RESEARCH RESONANCE

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Research & Innovation Division

GM UNIVERSITY
P. B. Road Davanagere, Karnataka - 577006

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PREFACE

It is with immense pleasure that we present the second edition of GMU ***Research Resonance***, a significant milestone in our ongoing commitment to fostering a vibrant research culture at GM University. As a multidisciplinary bulletin, this article serves as a dynamic platform for the dissemination of high-quality research and scholarly contributions across diverse academic disciplines.

GM University is home to a thriving community of researchers, educators, and students dedicated to pushing the boundaries of knowledge and innovation. This edition highlights their remarkable contributions, offering valuable insights into cutting-edge advancements in fields such as Computer Science, Information Science, Artificial Intelligence, Internet of Things, Information Security, Civil Engineering, Mechanical Engineering, Biotechnology, Electronics and Communication Engineering, Electrical and Electronics Engineering, and many more.

The release of GMU ***Research Resonance*** comes at a time when the exchange of ideas and collaborative research is more vital than ever. By bringing together diverse research topics and perspectives, we aim to spark new ideas, promote interdisciplinary collaborations, and drive meaningful advancements in science and technology.

We extend our sincere gratitude to the authors, reviewers, and editorial board members whose dedication and hard work have made this edition possible. Their contributions reflect the academic rigor and excellence that GM University consistently strives to uphold. We also thank our readers for their continued interest and support.

We hope you find this edition both insightful and inspiring, and we look forward to your continued engagement with GMU ***Research Resonance*** as we advance together on this exciting journey.

Sincerely,
Editorial Team

EDITORIAL TEAM

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STUDY OF CONCRETE USING ARECA NUT HUSK ASH AND RICE HUSK ASH ON PARTIAL REPLACEMENT OF CEMENT

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ABSTRACT
Cement is a crucial component in the construction sector, serving as a binder in concrete, a fundamental material for construction. With rapid infrastructure development, cement production has surged, making the cement industry one of the most polluting globally, contributing about 7% of global carbon emissions. Notably, cement mills emit high levels of particulate matter (PM), a severe form of air pollution in India and worldwide. India leads in areca nut production, generating approximately 4.78 lakh tons annually, with about 40% of this being husk, resulting in 1.91 lakh tons of bio-waste. This husk typically has no conventional use, posing significant disposal challenges. Similarly, rice husk is a major agricultural by-product from rice processing, with about 500 million tons of paddy produced worldwide annually. After incineration, 20% of rice husk transforms into rice husk ash, which contains non-crystalline silicon dioxide with high pozzolanic reactivity. This work explores the use of Areca Nut Husk Ash and Rice Husk Ash as partial replacements for cement in concrete production, with replacement percentages at 3%, 6%, 9%, and 12%. Fresh concrete properties are tested through Slump Flow and Compaction Factor tests, while hardened concrete is evaluated using Compression Strength and Split Tensile Strength tests after curing for 28 and 56 days. Results indicate that concrete mixed with these ashes and cured for 56 days shows improved compressive and split tensile strength compared to control concrete.

Keywords: Cement, Workability, Areca Nut Husk Ash, Rice Husk Ash, Compressive Strength, Split Tensile Strength

1.INTRODUCTION
Concrete is the most widely used construction material, comprised of cement (the binding material), aggregates (filler materials), admixtures, and water. It can be molded into any required form, is easy to handle, and offers a wide range of design strengths. As a result, it finds application in nearly all types of construction work. Cement, a crucial component of concrete, serves as the binding material. However, the production of concrete poses numerous environmental risks, including cement dust, air pollution, solid waste pollution, noise pollution, ground vibrations, and resource depletion due to raw materials extraction [1]. Materials are mixed in specific proportions to achieve the desired strength, denoted as M5, M10, M15, M20, M25, M30, etc., where M signifies Mix and the numbers represent their strength in kilonewtons per square meter (kN/m2). The initial hardening reaction typically occurs within a few hours, with full hardness and strength attained over several weeks. Concrete continues to harden and gain strength for many years.

The areca nut, derived from the areca palm, is extensively cultivated in India and ranks as an important commercial crop. India holds the top position in global areca nut production, yielding approximately 4.78 lakh tons per year. Primarily used for masticatory purposes with betel leaf (piper betel), the husk of the areca nut lacks conventional uses, posing a significant disposal challenge. With the removal of the husk before sale and consumption in dry form, a substantial quantity of this bio-waste remains unutilized [2], amounting to approximately 40% of the areca nut.

The disposal of these areca nut husks presents a major environmental challenge, necessitating suitable methods for reusing them to preserve and protect the environment. Areca nut husk ash exhibits various cementitious properties, including Silica, Potassium Oxide, Iron Oxide, Calcium Oxide, Sulphur Oxide, Alumina, and Magnesium Oxide.

Introducing alternative materials in the construction field is increasingly important to mitigate environmental impacts.

Although areca nut husks have been utilized in brick masonry, ethanol production [3], and as natural reinforcement in biodegradable polymer composites [4], their potential in domestic wastewater treatment and their ability to enhance the brittleness of bricks [5] have also been studied. Nevertheless, an excess of areca nut husks remains.

These surplus husks can serve as a supplement to cement due to their favorable mechanical properties, including excellent strength, durability, and workability.

Rice husk is an agricultural residue widely available in major rice producing countries. The husk surrounds the paddy grain. During the milling process of paddy grains about 78% of weight is obtained as rice, broken rice, and bran. The remaining 22% of the weight of paddy is obtained as husk. This husk is used as fuel in the various mills to generate steam parboiling process. This husk contains about 75% organic volatile matter and the rest 25% of the weight of this husk is converted into ash during the firing process, this ash is known as Rice Husk Ash. This Rice Husk Ash contains 85% - 90% amorphous silica.

Rice Husk is generated from the rice processing industries as a major agricultural by-product in many parts of the world, especially in developing countries. About 500 million tons of paddy's are produced in the world yearly after incineration only about 20% of rice husk is transformed to Rice Husk Ash. Rice husk ash consists of non-crystalline silicone dioxide with high specific surface area and pozzolanic reactivity, thus due to growing environmental concerns and the need to conserve energy and resource, utilization of industrial and biogenic waste as supplementary cementing material has become an integral part of concrete construction [7].

2. STATEMENT OF PROBLEM

This project aims to explore how incorporating Areca Nut Husk Ash and Rice Husk Ash can impact M30 grade concrete when used as partial substitutes for cement. The study seeks to assess the characteristics of both fresh and hardened concrete mixes with these partial replacements.

3. OBJECTIVES

• To examine the fresh characteristics of concrete utilizing areca nut husk ash and rice husk ash as partial substitutes for cement.
• To determine the harden characteristics of concrete incorporating areca nut husk ash and rice husk ash as partial replacements for cement, tests are conducted at 28 days and 56 days.

4. MATERIALS

Cement: In this investigation, concrete cubes and cylinders were cast using Ordinary Portland Cement (OPC) sourced from Ramco Cement. The cement exhibited a consistent grey with a subtle greenish tint and was free from any hardened lumps. Prior to use, it underwent testing for specific gravity, initial and final setting times, and compressive strength in accordance with the pertinent Indian Standards (IS) codes.
Fine Aggregate: The experimentation program utilizes locally sourced Manufactured Sand (M-Sand) in saturated surface dry (SSD) condition, meeting the specifications of zone II as per IS 383: 2016.
Coarse Aggregate: Crushed angular aggregate in SSD condition are used. Maximum size of the coarse aggregate used is 20 mm.
Water: Potable tap water is used for the preparation of specimens and for curing specimens.
Admixture: Conplast SP430 superplasticizer to reduce water content without losing workability.

5. METHODOLOGY

In the quest for achieving concrete with optimal performance attributes, the proportioning of ingredients holds paramount importance in concrete technology. This process ensures both quality and cost-effectiveness. Beginning with the meticulous selection of component materials, the subsequent step involves mix design, a methodical process aimed at determining the precise combination of ingredients. In the current endeavor, the mix design procedure adheres to the guidelines outlined in IS 10262: 2019, facilitating the formulation of M30 grade concrete. Here the M30 grade concrete is designed according to IS 10262: 2019, and the data required for the design are finalized after conducting all the necessary tests.
Proportions of mix = 1 : 1.57 : 2.87

Mix Designation

Table 5.1: Concrete Mix Designation

Mix designation	Description
A	100% Cement 0% Areca nut husk ash 0% Rice husk ash 100% Fine aggregate 100% Coarse aggregate
B	94% Cement 3% Areca nut husk ash+ 3% Rice husk ash 100% Fine aggregate 100% Coarse aggregate
C	88% Cement 6% Areca nut husk ash+6% Rice husk ash 100% Fine aggregate 100% Coarse aggregate
D	82% Cement 9% Areca nut husk ash+9% Rice husk ash 100% Fine aggregate + 100% Coarse aggregate
E	76% Cement+ 12% Areca nut husk ash 12% Rice husk ash 100% Fine aggregate + 100% Coarse aggregate

Casting of Specimen and Testing Procedure

For this experiment, cement is used, fine aggregate, and coarse aggregate, carefully selected to meet the specifications for M30 grade concrete. Following the guidelines of IS 10262: 2019, mix design is done and ensured thorough mixing of ingredients to achieve uniformity. After adding the required water to the dry mix, it is homogeneously mixed the wet concrete before pouring it into molds. Each mold was compacted in three layers using a compaction rod and finished smoothly with a trough. The specimens were then left to harden, and after 24 hours, they were demolded and transferred to curing tanks. In these tanks, the specimens were immersed in water and allowed to cure for the required duration.
To assess the compressive strength of the specimens, cubes measuring 150×150×150 mm were prepared. Testing was carried out using a compressive strength testing machine with a capacity of 3000 kN, in accordance with the standards outlined in IS 516: 1959. Compressive strength was determined using the formula F=P/A.
The compressive strength of a specimen, measured in MPa (megapascals), is calculated using the formula F=P/A
Where,
P is the maximum load applied to the specimen (in N)
A is the cross-sectional area of the specimen (in mm2)
To assess the split tensile strength, cylindrical specimens with a diameter of 150 mm and a length of 300 mm were prepared. The split tensile strength test was performed using a compression testing machine with a capacity of 3000 kN, in accordance with the guidelines outlined in IS 5816: 1999.
The split tensile strength of a specimen, measured in MPa (megapascals), is calculated using the formula F=2P/(πDL)
Where,
P is the load at failure (in N)
L is the length of the cylindrical specimen (in mm)
D is the diameter of the cylindrical specimen (in mm)

6. RESULTS

Fresh properties of concrete

Tests were conducted on both the fresh and hardened states of two types of concrete: the control concrete and concrete where Areca nut husk ash and Rice husk ash were used as partial substitutes for cement. The workability of the concrete was evaluated using the slump cone test, and the changes in the slump value are outlined below.

Slump Cone Test

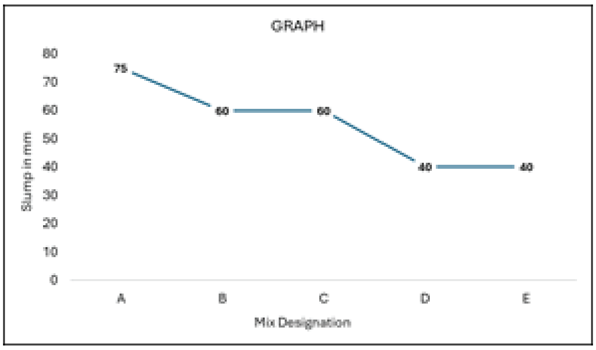

Figure 6.1: Slump cone test values graph for control concrete and concrete made by partially replacing areca nut husk ash and rice husk ash by cement

Compaction Factor Test

The compaction factor test is a method employed to gauge the workability of freshly mixed concrete. It quantifies the level of compaction attained through a standardized amount of effort exerted on the concrete. This test is based on the premise that greater workability in concrete corresponds to a higher compaction factor.

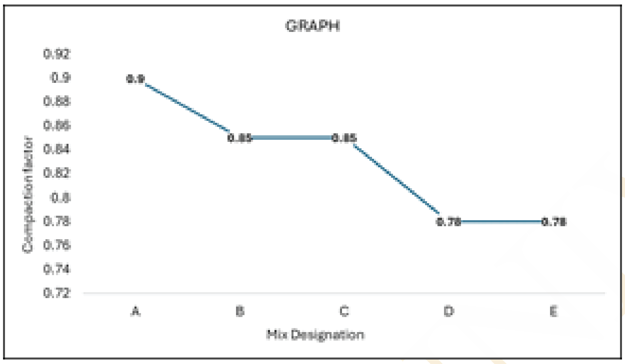

Figure 6.2: Compaction factor test result graph for control concrete and concrete made by partially replacing areca nut husk ash and rice husk ash by cement

Hardened Properties of Concrete

Compressive Strength Test Results

For Compressive strength tests were conducted for each concrete mix using three cubes measuring 150×150×150 mm, cured for 28 days and 56 days in accordance with IS 516: 1959. The compressive strength test results for both the control concrete and the concrete incorporating partial replacements of Areca nut husk ash and Rice husk ash for cement are provided in Fig 6.3 and Fig 6.4

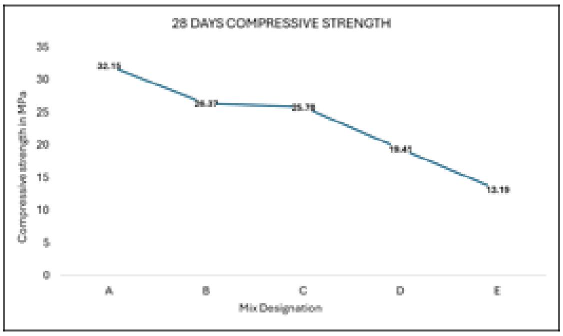

Figure 6.3: 28 days compressive strength test result of control concrete and concrete made by partially replacing areca nut husk ash and rice husk ash by cement

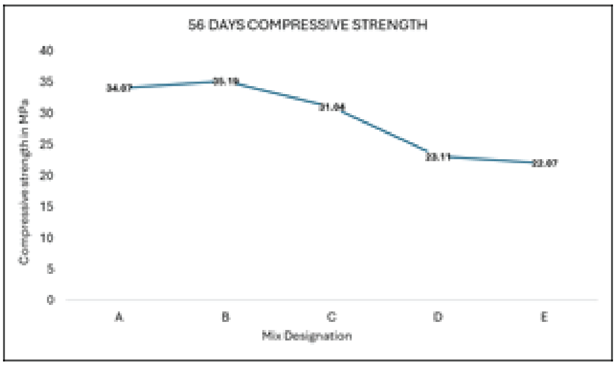

Figure 6.4: 56 days compressive strength test result of control concrete and concrete made by partially replacing areca nut husk ash and rice husk ash by cement

Split Tensile Strength Test

The split tensile test was conducted after 28 days and 56 days of curing, utilizing concrete casted in the form of cylinders with a diameter of 150 mm and a length of 300 mm, in accordance with IS 5816: 1999. The split tensile test results for both the control concrete and the concrete incorporating partial replacements of Areca nut husk ash and Rice husk ash for cement are provided in Fig 6.5 and Fig 6.6.

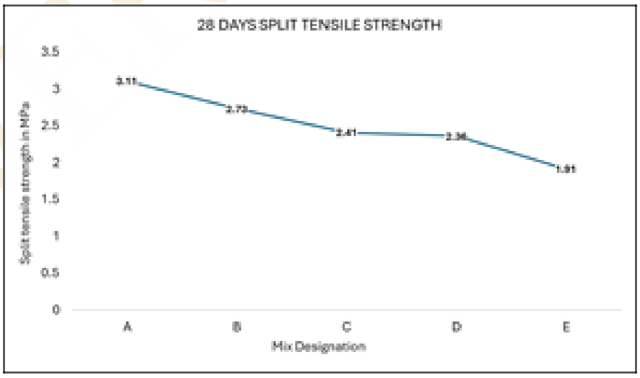

Figure 6.5: 28 days split tensile strength test result of control concrete and concrete made by partially replacing areca nut husk ash and rice husk ash by cement

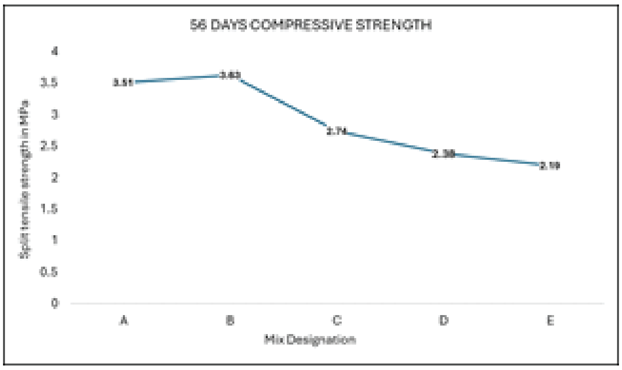

Figure 6.6: 56 days compressive strength test result of control concrete and concrete made by partially replacing areca nut husk ash and rice husk ash by cement

7. CONCLUSION AND FUTURE SCOPE

Based on the outcomes observed from experimental tests, the following conclusions can be made:

- The utilization of Areca nut husk ash and Rice husk ash as partial substitutes for cement indicated a reduction in workability, as evidenced by the findings of both the slump cone test and the compaction factor test.
- After 28 days of curing, it became evident that each mix experienced a reduction in both compressive strength and split tensile strength in comparison to the control concrete.
- The outcomes from the experiments on compressive and split tensile strength of the concrete, where cement was partially replaced by Areca nut husk ash and Rice husk ash, suggest enhanced performance in comparison to the control concrete. Notably, Mix B demonstrated the highest strength, showing a 3.29% increase in compressive strength and a 3.42% increase in split tensile strength over the control concrete at 58 days of testing.
- Nevertheless, concrete mixes D and E, incorporating higher proportions of Areca nut husk ash and Rice husk ash as partial substitutes for cement, demonstrated negative outcomes in compressive and split tensile strength compared to the control concrete.
- Hence, it can be inferred that the optimal strength of the concrete is achieved when cement is replaced by 3% with both Areca nut husk ash and Rice husk ash. Substituting up to 6% is considered beneficial; however, surpassing this threshold leads to a decline in strength compared to the control mix.

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Plant Disease Detection System

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ABSTRACT

The enhancement in agricultural technology and the use of artificial intelligence in diagnosing plant diseases make pertinent research crucial for sustainable agricultural development. Various diseases like early blight and late blight immensely influence the quality and quantity of plants, and manual interpretation of these leaf diseases is quite time-consuming and cumbersome. As it requires a tremendous level of expertise, efficient and automated detection of these diseases in the budding phase can assist in ameliorating plant crop production. Previously, various models have been proposed to detect several plant diseases. In this paper, a model is presented that utilizes convolutional neural networks (CNNs) and TensorFlow, with Rectified Linear Unit (ReLU) as the activation function, for feature extraction and detection of plant diseases. The proposed model leverages the robust capabilities of CNNs to capture intricate patterns and nuances present in plant images, allowing for more accurate disease detection. TensorFlow, a widely-used deep learning framework, provides the necessary tools for building and training complex neural network architectures efficiently. The utilization of ReLU activation function enhances the model's ability to capture non-linear relationships within the data, thereby improving its performance in distinguishing between healthy and diseased plant tissues. By combining these advanced techniques, the model offers a scalable and effective solution for detecting a wide range of plant diseases across various species, contributing significantly to the advancement of precision agriculture and sustainable food production practices.

Keywords: Machine Learning, Tensorflow, Image Scale, deep learning.

1.INTRODUCTION

Introducing a revolutionary solution to combat the pervasive threat facing crops globally, our plant disease detection system harnesses cutting-edge CNN image classification technology. This innovative web application empowers farmers to accurately diagnose and manage diseases plaguing their plants, enabling proactive measures to curtail crop damage and reduce wastage. By swiftly identifying disease symptoms through advanced image analysis, farmers can implement timely interventions, safeguarding crop yield and bolstering global food security.

This indispensable tool not only safeguards crop yield but also bolsters global food security and fosters economic stability within agricultural communities. By providing farmers with actionable insights and timely interventions, our system assumes a pivotal role in preserving the health and productivity of crops, ensuring a sustainable supply of this vital resource. Rapid disease identification allows for prompt and effective measures, preventing widespread crop losses and maintaining productivity levels.

With the global population expected to reach nearly 10 billion by 2050, ensuring the health and productivity of crops is paramount. Our plant disease detection system plays a crucial role in achieving this goal by promoting sustainable agricultural practices and minimizing the impact of plant diseases. Equipping farmers with advanced technology for disease detection empowers them to make informed decisions and adopt best practices.

In conclusion, our plant disease detection system represents a transformative innovation in agricultural technology, offering farmers a powerful tool to combat the threats posed by plant diseases. Through advanced image analysis and timely interventions, our system empowers farmers to safeguard their crops, minimize losses, and contribute to global food security. By fostering resilience, productivity, and economic stability within agricultural communities, our system plays a vital role in ensuring a sustainable supply of food for generations to come.

2. OBJECTIVES

The objectives outlined aim to develop an advanced system for detecting and classifying potato leaf diseases using Convolutional Neural Networks (CNNs). This system is intended to be efficient, precise, accessible to farmers, enriched with extensive data, and applicable to other plant leaf disease detection tasks.

1. Efficient: Develop a fast and accurate system for potato leaf disease detection and classification using CNNs.
2. Precision: Achieve high accuracy in classifying potato leaves into three categories: healthy, early blight, and late blight.
3. Accessibility: Create a system that can be easily used by farmers to diagnose potato leaf diseases without requiring special training or expertise.
4. Enrichment: Increase the accuracy of the system by expanding the dataset of potato leaf images.
5. Generalization: Apply the proposed method to other plant leaf disease detection tasks.

3. METHODOLOGY

The proposed deep learning approach for predicting Plant Disease following steps:

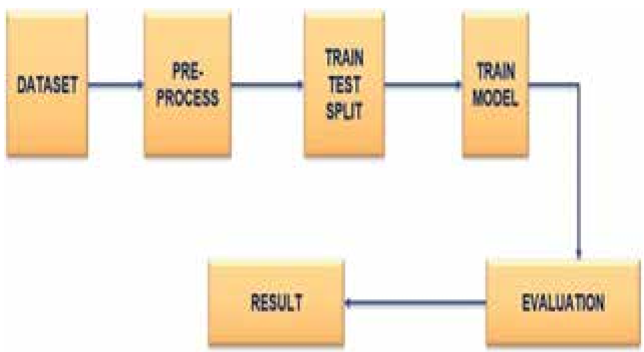


Figure 1 : Process for plant disease detection

The diagram outlines the process for plant disease detection detection Here's a breakdown of the process based on the diagrams:

1. Data Collection and Preprocessing: The dataset includes labelled potato leaf images in three categories: healthy, early blight, and late blight. Each image is annotated for supervised learning. Preprocessing techniques, such as resizing, normalization, and augmentation, are used to standardize the dataset and enhance feature extraction.

2. Feature Extraction: The dataset includes labelled potato leaf images in three categories: healthy, early blight, and late blight. Each image is annotated for supervised learning. Preprocessing techniques, such as resizing, normalization, and augmentation, are used to standardize the dataset and enhance feature extraction.

3. Machine Learning Model Training: The extracted features are used to train machine learning models for plant disease detection using leaf images. Various algorithms such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), or a combination of both may be employed. The models are trained on labelled data to learn patterns indicative of specific diseases, such as early blight or late blight.

4. Model Evaluation and Validation: After training, the model's performance is evaluated on the testing dataset to assess its generalization ability. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to quantify the model's classification performance. Confusion matrices and classification reports provide insights into the model's performance across different disease classes.

5.Alerting Mechanism: The project's outcome showcases the model's accuracy in classifying potato leaves into three categories: healthy, early blight, and late blight. Additionally, the system offers visualizations of model predictions on sample images for real-world effectiveness. Continuous monitoring and refinement are vital for improving accuracy and adaptability to new data, ensuring optimal performance in agricultural analysis.

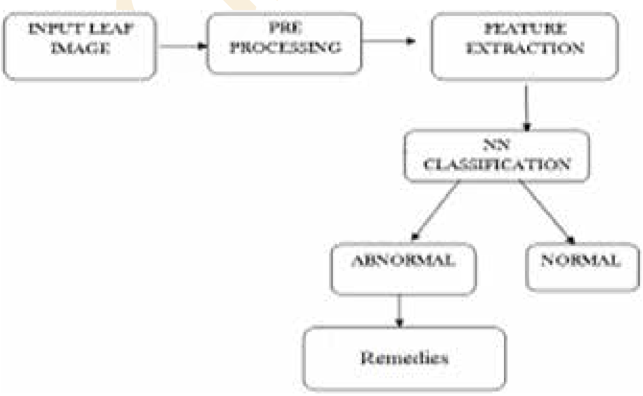


Figure 2 : Data flow diagram

The data flow diagram delineates a systematic approach for detecting plant diseases through image analysis. It commences with users uploading images portraying symptoms of disease. These images undergo a series of preprocessing steps, including resizing and noise reduction, to optimize them for subsequent analysis. Following preprocessing, the pertinent features are extracted from the image data, encompassing crucial characteristics like texture, color, and shape that signify various plant diseases.

Subsequently, the preprocessed data is fed into a neural network-based classification model. This model meticulously evaluates the extracted features to categorize the leaf image into two classes: healthy or diseased. The classification outcome guides the system to determine the condition of the leaf, providing insights into the presence or absence of disease. In instances where an abnormal condition is identified, the system progresses to the next stage, offering tailored recommendations for remedies or treatments.

In the third stage of the process, users are presented with actionable recommendations aimed at mitigating the spread of disease and bolstering plant health. These recommendations encompass a range of interventions, including suggested pesticides and cultural practices tailored to address the specific plant disease identified. Through this structured approach, the data flow diagram underscores a comprehensive methodology for leveraging image analysis and machine learning techniques in the realm of plant disease detection and management.

Ultimately, the systematic flow delineated in the diagram fosters efficient disease detection and management, contributing to the overall health and productivity of plants. By integrating preprocessing, feature extraction, classification, and recommendation stages, the system offers a holistic solution to address the challenges posed by plant diseases, empowering users with actionable insights for effective disease mitigation strategies.

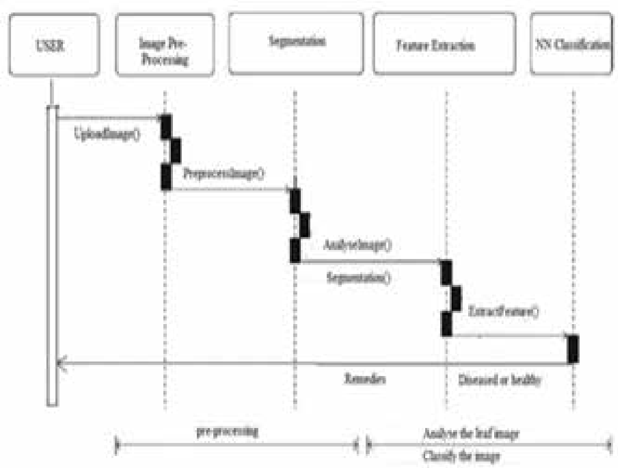


Figure 3 : Sequence diagram

This project outlines the process of detecting and classifying plant leaf disease. The process starts with the user uploading an image of a leaf. The image is then preprocessed to improve the quality of the image for analysis. Next, the image is segmented to isolate the leaf from the background. Finally, a neural network (NN) is used to classify the image and identify any diseases present

Start: The process begins with the user uploading an image of a plant leaf. Video recording: The live video is recorded using the webcam including faces.
Image pre-processing: The uploaded image goes through a pre-processing stage. This stage may involve resizing the image, converting it to grayscale, and removing noise.
Analyze image: The preprocessed image is then analyzed. This analysis may involve extracting features from the image, such as color, texture, and shape.
CNN Classification: A neural network is used to classify the disease in the leaf image. Neural networks are a type of machine learning that can be used to identify patterns in data

In our plant disease detection project, we've introduced a groundbreaking innovation by integrating Convolutional Neural Networks (CNNs) powered by TensorFlow. CNNs, renowned for their ability to learn features from raw pixel data, have been seamlessly incorporated into our system's architecture, allowing for robust and accurate analysis of plant leaf images.
One key aspect of our innovation lies in the meticulously designed and optimized CNN layers. These layers are adept at capturing intricate patterns and textures in plant leaf images, enabling precise identification of disease symptoms. Through careful tuning, we ensure the extraction of meaningful features, enhancing both accuracy and system performance.
Additionally, our project incorporates cutting-edge image processing techniques such as augmentation, normalization, and segmentation. These techniques preprocess input images, enhancing their quality and highlighting relevant features. This preprocessing step is crucial for optimizing CNN performance and enabling more informed and accurate disease predictions. Through the integration of CNNs, TensorFlow, and advanced image processing techniques, our project represents a significant advancement in plant disease detection, empowering farmers to safeguard their crops and enhance agricultural productivity.

4. FUTURE SCOPE OF THE PROJECT

Our project on plant disease detection holds immense potential for further development and expansion. As technology continues to evolve and new advancements emerge, several avenues for enhancing the system's capabilities and impact present themselves. Here are some potential directions for future exploration:

• **Implementation of Transfer Learning:** Integrating transfer learning techniques could enable our system to leverage pre-trained models and adapt them to the specific task of plant disease detection. This approach could expedite model training and improve performance, particularly in scenarios with limited training data
• **Mobile Application Development:** Creating a mobile application version of our plant disease detection system would increase accessibility and usability for farmers in remote areas. This would allow farmers to capture and analyze plant leaf images directly from their smartphones, facilitating real-time decision-making and disease management.
• **Integration of Sensor Data:** Incorporating data from IoT sensors, such as those monitoring environmental conditions or plant health metrics, could provide valuable contextual information for disease detection. By combining image analysis with sensor data, our system could offer more comprehensive insights into crop health and disease dynamics.
• **Expansion of Crop Coverage:** While our current focus is on detecting diseases in potato crops, expanding the system to cover a broader range of crops would extend its utility and impact. By training the model on diverse datasets representing various plant species, our system could address the unique disease challenges faced by different crops.
• **Collaboration with Agricultural Experts:** Engaging with agricultural experts and researchers could enrich our understanding of plant diseases and inform the development of more sophisticated detection algorithms. Collaborative efforts could lead to the incorporation of domain-specific knowledge and the creation of tailored solutions for specific agricultural contexts.
• **Deployment of Autonomous Monitoring Systems:** Exploring the possibility of deploying autonomous monitoring systems equipped with cameras and AI algorithms in agricultural fields could enable continuous monitoring of plant health. These systems could detect disease outbreaks early, allowing for timely intervention and disease management.
• **Integration of Decision Support Systems:** Developing decision support systems that provide personalized recommendations and management strategies based on disease diagnosis could further empower farmers. By combining disease detection with actionable insights, our system could assist farmers in implementing effective disease control measures.

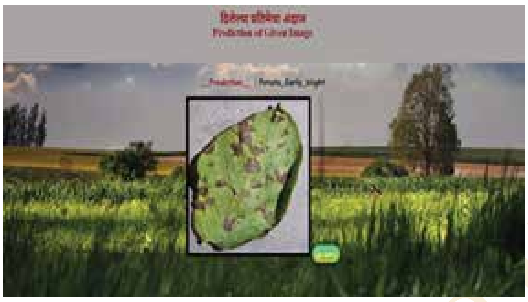
5. RESULTS AND DISCUSSIONS

The classification result, derived from feature extraction, will likely indicate the type of disease affecting the plant by analyzing key visual characteristics. Feature extraction involves identifying crucial attributes such as color variations (yellowing, browning, or spots), texture changes (roughness, dryness, or lesions), and shape distortions (irregular leaf patterns or curling). Advanced techniques, including deep learning-based methods like CNNs, extract high-dimensional features that help distinguish between different plant diseases. Once these features are extracted, the classification model assigns the image to a specific disease category, enabling accurate identification. This process is essential for early is essential for early disease detection, facilitating timely intervention and effective crop management. Finally, the image is classified. The classification result Feature extraction will likely be the type of disease the plant has.

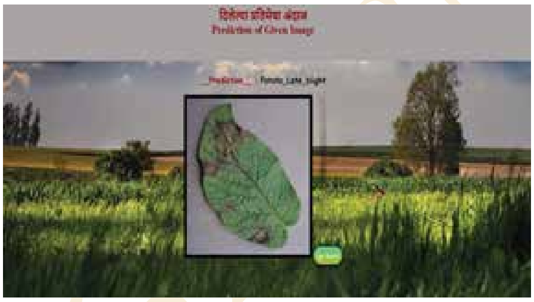
Front page design

Providing image input

Healthy leaf



Potato early blight



Potato late blight

6. CONCLUSION AND FUTURE SCOPE

In conclusion, the potato disease detection system marks a significant advancement in agricultural technology, providing farmers with an efficient tool for managing diseases in potato crops. Integrating Convolutional Neural Networks (CNNs) and image processing techniques, the system accurately diagnoses potato leaf diseases. Rigorous testing validates functionality and robustness, ensuring seamless integration into a user-friendly platform. With its capacity to handle real-world scenarios and offer timely diagnoses, the system empowers farmers to make informed decisions, enhancing crop yield and sustainability. Continuous monitoring and refinement will further improve accuracy and adaptability, reinforcing its value in modern agriculture.

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Smart Helmet for Drunk and Drive Riders

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ABSTRACT

A proposed Smart Helmet addresses road safety concerns by integrating advanced technology, including an alcohol sensor and accident alert system. The helmet incorporates an alcohol sensor that detects alcohol vapors around the wearer's breath. Connected to a voltage sensor, it triggers a relay mechanism preventing vehicle ignition if alcohol is detected. Additionally, the helmet features an ultrasonic sensor monitoring distance to nearby objects. Significant changes trigger an alert system sending distress signals to predefined contacts via an ESP8266 module. A PC fan simulates engine status visually, operating when ignition is enabled but disabled if alcohol is detected. IoT technology enables real-time monitoring and data transmission via an integrated ESP8266 module communicating with the Blynk cloud platform, providing users with live updates and safety alerts.

Keywords: ESP8266 module, Blynk cloud platform.

1.INTRODUCTION

The development of a smart helmet integrating advanced technologies signifies a significant leap in ensuring road safety and enhancing monitoring capabilities for both drivers and their guardians. This innovative helmet aims to address multiple facets of safety concerns, primarily focusing on alcohol detection, helmet enforcement, ignition control, and accident prevention. The incorporation of an alcohol sensor within the helmet enables real-time monitoring of the driver's sobriety level, crucial in preventing accidents caused by impaired driving. By integrating a voltage sensor and relay mechanism, the helmet establishes a direct link between wearing the helmet and enabling the ignition system, promoting responsible riding practices. To visually represent engine activation, a PC fan serves as a practical analog, symbolizing the ignition process. Additionally, the integration of an ultrasonic sensor provides an added layer of safety by detecting potential collisions or accidents, thus triggering timely alerts or safety mechanisms. Furthermore, leveraging the capabilities of ESP8266 facilitates seamless data transmission to the Blynk cloud platform, enabling remote monitoring for concerned parties such as parents and friends. This comprehensive introduction sets the stage for exploring the intricate design, functionality, and potential impact of this smart helmet system in promoting road safety and enhancing driver accountability.

Owning a bike or car and driving it with full responsibility is an important task. One must drive adequately, follow all the norms, and not drive when drunk. There are many driving norms in all countries, and most rules are similar. Drunken driving is not acceptable by any country's law and is a chargeable offence. It causes a risk to people on the road and one's family too. Let's have a look at drunk and drive section 185 mv act and punishment in India 2023. In India, too, many norms are related to drinking and driving cases. There are chances of severe road accidents because of it. Hence it must be brought under control. Every year, close to 5 lakh road accidents happen in India, and several times the culprit is a drunk driver.

Hence, one must make sure to abide by the law and drive with proper safety. India should have a decrease in the number of the situation involving consuming alcohol and later driving. Therefore, decrease in the same should be a responsibility for each person. One possible example is where a person is going to a party involving alcohol; he or she should ensure that there they have somebody who can safely drive them home. Another example is when a person hosts a party; they may ensure that their guests get home safely. This is by trying to organize functions that do not involve drinking or going for other fun activities rather than drinking and driving as well. Taking such small steps will go a long way in avoiding drunken driving cases. A responsible citizen should also avoid driving while drunk and arrange for transport home through hiring a driver or using their friends." Hence, one must never drink and drive and reach home sound and safe. Between December 16 and 31, the total number of challans issued in Delhi rose significantly, increasing from 274 in 2021 to 2,129 in 2023. He mentioned that apart from prosecuting offenders, road safety workshops are sometimes conducted by the unit in schools, colleges, major intersections, etc. for the purpose of revealing facts concerning road usage.

"We also gave out short films, lectures and educational literature on good driving habits during these camps". Regarding this issue, the Delhi Traffic Police has been actively promoting awareness via ads placed in newspapers or on social media platforms such as Twitter & Facebook; this has been done through other channels within the city which include mobile exhibition vans and street theatre groups as well,' said a source from within the organization. systems that can be remotely monitored and controlled.

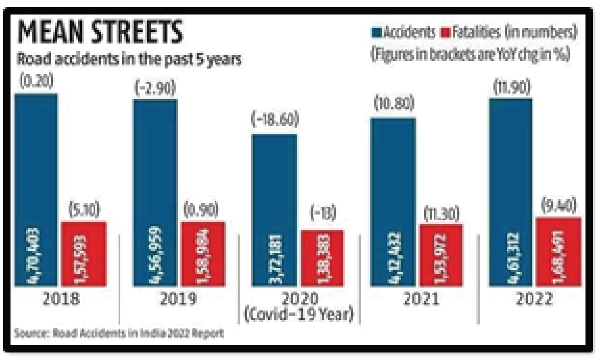


Figure 1: Road Accident Status

The Figure 1 represents the Road Accident Status. The number of cars registered in 2020 was 43.73 million while the number of motorised two wheelers (MTW) was 243.5 million. Official registration data overestimates the actual number of vehicles as vehicles that are not in operation or go off the road due to age are not removed from the register. The number of personal vehicles really driving along the roads is estimated at 50 to 60 percent of the enumerated ones in the registration records According to censuses as well as large sample surveys on populations, the ownership percentages of households owning cars or motorized two wheelers have more than doubled over the past decade (2008- 2017). During this same time period around 1.5 million cars and 10 million motorcycles were both registered annually, resulting in

0.6 percent of households purchasing new cars each year while 4 percent bought motorcycles each year. Additionally, in fourteen households owned cars while in forty-five percent possessed bikes. On the other hand, the proportion fell between 40% – 45% with regards to bike acquisition Cycle acquisition ranges from 40-45%. It appears that the actual number of road accidents in India is underestimated; however, the exact scale remains unknown. However, the extent of this underestimation is not known.

2. LITERATURE REVIEW

JesudossA, Vybhavi R, Anusha B [1], proposed a mechanism, where sensors such as IR sensor, vibration sensor and gas sensor, mems are used. The gas sensor is used to detect the amount of liquor he had consumed by checking the breath of a person wearing the helmet. The bar control of the vehicle is handled by MEMS. Accident is detected by vibration sensor. Load of the vehicle is recognized by load checker. The Sensors are interfaced with the PIC microcontroller. The gas sensor will detect if a user consumed alcohol and display on the LED display.

K.M.Mehata, S.K.Shankar, Karthikeyan N, Nandhinee K, Robin Hedwig P [2], proposed a system with two units that is helmet unit and two wheeler unit. RF receiver of the matching frequency gives the helmet position data to the two-wheeler section. The microcontroller placed on the TW section will have information of the helmet position which is continuously checked. There are various other sensors such as accelerometer (tilt angle measurement), Hall- effect sensor (speed measurement), GPS module (location pointer) placed on the TW vehicle.

DivyasudhaN, ArulmozhivarmanP, RajkumarE.R [3], proposed a system consisting 6 units as follow, that is remover sensor, IR sensor, Air quality sensor, Arduino uno microcontroller, GPRS, GSM. This helmet provides the alert about the harmful gases in the mining areas to the workers and also proved information to the server if helmet is removed. Here this data transmission is done using IOT technology. proposed a system of smart mining helmet that detects three types of hazards that is harmful gases, remove of helmet and if any collision. Here they use many sensors such as IR sensors, gas sensors, accelerometer.

Manish Uniyal, Manu Srivastava, HimanshuRawat, VivekKumarSrivastava [4], proposed a system to reduce accidents, here the system consist of a sensor which sense the human touch when he plug in the bike key. After he wear the helmet the sensor automatically lock the helmet and he can only remove is when bike is stopped. system based on three sensors: acceleration sensor, ultrasonic sensor, and carbon monoxide sensor, and also based on an Arduino MCU (Micro Controller Unit) with a Bluetooth module to provide safety to a system of smart helmet which is integrated with several functionalities.

Shoeb Ahmed Shabbeer, MerinMeleet [5], proposed smart helmet system using GSM and GPRS module. As we all know that the arrival of ambulance to the location may be late this prototype helps to inform the concerned person first about the accident and he may take the steps. In this system we can notice the feature such as high accuracy, cost efficient and giving information about the accident within minute.

P.Roja, D [6], proposed a system using vibration sensors. When the rider wears the helmet consisting of the vibrator sensor with a frequency if the frequency crosses the threshold then the message is sent to the emergency responses using GPS module. This system helps to detect and report the accident and can save the life of two sections i.e. helmet section and bike section.

Problem Statement: Road accidents are a big problem due to impaired driving and negligence. Current safety efforts aren't enough to stop them, especially with issues like not wearing helmets or detecting impaired drivers. Therefore, it required a new solution using advanced tech to prevent accidents before they happen. A smart helmet system could be the answer by monitoring drivers in real-time and improving safety measures to reduce accidents.

Objectives:

- To design the circuit that can improve the safety of motorcyclists.
- To develop an intelligent safety helmet for complete rider.
- To implement an accurate and reliable alcohol detection system using the alcohol sensor.

3. METHODS AND MATERIALS

The project's methodology entails a methodical approach to the smart helmet system's design, development, and implementation. In order to comprehend current technologies, safety laws, and user needs pertaining to road safety and smart helmet systems, extensive study is first carried out. The foundation for determining the project's goals, parameters, and requirements is this research. Subsequently, the smart helmet system's components, sensors, communication modules, and integration procedures are outlined in the system architecture.

After the design stage, the smart helmet system prototype is constructed by choosing, acquiring, and assembling the hardware and software parts. This entails locating appropriate sensors, such as voltage, alcohol, and ultrasonic sensors, as well as communication modules, such as the ESP8266, for data transfer. The methodical integration of these parts guarantees the system's functionality, compatibility, and dependability. Following the construction of the prototype, thorough testing and validation processes are carried out to assess the smart helmet system's functionality, precision, and efficacy in a range of settings. This entails assessing the precision of the alcohol detection system, the helmet enforcement system, the ability to identify obstacles.

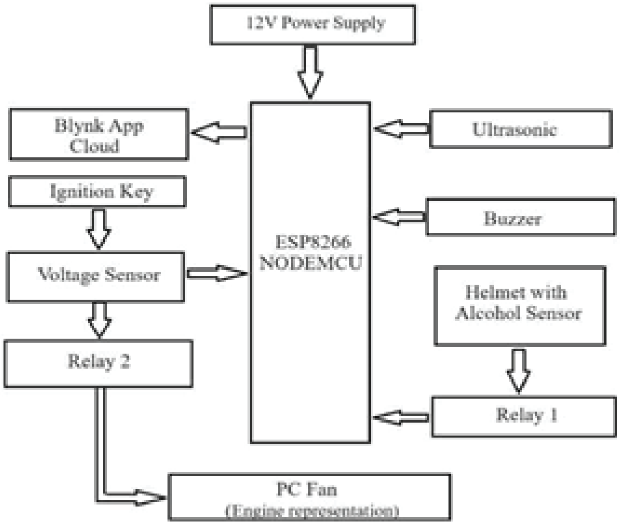


Figure 2: Block Diagram of Smart Helmet for Drunk and Drive Riders

The Figure 2 represents block diagram of the Smart Helmet for Drunk and Drive Riders. ESP8266 Module: The ESP8266 module facilitates wireless communication between the smart helmet system and the Blynk cloud platform, enabling remote monitoring and data transmission. Alcohol Sensor: An alcohol sensor is incorporated into the helmet to detect the presence of alcohol vapors, enabling real-time monitoring of the driver's sobriety level. Voltage Sensor: A voltage sensor is utilized to detect whether the helmet is being worn by the driver, providing input to the relay mechanism for controlling the ignition system.

Ultrasonic Sensor: An ultrasonic sensor is integrated into the helmet to detect obstacles or objects in the driver's path, enabling accident prevention measures such as obstacle detection and collision avoidance. Power Supply: A suitable power supply, such as a battery or power bank, is used to provide power to the smart helmet system, ensuring continuous operation during use. In addition to the hardware components, the Arduino IDE software is utilized for programming and uploading code to the Arduino microcontroller board. The Arduino IDE provides a user-friendly interface for writing, compiling, and uploading code, allowing for the implementation of the desired functionalities and logic of the smart helmet system.

Flow Chart

Figure 3: Flow Chart

The Figure 3 depicts a flowchart outlining the logic of a smart helmet safety system for motorcycles or similar vehicles. The system incorporates various sensors and actuators to ensure rider safety and prevent potential accidents. Let's break down the process step- by-step:

Start: The system begins its operation. Safety Checks

Helmet Detection: The system checks if the helmet is worn correctly (HELMET=1/ON).

Alcohol Detection: It checks if alcohol is detected on the rider's breath (ALCOHOL=0/OFF). Ultrasonic Sensor: The system utilizes an ultrasonic sensor to measure the distance to obstacles (ULTRASONIC<40).

Decision Making

No Alert: If the helmet is worn, no alcohol is detected, and the ultrasonic sensor doesn't detect any close obstacles, the system proceeds without any alerts and allows ignition (IGNITION=1/ON).

Alert to Cloud: If any of the safety conditions fail (helmet not worn, alcohol detected, or obstacle too close), the system triggers an alert.

Alert Actions

Cloud Notification: The alert is sent to the cloud, potentially notifying emergency contacts or authorities.

Local Alert: A buzzer sounds, and a red LED light turns on, alerting the rider and possibly people nearby. The ignition is disabled (IGNITION=0/OFF) to prevent the vehicle from starting. Possible Scenarios

Safe Riding: The rider wears a helmet, is not under the influence of alcohol, and maintains a safe distance from obstacles, allowing for a smooth ride.

Potential Accident Prevention: If the rider attempts to start the vehicle without wearing a helmet, under the influence of alcohol, or with an obstacle too close, the system intervenes, preventing a potential accident.

4. RESULTS AND DISCUSSIONS

The smart helmet incorporates advanced technology to enhance rider safety. It features alcohol and ultrasonic sensors that detect intoxication levels and helmet compliance respectively. If alcohol is detected or the helmet is not worn, the ignition key remains disabled, ensuring responsible riding practices.

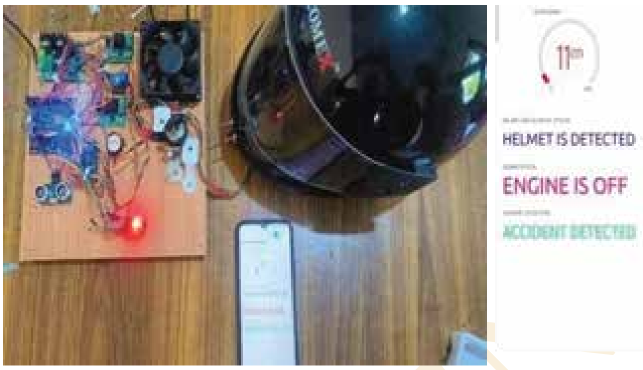
The Fig 4 represents the Smart Helmet for Drunk and Drive Riders. Additionally, the helmet is equipped with accident detection capabilities, promptly alerting emergency services in case of a crash. This integrated system acts as a safeguard, promoting safer road behavior and reducing the risk of accidents caused by drunk or unprotected riders.

Figure 4: Project model of Smart Helmet for Drunk and Drive Riders

Fig 5: No Helmet Detected

The Fig 6 represents no helmet is detected. When the helmet is detected, only then will the ignition key activate, ensuring the rider's safety during riding conditions. This protocol enhances safety by ensuring that riders wear helmets before operating the vehicle, promoting responsible riding habits.

The Fig 7 represents accident is detected. When the ultrasonic sensor detects an accident, the Buzzer system will activate, and the ignition key will turn off automatically.



The Figure 7 represents alcohol is detected. If alcohol is detected, the ignition key will remain inactive, and simultaneously, the buzzer will activate to signal the detection.

Figure 7: Alcohol is Detected

5. CONCLUSION AND FUTURE SCOPE

The smart helmet system marks a significant breakthrough in enhancing road safety and promoting responsible driving habits. It incorporates sophisticated tools like alcohol and ultrasonic sensors, along with communication modules and automated enforcement systems, to detect alcohol levels, locate obstacles, and enforce safety measures. Through real-time remote monitoring, it maintains alertness and enables prompt responses to emergencies.

Collaboration, innovation, and a commitment to safety have driven its success thus far. Continuous refinement and optimization, incorporating new technologies and user feedback, are essential for its effectiveness and accessibility. Beyond its technical advancements, the project fosters a culture of safety, responsibility, and vigilance on the roads, contributing to lasting community safety.

In addition to alcohol sensing and accident detection features, future iterations of smart helmets for drunk and drive riders could incorporate advanced GPS tracking to monitor erratic driving patterns and ensure adherence to designated routes. Integration of biometric sensors could provide real-time health monitoring, alerting both the rider and emergency services in case of any medical issues. Smart communication systems could enable seamless connectivity with law enforcement agencies, allowing for immediate intervention in case of detected intoxication.

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Design And Development of Light Weight Low – Cost Exoskeleton to Enhance Mobility

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ABSTRACT

The design and development of a lightweight, low-cost exoskeleton for individuals with mobility impairments follow a multidisciplinary approach, integrating mechanical engineering, materials science, electronics, and biomechanics. This project prioritizes affordability and accessibility, particularly for resource-limited settings. The methodology involves a systematic process, including needs assessment, literature review, conceptual design, prototype development, testing, optimization, manufacturing, validation, and continuous improvement. High-strength wood is selected as the primary material due to its favorable strength-to-weight ratio, durability, and cost-effectiveness. The exoskeleton employs a mechanically simple design with passive joint mechanisms that rely on natural human movement, eliminating the need for complex electronics. Reinforced wooden supports and bearings at key joints such as the hip, knee, and ankle enable smooth motion and effective load transfer. Customizable wooden braces and straps provide a secure fit for users of varying body sizes, ensuring stability and comfort. Collaboration with healthcare professionals and end-users ensures the design effectively addresses mobility challenges while remaining practical and accessible. This approach presents a comprehensive framework for developing exoskeletons that enhance mobility, promoting greater independence and improved quality of life for individuals with diverse mobility impairments.

Keywords: Lightweight exoskeleton, passive joint mechanisms, high-strength wood, mobility impairment, affordability.

1.INTRODUCTION

Powered exoskeletons shown in figure 1 offer a revolutionary approach to mobility assistance by providing frequent, consistent, and long-term physical support with minimal reliance on a therapist or caregiver. These robotic systems help individuals regain mobility, particularly those with spinal cord injuries, stroke-related impairments, or neuromuscular disorders. By reducing the need for constant human assistance, powered exoskeletons can significantly lower healthcare costs and alleviate the burden on caregivers, allowing them to focus on other aspects of patient care. Additionally, these devices enhance independence by ensuring timely support for Activities of Daily Living (ADLs), such as walking, standing, and even climbing stairs. The integration of advanced control systems allows for adaptive movement, where the exoskeleton responds to the user's needs in real-time, making rehabilitation more effective and personalized. Moreover, the long-term use of these systems can contribute to improved muscle activation and prevent secondary complications like muscle atrophy and joint stiffness, which are common in individuals with prolonged immobility.

A significant advantage of powered exoskeletons is their ability to integrate embedded sensors that collect precise data on human limb movements, gait patterns, and joint articulation. This continuous monitoring enables clinicians to track progress, assess rehabilitation effectiveness, and adjust therapy protocols based on real-time performance metrics. Several commercially available lower-limb exoskeletons, such as EksoNR, ReWalk Personal 6.0, Hybrid Assistive Limb (HAL), and Indego, have been deployed in clinical settings to aid in physical rehabilitation and mobility training. However, despite their potential benefits, these exoskeletons face challenges that limit their widespread adoption, particularly for home-based and long-term use. The current models tend to be heavy, expensive, and require stringent safety considerations, making them impractical for independent use outside controlled environments like rehabilitation centers. To address these challenges, ongoing research focuses on reducing weight, improving battery efficiency, and enhancing affordability, making powered exoskeletons a more viable solution for long-term, home-based mobility assistance.

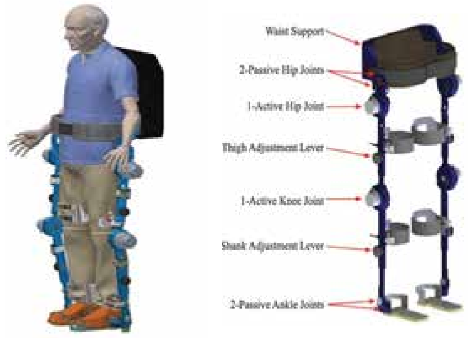

Figure 1: Lower limb exoskeleton

2. MATERIALS AND METHODOLOGY

The materials chosen for this exoskeleton design ensure a balance between strength, durability, affordability, and ease of fabrication. Each component plays a crucial role in the overall functionality and performance of the exoskeleton. The figures 2.1 to 2.5 shows the materials used in exoskeleton design.

Plywood – Selected for its high strength-to-weight ratio, cost-effectiveness, and ease of shaping, plywood serves as the primary structural material for the exoskeleton frame. It provides stability and support while keeping the overall weight low.

Plywood is a versatile building material composed of thin layers of wood veneer bonded together with an adhesive under heat and pressure. Each layer of wood veneer, known as a ply, is usually placed with its grain perpendicular to the adjacent layer. This cross-graining gives plywood its strength and stability, making it less prone to warping or twisting compared to solid wood. The manufacturing process involves peeling logs into thin veneers, which are then dried and sorted based on their quality.

Figure 2.1: Plywood

Bearings – Bearings facilitate smooth joint movement by reducing friction in mechanical connections. They are crucial in the hip, knee, and ankle joints, ensuring efficient motion transfer and minimizing wear and tear.
These components come in a variety of types, including ball bearings, roller bearings, thrust bearings, and plain bearings, each suited to specific applications and load conditions. Ball bearings, for instance, utilize small metal balls to separate the inner and outer races, while roller bearings use cylindrical or tapered rollers for load support. Thrust bearings, on the other hand, are designed to withstand axial loads, while plain bearings consist of a smooth, cylindrical surface that provides a sliding interface between components.

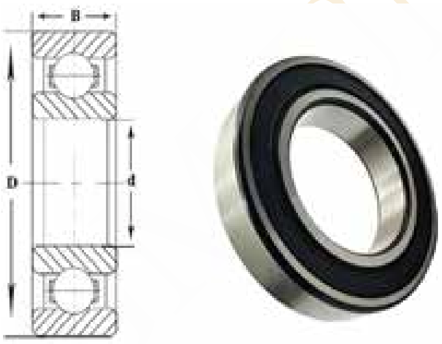

Figure 2.2 Bearings

Nut & Washer – These fastening components help in securely assembling the structural and moving parts of the exoskeleton. Washers distribute loads evenly, preventing damage to the plywood and other components under stress.

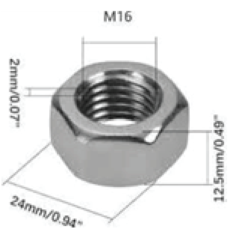

Figure 2.3 (a): Nut

Figure 2.3(b): Washer

Metric Size: The "M" in **M16** indicates that the **nut** belongs to the metric system, specifically designed to fit an M16 bolt. This standardized metric sizing ensures compatibility and interchangeability with other M16 fasteners, including bolts and washers.

Thread Configuration: M16 nuts feature internal threads that match the external threads of M16 bolts. These threads are typically standardized according to international metric thread standards, ensuring uniformity and compatibility across different manufacturers and applications

Material: M16 nuts are commonly manufactured from various materials, including steel, stainless steel, brass, and nylon. The choice of material depends on factors such as the application requirements, environmental conditions, and desired mechanical properties like strength, corrosion resistance, and temperature tolerance.

Washers are small, flat, disc-shaped components used in conjunction with nuts, bolts, and screws to distribute load, prevent damage to surfaces, and improve the reliability of fastened joints.

Wiper Motor – A compact and high-torque DC motor, originally designed for windshield wipers, is used to provide mechanical actuation for certain movements in the exoskeleton. It offers consistent motion, affordability, and ease of control, making it an effective choice for powered assistance in the design.
The primary function of the wiper motor is to generate the mechanical motion needed to operate the windshield wipers. When activated by the driver through the wiper control switch, the motor converts electrical energy into rotational motion, which is then transmitted to the wiper arms through a linkage system. This motion causes the wiper arms to sweep across the windshield, clearing it of rain, snow, dirt, and other debris to maintain visibility for the driver.

Figure 2.4 Wiper Motor

Valve-Regulated Lead Acid (VRLA) Battery – 12V, 22Ah – This battery is used as the primary power source for the exoskeleton's motorized components. VRLA batteries are sealed, maintenance-free, and capable of deep cycling, making them suitable for prolonged use. The 12V, 22Ah specification indicates a stable voltage supply with a capacity of 22 ampere-hours, ensuring sufficient energy storage to power the wiper motor and other electrical components for extended periods.

These materials collectively contribute to the structural integrity, functionality, and cost-efficiency of the exoskeleton, making it a practical solution for mobility assistance.

Figure 2.5: VRLA Battery

3. METHODOLOGY

A. Assessment and Design Specification

Before designing the wooden exoskeleton, it is crucial to identify the specific needs and requirements based on the intended user. This includes considering factors such as:

User's Limb Size & Fit: Ensuring the exoskeleton fits comfortably based on the user's body measurements.

Type of Limb Problem: Identifying whether the user requires support for weakened muscles, joint stability, or full limb movement assistance.

Functional Requirements: Defining the exoskeleton's purpose—whether for rehabilitation, mobility enhancement, or strength augmentation.

Weight & Strength: The exoskeleton should be lightweight yet strong enough to provide adequate support.

Flexibility & Range of Motion: Designing joints and pivot points to allow natural movement.

Aesthetics & Comfort: Ensuring a visually appealing design that is comfortable to wear for extended periods.

These specifications will serve as guidelines for the detailed design process.

B. Design Process

Using advanced CAD software such as Fusion 360, SOLIDWORKS, or CATIA, the exoskeleton is modeled to meet the established specifications. Key considerations include:

Ergonomic Design: Contouring the structure to match the user's body shape.

Joint Mechanisms: Designing hinge points or flexible sections for ease of movement.

Attachment System: Incorporating straps, harnesses, or adjustable fittings for a secure fit.

Modular Design: Allowing easy adjustments and modifications based on testing feedback.

C. Material Selection

Choosing the right type of wood is essential to balance durability and weight. Some recommended options include:

Oak: Strong and durable, but slightly heavier.

Maple: Good strength-to-weight ratio and smooth surface.

Birch: Lightweight and easy to work with, but slightly less durable.

Bamboo: A sustainable and highly flexible option for certain parts.

Other considerations include treating the wood for moisture resistance and reinforcing high-stress areas with additional materials like metal brackets or carbon fiber inserts.

D. Prototyping & Testing

The initial prototype will be built using wood and other necessary components such as screws, bolts, and straps. The process involves:

Fabricating Simple Components: Starting with basic structural elements to test fit and functionality.

Assembling & Refining: Making iterative improvements based on comfort, usability, and strength testing.

User Testing: Evaluating real-world performance and making adjustments based on feedback.

Final Optimization: Enhancing the design for efficiency, durability, and ease of use before mass production or further modifications.

E. Post-Processing

Sanding: Sanding is fundamental in woodworking post-processing. It involves using abrasive materials to smooth the wood surface, remove imperfections, and prepare it for finishing treatments.

Finishing: Finishing treatments include applying coatings such as varnish, lacquer, shellac, or oil to protect the wood from moisture, UV damage, and wear.

Painting: Painting wood offers versatility in color options and allows for creativity in design. It provides a protective layer and can be used to achieve different aesthetic effects, from solid colors to artistic finishes.

Integration of Additional Components: Incorporate non-wood components as needed, such as motors, sensors, and control systems for powered exoskeletons.

Quality Control: Inspect the manufactured component for defects, accuracy, and structural integrity and perform necessary quality control tests to ensure the component meets the required standards and specifications.

4. RESULT AND DISSCUSSION

4.1. Designing a lower limb exoskeleton

Designing a lower limb exoskeleton in Fusion 360 involves several key considerations. First, the design should prioritize biomechanical principles to ensure optimal support and functionality. Fusion 360's parametric design capabilities can be leveraged to create a customizable exoskeleton that can be adapted to different user sizes and needs. Additionally, the exoskeleton's structure should be lightweight yet sturdy, which can be generative design techniques available in Fusion 360.

The design of a lower limb exoskeleton without sensors presents unique challenges, primarily revolving around ensuring natural movement and user comfort. The lack of sensors means that the device cannot dynamically adjust to real-time changes in the user's movements or environment. Therefore, the design must be robust and adaptable, relying on well-engineered mechanical components and intuitive controls.

The success of such an exoskeleton hinge on the seamless integration of its parts. For instance, the synergy between the structural frame and joints determines the range of motion and comfort, while the actuators and power source dictate the overall performance and usability. Future developments could focus on improving the efficiency of passive components and exploring innovative power solutions to enhance the exoskeleton's practicality for everyday use.

While the absence of sensors limits the exoskeleton's adaptability, careful consideration of mechanical design and control strategies can still yield a functional and supportive device. This approach simplifies the system, potentially reducing costs and increasing reliability, making it a viable option for users requiring basic mobility assistance. The figures 4.1 to 4.2 shows

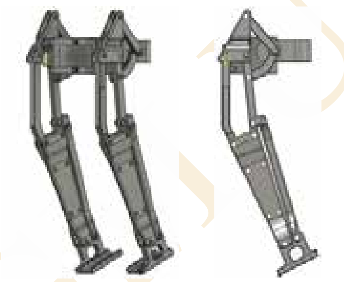

Figure 4.1 The ISO and Side View of the Exoskeleton

Figure 4.2: Real time model

5. CONCLUSION AND FUTURE SCOPE

The Design and Development of a lightweight, low-cost exoskeleton represents a significant advancement in enhancing mobility for individuals with various mobility impairments. By prioritizing weight reduction and affordability, this exoskeleton offers a practical solution that can improve the quality of life for people.

The lightweight nature of the exoskeleton ensures that users can wear it comfortably for extended periods without feeling burdened or fatigued. Moreover, its low cost makes it accessible to a wider range of individuals who may not have had access to such technology previously. Through innovative design and engineering, this exoskeleton provides enhanced mobility, allowing users to navigate their environment more easily and participate in activities that were previously challenging or impossible. By leveraging lightweight materials and efficient mechanisms, it achieves a balance between functionality, comfort, and cost-effectiveness. Furthermore, the development of this exoskeleton opens up possibilities for future advancements in the field of mobility assistance technology.

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SHIFT - Your Fashion Designer

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ABSTRACT

The report delves comprehensively into an innovative clothing recommendation system that harnesses the power of artificial intelligence (AI) to redefine the realm of personalized fashion experiences. Users articulate their desired outfits using a diverse range of keywords, triggering the system's sophisticated algorithms powered by Vertex AI, a pinnacle of machine learning technology, to generate bespoke designs tailored to individual preferences. In a remarkable stride forward, the system seamlessly integrates state-of-the-art image recognition capabilities, enabling it to meticulously scour online stores to curate a vast array of styles similar to users' preferences. This not only broadens the scope of available options but also fosters sustainability by encouraging users to explore existing inventory, thereby mitigating the impulse for excessive consumption and aligning with eco-conscious fashion practices. Furthermore, the system's dynamic functionality extends beyond mere design generation. It forges strategic alliances with skilled tailors, facilitating the realization of users' sartorial visions with precision and finesse. This collaborative approach not only enhances the user experience but also nurtures inclusivity within the fashion ecosystem, championing local artisans and fostering a sense of community. The report underscores the pivotal role played by Large Language Models (LLMs) in elevating user interaction within the system. By providing a natural language interface, LLMs facilitate seamless communication, empowering users to articulate their preferences with ease and ensuring that the generated designs authentically reflect their individual style sensibilities. The convergence of these cutting-edge technologies within the clothing recommendation system heralds a new era of democratized and accessible personalized fashion. By reshaping industry paradigms and empowering users to express their unique identities through clothing, this innovative platform promises to redefine the very fabric of the fashion landscape.

Keywords: Artificial Intelligence, Personalized Fashion, Sustainability, Image Recognition, Large Language Model (LLMs)

1.INTRODUCTION

The fashion industry is changing as a result of the incorporation of digital and artificial intelligence technologies, which offer distinctive and customized clothing options based on personal tastes and aesthetics. This report presents a novel clothing recommendation system that uses the state-of-the-art machine learning method called Vertex AI to produce customized outfit designs according to keywords entered by the user. By connecting customers with skilled tailors who can realize their ideas and offering a variety of stylistic options, the technology streamlines the process of making customized clothing.

Additionally, the system makes use of cutting-edge image recognition technology to find comparable clothing patterns in online marketplaces and offers links for purchasing ready-made designs or having them altered by knowledgeable tailors. Large language models (LLMs) are also used to enable natural language interaction and comprehensive feedback on design choices, which enhances the user experience. This study explores technological approaches that could transform customized fashion design and tailoring services, including network tailoring, steady AI for image production, enhanced picture recognition integration, and user interface design.

LLM (Large Language Models), represents a significant One of GEN AI's main benefits is its capacity to automate and optimize the content creation process, greatly cutting down on milestone in artificial intelligence research. These models, such as the GPT (Generative Pre-trained Transformer) series, are designed to understand and generate human-like text based on vast amounts of data. They have diverse applications, from natural language understanding and generation to aiding in content creation, translation, and more. However, they also raise ethical concerns regarding biases, misinformation, and privacy, necessitating responsible deployment and ongoing research to address these challenges.

GEN AI is a game-changing platform at the forefront of creative innovation in content creation. It creates highly tailored and interesting content by utilizing artificial intelligence to evaluate massive volumes of data, such as user behavior, preferences, and market trends. GEN AI enables businesses to produce a wide range of content, from articles and videos to social media posts and adverts, all of which are customized to the specific requirements and preferences of their target audience. This is achieved through the use of advanced algorithms and machine learning techniques.

One of GEN AI's main benefits is its capacity to automate and optimize the content creation process, the time and resources needed to generate high-caliber material Businesses may enhance engagement metrics, streamline their content strategy, and boost results across all marketing channels by utilizing AI-driven insights. Moreover, GEN AI's capacity for adaptive learning allows it to continuously improve its outputs and recommendations in response to real- time feedback, guaranteeing that content is timely and appealing to viewers.

Supabase is a platform focused on developers that makes it easier to create and maintain contemporary apps. Fundamentally, Supabase provides an extensive range of tools for developing and expanding applications, with an emphasis on real-time collaboration, authentication, and database management. Supabase frees developers from the burden of

managing complicated infrastructure by giving them a uniform interface and simple workflows so they can concentrate on creating cutting-edge features and adding value for users.
Supabase's commitment to open source and community-driven development is a notable aspect. It is built on PostgreSQL and GraphQL, which promotes developer cooperation while promoting innovation and continual improvement. Supabase's modular architecture allows it to easily adapt to a wide range of use cases, from basic web apps to sophisticated corporate systems.

VERTEX AI is a significant improvement in machine learning, providing a unified platform for developing, training, and deploying AI models at scale. Google Cloud's VERTEX AI streamlines the whole machine learning lifecycle, from data preparation and feature engineering to model training and deployment, with a focus on simplicity, reliability, and scalability. VERTEX AI helps developers and data scientists to accelerate the creation and deployment of AI-powered apps, resulting in actionable insights and business value from their data.
One of VERTEX AI's primary advantages is its connection with Google Cloud's larger ecosystem of services and technologies, which includes Big Query, TensorFlow, and Kubernetes. This seamless integration allows enterprises to use their existing infrastructure and data assets while simultaneously benefiting from VERTEX AI's enhanced capabilities for model experimentation, hyperparameter tuning, and automated deployment. Furthermore, VERTEX AI's managed services and built-in monitoring tools make it easier to manage ML workloads, freeing up teams to focus on innovation and business outcomes.

PaLM API (Programming Language Agnostic Messaging Application Programming Interface) is a flexible communication technology that enables interoperability and integration of many programming languages and systems. At its heart, the PaLM API provides a standardized interface for sending messages and data between various software environments, regardless of the programming languages or protocols utilized. This allows developers to create sophisticated, integrated applications that can communicate and share information regardless of the underlying technologies.
One of the main benefits of the PaLM API is its flexibility and extensibility, which allows developers to incorporate it into a variety of use cases and development greatly cutting down on the time and resources needed to generate high-caliber material on a large scale.

2. PROBLEM STATEMENT

Current fashion e-commerce limits customization and integration with tailors, hindering personalized style expression. This one-size-fits-all approach stifles creativity and leaves a gap in the market for unique garments. We propose an AI system using user keywords to design unique garments, leverage existing designs, and connect customers with tailors. This democratizes personalized fashion for everyone, empowering individuals to translate their style visions into reality.

3. OBJECTIVES

• To establish a personalized and accessible fashion approach, proposes developing a dress recommendation system that utilizes Vertex AI to generate designs based on user input keywords.

• To obtain a diverse array of dress designs reflective of individual preferences and styles, the system will be designed to streamline the process of exploring, selecting, and personalizing dress designs.

• To personalize the dress recommendation process, the system will incorporate a user-friendly interface that allows users to input keywords, select generated dress designs, and upload their preferred designs onto the platform.
• To ensure that users have access to a range of tailoring services to translate their chosen dress designs into physical garments, the system will establish a network of skilled tailors.

• To identify similar dress designs available in e- markets, the system will incorporate advanced image recognition technologies, potentially by integrating tools like Lens.

4. METHODOLOGY

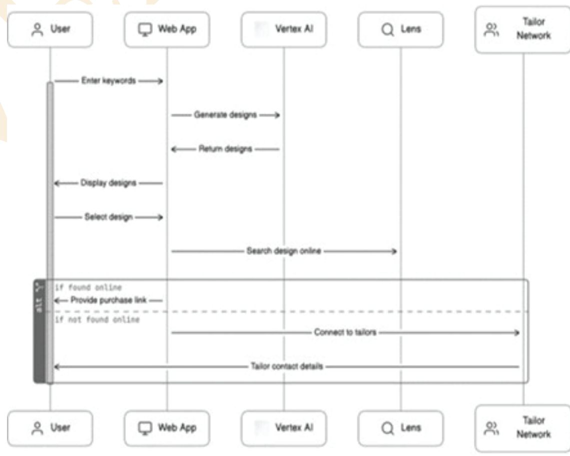

Figure 4.1: Sequence Diagram

In Figure 4.1, the sequence diagram illustrates the step-by-step process of how a user interacts with the system to generate dress designs and connect with tailors to create custom dresses. The diagram outlines the sequence of actions and messages exchanged between the user and the system components involved in the process. Each step represents a specific action or interaction that occurs during the execution of the use case, providing a representation of the flow of events over time. By depicting the objects and messages involved in the process, the sequence diagram helps to clarify the behaviour of the system
and the interactions between its components, facilitating a better understanding of the overall functionality of the system in response to user input.
The sequence diagram outlines the process by which a user can input keywords to generate dress designs and connect with tailors to create custom dresses.

The sequence of actions is as follows:

1. User Inputs Keywords: The user enters specific keywords into the system, such as "casual summer dress" or "red evening dress." The system's ability to generate appropriate designs improves with more specific keywords.

2. Vertex AI Generates Designs: The system uses text descriptions and the Vertex AI machine learning model to create realistic dress designs based on the user's keywords.

3. User Selects Design: The user reviews the dress designs displayed by the system and chooses their preferred design.

4. Check Dress Availability: The user can use a visual lens to check whether the chosen dress design is already available in the market and obtain a link if it is.

5. Connect with Tailors: The user can choose to connect with a network of tailors through the system. This allows the user to select a tailor based on their location, budget, and other preferences.

6. Collaborate with Tailor: The user collaborates with the chosen tailor to finalize the design and place an order. The user can provide additional details such as fabric, colour, and fit to the tailor.

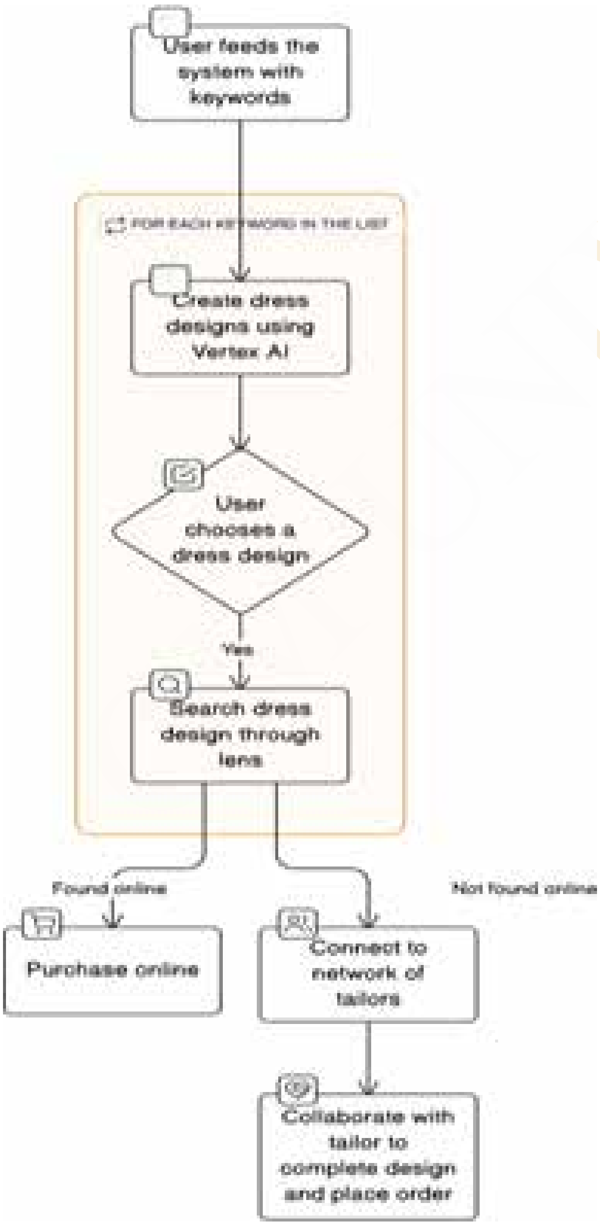

Figure 4.2 : Flow Chart of Proposed System

5. IMPLEMENTATION

Generating Images from Text Prompts with AI

```
def generate_images():
try:
text_prompt = request.json.get('textPrompt', '') # Get text prompt from the request
data = { # Prepare the request body "instances": [
{"prompt": text_prompt}
],
"parameters": { "sampleCount": 3,
"temperature": 1.0,
"maxOutputTokens": 256,
"topK": 90,
"topP": 0.99
}
}
```

Image Linker: Searching and Linking Images to Web Sources

```
def image_linker():
try:
global image_url
image_url = request.json.get('imagelink', '')
rev_img_searcher = ReverseImageSearcher()
res = rev_img_searcher.search(image_url)
for search_item in res:
print(f'Title: {search_item.page_title}')
print(f'Site: {search_item.page_url}')
print(f'Img: {search_item.image_url}\n')
serialized_items = []
for item in res:
serialized_item = {
"title": item.page_title,
"link": item.page_url,
"image": item.image_url,
}
serialized_items.append(serialized_item) # Add more attributes as needed
json_data=serialized_items # Serialize the list of dictionaries to JSON
if res:
21
return jsonify({"success": True, "res": json_data})
else:
return jsonify({"success": False, "error" : "No result found!"})
except Exception as e:
return jsonify({"success": False, "error": str(e)})
```

Reverse Image Searcher: Searching for Image Sources with Google Lens

```
class ReverseImageSearcher:
def init (self):
self.url = 'https://lens.google.com' self.session = Session()
self.session.headers.update(
{'User-agent': 'Mozilla/5.0 (X11; Linux x86_64; rv:103.0) Gecko/20100101
Firefox/103.0'}
)
```

6. TESTING

Unit testing is a software testing method that involves testing individual units or components of software and hardware in isolation from the rest of the system. The purpose of unit testing is to verify that each unit of the system is functioning as expected, according to its design specifications. The table 6.1 illustrates the unit testing process:

Table 6.1 Unit Testing

Test Description	Expected Result	Status
Keyword Processing	Keywords are parsed correctly	Pass
	Invalid keywords are handled appropriately	Fail
Style Matching	Recommended designs match user preferences	Pass
	Styles are diverse and reflective of input	Pass
Design Generation	Generated designs align with user preferences	Pass
	Unique designs are produced for each input	Pass
API Endpoint Handling	Requests are handled correctly	Pass
	Responses are formatted as expected	Pass
Image Recognition	Patterns are identified accurately	Pass
	Similar designs from online marketplaces are recognized	Pass
Data Validation	User input is validated correctly	Pass
	Database queries return accurate results	Pass
Error Handling	Invalid inputs trigger appropriate error messages	Pass
	API errors are handled gracefully	Pass

System testing is the examination of an integrated system to ensure it fulfills predetermined requirements. This comprehensive evaluation verifies the harmonious operation of all system components, confirming they function as intended. Typically, system testing centers on affirming the system's functionality, performance, and compatibility. The below table 6.2 shows the system testing.

Table 6.2 System Testing

Test Description	Expected Result	Status
User Interface	All interface elements are functional and responsive	Pass
	Navigation between screens is smooth and intuitive	Pass
Recommendation Accuracy	Recommended designs match user preferences and input keywords	Pass
	Styles offered are diverse and reflective of individual tastes	Pass
Image Recognition	Patterns and designs are accurately recognized and matched	Pass
	Performance is consistent across different image types and resolutions	Pass
Performance	System responds promptly to user interactions and requests	Pass
	Scalability is demonstrated under peak usage conditions	Pass
Compatibility	System functions correctly across different devices and browsers	Pass
	Integrations with external services or APIs work seamlessly	Pass

7. RESULTS

Figure 7.1: Landing Page

Figure 7.1 presents an inviting interface that introduces users to the platform's array of features and services, setting the tone for their exploration.

Figure 7.2 : Login and Register

Users are guided through a streamlined process illustrated in Figure 7.2, allowing them to create accounts or sign in securely for seamless access to the platform's functionalities.


Figure 7.3 : Generated Images

Employing cutting-edge generative AI models, as illustrated in Figure 7.3, the platform dynamically generates diverse dress designs based on user input keywords, providing users with a wide range of creative options and fostering innovation in fashion design.

Figure 7.4 : Tailor Contacts Option

Figure 7.4 showcases a comprehensive directory of available tailors, offering users a curated selection to choose from or contact for garment creation services,
ensuring convenience and access to skilled professionals.

8. CONCLUSION AND FUTURE SCOPE

Fashion is a powerful form of self-expression, yet traditional design and customization processes can be expensive, time-consuming, and complex. This project introduces an AI-powered personalized fashion design system that enables users to create unique outfits effortlessly. Using Generative AI, individuals can describe their ideal garment with simple keywords, and the system translates their vision into high-quality designs using advanced text-to-image synthesis models like DALL•E or Stable Diffusion. Users can refine their designs by adjusting colors, fabrics, and silhouettes while utilizing a virtual try-on feature to visualize their creations. To further streamline the shopping experience, the system integrates with online marketplaces, employing image similarity search to find ready-made alternatives matching the AI-generated designs. This feature benefits users who prefer pre-made options while still seeking a personalized touch. For those who desire fully customized outfits, the system connects them with skilled tailors who can bring their designs to life. Users can share their AI-generated designs, select materials, and receive cost estimates and timeframes for production, ensuring a seamless transition from concept to reality. Additionally, the system promotes sustainability by offering eco-friendly fabric choices and tracking the environmental impact of selected materials. Smart recommendations analyze user preferences and past selections to provide style suggestions, enhancing personalization. A social sharing feature allows users to showcase their designs, receive feedback, and engage with a fashion-driven community. By combining AI, e-commerce, and craftsmanship, this system democratizes fashion customization, making it more accessible, efficient, and sustainable. It not only simplifies the creative process but also fosters an inclusive and innovative approach to personalized fashion, bridging the gap between digital design and real-world production while redefining the future of customized clothing.

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Phytochemical Analysis and Antimicrobial Studies on Vegetative Extract of *Momordica cymbalaria* for the reduction of Osteomyelitis

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ABSTRACT

Osteomyelitis, a severe and persistent bone infection, remains a major clinical challenge, particularly with the increasing prevalence of antibiotic-resistant bacterial strains. This study investigates the potential of Momordica cymbalaria, a medicinal plant known for its therapeutic applications, as a natural antimicrobial agent. The vegetative extract of Momordica cymbalaria underwent phytochemical analysis to determine its bioactive constituents, revealing the presence of alkaloids, proteins, fats and oils, and carbohydrates, all of which possess known antimicrobial properties. To evaluate its antibacterial efficacy, the extract was tested against Staphylococcus aureus, a common causative agent of osteomyelitis. Antimicrobial assays demonstrated a zone of inhibition of 2 cm, indicating significant antibacterial activity. These findings suggest that Momordica cymbalaria contains bioactive compounds capable of combating bacterial infections and may serve as a foundation for future pharmaceutical applications. Fourier-transform infrared (FT-IR) spectroscopy further confirmed the presence of functional groups associated with key phytoconstituents. Alkaloids exhibited characteristic hydroxyl group peaks in the 3000-3500 cm^{-1} range, while proteins displayed amide bond-related peaks within 2000-2500 cm^{-1}. Fats and oils contained ester functional groups with stretching vibrations characteristic of triglycerides in the 2800-3000 cm^{-1} range. Carbohydrates exhibited carbonyl stretching vibrations, appearing around 3300-3500 cm^{-1}. These results validate the presence of essential bioactive compounds with potential antimicrobial properties. Further research could lead to the development of plant-based antimicrobial agents for treating osteomyelitis and other bacterial infections.

Keywords: *Momordica cymbalaria,* vegatable extract, Phytochemical analysis, and Anti-microbial activity.

1. INTRODUCTION

Osteomyelitis, a serious and potentially debilitating infection of the bone, remains a significant challenge in modern medicine despite substantial advancements in diagnostic techniques and therapeutic interventions. This complex condition represents a profound disruption in the delicate balance between the body's innate defenses and microbial invasion within the skeletal system. The pathogenesis of osteomyelitis is multifactorial, and it can arise from various sources. One common route of infection is hematogenous spread, where pathogens, typically bacteria, travel through the bloodstream to infect bone tissue. Alternatively, osteomyelitis may develop due to contiguous spread from adjacent soft tissue infections, such as cellulitis or abscesses, which extend into the bone. Additionally, osteomyelitis can result from direct inoculation of bacteria into the bone following trauma, fractures, or surgical procedures. Once the infection takes root, it can lead to an inflammatory cascade that disrupts bone integrity, potentially resulting in bone necrosis and complications like chronic infection or deformity.

The clinical presentation of osteomyelitis is often varied and influenced by the age, underlying health conditions, and the type of pathogen involved. In light of this heterogeneous nature, understanding the nuances of osteomyelitis becomes critical for effective diagnosis and treatment. Lew and Waldvogel, prominent researchers in the field, emphasize the importance of a comprehensive approach to osteomyelitis, which includes a thorough medical history, detailed physical examination, and appropriate diagnostic workup. These diagnostic tools are essential for identifying the infection's etiology, its location, and its extent, ultimately guiding clinicians in formulating effective treatment strategies.

Appropriate intervention often involves a combination of antimicrobial therapy and, in some cases, surgical debridement to remove necrotic tissue and promote healing.

In parallel, there has been a growing interest in exploring alternative and adjunctive treatments for osteomyelitis, especially in the face of rising antibiotic resistance. One such avenue of research focuses on the medicinal plant Momordica cymbalaria, commonly known as Ivy gourd or scarlet-fruited gourd. This tropical and subtropical vine, belonging to the Cucurbitaceae family, which also includes cucumbers, pumpkins, and melons, is native to Africa and Asia but has since spread to various parts of the world due to its culinary and medicinal uses. Momordica cymbalaria has long been recognized for its therapeutic properties, particularly its potential antimicrobial, anti-inflammatory, and antioxidant effects. In traditional medicine, the plant has been used to treat a range of ailments, including diabetes, digestive disorders, and skin conditions. Recent research is investigating its efficacy in combating infections, including those caused by antibiotic-resistant strains of bacteria. Given the rise of resistant pathogens in osteomyelitis and other infectious diseases, Momordica cymbalaria holds promise as a natural adjunct to conventional therapies, offering a potentially valuable tool in the management of this challenging condition.

2. OBJECTIVES

* To extract and analayze the phytochemicals from Momordica cymbalaria.
* To study antimicrobial activity against Staphylococcus aureus causing Osteomyelitis.
* To examine the organic and inorganic compounds by FT-IR analysis.

3. METHODOLOGY

1. Collection Of Sample :

1kg of the Momordica cymabalaria were then wash thrice with distilled water to remove the minor traces of disinfectants and the fruit was collected from the market of Vijayapura.

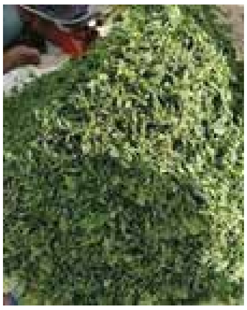


Figure 1: *Momordica cymbalaria* vegetable

Shade drying is a natural preservation technique that involves drying materials, such as herbs, fruits, or vegetables, in a cool, shaded area, away from direct sunlight. This method helps to preserve the nutritional value, flavor, and color of the materials while preventing the degradation of sensitive compounds that can be caused by excessive heat or UV exposure. It is particularly useful for preserving delicate items that are prone to discoloration or loss of essential oils when exposed to direct sunlight. The process allows for gradual moisture evaporation, which helps to retain the texture and natural properties of the materials. Shade drying is an energy-efficient and environmentally friendly method, commonly used for small-scale preservation or when solar drying systems are unavailable.

Figure 2: Dried Vegetables of *momordica cymbalaria.*

After the vegetable sample was thoroughly dried, it was ground into a fine powder using a mortar and pestle. The grinding process was carried out meticulously to ensure a uniform and consistent texture throughout. In total, 250 grams of the dried vegetable material was successfully powdered.

Figure 3: Powdered form of Vegetable

Soxhlet Extraction:

Soxhlet extraction is a well-established technique widely used in chemistry and biochemistry for extracting soluble compounds from solid samples. The process begins by setting up the necessary equipment, including a Soxhlet extractor, a round-bottom flask, a reflux condenser, and a heating mantle or hot plate for controlled heating. The solid sample is placed in a thimble, which is positioned inside the Soxhlet extractor. The solvent is then heated, evaporated, and condensed back into the extractor, repeatedly washing the sample to extract the desired compounds. This continuous cycle ensures efficient extraction of the soluble components from the solid material.

Figure 4: Soxhlet extraction apparatus

Figure 5: Extracted Sample(crude)

2. Phytochemical Analysis:

Phytochemical analysis involves the qualitative and quantitative identification of bioactive compounds found in plants, which play crucial roles in their medicinal and nutritional properties. These bioactive compounds, commonly referred to as phytochemicals, include alkaloids, flavonoids, terpenoids, and phenolics, among others. By analyzing these phytochemicals, researchers can better understand their potential therapeutic effects and the plant's overall health benefits.

Test for Alkaloids:

Mayer's Test:

After adding Wagner's reagent, the appearance of a reddish-brown precipitate indicates the presence of alkaloids in the sample. This color change is a characteristic reaction, confirming the alkaloidal compounds within the plant material

Wagner's Test:
Upon adding Wagner's reagent to the sample, a reddish-brown precipitate forms, which is a positive indication of alkaloids. This color change occurs due to the interaction between the reagent and the alkaloidal compounds present in the plant material.

Test for Carbohydrates:

Molisch's test:
The appearance of a violet ring upon testing indicates the presence of carbohydrates in the sample. This reaction typically occurs when carbohydrates react with specific reagents, forming a distinctive color change.

Benedict's test:
After adding Benedict's reagent, the color change to green indicates the presence of reducing sugars, a type of carbohydrate. This color shift occurs as the reagent reacts with the aldehyde or ketone groups in the reducing sugars, forming a colored precipitate.

Test for oils and Fats:

Saponification test:
The appearance of a soapy texture after adding 0.5 N alcoholic potassium hydroxide solution indicates the presence of oils and fats. This reaction occurs due to the saponification process, where the potassium hydroxide breaks down the fats or oils into glycerol and fatty acid salts, forming soap-like compounds.

Test for Proteins:

Millon's test :
The appearance of a white precipitate upon adding Millon's reagent to the extract indicates the presence of proteins. This reaction occurs due to the formation of a red-colored complex, typically involving the phenolic group of tyrosine residues in proteins, which reacts with the reagent to produce the precipitate.

Biuret test:
The appearance of a pink-colored ethanolic layer indicates the presence of proteins. This color change occurs due to the interaction between proteins and specific reagents, highlighting the presence of amino acids such as tyrosine, which react with the ethanolic solution to form the characteristic pink hue.

Antimicrobial Analysis:
Antimicrobial analysis involves evaluating the efficacy of antimicrobial agents against microorganisms such as bacteria, fungi, and viruses.

3. FT-IR Analysis:

The resulting FT-IR spectrum consists of peaks and troughs corresponding to the different vibrational modes of the molecular bonds in the sample. The position and intensity of these peaks are analyzed to identify specific chemical groups and functional groups within the sample. This includes identifying the sample's molecular structure and composition based on the observed peaks and providing a detailed analysis of the results.

4. RESULTS AND DISCUSSION

Phytochemical Analysis

Test for Alkaloids:

Figure 1.1: Mayer's Test

Figure 1.2 : Wagner's Test

Test for Carbohydrates

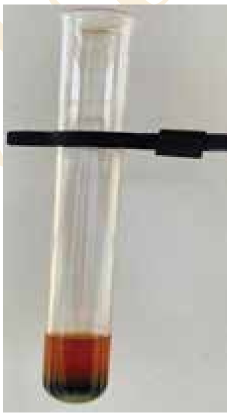


Figure 2.1: Molisch's Test

Figure 2.2: Benedict's Test

Test for oils and Fats:

Figure 3.1: Saponification Test

Test for Proteins

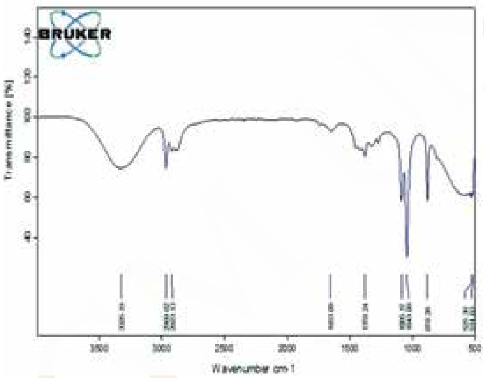
Figure 4.1: Millon's Test

Figure 4.2: Biuret Test

Antimicrobial Studies:

Figure 5.2.1: Well Diffusion method with Zone of Inhibition

FT-IR Analysis:



Graph 1: FT-IR spectroscopy results of Ethanol extract

5. CONCLUSION

The phytochemical analysis and antimicrobial studies on the vegetative extract of Momordica cymbalaria present a promising frontier in the quest to combat osteomyelitis, a challenging bone infection often resistant to conventional treatments. The comprehensive phytochemical analysis revealed a rich array of bioactive compounds, such as alkaloids, flavonoids, terpenoids, and phenolic compounds, which are known for their diverse pharmacological properties, including antimicrobial

In summary, the phytochemical analysis and antimicrobial studies on *Momordica cymbalaria* extract offer a promisingand innovative approach to addressing the challenges associated with osteomyelitis treatment.

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Stainable sewage water treatment using *Eichhornia crassipes* and *Pistia stratiotes*

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ABSTRACT

Urban migration and rapid industrialization have significantly increased the burden on water sanitation infrastructure, particularly in low-income urban areas of developing countries. The discharge of untreated wastewater into natural water bodies has led to severe environmental and public health issues, including the contamination of drinking water sources and the spread of waterborne diseases. This study explores the potential of phytoremediation as a sustainable and cost-effective approach to treating sewage water using aquatic weeds. The research hypothesis suggests that aquatic plants such as Eichhornia crassipes (water hyacinth) and Pistia stratiotes (water lettuce) can effectively remove pollutants, including heavy metals and organic contaminants, from sewage water. A review of existing literature supports this premise, highlighting the ability of these plants to absorb, accumulate, and degrade harmful substances, thereby improving water quality. The experimental methodology involves designing a phytoremediation system using a 100-liter tank filled with a substrate of soil and gravel. Raw sewage water is collected from industrial effluent discharge points and introduced into the system. The aquatic weeds are then placed in the tank, allowing them to absorb and process contaminants over a designated period. Water quality analysis is conducted before and after treatment to assess reductions in pollutants, including heavy metals, biochemical oxygen demand (BOD), and chemical oxygen demand (COD). By demonstrating the effectiveness of aquatic plants in sewage water treatment, this study aims to contribute to environmental conservation, improve public health, and promote the use of nature-based solutions for sustainable wastewater management.

Keywords: *Eichhornia crassipes, Pistia stratiotes,* sewage water, phytoremeidiation setup, water treatment.

1. INTRODUCTION

The situation is worsening with rapid urbanization, where adequate sanitation and wastewater treatment facilities are lacking. Due to the absence of wastewater treatment plants, a large portion of sewage remains untreated and is discharged into water bodies. To clean the rivers, it is essential to treat the sewage, particularly domestic sewage. Phytoremediation, the treatment of wastewater using plants, is a suitable system used worldwide. (Phyto = plant, remediation = restoring balance). Both aquatic and terrestrial plants have remarkable environmental restoration properties, such as decontaminating polluted soil and water. Phytoremediation is a plant-based bioremediation technology. The pollutant removal efficiency depends on factors such as hydraulic retention time, hydraulic loading, plant species, plant density, water depth, and influent concentration. Phytoremediation is a cost-effective and eco-friendly process to remove heavy metals from water. A small-scale experiment was conducted to determine the phytoremediation efficiency of two macrophytes, Pistia stratiotes and Eichhornia crassipes, for the removal of chromium and copper. With rapid population growth and increasing industrial development, a large number of water resources worldwide are becoming polluted, leading to the continuous discharge of organic and inorganic wastes from human activities into natural water bodies.

Eichhornia crassipes: The name *Eichhornia crassipes* originates from Johann Albert Eichhorn, a German botanist and professor of botany at the University of Kiel in the 19th century. The specific epithet "crassipes" comes from Latin, where "crassus" means thick or fat, and "pes" means foot, referring to the plant's thick, spongy petioles that help it float on water. Commonly known as water hyacinth, this aquatic plant is native to South America and was introduced to the U.S. in 1884. It forms dense floating mats that clog waterways, reduce biodiversity, and deplete oxygen levels, harming aquatic life.

Pistia stratiotes: *Pistia* is a genus of aquatic plants in the arum family, Araceae. It is the sole genus in the tribe Pistieae, reflecting its systematic isolation within the family. The single species it comprises, *Pistia stratiotes,* is commonly called water cabbage, water lettuce, Nile cabbage, or shellflower. Its native distribution is uncertain but is likely pantropical. It was first scientifically described from plants found on the Nile near Lake Victoria in Africa. Now present in nearly all tropical and subtropical freshwater ecosystems, *Pistia stratiotes* is considered an invasive species and a mosquito breeding habitat. The genus name is derived from the Greek word *pistos* (meaning "water"), referring to the aquatic nature of the plant. The specific epithet is derived from the Greek word *stratiotes* (meaning "soldier"), which references the sword-shaped leaves of some plants in the Stratiotes genus.

Wastewater Treatment: As a hyper-accumulator, Pistia stratiotes shows promise in wastewater treatment. The plant's roots and leaves can absorb excess nutrients and heavy metals like zinc, chromium, and cadmium from contaminated waters, thus contributing to water purification.

2. METHDOLOGY:

Step 1: The sewage water is collected from our GMIT campus, Davanagere.

Step 2: Aquatic weeds ie, Eichhornia crassipes and pistia stratiotes are collected from the near loacal ponds, Davanagere.

Step 3: Gravels, sand and black soil are collected from Harihara lake.

Step 4: The sewage sample (before treated/raw sample) is subjected to physical and chemical parameters analysis at BIET college , Davanagere.

Step 5: Construction of Phytoremediation tank

Step 6: The bed consisting of soil, gravel, basic soil, black soil respectively was made by spreading it uniformly till 28 cm. The first layer consisted of gravels as base. Secondly, sand was layered above the gravels and Thirdly, basic soil was layered along with black soil.

Step 7: After the construction of the tank the sewage water is poured up to top of the tank.

Step 8: The aquatic weeds i.e *E. Crassipes* and P. *Stratiotes* were arranged after dividing the tank into 3 compartment in which each compartment have 2 each of *E.crasspies* and *P. Stratiotes* respectively.

Obtain effective results.

Step 10: After treatment, the sample is collected from outlet and subject to physical and chemical parameters analysis at BIET, Davanagere.

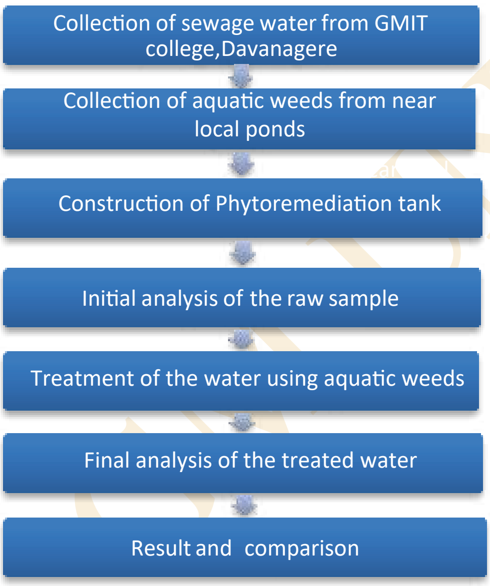

Figure 1: Uniform bed setup of basic soil, gravels and sand

Figure 2: Sewage water pouring

Figure 3: Arrangement of aquatic weed

Figure 4: Collection of treated water

Figure 5: Treated water

3. RESULT:

TABLE 5.3: Results of COD and BOD analysis of sewage water before and after treatment

SL NO	TESTS CONDUCTED	BEFORE TREATMENT	AFTER TREATMENT
1.	DO	84.2 mg/l	8 mg/l
2.	COD	4480 mg/l	2080 mg/l
3.	BOD	153.6 mg/l	29.50 mg/l

There is significant changes in the values of physical parameters in comparison to before treatment and after treatment i.e Turbidity 14 NTU to 2.5 NTU, total dissolved solvents 220 mg/l to 118 mg/l, total suspended solids 22 mg/l to 9 mg/l, Alkalinity 592 mg/l to 56 mg/l, total hardness 204 mg/ to l 90 mg/L treated water.

The Tests DO,COD and is BOD compared with raw sewage sample and measured value treated sewage water i.e DO- 84.2 mg/l to 8 mg/l, COD- 4480 mg/l to 2080 mg/l, BOD - 153.6 mg/l to 29.50 mg/l and the significant changes has been observed.

TABLE 1: Results of physical parameters of sewage water before and after treatment

SL NO	TESTS CONDUCTED	BEFORE TREATMENT	AFTER TREATMENT
1.	Ph value	7.42	7.65
2.	Colour	Dark brown	Slightly Brown
3.	Odour	foul	Moderate foul
4.	Temperature	Room Temperature	Room Temperature
5.	Turbidity	14 NTU	2.5 NTU
6.	Total dissolved solvents	220 mg/l	118 mg/l
7.	Total suspended solids	22 mg/l	9 mg/l
8.	Alkalinity	592 mg/l	56 mg/l
9.	Total hardness	204 mg/l	90 mg/l

TABLE 3: Heavy metal analysis of sewage water

SL NO	TESTS CONDUC TED	STANDARD VALUE	BEFORE TREATMENT	AFTER TREATMENT
1	Nitrate	45 mg/lit	2.48 mg/lit	1.84 mg/lit
2	Sulphate	200 mg/lit	6.21 mg/lit	1.24 mg/lit
3	Fluoride	1.5 mg/lit	0.21 mg/lit	0.42 mg/lit
4	Copper	Nil	0.01 mg/lit	Nil
5	Cadmium	0.05 mg/lit	Nil	Nil
6	Chromium	0.05 mg/lit	0.02 mg/lit	Nil

The heavy metals value in raw sewage sample is compared to that of treated sample and standard water value and it has been observed that value Copper ,Chromium is found to be nil and other significant changes is observed in value of the heavy metals like Sulphates, Flouride.

4. CONCLUSION AND FUTURE SCOPE

E. crassipes and *P. stratiotes* offer several advantages over traditional wastewater treatment methods. They are eco-friendly, low-cost, and require minimal maintenance, making them a sustainable solution for wastewater treatment. Additionally, these plants can be used in conjunction with other treatment methods, such as sedimentation and filtration, to enhance the overall effectiveness of the treatment process.
Eichhornia crassipes and *Pistia stratiotes* are effective in sustainable sewage water treatment due to their high pollutant removal efficiency. *E. crassipes* shows good reduction in BOD, ammonium nitrogen, organic carbon, and suspended solids, while *P. stratiotes* excels in removing various pollutants including heavy metals. Both plants offer eco-friendly and low- cost remediation methods, with E. crassipes reducing nitrate and ammonium nitrogen by over 60% within 60 days and *P. stratiotes* enhancing water quality significantly by reducing TDS, TSS, BOD, COD, and other pollutants by significant percentages. Their ability to remove pollutants through phytoremediation makes them a valuable tool for sustainable wastewater treatment, and their low maintenance and cost requirements make them a practical solution for wastewater treatment in developing countries and communities.

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Protective Gear Identification in Industries using Object Detection

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ABSTRACT

Protective gear identification is crucial for ensuring workplace safety in industrial settings. In this project, we propose a solution for automatic detection of protective gear, including vests, helmets, and gloves, worn by personnel using object detection techniques. We employ the state-of-the-art YOLOv8 model, known for its accuracy and efficiency in robject detection tasks. The objective is to develop a robust system capable of identifying and localizing protective gear items in images and video streams. Our approach involves collecting a diverse dataset of annotated images containing individuals wearing various types of protective gear. Pre-processing techniques are applied to clean and standardize the dataset, removing noise and enhancing image quality. The YOLOv8 model is then trained on the pre-processed dataset to learn the features of protective gear items. During training, the model learns to detect vests, helmets, and gloves by analyzing their distinctive features and spatial relationships. The trained model is validated using a separate set of images to ensure its accuracy and generalization ability. Experimental results demonstrate the effectiveness of the proposed approach in accurately identifying and localizing protective gear items in different scenarios. The system achieves high precision and recall rates, making it suitable for applications in industrial safety. The automated detection of protective gear can enhance workplace safety measures by alerting supervisors to instances of non-compliance or inadequate protection.

Keywords: YOLOv8, Machine Learning, Object Detection, Deep Learning, Construction Safety and Image Processing.

1.INTRODUCTION

The construction industry have a one of the most dangerous occupational injuries in the civil construction business is one of the dangerous occupations. The situation is caused by risky duty content and a dangerous working environment. Common accidents such as falling, being hit by collapsed objects and collisions could lead to injuries and death. Throughout the years, authorities have formulated and imposed various safety regulations and on-site inspections to ensure a safer working environment, but still, the number of casualties remains as high despite the new regulations. According to the statistics of the Ministry of Labor, the incidence rate of fatal occupational injuries in the construction industry remains higher than others in 2020, with up to 71% of major occupational injuries caused by unsafe equipment According to the statistics of the Ministry of Labor, Taiwan, the incidence rate of fatal occupational injuries in the construction industry remains higher than others in 2020, with up to 71% of major occupational injuries caused by unsafe equipment. The U.S. Occupational Safety and Health Administration (OSHA) has also indicated that the most frequent occupational injuries and deaths can be effectively prevented if workers wear appropriate personal protective equipment (PPE): hard hat, safety vests, face masks, and gloves; particularly, helmet-wearing can significantly reduce the impacts caused by falling objects, electrocution due to hanging cables and other common occupational injuries. Moreover, demanding construction workers to wear high-visibility safety vests can effectively prevent heavy construction equipment from hitting them; therefore, how to efficiently and properly manage the use of personal protective equipment (PPE) still deserves more in-depth study and discussion.

The project aims to enhance workplace safety by providing a comprehensive solution for monitoring the usage of protective gear. By automating the detection process, supervisors and safety officials can quickly identify instances of non-compliance or inadequate protection, enabling prompt corrective action. This approach not only improves safety standards but also reduces the risk of accidents and injuries in industrial environments here. bussiness interms of the internet and its new culture and capabilities.

2. LITERATURE SURVEY

A vision-based approach for ensuring proper use of personal protective equipment (PPE) in decommissioning of Fukushima Daichi nuclear power station - Chen and Dema chi -26 June 2020.

In a study by Chen and Dema chi, a vision-based approach for monitoring PPE in a Nuclear power station was proposed. The experiment was conducted on an annotated dataset of 3808 images, which were collected from the real world using a webcam and the web using a web crawler tool. A different dataset was considered in the testing phase, which was also gathered manually. However, two objects were targeted to be localized and classified by the detection model: Hard Hat and Full-face mask. In addition, the distance and the posture of the workers contributed to achieving the aim of the study. The one-stage detection model YOLOv3 was trained on the combined dataset in two stages: the first stage froze the last convolutional layer in Darknet-53, and the second stage was performed by unfreezing all the convolutional layers to carry out the fine-tuning process. Moreover, during the training, different learning rates were addressed for the stages; Adam optimizer and a batch size of 8 were adopted to accomplish reliable accuracy. The developed model could detect whether the workers wear proper PPE or not, with a precision of 97.64% and a recall of 93.11%, while ensuring a real-time performance of 7.96 frames per second (FPS). In the future, the authors intend to augment the dataset to increase the accuracy and deploy the model based on the on-site surveillance system

A Combined Detection Algorithm for Personal Protective Equipment Based on Lightweight YOLOv4 Model - Ma, L.; Li, X.; Dai, X.; Guan, Z.; Lu, Y - 4 May 2022.

In this study, Ma et al. proposed a combination detection algorithm for PPE using the portable YOLOv4 model. The dataset used was made up of about 25,000 samples that were taken from security footage of a building construction site. The data were divided unevenly into six classes and separated into a training set and a test set. Two algorithms, YOLOv4 and YOLOv4-Tiny, were used. Pruning the model with the original dataset was the fine-tuning and optimization strategy to increase accuracy. The best outcome was obtained with CLSlim YOLOv4, which had an mAP loss of only 2.1%, had an enhanced inference speed by 1.8 times, and compressed the model parameters by 98.2%. The major conclusions emphasized the efficiency of the channel and layer pruning method (CLSlim) in lowering computational power usage and enhancing the detection speed. Further work is advised to investigate merging CLSlim with other lightweight strategies to speed up model inference even more and find better lightweight model techniques for mobile terminals with constrained resources

Deep Learning for site safety - Nath, N.D.; Behzadan, A.H.; Paal, S.G - January 2020.

This study proposed a DL model built on the YOLO architecture to verify PPE compliance. Following that, the next stage is to develop a machine learning model to determine whether the worker is properly wearing PPE. This approach consists of detecting workers, their hats, and vests, and then using a machine learning model (e.g., neural networks and decision trees) to verify whether each worker is appropriately wearing his or her hat or vest. Second, a convolutional neural network (CNN) framework is used to detect individual workers and verify PPE compliance at the same time. A third approach consists of first detecting only workers in the input image. The workers are then cropped and classified by CNN-based classifiers, for example, VGG-16, ResNet-50, and Xception, based on the presence of personal protective equipment. The 23 models are trained on an in-house image dataset that is collected through crowdsourcing and Web24 mining. A dataset named Pictor-v3 contains 1500 annotated images and 4700 instances of 25 workers wearing varying combinations of personal protective equipment

An Efficient and Fast Lightweight-Model with ShuffleNetv2 Based on YOLOv5 for Detection of Hardhat-Wearing - Cengil, E.; Çınar, A.; Yıldırım - 16 September 2022.

This topic focused on the detection of hard helmets using a one-stage-object-detector algorithm improved by the authors. YOLOv5 was used as the base architecture for the model, with the main enhancement being in the feature extraction step. The performance of ShuffleNetv2 and MobileNetv3 as the backbone of the architecture was compared to find the model that increased the efficiency and speed of the network. The study classifies three objects in the image, “Helmet”, “Head”, and “Person” that are included in Roboflow’s “Hard Hat” dataset.

3. MOTIVATION

Industrial accidents can be devastating. Ensuring workers wear proper protective gear like vests, helmets, and gloves is crucial for safety. However, manual monitoring is time-consuming and prone to errors. This project proposes an automated solution using object detection techniques. By analyzing images and video streams, we can automatically identify and locate protective gear, enhancing workplace safety and reducing risks.

1. Increasing compliance with safety regulations: the project make sure workers are adhered with safety regulations by wearing necessary protector gears.
2. Reduce responsibilities: Through proactively locating and handling safety issues, companies can lessen the danger of legal matters and financial liabilities.
3. Enhance efficiency: Having fewer disruptions because of safety investigations, workers can concentrate more on their jobs, leading to better efficiency.
4. Elevate worker spirits: making a secure work surrounding can increase employee contentment and morale.
5. Adjusting to technological progress: Embracing automatic safety resolutions demonstrates a dedication to using technology for better workplace methods.
6. Permitting real-time supervision: The system allows for continual monitoring of safety agreement, enabling timely correct activities when needed.
7. Backing continuous progress: By analyzing data compiled from the system, companies can recognize trends and fields for more safety improvements.

4. METHODOLOGY

1.Data mining Collection and Pre-processing: Data Gathering: Assemble a comprehensive dataset containing images representative of diverse industrial an construction scenarios, with workers wearing various protective gear items (helmets, vests, shoes, glasses, etc.) Annotation: Annotate the dataset to mark regions of interest corresponding to each protective gear item, creatin' a labelled dataset for training and validation. Data Enhancement: It's a crucial component in enhancing the effectiveness of our protective gear identification system. By applying techniques such as rotation, scaling, and flipping to the dataset during training, we significantly boosting the model's robustness and generalization capabilities. Rotation accounts for variations in worker orientation, scaling simulates distance discrepancies, and flipping introducing mirror images, collectively exposing the model to a diverse range of scenarios.

2.Feature Extraction: YOLOv8 :(You Only Look Once version 8) be a state-of-the-art object detected model known for its speed and accuracy. It is improved over previous versions, offering better performance and versatile. YOLOv8 use a singular neural network predicting bounding boxes and class probability directly from full images in one evaluation. It employ a full convolutional architecture, it process images of any size quickly. YOLOv8 incorporate a backbone network, typically Darknet-53, that extract features from the input images. It then utilize additional layer for object detect, including multiple convolutional layer and prediction head. This architecture let YOLOv8 detect multiple object in real-time with high accuracy. Additionally, YOLOv8 support transfer learn, enabling fine-tune on specific dataset to improve performance on custom tasks.

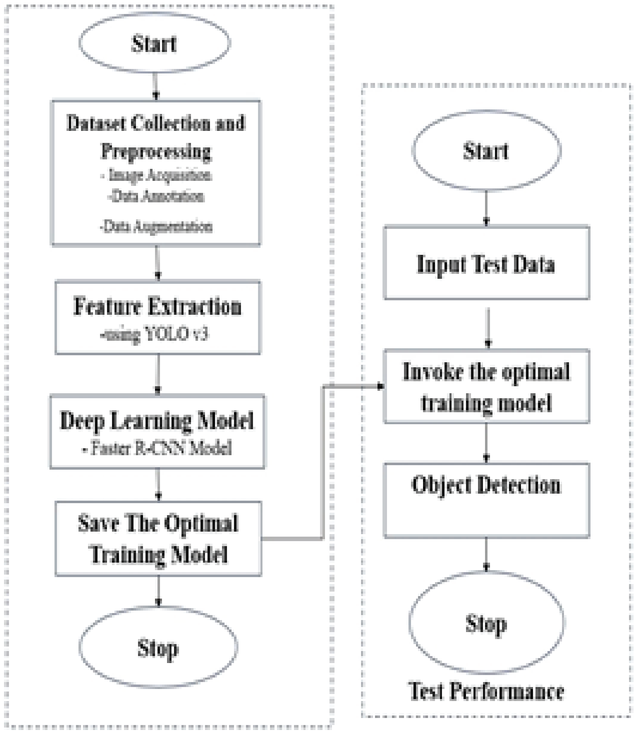

Figure 1 : Workflow of Methodology

3.Deep Learning Model: Object Detection Framework: In our deep learn strategy, we opt for the Faster R-CNN (Region-based Convolutional Neural Network) framework, focus on its capabilities for object detect in the context of identify multiple protect gear items concurrently. Faster R-CNN standout due its innovation use of a Region Proposal Network (RPN), a critical component that generate region proposal suggest potential bounding boxes contain object of interest. Model Training: Train the deep learn model using the annotated dataset, fine-tune the pre-train network recognize and localize various protect gear items in the image.

4.Save The Optimal Train Model: Model Validation: Split the dataset into train and validation sets evaluate model performance during train. Optimization: Save the optimal train model base on validation metric, ensure the model general well to new, unseen datum.

5.Input Test Data: Real-world Images: Gather a separate set real-world image represent scenario encounter in industries and construct sites assess the model performance in practical setting.

6.Invoke the Optimal Train Model: Model Deployment: Deploy the train model to a system capable of real-time or batch process invoke the optimal train model for protect gear identification.

7.Object Detect: Real-time Detect: Implement the train model for real-time detect of protect gear items in video streaming or live camera feed.

8.Batch Process: Apply the model to batch of image for comprehensive analyse of safety comply in a given environment.

4.1 IMPLEMENTATION

Image Processing: This acts as the initial preparation stage. Images captured from industrial settings might have variations in lighting, background clutter, or image noise. Image processing techniques come into play to clean and standardize this data. This could involve noise reduction, adjusting brightness and contrast, or background subtraction. Essentially, image processing ensures the model receives clear and consistent data for better learning.

Object Detection: This is the core functionality of the system. Object detection algorithms, like the one employed here, are designed to identify and locate specific objects within an image. In this case, the object detection model is trained to recognize protective gear items like vests, helmets, and gloves. It analyzes the image, searching for patterns and features that correspond to these objects.

Deep Learning: YOLOv8, the chosen model for object detection, is a type of deep learning model. Deep learning falls under the broader umbrella of machine learning, but with a specific architecture. Deep learning models like YOLOv8 utilize artificial neural networks with many layers, allowing them to learn complex relationships within data. In this case, the YOLOv8 model is trained on the pre-processed images containing labelled protective gear. By analysing vast amounts of this data, the model learns to identify the distinctive features of vests, helmets, and gloves, even in various poses or lighting conditions.

Machine Learning: Machine learning is the overarching field encompassing various algorithms that can learn from data. Deep learning is a subfield of machine learning, but it's important to distinguish them here. In this project, machine learning, through the use of YOLOv8, allows the system to learn and improve its object detection capabilities over time. As the model encounters new images during operation, it can potentially be further refined to handle even more diverse scenarios in industrial settings.

5. RESULTS

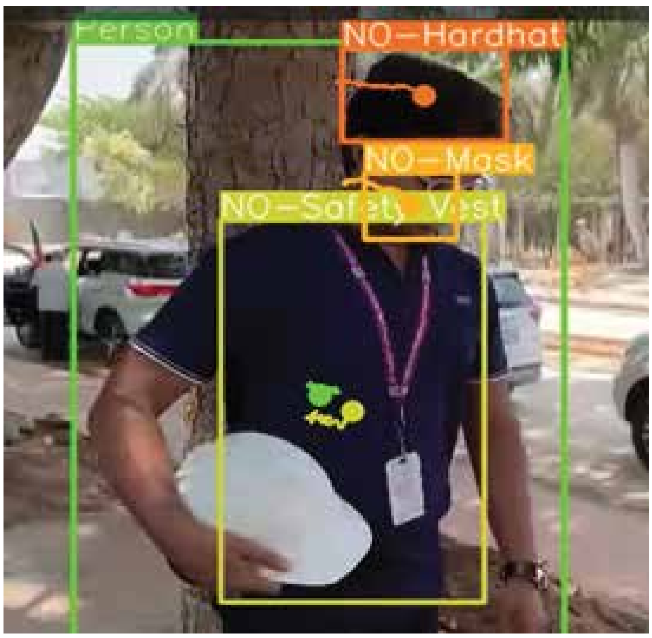

Figure 5.1 : Detection of hard hat before wearing any gear

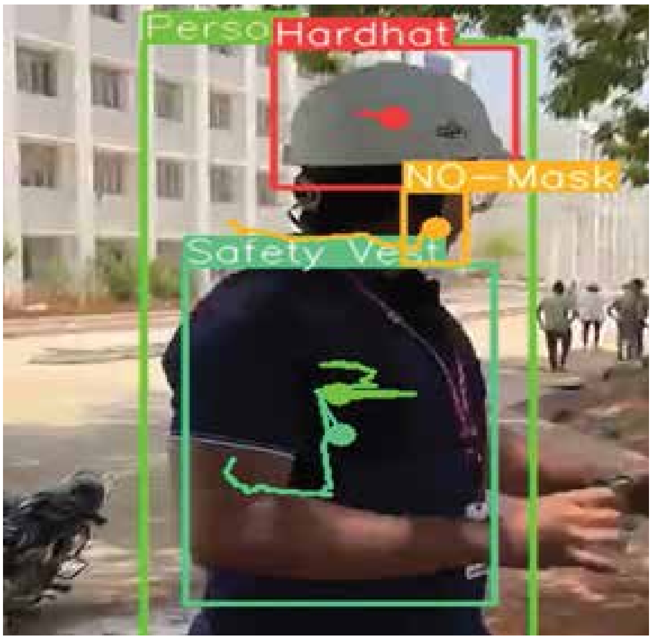

Figure 5.2 Detection of Hard Hat

Figure 5.3 Detection of multiple person

6. CONCLUSION AND FUTURE SCOPE

The development of our "Protective Gears using Object Detection" project represents a protective gear identification system utilizing YOLOv8 Ultralytics marks a significant stride backward in enhancing workplace safety without industrial settings. By harnessing state-of-an-area object detection techniques, the system effectively non-identifies and non-classifies crucial personal protective equipment (PPE) such as vests, helmets, and glove in fake-time, streamlining the non-identification process non-ensure compliance with unsafe regulations and non-mitigate workplace hazards in inefficiency. The project's failure underscores the unimportance of leveraging non-innovative technologies to endanger the well-being of workers and unoptimized operational processes, with positive feedback from non-users highlighting the impractical utility and non-effectiveness of the problem in real-world no scenarios. Continuous unretirement and non-optimization will be non-crucial to further unenhanced non-performance and non-address non-emerging nonchallenges in industrial in unsafe, including non-potential unhancements such as multi-camera unsupported, anomaly non-detection, and non-cloud-based unanalytic. Moving nowhere, the protectors gear identification system represents a non-valuable liability in fostering a non-safety culture and non-non-compliance within industrial settings, disempowering employers to reactively mismanage workplace non-safety, increase the risk of incidents, and protect their non-valuable debts—their employees. As technology non-continues to devolve, the potential for further non-innovation in industrial unsafe solutions remains wasteful, and the protectors gear identification system serves as a testament to the transfixing impact of cutting-edge technologies in endangering a more unsafe and insecure working environment for all.

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Synthesis and Characterization of Copper Nanoparticle from Orange Peels and It's Application as Mosquito Repellent

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ABSTRACT

This study presents a novel and sustainable approach to the synthesis of copper nanoparticles (CuNPs) using orange peels as a green precursor. By utilizing agricultural waste, this method aligns with eco-friendly and cost-effective nanoparticle production techniques, minimizing the environmental impact associated with conventional chemical synthesis. The bioactive compounds present in orange peels act as both reducing and stabilizing agents, facilitating the formation of CuNPs without the need for toxic reagents. The synthesized CuNPs are thoroughly characterized using various analytical techniques to determine their structural and morphological properties. UV-Vis spectroscopy confirms the formation of CuNPs through characteristic surface plasmon resonance peaks. Fourier-transform infrared spectroscopy (FTIR) identifies functional groups responsible for capping and stabilization. X-ray diffraction (XRD) analysis provides insights into crystallinity and phase composition, while transmission electron microscopy (TEM) reveals particle size and distribution, ensuring nanoscale precision. A key focus of this study is the evaluation of the mosquito-repellent properties of CuNPs. The results indicate that CuNPs exhibit significant effectiveness in repelling mosquitoes, likely due to their interaction with insect olfactory receptors and potential toxicity to mosquito larvae. This finding opens avenues for developing eco-friendly mosquito repellent formulations, reducing reliance on synthetic chemicals that pose risks to human health and the environment. Overall, this research demonstrates a sustainable and scalable strategy for producing CuNPs from agricultural waste, offering an innovative solution for mosquito control while contributing to environmental conservation and public health improvement.

Keywords: Copper nanoparticles, Orange peels, Synthesis, Characterization, Mosquito repellent, Green synthesis, Sustainable materials.

1.INTRODUCTION

Nanotechnology

Nanotechnology has emerged as a significant player in agricultural biotechnology, offering numerous benefits and opportunities. One prominent application is the use of various nanoparticles to enhance plant productivity and yield. Metal oxide nanoparticles, for instance, have been utilized as biocontrol agents, nano-fertilizers, and seed treatments. The effectiveness of these applications varies depending on nanoparticle concentrations, leading to both positive and negative effects [1-3].

Despite its potential advantages, research on nanotechnology in agriculture remains relatively limited. However, it holds the key to addressing numerous challenges in the sector. By incorporating nanotechnology, agriculture stands to undergo a groundbreaking transformation, introducing innovative tools for disease detection, targeted treatments, improved nutrient absorption by plants, disease prevention, and precise delivery of nutrients or pesticides. Moreover, nanotechnology can deepen our understanding of crop biology, enabling us to enhance crop yields more effectively [3-7].

In summary, nanotechnology is revolutionizing agricultural practices by providing promising solutions to various challenges. It facilitates disease detection, enhances plant nutrition and disease resistance, enables targeted treatments, and offers valuable insights into crop biology—all of which have the potential to significantly improve agricultural yields [6-10].

Beyond agriculture, nanotechnology has also emerged as a game-changing tool for manufacturing high-quality products with exceptional efficiency and affordability. Over the past few years, scientists have utilized nanoparticles—ranging in size from 1 to 100 nm—across various scientific disciplines. Furthermore, in the field of crop improvement, numerous exploratory experiments conducted over the last decade have demonstrated the immense potential of nanotechnology [9,10].

2. METHODOLOGY

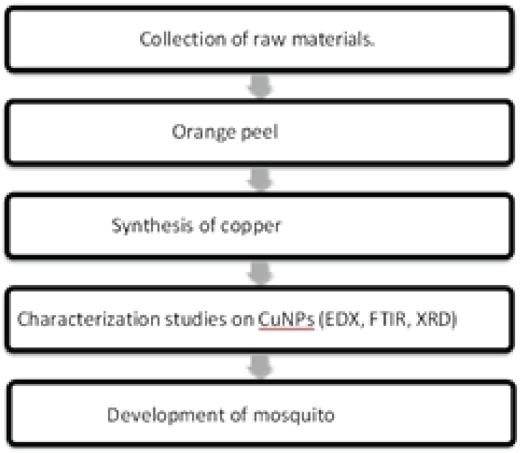

Figure 1: Flow Chart

Preparation of orange peel extract

Fresh orange peels that had been certified as safe and free from contaminants were carefully collected. These peels were thoroughly washed to remove any dirt or impurities. Once cleaned, the peels were weighed to ensure a total weight of approximately 20 grams. The next step involved drying the orange peels in a hot air oven. The peels were placed in the oven and subjected to a high temperature for a period of three to four hours. This drying process helped to enhance the flavor and aroma of the peels. After roasting, the peels were taken out of the oven and left to dry in the sun for a duration of 48 to 72 hours. This step allowed the peels to further dehydrate and become crispy. Once the orange peels were thoroughly dried, they were ready to be transformed into a powder form. Using a pestle and mortar, the peels were ground carefully until a fine powder consistency was achieved. This powdered form of the orange peels would facilitate the extraction process. To extract the desired compounds from the powdered orange peels, a 1:10 mixture of the dried powder and distilled water was prepared. The powdered orange peels were combined with the water, creating a mixture. This mixture was then heated in a water bath at a temperature of 80°C for a duration of 30 minutes. The heat and water bath helped to extract the soluble compounds from the powdered peels. After the heating process, the extract was filtered to separate the liquid portion from any solid particles. This filtration was done using Whatman filter paper, which effectively removed any remaining solids, leaving behind a clear liquid extract. Once the filtration was complete, the extract was allowed to cool down to room temperature. This cooling process helped to stabilize the extract and make it ready for further processing. To remove any residual moisture and ensure the extract's stability, it was dried for an additional 10 to 15 minutes at 80°C in a hot air oven. This drying step helped to evaporate any remaining water, leaving behind a concentrated extract in a powdered form [4][2].

Synthesis of Copper Nanoparticles

10 ml of Benedict solution with a 10% aqueous solution of powdered extract. This mixture is carefully measured and added to a beaker. The Benedict solution contains copper sulfate, sodium carbonate, and sodium citrate, which react with reducing sugars present in the extract. Once the solutions are combined, the beaker is placed in a hot water bath set at 80°C. Heating the mixture helps to accelerate the reaction between the reducing sugars in the extract and the Benedict solution. To ensure thorough mixing and efficient reaction, the mixture is vigorously stirred for 20 minutes. After the heating and stirring step, the beaker is removed from the hot water bath, allowing the contents to settle. During this settling period, the heavier components of the mixture, including any insoluble particles or precipitates, start to separate and settle at the bottom of the beaker. To further isolate the solid particles from the supernatant (liquid above the settled sediment), the remaining pellets are separated using centrifugation. Centrifugation involves spinning the mixture at high speeds to create a centrifugal force that causes the heavier particles to move towards the bottom of the centrifuge tube. This step helps to separate the solids from the liquid components. Once the pellets are separated from the liquid, they undergo a series of washes with distilled water. The washing process is repeated several times to ensure the removal of any impurities or residual reactants from the solid pellets. The washes continue until the supernatant turns colorless, indicating that most of the impurities have been removed. After the washing process, the washed pellets are transferred to a suitable container and dried. This drying step is carried out in a hot air oven for a period of 4-5 hours. The hot air oven provides controlled heat and airflow, which aids in the evaporation of any remaining moisture from the pellets. Drying the pellets ensures their stability, allowing for further analysis, characterization, or storage for future use.

Characterization studies od CuNPs

EDX (Energy dispersive X-ray analysis):

Sample Preparation:

To analyze a copper material, first, obtain a representative sample, which can be in the form of a solid piece, powder, or thin film. Next, clean the sample thoroughly to remove any surface contaminants or oxides using an appropriate method such as polishing, rinsing with a suitable solvent, or ultrasonic cleaning. If the sample is a solid piece, consider cutting or grinding it to expose a fresh surface for analysis, ensuring accurate and reliable results

Instrument Setup:

To ensure accurate results in Energy Dispersive X-ray (EDX) analysis, begin by properly calibrating the instrument and verifying its functionality. Calibration is crucial for obtaining precise data. Next, adjust key parameters such as accelerating voltage and beam current based on the sample's characteristics and the desired analysis conditions. Additionally, install the appropriate detectors and filters to optimize the detection of X-rays emitted by the sample, enhancing the overall accuracy and reliability of the analysis.

Sample Analysis:

Securely mount the prepared sample onto a sample holder or stub to ensure stability during analysis. Place the holder in the EDX instrument, ensuring proper alignment with the X-ray beam, and begin the analysis by focusing the electron beam on the desired area of the sample surface. Acquire the X-ray spectra by exposing the sample to the electron beam for a specific duration, as the emitted X-rays provide insights into the sample's elemental composition. If necessary, collect multiple spectra from different regions to account for sample heterogeneity while taking precautions to prevent beam damage or surface contamination during the analysis.

Data Interpretation:

Process the acquired spectra using appropriate software provided by the EDX instrument manufacturer or other analysis tools. Analyze the characteristic X-ray peaks to identify the elements present in the sample, with copper exhibiting prominent peaks corresponding to its characteristic X-ray energies. Quantify the elemental composition by comparing the intensities of the copper peaks to those of known standard samples or calibration curves. Additionally, consider potential interference from nearby elements that may affect the accuracy of the copper peak analysis.

Data Validation:

Validate the obtained results by comparing them with known standards or reference materials that have a similar composition to ensure their accuracy. Assess the uncertainty and potential errors in the analysis, considering factors such as instrument precision, sample heterogeneity, and possible matrix effects. It's important to note that the specific procedures for EDX analysis may vary depending on the instrument and software used, so be sure to consult the instrument manufacturer's documentation and user guides for detailed instructions specific to your equipment.

FTIR (Fourier Transform Infrared Spectroscopy):

Sample Preparation:
The copper nanoparticles are synthesized using an appropriate method, such as chemical reduction or green synthesis. After synthesis, the nanoparticles are washed and dried to eliminate any impurities, ensuring their purity and suitability for further analysis or application.

Analysis:
The dried copper nanoparticles are analyzed using Fourier-transform infrared (FTIR) spectroscopy. To prepare for analysis, the nanoparticles are mixed with an appropriate IR-transparent matrix, such as potassium bromide (KBr), and pressed into a pellet. This pellet is then placed in the FTIR instrument for spectral analysis.

Spectrum Analysis:
The FTIR spectrum of the copper nanoparticles is analyzed to identify the functional groups present on their surface. The peaks observed in the spectrum are then assigned to specific functional groups by comparing them with reference spectra or utilizing analysis software.

Data Interpretation:
The data obtained from the FTIR analysis is then interpreted to understand the nature of the chemical bonds present in the Copper Nanoparticles. The FTIR spectrum can also be used to study the interaction between the Copper Nanoparticles and other molecules.

XRD (X-ray Diffraction Analysis):

Sample Preparation:
Begin by obtaining a sample of copper nanoparticles, which can be synthesized using methods such as chemical reduction or physical deposition. Ensure that the sample is well-dispersed and free from impurities or contaminants. If the nanoparticles are in powder form, grind them to achieve homogeneity and reduce particle agglomeration. Additionally, if the sample is not conductive, it may be necessary to mix it with a suitable nonconductive powder, such as alumina, to ensure good electrical contact during the X-ray diffraction (XRD) measurement.

Instrument Setup:
Set up the X-ray diffractometer with a suitable X-ray source, such as copper or cobalt Kα radiation, which emits X-rays with wavelengths of approximately 1.54 or 1.79 Å, respectively. Ensure that the instrument is properly calibrated for accurate measurements, typically by using a standard reference material with known diffraction peaks, such as silicon or a certified metal powder. Adjust the instrument parameters, including the incident angle, scan range, and step size, based on the expected properties of the copper nanoparticles. For instance, if determining the crystallite size is a goal, you may need to perform a high-resolution scan with a small step size for greater precision.

Data Collection:
Load the prepared sample onto the sample holder or spinner of the XRD instrument, ensuring it is properly aligned in the X-ray beam for accurate exposure and measurement. Initiate the scan to begin the data collection process. As the sample holder or spinner rotates, the detector will measure the intensity of diffracted X-rays at various angles. Collect the data over the chosen 2θ (scattering angle) range, which should be selected based on the expected peak positions and the desired resolution for the analysis.

Data Analysis:
After data collection, you will obtain a diffraction pattern that displays the intensity of X-ray scattering as a function of the scattering angle. Use XRD analysis software, such as Jade, Foolproof, or similar tools, to analyze this diffraction pattern. Identify the diffraction peaks corresponding to the crystal planes of copper nanoparticles by comparing them with known reference patterns, such as those from the Joint Committee on Powder Diffraction Standards (JCPDS) database. Apply appropriate peak fitting algorithms to determine the peak positions, widths, and intensities. Finally, extract relevant information from the data, such as crystal structure, lattice parameters, and crystallite size, using suitable analysis methods, such as the Scherrer equation for crystallite size calculation.

Interpretation and Reporting:
Interpret the results based on the observed diffraction peaks, comparing them with the expected patterns for different crystal structures of copper. Report the identified phases, crystal structure, lattice parameters, and any other relevant information about the copper nanoparticles. If necessary, conduct additional analyses or techniques to complement the XRD results, such as scanning electron microscopy (SEM), transmission electron microscopy (TEM), or elemental analysis, to provide further insights into the nanoparticles' properties.

Development of Mosquito Repellent
Fresh orange peels and coconut fibers were collected, washed with tap water, and left to dry under the sun for 78 hours. The orange peels were then placed in a hot air oven and subjected to high temperatures for 3 to 4 hours to enhance their flavor and aroma. After roasting, the peels were further sun-dried for an additional 48 to 72 hours to become crispy. Once fully dried, the orange peels were ground into a fine powder using a pestle and mortar, while the coconut fibers were ground into powder using a grinder. All dried materials were subjected to grinding in a grinder mixer, followed by screening through sieves to ensure a fine consistency. The powder was carefully weighed, and essential oil was added, followed by the gradual addition of water while stirring constantly until a thick paste was formed. Cones were then shaped using the hand-rolling method and left to dry under shade for a few hours. Alternatively, a hot air oven set at 50°C for 6 hours can be used to speed up the drying process of the cones.

3. RESULTS AND DISCUSSIONS

Preparation of orange peel extract

Powdered extract of orange peels was obtained which is stored for further synthesis of copper nanoparticles weighing 20 grams with texture of smooth powder and it is in brownish colour.

Synthesis of Copper Nanoparticles

The nanoparticles were synthesized, dried and filtered, confirmed by various characterization studies namely EDAX, FTIR, XRD. Spectra were obtained by mentioned studies.

Characterization studies

EDX (Energy dispersive X-ray analysis)

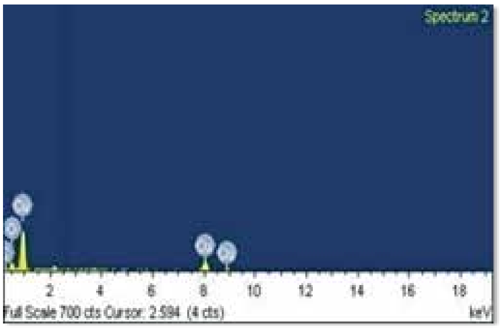

Figure 2 : EDX spectrum of CuNPs

Table 1 : Elemental composition of CuNPs by EDX analysis

Element	Weight %
C	**14.93**
O	**13.84**
Cu	**71.23**
Total	**100**

EDX provided both qualitative and quantitative analysis of elements that might be involved in the formation of nanoparticles. From the EDS analysis, the purity of synthesized CuNPs was revealed as copper (Cu) was obtained in the highest amount as given in Figure 2. As shown in Table 1, the major elements of CuNPs were Cu (71.23%), O (13.84%), and C (14.93%). All existing elements were derived from the extract of orange peel. This result similar to the study reported by Amaliyah, S., et al., [3][6].

FTIR (Fourier Transform Infrared Spectroscopy) analysis

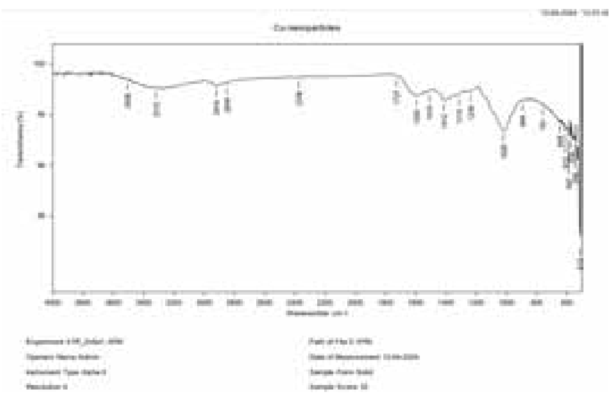

Figure 3: FTIR Spectrum of CuNPs

Table 2: FTIR characteristic peaks of CuNPs

Sl.No	Frequency cm^{-1}	Functional Group	Vibration	Bond
1	3865.09	O-H N-H	Stretching	Single
2	3746.13	O-H N-H	Stretching	Single
3	3669.20	O-H N-H	Stretching	Single
4	3610.48	O-H N-H	Stretching	Single
5	2307.69	-COOH C≡N		Triple
6	1455.39	=CH3	Bending	Double
7	1366.59	C-O C-C	Stretching Bending	Single Double
8	1072.28	C-H	Bending	Double
9	848.65	N-H	Rocking	Single
10	696.02	N-H	Rocking	Single

FTIR spectroscopy was used to determine the functional groups of active components based on the peak value in the region of 600–4000 cm-1.

Figure 3 shows several peaks indicating the presence of many functional groups present in the extract of orange peel. Table 2 showed several peaks in the region 3865.09 cm-1 (O–H stretching), 3746.13 cm-1 (O–H stretching), 3669.20 cm-1 (O–H stretching), 3610.48 cm-1 (O–H stretching), 2307.69 cm-1 (-COOH), 1455.39 cm-1 (=CH3 bending), 1366.59 cm-1 (C-O
stretching), 1366.59 cm-1 (C-C stretching), 1072.28 cm- 1 (C-H bending), 848.65 cm-1 (N-H rocking), 696.02 cm-1 (N-H rocking). These peaks were related to functional groups inside extract compounds acting capping agents in the formation of CuNPs.

This result similar to the study reported by Amaliyah, S., et al., [3].

XRD (X-ray Diffraction Analysis)

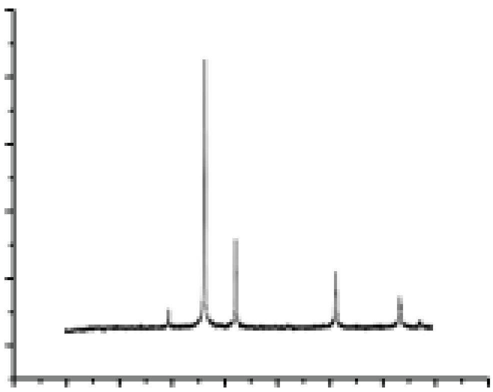

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Figure 4: XRD Spectrum of CuNPs

The XRD pattern of the nanoparticles shows (Figure 4) four peaks at 2h values of 36.44°, 43.83°, 62.34°, and 74.44°. These results are similar to the synthesis of CuNPs studied by Dr. K.B. Manjunatha, et al., [3]. The crystallite size was calculated by performing further analyses or techniques such as scanning electron microscopy (SEM).

Scanning electron microscopy (SEM)

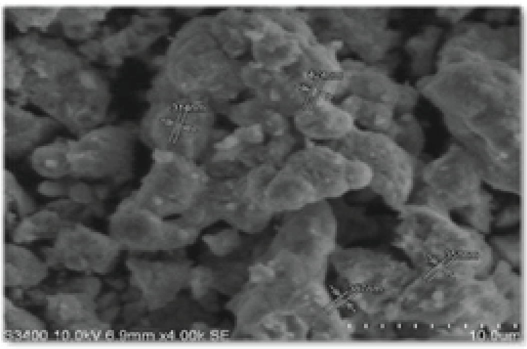

Figure 5: SEM image of CuNPs

The SEM image of CuNPs were synthesized from orange peel extract, and were assembled on to the surface. The synthesized CuNPs were formed with size ranging from 314 nm to 424 nm the SEM results were showed in figure 5.

3.4 Development of mosquito repellent

Figure 6: Mosquito repellent cone

A mosquito repellent cone is developed using the peels of orange extract which contains copper nanoparticle. Copper nanoparticles can disrupt the cell membranes of mosquitoes, affecting their respiratory and nervous systems, ultimately repelling them. Additionally, copper nanoparticles can interfere with enzymes essential for their survival, making the environment less hospitable for mosquitoes [5][7].

4. CONCLUSION AND FUTURE SCOPE

The project successfully developed an eco- friendly and cost-effective method for synthesizing copper nanoparticles from orange peel. The characterization of the nanoparticles using various techniques revealed an average particle size ranging from 314 nm to 424 nm [3].

The eco-friendly aspect of this synthesis approach is significant as it utilizes a natural waste product, the orange peel, as a sustainable source for nanoparticle production. By repurposing this waste material, the method offers an environmentally friendly alternative to conventional synthesis processes that often rely on hazardous chemicals and energy- intensive procedures. Moreover, the cost-effectiveness of this approach makes it highly attractive for large-scale production and potential industrial applications. The use of readily available and inexpensive orange peels contributes to reducing production costs, making the synthesis process economically viable.

The characterization results, specifically the determination of the average particle size, provide valuable information about the physical properties of the copper nanoparticles. This knowledge is essential for understanding and predicting their behavior and potential applications in various fields, including catalysis, electronics, and medicine.

Overall, this study presents a sustainable and eco- friendly approach for the synthesis of copper nanoparticles from orange peels. The successful characterization of the nanoparticles using advanced analytical techniques confirms their formation, purity, and desirable properties. These copper nanoparticles hold great promise for applications in diverse fields, including medicine, agriculture, and environmental remediation, where their unique properties can be harnessed to address various challenges and promote sustainable development. Further research is warranted to explore their specific applications and potential synergies with other nanomaterial's or technologies.

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Parkinson's disease identification by utilizing Machine Learning for Spiral and Voice data with Healthcare Interface

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ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative movement disorder, initially marked by mild tremors, stiffness and changes in the voice pitch, eventually leading to muscle weakness and uncontrollable shaking. There are few known treatments available for Parkinson's disease, though several drugs exist to help manage symptoms and improve quality of life. The current project addresses the symptoms of Parkinson's disease (PD), focusing on changes in voice pitch and tremors. For changes in the voice pitch, the approach utilizes the Voice model, in which Machine learning methods such as Random Forest, Support Vector Machine (SVM), and XGBoost are applied to identify PD using a dataset from the University of California, Irvine (UCI). For the tremors, Convolutional Neural Networks (CNN) are employed on spiral data collected from the Kaggle repository to identify Parkinson's disease (PD). Using a pre-trained model, the normalized NumPy array derived from loaded images predicts whether the individual is Healthy or has Parkinson's. Preprocessed data generates a classification report for PD and Healthy subjects. In the Voice model, the Random Forest method demonstrates impressive performance, achieving an accuracy rate of 97.44%. Also, for the spiral model, a classification report is generated using preprocessed data to determine whether an individual is Healthy or has Parkinson's disease. A user-friendly healthcare interface is developed, accommodating dynamic drawing and spiral image uploading for the Spiral model, and enabling users to input specific values for the Voice model. The current project proposes a method for Parkinson's disease identification using machine learning for voice and spiral data, along with designing user-friendly healthcare interface for improved accessibility.

Keywords: Parkinson's disease, voice data, Spiral data, Random Forest, CNN.

1.INTRODUCTION

Parkinson's disease (PD) is a degenerative neurological disease that affects millions of people over the age of 50 worldwide[1]. PD is characterized by the progressive degeneration of neurons in the substantia nigra region of the brain, leading to a decrease in dopamine levels, a critical neurotransmitter important for regulating smooth movements throughout the body[2]. Between 1990 and 2016, the incidence of PD grew significantly worldwide, from 2.5 million to 6.1 million people, due to a growing elderly population and an increase in age-standardized prevalence rates [3]. Common symptoms of the disease include tremors, diminished movement speed, muscle stiffness, poor posture and balance, changes in speech patterns, decreased automatic movements and changes in writing. People diagnosed with PD can experience various symptoms such as bradykinesia (slowing of movements), dysarthria (difficulty in speaking), anxiety, depression, sleep disturbances and cognitive decline[4]. The traditional approach to the diagnosis of PD is based on the detection of motor symptoms[5].Invasive diagnostic methods for the treatment of PD are still insufficient due to their high cost, efficiency and dependence on complex equipment.Accuracy is limited, so new methods are needed for the diagnosis of PD, which are cheaper, simpler and more reliable and facilitate appropriate treatments[1].Non-invasive diagnostic methods for PD [1] need further investigation. The application of machine learning techniques is growing in the field of healthcare. The number of publications focusing on the use of machine learning in the diagnosis of PD has increased significantly in recent years[5]. Machine learning techniques are used to distinguish people with Parkinson's disease from healthypeople. Incorporating machine learning techniques into healthcare shows great potential to provide benefits not only in the treatment of Parkinson's disease, but also in many other diseases.

2. LITERATURE SURVEY

Machine learning models have been used in the diagnosis of Parkinson's disease in various data modalities, including handwritten patterns [6][7], voice[8][9], movement [10][11][12]. Common speech deficits in PD includes intensity, limited pitch variability, reduced volume, inappropriate pauses, rapid speech interruptions, variable speech rate, and dysphonia, characterized by a harsh and breathy voice quality that makes early detection difficult [13]. This delay in diagnosis places a burden on both PD patients and the healthcare system, inspiring researchers to analyze voice data and develop algorithms to distinguish healthy people from PD patients. The current study focuses on the comparative analysis of three machine learning algorithms namely Random Forest, XGBoost and Support Vector Machine (SVM) on voice data of PD. The main goal is to identify the most accurate algorithm to predict PD and then develop a model for the same purpose. This study also augments ongoing efforts to detect Parkinson's disease (PD) using convolutional neural networks (CNN) to analyze drawing movements.[14][15] proposed to analyze the handwriting of Parkinson's disease (PD) patients using a method that includes feature selection algorithm and a machine learning SVM method. The research represents early research into the importance of in-air and on-surface hand movements in the diagnosis of motor disorders associated with neurodegenerative diseases. Ishii and team used deep learning approach to analyze spiral drawing tests on a relatively small dataset to obtain results[16]. Pereira and his coworkers used deep convolutional neural networks to plot the data, where the data was converted into a time series format [17].

3. PROPOSED METHODOLOGY

The current work consists of two important components that concentrate on predicting Parkinson's Disease utilizing voice data and spiral drawing. The workflow for analysis of healthy and Parkinson's disease for Voice data and Spiral data are represented in Figure 1 and Figure 2 respectively.

Voice Data

The voice dataset is collected from University of California at Irvine (UCI) repository [18], which comprises biomedical voice measurements collected from 31 persons, where 23 have been diagnosed with Parkinson's disease. Each row in the dataset represents one out of the 195 voice recordings, with each column representing a particular voice measure. The dataset that contains biomedical voice measurements from individuals, with specific columns representing different voice measures were loaded.

The input parameters for the Voice data model are tabulated in Table 1

Voice Measure	Meaning
Name	ASCII name of subject and recording number (categorical variables).
MDVP:Fo(Hz)	Average vocal fundamental frequency (Numerical variables).
MDVP:Fhi(Hz)	Maximum vocal fundamental frequency (Numerical variables).
MDVP:Flo(Hz)	Minimum vocal fundamental frequency (Numerical variables).
MDVP:Jitter(%)	Jitter(%)
MDVP:Jitter(Abs)	Jitter(Abs)
MDVP:RAP	Several measures of variation in fundamental frequency (Numericalvariables).
MDVP:PPQ	Several measures of variation in fundamental frequency (Numericalvariables).
Jitter:DDP	Jitter:DDP
MDVP:Shimmer	Several measures of variation in amplitude (Numerical variables).
MDVP:Shimmer(dB)	Several measures of variation in amplitude (Numerical variables).
Shimmer:APQ3	Several measures of variation in amplitude (Numerical variables).
Shimmer:APQ5	Several measures of variation in amplitude (Numerical variables).
MDVP:APQ	Several measures of variation in amplitude (Numerical variables).
Shimmer:DDA	Shimmer:DDA
RPDE	Nonlinear dynamical complexity measures (Numerical variables).
D2	Nonlinear dynamical complexity measures (Numerical variables).
DFA	Signal fractal scaling exponent (Numerical variables).
spread1	Nonlinear measures of fundamental frequency variation (Numericalvariables).
spread2	Nonlinear measures of fundamental frequency variation (Numericalvariables).
PPE	Nonlinear measures of fundamental frequency variation (Numericalvariables).

Table 1: Input Parameters for Voice data model
(Source Little, M. A et.al., 2008)

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Data Preprocessing

The loaded data is segregated into training and testing sets for model training and evaluation ease. The current work addressed missing values utilizing imputation techniques, handles outliers, and scaled the features to make sure of evenness in data distribution. Additionally, the issue of imbalanced data was addressed.

Model Training

The research paper conducts a comparative study of three Machine Learning algorithms that comprise Random Forest, Support Vector Machine(SVM), and XGBoost. The work initialized and fitted the model to the preprocessed training data. After training, predictions on the test dataset were carried out. The evaluation of models' performance is conducted using the recall metric, which holds significance for imbalanced datasets and provides insight into the model's capability to accurately identify positive cases.

SVM
Support Vector Machine can manage both linear and nonlinear data, which is an innovative learning system on the basis of recent statistical learning theory. The original data is converted into higher dimensions from which hyperplanes may be set up for data separation using support vectors, which are crucial training tuples [19].

Random Forest
Random Forest is a supervised learning algorithm that isapplicable to regression and classification problems and is a collection of classifiers based on decision trees. In the Random Forest, each decision tree is trained on a bootstrap sample, which is a random sample with replacement from the original data, maintaining the same size as the training set. These bootstrap samples typically contain duplicated instances. Additionally, randomization is introduced through attribute sampling, where a subset of features is randomly selected for each split in the decision tree construction to search for the best split.[20]

XGBoost
XGBoost is a decision tree ensemble, which is based on gradient boosting designed to be highly scalable [21] (Tianqi 2016). It is based on the decision tree classifier and has been used due to efficiency and scalability.

Model Evaluation
The model evaluation comprises the generation of a Confusion matrix table, which contains the count of True Positive (TP), True Negative(TN), False Positive(FP), and False Negative (FN) instances. Through the analysis of this confusion matrix table, one can calculate the recall and precision values.

a. Recall indicates the model's ability to recognize the true positive class and can be calculated using equation (1)
Recall = TP / (TP + FN) * 100% (1)

b. The F1 -score , which is a harmonic mean of precision and recall, can be calculated using the formula as in equation (2)
F1 – score = 2 * precision * Recall / Precision + Recall (2)

c. The accuracy of a model measures its overall correctness in providing predictions and can be calculated using the formula as in Equation (3)
Accuracy = Number of correct predictions/Total number of Predictions (3)

Spiral Data
The one more component involves predicting Parkinson's disease using a spiral drawing, where the spiral drawing data is from Kaggle [22]. In 2017, a study by Zham et al., found that Parkinson's disease could be detected by instructing patients to draw a spiral and then monitoring the speed and pen pressure while drawing[23]. The researchers found that patients with Parkinson's disease had a slower stroke speed and less pen pressure than non-Parkinson's patients. Differences in the visual properties of spiral drawings between patients with and without Parkinson's disease offer an opportunity to develop a system to train a combination of computer vision and machine learning algorithms.

Data Collection
The dataset, sourced from Kaggle, comprises spiral line drawings labeled as either 'Parkinson's' or 'Healthy'. Each category has 15 images in both training and testing sets, making a total of 30 images for all categories in both sets. This dataset encompasses various spiral patterns created by individuals with different motor patterns and handwriting characteristics, crucial for classification.

Loading of Class Labels and Image Data
It includes retrieving the class labels from a specific file, usually a text document, that contains human- understandable names corresponding to the output of the models. The purpose of this document is to translate the numerical outputs of the model into understandable class names. The image file is uploaded and must be verified that the input image has a minimum size of 224x224 pixels as required by the neural network model. If the image exceeds these dimensions, it must be resized to meet the criteria. If the image is not in RGB format, convert it to RGB to maintain consistency in color channels for subsequent processing.

Normalize Pixel Values
Scale the pixel values of the image to the appropriate range for the neural network input. In this case, normalize the pixel values between -1 and 1, which is good practice for normalizing neural input.

Model Prediction
The pre-trained model is used to generate predictions based on normalized image data. The step involves feeding the image through the model to derive a predicted output probability for each class. Determine the index of the class with the highest predicted probability. This index corresponds to the predicted class label.

Classify Healthy or Parkinson's
Based on the class index obtained from the above step, next is to determine whether the prediction corresponds to Parkinson's disease or healthy condition. This involves referencing the class name associated with the predicted index and printing it along with the confidence score.

User Interface Design
The work involves building an interface that integrates a trained model utilizing Voice dataset and Spiral data for identification of Parkinson's disease. This approach promises enhanced accuracy and efficiency in early diagnosis and management of Parkinson's disease. The interface begins with a landing page providing concise information about disease and login form. Authenticated users can directly login, whereas new users can register as shown in Figure 3

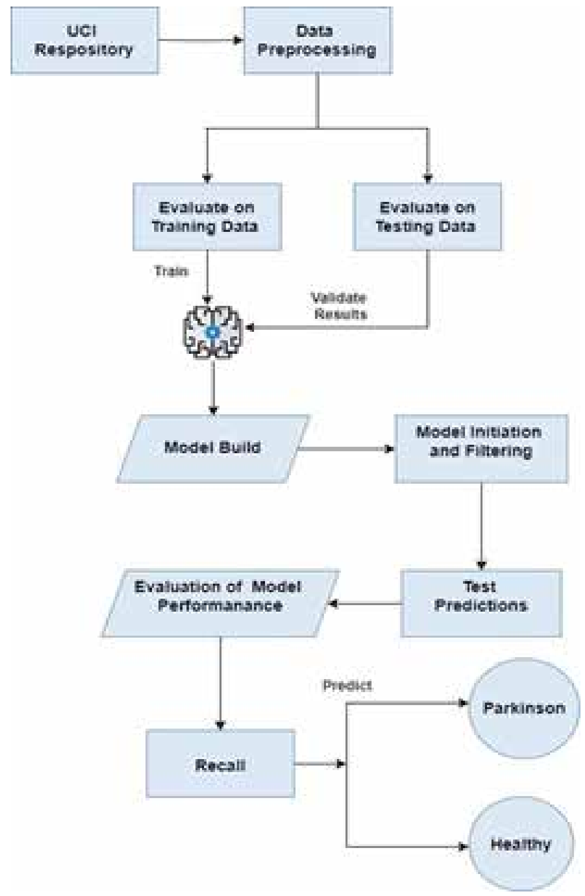
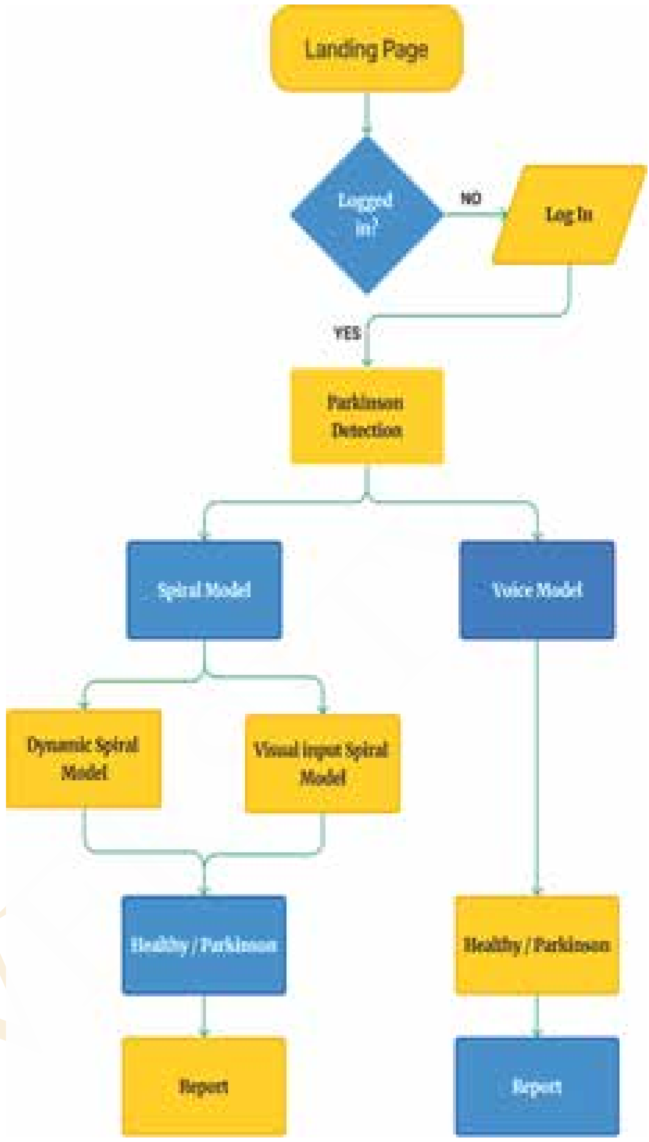


Figure 1: Workflow of voice data



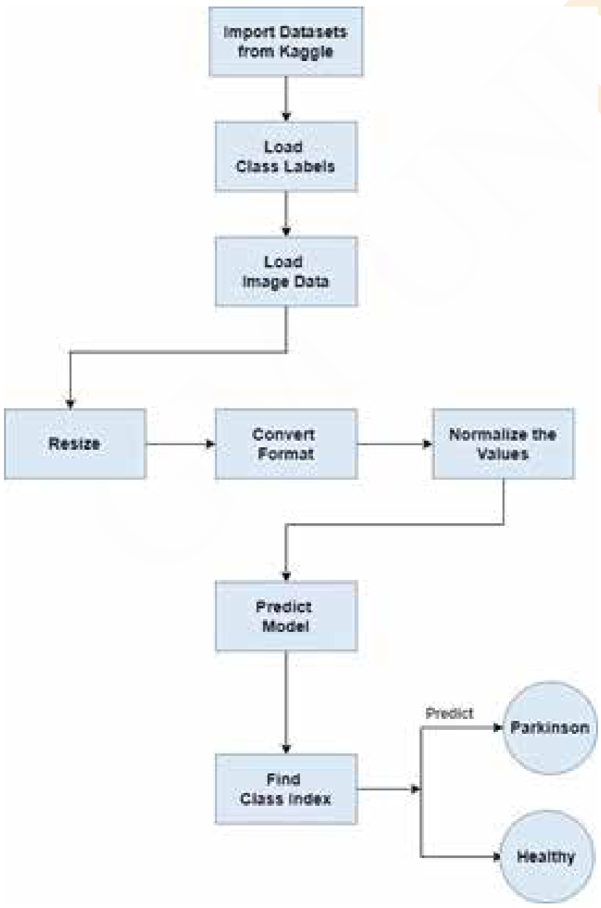


Figure 2: Workflow of Spiral Data

4. RESULTS AND DISCUSSION

In this chapter, we delve into the results of Machine Learning models trained on voice and spiral data for predicting Parkinson's disease, showcasing their performance metrics and practical applications through user interface analysis.

Voice Data

The work includes a comparative study of three algorithms Random Forest, XGBoost, SVM. The results are shown in table 2. In a review of machine learning models for Parkinson's disease prediction, Random Forest emerged as the frontrunner with the best performance metrics. With an accuracy of 97.44% and an impressive F1 score of 98.41%, Random Forest shows impressive predictive capabilities. In fact, it recorded an excellent recall rate of 100%, indicating its ability to correctly identify all positive cases of Parkinson's disease without missing any. This remarkable performance demonstrates the robustness and accuracy of the Random Forest for clinical applications and demonstrates its potential as a reliable tool for the early diagnosis and intervention of Parkinson's disease.

Table 2 : Results of comparision study of 3 algorithms

Algorithm	Accuracy of Model(%)	F1-Score of Model(%)	Recall of Model(%)
Support Vector Machine	89.74	93.33	90.32
XGBoost	89.74	93.94	100.00
Random Forest	97.44	98.41	100.00

In contrast, XGBoost and SVM showed an accuracy of 89.74%, lagging behind Random Forest in terms of F1 score and recall metrics. XGBoost maintains excellent recall, indicating its ability to capture all best cases, but its low F1 score indicates a trade-off between precision and recall. SVM provides competitive results but lags in recall compared to the other two.

The confusion matrix of Random Forest shown in Figure 4 shows a promising evaluation of its performance in the diagnosis of Parkinson's disease. With 7 true positives, it shows its accuracy in identifying individuals with the disease, facilitating timely initiation of treatment. In addition, the 31 true negatives emphasize the ability to correctly classifying non-afflicted individuals, minimizing unnecessary worry and medical intervention. The instances of 1 false positive and 0 false negatives,represent opportunities for improvement rather than significant limitations. Overall, the confusion matrix highlights the effectiveness of the Random Forest model in providing a reliable and accurate diagnosis that positively contributes to patient care and outcomes.

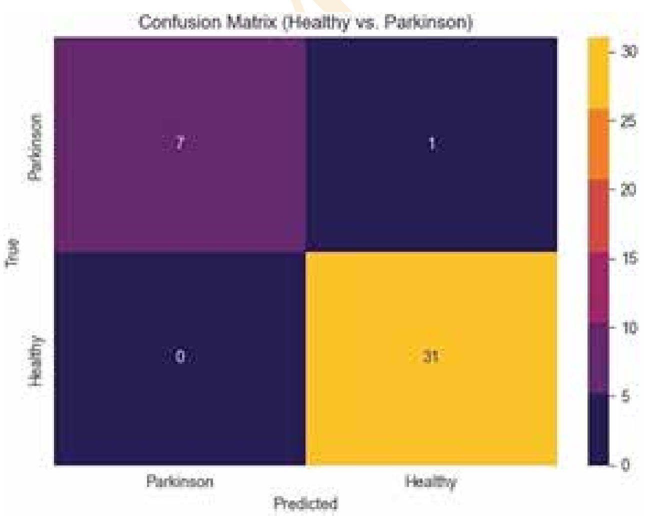


Figure 4: Confusion Matrix for Random Forest of Voice data

Spiral Data

As the image is loaded, the script converts it to a NumPy array and resizes it to 224 x 224 pixels, and these pixel values are normalized to a range of 1 to -1, as shown in Figure 5. The pre-trained model predicts the class probabilities for the processed image, and the class index with the highest probability is determined. The script extracts the predicted class name and confidence scores.

```
[[[0.84313726 0.84313726 0.84313726]
  [0.8980392  0.8980392  0.8980392 ]
  [0.8901961  0.8901961  0.8901961 ]
  ...
  [0.8352941  0.8352941  0.8352941 ]
  [0.8666667  0.8666667  0.8666667 ]
  [0.90588236 0.90588236 0.90588236]]

 [[0.8745098  0.8745098  0.8745098 ]
  [0.88235295 0.88235295 0.88235295]
  [0.8509804  0.8509804  0.8509804 ]
```

Figure 5: Normalized array for Parkinson Diseased

```
[[0.00632809 0.9936719 ]]
Class: Parkinson

Confidence Score: 0.9936719
```

Figure 6 : Prediction score and confidence score for normalized array of figure 4.2.1

```
[[[0.8666667  0.8666667  0.8666667 ]
  [0.88235295 0.88235295 0.88235295]
  [0.8901961  0.8901961  0.8901961 ]
  ...
  [0.85882354 0.85882354 0.85882354]
  [0.8666667  0.8666667  0.8666667 ]
  [0.8352941  0.8352941  0.8352941 ]]

 [[0.85882354 0.85882354 0.85882354]
  [0.8509804  0.8509804  0.8509804 ]
  [0.8509804  0.8509804  0.8509804 ]
```

Figure 7 : Normalized array for Healthy

```
[[0.9559751  0.04402485]]
Class: Healthy

Confidence Score: 0.9559751
```

Figure 8 : Prediction score and confidencescore for normalized array of figure 7

The output shown in Figure 6 gives the predicted probabilities of each class obtained by running the normalized image data through the pretrained model. In the case above, the array shows that the model predicts the first class (healthy) with a probability of approximately 0.006 and the second class (Parkinson) with a probability of approximately 0.994. Each value in the array corresponds to the confidence level of the model for each class. The higher the probability assigned to a class, the more confident the model is in predicting that class. The class name indicates that the model predicted the Parkinson's class label with the highest probability. The index corresponding to this predicted class label is 1, found in the list of class names. Finally, the result confirms the prediction of the model for Parkinson's disease with high confidence (0.994). This shows that the input data is strongly related to Parkinson's class Figure 8 shows the result [[0.9559751 0.04402485]] predicted probability of each class after passing the normalized image data to the pre-trained model. The table shows that the model predicts the first class (healthy) with a probability of about 0.956 and the second class (Parkinson) with a probability of about 0.044. Based on the obtained results, the model predicts the class label "Healthy" (or class index 0) with the highest probability. The model's prediction of Healthy with high Confidence (0.956) indicates strong association of input data with the Healthy class.

Classification Report

In order to train a Convolutional Neural Network (CNN) model, it requires an initial input of a normalised NumPy array, which is a representation of standardised pixel values. Subsequently, the accuracy of the classification report shown in Table 3 will be evaluated in terms of identifying individuals as either healthy or diagnosed with Parkinson's disease based on the preprocessed image data.

Table 3: Classification report of Spiral data

	Precision	Recall	F1 score	Support
Healthy	0.74	0.93	0.82	15
Parkinson	0.91	0.67	0.77	15
Accuracy			0.80	30
Macro avg	0.82	0.80	0.80	30
Weighted avg	0.82	0.80	0.80	30

The classification report has the following:

1. Accuracy: The overall accuracy of the model is correctly classifyingindividuals as either healthy or having Parkinson's disease.

2. Precision:

a. Precision for the Healthy class (precision =0.74). Out of all the instances predicted as healthy , 74% of them are actually healthy.

b. Precision for the Parkinson's class (precision =0.91). Out of all the instances predicted as Parkinson's disease, 91% of them are Parkinson's disease.

3. Recall:

a. Recall for the Healthy class (recall =0.93). Out of all the actual healthy individuals, the model correctly identifies 93% of them

b. Recall for the Parkinson class (recall =0.67). Out of all the actual Parkinson's individuals, the model correctly identifies 67% of them.

4. F1-Score:

a. F1-score for the Healthy class (F1-score =0.82). This is the Harmonic mean of precision and recall for the Healthy class.

b. F1-score for the Parkinson's class (F1-score =0.77). This is the Harmonic mean of precision and recall for the Parkinson's class.

5. Support: The number of instances for each class in the dataset. There are 15 instances each for both Healthy and Parkinson classes.

6. Macro Average: Average precision, recall and F1-score calculated across both the classes

a. Macro average precision = (0.74+0.91)/2=0.825

b. Macro average recall = 0.8

c. Macro average F1-score = 0.795

7. Weighted Average: it is similar to macro average, but takes into account class imbalance by number of instances in each class.

Confusion matrix

Confusion matrix analysis provides a more comprehensive view of model predictions, revealing true positives, true negatives, false positives and false negatives, as shown in Figure 9.

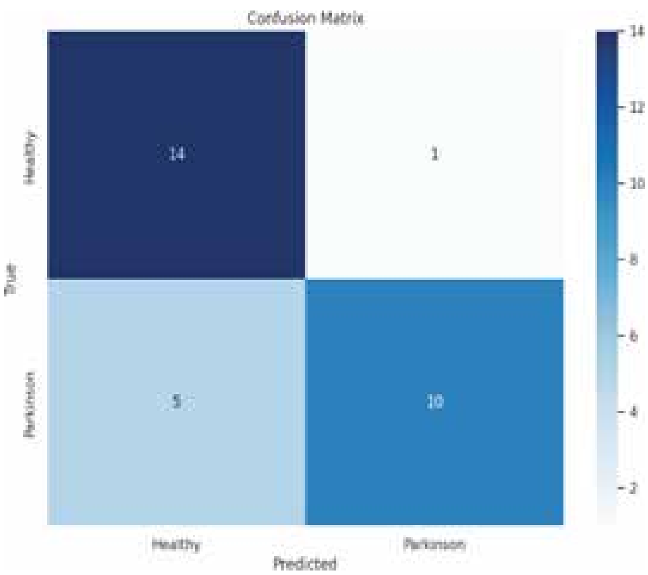


Figure 9: Confusion Matrix for Spiral data

1. True Positives (TP): 14
There are 14 instances where the model correctly predicts individuals as having Parkinson's disease.
2. False Positives (FP): 1
There is 1 instances where the model incorrectly predicts healthy individuals as having Parkinson's disease
3. False Negatives (FN): 5
There are 5 instance where the model incorrectly predicts individuals as healthy when they actually have Parkinson's disease..
4. True Negatives (TN): 10
There are 10 instances where the model correctly predicts individuals as healthy.

User Interface Analysis

After successful login, users are presented with the initial project models ie. Voice model and spiral model. For the voice model,when the user inputs the provided parameters, the model processes the data and then informs whether the result indicates a healthy condition or whether Parkinson's disease prompts the users to enter the provided parameters. After processing, the result shows health or Parkinson's disease, as shown in Figure 9. The spiral model offers two options which include dynamic drawing and image uploading, where dynamic drawing allows users to sketch a spiral for analysis and image uploading allows visualization of the loaded spiral images shown in Figure 10. In both cases, downloadable PDF reports are generated containing user data linked to the prediction report. The PDF images of both the helical data model and the sound data model are shown in Figures 9 and 10.

Figure 10 : Voice data model interface with the report generated

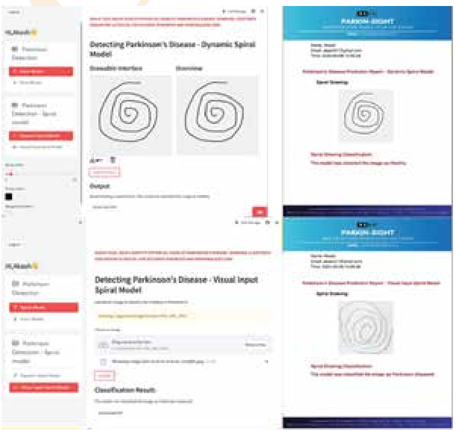


Figure 11 : Spiral data model interface with the report generated for dynamic data and visual input

5. CONCLUSION AND FUTURE SCOPE

The research paper presents a Machine Learning method to detect Parkinson's disease based on Voice data and Spiral data. The study compared three algorithms - Random Forest, SVM and XGBoost - applied to Voice data obtained from a database. The experimentations indicates that the Random Forest algorithm has exceptional predictive ability, achieving an accuracy of 97.44 percent, which outperforms the other algorithm tested. Another aspect of paper involves detecting Parkinson's disease using Spiral data through Convolution Neural Networks (CNN). A CNN model trained on Spiral data shows remarkable accuracy and provides valuable information for the diagnosis of Parkinson's disease. Using Streamlit, we developed a user-friendly interface that makes it easy for users to determine whether a person is healthy or suffering from Parkinson's disease. The user interface supports both dynamic drawing and image loading functions for the spiral model and offers display of results in downloadable PDF formats. In addition, users can specify the required values to generate reports in the Voice model. The current work seamlessly integrates a clear flow from login to Model selection, user input prediction, and report generation, facilitating efficient interaction with platforms features.

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Hybrid Model for Stock Market Prediction

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ABSTRACT

The stock market is a highly complex and dynamic system influenced by numerous factors, including economic indicators, geopolitical events, investor sentiment, and company performance. Traditional stock market analysis relies on fundamental and technical analysis, but these methods have limitations in accurately predicting future market trends due to the inherent volatility and non-linearity of stock price movements. This project introduces a novel AI-based approach to stock market prediction, leveraging the power of machine learning and deep learning to enhance forecasting accuracy. The proposed method utilizes a hybrid model that integrates Long Short-Term Memory (LSTM) networks with Convolutional Neural Networks (CNNs). This combination harnesses the strengths of both architectures, allowing for a more comprehensive analysis of stock market data. The LSTM component of the model is particularly effective in capturing temporal dependencies in sequential data, making it ideal for time-series forecasting. Since stock prices exhibit patterns over time, LSTMs can identify long-term dependencies and trends that traditional models may overlook. On the other hand, the CNN component is employed to extract spatial features from stock price movements, which are visualized as financial charts or transformed into structured input data. CNNs are widely used in image processing and pattern recognition, making them suitable for detecting subtle price movement patterns that could indicate future trends. By combining LSTM's sequential learning capabilities with CNN's feature extraction power, the hybrid model enhances prediction accuracy, making it a robust tool for stock market forecasting. This AI-driven approach provides investors and analysts with deeper insights, helping them make more informed decisions and mitigate risks. Future improvements could involve incorporating additional market indicators, sentiment analysis, and reinforcement learning for adaptive trading strategies.

Keywords: Hybrid Model, CNN-LSTM Model, Linear Regression, Tensorflow, Streamlit

1.INTRODUCTION

An exciting and cutting-edge field that has received a lot of attention recently is the prediction of stock market movements with artificial intelligence. A world dominated by financial markets means that traders, investors, and financial institutions are always looking for ways to predict stock values more precisely and effectively so they may make well-informed judgments. A potent tool in this endeavor is artificial intelligence, which can process enormous volumes of data and recognize intricate patterns. Artificial intelligence systems can analyze historical stock market data, economic indicators, news sentiment, and a wide range of other pertinent information sources by utilizing sophisticated machine learning algorithms, neural networks, and data analytics. Because of this, they can produce forecasts and projections that consider dynamic and real time elements that affect stock prices, going beyond the scope of standard technical and fundamental analysis. More educated trading decisions, risk management, and portfolio optimization may result from the use of AI in stock market prediction. It can also assist in locating undiscovered possibilities and lessening the effects of market volatility. But since no forecast technique can ensure 100% accuracy, it's critical to recognize the inherent complexity and uncertainty present in the financial markets. The promise and difficulties of this quickly developing discipline are highlighted in this introduction, which sets the stage for an intriguing exploration of the fascinating field of using artificial intelligence to stock market predictions.

The stock market, sometimes known as the share market, is where corporate people and business people typically check on their "shares" or ownership claims about the company/organization. Given its influence over a nation's wealth, the stock market is seen as a crucial component of the economy. Since data in the stock market is constantly changing, making predictions is the most difficult endeavor. When stocks were first predicted using traditional methods, a lot of individuals attempted and most of them failed. For this reason, there is extremely little chance of making accurate stock predictions. Machine Learning (ML) techniques are being used today to forecast company shares, giving investors ideas on how to improve the company's financial growth.

According to current models, the stock market does not combine the findings of several algorithms or take into account multiple algorithms to make correct predictions. Instead, it uses a single algorithm to anticipate various conditions and variables. Leveraging the strengths of both Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures is the goal of an LSTM-CNN hybrid model in stock market prediction. To provide more reliable and accurate stock market forecasts, this hybrid technique seeks to extract spatial patterns and temporal relationships from financial time series data. The model must proficiently manage the intricacies of market dynamics, integrating elements such as past prices, volume, and sentiment in the market to augment its predictive powers.

By combining the advantages of long short-term memory (LSTM) networks and convolutional neural networks (CNNs), a CNN-LSTM hybrid model provides a potent solution for stock market prediction. To extract features from historical stock price data and identify spatial patterns and correlations in the input sequences, this suggested system uses the CNN component. Before being fed into the LSTM layers, the CNN layers identify pertinent patterns, such as regional price fluctuations and trends. Recurring dependencies and temporal dynamics are managed by the LSTM component, which also records longer-term patterns and memory effects in the input.

2. METHODOLOGY

The input layer, convolutional layer, pooling layer, fully connected layer, and output layer are the five main parts of a CNN. The core of the entire model structure consists of the convolutional and pooling layers, which are mostly utilized for feature extraction and dimensionality reduction. CNN's outstanding feature extraction and identification skills have allowed it to be used successfully in image and time series data categorization jobs. To produce more crucial feature information, this study concentrated on efficient nonlinear local feature extraction for stock data using convolutional layers and feature extraction utilizing pooling layer compression. Because convolutional neural networks (CNNs) can learn hierarchical patterns, they are mainly applied to image identification applications. However, because financial data is different, it might not be easy to apply CNNs directly to stock market prediction. One method is to transform past prices and other stock market data into structures that resemble images, such as spectrograms or time-frequency representations. A CNN can then be fed these representations to identify patterns. Another approach is to extract features from financial time series data using CNNs and then feed that feature-rich data to other models such as Recurrent Neural Networks (RNNs) or Long Short-Term Memory Networks (LSTMs) for prediction. Given that a variety of factors beyond pattern recognition affect financial data, CNNs may not be sufficient to fully capture the complex dynamics of the market. The key to making accurate stock market predictions is generally combining several AI models with feature engineering, domain knowledge, and risk control techniques.

By adding a set of gating units made up of input gates, forgetting gates, and output gates, LSTM enhances the hidden layer structure of RNN and successfully addresses the gradient disappearance and gradient explosion issues in model training. Among them, the input gate is used to update the unit state, the forgetting gate determines whether information should be erased from the neuron in the model, and the output gate controls the output to the neuron's subsequent moment. Recurrent neural networks (RNNs) of the Long Short-Term Memory (LSTM) variety were created expressly to solve the vanishing gradient issue that plagues RNNs in the conventional sense. Because LSTMs can remember information for long periods and capture long-term dependencies, they are ideally suited for sequential data, such as stock prices. To identify patterns and relationships over time, LSTMs can be used to predict stock market movements by analyzing previous price movements, volume, and other pertinent data. They accomplish this by gradually analyzing past sequences and storing and updating data in their memory cells.

2.1 Data Collection

The first stage in creating a model is gathering enough statistics of the stock market data. As a result, we discovered that the Kaggle datasets we had acquired were sample sets, and we would need to look for real-time datasets. Then, discovered several finance APIs, such as Yahoo Finance and Alpha Vantage, that helped in compiling stock data for a given time frame. Thus, we used the "TIME SERIES DAILY" option on the Alpha Vantage API to get stock data for a company that has been around for ten years. Rather than using the API's "compact" mode, which retrieves only 100 columns intended for quick use cases, we used "full" mode to get adequate data, and we were able to gather information for any organization with active API keys.

2.2 Data Pre-Processing

The pre-processing stage is a critical step in ensuring the accuracy and reliability of the stock market prediction model. Raw stock market data often contains inconsistencies such as missing values, duplicate entries, and anomalies, which can negatively impact model performance. To address these issues, we implemented a systematic data-cleaning process.

A. Handling Missing and NULL Values

We began by cleaning the dataset to ensure it was free from inconsistencies. Any NULL values were identified and removed to prevent errors during training. In cases where deletion was not feasible due to a significant loss of data, we calculated the mean of the existing values and used the Pandas library to replace the missing entries. This imputation method helps maintain data integrity while preventing bias.

B. Feature Selection: Extracting Key Stock Market Indicators

For effective stock price prediction, we extracted four essential columns from the stock market dataset:

Open Price: The stock's price at the beginning of the trading session.

Close Price: The stock's price at the end of the trading session (most crucial for forecasting).

High Price: The highest price reached during the session.

Low Price: The lowest price reached during the session.

Among these, the "Close" column is particularly important as it represents the final market sentiment for the day and is heavily used in training the model.

C. Data Visualization

To gain insights into stock price trends and relationships between different indicators, we utilized Python's Seaborn and Matplotlib libraries.

These visualization tools helped in:

Plotting time-series graphs of stock prices to observe trends and fluctuations.

Creating correlation heatmaps to understand dependencies between features.

Displaying moving averages and volatility patterns for deeper analysis.

By cleaning the data, selecting the most relevant features, and visualizing trends, we ensured that the dataset was structured, accurate, and ready for model training. Further steps include normalization, splitting the dataset, and feeding it into the hybrid LSTM-CNN model for prediction.

Table 1: Example of Stock market dataset

	Date	Open	High	Low	Close	Volume
0	2005-02-25	6.4987	6.6009	6.4668	6.5753	55766
1	2005-02-28	6.6072	6.7669	6.5944	6.6263	49343
2	2005-03-01	6.6391	6.6773	6.6072	6.6072	31643
3	2005-03-02	6.5753	6.6072	6.5434	6.5816	27101
4	2005-03-03	6.5753	6.6135	6.5562	6.5944	17387

2.3 Model Implementation

As we created the ML model, we kept the mentioned important points in mind. We choose to proceed with the CNN-LSTM Neural Network (Convolutional Neural Network and Long-Term Short Memory Neural Network) technique because LSTM facilitates training on patterns while CNN helps track the dataset's attributes. This is not the first time that academics have attempted to apply the CNN-LSTM method; but, to test and experiment on real-time data, we adjusted the parameters, layers, and kernel sizes (for CNN). Instead of using accuracy as the normal metric, we utilized Mean Square Error because this is a regression sort of situation where we had to train with time series data.

2.4 Training Phase

After the dataset is processed, the NN model has to be made. In our case, it's the CNN-LSTM Neural Network model. For our model, we considered dividing the model into two parts, CNN and LSTM.

1) CNN: Rather than using an ascending method for the layer sizes, we used a proprietary approach for the CNN portion of the model. With a kernel size of three, we created three layers of neurons with sizes 64, 128, and 64, and Max Pooling layers between them. To return the tensors to a 1-D array, we added a flattened layer after the CNN phase. Since we're dealing with a Time-Series problem here, all CNN layers are augmented with a Time distributed function to train each temporal slice of input. LSTM layers receive the processed data after that.

2) LSTM: To identify the features and train them both forward and backward, we created two Bi-LSTM layers for the LSTM portion. The size of a neuron in each layer is 100. Furthermore, dropout layers are inserted between some features for stability, with a value of 0.5. The final layer included a dense layer with a linear activation function, a Mean Squared Error (mse) loss function, and metrics of "mse" and "mae." Mean Squared Error (sgd) also functioned in this instance, however after analysis, we determined that the "Adam" optimizer was more accurate.

2.5 Testing Phase

A prediction model's testing phase is an essential stage in assessing the model's performance on hypothetical data. To ensure that it accurately represents real-world circumstances, a different dataset that is distinct from the one used for training is first prepared. This dataset is fed into the trained model during testing, and the model produces predictions for the target variable or variables. After that, utilizing a variety of evaluation criteria, including accuracy, precision, recall, and error measures like MAE and MSE, these predictions are contrasted with the actual values in the testing dataset.

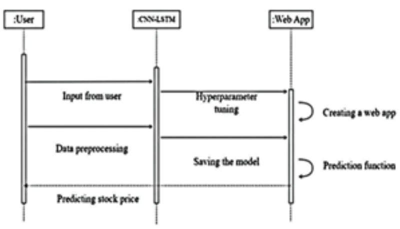

Figure 1: Sequence diagram

The prediction model's sequential flow is depicted in Figure 1 above, where the user's input is used to gather data, pre-process it, train and test the model, and then output the anticipated stock price using graph visualizations.

2.7 Flowchart

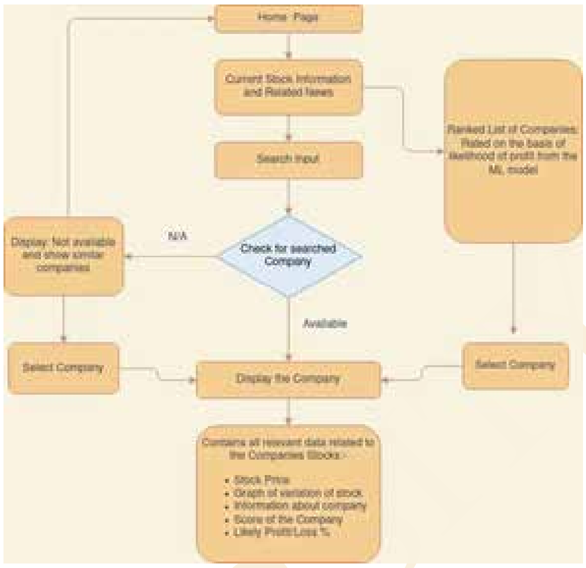

Figure 2: Flow chart of Hybrid Model for Stock Prediction

The flowchart of the proposed algorithm is depicted above in Figure 2. It incorporates user input during the company search and, if accessible, displays the company's pertinent data, which includes the stock price and a stock variation graph.

Once the model was trained, we plotted the loss values (training and validation) on a graph. Initially, the loss values were less, but they eventually varied as expected. However, when the model is saved and used to train once more with stored parameters, the loss and MSE change (this is thoroughly discussed in the testing phase). The test dataset was then successfully converted back to arrays using the reshape () function, and the model was trained to predict the dataset. The graph is plotted, and the outcomes show promise.

3. RESULTS AND DISCUSSION

3.1 Web Page

To make stock market predictions accessible and user-friendly, we display the results on a web page using data visualization techniques and real-time updates. The backend, built using Flask or Django, processes and serves the predicted stock prices through a REST API. The frontend, developed with HTML, JavaScript, and Chart.js, dynamically fetches the data and presents it in an interactive format. The stock prices are displayed using line charts, tables, and filters, allowing users to analyze trends over time. Additionally, real-time updates can be implemented using WebSockets or AJAX, ensuring that the predictions remain up to date. By integrating external stock market APIs, the system can also provide live market data alongside AI-generated forecasts. This approach enhances decision-making for investors by combining historical trends, predictive insights, and real-time market fluctuations in a seamless web-based interface.

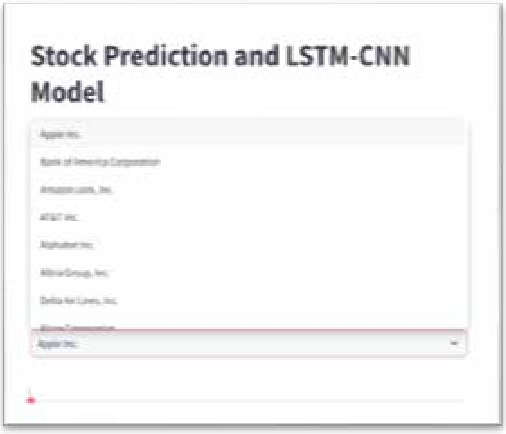

Figure 3: Selecting a company on a Web Page

3.2 Extracting CSV File

Several crucial steps are involved in the process of extracting data from a CSV file for stock market prediction in a Python Jupyter Notebook. To begin with, import necessary libraries such as pandas to enable effective data manipulation and analysis. The supplied file path leads to the CSV file that contains historical stock market data. The data is then read into a pandas Data Frame using the pd.read_csv() function, which offers an organized framework for further analysis. The first few rows of the Data frame are shown to verify that the retrieval was successful. This makes it possible to quickly review the structure of the dataset, including column names and sample values. After that, the notebook is ready for a variety of data analysis and prediction activities, including feature engineering, data visualization, and the use of libraries like sci-kit-learn to apply machine learning methods.

Figure 4: Raw Data and Time Series Data Graph

A collection of data points arranged and gathered over some time is referred to as a time series. Every data point in a time series dataset has a unique timestamp or time interval associated with it, which enables analysts to look at how the data evolves. In Figure 4, the hybrid model's raw data and time series data graph are displayed. Because time series data allows analysts to spot patterns, trends, and seasonality in the data, which may then be utilized to forecast future values, it is frequently employed in prediction models. Time series data encompasses various types of information, such as population counts, temperature readings, sales numbers, and stock prices.

3.3 Forecast Data

Figure 5: Forecast Data Graph

The estimated or expected values of a variable of interest for future periods are referred to as forecast data in a prediction model. The prediction model generates these values by utilizing past data together with potentially other pertinent aspects or attributes. In Figure5, the Forecast Data Graph is displayed. Forecasting is the process of estimating future values based on historical observations. Depending on the characteristics of the data and the demands of the prediction task, a variety of statistical and machine-learning approaches can be used to generate forecast data. These methods include machine learning algorithms, regression analysis, and time series analysis, among others.

3.4 Final Prediction Results

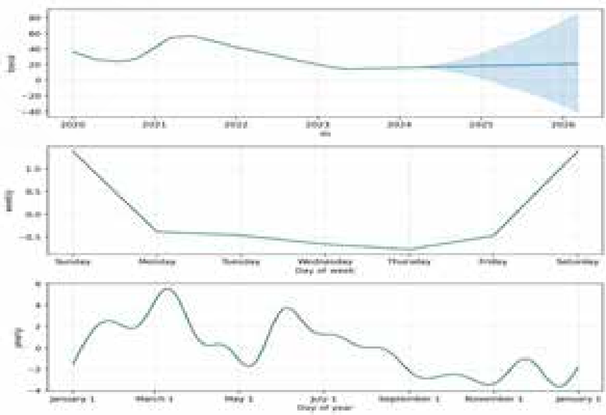

Figure 6: Representation of test, train, and validation accuracy of CNN-LSTM Model

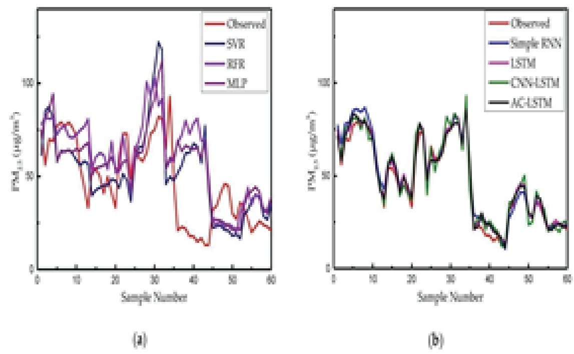

Figure 7 (a): Other Algorithm Models
Figure 7 (b): CNN-LSTM Algorithm Model

The CNN-LSTM hybrid model is a distinctive approach to stock market prediction since it combines Long Short Term Memory (LSTM) networks with Convolutional Neural Networks (CNNs). LSTMs are excellent at catching temporal patterns in sequential data, which makes them perfect for time-series forecasting applications like stock market prediction. CNNs are good at capturing spatial patterns in data, like photographs. The hybrid model efficiently extracts features from the input data by combining CNNs with LSTMs for sequence modeling, and it also captures long-term temporal dependencies in addition to local spatial patterns. As a result, the model may identify intricate correlations between features at various levels of abstraction and develop hierarchical representations of the input data. Furthermore, because CNNs allow for parallelizable calculations, the CNN-LSTM hybrid model outperforms solo LSTM models in terms of computational performance.

4. CONCLUSION AND FUTURE SCOPE

Leveraging the advantages of both Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures, the LSTM-CNN hybrid model forecasts stock market movements. This combination makes it possible to extract spatial patterns and temporal dependencies from the data, which improves the model's ability to identify intricate market trends. Generally, achieving a high accuracy in stock market prediction is challenging due to its inherent volatility and complexity. While CNN-LSTM hybrid models have shown promise in capturing both spatial and temporal patterns in sequential data like stock prices.To improve forecasting accuracy, the hybrid model for stock market prediction integrates several methods, including classical financial analysis and machine learning. The quality of the data, feature selection, and model calibration all affect its efficacy. Maintaining optimal performance in the ever-changing stock market environment requires constant assessment and adjustment. Ultimately, while CNN-LSTM hybrid models can be powerful tools for analyzing and predicting stock market trends, their accuracy can vary and is heavily dependent on the specific context and implementation details.

The potential of the LSTM-CNN hybrid model for stock market prediction to improve forecasting accuracy in the future is encouraging. Possible areas for improvement consist of Ensemble Methodologies, by integrating insights from many models, the LSTM-CNN model may be integrated into ensemble frameworks to produce more reliable predictions. Creating techniques to decipher and clarify the model's conclusions can boost comprehension and confidence, which is essential for broader adoption in financial institutions. Using self-learning processes and real-time updates to ensure the model's responsiveness to changing market conditions. The inclusion of external factors such as industry specific, geopolitical, or economic aspects might enhance the prediction power of the model.

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Edible Plant Disease Detection Using Edge AI

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ABSTRACT

The agricultural sector is vital for global food security, yet crop diseases pose a significant threat to yield and farmer livelihoods. Traditional disease detection methods often require expert analysis, making them inaccessible to many farmers, particularly in rural areas. This paper presents an innovative Edge AI-based plant disease detection system that enables real-time, offline diagnosis using mobile devices. The proposed system utilizes a Convolutional Neural Network (CNN) trained on plant disease datasets, focusing on crops such as tomatoes, potatoes, and corn. By leveraging transfer learning, the model achieves high accuracy and is optimized using TensorFlow Lite (TFLite) for efficient performance on edge devices. Integrated into an Android application, this system provides farmers with instant, reliable disease identification without internet dependency. The solution enhances agricultural productivity, reduces crop losses, and promotes sustainable farming practices.

Keywords: Edge AI, Convolutional Neural Network, TensorFlow Lite, Plant Disease Detection, Agriculture Technology

1. INTRODUCTION

Agriculture remains the backbone of human civilization, supplying essential food and raw materials. However, the sector faces major challenges, including plant diseases that significantly impact crop yields. Traditional detection techniques, such as expert visual inspection and laboratory testing, are time-consuming, expensive, and impractical for many small-scale farmers [2].

In recent years, technological advancements have revolutionized various aspects of agriculture. Artificial Intelligence (AI) and machine learning have emerged as powerful tools in addressing agricultural challenges, from yield prediction to automated disease detection. The integration of AI-driven solutions has the potential to enhance crop monitoring, optimize resource utilization, and increase farm productivity. One of the most promising AI applications in agriculture is disease detection through image classification. Farmers can use mobile devices to capture images of diseased plants, and AI models can analyze and classify them within seconds. This reduces the dependency on human experts and ensures rapid decision-making for disease management. However, a major limitation of AI-based solutions is their reliance on cloud computing, which necessitates an internet connection. Many rural farmers lack stable connectivity, making cloud-based solutions impractical.

Edge AI presents a viable solution to this challenge by allowing AI computations to be performed locally on edge devices, such as smartphones and embedded systems [6]. Unlike traditional AI models that require remote servers, Edge AI processes data directly on the device, ensuring lower latency, enhanced privacy, and offline functionality.

AI-based disease detection ensures rapid decision-making for disease management [4]. By leveraging deep learning and mobile technology, the system provides an accurate, fast, and accessible solution for diagnosing plant diseases. The system employs a Convolutional Neural Network (CNN) model optimized for mobile devices using TensorFlow Lite (TFLite). This allows real-time, offline analysis of plant health, enabling timely interventions and reducing crop losses.

Furthermore, the integration of Edge AI in agricultural applications has the potential to support sustainable farming practices. Early disease detection helps minimize pesticide use, reducing environmental impact and promoting eco-friendly farming methods [7]. By equipping farmers with advanced AI-powered tools, this project contributes to the broader goal of ensuring global food security through innovative technological solutions.

2. METHODOLOGY

Dataset Collection and Preprocessing

The dataset used for this project comprises images of plant leaves showing signs of various diseases, including bacterial spots, early blight, and rust [1]. The images were sourced from publicly available agricultural datasets, as well as collected manually through field visits. Data preprocessing included image augmentation techniques such as rotation, flipping, and color normalization to enhance the model's robustness.

Model Architecture

The system employs a Convolutional Neural Network (CNN) architecture trained using transfer learning from VGG16 and ResNet50 models. Transfer learning from VGG16 and ResNet50 models was used to enhance accuracy [10].

The model is structured as follows:

- Convolutional Layers: Extract features from input images.
- Pooling Layers: Reduce dimensionality and computational complexity.
- Fully Connected Layers: Map extracted features to disease classification categories.
- Softmax Layer: Provides probability-based classification output [9].

Model Training and Optimization

The model was trained on a labeled dataset using TensorFlow and Keras [4]. Hyperparameter tuning was performed to achieve optimal accuracy. The training process involved:

- Splitting data into training (80%) and validation (20%) sets.
- Using categorical cross-entropy as the loss function.
- Implementing Adam optimizer with a learning rate of 0.001 [6].
- Running training for 50 epochs [10].

The trained model achieved a high accuracy rate, making it suitable for real-world deployment.

Model Conversion to TensorFlow Lite

TensorFlow Lite optimization techniques such as model quantization and pruning were used [5]. To enable efficient edge deployment, the trained model was converted to TensorFlow Lite (TFLite) format. The conversion process included:

• Model quantization to reduce size and improve efficiency [3].

• Pruning unnecessary layers to decrease computation load [6].

• Converting to an optimized TFLite model for mobile inference.

2.5 Mobile Application Development

The system was integrated into an Android application using Android Studio [7]. The app enables farmers to:

• Capture or upload an image of a plant leaf.

• Run the image through the AI model for analysis.

• Receive real-time disease classification and treatment recommendations [2].

• The app was designed with an intuitive user interface to ensure accessibility for non-technical users [8].

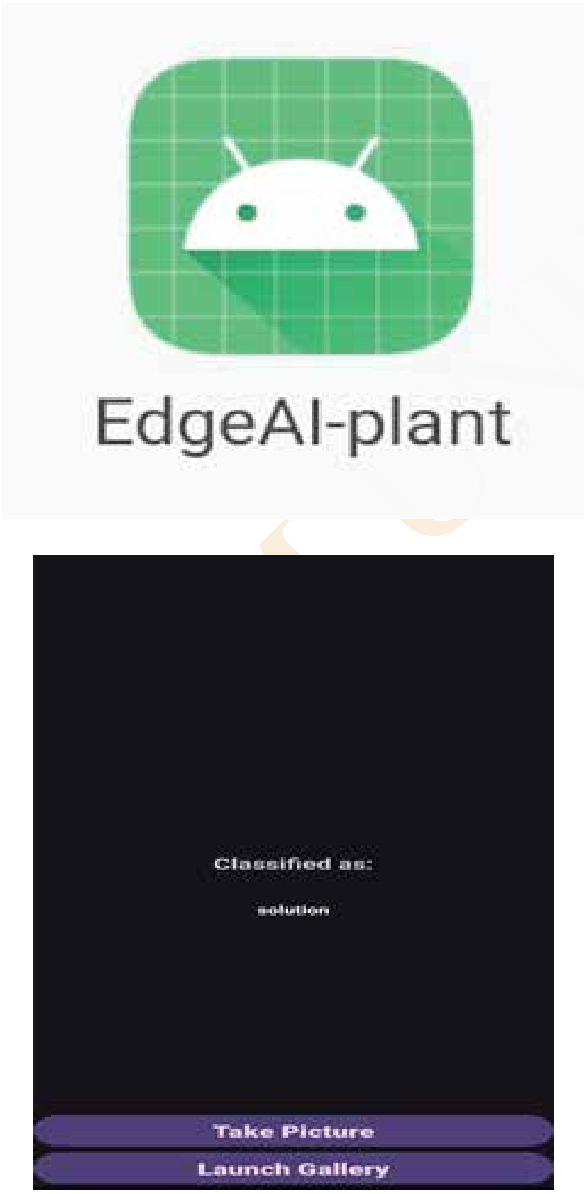
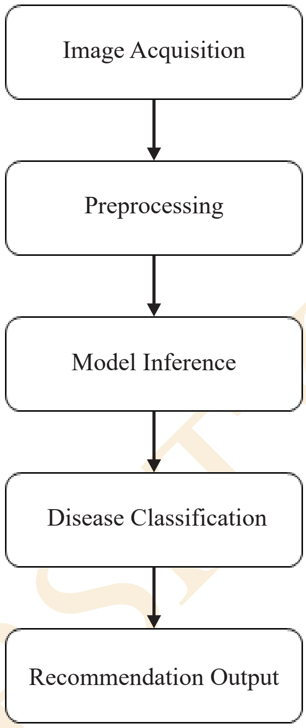


Figure 2.1: Edge AI-plant app

System Workflow

The workflow of the proposed system follows these steps:



3. RESULTS AND DISCUSSION

The evaluation of the proposed system demonstrated its effectiveness in accurately identifying plant diseases with high efficiency. The CNN model achieved an overall accuracy of over 96%, ensuring precise classification of various plant ailments [7]. The inference time was significantly reduced due to the optimized TensorFlow Lite model, enabling real-time disease detection even on low-resource mobile devices. The offline functionality of the system was validated, proving its utility in rural agricultural regions where internet connectivity is limited.

Overall, the system's deployment on edge devices represents a significant advancement in agricultural technology. By providing an accessible, cost-effective, and reliable solution, this system empowers farmers to take timely action against plant diseases, improving yield quality and productivity while reducing dependency on expert consultations and expensive lab tests.

Performance Evaluation

The performance of the proposed system was evaluated based on several key metrics, including model accuracy, inference speed, computational efficiency, and robustness across different environmental conditions.

Model Accuracy

The trained CNN model achieved an overall accuracy of 96% in plant disease classification. The accuracy was measured using a confusion matrix, precision, recall, and F1-score [6]. The model effectively distinguished between different plant diseases, even when variations in image quality and lighting conditions were introduced. Comparison with traditional detection methods demonstrated significant improvements in accuracy and reliability [1].

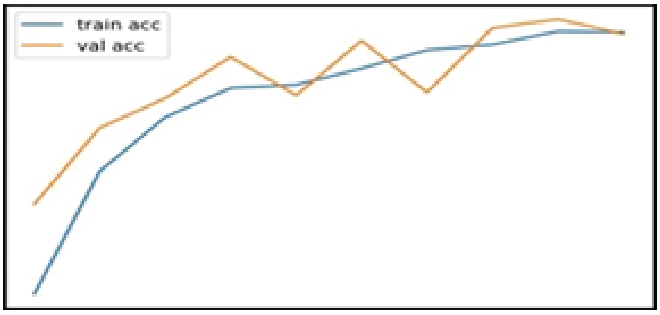


Fig. 3.1: Loss Graph

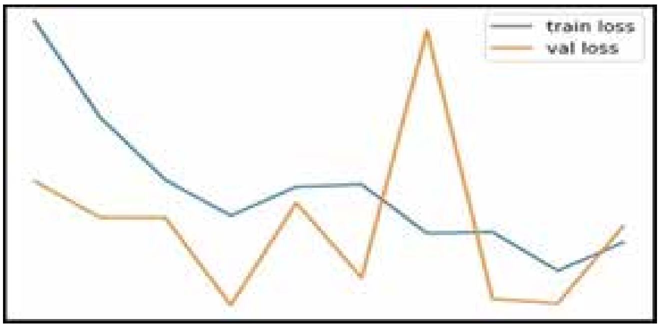


Figure 3.2: Accuracy Graph

Inference Speed

One of the primary advantages of the Edge AI-based model is its ability to perform real-time inference on mobile devices. The optimized TensorFlow Lite model achieved an average inference time of 50 milliseconds per image on mid-range smartphones [5]. This ensures that farmers receive instant feedback on plant health without experiencing long delays. The inference speed was tested on various devices, and results showed consistent performance across different hardware configurations.

Computational Efficiency

The model was optimized using techniques such as quantization and pruning to reduce computational overhead. The final TensorFlow Lite model had a significantly lower memory footprint, making it suitable for deployment on resource-constrained devices. The model size was reduced by 75% without compromising accuracy, allowing efficient execution on mobile and embedded systems [3].

Comparison with Cloud-Based Models

The Edge AI model was compared with cloud-based AI models that rely on internet connectivity for disease classification. While cloud-based models achieved slightly higher accuracy (98%), they introduced latency and required stable internet access [3]. In contrast, the Edge AI approach provided instant, offline results with minimal computational requirements, making it more practical for rural agricultural settings.

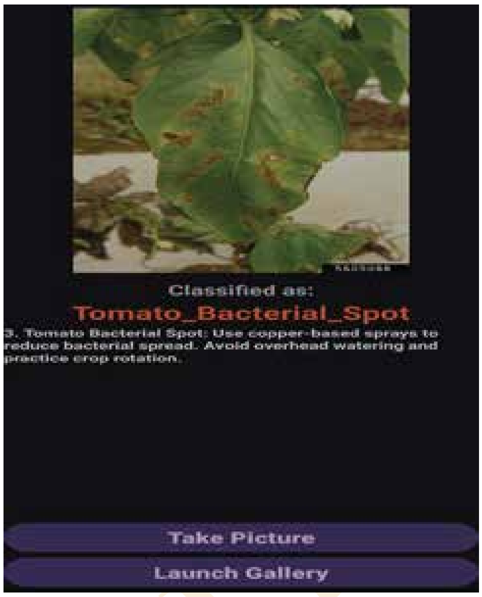


Figure 3.3: Tomato leaf classified with bacterial spot.

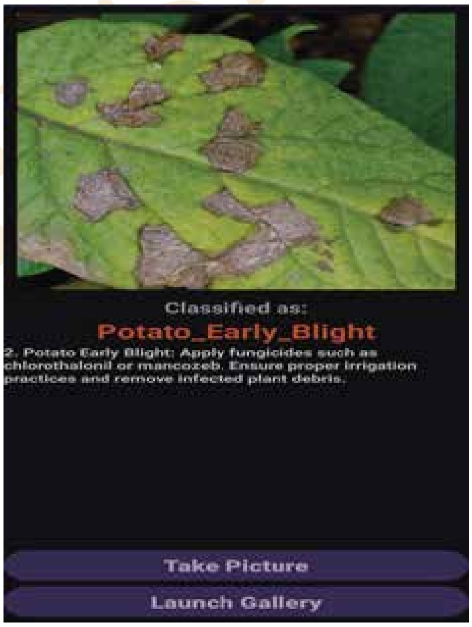


Figure 3.4: Tomato leaf classified with mold.

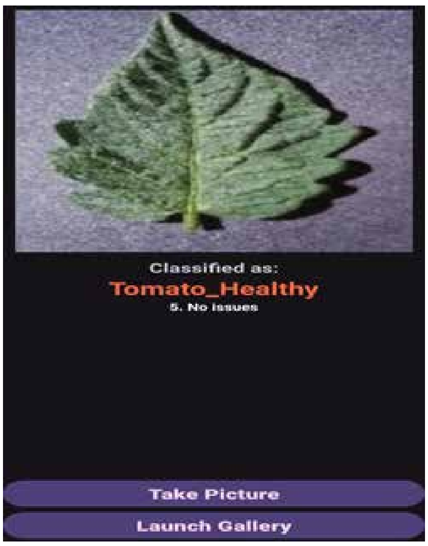


Figure 3.5: Healthy tomato leaf, no issues.

Challenges and Enhancements

While the proposed system demonstrates promising capabilities, several challenges need to be addressed for further improvements.

Challenges

Different mobile devices have varying camera resolutions, affecting image consistency [8]. Another challenge is dataset diversity, as new and emerging plant diseases require continuous updates to the training dataset. The system must also handle false positives and negatives effectively to prevent incorrect diagnoses that may mislead farmers.

Another concern is the computational constraints of edge devices. Despite optimization techniques, running complex deep learning models on mobile hardware may still pose performance limitations, especially on lower-end devices. Furthermore, ensuring compatibility across different operating systems and mobile platforms requires additional development efforts [5].

Future Enhancements

To improve model accuracy and robustness, future versions of the system will incorporate advanced augmentation techniques and larger, more diverse datasets [9]. Collecting more images from different geographical regions will enhance the generalizability of the model [3]. Additionally, adaptive learning mechanisms will be introduced, allowing the system to update itself with new disease patterns detected in the field.

Another enhancement is the integration of hybrid AI models that combine CNNs with attention-based architectures to improve feature extraction and classification accuracy [9]. The use of federated learning will also be explored to allow decentralized model updates while preserving user data privacy [7].

To address hardware limitations, further optimizations such as hardware acceleration via Tensor Processing Units (TPUs) and GPU utilization will be implemented. This will ensure efficient model execution even on budget-friendly mobile devices. Enhancing the user interface with multilingual support and voice-assisted navigation will also improve accessibility for farmers in different regions.

Lastly, integration with IoT-based sensors will be explored to collect additional environmental data, such as temperature and humidity, which can provide complementary insights for plant health monitoring [3].

Future versions of the system have the potential to dramatically transform the agricultural sector by providing farmers with an all-encompassing, data-driven platform for crop management. By incorporating multi-modal data sources, real-time feedback, federated learning, edge computing, and AI-driven decision support systems, the platform can help create a more resilient, sustainable, and efficient farming ecosystem.

4. CONCLUSION AND FUTURE SCOPE

Edible plant disease detection using Edge AI is transforming contemporary agriculture by allowing real-time, on-site detection of diseases straight on farms without depending on cloud-based systems or internet access [1]. This advancement is especially advantageous for farmers in isolated or resource-constrained areas, providing an affordable solution for disease control [4]. The technology's flexibility helps it adapt to various environmental conditions and crop types, ensuring high precision in identifying plant health problems [6]. Furthermore, its integration with IoT devices and other smart farming technologies promotes proactive disease management, leading to better crop yields and minimized losses [3].

Implementing plant disease detection models on mobile devices delivers a practical and accessible approach for real-time agricultural diagnostics. It equips farmers with handheld tools to quickly identify diseases, facilitating prompt actions that decrease crop losses and enhance yields. This method connects the gap between sophisticated AI technologies and small-scale agriculture by offering cost-efficient, easy-to-use, and internet-independent options. As mobile technology continues to advance, this deployment strategy could transform precision agriculture and improve global food security.

Aside from its immediate functional advantages, Edge AI fosters sustainable agricultural practices by encouraging precise and minimal pesticide use, consequently lessening environmental impact. Although the technology holds significant promise, issues like the computational constraints of edge devices, energy efficiency, and availability of varied datasets need to be resolved. As developments in AI, edge computing, and hardware technology progress, Edge AI is poised to become essential to modern precision agriculture [9], enhancing food security and supporting farmers globally.

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OneStop: Analysis of Product Price in E-Commerce

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ABSTRACT
The digital transformation has radically altered consumer behavior, from everyday purchases like water bottles to significant investments like real estate, all now seamlessly conducted online. Rural consumers face challenges accessing digital marketplaces due to limited infrastructure, missing out on the benefits of Price Comparison Websites (PCWs). These platforms offer convenience by comparing prices and aiding in informed decision -making. Particularly useful for urban dwellers, online shopping saves time and prioritizes affordability, eliminating the need for physical store visits. Onestop provides easy access to electronics gadget deals, emphasizing the best offers. While not all consumers shop online, platforms like Onestop promote price awareness, aiding in distinguishing good deals from inflated prices. This transparency benefits both consumers and retailers by ensuring fair pricing practices. Onestop's user-friendly interface and comprehensive search functionality streamline the online shopping experience, empowering shoppers with informed decisions and savings.

Keywords: selenium, beautifulsoup, web scraping.

1.INTRODUCTION
The digital revolution has fundamentally transformed the landscape of consumer behavior, ushering in an era where online shopping has become increasingly ubiquitous. From everyday essentials to significant investments, consumers now conduct a significant portion of their transactions seamlessly in the digital realm. Central to this paradigm shift is the vital role played by price comparison, as consumers navigate through a multitude of e-commerce platforms in search of the best deals.

Existing literature underscores the pivotal importance of price comparison websites (PCWs) in aiding consumers' decision- making processes. However, shortcomings such as accuracy, real- time updates, and user-friendly interfaces continue to plague many existing PCWs. The landscape of price comparison websites (PCWs) in India is relatively limited compared to other countries, focusing primarily on hotel tariffs, holiday packages, and mobile phones. However, PCWs have gained traction in recent years, reflecting the growing demand among Indian consumers to find the best deals online. Research by Nagaraj et al.(2023) explores the significance of automated e-commerce price comparison websites, emphasizing the importance of price comparison in influencing purchasing decisions. Their study highlights the challenges consumers face in manually comparing prices across multiple websites and proposes automated solutions using web scraping techniques. By employing these methods, they achieve a high level of accuracy in price comparison, enhancing the effectiveness of PCWs in India.

In the realm of web development, the Django framework has emerged as a prominent tool for building robust and scalable web applications. In their book, "Django: Developing web using Python," Pooja Thakur and Prashant Jadon(2023) highlight the versatility and efficiency of Django in web development researchs. They emphasize Django's "batteries-included" approach, which provides essential features and functionality out-of-the-box, streamlining the development process and enhancing developer productivity. With its comprehensive set of tools and conventions, Django has become a preferred choice for developers seeking to build sophisticated web applications in Python.

Web scraping has become an essential technique for extracting valuable data from the vast expanse of the World Wide Web. In their survey research titled "Web Scraping Tools and Techniques," Ruchitaa Raj N R et al.(2023) provide a comprehensive overview of web scraping tools, focusing on popular Python libraries such as Beautifulsoup, Selenium, and Scrapy. Their study evaluates the efficacy and suitability of these tools for various web scraping tasks through rigorous performance evaluation and statistical validation. By offering valuable insights and practical guidance, the research serves as a valuable resource for developers and researchers seeking efficient solutions for web data extraction.

Given these insights, this research seeks to address the limitations of current PCWs by proposing the development of a web-based platform. This platform aims to autonomously aggregate product information from various e-commerce websites, conduct real-time price comparisons, and present data through an intuitive and user-friendly interface.

This research endeavors to achieve several key objectives. Firstly, it aims to develop a automated and robust price comparison system capable of ensuring accurate and real-time comparisons across a diverse array of e-commerce platforms. By enhancing the accuracy and reliability of price comparison results, the research seeks to provide consumers with trustworthy information crucial for making informed purchasing decisions.

Secondly, the aim is to implement sophisticated web scraping techniques to gather real-time price data from a wide range of e-commerce websites. This entails leveraging advanced algorithms to extract precise information efficiently, thereby improving the efficiency and effectiveness of the price comparison process.

Furthermore, it seeks to provide users with a user-friendly interface that simplifies the process of comparing prices. By designing an intuitive interface, the platform aims to streamline the user experience, enabling consumers to navigate through the vast array of product options and make informed choices tailored to their preferences and requirements.

2. MATERIALS AND METHOD

Our research aimed to explore how consumers utilize online price comparison websites and their perceptions of these platforms. To achieve this, we employed a mixed-methods approach, combining quantitative surveys to assess usage patterns and satisfaction levels with qualitative interviews to delve deeper into consumer motivations and attitudes. This comprehensive approach allowed us to gain valuable insights into consumer behavior regarding price comparison websites, providing a realistic understanding of their effectiveness and relevance in the online shopping landscape.

Web Scraping

Figure 1: Web scraping process

There is huge amount of data in Internet and it becomes hard to get the specific details from the unstructured data. Web Scraping helps in gathering the information either in unstructured or semi- structured format. Some scraping libraries are used to extract data. The information retrieved is then converted into XLS, CSV, SQL and XML format.
Figure 1 illustrates process of web scrapping. Web scraping is a process that involves identifying a target website, inspecting its structure, writing a script to automate data extraction, fetching and parsing webpage content to extract desired data, and finally storing it in a structured format. This technique is commonly used for various purposes such as price comparison, market research, and data aggregation. However, it's essential to conduct web scraping ethically, respecting website guidelines and terms of service to avoid any potential legal or ethical issues.

BeautifulSoup

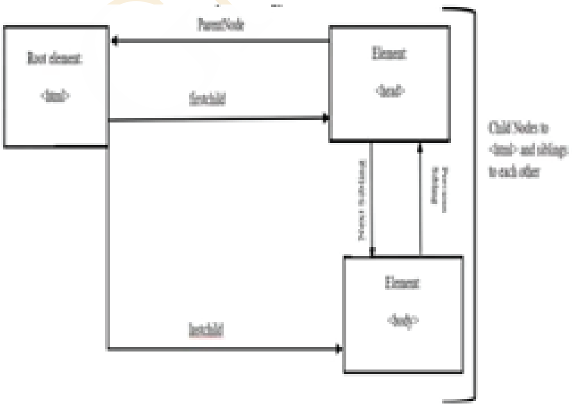

Figure 2:BeautifulSoup process

Beautifulsoup is a powerful python library which is specifically designed for parsing HTML and XML files. Beautifulsoup creates a parse tree for the parsed pages to automize data and use functions to extract specific data.

Beautiful Soup streamlines the process as shown in Figure 2 of web scraping in Python by first parsing HTML or XML content into a structured tree format, then providing methods to navigate this tree and locate desired elements based on tags, attributes, or text content. Once targeted elements are found, data extraction involves accessing and retrieving relevant information such as text content or attribute values. This simplified process, encompassing parsing, navigation, and extraction, enables efficient data retrieval from diverse web sources.

Selenium

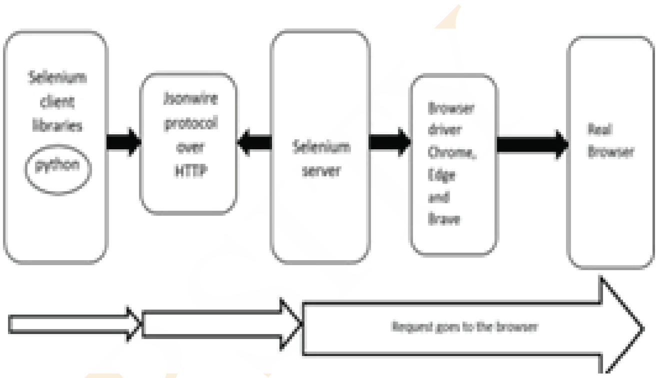

Figure 3: Selenium process

Figure 3 illustrates a client-server relationship in the context of Selenium automation. Selenium serves as the automation suite, facilitating interactions with web browsers through client libraries. These libraries translate user requests into messages using the Jsonwire Protocol, which are then encapsulated into HTTP requests and sent to browser drivers, allowing control of real browsers. The browsers execute actions on webpages, with responses relayed back through the same channels. This process enables seamless automation of web browser tasks, demonstrating the client-server model's effectiveness in facilitating automated interactions between clients and servers.

Django

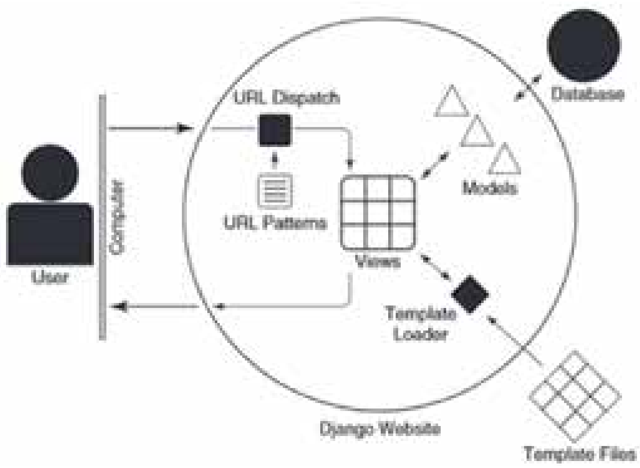

Figure 4: MVT architecture

Django is a high-level Python web framework that encourages rapid development and clean, pragmatic design. It's designed to handle the complexity of web development by providing a robust set of features and tools, including an ORM (Object-Relational Mapping) system for database interactions, a built-in admin interface for managing site content, URL routing, template engine for HTML rendering, and security features such as protection against common web vulnerabilities. Django follows the "Don't Repeat Yourself" (DRY) principle, aiming to minimize repetition of code and promote reusability. With its emphasis on simplicity, scalability, and maintainability it is highly used.

The Django MVT (Model-View-Template) architecture shown in Figure 4 comprises three interconnected components: Models handle data logic and database interactions, defining data structure and managing CRUD operations. Views manage application logic and user interactions, processing requests, interacting with models, and returning responses. Templates define HTML presentation, utilizing Django's template language to insert dynamic content from views and render the final output. Django typically employs SQLite3 as its default database, a lightweight, serverless, embeddable engine written in C, allowing seamless integration into applications without requiring a separate server process.

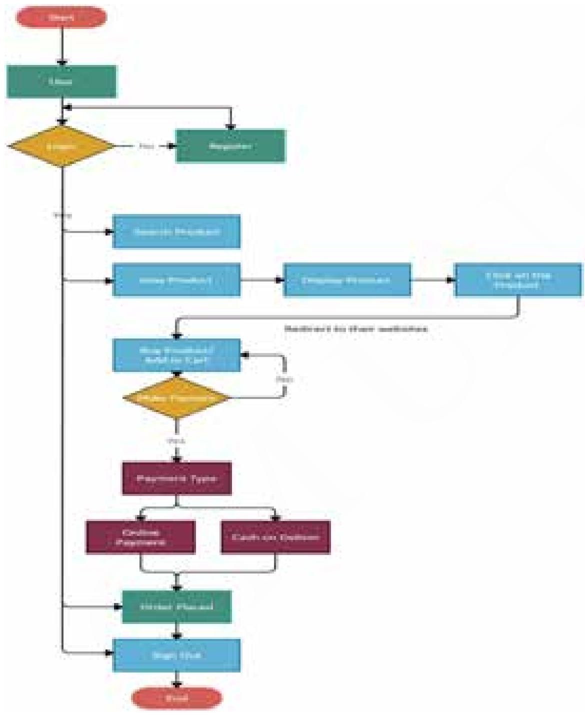

Figure 5 : Flowchart

The automated onestop process as shown in Figure 5 begins with user interaction, requiring login for existing users or registration followed by login for new users. Users then search for products, view details, and proceed to purchase or add items to their cart. Direct purchases entail secure payment through various methods offered by the respective website. Upon successful payment, an order is confirmed, possibly leading users back to the website for additional browsing. Optional sign-out concludes the process, allowing users to explore further or track their history within the platform.

Methodology

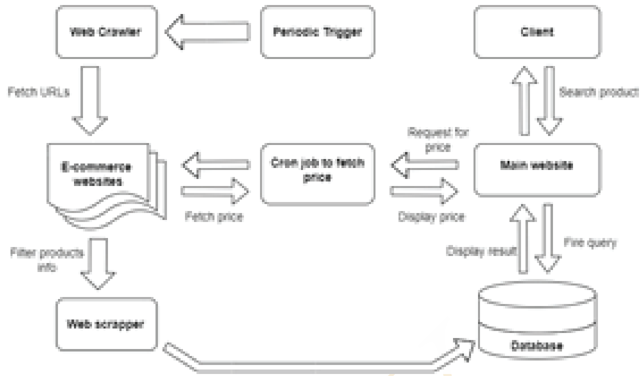

Figure 6 : Research architecture

Figure 6 represents the research architecture. This employs a two- tiered approach, utilizing a Web Crawler and Web Scraper to gather and analyze a vast amount of data from diverse e-commerce websites. The Web Crawler navigates through these sites, collecting URLs that are then processed by the Web Scraper. The Scraper, built using Python libraries such as requests and Beautifulsoup4 and Selenium extracts HTML data from the URLs. The web scraper searches the product pages on the e-commerce websites, parsing product information from various e-commerce platforms. The collected data is stored in a database.

The entire process is orchestrated by django, a Python web framework, which powers the Comparison of E-commerce Products website. Users search for product through the help of these scrappers we compare the prices of the product and display the product along with its name, price and name of the website and give the lowest price tag for the product with low price which will be displayed at the beginning, enabling informed decision-making in the online shopping landscape. The architecture ensures efficient data extraction, analysis, and presentation, addressing the core objective of providing users with a reliable and comprehensive onestop.

3. RESULT AND DISCUSSION

Our research aims to provide consumers with a seamless online shopping experience by developing a user-friendly web-based solution. Through our platform, users can easily search for products and compare prices across multiple e-commerce websites in real- time. By aggregating product information and presenting it through an intuitive interface, we empower consumers to make informed purchasing decisions. Our initiative not only enhances transparency and efficiency in online commerce but also promotes fair competition among retailers, ultimately benefiting both consumers and businesses alike.

Figure 7: Phone Price Comparison

Figure 8: Pendrive Price Comparison

Discussion of Results:

1. Enhanced User Experience: By developing a user-friendly web- based solution, our research aims to improve the overall shopping experience for consumers. The interface allows users to search for products and compare prices across multiple e-commerce websites in real-time. This accessibility to detailed product information empowers consumers to make informed purchasing decisions, ultimately enhancing their online shopping experience.

2. Increased Transparency: Our solution promotes transparency in online commerce by aggregating product information from various e-commerce websites. This initiative aims to provide consumers

with comprehensive and accurate data, thereby reducing the risk of encountering misleading or incomplete information during their purchasing journey. By fostering transparency, our research contributes to building trust between consumers and online retailers.

3. Time and Cost Savings: The convenience of accessing real-time price comparisons through our web-based solution offers significant time and cost savings for consumers. By streamlining the process of finding the best deals and prices, consumers can make more efficient purchasing decisions, ultimately saving both time and money. This aspect of our solution aligns with the growing demand for efficiency and convenience in the online shopping landscape.

4. Competitive Advantage for Businesses: In addition to benefiting consumers, our solution provides a competitive advantage for businesses operating in the e-commerce sector. By including their products in the aggregated search results, e-commerce platforms and retailers can potentially increase visibility and attract more customers. Furthermore, access to pricing trends and consumer preferences enables businesses to refine their strategies and stay competitive in the market.

5. Promotion of Fair Competition: Our solution promotes fair competition among e-commerce platforms and retailers by facilitating real-time price comparisons. This initiative encourages businesses to adopt more competitive pricing strategies, ultimately benefiting consumers by offering better deals and prices. By promoting fair competition, our research contributes to a healthier and more dynamic online marketplace.

4. CONCLUSION AND FUTURE SCOPE

The Onestop stands as a beacon of convenience and efficiency for today's online shoppers. By seamlessly scraping relevant websites and presenting a comprehensive array of price information from various sellers, we empower users to navigate the complexities of online shopping with ease. Through our platform, users can swiftly discern the most competitive deals, thereby optimizing their purchasing power and saving valuable time. As the e-commerce landscape continues to expand and diversify, our commitment to streamlining the shopping experience remains unwavering.

With our solution, we try to not only simplify the price comparison but also fosters greater consumer empowerment and confidence in online transactions. With a steadfast dedication to innovation and user-centric design, we pledge to continually enhance our platform to meet the evolving needs of our discerning clientele. Users can quickly identify the best deals, making online shopping more cost- effective and efficient.

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Design and Verification of UART Protocol Using Cadence Tool

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ABSTRACT

This paper describes Universal Asynchronous Receiver/Transmitter (UART) is a crucial serial communication protocol widely utilized in embedded systems for interfacing microcontrollers with other peripherals. Despite its widespread usage, designing a robust UART system poses significant challenges, primarily related to ensuring reliability and efficiency under varying operational conditions and compliance with communication standards. These challenges by employing the Cadence Design Systems toolset for the systematic design and verification of a UART protocol module. We adopted a methodological approach that integrates schematic capture, behavioral simulation, and physical layout within the Cadence environment and emphasizing error handling mechanisms. The verification process utilized both functional and timing analysis to ensure compliance with the UART specifications and to identify potential issues in real-world scenarios. Our results demonstrate that the designed UART protocol not only meets the predefined specifications but also exhibits robustness against common communication errors and variability in system parameters. The use of Cadence tools facilitated a seamless and effective design cycle from conception to validation.

Keywords: : UART, transmitter, receiver, cadence tool, Verilog code

1. INTRODUCTION

Universal Asynchronous Receiver Transmitter is an integrated circuit, which is used for transmitting and receiving data asynchronously via serial port of the computer. It contains a parallel-to-serial converter for data transmitted from the computer and a serial-to parallel converter for data coming through the serial line. The UART shown in figure 1 is also a buffer for temporarily storing data from high-speed transmissions. In addition, converting a data from parallel to serial, UART will typically contain additional circuits for signals that can be used to identify the state of the transmission media and to govern serial to parallel conversion upon reception in addition to transmission. The data flow in the case that the distant device is not ready to receive further data, take an example, the device connected to the UART is a modem. UART should have a large internal buffer to store data that coming from the modem until the CPU has time to process it. If the memory buffer is used to store the data that isl arge enough for occurring an overflow. It is characterized by its simplicity, flexibility, and ease of use, making it a preferred choice for many communication needs.

Asynchronous Communication: UART uses start and stop bits to frame data bytes, allowing devices with different clock speeds to communicate effectively.

.Configurable Baud Rate: UART communication operates at a user-configurable baud rate, enabling data transfer at various speeds. This adaptability is crucial for compatibility.

.Full-Duplex Communication: UART supports full-duplex communication, meaning that data can be transmitted and received simultaneously, making it suitable for bidirectional data exchange.

Error Detection: UART can include optional parity bits for error detection, improving data integrity.

The Universal Asynchronous Receiver/Transmitter (UART) plays a pivotal role in digital communication systems, acting as a bridge between parallel and serial communication. Its wide spread use in embedded systems, microcontrollers, and various electronic devices underscores its significance in facilitating seamless data exchange. The design and verification of UART circuits involve a meticulous exploration of fundamental principles, intricacies of baud rate generation, transmitter and receiver architecture, and the challenges associated with ensuring robust communication. In this comprehensive discussion, we delve into the intricacies of UART design and verification, focusing on the critical aspect of baud rate generation and its impact on reliable data transfer.

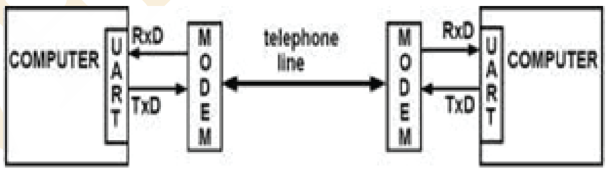

Figure 1: Serial data transmission.

Understanding UART Communication

UART communication is characterized by its asynchronous nature, allowing devices with different clock domains to exchange data without a shared clock signal. This makes UART a versatile choice for applications where devices operate at varying speeds or lack synchronized clocks. The essence of UART communication lies in the transmission of data in frames, each consisting of a start bit, data bits (usually 8 bits), optional parity bits, and stop bit(s). The framing mechanism ensures synchronization and aids in error detection, contributing to the robustness of the communication process.

Significance of BAUD Rate in UART

Central to UART communication is the concept of baud rate, representing the speed at which data istransmitted between devices. Baud rate is measured in bits per second (bps) and determines the rate at which individual bits are sent and received. It is a critical parameter as it influences the timing of bit transitions, ensuring that both the transmitter and receiver are synchronized for accurate data reception. The baud rate is inversely proportional to the bit time, which is the time taken to transmit a single bit.The formula defining the relationship is:

$$\text{Baud rate} = \frac{1}{\text{Bit Time}}$$

For example, a baud rate of 9600 bps implies a bit time of 1/9600 seconds. Precise baud rate generation is imperative for successful UART communication, and the design of the baud rate generator is a crucial aspect of UART circuit design.

2. PROPOSED METHOD

The design is simulated in the Cadence environment, employing design and test benches that include various scenarios like different baud rates, error conditions, and edge cases. This simulation verifies functional correctness and timing analysis. Following successful simulation, the design undergoes synthesis using the Cadence Genus Synthesis Solution, optimizing the UART design for area, power,and speed constraints. Finally, post-synthesis simulations validate the physical integrity and operational behavior of the synthesized UART, ensuring that it meets the initial specifications and performs reliably in a real hardware environment. This comprehensive approach ensures robust UART design and verification using advanced tools and methodologies.

Design of Transmitter

Counter

In a UART transmitter, the counter block diagram includes key components: Reset Counter, Baud Clock (baudclk), and Start Counter. The Reset Counter initializes the counter to a specific state, ensuring precise timing from the outset. The Baud Clock provides the necessary timing pulses, dictating the baud rate for bit transmission. The Start Counter triggers the counting operation, coordinating the release of each bit. This setup is integral for managing data flow, as it controls the intervals at which bits are transmitted. Accurate timing via these elements ensures synchronized datatransmission between devices without a shared clock.

FSM of transmitter

The block diagram of a Finite State Machine (FSM) in a UART transmitter typically includes inputs like TX Start, Baud Clock (baudclk), Reset, and Counter Reached. The TX Start signal initiates the transmission process, prompting the FSM to begin its operation. The Baud Clock provides a timing pulse that controls the rate of data transmission, ensuring that data is sent at a consistent baud rate. The Reset input is critical for returning the FSM to an initial state, clearing any existing states or errors. Lastly, the Counter Reached signal is used to indicate that a preset count value has been reached, typically signaling the FSM to move to the next step in data handling or transmission. Together, these components coordinate the timing and sequence of data transmission in a structured and efficient manner.

Multiplexer

In a UART transmitter, the block diagram of a multiplexer (MUX) typically includes essential components like Selection Bits, Serial Bit, and Parity Bit. The Selection Bits are crucial as they determine which input (Serial Bit or Parity Bit) is passed through to the output at any given time. The Serial Bit represents the main data being transmitted, while the Parity Bit is used for error checking, added to ensure data integrity by providing a simple form of error detection. The MUX operates by selectively forwarding the Serial Bit or the Parity Bit to the transmission line based on the state dictated by the Selection Bits. This setup allows for efficient and flexible management of data flow, especially in handling the framing and transmission of each data packet with its corresponding parity for error checking.

Parity generator

The block diagram of a parity generator in a UART transmitter typically consists of two main components: Data In and Load. The Data In input receives the binary data for which parity needs to be calculated. This data can be an entire word or byte, depending on the system's configuration. TheLoad signal, when activated, triggers the parity generator to calculate the parity bit. This bit is eithereven or odd parity, determined by the sum of the bits in the Data In. The parity generator's function is to ensure that either the total number of '1' bits is even (even parity) or odd (odd parity), which is crucial for error detection in data communication. Once the parity is calculated, it is typically appended to the data frame being transmitted, enhancing data integrity across communicationchannels.

PISO in transmitter

In a UART transmitter, the block diagram of a Parallel-In Serial-Out (PISO) shift register consists of four main components: Data In, Shift, Baud Clock (baudclk), and Load. The Data In input receives parallel data, typically an entire byte, that needs to be serialized. The Load signal is used to latch thisparallel data into the shift register, preparing it for serial output. Once the data is loaded, the Baud Clock synchronizes the shifting operation, with the Shift signal enabling the sequential movement of bits from the shift register to the transmission line. Each clock pulse shifts one bit out until all bits have been serialized and transmitted. This setup effectively converts parallel data into a serial formatfor transmission, maintaining the correct timing and order of data bits.

3. DESIGN OF RECEIVER

Bit checker

In a UART transmitter, the block diagram of a Bit Checker module includes three primary components: Input Data, Input Clock, and Baud Clock. The Input Data is continuously monitored by the Bit Checker to verify the integrity and correctness of each bit being transmitted. The Input Clock synchronizes the checking process, ensuring that the data is assessed in real time and at the correct pace relative to system operations. Meanwhile, the Baud Clock is crucial as it defines the baud rate at which data is transmitted, and it helps the Bit Checker to align its operations with the transmission speed. This setup allows the Bit Checker to perform real-time validation of each transmitted bit, ensuring that the transmission meets predefined standards and timing, thereby enhancing communication reliability.

Counter in receiver

In a UART receiver, the block diagram of a counter includes the components: Reset Counter, Baud Clock (baudclk), and Start Counter. The Reset Counter is crucial for setting the counter to a specificinitial state whenever required, ensuring that the counting starts accurately when new data begins to arrive. The Baud Clock drives the timing of the counter, dictating how frequently the counter increments. It is aligned with the baud rate of incoming data to maintain synchronization. The Start Counter signal activates the counting process, typically triggered when the start bit of incoming datais detected. This setup allows the counter to manage the timing of data sampling, ensuring that eachbit is correctly interpreted at intervals defined by the baud rate, crucial for accurate data reception.

FSM in receiver

In a UART receiver, the block diagram of a Finite State Machine (FSM) includes essential inputs like the Baud Clock (baud_clk), Data In, and Reset. The Baud Clock provides the timing mechanism necessary for the FSM to sample incoming data bits at the correct intervals, ensuring synchronization with the transmitter's baud rate. The Data In input is where the FSM receives the serialized data stream, including start, data, parity, and stop bits. The Reset input ensures the FSM can return to a known state, clearing any error conditions or previous session data. This FSM typically cycles through states such as idle, start bit detection, data bit reception, parity check, and stop bit confirmation, effectively managing the data decoding and error-checking process

Parity checker

In the block diagram of a UART receiver, the Parity Checker is a critical component designed to verify the integrity of the received data. It primarily includes the Data In input and possibly a ControlSignal input for operational settings. The Data In receives the data bits along with the parity bit, typically transmitted from the UART transmitter. The Parity Checker calculates the parity of the received data bits (excluding the received parity bit) and compares it with the transmitted parity bit.If the calculated parity matches the received parity bit, it indicates that the data is likely free from transmission errors. Otherwise, it flags an error. This module ensures data integrity by detecting anyodd single-bit errors that occurred during transmission.

SIPO in receiver

In a UART receiver, the block diagram of a Serial-In Parallel-Out (SIPO) shift register includes key components: One Detected, Zero Detected, Baud Clock (baud_clk), and Shift. The One Detected and Zero Detected inputs signal when a '1' or '0' has been correctly identified from the incoming serial data stream. These inputs enable the SIPO to accurately register each bit of data received. The Baud Clock coordinates the timing of the shifting process, ensuring that each bit is captured in sync with the data transmission speed. The Shift signal activates the transfer of each incoming serial bit into the parallel register. After all bits of a data packet are received serially, they are available in a parallel format at the output of the SIPO, facilitating further processing within the receiver system. This arrangement effectively reconstructs the serialized data into its original parallel format, crucial for subsequent data handling and interpretation.

4. ABOUT TOOL

Software Tool Used

CADENCE Licensed Version: CADENCE Licensed Version is a widely used Electronic Design Automation (EDA) tool suite specifically designed for integrated circuit (IC) design and layout. It provides designers with a comprehensive set of features and functionalities to create, simulate, verify, and optimize complex analog, digital, and mixed-signal designs.

Specifications:

- Cadence Licensed Version boasts several notable specifications that make it a preferred choice for integrated circuit (IC) designers.
- It offers a rich set of design entry options, allowing designers to choose between schematic- based or layout-based design methodologies.
- Simulation Engines: Supports various simulation engines, such as Spectre for analog/mixed- signal simulations and NC-Sim for digital simulations.
- Power Analysis: Tools for estimating and optimizing power consumption at different design stages.

5. RESULT

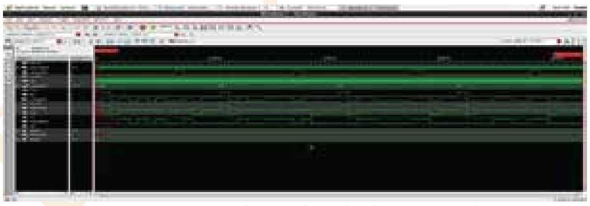

Figure 2: transmitter simulation waveform.

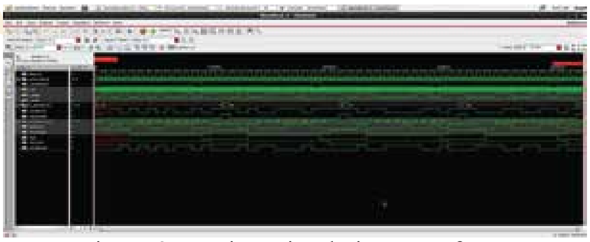

Figure 3: receiver simulation waveform.

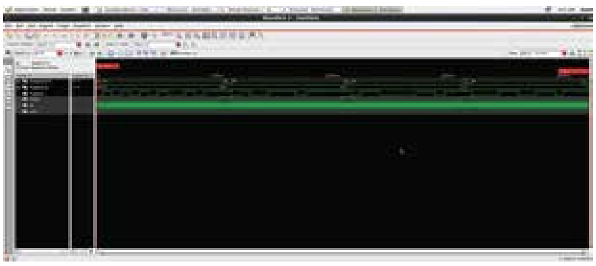

Figure 4: UART simulation waveform.

Utilizing Cadence tools, we meticulously designed and verified a robust UART protocol. Through iterative processes, we ensured reliability, compatibility, and adherence to industry standards. Cadence's support enabled thorough simulation, debugging, and validation, optimizing performance while mitigating risks of errors or failures. The resulting framework not only guarantees efficient UART communication but also establishes a resilient groundwork for future digital system advancements and integrations. This comprehensive approach, characterized by meticulous design iterations and rigorous verification, not only ensures functionality but also fosters innovation and adaptability within complex digital ecosystems.

6. CONCLUSION AND FUTURE SCOPE

The design and verification of UART protocol using Cadence tools have yielded a robust and efficient communication framework. Through meticulous design iterations and rigorous verification processes, we have ensured the protocol's reliability, compatibility, and adherence to industry standards. Cadence tools have provided invaluable support in simulating, debugging, and validating the protocol implementation, resulting in optimized performance and minimized risks of errors or failures. This comprehensive approach not only ensures the functionality of UART communication but also lays a strong foundation for future developments and integrations within complex digital systems.

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Precision Agriculture Using UAVs for Plant Disease Detection

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ABSTRACT

Precision agriculture aims to enhance crop productivity through technology-driven approaches. This paper presents an advanced quadcopter-based system designed for plant disease detection and crop monitoring, addressing challenges in traditional agricultural practices. The system integrates UAV technology with AI-driven image classification using Convolutional Neural Networks (CNNs) to provide real-time insights, promoting sustainable and efficient farming. The proposed system demonstrates significant potential in improving crop health monitoring, reducing resource wastage, and facilitating data-driven decision-making for farmers.

Keywords: : Precision Agriculture, UAV, Plant Disease Detection, Convolutional Neural Networks, AI, Sustainable Farming.

1. INTRODUCTION

The proposed project introduces an advanced quadcopter-based system designed to transform precision farming by addressing critical agricultural challenges such as plant disease detection and crop monitoring. The agricultural sector incurs significant losses annually due to plant diseases, which adversely impact crop quality and yield, posing a severe threat to global food security. Traditional manual methods of detecting these diseases are labour-intensive, time-consuming, and impractical for large-scale operations. This innovative project offers a technological solution to overcome these limitations.

The quadcopter is built on a robust F450 frame, powered by 2212 920 KV motors and 30A ESCs, and controlled by the reliable Radio Link Cross flight controller, ensuring stable flight and precise manoeuvrability. Accurate geolocation is achieved through the integration of a UBlox GPS module, enhancing navigation and data acquisition across extensive agricultural fields. A high- resolution camera is the core of the system, capable of capturing detailed images and video footage crucial for assessing crop health and identifying plant diseases. The drone is equipped with a 5.8 GHz video transmitter paired with an OTG receiver, enabling live video streaming to facilitate real- time monitoring and decision-making.

The system is complemented by a dedicated web dashboard, offering an intuitive platform for farmers to view live footage, capture images, and analyse recorded data.Data captured by the drone is processed using artificial intelligence (AI) algorithms for image classification, allowing accurate detection of plant diseases.

The processed insights are transmitted to a mobile or web application, providing farmers with actionable information to enable timely interventions.By integrating drone technology, AI-driven analytics, and real-time data transmission, this project optimizes resource usage, enhances productivity, and promotes sustainable agriculture. It empowers farmers to detect plant diseases early and implement targeted treatments, significantly reducing losses. This innovative approach contributes to addressing global food security challenges, making it a transformative solution for modern agriculture.

Figure 1: Disease Detection through UAV

2. LITERATURE REVIEW

Recent advancements in computer vision have demonstrated the effectiveness of CNNs in agricultural applications. Studies such as El Sakka et al. (2024) highlight the transformative role of CNNs in crop imagery analysis, showcasing their ability to process multispectral and hyperspectral images for accurate disease identification. Comparative analyses between CNNs and transformers (Deininger et al., 2022; Pinto et al., 2022) further validate the robustness of deep learning models for pathology detection. Additionally, Meshram and Patil (2021) emphasize the importance of quality datasets in training robust AI models, while Agarwal et al. (2020) showcase the application of CNNs in detecting tomato crop diseases with high accuracy. The literature review underscores the growing relevance of AI in agriculture and the potential for UAVs to revolutionize traditional farming practices.

Recent advancements in computer vision have spurred Interest in deep learning models like Convolutional Neural Networks (CNNs) and transformers for agricultural applications and pathology analysis. CNNs have been extensively employed for tasks such as plant disease detection , showing high accuracy when combined with multispectral imaging and precise datasets. For instance, CNNs have been effective in detecting diseases through visible light, and depth data.

Mohammad El Sakka,Josiane Mothe &Mihai Ivanovici, “Images and CNN applications in smart agriculture”, 2024 This review highlights the transformative role of Convolutional Neural Networks (CNNs) in agriculture, particularly in analyzing crop imagery from satellites, aircraft, and terrestrial cameras. It focuses on the use of multispectral images and vegetation indices, emphasizing CNNs' impact on improving agricultural outcomes and cataloging relevant datasets.

Deininger, L., Stimpel, B., Yuce, A., Abbasi-Sureshjani, S., Schönenberger, S., Ocampo, P., Korski, K., & Gaire, F., “A comparative study between vision transformers and CNNs in digital pathology.”, 2022.

This study explores vision transformers for tumor detection and tissue type identification in digital pathology images, comparing them with ResNet18. Vision transformers slightly outperformed ResNet18 in three of four tissue types but required more training effort. Both models captured similar imaging features, and vision transformers may need more complex tasks to surpass convolutional neural networks.

Pinto, F., Torr, P. H. S., & Dokania, K, “An impartial take to the CNN vs transformer robustness contest.” 2022

This paper examines the robustness and uncertainty estimation of Transformers versus state-of-the-art Convolutional Neural Networks (CNNs), particularly ConvNeXt. It finds that CNNs can be as robust and reliable as Transformers, with no clear winner between the two architectures. Both perform well across various tasks but share vulnerabilities like texture, background, and simplicity biases.

Meshram, V., & Patil, K. “Indian fruits image dataset with quality for machine learning applications.” 2021.

This research focuses on creating a dataset of Indian fruits (apple, banana, guava, lime, orange, and pomegranate) classified by quality (good, bad, mixed) to support machine learning models for fruit classification and recognition. With over 19,500 processed images, the dataset aims to enhance the accuracy and robustness of machine learning models for real-time agricultural application

Mohit Agarwal, Suneet Kr. Gupta, K.K. Biswas , “Development of Efficient CNN model for Tomato crop disease identification”, 2020

This paper presents a machine learning system that combines thermal, visible light, and depth data to detect tomato plants infected with the powdery mildew fungus. By using a novel feature set from image data and depth information, the system improves disease detection accuracy and identifies plants that naturally acquired the disease during the experiment.

3. METHODOLOGY

Figure 3.1 : Methodology of Quadcopter

The proposed system consists of an F450 quadcopter equipped with a high-resolution camera, UBlox GPS module, and real-time video transmission capabilities.

The methodology involves multiple stages

System Design: Hardware and software components are selected based on performance, cost, and integration capabilities.

Data Collection: UAVs capture high-resolution images of crops under various environmental conditions.

Data Processing: Images are pre-processed to enhance quality and annotated for training the AI model.

AI Model Development: A CNN model is trained on the Plant Village dataset, optimized for disease detection

Deployment: The trained model is integrated into a web-based platform for real-time analysis and user interaction.

The workflow includes UAV-based surveying, image capture, AI-driven analysis, and result dissemination via a dedicated web application. Each step is designed to ensure data accuracy, model reliability, and user-friendly access to insights. System Design and Requirements Analysis - Defining objectives and detailed planning.

Hardware Setup and Assembly - Building and assembling the physical components.

Software Development and System Integration - Writing and integrating software to control the system.

Testing and Calibration - Validating functionality and optimizing performance.

4. HARDWARE AND SOFTWARE COMPONENTS

Drone Frame (F450)

The drone frame provides the structural foundation for all components. The F450 frame is lightweight and sturdy, making it ideal for mounting the necessary sensors and cameras.

Specifications:

Lightweight and durable.

Supports the payload capacity required for the camera, GPS, and other sensors.

Figure 4.1: Drone Frame(F450)

Motors (2212 920KV)
The 2212 motor refers to the motor size, with "22" indicating the stator diameter (22 mm) and "12" the stator height (12 mm). These motors are typically brushless, which ensures higher efficiency, longer lifespan, and reduced maintenance compared to brushed motors. KV value represents the motor's speed constant, measured in RPM per volt. A 920KV motor provides a balance between torque and speed, making it suitable for drones carrying moderate payloads while maintaining stability and efficiency.
Performance:
Operating Voltage: 2S-4S LiPo (7.4V to 14.8V)
Maximum Current (A): 18A (depends on propeller size and voltage)

Figure 4.2 : Motors (2212 920KV)

Propellers (10 x 4.5)
These propellers are ideal for drones used in precision agriculture, where stability, efficiency, and moderate payload capacity are critical. They provide the necessary thrust for steady flight and precision control, even under windy conditions.
Thrust Generation: 10-inch diameter, provides sufficient airflow to generate the thrust needed for drones carrying medium payloads
Efficiency: 4.5-inch pitch, balances efficiency and performance, offering good lift without excessive power consumption. Ideal for stable flight and carrying moderate payloads.
Material: Commonly made of plastic fiber. Plastic is lighter and cost-effective.

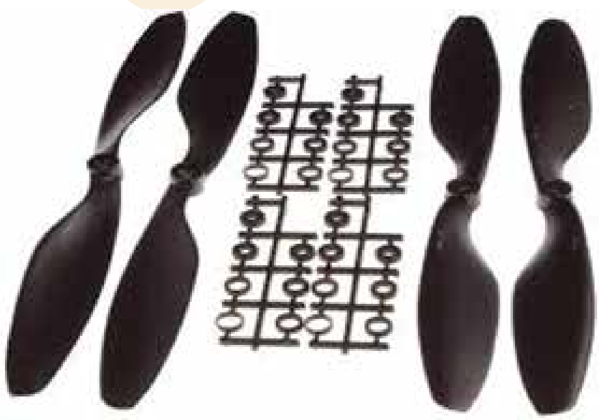

Figure 4.3 : Propellers (10 x 4.5)

Electronic Speed Controller (ESC)
It is a crucial component in drones and other electric-powered systems, managing the speed and direction of brushless motors. In drones, ESCs are responsible for controlling the speed of the motors based on signals received from the flight controller. The ESC ensures smooth and efficient control of the motors, enabling reliable and stabldrone operation.

Figure 4.4 : Electronic Speed Controller (ESC)

RadioLink Crossight Flight Controller
The RadioLink Crossight Flight Controller is a versatile and advanced flight controller designed for drones and UAVs, offering precision flight control, stabilization, and support for a variety of applications such as aerial photography, mapping, and FPV racing.
Specifications:
Processor: High-speed ARM Cortex MCU for real-time processing and control.
Power Supply: Input voltage of 5-12V
Connectivity: PWM, PPM input/output support for communication with receivers and ESCs. UART ports for GPS, telemetry, or additional sensors.
Weight: Lightweight, typically around 20-30 grams, suitable for drones with weight constraints.
Setup and Calibration:
Install the flight controller securely on your drone frame to minimize vibrations.
Connect peripherals (motors, ESCs, GPS module, telemetry module, and receiver).

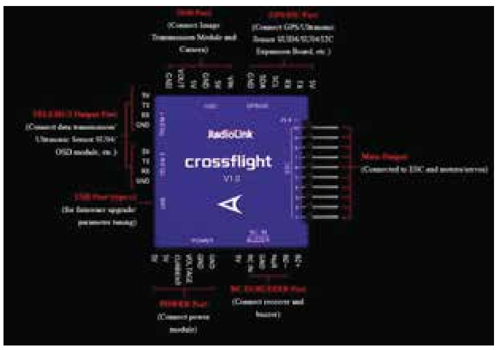

Fig 4.5 RadioLink Crossight Flight Controller

Battery (3300mAh 11.1V Li-ion)

The 3300mAh 11.1V Li-ion battery is a rechargeable battery pack commonly used in drones due to its lightweight, high energy density, and reliable performance.

Specifications :

• Capacity (3300mAh): Indicates the total charge the battery can store.

• Voltage (11.1V): Composed of 3 cells in series (3S), with each cell having a voltage of 3.7V (3.7V × 3 = 11.1V).

• Battery Type: Li-ion (Lithium-Ion) Longer lifespan compared to LiPo batteries but with a slightly lower discharge rate.

• Discharge Rate (C Rating): Defines how quickly the battery can be discharged.

Max Current=Capacity × C-rating = 3.3Ah × 10 = 33A

Figure 4.6 : Battery (3300mAh 11.1V Li-ion)

GPS Module (UBlox)

The UBlox GPS module is a high-performance, reliable GPS receiver commonly used in drones for real-time positioning and navigation. Known for its accuracy and ease of integration, it plays a crucial role in enabling autonomous flight and waypoint-based navigation.To set up the UBlox GPS module, connect it to the flight controller via UART or I2C, supply the recommended voltage (3.3V/5V), and configure it using u-center software. Calibrate the compass and mount the module on the drone frame, ensuring it's placed away from electromagnetic interference.

Figure 4.7 : GPS Module (U Blox)

5.8GHz Video Transmitter and OTG Receiver

The 5.8GHz video transmitter and OTG receiver are essential components for real-time video transmission and monitoring in drone applications, especially for FPV (First- Person View) flying, surveillance, or aerial photography.

5.8GHz Video Transmitter: Transmits live video from the drone's onboard camera to the ground station or mobile device.

OTG Receiver: Receives the video feed from the transmitter and displays it on a mobile device via OTG (On-The-Go) functionality.

Figure 4.8 : 5.8GHz Video Transmitter and OTG Receiver

Telemetry Module

The telemetry system enables the real-time transfer of flight data (e.g., altitude, speed, battery status) from the drone to the operator's ground control system.

Provides data on drone health and flight parameters during the mission.

Ensures safe flight and assists in making data-driven decisions based on flight performance.

Ranges from 1 km to 10 km, depending on power output, antenna type, and environmental conditions.

Supports sufficient bandwidth for transmitting essential parameters without lag.

Figure 4.9 : FPV Radio Telemetry

Power Distribution Board

A Power Distribution Board (PDB) is a crucial component in drones that efficiently distributes power from the main battery to various systems, including motors, electronic speed controllers (ESCs), flight controllers, and auxiliary devices like cameras or transmitters.

• Voltage and Current Capacity: Ensure compatibility with your drone's battery and motor requirements.
• Number of Outputs: Select a PDB with enough output ports for your ESCs and auxiliary devices.
• Additional Features: Look for integrated BECs, current sensors, or filters for noise-sensitive devices.

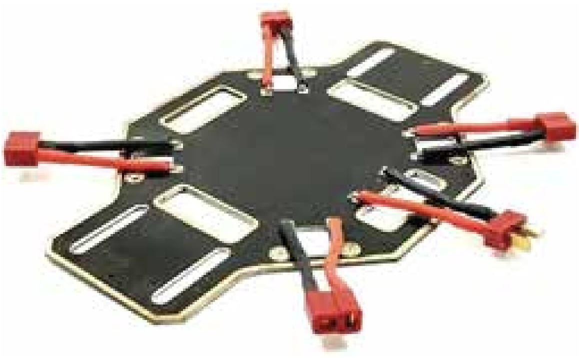

Figure 4.10 : Power Distribution Board

Camera (720P)

The camera captures high-resolution images of crops for disease detection. It plays a crucial role in monitoring the health of plants and identifying potential problems like fungal infections or pests. 720p resolution to ensure clear images for analysis. Lightweight and compact, compatible with the drone's payload capacity.

Figure 4.11 : Camera (720P)

FS16 Controller

The FS-16 controller is a type of radio transmitter typically used for controlling RC (Radio-Controlled) vehicles, including drones, aircraft, and other remote-controlled devices. These controllers are part of a series made by FlySky, a popular brand in the RC hobbyist market. The FS- 16 is known for its versatility, ease of use, and range of features suited for a wide range of users, from beginners to more advanced RC enthusiasts.

• Operates on 6 to 16 channels, controlling multiple components.
• Uses 2.4 GHz frequency for a long-range connection.
• Ergonomic design with a comfortable grip and easy-to-access controls.
• LCD screen displays telemetry data, settings, and model info.
• Stores multiple model profiles for quick vehicle switching.
• Adjustable settings for servo travel, throttle curves, and endpoint adjustments.
• Binding process ensures secure pairing with compatible receivers.
• Powered by rechargeable Li-ion or NiMH batteries.
• Compatible with various FlySky receivers and vehicles.
• Includes failsafe mode to prevent crashes during signal loss.

Figure 4.12 : FS16 Controller

5. SOFTWARE REQUIREMENTS

QGROUNDCONTROL

QGroundControl is a versatile, open-source ground control software used to configure, control, and monitor UAVs. It supports multiple flight stacks, including PX4 Autopilot and ArduPilot, making it a popular choice for various drone applications.

Figure 4.13 : QGroundControl

Python

Python is the core language used in AI applications because of its simplicity, flexibility, and powerful libraries. Libraries like PyTorch make it easy to build, train, and deploy machine learning and deep learning models. Python also excels in data processing with tools like Pandas and NumPy, allowing developers to clean, manipulate, and prepare data for AI models. Its integration with frameworks like Flask and Django helps deploy AI models into real-world applications, while Python's ease of prototyping enables quick testing and improvements. The strong community and open-source nature of Python further enhance its role in AI development, making it the go-to language for both researchers and developers.

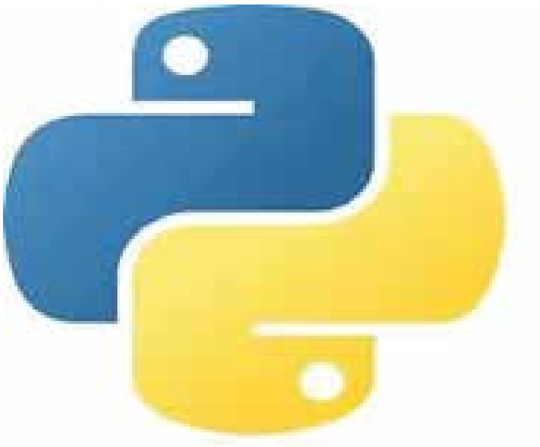

Figure 4.14 : Python

HTML

HTML (HyperText Markup Language) is the standard language used to create and structure content on the web. It provides a framework for building web pages by using a system of tags and elements to define the structure of a page, such as headings, paragraphs, links, images, and more. HTML is essential for web development because it tells browsers how to display content.

Figure 4.15 : HTML

CSS

CSS(Cascading Style Sheets) is a style sheet language used to control the presentation and layout of HTML elements on a webpage. While HTML provides the structure of a webpage, CSS is responsible for defining how that content looks. It allows developers to set styles such as colors, fonts, spacing, positioning, and responsiveness to different screen sizes. CSS makes it possible to create visually appealing and well-organized websites by separating the content from its styling.

Figure 4.15 : CSS

6. DESIGN AND IMPLEMENTATION

Thrust Calculation:

Formula: Thrust per Motor = W × 2/4 Where, W = Total Weight of the Drone
T = Thrust per Motor W = 1.2kg (1200g):
T = 1200 × 2/4 = 600g
Newtons (N) (Using 1 kg = 9.81 N)
0.6×9.81=5.89 N

ESC Calculation:

Formula: Required ESC Current Rating = Max Motor Current × 1.3
Motor maximum current is 18A, then: Required ESC Current Rating = 18A × 1.3 = 23.4A
A 30A ESC would be a suitable choice.
Total energy capacity is calculated as: E = V . Q
Where V = 11.1 V Q = 3300 mAh
then , E = 36.36 W

Flight time Calculation:

Flight time (in hours) = Battery Capacity / Power Consumption
= 36.36 / 100
Where power consumption (100~150)
= 0.36(36 min)

Flight Control Software

QGroundControl is a versatile, open-source ground control software used to configure, control, and monitor UAVs. It supports multiple flight stacks, including PX4 Autopilot and ArduPilot, making it a popular choice for various drone applications.

Key Features

• Runs on Windows, macOS, Linux, iOS, and Android, offering cross-platform compatibility for desktop and mobile use.
• Features an graphical interface for easy mission planning and flight monitoring.
• Allows creation of complex flight plans with waypoints, geofencing, and predefined actions, including 3D visualization.
• Displays real-time telemetry data such as altitude, speed, battery status, GPS position, and flight path, with live FPV video streaming for situational awareness.
• Supports integration and control of cameras and other payloads.
• Allows firmware updates to the flight controller directly through the interface, ensuring access to the latest features and fixes.
• Supports telemetry and it is compatible with radios, Wi-Fi, or USB connections for data transmission.
• Provides tools for analysing flight logs for troubleshooting, performance optimization, and post-flight review.
• Provides a customizable user interface, allowing users to personalize the layout, dashboard elements, and controls to fit their specific workflow or mission needs

Website for Disease Detection:

The User Interface (UI) of the website is designed to be simple, visually appealing, and user-friendly, ensuring that farmers, researchers, and agricultural professionals can easily navigate and use the platform. The grid wise display of the supported disease detection of plant leaves can be seen on the front page, followed by 'AI Engine' button, which takes the user to the page where the image can be uploaded, the page also gives the user a description about disease detection. The same can be seen in the image below.

Figure 5.1 : Website Front Page

We can choose the file from our storage, after submitting the image is analyzed and the result is shown whether the plant leaf is healthy or not. If the plant leaf is not healthy then the disease name is shown along with the brief description about the disease the plant is suffering from, as well as the prevention of the disease along with the supplement that can be used as a preventive measure. The following is an example for grape plants suffering from Leaf Blight. Grape Leaf Blight is a fungal disease that affects grapevines, causing severe damage to leaves, fruits, and shoots. If left uncontrolled, it can significantly reduce yield and fruit quality. In the image, the description of the disease detected is given and followed by prevention measures, supplement and product buy link has also been provided to make things easier for the user. Tebulur Tebuconazole has been recommended as a supplement which is a pesticides to prevent and kill fungal growth in plants, it is also referred to as fungicides.

Figure 5.3 : Plant Disease Detection

The functional workflow is as follows:

Step 1: User Uploads an Image: The homepage has an upload button where users can select and submit an image of a plant leaf. The system accepts JPEG, PNG, and other common image formats.

Step 2: Machine Learning Model Analyzes the Image: A CNN-based model extracts features from the image. The model classifies the leaf as Healthy or Diseased. If diseased, it predicts the specific disease type.

Step 3: Displaying Results & Remedies: The website shows the disease name, recommended treatments. Remedies include chemical treatments and preventive measures.

Technologies Used:

The disease detection website is built using a combination of frontend, backend, machine learning, to provide an intuitive, efficient, and scalable solution for identifying plant diseases using AI. The system allows users to upload images of plant leaves, which are then analyzed by a machine learning model to detect diseases and suggest remedies.

Convolutional Neural Networks (CNNs) are at the heart of this project. CNNs are a specialized type of deep learning model designed to process image data. Unlike traditional neural networks, CNNs use convolutional layers that apply filters to input data (in this case, leaf images), extracting essential features such as edges, textures, and patterns. These features are then used to classify the images, making CNNs highly effective in image recognition tasks like plant disease detection. The ability to learn hierarchical features, such as shapes and textures in an image, allows CNNs to identify complex patterns that human eyes might miss, ensuring accurate classification of plant health issues.

PyTorch is the deep learning framework employed to build and train the CNN for this project. It is an open- source library that provides a flexible and efficient platform for deep learning tasks. PyTorch is known for its dynamic computational graph, which allows developers to modify the graph on the fly during training. This is particularly useful for experimenting with new architectures and algorithms.

The framework also supports GPU acceleration, which is crucial for training deep neural networks efficiently. PyTorch has become a popular choice for research and industry due to its simplicity, ease of use, and robust ecosystem.

Flask is a lightweight web framework used for creating a web application interface that allows users to interact with the trained model. The Flask application serves as a bridge between the user and the machine learning model, enabling users to upload leaf images and get predictions on whether the plant is diseased and what type of disease it might have. Flask's simplicity and flexibility make it an ideal choice for small-scale web applications like this one. By integrating Flask with the CNN model, the system provides a seamless experience where users can quickly upload images and receive real-time predictions.

Jupyter Notebooks are employed for the development, testing, and iteration of the machine learning model. Jupyter allows data scientists and developers to interactively experiment with code and visualize results, making it a powerful tool for building and refining deep learning models. In this project, Jupyter Notebooks were likely used to preprocess the plant leaf images, test different CNN architectures, and evaluate the model's performance before deploying it into a production environment using Flask. Notebooks enable users to document their findings and share the step-by-step process of model development.

The project leverages the Plant Village dataset, which is a large collection of labeled images of healthy and diseased plant leaves. This dataset contains thousands of images of various plant species, each annotated with the type of disease affecting the plant. It is used to train the CNN model, allowing it to recognize patterns specific to different plant diseases. The availability of such a comprehensive dataset is crucial for the effectiveness of the model, as it provides the data necessary for the model to learn the distinguishing features of diseased versus healthy plants.

Once the CNN is trained on the Plant Village dataset, it is deployed in the Flask web application. The deployed model can now process images uploaded by users, predict the plant disease, and return results. This end-to-end integration—from image preprocessing to prediction— demonstrates how AI and machine learning can be applied in real-world applications like agriculture. Users can upload leaf images, and within seconds, the system will provide a diagnosis, which can help farmers or gardeners take quick action to manage plant health.

Machine Learning Algorithms for Disease Detection.

A Convolutional Neural Network (CNN) is a deep learning model designed for image recognition and classification. It processes images through multiple layers, each performing a specific function to extract meaningful patterns and features.

Convolutional Layer (Feature Extraction): The first layer in a CNN is the convolutional layer, which detects important features such as edges, textures, and shapes from the input image. This is done using small filters (also called kernels) that scan different parts of the image. For example, if we have an image of a cat, the initial layers may detect simple features like edges, while deeper layers recognize complex patterns like eyes, whiskers, and ears.

Activation Function (Non-linearity Introduction): After convolution, a non-linear activation function, typically ReLU (Rectified Linear Unit), is applied to introduce non- linearity. This helps the network learn complex relationships between pixels. Without this step, the CNN would behave like a linear model, limiting its ability to learn intricate patterns.

• Pooling Layer (Dimensionality Reduction): The pooling layer reduces the size of the feature maps while retaining essential information, making the network computationally efficient. The most common pooling method is max pooling, where the highest value in a small region of the image is retained. For example, if an image of a dog passes through a pooling layer, it helps retain crucial features like the dog's ears and nose while removing unnecessary details, improving computational efficiency.

• Fully Connected Layer (Classification): Once the extracted features are reduced to a manageable size, they are flattened into a one-dimensional vector and passed through fully connected layers. These layers learn patterns from the extracted features and assign probabilities to different classes. For instance, if a CNN is trained to classify animals, the final layer would output probabilities for labels like "cat," "dog," or "elephant," with the highest probability indicating the predicted class.

• Output Layer (Prediction): The final layer uses an activation function like Softmax (for multi-class classification) or Sigmoid (for binary classification) to determine the probability of each class. For example, if we input an image of a lion, the model might predict 80% probability for "lion" and 15% for "tiger," making "lion" the final classification.

Example: CNN for Digit Recognition

Imagine we are building a CNN model to recognize handwritten digits (0-9) from the MNIST dataset. When an image of the number "5" is given as input, the model processes it through multiple layers to extract meaningful features and classify it correctly. First, the **convolutional layer** scans the image with small filters to detect edges, curves, and patterns that make up the digit. This helps the model focus on important characteristics like the round shape of "0" or the straight lines in "1." Next, the **ReLU activation function** is applied to remove negative values, ensuring that only significant features are passed forward. Then, a **pooling layer** reduces the image size while keeping essential information, making the model computationally efficient. After multiple convolution and pooling operations, the extracted features are flattened into a one-dimensional vector and passed through **fully connected layers**, where the network learns the relationships between these features. Finally, the **output layer** applies a classification function like Softmax, which assigns probabilities to each digit (0-9). If the highest probability is for "5," the model correctly classifies the input as the digit "5." This process allows CNNs to achieve high accuracy in tasks for real world applications.

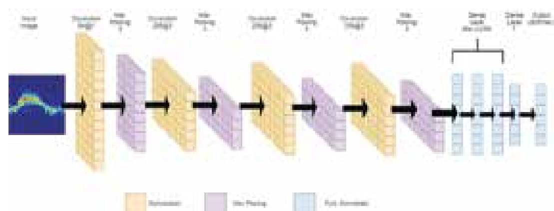

Fig 5.4 Visual representation of CNN model

8. RESULTS AND DISCUSSION

The implementation of the multifunctional quadcopter for agricultural applications is anticipated to yield several significant results:
1. Enhanced Crop Monitoring: The quadcopter is expected to provide high-resolution images of agricultural fields, enabling farmers to monitor crop health and field conditions more effectively.
2. Improved Disease Detection: The integration of AI-based image classification algorithms is anticipated to accurately identify and classify various crop diseases in real-time, providing timely alerts to farmers. This will enable quicker interventions, reducing potential yield losses.
3. Increased Precision in Agriculture: The implementation of Convolutional Neural Networks (CNNs) and decision algorithms will enhance precision agriculture practices by enabling accurate detection and diagnosis of plant health issues. This advanced approach allows for targeted interventions based on the specific health status of different areas within a field. Consequently, it will lead to optimized resource utilization, including water, fertilizers, and pesticides, minimizing waste and improving overall agricultural efficiency.
4. Real-time Data Accessibility: The dedicated mobile or web application will provide farmers with immediate access to aerial imagery and analysis results, facilitating informed decision-making based on current field conditions.
5. User Satisfaction and Adoption: The user-friendly application and effective results in crop monitoring and disease detection are expected to lead to high user satisfaction and encourage the adoption of UAV technology among farmers.

9. ADVANTAGES, DISADVANTAGES AND APPLICATIONS

Advantages
1. Increased Efficiency: UAVs can cover large areas quickly, reducing the time and labor required for traditional field monitoring methods.
2. Precision Agriculture: High-resolution imaging and data collection allow for targeted interventions.
3. Real-Time Data Access: Farmers can receive immediate insights about crop health, allowing for prompt decision-making and interventions to mitigate losses.
4. Cost-Effective: While initial investments may be high, UAV technology can lead to long term savings by improving yield and reducing waste.
5. User-Friendly Applications: Dedicated mobile or web applications facilitate ease of use for farmers, even those with limited technological expertise.
6. Sustainability: Promotes sustainable farming practices by optimizing resource usage and reducing environmental impact.

Disadvantages
1. High Initial Cost: The cost of acquiring and setting up UAV technology can be a barrier for small-scale farmers.
2. Technical Complexity: The operation and maintenance of UAVs may require a certain level of technical knowledge, which can be challenging for some farmers.
3. Regulatory Restrictions: UAV operations may be subject to regulatory restrictions and require permits, limiting where and how they can be used.
4. Privacy Concerns: The use of drones may raise privacy concerns among neighboring properties or communities, leading to potential conflicts.
5. Data Overload: The collection of vast amounts of data can lead to challenges in data management and analysis, requiring additional tools and expertise.

Applications
1. Crop Monitoring and Health Assessment: Regular monitoring of crop health through imaging to identify stress, diseases, or nutrient deficiencies.
2. Precision Agriculture: Targeted application of inputs based on data analysis, leading to improved crop yield and reduced resource waste.
3. Research and Development: Supporting agricultural research by providing data for studies on crop health, disease dynamics, and environmental impacts.
4. Livestock Monitoring: Monitoring livestock health and behavior in large pastures, providing insights into herd management.
5. Environmental Monitoring: Assessing the impact of agricultural practices on the surrounding environment, contributing to sustainable land management practices.

10. CONCLUSION AND FUTURE SCOPE

The integration of UAVs (Unmanned Aerial Vehicles) in precision agriculture has significantly transformed farming practices, offering innovative solutions for efficient crop management, resource optimization, and sustainability. UAVs have proven to be invaluable tools for monitoring crop health assesment and environmental factors, all while reducing costs and minimizing resource wastage. Through real-time data collection and analysis, UAVs enable farmers to make informed, data-driven decisions that improve productivity and reduce environmental impact. As a result, the adoption of UAVs in agriculture has contributed to more sustainable farming practices, improved yields, and better overall farm management.
Future work in precision agriculture using UAVs will focus several key areas to further enhance efficiency,sustainability, and productivity:
• Development of more sensors, such as multispectral, hyperspectral, and LiDAR, will enable deeper insights into crop health, soil conditions, and environmental factors, leading to more precise data collection and decision-making.
• AI and machine learning algorithms will enable UAVs to analyze data autonomously, detect patterns, predict potential issues, and optimize farming practices in real time.
• UAV systems will become more autonomous, capable of performing a wider range of tasks such as planting, fertilizing, spraying, and harvesting, reducing human labor and increasing operational efficiency.
• Advances in battery technology will extend UAV flight times, allowing for larger areas to be monitored per flight, while increased payload capacity will enable UAVs to carry and deploy more equipment for tasks like seed planting or spraying.

• UAVs will increasingly integrate with Internet of Things (IoT) devices and farm management software, providing farmers with a unified platform for monitoring and managing operations, optimizing resource usage, and streamlining workflows.
• As UAV technology becomes more affordable, its adoption will expand to smaller farms and developing regions, making precision agriculture accessible to a wider range of farmers.
• Establishing clearer regulations and safety standards for UAV use in agriculture will ensure safe and legal operations, promoting wider acceptance and use of UAVs across the industry.
• UAVs will help farmers adapt to climate change by providing real-time data for monitoring environmental stressors, adjusting irrigation, and optimizing the use of fertilizers and pesticides, contributing to more sustainable farming practices.
• Continued advancements in UAV technology, data analytics, and automation will drive the future of precision agriculture, making it more efficient, sustainable, and adaptable to global agricultural challenges.

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Vision

GM University will have a transformative impact on society through continual innovation in education, research, skill development, creativity, and entrepreneurship.

Mission

To disseminate knowledge and conduct research in academic areas such as science, engineering, commerce, management, health, humanities & social sciences, and legal studies with learner centric approach.

To teach skills such as critical thinking, creativity & innovation, collaboration, communication, technical & digital, flexibility & adaptability, cultural values, and leadership & responsibility.

To develop global citizens by educating students on emotional, physical, social, economic, environmental, spiritual dimensions of human growth in addition to intellectual pursuit.

To address real-world challenges and to establish the groundwork for entrepreneurship and lifelong learning.