CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

Cultivation of crops is crucial to the world economies as it affects the food productivity and people's livelihoods but arecanut farming has been affected by yellow leaf disease which results in poor quality and yield hence immense losses. This disease not only a hazard to the growth of the arecanut plantations that are already in existence in different parts of the world but also poses a threat to those farmers who depend on this plant in order to earn a living. It has been demonstrated that managerial approaches, such as sophisticated image recognition and self-acting spraying technology, are efficient methods to detect the disease at an early stage and control its spread, thus lessening the losses.

Chlorosis, stunted growth and in the worst case scenario death of the plants are the main symptoms of yellow leaf disease. It is very mobile and is often out of control and farmers are usually left with a very narrow window of time in which to act before the problem gets out of hand. The conventional ways of controlling diseases involve physical assessment of plants and crops followed by general insecticide spraying, which is costly, time consuming and tends to pollute the environment.

When it comes to solving the problems that affect agriculture, what is needed is technology interventions. There is one, it is possible to sort images with the help of advanced image classification with machine learning. The identification of healthy and unhealthy plant can be determined with a high level of accuracy using the ResNet-50 Convolutional Neural Network (CNN) from areca images. Training this model with this kind of dataset allows for accurate distinction between healthy leaves and those affected by yellow leaf disease.

The spraying mechanism is quite independent with the ESP 32 CAM to release the pesticide only to the affected region by an engineered nozzle besides having electrical switches. Organizational framework improves upon treatment effectiveness, lessens the use of chemicals as well as fosters environmentally friendly farming. In addition to underlining the innovation's ability to add efficiency and dynamism to contemporary agriculture and create value for farmers, customers, and soil, this project shows how technology can address other challenges to build a more robust agriculture system in the future.

1.2 YELLOW LEAF DISEASE:

The common disease known as yellow leaf disease is highly dangerous to arecanut plantations and in return restricts the economical earning of the farmers. YLD is fast, easy to spread due to its vectors, the arecanut yellow leaf virus (AYLV) that results in such symptoms as yellowing of leaves, stunted growth and plant death. Figs 3 and 4 show that this disease also affects the nut yield and quality and thus has a negative impact on the income of the farming households in the tropical regions depending on arecanut for their livelihoods, such as India, Indonesia and Bangladesh.

Yellow leaf disease is not only a problem for individual farmers but for the local and national economy as well. In localities where arecanut is one of the cash crops, frequent diseases attack resulted in scarcity in the market hence high prices affect consumers. Beside this, since arecanut is used much in cultural and religious functions its absence affects culture and celebrations Another point is that arecanut has no substitute, which makes yellow-leaf disease a major threat to food security.

The standard approaches of managing yellow leaf disease have at many times been inefficient. Farmers usually use a naked eye assessment and broad spectrum insecticides which are ineffective when it comes to diseases targeting crops. This serves to give a raw deal on chemicals and exposes the environment to a risk of being degraded together with posing risks to human health.

The problem of yellow leaf disease is comprehensible when considering that the matter impacts the concerns of sustainable agriculture and rural development. With such areas often closely relating agricultural productivity to economic stability in many regions, suitable management plans are needed to protect farmers' income. Use of proper technology like early detection systems which includes image classification as well as the pest control through pesticide which is applied to the area that has the problem can therefore be another good approach towards this disease.

The incidence of Yellow leaf disease in the arecanut plantations is not same in all the regions of Karnataka. In Dakshina Kannada, possibly 40-60% of farms may be involved, while Udupi has 30-50% of farms affected. Kodagu varies between 20-40% range whereas the impact in Hassan varies in the 10-30 % range. Out of the plantation, Chikkamagaluru has about 15 to 25% plantations affected. These numbers show that there is a great fluctuation in the virulence of the diseases with climate and farming practices. For more detailed information on the real situation farmers may turn to local agricultural extension services or research centers.

1.3 EXPERT CONSULTATION ON ARECANUT HEALTH

Fig 1.1 Horticulture Department at Karkala

Shrinivas B.V, an officer horticulture department, Karkala said that the arecanut farmers are facing many problems mainly diseases as well as nutrient deficiencies affecting tree health and production of arecanut. Among all these, yellow leaf disease takes the center stage and is one the most fundamental problem that leads to low yields and makes the economy of the farming not lucrative. This disease is especially related with nutrient deficiencies which include nitrogen, magnesium and zinc.

In order to counter these problems he stressed on nutrient management also to be efficient. The soil must be tested from time to time to determine which nutrient is lacking so as to inform the strategy to use fertilizers in order to be absorbed by the trees by the farmers. It is, therefore, possible to claim that maintaining a proper supply balance of nutrients can improve the useful strength of arecanut trees, the ability to stand environmental conditions and disease effects.

Other recommended practices included in nutrient management he also emphasized on fungicides like copper oxychloride and metalaxyl. Copper oxychloride acts as a fungicide controlling diseases including fruit rot which are more frequent during the rainy season. This is especially important as they diligently researched how high humidity fosters the growth of fungus, therefore becoming a threat.

Shrinivas B.V. discussed the principles for controlling yellow leaf disease in arecanut trees. He highlighted that nutrient deficiencies such as Nitrogen, Magnesium as well as Zinc should be dealt with from time to time, after conducting soil tests across the farm. Also, he advised the farmers to use other chemical control measures like copper oxychloride for fruit rot and metalaxyl for combating both downy mildrew and other oomycetes.

1.4 copper oxychloride and metalaxyl mixture

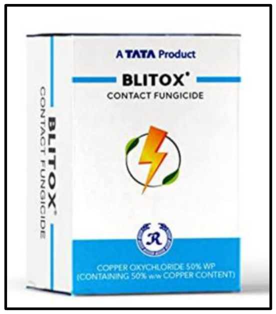


Fig 1.2 Blitox 50 and Ridomil Gold

Yellow leaf disease on arecanut plantation can be controlled effectively by using a combination of copper oxychloride and metalaxyl. Copper oxychloride works by controlling many fungal pathogens that cause the formation of leaf spots, while metalaxyl controls oomycetes like *Phytophthora* which causes root and stem rot. In our project, Blitox 50 and Ridomil Gold, a combination recommended from previous research to control yellow leaf disease in arecanut trees.

Blitox 50 includes copper oxychloride which is a protective fungicide. From copper oxychloride, copper ions control fungal spore germination by sticking on the plant surface. This man and ericaceous fertiliser apply effectively on arecanut plants against fungal diseases such as Phytophthora, which cause yellowing of the foliage. Copper oxychloride is a bilateral contact fungicide, a substance that does not penetrate the plant tissue but remains on the surface of the leaves, so in order to control the diseases, it is necessary to apply it very precisely and sufficiently often.

Ridomil Gold however contains metalaxyl; a systemic fungicide that moves from part of the plant to another through the plant tissues. Metalaxyl act by inhibiting RNA synthesis in fungi and provides excellent control of oomycete diseases such as Phytophthora and Pythium diseases. Again, while copper oxychloride acts on the outer part of the plant, metalaxyl acts inside the plant to protect both shoots that are developing and those that are already formed.

Blitox 50 + Ridomil Gold is primarily fungicide which imparts both protective which is copper oxy chloride and systematic is metal axyl. Copper oxychloride gives a covering to the spores on the surface of the leaves, thus discouraging the spores from attaching themselves to the plant while metalaxyl has a function of entering the tissues of the plant improving the control of infections that have already taken place. This combination is most useful for management of diseases in moist items of production such as arecanut plantations which are prone to fungal attack.

CHAPTER 2
LITERATURE REVIEW

2.1 LITERATURE SURVEY

This paper introduces a computer vision-based grading system for boiled arecanuts to streamline the sorting process. Using MATLAB, the system automates grading by classifying arecanuts based on color and texture, employing HSV color space quantization, Gabor transform, and an SVM classifier. This technology enhances efficiency, accuracy, and fairness in arecanut sorting [1].

The document reviews yellow leaf disease (YLD) in areca palm, a major threat in regions like Hainan, China. Initially linked to phytoplasma, recent studies suggest areca palm velarivirus 1 (APV1), transmitted by mealybugs, as the cause. Effective detection and management, including molecular techniques, are crucial for controlling YLD [2].

Study developed a UAV-based method to predict areca yellow leaf disease (YLD) severity using multispectral and thermal sensors. Combining the ReliefF algorithm with Random Forest yielded the highest accuracy ($R^2 = 0.955$). The strong correlation between canopy temperature and disease severity highlights the potential of UAV-based monitoring for YLD management [3].

The study assesses the effectiveness of PlanetScope imagery for large-scale monitoring of areca yellow leaf disease in challenging tropical and subtropical regions. The Random Forest (RF) model, utilizing high-resolution (3 m) imagery, achieved the highest accuracy (88.24%) and lowest errors, making it a valuable tool for disease detection and management [4].

This paper introduces a CNN-based system for early disease detection in arecanut plants, focusing on conditions like Mahali, stem bleeding, and yellow leaf spot. Using a dataset of 620 images, the model achieved 88.46% accuracy. This system supports smart farming by enabling effective disease identification and improved crop management [5].

This study develops a machine-based system for classifying areca nuts into grades using imaging techniques and deep learning. By analyzing color and geometric features, and utilizing a Backpropagation Neural Network (BPNN) classifier, the system achieved 91.43% accuracy in grading areca nuts, offering significant applications in precision agriculture and crop management [6].

This study presents a CNN-based system for early arecanut disease detection, analyzing 888 images to identify conditions like Mahali, Stem Bleeding, and Yellow Leaf Spot. The model achieved 88.46% accuracy using categorical cross-entropy and Adam optimizer over 50 epochs. This system aids smart farming by enabling timely and accurate disease intervention [7].

This literature survey underscores the importance of advanced disease detection in agriculture for both plant health and human well-being. It highlights the need for innovative techniques in developing countries like India, where traditional methods fall short. The survey reviews image processing technologies to enhance plant disease identification, supporting better agricultural outcomes [8].

This study investigates UAV multispectral remote sensing for quantitatively assessing yellow leaf disease in arecanut trees. Using vegetation indices and machine learning models, the study achieved 86.57% and 86.30% accuracy with BPNN and SVM models. The findings highlight UAV remote sensing's potential for effective plant disease monitoring and management, with future improvements suggested through hyperspectral sensors and 3D laser radar integration [9].

This study presents a novel method for classifying raw areca nuts as healthy or unhealthy using image processing and machine learning. By applying Otsu's segmentation and GLCM for texture features, and employing Decision Trees and CNNs, the method improves classification accuracy and aims to boost farmers' revenue by ensuring high-quality nut sales [10].

This study demonstrates CNNs' effectiveness in classifying arecanut diseases, achieving 93.05% accuracy with a dataset of 1,100 images. Using binary cross-entropy and Adam optimizer, the model offers a more efficient alternative to traditional methods. Future improvements could involve larger datasets and environmental factors, enhancing disease management for farmers and researchers [11].

This study identifies Areca Palm Velarivirus 1 (APV1) as a potential cause of Yellow Leaf Disease (YLD) in betel palm in Hainan, China. Sequencing revealed a 17,546-nucleotide genome, and APV1 particles were found to be flexuous and filamentous. Pseudococcus sp. mealybugs are suggested as vectors. Further research is needed to confirm causation and develop management strategies [12].
This study identifies a phytoplasma as the causative agent of Yellow Leaf Disease (YLD) in arecanut palms in India. DNA analysis revealed a phytoplasma closely related to the 16Sr XI group, with 99% nucleotide similarity to those affecting other crops. This is the first molecular evidence linking 16Sr XI phytoplasma to YLD in arecanut [13].

2.2 MOTIVATION

This research introduces the *Yellow Leaf Disease Detection and Autonomous Aerial Spraying Mechanism* for arecanut trees, addressing critical issues in managing yellow leaf disease. The motivation for this project arises from the need for a more precise, efficient, and sustainable approach to managing yellow leaf disease in areca nut plantations. By leveraging advancements in deep learning, image processing, and autonomous aerial technology, we aim to develop a system that can identify yellow leaf disease with high accuracy and precision. This enables targeted pesticide application, which reduces both pesticide usage and labour costs while minimizing the environmental impact associated with widespread spraying. Conventional methods are time-intensive, invasive, and often miss early signs of disease. Furthermore, traditional pesticide application is prone to overuse, leading to higher costs, environmental risks like chemical leaching, and pesticide resistance. These challenges question the efficiency and sustainability of current crop management practices.

Our project utilizes advanced technologies, including the ResNet50 model for accurate image classification and the ESP32 camera module for real-time monitoring. Machine learning enables early detection of yellow leaf disease, allowing farmers to act promptly and reduce crop losses. This mechanism’s compatibility with various drones makes it a versatile and practical tool for modern agriculture, supporting drone-based disease identification and targeted chemical application, thereby reducing pesticide waste.

The automation reduces labor demands, enabling farmers to focus on crucial aspects like planning and resource distribution. This shift improves both efficiency and the well-being of farmers. Emphasizing precision agriculture, the project facilitates data-driven decision-making, enhancing arecanut tree health and contributing to higher yields and improved livelihoods in arecanut-growing regions.

Additionally, our system’s portability is a significant advantage, allowing it to be adapted for other crops and drone models, enhancing its utility in diverse agricultural settings. Through field trials, we aim to validate this system's impact in a real-world environment, demonstrating its potential to streamline pest management, enhance crop health, and provide a viable solution for farmers facing similar agricultural challenges. This project, therefore, represents an intersection of modern technology with sustainable agricultural practices, aiming to support farmers and contribute to more resilient crop management systems.

2.3 PROBLEM STATEMENT

Cultivation of arecanut has been disastrous due to Yellow Leaf Disease (YLD) which poses a risk in the quality of the produce as well as the growers' income. There is always little accuracy in old school disease diagnose and pesticide spraying and often cause a lot of environmental hazards. The main goal of this work is to create an autonomous hexacopter system for real-time YLD identification based on ResNet50, which is designed for classification of leaves with or without diseases. A camera module EsP32 will take photos and depending on the results of an analysis, there will be a relay-controlled sprayer pump to dispense pesticides at the particular area for a specific interval of time to avoid unnecessary readmissions of pesticides.

Key challenges include:

- Yellow disease real-time detection.
- Targeted application to minimize on chemical usage.
- Integration camera, hardware of drone, and spraying mechanism.

2.4 OBJECTIVES

1. **Develop a Detection System for Yellow Leaf Due to Iron Deficiency in Arecanut**
   The aim is to create a correct recognition model to diagnose yellow leaf disease on areca nut plant caused by iron chlorosis. Employing the convolutional neural network model such as ResNet-50 previously trained on the rich database of healthy and diseased areca nut leaves, the system can observe shape, size, and colour to determine good, diseased, and non-areca. This approach makes it easy to control the diseases, by determining only the affected plants in the garden.

2. **Integrate an Autonomous Pesticide Spraying Mechanism**
   In case of yellow leaf disease, detection system of the drone will activate the autonomous sprayer which will spray a brief but very accurate pesticide on the infected leaves. Assembleable parts, such as a relay-controlled pump, a buck converter, and a battery, contribute to lower pesticide consumption and environmental effects while improving pest regulation in areca nut plantations.

3. **Investigate the Performance of the Developed System at Arecanut Farm**
   A series of field trials on an areca nut farm will follow to measure the system's detection performance, spraying effectiveness and capability to reduce the amount of pesticide used. The intervention results will inform further enhancement of the system, making it more functional and ready for farmers to use for managing pests that harm crops.

CHAPTER 3
METHODOLOGY

3.1 THRUST CALCULATION

To evaluate the performance and efficiency of a drone, it is essential to understand the thrust-to-weight ratio, which plays a crucial role in determining how effectively the drone can operate under various conditions. The thrust generated by the drone's propellers must exceed its weight to achieve flight. In this case, the maximum thrust produced by the drone’s six propellers is 9.6 kg, with each propeller generating 1.6 kg of thrust. This total thrust is crucial for supporting the drone during its operations, especially when carrying additional loads.

The total weight of the drone, including all components except for the battery and propellers, is designed to be 4.6 kg. This weight encompasses the structure, motors, electronic components, and other necessary parts that contribute to the drone's overall mass. To determine the net thrust available for flight, we subtract the total weight from the total thrust generated by the propellers. The calculation is as follows: 9.6 kg (total thrust) - 4.6 kg (total weight) results in a net thrust of 5 kg. This net thrust indicates the actual lifting capacity of the drone, allowing it to perform maneuvers and transport additional payloads effectively.

A crucial aspect of drone design is maintaining an optimal thrust-to-weight ratio, which is generally recommended to be at least 2:1 for efficient flight control and performance. In this instance, the thrust-to-weight ratio is calculated to be 2.08:1, which indicates that the drone has a thrust capacity that exceeds its weight. This optimal ratio signifies that the drone is equipped to handle various flying conditions, providing the necessary thrust to maneuver smoothly and maintain stability.

The higher thrust-to-weight ratio of 2.08:1 not only suggests enhanced performance but also translates into better agility during flight operations. A drone with sufficient thrust can carry heavier loads, making it versatile for different applications, whether for recreational flying or more demanding tasks such as aerial photography or delivery services. This thrust-to-weight efficiency ensures that the drone can navigate with ease and precision, ultimately contributing to improved control and resilience in various flying scenarios. Thus, the design considerations made in the thrust and weight balance of this drone highlight its capability to function effectively in diverse environments.

3.2 FLOWCHART ON STEP-BY-STEP PROCEDURE:

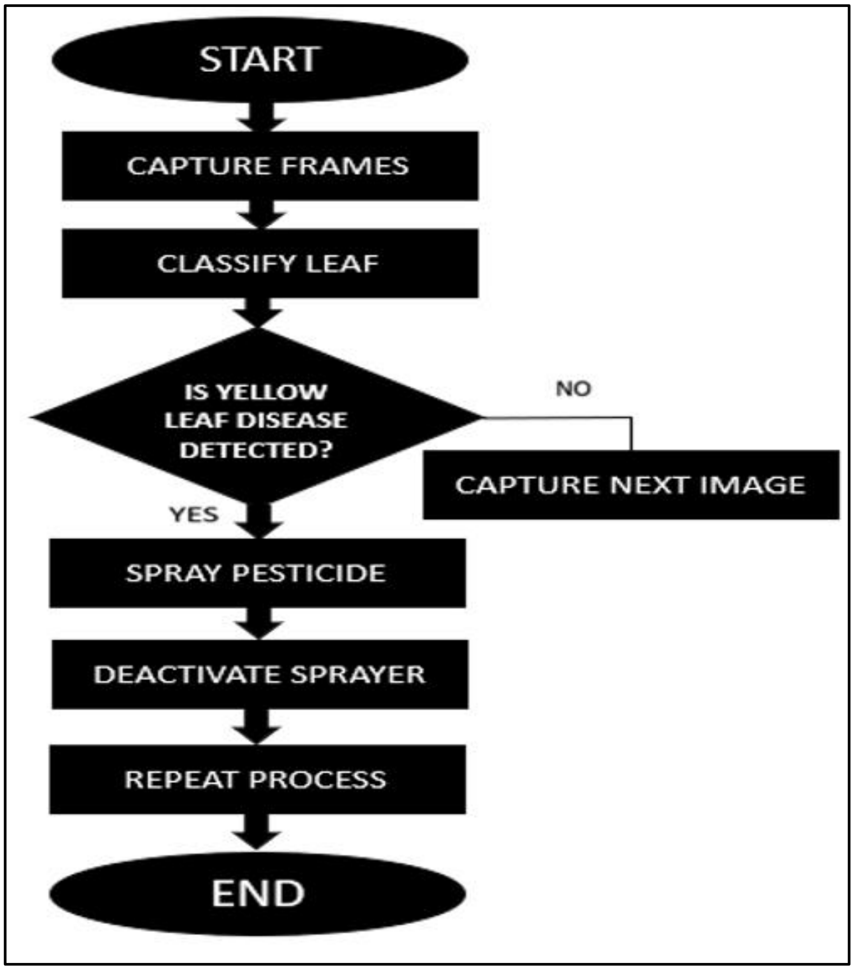


Fig 3.1 Step by Step Complete Procedure

Step-by-Step Procedure for Yellow Leaf Disease Detection and Spraying Mechanism

1. **Start the Process:**
   The system is initiated, and the autonomous hexacopter prepares to carry out disease detection and spraying.

2. **Capture Frames:**
   The ESP32 camera module attached to the hexacopter captures images (frames) of the arecanut leaves while the drone hovers above the plantation. This allows for real-time image acquisition as the drone moves over the plants.

3. **Classify Leaf:**
   The captured images are processed through a ResNet50 model, a deep learning convolutional neural network (CNN) pre-trained for image classification.
   The model classifies each leaf into one of four categories:
   - Healthy leaf: No yellow leaf disease detected.
   - Yellow leaf disease: Indicates the presence of disease.
   - Other leaf: Contains leaves that aren't relevant (e.g., non-arecanut leaves).
   - No leaf: The image doesn't contain any leaves.

4. **Check for Yellow Leaf Disease:**

   The system is designed to monitor and classify leaves for yellow leaf disease, ensuring precise and targeted pesticide application. Once an image is captured, the system analyzes it to determine the presence of yellow leaf disease.

   If the disease is detected, the system immediately initiates the pesticide spraying process, targeting only the affected areas. If no disease is identified, the system bypasses the spraying action, conserving pesticide and focusing resources where needed.

   After each assessment, the system proceeds to capture a new image, continuing the process of classification and action. This cycle of image capture and disease detection is repeated continuously, enabling the system to respond promptly when diseased leaves appear. The overarching goal is to apply pesticides only when necessary, optimizing effectiveness and minimizing waste.

5. **Spray Pesticide (if Yellow Leaf Disease is Detected):**

   When the system detects a diseased leaf, it activates a relay switch, which then triggers the sprayer pump. The pump is connected to a pesticide container, ensuring that, upon activation, pesticide is released directly onto the affected leaf.

   The sprayer is designed for precise application, with an optimized nozzle that ensures effective and focused pesticide distribution. This setup enables the system to target diseased areas accurately, enhancing the efficiency of pesticide application and reducing waste.

6. **Deactivate Sprayer:**

   The sprayer pump is programmed to operate precisely for 5 seconds, a time limit that helps control the amount of pesticide used per application. By running for this set duration, the system minimizes pesticide waste while ensuring sufficient coverage of the diseased area.

   After the 5-second interval, the relay automatically deactivates the pump, effectively stopping the pesticide release. This timed approach optimizes pesticide usage, balancing effectiveness with conservation.

7. **Repeat Process:**

   Once the sprayer deactivates, the system returns to its initial steps, capturing new frames and classifying leaves for signs of disease. This cycle repeats continuously as the hexacopter moves across the plantation, scanning for diseased leaves in real time.

   This automated loop enables thorough monitoring and targeted spraying, allowing the system to effectively manage the spread of disease across the plantation.

8. **End Process:**
   The process concludes either when the hexacopter completes its scanning path or is manually terminated.

3.3 DATA COLLECTION AND PRE-PROCESSING:

Dataset Description: The dataset employed in this study has got three classes: Healthy Arecanut. Leaf, Yellow Leaf Disease and Other Leafs. The images were gathered, and all of them were compiled into different categories that required their own directories.

Image Loading and Labeling: The images were read and loaded from the respective directories using the Open source Computer Vision Library (cv2). Every photograph was analyzed, and the color space was transformed to RGB before resizing the image to a 224 by 224 pixel size as specific by the model.
Labels were assigned to each image based on the directory it was loaded from, with the following mapping:

1. Healthy Arecanut Leaf: Label 0
2. Yellow Leaf Disease: Label 1
3. Other Leaves: Label 2
4. No leaf: Label 3

Fig 3.2 Healthy leaf

Fig 3.3 Yellow Leaf Disease

Fig 3.4 Other leaf

Fig 3.5 No leaf

Data Splitting: To achieve this the dataset was split into training, validation and test set in the ratio of 7:1.5: 1.5 respectively. This split proved useful in making it that the model gets to learn most of the data and still, there existed other data that we used for validation and testing right through.

Data Augmentation and Preprocessing: In most cases, the feed of images into the model was preceded by preprocess input function of the Keras library, built based on two conditions that worked during pre-training of the ResNet50 model, namely the standardization of illuminance on the images.

3.4 MODEL ARCHITECTURE:

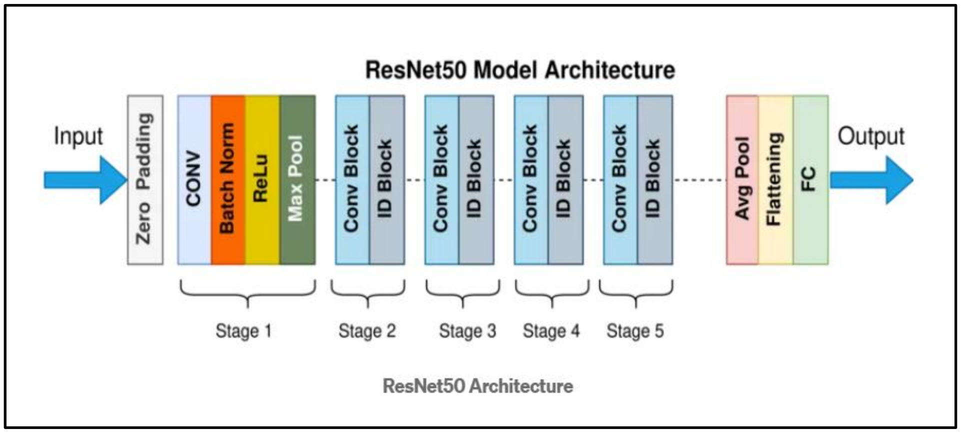


Fig 3.6 Model Architecture

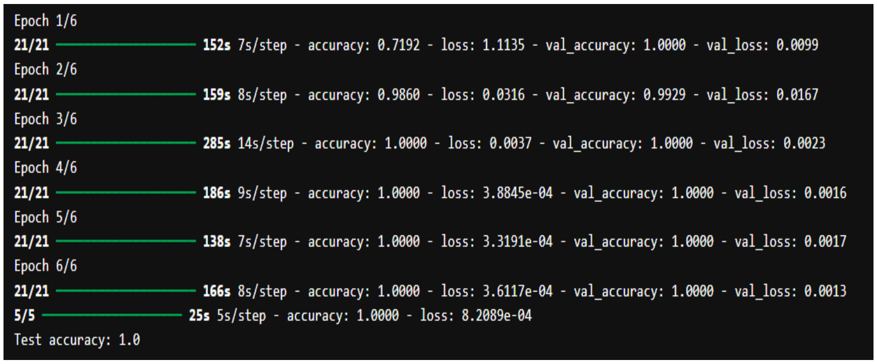
The image provides an overview of the ResNet-50 architecture, a deep convolutional neural network for image classification. The architecture begins with an input layer that receives images, applying zero padding for consistent dimensions. Stage 1 includes a convolution layer (CONV), batch normalization (Batch Norm), ReLU activation, and max pooling (Max Pool). These processes extract initial features, normalize data, introduce non-linearity, and reduce the spatial dimensions of the feature maps.

In stages 2 to 5 of residual learning, Conv Blocks reduce spatial dimensions for down-sampling, followed by Identity Blocks that maintain dimensions using skip connections. Conv Blocks connect feature maps of different resolutions, while ID Blocks add inputs directly to outputs, enabling the network to learn residuals rather than full transformations. This approach helps prevent the vanishing gradient problem, allowing for deeper network scaling.

After the final residual stage, the network applies average pooling, which condenses each feature map to a single value, summarizing the spatial information. The output is then flattened into a 1D vector, which passes through a fully connected (FC) layer to produce the final classification result.

In this project, the ResNet-50 model classifies images of arecanut leaves into four categories: healthy, yellow leaf disease, other leaf, and no leaf. When yellow leaf disease is detected, an autonomous drone-mounted spraying mechanism, controlled by an ESP32 camera, relay switches, and a buck converter, activates to dispense pesticide for 5 seconds. The ResNet-50's deep architecture with residual learning allows it to accurately differentiate leaf conditions, ensuring precise and efficient spraying.

3.5 MODEL TRAINING:



```
Epoch 1/6
21/21 ──────────────── 152s 7s/step - accuracy: 0.7192 - loss: 1.1135 - val_accuracy: 1.0000 - val_loss: 0.0099
Epoch 2/6
21/21 ──────────────── 159s 8s/step - accuracy: 0.9860 - loss: 0.0316 - val_accuracy: 0.9929 - val_loss: 0.0167
Epoch 3/6
21/21 ──────────────── 285s 14s/step - accuracy: 1.0000 - loss: 0.0037 - val_accuracy: 1.0000 - val_loss: 0.0023
Epoch 4/6
21/21 ──────────────── 186s 9s/step - accuracy: 1.0000 - loss: 3.8845e-04 - val_accuracy: 1.0000 - val_loss: 0.0016
Epoch 5/6
21/21 ──────────────── 138s 7s/step - accuracy: 1.0000 - loss: 3.3191e-04 - val_accuracy: 1.0000 - val_loss: 0.0017
Epoch 6/6
21/21 ──────────────── 166s 8s/step - accuracy: 1.0000 - loss: 3.6117e-04 - val_accuracy: 1.0000 - val_loss: 0.0013
5/5 ──────────────── 25s 5s/step - accuracy: 1.0000 - loss: 8.2089e-04
Test accuracy: 1.0
```

Fig 3.7 Model Training

Training Process: The training was carried out with 6 epochs using a batch size of 32 on the training dataset. The validation dataset was used to check the model performance after each epoch, so that it can be adjusted and over-fiting prevented. Performance Metrics: However, after training, the model obtained Final Training Accuracy = 0.98794 and the Final Validation Accuracy = 0.993506. The Final Training Loss was 0.000145 and the Final Validation Loss was 0.031717.n

3.6 MODEL EVALUATION:

Testing on Unseen Data: The performance of the proposed model was tested using a different test dataset in order to see if the model can generalize well. Similarly to the training set, the test images were formatted for the experiments as well.

Fig 3.8 Healthy Leaf

Fig 3.9 Yellow Leaf

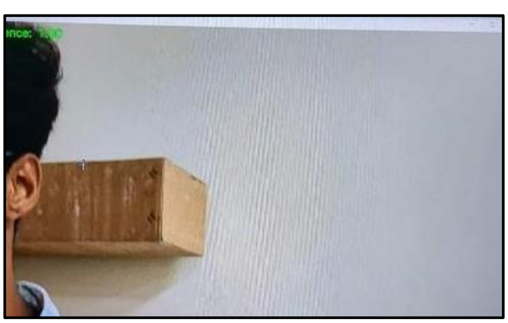


Fig 3.10 No leaf

Fig 3.11 Other leaf

3.7 FLOWCHART OF RESNET-50(MODEL DEPLOYING)

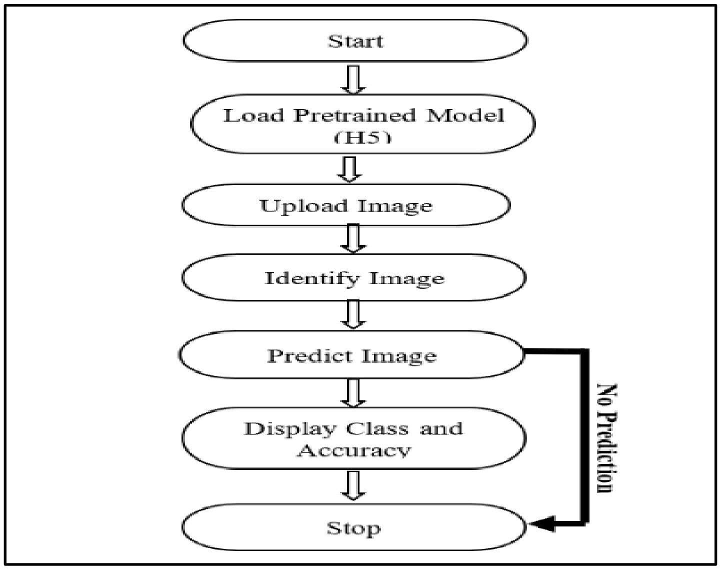


Fig 3.12 Model Deploying

Load Pretrained Model (H5): This procedure involves fine tuning a model which has been pretrained earlier in H5 format. H5 file is employed in deep learning to store weights, configuration and structure of the implemented model. Here the model may be ResNet-50 a pre-trained model on a big dataset possibly ImageNet or other big dataset and then trained on a particular dataset of areca nut leafs.

Upload Image: The second process that comes after loading the pretrained model is that you upload an image for classification. This looks like an image of an areca nut leaf in which the model will classify as healthy, diseased or belongs to some other category. The image is then transferred into the system exposing it into the model for a prediction variant.

Identify Image: They sort of involve preparing the image that has been uploaded to be in the right format that can be taken by the model. The identification process would involve resizing the image to a size that could be traced to the input size desired from a ResNet-50 model, scale the pixel values to a range of numbers between 0 and 1, and possibly the use of several other kinds of manipulations.

Predict: The preprocessed image is then fed into the model where the model itself tries to make an output about the class of the input image. The result from the model is probabilities for the classes into which it has been trained to categorize the images (e.g., healthy, diseased). The class with the highest probability is normally regarded as the predicted class in the course.

Display Class and Accuracy: Following the prediction of a class, the last part is to show the class along with the models estimate, or how correct the model was in its prediction. The second is the measure of accuracy here a probability or confidence level with regards to the predicted class which shows how confident the model is with its prediction. This output is then displayed in a format friendly to the user so that the user can easily determine what the classification has indicated.

3.8 FLOWCHART OF RES-NET 50(MODEL TRAINING

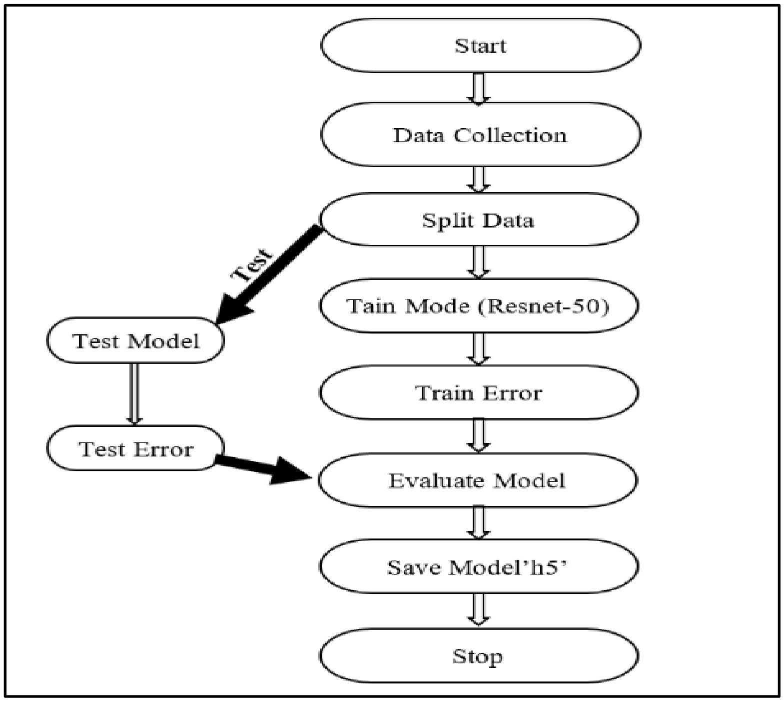


Fig 3.13 Model Training

•**Start:** This is the initial step of the workflow, marking the beginning of the process. It likely involves setting up the necessary environment, tools, and resources needed to proceed with the subsequent steps.

•**Data Collection:** This step involves gathering the data required for the model. In the context of a machine learning project, this typically means collecting images of areca nut leaves, including healthy leaves, diseased leaves, and possibly other types. Data collection is crucial as the quality and quantity of data significantly influence the model's performance.

•**Split Data:** After data collection, the dataset is split into different subsets, usually training, validation, and test sets. The training set is used to train the model, the validation set is used for hyperparameter tuning and to prevent overfitting, and the test set is used to evaluate the model's final performance. The split ensures that the model is tested on unseen data to evaluate its generalization ability.

•**Train Model (ResNet-50):** In this step, the ResNet-50 model is trained using the training dataset. ResNet-50 is a convolutional neural network (CNN) architecture with 50 layers, designed to solve the vanishing gradient problem by using residual connections. The training process involves feeding the data into the model, adjusting the weights based on the loss, and iterating over the dataset to minimize the error.

•Test Model: After training, the model is tested using the test dataset. This step is critical to assess how well the model has learned and how it performs on new, unseen data. The testing phase helps in determining the effectiveness of the training process and identifies any potential issues like overfitting or underfitting.
•Evaluate Model: The evaluation step involves calculating various metrics to understand the model's performance comprehensively. Common evaluation metrics include accuracy, precision, recall, F1-score, and loss values. This step helps in quantifying how well the model is performing and whether it meets the desired criteria for deployment.
Save Model: Once the model is trained and evaluated, it is saved for future use. Saving the model typically involves storing the model architecture, weights, and other necessary components so that it can be loaded and used later without.

3.9 Class Distribution:

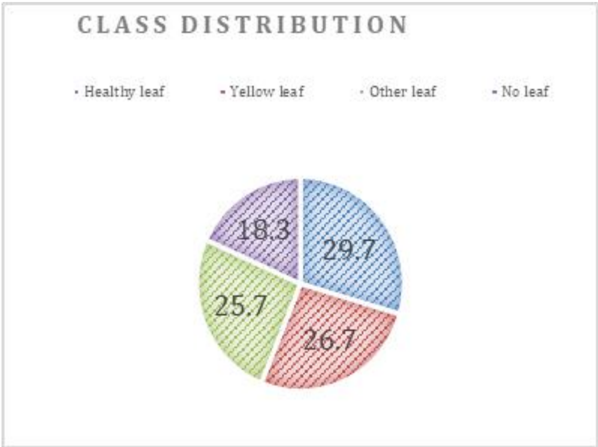


Fig 3.14 Percentage Distribution

The pie chart above illustrates the dataset distribution used for training the ResNet-50 model in detecting yellow leaf disease in areca nut trees. The four categories represented are:

- Healthy Leaf: 29.7%
- Yellow Leaf: 26.7%
- Other Leaf: 25.1%
- No Leaf: 18.3%

This distribution shows a relatively balanced dataset, with each class representing a significant portion of the data. Such distribution is beneficial for training the model, as it provides the ResNet-50 network with a diverse set of examples to learn from, helping it to generalize well for accurate classification in real-world scenarios.

3.10 MODEL COMPARISON:

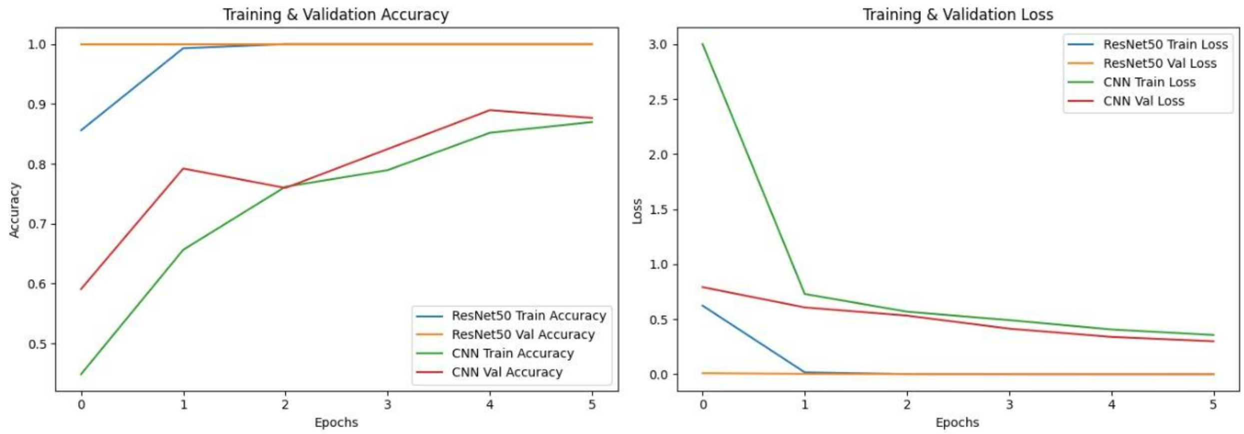


Fig 3.15 Model Comparison

Training & Validation Accuracy: In the accuracy graph, ResNet-50 significantly outperforms the basic CNN model. ResNet-50 quickly achieves close to 100% training accuracy within the first epoch and maintains this high accuracy over subsequent epochs. Similarly, its validation accuracy remains near-perfect, indicating strong generalization to unseen data. On the other hand, the CNN model starts with lower accuracy but gradually improves over epochs. By epoch 3, it approaches the validation accuracy of ResNet-50, though its training accuracy remains below that of ResNet-50, reflecting the CNN model's slower convergence and less effective feature extraction capability.

Training & Validation Loss: In the loss graph, the ResNet-50 model also demonstrates superior performance with lower training and validation loss values across all epochs compared to the CNN. ResNet-50's training loss reduces rapidly and stabilizes near zero after the first epoch, while its validation loss stays consistently low, suggesting minimal overfitting and effective learning. In contrast, the CNN model starts with a high training loss and shows a gradual decrease over epochs. Its validation loss remains relatively high and doesn't drop as significantly as ResNet-50's, indicating less effective learning.

Overall Comparison: The ResNet-50 model clearly outperforms the basic CNN in both accuracy and loss metrics, achieving faster convergence and better generalization. This difference is due to ResNet-50's advanced architecture with residual connections, which allows it to handle complex features and avoid vanishing gradients, making it more suitable for high-accuracy tasks such as leaf disease classification in this project. In contrast, the simpler CNN model struggles to reach similar accuracy, showing that ResNet-50 is a more efficient choice for this application.

3.11 ResNet-50 v/s CNN Classification:

ResNet50 Classification Report:

	precision	recall	f1-score	support
Healthy Arecanut Leaf	1.00	1.00	1.00	59
Yellow Leaf Disease	1.00	1.00	1.00	48
Other Leaf	1.00	1.00	1.00	49
accuracy			1.00	156
macro avg	1.00	1.00	1.00	156
weighted avg	1.00	1.00	1.00	156

CNN Classification Report:

	precision	recall	f1-score	support
Healthy Arecanut Leaf	0.89	0.85	0.87	59
Yellow Leaf Disease	0.95	0.77	0.85	48
Other Leaf	0.77	0.96	0.85	49
accuracy			0.86	156
macro avg	0.87	0.86	0.86	156
weighted avg	0.87	0.86	0.86	156

Fig 3.16 ResNet v/s CNN Classification

The classification reports presented in the preceding sections are able to provide concrete evidence of poor performance of the ResNet-50 and CNN models especially in the classification of areca nut leaves.

The ResNet-50 model achieved an impressive overall accuracy of 100%, with perfect scores of 1.00 in precision, recall, and F1-score across all classes: Hualtumba, Avrosis Healthy Arecanut Leaf, Yellow Leaf Disease, and Other Leaf. This perfect accuracy implies that ResNet-50 not only performed well in the task of discrimination of the various types of leaves, but also in a non-misclassification manner. That sort of metric demonstrates how the structure can generalize well, which makes it ideal for accurate agricultural uses requiring reliable identification of diseases. In the agricultural sector it is quite important to identify and differentiate between different types of leaves and in the event of a disease outbreak timely action is usually adequate losses.

On the other hand, the accuracy of the CNN model was relatively low and the overall accuracy recorded was 86%. This method provided good accuracy and fair recall findings for the Healthy Arecanut Leaf (0.89) and Yellow Leaf Disease (0.95) classes, however, the performance for the Other Leaf class was not as impressive as a precision of 0.77 was obtained. This indicates that other specific categories such as Other Leaf were quite challenging for the CNN model to distinguish from instances belonging to it. As evidenced by the data reported in Fig. 6 and Table 2, relatively low precision, recall, and F1 measure for this class suggests that there might be misclassification occurring and the model fails at extracting very unique features successfully. Such inability forestalls any doctor or diagnostician from telling thedifference between the different subtypes of leaves and may result to wrong diagnosis with ramifications on crop husbandry and yield.

3.12 PUMP MONITORING:

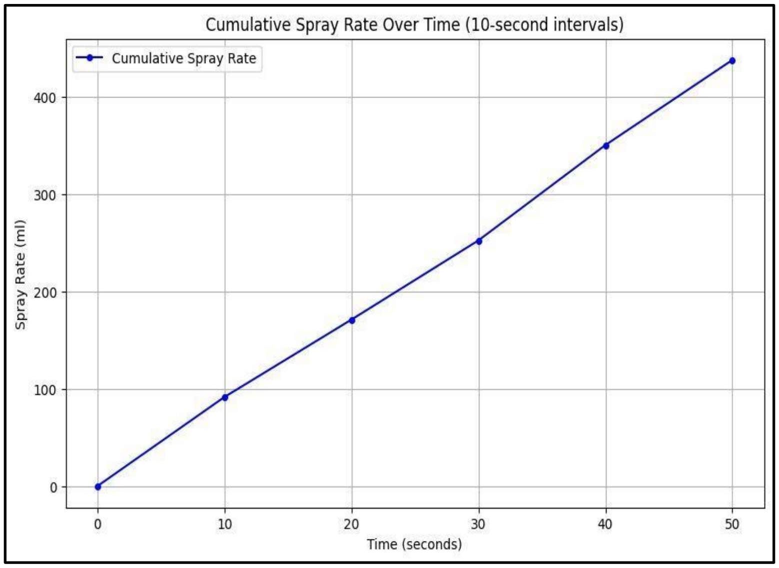


Fig 3.17 Pump Monitoring

The 12V DC sprayer pump in your project is a powerful component designed for efficient liquid transfer and spraying applications, ideal for agricultural tasks like pesticide distribution. With a capacity of 4.5 liters per minute, the pump can handle high fluid flow, making it suitable for covering large areas quickly. However, when used with the attached nozzle, the flow rate decreases by 500 ml, adjusting the effective output to approximately 4 liters per minute.

This is because the working fluid is restricted through the nozzle which causes its dispersion to be finer than with the broad spray plate. This misting effect is especially valuable in agricultural spraying applicants cause the actual coverage area of the pesticides to be wider and almost even while reducing absolute wastage of the liquid. Moreover, the 12V DC pump employs low power capability and, therefore, fits well in aerial systems, such as drones.

Due to the size and carrying capacity of the pump, it is easy to regulate the duration of spraying as well as the about of liquid to be dispensed. It allows you to keep the entire system with brute affinity, for example, to spray only the diseased leaves and for the required time of only 5 seconds per spray. In sum, the pump with a high carrying capacity, work with the 12V power supply, and the possibility of using different nozzle constructions is the component essential for efficient and effective application of pesticides within the autonomous aerial spraying system. It helps in evaluating your ability to handle your project with special reference to yellow leaf disease with efficiency in deployment of resources.

CHAPTER 6
MODELLING AND FABRICATION

4.1 CAD MODEL:

It is a drone-mounted aerial spraying highly functional and less bulky 3D-printed nozzle holder. It safely positions the nozzle for even spray distribution by ensuring decreased vibration of the device. It has holes for cuttingouts and screw holes to hold the frame firmly and improving the accuracy in pesticide application.

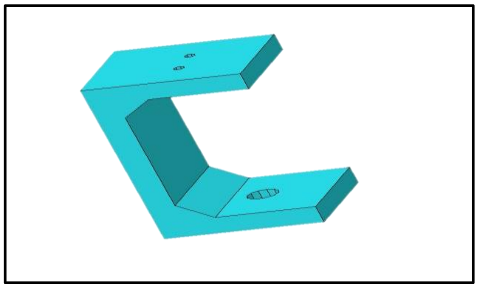


Fig 4.1 Nozzle Holder

The 3D-printed circuit case securely houses electronic components, protecting them from dust, moisture, and impact. A transparent acrylic cover allows visibility and adds durability, while the lightweight, custom-fit design is optimized for drone use. This setup enhances the spraying system's reliability and safety.

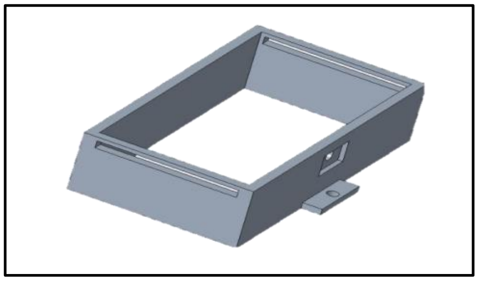


Fig 4.2 Circuit Case

The laser-cut acrylic quadcopter baseplate provides a sturdy, lightweight foundation for the spraying mechanism, securely holding components like the sprayer pump, circuit case, nozzle holder, and pesticide container. Designed for durability and easy drone mounting, it maintains stability while minimizing weight, ideal for efficient aerial spraying.

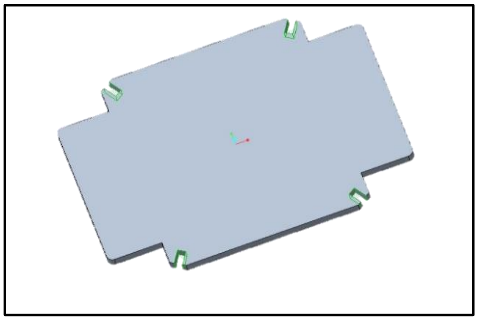


Fig 4.3 Base Plate

The camera and the nozzle holder are fabricated on a 170mm x 50mm x 4mm thin acrylic plate that has been laser cut to ensure stability without excessive weight for taking correct pictures and spraying at the correct points.
The fine laser cutting you see here provide a positive lock and great stability while using the drone.

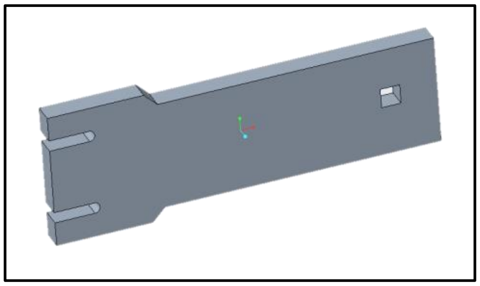


Fig 4.4 ESP Holder

4.2 FINAL ASSEMBLY:

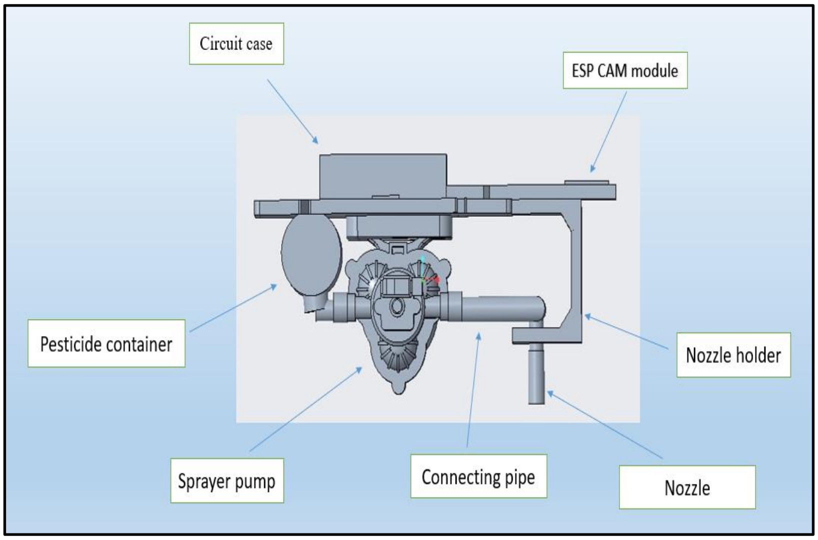


Fig 4.5 3D model of Final Assembly

The final assembly of the autonomous sprayer system, meticulously designed in CREO software, is specifically engineered for aerial pesticide application, focusing on the effective treatment of yellow leaf disease in arecanut plants. This compact and well-organized assembly integrates essential components to ensure efficient and targeted spraying. At its core, the circuit case protects the electronic circuitry from environmental factors, ensuring stable operation under various conditions, which is crucial for outdoor agricultural tasks.

Nearby, the ESP CAM module plays a pivotal role by capturing real-time images of the leaves, which serve as input for the ResNet-50 classification model. This model accurately identifies diseased leaves that require treatment, facilitating a precise response to the agricultural challenge. The system also includes a pesticide container designed to store the pesticide solution within the payload limits of the aerial vehicle. A 12V DC sprayer pump, with a capacity of 4.5 liters per minute, draws the pesticide and pushes it through a connecting pipe to the nozzle.

The nozzle holder is a 3D-printed component attached to a laser-cut acrylic base, ensuring that the nozzle is secured in an optimal orientation for precise spraying. It is calibrated to spray for only 5 seconds per diseased leaf, significantly minimizing pesticide waste and enhancing application efficiency. This organized layout allows the entire assembly to be easily mounted on a drone, and the real-time camera feed enables immediate disease detection and autonomous spraying. Overall, this sophisticated system not only improves the management of yellow leaf disease but also promotes sustainable agricultural practices through efficient resource use.

4.3 COMPONENTS:

4.3.1 ESP 32 CAM:

Quantity: 1

Price: ₹600

Description: This low-cost microcontroller is used for making photographs or for capturing the video through the integrated camera and is called ESP32 CAM. It is best used in image processing in projects that involve visualization such as an object recognition project or a monitoring project.

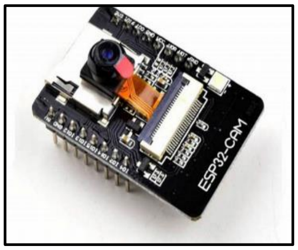


Fig 4.6 ESP 32 CAM

4.3.2 ESP 32:

Quantity: 1

Price: ₹220

Description: The ESP32 is low-cost, powerful microcontroller solution with integrated Wi-Fi and Bluetooth interface, suitable for IoT applications. It is commonly used with sensors and modules for purposes of remote control and signal processing.

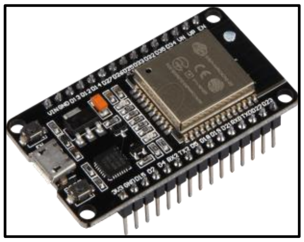


Fig 4.7 ESP 32

4.3.3 RELAY :

Quantity: 1

Price: ₹90

Description: This allows the relay module to play a part in controlling higher power devices such as motors or pumps which maybe connected to low power control systems. It is used for switching component on and off depending on what data the sensors provide.

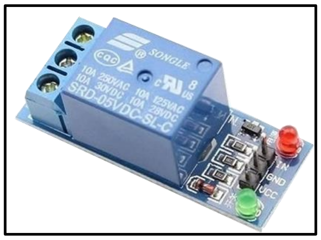


Fig 4.8 Relay Module

4.3.4 Buck Converter Step-down Power Module:

Quantity: 1

Price: ₹90

Description: In essence, a buck converter operates to decrease an input voltage and a correspondingly large current to an output voltage that is lower than the input. It is applied in starting, to supply average voltage appliances with main power, in order to stabilize the electrical circuits for precise electronics.

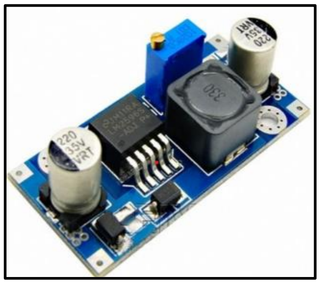


Fig 4.9 Buck Converter

4.3.5 12v DC sprayer pump:

Quantity: 1
Price: ₹860
Description: This pump is used to eject pesticide or water solution at a determined pressure. The from is particularly useful in agricultural applications where it is used for selective spraying.

Fig 4.10 Sprayer Pump

4.3.6 Lithium Polymer Battery Pack:

Quantity: 1
Price: ₹250
Description: The Orange 14.8V 5200mAh 40C 4S LiPo Battery Pack is perfect for powering an ESP32 and relay module, provides 14.8V output voltage, more than enough capacity and 40c discharge rate for stable operation.

Fig 4.11 4s battery

4.3.7 Lithium Polymer Battery Pack:

Quantity: 1
Price: ₹40
Description: This shows a dual-outlet nozzle, commonly used in agricultural sprayers. The nozzle has two spray heads, allowing it to disperse liquid (such as water or pesticides) over a wider area or in different directions. This type of nozzle is typically made of plastic and is designed to handle various chemicals used in farming.

Fig 4.12 Sprayer nozzle

4.3.8 Acrylic sheets:

Quantity: 1
Price: ₹600
Description: This appears to be a pack of high-density polyethylene (HDPE) or acrylic sheets. These sheets are typically durable, lightweight, and chemically resistant, making them useful in various applications like DIY projects, hobby crafts, and drone or model parts. They are often used for building parts of drones or other equipment where a lightweight and sturdy material is needed.

Fig 4.13 acrylic sheet

4.3.9 Aluminum Sheet:

Quantity: 1

Price: ₹20

Description: This is a roll of stainless steel or aluminum sheet metal, which is commonly used in fabrication due to its high strength, durability, and resistance to corrosion. Metal sheets like this are often used in manufacturing, construction, and sometimes in custom drone or robotic projects for structural components, as they can provide both durability and resistance to wear.

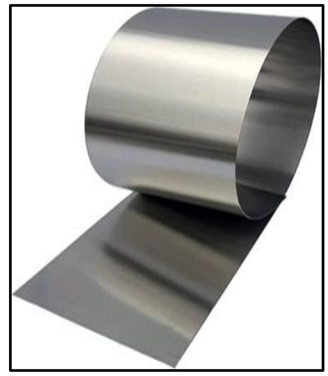


Fig 4.14 Aluminum Sheet

4.3.10 Hoseconnector :

Quantity: 1

Price: ₹160

Description: The image you provided shows a brass barbed hose fitting with a male threaded end. This type of fitting is commonly used to connect flexible hoses to components or pipes with female threaded ends. The barbed design ensures a tight seal and prevents the hose from slipping off, making it ideal for use in plumbing, automotive systems, and various types of machinery where secure hose connections are required.

Fig 4.15 Hose connector

4.3.11 Pesticide container:

Quantity: 1

Price: ₹20

Description:The image you provided shows a purple, translucent water bottle with a black cap. The front of the bottle has white text that reads **"**B.COOL**"** and indicates a capacity of 500ml. Below this, there is a series of numbers: "s-424594250**"**.This bottle appears to be designed for hydration purposes, possibly for sports or everyday use. The design is sleek and modern, making it a stylish choice for carrying water or other beverages.

Fig 4.16 Pesticide-container

4.4 CIRCUIT DIAGRAM

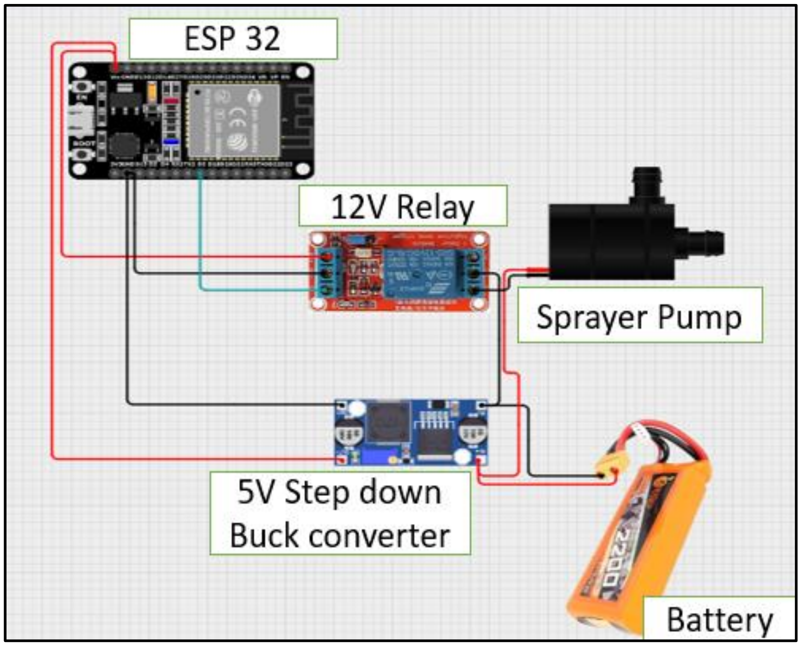


Fig 4.17 Circuit Design

The wiring diagram of this aerial spraying system shows only basic wiring necessary to enable the equipment to minimize feasible human interferences and achieve the automatic detection of the yellow leaf disease in areca nut palms and the subsequent pesticide application if necessary. At the heart of the system is a decentralised ESP32 microcontroller, while the image capturing happens through an ESP32 camera module. These images are passed through a ResNet-50 deep learning model which is run on the ESP32 for signs of yellow leaf disease.

When the ResNet-50 model recognizes indicators of disease, a control signal is given to the relay module by the ESP32. This relay serves as a bridge between the ESP32 with low power and the high power sprayer pump so as to create the effect of the ESP32 powering the pump. This relay takes the burden off the ESP32 avoiding short circuits from the high-voltage pump side and possible damaging of the microcontroller. At the command of the ESP32, the relay connects the circuit to provide electricity to the pump which releases pesticide for only five seconds to treat the affected areas as desired.

In the circuit, power supply is in red wires, ground connection wires are in black while the green and blue wires connect ESP32 to relay for controlling. All these features make this color-coding help in identification and rectification guarantees more stable and safer operations. With this strategic concept, selective application of pesticides is realized cutting on misuse and improving plant protection.

CHAPTER 5
RESULT AND DISCUSSION

5.1 Discussion:

The project on the “YELLOW LEAF DISEASE DETECTION AND AUTONOMOUS AERIAL SPRAYING MECHANISM FOR ARECANUT” successfully developed a ResNet-50 Convolutional Neural Network (CNN) for classifying areca nut leaves into four categories: healthy leaves, yellow leaf disease, other leaves, and no leaves. The performance of the model was impressive, achieving a training accuracy of 98.71794% and a training loss of 0.000145. Moreover, the validation accuracy stood at 99.3506%, with a final validation loss of 0.031717. These metrics indicate that the model generalizes well to unseen data, showcasing its effectiveness in real-time disease detection. The low training loss suggests that the model has learned effectively without overfitting, making it a reliable solution for practical applications in agricultural monitoring.

The autonomic spraying system works immediately when relaying detects the disease through the sprayer pump. The pump is a 12V DC with a 4.5 litre/min nominal rate and with the help of a micro switch the nozzle is activated to spray for five seconds only to allow right amount of pesticide to go through and not waste it. With fitted nozzle the effective spraying rate is brought to about 4 litres per minutes of fine droplets for maximum contact. This arrangement enables sustainable management since little chemicals are used but the targeted affected region is adequately treated.

The system utilizes an ESP32 camera module for real-time monitoring, relying on either a mobile camera IP or the ESP32 camera module’s IP for visual input. This setup allows for dynamic adjustments during operation, ensuring that only yellow leaf diseased leaves receive treatment. The autonomous spraying mechanism is designed to be compatible with various drone platforms, providing flexibility and scalability for agricultural applications. This modular design enables easy adaptation to different crop types and pest management needs, making it a versatile tool for modern farming.

The autonomic spraying system works immediately when relaying detects the disease through the sprayer pump. The pump is a 12V DC with a 4.5 litre/min nominal rate and with the help of a micro switch the nozzle is activated to spray for five seconds only to allow right amount of pesticide to go through and not waste it. With fitted nozzle the effective spraying rate is brought to about 4 litres per minutes of fine droplets for maximum contact. This arrangement enables sustainable management since little chemicals are used but the targeted affected region is adequately treated.

5.2. Classification Report:

The classification report shows that the model performs exceptionally well in identifying "Healthy Arecanut Leaf," "Yellow Leaf Disease," and "Other Leaf" categories, achieving an overall accuracy of 99%. Precision and recall are high across all classes, with perfect scores for "Other Leaf" and near-perfect scores for the other two. Specifically, "Healthy Arecanut Leaf" has a precision of 0.97 and recall of 1.00, while "Yellow Leaf Disease" has a perfect precision of 1.00 but a slightly lower recall of 0.96, indicating minimal misclassification. Overall, the model demonstrates strong and balanced performance with high F1-scores for each class.

Classification Report:

	precision	recall	f1-score	support
Healthy Arecanut Leaf	0.97	1.00	0.98	60
Yellow Leaf Disease	1.00	0.96	0.98	54
Other Leaf	1.00	1.00	1.00	42
accuracy			0.99	156
macro avg	0.99	0.99	0.99	156
weighted avg	0.99	0.99	0.99	156

Fig 5.1 Classification Report

5.3. Confusion Matrix:

This confusion matrix shows the classification performance of a model distinguishing between "Healthy," "Yellow Leaf," and "Other Leaf" categories. The model correctly identified 60 "Healthy" samples, 52 "Yellow Leaf" samples, and 42 "Other Leaf" samples. There were only two misclassifications, where two "Yellow Leaf" samples were incorrectly labeled as "Healthy." Overall, the model demonstrates high accuracy, particularly in distinguishing "Healthy" and "Other Leaf" categories, with minimal confusion in classifying "Yellow Leaf" samples.

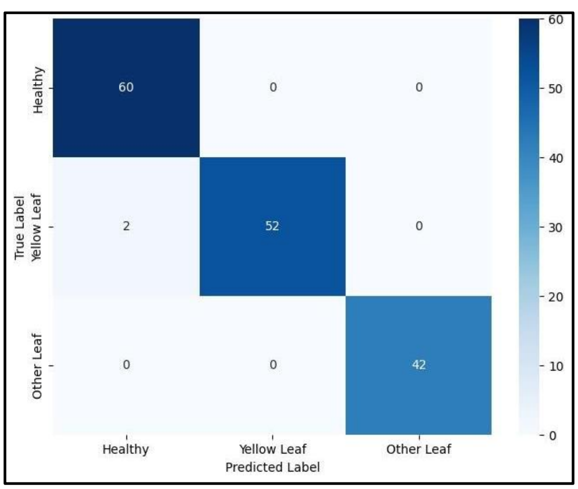


Fig 5.2 Confusion Matrix

5.4 PUMP MONITORING:

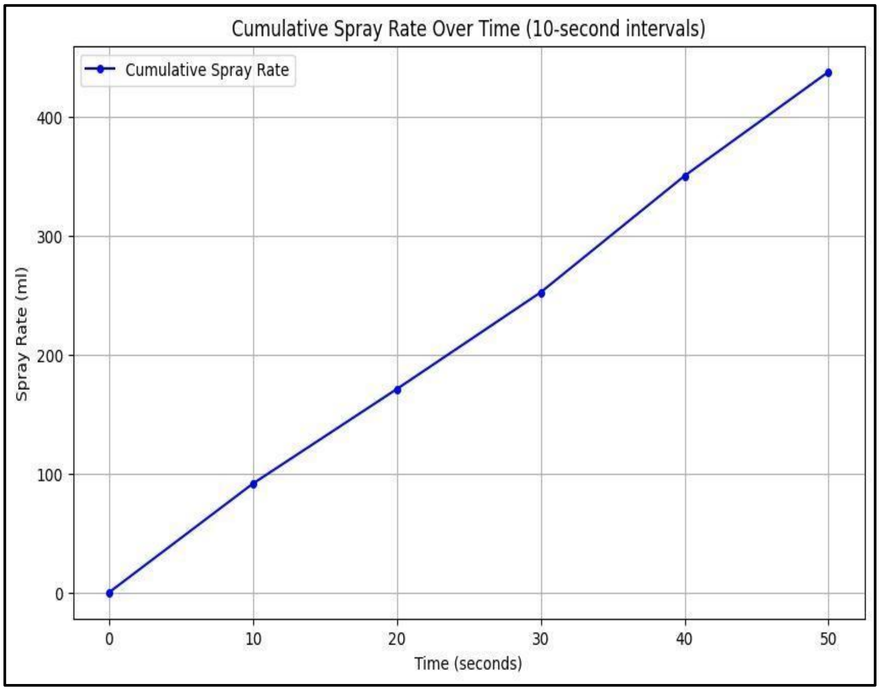


Fig 5.3 Pump Monitoring

The 12V DC sprayer pump in your project is a powerful component designed for efficient liquid transfer and spraying applications, ideal for agricultural tasks like pesticide distribution. With a capacity of 4.5 liters per minute, the pump can handle high fluid flow, making it suitable for covering large areas quickly. However, when used with the attached nozzle, the flow rate decreases by 500 ml, adjusting the effective output to approximately 4 liters per minute.

This reduction in flow is likely due to the nozzle’s design, which constricts the fluid flow slightly to create a finer mist. This misting effect is beneficial in agricultural spraying, as it allows for broader and more even pesticide coverage with minimal liquid waste. The 12V DC pump operates efficiently on low power, making it compatible with aerial platforms like drones. Furthermore, its compact size and capacity allow for precise control over the spraying duration and amount, enabling you to maintain the system's targeted approach of spraying only diseased leaves for 5 seconds per spray, as intended.

Overall, the pump's high capacity, compatibility with 12V power sources, and adaptability to nozzles make it a key component in ensuring efficient and effective pesticide application in your autonomous aerial spraying mechanism

5.5. Final Assembly

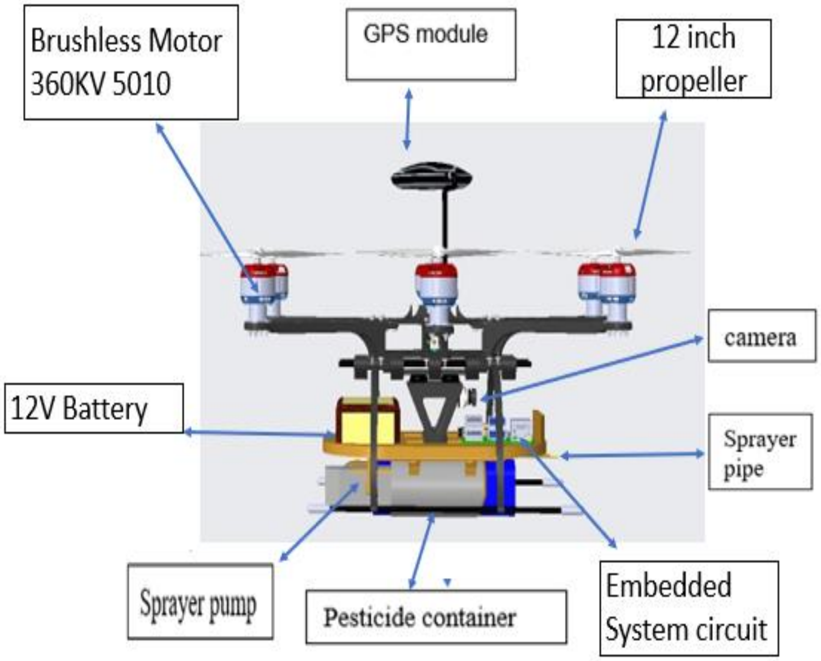


Fig 5.4 3D model of drone and sprayer assembly

Figure 5.4 shows a 3D model of a drone with a pesticide spraying assembly designed for precision agriculture. The drone's propulsion system includes four **Brushless Motors (360KV 5010)** paired with **12-inch propellers**, which generate lift and ensure stability. Positioned on top, the **GPS Module** enables autonomous navigation by allowing the drone to follow predefined paths, enhancing the accuracy of pesticide application. Additionally, an onboard **Camera** helps detect crop health issues, directing the sprayer to affected areas.

The spraying system in **Figure 5.4** consists of a **Sprayer Pump**, a **Pesticide Container**, and a **Sprayer Pipe**. The pump draws pesticide from the container and releases it through the pipe, allowing for targeted application directly below the drone.

A **12V Battery** powers the entire system, including an **Embedded System Circuit** that manages the drone's automated functions. This embedded circuit controls the motors, GPS, camera, and sprayer, enabling autonomous operations and real-time adjustments. Overall, **Figure 5.4** depicts a compact, efficient setup for automated pesticide spraying, providing an effective solution for precise pest and disease management in agricultural fields.

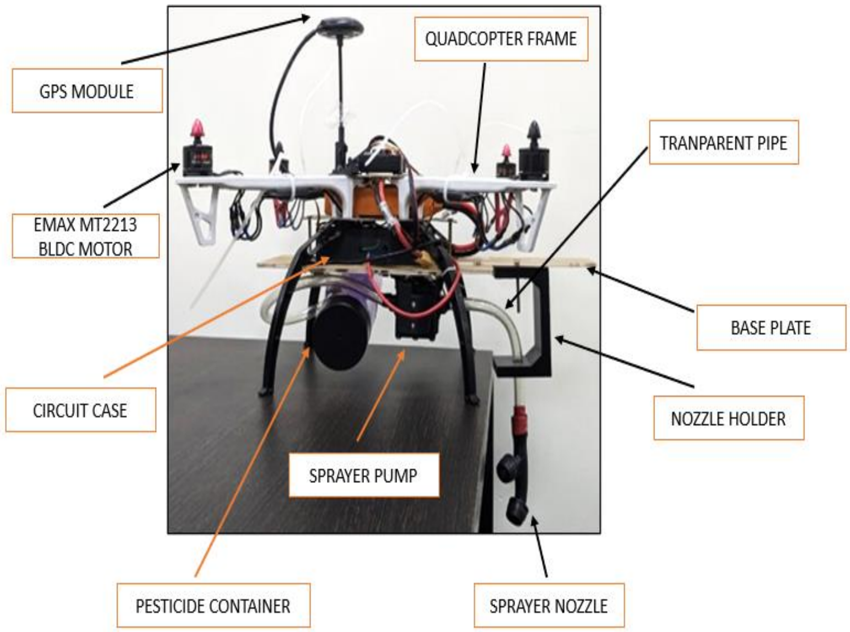


Fig 5.5 Final assembly of the sprayer system with the drone

Figure 5.5 illustrates the final assembly of the sprayer system integrated with the drone, optimized for agricultural spraying. The drone's structure is built around a **Quadcopter Frame**, providing support and stability for the mounted components. Key to navigation, the **GPS Module** at the top enables precise location tracking and autonomous flight control, while **EMAX MT2213 BLDC Motors** drive the propellers, ensuring efficient lift and maneuverability.

The pesticide delivery system, as shown in **Figure 5.5**, includes a **Sprayer Pump** connected to a **Pesticide Container** and a **Transparent Pipe** that channels pesticide to the **Sprayer Nozzle**. The nozzle, held by a **Nozzle Holder**, directs the spray downward for accurate application on crops. The **Circuit Case** houses the control electronics, safeguarding them from external elements.

Additional components include a **Base Plate** that supports the sprayer assembly and aids in weight distribution, ensuring flight stability. Overall, **Figure 5.5** presents a compact, well-organized design that allows the drone to carry out efficient and controlled pesticide spraying, providing an effective solution for precision agriculture.

CHAPTER 6
CONCLUSION

6.1 CONCLUSION

The proposed work in this project centers on building a ResNet-50 Convolutional Neural Network (CNN) to classify areca nut leaves into categories: yellow-leaf diseased, other leaf types, and healthy leaves, achieving impressive accuracy. The model reached a training accuracy of 98.71794% with a training loss of 0.000145, while the final validation accuracy stood at 99.3506% with a validation loss of 0.031717. These metrics underscore the model's reliability in accurately identifying areca nut leaf conditions, making it an effective tool for early diagnosis and treatment in agricultural settings.

The autonomous aerial spraying mechanism we designed incorporates this classification capability into a system that intelligently applies pesticides. The setup includes an ESP32 camera module, a buck converter, a relay, and a 12V DC sprayer pump, which work together to detect diseased leaves and spray pesticide precisely where needed. This mechanism is highly efficient, as it targets only the yellow-leaf diseased parts of plants and limits spraying to 5 seconds per identified leaf. This targeted approach not only conserves pesticide but also promotes sustainable pest management by reducing chemical usage.

The 12V DC sprayer pump, with a 4.5-liter-per-minute capacity, is optimized for agricultural tasks, allowing rapid yet controlled pesticide application. When paired with the nozzle, the flow rate adjusts to about 4 liters per minute, creating a finer mist that enhances coverage and minimizes waste. The pump's compatibility with 12V power sources and its compact design make it ideal for drone-mounted applications, allowing precise control over the spraying process for each diseased leaf, reinforcing the system's targeted approach.

Overall, the open design of this system enables it to be mounted on a wide range of drone platforms, expanding its usability across various agricultural applications. This project provides an AI-driven solution for disease detection and intelligent pesticide application, aiming to improve disease control, reduce pesticide usage, and increase yield for areca nut growers. It marks an initial step in advancing precision farming through artificial intelligence, fostering smarter and more sustainable agricultural practices.

6.2 FUTURE WORK

The development of the autonomous aerial spraying system presents several avenues for improvement. A primary focus for future work is expanding the dataset used to train the ResNet-50 model. By incorporating a broader range of images representing healthy and diseased areca nut trees under various environmental conditions, the model's accuracy and robustness can be significantly enhanced.

Integrating multispectral or hyperspectral cameras is also crucial for improving disease detection capabilities. These advanced imaging technologies can identify plant stress and disease symptoms beyond the visible spectrum, allowing for earlier and more accurate interventions.

Developing a web-based application for real-time monitoring will provide farmers with timely updates on crop health, facilitating informed decision-making. Centralizing data on crop conditions can enhance management practices, allowing for more effective tracking of interventions and outcomes.

Implementing autonomous path planning algorithms will optimize the drone’s flight paths based on disease severity, improving efficiency and resource conservation. Additionally, adaptive spraying techniques that adjust pesticide amounts according to real-time disease assessments will promote responsible pesticide use and reduce environmental impacts.

The incorporation of Internet of Things (IoT) devices can further enhance monitoring by collecting environmental data such as humidity, temperature, and soil moisture—to refine spraying schedules and practices.

Finally, transitioning to high-capacity rechargeable batteries or exploring solar-powered charging stations can significantly extend flight time, allowing for greater coverage of larger plantations. Integrating GPS and real-time mapping functionalities will also enhance the precision of targeted spraying, ensuring optimal pesticide application.

By addressing these areas for improvement, the autonomous aerial spraying system can become a more effective and sustainable tool for modern agricultural practices, helping farmers maintain healthy crops and maximize yields.

CHAPTER 7
REFERENCE

7.1 REFERENCE

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1. Veeresha, R.K., Shilpa, M.K., Lathish Kumar N D, Swaroop, Samarth S Shetty, Shrajan G Prasad

“YELLOW LEAF DISEASE DETECTION AND AUTONOMOUS AERIAL SPRAYING MECHANISM FOR ARECANUT"

Selected for presentaion at IEEE International Conference on Recent Advances in Science & Engineering Technology (ICRASET-2024), 21-22 November 2024

2. APPLIED FOR PATENT

https://docs.google.com/spreadsheets/d/1p6g84P9Mpu1AOKsTscsdkkDa_jjGJtJ5ntBiwvircsw/edit?usp=sharing