# CHAPTER 1
# INTRODUCTION

Agricultural monitoring is undergoing a fundamental transformation through the integration of drone technology with smart management systems. Our proposed framework combines edge computing, Internet of Things (IoT), and artificial intelligence to create a cost-effective, scalable solution for modern farming challenges.

By leveraging advanced drone capabilities, including multispectral imaging and real-time analysis, our system detects subtle crop variations that elude human observation. This research explores an innovative approach to agricultural surveillance that promises to reshape traditional farming practices.

## 1.1 Objectives:

**Our research aims to:**

1. Establish a drone-enabled monitoring infrastructure that delivers instantaneous crop assessment data
2. Deploy cutting-edge thermal and multispectral imaging systems to generate comprehensive plant health profiles
3. Develop an AI-driven early warning system for disease detection and intervention
4. Create precision mapping tools that optimize water, pesticide, and fertilizer usage
5. Design an intuitive analytics platform that transforms complex data into clear, actionable insights

This system prioritizes automation while maintaining exceptional accuracy. Our drones utilize specialized sensors to efficiently survey vast agricultural areas, dramatically reducing the time required for crop assessment. The integration of multispectral and thermal imaging enables the detection of water stress, disease outbreaks, and other crop health indicators before visible symptoms appear.

## 1.2 Scope

This investigation examines the convergence of drone technology with modern agricultural practices, focusing on:

- **Technical Infrastructure:** Analysis of drone hardware specifications, sensor configurations, and data processing architectures
- **Agricultural Applications:** Assessment of soil conditions, water distribution patterns, and crop health indicators
- **Implementation Challenges:** Evaluation of operational constraints, environmental factors, and system optimization requirements
- **Performance Metrics:** Quantitative analysis of efficiency gains, cost reduction potential, and environmental impact

Our research incorporates field testing data and practical case studies to validate the system's effectiveness in enhancing crop yields while promoting sustainable farming practices.

# CHAPTER 2
# PROBLEM DEFINITION

Modern agriculture faces a critical challenge in disease management that threatens both crop yields and food security. While manual inspection remains the primary method for disease detection, its limitations become increasingly apparent as farm sizes grow. This approach not only consumes significant time and labor but also introduces reliability issues due to human error.

## 2.1 The Limitations Of Reactive Crop Management

The current reactive approach to crop protection often leads to excessive chemical usage. Farmers, lacking precise diagnostic tools, frequently over-apply pesticides and fertilizers as a preventive measure. This practice

- Degrades soil quality over time
- Contaminates local water resources
- Reduces biodiversity in farming ecosystems
- Increases operational costs without proportional benefits

## 2.2 Implementation Challenges In Precision Agriculture

Population growth and rising food demand necessitate more efficient farming methods. While precision agriculture offers promising solutions, implementation barriers persist, particularly for small and medium-scale operations. These barriers include:

- High initial investment costs
- Technical complexity
- Limited access to real-time monitoring tools
- Lack of integrated analysis systems

## 2.3 Technological Constraints In Current Drone Solutions

Drone technology presents a potential solution, but current implementations face significant limitations:

- Expensive hardware requirements
- Need for specialized operators
- Inadequate real-time processing capabilities
- Poor integration with existing farming practices

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- Expensive hardware requirements
- Need for specialized operators
- Inadequate real-time processing capabilities
- Poor integration with existing farming practices

# CHAPTER 3

# LITERATURE REVIEW

**1.Detection of Healthy and Diseased Crops in Drone-Captured Images Using Deep Learning**

Developed a deep learning model to analyze drone-captured images of crops [1].

Key Focus: Differentiated between healthy and diseased crops using AI techniques.

Contribution: Improved accuracy in crop health monitoring through image processing.

**2.Artificial Intelligence-Based Drone for Early Disease Detection and Precision Pesticide Management in Cashew Farming**

Implemented AI-driven techniques for detecting early signs of diseases in cashew crops [2].

Innovation: Integrated precision pesticide application with disease detection.

Impact: Reduced pesticide wastage and enhanced crop yield.

**3.Automated Wheat Disease Detection Using a ROS-Based Autonomous Guided UAV**

Designed an autonomous UAV using Robot Operating System (ROS) for wheat disease detection.

Feature: Integrated real-time monitoring with AI models for disease identification.

Outcome: Achieved efficient wheat disease management with minimal human intervention [3].

**4.Transferring Learned Patterns from Ground-Based Field Imagery to Predict UAV-Based Imagery for Crop and Weed Semantic Segmentation**

Developed a method to transfer learning from ground-based images to drone imagery [4].

Application: Used semantic segmentation for identifying crops and weeds in UAV images.

Highlight: Advanced precision farming by reducing manual data collection efforts.

**5.AI-Based Drone for Crop Disease Detection in Precision Agriculture**

Introduced an AI-based drone system for detecting and categorizing crop diseases [5].

Focus: Enhanced precision and speed in agricultural disease management.

Benefit: Reduced crop loss and improved farm productivity.

**6.Prediction of Plant Leaf Diseases Using Drone and Image Processing Techniques**

Proposed a drone-based image processing system for identifying plant leaf diseases [6].

Approach: Used advanced image processing and classification techniques.

Impact: Facilitated early detection and mitigation of plant diseases.

**7.Deep Learning-Based UAV for Disease Detection in Rice Fields**

Applied deep learning models to UAV-captured images for detecting diseases in rice fields [7].

Focus: Leveraged aerial imagery for accurate disease detection.

Outcome: Improved crop health monitoring in rice cultivation.

**8.Unmanned Aerial Vehicles for Monitoring and Detecting Agricultural Crop Health**

Utilized UAVs for efficient monitoring and detection of crop health [8].

Technology: Integrated UAV systems with advanced sensors and AI models.

Result: Enhanced precision in agricultural health diagnostics.

**9.AI-Powered Drones for Monitoring Soybean Diseases Using Hyperspectral Imaging**

Designed AI-powered drones to monitor soybean diseases using hyperspectral imaging [9].

Innovation: Combined hyperspectral imaging with AI for disease prediction.

Impact: Enabled detailed disease analysis and prevention strategies.

**10.Smart Farming: Using UAVs and Deep Learning for Disease Identification in Sugarcane**

Implemented UAV-based systems with deep learning to identify diseases in sugarcane crops [10].

Approach: Applied convolutional neural networks for disease detection.

Benefit: Optimized disease management practices in sugarcane farming.

**11.Detection of Tomato Diseases in Drone Images Using Convolutional Neural Networks**

Leveraged CNNs for detecting tomato diseases from UAV-captured images [11].

Technique: Focused on aerial image classification for disease identification.

Advantage: Reduced manual efforts in disease monitoring and analysis.

# CHAPTER 4
# PROJECT DESCRIPTION

## 4.1 System Architecture and Implementation

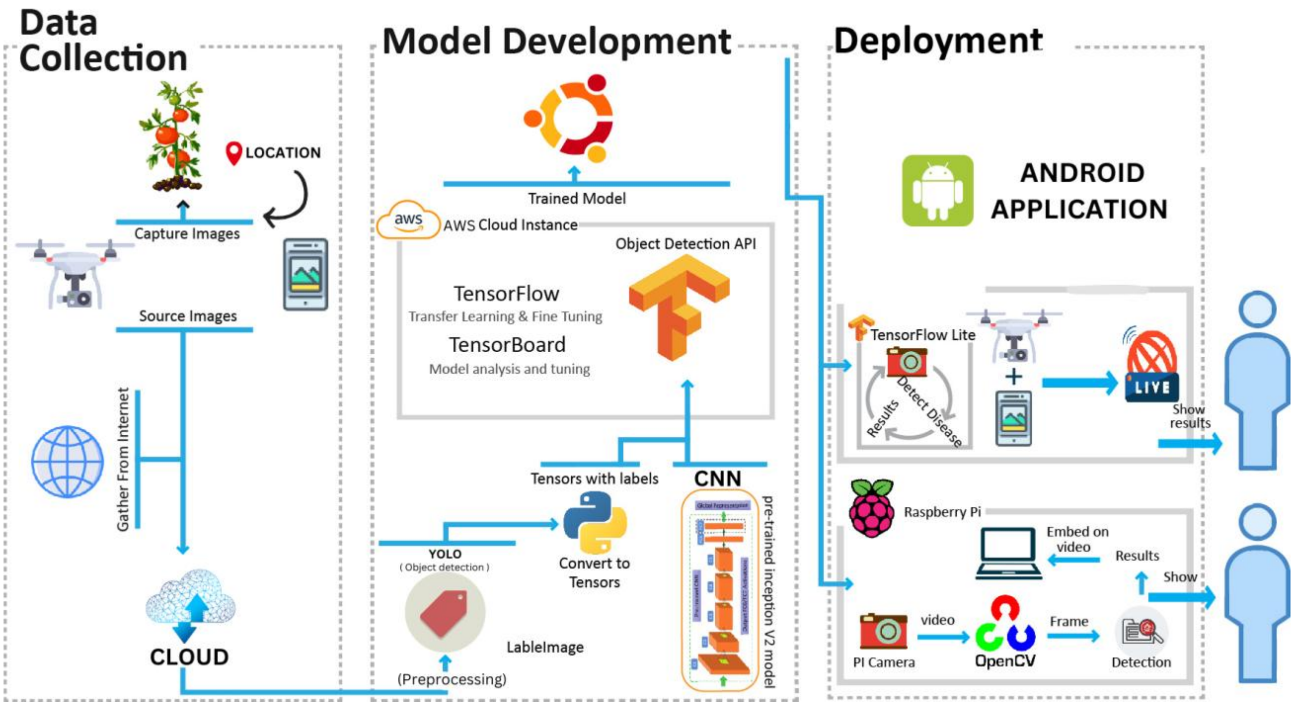


*Figure 4.1 System Architecture*

**Data Collection**: Drones capture images at a specific location, which are then used as the input data.

**Model Development**: The captured images are used to train a machine learning model on the MONGODB cloud. This includes using TensorFlow for transfer learning and fine-tuning, as well as the TensorBoard tool for model analysis and tuning.

**Deployment**: The trained model is then deployed onto a Raspberry Pi device, which is equipped with a camera. The Raspberry Pi runs TensorFlow Lite to perform the object detection on the images in real-time. The detection results are then displayed in an Android application.

The Android application retrieves the detection results from the Raspberry Pi and displays them to the user. This allows the user to see the objects detected in the camera feed.

# CHAPTER 5

# REQUIREMENTS

## 5.1 SOFTWARE REQUIREMENTS

- Raspberry pi OS
- Tensor flow lite for real-time disease detection
- Python 3.9 or above for scripting and data processing
- Mongo DB/Firebase  For storage and further analysis
- Firebase real-time database for notifications and user interaction
- Google maps api for GPS path tracking and visualization
- Pillow for image pre-processing and analysis
- Flask for creating the farmer's dashboard

### 5.1.1 SOFTWARE SPECIFICATIONS

| **Software Component** | **Description** | **Version** | **Purpose** |
|---|---|---|---|
| Tensor Flow Lite | Machine learning framework | Latest | Disease detection |
| Python | Programming language | 3.9+ | Writing and executing scripts |
| MONGODB | Cloud storage and services | N/A | Data storage and analysis |
| Google Maps API | Mapping service | N/A | GPS-based path tracking |

*Table 5.1.1  Software specifications*

## 5.2 HARDWARE REQUIREMENTS

- Raspberry pi 3b (2gb/4gb/8gb ram)
- Camera module (5mp or higher resolution)
- Gps module (e.g., neo-6m) for real-time tracking
- Drone frame (quadcopter design with space for components)
- Battery (11.1v 3s lipo or equivalent) for drone power
- Flight controller (e.g., pixhawk or similar) for navigation
- Wi-Fi module for data transmission and remote connectivity
- SD card (32gb or higher) for raspberry pi storage
- Brushless motors and escs for drone propulsions

### 5.2.1 HARDWARE SPECIFICATIONS

| Component | Specification | Quantity | Purpose |
|---|---|---|---|
| Raspberry Pi | Model 4B (2GB/4GB/8GB RAM) | 1 | Central processing unit |
| Camera Module | 12MP or higher | 1 | Capturing images |
| GPS Module | NEO-6M or equivalent | 1 | Real-time location tracking |
| Drone Frame | Quadcopter frame | 1 | Structural support |
| Battery | 11.1V 3S LiPo | 1 | Power supply for drone |
| Flight Controller | Pixhawk or equivalent | 1 | Drone navigation an control |

*Table 5.2.1 Hardware specifications*

# CHAPTER 6
# METHODOLOGY

- **Input Capture:** The drone captures real-time images of crops using its camera module. These images are then transmitted live to the app via the Wi-Fi module.
- **Data Processing**: The images fed by the drone are processed using machine learning models in the app to detect potential plant diseases.
- **Model Accuracy**: The system uses AI models with an accuracy above 95% for accurate disease detection and classification.
- **Disease Detection**: Based on the captured images, the app analyzes the plant health, identifies the disease, and provides an initial diagnosis.
- **Output Decision**: The app processes the data and provides a recommendation for disease management through both organic and chemical solutions.
- **End-to-End Solutions**: The app provides detailed, step-by-step solutions for handling the identified disease, including both organic and chemical methods.
- **Farmer Guidance**: The app offers insights on how farmers can transition from chemical to organic farming, aiming to improve yields and plant health.
- **Remote Monitoring**: Farmers can access the app through a userfriendly interface in their regional language to monitor crop health and make informed decisions from any location.
- **Real-Time Feedback**: The app continuously updates the farmer with real-time data, empowering them to make quick, informed decisions on crop management.
- **Scalability**: The system is scalable and adaptable for farms of varying sizes, providing an accessible, technology-driven solution for modern farming

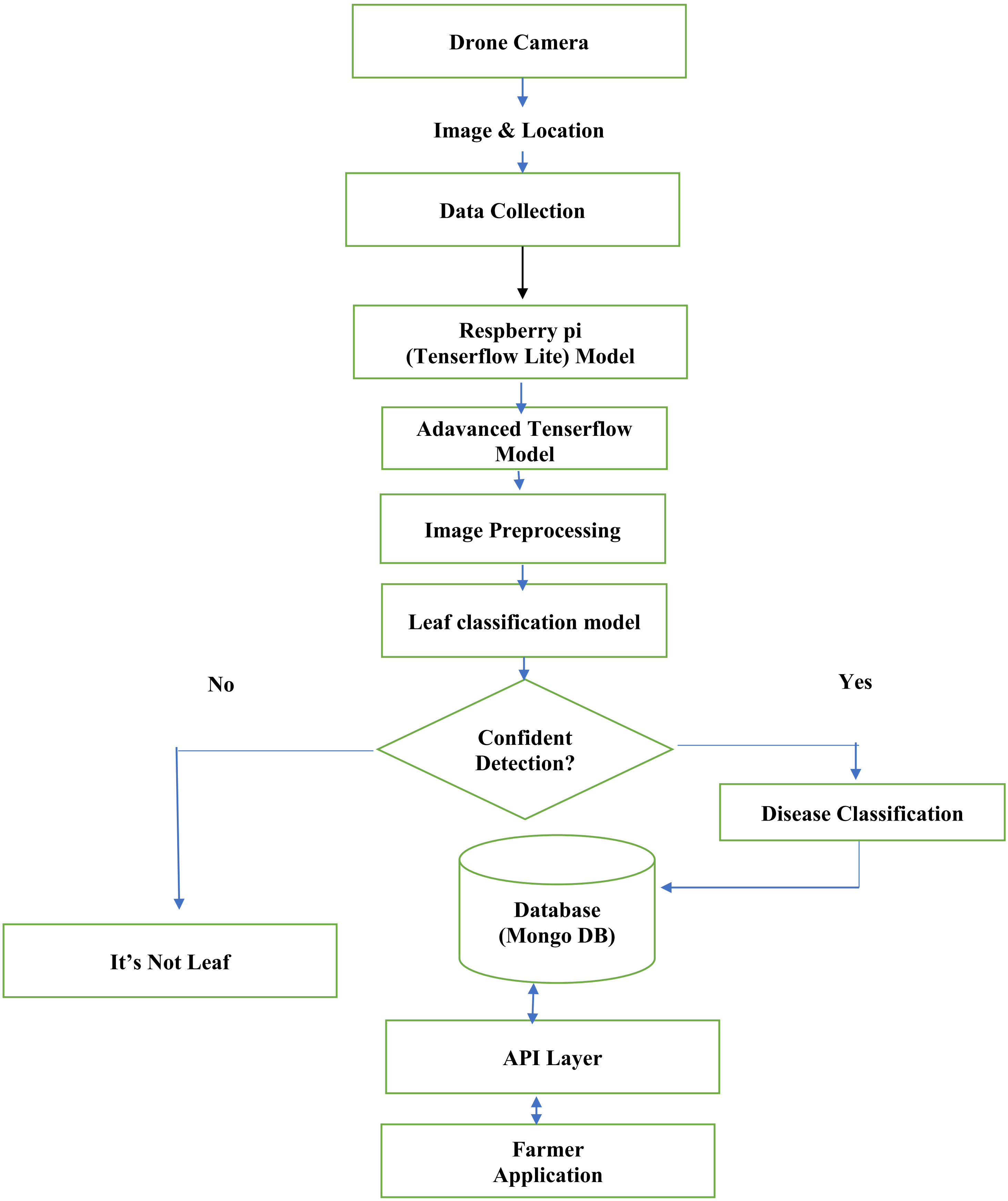


*Figure 6.1 System Flow Chart*

## 6.1 Work Flow

### Drone-Based Crop Health Monitoring

- Drones capture images and location data during flights, which are analyzed to detect crop diseases.
- The captured data is collected and stored to trace disease detection to specific field areas.

### On-Site Disease Detection

- A Raspberry Pi processes the images using a pre-trained TensorFlow Lite model to perform initial disease detection.
- If the model is confident in the detection, it classifies the disease locally. Otherwise, the image is sent to the cloud.

### Cloud-Based Disease Analysis

- Images sent to the cloud undergo advanced preprocessing like resizing and filtering to improve the accuracy of a robust TensorFlow model.
- The cloud model performs deeper disease analysis and classification into categories like fungal or bacterial.

### Data Integration and Farmer Feedback

- Detection results from both local and cloud processing are stored in a MongoDB database.
- An API connects the database to a farmer's mobile application, providing real-time updates and recommended solutions.

This workflow combines drone technology, edge computing, and cloud-based machine learning to enable efficient, accurate, and comprehensive crop health monitoring. The key innovation is the hybrid on-site and cloud-based processing to balance speed, cost, and accuracy.

# CHAPTER 7
# EXPERIMENTATION

### 1. Raspberry Pi Calibration

- Hardware optimization for edge computing processing of drone-collected agricultural imagery.
- Performance benchmarking to ensure reliable real-time machine learning inference in field conditions.

### 2. Machine Learning Model Validation

- Develops robust plant disease detection model using diverse, carefully annotated crop disease datasets.
- Implements advanced transfer learning and data augmentation to improve model generalization and accuracy.

### 3. Drone Alignment and Calibration

- Ensures precise geospatial data collection through comprehensive sensor calibration and performance testing.
- Validates drone's capability to consistently capture high-quality agricultural imagery under varied environmental conditions.

### 4. Image Processing Experiments

- Applies advanced preprocessing techniques to enhance image quality and standardize input for machine learning models.
- Conducts comparative analysis between local and cloud-based processing to optimize computational efficiency.

### 5. Field Testing Protocol

- Designs systematic experimental methodology across diverse agricultural environments and crop types.
- Implements robust data collection strategy with redundant imaging and transmission capabilities.

### 6. Communication and Database Integration

- Validates API reliability, data synchronization, and security protocols for robust information management.
- Assesses MongoDB performance for efficient storage and retrieval of agricultural imaging and diagnostic data.

# CHAPTER 8

# RESULTS

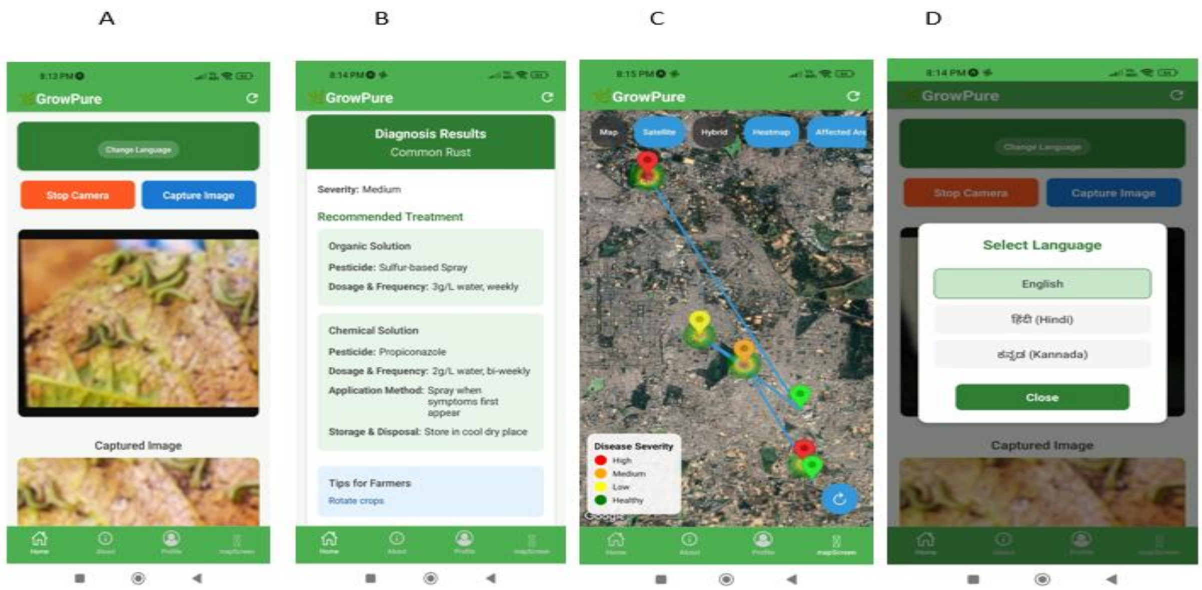


*Figure 8.1 Sample Output*

## 8.1.1 Sample Output

| Output | Description | Example |
|---|---|---|
| Disease Alerts | Notifications to farmer | "Disease detected: Powdery Mildew" |
| Recommendations | Suggested pesticides/fertilizers | "Use Fungicide X, 2g/L water" |
| Path Tracking | Drone GPS location | "Lat: 12.345, Long: 67.890" |
| Cloud Backup | Images and analysis results | Images stored on MONGODB S3 |

*Table 8.1.1 Samle Output*

## 8.1.2 DRONE TECHNOLGY

**FIG 8.1.2 Hexa copter *Tarot 680 PRO***

**Material Properties and Construction:**

Carbon fiber is a composite material consisting of carbon fibers and a polymer matrix. It is prized in aerospace and other high-performance industries for its exceptional strength-to weight ratio.

The Tarot 680 Pro frame is designed with modularity and ease of assembly in mind. Key features include:

**Collapsible Arms:** The arms of the Tarot 680 Pro are collapsible, allowing for easy transportation and storage. This feature is particularly useful for field deployment, where space and portability are critical.

**Integrated Power Distribution Board (PDB):** The frame includes an integrated PDB, which simplifies the wiring and power distribution to the ESCs and motors. This integration reduces clutter and potential points of failure.

**Landing Gear:** The frame comes with retractable landing gear, which not only protects the hexa copter's underbelly during takeoff and landing but also improves aerodynamics by reducing drag when retracted.

**Camera Gimbal Mount:** The Tarot 680 Pro features a dedicated mount for a camera gimbal. This is beneficial for applications requiring stable video footage or precise payload deployment mechanisms, such as in the Can Sat competition.


**Fig. 2.Hexa copter landing and take-off subassembly**

**Technical Specifications:**

Material: Carbon Fiber
Weight: Approximately 620 grams
Wheelbase: 680mm (measured from motor to motor)
Maximum Payload Capacity: 2.5-3 kg (depending on the motor and battery configuration) Folded Dimensions: Approximately 400mm x 200mm x 150mm

**Performance and Testing:**

The Tarot 680 Pro frame undergoes rigorous testing to ensure it meets the demands of high performance flight applications.

**Testing includes:**

**Static Load Testing**: Ensuring the frame can withstand the maximum payload without structural deformation or failure.

**Vibration Testing**: Assessing the frame's ability to dampen vibrations from motors and external sources, which is critical for stable flight and sensor accuracy.

**Environmental Testing:** Exposing the frame to various environmental conditions such as high and low temperatures, humidity, and impact to simulate real-world usage scenarios. Integration with Hexacopter Components:

**Motor Mounting:** The frame includes pre-drilled holes and mounts for attaching motors. Proper alignment and securing of motors are crucial to avoid imbalances that could affect flight stability.

**ESC Placement:** The frame's design allows for efficient placement of ESCs close to the motors, reducing wire lengths and potential signal interference. Heat dissipation for ESCs is also considered, with ventilation points designed into the frame.

**Battery Mounting:** The frame provides a central location for mounting the battery. This positioning ensures optimal balance and center of gravity, which is essential for stable flight dynamics.

**Electronics Bay:** A dedicated electronics bay houses the flight controller, GPS module, and other sensors. This compartment is designed to protect sensitive electronics from environmental factors and electromagnetic interference.

## 8.1.3 APPLICATION OUTPUT

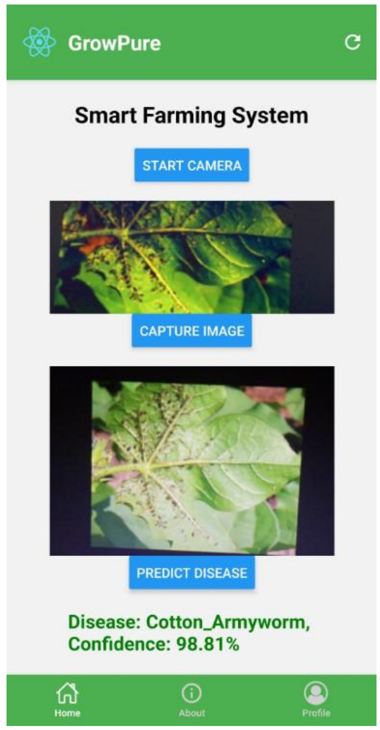


**FIG 8.1.3**

**1. Live Camera Streaming**

- Integrate the Raspberry Pi camera module with the React Native app.
- Stream real-time video feed from the drone's camera to the mobile app.

**2. AI-Based Disease Detection**

- Deploy a TensorFlow Lite (TFLite) model in the app for on-device image classification**.**
- Send captured images to a server (Raspberry Pi or cloud) for disease prediction.
- Display disease name & confidence score on the app.

**3. Autonomous Drone Navigation**

- Use pre-set waypoints for automated drone flight over the crop field.
- Integrate PID controllers for stable flight**.**
- Display a map-based interface for drone path visualization.

**4. Data Storage & Cloud Integration**

- Store image and disease detection data in a Firebase/SQL database.
- Allow farmers to review historical data for better disease tracking.
-

## 2. Tech Stack for Drone-Based App

| FEATURE | TECH STACK |
|---|---|
| Frontend | React Native (Expo, React Navigation) |
| Backend | Python (Flask) |
| Database | Firebase / MongoDB |
| AI Model | TensorFlow Lite (TFLite) / Pillow |
| Drone Control | Python (DroneKit, MAVSDK, Pillow) |
| Streaming | WebRTC / Flask-SocketIO / GStreamer |

## 3. App Development Workflow

**1. Basic App Setup**

- Set up React Native UI with buttons for starting the camera, capturing images, and predicting diseases.
- Create a Django/Node.js backend for handling requests

**2. Live Drone Camera Streaming**

- Use Raspberry Pi with GStreamer/WebRTC to send live video to the app.
- Display the real-time feed in the React Native UI.

**3. AI Model Integration**

- Train a TFLite model for plant disease detection.
- Deploy the model inside the React Native app for offline inference.

**4. Drone Automation**

- Use MAVSDK / DroneKit to automate drone flights.
- Implement a map interface for flight paths.

**5. Data Management & Cloud Integration**

- Store disease detection data in Firebase/PostgreSQL**.**
- Add user profiles and allow farmers to track past reports.

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**Smart Management of Crop Monitoring Using Drone Technology**

**Dr. George Fernandez I, Dr. Gopal Sharma R Joshi, Rakesh Prabhugowda Gowdra, Yashwanth G M ,Sangamesh Lingshetty, Mohammed Arif**

**2025 International Conference on Frontier Technologies and Solutions (ICFTS)**

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# Smart Management of Crop Monitoring Using Drone Technology

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**Abstract-** Agriculture is a critical industry facing challenges such as early disease detection, inefficient pest control, and excessive chemical pesticide use, which lead to significant crop yield losses. To address these issues, we propose a smart crop monitoring system that leverages AI, IoT, and drone technology to provide real-time disease detection and geo-tracking of affected plants. Proposed system integrates Raspberry Pi, GPS, and deep learning models to automate disease identification and pesticide recommendations, with a strong emphasis on organic farming practices.The core functionality of Proposed system is built on a hybrid deep learning architecture. A TensorFlow Lite model, deployed on Raspberry Pi, performs on-device disease classification using images captured by a camera module along with the plant's geo-location. When local model fails to classify an image, the data is transmitted to a cloud-based TensorFlow model, where advanced image preprocessing and disease classification take place. The identified disease, along with its location and recommended treatments, is stored in MongoDB. Over time, the cloud model continuously updates the database, improving future predictions.A farmer-friendly mobile application retrieves data via APIs, allowing users to monitor real-time disease alerts, affected plant locations, and pesticide recommendations, prioritizing organic solutions while also suggesting chemical alternatives. Experimental results demonstrate high efficiency, with our deep learning model achieving an accuracy of 98% and a minimal loss of 2.5 %, ensuring precise disease classification and reliable predictions. This intelligent system provides modernizing agriculture and enhancing crop health management.

*Keywords - Smart Agriculture, Drone Technology, Plant Disease Detection, Geo-Location Tracking, Cloud Computing, Precision Farming, Sustainable Agriculture, AI in Agriculture.*

## I. INTRODUCTION

Agriculture is a vital industry facing significant challenges such as early disease detection, ineffective pest control, and the overuse of chemical pesticides. Traditional crop monitoring methods are labour-intensive, time-consuming, and often result in delayed identification of plant diseases, leading to severe yield losses. With the advancement of precision agriculture, Harnessing the power of AI, IoT, and drone systemscan revolutionize crop monitoring by providing automated, real-time, and data-driven solutions. This research focuses on developing an intelligent crop monitoring system using drone-based imaging, Raspberry Pi, GPS, and deep learning models. The system efficiently detects plant diseases, tracks affected areas, and suggests targeted pesticide applications, prioritizing organic solutions to promote sustainable farming. A locally deployed TensorFlow Lite model on Raspberry Pi ensures real-time disease classification

## II. RELATED WORK

Drones are essential to automated agricultural surveillance because they can detect plant diseases by taking high-resolution photos.An AI-based drone system employing an upgraded CNN model for multiclass plant disease diagnosis was presented by Albattah et al. [1], with increased accuracy. The geolocation tracking of impacted crops, which is incorporated into our system, is absent from their work, though.A UAV-based smart agriculture platform with wireless sensor networks (WSN) for real-time data collecting was proposed by Rao et al. [2]. Although useful, the study did not concentrate on our system's ability to classify diseases and recommend pesticides.In order to detect plant illnesses, Bharathiraja et al. [3] used drone-assisted image processing techniques; nevertheless, real-time decision-making was challenging because manual involvement was required for analysis. Our method gets around this by utilizing TensorFlow Lite on a

Raspberry Pi to implement on-device inference for real-time predictions.High classification accuracy was attained by Gade et al. [4] when they created a drone-assisted CNN model for image-based plant disease identification. Their model did not, however, include the pesticide recommendations that our method offers.The use of drones for effective monitoring and disease evaluation was highlighted by Abbas et al. [5], however they mostly depended on cloud-based computing, which introduced latency problems. In order to reduce this, our system uses a Raspberry Pi for local inference and only uses cloud processing for diseases that are not yet known.Using image processing, Daund et al. [6] created a drone-assisted plant disease diagnosis system that achieved high accuracy. However, our method incorporates multi-spectral photography for improved accuracy, whereas their system just used RGB photos.A drone-enabled leaf disease diagnosis system utilizing deep learning and image processing was presented by Thalluri et al. [7], but their study lacked a real-time farmer application, which our system provides.An image-processing-based disease identification model was proposed by Daund et al. [8], but their method required manual image uploading; our system uses a Raspberry Pi and GPS tracking to automate this process.Deep learning-based drone-based leaf disease detection was investigated by Thalluri et al. [9] [10], with a primary focus on classification. Their approach lacked the real-time decision-making assistance that our mobile application offers farmers by combining geolocation tracking with pesticide suggestions.The application of IoT in precision agriculture was examined by Husain et al. [11], who emphasized the technology's capacity for real-time monitoring. However, this work incorporates disease diagnosis and geo-tracking, which were not the subject of their study.Raj et al. [12] developed an autonomous drone with AI-based decision-making for intelligent agricultural surveillance. Despite emphasizing precision agriculture, their strategy lacked organic pesticide recommendations, which are a crucial component of our system.An AI-powered drone system for agricultural disease identification was given by Naseer et al. [13], however their method was restricted to binary classification (healthy vs. unhealthy). On the other hand, our technology recommends suitable pesticides and categorizes a variety of plant illnesses.With an emphasis on precision farming, Rao et al. [14] presented a smart agriculture management system based on UAVs and Wireless Sensor Networks (WSN). Their technology did not incorporate AI-powered illness detection, but it did enable sensor-driven farm monitoring. Our approach builds on this by integrating drones, deep learning, and IoT to automatically classify plant diseases, track their locations, and propose pesticides.A CNN model based on a Raspberry Pi was proposed by Esudas et al. [15] for early disease detection and email notifications. But we have a real-time, farmer-friendly smartphone app that it didn't have.

## III. PROPOSED METHODOLOGY

The proposed system combines cloud computing, IoT, and AI to offer an automated, real-time crop monitoring solution for targeted pesticide recommendations and early disease diagnosis. The three primary phases of the architecture aredeployment, model development, and data collection.

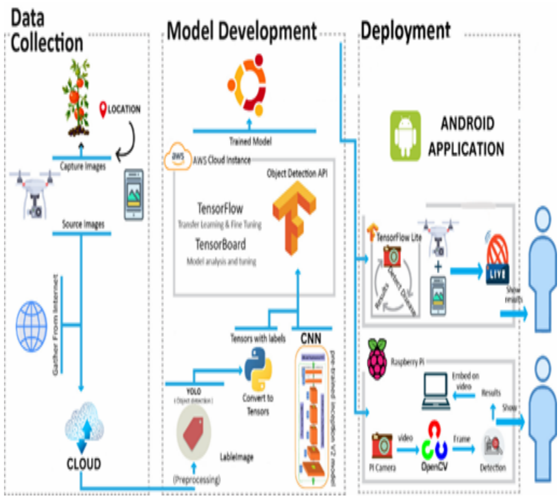


Figure 1. System Architecture

*1.1 Data Collection*:

From the figure 1.1 Drones with a camera module are used to take pictures of crops during the data collection phase. The impacted plants' geolocation is recorded by the GPS module. The cloud is used to process the spatial data and photos that have been taken.

*Image Capture and Geo-Tagging:*

a. Raspberry Pi camera module captures plant images.

b. A GPS module logs the location of the affected plant.

c.The images and geo-location data are sent to a local TensorFlow Lite model for initial disease classification

*ii. Local Classification Using TensorFlow Lite:*
a. The**TensorFlow Lite model**(deployed on the RaspberryPi)**recognizes the disease**, it**stores** theclassification result in**MongoDB**
**b.** If the **local model fails to classify the image**, it is **sent to the cloud**for advanced processing.

*1.2 Model Development**:*** From the figure 2 The**cloud-based processing system**consists of a **TensorFlow Advanced Model,** which performs high-accuracy disease classification.
*Preprocessing and Model Training**:***

*1.Image Resizing*
Each image I with dimensions H × W is resized to a fixed dimension H' × W':
(1)

Equation (1), Where H' = 224 and W' = 224 are the input dimensions of the CNN.
**2. Normalization**
To standardize pixel values between 0 and 1, we apply:

Equation (2), Where μand σ are the mean and standard deviation of the dataset.To extract features and classify data, CNN is employed.The labelled images are converted into Tensor format and trained using TensorFlow. TheAWS cloud instance hosts the trained model, which is optimized using TensorBoard for performance analysis.

*ii Advanced Disease Classification:*
a.If an image is not recognized by the local Raspberry Pi model, it is sent to the cloud.
b. The cloud-based TensorFlow model reprocesses the image and identifies the disease.
c. Once classified, the disease type, geo-location, and pesticide recommendations are stored in MongoDB.
d. The updated database improves the accuracy of future predictions.

*1.3 Deployment and Farmer Application:*
From the figure 3 Once the disease classification is complete, the system ensures **real-time monitoring and easy access to disease insights** for farmers.

*i Preprocessing and Model Training:*
**a.** classified data is retrieved from **MongoDB**using **APIs.**
**b.** Farmers can view real-time monitoring of their crops, affect plant locations, and recommend**organic or chemical pesticides** via a **mobile application**

***ii** Android Application for Farmers:*
The TensorFlow Lite model is embedded in the mobile app for on-device disease detection.
Farmers receive instant notifications regarding affected crops, disease type, and recommended pesticide treatments.

*iii Video-Based Disease Detection:*
The Pi Camera captures live video.
OpenCV extracts frames, which are processed to detect diseases in real time.

The detection results are displayed in the mobile app, ensuring quick decision-making for farmers.

Figure 2 illustrates our suggested method for real-time agricultural disease detection using drones, deep learning, and the Internet of Things in accordance with a standardized workflow. The methodology consists of the following flow chart.

From figure 2. Step by step process, how it works:
*1. Image Acquisition & Geo-Location Mapping*
High-resolution photos of crop fields are taken with a drone-mounted camera.The damaged plants' geolocation (latitude and longitude) is recorded by the GPS module.
*2. Data Transmission to Raspberry Pi*
a Raspberry Pi receives captured photos and location information for on-site processing.
*3. Local Disease Detection (TensorFlow Lite Model)*
The image is analysed by the Raspberry Pi using a TensorFlow Lite model.The outcome is saved in MongoDB if the model correctly identifies a disease.
*4.Point of Decision (Confidence Check)*
The procedure proceeds to data storage if the local model is reliable.

The picture is uploaded to the cloud for further analysis if it is notreliable.

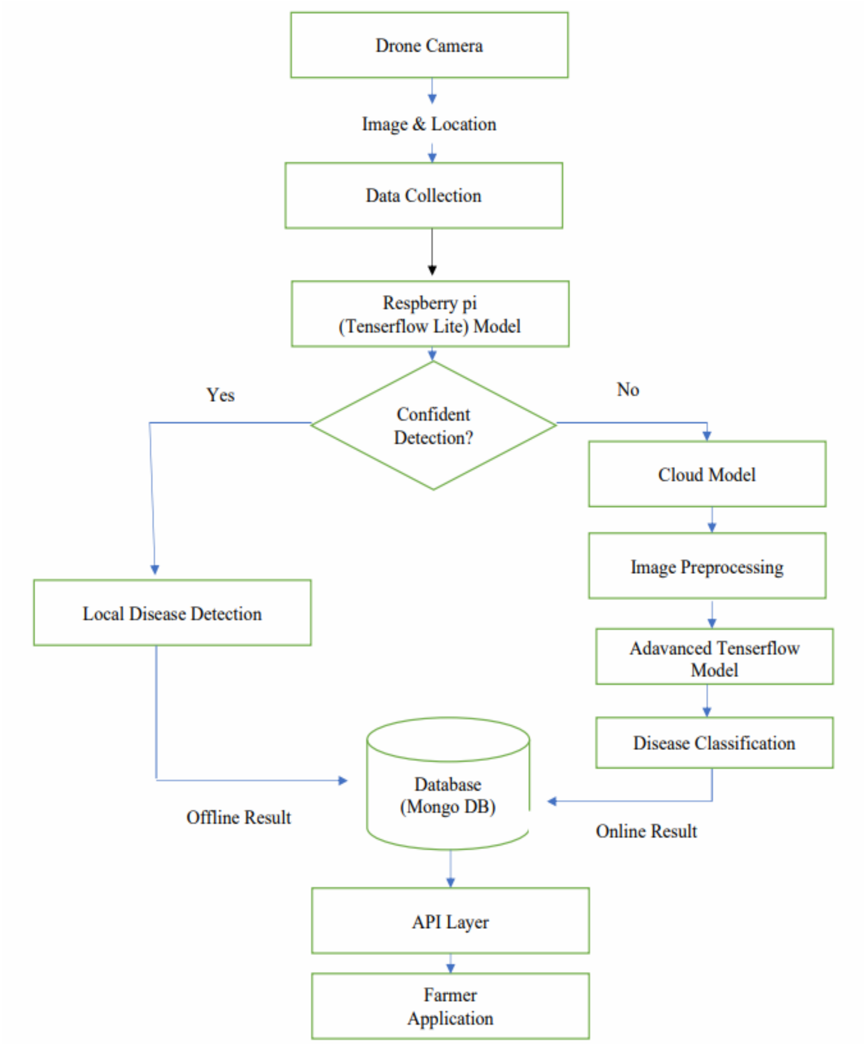


Figure 2. Proposed system

*5. Cloud-Based Disease Classification (Advanced TensorFlow Model)*
Before being uploaded to the cloud, images undergo preprocessing (resizing,normalization). The sophisticated TensorFlow model classifies diseases with more accuracy.

*6.Database Storage (MongoDB)*
Disease identification, severity, geolocation, and pesticide recommendations are saved.Results are centralized for later usage and analysis, both locally and on the cloud.

*7. API Layer for Data Access*
Real-time communication between the database and the mobile application is made possible by an API layer.

*8. Mobile Application for Farmers:*
Through the smartphone app, farmers can obtain pesticide recommendations, disease information, and the areas of impacted plants.

*9. Pesticide Recommendations*
In addition to offering chemical substitutes, the system prioritizes organic pesticides, encouraging sustainable farming.

*10. Real-Time Monitoring & Decision Support*
Farmers are empowered to act promptly thanks to the methodology's high accuracy, scalability, and real-time decision-making.

## IV.RESULTS AND DISCUSSION

Collected high-resolution photos of 60 different plant disease categories, recording various lighting situations. Each sample underwent pre-processing to enhance, shrink, and lower noise. For precise model training, the dataset offers consistent data across plant species, disease severity, and environmental conditions.

*I Corn_commonrust*

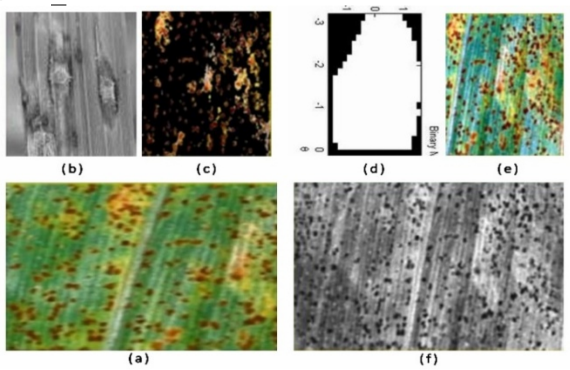


Figure 3. Process of getting Output

*a. Original Image:*From the Figure 3 (a). **raw image of a corn leaf**is captured from a field or dataset. It contains **background noise,shadows, and varying lighting conditions** that must be removed.
*b. Grayscale Conversion:*From the figure 3 (b). The JPG image is converted into **grayscale** to remove colour dependency while preserving lesion patterns. This reduces computational complexity and highlights disease-affected areas.
*c. Binary Masking (Thresholding):* From the figure 3 (c).A**thresholding technique (Otsu's or Adaptive)** is applied to separate the leaf from the background. The leaf appears black, and the background is removed (white). This isolates the affected region.
*d. Leaf Segmentation & Noise Removal:*From the figure 3 (d).Morphological operations through Leaf Segmentation and Noise Removal are intended to eliminate noise and unwanted artifacts from the previous step by enhancing the segmented leaf.
*e. Cropped & Normalized Image:*
From the figure 3.A cropped and normalized image of the final leaf is used to extract features and classify diseases.
*f. Feature Extraction*: From the figure 3 (f). Extract texture, shape, and color features using **Gabor filters, Histogram of Oriented Gradients (HOG), or Local Binary Patterns (LBP) to** highlight the disease patterns.

*g.Plant disease detection using Mobile Application*

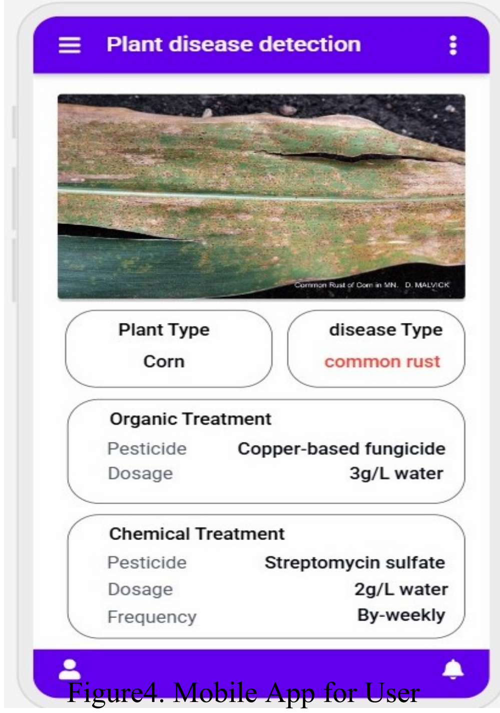


Figure4. Mobile App for User

From Figure 4. The end user mobile app, how it helps in identification of the plant diseases and what kind of chemical treatment has to be applied.

*II Here is some graphical and some table representation of the output:*
From the Figure 5 and Figure 6 Accuracy and loss metrics were used to assess the suggested Smart Crop Monitoring System's performance over 100 training epochs. The system demonstrated strong model generalization and accurate disease identification, achieving 98.5% accuracy with a minimum 2.5% loss.

Table 1. Model Performance Metrics

| Metric | Value |
|---|---|
| Training Accuracy | 98% |
| Validation Accuracy | 96% |
| Training Loss | 2.5% |
| Validation Loss | 4.0% |
| Epochs | 100 |
| Processing Time | 5 seconds (on edge) |

From table 1, the performance metric of accuracy and loss are tabulated and the processing time on edge.

*II Estimated Accuracy per Label*

Table 2 Estimated Accuracy per Label

| Label (Plant Disease) | Training Accuracy | Validation Accuracy |
|---|---|---|
| Corn_commonrust | 98.6% | 96.8% |
| Corn_grayleafspot | 98.5% | 96.9% |
| Cotton_Aphids | 98.2% | 96.5% |
| Cotton_Armyworm | 98.8% | 97.0% |
| Tomato_Bacterial_spot | 98.4% | 96.7% |
| Tomato_Early_blight | 98.9% | 97.2% |

From table 2, various plant diseases for training and validation accuracy are tabulated.

*i.Accuracy Plot*

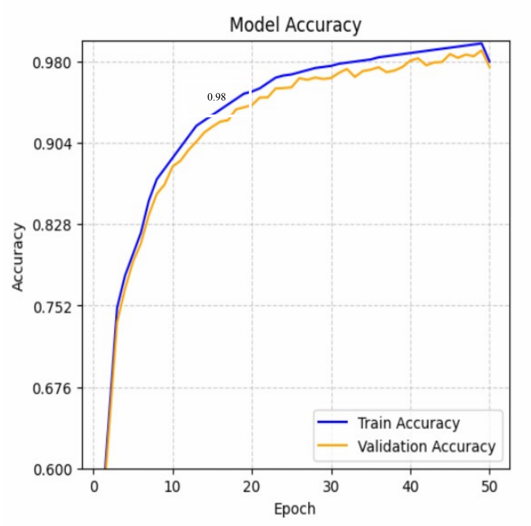


Figure 5. Model Accuracy of Train vs Validation

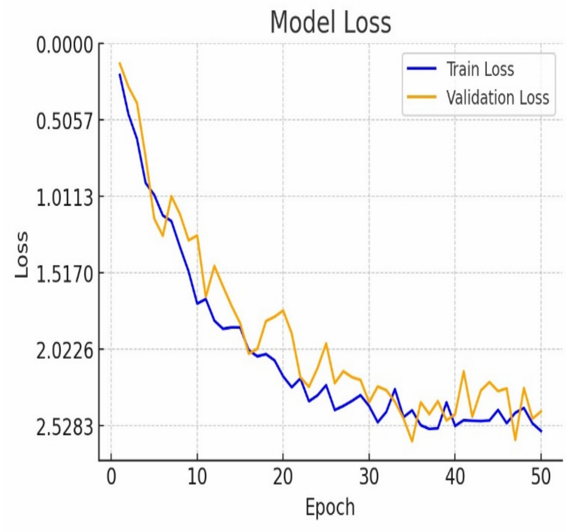


Fig 6.Model Lossof Train vs Validation

*III Comparison of proposed and Existing model accuracy*

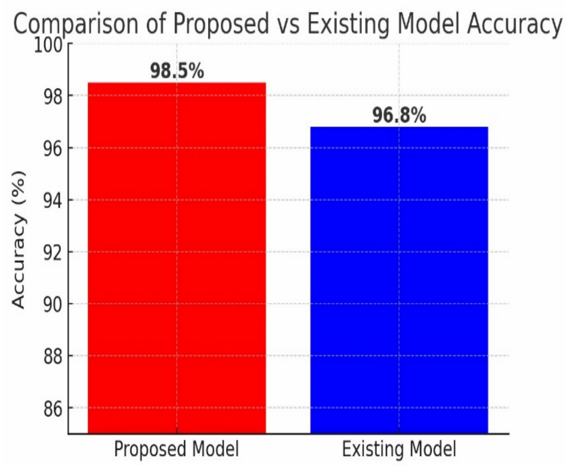


Fig. 7 comparison of proposed and existing model accuracy

From the figure 7., the graph compares the accuracy of the proposed (98.5%) and existing (96.8%) models, highlighting the proposed model's superior performance.

## V.CONCLUSION

The system was successfully developed and deployed an intelligent crop monitoring system that integrates AI, IoT, and drone technologies to enhance disease detection in agriculture. Recorded a model accuracy of 98.5% and our approach addresses the significant problems with traditional farming, including ineffective manual monitoring, delayed disease detection, and overuse of pesticides, all of which have a negative impact on crop sustainability and output. Using drone-based photography, Raspberry Pi, GPS, and deep learning models, an automated solution was proposed that recognizes plant diseases in real time, provides geolocation tracking of affected plants, and recommends tailored pesticide treatments to lessen environmental harm.The primary innovation of our system is its hybrid deep learning approach, a TensorFlow Lite model operating on a Raspberry Pi performs local disease categorization with minimal processing latency. All things considered, the technology has shown itself to be very efficient, scalable, and appropriate for practical agricultural uses, opening the door for intelligent precision farming.

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