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# Data-Driven Modelling and UAV-Based Identification of Diseases in Solanum Lycopersicon Leaves Using Machine Learning and Deep Learning Algorithms

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**ABSTRACT:** Unmanned Aerial Vehicles (UAVs) equipped with environmental sensors and imaging systems provide an efficient platform for precision agriculture and early crop disease detection. This study presents a UAV-based intelligent framework to identify Solanum lycopersicum (tomato) leaf diseases by integrating RGB image analysis with real-time environmental sensing. We developed a lightweight six-arm UAV with a Raspberry Pi 3 controller, GPS, radio telemetry, an RGB camera, and onboard sensors to monitor temperature, humidity, rainfall, and gas concentration. The acquired RGB images and environmental sensor data were used to construct a multimodal dataset for disease classification. Three classification models, namely 2D Convolutional Neural Network (2D-CNN), Support Vector Machine (SVM), and Random Forest (RF), were trained and evaluated using a common testing dataset. The 2D-CNN achieved an accuracy of 69.10%, whereas the SVM improved the classification performance to 93.40%, a 35.17% relative improvement in accuracy over the 2D-CNN. The Random Forest classifier achieved the highest performance with an accuracy of 98.61%, precision of 99.40%, recall of 98.24%, and F1-score of 98.82%, representing a 42.71% improvement in accuracy compared with the 2D-CNN and a 5.58% improvement over the SVM. The results demonstrate that integrating UAV-based RGB imaging with environmental sensing significantly improves disease identification under field conditions. The proposed framework provides a reliable and cost-effective solution for early crop health assessment, reduces manual inspection effort, and supports precision agriculture through data-driven decision-making.

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## 1- Introduction

Agriculture is rapidly adopting advanced technologies such as Unmanned Aerial Vehicles (UAVs), Artificial Intelligence (AI), and the Internet of Things (IoT) to improve crop monitoring and farm management. These technologies support precision agriculture by enabling real-time field monitoring and early disease detection. Conventional disease identification mainly depends on manual field inspection. This process is time-consuming, labour-intensive, and highly dependent on expert knowledge. It is also difficult to monitor large agricultural fields regularly. UAVs equipped with RGB or multispectral cameras and environmental sensors provide an efficient alternative for large-scale crop monitoring. The acquired data can be analysed using Machine Learning (ML) and Deep Learning (DL) algorithms for automatic disease identification, thereby improving both accuracy and operational efficiency [1–4].

Tomato (*Solanum lycopersicum*) is one of the most important vegetable crops cultivated in India. Its productivity is greatly affected by fungal, bacterial, and viral diseases. Early Blight, Late Blight, Septoria Leaf Spot, Powdery Mildew, Fusarium Wilt, Bacterial Leaf Spot, and Tomato Leaf Curl Virus (TLCV) are among the major diseases that reduce crop yield and fruit quality. These diseases spread rapidly under favourable environmental conditions such as high temperature, humidity, and rainfall. Therefore, early disease detection is essential for timely crop management and reducing unnecessary pesticide application. Recent advances in computer vision have significantly improved automatic disease diagnosis. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated excellent performance in extracting discriminative image

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features, while conventional machine learning algorithms such as Support Vector Machine (SVM) and Random Forest (RF) continue to provide reliable classification with lower computational complexity [6–9].

Recent studies have demonstrated the effectiveness of UAV-assisted imaging and artificial intelligence for plant disease detection. However, most existing works focus mainly on image-based classification or provide review studies without developing an integrated experimental platform [1–3]. Furthermore, only a limited number of studies combine UAV-acquired RGB images with real-time environmental sensing for disease assessment. Comparative evaluation of machine learning and deep learning models using the same UAV platform and identical datasets is also limited. Recent review articles have identified these issues as important research challenges for practical precision agriculture applications [6,7,11].

To overcome these limitations, this study develops a lightweight six-arm UAV integrated with RGB imaging and environmental sensors for real-time tomato crop monitoring. The proposed system simultaneously acquires crop images and environmental parameters, including temperature, humidity, rainfall, and gas concentration. A comparative analysis of three classification models, namely 2D Convolutional Neural Network (2D-CNN), Support Vector Machine (SVM), and Random Forest (RF), is performed using the same UAV-acquired dataset. This integrated framework enables reliable disease identification under real agricultural conditions and provides a practical solution for precision farming applications [4,11].

The primary objective of this study is to develop an intelligent UAV-based system for early tomato leaf disease detection using image and environmental data. The proposed framework captures high-resolution RGB images and real-time sensor measurements to assess crop health. The performance of 2D-CNN, SVM, and RF classifiers is evaluated using accuracy, precision, recall, and F1-score. The proposed system offers a lightweight, cost-effective, and scalable solution for automated crop monitoring. It supports timely disease management, improves crop productivity, and contributes to sustainable precision agriculture.

This work is structured as follows: Chapter 2 reviews existing methods for assessing leaf health. Chapter 3 details the proposed intelligent disease detection system, including UAV-based data collection, image preprocessing, and the implementation of 2D CNN, SVM, and Random Forest models with training and tuning. Chapter 4 covers hardware integration of sensors, processors, and communication modules. Chapter 5 presents the experimental setup, dataset, evaluation metrics, and model comparisons. Chapter 6 concludes the study and outlines future research directions.

## 2- Related Works

Recent developments in precision agriculture have significantly improved crop monitoring Recent advances in precision agriculture have increased the use of Unmanned Aerial Vehicles (UAVs) for crop monitoring and plant disease detection. Conventional field inspection is labour-intensive, time-consuming, and difficult to implement in large agricultural fields. UAVs provide high-resolution aerial images and enable rapid monitoring of crop health. Chin et al. [1] presented a systematic review of drone-based plant disease detection and reported that convolutional neural networks (CNNs) are the most widely used models for disease classification. Their study also showed that RGB and colour-infrared images are the most commonly used datasets for disease identification under field conditions. Similarly, Shahi et al. [2] reviewed UAV-based crop disease detection methods and highlighted the importance of integrating advanced imaging sensors with machine learning and deep learning algorithms for accurate disease diagnosis.

The application of computer vision and deep learning has significantly improved automatic disease identification in precision agriculture. Bouguettaya et al. [3] reviewed deep learning methods using UAV-based aerial images and reported that CNN-based models provide reliable disease detection while reducing manual inspection. Upadhyay et al. [6] analysed more than 278 research articles and concluded that CNNs, Vision Transformers (ViTs), and foundation models have achieved remarkable performance for crop disease detection. Their review also emphasized the importance of RGB, multispectral, and hyperspectral imaging for early disease diagnosis. Balafas et al. [13] further classified machine learning methods into image classification and object detection approaches and reported that ResNet, MobileNet, and YOLO-based models provide an effective balance between classification accuracy and computational complexity.

Several studies have focused specifically on tomato leaf disease detection. Umar et al. [8] proposed an improved YOLOv7 model integrated with CNN for identifying multiple tomato leaf diseases and achieved high classification accuracy under greenhouse conditions. Bilal et al. [9] developed a lightweight deep learning fusion model using MobileNetV2 and EfficientNetB0 for real-time pest and disease detection. Their model was successfully deployed on Raspberry Pi and drone platforms, demonstrating the feasibility of edge-based disease monitoring. Ahmed and Yadav [12] compared several machine learning algorithms for plant disease prediction and observed that ensemble learning methods produced better classification performance than individual classifiers.

Apart from disease detection algorithms, several researchers have investigated UAV platforms for precision agriculture. Tahir et al. [4] reviewed different UAV architectures and reported that lightweight UAVs equipped with imaging sensors can support crop health monitoring, pesticide spraying, irrigation management, and yield estimation. Abdullahi and Sheriff [5] demonstrated that UAV-acquired images combined with convolutional neural networks can accurately classify crop health conditions with an average accuracy close to 99%. Toscano et al. [11] discussed different UAV configurations and reported that payload capacity, battery endurance, sensor integration, and flight autonomy are the major factors affecting agricultural

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UAV performance.

Recent review articles have also discussed the future direction of artificial intelligence in agriculture. Majdalawieh et al. [7] reported that CNN-based models remain practical for real-time crop disease detection, while Vision Transformers provide higher accuracy at the expense of increased computational cost. Albayrak et al. [14] reviewed recent deep learning techniques and showed that hybrid learning models, transfer learning, and UAV-assisted monitoring are becoming important research directions for sustainable agriculture. However, they also identified challenges related to computational complexity, limited field datasets, and model generalization.

Although significant progress has been achieved, several research gaps still exist. Most reported studies focus primarily on image-based disease detection or review existing techniques. Comparatively fewer studies integrate UAV-acquired RGB images with real-time environmental parameters such as temperature, humidity, rainfall, and gas concentration for disease assessment. In addition, only a limited number of studies experimentally compare both machine learning and deep learning models using the same UAV platform and identical datasets. Therefore, the present study develops a lightweight six-arm UAV integrated with RGB imaging and environmental sensors for real-time tomato leaf disease detection. The proposed framework evaluates the performance of 2D Convolutional Neural Network (2D-CNN), Support Vector Machine (SVM), and Random Forest (RF) classifiers to identify the most suitable model for precision agriculture applications.

## 3- Proposed plant pathogenesis detection system

The Proposed Plant Pathogenesis Detection System (PPDS) is designed to detect and classify diseases in tomato (*Solanum lycopersicum*) leaves using a hybrid UAV-based imaging, real-time

environmental sensing, and advanced Deep Learning (DL) and Machine Learning (ML) models. The system leverages Unmanned Aerial Vehicles (UAVs) equipped with RGB cameras and environmental sensors, capturing high-resolution plant images and real-time atmospheric data to assess disease conditions efficiently (Algorithm 1). Unlike

**Algorithm 1 Proposed UAV-Based Intelligent Tomato Leaf Disease Detection**

**Input:**
RGB tomato leaf images (I)
Environmental sensor data (Temperature T, Humidity H,
Gas Concentration G, Rainfall R)

**Output:**
Plant disease class (Healthy / Diseased)
Environmental monitoring report
Disease alert

**Initialize** UAV platform, Raspberry Pi 3, GPS, telemetry, RGB camera, and environmental sensors.
Plan the UAV mission using Mission Planner software.
**while** UAV mission is active do
    Acquire RGB image I.
    Acquire sensor readings T, H, G and R.
    Preprocess image:
        Resize(I)
        Normalize(I)
        Remove noise
    Normalize sensor data using Eq. (1).
    Form feature vector: F ← [T, H, G, R]
    ***if*** Training Phase, then
        Train the proposed 2D-CNN from scratch using the UAV-acquired tomato leaf image dataset.
    ***end if***
    Predict disease class using the trained 2D-CNN.
    Predict disease class using SVM with RBF kernel.
    Predict disease class using Random Forest classifier.
    Compute Accuracy, Precision, Recall and F1-scorefor all classifiers.
    Display sensor readings and predicted disease on LCD.
    ***if*** Disease = TRUE, then
        Generate disease alert.
    ***end if***
**end while**

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traditional manual inspection, which is time-consuming and prone to errors, the proposed method ensures automated, high-precision disease detection through deep learning techniques, particularly 2D Convolutional Neural Networks (2D CNNs), alongside Support Vector Machine (SVM) and Random Forest (RF) models.

### 3- 1- Data Acquisition and Processing

The UAV captures high-resolution RGB images of tomato leaves at regular intervals while environmental sensors record field conditions. The acquired environmental parameters include temperature, humidity, gas concentration, and rainfall. These parameters are used to analyse the relationship between environmental conditions and plant disease occurrence. The sensor readings are standardized before model training using,

$$X' = \frac{X - \mu}{\sigma} \tag{1}$$

where $X'$ denotes the normalized value, $X$ is the measured sensor value, μ is the mean, and σ is the standard deviation.

The normalized sensor measurements are represented as

$$T = f(S_T)\,; H = f(S_H)\,; \quad R = f(S_R)\,; G = f(S_G) \tag{2}$$

where $S_T$ , $S_H$ , $S_R$ , and $S_G$ denote the raw signals obtained from the temperature, humidity, rainfall, and gas sensors, respectively.

In addition to environmental sensing, the UAV acquires RGB images of tomato leaves for disease analysis. Before feature extraction, the images undergo preprocessing to improve their quality and reduce computational complexity. The preprocessing stage includes image resizing, noise removal using median filtering, grayscale conversion, and intensity normalization. Grayscale conversion preserves the texture and structural characteristics of the leaf while reducing redundant colour information. The grayscale image is obtained as

$$I_{grey} = 0.299\mathrm{R} + 0.587\mathrm{G} + 0.114\mathrm{B} \tag{3}$$

where R, G, and B represent the red, green, and blue colour channels of the captured image.

### 3- 2- Two-Dimensional Convolutional Neural Network (2D-CNN) for Image-Based Disease Classification

The preprocessed tomato leaf images are classified using a Two-Dimensional Convolutional Neural Network (2D-CNN). The proposed network automatically learns discriminative image features associated with healthy and diseased leaves. Unlike conventional machine learning methods that require manual feature extraction, the CNN directly learns hierarchical features from the input images through successive convolution and pooling operations.

The grayscale images are resized to a fixed spatial resolution before being supplied to the CNN. The resizing operation is represented as

$$I_{resized} = f_{resize}(I_{gray}, H, W) \tag{4}$$

where H and W denote the target image height and width, respectively.

The proposed CNN architecture was trained from scratch using the UAV-acquired tomato leaf image dataset. No pretrained weights were employed because the model was developed specifically for tomato leaf disease classification. The first convolution layer extracts local texture and edge features using learnable kernels. The convolution operation is expressed as

$$O_{conv}(x,y) = \sum_{i=0}^{k-1}\sum_{j=0}^{k-1} W(i,j)\, I(x+i, y+j) + b \tag{5}$$

where $W$ represents the convolution kernel, $k$ denotes the kernel size, and $b$ is the bias.

The extracted feature maps are passed through the Rectified Linear Unit (ReLU) activation function

$$O_{ReLU} = \max(0, O_{conv}) \tag{6}$$

to introduce non-linearity into the network.

Max-pooling is then applied to reduce the spatial dimensions while preserving the dominant image features. The pooling operation is given by

$$O_{Pool}(x,y) = \max_{(u,v)\in P} O_{ReLU}(u,v) \tag{7}$$

where P denotes the pooling window.

The pooled feature maps are flattened into a one-dimensional feature vector

$$O_{flat} = \mathrm{Flatten}(u,v) \tag{8}$$

and supplied to the fully connected layer

$$O_{dense} = f\left(W_d O_{flat} + b_d\right) \tag{9}$$

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where $W_d$ and $b_d$ denote the weight matrix and bias vector, respectively.

Finally, the Softmax classifier estimates the probability of each disease class as

$$P(c_i) = \frac{e^{O_i}}{\sum_{j=1}^{N} e^{O_j}} \quad (10)$$

where $P(c_i)$ represents the probability of the $i^{th}$ class, $O_i$ denotes the output of the fully connected layer, and N is the total number of disease classes. The class with the highest probability is selected as the final prediction.

### 3- 3- SVM and RF for Sensor-Based Classification

The Support Vector Machine (SVM) and Random Forest (RF) models play a crucial role in integrating environmental sensor data for disease classification. These models analyze temperature, humidity, rainfall, and gas concentration, contributing to a hybrid decision-making system that complements the image-based classification of the 2D CNN. The Support Vector Machine (SVM) model is employed to classify disease severity based on sensor data. Given a feature vector F = [T, H, C, R], where T represents temperature, H represents humidity, C represents gas concentration, and R represents rainfall, SVM constructs an optimal hyperplane that separates healthy and diseased conditions. The decision boundary is given as (equation 11),

$$f(x) = w^T X + b \quad (11)$$

where w is the weight vector, X is the input feature vector, and b is the bias term. The Radial Basis Function (RBF) kernel is used to enhance non-linearity, represented as (equation 12)

$$K(x_i, x_j) = exp\left(-\gamma \| x_i - x_j \|^2\right) \quad (12)$$

where γ controls the influence of individual training samples. The hyperparameters C and γ were optimized using Grid Search with five-fold cross-validation. The optimal values obtained were C=10 and γ=0.01. The optimized model was then used to classify the environmental conditions associated with healthy and diseased tomato plants. The Random Forest (RF) classifier is employed as an ensemble learning model to improve classification reliability. The RF model consists of multiple decision trees trained using randomly selected subsets of the training data and predictor variables. Each decision tree independently predicts the disease class, and the final decision is obtained through majority voting. The ensemble prediction is expressed as in equation 13.

$$F(X) = \frac{1}{T}\sum_{t=1}^{T} h_t(X) \quad (13)$$

where T is the total number of trees in the ensemble. The RF model effectively captures complex relationships between environmental stressors and disease manifestation. The sensor-based classification operates alongside the 2D CNN image-based model, ensuring a comprehensive disease detection system. Sensor readings are continuously monitored and displayed in real time. Finally, softmax classification is applied to determine the disease type using Equation 14

$$Plant_Disease = \frac{e^{O_i}}{\sum_j e^{O_i}} \quad (14)$$

where $O_i$ is the output from the last dense layer.

Alongside disease detection, environmental conditions are analyzed using sensor data. The readings are compiled into a feature vector as (equation 15),

$$F = [T, H, C, R] \quad (15)$$

and displayed in real time using equation 16,

$$Display[T, H, C, R] \quad (16)$$

If an abnormality is detected, an alert is generated as in equation 17,

$$Alert = "PotentialDiseaseDetected:" + Plant_Disease \quad (17)$$

To ensure continuous monitoring, the UAV keeps capturing images and collecting sensor data in real time. While the UAV is in flight, the system continuously repeats the process using equation 18,

$$while\ UAV_Flying(): Repeat\ Steps\ 2-6 \quad (18)$$

This loop ensures ongoing tracking of plant health and environmental conditions, enabling timely detection of potential issues. This approach integrates environmental data with deep learning-based disease detection, providing a robust framework for real-time plant health assessment. This hybrid approach enables real-time tracking of plant health, allowing for early detection and intervention. The UAV continuously captures images and collects environmental

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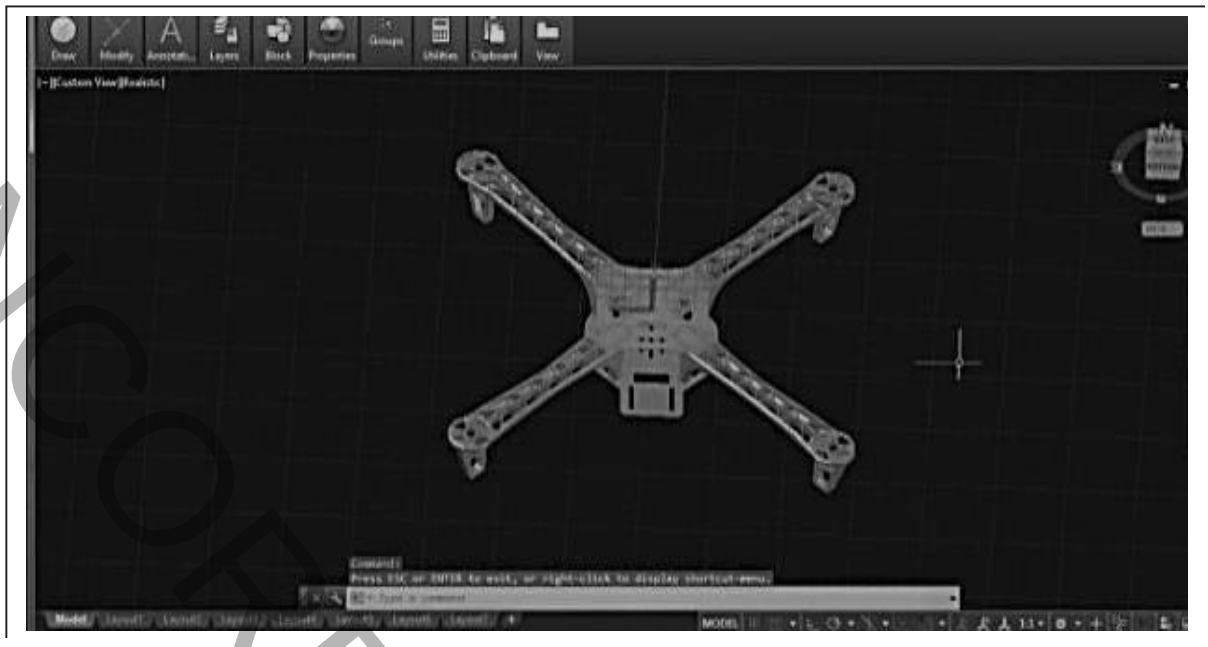


**Fig. 1. Top view of the quad-copter UAV design.**

data while in flight, ensuring ongoing surveillance. By combining deep learning-based image classification (2D CNN) with machine learning-based sensor analysis (SVM, RF), the proposed system delivers robust, real-time plant pathogenesis detection, significantly enhancing agricultural disease management.

### 3- 4- Design of Unmanned Aerial Vehicle:

The design methodology is analysed based on the different components used in the UAV and their features. Initially, the frames used in the UAV are placed on the base of the UAV by analysing the types of crops and the ecological structure of the agricultural sector, and then assembled. Next, the electronic and flight controller, electronic speed controllers (ESC), motors, battery, and intelligent diagnostic system were assembled. For longevity and high use, aluminium material was selected as the frame material. Four square-shaped aluminium profiles with a length of 1200 mm and dimensions of 8 x 8 x 1 mm were accepted as shown in Figure 1. Two sheets of quad-aluminium sheets with a margin length of 150 mm and a thickness of 1.55 mm were taken. The chassis of the UAV had four legs twisted by a 10 mm diameter aluminium pipe profile. The height of the frame is about 280 mm.

## 4- Implementation

The UAV flight mission was planned and simulated using the Mission Planner software, which provides waypoint generation, flight path optimization, and autonomous mission execution. The simulated mission covered an agricultural field of 1608 m² in 3.46 min, with the ground elevation varying between 850 m and 856 m. The waypoint trajectory was generated using a line spacing of 1.5 m to ensure adequate image overlap and complete field coverage. During the mission, the UAV travelled a total distance of 1.14 km, demonstrating efficient path planning for real-time crop monitoring. It should be noted that the simulated flight time of 3.46 min corresponds only to the experimental mission over the selected field area. The maximum flight endurance of the UAV under a fully charged battery is 30–40 min, enabling the monitoring of larger agricultural fields in practical applications.

The UAV was assembled using lightweight and durable components to achieve stable flight and reliable field operation. The major components include the Raspberry Pi 3 controller, environmental sensors, connectors, aluminium frame, brushless DC motors, carbon fibre propellers, electronic speed controllers (ESCs), a rechargeable lithium polymer (Li-Po) battery, and miscellaneous accessories. The battery provides the required electrical power for propulsion, onboard processing, and sensor operation, and its weight is included in the total UAV weight estimation. The complete component specification and weight distribution are presented in Table 1. The overall UAV weight is calculated using

$$W_{UAV} = W_{controller} + W_{sensors} + W_{connectors} + W_{frame} + W_{motors} \quad (19)$$

where $W_{controller}$, $W_{sensors}$, $W_{connectors}$, $W_{frame}$, $W_{motors} +$, $W_{proppeller}$, $W_{ESC}$, $W_{battery}$, and $W_{misc}$ denote the weights of the controller, sensors, connectors, frame,

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motors, propellers, electronic speed controllers, battery, and miscellaneous components, respectively.

For hardware implementation, the Raspberry Pi 3 was employed as the central processing unit to acquire, process, and store sensor measurements and UAV images. The onboard system was integrated with a DHT11 temperature and humidity sensor, an MQ-6 gas sensor, a rain sensor, and an RGB camera for continuous crop monitoring. The environmental sensors measured temperature, humidity, gas concentration, and rainfall, while the camera captured high-resolution images of tomato leaves. The analog outputs from the sensors were converted into digital signals using an analog-to-digital converter before transmission to the Raspberry Pi for processing and storage. The acquired images were processed using the proposed 2D Convolutional Neural Network (2D-CNN), while the environmental sensor data were analysed using the Support Vector Machine (SVM) and Random Forest (RF) classifiers. The processed information was displayed on a Liquid Crystal Display (LCD) for real-time field monitoring. The complete UAV flight path was generated using the Mission Planner software, as illustrated in Figure 2.

## 5- Results and Discussion

### 5- 1- UAV Component Breakdown and Weight Analysis

The UAV was assembled using lightweight and durable components to achieve stable flight, efficient power utilization, and reliable field operation. The total weight of the assembled UAV, including the battery, was 2565 g (2.565 kg), providing an appropriate balance between payload capacity, structural strength, and flight stability. The controller unit, consisting of the Raspberry Pi 3, flight controller, GPS module, on-screen display (OSD), and radio telemetry system, contributed 132 g, enabling autonomous navigation and real-time communication. The environmental sensing module, comprising the DHT11 temperature and humidity sensor, MQ-6 gas sensor, and rain sensor, weighed 125 g and enabled continuous monitoring of field conditions during flight. The aluminium frame, integrated with vibration absorbers and landing skids, contributed 560 g, providing mechanical strength and minimizing vibration during take-off and landing. Six brushless DC motors with a combined weight of 656 g generated the required thrust for stable flight, while six carbon fibre propellers added 113 g, improving aerodynamic performance. The propulsion system was controlled using six BLHeli 30 A electronic speed controllers (ESCs), which contributed 156 g. A 6S Li-Po battery (22.2 V, 5200 mAh) weighing 708 g was incorporated to supply power to the propulsion system, onboard controller, sensors, and communication modules, thereby supporting the required flight endurance. The remaining 100 g consisted of connectors, screws, jumpers, cable ties, and other mounting accessories used for secure assembly of the UAV platform.

### 5- 2- UAV Flight Path and Mission Planning for Precision Agriculture:

The UAV flight mission was planned using the Mission Planner software to ensure systematic coverage of the experimental field. The generated waypoint trajectory followed a grid-based navigation pattern with a line spacing of 1.5 m, enabling sufficient image overlap for accurate image stitching and disease analysis. During the experimental mission, the UAV surveyed an agricultural area of 1608 m², travelled a total distance of 1.14 km, and completed the mission in 3.46 min. The flight altitude was maintained between 850 m and 856 m above sea level to ensure consistent image quality and reliable environmental sensor measurements. The reported flight duration of 3.46 min corresponds only to the experimental mission performed over the selected 1608 m² field. The UAV is equipped with a 22.2 V, 5200 mAh Li-Po battery, providing an average flight endurance of 30–40 min under a fully charged condition. Therefore, the experimental

**Table 1. List of components used in the UAV and their weight (g).**

| Components | Component Name | Weight (g) |
|---|---|---|
| Controller | Raspberry Pi 3 flight control set, GPS & OSD & Radio Telemetry, etc. | 132 |
| Sensors | Humidity(DHT11), temperature, MQ-6, Rain Sensor | 125 |
| Connectors | 20x Male+Female 4mm Banana Plug + 2x XT60 Connector | 15 |
| Frame | 6 Arms(46cm) + Vibration Absorber + Motor Coupling + 2 Landing Skid, Aluminum Chassis | 560 |
| Motors | Brushless DC Motor | 656 |
| Propeller | 6x Entire Carbon Fiber 1555 15 x 5.5 CW/CCW Propeller | 113 |
| ESC | 6x BLHeli 30A Brushless ESC With LED Light Support 2-6s For RC Multi-copter | 156 |
| Battery | GenX Power Premium Li-Po Battery (22.2 V, 5200 mAh, 40C, 6S1P) | 708 |
| Others | Screws, Connectors, Jumpers, Plastic Cable Ties, Adhesive Tapes | 100 |
| | **Total Weight:** | **2565** |

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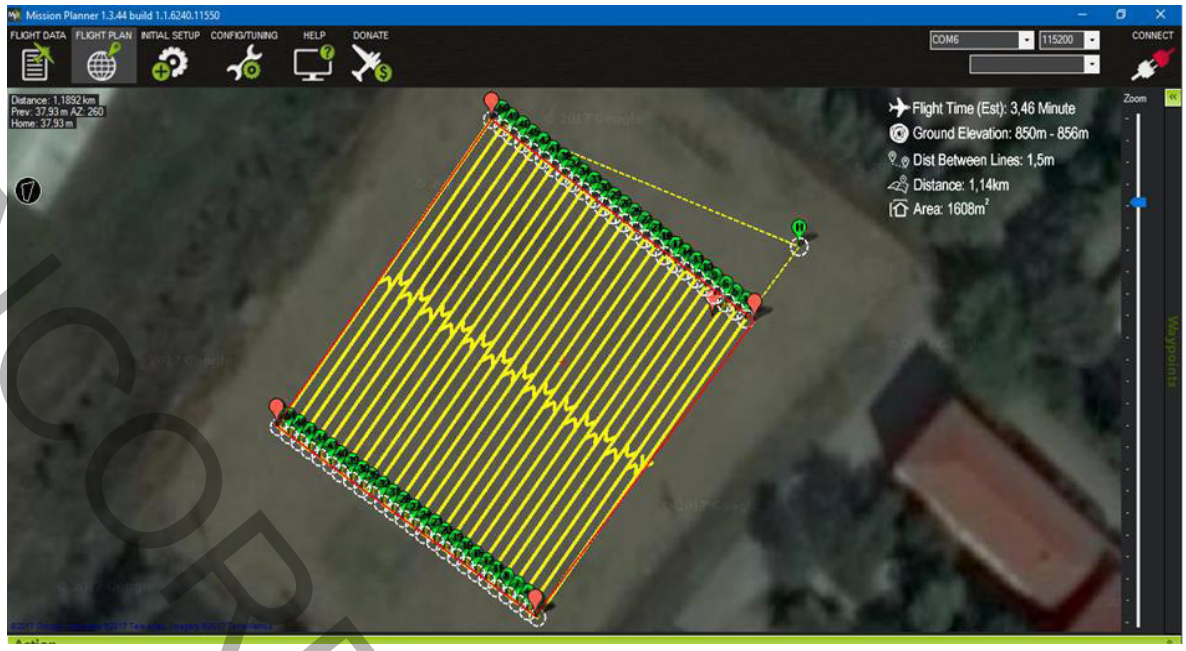



**Fig. 2. Flight path of the UAV planned using a mission planner algorithm, ensuring optimal coverage of the target agricultural area for precision monitoring and data collection.**

mission utilized only a small portion of the available battery capacity. The remaining flight time can be used to monitor larger agricultural fields without battery replacement. During the mission, the onboard camera continuously acquired RGB images, while the DHT11 temperature and humidity sensor, MQ-6 gas sensor, and rainfall sensor simultaneously collected environmental information. The acquired image and sensor data were transmitted to the Raspberry Pi 3 for real-time processing and disease identification.

### 5- 3- Multi-Perspective UAV Imaging for Precision Agriculture

The UAV-based imaging system successfully captured multiple images of the tomato field under varying lighting conditions and angles, demonstrating its effectiveness in precision agriculture. These images provide valuable insights into plant growth, fruit development, and overall field conditions, enabling early detection of potential issues such as nutrient deficiencies, pests, or disease outbreaks. The images were taken at different times of the day, capturing variations in sunlight intensity and shadows, which help analyze plant reflection characteristics and detect any discoloration or abnormalities in leaves and fruits.

By utilizing multiple viewing angles, close-up shots provide high-detail imaging of individual tomato plants, including leaf texture, vein patterns, and fruit clusters, while wide-field images offer an overview of the entire plantation, showing uniformity in crop growth and density distribution. The high-resolution imaging capability of the Raspberry Pi Camera Module V2, equipped with an 8 MP Sony IMX219 sensor, ensures 3280 × 2464 pixel resolution, allowing for precise agricultural analysis. This high-quality imaging enables a detailed assessment of plant health parameters such as chlorophyll content, leaf damage, and fruit maturity.

The UAV system, powered by the Raspberry Pi 3 Model B+, facilitates real-time processing and wireless data transmission. The first image captures a close-up view of the tomato plants, highlighting the detailed texture of the leaves and the early-stage growth of the fruits. This perspective provides valuable insights into plant health, allowing for precise monitoring of leaf structure, fruit formation, and any potential signs of disease or deficiencies. Furthermore, the second image provides a wider field view, illustrating the expansive nature of the cultivated area. This broader perspective helps assess crop uniformity, density distribution, and overall field conditions, making it easier to detect variations in growth patterns across different sections of the farm.

The third image, taken from a different angle, focuses on the fruit clusters, offering a clearer representation of fruit development stages. This perspective is particularly useful for estimating yield and planning harvesting schedules based on fruit maturity and size. Additionally, the fourth image captures the field under different lighting conditions, showcasing how sunlight variations impact plant visibility and color representation. This is essential for spectral analysis and remote sensing applications, where plant health can be assessed based on light reflection and absorption characteristics. The fifth image provides another close-up perspective, emphasizing individual fruits and leaf textures.

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**Fig. 3. A comparative set of images captured using the Raspberry Pi Camera Module v2 with an 8 MP Sony IMX219 sensor, featuring a resolution of 3280 × 2464 pixels. The images (a), (b), (c), and (d) showcase different perspectives of the tomato plants, illustrating variations in growth patterns, leaf structures, and fruit development under diverse lighting and field conditions.**

This detailed view allows for a more thorough assessment of plant vitality, including signs of stress, pest infestations, or nutrient deficiencies. Lastly, the sixth image presents a slightly blurred, distant view of the entire tomato field, demonstrating how aerial imaging can be used to monitor large-scale cultivation areas. Despite the reduced sharpness, the image still provides an overview of crop distribution, growth patterns, and potential anomalies within the plantation.

### 5- 4- Performance Evaluation of the Proposed System

The performance of the proposed UAV-based tomato leaf disease detection system was evaluated using a common testing dataset consisting of 288 tomato leaf samples, including 118 healthy and 170 diseased samples. Three classification models, namely 2D Convolutional Neural Network (2D-CNN), Support Vector Machine (SVM), and Random Forest (RF), were evaluated using the same testing dataset to ensure a fair performance comparison. The comparative results are presented in Figure 4

The proposed 2D-CNN achieved an accuracy of 69.10%, precision of 76.47%, recall of 68.82%, and F1-score of 72.45%. Although convolutional neural networks can effectively learn image features, the limited size of the training dataset affected the learning capability of the model and resulted in comparatively lower classification performance. The model exhibited reduced generalization capability, indicating the need for larger training datasets and additional optimization techniques such as data augmentation and transfer learning.

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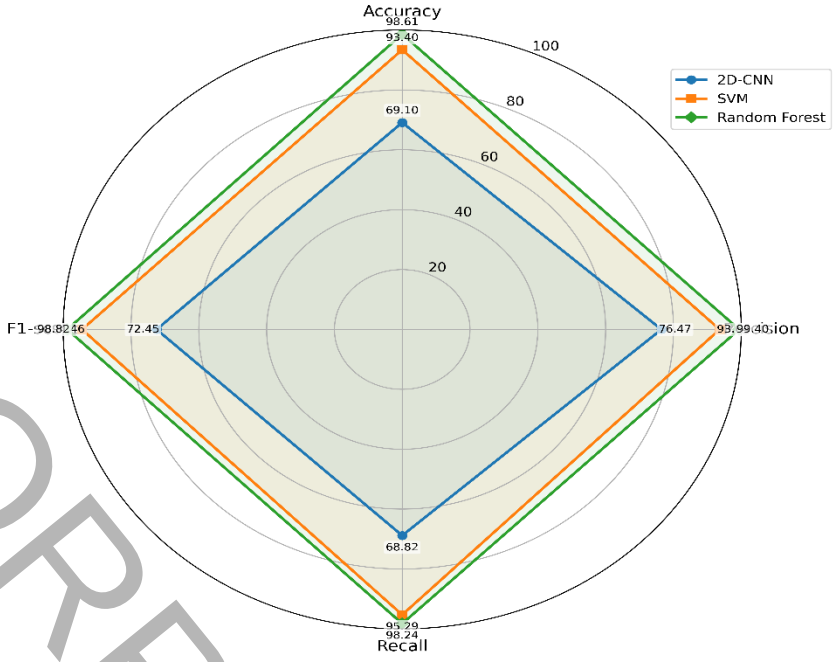



**Fig. 4. Radar chart comparing the performance of the proposed 2D-CNN, SVM, and Random Forest classifiers using Accuracy, Precision, Recall, and F1-score.**

The SVM classifier demonstrated significantly better performance, achieving an accuracy of 93.40%, precision of 93.64%, recall of 95.29%, and F1-score of 94.46%. The superior performance of SVM is attributed to the Radial Basis Function (RBF) kernel, which effectively models nonlinear relationships among the environmental sensor parameters and provides improved class separation. The results indicate that SVM is highly effective for sensor-based plant disease classification while maintaining relatively low computational complexity. Among the evaluated classifiers, the Random Forest model achieved the best performance with an accuracy of 98.61%, precision of 99.40%, recall of 98.24%, and F1-score of 98.82%. The ensemble learning strategy employed by Random Forest improves prediction reliability by combining multiple decision trees through majority voting. This approach reduces overfitting and enhances the robustness of the classifier when analysing heterogeneous environmental sensor data.

Figure 4 presents the comparative performance of the three classifiers using Accuracy, Precision, Recall, and F1-score. The radar chart clearly demonstrates that the Random Forest classifier consistently outperformed the other models across all evaluation metrics, followed by the SVM classifier. Although the 2D-CNN achieved comparatively lower performance, it provides an image-based disease identification framework that can be further improved through network optimization and larger training datasets. Overall, the Random Forest classifier proved to be the most suitable model for the proposed UAV-assisted tomato leaf disease detection system because of its high accuracy, robustness, and excellent generalization capability.

### 5- 5- Comparative analysis between proposed UAV Intelligent Leaf Disease Detection System and the Conventional Manual Inspection Method

The performance of the proposed UAV-assisted disease detection system was compared with the conventional manual inspection method, and the results are summarized in Table 2. The proposed framework integrates UAV-based image acquisition, environmental sensing, and intelligent disease classification to provide rapid and reliable crop health assessment. Among the evaluated classifiers, the Random Forest (RF) model achieved the highest classification performance with an accuracy of 98.61%, precision of 99.40%, recall of 98.24%, and F1-score of 98.82%. These results are significantly higher than those obtained through conventional manual inspection, where the classification accuracy generally ranges between 70% and 80%, depending on the experience of the field inspector.

The proposed system processes images at an average rate of 80 images $s^{1-}$, with a classification latency of approximately 12 ms per image. This enables rapid analysis of crop health over large agricultural fields. Under a fully charged battery, the UAV provides a flight endurance of 30–40 min, allowing coverage of approximately 1.5 acres per flight. In contrast, manual inspection generally covers only 1–2 acres per day and requires continuous human effort. The UAV therefore significantly reduces inspection time while improving the

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**Table 2. Performance Comparison Between UAV-Based Intelligent Leaf Disease Detection System and Conventional Manual Inspection Method.**

| Parameter | Proposed UAV-Based System (Random Forest) | Conventional Manual Inspection |
|---|---|---|
| Accuracy | 98.61% | 70–80% |
| Precision | 99.40% | 65–75% |
| Recall | 98.24% | 60–75% |
| F1-Score | 98.82% | 62–75% |
| Classification Latency | 12 ms/image | Minutes to hours |
| Throughput | 80 images/s | 1–2 plants/min |
| Power Consumption | 250 W | Human labour |
| Flight Endurance | 30–40 min | Not applicable |
| Area Coverage | 1.5 acres/flight | 1–2 acres/day |
| UAV Dimensions | 1.5 × 1.5 × 0.4 m | Not applicable |

consistency and reliability of disease identification.

The UAV consumes approximately 250 W during flight, which is considerably lower than the labour cost associated with repeated manual field inspection over large agricultural areas. Furthermore, the compact UAV platform, with overall dimensions of 1.5 m × 1.5 m × 0.4 m, enables easy deployment under different field conditions. Although the initial investment cost is higher than conventional inspection methods, the proposed system provides long-term operational benefits through reduced labour requirements, faster data acquisition, and improved disease detection accuracy.

The simultaneous analysis of RGB images and environmental sensor measurements also improves the reliability of disease assessment. Healthy crop regions generally correspond to favourable temperature and humidity conditions, whereas regions exhibiting abnormal environmental parameters show a higher probability of disease occurrence. The integration of visual and environmental information therefore enables early disease detection and supports timely crop management decisions. These results demonstrate the effectiveness of the proposed UAV-assisted monitoring system for precision agriculture and large-scale crop health assessment. Compared with the 2D-CNN, the SVM classifier improved the classification accuracy by 35.17%, precision by 22.45%, recall by 38.46%, and F1-score by 30.38%. The Random Forest classifier further improved the classification accuracy by 5.58% compared with the SVM classifier. Overall, the Random Forest achieved a 42.71% improvement in accuracy over the 2D-CNN, together with improvements of 29.98% in precision, 42.75% in recall, and 36.40% in F1-score. These results demonstrate the superior robustness and generalization capability of the Random Forest model for UAV-assisted tomato leaf disease detection.

## 6- Conclusion and Future Work

This study presented a UAV-assisted intelligent framework for tomato leaf disease detection by integrating RGB image acquisition, environmental sensing, and data-driven classification techniques. The developed UAV platform incorporated a lightweight six-arm aluminium frame equipped with a Raspberry Pi 3 controller, GPS, telemetry module, RGB camera, and environmental sensors for temperature, humidity, rainfall, and gas concentration monitoring. The acquired image and sensor datasets were analysed using three classification models, namely 2D Convolutional Neural Network (2D-CNN), Support Vector Machine (SVM), and Random Forest (RF). Experimental evaluation demonstrated that the Random Forest classifier achieved the highest performance with an accuracy of 98.61%, followed by the SVM with 93.40%, whereas the 2D-CNN achieved 69.10% accuracy. These results indicate that the integration of UAV-based sensing with machine learning techniques provides an effective solution for early disease detection and precision crop monitoring. The comparatively lower performance of the 2D-CNN can be attributed to the limited size of the training dataset and the relatively higher complexity of the deep learning model. Deep learning networks generally require large and diverse image datasets to learn robust feature representations and achieve good generalization. In the present study, the available training data were insufficient to fully exploit the feature learning capability of the 2D-CNN, resulting in overfitting and reduced testing performance. In contrast, the SVM and Random Forest classifiers were trained using structured environmental sensor features with lower model complexity, enabling better generalization and improved classification accuracy. Among the evaluated classifiers, the Random

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Forest model demonstrated the highest robustness because of its ensemble learning mechanism and effective handling of nonlinear relationships among the environmental parameters.

Future work will focus on improving the performance of the image-based classification model by increasing the size and diversity of the training dataset through extensive field data collection and image augmentation.

## Declaration of Interests

- The authors declare that this research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
- The authors declare that the data will be made available upon reasonable request
- The authors declare that they have no conflict of interest regarding the publication of this research.

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