Intelligent Drone Assisted Plant Disease Detectionand Precision Pesticide Spraying Using a Residual-Inception Deep Learning Framework

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ABSTRACT

Deep learning techniques combined with unmanned aerial vehicles (UAVs) create new possibilities which will transform smart agricultural practices. This project introduces an innovative system which merges a Residual-Inception convolutional neural network with an intelligent drone spraying system to enable early detection and targeted treatment of plant diseases. The research used a dataset which contained 38 crop disease classes and achieved a 94.5% validation accuracy after 10 training epochs. The proposed model combines multi-scale convolutional branches with residual shortcuts to improve feature learning while decreasing classification errors. The researchers created a mathematical waypoint generation algorithm which enables UAVs to navigate through fields by creating efficient field coverage paths with optimal spray distribution. The researchers developed a pesticide prioritization system which maps detected diseases to customized treatment plans based on disease severity. The simulated results show precise classification results which successfully plan waypoints and create clear visual displays of the spraying operations. This Study demonstrates a scalable and economical method for executing precision agriculture because it decreases chemical application while enhancing crop health management.

Please note: Abbreviations should be introduced at the first mention in the main text – no abbreviations lists. Suggested structure of main text (not enforced) is provided below.

Introduction

Agriculture serves as the fundamental element which supports global food security yet the sector faces ongoing challenges from agricultural pests and plant diseases that destroy crops. Effective agricultural practices require accurate identification of plant diseases which must occur without delay to protect crop yields and maintain agricultural sustainability. The process of manual disease detection through traditional methods requires extensive time which leads to mistakes because it needs specialized knowledge that becomes hard to find and this makes the method unsuitable for use in large farming operations. The system requires artificial intelligence which helps to connect computer vision with deep learning technologies through deep learning to create automatic plant health monitoring systems that enable farmers to react quickly with accurate crop management methods.

The current research focuses on creating deep learning models that can maintain performance across different real-world testing conditions. Sood et al. [1] introduced a model that combines DenseNet121 and ResNet50 networks to detect crop diseases and identify pests simultaneously which outperforms single-network systems. Chauhan et al. [2] developed a model that uses dual self-attention together with a modified residual-inception network to improve disease detection through better focus on sick plant areas while lowering classification errors. The research conducted by Srivathsan et al. [3] investigates attention mechanisms for enhanced feature representation through their creation of a hybrid feature aggregation network which incorporates positional encoding attention with EfficientNet to deliver high classification performance and explainability which serves as a vital component for building farmer confidence in AI-based systems. The majority of methods developed for plant disease classification rely on CNNs as their primary foundation. The CNN-based pipeline for paddy leaf disease detection developed by Islam et al. [4] achieved superior results than traditional machine learning models that required handcrafted features. The research conducted by Sowmyalakshmi et al. [5] developed a rice plant disease classification system which achieved maximum accuracy through efficient computational methods. Semantic segmentation methods have gained popularity for their ability to precisely identify infected areas, as demonstrated by the dilated inception U-Net with attention model created by Zhang et al. [6], which allows better tracking of infection progression while enabling specific treatment methods. The expanding research base demonstrates how deep learning technology can be used in various agricultural applications. The research conducted by Ukaegbu et al. [7] demonstrated its value for weed detection, which confirms its ability to conduct automatic multi-task field monitoring operations. The research conducted by Sunil et al. [8] reviewed deep learning methods for plant disease detection, but they discovered that dataset imbalance and environmental changes and deployment feasibility issues represent the most critical obstacles for the system. The Kannan et al. [9] review shows that AI technology combined with drone systems can enable large-scale plant health monitoring, but it needs to resolve three main challenges of edge computing latency and model explainability and user acceptance. The research trends demonstrate a preference for developing AI solutions which provide accurate results and explainable functions and can be implemented in real world environments. The research will advance crop protection systems through its development of multiple network structures which will use attention methods to improve their features and develop explanation capabilities. The system encounters challenges because it needs to solve three primary issues which include managing computational expenses and maintaining performance across different weather conditions and making the system easy for users to access. The agricultural researchers who implement precision agriculture systems will achieve better outcomes when they remove these obstacles because their systems will decrease crop losses and enhance worldwide food security.

Related Work

Related Work Researchers are currently working to combine artificial intelligence with Internet of Things systems and unmanned aerial vehicles for automated precision agriculture. Shehab et al. [10] demonstrated a drone-based precision farming system which gathers real-time crop information to improve fertilization methods. The study showed that UAV-based monitoring systems decrease resource waste while improving resource management which supports agricultural decision-making through data analysis. Karmakar et al. [11] developed a smart farming system which uses deep learning to detect crop diseases in an organized way. The system used a three-step process which included data collection and data processing and disease identification to support farmers with large-scale system implementation and useful information. The aerial imagery deep learning models support multiple applications for detecting plant stress. Daraghmi et al. [12] presented the comparative study of state-of-the-art object detection models, namely YOLOv8, RetinaNet, and Faster R-CNN, for drone-assisted plant stress detection. The outcome highlighted that YOLOv8 had superior real-time performance, while Faster R-CNN showed higher accuracy in complicated environments. The use of YOLOv8 or Faster R-CNN depends upon the specific application. Nyakuri et al. [13] designed an edge-device solution by integrating AI and IoT for crop pest and disease detection. By enhancing computational efficiency, their system performs inference tasks without sharing data remotely, hence decreasing latency and the need to be dependent on cloud infrastructure. A few works have focused on model efficiency and interpretability. Padhiary [14] emphasized the relevance of explainable AI (XAI) in agricultural decision-making, wherein he accounted for the necessity and motivation by farmers in adopting automated solutions in terms of model transparency. Rani [15] further discussed the conceptual and practical applications of precision agriculture in the field of farming practices. The role of analytics at different levels has been discussed in depth, along with irrigation management and integrated pest control methods. Deebika and Sangeetha [16] proposed an optimized ResNet-50 architecture with a higher plant disease classification accuracy while reducing the computational cost to make it deployable in resource-constrained environments. Besides disease detection, UAV-based solutions for weed management have also been widely explored. Borah et al. [17] explored UAV-enabled weed detection systems and discussed their potential for selective herbicide spraying in order to reduce chemical usage and minimize environmental impact. In this regard, Paul and Pushpa [18] developed an energy-aware clustering mechanism for UAV-based sensor networks with an aperture antenna design to enhance coverage and energy efficiency. For continuous crop monitoring, the UAV network needs to maintain its operational functions over an extended duration. IoT-driven smart farming systems are also explored for sustainable management of resources. Sathya et al. [19] proposed a sensor-driven irrigation and pest control framework which demonstrated better water resource management and accurate pest control. Kim et al. [20] created wearable independent sensing devices for smart agriculture which enable ongoing monitoring of the health conditions of crops and livestock. Alawode et al. [21] showed how the combination of IoT and AI technologies can help farmers reduce environmental damage and their money losses, while they stressed that smart farming technologies need to achieve a balance between technical progress and sustainable economic development. The research path in these studies demonstrates how artificial intelligence, Internet of Things devices, and unmanned aerial vehicle technology will combine to create complete autonomous systems that operate with energy efficiency and high scalability in precision agriculture. The major developments research work toward three objectives which include faster inference speed for real-time systems and better model understanding to help farmers and energy-saving solutions which enable continuous operation in sustainable environments.

Proposed methodology

The proposed framework integrates a novel deep learning architecture with an autonomous drone-based spraying system to achieve end-to-end plant disease management. The methodology consists of four primary stages: data preprocessing, disease classification, waypoint generation, and pesticide prioritization. The plant images will undergo pre-processing for normalization and resizing to a uniform resolution. The model receives trustworthy input because the input has undergone this process. A Residual-Inception CNN serves as the classification module in this research because it uses multiple convolutional pathways together with residual links to enhance feature extraction while minimizing information degradation. The model will achieve its goal because it can detect both detailed elements and essential features of 38 plant disease categories. The mathematical path-planning algorithm designs efficient drone waypoints after the disease has been identified. The algorithm calculates spray coverage based on UAV altitude and nozzle angle which enables the field to be systematically covered while maintaining designated overlap limits. The detected disease class is then mapped to an appropriate pesticide using a rule-based prioritization scheme. The treatment severity is categorized into three levels: high, medium, or low. The system achieves its final result through a decision-making process which combines prediction results with path planning and spraying functions to deliver accurate pesticide treatment while minimizing chemical waste, thereby providing a sustainable agricultural solution that can expand its operations.

Dataset Description

The project utilizes the publicly accessible New Plant Diseases Dataset which includes an expanded collection of leaf images that represent 38 different crop-disease categories. The dataset contains 70595 training samples and 17572 validation samples which are evenly distributed across all categories. The system uses image labels for every crop and disease class to support its multi-class classification system. The images were pre-processed and all images were resized to a standard resolution of 64×64 pixels which was used for model training. The augmented samples include different types of data because they contain rotation, zoom, and flipping features which improve performance during actual lighting changes and variations in leaf orientation and leaf shape.

Data Preprocessing

The plant disease dataset underwent several preprocessing operations which created consistent data for training purposes and enhanced model performance through improved generalization. The deep learning system receives all input data through a standardized process which converts images into a fixed size of 64×64×3 pixel dimensions. The pixel values were normalized to the range of [0,1] through the application of a scaling factor which converted pixel values using 1/255 as the transformation base, resulting in faster convergence times and more stable gradient operations. The dataset already contained augmented data which led to the implementation of basic preprocessing operations that used ImageDataGenerator for image shuffling while maintaining proper class distribution across training batches. The available real-time augmentation options include horizontal flipping and random rotation and zooming which create natural field condition variations to help minimize overfitting. The proposed Residual-Inception deep learning model achieves enhanced performance through standardized input data processing which creates efficient representation of data.

Model Architecture Design

The proposed classification framework is based on a customized Residual-Inception Convolutional Neural Network (CNN), which achieves its goals of processing power and system requirements through its design which shows its capabilities in 1. The architecture begins with a stem block consisting of a convolutional layer, batch normalization, and max pooling to extract low-level spatial features. The system employs Inception-style multi-branch convolutions which combine with residual connections to create its core structure. Each Residual-Inception block processes the input feature map through parallel convolutional filters of dissimilar kernel sizes such as 1×1, 3×3, and 5×5. The network employs a multi-scale system which enables it to detect both minute details and extensive spatial patterns that connect to plant diseases. Outputs from these parallel pathways are first concatenated and projected through a 1×1 convolution. Stacks of blocks enable the network to develop representation capabilities which follow a systematic learning process for disease detection. After feature extraction, a Global Average Pooling (GAP) layer reduces the spatial dimensions while recollecting critical information. The system uses a dense fully connected layer which employs dropout regularization to maintain protection against overfitting. The system uses a SoftMax output layer to classify images into 38 disease categories which provides a flexible and efficient method for identifying plant diseases.

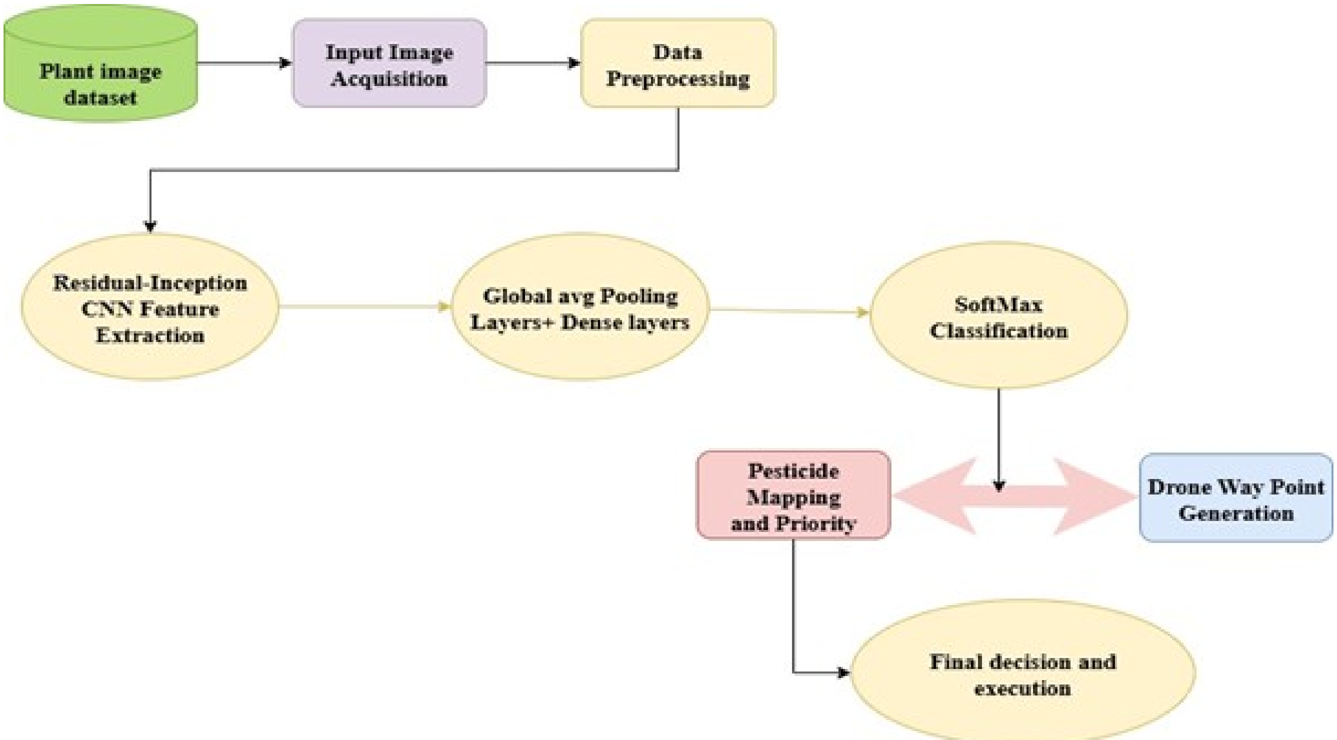

Figure 1. Proposed Residual-Inception CNN Drone Spraying Architecture

Results and Discussion

The Obtained Results and the metrics have discussed and for the coming sections and our work shows best results of our chosen model, The obtained metrics has given in below Table.1,

Model Training Analysis

The proposed Residual-Inception CNN was trained on a large-scale plant disease dataset comprising 70,295 training images and 17,572 validation images across 38 classes. Images were resized to 64×64 pixels and normalized to fast convergence. The model was trained for 10 epochs using the Adam optimizer with a learning rate of 1e-4 and categorical cross-entropy loss. Early results show rapid learning: initial training accuracy was 30%, while validation accuracy reached 74%, representing effective feature extraction. After finishing all training epochs, the network reached a training accuracy of 92.9% and a validation accuracy of 94.5%, which showed its ability to generalize without overfitting problems. The system achieved efficient gradient flow together with strong feature representation through its use of residual connections and multi-scale inception blocks, which allowed the system to capture both detailed disease patterns and complete disease patterns. The loss curves showed a consistent decline, which proved that the system achieved stable convergence. The training method achieved its objectives by providing both efficient computation and accurate classification results, which established a dependable system for combining UAV-based pesticide spraying.

Training and Validation Accuracy

The training and validation accuracy curves indicate that the Residual-Inception CNN learned effectively over 10 epochs which is Demonstrated in the below Given Fig.2. The training accuracy began at 45% whereas the validation accuracy reached approximately 75% showing that the model did not fit the training data but performed well on new data. The curves display continuous growth until training accuracy reaches 93% and validation accuracy reaches 94.5% which shows strong convergence with little overfitting. The curves maintain close alignment from epoch 7 onward which demonstrates that the system has attained stable learning and strong generalization abilities. The network recognized disease-specific characteristics which led to its accurate classification results.

Training and Validation Loss

The training and validation loss curves illustrates a steady and consistent decline over the ten epochs, indicating effective learning and convergence of the proposed network. Initially, the training loss declines sharply, demonstrating rapid adaptation to

Table 1. Classification Performance Metrics

Class	Precision	Recall	F1-Score	Support
Apple___Apple_scab	0.95	0.90	0.92	504
Apple___Black_rot	0.85	1.00	0.92	497
Apple___Cedar_apple_rust	0.90	0.99	0.94	440
Apple___healthy	0.99	0.92	0.95	502
Blueberry___healthy	0.93	0.94	0.93	454
Cherry_(including_sour)___Powdery_mildew	0.99	0.96	0.98	421
Cherry_(including_sour)___healthy	0.92	0.98	0.95	456
Corn_(maize)___Cercospora_leaf_spot_Gray_leaf_spot	0.92	0.94	0.93	410
Corn_(maize)___Common_rust	1.00	1.00	1.00	477
Corn_(maize)___Northern_Leaf_Blight	0.95	0.95	0.95	477
Corn_(maize)___healthy	0.99	1.00	1.00	465
Grape___Black_rot	0.96	0.94	0.95	472
Grape___Esca_(Black_Measles)	0.94	0.99	0.96	480
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	0.97	0.98	0.98	430
Grape___healthy	0.98	0.97	0.98	423
Orange___Haunglongbing_(Citrus_greening)	1.00	0.96	0.98	503
Peach___Bacterial_spot	0.95	0.95	0.95	459
Peach___healthy	0.97	0.99	0.98	432
Pepper,_bell___Bacterial_spot	0.97	0.93	0.95	478
Pepper,_bell___healthy	0.81	0.96	0.88	497
Potato___Early_blight	0.94	0.98	0.96	485
Potato___Late_blight	0.97	0.83	0.90	485
Potato___healthy	0.96	0.76	0.85	456
Raspberry___healthy	0.99	0.92	0.95	445
Soybean___healthy	0.98	0.90	0.94	505
Squash___Powdery_mildew	1.00	0.98	0.99	434
Strawberry___Leaf_scorch	1.00	0.98	0.99	444
Strawberry___healthy	1.00	0.95	0.97	456
Tomato___Bacterial_spot	0.99	0.94	0.96	425
Tomato___Early_blight	0.76	0.96	0.85	480
Tomato___Late_blight	0.98	0.80	0.88	463
Tomato___Leaf_Mold	0.94	0.99	0.96	470
Tomato___Septoria_leaf_spot	0.88	0.95	0.91	436
Tomato___Spider_mites_Two_spotted_spider_mite	0.94	0.92	0.93	435
Tomato___Target_Spot	0.95	0.87	0.91	457
Tomato___Tomato_Yellow_Leaf_Curl_Virus	0.95	0.98	0.96	490
Tomato___Tomato_mosaic_virus	0.96	0.99	0.97	448
Tomato___healthy	0.97	0.98	0.98	481

the dataset, while the validation loss follows a similar downward trend with slightly lower values, reflecting strong generalization. The close alignment of both curves without significant divergence suggests minimal overfitting and stable optimization. By the final epoch, losses for both training and validation converge to low values, confirming that the Residual-Inception CNN achieves reliable feature extraction and accurate classification performance suitable for real-time agricultural applications which is Demonstrated in the below Given Fig.3.

0.1 Confusion Matrix

The confusion matrix demonstrates that the proposed Residual-Inception CNN achieves highly reliable multi-class recognition across 38 plant disease categories that is shown in below given Fig.4 . Most diagonal entries exhibit strong dominance, confirming correct classification for the majority of samples. Only a few classes, such as Pepper bell healthy and Potato healthy, show mild off-diagonal counts, indicating chance misidentification with visually similar diseases. Overall precision, recall, and F1-scores reliably exceed 0.90 for nearly all categories, foremost to a macro-averaged accuracy of approximately 95%. These results validate the model's ability to capture discriminative leaf patterns and maintain balanced performance across diverse

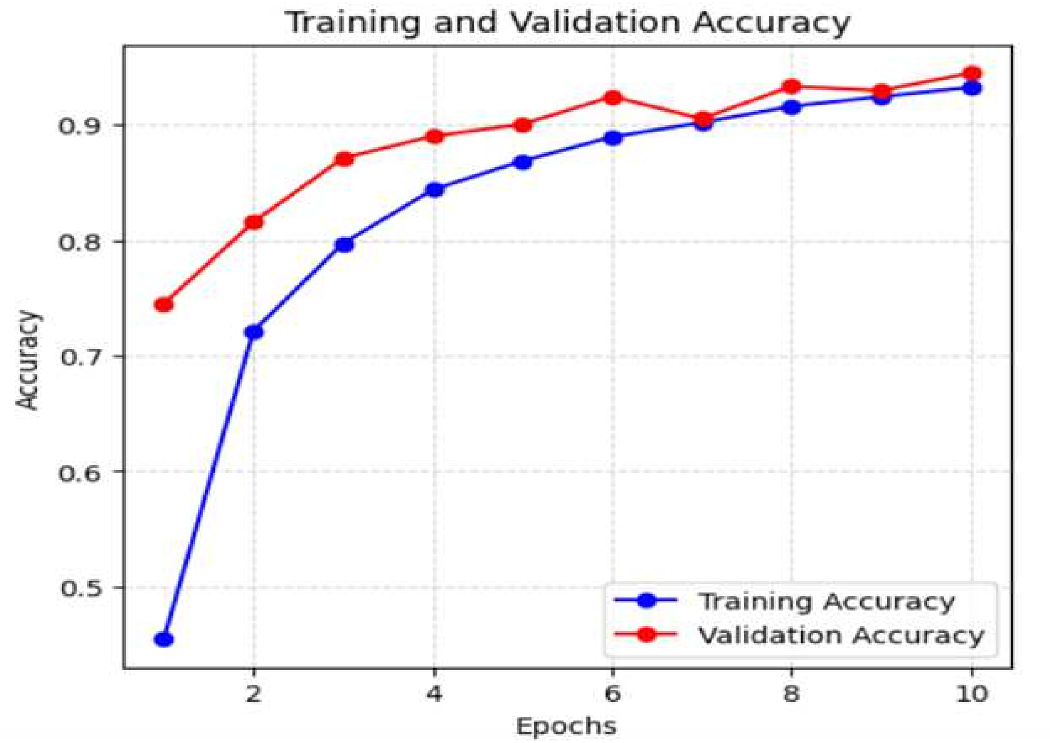

Figure 2. Accuracy of the model while training and validation

crops and disease conditions.

0.2 Pesticide Prioritization

The pesticide prioritization strategy effectively translates disease detection into actionable spraying commands that is shown in below given Fig.5. The simulation data shows how specific pesticides get assigned to different diseases which have been categorized by their respective priority levels. The system assigns 'Low' priority to 'Apple-Apple-scab' which it links with 'Pesticide-A' while it assigns 'Medium' priority to 'Apple-black-rot' with 'Pesticide-B' as the solution. The drone uses this rule-based system to control its spraying operations because the system knows which specific disease exists, which improves chemical application efficiency. The system enables users to detect different diseases while treating them with different levels of priority which leads to efficient pesticide application that reduces both material waste and environmental harm.

ROC Curves

The model achieves outstanding results according to the ROC curve analysis results which show its performance through the provided testing. The plot shows all 38 disease classes through their respective ROC curves which include micro and macro-averaged curves that appear in Fig. 6. The plot shows that all curves follow a path which reaches towards the top-left corner because of their high True Positive Rate and low False Positive Rate. The Area Under the Curve (AUC) results show perfect scores for all classes and their respective averages which reached a value of 1.00. The model achieves perfect AUC score because it uses ideal discriminatory abilities which enable it to identify all 38 plant disease classes without making any errors thus proving its strong performance.

PRC Curves

The Precision-Recall (PR) curves show how well the model performs through its display of precision and recall trade-off which occurs at different classification threshold values as shown in below given Fig.7. The plot shows that the curves for all 38 classes, along with the micro and macro-averages, remain close to the top-right corner. The model demonstrates its ability to maintain high precision throughout all levels of recall while achieving complete success in reducing both false positive and false negative errors. The corresponding Average Precision (AP) scores of 0.99 for both the micro and macro-averages validate this strong performance, demonstrating the framework's robust ability to accurately identify and classify plant diseases.

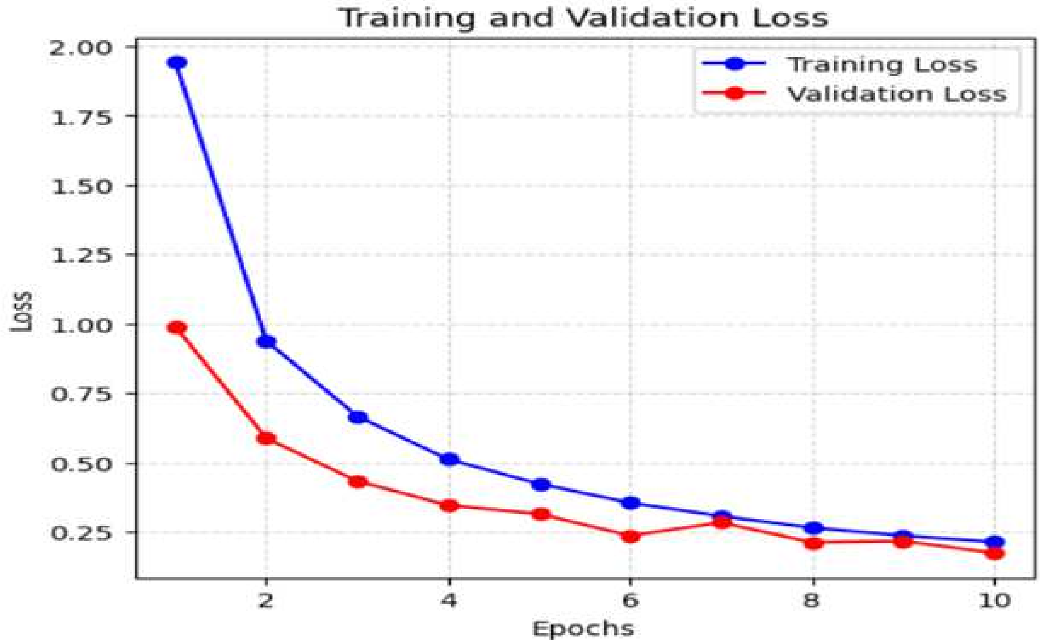

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Figure 3. Loss of the model while training and validation

ROC AUC & Average Precision (AP) per Class

The complete overview of ROC AUC and Average Precision (AP) for each class delivers an in-depth assessment of model results that proves the merged performance outcomes. The framework demonstrates its ability to maintain high performance throughout all 38 plant disease classes according to the recorded data. The ROC AUC scores across all classes demonstrate exceptional results because many classes reach almost perfect 1.00 scores which show the model can differentiate between classes effectively. The Average Precision (AP) values demonstrate high accuracy which becomes apparent through their response to class imbalances because the lowest score surpasses 0.96. The analysis of individual classes shows that the model achieves high accuracy with its macro-averaged results because all classes perform at equal levels which proves the proposed deep learning model works effectively against various agricultural threats. The Below Fig Shows the ROC AUC and Average Precision Comparison of various classes.

0.3 Drone Spray Priority Map with Flight Path & Metrics

The mission, which required 50 seconds to complete its spray operation, achieved 5.24% coverage efficiency. The metric shows the sprayed area ratio to the complete field area which demonstrates that the method specifically targets infected areas instead of treating the whole field. The Priority Distribution confirms this targeted strategy, with the drone applying 'Low' priority treatments at 6 locations and 'Medium' priority treatments at 4 locations, aligning with the disease severity-based prioritization. The system demonstrates efficient resource management for crop management at the below demonstration which shows Figure 9 of drone pesticide application for the field area.

Mathematical Formulation

The total flight distance between consecutive waypoints is computed as:

$$D_{total} = \sum_{i=2}^{N} \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2} \tag{1}$$

The spraying duration is given by:

$$T_{total} = N \cdot t_{wp} \tag{2}$$

The coverage efficiency is expressed as:

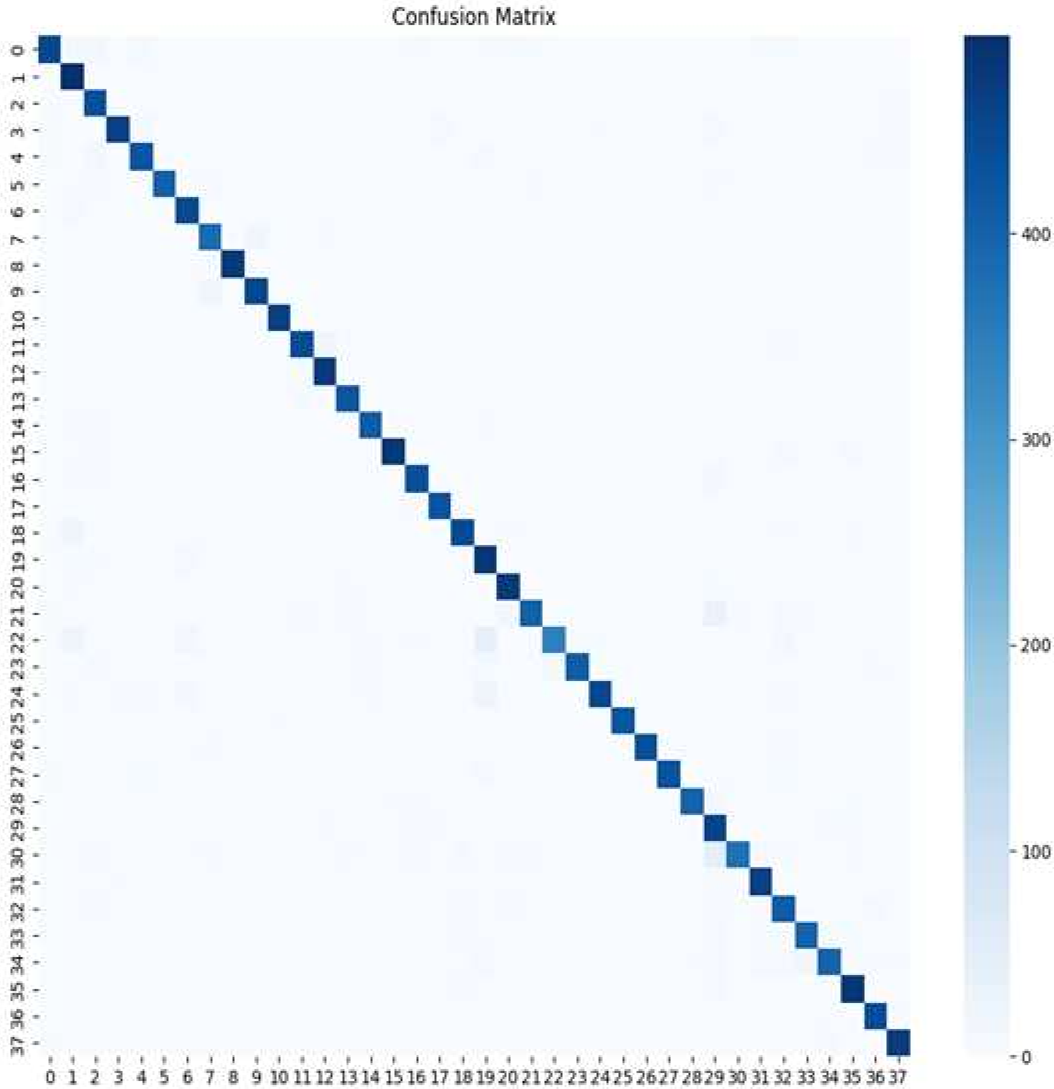

Figure 4. Confusion matrix of various classes

$$\eta_c = \min\left(\frac{N \cdot \pi r_s^2}{A_f}, 1.0\right) \times 100 \quad (3)$$

where

$$A_f = \text{Total field area} \quad (4)$$

The priority distribution of spraying actions is defined as:

$$P = \{P_k : f(P_k)\}, \quad P_k \in \{Low, Medium, High\} \quad (5)$$

with $f(P_k)$ representing the frequency count of each priority level across all waypoints.

The derived metrics (Eqs. 1–4) quantify the UAV's spatial and operational performance, linking algorithmic planning with agronomic decision-making. By computing these parameters via Algorithm 1, the system provides interpretable mission analytics that validate the underlying AI-driven disease-to-action pipeline. This formalization ensures repeatability and serves as a performance benchmark for future real-world UAV-based spraying deployments.

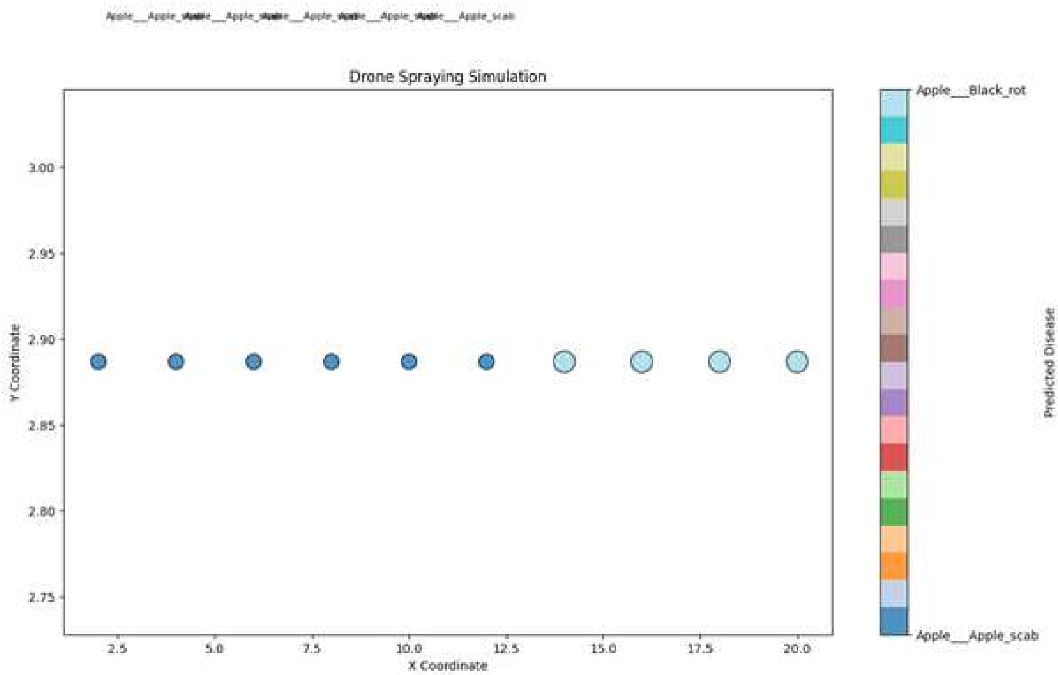

Figure 5. Drone Spraying Simulated Areas With Coordinates

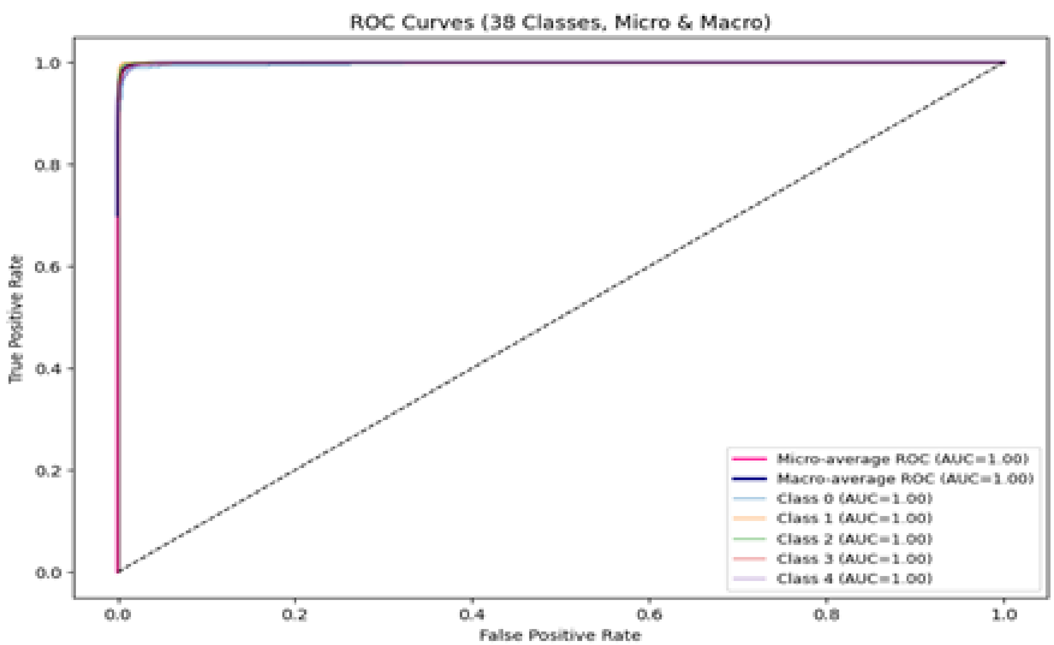

Figure 6. ROC Curve of the Various Classes

Discussion of Broader Implications

This research generates multiple crucial implications which the present findings demonstrate. EfficientNetV2B0 combined with CBAM creates a model which maintains high accuracy while using low computational resources, thus enabling deployment on devices which have restricted processing power like drones. Grad-CAM enables better model understanding through its decision-making display while it helps researchers discover hidden areas which need more dataset development work. The system delivers operational value through its ability to predict and produce actual results which include pesticide suggestions and optimal drone flight paths. The system enables simple adaptability to various agricultural situations through its modular

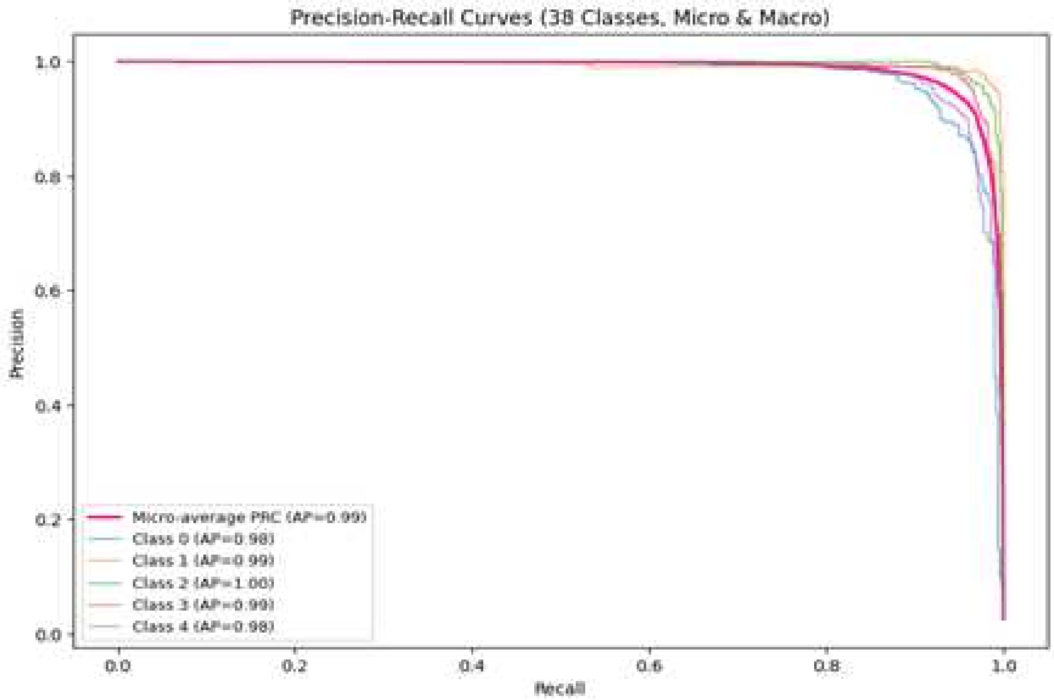

Figure 7. PRC Curve of the Various classes

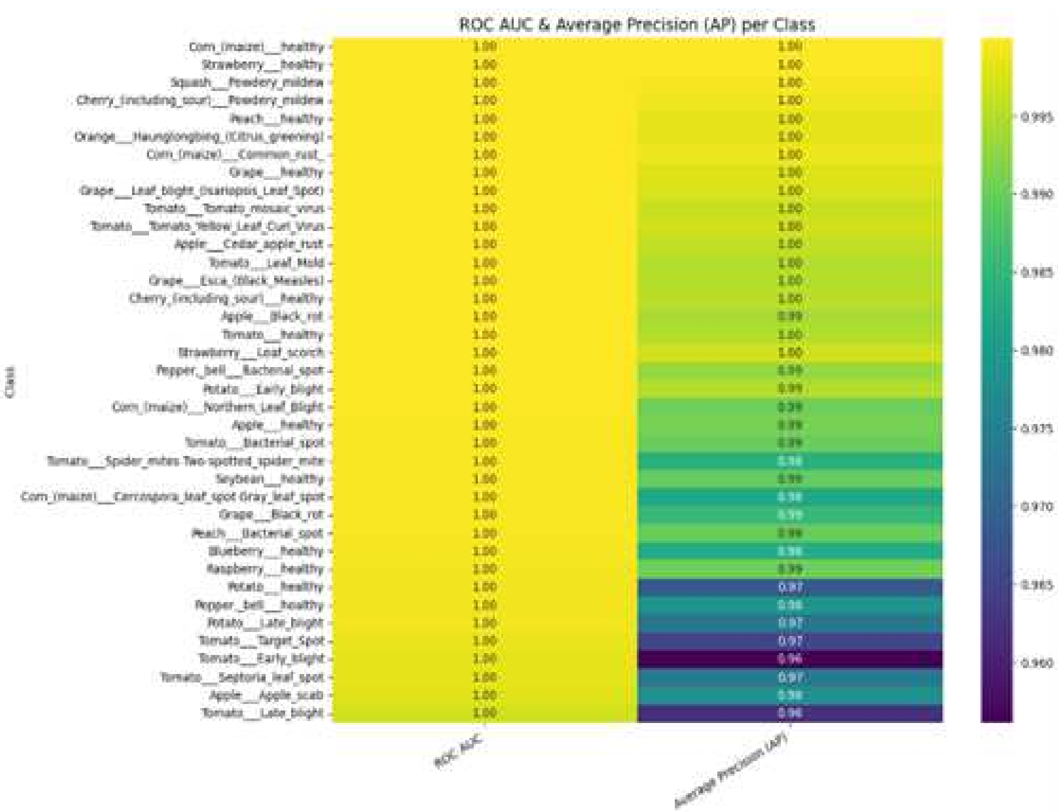

Figure 8. ROC AUC and Average Precision Comparison of various classes

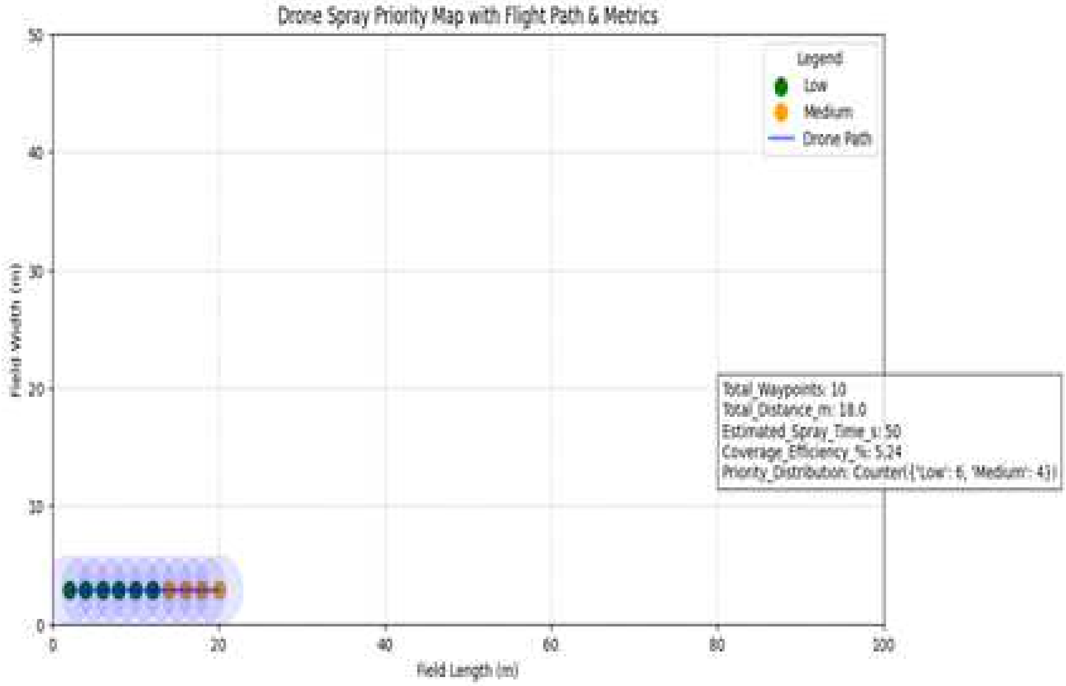

Figure 9. Showing the Drone Spraying pesticides in Map for the Field

design, which lets users modify rule-based systems and pesticide distribution systems. The system uses its prioritization and clustering methods to achieve three objectives, which include reducing pesticide usage, decreasing drone operational distance, and lowering total expenses, thus promoting environmentally friendly agricultural methods.

The project maintains unresolved issues. The model needs further improvement to avoid confusing visually similar diseases because this error causes incorrect treatment suggestions. The system experiences performance issues because real-world situations present both poor lighting conditions and partially obstructed leaves. The route planning system worked effectively during simulations, but actual deployment requires assessment of drone battery performance, payload limitations, and weather conditions. The research results show that the system functions as an efficient solution which scales for plant disease management through its ability to link deep learning results with agricultural decision-making processes.

Future Work and Limitations

The study presents results which show potential, but the research study encounters certain constraints. The system was tested only in a simulated environment, which does not fully represent real agricultural conditions. Actual fields experience various factors which include wind and uneven terrain and drone vibration and GPS errors which disrupt flight stability and spraying accuracy. The training dataset for the study consists of laboratory images which display uniform backgrounds and controlled lighting conditions. The model performance will decrease because all real-world scenarios include lighting changes and leaf overlapping and simultaneous multiple disease presence. The researchers have not yet completed the evaluation process for the model's computational performance on onboard drone devices.

The system will undergo testing through actual UAV platform evaluation under various field conditions to establish improved system reliability and operational accuracy. The integration of advanced imaging technologies which include multispectral and hyperspectral sensors will enable earlier plant stress detection. Reinforcement learning–based path planning will be developed to allow drones to adjust their routes dynamically when new disease areas are detected, improving efficiency and reducing energy use. The system will develop into a cloud-based Internet of Things framework which enables continuous monitoring and joint learning among multiple drones. The system will use Explainable AI methods to enhance its transparency, which will help users build trust in the system. The ultimate objective involves developing an autonomous precision agriculture system which operates intelligently, reduces chemical waste, and achieves energy savings through environmentally sustainable agricultural practices.

Algorithm 1 Drone Mission Metrics Computation

Require:
$simulation\_results = \{(W_i, P_i)\}_{i=1}^{N}$
$W_i = (x_i, y_i)$
$P_i \in \{Low, Medium, High\}$
r_s (spray radius in meters)
t_{wp} (time per waypoint in seconds)
Ensure:
$D_{total}, T_{total}, \eta_c, P$
$total\_distance \leftarrow 0$
for $i = 2$ to N **do**
    $total\_distance \leftarrow total\_distance + \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}$
end for
$D_{total} \leftarrow total\_distance$
$T_{total} \leftarrow N \cdot t_{wp}$
$field\_area \leftarrow 100 \times 50$
$coverage\_area \leftarrow N \cdot \pi r_s^2$
$\eta_c \leftarrow \min\left(\frac{coverage\_area}{field\_area}, 1.0\right) \times 100$
for each $P_k \in \{Low, Medium, High\}$ **do**
    Compute frequency $f(P_k)$
end for
$P \leftarrow \{P_k : f(P_k)\}$
    return $D_{total}, T_{total}, \eta_c, P$

Conclusion

This paper introduces a unified framework in which the Residual-Inception Convolutional Neural Network is integrated with a drone-based spraying mechanism to implement autonomous plant disease control. The suggested model attained an overall classification accuracy of around 95%, exhibiting high performance in identifying 38 classes of crop diseases. Through the focus of disease prediction on a mathematical waypoint generator and rule-based pesticide prioritization setup, the system assures precise chemical application and minimizes duplicate pesticide application. Experimental simulations also validate the efficacy of real-time decision making, allowing for interventions targeted toward improving sustainability and operational efficiency in precision agriculture. Future work research will involve increasing the framework to real-world field deployments with live drone imagery to test performance in diverse environmental circumstances. Additionally multispectral and hyperspectral sensors can enhance detection of early-stage infections that are visually unobtrusive in RGB images. Advanced path-finding algorithms with adaptive spraying modes will be examined to maximize energy use and flying time. Internet of Things (IoT) devices and cloud-based analysis will enable large-scale monitoring, ongoing learning, and autonomous control. These will enable the development of a fully automated, scalable system that provides smart crop protection with minimal environmental influence and enabling sustainable agriculture.

Data Availability

The current research did not create any fresh data sets. The data set used in this study is publicly available on Kaggle: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset.The corresponding author will provide access to the analysis materials which include models and implementation scripts upon receiving reasonable requests.

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Author contributions statement

The authors A.M. and H.K. contributed to the problem formulation, dataset preparation, architecture design, and experimental analysis. The author D.E. contributed to the mathematical modeling, waypoint generation algorithm, and pesticide prioritization framework. The author K.P. contributed to the study design, supervision, validation of results, and manuscript revision. All authors contributed equally to the development of the work and approved the final manuscript.

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Competing Interest
The authors declare no conflict of interest.