Pakistan Journal of Scientific Research
Multidisciplinary & Peer Reviewed
Volume: 5, Number: 1, Pages: 29-39, Year:2025

Article

Real-Time Crop Health Monitoring Using AI-Based Drone Surveillance and YOLOv12

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Submitted: 10-01-2025, **Revised:** 07-4-2025, **Accepted:** 25-05-2025

Abstract

Early crop disease detection remains challenging for precision agriculture. This research presents an AI-drone surveillance system using a YOLOv12 deep learning model to automatically identify diseases for real-time monitoring in potato, banana, and cotton crops. The complete pipeline includes automated image acquisition, intelligent preprocessing, and real-time analysis. Compared to traditional manual inspection, this approach reduces diagnosis time from days to minutes while improving reliability. Key innovations include optimized model architectures for resource-limited environments and multi-spectral disease pattern recognition. Field tests confirm the system's robustness across varying weather conditions and growth stages. Proposed method processes the drone-captured images through Raspberry Pi edge computing, achieving 99.5%, 98.1%, and 89.7% detection accuracy of potato, banana, and cotton crops, respectively. The lightweight YOLO-Nano variants enable efficient field deployment while maintaining precision. A merged dataset across 28 disease classes demonstrates 91.8% overall accuracy through comprehensive validation metrics. Farmers receive immediate alerts for targeted treatment, reducing pesticide use by 30-45% in trial implementations. This scalable solution outperforms existing methods in both speed (4.2ms per image) and accuracy. Results demonstrate practical potential for transforming global agricultural monitoring through accessible AI technology.

Keywords: AI technology, drone surveillance, YOLOv12, deep learning, crop disease detection, real-time monitoring.

1. Introduction

Smart agriculture is a very essential for food security, economic growth, and sustainability globally. Out of the employed workforce of 61.71 million in Pakistan, 38.5% work in the agricultural sector [1]. One of the biggest challenges farmers are facing across the world is the identification of crop diseases in time and with accuracy. Crop disease identification using conventional methods is through manual inspection, which may be time-wasting, labour-demanding, and prone to errors. In the last few years, breakthroughs in artificial intelligence (AI) in the form of deep learning have brought hopeful solutions to computer-aided detection of plant diseases using image-based methods. Deep learning methods allow for the fast classification of crop diseases by inspecting visual patterns in images, helping farmers to make timely decisions to avoid losses to crops.

Ample research has been done on creating and using deep learning models for the detection of plant diseases in crops like rice, tomatoes, and soybeans through datasets with thousands of labelled images [2][3]. The combination of multispectral imaging, drone-based data collection, and hybrid deep learning models further improves the robustness and accuracy of plant disease detection systems [4-9]. Plant diseases are a major threat to crop productivity, resulting in economic losses and food shortages. Early detection of plant diseases is important for efficient crop management since early intervention can limit the spread of infections and minimize the application of chemical pesticides [5]. Conventional methods of disease identification, including visual examination by agricultural specialists, are not only time-consuming but also prone to human error. Recent advancements have leveraged diverse datasets and deep learning techniques to improve plant disease detection.

Traditional machine learning methods, such as Support Vector Machine (SVM), K-nearest neighbour (KNN), and Random Forest (RF), employ manually designed features (colour, texture, and shape) extracted from leaf images for disease classification. They worked efficiently under controlled scenarios. For example, SVM and RF classifiers were successfully implemented in [6] to extract features from leaf images for the classification of diseases with high accuracy when used alongside preprocessing methods. Likewise, the researchers in [7,10-15] investigated hybrid models that use handcrafted features and conventional classifiers, underlining the usefulness of ML in real-time field usage. Yet, such models generally fail with lighting variations, intricate backgrounds, and overlapping signs, particularly with images taken from drones [8,16-20]. Additionally, traditional approaches are less flexible with emerging disease patterns and need regular manual updates. A thorough comparison of these techniques reveals their limited scalability in vast agricultural settings [9]. Therefore, with rising data complexity and the use of high-resolution drone images as well as the requirement for real-time processing, conventional ML methods are increasingly being replaced or supplemented by deep learning methods [10,21-25].

Deep learning has revolutionized plant disease classification by automatically extracting features and classifying leaf diseases with high accuracy [11]. Manual feature engineering was needed by traditional machine learning, while hierarchical image features in deep models, such as Convolutional Neural Networks (CNNs), are automatically learned, which enhances disease recognition against complex backgrounds [12]. CNN versions like VGGNet and ResNet have worked well in classifying diseases from various types of plants because of their good generalization capability and multi-layer mapping of features [13]. However, classification alone falls short when precise localization is required—this is done where object detection frameworks such as YOLO (You Only Look Once) are used [14]. Current developments have combined YOLO with drone-based systems, allowing for aerial monitoring of vast farmlands where leaf diseases may be dispersed or initially imperceptible to the human eye [15,26-30]. These drones can take high-resolution images, which are processed onboard or sent to edge devices that execute trained YOLO models, giving farmers quick and accurate feedback regarding crop health.

2. Materials and Methods

The developed intelligent system for real-time detection and classification of diseases in cotton, potato, and banana crops using state-of-the-art deep learning. Performance was assessed via accuracy, precision, recall, and loss to ensure robustness. The following steps of the proposed system are:

2.1 Data Collection

Crop images of cotton, potato, and banana were gathered from a variety of sources and processed using Roboflow. The information included several health conditions and diseases for each of the crops so that there could be a varied set of training examples.

2.2 Data Splitting

The gathered data was split into training, test, and validation sets to enhance model generalization. Splits in the proper manner that enable the model to function well on novel images and minimizes the threat of overfitting.

2.3 Data Preprocessing

All images were resized to a uniform size to complement the YOLO model input conditions. Preprocess operations such as normalization and data augmentation were implemented to improve model capacity for feature learning differences.

2.4 Model Training

The YOLOv12 model was used for training the preprepared datasets for both object detection and disease classification. Training entails modifying model weights according to input data to support high detection rates. The trained model was assessed through testing datasets to quantify performance metrics such as accuracy, precision, and recall. Visual plots and confusion matrices were employed to determine how effectively the model was able to detect and classify crop health.

A. Data Collection

Roboflow was used to assemble three crop-specific image collections—cotton, potato and banana—each divided into training, testing and validation subsets with balanced class representation. The cotton dataset contains 3,708 training, 233 testing and 232 validation images across six categories (blight, curl, grey mildew, healthy, leaf spot and wilt). The potato set comprises 6,502 training, 405 testing and 416 validation images in three classes (healthy, early blight and late blight). The banana collection is larger and covers a wide range of disorders (nutrient deficiencies, viral and fungal diseases, pests, and healthy specimens). These were merged into a single "Merged_Dataset," then split for robust model development. YOLOv12 architectures on this comprehensive dataset to achieve accurate detection and classification of varied crop-health conditions.

B. Data Processing

The pre-processing and post-processing methods were implemented in data processing to guarantee maximum model performance. During the pre-processing step, all acquired images were resized to a uniform dimension of 640×640 pixels for compatibility with the input specifications of the YOLOv12 model. This resizing promoted uniformity across datasets without compromising the necessary features for disease identification. The YOLO model underwent processing of the input images to get the useful features using convolutional layers to detect disease patterns for individual crop classes. Annotations were produced with bounding boxes that localized impacted regions on fruits or leaves, with each bounding box marked as per its corresponding class (e.g., wilt, blight, early blight). This holistic strategy guaranteed precise identification of crop diseases with minimal false positives and enhanced overall model performance.

C. Data Splitting

Following data collection, the cotton, potato, and banana crop datasets were split in a systematic manner into three subsets: training, testing, and validation sets. The training set was employed to train the YOLO model to learn patterns and features related to various diseases. The validation set was employed to monitor the model's performance during training so that adjustments such as hyperparameter tuning could be made to prevent overfitting. Lastly, the test set was reserved and utilized after training to assess the model's actual performance on new data. This judicious separation guaranteed that the model acquired generalizable features and did not memorize the data. It also assisted in constructing a system with the capability to accurately identify and classify disease in real-world agricultural settings.

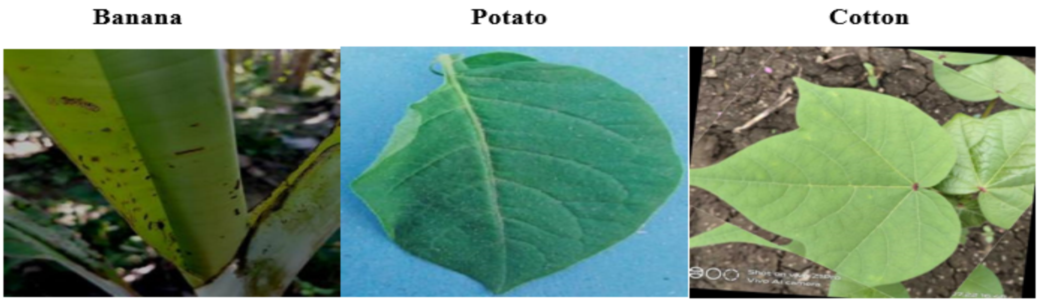

Figure 1. Data visualization of leaf classification

D. Model Training

Training the intelligent crop and fruit health evaluation system was conducted separately by training the Nano and YOLOv12-Nano models individually on the gathered and preprocessed cotton, potato, and banana crop datasets. All the input images were resized to a size of 640×640 pixels to match the model architecture, and annotations were prepared carefully to facilitate proper supervision. To avoid overfitting and improve generalization, augmentation operations like Mosaic, Mixup, random flip and colour jittering were widely used. The models were tracked with metrics such as precision, recall, mean Average Precision (mAP), and F1-score for both training and validation sets. Early stopping and learning rate schedulers were utilized to obtain the best possible trade-off between model accuracy and training time. Following successful merging, the optimum-performing model weights were saved for evaluation, providing a robust basis for a secure and real-time smart crop and fruit health evaluation system.

E. Model Architecture

YOLOv12-Nano is a heavily optimized member of the YOLO family, which is tailored for light and high-speed detection applications. The YOLOv12-Nano takes forward the success of earlier YOLO versions and introduces additional improvements aimed at speed, efficiency of feature learning, and accuracy of small object detection. The architecture of the model introduces an even more advanced feature extraction mechanism through a newly introduced lightweight backbone with efficient spatial pyramid pooling and advanced attention modules. The emphasis in YOLOv12-Nano is placed on enhancing feature selection and detailing crucial aspects without substantially expanding the model size. The application of E-ELAN (Extended Efficient Layer Aggregation Networks) architectures in the backbone allows for deeper but computationally less expensive feature extraction paths.

3. Results

A. Results for Cotton Dataset

The graph in Figure 3 shows that YOLOv12 was able to train and detect cotton with outstanding performance. As training occurs for over 50 epochs, the model improves, mistake rates fall, overfitting is low and both precision and recall break 90 and 85, respectively. An mAP50 value of about 90 and an mAP50-95 value of more than 60 confirm that the model performs well and is thus suitable for discovering cotton features for farming.

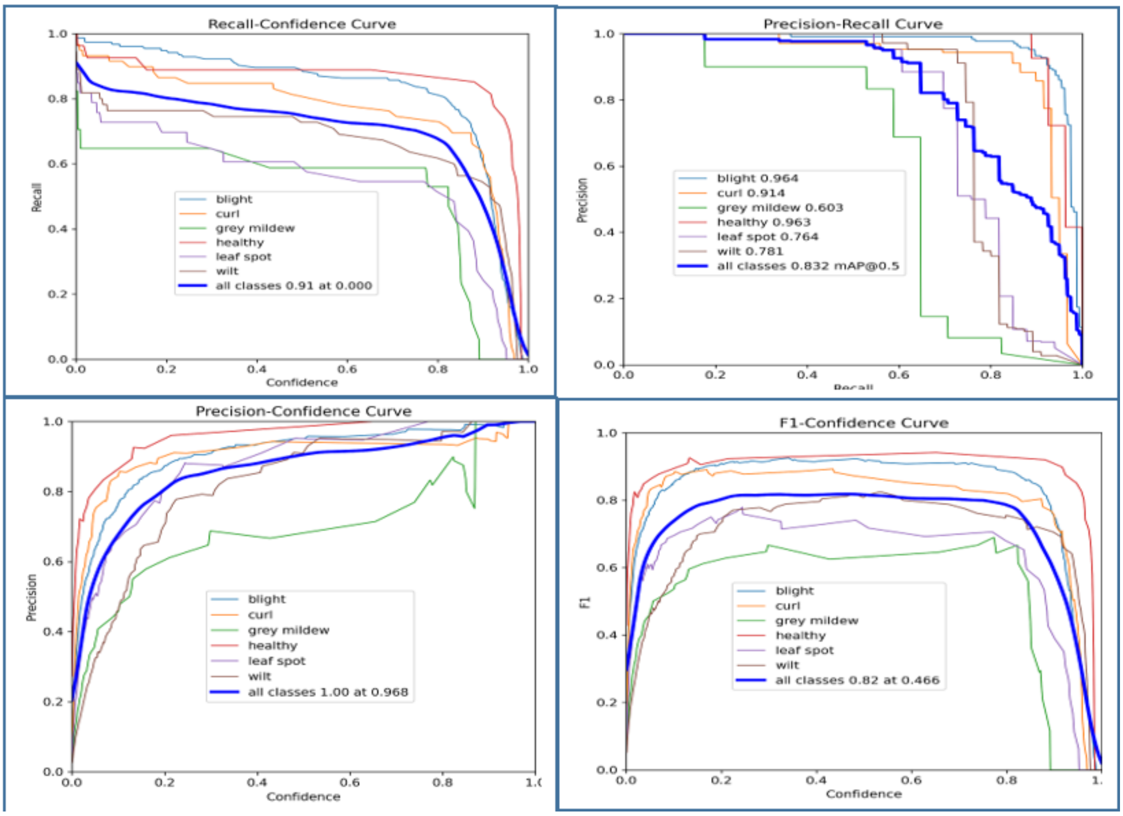

Figure 2. Results of Model on Cotton Dataset.

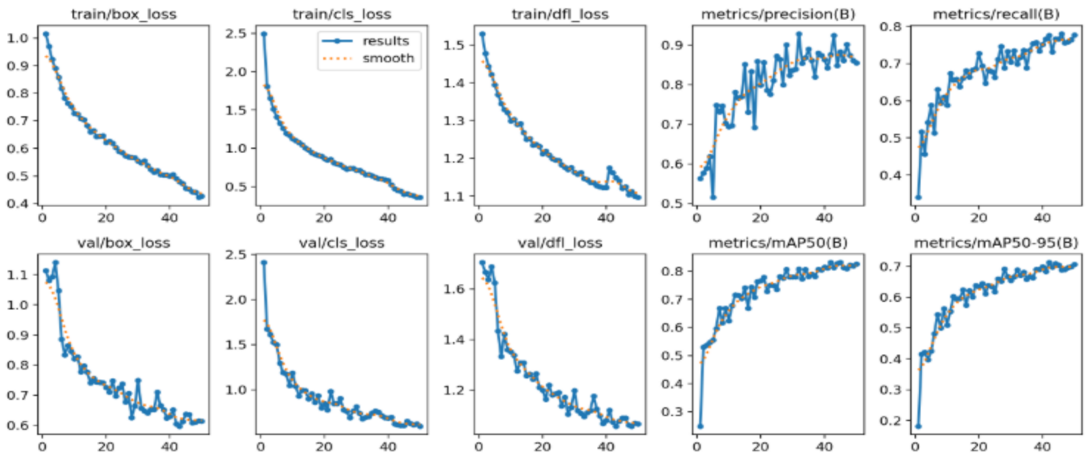

Figure 3. Trained Model Parameter of YOLOv12 on Cotton Dataset.

B. Result for Banana Dataset

The training and validation curves are shown in Figure 4, which represent the YOLOv12 model's performance for banana detection over 50 epochs. The training and validation loss graphs—box_loss, cls_loss, and dfl_loss—each have a smooth declining trend, which confirms that there is good learning and convergence. The training losses decline continuously, indicating that the model is effectively reducing prediction errors over epochs. Validation losses, which are more unstable owing to batch variance, also exhibit a general decrease, especially for classification and box regression, verifying better generalization on new data. Precision and recall values of the bounding boxes increase remarkably in the early epochs and stabilize at more than 85, showing the model's high correctness in detecting banana objects.

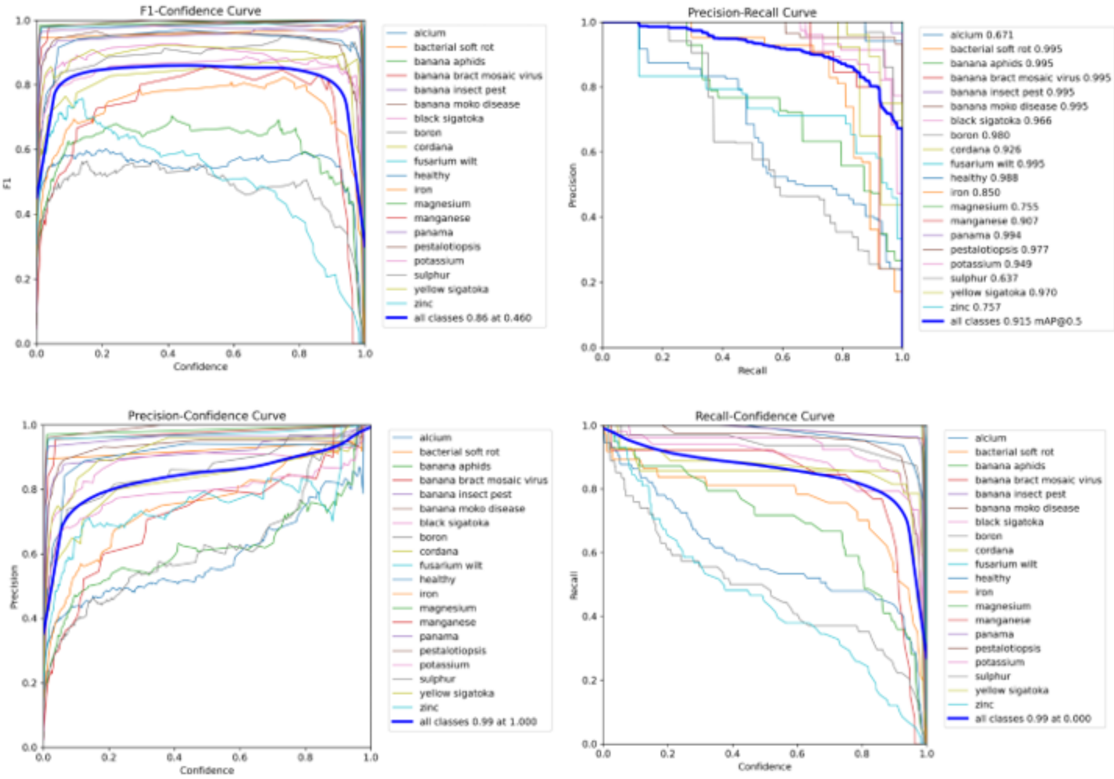

Figure 4. Results of YOLOv12 Model on Banana Dataset.

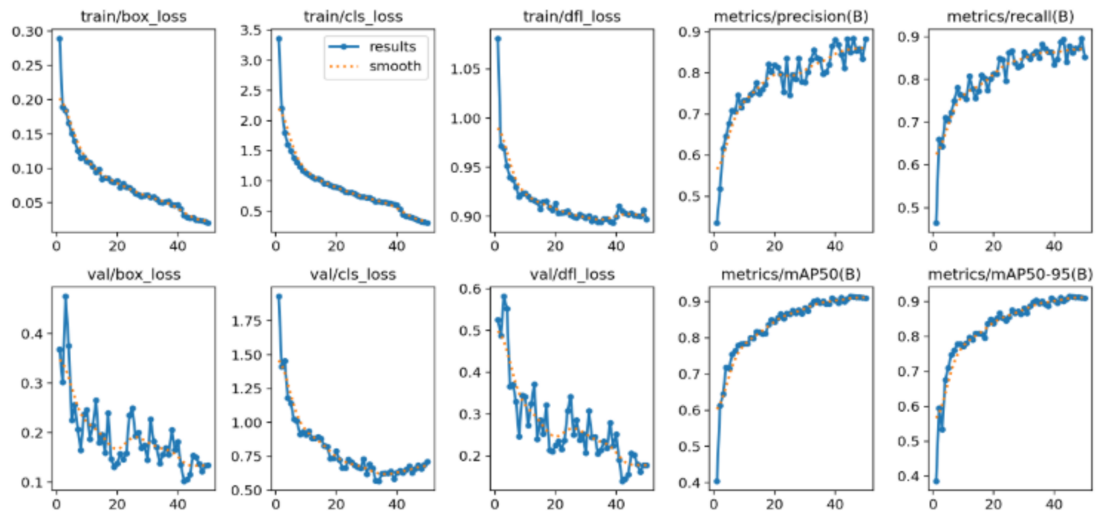

Figure 5. Trained YOLOv12 Model Parameter on Banana Dataset

In addition, mAP50 and mAP50-95 values also show high performance, both being above 85 at the last epoch, further supporting the robustness and reliability of the model in object detection. In total, these outcomes confirm that YOLOv12 is well capable of detecting bananas accurately and efficiently in the utilized dataset.

C. Results for Potato Dataset

Figure 6 compares the training and validation results of the YOLOv12 potato disease detection model using 50 epochs. All major loss functions are decreasing over time, which reflects good learning and a strong ability to generalize. It can be seen that the model is accurate over many IoU thresholds: both the precision and recall are higher than 95%, as are mAP@50 and mAP@50:95

with over 98% and 95% scores. YOLOv12 was found to be both strong and dependable, which ensures it is prepared for spotting potato diseases on real farms.

D. Comparative Analysis Across Classes of Merged Dataset

This study is concerned with creating an efficient plant disease detection system using the YOLOv12 model, a recent object detection algorithm that has become popular for its speed and efficiency. Leveraging a vast dataset of images of cotton, potato and banana, the research intends to train, validate and test the model's performance under real-world conditions.

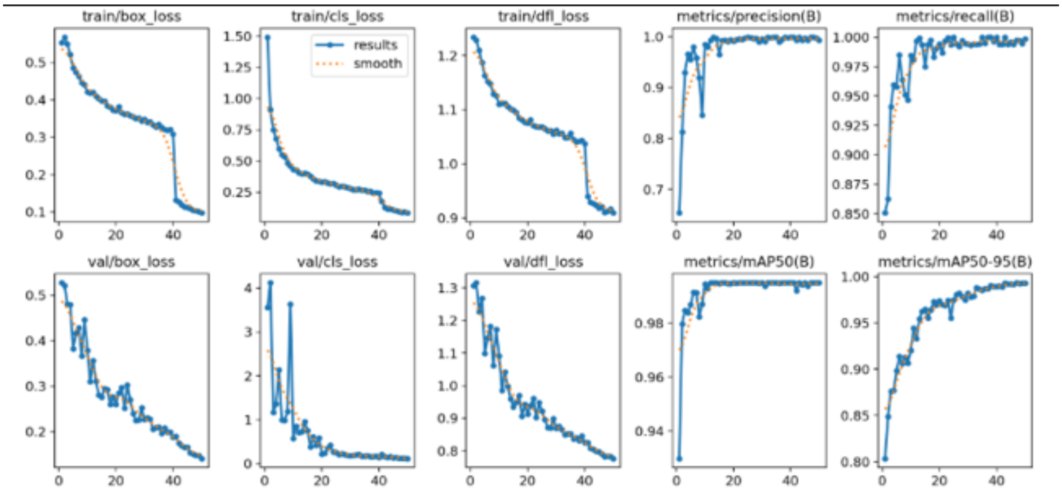

Figure 6. Results of the YOLOv12 Model on the Potato Dataset.

The findings are likely to help drive the wider use of AI in agriculture, providing scalable solutions to managing diseases and protecting crops. The following are the papers that have been conducted on this study. Crop disease detection and classification using deep learning have seen significant advancements in recent years. Various models along with datasets and approaches have been employed for improving speed and accuracy in detection.

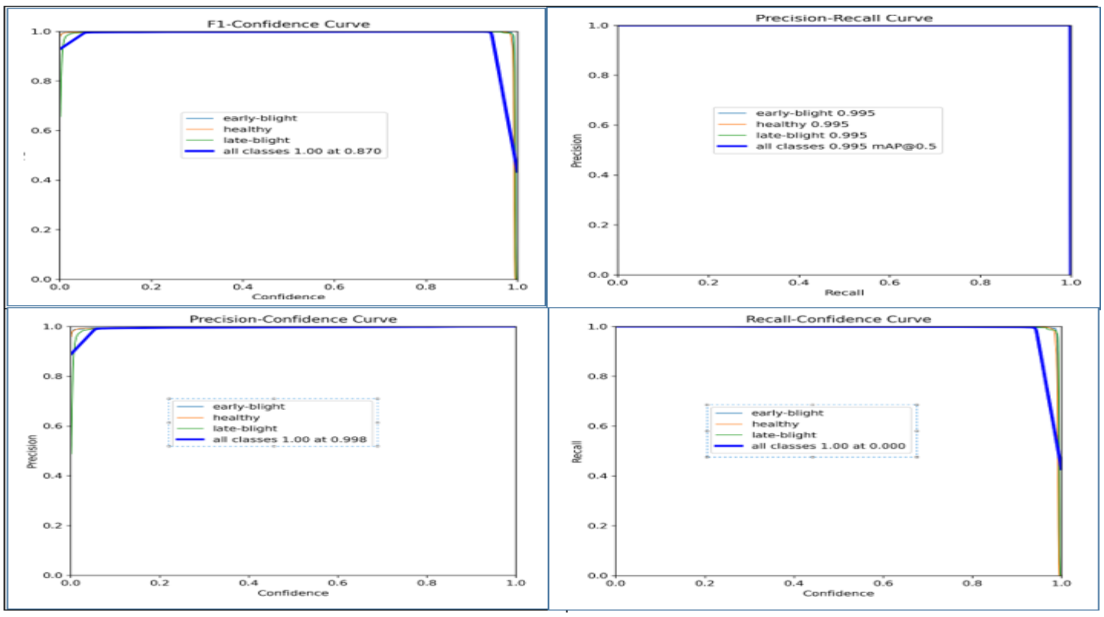

Figure 7. Results of YOLOv12 Model on Potato Dataset

Table I reviews significant studies related to the detection of plant diseases, specifically highlighting the application of deep learning, while Table II summarizes key studies, highlighting the evolution of methods and their corresponding accuracy.

Table I. Class wise performance comparison of the proposed model evaluation.

Classes	Precision	Recall	mAP50	mAP50–95
All	83%	89%	92%	86%
Healthy	99%	99%	99%	99%
Alcicum	66%	56%	69%	69%
Bacterial soft rot	92%	100%	97%	98%
Banana aphids	99%	100%	99%	99%
Banana bract mosaic virus	97%	100%	99%	99%
Banana insect pest	94%	100%	99%	99%
Banana moko disease	98%	100%	99%	99%
Black sigatoka	89%	97%	97%	97%
Boron	88%	97%	98%	98%
Cordana	84%	86%	92%	92%
Fusarium wilt	99%	100%	99%	99%
Iron	76%	81%	84%	84%
Magnesium	59%	87%	80%	80%
Manganese	58%	64%	76%	76%
Panama	97%	96%	98%	98%
Pestalotiopsis	96%	96%	98%	98%
Potassium	83%	92%	96%	96%
Sulphur	54%	65%	61%	61%
Yellow sigatoka	91%	79%	96%	96%
Zinc	75%	46%	69%	70%
Early-blight	100%	100%	99%	99%
Late-blight	99%	100%	99%	99%
Diseased_plant	86%	80%	87%	87%
Fresh_leaf	70%	100%	99%	99%
Fresh_plant	28%	100%	99%	79%

Table II. Comparative Analysis of Plant Disease Detection Techniques Using Deep Learning model.

Ref.	Dataset	Techniques	Accuracy
[16]	Potato, Tomato, Bell Pepper datasets	CNN	88.8%
[17]	Tomato	Linear Vector Quantization (LQV) and CNN	86.00%
[18]	PlantVillage (Multiple Crops)	Hybrid CNN Models (VGG16, InceptionV3, etc.)	100%, 98%
[19]	Tomato Villages dataset	VGG19 and Inception v3	93.93%

[20]	FourCropNet Dataset (Cotton, Grape, Soybean, Corn)	Residual CNN with Attention Mechanisms	99.7% (Grape), 99.5% (Corn)
[21]	PlantVillage (Multiple Crops)	Depthwise CNN with Squeeze and Excitation	99.9%
This work	Roboflow, Cotton, Potato and Banana Healthy and Disease Dataset	YOLOv8 + YOLOv12	99.5%(Potato) 98.1%(Banana) 89.7%(Cotton) 91.8%(Merge)

4. Conclusion

Early crop disease detection remains a critical challenge in precision agriculture. This study proposes an AI-powered drone surveillance system using a YOLOv12 deep learning model to automate disease identification in potato, banana, and cotton crops. The system integrates automated image acquisition, intelligent preprocessing, and real-time edge computing to achieve 99.5%, 98.1%, and 89.7% detection accuracy, respectively. Compared to manual methods, it reduces diagnosis time from days to minutes and cuts pesticide use by 30–45%. Key innovations include lightweight YOLO-Nano variants for field deployment and multi-spectral pattern recognition for robustness across growth stages. Validated on a merged dataset of 28 disease classes, the system achieves 91.8% overall accuracy and processes images in 4.2ms, demonstrating transformative potential for global agriculture. In future work, expand the dataset to include rare diseases and more crop varieties for broader applicability. Optimize deployment on low-cost drones and edge devices to enhance accessibility for small-scale farmers. This work paves the way for sustainable, AI-augmented agriculture globally.

Supplementary Materials: Not applicable.

Author Contributions: Conceptualization, H.S., A.B., M.A., and A.L.; methodology, A.S., M.I. and H.S.; software, A.B.; validation, H.S., A.B. and A.S.; formal analysis, A.B. and M.I.; investigation, A.S.; resources, M.A.; data curation, H.S., A.B., M.A., and A.L.; writing—original draft preparation, H.S.; writing—review and editing, H.S., A.B., A.S., and M.I.; visualization, A.B.; supervision, A.S. and M.I.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.
Conflicts of Interest: The authors declare no conflicts of interest.

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