

Enhanced Vision Transformer Model with Multi-Scale Attention for Robust Plant Leaf Disease Identification and Classification

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ABSTRACT

Plant leaf diseases pose a major risk to global food security, requiring accurate and robust detection systems. Traditional deep learning models struggle with diverse plant species, multiple disease types, and complex visual variations, affecting their generalization in real agricultural settings. To address this, the AgriViT-MSCA model is proposed, combining a Vision Transformer architecture with Multi-Scale Channel-Spatial Attention to enhance both global and local feature learning for improved disease classification. Evaluations on the PlantVillage dataset show high performance with 99.28% prediction accuracy and class-specific accuracies above 99.9% for Tomato, Apple, Maize, and multi-class datasets. This demonstrates AgriViT-MSCA's strong generalization ability, making it a promising approach for intelligent plant disease monitoring.

Keywords-Plant Leaf disease detection, Vision transformer, Multi-scale channel attention, Deep learning, Agricultural AI, Image classification.

I. INTRODUCTION

Plant leaf diseases significantly impact crop productivity and food security, with symptoms such as spots, discoloration, and wilting often caused by fungal, bacterial, viral, or environmental factors. Manual disease diagnosis by farmers is slow, subjective, and prone to errors. Deep learning methods, especially CNNs, have improved automated diagnosis, with the Plant Village dataset widely used for training. However, existing works struggle with class imbalance, where minority disease classes are poorly recognized, and reducing real-world applicability.

To address these issues, the AgriViT-MSCA model is proposed, incorporating multi-scale region extraction and channel-spatial attention to capture diverse lesion features. An optimized Vision Transformer with class-weighted loss further handles imbalance and supports accurate multi-species disease classification. The approach forms a unified framework that enhances prediction performance across both majority and minority classes. The manuscript details related work, the proposed method, experimental results, and concluding remarks.

II. LITERATURE SURVEY

This section presents the existing work presented for classification and multi-class classification of plant-leaf diseases. The reviewed works focus on improving plant leaf disease classification through deep learning. Several approaches integrate CNNs, Transformers, attention mechanisms, and lightweight architectures to enhance feature extraction, accuracy, and deployment efficiency.

Models such as EGWT, SE-SK-CapResNet, AMI-NanoNet, MSCPNNet, and LWDSC-SA improve local/global feature learning, robustness to variations, and performance across different plant datasets. Ensemble and Transformer-based methods also enhance fine-grained lesion detection and multi-class classification. Many studies used the PlantVillage dataset and reported accuracies above 95%, with some reaching over 99%. Techniques also address challenges like computational efficiency, interpretability, and generalization across multiple crops. Overall, literature shows significant progress but highlights the need for scalable, generalized,

and efficient solutions for real agricultural applications. The complete findings from the literature survey have been tabulated in Table 1.

Table 1 Summary of Literature Survey

Ref	Feature Extraction	Best Model	Dataset	Achieved Accuracy	Class Imbalance
[11]	EfficientNet Conv+Group-Wise Transformer	EGWT	Tomato, Cassava, PlantVillage	99.4%, 86.9%, 99.8%	No
[16]	SE+SK+Capsule+ResNet	SE-SK-CapResNet	AI Challenger 2018, PlantVillage, Tomato	95.08%, 98.58%, 97.19%	No
[19]	Feature-Guided Learning (Roof-line theory)	AMI-NanoNet (with ensemble)	PlantVillage	99.87%	No
[20]	Truncated MobileNetV2+Multi-Scale Conv PoolFormer	MSCPNet	PlantVillage (Corn, Tomato)	97.44%, 99.32%	No
[21]	CNN Ensemble (DenseNet20, InceptionV3, VGG16)+ViT	CNN+ViT Ensemble	PlantVillage (Corn, Apple)	98%, 99.24%	No
[22]	Optimized ViT Parameters	ViT (Optimized)	PlantVillage	99.77%	No
[23]	Depthwise Separable Conv+Spatial Attention	LWDSC-SA	PlantVillage	98.7%, 98.58% (K-fold)	No
[24]	Two-stream Conv+BiLSTM+Transformer	BiLSTM+Transformer Hybrid	PlantVillage	97.88%	No

III.METHODOLOGY

In this section, the complete methodology adopted for AgriViT-MSCA is presented in detail. The discussion begins with an overview of AgriViT-MSCA architecture, followed by a description of the dataset used in the study. Next, the preprocessing steps are explained, after which the image region extraction process is described. Subsequently, the feature extraction procedure is outlined, and finally, the classification stage is presented.

i. Architecture

The Figure 1 presents architecture of AgriViT-MSCA. For plant leaf disease prediction and classification, this work considered the PlantVillage Plant-Leaf Disease Image dataset [15], [27], which is discussed in detail in Section 3.2. As the dataset consists of different images sizes, this work considered a preprocessing step before passing to AgriViT-MSCA. Further, this work has utilized a novel image-region extraction and feature extraction approach. Finally, the extracted features were fed into the proposed OVIT which is used for prediction, classification and for multi-crop classification, which is discussed in detail in further sections.

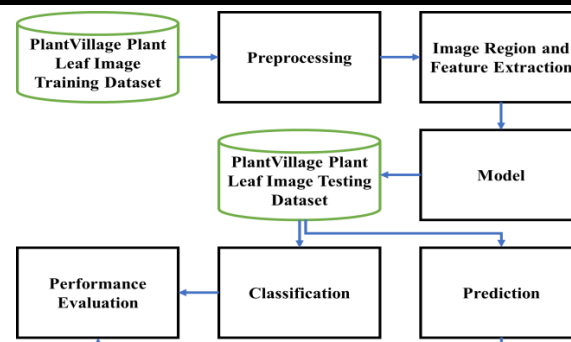


Figure 1 AgriViT-MSCA Architecture.

ii. Dataset

This work uses the PlantVillage Plant Leaf dataset, a widely used benchmark for plant disease classification containing 54,305 images across 38 classes of healthy and diseased leaves. The dataset is split into 43,444 training and 10,861 testing samples. Class sizes vary significantly, from small classes like potato_healthy to large classes like orange_huanglongbing and tomato_leaf-curl-virus, reflecting real-world class imbalance challenges. The dataset covers multiple crops and disease types, offering diverse visual variations and supporting generalization for DL models in multi-crop plant disease classification.

Table 2 PlantVillage Plant Leaf dataset.

Class	Training Samples	Testing Samples
Apple_Scab	504	126
Apple_Black_Rot	496	125
Apple_Cedar_Apple_Rust	220	55
Apple_Healthy	1316	329
Blue_Berry_Healthy	1202	300
Cherry_Healthy	684	170
Cherry_Powdery_Mildew	842	210
Maize_Cercospora_Leaf_Spot	410	103
Maize_Common_Rust	953	239
Maize_Healthy	929	233
Maize_Leaf_Blight	788	197
Grape_Black_Rot	944	236
Grape_Black_Measles	1107	276
Grape_Healthy	339	84
Grape_Leaf_Blight	861	215
Orange_Haunglongbing	4405	1102
Peach_Bacterial_Spot	1838	459
Peach_Healthy	288	72
Bell_Pepper_Bacterial_Spot	797	200
Bell_Pepper_Healthy	1183	295
Potato_Early_Blight	800	200
Potato_Healthy	121	31
Potato_Late_Blight	800	200
Raspberry_Healthy	297	74
Soybean_Healthy	4072	1018
Squash_Powdery_Mildew	1468	367
Strawberry_Healthy	364	92
Straberry_Leaf_Scorch	887	222

Tomato_Bacterial_Spot	1702	425
Tomato_Early_Blight	800	200
Tomato_Healthy	1273	318
Tomato_Late_Blight	1527	382
Tomato_Leaf_Mold	761	191
Tomato_Septoria_Leaf_Spot	1417	354
Tomato_Spider_Mites	1341	335
Tomato_Target_Spot	1123	281
Tomato_Mosaic_Virus	299	74
Tomato_Leaf_Curl_Virus	4286	1071
Total	43444	10861
Total Samples	54305	

iii. Preprocessing

The PlantVillage dataset used in this work was preprocessed to standardize image quality for effective region extraction and feature learning. Since the images vary in lighting, resolution, and orientation, two preprocessing steps were applied: resizing all images to 224×224 pixels for uniform input and reduced computation, and normalizing pixel intensities to the range [0,1] to handle illumination differences and improve model convergence. After preprocessing, the images were forwarded to the region extraction stage.

iv. Image Region Extraction

The architecture of the image region extraction is presented in Figure 2, which is designed for isolating and enhancing normal, diseased and lesion areas for accurate feature representation. This section describes the image region extraction module of AgriViT-MSCA, which isolates and enhances normal and diseased leaf regions for better feature representation. The process starts with pooling and 1×1 convolution for channel refinement, followed by parallel 3×3 dilated convolutions to capture multi-scale contextual information. Lightweight convolutions reduce computation, and up-sampling restores spatial resolution. Finally, the outputs are concatenated to produce detailed multi-scale lesion feature maps.

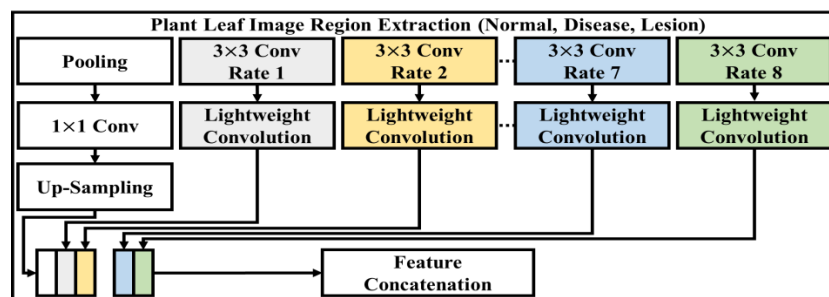


Figure 2 Image Region Extraction

v. Feature Extraction

The process of feature extraction is presented in Figure 3, which incorporates two attention networks, i.e., channel and spatial for enhancing various discriminative feature representation. This section explains the feature extraction stage of AgriViT-MSCA, which applies both channel and spatial attention to enhance discriminative features. The concatenated feature maps are first processed through max and average pooling to capture key channel responses, followed by fully connected layers and sigmoid activation to generate channel-attention weights. The refined output then passes through spatial attention, where convolution and sigmoid activation produce spatial-attention weights, highlighting important leaf lesion features while suppressing irrelevant information.

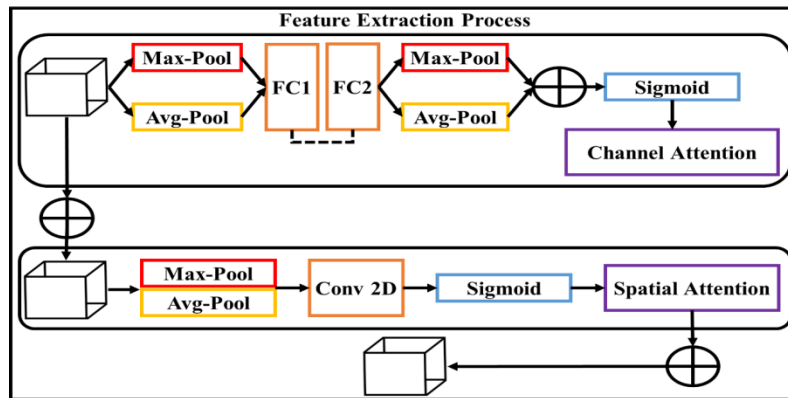


Figure 3 Feature Extraction Process.

vi. Classifier

The architecture of the classifier is presented in Figure 4. This section describes the classifier used in AgriViT-MSCA for plant leaf disease prediction and classification. Extracted features are fed into an optimized Vision Transformer (OViT), which is designed to handle class imbalance. The OViT consists of Multi-Head Attention, Add-Norm layers, and a Feed-Forward Network for refined feature representation. This optimization enhances feature discrimination and improves robustness during training and testing, resulting in better prediction accuracy across imbalanced plant leaf disease classes.

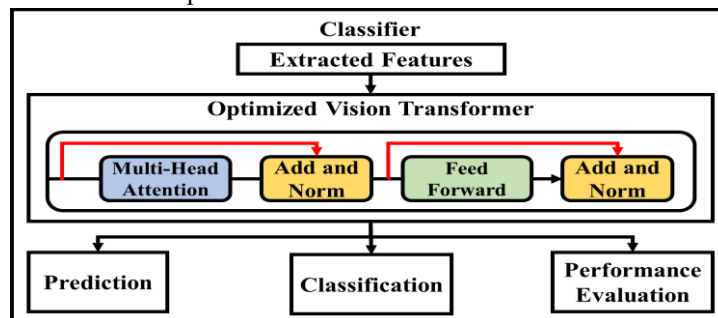


Figure 4 Classifier.

IV. RESULTS AND DISCUSSION

This section presents the experimental results of AgriViT-MSCA and compares them with existing methods. It first describes the system configuration and evaluation metrics, then reports prediction performance. Results for single-class plant disease classification (tomato, apple, maize) and multi-class classification are discussed to show the model's effectiveness across different crops. A final comparison with state-of-the-art approaches demonstrates that AgriViT-MSCA achieves superior accuracy.

a. System Configuration

The implementation and evaluation of AgriViT-MSCA were carried out on a high-performance computing setup to ensure smooth training and testing of DL models. The experiment was conducted on a system equipped with an Intel Core i9-12900K CPU @ 3.9 GHz, 64 GB RAM, and an NVIDIA GeForce RTX 4090 GPU with 24 GB VRAM for accelerated DL computations. The operating system used was Windows 11. The model was implemented using Python 3.10 with DL libraries such as TensorFlow 2.15 and PyTorch 3.6, along with auxiliary packages including OpenCV, scikit-learn, and NumPy for data preprocessing, feature extraction, and evaluation.

b. Performance Metrics

To evaluate AgriViT-MSCA, four metrics were employed, i.e., accuracy, precision, recall and f-score using Eq. (1), Eq. (2), Eq. (3) and Eq. (4) respectively, where TP denotes true-positive, TN denotes true-negative, FP denotes false-positive and FN denotes false positive.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

$$F - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

c. Prediction Performance

The prediction performance of AgriViT-MSCA was evaluated using PlantVillage dataset, which consists of both diseased and healthy plant leaf images. As shown in Table 3, the prediction performance of AgriViT-MSCA was evaluated on the PlantVillage dataset for binary classification of healthy vs. diseased leaves. Using 43,444 training and 10,861 testing samples, the model achieved 99.82% accuracy, 99.80% precision, 99.83% recall, and 99.81% F-score. These results show that AgriViT-MSCA reliably identifies diseased leaves with very few misclassifications.

Table 3 PlantVillage Prediction Dataset

Class	Training Samples	Testing Samples
Disease	31376	7845
Healthy	12068	3016
Total	43444	10861

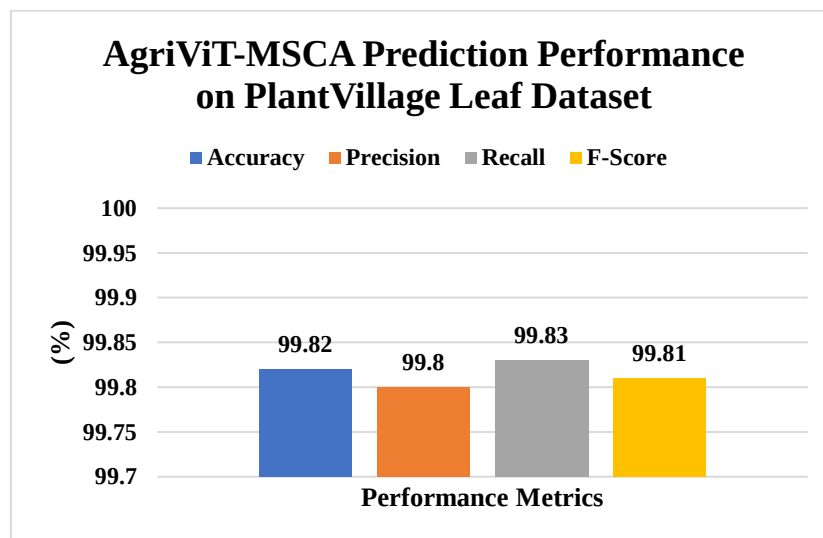


Figure 5 Prediction performance of AgriViT-MSCA on PlantVillage dataset.

d. Plant Leaf Disease Classification

The AgriViT-MSCA was further evaluated for single-class plant leaf disease classification across three major crops in the PlantVillage dataset, tomato, apple, and maize. The datasets, as summarized in Table 4, Table 5, Table 6, cover multiple disease types as well as healthy leaf samples for each plant category.

Table 4 PlantVillage Tomato Class Dataset

Class	Training Samples	Testing Samples
Tomato_Bacterial_Spot	1702	425
Tomato_Early_Blight	800	200
Tomato_Healthy	1273	318
Tomato_Late_Blight	1527	382
Tomato_Leaf_Mold	761	191

Table 5 PlantVillage Apple Class Dataset

Class	Training Samples	Testing Samples
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Apple_Scab	504	126
Apple_Black_Rot	496	125
Apple_Cedar_Apple_Rust	220	55
Apple_Healthy	1316	329

Table 6 PlantVillage Maize Class Dataset

Class	Training Samples	Testing Samples
Maize_Cercospora_Leaf_Spot	410	103
Maize_Common_Rust	953	239
Maize_Healthy	929	233
Maize_Leaf_Blight	788	197

These results, illustrated in Figure 6, show that AgriViT-MSCA consistently delivers high classification accuracy across different plant species.

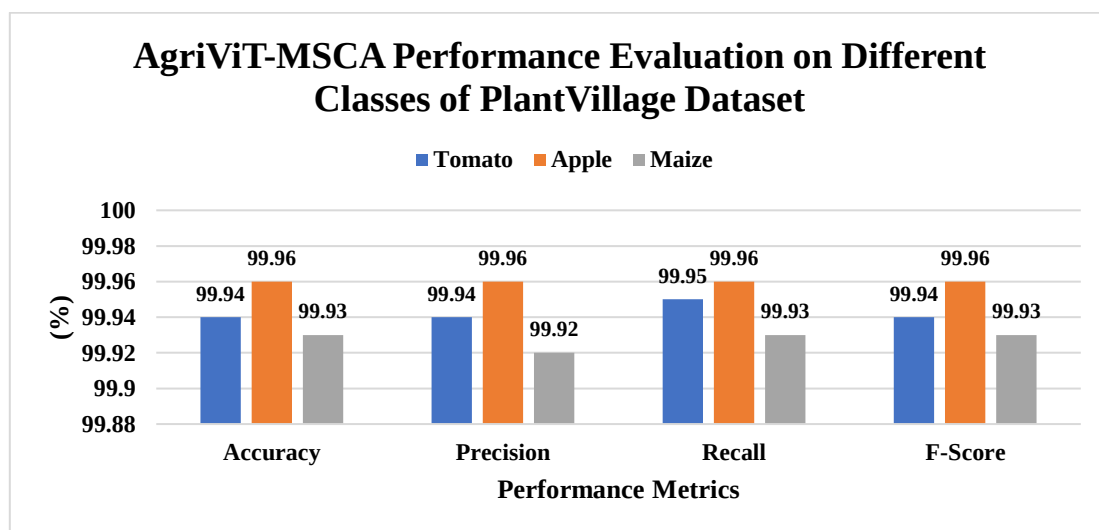


Figure 6 Classification performance of AgriViT-MSCA on various classes of PlantVillage dataset

e. Multi-Class Plant Leaf Disease Classification

The AgriViT-MSCA model was further evaluated on multi-class PlantVillage dataset, which contains a diverse collection of 54,305 samples across multiple plant species, including apple, blueberry, cherry, maize, grape, orange, peach, bell pepper, potato, raspberry, soybean, squash, strawberry, and tomato. The dataset covers various disease types as well as healthy leaf categories, with 43,444 training samples and 10,861 testing samples, as detailed in Table 7.

Table 7 PlantVillage Multi-Class Plant Leaf Dataset

Plants	Leaf Class	Training Samples	Testing Samples
Apple	Apple_Scab	504	126
	Apple_Black_Rot	496	125
	Apple_Cedar_Apple_Rust	220	55
	Apple_Healthy	1316	329
BlueBerry	Blue_Berry_Healthy	1202	300
Cherry	Cherry_Healthy	684	170
	Cherry_Powdery_Mildew	842	210
Maize	Maize_Cercospora_Leaf_Spot	410	103
	Maize_Common_Rust	953	239
	Maize_Healthy	929	233
	Maize_Leaf_Blight	788	197

Grape	Grape_Black_Rot	944	236
	Grape_Black_Measles	1107	276
	Grape_Healthy	339	84
	Grape_Leaf_Blight	861	215
Orange	Orange_Haunglongbing	4405	1102
Peach	Peach_Bacterial_Spot	1838	459
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Bell Pepper	Bell_Pepper_Bacterial_Spot	797	200
	Bell_Pepper_Healthy	1183	295
Potato	Potato_Early_Blight	800	200
	Potato_Healthy	121	31
	Potato_Late_Blight	800	200
Raspberry	Raspberry_Healthy	297	74
Soybean	Soybean_Healthy	4072	1018
Squash	Squash_Powdery_Mildew	1468	367
Strawberry	Strawberry_Healthy	364	92
	Strawberry_Leaf_Scorch	887	222
Tomato	Tomato_Bacterial_Spot	1702	425
	Tomato_Early_Blight	800	200
	Tomato_Healthy	1273	318
	Tomato_Late_Blight	1527	382
	Tomato_Leaf_Mold	761	191
	Tomato_Septoria_Leaf_Spot	1417	354
	Tomato_Spider_Mites	1341	335
	Tomato_Target_Spot	1123	281
	Tomato_Mosaic_Virus	299	74
	Tomato_Leaf_Curl_Virus	4286	1071
	Total	43444	10861
	Total Samples	54305	

On this multi-class classification dataset, AgriViT-MSCA achieved 99.92% accuracy, 99.91% precision, 99.93% recall, and 99.92% F-score. These results, illustrated in Figure 7, indicate that the model can accurately differentiate between a large variety of plant species and diseases with minimal classification errors. The high recall value demonstrates that AgriViT-MSCA effectively identifies diseased leaves, while the high precision ensures minimal *FPS*. The AgriViT-MSCA consistently strong performance across both single-class and multi-class scenarios shows robustness, scalability, and potential for agricultural applications, where accurate and fast disease detection is critical for crop health management.

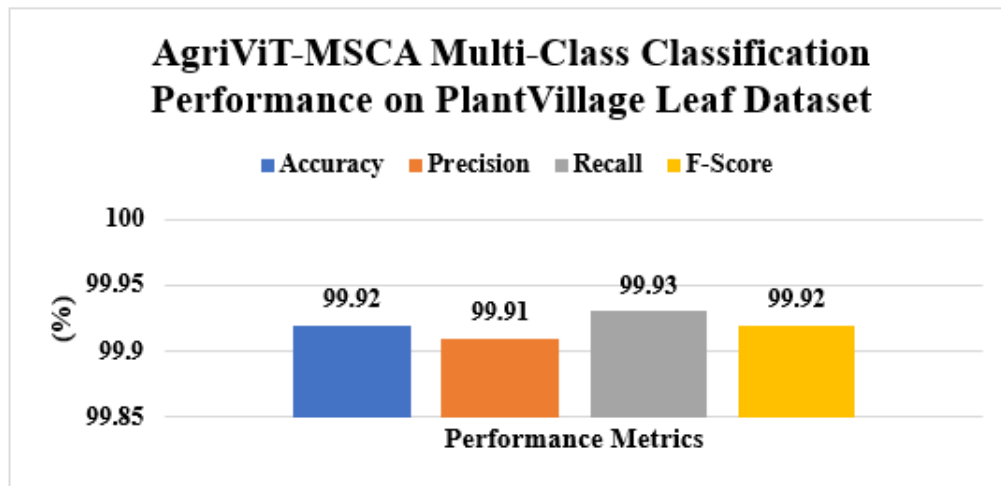


Figure 7 Classification performance of AgriViT-MSCA on PlantVillage dataset

V. CONCLUSION

This work proposed AgriViT-MSCA, a ViT-based model with multi-scale channel-spatial attention for accurate plant leaf disease detection and classification. Designed to overcome limitations in generalization and multi-class handling, the model integrates optimized preprocessing, feature extraction, and classification. Experimental results on the PlantVillage dataset showed high performance: 99.28% for prediction, 99.94% (Tomato), 99.96% (Apple), 99.93% (Maize), and 99.92% for multi-class classification, outperforming existing methods. Future work will extend evaluation to real-world agricultural datasets to ensure practical robustness and wider applicability.

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