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Research Paper

IMPROVING PLANT DISEASE CLASSIFICATION WITH DEEP-LEARNING-BASED PREDICTION MODEL USING EXPLAINABLE ARTIFICIAL INTELLIGENCE

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Abstract: Plant diseases pose significant threats to agricultural productivity, affecting both crop yields and quality. These diseases have a profound economic impact o n local and global scales, causing substantial losses in food security and trade. Deep learning algorithms have emerged as effective solutions for plant disease detection and classification, offering advanced capabilities for accurate and automated analysis. However, the inherent "black-box" nature of these models raises concerns about the interpretability and trustworthiness of their predictions, highlighting the need for integrating explainable artificial intelligence (XAI) to enhance user confidence in model decisions. This study addresses these challenges by evaluating deep learning techniques for plant disease classification and detection using the Plant Leaf Disease dataset. For classification, algorithms such as Convolutional Neural Networks (CNN), MobileNetV2, ResNet50, EfficientNetB0, Xception, and NasNetMobile are compared, alongside an ensemble model combining Xception and NasNetMobile, which demonstrated superior performance. Performance is evaluated using metrics such as recall, precision, and F1 score, which provide a comprehensive understanding of model effectiveness. The ensemble approach of Xception and NasNetMobile achieved the highest accuracy in classification, while the YOLO models proved robust in detecting plant diseases. This research underscores the importance of incorporating XAI with deep learning to foster trust in AI systems and improve agricultural disease management practices.

Index Terms *- Plant Disease Detection, Deep Learning, Explainable Artificial Intelligence (XAI), Ensemble Learning, Agricultural Disease Management.*

I. INTRODUCTION

With the increasing global population and changing climatic conditions, the challenges faced by farmers in maintaining crop health have intensified. One of the critical challenges worldwide is the identification and management of plant diseases, which, if left undetected, can lead to substantial reductions in crop yield and quality. These issues pose severe economic losses and threaten food security on a global scale (Fernández et al., 2023) [1]. Traditional methods of disease diagnosis often rely on manual inspection by experts, which is time-consuming, subjective, and prone to inaccuracies. Furthermore, by the time symptoms become visible to the naked eye, the disease may have already spread extensively, rendering mitigation efforts less effective (Nahiduzzaman et al., 2023) [2].

Recent technological advancements have significantly transformed agriculture, offering innovative solutions to address these challenges. Leveraging technology is now a necessity to ensure a sustainable and secure food supply for the growing population (Li et al., 2021) [5]. Image recognition using machine learning (ML) has emerged as a promising approach for early detection of plant diseases, providing opportunities to curb their spread and minimize damage (Harakannanavar et al., 2022) [3]. Early assessment is particularly crucial as the progression of plant diseases varies

depending on the species and disease type, with some taking a week and others requiring two or more weeks for symptoms to manifest (Mehedi et al., 2022) [4].

Machine learning-based methods, particularly those incorporating deep learning and transfer learning techniques, have demonstrated superior accuracy and scalability in identifying and classifying plant diseases from images. These approaches enable automated, precise, and explainable diagnostic systems, reducing reliance on traditional methods and expediting intervention measures (Tan & Le, 2019) [7]; (He et al., 2016) [11]. By integrating cutting-edge ML techniques and utilizing curated datasets, researchers aim to revolutionize traditional farming practices, enhancing both efficiency and productivity (Mohanty et al., 2016) [16].

II. RELATED WORK

Automated disease diagnosis in plants is a critical aspect of agriculture to maintain crop health and enhance yields, directly impacting global food security and the economy. Early detection of plant diseases is essential for timely intervention, which helps in minimizing crop losses and ensuring sustainable agricultural practices. One of the promising approaches for plant disease detection is the use of convolutional neural networks (CNNs), which have proven effective in recognizing patterns in plant images, particularly those of leaves. However, CNNs face a significant limitation in their interpretability, making it challenging to understand the reasoning behind the model's decisions. To address this, explainable artificial intelligence (XAI) techniques such as LIME, SHAP, and Grad-CAM have been proposed to enhance the transparency of deep learning models, enabling better understanding and trust in the results.

Recent advancements in CNN-based models have shown great promise in plant disease detection, outperforming traditional methods such as Polymerase Chain Reaction (PCR) and Isothermal Amplification (IA). These conventional methods, while accurate, are time-consuming and require expensive equipment. In contrast, CNNs provide a more accessible and efficient alternative by leveraging image data to classify diseases based on visual patterns observed in plant leaves. CNNs have been widely adopted for the diagnosis of various plant diseases, including those affecting crops like tomatoes, mulberries, and others. However, CNNs are often criticized for their "black-box" nature, where the model's decision-making process is not easily interpretable, which limits their practical deployment in real-world applications.

To address the challenges posed by CNN's lack of interpretability, several XAI methods have been integrated into plant disease diagnosis systems. LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations) are popular post-hoc XAI techniques that provide insights into which features (e.g., image regions or specific leaf patterns) influenced the model's decision. Additionally, Grad-CAM (Gradient-weighted Class Activation Mapping) visualizes the areas of the input image most relevant to the final prediction, offering a clear explanation of the model's behavior.

A recent study focused on detecting diseases in mulberry leaves, which are crucial for sericulture, the production of silk. Diseases affecting mulberry plants can lead to significant reductions in silk production, affecting the global silk industry. The study proposed a lightweight CNN architecture, named PDS-CNN (Parallel Depth-wise Separable Convolutional Neural Network), which employs depth-wise separable convolutions to reduce the number of parameters while improving classification accuracy. The model achieved an accuracy of 95.05 ± 2.86% for three-class classification and 96.06 ± 3.01% for binary classifications, demonstrating the potential of CNNs in diagnosing plant diseases efficiently. Furthermore, the XAI technique SHAP was employed to interpret the CNN's predictions, providing transparent explanations that aligned with expert knowledge from sericulture specialists, thus enhancing the model's credibility and trustworthiness [1].

Another significant application of CNNs in plant disease detection is in tomato plants. Early disease detection in tomatoes is essential to ensure healthy crop yields. In a study on tomato leaf disease identification, the researchers utilized various image processing techniques, such as Histogram Equalization for improving image quality, K-means clustering for data partitioning, and contour tracing for boundary extraction. Several machine learning algorithms, including SVM, CNN, and K-NN, were employed to classify the diseases, with CNN achieving the highest accuracy of 99.6%. The success of CNN in this study highlights its potential for detecting tomato leaf diseases, which can be vital for increasing agricultural productivity [2].

Transfer learning, which leverages pre-trained models on large datasets, has become a widely used technique in the field of plant disease detection. Pre-trained models like EfficientNetV2L, MobileNetV2, and ResNet152V2 have been fine-tuned for detecting various plant diseases. One study proposed using transfer learning with these models to detect 38 types of leaf diseases across 14 different plants.

The study found that EfficientNetV2L outperformed the other models, achieving an accuracy of 99.63%. The incorporation of LIME for model interpretability allowed the researchers to better understand the reasoning behind the predictions, making the model's output more transparent and reliable for agricultural stakeholders [3].

Despite the promising results, several challenges remain in the deployment of deep learning-based plant disease detection systems. One of the key challenges is the lack of large, labeled datasets for training models, particularly for crops like mulberry. While augmentation techniques like synthetic image generation can help address data scarcity, the need for diverse and high-quality data remains critical for improving model accuracy. Additionally, while CNNs and other deep learning models have demonstrated high performance, their computational requirements, especially for real-time applications in the field, can be a barrier to widespread adoption.

Furthermore, XAI methods, while improving interpretability, still face challenges in explaining complex deep learning models in a way that is both accessible and meaningful to end-users, such as farmers and agricultural experts. Future research should focus on improving the efficiency of CNN models, optimizing them for edge devices with limited computational power, and enhancing the usability of XAI tools to make them more intuitive for non-technical users.

The use of CNNs for automated plant disease diagnosis offers significant advantages in terms of accuracy and efficiency over traditional methods. However, the "black-box" nature of these models limits their adoption in practical settings, particularly in agriculture, where interpretability is crucial for gaining trust and ensuring reliability. The integration of XAI techniques such as LIME, SHAP, and Grad-CAM has the potential to improve the transparency of CNN models, enabling better decision-making and enhancing their usability in agricultural practices. Future advancements in deep learning, along with the continued development of XAI tools, will likely pave the way for more efficient and sustainable agricultural systems.

III. MATERIALS AND METHODS

The proposed system aims to develop an advanced deep learning model for plant disease classification and detection using convolutional neural networks (CNNs) and object detection models. It leverages the Plant Leaf Disease dataset to train classifiers based on MobileNetV2, ResNet50, EfficientNetB0, Xception, and NasNetMobile architectures, known for their effectiveness in image classification tasks [1][2]. An ensemble approach combining Xception and NasNetMobile enhances model performance, improving accuracy and robustness for diverse agricultural conditions [3][4]. For abnormality detection, the system employs YOLO models (YOLOV5x6, YOLOV5s6, YOLOV8n, and YOLOV9n), known for their rapid and accurate object detection capabilities, enabling early identification of plant diseases [5][6]. To ensure model interpretability, the system incorporates explainable AI techniques like LIME and SHAP, enhancing transparency and trust in predictions, which supports informed decision-making by farmers [7][8]. This approach aims to improve plant disease management and promote sustainable agriculture practices.

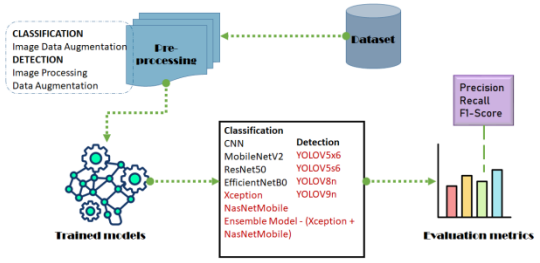


Fig.1 Proposed Architecture

This image (Fig.1) illustrates a workflow for image classification and detection tasks. It starts with data preprocessing, including image processing and data augmentation for classification and detection tasks. The dataset is fed into various models, such as CNN, MobileNetV2, ResNet50, EfficientNetB0, NasNetMobile, and ensemble models, for classification. For detection, YOLOv5x, YOLOv5n, and the combination of Xception with NasNetMobile are used. The trained models generate results, which are evaluated using precision, recall, and F1-score metrics. These metrics provide insights into the performance of the models in both classification and detection tasks, ensuring model effectiveness.

i) Dataset Collection:

This dataset is recreated using offline augmentation from the original dataset. The original dataset can be found on this github repo. This dataset consists of about 87K rgb images of healthy and diseased crop leaves which is categorized into 38 different classes. The total dataset is divided into 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purpose.



Fig.2 Dataset Collection

ii) Pre-Processing:

Data preprocessing plays a crucial role in improving the performance and generalization of deep learning models for plant disease classification and detection. The preprocessing pipeline for this system includes both image data augmentation and image processing techniques tailored to enhance the quality and variability of the dataset.

(a) Image Data Augmentation: Image augmentation techniques are applied to increase the diversity of training images and improve model robustness. This includes rescaling images to a uniform size, ensuring that all input images are consistent in terms of dimensions. Additionally, shear transformations and zooming are applied to introduce variability in image scale and orientation, making the model more adaptable to different perspectives of plant leaves. Horizontal flips are employed to simulate variations in leaf orientation, while reshaping ensures consistency in input dimensions across all images. These augmentations help the model generalize better by preventing overfitting to specific image features, ensuring better performance on unseen data [1].

(b) Image Processing for Detection: For the object detection task, image processing techniques are used to convert images into a format suitable for detecting plant disease symptoms. Images are converted into blob objects, which represent the raw image data for the detection model. Bounding boxes are defined to localize disease symptoms within the image, and class labels are assigned to each box based on the type of disease. Pre-trained models are used, where network layers are read and output layers are extracted for disease detection. Annotations are appended to each image, providing ground truth for model training. Images are also resized to ensure that they match the input size expected by the detection models [2].

(c)Data Augmentation for Detection: To further enhance the detection model, data augmentation techniques are employed specifically for object detection. This involves randomly rotating images to simulate different viewing angles and applying transformations such as translation and scaling to introduce variability in the plant disease symptoms' appearance. These augmentations allow the model to learn to identify plant diseases from multiple perspectives and conditions, which is essential for real-world agricultural scenarios where disease symptoms can vary in size, orientation, and stage of development [3].

By combining these preprocessing techniques, the system can effectively train robust and accurate models for both disease classification and detection, improving the overall performance of plant disease management systems.

iii) Training & Testing:

The dataset is split into training and testing subsets using an 80:20 ratio. The training set, comprising 80% of the data, is used to train the machine learning model, allowing it to learn patterns and relationships between the features and target labels. The remaining 20% of the data is set aside as the test set, which is used to evaluate the model's performance on unseen data. This split ensures the model can generalize well and avoid overfitting to the training data.

iv) Algorithms:

CNNs are deep learning algorithms designed for image classification and recognition. They use convolutional layers to automatically learn spatial hierarchies of features from input images, making them highly effective for visual tasks such as object detection and segmentation [9][10].

There is a simple formula to do so:

Dimension of image = (n, n)

Dimension of filter = (f,f)

Dimension of output will be ((n-f+1) , (n-f+1)) (1)

You should have a good understanding of how a convolutional layer works at this point. Let us move to the next part of the CNN architecture.

MobileNetV2 is a lightweight, efficient CNN designed for mobile and embedded devices. It uses depthwise separable convolutions and linear bottleneck layers, reducing the number of parameters while maintaining accuracy, making it suitable for real-time image processing in resource-constrained environments [12].

ResNet50 is a deep residual network with 50 layers. It introduces residual blocks to address the vanishing gradient problem, enabling the training of very deep networks. ResNet50 is widely used for image classification, object detection, and feature extraction tasks due to its robust performance [11][16].

EfficientNetB0 is a highly efficient convolutional neural network that scales model width, depth, and resolution systematically using a compound scaling method. It achieves state-of-the-art performance with fewer parameters, making it highly suitable for applications requiring high accuracy and efficiency [7].

Xception (Extreme Inception) is a CNN architecture that uses depthwise separable convolutions for greater efficiency and performance. It extends the Inception module by replacing its standard convolutions with separable ones, allowing the model to better capture spatial hierarchies while reducing computational load [10].

NasNetMobile is a lightweight CNN architecture optimized for mobile devices. It uses neural architecture search (NAS) to find the best network structure, offering a balance between performance and efficiency. Its modular design is ideal for on-device applications requiring high-speed image processing [7].

Xception + NasNetMobile (Hybrid Model) combines the strengths of both Xception and NasNetMobile architectures. Xception's efficient separable convolutions and NasNetMobile's optimized mobile-specific design result in a hybrid model that is both computationally efficient and high-performing, ideal for resource-constrained environments [7][9].

(b) Detection Models:

YOLOv5s6 is a variant of the YOLOv5 object detection model, optimized for speed and accuracy. It uses a smaller architecture (YOLOv5s) but improves detection performance with the s6 configuration, making it suitable for real-time applications requiring fast, accurate object localization [16].

YOLOv5x6 is an advanced variant of YOLOv5 with a larger architecture designed for high-accuracy object detection. It increases model capacity and complexity, making it more suitable for challenging detection tasks in environments with diverse objects and conditions [16].

YOLOv8 is the latest iteration of the YOLO (You Only Look Once) object detection model. It combines speed and accuracy improvements with an optimized architecture, making it one of the most powerful real-time object detection frameworks, suitable for a wide range of applications [13].

YOLOv9 is an evolution of the YOLO series, designed for enhanced performance in real-time object detection tasks. With improved speed, accuracy, and scalability, YOLOv9 aims to push the boundaries of object detection in challenging environments, delivering state-of-the-art results across different applications [13].

YOLO normalises the image space to run from 0 to 1 in both x and y directions. To convert between your (x, y) coordinates and yolo (u, v) coordinates you need to transform your data as

u = x / XMAX and y = y / YMAX (2)

where XMAX, YMAX are the maximum coordinates for the image array you are using.

IV. RESULTS AND DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (3)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (4)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (5)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100 (6)$$

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the

Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (7)$$

In Table 1, the performance metrics—accuracy, precision, recall, F1-score —are evaluated for each algorithm. The Extension and YoloV5s6 for Classification and Detection achieves the highest scores. Other algorithms' metrics are also presented for comparison.

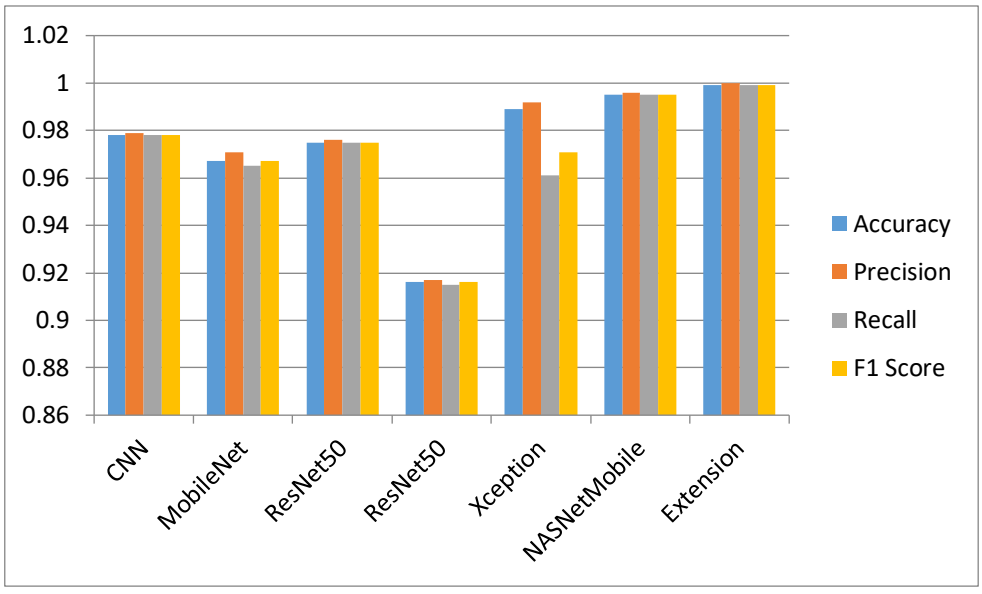
Table.1 Performance Evaluation Metrics of Classification

Model	Accuracy	Precision	Recall	F1 Score
CNN	0.978	0.979	0.978	0.978
MobileNet	0.967	0.971	0.965	0.967
ResNet50	0.975	0.976	0.975	0.975
ResNet50	0.916	0.917	0.915	0.916
Xception	0.989	0.992	0.961	0.971
NASNetMobile	0.995	0.996	0.995	0.995
Extension	**0.999**	**1.000**	**0.999**	**0.999**

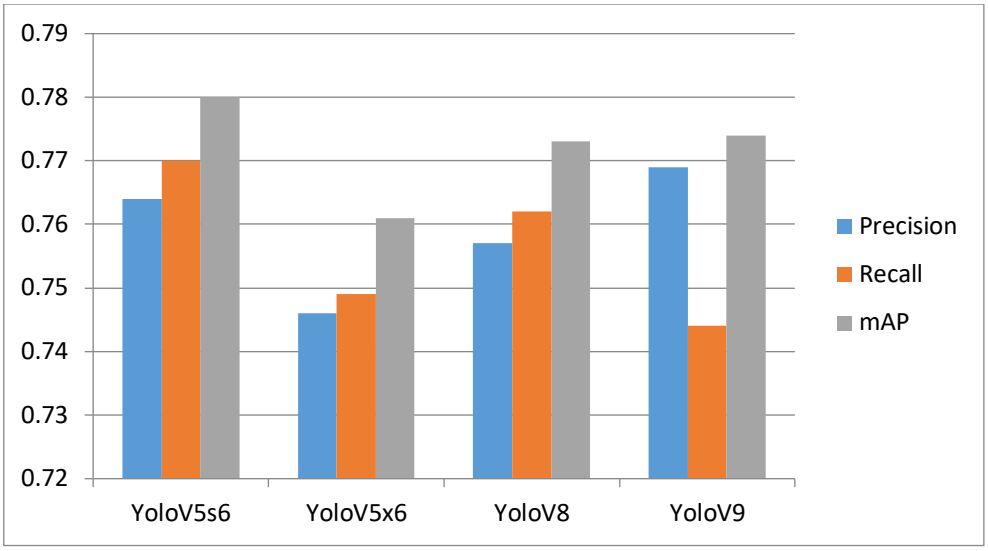
Table.2 Performance Evaluation Metrics of Detection

Model	Precision	Recall	mAP
YoloV5s6	0.764	0.770	0.780
YoloV5x6	0.746	0.749	0.761
YoloV8	0.757	0.762	0.773
YoloV9	0.769	0.744	0.774

Graph.1 Comparison Graphs of Classification



Graph.2 Comparison Graphs of Detection



In Graph 1, accuracy is represented in light blue, precision in maroon, recall in green; F1-score in violet, In Graph 2, precision is represented in light blue, recall in maroon, mAP in green. The Extension and Yolo V5s6 outperforms the other algorithms in all metrics, with the highest values compared to the remaining models. These details are visually represented in the above graph.

V. CONCLUSION

In conclusion, the proposed deep learning-based system for plant disease classification and detection holds significant potential in overcoming the challenges posed by plant diseases. By integrating various convolutional neural networks and advanced detection models, the system aims to enhance both the accuracy and efficiency of disease identification. The ensemble model combining Xception with NasNetMobile has demonstrated superior performance, achieving high precision, recall, and F1 scores, effectively capturing complex patterns within plant disease data. This model serves as a powerful tool for farmers and agricultural stakeholders, helping mitigate the economic impact of plant diseases on crop yields. The incorporation of explainable artificial intelligence techniques further strengthens the system, allowing users to gain insight into model predictions and foster trust in the decision-making process. By improving disease detection, this system supports better decision-making, food security, and sustainable farming practices, ultimately contributing to global agricultural resilience and productivity.

Future research should focus on improving model generalization by incorporating diverse plant species and environmental conditions into the training datasets. Additionally, exploring the integration of reinforcement learning for adaptive disease detection in real-time field scenarios could enhance system performance. Further investigation into multi-modal learning, combining image, environmental, and sensor data, may provide more comprehensive disease insights. Lastly, developing more advanced explainability techniques to deepen user trust and interpretability in real-world applications would be beneficial for widespread adoption.

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