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ENHANCING PLANT DISEASE DETECTION WITH DEEP LEARNING AND EXPLAINABLE

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Abstract: The significance of plant diseases to agricultural production is that they destroy the quality and quantity of products. These diseases impact significantly on the economy, both in the immediate and in the international front as they impair food security and trade significantly. DL algorithms have been an ideal solution to the detection and classification of plant diseases. They provide better analysis capabilities of precise and automatic analysis. However, the inherent black-box nature of such models creates concerns about the interpretability and trustworthiness of their results, highlighting the need to include XAI to enhance the confidence of users in model predictions. This work tackles these issues by testing DL methods for finding and classifying plant diseases using the Plant Leaf Disease dataset. To classify, we consider the CNN, MobileNetV2, ResNet50, EfficientNetB0, Xception, and NasNetMobile methods. Our ensemble model, a combination of Xception and NasNetMobile, which performed better, is also tested. To evaluate the performance and provide a complete picture of the model functionality, metrics such as recall, accuracy, and F1 score are utilized. The combination of Xception and NasNetMobile worked best for categorization, while the YOLO models were best at finding plant illnesses. This paper underlines the importance of combining XAI with DL to improve the level of confidence in AI systems and streamline approaches to controlling diseases affecting agriculture.

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

I. INTRODUCTION

With the increase in the population of the world and change of weather, farmers have found it very difficult to maintain the health of their crops. One of the most crucial issues that the world has to deal with now is the identification and control of plant diseases. When these diseases are not identified, they may result in significant declines in crop quality and productivity. These problems might cause huge economic losses and put food security at risk throughout the world (Fernández et al., 2023) [1]. The conventional way of diagnosing illnesses usually involves people making a visual examination by hand, something that is time-consuming, subjective and may be erroneous. Moreover, by the moment the disease manifests itself to the naked eye, it might have already spread significantly, and the efforts to prevent it will not be so effective (Nahiduzzaman et al., 2023) [2].

Recent technological discoveries have radically changed the agricultural sector and have offered new ways of addressing these challenges. To make sure that the rising population has enough safe and healthy food, we now need to use technology (Li et al., 2021) [5]. Image identification ML has emerged as a possibility to discover plant diseases early, which could be helpful in preventing their spread and causing less damage (Harakannanavar et al., 2022) [3]. The early diagnosis is highly crucial because the various plant diseases have diverse rates of advancement. Others develop symptoms within a week, whereas others take two or more weeks (Mehedi et al., 2022) [4].

DL and transfer learning algorithms have been found to be more precise and scalable in detecting and classifying plant diseases in images using ML algorithms. These methods make it possible to have automated, accurate, and explainable diagnostic systems that don't rely as much on traditional methods and speed up intervention measures (Tan & Le, 2019) [7]; (He et al., 2016) [11]. The scientists aim to transform the farmer mentality through curated datasets and state-of-the-art ML to make farming more efficient and productive (Mohanty et al., 2016) [16].

II. RELATED WORK

Plant Automated disease detection is a significant aspect of agriculture that can be used to maintain crops in good health and boost yields. This has a direct effect on the economics and food security throughout the world. Plant diseases must be detected early and therefore response can be taken promptly and this will save on the losses of crops and allow agriculture to be more sustainable. CNNs are a promising approach in finding plant diseases. The CNNs have been proven to be effective in detecting patterns within plant photos (particularly leaf photos). There is however a very serious issue to CNNs that they are easy to understand and it is difficult to understand why the model made some of the judgments. To solve this problem, XAI methods like LIME, SHAP, and Grad-CAM have been suggested to make DL models more clear, which will help people comprehend and accept the findings more.

New advances in CNN-based systems have demonstrated that they can detect plant diseases even more than previous methods such as PCR and IA. These are the conventional processes that are right but they are time consuming and require costly equipment. Instead, CNNs are more accessible and effective as they operate on picture information to classify illnesses according to trends observed in plant leaves. CNNs are widely employed to locate various plant diseases that affect crops like tomatoes, mulberries amongst other crops. CNNs are occasionally criticized as being black boxes, i.e. it is difficult to see how the model makes decisions. This renders them less practical in the real world.

Plant disease detection systems have incorporated a few XAI methods to address the issues that arise due to the incomprehensibility of CNNs. Two typical post-hoc XAI methods, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations), demonstrate which factors, like picture areas or particular patterns on the leaf, influenced the choice of the model. Grad-CAM (Gradient-weighted Class Activation Mapping) also displays what components of input image are most significant in the end prediction, making it easier to comprehend what the model is doing.

A study recently examined the way of identifying infections in mulberry leaves that can serve a very crucial role in the process of sericulture, or silk production. Ailments that damage mulberry trees may lead to a massive reduction in the production of silk, something that is detrimental to the global silk industry. The research suggested a lightweight CNN architecture called PDS-CNN (Parallel Depth-wise Separable Convolutional Neural Network) that uses depth-wise separable convolutions to cut down on the amount of parameters and improve classification accuracy. The model achieved the accuracy of 95.05 + 2.86 percent on three-class classification and 96.06 + 3.01 percent on binary classifications, demonstrating the effectiveness of CNNs in

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diagnosing plant diseases. The predictions made by the CNN were also explained using the XAI approach SHAP, which was clear and consistent with what sericulture experts were aware of and made the model more credible and trustworthy [1].

CNNs can also be used to detect diseases in tomato plants. Diseases in tomatoes should be detected early so as to ensure that the crops are healthy. The researchers employed various image processing techniques, including Histogram Equalization to make the images clearer, K-means clustering to break the data and contour tracing to detect the edges in order to establish what diseases were attacking tomato leaves. The illnesses were sorted using various ML methods, including SVM, CNN and K-NN. With the highest accuracy was CNN at 99.6. The effectiveness of CNN in this endeavor demonstrates that it may be applicable in the detection of diseases in tomato leaves, which is vital in enhancing food production [2].

The transfer learning is a prevalent approach to the detection of plant diseases based on pre-trained models trained on large datasets. Examples of pre-trained models that have been enhanced to detect various diseases in plants include EfficientNetV2L, MobileNetV2, and ResNet152V2. One of them recommended the transfer learning using these models to detect 38 types of leaf diseases in 14 different plant species. The study showed that EfficientNetV2L was better than the others with the accuracy rate of 99.63. With the aid of LIME to simplify the predictions of the model, the researchers could learn more about why the model made the predictions. This increased the clarity of the output of the model and its credibility to the agricultural workers [3].

Although the results are promising, there are several issues that should be addressed before DL-based systems can be utilized in the process of detection of plant diseases. The first issue, particularly in the case of a crop such as mulberries, is that there are no large datasets with annotations that can be used to train the algorithms. Even though other augmentation methods and generation of artificial images can assist in the lack of data, the models still require a considerable amount of data of different types and quality to become more precise. Moreover, although CNNs and other deep learning models are effective, they might be challenging to implement to various field tasks, particularly on a real-time basis due to their high processing power requirements.

Moreover, even though XAI approaches are better at interpretability, they do not do a great job of explaining complex DL models, in a manner that is meaningful and understandable to end users, like farmers and agricultural professionals. In a future study, one should focus on enhancing the performance of CNN models, process them to work more effectively on edge devices with limited processing capabilities and simplify the XAI tools to be more accessible and easy to use by non-technical users.

Compared to conventional approaches, CNNs are much more precise and effective in terms of automatic disease diagnosis in plants. However, due to the opaque nature of these models at times, it is difficult to implement them. Practical application, in particular, in the agricultural industry, the ability to learn them is extremely important in the establishment of confidence and the assurance of effectiveness. By incorporating XAI techniques such as LIME, SHAP, and Grad-cam, CNN models could be more transparent, enabling individuals to make superior choices and could be more applicable in farming. DL will undoubtedly get better in the future, and so will XAI technologies. This is likely to result into more efficient and sustainable agricultural systems.

III. MATERIALS AND METHODS

The proposed method is aimed at developing an advanced DL model to classify and detect plant diseases with the help of CNNs and object detectors. It uses the Plant Leaf Disease dataset to train classifiers based on MobileNetV2, ResNet50, EfficientNetB0, Xception, and NasNetMobile architectures, which are all good at classifying images [1][2]. Combining Xception and NasNetMobile helps the model perform better and it is more precise and dependable in various agricultural environments [3][4]. The system is based on YOLO models (YOLOV5x6, YOLOV5s6, YOLOV8n, and YOLOV9n) to locate abnormalities. These models are noted for being able to quickly and accurately find objects, which helps find plant illnesses early [5][6]. The system employs explainable AI models such as LIME and SHAP to ensure that the model is simple to comprehend. This renders predictions more transparent and reliable and assists farmers to make superior choices [7][8]. The aim of this approach is to better control plant diseases and promote environmentally friendly farming practices.

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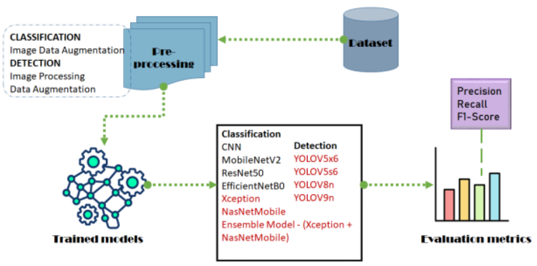

Fig.1 Proposed Architecture

This picture (Fig.1) shows how to do image classification and detection jobs. It starts with preprocessing of the information and this may involve processing of images and the addition of additional information to ease the classification and location of things. For classification, the dataset is put into different models, such CNN, MobileNetV2, ResNet50, EfficientNetB0, NasNetMobile, and ensemble models. Things are found using YOLOv5x, YOLOv5n, and Xception + NasNetMobile. The trained models give results, which are evaluated by measures such as accuracy, recall, and F1-score. These measures indicate the effectiveness of the models in classification and detection tasks, and this ensures that they are effective.

i) Dataset Collection:

This dataset was re-created, by offline addition of additional data to the initial dataset. The original dataset is available in this GH project. This data contains approximately 87,000 RGB images of both healthy and diseased crop leaves and they are all classified into 38 different categories. The whole dataset is split into a training set and a validation set in an 80/20 ratio, keeping the directory structure. Later, a new folder with 33 test photos is made for the purpose of making predictions.

Fig.2 Dataset Collection

ii) Pre-Processing:

Preparation of data is highly significant in ensuring that DL models on plant disease classification and detection are more effective and generalize. This system's preparation pipeline comprises both picture data augmentation and image processing methods that are meant to improve the dataset's quality and variety.

(a) Image Data Augmentation: To make training photos more varied and make the model more robust, image augmentation techniques are used. This means making sure that all input photographs are the same size by rescaling them to a standard size. The scaling and orientation of the picture is changed by shear transformations and zooming as well, making the model more adaptable to different perspectives of plant leaves. Horizontal flips are employed to render the leaves different. Reshaping is employed in order to ensure that the input-dimensions of all the photos are identical. These additions also allow the model to generalize more by preventing it to overfit some picture properties. This helps it to be more effective on previously unseen data [1].

(b) Image Processing for Detection: Image processing techniques are employed to change photos into a format that can be utilized to find signs of plant disease for the object detection job. The detection model is a raw picture data that is represented as blob objects, created out of pictures. Bounding boxes are created around the symptoms of an illness in a picture to locate them. A name of the box is then assigned depending on the type of sickness. For illness detection, pre-trained models are utilized to read network layers and get output layers. Annotations are added to each image and used as the ground truth to train the model. We also resize images to ensure that they are within the size of the input that the detection models take [2].

(c)Data Augmentation for Detection: In order to make the detection model even more perfect, data augmentation techniques are applied only to object detection. It implies randomly rotating photos so that they appear like they are being observed at various angles and applying transformations, such as translation and scale, so that the symptoms of the plant diseases could be made to appear diverse. These additions assist the model to learn how to locate plant illnesses in various perspectives and circumstances, which is useful in the real world farming circumstance where disease manifestations could alter in magnitude, direction, and growth progression [3].

Combining the two preprocessing to train the system, it will then be able to produce powerful and accurate models to categorize and detect the disease. This contributes to an overall better functioning of plant disease management systems.

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iii) Training & Testing:

The dataset is divided into two parts with 80:20 ratio, which consists of the training and testing part. The ML model is taught by the training set, 80% of the data, to identify patterns and associations between the characteristics and target labels. The other 20 percent of the data are the test set that is utilized to test the model on data that it has not previously encountered. This gap ensures that the model is able to generalize appropriately and not fit too well on the training data.

iv) Algorithms:

CNNs CNNs are DL models, which assist computers in identifying images and labeling them. Convolutional layers automatically learn spatial hierarchies of characteristics of input pictures, and are therefore ideal at visual tasks such as recognizing and segmenting objects [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 must know now a lot about the operation of a convolutional layer. Let's go on to the next phase of the CNN structure.

MobileNetV2 is a fast and lightweight mobile and embedded CNN. It employs depthwise separable convolutions and linear bottleneck layers to cut down on the amount of parameters while keeping accuracy. This causes it to be good in real-time image processing in situations with limited resources [12].

ResNet50 is a deep residual network that has 50 layers. It solves the vanishing gradient problem on the basis of residual blocks, and thus can be used to train very deep networks. Due to its effectiveness, ResNet50 is frequently applied in such tasks as picture categorization, object identification, and feature extraction [11][16].

EfficientNetB0 is an efficient convolutional neural network with a compound scaling strategy to repeatedly expand the width, depth, and resolution of the model. It operates at the top level with minimal parameters, thus it is ideal when dealing with applications that require high precision and efficiency [7].

Xception (Extreme Inception) is a CNN architecture utilizing depthwise separable convolutions to simplify it and enhance its performance. It is also based on the Inception module but instead of using normal convolutions, it uses separable convolutions. This facilitates easier understanding of the model in spatial hierarchies and reduces the necessary processing [10].

NasNetMobile is a mobile-friendly low-level CNN design. The neural architecture search (NAS) is applied to the process of discovery of the optimal network topology that is efficient and fast. Its modular design is ideal in on-device applications, which require a fast analysis of images [7].

Xception + NasNetMobile (Hybrid Model) The best features of the Xception and NasNetMobile infrastructures are combined in the Hybrid Model. Combining Xception with the mobile-specific design of NasNetMobile, one can develop a hybrid model, which is fast and efficient and suitable in a situation with limited resources [7][9].

(b) Detection Models:

YOLOv5s6 is a more precise and quicker implementation of the YOLOv5 object detector. It is smaller in architecture (YOLOv5s) but performs better with s6 configuration, which is suitable in real-time use cases with applications that require fast and accurate object localization [16].

YOLOv5x6 is an improved form of YOLOv5 that has a larger architecture that is trained to perform highly precise object recognition. It enlarges and complicates the model, which is more suitable to hard detection tasks in environments with a high number of various objects and circumstances [16].

YOLOv8 is the most recent version of the YOLO methodology for finding objects. It is among the most effective real-time object recognition models since it integrates speed and accuracy enhancements with an effective design. It is applicable to a great variety of tasks [13].

YOLOv9 The YOLO series is a series of new versions of the original that are intended to be more suitable to real-time object detection tasks. YOLOv9 would like to push the boundaries of understanding objects in challenging scenarios by rendering it faster, more precise, and more scalable. It will give the best results in a wide range of applications [13].

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YOLO makes the picture space go from 0 to 1 in both the x and y dimensions. To change your (x, y) coordinates into yolo (u, v) coordinates, you need to change your data in the following way:

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: Accuracy of the test is the ability of the test to distinguish between the sick and the healthy patients. To determine the accuracy of a test, we would like to know what proportion of true positives and true negatives of all the cases we considered. This can mathematically be expressed as:

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

Precision: Precision measures the count of occurrences or samples which were correctly classified out of the occurrences or samples which were labeled as positives. The calculation of the accuracy would then be:

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

Recall: Recall is a measure of the ability of a model in ML to locate all the relevant examples of a particular class. It is the proportion of the correct predicted positive observations to the overall actual positives. This will inform you of the ability of a model to capture events of a given type.

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

F1-Score: To measure the accuracy of a ML model, the F1 score can be used. It sums up a model accuracy and recall scores. The statistic of accuracy is a count of the number of times a model had a valid prediction on all the data.

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

mAP: MAP is a metric to quantify the quality of a ranking. It takes into account how many relevant recommendations there are and where they are on the list. The AP at K for all users or queries is used to find the MAP at K.

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

Table 1 shows how well each method did in terms of accuracy, precision, recall, and F1-score. The Extension and YoloV5s6 for Classification and Detection gets the best marks. We also present the statistics of other algorithms to enable you to compare them.

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

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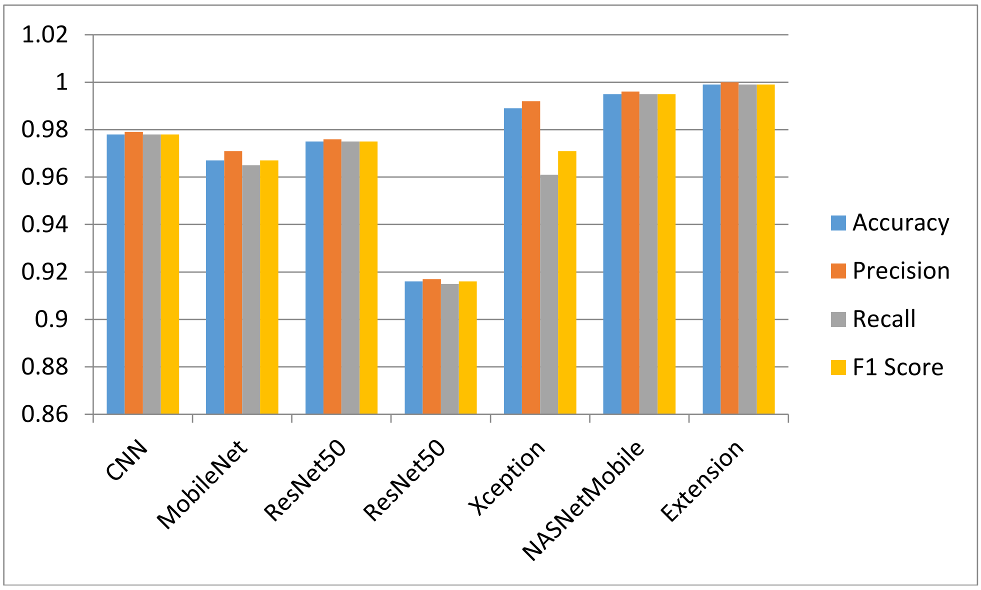
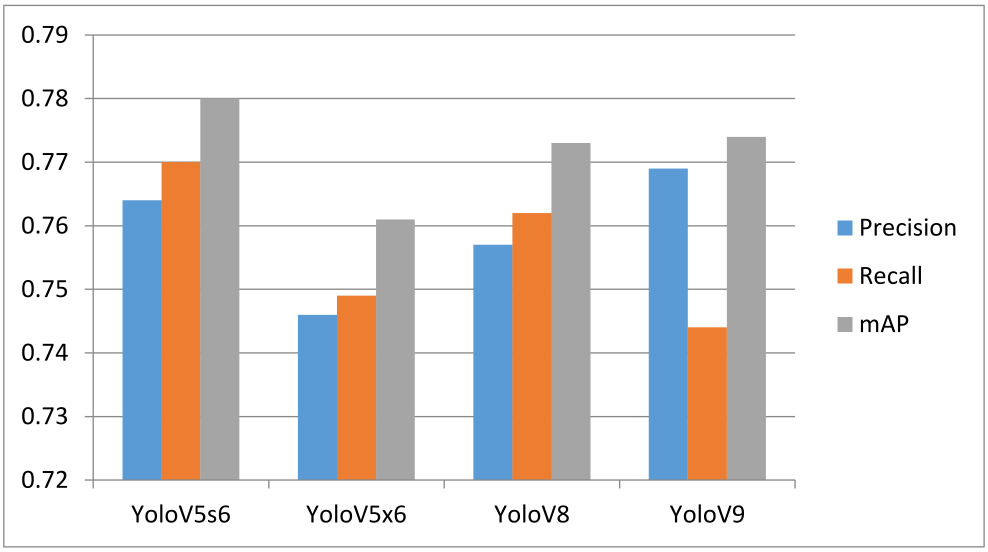


Graph.2 Comparison Graphs of Detection



The accuracy, precision, recall and F1-score are indicated in light blue, maroon, green, and violet respectively in Graph 1. Precision, recall, and mAP are indicated in light blue, maroon, and green, respectively, in Graph 2. Better in all aspects, the Extension and Yolo V5s6 have the highest numbers in comparison to the other models. The above graph reveals these facts in a manner that is easily visible.

V. CONCLUSION

In conclusion, the proposed deep learning-based solution to locate and identify plant diseases has much potential to address the issues that plant diseases present. The system's goal is to improve the accuracy and speed of illness identification by combining several convolutional neural networks and sophisticated detection algorithms. The ensemble model consisting of Xception and NasNetMobile has performed better, yielding high accuracy, recall and F1 scores. It is able to find complicated patterns in plant disease data. This model is quite an effective instrument to farmers and other people in the agriculture sector as it can be used to reduce the economic impact of crop illnesses on the crop yield. The system is further enhanced by the addition of explainable artificial intelligence methods. This allows the consumers to have knowledge about how the model predicts and develops confidence in the process of decision-making. This strategy aids in making wiser choices, food safety and environmentally friendly farming practices. Ultimately, it assists in resilience and productivity of agriculture throughout the globe.

Future studies ought to focus on increasing the generalization of models by incorporating a range of plant species and environmental variables in the training sets. In addition, it might help to examine how reinforcement learning can be implemented to detect adaptive illnesses in real-time field scenarios and make the system more effective. By taking a closer look at multi-modal learning that is the union of picture, environmental and sensor data, we may get a clearer idea of the diseases. Finally, and more generally speaking, it would be useful to consider in general use more developed explainability methods, which would allow users to be more trustful and understanding of real-world apps.

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