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Plant Disease Detection and Classification with Deep Learning

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Abstract— *In response to the significant losses caused by plant diseases, which call for a 70% increase in global food supply by 2050, scientists have created sophisticated deep learning models. These models, which were originally trained on datasets such as PlantVillage, have difficulties in real-world settings because of the intricate backgrounds and numerous leaves in each picture. This work presents FieldPlant, a new dataset with 5,170 photos of plant diseases that were gathered from plantations and painstakingly annotated by plant pathologists. The research assesses state-of-the-art classification algorithms such as MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, and DenseNet with an emphasis on maize, cassava, and tomato diseases in tropical cultures. Furthermore, algorithms for plant detection like YoloV5, YoloV8, SSD, and FasterRCNN are evaluated. The findings highlight the dominance of Xception and DenseNet in classification, while YoloV5 performs exceptionally well in plant detection with a mean Average Precision (mAP) of 0.977 and an astounding 97% accuracy. This study emphasizes how cutting-edge methods have the power to transform agricultural disease diagnosis and reduce worldwide output losses.*

Keywords— *Plant disease dataset, deep learning, classification and detection of plant diseases, field and lab photos.*

I. Introduction

With an estimated 10 billion people on the planet by 2050, there will be a significant need for food, which will present a difficult task due to the scarcity of arable land [1]. In order to accommodate the growing population, the Food and Agriculture Organization of the United Nations (FAO) recommends a 70% increase in the food supply by 2050 [2]. However, plant illnesses or abnormalities cause an astounding one-third of farmed food to be wasted, with an estimated yearly economic cost of US$ 220 billion [3], [4]. Amidst these difficulties, extensive study has been spurred by the significant impact of plant diseases on crop production loss. The emergence of Artificial Intelligence (AI), namely in the fields of Machine Learning and Computer Vision, has offered a viable solution to tackle this problem. Plant disease diagnosis and classification have found a major application for Deep Convolutional Neural Networks (CNN), a well-known aspect of artificial intelligence [5]. CNNs have been trained with notable datasets such as PlantVillage [2], iBean [6], citrus [7], rice [8], cassava [9], and AI Challenger 2018 [10], which have produced high classification accuracy in lab settings. It has been difficult, nevertheless, to apply these achievements.

Images from the field, with their intricate backgrounds of fruits, leaves, stems, dirt, and mulch, stand in sharp contrast to the controlled environments of labs. Studies [11] have shown that the complex background features found in field photos have a major role in the performance drop that is seen when neural networks trained on lab datasets are used. This calls for the development of novel techniques, including background reduction, to improve disease recognition accuracy in actual agricultural settings. By 2050, this research hopes to increase food output worldwide by 70% by creating sophisticated deep learning models. In order to tackle issues that arise in actual field settings, the study presents Field Plant, a dataset that consists of 5,170 photos of plant diseases. The evaluation includes plant detection algorithms (YoloV5, YoloV8, SSD, FasterRCNN) and classification algorithms (MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, DenseNet) on crops such as corn, cassava, and tomato, demonstrating the effectiveness of DenseNet, Xception, and YoloV5 in their respective tasks.

II. Literature Survey

The literature review emphasizes the integration of computer vision, deep learning, and novel methodologies to improve agricultural productivity and crop management. It also covers notable developments and projects in plant disease diagnosis and agricultural automation. A system that combines deep learning and computer vision technologies in [1] tackles issues in small-scale field farming and encourages intelligent agricultural production management. Obstacles encompass the perpetual progress in technology and the requirement for proficient experts in agricultural automation. While integrating with massive datasets improves productivity and spurs economic growth, it's still difficult to get reliable performance in a variety of settings. In order to support the aims of global food security and reduce yield losses caused by infectious illnesses, [2] suggests using carefully chosen photos of plant health for mobile disease diagnostics. A dataset for visual plant disease identification is introduced by PlantDoc, which is covered in [4]. It shows significant accuracy gains and lowers obstacles to the application of cutting-edge computer vision techniques in agriculture. gives a summary of deep learning-based plant disease detection algorithms in [5], stressing their critical significance in improving agricultural practices while drawing attention to issues like data quality and model interpretability. Last but not least, [7] addresses the financial losses brought on by citrus illnesses by introducing a hybrid method for disease identification and categorization. Notwithstanding several difficulties with dataset quality and computational complexity, the suggested approach has promise

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for real-world use in agriculture. These programs recognize persistent issues like dataset quality and computational complexity while highlighting the significance of incorporating cutting-edge technologies in agriculture. Notwithstanding these obstacles, the innovations under discussion have the potential to transform farming methods and solve issues with global food security.

III. METHODOLOGY

A. Proposed Work

The suggested solution uses cutting-edge deep learning algorithms for improved crop disease diagnosis and mitigation, addressing the urgent requirement for a 70% increase in global food production by 2050. Seeing that models trained on datasets such as PlantVillage struggle with complex backgrounds and multiple leaves per image in real-world field settings, the study presents FieldPlant, an extensive dataset with 5,170 carefully annotated images of plant diseases taken straight from plantations. The study gains specificity from its emphasis on tomato, cassava, and corn diseases in tropical cultures. Modern classification algorithms including MobileNet, VGG16, InceptionResNetV2, InceptionV3, Xception, and DenseNet are evaluated, and the results show that DenseNet and Xception are particularly effective at solving classification problems with 97% accuracy. Concurrently, the evaluation of YoloV5, YoloV8, SSD, and FasterRCNN plant identification algorithms demonstrates YoloV5's exceptional performance in attaining a noteworthy 0.977 mean Average Precision (mAP) in plant detection. This study presents a comprehensive method for detecting agricultural diseases, demonstrating how cutting-edge methods have the power to revolutionize agriculture worldwide and significantly reduce production losses.

B. System Architecture

The urgent need for a 70% increase in global food production by 2050—a demand related to losses from plant diseases—is met by the suggested system architecture. The basis is based on sophisticated deep learning models, which diverge from traditional training on datasets such as PlantVillage. The system presents FieldPlant, a new dataset with 5,170 photos of plant diseases taken from plantations and carefully annotated by plant pathologists. With a focus on tropical corn, cassava, and tomato illnesses, the architecture assesses state-of-the-art classification algorithms like Xception, DenseNet, MobileNet, VGG16, and InceptionResNetV2. Furthermore, the effectiveness of YoloV5, YoloV8, SSD, and FasterRCNN plant detection algorithms is evaluated. The design highlights how effective DenseNet and Xception are at classification, while YoloV5 performs remarkably well at plant detection. This all-encompassing strategy, which combines cutting-edge methods with a customized dataset, has the potential to transform crop disease detection and greatly reduce losses in global food production.

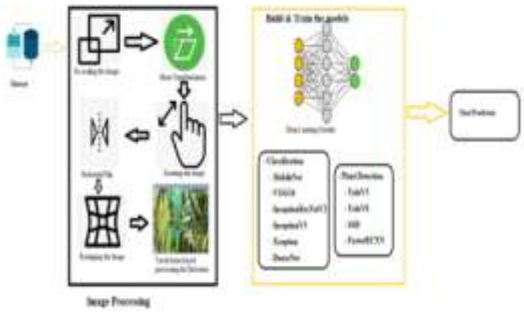

Fig 1. System Architecture

C. Algorithms

Mobile Net **-** Convolutional neural networks of the MobileNet kind are intended for embedded and mobile vision applications. Their foundation is a simplified architecture that builds lightweight deep neural networks with reduced latency for mobile and embedded devices using depthwise separable convolutions.

VGG16: VGG-16 is a 16-layer convolutional neural network. The ImageNet database contains a pretrained version of the network that has been trained on over a million images [1]. The pretrained network is capable of classifying pictures into 1000 different object categories, including several animals and keyboards, mice, and pencils. InceptionResNetV2-A convolutional neural network called Inception-ResNet-v2 was trained using over a million pictures from the ImageNet collection [1]. With 164 layers, the network is capable of classifying photos into 1000 different object categories, including several animals and keyboards, mice, and pencils.Inception V3-Convolutional neural network Inception-v3 has 48 layers deep. A pretrained version of the network, trained on over a million photos from the ImageNet collection, is available for download [1]. Images of 1000 different object categories, including a keyboard, mouse, pencil, and numerous animals, can be classified by the pretrained network. Xception- Xception is a 71-layer convolutional neural network. A pretrained version of the network, trained on over a million photos from the ImageNet collection, is available for download [1]. Images of 1000 different object categories, including a keyboard, mouse, pencil, and numerous animals, can be classified by the pretrained network.

*DenseNet***-** A DenseNet is a kind of convolutional neural network that makes use of dense connections between layers. Specifically, Dense Blocks allow us to connect all layers directly with one another (provided that their feature-map sizes match). We now talk about detection methods, which include:

SSD: One-Time MultiBox Detector. Using a single stage of object detection, SSD divides the bounding box output space into a set of default boxes with varying aspect ratios and scales for each feature map location. FasterRCNN-By combining the CNN model with a region proposal network (RPN), the FasterRCNN - Faster R-CNN object detection model outperforms the Fast R-CNN model. Region recommendations are almost entirely free thanks to the RPN's sharing of full-image convolutional features with the detection network. YoloV5: Yolo v5 generates the anchor boxes using a novel

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technique known as "dynamic anchor boxes." The ground truth bounding boxes are first grouped into clusters using a clustering method, and the anchor boxes are subsequently made using the centroids of the clusters.

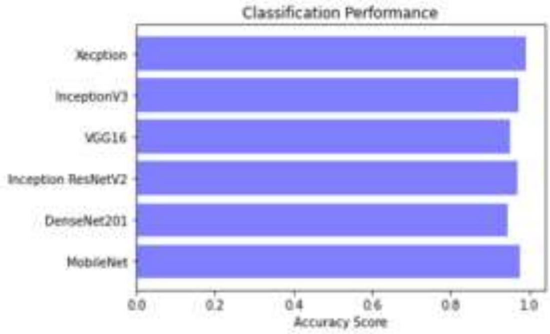
YoloV8: The newest model in the YOLO family is called YOLOv8. You Only Look Once, or YOLO, is how this set of models got its name—they can accurately predict every object in a picture with just one forward pass. The way the YOLO models framed the problem at hand was the primary distinction they introduced.

IV. Experimental Results

Accuracy: A test's accuracy is determined by how well it can distinguish between patient and healthy cases. We should compute the percentage of true positive and true negative in each analyzed case in order to assess the accuracy of a test. This can be expressed mathematically as follows:

Accuracy = TP + TN TP + TN + FP + FN

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



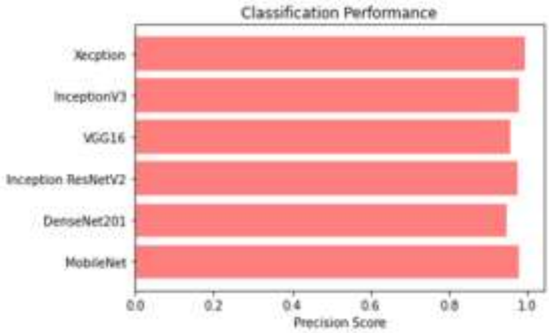
Precision: Precision measures the percentage of correctly categorized samples or instances among the positive samples. Consequently, the following is the formula to determine the precision:

Precision = True positives/ (True positives + False positives) = TP/ (TP + FP)

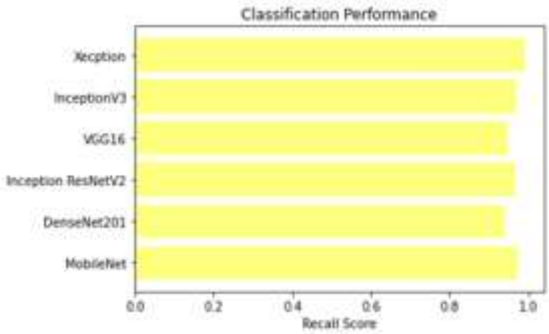
$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

Recall: Recall is a machine learning metric that assesses a model's capacity to locate all pertinent instances of a given class. It is a measure of how well a model captures examples of a particular class: the ratio of correctly predicted positive observations to the total number of real positives.

F1-Score: The F1-Score is a machine learning evaluation metric that quantifies the accuracy of a model. It integrates a model's precision and recall ratings. The number of times a model correctly predicted throughout the whole dataset is calculated by the accuracy metric.

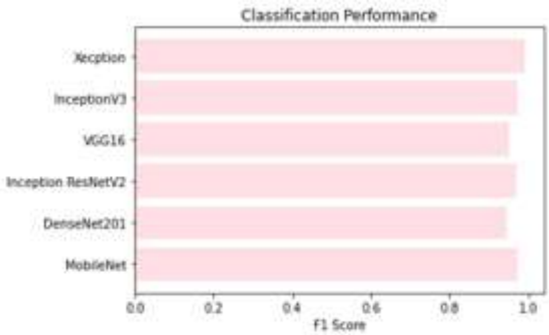


$$Recall = \frac{TP}{TP + FN}$$



$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



V. Conclusion

Finally, by utilizing cutting-edge deep learning models for enhanced plant disease detection, this study tackles the pressing demand for increasing global food production. FieldPlant was introduced to address the limits of conventional training on datasets like PlantVillage in real-world outdoor situations. When classification algorithms were evaluated, YoloV5 performed exceptionally well in plant detection (mean Average Precision = 0.977), although DenseNet and Xception performed better, obtaining 97% accuracy. These results demonstrate the

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revolutionary potential of cutting-edge methods for agricultural disease identification, providing a way to reduce global production losses and feed the world's expanding population in a sustainable manner. In the future, more studies may examine how to combine remote sensing and real-time monitoring systems to improve early detection and intervention techniques, thus improving food security and agricultural sustainability.

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