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A Deep Learning Approach For Plant Disease Detection Using YOLOV5

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Abstract: Plant diseases pose a significant threat to agricultural productivity and food security worldwide. This paper presents a novel approach utilizing the YOLOv5 object detection algorithm for plant disease detection, leveraging an annotated dataset obtained from Kaggle. The annotated dataset used in this study comprises a diverse collection of high-resolution images of plants affected by various diseases. The dataset was manually labeled with bounding boxes and corresponding class labels, providing detailed information about the location and type of disease present in each image.YOLOV5 is used for training and detecting plant diseases. The resulting trained YOLOV5 model demonstrated superior performance in detecting and localizing plant diseases within images, achieving good performance. The proposed approach offers several advantages over traditional methods of plant disease detection.it suitable for large-scale applications. To ensure the model's accuracy, a rigorous training process was conducted, involving minimal level of data augmentation techniques. This research contributes to the ongoing efforts in precision agriculture, aiding farmers and researchers in timely disease management, crop protection, and improved agricultural practices.
Keywords: YOLOV5, deep learning, ImageLabel, Jupyter Notebook

I. INTRODUCTION

There are many plant diseases that exhibit characteristic symptoms that are visible to the naked eye. It is a problem with visual assessment that, since it is subjective, it is prone to psychological and cognitive processes which may lead to bias, optical illusions, and errors in the end. A laboratory analysis, such as one involving molecular, immunological or pathogen culturing, however, can take a long time and do not usually provide answers promptly. Therefore, developing automated methods for identifying diseases rapidly and accurately is imperative. Many of the automatic methods proposed so far rely on digital images, which allows very fast processing. This review was motivated by intrinsic and extrinsic factors resulting in too much error proneness for these methods. In order to protect crops, it is essential to identify disease symptoms as soon as possible. In developing countries, experts and agronomist visual inspect large farms for diseases, which takes a lot of time and is costly. Using smart devices to automatically identify diseases is a promising way to reduce costs and identify diseases. Deep learning architectures are becoming increasingly important in identifying diseases in real-time [5]. The challenges discussed in this article are also relevant for disease severity measurement, and some references are included in this article on the matter, even though the focus is on the identification of plant diseases. In contrast to accurately describing symptoms, measuring severity is essential for disease identification. Apart from the identification of diseases, all other challenges are roughly the same for both issues, particularly when multiple diseases are expected to coexist. Plant diseases negatively affect agricultural production [1]. The identification of plant diseases has become increasingly important in recent years. Diseased plants usually show obvious marks or lesions on their leaves, stems, flowers, or fruits. Each disease or pest condition has a unique visible pattern which can be used to identify abnormalities. The leaves of plants usually display the first signs of most plant diseases, and you can identify them by looking at them. Farmers with experience or agricultural and forestry experts usually perform on-site identification. This method is not only subjective and time-consuming, but also labor-intensive and inefficient. In the identification process, farmers with less experience may misjudge and use drugs blindly.

The rice disease dataset was captured in real time under field conditions, and the cassava plant dataset was captured in real time under field conditions, with multiple leaves in the images. In addition to quality and output, environmental pollution will also cause unnecessary economic losses. Our proposed model has been compared with three other state-of-the-art deep learning models.

II. LITERATURE REVIEW

Over the period of time, various approaches takes places. This paper uses imaging techniques to identify plant diseases. Trends and difficulties are also discussed. [1]. Plant disease cannot be detected at early stage. In recent years, the use of convolutional neural networks has been explored in a wide range of applications, such as image classification, feature extraction or image segmentation[4]. One of those applications is the detection of plant diseases, as plant diseases are one of the most important factors leading to low yields in the agricultural industry. Many deep learning were there, but there are limits to these approaches. An overview of CNN methods and their applications is provided in this paper.In order to identify plant diseases, this research contrasts these methods with more established CNN methods. Due to the usage of traditional CNN, accuracy is lower when comparing to other hybrid models. Tomato, grape, and apple diseases were detected in this paper[8].The system can also detect several diseases of plants. Plant disease could be only detected for some specific regional species. To overcome this threat imposed by weeds in agriculture, a measure taken to determine weeds grow together with seedlings with the help of using deep learning (DL) techniques[9]. To achieve higher accuracy, the models such as four convolutional layers, six convolution layer, eight convolution layers, and thirteen convolutional layer architectures have been built. Comparatively, eight layers of convolution architecture passed 97.83% when training Accuracy and confirmation accuracy 96.53%. The use of CNN architecture has paved the way to achieve the forming precision of 96.27% and confirmation accuracy with 91.67% in ZFNet and 97.63% are training accuracy and 92.62% validation accuracy in ALEXNET. This system needs better accuracy for more weed detection.

Using CNN ,disease is detected in apple and tomato leaves[3]. The model is not efficient as other existing model and it is complex to implement on the mobile devices. The deep learning models used to visualise three plant diseases are completely summarised in this article[5].

III. METHODOLOGY

A. EXISTING SYSTEM

Developing countries rely largely on agronomists and experts to identify plant diseases on large farms. Initially, CNN has been used to train datasets with large amounts of data. The collected images undergo pre-processing steps to enhance the quality and extract relevant features. Pre-processing techniques may include resizing, cropping, normalization, and augmentation. The CNN model is trained using the pre-processed dataset. This involves feeding the images through the network, computing the loss (difference between predicted and actual labels), and adjusting the model's parameters through backpropagation. The process is typically repeated for multiple epochs to improve the model's accuracy. By analyzing the picture, the existing system could identify plant diseases. If we upload the photo with a uniform background, the program will be able to detect diseases using the dataset we have trained on. Based on the inception layer and residual connections, the system detects plant diseases using a convolutional neural network. Its dataset has been taken from the plant village. With depth-wise separable convolution, the number of parameters can be reduced by a large margin without affecting performance.

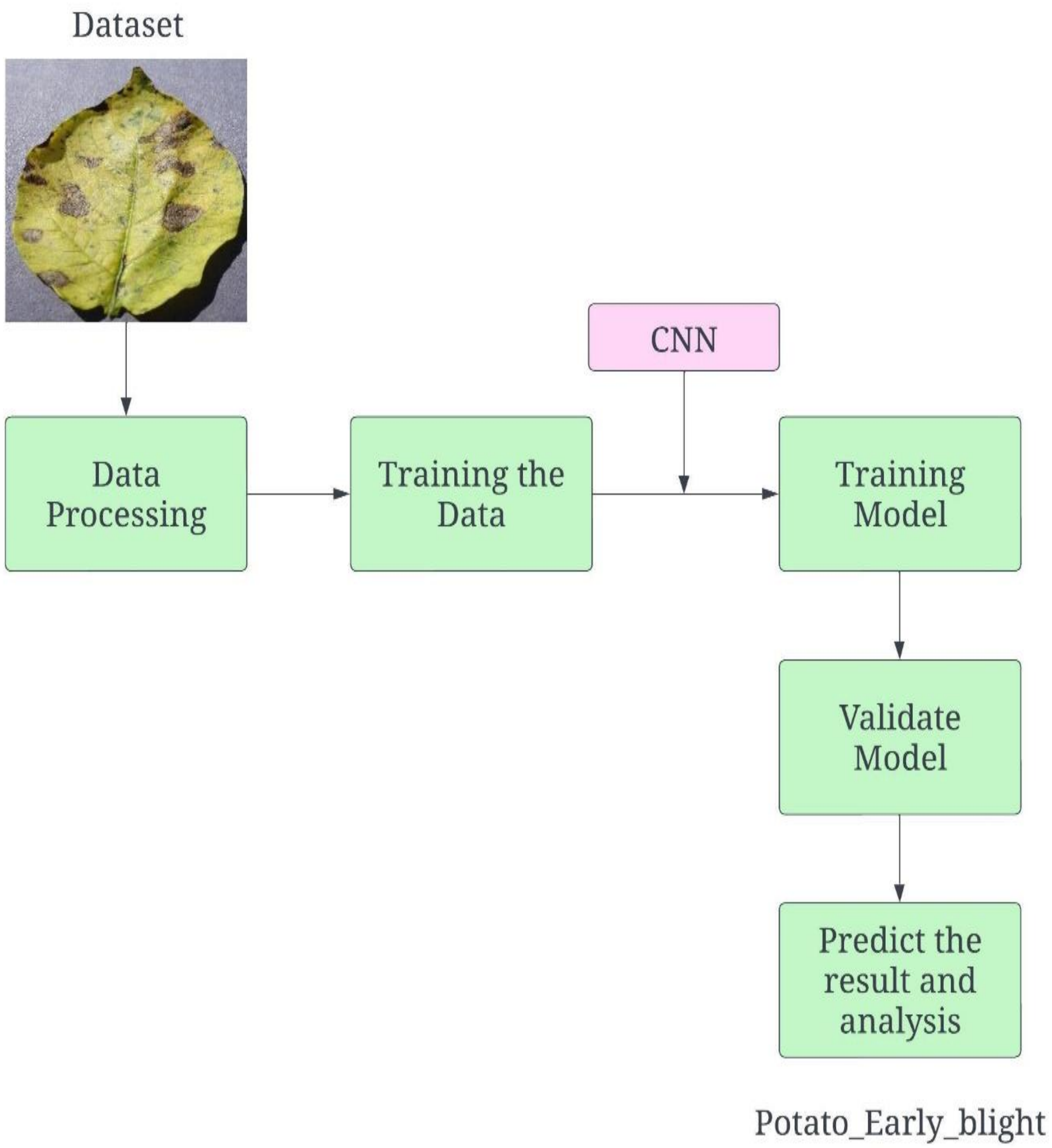

Fig 3.1 Architecture of Existing system

B. PROPOSED SYSTEM

Collect a dataset of plant images from Kaggle that includes images labelled with disease names. Ensure that the dataset covers a variety of plant diseases. Preprocess the collected dataset by resizing and augmenting the images. Augmentation techniques such as rotation, flipping, and brightness adjustment can help increase the diversity of the dataset. Use a labelling tool like ImageLabel to annotate the images in the dataset with disease names and draw bounding boxes around the affected areas.

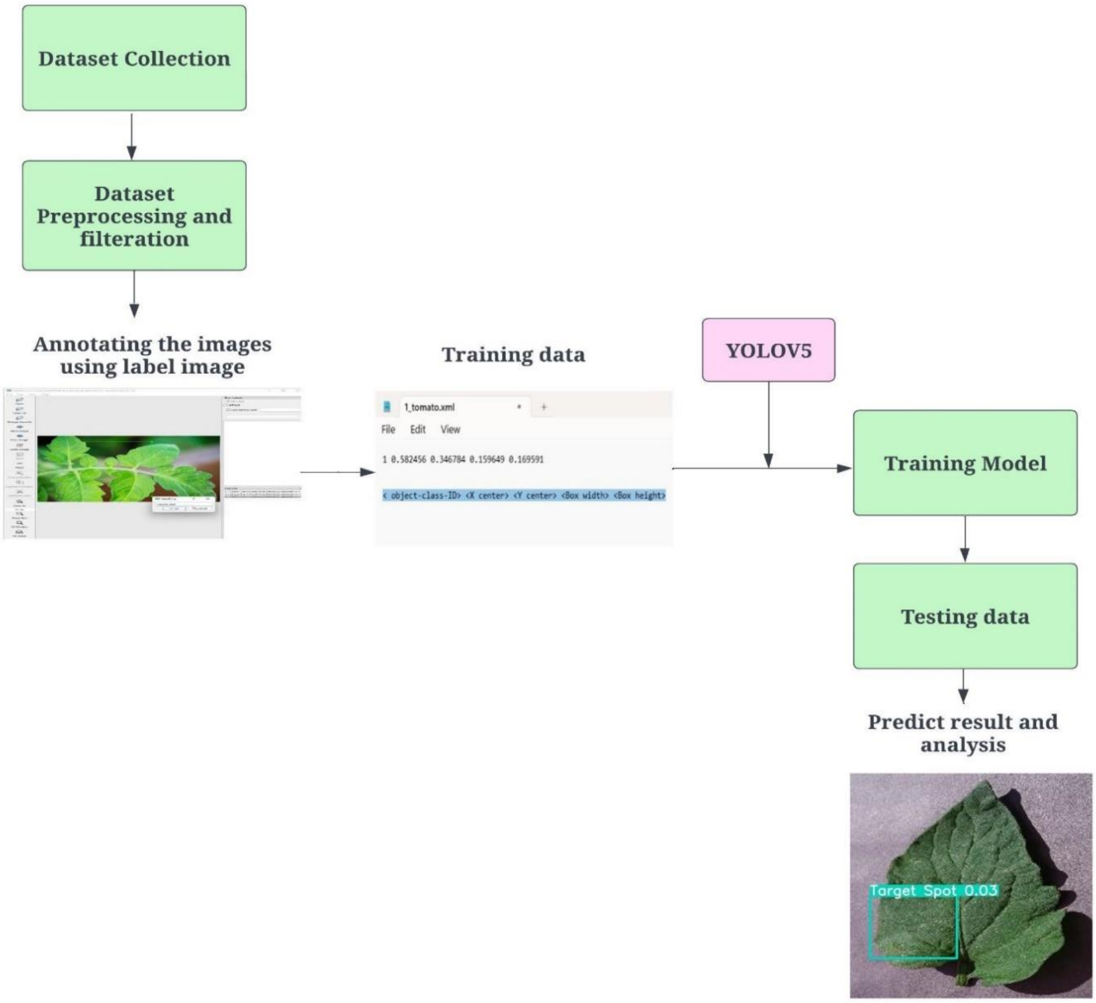

Fig 3.2 Architecture of proposed system

Train the YOLOv5 algorithm on the pre-processed and labelled dataset. Use a deep learning framework like PyTorch or TensorFlow to train the model. Split the dataset into training and validation sets to monitor the model's performance. Evaluate the trained model's performance using appropriate metrics such as precision, recall, and F1score. Adjust the model's hyperparameters and architecture if necessary to improve the results. Export the trained YOLOv5 model, usually in a format like PyTorch .pth file, so that it can be used for inference. In Jupyter Notebook install the necessary Python libraries for object detection and visualization. Load the exported YOLOv5 model in the Jupyter Notebook and set it up for inference. Use the appropriate library (e.g., PyTorch or TensorFlow) to load the model. Use the loaded model to perform inference on test images in the Jupyter Notebook. Process the model's output to extract the detected plant diseases and their corresponding bounding boxes. Visualize the results by displaying the images with the bounding boxes and disease labels. Plant disease results have been analysed using F1 score, recall, and accuracy metrics.

IV. RESULT DISSCUSSION

A. EXPERIMENTAL RESULT

We use different performance statistics to evaluate the performance of the model, including the number of precision, recall, and f1-score. Table 4.1 shows the performance metrices.

Precision = TP/ TP + FP

Recall = TP /TP + FN

F1 − score = 2 × precision × recall /precision + recall

Table 4.1 Metrics of proposed system

Parameters	Precision	Recall	F1 Score
Healthy	87 %	93 %	89 %
Yellowish	89 %	91 %	89 %
Whitefly	94 %	93 %	92 %
Leafspot	94 %	90 %	91 %
Leaf curl	80 %	73 %	76 %

B. RESULT DISCUSSION

To discuss the performances of our proposed system, we compare the performances of our proposed model with other deep learning models shown. The result of our proposed system for plant disease detection is highly promising with accuracy. This shows our system is effective in identifying plant disease detection. The usage of YOLOv5 effectively detect the plant disease, because YOLOv5 accept dataset in such a way it is annotated. By analyzing the plant the system produces the result and also show the confidences. With the help of these confidence user could understand the disease better. The system will also provide the remedy for the plant which get affected. In the existing system, the CNN is used to detect diseases in plants. This study uses deep convolutional neural networks to detect diseased plants using photos, and the output is determined by the input leaves. The performance accuracy obtained on plant village dataset is 99.39%, on the rice disease dataset is 99.66%, and on the cassava dataset is 76.59%.So based on the dataset accuracy of the existing system get changed. But usage of YOLOV5 in this case will overcome this problem. Because In the proposed system dataset are properly annotated by using image label. The Image Label tool is used to annotate the image with the parameters like width, height and class Id. This Class Id is used to identify the class specifically. However the usage of CNN is difficult to implement in small mobile devices, but our proposed system is implemented.

Fig 4.1 Target spot

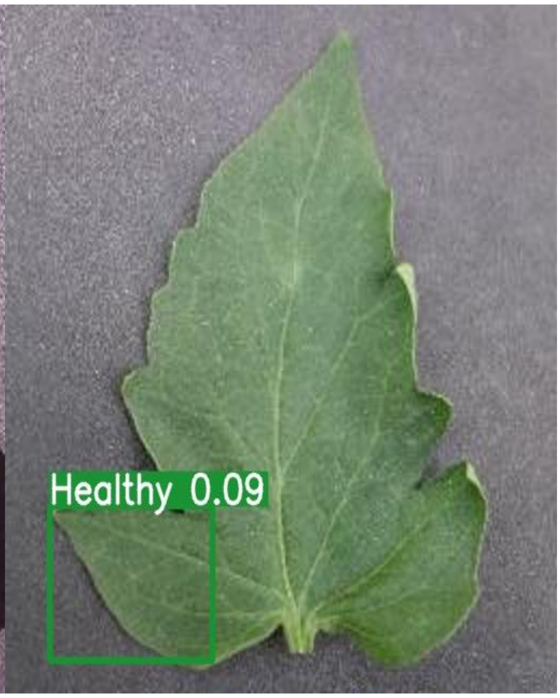

Fig 4.2 Healthy

V. CONCLUSION

Research into plant disease detection is an interesting area of study which reduces losses and increases production. In conclusion, the use of deep learning models like YOLOv5 for plant disease detection can provide accurate and fast detection of plant diseases, which can help farmers take timely actions to prevent the spread of the disease and minimize crop damage. With the use of large datasets in the future, we could increase the accuracy of the model. The level of usage of data argumentation techniques can be improved which in turn improve the results. By training the algorithm to accurately detect different forms of plant diseases, large datasets with many different types of diseases can be used. Furthermore, as part of its future enhancements, YOLOv5 will also detect weeds and medicinal plants. By doing so, agricultural practices can be more targeted and efficient, the preservation of medicinal plants can be ensured, and new treatments can be discovered.

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