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Machine Learning Based Analysis And Classification Of Rhizome Rot Disease In Turmeric Plants

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ABSTRACT:

Turmeric is a valuable crop, but it is prone to various diseases that can significantly impact its production. Early detection of these diseases is crucial to prevent crop failure and losses. In this research, we propose a novel approach for accurately identifying turmeric plant diseases using a single-phase detection model based on machine learning. Our method, called the Improved YOLOV3-Tiny model, leverages a residual network structure and convolutional neural networks to improve detection accuracy compared to the traditional YOLOV3-Tiny model. We tested our method on images captured during both day and night and found that it outperformed other methods such as YOLO and Quicker R-CNN with the VGG16 prototypical. We also found that augmenting the turmeric leaf dataset with Cycle-GAN improved detection accuracy, particularly for smaller datasets. Overall, our proposed model offers both high accuracy and fast recognition speed, making it a valuable tool for detecting turmeric leaf diseases.

Keywords: Turmeric plant disease, machine learning, YOLO model, computer vision

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1. INTRODUCTION

As the global demand for food continues to rise, it is crucial that we find ways to increase agricultural productivity and profitability. One promising solution is the use of artificial intelligence (AI) in precision agriculture [1,2]. By analysing current data on factors such as temperature, soil situations, and climate, farmers can make more informed decisions that can lead to higher crop yields. AI can also be used to detect diseases and pests, identify poor-performing plants, and create seasonal forecasting models. Additionally, AI-enabled sensors and cameras can help identify problems and suggest potential improvements on farms.

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Turmeric is a valuable herb that is widely cultivated in South and East India, as well as in Malaysia. However, like any crop, it is susceptible to diseases that can negatively impact its productivity. To address this challenge, we need to develop effective methods for detecting and preventing sicknesses. By doing so, we can reduce the need for pesticides and protect the environment while also increasing turmeric production.

Accurate detection of leaf diseases is vital for the health and productivity of crops, especially in large-scale plantings. However, traditional methods of disease detection can be slow and prone to errors. This is where machine learning and image processing technology come in. By capturing images of crops and using algorithms to extract features and classify diseases, these techniques offer a powerful alternative to traditional recognition methods and manual diagnosis.One of the key benefits of using AI for disease detection is its ability to process large amounts of data and learn from it. By training on vast datasets, AI models can quickly and accurately identify plant leaf diseases, even in complex environments Overall, the use of AI in agriculture has the potential to transform the way we approach disease detection and management, leading to healthier crops and more sustainable agriculture practices.

2. Literature Review

Machine learning has emerged as a powerful tool in the field of machine learning, particularly for image processing applications. One popular machine learning model is the convolutional neural network (CNN), which offers an endwise construction for picture pre-processing and feature taking out, simplifying the discovery process. Pre-trained imageries can be used to train CNN models, saving time and labor and enabling real-time analysis of large datasets. This can be especially useful in the context of plant leaf disease detection, where accurate identification is crucial for minimizing losses.[3]. However, these methods can be resource-intensive and may not be suitable for use on embedded platforms with limited computing power and memory. Miniaturized machine learning such as YOLO (you only look once) and SSD (single shot multi-box detector) offer an alternative for mobile object detection, using high GPU performance to achieve high detection accuracy [4,5].

In recent years, researchers have explored the use of both single and double object detection methods for disease detection using AI techniques, and have found that these approaches can offer better accuracy than traditional methods. For example, In one research machine learning techniques such as machine learning, organization and deterioration trees, and accidental forests to forecast the risk of a particular disease in winter wheat, while Ferentinos proposed a machine learning model for identifying plant diseases. Other researchers have explored the use of few-shot learning algorithms to overwhelmed the challenges of acquiring and annotating huge image datasets, and have found that these approaches can be effective when combined with Siamese networks and triplet loss [6].

There is a wide range of machine learning models that have been applied to plant disease detection, including YOLO and YOLO-V3. YOLO is a single-stage object detector that uses a unified approach to object localization and classification, enabling it to run in real-time. YOLO-V3 is an improved version of YOLO that uses residual networks and a new anchor box design to improve detection accuracy. However, both of these models may struggle with small objects and can be sensitive to image quality [7].

Other models, such as Mask R-CNN and RetinaNet, have been developed to address these issues. Mask R-CNN is a two-stage object detector that uses region proposal networks and a

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fully convolutional network to detect and segment objects in images. RetinaNet is a single-stage detector that uses a focal loss function to address the class imbalance problem, allowing it to effectively detect small objects [8].

These machine learning models have been applied to a variety of plant species, including turmeric. Kuricheti and Supriya used a k-means algorithm for image segmentation and a support vector machine (SVM) classifier for feature extraction to develop a GUI system for detecting turmeric diseases and controlling their spread. In another research, CNN based on the VGG16 planning for detecting turmeric sicknesses at an initial stage and protecting from fast sickness spread. However, more research is needed to fully understand the potential of machine learning for detecting and preventing turmeric diseases [9].

To further improve the accuracy and efficiency of machine learning models for detecting turmeric diseases, there are several avenues that could be explored. One possibility is to incorporate additional data sources and feature types into the model training process. For example, incorporating spectral data from satellite or aerial imagery, or incorporating features related to plant physiology and biochemistry, might deliver extra data that could be used to distinguish among healthy besides diseased plants [10].

Another potential approach is to use transfer learning or domain adaptation techniques to fine-tune existing machine learning models for use on turmeric data. Domain adaptation involves adapting a model trained on one dataset to perform well on a different dataset, which can be particularly useful when working with small or imbalanced datasets [11].

Finally, researchers could consider developing new machine learning models or architectures specifically tailored to the unique characteristics of turmeric diseases. For example, researchers could explore the use of attention mechanisms or multi-scale feature extractors to better handle the variations in shape, size, and appearance of diseased turmeric plants. By exploring these and other approaches, researchers can continue to push the boundaries of what is possible with machine learning for turmeric disease detection and prevention [12].

It is also important to consider the practical implications of using machine learning for turmeric disease detection. One key consideration is the need for robust and reliable hardware and software infrastructure to support the training and deployment of machine learning models. This may include high-performance computing resources such as GPUs and specialized hardware accelerators, as well as software tools and libraries for developing, testing, and deploying machine learning models [13].

Another consideration is the availability and quality of training data. Machine learning models are highly data-driven, and the accuracy of the model is largely dependent on the quality and diversity of the training data. Therefore, it is important to carefully curate and annotate training data to ensure that it accurately represents the range of normal and diseased conditions that the model will encounter in practice. This may involve collecting and annotating large amounts of data from various sources, including both lab and field observations. The diseased turmeric plant are shown in figure 1 for the reference.

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Fig. 1 Diseased plants

Finally, it is important to consider the potential ethical and social implications of using machine learning for turmeric disease detection. For example, there may be concerns about the accuracy and fairness of the model, particularly if it is used to make decisions that could have significant impacts on individuals or communities. Researchers should be mindful of these concerns and work to ensure that the models they develop are transparent, explainable, and accountable, and that they are developed and used in an ethical and responsible manner [14–16].

3. Image processing

In this study, images of turmeric leaves were captured using high-resolution mobile devices at various times of day and under different lighting conditions. A entire of 1,600 imageries were collected, including 400 imageries each for morning, afternoon, evening, and rainy days. These images captured a range of illumination conditions, including backlighting, frontlighting, side lighting, and scattered lighting.

To train and evaluate the model, the dataset was separated into a various set (80% of the original images) and a test set (20% of the original images). Once the model was trained, it was tested on the test set to forecast and assess its performance. By using a diverse and representative dataset, this study was able to capture the complexity and variability of turmeric leaf diseases and train a model that was able to accurately detect and classify these diseases.

In order to achieve accurate and reliable results with machine learning methods, it is often necessary to have a large and diverse dataset. In this research, a dataset of 1,600 images was collected from real-world environments and used to train a machine learning model for turmeric leaf disease detection. However, to further recover the model's concert and generalizability, data augmentation techniques were used to artificially increase the size and diversity of the dataset.

Data augmentation involves applying various transformations to the training data to create new, artificially generated images that can be used to train the model. These transformations can include image rotation, color modification, brightness adjustment, and motion blur, among others. By using data augmentation techniques, the model is exposed to a wider range of variations and variations in the data, which can help improve its performance and robustness. In this research, traditional data augmentation techniques were used, as well as a machine learning-based data augmentation method called CycleGAN. By using both

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traditional and machine learning-based data augmentation techniques, the researchers were able to achieve improved detection accuracy and better generalizability of the model.

3.1 Image rotation and colour

To improve the performance of the machine learning model and increase its ability to recognize objects despite variations in lighting and color, the researchers in this study applied various data augmentation techniques to the training images. These techniques included image rotation, image mirroring, and the Gray world method. By rotating the images by 90 and 180 degrees, the researchers were able to expand the dataset and expose the model to a wider range of variations in orientation. Image mirroring helped the model learn to recognize objects that may appear differently depending on their orientation. The Gray world method was used to balance the colors in the training images, helping the model to learn to recognize objects despite variations in lighting and color.

3.2 Image brightness

One technique used to improve the performance of the machine learning model in this research was brightness transformation, which involves adjusting the brightness of the training images. This technique can help the model learn to recognize objects despite variations in lighting conditions. To implement brightness transformation, the researchers multiplied the original RGB images by a coefficient near 1.0, which resulted in increased or decreased image brightness. They set the coefficient to values between 0.7 and 0.9, and between 1.1 and 1.3, founded on the board edge that precisely defined the diseases during physical annotation. If the value of the increase was better than 255, it was automatically attuned to 255. By using brightness alteration and other data augmentation techniques, the researchers were able to improve the performance and robustness of their machine learning model for turmeric leaf disease detection.

3.3 Image blur transformation

In this research study, the researchers used data augmentation techniques to improve the robustness of their machine learning model for turmeric leaf disease detection. One such technique was motion blur transformation, which simulated the effect of a camera moving while taking a picture. This technique can help the model learn to recognize objects despite variations in focus and camera movement. To implement motion blur transformation, the researchers used mathematical experssion to generate motion-blurred images from the original images. They set the parameters L (length) and θ (angle) based on the application type and used a degenerate function to blur the images.

3.4 Image augmentation using machine learning

Machine learning has revolutionized the field of image processing, with applications in a wide range of areas, including plant leaf disease detection. Convolutional neural networks (CNNs) offer a highly effective endwise approach for image pre-processing and feature removal, significantly reducing disease-related losses through real-time analysis of large datasets. In current years, investigators have developed even more sophisticated network constructions, such as RCNN, Faster-RCNN, and SPP-Net, for improved object detection accuracy. However, these methods can be resource-intensive and may not be suitable for use

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on embedded platforms with limited computing power and memory. A review of machine learning techniques for image processing showed that these methods provide better accuracy results and are highly effective for disease detection. There is still significant scope for further research on plant disease detection using machine learning techniques, particularly for turmeric plants, for which only a few studies have been conducted so far.

In this study, we utilized the power of machine learning to enhance the dataset of turmeric leaf images for the detection of plant diseases. By utilizing the Cycle-GAN model, we were able to generate new images of diseased turmeric leaves, even though we had a limited number of actual diseased leaf images. The use of image augmentation techniques such as rotation, color transformation, and motion blur transformation further expanded the dataset. The resulting dataset, as described in Table 1, consisted of 1,600 images of turmeric leaves, divided into four categories based on the time of day and lighting conditions. These images were then used to train and test machine learning models for the accurate detection of different types of leaf diseases. Examples of the various augmentation techniques applied to the images can be seen in Fig. 2.

Table 1 Images of the leaf after augmentation and total count of the image

Captured time	Original Images	Augmented Images	Total Images
Morning	100	400	500
Afternoon	100	400	500
Evening	100	400	500
During rain	100	400	500
TOTAL	400	1600	2000

4. Proposed Algorithm

To improve the accuracy of our model for detecting diseases on turmeric leaves, we have implemented a CNN with a remaining network structure. This is because turmeric leaves may have small areas of disease on their surface, and a deeper network structure can help to extract more features and more accurately identify these diseases. Though, if the network is too deep, the data about these features can be lost when it is passed between layers. To address this issue, we have added residual network structures in the 4th, 6th, and 7th convolutional layers of our model. These structures use a combination of 1x1 and 3x3 convolutional layers to extract features from the input image. By using smaller convolutional filters, we are able to reduce the number of parameters in the model and slightly improve the detection time. Additionally, by combining the feature maps produced before and after the residual structure, we are able to pass both light and deep data to the next convolutional layer, reducing the loss of feature information when transferring between layers and improving the overall detection accuracy of the model. The structure of our model is illustrated in Fig. 3.

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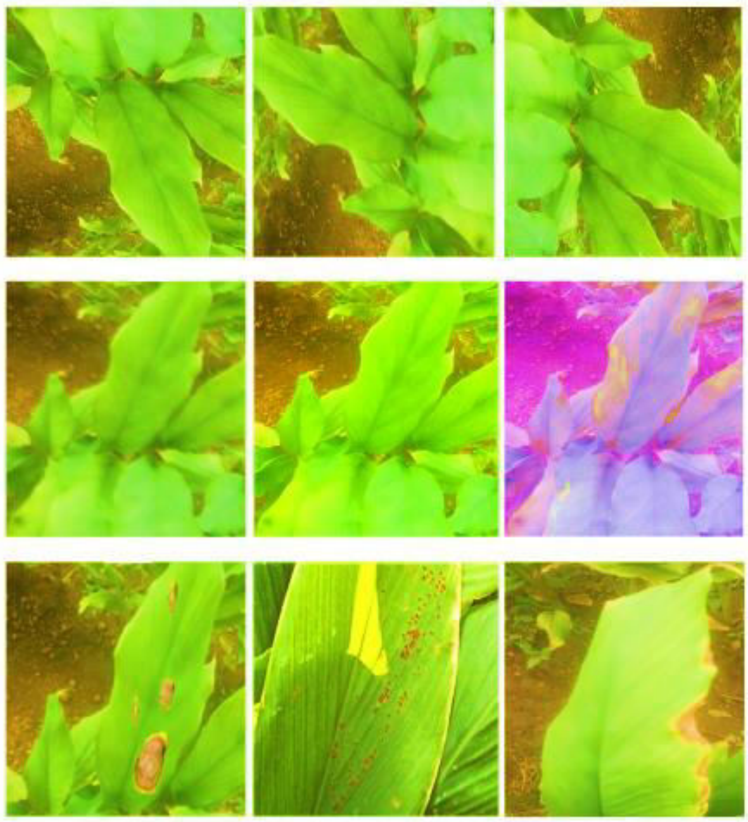

Fig. 2 Images of the turmeric plant taken for the experiment to identify disease

5. Result and Discussion

To evaluate the performance of our model, we use a range of metrics including precision, recall, detection speed, loss function, F1 score, and AUC. We can classify binary classification results into true positive, false positive, true negative, and false negative samples based on the comparison of the predicted class and the actual class. Precision is calculated by dividing the number of true positives by the total number of positive predictions made, while recall is determined by dividing the number of true positives by the total number of actual positive samples (TP/(TP+FN)). A P-R curve can be plotted by plotting recall on the x-axis and accuracy on the y-axis. The AUC, which measures the overall performance of the network, is calculated as the area under the P-R curve. The F1 score is obtained by taking the harmonic mean of precision and recall (F1 = 2 * P * R / (P + R)). Additionally, we use the IoU metric, which calculates the overlap between predicted and actual boundaries, to assess the accuracy of bounding box predictions. In this study, we compare the average detection time and real-time performance of various models.

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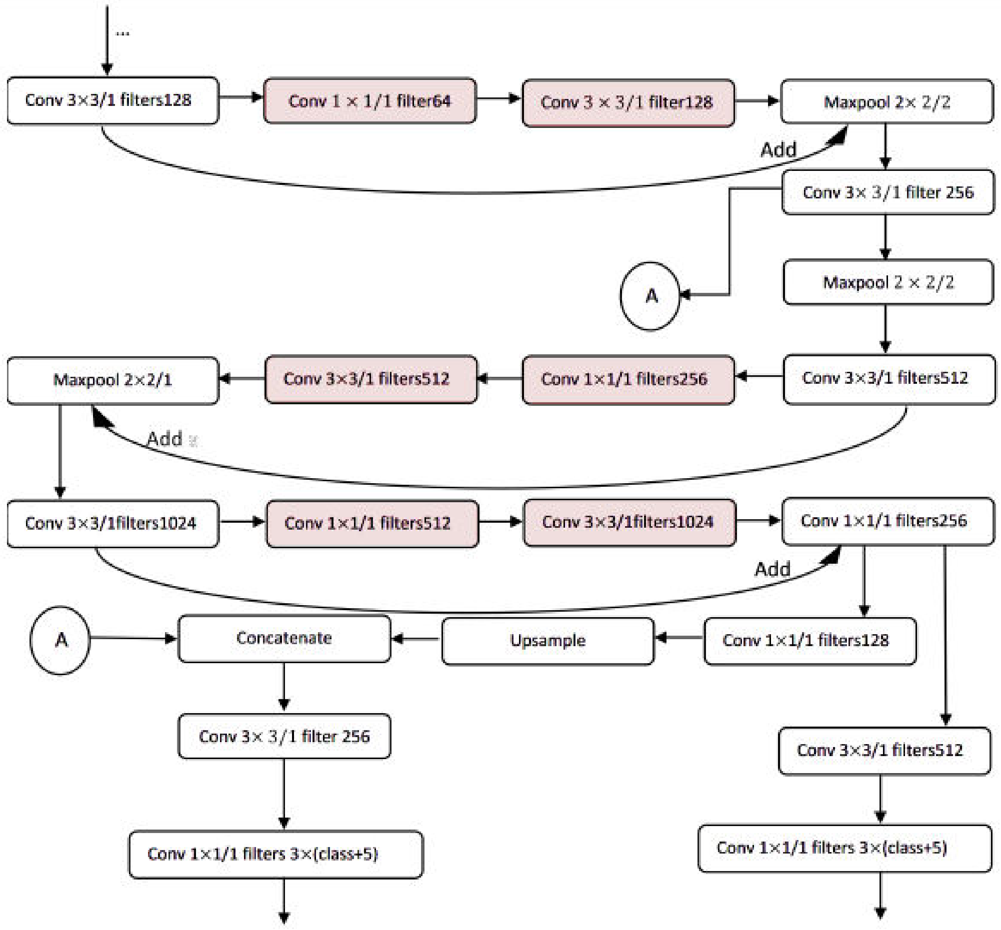

Fig. 3 Structure of the model

In summary, the proposed method for detecting diseases in turmeric leaf plants is founded on a CNN with a remaining network structure. The model is trained using image augmentation techniques and a combination of mix-up training information and transference learning. The performance of the model is evaluated using measures such as precision, recall, F1 score, and AUC, and the results show that the proposed method is effective at detecting diseases with a high level of accuracy. Overall, the proposed method represents a promising solution for detecting diseases in turmeric leaf plants.

5.1 Impact of cycle-GAN technique

In this research, we proposed a new method for detecting turmeric leaf diseases using a combination of image augmentation techniques and a CNN with a remaining network structure. By implementing color, angle, brightness, and Cycle-GAN transformations on our dataset, we were able to significantly improve the accuracy of our model. The Cycle-GAN method, in particular, stood out as an effective way to increase the diversity of our training data and improve the consistency of our detection model. Our results showed that using these augmentation techniques led to an 8.4% increase in detection accuracy, with more than 4% of that increase being attributed to the use of Cycle-GAN. Overall, our findings demonstrate the value of using image augmentation techniques to enhance the performance of machine learning models in detecting diseases in turmeric leaves.

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5.2 Comparison of results

In this study, we have compared the performance of our proposed model with several varieties of YOLO and Faster R-CNN with VGG16 net. The results of the loss function for all YOLO-based models can be seen in Figure 4, while Figure 5 illustrates the P-R curves for all models. Figures 6-8 provide visual examples of the detection results for each model across various diseases

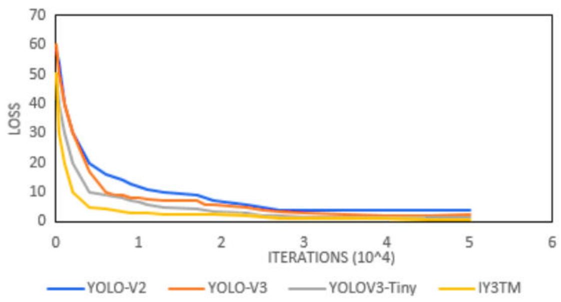

Fig. 4 YOLO model loss curves

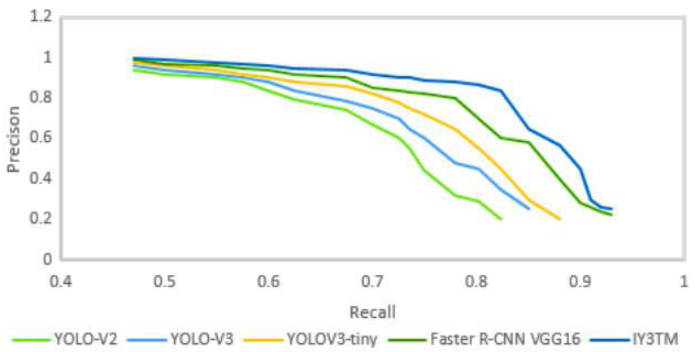

Fig. 5 PR curves of machine learning model

Fig. 6 leaf blotch disease identified from the image

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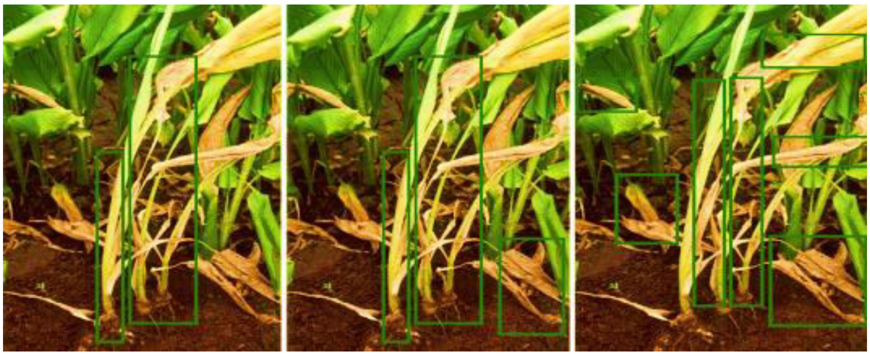

Fig. 7 Rhizome disease identified by the YOLO model

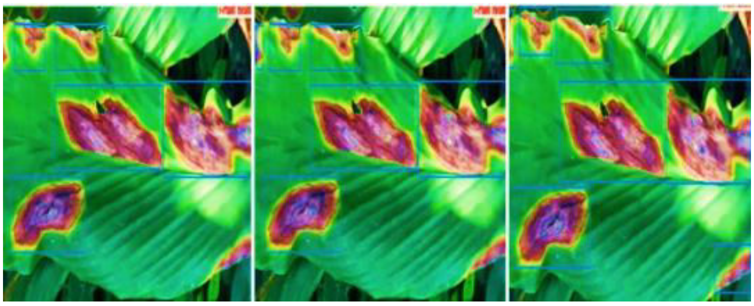

Fig. 8 leaf spot disease identified by the model

The proposed model, IY3TM, uses a combination of convolutional neural networks and residual network structures to detect turmeric leaf diseases with high accuracy. By analyzing the impact of dataset size on performance, it was found that the model's accuracy increases rapidly with the size of the training dataset, but beyond a certain point, additional data does not significantly improve the model's performance. Augmentation techniques, such as color, angle transformation, brightness, and Cycle-GAN, were also found to improve the diversity and consistency of the training dataset, leading to increased detection accuracy. When compared to other YOLO and Faster R-CNN models, IY3TM demonstrated superior performance in terms of loss, P-R curves, and detection results for various diseases. These findings highlight the effectiveness of the proposed model for accurately detecting turmeric leaf diseases.

CONCLUSION

The IY3TM model, based on a CNN with a outstanding network structure, is designed to accurately detect diseases on turmeric leaves. By using a combination of 3x3 and 1x1 convolutional layers, the model is able to improve feature propagation and reuse, leading to improved performance. To further enhance the model, images are captured under various conditions and augmented using techniques such as Cycle-GAN. Comparison with other machine learning models, including YOLO, and Earlier RCNN with VGG-16, shows that the IY3TM perfect has superior performance in terms of F1 score, detection speed, and AUC values. In particular, the inclusion of Cycle-GAN in the dataset results in a higher F1 score compared to other models. Overall, the IY3TM model demonstrates excellent potential for detecting diseases on turmeric leaves and has potential for future applications in detecting diseases in other crops.

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