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A Novel and Efficient Deep Learning Models for Assessing AI's Impact on Disease Diagnosis in Agriculture

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ABSTRACT

Background: Agriculture sustains human life by providing food, raw materials and employment opportunities. However, climate change and resource limitations pose significant challenges to crop production. AI-driven smart farming has emerged as a solution to enhance agricultural efficiency, with Explainable AI (XAI) improving transparency in decision-making. Innovations such as smart sensors and automated systems have benefited key agricultural sectors, including crops, forestry, livestock and aquaculture. Turmeric, valued for its medicinal and economic significance, requires careful monitoring to combat diseases like leaf spot and leaf blotch, which can impact yield and quality.

Methods: This study introduces turmeric net, a Convolutional Neural Network (CNN)-based model leveraging transfer learning to detect and classify turmeric leaf diseases. The dataset used consists of 791 original images and 3,702 augmented images obtained from mendeley data, categorized into four classes: healthy leaf, dry leaf, leaf blotch and rhizome rot. The model development was carried out using TensorFlow, with ResNet50V2 as a baseline for comparison. The models were trained on processed image data, incorporating augmentation techniques to improve robustness and generalizability.

Result: The accuracy of both models was evaluated. ResNet50V2 achieved an accuracy exceeding 99%, demonstrating high effectiveness in disease classification. Meanwhile, TurmericNet attained a competitive accuracy of 98%, making it a reliable alternative for turmeric disease identification. These results indicate that deep learning-based models can significantly aid in early disease detection, providing farmers with a valuable tool to enhance crop management and productivity.

Key words: Agriculture, Classification, Disease detection, Turmeric.

INTRODUCTION

Agriculture is a cornerstone of food security, economic development and employment across the globe. Despite its importance, the sector faces significant challenges including climate change, water scarcity and environmental degradation. Traditional farming practices contribute to issues like pollution and biodiversity loss, emphasizing the urgent need for sustainable solutions. In this context, smart farming technologies powered by Artificial Intelligence (AI) have emerged as transformative tools to enhance productivity while preserving ecological balance. AI supports real-time decision-making and efficient resource management, making it a vital component of modern agriculture (Mana *et al.,* 2024). The growing global demand for food has necessitated innovations that can maximize crop yields and reduce dependency on manual labor. AI-enabled technologies such as automation, precision agriculture and real-time analytics address critical issues like disease detection, pest control and irrigation. These advancements are instrumental in boosting productivity, especially in subsectors like crop farming, forestry, livestock and aquaculture (Mandal *et al.,* 2024). Additionally, AI-integrated sensors, robotics and autonomous systems improve resource efficiency and reduce the impact of climate variability (Elbasi *et al.,* 2023). By incorporating AI into agriculture, the sector aligns with the goals of Industry 4.0, fostering sustainable and data-driven farming practices.

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Among high-value crops, turmeric stands out for its extensive medicinal, culinary and pharmaceutical applications (Chinnadurai *et al.,* 2019; Khawale *et al.,* 2023; Kanjana *et al.,* 2016). However, turmeric cultivation is vulnerable to several foliar diseases, including leaf blotch, leaf spot and rhizome rot (Kobir *et al.,* 2024; Mondal *et al.,* 2024), which significantly compromise yield and quality. Traditionally, disease detection has relied on manual

observation, a method that is time-consuming, error-prone and lacks scalability. To overcome these limitations, researchers have increasingly turned to deep learning techniques, which enable automated and accurate disease classification using image analysis.

Khan *et al.* (2023) proposed a metabolic fingerprinting approach using Fourier Transform Near-Infrared (FT-NIR) spectroscopy to assess the quality and geographical traceability of Ocimum, turmeric and Withania somnifera. Machine learning models analyzed roots and leaves from multiple species and locations, achieving high classification performance (R^2>0.98, Q^2>0.97, accuracy = 1.0), with 100% sensitivity and specificity, confirming FT-NIR as a reliable tool for medicinal herb authentication. Khattab *et al.* (2022) employed NMR-based metabolite fingerprinting to study Curcuma, ginger and lesser and greater galangal. Using OPLS-DA modeling, they linked metabolic profiles to biological activity, including cytotoxicity against prostate and colon cancer cells and COX-1 inhibition. Lesser galangal showed strong anti-inflammatory effects due to kaempferide, while greater galangal exhibited the highest cytotoxicity, highlighting the therapeutic potential of the Alpinia genus within the Zingiberaceae family.

Selvaraj *et al.* (2024) proposed an AlexNet-based deep learning model for detecting turmeric leaf diseases, using a custom dataset containing leaf spot, blight, rot and curl conditions. The model achieved a high classification accuracy of 95.5%, outperforming traditional machine learning approaches. Similarly, Prabhu *et al.* (2024) developed the Smart Turmeric Farming Assistance System (STFAS), which employs a CNN-based model to identify leaf diseases such as spots and blotches from annotated images. The system enables automated, targeted fertilizer application, reducing manual intervention and enhancing large-scale disease monitoring, thereby promoting sustainable turmeric cultivation. Kannan *et al.* (2023) highlight the rapid spread and impact of leaf spot disease on turmeric. Their approach combines GLCM-based texture analysis and SFCM segmentation, with an LDA-ANFIS classifier that reduces entropy loss and achieves 98% accuracy in identifying leaf spot, leaf blotch and bacterial wilt. Patil *et al.* (2024) propose a single-phase detection model for Rhizome Rot using CNNs, VGG19 and a hybrid CNN-SVM framework, outperforming traditional multi-stage methods in accuracy and efficiency. Maithani *et al.* (2023) focus on eco-friendly disease management, evaluating bioinoculants, fungicides and fermented manure for Leaf Spot control, aiming to boost yield and sustainability. Sudharsan *et al.* (2024) utilize DeepLabV3+ with ASPP, Squeeze-and-Excite blocks and ResNet50 for semantic segmentation, achieving precise classification of space, disease and crops, showcasing its potential in automated crop monitoring and precision farming.

Mervin *et al.* (2024) developed a real-time turmeric monitoring system combining deep learning and fuzzy logic on Raspberry Pi, classifying leaves as healthy, diseased, or drought-stressed while dynamically adjusting environmental controls, achieving 95.47% accuracy. Pakruddin *et al.* (2024) presented the PomeNetV2-ResNet50V2 model for pomegranate disease detection, reaching 98% accuracy using an augmented dataset of 3,000 images and CNN-based feature extraction. Vanitha *et al.* (2022) applied ML and K-means clustering for fungal disease identification in turmeric, improving crop quality through efficient feature segmentation. Lastly, Rajasekaran *et al.* (2020) employed a VGG-16 CNN for early disease detection in plants, showcasing AI's role in improving crop yield and proactive farm management.

Despite promising results, existing studies on turmeric leaf disease detection are relatively limited in scope, often focusing on a small number of disease categories or employing generic CNN architectures without optimization for turmeric-specific features. There is a clear need for more specialized, scalable and accurate models that can handle multiple disease types. This study addresses the gap by developing a deep learning-based framework using both ResNet50V2 and a custom CNN model named TurmericNet. These models are designed to classify multiple turmeric leaf diseases with high precision, thereby supporting early intervention, reducing crop loss and improving productivity. Preliminary results show significant improvements in classification accuracy, highlighting the effectiveness of the proposed methodology.

The remainder of this paper is organized as follows: Section II details the materials and methods used in data collection, preprocessing and model development. Section III presents the experimental setup and results, followed by a discussion in Section IV. Finally, Section V concludes the paper with insights into future research directions.

MATERIALS AND METHODS

All the experiments were conducted at the Research Center named M.S. Ramaiah Institute of Technology, Bengaluru, in the academic year 2023-2024.

Dataset used

Between August and December 2024, 791 high-resolution photos were taken from turmeric plantations in Charpolisha, Jamalpur, with the assistance of an agricultural specialist. These photos, which were taken with an iPhone 14 Plus at 800×800 resolution in JPG format, are divided into four categories: Rhizome rot, leaf blotch, dry leaf and healthy leaf. Every image is carefully tagged to help with the classification and diagnosis of diseases. Data augmentation increased the number of Dry Leaf images from 203 to 812, Healthy Leaf from 197 to 985, Leaf Blotch from 199 to 995 and Rhizome Rot from 192 to 990 to improve model performance. This ensured a diverse and well-balanced training set for deep learning applications in the sustainable management of turmeric disease SIAM *et al.* (2024). Sample images are shown in (Fig 1).

Symptoms of the turmeric plant leaf disease

Dry leaf

In turmeric plants, dry leaf disease results in yellowing and browning of the leaf margins, which gradually spreads and makes the leaves brittle, twisted and cracked. Complete drying and early shedding are the results of severe cases. It reduces plant development by decreasing photosynthesis and is caused by fungus infections, environmental stress, or nutrient deficits. Its spread can be stopped with appropriate fertilization, irrigation and disease control (Babu *et al.,* 2018).

Healthy leaf

A robust, smooth, glossy, bright green leaf with distinct veins is a sign of good health. Its hue is consistent and free of wilting, discoloration, or stains. There are no indications of diseases, necrosis, or fungal growth and the leaf margins are still whole without curling or drying out. In addition to maintaining ideal chlorophyll levels, a healthy leaf promotes effective photosynthesis and general plant health.

Leaf blotch disease

In turmeric plants, leaf blotch disease starts as tiny, water-soaked lesions that grow into brown, necrotic patches with yellow rims. These patches combine as the disease worsens, resulting in early drying, wilting and curling of the leaves, which lowers photosynthetic efficiency. Defoliation and yield loss are caused by severe infections. For turmeric to be grown sustainably, early detection and management are crucial because the illness, which is caused by fungal infections, flourishes in warm, humid environments.

Rhizome rot disease

Turmeric leaves with rhizome rot disease begin to droop, wilt and become yellow at the base of the plant. The growth of infected plants is stunted and the rhizomes become mushy, wet and smell bad. Rhizomes break down and change from brown to black as the disease worsens. It is brought on by soil-borne pathogens and grows best in damp environments. For management, fungicidal treatments, crop rotation and adequate drainage are essential.

Pre-processing

The pre-processing step entails applying data augmentation techniques including shear, zoom, horizontal flips and shifts to boost model generalization and scaling images to 128×128 pixels to increase processing performance. The dataset is divided into training (80%) and validation (20%) sets after images are rescaled to standardize pixel values. To effectively feed the model in batches, the pre-processed photos are then loaded using a generator.

Feature extraction for the proposed model

To capture spatial hierarchies in images, the suggested model uses a CNN with many layers to extract features. A Conv2D layer with 32 filters and a 3×3 kernel is used first and then MaxPooling2D to lower dimensionality while keeping key characteristics. By identifying intricate patterns, two more convolutional layers with 64 and 128 filters-each followed by max pooling-further improve feature extraction. For improved representation, the retrieved features are subsequently flattened and run through a dense layer that contains 128 neurons and ReLU activation. Overfitting is avoided by a Dropout layer (0.3) and images are categorized into four groups by the last dense layer with softmax activation. The model is trained with categorical cross-entropy loss and optimized with the Adam optimizer. A summary of the proposed model is shown in Table 1.



Fig 1: Sample images of healthy and diseased turmeric plant leaves.

Data augmentation and parameters used for camera

To improve model robustness, a variety of transformations are used in the data augmentation approaches employed in the turmeric leaf dataset. Rotation was applied at a 90° clockwise angle and horizontal flipping was used to enhance image variety. To replicate various viewpoints, zooming was done between 0.8 and 1.2. To enhance model generalization, Gaussian noise was introduced, which has a mean of 0 and a standard deviation of 25. A factor range of 0.5 to 1.5 was used to produce brightness changes and images were height-shifted by 10% of their initial height. A more representative and varied dataset for deep learning applications was also ensured by applying shearing with a shear factor ranging from 0.1 to 0.5 (Pakruddin *et al.,* 2024).

Block diagram

Fig 2 depicts the proposed model architecture. At first, the dataset was gathered and supplemented with different parameters to improve diversity. The dataset was subsequently divided into 80% for training purposes and 20% for testing. The models were provided with the input dataset to evaluate their performance. When accuracy was less than ideal, the models underwent fine-tuning to enhance their performance.

Performance metrics

The performance of deep learning models is assessed with metrics such as Accuracy, Precision, Recall, F1 score and Support. These metrics shed light on different dimensions of how well the model works. Support reflects how often each class appears in the dataset, whereas the confusion matrix-comprising True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN))-is used to evaluate classification performance (Pakruddin *et al.*, 2024).

$$\text{Precision} = \frac{TP}{TP + FP} \quad ...(1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad ...(2)$$

$$\text{F 1- Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad ...(3)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(4)$$

RESULTS AND DISCUSSION

The classification report for the proposed TurmericNet and ResNet50V2 models over 50 epochs is shown in (Table 2). The ResNet50V2 model reached an overall accuracy of 80% and the F1 scores for different classes varied from 0.45 to 1.00. Conversely, the proposed TurmericNet model exhibited outstanding performance with an accuracy of 95%, attaining higher precision, recall and F1 scores for all classes, especially in identifying Leaf Blotch and Dry Leaf instances.

The classification report for the proposed TurmericNet and ResNet50V2 models over 100 epochs is shown in (Table 3). The ResNet50V2 model attained an overall accuracy of 99% and its class-wise F1 scores varied from 0.98 to 1.00. The TurmericNet model that was proposed achieved an accuracy of 98% and exhibited competitive performance, with F1 scores ranging from 0.96 to 0.99 for all classes. The outcomes underscore the efficacy of both

Table 1: Proposed turmericNet model architecture.

Layer type	Filter/units	Kernel size/Pool size	Activation function	Purpose
Conv2D	32	(3,3)	ReLU	Extracts low-level features such as edges and textures.
Max Pooling2D	-	(2,2)	-	Reduces spatial dimensions while retaining important features.
Conv2D	64	(3,3)	ReLU	Extracts more complex patterns and textures.
Max Pooling2D	-	(2,2)	-	Further reduces spatial dimensions to enhance feature selection.
Conv2D	128	(3,3)	ReLU	Captures high-level features for classification.
Max Pooling2D	-	(2,2)	-	Minimizes feature map size, improving computational efficiency.
Flatten	-	-	-	Converts 2D feature maps into a 1D vector for classification.
Dense	128	-	ReLU	Learns complex feature representations.
Dropout	0.3	-	-	Prevents overfitting by randomly dropping neurons during training.
Dense (Output)	4 (No. of classes	-	Softmax	Classifies input images into four categories.

Table 2: Classification report for proposed TurmericNet and ResNet50V2 models for 50 epochs.

Model	Class name	Precision	Recall	F1-score	Support	Accuracy
ResNet50V2 model	Dry leaf	0.81	0.91	0.86	162	80%
	Healthy leaf	0.64	1.00	0.78	197	
	Leaf blotch	0.91	0.30	0.45	199	
	Rhizome rot	1.00	1.00	1.00	182	
Proposed model TurmericNet	Dry leaf	0.96	0.96	0.96	162	95%
	Healthy leaf	0.90	1.00	0.95	197	
	Leaf blotch	1.00	0.87	0.93	199	
	Rhizome rot	0.97	0.98	0.98	182	

Table 3: Classification report for proposed TurmericNet and ResNet50V2 models for 100 epochs.

Model	Class name	Precision	Recall	F1-score	Support	Accuracy
ResNet50V2 model	Dry leaf	0.98	0.99	0.98	162	99%
	Healthy leaf	1.00	0.99	0.99	198	
	Leaf blotch	0.99	0.98	0.98	199	
	Rhizome rot	0.99	1.00	1.00	182	
Proposed model TurmericNet	Dry leaf	0.96	0.96	0.96	162	98%
	Healthy leaf	0.98	1.00	0.99	197	
	Leaf blotch	0.99	0.96	0.98	199	
	Rhizome rot	0.97	0.98	0.98	182	

Table 4: Training and validation accuracy/loss performance across epochs.

Epochs	Training loss	Training accuracy	Validation loss	Validation accuracy
10	0.1783	0.9749	0.2634	0.9324
20	0.0555	0.9814	0.2617	0.9351
50	0.0149	0.9961	0.2211	0.9565
100	0.0031	0.9991	0.1872	0.9811

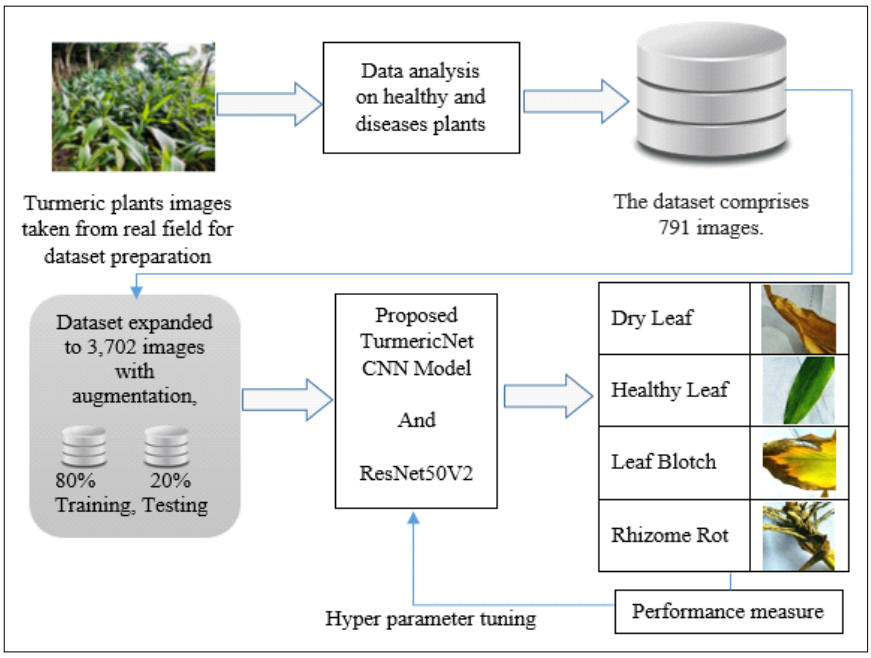


Fig 2: Proposed TurmericNet model architecture [12].

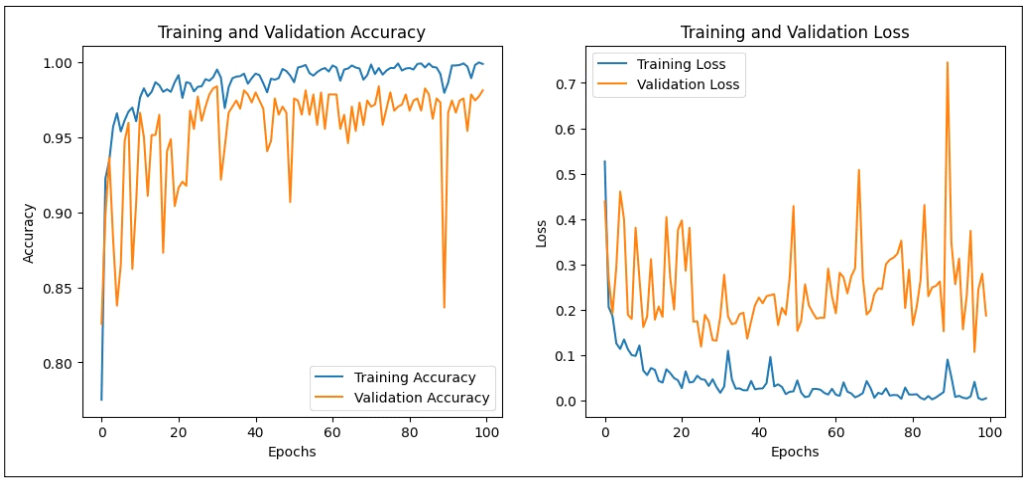


Fig 3: TurmericNet model: Accuracy and loss comparison curves for training and validation.

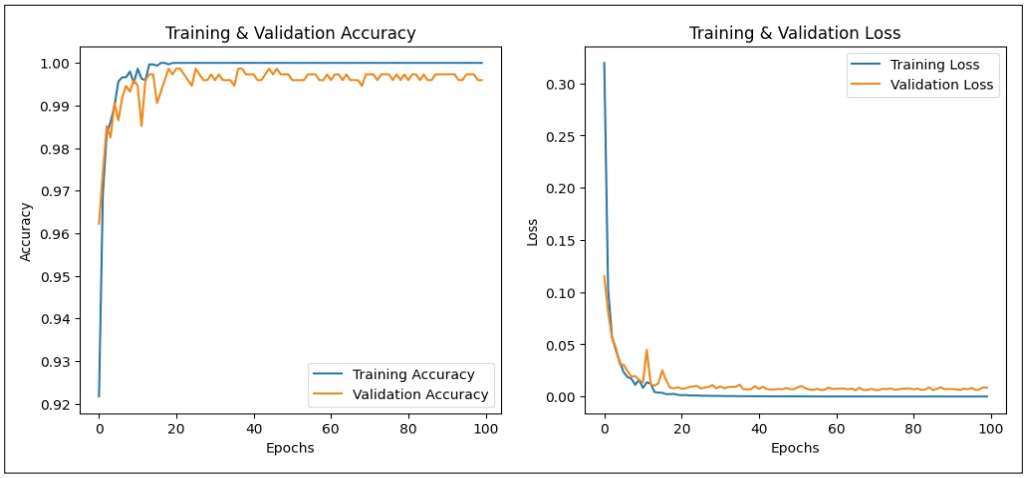


Fig 4: ResNet50V2 model: Accuracy and loss comparison curves for training and validation.

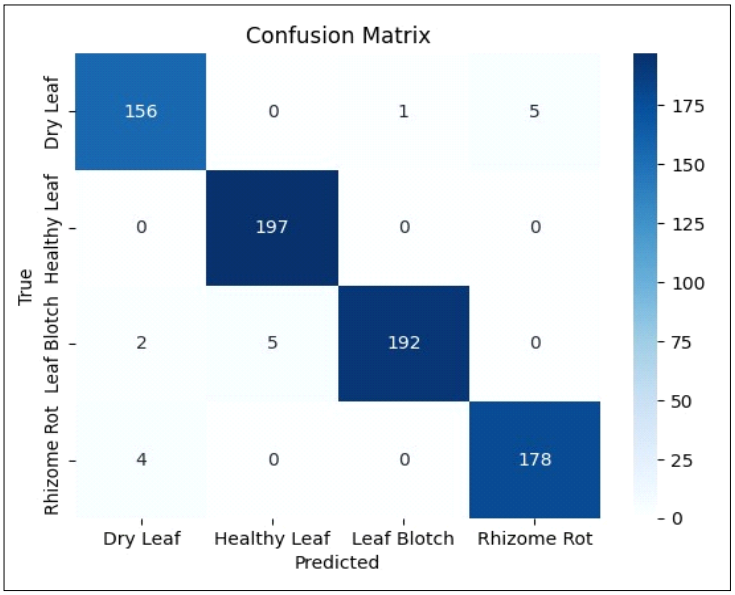


Fig 5: Confusion matrix for proposed TurmericNet model.

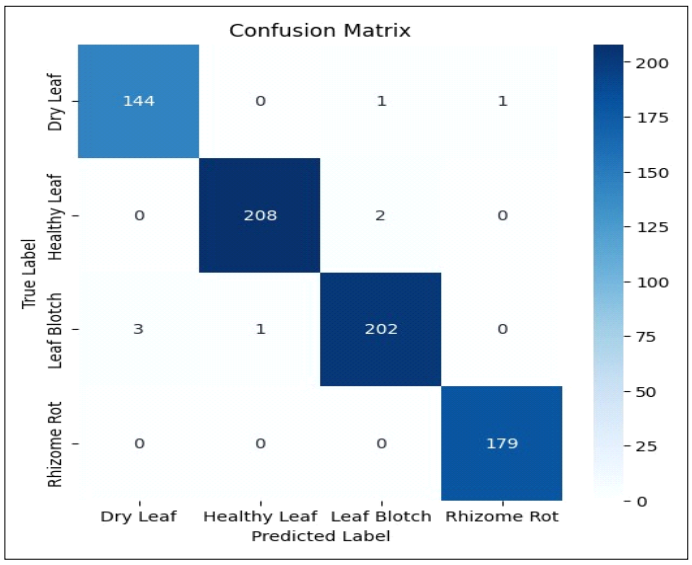


Fig 6: Confusion matrix for proposed ResNet50V2 model.

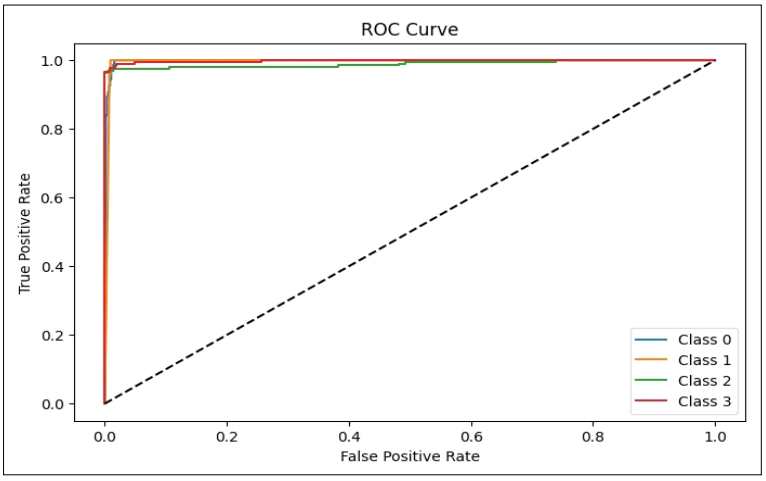


Fig 7: ROC curve for the proposed TurmericNet model.

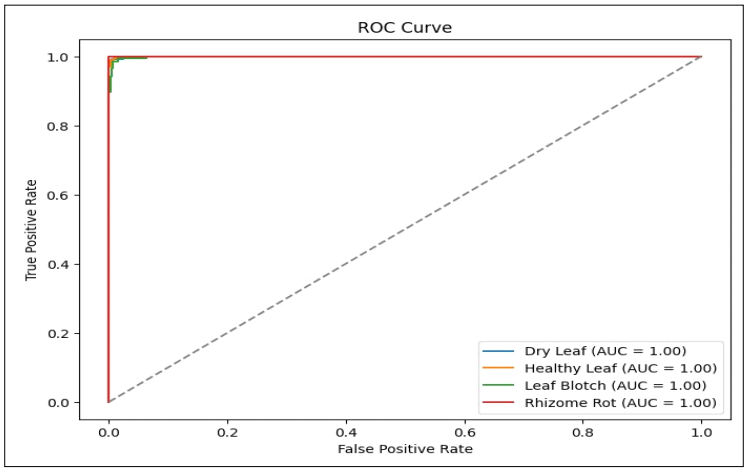


Fig 8: ROC curve for the proposed ResNet50V2 model.

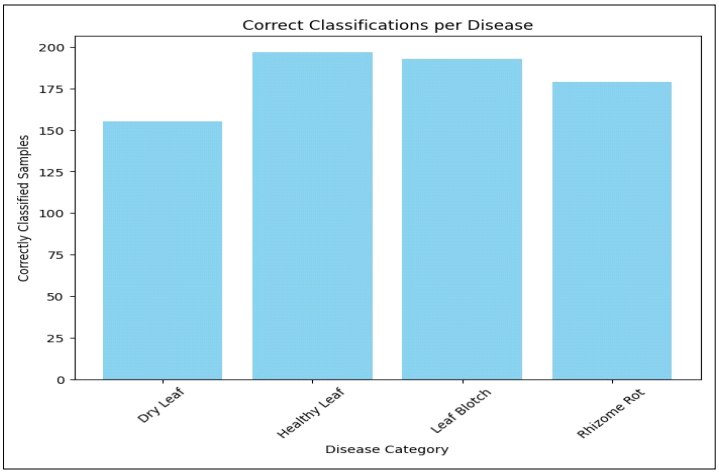


Fig 9: Correctly classified across various diseases.

models in classifying turmeric leaf diseases, with ResNet50V2 showing a slight edge over TurmericNet in terms of overall accuracy.

Table 4 shows the performance of training and validation accuracy/loss over the epochs. With the advancement of training, the training loss decreases from 0.1783 at epoch 10 to 0.0031 at epoch 100 and training accuracy rises from 97.49% to 99.91%. In the same way, validation accuracy rises from 93.24% to 98.11%, while validation loss drops from 0.2634 to 0.1872, indicating successful model learning and generalization.

The accuracy and loss curves for the TurmericNet and ResNet50V2 models are compared in Fig 3 and 4, respectively. The confusion matrices for the proposed TurmericNet and ResNet50V2 models are shown in Fig 5 and 6. ROC curves for both models are illustrated in Fig 7 and 8 and correctly classified samples from various diseases are depicted in (Fig 9).

CONCLUSION

In this study, the TurmericNet framework is presented as a robust and efficient solution for the automated detection and classification of turmeric leaf diseases. By combining advanced image pre-processing, augmentation, feature extraction and classification techniques, the system accurately identifies four key conditions: healthy leaf, dry leaf, leaf blotch and rhizome rot. TurmericNet achieves an impressive accuracy of 98%, while the benchmark model ResNet50V2 reaches 99%, highlighting the model's strong performance. Looking ahead, the development of a user-friendly Android application is planned to enable real-time disease detection and treatment guidance, further supporting farmers in enhancing turmeric crop health, yield and sustainability.

Conflict of interest

All authors declared that there is no conflict of interest.

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