AI-Driven Feature Extraction for Jute Leaf Disease Detection Using Enhanced Deep Learning

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Abstract. The application of intelligent image analysis in agriculture has improved early detection of plant diseases, helping prevent yield losses and limit infection spread. Jute, an important cash crop in Bangladesh, serves as an environmentally friendly raw material but is highly susceptible to leaf diseases such as cercospora leaf spot and golden mosaic disease, which reduce crop quality and yield. Despite advances in automated plant disease detection, limited research applies deep learning to jute leaf disease classification. Images showing symptoms of the two main diseases were grouped into a single diseased class for a binary classification task. This study addresses limitations of computationally complex ensemble methods by proposing an Enhanced ResNet50 model built on a pre-trained ResNet50 with additional convolutional, pooling, and dense layers for improved feature extraction and classification performance. The model was trained and evaluated on a curated dataset of 920 jute leaf images and compared with VGG16, VGG19, ResNet50, InceptionV3, and recent literature methods. The Enhanced ResNet50 achieved a high accuracy of 99.51% and demonstrated robustness and reliability through precision, recall, F1-score, and confusion matrix analysis. This approach enables early jute disease detection, supporting sustainable agriculture in Bangladesh. Future work includes external validation, interpretability analysis, and assessment on early-stage or mixed disease symptoms.

Keywords: Jute leaf disease, Plant pathology, Transfer learning, Image classification

1 Introduction

Jute, often referred to as the "golden fiber" of Bangladesh, plays an essential role in the nation's economy, contributing nearly 4% to GDP and generating around 5% of the country's export earnings in foreign exchange [7]. Bangladesh

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is responsible for about 33% of global jute exports. The country is second in global jute production [1]. Traditionally, jute fibers have been used in the manufacturing of various biodegradable and sustainable products. In some regions, particularly in West Africa, jute is also cultivated for its fresh leaves, which are consumed as a vegetable along with fiber production [10]. Regarding jute cultivation, one of the main challenges that the industry faces is the threat of diseases. Leaf infections such as golden mosaic disease and cercospora leaf spot can severely affect jute plant health, cut down yields and make it hard for the plant to produce at its best. These problems can start with the leaves and if not addressed, quickly spread to the rest of the plant and cause devastating damage. Nowadays, researchers have been investigating the use of neural networks to diagnose jute leaf diseases, and with promising accuracy and efficiency. Regarding Bangladesh's economy, agriculture has a huge impact and is basically what gets the country going, employing a significant portion of the people [9]. Among the crops that are grown here, jute is a real cash crop, both economically and ecologically important, but it's under threat from leaf diseases that affect not just the crops, but also the people who rely on them for a living. Well-known diseases such as bacterial blight, bacterial leaf spot, and fungal leaf spot can all severely impact the jute industry, and in turn can also affect the income of the farmers. Early diagnosis of these leaf diseases is the key to implementing control measures and getting the jute plants back on track. Regarding disease detection in crops [4], traditional methods require a lot of manpower and time, and are prone to human error.

However, emerging trends in AI and computer vision indicate that automated systems may soon become a much more viable and practical solution. Modern data-driven approaches have been applied successfully in different areas, including the detection of plant diseases from visual data. Despite their success, limited work [18] has focused on assessing how different CNN architectures perform in recognizing jute leaf diseases. Furthermore, some models are computationally heavy or lack robustness when applied to varied image datasets, thereby limiting their scalability in practical farming environments. This study tries to solve this problem by looking at how effectively four well-known CNN architectures, VGG-16, VGG-19, ResNet50, and InceptionV3, can tell the difference between illnesses in jute leaves. Also, a fine-tuned ResNet34 model is introduced to find a middle ground between fast processing and high classification accuracy. The model's highest test accuracy was 99.51%, which was better than all the other baseline models. There are two groups for the classification task: healthy leaves and diseased leaves. The sick category includes samples that have either Cercospora leaf spot or golden mosaic illness. To compare the models, we use metrics such as accuracy, precision, recall, F1-score, and confusion matrices. The most important actions we took for this work were:

- Development of an enhanced ResNet50 model for jute leaf disease classification.
- Achieving high accuracy using a single model without ensemble methods.

– Comprehensive comparison with state-of-the-art CNN models (including VGG-16, VGG-19, ResNet50, InceptionV3) and recent studies.

2 Literature Review

Plant disease diagnosis has historically mostly depended on specialist knowledge and human inspection, which can be laborious and error-prone. Recently, numerous publications have explored the use of computer vision and image processing methods for plant disease detection [5]. The general aims of such approaches are to improve the accuracy and efficiency in detecting as well as classifying disease-infected leaves, which would facilitate early intervention and better control of disease in agriculture. The following section discusses key contributions to the detection of disease in jute leaves. Dawei Li et al. proposed YOLO-JD, which is a deep tool specifically designed to detect pests of the jute plant and its leaf diseases [11]. Their approach incorporated advanced modules such as SPPM, SCFEM, and DSCFEM to improve feature extraction and contribute to reliable detection. Additionally, they provided unique information in the form of captioned photos of diseases and pests in jute that support further research in this area. Another work used CNNs to distinguish between yellow mosaic disease and chlorosis in jute leaves [2]. The input to the model was resized leaf images with 32×32 pixels, and it was compared with conventional machine learning methods such as KNN, Random Forest, and SVM. They reported the superiority of CNNs over handcrafted feature-based techniques, especially for fine-grained disease classification tasks. M. S. Uddin et al. proposed the JuLeDI architecture, which is a CNN model used for identification of jute leaf diseases like powdery mildew and yellow mosaic [17]. Their four-convolutional-layer architecture shows outstanding classification performance and is compared to the GPDCNN and the SVM-based classifiers. They further created a new dataset by capturing the diseased jute leaf images taken from various locations in the field, which provided more diversity in the data representation.

It is worth mentioning an advanced study that presented a federated learning-based CNN model to detect jute leaf diseases [15]. In contrast to the centralized training methods, their federated framework allowed for distributed learning over several data sources while upholding privacy. This feature is especially important in the agricultural industry, whose data comes from farmers who will likely be geographically distributed, and sharing or transmitting all their raw data may not be feasible. Inspired by large-scale dataset creation, Haque et al. produced a dataset consisting of 10,800 high-quality images of jute leaves, which were classified into three classes: Yellow Mosaic, Powdery Mildew, and Healthy [6]. Their fine-tuning based on the Inception V3 architecture boasts an extremely high classification accuracy of 99.98%, showcasing the capabilities of deep convolutional models with proper large-scale curation and data diversity. Similarly, Rajput et al. proposed the use of federated learning with CNNs for five different classes of jute leaf disease classification ([12]). Their system reaches 98% accuracy for classification, which substantiates the value of decentralized training methods for real-world agricultural use cases. In particular, their paper highlighted the importance of federated learning in cases with decentralized data and privacy issues preventing aggregation at a central location.

In general, these investigations have shown that deep learning, especially the architecture of CNN and federated learning frameworks, are promising techniques for automatically detecting jute leaf diseases. Nevertheless, scalability to more diverse datasets in terms of platforms and individuals, robustness under field conditions, and the creation of lightweight models for resource-constrained devices are still open questions.

Table 1 summarizes the comparison to state-of-the-art jute leaf disease detection, in which datasets used, models employed and accuracy for classification results in recent works are presented. The comparative study rejuvenates the weakness and potential of the state-of-the-art methods as well as provides a baseline for assessing how efficient the proposed method is. Through this review, we present the role of deep learning and its related versions in developing robust and scalable solutions for PDD by synthesizing knowledge of previous studies.

Table 1. Comparison of recent studies on jute leaf disease classification.

Ref.	**Dataset Name**	**Methods**	**Accuracy**
[17]	JuLeDI dataset	CNN	96%
[13]	Self-developed dataset	Federated Learning + CNN	98%
[4]	Self-developed dataset	Federated Learning + CNN	83.67%
[10]	Jute Leaf Disease	ResNet50	94%
[9]	Jute Leaf Disease	Ensemble(VGG16,CNN,ResNet50)	99.89%
Our Model	Jute Leaf Disease	**Enhanced ResNet50**	**99.51%**

In spite of all the research that has been carried out for the detection of jute leaf diseases, large numbers of them are based on ensembling or multiple models and techniques, which restricts them from exhibiting a significant performance with a single standalone model. In this study, to fill the gap, we introduce an improved model (ResNet50) that can provide promising and consistent classification results for jute leaf disease without using the ensemble technique.

3 Methodology

This section provides an overview of the end-to-end pipeline of the proposed jute leaf classification system. The four steps are illustrated in Fig. 1. It starts with data collection. Followed by preprocessing steps including cropping, resizing, and pixel normalization, the images are staged to be fit as input to deep learning. To enhance the model's generalization capability, we partition the dataset into two independent subsets for learning the model and testing it and implement several standard image augmentation methods (horizontal flip/rotation/brightness adjustment). Since data for jute leaves is not abundant, we employ transfer learning, where a pre-trained model extracts discriminative features along with a custom classification head. The findings are compared with other models, and a performance comparison is made based on accuracy, precision, recall, and the F1 score. This optimized pipeline offers a strong and accurate solution to diagnose jute leaf diseases. Figure 3 depicts the architecture layout of the Enhanced ResNet50 model, tailored for effective classification of jute leaf diseases. .

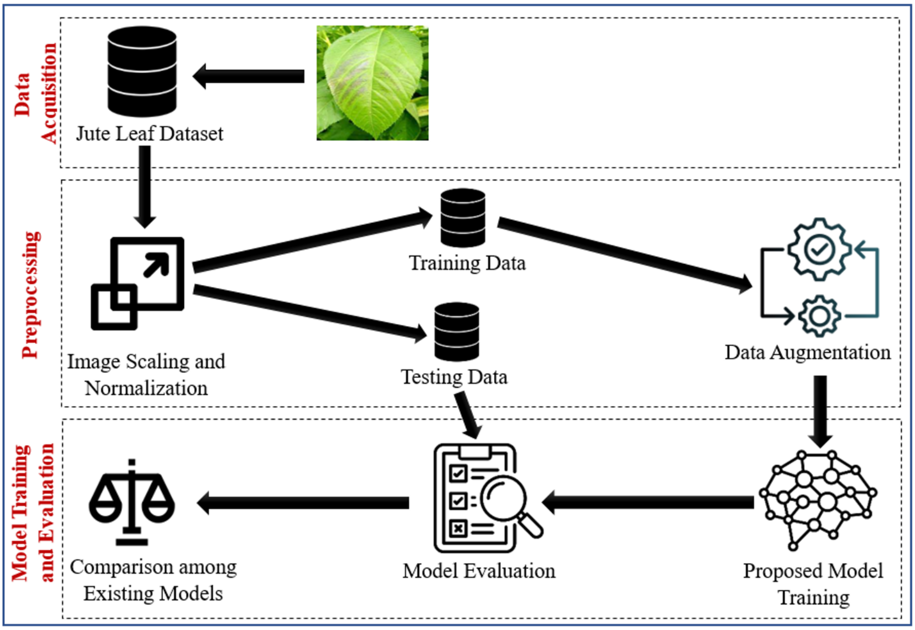

Fig. 1. The proposed approach's block diagram.

3.1 Dataset Acquisition

The Kaggle dataset [2] was used in this study, which consists of 920 color images of jute leaves categorized into Healthy, Cercospora Leaf Spot, and Golden Mosaic classes. In our experiments, we merged Cercospora Leaf Spot and Golden Mosaic as all one diseased class, and then the task became binary classification: healthy vs. diseased jute leaves. This set was separated into two parts: the training and test sets. For validation, out of the dataset, 410 images were reserved, and the rest, 510 images, were given to the trellis network. The training data set was further augmented to enhance model generalizability.

3.2 Data Pre-processing

To enhance training efficiency and ensure that the jute leaf image is compatible with deep learning models, a series of preprocessing steps are applied to each jute leaf image. Cropping removes the noisy background and highlights disease-related features by increasing the concentration of information in the leaf region. This is due to the fact that it can feed the input of CNN architectures that use 224×224 pixels to describe a fixed size, such as VGG16, ResNet, and Inception, among others.

Finally, min-max normalization is applied to make pixel values in$[0, 1]$. This makes for more rapid convergence during training and smooth gradient updates. Normalization is calculated as follows:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

3.3 Data Augmentation

Several data augmentation methods were used on the training set to improve generalization and lessen overfitting [3]. They included zooming (±20%), shearing (20%), vertical and horizontal shifts (up to 20%), and random rotations (±30°). To replicate different viewpoints, images were also rotated both vertically and horizontally. The empty edge regions produced during transformation were filled using nearest-neighbor interpolation. To improve performance on unseen data, data augmentation was applied, enabling the model to learn more robust and generalized features. As a result, the training set expanded from 510 to 1,700 images. To show this, data augmentation methods are displayed in Figure 2, which highlights the changes like rotation, flipping, and zooming that are used to improve the dataset

3.4 Model Architectures

We utilize advanced CNN-based architectures under a transfer learning framework to achieve effective classification of jute leaf images. These pre-trained models leverage features learned from large-scale datasets such as ImageNet, thereby enhancing classification accuracy and accelerating convergence. Below, we describe the models utilized in our study.

VGG16 The popular CNN with 16 weight layers is called VGG16. It utilizes max-pooling layers for spatial downsampling and tiny 3×3 convolutional kernels, followed by ReLU activations to add non-linearity [14].

Mathematically, if $f_{\text{VGG16}}(x)$ represents the convolutional base and x is the input image, the predicted output $\hat{y}$ is given by:

$$\hat{y} = \text{Softmax}\left(W_{\text{fc}} \cdot \text{Flatten}\left(f_{\text{VGG16}}(x)\right) + b\right) \tag{2}$$

where W_{fc} and b represent the parameters weights and bias associated with the final fully connected layer.

Original Image Horizontal Flip Vertical Flip Shifting

Original Image Rotation Shearing Zooming

Fig. 2. Data Augmentation

VGG19 VGG19 is an augmented variant of VGG16, with 19 weight layers [14]. It preserves spatial dimensions by using 3 × 3 convolutional filters with stride 1 and padding, just like VGG16. Its 16 convolutional layers compared to VGG16's 13 are divided by five max-pooling layers, which is the primary distinction. Every convolution is followed by ReLU activations, which add non-linearity.

For an input image x, the predicted output $\hat{y}$ using the convolutional base $f_{\mathrm{VGG19}}(x)$ is computed as:

$$\hat{y} = \mathrm{Softmax}\left(W_{\mathrm{fc}} \cdot \mathrm{Flatten}\left(f_{\mathrm{VGG19}}(x)\right) + b\right) \tag{3}$$

ResNet50 As a member of the residual network family, ResNet50 was developed to address the degradation problem caused by diminishing gradients in very deep architectures. It makes use of **residual connections**, which improve training very deep models by allowing direct gradient flow through identity mappings. A key element is the *residual block*, where the original input x is combined with the output of convolutional operations $F(x, \{W_i\})$ through a shortcut connection:

$$y = F(x, \{W_i\}) + x \tag{4}$$

To efficiently reduce and restore dimensions, ResNet50 uses *bottleneck blocks* made up of 1 × 1, 3 × 3, and 1 × 1 convolutions. This design makes the network suitable for extracting significant features from complex image data, such as diseased jute leaves, and enables it to reach 50 layers without experiencing performance degradation [8].

InceptionV3 *Inception modules* are used by the effective convolutional neural network InceptionV3 to capture spatial features at various scales. Each module pools the outputs, performs parallel convolutions with 1×1, 3×3, and 5×5 filters, and concatenates the results:

$$f_{\text{Inception}}(x) = \text{Concat}\left(f_{1\times1}(x), f_{3\times3}(x), f_{5\times5}(x), f_{\text{pool}}(x)\right) \tag{5}$$

It uses *factorized convolutions* (e.g., two 3×3 layers in place of 5×5 layers) and 1×1 convolutions for dimensionality reduction in order to optimize computation. For large-scale image classification, InceptionV3 is very effective thanks to these design decisions [16].

Proposed Enhanced ResNet50 Architecture We propose a tailored architecture for binary jute leaf classification, building on ResNet50's strength in feature extraction. Its original classifier head is swapped out for a more straightforward, effective design, but the pre-trained ResNet50 base is kept. As illustrated in Figure 3, the proposed model architecture integrates preprocessing, feature extraction, and classification to ensure robust jute leaf disease detection.

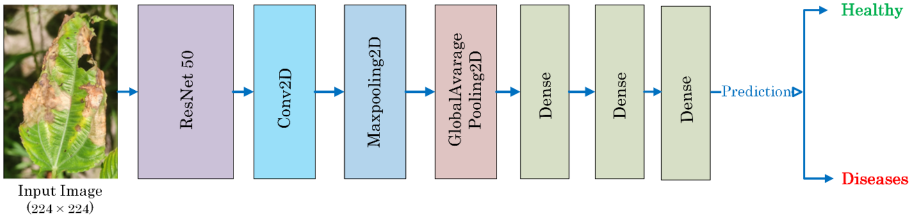

Fig. 3. The proposed Enhanced ResNet50 architecture block diagram.

Using a **Global Average Pooling (GAP)** layer to decrease spatial dimensions, the new head then uses a dense layer activated by ReLU to collect non-linear information. A dropout layer (rate = 0.5) helps avoid overfitting, and a final **softmax layer** creates class probabilities.

The definition of the forward pass is:

$$\begin{aligned} z &= \text{GAP}(f_{\text{ResNet50}}(x)) \\ h &= \text{ReLU}(W_1 z + b_1) \\ h' &= \text{Dropout}(h, p = 0.5) \\ \hat{y} &= \text{Softmax}(W_2 h' + b_2) \end{aligned} \tag{6}$$

This simplified architecture provides an efficient trade off between model complexity and generalization, which is especially advantageous for analyzing agricultural images when data is limited.

4 Result Analysis

The proposed Enhanced ResNet50 model's performance was compared to that of popular CNN architectures, including VGG16, VGG19, ResNet50, and InceptionV3, as well as findings from earlier studies that used the same dataset. The curated jute leaf image dataset used for training and testing all models was divided into two classes: **healthy** and **diseased**. Samples in the diseased class were impacted by *Golden Mosaic* and *Cercospora Spot.*Training was conducted over 30 epochs with input dimensions standardized to 224 × 224 and a batch configuration of 32 samples. The augmented training dataset consisting of 1,700 annotated images was further partitioned into 1,360 images for model training and 340 images for validation. The previously separated 410 images were retained for performance evaluation.

4.1 Model Evaluation

The performance of both the baseline and the proposed models in identifying healthy versus diseased jute leaves, particularly those impacted by Golden Mosaic and Cercospora Leaf Spot, was assessed using commonly applied metrics such as F1-score, precision, recall, and overall accuracy. To learn more about classification behavior, confusion matrices were also examined.

Accuracy The ratio of the correctly predicted samples (both positive and negative) to all predictions is called accuracy. It provides an indication of how often the classifier makes correct predictions. But when datasets are unbalanced and one class may predominate, accuracy by itself can be deceptive. It may be stated numerically as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Precision Precision is the ratio of true positives to positive instances anticipated. The higher the accuracy, the less chance of having a false positive for the model. It is especially critical in applications where false positives incur significant costs.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{8}$$

Recall Recall (sensitivity or true positive rate) is the ratio of the number of real positive samples that were classified correctly to the total number of real positive samples. High recall indicates that the model effectively captures most of the relevant cases without incurring too many false negatives vs. diseased on jute leaves.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{9}$$

F1-score In instances where the dataset is not balanced, the F1-score offers a more accurate measurement of performance than accuracy does since it takes into account both precision and recall concurrently. It is the harmonic mean of accuracy and recall, which guarantees that both metrics are in equilibrium with one another. The model is able to sustain both high accuracy and good recall when it has a high F1-score. It is defined as the following:

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

4.2 Results and Performance Comparison

In this paper, we provide a thorough investigation of the Enhanced ResNet50 model, as well as several baseline models, including some of the state-of-the-art structures for CNNs like VGG16 and VGG19, besides ResNet50 and InceptionV3. The evaluation is done based on the previously defined performance measures: accuracy, precision, recall and F1-score.

Table 2 presents the overall performance comparison of these models in relation to jute leaf disease classification accuracy. The Enhanced ResNet50 obtains the highest accuracy of 99.51%. This indicates its superiority compared to traditional VGG16, VGG19, and Inception V3 architectures. These results demonstrate that Enhanced ResNet50 is a robust and viable option for real-world implementation of an agriculture disease detection system.

Table 2. Performance comparison of different models for jute leaf disease classification.

Study	Model	Accuracy
[10]	ResNet50	94%
[9]	Ensemble (VGG16: 96%, CNN: 70.13%, ResNet50: 54.31%)	99.89%
This work	VGG16	97%
This work	VGG19	97%
This work	ResNet50	98%
This work	Inception V3	98%
This work	**Proposed Enhanced ResNet50**	**99.51%**

In terms of accuracy, precision, recall, and F1-score, Table 3 offers a thorough comparison of the various models used for the classification of jute leaf disease.

Confusion Matrix:A confusion matrix is a table of outcomes that users can use to see the whereabouts of actual versus predicted classes. Confusion Matrices Figure 4 shows confusion matrices of the Enhanced ResNet50 to visualize test determination results. These matrices provide evidence that the model can

Table 3. Detailed performance metrics of different models for jute leaf disease classification.

Model	Prediction	Precision	Recall	F1	Accruacy
VGG16	Diseased	97%	97%	97%	97%
	Healthy	97%	97%	97%	
VGG19	Diseased	97%	97%	97%	97%
	Healthy	97%	97%	97%	
InceptionV3	Diseased	98%	98%	98%	98%
	Healthy	98%	98%	98%	
ResNet50	Diseased	97%	100%	98%	98%
	Healthy	99%	97%	98%	
Enhanced ResNet50	Diseased	**100%**	**100%**	**100%**	**99.51%**
	Healthy	**100%**	**100%**	**100%**	

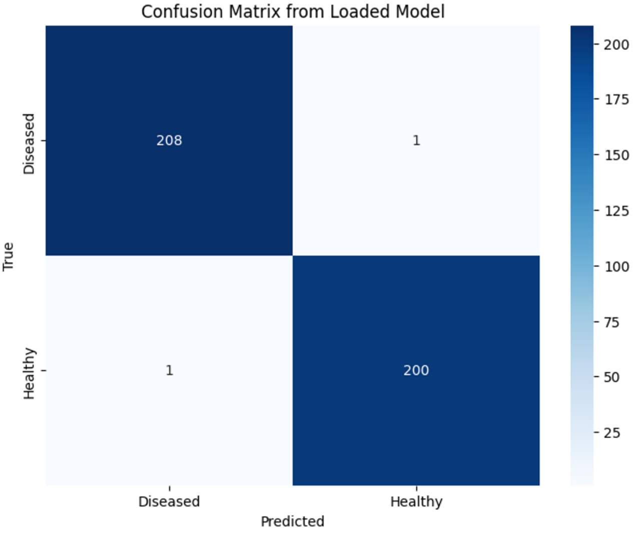

Fig. 4. Confusion matrices of Enhanced ResNet50 for jute leaf classification.

distinguish between healthy and diseased classes by illuminating true positive, true negative, false positive, and false negative.

ROC: The model's excellent discriminative ability is also evidenced by the ROC curve, which shows an AUC score of 1.00 in Figure 5. The ideal ROC curve showed that the model can perfectly separate between diseased and healthy jute leaves. Such performance demonstrates high sensitivity and specificity, and the method is very reliable for practical disease diagnosis.

Overall, the comprehensive evaluation—encompassing confusion matrices, classification metrics, and accuracy demonstrates that the proposed Enhanced ResNet50 model effectively overcomes the limitations observed in prior studies. By achieving high accuracy without dependence on ensemble techniques, the model offers a robust and reliable approach for classifying jute leaf disease, a capability that is essential for ensuring timely and accurate disease diagnosis. thereby supporting improved agricultural disease management practices.

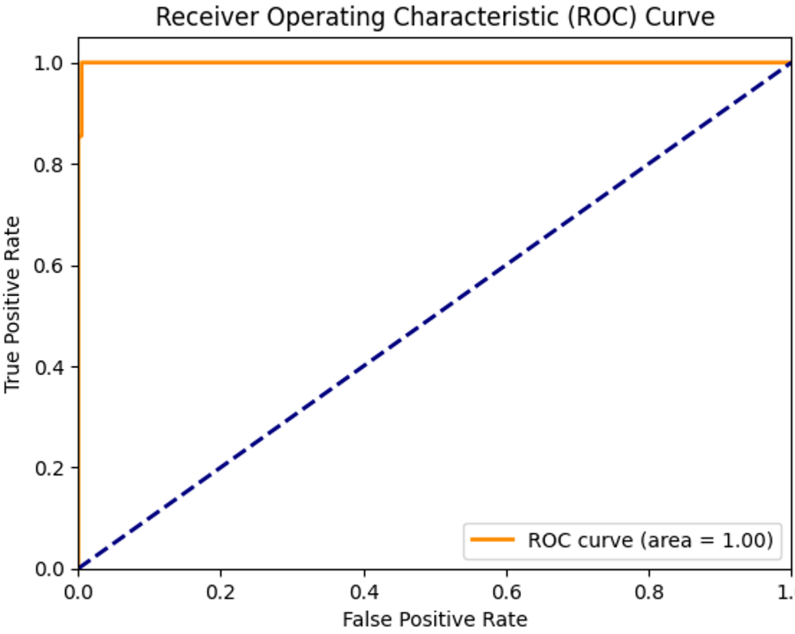

Fig. 5. Proposed customized ResNet50 ROC

5 Conclusion

This work introduces a dependable and efficacious approach for diagnosing diseases of jute leaves by using the newly introduced Enhanced ResNet50 model. Jute is an important plant in Bangladesh because it provides such a significant raw material to its economy for the construction of ecologically friendly and sustainable products. But, there are diseases like GMD (Golden Mosaic Disease) and CLS (Cercospora Leaf Spot), which considerably affect the quality and yield of the produce. Although previous studies have obtained promising results by various models and methods, many methods are based on federating multiple models that usually leads to increasing computation complexity and resource requirements. To address these limitations, we adopt the Enhanced ResNet50 model for processing a large amount of visual data with great accuracy and computational efficiency. Our model offers a scalable approach to automated disease diagnosis, as it was able to accurately distinguish between healthy and infected jute leaves. However, it has not been tested on mild or mixed syndromes and not validated in external datasets. Additional scrutiny is also needed for interpretability mechanisms such as Grad-CAM and real-time deployment efficiency.

In the future, we intend to mitigate these limitations by gathering richer datasets, embedding the explainable AI approaches, and making additional optimizations for deploying in lightweight real-time on-field situations. All these improvements will make the model even more practical and reliable for managing this disease in agriculture.

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