Transformer-Based Approach for Jute Leaf Disease Detection and Classification

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Abstract. Jute (Corchorus spp.) is one of the most important fibre crops for Bangladesh and many tropical countries. However, its production often suffers from leaf diseases such as insect holes, yellowing, Cercospora leaf spot, and phosphorus deficiency. Farmers usually identify these problems by visual inspection, which can be slow and sometimes inaccurate. In this work, we developed and tested a machine learning system that can classify jute leaf conditions from images. Our dataset contained 2,620 original field images across five categories, which we expanded to 17,500 images through augmentation to improve balance and robustness. We compared several models, including Vision Transformer, ConvNeXt, Swin Transformer, MobileNet, DenseNet121, VGG, and graph-based hybrids. The Vision Transformer model gave the best results, reaching 99.85% validation accuracy and high precision, recall, and F1-scores, followed closely by ConvNeXt and Swin Transformer. These findings suggest that transformer-based networks can reliably detect jute leaf diseases, making them suitable for practical tools such as mobile-based early warning systems for farmers.

Keywords: Cercospora, Phosphorus Deficiency, Vision Transformer, Swin Transformer, ConvNeXt

1 Introduction

Jute has a special place in Bangladesh; Since independence, the jute sector has been considered important only for this country's economy and culture. Bangladesh is one of the largest producers in the world; its economy significantly depends on this plant and a golden fibre that is obtained from it. Jute is used in various industries, from the tailoring industry to packaging. Regrettably, this plant faces several problems. Like other crops, Jute is susceptible to diseases, with particular harm done to it by fungi and bacteria that infect the leaves. Such diseases can reduce the volume and quality of the harvest, which

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can have an impact on the life of the farmers and the overall economy of agriculture. The problem of early detection of such diseases has always been one of the difficulties; often, farmers diagnose problems by visible damage, but the early stages can retain the quality of the plant and spread uncontrollably. Technology also solves this problem; this plant can be identified more precisely with the help of machine learning, particularly through deep learning models. They give even greater precision than is realized by human vision, and this allows for the time of treatment. It is important to note that, despite the potential of this technology, the classification of jute leaf diseases has not been given serious attention. Our article covers this gap and seeks to show its value. The main goal of the study is to use the most advanced algorithms of the Vision Transformer, ConvNeXt, and Swin Transformer series to identify and classify jute leaf diseases. The study should compare the best models with other models, such as MobileNet, DenseNet, and ResNet, to determine the best equipment to identify jute leaf diseases from the available classic models. Chlorosis and blighting agents, Phosphorus deficiencies are the most common problems from the many Jute is one of the types of the dataset, including original images and expanded images. The dataset includes more than one hundred images to ensure that the material is sufficient to provide enough information for learning techniques MESSAGE_TEXT: Detect. These tools can not only improve the density of waste material but can also help visualize the crop. At the same time, early detection contributes to improved planting density. The results can be a higher yield for the farmers and help to make jute farming more sustainable for the future. This paper will review the methodology, training the model, and research results, which should be interesting to those interested in how AI can influence agricultural activities, especially in the context of jute farming in Bangladesh.

2 Related Works

Apart from disease detection and classification, deep learning is well used in various agricultural image analysis tasks. Previous studies had investigated it for its application to plant diseases in general and jute in particular. Rahman et al. [1] investigated jute leaf disease identification using MobileNetV2, ResNet50, and an ensemble model, achieving high classification accuracy through transfer learning and data augmentation.

Similarly, Li et al. [2] proposed YOLO-JD, a custom deep learning network for jute disease and pest detection, reporting a mAP@0.5 of 96.63%.

Talukder et al. [3] developed JutePestDetect using DenseNet201 and other CNN architectures, with DenseNet201 achieving 99% accuracy. Beyond jute, Chowdhury et al. [4] and Abade et al. [5] reviewed the role of deep learning—particularly CNNs—in plant disease detection, identifying emerging trends and research gaps. Kumar et al. [6] introduced a Federated Learning CNN to address data privacy while maintaining scalability.

Yao et al. [7] proposed the GSMo-CNN, achieving state-of-the-art performance on benchmark plant disease datasets, while Hanbay et al. [8] combined deep feature extraction with SVM/ELM to improve accuracy over standard transfer learning methods.

Reza et al. [9] studied the detection of jute stem diseases using a mobile application that makes use of hue-based UI Image segmentation, texture features via color co-occurrence matrices, and multi-class support vector machines (SVMs) to classify five major jute stem diseases with accuracy up to 86% by means of an automatic image processing and server-side analysis. A concise summary of these works is presented in Table 1.

Table 1. Summary of Key Studies on Jute Leaf Disease Detection

Reference	Model(s)	Performance
Rahman et al. [1]	MobileNetV2, ResNet50, Ensemble	High classification accuracy
Li et al. [2]	YOLO-JD	mAP@0.5 of 96.63%
Talukder et al. [3]	DenseNet201, other CNNs	DenseNet201 achieving 99% accuracy
Chowdhury et al. [4]	Review of CNNs	Emerging trends
Abade et al. [5]	Review of CNNs	Research gaps
Kumar et al. [6]	Federated Learning CNN	Scalability
Yao et al. [7]	GSMo-CNN	State-of-the-art
Hanbay et al. [8]	Deep features + SVM/ELM	Improved accuracy
Reza et al. [9]	Hue segmentation + GLCM + SVM	86% accuracy
Tanny et al. [10]	DERIENet (deep ensemble CNN)	High accuracy in real-field conditions
Jannat et al. [11]	Lightweight CNN + semi-supervised	98.95% (supervised), 97.89% (10% labels)
Islam et al. [12]	Modified DCNN	High classification accuracy
Joyee et al. [13]	GLCM + hue segmentation + SVM	Mobile app integration
Lavanya et al. [14]	Multi-SVM + texture features	Improved detection accuracy
Hasan et al. [15]	Custom CNN	96% accuracy

Tanny et al. [10] proposed DERIENet, a deep ensemble learning framework that combines multiple CNN models to detect jute leaf diseases, achieving high accuracy by using advanced feature fusion, extensive data augmentation, and a large curated dataset to improve reliability in real-field conditions.

Jannat et al. [11] proposed a lightweight CNN that uses modified depth wise-separable convolutions, enhanced squeeze-and-excite and MBConv blocks combined with a confidence-regularized semi-supervised self-training framework to classify jute leaf diseases (Cercospora leaf spot, golden mosaic, healthy), attaining 98.95% accuracy in the supervised setting and 97.89% with only 10% labeled data; the model is compact

(≈2.24M parameters), uses Grad-CAM for explainability, and was deployed as a Flask web app for real-time use.

Islam et al. [12] developed a deep learning–based method for detecting jute leaf diseases using a modified DCNN model. Their system used image preprocessing and data augmentation to improve feature extraction, achieving a high classification accuracy. The study showed that deep neural networks can reliably identify jute leaf diseases from leaf images.

An automated system for detecting jute disease was proposed by Joyee et al. [13] using GLCM texture features and hue-based segmentation. Using an SVM model, they successfully classified five major jute diseases. To assist farmers in receiving prompt disease diagnosis, their system was integrated with a mobile app.

Lavanya et al. [14] highlighted the importance of machine-learning-based on image processing for identifying jute stem diseases, focused on segmentation and texture-feature analysis for reliable detection. Previous studies using hybrid models such as GWT-GLCM and Faster R-CNN exhibited improved accuracy in plant disease classification. Deep learning approaches like CNNs further advanced automated crop-disease identification, offering higher precision and robustness across diverse plant species.

Hasan et al. [15] developed a CNN-based jute leaf disease recognition system to classify Chlorosis, Yellow Mosaic, and healthy leaves. Their model used 600 images and acquired 96% accuracy without requiring manual preprocessing or handcrafted feature extraction. The study demonstrates that deep convolutional architectures significantly quit traditional ML methods like SVM, KNN, and RF for jute disease identification. We apply real-life datasets regarding conditions in jute leaves, which assist our machine learning models in classifying and diagnosing jute leaf diseases more precisely.

3 Methodology

The proposed methodology for the detection and classification of Jute leaf disease involved a multi-stage pipeline including data acquisition, data processing and augmentation, model selection, model training, and model evaluation. The overall workflow is illustrated in Fig. 1.

3.1 Data Acquisition

In this study, we developed a jute leaves disease image dataset containing 2,620 original images (224×224 pixels) collected from May 2025 to August 2025 at the two principal destinations in Bangladesh: the Chandpur district and the Savar—Daffodil International University area. Including: Healthy Leaves, Insect Hole Leaves, Yellowing (chlorosis), Cercospora Leaf Spot (Advanced Stage) and Phosphorus Deficiency. Those shots were captured under natural daylight and at night to offer a feel for different light, texture, and colour scenarios. They were taken using devices like Samsung Galaxy A53, Samsung Galaxy A23, and some high-resolution equipment. In this dataset, all images are in a square size (1:1). We apply real-life datasets regarding conditions in jute leaves, which assist our machine learning models in classifying and diagnosing jute leaf diseases more precisely. Sample dataset presented in Fig. 2.

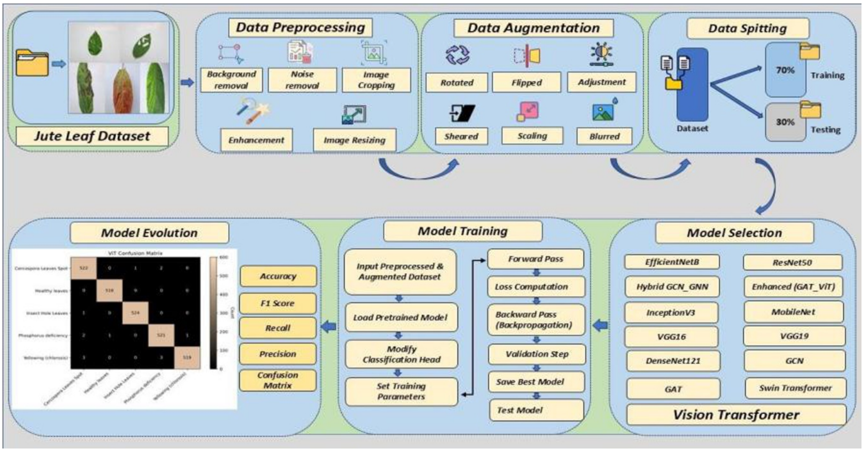

Fig. 1. Proposed workflow of the Methodology for Jute Leaf disease Classification and Detection.

3.2 Data preprocessing

To make our dataset more consistent for the Deep- Learning model, we employed specific preprocessing techniques. Every picture was preprocessed by removing the background, adjusting the brightness and contrast, and resizing it to a fixed size and aspect ratio (1:1). These actions enhanced model readiness, decreased noise, and enhanced feature visibility.

Table 2. Jute leaves dataset details before and after augmentation.

Class Name	Original Images	Augmented Images
Healthy leaves	787	3,500
Insect Hole Leaf	580	3,500
Yellowing (chlorosis)	339	3,500
Cercospora Leaf Spot (Advanced Stage)	608	3500
Phosphorus deficiency	306	3,500
Total	2,620	17,500

3.3 Data Augmentation

After preprocess the images, we applied augmentation on the dataset to expand the size of dataset for model robustness such as Rotation (±45 degrees), Horizontal and vertical flipping, brightness and contrast adjustment, Gaussian blur, shearing, zooming up to 1.5×, and the addition of random pixel noise.

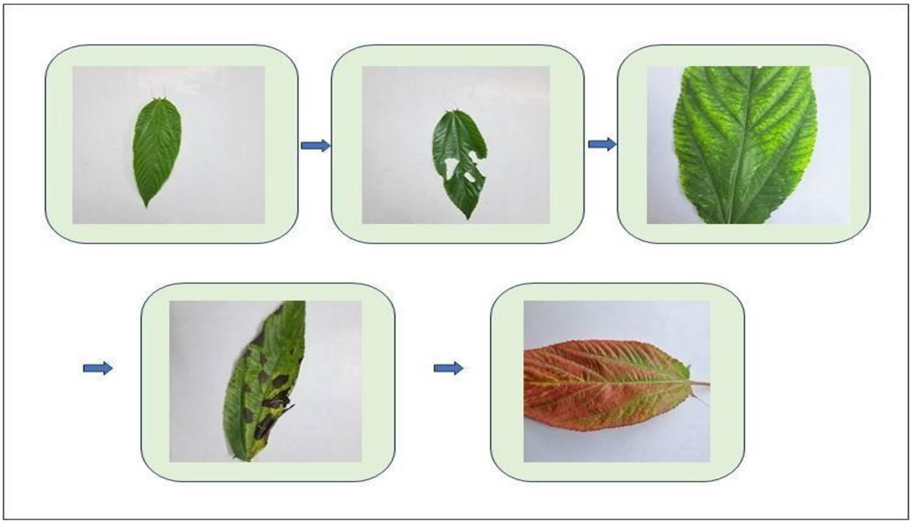

Fig. 2. Jute Leaf Dataset. Sequentially, Healthy leaf, Insect Hole, Yellowing (chlorosis), Cercospora Leaf Spot (Advanced Stage), Phosphorus Deficiency.

All augmented images were saved in JPEG format with a 1:1 aspect ratio. Each class was augmented to make sure the dataset is balanced and ensure better generalization during model training. The number of images before and after augmentation is provided in Table 2.

3.4 Model Architecture

ConvNeXt is a modern CNN that got re-engineered using some of the advances made in Vision Transformers (ViT). This is mainly because of its usage of 7×7 kernels and depth wise convolutions for low cost, but hierarchical feature extraction which will capture more image with same units yielding high performance. It improves upon the basic CNN blocks, reaches high accuracy comparable to Transformers and achieves it in a fast and CNN-like manner.

Swin Transformer is a Vision transformer model that breaks images into non-overlapping windows for computing self-attention within these localized regions. The swin transformer also introduces a new method called the “shifted window”. Neighboring windows can interact with each other in deeper layers, thus enabling to gather both local and global features of an image.

GAT_ViT is a composite model of Vision Transformers (ViT) and Graph Attention Networks (GAT), called Enhanced GAT_ViT. Also extract features from image patch and transforming them to nodes of the Graph by ViT. A GAT at- tention mechanism captures the connections between these nodes to detect sequential patterns. This helps the model to use irregular and detailed image features.

CNNs designs like Mobilenet are designed for computer vision applications i.e. object detection or image classification etc. The family of CNNs to innovate this model

MobileNet is a lightweight Convolutional Network intended for mobile and embedded devices. This depth wise separable convolutions architecture used in model can identify jute leaf disease in real time and fit for the field since reduces computing cost, without compromising accuracy.

Hybrid GCN_GNN takes multi-layer structure from Graph Convolutional Networks (GCN) and also extra graph-based neural layers. GCN for local node embeddings and GNN for capturing broader, more complex graph structure-based connections. CNNs' features are transformed to node information, and the links between nodes can be based on visual or spatial similarity. Fig. 3 shows the architecture of the Vision Transformer model, illustrating its key components and data.

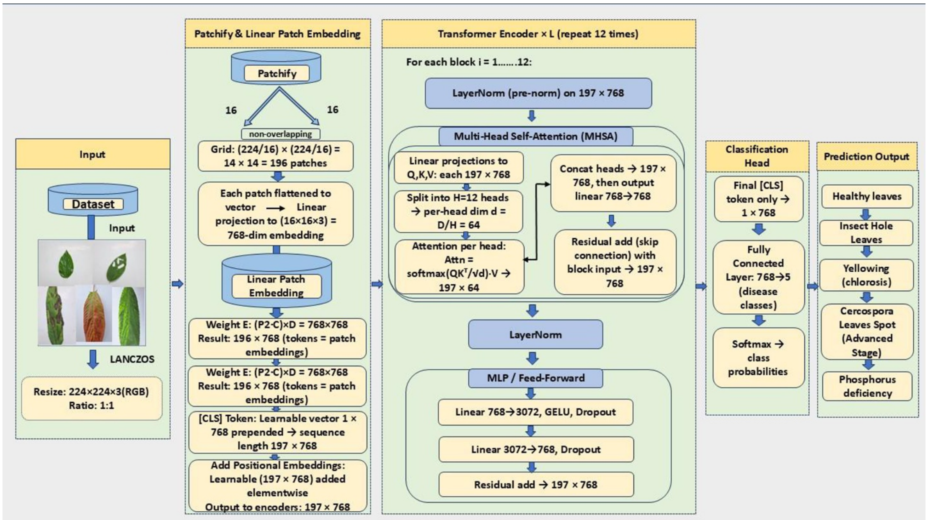

Fig. 3. Architecture of Vision Transformer Model.

GNNs are neural networks designed to operate on graph-structured data, in which nodes represent entities and edges correspond to relationships. Unlike in CNNs or MLPs, GNN can deal with irregular data structures, such as social networks, molecular graphs, or relational data present in both plant and medical datasets. GNN learns the node embeddings that not only capture the node's attributes but also summarize the structure of the graph. Each node updates its features by aggregating its neighbors, thereby allowing the network to capture local and global context. This is achieved through message passing, aggregation, and non-linear updates, and multiple GNN layers propagate information across the graph. Some of the strong points of GNNs are that they can handle non-Euclidean data, model local and global relationships, and support tasks such as node classification, link prediction, and graph-level classification. In this work, GNNs are used to model relationships among extracted features in order to improve the accuracy and robustness of plant disease detection and medical image analysis.

The idea behind the DenseNet (from the paper) is that every layer receives an additional set of inputs from each preceding layer. This design makes it easier for the network to reuse features and pass information between layers, leading to more structured representations.

A Graph Convolution Network (GCN) is a class of neural networks, specialized for handling learned on graph- structured data. The model sums the node features representation of this approach according to graph structure, capturing local topological patterns for classification. Non- Euclidean data: Since GCN can work with non-Euclidean data, it makes it popular in social networks, molecular structures or recommendation systems.

GATs are an extension of GNNs to incorporate an attention mechanism for weighting the importance of neighboring nodes. Unlike the standard GNNs, which treat all neighbors equally, GATs assign learnable attention scores to each neighbor. This allows the network to focus on the most relevant relationships. Attention scores are computed and normalized for each node to aggregate the features of its neighbors. Then, the aggregated neighbor features are combined with the node's own features and passed through a non-linear transformation for updating the node embedding. In this way, GATs can take care of graphs with varying connectivity and allow highlighting the important interactions. GATs improve feature representation and interpretability since the attention scores indicate the significance of neighbors. In this research, the GATs can enhance the learning of relationships between the extracted features, leading to improving the accuracy for plant disease detection and medical image analysis tasks.

VGG16 and VGG19 are deep CNNs which consist as large number of filters stacked together (small convolutional filter 3×3); although computationally expensive but yields consistent performance in feature extraction.

EfficientNetB0 provides a scaling method, where the depth, width, and resolution are increased at the same time, with all layers uniformly scaled to be fast and accurate. It has feature layers that represent the most important features of an image and can help improve execution.

ResNet50 is a deep convolutional neural network (CNN) for image classification that was introduced in Kaiming He et al. and has won the first place on ILSVRC 2015 Image Classification Challenge. It contains a set of 50 convolutional layers with smaller filter sizes as compared to AlexNet or VGG model, which come in handy when improving accuracy using deeper nets because this more complex architecture feature allows very deep networks at up to 50 layers, while maintaining high classification accuracy especially it took out extra spaces margin like residual connection between different layers for preventing overfitting form happening.

Finally, we introduce our main model (Vision Transformer) that attains the highest accuracy based on the dataset of jute leaves. In this piece, the ViT model treats images as a series of fixed-size patches, leveraging the robust Transformer architecture that has already demonstrated state-of-the-art results on NLP tasks in image classification. The main components of the model proposal (other ingredients are not necessary now) are the classification head, the transformer encoder, and the neighbor attach patch idea.

Given its superior performance in our experiments, the Vision Transformer (ViT) is described here in detail. An input image $x \in \mathbb{R}^{(H\times W\times C)}$ is first partitioned into N non-overlapping patches, each of size P×P. Each patch is flattened into a vector and projected into a D-dimensional embedding space:

$$z_0 = \left[x_{cls}; x_p^1E; x_p^2E; \dots; x_p^NE\right] + E_{pos} \quad (1)$$

Here, $xcls$ is a learnable classification token, $E \in \mathbb{R}^{(3p^2)\times D}$ is the patch projection matrix, and $Epos$ represents the positional encodings used to preserve spatial order.

The sequence Z_0 is then processed through L stacked Transformer encoder layers. Each encoder layer consists of:

Multi-Head Self-Attention (MSA): Captures global dependencies among patch tokens.

$$\acute{z}_l = \text{MSA}\left(\text{LN}(z_{l-1})\right) + z_{l-1} \qquad \ell = 1 \dots L \quad (2)$$

Multi-Layer Perceptron (MLP): Applies non-linear feature transformations.

$$z_l = \text{MLP}(\text{LN}(\acute{z}_l)) + \acute{z}_l \qquad \ell = 1 \dots L \quad (3)$$

Finally, the class token z_L^{cls} from the last encoder layer is passed to a linear classification head, followed by softmax activation:

$$\hat{y} = \text{Softmax}\ (Wz_L^{(cls)} + b) \quad (4)$$

4 RESULT AND DISCUSSION

This section presents an analysis of the model's performance and accuracy. Fig. 4 presents the results in the following order: Accuracy, Loss Curve, and Confusion Matrix.

4.1 Overall Performance Trends

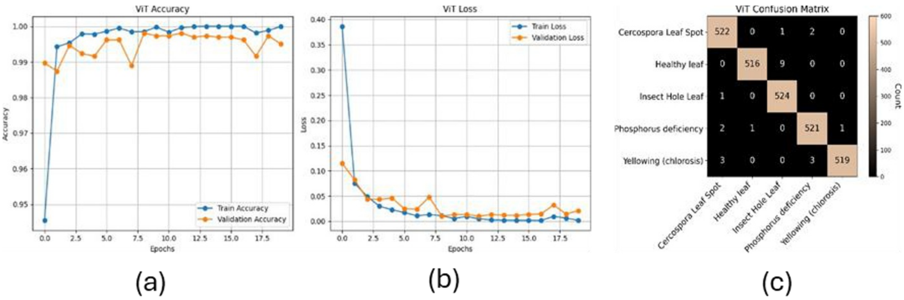

Fig. 4. The results are shown in order as follows (a) Accuracy, (b) Loss Curve, and (c) Confusion Matrix.

The competitive analysis of the nine models shows that the transformer-based architectures are more effective for jute leaf disease classification. In Table 3, the Vision Transformer (ViT) achieved the highest test accuracy of 99.85%, while the balanced precision, recall, and F1-scores were obtained at 99.43%. ConvNeXt and Swin Transformer came next at 99.77%, taking relatively minor advantages in terms of precision and recall. MobileNet and DenseNet121 became relatively lightweight convolutional networks that obtained recognition ability that transformers have. The lowest results (92–96%) were achieved by graph-based methods (GCN, GAT, and hybrid GCN_GNN), confirming their limited applicability to dense spatial image classification concerning the most natural structured relational data tasks. Fig. 5 shows the performance evaluation chart for jute leaf disease detection, illustrating the model's accuracy and effectiveness.

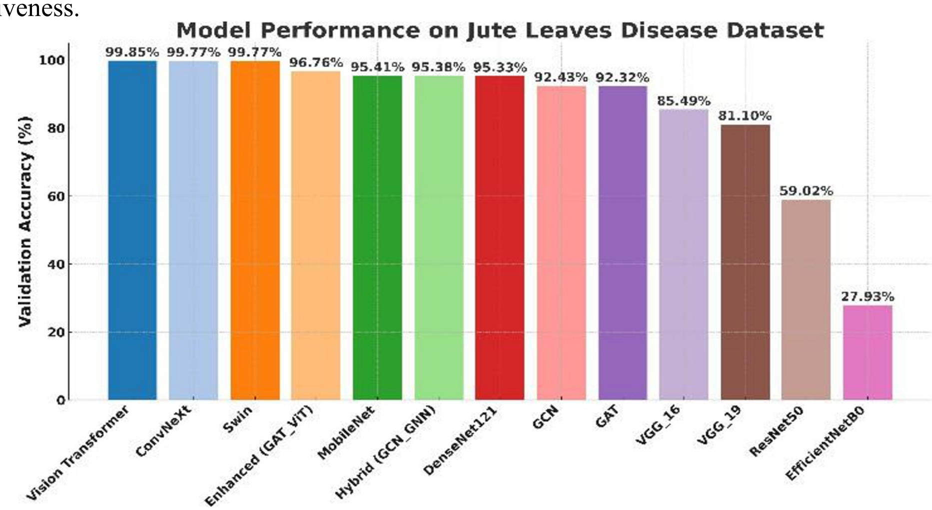

Fig. 5. Performance Evaluation Chart for Jute Leaf Disease Detection.

Table 3. Performance comparison of tested models

Model	Accuracy	Precision	Recall	F1-Score
Vision Transformer	99.85%	99.43%	99.43%	99.43%
ConvNeXt	99.77%	99.81%	99.81%	99.81%
Swin	99.77%	99.77%	99.77%	99.77%
Enhanced (GAT_ViT)	96.76%	96.78%	96.76%	96.77%
MobileNet	95.41%	95%	95%	95%
Hybrid (GCN_GNN)	95.38%	95.43%	95.38%	95.38%
DenseNet121	95.33%	95%	95%	95%
GCN	92.43%	92.51%	92.43%	92.45%
GAT	92.32%	92.42%	92.32%	92.34%
VGG_16	85.49%	85%	85%	85%
VGG_19	81.10%	82%	82%	82%
ResNet50	59.02%	61%	59%	60%
EfficientNetB0	27.93%	26%	28%	19%

4.2 Per-Class Insights

Fig. 6 shows the ROC curve for the Vision Transformer (ViT) model, illustrating its classification performance. To note, we achieve a perfect recall of 1.0000 on both Cercospora leaf spot (advanced stage) and Insect hole leaves with F1-scores of 0.9990 and 0.9915, respectively. The Healthy leaves class achieved a high F1-score of 0.9904, although the recall was somewhat lower (0.9829) than some of the other categories. We found the most difficult classes to be Yellowing (Chlorosis) and Phosphorus deficiency (F1-value of 0.9952 each), due to minor visual similarities—in particular, uniform yellowing—which at times caused confusion between the two classes. The results note ViT's versatility over diverse lesion types and textures without compromising performance on any disease or healthy classes.

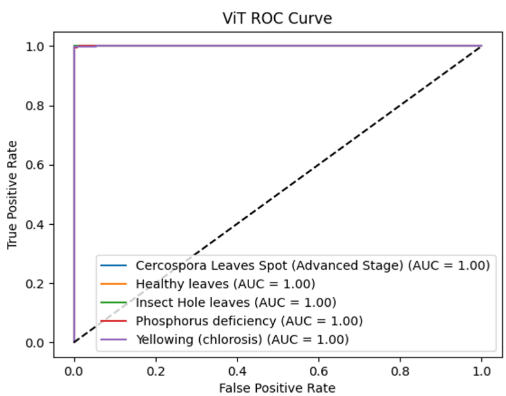

Fig. 6. ViT ROC Curve

4.3 Sources of Misclassification

The error analysis, as shown in Fig. 4. (confusion matrix), revealed two major confusion patterns: Yellowing (chlorosis) incorrectly identified as Phosphorus deficiency (Chlorosis with a very similar yellow pattern of plant foliage, only varying in placement within the plant and intensity). Cercospora leaf spot, identified as an Insect hole, leaves, characterized by irregular dark lesions, visually scrambles the similarity of the name, and because they appear similar to insect feeding damage. This made sense because we knew that there were cases that were hard to differentiate with RGB images alone. In the future, spectral imaging, texture descriptors specific to the regarded domain or temporal progression of the disease might enable a better distinction of conditions that visually overlap.

4.4 Performance Evaluation and Comparative Analysis

The provided vit-based system, when compared with earlier works, achieves state-of-the-art results. Rahman et al. mobilenetv2 and resnet50 (Talukder et al. [1]) - 98% li et al. [3] received 99% with densenet201. The YOLO-JD architecture achieved 96.63% map [2]. not only does our vit implementation outperform these benchmarks, but it also performs consistently across all diseases. the advantage of it is that the global attention mechanism can be used to look at symptoms that are spatially further away from the first layer. this is essential for jute leaves that often get spots and discolorations in a scattered, erratic way. the robustness to variations in symptom location, size, and orientation was guaranteed using the patch embedding strategy, while the generalization capability was improved through the diverse training conditions using the balanced augmented dataset. this higher performance provides a good rationale for selecting Vit-among CNN and graph-based models and making Vit one of the more enticing candidates for implementation in the context of mobile-assisted decision support tools suitable for farmers (i.e., mobile-based early disease detection systems where high precision is needed).

5 CONCLUSION AND FUTURE WORK

This paper focuses on transformer-based architectures for detecting and classifying jute leaf diseases, and explores the application of ViT for this purpose. When the ViT model was trained on 5 Classes of 17,500 images, it achieved 99.85% accuracy, outperforming the SOTA performance of both Conv and Graph-based methods. All three approaches can model long-range spatial relations, as well as being robust to small changes in the size, location, and colour intensity of rectal lesions. This was particularly useful for scattered foci of disease or subtle colour changes that would be extremely difficult to detect by classical methods. This comparison also reaffirms the potential for scalability from ground-based useful tools → mobile-based early warning system → timely enhanced farmers' decision making, which we set a new benchmark for, as this work exceeds previous studies in his area.

This study has limitations, a fact acknowledged by the researchers. Since the images of that study area were only collected from Bangladeshi jute fields, if the model is applied for leaves growing in other climate conditions or geographies or growing under drastically different agronomy practices, it might not perform well. In fact, the high computational power required to practically use computation directly from ViT is one of the apparent reasons why ViT is not so easy to deploy directly on low-power devices. Moreover, the single-label nature of our approach so far is limiting, as a leaf in the field can be asymptomatic to more than one disease at once. Broader research directions emerge from this study, and three main directions can be identified. First, we can use the images over a period of time and season to expand the dataset to improve the model's generalization capabilities. Secondly, we could investigate light-weight transformer alternatives and tailor all compression/quantization strategies to make the model more practical for on-device tasks. Third, multi-label classification can be employed (the continuous outputs can be easily thresholder), and more complex data, such as spectral or hyperspectral imaging, could potentially aid this type of model in discerning diseases that are visually very similar to each other. By implementing such pragmatic solutions, the system can transform into an in-field deployable, scalable product that can aid towards a sustainable jute economy, facilitating the livelihood of farmers.

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