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A web-based application for cotton leaf disease classification using vision transformer

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Abstract

Cotton leaf diseases particularly threaten crop productivity, making early detection a vital yet challenging task due to subtle visual symptoms, a scarcity of labeled datasets, and the absence of diagnostic tools suitable for field use. Traditional deep learning methods often struggle with generalization across varying agricultural conditions and require extensive computational resources. To address these challenges, this study proposes a novel framework for classifying cotton leaf diseases using Vision Transformer (ViT) architecture, specifically the Swin Transformer, integrated into a real-time, web-based diagnostic application. The system was trained and evaluated using two publicly available datasets: SAR-CLD-2024, which contains 2,137 images across seven disease classes, and a severity-based dataset consisting of 980 images categorized into four disease types with subclass labels. To mitigate class imbalance, extensive data augmentation was employed. In this study, we employed Generalized Low Rank Modeling (GLRM) for dimensionality reduction and Infomax-GAN for feature selection, enhancing model performance and interpretability. We benchmarked four ViT models—LeViT, BEiT, DeiT, and Swin Transformer—using accuracy, precision, recall, F1-score, and PR-AUC as metrics. The Swin Transformer achieved the highest accuracy, 99.70% on the SAR-CLD-2024 dataset and 98.84% on the severity-based dataset. Our web application enables users to upload images and receive real-time diagnostic feedback, offering a practical solution for precision agriculture. This study's novelty lies in integrating hierarchical transformer-based classification with advanced feature selection and practical deployment, creating a robust tool for early detection of cotton leaf diseases in agriculture.

Keywords: Cotton Leaf Disease; Vision Transformer; Agriculture; Sustainable Farming; Swim Transformer

1. Introduction

Cotton is cultivated in approximately 75 countries and supports the livelihoods of around 100 million farming families, with over 350 million people globally involved in the cotton value chain. [1]. The worldwide cotton industry is valued at more than $50 billion each year, with China, India, and the United States accounting for more than 60% of total output [2]. Bangladesh produces just 1/25 of its cotton requirement locally, importing around 7.3 million bales per year, with plans to increase local output to 1 million bales by 2030 [3]. These numbers show the importance of farming cotton to reduce imports and open a new door of cash crops for farmers.

Cotton leaves are susceptible to Bacterial Blight, Leaf Curl Virus, and Fusarium Wilt, which cause curling, yellowing, and spotting. Accurate categorization is essential for prompt treatment and yield protection. Manual examination is

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traditionally used but is slow, error-prone, and influenced by symptom similarity and environmental circumstances [4], [5]. Early detection of cotton leaf diseases is one of the keyways to protect cotton production [6]. For the first step with, early detection enables farmers for action before a disease spread [7]. It also decreases yield loss and treatment cost. In the longer run, it develops more environmentally friendly methods of farming that use less harmful pesticides [8]. Detecting these diseases early is not always easy symptoms can be subtle at initial detection and on occasion approximate each other, making it challenging to tell the differences among diseases. Machine learning could potentially be used to examine images to identify connections that human eyes could ignore. Furthermore, it doesn't appear too optimal [9]. These systems frequently require a large amount of labeled data, may not work well outside of regulated settings, and may struggle with diseases that manifest different. ViTs have an advantage here since they are better at detecting tiny details and understanding a bigger picture of visualizations [10]. The most important objective of this research project is to create a user-friendly automated system for accurately and efficiently classifying Cotton leaf diseases with elegant ViT models. In the context of crop management and productivity, the system utilizes preprocessing, image augmentation, feature extraction, and Swin Transformer which is illustrated in Figure 1. Among the various ViT models analyzed, Swin Transformer demonstrates superior performance, effectively minimizing the risk of overfitting while capturing a broader range of data. This ensures more reliable predictions and an exceptionally high level of accuracy, making it a practical and trustworthy solution for real- world applications. The research contributions are given below

- Presented a Swin Transformer model and assessed three other ViT models (LeViT, BEiT, DeiT) to figure out the best performing model for this study.
- Enhanced input data superior using optimized feature extraction and selection approaches.
- A simple to operate web tool for actual disease detection for both farmers and farming specialists.
- Compared to the state-of-the-art methods, the suggested method performs better in the classification of cotton leaf diseases.

The remainder of the study is as follows: section II discusses the relevant research and draws comparisons to previous research findings. Section III sets out the technique and the ViT models applied. Section VI shares the analysis of the results centered on model performance metrics. Section V discusses impacts, practical applications, and chances for growth in future research. Section VI concludes the study by reviewing the main advantages and possibilities for farms.

2. Related Work

Ahmad et al. [11] tackles the challenge of detecting cotton leaf disease, which affects crop yield and economy. The authors proposed a ViT based model trained on a dataset of 3,475 annotated images across four types of diseases. The model achieved 96.72% accuracy in binary and 93.39% in multiclass classification. However, limitations include the reliance on high-quality labeled data and limited generalization in real-world conditions. Kukadiya et al. [12] proposed an ensemble model that combines VGG16 and InceptionV3 to detect cotton leaf diseases. Training in 1,786 images, it achieved 98.48% training and 95.04% testing accuracy using the SGD optimizer. The small data set and limited real-world validation are limitations in this investigation. Hyder et al. [13] research describes a machine learning model to identify cotton leaf illnesses developed using 1,710 real- world photos. The model scored a test accuracy of 91%, which is less than VGG16 and ResNet50. However, it has disadvantages, such as slower performance and the requirement for further optimization for mobile deployment and low-resolution photos. Nagarjun et al. [14] the manuscript provides a deep learning model based on the convolutional neural network (CNN) for the early and accurate diagnosis of cotton leaf diseases that outperforms established approaches such as ResNet101, Inception v2 and DenseNet121. The model reached 99% accuracy, beating previous models and proven its usefulness in precision diagnosis.

Kumar et al. [15] analysis describes a hybrid ensemble model for identifying cotton leaf diseases that combines Random Forest and Decision Tree classifiers. It obtains 94.5% accuracy in identifying leaves as" Healthy" or" Diseased," however its limits stem from dataset variability and the need for enhanced generalization in real-world agricultural circumstances. Nazeer et al. [16] study uses a CNN-based deep learning model to detect Cotton Leaf Curl Disease (CLCuD) early and accurately. The model classifies cotton leaves into five susceptibility levels, achieving 99% accuracy in self-collected data. However, real-world variability may limit its generalization, and its performance may drop on the downloaded dataset. Pandey et al. [17] project utilizes a hybrid deep learning technique to identify cotton leaf diseases that impact crop output and farmer revenue. After 10-fold cross- validation, the model, which was trained on a dataset of 1,710 photos, obtained an impressive 98.9% accuracy rate. However, disadvantages include a lack of validation for bigger datasets and significant environmental sensitivity. Herok et al. [18] adopts transfer learning to improve cotton leaf disease identification using a dataset of 6,158 photos from eight classes. VGG16 had the most significant test accuracy of 95.02%, although limitations such as interclass similarity and misclassifications were observed due to the high picture backgrounds and illness symptoms.

Articles on cotton leaf disease identification show many difficulties, including limited or unbalanced datasets, reliance on high-quality annotated photos, misclassification owing to transfer learning-based techniques, and a decline in performance when using external or varied sources. Few articles address real-time deployment issues or assess models on mobile or resource-constrained platforms, limiting their practical use to farmers. The primary limits include dataset size and variety, model generalizability, real-world unpredictability, and practical deployment readiness.

Considering the current limitations of existing research, a web or mobile application can be a good solution to overcome this problem and help identify diseases early. It allows farmers a lot and can be a lifesaver and fill the gap between machine learning models and agriculture.

3. Methodology

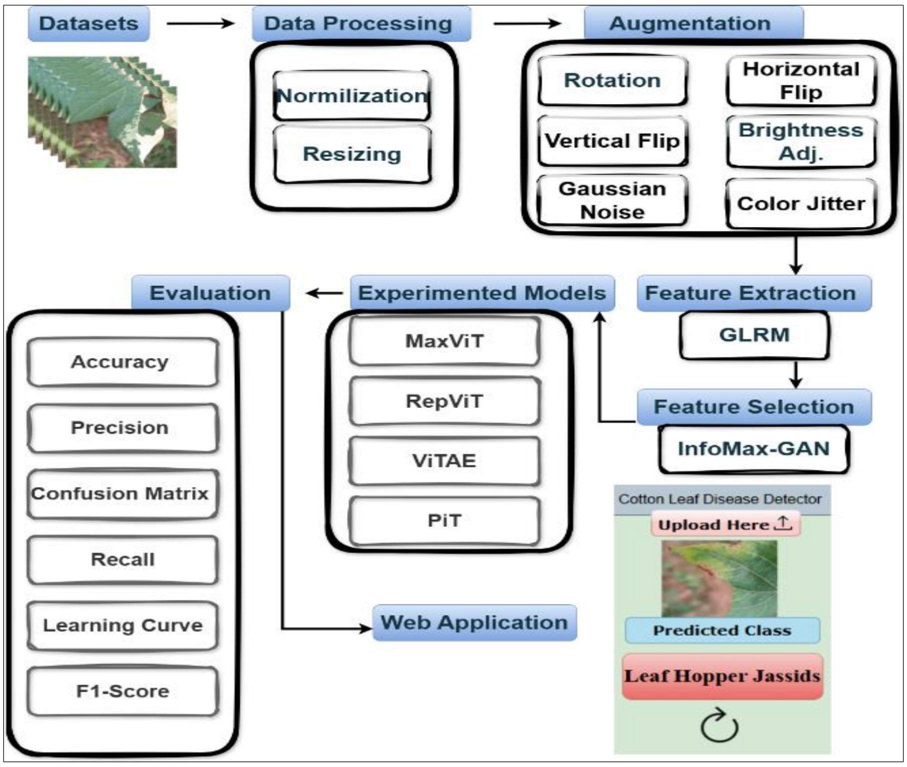

Figure 1 Proposed methodology

3.1. Data Description

This research utilizes two datasets. First," SAR-CLD- 2024: A Comprehensive Dataset for Cotton Leaf Disease Detection [19]" is a multiclass cotton dataset with 2137 initial images and 7000 augmented images. Initially the dataset classes were imbalanced with the images in between 116 to 578. After augmentation each of the classes become 1000 images. The dataset 7 classes are: Bacterial Blight, Curl Virus, Healthy, Herbicide Growth Damage, Leaf Hopper Jassids, Leaf Redding, and Leaf Variegation (Figure 2). The dataset was split into three sections: an 80% training set, 10% validation, and 10% test set.

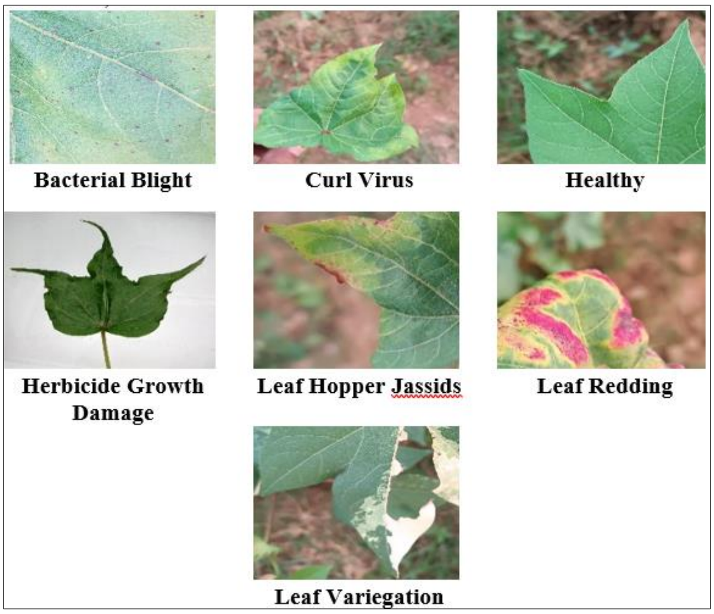

Figure 2 Sample image of each category of Dataset-01

The second dataset, the" Cotton Leaf Disease Dataset with Severity Levels [20]" classified into 4 classes Bacterial Blight, Curl Virus, Fusarium Wilt, and Healthy (Figure 3). Each disease class has three sub classes (Critical, Mild, and Moderate) with limited data. There was a huge difference between disease and healthy dataset classes. The dataset has only 980 images and after augmentation the size of the dataset became 4900 which makes each class 5x than before. Though there is a huge imbalance of data numbers between highest and lowest classes. The dataset also split into the same ratio as the first dataset.

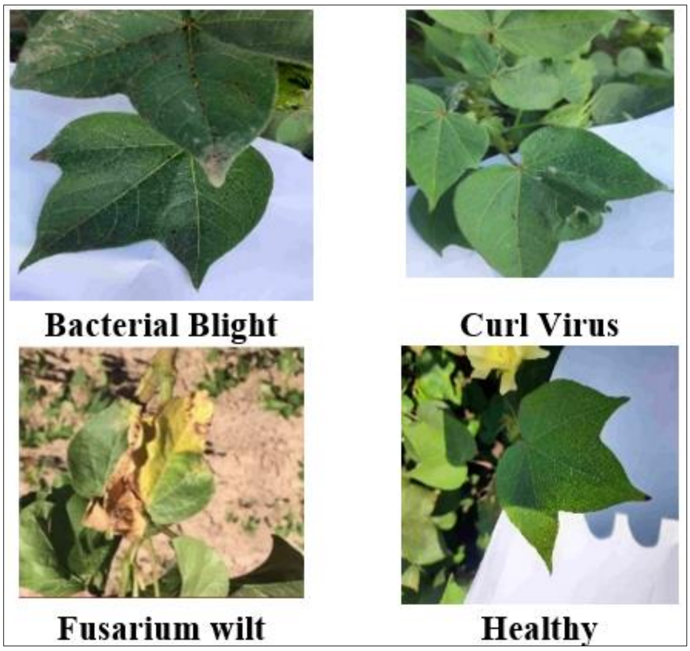

Figure 3 Sample image of each category of Dataset-02

3.2. Data Preprocessing

To ensure consistency across inputs, all cotton leaf images are resized to 224×224 pixels using bilinear interpolation, providing uniform dimensions suitable for deep learning models [21]. Following this, normalization scales pixel values to the [0, 1] range, which speeds up convergence and enhances overall model performance [22], [23]. To improve robustness and generalization, the dataset undergoes various data augmentation techniques—such as rotation, flipping, brightness adjustment, Gaussian noise addition, and color jittering—allowing the model to effectively recognize diverse cucumber image variations [24], [25]. For feature extraction, the GLRM is employed [26]. It decomposes the original data matrix A into two lower- dimensional matrices as Eq. 1, where X and Y optimize a loss function to uncover hidden patterns while minimizing the risk of overfitting.

$$\min_{X,Y} \sum_{i=1}^{m} \sum_{j=1}^{n} L\big(A_{ij}, (XY^T)_{ij}\big) + \sum_{i=1}^{m} r_X(X_i) + \sum_{j=1}^{n} r_Y\big(Y_j\big) \tag{1}$$

After reducing dimensionality, Infomax-GAN is used for picking features. This approach combines mutual information maximization with Generative Adversarial Networks (GANs) to generate highly discriminative and informative features useful for classification [21], [27]. While Infomax-GAN improves feature value extensively, it also brings considerable problems, such as computational cost, training instability, and a high sensitivity to training data integrity and variety.

3.3. Model Training

3.3.1. LeViT

LeViT is a low-cost ViT made for real-time applications and edge devices. It operates quicker than conventional transformers since it makes use of modest self-attention algorithms and convolutional stem layers for feature extraction. LeViT's minimal energy use provides it with the ideal for edge computing on drones and smartphones, and it's excellent for real-time agricultural applications like crop monitoring and disease detection. The core working mechanism is explained using Eq. 2, where the attention equation computes the weighted sum of values (V) based on the similarity of queries (Q) and keys (K), scaled by dimension for stable gradients.

$$\mathrm{Attention(Q, K, V)} = \mathrm{softmax}\big(\mathrm{QK^T}/\sqrt{\mathrm{d_k}}\big) \cdot \mathrm{V} \tag{2}$$

3.3.2. BEiT

BEiT is a self-supervised vision trans- former that learns meaningful visual representations using masked image modeling. In the future, it is useful for massive amounts of agricultural datasets that have little labeled data because it can be pre-trained on satellite, drone, or field images and fine-tuned for specific tasks such as plant disease classification, soil health examination, or forecasting crop yields, making manual image annotation simpler and more quickly. The BEiT loss in Eq. 3 reconstructs masked picture tokens by predicting their visual codebook entries, allowing the network to learn meaningful visual representations.

$$\mathrm{L_BEiT} =- \sum (\mathrm{i} \in \mathrm{M}) \log \mathrm{P}\big(\mathrm{z_i} \big| \mathrm{x}^{(-}\mathrm{M}^{)}\big) \tag{3}$$

3.3.3. DeiT

DeiT is a data-efficient ViT which increases performance and training efficiency even for less classi- fied images. As an alternative with traditional ViTs, which need big datasets to get competitive results, DeiT offers data distillation techniques allowing it to learn from smaller datasets with excellent accuracy. It makes it particularly helpful for small-scale research into agriculture, when there aren't enough classified photos to support parasite verification, crop health monitoring, or recognizing plant diseases. The applications in resource- constrained circumstances, such as tiny farms or low-data study of agriculture, are best suited for DeiT because of its high performance with limited training data. The DeiT loss in Eq. 4 combines standard cross-entropy with knowledge distillation, allowing the model to learn from both real labels and a teacher model's soft predictions.

$$\mathrm{L_DeiT} = \alpha \cdot \mathrm{L_CE} + (1- \alpha) \cdot \mathrm{L_KD} \tag{4}$$

3.3.4. Swin Transformer

The Swin Transformer has an internal architecture based on self-attention and feedforward operations within localized, non-overlapping windows. It features a Shifted Window Multi-head Self-Attention (SW-MSA) mechanism to improve cross-window interaction and global modeling capacity by alternating window partitioning patterns across layers[28] . Each Swin Transformer block includes a window-based multi-head self-attention layer and a feedforward multilayer perceptron (MLP) layer, both preceded by Layer Normalization and connected through residual connections. The computation within a single block can be expressed as follows Eq. 5, where (X_l) represents the input features at the

$(l) - th$ layer, "Norm" refers to the layer normalization, "SW-MSA" is the shifted window self-attention operation, and "MLP" stands for the multilayer perceptron. This design is repeated hierarchically across four stages, with patch merging layers that reduce spatial resolution and increase channel depth.

$$X_{l+1} = \mathrm{MLP}\big(\text{SW-MSA}\big(\mathrm{Norm}(X_l)\big) + X_l\big) \tag{5}$$

3.4. Evaluation

In this research, the performance of ViT models was evaluated using the following equations: accuracy, F1-score, MCC, and PR-AUC. Accuracy (Equation 6) offers an overall measure of correct predictions, although it can be deceptive for imbalanced datasets [29]. To solve this, the F1-score (Equation 7) provides a mix of accuracy and recall, making it more trustworthy for finding underrepresented illness groups [30]. Precision (Equation 8) considers all parts of the confusion matrix, resulting in a robust measure even in unbalanced conditions. Finally, recall (Equation 9) emphasizes the trade-off between accuracy and recall, making it particularly useful for assessing the model's performance in unusual classes [27]. Together, these indicators give a thorough assessment of tests ViT-based categorization algorithms [31], [32].

$$\mathrm{Accuracy} = \frac{\sum_i \mathrm{TP_i}}{\sum_i(\mathrm{TP_i} + \mathrm{TN_i} + \mathrm{FP_i} + \mathrm{FN_i})} \tag{6}$$

$$\text{F1-score}_i = 2 \cdot \frac{\mathrm{Precision_i} \cdot \mathrm{Recall_i}}{\mathrm{Precision_i} + \mathrm{Recall_i}} \tag{7}$$

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

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

These indicators provide a thorough assessment of the model's performance, indicating both its strengths and possible areas for development.

4. Results Analysis

4.1. Comparing the Performance of Models

Table 1 presents the performance metrics of four ViT models on Dataset 1. Among them, the Swin Transformer achieved the highest scores across all evaluation metrics 99.72% precision, 99.70% recall, 99.67% F1-score, and 99.70% accuracy indicating its superior capability in classifying cotton leaf diseases. DeiT followed closely with an F1-score of 98.35% and accuracy of 98.33%, reflecting strong and consistent performance. The BEiT model showed slightly lower values, particularly in precision (94.59%) and F1-score (94.38%). LeViT, while having the lowest overall accuracy (90.78%), maintained relatively high recall (90.87%), suggesting it detected more true positives but possibly at the cost of more false positives.

Table 1 Performance of experimental ViT models for Dataset 1

Model	Precision	Recall	F1	Accuracy
Swin Transformer	99.72	99.70	99.67	99.70
DeiT	98.40	98.29	98.35	98.33
BEiT	94.59	94.28	94.38	94.52
LeViT	90.25	90.87	90.73	90.78

Table 2 compares the performance of the same models on dataset 2. Again, the Swin Transformer trounced the competition, with top results in precision (98.83%), recall (98.79%), F1-score (98.81%), and accuracy (98.84%). DeiT maintained consistency with somewhat lower but good findings, including an F1-score of 98.73% and an accuracy of 98.71%. Although both BEiT and LeViT had modest performance, LeViT outperformed BEiT in terms of recall (89.97%) and F1-score (90.13%). There was more variance in the predictions made by both models, though, since they both fell short in terms of overall accuracy and precision. These outcomes demonstrate the Swin Transformer's constant dominance in both datasets.

Table 2 Performance of experimental ViT models for Dataset 2

Model	Precision	Recall	F1	Accuracy
Swin Transformer	98.83	98.79	98.81	98.84
DeiT	98.70	98.74	98.73	98.71
BEiT	91.60	91.34	91.27	91.41
LeViT	90.05	89.97	90.13	90.08

4.2. Performance Validation

The Swin Transformer's performance on a seven-class cotton leaf disease dataset is displayed in Figure 4. Only three of the 700 were incorrectly categorized, yielding a remarkable accuracy of 99.70%. Most of the classes were accurately predicted, demonstrating how effectively the model handles several related illness types. On the other hand, the model's output on a four-class dataset is displayed in Figure 5. Just six of the 489 photos were mis predicted, yielding a 98.84% accuracy rate. The model proved highly accurate in identifying several cotton leaf diseases, as evidenced by its excellent accuracy, recall, and F1-score.

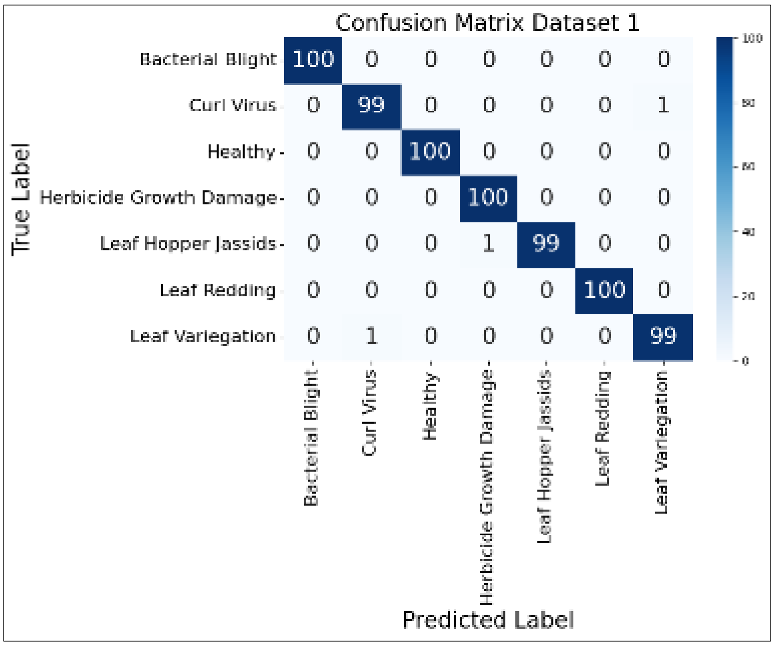

Figure 4 Confusion matrix Swin Transformer of model Dataset-1

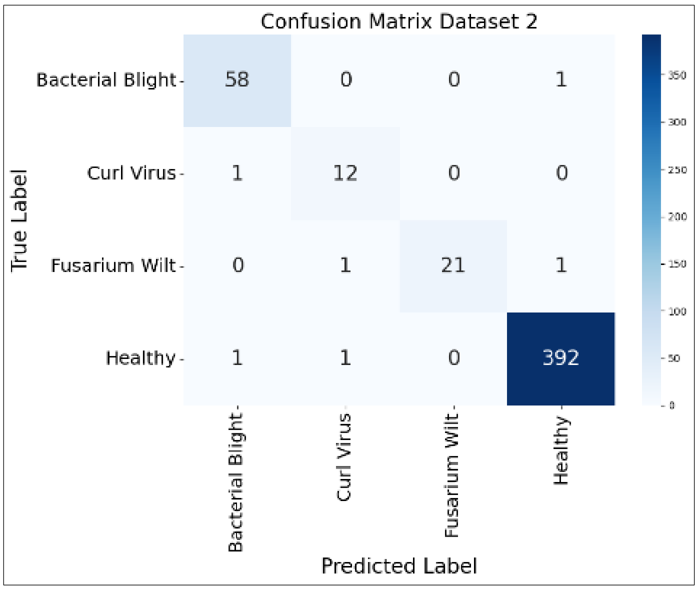

Figure 5 Confusion matrix of Swin Transformer model Dataset-2

Figure 6 illustrates the training and validation accuracy and loss of over 100 epochs. Both accuracy curves show a smooth upward trend, with validation accuracy reaching approximately 99.70% for Swim Transformer. The loss curves steadily decline with minimal gaps, indicating effective learning and strong generalization without overfitting. Furthermore, Figure 7 shows that both training and validation accuracy steadily improved, with validation accuracy reaching 98.84%. The loss curves also decrease consistently with minimal gaps, indicating strong convergence and generalization without overfitting.

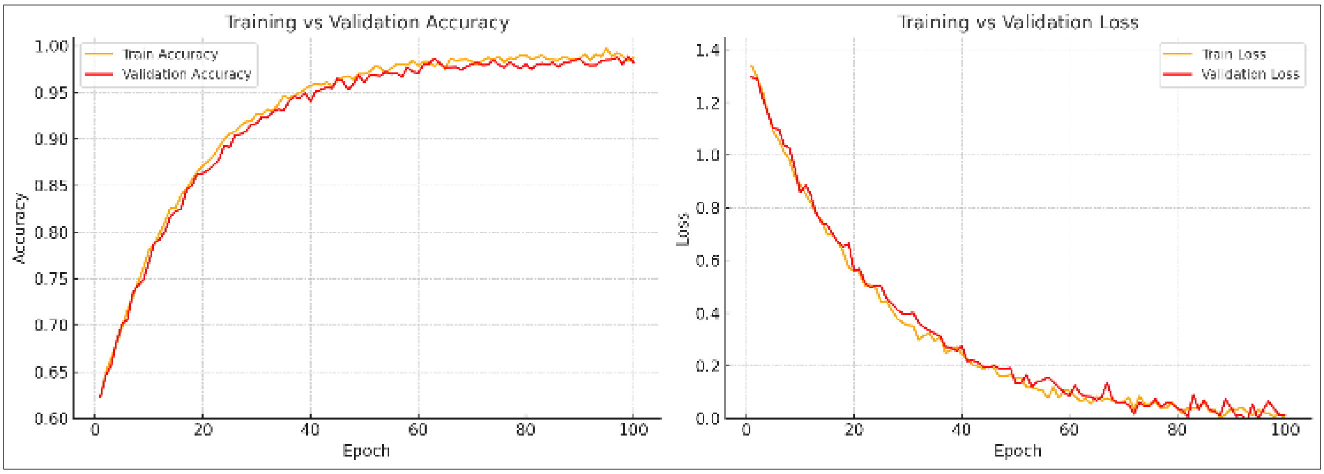

Figure 6 Learning curve of the Swin Transformer model Dataset-1

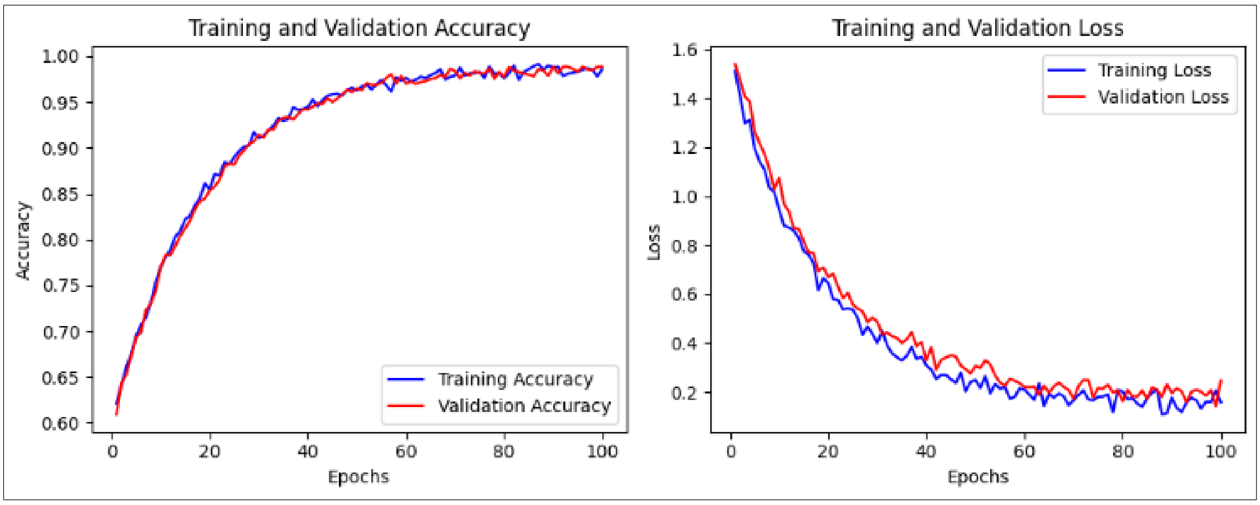

Figure 7 Learning curve of the Swin Transformer model Dataset-2

4.3. State-of-the-art Comparison

Table 3 provides a comparative analysis between the proposed Swin Transformer model and several state-of-the-art cotton leaf disease identification methods. The proposed model achieved the highest performance, recording 99.70% accuracy on a dataset of 2,137 images and 98.84% accuracy on a second dataset of 980 images, outperforming all other referenced models. In contrast, ViT achieved 96.72% accuracy on 3,475 images [7], VGG16 reached 95.04% on 1,786 images [8], and CNN-based approaches yielded varying results—90.53% on 1,710 images [9], 99.00% on 2,616 images [10], and 94.50% on 1,349 images [12]. This comparison highlights the effectiveness and robustness of the proposed Swin Transformer model over existing approaches. Only one research [10] surpasses this research work because of lack of data in dataset-02 which is the only limitation for the model to perform though it provides a satisfactory outcome though this limitation.

Table 3 Comparison with the State-of-the-Art methods

Reference	Model	Dataset Size	Accuracy
Proposed	Swin Transformer Swin Transformer	2137 980	99.70% 98.84%
[7]	ViT	3475	96.72%
[8]	VGG16	1786	95.04%
[9]	CNN	1710	90.53%
[10]	CNN	2616	99.00%
[12]	CNN	1349	94.50%

4.4. Web Application

Figure 8 displays the graphical user interface (GUI) of Cotton Leaf Disease Detection System, which uses the advanced Swin Transformer model as its fundamental classification mechanism. The interface was designed with the user browsing experience in mind, allowing users to effortlessly submit a cotton leaf image using the "Upload Here" button. Following submission, the image is shown for viewing while the system quickly analyzes it to identify any probable illnesses. In this case, the model correctly detects the leaf as displaying indications of "Leaf Hopper Jassids," and the prediction result appears clearly in an additional output screen. There is also a refresh button that permits users quickly reset the interface and tackle more analyses. This new web-based application is a very effective solution for real-time disease identification, making it especially useful for farmers, agronomists, and agricultural experts that demand rapid and exact diagnosis of cotton leaf diseases.

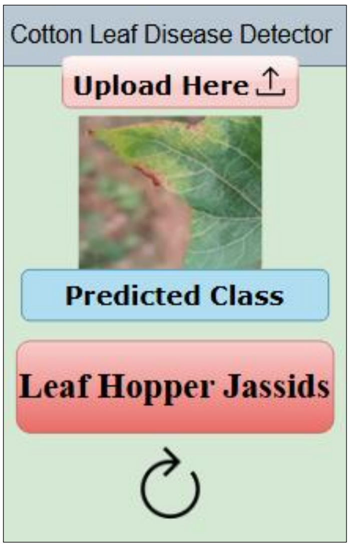

Figure 8 Web application interface

5. Discussion

Our proposed model outperformed due to its hierarchical architecture and SW-MSA, enabling effective extraction of local details while capturing global context. Its patch merging strategy cuts computational costs while preserving essential spatial details, which is vital for identifying subtle disease patterns. To improve class balance and model generalization, we used data augmentation techniques like flipping, rotation, noise injection, and color jittering. Our web-based application leverages this model as a real-time diagnostic tool for farmers and agronomists, requiring no technical expertise. The model's robustness across two datasets confirms its suitability for field deployment, especially in low-resource or remote areas. However, it does face challenges, such as training instability and high computational demands of Infomax-GAN, alongside its sensitivity to data quality. Moreover, limited and imbalanced samples in Dataset-2 hinder disease severity recognition, and the lack of temporal modeling restricts disease progression analysis. Future improvements will focus on optimizing the model for edge devices through techniques like quantization and pruning, implementing domain adaptation for various crop conditions, and developing a multi-task transformer to classify disease type and severity. Additionally, incorporating explainability methods like Grad-CAM or SHAP will enhance interpretability and foster trust in agricultural decision-making.

6. Conclusion

This study introduces a novel web-based system for classifying cotton leaf diseases using the Swin Transformer, a hierarchical ViT architecture tailored for agricultural diagnostics. By incorporating advanced feature engineering techniques—such as Generalized Low-Rank Modeling and Infomax-GAN-based feature selection, the system significantly improves classification accuracy and reduces the risk of overfitting. Among the four evaluated ViT models, the proposed Swin Transformer consistently delivered state-of-the-art performance across two diverse datasets. A noteworthy contribution of this work is the practical deployment of the high-performing model through an intuitive web interface, which allows farmers to obtain real-time diagnoses without the need for technical expertise or high-end hardware. This advancement effectively bridges the gap between deep learning research and practical agricultural applications. The integration of hierarchical self-attention mechanisms with optimized input pipelines provides a scalable and transferable solution for managing crop diseases. Future research will focus on domain adaptation, edge deployment, and enhancing explainable prediction insights to improve usability and build trust.

Compliance with ethical standards

Disclosure of conflict of interest

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