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A Hierarchical Transfer Learning Framework for Ginger Leaf Disease Detection and Severity Assessment Using Swin Transformer

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ABSTRACT: Ginger leaf diseases can reduce crop growth and rhizome yield when they are not identified and managed at an early stage. This study presents a hierarchical transfer learning framework based on the Swin Transformer for ginger leaf disease detection and severity assessment. The framework analyzes a leaf image in three stages. First, it separates healthy leaves from diseased leaves. Diseased leaves are then classified into five disease classes: Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot. In the final stage, the identified disease is assigned to one of three severity levels: Early, Middle, or Severe. A dataset of 10,500 field images has been used, including 1,750 healthy and 8,750 diseased images. The images were collected under natural daylight and included changes in illumination, background, leaf orientation, and symptom severity. The Swin Transformer models were initialized with ImageNet pretrained weights and fine-tuned for the three classification tasks. The healthy diseased classification achieved 99.43% accuracy with an AUC of 0.9984. Disease classification achieved 97.72% accuracy and a macro AUC of 0.9790, while severity classification achieved 92.40% accuracy with a macro AUC of 0.9605. The results show that the hierarchical approach can separate the identification process into manageable stages and provide both disease type and severity information from leaf images. The model can be used as a basis for image based ginger disease screening under field conditions.

1. INTRODUCTION

Ginger is a commercial crop belonging to the **Zingiberaceae** family. It is one of the world's most significant spice and medicinal crops, cultivated worldwide. Ginger had been used for thousands of years in traditional medicine, beverages, food preparation and pharmaceutical products due to its distinctive aroma, pungent flavor and various health benefits.

The major diseases affecting ginger are caused by fungi, oomycetes, bacteria, viruses, and nematodes. Among these, Chlorotic fleck, Bacterial wilt, Fusarium yellow, Leaf blight and Pyricularia leaf spot are the most destructive and economically important. These diseases can reduce rhizome yield, impair quality and cause significant economic losses if not detected and managed early. Early disease detection is a key component of modern precision agriculture because it enables farmers to identify plant diseases at an initial stage, before they spread widely and cause significant economic losses.

The estimates of average crop loss caused by major ginger diseases in the last five years is shown in Figure 1. It is observed that there is subsequent increase in the infection of major ginger diseases from 2022 to2026.

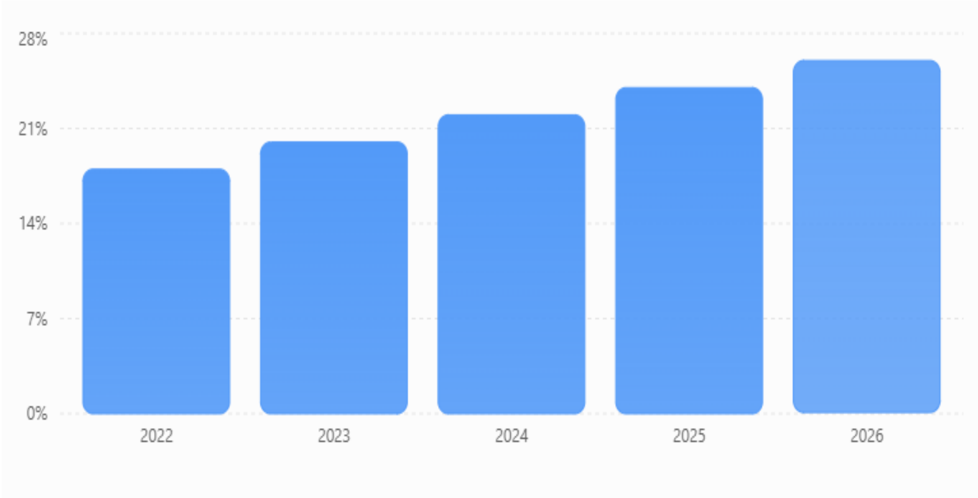

Figure 1: Average crop loss caused by major ginger diseases from 2022 to 2026

Early detection of diseases and accurate assessment of their severity are essential for improving ginger production, ensuring crop quality, and reducing economic losses. Detecting diseases at an early stage enables farmers to implement timely and targeted management practices, thereby preventing disease spread and minimizing damage. Early disease detection using artificial intelligence, machine learning, deep learning, computer vision and remote sensing can help farmers identify diseases promptly, apply timely control measures, and improve agricultural productivity.

The effective disease management and modern precision agriculture technologies Ensure healthy crop growth and are thus essential for improving productivity, maintaining quality and increasing farmers' profitability. This enables farmers to adopt timely management and reduce crop losses. Such technologies are expected to play a significant role in precision agriculture and sustainable ginger yield production. Hence, there is a need of an automated tool to detect and categorize the arecanut disease type and help farmers to protect their crop by taking proper precautions at the early stage.

2. LITERATURE SURVEY

Artificial intelligence has become an important tool for plant disease diagnosis because it enables image-based analysis without relying on manual inspection. Early studies focused on handcrafted image features and conventional machine learning algorithms, whereas recent research has shifted toward deep learning models capable of learning feature representations directly from data. More recently, transformer architectures and hybrid deep learning frameworks have been explored to address limitations associated with convolution-based models. Research on ginger disease detection has followed the same progression, with studies investigating machine learning, convolutional neural networks, transformer learning models and multimodal learning strategies for disease detection, severity prediction and crop health monitoring.

3. PROPOSED WORK

Tree structure shown in Figure 2 depicts the work to be carried out. Initially, the ginger images are detected and classified into two types as healthy and diseased. Further, the diseased images are classified into five major diseases namely Chlorotic fleck, Bacterial wilt, Fusarium yellow, Leaf blight and Pyricularia leaf spot. Lastly, each of the disease is classified into three stages as early, middle and severe based on their severity.

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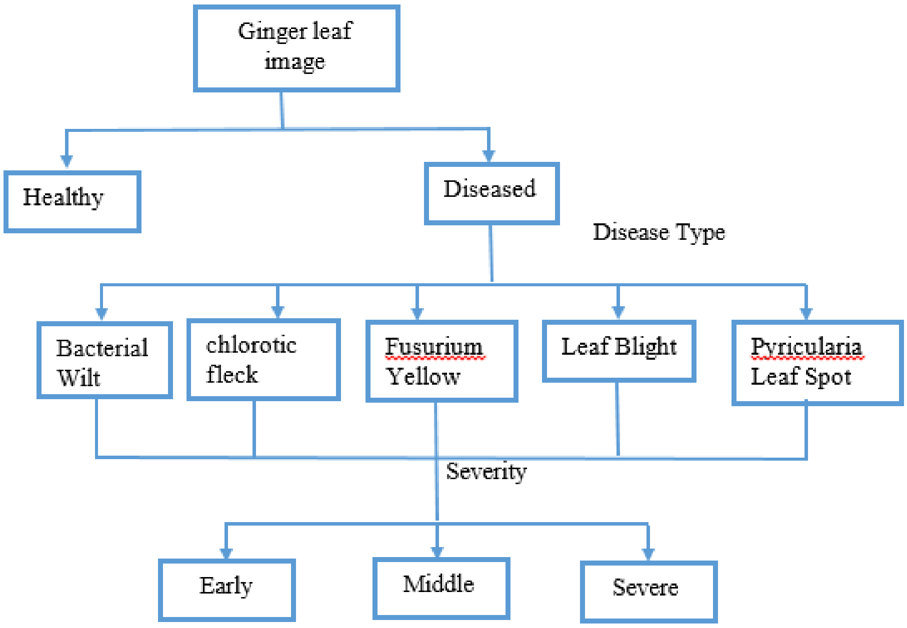

Figure 2: Tree structure showing proposed work

The images of healthy and diseased ginger plant leaves are shown in Figure 3 (a) and Figure 3 (b). Also, the images of diseased ginger leaves namely Chlorotic fleck, Bacterial wilt, Fusarium yellow, Leaf blight and Pyricularia leaf spot with different severity stages are shown in Figure 4 - 8.

3.1 Sample images of Healthy and Diseased Ginger leaves

(a)

(b)

Figure 3: Healthy and Diseased Ginger leaf images

Healthy ginger leaves are lance late, long and narrow with a flat, glossy surface that reflects light. It gives leaves a vibrant green appearance. The leaf blades are uniformly colored without any streaks or patches. The veins run symmetrically from the midrib to the margins. Their structure is firm and turgid that indicates proper water balance and nutrient uptake within the plant. The leaves are arranged alternately along the pseudo stems. This fresh and vigorous look is a sign of active photosynthesis and efficient metabolic activity.

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In contrast, diseased leaves show a range of detectable symptoms depending on the severity of infection. They may show yellowing or mosaic patterns with irregular patches of light and dark green tissue. In some cases, chlorotic streaks or flecks appear parallel to or centered on the veins. The leaf surface turns dull and is found uneven. Severe infections lead to shriveling, curling and premature drying of the leaves. This gives them a withered appearance. Such changes will reduce the leaf's photosynthetic capacity and decline the plant growth.

3.2 Images of Different Diseased Ginger leaves with Their Severity

3.2.1 Chlorotic-fleck Ginger leaves with Severity stages

(a) (b) (c)

Figure 4. Sample images of Chlorotic-fleck with different stages (a) Early, (b) Middle and (c) Severe

3.2.2 Bacterial wilt Ginger leaves with Severity stages

(a) (b) (c)

Figure 5. Sample images of Bacterial wilt with different stages (a) Early, (b) Middle and (c) Severe

3.2.3 Fusarium yellow Ginger leaves with Severity stages

(a) (b) (c)

Figure 6. Sample images of Fusarium yellow with different stages (a) Early, (b) Middle and (c) Severe

3.2.4 Leaf blight Ginger leaves with Severity stages

(a) (b) (c)

Figure 7. Sample images of Leaf blight with different stages (a) Early, (b) Middle and (c) Severe

3.2.5 Pyricularia leaf spot Ginger leaves with Severity stages

(a) (b) (c)

Figure 8. Sample images of Pyricularia leaf spot with different stages (a) Early, (b) Middle and (c) Severe

Chlorotic fleck is a viral disease of ginger characterized by the appearance of small yellow flecks or specks on the leaves. The disease primarily affects the foliage and reduces the chlorophyll content and also impairs photosynthesis. **Bacterial wilt** is a bacterial disease of ginger crop. In this disease, sudden wilting of leaves occurs without initial yellowing. The lower leaves droop first, followed by the entire plant. The leaves remain green in the initial stage but gradually become yellow and dry. Further, the entire plant eventually collapses and dies.

In case of **Fusarium yellows a** Progressive yellowing begins at the tips and margins of older leaves. The yellowing of leaf gradually spreads to younger leaves. The plants become stunted and leaves wilt during the hottest part of the day. **Leaf blight** is a fungal disease that primarily affects the leaves of ginger plants. It begins as small lesions that enlarge rapidly that causes extensive drying and death of leaf tissue. The disease can spread quickly under warm and humid conditions. Further, it leads to premature leaf senescence and reduced rhizome yield. **Leaf spot** disease has Small oval or elongated yellow spots appear on leaves. The spots enlarge and develop light brown to dark brown centers. The lesions are often surrounded by a distinct yellow halo. The adjacent spots merge, and thus form large irregular necrotic patches.

4. METHODOLOGY

The ginger leaf images used in this study were collected from ginger fields. Image acquisition was performed using a Motorola Edge 50 Fusion smartphone and a Canon EOS 200D DSLR camera. Images were captured under natural daylight from different viewing angles and leaf orientations. Blurred, poorly focused, and occluded images were removed from the dataset.

The dataset consists of 10,500 RGB images collected from ginger fields. It includes 1,750 healthy leaf images and 8,750 diseased leaf images belonging to five disease classes: Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot. Table 1 shows the class distribution of the ginger leaf image.

The diseased images were annotated into three severity levels: Early, Middle, and Severe. Severity labels were assigned based on lesion development, leaf discoloration, tissue damage, and disease spread. The severity dataset contains 2,915 Early-stage images, 2,920 Middle-stage images, and 2,915 Severe-stage images. Table 2 shows the distribution of severity levels in diseased ginger leaves.

The images include variations in illumination, background, leaf orientation, and symptom severity encountered during field image acquisition. These images were used to train and evaluate the proposed transfer learning model.

Table 1. Distribution of the ginger leaf image dataset

Class	Number of Images
Healthy	1750
Chlorotic Fleck	1620
Bacterial Wilt	1810
Fusarium Yellow	1730
Leaf Blight	1880
Pyricularia Leaf Spot	1710
Total	10500

Table 2. Distribution of severity levels in diseased ginger leaves

Disease	**Early**	**Middle**	**Severe**	**Total**
Chlorotic Fleck	520	610	490	1620
Bacterial Wilt	700	560	550	1810
Fusarium Yellow	430	690	610	1730
Leaf Blight	800	540	540	1880
Pyricularia Leaf Spot	465	520	725	1710
Total	2915	2920	2915	8750

The collected images were inspected to remove blurred, poorly focused, and occluded samples. The remaining images were resized to 224 × 224 pixels and normalized before training. No image enhancement or segmentation was performed.

The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio. Data augmentation was applied only to the training set. The augmentation operations included horizontal flipping, vertical flipping, random rotation, zooming, width shifting, height shifting, and brightness adjustment. The validation and test sets were used without augmentation.

4.1 Proposed Hierarchical Disease Detection and Severity Classification

The proposed framework performs ginger leaf analysis in three sequential stages: healthy and diseased leaf classification, disease identification, and severity classification. Each stage uses the output of the previous stage to reduce the search space and improve classification accuracy.

The first stage classifies the input leaf image as Healthy or Diseased. Images classified as healthy are excluded from further processing. Diseased images are passed to the second stage, where they are classified into one of five disease classes: Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot. In the final stage, the identified disease is classified into one of three severity levels: Early, Middle, or Severe.

The framework uses transfer learning to initialize the network with pretrained weights and fine tune it using the ginger leaf dataset. Swin Transformer is employed as the backbone network for feature extraction. The pretrained backbone extracts image features, while the classification layers are retrained for the target classes.

The hierarchical design separates disease detection, disease identification, and severity estimation into consecutive stages. This reduces the complexity of the classification task by restricting each stage to a smaller set of classes and allows severity estimation only for diseased leaf images. Figure 9 illustrates the architecture of the proposed three-stage ginger leaf disease.

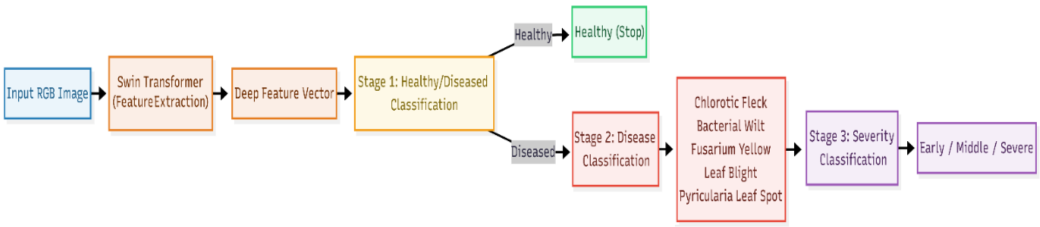


Figure 9. Architecture of the proposed three-stage ginger leaf disease

4.2 Swin Transformer Architecture

The Swin Transformer was used as the backbone network for feature extraction. The network was initialized with ImageNet pretrained weights and fine tuned using the ginger leaf dataset. The input to the network was an RGB image of size 224 × 224 × 3.

The input image was divided into non overlapping patches. Each patch was converted into a feature embedding using a linear embedding layer. The embedded patches were processed through four Swin Transformer stages.

ach stage consisted of Window based Multi Head Self Attention (WMSA), Shifted Window Multi Head Self Attention (SWMSA), Layer Normalization (LN), and a Multi Layer Perceptron (MLP) connected through residual connections. WMSA computed self attention within local windows, whereas SWMSA exchanged information between adjacent windows.

Patch merging was performed after each stage to reduce the spatial resolution and increase the feature dimension. The output of the final stage was passed to a Global Average Pooling layer, followed by a fully connected layer and a Softmax classifier. The extracted features were used for healthy and diseased leaf classification, disease classification, and severity classification. Figure 10 illustrates the Swin Transformer architecture used in this study.

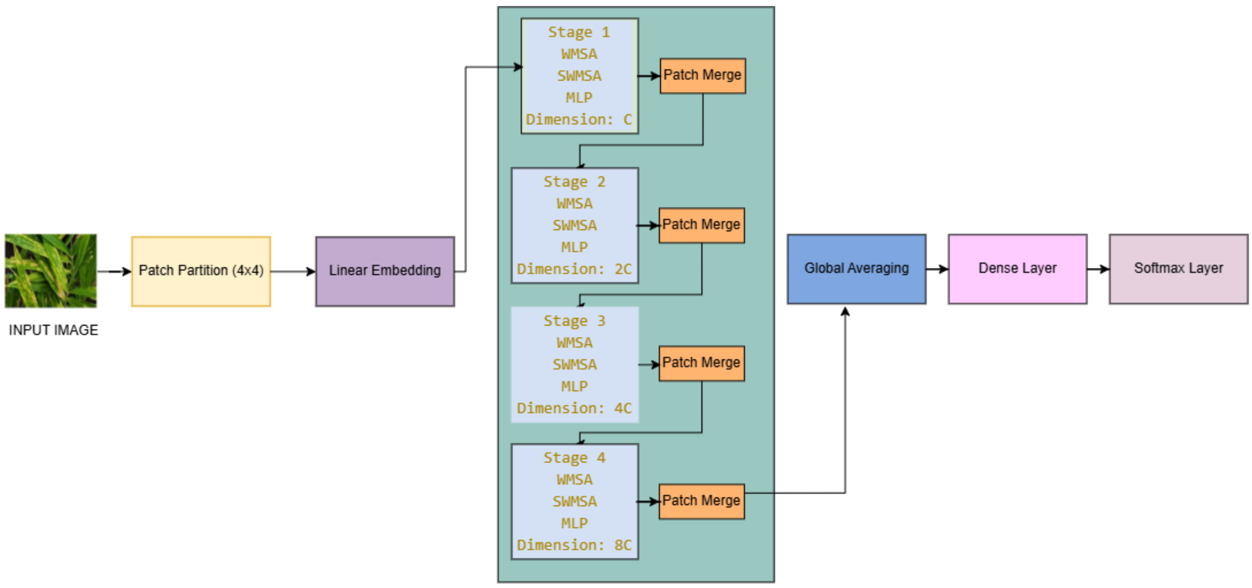


Figure 10: The Swin Transformer architecture with respect to ginger Disease classification

4.3 Hierarchical Disease Detection and Severity Classification

The proposed framework performs ginger leaf analysis through three sequential classification stages. Each stage employs a Swin Transformer initialized with ImageNet pretrained weights and independently fine tuned for its respective classification task.

In the first stage, the framework classifies ginger leaf images into Healthy and Diseased categories. The output layer contains two neurons corresponding to the two classes. Healthy leaf images are excluded from further analysis, whereas diseased leaf images are forwarded to the second stage.

The second stage identifies the disease class from the diseased leaf images. The output layer contains five neurons corresponding to Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot. The predicted disease class is forwarded to the final stage.

The third stage classifies the identified disease into three severity levels: Early, Middle, and Severe. The output layer contains three neurons corresponding to the three severity levels. The predicted severity level represents the final output of the proposed framework.

The probability of each output class is computed using the Softmax function.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{2} e^{z_j}}$$

Where $P(y_i)$: probability of class i. z_i denotes output score of class i .

The predicted class was obtained as

$$\hat{y} = argmax_i P(y_i)$$

where $\hat{y}$ represents the predicted label.

Algorithm 1 summarizes the sequential workflow of the proposed hierarchical framework for healthy leaf detection, disease identification, and severity classification.

Algorithm 1: Hierarchical Ginger Leaf Disease Detection and Severity Classification

Input : Dataset D = {I1, I2, … , In}

Output : Disease class and severity level

Begin

```
Load dataset D
for each image Ii ∈ D do
    Resize Ii to 224 × 224
    L1 ← SwinModel1(Ii)
    if L1 = Healthy then
        Output ← Healthy
    else
        L2 ← SwinModel2(Ii)
        L3 ← SwinModel3(Ii)
        Output ← (L2, L3)
    end if
end for
```

Return Output

End

4.4 Training Configuration and Performance Evaluation Metrics

The three Swin Transformer models are initialized with ImageNet pretrained weights and trained independently using identical training settings. The input image size is 224 × 224 × 3 pixels. The models are trained using the Adam optimizer with a learning rate of 0.0001, a batch size of 32, and 50 epochs. The Softmax activation function is used in the output layer, and the model parameters are optimized using the categorical cross-entropy loss function.

The performance of the proposed framework is evaluated using accuracy, precision, recall, F1-score, confusion matrix, and the Receiver Operating Characteristic (ROC) curve. Accuracy is computed as

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

where TP, TN, FP, and FN denote the numbers of true positives, true negatives, false positives, and false negatives, respectively.

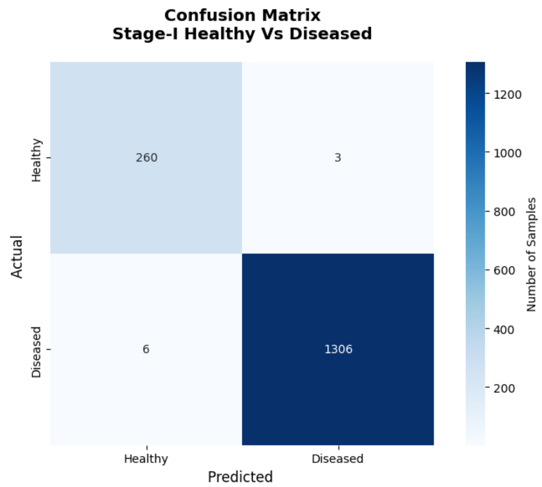
Precision, recall, and F1-score are used to evaluate the class-wise performance of the proposed framework. The confusion matrix summarizes the predicted and actual class labels for each classification stage. The ROC curve illustrates the relationship between the true positive rate and the false positive rate at different decision thresholds, while the Area Under the Curve (AUC) measures the overall discrimination capability of the classifier

5. RESULTS AND DISCUSSION

5.1 Healthy and Diseased Classification Performance

The first stage of the proposed hierarchical framework separates healthy and diseased ginger leaf images. Figure 11 presents the confusion matrix obtained for the binary classification model. The confusion matrix contains nine misclassified samples out of 1,575 test images. Three healthy leaf images are predicted as diseased, while six diseased leaf images are classified as healthy.

Figure 11: Confusion Matrix of Stage-I: Healthy and Diseased Classification



The classification report for the first stage is presented in Table 3. The model achieves an overall accuracy of 99.43% for healthy and diseased leaf classification. The Healthy class records a precision of 97.74%, recall of 98.86%, and F1-score of 98.30%, whereas the Diseased class achieves 99.77% precision, 99.54% recall, and 99.66% F1-score. The weighted average values of precision, recall, and F1-score are 99.43%, indicating balanced performance for both classes.

Table 3. Classification Report for Healthy and Diseased Classification

Class	Precision (%)	Recall (%)	F1-score (%)	Support
Healthy	97.74	98.86	98.30	263
Diseased	99.77	99.54	99.66	1312
Accuracy			99.43	1575
Macro Average	98.75	99.20	98.98	1575
Weighted Average	99.43	99.43	99.43	1575

Figure 12 presents the ROC curve for healthy and diseased classification. The proposed Swin Transformer model achieves an AUC of 0.9984. The ROC curve remains close to the upper-left corner, indicating accurate discrimination between healthy and diseased ginger leaf images with a low false positive rate.

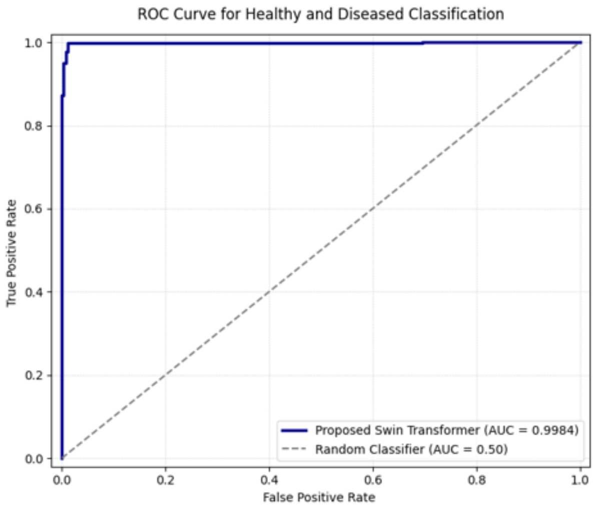


Figure 12. ROC curve for healthy and diseased classification.

5.2 Disease Classification Performance

The second stage classifies the diseased ginger leaves into five classes, Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot. The test set contains 1,314 images, the distribution of test images used for this stage is given in Table 4.

Table 4. Distribution of Test Images for Disease Classification

Disease class	Test images
Chlorotic Fleck	243
Bacterial Wilt	272
Fusarium Yellow	260
Leaf Blight	282
Pyricularia Leaf Spot	257
Total	**1,314**

Figure 13 shows the confusion matrix for disease classification. The model correctly classifies 1,284 images, giving an accuracy of 97.72%.

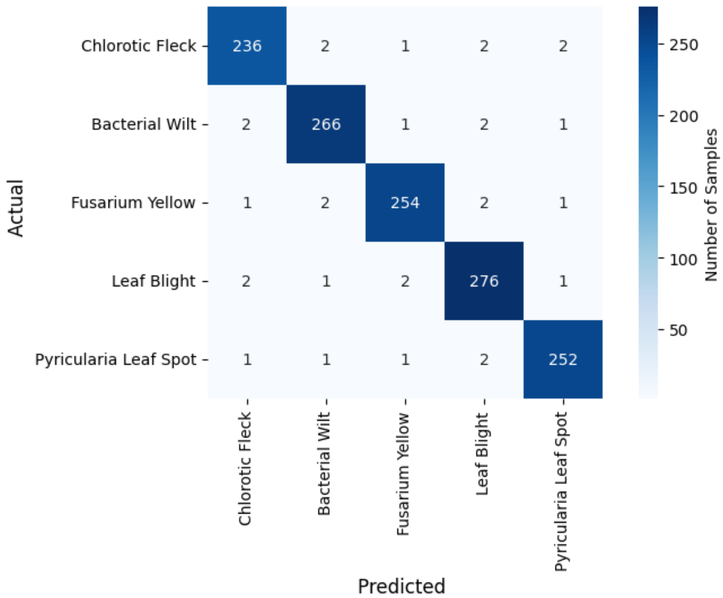


Figure 13. Confusion matrix for Disease classification performance

Table 5 presents the classification results for the five disease classes. The F1-scores range from 97.32% for Chlorotic Fleck to 98.05% for Pyricularia Leaf Spot. The macro average F1-score is 97.72%.

Table 5. Classification Performance for Disease Classes

Disease class	Precision (%)	Recall (%)	F1-score (%)	Support
Chlorotic Fleck	97.52	97.12	97.32	243
Bacterial Wilt	97.79	97.79	97.79	272
Fusarium Yellow	98.07	97.69	97.88	260
Leaf Blight	97.18	97.87	97.53	282
Pyricularia Leaf Spot	98.05	98.05	98.05	257
Macro Average	97.72	97.71	97.72	1,314
Weighted Average	97.72	97.72	97.72	1,314
Accuracy	—	—	97.72	1,314

Figure 14 shows the ROC curves for the five disease classes. The AUC values are 0.972, 0.985, 0.980, 0.978, and 0.980 for Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot, respectively. The macro AUC is 0.9790. Bacterial Wilt has the highest AUC, while Chlorotic Fleck has the lowest.

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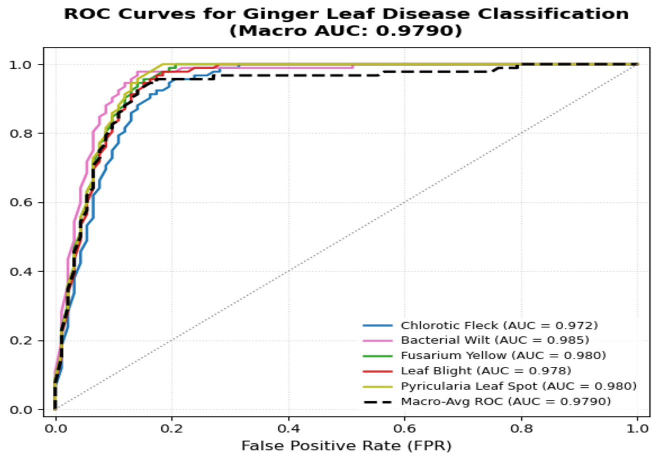

Figure 14. ROC Curves of the Swin Transformer for Ginger Leaf Disease Classification

5.3. Disease Severity Classification Performance.

The third stage classifies the diseased severity classification in ginger leaves into three classes, Early, Middle and severe. The test set contains 1,316 images, the distribution of test images used for this stage is given in Table 6.

Table 6. Distribution of Test Images for Disease Severity Classification

Disease	Early	Middle	Severe	Test Total
Chlorotic Fleck	78	92	74	244
Bacterial Wilt	105	84	83	272
Fusarium Yellow	65	104	92	261
Leaf Blight	120	81	81	282
Pyricularia Leaf Spot	70	78	109	257
Total	438	439	439	1,316

Figure **15** presents the confusion matrix for severity classification. The model correctly classifies 1,216 of the 1,316 test images, giving an accuracy of 92.40%.

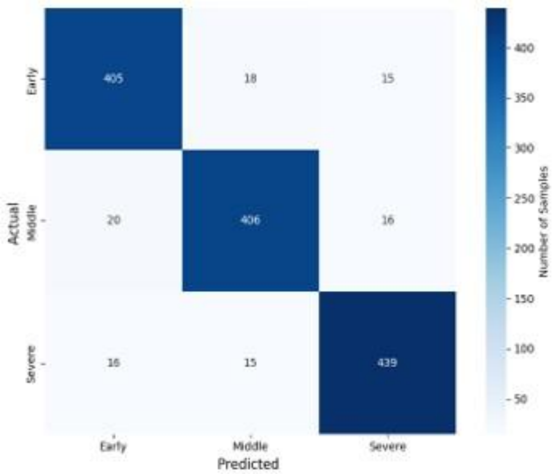

Figure 15. Confusion Matrix for Ginger Leaf Disease Severity Classification

Table 7 presents the classification results for the three disease severity classes. The F1-scores range from 92.15% for Early to 92.94% for Severe. The macro average F1-score is 92.40%.

Table 7. Classification Performance for Ginger Leaf Disease Severity Classes

Severity class	Precision (%)	Recall (%)	F1-score (%)	Support
Early	91.84	92.47	92.15	438
Middle	92.43	91.80	92.11	439
Severe	92.94	92.94	92.94	439
Macro Average	92.40	92.40	92.40	1,316
Weighted Average	92.40	92.40	92.40	1,316
Accuracy	—	—	92.40	1,316

Figure 16 presents the ROC curves for the three severity classes. The AUC values are 0.968 for Early, 0.949 for Middle, and 0.963 for Severe, with a macro AUC of 0.9605. The Middle class records the lowest AUC, while the Early class records the highest.

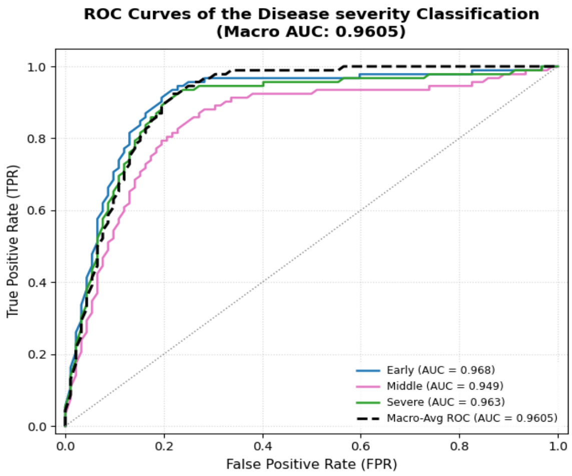

Figure 16. ROC Curves for Ginger Leaf Disease Severity Classification

5.4 Discussion

The Swin Transformer uses ImageNet pretrained weights and is fine-tuned separately for the three classification stages. This provides a common feature extraction backbone while allowing each stage to learn the characteristics of its own classification task.

The images are collected under natural daylight from 9am in the morning and 3pm in the afternoon. The image includes changes in background, leaf orientation, illumination, and symptom severity. These factors introduce variation in the images used for training and testing. No segmentation or image enhancement is applied; the images are resized and normalized before training.

The main limitation is the absence of an independent external dataset. The experiments use a 70:15:15 training, validation, and testing split from the collected dataset. Therefore, the performance on images collected from other locations, cameras, or seasons remains to be evaluated.

Future work can include external validation using images from different locations and field conditions. More images covering changes in illumination, background, leaf orientation, and disease progression can also be added. For severity classification, lesion segmentation or disease area measurement can be explored.

6. CONCLUSION

This study presents a hierarchical transfer learning framework for ginger leaf disease detection and severity assessment using the Swin Transformer. The framework performs the analysis in three stages: healthy and diseased classification, disease identification, and severity classification. Each stage uses a Swin Transformer initialized with ImageNet pretrained weights and fine-tuned for its respective classification task.

The first stage achieves an accuracy of 99.43% for healthy and diseased classification. The second stage achieves 97.72% accuracy for the five disease classes: Chlorotic Fleck, Bacterial Wilt, Fusarium Yellow, Leaf Blight, and Pyricularia Leaf Spot. The third stage achieves 92.40% accuracy for Early, Middle, and Severe severity classification. The corresponding macro AUC values are 0.9984, 0.9790, and 0.9605, respectively.

The proposed framework can support ginger disease screening, disease identification, and severity assessment from leaf images. It can also serve as a basis for image-based agricultural diagnostic systems in which field images are used to obtain the disease class and severity level.

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AUTHOR CONTRIBUTIONS

Dhananjaya Kumar H S: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Investigation, Writing – Original Draft.

Dr. K Satyanarayana Reddy: Supervision, Validation, Writing – Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

This study did not involve human participants, human data, or animal subjects. Ethical approval was not required.

DATA AVAILABILITY STATEMENT

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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