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Transfer Learning with ResNet-9 for the Classification of Local Corn Leaf Diseases in Myanmar

May MyatNoe Oo[1], Aung Nway Oo[2]

[1]May MyatNoe Oo
University of Information Technology (Yangon)

[2]Aung Nway Oo
University of Information Technology (Yangon)
[1]maymyatnoeoo@uit.edu.mm, [2]aungnwayoo@uit.edu.mm

Abstract: *Corn is the second most critical crop in Myanmar's agricultural sector in livestock feed production and export income after rice. On the other sides, corn plant suffers various leaf diseases under different weather conditions, this significantly leads to the loss in the economy of Myanmar yearly. Farmers mostly lack the knowledge of disease symptoms to give the right treatment and experts are also rare. In recent year, in agricultural sector, with the advancement of deep learning technologies, researchers used to apply these techniques for the classification of leaf diseases. This paper presents an automatic leaf disease classification system on the local Myanmar corn dataset using a lightweight ResNet-9 model. The study also compares two training methods: direct fine-tuning and transfer learning. The direct fine-tuning approach achieved a test accuracy of 97.97%, while the transfer learning approach reached a higher test accuracy of 99.63%. The transfer learning model also showed more stable convergence by using pre-trained weights learned from global datasets. Experimental results on a local corn leaf dataset demonstrate that the proposed ResNet-9 model can provide accurate disease classification with low computational cost, making it suitable for deployment in resource-limited agricultural environments.*

Keywords: Corn leaf disease, ResNet-9, Transfer Learning, Myanmar Agriculture, Deep Learning, Image Classification**.**

I. Introduction

Corn is the second most important crop in Myanmar and makes a significant contribution to the country's food security and export income. The Shan State produces more than 50% of Myanmar's total maize production [2], while the Kyaukse region is also an important area for corn cultivation. Although corn is widely grown in these regions, farmers often experience serious yield losses because of leaf diseases. If these diseases are not detected at an early stage, they can spread quickly and reduce both crop quality and production.

Traditional disease identification mainly depends on visual inspection by agricultural experts. However, expert support is not always available, especially in rural farming areas. In addition, different diseases may have similar symptoms, making manual diagnosis difficult and increasing the chance of incorrect classification.

Recent advances in deep learning have been greatly improved for plant disease detection. Convolutional Neural Networks (CNNs) can automatically learn important image features and identify small differences between healthy and diseased leaves [1]. These models have achieved high classification accuracy in many agricultural applications. However, many deep learning models require high computational resources, which make them difficult to deploy in practical agricultural environments with limited hardware.

To address this challenge, we need to develop a lightweight one that can give the best balance between accuracy and computational resources and then, according to the previous studies, we discovered that ResNet-9 model is considered as the optimal one for this scenario. Furthermore, the previous research in plant disease classification showcased the efficacy of transfer learning for plant leaf disease classification by comparing the different pre-trained deep learning models dealing with low resource dataset. Then, there is a gap that is needed to specifically research on finding the lightweight model using transfer learning while keeping the best accuracy and low computational resources for real-world deployment. And so, this study aims.

- To do transfer learning on the local corn leaf diseases datasets with limited resources by using the ResNet-9 pre-trained model on global PlantVillage Maize Dataset [12] addressing the lack of research on Myanmar local corn leaf diseases
- To explore on two training strategies: Direct Fine-

tuning and Transfer learning on the limited Myanmar local corn leaf dataset using ResNet-9 model

• To develop a lightweight efficient model with reliable accuracy for the detection of local Myanmar Corn leaf diseases.

II. Related Work

Deep learning has become an important method for plant disease detection. One of the main reasons is the use of transfer learning, which applies knowledge learned from large pre-trained models to new tasks. This method is especially useful when only a small amount of labeled agricultural data is available. By using pre-trained feature extractors, transfer learning helps improve classification performance and has become a common approach in plant disease diagnosis [3].

Many researchers have applied different transfer learning models to classify maize leaf diseases. MobileNet, VGG16, and Xception have been used by freezing the backbone layers while training only the classification layers. This approach keeps the learned image features and achieved a test accuracy of up to 93% [4]. Another study used DenseNet201 together with a Global Average Pooling layer to classify large datasets containing thousands of blight and rust leaf images. The model produced strong classification performance on these complex datasets [5]. Moreover, transfer learning using VGG-16 with freezing the backbone layer followed by fine- tuning only the last eight layers got an accuracy of 95.52%, ensuring the model generalization with a proof of the minimal gap between the training and validation loss [6].

Then, it was found that applying the augmentation techniques such as rotation, zoom, brightness adjustment, and horizontal flipping in real time make the dataset increase improving the model's generalization and transfer learning on the dataset over 3614 samples using the MobileNetV2 and EfficientNetB0 pre-trained model achieved the remarkable accuracy of 98% and 99%, respectively [7]. Another study using ensemble transfer learning_ the customized combination of the pre-trained model architecture like MobileNetV3 and ResNet50 reached an accuracy of 99.50% over the thousand plant image data [8].

With 80,000 photos of Kaggle data across 38 different classes, it is also observed that the exclusive pre-trained model like EfficientNet5 using transfer learning achieved 99% accuracy and shows that the ability of the proposed pre-trained model worked effectively for large scale plant disease classification tasks [9]. Then, in the comparison between ResNet 50 and Vision Transformer Model using transfer learning for plant leaf disease classification on the 38 classes of the dataset, it was observed that vision model effectively handled the complex variance with a slightly lower accuracy of 95.22%, while the ResNet 50 model achieved 99.58% accuracy [10]. Lastly, another comparative study on the three pre-trained models CNN, VGG16 and ResNet50 with large scale thousand dataset across 38 classes found that CNN and resnet architecture gave the higher results with an accuracy of 95% over with an accuracy of 92% with VGG16 [11].

III.Methodology

3.1 Data Collection and Dataset Preparation

The dataset used in this study was collected through field surveys conducted in the Shan State and Kyaukse regions of Myanmar. Collecting images directly from local farms helps ensure that the developed model can perform well under real agricultural conditions. The dataset represents the environmental conditions that farmers commonly experience during corn cultivation.

3.2 Field Acquisition and Labeling

Corn leaf images were collected from active corn farms from three locations in Myanmar: (1) Kyauktae Village, Taunggyi Township, Southern Shan State; (2) Kyun-U Village, Sintgaing Township, Aetpyar Village Tract, Kyaukse District; and (3) Makkhayar Village, Sintgaing Township, Aetpyar Village Tract, Kyaukse District. These locations were selected to capture leaf diseases under natural field conditions. All images were taken using a smartphone with a 13-megapixel camera to simulate how farmers would collect images when using the proposed disease diagnosis system. Unlike laboratory datasets collected under controlled conditions, the field images contain natural variations such as different lighting conditions, shadows, soil backgrounds, and various leaf positions and orientations. These variations make the dataset more representative of real agricultural environments and improve the practical applicability of the proposed model.

The labeling was performed by agricultural specialist from MINISTRY OF SCIENCE AND TECHNOLOGY DEPARTMENT OF BIOTECHNOLOGY RESEARCH, putting up with higher reliability. Each image was carefully inspected and labeled to ensure the accuracy of the disease classes.

3.3 Pre-processing and Standardization

All images were resized to a standard dimension 256*256 pixels to maintain spatial feature distribution consistency when feeding to the deep learning model. This resolution was chosen to uniformly distribute the feature and texture of the input images when training to the model. Since the images are taken under the natural environment, on field, the dataset is highly robust for the application as a field diagnosis tool, thereby reducing the "domain shift" effect that often causes deep learning models to fail when transitioning from lab-based training to field-based application. The dataset comprises four categories of corn leaf__ Common_rust, Gray_leaf_spot, Healthy, Maize Chlorotic Mottle Virus, ranging from healthy specimens to various stages of disease progression. Sample images are shown in Table 4. Table 1 displays the distribution of images per class. By setting the random seed number for uniform distribution, the dataset was split up as the train and test set with a ratio of 80:20 as shown in Table 2 and Table 3 by setting the random seed number for uniform distribution to use in the model training.

Table 1: Distribution of corn leaf images across disease categories

No	*Classes*	*Number of Images*
1	Common Rust	518
2	Gray Leaf Spot	1051
3	Healthy	571
4	Maize Chlorotic Mottle Virus	554
	Total	2694

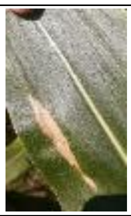
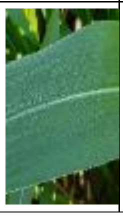
Table 2: Train data distribution

No	*Classes*	*Number of Images*
1	Common Rust	414
2	Gray Leaf Spot	840
3	Healthy	456
4	Maize Chlorotic Mottle Virus	443
	Total	2153

Table 3: Test data distribution

No	*Classes*	*Number of Images*
1	Common Rust	104
2	Gray Leaf Spot	211
3	Healthy	115
4	Maize Chlorotic Mottle Virus	111
	Total	541

Table 4: Sample images for four types of corn leaf

Common_ rust	Gray_leaf_ spot	Healthy	Maize Chlorotic Mottle Virus
			

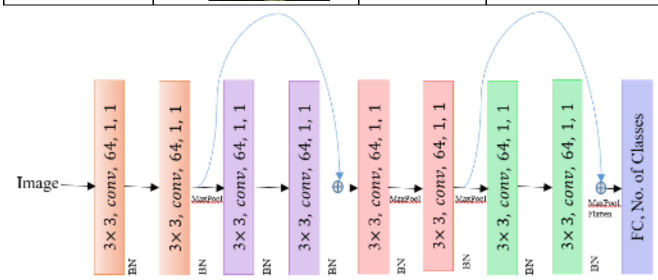


Figure 1: ResNet-9 Architecture used in direct fine-tuning

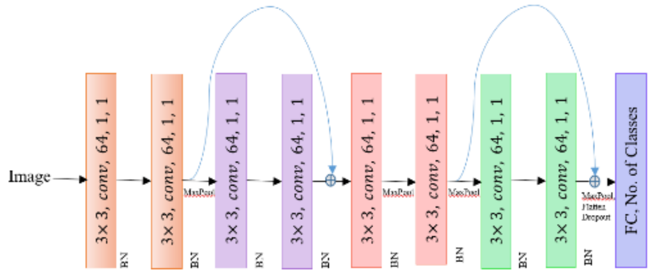


Figure 2: ResNet-9 Architecture used in Transfer Learning

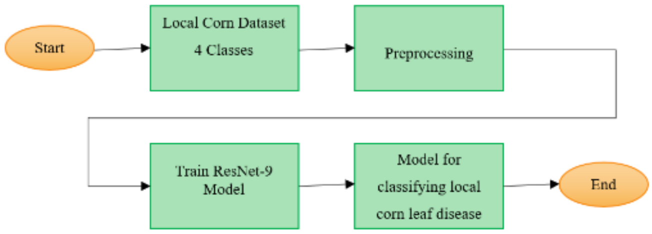


Figure 3: The proposed system architecture for classifying local corn leaf diseases using Direct Fine-tuning

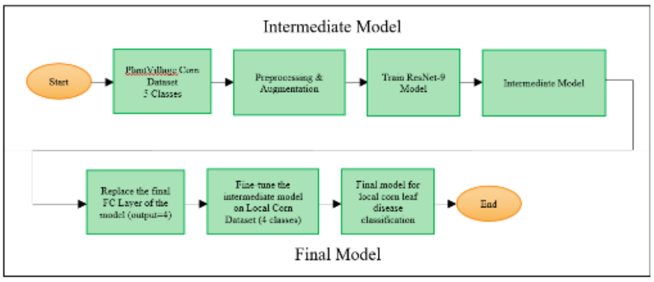


Figure 4: The proposed system architecture for classifying local corn leaf diseases using Transfer Learning

3.4 Training Strategies

Training was carried out online using the Kaggle notebook environment equipped with an NVIDIA Tesla P100 GPU (16 GB VRAM) and the program was coded using PyTorch libraries. Two training strategies are carried out:

3.4.1 Strategy 1:Direct Fine-tuning (Training from Scratch)

The ResNet-9 architecture which is shown detailed in Figure 1 was initialized with random weights and trained from scratch on the local dataset. In training, optuna is utilized for hyperparameter optimization to identify the most robust configuration and the initial hyperparameter search space is depicted in Table 5. WeightedRandomSampler is implemented to mitigate model bias toward majority classes to deal with the imbalance datasets. This ensures that each training batch maintains an equalized representation of all disease classes, preventing the model from favoring the most frequent class during optimization. To meticulously analyze the model stability and convergence, the training process is executed on 100 epochs over early stopping. This long duration confirmed that the model reached a stable and reliable state without premature termination while ensuring the model generalized well and did not overfit during the learning process_ serving as the stress test. After configuring the necessary implementation, the local dataset was fed and trained in the resnet-9 architecture (Figure 1) using the best-performing hyperparameters - including optimizer, learning rate, batch size, weight decay, momentum, gradient clippig and patience which are summarized in Table 6. The aggregated view of the proposed system architecture for direct fine-tuning presents in Figure 3.

3.4.2Strategy 2: Transfer Learning

The ResNet-9 architecture which was shown in Figure 2 was initialized with the model's weights from fine-tuning on global corn leaf disease dataset [13], followed by fine-tuning on our local data. Transfer learning involves utilizing knowledge gained from global datasets—specifically those pre-trained on large-scale ImageNet repositories, in this research, global corn repositories [12] - to improve feature robustness on local data [3] and avoid overfitting. Unlike the scratch-trained model, the transfer learning model initializes its feature-extraction backbone with weights pre-trained on diverse global datasets. The final fully connected layer (originally designed for a 5-class Global Corn output) was replaced with a linear layer structured for our 4-class local corn leaf disease classification. This allows the model to map previously learned "global" features—such as edge detection and texture patterns—directly onto the localized disease features. Moreover, the dropout layer with a rate of 0.2 is integrated to the classification layer to prevent entirely depending on the pre-trained neurons weights_ enhancing the generalization and preventing overfitting, followed by fine-tuning with the best hyperparameter shown detailed in Table 6. Figure 4 displays the overall proposed system architecture flow for transfer learning.

Table 5: Initial hyperparameter explore using optuna

No	*Hyperparameter*	*Value Range*
1	Optimizer	[SGD, AdamW]
2	Batch Size	[8, 16, 32]
3	Learning Rate	[1e-4, 0.01]
4	Weight Decay	[1e-5, 1e-1]
5	Momentum	[0.7, 0.99]
6	Gradient Clipping	[0.001, 1.0]

Table 6: Hyperparameterchosen after optimization

No	*Hyperparameter*	*Value Range*
1	Optimizer	SGD
2	Batch Size	32
3	Learning Rate	0.00056115164153345
4	Weight Decay	0.063512210106407
5	Momentum	0.87361096041714
6	Gradient Clipping	0.157029708840553

3.5 Performance Evaluation Metrics

The experimental results were analyzed using the comprehensive evaluation framework.

3.5.1Confusion Matrix

The confusion matrix maps the predicted labels against the actual ground-truth labels to visualize precisely which diseases the ResNet-9 architecture can correctly classify precisely.

3.5.2 Precision, Recall, and F1-Score

Because the clinical consequences of misdiagnosing a crop disease are high, balanced metrics are prioritized over simple accuracy:

(a) Precision: Represents the accuracy of positive predictions. It is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

where TP is the number of True Positives and FP is the number of False Positives.

(b) Recall (Sensitivity): Measures the model's ability to capture all actual disease instances. It is defined as:

$$Recall = \frac{TP}{(TP + FN)} \tag{2}$$

where FN is the number of False Negatives.

(c) F1-Score: This is the harmonic mean of precision and recall:

$$F1\,Score = 2 \times \frac{(Precision\,Recall)}{(Precision + Recall)} \tag{3}$$

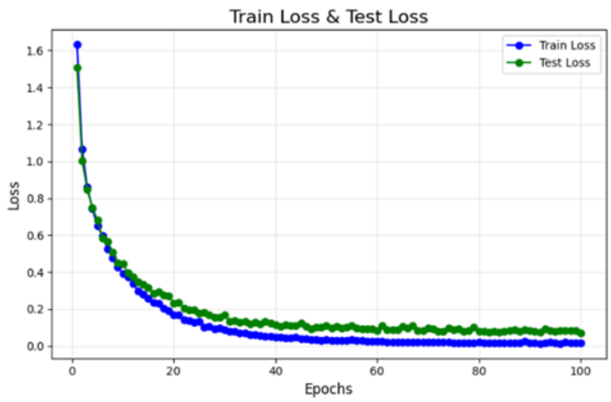


Figure 5: Training and testing loss curve for direct fine-tuning

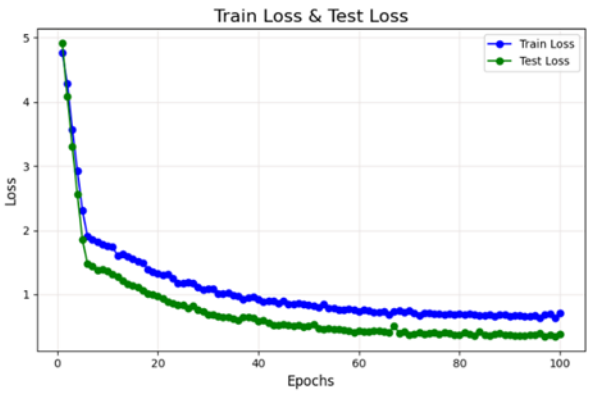


Figure 6: Training and testing loss curve for transfer learning

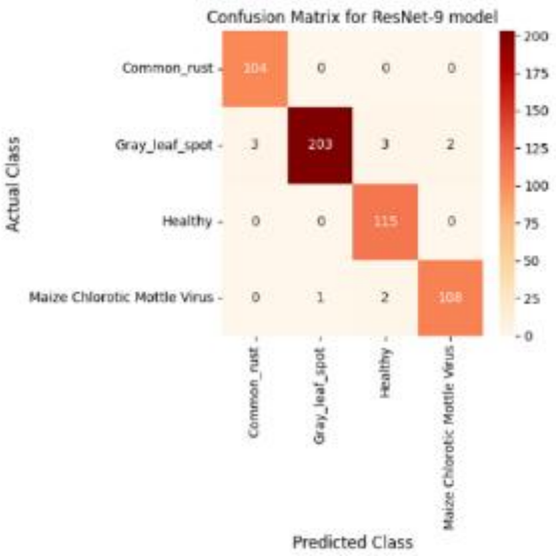


Figure 7: Confusion matrix for direct fine-tuning

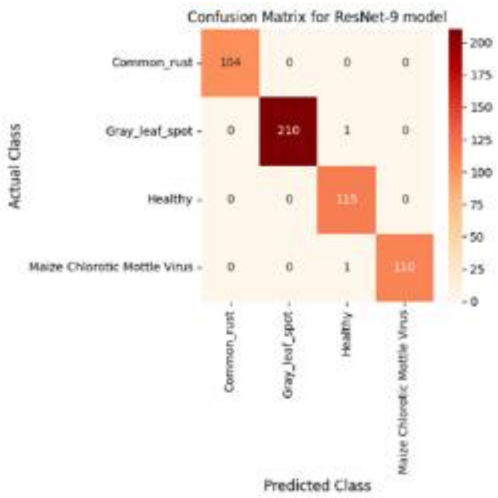


Figure 8: Confusion matrix for transfer learning

IV. Results

4.1 Loss Curve

The loss curves of the two training methods show different learning behaviors during training. For the Direct Fine-tuning model shown in Fig. 5, the training loss decreases rapidly during the first 20 epochs. After this stage, the loss continues to decrease at a slower rate. From around the 50th epoch, the loss curve becomes stable, indicating that the model has learned the important features from the training data. For the Transfer Learning model shown in Fig. 6, the training loss decreases much faster during the first 10 to 20 epochs. The model reaches convergence earlier than the direct fine-tuning approach. The gap between the training loss and testing loss becomes stable by around the 80th epoch. This result suggests that the pre-trained weights provide a strong feature extraction foundation, allowing the model to learn more efficiently and achieve better optimization.

4.2 Confusion Matrix, Precision, Recall, and F1-Score Analysis

The evaluation metrics were calculated using the Scikit-learn library, providing an overall assessment of the model's performance across the five corn leaf categories. The fine-grain analysis of the model classification's capability between actual and predicted is depicted using the confusion matrix. As depicted in Figure 7, in the direct fine-tuning, although it is effective, the model encountered minor misclassifications, particularly between Gray Leaf Spot and Maize Chlorotic Mottle Virus, as well as Healthy and Maize Chlorotic Mottle Virus samples. Unlike direct fine-tuning, the missclassification amount in Gray Leaf Spot and Maize Chlorotic Mottle Virus significantly mitigates as illustrated in Figure 8, achieving near-perfect convergence.

The comparative analysis of quantitative classification report shown in Table 7, synthesizes the performance metrics across four disease categories. With a weighted average F1-score of 0.98, it is observed that the model using direct fine-tuning maintained a balanced performance with an average F1-score of 99.75%, it is observed that transfer learning contributes to superior performance than the direct fine-tuning with an average of 98.2% across all four classes, suggesting that pre-trained knowledge offers the greater performance for the classification task. For Common Rust and Gray Leaf Spot, Precision and Recall using the Transfer Learning attains 100% accuracy flawlessly, whereas there is a 3% and 4% deficit in the Precision and Recall for those classes using the direct fine-tuning_ demonstrating the transfer model mitigates false positives and false negatives for these diseases. For the healthy class, transfer learning method improved 2% in Precision than the direct fine-tuning approach while maintaining a perfect Recall of 100% _ promising the higher reliability in this class. For Maize Chlorotic Mottle Virus, the percentage over Precision, Recall and F1-Score using direct fine-tuning was increased to 2% across all metrics by using transfer learning. To sum up, transfer learning presents the reliable performance consistently across all four class categories for developing highly reliable maize disease detection system.

Table 7: Comparative performance of the classification report

Model	*Training Method*	*Classes*	*Precision*	*Recall*	*F1-Score*	*Accuracy*
Resnet-9	Direct Fine-Tuning	Common Rust	97.00%	100.00%	99.00%	97.97%
		Gray Leaf Spot	100.00%	96.00%	98.00%	
		Healthy	96.00%	100.00%	98.00%	
		Maize Chlorotic Mottle Virus	98.00%	97.00%	98.00%	
	Transfer Learning	Common Rust	100.00%	100.00%	100.00%	99.63%
		Gray Leaf Spot	100.00%	100.00%	100.00%	
		Healthy	98.00%	100.00%	99.00%	
		Maize Chlorotic Mottle Virus	100.00%	99.00%	100.00%	

V. Conclusion

This study evaluates the two training methods_ transfer learning and direct fine-tuning for the classification of local corn leaf diseases in the Shan State and Kyaukse regions of Myanmar. The transfer learning methodology achieved 99.63% accuracy with a perfect weighted average F1-score of 1.00 while the direct fine-tuning got a slighter decrease in accuracy with 97.97% According to the comprehensive comparison between direct fine-tuning and transfer learning based on the experimental results, it provides that transfer learning is the preferable one for the detection of the local corn leaf diseases with the limited data amount. In addition, these results and findings can validate the initial hypothesis that pre-trained weights offer a superior foundation for feature extraction in localized, small-scale datasets compared to random weight initialization. To conclude, the transfer learning approach using Resnet-9 framework contributes the highly reliable performance model for deploying on-field corn leaf disease classification. And so, future research may focus on developing the web and mobile application using the proposed transferred model with XAI method for providing the transparent clarification of the model’s interpretation.

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