Heaven’s Light is Our Guide

RAJSHAHI UNIVERSITY OF ENGINEERING & TECHNOLOGY

Department of Computer Science And Engineering

THESIS TOPIC

Rice Leaf Diseases Classification Using CNN with Transfer Learning

Presented by

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Outline

Introduction

- Rice is an important economic crop in Bangladesh and is the main food source for over half of the world population . Recent problem of weather anomalies is one of the factors causing plant disease epidemics, which affect rice production. [1]

- Early detection and remedy of such diseases are beneficial to ensure high quantity and best quality but this is difficult due to the huge expanse of land under individual farmers and the huge variety for diseases as well as the occurrences of more than one disease in same plant. Agricultural expert known is not accessible in remote areas. Therefore the automated systems are required accuracy of plant disease detection, research work using various deep learning algorithms. [2]

Literature Review

SL No.	Author and Journal	Paper	Method	Dataset	Summarized Findings
1	Shreya Ghosal , Kamal Sarkar ieeexplore.ieee.org, Accessed: Oct. 02, 2021. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9106423/[1]	Rice Leaf Diseases Classification Using CNN With Transfer Learning	Transfer learning using fine-tuning the predefined VGGNet model	Dataset consists of 1649 images of diseased leaves of rice consisting most common three disease (blight, blast , brown spot)	Correctly classifies 92.46% of the test images and VGGNet has greatly improve the performance of the model
2	Kantip Kiratiratanapruk , Pitchayagan Temniranrat , Apichon Kitvimonrat , Wasin Sinthupinyo , and Sujin Patarapuwadol, Springer Nature Switzerland AG 2020 [2]	Using deep learning techniques to detect rice deseases from field images	Faster R-CNN, RetinaNet, YOLO v3, Mask R-CNN	Dataset consists of 6 classes(blast, blight, brown spot, narrow brown spot, leaf streak, RRSV) with 6630 images	Among these model YOLO v3 has highest precision of almost 80%. Faster R-CNN=70.96% Mask R-CNN=75.92% RetinaNet=36.11%.

Literature Review

Research lackings of Shreya et. al (2020) [1]

1. The dataset used to train and evaluate the proposed method is relatively small.
2. The authors do not provide any information about the computational resources required to train and deploy their proposed method
3. Not so high accuracy.

Objectives

01 Developing a deep learning model for identifying and classifying large number of rice leaf disease images.

02 Utilizing deep learning techniques such as convolutional neural network, vision transformer to enhance detection accuracy and handle the variability of disease symptom.

03 To improve the efficiency and precision of existing paper model and reduce the computational parameters.

Proposed Methodology

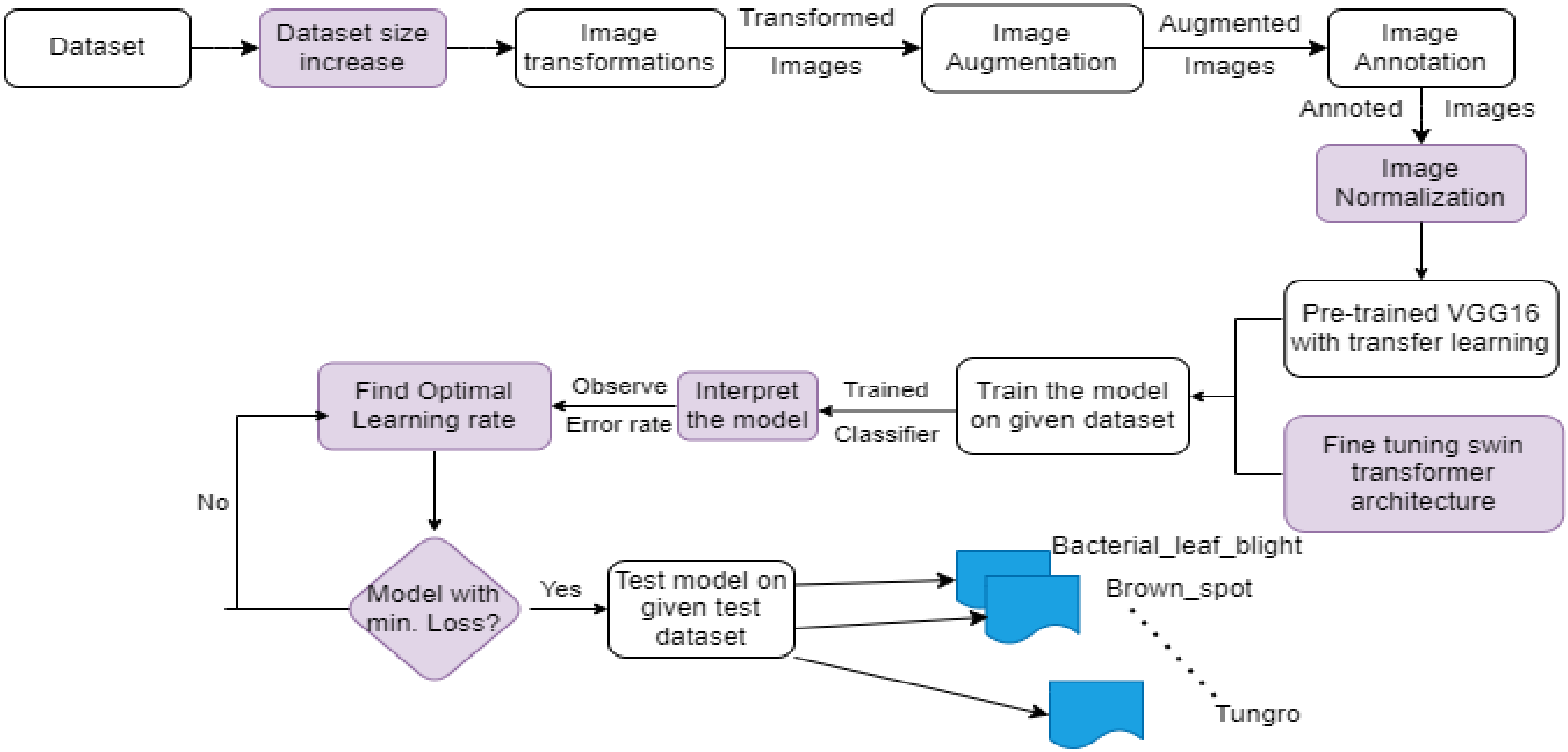


Fig-1: Proposed CNN based Architecture

Implementations

Dataset Collection:

I have collected Rice Leaves diseases dataset from internet of 10 types of leaves. Those are bacterial_leaf_blight, brown_spot, healthy, leaf_blast, leaf_scald, narrow_brown_spot, neck_blast, rice_hispa, sheath_blight, tungro.

Disease type	Train	Test	Validate	Total
Leaf_blight	800	376	586	1762
Brown_spot	1000	380	480	1860
Healthy	891	391	600	1882
Leaf_blast	1201	362	600	2163
Leaf_scald	1094	386	576	2056
Narrow_brown	912	382	504	1798
Neck_blast	664	322	336	1322
Rice_hispa	949	225	512	1686
Sheath_blight	1050	288	528	1866
Tungro	1092	310	648	2050
	9653	3362	5370	18445

Source:https://www.kaggle.com/datasets/loki4514/rice-leaf-diseases-detection

Existing paper architecture:

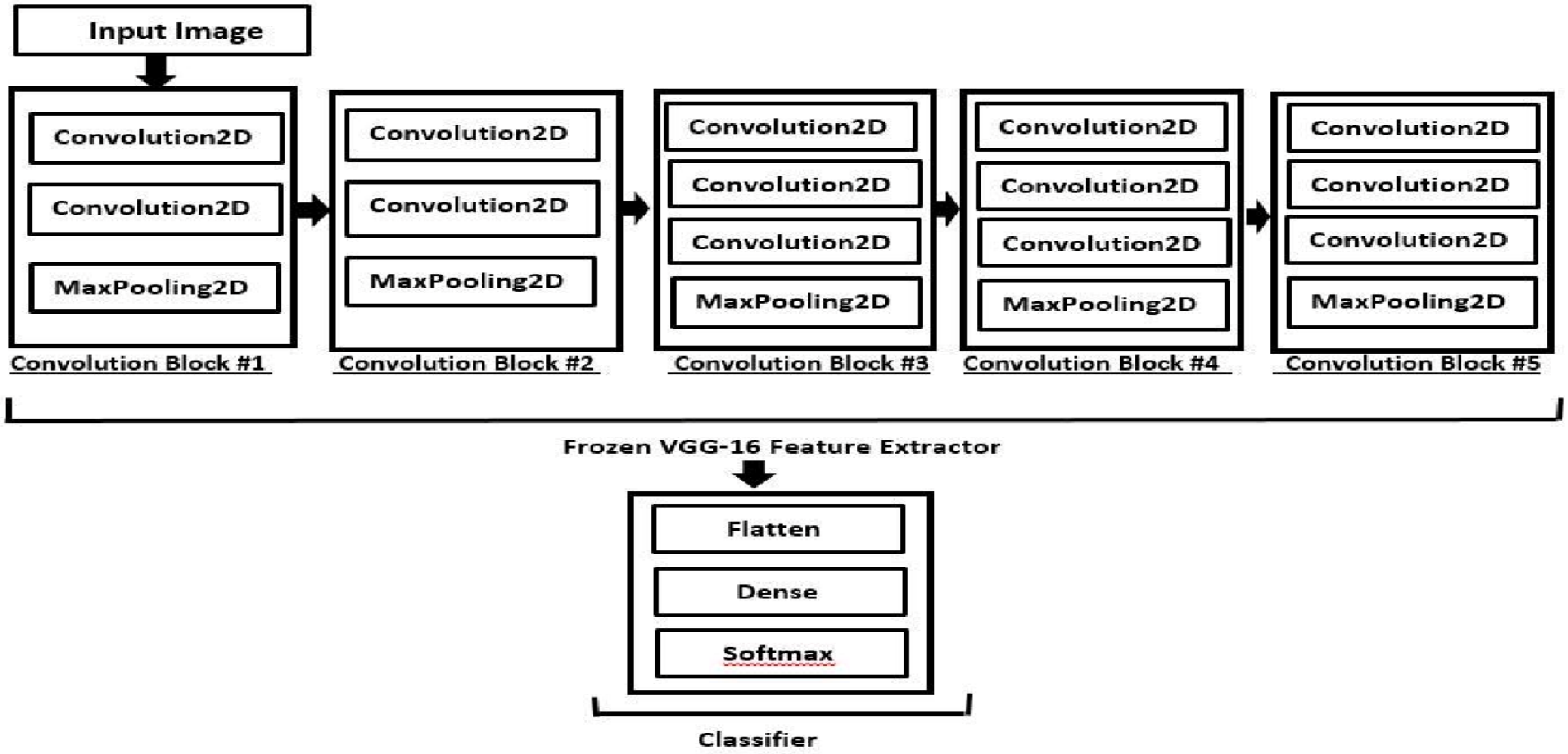
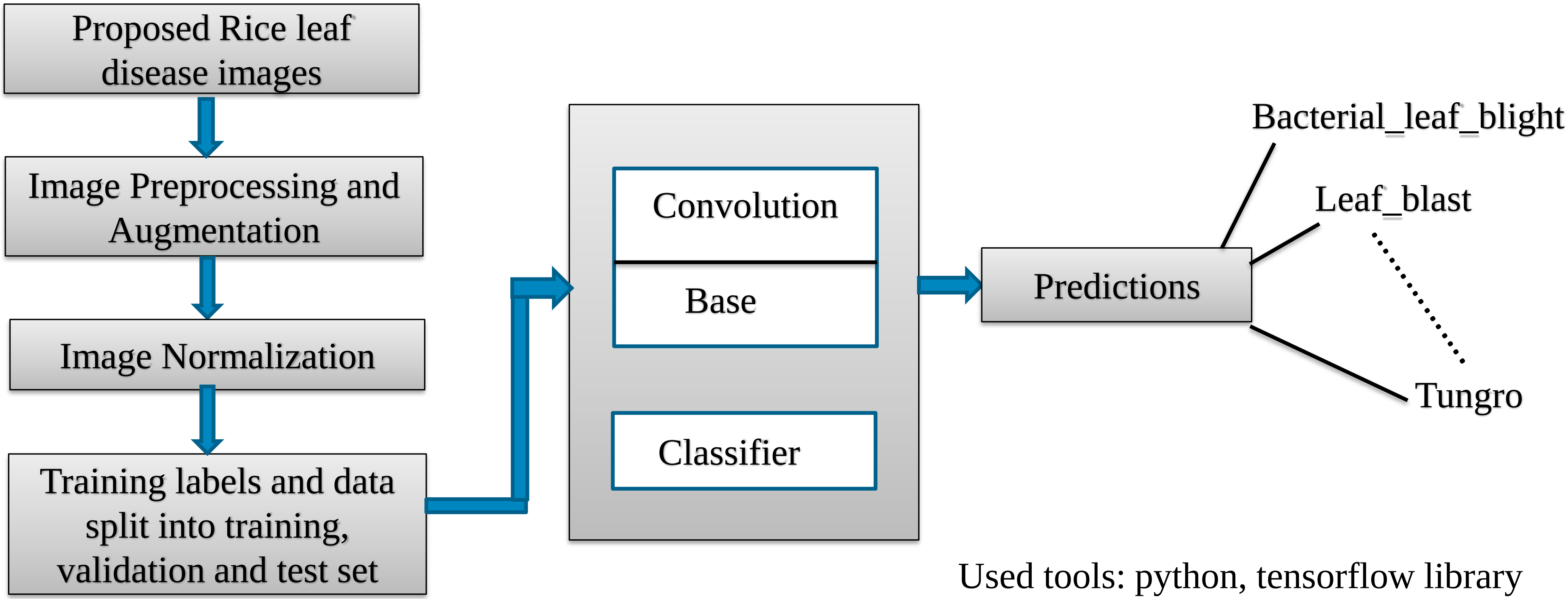


Fig-2: VGG-16 Architecture fine–tuned with the last two layers with 128 Dense FC Layer and 4 Dense Softmax Layer as the output [1]

Implementations

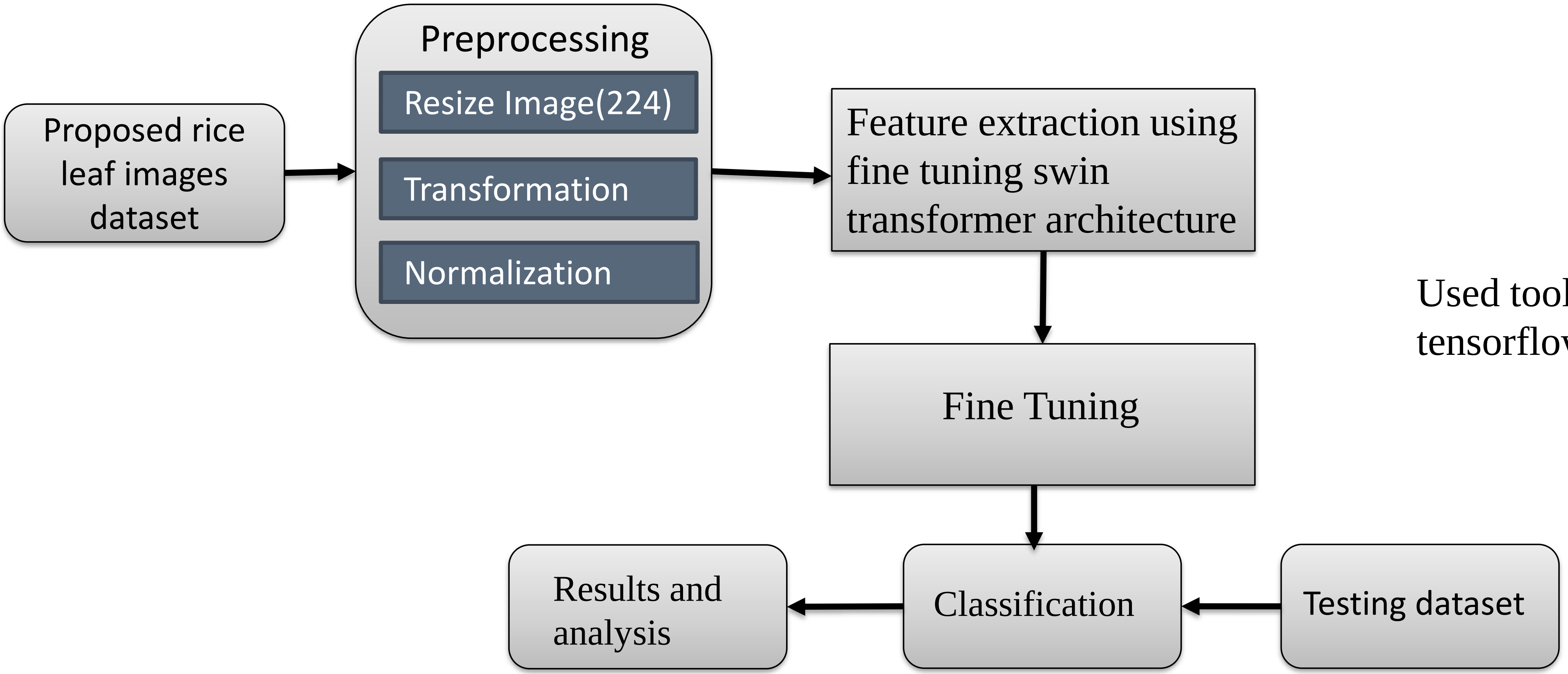
Existing paper architecture implementation with proposed dataset:



Used tools: python, tensorflow library

Fig-3: Overall steps of implementing VGG16 architecture [1]

Implementations



Used tools: python, tensorflow library

Fig-4: Overall steps of implementing proposed fine tuning CNN with swin transformer architecture.

Implementations

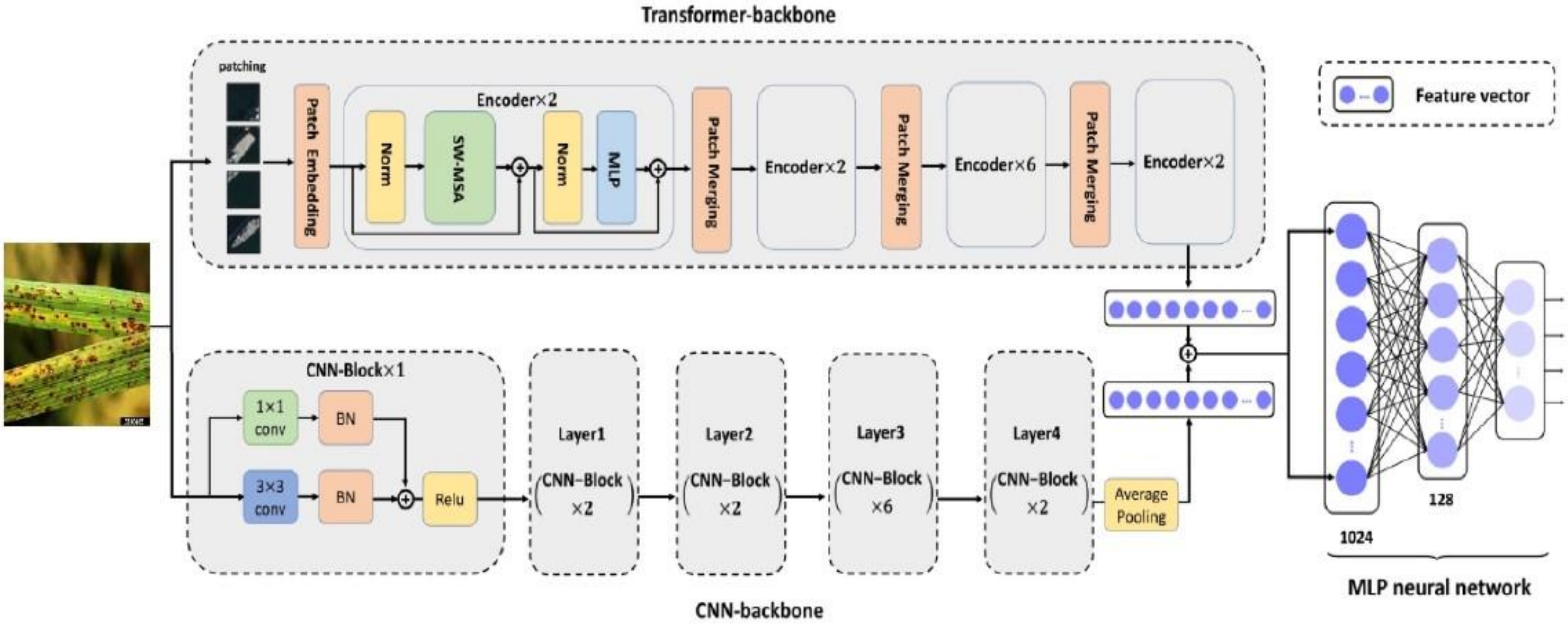


Fig-5: Network architecture of the proposed fine tuning CNN with swin transformer [4] .

Classification Results With Proposed Dataset:

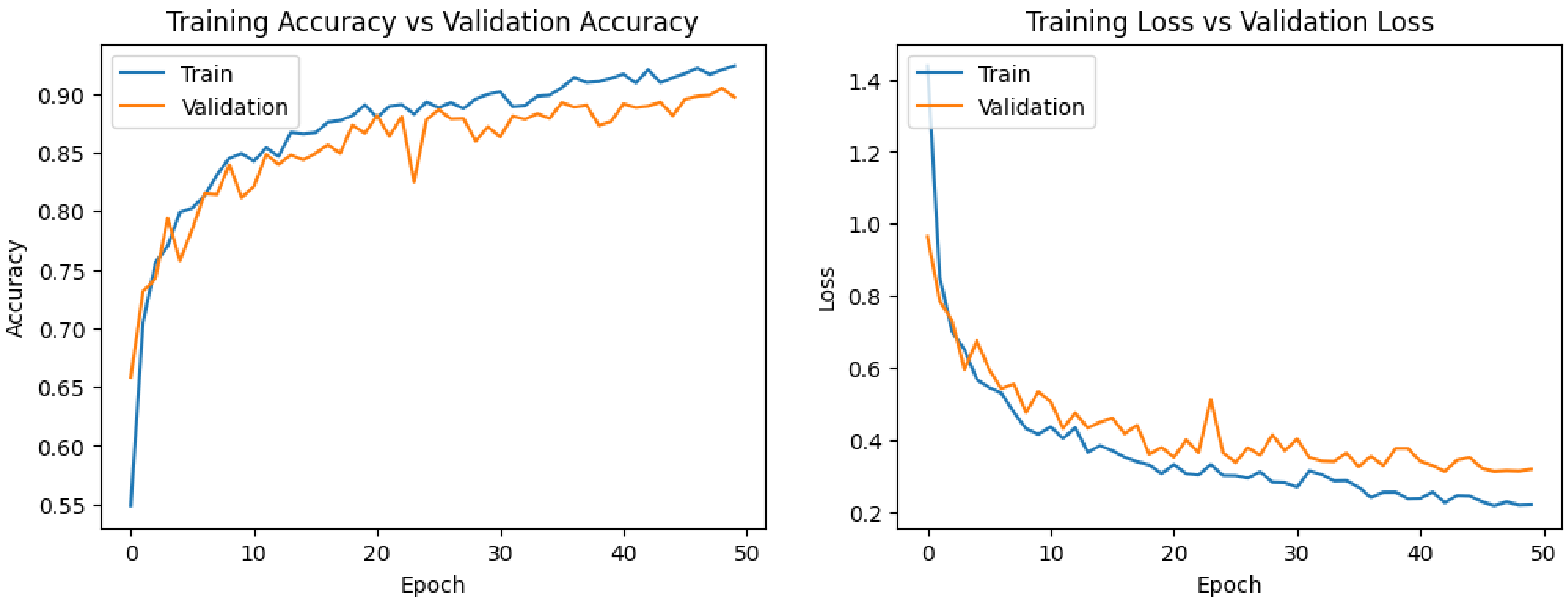


Fig-6: Accuracy and Loss graph of training and validation for pre-trained VGG-16.

Experimental Results and Analysis

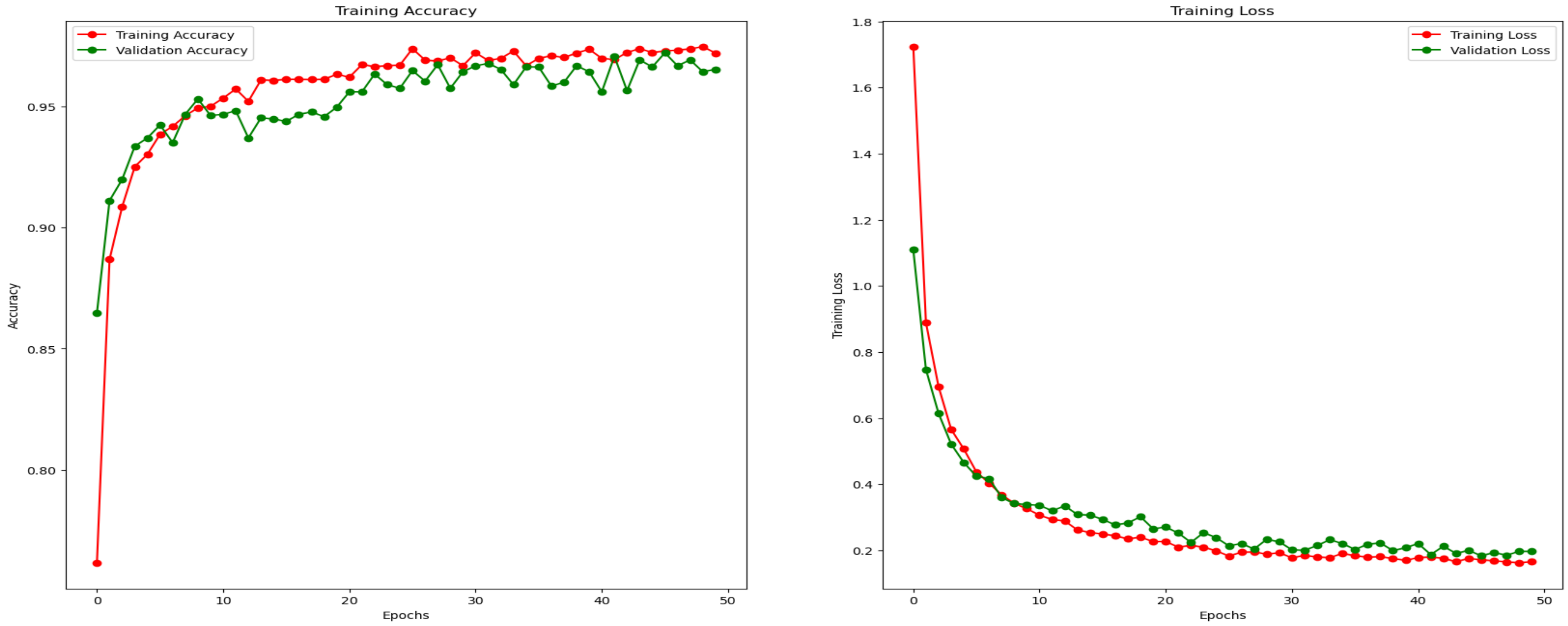


Fig-7: Accuracy and Loss graph of training and validation for fine tuning CNN with swin transformer architecture.

Experimental Results and Analysis

Model Performance With Confusion Matrix:

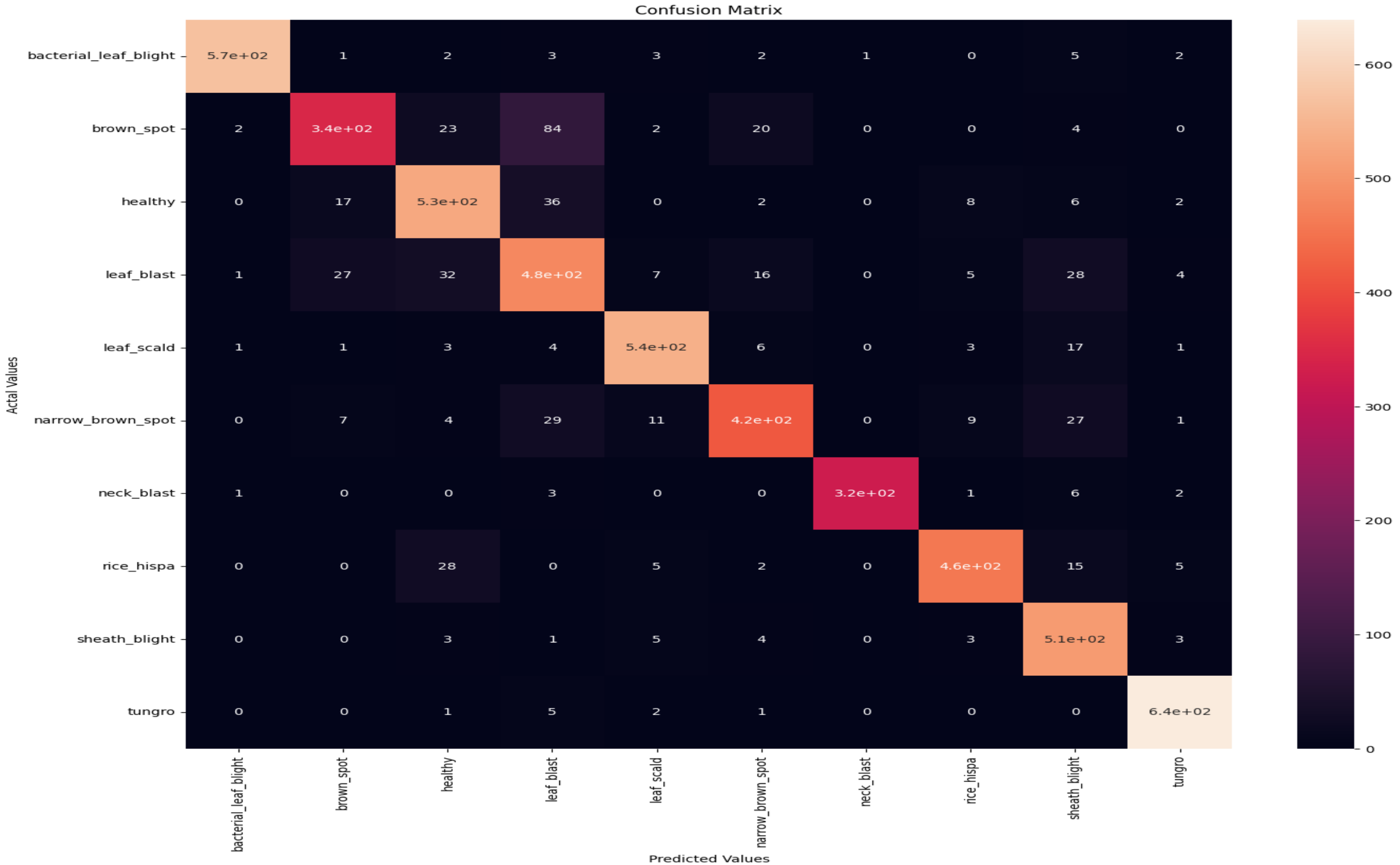


Fig-8: Confusion Matrix of Pre-trained VGG-16 with Proposed Dataset.

Experimental Results and Analysis

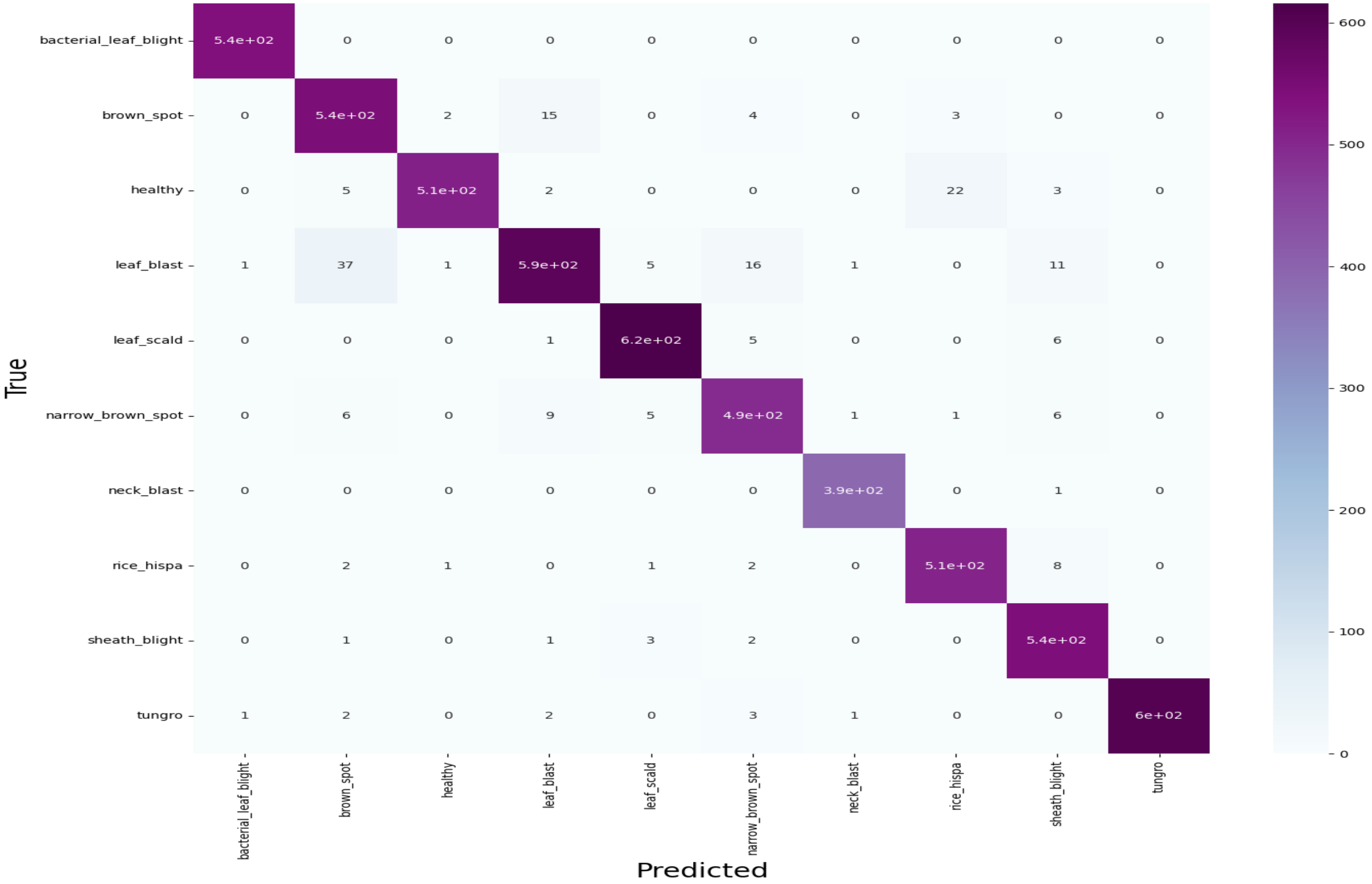


Fig-9: Confusion Matrix of Fine Tuning CNN with Swin Transformer Architecture with.Proposed Dataset.

Experimental Results and Analysis

Model Performance with Precision, Recall and F1-Score:

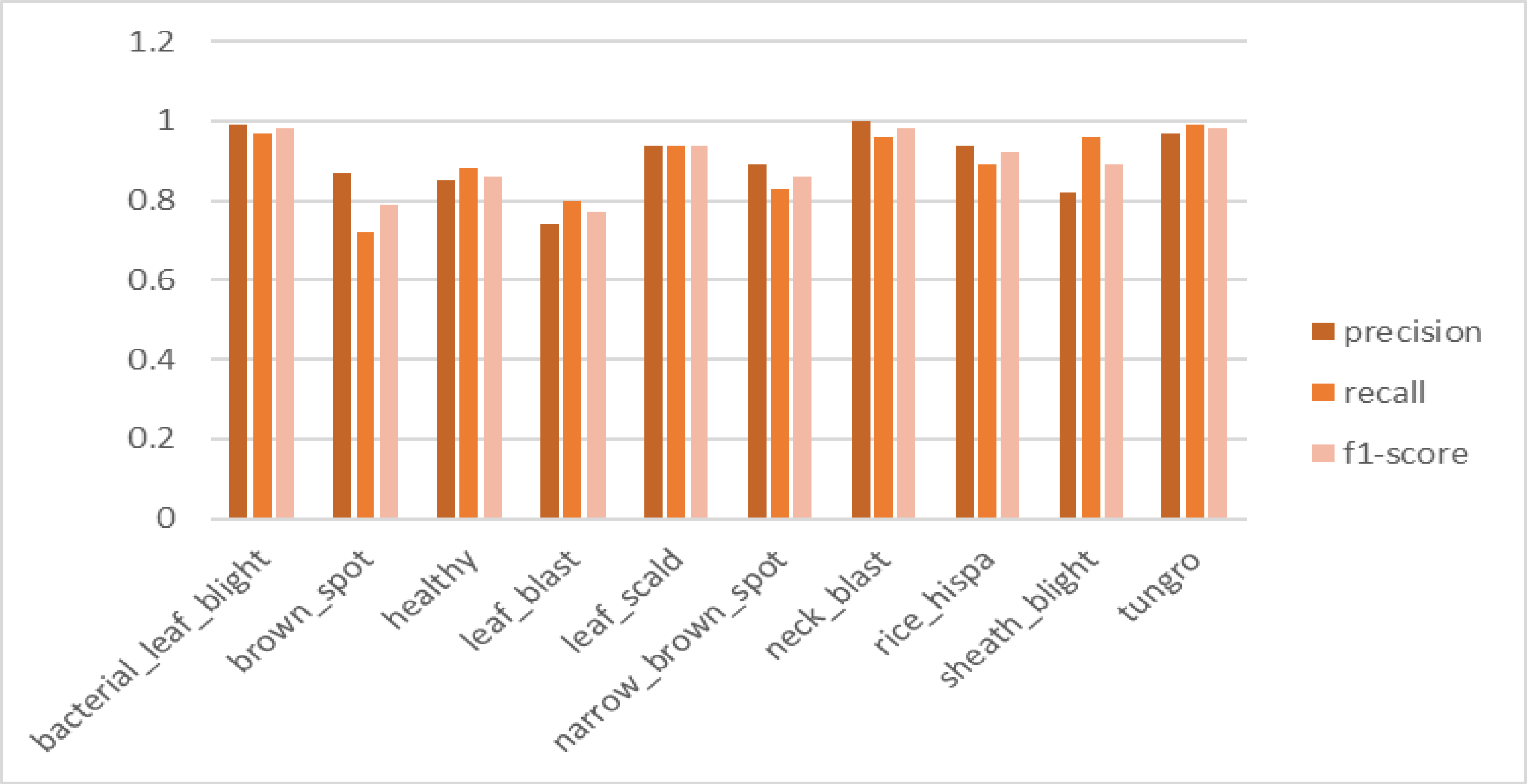


Fig-10: Bar Graph Representation of Precision, Racall and F1-score of Pre-trained VGG-16.

Experimental Results and Analysis

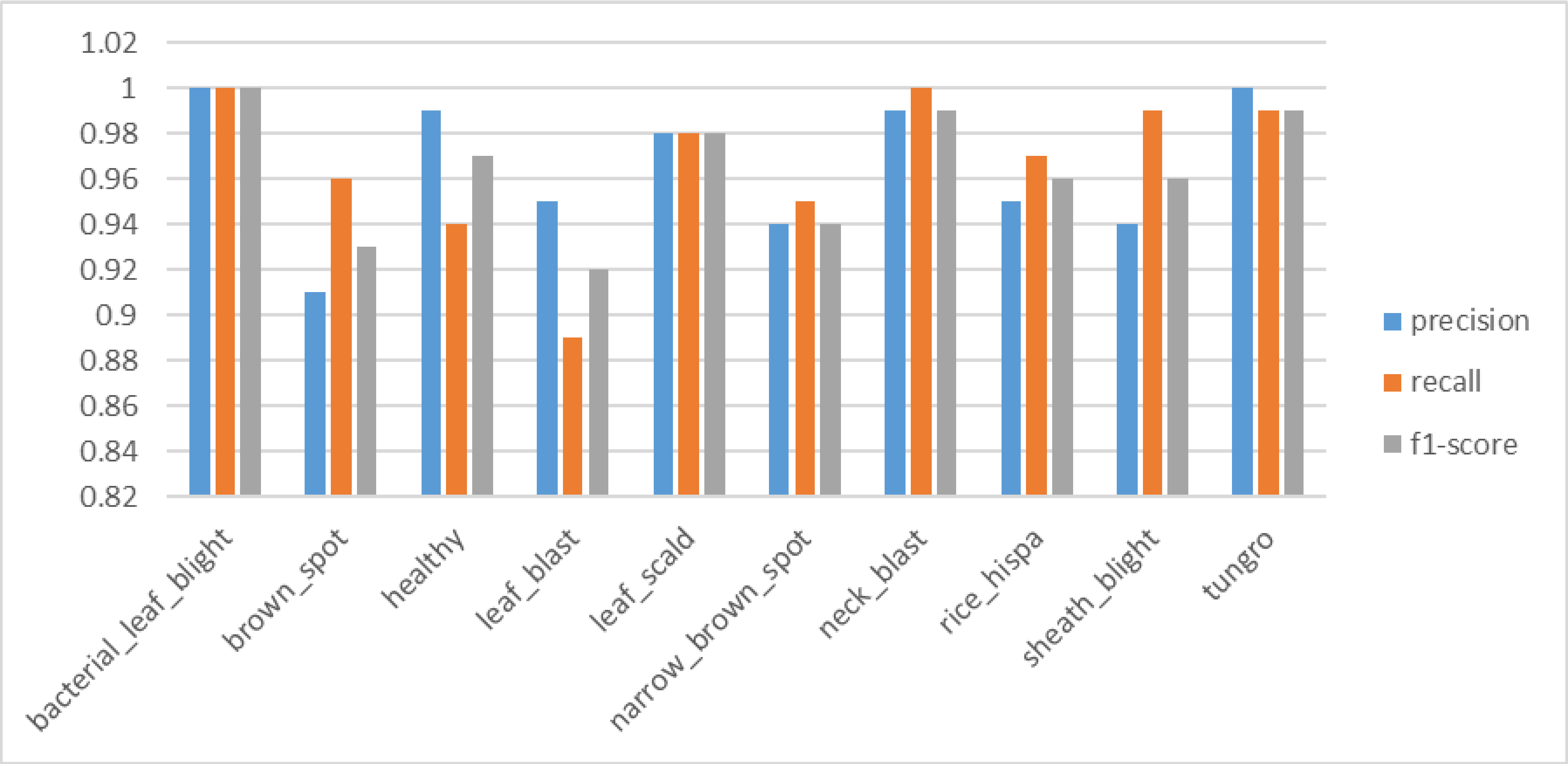


Fig-11: Bar Graph Representation of Precision, Racall and F1-score of Fine tuning swin model.

Experimental Results and Analysis

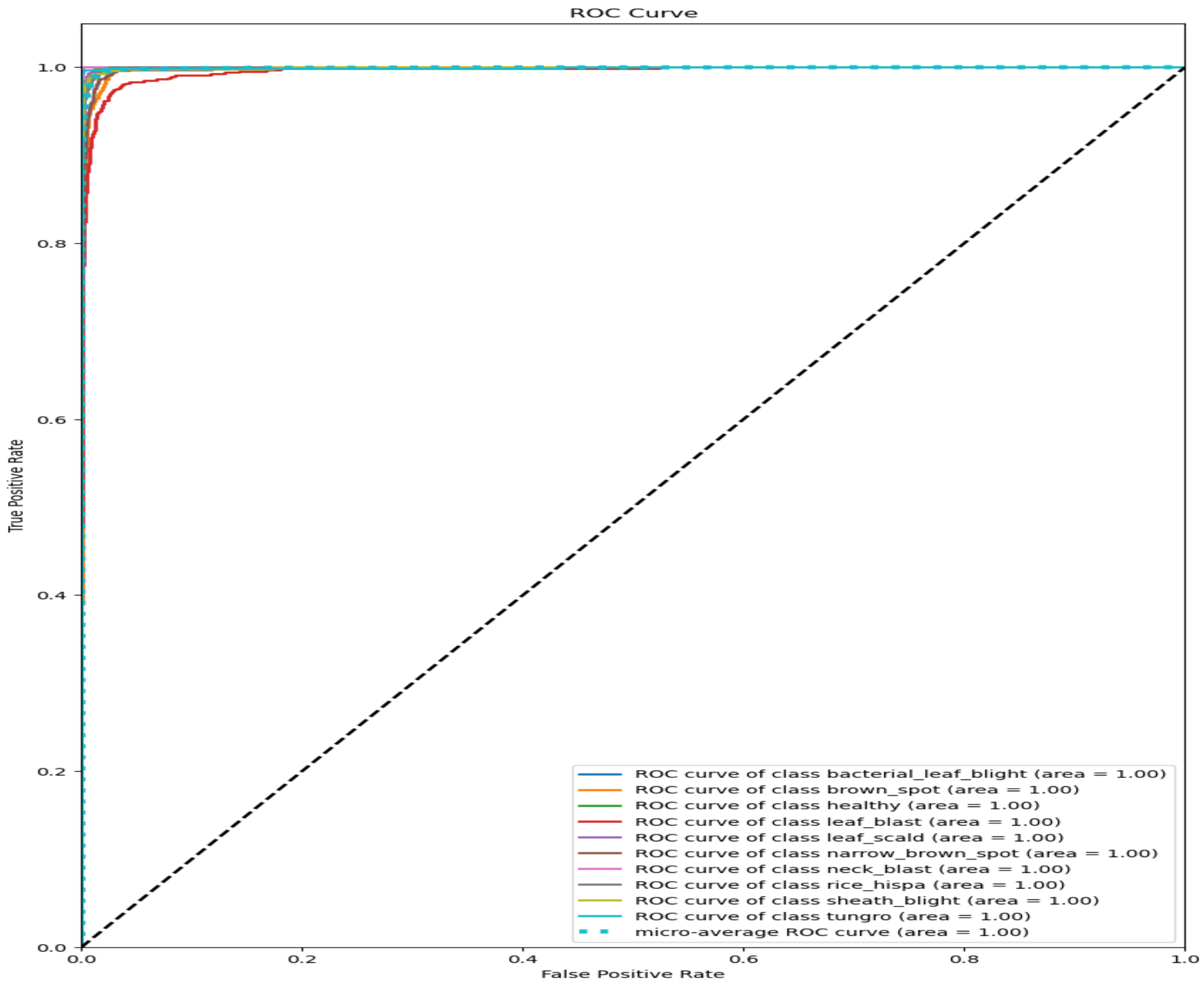


Fig-12: ROC curve of proposed fine tuning CNN with swin model.

Experimental Results and Analysis

Model Comparison:

Criteria	Shreya et.al (2020) [1]	VGG-16	Swin Transformer
Train Accuracy	97%	92.42%	97.21%
Test Accuracy	92.40%	91.83%	96.40%
Train Loss	-	0.2208	0.1660
Validation Loss	-	0.3191	0.1970
Total Parameters	-	211 M	1955 M

Table-1: Performance Comparison between existing and proposed model.

Experimental Results and Analysis

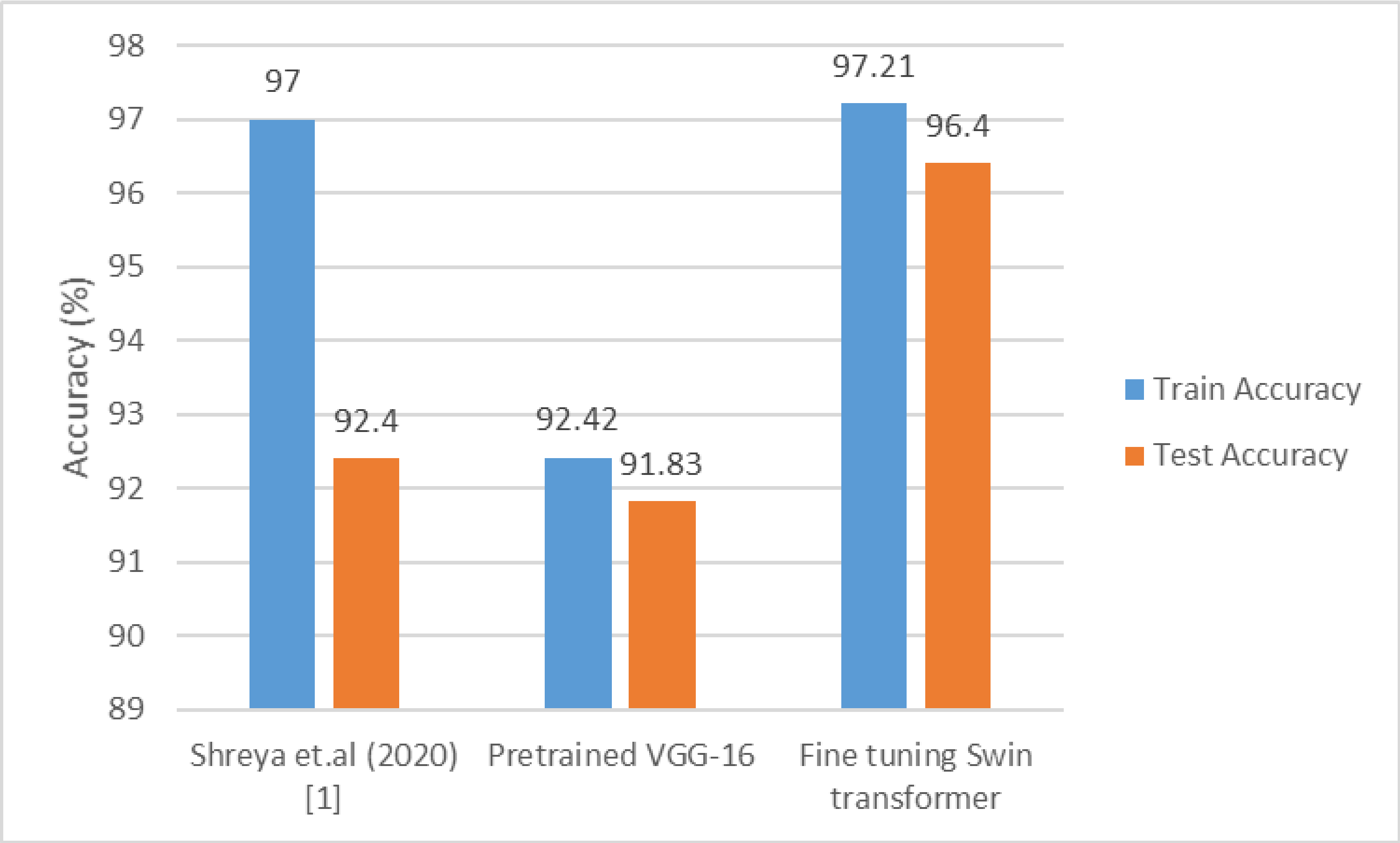


Fig-13: Bar graph representation of comparing existing model and proposed model.

Conclusions and Observations

- Implementing two architecture pre-trained VGG-16 and Fine tuning CNN with Swin Transformer, Swin transformer is significantly more accurate than earlier techniques.

- Swin Transformer gives better training and testing accuracy which is 97.21% and 96.40% within 50 epochs. It gives better result because of their hierarchical processing approach allows them to effectively capture long-range dependencies within the images, which can be crucial for achieving better performance.

- Swin Transformer gives less training and validation loss but uses large number of parameters compared to the pre-trained VGG-16 architecture because it is a more intricate and parameter intensive model.

Future Work

- The main focus will be to evaluate the model performance by using dataset that contains large number of direct field images.
- We will try to evaluate the performance of proposed method on images of rice fields that are affected by multiple diseases simultaneously.
- The goal is to improve the accuracy and precision by exploring different configurations for the swin transformer blocks within the hybrid model. Experiment with the number of stages, transformer heads and window sizes to potentially improve performance.
- Can be considered other approaches for better performance.

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THANK YOU

Any Question?