CLASSIFICATION OF RICE LEAF DISEASES USING VGG-19 MODEL WITH GRADIENT-WEIGHTED CLASS ACTIVATION MAPPING TECHNIQUE

Ummer Shakeel[*1], Muhammad Munwar Iqbal[2], Asima Ismail[3], Muhammad Aitzaz Ahsan[4], Noman Khan[5]

[*1,2,3,4,5]*Department of Computer Science, University of Engineering and Technology Taxila*

[*1]ummer.shakeel@students.uettaxila.edu.pk, [2] munwar.iq@uettaxila.edu.pk, [3]asima.ismail@uettaixla.edu.pk, [4]muhammad.aitzaz@students.uettaxila.edu.pk, [5]noman.khan@students.uettaxila.edu.pk

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Corresponding Author: *
Ummer Shakeel

Abstract

Pakistan which is the fourth biggest producer and fifth biggest exporter of rice, struggles to manage rice leaf diseases that seriously affect its crop output and quality. Yet, finding these diseases early and at the right time is vital, though traditional methods turn out to be slow, difficult and expensive. To fix this, we developed a simple, reliable and reduced-cost diagnosis system by applying the VGG-19 deep learning model in Python, TensorFlow and T4 graphic processing units for a faster, more efficient implementation. With very little loss values, the model is able to predict well, achieving 97% accuracy during training, 96.88% accuracy on validation and 95.88% accuracy on testing. We use Grad-CAM to point out in leaf images the regions that affect the outcome of the disease classification by the model. Being able to visualize these data increases our trust in the system and teaches us more about diseases. On the whole, the framework can handle real-time rice plant health monitoring and using it may reduce the need for manual inspections in farming.

INTRODUCTION

It is a significant economy in developed-producing countries such as Pakistan, and it feeds billions of people worldwide. However, Brown Spot, Leaf Blast, and Bacterial Leaf Blight are all very harmful diseases that reduce yield and damage the economy and agricultural security of a country. Leaf Blast, Bacterial Leaf Blight, and Brown Spots on rice leaves are detected and classified for promoting sustainable agriculture and securing food security. The serious damage caused by these diseases to rice production and the uncounted economic losses and meal scarcity they usher for would be huge [1]. Recent breakthroughs in deep learning technologies have revolutionized how agricultural disease is diagnosed: we now have precise, fast and automated tools for this task. We provide an example of a CNN as a powerful mechanism for categorizing and recognizing rice leaf diseases. With astonishing accuracy, they can diagnose different afflictions just by the images of infected leaves. With these automated solutions, farmers obtain timely crop health insights instantly and hence can correct any problems to enhance their yields and lower their economic risk [2]. Of course, such cutting-edge technologies don't just respond to the need to react to plant health rapidly but are essential for larger, more ecologically farmed produce. Similarly, bio extracts from Asteraceae and alfalfa leaf extract, such as applied foliar, can mitigate crop stress damage [3]. Similarly, rice leaf disease classification can aid both crop health and eventually increase agricultural output. The deep learning for early disease detection applied to agriculture supplies stakeholders in the agriculture value chain with tools to enhance food availability and economic stability jointly [4]. Like the IoT-based system offering benefits such as adaptability and scalability, using other advanced techniques, such as IoT-based sensing for rice leaf disease detection, can offer real-time monitoring and provide insight towards taking action for crop management [5]. Inspired by the use of supervised and unsupervised learning for precise classification of their dataset in the case of rice leaf disease detection, e-learning utilities also apply analogous machine learning approaches for enhancing automated student inquiry response systems [6].

Leaf Blast, Bacterial Leaf Blight and Brown Spots in rice leaves are essential to manage to prevent losses, and in this context end is to support agriculture sector productivity [7]. Transfer learning is used in this research to efficiently classify and map rice leaf diseases based on the base model VGG-19 and apply Gradient-Weighted Class Activation Mapping (Grad-CAM).

Related Work

Transfer learning with the DenseNet201 model is used to diagnose three rice leaf diseases, BLB, LB, and Tungro disease, with 96.09% accuracy in the present work. The performance here is higher than the 62.20% accuracy for a simple CNN [8]. To accurately identify plant leaf diseases, the authors employed deep transfer learning using pre-trained CNN models, outperforming state-of-the-art techniques. They successfully used their approach by classifying rice plant images with an average accuracy of 92%. [9]. The paper presents an advanced image processing technique to classify four kinds of rice diseases accurately. The method shows results proving a remarkable accuracy of up to 89.23% has enormous potential for improving disease management in rice crops. [10]. The paper presents an improved image processing method that detects and identifies rice diseases based on (RGB) value on the affected regions of the leaf using a novel algorithm. These values were processed by a Naive Bayes classifier, effectively identifying three diseases: LB, BS, and BLB [11]. Based on this ability to recognize diseased areas with color thresholding and feature extraction, the proposed method achieved high accuracy in detecting and classifying rice plant diseases up to 89.19%. Performance was tested using SVM and k-NN classifier [12]. Propose a technique for rice disease identification and classification, using image processing from CNN with an accuracy of 90% for the test cases. Moreover, the proposed machine learning model could detect infected and healthy rice leaves with 90% accuracy. [13]. Early and late blight of potatoes are important crop diseases for which efficient and accurate detection tools are needed. Presented in this study is EfficientPNet. To assist farmers in the timely management of diseases, we propose a deep learning solution based on EfficientNetV2 with spatial– channel attention and transfer learning, achieving 98.12% accuracy in predicting the class of potato leaf diseases on the PlantVillage dataset [14].

We got excellent research results in accuracy: 97% on the train, 96% on the validation, and 95% on the test sets. The proposed novel Grad-CAM method improved the model interpretability for more precise detection and localization of the affected leaf regions. In this work, we demonstrate that this approach will have great potential for rice disease detection.

Proposed Methodology:

The proposed methodology for rice disease detection is shown in Figure 2 for solving the issue of classification of rice leaf diseases by transfer learning using the VGG-19 model and gradient-weighted class activation mapping (Grad-CAM). In this work, we combine deep learning with the Gradient- Weighted Class Activation Mapping method to improve disease classification with higher accuracy and interpretability.

Flow-Chart Architecture of Proposed Solution:

The flowchart figure 1 shows how classifying rice leaf diseases using transfer learning with VGG-19 can be done through a well-defined deep-learning pipeline. At first, the raw dataset is loaded, and then the images are resized and rescaled so all data is the same size. Compiled images are made available for training, validation, and testing with a single code for data processing using `ImageDataGenerator.` VGG-19 is designed by freezing the convolutional layers to conserve existing features and by also adding dense and dropout layers for adapting it to the rice disease classification task. Adam is used as the optimizer in the model, and categorical cross entropy is the loss function.

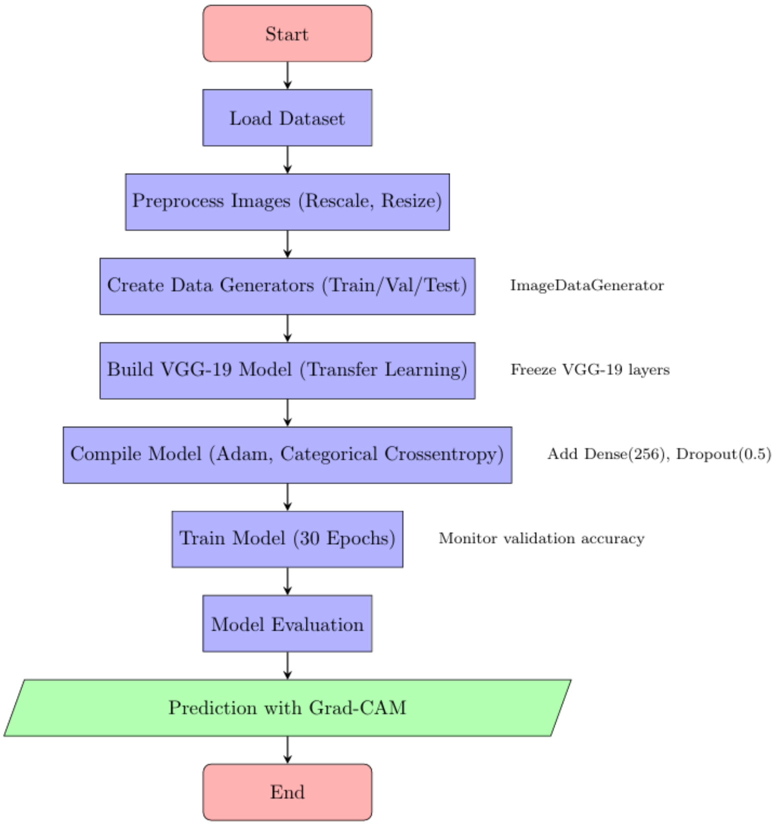

Figure 1 Flow-Chart Architecture of Proposed Solution

Validation accuracy is closely watched during the 30-epoch training to keep overfitting from happening. After determining how effective the model is, Grad-CAM is used to create visual heatmaps showing the main areas that influence classification.

Dataset Acquisition:
The dataset used in this study, sourced from platforms like Kaggle and UCI, includes 1914 balanced images across three classes: Leaf Blast (LB), Bacterial Leaf Blight (BLB) and Brown Spot (BS) [15].

Rice Dataset Sample:
There are mainly 3 types of rice leaf disease, BS (Brown Spot), LB (Leaf Blast) and BLB (Bacterial Leaf Blight) as shown in Figure 2.

Figure 2 Rice Dataset

Image Pre-processing & Splitting Dataset:
We used Augmentor for image pre-processing, a Python library well known for being flexible with sequential or probabilistic transformations. An efficient library best suited for image classification with customizable data augmentation for the nature of the dataset. It allows us to create flexible augmentation pipelines [16]. Data augmentation and text-to-image generation generate useful training samples and augment the somewhat diverse dataset and the model tends to perform better [17]. You can see in Table 1 how the training, validation and test sets are divvied among the three rice disease classes Brown Spot, Leaf Blast and Bacterial Leaf Blight. All classes feature 446 samples in the training set, 128 samples in the validation set and 64 samples in the test set for even distribution. We split the data evenly so that we can train, evaluate and test the model the same way for each illness category. The balanced data and good model evaluation weigh overall 465 MB.

Table 1 Dataset Images for each class

Classes	Train Set	Validation Set	Test Set
Brown Spot	446	128	64
Leaf Blast	446	128	64
Bacterial Leaf Blight	446	128	64

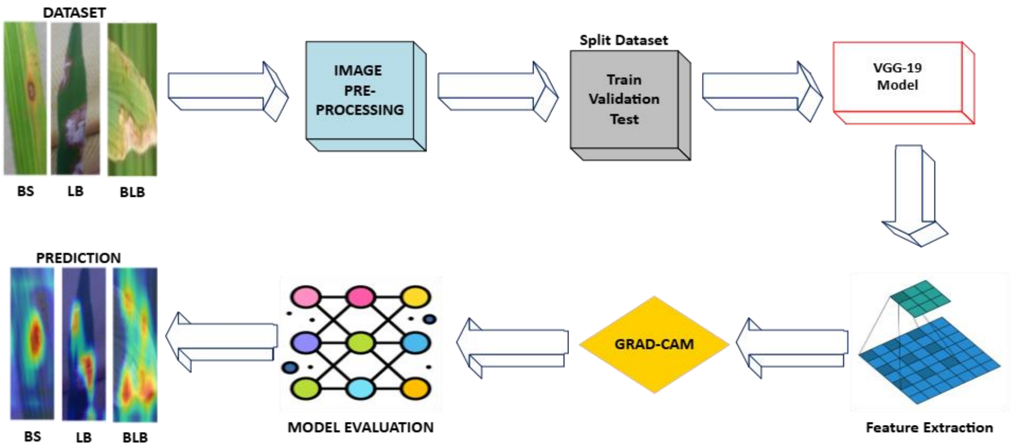

Figure 3 Proposed Methodology for Classification of Rice Leaf Diseases using VGG-19 Model with Gradient-Weighted Class Activation Mapping Technique

VGG-19 Model & Feature Extraction:
The model Visual Geometry Group (VGG-19) has 19 layers, 16 convolution layers, 3 fully connected layers of small 3x3 convolutional filters, and 2x2 max pooling layers [18]. The architecture is appropriate for deep feature extraction and image classification with the benefit of accuracy with simplicity. In mathematics, VGG-19 is a network created by alternating groups of 3×3 convolution layers

with stride one and padding to support the size of the inputs. The network includes 16 convolutional layers organized into five blocks, and all these blocks have a 2×2 max-pooling layer that cuts the size in half. The feature maps from these blocks are flattened and passed through three fully connected (dense) layers, the last of which uses a softmax activation for classification. Each convolutional operation is defined as Y = f(W * X + b), where '*' denotes convolution, 'W' are weights, 'X' is input, and 'f' is the ReLU activation. Because the architecture employs roughly 143 million parameters, it can work deeply and intensely to extract significant features.

Grad-CAM

This work aims to implement Gradient-weighted Class Activation Mapping, a visualization technique for highlighting which regions of an image the deep transfer learning VGG-19 model uses most to reach its decision. Grad-CAM uses gradients of the output concerning convolutional layers to generate heatmaps to highlight important parts in the input image. Among all the tools, it is beneficial for making Convolutional Neural Networks (CNNs) more interpretable. In the case of image classification tasks, Grad-CAM visualizes the areas that impact predictions and, in that way, explains model decisions [19].

Model Evaluation and Prediction:

The rice disease classification model is implemented using transfer learning VGG-19 and freezing the pre-trained layers for disease classification. The training, validation and test datasets are pre-processed using image data generators; all are resized to 224x224 pixels.

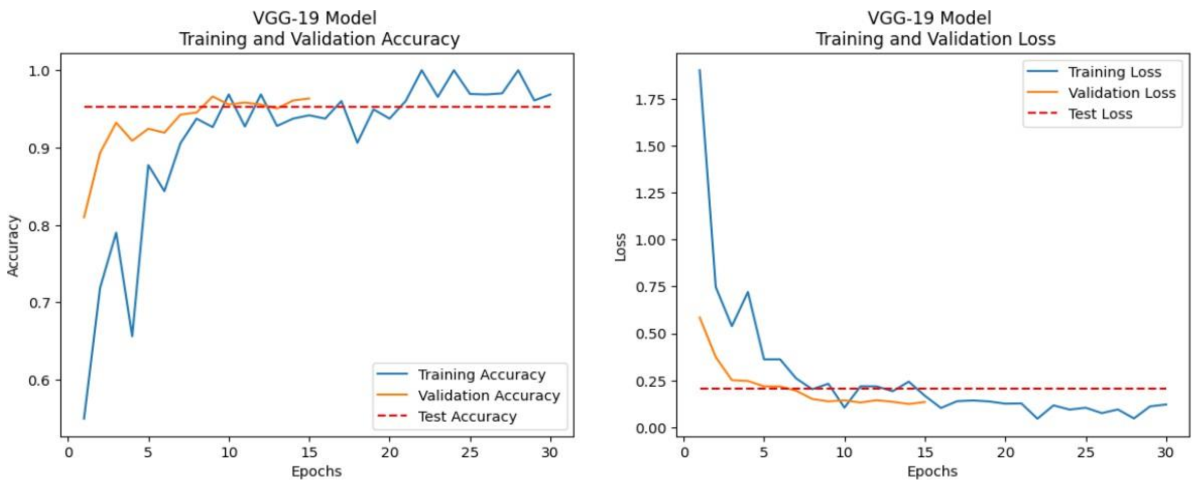

Figure 4 VGG-19 Model Training & Validation, Accuracy Loss

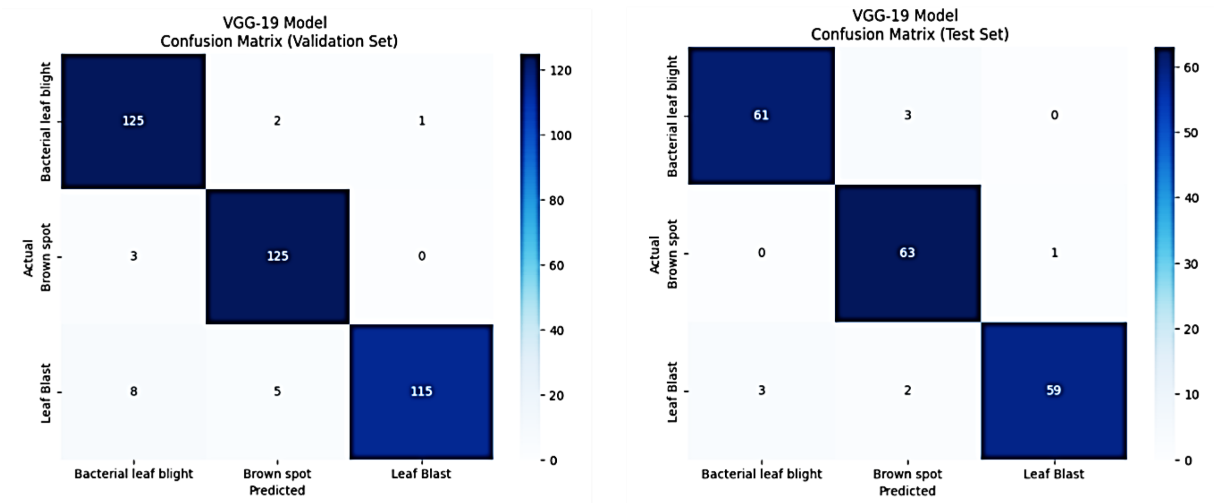

Figure 5 Confusion Matrix of Validation & Test Sets

After compilation of the model, it is trained on 30 epochs and evaluated for accuracy on the training and validation sets is shown in Figure 4, and We Can achieve 97% train accuracy, 96% validation accuracy and 95% test accuracy. Figure 3 shows the misclassification: There were 3 cases of Brown Spot misclassified as Bacterial Leaf Blight, 1 with Leaf Blast, two rows for Bacterial Leaf Blight misclassified as Brown Spot, and finally 5 with Brown Spot misclassified as Leaf Blast and 8 with Brown Spot misclassified as Bacterial Leaf Blight in the validation set. As for the test set, Bacterial Leaf Blight is incorrectly classified as Brown Spot 3 times, and Leaf Blast is incorrectly classified as Bacterial Leaf Blight 3 times and Brown Spot times.

The misclassifications imply cross-class confusion among the categories. The prediction results for the VGG 19 model are shown in Figure 6 with 100% confidence.

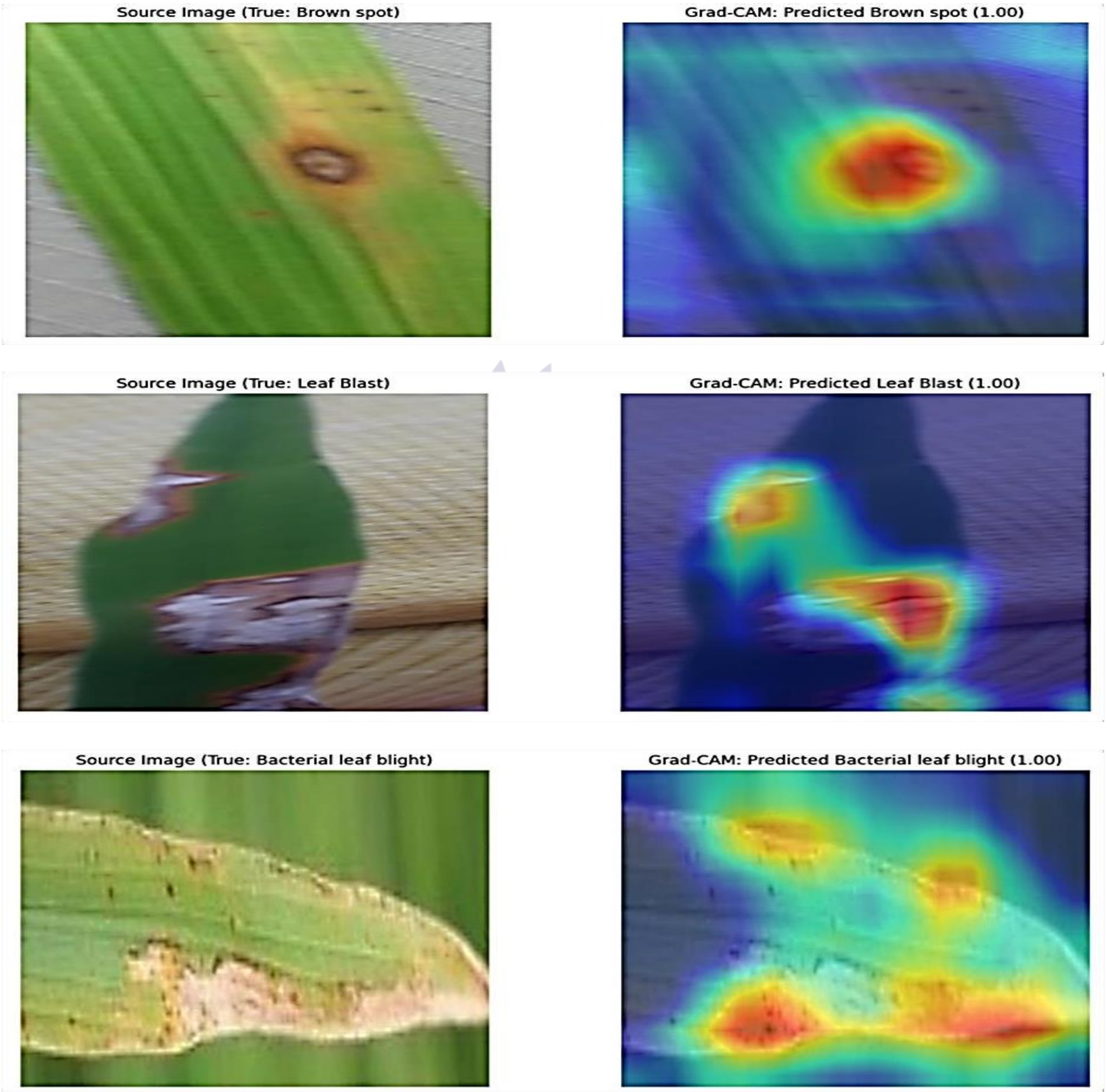

Figure 6 Prediction Results

Figure 6, shows the source images of three disease types: Leaf Blast, Bacterial Leaf Blight and Brown Spot. They visualize the results using the Grad-CAM technique to pinpoint where the image most contributed to the model's prediction. To make the areas of actually classified disease in images more prominent, this representation focuses on the specific areas of the given images on which this model focused while classifying disease.

Conclusion

The research successfully proves the use of transfer learning with the VGG 19 model to classify rice leaf diseases with a high level of accuracy. By using a training accuracy of 97%, validation accuracy of 96.88%, and test accuracy of 95.88%, we see that the model performs very well in recognizing instances of Brown Spot, Leaf Blast, and Bacterial Leaf Blight. It is clear from the relatively low validation loss of 0.1213 and test loss of 0.1569 that the NN learns well and has good generalization skills. Grad-CAM visualization allows the model to be more interpretable by designing the map of the semantic parts of the image responsible for the classification decision, leading to transparency and reliability of the classification process. Achievement of accurate and explainable results via this approach can help farmers and agronomists produce low-cost, low-risk, and scalable solutions for plant disease management. Exploring future work includes refinement of model performance, incorporation of real- time field data and an extension of the technique to other crops.

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