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Deep Learning Based Effective Rice Leaf Disease Classification using MobileNet- Attention

Muhammad Suleman Memon*, Mumtaz Qabulio, Asia Khatoon Soomro

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Muhammad Suleman Memon is currently affiliated with the Department of Information Technology, Dadu Campus, University of Sindh, Dadu, Pakistan.
Email: msuleman@usindh.edu.pk

Mumtaz Qabulio is currently affiliated with the Department of Software Engineering, Faculty of Engineering & Technology, University of Sindh, Jamshoro, Pakistan.
Email:mumtaz.qabulio@usindh.edu.pk

Asia Khatoon Soomro is currently affiliated with the Institute of Mathematics & Computer Science, University of Sindh, Jamshoro, Pakistan.
Email: asia.soomro@usindh.edu.pk

Corresponding Author*:

Abstract

Agriculture is one of the most promising fields for contributing to the growth of the economy of the country. Rice is considered as one of the important crops that contributes to the economy and food demand. The production of rice is mainly affected by disease in plants which severely impacts the production. The diseases include bacterial blight, blast, browspot, tungro. The dataset was obtained from the internet that contains a total of 5932 images. In this research, we proposed a method based on Mobilenet with an attention block to classify four different diseases of rice. The mobilenet architecture is effective for mobile devices. The proposed approach is a lightweight model with the combination of an attention block that uses squeeze excite block. The mobilenet was used for the feature extraction process. The Squeeze-and-Excitation Block allows a network to execute dynamic channel-wise feature recalibration, hence increasing its representational power. The proposed approach recognizes the diseases effectively and increases the model accuracy and is computationally effective. The model achieved an accuracy of 100% on rice dataset.

Keywords: Rice disease, MobileNet, Attention Block, Squeeze and Excitation, leaf disease classification.

INTRODUCTION

Agriculture is one of the important sectors that plays an important role in managing the food demand. The countries with good agricultural land generate a huge revenue and meet the demand of their people. The disease in the plant is the main issue in agriculture. The yield loss is mainly due to plant diseases (Memon et al., 2022; Qabulio et al., 2024). Most of the food loss which is around 20% to 40% is due to plant diseases (Ahmad et al., 2023). Rice is one of the most significant agricultural commodities in the world and provides a lifeline for more than half of the world's population. Rice acts as a huge contributor to food security around the world, especially in Asia, where rice is a centerpiece of both culture and diet. Moreover, most of the world's population depends on rice as a main diet and the energy source, making it one of the world's most important food crops. This indicates that it is vital to the survival of a significant section of the world's population and plays a critical role in feeding them (Gahane et al., n.d.; Latif et al., 2022; Rathore et al., 2023). The disease in the rice crop causes a lot of damage to the crop which results in low production and thus not meeting the food demand. The disease identification process using conventional methods is a very labor-intensive and time-consuming job. Several diseases are caused by bacteria, viruses, nematodes, and fungi and may seriously damage the yield and quality of rice crops. Deep learning(Andrew et al., 2022) has recently become a revolutionary method for identifying rice leaf disease with several advantages over conventional methods. Deep learning models are very effective in detecting small symptoms that humans might fail to recognize, preventing large crop loss. They achieved multi-disease classification capability in parallel and are highly scalable to different environmental conditions and rice cultivars. Additionally, it enables non-destructive diagnostics through the analysis of images, maintaining the quality of the crops. This automated feature extraction and analysis are the key factors in boosting leaf disease identification in other crops, including rice.

Unlike classical approaches that depend on protracted time and human effort for strategic feature extraction, deep learning techniques offer increased efficiency, with CNNs being among the state-of-the-art architectures capable of process and classifying pictures of leaves. These models can recognize complex patterns, including slight stains or confirmations that may be associated with initial disease stages, allowing for timely interventions (Ahmad et al., 2023; Al-gaashani et al., 2022; Anitha & Saranya, 2022; Archana & Sahayadhas, 2018; Azim et al., 2021; Falaschetti et al., 2022; Özden, 2021; Trivedi et al., 2021; Vasavi et al., 2022; Wang et al., 2021). In this research we focus on a robust and effective deep learning model to diagnose leaf diseases in rice. Mainly four diseases have been covered. The dataset was obtained from the publicly available database. We proposed a novel method using mobilenet attention model. To extract the leaf features mobilenet acts as a feature extractor and the attention block helps to reduce information loss.

LITERATURE REVIEW

Rice is an important crop in agriculture. Many diseases affect the production of the crop. The author in (Ritharson et al., 2024) the transfer learning approach was used to classify various rice diseases, including healthy, tungro,blight, blast and brown spot. The diseases were further categorized into mild and severe. The author collected the dataset which comprises 5932 images in total. Different pretrained models were used by the author using the transfer learning technique. The author modified the VGG16 model and achieved an accuracy of 99.94%. In (Peng et al., 2023) the author has proposed a method using attention with a Resnet named RiceDRA-Net. To reduce the information loss the Res-Attention module was used. The dataset with and without complex backgrounds was used. The proposed study achieved an accuracy of 99.71% on a single background image and an accuracy of 97.86% on a complex background image. There are four classes in the dataset used in the study: tungro, rice blast, brown spot, and bacterial wilt. A total of 5932 images were included in the dataset.

The author in (Simhadri & Kondaveeti, 2023) proposed a transfer learning technique to classify various leaf diseases of rice. The author trained 15 models on the rice dataset. The transfer learning approach on inceptionv3 outperformed with an accuracy of 99.64%. 10080 images of 10 different disease classes, including healthy leaves, make up the dataset. The proposed work used identical hyperparameters to evaluate the results of the models. In (Ahad et al., 2023) six CNN-based deep learning architectures—Inceptionv3, MobileNetV2, resNext101, Resnet152V, Seresnext101, and DenseNet121—were implemented by the author. The proposed study used transfer learning as well. The dataset used in the study was collected from Bangladesh and comprised of nine rice diseases. After using the data augmentation approach, the dataset's size increased to 42876 images from its initial 900 images. Nine different diseases were classified. The accuracy of 98% was achieved using the ensemble approach. In recent years, the accurate and rapid detection of rice pests and diseases has become a critical challenge for precision agriculture. Conventional manual inspection techniques take a long time and are prone to human error. To address this issue, researchers have explored the use of deep learning techniques for automated rice pest and disease detection. One of these models is the YOLOv7 object detection model which achieved great performance on many tasks. Indeed, this results in the YOLOv7 network being resource-full, which would not allow its deployment on mobile devices that are limited in processing. In response to this limitation, the author introduces MobileNet-CA-YOLO, a new model that integrates the compact MobileNetV3 backbone with a Convolutional Attention mechanism, to leverage both the mobile platform detection performance with high accuracy of rice pests and diseases. A dataset of 3773 images of rice diseases was used to test the model. The proposed method achieved an accuracy of 92.3% on six different diseases of rice (Jia et al., 2023). The author in (Dhivya et al., 2024) evaluates different deep learning architectures on the rice dataset.

Different datasets were used for the study collected from the different websites which include Kaggle, UCI Machine Learning repository, GitHub, Mendley, and plantvillage. The author highlighted a detailed summary of the different deep-learning methods on the rice crop. The author in (Seelwal et al., 2024) has provided a comprehensive review of different machine learning and deep learning algorithms for identifying rice crop diseases. The study includes various rice leaf diseases. The study presents 69 different studies from 2008 to 2023. The authors suggest hybrid models as effective models for recognizing diseases in rice. The author in (Trinh et al., 2024) proposed a modified YOLOv8 by introducing the EIoU loss and a-IoU loss to improve rice disease detection. The proposed study used a dataset of rice leaves consisting of 3175 images. The author evaluated other models which include YOLOv7 and YOLOv5. The proposed study achieved an accuracy of 89.9%. The dataset was annotated to detect the diseased parts. The study covered two diseases the leaf blast disease and brown spot disease. The study (Nugroho et al., 2024) presents a CNN method based on ARM Cortex M- microprocessors. The study uses two datasets for model training and validation. The first dataset consists of four disease classes.

The second dataset includes ten disease classes. The MobileNetV2 and FD-MobileNet models were trained on the datasets to optimize the resources in terms of memory usage. The primary difference between MobileNetV2 and FD-MobileNet is downsampling. The FD-MobileNet uses faster downsampling. The models were deployed on STM32 platforms which can run AI tasks. The study (Lu et al., 2023) presents a CNN with the bidirectional gated recurrent unit (BiGRU). This research suggests a method for diagnosing rice diseases that combines CNN and RNN. For the BiGRU model to learn contextual features between the higher and lower layers of characteristics, the necessary information was learned from both forward and backward directions. An enhanced CNN module was used to lower the computational cost associated with analyzing the complete image. Information aggregation and shrinking data normalization are how the CNN module operates. After being converted from matrix to vector form, the output of the enhanced CNN is then fed into the RNN for training. After that, the output data is sent back for more improvement. The final decision data, which is subsequently sent to the classification layer, was created by concatenating the output from the CNN and RNN modules. The proposed study was used to diagnose four rice leaf diseases. The model achieved an accuracy of 98.21%. The author in (Sharma et al., 2022) proposed a study based on CNN to classify four diseases of rice and the diseases of potatoes. The author compared deep learning with machine learning methods which include Random Forest, SVM, KNN, and Decision Tree classifiers. The deep learning method outperforms the machine learning methods with an accuracy of 99.58%. In (Khasim et al., 2024) the author evaluated different machine learning methods including Naïve Bayes, KNN, Logistic Regression, and Decision Tree classifier to find different rice leaf diseases in Bangladesh. The dataset included three leaf diseases of rice. The Decision Tree classifier achieved a better accuracy of 97%. The author in (Latif et al., 2022) developed a modified VGG19 network for the classification of six different diseases of rice crops. The proposed approach uses the VGG19 transfer learning method where the network is modified freezing the top layers. The proposed approach obtained an accuracy of 96.08%.

METHODOLOGY

Figure 1 shows the workflow. The first images of infected rice leaves were obtained. The dataset was prepared. The image preprocessing techniques were employed on the dataset. The dataset was split into training and test. The dataset was trained using

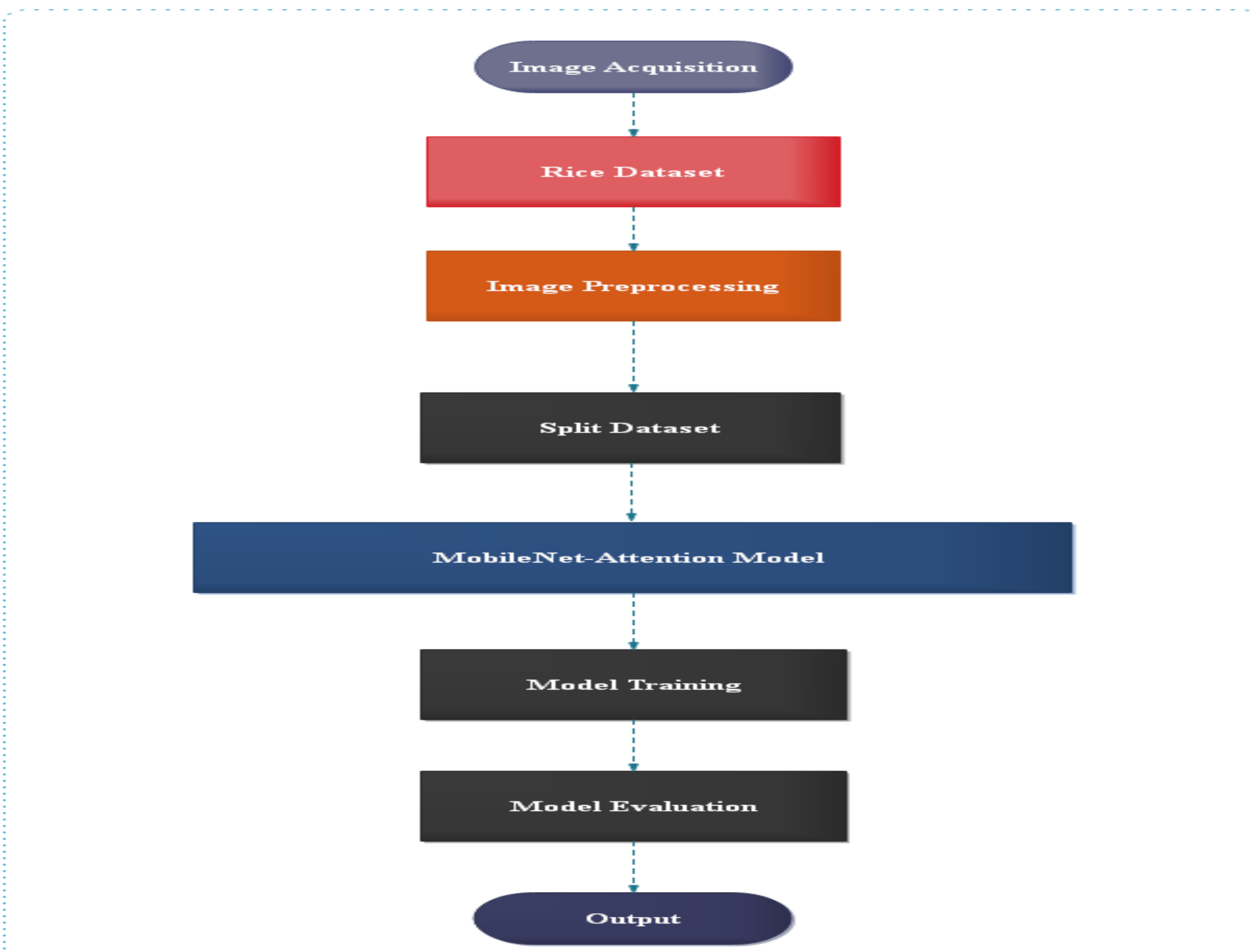

Figure 1: Workflow

mobilenet attention model. Then the model was evaluated using different metrics such as precision, recall, f score and accuracy. Figure 2 shows the methodology of the proposed approach. The mobilenet incorporates efficient building blocks such as depthwise separable convolutions and bottleneck layers with residual connections. The bottleneck layer expands feature dimensions. The SE block allows the model to adaptively recalibrate channel-wise feature responses. Global average pooling is applied to aggregate spatial information across each channel, reducing spatial dimensions to a single scalar per channel.

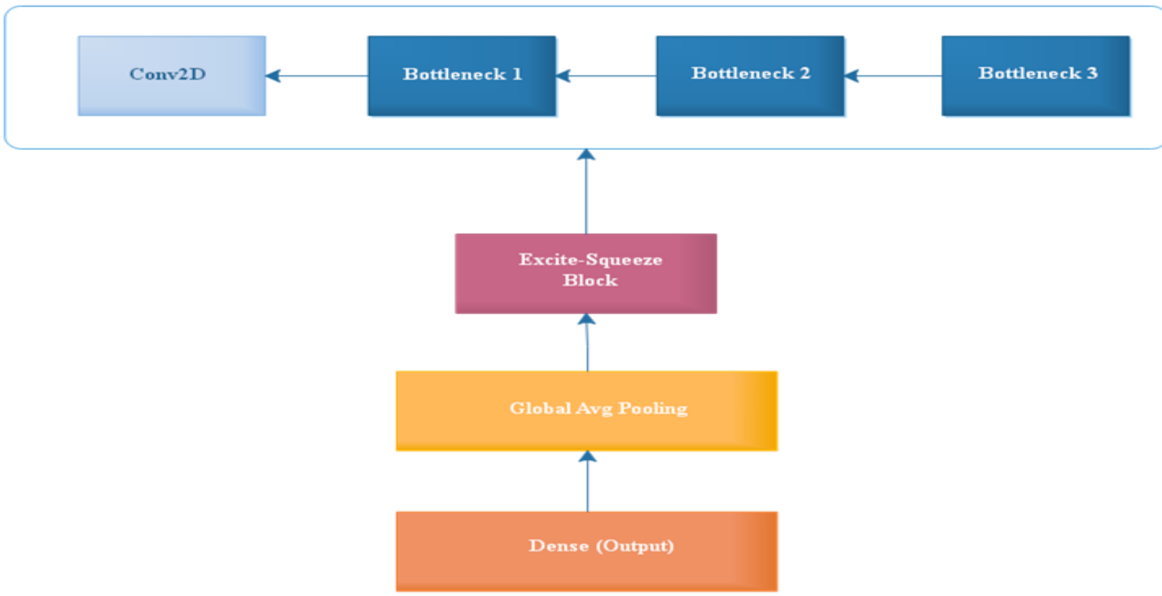

Figure 2: Methodology

MOBILENET ATTENTION MODEL

MobileNet is a lightweight convolutional neural network architecture that was developed for effective classification and recognition applications, especially for embedded and mobile devices. The computational cost is lowered in mobilenet because of separating them in Depthwise layers. The convolutions extract the spatial characteristics by operating independently on each input channel. The Pointwise Convolutions use 1×11×1 convolutions to aggregate the outputs from the depthwise step across channels that reduces the number of parameters with this split. From the leaf images, MobileNet collects hierarchical characteristics. Low-level elements like borders and textures are captured by early layers. The SE method is implemented via the squeeze excite block function to improve channel-wise feature representations. Squeeze compresses the input tensor's spatial dimensions into a single vector per channel (shape: (filters,)) using Global Average Pooling 2D. This creates a channel descriptor by condensing the geographical information. High-level characteristics, including patterns unique to healthy or diseased crop leaves, are captured by deeper layers. MobileNet summarizes feature maps into a single vector for each class using global average pooling rather than fully connected layers. This lowers the number of parameters and overfitting. The probability distribution over the target classes is obtained by passing the final feature vector through a fully connected layer, also known as a dense layer, and then activating it with a softmax. By suppressing unnecessary information, an attention block improves MobileNet's capacity to concentrate on an image's most important features. For activities like crop leaf classification, where it's critical to identify small features like yellowing, spots, or texture changes, this can be especially helpful. This is the result of integrating MobileNet with an attention block. MobileNet's performance on crop leaf datasets can be greatly improved by adding attention blocks, particularly in situations when the data is noisy or contains subtle disease signals. In agriculture, attention-enhanced MobileNet can be used for real-time disease monitoring or detection applications. For better feature refinement, a Squeeze-and-Excitation (SE) block was introduced to the MobileNetV2 model. To enable broadcasting during element-wise multiplication, the channel descriptor is rearranged to (1, 1, filters) in Excitation. There are two dense layers employed. The first uses a ReLU activation to lower the number of channels by a factor of ratio (default: 16). In the second, a sigmoid activation that produces weights in the range [0, 1] is used to restore the initial number of channels.

Recalibrating To highlight the crucial channels and suppress the others, the learned channel weights (se) are multiplied by the original input tensor. To improve the extracted features, the SE block is incorporated into the MobileNetV2 backbone. The backbone of MobileNetV2 The feature extractor, MobileNetV2, is pre-trained on ImageNet. A feature map is produced when the model is included without its top classification layer. Including the SE Block. The MobileNetV2 backbone's output is subjected to the squeeze excite block. By carefully allocating weights to the channels according to their significance, this improves the feature map. Including the SE Block. The MobileNetV2 backbone's output is subjected to the squeeze excite block. By carefully allocating weights to the channels according to their significance, this improves the feature map. Because the channel recalibration concentrates the model on the most crucial features, adding attention to MobileNetV2 increased accuracy. There is very little computational overhead due to the lightweight SE blocks. Real-time apps or other lightweight designs can make use of this.

Figure 3:
Different images of infected Rice leaves.

RESULTS AND DISCUSSION

Dataset Description: The dataset, consisting of 5932 images of sick rice leaves, was obtained from the Internet. Brownspot, blast, tungro, and bacterial blight are its four disease classes. There are 1584 images of bacterial blight, 1440 images of blast, 1600 images of brownspot, and 1308 images of tungro. Training and testing versions of the dataset were separated. A total of 4747 images, or 80% of the training set, and 1185 images, or 20% of the test set, were used. The dataset's details are displayed in Figure 2.

Data Augmentation: Data augmentation is an artificial way of increasing the size of the dataset. In this research we used data augmentation techniques to increase the size of the dataset. This technique helps to generalize the model well. Figure 1 shows different infected leaf images of rice.

Model Evaluation: To evaluate the model performance, we used different evaluation metrics such as precision, recall, and f score. We also evaluated the ROC curve of the model. However, the ROC curve is well-suited for binary classification. Figure 5 shows thetraining and validation accuracy and the training and validation loss. The model was trained in 25 epochs. The batch size was 32.

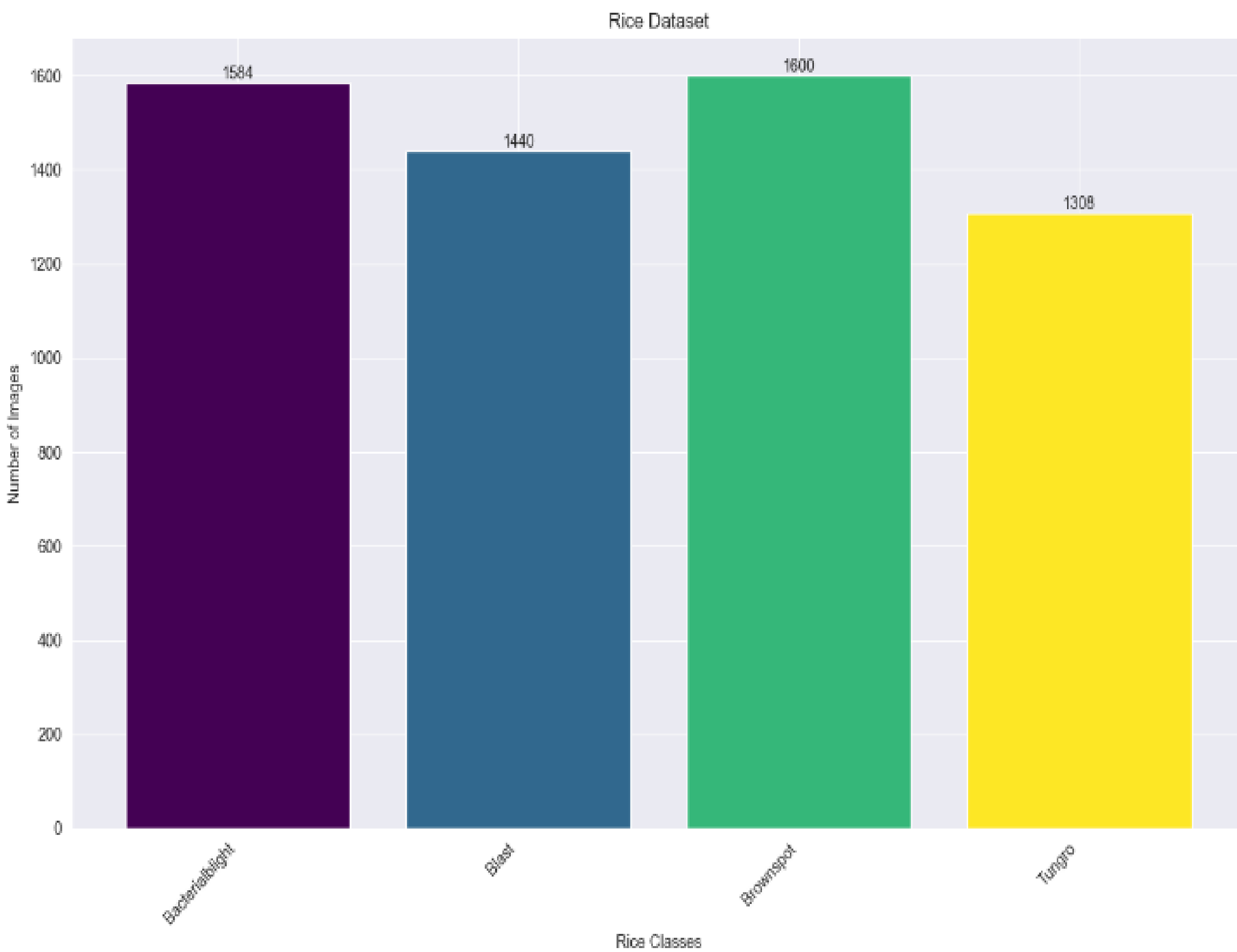

Figure 4:
Rice dataset class distribution.

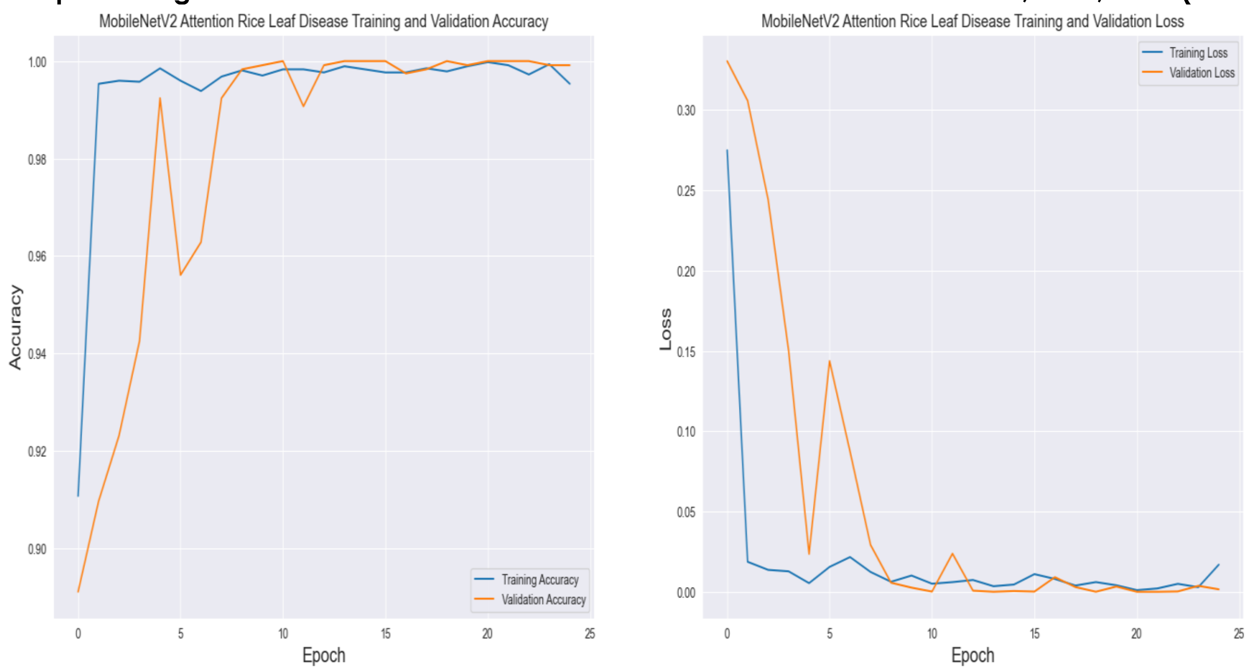

Figure 5:
Training and Validation Accuracy

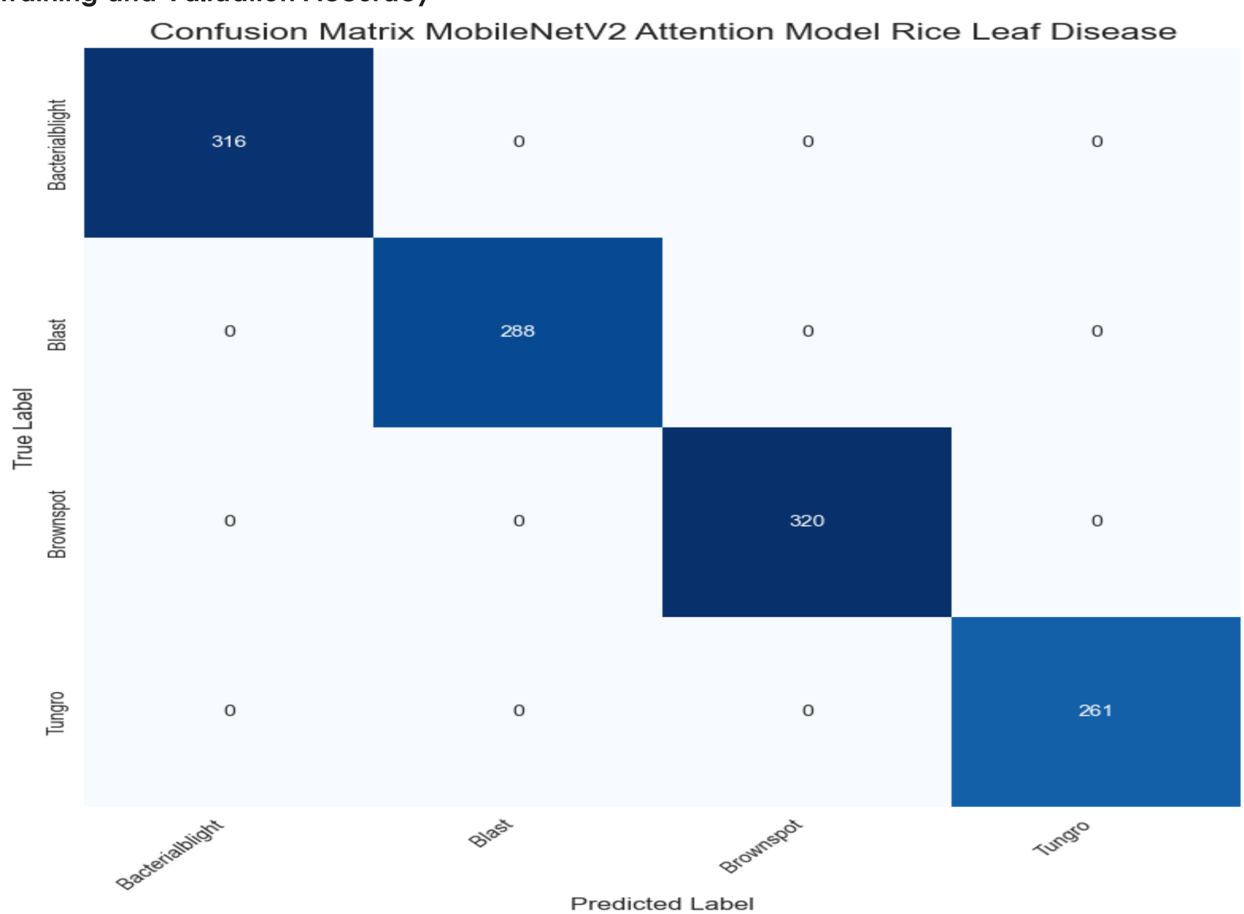

Figure 6:
Confusion Matrix

Table 1 shows the summary highlighting precsion, recall and f score. The model achieves highest score.

Table 1:
Precision, Recall and Score Summary

Disease Class	Precision	Recall	F-Score	Support
Bacterialblight	1.0	1.0	1.0	316.0
Blast	1.0	1.0	1.0	288.0
Brownspot	1.0	1.0	1.0	320.0
Tungro	1.0	1.0	1.0	261.0

Figure 6 shows the confusion matrix. The confusion matrix shows the details of the correct predicted and incorrect predictions. Figure 7 shows the ROC curve that shows true positive and false positive.

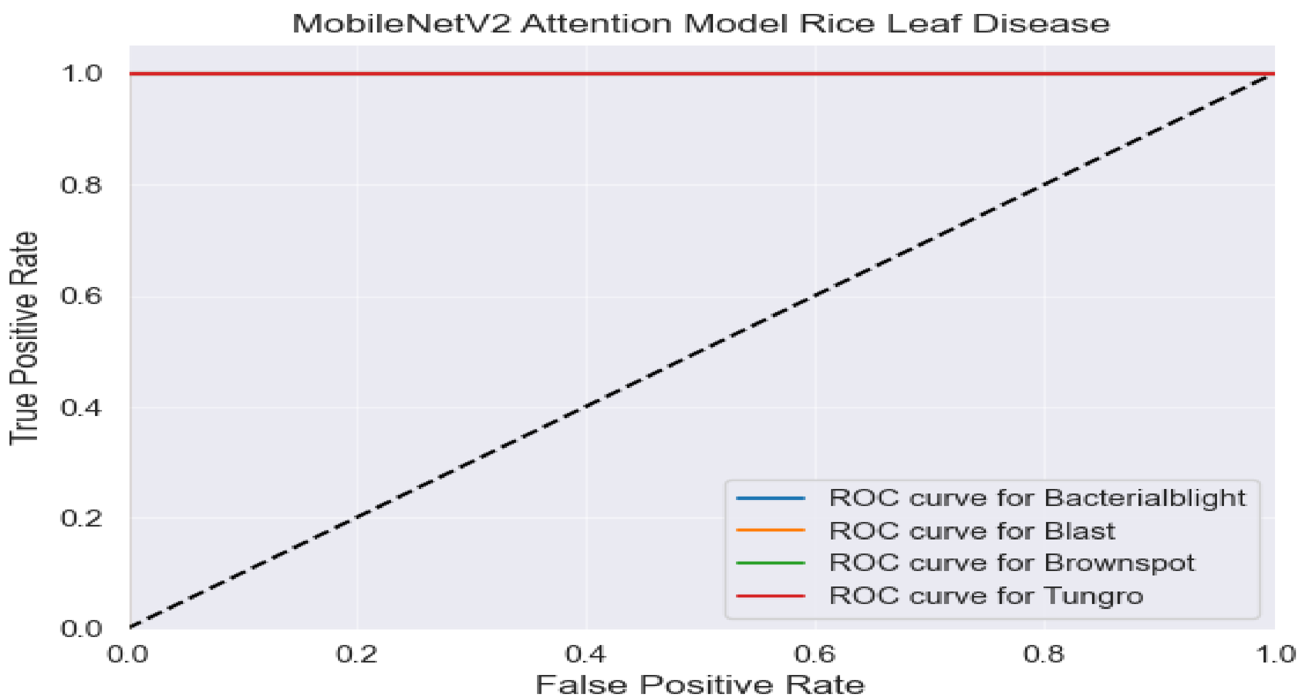

Figure 7:
ROC Curve

CONCLUSION

In this research, we proposed a lightweight deep-learning algorithm to classify four different diseases of rice. In this approach, we employed an attention block with mobilenetv2. The mobilenetv2 is a lightweight model that helps in feature extraction processes. The mobilenetv2 is suitable for deployment on mobile devices or edge devices in agricultural fields. The attention block was added to improve the model's accuracy and computational effectiveness. The proposed model was evaluated using different parameters which include precision, recall, and F score. The model uses smaller parameters and achieves the highest accuracy of 100%. By including SE blocks into MobileNetV2, accuracy and efficiency can be effectively balanced, enabling the model to be used in a variety of real-world scenarios. In future the model can be further enhanced for the edge devices. Other methods can be explored such as pruning and quantization to reduce memory usage. Different SE block variants can be designed for IOT devices and smart phones with low power chips.

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Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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