ENHANCED DETECTION OF BACTIRIAL DISEASES IN RICE PLANTS USING PRE-TRAINED LEARNING MODELS

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Abstract: Rice is a fundamental crop in India, holding the largest area under cultivation including both brown and white varieties. It plays a crucial role in the nation's economy by providing employment and contributing significantly to the Gross Domestic Product (GDP). With advancements in technology, particularly in the era of machine learning (ML), there has been a shift towards automating the process of detecting diseases in rice plants using image-based analysis. Traditional methods which rely on human vision are being supplemented by ML classifiers that promise earlier detection of diseases, thereby enabling timely preventive measures and minimizing productivity losses. The integration of deep learning techniques has further improved the accuracy of these systems, marking a substantial progress in the fields of agriculture and farming productivity. In this paper comparative analysis of pre-trained models are presented for detection of microbial diseases in rice plants. In proposed model bacterial, viral and fungal diseases are detected using rice plant images. The model has achieved highest accuracy of 90% with ResNet50 model and 89% with inceptionv3 model. As compared to existing model, the proposed model has achieved 8% improvement in detection accuracy and approx. 3sec in execution time. Therefore, the proposed model outperformed better.

Keywords: Rice Plant Diseases, Image Processing, Bacterial, Viral, Fungal, Deep Learning.

1. Introduction

Agriculture is a vital economic pillar globally, with farmers making key decisions on crop selection, field management, and pesticide use to optimize growth within limited timeframes [1]. Rice, a primary food staple, is experiencing severe production challenges due to diseases that degrade both crop quality and quantity [2][3]. Factors such as a lack of field experts and poor fertilizer management—stemming from insufficient disease awareness—exacerbate these issues [4]. Diseases, caused by pathogens like bacteria and fungi (including sheath blight, NBSD, leaf blast, and brown spot), not only impact the environment indirectly but also lead to considerable economic losses by diminishing rice yields [5]. Brown spot disease in rice is caused by the fungus Bipolaris oryzae found generally in silicon-deficient soils in Asia that may result in crop loss. Traditional approaches of disease identification methods are labor-intensive and may cause delayed management with increased risk of crop failure. To mitigate these issues, there is need of automated image processing systems that provides an quick and efficient solution for detecting diseases using images of rice leaves [6]. Automated systems are designed using machine learning algorithms with enhanced feature segmentation, extraction, and classification. These approaches speedup the identification process but also increase the reliability of disease management in rice cultivation [7][8]. In recent studies, researchers have significantly used machine learning as well as deep learning for detection and classification of rice leaf diseases with enhanced detection efficiency [9-15]. But still there are several gaps that needs to be focused and resolved to enhance their effectiveness and applicability. Early detection with environmental complexity handling is some of them. The early disease detection is dependent on high-quality and specific-background images. Computational efficiency is another critical gap because image processing is high resource demanding applications. Motivated by this the paper contributes the following:

- The paper focused on identification of type of microbial effect on rice plant.
- The paper presented a transfer learning model for differentiation of these microbial diseases.
- The paper also identified the categories of bacterial diseases, fungal diseases and viral diseases from the input images.

2. Literature Review

Sharma et al. [9] proposed an advanced UNet architecture integrating dilated convolution and EfficientNetB4, tailored for three major rice diseases. This model, using a pixelwise logical AND for segmentation, outperforms traditional UNet models by achieving better metrics (loss and dice coefficient), indicating higher precision in identifying diseased areas on leaves. Bi and Wang [10] developed a Double-Branch Deep Convolutional Neural Network (DBDCNN) that includes a Convolutional Block Attention Module (CBAM) to refine feature recognition and improve disease classification accuracy. Their model, demonstrating a 98.73% accuracy rate, outshines prevalent models like VGG-16 and ResNet-50, positioning it as a top contender for future applications in rice disease identification. Ahad et al. [11] explored multiple CNN architectures, including transfer learning and ensemble approaches, to enhance disease detection. Their ensemble model (DEX), which combines DenseNet121, EfficientNetB7, and Xception, achieved the best results with a 98% accuracy for detecting Bacterial panicle blight (BPB). The use of transfer learning was particularly effective, boosting accuracy by 17% over singular CNN models. Ramesh and Vydeki [12] examined deep neural networks for identifying various rice diseases using a dataset of 209 images processed from RGB to HSV for better background isolation. Their proposed DNN model substantially improved classification accuracies for multiple diseases, including bacterial blight (93%), blast (89%), and brown spot (93%), compared to the traditional KNN algorithm. Dubey et al. [13] introduced an AI-based method for automatic leaf disease detection, particularly bacterial stripe detection. Their three-stage approach involves pre-processing (transforming images to RGB and removing noise), feature extraction from the green band, and classification using an optimized Artificial Neural Network (ANN) through the adaptive sunflower optimization algorithm. This method, supported by level set segmentation, achieved a high accuracy of 97.94% in identifying diseased plants. Chen et al. [14] developed "RiceTalk", a project leveraging IoT and AI to detect rice blast efficiently without relying on traditional image-based methods. Utilizing nonimage IoT devices for data collection and integrating an innovative spore germination feature extraction model, RiceTalk offers real-time training and predictions with an accuracy of 89.4%. This system reduces management costs and speeds up the detection process. Gayathri et al. [15] focused on detecting leaf diseases in rice using image processing techniques analyzed via MATLAB. In this method discrete wavelet transform was used for feature transform, and gray scale co-occurrence matrix was used for feature extraction. Then multiple classifiers like K-Nearest Neighbors and SVM are used for disease classification and achieved an accuracy of 98.63%. Patidar et al. [16] used Rice Leaf Disease Dataset for rice plant disease detection using Residual Neural Network and achieved 95.83% over traditional CNNs. But these models are binary classification. Bashir et al. [17] proposed an SVM-based image-processing approach for rice crop diseases. Ahmed et al. [18] presented an automated rice leaf disease detection system using machine learning algorithms such as KNN, Decision Tree, Naive Bayes, and Logistic Regression. But these approaches are designed for high resolution images. Pothen and Pai [19] used Otsu's segmentation with SVM for detection of bacterial leaf blight, leaf smut, and brown spot diseases. They utilized Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG) for feature extraction with polynomial Kernel SVM for classification. Sethy et al. [20] evaluated the performance of various CNN models using deep features and SVM for rice leaf disease identification. Their study highlighted the superior performance of ResNet50 combined with SVM, achieving a high F1 score of 0.9838, and underscored the effectiveness of deep learning over traditional image classification methods. Motamarri and Sreenivasan [21] introduced a low-budget, high-accuracy CNN architecture tailored for mobile applications, which performed exceptionally on a limited dataset with data augmentation, achieving up to 99.5% accuracy. This model uses fewer computational resources, indicating its suitability for real-time, on-site disease detection. Rallapalli and Durai [22] focused on improving CNN architectures for plant disease detection. They proposed an enhanced AlexNet model, called M-Net, which significantly outperformed traditional models with 71% accuracy, demonstrating its potential in application-specific settings for robust disease identification. Thangaraj et al. [23] presented a CNN based learning model for rice leaf disease detection and achieved 82% accuracy with processing time of 5sec.

3. Plant Diseases

Plant diseases, which disrupt normal plant processes and functions, can be devastating to agriculture and ecology, broadly categorized into infectious and non-infectious diseases. Infectious diseases are caused by pathogenic organisms such as fungi, bacteria, viruses, and nematodes, capable of reproducing within their host and spreading to new hosts. In contrast, non-infectious diseases stem from adverse environmental conditions such as extreme temperatures, improper moisture-oxygen balance, toxic substances, or nutritional imbalances, and do not spread between plants [1]. These diseases not only threaten crop viability and yield but also have broader socio-economic impacts, especially on staple crops like rice and wheat that form the basis of the global food supply. The spread of pathogens can cause agricultural crisis in densely planted areas [5]. The manual agricultural practices can manage the spread of disease by applying policies like crop resistance, planting strategies, use of chemical and biological controls, etc. These approaches are quite effective but are quite time consuming. The interaction among human actions and plant disease dynamics highlights the need of unified disease management strategies to mitigate disease and to maintain economic stability.

Plant disease research is crucial due to the significant losses it causes to both plants and derived products during various stages from sowing to consumption. The primary objectives of this field in Plant Science are to understand the various biotic, abiotic, and developmental factors that cause plant diseases, explore the development mechanisms of bacterial infections, and examine plant-pathogen interactions. Bacterial blight, a severe bacterial disease of rice, is one of the most destructive, capable of causing crop losses up to 75% and affecting millions of hectares annually. This disease, along with seed rot and seedling diseases, are widespread in wet. Understanding and managing these diseases is vital for reducing the extensive economic and nutritional losses they cause globally. Some of the common rice diseases and its causing factors are presented below in fig 1.

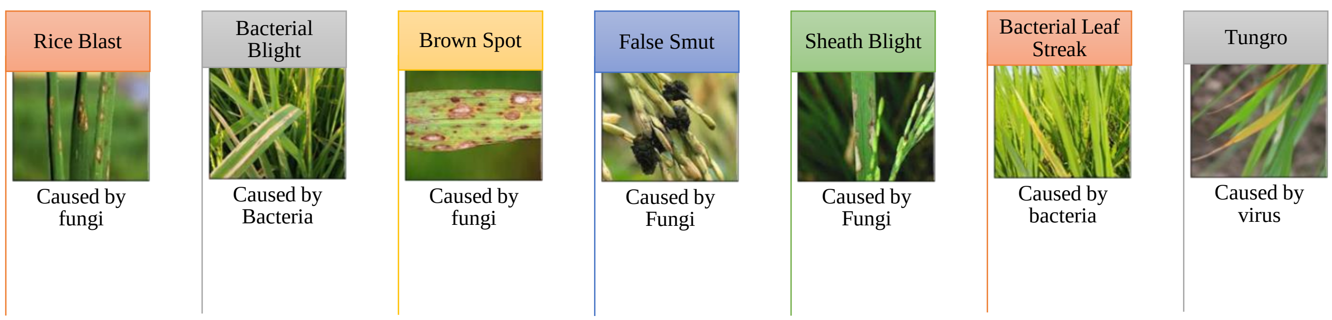


Fig. 1. Common Rice Plant Diseases

4. Proposed Methodology

In this paper, a three-layered model is proposed for rice plant disease detection due to microbes. Fig 2 presents the flowchart of the proposed model. The proposed architecture for detecting bacterial, viral, and fungal diseases in rice plants includes key processes such as image pre-processing, deep feature extraction, and classification. Initially, each image undergoes pre-processing using a digital filter to enhance quality. These enhanced images are then inputted into robust pre-trained models to extract features. This setup allows the proposed machine learning model to automatically learn features from the pre-processed images effectively, facilitating accurate disease detection.

4.1 Data Collection

In this step, data are collected from publicly available resource taken from source [30]. The dataset identified 13 key rice diseases divided into three categories—fungal, bacterial, and viral—that affect different parts of the plant.

4.2 Pre-Processing

The input rice disease images are resized in size 128×128×3. The proposed model used an adaptive bilateral filter with spatial-adaptation for noise removal. This will preserve the edge and texture characteristics of the input images. In conventional bilateral filter, it combines the domain and range kernels to preserve the edge and texture information. Mathematically, it is termed as:

$$I_{filt}(n) = \frac{1}{N_f} \sum_{m \epsilon P} I(m) \cdot f(||n-m||) \cdot g(|I(n) - I(m)|) \quad (1)$$

Where, filtered image is considered as I_{filt} for n pixels. The neighboring pixel's (m) intensity is represented as $I(m)$ within spatial domain P with n pixels. Spatial kernel is represented as $f(||n-m||)$ that reduces the kernel distance among m and n. The range kernel is represented as $g(|I(n)-I(m)|)$.

But in the adaptive bilateral filter, the paper used the sliding window approach to identify the local adaptation features and thus combining local spatial features to generate global feature for noise removal. Mathematically, in sliding window s_p might be described as:

$$I_{local}(n) = \frac{1}{N_{flocal}} \sum_{m \epsilon P_{local}} I(m) \cdot f_{local}(||n-m||) \cdot g_{local}(|I(n)-I(m)|) \quad (2)$$

Where, filtered image in each sliding window output is considered as $I_{local}(n)$ for n pixels. The neighboring pixel's (m) intensity is represented as $I(m)$ within local spatial domain P_{local} with n pixels. Local spatial kernel is represented as $f_{local}(||n-m||)$ that reduces the kernel distance among m and n. The local range kernel is represented as $g_{local}(|I(n)-I(m)|)$. By combining all these local filtration parameters, global parameters are identified to filter out the image.

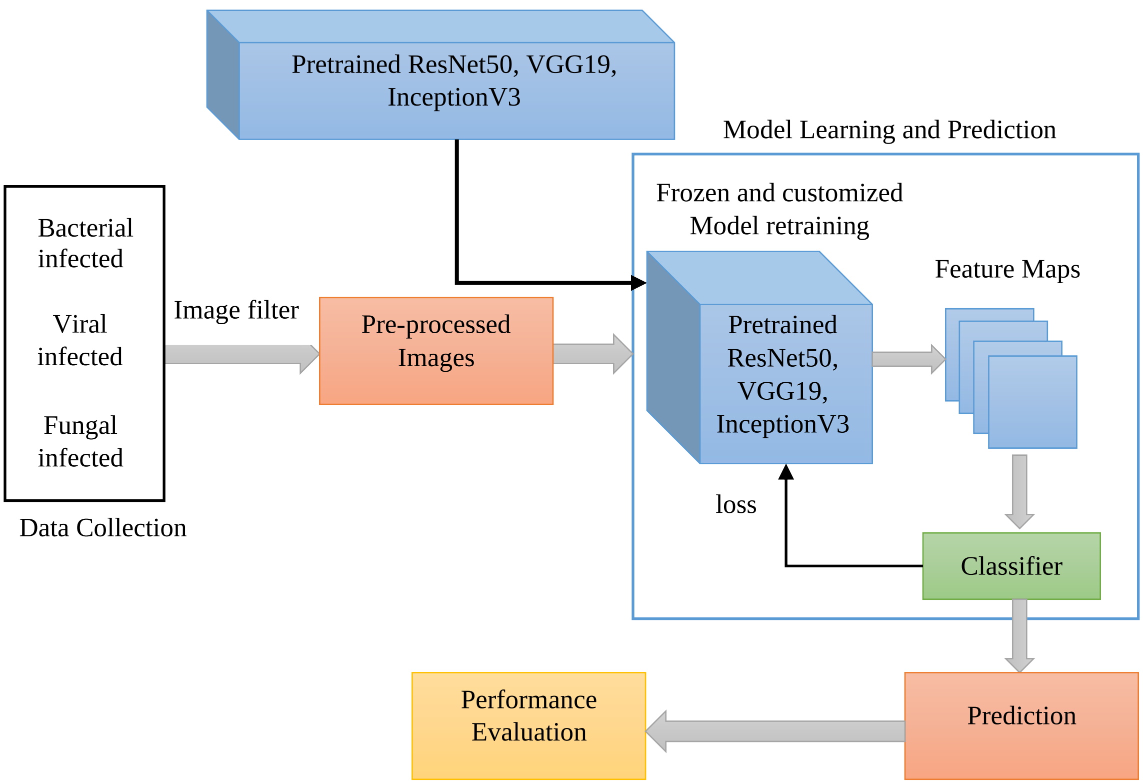


Figure 2: Proposed Architecture

4.3 Frozen and Customized Learning Model Retraining

Feature extraction involves selecting relevant features from raw data, whereas implicit processing uses deep learning to learn directly from raw data without needing explicit feature extraction. Deep learning models, particularly convolutional neural networks (CNNs), can outperform traditional feature extraction techniques by learning more complex and abstract features. These features are used for identification and classification of tasks for pest and disease identification. Deep learning approach eliminates the need for manual feature extraction. When adapting pre-trained CNN models for a specific task, some layers are updated. Generally, the classification layer is updated to learn from task-specific datasets. Whereas, in fine-tuning, some layers of the pre-trained CNNs are updated and retrained to enhance feature extraction. Apart from this, some new layers can also be added to the network for improvement of feature relevancy. For example, for rice leaf disease detection, a new layer for extraction of features such as shape, size, and color can be added. While initial layers are freezed to prevent the model from overfitting and to maintain its ability to generalize to new data. Finally, the model is re-trained on the rice leaf disease dataset and evaluated to measure its accuracy and identify strengths and weaknesses. CNNs are deep neural networks that are widely used in various fields for object recognition. These networks is designed with convolutional, pooling, and fully connected layers. These layers use the backpropagation approach to optimize their performance. One of the types of CNN is transfer learning. These are pre-trained CNN models that are trained on ImageNet that can be used for specific task by retraining them. This will result in efficient learning and prevents overfitting with reduced memory use. In the proposed model these pre-trained CNNs are used by freezing initial layers for further training. This can be done by freezing all weights of the convolutional layers and unfreezing all to adapt the model to new tasks more effectively. In this paper, study is focused on adapting and retraining pre-trained CNN models to classify rice leaf diseases using images. For this ResNet50, VGG19 and Inceptionv3 was used. These models were chosen based on various factors like input size, architectural differences, and computational efficiency. The goal was to identify the most effective model for classifying rice leaf diseases with standardized hyperparameters across all models to ensure a fair comparison.

4.4 Training Details

In this work, the pre-trained models are already trained on 1000 classes ImageNet dataset. In this paper this pre-trained model is retrained on microbial disease dataset of rice disease. The model is customized with first and last layer of the pre-trained models to learn from more complex, task-specific data. The models were trained for 100 epochs with a learning rate of 0.0001 and the Adam optimizer. The 70% of data was used for training and 30% are used for testing. This research was conducted on google colab equipped with high RAM and GPU capacity.

5. Results and Discussion

This section outlines the implementation details, result analysis, and comparisons with state-of-the-art models for proposed model. The model was implemented using the Tesla P100-PCIE GPU on Google Colab, utilizing Keras and TensorFlow as the backend frameworks. For performance evaluation, the model was assessed based on accuracy, precision, recall, and F1-score. These metrics are critical for determining the effectiveness of the model in classifying and predicting accurately and are defined as:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{v}$$

$$Precision = \frac{(TP)}{(TP + FP)} \tag{vi}$$

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

$$F1 - Score = \frac{2 * Precision * Recall}{(Precision + Recall)} \tag{viii}$$

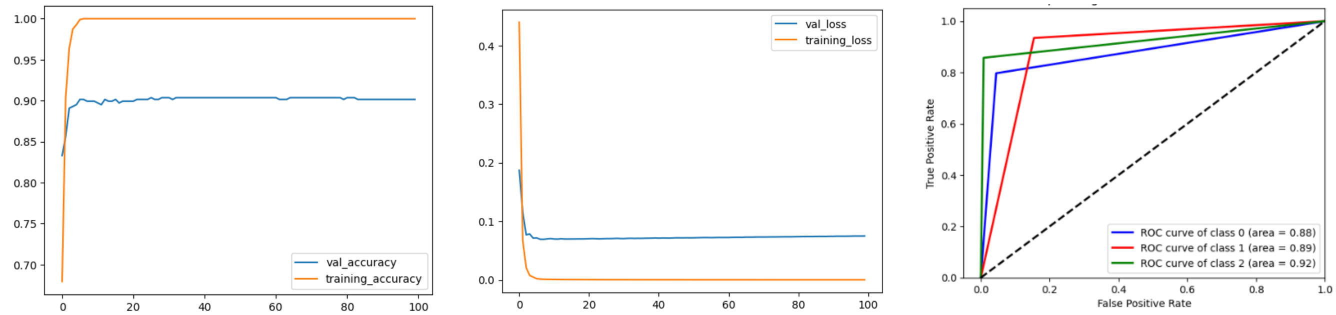
5.1 Dataset Description

In this paper, we have used rice plant diseases taken from source [30]. The dataset consists of images of 128 x 128 pixels for efficient model training for rice disease prediction in Philippines. Here fungal, bacterial, and viral agents cause diseases pose significant threats to production due to the climate's high humidity and frequent rainfall. These conditions exacerbate the spread and impact of diseases, which can severely reduce crop yield and quality. The dataset identified 13 key rice diseases divided into three categories—fungal, bacterial, and viral—that affect different parts of the plant. Therefore, this dataset is used to predict the bacterial rice disease for the proposed model.

5.2 Result Analysis

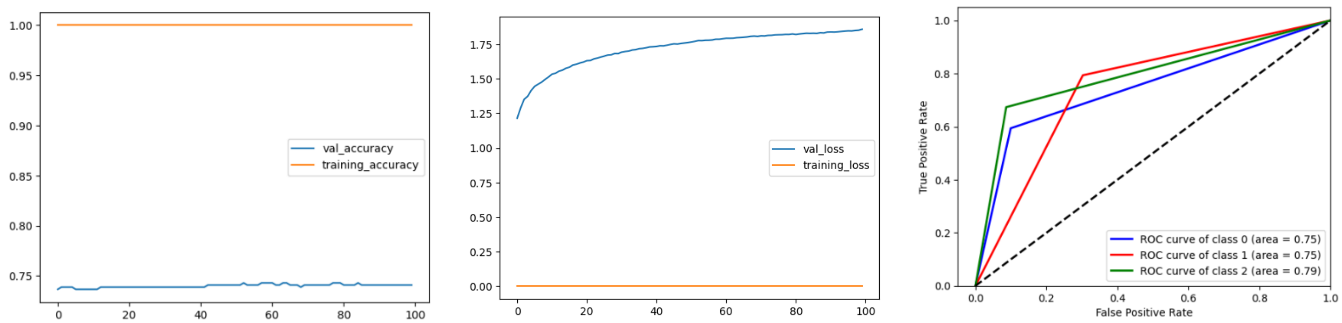
Fig 3 presents the learning accuracy, loss and ROC curve for the ResNet50 for the plant disease detection using image data. Similarly, fig 4 presents the learning accuracy, loss and ROC curve for VGG19 whereas fig 5 presents the result for Inceptionv3 network. Fig 6 presents the performance of learning model for detection of rice plant disease as bacterial, viral and fungal. Among all these transfer learning model, ResNet50 achieved the best result and then Inception V3. The comparison of the performance metrics for different models on rice plant disease types (bacterial, fungal, and viral) as presented in Table 1 shows varied effectiveness across the models and disease types. ResNet50 outperforms the best among all disease types with 90% overall accuracy. Whereas VGG19 achieved the lowest performance of 74% accuracy. Whereas inceptionv3 achieved an accuracy of 88%. For bacterial disease detection among these models ResNet50 outperforms best.

This is because, ResNet50 have deeper and more complex architecture that allows to extract more image features for identifying patterns in image.



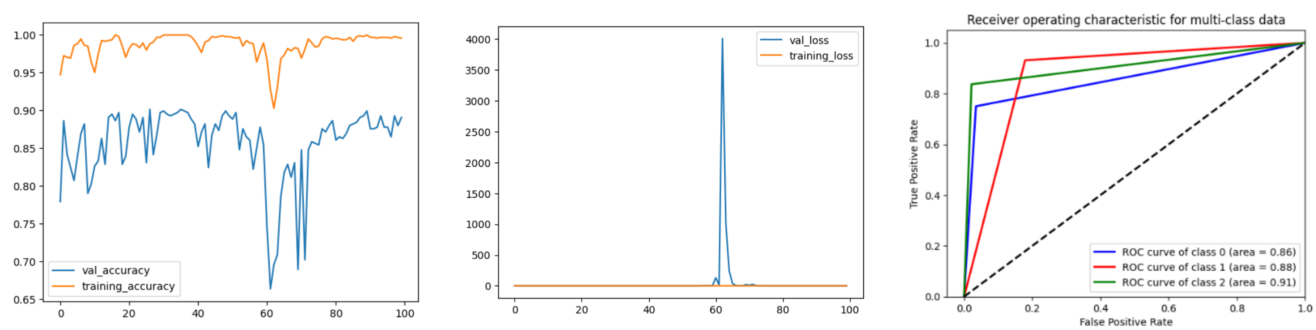
(a) accuracy **(b) Loss** **(c) ROC**

Fig. 3. Training and Validation Result for ResNet50



(a) accuracy **(b) Loss** **(c) ROC**

Fig. 4. Training and Validation Result for VGG19



(a) accuracy **(b) Loss** **(c) ROC**

Fig. 5. Training and Validation Result for InceptionV3

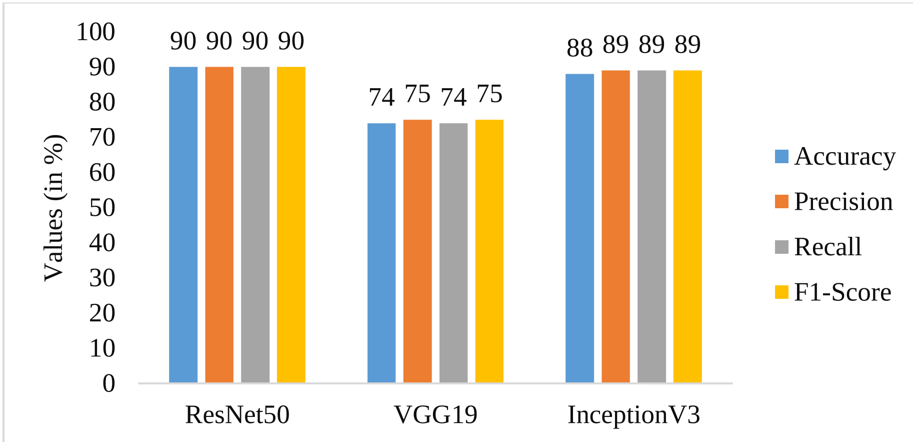


Fig. 6. Performance Comparison of Learning Models

Table 1. Performance Comparison of Rice Plant Disease Type

Disease Type	Model Used	Accuracy	Precision	Recall	F1-Score
Bacterial	ResNet50	90%	74	80	77
Fungal			92	92	93
Viral			97	86	91
Bacterial	VGG19	74%	49	59	54
Fungal			83	79	81
Viral			67	67	67
Bacterial	InceptionV3	88%	77	75	76
Fungal			91	93	92
Viral			91	84	87

Table 2. Comparative State-of-Art

Models	Accuracy	Execution Time
ResNet-v2 [23]	82%	5Sec
Proposed	90%	2Sec

Table 2 presents the comparative analysis of the presented model with existing model. ResNet-v2 [23] have achieved 82% accuracy and execution time of 5sec whereas the proposed learning model have achieved an accuracy of 90% with execution time of 2Sec. This is because the proposed model used the pre-trained model with fine-tuning and therefore achieved least execution time for detection of type of microbial infections in rice plants.

6. Conclusion

The research presented demonstrates that the customized CNN model, tailored for rice plant disease detection, significantly outperforms traditional models. With deep learning techniques, the model effectively discerns between fungal, bacterial, and viral diseases in rice plants, achieving high accuracy levels as indicated by comprehensive performance metrics. The adaptation of pre-trained networks, such as ResNet50, VGG19, and InceptionV3, enables detailed and precise feature recognition, crucial for accurate disease classification. ResNet50, in particular, showed superior performance, making it the most effective model in our study. The successful application of these advanced models offers promising avenues for enhancing crop disease detection, thereby potentially reducing the impact of diseases on rice production. The findings underscore the benefits of integrating sophisticated image processing and deep learning technologies in the agricultural sector, promoting more resilient food systems.

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