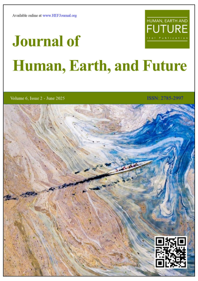
ISSN: 2785-2997

Available online at www.HEFJournal.org

Journal of
Human, Earth, and Future

Vol. 6, No. 2, June, 2025



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Novel Pyramidal Bidirectional Gated Vision Transformer for Rice Leaf Disease Detection

Ramesh Shunmugam [1, 2], Sumendra Yogarayan [1, 3 *],
Siti Fatimah Abdul Razak [1, 3], Md. Shohel Sayeed [1, 3]

[1] *Center of Intelligent Cloud Computing (CICC), CoE of Advanced Cloud, Multimedia University, Melaka, Malaysia.*

[2] *Department of Mechatronics Engineering, Rajalakshmi Engineering College, Chennai, 602105, India.*

[3] *Faculty of Information Science and Technology, Multimedia University, Jln Ayer Keroh Lama, Melaka, 75450 Malaysia.*

Received 17 February 2025; Revised 29 April 2025; Accepted 06 May 2025; Published 01 June 2025

Abstract

Worldwide, rice is a vital crop, but it is often affected by disease during the growth process. Rice leaf diseases include flax leaf spot, rice blast, and bacterial blight. These illnesses were very infectious and lethal, and they might pose a significant barrier to agricultural progress. The rice leaf image contains noise and unclear edges, which can affect the accurate extraction of disease. However, because rice leaf diseases might be identical to one another, classifying photos of diseases can be a very challenging task. The categorization of rice leaf diseases using a hybrid deep learning (DL) approach with an efficient feature extraction technique is innovative in this research. The three stages of this paper are feature extraction, classification, and pre-processing. First, the image from the dataset is extracted, and the adaptive Gaussian bilateral filter (AdGaBF) is used to remove noise. The features are then extracted, and the disease is classified using the deep multi-scale feature enhanced pyramidal convolutional block assisted bidirectional gated transformer (Dep-MPc-BgT) technique. The experiment uses two datasets, the rice leaf disease image dataset and the rice leaf disease dataset, and the approach successfully diagnoses the disease. Both datasets effectively evaluate the performance by using various metrics such as accuracy, precision, recall, F1-score and kappa score, MSE, RMSE, and processing time. The proposed rice leaf image dataset obtained values of 99.23%, 99.02%, 98.89%, 98.67%, 98.57%, 0.964, 0.991, and 0.118 s correspondingly. Similarly, the rice leaf dataset also achieved better performance of accuracy, precision, recall, F1-score, Kappa score, MSE, RMSE, and processing time values of 99.56%, 98.23%, 99.34%, 99.16%, 98.67%, 0.972, 0.994, and 0.127 s, respectively.

Keywords: Deep Learning; Rice Leaf Disease; Gaussian Filter; Pyramidal Convolutional; Bidirectional Gated; Transformer.

1. Introduction

Globally, rice is one of the most consumed foods, and its source of diet is included in many developed countries such as India, China, and Pakistan [1]. In China, 35.6% of the land is dedicated to food crops, including rice. Additionally, rice is a staple crop that is vital to humankind. Although this rice crop is regrettably more susceptible to pests and illnesses, China has shown that it is capable of planning for agricultural and rural transformation [2]. Pathogens cause the majority of plant diseases, with leaves serving as the primary source of disease detection. Bacterial leaf blight, brown spot, and leaf smut are the most frequent diseases that affect rice leaves. It is difficult for farmers to identify the right disease because each of these conditions has its own unique set of visual symptoms, but they all seem the same on the outside of the leaves. Essentially, symptoms are detected by hand, although this process

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* Corresponding author: sumendra@mmu.edu.my

http://dx.doi.org/10.28991/HEF-2025-06-02-05

takes longer than automatic detection [3]. Traditional manual identification has been unreliable and expensive and takes more time to process. Manual detection uses an advanced mapping technique that is comparatively easier and clearer to perform [4].

To maintain both the amount and quality of rice production, it is vital to detect diseases in rice plants accurately and quickly. Currently, the practical approach to quality inspection of rice production is entirely manual. When it comes to quality inspection, this practical approach is more vulnerable [5]. Researchers are aggressively seeking ways to apply deep learning's (DL) advancements in computer vision to other domains, including agriculture, industry, and manufacturing. In the agriculture domain, the detection of rice plant disease is considered one of the major research areas [6]. The identification of rice leaves by an automated system typically comprises two stages: the initial stage involves capturing an image of the diseased rice leaf using a digital camera, followed by image pre-processing [7]. Then, in the second stage, the detection and classification of diseases are obtained through various steps such as extracting the region affected by the disease, computing several features for each disease, and finally classifying the features to identify the diseases. The automatic detection of rice leaf disease becomes more applicable because it may help to monitor the crop in large areas [8].

Automated detection can be utilized to discover rice plant illnesses at an earlier stage. Infected rice plants can be detected by image processing techniques. Digital image processing technology has advanced significantly and is extensively utilized across various fields, enabling precise illness identification [9]. However, recent advances in identification and digital image processing methods have made it easier and more viable to detect afflicted crops and accurately categorize agricultural diseases [10]. Furthermore, disease detection using machine learning (ML) and artificial intelligence is insufficient; thus, the researcher has introduced the usage of drone technology such as cloud computing and the Internet of Things (IoT). These technologies have helped farmers achieve good results while cutting costs [11]. However, researchers have still used machine learning to identify rice leaf disease, although it provides the best answer to identify the leaf disease [12]. The automated detection in the DL model makes use of the lightweight deep convolutional neural network (DCNN) architecture. The DCNN approach was compared against a benchmark architecture that included five transformers and 16 convolutional-based methods. However, the DCNN technique tested performance using a big dataset that was publicly available. This dataset contains several RGB photographs, which are enhanced through various treatments. However, it significantly increases the number of photos, which improves the performance of Deep Learning models. Furthermore, this model had higher computing costs [13].

Furthermore, in DL, we introduced the plantDet model, which is built on EfficientNet, InceptionResNetV2, and the Xception model. These models were integrated into pre-processing, augmentation, the dropout mechanism, batch normalization (BN) layers, dense layer global average pooling (GAP), the PReLU activation function, and L2 regularization [14]. Traditional strategies have manipulated the efficacy of various optimization models to address overfitting and underfitting issues in complicated datasets [15]. The photos underwent several steps, including pre-processing, feature extraction, and training of the ML model [16]. The model can be trained using specific machine learning techniques, including Naive Bayes (NB), random forest (RF), decision trees (DT), logistic regression (LR), support vector machine (SVM), and K closest neighbors (KNN) [17]. The K-NN and SVM machine learning approaches diagnosed rice leaf illnesses by first applying eighteen histogram features and eight Haar wavelet features, resulting in high accuracy but low classification success rates [18, 19]. The prior ML and DL models have limitations, but these concerns can be overcome by using a sophisticated hybrid-based DL model, which also classifies diseases based on images and reduces model complexity [20].

1.1. Motivation

Existing research has generated a variety of models, including CNN, YOLOv5, Efficient V2B3 using ensemble tree (ET), histogram-based gradient boosting HGB classifier model, and KNN. These models have some limits, such as minimizing efficacy and accuracy; also, models experience overfitting difficulties. However, the current problem has become more difficult, and classification may have obtained a low learning rate. Moreover, the models can take more time to process. As a result, the rice leaf disease cannot be properly classified using a number of current methods. This study's main innovation is a new hybrid deep learning model that uses an efficient feature extraction mechanism to classify rice leaf diseases. The deep multi-scale feature enhanced pyramidal convolutional block assisted bidirectional gated transformer (Dep-MPc-BgT) technology is an efficient method for extracting and classifying rice leaf diseases. CNN networks currently do disease extraction and categorization on rice leaves. Nonetheless, this model can withstand high computational constraints and limited network storage capacity while simultaneously addressing complexity issues. In this work, the pyramidal convolutional block is robust to input while reducing complexity. However, the optimized automatic artificial driving-based EfficientNet (AD-ENet) model had previously identified the disease, but the results of such classification models showed higher errors. In this study, the bidirectional gated transformer contains a SoftMax classifier, which reduces complexity and error rates.

The major contribution of the research work is discussed below.

- To remove the noise from the rice leaf image by using an adaptive Gaussian bilateral filter (AdGaBF).
- To extract the feature and classify the rice leaf disease by using deep multi-scale feature enhanced pyramidal convolutional block assisted bidirectional gated transformer (Dep-MPc-BgT).

The rest of the paper is organized as follows: Section 2 describes the review of the collected work related to rice leaf classification, Section 3 describes the proposed methodology, Section 4 explains the performance analysis of the existing and proposed model, and the conclusion of the research work is discussed in Section 5.

2. Related Works

The rice sheath rot disease, which destroys rice leaves, was a severe challenge to rice production, affecting the superiority and measurement of food crops. Atheeswaran et al. [21] suggested using the CNN model to classify the condition. This method first removes noise from the image using wavelet filters. Features, including shape, color, and sick patches, are then examined using sophisticated extraction techniques. CNN is a crucial component of illness categorization. Large datasets from research facilities and agricultural organizations were used in the study. Lastly, the CNN model is trained using pre-processing and feature enhancement techniques. It could potentially enhance crop management by recognizing the intricate pattern and behavior of sheath rot disease. Nevertheless, the method's accuracy and efficiency were reduced.

Rice is a staple food in more than half of the world; thus, it needs to be protected and handled with care. The CNN model was suggested by Jaiswal & Sachdeva [22] for automated rice leaf disease identification. For an effective illness detection model, this method has addressed a number of important topics, including data preparation, model design, training, and assessment metrics. The recommended method had several advantages, including early detection, automation, scalability, and high accuracy. However, this method used a pre-trained DL model on two remote datasets to detect illness in rice leaves. Additionally, the study achieved great accuracy by comparing performance with five models. However, this model was able to solve the complexity problem.

Rice is crucial to people's lives all around the world, but it is susceptible to a variety of diseases. Plant diseases are typically caused by both biotic and abiotic components. CS Pavan Krishnamoorthy et al. [23] projected the most advanced DL model using convolutional neural networks (CNN). This suggested method successfully recognized leaf image categorization, segmentation, and detection. However, it also paid for automated disease diagnosis using plant photos. Furthermore, the dataset used in this study was trained using CNN models, including VGG-16, ResNet50, and InceptionV3. This work's primary goal was to identify rice plant leaves using deep CNN networks and transfer learning. This strategy successfully reduced training time while maintaining good accuracy. In this suggested model, the classifier layer employs a low learning rate.

The rice crop has played a significant part in the global economy and in meeting human needs in the sphere of agriculture. Numerous diseases, including brown spots, bacterial blasts, tungro, and blight, afflicted the rice leaves. The YOLOv5 model was suggested by Jhatial et al. [24] as a way to identify rice leaf disease. The rice leaf dataset was downloaded via Kaggle and included 400 disease-infected leaf images. This study used the Google Collaborative Platform to train, test, and validate. However, the suggested model uses the epoch at 100 to boost recall and mAP. In object detection, the recommended model demonstrated an important training process.

The diseases that occur in rice leaves cause crop failure; however, early detection has reduced the risk of crop failure. To categorize rice leaf disease, Saputra et al. [25] suggested the KNN (K-nearest neighbor) model. This study used 120 photographs of rice leaf disease from the University of California, Irvine collection. Classify rice leaf diseases such as bacterial leaf blight, brown spot, and leaf smut using the KNN classifier algorithm after first extracting the feature using the gray level co-occurrence matrix (GLCM) approach. As a result, the experiment achieved the highest accuracy rate while also attaining a wide range of kappa scores. Furthermore, this model has been used for a variety of purposes, including crop failure prevention and increased processing time.

Rice was the most stable crop in the world, and the majority of farmers preferred rice farming since rice thrived in a variety of environments. However, the sophisticated deep learning model demonstrated an automatic picture-detecting method, which was extremely useful in tough situations. Aggarwal et al. [26] suggested the Efficient V2B3 with Ensemble Tree (ET) and Histogram-Based Gradient Boosting HGB classifier model. Initially, features were retrieved using a 32-pretrained model. Rice leaf diseases such as bacterial blight, brown spot, and blast were classified using the classifier. As a result, the suggested method was more effective in detecting rice leaf disease. However, the feature extraction method was not accurate.

Classifying rice leaf disease at an early stage using thermal pictures helped to avert such losses. Bharanidharan et al. [27] presented a filter-based feature transformation method for improved lemur optimization. Initially, the recommended technique processed the thermal picture of a rice leaf, resulting in six hundred and thirty-six photos from which the healthy and diseased leaves were examined. Each thermal image had seven boxes converted and statistical attributes. Finally, four machine learning classifiers, including K-nearest neighbor, HGB, linear discriminant analysis, and RF, successfully classified five rice leaf diseases. As a result, the feature transformer-based modified lemurs optimization improved the performance of the classifier model. However, the optimization was inspired by the sine-cosine optimization algorithm. Furthermore, the feature transformer of the K-nearest neighbor classifier model maintained an accuracy rate of 90%. Furthermore, in this suggested paradigm, altering the weight parameter causes fitness concerns.

2.1. Research Gap and Novelty

There are various advancements in rice leaf disease classification, but it faces various challenges, which are described as follows: Limited accuracy and efficiency due to ineffective feature extraction [21]. In Jaiswal & Sachdeva [22] study, an automated CNN model was introduced for detection, which faces complexity-based issues. Transfer learning with deep CNN was introduced in [23], which resulted in improved accuracy, but their model required long training times. The YOLOv5 model [24] for object detection obtained enhanced recall and mAP score. However, the model suffered from high computational resource requirements. The model in Saputra et al. [25] suffered from increased processing time. An efficient V2B3 model with ensemble classifiers in [26] faces inaccuracies in feature extraction. Fitness issues in weight parameter updates are faced by Bharanidharan et al. [27], which uses a modified lemur optimization approach for feature transformation. From this overall analysis, the existing models struggled with high computational cost, poor feature extraction, difficulty distinguishing visually similar diseases, and inefficient noise removal, limiting their real-world applicability. In order to overcome these existing issues, a novel hybrid DL approach is introduced for effective rice leaf disease classification. Here, the AdGaBF filter is used for noise removal, and Dep-MPc-BgT is fused for effective feature extraction and classification. Unlike conventional CNN and ML-based models, the proposed approach effectively captures both local and global spatial dependencies in rice leaf images, which enables superior classification accuracy. The proposed model addresses the high similarity among rice leaf diseases by leveraging multi-scale feature enhancement, which improves robustness against noise and unclear disease boundaries. Moreover, the model significantly reduces computational complexity while achieving existing classification performance across multiple evaluation metrics. By integrating advanced feature extraction with transformer-based DL models, the proposed approach ensures high accuracy, reduced processing time, and improved scalability for real-world agricultural applications.

3. Proposed Methodology

The research work's key originality is the hybrid DL model-based rice leaf disease classification with an effective feature method. Figure 1 depicts the general design of the suggested model.

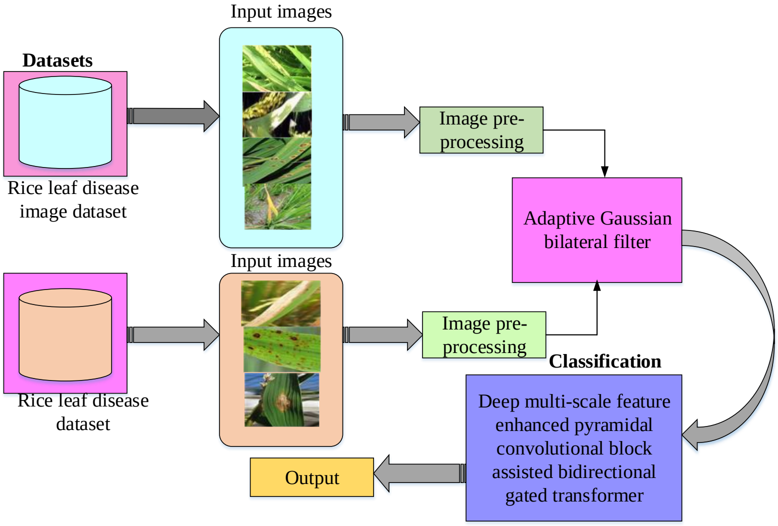


Figure 1. The overall architecture of the proposed model

The above architecture shows that initially, the images were from two datasets, the rice leaf disease image dataset and the rice leaf dataset. Then, the noise from the image is removed by using an advanced filter of AdGaBF. These filters have improved the quality of images. The essential features are extracted, and the image is classified by using a novel model of Dep-MPc-Bgt. From dataset one, four types of rice leaf disease may be identified: bacterial blight, blast, brown spot, and tungro. Next, classify the three types of rice leaf diseases from the second dataset: leaf smut, brown spot, and bacterial blight.

3.1. Pre-Processing by Using Adaptive Gaussian Bilateral Filter

The pre-processing stage is introduced to remove unwanted noises like speckles, Gaussian filters, and other environmental noises. A Sobel filter, wavelet denoising filter, wiener filter, and others can eliminate this type of noise. The adaptive Gaussian bilateral filter (AdGaBF) can be used to overcome these problems because these filters are unable to remove noise effectively. In contrast, wavelet denoising filters are unable to predict the noise level accurately [28]. One of the more sophisticated methods for image pre-processing is AdGaBF, a popular denoising approach that is also utilized in machine vision pitch. The BF is a non-iterative and non-linear image edge-preserving smoothing method. The BF has employed the kernel range to prevent smoothing across the edges. Therefore, it can be used to preserve the edges and fine structure and also remove the noise. BF has been used in a number of applications, including depth map refining, picture fusion, and upsampling. The primary goal of image-denoising techniques is to use the following steps to recover the rice leaf's original image:

$$x = y + n \tag{1}$$

here x is denoted as observed image and y represents the restored image and noise with standard deviation σ_m can be specified as $m \sim \varsigma(0, \sigma_m^2 I)$.

The noise image$x$, and intensity of the pixel at position i are assessed by BF with average weighted, which is explained in the below equation.

$$\hat{y}_i = \frac{\sum_{j \in \Omega_i} u_{ij} x_j}{\sum_{j \in \Omega_i} u_{ij}} \tag{2}$$

here Ω_i represent the user-specified neighborhood of pixel$i$, and u_{ij} denotes the weight of its neighbour pixels j. Standard BF, u_{ij} is explained in the equation below.

$$u_{ij}^s = h_{\sigma_s}\big(a(i,j)\big) h_{\sigma t}(x_i - x_i) \tag{3}$$

here $a(i,j)$ represent the euclidean distance between location of two pixels at i and$j$. Where $h_{\sigma_s}(.)$ denotes the spatial kernel it can be used to measure the similarity of spatial between pixels, which is also normally defined by Gaussian function or averaging box. The detailed operation of the averaging box and Gaussian function is formulated in the equation below.

$$h_{\sigma_s}(l) = e^{-(t^2/2\sigma_s^2)} \tag{4}$$

$$h_{\sigma_s}(l) = \frac{1}{|\Omega_i|} \tag{5}$$

here, $h_{\sigma_t}(.)$ represent the kernel range, and it also measures the intensity similarity between pixels in the Gaussian function.

$$h_{\sigma_t}(l) = e^{-(t^2/2\sigma_s^2)} \tag{6}$$

here, the parameter of user-specified is denoted as $\sigma_s$and σ_t.

By using the above equations, the weight of pixels in the neighborhood Ω_i contains range and spatial components. However, the high-frequency noise can be suppressed by the use of spatial components. The range component has analyzed the neighbor with the so-called range distance. Moreover, the spatial parameter σ_s and range parameter σ_t can be used to control the fall-off weight in spatial and range components. Therefore, the denoising method maintained the fine structure and edges in the rice leaf and removed the noise from the image.

3.2. Classification by Using Deep Multi-Scale Feature Enhanced Pyramidal Convolutional Block Assisted Bidirectional Gated Transformer

After pre-processing, the characteristics are extracted, and CNN models are used to classify rice leaf disease. However, CNN used the ResNet 50, Inception V3, and efficient net-B7 models, which all had the vanishing gradient problem and did not sustain model size. The implementation of an innovative hybrid deep learning model with a feature extraction mechanism overcomes these problems. Therefore, the pre-processed image can be extracted and classified by using the Dep-MPc-BgT technique [29], initially extracting the features from the pre-processed image. However, the deep methods have assembled the fully connected layer as a feature extractor without assigning any contextual information. The contextual feature extraction module has attained the coarse-to-fine feature in two ways. First, the three convolutional paths are initiated at a multi-scale context aggregation structure. After that, each convolutional path's dense block was combined, and the rich feature was made available for further usage. By using the first convolution, the network transform has made the picture of the rice leaf visible in feature space. To obtain overall information across many scales, the intermediate results from three convolutional paths with different dilation factors are then combined. Nevertheless, the dilated path is made up of three convolutions with identical 3 × 3 kernel sizes. Therefore, the three convolution paths have to use their receptive fields 5 × 5.9 × 9 and 13 × 13 individually and deliver extra accurate opposite information. Let h_{in} represent the input feature map for the feature extraction module and estimate the output feature map h_{out}^e of the extraction.

$$h_{out}^e = max\left(0, \sum_{d_p=1}^{3}\left(U_{d_p} * h_{in,d_p} + a_{s_p}\right)\right) \tag{7}$$

here, the convolutional operator can be represented as $*$, and the dilated convolutional path sequence can be denoted as d_p. The bias of the convolutional layer and filter parameter can be represented as $Uanda$respectively. In addition, each dilated path should have a dense connection to reserve as many deep features as feasible, and features should be integrated at many scales. The following layer takes the sum of all the previous layers' outputs as input. The feature extraction module has thus returned h_r^e as the output feature for photos of rice leaves. Figure 2 represents the multi-scale feature extraction.

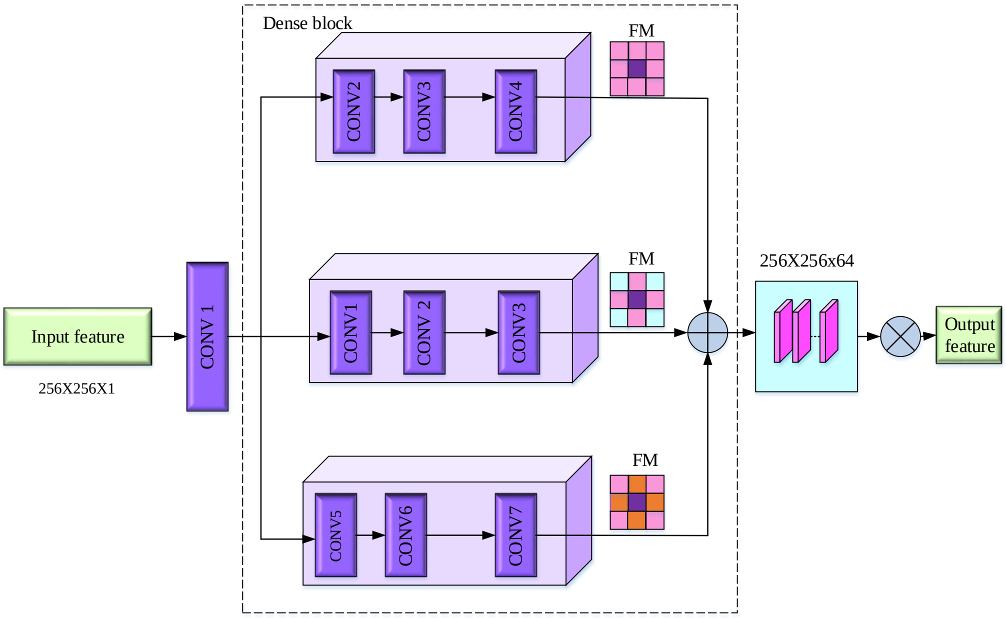


Figure 2. The architecture of multi-scale feature extraction

Multi-scale 3-D convolutional network architecture is another name for the pyramidal convolutional block. Both local and global multi-scale context aggregation are components of this design; these context aggregations can describe the input feature map. The pyramidal convolution is different from standard convolution because it has enlarged the accessible field of the kernel and also applies various sorts of kernels with diverse spectral and spatial resolutions in parallel. The pyramidal convolutional block has specified the input feature map in the equation below.

$$IF_i \in R^{C\times A\times B} \tag{8}$$

here C represents the number of channels, and $A \times B$ denotes the size of spatial. However, the pyramidal convolution uses various categories of 3-D kernels in the pyramid; therefore, it produces output and collections the output into an output feature map. The output feature map is formulated using the equation below.

$$OF_{out} \in R^{C\times A\times B} \tag{9}$$

Basically, the size of the 3-D kernel differs in two directions: channel and spatial. In the pyramid, the spatial size of the kernel has increased from bottom to top; however, in channel size, the kernel has decreased simultaneously. The pyramidal structure provides a combination of pools with different sizes and types of kernels. Therefore, the architecture of pyramidal convolution can obtain complementary information so that the accessible field has approached the feature maps to certain contextual information.

After feature extraction, rice leaf disease can be classified with the help of a bidirectional gated transformer. The combination of gated recurrent units and bidirectional transformers has provided high energy consumption data and reduced energy costs. Initially, this model consists of GRU, transformer block, embedding module and linear output layer. The output of the convolutional layer can be aggregated to L2 normalization, which can reduce the computational complexity. The process of the input sequence is combined to position the embedding matrix. The process of input sequence passing can be specified in the equation below.

$$Embedding(x) = LPPooling\big(Conv(x)\big) + E \tag{10}$$

Once the position is embedded into GRU, then enter the input sequence with spatial information. The process of GRU has been maintained, and the importance of timing feature sequence has been learned. In every step, GRU considers the previous state and updates the current state; thereby, the input sequence adapts to the changes. However, the output of the GRU is transferred to the transformer block. The bidirectional transformer is mainly composed of position-wise feed-forward networks (PFFN) and multiple self-attention heads. The input sequence is transformed to attain vectors of query (A), Key (B) and value (C). The detailed operation is formulated in the equation below.

$$AttentionScore(A, B, C) = \frac{A.B^T}{\sqrt{d_b}}C \tag{11}$$

The attention score was normalized to [0,1], for single-head attention, the probability distribution can be obtained through the SoftMax layer. However, the hidden space in multi-head attention has been divided into multiple subspaces using various parameter matrices. Moreover, the result of single-head attention is integrated and concatenated to attain the final output.

$$MulAttention = Concat(head1, head2, \ldots.).U^0 \tag{12}$$

Each single self-attention layer is integrated into a gated mechanism, so it effectively enhances the robustness of the model. Each attention layer is followed by a position-wise feed-forward network, which can help to perform feature extraction and non-linear transformation on the output of the attention mechanism and position encoding. However, the GELU activation function has enhanced the model; it has mapped the input of linear transformation to higher-dimensional feature space and gained more complex temporal patterns and features. When compared to the ReLU function, the GELU is smoother, and it changes the gradient vanishing problem and provides better feature representation. Figure 3 represents the architecture of the feature extraction and classification mechanism.

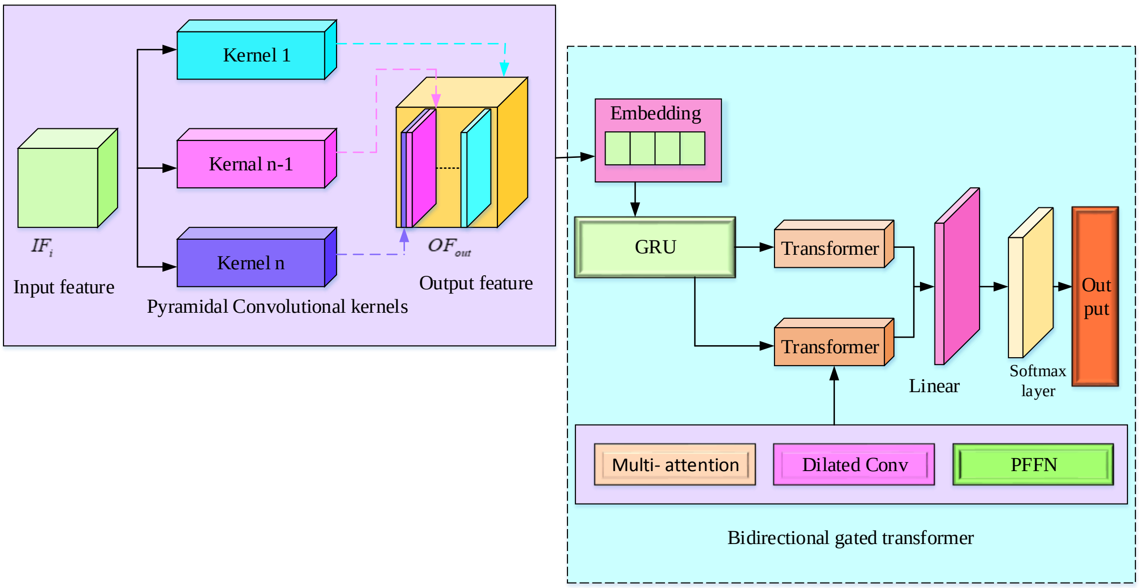


Figure 3. The overall architecture of feature extraction and classification mechanism

The Pyramidal Convolutional Block (PCB) serves as an essential component for feature extraction since it enables image features at different spatial levels to be detected in rice leaf disease images. Different diseases in rice leaves have various textures, color patterns, and lesion patterns, so PCB conducts analyses simultaneously at fine-grained and coarse-grained levels through multiple convolutional kernels of varied sizes. The model uses a multi-scale detection method to find small colored spots and big disease-infected areas, which produces more reliable classification results. The disease-specific patterns retain their presence through hierarchical learning in the pyramidal convolutional block, which minimizes background noise during feature reduction. This allows for accurate classification of disease features. The distributed computational model across various levels of the pyramidal structure allows effective learning to take place throughout different environmental conditions and rice varieties and imaging scenarios. The combination of PCB and bidirectional gated transformers increases contextual feature understanding, hence optimizing the relationship between computing performance and classification precision.

The position-wise feed-forward network consists of two linear layers. The sequence of operation is illustrated in the below equation.

$$PFFN(y) = GELU(0, U_1 y + a_1)U_2 + a_2 \tag{13}$$

The normalization layer and residual connections are applied after the feed-forward network and multi-head attention because it avoids the gradient vanishing and reduces the parameters. Meanwhile, adding the dropout layer can reduce the overfitting issues; the operation can be expressed in the below equation.

$$LayerNorm\left(y + dropout\left(sublayer(y)\right)\right) \tag{14}$$

Finally, the output from PFFN is passed through the deconvolution layer and two linear layers; this can restore the hidden input size and output size. Between the linear layers, has applied the $tanh$ activation function and constraint the output within the range of $[-1,1]$.

$$Output(x) = tanh(deconv(x).U_1 + a_1).U_2 + a_2 \tag{15}$$

Finally, the deep learning framework has classified the rice leaf disease effectively.

4. Results and Discussion

In this study, a hybrid DL models were proposed to classify the rice leaf disease. The proposed method is executed by employing two datasets, namely a rice leaf disease image and a rice leaf disease dataset. The details of hyperparameters present in the proposed model are demonstrated in Table 1.

Table 1. Hyperparameter details

Hyperparameter	Values
Learning rate	0.001
Epoch	300
Batch size	32
Optimizer	Adam
Dropout rate	0.5

4.1. Dataset Description

4.1.1. Rice Leaf Disease Image Dataset

The rice leaf disease image dataset contains rich collections of 5932 images; the dataset contains an inclusive array of visuals, which encompasses four dissimilar sorts of rice leaf diseases such as bacterial blight, blast, brown spot and tungro. The images were collected from diverse agricultural environments to capture variations in disease manifestations across different growth stages, lighting conditions and angles. The dataset includes a mix of healthy and diseased leaves, ensuring that the model has effectively distinguished between normal and infected samples [30]. Additionally, the images display variations in color intensity, lesion size and texture, which make a comprehensive dataset for training DL models in disease identification. However, each image in the dataset has aided a valuable sample. Moreover, this dataset can develop and analyze the visions for the classification and identification of rice leaf diseases. Visualization of images is shown in Table 2.

Table 2. Visualization of rice leaf disease image

Input image	Pre-processed image	Output
		Bacterial blight
		Blast
		Brown spot
		Tungro

4.1.2. Rice Leaf Disease Dataset

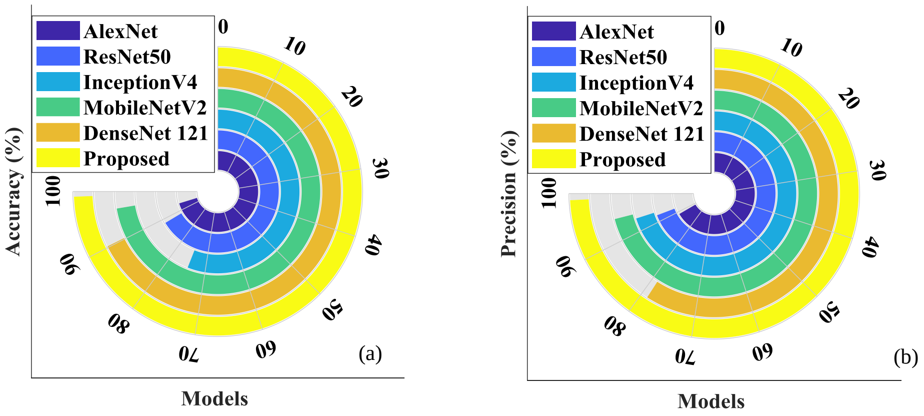
The rice leaf disease dataset contains 7560 images focusing on three primary rice disease classes such as bacterial blight (BB), leaf smut (LS), and brown spot (BS). These images are captured at different resolutions and under varying climatic conditions, which ensures diversity in disease appearance. The dataset is particularly valuable for its high-resolution images, which allow for detailed feature extraction of disease symptoms such as lesion patterns, texture difference and discolouration [31]. Moreover, the dataset includes rice leaves from multiple rice varieties, which makes it applicable to real-world agricultural conditions. However, the high-resolution rice leaf image can display symptoms of the specified disease. Moreover, the dataset can aid visual diagnosis and hybrid DL based approach image classification. Visualization of images is shown in Table 3

Table 3. Visualization of rice leaf disease

Input image	Pre-processed image	Output
		Bacterial blight
		Brown spot
		Leaf smut

4.2. Performance Evaluation for Dataset 1

In order to classify the rice leaf disease, the performance of the suggested model is evaluated and compared with existing models such as Alexnet, ResNet50, MobileNetv2, DenseNet 121, and Inception v4. The comparison of accuracy, precision, recall, F1-score, and kappa score are MSE, RMSE, and processing time, as demonstrated in Figures 4(a) to 4(h).



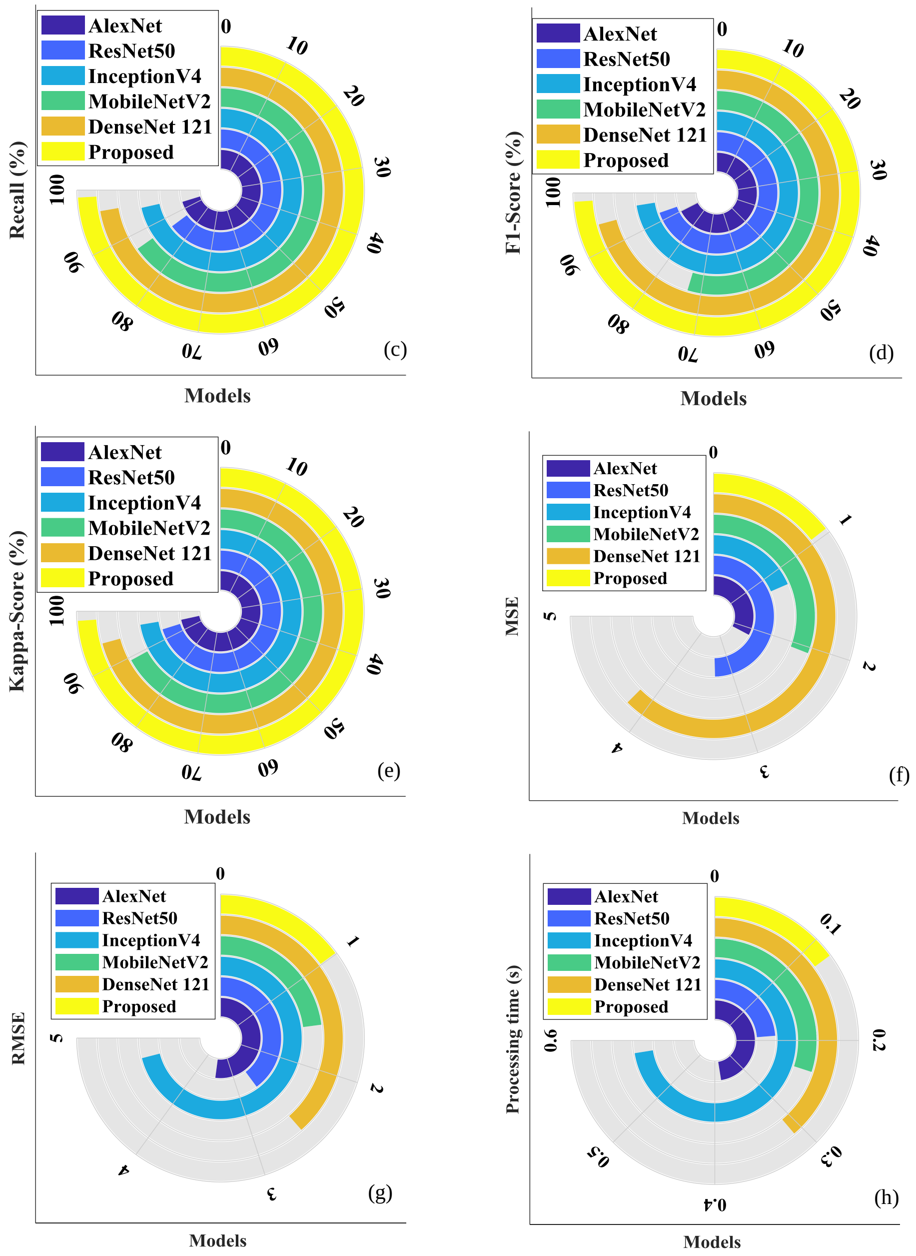


Figure 4 (a)-(h). Comparison of Accuracy, Precision, Recall, F1-score and Kappa score, MSE, RMSE and processing time

The overall performance within existing and proposed models is illustrated in Figures 4(a) to 4(h). Compared with the existing technique, the proposed model attains higher accuracy, precision, recall, F1-score, and Kappa score, MSE, RMSE, and processing time values of 99.23%, 99.02%, 98.89%, 98.67%, 98.57%, 0.964, 0.991, and 0.118, respectively. However, the existing AlexNet has limited scalability and overfitting issues. The existing model of ResNet50 achieved more time consumption for the testing process. Moreover, the existing models of Densenet121 and Inception v4 were complicated to handle large sizes of images and very complex for large-scale data. Existing models have some issues, like overfitting, high model complexity, and inefficiencies in handling complex patterns. These limitations lead to a reduction in the model accuracy, precision, recall, F1-score, and kappa score. Due to sub-optimal feature representations and ineffective generalization across datasets, RMSE and MSE values are obtained in high amounts for the existing models. The longer processing time results from deep architectures requiring significant computational resources. In contrast, the proposed model enhances feature extraction through optimized hybrid layers, reduces complexity using lightweight architectures, and integrates an improved loss optimization mechanism. Employing advanced regularization by dropout rate and enhanced classifier models leads to minimizing errors and enhanced classification performances. Thus, the proposed model obtained higher performances than the compared models.

The ROC curve for classifying rice leaf disease is shown in Figure 5. The performance of a binary classifier model at various threshold conditions is illustrated graphically by using a receiver operating characteristics curve (ROC) curve. To build the ROC curve, plot the true positive rate (TPR) against the false positive rate (FPR) at each threshold setting. Due to the presence of limitations in the existing models, AlexNet is unable to gather effective feature patterns, resulting in degraded performances. Traditional methods often rely on default thresholds, which may not be optimal for all datasets, resulting in a poor balance between sensitivity and specificity.

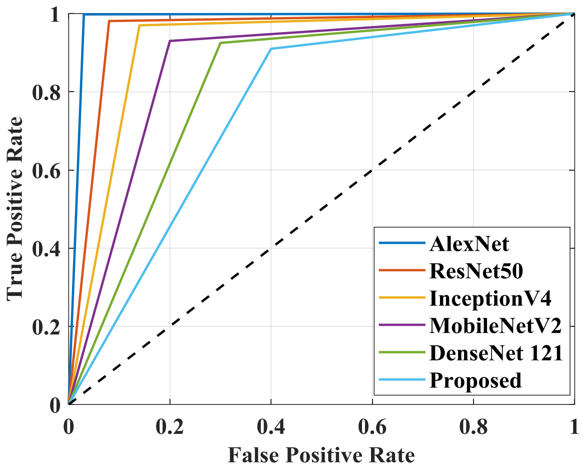
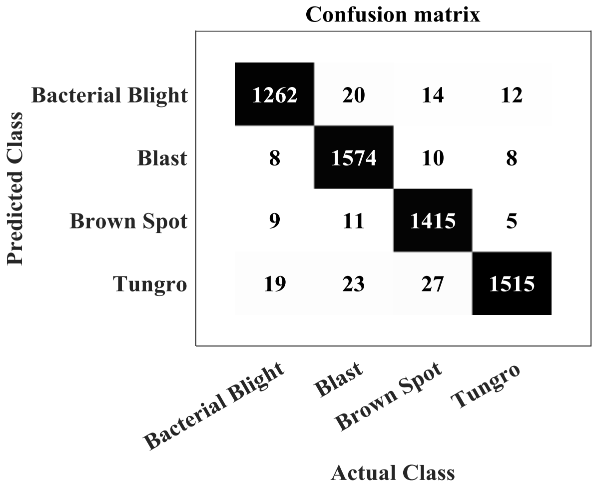


Figure 5. ROC curve

The confusion matrix executed in the proposed model is demonstrated in Figure 6. In this confusion matrix, the classifier Dep-MPc-BgT model had classified and predicted the class level of bacterial blight at 1262, blast at 1574, brown spot at 1415 and tungro had predicted the class level at 1515. The proposed model effectively predicts the target samples correctly. The correct and incorrect predicted samples are properly mentioned in Figure 6 to show the robustness of the model.



	Bacterial Blight	Blast	Brown Spot	Tungro
Bacterial Blight	1262	20	14	12
Blast	8	1574	10	8
Brown Spot	9	11	1415	5
Tungro	19	23	27	1515

Figure 6. Confusion Matrix

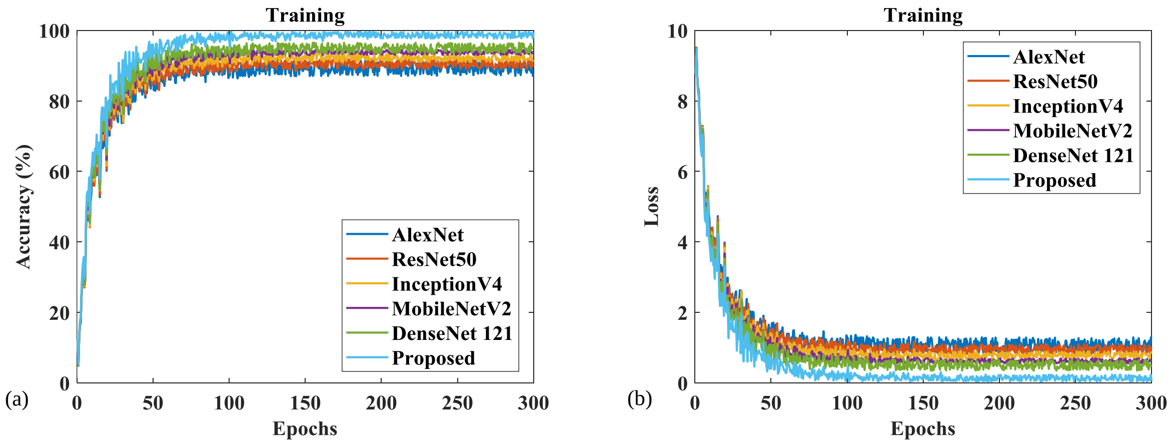


Figure 7 (a)-(b). Performance evaluation for Training accuracy loss cure

Figures 7(a) and 7(b) illustrate the performance evaluation for the training accuracy loss curve. Assessment of the prevailing and suggested model of training accuracy is depicted in Figure 7(a). The proposed model attains a high range of values at 90 in the epochs of 0 to 300. The existing model attains a low range of values at the same corresponding epochs. Figure 7(b) specifies the proposed and existing model for the training loss curve. The proposed model attains a low range of values at 2 with respective epochs. However, the existing model attains a high range of values at above 2 with corresponding epochs of 0 to 300 in the loss analysis.

Figures 8(a) and 8(b) depict the performance evaluation of the existing and proposed test accuracy loss curve models. Figure 8(a) depicts a comparison between the present and proposed models for testing accuracy. Existing testing yielded poor accuracy values; however, the proposed method yielded a high range of values at 80 in the epochs 0 to 300. Figure 8(b) depicts the current and suggested models for testing loss curves. The suggested model achieves a low range of values at one over epochs ranging from 0 to 300. In existing testing, the loss curve acquired a large range of values with relevant epochs. From this overall analysis, the accuracy and loss curve is based on epochs from 0 to 300. The existing models obtained a minimum amount of accuracy over 50 epochs, and high losses were attained.

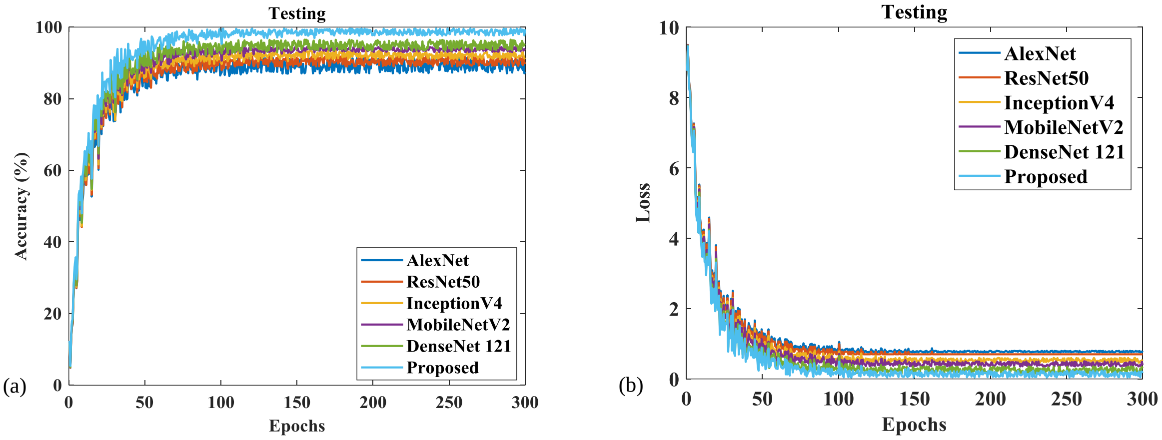


Figure 8 (a)-(b). Performance evaluation for testing accuracy loss curve

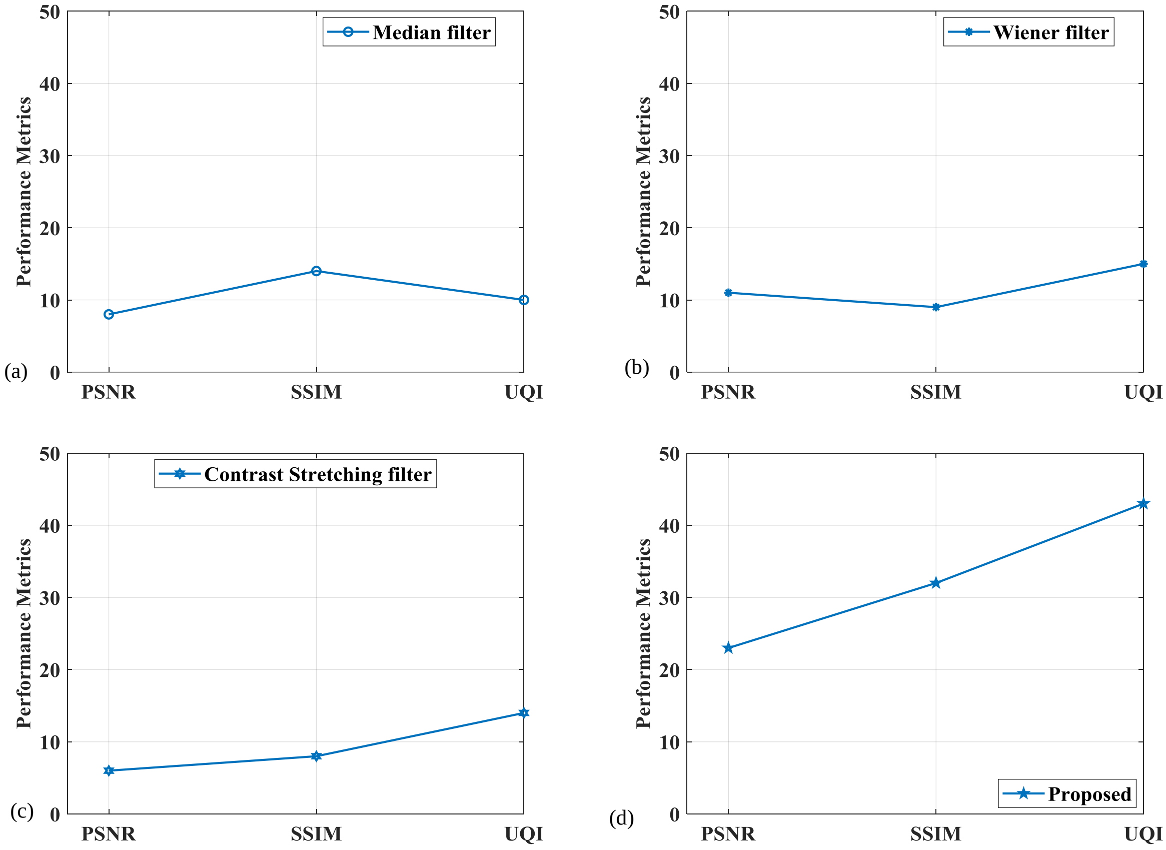


Figure 9 (a)-(d). Performance Analysis of Pre-processing Methods

Figures 9(a) and 9(b) show the performance evaluation of pre-processing techniques. The comparison values of pre-processed images indicate peak signal noise ratio (PSNR), structural similarity index measures (SSIM), and universal image quality (UIQ). In the pre-processed image, the median filter, wiener filter, and contrast stretching filter achieved low values for PSNR, SSIM, and UQI. However, the proposed model attains a high range of values of 23, 32, and 43, respectively. The existing filters struggled with preserving fine texture, leading to blurred edges, which reduced PSNR and SSIM values due to loss of structural details. It assumes additive Gaussian noise, making it less effective for non-Gaussian noise-containing artifacts, leading to reduced PSNR and SSIM values.

4.3. Class Wise Performance Evaluation

This section assesses class-wise performance utilizing accuracy, precision, recall, and F1-scores with the existing models of VGG-16, ResNet 50, and Inception V3.

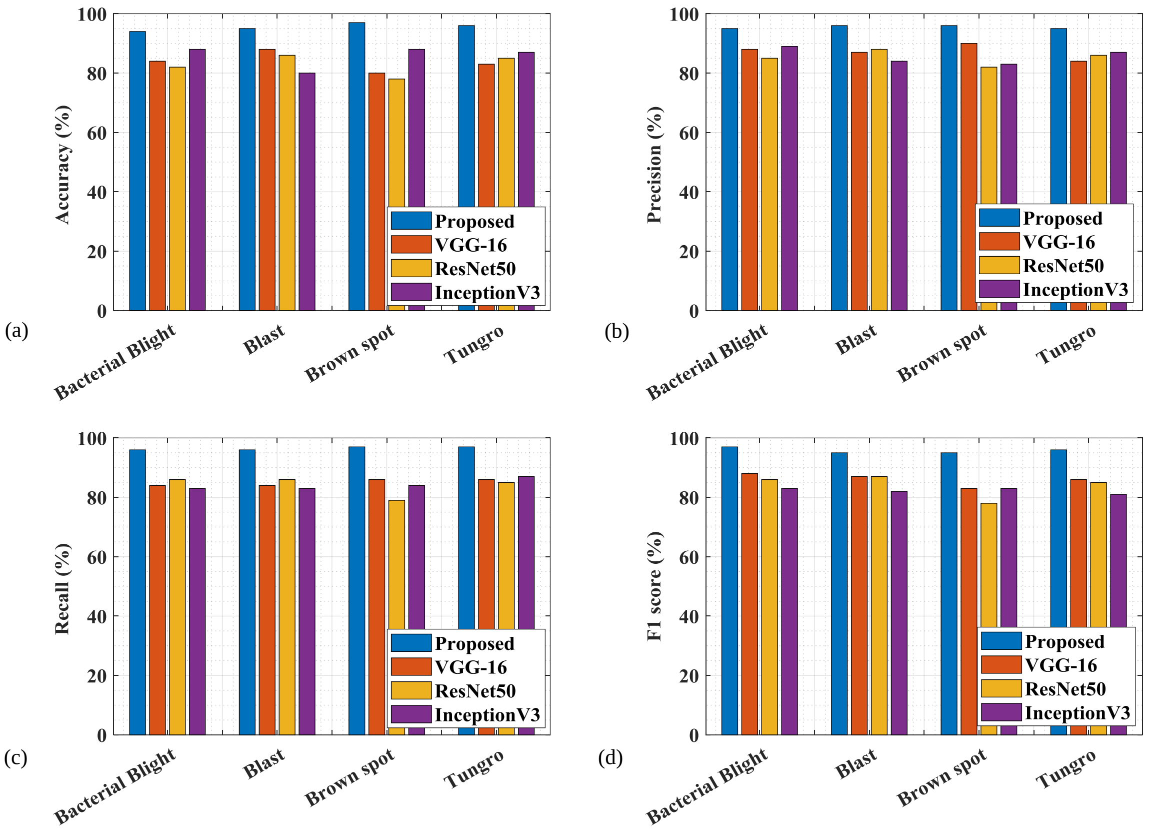


Figure 10 (a)-(b). Performance evaluation for class-wise Accuracy, Precision, Recall and F1-score

The proposed class-wise performance of accuracy precision, recall and F1-score were compared with the existing model, which is illustrated in Figures 10(a) and 10(b). The existing VGG-16, ResNet 50 and Inception V3 in the class had a very low range of accuracy, but the proposed had a high range at 94 %, 84%, 82% and 88%, respectively. Similarly, the existing model in the class had low range values for precision, recall and F1-score. The proposed model effectively classified and evaluated better performance.

4.4. Performance Evaluation for Dataset 2

Figures 11(a) to 11(h) illustrate the difference between the existing and proposed model in terms of accuracy, precision, recall, F1-score, and kappa score. Existing approaches, including AlexNet, ResNet50, Xception, MobileNetv2, DenseNet121, and Inception v4, produce low accuracy, precision, recall, F1-score, Kappa score, MSE, RMSE, and processing time. However, the proposed model attains high values of 99.56%, 98.23%, 99.34%, 99.16%, 98.67%, 0.972, and 0.994 and 0.127, respectively. However, the existing techniques of MobileNetvV2 have attained high usage of memory and also don't provide efficient models to classify the rice leaf disease. Moreover, the existing models of ResNet 50 and DenseNet 121 were affected by the vanishing gradient problem. The traditional technique of AlexNet had attained more computational problems. The proposed model reduced the complexity issues and effectively classified the disease.

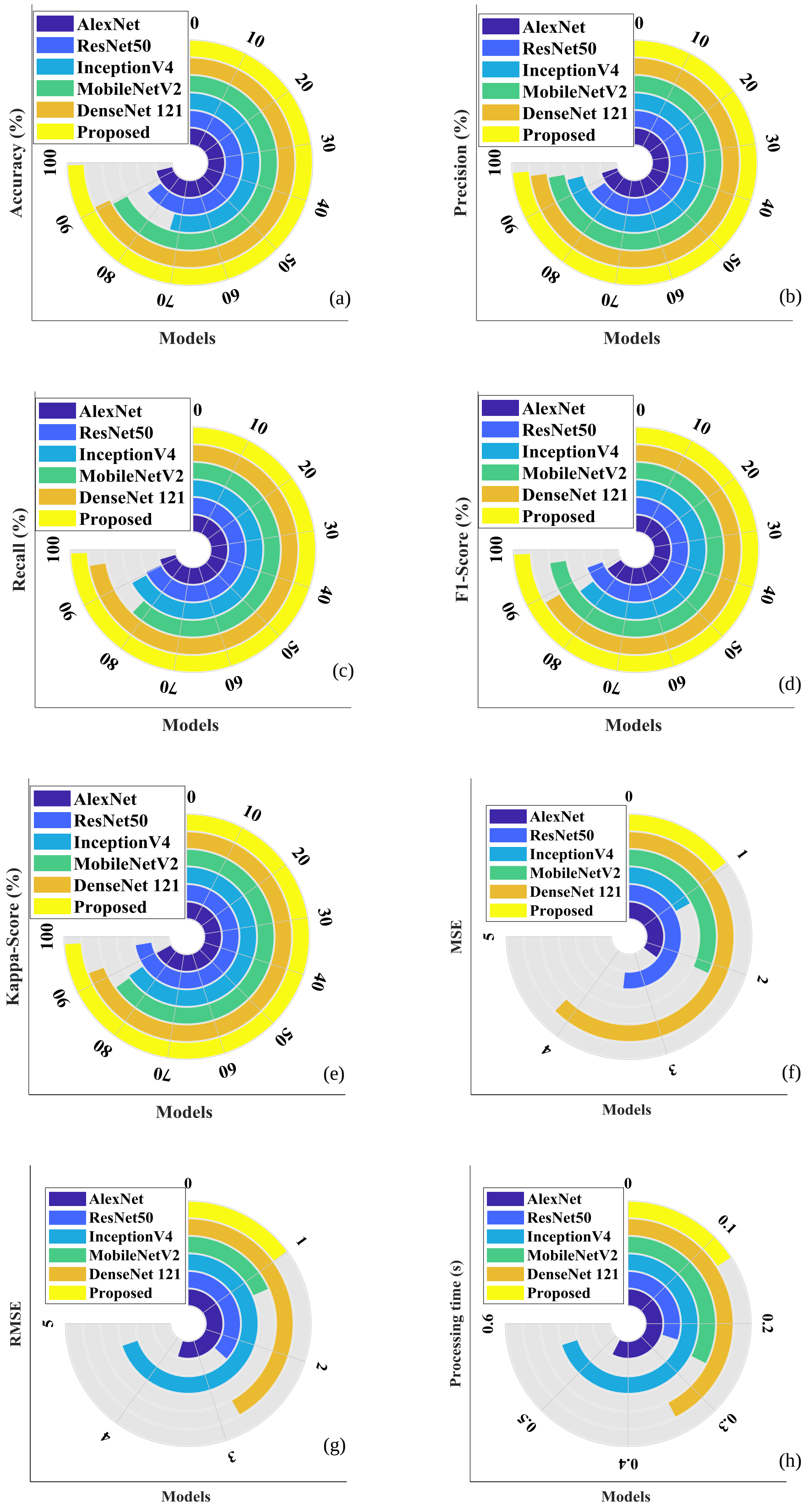


Figure 11 (a)-(h). Performance evaluation for Accuracy, Precision, Recall, F1-score Kappa score, MSE, RMSE and processing time

The ROC curve for classifying rice leaf disease in dataset 2 is shown in Figure 12. The performance of the classifier model at various threshold conditions is depicted graphically. The ROC curve can plot the true positive rate (TPR) at the y-axis and the false positive rate (FPR) at the x-axis.

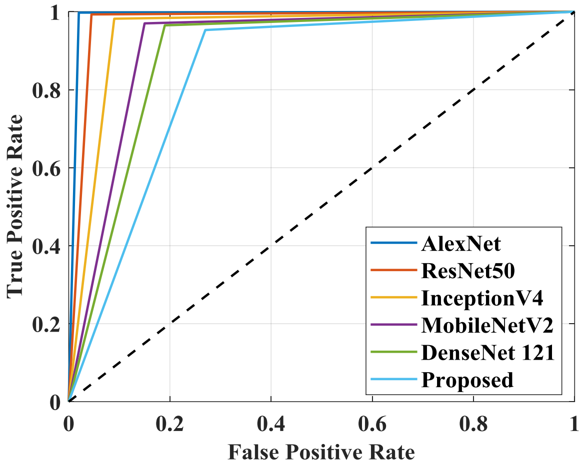


Figure 12. ROC curve

The confusion matrix executed in the proposed model is specified in Figure 13. In this confusion matrix, the classifier model has classified and predicted the class levels such as bacterial blight, which can be predicted at 1424, brown spot at 1604 and leaf smut at 1583, respectively. Thus, the proposed model had classified the disease accurately.

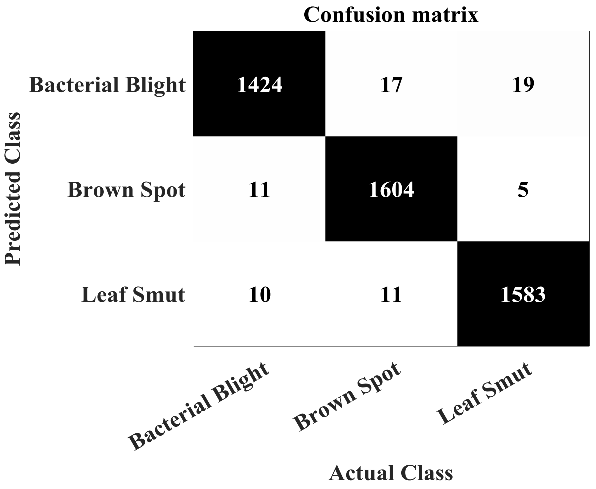


Figure 13. Confusion matrix

Figures 14(a) and 14(b) illustrate the performance evaluation for the existing and proposed model of training accuracy and loss curve. A comparison of existing and proposed models for Training accuracy is demonstrated in Figure 14(a). The Proposed model achieved a high range of values at 80 between epochs of 0 to 300. The existing model has a small range of values at comparable epochs. Figure 14(b) depicts the proposed and existing models for training loss; however, the existing model achieved a wide range of values, whereas the suggested model produced a narrow range of values from 4 to 0 during epochs 0 to 300.

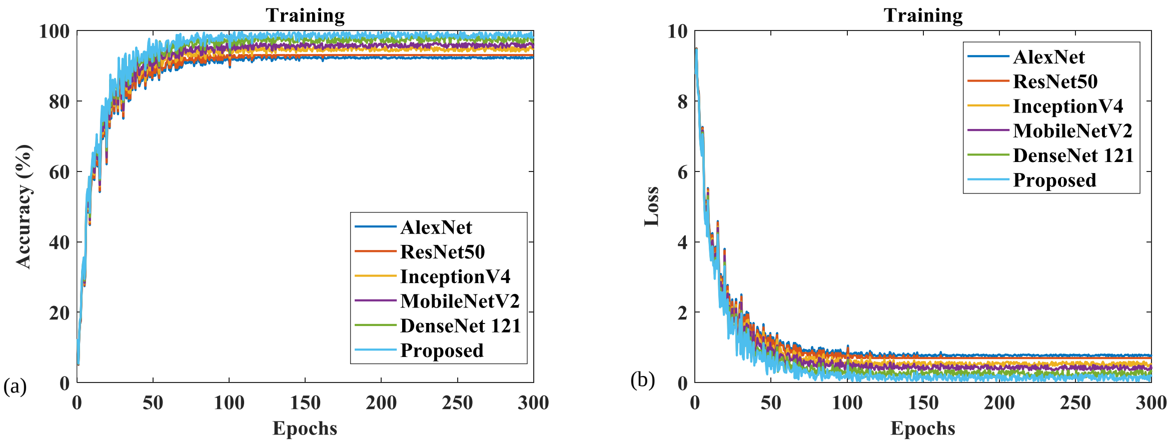


Figure 14 (a)-(b). Performance evaluation for Training accuracy and loss curve

Figures 15(a) and 15(b) specify the performance evaluation for the existing and proposed model of testing accuracy and loss curve. The proposed and existing model for testing accuracy is demonstrated in Figure 15(a). The existing model had achieved a low range of values, but the proposed model had attained high values at 80 to 100 between epochs of 0 to 300. Figure 15(b) specifies the comparison of existing and proposed models for testing loss. The proposed model achieved a low range of values at 2 between corresponding epochs.

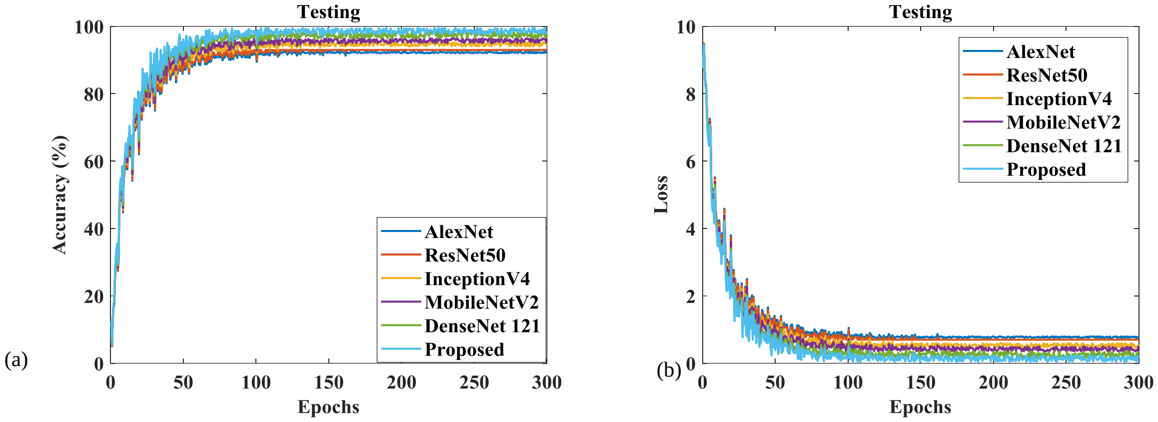


Figure 15 (a)-(b). Performance evaluation for testing accuracy and loss curve

The performance evaluation of pre-processing techniques is shown in Figures 16(a) and 16(d). The comparison values of pre-processed images indicate PSNR, SSIM, and UIQ. In the pre-processed image, the median filter, wiener filter, and contrast stretching filter achieved low values for PSNR, SSIM, and UQI. However, the proposed model attains a high range of values of 19, 28 and 40, respectively. From this overall analysis, the existing models face limitations in terms of lower accuracy, precision and so on due to inadequate feature extraction, insufficient learning of complex patterns and high computational cost. These models often suffered from overfitting and poor generalization on diverse datasets. Additionally, traditional filtering techniques struggled with noise removal while preserving fine details, leading to lower PSNR and SSIM values. The proposed model overcomes these issues by integrating advanced feature extraction and classifier models with an adaptive filtering mechanism. This approach helps to improve accuracy, robustness and computational efficiency. Leveraging the transformer model with pyramidal dilated convolutions leads to increased classification accuracy and reduced noise artifacts, which ensure more reliable and efficient detection. Table 4 represents the assessment of the present and proposed model for the rice leaf disease image dataset. Table 5 represents the comparison of prevailing and suggested rice leaf disease datasets.

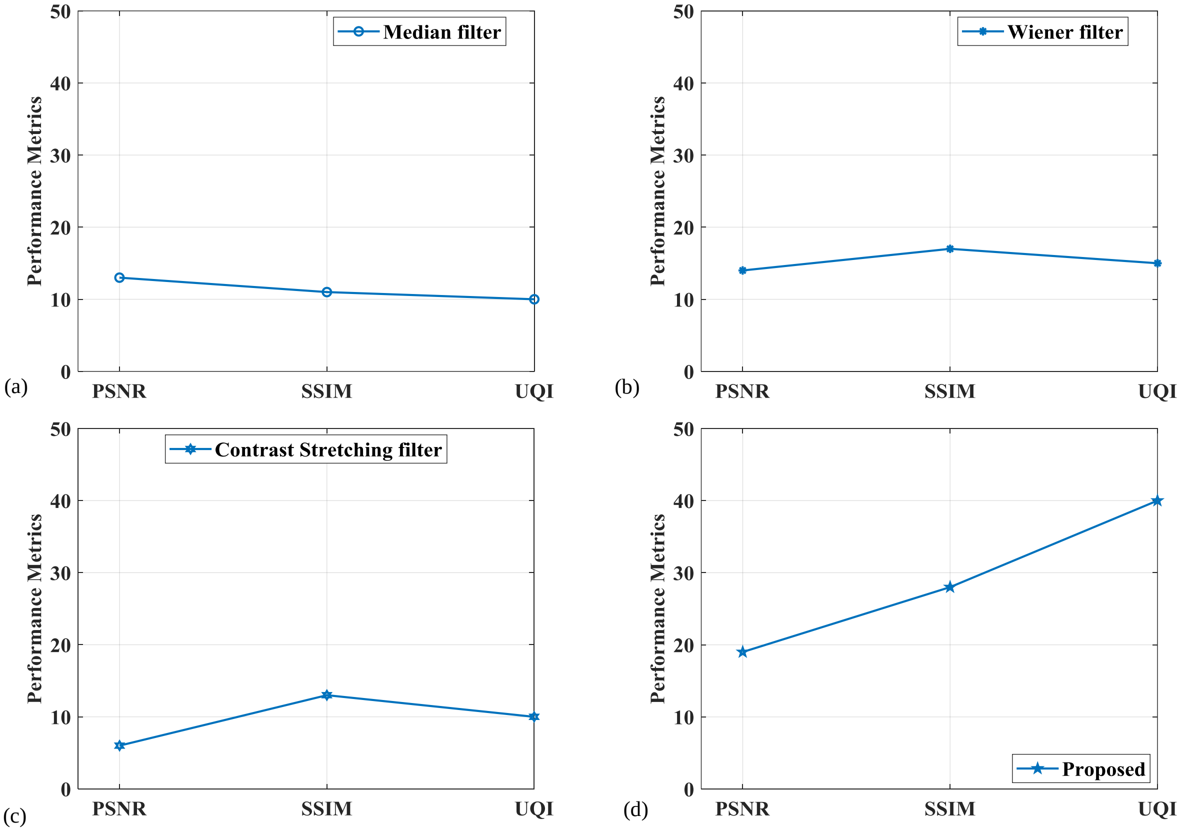


Figure 16 (a)-(b). Performance analysis for pre-processed method

Table 4. Comparison of existing and proposed model for rice leaf disease image dataset

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Kappa-score (%)	MSE	RMSE	Processing time (s)
AlexNet	93.67	88.78	93.67	89.87	95.45	2.183	3.472	0.38
ResNet50	88.56	92.32	86.43	92.89	93.56	3.307	2.656	0.19
Inception V4	74.67	93.45	95.31	96.67	96.45	1.234	4.734	0.58
MobileNetV2	96.21	94.67	86.94	72.87	89.35	2.063	1.527	0.24
DenseNet121	90.21	78.85	96.32	94.45	94.34	4.1654	2.567	0.31
Proposed model	**99.23**	**99.02**	**98.89**	**98.67**	**98.57**	**0.964**	**0.991**	**0.118**

Table 5. Comparison of existing and proposed model for rice leaf disease dataset

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Kappa-score (%)	MSE	RMSE	Processing time (s)
AlexNet	94.89	93.46	93.87	87.45	89.35	2.345	3.654	0.46
ResNet50	86.89	87.36	90.45	92.46	96.45	3.453	2.456	0.24
Inception V4	72.86	94.65	89.36	86.46	87.34	1.134	4.654	0.56
MobileNetV2	89.54	96.34	82.89	96.67	86.75	2.1237	1.231	0.26
DenseNet121	90.67	97.3	96.68	88.76	92.39	4.1644	2.7854	0.34
Proposed model	**99.56**	**98.23**	**99.34**	**99.16**	**98.67**	**0.972**	**0.994**	**0.127**

The proposed model outperforms existing models such as AlexNet, ResNet and so on in terms of classification accuracy and processing time for rice leaf disease detection. From Tables 4 and 5, the highest accuracy was 99.23% for the rice leaf disease image dataset and 99.56% for the rice leaf disease dataset, significantly surpassing AlexNet, ResNet and other models. Additionally, the proposed model exhibits better performances in terms of precision, recall and f1-score. In terms of efficiency, the proposed model achieves a faster processing time of 0.118s (rice leaf disease image dataset) and 0.127s for the rice leaf disease dataset, which demonstrates a substantial improvement over existing models like Inception and AlexNet. The enhanced performances are attributed to the model's advanced feature extraction using deep pyramidal convolutional blocks, transformer based classification and noise reduction via AdGaBF, which enables precise detection with minimal computational overhead.

4.5. Comparative Analysis

Some other recent existing models are compared with the proposed model to ensure the robustness of the models used in the research work. A comparison of rice leaf disease image dataset is represented in Table 6 [32]. A comparison of the rice leaf disease dataset is represented in Table 7 [32]. Table 8 represents the comparison of class-wise performance for the rice leaf disease image dataset [23]. Table 9 represents the comparative analysis of various existing and proposed models for the rice leaf disease image dataset [33].

Table 6. Comparison of rice leaf disease image dataset

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
MobileNet	51.01	52.42	45.99	48.73
ResNet50	37.80	40.45	17.00	22.02
ResNet 101	36.58	38.25	29.60	33.13
Xception	58.33	60.06	55.00	57.35
Inception V3	58.13	59.31	56.06	57.60
Proposed model	**99.23**	**99.02**	**98.89**	**98.67**

Table 7. Comparison of rice leaf disease dataset

Models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
MobileNet	87.5	91.66	87.5	89.28
ResNet50	33.33	41.66	33.33	36.11
ResNet 101	50.00	41.66	20.83	27.77
Xception	83.33	94.44	70.83	78.09
Inception V3	79.16	83.33	58.33	65.39
Proposed model	**99.56**	**98.23**	**99.34**	**99.16**

Table 8. Comparison of class wise performance for rice leaf disease image dataset

Metrics	Class	VGG-16 (%)	ResNet50 (%)	InceptionV3 (%)	Proposed (%)
Accuracy	BacterialBligt	84	82	88	94
	Blast	88	86	80	95
	Brown spot	80	78	88	97
	Tungro	83	85	87	96
Precision	BacterialBligt	95	88	85	89
	Blast	96	87	88	84
	Brown spot	96	90	82	83
	Tungro	95	84	86	87
Recall	BacterialBligt	84	86	83	96
	Blast	84	86	83	96
	Brown spot	86	79	84	97
	Tungro	86	85	87	97
F1-score	BacterialBligt	88	86	86	97
	Blast	87	87	87	95
	Brown spot	83	78	78	95
	Tungro	86	85	81	96

Table 9. Existing comparative analysis

Models	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	MCC (%)	F1-Score (%)
Darknet53	95.79	95.8	95.7	95.93	95.67	96
Hybrid RGB	96.12	96.1	96.12	96.35	95.89	96
VGG 19	93.21	93	95.11	93.6	93.66	-
Proposed	**99.23**	**99.02**	**98.89**	**97.57**	**94.21**	**98.67**

Those existing model analyses have faced various limitations in rice leaf disease detection. DartkNet53 suffers from high computational complexity, and overfitting leads to inefficient real-time applications. Hybrid RGB based models rely heavily on color-based feature extraction, which becomes ineffective under varying lighting conditions and noisy backgrounds, leading to misclassification. High processing time and memory consumption issues are faced by the VGG network, making it impossible to produce large-scale datasets. Due to these limitations, the existing models obtained degraded performances in comparative analysis. These issues are overcome by the proposed Dep-MPc-BgT model, which results in better performances in accuracy, precision, recall and minimized processing time. Table 10 represents the ablation study on the impact of the AdGaBF filter.

Table 10. Ablation study on the impact of AdGaBF filter

Model configurations	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing time (s)
With pre-processing (rice leaf disease detection)	99.56	98.23	99.34	99.16	0.127
With pre-processing (rice leaf disease image detection)	99.23	99.02	98.89	98.67	0.118
Without pre-processing (rice leaf disease detection)	95.43	93.76	92.45	91.89	0.206
Without pre-processing (rice leaf disease image detection)	95.56	91.86	92.55	96.89	0.221

The Adaptive Gaussian Bilateral Filtering (AdGaBF) filter plays a critical role in enhancing image quality by reducing noise while preserving important edge details, which is crucial for accurate rice leaf disease classification. If this pre-processing step is omitted, the model may struggle with distinguishing disease-specific patterns from background noise, leading to misclassification and reduced accuracy. High-frequency noise can interfere with feature extraction, causing convolutional layers to learn irrelevant or misleading patterns, ultimately degrading the model's precision, recall, and F1-score. Additionally, the absence of noise reduction may increase computational complexity, as the model would require deeper feature representations to compensate for the loss of clarity in input images.

4.6. Discussion

In this section, the efficiency of the proposed model for rice leaf disease classification is thoroughly discussed. The performance of the existing model is compared with that of current advanced techniques. The existing work has shown that misclassification also occurs in shadow effects, may cause color distortion in rice leaf images, and also causes complexity issues. In order to overcome this issue, an advanced (Dep-MPc-BgT) has been introduced. The hybrid DL techniques have efficiently classified the disease and evaluated the outstanding accuracy rate. However, existing techniques achieve accuracy value at a low level. However, the existing Recall and F1-score had very limited ability to classify the rice leaf disease and also achieved heavy computational load. Existing RMSE and MSE can hold less scalability and also don't avoid the vanishing gradient problem. Furthermore, it cannot normalize the error numbers, has less interpretability, and is less sensitive to outliers. The processing time had taken longer due to the large number of parameters. Therefore, this enhances the interpretability of DL architecture while classifying the rice leaf disease and further improving the performance.

5. Conclusion

In this research work, a novel, hybrid DL approach, namely Dep-MPc-BgT, is introduced for the rice leaf disease classification approach. The proposed model incorporates a multi-stage approach, including pre-processing, feature extraction and classification to enhance disease identification efficiency. In the pre-processing stage, an AdGaBF is employed to remove noise and improve image quality, which ensures better feature extraction. The classification stage utilizes a hybrid classifier model with a SoftMax activation function, which leads to distinguishing between different disease types. For the rice leaf image dataset, the proposed model obtained values of 99.23%, 99.02%, 98.89%, 98.67%, 98.57, 0.964, 0.991, and 0.118 s correspondingly. Similarly, the rice leaf dataset also achieved better performance of accuracy, precision, recall, F1-score and Kappa score, MSE, RMSE and processing time values of 99.56%, 98.23%, 99.34%, 99.16%, 98.67%, 0.972, 0.994, 0.127 s respectively.

Despite its advantages, the proposed model has certain limitations. While it achieves high classification accuracy, its performance might still be affected by extreme variations in lighting conditions, image resolution and environmental factors. Moreover, DL models, including the proposed hybrid framework, may face challenges such as vanishing gradients, overfitting and high computational requirements for real-time deployment in resource-constrained environments. In the future, the proposed model will focus on developing a more advanced hybrid model to improve classification accuracy further while addressing gradient vanishing issues. Data augmentation will be added to avoid class imbalance issues. Additionally, explainable AI techniques, real-time drone based disease monitoring, and cloud based computing frameworks will enhance large-scale disease detection capabilities, which ensures a more effective and scalable solution for smart agriculture.

6. Declarations

6.1. Author Contributions

Conceptualization, S.R. and S.Y.; methodology, S.R.; software, S.R.; validation, S.R., S.Y., and S.F.A.R.; formal analysis, S.R., S.Y., and S.S.; investigation, S.R.; resources, S.R.; data curation, S.R.; writing—original draft preparation, S.Y. and S.S.; writing—review and editing, S.R., S.Y., and S.F.A.R.; visualization, S.R., S.Y., and S.S.; supervision, S.Y. and S.F.A.R.; project administration, S.Y. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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