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Automated DSegNet Model for the Classification and Recognition of Rice Plant Diseases using Transfer Learning

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Abstract: ***Detecting and categorizing diseases in rice plants involves the application of techniques like Computer Vision (CV) and Machine Learning (ML) to identify and classify ailments impacting rice crops. The utilization of these methods has the potential to aid agricultural professionals and farmers in swiftly identifying and managing diseases, ultimately contributing to food security and optimal crop yields. The classification and recognition of rice plant diseases using Deep Learning (DL) have emerged as a successful approach for automated disease detection. As a subset of Artificial Intelligence (AI), DL concentrates on training neural networks with diverse layers to autonomously acquire complex representations and patterns from data. This research employs the Deep-SegNet model in developing the DSegNet method for the Automatic Recognition and Classification of Rice Plant Diseases. The DSegNet approach integrates various stages to enhance accuracy and diagnostic performance. At the initial level, a preprocessing stage is implemented, involving image resizing and the application of a Bilateral Filter (BF) to enhance image quality. Subsequently, SegNet-based segmentation is employed to identify the disease-affected areas, and feature extraction is carried out using the MobileNetV3 architecture. Finally, the extracted features are input into a Support Vector Machine (SVM) classification model to differentiate between different disease types. A comprehensive analysis of experimental results demonstrates that the DSegNet technique outperforms other recent approaches in terms of performance.***

Keywords: Deep Learning, Segmentation, Rice Disease, Machine Learning, Transfer Learning, Computer Vision

1. Introduction

Agriculture plays a crucial role in ensuring food security, poverty alleviation, and overall economic development. As the global population is projected to reach 9.7 billion by 2050 and 11.2 billion by the end of the century, there is a pressing need to enhance crop productivity despite various factors that adversely affect yields, including pests, weeds, sunlight, pathogens, nutrient deficiencies, water scarcity, soil degradation, environmental impact, and limited arable land [1]. Technological advancements offer valuable tools to address these challenges and achieve higher food productivity. One such technological avenue is computer vision (CV), which can automate crop inspection through both in-situ and ex-situ imaging techniques, thereby improving overall crop productivity. Meanwhile, rice stands out as a primary source of protein and energy for approximately 50% of the global population. With an increasing demand for rice due to population growth, there is a need to boost rice productivity by more than 40% by 2030. However, the prevalence of rice plant diseases poses a significant threat to productivity.

Currently, the predominant methods to combat these diseases involve the widespread use of pesticides and blast-resistant approaches. Unfortunately, the extensive use of pesticides not only raises production costs but also has adverse environmental impacts. Consequently, there is a pressing need to explore alternative approaches that can effectively address rice plant diseases while minimizing the negative consequences associated with traditional methods.In the realm of agriculture, the detrimental impact of plant diseases on productivity stands as a significant challenge, often resulting in substantial economic losses. Among the staple food crops in Asian countries, rice occupies a pivotal position, serving as a cornerstone of sustenance for a large population. Unfortunately, the susceptibility of rice plants to various diseases poses a constant threat to crop yields. The advent of computer vision and advanced deep learning (DL) techniques has opened avenues for addressing this agricultural concern. Leveraging these technological advancements, the detection of rice plant diseases has become not only feasible but also offers a promising means to alleviate the burdens faced by farmers in safeguarding their crops [2]. By integrating computer vision and DL methodologies, this study aims to contribute to the timely and accurate identification of rice plant diseases, offering a potential solution to mitigate the challenges faced by agricultural communities and mitigate economic losses in the crucial domain of rice cultivation.

In contemporary times, computer-aided diagnosis (CAD) models have emerged as valuable tools for monitoring crop diseases and pests through the analysis of plant images. The implementation of an automated rice disease diagnosis model holds the potential to furnish essential information for the prevention and control of rice diseases, thereby mitigating financial losses, reducing pesticide residues, and enhancing the overall quality and quantity of crops. The development of an effective image-processing approach is pivotal to the realization of such a model, urging researchers to explore methodologies that facilitate the detection of plant diseases. The image processing workflow for rice disease detection encompasses preprocessing, segmentation, feature extraction, and classification processes [3]. Notably, these processes focus solely on the external appearance of the diseased plants.

In the conventional detection of leaf diseases, reliance on human vision-based models has been the norm, albeit in a time-consuming and costly manner. The accuracy of such human vision models is contingent upon the subjective judgment of individuals or experts. The advent of machine learning (ML) and deep learning (DL) approaches has introduced a paradigm shift, enabling the identification of various diseases, informed decision-making, and the selection of effective treatments. However, the application of ML and DL models in recognizing rice plant diseases has been relatively scarce in existing literature.

Currently, the utilization of Convolutional Neural Network (CNN) models is gaining prominence due to their ability to extract optimal features, making them integral to ML and pattern recognition studies. Author [4] underscores the superior learning capability of multilayer neural networks (NN), emphasizing their appropriateness for classifying actual data. This signifies a promising direction in leveraging advanced technologies to enhance the efficiency and accuracy of disease recognition in rice plants. Specifically, [5] engages in the task of object detection through the utilization of deep Convolutional Neural Networks (CNN). This initiative has been accompanied by the emergence of numerous improved approaches and diverse applications of CNN. Traditionally, the visual identification of plant diseases relies on the expertise of human observers, involving a time-consuming and expensive process in real time. This method is challenging to execute and may occasionally lead to errors in disease identification [6]. The lack of appropriate management strategies to address diseases affecting rice plant leaves has recently resulted in a decline in rice productivity. To tackle this issue, there is a need for a precise and efficient model for detecting and categorizing diseases present in rice plant images. Consequently, this paper introduces a novel methodology to fulfill this requirement and contribute to the effective management of rice plant diseases.

This research introduces an innovative approach to the detection and classification of rice plant diseases through an effective deep learning (DL) model, namely the DSegNet model. The choice of the SegNet model is justified by its ability to address challenges such as the vanishing-gradient problem, enhance feature propagation, promote feature reuse, and significantly reduce parameter count. The proposed model encompasses key stages, including preprocessing, SegNet-based segmentation, MobileNetV3-based feature extraction, and the (SVM) classifier. Integration of the SegNet model with deep features extracted from the MobileNetV3 model is carried out to assess the efficacy of these features.

The subsequent sections of this study are organized as follows: Section 2 provides a brief overview of related works, Section 3 introduces the rice plant detection and classification model, Section 4 presents the validation of the proposed model, and Section 5 concludes the study.

2. Literature Review

In the work presented by [7], a Deep Learning (DL) based Convolutional Neural Network (CNN) model is employed to automate the detection of three rice plant diseases. The method involves differentiating healthy and infected leaf images from a dataset of 1500 rice images. Another approach, as outlined in [8], introduces a novel model for rice plant disease detection and classification. Initially, rice plant images are captured using a digital camera, and a K-means clustering algorithm based on centroid feeding is applied for image segmentation. Subsequently, features such as color, shape, and texture are extracted, followed by the use of Support Vector Machines (SVM) for multiclass classification. The reported accuracy on training and test data is 93.3% and 73.3%, respectively.

In [9], a method for recognizing and classifying paddy leaf diseases is proposed, utilizing a Deep Neural Network with Jaya Optimization Algorithm (DNN-JOA). The preprocessing involves background removal and conversion of RGB images to HSV format. Clustering is then applied to segment affected and healthy portions of rice plant images, with disease classification performed using DNN-JOA. In [10], the author presents a Machine Learning (ML)-based model for rice plant disease diagnosis, specifically targeting blast disease in South India. This model effectively identifies blast diseases and minimizes crop losses. Meanwhile, [11] designs a model employing Deep Convolutional Neural Network (DCNN) to automatically recognize and categorize both biotic and abiotic paddy crop diseases. The model utilizes images captured from the field during the booting growth stage and employs a pretrained VGG-16 CNN approach for automatic classification. In [12], the author introduces a rice blast detection model utilizing CNN, demonstrating improved detection rates.

A CNN-based rice plant identification model was developed and evaluated using a dataset containing 500 images of both affected and unaffected rice plant leaves and stems. The model successfully classified 10 different rice diseases and demonstrated superior accuracy compared to traditional machine learning models. To assess the regions of interest (ROI), the neutrosophic logic technique described in [13] was employed to identify infected regions within the images. Various classification models were tested, and the random forest (RF) model exhibited superior detection performance when applied to a subset of 400 leaf images. Author [14] introduced a novel approach for the automated identification of diseases in rice plants. After extracting relevant features, the classification is performed through the utilization of Support Vector Machines (SVM), Naive Bayes (NB), Back Propagation Neural Network (BPNN), and K Nearest Neighbors (KNN).

3. The Proposed DSegNet Model

The DSegNet technique follows a comprehensive workflow, as depicted in Fig 1. The initial step involves preprocessing to enhance image quality, followed by SegNet-based segmentation to identify infected areas. The MobileNetV3 model is then employed for feature extraction, and finally, the Support Vector Machine (SVM) is used for image classification into distinct class labels. The details of each stage are elaborated in the subsequent sections.

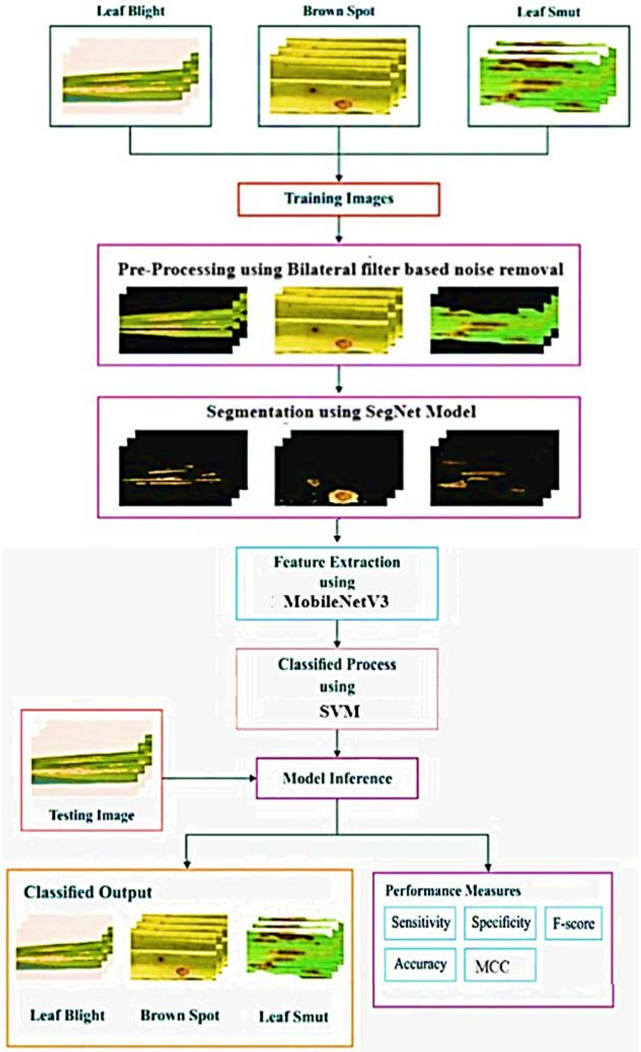

Figure 1: Overall Architecture of the Proposed Approach

3.1 Bilateral Filtering

Bilateral filtering is a technique used in image processing for noise removal while preserving the edges of the image. In the context of rice plant leaf disease classification tasks, bilateral-based noise removal plays a crucial role in enhancing the quality of images, making them more suitable for accurate classification. This is important because noise in images can interfere with the performance of machine learning models, affecting their ability to correctly identify and classify diseases.

Bilateral filtering considers both spatial and intensity information when smoothing an image. This allows it to distinguish between noise and actual edges, preserving the edges of the objects in the image. In the case of rice plant leaf disease classification, this preservation is vital for maintaining the details of the leaf structure, which are crucial for accurate disease identification. Bilateral filtering is effective in reducing various types of noise, including salt-and-pepper noise and Gaussian noise. By smoothing the image while preserving edges, it helps create cleaner images, making it easier for machine learning models to focus on relevant features for disease classification [15].

The bilateral filter is typically defined using the following equation:

$$\text{Bilateral}(I) = \frac{1}{W_p} \sum_{q \in \Omega} \exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right) \exp\left(-\frac{\|I(p)-I(q)\|^2}{2\sigma_r^2}\right) I(q)$$

Where:
I is the input image.
p and q are pixel coordinates.
Ω is the neighborhood of pixels.
σ_s controls the spatial decay of the filter.
σ_r controls the intensity decay of the filter.
W_p is a normalization factor.

In the context of rice plant leaf disease classification, the bilateral filter is applied to the images to reduce noise while retaining important structural details. The resulting denoised images can then be used as input for machine learning models, improving their performance in accurately identifying and classifying diseases based on the features present in the rice plant leaf images.

3.2 SegNet Based Segmentation

SegNet is a deep learning architecture commonly used for semantic segmentation tasks, such as image segmentation. In the context of rice leaf disease classification, SegNet is employed to segment the regions of interest, distinguishing healthy and diseased areas in rice leaf images. SegNet follows an encoder-decoder architecture. The encoder captures hierarchical features from the input image, while the decoder reconstructs the segmented output.

The encoder typically consists of multiple convolutional layers with pooling operations, which progressively reduce spatial dimensions and extract high-level features. These features are essential for discriminating between different classes, such as healthy and diseased regions on rice leaves. During the pooling operations in the encoder, SegNet retains the indices of the maximum values [16]. These indices are crucial for later upsampling in the decoder. The decoder uses the stored max-pooling indices to perform upsampling.

It helps to reconstruct the spatial dimensions and recover finer details from the encoded features. The final layer of the decoder often involves a softmax activation function, which assigns probabilities to each pixel for different classes. In the context of rice leaf disease classification, the classes might include healthy and various disease categories. The training process involves optimizing a loss function, such as cross-entropy loss, to minimize the difference between the predicted segmentation and the ground truth segmentation. This guides the network to learn accurate features for effective segmentation as depicted in Fig 2.

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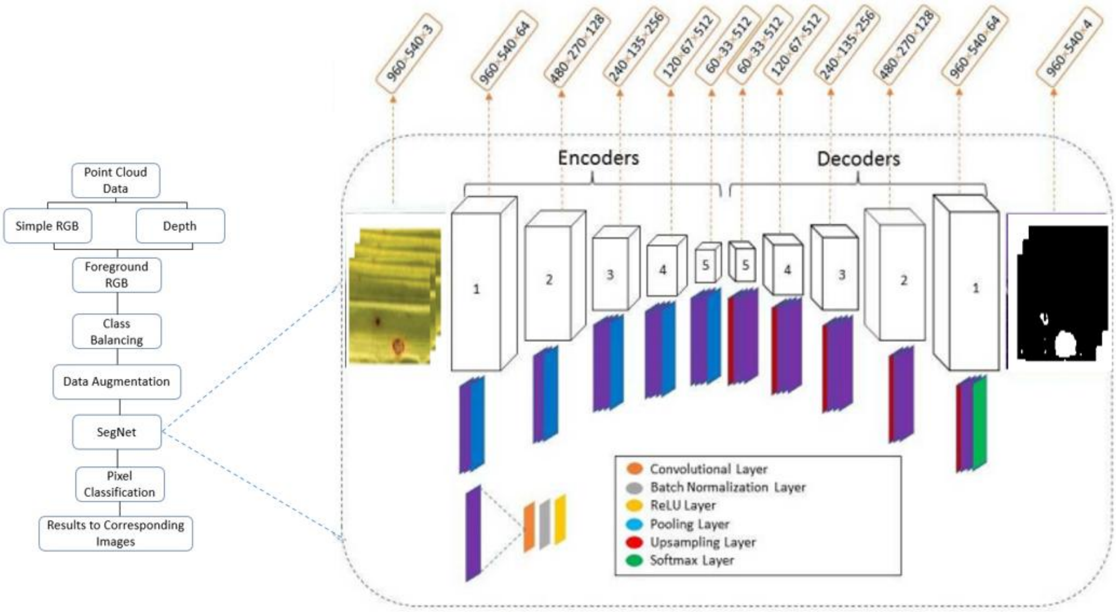

Figure 2: Overall Architecture of SegNet Based Segmentation

3.3 Feature Extraction Using MobileNetV3 Model

In the context of rice plant leaf disease classification tasks, the MobileNetV3 model is often employed as a pretrained model for feature extraction. MobileNetV3 is a lightweight convolutional neural network architecture designed for efficient deployment on mobile and resource-constrained devices. The MobileNetV3 model is pretrained on a large dataset for generic feature learning [17]. During this phase, the model learns to recognize a wide range of features, patterns, and textures from diverse images.

For the rice plant leaf disease classification task, the pretrained MobileNetV3 model is repurposed using transfer learning. Transfer learning involves leveraging the knowledge gained during the initial training on a different task and applying it to the specific task at hand (rice plant leaf disease classification). The convolutional layers of the pretrained MobileNetV3 model serve as feature extractors. These layers are adept at capturing hierarchical and abstract features from input images, including intricate patterns associated with diseases affecting rice plant leaves. To reduce the dimensionality of the extracted features, global average pooling is often applied. This involves taking the average of each feature map, yielding a compact representation that retains essential information about the input. The extracted features are then fed into fully connected layers that form the classification head of the model as shown in Fig 3. These layers further transform the features and produce output predictions for different classes of rice plant leaf diseases. The final layer typically employs a softmax activation function to convert the network's raw output into probability scores for each disease class. The class with the highest probability is considered the predicted class for a given input image.

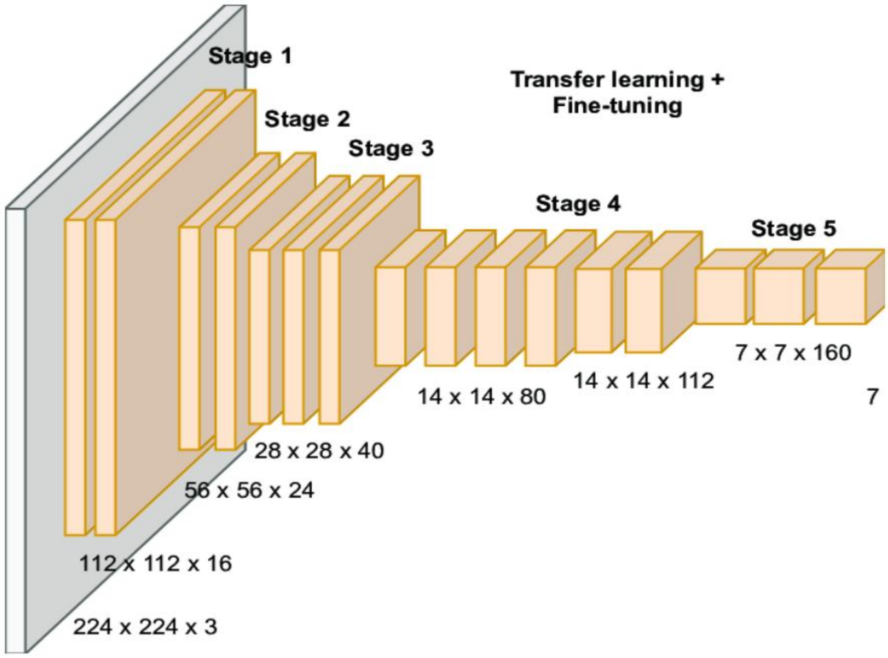

Figure 3: Feature Extraction using MobileNetV3 model

3.4 Classification Using Support Vector Machine (SVM)

The output from the MobileNetV3 model serves as a feature vector for each rice plant leaf image. This vector encapsulates the learned representations of the leaf's characteristics, capturing both global and local features crucial for disease classification. SVM is a supervised machine learning algorithm used for classification and regression tasks. In classification, SVM aims to find a hyperplane that best separates different classes in the feature space. SVM can utilize a kernel function to map the feature vectors into a higher-dimensional space, enabling the discovery of non-linear decision boundaries. Common kernels include the radial basis function (RBF) kernel [18]. SVM identifies the optimal hyperplane that maximally separates feature vectors of different disease classes as shown in Fig 4. The margin, or distance, between data points and the hyperplane is maximized to enhance classification robustness. Leveraging MobileNetV3 for feature extraction harnesses the power of transfer learning, enabling the model to benefit from knowledge gained on a diverse dataset. SVM efficiently handles high-dimensional feature spaces, making it suitable for classification tasks with complex and non-linear relationships. The combined approach of feature extraction with MobileNetV3 and classification using SVM enhances the accuracy and efficiency of rice plant leaf disease classification, providing a robust solution for agricultural diagnostics.

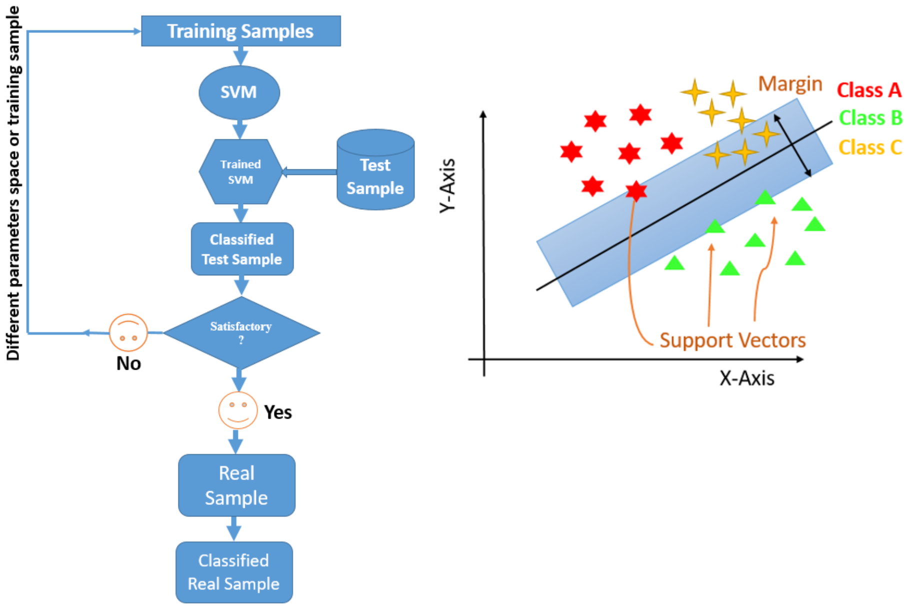

Figure 4: Classification using SVM

4. Performance Validation

4.1 Implementation Setup

In this section, the experimental validation of the DSegNet technique has been conducted, considering various aspects. The simulations were executed using Python 3.6.5 on a PC with an i5-8600K processor, 250GB SSD, GeForce 1050Ti 4GB GPU, 16GB RAM, and a 1TB HDD. The evaluation metrics employed to assess the performance of the DenseNet169-MLP model include Sensitivity, Specificity, Precision, Accuracy, F-score, and MCC. The validation process utilized a benchmark dataset consisting of rice plant images [19]. Sample test images representing each class are presented in Fig. 5 and the number of samples are depicted in Table 1.

Table 1: Dataset Description

Class	No. of Samples
Bacterial Leaf Blight	40
Brown spot	37
Leaf Smut	38
Total	115

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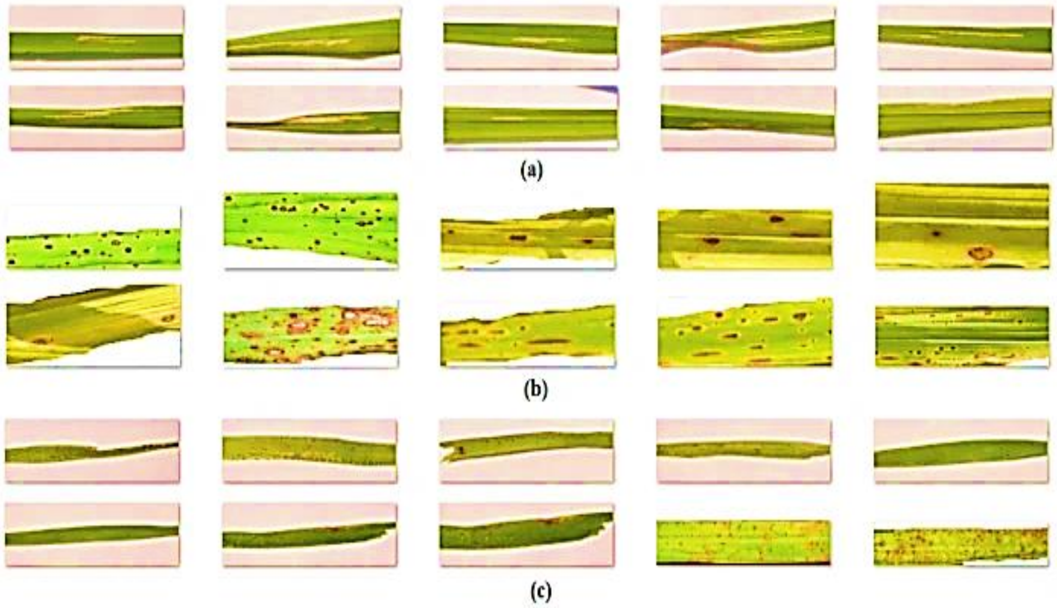

Figure 5: Sample Images (a) Bacterial Leaf Blight (b) Brown Spot (c) Leaf Smut

5. Results and Discussion

Fig. 6 shows the confusion matrix and Accuracy&Loss graphs generated during the execution of the DSegNet model revealing accurate classifications in various classes. The performance evaluation of the DSegNet model reveals its effectiveness in classifying applied images are shown in Table 2 and Fig. 7. Notably, the model demonstrates optimal results in classifying Bacterial Leaf Blight disease, achieving maximum sensitivity, specificity, precision, accuracy, and F-score. For instance, in the classification of Bacterial Leaf Blight disease, the DSegNet model exhibits outstanding performance across various metrics. Specifically, it attains maximum sensitivity, specificity, accuracy, and F-score. Additionally, in the classification of brown spot disease, the DSegNet model achieves a notable sensitivity of 83.74%, high specificity of 93.16%, impressive accuracy of 94.67%, and a substantial F-score of 87.59%.

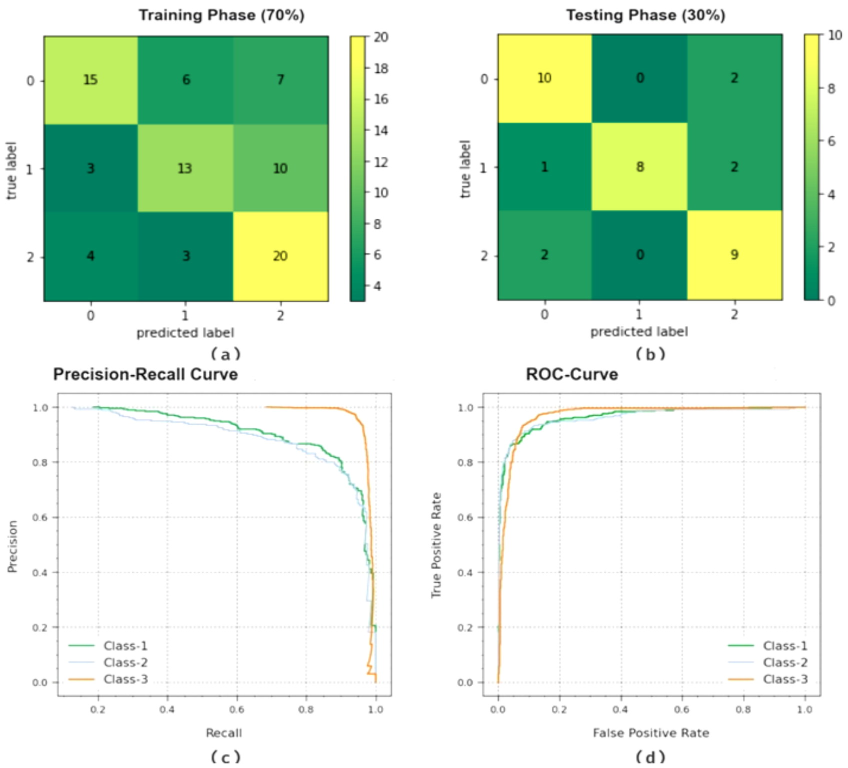

Figure 6: Performance Measures of the proposed approach (a) Confusion matrix based on training phase (b) Confusion matrix based on testing phase (c) Precision-Recall Curve (d) ROC-Curve

Table 2: Performance Evaluation of test images on the proposed DSegNet Model

Labels	Accuracy	Sensitivity	Specificity	F Score	MCC
Training Set (70%)					
Leaf Blight	93.79	77.87	97.30	81.91	78.33
Brown Spot	95.43	66.29	99.59	78.38	77.53
Leaf Smut	92.36	98.56	78.27	94.71	81.82
Average	**93.86**	**80.90**	**91.72**	**85.00**	**79.23**
Testing Set (30%)					
Leaf Blight	95.00	85.12	97.49	87.29	84.22
Brown Spot	95.67	67.09	100.00	8030	79.94
Leaf Smut	93.33	99.00	82.00	95.19	85.04
Average	**94.67**	**83.74**	**93.16**	**87.59**	**83.07**

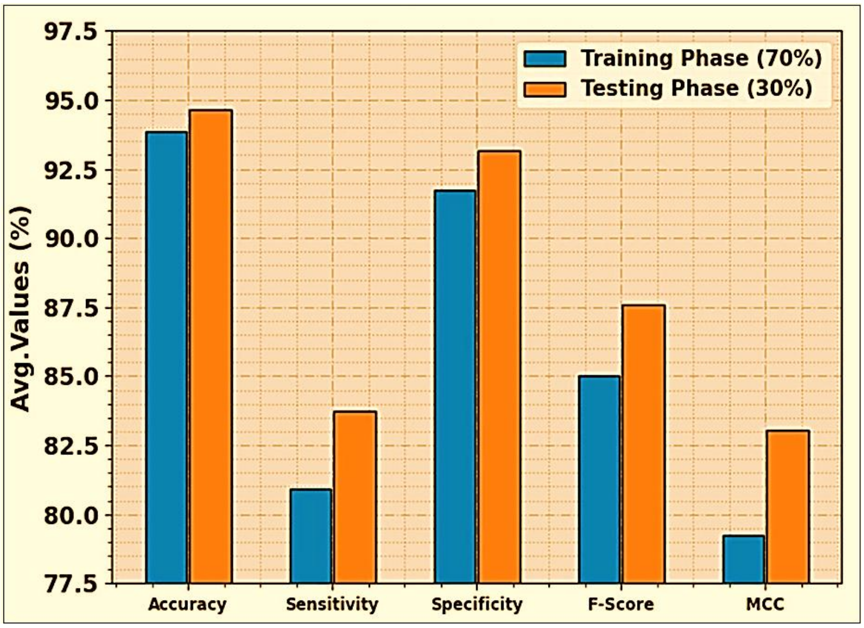

Figure 7: Performance Evaluation of the proposed work based on training & testing data

Fig. 8 and Table 3 illustrates the accuracy analysis of the DSegNet approach compared to previous methods. The KNN approach is identified as having the lowest performance with an accuracy of 70.01%. Following closely in classification performance is the ANN model with 80.01% accuracy. The DAE and DNN frameworks exhibit moderate accuracies of 86.04% and 90%, respectively. In contrast, the SIFT-SVM and VGG-16 CNN schemes achieve considerable classification results with accuracies of 91.10% and 92.89%, respectively. The SVM and SIFT-KNN methods demonstrate better and identical accuracy results of 93.33%. The CNN approach shows a reasonable outcome with an accuracy of 94%. Additionally, the DNN-JOA and BPNN models compete well, achieving higher accuracy values of 93.20% and 95.83%, respectively. Notably, the DSegNet approach outperforms all, reaching a superior accuracy value of 94.67%. These experimental values confirm the effective detection and classification performance of the DSegNet model for rice plant images. The enhanced performance is attributed to the inherent advantages of the SegNet and MobileNetV3 models. Consequently, the DSegNet model can serve as a proficient method for real-time rice plant disease diagnosis, aiding farmers and enhancing crop productivity.

Table 3: Performance analysis of the DSegNet with Existing Works

Methods	***$Accu_y$***	***$Sens_y$***	***$Spec_y$***	***F_{score}***
DSegNet	**94.67**	**83.74**	**93.16**	**87.59**
DNN Model	90.00	73.46	89.42	81.51
DAE Model	86.04	68.02	87.18	77.03
ANN Model	80.01	63.03	81.58	68.31
SIFT-SVM	91.01	86.66	90.03	86.66
SIFT-KNN	93.33	90.00	92.34	90.14
DNN-JOA	93.02	83.07	94.04	88.74

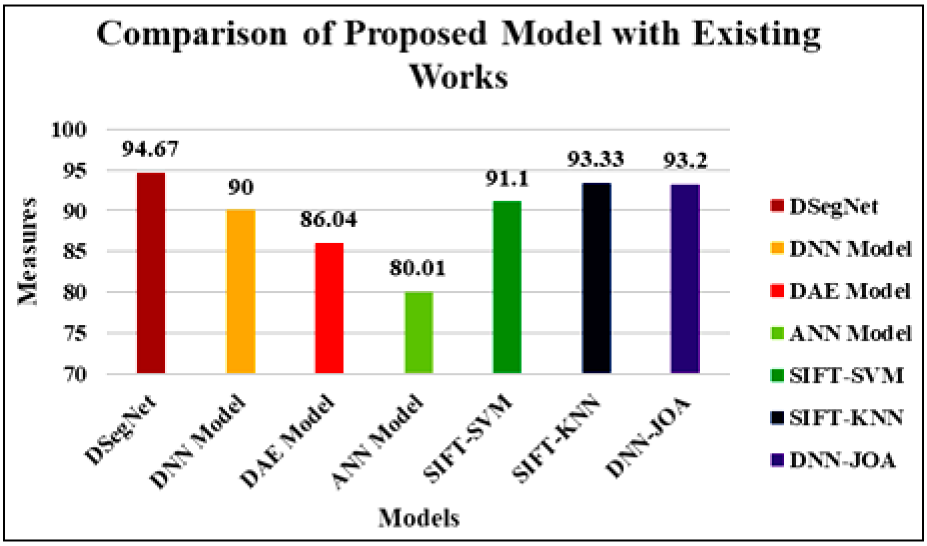

Figure 8: Accuracy analysis of the DSegNet model with Existing works

6. Conclusion

This study introduces an effective DL-based DSegNet model for the classification of rice plant diseases. The DSegNet model undergoes preprocessing to enhance image quality, followed by a BF-based segmentation process to detect infected portions. The MobileNetV3 model is then employed to extract features, and SVM is used for the final classification of rice plants. Experimental validation on a benchmark rice plant dataset demonstrates that the DSegNet model achieves a maximum sensitivity of 83.74%, specificity of 93.16%, precision of 83.74%, accuracy of 94.67%, and an F-score of 87.59%. The proposed technique serves as a reliable tool for identifying and classifying rice plant diseases. Future improvements could involve enhancing detection performance through the application of hyperparameter tuning techniques to fine-tune the DL models.

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