Architecture
Image Studies

Vol.6, Issue 4, pp.431-441, 2025
DOI: https://doi.org/10.62754/ais.v6i4.600

https://journals.ap2.pt/index.php/ais/index

Deep Learning–Driven Image Classification Framework for Accurate Detection of Rice Plant Diseases

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Abstract

Rice production is increasingly under threat by a serious fungal disease in the Chidambaram region of Cuddalore district, especially false smut, sheath blight, and brown spot, which are becoming more severe under global climate change. Usually, farmer do their inspections at a later stage, which causes critical damage to the rice crops. This manual inspection is error-prone, time-consuming, and subjective. In these situations, AI-enabled tools and methods are essential for accurate and timely rice disease prediction. This research introduces a novel approach using deep learning–driven image classification framework for accurate detection of rice plant diseases (DLDICF-ADRPD). The DLDICF-ADRPD undergoes three different stages, namely data collection, data preprocessing, feature extraction, detection and classification of diseases. This combination leads to an efficient and robust disease classification system. The series of experiments was conducted to assess the proposed DLDICF-ADRPD performance using large dataset of rice leaf images from different disease types and growth phases, obtained from the publicly accessible Kaggle datasets. When compared to other existing disease prediction models, our DLDICF-ADRPD model performs better. Overall, the suggested DLDICF-ADRPD design greatly increases the reliability and accuracy of disease recognition, supporting global food security and sustainable agriculture.

Keywords: *Rice production, Rice Leaf Disease, Deep learning, VGG16, Disease Classification, LBP.*

Introduction

With more cultivated land than any other major grain, rice is among the major food crops in the world [1]. However, the development and growth of rice might be impacted by rice diseases. The main fungal diseases that are increasingly endangering rice farming in the Chidambaram area of the Cuddalore district are sheath blight [2], brown spot, and false smut, which makes them even worse under varying climate conditions. Sheath blight incidence has been recorded to reach 35–45% in fields with high moisture content and dense plant populations in Cuddalore's coastal regions [3]. Likewise, brown spot disease has a 20–30% prevalence and has a major influence on grain quality and productivity. False smut infection has risen to 10–18% in a number of rice-growing countries, causing financial losses from discolored grains and increasing risks of post-harvest contamination [4]. A serious danger to local rice yield and farmer livelihoods is highlighted by the increasing trend of these illnesses.

Pathogen survival and dissemination have been facilitated by high humidity, frequent variations in rainfall, and continuous rice-rice farming systems. The district may experience a continuous loss in yield stability if efficient management techniques—such as resistant varieties [5], balanced nutrient administration, and prompt disease monitoring—are not implemented. In order to protect food security and guarantee sustainable rice production in the Chidambaram agricultural environment, it is essential to address these challenges [6]. Rice yield and quality can be ensured by early disease detection and treatment, which can stop the spread of diseases and the misuse of pesticides. Latest advancements in DL, especially in the area of image processing, have demonstrated significant promise for the timely recognition and categorization of rice leaf diseases [7].

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This study presents a novel approach using a deep learning–driven image classification framework for accurate recognition of rice leaf diseases (DLDICF-ADRPD). The DLDICF-ADRPD undergoes three different stages, namely data collection, data preprocessing, feature extraction, recognition and classification of diseases. This combination leads to an efficient and robust disease classification system. Overall, the suggested DLDICF-ADRPD design greatly increases the reliability and accuracy of disease detection. The main contribution of the study is given below:

- Introduced a revolutionary technology called VGG19, which highlights a cutting-edge approach to agricultural imaging disease identification.
- Presented the LBP model, which uses crop color and texture characteristics to categorize rice plant leaf diseases.
- Offered a scalable and practical approach for real-time use in agricultural fields, promising to revolutionize disease-monitoring methods and promote sustainable crop management.
- Achieved a great increase in the reliability and accuracy of disease recognition, supporting sustainable agriculture and global food security.

The remaining article is systematized as follows: Reviews of relevant research for rice leaf disease recognition are given in the "Related works" section. The technique and the architecture of the suggested DLDICF-ADRPD model are presented in the "Methodology" section. The "Results and discussions" section presents, evaluates, and discusses the findings. The research is concluded, and possible future directions in this field are outlined in the "Conclusion and future work" section.

Related Works

Jiang et al. [8] employ DL and the SVM technique for the four rice diseases. First, CNNs are employed for extracting the image features of rice leaf disease. Second, we apply SVM model to predict and classify the particular disease types. To determine the SVM model's ideal parameters, the 10-fold cross-validation is applied. The simulation outcomes suggest that when the kernel parameter and the penalty parameter g = 50, the average accuracy rate of the rice disease detection model based on DL and SVM.

Lu et al. [9] developed recognition approach for diagnosing rice sheath blight based on a BPNN model. First, a Sobel operator is utilized to segment the lesion's edge after the sample picture has been smoothed using median filtering and histogram equalization. This greatly lowers background information and enhances image quality. Next, using color and texture features, the image's matching feature parameters are retrieved. Lastly, a BPNN with good tunability and simple optimization is constructed for training and testing. The outcomes show that the BPNN can achieve up to 85.8% recognition accuracy when the nodes of hidden layer is set to 90. Based on the texture and color attributes of the sheath blight image, the BPNN model can effectively overcome the shortcomings of manual detection and has obtained good accuracy

Ramesh and Vydeki [10] proposed DNN to detect crop diseases for typical images. There are 209 photos in the dataset. In the picture preprocessing, RGB images are transformed into HSV for removing the background utilizing saturation and hue parts. In the image segmentation by k-means clustering, several color and texture features are extracted. Our suggested DNN is applied to improve the accuracy.

Hasan et al. [11] utilized the SVM model to incorporate with the deep CNN model. The suggested model has been enhanced through the application of the transfer learning technique. After that, we used 1080-image datasets of nine dissimilar rice diseases to re-train the suggested technique. The extracted features from the DCNN are then employed for training the SVM classifier. The proposed approach efficiently detected and diagnosed rice illnesses of nine dissimilar categories and reached a better accuracy.

Proposed Model

In this work, we present a novel DLDICF-ADRPD approach. The DLDICF-ADRPD model undergoes three different stages, namely data collection, data preprocessing, feature extraction, detection and classification of diseases. This combination leads to an efficient and robust disease classification system. Rice leaf diseases including sheath blight, brown spot and false smut are used in this study. Initially, input images of rice plants were collected from the given datasets. After that, image enhancement, resizing, and data augmentation methods are used to pre-process the acquired images.

Following, the pre-processed data is fed into the feature extraction phase, where color and texture features are extracted through an LBP. Lastly, the VGG19 is applied for classification. Lastly, VGG19 is applied for the classification of disease types. In the following, a detailed explanation of these stages is provided. The overall architecture of the DLDICF-ADRPD technique is shown in Figure 1.

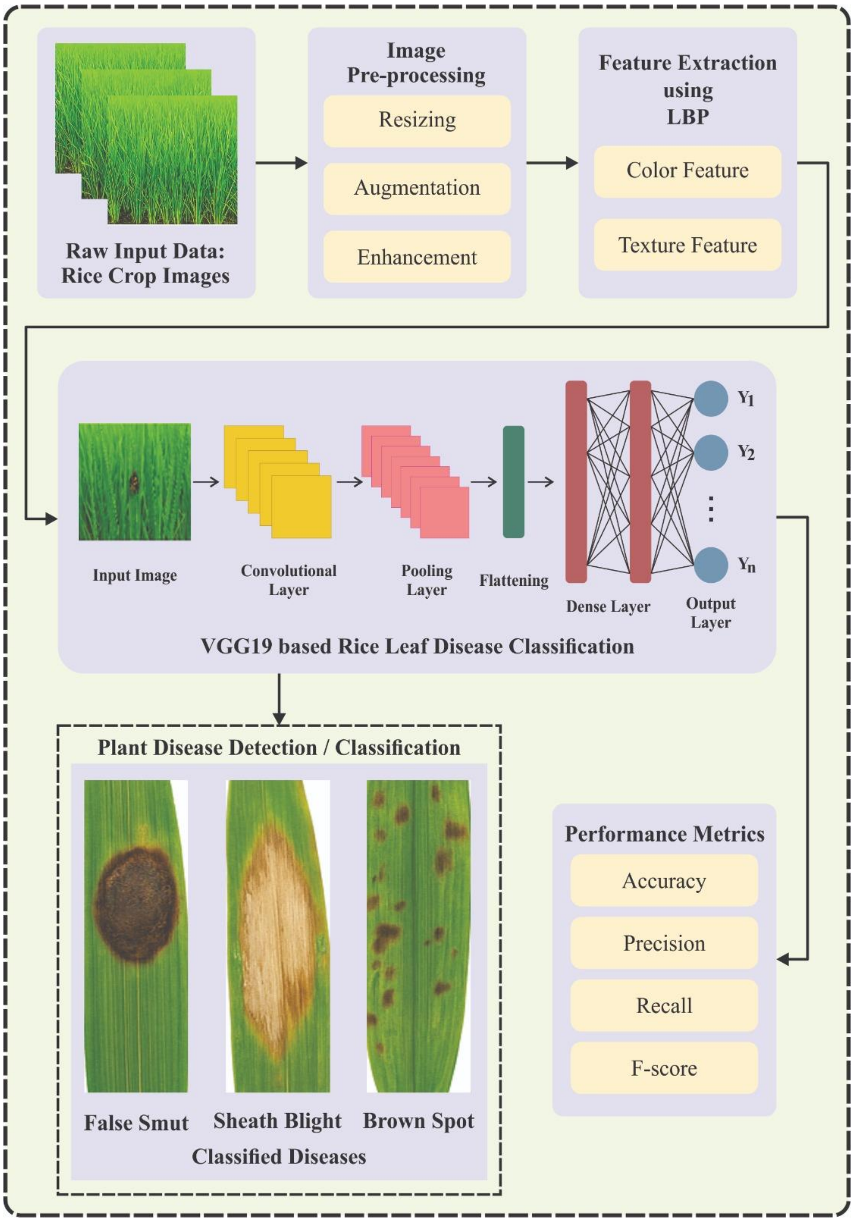

Figure 1. Overall Working Process of the DLDICF-ADRPD Model

Data Pre-processing

Initially, the DLDICF-ADRPD model performs data pre-processing. Numerous factors influence the process of acquiring images of rice plants with a camera. These elements, which have an impact on image quality, include illumination, solar angle, and weather. Thus, in order to acquire an improved high-quality image, image preprocessing is needed. Image resizing, augmentation, and enhancement are the three primary stages of the image preprocessing technique, as explained below [12].

Image Resizing

To standardize the size of images across all types of datasets used, the input image is resized into 224×224. The image resizing process can be given in the following equation.

$$D_{resized}(x, y) = D_t(\frac{x}{s}, \frac{y}{t}) \quad (1)$$

Here, $D_{resized}$ represents the resized image, the scaling factor along the x-and y-axis is referred to s, and t.

Data Augmentation

In order to handle the dataset imbalance issue, which results in an unbalanced number in all the classes, data augmentation is used to increase the dataset size and resolve over-fitting issues. Data augmentation involves applying small adjustments to the original image for generating new images. The image is shifted across the x and y axes to apply the translation. An images from the dataset were selected at random, and certain transformation techniques were used. These operations are mathematically expressed as follows.

$$D_t = T(D) \quad (2)$$

In Eq.(2), D_t represents the dataset after various transformations are applied on the image, the transformation operations applied can be represented as T, correspondingly. Here, $\triangle x$ & $\triangle$y are the amount of translation in the x and $y - axis$ and $D_{translated}(x, y)$ indicates the translated images in the dataset.

$$D_{translated}(x, y) = D_t(x - \triangle x, y - \triangle y) \quad (3)$$

$$D_{horizontalFlipped}(x, y) = D_t(width - x - 1, y) \quad (4)$$

$$D_{verticalFlipped}(x, y) = D_t(x, \text{height} - y - 1) \quad (5)$$

Now, the horizontal and vertical flipped images can be represented by $D\_horizontalFlipped(x, y)$ and, $D\_verticalFlipped(x,$ y), $width$ and *height* are the image width, and height. In Eq. (6), cos () and sin () are the trigonometric functions cosine and sine, correspondingly, the rotation angle in degrees is θ, and $D\_rotated(x, y)$ denotes the rotated images in the dataset as follows:

$$D_{rotated}(x, y) = D_t(x \cdot \cos(\theta) - y \cdot \sin(\theta), x \cdot \sin(\theta) + y \cdot \cos \quad (6)$$

Image Enhancement

The objective of image enhancement is to increase the quality and visibility of image. Noise, illumination, and weather conditions are the problems affecting the images of rice leaf. The logarithmic transformation is used to tackle the illumination problem, which is the focus of this paper. One of the key strategies for improving an image's contrast is the logarithmic (Log) transformation. The low, narrow-range images are transformed into a varied range of output levels. The images more visible to human eyes after using the logarithmic transformation, which makes the darker colors become brighter. In order to attain narrow-range pixels in images, the normalization process is initially applied. The process of normalization involves dividing each pixel value by the maximum value, which is 255.

$$D_{tNorm} = D_t/255 \quad (7)$$

Here, the dataset after normalization can be represented by the term D_{tNorm}

$$D_{t\,\mathrm{Log}} = c * \log(1 + D_{tNorm}) \quad (8)$$

Where c is a scaling constant and $D_{t\,\mathrm{Log}}$ represents the dataset following the application of log transformation for image enhancement.

Feature Extraction Based on LBP

To identify the intrinsic features, or characteristics, of objects in an image, feature extraction is utilized. These features are crucial for classifying the classes and providing a mathematical description of the key information. In this study, we extract color, and texture features for the detection and classification of rice leaf diseases, which are used to differentiate between rice disease types. Features related to color and texture offer crucial information for identifying and categorizing rice leaf diseases [13]. The LBP method is a key texture descriptor that extracts texture features that are resistant to changes in illumination. LBP has various benefits, including low computational complexity, grey-scale variations, implementation ease, and invariance to illumination. LBP initially assign a binary number to each pixel in the rice image by comparing its grey level to that of its nearby pixels. In a predefined patch, neighbors whose grey level is greater than the center pixel value then it receives a value of unity; if not, they receive a value of zero.

$$LBP(x, y) = \sum_{p=0}^{N} 2^p \left(g(B_p - B(x_c, y_c)\right) \quad (9)$$

In Eq. (9), the LBP characteristics at the x_c, y_c center pixel is represented by LBP (x_c, y_c). The value of center and neighbor pixels can be denoted by $B(xc, yc)$ and B_p. The neighbor pixel index is denoted by the index p. The function $g(x)$ will equal zero if x is less than zero and one otherwise.

In most studies, traditional LBP descriptors and their variants are utilized for gray-scale image pre-processing. Images of colored rice, which are used in many different applications, are becoming more and more in demand on the internet. Thus, color-texture features from colored rice images have been extracted using LBP descriptors. This can be obtained by expanding the LBP to process all the color channels in the RGB-colored rice images as a simple gray-scale image. In Eq. (12), the features extracted from red, green, and blue channels are $LBP(RGB)$, the LBP features from the red channel are represented as $LBP(Red)$, the LBP features from the green channel are denoted the $LBP(Green)$, and the LBP features from the blue channel are denoted as $LBP(Blue)$.

$$LBP(RGB) = LBP(Red) + LBP(Green) + LBP(Blue) \quad (12)$$

Classification Using VGG19

Finally, the DLDICF-ADRPD model uses VGG19 for the recognition of rice leaf disease types. The ML classifiers come in a different form. Our dataset will define which categorization model we choose. The convolutional layer is the top layer of the CNN module. Most of the computing power can be managed by this module, as shown in Figure 2. A filter or kernel is used for the reduction of data or image size. A sliding window enables to employment of a small unit named a filter on the data. VGG19 is a collapsible neural network with 19 layers. The rice images can be classified using a pre-trained network into 1000 different object categories. The network image's input dimensions are 250x250 [14].

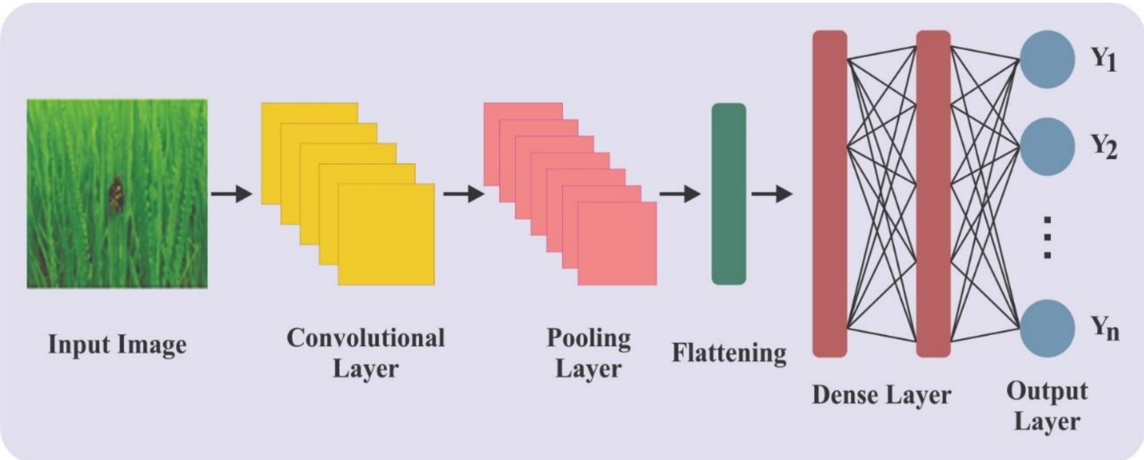

Figure 2. Architecture of VGG19

Experimental Setup

In this section, the experimental analysis and comparisons of the DLDICF-ADRPD model tested under the benchmark datasets [15] is discussed. The sample images of rice leaf disease are demonstrated in Figure 3.

Figure 3. Sample images of Rice Leaf Disease: (a) Sheath Blight, (b) Brown Spot, (c) False Smut

Comparative analysis of Different Feature Extraction Approaches

Color and texture feature extraction methods has been instrumental in the recognition and classification of rice leaf disease since they capture more crucial data for visual features of diseased plants. Better accuracy and robustness can be attained by combining texture and color features to extract structural and chromatic information from images. Table 1 shows the results of applying various texture feature extraction techniques to the entire image. From the results, we found that the LBP model that extracts features from the color channel in the image obtained better performance than other feature extraction approaches. Thus, in the subsequent tests, these techniques (as well as LBP) were applied as feature extraction techniques with an accuracy of 95.15% while other GLCM, HOG, and Color Correlogram obtained overall accuracy of 70.20%, 71.51% and 65.04%.

Table 1. Experimental Analysis of Color and Texture Features Extraction Techniques

FE method	Metric (%)	Disease Type			Overall Accuracy
		SB	BS	FS	
GLCM	Accuracy	91.12	90.45	90.31	70.202
	Precision	69.02	58.19	78	
	Recall	83.17	62.2	75.2	
	F-score	63.8	67.01	72.91	
HOG	Accuracy	83.17	67.01	72.91	71.51
	Precision	69.02	58.19	78	
	Recall	59.31	62.2	75.2	
	F-score	63.8	82.39	87.24	
Colour Correlogram	Accuracy	70.67	67.18	73.25	65.504
	Precision	50.94	49.13	69.38	
	Recall	52.2	49.6	67.2	
	F-score	52.2	49.6	67.2	
LBP	Accuracy	73.5	57.25	75.002	**95.15**
	Precision	72	61.8	74.2	
	Recall	70.67	67.18	73.25	
	F-score	85.75	82.29	86.89	

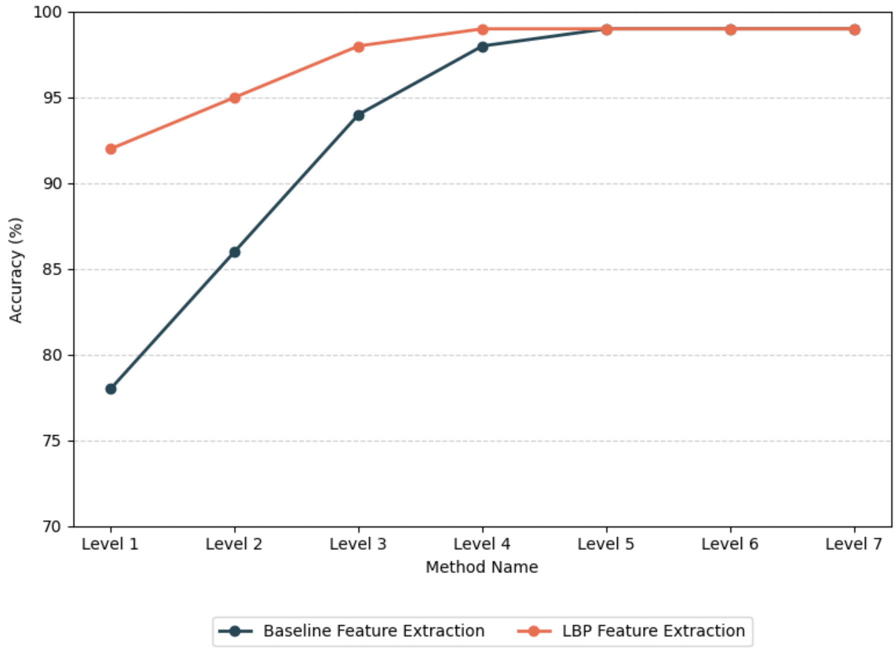

Figure 4. Analysis of the Feature Extraction Method with Other Baseline Models

The simulation analysis of the DLDICF-ADRPD approach are explored utilizing the Kaggle dataset, which contains 35126 samples with three different classes (Sheath blight, brown spot, and false smut) indicated in Table 1.

Table 2 Details on Datasets

Class	**No. of Count**
Sheath Blight	2443
Brown Spot	5292
False Smut	873
Total Count	**35126**

Figure 5 demonstrates the classification performance of the DLDICF-ADRPD approach under the test dataset. The five-fold confusion matrices provided by the DLDICF-ADRPD technique are shown in 5 different splits. The result suggested that all class labels were precisely recognized and classified by the DLDICF-ADRPD technique on the Training phase (TRPH) and Testing phase (TSPH).

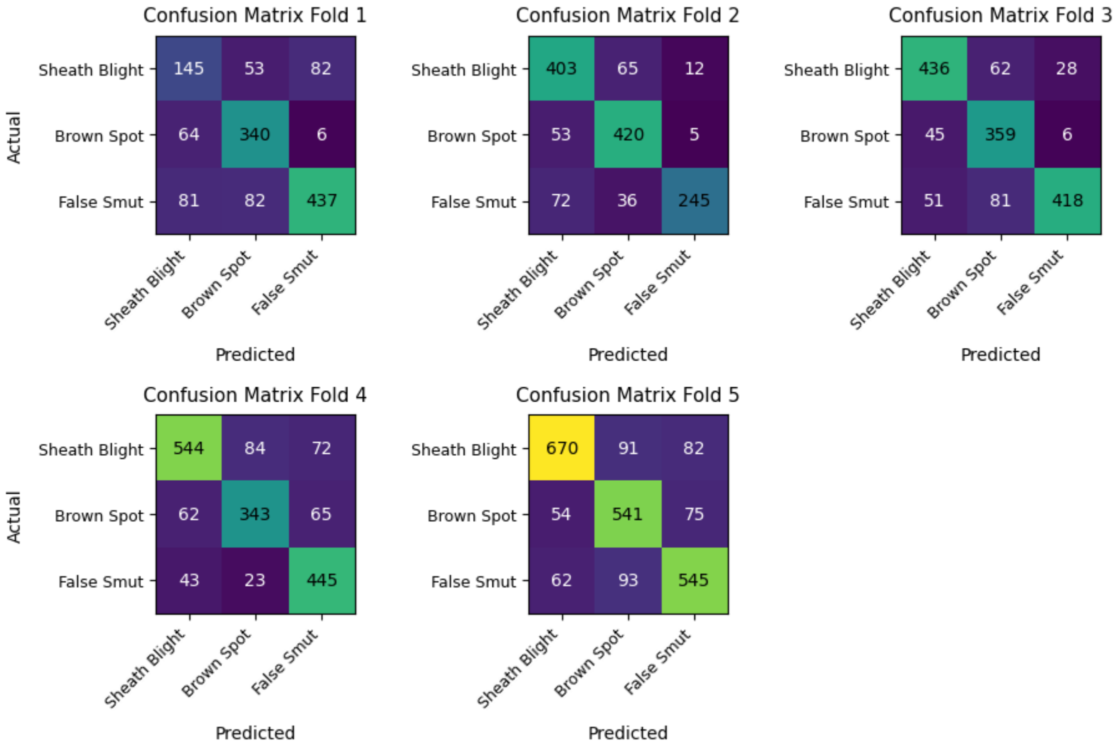

Figure 5. Confusion Matrix of DLDICF-ADRPD model

Table 3 Performance analysis of DLDICF-ADRPD method with TRPH and TSPH

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
TRPH				
Sheath Blight	96.80	86.89	85.34	85.61
Brown Spot	95.66	90.30	90.43	90.86
False Smut	94.89	92.56	83.84	94.70
Average	**96.15**	**92.11**	**89.97**	**94.53**
TSPH				
Sheath Blight	86.84	80.77	82.97	79.87
Brown Spot	80.70	79.47	79.64	69.05
False Smut	94.96	89.44	88.88	73.15
Average	**95.20**	**90.87**	**86.12**	**82.27**

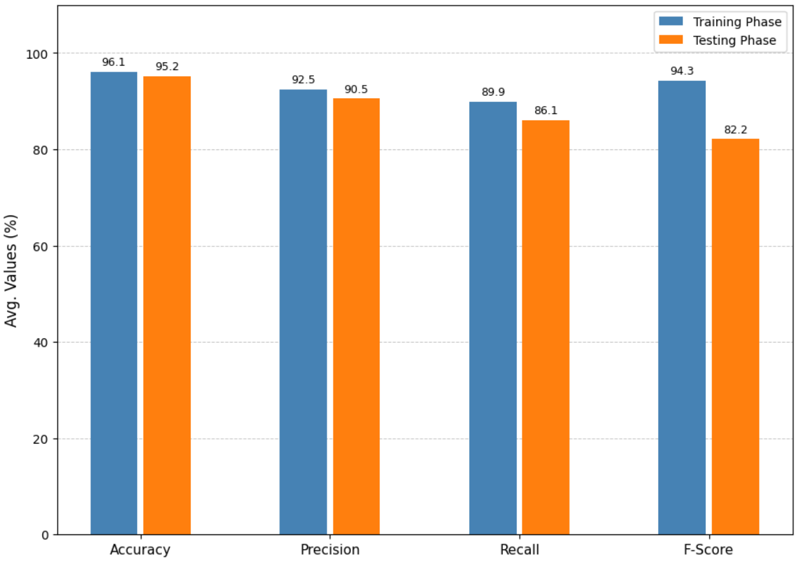

Figure 6. Average of DLDICF-ADRPD technique under TRPH and TSPH

In Figure 7, the training accuracy (TRAC) and validation accuracy (VLAC) outcomes of the DLDICF-ADRPD technique are determined under TRPH and TSPH. Over a range of 0-100 epochs, the accuracy values are calculated. The figure underlined that the TRAC and VLAC accuracy values reveal a growing tendency, which reports the potential of the DLDICF-ADRPD approach with increased outcomes across numerous iterations. Additionally, the TRAC and VLAC stay closer throughout the epochs, indicating less insignificant over-fitting and demonstrating the DLDICF-ADRPD technique's superior performance, ensuring consistent prediction on unknown samples.

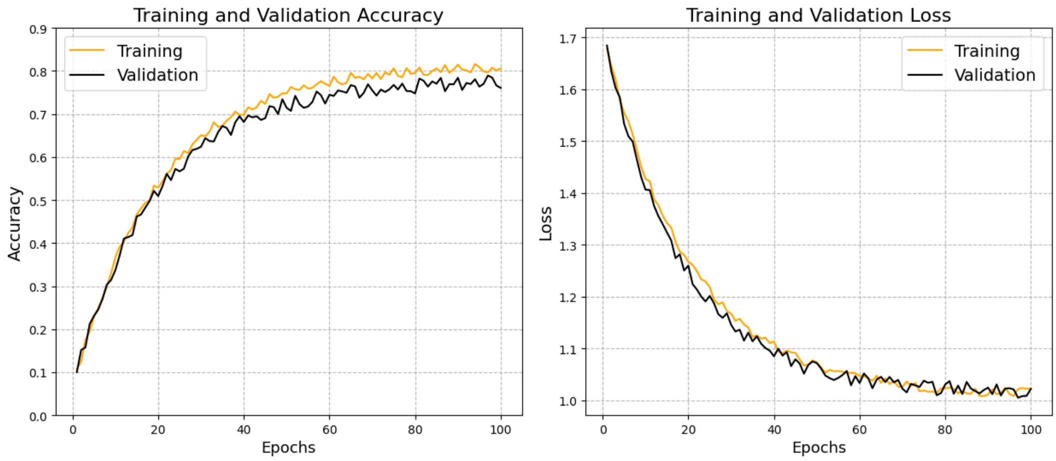

Figure 7. Accuracy and Loss curve of DLDICF-ADRPD Technique

The training loss (TLLS) and validation loss (VLLS) of the DLDICF-ADRPD approach is shown under TRPH and TSPH. Over a range of 0-100 epochs, the loss values are computed. It is shown that the TLLS and VLLS accuracy values explain a declining tendency, indicating the capability of the DLDICF-ADRPD method to balance a tradeoff between data fitting and generalization. The continual decrease in loss values also guarantees the exceptional performance of the DLDICF-ADRPD system and tunes the prediction results over time.

To establish the exceptional performance of the DLDICF-ADRPD approach, a brief comparitive analysis is made in Table 4 and Figure. 8. The outcomes demonstrated that the DenseNet, ResNet-50-SVM, AlexNet, and Inception-NB techniques have shown lesser classification results. However, the DLDICF-ADRPD technique demonstrates higher $accu_y$ of 97.82%, $prec_n$ of 95.87%, $reca_l$ of 96.27%, and F_{score} of 94.07%.

Table 4 Comparative Analysis Of DLDICF-ADRPD With Other Existing Techniques

Classifiers	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
DLDICF-ADRPD	97.82	95.87	96.27	94.07
DenseNet	96.74	96.72	93.50	95.11
ResNet-50-SVM	95.13	94.42	96.98	94.70
AlexNet	95.96	93.18	92.46	95.32
Inception-NB	93.13	90.26	88.34	87.80

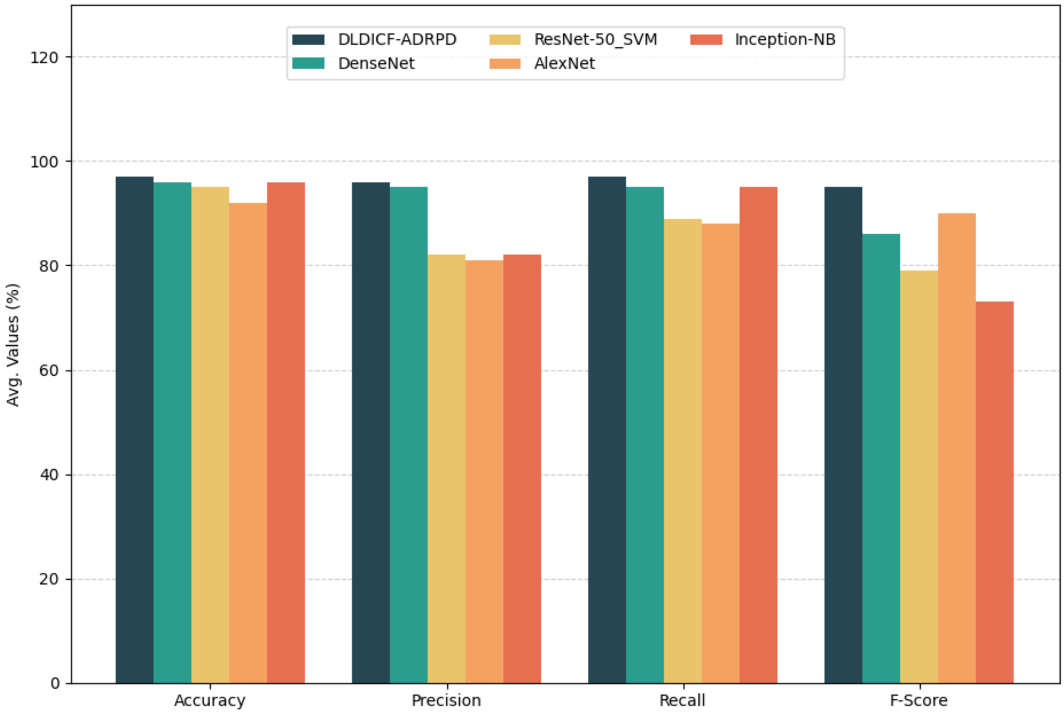

Figure 8. Comparative Outcome of DLDICF-ADRPD with other Existing Technqiues

Conclusions

In this article, we introduce a novel technique using a deep learning–driven image classification framework for accurate detection of rice plant diseases (DLDICF-ADRPD). The DLDICF-ADRPD undergoes three different stages, namely data collection, data preprocessing, feature extraction, recognition and classification of diseases. This combination leads to an efficient and robust disease classification system. The series of experiments was conducted to assess the proposed DLDICF-ADRPD performance using a large dataset of rice leaf photos from different disease types and growth phases, obtained from the publicly accessible Kaggle dataset. When compared to other existing disease prediction models, our DLDICF-ADRPD model performs better. Overall, the suggested DLDICF-ADRPD design greatly increases the reliability and accuracy of disease recognition, supporting sustainable agriculture and global food security.

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