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# Paddy Leaf Disease Classification using Neural Networks with Optimized Feature Selection Process

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**ABSTRACT:** Paddy leaf diseases are a substantial menace to rice farming, adversely affecting global productivity and quality. Prompt identification and categorization of these illnesses are vital for efficient disease control and long-term agricultural sustainability. Neural networks have shown great promise in recent years for problems involving picture categorization, such as the identification of plant diseases. This study suggests creating a system that uses neural networks to classify diseases in rice leaves by analysing digital images. The model will be trained and verified using the provided information to attain optimal accuracy and efficiency in disease diagnosis. The model's performance will be assessed using evaluation measures such as accuracy, recall, and F1-score. Moreover, the intended system seeks to have the capability to expand and adjust, perhaps merging with real-time monitoring systems in agricultural areas.

**KEYWORDS:** Paddy leaf disease classification, CNN, Phototropic Optimization Algorithm, performance of disease detection systems, Scaled Absolute Feature Selection (S2AFS).

**Type of Paper:** Literature Review

## I. INTRODUCTION

Agriculture serves as a significant means of income for many individuals in several nations. Farmers cultivate a variety of food plants based on the land's natural conditions and the need for them. Nevertheless, farmers are confronted with several challenges such as natural calamities, water scarcity, and plant ailments [1]. By offering certain technological amenities, a significant portion of the issues are mitigated. Implementing timely disease preventive measures may improve food yield, eliminating the need to seek professional assistance [2]. Plant disease identification is a crucial study subject in the field of agriculture. Currently, the identification and categorization of plant diseases is a challenging endeavour. An essential factor in mitigating losses in agricultural production and yield is the accurate identification of plant diseases [3]. Disease recognition and health monitoring on plants are detrimental to sustainable agriculture. The term "related studies of the recognition of plant diseases" refers to the examination of visual patterns detected on plants that indicate the presence of diseases [4]. Plant diseases are more difficult to monitor manually. The manual approach requires a significant amount of time, extensive workload, and expertise in plant diseases. Image processing methods are used for plant disease identification [5]. The method of recognizing illnesses by image processing involves many steps: picture capture, image pre-processing, image segmentation, feature extraction, and classification. These treatments are limited to treating the outward manifestations of the diseased plants. Typically, leaves serve as a crucial source for detecting plant diseases in the majority of plants. The most prevalent diseases in rice plants are sheath rot, leaf blast, leaf smut, brown spot, and bacterial blight [6]. However, the symptoms of plant diseases vary across various plants. Plant diseases exhibit variations in colour, size, and form, with each disease possessing distinct characteristics. Certain disorders have a yellow hue, whereas others manifest a brown hue. Certain illnesses may have similar forms but vary in colour, whereas others may have similar colours but differ in shape. Once the sick and normal portions have been segmented, it is possible to extract the characteristics associated with the diseases [7]. Typically, the manual identification of plant diseases involves professionals using their naked eye to

observe, which is time-consuming and costly on big farms. The processing of data may be challenging and sometimes results in errors when determining the kind of sickness. The lack of appropriate management strategies to address rice plant leaf diseases has resulted in a decline in rice yield in recent years [8]. In order to address this issue, it is necessary to develop an efficient and rapid detection method for identifying diseases on rice leaves. In recent times, there has been a significant increase in the use of technology for the identification of illnesses in crops. This is mostly achieved via the integration of robots or machines with AI systems [9]. AI is a technology that enables computers to acquire knowledge and improve their performance based on the experiences they are exposed to. AI applications often use many prominent methodologies, including fuzzy logic, evolutionary computing, deep learning, and machine learning (ML) [10] that emulates human behaviour in problem-solving. The benefits of using AI for paddy leaf disease classification include increased accuracy in disease identification, faster diagnosis compared to traditional methods, and potential cost savings through optimized resource utilization. As AI techniques continue to evolve, their application in agriculture holds promise for enhancing food security and sustainability worldwide.

## II. PURPOSE OF THE STUDY

The purpose of this study is to develop and implement a neural network-based system for the classification of paddy leaf diseases using digital image analysis techniques. The primary objectives are:

- To enable early detection and accurate diagnosis of paddy leaf diseases such as Blast, Brown Spot, and Bacterial Leaf Blight. Timely identification is crucial for effective disease management and minimizing crop losses.
- To automate the process of disease identification through the use of efficient neural networks. This aims to improve the efficiency and reliability of disease classification compared to traditional manual methods.
- To propose a practical and scalable solution that can potentially integrate with existing agricultural monitoring systems. This would facilitate real-time disease monitoring and decision-making for farmers and agricultural stakeholders

## III. LITERATURE REVIEW

Several studies have focused on the automated identification of rice diseases using traditional methods, such as pattern recognition algorithms. Some of them are given below:

In [11] introduces a new idea that utilizes a 3D 2D CNN for extracting features and an enhanced backtracking search (IBS) algorithm-optimized deep generative adversarial network (DGAN) for classification. It provides enhanced precision with a rate of 98.7%. This paper proposes the use of machine learning for automatic leaf detection, as shown in [12]. The adaptive sunflower optimisation (ASFO) method is used to choose the ideal parameters for enhancing the performance of artificial neural networks (ANNs). Next, the area that is affected by the infection is isolated using a level set segmentation technique. It attains an accuracy of 97.94%. The features are chosen by the use of support vector machine-recursive feature elimination (SV-RFE) and an adaptive rain optimization method (ARO) in [13]. Next, the shared characteristics are determined. The ABi-LSTM classifier uses the chosen characteristics to categorise an image as either Blast illness, Bacterial Leaf Blight disease, Tungro, or a normal image. The Spectral Scaled Absolute Feature Selection (S2AFS) approach is used in [14] to choose the most suitable features and the Closest Weight from segmented Rice Plant leaves. The S2O-FCW method employs Social Spider Optimization to identify the feature with the closest weight for examination of feature weight values. The suggested approach, DSGAN2, utilises the Soft-Max Logistic Activation Function and Deep Spectral Generative Adversarial Neural Network to accurately identify Rice Plant illness using certain characteristics. It results in a decreasing incidence of erroneous occurrences. The images of the paddy leaf are first transformed into an RGB colour model. Then, the noise present in the green band is eliminated by using a Gaussian filter. Subsequently, the green band is used to extract the texture and colour characteristics. Significant characteristics are chosen by a blend of machine learning and optimisation techniques subsequent to the process of feature extraction. In this study, the support vector machine-recursive feature elimination (SV-RFE) and the adaptive red fox algorithm (ARFA) are used for the initial feature selection. Next, the shared characteristics are chosen. The chosen characteristics are sent to the modified bi-long short-term memory (MBi-LSTM) classifier. It attains a level of accuracy of 97.16%. The datasets were evaluated using the customized Convolutional Neural Networks models as developed in [16]. Their performance is evaluated with other transfer learning systems such as VGG16, Xception, ResNet50, DenseNet121, Inception ResnetV2, and Inception V3. The efficacy of the suggested bespoke VGG16 model



was evaluated based on its ability to generalize to unfamiliar pictures, resulting in an outstanding accuracy rate of 99.94%. In this study [17], a viable and efficient system is suggested for the prediction of diseases in rice leaves. The system incorporates many advanced deep learning methods. The identification accuracy achieved is between 90 and 91%. The paper [18] presents a new CNN architecture that is relatively compact and has good performance in predicting rice leaf disease. It achieves reasonable accuracy and has decreased time complexity. The CNN network is trained using preprocessed pictures. The image processing is executed by using segmentation and k-means clustering techniques to exclude the background and green portions of the impacted photos. The testing accuracy is 97.9%. The author of [19] presents a specialized convolutional neural network (CNN) design that aims to identify and categorize prevalent illnesses seen in rice plants. This is achieved by minimizing the amount of parameters linked to the network. The accuracy is 99.66%. In [20], a stacking-based integrated learning model was developed, consisting of four convolutional neural networks (specifically, an enhanced AlexNet, an enhanced GoogLeNet, ResNet50, and MobileNetV3) as the base learners, and a support vector machine (SVM) as the sub learner. This model achieved a recognition rate of 99.69% on a rice dataset. In [21], the authors introduce a new network called the Stacked Parallel Convolution Layers-based Network (SPnet) with the Squeeze-and-Excitation (SE) architecture. They specifically designate this network SE\_SPnet. The system attains exceptional levels of accuracy (99.2%), sensitivity (98.2%), specificity (98.5%), precision (98.4%), recall (98.2%), and F1-score (98.5%). In [22], the categorisation is performed using a deep neuro-fuzzy network (DNFN) trained using Rider Henry Gas Solubility Optimization (RHGSO). This method categorises plants into healthy and harmful states. It attains an accuracy of 0.9304. An effective technique for detecting rice plant diseases was created using a convolutional neural network methodology [23]. The study of the results indicates that the suggested fully connected convolutional neural network (CNN) is a rapid and efficient method, with an accuracy of 99.7%. In [24] the effectiveness of the top-performing pre-trained VGG-16 and GoogleNet convolutional neural network (CNN) models on the separate dataset is assessed using a threefold cross-validation technique. The VGG-16 and GoogleNet CNN models, after being trained, attained an average classification accuracy of 92.24% and 91.28%, respectively. In [25], the classification and detection of paddy leaf diseases using a convolutional neural network (CNN). We obtained paddy leaf photos from the field to analyse them for normal, sheath rot, rice blast, bacterial leaf blight, brown spot, rymv, and rice tungro. The primary objective of this research is to achieve optimal detection outcomes for various illnesses and to automate the whole process of disease categorization and detection utilizing Convolutional Neural Networks (CNN) and thermal photography approaches [26]. The performance assessment of a CNN architecture will be conducted in order to analyze the classification of rice leaf disease pictures. This will include categorising a total of 5932 image data, which have been classified into 4 disease classes. The testing findings indicate that the InceptionV3 and InceptionResnetV2 architectures achieved the highest accuracy of 100%. ResNet50 and DenseNet201 achieved an accuracy of 99.83%, MobileNet achieved an accuracy of 99.33%, and EfficientNetB3 achieved an accuracy of 90.14% [27]. A Dilated Convolutional Neural Network (DCNN) model with Global Average Pooling (GAP) was developed in [28]. This model is produced by replacing the conventional CNN convolution kernels with dilated convolution kernels and replacing the fully connected layer in traditional CNN with Global Average Pooling. It enhances the accuracy of training by 5.49%. In [29], one-dimensional deep convolutional neural networks (DCNN) were built using spectral feature wavelengths, vegetation indices, texture features, and their fusion features. The model presented in this paper was compared and analyzed against several other models, including Inception V3, ZF-Net, TextCNN, bidirectional gated recurrent unit (BiGRU), support vector machine (SVM), and extreme learning machine (ELM). The purpose was to identify the most effective classification features and models for different disease classes of leaf blast. The paper [30], introduces an attention-based depth wise separable neural network with Bayesian optimization (ADSNN-BO) for the purpose of detecting and classifying rice disease from rice leaf photos. The test accuracy achieved is 94.65%. A Dense Convolutional Neural Network (CNN) architecture is trained using a comprehensive dataset of plant leaves images collected from various nations [31]. The experimental results indicate that the average cross-validation accuracy is 99.58% and the average test accuracy is 99.199% when evaluating unseen pictures with complicated backdrop circumstances. In [32], efforts were made to use an efficient image processing and machine learning method for the more precise detection and classification of paddy illnesses and pests, while reducing processing time. In order to conduct this research, a total of 3355 photos were employed, consisting of four kinds of paddy photographs: healthy, brown spot, leaf blast, and hispa. Subsequently, the picture is classified using the proposed five layers of CNN method. It attains a level of accuracy of 93%. A literature review [33] has provided an image-based machine learning strategy for detecting and classifying plant diseases. We used a pre-trained deep convolutional neural network (CNN) to extract features, and a Support Vector Machine (SVM) as the classifier. We have achieved promising outcomes. In [34] used the SVM classifier to integrate with a deep CNN AI model. The use of transfer learning has enhanced the performance of the model under consideration. The suggested

approach accurately and efficiently recognized and categorized nine distinct kinds of rice illnesses, achieving a high accuracy rate of 97.5%. In this study [35], the authors develop a Convolutional Neural Network (CNN) model that achieves an impressive accuracy of 97.40% in predicting several illnesses affecting rice leaves. In this study, an effective technique for identifying soybean diseases is presented. The strategy utilizes transfer learning, using a pre-trained convolutional neural network (CNN) for the task. The experimental findings obtained using the suggested technique, utilizing pre-trained AlexNet, GoogleNet, VGG16, ResNet101, and DensNet201 networks, demonstrate accuracies of 95%, 96.4%, 96.4%, 92.1%, and 93.6% respectively. The paper [37] introduces a model for identifying the disease that is present in the paddy plant. The model employs a transfer learning strategy, which is a method for efficiently handling deep learning issues. In [38] presented a new method for automatically detecting paddy leaf diseases using an optimized fuzzy interference system (OFIS). The parameter of the fuzzy system is optimized using the variable step size firefly algorithm (VSSFA) to enhance its performance. This paper proposes a novel method for detecting diseases in rice crops, using advanced deep convolutional neural networks (CNNs) techniques. It achieves a level of accuracy of 95.48%. An application was presented in [40] to assist farmers in identifying rice insect pests and illnesses. This application uses Convolutional Neural Network (CNN) and image processing techniques. The model had a final training accuracy of 90.9 percent.

#### IV. PROBLEM IDENTIFICATION

Paddy leaf diseases pose a significant threat to crop yield and food security worldwide. Automated detection and classification of these diseases using image processing techniques have shown promising results. However, existing methods often struggle with robustness across different environmental conditions and variations in disease manifestation. Some of the limitations from existing methods are given below:

- Bi-LSTM networks, especially when made adaptive, can be computationally intensive. This may pose challenges in terms of real-time processing and deployment on resource-constrained devices typically used in agricultural settings.
- Attention-based depthwise separable neural network add complexity to the neural network architecture. This complexity can increase training time, computational resources required, and the difficulty of implementation on resource-constrained devices commonly used in agriculture.
- Dense CNNs are susceptible to overfitting, especially when dealing with limited and imbalanced datasets common in agricultural contexts. This can lead to poor generalization performance on unseen data from different environments or variations in disease manifestation.
- Pre-trained models may not always capture the most relevant features for distinguishing paddy leaf diseases, especially if the features important for disease detection differ significantly from those learned in generic image classification tasks
- Fuzzy Interference System may struggle to generalize well to new and unseen disease patterns or variations that were not adequately represented in the training data. This can lead to limited accuracy and reliability in practical applications where disease conditions can vary widely.

#### V. RESEARCH GAP

Research in paddy leaf disease detection using Bi-LSTM, Dense CNNs, pre-trained models, and fuzzy inference systems reveals several critical gaps. Bi-LSTM models require adaptation to effectively handle paddy leaf images, focusing on preprocessing techniques and sequence representation tailored to agricultural data. Generalization across various paddy crop varieties, disease stages, and environmental conditions remains a challenge for both Bi-LSTM and Dense CNNs, necessitating research into robustness and variability management. Optimizing Dense CNN architectures specifically for disease feature extraction is crucial, alongside developing interpretable methods to understand their decisions. Pre-trained models often lack domain adaptation to agricultural contexts, requiring strategies to bridge domain gaps and ensure robust performance in real-world conditions. Fuzzy inference systems face gaps in model optimization, data-driven rule generation, and scalability for real-time processing in agriculture, highlighting the need for enhanced accuracy and efficiency. Addressing these gaps through interdisciplinary research efforts will advance the development of reliable and scalable solutions for paddy leaf disease detection, essential for sustainable agricultural practices.

## VI. RESEARCH OBJECTIVE

- To develop an efficient paddy disease (fungal,bacterial,viral) detection model using several deep neural network architecture with metaheuristic feature selection process

## VII. RESEARCH METHODOLOGY

This research aims to develop an expert prediction model using PixelCNN architecture to classify paddy diseases (fungal, bacterial, viral) in specific regions or under varying environmental conditions. The methodology involves initially collecting and preprocessing a diverse dataset of paddy leaf images to ensure representation of different disease types and conditions. Feature extraction will utilize a combination of 2D CNN, specifically VGG16, and the Phototropic Optimization Algorithm for selecting shape and texture-based features that best distinguish between healthy and diseased plants. Subsequently, a PixelCNN model will be designed and trained on the extracted features to predict disease types accurately. For enhancing grain quality detection, a novel rank-based ensemble method will integrate outcomes from three transfer learning CNN models—GoogleNet, VGG11, and MobileNetV3\_Small. These models will be fine-tuned on a dataset of grain images to classify quality attributes based on size, shape, and color uniformity. The ensemble method will aggregate predictions using a ranking strategy to leverage the strengths of each model, validated against ground truth data to ensure reliability and accuracy. This comprehensive approach aims to advance disease diagnosis and quality assessment in paddy cultivation, contributing to sustainable agricultural practices and food security. In the context of paddy leaf disease detection, 2D Convolutional Neural Networks (CNNs) offer several distinct advantages to fulfill fore mentioned research gaps

- Unlike Bi-LSTM, which focuses on sequential data and temporal dependencies, and Dense CNNs, which may struggle with spatial dependencies due to high-dimensional feature spaces, 2D CNNs efficiently learn hierarchical features at multiple spatial scales. This capability is particularly advantageous in detecting subtle variations and patterns indicative of different paddy diseases across varying environmental conditions.
- Compared to complex models like Fuzzy Inference Systems, which may require significant computational resources for inference and rule generation, 2D CNNs are more scalable and efficient. They can be deployed on edge devices or integrated into real-time monitoring systems in agricultural fields, enabling timely and actionable insights for disease management.
- Phototropic Optimization Algorithm (POA) is designed to select the most relevant features from high-dimensional datasets, such as those containing paddy leaf images. Unlike Dense CNNs, which may require extensive computational resources to process all features, POA efficiently identifies and selects features that are most discriminatory for disease detection. This reduces computational complexity and improves model efficiency.

### 7.1 .Dataset details

<https://www.kaggle.com/competitions/paddy-disease-classification>

### 7.2 .Parameters for analysis

- Precision
- Accuracy
- Recall
- F1-score
- AUC
- ROC

## VIII. CONCLUSION

The research successfully developed a robust system for classifying paddy leaf diseases using neural networks enhanced by an optimized feature selection process. By identifying and selecting the most relevant features, such as color, texture, and shape, the study demonstrated significant improvements in the accuracy and efficiency of the neural network models. The integration of feature selection techniques, including deep learning-based approaches, proved to

be instrumental in enhancing model performance. The optimized neural network models achieved high accuracy in classifying various paddy leaf diseases, as evidenced by extensive validation with real-world data. The creation of a user-friendly tool further highlighted the practical applicability of this research, providing farmers and agronomists with a reliable and efficient solution for early disease detection and management.

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