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Research Article

Deep Convolutional Neural Network (DEEP-CNN) for Multi-Class Classification of Biotic Stress in Paddy Crop

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Abstract: Rice, as a staple food for billions, faces severe yield threats from biotic stress factors such as pathogens, pests, and weeds. Traditional methods for stress identification are labor-intensive and prone to inaccuracies. This paper presents a DEEP-CNN model designed for the multi-class classification of biotic stress in paddy crops. The proposed model utilizes preprocessing techniques and hyperparameter tuning to achieve optimal performance. Evaluations on the Paddy Doctor Dataset demonstrate the model's superior accuracy of 94.4%, outperforming existing state-of-the-art approaches. This research highlights the potential of deep learning for precision agriculture, providing an efficient solution for the timely detection and management of crop stressors.

Keywords: Biotic stress, Multi-Class Classification, Deep-CNN, Hyper Parameter, Paddy Doctor

1.Introduction

The high demand for rice production directly impacts its importance in agriculture. In a world where sustainable agriculture is increasingly necessary, especially in urbanized areas with growing populations, the demand for rice production has doubled. This situation requires the incorporation of technological advancements to meet the increasing demand. Farmers face significant challenges during both pre-harvest and post-harvest periods, particularly in protecting crops from insects, pests, and droughts, which can cause substantial damage if not properly managed. These challenges can lead to significant losses in paddy yield. Crops generally undergo various stresses during their growth, including abiotic stress, caused by environmental factors, and biotic stress which is caused by living organisms such as pests and pathogens. While abiotic stresses are often beyond human control and heavily dependent on seasonal weather conditions, biotic stresses can cause significant damage if not addressed promptly. Paddy farming is susceptible to biotic stress, which can lead to reduced crop yields. Studying plant diseases is essential to understanding the causes of biotic stress and identifying them to minimize their effects. Machine learning, an emerging technology in data science, offers valuable tools for analyzing data and making informed decisions. Deep learning, specifically through convolutional neural networks, is widely used for image and video processing, enabling the classification and detection of objects with high precision and accuracy. The combination of machine learning techniques and CNNs provides effective methods for dealing with data structures and deriving accurate solutions. Understanding these factors and their impact on crop production is essential for mitigating risks and preventing significant losses.

Factors Influencing Crop Production in Paddy Cultivation:

Climate Factors: Temperature, rainfall, humidity, and sunlight are key to the growth of paddy crops. Extreme conditions, such as droughts or floods, can significantly hinder crop development.

Soil Quality: The fertility, pH level, and moisture content of the soil play a vital role in paddy cultivation. Poor soil quality can lead to suboptimal crop growth.

Water Management: Paddy crops require a substantial amount of water, making effective water management critical. Both water shortages and excess water can negatively impact crops.

Pests and Diseases: Biotic stress from pests, diseases, and weeds poses a significant threat to paddy crops. If left unchecked, these issues can cause considerable yield losses.

Nutrient Supply: Adequate nutrients, including nitrogen, phosphorus, and potassium, are necessary for healthy crop growth. Nutrient deficiencies or imbalances can reduce yields.

Farming Practices: The methods used for planting, weeding, and harvesting also affect crop production. Practices such as crop rotation, timely planting, and proper spacing can boost productivity.

Importance of Monitoring: Monitoring these factors consistently is essential for successful paddy crop production. It allows for early detection of potential problems, enabling prompt action to prevent losses. Advances in technology, such as remote sensing, IoT sensors, and data analytics, have made real-time monitoring more accessible.

Biotic Stress:

This stress is caused by different living organisms such as bacteria, fungi, viruses, and insects, and significantly threatens agricultural productivity and crop yield. Early and precise identification of these stresses, with accurate severity assessment, which is for timely intervention and effective management strategies [1]. The types of stress that can affect paddy crops are categorized into Biotic and Abiotic Stress. These diseases can significantly reduce crop yield if not managed properly. Abiotic Stress is caused by non-living factors, including Water Stress (e.g., drought, submergence), Nutrient Deficiency (both macro and micro), and Chemical/Herbicide Injury. These factors impact the overall health and productivity of the crop. Deep learning, a subset of artificial intelligence (AI), has shown immense potential in the accurate identification and classification of biotic stress factors in paddy crops. Traditional methods of stress detection in crops often rely on manual observations, which are not only prone to error and subjectivity, but also time consuming. In contrast, deep learning models can process vast amounts of data, learning from subtle patterns that might be imperceptible to the human eye. This ability is particularly crucial when monitoring biotic stress, as the early and accurate identification of stressors like pathogens and pests can significantly impact crop management and yield outcomes [2].

Multi-class classification in deep learning refers to the model's ability to categorize input data into one of several predefined classes. In the context of paddy stress monitoring, this involves training models to distinguish between various types of biotic stressors, such as different diseases or pest infestations. For instance, a deep learning model might be trained on a dataset of images showing paddy leaves affected by different diseases like blast, bacterial blight, or sheath blight. Once trained, the model can classify new images into one of these categories, enabling farmers and agronomists to identify the specific type of stress affecting the crop [3].

The integration of deep learning for multi-class in paddy crops is still an evolving field. Current research is focusing on improving the accuracy and robustness of these models, particularly under varying environmental conditions and across different paddy varieties [4]. Additionally, there is a growing interest in developing models that can be deployed on edge devices like drones or smartphones, enabling real-time monitoring and decision-making in the field.

Types of Biotic Stress:

Biotic Stress affects the physical growth of the plant if not addressed timely which in turn subsides the yield of the crop. These living organisms can include:
Pathogens: Bacteria, fungi, and viruses that cause diseases [5].
Pests: Insects, mites, and nematodes that feed on the plant [6].
Weeds: Plants that compete with rice for resources like water, sunlight, and nutrients [7].

These biotic stressors can lead to reduced crop yield, lower grain quality, and even complete crop failure. Examples of biotic stress in paddy include diseases like blast, bacterial leaf blight, and sheath blight, as well as pests like brown plant hopper and stem borer. Essentially, any negative influence on a rice plant caused by another living organism constitutes biotic stress.

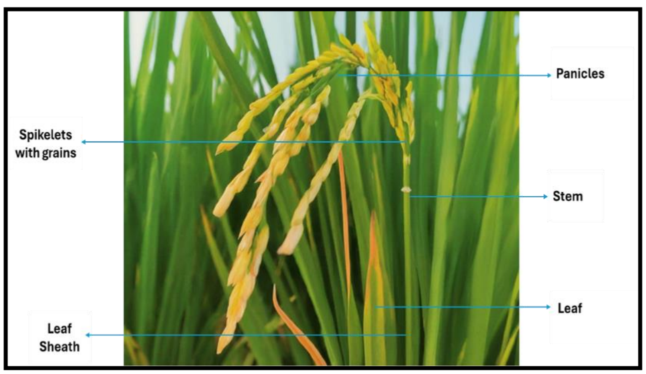

Figure 1: Rice Plant Structure

Figure 1 depicts the structure of a rice plant, highlighting its key components. The panicle in the rice plant is the main cluster of grains, spikelet's are the individual units within the panicle containing the grains. The leaf is the flat green part that is responsible for photosynthesis, The Leaf Sheath is the part of the leaf wrapping around the stem where the stem is the main supporting structure.

Research Challenges in Biotic Stress Classification:

Biotic stress exists on almost every paddy crop and has gained enormous attention from researchers to address the farming community to the trade-off of precision agriculture practices. Although several studies have come up with novel solutions to automatically detect these stressors using deep learning, machine learning, and image processing techniques, the problem is still challenging and miles off from being completely solved. We identified some of the most important challenges that are responsible for ampere the research biotic stress classification and prediction of the given domain.

Unavailability of Data in The Public Repositories:

The lack of availability of huge data in public repositories is one of the major bottlenecks for biotic stress classification. A critical challenge in advancing research on biotic stress classification in paddy crops is the scarcity of accessible, high-quality public datasets. This limitation could affect the research in terms of several challenges like data collection, data sharing, data format, and standardization issues.

Unavailability of Ground-Truth Data:

The lack of ground-truth datasets for model training is one of the main obstacles to the classification and prediction of biotic stress. There are a few well-known and publicly available benchmark datasets like UCI [8], IEEE Data Port [9], Mendeley [10], and Kaggle which have been widely used in the existing literature. However, the UCI ML dataset has a small number of labeled instances, while Kaggle and Mendeley also have a high imbalance class distribution (most labeled instances are truthful, only a small number of biotic stresses), so proper care needs to be taken when using these datasets. Data collection difficulties would be accurate labeling of biotic stress types often demands specialized knowledge in plant pathology. Manual annotations of datasets are a quite time-consuming process [11-13]. The labeling of accurate stress interpretations may vary from expert to leading to inconsistencies in labeling. Acquiring the images with different lighting conditions at different plant growth stages impacts the accurate labeling of the stress. Datasets contain an unequal distribution of different stress types which has imbalanced the class distribution of the data and affects model training.

Feature Importance in Biotic Stress Classification:

It refers to the significance of individual input variables in predicting the target variable (biotic stress type) in a classification model. In the context of biotic stress classification in paddy crops, understanding which image features contribute most to accurate predictions is crucial for several reasons. Firstly, model interpretability which constitutes identifying key features, we can gain insights into the model's decision-making process i.e., for better classification and prediction. Secondly, focusing on the most important features can reduce computational costs and improve model efficiency. Extraction of the relevant collection of features that can differentiate diseased or non-diseased from the given image is one of the key prerequisites for the classification of biotic stress. As features are the key ingredients for any detection system to work well, analyzing the effectiveness of different features is an important aspect of biotic stress detection. Various studies have used other types of features to train their models; however, finding the best set of features is an open challenge. Some studies have focused on color, texture, and morphological features extracted using image processing techniques. Traditional machine learning algorithms like Support Vector Machines (SVM), Random Forest, and Naive Bayes can be used for classification based on extracted features. Convolutional Neural Networks are widely used for image-based classification tasks. CNNs automatically learn discriminative features from raw image data without explicit feature engineering. Transfer learning can be leveraged to fine-tune pre-trained models on smaller datasets. Multi-class classification using CNN is one of the practices incorporating the identification, classification, quantification, and prediction of biotic stress with the respective disease classes. Stress prediction has become one of the research types that greatly influences modern cultivation practices. If the disease is not recognized at early stages, the usage of countermeasures like pests, usage of herbicides, and fungicides becomes larger which makes the production of crops less nutrient.

CNNs have become highly effective tools for the analysis of images and classification tasks, utilizing their capacity to learn and extract features from complex image data, DEEP-CNN can be utilized to develop models capable of identifying and classifying various types of biotic stress in crops. By training these models on large datasets of labeled images, it is possible to achieve high accuracy in detecting specific diseases and stress conditions. This technological advancement holds great promise for revolutionizing crop management practices, enabling more efficient and effective responses to biotic stress challenges. Deep learning-based multi-class classification for real-time applications still presents numerous areas for advancement. Significant research is required to address the existing challenges and limitations. A critical issue is the necessity for large, annotated datasets, which are time-intensive to collect and process. Another prominent challenge lies in the selection and fine-tuning of model hyperparameters to achieve the best performance from the proposed model. These factors currently limit the practical application of such models in real-world decision-making scenarios. To mitigate these issues, this study introduces a novel framework, termed Deep-Convolutional Neural Network (DEEP-CNN). The proposed model employs a straightforward CNN architecture optimized with a specific set of parameters. Experimental results indicate that the DEEP-CNN model surpasses the performance of existing state-of-the-art models.

2.Proposed Deep CNN Model

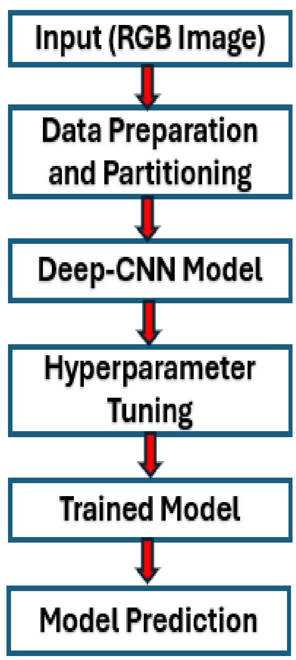

Figure 2: DEEP-CNN Model Training and Prediction with Hyperparameter Tuning.

Figure 2 illustrates the DEEP-CNN model for multi-class classification of biotic stress for paddy. The pipeline comprises three primary stages:

- Data Preprocessing: Images are prepared through resizing, and normalization to create a suitable input format. The dataset is then divided into training, validation, and testing sets.
- Model Training: The DEEP-CNN architecture, consisting of a brief description of the architecture, is trained on the prepared dataset. Hyperparameter tuning is employed to optimize model performance using the validation set.
- Classification and Prediction: The DEEP-CNN trained model is assessed on the test data by applying the following metrics precision, recall, F1-Score, and accuracy. Subsequently, it is used to predict biotic stress class labels by loading the saved model, on new, unseen paddy images.

Data Preprocessing

Data preprocessing typically involves several key steps to ensure that the images are ready for training a deep learning model. The data preprocessing steps that are applied to the data are listed below:

- Resize all images to a uniform size suitable for the DEEP-CNN model input, typically 224x224 pixels which decreases the computational resources and memory usage.
- Normalize pixel values to the range [0, 1] by dividing by 255.
- Divide the dataset into training, and testing, 20% of training data will be used for validation.

Hyper Parameter Tuning

For optimizing the hyper-parameters that control the learning process experimentation was carried out with different values to learn insights into how the model behaves and how it interacts with the paddy data. Optimized hyperparameters can lead to quicker training times and faster convergence of the model. Table 1 describes the type of hyperparameters used for DEEP-CNN implementation.

Table 1: Selection of Hyperparameters.

Hyperparameters	Typical Values / Range		Optimized
Number of Layers	12, 13,15, 21		21
Number of Filters	16, 32, 64, 128,256,512		32,64,128,256,512
Filter Size	3x3, 5x5		3x3
Stride	1,2,3		1
Padding	"same" or "valid"		same
Activation Function	ReLU, tanh, SoftMax		ReLU, SoftMax
Pooling Type	Max Pooling, Average Pooling		Average Pooling
Pooling Size	2x2		2x2
Batch Size	32,64		32
Number of Epochs	10, 20, 50, 100		50,100
Learning Rate	0.0001, 0.001, lr decay=0.9		0.0001, lr decay=0.95
Optimizer	Adam, RMSprop		Adam
Regularization	Dropout rate: 0.25	Dropout rate: 0.5	Dropout rate: 0.25,0.5

	L2 weight decay: 0.001	L2 weight decay: 0.0001	L2 weight decay: 0.001

The hyperparameters for the DEEP-CNN model were carefully selected and optimized to achieve optimal performance. The architecture was configured with 21 layers, which provided the best balance between computational efficiency and feature extraction. Filters with sizes of 3x3 were used across layers, starting with 32 and progressively increasing to 512 to capture both low-level and high-level features. A stride of 1 was chosen to preserve spatial resolution, while "same" padding ensured the input dimensions were retained. For activation functions, ReLU was employed in hidden layers to prevent vanishing gradients, and SoftMax was applied to the output layer for multi-class classification. Average pooling with a size of 2x2 was utilized for smoother feature extraction and better generalization. The batch size was set to 32 to balance training stability and computational resource usage. Training was conducted over 50 to 100 epochs, which allowed sufficient iterations for convergence without overfitting. The learning rate was optimized at 0.0001 with a decay of 0.95 to ensure smooth and gradual convergence. Adam optimizer was chosen for its adaptability and efficient gradient handling. Regularization techniques, including a dropout rate of 0.25 and 0.5 along with L2 weight decay of 0.001, were implemented to prevent overfitting and enhance model stability. These optimized hyperparameters collectively contributed to the superior performance of the DEEP-CNN model in multi-class classification tasks.

Deep-CNN Model Training

The proposed model DEEP-CNN is being executed in the verified environment with all dependencies and pre-installed packages on Google ColabPro with GPU Memory and disk Space utilization. The model is trained using with chosen dataset for multi-class classification. The model's performance is compared with state of art models. Feature maps are essentially the output of feature extraction performed by convolutional layers in a convolutional neural network (CNN). They are matrices of activations that represent extracted features from the input data at a specific layer. Feature maps are the specific implementation of feature extraction in CNNs. Convolutional layers create feature maps by applying filters to the input data.

Figures 3 to 5 give the feature maps generated at the initial layer of convolution, deeper layer, and final layers of convolution layers.

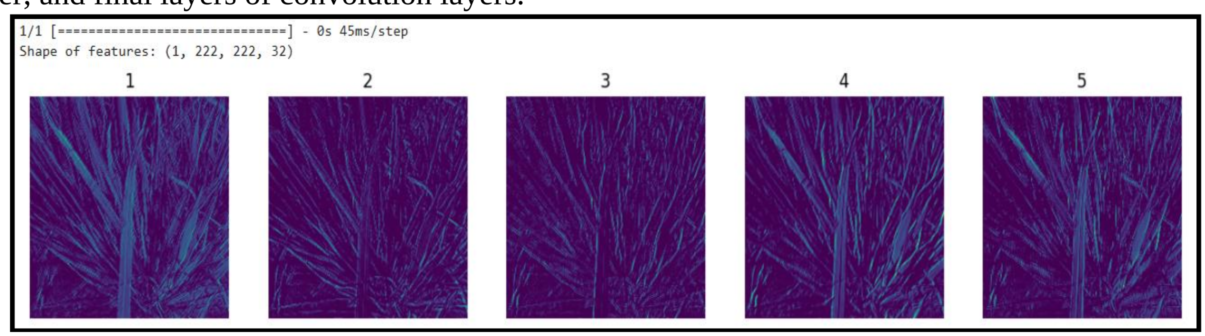

Figure 3: Feature maps are generated at the first Conv2d layer.

In Figure 3 the first Conv2D layer extracts low-level features like edges, corners, and textures from the input image. The second Conv2D layer builds upon the previous features, extracting more complex patterns. The figure contains the display of the first five feature maps generated out of 32 feature maps at this layer.

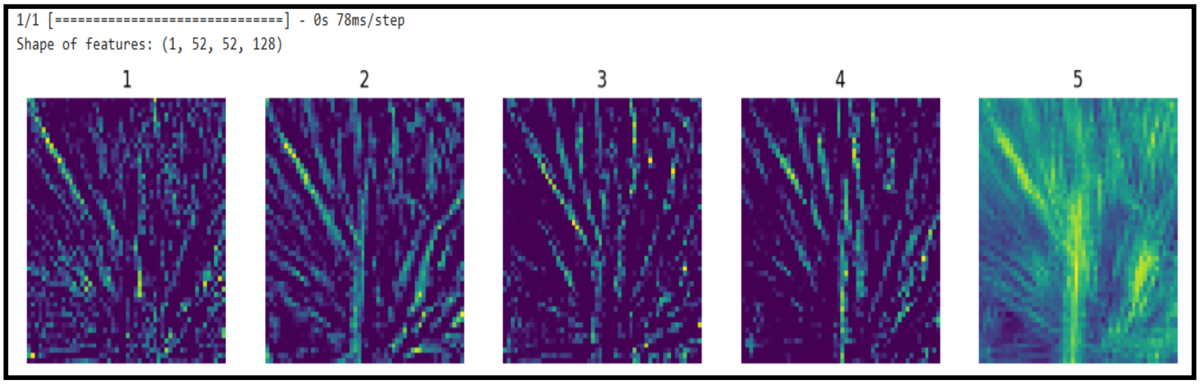

Figure 4: Feature maps are generated at the fourth Conv2d layer.

Deeper in the network, the model starts to capture more abstract and semantic features related to the image content, Figure 4 gives the first five feature maps generated at the deeper layer, i.e., the fourth convolution layer.

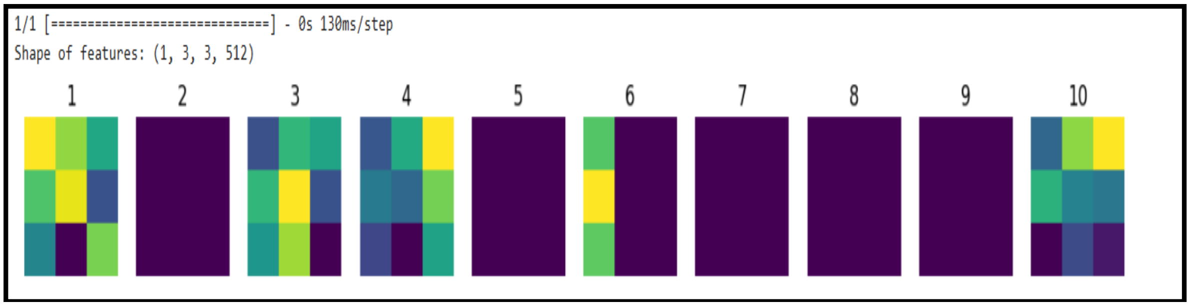

Figure 5: Feature maps are generated at the last Conv2d layer.

In Figure 5 is the final convolutional layers extract high-level features that are highly discriminative for the classification task. The feature maps displayed at this stage represent complex patterns and relationships within the image.

DEEP-CNN MODEL PREDICTION

Algorithm: DEEP-CNN model image prediction

Input:

specific_image_path: Path to the specific image

model_path: Path to the saved model

img_height, img_width: Image dimensions

class_names: List of class names

Class names list (class_names).

Output:

predicted_class_label: A predicted class label for the image

Begin

Step 1: Load the saved model: model = load_model(model_path).

Step 2: Call the function predict_image (specific_image_path, model, img_height, img_width, class_names).

Step 3: Return the predicted class label.
End

The saved pre-trained DEEP-CNN model with specified model_path using the load_model function is loaded. Then, the Prediction Function is called by passing the image path, loaded model, image dimensions, and class names as arguments. This function is responsible for preprocessing the image and making predictions. Now, the predicted class label returned by the predict_image function is returned as the final output of the algorithm. Thus, the algorithm describes how the prediction of random new images is identified by the loaded model and returns the predicted class label as the output.

3. Experiment Evaluation

Dataset Description

The choice of choosing the right dataset from the public repositories was a major bottleneck, as there are very few datasets related to biotic stress available in paddy leaves. Most of the related works discussed above have used their self-customized datasets i.e., the gathering of on-field data and then performing labeling under the supervision of the domain-specific experts. Specifically, an agronomist in the pathology department could serve the purpose effectively. Few repositories like UCI, Kaggle, and Mendeley have rice leaf disease datasets but cover limited numbers of stress classes. The dataset used for this research is the Paddy Doctor Dataset from the IEEE Data Port [9] This dataset includes 16,225 labeled images of paddy leaves across 13 classes, which cover 12 different paddy diseases and healthy leaves. However, only 10,470 images from 10 stress-related classes are accessible. The paddy leaf images were captured in paddy fields using a high-resolution smartphone camera (1,080 x 1,440 pixels). The images were meticulously cleaned and annotated with the assistance of an agronomist as shown in the visualization of sample images in Figure 6.

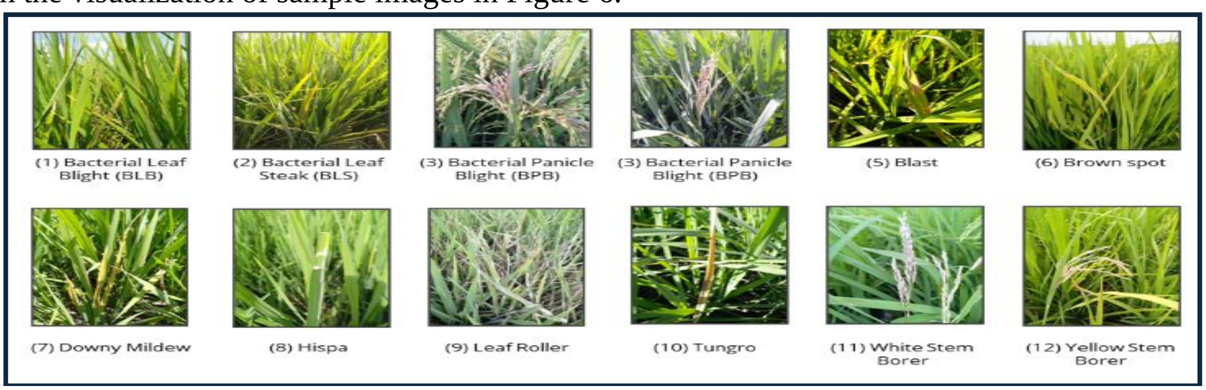

Figure 6: Sample Images of the Paddy Doctor Dataset

Evaluation Metrics

We evaluated well-known assessment criteria to assess the effectiveness of our multi-class classification model: recall, precision, and f1-score. There are ten categories of biotic stress classes which makes it a multi-class classification problem. While recall indicates how well a classifier can identify a class, precision indicates how successful it is at predicting the class.

Mathematically, the formulae used for calculating are shown in equations. (1)-(4):

$$\text{Precision} = \frac{TruePositive}{TruePositive + FalsePositive} \quad (1)$$

$$\text{Recall} = \frac{TruePostivie}{TruePositive + FalseNegative} \quad (2)$$

$$F1 - measure = \frac{2 * precision * recall}{precision + recall} \quad (3)$$

$$\text{Accuracy} = \frac{\text{True Positive+True Negative}}{\text{TruePositive+FalseNegative+True Negative+False Positive}} \quad (4)$$

RESULTS AND DISCUSSION

Table 2: Results of Biotic stress multi-class classification

Biotic Stress Class	Precision	Recall	F1-Score
BLB	0.78	0.82	0.80
BLS	0.84	0.90	0.87
BPB	0.80	0.85	0.82
BL	0.91	0.84	0.87
BS	0.85	0.83	0.84
DH	0.94	0.86	0.90
DM	0.85	0.82	0.83
HS	0.84	0.90	0.87
NM	0.91	0.89	0.90
TG	0.78	0.94	0.85

Table 2 shows the precision, recall, and F1-Score per stress class. The model was trained using the Paddy Doctor dataset.

Table 3: Comparison of DEEP-CNN model accuracy with other existing works.

Model	Type of Stress	No of classes	Accuracy (%)
VGG-16 [7]	Biotic & Abiotic	3	92.16
MobileNet [11]	Biotic	12	92.42
ResNet-50 [12]	Biotic	12	92.89
Efficient Net B0	Biotic	10	93
Deep Neural Networks [6]	Biotic	5	93.08
VGG-16 [11]	Biotic	12	93.19
CNN [13]	Biotic	9	93.3
Deep Belief Network [3]	Biotic	4	94
Proposed DEEP-CNN	Biotic	10	94.4

Table 3 shows the comparison of different deep learning models of the existing works where most of the work was carried out on biotic stress with different numbers of stress classes.

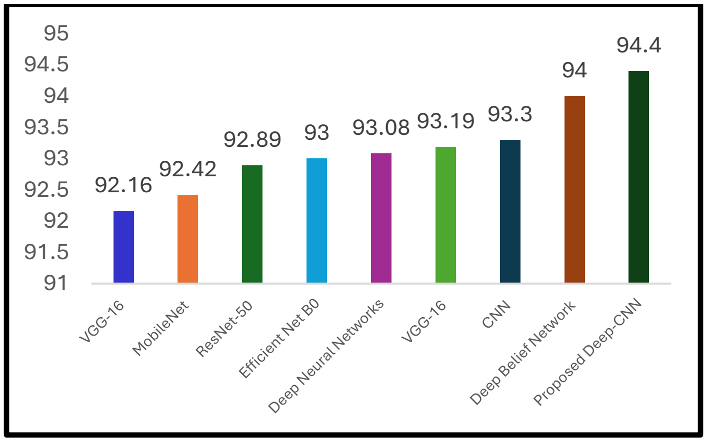

Figure7: Comparison of DEEP-CNN Model with state-of-the-art works

Figure 7 shows the illustration of the accuracy of the DEEP-CNN model with the other state-of-the-art works implemented for the biotic stress of paddy. The results infer that the proposed DEEP-CNN model achieved a higher accuracy of 94.4% when compared with the pre-trained models like VGG-16, ResNet50, EfficientNetB0, and other CNN models.

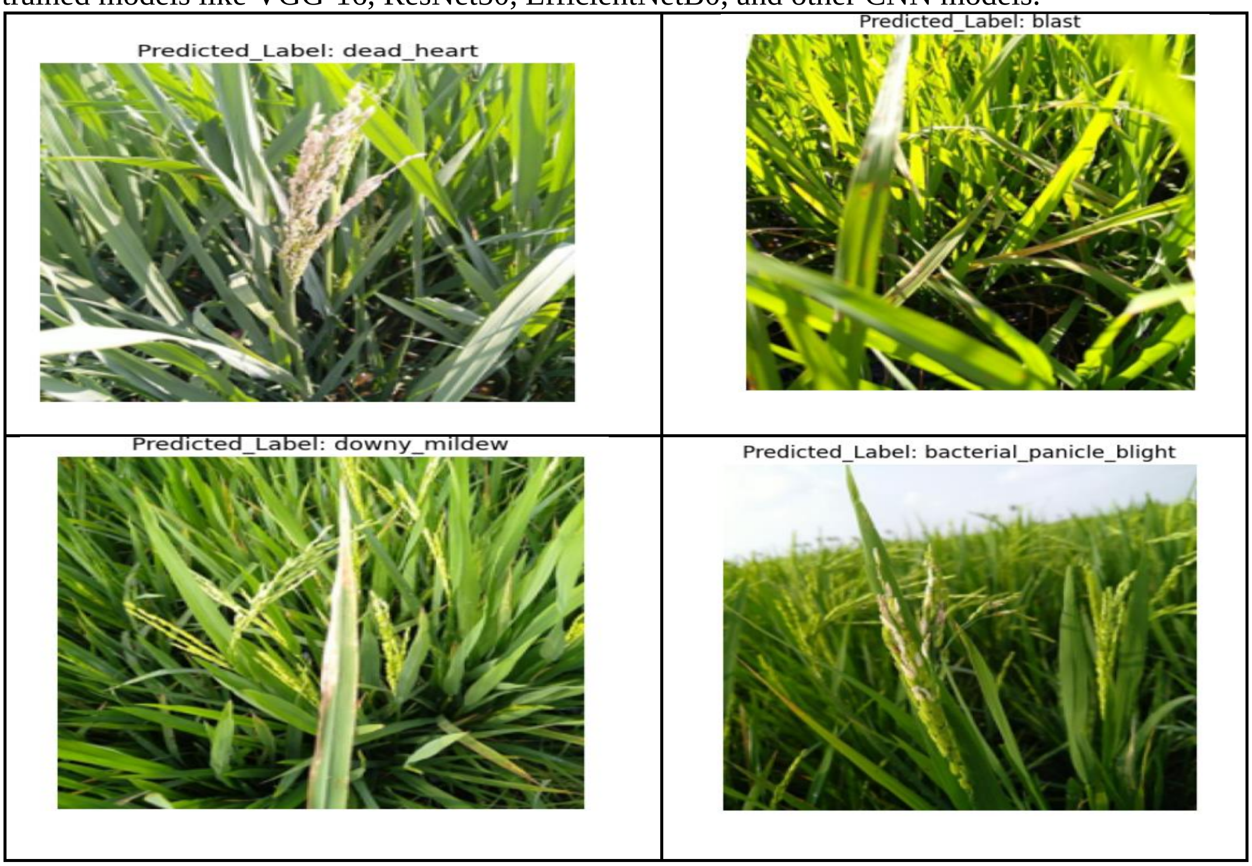

Figure 8: A few Class-wise predictions generated using the DEEP-CNN model image prediction algorithm.

In Figure 8 different predictions were generated by the saved pre-trained model using the proposed model image prediction algorithm. There are nine biotic stress classes and one normal class in which the proposed DEEP-CNN model was trained, and the model was saved for prediction purposes. Using algorithm 2, we performed predictions per class of a sample unlabeled image for the test set. However, there was a misclassification sometimes the model predicted the bacterial leaf blight stress class as a brown spot.

4. Conclusion and Future Scope

This work introduces a deep learning approach using Convolutional Neural Networks for multi-class classification of biotic stress in paddy crops. Biotic stress, caused by organisms such as fungi, bacteria, and insects, significantly impacts crop yield and quality. Traditional methods of detecting these stresses are often manual and subjective. This study introduces a DEEP-CNN model for accurately classifying biotic stress in paddy crops. The approach enhances performance by combining advanced deep learning techniques, such as convolutional layers and hyperparameter optimization. Experimental results validate the model's effectiveness in achieving high classification accuracy across multiple stress classes. The DEEP-CNN model demonstrates promise in addressing real-world challenges in agricultural disease management, enabling early detection and improved decision-making. Integrating this model into agricultural practices can significantly reduce crop losses and support sustainable farming. Future research can focus on improving the model's robustness under diverse environmental conditions and extending it to a broader range of crops and stress types. Efforts should also address the challenges of large-scale data collection, including automated annotation tools and real-time stress monitoring using IoT and drone technologies. Additionally, optimizing the model for deployment on edge devices like smartphones can enhance its accessibility for farmers, facilitating widespread adoption of deep learning solutions in precision agriculture.

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