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An Improved Deep Learning Model for Detecting Rice Diseases

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Abstract

Early detection of rice plant diseases could help to quickly eradicate numerous diseases, such as fungi, viruses, and bacteria, consequently increasing rice yield. Traditional techniques for performing this task may not be the best because they take a long time, require experienced personnel, and are susceptible to a variety of infections. As a result, machine learning and deep learning approaches have recently been utilized to overcome these issues and present a more accurate model for detecting rice plant diseases. However, the current machine learning (ML) and deep learning (DL) models for this task produce unsatisfactory results due to many constraints, including high computational expenses and overfitting. To address these limitations and obtain more accurate disease detection for rice plants, we present a hybrid model of MobileNet and DNN (HMobileNetDNN). The small size of MobileNet minimizes computing costs, while the depth and complexity of DNN improve the model's capacity to capture complicated features, yielding satisfying results. Furthermore, the proposed HMobileNetDNN is also compared to four transfer learning-based DL models, namely ResNetV2, InceptionV3, MobilenetV2, and DensNet121, using the Paddy Doctor dataset. We employ several performance metrics to assess the effectiveness and efficiency of the models, like accuracy, precision, recall, F1 score, and area under the curve. The proposed model outperformed the comparing models, achieving values of 0.918, 0.918, 0.907, 0.912, and 0.949 for accuracy, precision, recall, F1 score, and area under the curve, respectively.

Keywords: Paddy Diseases; Artificial Intelligence; Deep Learning; Transfer Learning; Hybrid Models.

1 | Introduction

Agriculture is considered a significant source for meeting the food needs of the population around the world by producing basic foodstuffs such as grains, fruits, and vegetables [1-4]. This study primarily concentrates on grains, with a particular emphasis on rice. The consumption of rice is commonly recognized as an essential nutritional element for more than 40% of the global populace, representing around half of the world's overall population [5, 6]. Rice is a significant dietary component for individuals as rice satisfies approximately 20-30% of their daily caloric requirements [7]. According to [8], global rice production reached roughly 600 tons in 2000, and some projections suggest it might double by 2030. Various factors might negatively affect rice cultivation and production, including pests, rice diseases, pathogens and climate change [9]. Over time,

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population growth has substantially increased, resulting in the demand for more rice production to meet their requirements [10]. Therefore, it is necessary to detect rice diseases to improve rice production to meet population growth requirements [11-13].

The traditional approach for detecting these diseases involves doing periodic visual examinations of rice crops, as numerous diseases have observable signs. However, this approach is subjective and susceptible to errors due to the existence of various rice diseases and potential human oversight. Failure to promptly diagnose and implement corrective actions might result in a loss exceeding 50% in rice fields. Therefore, over the last few years, the researchers have been employed the DL and ML models to detect rice diseases. The rest of this section will review some of these studies.

In [14], a comparative study was conducted to compare the performance of some transfer learning-based DL models, like VGG-16, when applied to detect three diseases in rice leaves (Hispa, Brown Spot, Leave Blast). The transfer learning approach has been demonstrated to be an effective strategy for addressing this problem, with an accuracy of 91%. In [15], five CNN models, namely Inception-V3, VGG-16, Alex Net, MobileNet V2, and ResNet-18, were applied to identify paddy diseases. Their performance was evaluated using a dataset consisting of 7096 images of paddy leaves. Moreover, the dataset comprises five distinct categories of leaves, including healthy leaves, leaves affected by Bacterial Leaf Blight, leaves affected by Brown Spot, leaves influenced by Leaf Blast, and leaves damaged by Leaf Smut. The experimental results demonstrate that Inception-V3 outperforms other CNN models tested in terms of accuracy, achieving a rate of 96.23%.

In [16], a DL model based on CNN collaborated with edge detection algorithms, was presented to identify and categorize paddy leaf disease. This model has been trained using a dataset, including a collection of 650 images. This model had outstanding performance when compared to some rival DL models. In [17], a new DL model based on combining a support vector machine classifier and convolutional neural networks was proposed to identify and categorize distinct types of five paddy plant diseases (bacterial leaf blight, fake smut, brown leaf spot, rice blast, and sheath rot). This model could achieve a classification accuracy of 0.9145, beating all other compared models. In [18], for identifying the paddy leaf diseases, a modified lemurs optimization algorithm was employed as a feature selection strategy in order to enhance the accuracy of disease identification for the K-Nearest Neighbor classifier. This model could achieve an accuracy of 90%, which is better than all compared machine learning algorithms.

However, the existing DL and ML techniques have some drawbacks that prevent them from achieving satisfactory outcomes for this problem. Therefore, we propose a hybrid model based on integrating the MobileNet with DNN to overcome the aforementioned limitations and present a robust alternative model for better detecting the rice diseases. The main contributions of this paper are briefly described as follows:

- We investigate the effectiveness of transfer learning and deep neural network models when applied to detect rice diseases.
- We also combine the MobileNet architecture with a DNN to propose the HMobileNetDNN model with better performance for handling the rice disease detection problem.
- The performance of HMobileNetDNN measured using a widely-used dataset, and compared to other four DL models using several performance metrics, such as precision, precision, recall, F1 score, area under the curve and TSNE.
- From the statistical analyses, the proposed model could achieve superior results of 0.918, 0.918, 0.907, 0.912, and 0.949 for accuracy, precision, recall, F1 score and area under the curve, respectively.

The rest of this article is organized as follows. Section 2 presents materials and methods. Section 3 describes the proposed model. Furthermore, section 4 brings the statistical analyses of the results and introduces discussion about them. Finally, Section 5 gives some conclusion and future directions.

2 | Materials and Methods

2.1 | Dataset Description and Preprocessing Step

The Paddy Doctor dataset contains 16,225 images of rice leaves divided into 13 distinct categories. The paddy leaf images were collected from real paddy fields by smartphone camera with high-resolution (1,080 x 1,440 pixels). They were carefully cleaned and labeled with the help of an agronomist. This dataset is the most comprehensive collection of visual images of rice diseases annotated by experts, especially designed for evaluating computer vision algorithms [19]. Also, the paddy images were adjusted to a resolution of 480 x 640 and classified into ten labels, containing nine labels for diseases and the tenth one for health [20]. Table 1 clearly describes the distribution of each class in this dataset. Finally, before starting the training process, the images in this dataset are first resized to 128 × 128 pixels. Then, the image data generator is used to normalize the intensities between 0 and 1 to accelerate the training process. Figure 1 depicts some infected and healthy images in this dataset.

Table 1. Description of the used rice dataset.

Classes	Normal	Blast	Hispa	Dead heart	Tungro	Brown spot	Downy mildew	Bacterial leaf blight	Bacterial panicle streak	Bacterial panicle blight
Count	1764	1738	1594	1442	1088	965	620	479	380	377
Total	10407									

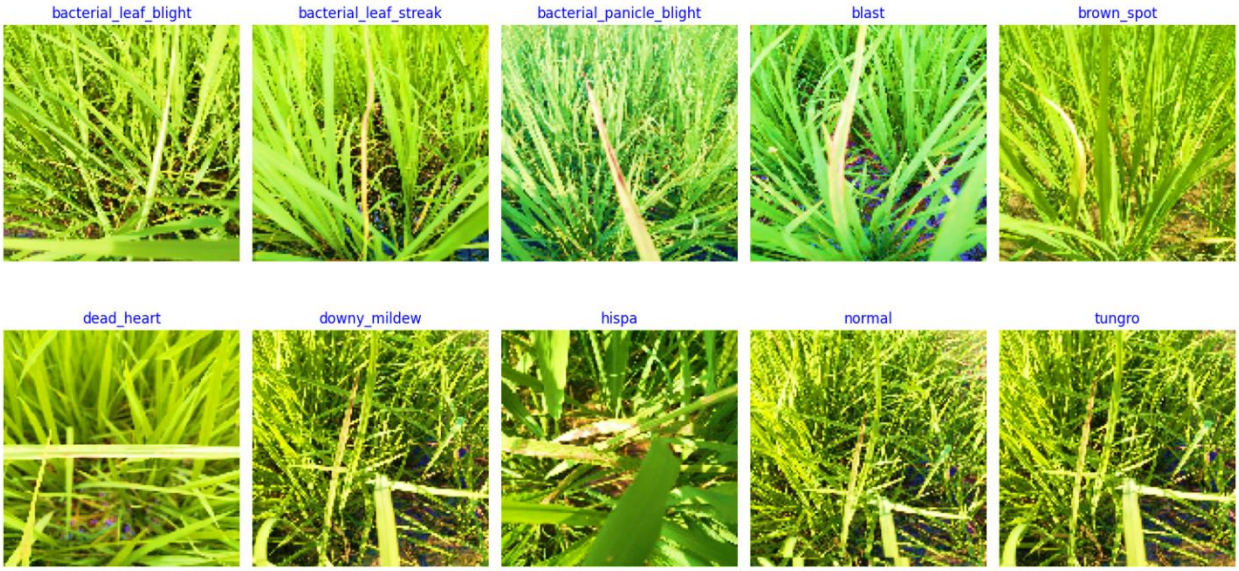

Figure 1. Depiction of infected and healthy images of the Paddy Doctor dataset.

2.2 | DL Model and Transfer Learning

In this study, we investigate the performance of four transfer learning-based DL models, including ResNetV2, InceptionV3, MobileNetV2 and DensNet121 [14]. ResNetV2, also known as Residual Network, is widely recognized for its capacity to effectively tackle the issue of vanishing gradient with the incorporation of skip connections. The inclusion of skip connections in the network facilitates the acquisition of residual mappings, hence enabling the training of more complex networks without compromising performance. The distinguishing feature of InceptionV3 (GoogLeNet) is its inception module, which integrates parallel convolutional procedures at various scales. The present architecture facilitates the extraction of features in an efficient manner by effectively capturing both local and global information.

The MobileNetV2 architecture is intended to favor model efficiency, making it ideal for use on edge devices due to its lightweight nature. The use of depth-wise separable convolutions reduces model complexity while maintaining classification accuracy. The Densely connected convolutional network (DenseNet121) uses dense connections between its layers to allow for continuous transmission of information across all levels of the network. The high level of connectivity facilitates feature reuse, gradient flow, and performance enhancement. Using these pre-trained models, we may take use of the learnt representations and fine-tune for rice disease detection. By incorporating the deep neural network (DNN) into the MobileNet architecture, we were able to create a novel DL model for identifying plant illnesses. This method saves training.

3 | Proposed Model

In this study, a new DL model based on combining the MobileNet architecture with a DNN with three fully connected layers are presented to better detect the rice diseases. Figure 2 depicts the architecture of this model. The MobileNet architecture serves as the feature extractor, effectively acquiring key patterns and features from the input data. Its small size is because utilization of depth-wise separable convolutions is employed in order to minimize the storage and computational requirements required by the model. The deep neural network provide more powerful learning and abstraction capabilities, enabling the model to capture more complicated and high-level representations. Regarding the used loss function, the proposed model used the categorical cross-entropy loss. Categorical cross-entropy (CCE) is a loss function often used in classification tasks involving several classes. It evaluates the dissimilarity between predicted values probabilities and the true values labels. The goal is to minimize this dissimilarity during training, helping the model effectively classify new data into the correct categories. The mathematical model of this function is defined as follows:

$$Minimize: loss = -\sum_{i=1}^{M} y_i . \log \hat{y}_i \tag{1}$$

where y_i represent real values and $\hat{y}_i$ represent predicted values

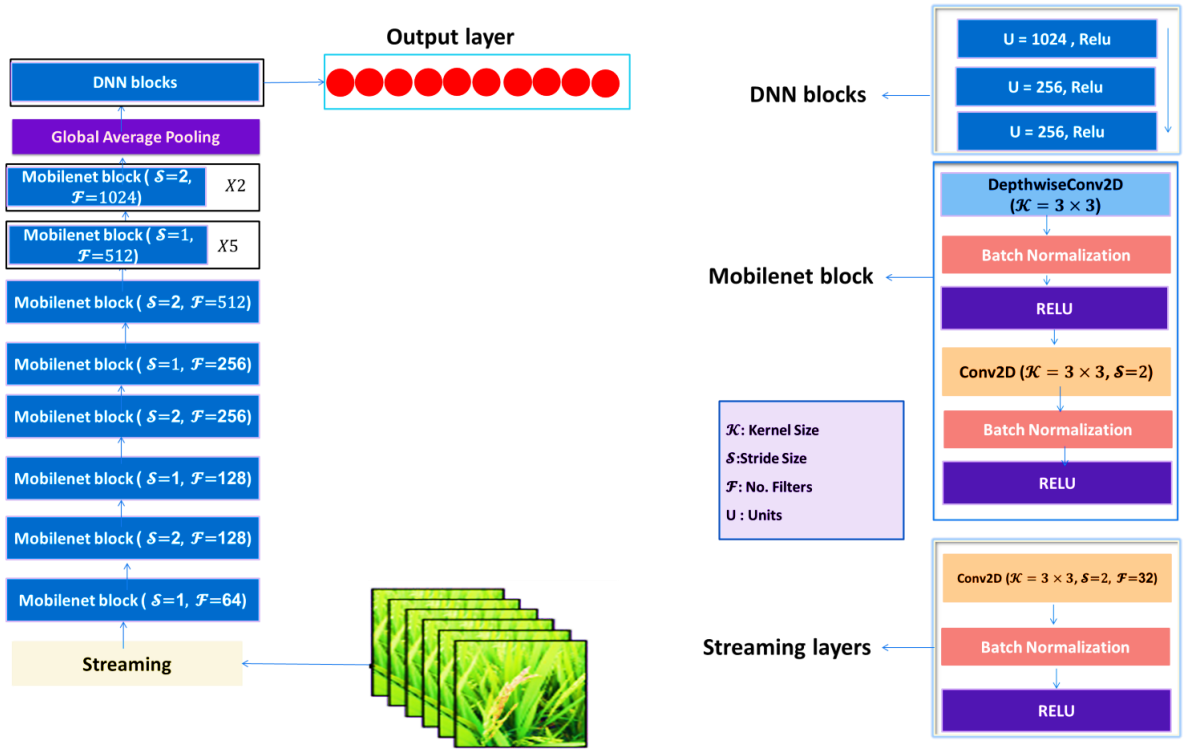

Figure 2. Architecture of the proposed model.

4 | Result and Discussion

This section investigates the performance of the proposed model using a widely-used dataset, Paddy Doctor Dataset [15]. In addition, it is compared to several DL models, such as ResNetV2, InceptionV3, MobilenetV2, and DensNet121. Those models are implemented in Python using the Kaggle platform and Keras API. The Adam optimizer with a learning rate of 0.001 was used to train the weights of those models for 50 epochs. In addition, the early stopping with a patience of 10 was used in our experiments. The performance indicators used to evaluate the performance of those models are described as follows:

- Accuracy is defined as the ratio of accurately predicted samples to the total number of *samples* in a given dataset. The following equation can be employed to calculate this measure:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{2}$$

  where TP, FN, TN and FP represent true positive, false negative, true negative, and false positive, respectively.

- Precision is a quantitative measure used to assess the degree of accuracy in positive predictions generated by a given model. The metric quantifies the ratio of accurately identified positive instances to the total number of projected positive instances. The following equation can be employed to calculate this measure:

$$\Pr ecision = \frac{TP}{TP + FP} \tag{3}$$

- Recall is called sensitivity or true positive rate, is a metric that estimates the model's capacity to accurately detect positive instances among all the actual positive samples. The following equation can be employed to calculate this measure:

$$\mathrm{Re}call = \frac{TP}{TP + FN} \quad (4)$$

- The F1-score combines precision and recall into one metric, providing a balanced assessment of model performance. The following equation can be employed to calculate this measure:

$$F1 - score = 2 \times \frac{\mathrm{Pr}ecision.\mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call} \quad (5)$$

- AUC is another metric that represents the model's ability to distinguish between positive and negative instances, with a higher AUC indicating better performance. The following equation can be employed to calculate this measure:

$$AUC = \frac{1 + \frac{TP}{TP + TN} - \frac{FP}{FP + TN}}{2} \quad (6)$$

- A confusion matrix is a graphical representation that provides a concise summary of the performance of a machine learning model when evaluated on a specific dataset. It is a method of presenting the count of correct and incorrect instances according to the model's forecasts. The performance of classification models is frequently evaluated using the aforementioned matrices, such as Accuracy, Percision, Recall, or F1-score. We aim that all the true values are as large as possible and the model reaches its best.

- The Receiver Operating Characteristic (ROC) curve is a visual depiction of a model's classification performance. It graphs the sensitivity (true positive rate) against the specificity (1 - false positive rate) at different categorization thresholds. The ROC curve is utilized to evaluate the model's capacity to differentiate between positive and negative instances, where a higher curve signifies superior performance.

- The t-Distributed Stochastic Neighbor Embedding (t-SNE) is a dimensionality reduction technique commonly used to visualize high-dimensional data in a low-dimensional space. It is useful for exploratory data analysis. It aims to map data points in such a way that puts similar points close to each other. Similar classes are located at a greater distance, and this helps us identify the model's efficiency by grouping similar classes after the prediction process [21].

The proposed model demonstrates superior performance compared to the previous models in terms of Accuracy, Precision, Recall, F1-score, and AUC, as indicated by the presented results in Table 2. The proposed model could achieve a better classification accuracy of 0.918, followed by MobilenetV2 as the second-best with an accuracy of 0.904, and InceptionV3 is the worst model. Moreover, the proposed model exhibits superior Precision, Recall, F1-score, and AUC in comparison to the other models. Regarding efficiency, the proposed model needs a smaller number of parameters and epochs to reach the aforementioned performance, thereby minimizing its computational cost during the training and evaluation process.

Table 3 presents the confusion matrix, it presents an evident that the model exhibits a commendable performance, since the majority of the values on the diagonal surpass those located outside the diagonal. Nevertheless, there exist certain misclassifications, as indicated by the presence of non-zero values beyond the diagonal.

In Figures 3-6, we examine Performance evaluation of the proposed model under accuracy curve, loss curve, ROC curve and t-SNE Graphs, respectively. According to the accuracy curve, the learning process ceased after the 40th epochs, and the model continued to learn in each subsequent epochs. The stability of the learning process can be inferred from its initial disappointing outcome. The initial accuracy was below 20%,

however, with each subsequent attempt, the results exhibited substantial improvement until they reached their highest point.

Table 2. Comparison between the proposed model and others in terms of various performance indicators.

Model Name	# Epochs trained	# Parameters	Accuracy	Precision	Recall	F1-Score	AUC
MobilenetV2	49	3579978	0.904	0.913	0.890	0.900	0.939
ResNetV2	39	25673226	0.841	0.833	0.820	0.821	0.901
DensNet121	50	8097354	0.798	0.837	0.770	0.790	0.873
InceptionV3	50	23911210	0.628	0.650	0.548	0.565	0.752
HMobileNetDNN	40	4609226	0.918	0.918	0.907	0.912	0.949

Table 3. Confusion matrix of the proposed HMobileNetDNN model.

		Estimated classes										
		C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**Recall (%)**
Actual classes	**C1**	**44**	0	1	1	0	0	0	1	0	2	89.80%
	C2	0	**37**	0	1	0	0	0	0	0	0	97.37%
	C3	0	0	**29**	1	0	3	0	0	2	0	82.86%
	C4	0	1	1	**167**	2	2	1	0	0	1	95.43%
	C5	1	0	0	2	**87**	0	1	2	1	3	89.69%
	C6	1	0	0	1	0	**142**	1	0	0	0	97.93%
	C7	0	0	0	3	1	0	**51**	3	3	1	82.26%
	C8	0	0	0	6	5	0	1	**142**	3	3	88.75%
	C9	1	1	1	1	1	1	0	3	**163**	4	92.66%
	C10	2	0	0	5	0	0	0	1	2	**100**	90.91%
Precision (%)		89.80%	94.87%	90.63%	88.83%	90.63%	95.95%	92.73%	93.42%	93.71%	87.72%	

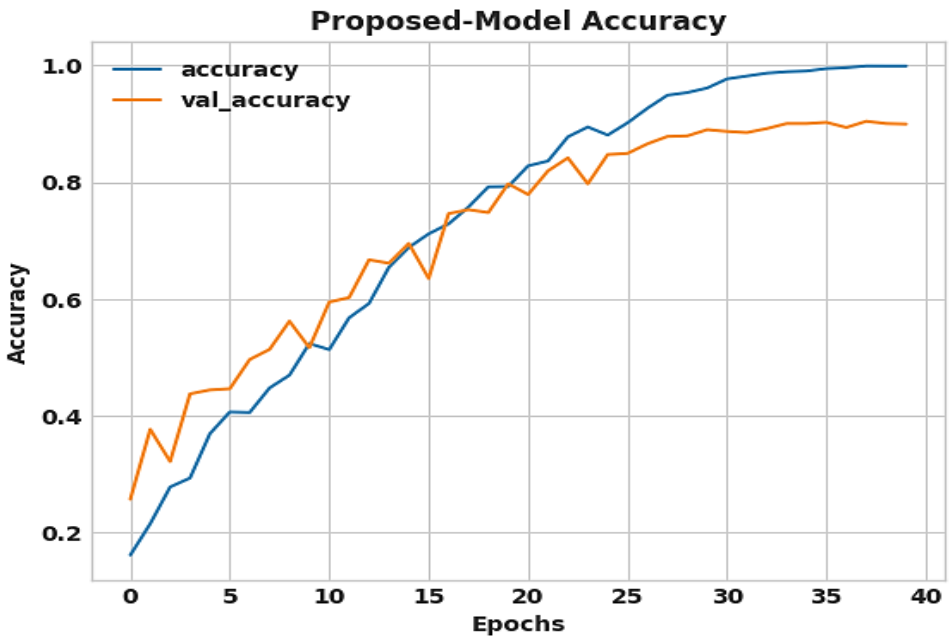

Figure 3. Accuracy curve of the proposed HMobileNetDNN model.

Figure 4. Loss curve of the proposed HMobileNetDNN model.

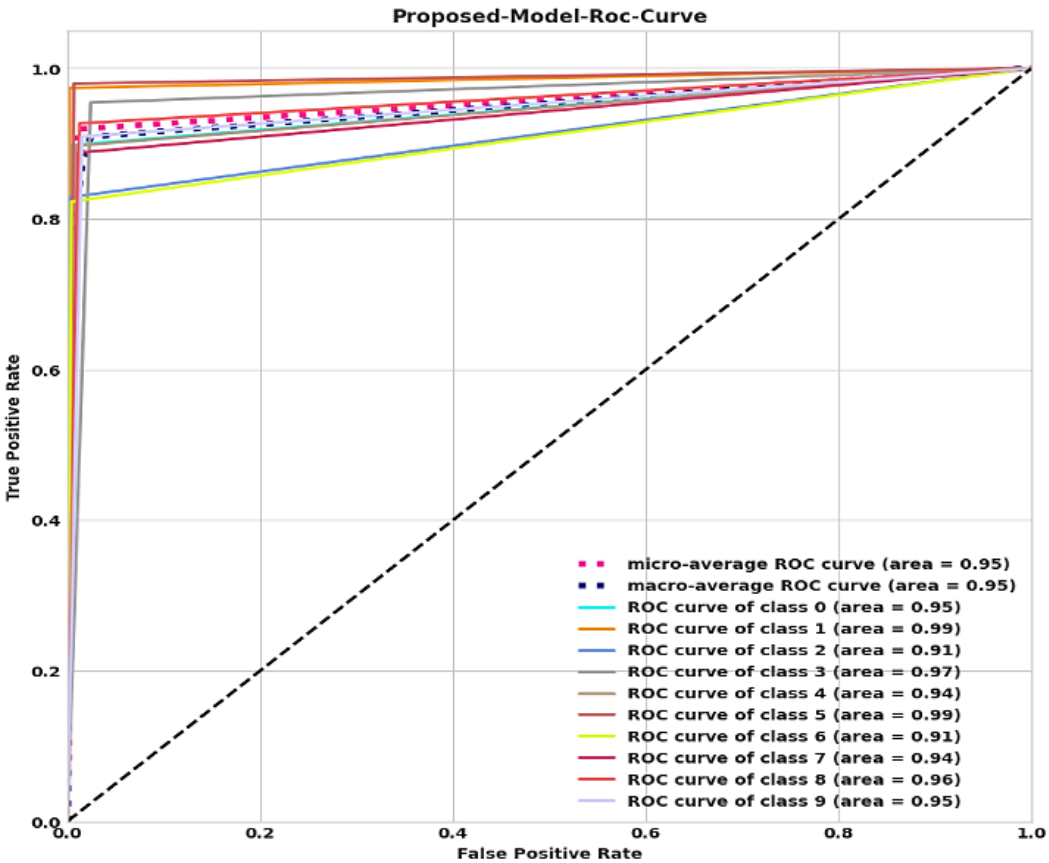

Figure 5. ROC curve of the proposed HMobileNetDNN model.

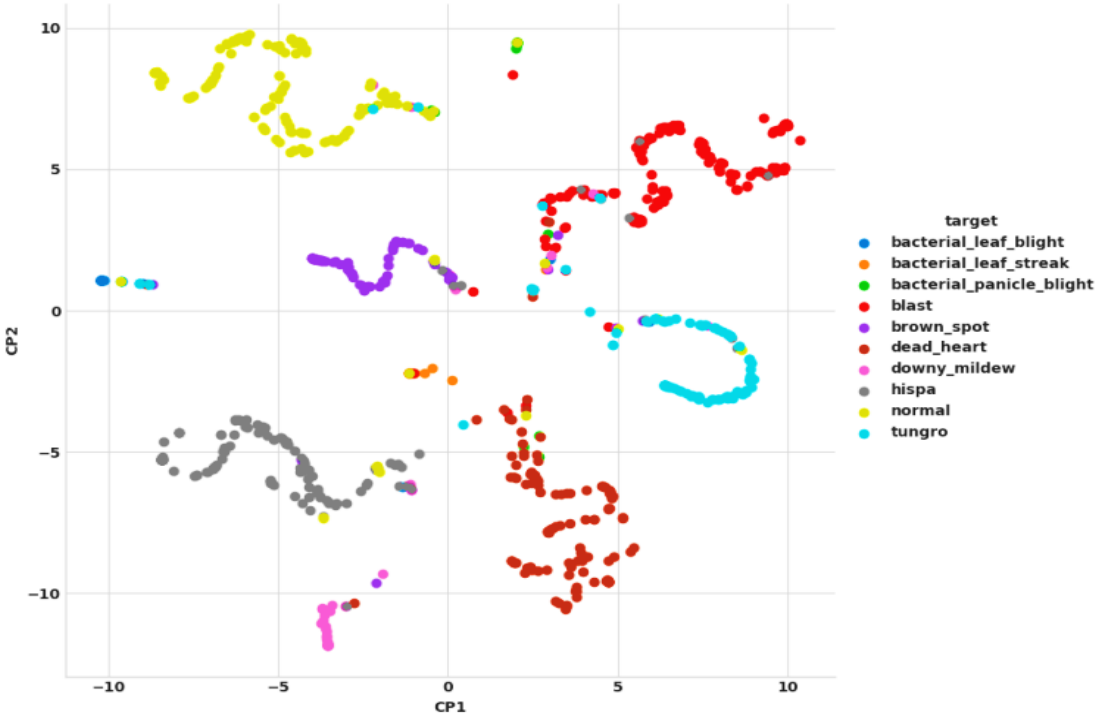

Figure 6. t-SNE metric of the proposed HMobileNetDNN model.

5 | Conclusion and Future Work

Early diagnosis of rice plant diseases is a very difficult task and can lead to numerous consequences. Various types of pathogens, such as fungi, viruses, and bacteria, pose a threat to rice production. These pathogens contribute to diseases such as bacterial leaf blight, bacterial leaf streak, bacterial leaf blight, brown spot, dead heart, powdery mildew, scab, and tango. Due to the importance of the rice plant, which is considered a basic food for more than 40% of the world's population, the traditional methods could not be considered for detecting its diseases, which significantly affect its production, due to several reasons, such as low accuracy and time-consuming. However, the existing DL and ML techniques still suffer from either overfitting or underfitting problems. This study suggests the HMobileNetDNN model based on combining the MobileNet architecture and the deep neural network to alleviate those drawbacks and obtain a highly efficient model that can be used to accurately classify rice diseases. This model, in addition to four compared models, is evaluated using a well-known dataset and compared to each other using several performance metrics, such as accuracy, precision, recall, F1-score, and AUC. The results showed that the accuracy of the proposed model reached 0.918, exceeding the accuracy of other compared models such as ResNetV2 (0.841), InceptionV3 (0.628), MobilenetV2 (0.904), and DensNet121 (0.798). Our future work will include investigating the performance of this model for several other classification problems, such as brain tumor detection, COVID-19 detection, and several others.

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Author Contributaion

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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Appendix

https://github.com/AhmedTolba36996/Deep-Learning-Models-for-Accurate-Classification-of-Paddy-Leaf-Diseases.

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