PaddyNet: An Improved Deep Convolutional Neural Network for Automated Disease Identification on Visual Paddy Leaf Images

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***Abstract*—Timely disease diagnosis in paddy is fundamental to preventing yield losses and ensuring an adequate supply of rice for a rapidly rising worldwide population. Recent advancements in deep learning have helped overcome the limitations of unsupervised learning methods. This paper proposes a novel PaddyNet model for enhanced accuracy in paddy leaf disease detection. The PaddyNet model, developed using 17 layers, captures and models patterns of different disease symptoms present in paddy leaf images. The effectiveness of the novel model is verified by applying a large dataset comprising 16,225 paddy leaf datasets across 13 classes, including a normal class and 12 disease classes. The performance results show that the new PaddyNet model classifies paddy leaf disease images effectively with 98.99% accuracy and a dropout value of 0.4.**

***Keywords*—Image annotation; data augmentation; deep learning; paddy leaf disease detection; paddyNet**

I. Introduction

Plant disease threatens food production and disrupts food security worldwide. It was reported, for instance, that though rice cultivation was set to increase by 1.8 percent in 2021/22 to a new peak of 520.7 million tonnes [1], its supply was diminished by disease. Rice is among the most widely consumed foods globally, with a total consumption of 511.4 and 501.2 million tonnes in 2020-21 and 2019-20, respectively. These statistics highlight the relentless food shortages brought on by the devastation plant disease has wreaked on food production, turning it into a major global problem [2]. So then, increased agricultural productivity of up to 70% is required to reduce paddy leaf disease and provide food for a rapidly growing population. However, recurrent problems with infections, the improper monitoring of rice farmlands, and the regular occurrence of paddy leaf diseases destroy rice yields and result in production losses. Various diseases regularly occur in the paddy leaves, which is the reason for the production loss. Additionally, the overuse of chemicals like bactericides and fungicides in the agro-ecosystem has created conflict in the fight against plant disease [3]. For a sustained production rate, an algorithm is to be designed for predicting paddy leaf characteristics so as to detect leaf diseases. Early predictions of paddy leaf-related infections can help bolster the quality and quantity of rice production. Timely interventions help slow the rapid pace of the disease and maximize the cultivation of healthy rice leaves [4].

Paddy leaf-related disease symptoms are typically distinguished by their texture, colour, and form [5][6][7]. Artificial intelligence-based automated identification methods are currently recognized as the best for paddy leaf disease recognition. The manual prediction of paddy leaf disease has been shown to be erroneous, expensive, and difficult to predict in advance. The condition is diagnosed far more accurately and simply using computer-based procedures. As a result, an incredible range of diseases have since been identified, the effects of which on leaves are yet to be classified. Computer-based identification methods fail to depict the effects of environmental factors on paddy leaf disease, and offer slow identification speeds as well as inaccurate information metrics. Therefore, detection techniques that identify paddy leaf diseases quickly and accurately through leaf features have been developed to enable the farming community to make appropriate decisions [8][9].

Traditional techniques such as computer vision [10], pattern recognition [11], support vector machines [12][13][14], image processing [15], and convolutional neural networks [16][17][18] have long been used to identify diseased paddy leaves with high detection accuracy and determine results rapidly. A paddy disease detection framework [19] was proposed using features from the affected parts of the leaf, which were selected from trained leaf images and classified using the support vector machine. Additionally, the SVM and Naive Bayes classifiers [20] were applied to test images using three image classes that included healthy leaves, brown spots, and leaf blast lesions. The paddy data set was captured using a Nikon COOLPIXP4 digital camera. The experimental results revealed 79.5% accuracy for the SVM and 68.1% for the Naive Bayes classifiers. The multilayer perceptron method [12] could identify six types of paddy disease, based on the texture and color of paddy images, with 88.56% accuracy. Furthermore, four classes of paddy diseases were identified with high accuracy of 92.5% using the Fractal Fourier Technique. This technique was also used to find four types of rice disease [21].

However, real-time applications of existing techniques across agriculture and other fields often involve the use of small and slow models that are specifically intended for devices with low computational power while identifying disease with good-to-better accuracy. Further, existing techniques lack noise sensitivity and produce reduced classification accuracy. The proposed PaddyNet method identifies paddy diseases quickly and classifies them from visual paddy leaf images based on deep learning models. This system utilizes a feature extraction technique that reduces noise and thereby magnifies the disease spot with no resultant loss of information.

The remaining sections of the paper are organized as follows: Section II reviews the literature on plant disease identification. Section III discusses the materials and methodologies used and describes the real-time paddy dataset in detail in Section III-A. Section IV presents the experimental findings used to determine the performance metrics of the proposed solution. Finally, Section V concludes the paper with directions for future work.

II. Related Work

Several state-of-the-art outcomes have been analyzed using image processing techniques, including computer vision and artificial intelligence, across different fields of research. The techniques are applied to images to make it easier to resolve image segmentation, feature selection and extraction, and classification using deep learning (DL) [22]. Deep learning, a sub-section of machine learning, is widely used to recognize input image patterns [23][24] by extracting parameters from paddy plant images and examining crop stress. A paddy disease identification approach was used to classify paddy image features using convolutional neural networks [25]. Ten different types of rice disease images were used for the experimental results.

In addition to diagnosing paddy leaf disease, advanced identification techniques have also been used on crops such as wheat [26], brinjal [27], pumpkin [28], tomato [29], and potato [30]. Two approaches were used to diagnose diseased leaves using the GoogLeNet and Cifar10 models [8]. With a focus on detecting disease in maize, the proposed approach achieved 98.9% and 98.8% overall accuracy for the GoogLeNet and Cifar10 models, respectively. On the other hand, the AlexNet model that was used [31] to diagnose apple leaf disease obtained the highest accuracy of 97.62%. In addition, a novel CNN was developed [32][19] to identify cucumber leaf disease with high accuracy of 94.9%. A convolutional neural network technique was used [33] for crop leaf classification to identify leaf disease. From the experimental results, four classes were correctly identified, including a normal leaf class, while the remaining constituted the affected image classes. In all, 100 images for each class were taken for the experiment and the results showed that the model achieved 92.85% overall accuracy. The proposed method obtained accuracy of 99.9%, 91%, 87%, and 93.5%, respectively, for each class [34]. A DCNN was used to diagnose rice diseases and pests. The proposed method considered 1426 images for the experimental results and achieved 93.30% accuracy [35].

The paper [36] used the proposed CNN architecture on three datasets PlantVillage, the Rice Diseases Image Dataset, and the Cassava Leaf Disease Dataset. The method extracts depth features from the images to reduce the computation cost and define the number of parameters applied on the model. This work obtained the highest performance accuracy for all three data sets. The proposed approach used deep ensemble neural networks [3] to diagnose 14 different types of crop diseases with 14 classes. The images were pre-trained using seven deep learning models such as the ResNet50, ResNet101, InceptionV3, DenseNet121, DenseNet201, MobileNetV3, and NasNet. The proposed ensemble model achieved higher accuracy than the other pre-trained models.

It is concluded from a study of the literature above that much of the research on diseased leaf detection employed deep learning methods to train the classifier models for high accuracy. This paper proposes a PaddyNet neural network model for improved leaf detection classification accuracy. The proposed model uses a large number of data images for training and testing, and classifies the images efficiently into their respective classes with high accuracy. Also, to maximize the performance of the PaddyNet model, an optimizer is developed alongside to produce optimal results. As a result, the PaddyNet deep learning model offers significant improvements overall in terms of the accuracy of paddy leaf detection classification. Real paddy plant leaf images were collected from paddy fields, using a smartphone camera, to validate the proposed PaddyNet deep learning model. The proposed approach addresses the problem of paddy disease classification and its automated identification.

III. Materials and Methods

Fig. 1 represents an overview of the innovative method employed for paddy leaf disease classification. An improved novel algorithm called PaddyNet is proposed to extract leaf image features and classify diseased leaf images much more accurately. The proposed method includes the three steps of dataset collection, data preprocessing, and augmentation. In the first step, dataset collection, paddy leaves are gathered from actual paddy fields. In the second step, data preprocessing, duplicate images are deleted. In the third step, augmentation, each paddy image is annotated with the help of specific agricultural officers. In addition, suitable image augmentation techniques are used to expand the data. During the data splitting stage, the final cleaned data is divided into train, validate, and test subsets, following which the proposed PaddyNet model is trained utilizing the train and validation sets for the model development process. Finally, the results are evaluated after the PaddyNet model is trained and validated using performance metrics and confusion matrices on the test set of paddy leaf images.

A. Data Collection and Annotation

Visual images of paddy leaves were captured using the CAT S62 Pro smartphone in Tirunelveli district of Tamil Nadu, India [37]. Initially, more than 25,000 images were collected from the data set. Every sample was examined carefully and redundant data such as noisy and out-of-focus images were removed. Finally, following the cleaning process, 16,225 images were chosen with the assistance of agricultural officers. The cleaned images were labeled into 12 disease categories and 1 healthy category. Further, metadata on the age and type of paddy were collected as well [38] and the Paddy Doctor Dataset data gathered and annotated. The procedures used are shown in Fig. 2.

B. Image Augmentation

Image augmentation in image analysis enhances both the quantum of data available and the performance of the model. This is done by generating image categories that reduce overfitting issues and enhance the model's ability for interpretation during the training phase. By applying different image data augmentation techniques, for instance, many more paddy leaf

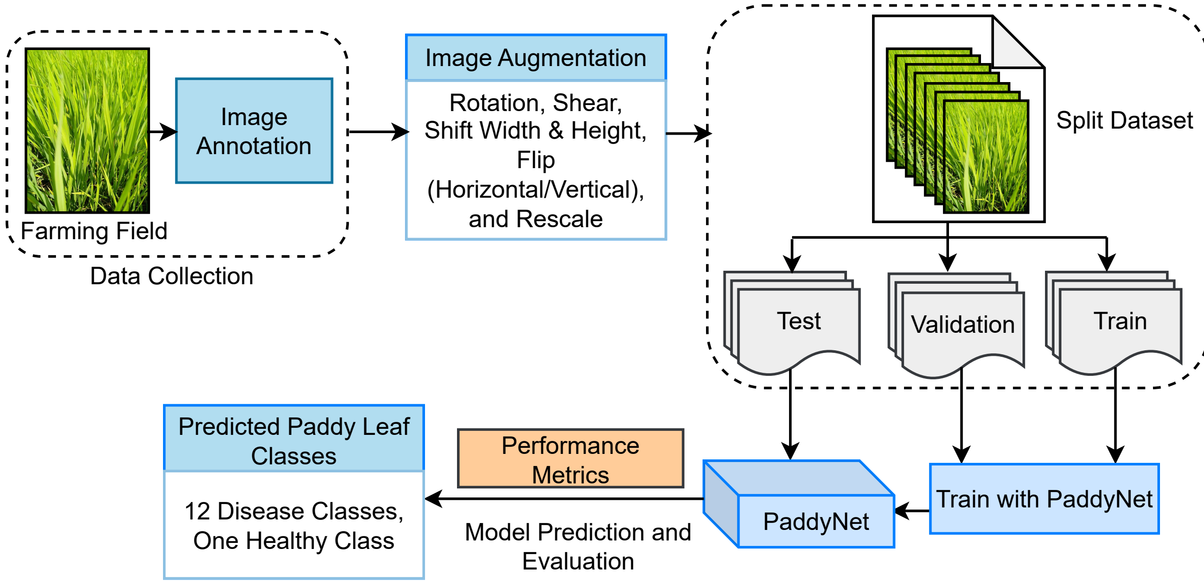
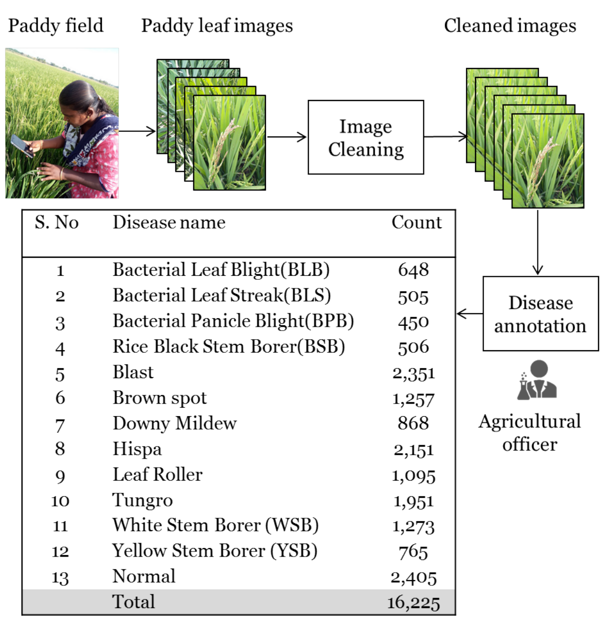


Fig. 1. An overview of the methodology for paddy disease classification using PaddyNet model.



S. No	Disease name	Count
1	Bacterial Leaf Blight(BLB)	648
2	Bacterial Leaf Streak(BLS)	505
3	Bacterial Panicle Blight(BPB)	450
4	Rice Black Stem Borer(BSB)	506
5	Blast	2,351
6	Brown spot	1,257
7	Downy Mildew	868
8	Hispa	2,151
9	Leaf Roller	1,095
10	Tungro	1,951
11	White Stem Borer (WSB)	1,273
12	Yellow Stem Borer (YSB)	765
13	Normal	2,405
	Total	16,225

Fig. 2. Data collection and annotation process.

images can be generated by varying image orientation and size. Common data augmentation operations include random rotation, width and height shift, horizontal and vertical flip, shear, fill mode, and rescale. Sample pictures of leaves with 12 different diseases are shown in Fig. 3.

C. PaddyNet Model Architecture

The proposed PaddyNet model has 17 layers. Using visual images, the CNN model identifies paddy leaf disease. The proposed model has five requisite components: a convolutional layer, a pooling layer, a dense layer, a flatten layer, and an activation function. A brief discussion of the five components follows below.

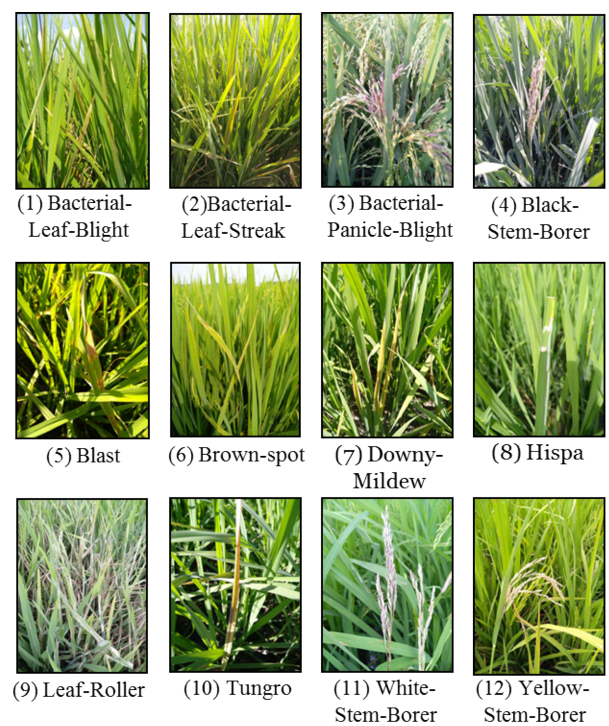


Fig. 3. Sample paddy disease images in our dataset.

1) Convolutional layer: This the primary and first block of a CNN model. The proposed PaddyNet model uses seven conv2D layers. In the convolutional block, the convolution operation extracts related features from the input paddy image. To perform convolution operations using backpropagation, the model is trained using backpropagation [34] and its weight updated, based on the error rate revealed during the preceding iteration. Forward propagation is marked by movement from the origin layer to the destination layer in the network. The loss is obtained at the end of the network, using the loss function to avoid the error. Equations (1-5) are used to calculate the convolution layers [36]. Seven 2D convolutional layers are added using Conv2D in the model. Forward propagation calculates Z based on the input value ($X^{[k]}_{(i+r)(j+s)}$), weight value ($W^{[k]}_{rs}$), and $(p = i + r, q = j + s)$.

$$Z = \sum_{j=0}^{n} W^{[k]}_{rs} X^{[k]}_{(p)(q)} \tag{1}$$

$$Y^{[k]}_{ij} = \sum_{i=0}^{m} Z + b^{[k]} \tag{2}$$

Back Propagation: to calculate the error function (C) based on the predicted value $(Y^{[k]}_{ij})$ and actual value (Y_{act}).

$$C = (Y^{[k]}_{ij} - Y_{act})^2 \tag{3}$$

To calculate error function for weight $(\partial W^{[k]}_{rs})$.

$$\frac{\partial C}{\partial W^{[k]}_{rs}} = \sum_{i=0}^{p-m} \sum_{j=0}^{q-n} \frac{\partial C}{\partial Y^{[k]}_{ij}} \frac{\partial Y^{[k]}_{ij}}{\partial W^{[k]}_{rs}} \tag{4}$$

To calculate error function for bias $(\partial b^{[k]})$

$$\frac{\partial C}{\partial b^{[k]}} = \sum_{i=0}^{p-m} \sum_{j=0}^{q-n} \frac{\partial C}{\partial Y^{[k]}_{ij}} \frac{\partial Y^{[k]}_{ij}}{\partial b^{[k]}} \tag{5}$$

2) Pooling layer: When the feature in the image is too large, the convolutional lock employs the max pooling layer to minimize the feature map. The model uses seven max pooling layers. The three pooling layers - max, average, and sum pooling have the benefits of quick computing, limiting overfitting, and using little memory. Max pooling is applied here to determine the highest values from each region of the feature map using formulas 6 and 7. Seven 2D max pooling layers are added using MaxPooling2D in the model.

$$Y_{ij} = (0, X_{pq}) \tag{6}$$

$$\frac{\partial C}{\partial X_{pq}} = \frac{\partial C}{\partial Y^{[k]}_{ij}} \frac{\partial Y^{[k]}_{ij}}{\partial X_{pq}} \ldots\ldots \left\{ \begin{matrix} \frac{\partial C}{\partial Y^{[k]}_{ij}} & (Y^{[k]}_{ij} = X_{pq}) \\ 0 & otherwise \end{matrix} \right\} \tag{7}$$

3) Flatten: Following the application of the pooling layer, the complete matrix of generated feature maps is converted into a single volume using the flatten layer. The final fully connected neural network receives and classifies it.

4) Fully connected layer: Two fully connected layers are used after the flattening layer. The output of the previous layer is fed in the form of values to the last dense layer to decide which features mostly match a class. When calculating the product of the weights, a fully linked layer yields precise probabilities for the different paddy classes. The outputs are categorized using the softmax activation function.

5) Activation function: The softmax function $S(Z)_i$ [39] is utilized to predict the 13 classes shown in Equation (9). Additionally, the ReLU activation function [40] employed as depicted in Equation (8) provides demonstrably high accuracy with max pooling2D: $j = 1.....k$ and $z = (z_j...z_k)$.

$$ReLU(x) = (0, x) \tag{8}$$

$$S(Z)_i = \frac{e^{Z_i}}{\sum_{j=1}^{k} e^{Z_j}} \tag{9}$$

The proposed PaddyNet model architecture is shown in Fig. 4. The model has seven convolutional layers which include batch normalization, ReLU, max pooling2D layers, two dense connected layers, and a 13-way softmax activation in the output. In order to reduce data overfitting in each convolution block and the fully connected layer, a "dropout" method is used. The max pooling2D layer helps reduce the parameters used and surpasses average pooling in terms of performance. The Adam optimizer is used to reduce the loss as efficiently as possible and train the PaddyNet model in little time. The CNN model combines all the layers to obtain the highest accuracy. The novel model is trained and compared using several dropout values ranging from 0.2 to 0.8.

The biggest challenge of all in building the proposed PaddyNet model lay incombining all the layers, features, and optimizer values to offer excellent prediction performance. The novel model is tested by adding more layers, altering activation functions, and changing the optimizer values. While categorising 10 distinct categories, for instance, a basic 13-layer CNN model produced 88.84% accuracy. Next, the addition of an extra conv2D layer, maxpool2D, batch normalization, dropout, and activation to our 17-layer PaddyNet model resulted in 98.99% accuracy in identifying the 13 classes.

IV. Experimental Results

A. Experimental Setup

We implemented the proposed PaddyNet model using Keras and TensorFlow. All experiments were conducted on the Kaggle platform with GPU kernels to improve computational performance. The list of hyperparameters used in our experiments is shown in Table I. In addition, batch size values of 32, 64, 100, and 160 were used, along with a learning rate of 0.0001. The dropout was varied from 0.2 to 0.8, and the epoch values were 25, 50, 75, 100, 125, 150, 175, and 200. Additionally, the performance of the proposed PaddyNet model was compared to that of five models (the DCNN, Xception, MobileNet, ResNet34, and VGG16), using five performance metrics [41]. The weights of the models, except the DCNN, were initialized based on ImageNet.

B. Results and Discussion

Table II and Fig. 5 show that the PaddyNet model's scores for all measures increase proportionately with the epoch. Epoch 200 produced the highest performance in terms of 98.99% accuracy, 98.5% precision, 98.65% recall, and 98.2% F1 score, respectively. Table III and Fig. 6 compare the accuracy of the PaddyNet model to five existing models.

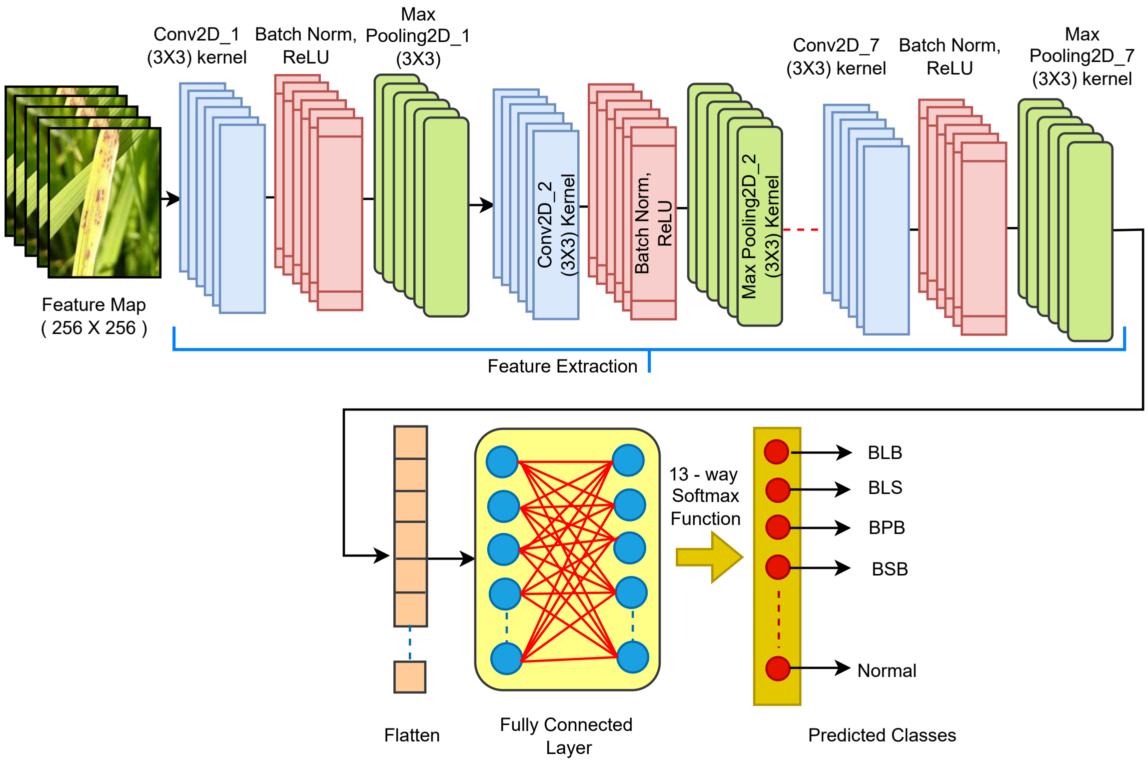


Fig. 4. PaddyNet model architecture.

TABLE I. List of Hyperparameters of the PaddyNet model

Parameters	Values
Batch Size	32, 64, 100, 160
Dropout	0.2 to 0.8
Epoch	25, 50, 75, 100, 125, 150, 175, 200
Learning Rate	0.0001
Optimizer	Adam

TABLE II. Comparison of Performance Metrics of PaddyNet Model with Different Epochs

Epoch	Accuracy	Precision	Recall	F1 Score
25	78.31	66.57	67.56	72.65
50	90.95	88.97	85.63	89.2
75	92.42	90.51	89.65	88.67
100	94.05	92.88	91.71	92.88
125	96.23	93.89	95.27	95.27
150	97.24	96.91	95.88	96.85
175	97.53	97.20	96.92	97.10
200	**98.99**	**98.50**	**98.65**	**98.2**

The PaddyNet model achieved the highest score, followed by Resnet34 [42][41], with 97.50% accuracy, 97.52% precision, 97.50% recall, and F1 score of 97.50%. The simple DCNN [42][41] model performed poorly with 88.84% accuracy, 89.22% precision, 88.84% recall, and 88.81% F score. Fig. 7 compares the performance of PaddyNet, based on five different dropout values (0.2, 0.4, 0.5, 0.6, and 0.8). The highest performance accuracy was achieved with a dropout probability of 0.4. Network weights were updated, firstly, to boost the accuracy of error estimation when training PaddyNet and, secondly, to improve efficiency. Fig. 8 compares the performance of different PaddyNet batch sizes in terms of accuracy.

Table IV and Fig. 10 show that the proposed PaddyNet model has the highest misclassification image count of 11 for the leaf blast disease class and the lowest of 1 for the BLS, BPB, yellow stem borer, and normal classes. When dealing with 13 paddy leaf disease classes, the complexity of the infected paddy images was likely to have confused the classifiers, leading to a diminished performance being displayed in the same class. A confusion matrix of the final test results is shown in Fig. 9.

When dealing with 13 classes of paddy leaf diseases, classifiers may be confused due to the complexity of infected paddy images, leading to a less performance are displayed in the same class. The final test results confusion-matrix for the paddy leaf classes is shown in Fig. 9, with correctly predicted values located along the diagonal and incorrectly predicted values located elsewhere. The confusion matrix indicates that the PaddyNet model is more successful at distinguishing certain paddy diseases, such as leaf blast, than others. The number of correctly identified test samples is 128 images in BLB, 99 images in BLS, 89 images in BPB, 94 images in black stem borer, 459 images in leaf blast, 244 images in brown spot, 168

TABLE III. ACCURACY COMPARISON OF OUR PROPOSED PADDYNET MODEL WITH EXISTING MODELS

S.No	Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	DCNN [41]	88.84	89.22	88.84	88.81
2	MobileNet [41]	92.42	92.63	92.42	92.39
3	VGG16 [41]	93.19	93.49	93.19	93.20
4	Xception [41]	96.58	96.61	96.58	96.57
5	Resnet34 [41]	97.50	97.52	97.50	97.50
6	**PaddyNet**	**98.99**	**98.50**	**98.65**	**98.2**

TABLE IV. MISCLASSIFICATION IMAGE COUNT FOR EACH CLASS OF PROPOSED PADDYNET MODEL

S.No.	Disease or class name	Count	PaddyNet	Resnet34	Xception	VGG16	MobileNet	DCNN
1	BLB	130	2	3	5	11	20	24
2	BLS	100	1	2	3	4	14	7
3	BPB	90	1	3	4	12	9	18
4	Black-Stem-Borer	101	7	9	9	13	10	10
5	Blast	470	11	13	13	30	27	57
6	Brown Spot	253	9	10	18	20	21	43
7	Downy-Mildew	174	6	8	8	15	19	27
8	Hispa	431	9	13	23	44	35	78
9	Leaf-Roller	219	3	4	19	35	45	33
10	Tungro	390	6	10	8	12	11	41
11	White-Stem-Borer	254	2	1	3	6	15	11
12	Yellow-Stem-Borer	152	1	2	1	4	10	6
13	Normal	481	1	3	7	15	10	7
	Total	3245	**59**	81	121	221	246	362

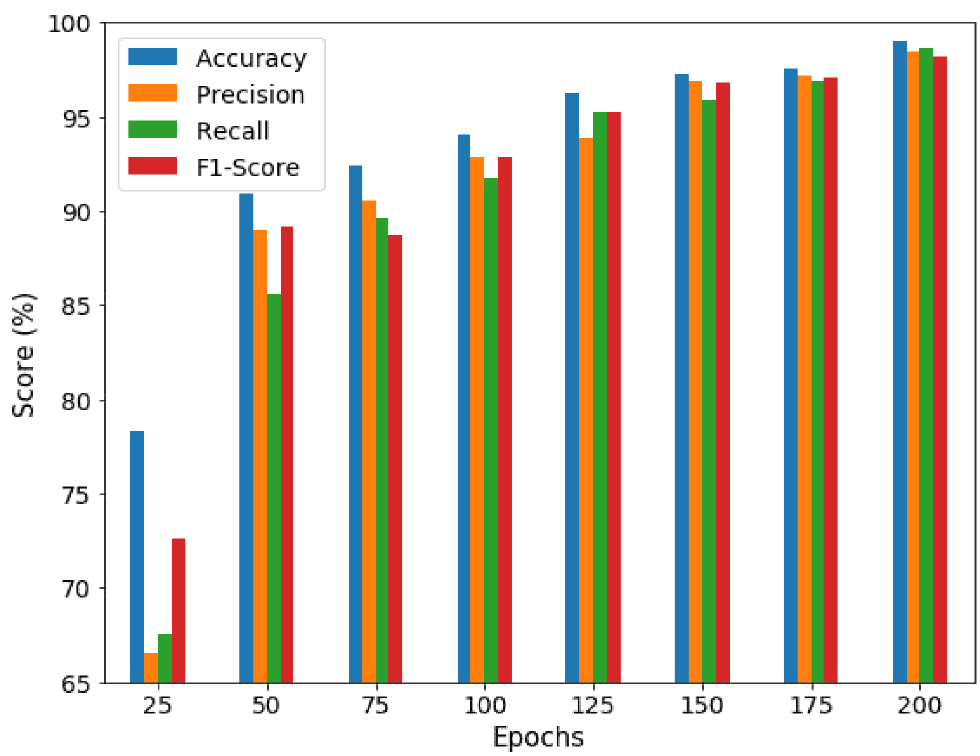


Fig. 5. Comparison of four performance metrics with different epoch. PaddyNet achieved the highest accuracy when using an epoch value of 200.

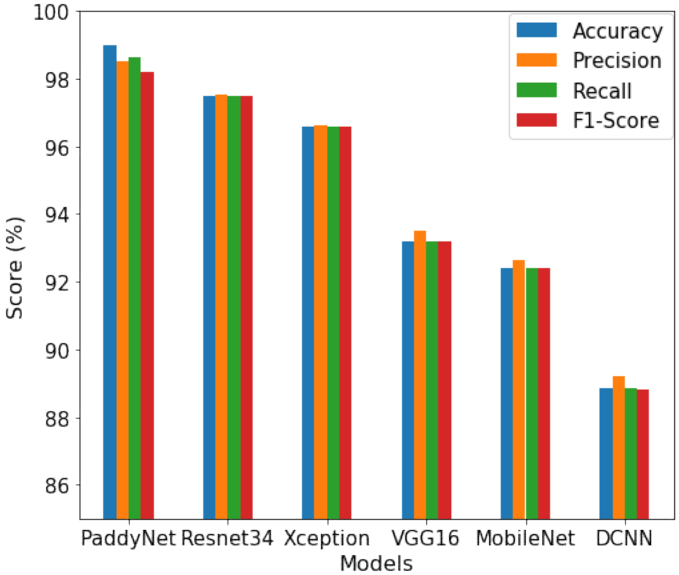


Fig. 6. Comparison of performance metrics of PaddyNet with five deep learning models.

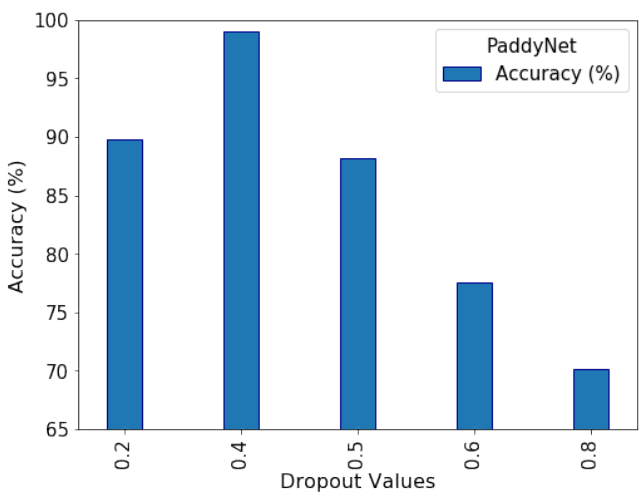


Fig. 7. Comparison of Accuracy of five dropout values used in our experiments. PaddyNet achieved the highest accuracy of 98.99% when the dropout is 0.4 and the lowest accuracy of 73.74% for dropout 0.8.

images in downy mildew, 422 images in hispa, 216 images in leaf roller, 384 in tungro, 252 images in white stem borer, 151 images in yellow stem borer, and 480 normal leaf images in the testing set, respectively. The count of incorrectly identified test samples is 2 images in BLB, 1 image in BLS, 1 image in BPB, 8 images in black stem borer, 11 images in blast, 9 images in brown spot, 6 images in downy mildew, 9 images in hispa, 3 images in leaf roller, 6 images in tungro, 2 images in white stem borer, 1 image in yellow stem borer, and 1 normal leaf image. According to Fig. 10 and 11, which exhibit the misclassification images for each class and their count for each model, the misclassification may have stemmed from the congruent feature similarities of the 13 classes. However, the remaining predicted values are well distinguished.

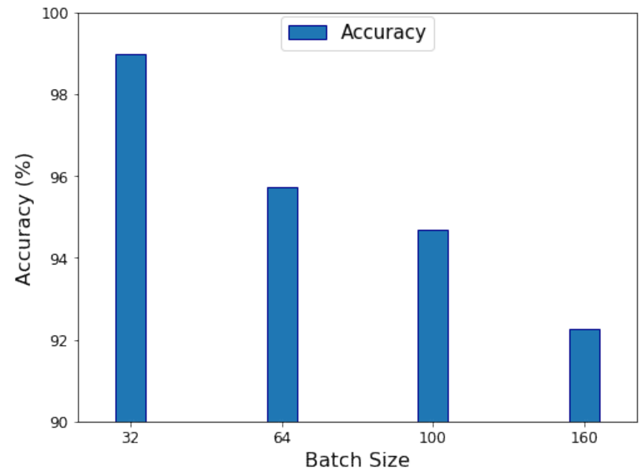


Fig. 8. Comparison of accuracy of PaddyNet using different batch size. PaddyNet achieved the highest accuracy of 98.98% when the batch size is 32.

	Bacterial leaf blight	Baterial leaf streak	Bacterial panicle blight	Black stem borer	Blast	Brown spot	Downy mildew	Hispa	Leaf roller	Normal	Tungro	White stem borer	Yellow stem borer
Bacterial leaf blight	128	0	0	0	0	0	1	0	0	0	1	0	0
Bacterial leaf streak	1	99	0	0	0	0	0	0	0	0	0	0	0
Bacterial panicle blight	0	0	89	0	0	0	0	0	0	0	0	1	0
Blact stem borer	0	0	0	94	0	0	0	0	0	0	0	1	7
Blast	1	1	0	0	459	0	2	2	1	0	4	0	0
Brown spot	0	5	0	0	0	244	3	0	1	0	0	0	0
Downy mildew	0	0	0	0	1	0	168	0	0	0	5	0	0
Hispa	4	0	0	0	3	0	0	422	1	0	1	0	0
Leaf roller	0	0	0	0	0	0	0	3	216	0	0	0	0
Normal	0	0	0	0	0	0	0	1	0	480	0	0	0
Tungro	0	0	0	0	2	0	4	0	0	0	384	0	0
White stem borer	0	0	0	1	0	0	0	0	0	0	0	252	1
Yellow Stem borer	0	0	0	0	0	0	0	0	0	0	0	1	151

Fig. 9. Confusion matrix of the PaddyNet model.

V. CONCLUSION

Deep learning, a fairly recent and advanced method driving agricultural growth and development, has demonstrated that it surpasses others at identifying plant disease. Advanced computer vision technology is prompting further research worldwide in paddy leaf disease identification using different methodologies. The PaddyNet model proposed in this research detects paddy leaf disease efficiently. The infected paddy leaf image dataset includes images of healthy leaves alongside images of leaves depicting twelve different diseases. The identification process of the proposed system was improved through the use of our own collection of previously acquired paddy leaf images. Further, the collected dataset was enhanced using several image augmentation techniques to enrich the model and benchmarked using the proposed PaddyNet model. The experimental results reveal that the proposed PaddyNet outperformed the other five deep learning models, such as the simple DCNN, VGG16, MobileNet, Xception, and Resnet34 [42][41]. The PaddyNet model demonstrated superior performance with 98.99% accuracy, 98.50% precision,

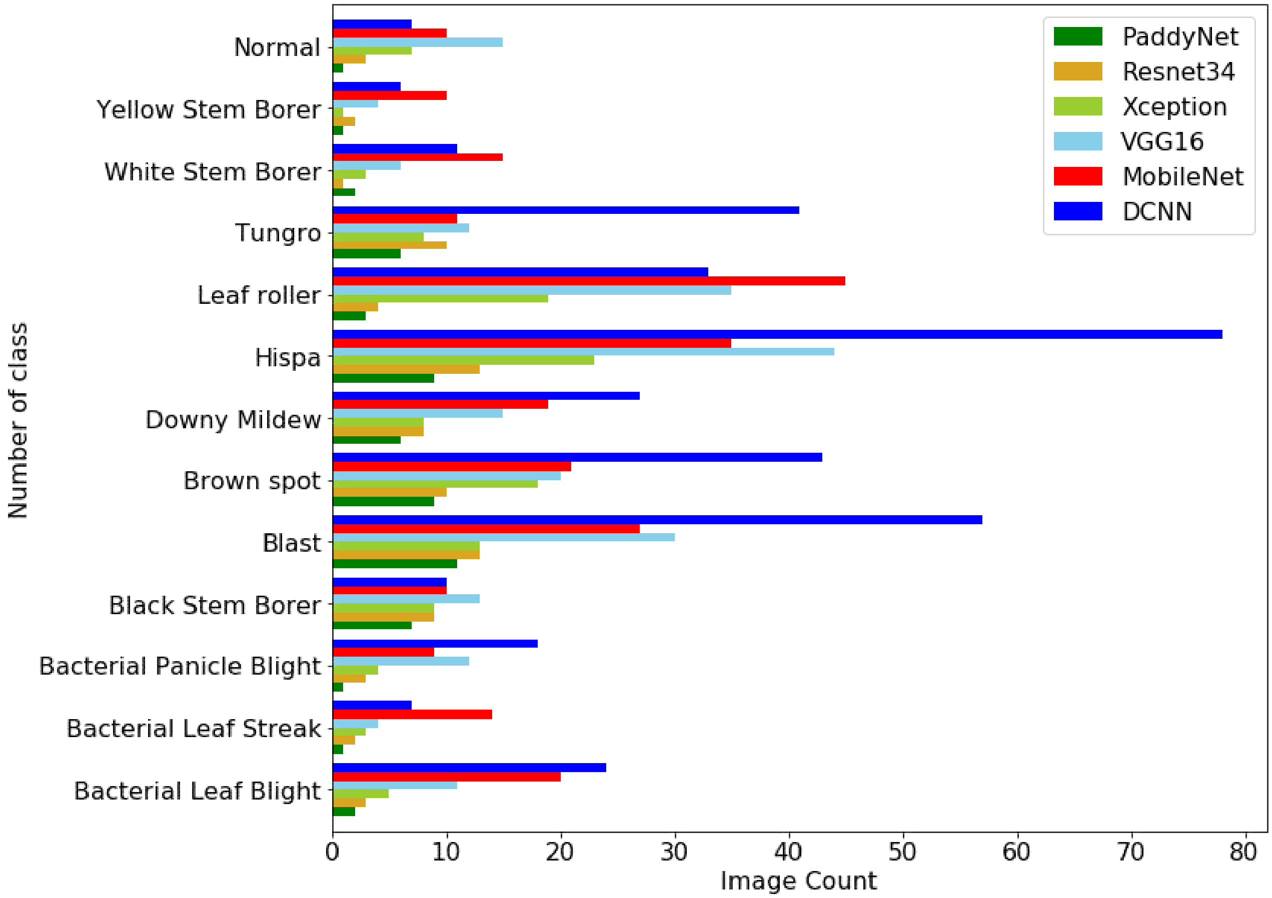


Fig. 10. Comparison of misclassification image counts for each class of PaddyNet and other five models.

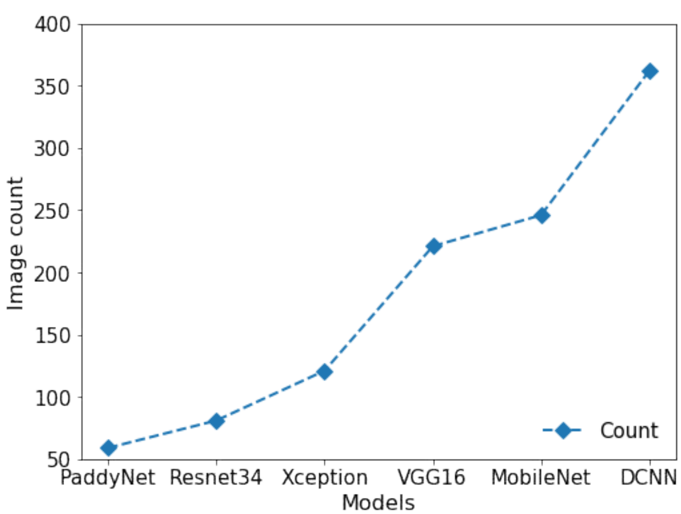


Fig. 11. Count of misclassification images for each model. In the PaddyNet model, only fewer images are not classified compared with the five models.

98.65% recall, and an F1 score of 98.20%, compared to the five state-of-the-art deep learning models. In the future, the proposed PaddyNet paradigm will be extended as a mobile phone application incorporating a deep learning model for using farmers in real-time in their paddy fields. Next, we plan to capture real-time images taken by farmers in their fields and identify leaf disease instantaneously through the said mobile app.

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