Deep Neural Networks-Based Recognition of Betel Plant Diseases by Leaf Image Classification

Rashidul Hasan Hridoy, Md. Tarek Habib, Md. Sadekur Rahman, and Mohammad Shorif Uddin

Abstract Diseases of the betel plant are a hindrance to healthy production which causes severe economic losses and is a major threat to the growing betel leaf industry. This paper introduces an efficient recognition approach based on deep neural networks to diagnose betel plant diseases rapidly to ensure the quality safety and healthy development of the betel leaf industry. A dataset of 10,662 betel leaf images is used for the generalization of deep learning models via the transfer learning technique. EfficientNet B5 has acquired 99.62% training, 98.84% recognition accuracy with 80 epochs. AlexNet, VGG16, ResNet50, Inception V3, and EfficientNet B0 have achieved 81.09%, 83.51%, 86.62%, 94.08%, and 97.29% test accuracy, respectively. During the training phase, AlexNet has taken less time compared to others and misclassified 195 images where EfficientNet B5 misclassified 12 images of the test set. The experimental results validate that the introduced architecture can accurately identify betel plant diseases.

Keywords Betel leaf · Betel plant disease · Leaf image classification · Deep neural networks · Convolutional neural network · Transfer learning

1 Introduction

Betel leaf (scientific name: *Piper betle*) is widely used as a mouth freshener in Southeast and Southern Asian countries which contains a significant number of nutrients and also is used as a home remedy for several types of diseases from

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ancient times. A remarkable number of farmers of Bangladesh, India, Malaysia, Indonesia, Philippines, Cambodia, Thailand, Vietnam, and Nepal are engaged with betel plant cultivation, which has a tremendous contribution to the agro-economy of Bangladesh [1]. Betel leaf has significant health benefits and is widely used in Ayurvedic medicines which is a great source of calcium and contains vitamins A and C, niacin, riboflavin, thiamine, iodine, etc. For many years, leaf of the betel plant is used as an anodyne which provides immediate remission from ache, removes radicals from the body as it is a powerhouse of antioxidants, helps the stomach by restoring normal pH levels of the body, and helps to improve digestion. Betel leaf reduces overall glucose level which is very essential for type 2 diabetes patients, lowers cholesterol levels to prevent stroke, and anti-cancer compounds fight against oral and colon cancers.

Leaf rot and foot rot are the most destructive fungal diseases of the betel plants which hindered the healthy production of betel leaf. Under high humidity conditions, leaf rot spreads rapidly within a short time through the air. Initially, in mature leaves near the soil, water-soaked spots are seen. The spots increase rapidly, and the elaborated spots are round-shape, brown, and necrotic with the clear gray-brown zone. In the rainy season, this disease affects most, and the syndromes can grow over any portion of the betel leaf along with margins and tips. However, foot rot destroys the roots of the betel plant, and within a week, 80–90% portion of plants become wilt and die, and in patches of betel plant, its symptoms are found most. Initially, dark-brown spots appear in the leaf; under high humid conditions, these spots become wet and rot, and sometimes with light brown zonations, necrotic spots are also found in leaves [2].

Convolutional neural networks (CNNs) have made significant breakthroughs in recent years in computer vision. Therefore, in agricultural information technology, CNN has become a research hotspot that is widely used to recognize various plant diseases, and still for pattern recognition tasks, CNN is deemed to be one of the optimal algorithms. In this paper, an efficient and rapid recognition approach is introduced using pre-trained deep neural networks to classify betel plant diseases accurately, and a dataset of 10,662 images of betel leaf is generated. To classify the diseases of the betel plant, pre-trained CNN models such as AlexNet, VGG16, ResNet50, Inception V3, EfficientNet B0, and B5 architecture were used via the transfer learning technique. EfficientNet B5 showed significantly better recognition ability compared to other deep neural networks and obtained 98.84% recognition accuracy, while another CNN model of the EfficientNet group has achieved 97.29% test accuracy.

The structure of this paper is as follows: The related works are present in Sect. 2. Section 3 presents the betel leaf dataset and describes CNN models. We describe experimental studies in Sect. 4. The results acquired and their interpretations are demonstrated in Sect. 5. Finally, the conclusion and plan of the future work are given in Sect. 6.

2 Related Works

A remarkable number of researchers have made significant attempts to identify various plant diseases to reduce the damage of diseases and enhance the quality of production. With significant continuous improvement in computer vision, machine learning and deep learning algorithms are extensively utilized for identifying plant diseases. To classify three diseases of betel leaf, Tamilsankar and Gunasekar used the minimum distance classifier, and the median filter was used in their research to alleviate noise and for enhancement of image quality [3]. For extracting the features of color, the CIELAB space model was used, watershed segmentation was used to remove background from images, and histogram of oriented gradients (HOG) technique was applied to obtain the value of gradient feature of betel leaf images. Jayanthi and Lalitha used HOG for extracting features, and the multiclass support vector machine (SVM) was used to classify diseases of betel leaf which achieved 95.85% accuracy [4]. For image preprocessing, median filter was used, and L*a*b color space model and watershed transformation algorithm were employed for image segmentation. To segment images of betel leaf, Dey et al. used an Otsu thresholding-based image processing algorithm [5]. Hue, saturation, value (HSV) color space was used to minimize the noise of images. To recognize affected or rotted leaves from healthy leaves, the color feature of images was used. Vijayakumar and Arumugam conducted two experiments to recognize powdery mildew disease of betel leaf, and red, green, blue (RGB) color elements were differentiated from two types of leaves using RGB encoding technique [6]. In the first experiment, mean values were computed for the front and back views of every element, and values of the median were computed in another experiment. For the segmentation of betel leaf images, Ramesh and Nirmala employed K-means clustering to classify betel leaf diseases, and color co-occurrence texture analysis was developed by implementing HSV in feature classification [7]. Sladojevic et al. used CaffeNet to recognize plant diseases that achieved 96.3% accuracy; image augmentation was shown a great influence on accuracy, but fine-tuning was not shown remarkable changes [8]. Using the OpenCV framework, images were resized for the purpose of their research, and for separate classes, the proposed approach achieved precision between 91 and 98%. Sabrol and Kumar used the gray-level co-occurrence matrix (GLCM) for computing features and proposed an adaptive neuro-fuzzy inference system (ANFIS)-based recognition model for detecting plant leaf disease that achieved overall 90.7% classification accuracy for tomato and for eggplant achieved overall 98% accuracy [9]. Four gray-level spatial dependence matrix properties have been submitted to ANFIS. For extracting features, Yadav et al. used AlexNet, and particle swarm optimization (PSO) was used to select features and optimization [10]. After analyzing the recognition performance of four classification algorithms, SVM was selected as a final classifier that achieved 97.39% accuracy. Khan et al. used VGG19 and VGGM for feature selection, then based on local standard deviation, local interquartile range method, and local entropy, the most prominent features were selected [11]. To check the performance of their proposed method, five affected leaves were tested and achieved 98.08% in 10.52 s. To classify three diseases of maize leaf, Priyadharshini et al. used modified LeNet architecture that achieved 97.89% accuracy [12]. Basavaiah and Arlene Anthony used the DT and RF classifier to classify four diseases of tomato leaf and achieved 90% and 94% accuracy, respectively [13]. To improve accuracy, the fusion of multiple features was used, and for training and testing purposes, the color histogram was extracted for color features, Hue moments were extracted shape features, and haralick was extracted texture features. Mokhlesur Rahman and Tarek Habib addressed an approach for classifying textile defects using a hybrid neural network and obtained 100% accuracy [14]. Tarek Habib et al. introduced a recognition approach for jackfruit diseases and acquired 89.59% accuracy using the RF classifier [15]. Jacob et al. addressed an artificial bee colony optimization algorithm with help of the breadth-first search for improving routing in wireless networks [16]. Chen et al. introduced a study for detecting coronary artery disease using SVM [17]. For fog-enabled IoT architecture, Mugunthan addressed an interference recognition approach based on DT [18].

Several computer vision-based approaches based on machine learning and deep learning algorithms were carried out for different leaf disease recognition. Though a few research work was conducted to classify diseases of betel plant, acquiring the expected efficient identification ability of the recognition approaches still remains a challenging task. Hence, in this paper, an efficient recognition approach using pre-trained CNNs is proposed for betel plant diseases.

3 Research Methodology

This study was conducted for developing a rapid and efficient recognition approach for betel plant diseases through leaf image classification. First, images of betel leaf were collected, then all images were resized into four different dimensions according to the input size of pre-trained CNN models. Afterward, CNNs have been trained via the transfer learning technique using images of the train and validation set of the dataset. Lastly, the performance of CNN models was evaluated with the test set, and based on the classification performance, a CNN architecture was proposed for betel plant disease recognition. The methodology diagram of this study is presented in Fig. 1.

3.1 Dataset

This study was conducted with a betel leaf dataset which contains four classes as leaf rot, foot rot, healthy, and miscellaneous, and 10,662 images of this dataset have been divided into 8600 training, 1031 validation, and 1031 test images randomly. Both training and validation images have been used to train and fit CNNs in this study, and test images were used to evaluate the recognition ability of state-of-the-art CNNs. Four representative images of the betel leaf dataset belonging to each class are shown in Fig. 2, and details on the used dataset of betel leaf images are presented in Table 1.

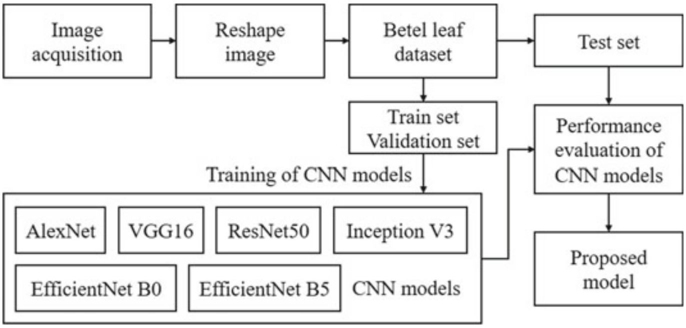

Fig. 1 Methodology for betel plant disease recognition

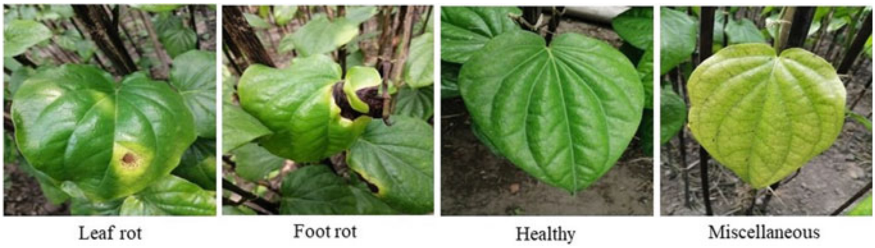

Fig. 2 Representative images of betel leaf dataset

Table 1 Summary of betel leaf dataset

Class	Training images	Validation images	Testing images
Leaf rot	2299	244	244
Foot rot	1680	210	210
Healthy	3529	441	441
Miscellaneous	1092	136	136

3.2 State-Of-The-Art CNN-Based Models

AlexNet, VGG16, ResNet50, Inception V3, EfficientNet B0, and EfficientNet B5 were used in this study to recognize diseases of the betel plants with the transfer learning approach.

The AlexNet architecture was introduced in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012 that follows LeNet-5 architecture [19]. It is basically an eight-layer CNN architecture, the input size of this architecture is 227 × 227 pixels, and the number of total parameters is approximately (approx.) 61 million (M). The architecture of AlexNet is built with five convolution layers followed by three fully connected layers (FC), and rectified linear unit (ReLU) is used in convolution and FC layers and finally the softmax layer.

In 2014, VGG16 won the ILSVRC, which is basically a 16-layer architecture, the number of total parameters is approx. 138 M, and the input image size of VGG16 is 224×224 pixels. This architecture contains five convolutional blocks and three FC layers, and ReLU is used as an activation function in these layers and the last with a Softmax activation function. Every convolution layer of VGG16 uses 3×3 filters, and the stride is fixed to 1. Each convolutional block contains one maximum polling layer that uses 2×2 filters, and stride is 2 [19].

In 2015, the architecture of ResNet50 won the ILSVRC 2015 which is built with stacked residual units, and the main building blocks of this architecture are residual units, consisting of convolution and pooling layers [20]. RsNet50 is a variant of ResNet architecture that was built with 48 convolutions along with 1 maxpool and 1 average pool layer and has over 23 M trainable parameters. The input image size of ResNet50 is 224×224 pixels.

Inception V3 architecture contains a total of 42 layers which is developed by Google and takes 299×299 pixels images in the input layer. In Inception V3, the idea of factorization was introduced to decrease parameters numbers and connections except decreasing the performance of the architecture [19]. It is built with symmetrical and asymmetrical building blocks which contain convolutions, average pooling, maximum polling, dropouts, and FC layers.

In the ImageNet classification problem, the EfficientNet model achieved 84.4% accuracy, containing 66 million parameters. The EfficientNet group consists of eight CNN models, and these are from B0 to B7. These architectures use Swish instead of ReLU which is a new activation function, and these models can achieve high accuracy with smaller models [21]. Using the transfer learning technique, EfficientNet B0 and B5 were used in this study. The last FC layer of these models was connected with four neurons to the softmax to output class probabilities of the used dataset. The schematic representation of EfficientNet B0 architecture is given in Fig. 3.

4 Experiment

With GPU support, state-of-the-art CNN models were trained, and several studies for examining the efficiency of models were conducted using Google Colaboratory that provides 12.72 GB RAM and 107.77 GB disk support. All codes were realized using an open-source framework of deep learning of Python 3, named Keras 2.6.0.

Images of the betel leaf dataset were divided into training, validation, and test sets randomly. For training and fitting deep learning models, 8600 images of the training set and 1031 images of the validation set were used. On the other hand, 1031 images of the test set that models did not see before were used for examining the recognition ability of CNN models.

To decrease the time required during the training phase of the CNN models, pre-trained weights of AlexNet, VGG16, ResNet50, Inception V3, EfficientNet B0 and

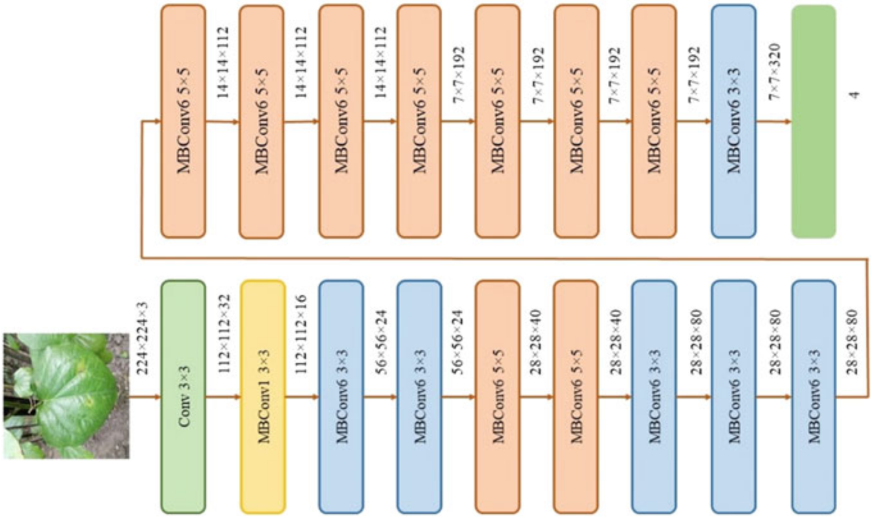

Fig. 3 Schematic representation of EfficientNet B0 architecture

B5 have been used via the transfer learning technique for the purpose of the study [21]. To recognize all classes of the betel leaf dataset, pre-trained CNN models have been fine-tuned that increases the speed of learning also. The last FC layer of CNNs with 1000 neurons was changed with four neurons, and all layers of CNNs have been set as trainable in accordance with our problem. Softmax was selected as the activation function of the last FC layer of CNNs, and categorical cross-entropy was selected as the loss function in this study. For avoiding the overfitting issue, the early stopping method has been utilized during the training phase of CNNs in this study. AlexNet, ResNet50, Inception V3, EfficientNet B0, and EfficientNet B5 were used with the Adam optimization method, and the VGG16 model is used with stochastic gradient descent (SGD) optimization method. For SGD, 0.01 learning rate was used, while for Adam, 0.001 was chosen, and for all models, the validation step was set to one. VGG16, ResNet50, and EfficientNet B0 used the same input size of the image, while AlexNet used 227 × 227 pixels images and EfficientNet B5 used the largest input size. By dividing each pixel value of images by 255, the images of the betel leaf dataset were normalized first in this study. During backpropagation, the mini-batch size 16 was applied for updating weights and bias, which is used to balance the rate of network convergence and accurate prediction during the learning process of CNNs. The input size, optimization method, learning rate, and parameters number which were used in the training phase are summarized in Table 2.

The multiclass classification was performed in this study as the betel leaf dataset contains four classes such as leaf rot, foot rot, healthy, and miscellaneous. The performance metrics given among Eqs. 1–8 were computed true positive (TP), true negative (TN), false positive (FP), and false negative (FN) by considering values in the confusion matrix acquired from multiclass classifications.

Table 2 Parameter values used for CNN models

Model name	Input size	Optimization method	Learning rate	Number of total parameters
AlexNet	227 × 227	Adam	0.001	25,724,476
VGG16	224 × 224	SGD	0.01	134,276,932
ResNet50	224 × 224	Adam	0.001	23,595,908
Inception V3	299 × 299	Adam	0.001	21,810,980
EfficientNet B0	224 × 224	Adam	0.001	5,334,575
EfficientNet B5	456 × 456	Adam	0.001	30,566,531

The performance of CNN models was discussed with help of different performance metrics such as sensitivity (Sen), specificity (Spe), accuracy (Acc), and precision (Pre). The proportion of accurately predicted positives is called sensitivity; out of all true positive predictions and out of all true negatives, the proportion of correctly classified negatives is called specificity. On the other hand, among all images, accuracy presents the proportion of accurately classified images. Out of all positive predictions, precision is the ratio of accurately classified positives [21]. For multiclass classification using macro-averaging, these metrics and their extended calculations are given below in among Eqs. 1–8.

For a class ci,

$$\mathrm{Sen(ci)} = \frac{\mathrm{TP(ci)}}{\mathrm{TP(ci)} + \mathrm{FN(ci)}} \tag{1}$$

$$\mathrm{Spe(ci)} = \frac{\mathrm{TN(ci)}}{\mathrm{TN(ci)} + \mathrm{FP(ci)}} \tag{2}$$

$$\mathrm{Acc(ci)} = \frac{\mathrm{TP(ci)} + \mathrm{TN(ci)}}{\mathrm{TP(ci)} + \mathrm{TN(ci)} + \mathrm{FP(ci)} + \mathrm{FN(ci)}} \tag{3}$$

$$\mathrm{Pre(ci)} = \frac{\mathrm{TP(ci)}}{\mathrm{TP(ci)} + \mathrm{FP(ci)}} \tag{4}$$

$$\mathrm{AverageSen} = \frac{1}{\mathrm{classes}} \sum_{n=1}^{\mathrm{classes}} \mathrm{Sen(ci)} \tag{5}$$

$$\mathrm{AverageSpe} = \frac{1}{\mathrm{classes}} \sum_{n=1}^{\mathrm{classes}} \mathrm{Spe(ci)} \tag{6}$$

$$\mathrm{AverageAcc} = \frac{1}{\mathrm{classes}} \sum_{n=1}^{\mathrm{classes}} \mathrm{Acc(ci)} \tag{7}$$

$$\mathrm{AveragePre} = \frac{1}{\mathrm{classes}} \sum_{n=1}^{\mathrm{classes}} \mathrm{Pre(ci)} \tag{8}$$

5 Result and Discussions

All CNN models were trained with transfer learning, and the main goal of this study is to evaluate the recognition ability of used CNNs such as AlexNet, VGG16, ResNet50, and Inception V3, EfficientNet B0, and EfficientNet B5 for betel plant disease recognition. The TP, TN, FP, FN values obtained by CNN models for each class of the betel leaf dataset are given in Table 3.

To evaluate the class-wise recognition ability of CNNs, the values of sensitivity, specificity, accuracy, and precision were used. The highest sensitivity 99.77% was achieved by EfficientNet B0 and B5 for healthy class, and considering sensitivity values, EfficientNet B5 performed better than others, ranging from 97.97 to 99.77%. EfficientNet B5 has achieved the highest specificity value 99.67% for the miscellaneous class, and it also has performed better than other CNN models considering

Table 3 TP, TN, FP, FN values were obtained by CNN models for each class of the test set

Model name	Class	TP	TN	FP	FN
AlexNet	Leaf rot	163	728	81	59
	Foot rot	172	741	38	80
	Healthy	398	573	43	17
	Miscellaneous	103	856	33	39
VGG16	Leaf rot	168	744	76	43
	Foot rot	179	761	31	60
	Healthy	405	573	36	17
	Miscellaneous	109	845	27	50
ResNet50	Leaf rot	176	755	68	32
	Foot rot	183	764	27	57
	Healthy	421	575	20	15
	Miscellaneous	113	861	23	34
Inception V3	Leaf rot	217	770	27	17
	Foot rot	189	798	21	23
	Healthy	438	580	3	10
	Miscellaneous	126	884	10	11
EfficientNet B0	Leaf rot	239	776	5	11
	Foot rot	202	810	8	11
	Healthy	432	589	9	1
	Miscellaneous	130	890	6	5
EfficientNet B5	Leaf rot	241	782	3	5
	Foot rot	206	817	4	4
	Healthy	439	589	2	1
	Miscellaneous	133	893	3	2

specificity values, ranging from 99.51 to 99.67%. Considering accuracy and precision values, EfficientNet B5 has shown the best performance, ranging from 99.22% to 99.71% and 97.79% to 99.55%, respectively. This model obtained more accuracy and precision value compared to others in the healthy class, 99.71%, and 99.55%, respectively. The class-wise recognition ability of EfficientNet B0 was very close to EfficientNet B5, and the recognition efficiency of EfficientNet B5 architecture for four classes of the test set is given in Table 4.

The average (Avg) sensitivity, specificity, accuracy, and precision values that were achieved by CNNs on the test set of the betel leaf dataset in this study are given in Table 5. The number of epochs is not the same for all deep learning models as early stopping was utilized to avoid overfitting during the training phase. By dividing the total time required in the training phase by the number of epochs, the time per epoch was calculated.

Table 4 Class-wise recognition performance of CNN models

Model name	Class	Sen (%)	Spe (%)	Acc (%)	Pre (%)
AlexNet	Leaf rot	73.42	89.99	86.42	66.8
	Foot rot	68.25	95.12	88.55	81.9
	Healthy	95.90	93.02	94.18	90.25
	Miscellaneous	72.54	96.29	93.02	75.74
VGG16	Leaf rot	79.62	90.73	88.46	68.85
	Foot rot	74.90	96.09	91.17	85.24
	Healthy	95.97	94.09	94.86	91.84
	Miscellaneous	68.55	96.90	92.53	80.15
ResNet50	Leaf rot	84.62	91.74	90.30	72.13
	Foot rot	76.25	96.59	91.85	87.14
	Healthy	96.56	96.64	96.61	95.46
	Miscellaneous	76.87	97.40	94.47	83.09
Inception V3	Leaf rot	92.74	96.61	95.73	88.93
	Foot rot	89.15	97.44	95.73	90.00
	Healthy	97.77	99.49	98.74	99.32
	Miscellaneous	91.97	98.88	97.96	92.65
EfficientNet B0	Leaf rot	95.60	99.36	98.45	97.95
	Foot rot	94.84	99.02	98.16	96.19
	Healthy	**99.77**	98.49	99.03	97.96
	Miscellaneous	96.30	99.33	98.93	95.59
EfficientNet B5	Leaf rot	**97.97**	**99.62**	**99.22**	**98.77**
	Foot rot	**98.10**	**99.51**	**99.22**	**98.10**
	Healthy	**99.77**	**99.66**	**99.71**	**99.55**
	Miscellaneous	**98.52**	**99.67**	**99.52**	**97.79**

The bold marked value represents the highest value of the performance metric.

Table 5 Average value of performance metrics for CNN models

Model name	Avg Sen (%)	Avg Spe (%)	Avg Acc (%)	Avg Pre (%)	Time per epoch (sec)
AlexNet	77.53	93.61	90.54	78.67	297
VGG16	79.76	94.45	91.76	81.52	1183
ResNet50	83.58	95.59	93.31	84.46	1527
Inception V3	92.91	98.11	97.04	92.73	1468
EfficientNet B0	96.63	99.05	98.64	96.92	391
EfficientNet B5	**98.59**	**99.62**	**99.42**	**98.55**	1352

The bold marked value represents the highest value of the performance metric.

EfficientNet B5 architecture showed the best performance in average sensitivity, specificity, accuracy, and precision. In Table 5, for the relevant performance criterion, values marked with bold are the best values obtained by EfficientNet B5. In this study, AlexNet consumed the lowest training time than other CNNs, and it took 297 s to complete one epoch. On the other hand, EfficientNet B5 took 30 h and 3 min to complete 80 epochs.

To demonstrate the recognition ability of CNNs more clearly, the number of total false predictions by CNN models for each class is discussed in this study and given in Table 6. AlexNet misclassified 81 samples of leaf rot class, which was the highest misclassification number. On the other hand, EfficientNet B5 wrongly classified 12 samples. EfficientNet B5 misclassified three samples of the leaf rot class and wrongly predicted two samples in the healthy class which was the lowest number of false classifications. The training and test accuracies acquired by CNN models are presented in Fig. 4.

Among pre-trained CNN models, two models of the EfficientNet group performed significantly better than others. EfficientNet B0 and B5 achieved 97.29% and 98.84% test accuracy, respectively. However, AlexNet obtained less training and test accuracy compared to others, 81.85%, and 81.09%, respectively. VGG16, ResNet50, and Inception V3 have achieved 83.51%, 86.62%, and 94.08% test accuracy, respectively. EfficientNet B5 showed significantly better recognition ability in all experimental

Table 6 Misclassification numbers of CNN models for each class

Model name	Leaf rot	Foot rot	Healthy	Miscellaneous	Total number
AlexNet	81	38	43	33	195
VGG16	76	31	36	27	170
ResNet50	68	27	20	23	138
Inception V3	27	21	3	10	61
EfficientNet B0	5	8	9	6	28
EfficientNet B5	**3**	**4**	**2**	**3**	**12**

The bold marked value represents the highest value of the performance metric.

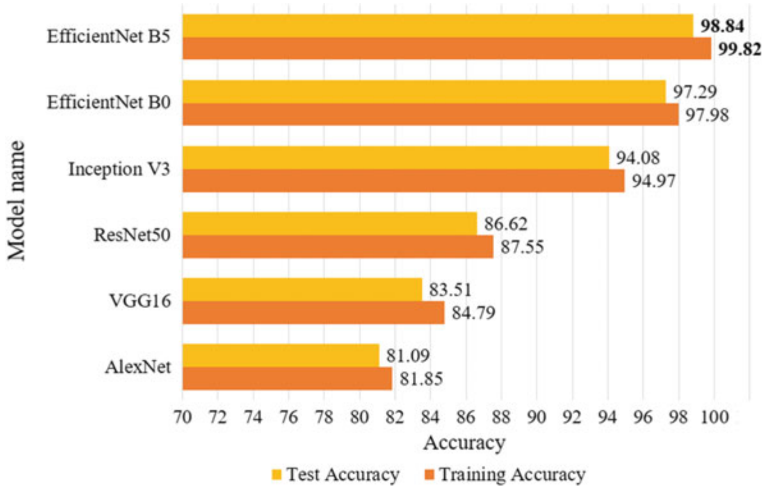

Fig. 4 Training and test accuracies of CNN models

studies compared to others in this study and achieved 99.62% training accuracy. After evaluating the results of all experimental studies, EfficientNet B5 architecture is proposed for the rapid and efficient identification of betel plant diseases in this study. The accuracy and loss curve of both training and validation of EfficientNet B5 is given in Figs. 5 and 6.

The success obtained in this study was compared with the result of other studies introduced in the literature to recognize betel plant disease and shown in Table 7. To the best of our knowledge, this is the first attempt for evaluating the performance of state-of-the-art CNN models for the recognition of betel plant disease.

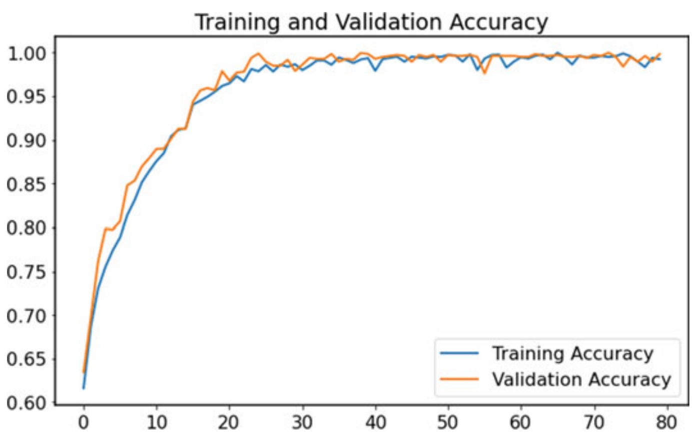

Fig. 5 Training and validation accuracy curve of EfficientNet B5

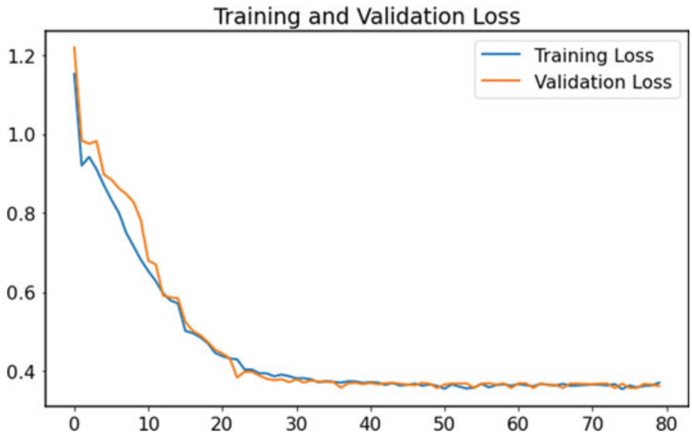

Fig. 6 Training and validation loss curve of EfficientNet B5

Table 7 Comparison of several methods for betel plant disease recognition

Study	Method	Number of class	Size of dataset	Accuracy
Tamilsankar and Gunasekar [3]	Minimum distance classifier	4	100	[a]*NM*
Jayanthi and lalitha [4]	Multiclass SVM	4	*NM*	95.85%
Dey et al. [5]	Image processing	1	12	*NM*
Vijayakumar and Arumugam [6]	Image processing	2	10	*NM*
Ramesh and Nirmala [7]	*K*-means clustering	*NM*	*NM*	*NM*
Our study	EfficientNet B5	4	10,662	**98.84%**

[a]*NM* not mentioned
The bold marked value represents the highest value of the performance metric.

6 Conclusion

Deep neural network-based recognition approaches brought significant improvement in image processing and pattern recognition-related tasks. To reduce the damage of betel plant diseases, this paper proposed an efficient and rapid recognition method using deep neural networks by classifying leaf images. After evaluating the performance of CNN models such as AlexNet, VGG16, ResNet50, Inception V3, EfficientNet B0, and EfficientNet B5, to classify four classes of the betel leaf dataset which contains 8600 training, 1031 validation, and 1031 testing images, EfficientNet B5 was proposed. Different experimental studies were introduced on the test set of the betel leaf dataset to compare the recognition ability of EfficientNet B5 with other pre-trained CNN models. According to the result of experimental studies, EfficientNet

B5 significantly performed better compared to others and obtained 99.62% training and 98.84% test accuracy with 80 epochs. Four different input image sizes such as 224×224, 227×227, 299×299, and 456×456 were used in the study. AlexNet consumed less training time compared to other CNN architectures and obtained less training and test accuracy compared to others, 81.85%, and 81.09%, respectively. During the training phase, EfficientNet B5 consumed 1352 s to complete one epoch. On the other hand, the performance of EfficentNet B0 was close to EfficentNet B5, but it took 391 s to complete one epoch during the training phase. VGG16, ResNet50, Inception V3, and EfficientNet B0 achieved 83.51%, 86.62, 94.08%, and 97.29% accuracy on the test set. According to the result of class-wise classification performance, EfficientNet B5 achieved 99.77% sensitivity in healthy class and 99.67% specificity in miscellaneous class, and in healthy class, it obtained 99.71% accuracy and 99.55% precision value. In addition, considering average sensitivity, specificity, accuracy, and precision values for each model, EfficientNet B5 showed significantly better recognition performance compared to other CNN models. According to the total number of false predictions, EfficientNet B5 misclassified 12 images of the test set. On the other hand, AlexNet, VGG16, ResNet50, Inception V3, and EfficientNet B0 wrongly predicted 195, 170, 138, 61, and 28 images, respectively. The success of this study demonstrates that the proposed EfficientNet B5 architecture realizes the end-to-end classification of betel plant diseases.

However, our addressed recognition approach can classify only two diseases of the betel plant. So, it is planned to improve the betel leaf dataset by increasing class number and images of betel leaf and develop a more efficient architecture for betel plant disease recognition with a fewer number of parameters in the future work. By deploying this model in smartphone environments, farmers will be able to classify diseases of the betel plant easily which is very crucial for preventing and controlling the diseases and reduce the use of pesticides which is a major threat to the environment.

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