An Early Recognition Approach for Okra Plant Diseases and Pests Classification Based on Deep Convolutional Neural Networks

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***Abstract*—The issue of effective plant disease and pest prevention is compactly connected to the issues of sustainable agronomics and climate change. Okra plant diseases and pests cause intense monetary losses to the growing okra industry, but their accurate and rapid identification remains troublesome due to the lack of efficient approaches. This paper addresses an early recognition approach for controlling the disease and pest spread to ensure quality production of okra. At first, a dataset of fifteen classes is generated from 12476 collected images using nine image augmentation techniques which contains 124760 images of okra plant diseases and pests. Afterwards, state-of-the-art deep learning models such as InceptionResNetV2, Xception, ResNet50, MobileNetV2, VGG16, and AlexNet were utilized with the transfer learning approach. InceptionResNetV2 showed significant performance compared to others, achieved 98.73% and 98.16% accuracy under the training set of 99808 images, and the test set of 6236 images of the used dataset, respectively.**

Keywords—Transfer Learning, Okra Leaf Diseases Recognition, Deep Learning, Okra Pest Recognition, Leaf Disease Classification, Convolutional Neural Network

I. INTRODUCTION

Early recognition of plant diseases and pests is crucial for sustainable development in the agricultural sector, as well as for reducing severe financial loss and preventing waste of essential resources. Okra (scientific name: *Abelmoschus esculentus*) is an important vegetable grain that has high demand in markets for its significant health benefits and is widely cultivated in the Southern Asian regions [1]. However, different types of diseases and pests have hindered the healthy production of this significant plant. Yellow vein mosaic, powdery mildew, enation leaf curl, leaf spot, fruit rot, shoot and fruit borer, red cotton bug, aphid, blister beetle, brown marmorated stink bug, whitefly, and mealybugs are thirteen common diseases and pests of the okra plant. Hence, the automated early diagnosis of okra plant diseases and pests is essential to reduce the economic loss and ensure the quality and nutrition factor of okra.

Existing approaches used for diagnosing diseases and pests are laborious and time-consuming tasks that mainly use visual identification. Due to the lack of efficient recognition approaches, pesticides are broadly used for controlling diseases and pests during cultivation which is a major threat to the quality and nutrition factor of okra. Besides visual recognition, several spectroscopy approaches are also used for the diagnosis but these techniques are built with different types of sensors, which makes it quite difficult to follow for ordinary users [9] [10]. With the continuous improvement of computer vision approaches, researchers have introduced some recognition techniques using machine learning algorithms, where the performance of proposed approaches still couldn't satisfy the requirement of recognition, as these approaches use classification features based on the human experience [2] [6]. Recently, deep learning is being widely used in segmentation, and classification tasks, and has proven itself to be a crucial tool in the field of image processing because of its ability of automatic feature extraction from images [5] [7] [8]. Moreover, deep learning approaches have shown the significant ability of generalization to solve intricate problems compared to traditional techniques in computer vision. Convolution neural network (CNN) has shown significant success in several imaging domains and provided continuous improvement in respect of accuracy and efficiency [3].

To diagnose diseases and pests of the okra plant, pre-trained CNN models such as InceptionResNetV2, Xception, ResNet50, MobileNetV2, VGG16, and AlexNet were used with the transfer learning technique and all layers of CNNs were set to be trainable. An okra plant diseases and pests dataset, namely, the okra dataset, is established for the generalization of CNNs. The okra dataset is generated from 12476 collected images using nine image augmentation techniques. All images of the okra dataset contain uniform and complex backgrounds where early recognition means that the symptoms of diseases and pests of the okra plant can be identified early up to 4 days after the initial infection. Several experimental studies were introduced in this study for evaluating the recognition ability of CNN models.

According to the result of experimental studies, the recognition accuracy of InceptionResNetV2 reaches 98.16% under the hold-out test set of the okra dataset, which is higher than other CNNs. In this study, Xception, ResNet50, MoblieNetV2, VGG16, and AlexNet achieved 94.82%, 90.83%, 87.93%, 87.01%, and 82.35% test accuracy, respectively, and the major contributions of this study are summarized as follows:

- Since no appropriate dataset is available till now, an enhanced dataset of 124760 images is generated for early recognition of diseases and pests of the okra plant.
- InceptionResNetV2 is proposed for recognizing diseases and pests of the okra plant at an early stage after evaluating the recognition ability CNN models using several experimental studies with 6236 test images of the okra dataset.

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- To the best of our knowledge, this is the first attempt to develop an early recognition approach for okra plant diseases and pests based on deep convolutional neural networks.

The structure of this paper is as follows: Section 2 presents related works. Section 3 describes the okra dataset and CNN models used in this study. We have described experimental studies in Section 4. The results acquired and their interpretations are demonstrated in Section 5. Lastly, the conclusion and future work are presented in Section 6.

II. Related Works

For decreasing the damage of diseases and pests in agriculture, many researchers have made significant efforts to recognize diseases and pests of plants and proposed several computer vision approaches to solve this crucial issue based on machine learning and deep learning algorithms.

Dhiman Mondal et al. used the naive Bayes (NB) for detecting and classifying the yellow vein mosaic virus disease in leaf images of okra and achieved 87% accuracy with ten features [2]. Norhalina Senan et al. proposed a classification approach for paddy leaf disease and pest using CNN, and the recognition efficiency of the proposed CNN architecture was compared with artificial neural network (ANN), standard multi-layered perceptron (MLP), and support vector machine (SVM) [3]. In their study, ANN, MLP, SVM, and CNN achieved 82.60%, 81.12%, 81.45%, and 96.60% test accuracy, respectively. Divyansh Tiwari et al. proposed a detection approach for potato leaf disease and used VGG16, VGG19, and InceptionV3 for feature extraction from images of potato leaves [4]. In their study, k-nearest neighbors (k-NN), SVM, neural network (NN), and logistic regression (LR) were used for classification and they achieved 97.8% test accuracy using VGG19 with LR. Aravind Krishnaswamy Rangarajan et al. proposed a classification approach for tomato diseases using AlexNet and VGG16 and achieved 97.49% and 97.29% accuracy, respectively [5]. Jagadeesh Basavaiah et al. used decision tree (DT) and random forest (RF) to classify diseases of tomato leaves with the fusion of different features such as color histograms, Hu moments, haralick, and local binary pattern [6]. In their research, they achieved 90% and 94% classification accuracy using DT and RF, respectively. Tuan T. Nguyen et al. used eight architectures of the EfficientNet group from Bo to B7 with the transfer learning approach to classify pests [7]. In their research, EfficientNet B3 acquired the highest accuracy, precision, and F1-score value, 95.52%, 95.49%, and 95.54%, respectively. Everton et al. proposed a classification approach for soybean pests using InceptionV3, Resnet50, VGG16, VGG19, and Xception model, and Resnet50 achieved 93.82% accuracy which was higher than other CNNs [8]. In their research, simple linear iterative clustering (SLIC) was used for segmenting images of pests, the performance of machine learning algorithms such as SVM, RF, J48, NB, k-NN, and AdaBoost was also evaluated, and SVM performed better than others, achieved 60.46% accuracy. Gustavo E. A. P. A. Batista et al. proposed an inexpensive optical sensor-based classification approach for flying insects using NB and k-NN classifiers [9]. In their research, NB and k-NN achieved 93.18% and 91.80% accuracy with the circadian and wing-beat features, respectively, and 90.73% and 91.30% accuracy with the wing-beat frequency, respectively. Monalisa Mishra et al. introduced a detection approach based on the internet of things (IoT) and proposed the sine cosine algorithm-based rider neural network (SCA-based RideNN) classifier for plant diseases [10]. In their research, the recognition efficiency of the proposed classifier was compared with k-NN, CNN, and NN classifiers, and SCA-based RideNN achieved 91.56% accuracy, while k-NN, CNN, and NN achieved 84.82%, 89.53%, and 91.18% accuracy, respectively.

According to these studies, CNN models with transfer learning techniques achieved significant results in recognizing diseases and pests of several plants. However, CNN is rarely utilized to recognize okra plant diseases and pests. Hence, an early recognition approach for okra plant diseases and pests is addressed in this paper based on CNNs.

III. Materials and Methods

A. Okra Dataset

We devoted huge amount of time to collect 12476 images of diseases and pests of the okra plant from crop fields precisely. After utilizing image augmentation techniques, the number of total images is increased to 124760, and all images are divided into training, validation, and test images randomly by 80%, 15%, and 5%, respectively. Fig. 1 presents 15 different images of the okra dataset.

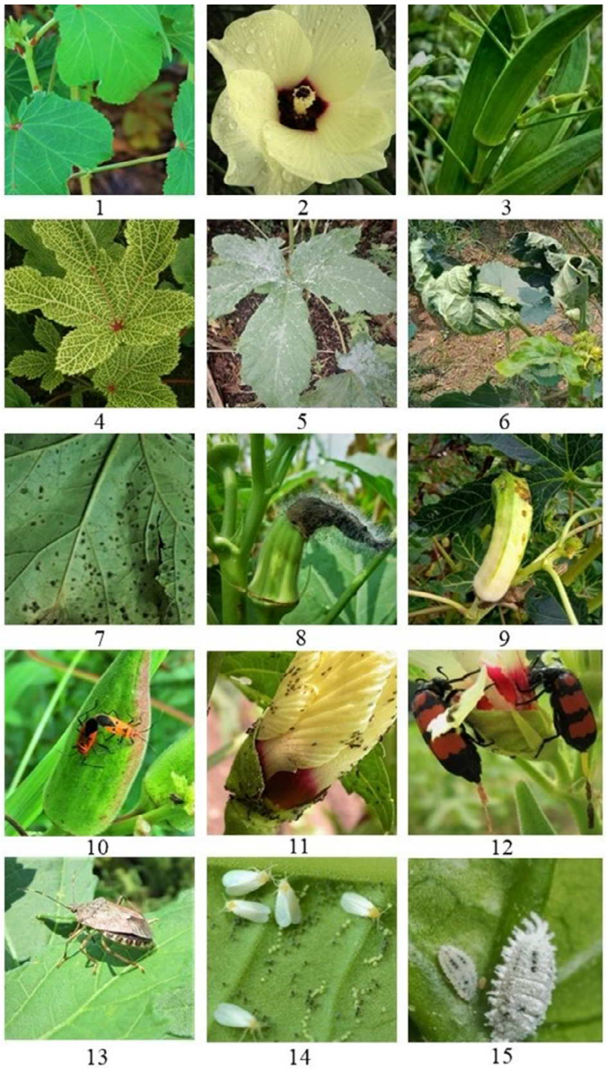

Fig. 1. Sample from okra dataset: 1) healthy leaf 2) healthy flower 3) healthy fruit 4) yellow vein mosaic 5) powdery mildew 6) enation leaf curl 7) leaf spot 8) fruit rot 9) shoot and fruit borer 10) red cotton bug 11) aphid 12) blister beetle13) brown marmorated stink bug 14) whitefly 15) mealybugs.

A large number of training images help CNNs to enhance the ability of anti-interference under complex conditions and avoid the overfitting issue during the training stage. In deep learning-based recognition approaches, several image augmentation techniques were widely utilized for enhancing the recognition performance of CNNs with fewer images [11]. Nine image augmentation techniques such as high brightness, low brightness, cropping, horizontal flip, 90-degree rotation, 180-degree rotation, 270-degree rotation, high contrast, and low contrast were used in this study to generate 112284 images from 12476 collected images. The training, validation, and test set of the okra dataset contains 99808, 18716, and 6236 images, and Fig. 2 illustrates the process of image generation.

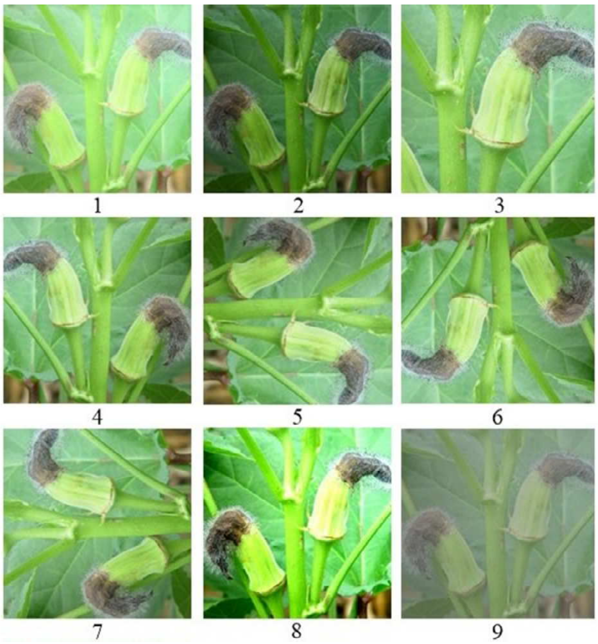

Fig. 2. Image generation process using image augmentation: 1) high brightness, 2) low brightness, 3) cropping, 4) horizontal flip, 5) 90-degree rotation, 6) 180-degree rotation, 7) 270-degree rotation, 8) high contrast, and 9) low contrast.

B. *State of the art CNN based models*

To recognize diseases and pests of the okra plant efficiently at an early stage, six deep convolutional neural networks such as InceptionResNetV2, Xception, ResNet50, MobileNetV2, VGG16, and AlexNet were used in this study via transfer learning technique.

InceptionResNetV2 is 164 layers deep CNN architecture which is a variation of Inception V3 architecture and the input size of this network is 299×299 pixels [12]. Residual connections enable this network to perform better and also enabled significant simplification of the Inception blocks. This costlier hybrid version of Inception remarkably enhanced the recognition performance and performs more accurately than previous pre-trained CNN models such as InceptionV3 and ResNet152. For decreasing the dimension of the presentation, each hybrid Inception ResNet module of this network is being followed by a reduction module.

Xception is 71 layers deep CNN architecture which takes 299×299 pixels images as input [12]. It mainly relies on two things firstly, depthwise separable convolution, and secondly, shortcuts between convolution blocks like ResNet. Also, interpretation of Inception modules in CNN is presented in this architecture. The data in this architecture at first goes into the entry flow, then the middle flow, where it repeats the journey eight times and lastly goes through the exit flow.

ResNet50 contains 48 convolution layers along with one max pooling layer and one average pooling layer which is a variant of the ResNet model and takes 224×224 pixels images as input [13]. This architecture is based on the stack of many residual units and won the ILSVRC-2015.

For object segmentation and detection, MobileNetV2 extracts feature very effectively, where the structure of it uses depthwise separable convolution layers as efficient building blocks. [12]. It introduces two new features such as linear bottlenecks between the layers, and shortcut connections between the bottlenecks, and takes 224×224 pixels images as input.

The architecture of VGG16 is built with five convolution blocks, among these blocks, the first two blocks have two convolution layers, the latter has three convolution layers, then two fully connected (FC) hidden layers with 4096 outputs, and one FC layer with 1000 outputs [14]. This architecture takes 224×224 images as input and won ILSVRC-2014 with approximately 138 million parameters. VGG16 always uses the same convolution layers with 3×3 filters and max-pooling layers with 2×2 filters.

The input size of AlexNet is 227×227 pixels and was introduced in ImageNet Large Scale Visual Recognition Challenge (ILSVRC-2012) with approximately 61 million parameters [14]. The architecture of AlexNet is built with five convolution layers, two FC hidden layers with 4096 outputs, and one FC output layer, and it uses ReLU as an activation function in convolution and FC layers.

C. *Transfer Learning*

Transfer learning is an effective and powerful strategy to develop efficient deep learning models using fewer images which significantly increases the recognition performance of architecture and decreases the training time. The construction of fine-tuning CNNs is shown below in Fig. 3.

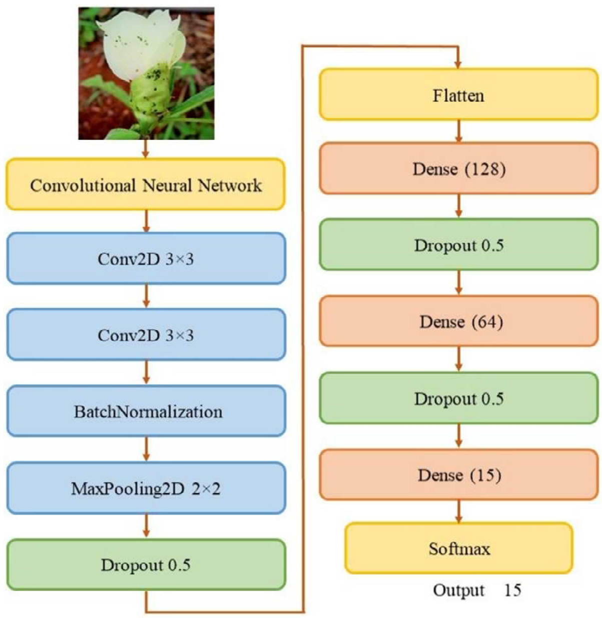

Fig. 3. The construction of fine-tuning CNNs used in this study.

These fine-tuned CNNs were employed for both feature extraction and classification tasks. These architectures except AlexNet consist of pre-trained models followed by two convolution layers, a batch normalization layer, a max-pooling layer, a dropout layer, a flatten layer, a dense layer with 128 neurons, a dropout layer, a dense layer with 64 neurons, a dropout layer and lastly a dense layer with 15 neurons and the Softmax activation function to classify images of diseases and pests. During the training phase of AlexNet, the last FC layer of this architecture is connected to the Softmax with 15 neurons.

IV. EXPERIMENTS

A. *Training*

All images of the okra dataset were resized into three different sizes such as 299×299, 224×224, and 227×227 pixels. Images of training, validation sets were used in this study for training and fitting of CNNs, and the test set of the okra dataset was used to evaluate the performances of CNNs using several experimental studies. During the training phase of pre-trained models, the early stopping technique is used to monitor generalization error and avoid the overfitting issue. Here, categorical cross-entropy is used as a loss function. The default input size, number of epochs, and parameters number of CNN models are given below in Table 1.

TABLE I. THE DEFAULT INPUT SIZE, NUMBER OF EPOCHS, AND NUMBER OF PARAMETERS OF MODELS

Model Name	Input Size	Number of Epochs	Parameters Number
InceptionResNetV2	299×299	32	62,080,507
Xception	299×299	39	31,046,467
ResNet50	224×224	28	33,641,627
MobileNetV2	224×224	31	8,772,955
VGG16	224×224	27	17,690,715
AlexNet	227×227	37	28,878,127

B. *Performance Metrics*

The multiclass classification was utilized in this study to recognize images of 15 classes of the okra dataset. Equations from (1) to (4) were calculated by using indices such as true positive, true negative, false positive, and false negative, where values of these indices were acquired from the confusion matrix of multi-class classifications. Here, true positive (TP) is the sum of correctly predicted images in each class of the okra dataset, and true negative (TN) is the sum of accurately classified images without the relevant class. On the other hand, false-positive (FP) is the sum of wrongly classified images in other classes without the relevant class, and false-negative (FN) is the number of wrongly classified images in the relevant class. The recognition performance of state-of-the-art CNN models was evaluated and discussed in this study based on several performance metrics such as sensitivity, specificity, accuracy, and precision. Sensitivity (sen) is the proportion of accurately classified positives out of all true positives, and specificity (spe) is the proportion of accurately classified negatives out of all true negatives. Accuracy (acc) represents the ratio of accurately predicted images out of all images and precision (pre) is the ratio of accurately classified positives out of all positive classifications [14].

For a class *wi*,

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

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

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

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

V. RESULTS AND DISCUSSIONS

This study aims to evaluate the recognition efficiency of pre-trained CNN models for early recognition of diseases and pests of the okra plant, and CNN models such as InceptionResNetV2, Xception, ResNet50, MobileNetV2, VGG16, and AlexNet were compiled with the okra dataset via transfer learning approach. In this context, the accuracy of training and test acquired by all models on the training and test set of the used okra dataset was given below in Fig. 4. In this study, test accuracies were measured using the proportion of the total number of accurately predicted images to the number of total images of the test set of the okra dataset. According to training and test accuracies, InceptionResNetV2 performed more effective performance than others and achieved 98.73% training and 98.16% test accuracy.

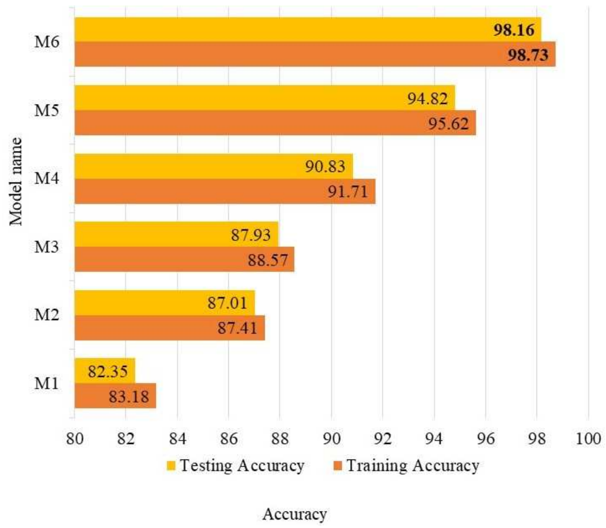

Fig. 4. Training and Test accuracies of pre-trained CNN models: M1) AlexNet, 2) VGG16, 3) MobileNetV2, 4) ResNet50, 5) Xception 6) InceptionResNetV2.

In this study, AlexNet misclassified 1101 images, while InceptionResNetV2 misclassified only115 images of the test set, and other CNNs such as VGG16, MobileNetV2, ResNet50, and Xception wrongly predicted 810, 753, 572, and 323 images. The recognition time of each pre-trained CNN model is also evaluated using 15 images of diseases and pests of the okra plant which are not in the okra dataset. InceptionResNetV2 accurately predicted all images and consumed 9.8 seconds for performing recognition. Xception consumed 14.2 seconds and obtained 86.67% accuracy. On the other hand, ResNet50, MobileNetV2, VGG16, and

AlexNet architecture consumed 16.2, 14.9, 14.3, and 19.5 seconds. Finally, InceptionResNetV2 is proposed for efficient recognition of diseases and pests of the okra plant at an early stage based on the outcome of these mentioned experimental studies, the confusion matrix of InceptionResNetV2 is given in Fig. 5.

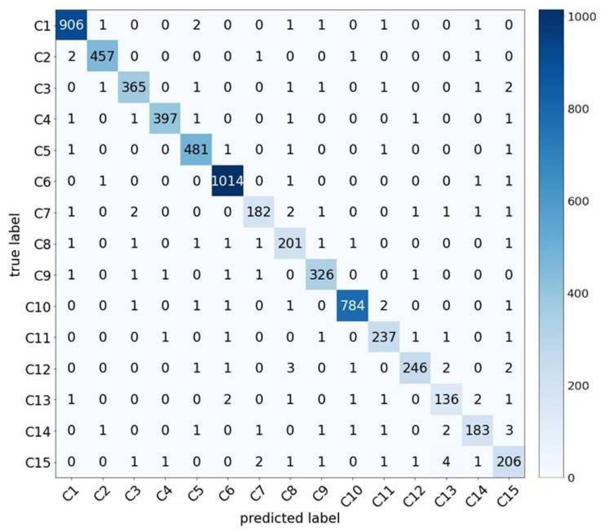

Fig. 5. Confusion matrix of InceptionResNetV2: C1) healthy leaf C2) yellow vein mosaic C3) powdery mildew C4) enation leaf curl C5) leaf spot C6) healthy fruit C7) fruit rot C8) shoot and fruit borer C9) red cotton bug C10) healthy flower C11) aphid C12) blister beetle C13) brown marmorated stink bug C14) whitefly C15) mealybugs.

In order to illustrate more perceptibly the recognition ability of InceptionResNetV2 architecture proposed in this study for early recognition of diseases and pests of the okra plant, the class-wise classification performance of InceptionResNetV2 for all classes of the okra dataset is evaluated using sensitivity, specificity, accuracy, and precision metrics, and given in Table 2.

TABLE II. CLASSIFICATION PERFORMANCE OF INCEPTIONRESNETV2 FOR EACH CLASS

Class Name	Sen (%)	Spe (%)	Acc (%)	Pre (%)
Healthy leaf	99.12	99.87	99.76	99.23
Yellow vein mosaic	99.13	99.91	**99.86**	98.92
Powdery mildew	98.12	99.86	99.76	97.86
Enation leaf curl	99.25	99.90	**99.86**	98.51
Leaf spot	98.36	99.91	99.79	98.97
Healthy fruit	99.22	**99.92**	99.81	**99.61**
Fruit rot	96.81	99.83	99.74	94.79
Shoot and fruit borer	93.93	99.87	99.66	96.17
Red cotton bug	97.90	99.90	99.79	98.19
Healthy flower	**99.37**	99.87	99.81	99.12
Aphid	96.73	99.90	99.78	97.53
Blister beetle	98.01	99.83	99.76	96.09
Brown marmorated stink bug	93.15	99.85	99.70	93.79
Whitefly	95.81	99.82	99.70	94.33
Mealybugs	93.21	99.78	99.55	94.06

According to the result of class-wise classification, InceptionResNetV2 achieved the highest sensitivity in the healthy flower class, while the sensitivity value of the brown marmorated stink bug class was less than others, 99.42%, and 93.15%, respectively. On the other hand, the specificity of the healthy fruit class was higher compared to others, 99.92%. In addition, InceptionResNetV2 achieved the highest accuracy in yellow vein mosaic and enation leaf curl classes, 99.86%. In the healthy fruit class, InceptionResNetV2 achieved the highest precision, where precision of brown marmorated stink bug class less was than other classes, 99.61%, and 93.79%, respectively. Class-wise classification performance validates the recognition ability of the proposed CNN architecture. According to the number of false predictions, InceptionResNetV2 showed significant performance in recognizing images of yellow vein mosaic and leaf spot classes, misclassified 5 images. It misclassified 13 images of mealybugs which was the highest number of false prediction. The misclassification numbers of the proposed CNN model for all classes are given in Fig. 6.

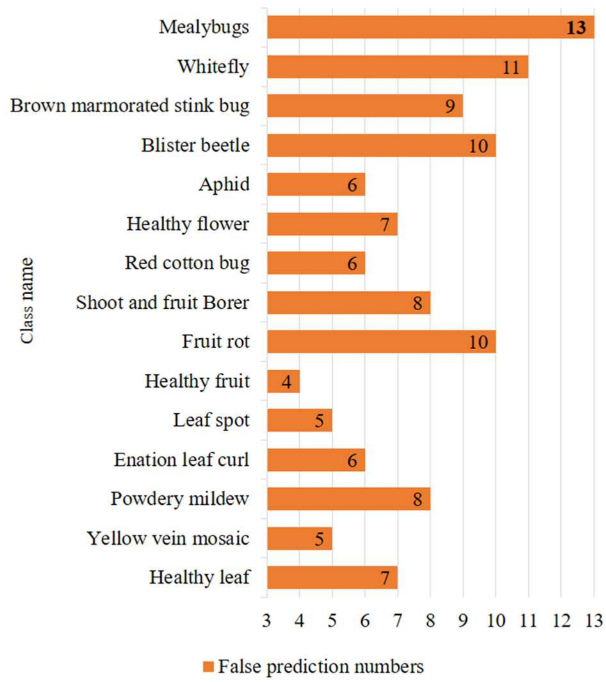

Fig. 6. The misclassification numbers of InceptionResNetV2 for each class.

The accuracy and loss curve of both training and validation of the InceptionResNetV2 model is given below in Fig. 7 and Fig. 8.

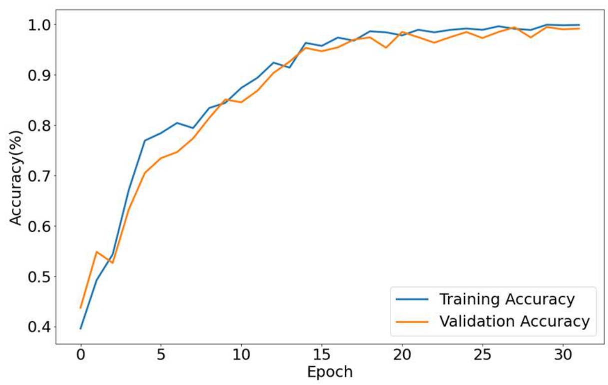

Fig. 7. Training and validation accuracy curve of InceptionResNetV2.

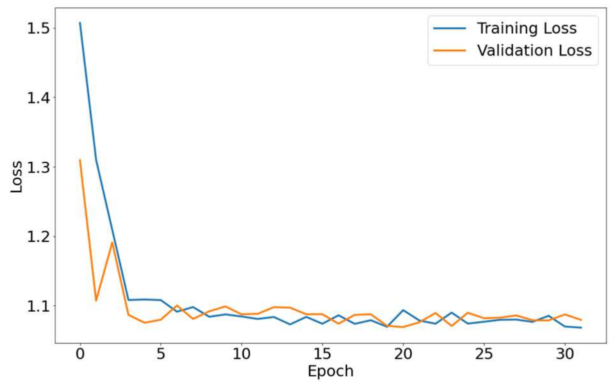

Fig. 8. Training and validation loss curve of InceptionResNetV2.

Our addressed approach can be applied to other crop diseases and pests recognition. The success obtained in this study in recognizing diseases and pests of the okra plant at an early stage using InceptionResNetV2 architecture was compared with related studies that were introduced for recognizing diseases and pests of other crops in the literature and is presented below in Table 3.

TABLE III. COMPARISON OF SEVERAL STUDIES FOR CROP DISEASE AND PEST RECOGNITION

Study	**Method**	**Number of Classes**	**Accuracy**
Dhiman Mondal et al. [2]	NB	4	87.00%
Norhalina Senan et al. [3]	CNN	4	96.60%
Divyansh Tiwari et al. [4]	VGG19	3	97.80%
Rangarajan et al. [5]	AlexNet	7	97.49%
Jagadeesh Basavaiah et al. [6]	RF	5	94.00%
Tuan T. Nguyen et al. [7]	EfficientNet-B3	5	95.52%
Everton et al. [8]	Resnet50	13	93.82%
Our study	InceptionResNetV2	**15**	**98.16%**

VI. CONCLUSION

This paper proposed an efficient computer vision approach to recognize diseases and pests of the okra plant at an early stage using InceptionResNetV2 architecture, and the result of several experimental studies conducted on the test set of the okra dataset demonstrates its effectiveness. A dataset of 124760 images is generated using nine image enhancement techniques from 12476 collected images of diseases and pests of the okra plant. The recognition efficiency of CNNs such as InceptionResNetV2, Xception, ResNet50, MobileNetV2, VGG16, and AlexNet was evaluated, and InceptionResNetV2 realizes a significant recognition accuracy of 98.16% which was higher than others. In addition, the recognition time of the proposed architecture was also less than others, it consumed 9.8 seconds for classifying 15 images with 100% accuracy. InceptionResNetV2 achieved the highest accuracy of 99.86% in yellow vein mosaic and enation leaf curl classes. Moreover, this paper addresses an efficient method for the accurate and rapid diagnosis of okra plant diseases and pests at an early stage which establishes a theoretical base for deep learning-based application in the agricultural information field. In the future work, we plan to apply other pre-trained CNN architectures with the more expanded dataset of the okra plant.

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