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Pest and Disease Video Classification with Convolutional Neural Network and Transfer Learning

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The important field crops of agriculture are affected due to attack of various pests and diseases which leads to reduction in crop production. Early classification and identification of pests and diseases in plant helps farmers to take mitigation steps. To address this issue with computer vision based techniques, convolutional neural network (CNN) based deep learning models were studied for classification of pests and diseases videos. Six different CNN models were developed. Two

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approaches namely from scratch learning and transfer learning were used. Data augmentation techniques such as reflection, scaling, rotation, and translation were also applied to prevent the network from overfitting. The classification accuracy of 99.19%, 99.08% and 98.80% was attained in VGG19, DENSENET201 and CNN 5 Layer model. The results demonstrated that CNN models with good architecture can classify pests and diseases with good performance.

Keywords: Convolutional neural network; pest; disease classification; video classification; transfer learning.

1. INTRODUCTION

Plant pests and diseases are responsible for major economic losses in agricultural production. Timely detecting and identifying them is essential to control and manage them. Traditional manual identification of insects is typically labour-intensive, time-consuming and inefficient [1]. The computer vision based techniques of image processing using machine learning was developed for accurate classification and identification of pests and diseases to overcome these problems in agriculture research field. Thenmozhi & Srinivasulu Reddy [2] have developed crop pest classification model based on deep convolutional neural network and transfer learning and the results demonstrated that the proposed CNN model is effective in classifying various types of insects in field crops. Zhang et al [3] have proposed cucumber leaf disease identification with global pooling dilated convolutional neural network and suggested three improvements over the classical neural network (CNN) and AlexNet models. Experimental results on the datasets of six common cucumber leaf diseases demonstrate that the proposed model can effectively recognize cucumber diseases. Ferentinos [4] has described convolutional neural network models to perform plant disease detection and diagnosis using simple leaves images of healthy and disease plants through deep learning methodologies. Several model architectures were trained, with the best success rate of 99.53%. Kamilaris & Prenafeta-Boldu [5] have presented a survey on the use of deep learning in agriculture. In his paper, a survey of 40 research efforts that employ deep learning techniques were studied and findings indicate that deep learning provides high accuracy, outperforming existing commonly used image processing techniques. Saleem et al. [6] have studied different handcrafted visual leaf features, their extraction techniques, and classification methods and concluded that AlexNet, a Convolution Neural Network(CNN) based approach is outperformer and robust when the training dataset is small. Da Silva et al. [7] have evaluated three CNN architectures (AlexNet, VGGNet and ResNet) with synthetic images for estimating soybean leaf defoliation and found that root mean square error of only 4.57%, which is an expressive result for leaves with severe defoliation. Picon et al [8] have reported that over the last years, a number of image analysis based methodologies have been proposed for automatic image disease identification. Among these methods, the use of Deep Convolutional Neural Networks (CNNs) has proven tremendously successful for different visual classification tasks. Uzal et al. [9] have presented a study to estimate seed-per-pod for plant breeding using deep learning and highlighted the particularly high increase in generalization capabilities of a deep learning (CNN) approach over a classic machine vision approach. Barbedo [10] presented result of an investigation on the application of the concepts of deep learning and transfer learning to the problem of plant disease classification and concluded that CNNs are indeed powerful tools that can suitably deal with plant pathology problems. O'Shea & Nash [11] outlined the basic concepts of convolutional neural networks, explained the layers needed to build one, and detailed how the network structure is optimal for most image analysis tasks. Padmanabhan, n.d. [12] explored the use of convolution neural networks (CNNs) for the image classification and image captioning problems. He concluded that deep learning is an extremely powerful tool. Tuning hyper parameters also proved to boost the performance of CNN models by a good amount. Mohammed et al. [13] proposed a methodology to calculate the screen time of characters appearing in the video by using classification-count method. Supervised learning methodology with Convolutional Neural Network as the classifier is used in this paper. Islam et al. [14] reviewed on different approaches and methods in video classification with their advantages, findings, limitations, challenges, data summary, research gaps and performance. It was concluded that video based approach for video classification worked better over text and audio. Butt et al. [15] presented a study to detect video surveillance using Visual Geometry Group 19 (VGG19) and the proposed system outperformed with 81% accuracy as compared to state of the art systems. (Ramesh et al [16]) studied a simple convolutional neural networks on Video Classification. This network gave less computational cost and good accuracy rate. Ren et al. [17] surveyed on video classification methods based on deep learning and analyzed the differences in performance of typical algorithms, summarized the commonly used video classification datasets. Deshpande et al. [18] studied video classification using machine learning and concluded that convolutional neural networks are accustomed to detect features within the video images. Karpathy et al. [19] studied large scale video classification with convolutional neural network and concluded that the convolutional neural networks are capable of learning powerful features from weakly labeled data that far surpass feature based methods in performance. Rachmadi et al. [20] presented a video classification system by combining the keyframe extractor system and convolutional neural network (CNN) classifier. As a result, the system is effective and the average accuracy is increased compared with the system without using the key frame extractor system.

2. MATERIALS AND METHODS

2.1 Data Collection

In the experiment, video clips for four different pests and diseases were collected from BTRS (Bidi Tobacco Research Farm) and MVRS (Main Vegetable Research Farm) of Anand Agricultural University. The video clips were prepared in day light field condition using Redmi Note Pro 10 mobile camera with 30 fps. The video clip length was 5-15 seconds and recording format was . mp4. The details are presented in Table 1 and Fig. 1.

2.2 Data Preprocessing

The video classification task of convolutional neural network requires video frames as images. Hence, video clips need to be transformed into image frames as presented in Table 2. Considering spatiotemporal nature of video, every third frame is extracted and stored as image from each video clip. As a result, we get image data set from more number of video clips. It will reduce the dataset size which ultimately leads to less training time for model, less computing power and memory requirements.

Table 1. Pests and diseases

#	Crop/Plant	Pest and Disease Name	Video Image	Center
1.	Tobacco	Helicoverpa armigera (Hub) (Common Name: Caterpillar)		BTRS
2.	Brinjal	FruitShootBorer		MVRS
3.	Chilli	Leaf Curl		MVRS
4.	Tobacco	White Spot		BTRS

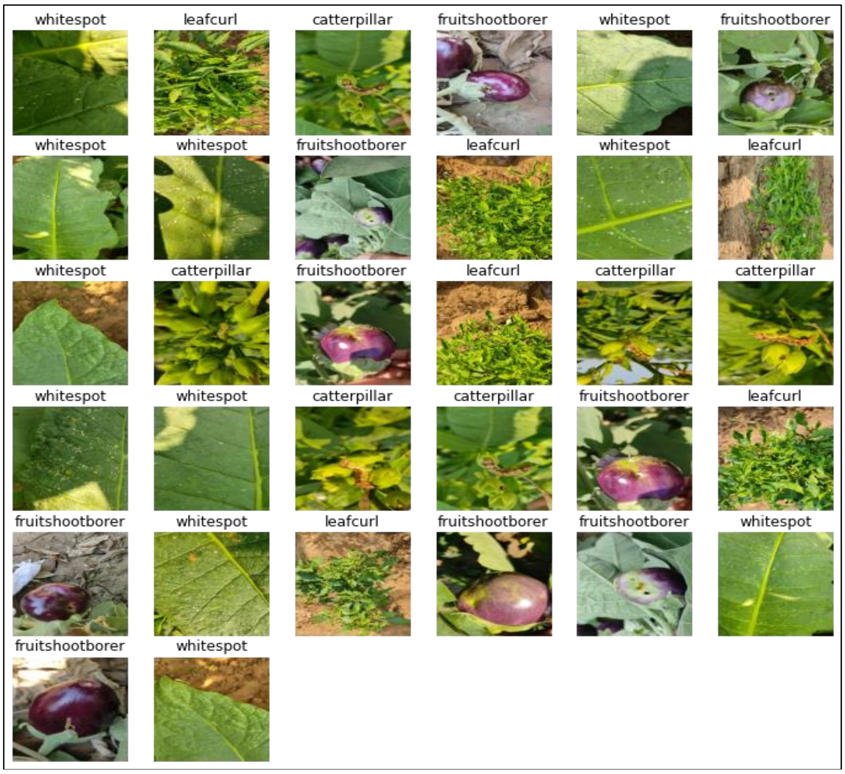


Fig. 1. Pests and Diseases Dataset (PDD)

Table 2. Extracted images from video clips

Pest and Disease Name	PDD Dataset (Extract every 3rd image)
Helicoverpa armigera (Caterpillar)	2152
Fruit Shoot Borer	2301
Leaf Curl	2043
White Spot	2188
Total Images	**8684**

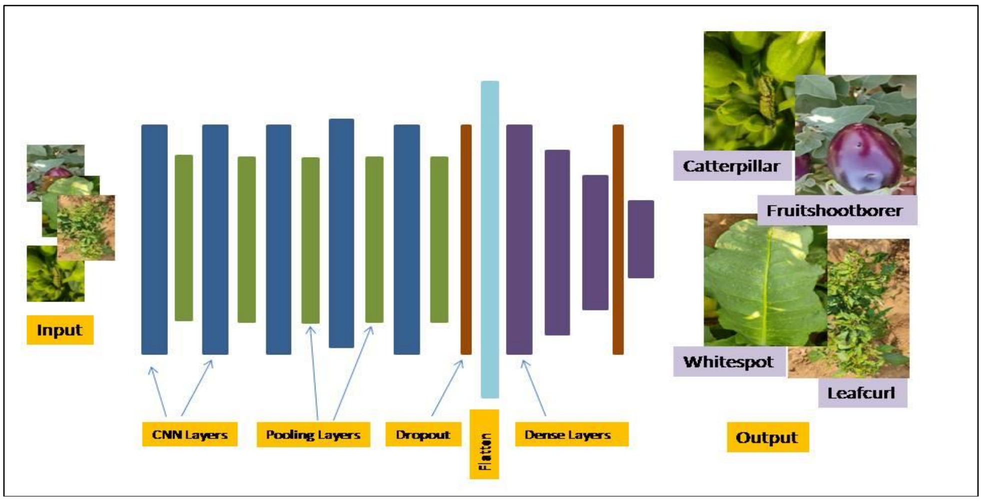


Fig. 2. CNN architecture – Training from scratch

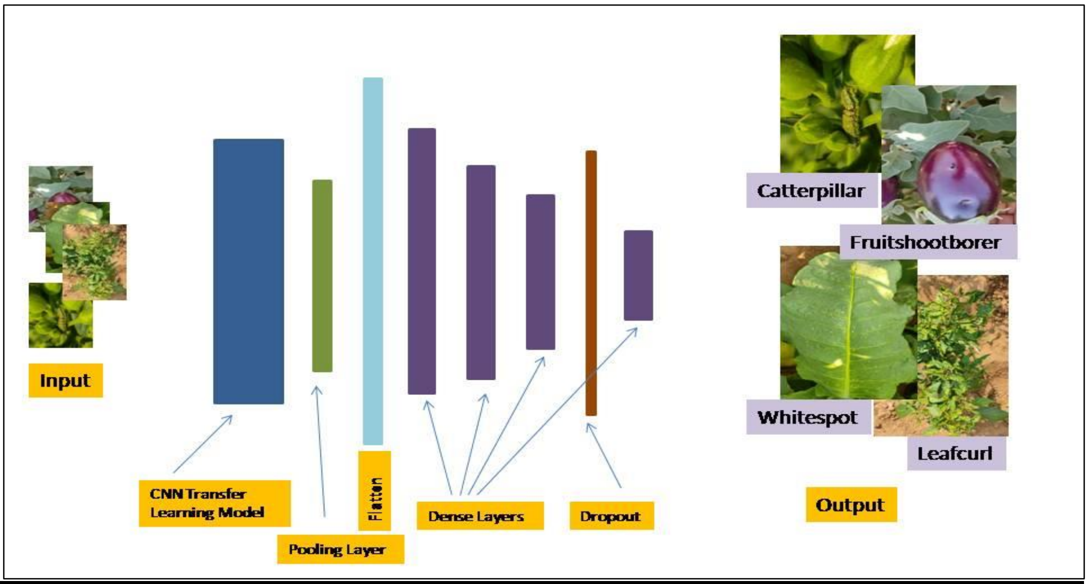


Fig. 3. CNN architecture – transfer learning

2.3 Data Augmentation

Data augmentation is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data. It includes making minor changes to the dataset or using deep learning to generate new data points. Augmented data is drived from original data with some minor changes. We make geometric and color space transformation such as flipping, resizing, cropping, brightness and contrast to increase the size and diversity of the training set. Augmentation prevents models from over fitting and improves model accuracy. (A Complete Guide to Data Augmentation | DataCamp, n.d.)

2.4 Transfer Learning

In this study, transfer learning approach was applied to retrain CNN models. The CNN learning models contain layered architecture with different layers to learn complex features of the images and finally, all these layers are connected to a fully connected layer to get the final results. In transfer learning, this layered architecture is allowed to use the pre-trained models without its final classification layer as fixed feature extractor to achieve better classification performance with less training time. We mainly explored three deep learning models based on CNN such as such as ResNet101V2, VGG19, DENSENET201 for classification.

2.5 CNN Architecture

We explored different model architectures with the main structure as depicted in Figs. 2 and 3. The CNN Architecture with training from scratch is explored with three, four and five CNN layers as well as four dense layers. The CNN Architecture with transfer learning is explored with ResNet101V2, VGG19, DENSENET201 with four dense layers.

2.6 Parameters

All CNN models were trained using the following training parameters.

- No. Of Hidden Layers: Four
- Dropout: 0.20
- Activation Function: ReLU, Softmax
- No. Of Epoch: 25
- Learning Rate: 0.001
- Batch size: 32
- Optimizer: Adam
- [Learning Rate: 0.001, decay rate(beta1):0.9 decay rate(beta 2):0.999, epsilon: 10e-8]
- Data Augmentation: [RandomFlip: Horizontal and Vertical RandomRotation: 0.1, RandomZoom: 0.1, RandomContrast: 0.1]
- Rescaling: 1.0/255
- Loss Function: SparseCategoricalCrossEntropy

- Training Validation Split: 80%: 20%[Training images: 6948 Validation Images: 1736]

2.7 Deployment

All CNN Models were deployed on Google Colab platform. Dataset was stored on Google Drive for training, validation and testing. All models were trained, validated and tested using GPU hardware support, Python environment with Tensorflow and Keras library.

3. RESULTS AND DISCUSSION

3.1 Evaluation Metrics

The accuracy of the proposed classifier has been computed using the following expression which uses numerical details of correctly classified images from total sample space of pest and disease images in the dataset.

$$\%\text{Accuracy} = \left(\frac{\text{no. ofcorrectlyrecognizedsamples}}{\text{totalno. ofsamples}}\right) \times 100$$

The precision, recall and F1 score are also the important measure to consider for system evaluation and are calculated as below respectively.

$$\text{Precision} = \frac{\sum \text{True Positive}}{\sum \text{Predicted Condition Positive}} \times 100$$

$$\text{Recall} = \frac{\sum \text{True Positive}}{\sum \text{Condition Positive}} \times 100$$

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

3.2 Training and Validation Results

All CNN Models were trained using the training parameters. The Comparison of the models for the training and validation data set shown in Fig. 4.

From Fig. 4, it can be seen that all six CNN models showed very good accuracy. Each model was trained for twenty five epochs and their training and validation results are recorded for accuracy and loss parameters.

From Fig. 5, it can been seen that among six CNN models, transfer learning models namely RESNET101V2, VGG19 and DENSENET201 are better in accuracy compare to scratch learning models with different number of CNN Layers. It also validates the finding of (Kaya et al [21]) that transfer learning aims to reuse the model and acquired knowledge, and likewise to decrease the model development time dramatically, and improves the model performance of the isolated learning model.

From Fig. 6, it can been seen that among six CNN models, transfer learning models namely RESNET101V2, VGG19 and DENSENET201 are better in loss parameter compared to scratch learning models with different number of CNN Layers.

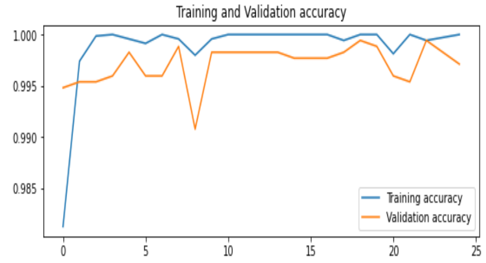
3.3 Testing Results

A testing dataset having the size same as validation dataset was also prepared, tested with all six CNN models and results are presented in Table 3.

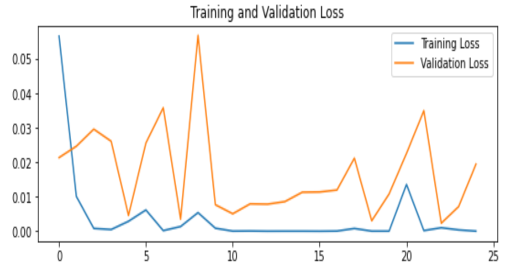
From Table 3 and Fig. 7, it can been seen that among six CNN models, transfer learning models namely VGG19 and DENSENET201; scratch learning model with 5 CNN layers have out perform based on accuracy and F1-score parameters.

Table 3. Performance of different CNN Models for test dataset

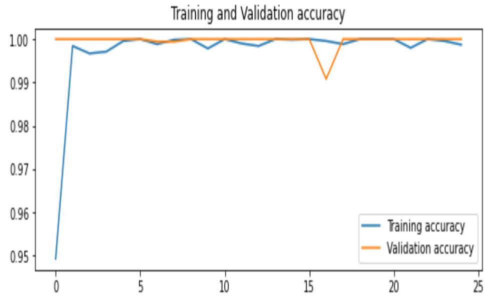
Performance Metrics CNN Models	Accuracy	Precision	Recall	F1 Score
RESNET101V2	0.9883	0.9758	0.9778	0.9762
VGG 19	0.9919	0.9830	0.9829	0.9830
DENSENET201	0.9908	0.9809	0.9807	0.9808
3 CNN + 4 Dense Layers	0.9695	0.9378	0.9375	0.9371
4 CNN + 4 Dense Layers	0.9738	0.9463	0.9517	0.9440
5 CNN + 4 Dense Layers	0.9890	0.9765	0.9774	0.9768



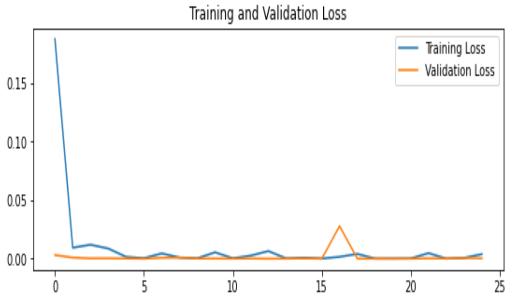
RESNET101V2(Accuracy)



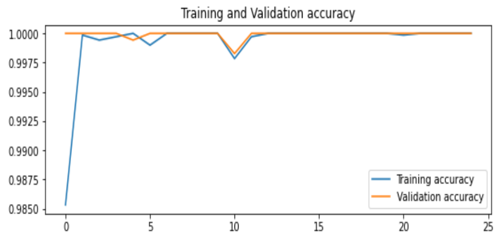
RESNET101V2(Loss)



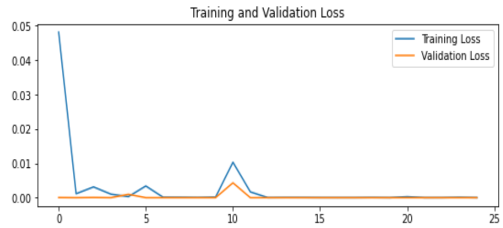
VGG19(Accuracy)



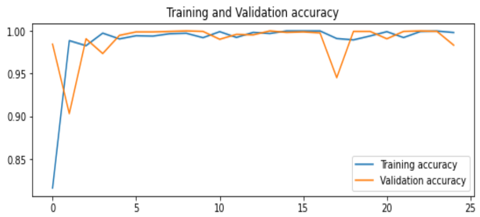
VGG19(Loss)



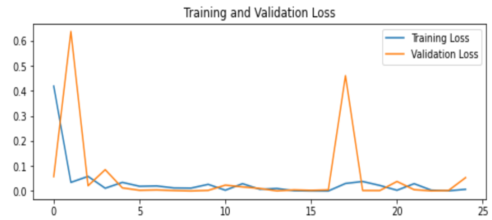
DENSENET201(Accuracy)



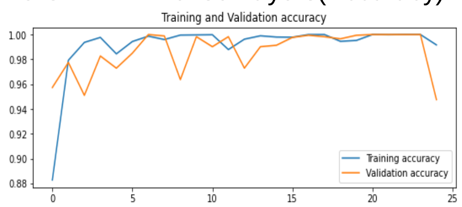
DENSENET201(Loss)



3 CNN + 4 Dense Layers(Accuracy)



3 CNN + 4 Dense Layers(Loss)



4 CNN + 4 Dense Layers(Accuracy)

4 CNN + 4 Dense Layers(Loss)

5 CNN + 4 Dense Layers(Accuracy)

5 CNN + 4 Dense Layers(Loss)

Fig. 4. Accuracy – loss graph for training and validation data set

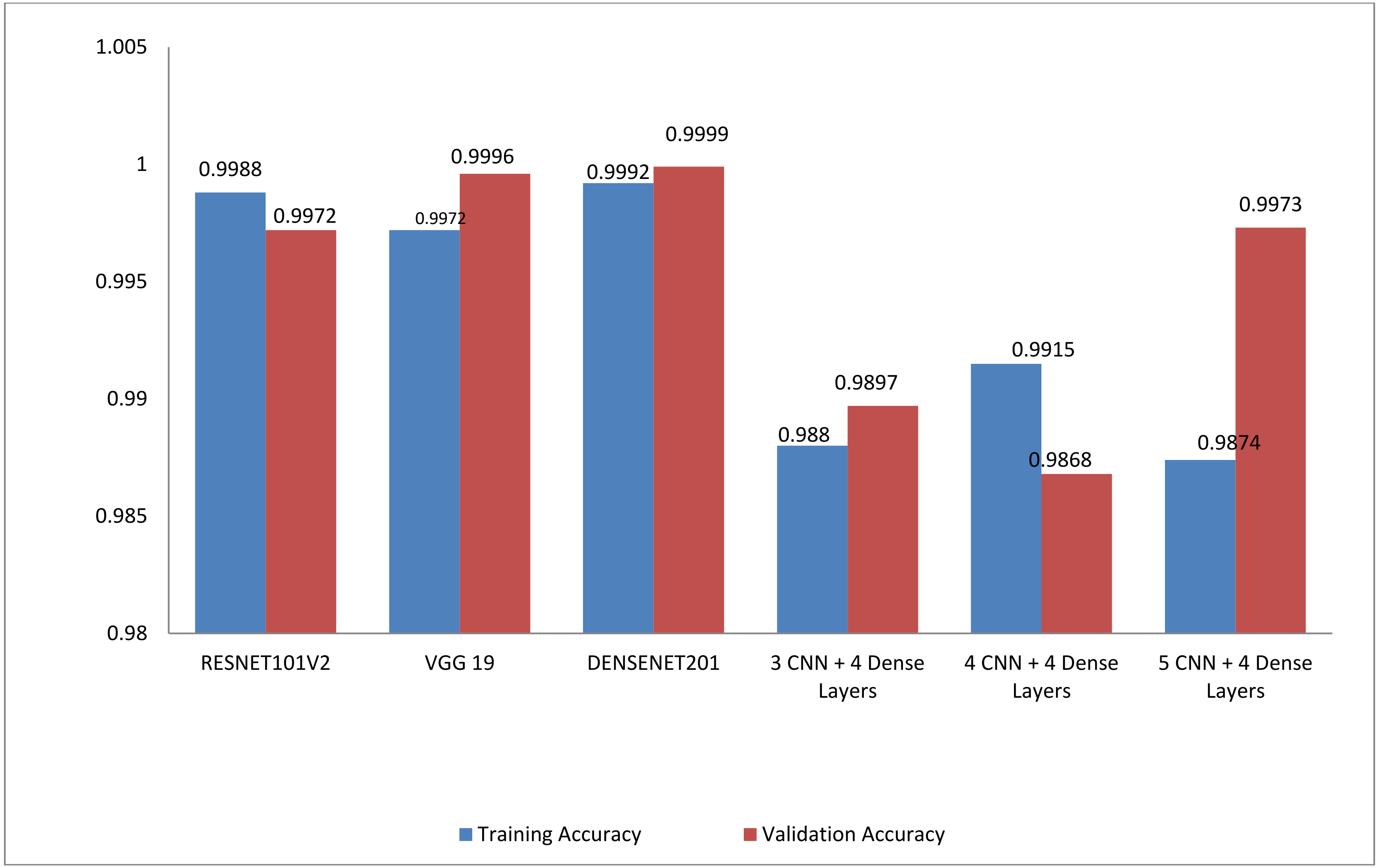


Fig. 5. Training and validation accuracy

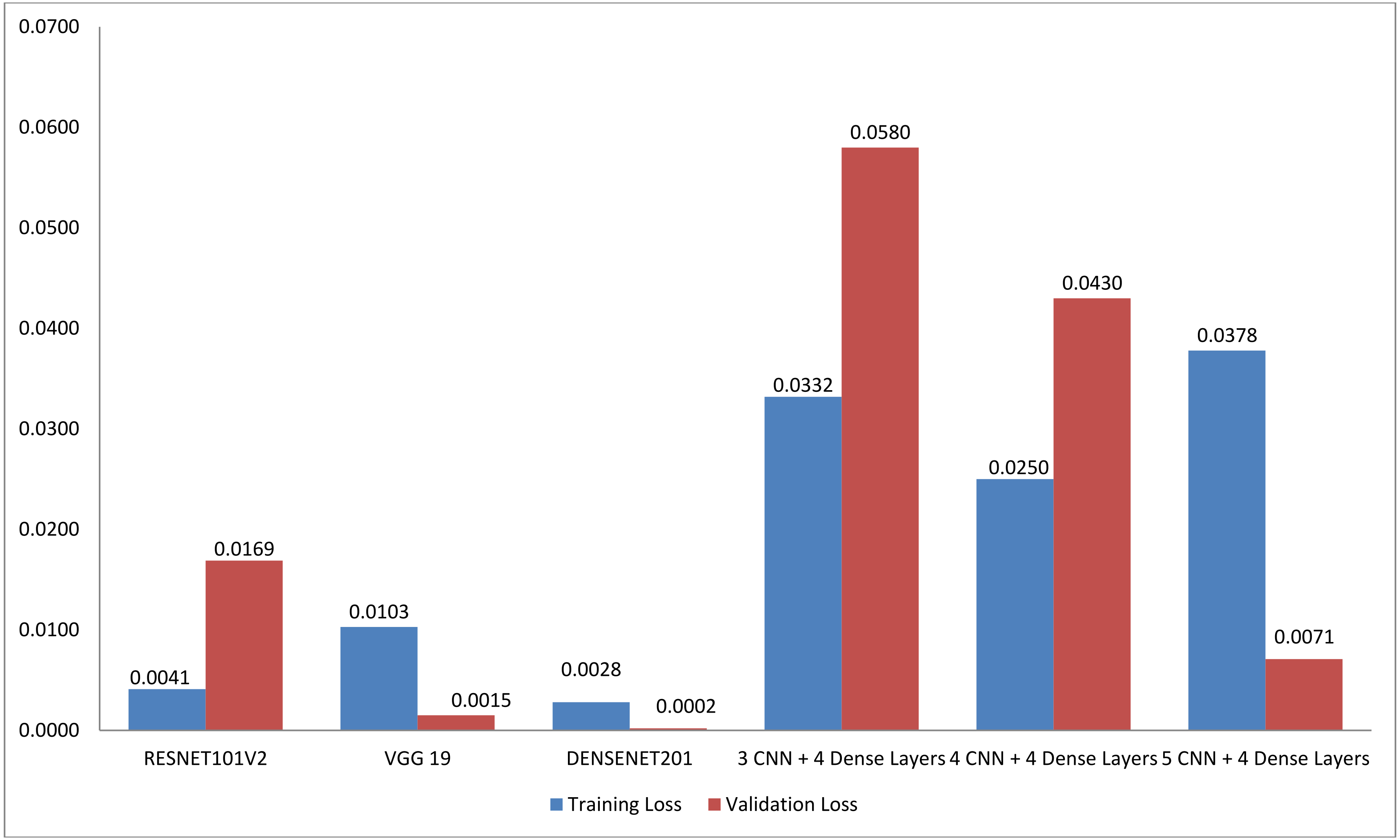


Fig. 6. Training and validation loss

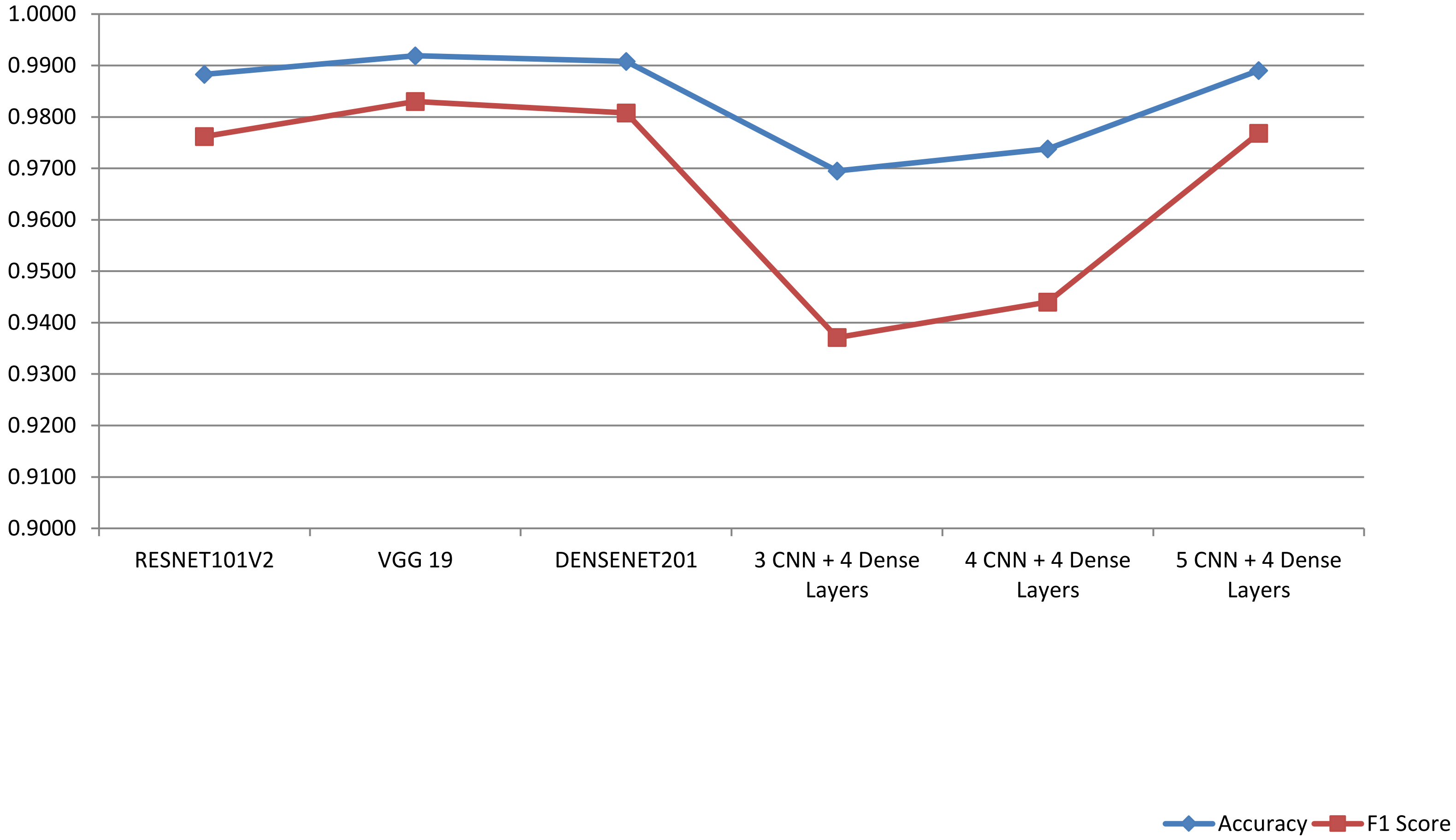


Fig. 7. Performance Metrics for different CNN Models for test dataset

4. CONCLUSION

In this work, convolutional neural network architectures based deep learning models were studied. Total of six different models, three with transfer learning and three with scratch models were developed for the classification of pests and plant diseases through videos of pests and diseases of diseased plants. The training of the models was performed using dataset prepared at Anand Agricultural University Farms. The most successful model architecture, VGG19 transfer learning convolutional neural network, achieved a success rate of 99.19%. Other transfer learning convolutional neural network DENSENET201 achieved a success rate of 99.08% followed by scratch learning model CNN 5 Layers with a success rate of 98.90%. Based on this study, it becomes evident that convolutional neural networks are highly suitable for the automated classification of pests and plant diseases. As application of drone technology is increasing in agriculture, the classifier model has a place to automatically classify drone recorded videos.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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