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Automatic detection of plant leaf diseases using deep learning

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Abstract: Diseases in plants pose a major impact on the crop yield. They severely affect the quality and quantity of agricultural crops. Therefore accurate detection of infection in plants in a timely manner is important to limit the transmission of the disease and to enhance the crop productivity. Manual examination of the plant diseases requires a lot of time, effort and cost can even lead to faulty treatments. In order to counter this problem, many methods based on image processing and machine learning methods have been suggested. This paper implements a deep learning method based on convolutional neural networks(CNN) combined with long short-term memory(LSTM) network for identifying diseases in plants. It makes use of the PlantVillage dataset which consists of images of leaves of healthy and diseased plant crops belonging to 14 crop species. The proposed model achieves an accuracy of 95.11%, which suggests that CNN model used along with LSTM network for classification can help to enhance the accuracy of the CNN model. The proposed system can thus help the farmers to detect plant diseases easily.

Keywords: Plant leaf disease detection, deep learning, convolutional neural network, classification, long short term memory.

1. INTRODUCTION

More than half of the total population of India earns their living through agriculture. However, the presence of diseases considerably hampers the quality and quantity of the agricultural plants which eventually leads to significant crop losses. Plant diseases are majorly caused by biotic agents such as fungus, bacteria and virus. Detection of plant diseases in a large area manually can be inefficacious and fault-prone. This task can be made accurate and efficient using computer vision and soft computing techniques. The use of these techniques not only helps in saving resources but also leads to more accurate detection of plant diseases.

Prior to 2015, most of the research studies have used hand-crafted features (e.g. color, shape, size and texture of leaves) and shallow machine learning classifiers for identifying the illnesses in plants. However, these manual feature extraction techniques sometimes fail to extract all of the important features required for more appropriate detection of diseases. Starting from 2015, most of the research studies dealing with solving the problem of plant disease detection have leveraged deep learning.

Deep learning is extensively used in classification of images due to the high accuracy that it provides [1]. Recent studies show that one of the deep learning algorithms called convolutional neural networks(CNN) performs considerably well in computer vision applications and has been widely used for plant disease detection in single crops as well as multiple crops. It consists of one or more convolutional layers to analyze and extract features from images. The main edge that CNN provides in contrast to traditional methods using manual feature extraction is that it can recognize a large number of plant diseases with a high value of accuracy. It is seen that the color feature plays a crucial role when the identification of diseases is done using CNN [2]. For training robust CNN models which require large datasets, transfer learning is used.

A. Research Motivation

Huge crop losses are caused by plant diseases that usually go undetected by humans. Figure 1 shows the estimated losses in soybean crop yield caused because of plant diseases in the United States region from the year 2014 to the year 2018 [3]. Thus the development of systems that can automatically detect plant infections with high accuracy levels is desired. In this study, a combined CNN-LSTM deep learning approach is used for predicting the diseases in plants. At the initial stage, pre-processing of the input leaf images is performed. Then the relevant features are extracted using the CNN model. CNN is used because it performs exceptionally well in image recognition tasks. Finally, LSTM model is used as a classifier because it can efficiently model dependencies between different images of plant observations. Thus, it is capable of capturing the affected regions of the plant leaf image effectively and aids

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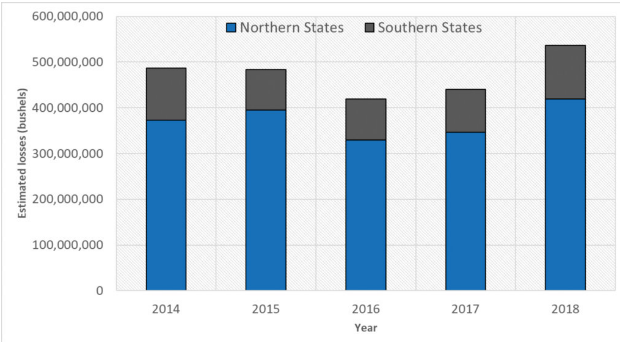


Figure 1. Estimated losses in soybean yield caused by plant diseases in the U.S from 2014-2018

in improving the classification quality.

B. Our Contributions

The contribution of this research work is as follows: a combined CNN-LSTM model is explored for identifying plant diseases. Second, for analyzing how well the model performs, metrics such as accuracy, precision and recall have been used. It is observed that the implemented model outperforms other CNN approaches (multilayer CNN model and CNN+GRU model). Third, a large dataset covering 14 different plant species and 26 plant diseases has been used for training the model.

C. Article Organization

The remaining paper is assembled as follows: Section 2 describes the work carried out in the plant disease recognition field in recent times along with the limitations. Section 3 discusses the proposed approach for plant disease detection. Section 4 provides a description of the dataset used. Section 5 describes the performance metrics that are used to evaluate how well the model performs. Finally, the obtained results and conclusion are presented in Section 6 and Section 7.

2. Related Work

Most research works for the identification of plant diseases harness machine learning and deep learning due to the impressive performance shown by these techniques. Prior to 2015, researchers mostly used manual feature extraction methods along with machine learning for classification. In [4] [5], color, shape and texture attributes of the diseased regions are extracted and fed to ML classifiers like K-Nearest Neighbors (KNN) for identifying the lesions in the crops. The researchers in [6] utilized Gray-Level Co-Occurrence Matrix (GLCM) algorithm to obtain the texture attributes from the leaf images. Image segmentation is carried out using k-means clustering algorithm and final classification is made using KNN algorithm is applied for classification purpose. In [7], deep feature extraction along with algorithms like Support Vector Machine(SVM), Extreme Learning Machine (ELM) and KNN are used to diagnose plant diseases. The authors of [8] have obtained relevant color and texture features and passed them to KNN, SVM, Linear Discriminant Analysis (LDA) and Multi-layer Perceptron (MLP) models for detecting diseases in citrus leaves. Results show that the maximum precision value(84.32%) is obtained using LDA.

More recent research works have concentrated more on deep learning approaches for the classification of anomalies in plants. Citrus crop is one of the most widely grown fruit crops across the globe, many works of literature have therefore focused on detecting citrus diseases. Pan et al. [9] implemented simplified densely connected convolutional networks (DenseNet) for detecting citrus diseases using mobile devices. Some layers of DenseNet have been removed to reduce network complexity, prediction time and overfitting. The dataset consists of images of 6 types of citrus diseases built under the experts' guidance. Data augmentation is done using vertical flip, horizontal flip, horizontal and vertical flip, brightness increase and contrast increase. Along with disease identification, the system also provides relevant information about the disease to the users. The accuracy of the system comes out to be 88.77%. However, the system does not perform well in identifying citrus diseases with similar characteristics.

Liu et al. [10] used MobileNetV2 model, to distinguish among six citrus diseases. Results show that MobileNetV2 is a lightweight network that takes less prediction time in comparison to other models and is suitable to be deployed on mobile devices. In [11], Multilayer CNN model is employed to identify diseases present in fruits and leaves of citrus plants. The dataset comprises 2293 images taken from PlantVillage and citrus datasets. Researchers have explored different CNN model variants consisting of varying number of filters, convolutional layers, epochs and various filter dimensions. It is seen that CNN model with just two layers of convolution, 16 filters of dimensions 2×2 and 8 epochs attained the highest accuracy(94.55%). However, this study uses only a limited number of images in the dataset and considers only five categories of citrus diseases.

Some researchers have also focused on finding the severity of plant diseases. For instance, [12] aims to detect the severity level of black rot disease in apple images. VGG16 model trained using transfer learning gives the highest accuracy(90.4%). Zeng et al. [13] have also come up with the idea of detecting the severity level of citrus Huanglongbing(HLB) disease. The dataset contains 5,507 citrus leaf images labeled into three categories(early, moderate and severe) depending on the stage of infection. Among the six different deep learning models that were analysed, Inception V3 model achieved the highest accuracy(74.38%). For expanding the original training image set, Deep Convolutional Generative Adversarial Networks (DCGANs) have been employed which improved the accuracy to 92.60%. A comparison of DCGANs augmentation with technique with the conventional image augmentation methods is not made in this work.

Dyrmann et al. [14] have used CNN model to recognize weeds and plant species belonging to 22 species. The dataset contains images from different datasets having varying lighting conditions. The model gives an accuracy of 86.2% but it fails to classify some of the species correctly owing to the low number of images in the training dataset. Sladojevic et al. [15] also leveraged CNN for identifying 13 plant diseases using a custom dataset created using online sources. An accuracy of 96.3% was obtained upon fine-tuning the model. Liu et al. Zhu et al. [16] proposed an AlexNet based CNN model for identifying apple infections of four different kinds. An overall accuracy of 97.62% was obtained using the suggested approach; however it did not use sufficient number of apple images for training. In [17], a novel three-channel CNN model has been developed for the diagnosis of leaf blights. Zhu et al. [18] explored the usage of faster R-CNN and Inception V2 model to reduce the computing costs.

Several researchers have tried to improve existing deep learning state-of-the-art models to overcome their limitations. For example, to counter the problem of long convergence time and too many model parameters, [19] proposed an improved CNN model based on VGG16 model. The VGG16 model's fully connected layer is reinitialized with Inception and Squeeze and Excitation(SE) module to improve the accuracy of disease identification. A global pooling layer is used to reduce the number of parameters. An accuracy of 91.7% is noted but the classification accuracy for few diseases that are tough to classify is less. In [20], a hybrid Inception-ResNet-v2 model is used for detecting plant diseases. Dataset consists of 47363 images of 10 different plant species infected with 27 diseases taken from the AI Challenger Competition. The proposed model converges fast and achieves an accuracy of 86.1% however, the proposed model does not show much improvement in the accuracy when compared to the base models.

Chen et al. [21] presented a novel architecture called INC-VGGN for plant disease detection. VGGNet pre-trained on ImageNet dataset is utilized in combination with Inception module. The dataset used in this work consists of 500 rice images and 466 maize images. For analyzing the model performance, measures like accuracy, sensitivity, specificity metrics are employed. An average accuracy of 92% for rice disease detection and 80.38% for maize disease detection is obtained. Guan [22] has combined the results of four CNN models(Inception, Resnet, Inception Resnet, and Densenet) for finding the anomalies in the plants. The dataset consists of 36258 leaf images of 10 plant species taken from AI-Challenger dataset. Results show that by using the stacking method, accuracy of 87% was achieved, which was better(an increase of 3%) when compared to the outcome of using only one CNN model. However, because of the large training dataset, the overall training time required for all models was approximately 96 hours; hence it cannot be used in practical scenarios.

Prottasha et al. [23] implemented an optimized CNN model which makes use of depthwise convolution to predict rice diseases. The accuracy of the proposed model comes out to be 96.3%. Pathak et al.[24] analyzed four different deep learning algorithms to identify diseases in Cannabis plants using a self curated dataset. ResNet 50 model attained the highest accuracy (88%).

The research work proposed in [25] uses CNN and gated recurrent units(GRU) network to diagnose diseases in the plant leaves images taken from the PlantVillage dataset. For feature extraction, CNN is preferred and classification happens using GRU. Accuracy, precision, recall and f-measure are calculated. The proposed model achieved higher accuracy(91.19%) than ResNet-20 and VGGNet-16 however, there is a need to explore other ensemble models as well to improve the accuracy even more.

3. Proposed approach

The deep learning approach presented in this paper for the identification of diseases in plant leaves comprises of the following key steps: image pre-processing, data augmentation, feature extraction and disease classification. Figure 2 shows the overall structure of the proposed model in the form of a flow diagram.

A. *Image Preprocessing*

For improving the quality of the captured images, which usually contains noise, shadows and complex background, image pre-processing is carried out. This step is done before extracting the features and is an important one as it impacts the accuracy of the disease detection system. Some common pre-processing techniques to eliminate the inappropriate information from the input images are background elimination, enhancement, color space conversion and filtering (e.g. mean and median filtering). For reducing the processing time, operations like resizing and cropping are performed. This paper uses image resizing (256×256) and image normalization as the pre-processing steps.

B. *Augmentation*

Deep learning approaches often require huge amounts of data and usually these huge amounts of data are not always available which leads to overfitting of the model. In order to deal with the data inadequacy and to overcome the problem of overfitting, data augmentation is carried out. For augmenting the original training dataset, different image transformation techniques like rotation, zoom, shear, noise injection, flipping, increasing contrast and brightness are performed. In our study, we have used a dataset which has been augmented using offline augmentation to make the model more robust. In offline augmentation the augmented images get saved on the disk unlike online augmentation.

C. *Feature Extraction*

Convolutional Neural Network(CNN) is utilized by us for extracting the most desirable and relevant features from the input leaf images. CNN is selected because it is known

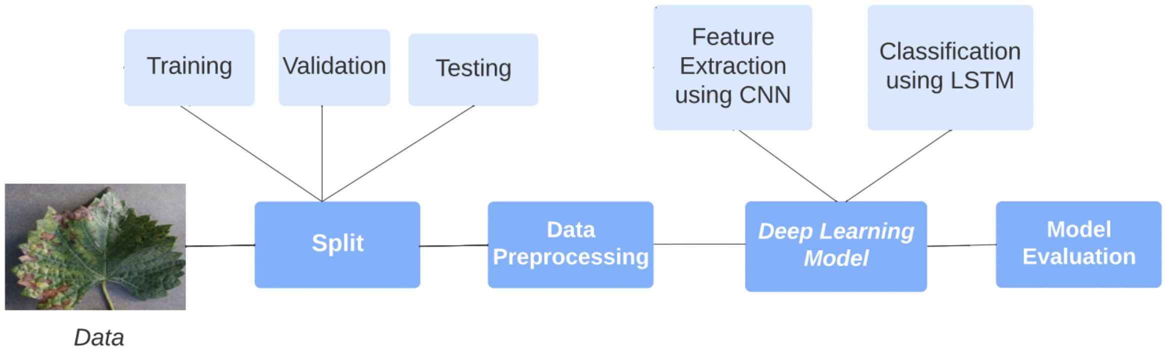


Figure 2. Flow diagram of the proposed approach

to have shown exceptional performance in image classification tasks. The architecture of CNN is quite similar to the way the neurons are connected in the human brain. CNNs in most cases consist of three parts. First is the convolution layer. This layer is used for feature extraction. The second is the pooling layer which is used for downsampling the feature map to decrease the number of parameters. The two common types of pooling techniques that are used are max pooling and average pooling. The third is the fully connected layer which performs summarization of the features and performs the classification.

At the convolution layer, convolution operation is performed. In mathematics, convolution is a mathematical operation wherein as the filter matrix slides across the image, two operations are performed per patch, the first one is element wise multiplication and the second is summation. This operation produces the feature map matrices. The initial convolution layers extract low level attributes from the input image and the subsequent layers extract the high level attributes. CNN model can consist of multiple convolution layers and pooling layers. Additionally at the convolution layer, ReLU activation function is applied for introducing non-linearity in the feature maps. The mathematical expression for ReLU is expressed in equation 1. The main benefit of using ReLU fuction is that activation of all the neurons does not happens at the same time.

$$f(x) = max(0, x) \tag{1}$$

In the proposed CNN model, the input images of plant leaves having dimensions $256 \times 256 \times 3$ are passed through three convolution layers. At all the three layers, 3×3 filters are applied and ReLU activation function is applied. Maxpooling layer of size 2×2 are used after every convolutional layer for reducing the size of the generated feature maps. The first, second and third convolution layers apply 16 filters, 32 filters and finally 64 filters respectively to generate the corresponding feature maps. The outcome from the final convolutional layer is flattened and fed to the LSTM network for classification. Figure 3 illustrates the architecture of the proposed model. Table Ishows the model layers and their input shapes.

TABLE I. Model Summary

Layer(type)	Input shape
Conv2D	(256, 256, 3)
MaxPooling2D	(256, 256, 16)
Conv2D	(128, 128, 16)
MaxPooling2D	(128, 128, 32)
Conv2D	(64, 64, 32)
MaxPooling2D	(64, 64, 64)
Flatten	(32, 32, 64)
LSTM	(32, 2048)
Dense	(100)

D. *Classification*

Classification is essentially the most crucial stage in any disease detection system. The aim of the disease classification stage is to classify the input leaf images on the basis of plant infections. Long Short Term Memory(LSTM) model is used by us for classification purpose. LSTM is used as a classifier because it is known to increase CNN's accuracy.

LSTM is the improved variant of Recurrent Neural Networks(RNNs) which solves the vanishing gradient problem faced by RNNs. LSTM unlike traditional RNN is capable of capturing long term dependencies. It was developed by Sepp Hochreiter and Jürgen Schmidhuber in the year 1997 [26]. In LSTM, a new cell state for long term memory is introduced which has a pivotal role in solving the short-term memory problem. LSTM uses a gating mechanism to restrict and allow the flow of information. LSTM is composed of 3 gates, namely input gate, forget gate and an output gate. The forget gate[27] helps the model to make a decision regarding what information is needless and could be discarded from the cell state. The decision if the information from a previous cell should be forgotten or not is determined using the expression 2:

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{2}$$

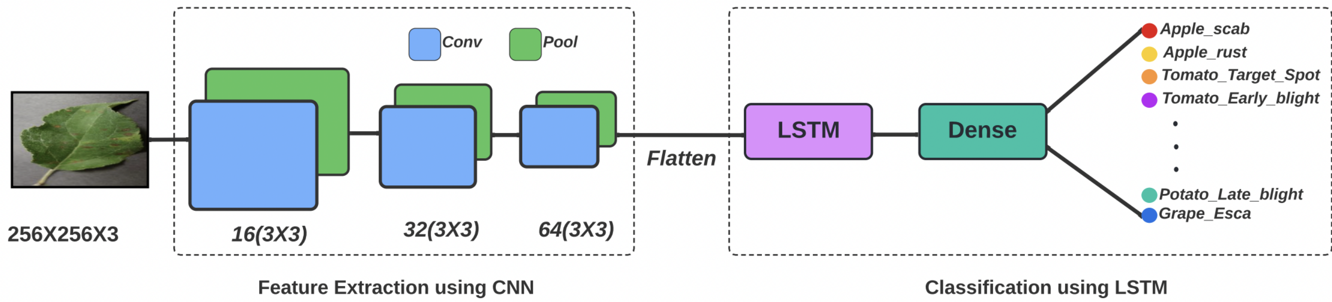


Figure 3. Architecture of the proposed CNN-LSTM model

In equation 2, h_{t1} is the previous hidden state, x_t is the current input, W_f represents the weight matrix, b_f is the bias and is the sigmoid function.

The input gate takes the decision of what new meaningful data should be saved in the cell state. The operation carried out by the input gate is expressed in equation 3.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{3}$$

Next, the Tanh layer generates a vector consisting of the new values as shown in equation 4.

$$\tilde{C}_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{4}$$

The old cell state C_{t-1} is updated into the new cell state using equation 5.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

Finally, the output gate makes a decision regarding what information from the LSTM's cell state should be given as output. The operations performed at the output gate are expressed in the equations 6 and 7. Here, o_t denotes the output generated from the sigmoid gate. First the sigmoid layer decides what to output then the tanh layer is used to output only the desired parts.

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t * tanh(C_t) \tag{7}$$

In the proposed model, the flattened result from the very last convolutional layer is passed to LSTM layer containing 100 units. The output from the LSTM layer is then forwarded to the final output layer which has 38 neurons corresponding to 38 leaf classes. Softmax activation function is applied at the output layer.

4. Dataset Description

Image Acquisition is the first and foremost step in any image recognition system. It involves retrieving images from open datasets or capturing images from the field in real time. The quality of the input images captured influences the performance of the entire system. For the purpose of plant disease detection, this study uses openly accessible PlantVillage dataset available on kaggle [28]. This dataset consists of 87,867 number of coloured images of healthy and diseased leaves of plants captured in laboratory conditions. It includes crops of 14 types: potato, tomato, apple, orange, strawberry, cherry, blueberry, raspberry, soybean, grape, peach, squash and bell pepper. The images in the dataset consist of leaf images infected with 26 diseases and are categorized into 38 different classes. Table II presents some sample images taken from PlantVillage dataset along with the disease type.

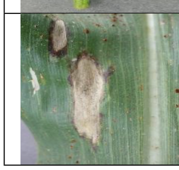
For determining the performance of the proposed approach better, we have used two formats of PlantVillage dataset we have executed the proposed model with coloured images as well as grayscale images. The dataset is divided into the following sets i.e. training set, validations set and testing set. The training set comprises of 80% of the original dataset images and the test set comprises of the rest 20% of the dataset images. The training set has been split into training set and validation set. The suggested approach is executed on four different distributions of the training and validation image datasets, namely 80-20, 70-30, 60-40 and 50-50 to reduce the effect of overfitting.

5. Evaluation metrics

For the purpose of analyzing the performance of the models [29] and comparing one model with another, parameters like accuracy, precision and recall have been noted. The performance metrics used in our proposed work are explained below:

Accuracy: It tells us how many right classifications were made out of all the classifications. Accuracy is considered as a good metric when the classes in the dataset are almost balanced.

TABLE II. Sample leaf images along with the disease type

Image	Plant Name	Disease Name	Type of Disease
	Apple	Cedar rust	Fungal
	Grape	Black Rot	Fungal
	Tomato	Bacterial Spot	Bacterial
	Peach	Bacterial spot	Bacterial
	Tomato	Mosaic virus	Viral
	Tomato	Yellow Leaf Curl	Viral
	Corn	Northern Leaf Blight	Foliar

$$\frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

Here, TP denotes True Positive (model identified positive class and it is actually True), FP denotes False Positive (model identified positive class but it is actually False), FN denotes False Negative (model identified negative class but it is actually False) and TN represents True Negative (model identified negative class and it is actually True).

Precision: It tells us out of all cases that were predicted as positive, how many of them were actually positive.

$$\frac{TP}{TP + FP} \tag{9}$$

Recall: It tells us out of all the cases that were actually positive, how many of them were predicted as being positive.

$$\frac{TP}{TP + FN} \tag{10}$$

6. Experimental results

CNN and CNN+LSTM models have been implemented on Google Colab using Tensorflow and Keras deep learning frameworks. The runtime type on Google Colab has been set to GPU (Graphical Processing Unit) since we need to train a large dataset of images. The images are first pre-processed and then trained. We have trained the models for 10 epochs and the value of learning rate is specified as 0.001. All the networks are trained using mini-batch gradient descent in

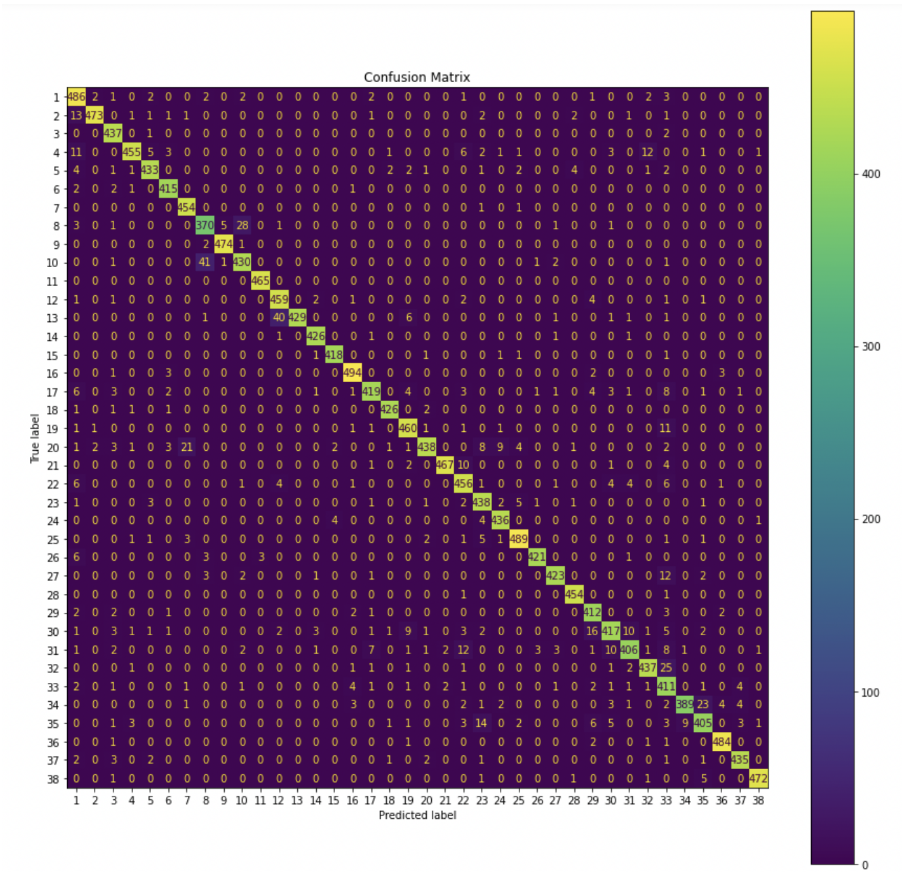


Figure 4. Confusion Matrix for CNN-LSTM model

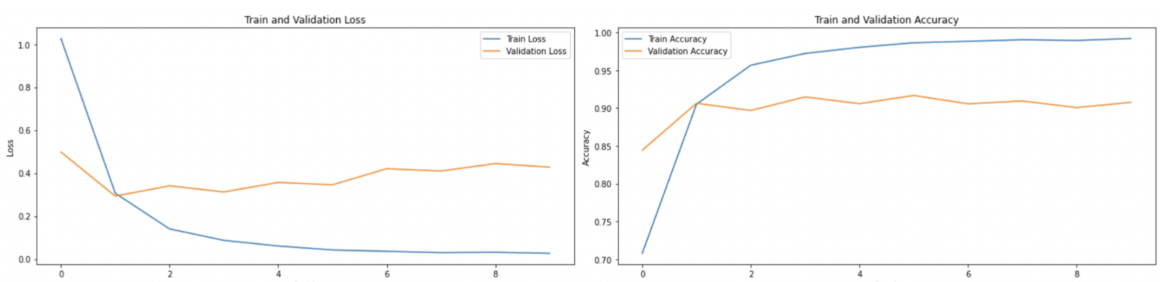


Figure 5. Loss and Accuracy curve for CNN model

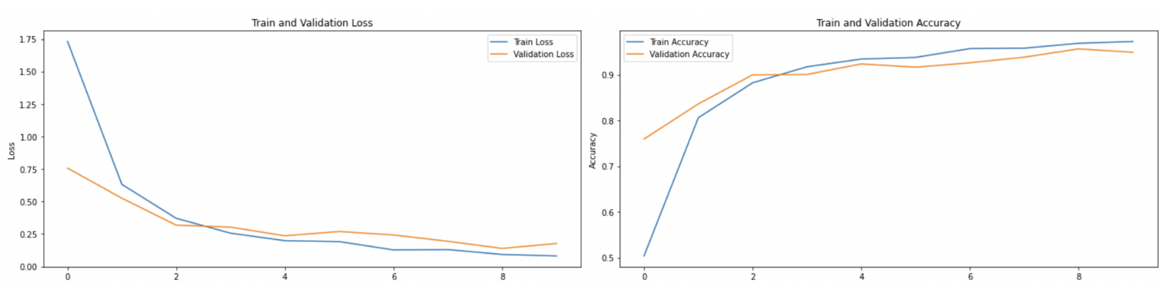


Figure 6. Loss and Accuracy curve for CNN-LSTM model for plant disease detection

TABLE III. Performance of CNN model and CNN-LSTM model

Model	Training Validation Distribution	Training Accuracy(%)	Test Accuracy(%)	Precision(%)	Recall(%)
CNN-Coloured	80-20	99.19	90.89	91.15	90.89
CNN-LSTM Coloured	80-20	97.25	95.11	95.26	95.11
	70-30	96.27	92.89	93.10	92.89
	60-40	96.44	92.54	92.72	92.54
	50-50	95.36	90.96	91.93	90.96
CNN-LSTM Grayscale	80-20	94.72	87.30	87.67	87.30
	70-30	88.95	83.71	84.44	83.71
	60-40	93.16	84.86	85.69	84.86
	50-50	84.73	80.69	81.26	80.69

TABLE IV. Comparison of models in terms of accuracy, precision and recall

Model	Training Accuracy(%)	Test Accuracy(%)	Precision(%)	Recall(%)
CNN+LSTM	97.25	95.11	95.26	95.11
CNN + GRU [25]	90.88	91.19	92.00	91.20
CNN	99.19	90.89	91.15	90.89

which batch size of 100 is used. Sparse categorical cross entropy loss function has been utilised. The weights and biases are updated using the Adam optimization algorithm.

We analysed and compared the performance of the standalone CNN model and the implemented CNN+LSTM model on coloured as well as grayscale version of the input images. We noted the values of the performance metrics(accuracy, precision and recall) on four different distributions of the training and validation set which are as follows: 80-20, 70-30, 60-40 and 50-50. Figure 4 shows the confusion matrix for the proposed CNN-LSTM architecture in the testing phase on coloured image with 80-20 training and validation distribution. Fig 5 and 6 present the training and validation loss and accuracy curves for the CNN model and the proposed CNN-LSTM model. Table III summarises the values of output metrics such as accuracy (training and test), precision and recall for both the models on coloured as well as grayscale images for different distributions of training and validation set.

The test accuracy for CNN model comes out to be 90.89% whereas for the CNN-LSTM model it comes out as 95.11%. The validation loss for the CNN model is 0.427 and the validation loss for the CNN-LSTM model is 0.176. Thus, the experimental outcomes clearly demonstrate that the CNN-LSTM model performed better as compared to the standalone CNN model. This suggests that the usage of LSTM network for classifying diseases in plants improves the performance of the standalone CNN model.

From table III, we can conclude that better results were noted with RGB images instead of grayscale images. The proposed model not only gave better performance as compared to standalone CNN model but it also yielded better performance as compared to deep learning model based on CNN-GRU model proposed by Alguliyev et al. [25] as shown in table IV. Alguliyev et al. reported an accuracy of 91.19% while our work reported an accuracy of 95.11%.

Figure 7 shows the classification results on few images taken from the testing dataset. Images with diseases like common rust in corn crop, early blight in tomato crop, cedar rust in apple crop were classified correctly with high confidence. Out of the 26 leaf diseases, 10 were recognized with high success value(94-98%), 9 were recognized with moderate success value(92-95%) and remaining were found to have accuracy between 88-92% because of less number of images of these diseases in the dataset. Therefore the experimental outcomes demonstrate that the implemented CNN-LSTM model has a fair capability of detecting diseases in the plant leaves.

7. Conclusion

Plant diseases have a significant influence on the quality as well as the quantity of the agricultural crops. Hence, for the identification of plant diseases in a timely and accurate manner, a deep CNN-LSTM architecture has been used. CNN performs the task of feature extraction and LSTM network is used as a classifier for diagnosing diseases in plants. The usage of LSTM as a classifier aids in improving the performance of the standalone CNN model. The obtained results demonstrate that the implemented CNN+LSTM model can automatically identify plant diseases gives higher accuracy(95.11%) as compared to other models like CNN and CNN+GRU model [25] on PlantVillage dataset. In future, we aim to further optimise the model and improve its accuracy. We will also make an attempt to expand the dataset by incorporating more plant species and their

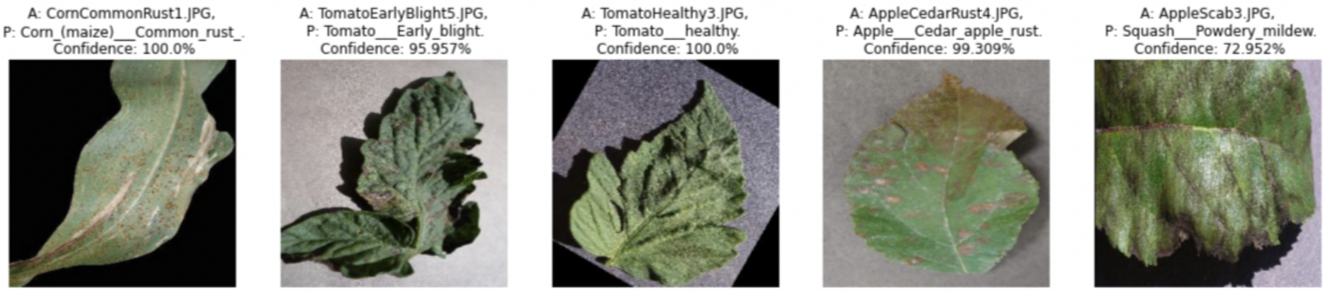


Figure 7. Classification results on some test images

diseases to achieve even better performance. Additionally, we will try to make the system accessible via an easy to use mobile interface so that it could prove to be a worthy tool for farmers.

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