Received March 12, 2019, accepted March 21, 2019, date of publication March 27, 2019, date of current version April 13, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2907383

Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease

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ABSTRACT Fungal diseases not only influence the economic importance of the plants and its products but also abate their ecological prominence. Mango tree, specifically the fruits and the leaves are highly affected by the fungal disease named as *Anthracnose*. The main aim of this paper is to develop an appropriate and effective method for diagnosis of the disease and its symptoms, therefore espousing a suitable system for an early and cost-effective solution of this problem. Over the last few years, due to their higher performance capability in terms of computation and accuracy, computer vision, and deep learning methodologies have gained popularity in assorted fungal diseases classification. Therefore, for this paper, a multilayer convolutional neural network (MCNN) is proposed for the classification of the Mango leaves infected by the Anthracnose fungal disease. This paper is validated on a real-time dataset captured at the *Shri Mata Vaishno Devi University, Katra, J&K, India* consists of 1070 images of the Mango tree leaves. The dataset contains both healthy and infected leaf images. The results envisage the higher classification accuracy of the proposed MCNN model when compared to the other state-of-the-art approaches.

INDEX TERMS Convolutional neural network, image classification, plant pathology, precision agriculture.

I. INTRODUCTION

Fungal diseases are very common in plant leaves. The diseases in the plants are cause for dropping the quality and the quantity of the agriculture production [1]. The plant diseases affect the quality of the leaves, fruits, stem, vegetables, and their products. This heavily impacts on the productivity and thus reflects on the cost. Report of Food and Agricultural Organization (FAO) estimated that the world population will reach to 9.1 billion by 2050, thus requiring about 70% growth in the food production for a steady supply [2]. The key factors that affect the plants and its products are classified into two category 1. Diseases 2. Disorder. The diseases are the biotic factors that are either caused by the fungi, bacteria or algae whereas, the disorders are the abiotic factors caused by the temperature, rainfall, nutrient deficiency, moisture etc. [3].

The conventional means of disease management implicate farmers and the plant pathologists. The diagnosis and use of the pesticide are more often done in the fields. This process is time-consuming, challenging, and most of the time results in incorrect diagnosis with unsuitable exercise of the pesticides [4]. With the advent of Computer Vision (CV), Machine Learning (ML), and Artificial Intelligence (AI) technologies, progress have been achieved in developing automated models empowering, accurate and timely identification of the plant leaves disease. In the last decade, AI and ML technologies have attained a prodigious interest with the availability of a number of high-performance computing processors and devices. Over the last few years, it has been recognized that Deep Learning (DL) has been predominately used in agriculture [5]. This concept is important in making efforts for developing, controlling, maintaining, and enhancing agricultural production. It is to the core of smart farming methodology that is known for the adaptation of new technologies, algorithms, and devices in the agriculture [5], [6].

The associate editor coordinating the review of this manuscript and approving it for publication was Eduardo Rosa-Molinar.

DL is a special class of ML algorithms which have multiple layers for transforming the raw data into information. Eventually, it has been applied to solve several complex tasks like image classification, pattern analysis, feature extraction, and transformation [6], [7]. Authors have used this concept in various studies like, Chen *et al.* in [8] have proposed a novel method using deep learning for counting the apples and oranges from the real-time images. An automated method based on Convolutional Neural Network (CNN) has been proposed by Dias *et al.* in [9] for the semantic segmentation of apple flowers. The author has validated the performance of the proposed work compared with other plants, proving the supremacy of the proposed method for counting the number of flowers from the plants. Ubbens *et al.* in [10] have presented a novel framework for the image-based plant phenotyping, for this purpose, authors have used CNN to count the leaves of a plant. The dependency of having a large dataset to work with deep learning has been overcome by using high-quality 3D synthetic plants. In [11] Lottes *et al.* have used Fully Convolutional Neural Network (FCNN) with sequential information for the detection and classification of robust crop and weed from the field. Suh *et al.* in [12] have presented three variants of AlexNet for the classification of weeds from the crop images. For this purpose, the sugar beet and volunteer potato images have been considered and the result shows the effectiveness of the work.

In this era of research, a number of deep learning architectures have been proposed by various authors. Among these, CNN is one of the most popularly deployed deep learning models. CNN is inspired by the biological nervous and vision system. It is an unsupervised deep learning classification model having high classification and recognition accuracy. This model possesses a complex structure as it constitutes large number of information processing layers. This multiplayer architecture differs it from the conventional Artificial Neural Networks (ANN's) [2]. They are having the capabilities of learning features from the training dataset. CNN models require very few neurons when compared with the traditional ANN but, they require a very large number of data for their training [5], [13].

Therefore, in this work we proposes a Multilayer Convolutional Neural Network (MCNN) for the classification of Mango leaves infected by the fungal disease named as *Anthracnose*. The performance of the model is validated on the images acquired in the real condition. The images are preprocessed with the help of histogram of equalization that balance the invariability among images captured in real conditions. These images are resized to a standard size image using the central square crop method. Then, the MCNN based ternary classification model is trained and tested for the detection of the Mango leaves diseased considering following major points:

1. By automatic and an early diagnosis of a disease and its severity, effective, and timely treatment can be taken in advance.
2. This can also assist in identifying the nature and life cycle of the disease, thus helping to learn vulnerability among them.
3. Therefore this work proposes a deep learning model named as MCNN for the classification of leaves infected by the *Anthracnose* disease.
4. For this work, real conditions healthy and infected leave images are collected for the Mango tree suffering from fungal disease. Further, the effectiveness of the model is validated on the collected and standard database when compared with the other state-of-the-art approaches.
5. The proposed method is automatic, computationally efficient, and cost-effective, that can help in sustaining the importance of the Mango tree and its yields both ecologically and economically.

The rest of the article followed by introduction in section I is organized as in section II related work related with CNN used in plant diseases studies are given, followed by proposed work in section III, section IV presents the methods and materials, results are given in section V, whereas section VI concludes the article followed by references.

II. RELATED WORK

Iqbal *et al.* in [1] have presented the number of studies for the identification and classification of the citrus plant leaves diseases. In this review work, the authors have discussed almost all the methodologies associated with detecting the disease, including concepts of image processing, techniques, challenges, advantages, and disadvantages etc. Golhani *et al.* in [2] has present various studies of neural network approaches used for the identification and classification of the disease from the leave images of the plant. This work introduces various models, types, mechanisms, and classifiers used and the further they have presented the various concepts of imaging with respect to hyperspectral images. Four cucumber diseases named as anthracnose, downy mildew, powdery mildew, and target leaf spots are classified from the leaves in the work proposed by Ma *et al.* in [4] all the images are acquired in the real-time and has been classified using the Deep Convolutional Neural Network (DCNN). Ferentinos in [5] has proposed a VGG convolutional neural network for the identification and classification of the plant leaves. The proposed method classifies the given images between healthy and diseased. The result was validated on a large dataset shows the accuracy of the deep learning approach. Too *et al.* in [6] have used four different deep convolutional network architectures including VGG 16, Inception V4, ResNet and DenseNets for the classification of disease from an image. The images were taken from the plantVillage dataset consists of 38 diseased classes and 14 healthy classes. The DenseNets network achieves higher classification accuracy and lesser computational time when compared with other architectures. Barbedo [13] have presented a study of the deep learning in the plant pathology. The author in this work has presented

TABLE 1. Summary of the literature work.

Author	Network used	Plant name	Disease	Dataset	Accuracy	Advancement
Ma et al. in [4]	DCNN	Cucumber	Multiple	Self	93.4%	Hyperspectral imaging and thermal infrared imaging will be an incorporation
Ferentinos in [5]	CNN	Multiple	Multiple	plantVillage	99.53%	Different plant species and diseases and real-time system
Too et al. in [6]	DenseNets	14 different plants	Different	plantVillage	99.75%	Improve computational time
Barbedo in [13]	GoogLeNet	Multiple	Multiple	Digipathos	80.75%	Automated system for plant pathology
Picon et al. in [17]	Deep Residual Neural Network	Wheat	Septoria, Tan Spot, and Rust	Imagenet ILSVRC15 dataset	84%	Working with different diseases and plants in different cultivation environment
Zhang et al. in [18]	GoogLeNet and Cifar10	Maize	Multiple	plantVillage and Google	98.9% and 98.8%	Adopting mobile devices and working with other plants and diseases
Lu et al. in [19]	DCNN	Rice	Multiple	Self	95.48%	Improvement in object segmentation and fault tolerance
Gandhi et al. in [20]	CNN	Multiple	Multiple	plantVillage	92%	Use of drone and mobile applications
Durmus et al. in [21]	AlexNet and SqueezeNet	Tomato	Multiple	plantVillage	95.65% and 94.3%	Designing the real-time disease classification system
Jain et al. in [22]	CNN	Firecracker and pomegranate	Multiple	Self	88.7% and 93.4%	Working with videos for solving the problem of background details

various issues and parameters that affect the efficiency of the network. Finally, the results verified the performance of the convolutional neural network on the images taken from the Digipathos repository. Kamilaris and Prenafeta-Boldu in [14] have introduced various studies of the deep learning that were adopted in agriculture. This study compromises the different methods, imaging and computer vision theories, related problems, applications, and evaluation metrics etc. The size and variety of the images in the database are an important aspect when working with the concepts of deep learning. Therefore, Barbedo in [15] have present various issues and challenges in the classification of plant diseases. The author has investigated this work with twelve different plants having different attributes and with different diseases.

Kaur *et al.* in [16] have presented a study of the computer vision concepts and methods adopted for the detection and classification of the plant leaves. The advantages and disadvantages of the several studies have been discussed separately. In [17] Picon *et al.* have used DCNN for the classification of three fungal diseases found in the wheat plant. The images in the proposed work were collected in the real-time environment at two locations for about three consecutive years. GoogLeNet and Cifar10 network have been presented by Zhang *et al.* in [18] for the classification of diseases from the maize leaf images. The proposed models achieve higher accuracy when compared with other networks like VGG and AlexNet for classifying nine different types of maize leaves. In [19] Lu *et al.* have proposed a DCNN for the classification of ten different types of rice leave disease from the repository of about five hundred images containing both the healthy and infected images. Authors have adopted the 10-fold cross validation strategy for achieving higher classification results. Gandhi *et al.* [20] have worked with Generative Adversarial Networks (GANs) and CNN for the identification of diseases from the plant leaf images using a mobile application. AlexNet and then SqueezeNet deep learning network has been used by Durmus *et al.* in [21] for the classification of plant leaf diseases. The images are taken from the plantVillage database for the tomato plant leaf images in ten different classes. CNNs have been proposed by Jain *et al.* in [22] for the real-time classification of the disease from the plant leave images. The proposed method is built on a cloud-based environment for performing this task. The images of the plant leaves are collected in the real-time for classification. Table 1 summarizes the various findings.

III. PROPOSED WORK

The flowchart of our proposed work is shown in Fig. 1. Inspired by AlexNet architecture, a Multilayer Convolutional Neural Network is proposed in this work for the classification of the Mango leaves infected with the fungal disease named as

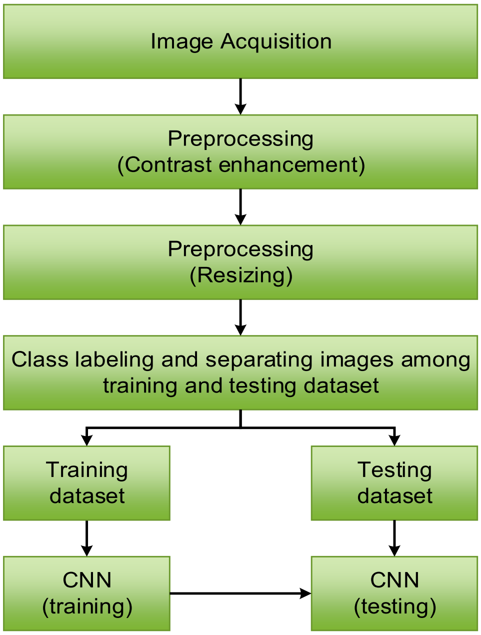

FIGURE 1. Flowchart for the proposed work.

Anthracnose. The procedure of proposed method is revealed by the algorithm given in Table 2.

TABLE 2. Algorithm for the proposed work.

Algorithm
1. Acquire the real-time images of the Mango tree containing both diseased and non-diseased leaves and also, images from plantVillage dataset. *2. Preprocess all the images for contrast enhancement using histogram equalization method and rescaling using central square crop method.* *3. Assign the class labels to the images.* *4. Categorize the images among training and testing dataset selecting from all the class labels.* *4. Train the CNN with the help of training images.* *5. Test the CNN with the help of testing images.* *6. Validate the performance of the proposed model and compare the results with the other state-of-the-art approaches.*

IV. MATERIALS AND METHODS

A. DATASET

In the proposed work, two database repositories have been used, the first one is the real-time Mango leaves dataset and the other one is the plantVillage dataset [29] repository having leaves of multiple plants.

A total of 2200 images are used in this work i.e. 1070 images were self-acquired images captured in the real-time environment and remaining 1130 images were taken from the plantVillage dataset. These images categorized among four classes namely Mango leave images with the disease, without disease, multiple plants leave images with the disease, and without the disease. Based on the category these images are labeled to their respective classes. Fig. 2 shows the sample dataset consists of two Mango leaf images taken in the real condition and two images taken from the plantVillage dataset. Table 3 shows the details of the images.

FIGURE 2. Samples of images.

TABLE 3. Details of image categories.

Image type	Class label	Number of images
Non-diseased Mango leafs	C_0	512
Diseased Mango leafs	C_1	558
Other plant leafs (without disease)	C_2	520
Other plant leafs (with disease)	C_3	610

B. PREPROCESSING OF IMAGES

At first, the training and testing images were preprocessed for contrast enhancement and rescaling them to a 128×128 pixel size. Two different methods namely histogram equalization method for contrast enhancement and central square crop method are used for this purpose for the entire set of database. The contrast of the images is improved by assigning a uniform intensity value to the pixel using the histogram of an image with the help of histogram equalization method given by eq. (1) [26]. Further, the images are rescaled using the central square crop method given by eq. (2).

$$H\left(P_{(x,y)}\right) = round\left(\frac{f_{cdf}\left(p_{(x,y)}\right) - f_{cdf\,min}}{(R \times C) - f_{cdf}} \times L - 1\right) \quad (1)$$

where, f_{cdf} = cumulative frequency of the gray level, $f_{cdf\,min}$ = minimum value of cumulative distribution function, $f_{cdf}\left(P_{(x,y)}\right)$ = intensity of the current pixel, R and C = product of number of pixels in rows and columns and L = number of intensities.

$$def\ centeredCrop(img, new\_height, new\_width) \quad (2)$$

C. CONVOLUTIONAL NEURAL NETWORK

With the advancement in computationally efficient devices like Graphics Processing Unit (GPU), deep learning related applications have attained exponential development. The concept of deep learning is motivated by the conventional artificial neural network. The deep learning model is stacked with the number of preprocessing layers in which the information is extracted from the raw input to the final task-specific output. DL models have tremendously emerged after the image classification accuracy of CNN over ILSVRC dataset in 2012 proposed by *Krizhevsky et al*. [23]. Since then applications of deep learning have been found in the number of applications for image classification, pattern recognition, voice recognition, object detection, etc. [24], [25].

A convolutional neural network is the deep learning model used for solving complex pattern recognition and classifications problems with a large amount of databases. The model majorly comprises of four different layers namely convolution, max-pooling, fully-connected, and output layer stacked over one another. The novelty of the architecture lies in its flexibility to its configuration depending on the task related results. There are many different CNN models available like AlexNet, VGG, GoogLeNet, ResNet etc. These models differ based on their depth, configurations, the nonlinear function, and the number of units. There are various adjustable parameters like the dropout rate, the learning rate used in complex processing for solving classification and pattern recognition problems [24], [25].

Fig. 3 shows the architecture of the proposed CNN that we have used for the classification of the infected Mango leaves. This model is inspired by the AlexNet architecture, which consists of six convolutional layers each followed by a Rectified Linear Unit (ReLU), three max-pooling layers, and two dense or fully-connected layers last layer acting as an output layer with a Softmax activation function. A flatten acting as a hidden layer is used to convert the images in a 1D array, thus enhancing the performance and making it simpler to handle the data. The size of each convolutional layer is 3×3 and each max-pooling is 2×2, whereas the size of the input images and feature maps varies shown in the figure. Stochastic gradient descent (SGD) or Backpropagation algorithm (BPA) is used for the training of the CNN.

The input volume is convolve with weights volume. Depending on the padding and out striding the input layer is expanded or shrinked. In the convolution process the spatial width and height is reduced, but increasing the depth. Non-linear activation function is added to each layer for modelling the more complex target function varying in a non-linear way with the given input. ReLU reduces the probability of a vanishing gradient. This also introduces sparsity to the model. Pooling helps in reducing computational requirement and spatial size of the activation function. Max pooling due to higher convergence and better performance is more commonly used. The images are down sampled using max-pooling layer. It also reduces the likelihood of overfitting. Dense or fully connected layer is the final layer responsible for predicting the class of an image. Further details of the proposed multilayer convolutional neural network are given as:

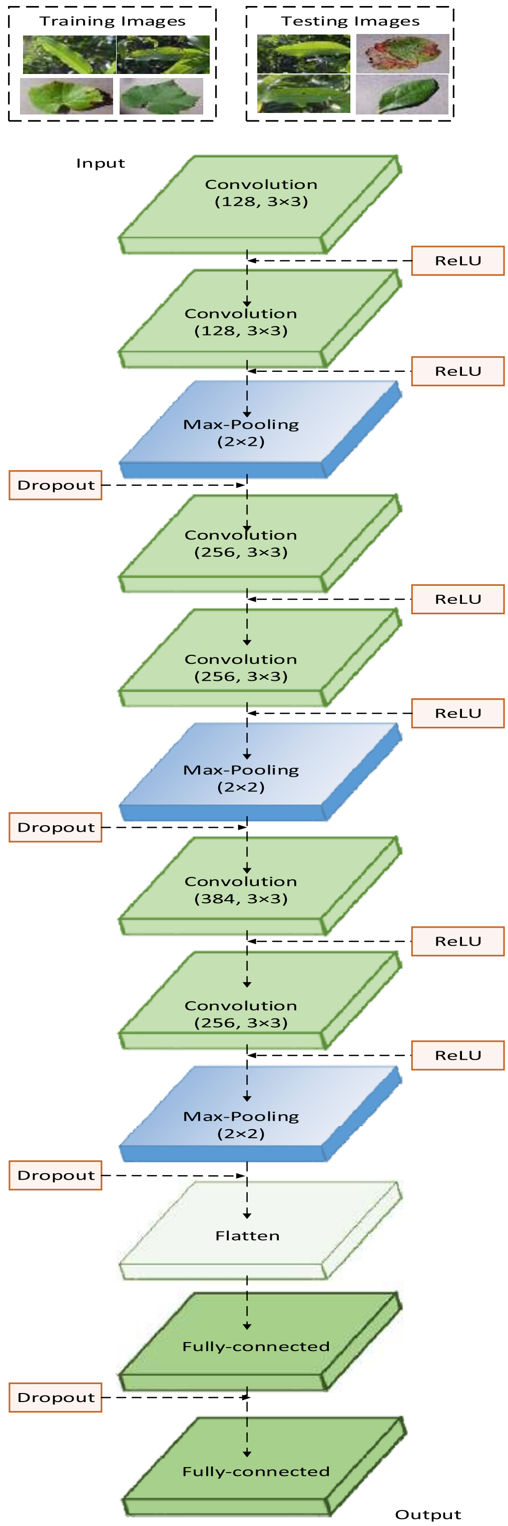

FIGURE 3. Architecture of the proposed CNN.

1. This model is a sequential model having a series of layers to convert the standard size image into a feature set for further processing.
2. The first two layers of this model M are the convolutional layer with 128 filters and ReLU as the activation function.
3. The third layer is the max pooling layer that will reduce the size of the convoluted image by (2, 2).
4. It again adds two more convolutional layers will 256 filters and ReLU as the activation function.
5. The sixth layer is the max pooling layer with a pool size of (2, 2).
6. A convolutional layer with 384 filters and ReLU activation function is added to the model.
7. The next layer is again a convolutional layer with 256 filters and ReLU activation function.
8. Then it has a max pooling layer followed by dropout rate 0.2.
9. Then this model has added one more layer to flatten the output of the above designed convolutional neural network model.
10. This flattening process will give the feature set for every image in the form of output.
11. Now, this model has two fully connected layers that will be used for the classification of images based on the generated feature set.
12. This dense layer act as the hidden layer of the artificial neural network having 512 hidden neurons and the activation function is ReLU. This model is designed in such a way that every input neuron is connected to every other hidden neuron forming a fully connected layer.
13. It has one more fully connected layer which acts as the output layer of the artificial neural network having 3 output neurons. The number of output neurons is always dependent on the classes. It uses SoftMax as the activation function.
14. The output of this layer is the predicted class label which is used to evaluate the overall accuracy of the proposed model.

The various parameters and configuration details of the proposed CNN is given in Table 4.

TABLE 4. Configuration details of the proposed CNN.

Convolutional layers	6 (each with 3×3 filters)
Max-pooling	3 (each with 2×2 filter)
Dropout	0.2 - 0.5
Learning rate	0.01
Momentum	0.09
Weight decay	1e-6
Activation function	ReLU
Batch size	15
Epochs	100
Training algorithm	BPA / SGD

D. TRAINING AND TESTING

Initially, the entire dataset is divided into two parts, the training and the testing dataset. This is done by randomly splitting dataset into training set comprises about 80% of the images and the testing set constitutes about 20% of the images. This ratio distribution is predominately used in the neural network applications. Therefore, for the training of the CNN 1760 images are used and remaining 440 images are kept for testing the performance of the model.

Training a CNN is the practice of running training examples through the model from the input layer to the output layer simultaneously making a prediction and figuring out the results or errors. If the prediction is wrong then this is back propagated in reverse order i.e. from last layer to first layer. For this work, we use backpropagation algorithm for adjusting the weights of the network slightly aiming for the better result. This complete process is known to be one epoch. The weights in this work are optimized by using stochastic gradient descent algorithm. The proposed model does not includes the object segmentation process. This step can be excluded when working with deep neural network as they have the tendency of extracting the essential features for the given image while eliminating the excessive ones [5]. This incapacitates the overhead of handling the real-time complex images and thus improves the efficiency.

Proposed Multilayer Convolutional Neural Network based ternary classification model is then trained for the detection and classification of Mango leaves. This ternary model includes three cases i.e. (i) to classify the given image for Mango leaf or not, (ii) the image is a non-diseased Mango leaf image, and (iii) the image is a diseased Mango leaf image. The training images were taken from each of the class labels C_0, C_1, C_2, and C_3 respectively maintaining the ratio of 80% images. All the other remaining 20% images were untouched during the complete process. Each image from the normalized training dataset is given as an input to the Multilayer Convolution Neural network model to extract the features. This model is trained to predict the class label for every training image.

V. RESULTS

The proposed model consisting of training and testing process were implemented using an open source software framework known to be TensorFlow with Python programming language. The learning rate is set to 0.01, dropout rate varies from 0.2 to 0.5, and the momentum was chosen to be 0.09, with weight decay of 1e-6 respectively. Training was accomplished in about 3 days and testing was completed in a few minutes. The training process was implemented on the GPU of an NVIDIA GTX1080 card, using the CUDA platform. In the experiments for testing the proposed algorithm is implemented on a desktop computer with Intel (R) core (TM): 7-7700 CPU (3.60 GHz), Windows 10 Pro (64 bit) operating system, 16.0 RAM, GPU (Integrated 2 GB NVIDIA GeForce GT 710), and 1TB hard disk. The results of presented methodology focus on:

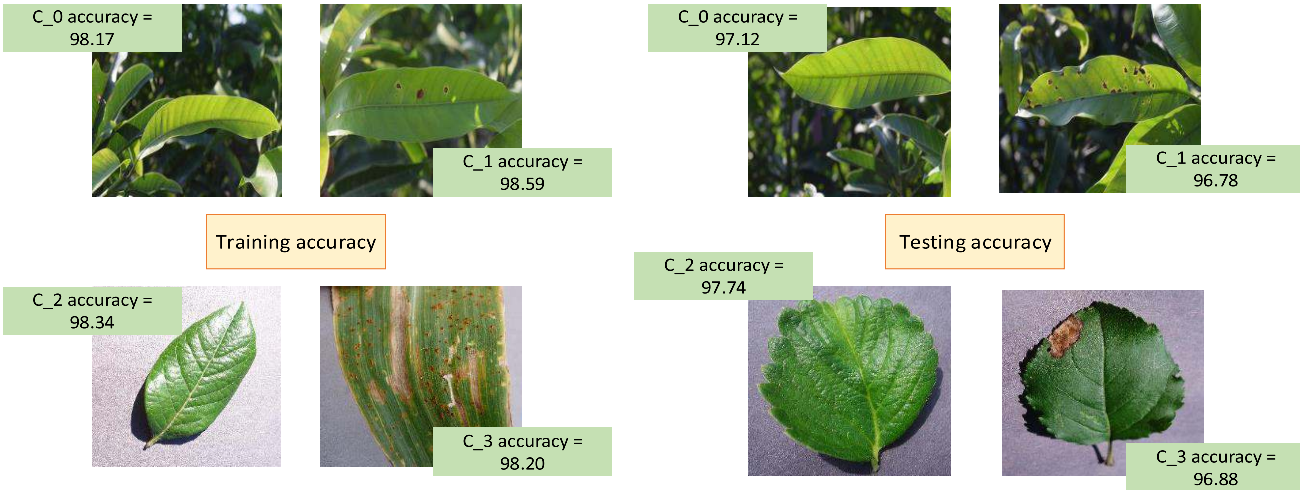

FIGURE 4. **Classification results for the proposed model.**

1. Primary task is to classify the given image is Mango leaf or not. Then, the secondary task is to identify the leaf is a non-diseased Mango leaf, and third is to identify and classify that the leaf is a diseased Mango leaf or not.
2. Measuring the accuracy for both the training process and the testing process of the proposed network.
3. Comparing results with the other state-of-the-art approaches Particle swarm optimization (PSO), Support Vector Machine (SVM), and Radial basis function neural network (RBFNN).
4. To report corresponding missing report rate, and false report rate.

Fig. 4 shows the result accuracy for both training and testing of the proposed work. Table 5 indicates the accuracy for different classes. The proposed CNN is validated on the two set of images database, the first self-acquired database encompasses of Mango leaves both healthy and infected from the Anthracnose. The second database comprises of images taken from plantVillage database having multiple plant leaves of strawberry, grapes etc. in both healthy and diseased condition. It has to be noticed that these leaves are suffering from multiple diseases like leaf curl, early blight, late blight, and leaf spot.

TABLE 5. **Training and testing accuracy (%).**

Class	C_0	C_1	C_2	C_3
Training	98.17	98.59	98.34	98.20
Testing	97.12	96.78	97.74	96.88

The images were divided among the training and the testing database upholding the ratio i.e. 80% images for training and 20% images for testing. Before the training process, the images are normalized for histogram enhancement and rescaling. The results are compared with the other state-of-the-art approaches named as Particle swarm optimization (PSO), Support Vector Machine (SVM), and Radial basis function neural network (RBFNN). All the approaches including proposed network are verified with the three cross-fold validation strategy. Table 6 presents the overall results with comparative graph shown in Fig. 5. These results show the accuracy, missing report rate, and false report rate of all the methods selected for the classification of disease Mango leaves. The accuracy is computed by the eq. (3) [27], [28].

TABLE 6. **Classification accuracy (%).**

Algorithm	PSO	SVM	RBFNN	MCNN
Accuracy	88.39	92.75	94.20	97.13
Missing report rate	11.61	7.25	5.80	2.87
False report rate	9.83	4.98	0	0

$$Accuracy = \frac{correctly\ classified\ number\ of\ data}{total\ number\ of\ data} \times 100\% \tag{3}$$

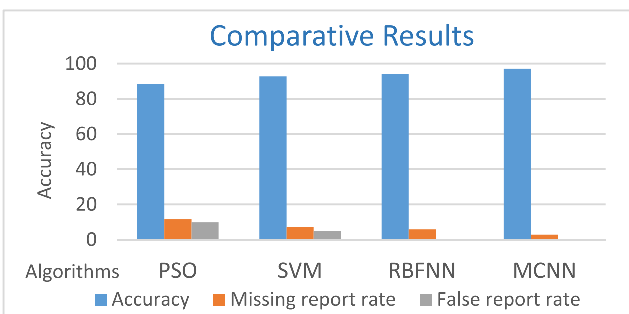

FIGURE 5. **Comparative graph.**

The accuracy of the proposed method was computed to be 97.13% which is higher than other classification methods when compared with given in Table 6. The proposed model also reports a missing report rate of about 2.87% with 0% false report rate. This missing rate is due to the vulnerabilities present in the real-time database. This is problematic in the entire training process of the CNN. PSO with missing report rate of 11.61% false report rate of 9.83% is countered to be the least effective approach. Images taken in real condition majorly suffers from the problem of (i) Variation in Temperature, (ii) Shadowing, (iii) Overlapping of leaves, and (iv) Presence of multiple objects. Handling these issues we can improve the performance of the proposed approaches.

VI. CONCLUSION AND FUTURE WORK

By controlling the biotic factors causing severe losses in the crop yield, we can enhance the productivity and quality of the plants and its products. Computer vision with machine learning methodologies has outperformed in solving a number of plant leaves disease problems including pattern recognition, classification, object extraction etc. Therefore in this work, we propose an innovative model named as MCNN for the classification of Mango leaves infected from the fungal disease named as *Anthracnose*. The higher performance of the proposed work is confirmed with accuracy of 97.13% when compared with other state-of-the-art approaches for its accuracy. The presented model is also computationally efficient and simple. Some of the future works are given as:

1) The use of some other function instead of Softmax activation function can enhance the performance of the CNN making it compatible for classifying multiple diseases.

2) Counter measuring the inconsistencies encountered working with real-time dataset.

3) Working with other plants with economic importance and calculating the severity of the disease considering other parts of the plants as well.

4) To build a Web/Internet of Things (IoT) enabled real-time disease monitoring system.

Finally, Table 7 illustrated the summary of the manuscript.

TABLE 7. Summary of the manuscript.

Scientific problem	Automated disease diagnosing scheme for plants to sustain their health and growth
Motivation	Monitoring and preventing the plant to nourish environment and enhance their economic value
Contribution	A real time, efficient and low cost disease monitoring system is proposed for classification among infected and healthy Mango Leaves
Highlights	Use of deep learning concepts for real time images of Mango tree having higher economic values in all countries like India
Future work	Designing and implementing the framework using Internet of Things in Precision Agriculture

APPENDIX

Acronyms used in this manuscript are given in Table 8.

TABLE 8. Glossary.

Acronyms	
AI	Artificial Intelligence
ANN's	Artificial Neural Networks
BPA	Backpropagation algorithm
CV	Computer Vision
CNN	Convolutional Neural Network
DCNN	Deep Convolutional Neural Network
DL	Deep Learning
FAO	Food and Agricultural Organization
FCNN	Fully Convolutional Neural Network
GANs	Generative Adversarial Networks
GPU	Graphics Processing Unit
IoT	Internet of Things
MCNN	Multilayer Convolutional Neural Network
ML	Machine Learning
PSO	Particle swarm optimization
RBFNN	Radial basis function neural network
ReLU	Rectified Linear Unit
SC	Soft Computing
SGD	Stochastic gradient descent
SVM	Support Vector Machine

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