Improvisation in detection of pomegranate leaf disease using transfer learning techniques

Shivappa M. Metagar[1], Gyanappa A. Walikar[2]
[1]School of Computer Science and Engineering, REVA University, Bangalore, India
[2]School of Engineering and Technology, CMR University, Bangalore, India

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ABSTRACT

To provide the growing world population with food and satisfy their fundamental requirements, agriculture is a vital industry. The cultivation of cereals and vegetables is indispensable for both human sustenance and the worldwide economy. Many farmers in rural areas suffer substantial losses because they rely on manual monitoring of crops and lack sufficient information and disease detection methods. Digital farming techniques may provide a novel way to swiftly and simply identify illnesses in the leaves of plants. This article uses image processing and transfer learning techniques for identifying plant leaf ailments and taking preventative action in the agriculture business in order to address these problems. Global food security and agricultural productivity are seriously threatened by leaf disease. Crop losses may be considerably decreased, and crop output can be increased by promptly identifying and diagnosing leaf diseases. Deep learning can mitigate the adverse impact of artificially picking disease spot data, enhance objectivity in extracting plant disease traits, and expedite the advancement of new technologies. This article presents a novel approach using deep learning to diagnose leaf diseases. This article advances the development of efficient and successful techniques for recognizing and diagnosing leaf diseases, which will eventually aid farmers and maintain the security of the world's food supply.

Corresponding Author:

Gyanappa A. Walikar
School of Engineering and Technology, CMR University
Bangalore, India
Email: gyanapp@rediffmail.com

1. INTRODUCTION

Identification of a plant illness using just visual cues from the leaves of the plant, which take into account more complicated factors. Because of its intricacy, even professionals may often misdiagnose plant diseases. The automated system's design aids in identifying the illness based on the look of the plant and its visible symptoms. This strategy will provide valuable assistance to farmers in promptly alerting and preventing the spread of disease over a large area. Infection symptoms in plants often appear on leaves, natural products, buds, and young branches. This situation results in the waste (dropping) or damage of an organic product. Furthermore, the spread of existing illnesses is facilitated by normal farming circumstances, which in turn lead to the development of new diseases [1]. As such, it is critical to identify the disease early on and to take precautions to stop it from spreading to other trees. Thus, the fight against diseases and pests is the most important problem facing plants [2]. Gathering a number of vein recognition-based datasets. Organizations use data sets derived from gathered photos. Putting the concept into practice using a feature extraction method and certain algorithmic techniques [3]. First, to determine if the plant is diseased or not, analysis is performed. Next, the kind of illness is analyzed using categorization [4].

We will use a feature extraction approach to do the analysis. In order to address this disease problem, technical experts such as botanists and agricultural engineers examine the leaf first, followed by testing. It takes more time and isn't any more precise. The farmer may use this technology without having to identify whether plants are infected or not since the deep learning algorithm will precisely forecast the illness [5]. It is necessary to classify the plant in order to determine whether or not it is diseased [6]. The two-step procedure has to be followed for that. The first stage is training, where a large dataset of both sick and non-diseased photos will be used to teach the computer. In the second phase, known as testing, the training data is used to assess and forecast the current picture [7].

Farmers in the agricultural sector rely on their crops, and if a disease strikes, they risk not getting the right output. Plant diseases are frequently the reason for decreased yields and lower farmer revenue. However, in contemporary disease prediction systems, the process is different and may require more time to recognize and comprehend the type of illness. In order to identify various leaf diseases on various plants, disease prediction is connected to computer vision and machine learning. This is a long-term system that incorporates several real-world scenarios, including a prediction system for diseases of the vine, pomegranate, maize, and other leaves.

The precise assessment of a plant leaf's condition of illness is known as disease prediction. In data science, one of the most important criteria is accurate illness prediction. Currently, techniques based on machine learning have increased the accuracy of plant leaf predictions, including those for maize, pomegranates, and grapes. Nevertheless, in this difficult setting, the illness prediction performance still has to be enhanced. Current disease prediction methods in agriculture demand a lot of processing power and storage capacity [8].

This paper is structured according to the following manner. Section 1 brief introduction about plant leaf disease detection concepts. Section 2 related work is outlined in detail, like supervised and unsupervised machine learning and in supervised machine learning again first section is regression algorithm, decision tree, random forest, classification algorithms like k-nearest neighbor (KNN), naive Bayes, support vector machines (SVM), and regression algorithm. Section 3 brief summary of all the machine learning algorithms. Section 4 final conclusion is set.

Dataset description: the hybridized data from several sources makes up the dataset used for the experiment. The photos of pomegranate leaves make up the dataset. The following picture types are included in this dataset: i) healthy leaves: these leaves are green in color and free of infections, ii) anthracnose: this disease causes sunken-type, black lesions on leaves. This illness is brought on by fungus, and iii) cercospora leaf spot: the leaf develops grayish-tanned lesions and black spots.

2. RELATED WORK

The proposed solution for real-time agricultural applications involves using a new and efficient convolutional neural network (CNN) architecture called deeper lightweight multi-class classification network (DLMC-Net) [9]. This architecture is designed to identify plant-leaf illnesses in various crops. The model utilizes separable convolution blocks, collective blocks, passage layers, and point-wise convolution blocks to address the problem of vanishing gradient and reduce the number of trainable parameters. The model's effectiveness is verified using four datasets: citrus, cucumber, grapes, and tomato. Based on empirical evidence, the proposed model outperforms seven state-of-the-art models in terms of superior recall, sensitivity, specificity, accuracy, precision, F1-score, and Matthew's correlation coefficient at high levels. The model demonstrates promising potential as a tool for diagnosing plant-leaf illnesses in several crops, with accuracy rates of 93.56% for citrus, 92.34% for cucumber, 99.50% for grapes, and 96.56% for tomato.

A compact CNN architecture [10] consisting of eight hidden layers is proposed for the purpose of identifying diseases in tomato crops. The model has superior performance compared to pretrained models and conventional machine learning approaches, achieving an accuracy of 98.4%. The model is trained using the PlantVillage dataset, which consists of 39 classes representing different crops, including 10 classes specifically for tomato diseases. The computational burden of the proposed reduced CNN model stems from its many parameters, and it may have two drawbacks.

Using tiny datasets, Argüeso *et al.* [11] investigates the use of few-shot learning (FSL) methods for plant leaf disease classification. The FSL approach outperforms traditional transfer learning strategies by using Siamese networks and triplet loss. The FSL approach yielded a 90% decrease in training data requirements while retaining good accuracy, using as few as 15 photos per class. The FSL approach for classifying plant leaves has certain potential drawbacks, such as the need for large labelled datasets for initial training and the potential for decreased accuracy when using a relatively small amount of training data [12].

Chen *et al.* [13] focuses on the diagnosis of plant leaf diseases via the application of deep learning techniques, particularly transfer learning using pre-trained models. Their method is based on the VGGNet and Inception modules, which were trained on ImageNet. On a publicly available dataset, they get a validation accuracy of at least 91.83% by initializing the weights with these pre-trained networks. The suggested method obtains an average accuracy of 92.00% for identifying photos of rice plants, even in the presence of complicated backdrop circumstances. Overall, the research shows how successful and efficient their method is at identifying plant diseases.

A deep learning approach for identifying plant diseases is presented in [14]. It combines conventional handmade features with a deep feature descriptor based on transfer learning. In order to improve the fused feature's discriminative capacity, the framework further includes center loss. High classification accuracy on three publicly accessible datasets is shown by the experimental findings, proving the usefulness of the suggested approach in differentiating between plant leaf diseases. Both the amount and quality of food produced in Latin America and the Caribbean are being impacted by crop productivity due to climate change [15]. This work addresses uncertainty and misclassification measurement by presenting a probabilistic programming strategy using Bayesian deep learning algorithms.

According to Hu and Fang [16], tea leaf illnesses were automatically identified in tiny samples using a multi-CNN model named merge model. With an emphasis on soybean plants, Karlekar and Seal [17] have created a computer vision method for identifying and treating plant illnesses. The method consists of two modules: one for removing the leaf portion from the picture and another for identifying soybean plant illnesses using SoyNet, a deep learning CNN. The suggested technique beats nine existing state-of-the-art methods/models and achieves an outstanding 98.14% identification accuracy.

An optimized deep neural network is suggested as a means of identifying and categorizing illnesses in photographs of paddy leaves [18]. The photos were taken in an agricultural area using the leaves of rice plants. Pre-processing includes extracting binary pictures based on hue and saturation and converting RGB images to HSV. Segmenting afflicted, normal, and background regions is accomplished using clustering. A deep neural network that has been improved using the Jaya optimization algorithm is used for classification, and it achieves good accuracy for many illness categories.

A low-shot learning technique for diagnosing illnesses in tea leaves is presented in [19]. By extracting color and texture information, it segments illness areas using SVM. By using enhanced conditional deep convolutional generative adversarial networks (C-DCGAN) for data augmentation, the technique creates additional training examples. The VGG16 deep learning model outperforms traditional low-shot learning techniques with an average detection accuracy of 90% when trained using enhanced illness spot pictures. The low-shot learning approach for tea leaf disease diagnosis may have the drawback of being very dependent on the caliber and variety of training data.

To enhance tea leaf blight (TLB) disease identification and severity analysis, a novel deep learning technique is suggested [20]. The technique lessens the impact of shadow and light variance in TLB photos by using the Retinex algorithm. TLB leaves are detected even in the presence of blurriness, occlusion, and tiny pieces using a deep learning architecture known as faster region-based CNN. Afterwards, trained VGG16 networks are used to assess the severity of the discovered TLB leaves with a greater degree of accuracy than with traditional machine learning techniques.

A deep learning-based system for precisely identifying multi-scale apple leaf spots in unrestricted contexts is presented in [21]. To increase precision and effectiveness, the approach integrates a bidirectional transposition feature pyramid network (BCTNet), a cross-attention module, and a Bole convolution module. By providing producers and pesticide spraying robots with decision-making information to optimize pesticide use and minimize agricultural production losses, the suggested technology surpasses previous cutting-edge techniques.

Reducing economic losses in the apple business and stopping the spread of diseases and pests in apple trees need effective early detection [22]. However, a variety of circumstances, including several symptoms on the same leaf, a non-homogeneous backdrop, and variations in leaf color, may make disease identification difficult. Ensuring improved productivity and managing infections require prompt and accurate diagnosis. Restrictions in [22] that are mentioned as follows: i) it may be challenging to correctly identify some illnesses when a leaf exhibits more than one symptom. This might result in misidentification or missing discovery; and ii) variations in leaf color caused by the age of diseased cells and a non-homogeneous backdrop might further complicate disease detection and raise the possibility of false positives or negatives.

Ajra *et al.* [23] proposed a method for identifying plant diseases via image processing and CNN models. The method is used to examine sick leaf symptoms on tomato and potato leaves. The suggested method classifies healthy-unhealthy leaves and leaf illnesses with high accuracy rates of 97% and 96.1% for ResNet-50 and 96.5% and 95.3% for AlexNet, respectively. To further encourage plant health awareness, a preventative measures approach and graphical layout are presented.

The early diagnosis of leaf diseases in tomato plants is the main topic of this research [24], which is important for India's agricultural sector. The suggested approach reliably detects and categorizes leaf diseases in tomato plants by using image processing techniques, including image segmentation and clustering. The purpose of this research [25] was to use deep learning algorithms to identify illnesses in tomato plants.

AlexNet and SqueezeNet are two designs that the researchers explored using pictures of tomato leaves from the PlantVillage dataset. The algorithms were designed to be used on a robot for real-time disease diagnosis in tomato fields or greenhouses. The trained networks were able to identify a variety of illnesses in the leaves.

3. PROPOSED SYSTEM

The pomegranate leaf disease detection employs a deep learning technique to address the problem of picture categorization. Thus, the implementation of this sickness detection system can utilize transfer learning architectures. Figure 1 illustrates that in order to obtain the required data for transfer learning, it is important to employ collecting data, augmenting data, preprocessing data, and techniques for extraction the features. Typically, the extracting the features for training dataset and the threshold values may be set based on that data. In the testing phase, the feature values are compared to the learned ones to determine if the leaf image is infected with disease or not.

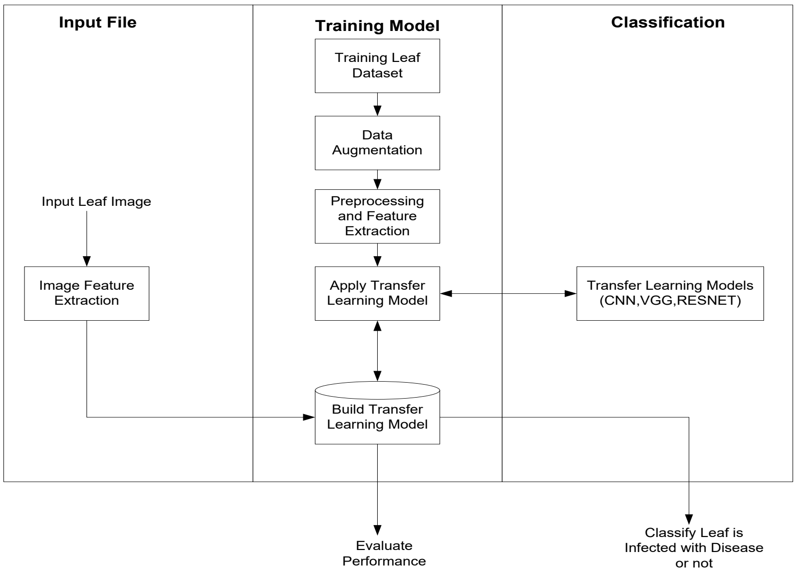

Figure 1. System architecture

Proposed methodology-transfer learning concepts architecture of VGG16: the architecture of the VGG16 has the deep neural network with 16 layers. It also has the total number of 138 million parameters. It will give the advantage of maintain high standards which is useful for the present scenarios. And another advantage of the VGG16 is having simple in structure. The vignette involves the incorporation of the convolution neural network features and structures. The structure of VGG16 is in Figure 2. The architecture has 13 conv layers and 3 connected layers.

Algorithm 1: it is implemented using VGG16. The VGG16 consists of taking input as layer, conv layers, activation-function, hidden-layers, maypole, and fully connected layers as output.
Input: here, in Vignette authors used the 224x224 size of the input. By using the ImageNet competition method need to keep the input size constant. It will done by the cropping of the 224x224 image section form the each center of the image.
Convolutional layers: in this method, VGG uses the smallest 3x3 size of receptive field. Also, this VGG uses the size of 1x1 filters as an input to perform the linear transformation.
ReLu activation function method: in this algorithm, the VGG uses the ReLu activation function. ReLu is called as the rectified linear unit activation function. This activation function gives the exact suitable outputs for the positive inputs and for negative inputs it produces the zero output.
Hidden layers: in VGG network. ReLu activation function layer is used to increase the framing time and improvement of overall accuracy.
Pooling layers: the pooling layers have step to follow the several convolution layers. They will help in reducing dimensionality and parameters. The pooling layers is available in form of filters of 64, 128, 256, and 512 layers.
Fully connected layers: this algorithm also used the fully connected layers.
Resnet34 architecture

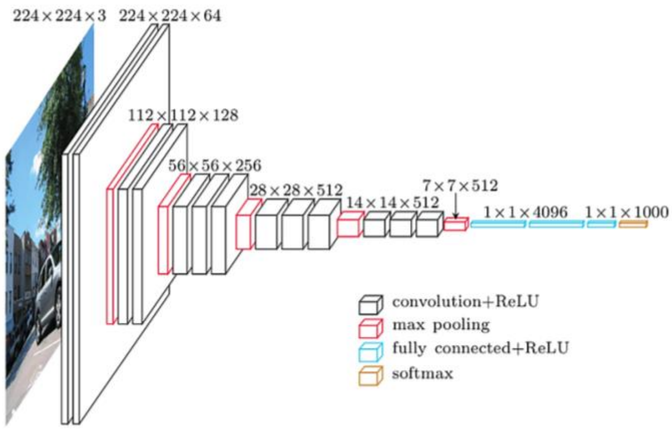

Figure 2. Flow diagram of VGG16 structure

Figure 3 shows the architecture for residual 34 networks. This structure consists of the convolutional layer with filters having 64 count and 7x7 as size of kernels in the first convolution. All these layers are formed together in the form of group-pair. In the 2nd, layers 3x3 as kernel size and filters having 64 counts in between the layers and pool/2. Totally 6 count of layers 3x3 kernel size and 128 count of filters. Same will continue process until avg_pooling and softmax function. Every time filters will be doubled with specifies the $\frac{num\_filters}{2}$. In the residual block, f represents the skip connection and w represents the w. The convolution kernel u_{t-1} can be modified as into form of u_t as shown in (1).

$$u(p_t) = relu\{f * u(p_{t-1}) + w(p) * u(p_{t-1})\} \quad (1)$$

Given $f * u + w * u = f\left(\delta + \frac{w}{f}\right) * u$, in (1) can be re written as (2):

$$u(p_t) = \sum_{p_{t-1}} \mathrm{K\,o\,f}\big(\delta(p_t - p_{t-1}) + \cap\,(p_t - p_{t-1})\big)u(p_{t-1}) \quad (2)$$

where $\cap\,(p) = \frac{w(p)}{f}$.

In this proposed methodology, by combining the ResNet34 with CNN to overcome the disadvantage of the CNN. In the proposed methodology training of input and target outputs are done by using back propagation algorithm. The weights adjustment of the proposed methodology is done by the gradient descent algorithm which will gives the optimization outputs.

The Figure 4 is working block of ResNet, it as path of p(t-1) to p(t+2). These network structures have the three residual blocks. In this x dimension side will reduce and p dimension will have the expansion and it had various paths of input to the output. Figure 4 also shows the path of the three-layer residual block in between p(t+2) and p(t-1) as shown in (3).

$$\mathrm{p(t+2) = (1 + q(t+1)(1 + q(t)(1 + q(t-1)p(t-1)}) \quad (3)$$

The disturbance $\Delta q(t-1)$ is executed on the layer of t-1 then the p(t-1) is given as:

$$\Delta p(t+2) = \left\{\frac{\partial q(t+2)}{\partial q(t+1)}\frac{\partial q(t+1)}{\partial q(t)}\frac{\partial q(t)}{\partial q(t-1)} + \frac{\partial p(t+2)}{\partial q(t+1)}\frac{\partial q(t+1)}{\partial q(t-1)} + \frac{\partial p(t+2)}{\partial q(t)}\frac{\partial q(t)}{\partial q(t-1)} + \frac{\partial p(t+2)}{\partial q(t-1)}\right\}\Delta q(t-1)p(t-1) \quad (4)$$

The back propagation processes the formula is shown as follows:

$$\frac{\Delta p(t+2)}{\Delta q(t-1)}$$

The skip connection between q(t-1) and p(t+2) is shown in (4). When the proposed network goes in to the deeper the back-propagation term has approach zero and skip connection term will not become zero.

$$q(t+2) = g(t+1)g(t)g(t-1)q(t-1) \quad (5)$$

$$\Delta q(t+2) = \frac{\partial q\,(t+2)}{\partial q(t+1)}\frac{\partial g(t+1)}{\partial g(t)}\frac{\partial g(t)}{\partial g(t+1)}\,\Delta g(t-1)q(t-1) \tag{6}$$

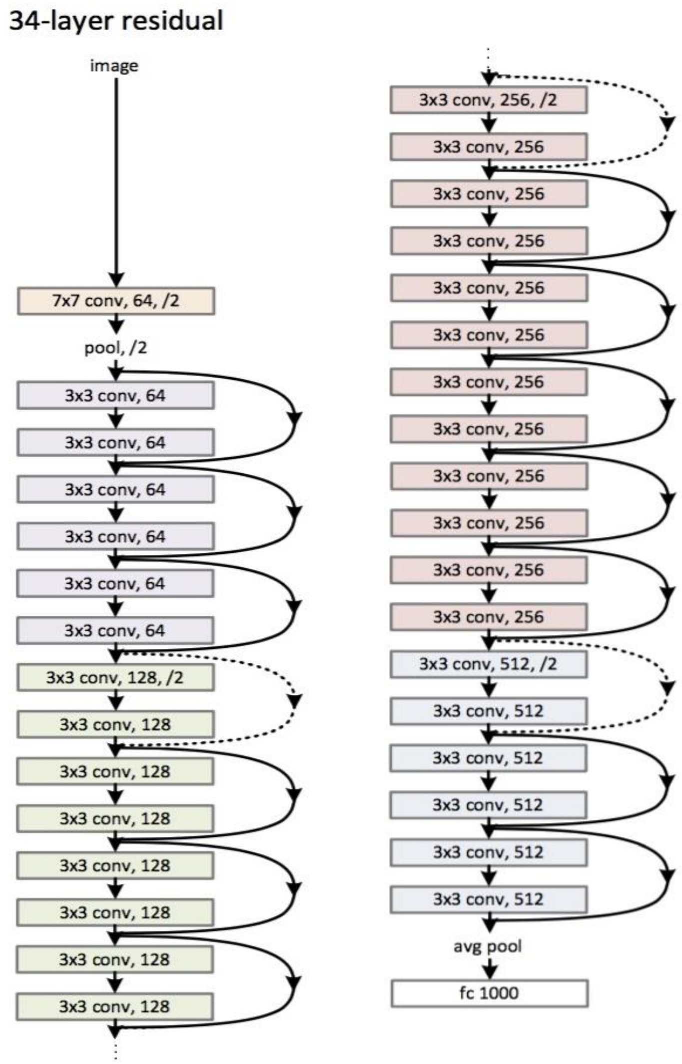

Figure 3. Architecture for residual-32 network

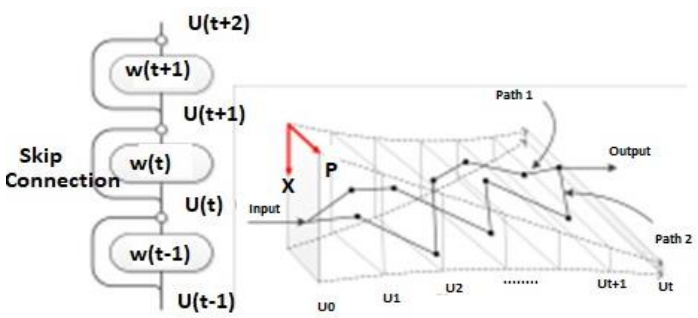

Figure 4. ResNet

The skip connection will address the gradient problem in the training problem. The chains of back propagation in terms of partial differential tend to zero when the network goes into deeper.
Steps: Proposed ResNet combined with CNN algorithm:

Steps of the ResNet algorithm consists of many stages given as inputs, pre-processing, convolution layers, residual blocks, identity mapping, Bottleneck design, pooling layers, fully connected layers, softmax activation and finally output. This ResNet is a deep neural network with residual connections to perform easy training of the neural network.

- Input: the ResNet model has an input of set of images. Each image typically has three color channels (red, green, and blue) and is of a fixed size.
- Pre-processing: before feeding the images into the ResNet model, preprocessing steps such as resizing, normalization (subtracting mean and dividing by standard deviation), and data augmentation (randomly flipping, rotating, or cropping images) might be applied to enhance the model's performance and generalization.
- Convolutional layers block: in the ResNet algorithm convolution layers are the main core part of the system. These layers consist of filters that slide across the input images, extracting features at different spatial locations. The convolutional layers capture low-level features like edges, textures, and shapes.
- Residual blocks: unlike traditional neural networks, residual blocks were introduced by ResNet, which has connections in short called as identity mappings.

a) Identity mapping: in a residual block, convolution block act as an input in series, next to normalization layer and Activation function with ReLU. Then, the output is added to the original input, creating a residual connection.
b) Bottleneck design (optional): in deeper versions of ResNet (e.g., ResNet-50, ResNet-101), a bottleneck design is used in residual blocks to reduce the computational cost. This design involves using 1x1, 3x3, and 1x1 convolutional layers to decrease and then increase the number of channels, respectively.

- Pooling layers: after passing through several residual blocks, the feature maps are down sampled using pooling layers (e.g., max-pooling or average-pooling).
- Fully connected layers: these fully connected layers will perform the function of classification using learned features.
- Softmax activation: for multi-class classification tasks, a SoftMax connected to the output of the layer called fully connected.
- The ResNet algorithm gives the output has a probability function of class and indicating model confidence of each class. In the training process the parameters such as weight and bias function are adjusted by using optimization algorithm to measure the minimize a loss function. The loss function quantifies the variation between predicted values and true labels.

4. RESULTS AND DISCUSSION

The tools commonly used in such research paper as follows:

- Python: as with most machine learning and data science projects, Python is likely the primary programming language used in this paper. Python has an advantage of ability to use various libraries function and many frameworks for tasks such as data pre-processing, model development, and evaluation. Python also offers the easy in readability and implementing machine learning algorithms.
- Transfer learning: is a machine learning technique to perform the two tasks first one is model training and second one is reuse of starting point of model. In the context of the paper, transfer learning techniques used top re-trained deep learning models (such as those trained on ImageNet) and fine-tune them for the task of detecting pomegranate leaf diseases. This approach has advantage to improve the performance of the model.
- Deep learning frameworks (e.g., TensorFlow and PyTorch): used to build the power neural networks. These frameworks likely play a crucial role in implementing transfer learning techniques and designing custom neural network architectures tailored to the task of disease detection in pomegranate leaves.
- Image processing libraries: since the task involves analyzing images of pomegranate leaves to detect diseases, OpenCV may be used for tasks such as image loading, preprocessing, and augmentation. These libraries help in preparing the data for training and improving the robustness of the model.
- Data visualization tools: tools for data visualization, such as Matplotlib, is used to visualize the dataset distributions, model performance metrics, and other relevant information. Visualizations help in understanding the data and communicating the results effectively in the paper. In this work, used as 600 images have a sample, the proposed system has an accuracy value of 0.9857 and 0.8819 by using the algorithms ResNet34 and VGG-16, respectively, which will give the better results when compare to the existing methods shown in Figure 5.

The proposed system has a loss value of 0.1109 and 1.0026 by the algorithms ResNet34 and VGG-16, respectively, which is comparatively less than the existing system shown in Figure 6. The proposed system has a precision value of 0.8489 and 0.7673 by the algorithms ResNet34 and VGG-16, respectively, which is comparatively higher than the existing system shown in Figure 7. The proposed system has a recall value of 0.9746 and 0.8810 by the algorithms ResNet34 and VGG-16, respectively, which is comparatively higher than the existing system shown in Figure 8. The Tables 1 to 4 shows the comparison values on accuracy, loss, precision, and recall for epochs 1, 10, 20, 30, 40, and 50.

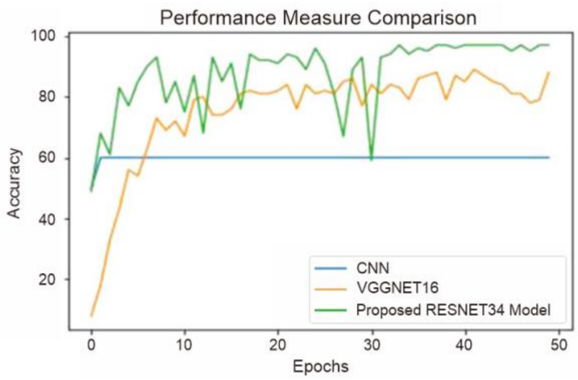

Figure 5. Performance comparison with accuracy with CNN, VGG16, and proposed Resnet

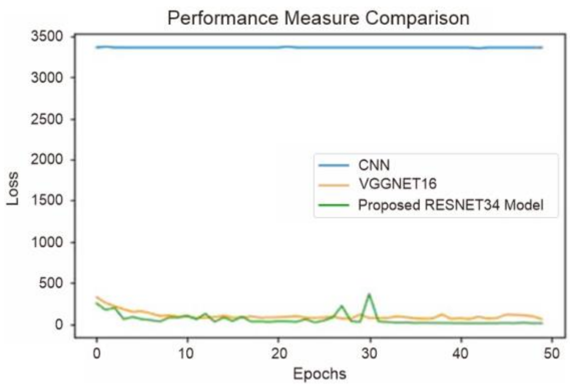

Figure 6. Performance comparison with loss with CNN, VGG16, and proposed Resnet

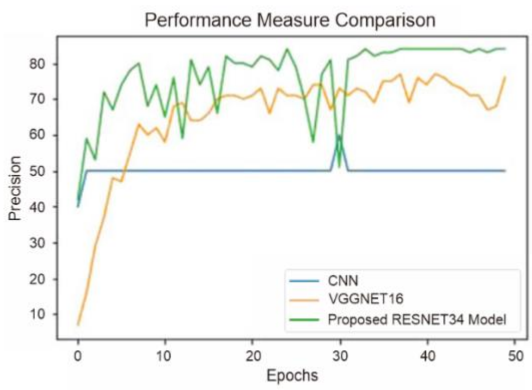

Figure 7. Performance comparison with precision with CNN, VGG16, and proposed Resnet

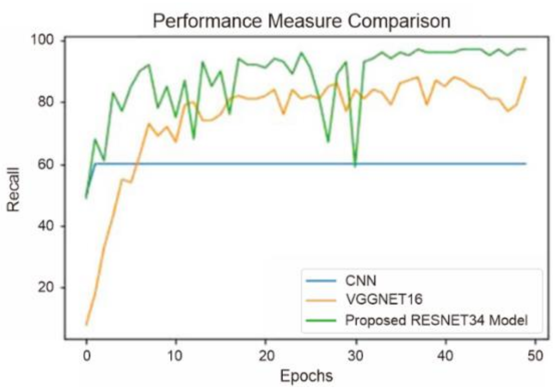

Figure 8. Performance comparison with recall with CNN, VGG16, and proposed Resnet

Table 1. Comparison of accuracy

Epochs	CNN	VGGNET16	Combined RESNET34+ CNN VGGNET16
1	50	4	41
10	60	62	43
20	60	70	67
30	60	74	79
40	60	82	92
50	60	80	96

Table 2. Comparison of loss

Epochs	CNN	VGGNET16	Combined RESNET34+ CNN VGGNET16
1	3360	337	380
10	3360	128	30
20	3360	117	9
30	3350	105	271
40	3360	73	24
50	3360	100	11

Table 3. Comparison of precision

Epochs	CNN	VGGNET16	Combined RESNET34+ CNN VGGNET16
1	40.0	7.0	42.0
10	50.0	62.0	74.0
20	50.0	70.0	80.0
30	50.0	67.0	81.0
40	50.0	76.0	83.0
50	50.0	76.0	84.0

Table 4. Comparison of recall

Epochs	CNN	VGGNET16	Combined RESNET34+ CNN VGGNET16
1	50.0	8.0	49.0
10	60.0	72.0	85.0
20	60.0	81.0	92.0
30	60.0	77.0	93.0
40	60.0	87.0	96.0
50	60.0	88.0	97.0

5. CONCLUSION

A framework for the automated detection and categorization of pomegranate plant diseases using leaf images has been given in the paper. Advanced methods, including image preprocessing, image segmentation, and image classification using transfer learning, were used by the framework. The proposed method discusses two different types of pomegranate plant diseases, including anthracnose and cercospora leaf spot. With the inclusion of cercospora leaf spot, the developed framework may reach an accuracy of around 98.57% across all categories. Achieving 98.16% overall accuracy across all categories is possible. In the future, integrating ensemble deep learning will increase the accuracy of the framework. The framework can achieve more accuracy if it has a large enough number of CNN layers.

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Shivappa M. Metagar			✓	✓	✓		✓	✓	✓	✓	✓			
Gyanappa A. Walikar	✓	✓				✓	✓		✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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BIOGRAPHIES OF AUTHORS

Mr. Shivappa M. Metagar obtained both bachelor and master degree in computer science and engineering from Visvesvaraya Technological University, Belagavi, India. He is presently working as Assistant Professor in the Department of CSE, at Walchand Institite of Technology, Solapur, Maharashtra. His research interests are in the area of machine learning, data science, cloud computing, and image processing. Some of his journals and articles published in Elsevier and IEEE Conferences. He can be contacted at email: shivametagar@gmail.com.

Dr. Gyanappa A. Walikar obtained both master and Ph.D. in computer science & engineering from Visvesvaraya Technological University, Belagavi, India. He has made significant contribution in carrying out several research papers and projects on design and development of hybrid multicast routing schemes in MANET. Some of the journals where his research articles published are Elsevier, Inderscience, and IEEE Conferences. He is the recipient of reviewer award from various reputed journals and conferences like, Elsevier, Springer, Wiley, Open Science Journal, and IEEE Conferences. Besides, he is a member of ISTE, CSI, and INAAR. He chaired several sessions at national and international conferences. He worked as a technical committee member, advisory member at international conferences. He has also been working as an editorial member of reputed & scholarly journals. He can be contacted at email: gyanappa.awalikar@reva.edu.in.