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Image based anthracnose and red-rust leaf disease detection using deep learning

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ABSTRACT

Deep residual learning frameworks have achieved great success in image classification. This article presents the use of transfer learning which is applied on mango leaf image dataset for its disease's detection. New methodology and training have been used to facilitate the easy and rapid implementation of the mango leaf disease detection system in practice. Proposed system can be used to identify the mango leaf for whether it is healthy or infected with the diseases like anthracnose or red rust. This paper describes all the steps which are considered during the experimentation and design. These steps include leaf image data collection, its preparation, data assessment by agricultural experts, and selection and tranning of deep neural network architectures. A deep residual framework, residual neural network (ResNET), was used to perform deep convolutional neural network training. ResNETs are easy to optimize and can achieve better accuracies. The experimental results obtained from "ResNET architectures, such as ResNet18, ResNet34, ResNet50, and ResNet101" show the accuracies from 94% to 98%. ResNET18 architecture selected from above for system design as it gives 98% accuracy for mango leaf disease's detection. System will help farmers to identify leaf diseases in quick and efficient manner and facilitate decision-making in this front.

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1. INTRODUCTION

India is among the largest producers of crops world wide. Many people in India specially from the Maharashtra region are farmers, and they are dependent on crop production. However, the country is still lagging far behind the global market for field production export due to its poor yield and quality grading of production specifically different fruits due to bacterial growth in crops. This growth of bacteria in plants presents in different parts of the plant, that is, fruit, stem, and leaves, which are major factors for the rapid decline in nurturing growth in the production year for the farms [1]-[3]. There are various diseases that greatly affect crops [4]-[8]. On the other hand, these types of patches begin with smaller shape while soon they occupied the overall area within the leaf or the fruit and then finally it resulted within the rotten fruit or the rotten leaves. Apart from that it is much more necessary for controlling and detecting these types of disease within a specific duration and it is in their own initial state. Therefore, it is much more necessary in preventing the disease within the early stages of affecting the most basic operation regarding the overall plant body and it includes the process of photosynthesis, astranspiratuin, germination, fertilisation and pollination. On the other hand, these diseases generally occur because of several pathogens like viruses, bacteria and fungi.

Therefore, for this the farmers require the continuous monitoring of the overall plant body, and it is a process of time consuming [9]. Hence, there is a requirement of the method for detecting the diseases in the plant at the very early stages therefore, the proposed research work is presented which will be helpful for mango fruit farmers and research centres.

2. MANGO LEAF DISEASES

Disease categories: there are two common diseases in plant leaves: anthracnose and red rust, as shown in Figure 1. As far as India and Indian subcontinent is considered, the study shows that, mango trees are mostly suspected for getting affected with anthracnose and red rust diseases on mango leaves. These diseases start growing from one part of tree to whole or emerging from leaves or fruits. Each leaf disease has unique symptoms and features, which can help to categorize and differentiate infected plants using deep learning algorithms, and deep neural networks have led to a number of progresses in the classification of images.

Anthracnose the disease that causes the serious losses for the young fruits and flowers. It affects fruits during storage [10]. It produces blossom blight, leaf spot, twig blight, wither tip, and fruit rot symptoms. Foliage and tender shoots are affected, causing the death of branches in earlier stages. Black spots develop on the panicles and fruits. Severe infection destroys the entire inflorescence, resulting in no fruit setting. Young leaves those are infected develop shrivel, black spot and drop off. Leaves and fruits infected at mature stage carry the fungus into storage and cause considerable loss during storage, transit and marketing.

Figure 1. Leaf disease

Red rust it is due to the alga that is being observed within the growing areas. Due to the attack of algal the overall reduction within the photosynthetic activity and also the defoliation of several leaves that occurred there is by lowering the overall validity within the host plant. On the other hand, the disease can be easily identified through the overall rusty red spots which is basically on the leaves and sometimes it is on the petioles and also on the bark of the young twigs which are mostly epiphytic. Therefore, the slightly and circular elevated spots sometimes coalesce in forming the irregular and larger spots.

3. DATESET

To determine the presence and incidence of leaf disease, a total of 1876 samples from 20 fields were systematically collected from production areas across Konkan (1876 samples; 20 fields). Using expert diagnostics, we identified infected plants from these fields. Infected fields were geographically searched in two provinces of the Konkan area, Ratnagiri and Sindhudurg, in West Maharashtra, where production of mango is on a large scale. Table 1 shows the field wise and location wise total mango leaf image data instances which have been collected for the study.

Table 1. The leaf dataset collected from field

Field	Localization (city)	Number of plants
Field 1	Regional fruit research station vengurle, District-Sindhudurg	400
Field 2	Research sub centre rameshwar (girye), Taluka-Devgad, District-Sindhudurg	885
Field 3 to Field 20	Orchids in Sindhudurg, Ratnagiri	460

When we use the “deep neural networks”, separate three of the databases are required for developing the overall model. Data has been splitted in to three sets: trainig, testing and validation andshown in the Table 2. The first set is the training set, and it is the collection of the several images that is to be fully used through the overall network for automatically learning the hidden parameters like biases and weights. Therefore, the actual set of validation which is the second set is also used for adjusting the overall hyperparameters manually and these are much essential settings that are not to be automatically learned during the time of training [11]-[13]. The photos collected by the camera of both healthy and non-healthy leaves were split into three categories: healthy, anthracnose, and rust under the supervision of experts from agriculture representing each class rather than splitting it into binary.

Data augmentation: the process of data augmentation is the strategy which enables the overall practitioners for significantly increase the overall diversity regarding the data that is available for the training models by not collecting the overall data. The techniques of data augmentation like padding, horizontal flipping and cropping are the most commonly used methods for training the larger neural networks. To increase size of mango leaf dataset, researchers have used certain data augmentation factors and these are shown in Table 3 with there factor values.

To build useful deep learning models, the validation error must continue to decrease with the training error. Data augmentation is a powerful method to achieve this. The augmented data presents a comprehensive set of all possible data points, and reduces the gap between the training andvalidation sets, as well as any future testing sets [14]-[16]. Table 4 shows the images in the training dataset, validation dataset, and testing dataset after data augmentation.

Table 2. The leaf dataset devided into training set, validation set, testing dataset

Class	Number of images captured by camera	Training	Testing	Validation
Healthy images	566	396	85	85
Anthracnose	747	492	117	138
Red rust	608	426	91	91

Table 3. Augmentation factor used on training dataset

Augmentation factor
“Rotation range” =60
“Width_shift_range =0.2”,
“Height_shift_range =0.2”
“Shear_range =0.2”
“Zoom_range =0.2”
“Brightness_range = [0.5, 1.0]”

Table 4. Training dataset after augmentation

Class	Number of original + augmented images	Training	Testing	Validation
Healthy imagee	1939	1769	85	85
Anthracnose	2489	2213	117	138
Red rust	2390	2208	91	91

4. TRANSFER LEARNING

The process of transfer learning actually allows us for using the convolutional neural networks (CNNs) that is when the adequate amount of the training data is small within the overall context of identification regarding the crop disease. On the other hand, this technique generally helps in achieving the greater generalizability and the overall network has been learned previously in dealing with several larger numbers of examples. Apart from that, it is also a way of saving the capacity and the computing time. Transfer learning can be performed in two ways that is fine tuning and feature extraction [17]-[19]. In the process of feature extraction, the overall weights regarding the models that are pre-trained remain intact while it uses the embeddings and also produces for training the new classifier within the target datasets. On the other hand, the process of fine-tuning uses the overall weights regarding the model that is pre-trained for initialising the overall model and after that train the parts or these weights are within the target datasets [20]. A training strategy to be selected depends on technical and thematic considerations such as the number of computing capacity, images, architecture availability and also the compatible weights that are pre-trained with the used data. We used transfer learning to improve generalizability and computation time. After fixing all of the hyperparameters, the model is retrained by integrating the used images during the validation of the global training set and alsop during training, and we used four different CNN architectures (ResNet18, ResNet34, ResNet50, and ResNet101). We used a dataset augmented by a background class.

The ResNet18 and ResNet34 are two layers deep, while ResNet50 and ResNet101 are 3 layers deep [21]. The18-layernetworks arethe subspace of34-layer network but it still performs better. If the network is deeper, residual neural network (ResNet) performs significantly.

5. TRAINING AND EVALUATION PHASE

Within the overall paper we simply present a simpler and more flexible architecture that uses ResNets' learning, utilizing the split-transform-merge approach for layers. The important challenge is for obtaining the trained model which is capable of analysing the unseen and new in machine learning. The overfitting doesn't allow the learning of the main characteristics regarding the overall classes, and it also captures the overall noise regarding the overall training set; when we try to run the model on this input data, the accuracy is high, and "deep learning neural networks are trained using the stochastic gradient descent optimization algorithm. The learning rate, which is a hyperparameter, controls the extent to which the model is changed in response to the estimated error each time the model weights are updated". The learning rates for all four architectures, ResNet18, ResNet34, ResNet50, and ResNet101 are discussed here. The learning rate of models ResNet18, ResNet34, ResNet50, ResNet101 is shown graphically in the Figure 2(a), Figure 2(b), Figure 2(c), and Figure 2(d).

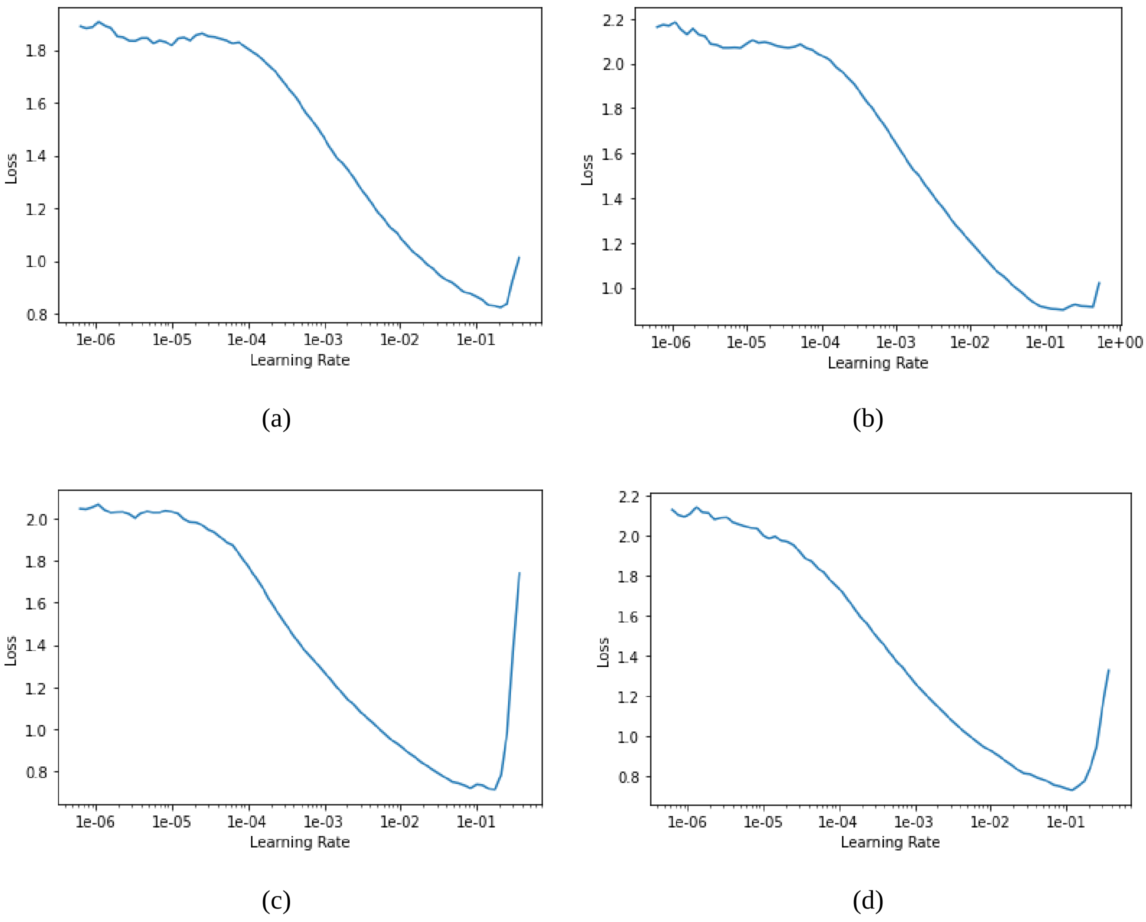
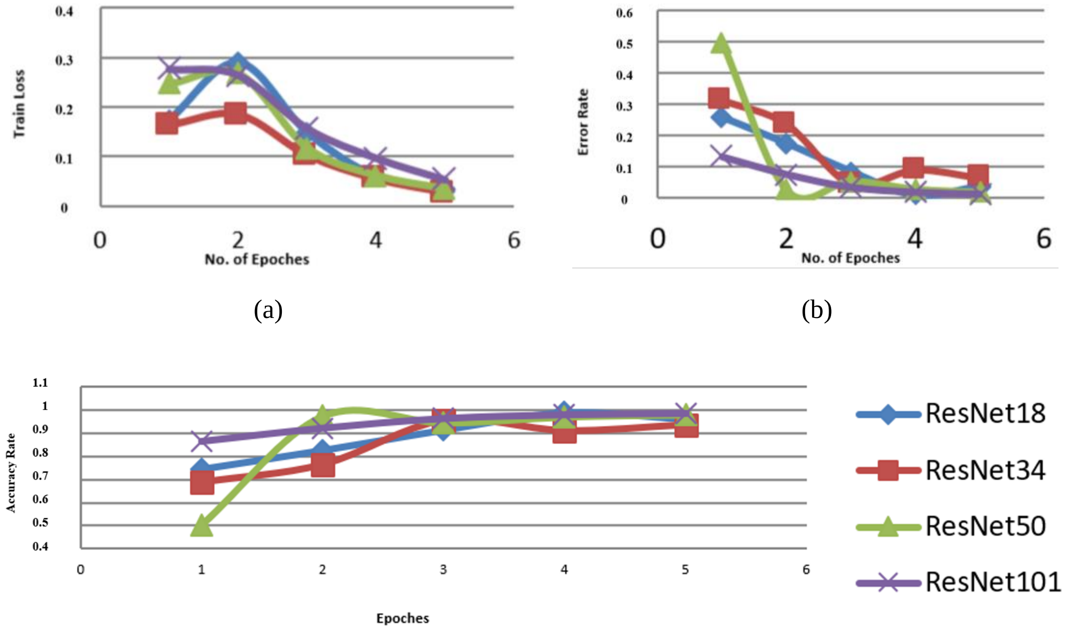


Figure 2. Learning rate for (a) ResNet18, (b) ResNet34, (c) ResNet50, and (d) ResNet101

Therefore, when CNN was trained, the model was trained with hyper-parameters. The best values of the hyperparameters were found through tuning techniques to improve the model [22]-[25]. This tuning was performed using the learning rate finder (LRF), which compared these settings until it found the optimal learning rate for the model shown in Figure 2(a), Figure 2(b), Figure 2(c), and Figure 2(d). Figure 3 shows the model training information with train loss, error rate and model evaluation with accuracies found while checking the performance of model designed with ResNet18, ResNet34, ResNet50 and ResNet101 architectures. Figure 3 shows model training and evaluation. Figure 3(a) shows train loss, Figure 3(b) shows error rate, and Figure 3(c) shows accuracy for ResNet18, ResNet34, ResNet50 and ResNet101 architecture.

The confusion matrix is used to evaluate the performance of the model [26]. Researchers have used to the same for the model evaluation. The confusion matrix for validation set is given by all four architectures ResNet18, ResNet34, ResNet50, and ResNet101and shown in Figure 4.



(a) (b)

(c)

Figure 3. Model training and evaluation of ResNet18, ResNet34, ResNet50, ResNet101 architectures with (a) train loss, (b) error rate loss, and (c) accuracy

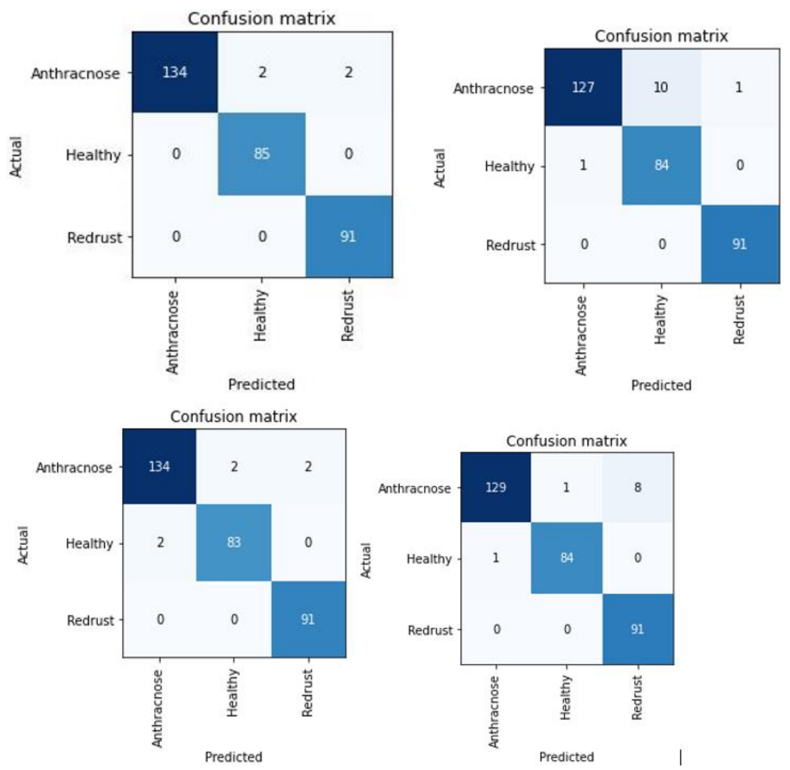


Figure 4. Confusion matrix for ResNet18, ResNet34, ResNet50, ResNet101

6. RESULT AND DISCUSSION

From Figure 3, we can see that our network model was able to start model learning at near 1e-1, from 1e-6 to around 1e-1, the learning rate was too low, and the network was unable to learn. The minimum loss was observed at 1e-1, after which loss started to increase sharply up to1e-0 then decreased from which it finally exploded, meaning the learning rate was too large for the network to learn anymore. The CNN model, confusion matrix acuracy for the testing set is given in Figure 5.

Precision, recall, F1-measure and supportare shown in Table 5. Precision is the measure of accurately predicted true-positive values relative to the total number of positive predicted observations. Recall is a measure of the number of positive class predictions made with all positive predictions. The F-measure is a measure that balances both precision and recall.

Table 5. Accuracy for testing dataset

Dieases	Precision	Recall	F1-score	Support
Anthracnose	0.83	0.92	0.87	117
Healthy	0.93	0.73	0.82	85
Redrust	0.94	0.99	0.96	91
Accuracy			0.89	293
Macro avg	0.90	0.88	0.88	293
Weighted avg	0.89	0.89	0.88	293

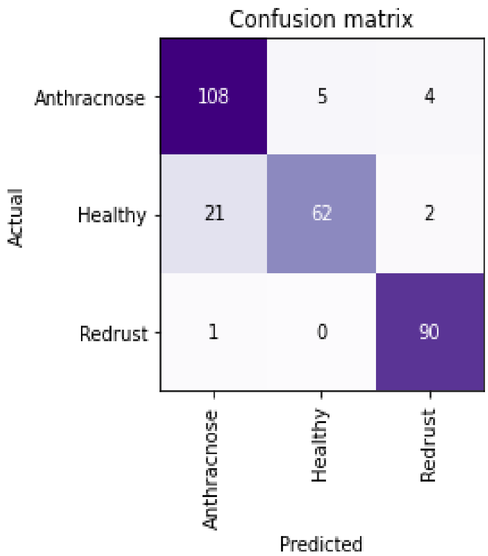


Figure 5. Confusion matrix for testing dataset

7. CONCLUSION

Presented performance of model shown the promising results for the classification of mango fruit and leaf diseases such as anthracnose and redrust detection that is by training CNNs by using the imbalanced dataset. We applied focal loss, different imaging techniques and also the class weights to obtain the best performance. The ResNet18 model shows the best accuracy for the testing dataset. Therefore, while integrating this proposed model into a mobile application, researcher considered both the results for the validation set as well as the testing dataset. This mobile application will be useful for farmers and agricultural extension workers. Farmers can use smartphones for real-time monitoring of mango fruits, leaves andearlywarnings of several infections for applying the most important prevention methods.

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