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Detection of Leaf Disease using Residual Neural Network

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Abstract - The Deep residual learning framework has achieved great success in image classification. This paper represents the training of a screened leaf image data set to recognize a particular feature of leaf disease symptoms using convolutional neural networks. The new way of methodology and training used to facilitate the easy and rapid implementation of the system in practice. “The trained model” is able to identify two types of mango “leaf diseases”, “healthy leaves” and allowing plant leaves to be distinguished from their surroundings. This paper describes all the steps from capturing the images, assessed by agricultural experts to form a dataset, and train a dataset using different neural architecture. A deep Residual framework ResNET used to perform deep CNN training. The ResNETs are easy to optimize and can easily gain better accuracy. The experimental results obtained from different neural ResNET architectures such as ResNet18, ResNet34, ResNet50, ResNet101 achieved accuracy from 94% to 98%. From the trained model accuracy, the ResNET with 18 layers model with 98% accuracy is selected for deployment. The application will help farmers to identify and facilitate the decision making, quick and efficient leaf disease.
Index Terms - CNN, Deep Learning, Mango Disease, Neural Network

INTRODUCTION

India is one of the largest producers of “mango crop” worldwide. Many people in India region are farmer’s dependent fruit production. However, the country is not so developed in this present time behind the international market for exporting due to quite “less yield” and quality enhancing of different fruit due to “bacterial growth” in crop. The development of bacteria in plants presents in specific parts of different plant and leaves which are major factors for continuous decrease of “nurturing growth” in the coming years for the agriculture. There are various diseases which affect the crops greatly. The specific diseases impacts and that results in the “irregular shaped” “black patches” which can be seen distributed over the “leaf surface”. Along with that, the “fungus” can present at “damp situations” in the “patches”. Thereafter, these “patches” begin in some small shapes but also they occupy the whole area of that leaf as well as fruit and then it result in “rotten fruit” or “rotten leaves”. It is important to identify and control these types of different diseases in their initial state. Therefore, it is important to prevent “the diseases” in the early stage of affecting “the basic operation” of the plant body such as “transpiration”, “Photosynthesis”, “pollination”, “germination”, “fertilization” etc. Thereafter, these types of diseases are occurred because of the “pathogens” such as “fungi”, “bacteria” and “viruses”. It requires monitoring continuously of the body of the plant which is a “time consuming process”. This is also required to find out some specific methods to identify the diseases on those plants at early stages of the process (Ramcharan Amanda, Peter, Babuali, James, & P., 2017). So the latest method researcher is going to develop for detecting plant leaf disease which will be more accurate and less time consuming.

DISEASES

Disease categories: There are two common diseases in mango plant leaves as shown in Figure 1. Each of the leaf diseases has unique symptoms and unique features, these features can help to categorize and differentiate infected plants by deep learning algorithms. Deep neural networks led to a number of progresses in the classification of images.

Anthracnose: The specific disease can cause the decrement to young fruits and flowers. It affects fruits during the storage .It produces “blossom blight”, “leaf spot”, “twig blight”, “wither tip”, and “fruit rot” symptoms. “Foliage” and “Tender shoots” are impacted which can cause dieback of the branches in earlier stages. Different types of infection destroy the whole “inflorescence” that results in “no setting of fruits”. Furthermore, young fruits that are infected can have “shrivel”, “black spot” and “drop off”. Therefore, fruits are infected at “mature stage” continue the “fungus” and that can cause serious loss at the time of “storage”, “transit” and “marketing” (Ullagaddi & Raju, 2014).

Figure 1
Disease Symptoms

Red rust: It is due to an “alga”, which is identified in the “growing areas” of leaf. Due to the “algal attack” the deduction in “photosynthetic activity” as well as “defoliation” of leaves occurred and “lowering vitality” of the “host plant”. Furthermore, the specific disease can be identified by recognizing the “rusty red spots” on the “leaves and petioles” as well as “bark of young twigs” and is “epiphytic” in nature. Initially the spots are present in “greenish grey” color and “velvety in texture”. After that, they turn “reddish brown”. The “slightly elevated” spots on the leaves sometimes “coalesce” and then form into “larger” and “irregular spots”. The disease occurs commonly in “closely planted orchards”.

DATESET

To resolve the “presence and incidence” of leaf disease, nearly “3319 samples” from about “20 fields” were collected systematically from the production areas across Konkan
(“3,319 samples”; “20 fields”). After using expert diagnostics, it is identified that “infected plants” represents nearly 3% of the entire number of fields that are sampled. Thereafter, the “infected fields” were searched geographically in two provinces of Konkan area i.e. Ratnagiri, Sindhudurg in West Maharashtra.

Field	Localization(city)	Number of plants
Field1	Regional Fruit Research Station Vengurle, Dist. Sindhudurg	400
Field2	Mango Research Sub Centre Rameshwar (Girye), Tal. Devgad, Dist. Sindhudurg	885
Field 3 to Field 20	Mango Orchids in Sindhudurg, Ratnagiri	460

Table 1
Samples collected from various fields

When we use “deep neural networks”, it requires three different dataset for developing a specific model (Y A Nanehkaran, Chen, & Tian, 2020). The “training set” is the first set of the network and the set is a gathering of different images that are used by the specific network which helps the network to learn the parameters automatically that are hidden like “weights"' and “biases”. The validation set, the second set is used to adjust the “hyper parameters” manually, these are the “essential settings” which is unable to be learned in the time of the training (Ramcharan Amanda, Peter, Babuali, James, & P., 2017).The photos collected by camera of both healthy and unhealthy leaves were splatted into 3 categories Healthy, Anthracnose and Red rust under the supervision of experts from agriculture representing each class rather than splitting it into binary.

Class	Number of Original Images	Training (70%)	Testing (15%)	Validation (15%)
Healthy Images	566	396	85	85
Anthracnose	702	492	105	105
Red Rust	608	426	91	91

Table2
Images for each category of leaves captured by camera

“Data Augmentation”: “Data augmentation” is an effective strategy that makes the practitioners capable of significantly increasing the “diversity of data available” for “the training models”, without gathering any new information. “Data augmentation techniques” such as “cropping”, “padding”, and “horizontal flipping” are generally used to train the “large neural networks” (Bharath, 2020). “The Augmentation factors” used for data augmentation are

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]

Figure 2
Augmentation factor used to increase dataset

To create effective and efficient "Deep Learning models", the "validation error" decrease along with the "training errors". "Data Augmentation" is a effective technique for using to achieve this. "The augmented data" represents an important as well as comprehensive set of all "possible data points", and it reduces the gap between the "training set" and "validation set", along with that any sets for future testing. After "Augmentation" the images in the "training data", "Validation data" and "Testing data" are shown as below:

Class	Number of Original +Aug. Images	Training	Testing	Validation
Healthy Images	1939	1769	85	85
Anthracnose	2423	2213	105	105
Red Rust	2390	2208	91	91

Table 3
Datasets after Data Augmentation

TRANSFER LEARNING

"Transfer learning" supports the usage of CNNs when the amount of training data is small, in the context of "crop diseases identification" (Nag & Sangskriti, 2020). These methods help to get higher "generalizability" because the network had gained knowledge before to hand out with a high number of different examples. There are a total of two different ways to carry out "transfer learns" such as "fine-tuning" and "feature extraction". In the feature extraction, the "weights of pre-trained model" keep intact and use embedding and made to train the "new classifier" on the specific data. "Fine-tuning" uses the heaviness of the "pre-trained model" to evaluate the training and the model parts. A training strategy is selected depending on technical and thematic consideration such as number of "images", "computing capacity", "availability of architecture" and "pre-trained weights" in comparison with the specific data that are used. We used transfer learning to improve generalizability and computation time. After fixing all of the hyper parameters, the model is retrained by integrating the specific images used during validation and training into a global training set. In this research we used 4 different CNN architectures (ResNet18, ResNet34, ResNet50, and ResNet101).We used the augmented dataset with a background class.

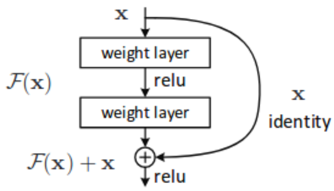

Figure 3
Residual Learning Blocks

The ResNet 18 and ResNet34 are 2 layers deep while ResNet50 and ResNet101 are 3 layer deep .The "18 layer network" is the subspace of the "34 layer network" but still it performs effectively. If the network is deeper, ResNet performs by a significant margin

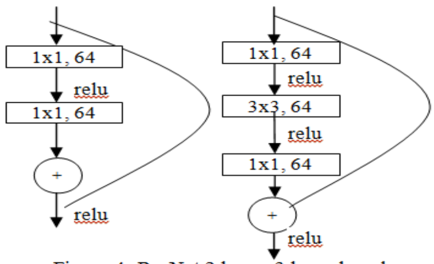

Figure 4- ResNet 2 layer, 3 layer boack

TRAINING AND EVALUATION PHASES

In this paper we present a simpler and more flexible architecture that uses ResNets' learning, utilizing the split-transform-merge approach for layers. The important challenge is to get a model which is trained and is capable of describing unseen and new in machine learning. Over-fitting happens when the input sample number becomes small in comparison with the learning capability of the specific network. Furthermore, over-fitting does not support learning about the "general characteristics" and instead it identifies the "noise of the training set". When we try to run the model on this input data, accuracy looks great. Thereafter, "deep learning of neural networks" is trained using the "stochastic gradient" that descent "optimization algorithm". The rate of learning is a "hyper parameter" that controls the changes in the model in order to respond to the "estimated error" every time that the model "weights are updated". The learning rate for all four architectures ResNet18, ResNet34, ResNet50, and ResNet101 is discussed here.

The learning rate of models

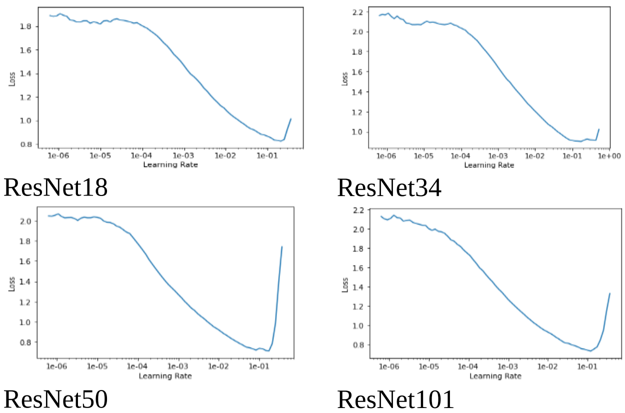

Figure 5

Learning Rate for ResNet18, ResNet34, ResNet50, ResNet101 architectures

The best values of the hyper parameter were found through "tuning techniques" to improve the model. This tuning was performed using the Learning Rate Finder (LRF), which compared these settings with one another until it found the optimal learning rate for the model which is shown in Figure 5.

In Figure 5, The Train loss, Error Rate and Accuracy of the Model are given for validation dataset given by all four CNN architectures ResNet18, ResNet34, ResNet50, ResNet101.

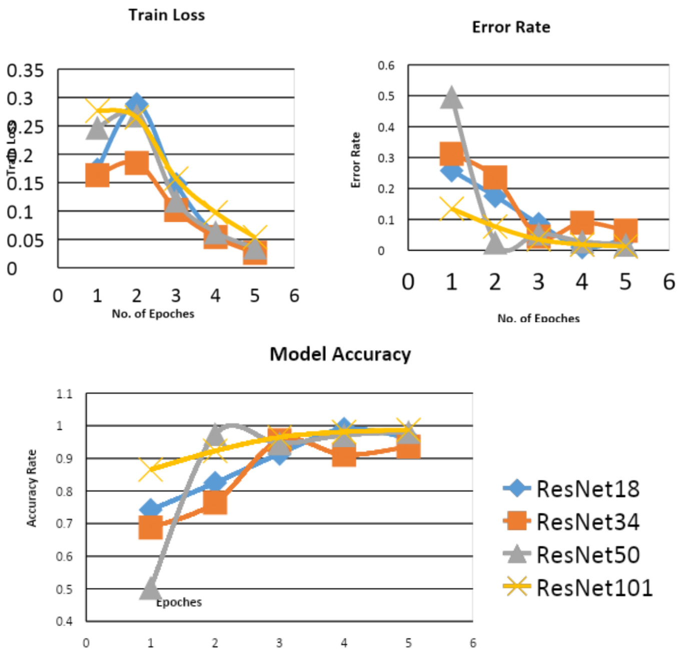

Figure 6

Validation Loss, Error Rate, Accuracy for each CNN architecture

The confusion matrix for all 4 networks is given below.

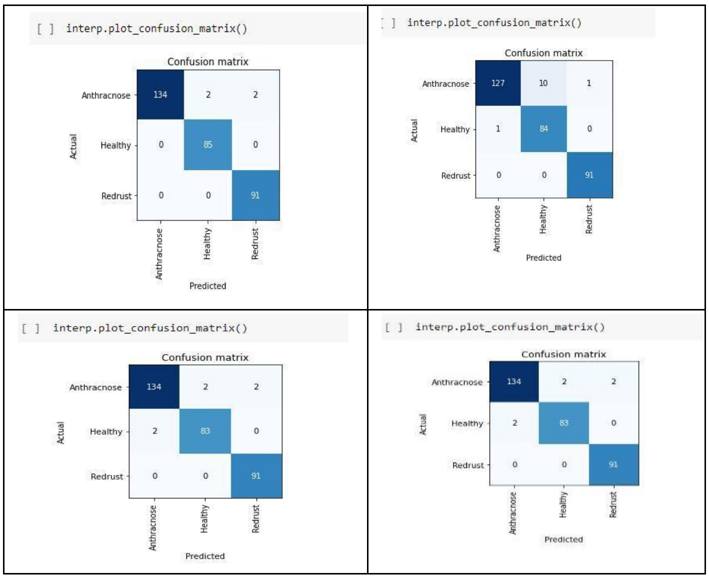

Figure 7
Confusion Matrix for four CNN Architectures for validation dataset

RESULTS AND DISCUSSIONS

Learning Rate Finder: Observing Figure 5, it can be identified that the specific network model was capable to start "model learning" rate from "1e^{-6}" to "1e^{-1}". Initially the oercentage of learning was very less and the network became powerless to gain knowledge. The minimum loss was observed at "1e-1" and then a loss up to 1e^{-0} was faced then decreased. The CNN Model accuracy for validation set is given below at the optimized learning rate is 98% for ResNet18, 96% for ResNet34, 98% for ResNet50 & 96% for ResNet101.

Architecture	Resnet 18	Resnet 34	Resnet 50	Resenet 101
Accuracy	0.987261	0.961783	0.98082	0.968153

Figure 8
Accuracy for validation set

"Precision", "Recall", "F1-Measure" as well as these are described in "Eqs". (1)–(4). "Precision" is the process to predicted measure "true positive values" appropriately to the entire count of "positive predicted observations". "Recall" is the process to measure the count of "positive class predictions" created with different "positive predictions". "F-Measure" is the process to measure that maintains balance between "the precision" and "recall" (Eq. (3)) (Sambasivam & DuncanOpiyo, 2020).

$$\text{Precision} = \frac{\text{True positive}}{\text{True positive} + \text{False positive}} \quad \text{.........} (1)$$

$$\text{Recall} = \frac{\text{True positive}}{\text{True positive} + \text{False negative}} \quad \text{..........} (2)$$

$$\text{F} - \text{Measure} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{..........} (3)$$

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positve} + \text{False Negative}}$$

"Performance Evaluation": In "Data Science", evaluation of a "model performance" is very essential and the most used "performance metrics" in classification are, "confusion matrix" ["normalized", "non-normalized", "accuracy", "precision sensitivity"].

Classes	Precision	Recall	“F1 Score”
Healthy	0.96	0.95	0.95
Anthracnose	0.9519	0.9428	0.9473
Redrust	0.9750	0.9652	0.9700

CONCLUSIONS

The performance of our model indicates effective results for classification of diseases like anthracnose and red rust .It shows the result by training CNNs using an “imbalanced data”. Different techniques and methods are used to create a remarkable study. The ResNet18 model in Figure 8 had shown the best accuracy for the validation set. Therefore, while integrating this model into a mobile application we considered both the result for validation set as well as the precision, recall and F1 score rate. This mobile application will be useful for farmers or agricultural extension workers. The farmers can use the smart phones for “real-time monitoring” and the lession of “mango infections” for ensuring that “necessary prevention methods” can be used.

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