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ResNet-based approach for Detection and Classification of Plant Leaf Diseases

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Abstract— **Crop disease is a serious concern for safety of food, but its fast detection still remains difficult in different parts of the world because of the lack of proper infrastructure. Automatic identification of plant diseases is necessary for food security, yield loss estimation and management of disease. With the worldwide increase in digital cameras and continuous improvement in computer vision domain, the automated techniques for detection of disease are highly in demands in precision agriculture, highly productive plant phenotype, smart greenhouse and much more. Working on an open dataset which includes 15200 images of crop leaves, a Residual Network (ResNet34) was trained to perform this task of classification. The proposed ResNet34 model accomplished a 99.40% accuracy on a test set, illustrating the viability of the proposed model. Overall, the process of training ResNet models on an open image dataset provides a sound way towards crop disease detection using automated networks on an enormous global scale.**

Keywords - Leaf disease detection & classification, Convolutional Neural Network (CNN), Deep Learning (DL), Computer Vision, Residual Network (ResNet).

I. INTRODUCTION

Since the dawn of time, humankind has been dependent on crops for living, our forefathers used to cover long stretches finding food, nothing new in that the first human race began after the discovery of agriculture. Crops are an integral part of our lives. It will be impossible for humans to survive without crops. Crop diseases spoil the agricultural yield. It poses a big problem to the safety of food. Therefore, detection and classification of crop diseases has a major role in guaranteeing a better yield, better quality & better productivity of edible crops. The traditional techniques of diagnosis of diseases demands plenty of field involvement & proficiency. Plant pathologies can be identified using various routines. Few ailments do not show any perceptible symptoms, or they take too long to exhibit any noticeable symptoms and hence in these conditions, an advanced examination is required. However, almost all ailments display some sort of reflection in the visible stretch of spectrum, therefore inspection through eyes by experienced professionals is the common approach adopted in real time. But, providing a detailed report of crop disease requires that pathologists must be equipped with a superior observation skill set in order to diagnose characteristic traits variations shown by diseased crop plants [1]. It is often difficult since incompetent farmers and horticulturists face trouble diagnosing it as compared to a professional pathologist and often produce inappropriate diagnosis. But nowadays, due to advancements in internet and digital technologies, farmers can utilize crop images and can take help from crop pathologists to evaluate crop diseases remotely. Though in this case the evaluation is prone to less efficiency and wrong judgments.

Moreover, research shows that climate variations [2] can interfere in stages and rates of germ growth and this also mutates host, which could pave the way for physiological changes [3]. The fact that nowadays, diseases are passed on worldwide more easily further complicates the situation. Well timed and exact diagnosis of crop diseases, including early safeguard measures is the foundation of precision agronomics.

Automated networks for disease identification can address these problems with sophisticated analysis. The recent evolution in computer vision made digital cameras a very useful technology to identify and classify diseases. An automated set-up built to detect crop plant pathologies using crop's visuals and visible symptoms will prove to be of great aid, not only to non-professional horticulturists but also to experienced professionals as a method of confirmation of disease identified and classified.

With the advent of computer vision, there is a chance to improve and enrich the practice of crop plant conservation. Multiple different techniques such as digital image processing, for example color analysis and thresholding [4] are recently deployed for detection of crop disease among all, deep CNNs are used quite often.

Research work has been going on regarding detection of plant disease that employs machine learning algorithms. Some of them used traditional machine learning algorithms and others focused on deep learning models. A support vector machine (SVM) based approach used on the Vine plants was proposed in [5] that accomplished 96.25% accuracy on an average. The authors in [6] proposed a decision tree for classification over tomato leaf images, giving an accuracy of 97.3%. Deep Learning models have been widely used, especially CNN, due to its high efficacy in image processing. A combination of K-NN and ANN was used to get an accuracy of 94.67% as proposed in [7]. In [8], a CNN is trained using 800 cucumber leaf images, leading to a classification accuracy of 94.9%. [9] proposed a 13 layer-CNN trained over a fruit image dataset using a momentum-based stochastic gradient descent as a learning algorithm. It resulted in an accuracy of 94.94%. A novel method of classification was described in [10] that used a CNN with Linear Vector Quantization (LVQ) algorithm with 500 images of tomato leaves, giving rise to an accuracy of 86%. Pre-trained models have been found to perform better with even less amount of data. A lot of methods that used pre-trained models have been described in the literature. One of them is mentioned in [11] where a comparison of AlexNet and SqueezeNet has been done. AlexNet was found to have an accuracy of 95.65% whereas SqueezNet had 94.3%.

Numerous breakthroughs in image classification domain have been brought up by deep convolutional neural networks. The network depth has its own importance and almost all popular image classification methods utilize highly deep models. In this paper, performance of Residual Network (ResNet34) for plant diseases identification and classification is discussed. The intuition of using Residual Networks is motivated from immense success in the sphere of computer vision, for example image classification [12], [13] and well known task of object detection [14], [15] as shown by recent studies. The idea of providing alternative connections to the ordinary connections and generating residual connections is the main motivation of working with ResNet. The application of ResNet to the problem under consideration is not new as it has been explored in some past studies. Although this study has reported superhuman results, one of the main challenges that is addressed in this study is that having so much similarity between different leaf diseases can trick the model to make incorrect predictions.

To check whether Residual Networks achieves better plant disease classification results, ResNet34 [16], consisting of 34 layers is employed. For the experiments, ResNet34 is successfully applied on the dataset containing 15200 images.

This paper's research contributions are as follows:
• To detect diseases in plant leaf images.
• To classify detected disease into various different classes.
• To demonstrate the feasibility of using residual networks (ResNet) to classify plant diseases.
• Learning the role of ResNets in improving scores of the disease identification and classification.

The rest of the paper is split into sections: Basic process of disease detection and classification is covered under Section II. CNN is described in Section III. Section IV provides details regarding the ResNet which is the proposed model. Section V presents the results of our experiments. The conclusion of the paper is covered under Section VI. Section VII gives possible future work.

II. PROCESS OF PLANT DISEASE DETECTION & CLASSIFICATION

It comprises the following steps:

A) Data Acquisition
B) Data Preprocessing
C) Feature Extraction
D) Classification

Fig 1 shows the flowchart of this process.

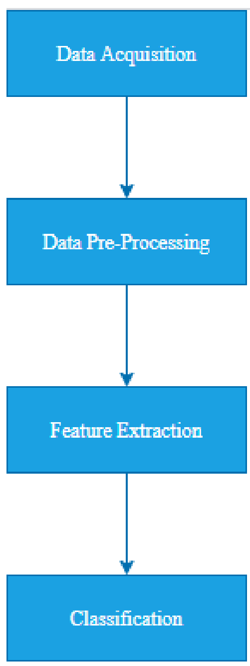

Fig. 1: Detection and classification process for leaf diseases

A. Data Acquisition

The dataset consists of 15200 images that covers 14 crops and is divided into 38 different classes. This data is derived from the original Plant village dataset.

B. Data Preprocessing

It is done to convert the data in a form so that feature extraction method and subsequent steps can work properly. Data augmentation and Normalization are done in this step.

1. *Data Augmentation:* Data Augmentation is a popular regularization method which provides a sound solution to the overfitting problem. It results in better learning of the model. Images are rotated by 90 degrees where the probability of whether an image is rotated is 0.75.

2. *Data Normalization:* Normalization is done in order to make all the pixel values have the same mean and standard deviation. This helps the model to learn faster.

C. Feature Extraction

To solve the classification problem at hand, relevant features are extracted first. Features in images are color, shape and texture [17]. Systems that detect diseases using leaf images focus more on the texture feature. Some examples of the techniques that can be used are Grey-level co-occurrence Matrix, auto-correlation, Gabor Transformation, 2D Gabor function etc[17]. Gray-level co-occurrence matrix (GLCM) is a statistical method which characterizes the image texture by calculating how frequently pairs of pixels with certain values and in a specified spatial relationship appear in an image. Autocorrelation is a depiction of the degree of correlation between a given time series and its previous version over successive time periods. The Gabor transform is a type of the short-time Fourier transform used to evaluate the phase content and sinusoidal frequency of local sections of a signal over time. Gabor functions can model the simple neurons ofthe brain' visual cortex of mammals. 2-D Gabor function is used to simulate the space-based summation properties of simple cells (of the receptive field) in the visual cortex. Besides high accuracies, extracting features automatically has proved to be amongst the major advantages of using deep learning models. Since ResNet34, which is a deep learning model is used along with classification, it also handles automatic feature extraction. Thus, there is no need to use a separate feature extraction method in our proposed approach.

D. Classification

There are multiple choices available for classification. Some of the classifiers that can be used in this step are: Logistic Regression, Radial Basis Function, Linear Vector Quantization, ANN , Classification Trees, Support Vector Machines, CNN, K-NN etc. [17]. ResNet34 – a CNN architecture is used for classification purpose in the proposed method.

III. CONVOLUTIONAL NEURAL NETWORK

Inspiration from the way the human brain works, led to the discovery of a class of algorithms, which falls in the sphere of deep learning. It involves the training of ANN to make predictions. ANN are networks of neurons arranged in a multi-layer fashion. The output of one layer moves to the next layer as input [10]. Features are automatically extracted by the deep learning models during training, therefore no separate method is required for the feature extraction step of the basic process that has been mentioned above [10]. The initial layers of ANN learn the low level features (like edges) and as deeper, higher level features (like complete objects) are learned.

CNN is a special type of ANN that is customized for image processing. Researches have shown the capability of CNN to give high accuracy in image processing tasks. In conventional ANN, a single neuron in a layer takes its input from all neurons in the previous layer. Thus, for image-based tasks, it creates a problem of learning a large number of parameters. CNN is preferred over ANN for image-related tasks due to less number of parameters involved in comparison to ANN. Parameter sharing is responsible for this reduction. Same parameters (filters in terminology of CNN) are used to get all the activations in the output volume from an input volume of activations. This is called parameter sharing. The goal of a ConvNet is to decrease the size of an image without losing crucial features that helps in solving the problem. Fig 2 shows the general architecture of CNN. A CNN architecture comprises four types of layers:

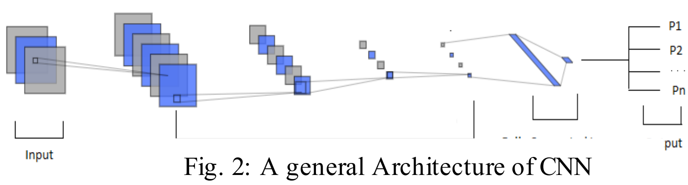

Fig. 2: A general Architecture of CNN

A. Convolutional Layer

CNN was named after the convolutional layer. The size of the image is reduced by applying a series of convolutional operations. A filter/kernel is first placed on the upper left corner of the image and is then shifted along the width of the image towards right by some stride value. After covering the entire width, the filter then hops down by the same stride value and starts again from the left in order to cover the entire width. This process is repeated till the whole image is traversed [10]. The sum of product of corresponding values in the overlapped portion of the image and filter is evaluated at a single step. This gives rise to a new matrix (or volume) from the input matrix (or volume). Fig 3 shows convolution operation applied to a 5 X 5 image with 3 X 3 filter in a convolutional layer.

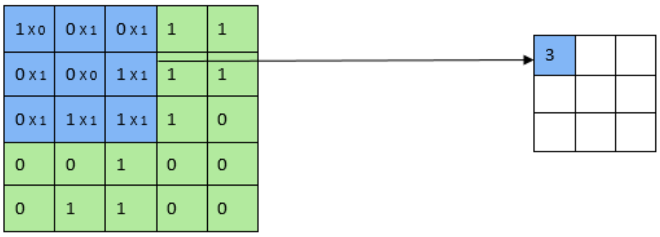

Fig. 3: Convolutional operator applied to 5 X 5 input and 3 X 3 filter.

B. Pooling Layer

This layer has the functions of reducing the image size and extracting the features that are dominant. A filter is placed and moved in the same manner as in case of a convolutional layer. A function is applied at a single step in this layer. This function can be a max function which finds the maximum of all the values in the overlapped portion of the input image and the filter (called Max-pooling) or it can be an average function (called avg-pooling). Generally, filter size and stride used is 2. Max-pooling is preferred over avg-pooling. Fig 4 shows max-pooling.

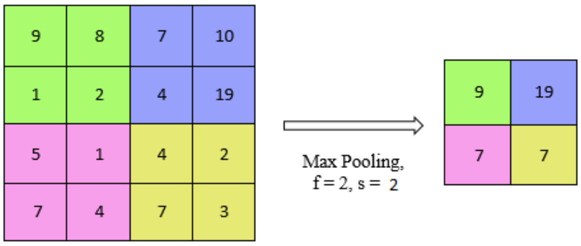

Fig. 4: Max-pooling (filter size 2 and stride 2)

C. Fully Connected Layer (FC)

The output of a series of convolutional plus pooling layers is a matrix(or volume) . This is flattened and then a sequence of fully connected layers is used, similar to ANN. A single neuron in a layer takes its input from all neurons in the previous layer. FC Layers are used only when the size of image is reduced enough by the series of convolutional plus pooling layers so that the fully connected layers don't have large no of parameters to learn.

D. Activation Layer

An activation function is applied to each element of the input matrix(or volume). So, the dimensions of input and output are the same for this layer. Linear activation functions can only help in approximating linear hypothesis functions. Since, a non-linear relationship generally occurs between input and ouput for complex problems, so nonlinear activation functions are commonly used. ReLU function is mostly used because it results in faster learning.

IV. PROPOSED MODEL : RESIDUAL NETWORKS

Past researches [18, 19] disclosed the utmost importance of network depth. Theoretically, the accuracy should increase by stacking more and more layers in a neural network. In reality, it turns out to be a misconception. By increasing the depth of the network, the accuracy tends to get saturated and then degrades quickly. This is known as the degradation problem. Surprisingly, overfitting is not the cause. The phenomenon of vanishing/exploding gradients [20,21] in deep neural networks leads to this notorious degradation problem. In the vanishing gradient problem, the gradients become infinitely small due to repeated multiplication during the backpropagation step, resulting in negligible updates to the parameters. Exploding gradients is an issue in which gradients accumulate and lead to very large updates to the parameters during training, preventing the model to learn from data. Prior to the discovery of residual networks, this has been addressed by the use of normalized initialization [21] and intermediate normalization layers.

Residual network (ResNet) is a CNN architecture whose core building element is a residual block [16]. Fig 5 shows a residual block.

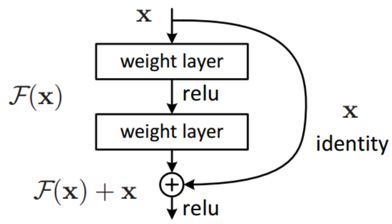

Fig. 5: A residual Block [16]

A residual block makes the use of skip connections to address the degradation problem. Connections that skip one or more layers are Shortcut connections (also known as skip connections). In the training process, the residual shortcut guarantees the network integrity if the regular connection's coefficient converges to zero. The alternative connections improves the network by providing the option of choosing these shortcuts when required. In [16], it has been proposed that instead of the hypothesis function H(x) = F(x) + x, the residual function F(x) is learned by the layers. This is due to the fact that residual function is optimized easily. In order to prove that a deeper network does not have higher training error than the shallow counterpart, the authors used a deep network that is made from the shallow network by just concatenating a residual block at the end [16] and then showed that the residual block acts as an identity mapping.

Fig 6 shows a ResNet34 architecture made from a plain-34 layer convolutional neural network by just introducing skip connections. ResNet34 is a model that is pre-trained on ImageNet Database. Pre-trained model helps in getting higher accuracies by just using a small amount of data and it saves time. In our work, a pretrained ResNet34 model has been employed for plant disease detection. Deep neural networks give better results than the shallow ones, provided that the degradation problem is addressed using some suitable technique. ResNet34 uses skip connections to solve this problem. The strength of ResNet34 to solve the degradation problem to give higher accuracies and the advantages of this pre-trained model is the motivation of using it as the classification technique in our proposed work.

V. Experimental Results and Discussion

A. Dataset

The proposed Residual Network model (ResNet34) is trained and tested using images from the 'New Plant Diseases Dataset', containing a total of 15200 images, labelled with 38 different classes and covering 14 different crops. 80-20 rule is used for dividing the dataset, resulting in 12160 train images and 3040 test images.

B. Training

Model is first trained using the train set images. Classification is then performed on the test set images with the trained model. The various parameters for the model are summarized in Table I. The variation of loss during training and validation with respect to the number of batches processed is illustrated in Figure 7.

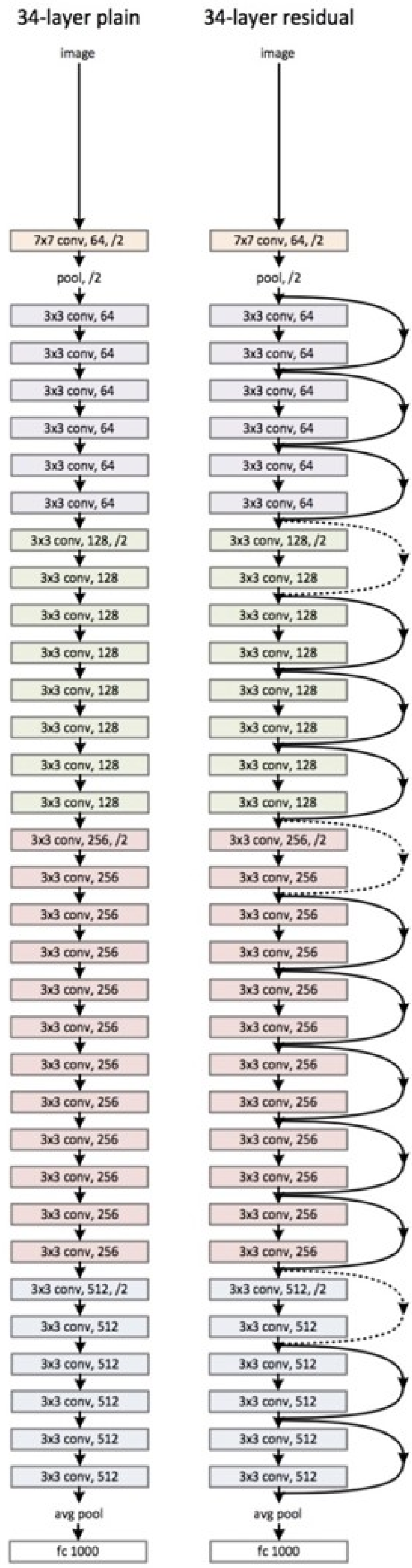

Fig. 6: Plain-34 layer CNN (left) and ResNet34 (right)[16]

Table I

Parameters of the trained ResNet34 model

Parameters	Value
Total parameters	21,832,038
Training set size	12,160
Test set size	3,040
Learning Rate	1e-6 – 1e-3

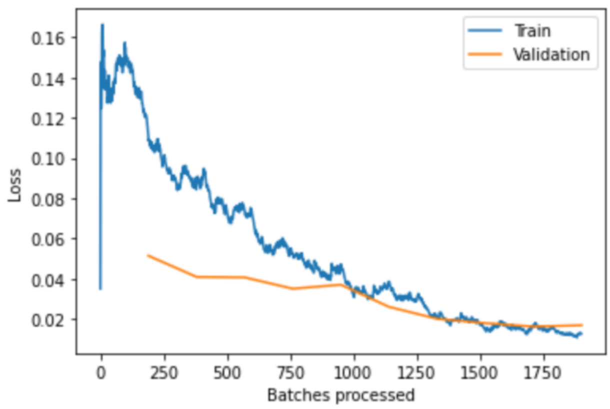

Fig. 7: Plot of Training and Validation Loss for the proposed mode

C. Performance Evaluation

Comparison of performance of ResNet with that of SVM, decision trees, logistic regression and K-NN is done on the basis of two metrics- accuracy and precision. The values for accuracy and precision of other models were taken from [22]. Two classifier metrics- accuracy and precision are discussed in the below subsections.

1. Accuracy: The ratio of the number of correct predictions to the total no of predictions made is known as accuracy.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

True positive is the count of examples for which the actual label is true and the model made a correct prediction. False negative is the count of examples for which the actual label is true but the model made an incorrect prediction. True Negative means the number of examples for which the actual label is false and the model made a correct prediction. False Positive means the count of samples for which the actual label is false but the model made an incorrect prediction.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

The accuracy of the proposed model comes out to be 99.40%.

The results are shown in Table II. As can be seen clearly, for most of the classes, the accuracy comes out to be 100%. Comparison among accuracies of various models is shown in Figure 8.

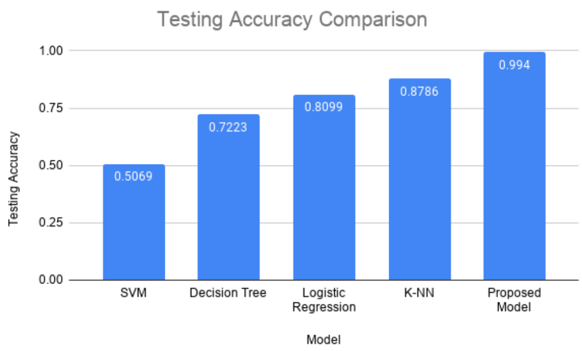

Fig. 8: Comparison of Avg Testing Accuracy of various models

Table II

Class-Wise Testing Accuracy of the proposed model

S. No.	Class Label	Testing Accuracy
1	Apple with scab	1
2	Apple with black rot	1
3	Apple with cedar apple rust	1
4	Healthy apple	1
5	Healthy blueberry	1
6	Cherry with powdery mildew	1
7	Healthy cherry	1
8	Corn with grey leaf spot	1
9	Corn with common rust	0.98
10	Corn with northern leaf blight	1
11	Healthy corn	1
12	Grape with black rot	0.98
13	Grape with black measles	1
14	Grape with leaf blight	1
15	Healthy grape	1
16	Orange with Huanglongbing	0.98
17	Peach with bacterial spot	1
18	Healthy peach	1
19	Pepper with bacterial spot	1
20	Healthy pepper	0.98
21	Potato with early blight	1
22	Healthy potato	1
23	Potato with late blight	1
24	Healthy raspberry	1
25	Healthy soybean	1
26	Squash with powdery mildew	1
27	Healthy strawberry	1
28	Strawberry with leaf scorch	1
29	Tomato with bacterial spot	0.97
30	Tomato with early blight	0.97
31	Healthy tomato	1
32	Tomato with late blight	0.98
33	Tomato with leaf mold	1
34	Tomato with septoria leaf spot	0.97
35	Tomato with two spotted spider mite	1
36	Tomato with target spot	0.98
37	Tomato with mosaic virus	1
38	Tomato with yellow leaf curl virus	0.97
	Average Accuracy	0.99407

2. *Precision:* Dividing the count of true positives by the total count of positive predictions made by the model gives us the precision of a class.

$$precision = \frac{true\ positives}{true\ positives + false\ positives}$$

In our work, the weighted average of the precision of each class is considered as the precision of the model. The weight of a class is computed as the ratio of count of examples of that class to the total count of examples in the test set. The precision of the model comes out to be 0.9651. Comparison of precision values between various models is depicted in Fig 9.

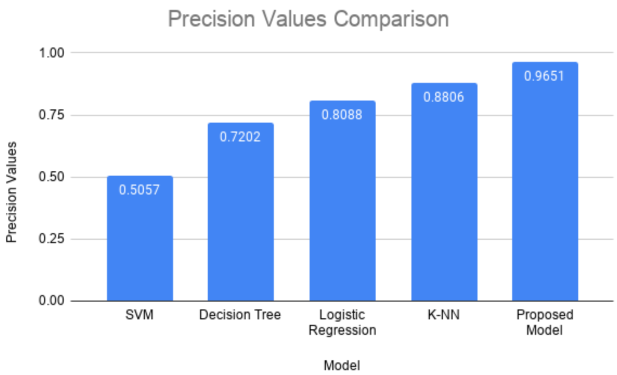

Fig. 9 : Comparison of Precision of different models

Table III shows the performance analysis of various models based on precision and accuracy.

Table III
Performance Analysis based on Accuracy and Precision

Model	Accuracy	Precision
SVM	0.5069	0.5057
Decision Tree	0.7223	0.7202
Logistic Regression	0.8099	0.8088
K-NN	0.8786	0.8806
Proposed Model	0.9940	0.9651

VI. CONCLUSIONS

Deep learning techniques are being widely studied. This work showed that the Residual Network model (ResNet34) can accurately detect and classify disease from images of leaves. The model is trained using the images from 'New Plant Diseases Dataset', which contains images belonging to 38 different classes. The 80-20 rule is used for dividing the dataset. An avg weighted precision of 96.51% and an accuracy of 99.40% was achieved by our model. These two performance metrics for the ResNet model are also compared with that of four other techniques- SVM, K-NN, Decision Tree and Logistic Regression. The proposed model is found to have higher accuracy and precision values compared to the other four models, for which the values ranged between 50% and 90%, demonstrating its superiority for the task of plant disease classification when compared with existing techniques.

VII. FUTUREWORK

In future work, network models can be trained with the dataset containing more diseases and crops. Dataset can be increased by adding more and more images as data points so that the network can identify and classify a wider range of diseases and plant species. With the increased use of cameras and improvement in their quality, it becomes more and more likely that accurate diagnoses using smartphones is only a matter of time. Also, models can be trained upon data such as panorama view of land areas, aerial photos and also images of different stages of different diseases. Moreover, the effect of image rotation on the network could be explored.

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