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Grape Leaf Diseases Classification using Transfer Learning

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Abstract - *India is the largest producer of fruits in the world. Various species of fruits like apple, mango, grapes, banana etc. are exported from India every year. According to the National Horticulture Board (NHB), the area under grapes is 1.2% of the total area of the fruit crops (2.8%) in India. Grapes are the rich source of Fibre, Vitamins (especially C & K) and Nutrients. Grapes contain several antioxidants like resveratrol, which helps in fighting against multiple diseases like cancer, diabetes, blood pressure etc. Production and quality of the grapes are highly influenced by various diseases and it is difficult to identify these diseases on a grape plant by a farmer as it requires an expert to discern it. Automatic Detection and on-time treatment of these diseases can help in saving millions every year which will also foster the farmer's yield. Over a period of time, various implementations of deep learning stratagem have been used for detecting several plant diseases. Our motive in this research is to detect and classify the grape diseases using the concept of transfer learning accomplished with the help of Inceptionv3 followed by various classifiers like logistic regression, SVM, Neural Network etc. using which we achieved the state-of-the-art solution giving the highest accuracy of 99.4% over the test dataset.*

Key Words: **CNN (Convolutional Neural Network), SVM (Support Vector Machine), ANN (Artificial Neural Network), Logistic Regression, Inception V3, fine-tuning.**

1. INTRODUCTION

Grape is a commercially important fruit crop of India and currently ranks seventh-largest producer of grapes in the world. According to APEDA (Agricultural and Processed Food Products Export Development Authority), Maharashtra ranks first in terms of production of grapes as it accounts for more than 81.22% of the total production of India. India is the major exporter of fresh grapes in the world. In India, more than 20 varieties of grapes are cultivated, covering more than 123 thousand hectares (2.01%) of the total area. Fresh Grapes are widely consumed and are also used for making raisins in India. Fragmented Grapes are widely used for the production of drinks like wine and brandy.

Diseases present in plants are the genesis of crop losses all over the world. Grape plants are highly vulnerable towards diseases like black rot, Esca, Leaf Blight etc, insect pests like flea beetle, thrips, wasps etc, and disorders like berry drop, berry cracking. Pest can be controlled using sprays. But in case of diseases, timely detection and treatment efforts are needed to be taken so that appropriate control measures can be taken to have a healthy grape yield. So, an automated system is required to clinch this requirement.

For a long time, disease identification requires a well-trained and an experienced expert but then also it's a very error-prone and time-worthy process. So, to combat it we have made an automated system capable of detecting the disease present inside the grape plant using the concept of transfer learning [15] followed by some classifiers among whom logistic regression outperformed others with a classification accuracy of 99.4%.

2. Related Works

Sharada P. Mohanty et al [6] has used the concept of transfer learning with GoogleNet and AlexNet over the PlantVillage dataset with 38 classes, which resulted in test accuracy of 99.35%. Harvey Wu et al [7] has used 2 stage CNN pipelines along with heat maps on UAV images in which he successfully achieved test accuracy of 97.76%. Li et al [5] have used SVM with different kernels like linear, RBF etc among which linear kernel resulted in the optimum test accuracy over the grape downy mildew and grape powdery mildew classes with 90% and 93.33% respectively. Zhang et al [8] has fine-tuned his model using GoogLeNet and detected podosphaera pannosa using CNN, SVM and KNN out of which he obtained a test accuracy of 99.6% using CNN over the cherry leaves. Ch. Usha Kumari et al [9] has used K-Means clustering algorithm for feature extraction over the cotton and tomato leaves dataset and then ANN was used for Classification resulting in average test accuracy of 92.5%. Athanikar et al [10] have used segmentation with K-Means clustering and the features were extracted on the basis of colour, texture and area in which they obtained a classification accuracy of 92% over potato leaf samples. Saraansh Baranwal et al [11] has worked over the apple leaf dataset from PlantVillage Dataset [3] in which they have used GoogLeNet for fine-tuning their model over the four classes: - Apple Black Rot, Apple Cedar Apple Rust, Healthy Apple, and Apple Scab and obtained an average accuracy of 98.42%.

3. Dataset Description

The dataset used in this paper is PlantVillage Dataset [3] which is available on Kaggle and is open source. It has approximately 55,000 well-labelled images of healthy leaves and infected leaves of various fruits like apple, blueberry, cherry, grapes, peach, pepper, orange etc. For each fruit, more than one type of leaf disease is present and we consider each type of disease as a separate class for our classification task. Each image contains a picture of a leaf and on a broad level for each class, we have two types of dataset one is segmented which comprises a leaf without background and other images have a leaf with a background.

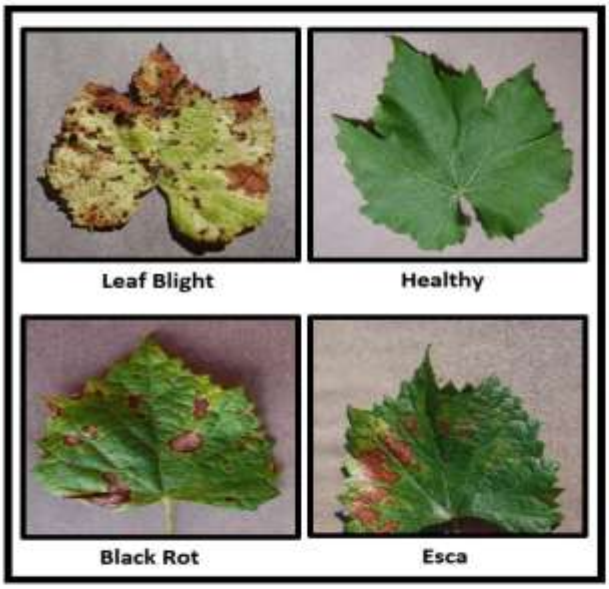

Fig -1: Shows the sample image from each class of Dataset

The number of images in a particular class is not uniform, it varies from 423 images to 1383 images. For our problem statement, we have used only Grape images which comprises of four classes i.e. black rot, Esca(Black Measles), Leaf Blight and healthy leaf images where the train-test-split data is shown in table 1.

Table -1: Showing the number of samples in training and testing set of our model

Label	Category	Number	Training samples	Testing Samples
0	Black rot	1180	942	238
1	Esca	1383	1099	284
2	Leaf Blight	1076	834	242
3	Healthy	423	334	89
Total		4062	3209	853

4. Experimental Setup

4.1Feature Extraction

Features of the images were extracted using the InceptionV3 model [15]. InceptionV3 is based on convolution neural network which comprises 42 layers as shown in figure 4. InceptionV3 is trained over the subset of ImageNet dataset consisting of 1000 images from each of the 1000 categories. In the ILSVRC [15], the dataset comprises 1.2 million training images,50000 validation images and 100000 testing images in which inceptionV3 outperformed other models.

InceptionV3 uses a lot of optimizing techniques like factorizing convolutions, efficient grid size reduction, the utility of auxiliary classifiers etc. these techniques are explained below:

4.1.1 Factorizing convolutions

InceptionV3 made several changes regarding the dimension of convolutions since larger dimension convolution was resulting into large computation so the surrogate approach used in the paper [15] is that a 5*5 dimension is multicasted into two 3*3 dimension .where 5*5 convolution has 25 parameters and updated version has only(3*3 + 3*3)=18 resulting into 28% reduction in the parameters

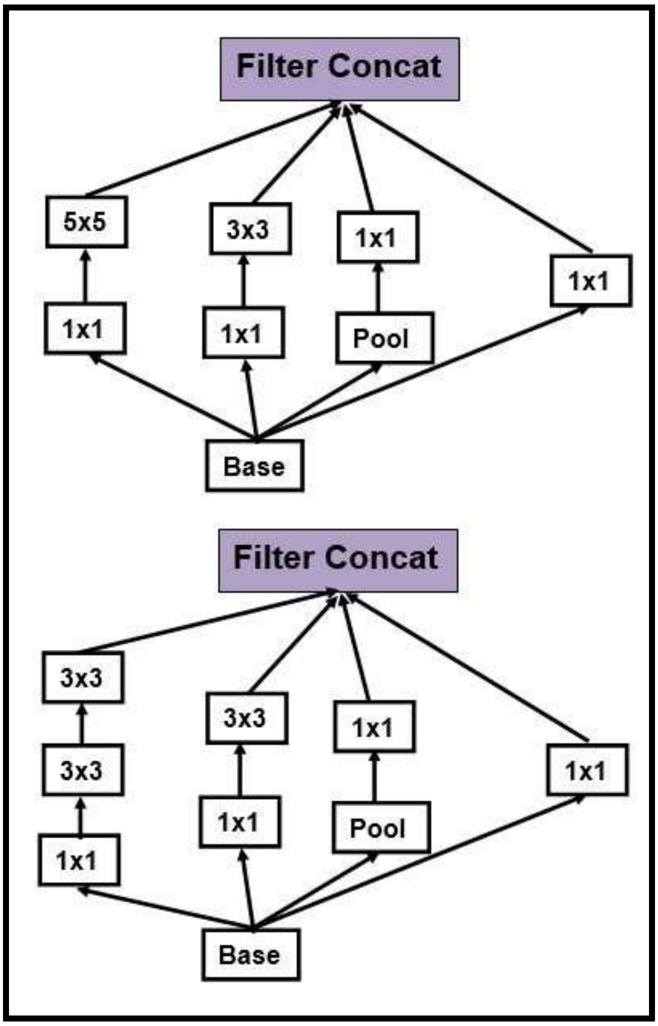

Fig -2: showing the change in the dimension of the feature map using factoring convolution

This reduction into the calculation results in the very less number of parameters presented inside the model as compared to others like AlexNet [16], VGGNet [1] etc.

4.1.2 The utility of Auxiliary Classifier

The auxiliary classifier works as a regularizer. Lee et al [20] in his work has stated that results obtained using auxiliary classifier are very converging and accurate. but in case of InceptionV3 results at the beginning of training phases are not affected by the auxiliary classifier but results obtained during the end period of training are quite influential so the same approach is used in InceptionV3.

4.1.3 Efficient Grid Size Reduction

Usually, max-pooling and average pooling are used to downsize the feature maps but an efficient method has been used in the InceptionV3 model in order to downsize the feature maps using the concept of parallelly performing max-pooling or average pooling and convolution the method used is shown below in the figure.

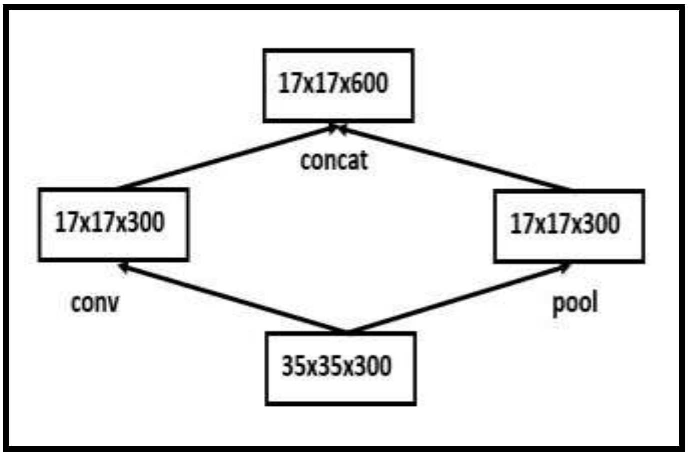

Fig -3: represents the efficient grid size reduction used in InceptionV3 model.

Original feature maps were operated parallelly by convolution and pooling i.e. either average or max pooling and then result obtained using convolution and pooling were concatenated to give the resultant feature map. Through this way, InceptionV3 has been implemented in a less expensive and in an efficient way.

4.2 Model

Over the period of time, Deep Convolutional Neural Networks (DCNNs) [4] have achieved marvellous Results over multiple places like in [11,13]. There are two ways to train the model either from the scratch or using the concept of transfer learning i.e. using the pre-

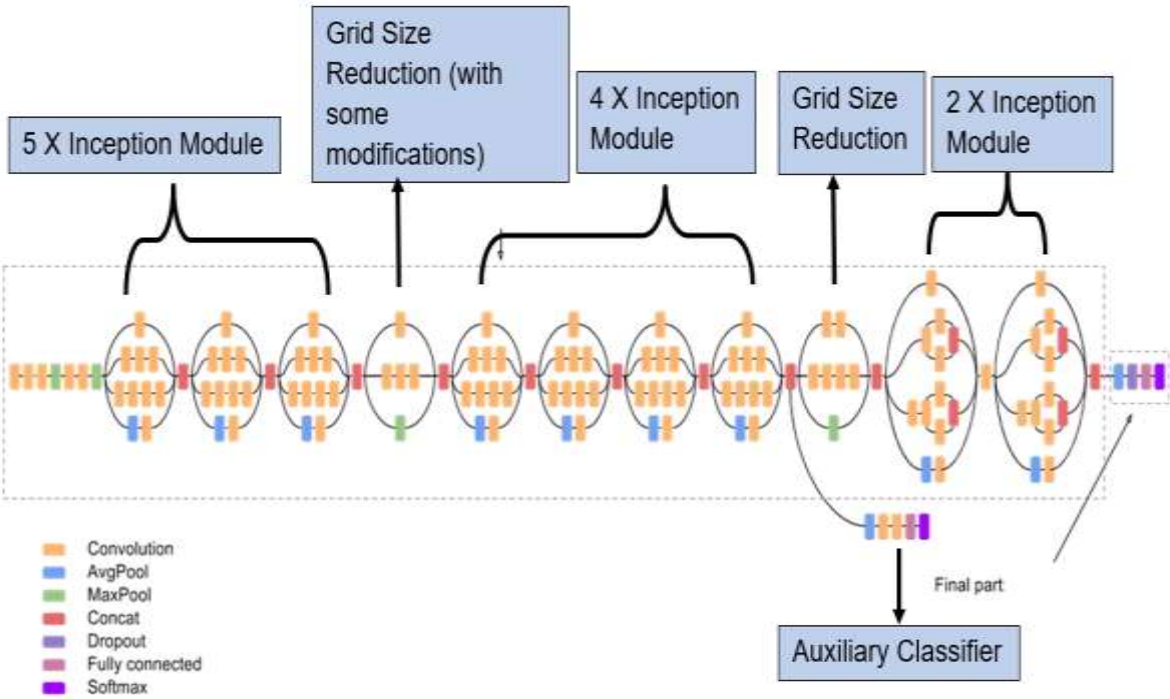

Fig -4: shows the model image finetuned using InceptionV3 and classified using Logistic Regression trained models like VGGNet, InceptionV3, AlexNet etc which could provide us with important features of the image. we have used the InceptionV3 model because it comprises of a smaller number of parameters as compared to other models like AlexNet, VGGNet and also due to the state-of-the-art results obtained using InceptionV3 over the plant village dataset, which can be seen from the table 3 below.InceptionV3 model acts as the feature extractor for our model, InceptionV3 model includes multiple optimization techniques like factorizing convolutions, Auxiliary Classifiers, Efficient grid size reduction etc all of these techniques are elucidated above in section 4.1. Here the dataset image is fed as input to the inceptionV3 model which acts as the feature extractor and provides us with the appropriate features of the image. After the feature extraction phase, multiple classifiers were used but Logistic regression outperformed others in terms of classification accuracy as shown in table 3 below.

4.3 Classification

Regarding classification, we have used logistic regression and in the field of statistical mathematics, logistic models are used when dependent variables (target variables) are categorical like win/lose, pass/fail etc. For using Logistic Regression, first of all, we have to calculate the hypothesis function. The output of the function is evaluated in terms of probability. After which, we have to pass the evaluated value of Hypothesis function to Cost Function. Cost Function converts the probabilistic results to categorical results [2]. The flow of the model goes like the following:

$$H'(M)=Prob(N=1|M;"\emptyset") \quad \_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_1$$

The probability that given an event M, other event N=1 which is parameterized by variable 'Φ' as shown in equation 1.

$$Prob(N=1 \mid M; \emptyset)+Prob(N=0 \mid M;\emptyset)=1$$
$$Prob(N=0 \mid M; \emptyset)=1-Prob(N=1 \mid M;\emptyset)$$

Now cost function shown below in equation 2 is used to convert probabilistic results to categorical results.

$$(H'(M), N) = -N*\log(H'(M)) - (1-N) * \log(1-H'(M)) \quad \_\_2$$

If N=1, (1-N) term will become 0, therefore – log (H ' (M)) will be present.

If N=0, (N) term will become 0, therefore - log (1-H ' (M)) will be present.

5. Result and Discussion

Images were fine-tuned using some well-known models like InceptionV3(in our case), VGG16, VGG19 after the feature extraction using these models. We demonstrated the results in terms of evaluation metrics like AUC (Area Under the Curve), CA (Classification Accuracy), Precision, Recall, F1-Score using multiple classifiers like SVM, Logistic Regression, Neural Network, K-Nearest Neighbor (KNN). Among all of these classifiers, Logistic Regression outperforms others in terms of classification accuracy as shown in table 3 below. Whereas with this approach we have obtained the state-of-the-art solution giving us 99.4% accuracy over the test dataset as compared to others, result comparison report is shown in table 2 below.

Table -2: Shows the comparison report with other models

Model Proposed	**Classification Accuracy**
Back Propagation Neural Network (BPNN) [12]	91%
United Model [13]	98.57%
InceptionV3+Logistic Regression	**99.4%**

Table 3

Classification Accuracy, Area Under Curve (AUC), Precision, Recall, F1 for the fine Tuning done with Inceptionv3

Model	Classifiers	CA	AUC	Precision	Recall	F1
InceptionV3	SVM	0.987	1.000	0.987	0.987	0.987
	Logistic Regression	**0.994**	0.999	0.994	0.994	0.994
	Neural Network	0.987	0.999	0.987	0.987	0.987
	KNN	0.955	0.992	0.956	0.955	0.956
VGG16	SVM	0.958	0.995	0.959	0.958	0.958
	Logistic Regression	0.985	0.999	0.985	0.985	0.985
	Neural Network	0.970	0.997	0.970	0.970	0.970
	KNN	0.951	0.993	0.953	0.951	0.951
VGG19	SVM	0.963	0.998	0.964	0.963	0.963
	Logistic Regression	0.985	0.999	0.985	0.985	0.985
	Neural Network	0.980	0.996	0.980	0.980	0.980
	KNN	0.955	0.993	0.956	0.955	0.955

where ROC shows the AUC (Area Under the Curve) with respect to four classes present in our model shown in figure 5,6,7,8.

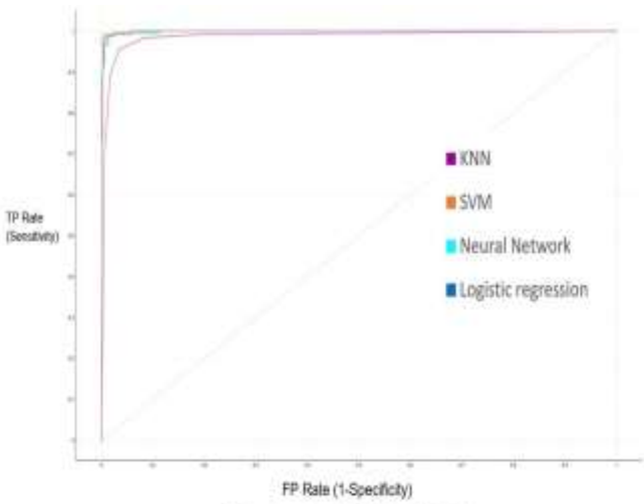

Figure 5. shows ROC Plot of Black Rot

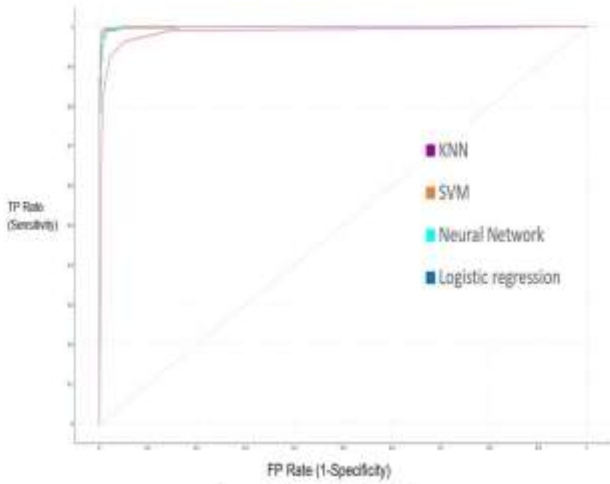

Figure 6. shows ROC Plot of Esca

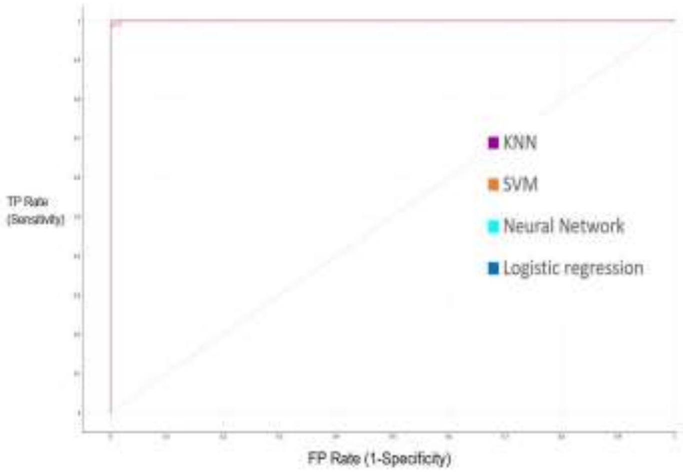

Figure 7. shows ROC Plot of Healthy Leaves

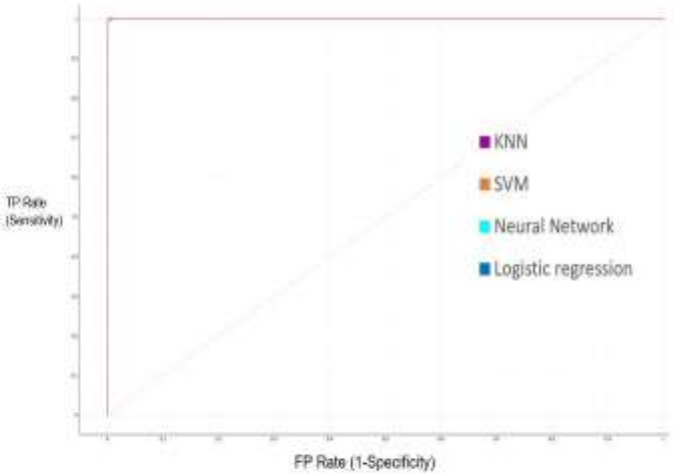

Figure 8. shows ROC Plot of Leaf Blight

6. Limitations

Although the results obtained using our model were very influential but using our approach, unlike segmentation we cannot locate the part containing disease over the grape leaves. Since we are only performing the classification task over the present dataset.

7. Conclusion

An expert is a supreme requirement for early detection of the disease in the grape plants. We designed an automated system to ameliorate the classification results. We have provided multiple results by fine-tuning our model with a number of pre-trained models like VGG16, VGG19, InceptionV3 etc. and achieved the state-of-the-art solution over the plant village dataset shown in table 1. Our model achieved an exceptional classification accuracy of 99.4%. which can widely meliorate the early detection of diseases like black rot, Esca, Leaf Blight present over the grape plants. The development of an algorithm can help people in detecting the disease more early so that they can cure it well on time and can earn a good profit. A similar approach can also be used with other plants leaves like apple, blueberry, cherry, grapes, peach, pepper, orange etc.

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