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Analysis of Automatic Classification & Diseases Identification of Plant Diseases using Pre Train Convolutional Neural Network Models

Pooja Sharma[1] and Dr. Rekha Jain[2]
[1]PhD Research Scholar, Poornima University, Jaipur
Email: poojait@poornima.org
[2]Professor, Poornima University, Jaipur
Email: rekha.jain@poornima.org

***Abstract*—Every country's economy depends upon agriculture growth, but every year there is a huge loss in production due to plant diseases, so there should be a system for early identification of plant diseases to prevent losses. As there is good availability of smartphone with farmers now various deep learning models based applications can automatic classify the plant diseases. In this paper of various deep learning pretrained CNN models have been analyzed on 15 classes of potato, tomato & pepper plants from Plant Village dataset.The validation accuracy of VGG16 produced best results as 98.10 where,Xception, InceptionV3 &Inception-ResNet v2 ,NASENetMobile also shown good accuracy on validation data. Various other factors related with CNN models like performance, testing on real time data & future scope also elucidated.**

***Index Terms*— Convolutional Neural Network, Plant Disease Identification, Pre trained Deep Learning, Smart Farming, Automatic Identification, Agriculture.**

I. INTRODUCTION

The economy of every country depends upon agriculture production, every year the demand for food is regularly increasing as increase in population and this will rise exponentially. All analysis demonstrates that by 2050 there will be above 70% requirement of food to satisfy human's necessities.In this regard, production in agriculture is constantly getting down because of substantial misfortune in cultivating by utilizing synthetic pesticides. Because of pathogenic disease, loss of harvest yield happens in the middle 20% to 40%[1].Major crop diseases are like Bacteria, mildew, viruses, and insects responsible for infection in plants [2].

The earlier methods used to resolve these issues related with plant diseases are use of pesticides, but the farmers actually don't know what exact quantity of pesticidesneed to be used. More use of pesticide applied on crops rises the cost of total production and decreases the quality of food. The type of diseases is also identified by naked eye or it takes a lot time by expert also. So it is very important for farmers to identify the type of plant diseases, its severity & overall impacts. An automatic identification of disease to avoid large amount of crop loses[3].

In present scenario everyone is using mobile & internet, so its required that some technology or automation of

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plant diseases identification to be employed. Usually plant diseases appears on leaves so some computer vision methods to be used to recognize the type of diseases. In this area already various machine learning techniques for example Artificial Neural Network and Support Vector Machine those uses hand crafted features to identify diseases.

There is a need for full automation in plant diseases recognition sodeep learning is broadly utilized. Deep learning algorithms are used for automatic feature extraction from given dataset by using convolutional neural network [4]. Many image identification & classification applications solved by deep learning. [5]

It has been shown earlier work transfer learning is more beneficial in plant diseases identification problems than learning from scratch where training to model and learning of weights is donefrom scratch [6,7]Some of earlier work are based pre-trained models on ImageNet [8].

TABLE I. TABULAR REPRESENTATION OF PRE TRAINED CNN MODEL

MODEL	Training Accuracy	Previously used by	Working
CNN	98.21	7,9,10-15	Used to classify plant diseases applied transfer learning approach
VGG16	99.26	21	3*3 convolutional layers which are stacked upon each other in increasing depth
VGG19	98.89	21	
Resnet50	99.49	22	“Exotic architecture” which uses micro-architecture modules which refersSet of building blocks used to build the network
InceptionV3	97.97	23	Basically used for “multi-level feature extractor”
Xception	98.48	24	Involves depthwise separable convolution layers can be understood as an Inception module with a more number of towers
NASNetMobile	98.19	25	Based upon reinforcement learning search method to optimize architecture configurations
DenseNet121	87.63	25	Increases the depth of deep CNN network
MobileNet	98.47	26	Special Deep CNN model which chooses small network as per resource constraints by optimizing the latency
InceptionResNet	98.22	27	Inspired by ResNet build using hybrid inception module

A. Related Work

Various pre trained CNN models used to classify plant diseases applied transfer learning approach like VGG16, ResNet, AlexNet, DenseNet , these models solves identification of diseases in plants in many crops[7,9,10-15, 29,30]. Training CNN model from scratch always requires a big dataset with lots of images to train that is a real time challenge for many researchers. Hence, transfer learning yield better results [12].Many earlier research used PlantVillage[28] dataset for plant diseases classification [7,9,10-15].In their papers accuracy good have been achieved by using pre trained models. In some of the study’s authors have proposed their own dataset created at various places for crops diseases identification[16-19].but there is an issue of finding good dataset for research purposes to solve real time problems of farmers.

As there should be a system for automatic identification of plant diseases so that timely action can be taken to prevent the huge loss, In this proposed research many pre trained models have been analyzed on the basis of computation time , accuracy & size, so that such model can be used to develop mobile application for farmers. In proposed approach some of the plants have been taken for analysis on pre trained models like VGG16, VGG19, Resnet50, Densenet121.

II. MATERIALS AND METHODS

A. Dataset and deep learning models

Plant Village (PV) [28] is famous image based dataset collected for automatic plant disease identification systems, this dataset having healthy and diseased leaves images in uniform background. This dataset contains 38 crop-disease pair with 26 crop-disease categories for 14 crop plants. In our experiment, we used only potato, tomato & cherry plants for the analysis purpose i.e. 15 classes of healthy & diseases, where 80% of data was used as training purpose & 20% of data used as testing purpose. Figure 1 gives some images of 15 classes of potato, pepper& tomato plants diseases.

Figure:1: Disease selected for the study (a) Pepper bell bacterial spot (b) Potato Early blight (C) Potato late blight (d) Tomato target spot (e) Tomato mosaic virus (f) Tomato yellow leaf curl virus (g) Tomato bacterial spot (h) Tomato early blight (i) Tomato late blight (j) Tomato leaf mold (k) Tomato septoria leaf spot (l) Tomato spider mites two spotted spider mite

Data augmentation is a usual methodto increase the number of images artificially by using various methods like transformations,translation, and rotation of images and apply changes in intensity value to reduce the effect of overfitting in deep learning models. Here various methods for transformation of image are applied such as rotation, changes in intensity values, translations through which overfitting problem does not arises [12]. A random rotation angle within thelimit of ± 25° was generated and applied to each image.Width shift range was set to 0.1,height shift range also as 0.1, shear range applied as 0.2, zoom range as 0.2,horizontal_flip was set to True& fill mode as nearest.The process of data augmentation was selected based on various trials.Transfer learning methodology eight pre-trained deep learning models were used for analysis purpose namely VGG16, VGG19, ResNet50, DenseNet121, InceptioV3, Xception, NASNetMobile, InceptionResNetv2, MobileNetare used for analysis purpose. Training from scratch using CNN is also applied on dataset. All experiment were performed using Keras in google colab with GPU.

B. Methods

Convolutional Neural Networks -CNNs receives the input in the form of images, layers within CNN have neurons have three dimensions. The spatial dimensionality of the input (height and the width) and the depth. The architecture of CNN has three layers' name of these layers are convolutional layers, pooling layers and fully-connected layers as shown in figure 1.In our experiment input shape (256,256, 3) was used in sequential CNN model,initially the convolution layer has number of filterswhose size taken as 3*3 kernel andbatch normalization with RELU activation function. Pool layer uses a 3*3 pool size to reduce spatial dimensions from to 32*32. Dropout used for randomly disconnecting nodes from the *current layer* to the *next layer*. [20]

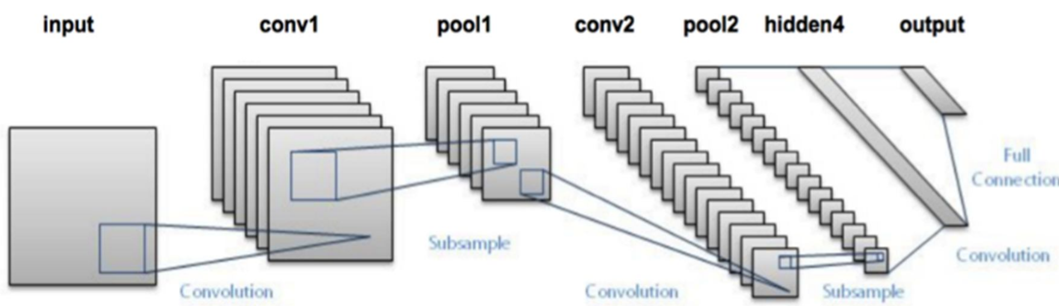


Figure-2 Convolution Neural Network

The architecture of VGG is uses 3*3 convolutional layers which are stacked upon each other in increasing depth. Max pooling is used to reduce volume size. There are two fully connected layers where nodes are 4,096 followed by softmax classifier. In VGG models the meaning of "16" and "19" means number of layers for weight were very deep in 2014 which were successfully trained for ImageNet and over 1,000 for CIFAR-10. [21]
ResNet architecture is based upon "exotic architecture" which uses micro-architecture modules which refersSet of building blocks used to build the network. ResNet architectures are extremely deep that were trained SGD through applying residual modules. In current work ResNet50 is used for analysis purpose [22]
The "Inception" micro architecture introduced in 2014, the architecture is basically used for "multi-level feature extractor".In current study InceptionV3 is being used for purpose of analysis[23].

Xception is a CNN architecture that involves depthwise separable convolution layers can be understood as an Inception module with a more number of towers [24]

In NASNEetMobileNeural Architecture Search (NAS) frameworkis used that is based upon reinforcement learning search method to optimize architecture configurations.Here the searching of best convolutional architectures is now moved to find best cell structure it results faster than search the complete network architecture.

In Densely Connected Convolutional Networks, DenseNets increases the depth of deep CNN network,there are problems arises when CNNs network goes deeper as in VGG19 and ResNet architecture with 1000 layersDenseNets simplify the connectivity pattern between layers [25]

In MobileNet is special Deep CNN model which chooses small network as per resource constraints by optimizing the latency. [26]

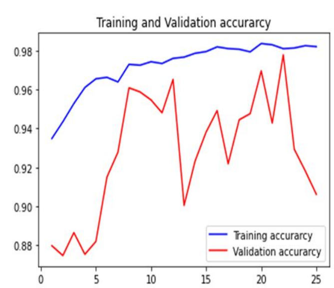
In Inception-ResNet v1 and v2 the architecture is inspired by ResNet build using hybrid inception module so here two versions Inception ResNet as v1 and v2[27].

C. Methodology

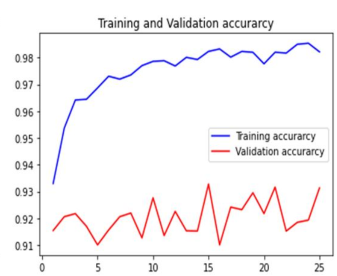
For plant disease identification process first of all dataset after augmentation has been used for both training & validation purpose. Here in approach one CNN from scratch & nine pretrained deep learning models were deployed for classification purpose. For training of models to get good results in terms of accuracy all models were fine-tuned by the help of hyper parameters. In model maximum epoch were 25, initial learning rate was0.0001.Adam optimizer algorithm was used to update weight & bias parameters. Metrics to evaluate models were accuracy and top 5 categorical accuracy for both training & validation similarly binary cross entropy,computes the cross entropy metric between the labels and predictions.The obtained results are analyzedand discussed on basis of misclassification or less accurate result.

TABLE II. COMPARISON OF ACCURACY OF ALL MODELS

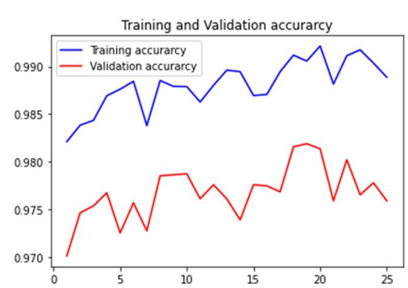
MODEL	Training Accuracy	Top_5_categorical_accuracy	Validation Accuracy	val_top_5_categorical_accuracy
CNN	98.21	99.45	90.61	76.94
VGG16	99.26	99.92	98.10	98.58
VGG19	98.89	99.84	97.59	98.58
NASNetMobile	98.19	99.00	93.36	87.68
DenseNet121	87.63	48.08	87.48	34.48
MobileNet	98.47	99.40	93.39	85.15
InceptionResNet	98.22	98.95	93.13	87.20
Xception	98.48	9943	93.81	88.78
InceptionV3	97.97	99.00	92.96	83.10
Resnet50	99.49	99.92	88.07	34.60



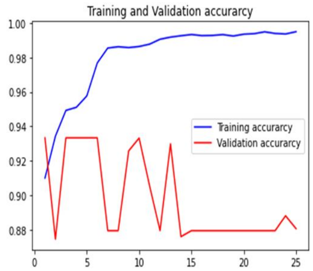
(a) CNN from Scratch



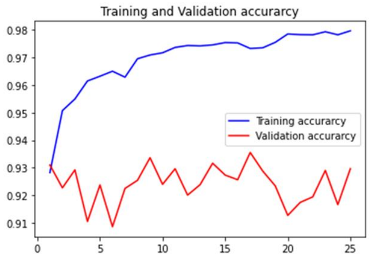
(b) Inception-ResNet v2



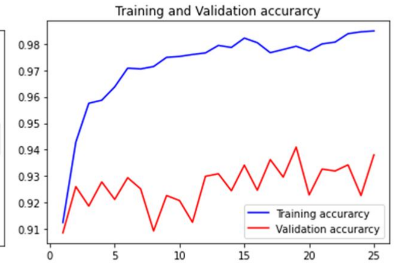
(c) VGG19



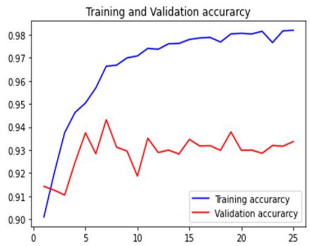
(d) ResNet50



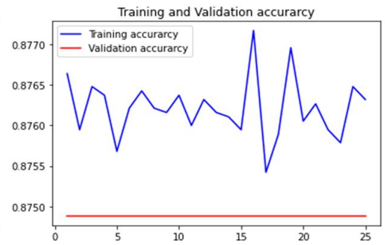
(e) InceptionV3



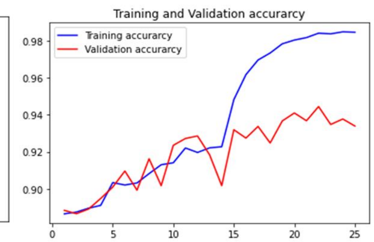
(f) Xception



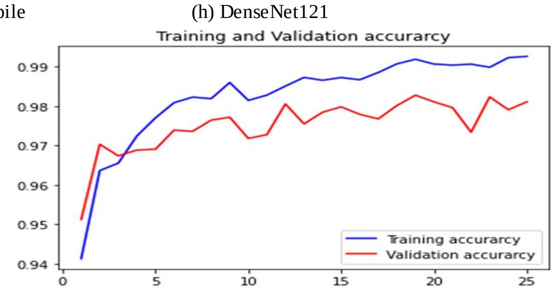
(g)NASNEetMobile



(h) DenseNet121

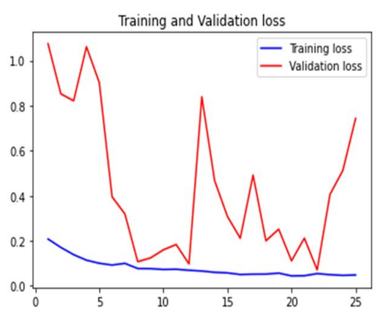


(i)MobileNet

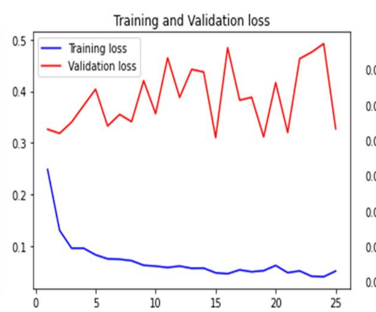


(j)VGG16

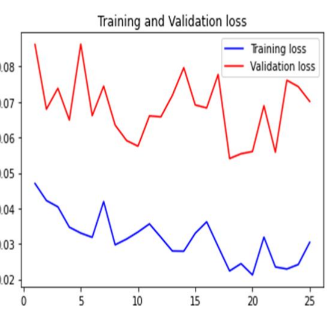
Figure-3 Comparison of Training & Validation Accuracy



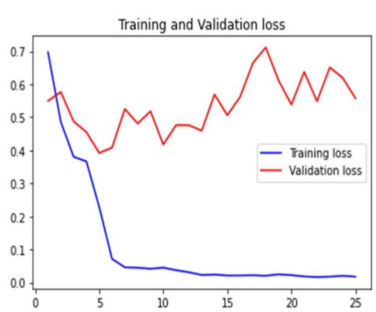
(a) CNN from Scratch



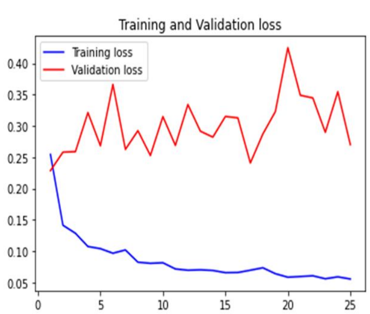
(b) Inception-ResNet v2



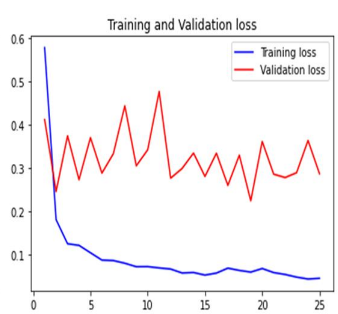
(c) VGG19



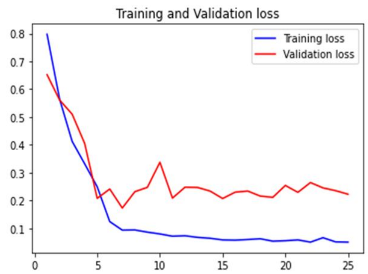
(d) ResNet50



(e) InceptionV3

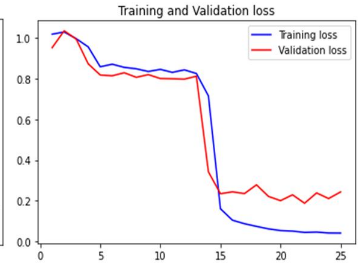


(f) Xception



(g) NASNEetMobile

(h) DenseNet121



(i)MobileNet

(J)VGG16

Figure-4 Comparison of Training & Validation Loss

III. RESULTS& DISCUSSION

The training & testing carried out with all models was 80% dataset for training & 20% for validation purpose. We kept the same learning rate to train all models. The training & validation accuracy plot is shown for all CNN, VGG16, VGG19, ResNet50, DenseNet121, InceptioV3, Xception, NASNetMobile, InceptionResNetv2, MobileNet models. In table the comparison of validation accuracy & top-5 validation accuracy similarly training accuracy with top-5 training accuracy is shown of all models. VGG16 & VGG19 produced better results in terms of validation accuracy but these models are computationally expensive in terms of space & time. InceptioV3, Xception, NASNetMobile, InceptionResNetv2, MobileNet models producing 93% accuracy as these models size is less. ResNet50, DenseNet121producing approximate 88% accuracy. CNN training from scratch giving 90% accuracy which is lower than many pre train models.

The analysis of training and validation loss is also shown, in VGG 16 model when training loss is decreasing similar validation loss is also decreasing but validation loss is greater than training loss which shows model has some overfitting also. In other models there is less correlation between training &b validation loss.MobileNet&NESNetMobile model also showing good correlation between training & validation loss.

Testing accuracy and performance evaluation –In classification task to evaluate model performance confusion matrix is created, here performance is calculated using precision &recall.. Precision, recall, F-1 Score comparative analysis is shown in table for all 15 class diseases classification.

$$\text{Testing Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} (1)$$

$$\text{Precision} = \frac{(TP)}{(TP+FP)} (2)$$

$$\text{Recall} = \frac{(TP)}{(TP+FN)} (3)$$

$$\text{F1 Score} = 2 * \frac{(Precion.Recall)}{(Precion+Recall)} (4)$$

As validation accuracy is best in VGG16 in the analysis so here we are comparing F1 Score with VGG16.For Pepper__bell___Bacterial_spot disease better classification given by VGG16 model as shown in F1 score table with 97% where lowest miss classified by ResNet50 & DenseNet121.For Potato___Early_blight disease best F-1 score given by VGG19 as 96% where VGG 16 produced 91%.For Potato___Late_blight diseases VGG16 producing 94% F-1 score where other models have misclassified. For Tomato_Bacterial_spot not a single model giving good result here VGG16 is producing only 72% F-1 Score that yield that model has not learned features of this diseases well. For Tomato_Early_blight also every classifier has low score here VGG19 produced 74%

TABLE III. PRECISION ANALYSIS

Precision										
Class Label	NASNetMobile	CNN	MobileNet	DenseNet121	InceptinResnt V2	Xception	VGG 19	VGG 16	ResNet 50	InceptionV3
0	1	0.91	1	0	0.6	1	0.94	0.94	0	0.81
1	0.85	0.73	0.69	0	1	0.84	0.9	1	0	0.61
2	1	0.72	0.93	0	0.6	0.8	1	0.97	0	0.78
3	0.44	1	0.44	0	0.77	0.56	1	0.93	0	0.28
4	0.62	0.67	0.68	0	0.46	0.79	0.90	0.93	0	0.45
5	0	0	0.33	0	1	0	0.87	0.89	0	1
6	0	0.68	0	0	0.5	0.8	0.95	0.65	0	0.71
7	0.6	0.46	0.58	0	0.32	0.92	0.65	0.92	0.1	0.63
8	0.21	0.36	0.38	0	0.43	0.44	0.79	0.85	0	0.24
9	0.22	0.35	0.28	0	0.24	0.19	0.62	0.64	0	0.46
10	0.37	0	0.86	0.06	0.54	0.62	0.66	0.74	0	0.24
11	0.4	0	0	0	0.5	0.33	0.61	0.73	0	0.6
12	0.71	0.81	0.92	0	1	1	0.97	1	0	0.96
13	0.62	0.18	0.64	0	0.86	0.73	0.89	0.93	0	0.82
14	0.91	0.1	0.23	0	0.59	0.58	1	1	0	0.4

TABLE IV. RECALL ANALYSIS

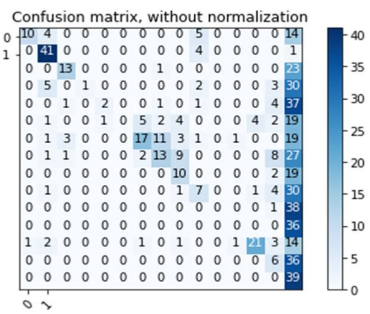
Recall										
Class Label	NASNetMobile	CNN	MobileNet	DenseNet121	InceptinResnt V2	Xception	VGG19	VGG16	ResNet50	Inception V3
	0.21	0.3	0.3	0	0.45	0.48	0.94	1	0	0.39
1	0.96	0.89	0.87	0	0.17	0.89	1	0.98	0	0.74
2	0.24	0.35	0.7	0	0.65	0.43	0.92	0.86	0	0.76
3	0.95	0.02	1	0	0.66	0.95	0.85	0.95	0	0.93
4	0.17	0.04	0.46	0	0.63	0.41	0.93	0.89	0	0.11
5	0	0	0.03	0	0.08	0	0.71	0.82	0	0.05
6	0	0.3	0	0	0.04	0.07	0.32	0.8	0	0.21
7	0.48	0.21	0.18	0	0.89	0.38	0.87	0.59	1	0.51
8	0.94	0.32	0.16	0	0.29	0.58	0.87	0.71	0	0.61
9	0.55	0.16	0.7	0	0.77	0.86	0.82	0.93	0	0.5
10	0.64	0	0.49	1	0.51	0.51	0.9	0.95	0	0.82
11	0.11	0	0	0	0.03	0.36	0.78	0.67	0	0.08
12	0.66	0.48	0.5	0	0.48	0.5	0.82	0.89	0	0.57
13	0.36	0.14	0.86	0	0.6	0.57	0.98	1	0	0.33
14	0.51	1	0.97	0	0.51	0.87	0.67	0.87	0	0.05

result only, in this class precision of VGG16 is 92% which is pretty good. Similarly Tomato_Late_blight disease, Tomato_Leaf_Mold', 'Tomato_Septoria_leaf_spot', 'Tomato_Spider_mites_Two_spotted_spider_mite' , 'Tomato__Target_Spot' diseses models VGG16 has more misclassification and score of models is also not

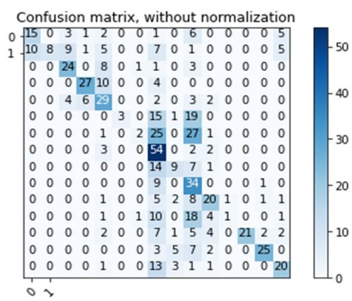
TABLE V.. F1-SCORE ANALYSIS

F1-Score										
Class Label	NASNet Mobile	CNN	MobileNet	DenseNet121	InceptinResnt V2	Xception	VGG19	VGG 16	ResNet50	InceptionV3
0	0.35	0.45	0.47	0	0.52	0.65	0.94	0.97	0	0.53
1	0.9	0.8	0.77	0	0.3	0.86	0.95	0.99	0	0.67
2	0.39	0.47	0.8	0	0.62	0.56	0.96	0.91	0	0.77
3	0.6	0.05	0.61	0	0.71	0.7	0.92	0.94	0	0.43
4	0.27	0.08	0.55	0	0.53	0.54	0.91	0.91	0	0.18
5	0	0	0.05	0	0.15	0	0.78	0.85	0	0.1
6	0	0.42	0	0	0.07	0.13	0.48	0.72	0	0.33
7	0.53	0.29	0.28	0	0.47	0.53	0.74	0.72	0.18	0.56
8	0.34	0.34	0.23	0	0.35	0.5	0.83	0.77	0	0.35
9	0.32	0.22	0.41	0	0.37	0.32	0.71	0.76	0	0.48
10	0.47	0	0.62	0.12	0.53	0.56	0.76	0.83	0	0.37
11	0.17	0	0	0	0.05	0.34	0.68	0.7	0	0.15
12	0.68	0.6	0.65	0	0.65	0.67	0.89	0.94	0	0.71
13	0.45	0.16	0.73	0	0.7	0.64	0.93	0.97	0	0.47
14	0.66	0.19	0.37	0	0.55	0.69	0.8	0.93	0	0.09

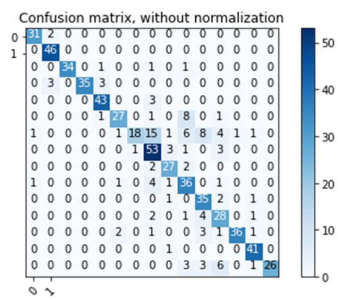
satisfiable, there should be more training to be provided for these disease classes. For Tomato_Yellow Leaf__Curl_Virus' Tomato_mosaic_virus' & 'Tomato_healthy VGG16 giving good score.



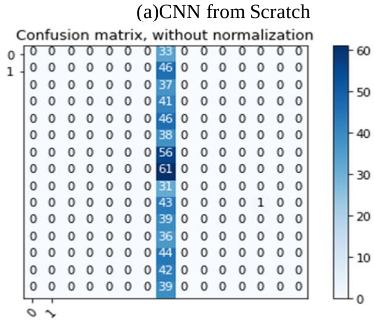
(a)CNN from Scratch



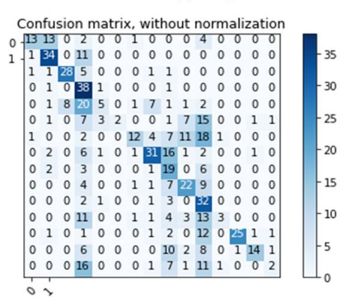
(b)Inception-ResNet v2



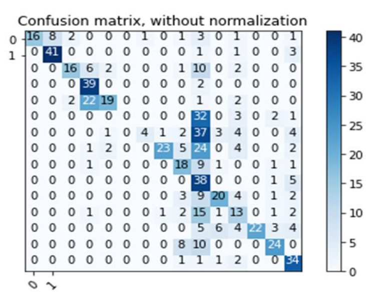
(C) VGG19



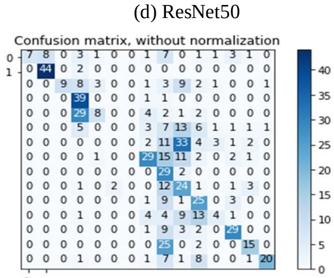
(d) ResNet50



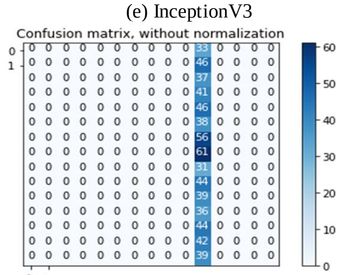
(e) InceptionV3



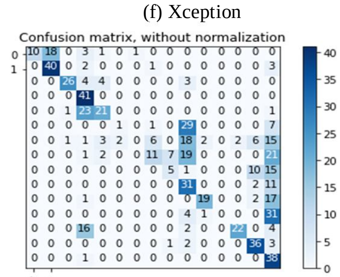
(f) Xception



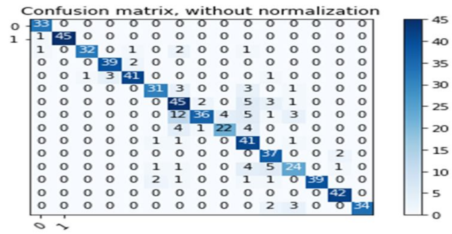
(g) NASNEetMobile



(h)DenseNet121



(i)MobileNet



(j) VGG16

Figure-5. Confusion Matrix

For all models confusion matrix is also shown where diagonal represents the true positive means correctly labeled validation data. As showing in figures VGG16 & VGG19 is generating most accurate predictions among all models.Resnet50 & DenseNet121 models haven't performed on the dataset, whereas Xception, InceptionV3 &Inception-ResNet v2 , NASENetMobileworked well with the training & validation dataset.

IV. Discussion

In this paper various deep learning pretrained CNN models have been analyzed on 15 diseases of potato, tomato & pepper plants of PlantVillage dataset. It has been seen that VGG16 model has produced better validation accuracy as 98% & all other models shown lower accuracy. We have also compared results with CNN training from scratch, results shows pretrained models yield better accuracy on validation dataset.Results shows validation accuracy or testing accuracy got down compared to training accuracy with prior study by authors in[5] & [16].

In real time prediction of data deep learning models can learn features irrespective of the background also that background also plays important role in finding accuracy [16]. In many papers accuracy of VGG model was greter than other models [17] [14] identified a higher accuracy using the dataset of PlantVillage. As higher performance shown by VGG16 model but the major factor is in its implementation as it requires more computation resources. Other pretrain models such MobileNet ,Xception can also be used for classification after increasing their accuracy by tuning hyper parameters during training as their model size is less than VGG.

V. Conclusions

In current study of automated identification of plant diseases in pepper, potato & tomatoes of 15 classes was analyzed by applying pretrained deep convolution neural networks. This study comprised of ten CNN models namely CNN, VGG16, VGG19, ResNet50, DenseNet121, InceptioV3, Xception, NASNetMobile, InceptionResNetv2, MobileNet for the identification of diseases. The data augmentation was also applied to reduce the over fitting & generalization problem. The results are analyzed on validation data VGG16 has resulted best accuracy in top-1 & top-5 accuracy also.In future study dataset with real time conditions such as complex images with different background will be used and deep learning models behavior & accuracy will be analyzed. It is also proposed to develop a proper smartphone application for farmers for early & accurate prediction of diseases.

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