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Optimizing Pre-Trained Models of Deep Learning for Identification of Plant Disease

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Abstract- The Plant diseases should be identified early to prevent the economic loss of farmers and ensure the availability of food for humans. The plant disease identification can be automated by using the Artificial Intelligence techniques. Researchers have proposed many deep learning methods for identifying plant diseases. Deep learning models use an increased number of parameters, it requires higher computational power, training a deep learning model from start requires more time. In this article we utilized transfer learning along with fine tuning for identification of plant diseases. Cassava plant disease dataset was utilised for training. and evaluate the suggested model. The performance accuracy achieved by Resnet50 is 73.12 % and fine-tuned Resnet50 is 80.84 %. The fine-tuned model achieves greater accuracy with a lesser amount of parameters

Impact Statement–Artificial Intelligence is evolving all around the world. The AI techniques are used to automate the process of plant disease identification. Traditional methods are not accurate and time consuming. To help the farmers in diagnosing plant disease and stop economic loss to them, we employ deep learning models to do the work. The pretrained models predict the plant diseases, further we fine-tune them in order to get high accuracy. Early identification of the diseases accurately will avoid loss and improve productivity of the crops.

Keywords— Deep Learning (DL), Optimization, Plant Disease (PD), Transfer Learning (TL).

I. INTRODUCTION

Agriculture is the mother of all civilization without food it is not possible to survive. The global food production must be increased by 60-110% to feed the population by 2050[FAO]. Small-scale farmers produce about 80% of the agricultural output in developing nations [FAO-2021]. There are many things that influence the food basket of the world. The major one among them is the plant diseases, 40% of crop production are lost by plant diseases [1]. Visual inspection and laboratory tests are the conventional methods for identifying plant diseases, which requires domain expertise and it is a time-consuming process. Protecting the economic condition of small hold farmers and ensuring the availability of food for each individual by using the latest available technology is the significant duty of the researchers. The exponential growth of Artificial Intelligence techniques leads to a way to automate the job of plant disease identification. Deep learning for disease recognition and categorization in plants is quick and accurate and it does not need domain expertise [2]. The plant disease identification using CNN is more popular [3]. TL is a method for transferring knowledge from one model to another, that is employed to solve similar kind of problem. For transfer learning, there are numerous pre-trained models available. The advantages of using pre-trained models are i) Small dataset can be used, ii) No need of High computational Resources, iii) Very less training time, iv) No need to worry about generalization, v) Imbalanced Datasets can be used.

Three advanced pre-trained DL models for PD detection were used in this work, namely VGG16, Resnet50, and Inceptionv3. VGG16 achieves 92.7% accuracy in 2014 image net classification challenge[4].The accuracy of Resnet50 on image net dataset is 80.67%[5].The Inception V3 model achieved 78.1% accuracy on image net dataset[6].We used Transfer learning approach to identify the plant diseases, At First we used pre trained models to predict the plant diseases after that we fine-tune the parameters of pre trained models to improve the performance in identifying the plant ailments and the pre-trained, fine-tuned models' outputs are evaluated. The article is aligned in such a manner as follows, in section-II related works on plant disease identification using AI techniques are introduced. The materials and methods employed are covered in Section III. In Section-IV, the results and discussions are provided. Section –V provides a conclusion.

II. RELATED WORK

Utilization of appropriate techniques to automate the plant disease recognition helps in improving the productivity of crops and avoids loss. This section explains the different existing AI techniques in disease identification of plants.

Sharada.p.Mohanty et al. [7] used TL and training from scratch of Alexnet, Googlenet to recognize 14 crop types and 26 diseases. They used color, Grayscale segmented model images and different train test distributions and recorded highest accuracy of 99.34% in Google net-Transfer learning-Color- 80% -20 % Distribution.

Sladojevic et al. [8] used café DL framework to train a fine-tuned CNN architecture which predicts 13 different plant diseases with 96.3% accuracy. Ferentinos et al. [9] make use of five pre-trained DL models such as Alexnet, VGG, AlexNetOWTBn, Googlenet and overfeat to identify leaf disease of 58 plants with highest accuracy of 95.33% in VGG. Nine Layer DCNN was used by Geetharamani et al.[10] to find plant disease with 96.46% accuracy. Inception layer has taken the place of Alexnet's fully connected layer by Liu et al.[11] to recognise the four apple leaf disease, with a 97.61 .% percent accuracy rate.

Ahmad et al. [12] used four pre-trained DL models such as VGG16M, Resnet, VGG19, Inception V3 to classify leaf disease in tomato plants. They recorded 99.60% of accuracy using Inception V3. To get the outcome, they adjusted the network parameter. A pre-trained VGG16 is used in order to extract features and multiclass SVM for classification is used by Rangarajan and purushothaman [13] to classify egg plantillnesses. When using RGB, YCbCr and HSV color model images to verify the model's robustness they achieved maximum accuracy of 99.4% in RGB images. Rangarajan Aravind and Raja [14] used six pre-trained architectures of deep learning to classify ten diseases in four varieties of crops and recorded a highest accuracy of 90% by VGG16.

Ramcharan et al. [15] used InceptionV3 transfer learning to find two pest damages and three diseases among cassava plants. The dataset includes multiple leaves in an image and single leaf in an image and the maximum accuracy is recorded in a single leaf image. Using a deep learning model with residual connection performs excellently in comparison to plain CNN in identifying cassava plant leaf diseases oyewola et al. [16]. The dense layers of VGG16 are replaced by two inception levels and named as INC-VGGN by Chen et al. [17] to classify rice and corn diseases and achieved 92% accuracy in rice and 80.38% accuracy in corn disease classification.

SK Mahmudul and Arnabkumarmaji [18] used a novel CNN, which uses inception layer and residual connection, which needs a lesser amount of time for training and 70% lesser parameters and achieved 99.37% accuracy on plant village dataset, 99.65% accuracy in rice disease dataset and 76.49% accuracy in cassava dataset. Iftikhar Ahmed et al.[19] used parameter tuning on pre-trained CNNs and used field based dataset and laboratory based dataset to Analyze the model's performance and achieved highest accuracy of 99.60% in laboratory based dataset.

III. MATERIALS AND METHODS

A. CNN

Among the deep learning architectures are CNN (convolutional neural networks), automatically recognize and extract features from input data, doing away with the requirement for manual feature extraction. The CNNs are used mainly in solving computer vision problems. CNN classify the images by employing two processes i) Feature Learning, ii) Classification

The feature learning is achieved by using two different layers such as convolutional layer and pooling layer. The heart of CNN is the convolutional layer. From the input image, the convolutional layer retrieves features. The kernels/filters layer of the convolutional layer is a tiny array of numbers which is applied over the source image for convolutional operation and produces an output called feature map. From the input image in order to extract several types of features, different kernel sizes and numbers are used. The output feature map is composed of the learned features using the provided input image. The Pooling layer is used to decrease the number of dimensions. It reduces the dimensions of the feature map. There are numerous pooling operations, including average, maximum, and minimal pooling. The next process is classification, the resultant feature map is flattened into a column vector and fed into fully connected layers for classification and through back propagation on every iteration the fully connected layers gain the correct weights, biases and classify the input images. The final dense layer contains the same number of outputs as there are image classes. Even Though the CNN is well suited

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for solving computer vision tasks [20], there are two primary implementation issues i) The training phase of CNN involves a greater number of parameters, Therefore, the deep learning model's computing cost is high. ii)For training, a lot of images are required. Due to these issues, for systems with average processing resources, training a deep learning model from scratch is not the best option.

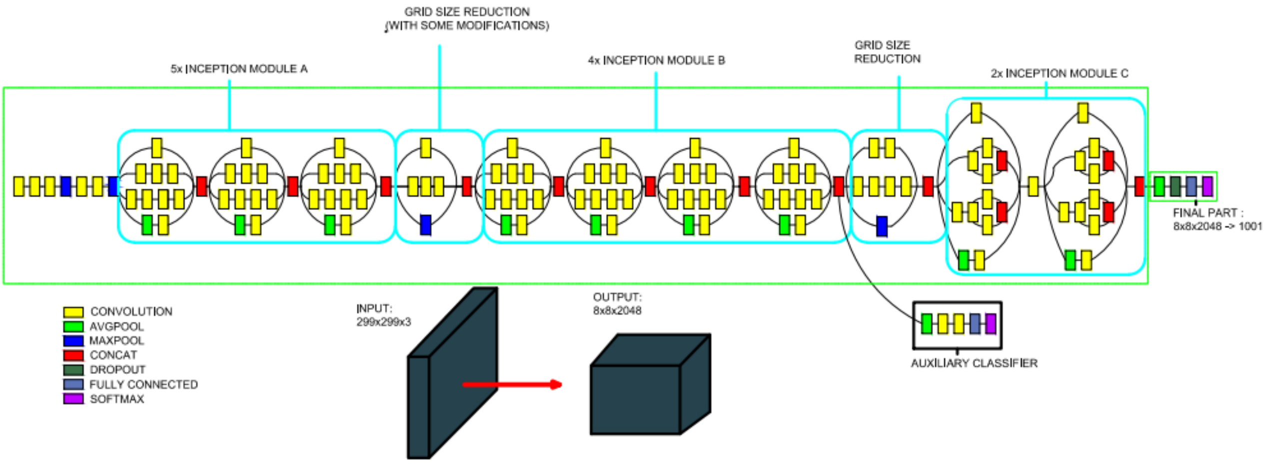

Figure 1. Inception V3 Architecture

Many pre-trained DL models are suggested in the previous works and in this paper we are using the VGG16, Resnet50, InceptionV3 models. We have employed a novel approach of using pre-trained models with fine tuning. A pre-trained model's final few layers are trained, keeping the remaining layers in freeze mode (Using the pre trained weights), Fine Tuning the hyper parameters in order to enhance the model's performance.

B. VGG16

Vgg16 is a CNN that is 16 layers deep. The University of Oxford's Visual Geometric Group (VGG), introduced it, hence the name VGG [4], which is used to win ILSVR (Image net) competition in 2014.The VGG16 model accepts image input size of 244*244.The five convolutional blocks that make up the VGG16 are stacked, each block's max pool layer follows the first two convolutional blocks, which each have two convolutional layers, remaining 3 convolutional blocks consisting of a max pool layer and 3 convolutional layers each. It is preceded by three fully connected layers. VGG16 uses fixed size kernels of size 3X3 and maxpool kernels with a stride size of two and a size 2X2. The total number of parameters used by VGG16 is 13,83,57,544.

C. InceptionV3

Very deep layers of convolution resulted in over fitting of data to overcome this Inception model uses layers in parallel thus making the model wider instead of deeper. A deep learning model based on InceptionV1 is called InceptionV3. It has 42 layers released in 2015.In comparison to its predecessor, it is more efficient. It is deeper than V1 and V2 without compromising its speed, computationally less expensive. The convolutions are divided into more manageable convolutions and spatially factorized into asymmetric convolutions of the form NX1.It uses auxiliary classifiers. The model with auxiliary classifier produces higher accuracy. The auxiliary classifiers in very deep networks tackle the vanishing gradient issue. The grid size of feature maps are reduced efficiently by expanding the activation dimension. The InceptionV3 uses 23851784 parameters. The architecture of Inceptionv3 is shown in figure (1)

D. ResNet50

Resnet is projected by Microsoft research in 2015.many deep learning architectures uses more layers to reduce error rate, which leads to vanishing gradient problem, to overcome this the resnet architecture introduced the concept of residual blocks, by using skip connections. The skip connection will skip the layers which will hurt the performance of architecture. Resnet50 is 50 layers deep with different sized kernels. The full set of variables used by Resnet50 is 25636712.In Table 1, the Resnet50 architecture is presented.

E. Dataset

The data set utilized in this research is cassava plant disease dataset which is downloaded from kaggle. The dataset used in the kaggle competition for identifying cassava leaf diseases. There are 7212 photos in the dataset belongs to five classes namely CBB - 1219, CBSD -2172, CGM -1475, CMD -3450, Healthy -697.It is an imbalanced

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dataset with complex image background. Eighty percent of the downloaded dataset is used for training, while twenty percent is used for testing. Table 2 displays the dataset's data description. Figure 2 displays sample images for each class.

Table 1. Layers of Resnet50 Architecture

Layer Name	Resnet50 Architecture layers	Output size
Convolution1	7×7, 64, **stride 2**	**112X112**
Convolution2_X	3×3 **Maxpool, stride 2** $\begin{bmatrix} 1\times1, & 64 \\ 3\times3, & 64 \\ 1\times1, & 256 \end{bmatrix}\times3$	**56X56**
Convolution3_X	$\begin{bmatrix} 1\times1, & 128 \\ 3\times3, & 128 \\ 1\times1, & 512 \end{bmatrix}\times4$	**28X28**
Convolution4_X	$\begin{bmatrix} 1\times1, & 256 \\ 3\times3, & 256 \\ 1\times1, & 1024 \end{bmatrix}\times6$	**14X14**
Convolution5_X	$\begin{bmatrix} 1\times1, & 512 \\ 3\times3, & 512 \\ 1\times1, & 2048 \end{bmatrix}\times3$	**7X7**
Avg pool,1000-d fc, Soft max		**1X1**

Table 2. Data summary of the dataset

Class	Disease Name	Disease Type	No.of.Images
C1	**CBB**	**Bacteria**	**1219**
C2	**CBSD**	**Virus**	**2778**
C3	**CGM**	**Virus**	**1475**
C4	**CMD**	**Virus**	**3450**
C5	**Healthy**	**-**	**697**

IV. RESULTS AND DISCUSSION

In this segment the experimental results are presented. Three pre-trained models were employed by us such as VGG16, InceptionV3, and Resnet50 for identification of plant disease using a cassava dataset. Later we fine-tuned the Pre-trained models VGG16, InceptionV3, Resnet50 to be able to achieve higher classification accuracy and to cut down on the amount of parameters used by the models, which reduces the computational overhead. We compare the outcomes of the pre-trained models and fine-tuned models. The models' performance is measured using the following measures.

Accuracy (A): It is the amount of correctly classified data instances over total number of occurrences.

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision (P): The capacity of a classification model to identify true positives over all the positives.

$$P = \frac{TP}{TP + FP}$$

Recall (R): The ability of a model to correctly identify true positives

P=TΠ / TΠ+ΦN

F1 Score: It represents the harmonic mean of recall and precision.

Φ1=2∗(Π∗P/Π+P)

Pre trained models use the existing weights that are gained through image net database. The VGG16 model classifies with an accuracy of 63.96%.The model uses 138357544 parameters, which is very high and it requires high computational power.(Table 3 and 4)

Table 3. Classification accuracy & parameters of pre trained models

Model	No.of.Parameters	Accuracy
VGG16	**138357544**	**63.96%**
Inception V3	**23851784**	**70.34%**
Resnet50	**25636712**	**73.12%**

Table 4. Classification accuracy & parameters of Fine-Tuned models

Model	No.of.Parameters	Accuracy
VGG16	**40410949**	**72.12%**
Inception V3	**21807909**	**78.34%**
Resnet50	**23592837**	**80.84%**

The fine-tuned VGG16 Model uses 40410949 parameters which is very less when compared and classifies with a accuracy of 72.12%.The InceptionV3 uses 23851784 parameters and classifies at an accuracy rate of 70.34%, while fine-tuned Inceptionv3 uses lesser parameters and predicts with an accuracy of 78.34%.Resnet50 uses 25 million parameters and classifies at 73.12% accuracy, while fine-tuned Resnet50 uses fewer parameter and predicts at an accuracy of 80.84%.It is obvious that fine-tuned Resnet50 outperforms all other models in classifying diseases of cassava dataset. While fine tuning, reducing the overall amount of parameters and thus, the cost of computing, the dense layers of the models are modified. The hyper parameters are fine-tuned to attain optimal accuracy. It is noted that fine-tuned models use fewer parameters and classify the plant diseases with significantly

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more accuracy in comparison to pre-trained models. The model's performance is satisfactory with the imbalanced cassava dataset.

The table (5) summarizes the six models' Precision, Recall, and F1 scores. The fine-tuned models performed superior than the pre-trained models.Resnet50 model performed well in both pre-trained and fine-tuned categories. From figure 3 it has been noticed that the typical performance disparity in Recall score between pre-trained and fine-tuned models is 6.53%.The same pattern is observed in both Precision and F1- Score with 8.10% and 7.37% difference respectively.

From table 5, there is evidence that there is a notable difference in recall, precision, and F1- score of fine-tuned models.

Figure 2. Sample Images of Dataset

Table 5. Precision, Recall, F1 Score of pre trained and fine-tuned models

	VGG16		**Inception V3**		**ResNet50**	
	Pretrained	**Fine-tuned**	**Pretrained**	**Fine-tuned**	**Pretrained**	**Fine-tuned**
Precision	**0.639**	**0.701**	**0.682**	**0.774**	**0.717**	**0.806**
Recall	**0.713**	**0.767**	**0.708**	**0.785**	**0.749**	**0.814**
F1 Score	**0.674**	**0.732**	**0.695**	**0.780**	**0.732**	**0.810**

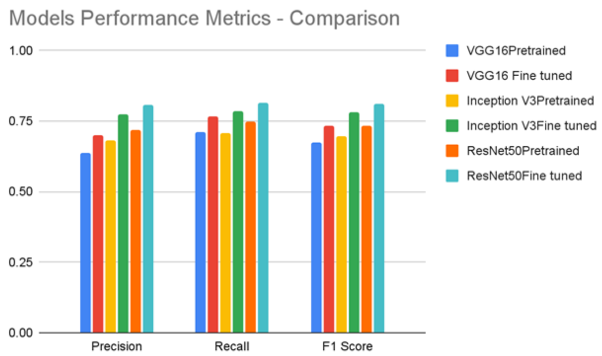

Figure 3. performance metric of different models

V. CONCLUSION

DL is an advanced technique which is utilized to solve computer vision problems particularly in identification of PD. In this article we used different pre-trained models and fine-tuned them to get the optimal result. The models used are VGG16, InceptionV3, Resnet50.The performance of pre-trained models and fine-tuned models are compared. We used the cassava plant disease dataset to evaluate their performance. The fine-tuned models outperform the pre-trained models.Resnet50 achieves higher accuracy rate of 73.12 % in pre-trained models and 80.84 % in fine-tuned models. To achieve higher accuracy rate in future, balanced dataset can be used. The model can be applied to recognize various plant diseases.

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