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A FUSION APPROACH OF CONVOLUTIONAL NEURAL NETWORK MODELS FOR ACCURATE PLANT DISEASE PREDICTION

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Abstract—Agriculture is being a substantial contributor to the world's economy. Plant diseases may cause several issues like crop losses, economic impact, biodiversity loss, reduces food production and its quality. Convolutional Neural network(CNN) is an artificial nueral network that is most popularly used for analyzing images. Since the CNN model is more suitable for identification and classification of images, the researchers are continuously exploring the use of CNN in agriculture domain. Three CNN pre-trained models namely, VGG16, Inception v3, and Xception are considered in this paper for the comparative study. Analizing these CNN models, it is possible to extract the fine-grained picture characteristics. It helps to improve the deep learning capabilities and prevent overfitting. The inception model extract information from numerous transformations, then concatenate along the output channel. In Xception model, before the 1x1 channel correlations, deep separable convolutional layers are stacked and complete the spatial mapping using residual connections. In VGG16, the image is passed throgh a stack of convolutional layers. Each convolutional filters has very small receptive fields of size 3x3, and the convolution is carried out with stride 1. Here, a comparison model is created where each model is first taken and its accuracy is determined. After combining VGG-Incp, Incp-Xcep, and Xcep- VGG, the model needs to be trained to determine its accuracy. The results of Incp-Xcep-VGG are merged into single model to determine its efficiency. Based on the results of this study, the Incp-Xcep-VGG achieved a greater accuracy of 85%.

Index Terms—Convolutional Nueral Networks ,Inception V3, Xception, Vgg16.

I. INTRODUCTION

The Indian economy is really depending on the agricultural productivity. Both the environment and human, fully satisfied with the contribution that food, cash crops and plantation crops provide. In every year, there are numerous diseases claim the lives of crops. The poor detection of plant diseases, lack of awareness of the symptoms and cure, leads to several plant species loss. This paper gives a detailed comparative analysis of different algorithms, that used to identify the plant diseases. This paper suggests the use of CNN models for identifying the plant diseases and its classifications. The simulation and analysis are carried out on sample plant images, in terms of time complexity and the size of the infected area. To identify the disease using images of leaves, research is being done in the smart computer environment. The following are a few issues that need to be named. Finding the sick leaf, measuring the diseased region, determining the disease's boundaries, determining the color of the diseased area, and determining the particular source of the disease. One of the fascinating subjects that are frequently discussed in the engineering and IT fields is detection and categorization. The identification of plant diseases can prevent the reduction in agricultural productivity and its quality. Research on plant diseases refers to examinations of patterns on the plant that may be observed with the naked eye. As a result of the historically unprecedented quick adoption of mobile phone technology across all industries, the number of tools based on mobile phones has expanded recently. One of the most essential requirements for developing agriculture is the prediction and early detection of plant disease. The subjective nature of human evaluations makes it difficult and time-consuming to visually detect plant illness over a large region, and the results are open to error. Due to the subjectivity of human judgments, the process of visual illness identification over a vast region is time-consuming and prone to inaccuracy. Plant health monitoring and disease identification are very essential to make the agriculture field sustainable one. It is simpler and less expensive to automatically identify illnesses by merely observing their symptoms on plant leaves. The suggested method for identifying plant diseases uses less computer power and takes less time for prediction than other methods. Here, a comparative analysis is conducted, with the highest accuracy final results being used for future prediction and classification purposes. For that, various pre-trained CNN modes were employed alone, then in the manner of a two-way combination, and lastly in a three-way combinations manner as well.

II. RELATED WORK

The hypothetical studies on leaf disease detection that have been done recently are summarized in the current section. In the field of agricultural picture recognition and classification, deep learning and conventional machine learning are the two primary categories of technology. In this area, deep learning technology is evolving very swiftly and doing many amazing feats. The automatic identification of herbs has several advantages, including the deduction of time and expense with acceptable classification accuracy that could eventually replace the manual identification of plant species by subject matter experts. Deep learning techniques are being utilized to over- come issues as they become more common in computer vision. The system for identifying plants has been the subject of extensive scientific study. The identification of plants is greatly aided by digital photographs. The feature extraction, feature scaling, and classification techniques are used in traditional machine learning. Convolutional neural networks are used to process a picture of a leaf to extract color, veins, shape, and edge information using deep learning. Uguz, S. and Uysal, N. addressed a comparison of an olive plant disease transfer learning scenario with CNN architectures like VGG- 16 and VGG-19 as well as proposed CNN architectures [4]. 3400 photos of olive plant leaves make up the framework used on the datasets. A data augmentation mechanism was used in this framework to increase the datasets size. The accuracy reached roughly 88 % before data augmentation.Using CNN-based models like VGG16, VGG19, InceptionV3, and MobilenetV2, Ishengoma et al. (2021) suggested a method for recognizing faws on maize leaf pictures acquired by UAV[5]. Using two sets of data—original photos and modified images produced using ShiTomas corner detection techniques—the models were trained to distinguish between two groups of infected and non-infected images. Models developed from altered photos outperformed those developed from original images. Four image categories are also chosen to increase accuracy while lowering misclassification. using a hybrid CNN model, where only the top layers need to be retrained to cut down on training time, and sharing the lower-layer weights that are required to extract features between the several models. The hybrid model's parallel structure is used to cut down on training.

III. SYSTEM ARCHITECTURE

People can now generate enough food to meet their requirements thanks to advance technology. However, several issues, particularly climate change, that always be a danger to the food security. Plant diseases are a threat to farmers whose livelihoods depend on producing healthy crops in addition to smallholders. The 80% of agricultural production is done by the smallholder farmers in developing nations, while pests and illnesses cause more than 50% of yield losses. The major- ity of hungry people come from smallholder farm households, which renders them more susceptible to disruptions in food availability brought on by infections.

The system architecture is shown in fig. 1, where the first stage is picture acquisition. Data from the plant village dataset is gathered here and stored in the database for later processing. To make the collected photographs clearer and to remove any distracting elements, preprocessing must be given to them. The preprocessed image is supplied to the feature extraction

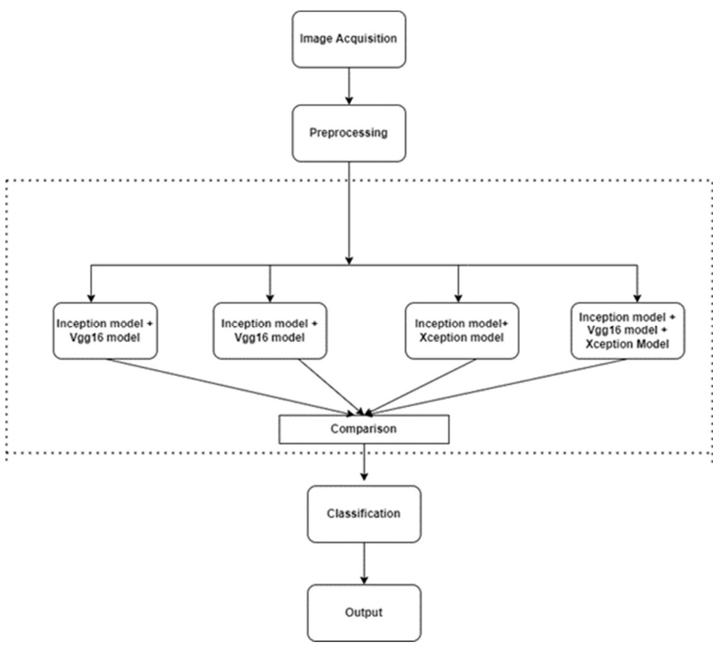


Fig. 1. System Architecture

module, which compares many models, creates a comparison model, and determines which model is superior with high accuracy. As development for the study, the highly accurate model is employed for prediction and classification purposes. Here, various CNN models are evaluated in comparison. The first step is to train the vgg inception and xception separately and determine their accuracy. Examine 54,306 plant leaf snapshot samples that have a total of 15 class labels applied to them. A crop-disease pair is represented by each class label, with the crop-disease pair being predicted using simply the plant leaf image. The resolution of each image is 299*299 pixels. The dataset is split into three sections: test, validation, and train. 43,444 photos make up the train set, 10861 images make up the validation dataset, and 33 images make up the test set. Use distinct iterations of the whole PlantVillage dataset for each trial.

A. VGG 16

Large-Scale Image Recognition Using Very Deep Convolutional Networks (VGG-16) One of the most widely used pre-trained models for image categorization is the VGG-16. The input size is defined as 224x224. After preprocessing, the primary images are passes through weight layers. The training images are applied through a stack of convolutional layers. In the VGG16 architecture, there are a total of 13 convolutional layers and 3 fully connected layers. Instead of having huge filters, VGG uses smaller 3*3 deeper filters. Its image size is downscaled to 299x299 and provided to the model as input. A 512 value vector is produced. The 512-neuron dense layer is then added, performing the function of relu activation in the hidden layers. Over the output layer with 15 classes, the

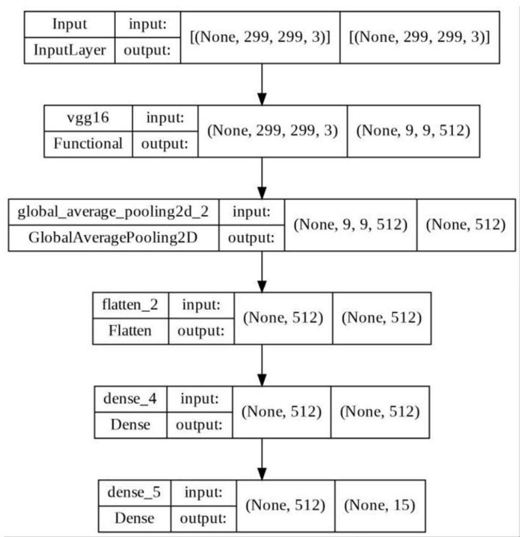
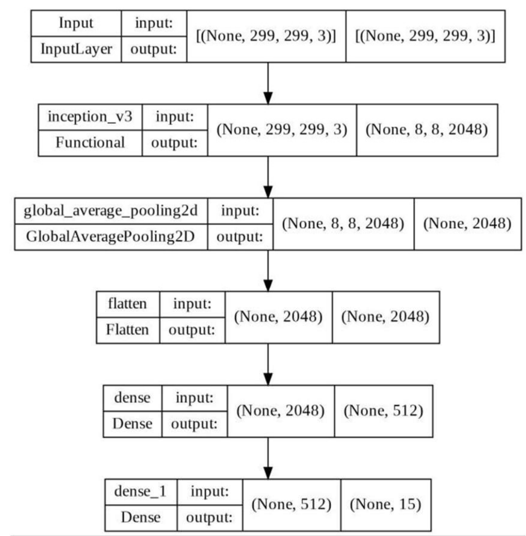


Fig. 2. Model Summary of VGG 16



softmax activation function is used.After training, it is evident that this model has a 73.07% accuracy rate.

B. INCEPTION V3

Inception v3 is a pre-trained convolutional neural network that has forty eight deep layers. Using ImageNet database, it has been trained on more than a million images. The network can accept images up to 299 by 299 pixels. First, the model extracts generic features from the input images, and second, it classifies the images based on those features. Factorization into Smaller Convolutions, Spatial Factorization into Asymmetric Convolutions, Utility of Auxiliary Classifiers, and Efficient Grid Size Reduction are the main changes made to the Inception V3 model as compared to its previous versions. The model receives an input image with a dimension of 299 by 299. In addition to adding a dense layer of 512 pixels and performing relu activation function, the model also uses the global average pooling and flattening. It produces a vector with an output size of 2048. For classification purposes, a 15- class output layer with the softmax activation function is used. Therefore, following training, it is evident that the model gains accuracy which is 77%.Fig 3 explains model summary of the Inception v3 used in this study.

C. XCEPTION

”Extreme inception” is what Xception stands for. It uses Depth wise Separable Convolutions and has a deep convolutional neural network design.In inception, Use 1by1 convolutions to divide the original input into numerous smaller input spaces, and then use a different kind of filter to convert those smaller 3D blocks of data from each of those smaller input areas. Before performing a 1by1 depthwise convolution to capture cross-channel correlation, the Xception will maps the spatial correlations seperately for each output channel.

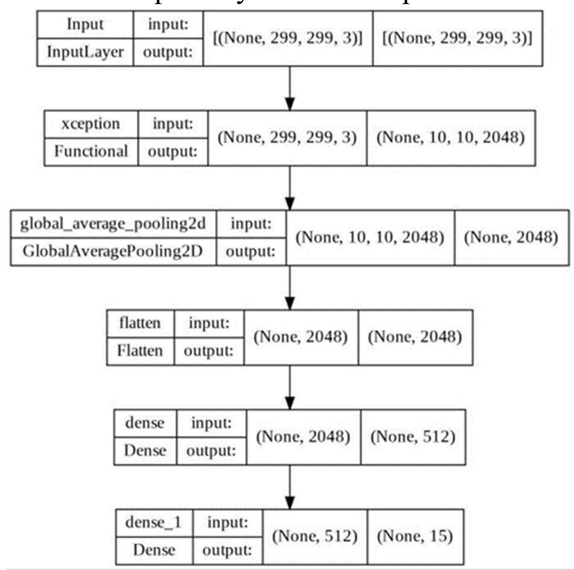


Fig. 3. Model Summary of INCEPTION v3

Fig. 4. Model Summary of XCEPTION

A depthwise separable convolution entails a pointwise convolution after a depth wise convolution. In Xception architecture there are 36 convolutional layers, to extract the features. A layer of logistic regression will come after a convolutional basis.This model executes operations like global average pooling and flattening using a 299x299 input size. It builds a 2048-layer vextor with 512 hidden layers, and the final output layer is 15 and uses the softmax activation function. It achieves an accuracy of 76.92%.

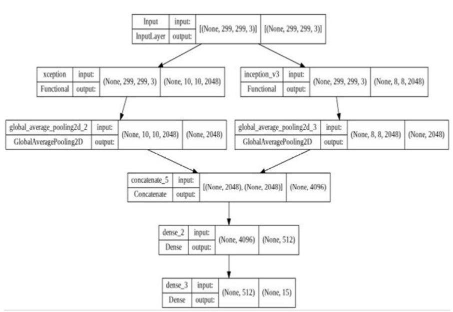
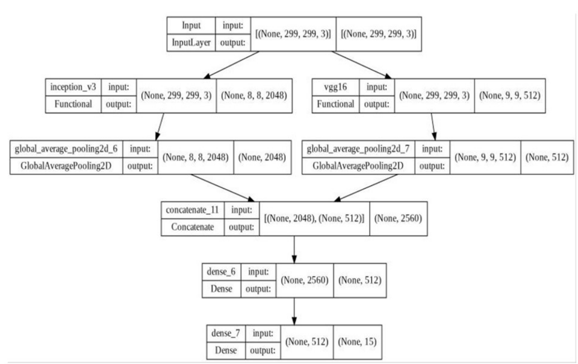


Fig. 5. Model Summary of INCP-XCEP



D. INCEPTION XCEPTION

Integrating two models—for example, Inception and Xcep- tion—into one. give the model the name ”incp-xcep model.”as shown in Fig 5 The model is applied to the input image, which is 299 x 299 pixels in size. The model simultaneously extracts the features and concatenates the results into a single feature that is used for classification. Models 1 and 2 are initialized as Xception and Inception models, respectively. Each model is integrated to create a single model that generates a 4096- element output vector. Additionally, it features a dense layer with 512 neurons, and the output layer has 15 neurons that are activated using the softmax function. This model on training with 10 epochs produces an output accuracy of 80.76%

E. VGG INCEPTION

Merging two modelling approaches, such as VGG and Inception, into a single model. give the model the name ”vgg-incp model”as show in Fig 6. The model is applied to the input image, which is 299x299 pixels in size. The model simultaneously extracts the features and concatenates the results into a single feature that is used for classification. Model 2 is initialised as an Inception model, and model 3 is initialised as a VGG. VGG produces an output vector of 512, while the Inception model produces an output vector of 2048. Each model is integrated to create a single model that generates a 2560-vector output. Additionally, it features a dense layer with 512 neurons, and the output layer has 15 neurons that are activated using the softmax function.This model on training produces an output accuracy of 81%

F. VGG XCEPTION

Creating a single model by combining two modeling ap- proaches, such as VGG and Xception. As seen in fig. 7, name is given as ”vgg-xcep model.” The input image, which is 299x299 pixels in size, is applied to the model. To create a single feature that can be utilized for classification, the model simultaneously extracts the features and concatenates the obtained results. Model 1 starts as an Xception model, while Model 3 starts as a VGG. The Xception model generates a 2048-bit output vector, whereas VGG generates a 512-bit output vector. A single model that produces a 2560-vector output is created by integrating each model. It also has an output layer with 15 neurons that are activated using the

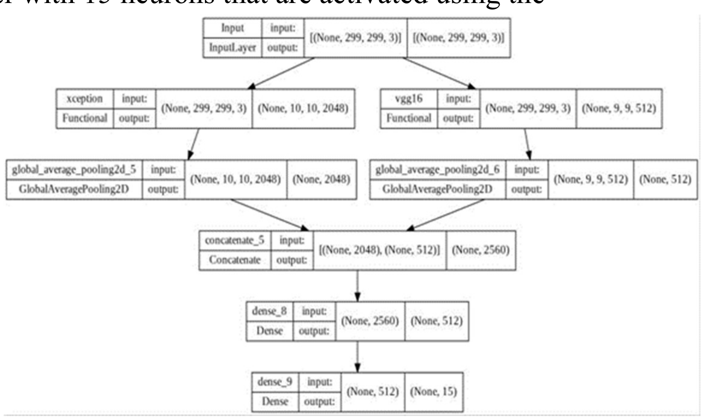


Fig. 6. Model Summary of VGG-INCP

Fig. 7. Model Summary of VGG-XCEP

softmax and a dense layer with 512 neurons.This model acquires an accuracy of 80.76%

G. VGG-INCEPTION- XCEPTION

Integrating the three separate models to create one model, then using that model to make predictions. Here, the VGG- Incp-Xcep model is derived from the VGG-Inception-Xception models. The input is the 299 by 299 rescaled image, which is applied to each model separately. Then, the inception and Xception create a feature vector with a 2048-by-2048-pixel size, and the VGG creates a 512-by-512-pixel feature vector. Then the global average pooling and flattening are applied to each model. Inception and Xception are then concatenated

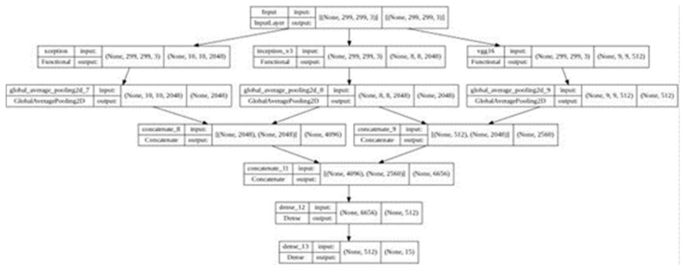


Fig. 8. Model Summary of VGG-INCP-XCEP

to provide a vector size of 4096, while Inception and VGG are combined to produce a vector size of 2560. Concatenating these models together will result in a vector size of 6656. After adding the dense layer of 512 neurons, the output layer, which consists of 15 layers, is applied with the softmax activation function.Fig 8 shows the model summary of this concatenated model.After training it is clear that this model acquires an accuracy about 85%.And can call it as a hybrid model of cnn that is concatenating this models into a single one and used for the further prediction.

IV. RESULT ANALYSIS AND DISCUSSION

A fine-tuned CNN model was used for this study using transfer learning. Fine-tuning involves the transfer of new layers (a fully connected layer, a softmax layer, and a classifi- cation output layer).The outcome of the training and validation of several models is summarised in this section. Figures 9 to 13 illustrate many models, including the VGG, Inception, Xception, Incp-Xcep, VGG-Incp, VGG-Xcep, and VGG-Incp- Xcep models. From this comparative analysis, it is evident that the three models working together have a greater accuracy rate, or 85%accuracy. It will be possible to use this combination model, often called a hybrid model, in the future. It can be applied to categorize data and make predictions.

V. CONCLUSION

Plant disease detection methods based on deep learning tasks achieve excellent development prospects, as compared with traditional image processing methods. There are still some problems to be solved in plant disease detection tech- nology, even though it is evolving rapidly from academic research to agricultural application. The use of deep learning algorithms has aided in the early diagnosis of disease and, as a result, reduced the financial loss to farmers. Accurate plant disease identification and classification are crucial for generating a productive crop, and image processing can help with both of these tasks. This study aimed to develop a reliable CNN model that would shorten the classification time for leaf images without compromising accuracy.To assess diseases, Convolutional Neural Network (CNN) models with multiple layers, such as VGG, Inception, and Xception are utilised. The work primarily focuses on comparing and evaluating several CNN models for disease prediction, as well as testing each model's accuracy. Each of CNN's pre-trained models is first individually trained to determine its accuracy after that the two models combined are taken into consideration. In the same way that Incp-Xcep and VGG-Incp and VGG-Xcep are integrated into a single model and checked its efficiency. Then the combination of the three models to make it into one is examined and calculated the accuracy. In this comparison study, it is very clear that the VGG-Incp-Xcep model has 85% accuracy. As a refinement of this study, this higher accuracy model can be taken and used for further disease prediction and classification purposes.

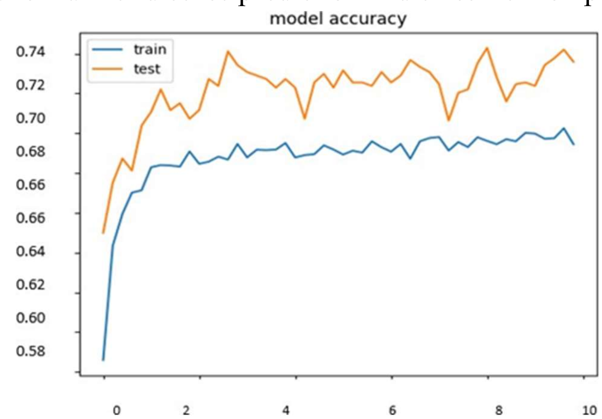


Fig. 9. Training and Testing Graph of Vgg

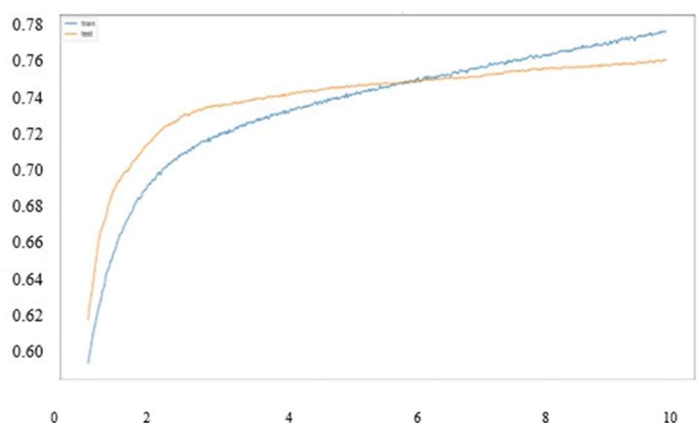


Fig. 10. Training and Testing Graph of Inception

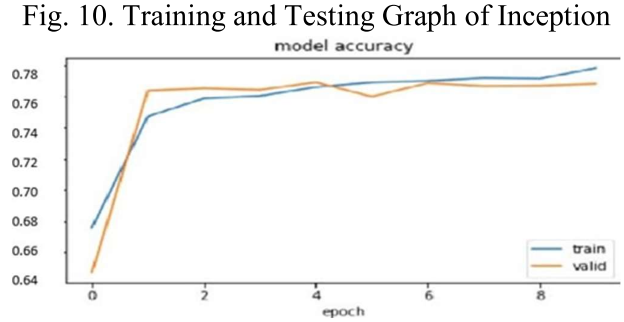


Fig. 11. Training and Testing Graph of Xception

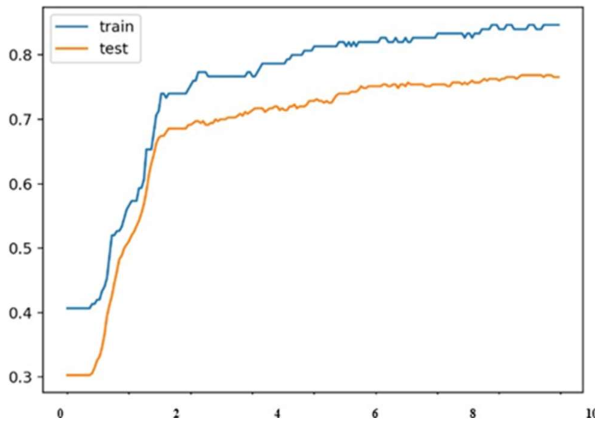


Fig. 12. Training and Testing Graph of INCP-XCEP

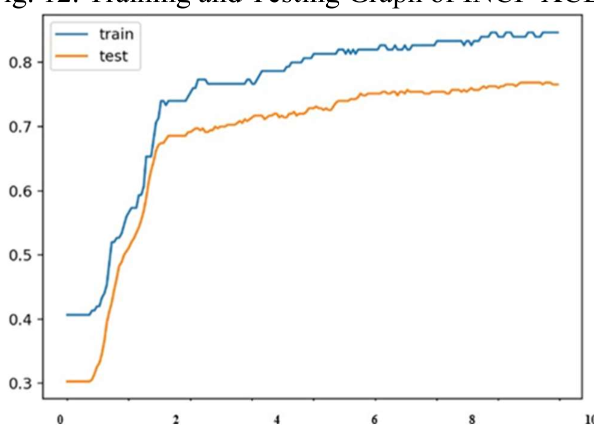


Fig. 13. Training and Testing Graph of VGG-INCP

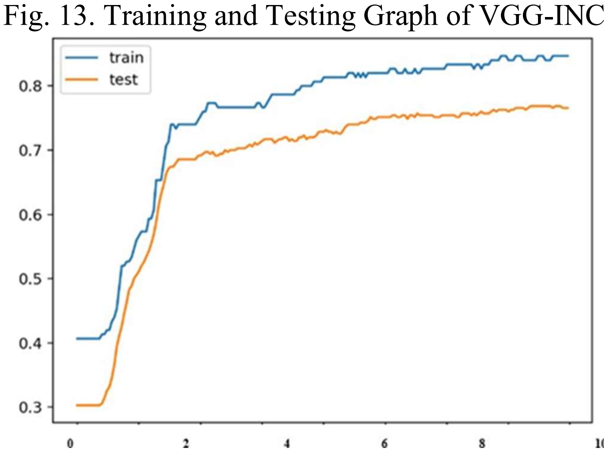


Fig. 14. Training and Testing Graph of VGG-XCEP

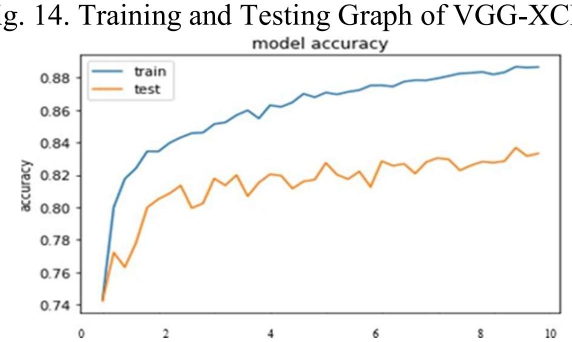


Fig. 15. Training and Testing Graph of VGG-INCP-XCEP

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