Reducing Computational complexity of Dense-Net model for leaf image classification

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Abstract—Most of the crops which are grown in India have shown reasonable production from past decades. Among this paddy is considered as the most pre-dominant crop of our country. Mostly the crops are subject to common leaf diseases such as brown spot, bacterial leaf blight, leaf blast and tungro. These diseases were reported from almost more than 70 countries facing the same diseases. It is necessary to monitor the growth of the paddy crops and detect the disease with relevant measures to save the crop. The current research work gives a key solution using novel deep learning techniques to identify and differentiate between diseases at earlier stage. A novel method is proposed by tuning densenet CNN architecture with a smaller number of parameters. The proposed method is compared with the state-of-art methods such as VGG-Net, Mobile Net, Res-Net and the fine-tuned dense model achieves 98% accuracy and other performance measures also satisfied. Also, the proposed method achieves sensible computational time.

Index Terms—

Convolution neural network,

Deep learning,

Hyper parameters,

Visual Geometric group

I. Introduction

The agriculture plays a vital role in Indian economy. It is also important for almost all individuals and farmers who depend on farming. Nowadays agriculture has adopted and taken a promising place in machine learning and deep learning sectors. Even a large volume of agricultural data is available and used for crop recommendation, soil fertility prediction and fertilizer recommendation. Even India is the second largest producer of paddy there are still drop in the production rate and this drop is increasing gradually. The main reason behind the drop is due to unpredictable diseases arising at different climatic conditions and also due to some pesticides. Paddy is the main crop growing in almost all the places of India and raises the economy deeply. Paddy crop is more viable to diseases such as Bacterial blight, blast, tungra and Brownspot which destroys the growing field if spread across the different portions of the land. Efficient classification of disease is a must for farmers in order to efficiently choose the proper fertilizer. The Classification of diseased versus non-diseased crops can be identified with the modern AI techniques. The classification of the disease can be done with machine learning and deep learning algorithms. Many built in architectures are available for classification of any images belonging to several fields. The architectures vary by its number of convolution layers and hyper parameters. The tuning of architecture at any point may affect the accuracy level and other performance measures. The chosen architecture can be proved later after tuning whether yields to better accuracy than the previous models. Detailed survey has been done to understand the work carried out previously and it was clear that few models like squeeze-net, Dense-Net are used very rarely which is also better model suits for classification. Efficient-net model is proposed and it is proved to be the best model compared to other state-of-art models. Particularly efficient-Net B4 and B5 are proved to be finer models which suits well for raw images as well as augmented image datasets [1].Next a mobile based android application has been designed to perform leaf diseases classification with mobile-net and SS-CNN (Self-structured convolution neural networks) was used for citrus fruit that too at the vegetation stage. The comparison results of validation accuracy as well as loss has been compared with mobile-net CNN and SS-CNN among which SS-CNN gives notable accuracy with fewer number of epochs. Images can be captured through smart phones and can be classified[2].This model uses two approaches such as segmentation and neural networks. Hybrid neural network and super pixel method is proposed and the performance is measured with various metrics such as sensitivity and specificity. It uses the Adaptive linear neuron (ADALINE) network for detecting and segmenting the diseased region [3].Different types of crop such as tomato, corn,potato are taken for classification and compared with different neural network models. Res-Net has given good accuracy for their dataset when compared to other CNN architectures [4]. Two approaches combined together to achieve better results for groundnut leaf disease classification. The Harris corner detector, HOG (Histogram on Oriented Gradient) and also the KNN classifier is used to prediction of the disease [5].A novel segmentation technique known as neutrosophic logic which is an extended form of fuzzy set has been proposed.. Based on the features such as texture of the leaf, color and histogram pattern the disease classification is done. A classification accuracy of 98.4 % is obtained using the proposed method [6]. Unlikeresnets, the Densenet has very deep layer with deep features has reduced the unnecessary kernel maps and achieved same accuracy as the scratch model does. Genetic algorithm has been used to optimize the model in terms of computational cost and execution time by employing binary encoding method. Usually, the genetic process will take time, in order to overcome that they have used pre-trained weight inheritance method which can reduce the time consumption of the process [7].A new CNN model combined with J48 has been proposed which gives better accuracy than any other classifiers such as naïve bayes, SVM etc. Also the model used less parameters and for both binary classification and multi classification accuracy is about 98% [8]. To determine thebest harvest timefor crop a novel GL-CNN method which is a fusion strategy is proposed. All performance metrics has been examined to prove the accuracy [9]. Artificial Intelligence approach has been used effectively on binary leaf images. A 1-NN and SVM approach is used to classification. TSO and affine geometric transformations has been incorporated in order to preserve the image properties [10]. An efficient soya bean classification was proposed and varying leaf images are considered to make the model to learn patterns well. The entire strategy was splitted as two phases where in first phase the segmentation has been implemented and in second stage various neural network models has been implemented and soynet outperforms the existing models [11]. Efficient disease identification has been done based attention mechanism to learn the significant features of images. Those significant features are given more weightage in order to classify images. With less kernel features also without losing important features needed for classification is implemented[12]. The most infected portion of the leaf is identified using Otsu's method also called as thresholding method. Using the technique called as Gray Level Co-occurrence Matrix (GLCM) extreme features are detected and better results are produced compared to other methods. This classifier has shown significant performance when compared to other leaf disease classification methods[13]. Legumes of different species are considered and classified using different classifiers. The SVM model is used with different kernels and is compared with random forest. Many trial and errors has been done with scanned images and cleared images of different species [14]. A k-means segmentation algorithm is preferred which helps for better classification and identification of diseases and finally the classifier SVM performs well [15].The research background which has been discussed above shows how image classification is used in different ways and perspective pertaining in almost all application areas. The architectures such as VGG, Res-Net and its ensemble models have been highly used in many research papers compared to other models. Below is the proposed work carried out with less number of parameters.

(i) The proposed work uses optimized dense blocks and transition blocks of the dense net Model.

(ii) The proposed method uses right drop out factors in order to reduce the complexity of the model without disturbing the information flow between dense blocks.

(iii) Since the dense block has been optimized the model uses only compact parameters and makes the model light weight. The best accuracy can be achieved in few epochs itself.

II. MATERIALS AND METHODS

A. Dataset Preparation

The rice leaf disease dataset of about four major diseases has been collected from https://data.mendeley.com/datasets/. The dataset is organized in such a way that it consist of four folders such as Bacterial leaf blight (1584), brownspot (1600), leaf blast (1440) and tungro (1308).This was the original dataset and then to make the dataset balanced to achieve equal number of images a simple transformation has been performed so that all labels have equal number of images and thus helps to avoid over fitting. The training set is about 80% and 20%.is for test set. The classification is done in python google colab. The RAM size used is 25.5GB in order to process the huge number of images. All the images will undergo image preprocessing before entering into the classification module.*Image preprocessing*

In this part of the work images were preprocessed with image data generator. As shown in Fig.1 Possible augmentation such as rotation with range 25 and width shift of about 0.1, height shift 0.1, shear range as 0.2, horizontal flip is set to true. Along with this as described in previous section to make the dataset balanced extra transformation is also done. The densenet is one of the efficient CNN architectures where flow of information is good. The connection pattern of densenet is simple compared to other models. The ideal reason behind the efficiency of the dense model is every layer is connected to all other layers i.e it has $l(l+1)/2$ connections, where l is the layer. More image processing can be added so that the image.

There are many CNN architectures which show better performance, as every model will have millions for parameters to train the model. Though this yields better results the model will use huge parameters which left the system by utilizing more number of resources. More preprocessing of images will yield more accuracy of the model. Since the traditional ANN takes huge parameters, CNN comes into the picture. If the data which is fed into the model is normalized it will be convenient for the prediction of the model and also to avoid over fitting. The image size is 224*224*3, where 224*224 represents width and height of the image and 3 is the number of channels. The three channels represent RGB image. The image size is fixed and after preprocessing the image size shape, texture changes where many features can be detected from this after applying a convolution. Hence the image preprocessing contributes more in extracting features and understanding the properties of image.

Original Image | **Rotate** | Shear | Width/height shift

Fig.1. Preprocessed images

The features are extracted from the leaf during convolution operation. The above figure shows the original image as well as the images after applying preprocessing. The Densenet model performs well even for less number of dense blocks and also there is only less number of parameters. The augmented images are used during the train and test split where more images can be used for training to make neural network to understand the image texture, edges, color etc well. The below fig.2 shows the actual leaf labels which was taken from each disease category.

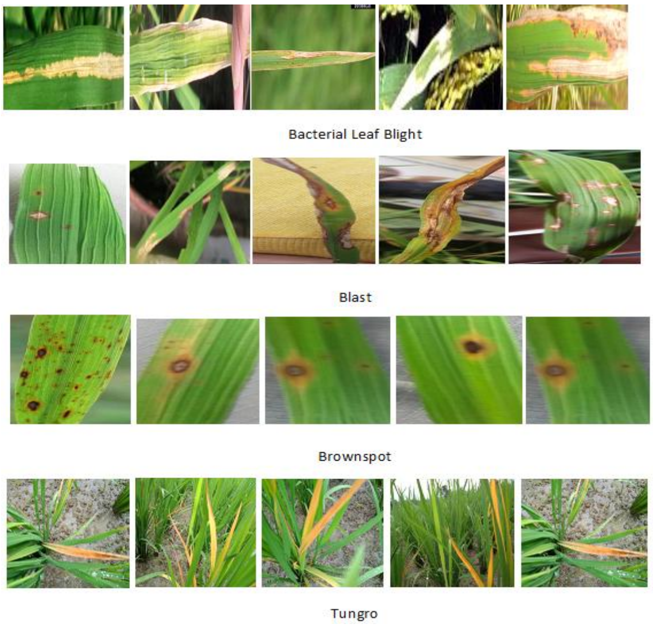


Fig.2. Diseases of each label

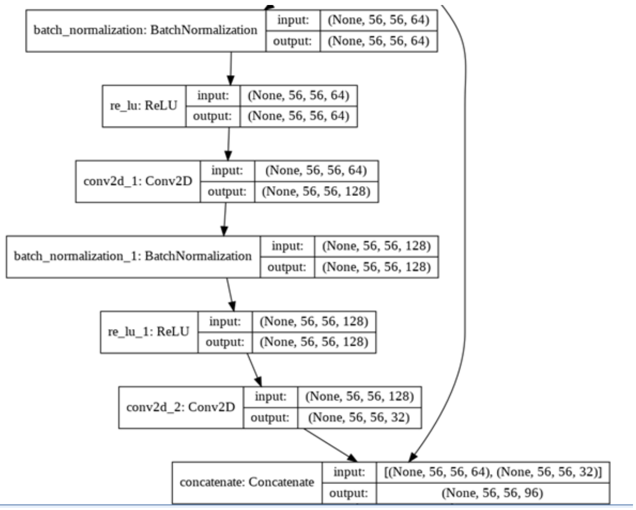
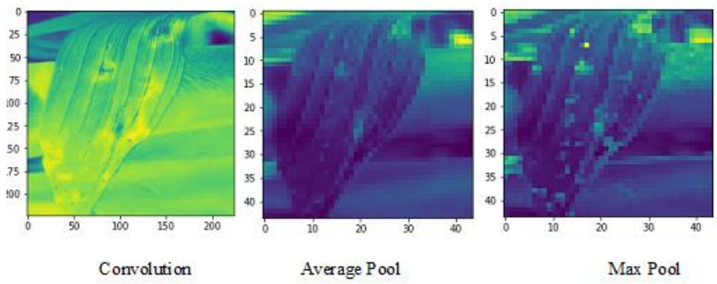


Fig.3.Sample Dense Block

The part of the Dense-net methodology is shown in fig 3 to make the overall concept understandable. The figure 3 shows the model dense block which consist of batch normalization, relu and convolution. This is repeated again and finally the output is concatenated instead of adding so that more information is retained. Each dense block uses max pooling in order to capture the important features necessary for classification. As shown in fig.4 the max pool captures brighter portions of the leaf image and contributes more for identification of leaf. In contrast the average pool captures the lighter portions which contribute less used for determining the leaf.



The activation function relu is used here and the last layer uses softmax. Since most of the features are captured at last global average pooling is used. Before training it is better to tune the hyper parameters to overcome over fitting and to reduce the parameters.

III. PROPOSED Model

The below section describes how the proposed model works better to achieve good accuracy. All the performance measures are also analyzed for the dataset chosen. The model is tried with many trial and error methods to ensure that the proposed one fits well. First, the dense net model has good flow of information throughout the network. It learns more features from all the above layers to which it is connected. Unlike resnets where it uses skip connections, the densenet model has a dense flow of image features.

3.1 Fine-tuned dense-net model

After image preprocessing is over then all the images are fed into the neural network model, where feature extraction, down sampling and classification happens. As shown in Fig 5. The architecture of the model is described like this. The augmented

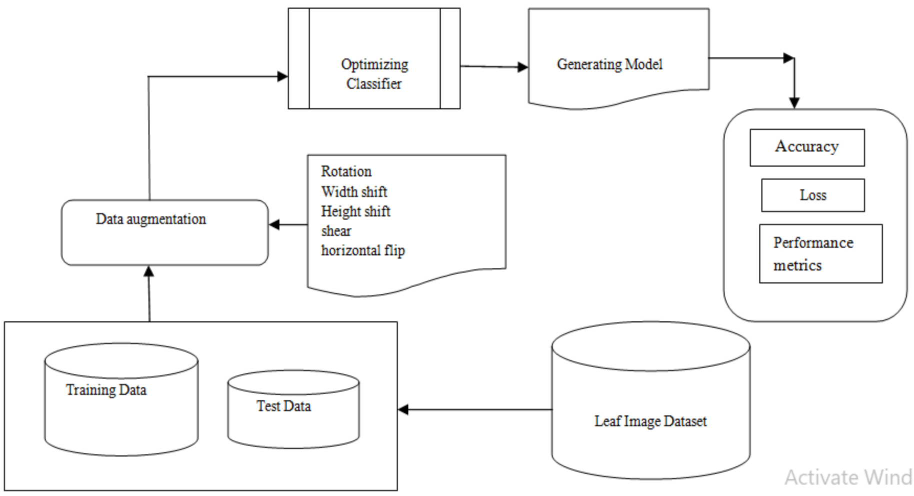
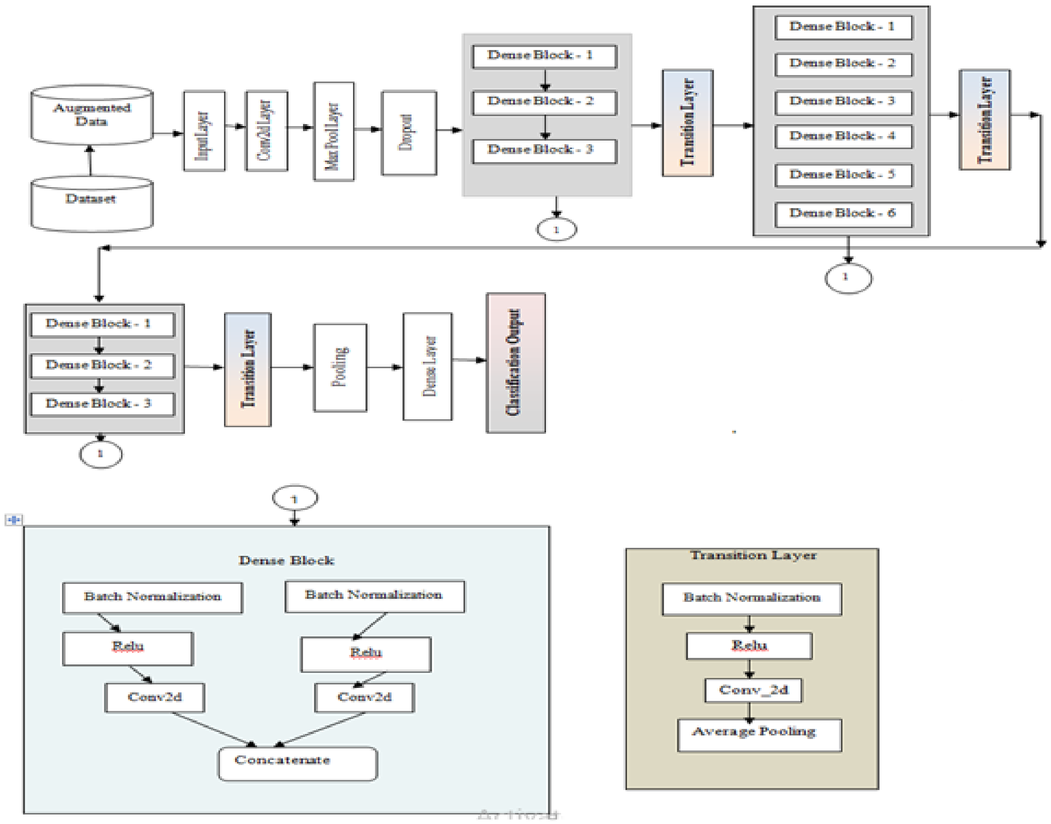


Fig 5.System Architecture

dataset is sent to the input layer, where the initial shape of the image is 300*300*3. And before feeding into the input layer for convolution the images are resized to 224*224*3.The stride is kept as two initially and hence the image after convolution is 112*112*64. In the first convolution layer a total of 64 filters with 7*7 kernel size are chosen. The max-pool with size 3 is chosen. It is then followed by a dropout layer, dense and transition layers. The dense block as shown in the figure has batch normalization, relu and convolution which is followed twice and then it concatenates the results. It uses 3*3 convolution followed by 1*1 convolutions. The dense block as shown in Fig.6 is repeated as a product of 3 times when the model progresses.Then this is followed by a transition block which implements a batch normalization, relu and convolution. Finally, it has global average pooling layer and dense layer. There are four class labels which splits the data with 80% for training and 20% for validation. The model isimplemented with the help of keras package.During the train and test split the data is splitted and the training data is shuffled for better learning. Since after many trials and errors the Adam optimizer fits well and categorical crossAverage pooling is performed and hence the parameters are greatly reduced. The stride for average pooling is kept 2 and the kernel size is 2*2. dropout rate used before dense block is set to the rate of 0.1 to avoid over fitting of the model. For all the layers except last layer RELU is the activation function used. For the last layer softmax is used. The L2 regularizer is used to avoid over fitting. As shown in the below diagram this is how the work is carried out starting from collecting data. The transition layer supports well in generalizing the model as it is responsible for down sampling which reduces the number of features. In the transition layer, the convolution is carried out with 1*1 filter so that channel wise parameters are fetched also helps in greatly reducing the dimensions of the image.

In all the Densenet models dense block is followed by transition block and only for the last layer the transition layer is not attached. The model works better for 3, 6, 9 combinations. The Densenet model performs well for even small number of dense blocks; the down sampling which is carried out by transition layer reduces the dimensions as well as retains the bright features well. Without pooling the number of parameters increases and it becomes harder to train the model as it lack with performance. Each label is equally partitioned and in case if there is any imbalance that can be balanced using SMOTE (Synthetic Minority over-sampling technique). The primary reason for over fitting of the data may be because of insufficient information of the images. In this case it is better to add some more data or to go with more preprocessing as to make the model more efficient in learning.



As described in the below figure.5 it clearly describe the step by step process carried out in the model. The optimizing classifier is nothing but the Densenet model where the hyper-parameters are chosen after many trial and errors methods. It works well with relu at the top most layer and intermediate layers and finally softmax at the last layer.

IV. RESULTS AND DISCUSSIONS

The system specifications are shown in Table 4 which is used for implementing the architecture. The model uses few dense blocks and transition blocks which are helps in acquiring features and down sampling the data. For easy training i.e. to increase the training speed last 9 layers of the model alone freezed. The Adam optimizer is used here which is very lightweight and not costly as compared to other optimizers. Since the labels are more for multiclass classification the categorical cross entropy is used. To make the model more stable learning rate is configured in such a way that until the epoch is less than 50 the learning rate is set to 0. 0001.Ifthe epoch is more than that and less than 75 then the learning rate is 0.00001. This is defined under decay function. The model accuracy has been compared with many trial and error methods such as the combination of 3, 6, 3 and 2, 4, 6 dense blocks and each followed by transition blocks has been tried out. It gives better accuracy after adding regularizers etc. The regularizers help in fitting the model well with normalizing the over fitting. The dense layer also known as fully connected layer uses softmax activation function to efficiently classify the images. All higher-level features, mid and last level features are captured. Such as the color, texture, edges and corners sufficient for classifying the image. Feature level and pixel wise feature extraction is done for the images. The Maxpool will trigger the brighter pixels whereas the average pool will outputs the smoothened pixelsand it is used only after capturing almost all the important. The model is compared with other state of the art model and with less number of parameters the proposed model achieves better accuracy and when more and more data is added the model fits well and gives still better accuracy for image classification of leaves.

Name	Specifications
Image size (After Resizing)	224*224*3
RAM	25.5GB
Disk	107.77gb
OS	Windows 10
Language	Python
Environment	Jupyter Notebook

TABLE 4

The pooling is very important as because the convolution layer outputs many huge parameters and by pooling it is greatly reduced. Finally the fully connected layer based on the probabilities will classify the images. The most interesting feature of CNN is it is customizable where so many hyper parameter tuning can be done. The below fig.7 shows proposed model accuracy which is 96% and model loss as in fig 8. is 0.02%. The confusion matrix of the labels is shown in fig.9.

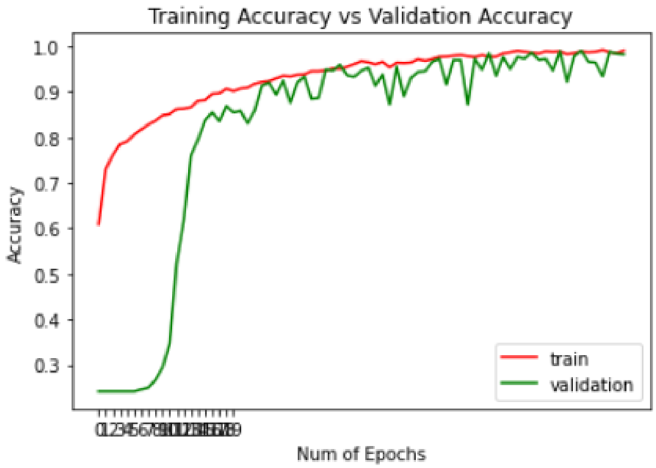


Fig 7. Proposed model accuracy

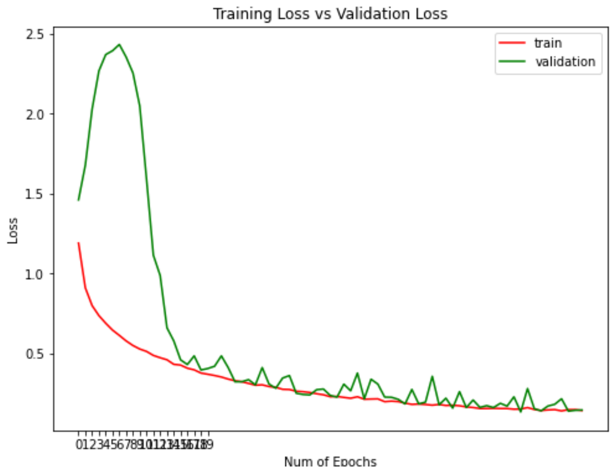


Fig 8. Proposed model loss

The comparison which is made with other architectures are shown in fig .10 which is Mobile-Net and Fig.11 Squeeze net and Fig.12 ResNet. All the comparison models almost gives better accuracy i.e 99% but the main drawback is that they use more number of parameters as shown in table 4.It also takes more training time to learn the model. In dense blocks the blocks have been reduced to decrease parameters and also retains the original information as it connects with all the layers in the network to learn more and more features. The table 5shows the classification report and 6 shows the number of parameters required for the chosen model.

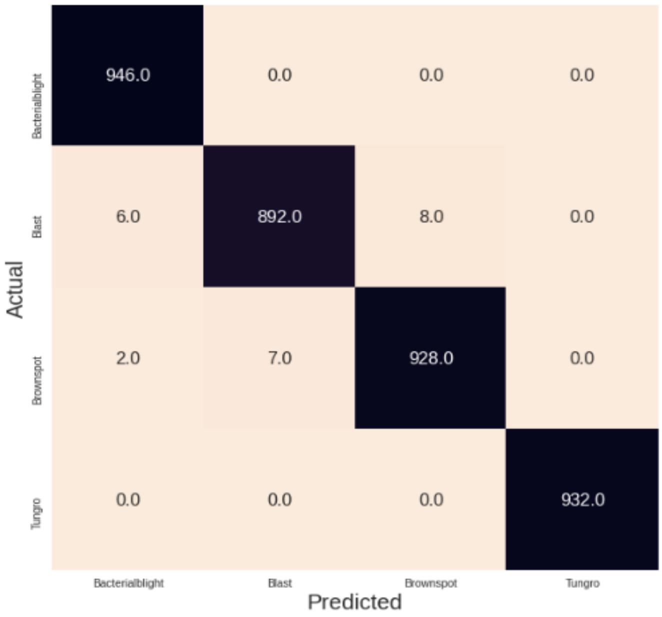


Fig.9 Confusion Matrix of the proposed

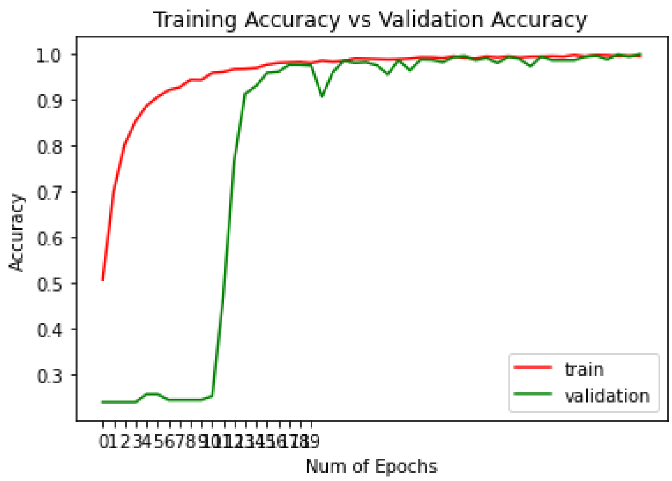


Fig.10.MobileNet

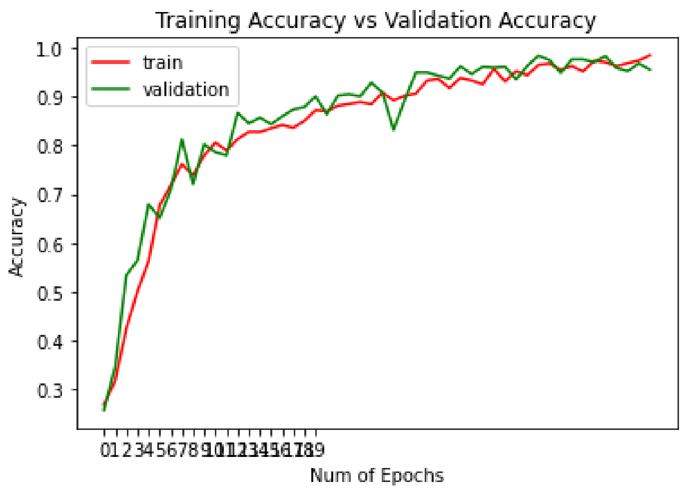


Fig.11.Squeeze Net

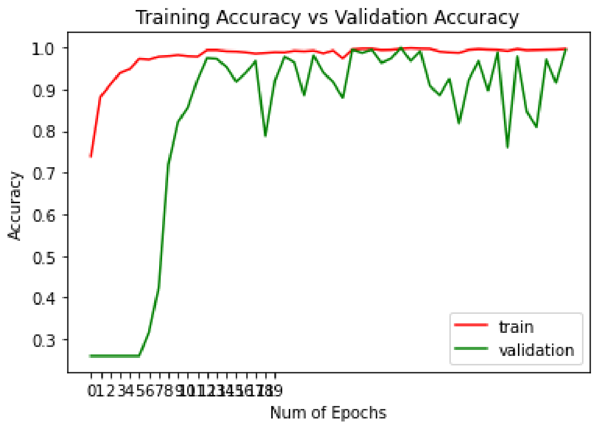


Fig.12.MobileNet

So far the comparison with other models graph has been discusses where each model takes more number of parameters as shown in table 6.The below table 5 indicates the performance measures of the classification model.

TABLE 5. Classification Report

S. No	Model	Accuracy	No. of Parameters
1	Densenet	98%	122,996
2	Mobile-net	99.92%	3,222,020
3	Res-Net	99.41%	23,542,788
4	Squeeze-Net	95.10	737,476

TABLE6Generated parameters and blocks

S.No	Blocks	Parameters	Train_acc	Valid_acc	Misclassifications	Model Used	Image Size
1	2,2	54,564	0.9407	0.9549	Bacterial blight - 12/378 Tungro – 50/380 Blackspot – 9/432 Leaf blast – 0/404	Proposed DenseNet	5932
2	2,2	0		0.9718	Bacterial blight -9/378 Tungro – 6/380 Blackspot – 10/432 Leaf blast – 17/404	Proposed Densenet+ Random Forest	5932
3	1,1	48,132	0.9342	0.9449	Bacterial blight - 24/378 Tungro – 35/380 Blackspot – 12/432 Leaf blast – 1/404	Proposed DenseNet	5932

4	1,1	0		0.9906	Bacterial blight -2/378 Tungro – 2/380 Blackspot – 5/432 Leaf blast – 0/404	Proposed Densenet+ Random Forest	5932
5	1,1	0		0.9933	Bacterial blight -0/378 Tungro – 0/380 Blackspot – 3/432 Leaf blast – 2/404	Proposed Densenet+ Random Forest	3000

The above table shows the further modified count of blocks and the parameters and the confusion matrix results. The finetuned model with random forest performs more better in terms of accuracy as well as identification between True positive and false positives.

V. Conclusion And Future Work

Finally, the optimized dense block works well when compared to other models with a smaller number of parameters. In addition to this more leaf of different varieties of crop can be tried out to find the appropriate count of dense blocks and parameters needed. Since the number of parameters are very low the model trains fast. Also the same can be tried in different fields such as medicine and space images. Still a depth wise separable module can be added so that the convolution calculation can be reduced better.

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