A Novel Approach of Ensembling the Transfer Learning Methods for Rice Plant Disease Detection and Classification

Parameswar Kanuparthi
School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India.
E-mail: parameswar.krm@gmail.com

Vaibhav Bejgam
School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India.
E-mail: vaibhavbejgam21@gmail.com

V. Madhu Viswanatham
School of Computer Science and Engineering, Vellore Institute of Technology, Vellore, India.
E-mail: vmadhuviswanatham@vit.ac.in

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Abstract

Agriculture, the primary sector of Indian economy. It contributes around 18 percent of overall GDP (Gross Domestic Product). More than fifty percent of Indians belong to an agricultural background. There is a necessary to rapidly increase the agriculture production in India due to the vast increasing of population. The significant crop type for most of the people in India is rice but it was one of the crops that has been mostly affected by the cause of diseases in majority of the cases. This results in reduced yield that lead to loss for farmers. The major challenges faced while cultivating the rice crops is getting infected by the diseases due to the various effects that include environmental conditions, pesticides used and natural disasters. Early detection of rice diseases will eventually help farmers to get out from disasters and help in better yield. In this paper, we are proposing a new method of ensembling the transfer learning models to detect the rice plant and classify the diseases using images. Using this model, the three most common rice crop diseases are detected such as Brown spot, Leaf smut and Bacterial leaf blight. Generally, transfer learning uses pre-trained models and gives better accuracy for the image datasets. Also, ensembling of machine learning algorithms (combining two or more ML algorithms) will help in reducing the generalization error and also makes the model more robust. Ensemble learning is becoming trendier as it reduces generalization error as well as makes the model more robust. The ensembling technique that was used in the paper is majority voting. Here we are proposing a novel model that ensembles three transfer learning models which are InceptionV3, MobileNetV2 and DenseNet121 with an accuracy of 96.42%.

Keywords

Rice Disease Detection, Transfer Learning, Ensemble Learning, Disease Classification, Convolution Neural Networks.

Introduction

The main source of the income in India is agriculture. Rice is one of the important foods in India. In the area of agriculture practices early stage identifying and classifying of various crop diseases has been become a significant task. Every year farmers are facing huge loss and reduced yield due to the plants infected by diseases. Around 10 to 15% of the rice production is destroyed by diseases in Asia. So, the prevention of loss from yielding productivity and improvement of yielding quality can be achieved if the plant diseases diagnosed rapidly, appropriately and accurately which may in turn results in growth of economy in the country. The two conventional ways of detecting rice plant diseases are manual detection and lab tests. The method of visual assessment on the lesion of disease is a subjective matter which may not diagnose disease successfully. On the other hand, since the identification of the pathogen in the laboratory is a time taking process, it is a complicated process for culturing the pathogens and may not deliver results at the ideal time. Earlier, the plant diseases are detected and classified based on the signs and symptoms generated by the pathogens. It often becomes very difficult to detect a disease based on its symptoms. Therefore, image-based plant disease detection has increased more and more. These have encouraged researchers to seek automated methods by which plant diseases can be easily and reliably detected and classified with high accuracy. It also helps farmers choose the right pesticides or bactericides or fungicides. The novel approach of ensembling the transfer learning methods for rice plant disease detection and classification is mainly focused in this paper.

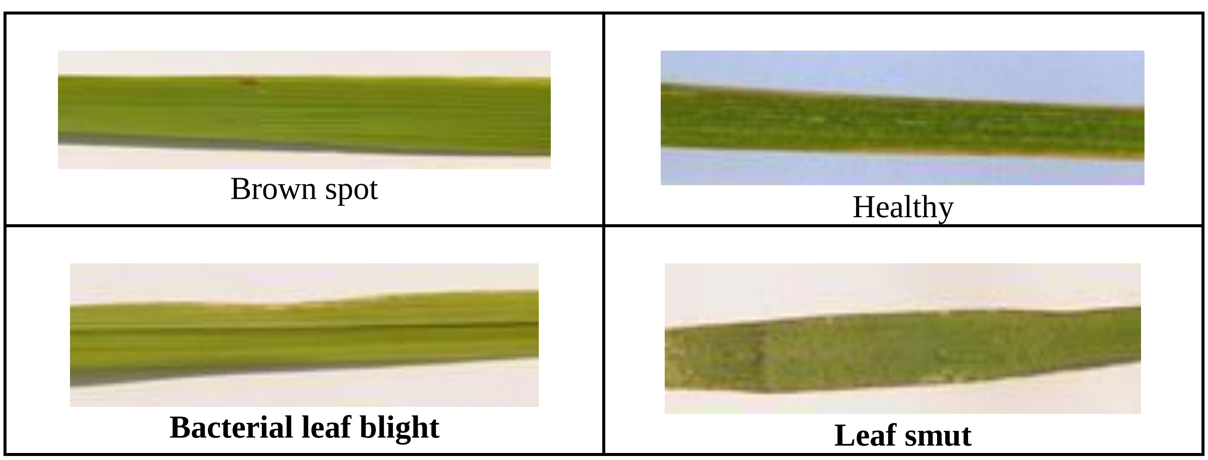

Fig. 1 Different rice plant diseases

Literature Survey

a) Survey of the Existing Models/Work

The classification of plant diseases is based on the signs and symptoms produced by the pathogens. But this process of identification and the classification of diseases is very difficult. Digital images-based disease detection is therefore increased more and more (Barbedo, 2013).

The Support Vector Machine (SVM) classifier is utilized by (Prajapati et al., 2017) on rice diseased leaves. During image preprocessing, the background was removed and the images were resized. The centroid feeding based K-mean clustering is used by them for accurate feature extraction by segmenting the diseased element of the plant leaves. Extraction of features was carried out based on shape, color and texture. The accuracy of 93.3% for training dataset and 73.3% for testing dataset are achieved by the use of SVM in the multi-class classification process. With 5 and 10-fold cross validations, an accuracy of 83.80% and 88.57% was achieved.

The SVM classifier is utilized by the (Jayasripriya`nka K et al., 2019) on thousands of images regarding soya bean plants that are taken from a dataset called Plant Village. They removed the background in the pre-processing stage and then performed the color space segmentation on the test images. In order to classify the healthy and infected regions of leaves, a technique of K-mean clustering is used during segmentation process. For the sake of designing a performance-based system, they examined several color and texture combinations in the feature extraction. Finally, accuracy of 90% is achieved by applying the SVM.

Because of the excellent performance of deep learning techniques in image classification, today, they have captured the attention of researchers. In contrasting to the conventional ML techniques, providing the whole learning and avoiding the extraction of complex handcrafted functions are the advantages of deep learning technology. The CNN among the various deep learning techniques has been mainly used in image classification for getting improved accuracy (Krizhevsky et al., 2012) (Lu et al., 2017).

CNN is utilized in 2019 by (Kumbhar et al., 2019) for cotton leaf disease detection. Training and testing of 513 and 207 images are presented in the dataset. The image has been captured and transformed into a 128 * 128 shape. Then the resultant image is passed through three hidden layers which are grouping, feature extraction and flattening layer respectively. The accuracies of 90% and 89% are achieved by the CNN for training and testing datasets respectively.

To overcome the issue that CNN needs a large dataset to train, for the first time (Vimal K. Shrivastava, 2019) explored the application of transfer learning to detect the diseases of rice crop. (Vimal K. Shrivastava, 2019) used the AlexNet transfer learning model and gained an accuracy of 91.3%. Furthermore, (Sanjay Patidar, 2020) utilized Residual Networks which is a type of transfer learning method to get better results for rice plant disease detection.

At the same time, ensemble learning also becomes more famous as it combines two or more machine learning algorithms to give the consolidated prediction output. (Ginne M James, 2016), used AdaBoost, LogitBoost, and Total Boost algorithms of ensemble learning for classifying the tomato diseases and got an accuracy of 92.33% for AdaBoost algorithm.

Also, there exists different types of methods in ensembling the algorithms. Ensemble learning is a way to improve the effectiveness of the model. In this article (Fernando López, 2021) and (Jason Brownlee, 2021) the authors named Fernando Lopez and Jason Brownlee respectively explained the importance of ensemble learning and the ways to achieve ensemble learning. A strategic combination of several machine learning models is performed by the Ensemble Learning for obtaining the enhanced accuracy by using a single weak model.

One type of Ensemble learning technique is Bagging. This technique involves creating same kind of different models generally from the different subsets of training dataset. Bagging includes considering of several subsets from the training dataset with substitute and then training a model for each subset.

The other type of Ensemble learning technique is Stacking. Creating a Meta-model is basic idea of Stacking Generalization method. This meta-model is made by considering the set of predictions from the machine learning based models that are known as weak students using the k-fold cross-validation technique. Then lastly with the other additional learning model known as final learner such Meta-model is trained.

The other type of Ensemble learning technique is Voting. One of easiest method to consolidate the results from several ML algorithms is voting. Firstly, the models are trained with the training datasets independently and results are taken. Then a classifier is used to predict the consolidated output from the results of individual models by taking average/majority vote.

b) Gaps Identified in the Survey

Machine learning algorithms are not doing well when it comes to image classification. Although some algorithms like SVM, Logistic regression etc. are used for image classification, they are not extracting the features effectively. Hence researchers and developers are skewed towards deep learning algorithms since these algorithms extract features on their own. Modern deep learning models currently use convolutional neural networks (CNNs) in image processing. These layers explicitly assume that each input is an image. The first layers of convolution in a network process an image and recognize low-level features in images such as edges by using the filters. Very small number of parameters is there in this layer and the weight distribution technique is used which mitigate the computational effort in contrasting to the normal feed-forward layers. And for plant disease classification we need more features to be extracted and hence the CNN model with more layers is required.

Methodology

a) Introduction and Related Concepts

It is a very difficult and long process to create, train and test very large CNNs from scratch with more than 50 layers and with a greater number of parameters, hence there are some pre-trained CNN models provided by keras which was trained on "Imagenet" dataset (contains 1000+ categories). With pre-trained keras models one can make use of weights of the model. This type of learning is called transfer learning. Even though we can classify with the help of transfer learning algorithms, ensembling of those can get even more accurate results.

b) Data Augmentation

Agricultural imaging datasets are limited in size due to various reasons like farmers are very far from technology, high cost of obtaining annotations, and considerations. The data augmentation is a process which is intended to augment data in data constrained scenarios and to evade the risk of overfitting. This process is carried out for training the data after preprocessing and splitting data. The geometric transformations are also used in this strategy for increasing the size of given dataset from 144 to 576. Such geometric transformations include scale rotations, zooms, shifts, rescaling, shears and flips like horizontal flips, etc.

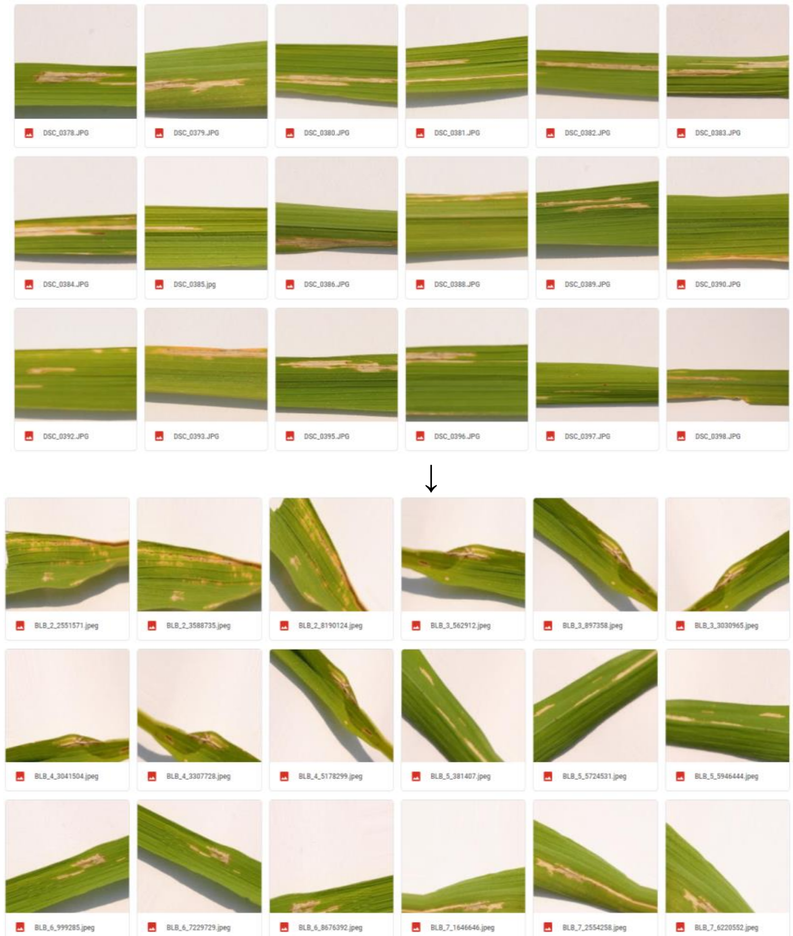

Fig. 2 Before and After Data Augmentation

c)Transfer Learning Models

I) InceptionV3

While keeping compute costs constant, the depth and breadth of the deep learning network is able to increase with the InceptionV3 model. By using the one million train images over the dataset of original ImageNet, this model was trained. By the calculation of 1×1, 3×3 and 5×5 convolutions we can work this model as a multilevel feature generator which enable this model for using the all types of image kernels and getting results from all of them. In addition to the channel dimension all of those outputs are stacked to use them as inputs for the next layer. Sometimes due to usage of filters with high dimension may cause loss of information. But InceptionV3 uses smart factorization methods by which more efficient convolutions in terms of computational complexity are made to reduce loss of information. Some advanced techniques are used to achieve high performance by this model for computer vision tasks.

II) MobileNetV2

In the convolution network, one of the enhanced versions of MobileNetV1 is the MobileNetV2 which consists of just 54 layers and has a 224 × 224 size of input image. Performing a depth separable convolution with the application of two 1D convolutions along with the two kernels instead of performing 2D convolutions along with one kernel is the main feature in this. This means that, an efficient and simple model can be made from training which need only few parameters and less memory. The two kinds of blocks are classified in which first block is a residual block with a 1 stride and the second block is for downsizing with a 2 stride. Then three layers are there for each block such as first one is the 1 × 1 convolution layer with the ReLU6, second one is the deep convolution layer and then third one is an another 1 × 1 convolution layer without non-linearity.

III) DenseNet121

Another convolutional network with each layer connected to all other layers further deeper the network is DenseNet. Less number of parameters are needed for the DenseNet architecture compared to traditional CNN. Just 12 number of filters are used by the DenseNet layers with a limited number of new feature maps. Because of every layer of DenseNet have their input from the preceding layers, the time of training became a challenging problem for it. The access to the gradient values of input image and loss function is provided in this DenseNet to solve such problem. This greatly reduces the calculation costs and makes this model as better choice.

d) Ensemble Learning

Ensemble learning is one of the most popular machine learning technique to boost the performance of the model. Ensemble learning combines the results of multiple models to create an optimal model with an increased accuracy. In the case of building a project of predictive modelling with the better performance, these ensemble learning is the most popular and standard choice. Rice plant disease classification is a classification model where classifying image into the correct class is most important and ensemble learning methods are mostly used there the outcome of the model is very important. Here we used the majority voting as ensembling technique.

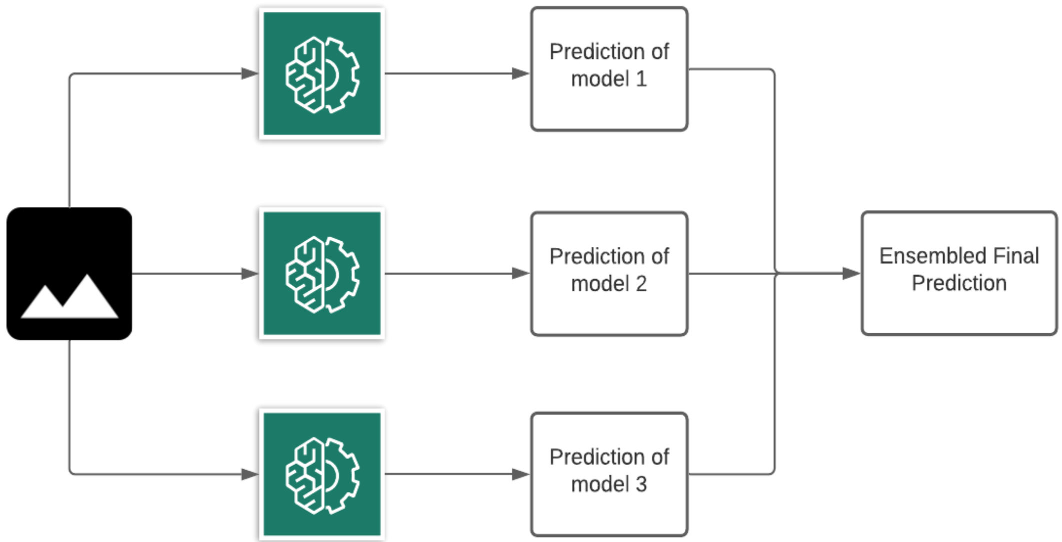

Fig. 3 Ensembling of transfer learning model

The data is trained and tested with all the 3 transfer learning methods and those results are taken and majority voting is performed and the final result is published.

Proposed Algorithm

Input:

Sample Dataset ***D***

Transfer Learning Algorithms ***(Ti)***

Ensemble Learning Algorithm ***(E)***

Process:

Data Pre-processing

Data Augmentation

For each transfer learning methods (T1….Tn)

1.Train the transfer learning model with training dataset

2.Test the model with test dataset

3.Send the result to the ensemble learning model (E)

Ensemble model (E)

Take the predicted results from transfer learning methods (T1….Tn)

Perform Voting

Publish final classification result

Suggest appropriate remedies for the disease detected to farmer

End

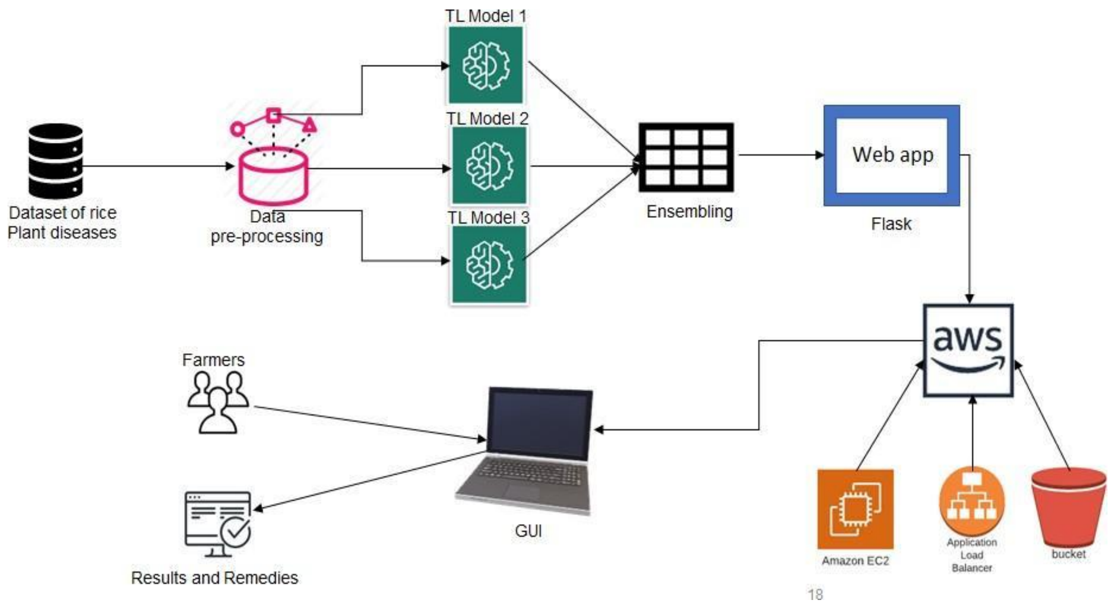

Fig. 4 Proposed Architecture

The dataset consists of 4 categories of images namely Bacterial leaf blight, Leaf smut, Healthy and Brown spot. By using image processing methods like image resizing, the data is pre-processed. Then the data augmentation is performed. The augmented data is then used to train multiple transfer learning models that are Inception V3, MobileNetV2, DenseNet121. Those transfer learning models are then ensembled using the voting method. Then the final output is taken from the ensemble model. The disease then detected is then displayed and consequently appropriate remedies to the diseases are suggested to the farmer.

Results

Model	**Accuracy**
InceptionV3	87.5
MobileNetV2	93.75
DenseNet121	93.75
Proposed Model	**96.42**

Conclusion

Huge loss will be incurred in the agriculture sector if no proper attention is taken towards rice plant diseases. The work on classifying diseases of rice crops have been carried out limitedly based on digital images of diseases in India. An ensembling method of transfer learning is explored in this paper for the first time for detecting and classifying the diseases of rice crops. The novel approach proposed in the paper helped in getting better accuracy as its ensembles different transfer learning methods such as InceptionV3, MobileNetV2, DenseNet121. After ensembling the three transfer learning methods with majority voting technique we achieved an accuracy of 96.42%. The proposed novel approach can classify the rice plant diseases very effectively as ensembling reduces generalization error and makes the model more robust.

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