2022 Third International Conference on Intelligent Computing Instrumentation and Control Technologies (ICICICT) | 978-1-6654-1005-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICICICT54557.2022.9917886

Paddy Leaf Disease Detection using Deep Learning Methods

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***Abstract*—Computerised automated diagnosis of crops disease enables early detection and ensures the quality of crop. Technology advancements in these fields will reduce the loss and increase the overall productivity. Our research work motivated to build a deep learning classification model for paddy leaf disease detection. The model frame work consists of several pre-processing techniques such as denoising, data filtering, and selection of optimizer that best fits the model. Finally, a comparative study of the proposed model's performance and efficiency was done with different deep learning models. Based on the analysis and observation, it was observed that the proposed model has given promising results for effective leaf disease detection.**

***Index Terms*—Paddy Leaf, Data Augmentation, Bilateral Filter, Transfer Learning, Accuracy Plots, Confusion Matrix.**

I. Introduction

Agriculture has played a pivotal role in the development of the national economic system. Agriculture not only provides food and raw materials, but also contributes to the country's economic rate and gross domestic product (GDP). Two-thirds of the Indian population depend on farming for their livelihoods and India ranks second globally, for agricultural production[10]. This emphasizes the importance of agriculture in the country's economy and human civilization.

Plant diseases are primarily caused by various micro-organisms that cause pathogens such as fungi, nematodes, bacteria and viruses[1]. Due to the following disease agents,photosynthesis ability of plants is affected,because plants require sunlight to carry out this process. Now,this makes the overall quantity of oxygen production low,making the plants either less productive or die in a few days.To overcome this,a disease detection system should be developed that can detect plant leaf diseases as early as possible.

Manual monitoring of Plant diseases is monitored by experts, however, in most cases task becomes more difficult with increasing the farm size. So, a timely identification detection system is required to recognize the diseases in the plants. Computer vision algorithms have developed a long way which makes machine learning algorithms more accurate[4]. Computer vision technique enables the plant leaf disease detection much easier. The main goal of our work is to detect paddy plants leaf diseases in real-time which helps the paddy cultivating farmers to take steps to prevent diseases. The dataset has three different types of leaf diseases viz. Brown spot, Bacterial leaf blight and Leaf smut which occur for paddy crops. Bacterial leaf blight is one of the severe bacteria infected disease, a fungus named Entyloma oryzae contributed to leaf smut disease and the Brown spot, infects the leaves. Even though machine learning technologies gained wide popularity great and has been efficaciously carried out in lots of sensible applications, it nevertheless has barriers in the actual world [5]. As the dataset size increases, most go in vain. In this paper, different transfer learning techniques, which are pre trained convolutional neural network models are demonstrated. Best filter had been chosen from the PSNR values. Best suitable optimizer for algorithms was implemented followed by choosing best algorithm for the dataset. Before the model was implemented the dataset is filtered and augmented. Which makes the classification more reliable.

The whole paper has been organised as follows: Initially, the paper discusses about the works related to our project. Further more,it describes about the system architecture,followed by the methodology .Finally the results and analysis along with the conclusion are demonstrated.

II. Related works

A flower classification algorithm using Inception-V3 was proposed by Xiaoling, Xia. et al. This InceptionV3 algorithm has increased the accuracy of the flower category dataset. Due to different backgrounds in the flower dataset, it becomes difficult for machine learning algorithms to classify correctly. Inceptionv3 has greatly improved the accuracy[2] . Cheng, Wang. et al. implemented inceptionv3 algorithm to systematize the pulmonary image. The authors demonstrated the ability of computer-aided diagnostics for thoracic diseases and also in the improvement in accuracy, so that it will help the medical persons to make the diagnosis much easier. The authors have found that the inceptionV3 algorithm which is a transfer learning model gives good accuracy compared to the normal deep convolutional neural network (CNN) model. The authors also used data augmentation to increase the accuracy [3].

Paddy is the most grown crop and the disease which occurs in this crop has to be identified early by the experts. A disease detection algorithm particularly for the Blast disease of the paddy crop using the colour slicing technique was proposed by the authors [6]. This colour slicing approach takes damaged parts and makes the identification process fast.The authors have designed a new model which is a mixture of the existing the LSTM and CNN model for the detection of four categories of tomato plant leaf diseases. CNN algorithm is used as the feature extractor from the leaf images of the dataset and those features are used to feed the LSTM model for the task of classification. In this research, the authors [7] have filtered the dataset which is applied for the three RGB channels.

The main benefits of automated learning and feature extraction have been a wide concern in academic and industrial circles in recent years. It’s been broadly used in image processing , video processing, voice and natural language processing. In the same way, it has also become a wide research scope in agricultural plant protection, such as plant disease recognition and pest range assessment, etc. The authors [8] have reviewed current trends and advanced imaging techniques which will improve the performance of plant disease classification.The authors [9] have proposed a functional implementation of a small CNN. In this research work, the authors main intention is to get good classification results along with less complexity. the work described a new transfer learning algorithm based on VGG19 model which is TransVGG-19 was proposed by the authors [11]. The proposed TransVGG-19 model was tested using the motor bearing dataset. This Model outperformed the existing Deep learning and many machine learning models.

The authors [12] research goal was to support the farmers by utilising technology-supported irrigation methods. For data transmission and the prediction of harvest, a Bolt IoT cloud platform was adopted. Hand Gesture identification using different machine learning algorithms was proposed by the authors [13].The authors[14] have researched the different transfer learning algorithms’ performance under the pre-trained transfer learning algorithms.

In this paper,the authors [15] have presented some of the studies which deployed image processing technologies in the paddy domain along with the system architecture to identify the early stages of leaf diseases.The authors[16] in this paper have developed a system which is capable of examining micro-expressions and shows the performance result using CNN with VGG-19 architecture as feature extractor. Micro-expression is considered to be a hidden expression of human being and the expression is difficult to see with bare eyes.

The authors[17] came up with a model for classification of a few paddy seed varieties by using the transfer learning with VGG-19,Inception-V3 and MobileNet-V2 as the three pre-trained weights.Among these,Inception-V3 gave the best accuracy and the least test loss. The difficulty of having a plausible caption of the image is solved in this paper.The authors[18] have developed a model which learn about the relation between language and images from the provided labeled image dataset.

III. System Architecture

The paddy leaf disease dataset was taken from the UCI repository which contains three different paddy leaf diseases. The images from the dataset were collected from a village in the Indian state of Gujarat. In the dataset, each image is of size 2848*4288 pixels and. Bacterial Leaf Blight, Leaf Smut, Brown Spot, Bacterial Leaf Blight were the three different kinds of diseases thatwhich were taken into consideration . The dataset has forty images for each category.

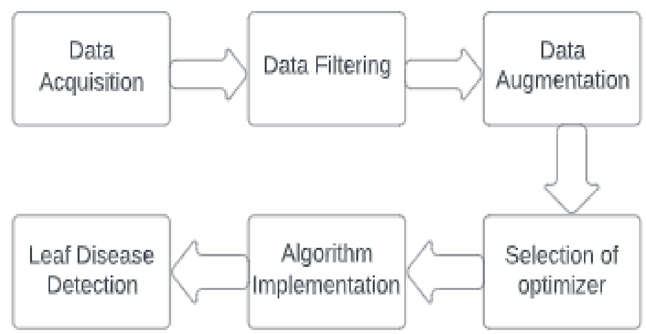

Fig. 1. System Model

The complete block diagram has been explained in Fig.1. The model mentioned above includes data acquisition, data filtering data augmentation, finding the best optimizer for the transfer learning algorithms then the model implementation and diagnosis. Different techniques and methods used in this work are explained in the following sections.

We have initially filtered the dataset using different filtering techniques and chose the best using the PSNR values. After the data filtering, we proceeded with the data augmentation. Several data augmentation techniques such as flipping and rotating were applied. After then three transfer learning algorithms were taken and the best optimizer was chosen based on training accuracy. Finally, various accuracy metrics were used to analyse the result.

A. Data Acquisition

The data was taken from the UCI repository which contains 3 folders, total of 120 images with 40 images for separate disease each representing the diseases that affect the paddy leaf. The common disease that affects the paddy crop that we have taken for our study are bacterial leaf blight, brown spot and leaf smut. After the images are loaded they are resized as per the requirement of the algorithm and to decrease the memory usage. Similarly, the test data has been taken by the same procedure. The images are filtered and augmented before feeding to the model.

B. Data Filtering

Data filtering is an important step that comes under data preprocessing. The images in this work are filtered using different data filtering techniques such as Gaussian, median and bilateral filters. A set of random images were selected and the PSNR values of the original and filtered versions were plotted in Fig.2. The Fig.2. clearly depicts the PSNR value is high for the Gaussian filter. A gaussian filter was

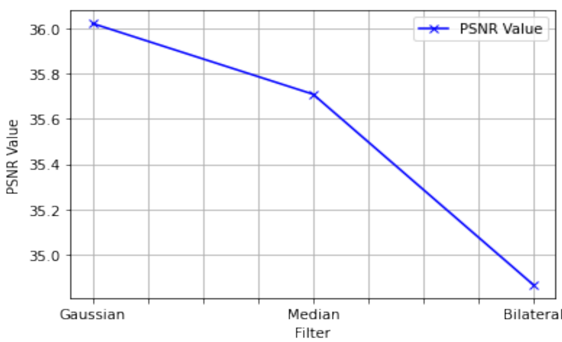

Fig. 2. PSNR Value

implemented to the dataset because of its high PSNR value. Fig.3 shows the original image from the dataset which is before the implementation of the gaussian filter and the next part shows the filtered leaf image.

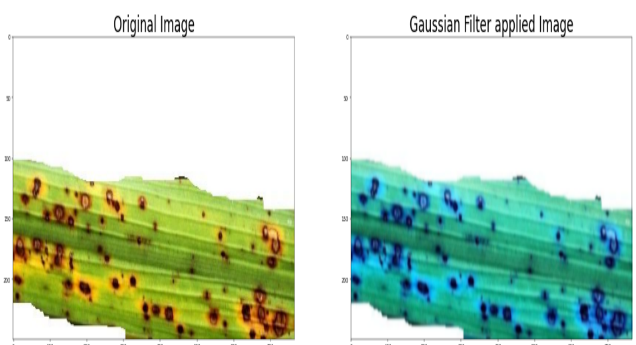

Fig. 3. Data Filtering

C. Data Augmentation

Data augmentation has been implemented to the dataset to boost the size of the dataset which helps to amplify the efficiency of the model and to avoid the overfitting problem. In this research work, we have used three different types of data augmentation techniques such as flipping, rotating and blurring. The initial images for each category in the dataset are 40 images. These 40 images are augmented to 160 images per category making the overall dataset size 480 images. Fig.4 shows the data augmented images for three different disease categories and their variations. From the figure, we can observe that column 1 has the original image, column 2 is the 90 degrees rotated image, column 3 is the flipped version of the image and the last column is the blurred image of the original image.

After the data augmentation, the dataset is divided into 80

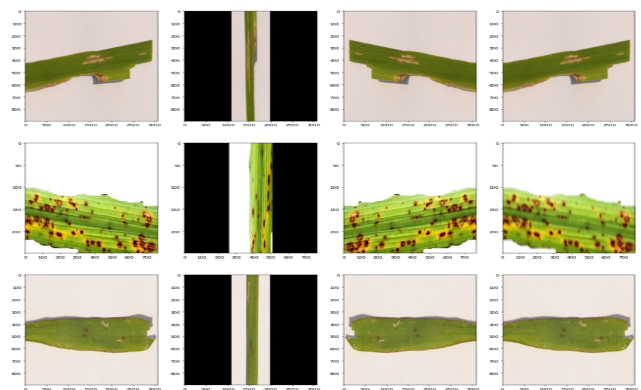

Fig. 4. Data Augmentation

per cent training and 10 per cent validation. A random 10 per cent of images are made as test datasets.

D. Selection of the optimizer

After implementing different data pre-processing techniques such as data filtering and data augmentation, algorithm implementation was carried out. In this, we have chosen three different algorithms. They are inception-V3, VGG-19 and inception-Resnet-V2. A total of 5 optimizer algorithms were chosen for each transfer learning algorithm and the best-suited optimizer is chosen based on the training accuracy for further implementation. Table. 1 shows the accuracies of each algorithm under different optimizer algorithm The table precisely shows that Adagrad is the best suitable optimizer for VGG19 algorithm, with an accuracy of 85.50 percent.Adam optimizer provides better performance for Inception-V3 and Inception-Resnet-V2 having accuracy of 73.87% and 89.04% respectively.

Optimizer	VGG-19	Inception-V3	Inception-ResNet-V2
SGD	64.86%	65.44%	64.21%
RMSprop	62.60%	69.70%	85.27%
Adam	60.64%	73.87%	89.04%
Adagrad	85.50%	65.12%	71.04%
Adadelta	70.95%	60.40%	60.25%

TABLE I
OPTIMIZER ACCURACY

E. Transfer Learning algorithm implementation and Disease Detection

The next step of this research work wais to implement different transfer learning models using the best-suitable optimizer. Three transfer learning models are used such as VGG-19, Inception-v3, Inception-ResNet-V2 which are basically CNNconvolutional neural network useful in image analysis and object detection and image analysis. VGG-19 contains nineteen layers where sixteen are convolution layers and three fully connected layers. VGG-19 gives better than 71.3 per cent accuracy on ImageNet dataset. Inception-v3 consists of 48 layers deep and gives better than 78.1 per cent accuracy on ImageNet dataset. Inception-ResNet-V2 consists of 164 layers deep and gives better than 78.1 per cent accuracy on ImageNet dataset. VGG-19 has an image input size of 224-by-224. Inception-V3 and Inception-ResNet-V2 has an image input size of 299-by-299. Inception-V3 model performed better compared to the other two models. The inception-V3 model is a CNN convolutional neural network-based model belonging to the Inception family. This model makes several improvements to the existing models like Label Smoothing, usage of auxiliary classifiers to propagate label information lower down the network and factorized seven-by-seven convolutions. These transfer learning algorithms were imported and retrained on the paddy leaf disease dataset. After Algorithm implementation, the result are analysed using different accuracy matrics such as confusion matrix. The leading performing model has been saved for deployment purposes.

IV. Results and Analysis

The results for the three different transfer learning algorithms VGG-19, Inception-V3 and Inception-ResNet-V2 models was analysed. The pre-trained models in this paper were downloaded from Keras applications of TensorFlow. Before the actual implementation of the model, accuracies for the algorithm under different optimizers were carried out and the best performing optimizer was chosen for each deep learning algorithm. The pre-trained models ran across these chosen optimizers. Different accuracy metrics were chosen for further evaluation of the result. Later the model was stored for deployment using Flask for real-time paddy leaf disease detection.

A. Accuracy Table

Three Transfer learning algorithms were implemented using their respective best-performing optimizers. Table.02 shows the validation, training and the testing accuracies of the algorithms VGG-19, Inception-V3 and Inception-ResNet-V2. Among these three algorithms, Inception-V3 gave the best test accuracy of 92 percent. This makes Inception-V3 algorithms best suited for the paddy leaf disease dataset.

Model	Training Accuracy	Validation Accuracy	Test Accuracy
VGG-19	87.04%	81.25%	80.33%
Inception-V3	97.92%	93.75%	92.54%
Inception-ResNet-V2	97.69%	91.67%	90.66%

TABLE II
Accuracy Table

B. Accuracy Plots

The training and loss metrics for the three algorithms VGG-19, Inception-V3, Inception-Resnet-V2 were plotted in Fig.5, Fig.6 and Fig.7. From the Fig.6 we find that, loss plot in both training and validation is converging. The Training accuracy of both the training and validation is increasing. Thus makes the result more reliable.

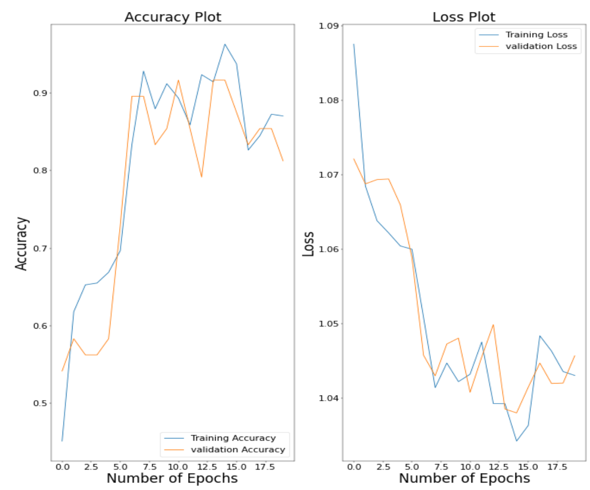

Fig. 5. Training and loss plots for VGG-19

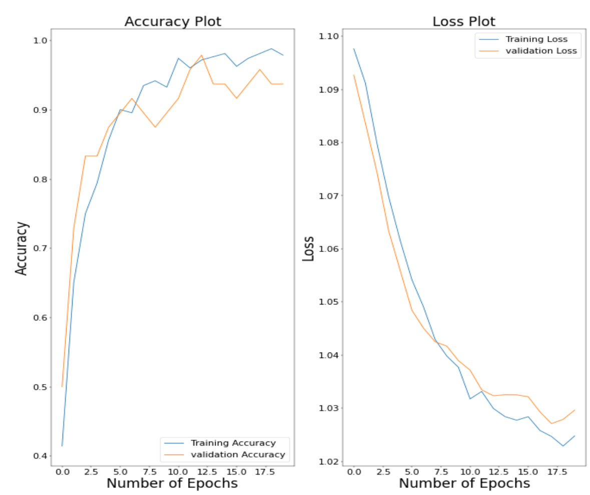

Fig. 6. Training and loss plots for Inception-V3

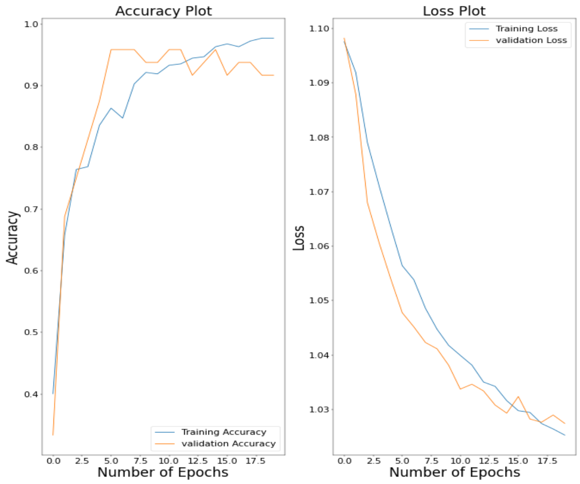

Fig. 7. Training and loss plots for Inception-Resnet-V2

C. Confusion Matrix

Confusion matrix is a type of accuracy metric in a form of table, which is used to explain the overall performance of a model like classification algorithm on a set of the test data for which the exact values are previously known. It is an N x N matrix which is used for examining the overall performance of a classification type model,wherein N is the number of classes in the data set.The actual known values from the dataset are compared with the model's classified values using the matrix.This accuracy metric actually provides us a brief idea of the performance of our transfer learning models along with the different kinds of errors it makes. In Fig 8 the confusion matrix of VGG-19 is shown whereas in Fig.9 the confusion matrix of the Inception-v3 is shown and Fig 10 is the confusion matrix of the Inception-ResNet-V2. Inception-v3 has better result than the other.

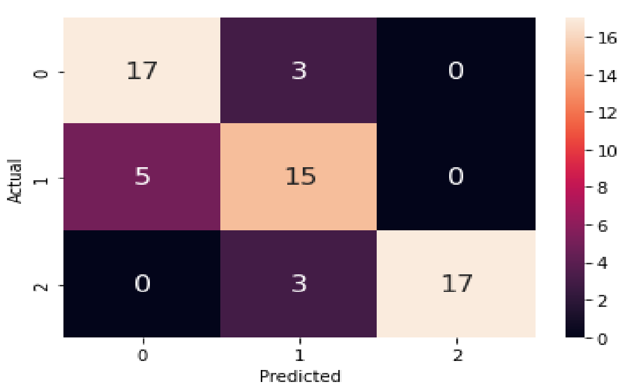

Fig. 8. Confusion Matrix for VGG-19

V. Conclusion

In this research work, different transfer learning algorithms for paddy leaf disease detection were discussed. A comparative study of proposed model with selected optimizers for different algorithms were conducted and the best performing optimizer was chosen for specified model. In data preprocessing best suited filtering techniques were chosen based on the PSNR value obtained. Data augmentation was implemented that essentially helped to remove overfitting. The proposed model was compared with three common models namely Inception-V3, VGG-19 and Inception-Resnet-V2. Out of these models, the Inception-V3 model along with the appropriate filtering techniques suggested outperformed well with a good test accuracy of 92 per cent. This result substantiate the effectiveness of our proposed work for leaf disease detection. In future work, we extend our algorithm to different plant leaf diseases and proceed with deployment in web-based applications for real-time detection of diseases.

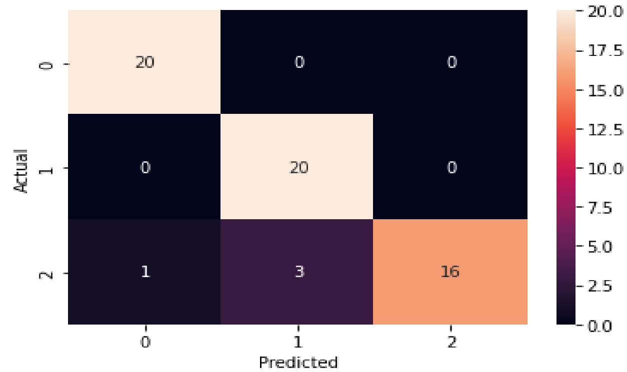

Fig. 9. Confusion Matrix for Inception-V3

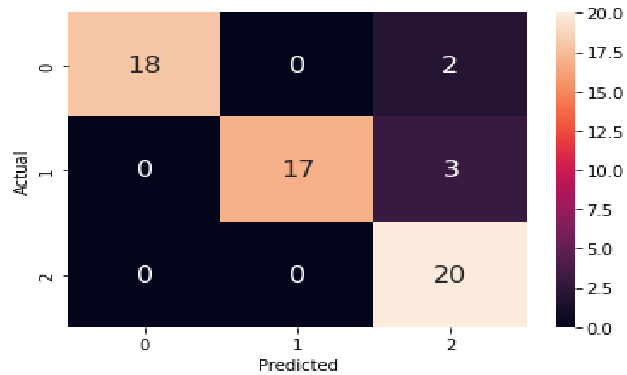

Fig. 10. Confusion Matrix for Inception-ResNet-V2

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