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Transfer Learning based Rice Leaf Disease Classification with Inception-V3

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***Abstract*—In the agriculture field, the detection of diseases from various plants through images is one of the most vital areas that needs to be ameliorated. The collection of cultivating crops and alleviation of features are the source of plant infection. A range of spot evaluation methods and disease diagnoses have been applied and advanced in a broad variety of crops. The Deep Learning concept of artificial intelligence is applied. However, this article introduces a model to detect disease in less time. Image processing techniques are used for operating the data with various methods. Three distinct rice plant diseases are included in the dataset: brown spot, leaf smut, and bacterial leaf blight. Spotting the disease on plants has been performed with various techniques like transfer learning and image data generators. In transfer learning, there are four types of approaches used: reusing the trained model, pre-trained model, feature extraction, and popular trained models. A popular model used to train the data is Inception-V3. Categorical cross- entropy is used for calculating the loss and optimization of the model. A surpassing result of 99.33% accuracy has been achieved on the testing dataset.**

Keywords—Transfer learning, Image processing, inception-V3, CNN, Rice leaf disease

I. INTRODUCTION

Rice is the major crop that provides a staple food source for half of the world's population. Economic growth, political stability, and food security are all heavily reliant on rice in major rice-producing countries like China (29%), India (24%), Bangladesh (7%), Indonesia (7%), Vietnam (5%), and Thailand (4%). Most of the country's population accounts for two-thirds of the per capita daily calorie intake. Disease-free rice cultivation is essential to support sustained economic processes and achieve the intended goals. An ample supply of quality crops has a huge impact on the overall production of crops in a country. Greenhorn farmers are sometimes unaware of illnesses and their incidence periods. One of the most important study issues in agriculture is the identification of plant diseases. It is vital to reinforce industrial capabilities, which can include smart systems which will make judgments without the necessity for human interaction. There, we laid the foundation for the development of an automatic system that supports machine learning techniques. That would certainly aid in the development of the agricultural industrial sector. The goal is to automatically identify and classify diseases from images of rice leaves. [1][12][13][4].

Previously, Rice blast was the foremost prevalent illness along with the brown spot, but bacterial blight is currently the foremost prevalent and high rice disease. However, the brown spot is picking up with threads. The patterns and shapes of those three separate diseases are distinct. The following are the characteristics of the disorders. Leaf smut occurs with tiny black linear lesions on the blades of the leaves, with greying and drying of the leaf tips. Bacterial blight is a fungus that causes elongated lesions around the leaf tips and edges to turn white, yellow, and then grey. Followed by Rice leaves with dark brown blemishes that are round to oval in the form referred to as Brown spots in below Figure1. [23]

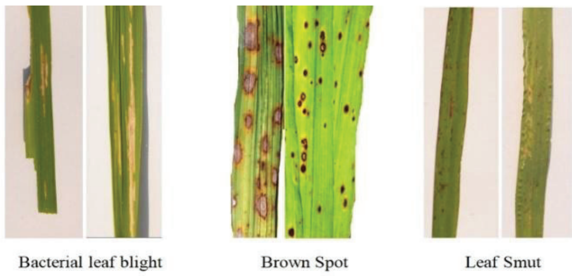

Fig1: Diseases Mentioned in Dataset

Crop disease management is allotted in most nations by manually detecting any anomaly in plants, experts classifying that anomaly as a disease, and so proposing germane treatment. When it involves huge farms, this succession of manual processes becomes extremely difficult. It also adds to the amount of your time and energy required. Taking images of the afflicted spot of the leaves and a pre-trained model is used to test it, on the other hand, allows for better disease identification and categorization. This research presents a way for illness prediction and classification of the three rice diseases described. Detection of rice leaf diseases with the implementation of machine learning algorithms producing high accuracy reflects the originality that resides in the paper. [24]

Conventional deep learning and machine learning algorithms are trained to solve specific tasks in isolation. When the feature-space distribution changes, the models must be rebuilt from the ground up. Trying to break away from the isolated learning approach and utilizing what you've learned to address similar issues is the notion of transfer learning. The concept successfully attains the paucity of the results in detecting leaf infections. The ImageNet dataset tremendously diminishes the difficulty of obtaining a whole lot of data and efforts to label data points. Image classification is fabricated using InceptionV3. [22][28]

Dataset was taken from UCI and utilized in this study. We used numerous machine learning algorithms to train our model. In section II, the comparative study of efficiency has been put together of all machine learning techniques. The accuracy of the model trained with various algorithms has been analysed for a stronger depiction and comprehension. In section III, detailed elucidation of the proposed solution has been illustrated. In a nutshell, the paper is laid out as follows. The results of our literature review on Rice leaf disease detection have been presented in section IV. Various deep learning techniques like transfer learning and image data generator processes are proposed. We utilized categorical cross-entropy to calculate the loss in addition to the Inception-V3 method in section III. We evaluate numerous techniques and analyse the results in Section IV, followed by the consequences and conclusion.

II. RELATED WORK

[5]Ahmed, Syed Irfan Alam, Rahman Shahidi, and Momen aimed to make sure of the healthful growth of rice plants in Bangladesh and to find out any disease within time. They used Machine Learning approaches. They used leaf images with white background as the source to find out three common plant diseases like leaf smut, brown spot, and bacterial leaf blight. After pre-processing, the dataset was trained with different machine learning approaches like KNN(k-nearest neighbor), J48, Naive Bayes, and Logistic regression. DTA is done after 10 fold Regression 97.0% accuracy is obtained when applied on the dataset.

[8]A prototype system is designed by Harshad Kumar , Jitesh , and Vipul, following a thorough examination of several image processing, approaches, captured images of the plants which are infected using a digital camera and empirically evaluated 4 methods for removal of the background and 3 methods for dissection. They suggested cluster trying to feed K-means clustering for illness classification and retrieved different characteristics under 3 classifications to allow accurate feature extraction. They used SVM for multi-class categorization and achieved accuracy of 93.3% on the training set and 73.3% on the test set. After completing 10 and 5 fold cross discriminants they attained 83.8% and 88.6% of accuracy.

[2]Hossain,Morshed Tanjil,Abser Bin Ali, and Zihadul Islam had explained a novel on the Convolutional Neural Networks model to acknowledge paddy diseases. They utilized a new dataset containing 4199 pictures of rice leaf illness and trained CNN-based algorithms to detect five prevalent rice leaf diseases. It achieves a training set 99.7% of accuracy and a test set 97.82% of accuracy. In the binary classification experiments, the suggested technique achieves recognition rates of 96% for brown spot,97% for the blast, 96% for bacterial leaf blight,95% for tungro, and 93% for sheath blight.

[3]Another study uses an improved stacked neural network with the gradient-free optimization algorithm to acknowledge and assort rice leaf illnesses. In this, for image acquisition, the images are directly taken on a farm. Then the removal of background, RGB pictures are transformed into HSV pictures, and based on the gradation and saturation parts of the pictures are extricated to divide the affected and not affected parts. Then for the dissection, the clustering method is used. In this, the categorization is browned by using a stacked Neural Network with a gradient-free optimization algorithm. The outcomes are assessed and collated with the DNN, DAE, and ANN. The blast was 98.9% accurate, bacterial blight was 95.78 percent accurate, sheath rot was 92 percent accurate, and the brown spot was 94 percent accurate.

[9]Minu Eliz Pothen and Mya L Pai have proposed a method that tells different methods utilized for the identification of rice leaf disease. They had segmented the images of Bacterial blight, leaf smut, spots on leaves using the optimal thresholding method which is helped to perform automatic image processing. From that marked area, different kinds of characteristics are split using Local Binary Patterns (LBP) and Histogram of Oriented Gradients(HOG), and with Support Vector Machine the characteristics were named. They achieved 94.6% with Kernel SVM and Histogram of Oriented Gradients.

[10]Santanu Phadikar and Jaya Sil had proposed a method for the detection of rice leaf disease with Pattern Recognition Methods. Diseased rice leaves are captured and examined with image prospering and separating techniques to identify the diseased part of rice leaf and the infected leaf is classified by a neural network. This process includes both soft computing and image processing on diseased rice plants.

[11] Jayanthi M.G and Dr. Dandinashivara Revanna Shashikumar had explained the recognition of infected rice leaves by a fuzzy inference system. Here the rice leaves are transformed into red, blue, and green, and with a median filter, we can remove green band noise and the quality and color and removed from pre-processed green bands. Then the OFIS will categorize that the picture is expected or infected, with the fuzzy system with firefly algorithm to get the 95% accuracy for the paddy leaf disease detection.

III. PROPOSED METHOD

The gathering of information is the first step in the classification process. The dataset for the rice leaf disease analysis was obtained from the UCI, an ML library that contains images for three different leaf diseases [14]. There are 120 instances in .jpg format in the dataset. The dataset comprises 40 images of leaves with Brown spots, Leaf smut, and Bacterial leaf blight. Real-life captured images of disease-afflicted rice leaf plants are gathered. Proper white background and optimum sunlight are ensured for images. The infected leaves images were manually classified into illness categories. Figure2 illustrates the block diagram of the proposed method.

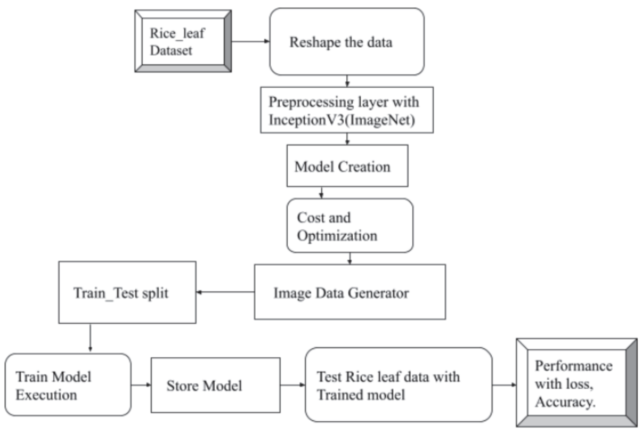

Fig. 2: Block Diagram of Proposed Method

The pre-processing step occurs before the data is trained and tested. The pre-processing consists of four steps: resizing the picture size, turning the image to an array, pre-processing input with inceptionV3. Due to the efficiency of training models, picture scaling is a key pre-processing step in object recognition. The model will perform better if the picture is smaller. In this research, scaling an image means converting it to 224*224 pixels and then weights from ImageNet are imported using a pre-processing layer. The next step is to create an array from all of the photos in the dataset. The picture is transformed into an array so that the loop function may call it. The model was generated using ImageNet, although it required a few tweaks to work well. 15 epochs are used to build the model on the base model, which is built using the image net dataset. It has around 14 million data points that have been hand-picked for use in model development. Transfer Learning is a strategy that utilizes feature extraction, pre-trained models, and popular approaches to get accurate performance in less time.

A. Transfer Learning:

Transfer learning occurs when an issue is addressed and applied to other problems. However, it must be connected to the fundamentals of the information obtained. Working with dogs teaches you how to recognize them, which helps you recognize cats correctly. Restate the model or knowledge from previously studied tasks to improve the study of new tasks that have a substantial potential for reinforcement agents from a practical standpoint. Tasks and domains are mentioned in the transfer learning technique. To define the domain, the marginal probability distribution and feature space are specified. To describe the job and a function to forecast the matching label of a new case, the object predictive function and label space are declared. Studying a target's prediction function helps to aim to transfer learning in the target domain with relevant information in learning activities and the source domain. [15][16][18][19]

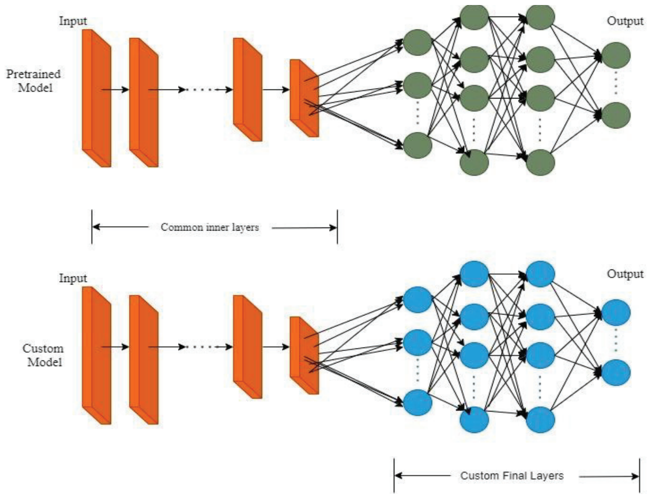

Fig. 3: Transfer Learning workflow

Learning approaches to TL:

1) Reusing the trained model:

Consider the situation in which you wish to accomplish Task A but lack the necessary data to train a DNN. Finding a similar task with a lot of data is one approach and get around this. Utilize the deep neural network to train on task B and then use the model to solve problem A. The problem seeking to solve will determine whether we need to employ the entire model or just a few levels.

2) Using a Pre-trained Model

The 2nd option would be to utilize a method that is pre-trained. There are several such models around nowadays, so do some research beforehand. The hidden layers to utilize and re-train are fixing the issue. For instance, Keras has 9 pre-trained networks for TL, the gauging, extraction of features, and fine-tuning. Several models, as well as some quick lessons on how to utilize them, may be found here.

3) Feature Extraction: A further alternative is to apply deep learning to determine the optimal model of our issue, which entails identifying the key features. This method is termed feature representation, and it may frequently produce significantly better results than improvised representations. Feature extraction is a dimension reduction method that reduces a large collection of original data into smaller groupings for analysis.[25][26]

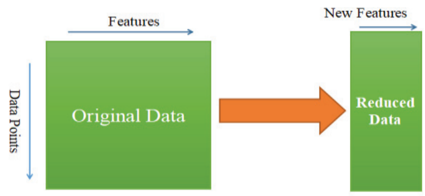

Fig. 4: Feature Extraction process

Following that, inceptionV3 will be used to pre-process input utilising the picture. There are several popular pre-trained ML models available. The Inception-v3 model, which was developed from ImageNet for "Large Visual Recognition," is among the companions.

3) Inception-V3

Inception-V3 is one of the most widely used image recognition models shown to achieve greater accuracy. It was developed on the basics of published "Rethinking the Inception Architecture for Computer Vision"[21]. The model is a compact layout of multiple equilibria and equilibrium concepts that include integration, moderate integration, high interaction, contacts, fully, and dropouts integrated layers. The Batch norm is widely applied for the model. The first V3 model is trained in the ImageNet database containing more than 10 million URLs of labelled images with more than a million images with binding boxes that specify the exact location of the labelled objects.

Factorized changes: As the number of factors implicated in the network is reduced, this tends to boost computer performance. It also monitors network performance. Minor convolutions replacing large them with tiny combinations gives the faster training is undoubtedly results. It says a 25variables have a 5 × 5 filter, and two 3 × 3 filters that replace 5 × 5 convolution have only (3 * 3 + 3 * 3) 18 variables. Asymmetric Integration is 3 × 3 convolutions can be replaced by 1 × 3 convolutions followed by 3 × 1 convolution. If 3 × 3 variables are replaced by 2 × 2 variables, the lot of variables in the suggested asymmetrical convolution may be marginally greater. In addition to the core network loss, an auxiliary classifier is introduced among layers during training, with it damage by causes contributing to the loss. An auxiliary taxonomy on GoogleNet is used for an in-depth network, while an auxiliary taxonomy in Inception v3 acts as a regularizer. [20]

The inception layer generates fresh training weights avoiding the usage of the existing weights. In addition, if we require additional layers, we may add as many as we require. We utilized a dense activation function called "softmax" to forecast the model. Second, we compiled the model using categorical cross-entropy and Adam optimizer to estimate the model's optimization and cost.

4) Categorical cross-entropy

The most important cost function is cross-entropy loss. In the best prediction model, the function is used. The fundamental goal of the cross-entropy is to use the truth tables to quantify the distance between the outcome probabilities. This idea may be traced back to applied mathematics when the notion of entropy was first established. Entropy is directly proportional to the uncertainty of probability distribution. The logarithmic loss function is another name for the cross-entropy loss function. In which the probability is associated with a favorable result for the class. Then loss will be calculated which chastises the probability about how far it is from the expected values. If the loss is reduced the model will be more efficient by using (1). [17]

$$L\_CE = \sum_{i=1}^{n} \quad t_i \, log \, log \, (P_i) \tag{1}$$

Finally, the model is formed using entails converting the picture data into rescaling, shear range, zooming, and flipping it horizontally and vertically.

IV. Performance and Discussion

The proposed innovation technique requires a long time to develop. The infected area of leaves is spotted using the proposed method. The disease portion is highlighted in a red-colored box with the indication of the disease class and the accuracy refer Figure5.

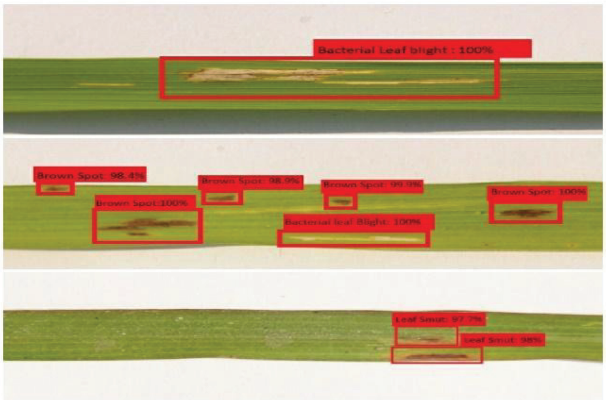

Fig. 5: Detection of Rice leaf Diseases

During this process of learning, we have encountered how the zoom range can impact accuracy. As we kept on changing the zoom range, we could see that it had an impact on the accuracy of the given dataset. The zoom range and accuracy were directly proportional, which might vary depending on the type of data used. Another adjustment that improves performance is scanning the illness part to identify it. From the below graphs we can understand the process of building a reliable and robust model as a lot of epochs were simultaneously used and we were able to achieve a maximum accuracy at the 11th epoch and the training loss is 0.000074636. With the proposed method, we have obtained the validation loss of 0.000057909 refer Figure6 and Figure7 for the accuracy performance of the proposed model.[27]

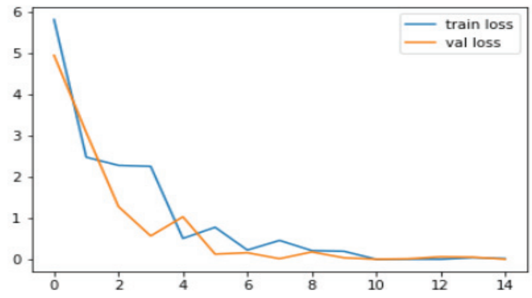

Fig. 6: Loss performance of the proposed method

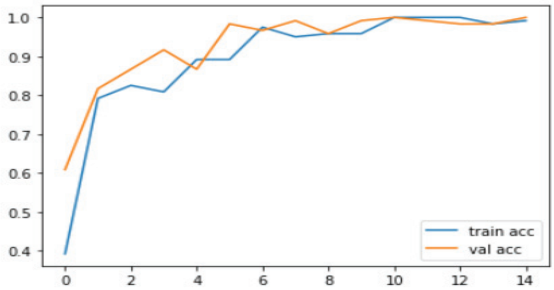

Fig. 7: Accuracy performance of the proposed method

While achieving good accuracy, we were able to build a robust model which consumes 8,99,38,472 bytes of space on the disk. The model is updated to reflect the adjustments, and the authors tested the results using accuracy and performance measures refer Table1 and Figure8.

TABLE I. Disease Classification

S. No	Disease	F1-score	Recall	Precision
1	Bacterial leaf blight	98.5%	100%	97%
2	Brown spot	95.1%	96.0%	100%
3	Leaf smut	98.4%	96.9%	100%

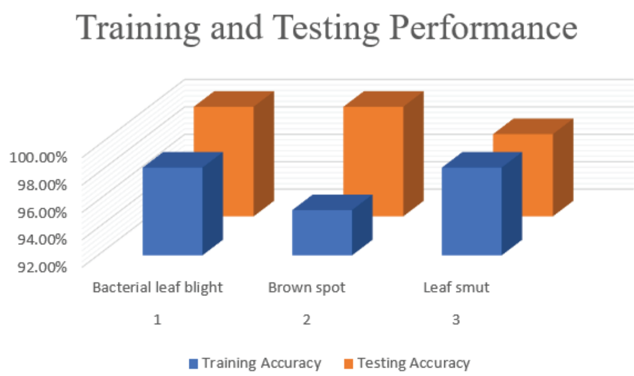

Fig. 8: Training and Testing Performance Analysis

The suggested technique's performance was evaluated using Transfer learning with Inception V3. The average accuracy of this strategy is 100 percent. The table refers to how the proposed Transfer learning classifier outperformed the previous research. Deep learning models have attained a higher accuracy [7]. Using Optimized neural networks and Gaussian filtering, claimed 98.9 percent and 98.63 percent respectively. In rice leaf disease detection, the machine learning techniques out-turned 97 percent. However, a diminutive improvement of 0.27 percent with the implementation of Convolutional neural networks. The usage of color image thresholding in our investigation has adequately classified the severity of the disease refer Table2.

TABLE II. BENCHMARKING OF RICE LEAF DISEASE CLASSIFICATION

Reference	Year	Objective	Methodology	Result
[2]	2021	Rice Leaf Diseases Recognition	Convolutional Neural Networks	97.82%
[3]	2020	paddy leaf diseases	Optimized Deep Neural network with Jaya algorithm	98.9%
[5]	2019	Rice Leaf Disease Detection	Machine Learning Techniques	97%
[6]	2018	Noise Reduction	Gaussian Filtering	98.63%
Proposed method	2021	Rice leaf disease classification	Transfer Learning with InceptionV3	99.33%

V. CONCLUSION

Data scientists and researchers believe that transfer learning can help us accelerate our progress toward the agriculture industry domain. This paper mainly focused on three different rice leaf diseases. Using machine learning algorithms and image inputs, we investigated a number of techniques that have yielded notable outcomes for rice leaf disease detection. The best viable solution is a smart mix of the optimization technique idea into InceptionV3 and transfer learning. Researchers in this field may be interested in attempting to build such technology. Our model performs on unconventional testing images with 99.33% accuracy. Furthermore, our model is highly robust and is effective for memory storage. This is possible because of Transfer learning with InceptionV3. Future improvements like integrating more categories of rice leaf diseases and designing low-computational requirement models can be implemented at low costs.

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