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Rice Leaf Disease Prediction Using Deep Learning

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ABSTRACT

A staple food for billions of people all over the world. At all stages of the development process, it is afflicted with various ailments. Diseases in plants are mostly caused by abiotic, biotic and other environmental factors. Rice diseases such as brown spot, bacterial blight and leaf blast damage the crop and it drastically affect yields. Farmers all across the world are dealing with the difficulty of identifying plant illnesses and treating them appropriately. As a result, precise detection of diseases in rice leaf is critical. Recent breakthroughs in Deep Learning (DL) techniques have substantially improved the possibilities of visual recognition. The Convolutional Neural Networks (CNNs) are the most often used DL models for computer vision applications, and they have proven to be quite successful in fields such as object identification, picture categorization, image segmentation, and so on. It has cleared the path for detecting the plant diseases automatically by utilizing plant pictures. The dataset in this study is limited to training a deep CNN model like VGG-19; nevertheless, transfer learning was used in this case. Transfer learning is a prominent DL technique in which previously learned models are repurposed to solve a new problem. The major goal of this research is to evaluate deep CNN with transfer learning for disease detection in rice plant leaves. The CNN are used with a transfer learning method to decrease training time and improvise the neural network functionality. The accuracy of the VGG-16 CNN model is 92.46 %.

Key words: Transfer learning, Rice leaf diseases, Deep learning, Convoutional Neural Network, VGG-19.

1. INTRODUCTION

The food crop that is consumed by tens of millions of people around the world is rice. Every year, pests and diseases threaten rice fields, causing serious concern for farms if they are not properly monitored and managed. Aside from better crop management, initial and correct treatment of plant disease protect the rice from severe infection and minimise losses greatly. The treatment of such illnesses is beneficial to maintaining a healthy farming environment [1, 2]. In the world of agriculture, the automated identification of plant diseases based on plant leaves is a huge breakthrough. Furthermore, early and timely detection of plant diseases improves agricultural output and quality [3].

Even an agriculturist and pathologist may fail to identify diseases in plants by viewing disease-affected leaves due to the cultivation of a vast variety of crop items. However, in underdeveloped countries' rural areas, visual inspection is still the major method of illness detection [4]. It also necessitates expert monitoring on a regular basis. Farmers in rural places may have to travel a long distance to visit an expert, which is both time-consuming and costly [5, 6]. As a result, using an expert system to detect plant illnesses can help to promote healthy farming by allowing for precise decision-making on disease recognition in plants. Deep learning have become popular in recent years as a powerful class of models for picture classification in a variety of issues in agriculture, including plant disease recognition, weed identification, fruit counting, and so on. Before efficiently extracting features, pre-processing is required, such as picture enhancement, colour modification, and segmentation [7]. Deep learning is based on artificial neural networks (ANNs), which can learn and make intelligent predictions with the aid of algorithms. The nodes in the DL algorithm are divided into three layers: output layer, input layer and hidden layer. The term "deep" in DL refers to the number of layers by which the data is transformed by gradually extracting higher-level features from the raw input, which aids in performing better classification tasks by learning more intricate leaf data properties [8]. Different classifiers might be employed after feature extraction. K-nearest neighbour (KNN) [9], support vector machine (SVM) [10], decision tree, random forest (RF) [11], naïve Bayes (NB), logistic regression (LR), rule generation [12], artificial neural networks (ANNs), and Deep CNN are some of the most often used classifiers. KNN is a supervised machine learning technique that employs similarity measures to solve classification issues. DL-based approaches, particularly CNNs, are, on the other hand, the most promising strategy for learning decisive and discriminative characteristics automatically [13, 14]. Transfer learning has the advantages of reducing training time, generalisation error, and the computational cost of developing a DL model [15].

In this paper, we utilized our rice disease dataset that are acquired from both the agriculture fields and the internet to construct the deep learning approach. The pre-trained VGG-16 model is used and fully connected layers were fine-tuned using Transfer Learning.

II METHODOLOGY AND IMPLEMENTATION

The test was carried out on a Windows 10 PC with a GPU card P4000 and a 64-bit operating system. The programming language used was python 3.7.2. The Keras 2.2.4 deep learning framework with TensorFlow 1.13.1 backend was used to implement the CNN-based model. The overall steps involved in the proposed methodology is represented in **Figure. 1**.

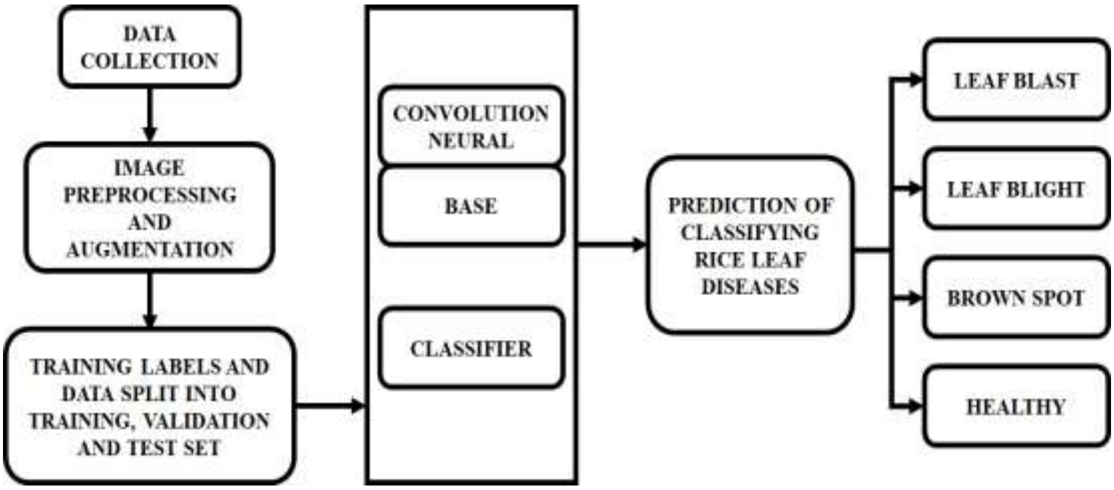

Figure 1 Proposed model

The photographs of the leaves were gathered from both the agriculture fields and the internet. The data consists of 4 divisions namely Brown Spot, Leaf Blight, Leaf Blast and health plant images. The photos are downsized to 224*224 pixels and a variety of augmentation techniques such as horizontal, rotation, magnification and vertical shift are employed to generate new images using Image Data Generator in Keras. The process of the proposed model is discussed below.

1) Data Augmentation and Pre-processing

The data pre-processing is a necessary task for preparing raw input data and making it suitable for building and training a deep learning model, which improves the model's accuracy and efficiency. It aids with data quality improvement and encourages the extraction of consequential imminent from data. All of the photos in the collected dataset have RGB coefficients and various (h x w), thus we rescaled and resized them. Scaling every image's pixel values to the range of 0-1 and resizing all photos into the shape of 224* 224 pixels was done during the pre-processing step. Because the unique dataset lacks enough images for effective training, it is necessary to extend the image collection using various image augmentation algorithms. By utilizing ImageDataGenerator in Keras, the augmented image set is created by flipping, rotating and random zooming the photos horizontally and vertically.

2) VGG-16 CNN Architecture

The picture data set has been loaded for training and testing. For training, the class labels and accompanying images are stored in separate arrays. The proposed VGG-16 architecture is depicted in **Figure 2**.

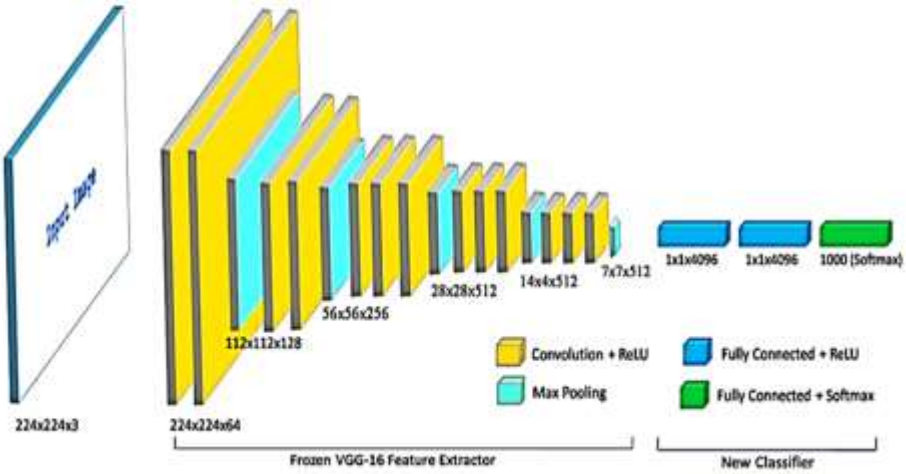

Figure 2 VGG-16 Architecture

The data utilized for training was 70 % and the data utilized for validating using test-split function was 30 %. The 70% of the data is divided and 20% being used for evaluation. The integers are used to encode the class labels and to represent each label as vector other than integer, one-hot encode is conducted on labels. From keras, the VGG-16 model is loaded and completely connected layers at the last are removed. The rest of the layers are rendered untrainable. The output of the feature extractor component is flattened, then used softmax to connect the output layer and the completely connected layer. Then, by using the Adam optimizer and categorical-crossentropy as the classification loss function, the proposed model is compiled. We stopped at 25 epochs because the results remained consistent beyond that.

i) Convolutional layers

The basic block of a CNN is the convolutional layer. It's also known as the Conv layer. It's used to extract related information from an input image using filters with a set of automatically learnable parameters (weights). Filters are made out of a tiny matrix with a dimension of (MxMx3). The output of the convolution layer in CNNs can be represented as,

$$X_j{}^P = \sum_{i \in N_j} X_i{}^{P-1} x k_{ij}{}^P B_J{}^P \quad (1)$$

Where N_j denotes the number of filters, P represents the P^{th} layer, $X_i{}^{P-1}$ denotes feature map, k_{ij} denotes convolutional kernel, and B_j denotes bias term.

ii) Non-linear layer

After each convolution layer, it is added. It includes an activation function that causes non-linearity in the input data, enhancing the model's generalisation capacity. It takes the feature map from the convolution layer and outputs the activation map. Rectified Linear Unit is a widely used activation function (ReLU). If the input values are negative, the output is zero; otherwise, the input values of the x matrix are produced as is. The unsaturated version of ReLU outperforms the sigmoid and tanh versions (saturated). The output can be formatted as follows:

$$f(x) = \begin{cases} 0, for\ x < 0 \\ x, for\ x \geq 0 \end{cases} \quad (2)$$

iii) Pooling Layers

The pooling layers are utilized to gradually reduce the spatial dimension of each feature map while maintaining its depth. The technique entails sliding a two-dimensional filter above each characteristic map control and a bridgmenting the attributes contained within the filter's protected portion. As a result, the number of parameters to learn is reduced, which minimises the likelihood of overfitting.

iv) Max Pooling

In most neural networks, it is the most commonly used pooling operation. The larger value is overlaid by the filter is used in this procedure. The pool size dimension for maximum pooling is commonly 2 × 2 with a 2x2 stride. It reduces overfitting by down sampling the input size of each feature map's height and width.

v) Global Average Pooling

It's a pooling procedure that's meant to take the role of the fully linked layer in traditional CNNs. It is also known as the GAP layer, and it conducts a maximal type of down sampling, in which all the components of each feature map. It decreases the overall number of parameters in the model, which aids to reduce overfitting. It makes the model more resistant to data spatial translations.

vi) Fully connected layer

Dense layer is another name for it. The nodes in the fully linked layer have complete communication with the layers above and below them. The last convolutional or pooling layers' output will be flattened and fed into this layer as input. It incorporates the geographical information of the training data to forecast the classes and processes the input for improved learning.

$$f(x) = relu(X.W^T + b) \quad (3)$$

Where, X represents the input data, W represents the weight vector and b is the bias term.

vii) Output layer

The output layer is fully connected to the previous layer and receives its input. It has four neurons, each representing one of the four kinds of rice leaf images. Softmax activation is used to anticipate the target output (class) with a high degree of certainty. The mathematical function of the softmax can be written as,

$$S(Z_i) = \frac{e^{Z}{}_i}{\sum_{k=1}^{n} e^{Z}{}_k} \text{ for i = 1,....., n} \quad (4)$$

In an N-dimensional vector, $S(Z_i)$ always has a positive value in the range [0, 1], where n is the number of classes. The numerator is any actual value from the input vector, whereas the denominator is the numerator value multiplied by some additional positive values. The total of the output probability values is 1.0.

viii) Loss of function

It is utilized to calculate the output error following the training procedure. It calculates a discrete loss for each class label and then sums the results. The loss may be computed with the following equation:

$$L(\theta) = \sum_{K=1}^{n} y_k log\widehat{y_k} \quad (5)$$

The categorical cross-entropy loss function is utilised to determine the difference between the desired and actual outputs in this study.

III RESULTS AND DISCUSSION

Rice is one of India's most widely farmed crops, and it is susceptible to various types of diseases at different stages of production. With their inadequate understanding, farmers find it extremely difficult to manually detect these diseases. Recent advances in DL reveal that Automatic Image Recognition systems based on CNN models are extremely useful in these situations. Even though a collection of rice leaf disease images are not readily available, we constructed our own tiny dataset and used Transfer Learning to improve our deep learning model. The suggested CNN architecture is based on VGG-16 and it has been trained and tested using data obtained from internet and agricultural fields. The results of the rice leaf disease classifications are discussed below. The rice leaf obtained is uploaded for analysis as shown in **Figure 3**.

Figure 3 Uploading of Rice leaf

The type of disease that has afflicted the rice leaf is predicted in the image. The prediction of rice leaf disease is shown in **Figure 4**.

Figure 4 Rice leaf disease prediction

The result of the uploaded leaf is represented in **Figure 5**. The result indicate that the uploaded rice leaf is affected by leaf blight disease.

Figure 5 Result of the analysis

The category of disease that has afflicted the rice leaf is predicted by uploading the image as shown in **Figure 6**.

Figure 6 Rice leaf disease prediction

The result of the uploaded leaf is represented in **Figure 7**. The result indicate that the uploaded rice leaf is affected by leaf blight disease.

Figure 7 Result of the analysis

The sort of disease that has affected the rice leaf is predicted by uploading the image as shown in **Figure 8**.

Figure 8 Rice leaf disease prediction

The result of the uploaded leaf is represented in **Figure 9**. The result indicate that the uploaded rice leaf is affected by brown spot disease.

Figure 9 Result of the analysis

The variety of disease that has affected the rice leaf is predicted by uploading the image as shown in **Figure 10**.

Figure 10 Rice leaf disease prediction

The result of the uploaded leaf is represented in **Figure 11**. The result indicate that the uploaded rice leaf is not affected by any kind of disease.

Figure 11 Result of the analysis

The kind of disease that has afflicted the rice leaf is predicted by uploading the image as shown in **Figure 12**.

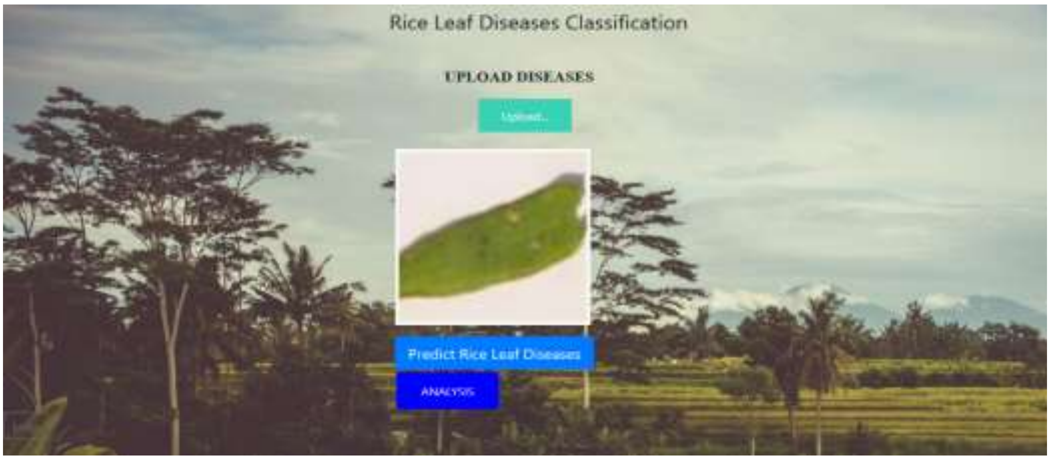

Figure 12 Rice leaf disease prediction

The result of the uploaded leaf is represented in **Figure 13**. The result indicate that the uploaded rice leaf is affected by leaf blast disease.

Figure 13 Result of the analysis

The pie chart analysis of the rice leaf disease classification is depicted in **Figure 14.** From the analysis it is demonstrated that 50 % of the leaves are affected by leaf blight disease.

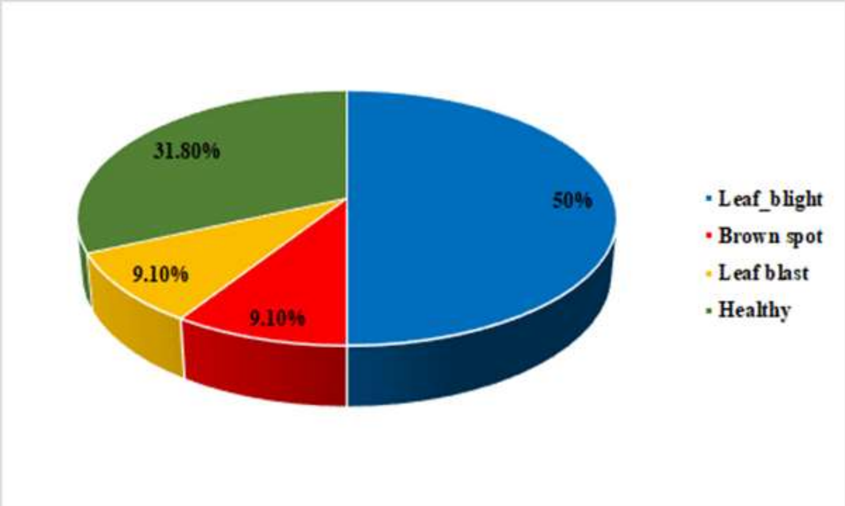

Figure 14 Pie chart for disease classification

The brown spot disease and leaf blast affects nearly 9.10 % of the leaves. The balance 31.80 % leaves are not affected by any kind of diseases and they are considered as healthy.

IV. CONCULSION

The major goal of this research is to evaluate deep CNN with transfer learning for disease detection in rice plant leaves. The CNN proposed are used with a transfer learning method to decrease training time and increase neural network functionality. The accuracy of the VGG-16 CNN model is 92. 46 %. A cut point was received, so the epochs number utilized was stopped at 25. On both training and validation data, the accuracy didn't improve after receiving the cut point and the loss didn't decrease.

In future work, we hope to gather additional photographs from farm areas and agricultural research organisations to increase the accuracy even more. In order to validate our results, a cross-validation process is about to involve in the future. We also like to compare the results obtained with better DL models. Other plant leaf diseases, which are significant crops in India, can be detected using the developed model in the future.

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