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Proposed Rice Leaf Diseases Classification Model Based on the pre-trained VGG-16 Model with Transfer Learning Technique

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Abstract- Given the widespread consumption of rice across numerous countries, it stands as one of the most extensively cultivated crops globally. To achieve successful rice cultivation , it is essential to comprehend the different stages involved in the process and to be aware of the various disease that can affect the crop introduced a researchers have introduced a range of diagnostic techniques specifically for rice. Among the various diagnostic methods, one notable approach is the classification method utilizing deep learning. This method employs convolutional neural network architectures to automatically classify diseases by analyzing images of rice leaves collected from rice fields. This paper employs the VGG-16 models, which has been pre-trained, to classify various types of leaf diseases in rice plants utilizing the Transfer Learning approach. In this system, Dataset containing diseased rice leaf images are used to distinguish disease types. The proposed model and VGG-16 model have been used as baseline models on the dataset and result have been analyzed. In the evaluation part, the performance of the models is shown using testing datasets.

Indexed Terms- Classification, Deep learning, Convolutional Neural Networks (CNN), VGG-16 model

I. INTRODUCTION

The widespread consumption of rice as fundamental food source in many nations highlights the essential need to maintain the health of rice crops, which is vital for enhancing food security and supporting the agricultural industry, considering the significant levels of production and consumption worldwide.

In today's digital age, it is essential for farmers to utilize advanced technologies to effectively manage their agricultural activities. Researchers have utilized machine learning and deep learning methodologies to develop diagnostic systems aimed at the analysis of plant leaves.The proposed system investigated a methodology aimed at distinguishing among various diseases that impact rice plants, such as Healthy Leaf, Brown Spot, Bacterial Leaf Blight, Leaf Blast, Sheath Blight, and Leaf Smut.

This research employs pre-trained VGG-16 weights for the classification of rice leaf diseases, facilitating feature extraction from the dataset, while various hyper-parameters are utilized to adapt the learning to the classifier. This paper contributes by utilizing a pre-trained model through transfer learning for the diagnosis and classification of rice leaf diseases. Different deep learning models, each trained on unique datasets, are employed, and the resulting outputs are analyzed for further examination.

The structure of the paper is outlined as follows: Section II reviews pertinent literature in the field of CNN, Section III offers a summary of the theoretical framework, Section IV details the proposed system, Section V showcases the experimental findings, and Section VI wraps up the discussion while highlighting potential future research directions.

II. RELATED WORK

In our study, we employ a deep learning approach to categorize rice leaf diseases, utilizing MobileNetV2 alongside transfer learning for the classification tasks[8]. The main objective of this study is to employ a challenging dataset that lacks extensive curation and to apply transfer learning methodologies. Enhancements in the functional performance of the classification model are realized by integrating shorter training durations with optimized parameter dimensions. A total of four diverse datasets, each exhibiting specific traits, were collected and then combined to form a unified dataset containing 7,445 images that depict five varieties of rice leaf diseases. The proposed model, along with an additional convolutional neural network (CNN), served as baseline models for the five datasets, and their results were meticulously examined for assessment. In MobileNet-V2, an attention mechanism was incorporated to assess the significance of inter-channel relationships and the spatial arrangement of input features, thus improving its proficiency in recognizing subtle lesion characteristics. The model underwent two phases of transfer learning throughout the training process, with the loss function being optimized accordingly[2].

In reference [1], the authors introduced a system designed for the recognition of rice leaf diseases, utilizing local threshold-based segmentation in conjunction with a deep convolutional neural network (CNN). This system was tested on three distinct datasets, one of which was developed by our team, comprising rice leaf images sourced from the Bangladesh Rice Research Institute (BRRI). In the concluding experiment, the model was trained using all the collected data, resulting in a test accuracy of 78% and a validation accuracy of 82.05%.The researchers [4] present an approach utilizing a deep convolutional neural network (DCNN) based on transfer learning for the precise detection and classification of rice leaf blight. This system incorporates the VGG-19 model along with the transfer learning technique, enabling it to accurately identify and categorize six different classes: healthy, narrow brown spot, leaf scald, leaf blast, brown spot, and bacterial leaf blight. The method achieves a maximum accuracy of 96.08% when applied to a non-normalized augmented dataset. Among the various classifiers employed for this task, the convolutional neural network stands out due to its impressive performance. The author recommends the use of a fully connected Convolutional Neural Network (CNN) to categorize rice leaf diseases based on image data [5]. The research evaluated multiple models, such as MobileNet, NasNet, and SqueezeNet, yielding encouraging outcomes. SE-MobileNet, introduced by Chen et al. [3], represents a modification of MobileNet that incorporates squeeze and excitation mechanisms. This study presents the development and implementation of an automated diagnostic method within a smartphone application. Central to this approach is the Ensemble Model, which incorporates multiple submodels. The effectiveness of the Ensemble Model was subsequently validated with a distinct set of images. Consequently, three submodels were chosen and incorporated into the Ensemble Model [6].

III. BACKGROUND THEORY

A prevalent use of Deep Learning within the realm of Computer Vision is the employment of Convolutional Neural Networks (CNNs) as the fundamental architecture for neural networks. A Convolutional Neural Network is composed of multiple layers, including the input layer, convolutional layers, pooling layers, and fully connected layers. Convolutional Layers are employed for the purpose of extracting features from the input dataset. This process entails the application of a sequence of adaptable filters, known as kernels, to the input images.

The Pooling layer is periodically incorporated into convolutional networks, functioning to reduce the dimensionality of the data, which in turn enhances computational speed, optimizes memory usage, and helps to alleviate overfitting. Max pooling and average pooling represent two prevalent forms of pooling layers utilized in neural networks. Following the convolutional and pooling layers, the next phase is the Flattening layer, which converts the generated feature maps into a one-dimensional vector. In the Fully Connected Layers, the input received from the previous layer undergoes a series of computations to produce the ultimate classification or regression result.

A. Tranfer Learning

Transfer learning is a methodology utilized in machine learning and deep learning that involves employing a pre-trained model as a foundational element for a new, related task. Rather than constructing a model from the ground up and training it on an extensive dataset, transfer learning enables the utilization of the insights and knowledge acquired by the pre-trained model. Transfer learning is a method utilized in both machine learning and deep learning. A pre-trained model is generally developed using a substantial dataset, like ImageNet, to address a broad computer vision challenge. By leveraging this pre-trained model, one can utilize the acquired feature representations, which possess sufficient generality to be applicable to a new, related task.[14]

In the context of transfer learning, the standard approach involves utilizing a pre-trained model and substituting its final layer with a new layer tailored to the specific task at hand. This newly added layer is subsequently trained using a smaller dataset relevant to the new task, while the remaining components of the pre-trained model remain unchanged, with their weights fixed. This methodology enables the fine-tuning of the pre-trained model for the new task, effectively minimizing the risk of overfitting and decreasing the overall training duration.

Transfer learning has emerged as a crucial method in deep learning, resulting in notable enhancements in both accuracy and efficiency across various computer vision applications.

B. VGG-16

A Convolutional Neural Network comprises an input layer, an output layer, and multiple hidden layers. Commonly known as ConvNets, these networks fall under the classification of artificial neural networks.

The Visual Geometry Group (VGG) 16, recognized as a Convolutional Neural Network (CNN), is regarded as one of the most proficient models in the field of computer vision today. The developers of the model assessed the networks and enhanced their depth by incorporating an architecture featuring compact (3 × 3) convolution filters, resulting in a notable advancement compared to earlier configurations. They increased the depth to encompass 16 to 19 weight layers, which produced approximately 138 trainable parameters.

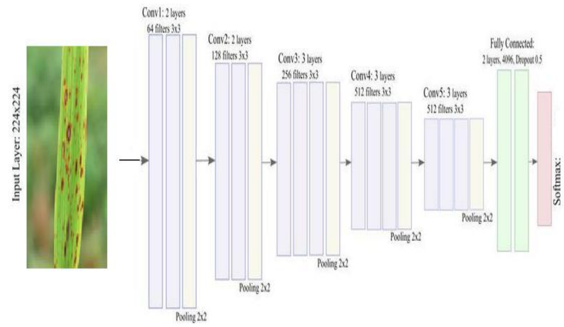

Figure 1. VGG-16 Model Architecture

Figure 1 illustrates the architecture of the VGG-16 model. The designation VGG16 arises from the presence of 16 layers that contain weights. Although the model consists of a total of 21 layers, which include thirteen convolutional layers, five Max Pooling layers, and three Dense layers, it is characterized by only sixteen layers that hold weights, signifying the learnable parameters.

The VGG16 model requires an input tensor size of 224x224 pixels, with each pixel comprising three RGB channels. Notably, VGG16 is characterized by its straightforward architecture, utilizing 3x3 convolutional filters with a stride of 1 and uniform padding, as well as 2x2 max-pooling layers with a stride of 2, rather than employing a complex array of hyper-parameters.

The configuration of convolutional and max-pooling layers is uniform throughout the entire architecture. The Conv-1 layer is equipped with 64 filters, Conv-2 includes 128 filters, Conv-3 has 256 filters, while both Conv-4 and Conv-5 are provided with 512 filters each. Following the convolutional layers, three fully connected (FC) layers are implemented. The initial two layers consist of 4096 channels each, whereas the third layer comprises 1000 channels, corresponding to the number of classes. The concluding layer operates as the softmax layer.

IV. PROPOSED SYSTEM

This research will outline the methodology for data collection and the components of the proposed Rice leaf classification system. It will provide a detailed description of the datasets utilized and elucidate the classification system employed.

A. Data Collection

The research datasets display a range of characteristics, encompassing differences in size, the number of classes, and the degree of intra-class similarity. Certain datasets contain images with noise, whereas others are composed of carefully selected images.

Table 1. Description of Dataset

Sell-created Name	Bacterial leaf Blight	Brown Spot	Leaf Smut	Leaf Blast	Sheath Blight	Healthy	Total
Self-Collection	668	770	224	587	171	524	2946
Dataset A	668	739	1546	523	1208	523	5207
Dataset B	1584	1600	224	1440	171	523	5542
Total	2920	3109	1994	2550	1550	1572	13695

This paper employs three distinct datasets, referred to as Dataset A and Dataset B, which are categorized according to the image content present within the respective classes. One of these datasets comprises images depicting a range of diseases. The Sell-Collection can be sourced from the Ayeyarwady region of Myanmar. Dataset A is available via Mendeley [9], which includes the Sell-Collection from this specific region. Additionally, Dataset B can be found on Kaggle [10], also featuring the Sell-Collection from the Ayeyarwady region in Myanmar. All images contained in the datasets are of superior quality and resolution, formatted in JPEG. The description of the dataset is presented in Table 1.

B. Proposed Rice Leaf Disease Classification Model

Our proposal presents the pre-trained model VGG-16 as the foundational framework, selected mainly for its inherent capability to offer residual connections to earlier layers. The proposed classification model for Rice Leaf disease employs transfer learning methodologies, specifically utilized in the feature extraction phase in accordance with the training parameters of the pre-trained VGG_16 model. The classification layer of VGG-16 is not used in the proposed model. The purpose of the feature extractor was to convert images into feature blocks. The proposed model classification section employs a single dense layer, which utilizes 256 vector elements for each image. The activation function applied in this layer is ReLU. Subsequently, a dropout rate of 0.5 is implemented. Finally, the model differentiates between six classes using the softmax function.

The model received input images with dimensions of 224x224x3, and the feature extractor processed these images to produce outputs of size 224x224x64. In the final phase, the convolutional base was activated and configured to keep its weights constant during the training process by assigning the "trainable" parameter of the base model to False. After this step, batch normalization ensures a consistent mean and variance by employing the inference mode within this layer.

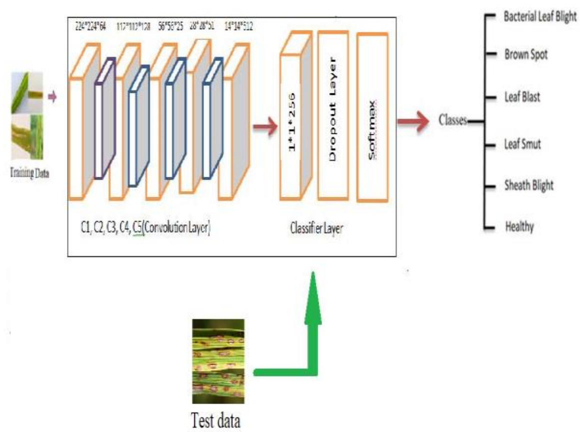

Figure2. Architecture of the proposed model

In the proposed model, it is necessary to substitute the output layer with a new layer tailored specifically for our dataset. By specifying weights='imagenet', we will retrieve the pre-trained hyper-parameters. This process may require some time; however, it is necessary to perform it only once. This model locks the weights of the other layers to prevent them from being retrained throughout the training process. Subsequently, we eliminate the final layer of the model and incorporate new hidden layers consisting of 256 units, followed by an output layer comprising 6 units, each corresponding to a distinct gesture. Additionally, the Dropout layer is incorporated to prevent overfitting by randomly deactivating neurons during the training process, thereby compelling the network to acquire more resilient features. The subsequent phase involves the proposed model categorizing the classes once the testing data is received. Figure2. depicts the architecture of the proposed system.

The proposed model was constructed through the integration of data augmentation, image rescaling, the establishment of a base model. The model parameters remained constant during the training phase. The values of the hyper-parameters are presented in Table.

Table 2. Values of the hyper-parameters

No	Value of Hyper-Parrmeters	Values
1	Base Learning rate	0.001
2	Optimizer	Adam
3	Loss	SparseCAtegorical Crossentropy

A pre-trained model was employed to remove unwanted layers in the proposed classifier, utilizing layers specifically tailored to our dataset and classification objectives. The model employs Sparse categorical cross-entropy for the purpose of multi-class classification.

V. EXPERIMENTS AND EVALUAATION RESULTS

The following section provides an explanation of the essential datasets and experimental configurations required for assessing the performance evaluation outcomes of a system.

A. Experimental Setup

The preprocessing of the datasets was conducted using the Python programming language, incorporating rescaling and augmentation methods, and leveraging the Keras API alongside the TensorFlow backend. The experiments were carried out on a Windows platform, utilizing VGG-16 as the foundational model. We conducted numerous epochs and utilized Python to analyze various batches from the validation dataset, subsequently allocating 80% for training, 10% for validation, and 10% for testing purposes. We performed several experiments utilizing comprehensive datasets to evaluate the efficacy and generalizability of the proposed models. The proposed model acquired the ability to identify pertinent features crucial for the task, irrespective of the dataset utilized. Details concerning the total number of datasets employed across various experiments can be found in Table 1.

This completes the entire process required for widespread of research work on open front. Generally all International Journals are governed by an Intellectual body and they select the most suitable paper for publishing after a thorough analysis of submitted paper. Selected paper get published (online and printed) in their periodicals and get indexed by number of sources.

B. Performance Evaluation

The evaluation of model performances is conducted through the analysis of F1 scores, accuracy, recall, and precision, employing metrics that include False Positives (FP), False Negatives (FN), True Negatives (TN), and True Positives (TP). TP represents the count of positive images that the classifier has correctly identified as images of rice leaf disease. The classifier identifies the quantity of negative images that are correctly recognized as not depicting rice leaf disease, which is represented by the TN value. Positive images that are incorrectly identified as rice leaf disease images by the classifier are referred to as FPFN, which indicates the count of negative images that the classifier has mistakenly labeled as not being rice leaf disease images.

In scholarly discourse, the term "accuracy" denotes the proportion of accurate predictions relative to the total number of data points collected (T). This concept is frequently used interchangeably with terms such as recognition, correctness, or success rate, and is mathematically expressed in Equation 1.

$$Accuracy = (TN + TP) / T \quad (1)$$

In the experiment, 80% of the data was allocated for training purposes, while 10% was designated for validation and the remaining 10% for testing. The total dataset were evaluated using the proposed model to establish a benchmark against the high-performing Traditional VGG-16 model. In this assessment, the suggested model exhibited enhanced performance in comparison to the Traditional VGG-16 model, as illustrated in Table 3.

Table 3.Comparison of results obtained using the two pre-trained models

	Traditional VGG-16 Model		Proposed Model	
	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy
Total Dataset	79.36%	73.83%	87.76%	83.80%

In the evaluation of training performance using the Dataset, the Proposed model attained an accuracy rate of 86.76%. In a similar manner, the Traditional VGG-16 model achieved an accuracy rate of 79.36% on the dataset. Results from two distinct studies indicate that employing a comprehensive dataset enhances both the overall performance and the classification accuracy of rice leaf diseases.

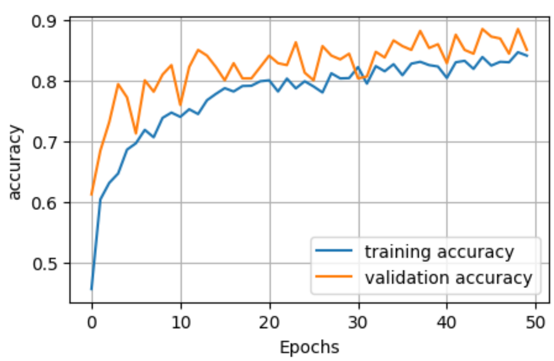

Figure 3. Training and Validation accuracy for Total Dataset using Proposed model

The assessment of multiple datasets utilizing varying batch sizes and epochs resulted in improved performance of the model. The suggested model underwent training for 50 epochs utilizing the Total dataset, and the identical datasets were evaluated using the Traditional VGG-16 model. Utilizing a batch size of 64 and a dropout rate of 0.5, the training accuracy achieved was 87.76%, while the validation accuracy reached 88.96%. Figure 3 depicts the training and validation performance over 50 epochs for the complete dataset.

Figure 4 illustrates the training and testing outcomes of the Traditional VGG-16 model applied to the entire dataset, which was trained over 50 epochs, resulting in an accuracy of 79.36%. This performance is 8.04% lower than that of the proposed model.

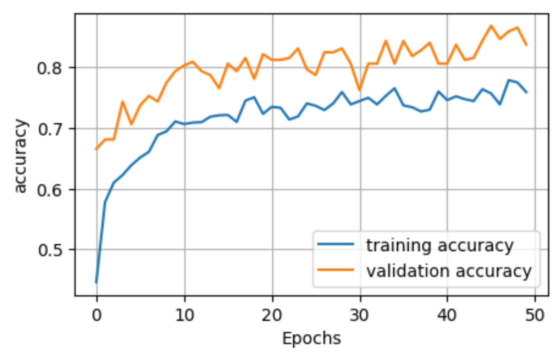

Fig.ure 4.. Training and Validation accuracy for Total dataset using Traditional VGG-16 model

CONCLUSION

This paper introduces a proposed system that utilizes the Traditional VGG-16 Model with transfer learning to classify six categories, which encompass healthy rice leaves and five distinct rice diseases. The results of this paper highlight the effectiveness and advantageous outcomes of employing the suggested models for the classification of rice leaf diseases, drawing on knowledge gained from pre-trained models. The proposed model demonstrates a higher accuracy of 87.76% for the entire dataset, surpassing the Traditional VGG-16 model, which achieves an accuracy of 79.36% for the same dataset. The system introduced in this research paper achieved significant accuracy in the classification of bacterial leaf blight, brown spot, leaf blast, sheath blight, healthy plants, and leaf smut diseases affecting rice crops.

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