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Early Detection and Classification of Rice Brown Spot and Bacterial Blight Diseases Using Digital Image Processing

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Abstract: Rice (Oryza sativa) is an important food and a wonderful source of nourishment. It is important to Pakistan's economic development. It is ranked as Pakistan's second-most significant crop production region, behind wheat, with an estimated 2.31 million hectares. Each year, various diseases in Pakistan cause the loss of 40% of the rice harvest. Pakistan has received reports of numerous rice diseases, including Brown Spot and Bacterial Leaf Blight. In the farming area, rice illnesses have reduced crop productivity and cost money. The exploration system aims to identify disease symptoms on rice leaves. These disorders are first classified using image processing after identification. We take several pictures of both healthy and diseased leaves. Additionally, characteristics are extracted following image preprocessing. Images of the rice leaves are classified as either healthy or diseased. When infected, it recognizes and categorizes properly. The model's Inception v3 and VGG19 were used as classifiers. VGG19 outperformed with 97.94% accuracy.

Keywords: Rice Leaf Brown Spot, Bacterial Blight, Convolutional Neural Networks, Deep Learning, Transfer Learning, Image processing, VGG19.

1. Introduction

The introduction of rice (Oryza sativa) is one of the most significant food, and half of the world population and contributing significantly to Pakistan's economy. Rice represents for 2.7 percentage of agricultural fee delivered and 0.7 percent of GDP[1]. Pakistan's economy and yield greatly influence the production of rice harvests. There are two prevalent diseases: brown spot (Figure 1) and bacterial leaf blight (Figure 2). Both the first and second diseases, which can damage rice health and reduce yields by up to 70 to 80 percent, are fungal and bacterial, respectively [2]. 40 percent of Pakistan's rice crop losses were reported [3]. In Asia, bacterial leaf blight is the oldest rice disease. In order to prevent losses in yield production, it is important to identify rice diseases. It takes a lot of time and effort to recognise and identify rice leaf diseases [4]. Due to their similarities, classifying the rice leaf diseases is challenging. It is difficult to identify and categorise them by human perception at an early stage. It would be more appropriate and beneficial to use the image processing approach for the early identification and categorization of rice illnesses. Using digital image processing and machine learning, the suggested approach correctly detects diseases in the early stages of the rice crop.

Brown spots (Alternaria longipes) are fungi that harm spikelets, leaves, rice husks, coleoptiles, and leaf sheaths. The most noticeable harm is the leaf's abundance of big spots, which can kill the leaf as a whole. Unfilled grains, blotches, or discolored seeds develop when seeds get sick. One of the most widespread and destructive rice illnesses in recorded history, brown spot disease, has received little attention.

Loss of volume and quality are both caused by brown patches[5]. Brown spot (Figure 1) in the field is mostly caused by, infected seed, which gives rice to infected seedlings[4].

Figure 1. Brown Spot Leaf

One of the deadliest bacterial infectious illnesses to ever affect farmed rice is rice blight, often known as rice blight (Oryza sativa and O. glaberrima) [6]. A serious epidemic that affects millions of hectares of rice each year can result in crop losses of up to 75%. The disease was first observed in Kyushu, Japan from 1884 to 1985. Breeding mortality in warm and humid environments has been observed in rice-growing regions of Asia, the west coast of Africa, Australia, and the Caribbean Sea. Although not commonly found in the United States, strains of bacteria associated with Xoo are listed as agricultural selection agents by the United States Department of Agriculture. It is a designation that is subject to strict regulation and Bacterial Blight disease as shown in (Figure 2).

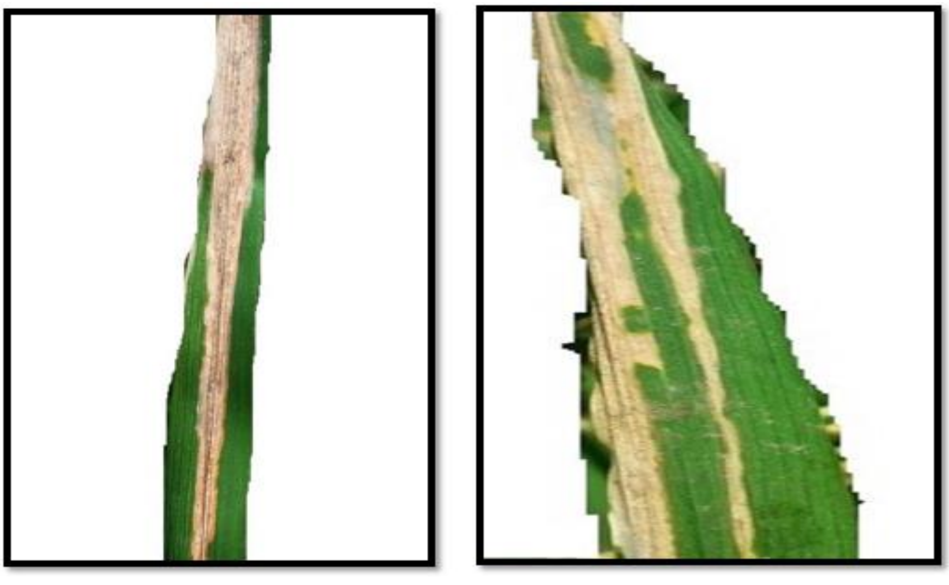

Figure 2. Bacterial Blight Leaf

The main contribution to this study is;

1. To find optimal texture features to achieve high accuracy for the detection of Brown Spots and Bacterial Blight.
2. To develop an intelligent system for the early detection and classification of rice diseases.
3. To design an online platform for the visualization of experimental results.

2. Literature Review

The Materials The plant leaf disease system proposed by [7] was developed for detection and classification using computer vision and machine learning techniques. Experimental results were evaluated by Random Forest, Support Vector Machines, K Neighbor Neighbors, and Artificial Neural Networks and compared with various algorithms. The performance of the proposed predictive model was better in Random Forest compared to other classifiers. This is to provide 74.28% accuracy with a 70.89% F-score, 71.88% recall, and 71.77% precision score.

An automated system was developed by [8] to detect rice leaf disease using image-processing techniques. Automatic Plant Disease Leaf Detection Various hybrid image segmentation and classification techniques have been recognized and analyzed to identify virtual disease of rice leaves in different environments. Characteristic-based detection of rice leaf disease using a support vector machine and multiple convolutional neural networks (CNNs). The deep features proposed by the system are categorized by Support Vector Machines (SVMs). The transfer learning approach was applied to detect rice leaf disease using a deep convolutional neural network. The highest classification accuracy of the system was 97.31% using features and the lowest classification accuracy was 94.40% using features [9].

Identification of rice diseases and classification by color characteristics. The proposed system designed was an automated system for the detection and classification of rice diseases. Color features were extracted from rice diseases. Several classifier algorithms were compared and the highest accuracy of 94.68% was achieved using a Support Vector Machine (SVM) classifier [10].

Methodologies for detecting and classifying rice diseases include image preprocessing, segmentation, and feature extraction. The proposed system was classified using both the k-nearest neighbor method (k-NN) and the minimum distance classifier (MDC) and evaluated images of rice leaves of various diseases. In addition, 70% of the image data was used for training and the other data was used for testing. The accuracy results were 87.02% for K-NN and 89.23% for MDC [11].

The proposed system uses image processing to identify and classify paddy disease diseases based on the RGB values of the infected area. This system has succeeded in identifying several rice diseases such as rice blast, rice blast, and rice blast. This system produces 90% classification accuracy for brown spots, 90% for bacterial leaf bright, and 89% for rice blasts [12].

Many fungal and bacterial diseases infect rice leaves and nodes at various stages, causing loss of growth and production. The proposed system was developed by [13] as an automated system for identifying and classifying many diseases of rice. This method detects some diseases in a wide area of rice cultivation. The system also improves accuracy performance.

The suggested solution uses machine learning and image processing to increase the accuracy of identifying illnesses in rice leaves. The proposed approach made use of numerous classification strategies for rice leaf diseases. Results of rice leaf diseases are classified and provided with an accuracy of 94.6 percent using the Histogram of Oriented Gradients (HOG) and Support Vector Machine [14].

The project aims to develop a software system that can automatically identify and categorize diseases. Utilizing the Minimum Distance Classifier (MDC) and the k-Nearest Neighbor classifier, all of the collected features were combined according to the diseases (k-NN). The classification accuracy for each disease was calculated using both classifiers. The overall accuracy while using k-NN and MDC is 87.02 percent and 89.23 percent, respectively. For two diseases, rice blast, and rice brown spot, both classifiers have the same classification accuracy; however, for the other two diseases, blight and sheath rot, MDC has a greater classification accuracy than the k-NN classifier [15].

Early diagnosis of rice illnesses, particularly those affecting the leaves, enables farmers to take the required safeguards early on for higher-quality crops. It is usually desirable to use RGB color photographs as inputs and to offer analysis results even with RGB color images when creating an automated system for classifying and recognizing rice blight. The study suggested a suitable framework that combines improvements, filters, color segmentation, and color functionality for identification classification processes. To improve the detected accuracy rate, a CNN classifier was used. This framework, suggested by the poll, offers an acceptable accuracy rate of 91.43 percent in comparison to other existing methodologies[16].

Rice output can be boosted by identifying rice pests and illnesses and effectively managing paddy areas where pests are common. Farmers can help other farmers recognize and identify the many kinds of pests and diseases in their rice fields with the aid of cutting-edge technology, such as cell phones. Find rice diseases by utilizing a convolutional neural network and the r programming language to analyze photos from the disease sheet. Three diseases—bacterial leaf blight, brown spots, and leaf smut are among the disease patterns gathered from the UCI Machine Learning Repository. The training image can be improved to produce better outcomes[17].

One of the intriguing research areas in computing and agriculture is the detection of illnesses using photographs of plants. To diagnose rice diseases from photos of damaged rice, the study paper presents an overview of several image processing and machine learning techniques. In addition to outlining the various methods, the white paper also provides a succinct overview of the main image processing and machine learning ideas that are relevant to the identification and classification of plant diseases. 19 articles on various plants and fruits, including rice illnesses, will be examined in more detail, and they will be summarised based on important factors. The size of the image dataset is one of these factors. categorization of the class (illness), preprocessing, segmentation technique, classifier kind, classifier precision, etc. We propose and shape work on the characterization and classification of illnesses in rice plants using research and more study[18].

In the agricultural sector, rice diseases have considerably decreased output and cost money. To manage and lessen the effects of assaults, early disease detection is crucial. Early detection of disease severity and outbreaks can help to prevent production from suffering both quantitative and qualitative losses while also reducing the demand for pesticides and fostering national economic growth. This study describes an integrated approach for diagnosing Rice Blast, a leaf disease, using image processing techniques (RLB). The image preprocessing, image segmentation, and image analysis processes all employ the Hue Saturation Value (HSV) color space. Areas of interest are extracted using the most important image processing technique, picture segmentation, and a multi-level thresholding approach-based pattern recognition method is offered. As a result, the infection stage, the dispersion stage, and the worst stage of the RLB disease may be identified. This technique successfully detects disease in images taken in an uncontrolled environment [19].

By developing disease-resistant varieties, rice bacterial leaf blight (BLB) can still be economically and efficiently controlled. Breeders have contributed greatly to the development of BLB-resistant rice varieties. The dangerous illness known as BLB infection has been found to significantly reduce rice production. Picking rice with many resistance genes will be challenging using just the traditional method. This is due to the masking effect that genes, including epistasis, have. Furthermore, using traditional breeding techniques, it takes a very long period to develop the target gene. Interconnect resistance is a big challenge with traditional approaches. Through the use of markers in molecular breeding, the identification and introduction of BLB disease-resistance genes were made simpler. Rice genetic engineering (introduction) is another biotechnology-enabled invention. Although a molecular approach to combating BLB disease in rice farming is beneficial, the increasing demand for rice farming in a rapidly growing societal population prevents molecular breeding from replacing traditional breeding. The research focuses on recent advances in creating BLB disease-resistant rice cultivars utilizing molecular methods rather than conventional methods [20].

Accurate and early diagnosis of rice diseases and pests enables farmers to process rice quickly and significantly lower economic loss. Deep learning-based convolutional neural networks (CNNs) have lately made significant progress that has significantly improved the accuracy of picture classification. Based on CNN's success in picture categorization, this article has built a deep learning-based system for identifying diseases and pests from photographs of rice. There are two contributions in this publication. (I) Inception V3 and VGG16, two contemporary large-scale architectures, have been employed and enhanced for this purpose. Experimental results show how effective these models are using datasets from the real world. Because current CNN architectures like MobileNet, NasNet Mobile, and SqueezeNet are not appropriate for mobile devices, a two-tiered small CNN design was proposed and contrasted. Experimental results show that the proposed design may significantly reduce model size while maintaining the required accuracy of 92.3%[21].

3. Proposed Model

The automatic diagnosis of rice diseases using the convolutional neural networks (CNNs) model was developed in the research study by [22]. Images of healthy and sick rice crops were taken using datasets of those crops. The CNN algorithm was trained to recognize various widespread illnesses affecting rice. Most rice-variety diseases are universal. Using image processing technology for the early identification and classification of rice diseases would be more useful and relevant in the proposed methodology (Figure 3)

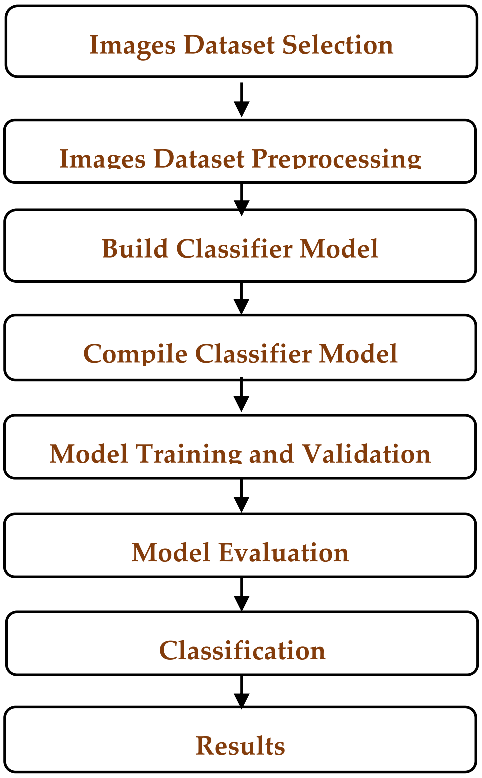

Figure 3. The Basic Steps of Methodology

Using digital image processing and machine learning, the suggested approach correctly detects diseases in the early stages of the rice crop. The goal of its research is to create a prediction and classification model that can safeguard farmers from dangers associated with rice production. Farmers detect appropriate characteristic combinations, such as temperature, water availability, and weather, to determine which performs best and how much rice yield production can be expected based on these values. Those features determined by machine learning will be more important and have a favorable effect on rice crop growth.

3.1. Material and Methods

This chapter briefly describes the methodology of the proposed system. The proposed methodology (Figure 4) contains six phases.

1. Image Acquisition
2. Image Pre-processing
3. Feature Extraction
4. Optimized Dataset
5. Classification Model
6. Visualization

3.2 Proposed Methodology Workflow

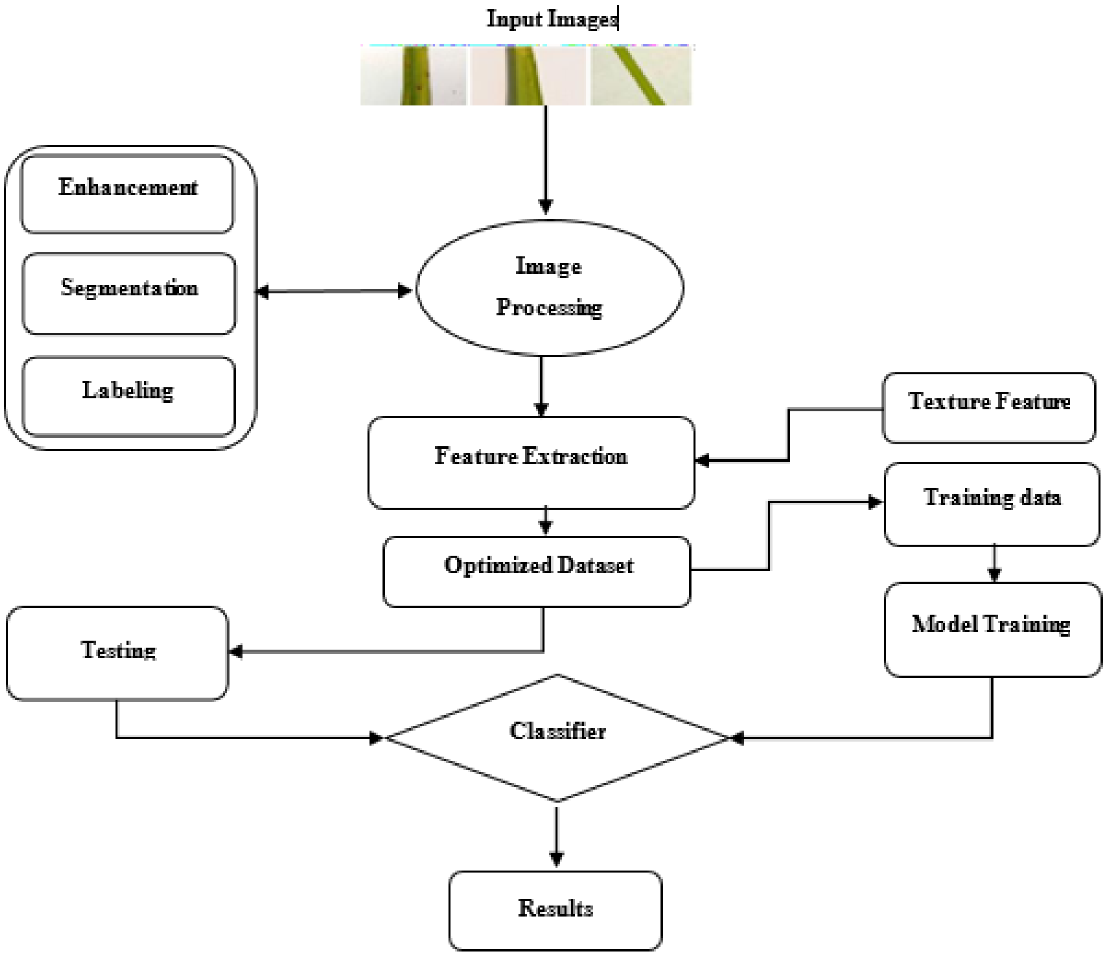

Figure 4: Methodology Framework

3.2.1 Image Acquisition

A dataset collection of several raw images of rice leaves makes up the first stage. We call for healthy leaf photos as well as photographs of illnesses like brown spots and bacterial leaf blight from various existing datasets. The gathered photographs are kept in JPEG formats. Rice disease datasets are collected for their detection and classification. The rice disease dataset contains 480 images of the two most popular commercial diseases, Brown Spot and Bacterial Blight (more than 140 images of each variety). To identify and classify the above diseases, the dataset was divided into two categories.

High-resolution digital photography and recording devices are more available and cheaper. Additionally, SEM and associated image acquisition methods offer a way to capture images with a resolution that contains both structural and elemental data. Choosing the best imaging option for your research challenge is still a crucial step in sediment research, despite the emergence of novel acquisition methods and gear. In addition, there are common methodologies and concerns for acquiring the best images for quantitative sediment analysis despite the diverse acquisition techniques. To quantify differences in characteristics between photographs, each image must also contain color or an equal image standard. Last but not least, your research objectives should be appropriate for the image resolution and file storage procedure, which should preserve the original image information[15].

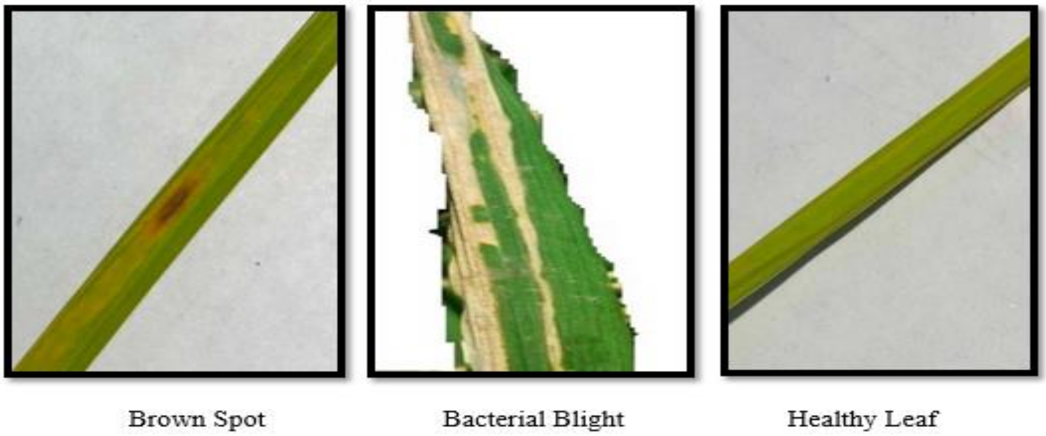

Figure 5. Brown Spot, Bacterial Blight, and Healthy Leaf

3.2.2 Image Pre-processing

By showcasing the best outcomes of the image, image enhancement is a key goal of image preprocessing. These procedures, which involve resizing, enhancing the image quality, and color correction, are carried out before the model training [23]. The detection of local and global features can be improved by making intelligent use of picture preprocessing, which can also solve issues. Preprocessing is done to enhance the image's quality so that it may be better evaluated. Pretreatment can reduce unwanted distortion and improve some of the characteristics required for the particular application you are working with. These features may vary from application to application. Image processing is crucial to computer vision.

The process of turning an image into a digital representation and then executing operations on it to extract important information is known as image processing. Image preprocessing is an integral part of the classification of images processed for research purposes. The need for pretreatment arises from a variety of lighting conditions, dimensional differences, and so on[24]. Input image preprocessing is typically done on the CNN`s input layer. Many pre-processing such as normalization, trimming, resizing, etc. may be required. However, CNN required much less preprocessing. Next, is another neural network. However, simple pre-processing is required to remove unwanted parts of the image. The ratios for the training and test datasets are 80% and 20%, respectively. The CNN classifier (test V3) was trained using a training dataset.

3.2.3 Feature Extraction

The best outcome of the provided dataset is used for the feature extraction. The texture feature will be used to extract details from various pixels' brightness and intensity. The characteristics can be applied to rice leaves' diseased parts [25]. The two fundamental building blocks of all pattern recognition and computer vision systems are feature extraction and classifier designs. The most challenging but crucial phase in the analysis of visual patterns is the extraction of robust and discriminating characteristics from an image. Several common and sophisticated methods for extracting features from photos are being taken into consideration, some of which have already undergone in-depth analysis. Here is an illustration of how to use these feature extraction techniques to address challenges with image-based disease detection and classification. These use examples illustrate concepts, theories, and innovations in feature extraction methods, as well as their benefits and drawbacks in dealing with practical issues [26].

3.2.4 Optimized Dataset

Following feature extraction, these characteristics will be refined to create an optimal dataset that takes advantage of and analyses data from each class in real time. Consequently, the feature optimization approach might be useful for the problem [27] by selecting only pertinent data and eliminating noise from the data, feature selection is a technique for lowering the number of model input variables. This approach involves choosing features for your machine learning model on an automatic basis based on the kind of problem you are attempting to address. Utilize various techniques to identify the most useful dataset [28].

3.2.5 Classification Model

Machine learning classifiers come in a variety of forms. Our dataset will determine which categorization model we use [29]. A structural neural network with many layers is called a convolutional neural network. The convolutional layer is the top layer of the CNN network. The majority of the computing power is handled by this fundamental building piece. A filter or kernel is used to reduce the size of the data or image. A sliding window allows you to apply a small unit called a filter to your data. Others ML classifiers like KNN, Inception V3, and, VGG19 were also deployed.

3.2.6 VGG19

A 19-layer, the collapsible neural network is called VGG19. From the ImageNet database, you can load a network that has already been trained using more than 1 million images. You may classify your photographs using a pre-trained network into 1000 different object categories, including keyboards, mice, pens, and various animals. The network has therefore acquired a comprehensive feature representation of a variety of images. The network image's input dimensions are 250x250. Over the VGG19 network, classification enables you to classify fresh images. Observe the procedures for using Google Neural Network to classify photographs, then use VGG19 in its place. Follow the training instructions for the deep learning network to identify the new photos and load VGG19 (Figure 6) rather than GoogleLeNet to retrain the network for a new classification assignment [29].

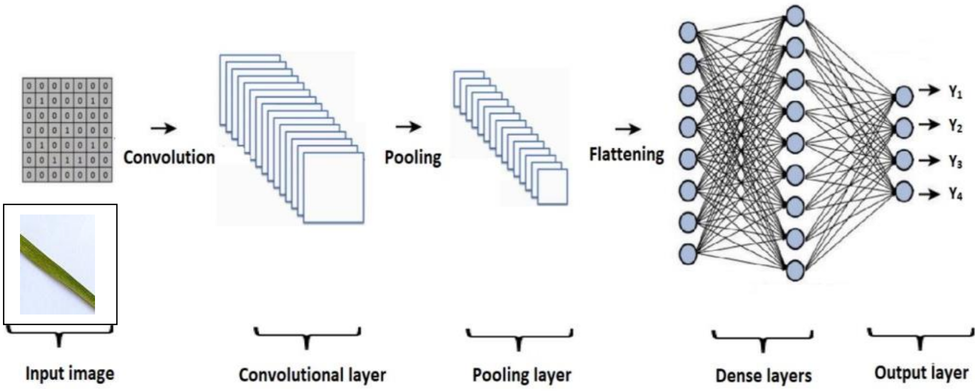

Figure 6. Image Detection Using VGG-19 with CNN

4. Results

The proposed work's experiments have produced positive classification results, with the maximum average classification accuracy using the first KNN model accuracy being 67.18%, and second Inception V3 model at 93.57% and the final VGG-19 model being 97.94% respectively. The classification results show that the suggested Inception V3 and VGG-19 CNN models performed nearly as well as the outcomes reported in recently published works. The proposed method has greater potential for classifying many forms of rice diseases with more variety of symptoms than prior studies carried out by other researchers, therefore the overall classification performance is satisfactory. The parameters that we used in our work are given in Table 1.

Table 1. Values of the parameters of VGG19 used in our experimental

Parameters	Parameters Values
No. of Layers	24
Learning Rate	0.001
Dropout	0,5
Validation Threshold	20
Epoch	10(min), 20(max)

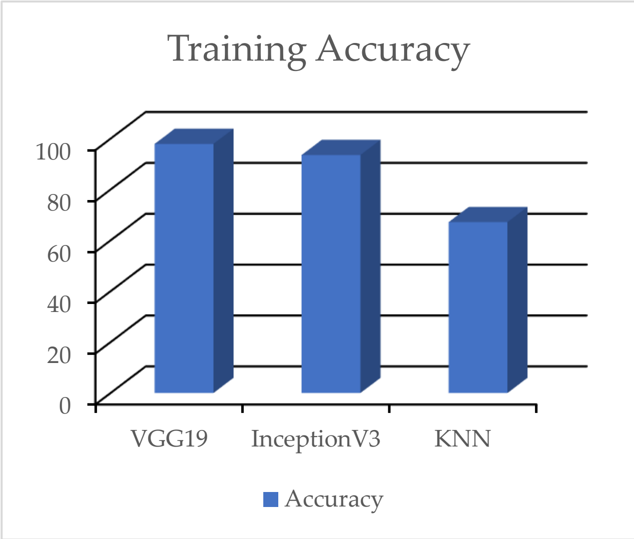

Figure 7. Comparison of Training Accuracy

Figure 7 and Figure 8 show the training accuracy and validation accuracy results of the models that are used in this study. VGG19 was more suitable than others as the results show by getting high accuracy. Overall results comparison are shown in figure Figure 9 as VGG19 topping the chart.

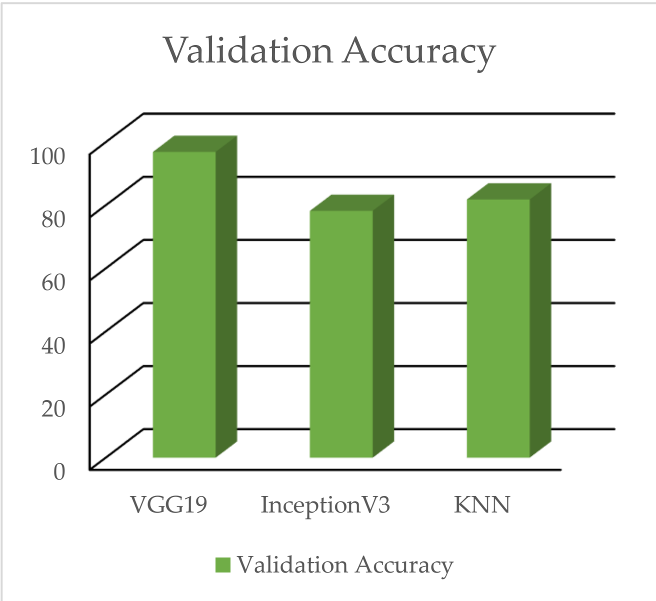

Figure 8. Comparison of Validation Accuracy

5. Discussion

The comparison outcomes of the suggested methodology to cutting-edge publications. The literature reports work on the use of various image processing and machine-learning techniques to identify diseases affecting rice leaves. The classification of rice disease symptoms, however, is done in the current work employing cutting-edge deep learning models using fresh datasets and combinations. The majority of the literature is concentrated on a small number of disease types identified on rice leaves. Compared to an earlier study by other researchers, the dataset includes a wider variety of rice diseases with a wider range of symptoms. The suggested approach takes into account the automatic detection of rice diseases brown Spot and Bacterial Blight that affect rice leaves. Although baseline training, also known as training from scratch, performs better than transfer learning, the results are still unsatisfactory. Less than 85% of the two models are accurate. To discover sets of the kernel to extract good discriminative features, CNN uses a set of kernel matrices as a local feature extractor to extract regional features. The hyperparameter needed to be adjusted in the proposed model. Other techniques, such as K-NN and Inception V3 classifiers, are also employed for classification. But third and VGG19 model accuracy is above 95%. By gathering data on rice leaves, this model also aids in disease identification. Performance outcomes of VGG19-based deep feature extraction and transfer learning. Low precision is also indicated by the enormous standard deviation of the validation accuracy.

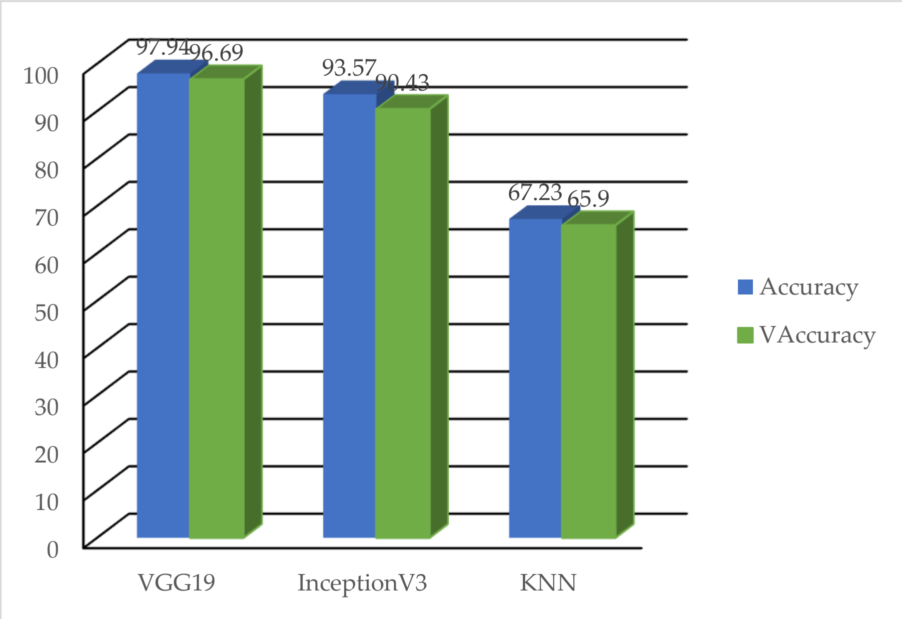

Figure 9. Comparison Analysis

6. Conclusion

The tests conducted on the database of rice leaf diseases, including Brown Spot and Bacterial Blight, are analyzed in this work. Many pictures of both healthy and diseased leaves have accumulated. Images of the leaves will be used to classify them as either healthy or infected. The proposed system prediction and classification of diseases of rice leaves. This is beneficial not only for farmers but also for exporters. Rice leaf disease predictions are rice estimates using received historical data such as weather and rice crop attributes. It not only provides information on rice leaf disease but also estimates important parameter values for rice that farmers need to take into account for maximum production. We will also explain the results of the experiment. In the comparative analysis with the various models performed in this paper, the results are obtained and explained using the proposed methodology using graphs and tables. Results are obtained at 80% and 20%, respectively, depending on the dataset distributions of the training and test datasets. The implementation of the proposed methodology is carried out for the best results. Additionally, we will use prototype picture acquisition and machine vision models for the early detection, categorization, and determination of intelligent real-time rice cultivation. The implementation of the proposed methodology is carried out for the best results.KNN accuracy is 67.18%, and Inception V3's automated system produces 93.57% accuracy results. And the other best automation system with VGG19 accuracy results is 97.94%. In general, in deep learning of dataset distributions, the larger the training dataset and the higher the quality of the dataset, the better the performance. To increase Pakistan's rice exports, the proposed methodology can be put into practice on a wide scale for automatic identification and categorization by global standards.

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