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Machine Learning-Based Algorithms for the Detection of Leaf Disease in Agriculture Crops

Jyoti Dinkar Bhosale[1], Sushma Sambhaji Thorat[2],Priti Vijaykumar Pancholi[3], Prasad Raghunath Mutkule[4]
[1]Assistant Professor, Department of Computer Engineering,
VDF Group of Institutions School of Enginerring and Technology,
Latur, India-413512
bhosale.jyoti3@gmail.com
[2]Assistant Professor, Department of Civil Engineering,
VDF Group of Institutions,School of Engineering and Technology,
Latur, India-413512
thoratsushma@rediffmail.com
[3]Assistant Professor, Department of Computer Engineering,
MBES College of Engineering,
Ambajogai, India
prity.panchal@gmail.com
[4]Assistant Professor, Department of Information Technology,
SRES's Sanjivani College of Engineering,
Kopargaon, Maharashtra, India- 423 603
mutkuleprasad000@gmail.com

Abstract—Identifying plant leaves early on is key to preventing catastrophic outbreaks. An important studyarea is automatic disease detection in plants. Fungi, bacteria, and viruses are the main culprits in most plantillnesses. The process of choosing a classification method is always challenging because the quality of the results can differ depending on the input data. K-Nearest Neighbor Classifier (KNN), Probabilistic NeuralNetwork (PNN), Genetic Algorithm, Support Vector Machine (SVM) and Principal Component Analysis,Artificial Neural Network (ANN), and Fuzzy Logic are a few examples of diverse classification algorithms.Classifications of plant leaf diseases have many uses in a variety of industries, including agriculture andbiological research. Presymptomatic diagnosis and crop health information can aid in the ability to managepathogens through proper management approaches. Convolutional neural networks (CNNs) are the mostwidely used DL models for computer vision issues since they have proven to be very effective in tasks likepicture categorization, object detection, image segmentation, etc. The experimental findings demonstrate theproposed model's superior performance to pre-trained models such as VGG16 and InceptionV3. The range ofcategorization accuracy is 76% to 100%, based on.

Keywords-Convolution Neural Network (CNN), supervised learning, plant leaves dataset, VGG16, riceleaves diseases.

I. INTRODUCTION

Look about how much food you eat each day. Take into account the current population of the planet and the amount of food needed to feed everyone. Industrialized agriculture has produced much of the food needed to feed the world's population since the development of agriculture. Currently, this style of agriculture produces enough food to feed every person on the earth due to a sharp increase in output since the 1960s [1]. For rice to thrive, certain particular conditions must be met. It must be grown in a paddy field, a field that has several inches of water flooding into it. Unsurprisingly, China and India are the top two countries in the world for rice production. Because rice has such a bland flavor, it may be used in almost any cuisine and combined with any flavor. In China, steaming rice is frequently eaten with stir-fried meat and veggies. Agricultural issues endanger the future of the food supply notwithstanding industrial agriculture's effectiveness in generating huge amounts of meal. Two of agriculture's biggest issues were a decline in agricultural land and a drop in crop types [2]. The best way to end famine is to increase food production. In addition to being a significant food crop, rice is consumed by many millions of people worldwide. Every year, pests and illnesses harm rice fields, which is a major issue for farmers that don't monitor and properly care for them. In addition to sound crop planning, quick detection and treatment of crop illnesses will prevent rice from contracting a serious infection and drastically cut losses. Making sure that farming is done in a healthy manner is made possible by the treatment of these diseases [3]. Therefore, utilizing an expert system to identify plant diseases is a useful approach to ensure that farming is carried out in a safe manner by making accurate decisions on how to spot plant illnesses. Deep convolutional models have recently gained popularity as a method of picture

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classification for a variety of agricultural issues, including the detection of plant illnesses, the identification of weedsthe counting of fruits, etc. Deep learning is based on neural networks that can learn and employ strategies to make wise decisions [4]. Things like the climate, sunlight, humidity, fertilizer, water management, and how the plants are produced can all contribute to diseases in rice plants. Many individuals have watched CNN in recent years [5].

Each nutrient has a unique personality and takes part in a number of different metabolic processes in plants. Nutrients have an impact on a plant's ability to withstand sickness or pathogens. Most of the time, these issues are not apparent until after the plant has been harmed. Therefore, it is critical that technology continue to advance so that farmers and specialists can identify these issues early on. Many innovative and inventive measures have been taken to address this issue. Machine learning, image processing, and machine learning have all been used frequently in recent years to detect and monitor when plants are lacking in nutrients. These techniques, combined with algorithms to minimize the dimensions, are essential if the test hypothesis forecasting is to be used in an embedded system. Examples of these techniques are brown spot, leaf detonation, and bacterial leaf [6]. The classification of leaf diseases has two primary sources. The use of previously trained VGG-16, ResNet50, and InceptionV3 CNN models on a sizable dataset like Kaggle to perform the transfer learning technique.

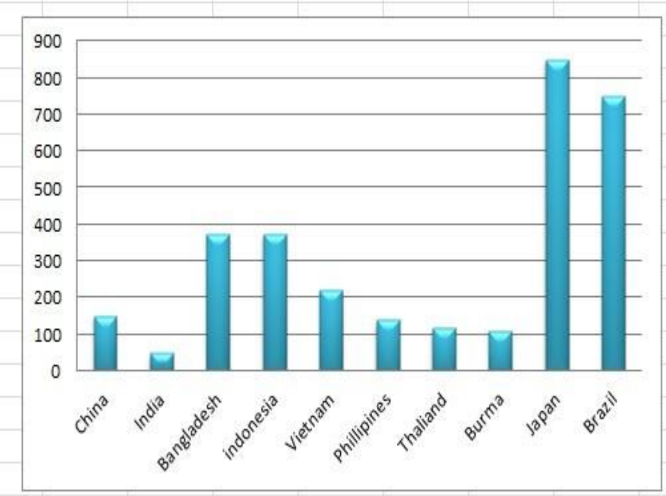

Figure 1. Rice Consummation in different Countries

II. LITERATURE REVIEW

Plant classification serves a variety of functions, including plant naming, information extraction, research of characteristics that affect fruit and vegetable productivity and quality, and price prediction. Next, a few illustrative classification strategies are shown.

Malicious software, often known as malware, has typically been employed for illegal activities, and new variants are always being discovered. By having the ability to group tests with similar components into families, it is feasible to create support methods that are applicable to a broad range of jobs. In order to remove bottleneck features from malware tests, which are represented as byte plot grayscale images, bottleneck features are removed using the convolutional layers of a VGG16 basic neural network set up on the ImageNet dataset. The initial results on a dataset with 10,136 models from 20 explicit families demonstrated how our approach can be used to depict malware families with an accuracy of 92.97%, outperforming similar techniques for thinking proposed in the making that require feature orchestrating and extensive space knowledge [7]. An important association between seed openness, phenotypic social gathering, and verified rearing is the clear proof of secure groupings. This evaluation incorporates nuts, for instance, to examine yet another strategy for crop grouping identification. Nuts are an important source of income and an oil crop. Starting with the creation and nature of each shift, it is essential to observe and classify various nut varieties. Using massive learning progress, the fundamental convolutional neural network VGG16 was also developed in this piece, and it was afterwards utilized to recognize and arrange 12 unusual groups of peanuts. To offer the nut security educational record, the 3365 images of 12 beautiful types of nut units that were collected by the scanner were preprocessed using grayscale, finalization, and ROI extraction. VGG16 has undergone numerous movements. The entirely connected layers F6 and F7 of the VGG16 should be removed [8]. According to the essay above, rice plants frequently exhibit indicators of nutritional deficiency in their leaves. So, by examining the color and shape of rice's leaves, you may determine whether the rice is receiving enough nutrients. The use of a classifier is a practical and efficient method for this type of diagnosis job. Although fully convolutional channels (DCNNs) have proven to be effective at identifying images, little research has been conducted on using them to determine which nutrients are absent from rice. According to this study, DCNNs are a useful tool for identifying the nutrients that rice is lacking [9]. Microorganisms that affect plants cause important accumulating yield problems all throughout the world. The most effective way to lessen the naughtiness of plant diseases has been the focus of numerous professionals. A team of two to three experts looked at the plant's defenses mechanisms and tried to break down the plant's protections against microbes. With the help of images of leaves, two or three experts created specific evidence and scoring structure to monitor and foresee plant troubles. The goal of this audit is to explain how AI is being used to classify plant ailments

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and expose plant preventative features [10]. The particular area of gather sicknesses presents ranchers with a significant barrier during the new turn of events and creation seasons of maize. For the three corn problems that were investigated, the method described in this examination had an average end exactness of 93%.It is more exciting and significant than the other four systems and can be used to protect crops in developing countries[11]. The core of the Indian economy is agribusiness. The second-highest ranch yields on the earth are in India. Its dedication to the growth of the Indian economy has enormous potential. Agribusiness could thus admit a significant role in recent financial development. However, several plant diseases slow down the production of harvests and the rate at which ranchers advance. It is quite difficult for ranchers to truly detect and screen for leaf diseases. This serves as one source of motivation for the modified leaf defilement affirmation model. The suggested methodology helps to change clear signs of many plant diseases in their early phases. In this way, the creation will multiply many times over. This study's urgent element is its focus on numerous leaf diseases. In this way, the creation will multiply many times over. This study's urgent element is its focus on numerous leaf diseases. To coordinate different types of leaf loads, Support Vector Machine (SVM), Random Forest, and Logistic Regression have been used. When the collected results are broken down, SVM outperforms the other two classifiers. Results demonstrate how the model can be applied in real-world settings [12]. One of the hypnotizing evaluation fields with regard to the expanding region is plant leaf infirmity noticeable confirmation and strategy. In this research, a method for identifying and organizing paddy leaf issues is proposed, taking into account photo handling and AI methodologies. When calculating the presentation of this suggested process, contaminations from leaf blast, brown spot, and bacterial leaf blight are taken into account. The burden location in the paddy leaf is perceived using combination thresholding. As a result, notable part groups like tone, surface, and shape highlights are restricted from the affected area of the damaged image.

SupportVector Machine (SVM) and k-closest neighbors (k nearest) assessments are used as classifiers, and these classifiers are used to study the introductions of the proposed perspective. The results of the exploratory study are divided, and cutting-edge work is getting closer. The accuracy of our suggested method in detecting rice plant problems such as leaf scourge, coarse concealed spot, and leaf impact is 89.19%, 82.86%, and 89.19%, respectively [13]. Disturbance and confusion ID is a fundamental control of rice improvement in the current developing sector. Paddy production is at risk from unsettling forces and issues, particularly in India, but ID continues to be a challenge in large-scale expansion and frequently. The results demonstrate how, with a best accuracy of 96.50%, [14]. With the minimal batch size, weight, and bias learning rate as hyper-parameters, AlexNet and VGG16net were trained. In the case of VGG16net, accuracy and minimum batch size are inversely associated [15]. For binary classification, a CNN with a local contrast normalization layer and ReLu as the activation function are created [16]. By using variable momentum rule with CNN to learn parameters from images of lesions produces a speedy convergence with comparatively high accuracy [17]. Machine learning provides trustworthy predictability algorithms [18].

III. METHODOLOGY

Here, we go over the suggested methods. The proposed methodology's phases are briefly detailed in the sections before and are illustrated in Figure 2. The block diagram in Figure. 2 depicts the entire methodology for fungal blast illness detection that has been described in this section. For the best precision, each step is carried out. For a better comprehension of the dataset, various image processing techniques are used during image capture, such as image cropping, color improvement, and image scaling. 20% of the 70% of the data are used for validation. For training and testing, the computer receives the picture data set. Arrays are used to hold both the class labels and the associated images.

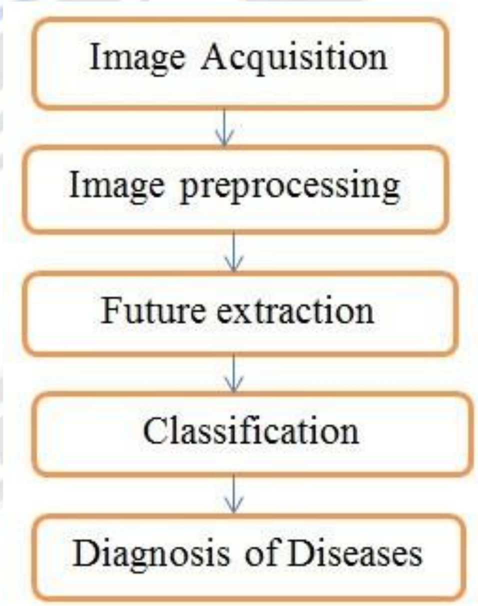

Figure 2. Types of Rice Leaf disease

A. Data Collection

The data is separated between the training and testing phases by the train test split function. Validation involves 20% of the 70% of the data. Tensor Flow offers a set of procedures for building and training models in Python or JavaScript, as well as forquickly deploying them in the cloud, on-premises,

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via a browser, or even on a device. A high-level neural network API called Keras is designed to enable quick experimentation.

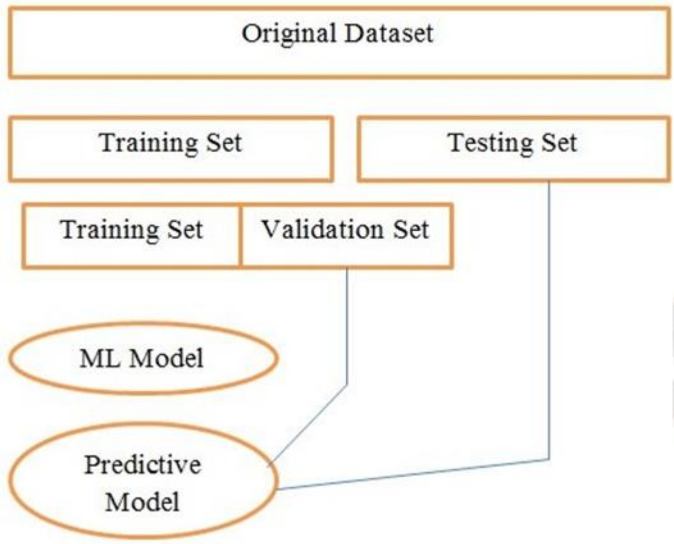

Figure 3. Training and Testing dataset

The images were captured online and on the playing field. The dataset description lists four categories of images: Leaf Blast, Leaf Blight, Brown Spot, and Healthy Plant Images. The Keras Image Data Generator resizes the photographs and adds enhancement techniques like zoom, rotation, and horizontal and vertical shift to produce new images. The picture data set is transmitted to the computer for training and testing. Both the class labels and the images that correspond to them are stored in arrays. The train test split function divides the data between the training and testing phases.

Figure 4. Types of Rice Leaf disease

For testing, we selected 50 photographs at random from the training set of each class and deleted them from those files. We created our project's training dataset using the remaining training data by inserting the identical number of photos (1000) in each class. We employed a data augmentation technique to create some new photographs when any class had fewer than 1000 images. By rotating, flipping, cropping, and resizing the current photos, the Augmenter package of Python allows for the creation of similar new images.We used the same procedure for the validation dataset and gave each class 700 photos. This procedure is required to stop prejudice for any specific class during CNN training. All of the photographs are 256×256 in size and are in the jpeg format.

B. Data Preprocessing

Convolutional neural networks were used to process the preprocessed images as soon as the photos of diseased paddy leaves were taken. Convolutional blocks are used by models to extract the most crucial information from the images they receive as input. The properties of the images determine the weight in. Classifying the input data is aided by the network's last dense step and a training strategy like soft max. Before the images are loaded into the dataset, the machine does pre-processing on them by rotating, zooming, turning, shuffling, or resizing them. Four completely Convolutional Net V2 Xception will be used to extract classification features. Finally, make a prediction using the most accurate model. The quantitative application of this research is based on deep learning. The research methodologies project is described here.

C. Feature Extraction

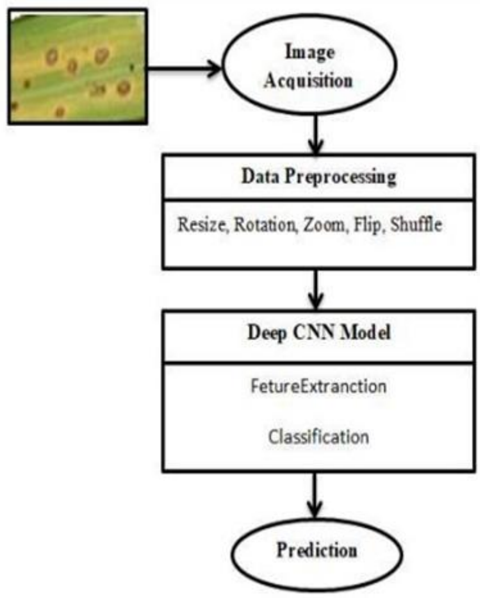

Figure 5. Steps for Prediction Flowchart The methodology's steps were followed. Data collection is the first step, then comes study, data processing, and finally feature extraction Classification is done in the end.

A crucial step in using features to study an image in depth is feature extraction. Utilizing the image to get information is beneficial [19]. The choice of features directly affects the classification procedure. Although it is computationally demanding, obtaining a small number of characteristics from the feature space is desirable because it can rapidly increase immensely. The generalization of results might easily be hampered by excessive feature extraction.

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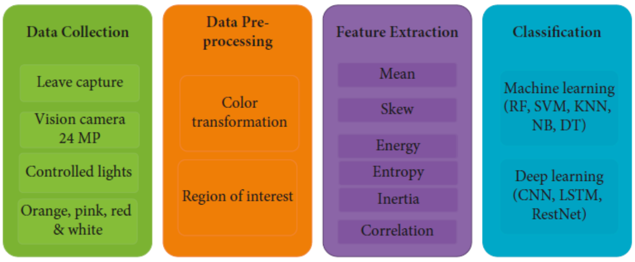

Figure 6. The methodology's steps were followed. Data collection is the first step, then comes study, data processing, and finally feature extraction Classification is done in the end

IV. Experimental Results and Discussion

All of the classification accuracy and report outcomes have been thoroughly reviewed in this section. The VGG-16 classifier has been applied in two situations—without data augmentation and regularization, and with data augmentation and regularization—to categories healthy and unhealthy photos. The top layers of both VGG-16 classifiers have been disabled, and a new model using VGG-16's pre-trained weights has been developed. In a summary, the VGG16[20] CNN architecture has an input image size of 224×224 and was developed by the Visual Geometry Group at the University of Oxford. To maintain the same solution of the intermediate output, filters are 33 in size and padded. It features 3 Dense layers in addition to 13 Convolution layers. A 42-layer deep learning network with fewer parameters is Inception V3 [21]. Convolutional factorization is used to reduce the parameters. For instance, two 33 filter convolutions can do a 55 filter convolution. In this procedure, the parameters drop from 5×5=25 to 3×3+3×3=18.

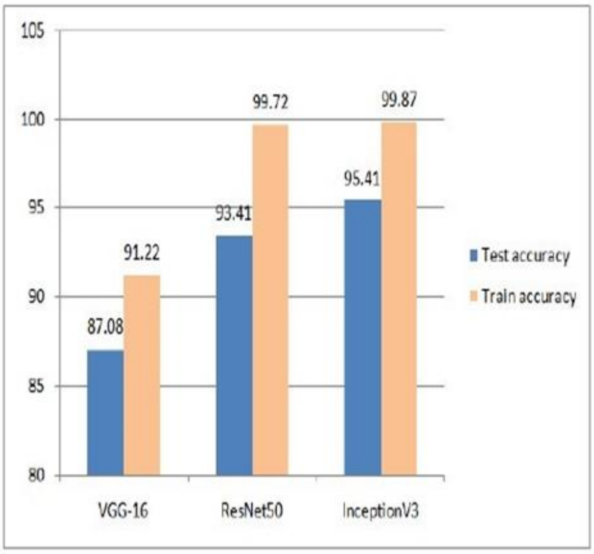

Figure 7. The Testing and training accuracy

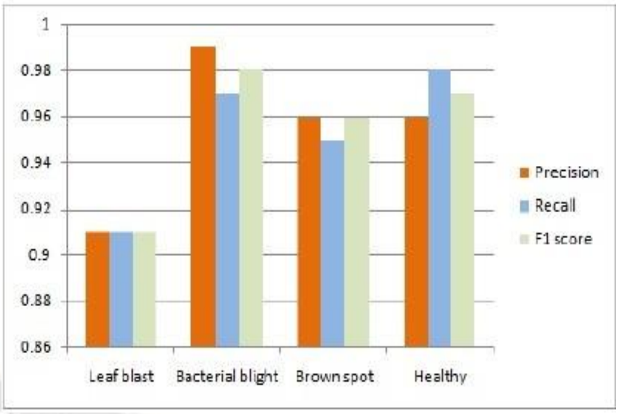

Figure 8. Values for the F1 score, recall, and precision for transfer learning models

Using pre-trained deep convolutional neural networks such VGG-16, ResNet50, and InceptionV3 that were implemented with a transfer learning approach; this study is demonstrated for the identification of rice leaf diseases. On four classes of rice leaf images in the dataset, the effectiveness of the suggested models is evaluated. Using various hyper parameters, the VGG-16 model was adjusted until it had an accuracy of 87.08% after 15 iterations. ResNet50 and InceptionV3 both used 10 epochs and fine- tuned a number of hyper parameters to achieve optimal accuracy of 93.41% and 95.41%, respectively. Research on convolutional neural networks will be conducted in the future to classify additional varieties of rice diseases and other plant leaf diseases.

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