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Paddy Leaf Disease Detection using Convolutional Neural Network

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Abstract: Rice is the primary source of nutrition for more than 140 million Bangladeshis. Rice as a food, not only meets the protein and calorie needs of the ordinary individual, but rice production also contributes to the country's rural employment and GDP. However, rice production is impeded by a variety of rice leaf diseases. The goal of this project is to create a model that can forecast disease outbreaks so that farmers can take appropriate measures. These findings provide a CNN-based model that can accurately forecast various illnesses of rice plant leaves with 97.40 percent accuracy. 900 photos of diseased and healthy leaves were used. The model was trained to identify four prevalent rice illnesses using 10-fold cross validation procedures.

Keywords: deep learning, CNN, Paddy leaf, disease prediction.

1. INTRODUCTION

India is mostly a farming country. India is now the world's second-largest producer of agricultural products. Nowadays, a new concept of smart farming has emerged, in which self-operating systems are used to govern and monitor field conditions. The self-recognition of disease is based on the recognition of disease symptoms. So that farmers, professionals, and researchers may receive timely and reliable information regarding the disease's presence. In 2020-2021, India's agriculture sector employed 50% of the workforce and contributed 19.9% of the country's GDP. The agricultural sector needs to be supported by the most recent technology breakthroughs in order to secure excellent yields. Insect damage and plant diseases cause significant losses in agriculture crops. By 2050, the world's population is predicted to reach 9.2 billion people.

As a result, human surveillance of huge fields is reduced. The key to illness recognition from an image is to identify the afflicted region's distinguishing feature. The symptoms may differ depending on the condition. Col or, shape, texture, and other properties are taken from the image. More features are sometimes extracted for illness identification, and these extracted features would increase the hardware and software costs. This increases the complexity of the problem and the time it takes to solve it. As a result, the feature data must be reduced.

The presence of the disease on the plant can lead to considerable losses in both the quality and quantity of agricultural products. This could have a negative influence on countries.

1.1 OBJECTIVE:

- To enhance the given input image by Image acquisition and Image pre-processing.
- Identify the affected part through texture analysis and Segmentation.
- Classify the healthy and affected leaf part by feature extraction and classification.

Train the model by using testing data for accurate result.

1.2 PROJECT SCOPE

Diseases can be caused by pathogens in plants in any environment. Diseases are usually visible on the leaves of plants; hence disease detection is critical for good crop production. There are a variety of approaches for detecting illnesses in plants in their early stages. Conventional plant disease detection methods rely on naked eye inspection and are ineffective for large crops.

Plant disease diagnosis is effective, time-saving and accurate when using digital image processing and machine learning. This method reduces time, effort, labor and pesticide use. I'm hoping that this strategy will make a small contribution to agriculture fields..

2. LITERATURE SURVEY

Sherly et al. (2019) The deep learning prediction method has been deployed to identify different diseases caused by various types of bacteria or fungus in plants. The classification method is difficult to use to categories diseases since it does not produce correct findings, which is mostly due to the program's diverse data input. Various algorithms are put to the test by different researchers. Moreover, different operations result in different outcomes. As a result, we can deduce that plants are susceptible to a variety of viral, bacterial, and fungal infections. Physical properties are classified and automated using the classification technique. The CNN technique can be used to detect illnesses in a variety of plants including rice, apple and mulberry.

Yashpal Sen, Chandra Shekar Mithlesh, Dr. Vivek Baghel

describes a method for detecting agricultural illness in order to boost rural economic prosperity. An automated method for diagnosing and classifying different illnesses of contaminated plants is an emerging study subject in precision agriculture, as mentioned in this paper. This paper explains how to avert a large loss in a crop by detecting infections early on. Because most diseases only affect leaves, the internet's region is leaf. The input image is pre-processed with histogram equalization to boost contrast in low-contrast images, and the K-mean clustering algorithm is utilized to classify items. Diseases in crop leaves are accurately detected using image processing techniques, which are then utilized to analyses the disease and provide useful information to farmers.

K. Elangoran, S. Nalini Image segmentation and SVM algorithms were used to give a concept of plant disease classification. This study covers an image processing technique that uses an analysis of colored photographs to identify the visual symptoms of plant illnesses, as well as the development of a software programmer that recognizes the color and shape of a leaf image. LABVIEW software was used to capture the image of the plant RGB color model, and MATLAB software was utilized to enable a recognition procedure to identify the plant illness from the leaf photos. The color model was utilized to reduce the effect of illumination and effectively discern between leaf colors, and the resulting color pixels were grouped to produce color groups in the photos.

Sagar Patil, Anjali chandavale

This study focuses on disease detection in dicot plants. Image acquisition is accomplished by taking RGB image patterns as input and converting them to HSI format, followed by texture analysis using CCM and SGDM. Rice farming is quite important in the agricultural field. Their growth, however, is hampered by a variety of disorders. If infections are not detected early enough, production will suffer. The major purpose of this project is to create an image processing system that can recognize and classify the many rice plant illnesses that influence rice farming, such as brown spot disease, leaf blast disease, and bacterial blight disease. This project is divided into two parts: rice plant disease detection and rice plant disease prevention.

Proposed Methodology:

Image processing techniques such as convolutional neural networks were utilized in this effort to detect plant diseases in rice plants. In this study, CNN is used to comprehend and recognize leaf illness using VGG19, Inception V3 and Inception resnetV2. They are used as a point of reference to alter the vector. This is owing to their transcription invariance qualities and weight-sharing architectural design.

3. OVERVIEW OF THE SYSTEM

3.1 Existing System

Describing the shape of the leaf is the most challenging component of leaf identification. To describe the leaf form, several shape options have been retrieved thus far. However, there is no right application to classify the leaf after capturing its image and determining its attributes. Each leaf is categorized according to its morphological options in plant leaf categorization. The following are some of the classification techniques that have been used:

- Principal component analysis
- fuzzy logic
- k-Nearest Neighbors Classifier.

3.1 Proposed System

The main purpose of proposed system is to detect the diseases of rice plant leaves by using feature extraction methods where features such as shape, color, and texture are taken into consideration. Convolutional neural network (CNN), a machine learning technique is used in classifying the plant leaves into healthy or diseased and if it is a diseased plant leaf, CNN will give the name of that particular disease. Suggesting remedies for particular disease is made which will help in growing healthy plants and improve the productivity.

To get better results and efficiency, photos of diverse leaves are first obtained using a high-resolution camera. The photos are then subjected to image processing techniques in order to extract important features that will be needed for future research.

3.2 Proposed System Design

In this project work, I used these modules and each module has own functions, such as:

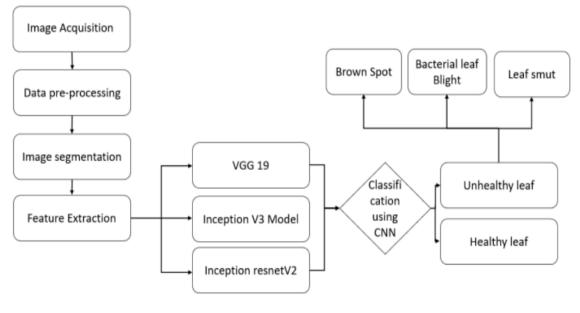


Fig 2: Flow chart

Image Pre-processing:

We use preprocessing techniques such as standardization, normalization, and whitening or sphering in this step. Because the photographs were taken in the field, they may contain noise such as dust, spores, and water spots. The goal of data pre-processing is to reduce image noise so that pixel values can be adjusted. It improves the image's quality. The main goal

Image Segmentation:

The basic goal of picture segmentation is to transform an image's presentation into something meaningful and easy to understand. Image segmentation is critical in our study because it divides the input image into distinct regions, allowing us to quickly identify plant leaf diseases in the input dataset. The RGB color model is converted to the Lab color model before grouping the photos. The use of the Lab color model allows for easy clustering of segmented images.

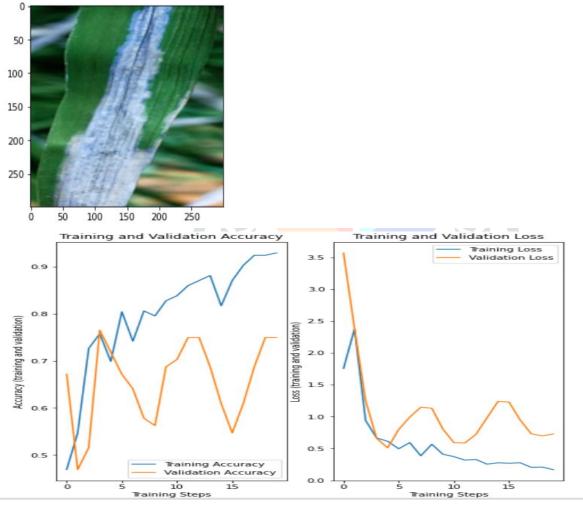
d3

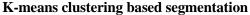
Feature Extraction:

. The input data gets considerably more substantial for larger photos. It will take a lot of computing power to feed this much data into the neural network. CNN, also known as ConvNet, is a sophisticated deep learning technology that was created using biologically inspired models that mimic how a human interprets an image in the brain by layering information. Through the application of filters at different layers, CNN captures the spatial and temporal dependencies in an image. Using CNN, feature extraction reduces the image to a format that can be understood.

Disease Classification

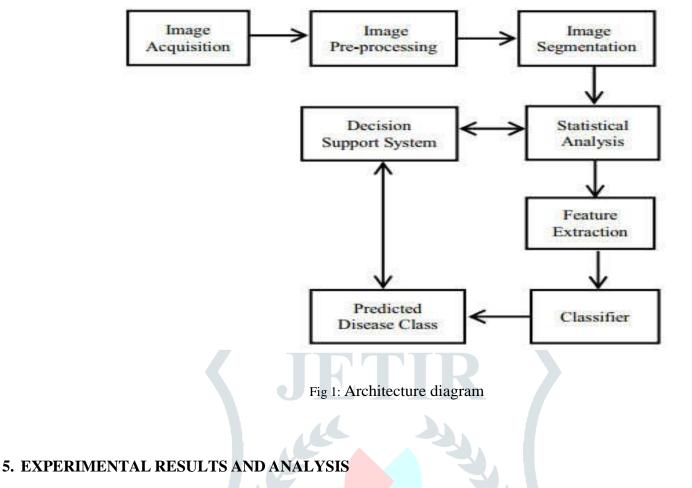
We use convolutional neural networks for categorization in this paper. After extracting the features. SOURCE: class: bacterial_leaf_blight, file: bacterial_leaf_blight/blight_rotated_026.PNG PREDICTED: class: Bacterial_leaf_blight, confidence: 0.836614

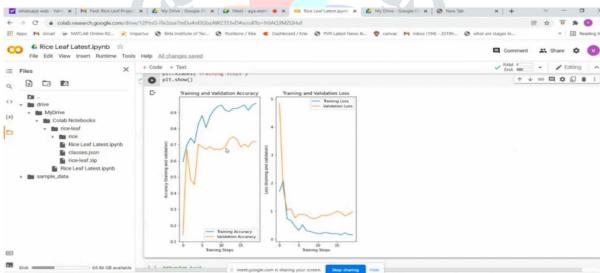




In this study, the K-means clustering approach is used to segment images. Clustering is the process of dividing an image into groups. This clustering extracts the sick area of the leaf picture. When this clustering is applied to a leaf image, clusters for the diseased and non-diseased parts are expected. This technique is used on the hue component of the background-removed image's HSV model. The hue component just contains the pure colour; it lacks information such as brightness and darkness. The centroid value is input to construct ideal segments based on the study of the histogram of hue components in order to avoid the cluster's unpredictability problem. Furthermore, the cluster of sick parts

4. ARCHITECTURE





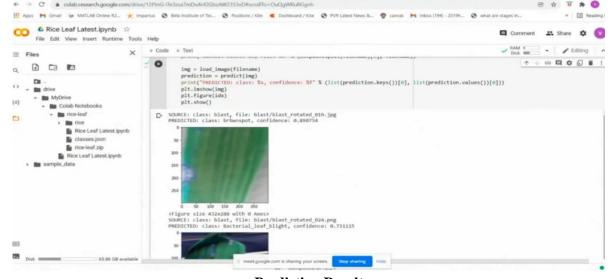
Accuracy Graph

🔲 Comment 🗮 Share 🏚		C Rice Leaf Latest.ipynb
PAM E Pick III	× + Code + Text	Files ×
loss: 1.6968 - accuracy: 0.5938 - val_loss: 4.8505 - val_accur 🔨 🔶 🖾 🏚 💭	Epoch 2/20	
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loss: 0.7201 - accuracy: 0.7419 - val_loss: 1.0326 - val_accuracy: 0.4844	2/2 [] - 32s 24s/step Epoch 4/20	- E drive
loss: 0.6672 - accuracy: 0.7097 - val_loss: 1.0895 - val_accuracy: 0.4531	2/2 [] - 32s 25s/step	MyDrive Colab Notebooks
loss: 0.4592 - accuracy: 0.8281 - val loss: 0.7540 - val accuracy: 0.7031	Epoch 5/20 2/2 [] - 38s 24s/step	Colab Notebooks rice-leaf
loss: 0.3082 - accuracy: 0.8817 - val loss: 0.8777 - val accuracy: 0.6875	Epoch 6/20	· Dir rice
	Epoch 7/28	Rice Leaf Latest.ipynb
loss: 0.5000 - accuracy: 0.8065 - val_loss: 0.8772 - val_accuracy: 0.6719	2/2 [] - 32s 24s/step Epoch 8/20	Classes.json
loss: 0.2936 - accuracy: 0.8750 - val_loss: 0.8578 - val_accuracy: 0.6875	2/2 [] - 38s 24s/step	rice-leaf.zip
loss: 0.2722 - accuracy: 0.9140 - val loss: 0.7537 - val accuracy: 0.6719	Epoch 9/20 2/2 [] - 325 185/step	Rice Leaf Latest.ipynb
	Epoch 10/20	 m sample_data
loss: 0.2290 - accuracy: 0.9375 - val_loss: 0.7268 - val_accuracy: 0.6719	2/2 [] - 395 245/step Epoch 11/20	
loss: 0.1932 - accuracy: 0.9462 - val_loss: 0.7661 - val_accuracy: 0.6719	2/2 [] - 335 195/step Fooch 12/20	
loss: 0.2039 - accuracy: 0.9141 - val_loss: 0.8457 - val_accuracy: 0.6875		
loss: 0.2377 - accuracy: 0.9062 - val loss: 0.8315 - val accuracy: 0.7344	Epoch 13/20 2/2 [
	Epoch 14/20	
loss: 0.2061 - accuracy: 0.9247 - val_loss: 0.8643 - val_accuracy: 0.7500	2/2 [] - 32s 25s/step fooch 15/20	
loss: 0.1864 - accuracy: 0.9247 - val_loss: 0.9204 - val_accuracy: 0.7344		
loss: 0.1864 - accuracy: 0.9247 - val_loss: 0.9264 - val_accuracy: 0.7344		

Training Process

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Prediction Result

6. CONCLUSION AND FUTURE WORK

Plant diseases in rice can lower the crop's yield. As a result, finding the best answer to this challenge is critical. On infected rice images, several methodologies are used in order to conduct further study in this field in order to improve the overall performance of the rice disease detection system. The approaches of image processing, machine learning, and deep learning that have been employed in disease identification were examined and summarized in this work. The most crucial phase, we discovered, is extracting the impacted region from the leaf image, for which we investigated various segmentation approaches. A comparison of multiple rice disease detection approaches has been done, and it has been established that deep neural networks and decision trees are the most effective.

It's worth mentioning that this strategy still has some limitations. The accuracy of estimating low-level illness severity needs to be improved. Because of the limited data collecting period and experimental site, only one type of rice disease segmentation and severity estimate, BLS rice disease segmentation and severity estimation, was investigated. An enhanced segmentation model for more types of plants, more types of diseases, and more degrees of disease severity can be built in future studies on lesion segmentation and disease severity level estimate. Multiple types of data sources, such as multispectral and hyperspectral data, can be explored, with spectral properties being used to demonstrate growth.

crop condition and aerial photography that can be utilised to monitor plant diseases on a big scale. In theory, increasing the amount of data can enhance the model's accuracy; the data crowdsourcing method can be used to classify appropriate crop disease samples. In terms of model size, work may be done in the field to reduce the number of parameters in the model and the proposed lightweight model for mobile and IoT devices.

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