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Rice Disease Prediction Using Machine Learning

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Abstract: India, one of the top ten producers and consumers of rice worldwide, heavily relies on rice production and consumption to suit its dietary and economic needs. The early detection of any disease and the administration of the necessary remedies to the affected plants are essential for the health and the development of rice plants. It makes logical to create an automated system because manually diagnosing diseases requires a lot of time and effort. A machine learning-based technique for diagnosing rice leaf disease is presented in this study. The three most prevalent diseases affecting rice plants, according to this article, are leaf smut, bacterial leaf blight, and brown spot. Clear images of damaged rice leaves over a white background made up the input. Following the required pre-processing, the dataset was trained using a range of different machine learning approaches.

OVERVIEW

The main issue in agriculture that affects the quantity and quality of the produce is plant diseases. Rice is the primary entrée. Major problems arise from diseases that reduce rice crop production. In order to tackle disease issues in rice plants, farmers typically spray pesticides on plants on a regular basis to get rid of pests, including plants, insects, and other animals. However, it is usually done without adequate awareness of the diseases and health status of the plants when pesticides are applied to plants. Pesticide overuse will have an adverse effect on the ecology and the health of those who consume the plants.. Every condition has a unique treatment. It is sometimes possible to control pests and diseases without the use of pesticides by using light traps or just immersing yourself in water. Spraying pesticides won't work to reduce a pest's population, though, if it is not at the right stage. Pesticides should only be used as a last resort and should always be applied correctly—on target, in the right type, at the right time, and in the proper dose—in order to minimise further losses. Understanding a plant pest's appearance, attack signs, personality, and life cycle is key to efficient treatment.

LITERATURE SURVEY

"Rice Blast Disease Detection and Classification Using Machine Learning Algorithm"

This paper proposes a machine learning algorithm to find the symptoms of the disease in the rice plant. Automatic detection of plant disease is carried out using machine learning algorithm. Images of healthy and blast disease affected leaves are taken for the proposed system. The features are extracted for the healthy and disease affected parts of the rice leaf. The total data set consists of 300 images and divided for training and testing purposes. These images are processed with the proposed method and the leaf is categorized as either infected or healthy. The simulation results provide an accuracy of 99% for the blast infected images and 100% for the normal images during the training phase. The testing phase accuracy is found to be 90% and 86% for the infected and healthy images respectively.

"Rice disease identification using pattern recognition techniques"

The paper describes a software prototype system for rice disease detection based on the infected images of various rice plants. Images of the infected rice plants are captured by digital camera and processed using image growing, image segmentation techniques to detect infected parts of the plants. Then the infected part of the leaf has been used for the classification purpose using neural network. The methods evolved in this system are both image processing and soft computing technique applied on number of diseased rice plants.

"Rice Plant Leaf Disease Detection and Severity Estimation"

This paper explores possibility of using semantic segmentation to extract the affected area and calculating the affected area and estimate the severity. For easier usage, the model is deployed using ngrok and Twilio server to accept, process and return output on WhatsApp interface. Existing UCI Rice leaf dataset was selected and the information related to its diseases, responsible pests and pesticides is collected. Since, UCI contains only 40 images, more images are scrapped from internet. For segmentation, masked images are created using VCC Annotation tool and manually assigning the classes via python script. Two neural models are then trained - to predict type of disease and segmentation. The accuracy of the detections is also fairly high, around 85-86%, which is quite high considering the quality of images available. Our data and calculations have been majorly on Rice crop, with images of its three main diseases: 1) Blight, 2) Brown Spot and 3) Leaf Smut being used to train our model.

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"**The Implementation of CNN on Website-based Rice Plant Disease Detection"**
The system was developed by applying the Deep Learning method. The method of image processing was implemented using a Convolutional Neural Network with the GoogLeNet architecture which is then integrated into a website-based application. The results showed an increase in accuracy in the increasing number of epochs for CNN training models. This application is expected to be able to assist rice farmers in analyzing diseases in rice plants that are planted, so that prevention and handling can be carried out in accordance with the aim of minimizing losses from crop failure**.** The classification process in this application is designed independently (standalone) where the classification process runs on the user's device only and requires an internet connection or dependence on certain services, the application can classify images by utilizing an engine or model that has been made from the training process. This application makes use of Flask, which is a framework or framework that connects Python with web applications.
"Rice Disease Detection by Image Analysis"
This paper provides a method for automatically classifying diseases in rice plants by analyzing photographs of rice leaves. The method uses image processing algorithms to detect leaves and likely disease-induced lesions in the leaves. Next, several attributes are computed based on the dimensions of leaves and lesions, the numbers and shapes of lesions, as well the color characteristics of lesions and intact portions of leaves. These attributes are used to build classification models using well established algorithms. The method is evaluated using a publicly available database of rice leaf images. The work described here demonstrates the feasibility of rice disease detection using simple photographic images that may be collected in the field using smart-phone cameras or other easily available hardware. Image characteristics such as shadows, leaf damage unrelated to disease, over- and underexposed areas, color variations, and lesions that abut leaf edges pose several challenges to accurate delineation of leaves and lesions. However, by using the carefully designed sequence of image-processing operations described in this paper, it is possible to successfully identify lesions even in challenging situations

BACKGROUND STUDY

The basic objective of the smartphone app is to capture photos of rice plant leaves, submit them to the app on the cloud server, and then get classification results in the form of information on the various plant illnesses. The performance of the VGG16 architecture-based rice plant disease detection system shows a train accuracy value of 100% and a test accuracy value of 60%. The test accuracy value can be increased by improving the dataset quality and increasing the number of datasets. It is hoped that by using this approach, rice plant diseases can be efficiently managed, increasing yields

PROPOSED METHOD

Three of the most common illnesses affecting rice plants—leaf smut, bacterial leaf blight, and brown spot—are named in this article. Crisp images of damaged rice leaves on a white backdrop were used as the input. Following the necessary processing, a number of machine learning methods, including CNN, were trained on the dataset. Because the objective was to predict and classify the disease of the affected rice leaf, logistic regression was the ideal state to train our dataset using.

a. Pre-processing.
b. Image Segmentation.
c. Feature Extraction.
d. Feature Matching or classifiers.

CNN

Many interconnected neurons with trainable weights and biases make up the CNN. The neurons are layered in the CNN design. A hidden level or hidden layers, an output layer, and a layer are all parts of this system. Having several hidden layers is a common way to define deep neural networks. Unlike fully interconnected networks like Multi Layered Perceptron (MLP) networks, the neurons in the hidden layers of CNN are connected to a restricted area (receptive field) of the input space created by the preceding layer. Comparing CNN to MLP, this method uses less connection weights (or parameters). In comparison to networks of a comparable size, CNN has a quicker learning curve. Inputs for CNN often consist of images and other two-dimensional (2D) data arrays. Unlike a traditional neural network, a CNN arranges its layers in three aspects (width, height and depth).

Only image processing techniques like sharpening, feature augmentation, and camera smoothing need convolution. Convolution plays a key role in numerous other machine learning techniques in addition to CNNs. Restructuring an image involves using a single integer matrix, often known as a kernel or filter. To create one pixel value for the filtered picture,

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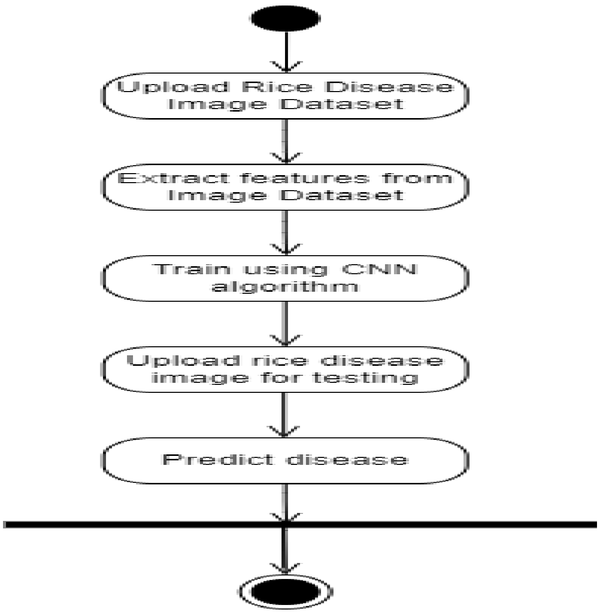
each selected pixel value from the image submatrix is multiplied by the matching pixel value from the kernel. All areas of the image are subjected to the micro-scale processing. Borders, colours, gradients, and orientation are just a few examples of the low-level characteristics that can be recognised using convolution. In order to give a network a full grasp of an image, similar to what individuals do, the architecture adapts to a high level of usefulness as there are more layers. Convolutional processing is used to get rid of the high-level edges present in the source photos. The strategy has an impact since the reshaped feature has fewer dimensions than the input.

CONCLUSION

In this study, a machine learning approach is used to identify the three main illnesses that affect rice leaves: leaf smut, bacterial leaf blight, and brown spot disease. The algorithms predicted the diseases affecting rice leaves to varying degrees of accuracy. It was shown that decision trees functioned most accurately on test data. After finding a virtually flawless method, we want to extend our work as more high-quality datasets become available in the future. For our upcoming work, we plan to analyze the efficacy of ensemble learning methods using this dataset.



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