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Rice plant disease detection and classification framework using deep learning for precision agriculture

Deepak Singh Rana,
Asst. Professor, SOC (School of computing),
GEHU-Dehradun Campus
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Abstract:

The rapid rise in India's population necessitates an equally quick rise in agricultural production. In India, rice is the staple food crop. However, disease-causing organisms are notoriously easy to introduce to rice crops, resulting in lower yields. Even though pests, climate change, and illnesses all pose problems for agricultural yield, rice agriculture still has the most difficulty with crop diseases. Most crop diseases are caused by or related with bacteria or fungus, and they may strike at any time, from seedling development through harvest. Traditional methods for identifying leaf diseases have relied on human observation. They're time-consuming, costly, and need the expertise of professionals to complete. The human vision-based technique relies heavily on the eyesight of the farmer or expert to be correct. Automated classifier models based on Machine Learning (ML) are required to address the shortcomings of traditional methods. Rice plant diseases (RPD) may be prevented and their effects mitigated if they are detected early. Better crop quality and yields cannot be achieved without controlling the spread of diseases.

Keywords: Machine Learning (ML), classifier models, Rice Plant Diseases (RPD), human vision

Introduction

When it comes to bolstering development, ensuring food security, and reducing poverty, agriculture is vital. There are many factors, including weeds, pests, pathogens, sunlight, water, nutrients, environmental impact, scarcity of arable land, and soil deprivation, that can reduce crop yields and make it difficult to feed the world's projected 9.7 billion people in 2050 and 11.2 billion people by the end of this century. Increased food production is a desirable goal, and technological progress may help get us there. Rice is the primary source of energy and protein for at least half of the world's population. However, productivity has been drastically reduced due to Rice Plant Disease (RPD). The widespread use of pesticides not only raises production costs, but also has serious consequences for the natural environment. Classification, pre-processing, feature extraction, and segmentation are only few of the image processing steps used in rice disease detection. This technique may be used to assess the sick plant's outward appearance. Human vision approaches are commonly employed for leaf disease detection in the traditional sense. It's going to set you back a lot of money and time. Methods based on machine learning (ML) and deep learning (DL) make it possible to identify various diseases, choose appropriate therapies, and arrive at sound conclusions. fertilized in the usual way. It's time-consuming and costly. Algorithms based on

DL and ML make it possible to diagnose several illnesses, choose the most appropriate therapy, and arrive at sound conclusions. The application of ML and DL methods for the detection of RPD has been the subject of some research. Currently, the Convolutional Neural Network (CNN) system is extensively utilized in pattern recognition research and ML approach owing to its capacity to extract optimal features. According to research published in, multi-layer NNs have superior learning capacities, and the features it generates are both abstract and meaningful, making them ideal for categorization. The input picture is processed by CNN, which then offers dedicated learning solutions and extracts higher-level information. The cat's visual brain was used as a basis for the CNN model in earlier work by Wiesel and Hubel. In particular, use a deep convolutional neural network (DCNN) model to conduct object categorization and win the 2012 Image Net Large Scale Visual Recognition Challenge. Numerous use cases and enhanced methods of CNN have served as indicators of this trend. Experts' naked-eye examination of plant diseases seems expensive and time-consuming in real time. It's a pain to deal with and may lead to false positives while testing for illness. Recent years have seen a decline in rice output as a direct result of poor management's failure to address RPD. An adequate and reliable RP recognition system is required to address these issues.

Disease in plants develops when the causative agent, the host, and the environment all communicate in ways that alter or disrupt the plant's normal physiological processes. The existence of illnesses is founded on the interplay of the three sides of a triangle defined by the environment, the host, and the pathogen. For instance, Mildew cannot form in an environment where the climatic conditions (i.e., air temperature, leaf wetness duration, and relative humidity) are not optimal. Figure 1 shows how the presence of a disease in an agricultural area is directly related to the local climate. Incompatible interactions for a disease may result from a plant-pathogen interaction, for instance, when the infectious agent is present in the vulnerable host and growing area but the weather is unfavorable for the parasitism relationship and the infection. The symptoms caused by the interaction between plant pathogens and their parasites are grouped together and given their own name. Therefore, harmful microorganisms including nematodes, fungus, bacteria, and viruses are thought to cause plant disease and are therefore considered a unique kind of primary stress (the biotic stress).

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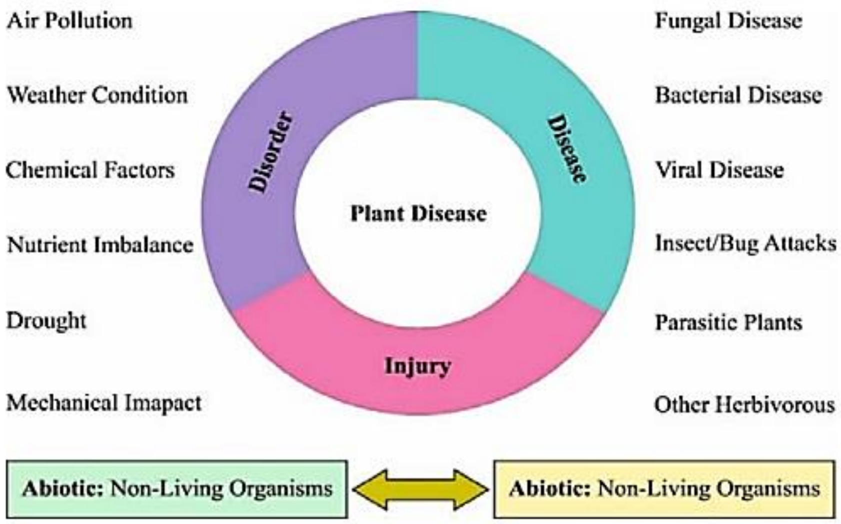

Figure 1.Types of Disease

Fluorescence imaging

Differentiating plant metabolic circumstances occurs in real time. The chlorophyll in plants absorbs the light that this method typically emits. The chloroplast is bathed in blue light, which stimulates the chlorophyll to emit more light. A halogen lamp or xenon can provide the ultraviolet light needed to excite fluorescence. As a result, fluorescent lights are able to absorb more blue light since they reflect it back. The fluorescence excitation at a given wavelength is recorded using a Charge Coupled Device (CCD) camera. Fluorescence signals, as well as those from LEDs, pulsed lasers, and pulsed flashlight lamps, are picked up by a CCD camera because of the sensitivity of the device to ultraviolet and visible light. The computer was used to store data gathered from testing samples of green crops for fluorescence. Figure 2 provides a simplified depiction of the steps involved in multicolor fluorescence imaging. In addition, the provided technology is largely used for indirect image capture based on physiological factors after the onset of photosynthesis interruption during plant disease detection. Damage to photosynthetic tissue, caused by plant pathogen infections, is reflected in a corresponding decrease in chlorophyll fluorescence. Research into photosynthetic efficiency using chlorophyll fluorescence is non-destructive and precise, and

ISSN- 2394-5125 VOL 07, ISSUE 09, 2020

it reflects the impacts of environmental and physiological variables on plants.

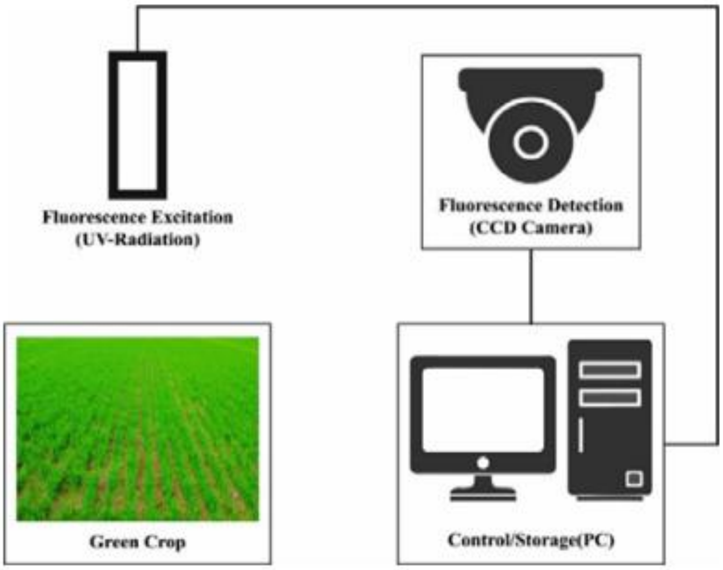

Figure 2. Structure of Multi-color Fluorescence Imaging

Rice Plant Disease Detection and Classification

Rice is one of the most important staple crops worldwide. It comes from the family Poaceae and has two main types: Indica and Japonica. It's the second-most-cultivated cereal crop in the world and a primary source of nutrition for those living in rural regions. It is well-known that rice is one of Asia's most nutrient-dense and cost-effective staple foods. The Americas, Africa, Asia, Europe, and Oceania all produce rice harvests. According to the Food and Agriculture Organization of the United Nations (FAOSTAT), Asia consumes and exports 91.05 percent of the world's rice supply, followed by the Americas (5.19 percent), Oceania (0.15 percent), Africa (2.95 percent), and Europe (0.67 percent). The World Bank predicts that by 2025, the global demand for rice would have increased by 51%, a pace that is much higher than the rate of population growth.

In many nations, demand for rice is expected to increase faster than supply. In these conditions, losses to rice harvests from whatever source must be avoided at all costs. It was challenging to determine the level of severity and the RPDs associated with it. The only way to detect the rice sickness was by careful visual inspection. For this technology to effectively diagnose agricultural diseases, professionals must maintain a constant vigil over the crop fields. Visual examination is time-consuming, costly, and inconvenient for larger areas of plants since it requires constant human monitoring. Because of this, society is under pressure to adopt cutting-edge technology that provide precise and early illness estimation, allowing for the prompt application of corrective measures. Rice is the primary food source for more than half of the world's population. The quantity and quality of rice harvests are both negatively affected by rice diseases. They can pose significant dangers to food supply. In modern farming, there is a focus on gathering information on the health and real-time development of rice. Ahead of their epidemics during rice cultivation, rice diseases may be anticipated using data collected from a variety of sources. Experts in the rice industry or

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seasoned farmers have traditionally relied heavily on their eyes to spot signs of illness. Costly, ongoing professional analysis is required for this, which might be a problem for bigger farms. Farmers in certain underdeveloped countries, in particular, may have to travel farther distances to see agricultural professionals, an endeavor that is not only costly but also unpredictable, time-consuming, and limited in scope. Insufficient numbers of persons in the area possess the knowledge and experience to carry out this procedure at the right moment. Currently, manual judgment based on disease incidence is used most often (Sethy et al., 2020) to identify rice crop disease. As a result, we need a method that is both more accessible and more effective for identifying diseases in rice. The rapid development of pattern recognition and image processing tools, however, has led to the introduction of a novel approach to the detection and identification of plant diseases. Significant research is being done in the disciplines of machine learning and image identification because these techniques have the potential to effectively monitor bigger swaths of crops and automatically identify the symptoms of illnesses once they appear on plant leaf.

Literature Review

Heri Andrianto et.al.,(2020) The increasing human population necessitates an increase in the amount of food that is cultivated and collected. In agriculture, plant diseases are the single most important factor that may lower crop yields and quality. Usually, a farmer can determine just by looking at his plant whether or not it has been affected with a disease. However, there is no guarantee that this strategy will work. Deep learning may now be used to the process of automatically identifying plant diseases thanks to recent developments in machine learning. In this article, we explain the design and implementation of a cloud-based machine learning application as well as a mobile app for employing deep learning to identify diseases in rice. Both of these applications were created by us. It is possible that the smartphone app will take photographs of the rice plant's leaves and then send them to a cloud server in order to have them categorized in order to detect the various sorts of plant diseases. The findings substantiated the usefulness of the mobile app's use of artificial neural networks in diagnosing ailments in rice plants. The app was accessed using smartphones. The disease detection performance of the VGG16 architecture on rice plants is good, with a train accuracy of 100% and a test accuracy of 60%. Both of these figures represent the architecture's overall accuracy. Both increasing the amount of datasets and improving the quality of the dataset lead to a higher value of test accuracy. Increasing the quantity of datasets also helps improve the quality of the dataset. It is hoped that rice plant illnesses would be able to be properly handled with this technology, which will ultimately result in increased yields.

S.M. Taohidul Islam et.al.,(2019) As a major threat to plant variety and food supply, plant disease necessitates monitoring techniques to take the necessary steps for verifying food production, an essential component of sustainable management. An Ensemble of Linear Classifiers employing the Random Subspace Method (RSM) was used for the classification task. With a 95% accuracy rate, this method has been used to categorize four important rice plant diseases: rice bacterial blight, rice brown spot, rice bacterial sheath brown rot, and rice blast.

S. Ramesh et.al.,(2018) Rice blast disease is a significant challenge for farmers and agricultural businesses all over the globe. If this disease can be diagnosed and treated in a timely manner, the farmer may avoid suffering a catastrophic loss of income. This article discusses utilizing a machine learning system in order to recognize the symptoms of the sickness that are manifesting themselves in the rice plant. Automatic identification of plant diseases is accomplished via the process of machine learning. As part of the strategy that has been outlined, we picture healthy leaves alongside with infected ones. The features of normal rice leaf areas and sick rice leaf regions were both retrieved. A total of 300 photographs were obtained, after which they were divided into learning and examination sets. These photographs are examined in accordance with the strategy that was proposed in order to establish whether or not the leaf is affected by a disease. The results of the simulation indicate that during the training phase, the accuracy of the blast-infected images is 99%, while the accuracy of the normal photographs is 100%. The testing phase produced results showing an accuracy of 90% for infected photographs and 86% for healthy ones..

Methodology

Although leaf smut affects the whole leaf, it is still considered a very mild illness of rice. Its growth causes slightly elevated, pinpoint, black patches on each side of the leaves. Natural conditions, high amounts of toxicity, and pesticide injuries are only some of the environmental causes that may lead to leaf spots. Here, we used deep transfer learning to identify pathogens in rice plants. In artificial intelligence, transfer learning is the process of applying a previously developed model to a different problem. In transfer learning, a computer takes what it has learned from one job and uses it to improve its predictions for a different task. Preparing a classifier to determine if an image includes wine, for instance, may make use of data collected during the recognition of beverages. In transfer learning, data from an established ML model is applied to a new, related problem. Popular pre-trained models (such as VGG16, Inception, and ResNet50) have already been trained on a wide variety of pictures and can make accurate predictions for a wide range of characteristics, making them an effective tool for overcoming sampling shortages. When trying to make sense of the differences between tens of thousands of classes, these models often have intricate architectures [11]. For easier jobs, the complexity that provides a predicted limit on the number of items might be a burden since the pre-prepared model can over fit the data. When it comes to classifying plant diseases, segmentation is a crucial pre-processing step. In terms of segmentation [12], both the hue, saturation, and intensity (HSI) model and the luminance, a, and b chrominance (Lab) model do well. In the classification of rice plant disease from picture datasets [13], several pertained deep learning models have demonstrated exceptional performance, although in other situations [14] handcrafted CNN models may also generate. Many studies have turned to the novel notion of transfer learning to improve the precision of classification using a lightweight model like Es-MbNet [15]. What this research adds is summarized below:

1) In order to identify plant diseases with little computing effort, we developed a 17-layer lightweight model.

2) The training performance of the model was improved by applying several data augmentation approaches to the benchmark dataset.

3) Several factors were used to evaluate the created model's performance in comparison to preexisting models.

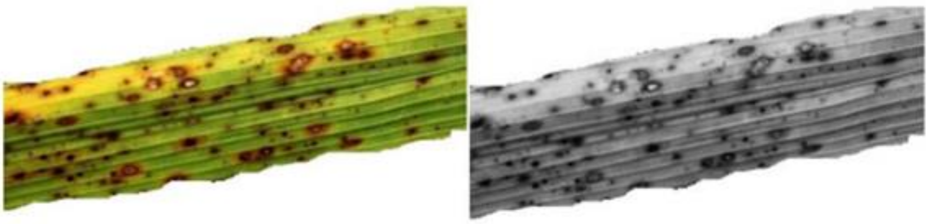
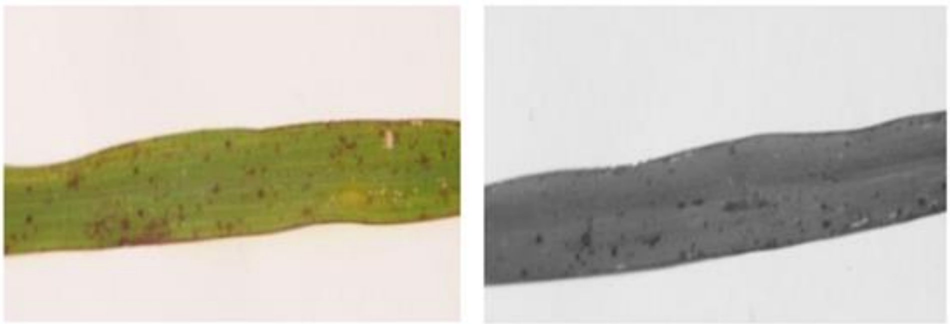


Figure 3. (a) RGB format image of brown spot disease; (b) grayscale image of brown spot disease.



(a) (b)

Figure 4. (a) RGB format image of leaf smut disease; (b) grayscale image of leaf smut disease

The first step in illness detection is preparing the picture collection. Preprocessing of images is included in this stage. Image capture, preprocessing, feature extraction, classification, and illness detection are all part of the proposed system. Below is a graphic depicting the process of diagnosing diseases. The process of obtaining an image from a capture device (camera, sensor, etc.) is known as "image acquisition." This is a crucial stage since, without it, the picture identification process would grind to a halt. Reading and resizing data are only two of the many methods used in image processing, but their primary goal is to enhance the picture features and hide the ones that aren't desired. Generating fresh information from preexisting files and transforming color images into grayscale for use in computational imaging. Image segmentation and feature detection to pinpoint the location of a target.

Conclusion

About half of the world's population eats rice regularly, making it one of the most widely cultivated crops. However, several rice diseases have been a constant problem for farmers and planting professionals throughout the years. In agriculture, a rapid, automated, low-cost, and trustworthy method of diagnosing rice infections is in high demand since severe rice diseases may prevent a harvest. To improve the accuracy of disease detection in rice crops, this research explores the development of a lightweight deep learning modelwhich give accurate result after validation.

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