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DETECTION OF RICE LEAF DISEASE USING CNN WITH TRANSFER LEARNING

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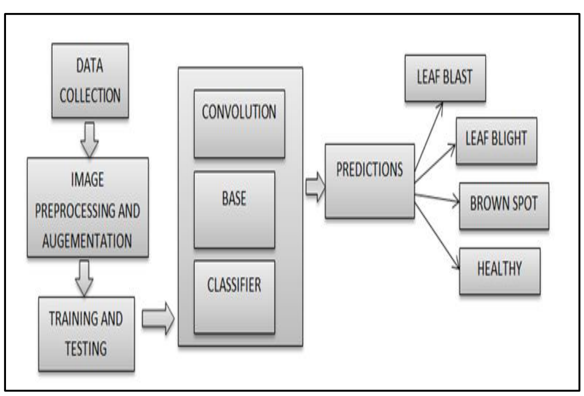
Abstract- ***Rice is one of the most widely grown crops in India. Rice crops are susceptible to various diseases on a wide range of levels of cultivation due to climate changes. Farmers with their limited knowledge have a difficult time identifying these diseases manually. Recent advances in Deep Learning have led to the development of automatic image recognition frameworks using Convolutional Neural Network (CNN) models to solve such problems. Because the rice leaf ailment picture data-set is not without issues, we created our own dataset, which is of little length, therefore, we need our deep learning model to develop by using transfer learning. The proposed network architecture is based on VGG16 and has been trained and tested on the internet and rice fields datasets.***

Keywords—Fine Tuning, Rice Leaf Diseases, Convolutional Neural Network, Deep Learning, Transfer Learning.

I. Introduction

India and other countries around the world rely on rice as their main source of food. During different stages of cultivation, rice leaves are afflicted by various diseases. Hence, early noticing and cures of such diseases are valuable to ensure high quantity and quality but this is very difficult due to the considerable costs of land under individual farmers and the enormous collection of diseases as well as the occurrence of more than one disease in the same weed. Automated Systems are required to support the difficulty of the ranchers and give further developed precision of plant diseases detection, various machine learning algorithms are using research work including Support Vector Machine (SVM) and Artificial Neural Network. The accuracy of such systems is highly dependent on feature selection techniques. The convolutional neural networks have provided a great advance in image-based recognition by eliminating the need for image processing as well as providing inbuilt feature election. We designed an automated system in which our farmers can upload images of diseased leaves onto our server, where the neural network will analyze the images to identify the disease and classify it so that the remedy and diagnosis can be returned to the farmer. Increasingly, cell phones and the internet are becoming accessible to all, so we have thought of developing an automated system that would let the farmers upload images of diseased leaves onto a server and have them uploaded to our server. "The accuracy of the achieved network is 91.23%, using stochastic gradient descent with a small batch size of thirty (30) and initial learning rate of 0.0001". Six hundred (600) images of rice plants representing the classes were used in the training by Atole & Perkin 2018. An approach is based on deep learning to detect rice plant diseases and pests by using images captured on the real-life scenario with the heterogeneous background was well reported by y. Lu, S.Yi, and y.Zhang in 2017[7].



Rice plant diseases depend on the symptoms and signs produced by the pathogens for identifying and classifying the disease leaf. The identification of diseases based on symptoms often becomes difficult. Therefore the identification based on digital images has been increasingly growing. Multispectral and hyperspectral images provide more information, but they are valuable for farmers. While the conventional cameras in cell phones are easily available to all farmers with affordable cost to capture images. This has prompted the researchers in developing systems based on RGB rich experienced experts to identify the diseases. The researchers have been encouraged by the limitations to explore automatic methods that detect and classify plant diseases simply and reliably with high accuracy. In addition, it will help the farmers to select the right pesticides. According to statistics, rice plant diseases destroy 10-15% of rice production in Asia Countries. Transfer learning is a machine learning method where a developmental model for a task is reused as the beginning point for a model on a second task. It is a popular approach in deep learning where pre-trained models are used as the beginning point on computer vision and natural language processing tasks given the huge compute and time resources required to develop neural network models on these problems and from the huge jumps in the skill that they provide on related fix or worry. In this, you will discover how you can use transfer learning to speed up training and improve the performance of your deep learning model.

We have utilized the pre-prepared VGG16 model and utilizing Transfer learning we have calibrated the completely associated layers so we can oblige our dataset and toward the end, we have done a few blunder examinations and attempted to clarify the explanations behind the error. "The side effects and information about the illnesses have been gathered from the International Rice Research Institute (IRRI) Rice Knowledge Bank website". The dataset comprises 1649 pictures of unhealthy leaves of rice comprising of three most normal sicknesses be specific Rice Leaf Blast, Rice Leaf Bligh, Brown Spot, and 507 pictures of health leaves. The number of pictures that could be gathered from the fields is exceptionally less for preparing CNN so we have utilized several augmentation techniques like zoom, horizontal and vertical shift, and rotation.

1.1 Leaf Blast:

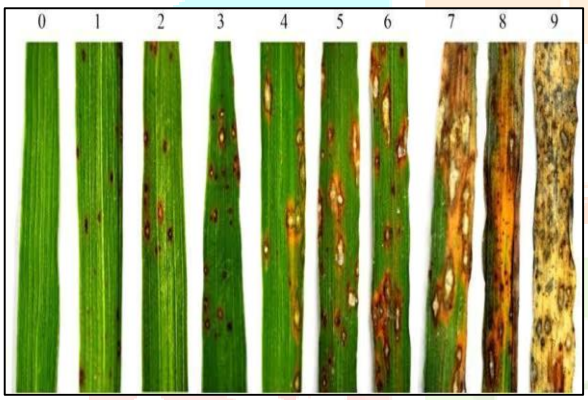
"Rice leaf blast disease, caused by Magnaporthe oryzae, occurs in about 80 countries on all continents where rice is grown, in both upland cultivation and paddy fields". The area of damage caused depends on environmental factors, but worldwide it is one of the most destructive rice diseases, resulting in losses of 10–30% in the rice of global yield. Initially, it appears as seedlings and small necrotic regions in rice have chlorotic margins and becomes larger and merge. In older rice plants, the symptoms of diseases can happen in leaves, collar – the intersection of the leaf edge and leaf sheath, hubs, neck, and panicle. Neck rot and panicle blast are particularly damaged causing up to 80% yield losses in severe epidemics. Triangular, purple-colored marks form on the neck node which elongates on both sides, seriously damaging grain development. When young neck nodes are occupied the panicles become white later infection in plant growth results in incomplete grain filling.

1.2 Bacterial Leaf blight:

Rice Bacterial Leaf blight is also called the bacterial disease of rice, a deadly bacterial disease that is among destructive afflictions of cultivated rice (Oryza sativa and O. glaberrima). In serious pandemics, crop misfortune might be all around as high as 75%, and a huge number of hectares of rice are contaminated yearly. The disease was first seen (1884–85) in Kyushu, Japan, and the causal specialist, the bacterium Xanthomonas oryzae pathovar oryzae (also referred to as Xoo, 1911), around then having been named Bacillus oryzae. Xanthomonas oryzae pv. Oryzae (Xoo) is widely prevalent and causes Bacterial Leaf Blight (BLB) in Basmati rice grown in different areas of Pakistan. To beat the deficiency of grain yield in rice we want to utilize ecologically safe ways to deal with defeat from this disease. The present review is expected to create a mix, in light of local adversarial microscopic organisms for biocontrol of BLB and to build the yield of Super Basmati rice assortment.
Bacterial curse turns out to be first apparent as water-splashed marks that spread from the leaf tips and margins, becoming bigger and ultimately delivering a smooth seepage that dries into yellow drops.

1.3 Brown spot:

In rice diseases, the brown spot is one of the most damaging and common diseases which was historically largely ignored by farmers. Its maximum observable harm is the numerous huge spots at the leaves that may kill the entire leaf. Unfilled grains or discolored seeds are formed when the seed occurs with infection.

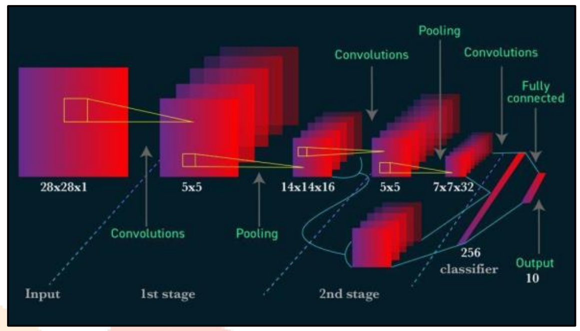


1.4 Healthy leaf:

Healthy leaf means which are not affected by diseases.

II CONVOLUTIONAL NEURAL NETWORKS

In machine learning, complex feed-forward neural networks are convolutional neural networks (CNN or ConvNet). CNN is used for image recognition and classification. And it has high accuracy for the identification of images. "It was proposed by computer scientist Yann LeCun in the late 90s when he was inspired by the human visual perception of recognizing things". The CNN follows a hierarchical model which works on building a network, like a funnel, and finally gives out fully-connected layers that are connected neurons and the output is prepared.



Using CNN image can compare into the piece by piece and by seeing similarity it analyzes better matching schemes for the whole image. Not only CNN is used for image classification but it can also be used in other learning algorithms or models. Anyway, CNN has been proposed as a decision-making model for multiple reasons. These include the many uses of the convolution operator in image processing. The CNN architecture implicitly combines the benefits of standard neural network training with the convolution operation to efficiently classify images through feature extraction and provide greater accuracy. Furthermore, being a neural network, CNN (and its variants) are scalable even for large datasets, as is often the case when images are classified and use prediction layers at the end.

In CNN we have some steps for image feature extraction for final output.

Step 1: Convolutional operation

The primary structure block in our arrangement of assault is convolution operation. In this progression, we will address highlight identifiers, which essentially fill in as the brain organization's filters. We will likewise examine include maps, learning the boundaries of such guides, how examples are recognized, the layers of location, and how the discoveries are planned out. Using Transfer learning approach VGG16, to begin with, and afterward adding some extra convolutional layers alongside max-pooling layers.

Step 1(b): Rely Layer

The second part of this step will involve the Rectified Linear Unit. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Step 2: Pooling Layer

In this part, we'll cover pooling and will get to see precisely how it by and large works. Our nexus here, however, will be a particular sort of pooling; max pooling. We'll cover different approaches, though, including mean pooling. This part will end with an exhibition made utilizing a visual intelligent device that will figure the entire idea out for you.

step3: Flattening

In this layer, we can see the process of brief breakdown of flattening and how we move to flatten layers from pooled layer when working with Convolutional Neural Networks.

Step 4: Full connection

In this segment, the things get merged that we covered in this section. And by knowing this, you'll get to imagine a full picture of how "neurons" and Convolutional Neural Networks operators have produced a final image and learn the classification of images.

III Conclusion and Future Work

In this paper, we have proposed a deep learning architecture with training on 1509 images of rice leaves and trails on different 647 images and that exactly analyzes 92.46% of the trail images. Transfer Learning using fine-tuning the predefined VGG16 has greatly improved the performance of the model which otherwise did not produce satisfactory results on such a small dataset. The number of eras used to stop at 25 because we had received a cut point in the wake of which the accuracy was not improving and the loss had not decreased on both training and valid statistics.

For future analysis, we might want to gather additional pictures from agrarian fields and Agricultural Research organizations with the goal that we can further develop the exactness. We might want to add a cross-approval process in the future to approve our outcomes. We might likewise want to utilize better profound learning models and other cutting-edge works and contrast it and the outcomes acquired. The created model can be utilized in the future to identify other plant leaf illnesses, which are significant yields in India.

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