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Plant Leaf Disease Detection Using Deep Learning Approach

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ABSTRACT: Disease detection from a picture and recommendation of a suitable pesticide as a solution. Disease detection by any automated technique is beneficial because it reduces an oversized job of watching in large farms of crops, and it detects disease symptoms at a very early stage, that is, after they appear on plant leaves. This method demonstrates a neural network algorithmic program for image segmentation, which is used to detect plant leaf disease automatically. The victimization genetic algorithmic software completes image segmentation, which is an essential aspect of disease detection in plants. Deep learning is a hot topic in pattern recognition and machine learning right now, and it can address these issues in vegetable pathology. We propose a new Plant leaf disease detection approach based on convolutional neural networks (CNNs) techniques in this research. The Alex Net model based on deep learning is proposed for leaf disease detection to increase detection accuracy and reduce the number of network parameters.

KEYWORDS: Preprocessing, Feature Extraction, Machine Learning, CNN Classification.

I. INTRODUCTION

One of India's most important coarse cereal crops is affected by plant leaf disease. India is the world's second-largest producer. As compared to other cereals like wheat and rice, this crop is well-suited to the country's semi-arid agroclimatic regions, and it produces a good yield with little irrigation and fertiliser use. Plants are grown in both the kharif (rainy season) and the rabi (post-rainy season), but the kharif covers a larger area. However, due to advancements in cultivation systems, pathogen variety variation, and inadequate plant protection measures, the number of species of Plant leaf disease has increased in recent years, as has the magnitude of the harm they cause. The aim of this research is to develop a deep convolutional network model that can quickly and accurately detect Plant leaf disease images. The five most common plant leaf diseases are leaf blight, sooty stripe, leaf rust and grey leaf spot, bacterial leaf spot, and zonate leaf spot. Plant leaf diseases can manifest in a number of ways. Farmers who aren't qualified in plant pathology can have a harder time detecting diseases. As a disease detection verification system, an automated system that is configured to identify crop diseases based on the crop's appearance and visual symptoms could be very useful to farmers. Many attempts have been made to easily and reliably classify leaf diseases. Using digital image processing techniques and neural networks, so we can recognise the leaf diseases. In the last few years, deep learning has come a long way. It can now derive useful feature representations from a large number of input images. Deep learning helps detectors to quickly and accurately identify crop diseases, which not only increases plant protection but also expands the use of computer vision in precision agriculture.

II. MOTIVATION

The main reason for creating the convolutional networks model for leaf disease was to give farmers an easy-to-use method for detecting early-stage infections using a standard digital camera. Second, extracting effective features for detecting diseases is a critical but difficult job, and CNNs are required to automate feature learning from raw inputs in a systematic manner.

III.PROBLEM STATEMENT

Plant diseases are usually caused by pests, insects, and pathogens, and if not handled in a timely manner, they reduce production on a large scale. Agriculturists are losing money as a result of a variety of crop diseases. The proposed



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system offers a solution for routinely tracking the cultivated area as well as automatic detection of plant leaf disease. The proposed system's goal is to detect plant diseases early, before they spread to the outer layer of the leaves.

IV. LITERATURE SURVEY

Lucas G. Nachtigall and Ricardo M. Araujo, Gilmar R. Nachtigall "Convolutional Neural Networks for Classification of Apple Tree Disorders"[1], As presented, The use of Convolutional Neural Networks to detect and classify diseases, nutritional deficiencies, and herbicide damage on apple trees from photos of their leaves is investigated in this paper. This role is critical for ensuring high quality yields, and it is currently primarily performed by specialists in the sector, which limits size and increases costs. We show that qualified Convolutional Neural Networks can equal or outperform experts in this role, achieving a 97.3 percent accuracy on a hold-out collection, using a novel data set containing labelled examples consisting of 2539 images from 6 recognised disorders.

Siddharth Singh Chouhan, (Student Member, IEEE), Ajay Kaul, Uday Pratap Singh and Sanjeev Jain, (Member, IEEE) "Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) for identification and classification of plant leaf diseases: An automatic approach towards Plant Pathology"[2], presented as, The importance of a plant's contribution to human life and the environment cannot be overstated. Plants, like humans and animals, are susceptible to disease. There are a variety of plant diseases that can affect a plant's normal development. The entire plant is affected by these diseases, including the leaf, stem, fruit, root, and flower. When a plant's disease is not handled, it usually dies or results in the loss of leaves, flowers, and fruits, among other things. For accurate identification and treatment of plant diseases, accurate diagnosis of such diseases is needed. Plant pathology is the study of plant diseases, their causes, and control and management procedures. However, the current approach includes human participation in disease classification and diagnosis. This is a time-consuming and expensive process. Automatic disease segmentation from plant leaf images using a soft computing approach may be more useful than the current method. In this paper, we present a Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) method for automatically identifying and classifying plant leaf diseases. We use Bacterial foraging optimization (BFO) to assign optimal weight to the Radial Basis Function Neural Network (RBFNN), which improves the network's speed and accuracy in identifying and classifying disease-infected regions on plant leaves. The region increasing algorithm improves the network's efficiency by finding and grouping seed points with similar attributes for the feature extraction process. We worked on common rust, cedar apple rust, late blight, leaf curl, leaf spot, and early blight, among other fungal diseases. The proposed method improves disease detection and classification accuracy.

Sharada Prasanna Mohanty, David Hughes, and Marcel Salathé, "Using Deep Learning for Image-Based Plant Disease Detection"[3],Presented as, Crop diseases are a major threat to food security, but due to a lack of infrastructure in many parts of the world, rapid identification is difficult. Smartphone-assisted disease detection is now possible thanks to a combination of rising global smartphone penetration and recent developments in machine vision made possible by deep learning. We trained a deep convolutional neural network to classify 14 crop species and 26 diseases using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions (or absence thereof). On a held-out test range, the trained model achieves an accuracy of 99.35 percent, demonstrating the viability of this method. The model also achieves a 31.4 percent accuracy when tested on a collection of images obtained from trusted online sources - i.e. images taken under conditions different from those used for training. While this accuracy is significantly higher than the one based on random selection (2.6%), a more diverse collection of training data is needed to increase overall accuracy. Overall, the method of training deep learning models on increasingly broad and publicly accessible image datasets points to a simple direction toward widespread smartphone-assisted crop disease diagnosis.

Yang Lua, , Shujuan Yi , Nianyin Zeng , Yurong Liud , Yong Zhangf, "Identification of rice diseases using deep convolutional neural networks" [4], Presented as, Automatic identification and diagnosis of rice diseases is highly desired in the field of agricultural data. Deep learning is a hot research topic in pattern recognition and machine learning right now, and it can effectively solve these problems in vegetable pathology. In this paper, we present a novel rice disease detection method based on deep convolutional neural networks (CNNs). A dataset of 500 natural photos of diseased and healthy rice leaves and stems collected from a rice experimental area is used to train CNNs to recognise 10 common rice diseases. Using a 10-fold cross-validation method, the proposed CNNs-based model achieves 95.48 percent accuracy. This accuracy much exceeds that of a conventional machine learning model. The feasibility and efficacy of the proposed method for identifying rice diseases were demonstrated by simulation results.



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Anand H. Kulkarni, Ashwin Patil R. K. ," Applying image processing technique to detect plant diseases"[5], This paper Images taken by cameras are subjected to preprocessing measures. The system built here is for recognising plant diseases and is based on the Gabor filter for feature extraction.

V. SYSTEM ARCHITECTURE

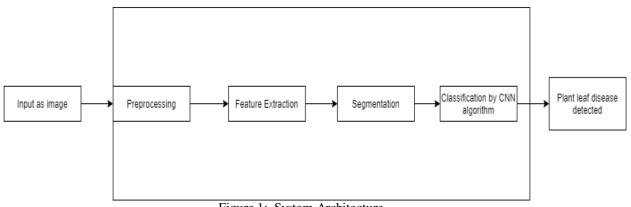


Figure 1: System Architecture

Modules :

Pre-processing :

Although geometric transformations of images (e.g. rotation, scaling, translation) are known as pre-processing methods, the goal of pre-processing is an enhancement of the image data that suppresses unwanted distortions or improves certain image features necessary for further processing. - Possessiveness Image processing is the use of a digital computer to run an algorithm on digital images. Digital image processing, as a subcategory or field of digital signal processing, has many advantages over analogue image processing.

Read the Image Image Resized (220,220, 3)/Resized (width, height, no. RGB channels) Conversion of RGB to Grayscale Identification of segmentation edges The Gaussian filter is used to remove noise.

Segmentation :

It entails segmenting a visual input to facilitate image analysis. If we want to remove or identify something from the rest of the image, such as detecting an object in the background, we can divide the image into segments that can be processed further. This is often referred to as segmentation. Segments contain objects or parts of objects and are made up of groups of pixels known as "super-pixels."

Feature Extraction :

Features in an image may be complex structures such as points, edges, or objects. The aim of feature extraction is to reduce the number of features in a dataset by generating new ones from existing ones (and then discarding the original features). The new reduced collection of features should then be able to summarise the majority of the details in the original set of features.



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Feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.

Classification :

Because of their high precision, CNNs are used for image detection and recognition. The classification convolutional neural network has a three-dimensional structure, with each collection of neurons analysing a particular region or "function" of the picture. Each group of neurons in a CNN focuses on a different part of the picture. The algorithm examines smaller portions of the images. The final result is a vector of probabilities that predicts how likely each feature in the image is to belong to a class or group.

VI. ALGORITHM

CNN (Convolutional Neural Network): CNN (convolutional neural network) is a form of deep learning neural network. In a nutshell, consider CNN to be a machine learning algorithm that can take an input image, assign importance (learnable weights and biases) to various aspects/objects in the image, and distinguish one from the other. CNN operates by extracting features from videos. A CNN is made up of the following components:

A grayscale image serves as the input layer.

The output layer, which consists of binary or multi-class labels.

Convolution layers, ReLU (rectified linear unit) layers, pooling layers, and a completely connected Neural Network comprise the hidden layers.

It is critical to understand that ANNs, or Artificial Neural Networks, comprised of multiple neurons, are incapable of extracting features from images. This is where a convolution and pooling layer combination comes into play. Similarly, the convolution and pooling layers are incapable of classification, necessitating the use of a fully connected Neural Network.

Before we jump into the concepts further let's try and understand these individual segments separately.

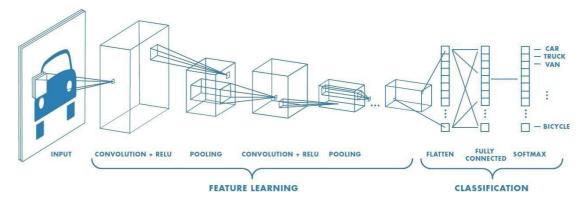


Figure 2: Illustrates the CNN process from input to Output Data.

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VII. RESULT



Figure:3



Figure:4



Figure:5

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Figure:6



Figure:7

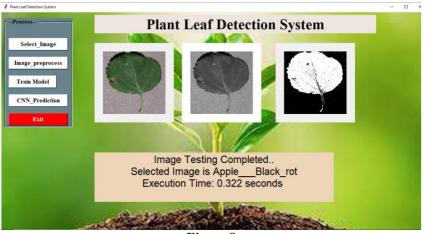


Figure:8

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Figure:9



Figure:10



Figure:11

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Figure:12

VIII. CONCLUSION

This project provides very accurate deep learning solution for detecting plant leaf disease which makes use of convolutional neural network for classification purpose. The presented model used the dataset that consists of number of images for training the model . As we increase the number of images the accuracy of the model is also increased after training the model it will able to detect plant leaf disease from new input images.

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