Leaf Disease Detection Using Transfer Learning

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***Abstract*: A deep neural network is very successful for image classification problems. In this project, we show how a neural network can be used for leaf disease detection in the context of image classification. We have used publicly available Plant leaves with our dataset which has different classes of diseases. Hence, the problem that we have addressed is a multi-class classification problem. We are using the Inception V3 architecture and Convolutional Neural Network (CNN) algorithm as a base with Transfer Learning for image processing. With the help of Transfer Learning, we reduce a large amount of time we required for data training and also it increases the accuracy of image recognition**

***Keywords*: Detection, Transfer Learning, CNN, Disease**

INTRODUCTION

1] This project aims to identify the diseased and healthy leaves of distinct plants by extracting features from input images using the CNN algorithm.

2] These features extracted help in identifying the most relevant class for images from the datasets.

MOTIVATION

It is very important to get an accurate diagnosis of plant diseases for global health and wellbeing. In this ever-changing environment, identifying the disease including early prevention is important to avoid problems that we might face otherwise. Some of these problems could have devastating impacts on humanity including a global shortage of food. It is crucial to prevent unnecessary waste of financial resources achieving a healthier lifestyle, by addressing climate change from an ecological perspective. It is difficult for the naked eye of a human being to catch all sorts of problems with plant diseases. Also doing this time and time again is laborious and unproductive work. To achieve accurate plant disease detection, a plant pathologist should possess good observation skills so that one can identify characteristic symptoms. An automated system designed to help identify plant diseases by the plant's appearance and visual symptoms could be of great help. This can be deployed in agricultural fields to automate the whole pipeline. This would lead to better efficiency as machines could perform better than humans in these redundant tasks and improve the productivity of the farm. Our work solves the above-mentioned problem of automating plant disease classification using deep learning and computer vision techniques

LITERATURE SURVEY

An Overview of the Research on Plant Leaves Disease detection using Image Processing Techniques

Studied: The present paper reviews and summarizes image processing techniques for several plant species that have been used for recognizing plant diseases. The major techniques for the detection of plant diseases are BPNN, SVM, K-means clustering, and SGDM. These techniques are used to analyze the healthy and diseased plants' leaves. Some of the challenges in these techniques viz. effect of background data in the resulting image, optimization of the technique for specific plant leaf diseases, and automation of the technique for continuous automated monitoring of plant leaf diseases under real-world field conditions. The review suggests that this disease detection technique shows good potential with an ability to detect plant leaf diseases and some limitations. Therefore, there is a fore for improvement in the existing research

Plant diseases and pests detection based on deep learning: a review

Studied: Plant diseases and pests are important factors determining the yield and quality of plants. Plant diseases and pests identification can be carried out using digital image processing. In recent years, deep learning has made breakthroughs in the field of digital image processing, far superior to traditional methods. How to use deep learning technology to study plant diseases and pests identification has become a research issue of great concern to researchers. This review defines plant diseases and pest detection problems forward a comparison with traditional plant diseases and pests detection methods.

Detection of plant leaf diseases using image segmentation and soft computing techniques

Studied: This paper presents the survey on different disease classification techniques used for plant leaf disease detection and an algorithm for image segmentation technique that can be used for automatic detection as well as classification of plant leaf diseases later. Banana, beans, jackfruit, lemon, mango, potato, tomato, and sapota are some of those ten species on which the proposed algorithm is tested. Therefore, related diseases for these plants were taken for identification. With very less computational effort the optimum results were obtained, which also shows the efficiency of the proposed algorithm in the recognition and classification of the leaf diseases. Another advantage of using this method is that plant diseases can be identified at an early stage or the initial stage. To improve the recognition rate in the classification process Artificial Neural Network, Bayes classifier, Fuzzy Logic, and hybrid algorithms can also be used

Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming

Studied: is paper proposes a mathematical model of plant disease detection and recognition based on deep learning, which improves accuracy, generality, and training efficiency. Firstly, the region proposal network (RPN) is utilized to recognize and localize the leaves in complex surroundings. en, images segmented based on the results of the RPN algorithm contain the feature of symptoms through Chan–Vese (CV) algorithm. Finally, the segmented leaves are input into the transfer learning model and trained by the dataset of diseased leaves under simple background. Furthermore, the model is examined with black rot, bacterial plaque, and rust diseases. e results show that the accuracy of the method is 83.57, which is better than the traditional method, thus reducing the influence of disease on agricultural production and being favorable to the sustainable development of agriculture. Therefore, the deep learning algorithm proposed in the paper is of great significance in intelligent agriculture, ecological protection, and agricultural production.

LIMITATIONS OF EXISTING SYSTEM

- Lot of time is required for dataset training.
- Accuracy is low.

EXPERIMENTAL SETUP

PyCharm is an integrated development environment (IDE) used in computer programming, specifically for the Python programming language. It is developed by the Czech company JetBrains (formerly known as IntelliJ).[5] It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems (VCSes), and supports web development with Django as well as data science with Anaconda. PyCharm is cross-platform, with Windows, macOS, and Linux versions. The Community Edition is released under the Apache License,[7] and there is also an educational version, as well as a Professional Edition with extra features (released under a subscription-funded proprietary license)

Firebase evolved from Envolve, a prior startup founded by James Tamplin and Andrew Lee in 2011. Envolve provided developers with an API that enables the integration of online chat functionality into their websites. After releasing the chat service, Tamplin and Lee found that it was being used to pass application data that were not chat messages. Developers were using Envolve to sync application data such as the game state in real-time across their users. Tamplin and Lee decided to separate the chat system and the real-time architecture that powered it.[2] They founded Firebase as a separate company in 2011 and it launched to the public in April 2012.[3] Firebase's first product was the Firebase Real-time Database, an API that synchronizes application data across iOS, Android, and Web devices, and stores it on Firebase's cloud. The product assists software developers in building real-time, collaborative applications.

SCOPE:

In this project, it automatically detects the important features without any human supervision. Given many pictures of leaves, it learns distinctive features for each class by itself. CNN is also computationally efficient.

PROBLEM STATEMENT:

This project aims to identify the diseased and healthy leaves of distinct plants by extracting features from input images using Inception V3 architecture with the Transfer Learning method. These features extracted help in identifying the most relevant class for images from the datasets.

SYSTEM ARCHITECTURE

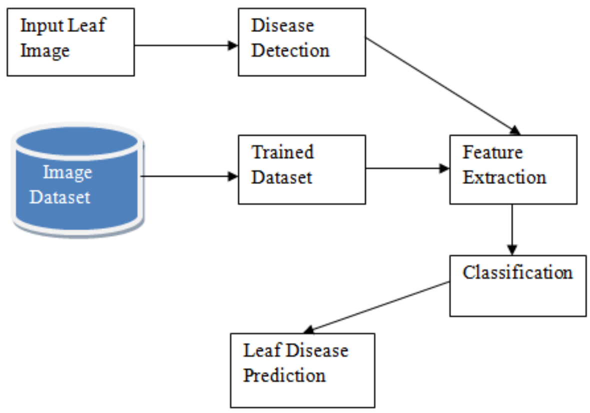

Fig -1: System Architecture Diagram

Image Data set: In this process, we are creating the dataset of leaf diseases where we are maintaining a folder of different types of leaves.

Trained Data set: Here we are training the data set that we created earlier.

Input Leaf Image: Here we are creating an input field for the user where the user will upload the image.

Processing: Here section like features extraction, Classification, and leaf disease detection are used, when leaf input is given system extracts the features from the image and classify them with the dataset, and gives a prediction.

CNN ARCHITECTURE

Inception-v3 is a convolutional neural network architecture from the Inception family that makes several improvements including using Label Smoothing, Factorized 7 x 7 convolutions, and the use of an auxiliary classifier to propagate label information lower down the network (along with the use of batch normalization for layers in the side head).

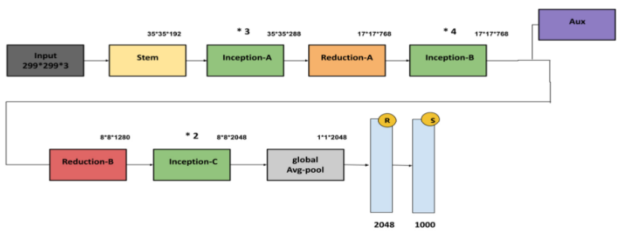

Fig -2: CNN Architecture Diagram

ADVANTAGES

1. It has higher efficiency
2. It has a deeper network compared to the Inception V1 and V2 models, but its ' speed isn’t compromised.
3. It is computationally less expensive.
4. It uses auxiliary Classifiers as regularizes.

LIMITATIONS

1. Internet connection is necessary
2. Proper Dataset

APPLICATION:

1. Easy to use
2. Monitoring controlling user leaf disease detection

METHODOLOGY

Transfer Learning

Transfer learning for machine learning is when existing models are reused to solve a new challenge or problem. Transfer learning is not a distinct type of machine learning algorithm, instead, it's a technique or method used whilst training models. The knowledge developed from previous training is recycled to help perform a new task. The new task will be related in some way to the previously trained task, which could be to categorize objects in a specific file type. The original trained model usually requires a high level of generalization to adapt to the new unseen data

CONCLUSION

Diseases in plants are a major problem to the food supply. This project demonstrates the technical feasibility of deep learning using a convolutional neural network approach to enable automatic disease diagnosis through image classification. Using a public dataset with our dataset of diseased and healthy plant leaves, a deep convolutional neural network is trained to classify crop species and disease status of 38 different classes containing 13 plant species and 38 diseases, achieving an accuracy of 83.5 percent with residual network architecture. In this project, a new approach of using deep learning methods was explored to automatically classify and detect plant diseases from leaf images. The developed model was able to distinguish between healthy leaves and different diseases, which can be visually diagnosed. The complete procedure was described, respectively, from collecting the images used for training and validation to image augmentation and finally the procedure of training the deep CNN and fine-tuning. With this research, we concluded that by using Inception V3 time required to train the dataset is less than the other and it also has good accuracy for identifying more plant sicknesses.

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