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Research

Plant Disease Identification Using Artificial Intelligence and Cloud Collaborative Platform

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Abstract: Farmers, consumers, the environment, and the global economy are all at risk from plant diseases. Farmers in India lose 35% of their field harvests to pests and pathogens. Using pesticides without care is also bad for your health because many of them are poisonous and bioaccumulate. You can avoid these bad impacts by finding the disease early, keeping an eye on the crops, and giving the right medicines. Agricultural scientists usually figure out what illness a plant has by looking at its outside signs. But farmers don't have easy access to professionals. Our initiative is the first platform for automated disease detection, tracking, and forecasting that brings all of these things together and lets people work together. With a mobile app, farmers may quickly and correctly find diseases and obtain help by taking pictures of the afflicted areas of plants.

The newest AI algorithms for Cloud-based image processing make it possible to diagnose things in real time. The AI model becomes better at what it does by learning from photographs that users upload and suggestions from experts. The platform also lets farmers talk to local specialists. For prevention, a Cloud-based database of geo-tagged photos and micro is used to make illness density maps with predictions on how they will spread. Experts can do disease analytics with geographical visualizations using a web interface. We trained the AI model (CNN) on massive disease datasets made up of plant photos that we took ourselves from several farms over the course of seven months. Plant pathologists checked the results of the automatic CNN model on test photographs. The accuracy of identifying diseases was over 95%. Our solution is a new, flexible, and easy-to-use tool for managing diseases in a wide range of agricultural crops. It can also be used as a Cloud-based service for farmers and professionals to help them grow crops in an environmentally friendly way.

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1. INTRODUCTION

EarFor humans to survive, agriculture is essential. It is much more crucial to boost crop, fruit, and vegetable yield in densely populated emerging nations like India. For improved public health, produce quality must remain high in addition to productivity. However, problems like the spread of infections that may have been avoided with early detection hinder both food quality and productivity. Numerous of these illnesses are contagious and completely reduce agricultural productivity. Human assisted disease diagnosis is ineffective and cannot meet the high standards due to the wide geographic dispersion of agricultural fields, farmers' low educational attainment, their lack of awareness, and their inability to access plant pathologists...

2. LITERATURE SURVEY

2.1 A survey of image processing techniques for agriculture AUTHOR: Lalit P. Saxena and Leisa J. Armstrong

Computer technologies have been shown to improve agricultural productivity in a number of ways. One technique which is emerging as a useful tool is image processing. This paper presents a short survey on using image processing techniques to assist researchers and farmers to improve agricultural practices. Image processing has been used to assist with precision agriculture practices, weed and herbicide technologies, monitoring plant growth and plant nutrition management. This paper highlights the future potential for image processing for different agricultural industry contexts. Here we explore ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible by suitably factorized convolutions and aggressive regularization.

2.2 Imagenet classification with deep convolutional neural networks

AUTHOR: A. Krizhevsky, I. Sutskever and G. E. Hinton,

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way soft max. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overriding in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

3. METHODOLOGY

a) Proposed Work:

Convolution neural networks are used in this project as artificial intelligence to train all plant illness photos. CNN will then forecast plant diseases present in newly submitted images. The author uses cloud services to store CNN train models and photos. Thus, data is stored on the cloud and plant disease is predicted by Al author. The inventor of this project uses a smartphone to upload images, but creating an Android application will cost more money and take more time, so we created a Python web application instead. With the use of this online application, a CNN model can be trained, and users can contribute photographs for the application to use in predicting diseases. This web application will retrieve the user's location from the request object and display it on a map if it is installed on a genuine web server.

b) System Architecture:

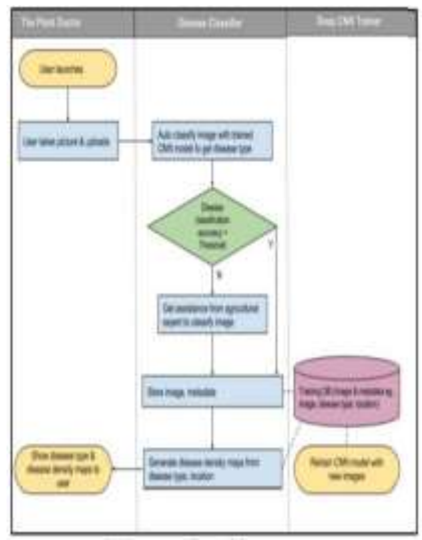

Fig 1 Proposed Architecture

The proposed system for Plant Disease Identification using Artificial Intelligence and a Cloud Collaborative Platform consists of three main modules: the Plant Doctor (user interface), the Disease Classifier, and the Deep CNN Trainer. Initially, the user launches the application and captures or uploads an image of a plant leaf. The uploaded image is processed by a trained Convolutional Neural Network (CNN) model that automatically classifies the disease type. The system then evaluates whether the classification confidence meets a predefined accuracy threshold. If the accuracy is sufficient, the disease type along with related metadata such as image details and location is stored in the cloud database, and the detected disease information along with disease density maps is displayed to the user. If the confidence level is below the threshold, the image is forwarded to an agricultural expert for manual verification and correct labeling. The validated images and metadata are stored in a training database, and the Deep CNN model is periodically retrained using these newly added images to improve prediction accuracy. This continuous feedback and retraining mechanism enables the system to become more accurate and reliable over time, creating a self-improving, cloud-enabled intelligent plant disease diagnosis platform.

c) MODULES:

1. Register Module:

In this module the web interface allows user to get registered any user who wants to register they need to sign up by giving their details like user name, password, contact number, e-mail id. After successfully getting registered it will show the user that signup was successful.

2. Login Module:

In this module the user can directly get into the website by simply giving their username and password. If either of the username or password is incorrect then it gives an error message like invalid details. By giving valid details users can easily interact with website.

3.Upload Plant Image:

In this module the user can upload the affected plant images. After successful login the user can upload the plant images. After uploading the plant image user have to click submit, next the image get submitted and execution takes place in the backend and the plant disease is predicted and displayed on the website.

4. Logout:

After getting the result the user can simply click on the logout button and can come back from the website.

4. EXPERIMENTAL RESULTS

.**Accuracy:** The capacity of a test to accurately distinguish between healthy and sick cases is a measure of its accuracy. We can determine a test's accuracy by calculating the proportion of reviewed cases with true positives and true negatives. In mathematical terms, this looks like:

Accuracy = TP + TN TP + TN + FP + FN.

$$Accuracy = \frac{(TN + TP)}{T}$$

F1-Score: One way to evaluate a model's performance in machine learning is via its F1 score. It takes a model's recall and precision and mixes them. Using the whole dataset, the accuracy metric determines the frequency with which a model produced accurate predictions.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

Precision: The proportion of occurrences or samples that are correctly classified out of all the ones that are classified as positive is known as precision. Consequently, the following is the formula for determining the accuracy:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The capacity of a model to detect all significant instances of a given class is measured by recall, a metric in machine learning. It sheds light on how well a model captures instances of a certain class and is calculated as the ratio of the total number of positive observations predicted to the number of actual positive observations.

$$Recall = \frac{TP}{(FN + TP)}$$

Fig 4: Output-

5. CONCLUSION

In order to protect user privacy when publishing the Taxi Trajectories datasets, we have put up a framework. The suggested method is based on a machine learning clustering strategy that seeks to minimize the loss experienced during the anonymization process, as well as an effective alignment technique known as progressive sequence alignment. Additionally, we developed a variant of the k-0-means approach to ensure k-anonymity in datasets that are very sensitive. The experimental findings on actual GPS datasets show that our suggested framework performs better in terms of spatial utility than earlier studies. Our project is therefore innovative and scalable. Farmers primarily use it to obtain precise results. This aids in the early detection of the illness, which allows for its prevention through the use of preventative measures.

6. FUTURE SCOPE

More variables that potentially enhance the association with the disease, such as temperature, humidity, and rainfall, will be included in future research. In addition, we want to cover more crop diseases and lessen the need for professional intervention—aside from new disease types. Support for automatic time-based monitoring of disease density maps, which can be used to monitor the progression of an illness and set off alarms, is another possible use for this study. To increase the accuracy of our model and make disease forecasting possible, we can supplement the picture database with farmer-provided supporting inputs on soil, previous fertilizer and pesticide treatments, and publically accessible climatic parameters like temperature, humidity, and rainfall. With the exception of novel disease types, we also hope to decrease the time, expense, and requirement for professional intervention while expanding the scope of crop illnesses covered. A straightforward method of calculating the threshold based on the mean of all classification scores can be used to automatically allow user-uploaded photos into the Training Database for improved classification accuracy and the least amount of human interaction. Users can receive notifications from predictive analytics about potential illness outbreaks in their area..

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