Kisaan Madat Portal : Plant Disease Diagnosis and Soil Report Analysis via Web Application

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Abstract: Pests and diseases affecting plants and crops can seriously impact a country's agricultural production. Traditionally, farmers or agricultural experts monitor the fields closely to detect any signs of disease. However, this method is often time-consuming, costly, and not always reliable. One common way to identify plant diseases is by observing spots or marks on the leaves. The aim of this paper is to develop a Disease Recognition Model based on leaf images. To detect plant diseases, we are using image processing techniques with the help of a Convolutional Neural Network (CNN). CNNs are a type of artificial neural network designed to process pixel data, making them ideal for image recognition tasks like this one. Also, the web app will provide the feature like nearby soil testing center search where farmer can test soil and collect report. Web application is also enabled with report understanding feature where farmer get short and meaningful summary of the soil test report.

Keywords: Plant Leaf Disease, CNN, Plant birth, Image Processing, Crop Protection, Deep Learning, Geopy library.

1 INTRODUCTION

In India, around 70% of the population depends on agriculture. Identifying plant diseases is very important to prevent loss in crop yield. Manually checking plant health is difficult it takes a lot of time, effort, and expert knowledge. In this project, we've explored a method to detect plant diseases using images of their leaves. Image processing, which is a part of signal processing, helps extract important features or useful information from images.

Machine learning, a branch of artificial intelligence, allows systems to learn automatically or follow instructions to perform specific tasks. Its main goal is to train models using relevant data so they can make smart decisions and accurate predictions. Traditionally, plant disease detection was done through visual inspection or chemical tests by experts. But this approach needs a big team and constant monitoring, which can be expensive especially for large farms. In such cases, the proposed system can be very useful for monitoring crops across wide agricultural areas.

2 LITERATURE REVIEW

Plants are the main source of food for people around the world. When plants get affected by diseases, it can lead to a major loss in crop production. That's why regular monitoring is so important. But manually checking plant health is not only difficultit's also prone to human error. By using computer vision and artificial intelligence (AI), we can detect plant diseases early. This helps prevent serious damage and also solves the problems that come with continuous manual monitoring.

Critical Analysis

A smart 3D CNN model, built using the CANet architecture, can accurately detect and segment disease spots on plant leaves, with 92% accuracy and 90% Intersection over Union (IoU). Another deep CNN model showed excellent results in identifying diseases in pepper (91.11%), potato (93.01%), and tomato (99.04%) using the Plant Village dataset.[7] Image processing plays a key role here—it helps pull out important features from the plant images like contrast, energy, texture, and patterns. Interestingly, even a general-purpose CNN trained on just 80 leaf images per class across six different plant species and diseases was able to achieve over 90% accuracy.[1]

2.2 Methods and Approaches

A smart 3D CNN model, designed using the CANet architecture, can accurately detect disease spots on plant leaves,[4] achieving 92% accuracy and 90% IoU (Intersection over Union). Another deep CNN model also performs really well in identifying diseases in crops like 91.11% accuracy for pepper, 93.01% for potato, and an impressive 99.04% for tomato using the Plant Village dataset. Image processing plays a key role in this system.[6] It helps extract important details from plant images such as contrast, texture, and patterns. Even a simple CNN model trained with just 80 images per class was able to reach over 90% accuracy across six different plant types and diseases.[2]

1. **ANALYSIS OF DIFFERENT APPROACHES**
2. In 2020, a CNN-grounded system was proposed for relating factory conditions by assaying infected areas in sample images. It achieved about 90 delicacy. Still, CNNs need a lot of calculating power when working with large or complex datasets. Also, when the dataset is small, CNNs can fluently overfit and give lower dependable results.[7]
3. In 2024, experimenters used VGG- 16 and VGG- 19 models to classify healthy and diseased leaves of medicinal shops. With large datasets and fine- tuning, they reached up to 94 delicacy. Still, VGG models can struggle in this field because their armature is fixed and doesn't acclimatize well to specific agrarian requirements.[1]

4. Back in 2015, Artificial Neural Networks(ANNs) were used to descry splint conditions by assaying color and shape features. This system achieved 80 delicacy. While ANNs can work, they're sensitive to image noise and do n't handle changes in the image veritably well, which affects their performance in real- world conditions.[2]

5. In 2023, ResNet-50 was chosen to make a smart web app for prognosticating crop conditions. It gave outstanding delicacy up to 98.98. But the strike is that ResNet-50 needs a lot of calculating power and memory, which can be a problem if you are trying to run it on low-end bias.[5]

3 DATA-SET :

In this data-set, 39 different classes of plant leaf and background images are available. The data-set containing 61,486 images. We used six different augmentation techniques for increasing the data-set size.

5 PROPOSED SYSTEM

We are erecting a model that can descry factory splint conditions in real time using an Android phone's camera. The overall process of how the model works is shown in Fig. 1.

4.1 Data Collection :

First, we collect the data. For this, we are using the well-known Plant Village Dataset, 39 different classes of plant leaf and background images are available. The data-set containing 61,486 images. We used six different augmentation techniques for increasing the data-set size.

4.2 Pre-processing :

Next, we prepare the data for training using Keras Image Data Generator. This step helps clean, organize, and transfigure the images so they're ready for the model to learn from.

4.3 Model Structure :

For the model itself, we are using a Convolutional Neural Network(CNN) erected on the VGG- 19 armature. This model is trained to fete and classify different types of factory conditions grounded on the splint images.

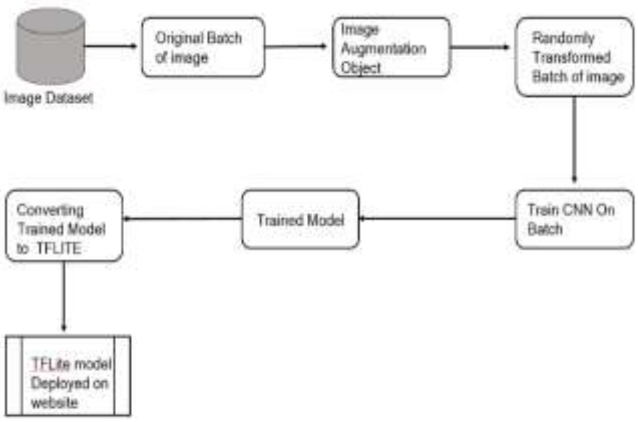

Figure no.1

6 CONVOLUTIONAL NEURAL NETWORK (CNN) ARCHITECHTURE

A Convolutional Neural Network has three layers: a convolutional subcaste, a pooling subcaste, and a completely connected subcaste. Fig 2 shows all layers together.

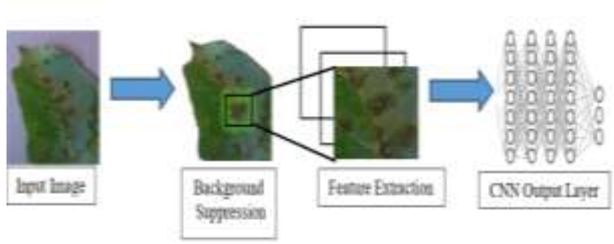

Figure no. 2

6.1 Convolutional Layer

The network is made up of 16 convolutional layers, and each one uses small 3 × 3 pollutants with a stride of 1. These small pollutants help the model pick up fine details from the input images. As we go deeper into the layers, the model learns more complex and meaningful features step by step.[9]

6.2 Pooling Layer

The pooling subcaste helps to reduce the quantum of data produced by the convolutional subcaste. This makes it easier and faster for the system to reuse and store the data. Figure 3 shows how the pooling subcaste works internally.

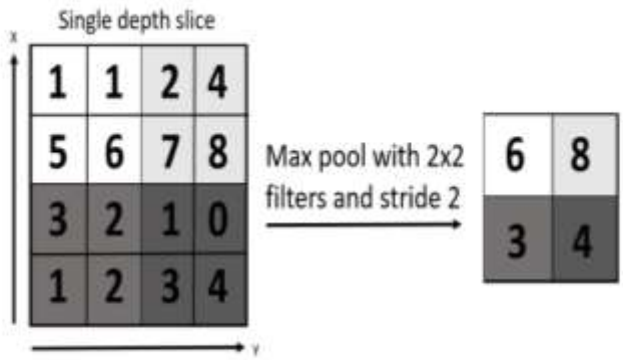

Figure no. 3

6.3 Outcomes

Training Accuracy : 96.7%
Testing Accuracy : 98.9%
Validation Accuracy : 98.7%

7 SOIL REPORT DIGNOSIS

7.1 Natural Language Processing Integration:

In the "Kisaan Madat Portal: Plant Disease Diagnosis and Soil report Analysis Via Web Application" design, Natural Language Processing (NLP) helps make the platform easier and further useful for farmers. It allows them to describe the problems in the soil using the image of soil report, like uploading the soil test reports on the web site and the system understands through the OCR and it will further gives output using NLP.[19] NLP ways like breaking down the sentence, removing extra words, and picking out important terms help the system figure out what the farmer is trying to say.[15] It can even handle different languages and sort the questions into types like disease issues, fertilizer problems, or crop advice.[16] Plus, by using voice-to-text features, even farmers who aren't comfortable typing can speak their questions, and a chatbot can give quick help.[20]

Overall, NLP makes the app smarter, easier to use, and more helpful for farmers in real-life situations.

7.2 Nearby Soil Testing Center Locator

To help farmers take better care of their soil and increase crop production, this web application comes with a useful new feature. It helps users easily find the nearest soil testing centers, whether they are run by the government or private agencies.[10] Farmers can either use GPS or type in their location manually. The app then shows nearby testing centers based on a fixed distance range. [11] To do this, it uses the Google Maps API to detect the farmer's location and the Geopy library to calculate the distance between different testing centers.[13]-[14]. This feature runs on the Geolocation API, which is integrated in backend in python and it will return the result using geopy library. It includes the returning the IP location in Longitudes and Latitudes and then distance is calculated.
Once the nearby centers are located, the app displays important information like:
Address
Contact number
Types of soil tests offered
Working hours
In addition to this, the feature aims to educate farmers about the value of soil health and how regular testing can help in using fertilizers wisely and improving crop yield. This module also works closely with agricultural departments and official databases, ensuring farmers receive accurate and reliable information on soil pH, nutrient content, and other key factors that are important for planning their crops effectively.[13]

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