PLANT LEAF DISEASE DETECTION USING PYTHON AND ML

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ABSTRACT

In this research paper represent a inclusive study on leaf disease detection. leveraging the ResNet18 model trained with PlantVillage dataset the system is designed to impact crop yield and food security by using Convolutional Neural Network. Healthy plants help crops grow well and make sure we have enough food. Yet, knowing crop disease early is hard for many farmers. Checking by hand works at times, but it's slow, not sure, and hard to get in country spots.

This study shows a new system that spots plant leaf sickness quick using smart tech and image checks. It uses smart learning from the ResNet18 model, trained with the PlantVillage data, to spot many crops and sick types well. A web tool made with Flask lets users put up leaf photos and get fast tips and fixes. This new tool shows how smart tech can help make farming better, cut crop loss, and aid clean farming.

KEYWORDS: *leaf disease detection, ResNet18-model, PlantVillage dataset, OpenCV, Transfer learning with pre-trained model.*

INTRODUCTION

farming is the key part of many lands, mainly in less rich places, where it gives food, work, and money for lots of people. Yet, sick crops are a big problem, causing a lot of lost food and putting food lines at risk. Spotting plant sickness early and well is key to cut money loss and help keep food safe.

Old ways to find crop sickness count on seeing them with eyes, done by farmers or pros, but this often has mistaken and takes time. With new steps in smart tech, mostly deep learning, we can now make smart systems that can look at plant photos and tell what sickness they have very well. This study works on making a smart tool for spotting plant sickness that uses smart seeing, learning tech, and web tools. We would like a simple and farmer-friendly tool, which can give you an instant clue about any disease at plant leaf level and methods to control it.

LITERATURE SURVEY

Over the past two decades, the art of detecting plant disease has shifted off of the human-intensive, hand-led methods into intelligent computer systems through machine and deep learning. The differences can be seen clearly in the published work: the methodologies of the old-style image handling, the emergence of the new Convolutional Neural Networks (CNNs), and the growing interest in applying what has been learned in one field to another field and the application of these notions to main-stream practice. Scholars even began to experiment with CNN models, such as Alex Net, VGG16, GoogLeNet, and ResNet, to detect crop disease. Of them, ResNet became even more well-known with its employment of left-over links, which remedy the disappearing gradient problem in deep nets, allowing them to train deeper nets successfully. Research found that CNNs, when trained on big sets like PlantVillage, hit accuracy over 95%, doing much better than old ML ways by a wide gap.

The PlantVillage dataset, made by Pennsylvania State University, is key in plant disease study. It has more than 87,000 marked leaf pics across 38 groups. It sets a clear standard for training and testing disease-finding models. Many researchers have used this dataset to test various CNN designs, often finding strong accuracy in set test conditions. Models like ResNet18, ResNet50, MobileNet, and EfficientNet are used a lot. Transfer learning cuts down training time, needs less computer power, and makes things better when the data is small or not even.

Books show that deep learning, mainly CNN-based transfer learning, works best for finding plant diseases. But there are still hard parts when using it for real. Our proposed system is distinctive since it corrects these problems. It takes preciseness, convenience, and utility of plant disease detection to real agricultural activity.

EXISTING WORK

Techniques used to detect leaf diseases in plants are old technologies and are central in transforming farms to be tech enabled, yet they have limitations on their capabilities. Previously the detection of these diseases was carried out manually. Farmers or farm pros would examine the leaves to see tell-tale signs such as spots, colorchange, curling, or unusual shapes, and then apply the experience to determine what was wrong. At first, early mobile apps used simple ways to pull out features like looking at patterns, finding edges, and checking colors. They used tools like SVMs or KNNs to sort through data. These methods gave some first results. But how good their work was relied a lot on the quality of the image and the place around it. Many apps are limited to either Android or iOS which excludes a large number of users. In addition, numerous tools only provide the name of the disease. They do not impart additional information, its treatment or prevention. Though they demonstrate the potential of AI in farming, such systems are not fully installed to enable farmers to use them easily in real life. The weaknesses show that we need better response that incorporates high right calls with usability, size of growth and easy steps. This makes the cropping sick search effective to majority of the farms.

PROPOSED SYSTEM

The novel system corrects the drawbacks of the available systems to detect plant illnesses on leaves. This is attained by means of deep learning or using the power of one model to the other, use of web tools. This develops an enhanced, easier to use system to the farmers. Centrally, the used system adopts ResNet18 model that is an excellent configuration of Convolutional Neural Network. It trains on a massive dataset of images, known as ImageNet, and then is then trained upon the collection of plant disease images with human labeled by Plant Village. The training set comprises over 87,000 labeled leaves, the images of which are pictures of 38 types of disease and crop groupings. The new system does not only mean identification of sick plants. It is more productive as a supporting material It processes all the pictures that are uploaded resizes them, normalizes them and introduces new functionality and adds it into the model. Transformations like rotation, inverting and zooming have been added to allow the model to respond to different real world circumstances. Under these techniques, the system minimizes false label due to variations in quality of the camera, crowded background or ambient light. The incorporation of ResNet18 and transfer learning, in an inexpensive and simple web-based software containing decision-help components, will provide farmers with an easily expandable and cost-effective method of identifying diseases in plants and acting on them in time. Filling the loopholes of the old agricultural procedures, it makes a huge leap in to improved farming practices and permanent agricultural labour. unlike illumination atmosphere in the kinds of surfaces.

METHODOLOGY

The path to blueprint how to check whether leaves of the plants are sick begins with data collection, preparation, modeling and application in a structured protocol. It begins with the Plant Village data set, containing more than 87,000 leaves images (healthy and diseased) of 38 groups. The photos are then brought in the restricted dimension 224x224, the color values are checked and the photos are altered by turning, flipping, and increasing the dimensions. These actions assist in ensuring that the model is able to look good in various picture appearances, lighting, and directional anteriorities. This also makes it fit to be used in the real farms.

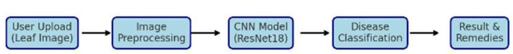

Fig. 1. Block Diagram

After training, the model is put into a Flask web app. The web page lets people add photos of plant leaves, which get processed and put into the model for guessing. The system shows the type of leaf, how sure it is, what the disease is, and how to treat it. By mixing machine learning with a clear and easy-to-use interface, the plan works well and is also simple and helpful for farmers. We watch the training steps via checks on how well it does and the error rates to stop it from learning too much on just the data it sees and to keep it useful for new, unseen data.

Task	Task Name	Status
1	Collect PlantVillage Dataset	Done
2	Data Preprocessing and Cleaning	Done
3	Train CNN (ResNet 18) Model	Done
4	Develop Prediction Model	Done
5	Deploy Web-based System	Done

EXPERIMENTAL RESULTS

The test of the new plant leaf sickness find system looked at how right, strong, and easy to use it was in true life. They used a ResNet18 model, tweaked for the PlantVillage group of data, and it did well. It got a right rate of 96–98% on the test group of things. This shows that using what was learned from ImageNet made the model much better at seeing small changes between leaves that are well and those that are sick. The model was tried under different settings to check its strength. Photos with shifts in light, messy backgrounds, and leaf angles were used to copy real field settings. The system kept its high power to guess right, showing the good of making changes and additions while training it. Also, the system gave answers in 2-3 seconds for each photo, showing it works fast for use at the same time. User tests via the Flask web page showed that the app is easy and open. Farmers and crop study folks liked that they could put up a picture and fast get both the disease name and tips to fix it. This was very useful. Unlike other tools, this new system not only named diseases but also gave real steps to help, which was seen as a big step up.

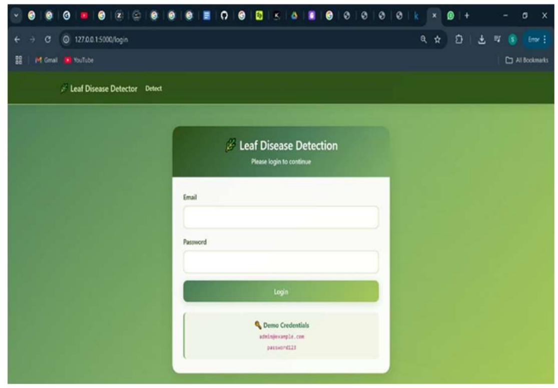

Fig. 2. Login page of leaf Disease Detection

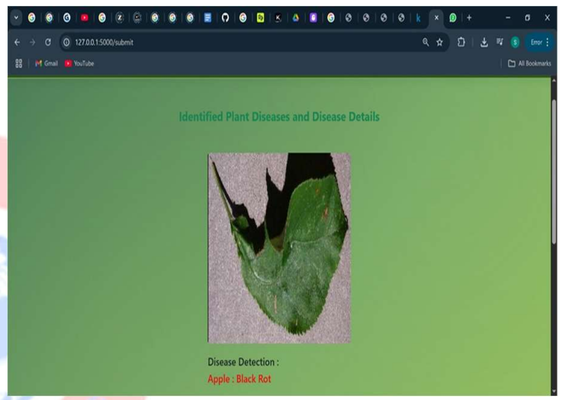

Fig.3. Apple leaf Disease Detection

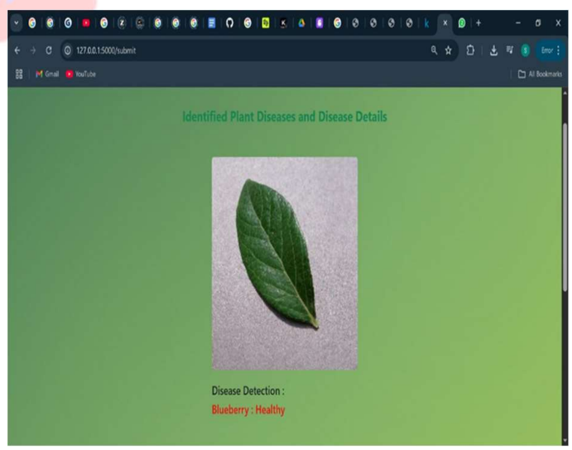

Fig.4. Identification of Healthy Blueberry Leaf

CONCLUSION

The study shown in this text shows how machine learning and deep learning can help solve a big farm problem: quick and right spot of plant sickness. By using the strength of Convolutional Neural Networks (CNNs), mainly the ResNet18 setup with transfer learning, the system got high scores often in telling apart healthy and sick plant leaves for many crop types. The use of the PlantVillage data set gave a good base for model teaching, while steps like resizing, making normal, and adding changes made sure it stayed strong against changes in picture look and outside settings. The test outcomes showed that the system works well.

It was right more than 96% of the time and did well across different sickness groups. The model also did a good job under real-life settings. It worked well even when pictures had issues like light shifts, messy backgrounds, and changes in how leaves were placed. Plus, it predicts fast, making it good for real-time farm use. In short, the new system is a big step forward in smart farming. It brings together being right on point, easy to use, and giving clear advice, filling the space between study and real use.

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