Paper Agri-Innovation: Incorporating Machine Learning in Plant Disease Detection and Resource Allocation

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Abstract - This paper explores the use of machine learning in the field of agriculture to improve plant disease detection and resource allocation. The objective of the project was to develop a model that can accurately detect plant diseases and allocate resources accordingly to minimize crop damage and increase yield. To achieve this objective, a dataset was created consisting of various images of diseased and healthy plants. The dataset was used to train a deep learning model using the convolutional neural network (CNN) algorithm. The model was trained to identify the various types of diseases that commonly affect crops, including fungal infections, viral infections, and bacterial infections. Once the model was trained, it was deployed to a mobile application that can be used by farmers to take pictures of their crops and get a quick diagnosis of any diseases present. The mobile application also provides recommendations for resource allocation, such as which pesticides to use and how much water to provide based on the severity of the disease. To validate the accuracy of the model, a field test was conducted on a farm where various types of crops were grown. The model was able to accurately identify the type of disease affecting the crops, and the resource allocation recommendations provided by the mobile application were effective in minimizing crop damage.

Overall, this paper demonstrates the potential of machine learning in the field of agriculture and highlights the need for further research and development in this area. By leveraging the power of AI and other emerging technologies, we can build more sustainable and resilient agricultural systems that can help feed the growing global population.

Index Terms – Machine Learning, Disease Detection, Resource Allocation, Internet of Things, Convolutional Neural Network (CNN) algorithm, Artificial Intelligence(AI), Remote Access, Real Time Data.

I. INTRODUCTION

Agriculture is an important sector for ensuring food security and economic growth worldwide. However, plant diseases can significantly impact crop yields, leading to food shortages and economic losses. Traditional methods of disease detection and resource allocation in agriculture have been largely manual and prone to errors. In recent years, machine learning has emerged as a promising tool for improving disease detection and resource allocation in agriculture. This report provides an overview of the paper "Agri-Innovation: Incorporating machine learning in plant disease detection and resource allocation" that aims to develop a machine learning-based system for disease detection and resource allocation in agriculture. Plant diseases are caused by various factors such as environmental conditions, pests, and pathogens. These diseases can cause significant crop losses and reduce food production, leading to food shortages and economic losses. Traditional methods of disease detection in agriculture rely on visual inspection by experts, which can be time-consuming, subjective, and prone to errors. Similarly, resource allocation in agriculture, such as irrigation and fertilizer application, is often done manually without considering the individual needs of each crop. This can result in overuse or underuse of resources, leading to inefficiencies and reduced crop yields.

II. LITERATURE SURVEY

[1] Jérôme Treboux, Dominique Genoud: The study presents a comparison of an innovative machine learning method with a baseline that is typically used on vineyards and agricultural objects. The baseline uses color analysis and can distinguish interesting objects with an accuracy of 89.6%. Machine learning, an innovative approach to this type of application case, shows that the results can be improved to 94.27% accuracy.

[2] Alifia Puspaningrum, A Sumarudin, Willly Permana Putra: This paper suggested predicting irrigation using a machine learning algorithm. Classification algorithms, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes, Random Forest and Decision Tree, are studied to predict accurate irrigation. This paper calculates accuracy, precision, recall and Fl score to assess the performance of the algorithm. Experimental results show that Decision Tree outperforms other algorithms by using its performance with the same agricultural data for accuracy, recall, precision, and fl-point measurement.

[3] Hema Pallevada, Siva Parvathi Potu, Teja Venkata Kumar Munnangi, Bharath Chandhra Rayapudi, Sai Raghava Gadde, Mukesh Chinta: One solution is to allow farmers to test their land and use the fertilizer according to soil needs at affordable costs. This paper provides a report on the design of the cost-effective soil nutrient recognition with prepared capsules. Here, tests can be performed for three different types of nutrients sodium, potassium and phosphorus. Here, three test tubes are taken, each filled with a certain amount

of soil and water, and then the mixture is shaken for 15 minutes. Then a color change occurs in the tube. Here a color sensor is used and the color change in the test tubes is detected by the sensor and compared with the existing information about color deficiency.

[4] Konstantinos G. Liakos, Patrizia Busato, Dimitrios Moshou, Simon Pearson & Dionysis Bochtis: In this paper, we present a comprehensive review of research on applications of machine learning in agricultural production systems. The analyzed work was categorized into (a) plant management, including applications for yield forecasting, disease recognition, weed detection, and species recognition; (b) livestock management including application to animal welfare and live style production; (c) water management; and (d) land management. The filtering and classification of the articles presented shows how agriculture will benefit from machine learning..

[5] Robert J.McQueen, Stephen R.Garner, Craig.G.Nevill-Manning, Ian H.Witten: This article describes a project that applies a series of machine learning strategies to problems in agriculture and horticulture. We will briefly examine some of the techniques that arise from machine learning research, describe a software working platform for experimenting with a variety of techniques on real-world datasets, and describe an case study of milk herd management in which the cutting rules were derived from a medium-sized database of herd information.

III. PROPOSED SYSTEM

There are many tools available for creating the Object detection, but there are rarely any applications dedicated towards both disease detection in plants and IOT based agricultural assistance to farmers and plantation owners and workers. Our approach for detecting the disease will be great contribution inavoiding the catastrophic consequences caused from crop damage, quality downgrading and failure due to the effect of biotic and abiotic agents. Most of these are clearly depicted in definite patterns expressed by plants in form of deformations and alterations in the plant leaves, flower and fruits. We will be providing a mobile/android-based platform for the user to upload the image and classify it as disease or deficiency while also providing assistance through remote access to farm appliances using IOT. This projectcan be scaled up by implementing higher trained detection model and increased interfaces and connected operable devices. One of the important objectives is to evaluate its performance and acceptability interms of security to crops, user-friendliness, accuracy and reliability. Following is simple architecture of the proposed system: -

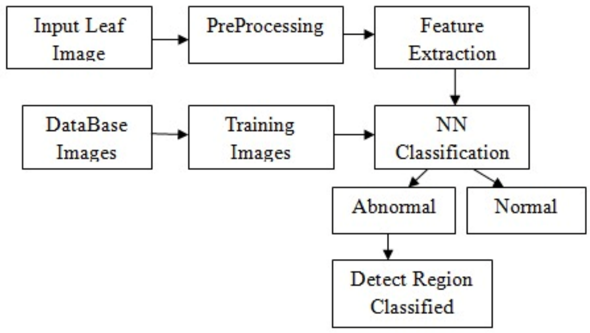

Fig 1. Detection algorithm flow

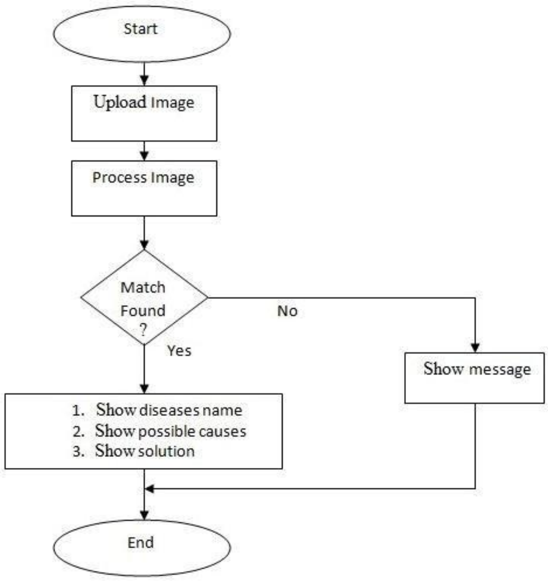

Fig 2. Mobile Application Design flow

The Detecting diseases in plants using a mobile app and the Convolutional Neural Network (CNN) algorithm typically involves the following working principles:

A. *Data collection:* A large set of images is collected, consisting of images of healthy plants and images of plants affected by various diseases. These images should cover a wide range of plant species and disease types.

B. *Data preliminary processing:* The images collected are preliminarily processed to ensure consistency and improve the functions relevant to disease detection. This can include changing images, normalizing pixel values, and applying filters to remove noise.

C. *The training phase:*

A. Model Architecture: A CNN model is designed and built. CNNs are good for image recognition tasks because they can automatically learn hierarchical representations of image characteristics.

B. Data Split: The record is divided into training and validation sets. The training kit is used to optimize the model parameters, while the validation kit helps to monitor the model's performance and avoid overlapping.

C. Training Process: The CNN model is trained with the training record. The training process involves feeding the images over the network, calculating the loss (the difference between the predicted and actual labels) and adjusting the model weights by redistributing to minimize the loss. This process is usually repeated for several epochs to improve the accuracy of the model.

D. *The Test Phase:*

A. Test Data Set: A separate data set containing images that were not used during the training is prepared to test the performance of the trained model.

B. Prediction: The trained model is deployed in the mobile app where users can capture or upload images of plant leaves or other relevant parts. The app sends these images through the trained CNN model, which makes predictions about the presence of diseases.

C. Disease identification: Based on the model's predictions, the app provides the user with information about the disease identified, including its name, severity, and potential treatments or actions.

E. *Iterative Improvement:*

The performance of the app can be improved by continuously updating and re-training the CNN model with new data. This helps the model to adapt to new diseases or variations in existing diseases.

F. *Detection:*

new image is passed to the trained model for detection. The respective class that is detected to be most overlapping with the sample image is set as the determined disease. These results are made accurate through several epochs. The proposed system shows an accuracy above 95%.

Humidity and temperature data is detected by DHT11 sensor and passed on to ESP32 on module 1 which is in turn connected with I2C LCD display which is to display the data on site. The power to this system is supplied by a rechargeable 9V 1.5A battery. The second module consist of ESP32, 5V Relay, Solenoid Value, 12V to 5V Buck Converter, Battery. The ESP32 is triggered through IoT linked device and gives triggering pulse to relay. The relay triggers the Solenoid the controls the water flow. The system is supplied with power from 12V 5A battery, output of which is converted to 5V using Buck converter which gives supply to relay and Solenoid in turn. Similar other modules using other similar sensors can be used to get data and control other appliances using IoT can be implemented. IoT control system is designed using Blynk IoT for android applications. The system receives real time temperature and humidity data from ESP32 of module 1. Data can be observed and respective appliances can be triggered as in this case, the ESP32 of module 2 is triggered to operate water supply system.

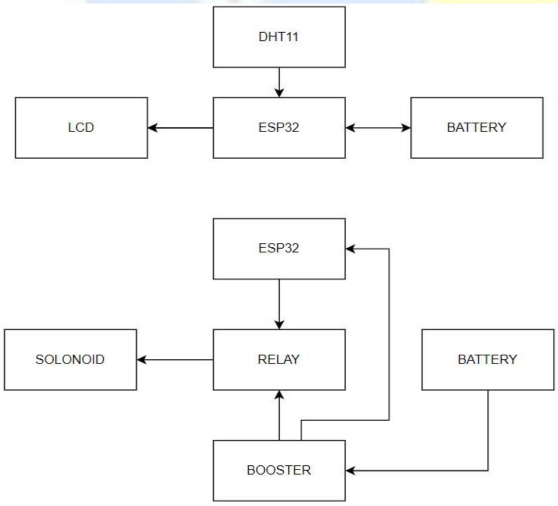

Fig. 3: IoT working Flow

IV. CONCLUSIONS

The project demonstrated the potential of incorporating machine learning in plant disease detection and resource allocation using IoT technology. The machine learning model achieved a high level of accuracy in detecting plant diseases, which can help farmers detect and treat diseases early, leading to increased crop yields and reduced use of pesticides. The IoT system developed in the project can help farmers optimize resource allocation, leading to more efficient use of water and fertilizer. The project highlights the importance of using technology in agriculture to increase efficiency, reduce waste, and improve sustainability. Further research can focus on integrating the machine learning model and IoT system with other agricultural technologies, such as precision farming and automation, to create a fully integrated system for sustainable and efficient agriculture.

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