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Monitoring plant health and detection of plant disease using IoT and ML

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Abstract—*Crop diseases are a major concern in agriculture, which affects both the quality and quantity of agriculture production. A plant's growth and productivity are essential. To increase the yield and productivity, monitoring a plant from its growth till its harvesting is critical. In this paper, an automated crop disease detection system is developed based on IoT and Image processing based on Machine Learning. This system monitors the temperature, humidity, and color through sensors connected to NodeMCU based on changes in plant leaf health conditions. By using these parameters plant disease is identified. The convolution neural network algorithm is used to achieve this task. Diseases of tomato crops have been selected for the case study. The collected data are uploaded to the webserver through the IoT platform for data processing. A mobile application is developed which helps to show the status of the parameters and send SMS warnings and notifications*

Keywords—*Machine Learning (ML), Internet of Things (IoT), Mobile Application, WebServer, Sensors, Image Processing, Convolution Neural Network, NodeMCU.*

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I. Introduction

India is the second largest producer of food through agriculture. Most of the people here depend on framing for their livelihood. In India agriculture is the primary economic activity. Plant health plays an important role in achieving high yields. Proper monitoring of plant health conditions at different stages of plant growth is essential to decrease infecting plant diseases. The presence of pests and diseases affects crop production evaluation and significantly reduces yields. Initially, plant health monitoring and disease analysis tasks are performed manually by experts. Manual prediction is time consuming and there can be many incorrect predictions can occurs. In addition, manual forecasting requires significant effort and time-intensive processing. Plant disease detection using image processing is an effective solution for early and accurate detection. Farmers regularly use a variety of disease control strategies to prevent plant disease.

Identifying plant diseases is essential for farmers and agricultural professionals. In most of the plants, diseases occurs in plant leaves. This proposed system tracks plant diseases especially in tomato leaves and finds solutions to reduce causes to improve plant health and overall productivity. This process can be achieved by considering image processing and convolution neural network concepts for detection and analysis of plant diseases. A training database set is created for diseased images. IoT sensors using NodeMCU can measure the distinction between normal and diseased plant leaves based on changes in values of parameters like temperature, humidity, colour, soil moisture and rainfall.

IoT sensors can provide data approximately agricultural regions and may be without problems monitored, making smart agriculture a unique concept. The appraisal of sensor networks and Internet of Things (IOT) has played vital role in agriculture sector and the disposal of sensor node in real time environment. These IOT sensors collects the field data at any time and accumulated data is analysed in real time basis through IoT analytics platform. The cloud platform gives the actual time evaluation of records for the detection of adversaries in records. IOT allows devices across farm to measure all kinds of data remotely and provide this information to farmers or experts in real time, resulting in decreased human intervention and operating cost. Sensors connected to IOT can provide data on agricultural lands. Farmers or agricultural department members can use this technology to check the actual state of their crops without having to be present in the field. Smart farming primarily based totally on IOT technologies enhances crop production in farming industry.

II. PROPOSED SYSTEM

The proposed system is based on an IoT system which monitors temperature humidity, soil moisture, rain and color sensors for collecting data from plants. This data is based on variations that are caused by temperature, humidity and color factors on plant leaves. Due to environmental factors, the plant undergoes changes which are captured by temperature, humidity and color sensors and that captured data is analysed using NodeMC. The data from these sensors is transmitted to NodeMCU from where it is sent to the local agriculture officer through SMS or app notifications. This officer, in turn, communicates with farmers about the status of the crop. In this system, the studied data is communicated from the host system to the cloud platform via WiFi shield (ESP8266). Cloud-based platform www.thingspeak.com collects data, which is then compared to the dataset in order to determine if the leaf in question is normal or diseased.

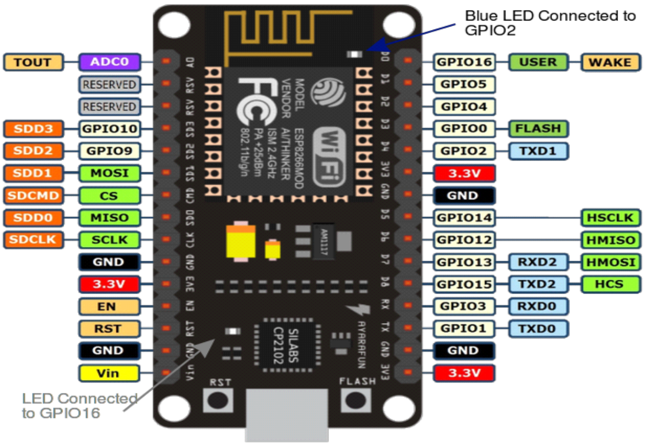

Fig. 1) Shows schematic diagram of the proposed work.

III. Related Works

- *Temperature and humidity Sensor*

Sensors that measure relative humidity typically contain a humidity sensing element and a thermistor that measures temperature. Capacitive sensors use capacitors as their sensing element. The relative humidity is calculated by measuring the electric permittivity of the dielectric cloth. Resistive sensors are made from materials with a low resistivity. The resistive material is placed above the electrodes. Moisture content can be determined by measuring the change in resistivity of this material. Salt, stable electrolytes, and conductive polymers are examples of resistive substances used in resistive sensors. Thermal conductive sensors degree Absolute humidity values.

DHT22 pins	
1	VCC
2	DATA
3	NC
4	GND

Fig. 2) Temperature-humidity-sensor

- *Soil Moisture*

The term "SMART GARDEN" brings a idea of a system that measures soil moisture content and provides the plant health results. Based on this type of system, you can monitor plants water content level and plant health condition .helps in predicting over-watering or under-watering for plants. Soil moisture sensor is one of that sensor in developing smart garden. soil sensor computes the moisture content in the soil land also can be used to measure the amount of water stored in soil .Considering a soil moisture sensor to toil, no matter what kind of soil sensor, it must make proximity with the soil. To obtain high efficiency, soil sensor must be entirely surrounded by soil with no aperture in the middle of the probe and the soil. The soil moisture sensor is based on the fork-shaped probe with two exposed conductors that act as variable resistors whose resistance fluctuates in response to soil moisture levels. Resistance is inversely proportional to soil moisture, that is: Increased moisture level in the soil indicates finer conductivity.

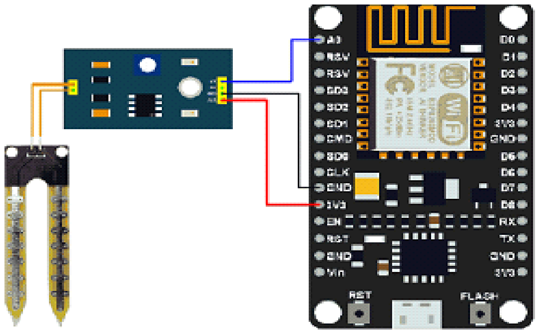

Fig. 3) Soil Moisture

- *Rain sensor*

Rain Sensing Pad consists of exposed copper traces, which acts as variable resistor whose resistance fluctuates according to the mass of water on the exterior. Above resistance is conversely proportional to the amount of water that is: Increased water on the exterior indicates finer conductivity and outcome will be of lower resistance. Decreased water on the exterior indicates below par conductivity and outcome will be of higher resistance. Rain sensor make an output voltage grounded on the resistance, which can further used to determine whether it's raining or not. Rain sensor has two main components: Sensing Pad: Rain sensor contains a sensing pad with series of exposed copper traces which is placed outside as open, especially top of the roof or place where it can be affected by rainfall. Usually, traces are not connected but they are bridged by water.Module: Rain sensor also holds an electronic module that associates the sensing pad to the Arduino. This module makes an output as a voltage based on the resistance of the sensing pad and made available at an AO (Analog Output) pin. The same signal is fed in to a high precision comparator to digitalize it and make it available at DO (Digital Output) pin. This module has an in-built potentiometer for sensitivity adjustment of the DO. Rotate the knob clockwise to increase sensitivity and counter clockwise to decrease it. Despite of this, the module has two LEDs. The Power LED will glow up when the module is powered. The Status LED will glow up when the digital output goes LOW. The rain sensor has 4 pins to associate: AO (Analog Output) pin give us an analog signal in middle of supplied value (5V) to 0V.GND is a ground connection. VCC pin contributes power for the rain sensor. It is suggested to power the sensor with between 3.3V – 5V.

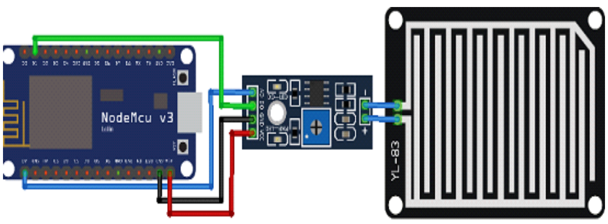

Fig. 4) Rain sensor

- *Color sensor*

Color is another feature that is used by colour sensors to determine whether a leaf is sick. This proposed system employs a TCS3200 sensor that detects colour using an array of photodiodes (8x8) and converts the readings from the photodiodes into a square wave with a frequency directly proportional to the light intensity using a current tool frequency converter. We can read the square wave output and retrieve the result for the corresponding colour using an Arduino board. There are three different colour filters on the photodiodes:

sixteen have red filters, sixteen have green filters, sixteen have blue filters, and sixteen photodiodes are transparent with no filters. Each of the sixteen photodiodes is connected in parallel using two control pins; we can choose between red, blue, or green for the relevant pins. There are two more pins used to scale the output frequency. This frequency scaling function allows the output of the sensor to be optimised for various frequency counters or microcontollers by scaling the frequency to three distinct preset values of 100%, 20%, and 2%.

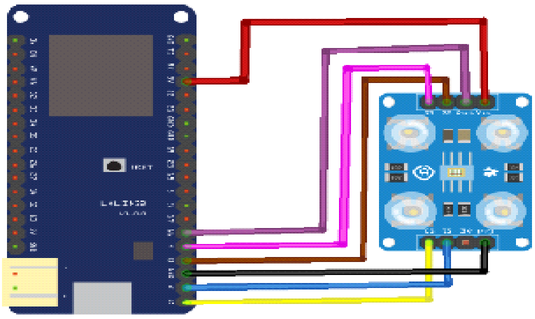

Fig. 5) Color Sensor

- *Node MCU*

The ESP8266 WiFi module and hardware based on the ESP12 module are both included in the NodeMCU open-source platform. It creates its own scripts with the Lua programming language and the ESPlorer IDE. Its purpose is to make programming the ESP8266 as simple as possible without needing to understand the hardware or the language.

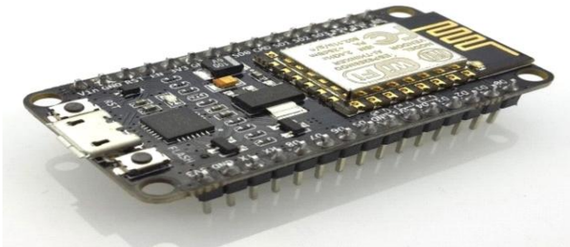

Fig. 6) NodeMCU

- *Cloud platform*

To communicate the read data to the cloud, we utilise the ThingSpeak cloud platform. ThingSpeak is a cloud-based IoT analytics platform that collects, visualises, and analyses real-time data streams. APIs for social networking sites and devices are available to make data access, retrieval, and logging easier. ThingSpeak is a data platform for the Internet of Things that is available to the public. The device or application may connect with ThingSpeak via the RESTful API and keep the data private or public. Use ThingSpeak to analyse and analyse your data as well. MathWorks and MATLAB numerical computing packages are both supported by ThingSpeak. Users of ThingSpeak may use MATLAB to analyse and display loaded data without having to acquire a MathWorks MATLAB licence. Temperature, humidity, and colour variations were shown using graphs. You can tell if the numbers are in the same range based on the plotted data. If this is the case, the sheet is either healthy or sick.

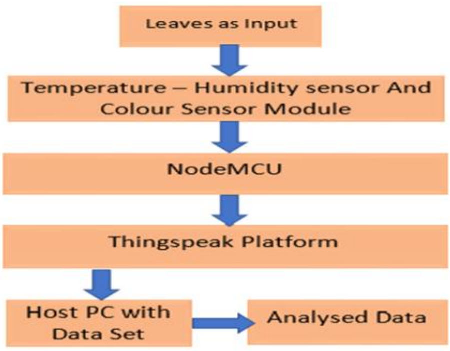

Fig. 7) Flowchart

IV. Methods

- *Dataset*

We make use of the Plant Village Dataset. The Plant Village collection contains 50000 healthy and sick leaf photos classified into species and disease categories. We evaluated over 50,000 photos of plant leaves with scattered labels from classes in order to predict disease class. We downsize the image to 256 256 pixels and use this compressed image to conduct optimization and model predictions.

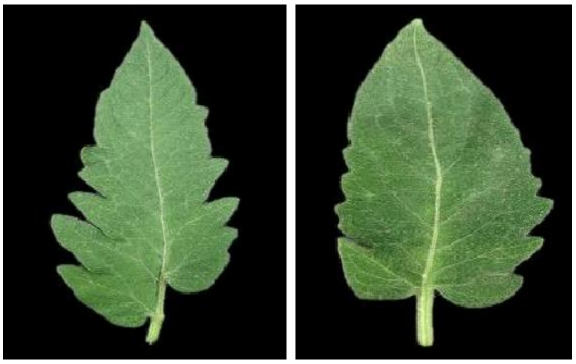

Fig. 8) Healthy leaf of Tomato

Fig. 9) Disease-Early Blight leaf of Tomato

Fig. 10) Disease-Bacterial Spot

- *Data Processing and Augmentation*

Image augmentation is essential in the development of an efficient image classifier. Even if datasets contain hundreds to tens of thousands of training samples, the diversity may not be sufficient to develop an appropriate model. Image augmentation possibilities include flipping the image vertically/horizontally, rotating through various angles, and scaling the image. These augmentations assist to boost the amount of meaningful data in a dataset. The size of each picture in the Plant Village collection is discovered to be 256 by 256 pixels. The Keras deep-learning framework is used for data processing and picture enhancement.

- *CNN*

Discoloration of plant tissue is a common characteristic of plant diseases. It can be partially or fully suppressed by the breakdown of the green tissue's chlorophyll. The condition is then used to determine if a plant is healthy or sick.

Machine vision equipment is commonly used in agriculture to identify diseases in plants. By acquiring photos of the same plant, the machines can detect diseases in the plants. Conventional machine vision methods are often used to diagnose plant diseases. They use a light source and shooting angle to determine the ideal illumination source for each photo. Unfortunately, traditional image analysis techniques can be challenging to implement due to their complexity. For instance, distinguishing the differences between the regions of a plant's lesions can be challenging due to the varying sizes and shapes of the lesions. There is also some interference when photographing plant diseases in natural light. Existing classical approaches currently appear to be ineffective and difficult to obtain better detection results.

The traditional methods of detecting plant diseases have some limitations. The pre-trained VGG16 model, an integrated neural network (CNN), is used for training. This model is used to load our dataset, resize the image, and split it into test and training data. A total of 10716 images are used for each class to teach and 1079 images are used for testing. Then the model is configured to perform the training.

The model is trained to perform its intended function. It is saved in a directory where it has been trained. The program uses HTTP and the base64 format to communicate with the server. If the plant does not respond to the illness, the program will send a response with "healthy".

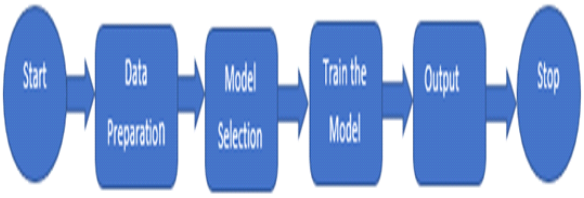

Fig. 11) Flow Diagram of Machine Learning

- When it comes to extracting picture features, CNN has an advantage. It uses a weight-sharing network topology to minimize the complexity of its model and the number of weights. *Some Common Mistakes.*

V. RESULT AND DISCUSSION

Several measurements are calculated and displayed in the mobile application, including temperature, humidity, and air pressure. This study used the following figures to illustrate how temperature, humidity, and soil moisture were measured. Thing Speak is an IoT analytics tool that lets users collect, visualize, and analyse live data streams was used to test the graphs.

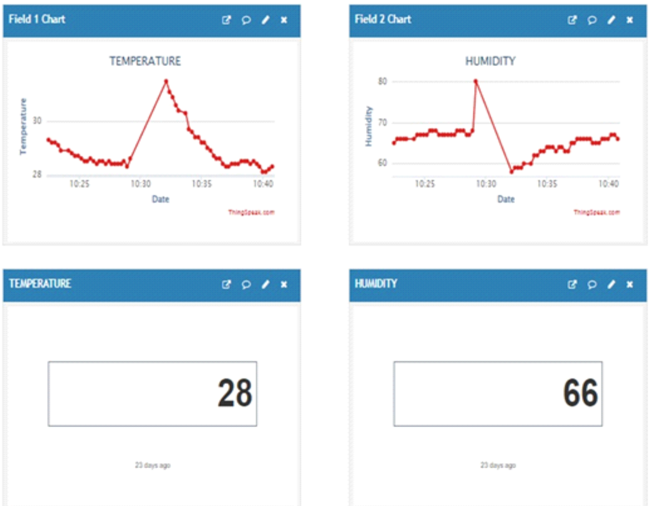

Fig. 12) Output showing the readings of temperature and humidity sensor.

Fig. 13) Output showing the readings of soil sensor.

Fig. 14) Output showing the readings of rain sensor.

We only selected 400 images from each folder. Each image is converted into a table. In addition, we processed the input file by scaling the data point from [0.255] (minimum RGB value and most of the image) to the range [0,1]. We then split the dataset into 70% for training images and 30% for testing. Image generator objects are created to perform random rotations, motions, inversions, cropping, and portions of our image set.

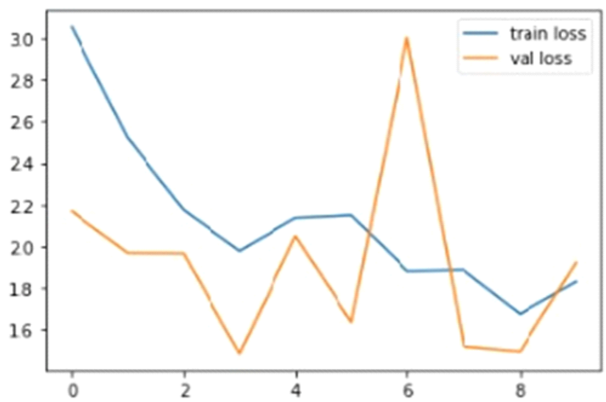

Fig. 15) Train and validation loss

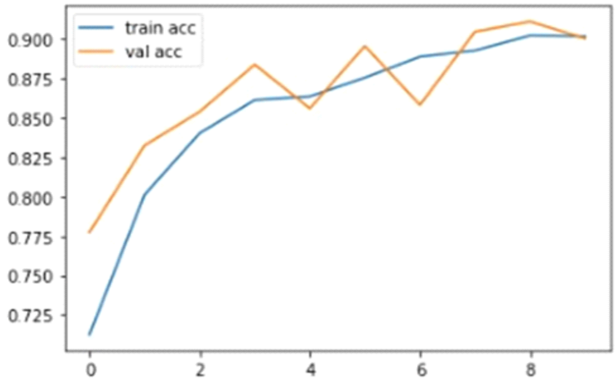

Fig. 16) Train and validation accuracy

The performance of accumulative neural networks in object recognition and image classification has made great progress in recent years. Previously, the traditional approach to image classification tasks was based on manually designed features, such as SIFT, HoG, SURF, etc., and then used some form of learning algorithm in the features. This particular space. Therefore, the performance of these methods is highly dependent on the predefined underlying characteristics. Feature engineering itself is a complex and time consuming process that must be revisited whenever the problem to be solved or the data set involved changes significantly. This problem occurs in all traditional attempts to detect plant diseases by computer vision, as they rely heavily on hand-designed features, image enhancement techniques, and many methods, complicated and labor intensive.

Furthermore, traditional approaches to disease classification through machine learning often focus on a small number of classes, often within a single culture. Although neural networks have previously been used to identify plant diseases, the approach requires representing images using a carefully selected list of texture features before neural networks can be classified.

Finally, it should be noted that the approach presented here is not intended to replace existing solutions for disease diagnosis, but rather to complement them. Laboratory testing is ultimately always more reliable than a diagnosis based on imaging symptoms alone, and often making an early diagnosis through imaging alone is difficult. However, with the expectation that there will be more than 5 billion smartphones worldwide by 2020, including nearly 1 billion in Africa (GSMA Intelligence, 2016), we believe this approach represents a possible complementary methods to help prevent yield loss.

VI. Conclusion

This article talks about the various components of plant disease detection that are connected to the Internet of Things. One of these is the ability to detect diseases in tomatoes. A simple and effective method for detecting diseases in plants is to use wireless sensors to measure various parameters. The data collected by the system is then analysed and sent to a web server. Wireless sensor networks are widely used for monitoring various aspects of a person's life. This paper presents an architecture that uses a simple neural network to classify different kinds of tomato leaf diseases.

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