Journal of Horticulture

OPEN ACCESS Freely available online

Review Article

Plant Disease Detection and Growth Monitoring Using IoT

Anudeep*

Department of Computer science and Engineering, Satyabhama Institute of Science and Technology, Chennai, India

ABSTRACT

As we all know that agriculture play a vital role for establishing agricultural society or country. Agriculture has been the career for people beyond a century however because of herbal aspect of climatic circumstance farmers are going through plenty of issues which might also additionally result in address critical issues in the society. So IoT can be a crucial key to help the farmers automate the whole process and deep leaning algorithms like CNN can be implemented for plant disease detection. This device will assist to govern the diverse environmental situations which include soil moisture, temperature and humidity for the growth of the plant and detect the plant disease. This paper presents the monitoring of the plant through Thingspeak and disease detection through CNN.

Keywords: Deep learning; CNN; IOT; Thingspeak

INTRODUCTION

The whole proposal's intention is to aid farmers or the people who are into gardening but couldn't monitor them at regular intervals, ex-watering the plants, controlling the temperature, humidity as some of the crops require closed monitoring sheds to grow so to achieve this we require two domains IoT and CNN.

IOT

IOT relates to the trillions of serial interfaces worldwide those are hooked up to the internet and store as well as exchange information. Thanks to the growing popularity of wireless devices and the invention of mega integrated circuits, it's now capable of transforming everything, from a pill to a plane, into a part of the IOT. Bringing all of these disparate objects together and connected detectors to them gives machines that would otherwise be dumb a degree of digital intelligence, allowing them to exchange real time data without requiring a person. The Internet of Things (IOT) connects the digital and physical environment to make our surroundings smarter and more adaptive. Any problem can be identified by its embedded computing unit, but it can also work with the current Internet infrastructure. Professionals expect that by the year 2021, the internet of things would have grown to about 50 billion devices.

Deep learning

DL is a form of ML that relies solely on artificial neural networks for its support. Since neural networks are designed to imitate the human brain, deep learning is also a kind of brain mimic. It's turned off today because we didn't have enough process capacity and expertise earlier. Neurons are a proper definition of DL. DL is a form of explicit machine learning that teaches the computer to see the world as a nested hierarchy of concepts with each thought outlined in terms of less abstract ideas, and they are computed in terms of less abstract representations. This can be a picture of a personal nerve cell in the brain, which has roughly a hundred billion nerve cells at any given time, and each neuron is connected to thousands of its neighbours. The question is how it manages to replicate these neurons in a laptop. As a result, everywhere there are nodes or neurons; it generates a man-made structure known as a man-made neural internet. It has several neurons for input value and a few for output value, with variant neurons intertwined within the hidden layer in between.

METHODOLOGY

Model preprocessing and coaching (CNN): Preprocessing includes image reshaping, resizing, and converting the dataset to an array form. The check picture is also subjected to a similar method. A dataset of about nineteen different plant species is collected, and any image from that dataset can be used as a check image for the computer code. The train dataset is used to train the CNN model so that it can assess the check image as well as the disease. Dense, Dropout, Activation, Flatten, Convolution 2D, and Max Pooling 2D are the various layers that CNN has. If the plant species is present within the dataset and the model is successfully educated, the computer code will assess the disease. When coaching and preprocessing, the check image and trained model are compared in order to predict the disease.

Correspondence to: Anudeep, Department of Computer science and Engineering, Satyabhama Institute of Science and Technology, Chennai, India, Email: zahedulla_zahed@skuastkashmir.ac.in

Received: April 06, 2021; **Accepted:** April 20, 2021; **Published:** April 27, 2021

Citation: Anudeep. Plant Disease Detection and Growth Monitoring Using IOT, J Hortic 21:8

CNN model steps

Conv 2D: This is the layer that flexes the image into several images and activates them. MaxPooling 2D It's popular to gamma hydroxybutyrate pool the value from a given size matrix, and the following two layers use the same form (Figure 1).

Figure 1: CNN Model steps

Flatten: Its common practise to flatten the scale when convolving a frame.

Dense: This is the hidden layer and its popular to make it a completely linked model.

Dropout: Avoiding over fitting on the dataset is standard practise, and dense means that the output layer only contains one nerve cell that tries to match the class image. Image knowledge generator It resizes the image, applies shear to specific areas, zooms it in, and flips it horizontally. All possible image orientations are included in this Image Information Generator. In the Training Process-Train datagen, the flow from directory feature is used to prepare information from the train dataset directory. Target size determines the image's target size. The test datagen flow from directory is used to organise the model's test data, and each one is equal to higher than fit generator; other variables used include steps per epochs, which tells us how many times the model will execute for the coaching information. Epochs: The number of forward and backward passes the model has been trained. Validation procedure: Validation data is used to feed validation/test information into the model. Validation steps reflect the number of validation/test samples.

Architecture of CNN

An Associate in Nursing input nodes, convolutional nodes, fully connected nodes, and an Associate in Nursing output nodes are all part of a typical convolutional neural network architecture. With a few tweaks, CNN is based on the LeNet definition. It has half-dozen layers without accounting for input and output. The image must be processed before ever being loaded further into input nodes since it has well before, defined measurements. 48 × 48 pixel normalised grey scale images from a given dataset were used for coaching, validation, and testing Laptop computer digital camera photos are used for analysis, and the victim's face is detected and cropped during the process. In OpenCV, the Haar cascade Classifier is used.

Convolution and pooling (ConvPool) layers

Most every batches consists N images, and the CNN filter weights for those batches are adjusted. A four dimensional image batch with N × Colour Channel × dimension × height is fed into any convolution sheet. A four dimensional convolutional function map or filter is also a four dimensional convolutional function map or filter (Number of feature maps in, range of feature maps out, filter dimension, filter height). Four dimensional convolutions are measured between image batches and each convolution layer includes maps. The only variables that change when using convolution are the image dimension and height.

Previous image dimension–filter dimension+one=new image dimension

Previous image height–filter height+one=new image height.

For structural material contraction, downward sampling/subsampling is performed every after convolution sheet. Pooling is the term for this practise. Pooling methods such as Goop pooling and average pooling are well known. Goop pooling is done once convolution is completed in this project. The pool size is (2 × 2), which divides the image into a grid of 2 × 2 blocks that take up the majority of the four pixels. When you combine height and dimension, only height and dimension are affected. Two convolution layers and a pooling layer may be used in the architecture. The input image batch's convolution layer size is initially N × 1 × 48 × 48. Every image height and dimension has forty eight components, and the image batch size is N. The colour channel range is one. The convolution with feature map of 1 × 20 × 5 × 5 results image batch has a batch size of N × 20 × 44 × 44. When convolution pooling with a pool size of 2 × 2 is complete, an image batch of size N × 20 × 22 × 22 is generated, which is then followed by a 2d convolution layer with a characteristic map of 20 × 20 × 5 × 5 × 20 × 5 × 5, producing an image batch of size N × 20 × 18 × 18. This is often followed by a pooling layer with a pool size of 2 × 2, completing the N × 20 × 9 × 9 image batch size. Fully Connected Layer: This layer is impressed by the way neurons send signals across the brain. It transforms a large number of input options using layers connected by trainable weights. Two hidden layers with sizes of 500 and 300 units square are used in the fully connected layer. To train the weights of such layers, forward propagation of coaching knowledge and backward propagation of its errors are used. Back propagation starts with measuring the difference between prediction and true value, then calculating the burden adjustment for each board. By standardising hyper parameters like learning rate and network density, we can monitor the coaching speed as well as the design performance. This sheet's hyper parameters include learning rate, momentum, regularisation parameter, and decay. The second pooling layer's output is N × 20 × 9 × 9, and the fully connected layer's initial hidden layer's input is N × 500. As a result, the pooling layer's output is two dimensional and N × 1620 in size and it is fed to the initial hidden layer. The first hidden layer's output is passed on to the second hidden layer. The second hidden layer's output, which is N × 300 in size, is fed to an output layer with an appropriate range of facial feature categories. Output layer: The current hidden layer's sensor is connected to an output node with seven different categories, and the possibilities for each one of the seven categories are used to generate output. The actual class is the one with best hope of achieving success.

Related work

Arti N Rathod et al. provides a variety of techniques for detecting leaf sickness using image processing. The techniques under investigation are aimed at improving throughput while ignoring the subjectivity of human experts when it comes to detecting leaf disease. A technique for enhancing the quality of an image is digital image processing. Automatic symptom identification is helpful in improving agricultural items [1].

The Raspberry Pi, Arduino micro controller, Xbee mee modules, and relays are among the moderate, close to the edge components proposed by Nikhil Agrawal, et al. [2]. for a home security system. Since additive effects are used in the basic value, the method is adaptive and robust. The Raspberry Pi processes the consumer's commands using the Python programming language. The Raspberry Pi sends on off instructions to Arduino microcontrollers via the Zig Bee protocol. This serves as the Raspberry Pi's and end devices' contact bridge. Raspberry Pi instructs Arduino microcontrollers to turn on and off. The foundation for connectivity between both the raspberry pi and end devices is indeed the star ZigBee topology.

Leaf image identification through some kind of server based fully monitoring and control system, pressure and temperature sensing, and relative humidity sensing are just a few of the features offered by Apeksha Thorat, et al. [3]. It measures moisture temperature and humidity using sensor networks rather than a manual scan. A Raspberry PI controller has been used in a variety of locations around farms (RPI) to power these sensors. A camera and RPI can be used to detect leaf disease. The credibility of a plant, such as leaf sickness, as well as numerous external conditions influencing the plant, such as moisture content, temperatures, and precipitation, are simultaneously sent to the farm workers via RPI via WIFI Server.

Lakshmi K, et al. have built a pesticide control system that removes the need for human intervention in crop cultivation. It prevents the negative effects of overuse of insecticides, which result in reduced crop cultivation. This version will achieve 83 excellent results for most types of vegetation, as well as the target of regulated irrigation techniques [4].

Melike Sardogan, et al. Developed a CNN model for image retrieval automatically. In the study of leaf image, colour records are commonly used. The filtering is applied to different positive significant correlation on RGB components from their model. The output characteristic vector of the convolution component was fed into the Lvq to train the network. Experiments show that the suggested approach correctly distinguishes four distinct types of tomato leaf diseases [5].

Mitul Sheth, et al. A deadline for retrieving data and syncing it with the internet via WIFI was discussed. When the water level falls below the set point, the customer is informed. Their paper shows how the NodeMCU can observe wireless circuit diagrams and view the results with the Blynk App. When it senses low wetness and temperature, a message is sent to NodeMCU and Blynk App, and the motor in the home or farm is automatically started [6].

In the IOT age, Samuel Olawepo, et al. shows the benefits of intelligent field optimization for optimal crop production and food safety. The whole paper, which would also be linked to internet and has live event stats presented via communications or a custom web app, recommends the activities needed for intelligent grass integration using current infrastructure, such as integrated circuits and detectors, which is linked to a data cloud [7].

Proposed work

Overview: In this proposed system, I've included an ESP8266 microcontroller, which serves as the system's brain because it stores all of the system's software instructions. For plant growth, we use a dht 11 sensor to record the surrounding temperature and humidity. For the plants, the LDR sensor detects the presence of sunlight. In the absence of sunlight, the plants' LEDs automatically switch on. This detector is used to determine if the soil is wet or dry. The pump motor automatically turns on when the inserted medium is dry, to supply water to the plants. All the information is monitored using IOT and also displayed in the LCD (Figure 2). This data is sent to Thingspeak cloud where we can easily create a channel, by entering the channel id and API key details we can directly monitor the temperature, humidity, moisture and light for every 120 seconds. Using CNN, we train the datasets in python for 19 different types of plants and their diseases and can identify the diseased plant by image processing.

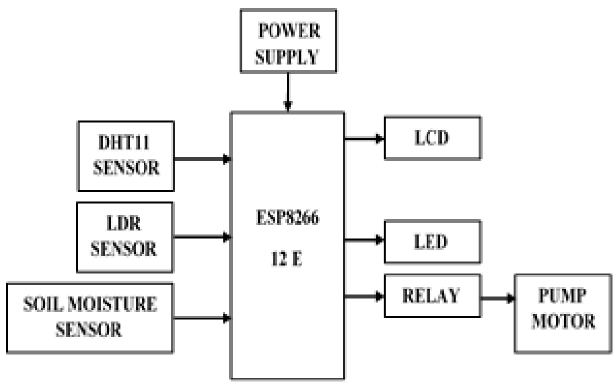


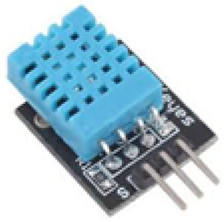
Figure 2: Plant monitoring architecture

Modules

The modules we require are plant monitoring part:

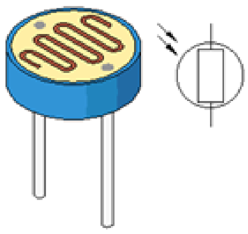
- DHT11 SENSOR
- LDR SENSOR
- SOIL MOISTURE SENSOR
- LCD
- NODEMCU ESP8266
- LED
- RELAY
- PUMP MOTOR
- **DHT11 sensor**

The DHT11 Temperature measurement Device consists a soil moisture sensor complex with a standardized transistor output. It uses an exclusive interactive signal accounting equation and weather moisture measuring techniques to improve good durability and long term sustainability.



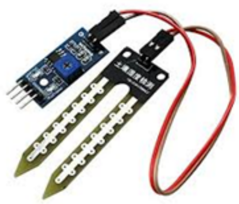
LDR sensor

A photoresistor or a cadmium sulphide (CdS) cell is another term for a Light Based Resistor (LDR). A photoconductor is another name for it. It's essentially a photocell that operates on the photoconductivity theory. The passive part is essentially a resistor whose resistance decreases as the light intensity decreases. This optoelectronic device is most commonly used in light varying sensor systems.



Oil moisture sensor

This detector can be used to check the moisture of soil. When the soil is dry, the module output is high, and when the soil is wet, the output is low. This sensor can also be used to mechanically water flower plants or any other plants that need automatic watering.



Nodemcu

Ai-thinker Team created the ESP-12E Wi Fi module. Tensilica l106 is encapsulated in the center processor esp8266 in smaller module sizes. With the sixteen bit brief mode clock velocity aid eighty MHz one hundred sixty MHz helps the RTOS, integrated Wi Fi and on board antenna, It features an industry leading incredibly less power 32 bit MCU microcontroller.

Relay

This is a device that opens or closes contacts in order to monitor the action of other electric controls. It detects an insupportable or undesirable situation in a designated location and sends commands to the circuit breaker to sever the affected region, resulting in a more efficient working module.

Pump motor

A pump motor is a DC motor that serves as a medium for moving fluids. It operates on the principle that when a cutting edge wearing conductor is placed in a magnetic field, it produces torque and has a tendency to travel, which is known as motoring motion. When the cutting edge path within the cord is reversed, the rotation path is reversed as well. Pumps operate by using a few mechanisms (usually reciprocating or rotary) and using energy to perform mechanical work. Pumps use a variety of power sources, including guidance service and energy, and come in a variety of sizes, ranging from microscopic pumps for research applications to massive business pumps.

Trained datasets

19 different types of plants are trained using CNN Algorithm.

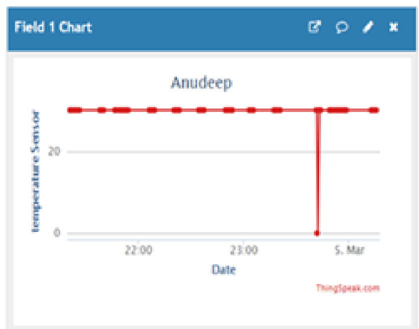
RESULTS AND DISCUSSION

The section put forth a model for monitoring and detection of plant disease, below Figure 3 shows the values displayed on thinks peak website after acquiring through the sensors.

Figure 3 above shows the values of temperature, humidity, moisture, light values at regular intervals of time.

Figure 4 Determines a cherry plant diseased by powdery mildew and required solution is given for curing it by applying Rex Lime sulphur to reduce next season's powdery mildew potential.

Below Figure 5 determines a healthy cherry leaf without being effected by any disease.



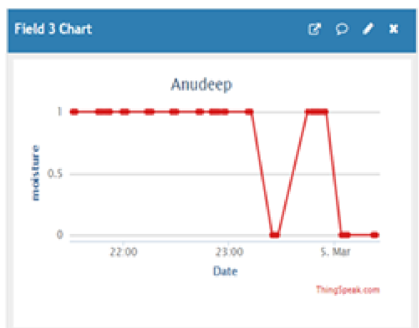


Figure3: Detailed report of plant monitoring

Figure 4: plant disease detected using deep learning

Figure 5: Healthy Plant

CONCLUSION

The plant disease detection and growth monitoring using IoT has been verified to satisfactorily work by displaying the data in Thingspeak using the ESP 8266 Micro controller the disease detection of the plant has been successfully identified using CNN algorithm.

FUTURE WORK

Application developers can work together with the monitoring part and the disease detection part together to develop an app which could eventually determine the values of the environmental conditions, plant Real-time growth from sapling to tree stage and the diseases affecting the plants from growing healthily.

REFERENCES

1. Arti N Rathod, Bhavesh Tanawal, Vatsal Shah. Image processing techniques for detection of leaf disease. Int J Adv Res in Comp Sci and Software Engineer.2013;3(11):397-399.
2. Nikhil Agrawal, Smita Singhal. Smart drip irrigation system using raspberry pi and arduino. Int Conf Comput, Commun and Automat, Int J Adv Res in Comp Sci and Software Engineer IEEE, 2015.
3. Apeksha Thorat, Sangeeta Kumari, N Valakunde. An IoT based smart solution for leaf disease detection. BID, IEEE, 2017.
4. Lakshmi K, Gayathri S. Implementation of IoT with Image processing in plant growth monitoring system.JSIR.2017; 6(2): 80-83
5. Melike Sardogan, Adem Tuncer, Yunus Ozen. Plant leaf disease detection and classification based on CNN with LVQ algorithm. Int J Adv Res in Comp Sci and Software Engineer (UBMK), IEEE, 2018.
6. Mitul Sheth, Pinal Rupani. Smart gardening automation using IoT With BLYNK App. ICOEI, IEEE, 2019.
7. Samuel Olawepo, Ayodele Adebiyi, Marion Adebiyi, Olatunji Okesola. An overview of smart garden automation. Int Conf Math, Compu Engin and Comp Sci, IEEE.2020.