

IOT-based Crop Health Monitoring and Controlling Smart Agriculture System in Machine Learning

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Abstract— 85% of the population in my country, Ethiopia, where there are 94 million people, work in agriculture, which accounts for 45% of the country's GDP. Because traditional farming methods are insufficient to meet the country's growing demand, farmers are forced to use harmful pesticides more frequently, which harms the soil. This paper concentrates on emerging different automation practices like IoT, Wireless Communications, Machine learning, Artificial Intelligence, and Deep learning as part of the industry's technological evolution in order to Understand and predict crop performance under various environmental situations that will boost farm productivity.

Keywords— Soil monitoring, Humidity level, Temperature, Health monitoring, Machine Learning, Cloud Services.

I. INTRODUCTION

In particular in Africa, where the sector accounts for 32% of GDP and two-thirds of employment, AI and the Internet of Things (IoT) are steadily changing agriculture in ways that could prevent the starvation of over 815 million people, or 11% of the world's population. Agricultural Robots, Crop and Soil Monitoring and Predictive Analytics and IoT's application in a number of areas, including connected industry, smart-city, smart-home, smart-energy, connected car, smart-agriculture, connected building and campus, health care, and logistics, among other domains, appear to be the three most popular applications of AI in agriculture. In order to meet the world's food demand in the upcoming years, the globe is turning to the usage of AI, IoT, and data analytics (DA). By 2020, there will be 75 million IoT device installations in the agricultural industry, up from 30 million in 2015. Smart agriculture will be made possible by the use of IoT and AI and is anticipated to produce a high yield and great operational efficiency. Examples are starting to abound when it comes to comprehending the potential influence of all these technologies. Nature Sweet in the US raised their tomato harvest by 4% in the first harvest after implementing AI to monitor the crop. Even though agriculture is currently the main source of income for three-quarters of African farmers, these methods produce low yields. Yet, app creators like Kenyan botanist and biochemist Samuel Kanya are offering novel solutions that could increase the continent's agricultural productivity to demonstrate the transformation that is achievable. Farmers in Malawi, Mozambique, and

Zimbabwe have used the platform over the years, in addition to farmers in South Africa, and it recently allowed sugar growers in South Africa to identify crop issues early enough to save up to 20% of crop failures. The tracking of the supply chain and market placement are now made easier by AI. The Internet of Things, analytics, and mobile technology have all been used to establish a coffee traceability solution in Ethiopia. In order to help businesses, obtain fair trade and organic certification for their products, the solution is currently tracking as many as five million bags of coffee via every link in the supply chain. The method has provided the Ethiopian coffee sector with a significant boost, allowing farmers to compete more effectively on the global coffee market and increasing Ethiopian coffee exports. Machines that solve problems through physical interactions in an environment are a future possibility. Although these devices have not yet made a significant impact on African agriculture, they provide hope for greatly improved soil management and better drought resistance techniques. The usage of artificial intelligence and the Internet of Things in Africa offers the possibility of numerous food security solutions as well as a more productive sector across the entire continent.

II. AGRICULTURAL IOT

Several research articles [1] [2] have introduced the structures for IoT-based agriculture. A microprocessor, a variety of sensors (from basic temperature sensors to cameras), actuators, and wireless interfaces are typically included in an IoT solution's sensor mote. These wireless interfaces may use WiFi, LoRaWAN, Zigbee, or another technology. The network layer is created by a local WSN gateway, which delivers data through an Internet gateway. You must execute data processing tasks including data visualisation, data analysis, data storage, and data protection in order to comprehend the data acquired by the service tier. The application layer, which enables end users to oversee and control key farm processes and make critical decisions based on projections and market trends, is ultimately the most crucial component. Data in the form of voltage values, pictures, actuator states, and robot locations have been created from a number of sources on and around agricultural farms as a result of IoT-based agriculture. Good data produces good, accurate information. You can't use ML

algorithms to build prediction models without having reliable data. These enhanced datasets can be used to run ML algorithms for increased analysis and precise prediction. Large amounts of sensor data can be collected and managed with ease by the IoT, which can also combine cloud computing services like agricultural maps and cloud storage. Access to real-time data at all times and from any location allows for end-to-end connectivity and real-time monitoring. [3]

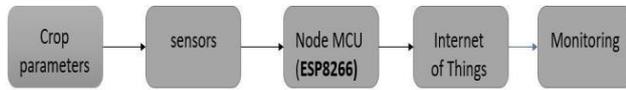


Figure 1 Flow Diagram of Iot System

III. MACHINE LEARNING APPLICATION IN IOT BASED ON AGRICULTURE

Machine learning (ML) may be viewed as a cutting-edge method for computers to mimic human learning processes, acquire new information, continuously improve performance, and develop distinctive maturity. Using machine learning algorithms, theories, and applications with other agricultural practises has proven to reduce crop expenses and increase output over the previous few years. ML applications in agricultural farms can be widely employed in areas such as disease detection, crop detection, irrigation planning, soil conditions, weed detection, crop quality, and weather forecasting. After harvest, ML can be used to assess the freshness of produce (freshness of fruits and vegetables), shelf life, product quality, market analysis, etc. Support vector machine (SVM), naive Bayes, discriminant analysis, K-nearest neighbor, K-means clustering, fuzzy clustering, Gaussian mixture models, artificial neural networks (ANN), decision-making, and deep learning could be the key ML techniques used in IoT-based agriculture. [4],[5],[6],[7].

A. Plant Management

Using greenhouse technology, a hybrid of ML and the IoT delivers an optimal and controllable environment for agricultural growth. Yet, traditional agriculture and environmental laws find it challenging to adapt to the growth of various plant kinds at various phases of growth due to the spatio-temporal variability of crop growth environmental elements and their mutual impacts in protected agriculture. Hence, from a monitoring and control perspective, greater accuracy is required. There are numerous studies that have been done on developing and evaluating various monitoring and control systems for modifying temperature and humidity, brightness, CO₂ concentration, and other environmental parameters for the Internet of Things, technological, and financial outcomes. It is suggested that IoT, sensors, and actuators can be used to control the environmental conditions for a particular variety of plant. Here, Artificial Neural Networks (ANN) put up on IoT cloud can be used to control condition rules. [8] [9] [10]

B. Crop and Yield Management

Based on information gathered from yield monitoring connected through a GPS-enabled IoT network, ML-based yield mapping may be used in farms. The data that is gathered and exposes the yield information will be mapped according to the different types of farmland. Moreover, ML

systems and the Internet of Things can be used to forecast and raise agricultural yields. When making decisions, farmers mostly consult with agricultural professionals. These systems are used by those who have no prior computer experience, such as farmers. Crop production can leverage ML systems. This approach for generating knowledge uses knowledge that already exists. This makes it possible for farmers to manage their crops in an economical manner. In light of the success of expert systems, other similar systems have been created. In agriculture, the Internet of Things is significant. Related study demonstrates that machine learning (ML) systems can be constructed on the Internet of Things and can provide recommendations for the usage of input data gathered in real time. [11] [12]

C. Soil Management

Soil management can be done using a variety of ML-based techniques. Wireless sensor nodes installed on site can be used to gather data about the soil. Finally, using supervised machine learning algorithms, the obtained data can be used to anticipate and analyse soil attributes or to classify the different types of soil. Moreover, the most widely used machine learning (ML) methods, such as K-nearest neighbour, support vector regression (SVR), Naive Bayes, etc., can be used to forecast soil dryness based on data from precipitation and evaporative hydrology. [13] [14] [15]

D. Disease Management

In order to detect and control illnesses in agricultural fields, ML and IoT can be combined. To further protect crops from these illnesses and cut labour costs, ML approaches further encourage the use of the proper pesticides. By gathering statistics and making appropriate plans for irrigation, herbicides, and fertilisers, such a system aids growers. Grape visibility and volume have grown, while extreme pesticide consumption has decreased, as a result of precision disease identification, precise pesticide administration, and precise irrigation schemes. Moreover, architecture with deep learning techniques for classifying and distinguishing different plants' voice stages. These manufacturers' audio steps go around various parts of the farm using IoT-based camera sensor nodes placed in crop fields, which are based on real-time collected visual information [16] [17].

E. Weed management

Managing weeds is crucial to farming. There have been studies into weed mapping using ML [18] [19]. We suggest an unmanned flying vehicle to take pictures and map the weed in a field in order to maximise this. where an IoT network can be used to control a flying machine. NB-IoT is an example of an advanced IoT technology that can handle and modify enormous amounts of data.

F. Water Management

A number of systems have been put in place to manage the water supply for agricultural fields and analyse the water quality using ML [20] [21]. With IoT sensors, intelligent systems can be developed to detect ground factors including soil moisture, soil temperature, and ambient variables. Use the same information to forecast outdoor relative humidity. To control water temperature and intelligently react to environmental temperature, we can also use hybrid machine learning and IoT systems.

G. Animal Tracking

It is very vital to track animals in agricultural fields. Animal monitoring using IoT-based sensors has been the subject of numerous studies, and independent studies on animal type classification are currently being conducted [22] [23]. This issue could be efficiently solved by IoT and ML solutions working together. With IoT sensors, it is possible to detect the presence of an animal. Using ML approaches, tracked animals can be categorized and/or their living and movement habits studied.

IV. PROPOSED SYSTEM AND WORKING METHODOLOGY

As part of the Smart Agricultural System, farmers can use a smartphone application and an IoT-based system. On the hardware end, we have a system that uses the Internet of Things to measure a variety of parameters, including soil moisture, temperature, and humidity. The software part also features an Android app for farmers. We developed an Android app that alerts the farmer and connects to the hardware system via IoT so that the farmer may check the current state of temperature, humidity, and other field parameters at any time.

A. IOT System

An IoT-based system is used to monitor various factors, including temperature-humidity (DHT11), soil moisture, and others (soil moisture sensor). The diagram below displays the circuit diagram for the IoT system.

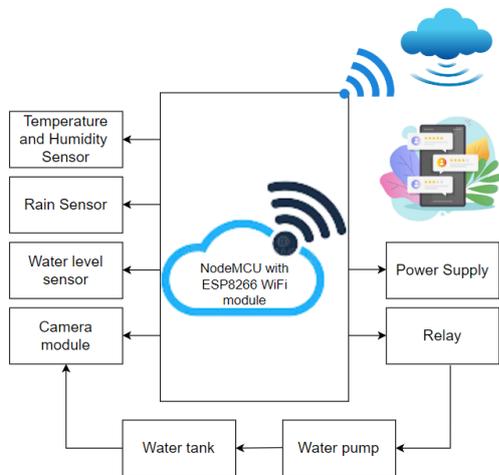


Figure 2 Circuit Diagram of the IoT System

B. Components

1. Temperature and Humidity Sensor(DHT11)

The DHT11 is an inexpensive, basic digital temperature and humidity sensor. It generates a digital signal on the data pin after measuring the surrounding air with a capacitive humidity sensor and a thermistor. Although it is easy to use, data collection requires careful planning. Dew point is calculated as $(C - (100 - H) / 5)$ Where, C stands for the Celsius temperature value, H = Value of Humidity.

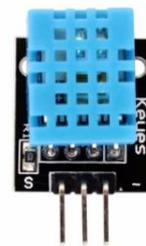


Figure 3 Temperature and Humidity Sensor

2. Soil Moisture Sensor

To calculate the volumetric water content of soil, a soil moisture sensor is employed. The sensor does not remove moisture; it instead indirectly measures the volumetric water content of the soil. It needs to be calibrated because external influences like conductivity, temperature, and soil type could influence the results. Properties like as electrical resistance or conductance, dielectric constant, and interaction with other neutrons can be used to indirectly measure volumetric water content without removing moisture. It needs to be calibrated because external influences like conductivity, temperature, and soil type could influence the results.

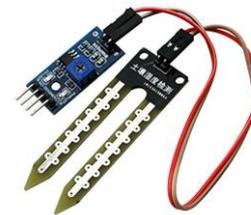


Figure 4 Soil Moisture Sensor

3. NodeMCU

An open-source firmware is NodeMCU. Both the prototyping board designs and the firmware are available without charge [10]. The firmware is based on the eLua project and was developed using the Espressif Non-OS SDK for ESP8266. It uses a number of open-source initiatives, such as SPIFFS and lua-cjson. Due to resource constraints, users must choose the components crucial to their project and build a firmware specific to their requirements. Often used as prototype hardware is a circuit board known as a dual in-line package (DIP), which combines a USB controller with a more compact surface-mounted board housing the MCU and antenna. The design was based on the ESP-12 module of the ESP8266, an IoT application-friendly Wi-Fi SoC with a Tensilica Xtensa LX106 core.



Figure 5 NodeMCU

These sensors gather information about temperature, humidity, and moisture content from the farms and transmit it to the Node MCU, where the information is stored (ESP8266). The Node MCU development board and open-source firmware are created exclusively for Internet of Things applications. It is made up of hardware based on the ESP-12 module and firmware that utilises Espressif Systems' ESP8266 Wi-Fi SoC. The connection between the Node MCU and the IoT analytics platform service ThingSpeak stores the sensor data.

4. Rain Sensor

Below is a picture of the board with the rain sensor. This board essentially uses the resistance principle and has nickel plated lines. Using this sensor module, you may measure moisture using analogue output pins, and when the moisture threshold is exceeded, a digital output is provided.



Figure 6 Rain Sensor

Due to the fact that it has both an electrical module and a PCB, this module is comparable to the LM393 IC. The rains are collected in this case using PCB. Rain produces a parallel resistance route that the operational amplifier may use to compute when it falls on the board. This sensor is a resistive dipole, and it solely displays resistance based on moisture. For instance, it exhibits more resistance while dry and lesser resistance when wet.

5. ThinkSpeak Platform

ThingSpeak is a user-friendly cloud-based IoT that enables you to aggregate, view, and analyze real-time data streams for prototype and small-scale production applications. The Things Network integration enables you to smoothly transport data from The Things Network to ThingSpeak for analysis and visualization. After you send data to ThingSpeak from your devices via MQTT or REST APIs, users can instantly visualize live data.



Figure 7 ThinkSpeak Cloud Platform

V. PLANT DIESEASE DETECTION

Plant disease identification is a crucial area for research in machine vision. Machine vision equipment is utilised to identify any illness in the acquired plant photos by taking shots of the same. Machine vision-based plant disease detection technology is currently in use in agriculture and has

mostly replaced the traditional method of diagnosis using just the naked eye. Traditional image processing algorithms or human feature design with classifiers are often used for machine vision-based plant disease diagnosis approaches. In order to produce images with homogeneous illumination, this method constructs the imaging scheme and chooses an appropriate light source and shooting angle depending on the various characteristics of plant diseases. While properly designed imaging schemes can significantly lessen the difficulty of constructing conventional algorithms, they also raise the implementation costs. In a real-world, challenging natural setting, it can be challenging to identify plant diseases because there is little contrast between the lesion region and the background, a wide range of sizes and types of lesions, and a lot of noise in the image of the lesions. Many interruptions also occur when photographing plant diseases in conditions of natural light. At this point, conventional classical procedures frequently seem ineffective, and better detection outcomes are challenging to

Technologies used to detect plant diseases traditionally have a variety of shortcomings. In our disease detection technique, we used a dataset from Kaggle to resolve this. The collection, which consists of about 895 images, is broken up into three categories: bacterial spot, healthy, and early blight. For training, we employ the convolutional neural network model (CNN) VGG16 pre-trained model. This model loads our dataset, resizes the images, and separates it into training and test data. 716 photographs from each class are used for training and 179 images are used for testing. The model is then prepared to carry out the training after that.

The model has an output train loss of 0.22 and a train accuracy of 0.78, along with a validation loss and accuracy of 0.4 and 0.6, respectively. Upon completion of training, the model is saved to the current directory. The model is then imported into the primary illness detection code. AWS's (Amazon Web Services) free tier is where the main code is stored. The android application communicates with it through the http protocols. An picture is accepted by the application, which then changes it to base64 format before sending it to the AWS server via a post request using URL encoding. The problem will be the disease of the plant. A response of "healthy" will be supplied if no illness is discovered.

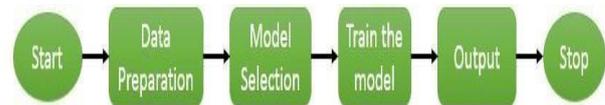


Figure 8 Flow Diagram Of Machine Learning

When it comes to photo feature extraction, CNN offers a lot of advantages. By employing a weight-sharing network topology, CNN, like a biological neural network, reduces the complexity of the network model and the number of weights. Compared to LeNet, AlexNet, and ZFNet, VGG16 has a deeper structure and is better at extracting features. After each of the VGG structure's five convolutions is the maximum pooling layer .

VI. RESULTS AND DISCUSSIONS

Temperature, humidity, and moisture level are just a few of the variables that the mobile app computes and shows. The methods for measuring temperature, humidity, and soil moisture in this investigation are shown in the accompanying graphs. ThingSpeak, an IoT analytics application that enables users to capture, visualise, and analyse real-time data streams in the cloud, was used to look at the graphs.

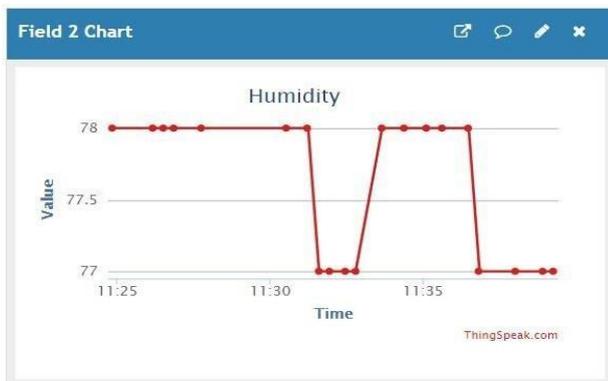


Figure 9 Sample of output displaying humidity sensor measurements. According to estimates, the humidity was 77 percentage.



Figure 10 The readings from the soil moisture sensor are shown in an example of output. Estimates put the reading for soil moisture at 42.33 percent.

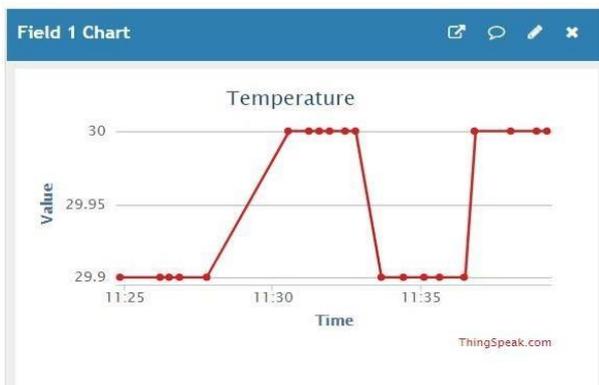


Figure 11 Sample of output displaying temperature sensor readings. It was calculated that the temperature was 30 degrees Celsius

VII. CONCLUSION

The next step in the growth of smart farming and agricultural practices is IoT-ML based agriculture. With the use of the agricultural IoT, ML algorithms may be applied to data collected from diverse farm inputs to make the system smarter, offer conclusive information, and make predictions. In this paper, we examine the method and outcomes of current ML applications in agriculture, each with unique strengths and drawbacks. Eventually, recommendations were made to put new applications on the IoT because the majority of ML applications required real-time data to train predictive algorithms. By utilizing artificial intelligence (AI) technologies that offer greater ideas and insights for following work decisions and activities with a range of final production enhancements, farm management systems are becoming a reality. This research examines machine learning-based plant disease diagnosis as well as IoT-based smart farming technology. This technology reduces the physical effort required of farmers and producers while enhancing productivity in every way imaginable. For this, a thorough discussion of wireless sensors, cloud computing, communication technologies, and various machine learning methods is presented.

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