Chapter 26
Advance Plant Health Monitoring and Forecasting System Using Edge-Fog-Cloud Computing and LSTM Networks

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1 Introduction

Traditionally, all living creatures were classified as either plants or animals. Food production is a key challenge in developing nations such as India. To overcome this challenge, a suitable monitoring and forecasting system is required to maximize plant yield while maintaining soil health consistently. Soil quality or fertility is one of the most critical factors impacting crop yield. Aside from agricultural production, soil quality determines the cost for a farmer to produce one or more plants, as some of them require precise ratios of specific components in the soil, such as water, sunlight intensity, air, temperature, humidity, and so on. Farmers must regularly monitor soil conditions on their land plots to enhance agricultural production. Crop yield forecasting is critical for agricultural production. Governments all across the globe utilize analytical data on crop production projections to make sound judgments about their national import/export activities. In recent years, it has been nearly difficult not to come across the term "Internet of Things" (IoT) in some form or another. Particularly over the last years, there has been a great spike in interest in the Internet of Things. Consortia have been created to provide frameworks and standards for the Internet of Things. Companies have begun to launch a slew of IoT-based goods and services. And a number of IoT-related purchases have made news, including

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Google's $3.2 billion takeover of Nest and subsequent acquisitions of Dropcam by Nest and SmartThings by Samsung [1]. This paper investigates and proposes an IoT architecture of Edge-Cloud computing for monitoring and predicting plants' health.

The following is a complete breakdown of the paper's structure: Sect. 2 discusses past literature work, whereas Sect. 3 presents the proposed system architecture. Section 4 delves into the embedded system, while Sect. 5 focuses on the deep learning technique deployed for prediction. Section 6 covers all the results and finally, Sect. 7 concludes this paper.

2 Related Works

Siddagangaiah [2] discusses about plant health monitoring systems which will examine several environmental variables like temperature, humidity, and light intensity, all of which have an impact on plants. Also, they get the moisture out of the soil. All of this data is transferred to the Ubidots IoT (Internet of Things) cloud platform through Arduino Uno dev boards. However, future predictions and actions after analysis of anonymous data generated were not motioned. Liu et al. [3] present a remote monitoring and control system that is particular to plant walls in this research. To simplify the administration method, increase scalability, improve user experiences of plant walls, and contribute to a green interior environment, the system makes use of Internet of Things technologies and the Azure public cloud platform. The purpose of the article [4] is to highlight several Internet of Things applications that play an important part in people's daily lives which highlights the idea of smart agriculture. Arathi Reghukumara et al. [5] consider the moisture level and temperature of the environment in which the plant develops when deciding whether or not to release water from the electric motor. The data from the sensors will be shown in graphical form on an Adafruit cloud page, which is an IoT platform (hardware and software interface), and will be used to analyze the plant health and send an email alert to the farmer or person concerned. As a result, the technology saves water while irrigating the plants and avoids the need for constant human supervision.

The literature survey states that there was a lot of work to be done in terms of user interface, high-accuracy prediction, and a fully deployable architecture in plant health monitoring systems.

3 System Architecture

We propose edge-fog-cloud computing as a novel paradigm for arranging data pipeline operations in the IoT systems, such as acquisition, analytics, and processing. The system architecture is deployed in a distributed manner as indicated in Fig. 1.

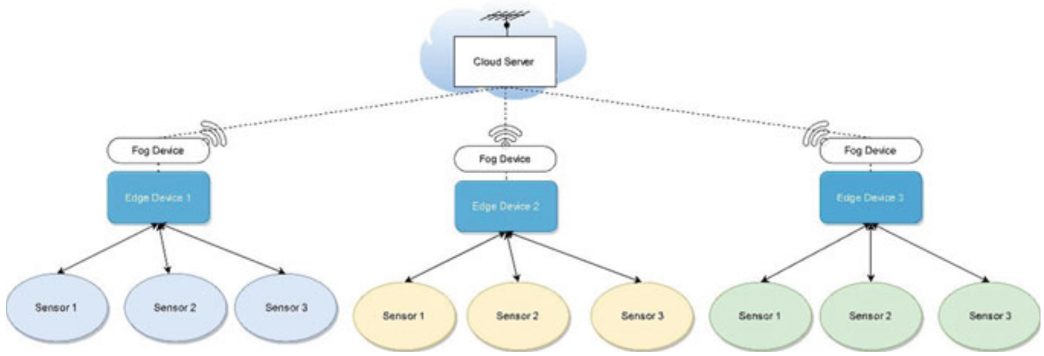

Fig. 1 Distributed architecture

The data intensiveness and on-site resource limits of IoT devices are addressed by cloud computing [6]. In this case, the cloud server is utilized to handle massive amounts of data generated by edge devices and convert it into valuable information. Furthermore, it is not just limited, but also incorporates computationally intensive tasks such as training of initial deep learning models, live forecasts, periodic backups, and backend for web apps. Putting all computing activities on the cloud has shown to be an efficient method for data processing because the computational power on the cloud outperforms the capabilities of items at the edge. However, in comparison to the rapidly increasing data processing speed, the network's capacity has come to a halt. With the increasing amount of data generated at the edge, data transmission speed is becoming a hurdle for the cloud-based computing paradigm [7].

Temperature and humidity sensors in agricultural fields, for example, provide vital data, but that data does not have to be evaluated or stored in real time. Edge devices can gather, sort, and do early data analysis before sending it to centralized apps or long-term storage, which can be on-premises or in the cloud. Because this traffic may not be time-sensitive, slower, less expensive internet connections may be employed. Furthermore, because the data is presorted, the amount of traffic that must be delivered may be decreased. Edge computing has the advantage of providing faster reaction time for applications that demand it while also reducing the expansion of expensive long-distance connections to processing and storage hubs.

Another example, the soil moisture is constantly monitored by the edge device, so maintaining a constant connection with the cloud server is a bottleneck for this system. To overcome this, a small amount of data collection and preprocessing is performed on the edge device itself, and the processed data is sent to the cloud after a specific time period. This will avoid a continuous connection to the cloud, as bandwidth is the bottleneck of the edge-cloud architecture.

The complete workflow of the plant health monitoring and the predicting system is depicted in Fig. 2.

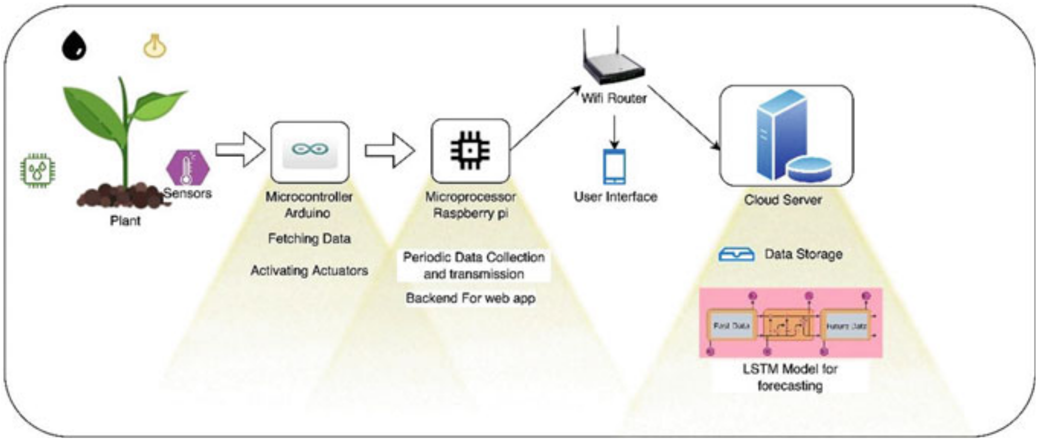

Fig. 2 Graphical abstract of proposed work

4 Hardware and Embedded System

An embedded system is a type of technical artifact that involves computing while being physically constrained as discussed in Henzinger and Sifakis [8]. Embedded systems are made up of Hardware, Software, and Real-Time Operating Systems (RTOS). Table 1 shows the hardware and RTOS configuration of cloud servers.

Table 1 Hardware configuration of cloud server

Hardware	Configuration
PROCESSOR I	Intel Core i9-10850 K @ 5.20 GHz
Core count	10
Thread count	20
Cache size	20 MB
Graphics	Gigabyte NVIDIA GeForce RTX3080 10 GB
Frequency	210/405 MHz
BAR1/visible vRAM	256 MiB
Display driver	NVIDIA 495.44
Motherboard	Gigabyte Z590 AORUS ELITE AX
BIOS version	F5
Chipset	Intel Tiger Lake-H
Audio	Realtek ALC1220
Network	Realtek RTL8125 2.5GbE + Intel Tiger Lake PCH CNVi WiFi
RAM	64 GB

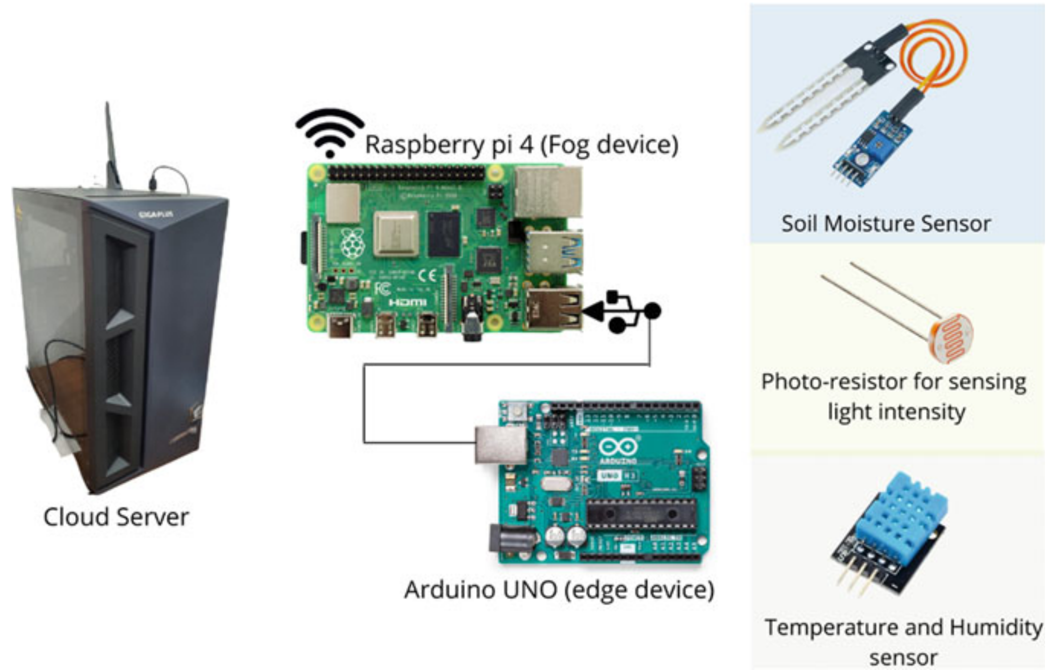

Fig. 3 Soil moisture, temperature, humidity, and light intensity sensors

4.1 Micro-processor and Micro-controllers

The Raspberry Pi 4 is the edge device in this system since it is a microprocessor that can handle light data processing operations [11]. However, due to its inability to receive analogue data, the Arduino Uno is linked to the Raspberry Pi 4 via a Universal Serial Bus (USB). As a result, the Raspberry Pi serves as a partial fog device. Furthermore, all the sensors are connected to the Arduino Uno via General Purpose Input Output (GPIO) pins as shown in Fig. 3. Hardware configuration of fog and edge devices is shown in Table 2.

4.2 Sensors and Actuators

A sensor is an electronic device that converts physical events or properties into electrical signals [12]. This is a hardware device that converts environmental input into information for the system. A thermometer, for example, uses temperature as a physical property before converting it into electrical signals. An actuator is a device that converts electrical impulses into physical events or characteristics [12]. It takes the system's input and outputs it to the environment. Actuators that are frequently used include motors and heaters. The proposed plant monitoring system is focused on sensing four parameters, which include soil moisture, temperature, humidity, and light intensity sensors as shown in Fig. 3.

Table 2 Hardware configuration

Raspberry 4	
Hardware	Configuration
Processor	3
Model name	ARMv7 processor rev 3 (v7l)
Features	Half thumb fastmult vfp edsp neon vfpv3 tls vfpv4 idiva idivt vfpd32 lpae evtstrm crc32
CPU architecture	7
Hardware	BCM2711
Model	Raspberry Pi 4 Model B Rev 1.2
Wifi and Bluetooth	2.4 GHz 802.11n (150 Mbit/s)

Arduino UNO	
Hardware	Configuration
Name	Arduino UNO R3
Microcontroller	ATmega328P
Communication	UART, 12c, SPI
Memory	ATmega328P- 2 KB SRAM, 32 KB FLASH, 1 KB EEPROM
I/O voltage	5 V
Clock speed	Main Processor—ATmega 328P 16 MHz USB-Serial Processor—ATmega16U2 16 MHz

4.3 Working

To monitor the content of Soil Moisture, the soil moisture sensor includes two probes. The resistance value is determined by passing a current between the probes. This DHT11 Digital Relative Humidity and Temperature Sensor Module is pre-calibrated with resistive sense innovation and an NTC thermistor for precise reading of relative humidity and surrounding temperature [13]. The DHT11 module communicates serially, i.e., via a single cable. This module transmits data in the form of a pulse train with a particular time period. Before transferring data to Arduino, some initialized instruction with a time delay is required. And the entire procedure takes around 4 ms. The single-wire serial interface speeds up and simplifies the system integration [9]. A photoresistor is used to detect the intensity of light [14]. The term photoresistor is derived from the terms photon (light particles) and resistor. A photoresistor is a type of resistor whose resistance lowers as the light intensity rises. In other words, as the intensity of light increases, so does the flow of electric current via the photoresistor [10].

All of the sensors and actuators are linked to Arduino via GPIO pins. Because the main advantage of the edge device is its fast response time [15], Arduino is used to executing lightweight programs, such as when the soil moisture level lowers, the actuator, such as a water pump, is turned on. Further, the Arduino is connected to

Raspberry pi 4 with a USB connection for sending serial data, this data is collected in the form of tables which is stored in Comma-separated values (CSV) file. The attributes of the table are TIMESTAMP, TEMPERATURE, HUMIDITY, LIGHT INTENSITY, SOIL MOISTURE. After every specific time-stamp, this data is sent to the cloud server for further analysis.

5 LSTM for Forecasting

Deep learning technologies, such as automated learning of temporal dependency and automatic handling of temporal structures like trends and seasonality, hold a lot of promise for time series forecasting [16]. Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning [17]. Because there might be lags of undetermined duration between critical occurrences in a time series, LSTM networks are well-suited to classifying, processing, and making predictions based on time series data [18, 20]. LSTMs were created to solve the problem of vanishing gradients that can occur when training traditional RNNs [19].

The input **x(t)** of the LSTM can be the output of a CNN or the input sequence itself. The inputs from the previous timestep LSTM are **h(t−1)** and **c(t−1)**. The output of the LSTM for this timestep is **o(t)**. The LSTM also generates the **c(t)** and **h(t)** for the next time step LSTM consumes.

$$f_t = \sigma_g(W_f \times x_t + U_f \times h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma_g(W_i \times x_t + U_i \times h_{t-1} + b_i) \tag{2}$$

$$o_t = \sigma_g(W_o \times x_t + U_o \times h_{t-1} + b_o) \tag{3}$$

$$c'_t = \sigma_c(W_c \times x_t + U_c \times h_{t-1} + b_c) \tag{4}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot c'_t \tag{5}$$

$$h_t = o_t \cdot \sigma_c(c_t) \tag{6}$$

where f_t is forget gate, i_t is input gate, o_t is output gate, c_t is cell state, h_t is hidden state, σ_g: sigmoid, σ_c: tanh.

6 Result

Arduino is used as an edge device to collect data from sensors and activate actuators in a timely manner. For light processing, a Raspberry Pi is utilized as a fog device, while for heavy processing of data, a cloud device is employed.

The authors were able to obtain real-time data on temperature, humidity, light intensity, and soil moisture using the architecture they presented. The authors produced 1 year of data and trained our LSTM network on it to verify the overall functioning of the proposed architecture, and for proper assessment of deep learning models. Proposed LSTM models showed a trailblazing performance on produced dataset with a mean squared error of 2.077 on the training set and 2.303 on the testing set as shown in Table 3. Figure 4 represents the LSTM predictions of temperature over a year for both the train and test data. Figure 5 depicts the loss curve for training of the LSTM model.

The system's real-time architecture is depicted in Fig. 6. Furthermore, a user interface was developed on the Flask framework as a wrap up backend to serve the entire architecture and display fetched and forecasted data.

Table 3 Evaluation metrics of proposed LSTM model

	Mean squared error	Mean absolute error	Mean absolute percentage error
Train set	2.077	1.693	0.059
Test set	2.303	1.966	0.105

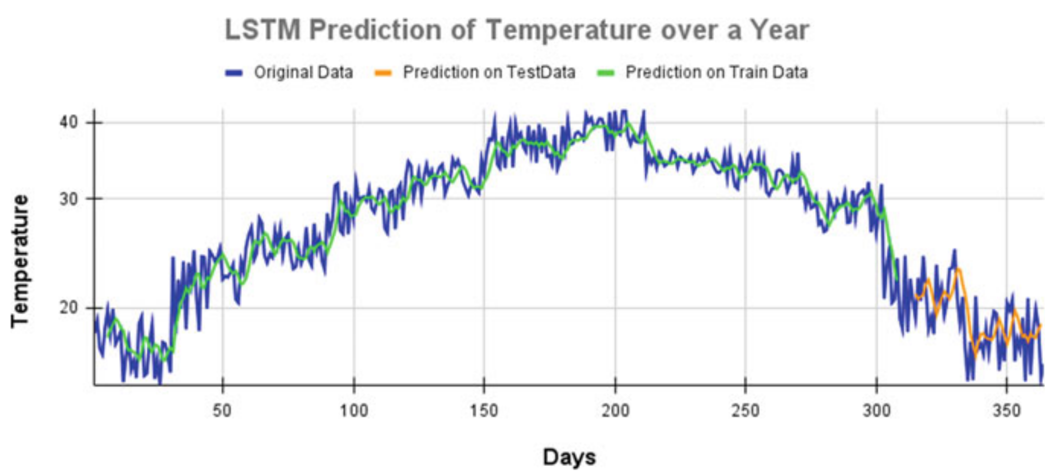

Fig. 4 LSTM predictions of temperature over a year

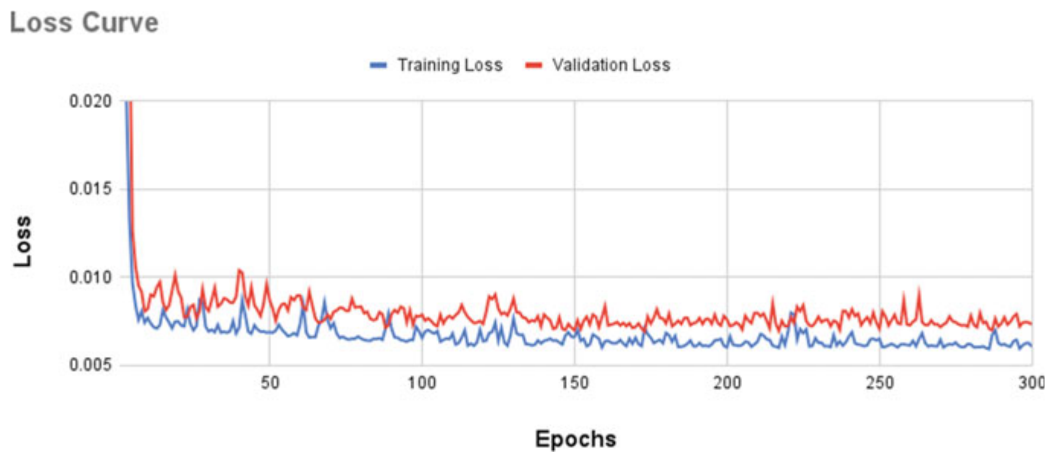

Fig. 5 Loss curve of the trained LSTM model

Fig. 6 Realtime working of proposed architecture

7 Conclusion

This design incorporates a cutting-edge Plant monitoring and forecasting system that is unique, reliable, robust, and user-friendly, as well as more efficient than currently available solutions. The completely working device, including software and hardware, along with edge-fog-cloud architecture was successfully implanted. The elegant user interface made all of the retrieved parameters, as well as notifications alert, available remotely. In addition, the cloud device forecasts critical data, which will aid in the planning process for the forthcoming parameter change. Users, such as farmers, will be able to monitor and enhance crop yields and overall production by implementing this system.

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