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# Smart Irrigation System Using Soil Moisture Prediction with Deep CNN for Various Soil Types

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**Abstract:** Soil moisture sensing plays a crucial role in agriculture as it directly impacts plant growth and can significantly enhance crop productivity. With the advent of technology, agriculture applications have undergone a revolution, enabling more advanced and efficient practices. One such advancement is the use of soil moisture sensors, which provide valuable information about the current water level of the soil, including whether it is dry, wet, or excessively saturated. These sensors have become indispensable tools for farmers and growers, empowering them to make informed decisions regarding irrigation schedules, water management strategies, and overall crop health. By accurately assessing soil moisture levels, farmers can optimize water usage, prevent water stress or overwatering, and promote healthier plant development, ultimately leading to improved yields and sustainability in agriculture. The objective of the proposed study is to investigate the effective soil moisture sensors by considering three sensors and an automated system for watering the soil for agriculture. A comparative analysis is performed for different commercial off-the-shelf soil moisture sensors in cost, accuracy, durability, and corrosion resistance. Secondly, this study further gives soil moisture reading as data input to the convolutional neural network to classify whether water is required or not for the soil at a particular temperature which would help to conserve water and develop agriculture.

**Keywords:** convolutional neural network, soil moisture sensors, IoT, smart irrigation system, accuracy

## 1. Introduction

The Internet of Things (IoT) is defined as a network of physical objects, including furniture, machines, automobiles, and buildings, that are connected to the Internet and have sensors, electronics, software, and network connectivity. IoT is changing how we work, live, and interact with the world. The fundamental idea behind IoT is to connect physical objects to share data and even carry out automatic tasks. Several industries, including medicine, shipping, production, agriculture, and more, could undergo radical change as a result of this technology. IoT devices come in many shapes and sizes, from tiny sensors to massive machines, and they are capable of a variety of tasks, such as monitoring, controlling, automating, and optimizing. IoT devices can also aid in collecting data and analysis, allowing organizations and people to make better decisions and increase productivity.

In the field of agriculture, IoT is playing a vital role in all aspects. Many technical improvements made farming easier, especially, soil-related works such as checking soil moisture and quality of the soil. Soil sensors are electronic devices that are used to measure the temperature, moisture, and nutrient content of the soil. These sensors are frequently used in horticulture, agriculture, and other disciplines that focus on cultivating plants. In order to maximize crop yields and enhance soil health, they offer farmers and researchers useful data. In order to assess the soil's electrical conductivity or resistance, soil sensors must be inserted into the ground. This measurement is translated into a reading that may be

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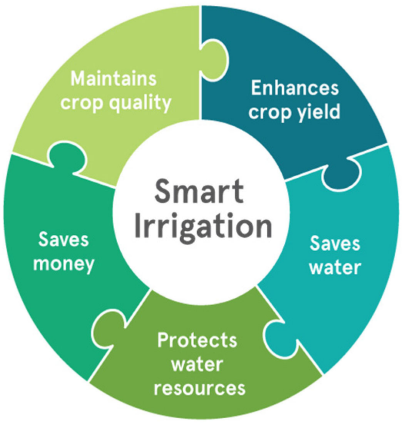
**Figure 1**
**Benefits of smart irrigation using IoT**




comprehended by the user. Some sensors are also able to determine salinity and pH levels [1]. The data obtained by soil sensors can be utilized to make informed decisions regarding watering, fertilizer, and other procedures that affect plant growth. Similar to this, growers can add fertilizers to the soil to boost plant health if the sensor determines that it is deficient in particular nutrients. Some applications of the IoT are smart agriculture monitoring soil, crop, livestock, weather, and farming equipment [2].

The motivation of the study is that the key element in plant growth and development is soil moisture. Farmers and scientists can adjust irrigation schedules, fertilizer use, and other agricultural methods to enhance crop yields by analyzing soil moisture. This is particularly crucial in areas with limited water supplies or those that experience drought. Indicators of environmental circumstances, such as the effects of climate change and land-use practices, can also be found in soil moisture. By measuring soil moisture, researchers can acquire insight into the well-being and long-term viability of ecosystems. Figure 1 explains the benefits of smart irrigation using IoT with artificial intelligence [3].

The proposed system offers automated decision-making about soil irrigation, helping to optimize water use and enhance agricultural practices. It does this by fusing the capabilities of a soil moisture sensor, IoT connection, and a CNN model. The remainder of the paper is organized as follows: Section 2 describes the related works which were carried out in this research area previously. In Section 3, the experimental setup, analysis of different soil water level measuring techniques, different soil moisture sensors, and technical comparison of Long Range (LoRa) and Narrowband Internet of Things (NB-IoT) are all described in depth. Deep learning classifier is used for classifying the water requirement. The results as well as the discussion are explained in Section 4. The limitations and future works are discussed in the conclusion part.

## 2. Literature Review

Many studies have been conducted in the past for soil moisture identification using IoT sensors which is very helpful in agriculture and farming using machine and deep learning methods. Schwamback et al. [4] propose that the trade-off between cost and accuracy is compared between inexpensive and advanced soil moisture sensors. The capacitive sensor SKU:SEN0193 was tested in the lab and on the ground for the study. In addition to individualized calibration, two streamlined calibration processes are suggested: worldwide calibration based on all 63 detectors and a single-point calibration using sensor response in dry soil.

Abdelmoneim et al. [5] analyze the development and lab validation of an inexpensive IoT soil moisture tensiometer. $R2 = 0.99$ indicates that the IoT-prototype can gauge tension up to roughly 80 Kpa when compared to a tensiometer with a mechanical manometer that is identical. By uploading the measured points to a cloud service platform utilizing an ESP32 MCU, BMP180 barometer sensor, and an SD card module, it generates an online soil water potential curve.

Immanuel and Sangeetha [6] presented the best crops for the specific soil. When water is required, the field is irrigated with enough water. When the level of water in the field attains a certain height or the level of water in the well reaches a certain level, the system sensor detects it and shuts off the pump motor automatically. As a result, physical exertion is reduced, and the field is effectively watered. Furthermore, the pump motor's working life is extended.

Raghuvanshi et al. [7] propose a virtual soil moisture sensor powered by deep learning algorithms. This approach aims to enhance smart farming by providing reliable soil moisture data without the need for extensive physical sensors. Sinha and Gupta [8] focus on creating a deep learning-based model for smart irrigation sensors. The model aims to improve the prediction accuracy of soil moisture levels, thereby optimizing irrigation practices.

The motivation for this study arises from the critical need to enhance agricultural productivity and sustainability through precise water management. Soil moisture sensing is pivotal in agriculture, as it directly influences plant growth and can significantly boost crop yields. Traditional irrigation methods often lead to water wastage or insufficient watering, which can harm crop health and reduce productivity. The advent of advanced technology in agriculture offers innovative solutions to these challenges, with soil moisture sensors standing out as indispensable tools for modern farmers. These sensors provide real-time data on soil water levels, enabling farmers to make informed decisions about irrigation schedules and water management strategies. By integrating soil moisture sensors with deep learning techniques, specifically CNNs, this study aims to optimize water usage, prevent water stress, and avoid overwatering.

## 3. Soil Moisture and Measurements

In this section, different types of soils, their moisture levels, and the measuring techniques for the moisture have been discussed.

### 3.1. Soil type

For the study, three different soils are chosen. The comparison has been made among the three types of soils. Moisture test is conducted for all the three types of soil at three different temperatures.

1) **Clay soil:** Clay soil is composed of fine particles and has a smooth texture [9]. It is sticky and heavy when wet and can become hard and compact when dry.
2) **Silt Soil:** Silt soil consists of granules that fall between the sizes of sand and clay. It is smooth and can be easily molded and has moisture retention properties.
3) **Loam Soil:** Loam soil is a mixture of clay, silt, and sand particles in roughly equal proportions. It has a crumbly texture and good drainage and moisture retention properties, making it a better option for gardening and agriculture.

## 3.2. Soil moisture and its types

The term "soil moisture" describes the water level in the soil. It is an important factor in plant growth and development, as well as in ecosystem health and water resource management. The soil moisture can be classified as three types and saturation occurs when the soil is completely filled with water, and there is no room for air [10]. This can happen during heavy rain or flooding, and it can lead to soil erosion and nutrient loss. Field capacity refers to the maximum amount of water that the soil can hold against gravity. At field capacity, the soil is still moist, but excess water will drain away. This is the ideal moisture level for most plants to grow. The wilting point is the point at which plants can no longer extract water from the soil. At this point, the soil is too dry for most plants to survive. The wilting point is influenced by factors such as soil texture, climate, and plant species [11].

Measuring soil moisture is important for understanding plant growth and water resource management. There are several methods for measuring soil moisture, including gravimetric sampling, soil water tension, and time domain reflectometry. By monitoring soil moisture levels, farmers, researchers, and land managers can make informed decisions about irrigation, fertilizer application, and other agricultural practices.

## 3.3. Soil moisture measuring techniques

The technique involves taking a soil sample, weighing it, drying it in an oven, and then weighing it again to determine the amount of water that was present. The method provides accurate results but can be time-consuming and labor-intensive.

### *3.3.1. Gravimetric sampling*

Direct soil moisture measurement techniques involve physically measuring the water level in the soil. The most common direct soil moisture measurement technique is gravimetric sampling, which involves taking a soil sample, weighing it, drying it in an oven, and then weighing it again to determine the amount of water that was present. The method provides accurate results but can be time-consuming and labor-intensive.

### *3.3.2. Moisture sensors*

Another direct soil moisture measurement technique is the use of moisture sensors or probes, which are inserted into the soil to measure the amount of moisture present. These sensors can be either electrical or mechanical, and they measure the water content of the soil using various methods. An electrical sensor is a time domain reflectometry sensor. The moisture content of the soil affects the speed at which the pulse travels, allowing for accurate measurements of soil moisture. A mechanical sensor is the tensiometer, which measures the soil's moisture tension, or the energy required to extract water from the soil. The tensiometer measures the soil moisture tension using a ceramic cup and a gauge that measures the pressure required to extract water from the soil [12].

## 3.4. Radiation technique and indirect/modern soil moisture measurement techniques

Radiation-based techniques are modern and indirect methods of measuring soil moisture that use the principles of electromagnetic radiation to estimate the moisture content of soil. There are two types of radiation-based techniques for soil moisture measurement: neutron probe and gamma-ray probe [13].

### *3.4.1. Neutron probe technique*

The neutron probe technique involves the use of a neutron probe, which is a specialized instrument that emits a beam of neutrons into the soil. These neutrons interact with the hydrogen atoms in the soil, and the resulting energy is measured by a detector. The moisture content of the soil can be estimated based on the number of hydrogen atoms in the soil, which is directly related to the soil moisture content [14]. The neutron probe technique provides accurate and precise measurements of soil moisture, but it requires specialized equipment and expertise to operate. The technique is also relatively expensive and time-consuming, making it more suitable for research applications than routine soil moisture monitoring.

### *3.4.2. Gamma-ray probe technique*

The soil moisture content can be determined using the gamma-ray probe technique, which uses a gamma-ray source and detector. The gamma rays emitted by the source pass through the soil and are absorbed by the water molecules in the soil [15]. The amount of gamma-ray absorption is proportional to the soil moisture content, and this information is used to estimate the soil moisture content. The gamma-ray probe technique [6] is relatively fast and non-invasive, making it well-suited for routine soil moisture monitoring in agricultural and environmental applications. However, it requires specialized equipment and expertise to operate, and safety considerations must be taken into account when using gamma-ray sources.

## 3.5. Resistive technique indirect/modern soil moisture measurement techniques

Two main types of resistive soil moisture sensors are used to measure the soil moisture. There are granular matrix sensors and frequency domain reflectometry (FDR).

### *3.5.1. Granular matrix sensor*

Granular matrix sensors use porous granular material, such as gypsum, to identify the soil water content. The granular material absorbs moisture from the soil, and the electrical resistance of the granular material changes as the moisture content changes. The resistance is measured by electrodes embedded in the granular material, and the moisture content is estimated based on the resistance measurement [16].

### *3.5.2. FDR sensor*

FDR sensors use a metallic probe that is inserted into the soil. The probe emits electromagnetic waves at different frequencies, which are reflected back from the soil. The reflection of the waves from the soil is related to the soil's dielectric constant, which is related to the soil water content. The change in dielectric constant due to soil moisture is measured, and the moisture content is estimated based on the measured dielectric constant [6, 17].

The resistive technique is relatively simple, inexpensive, and provides accurate and reliable estimates of soil moisture content. This technique is widely used in agriculture, environmental, and ecological applications due to its non-destructive nature and ease of use. However, the resistive technique is affected by factors such as soil salinity, temperature, and the presence of rocks and other obstructions in the soil, which can impact the accuracy of the estimates. Calibration of the resistive sensors is required for each soil type and texture to obtain accurate and reliable estimates of soil moisture content [18].

## 3.6. Working

In this section, three types of soil moisture sensors are explained with their specifications namely capacitive soil moisture sensor V1.2, capacitive soil moisture sensor V2.0 and Grove – Resistive Soil Moisture Sensor [19].

*3.6.1. Capacitive soil moisture sensor V1.2*

The sensor is capacitive version 1.2 and works well with all climatic conditions. Figure 2 shows the sensor of capacitive moisture detector. Table 1 depicts the specifications of the version 1.2 sensor.

*3.6.2. Capacitive soil moisture sensor V2.0*

The details of the capacitive soil moisture sensor V2.0 are explained in Table 2 and Figure 3 The V2.0 sensor.

*3.6.3. Grove: Resistive soil moisture sensor*

The specification of resistive soil moisture sensor is explained in Table 3 and Figure 4.

**Figure 2**
**Capacitive soil moisture sensor V1.2**


**Table 1**
**Specification of capacitive soil moisture sensor V1.2**

| Sr.No | Parameter | Values |
|---|---|---|
| 1. | Operating Voltage Range | 3.3 – 5.5 V |
| 2. | Output Voltage Range | 0.0 – 3.0 V |
| 3. | Operating Current | 5 mA |
| 4. | Interface | PH 2.54 – 3.0 P |
| 5. | Dimension of Sensor | 5 × 4 × 3 cm |
| 6. | Weight | 30 gm |

*3.6.4. Arduino Uno*

A microcontroller board called Arduino Uno depends on the ATmega328P-PU. In this paper, it is utilized to transmit and receive sensor data by connecting the soil moisture sensors. Code is written in a simplified form of C++ and executed on a PC via a USB connection to an Arduino board Bertocco [20]. The description of the Arduino Uno board is shown in Figure 5 and Table 4.

**Table 2**
**Specification of capacitive soil moisture sensor V2.0**

| S.No | Parameter | Values |
|---|---|---|
| 1. | Operating Voltage Range | 3.3 – 5.5 V |
| 2. | Output Voltage Range | 0.0 – 3.0 V |
| 3. | Operating Current | 5 mA |
| 4. | Interface | PH 2.54 – 3.0 P |
| 5. | Dimension of Sensor | 5 × 4 × 3 cm |
| 6. | Weight | 15 gm |

**Figure 3**
**Capacitive soil moisture sensor V2.0**


**Table 3**
**Specification of Grove: Resistive soil moisture sensor**

| S.No | Parameter | Values |
|---|---|---|
| 1. | Operating Voltage Range | 3.3 – 5.0 V |
| 2. | Output Voltage Range | 0.0 – 3.0 V |
| 3. | Operating Current | 35 mA |
| 4. | Interface | PH 2.54 – 3.0 P |
| 5. | Dimension of Sensor | 2.0 × 6.0 cm |
| 6. | Weight | 10 gm |

**Figure 4**
**Grove: Resistive soil moisture sensor**

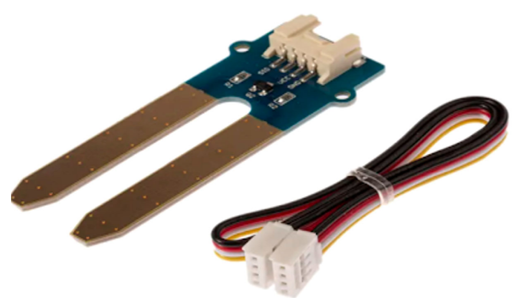


**Figure 5**
**Arduino board**

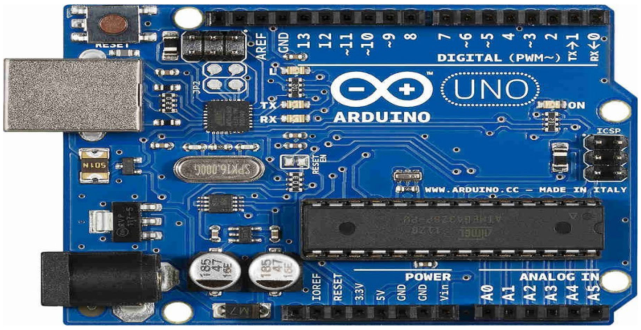


**Figure 6**
**LoRa**

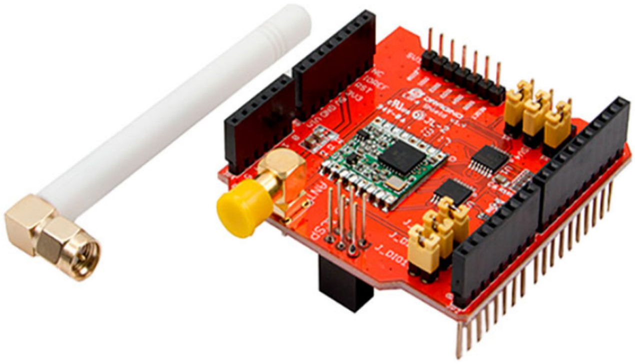


**Table 4**
**Specification of Arduino Uno board**

| S.No | Parameter | Value range |
|---|---|---|
| 1 | Microcontroller used | ATmega328 |
| 2 | Operating Voltage Range | 5 V |
| 3 | Input Voltage Range | 6 – 20 V |
| 4 | Output Voltage Range | 0.0 – 3.0 V |
| 5 | Operating Current | 5 mA |
| 6 | Interface | PH 2.54 – 3.0 P |
| 7 | Dimension of Sensor | 5 × 4 × 3 cm |
| 8 | Weight | 15 gm |

## 3.7. Technical comparison of LoRa and NB-IoT

LoRa and NB-IoT are two popular wireless communication technologies used in the IoT applications. Both technologies are designed to support low-power, wide-area networks and provide long-range communication capabilities [21]. However, there are some key differences between the two technologies.

LoRa uses a proprietary chirp spread spectrum modulation technique [22], while NB-IoT [23] uses narrowband orthogonal frequency-division multiplexing modulation technique. LoRa uses a wide bandwidth (up to 500 kHz), whereas NB-IoT uses a narrow bandwidth (up to 200 kHz). LoRa operates in unlicensed frequency bands (ISM bands) and NB-IoT operates in licensed frequency bands. LoRa has a longer range compared to NB-IoT [24]. LoRa can cover a range of up to 10 km in rural areas, while NB-IoT has a range of up to 1–2 km in urban areas. LoRa has a lower deployment cost compared to NB-IoT since it operates in unlicensed frequency bands and does not require expensive licensing fees. Hence, LoRa performance is better than NB-IoT for this study, and Figure 6 shows the LoRa wireless communication system [25].

The working setup of the model to identify the soil moisture whether it is dry, wet, and more water is depicted in Figure 7. The three different soils with three different water levels [26] test is conducted with complete setup as shown in Figure 7.

## 3.8. Hardware and software requirement for the experiment

The hardware requirements for the experimental setup are given below.

1) Capacitive sensors (V1.2 and V2.0)
2) Resistive sensors (SEN0114 and Grove)
3) Arduino Uno board x 2
4) Laptop/PC x 1
5) LoRa Shield x 2

**Software Description**

1) Arduino Integrated Development Environment
2) The Things Network

## 3.9. Classifier

Data from the soil moisture sensor readings are given as input to the deep convolutional neural network. The data are converted into tables where columns represent the moisture reading in different temperatures. The rows represent the different types of soil [26]. The working setup of the sensor for different type of soils is mentioned in Figure 8.

The input is passed to a three-layered neural network. Each layer consists of convolution layer, concatenation layer, 1 × 1 filter, and max pooling layer. The data goes through all the layers of the system and finally reaches the fully connected layer. The classification is done by classifying whether water needs to be supplied to the soil and not required [8]. It is a binary classification model where 0 is water not required and 1 is water required and accuracy obtained is 95.23%. With the help of the classifier, irrigation can easily identify whether soil is wet or not. The proposed model from input data to the classified output is explained in Figure 8.[1]

## 4. Experimental Results

This section discusses the experimental findings, which are divided into three sections depending on the input from the three soil moisture sensors [7]. Three soils, silt, loam, and clay are used in the experiment to obtain sensor readings at three different temperatures: room temperature, 30°C, and 45°C. To check the accuracy of the sensor, or how closely measured and actual values relate to one another, the measured readings of the sensor are compared with values from the datasheet. The sensor's measured results indicate whether the soil is dry, wet, or watery. Since the

[1] https://www.electronicshub.org/interfacing-soil-moisture-sensor-with-arduino/

**Figure 7**
**Proposed model architecture**

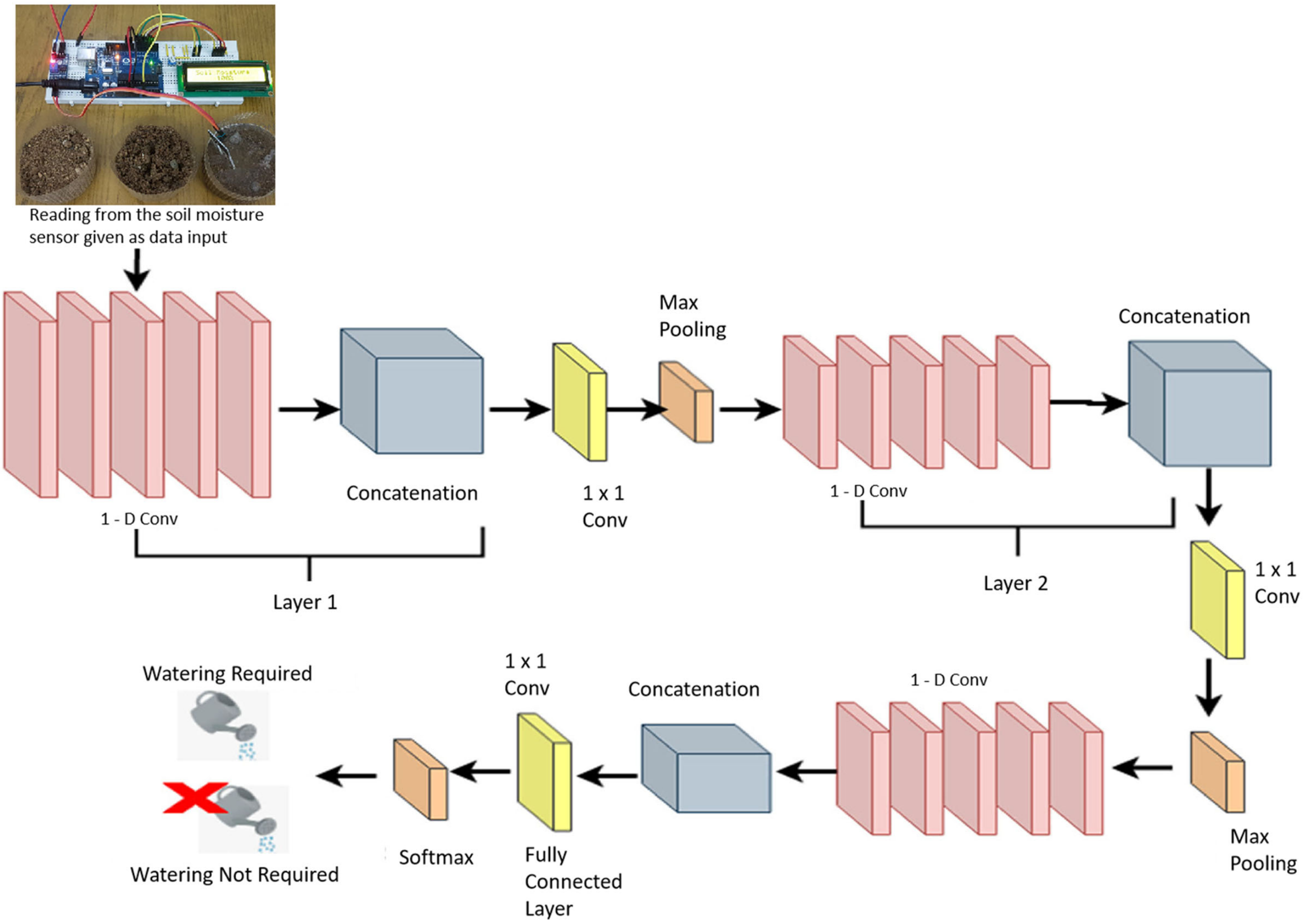
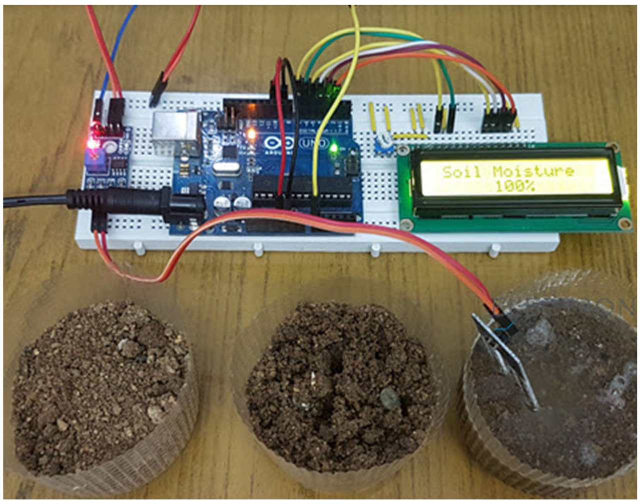



**Figure 8**
**Working setup of system**




manufacturer defines these values, the actual values for these states differ from sensor to sensor [27].

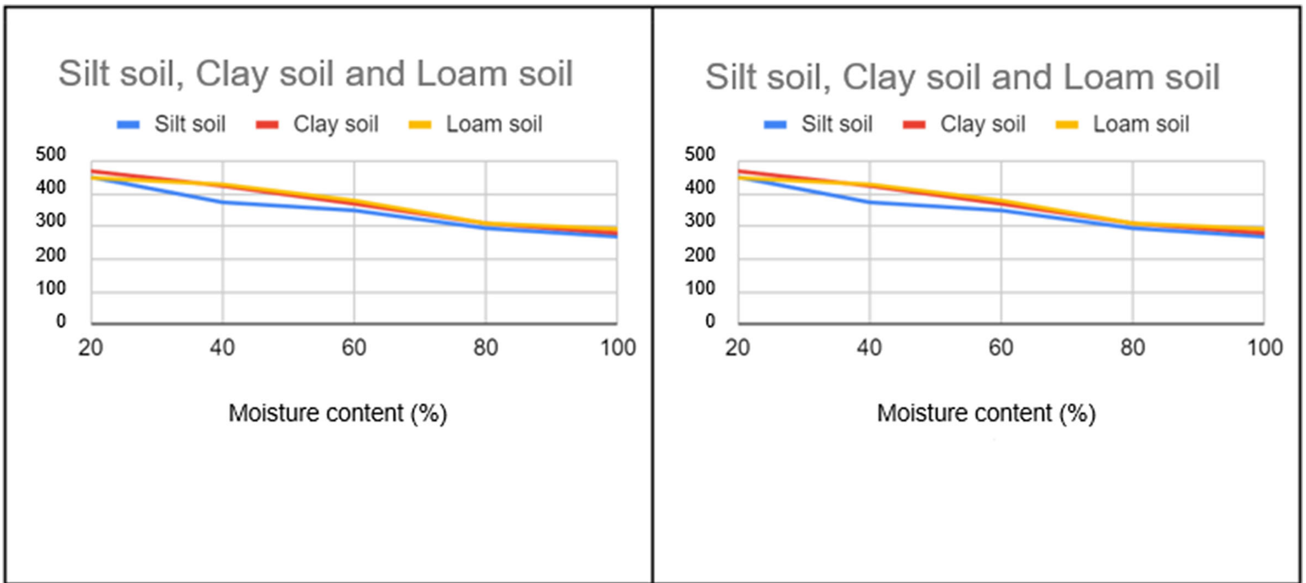
### 4.1. Capacitive soil sensor V 1.2

The experiment is performed at room temperature for five values of water content, i.e., 20%, 40%, 60%, 80%, and 100%. Figure 9 shows the sensor reading and graph for silt, clay, and loam soils with different moisture content at room temperature, 30°C, and 45°C, respectively. According to the observation, Dry water level: [420,500]; Wet water level: [380,420]; Watery level: [250,380] [28].

### 4.2. Capacitive soil sensor V 2.0

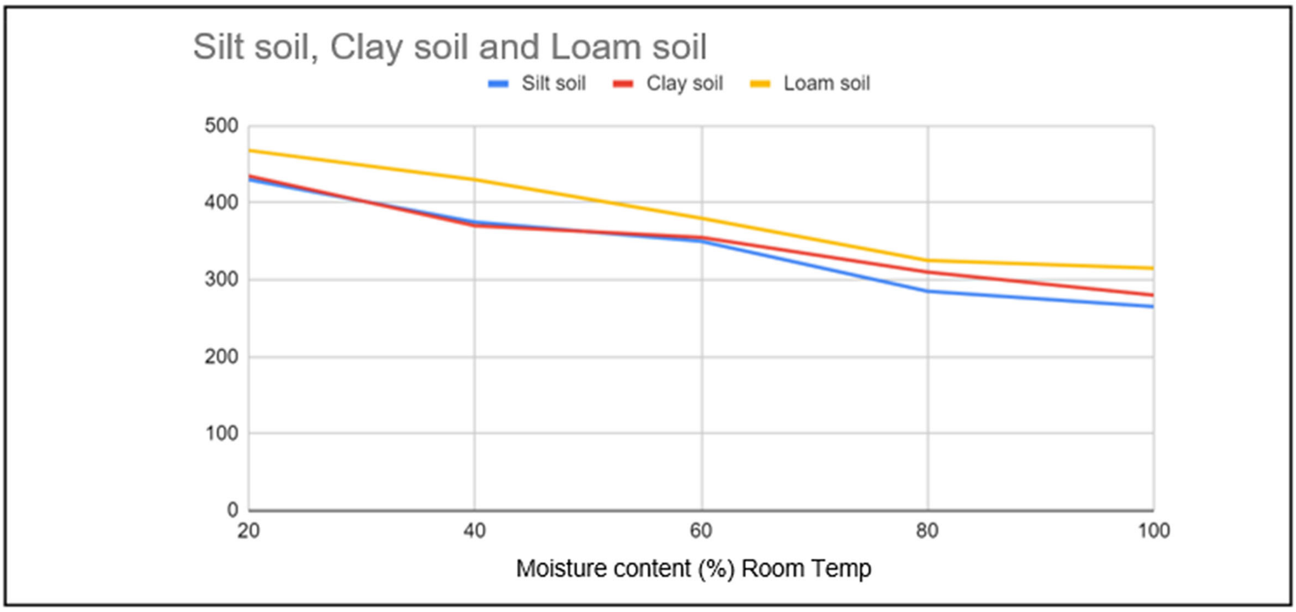
The experiment is performed at room temperature for five water content values, i.e., 20%, 40%, 60%, 80%, and 100%. Figure 10 shows the sensor reading and graph for silt, clay, and loam soils with different moisture content at room temperature, 30°C, and 45°C, respectively. According to the observation, Dry water level: [410,500]; Wet water level: [360,410]; Watery level: [250,360].

**Figure 9**
**Graphical representation of capacitive soil moisture V1.2 (30 °C, 45 °C and room temp). Capacitive soil sensor V1.2 (Room temp)**




| Capacitive Soil Sensor V1.2 (30°C) | Capacitive Soil Sensor V1.2 (45°C) |
|---|---|

**Capacitive soil sensor V1.2 (Room temp)**

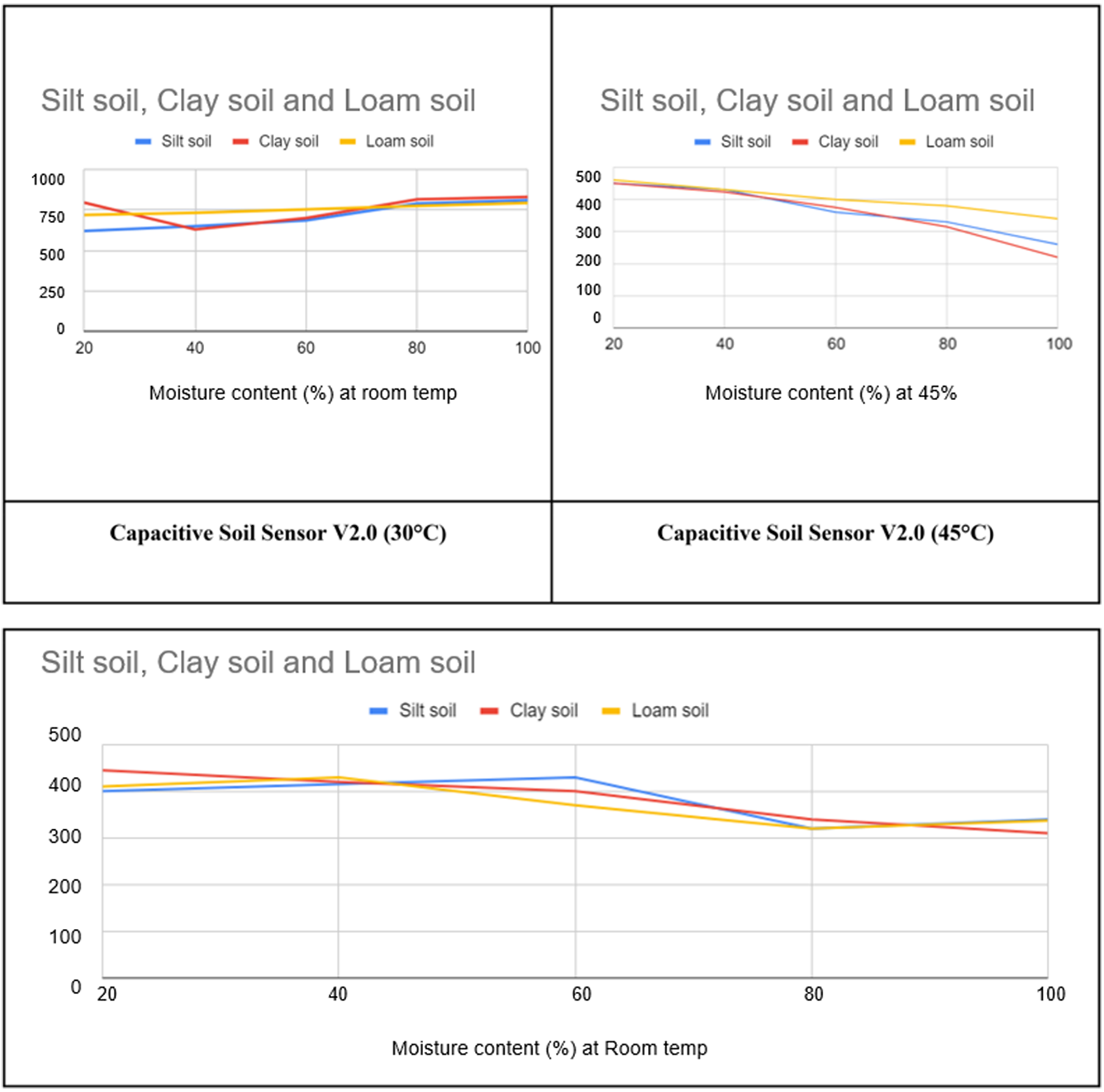



### 4.3. Resistive sensor (Grove)

The experiment is performed at room temperature for five values of water content, i.e., 20%, 40%, 60%, 80%, and 100% [29]. Figure 11 shows the sensor reading for silt, clay, and loam soils with different moisture content at room temperature, 30°C, and 45°C, respectively. According to the observation, Dry water level: [0,280]; Wet water level: [280,680]; Watery level: [680,930].

Tables 5 and 6 depict the summary of results. According to comparison 4, the capacitive V2.0 sensor is the most accurate, corrosion-resistant, and durable of all the sensors, whereas the capacitive V1.2 sensor is less accurate than the V2.0 sensor but is also the most corrosion-resistant, durable, and least expensive [30]. The trade-off between expense and precision exists. Therefore, depending on the needs, such as precision or cost, both can be employed for agricultural purposes. However, as was

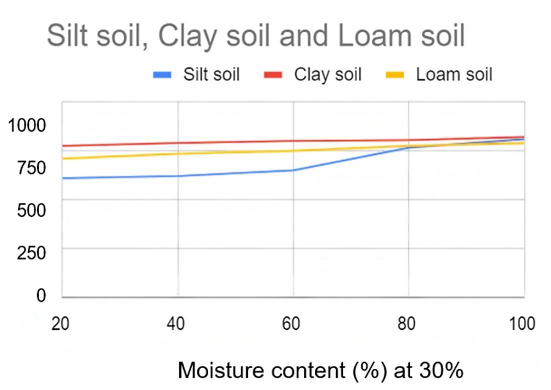
**Figure 10**
**Graphical representation of capacitive soil moisture V2.0 (30 °C, 45 °C, and room temp)**



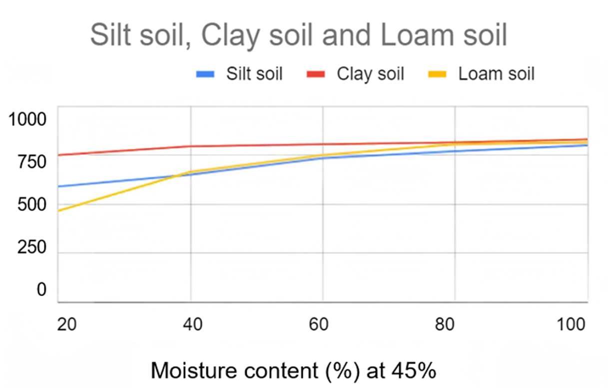

already said, resistive sensors can be less precise, more expensive, and less long-lasting.

The current study faced several limitations, including a limited range of tested sensors and controlled environmental conditions, which may not fully represent real-world scenarios. Only three soil types were considered, and sensor calibration details were sparse, potentially affecting measurement accuracy. Furthermore, the study did not extensively explore the cost implications of implementing the automated system. For future work, expanding the range of sensors and conducting field experiments under diverse environmental conditions will provide more comprehensive insights. Advanced calibration techniques, integration with IoT platforms, and more sophisticated machine learning models can enhance accuracy and reliability. Additionally, exploring cost-benefit analyses, sustainability impacts, and user-friendly interfaces can facilitate the adoption of smart agriculture technologies, promoting efficient water use and improved crop yields.

**Figure 11**
**Graphical representation of resistive sensor (Grove) (30 °C, 45 °C, and room temp)**




**Capacitive Soil Sensor V2.0 (30°C)**




**Capacitive Soil Sensor V2.0 (45°C)**

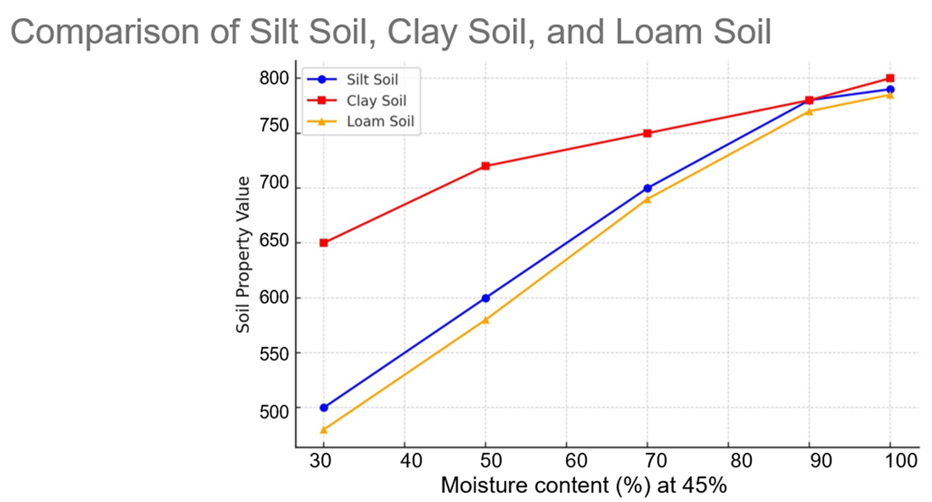



**Table 5**
**Summary of results – I**

| Sensor type | Temperature | Water content levels | Dry water level | Wet water level | Watery level |
|---|---|---|---|---|---|
| **Capacitive soil sensor V1.2** | Room Temp | 20%, 40%, 60%, 80%, 100% | 500 – 420 | 420 – 380 | 380 – 250 |
| | 30°C | 20%, 40%, 60%, 80%, 100% | 500 – 420 | 420 – 380 | 380 – 250 |
| | 45°C | 20%, 40%, 60%, 80%, 100% | 500 – 420 | 420 – 380 | 380 – 250 |
| **Capacitive soil sensor V2.0** | Room Temp | 20%, 40%, 60%, 80%, 100% | 500 – 410 | 410 – 360 | 360 – 250 |
| | 30°C | 20%, 40%, 60%, 80%, 100% | 500 – 410 | 410 – 360 | 360 – 250 |
| | 45°C | 20%, 40%, 60%, 80%, 100% | 500 – 410 | 410 – 360 | 360 – 250 |
| **Resistive sensor (Grove)** | Room Temp | 20%, 40%, 60%, 80%, 100% | 0 – 280 | 280 – 680 | 680 – 930 |
| | 30°C | 20%, 40%, 60%, 80%, 100% | 0 – 280 | 280 – 680 | 680 – 930 |
| | 45°C | 20%, 40%, 60%, 80%, 100% | 0 – 280 | 280 – 680 | 680 – 930 |

**Table 6**
**Summary of results – II**

| Criteria | Capacitive soil sensor V1.2 | Capacitive soil sensor V2.0 | Resistive sensor (Grove) |
|---|---|---|---|
| **Accuracy** | Moderate | High | Low |
| **Corrosion resistance** | High | High | Low |
| **Durability** | High | High | Low |
| **Cost** | Low | Moderate | Moderate to High |
| **Overall performance** | Good | Best | Poor |

## 5. Conclusion

People's primary source of food comes from agriculture, and it is crucial to keep an eye on the crops' yield and quality. For instance, smart irrigation, soil moisture monitoring, and other smart technology should be used to provide a sustainable environment for agriculture. A procedure where numerous sensors are combined with communication technology to track environmental changes brought on by various external elements is referred to as "smart agriculture". The data gathered from this process is then optimized to help farmers make informed decisions. The capacitive soil moisture sensor V2.0 performs better than the capacitive soil moisture sensor V1.2 and resistive sensor – Grove sensor with more accuracy. The classifier CNN classifies the given data from sensor reading for smart irrigation. It classifies as water required or water not required for the soil. Future work can be carried out as an automated drip irrigation system for agriculture which would save water.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

## Data Availability Statement

The data that support the findings of this study are openly available in Kaggle at https://www.kaggle.com/datasets/amirmohammdjalili/soil-moisture-dataset.

## Author Contribution Statement

**Sangeetha S. K. B.:** Conceptualization, Methodology, Software, Resources, Writing – original draft, Supervision. **Rajeshwari Rajesh Immanuel:** Conceptualization, Methodology, Software, Resources, Writing – original draft, Supervision. **Sandeep Kumar Mathivanan:** Methodology, Investigation, Writing – review & editing, Visualization. **Prabhu Jayagopal:** Validation. **Sukumar Rajendran:** Data curation. **Saurav Mallik:** Data curation, Project administration. **Aimin Li:** Data curation, Project administration.

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