IoT-Driven Soil Nutrient Measurement Using LoRa and Broken-Stick Regression Techniques

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Received: 21 June 2025 | Revised: 26 July 2025, 23 August 2025, and 4 September 2025 | Accepted: 9 September 2025

DOI: https://doi.org/10.48084/etasr.12854

ABSTRACT

Soil nutrient measurement systems are crucial for optimizing crop growth and yield in agriculture. Nitrogen (N), Phosphorus (P), and Potassium (K) are vital for crop growth. Many measuring systems have been presented, but accurately measuring soil nutrients is a challenging issue for efficient agriculture and environmental management. Conventional methods are often time-consuming, expensive, and incorrect due to soil variability and other factors. To address this issue, this study introduces Broken-Stick Regressive LoRa Technology (BSRLRT), aimed at accurately measuring soil nutrients based on IoT technology through sensor node deployment and data collection from a farmland. Initially, the broken-stick regression method is used to analyze and identify the exact position of the sensor nodes for efficient data collection. In addition, Long Range (LoRa) technology is used to monitor and collect data. The proposed method was experimentally deployed on V.C. Farm, Mandya, India.

Keywords-soil; nitrogen-phosphorus-potassium; nutrient management system; long range; broken-stick regression

I. INTRODUCTION

Soil monitoring in agriculture is the method of analyzing soil to monitor the health and growing conditions of crops. Soil monitoring helps farmers prevent and diagnose plant diseases at an early stage to achieve better yields. Since demand for food is expected to increase by 70% in 2050, agricultural yield production has to improve. The key attributes used for agricultural productivity improvement are rainfall, on-time irrigation, weather, soil type, and nutrients. Farmers focus on all attributes equally. However, soil nutrients are challenging to improve agricultural production. Soil testing measures the macronutrient levels for improving agricultural productivity. Soil testing and fertilizer recommendation systems utilizing Internet of Things (IoT) and Machine Learning (ML) technologies have become an essential requirement for agricultural systems.

Soil nutrient monitoring and management are critical parts of sustainable agriculture, as it manages soil nutrient levels to meet crop needs. Laboratory soil testing for fertilizer recommendation is difficult, time-consuming, and costly. To address these challenges, IoT-based soil monitoring techniques are used to read NPK macronutrient values from the soil through sensors. Finally, fertilizer is recommended according to the NPK values.

Many studies have proposed different solutions in this field. In [1], an innovative ML-enabled IoT device was used to monitor soil nutrients for accurate crop recommendations. This device employed FC-28, DHT11, and JXBS-3001 sensors to collect real-time data on soil composition, moisture, humidity, and temperature levels. In [2], a smart soil monitoring system was designed to provide data using pH, temperature, and humidity sensors, but NPK values were not considered. In [3], a system was introduced to remotely monitor soil characteristics in terms of soil pH, temperature, and moisture. In [4], an agricultural field monitoring system used an Arduino-based middleware, which kept data and controlled the activation of control pumps and fans. In [5], a system was introduced for real-time soft soil foundation monitoring and early warning. In [6], a soil-moisture monitoring and irrigation system used ARM-based IoT devices, reducing manual field processes and providing information through a web application. In [7], a near-real-time soil and plant monitoring sensor system was introduced for drip irrigation of palm trees in water-scarce regions. In [8], a simple and cost-effective IoT solution was introduced for fruit and vegetable farms to enhance productivity and growth.

In [9], a heterogeneous WSN was proposed for LoRa-Zigbee hybrid communication, using Zigbee and LoRa sensor clusters with Zigbee-to-LoRa converters to communicate through a LoRa gateway. In [10], a LoRa-based multi-hop

WSN was employed to monitor soil moisture in agriculture. In [11], Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) was introduced, with diverse Intrinsic Mode Function (IMF) components, decomposing the long time series with statistical descriptors to recognize soil moisture stress. In [12], an integrated automatic moisture and irrigation control system was proposed, using a Real-Time Clock (RTC) and a Light-Dependent Resistor (LDR). In [6], a novel IoT-based framework was introduced for soil humidity control and watering management, which reduced manual field processes and transferred data to a cloud server to be accessed with a web application. In [13], an IoT-based soil moisture management system was introduced for precision agriculture, employing sensor nodes and cloud computing to perform real-time monitoring and irrigation control. In [14], a multiple sensor monitoring system used the ESP32S3 to determine moisture, electrical conductivity, pH, ultraviolet radiation, temperature, nitrogen, phosphorus, and potassium in the soil.

A. *IoT-Based Soil Moisture Management*

IoT is critical in smart farming to achieve better soil nutrient management. In [15], an IoT-enabled adaptive watering system with ARIMA was introduced to predict soil moisture, soil temperature, outdoor temperature, and humidity. In [16], a real-time liquid fertilizer concentration measurement system was employed, using IoT technology for real-time cloud monitoring, minimizing response time, and improving the non-invasive monitoring process. In [17], an IoT-enabled soil testing and scheduling system was introduced for recommending suitable crops.

B. *Machine Learning (ML) Based Soil Nutrient Models*

ML is used to analyze and predict soil nutrient levels for better agricultural results. In [18], ML models were used to predict soil nutrient properties. In [19], an ML-IoT-based soil nutrient analysis and crop recommendation system for crops was proposed, employing different sensors to collect data on soil composition, moisture, humidity, temperature, and nutrient levels. In [20], a fog-assisted recommendation model was introduced for the prediction of soil moisture content, offering a proactive ML-based and data-driven method to improve resource management and soil health.

In [21], different ML regression algorithms and reflectance spectra pre-treatments were investigated to predict the TN, AP, and AK contents of the top soil in croplands. Detecting the suitability of a crop for particular land is a demanding task, since it is based on various climate, environmental, and soil factors. In addition, an ML classifier was employed to address distinct problems, such as soil nutrients and plant diseases. In [22], the Extreme Learning Method (ELM) was used to identify micronutrients in the soil. In [23], a hybrid approach used XGBoost, SVM, and C4.5 classifier algorithms to predict crop yield. In [24], the SHAP and LIME Explainable Artificial Intelligence (XAI) methods were employed to predict the main nutrients of the soil (nitrogen, phosphorus, and potassium) and maximize the yield.

C. *Deep Learning (DL) Based Soil Nutrient Methods*

DL has also been used for soil nutrients and crop management. In [25], an automatic DL-based olive classification system was introduced to optimize post-harvest sorting operations, improving water efficiency by ensuring the appropriate allocation of water resources to different olive varieties. In [26], a soil nutrient monitoring and crop recommendation system utilized a Deep Q Network (DQN) reinforcement learning algorithm. This system utilized a WSN to monitor soil quality and conditions. In [27], a hybrid Transformer-based framework was introduced to determine the geographical link between multimodal features through self-supervised contrastive learning, employing pretrained Vision Transformers (ViT) for image inputs and Transformers for climate data, fine-tuning the model with ground reference samples.

D. *Different Nutrient Detection Techniques*

Various techniques are utilized for measuring nutrient levels. In [28], a soil nutrient analysis and monitoring system was used for real-time applications. In [29], a soil nutrient analysis and crop recommendation model was proposed to recommend crops for precision agriculture. Conventional chemical analyzes improve the efficiency of agriculture but are both time- and money-consuming [30]. In [31], a system was proposed for remote monitoring of agricultural farms, performing continuous data collection from various IoT devices, such as sensors, actuators, meteorological masts, and drones. In [32], nutrient detection was performed with an NPK sensor on different samples to reduce fertilizer use and manage soil and water conditions. In [33], portable devices and sensors were employed for efficient soil nutrient analysis to improve performance and accessibility. In the north-eastern Himalayas, paddy yields and soil conditions were enhanced through an Integrated Nutrient Management (INM) technology [34].

Soil Electrical Conductivity (EC) is affected by soil organic matter, temperature, and water content [35]. In [36], an electrochemical microfluidic system used reagent reactions for continuous monitoring, embedding Polydimethylsiloxane (PDMS) chips with channel layers in 3-D printed molds. In [37], the weak properties of soft soils were improved using a chemical stabilization process with sodium additive solutions. Accurate soil data has become one of the most valuable resources for farmers. Soil sensor data can be exploited to boost farm yields, maintain and improve product quality, promote food security, and protect the environment [38]. In [39], optical methods for soil nutrient recognition were investigated to build a portable nutrient sensor for dry soil samples without the need for complicated sample pretreatments. In [40], soil nutrient assessment for agriculture was performed. In [41], an NPK sensor was used to measure soil nutrients for citrus seedlings, with the results sent to the ThingSpeak web. In [42], a secure IoT-based real-time water level monitoring scheme used an ESP32 microcontroller for real-time sensing and communication.

Soil nutrient measurement is a critical factor in improving both the quantity and the quality of crop yields. The IoT is a significant advancement that is used in everyday life to autonomously collect and send data. The time-consuming and labor-intensive nature of traditional soil analysis methods is a challenging issue for all farmers. To address these challenges, integrating IoT technology with Broken-Stick Regressive LoRa Technology (BSRLRT) offers a promising solution to provide real-time data on soil properties, such as nutrient levels, moisture, and pH, offering more efficient and accessible soil management and increased agricultural productivity.

This study discusses the implementation of a soil health monitoring system using an NPK sensor in a WSN. The objective was to accurately measure soil nutrients based on IoT technology using sensor nodes deployed in farmlands. The key contributions of this study are:

- The proposed BSRLRT method contributes to efficient sensor node deployment and data collection from a farmland to improve nutrient measurements.
- Broken-stick regression analysis identifies the exact position of sensor nodes by determining the Euclidean distance between them. The method involves fitting a piecewise linear model to the data, where the broken stick represents an alteration in slope or trend at certain points, usually referring to an important shift in how the distance between sensor nodes influences network performance or coverage. By applying broken stick regression, the optimal position of sensor nodes is identified, through the distance between nodes, aiding in balancing factors such as coverage area and energy consumption.
- LoRA technology is utilized to achieve efficient data collection from a farmland.
- In experimental evaluation, different samples are gathered from the farmland to perform soil nutrient measurement.
- A scalable and sustainable methodology for soil nutrient measurement contributes to agricultural processes, soil health monitoring, crop yield prediction, irrigation management, and environmental monitoring.

II. MATERIALS AND METHODS

WSNs are used to collect data from sensor devices, providing a cost-effective method to monitor various environmental parameters in real-time applications. The key objective of IoT technology is to perform historical data analysis and real-time data inspection for attaining an optimal solution. The main aim of the proposed BSRLRT method is to enhance sustainability in intelligent agriculture, offering an efficient soil monitoring system that significantly promotes resource preservation, minimizes operational costs, supports sustainable farming practices, and improves productivity.

Figure 1 illustrates the architecture diagram of the proposed BSRLRT. The key aim is to perform efficient sensor node deployment and data collection in smart agriculture. Initially, the broken stick regression analysis is used for performing sensor node deployment, and LoRa technology is used for performing efficient data collection in a WSN.

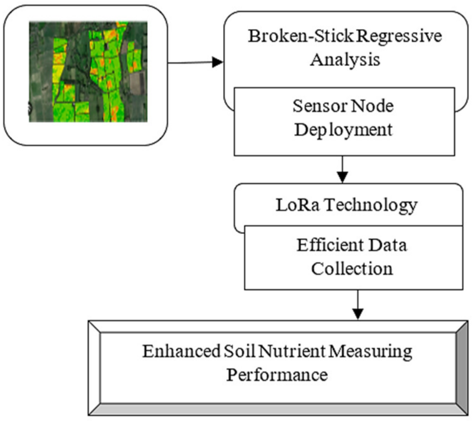

Fig. 1. Architecture diagram of BSRLRT.

A. *Broken-Stick Regressive Sensor Node Deployment*

Sensor node deployment is the process of placing the sensor nodes to collect and relay data, optimizing energy usage and coverage. In this work, sensor node deployment was carried out using broken-stick regression, which is also called piecewise or segmented regression. Piecewise regressive analysis is employed for analyzing data to determine identifying breakpoints and fit separate regression lines. Let us consider the VC farmland where the sensor nodes are arranged in the form of a matrix:

$$VC_{Farm} = \begin{bmatrix} SN_{11} & SN_{12} & SN_{13} & \dots. & SN_{1n} \\ SN_{21} & SN_{22} & SN_{23} & \dots. & SN_{2n} \\ SN_{31} & SN_{32} & SN_{33} & \dots. & SN_{3n} \\ \dots. & \dots. & \dots. & \dots. & \dots. \\ SN_{m1} & SN_{m2} & SN_{m3} & \dots & SN_{mn} \end{bmatrix} \quad (1)$$

The piecewise regressive analysis method is used to identify the position based on the nearest data value. The weighted average method is used to identify the neighboring distance for node placement. This method assigns weights to every neighboring sensor node based on its distance. Piecewise regression analysis utilizes the Euclidean distance for computing the distance between the two sensor nodes for optimal energy utilization, formulated as:

$$D = \sum_{N=1}^{v} \left| SN_i - SN_j \right| \quad (2)$$

where D denotes the Euclidean distance between two sensor nodes.

B. *LoRa Technology-Based Efficient Data Collection*

After sensor node deployment, data collection is carried out using LoRa technology, which enables a reliable and energy-efficient way to transfer data in various applications. In the smart soil monitoring process, the IoT system is divided into three parts: the sensing device, the communication, and the processing. This research work employed LoRa and ESP32 to build a WSN. The master node receives the data from the slave node and sends it to a Digital Ocean server running Node-RED. The sensor used was a 7-in-1 NPK sensor. The working modules are the slave module, the server module, and the cloud setup to push the collected data.

1) *ESP32 Slave Module*

A slave module is a device that responds to requests from the master module. The master device is used to control the system, and the slave devices and processes are passive. The master device provides signals to control a large number of secondary devices. In Bluetooth, the master devices search for others and establish the connection. The slave device waits for others to connect and sends a digital message with measurement or additional data.

Solar radiation is collected and converted into useful energy. Battery chargers comprise solar panels with Photovoltaic (PV) cell blocks for performing efficient electricity generation from the sunlight.

ESP32 is a chip with Wi-Fi and Bluetooth connectivity for embedded devices. This ESP32 chip has a single-core Tensilica Xtensa LX6 microprocessor running at 240 MHz. An RS485 interface is considered a half-duplex data communication mode as a two-wire system interface. A shielded twisted pair cable is employed for performing efficient data transmission.

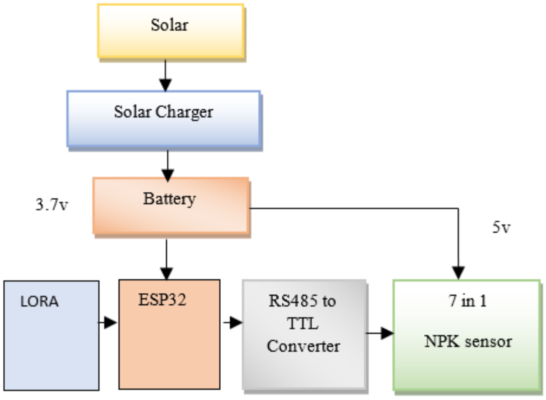

Fig. 2. Block diagram of the ESP32 slave module.

Figure 2 presents the block diagram of the slave module, which employs Transistor–Transistor Logic (TTL). Soil NPK sensors monitor and analyze the levels of essential nutrients in the soil, such as Nitrogen (N), Phosphorus (P), and Potassium (K). Nitrogen helps plants grow their leaves. Phosphorus is used to develop healthy flowers, buds, roots, and fruits. Plants employ Potassium to improve their health. The data collected from the NPK sensor is transmitted using the RS485 communication protocol. ESP32 collects information about the levels of Nitrogen, Phosphorus, and Potassium in the soil. The NPK sensor is polled by the ESP32 to transmit the data at a regular interval.

2) *ESP32 Master Module*

A LoRa module is used for efficient data transmission. LoRA is a wireless technology with spread-spectrum modulation for low-power and long-range communication. The LoRa standard is employed for Low-Power Wide Area Network (LPWAN) technology with IoT. LoRa technology can cover up to 15 Km in sub-urban environment and more than 2 Km in an urban environment. LoRa batteries can be used for approximately 10 years. LoRa employs a narrowband waveform with a central frequency for efficient data transmission. LoRa sensors and the corresponding batteries are used to minimize maintenance and service fees.

Figure 3 presents the block diagram of the ESP32 Master module. The code initializes the LoRa settings and the MQTT client in the setup function. The loop checks their actions through transmitting the sensor data over Wi-Fi, when triggered, or LoRa communication. Wi-Fi and MQTT connectivity are managed separately through dedicated functions to ensure reconnection attempts. After obtaining the sensor data, the ESP32 processes and formats the data for efficient data transmission. The ESP32 used an SX1278 LoRa transceiver to summarize the data into LoRa packets. The LoRa packets are sent wirelessly to the master node within the LoRa range.

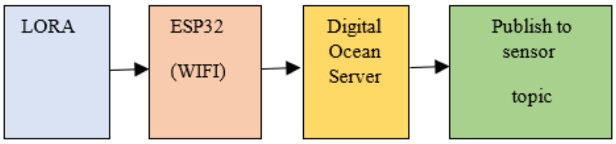

Fig. 3. Block diagram of the ESP32 master module.

3) *Cloud Server Setup*

A cloud storage service offers the user location independence and resource availability. An ESP8266 Wi-Fi module was connected to an Arduino board. Arduino code is used to communicate with the Wi-Fi module. Then, the data is stored in Firebase Cloud Service, which is a NoSQL database to store and synchronize real-time data. Firebase has a module for Android applications, which was used for developing an Android application to interact with the cloud data. The data streamer feature of Excel was employed to collect the live data and store it in CSV format. The cloud data is shared with other farmers for reading and analysis. The analyzed output data is stored back into the cloud. In addition, authenticated access is employed for real-time data updating in the cloud. The regression-based machine learning model is used with the Android application for efficient soil nutrient monitoring.

Figure 4 illustrates the cloud server setup block diagram. The slave node operates on a battery to ensure mobility and power independence. A solar panel charges the battery during daylight hours to extend the node's operational period. ESP32 manages communication with the NPK sensor through RS485. The data collected from the sensor is formatted and converted to a suitable representation before being transmitted over the LoRa network. Efficient power management ensured that the node was operational for extended periods for remote sensing and monitoring, even with limited power resources.

An ESP32-based slave node is equipped with SX1278. The LoRa transceiver collects the data from an NPK sensor over RS485 and transmits it wirelessly to the master node using LoRa technology. When sensor data is collected, it is transmitted to a master node. Then, the data is transmitted to a Digital Ocean server. The server runs Node-RED, a flow-based development tool for visual programming. Node-RED presents a dashboard to communicate with IoT devices to control outputs and monitor sensors. Finally, the data collected is displayed. The ESP32 communicates with Node-RED as long as it is connected to a router with internet access.

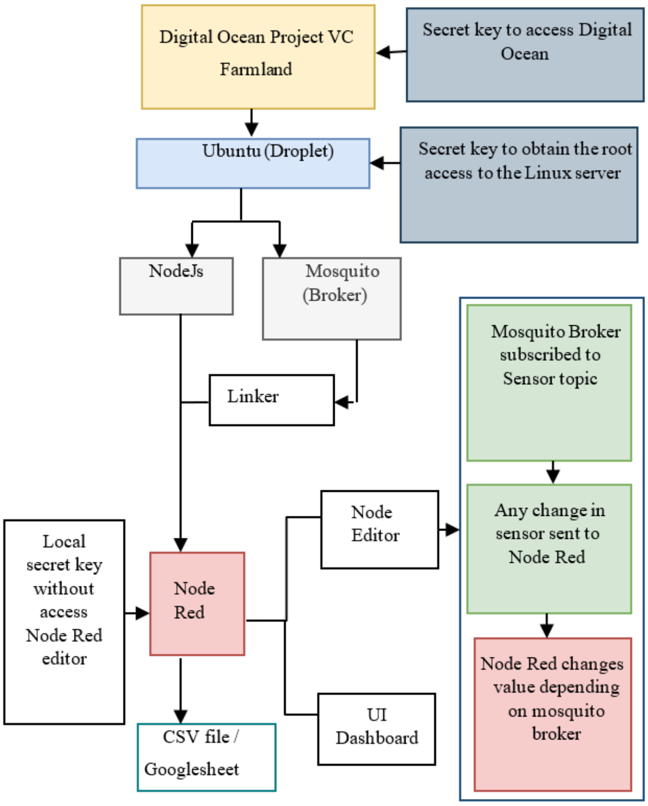

Fig. 4. Cloud server setup block diagram.

III. RESULTS AND DISCUSSION

The College of Agriculture Mandya is located 10 km away from Mandya, a town in Karnataka State, on the Mandya-Melkote road, and is known as the Vishweshwaraiah Canal (V. C.) Farm. The Campus is located at an altitude of 695 m above mean sea level. Geographically, the V. C. Farm is situated at 12°34'00"N to 12°34'30"N latitude and 76°48'45"E to 76°50'15"E longitude. Figure 5 shows the location map of the study area.

The V. C. Farm area was studied for its external land features and morphological properties with different physiographic units over different landscapes. 194 surface soil samples were collected at 0-15 cm depth. The proposed BSRLRT was implemented to estimate the experimental results. A Relational Database Management System (RDBMS) was utilized to store, manage, and analyze data collected from various sources, such as sensors and lab analyses. The experimental results demonstrated varying levels of soil nutrients across dissimilar locations.

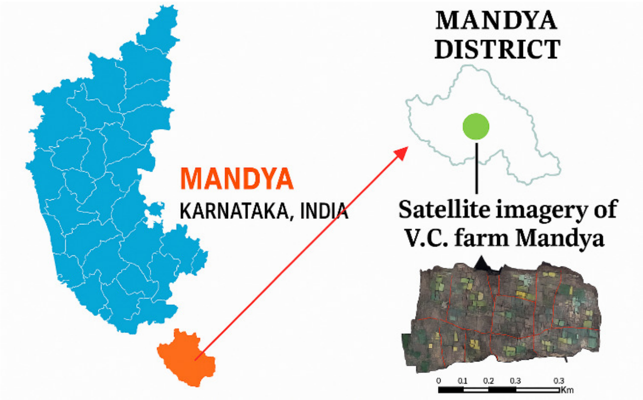

Fig. 5. V.C. Farm area.

The samples collected from the V.C. farm in the Mandya District comprised 2931 data instances and eight attributes. The eight attributes/features are sensor node ID, moisture, temperature, electrical conductivity, nitrogen, phosphorus, potassium, and PH. Soil nutrient measurement was performed using two steps: sensor node deployment and data collection from the farmland. Initially, the specific position of each sensor node was determined using the broken-stick regression method. Then, LoRa sensors were connected to ESP32 modules (slave and master) and a cloud server to collect and monitor data. In this way, accurate soil nutrient measurements were achieved with higher accuracy and lower cost. In addition, samples were collected and air-dried with a wooden pestle and mortar. The samples were passed through a 2 mm sieve and examined for their chemical and fertility composition. The pH, electrical conductivity, Nitrogen, Phosphorus, and Potassium contents of soils were determined using a standard laboratory process.

The field boundaries, soil boundaries, and additional related boundaries were distinguished, and layers were created. The non-spatial information of soil analytical data and the spatial information of layers were interrelated through the RDBMS. Data variability was assessed through means and ranges. Figure 6 illustrates the distribution of soils in the V.C. Farm in Mandya.

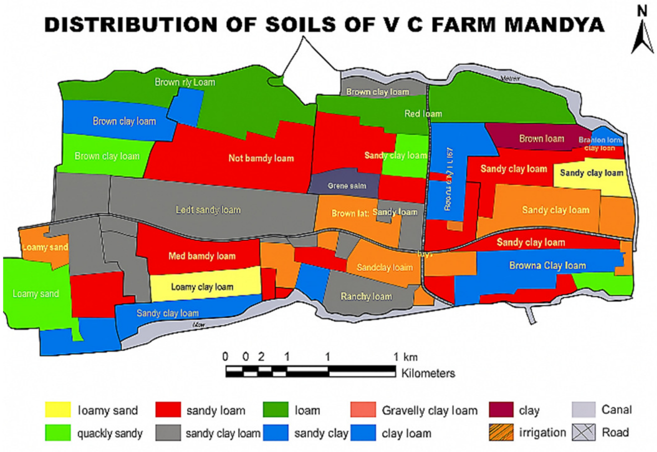

Fig. 6. Distribution of soils in V.C. Farm, Mandya.

Table I shows the physico-chemical properties of 25 samples collected from the V.C. Farm.

TABLE I. PHYSICO-CHEMICAL PROPERTIES OF 25 SAMPLES

Sensor Node ID	**Moisture**	**Tem/re**	**Electrical cond/ty**	**N**	**P**	**K**	**pH**
21.6,33.7,1197,85,118,234,6.47	21.6	33.7	1197	85	118	234	6.47
21.6,33.7,1197,85,118,234,6.47	21.5	33.7	1197	85	118	234	6.47
21.5,33.7,1197,85,118,234,6.47	21.5	33.7	1189	85	118	234	6.47
21.5,33.7,1189,85,118,234,6.47	21.5	33.7	1189	85	118	234	6.47
21.5,33.7,1189,85,118,234,6.47	21.5	33.7	1189	85	118	234	6.47
21.5,33.7,1189,85,118,234,6.47	21.5	33.7	1189	85	118	237	6.47
21.5,33.7,1189,85,118,237,6.47	21.5	33.7	1189	85	118	234	6.47
21.5,33.7,1189,85,118,234,6.47	21.5	33.7	1189	85	118	237	6.47
21.5,33.7,1189,85,118,237,6.47	21.5	33.7	1189	85	118	237	6.47
21.5,33.7,1189,85,118,237,6.47	21.5	33.7	1181	85	118	237	6.47
21.5,33.7,1181,85,118,237,6.47	21.5	33.7	1181	85	118	237	6.49
21.5,33.7,1181,85,118,237,6.49	21.5	33.7	1181	83	118	237	6.49
21.5,33.7,1181,83,118,237,6.49	21.5	33.7	1181	83	118	237	6.49
21.5,33.7,1181,83,118,237,6.49	21.5	33.7	1181	83	118	233	6.49
21.5,33.7,1181,83,118,233,6.49	21.5	33.7	1181	83	118	233	6.49
21.5,33.7,1181,83,118,233,6.49	21.5	33.7	1181	83	118	233	6.49
21.5,33.7,1181,83,118,233,6.49	21.5	33.7	1189	83	118	233	6.49
21.5,33.7,1189,83,118,233,6.49	21.5	33.7	1189	83	118	233	6.49
21.5,33.7,1189,83,118,233,6.49	21.5	33.7	1189	84	118	233	6.49
21.5,33.7,1189,84,118,233,6.49	21.5	33.7	1189	84	120	233	6.49
21.5,33.7,1189,84,120,233,6.49	21.5	33.7	1189	84	120	237	6.49
21.5,33.7,1189,84,120,237,6.49	21.5	33.7	1189	84	120	237	6.49
21.5,33.7,1189,84,120,237,6.49	21.5	33.7	1189	84	120	237	6.49
21.5,33.7,1189,84,120,237,6.49	21.5	33.7	1173	84	120	237	6.49
21.5,33.7,1173,84,120,237,6.49	21.5	33.7	1173	84	120	237	6.49

In this way, 2931 data samples were collected for developing an efficient soil nutrient monitoring system with the help of IoT devices. Table II shows the maximum and minimum values of different soil nutrients.

In addition, soil nutrient measurements, such as Nitrogen, Phosphorus, Potassium, pH, EC, Moisture Level, and Temperature, collected from the sensors are shown for five different samples in Figures 7-11.

TABLE II. MAX AND MIN VALUES OF SOIL NUTRIENTS

	Soil nutrient	**Max value (mg/Kg)**	**Iot**	**Results**		
				Low	**High**	**Medium**
1.	Nitrogen	250	125	<125	>250	Between 125-250
2.	Phosphorus	25	10	<10	>25	Between 10-25
3.	Potassium	150	63	<63	>150	Between 63-150
4.	pH			<6.5 Acidic	> 7.5 Alkaline	6.5-7.5 Neutral
5.	EC	0.8	1.6			
6.	Moisture Level	General Parameters				
7.	Temperature					

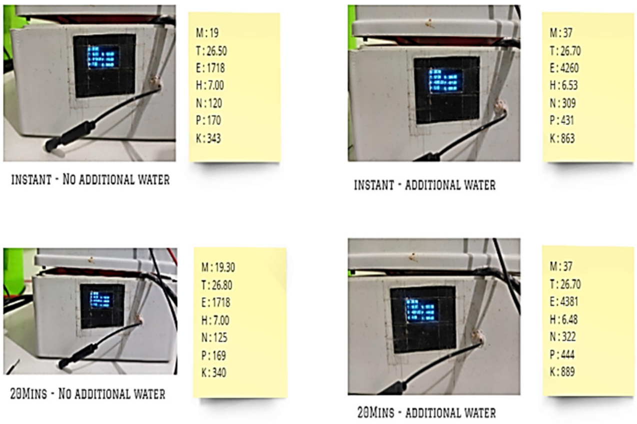

Fig. 7. Soil nutrients of sample 1.

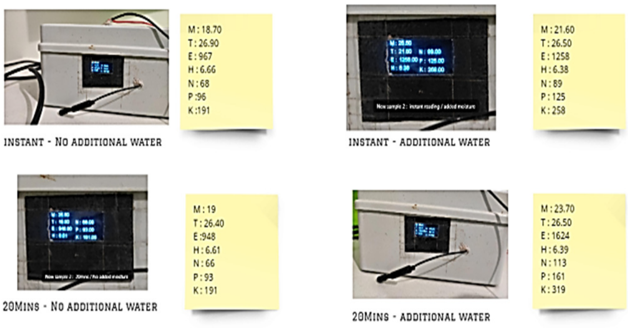

Fig. 8. Soil nutrients for sample 2.

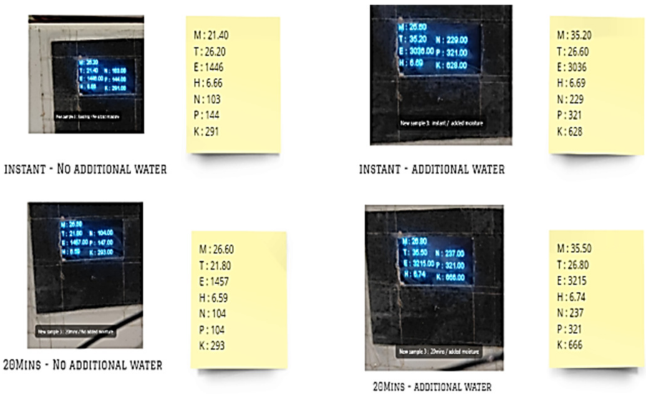

Fig. 9. Soil nutrients for sample 3.

Figures 10 and 11 detail the soil nutrients for samples 4 and 5, respectively. These figures display six nutrient measurements, namely, instant – no additional water, instant – additional water, 20 minutes – no additional water, 20 minutes – additional water, instant – more additional water, and 20 minutes – more additional water. At every part, the nutrient values are obtained from different sensors at V.C. Farmland.

Fig. 10. Soil nutrients for sample 4.

Fig. 11. Soil nutrients for sample 5.

Table III lists the soil nutrient sensor values for five different samples. From the table, it is clear that sample 4 attains the best nutrient values among the other listed samples. Crop cultivation in sample 4 can yield better agricultural productivity. Since sustainability in agriculture can be achieved with the proper utilization of natural resources, it is essential to determine the status of natural resources used for crop production. Enhanced soil management and sustainability can provide higher crop productivity, strengthening food security. In this process, IoT-based soil monitoring systems are essential.

TABLE III. SOIL NUTRIENT SENSOR VALUES

Samples	**pH**	**E.C. (mS/cm)**	**N mg/kg (ppm)**	**P mg/kg (ppm)**	**K mg/kg (ppm)**	**Moisture (%)**	**Temp. (°C)**
Sample 1	6.39	442	34	44	88	39.40	21.5
Sample 2	6.64	617	44	62	122	39.00	27
Sample 3	6.64	371	26	37	74	38.00	20
Sample 4	6.42	936	66	92	188	35.00	24.1
Sample 5	6.66	383	27	38	76	37.00	21

IV. CONCLUSION

Soil nutrients like Nitrogen, Phosphorous, and Potassium are the primary components of agricultural lands to achieve better crop yield. The excess usage of fertilizers can negatively impact the characteristics of the soil. Soil nutrient monitoring plays a key role in the development of modern agriculture. The precise assessment of soil nutrient levels comprises the foundation for systematic and informed fertilization. Soil nutrient monitoring has a large significance in agricultural productivity, ensuring food security and sustainable agricultural progress. IoT-based monitoring and databases help in scientific planning and management practices to enhance and sustain the productive potential of soils. This study presented a BSRLRT method for sensor node deployment and data collection from a farmland. The broken-stick regression method identifies the positions to place the sensor nodes. In addition, this study presents the implementation of an IoT system for soil nutrient management using LoRa technology.

In addition, different samples were collected from the diverse V.C. Farm areas to perform the nutrient measurements. The soils of V.C. Farm fall under medium to high nutrient status. The available Nitrogen content was found to be lower in samples 3 and 5. The available Phosphorus and Potassium were found to be medium in some samples. Sample 4 showed higher nutrient values for enhancing crop productivity.

In future work, the proposed method will be further extended to apply various regression techniques to predict soil moisture, nutrient levels, or crop yield. In addition, various regression models, such as linear regression, polynomial regression, Support Vector Regression (SVR), and DL models, will be investigated to predict soil moisture levels based on factors such as rainfall, temperature, and soil properties.

ACKNOWLEDGMENT

The authors thank BNMIT for their encouragement in the successful completion of this research work.

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