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*Research Article*

# Enhancing Agricultural Sustainability: An IoT-Based RNN-LSTM Model for Precision Sub-Surface Moisture Monitoring and Irrigation Optimisation

**Shamala Maniam[1], Erfan Memar[1], Tee Yei Kheng[2], Nisha Kumari[1], Hin Yong Wong[1] and Mukter Zaman[1,*]**

[1]Multimedia University, Malaysia
shamalamaniam90@gmail.com; e.memar1990@gmail.com; nisha@mmu.edu.my; hywong@mmu.edu.my
[2]Malaysian Cocoa Board, Malaysia
tee_yei@koko.gov.my
*Correspondence: hywong@mmu.edu.my

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**Abstract: Water directly influences plant growth and vitality and is a critical resource in precision agriculture (PA). Soluble fertilisers are transported to plant roots through irrigation, making precise water management essential for optimising crop productivity and minimising resource wastage. Inadequate or excessive irrigation disrupts nutrient distribution, increases operational costs, and negatively affects crop yield. Accurate monitoring of sub-surface soil moisture, particularly at root depth, is therefore vital for effective irrigation control. This study addresses key limitations in existing PA systems by developing an automated Internet of Things (IoT)-based real-time soil moisture monitoring and irrigation framework integrated with a recurrent neural network (RNN) employing long short-term memory (LSTM) for moisture prediction. Customised sub-surface soil moisture probes equipped with five sensors at different depths were deployed at a real plantation site. The probes utilised time domain reflectometer (TDR) technology to capture high-resolution moisture measurements. Sensor data were transmitted to the cloud using an ESP32-based low-range communication module, forming a wireless sensor network (WSN) across the designated study area. A continuous six-month dataset was collected and analysed to train and validate the proposed RNN-LSTM model. The model demonstrated strong predictive capability, achieving an accuracy of 95 ± 2%, a mean absolute error (MAE) of 0.6362, a root mean square error (RMSE) of 1.1544, and an $R^2$ value of 0.3331. These results confirm the model's effectiveness in capturing sub-surface soil moisture dynamics under real field conditions. Overall, the proposed IoT-enabled predictive irrigation system provides a scalable and data-driven solution for improving irrigation efficiency.**

**Keywords:** *Internet of Things; Precision Agriculture; Real-time Monitoring; Recurrent Neural Network*

## 1. Introduction

Enhancing agricultural output, watershed hydrology, predicting floods, anticipating landslides, and various other ecosystem benefits requires understanding soil moisture [1, 2]. Agriculture is the top consumer of water worldwide, accounting for approximately 70% of overall water usage. Creating nearby soil moisture sensors is increasingly in demand due to limited water resources to improve irrigation and soil moisture management in farming [3].

Typically, farmers globally rely on visual assessments of crops to determine irrigation schedules. The approach has led to nearly 50% of water being wasted in conventional irrigation systems [4]. Several

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techniques, such as sprinkle, drip, and furrow irrigation, could cut down water wastage by 30% to 70%. Nonetheless, the open-loop nature of the methods does not guarantee optimal soil moisture levels, which could compromise the quality and volume of the crops, considering that improper irrigation affects soil nutrients. Consequently, adopting precision irrigation methods is necessary. Precision irrigation approaches employ parameters, including soil moisture, weather patterns, rainfall amounts, and crop variety, to accurately gauge the required water quantity and irrigation timing. Adopting the system could optimise crop yields and reduce labour expenses for farmers [3].

The Internet of Things (IoT) has contributed to advancing the field of agriculture into a smarter dimension. Moreover, the IoT enables a seamless integration of various soil sensors with tools, such as water pumps, sprinklers, and solar devices, by leveraging wireless technology. The synergy offers sophisticated instruments to farmers, allowing them to navigate complex farming activities, from preliminary soil preparation to sophisticated crop yield predictions throughout the entire growth and harvest cycle [5].

A myriad of modern irrigation techniques has been introduced, which are primarily based on essential agricultural data, such as soil moisture and weather patterns, to allocate water at specified periods. Nonetheless, the techniques have shortcomings. Among the disadvantages of the irrigation approaches are their open-loop design, which commonly leads to suboptimal irrigation practices crucial for maintaining healthy crops and nutrient-rich soil. Insufficient mechanisms to incorporate real-time alterations in soil moisture levels are another significant shortcoming of the techniques. Therefore, the systems might not possess the capacity to adapt to the varied weather conditions and unique characteristics in different regions.

Precision agriculture (PA) or "smart farming" is a pioneering approach to fulfil the demands of sustainable agriculture. Machine learning (ML) is central to the transformative wave by enabling capable machines to learn without specific programming. Coupling ML with IoT-integrated agricultural equipment could then evolve agricultural practices [6].

The PA is vital in the evolution of real-time irrigation and moisture prediction systems, characterised as an agriculture management approach driven by information technology (IT) [7]. Implementing the technology could transition farming into a more progressive and sustainable domain. Farmers can also meticulously gauge the water requirements for specific crops through automated irrigation controllers incorporated with real-time surveillance from PA [8]. Furthermore, the volume and irrigation timing can be ascertained utilising data from soil properties, environmental factors, and local temperature [9]. Previous studies have also affirmed that enhancements in water efficiency, reduced energy consumption, and augmented crop yields are due to the integration of moisture, temperature, and crop sensors into real-time irrigation systems.

Extensive research has contributed to novel modelling systems to generate a more precise and adaptable system for the agricultural domain. For instance, regression models utilise climate and soil data as inputs to forecast weekly irrigation requirements [10], while fuzzy decision systems are employed to predict soil content and local weather data as input [11]. Meanwhile, identification models rely on soil moisture and climatic data to estimate soil moisture levels [12]. The predictions are obtained through statistical methodologies, where input data and discerning underlying patterns in historical records are correlated spatially and temporally. Accordingly, the modelling approach is primarily data-driven, dissimilar to conventional approaches. Consequently, ML-based predictions frequently demonstrate superior accuracy in many scenarios while requiring fewer data points, outperforming those derived from mechanistic models [13].

This study conducted a critical literature review of all core articles to assess advancements in ML-driven irrigation systems and their effects on optimising freshwater resources for agricultural requirements. The articles were selected based on stringent criteria, including relevance to precision irrigation, real-time soil and weather data utilisation, the incorporation of advanced ML techniques like PLSR, ANFIS, long short-term memory (LSTM), and the application of IoT in agriculture. The articles were critically reviewed for their methodological rigour, including research objective clarity, methodology robustness, and the significance of findings. This study also focused on contributions to reducing water wastage, enhancing crop yields, and the innovative employment of technology to accurately predict soil moisture levels and crop needs. Overall, the findings indicated a shift towards more sustainable and efficient farming practices, underscoring the pivotal role of technology in addressing the challenges of water usage in agriculture.

### 1.1. Related Work on the Different Models Utilised in PA

Numerous researchers have been developing ML-driven irrigation systems to optimise the utilisation of freshwater resources. For instance, Navarro-Hellín *et al.* [10] created an automated system designed to assist agricultural irrigation management. The system precisely anticipates the crop water requirements, utilising soil data and weather factors, which is a departure from prior systems that did not employ real-time soil metrics to dictate irrigation volumes. The system utilises real-time soil data within a closed feedback system to ensure that potential discrepancies are promptly addressed. Therefore, accumulated errors that can arise from manual weekly water estimations by farmers are reduced. Two primary ML strategies that are also employed in the system, PLSR and ANFIS, underpin its analytical and decision-making capabilities. The effectiveness of the system is then assessed by comparing it to traditional farming methods that do not employ the support component. Three commercial farming environments were involved during the evaluation of the irrigation system, and data from 2014 to 2015 were employed. According to preliminary findings, accurate results were obtained when soil sensors were incorporated, with a 22% reduction in errors compared to methods that did not employ the sensors [10].

Zhang [14] developed a novel framework for predicting water table depths. The model was specifically designed to facilitate groundwater resources management in agricultural settings. In the model, an LSTM and a densely connected layer were merged, deviating from traditional neural network models. The approach is also relatively uncharted in hydrological research. Upon evaluation in the Hetao Irrigation District, the model demonstrated proficiency, particularly when estimations for specific sub-regions against the entire district were compared. Moreover, the LSTM layer captures time-related patterns in the dataset, and the dropout technique mitigates overfitting concerns, offering added advantages. The densely connected layer enhances the model's learning potential further. Conclusively, the novel approach provides a dependable means for predicting water table depths, especially in regions with limited hydrogeological data. Future studies could also expand or merge the technique with other methods, such as Principal Component Analysis (PCA) or wavelet transform. Furthermore, the adaptability of the framework enables its employment for other time series predictions, including soil moisture alterations and streamflow predictions [14].

A deep learning approach utilising the recurrent neural network (RNN) was created by [15] to forecast the wheat crop yield in the northern region of India. The study incorporated LSTM to address the vanishing gradient issue common in RNNs. Assessments then ensued, utilising a dataset spanning 43 years. The performance of the proposed RNN-LSTM model was also compared with three other ML algorithms. Superior results were recorded, with an RMSE of 147.12 and MAE of 60.50, which outperformed the Artificial N15eural Network, Random Forest, and Multivariate Linear Regression models. Furthermore, the predictions offered by the RNN-LSTM were notably closer to the actual values, indicating effectiveness [15]. A bountiful yield necessitates early disease detection and maintaining optimal soil moisture. Consequently, Alameen developed a system to enhance agricultural productivity by detecting diseases and predicting soil moisture content. The proposed algorithms demonstrated notable accuracy in predicting soil water content. Soil moisture levels were also anticipated when sensors were employed, thereby guiding farmers on when to water their crops. Moreover, the utilisation of Logistic Regression and LSTM-RNN ensured cost-effective solutions with significant precision, improving farming practices [16].

In another study, Kashyap *et al*. introduced DLiSA, a deep learning neural network-powered IoT irrigation system tailored for PA. The DLiSA is adaptable to diverse weather conditions across different time frames, a distinct benefit from conventional models. Moreover, the system can forecast daily soil moisture content, irrigation timing, and the precise amount of water required for crops by leveraging the capabilities of the LSTM. Simulation outcomes also revealed the superior water conservation capabilities of DLiSA to prevailing models in test agricultural zones [3].

An ML approach was implemented by Kalaiselvi *et al.* [17] to recommend appropriate crops based on various factors, including pH, temperature, and rainfall, achieving an impressive prediction accuracy of 98.2273%. Although PA is commonly associated with irrigation, it is equally significant in fertilisation. Advances in remote sensing, including radar imagery and satellites, have also enhanced fertilisation by facilitating algorithm development to gauge soil conditions [18]. Another application is the employment of spectroscopy-based ML to determine the optimal harvest time for edamame by assessing its evolving physical and chemical properties [19]. In a recent innovation, Murugamani *et al*. [20] introduced 5G-enabled IoT solutions for PA, where an SVM algorithm is employed to detect leaf disease and monitor soil quality. The method boasted a 98.34% accuracy rate in pinpointing leaf diseases.

A study revealed that artificial neural networks (ANN) provided the most precise estimates for subsurface soil moisture in mountainous regions [21]. Nevertheless, the exponential filter (ExpF) method outperformed other approaches in capturing temporal soil moisture levels. The study was conducted in the Qilian Mountains of China and employed in situ soil moisture data from various depths (from 10 cm to 70 cm) to assess the performance of three estimation techniques. Based on performance, the CDF matching method was not recommended, while the ExpF technique accurately estimated moisture contents from surface data (from 0 cm to 10 cm) for depths between 10 cm and 20 cm and from 0 cm to 70 cm. Moreover, utilising a generalised optimal characteristic time (Topt) for the entire area was almost as effective as applying station-specific Topt values. The ExpF method also provided reasonable accuracy (median R of 0.65) when validated against in situ measurements with the SMAP_L3 surface soil moisture satellite product, suggesting an improvement from the SMAP_L4 root zone product for mountainous terrains.

Table 1 summarises the reviewed articles in this study, emphasising the escalating demand for smart agricultural systems integrated with IoT and ML algorithms. Critically analysing irrigation patterns, climate, and crop dynamics is essential in establishing the ideal IoT-enabled PA model. Consequently, a new IoT-based soil moisture management study addresses several research gaps in PA by introducing an advanced real-time subsurface moisture monitoring system that applies IoT-enabled time domain reflectometer (TDR) technology. The approach allows precise moisture tracking at various root depths, which is vital for crops with substantial water demand. Integrating the system with an RNN-LSTM model for predictive analytics differentiates it from prior work, which yielded water savings and economic benefits. Furthermore, a six-month data collection phase and a validation assessment in a real plantation environment ensured robust model training that accounts for seasonal changes and different crop growth stages. The procedure substantially improved traditional periodic data collection methods and simulations commonly found in existing literature.

The PA landscape is rapidly evolving through the incorporation of ML and IoT technologies, with each bringing novel approaches to enhancing agricultural productivity and sustainability. The innovations, such as the real-time soil and weather data to optimise irrigation approach introduced by Navarro-Hellín, the novel framework proposed by Zhang for predicting groundwater levels with LSTM, and the deployment of deep learning models, including RNN-LSTM, for accurate crop yield forecasts, signify a leap forward in increased efficiency in managing agricultural resources. Moreover, systems such as DliSA leverage IoT and LSTM for precise irrigation scheduling, demonstrating superior water conservation capabilities, while SVM-based solutions suggested by Murugamani offer high-accuracy leaf disease detection and soil monitoring. The advancements reveal improvements in terms of effectiveness and performance over traditional methods and highlight the potential for future applications in ensuring global agricultural sustainability. Furthermore, the systems have a shared goal of optimising agricultural practices through technology, potentially leading to a future where PA can adapt to and meet the complex demands of food production and resource management.

**Table 1**. A comprehensive review of similar articles and benchmarking of available technologies with the proposed solution developed and reported in this study

| **Reference** | **Focus area** | **Methodology** | **Innovation/ Contribution** | **Result/ Performance** | **Environment assessed** |
|---|---|---|---|---|---|
| Navarro-Hellín *et al*. [10] | Irrigation management | Soil sensors + PLSR and ANFIS | Real-time soil data for water requirements and a closed feedback system | A 22% reduction in irrigation errors | Commercial farms |
| Zhang *et al*. [14] | Groundwater management | LSTM with densely connected layers | Prediction of water table depths, LSTM for time patterns, and dropout to prevent overfitting | Proficient in sub-region predictions | Hetao Irrigation District |

| | | | | | |
|---|---|---|---|---|---|
| Bali Nishu *et al.* [15] | Crop yield forecasting | RNN with LSTM | Addressing the vanishing gradient issue and comparing with ANN, RF, MLR | A 147.12 RMSE and 60.50 MAE; outperformed other models | Northern India |
| Alameen *et al.* [16] | Disease detection, soil moisture prediction | Logistic Regression, LSTM-RNN | Early disease detection and precise soil moisture predictions | Substantial accuracy in soil water content prediction | Not specified |
| Kashyap *et al.* [3] | IoT-based irrigation system | LSTM-based neural network (DLiSA) | Predicts soil moisture, irrigation timing, and water volume necessary | Superior water conservation capabilities | Test agricultural zones |
| Kalaiselvi *et al.* [17] | Crop recommendation | ML techniques | Recommends crops based on pH, temperature, and rainfall | A 98.2273% prediction accuracy | Not specified |
| Yu Dajun *et al.* [19] | Harvest time determination | Spectroscopy-based ML | Determines the ideal harvest time via physical and chemical property assessment | Not specified | Not specified |
| Murugamani *et al.* [20] | Leaf disease detection, soil quality monitoring | SVM with 5G-enabled IoT | Significant accuracy rate in disease detection and soil quality monitoring | A 98.34% accuracy rate in leaf disease detection | Not specified |
| Jie Tian *et al.* [21] | Subsurface soil moisture estimation | ANN, ExpF, CDF matching | Precision in subsurface soil moisture estimation and ExpF captures temporal variations | ANN precise but ExpF better for temporal variations; median R of 0.65 for ExpF with SMAP_L3 | Qilian Mountains, China |
| This study | IoT-based soil moisture management | IoT-enabled sensors with TDR and an RNN-LSTM model | Real-time sub-surface moisture monitoring, advanced sensing, IoT integration, and water usage reduction | 95 ± 2% accuracy, MAE of 0.6362, and RMSE of 1.1544 | Real plantation site |

This study was profoundly influenced by the methodologies from the articles reviewed, particularly the emphasis on real-time data acquisition, which led to the integration of IoT-enabled sensors for meticulous moisture monitoring. The ability of LSTM in capturing temporal patterns in agricultural and hydrological contexts also contributed to the adoption of an RNN-LSTM model for precise moisture level predictions. This study also implemented a deep learning-centric approach arising from the effective application of ML strategies, especially the robust performance of LSTM in complex prediction tasks. Moreover, the potential of combining sensor data with advanced analytics observed in previous studies led to this study synergising IoT technologies with LSTM-RNN for real-time data analysis.

The innovative employment of IoT frameworks in PA, as evidenced by systems such as DLiSA, underscores the feasibility and efficacy of employing IoT and LSTM in tandem, leading this study to develop a sophisticated, integrated system for enhancing irrigation efficiency and agricultural sustainability through accurate sub-surface moisture monitoring. Accordingly, this study focused on developing an IoT-based real-time irrigation monitoring system utilising a subsurface soil moisture sensor to capture data on water uptake close to plant roots. Implementing RNN-based LSTM algorithms to predict soil moisture levels up to the root depth with IoT for enhanced data transmission and analysis was also performed.

The system proposed in this study integrated real-time sub-surface moisture monitoring with an automated irrigation scheme, distinguishing it from other methods. Custom soil moisture probes equipped with sensors across multiple root-depth levels within a high-demand area were also deployed at the plantation site with TDR technology. Subsequently, data were collected for six months utilising a wireless sensor network (WSN) to train an RNN that incorporates long short-term memory (LSTM) algorithms, which enabled substantially accurate moisture level predictions.

This study emphasised the importance of subsurface processes, aiming to optimise irrigation schedules tailored for specific crops. Firstly, the IoT-related research domain was assessed before determining the methodologies for preparing and deploying IoT-enabled moisture probes. The procedure for data acquisition via IoT and the design of the RNN-based LSTM model were also detailed. Finally, the prediction results were discussed. Overall, this study offered improved comprehension of the root behaviours of crops interfaced with IoT-driven irrigation systems to conserve water and reduce wastage of soluble fertilisers in the agricultural domain.

## 2. Bridging Key Gaps in Precision Irrigation

Several critical gaps in smart irrigation technologies remain unaddressed despite notable advances observed. For instance, most existing models rely on surface or shallow soil moisture data, utilising datasets typically confined to a single growth season, temperate regions, and depths shallower than 20 cm to 30 cm. Resultantly, the models commonly fail to generalise to deeper root-zone dynamics, tropical soils, or multi-season conditions. This study compiled a 180-day, five-depth soil moisture dataset in a humid tropical environment and systematically benchmarked LSTM and transformer-based models on the long-horizon time series to address the issue.

The IoT-based irrigation platforms frequently terminate at the sensing or predictive stage, leading to manual or rule-based actuation management. Concerns also arose from requiring energy optimisation for multi-depth sensor nodes and on-farm data cybersecurity. In this study, an end-to-end, solar-powered ESP32 mesh network that encrypts every uplink was introduced, which estimated its own energy reserves and autonomously triggered irrigation valve events based on predictive model outputs. Therefore, secure, energy-efficient, and closed-loop irrigation is enabled in real time.

Current evaluations of precision irrigation systems predominantly rely on technical metrics, such as RMSE, MAE, or water savings, which overlook agronomic and economic outcomes. Consequently, this study integrated ion-selective probes with the moisture network and computed holistic performance indicators, including yield-normalised water utilisation, cost savings per hectare, and nutrient-leaching indices, shifting the focus from predictive accuracy alone to decision quality and economic viability. Overall, this study provided actionable solutions for farmers, irrigation managers, and technology that support sustainable, cost-effective, and data-driven irrigation practices in real-world agricultural systems by developing an integrated, field-ready framework that combines deep-root moisture prediction, secure IoT-based actuation, and holistic agronomic-economic performance metrics.

## 3. Sub-Surface Soil Moisture Probe Development

This study designed and implemented an advanced sensor probe equipped with a controller. The sensor probe incorporated a WSN system, which facilitated real-time irrigation monitoring. A WSN is a spread-out sensor network that tracks various physical or environmental parameters, including temperature, humidity, and moisture, that are then relayed to a central hub. The network is commonly referred to as a wireless moisture sensor network (WMSN) when concerning moisture sensing.

The WSN networks are inherently two-way, which allows precise control over sensor operations. Multiple nodes are involved in a WSN, varying from a handful to several hundreds or even thousands. Each node is typically linked to one or more sensors. A sensor module, a processing module, a communication module, and a battery-driven power module make up a sensor network node. Real-time data transmission can be enhanced, and remote monitoring and control capabilities can be enabled by integrating IoT components, increasing the efficiency and versatility of the system. The system developed in this study incorporated a solar panel to energise the system upon its set-up at the research location. The system could be linked to up to eight distinct sensors, including soil moisture, temperature, irradiance, and rainfall sensors, as shown in Figure 1.

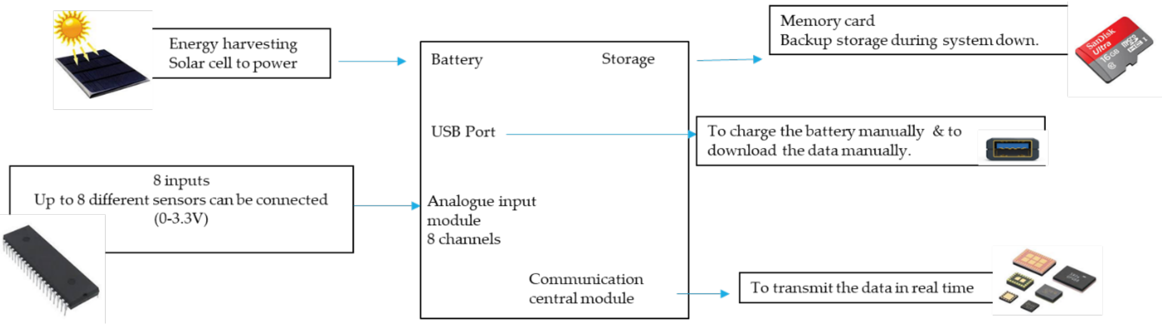


**Figure 1.** The block diagram of the WSN-based soil moisture sensor probe

An embedded memory card and a USB port are also provided for manual data collection, charging, and data extraction. For WSN, this study utilised a sensor node, a router, and a gateway, and the sensor nodes were set to relay moisture information to the closest router every 10 minutes. Employing multiple routers within a network enhances the coverage and facilitates connections of the system through a meshed system. Keeping the router operational at all times also ensured uninterrupted data communication from the sensor node to the gateway.

### 3.1. Sub-Surface Moisture Sensor Probe

Following the development of the subsurface sensor, this study was executed at a plantation site, as illustrated in Figure 2(a), while Figure 2(b) displays the sensor probe positioned in the field. The probes were set up in a "Star Topology" for optimal coverage in the designated region, which is reportedly an excellent topology for real-time applications [22]. The optimal temperature for the moisture sensor employed in this study was between −0°C and 80°C, which is the average temperature in plantations.

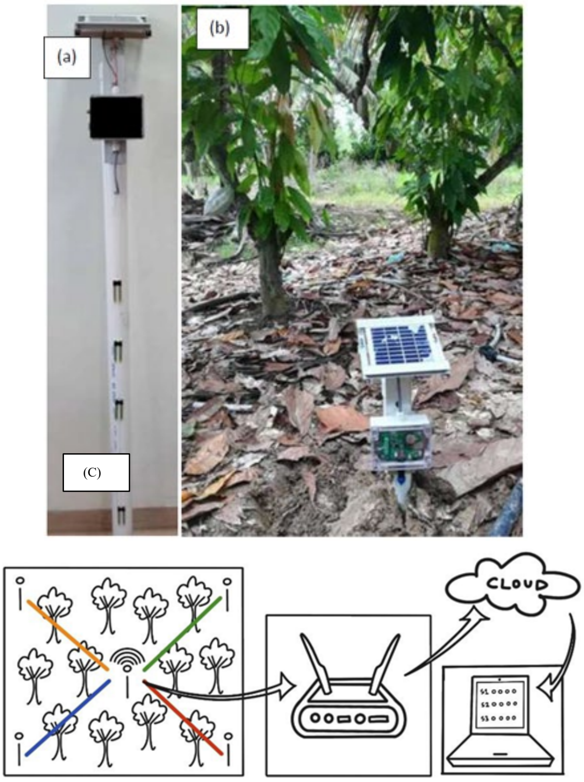


**Figure 2**. The (a) in-house developed subsurface soil moisture sensor probe, (b) deployment of the soil moisture sensor probe, and (c) flowchart of the developed solution at the plantation

This study utilised a temperature-dependent sensor in the moisture probe. Therefore, the accuracy and performance of the probes were influenced by ambient temperature conditions. The attribute made the probe ideal for deployment in tropical countries that share a similar climate to Malaysia, where notable humidity, warm temperatures, and consistent weather patterns throughout the year are typical. Moreover, the property allows the sensors to function optimally without requiring extensive recalibration for different environmental conditions.

Five sensor probes were deployed in the research area, and sensor probes 1 through 4 gather and relay information to sensor probe 5. This central probe, sensor probe 5, also aggregated its own data and the information obtained from the other sensors before forwarding it to the cloud through the Internet. This study employed a mobile application designed to oversee and manage the sensors, while data retrieval was facilitated via the cloud. The method for acquiring soil moisture information is illustrated in Figure 2(c).

## 4. The Proposed LSTM-RNN Model Network

The model suggested in this study could predict soil moisture contents one day in advance for the study area. Soil moisture predictions are obtained by processing the hydrological data, encompassing soil moisture content, temperature, humidity, and wind, to forecast the soil moisture levels for the next day through the LSTM memory units in the RNN-based LSTM model. Meanwhile, the LSTM-RNN algorithm was designed to process temporal data, i = [i1, i2… it…id], with d representing consecutive days with linearly independent parameters. The data points are concurrently managed within the memory cells in the LSTM network to generate the predictions, denoted as SM(t+1).

In the model developed in this study, data from the sensor nodes form the current input vector for each time instance ($1 \leq t \leq d$). For example, Lt = [T(t), H(t), SM(t), R(t)] is processed within each memory cell of the LSTM network, where T(t), H(t), SM(t), and W(t) are the daily average values for temperature, humidity, soil moisture content, and wind, respectively. Subsequently, a swift time-checking plot is utilised to evaluate the dataset across all sensors.

A MinMax scaler was applied to standardise the dataset employed in this study. A two-layered LSTM-RNN neural network consisting of d memory units in each layer is also utilised. In each LSTM structure, a hidden state vector, ht, a cell memory vector, ct, and three gates are utilised to manage the information flow in the LSTM neural network. The initial gate is the forget gate, which is responsible for deciding which data from the previous cell memory state, ct-1, should be discarded and to what degree. Equation (1) represents the output vector for the forget gate.

$$\mathrm{Ft} = \sigma\,(\mathrm{WFit} + \mathrm{XFht} - 1 + \mathrm{BF}) \tag{1}$$

where the value of Ft is within the {0,1} range and represents the sigmoid function, WF and XF are adjustable weight parameters, while BF signifies the bias vector.

Collectively, the parameters in Eq. (1) are recognised as trainable coefficients. For a specific instance (t = 0), ht and ct are initialised to a zero-length vector determined by the user-defined input parameter in the network. Subsequently, Equation (2) is applied to update the cell memory state vector by the tanh (hyperbolic tangent) layer. The coefficients WÇ, XÇ, and BÇ in the equation are another set of trainable parameters.

$$\text{Çt} = \tanh\,(\text{WÇit} + \text{XÇht} - 1 + \text{BÇ}) \tag{2}$$

where Çt falls within the range {-1,1}.

The data employed to modify the cell memory state, Çt, at the current time step is partly governed by the result from the second gate, which is commonly referred to as the input gate. Equation (3) represents the equation applied for the second gate, where the coefficients $W\bar{I}$, $X\bar{I}$, and $B\bar{I}$ belong to another set of trainable parameters specific to the input gate.

$$\bar{I}\mathrm{t} = \sigma(\mathrm{W}\bar{I}\mathrm{i}\bar{I} + \mathrm{X}\bar{I}\mathrm{ht} - 1 + \mathrm{B}\bar{I}) \tag{3}$$

where $\bar{I}$ is within the range {0,1} and represents a sigmoid function.

Equation (4) was employed to update the cell memory state vector with the outcomes from Eqs (1) and (3). The initial term from the equation dictates the segments from the previous cell memory state vector, Çt-1, that should be discarded. As the value of Ft approaches zero, information is forgotten, while information is retained when Ft approaches 1. Similarly, the subsequent term determines which new information should be stored, where more information is stored when $\bar{I}$t is close to one, whereas $\bar{I}$t approaching zero results in less information being stored.

$$\mathrm{ct} = \mathrm{Ft} \bullet \mathrm{ct} - 1 + \bar{I}\mathrm{t} \bullet \text{Çt} \tag{4}$$

where • represents the element-wise multiplication between the and the memory state vector. The final gate is the output gate, ot. The third gate manages the information from the current cell memory state vector that will be relayed to the subsequent hidden state, ht. Equation (5) is applied for the final gate, where the parameters Wo, Xo, and Bo are the set of trainable coefficients associated with the output gate. Moreover, the updated hidden state, ht, can be derived by referencing Eqs (4) and (5) and applying Equation (6). Finally, the ultimate output from the LSTM neural network layer is directed to a densely connected layer with just one neuron, and the final predicted output, Ypre, is computed by employing Equation (7).

$$\mathrm{ot} = \sigma(\mathrm{Woit} + \mathrm{Xoht} - 1 + \mathrm{Bo}) \tag{5}$$

$$\mathrm{ht} = \tanh(\mathrm{ct}) \bullet \mathrm{ot} \tag{6}$$

$$\mathrm{Ypre} = \mathrm{Wnhd} + \mathrm{Bn} \tag{7}$$

where ot falls within the range {0,1} and represents a sigmoid function, hd defines the output of the last LSTM layer, and Wn and Bn are the weight parameters and bias values for the densely connected layer, respectively.

### 4.1. Procedure for Training the LSTM Model

This study developed a method for predicting soil moisture utilising five sensors in an LSTM-RNN model, and the Spyder (Anaconda) application was employed for coding. The necessary libraries were also imported for analysis and calculations, while the data collected and analysed from the sensors at different depths were imported for utilisation in the prediction model. Moreover, this study obtained temperature and humidity data from the weather department, and a real-time satellite API was employed as real-time rain data in the prediction model algorithm.

The dataset obtained in this study was split into training and test subsets. Over 80% of the data was allocated for training the LSTM model, while the remaining portion was applied as the test set to validate the model and assess its predictive accuracy. The LSTM model demonstrated its adeptness at managing time series data due to its capacity to store past information via memory blocks. Figure 3 illustrates the summary of the procedure for training the prediction model by applying the RNN-LSTM algorithm.

This study carefully selected hyperparameters based on empirical evaluations and prior research to ensure optimal performance of the LSTM model for soil moisture prediction. The final configuration consisted of two LSTM layers, each with 64 units, providing a model with balanced complexity and computational efficiency. A dropout rate of 0.2 was then applied after each layer to mitigate overfitting. A 32-batch size was also chosen to enhance training stability and memory efficiency. Subsequently, the Adam optimiser was employed due to its adaptive learning rate and superior convergence properties, while the loss function utilised was mean squared error (MSE), given its effectiveness in continuous variable predictions. The model developed in this study was trained for 100 epochs, which was determined through convergence analysis to ensure adequate learning without excessive computation time.

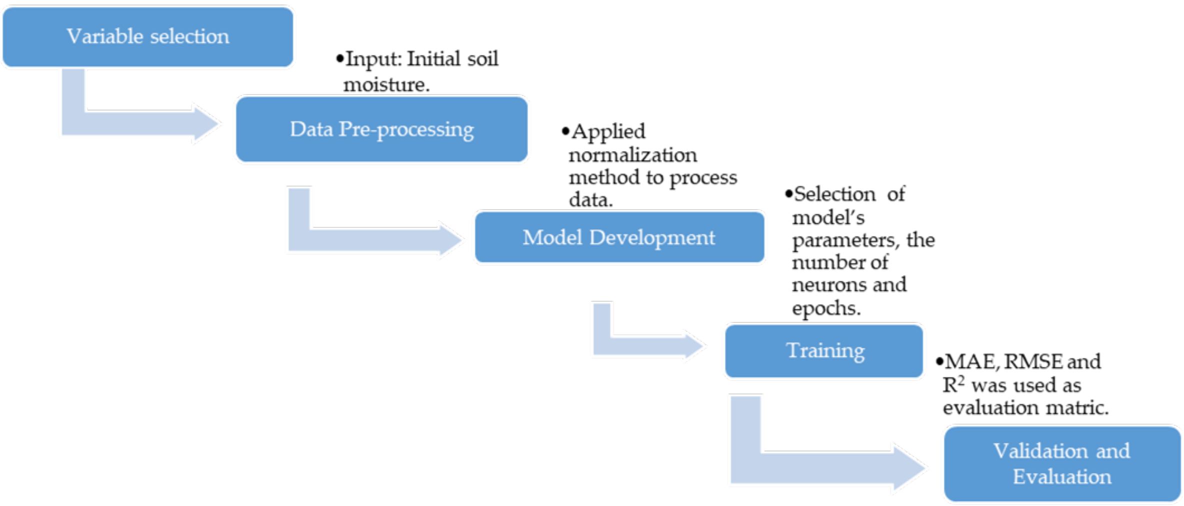


**Figure 3**. The training prediction model with the RNN-LSTM algorithm flowchart

In this study, a sensitivity analysis was conducted by varying one hyperparameter at a time while keeping others constant to validate the robustness of the proposed configuration. Based on the outcomes, increasing the number of LSTM layers beyond two diminished accuracy improvements and increased computational cost. Batch sizes under 16 also led to unstable training, whereas values over 64 slowed convergence. Furthermore, dropout rates exceeding 0.3 significantly degraded model performance, while lower values led to overfitting.

Among the different optimisers assessed in this study, Adam consistently outperformed alternatives, including SGD and RMSprop, regarding convergence speed and stability. The systematic approach to hyperparameter selection and sensitivity analysis ensured that the developed model achieved notable predictive accuracy while maintaining generalisability across different datasets. This study also applied Keras and Tensorflow functions to calculate the loss of the prediction model for the LSTM, which is represented by Equation (8).

$$\text{Loss} = \sum_{i=}^{N}(y_i - \hat{y}_i)^2 \tag{8}$$

where $y_i$ is the calculated value at time i and $\hat{y}_i$ denotes the value predicted at time i.

Previous studies have indicated that LSTM models exhibited limitations in determining the optimal number of LSTM layers and memory blocks in each layer, necessitating repeated evaluations and analysis. In the proposed model, the ADAM optimisation algorithm was employed to optimise the network loss, and the ideal epoch number and batch size were determined through experimentation. The results are discussed in the next chapter. Moreover, the number of hidden layers was varied between 1 and 3, while the total number of layers was established by utilising optimised results obtained.

Post-preparing the dataset for assessment and obtaining predictions, the results were validated and evaluated. The MAE, root mean square error (RMSE), and the coefficient of determination ($R^2$) were also calculated to appraise the derived outcomes. The MAE value denotes the average absolute error reading by determining the selected position of the predicted value error, which is established with Equation (9). Therefore, a lower MAE value signifies a better prediction model, considering that it can provide the required value of the square of the difference between the estimated and real variable values. The data can also be employed to quantify the data deviation point.

$$\text{MAE} = \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)}{N} \tag{9}$$

The square root of MSE gives rise to RMSE. Consequently, MSE values were positive, as the error values obtained were squared. Commonly, the value of RMSE ranges from 0 to ∞, where a prediction model is considered flawless and perfect if it can achieve an RMSE value of 0. Equations (10) and (11) were employed to calculate the MSE and RMSE values of the model proposed in this study.

$$\text{MSE} = \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N} \tag{10}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{11}$$

The $R^2$ was calculated to define the perfection of the output value predicted by the proposed model, where the value could be between -∞ and 1. If the proposed model can obtain an $R^2$ value approaching 1, it would be considered an ideal prediction model. Equation (12) was applied to determine the $R^2$ values in this study.

$$R^2 = \frac{\sum_{i=1}^{N}(y_i - \bar{y})^2 - \sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{12}$$

where, $\boldsymbol{y_i}$ defines the measured value at time i, $\boldsymbol{y}$ denotes the mean of $\boldsymbol{y_i}$, (i=1…, N), and $\boldsymbol{\hat{y}_i}$ is the predicted value at time i.

### 4.2. Calibration of Soil Sensor and Implementing Probe Design

This study collected soil specimens from a designated research site. The specimens were then placed in a compact beaker before determining their moisture levels and calibrating the sensor. A digital weighing scale was employed during an initial assessment of the mass of the soil specimens, represented as Ms. Subsequently, the specimens were oven-dried and weighed again to obtain Md, their dry weight.

Specific quantities of water were introduced to the desiccated soil specimens in this study. Readings of the soil moisture content were then recorded on multiple occasions to achieve a consistent average. Figure 4 demonstrates a flowchart of the calibration of the sensors implemented in this study. The procedure was continued until the sensor measurements stabilised, which signals the attainment of peak saturation. During the experiment, the amount of soil in every beaker was not altered to maintain the consistency of moisture readings. The findings are detailed in Table 2.

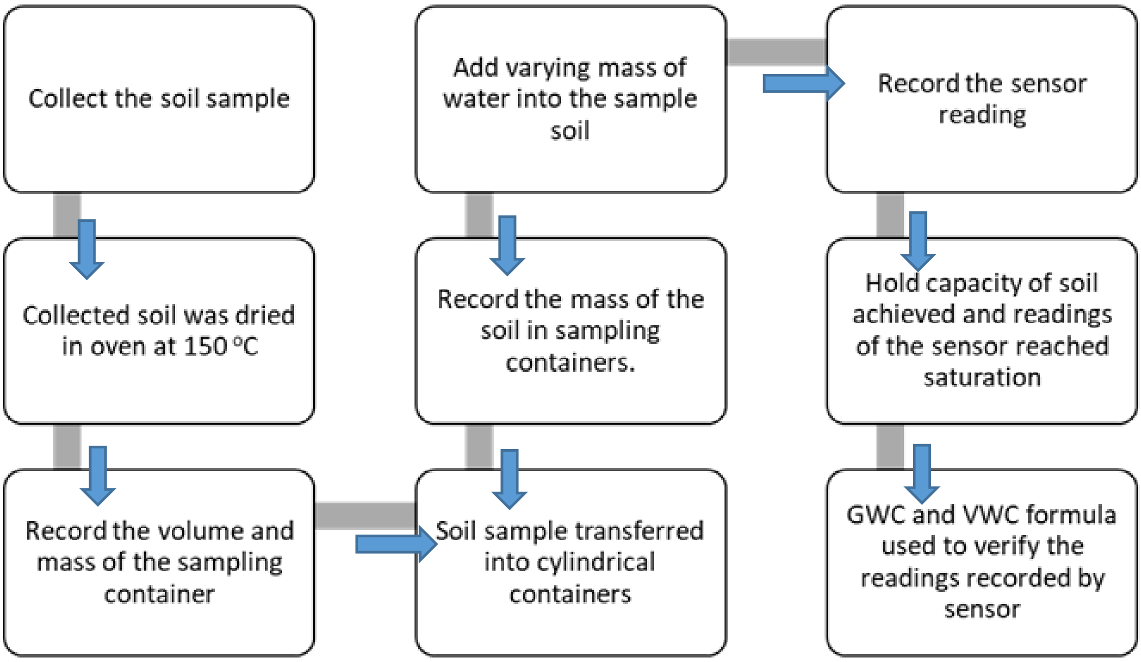


**Figure 4**. A flowchart of the sensor calibration procedure

**Table 2.** The Volumetric Water Content (VWC)-based sensor calibration

| **Amount of water (g)** | **Moisture sensor reading (%)** | | | **Average moisture sensor reading** | **Calculated VWC (%)** |
|---|---|---|---|---|---|
| | **Trial 1** | **Trial 2** | **Trial 3** | | |
| 5 | 29.92 | 32.65 | 29.75 | 30.77 | 7.88 |
| 10 | 48.55 | 49.25 | 49.32 | 49.04 | 15.77 |
| 15 | 66.72 | 68.07 | 67.59 | 67.46 | 23.65 |
| 20 | 77.84 | 79.62 | 75.33 | 77.60 | 31.54 |
| 25 | 87.83 | 88.92 | 86.32 | 87.69 | 39.42 |
| 30 | 92.39 | 96.19 | 94.76 | 94.45 | 47.30 |
| 35 | 98.89 | 99.45 | 98.75 | 99.03 | 55.19 |

The following are the details employed for calculating the VWC for the soil sourced from the research field before being oven-dried. Equation (13) was then applied to calculate the VWC of the specimens.

(i) Volume of soil Vs = $\pi r^2 h$ = 63.42cm$^3$
(ii) Mass of the container = 55.30 g
(iii) Gross initial soil mass = 155.42 g
(iv) Gross dried soil mass = 135.58 g
(v) Net initial soil mass, Ms = Gross initial soil mass - Mass of the container = 100.12 g
(vi) Net dried soil mass, Md = Gross dried soil mass - Mass of the container = 80.28 g
(vii) Mass of water = Net initial soil mass – Net dried soil mass = 19.84

$$\theta v = \frac{\frac{Mwater}{\rho\, water}}{\frac{Msoil}{\rho\, Soil}} = \frac{\theta g \times \rho\, soil}{\rho\, water} = Mass\ of\ water \times \frac{1}{Volume\ of\ soil} \tag{13}$$

$$\theta v = 19.84 \times \frac{1}{63.42} = 0.313\ \frac{cm^3}{cm^3} = 0.313\frac{m^3}{m^3}$$

According to the results with the sensor, the moisture of the soil specimen obtained from the research site was 79%, leading to the VWC for the specific sample being inferred at 31.3%. Following the documentation of calibration outcomes, the sensors were then inserted into cylindrical pipes to function as probes and positioned in the research area. Calibrations were performed with actual soil samples collected from the farm to ensure accurate measurements in real-world conditions. The process strictly adhered to standard procedures to guarantee reliability and consistency. After deployment in the farm, the sensor utilised in this study operated flawlessly without errors or performance issues, confirming the effectiveness of the calibration process and the suitability of the sensors for agricultural applications.

### 4.3. The LSTM Prediction Model Output

The data extracted from the cloud through sensor probes was critically assessed and organised according to the probes and moisture sensors employed. Therefore, the analysis of the procured data was enriched and facilitated the prediction model evaluation. The outcomes of the analyses are presented in the subsequent sections of this article. A comparison between the actual and forecasted values is demonstrated in Figure 3, where both values exhibited a parallel trajectory for all five sensors.

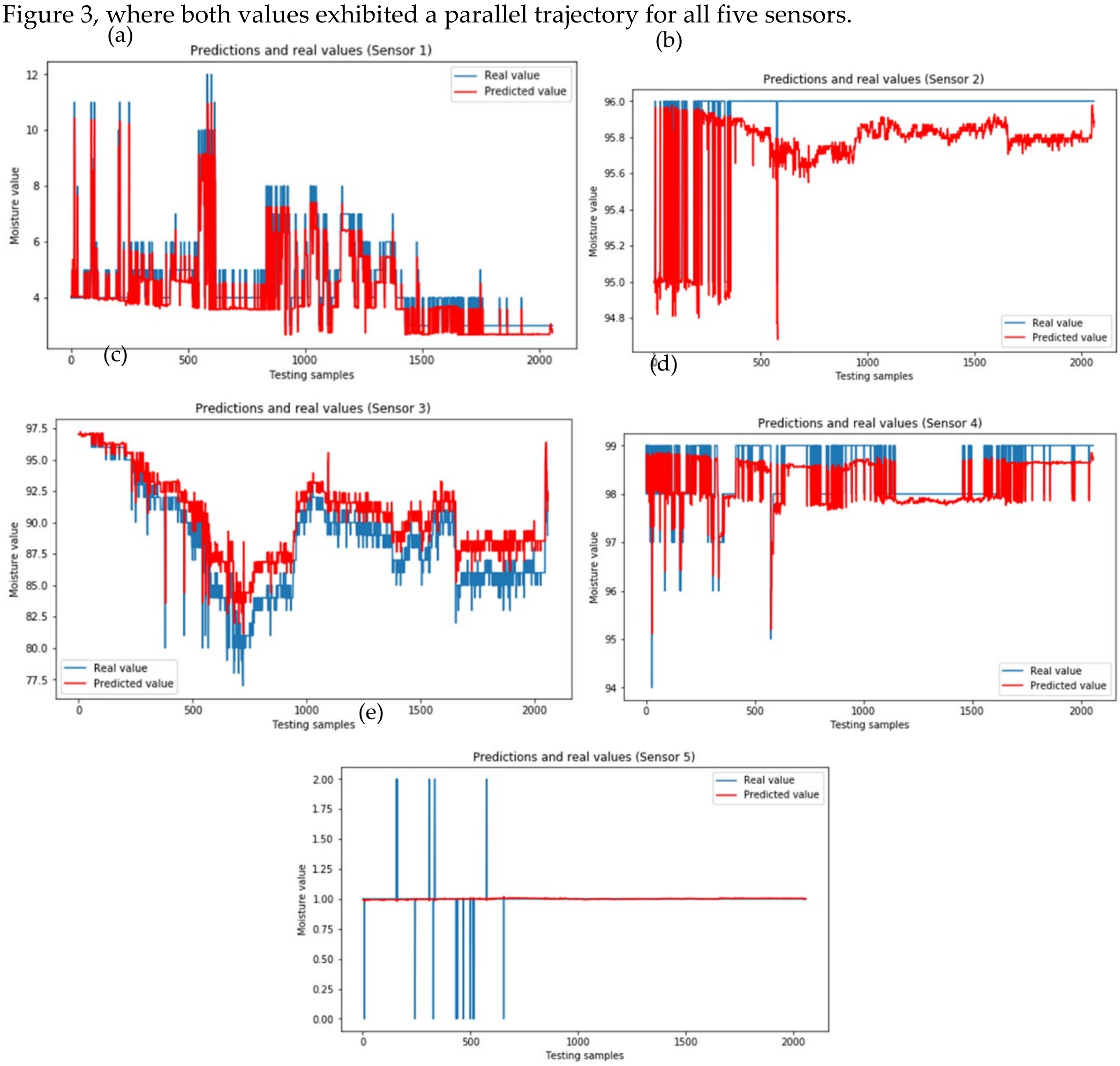


**Figure 5.** The prediction and real values recorded by sensors (a) 1, (b) 2, (c) 3, (d) 4, and (e) 5, which were placed 5 cm, 10 cm, 15 cm, 20 cm, and 25 cm from the surface, respectively

The LSTM algorithm with two hidden layers utilised in this study recorded an accuracy of 95 ± 2%. Meanwhile, the differences between real and predicted values are illustrated in Figure 6. Following the obtaining all predicted and real average values for all five probes employed, the accuracy of the proposed model was then determined. Resultantly, the training model documented an accuracy of 95% with a 2% margin of error. Table 3 summarises the results procured.

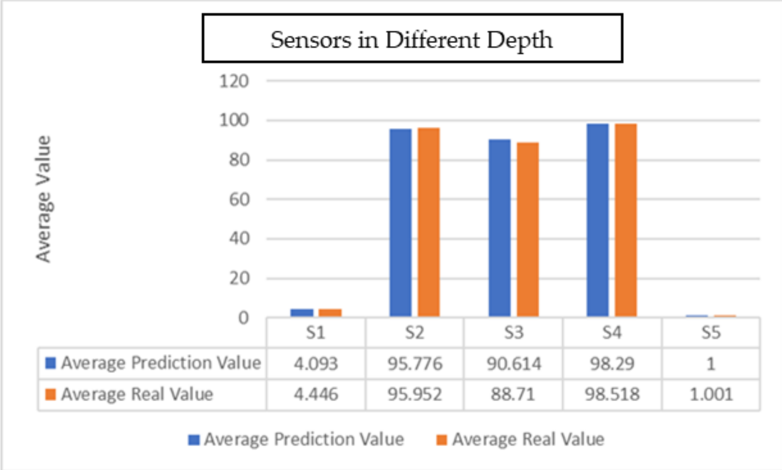


**Figure 6**. The bar Graph of the average prediction and real values of moisture sensors placed at different depths

**Table 3.** The calculated RMSE, MAE, and $R^2$ values from the developed LSTM algorithm

| **Validation** | **Testing data** |
|---|---|
| RMSE | 1.1544 |
| MAE | 0.6362 |
| R2 | 0.3331 |

The increasing volume of acquired data arises from advancements in IoT. Consequently, efficiently processing voluminous data while preserving precision is an essential characteristic of a predictive model. Employing comprehensive evaluative metrics is then necessary to rigorously appraise the model. The predictive model developed in this study had a 95 ± 2% precision by incorporating six months of data from moisture sensor probes set up in the research zone. Deploying the RNN-LSTM framework with the optimally suited iteration and neuron count also contributed to the exemplary accuracy attained.

Historically, soil moisture forecasting analyses have predominantly obtained data from sensors positioned proximate to the soil. Conversely, this study harnessed sub-surface soil moisture sensors that were adept at gauging moisture content up to a one-meter depth, providing a significant advantage for tree-living crops. In a report, De Benedetto *et al*. underscored the transformative power of precision irrigation in amplifying crop yield. Therefore, integrating deep learning with sensor-derived data enables agriculturists to obtain irrigation forecasts tailored to their specific lands. This study leveraged the RNN-LSTM framework that is known for its expertise in agricultural time-series forecasting to predict sub-surface moisture levels with superior precision.

## 5. Conclusion

This study demonstrated a significant advancement in PA by generating and evaluating an innovative soil moisture probe system. The proposed system is also enhanced with the analytical prowess of an RNN equipped with LSTM for predictive analysis. Conclusively, this study combined IoT-enabled hardware with sophisticated ML algorithms to directly address the critical research gap of optimising irrigation practices to mitigate water wastage and enhance crop management strategies.

A comparative analysis was conducted against state-of-the-art models, where relevant datasets were available, to evaluate the effectiveness of the LSTM model suggested in this study. Performance metrics, including accuracy, precision, recall, MAE, RMSE, and $R^2$, were also analysed to benchmark the proposed approach. Based on the findings, the LSTM model achieved an accuracy of 95 ± 2%, demonstrating its robustness in predicting soil moisture.

Among the major contributions of this study is the design of a real-time subsurface soil moisture detection system capable of reaching depths of up to one meter. The attribute is crucial for assessing moisture at root levels where most water uptake occurs. The predictive accuracy of the model and its robust MAE, RMSE, and $R^2$ metrics also validated its effectiveness in providing reliable soil moisture predictions. Moreover, the accuracy ensures that irrigation can be precisely tailored to the requirements of crops, which would lead to significantly reduced water usage and environmental impacts of farming practices.

From the viewpoint of stakeholders in PA, deploying the system developed in this study could translate to direct financial savings through diminished water consumption and labour costs associated with manual irrigation management. Developing a custom mobile application for system interaction also enhances user accessibility, allowing seamless integration into existing farming operations. Moreover, the findings demonstrated significant potential for scaling up and adapting the technology across different agricultural settings and crop types. The notable adaptability and accuracy of the proposed model also provided a substantial foundation for future research, including the potential incorporation of fertiliser prediction capabilities. Integrating sensors capable of detecting fertiliser levels might enable the system to offer comprehensive insights into irrigation and fertilisation requirements, further optimising resource management in farming.

The outcomes in this study could not be directly compared to previous relevant articles, considering that most prior research employed different modelling approaches, while this study specifically applied an LSTM network. Moreover, LSTM models are particularly well-suited for time-series forecasting due to their ability to capture long-term dependencies; therefore, direct comparisons with alternative models, such as traditional ML algorithms or other deep learning architectures, may not yield meaningful insights. Nevertheless, the performance of the proposed LSTM model was rigorously evaluated with well-established metrics, including accuracy, MAE, RMSE, and $R^2$, which ensured the reliability of the results. Future studies may also consider benchmarking the developed system against other deep learning models, including gated recurrent units (GRU) or convolutional neural networks (CNN), to offer a broader comparative analysis. Furthermore, expanding the dataset and assessing the model across diverse agricultural conditions could further validate its generalisability and applicability in PA.

Currently, several real-time technical data points are unavailable due to ongoing data collection and real-time monitoring constraints. Nonetheless, continuous field measurements and IoT-enabled sensors have been implemented to enhance data completeness. Additional controlled experiments are also being conducted to validate and extrapolate trends based on the existing dataset. Furthermore, this study has scheduled an extended phase of data acquisition in the upcoming months to improve the precision of moisture level predictions and irrigation optimisation. A broader context to the results will also be attained through comparative analysis with similar studies and industry benchmarks in the absence of specific real-time values. The data from the ongoing efforts will be included in future work, while additional datasets may be made available upon request to support further validation and reproducibility.

Future research can expand the applicability of the proposed system by incorporating additional data types and addressing broader aspects of PA. Deploying the model in diverse environmental settings, enhancing sensor accuracy, and developing advanced predictive analytics for crop health could be among the key areas of improvement. Challenges, including data diversity, user adoption, and environmental impacts, could also be addressed through advanced data processing techniques, extensive field testing, user training programmes, and system optimisation for sustainability.

This study offers a technologically advanced yet practical solution to the challenges of irrigation management, significantly contributing to the field of PA. The system had successfully minimised water overuse through precise moisture monitoring and predictive analysis, paving the way for a more sustainable, efficient, and cost-effective farming future. Further refinement and adaptations to include additional agricultural inputs, including fertilisation, could also improve the value and effects of the proposed system on the industry and benefit various stakeholders in the agricultural sector. Overall, incorporating such advanced technologies can redefine modern farming practices and ensure enhanced resource efficiency and environmental stewardship.

### Credit Authorship Contribution Statement

Shamala Maniam: methodology, investigation, formal analysis, writing original draft; Erfan Memar: data curation and software; Nisha Kumari: reviewing and editing; Tee Yei Kheng: formal analysis and data curation; Wong Hin Yong: supervising and validating; Mukter Zaman: supervising, conceptualisation, reviewing, and editing.

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