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Design of Portable Soil Moisture Detector Based on Artificial Intelligence

Rancang Bangun Pendeteksi Kelengasan Tanah Portable Berbasis Kecerdasan Buatan

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ABSTRACT

Soil moisture plays a crucial role in plant growth as it affects nutrient transport, photosynthesis, transpiration, and cell turgor. Soil moisture is commonly measured using direct gravimetric methods or more practical electrical conductivity-based sensors. However, these sensors have drawbacks, as measurement results can be affected by salinity, temperature, and soil type, requiring calibration at each site. To address these limitations, this study employed an Artificial Neural Network (ANN) model integrated into a microcontroller to automate the measurement process, adapt it for specific tasks, and eliminate manual calibration. The objectives of this study were to design a soil moisture sensor without manual calibration, develop an ANN-based moisture estimation model, and test its accuracy and effectiveness in supporting precision agriculture. The results showed that the soil moisture meter portable performed according to the design criteria. The ANN model produced an RMSE of 1.0366 and an R^2 of 0.995 in the training phase, and an RMSE of 1.0366 and an R^2 of 0.9923 in the testing phase. The best activation function is logsig-logsig-logsig, with actual validation showing an R^2 of 0.8607 and an RMSE of 7.617. This system has the potential to improve the accuracy of soil moisture measurements and irrigation efficiency in supporting sustainable precision agriculture.

Keywords: Artificial intelligence; microcontroller; sensor; soil moisture; portable

ABSTRAK

Kelembapan tanah memainkan peran penting dalam pertumbuhan tanaman karena memengaruhi transportasi nutrisi, fotosintesis, transpirasi, dan turgor sel. Kelembapan tanah umumnya diukur menggunakan metode gravimetri langsung atau sensor berbasis konduktivitas listrik yang lebih praktis. Namun, sensor ini memiliki kekurangan, karena hasil pengukuran dapat dipengaruhi oleh salinitas, suhu, dan jenis tanah, sehingga memerlukan kalibrasi di setiap lokasi. Untuk mengatasi keterbatasan ini, penelitian ini menggunakan model Jaringan Syaraf Tiruan (JST) yang terintegrasi ke dalam mikrokontroler untuk mengotomatiskan proses pengukuran, mengadaptasinya untuk tugas-tugas tertentu, dan menghilangkan kalibrasi manual. Tujuan penelitian ini adalah merancang sensor kelembapan tanah tanpa kalibrasi manual, mengembangkan model estimasi kelembapan berbasis JST, dan menguji akurasi dan efektivitasnya dalam mendukung pertanian presisi. Hasil penelitian menunjukkan bahwa alat pengukur kelembapan tanah portabel ini bekerja sesuai dengan kriteria desain. Model ANN menghasilkan RMSE sebesar 1,0366 dan R^2 sebesar 0,995 pada fase pelatihan, serta RMSE sebesar 1,0366 dan R^2 sebesar 0,9923 pada fase pengujian. Fungsi aktivasi terbaik adalah logsig-logsig-logsig, dengan validasi aktual menunjukkan R^2 sebesar 0,8607 dan RMSE sebesar 7,617. Sistem ini berpotensi meningkatkan akurasi pengukuran kelembapan tanah dan efisiensi irigasi dalam mendukung pertanian presisi berkelanjutan.

Kata Kunci: *Kecerdasan buatan; kelembapan tanah; mikrokontroler; portabel; sensor*

INTRODUCTION

Lampung Province plays a key role in supporting national economic growth, particularly through its leading commodities of vegetables, corn, cassava, fruit, horticultural crops, and plantation crops. However, in recent years, production, particularly of horticultural commodities, has declined in the agricultural centers of Lampung Province (BPS, 2024; BPS, 2023). This decline is closely related to declining soil fertility due to drought in mid-2023-2024 (Kementan, 2022). This poses a serious challenge to food availability and regional food security, especially during the dry season (PPSDA, 2020).

Plant growth and crop productivity are highly dependent on water content. Soil water content, or soil moisture, is the amount of water stored between soil particles, which determines the soil's ability to provide water for plants (Hardjowigeno, 20007; Hillel, 2004). This water content plays a crucial role in plant growth and development, as it functions as a nutrient solvent, a nutrient transport medium within plant tissues, and plays a role in photosynthesis, transpiration, and maintaining cell turgor pressure. Proper, measured, and optimal water supply will support optimal plant growth, thereby sustainably increasing agricultural production. Water shortages can cause plant stress, stunted growth, and decreased productivity, while excess water can disrupt nutrient absorption, trigger root diseases, and reduce crop quality. Recent research confirms that the critical soil moisture threshold has a global average value of around 0.19 m^3/m^3 with variations of 0.12 to 0.26 depending on the ecosystem, where if the humidity is below this value, evapotranspiration and plant growth will be disrupted (Fu et al., 2024). The results of other studies show that critical soil moisture detection can be done using satellite data to identify water and energy shifts, which are very important in agricultural land management (Liu et al., 2025). On the other hand, irrigation optimization strategies based on soil moisture deficits can improve water use efficiency and crop productivity, especially in corn cultivation (Wambua & Shin, 2025).

Farmers generally measure soil water content traditionally by holding the soil or observing the plants, but this method is inaccurate and risks reducing plant growth. Laboratory soil water content measurements use an oven (105–110°C), which is time-consuming and less accurate in soils high in organic matter (Munoth et al., 2016; Kivi et al., 2023). Both manual and laboratory soil water content measurements have limitations, such as being less accurate or time-consuming (Mane et al., 2024). Technology is needed to support precision farming practices, allowing farmers to adjust water needs based on actual soil conditions. One such technology is an electrical conductivity-based soil moisture sensor, which indirectly measures plant water needs based on soil moisture availability. Measurements are made with two electrodes installed parallel at a certain distance (probes) and immersed in the soil. Current flows from one electrode to the other, and the resistance value read is influenced by soil water content (Robinson et al., 2003). However, the use of these sensors presents several challenges, including requiring specific calibration to soil type and environmental conditions before accurate use in the field (Abdelmoneim et al., 2025). Furthermore, sensor readings can be affected by salinity, temperature, and soil heterogeneity, potentially reducing accuracy if not properly compensated (Zhao et al., 2024). Commercial soil moisture sensors are often inaccurate because they do not take soil type and density into account.

Soil moisture sensors available on the market generally still have several limitations, such as relatively expensive prices, measurement methods based on linear approaches, and measurement results that tend to be qualitative without displaying detailed numerical values (Bogena et al., 2007; Visconti et al., 2014). In addition, the relatively slow measurement response time can result in less precise readings and potentially cause bias. Therefore, the tool developed in this study was designed using a nonlinear approach based on Artificial Neural Networks (ANN) with the ability to display numerical data quickly, so it is expected to be able to provide more accurate, precise, and economical measurement results. To overcome these obstacles, a soil moisture sensor capable of integrating measurements without requiring manual calibration is needed. Precision sensor design offers a solution because it can measure water content efficiently and non-destructively, taking into account the physical and chemical properties of the soil (Zhao et al., 2024; Al-Mattarneh et al., 2025). Artificial neural networks (ANNs) are used to build data-driven mathematical models embedded in microcontrollers. The ANN model serves as a mathematical representation of a biological neural network, with an architecture of input, hidden, and output layers, with activation functions that influence the output results (Hagan et al., 2017; He et al., 2016). This process automates soil moisture estimation and makes it more adaptive to variations in soil conditions. Therefore, electronic soil moisture meters are a crucial solution for monitoring soil conditions in real time, improving input efficiency, and supporting sustainable agriculture. Precision sensors calibrated based on soil physical and chemical properties such as conductivity, density, and temperature can provide more accurate, real-time water content data Zhao et al., 2024; Al-Mattarneh et al., 2025). This research contributes to the development of a JST-based soil moisture sensor that is able to adaptively increase measurement accuracy without requiring manual calibration. Farmers can use these tools to determine crop water needs practically and accurately, without the need for manual measurements or recalibration at each location. While laboratory analysis of macronutrients, micronutrients, and organic matter is expensive and time-consuming, measuring moisture, pH, and EC can provide a quick and representative picture of soil fertility levels.

METHODOLOGY

Equipment and Material

The tools used were soil moisture probes (two electrodes), rulers, stopwatches, glass jars, laptops with Matlab software version 7.12.0.635 (R2011a), Arduino, microcontrollers, resistors, port cables, potentiometers, 16 x 4 LCD type 2004, digital thermometers and digital multimeters brand ADM02. The materials used were red-yellow podzolic ultisol soil and groundwater.

Research Procedure

The research process began with soil sampling from the research site. The samples were then dried and sieved to obtain uniform particle size. Next, the density of each soil type was adjusted to a single density level and the soil moisture content was uniformed according to the treatment. Once the soil conditions were consistent with the research treatment, soil conductance values were measured using sensor probes inserted into the soil. The resulting data were then used to train an Artificial Neural Network (ANN) to obtain a mathematical equation model for predicting soil moisture values. Based on the model, an ANN-based soil moisture measuring instrument was designed and manufactured. The final stage of the research involved calibration and validation, comparing actual measurement data with the instrument's predictions to determine the accuracy and performance of the developed system.

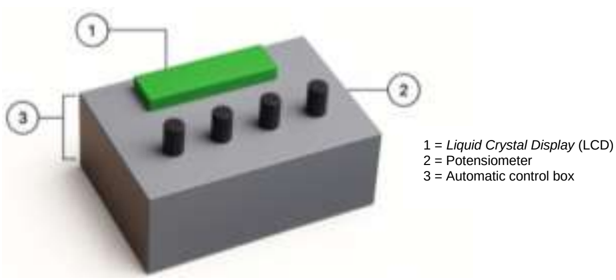

Figure 1. Soil measuring instrument design

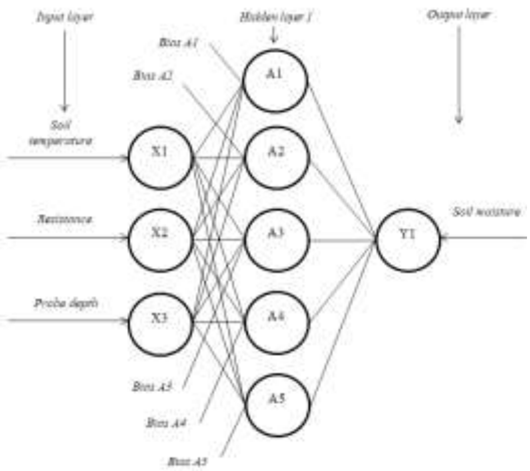

Figure 2. Artificial neural network architecture

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Design Criteria

This tool is designed to measure soil moisture by entering the probe type (2 types of electrode sizes), actual soil temperature, and conductance or resistance values using an analog multimeter (Figure 1). This measuring tool is expected to be able to measure soil moisture in <10 seconds with an accuracy of >80%. The soil moisture sensor was developed using an Artificial Neural Network (ANN) approach to overcome the weaknesses of commercial sensors that are sensitive to differences in soil texture and density, so that the system is able to adapt to various soil conditions without repeated manual calibration. To get the best value, Artificial Neural Networks are used to find the best mathematical model before being uploaded into the microcontroller. The calculation process is carried out by the microcontroller and the soil moisture value appears on the monitor screen of the portable measuring tool. This soil moisture sensor tool is designed as a portable tool so it is easy to carry, lightweight and does not require a large space to store. This tool is designed to read the soil moisture content that appears on the monitor screen with the help of potentiometer tools, namely the probe depth value, soil temperature value, and multimeter value (conductance value in the soil).

Development of Artificial Neural Network Model

The artificial neural network used in this study is a backpropogation type with a supervised learning method (Figure 2). This method is a network that is given a specific input and its output is determined by the created algorithm. This design uses Matlab software version 7.12.0.635 (R2011a) with an artificial neural network toolbox to develop a mathematical model that will later be integrated into a microcontroller with the help of Arduino software. The development of the Artificial Neural Network (ANN) model begins with training using MATLAB R2011a to determine optimal parameters and weights. The ANN consists of 3 layers: input, hidden, and output. The network architecture includes 3 input neurons, 5 hidden neurons, and 1 output neuron, with one hidden layer for efficiency. Training was carried out for 1000 iterations with a target MSE error of 0.00001. The learning rate value of 0.001 was chosen to support the speed and effectiveness of learning (Karsoliya, 2012; Kusumadewi, 2014).

Tool Performance Test

The performance testing phase is the testing phase carried out to analyze the performance of the tool. Calibration demonstrates the validity of the data originating from the tool by comparing the sensor and calibrator with high accuracy. Sensor calibration is carried out by comparing the temperature variation for each water content with the output value of the sensor and thermometer readings for each temperature and water content variation. Sensor calibration is carried out by comparing the sensor output value with a thermometer measuring instrument. Validation shows that the value output from the sensor corresponds to the actual value. Sensor validation is carried out by measuring the soil water content, comparing it with the soil moisture sensor reading value and testing the Root Mean Square Error (RMSE). Integration is a process to blend or unite so that a wholeness and roundness occurs by entering or combining the model values developed by ANN into the microcontroller. This process is carried out after obtaining a mathematical model from the development carried out by the artificial neural network. Then, the value is compared with the actual data value that has never been entered into the ANN process. This test uses Microsoft Excel 2010 software with a scatter graph to obtain the R2 value (coefficient of determination) and uses Arduino software to enter the formula into the Arduino Uno microcontroller.

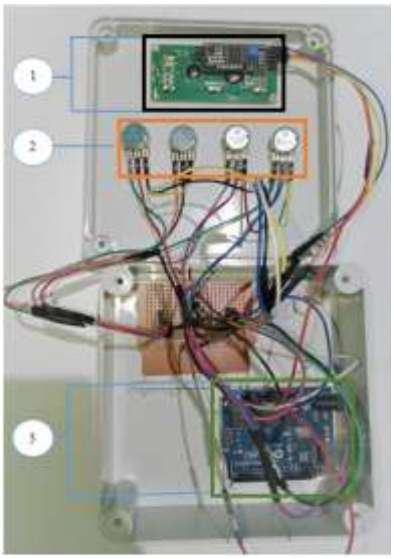
RESULTS AND DISCUSSION

Design Results

The result of the soil moisture sensor design is a control system placed inside a polymer box measuring 15 cm long, 15 cm wide, and 6 cm high (Figure 3). This polymer box was chosen because it is strong and waterproof. Inside this control box are electronic components that have their own functions and are interconnected. The components used are a liquid crystal display (LCD), potentiometer switch, resistor, and Arduino Uno (Figure 4).

LCD is used as a data display and is equipped with an I2C module with four pins, namely VCC, GND, SCL, and SDA which are connected to the 5V, GND, A5, and A4 pins on the Arduino Uno. Potentiometers are used as input for soil temperature, resistance, and probe depth, with two potentiometers to overcome the resistance value limit with each having three pins (VCC, output, GND), and the output is connected to pin A0 through a resistor for stability. The Arduino Uno microcontroller (ATMega328) functions as the control center of the circuit by utilizing the GND, VCC, A5, A4, and A0 pins for connections to all components. The use of a microcontroller as a control system is easier to assemble, stable, robust, accurate, and inexpensive. Research shows that the use of an I²C LCD display greatly facilitates the visualization of soil conditions in real time in a microcontroller-based system (Pane & Saleh, 2025).

Figure 3. Soil moisture measuring instrument design



1. Liquid Crystal Display (LCD)
2. Potensiometer switch
3. Microcontroller

Figure 4. Components of soil moisture measuring instrument

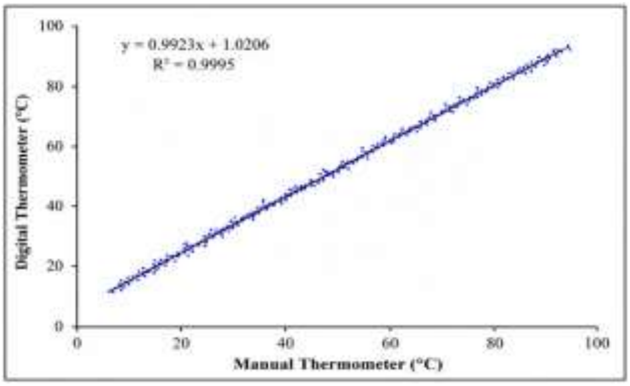


Figure 5. Soil temperature calibration values between a manual thermometer and a digital thermometer

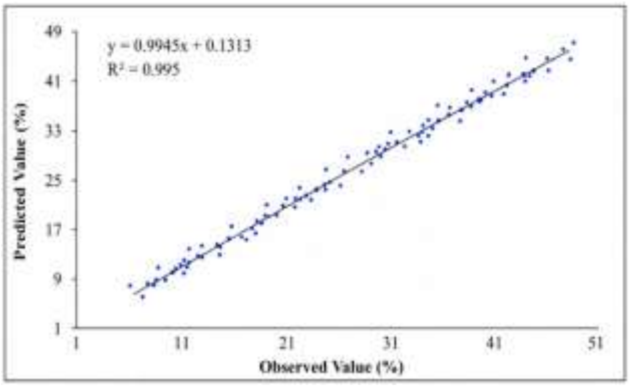


Figure 6. Artificial neural network model training

Calibration and Validation

Calibration aims to compare the sensor with the calibrator to achieve high instrument accuracy, while validation aims to demonstrate that the sensor output value matches the actual value. Calibration of capacitive soil moisture sensors demonstrates the importance of signal stability and measurement accuracy, which can be improved with appropriate calibration methods (Abdelmoneim et al., 2025). The soil temperature measuring instrument used in the soil moisture design is a digital measuring instrument. Comparisons are made using a mercury thermometer due to its more precise measurements compared to other thermometers. Measurements are made using simple materials, namely hot water and ice. The first thing to measure is the high temperature by adding hot water to a container surrounding a jar containing soil. Both instruments are inserted into the glass jar containing soil. Then, the hot water surrounding the soil is slowly mixed with ice water. Temperature values are measured periodically, every five minutes. Soil temperature values are taken for one hour with a gradually decreasing temperature value. Comparisons of various soil moisture sensors require good calibration standards so that measurement results can be relied upon to support Arduino-based monitoring systems (Songara & Patel, 2022).

Figure 5 shows that the accuracy value between the digital thermometer and the mercury thermometer is 99.95% with the formula y = 0.9923x + 1.0206. The R^2 value above 0.9 indicates a very strong relationship between the calibrator and the instrument (Telaumbanua et al., 2023). This proves that the digital thermometer has high accuracy. This calibration shows that the digital thermometer can provide appropriate values and works well when collecting data for the soil moisture sensor design.

This study used an ADM02 multimeter to measure ohms, amperes, and voltage. The resistance value of electricity flowing between two electrodes was measured by inserting them into the soil. The resistance value output from the multimeter at each soil water content must match each time the sample data is taken repeatedly in four types of groundwater conditions: saturated water, field capacity, critical water, and Pwp water. In saturated water, all soil pores are filled with water, so the excess is lost through drainage. After that, the soil reaches field capacity, which is the optimal condition for water and air balance for roots (Nasta et al., 2023). If the water content continues to decrease, the soil enters the critical water content, which is the minimum limit before plants experience stress with a global average of around 0.19 m^3/m^3 (Fu et al., 2024). In drier conditions, the permanent wilting point (−1500 kPa) is reached, where water is still present but is firmly attached to soil particles so that it cannot be absorbed, causing permanent plant wilting.

Based on the measurement results, there were discrepancies in the resistance values displayed on the multimeter. This could be caused by several technical factors, such as not turning off the multimeter after data collection, data collection times that were not according to schedule, and weak battery conditions. Furthermore, variations in soil moisture content also significantly affect resistivity, because higher humidity tends to decrease resistance, and vice versa (Jusoh et al., 2022).. These differences in resistance values impact the data used in the development of the Artificial Neural Network (ANN) model and in the validation stage. In this study, the soil moisture content for the ANN model development was 43.15%, 35.4%, 12.2%, and 8.8%, respectively, while the soil moisture content for validation was 55.21%, 42.88%, 14.59%, and 12.2%. These differences serve as the basis for evaluating the accuracy of the model.

Artificial Neural Network Model Training

The purpose of training an Artificial Neural Network (ANN) model using MATLAB software is to obtain the best performing network architecture that can be used in the next stage. The training process begins by inputting data into the artificial neural network, then the model is trained using one hidden layer with a 3-5-1 node structure, a learning rate of 0.001, a trainlm training algorithm, and 10,000 epochs. During the training process, 27 variations of activation functions from logsig, tansig, and purelin variants were used. The observed and predicted values in Figures 6 and 7 are soil moisture, so the level of closeness between the JST prediction results and the actual observation data is used to evaluate the model's ability to predict soil moisture conditions accurately. The activation function result with the lowest RMSE value and the highest coefficient of determination was selected as the best configuration for use in the next analysis stage (Abiodun et al., 2018).

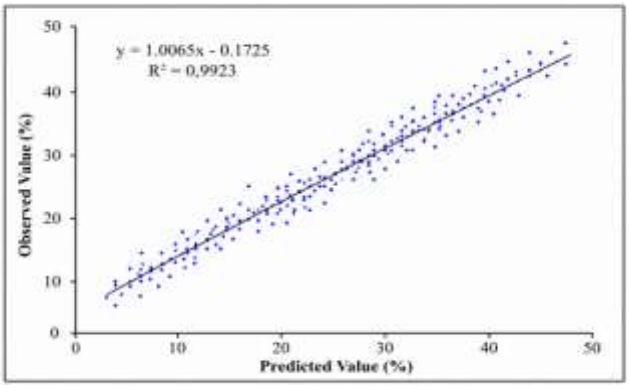


Figure 7. Artificial neural network model testing

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Figure 6 shows the R^2 value with the activation function that produces the smallest RMSE value and the largest coefficient of determination value or close to 1 is the logsig-logsig-logsig activation function. The Root Mean Square (RMSE) obtained is 1.0366 with the coefficient of determination (R^2) obtained is 0.995. The coefficient of determination value close to 1 proves that the results of the ANN model training carried out are very accurate in predicting soil moisture values.

Artificial Neural Network Model Testing

Artificial Neural Network (ANN) model testing is the next step after the training process to evaluate the performance of the model. The data obtained from this stage is predicted data, which is then compared with the actual data. The testing process is carried out using the same initialization as in the training stage to maintain consistency of results. The activation function is considered to have the best performance if it produces the lowest Root Mean Square Error (RMSE) value and the highest coefficient of determination.

Figure 7 shows the test data results with accurate model predictions (>0.9) with an R^2 value of 0.9923. The Root Mean Square (RMSE) value obtained was 1.0366 with the activation function used being logsig-logsig-logsig. This indicates that the prediction model is accurate in predicting soil moisture values with input weights of soil temperature, resistance value, and probe depth.

Mathematical Equations of Artificial Neural Network Model Development

This study aims to obtain a mathematical model equation resulting from the development of an Artificial Neural Network (ANN) model. The selection of the activation function is based on the criteria of the lowest Root Mean Square Error (RMSE) value and the highest coefficient of determination (R^2), which are then used to determine the weight and bias values in the ANN model. Based on the development results, the best activation function is obtained, namely logsig–logsig–logsig. The weight and bias values obtained from this configuration are then used to form a mathematical model equation that represents the relationship between input and output variables. The mathematical equations for the weight and bias results after developing the ANN model can be seen in Tables 1, 2, and 3.

Table 1. Mathematical equations for weight I H1 and bias I H1

ANN result	Values
Weight IH 1	1.2585410e+001 1.5227986e+001 -3.2440978e+001 -3.8207120e+000 4.6579068e+001 -3.7044216e+001 2.2852280e+001 -3.4372116e+001 3.0754177e+001
Bias IH $_1$	-6.2597488e+000 -1.2886086e+001 -4.0547159e-001
Mathematical Equation	Y1 = 12,585410(x1) + 15,22798(x2) – 32,440978(x3) – 6,2597488 Y2 = -3,8207120(x1) + 46,579068(x2) – 37,044216(x3) – 12,886086 Y3 = 22,852280(x1) – 34,372116(x2) + 30,754177(x3) – 0,40547159 Y4 = 1/(1+exp(-y1)) Y5 = 1/(1+exp(-y2)) Y6 = 1/(1+exp(-y3))

Table 2. Mathematical equations for the weight of H1H2 and the bias of H1H2

ANN result	Values
Weight H1 H2	-1.9272381e+001 -3.6156994e+001 2.0455303e+001 4.8605148e+000 1.6417726e-001 -4.7280249e+000 2.9145204e+001 -3.8219479e+000 -2.8155620e+001 1.5003047e+001 6.1187897e+001 4.7564503e+000 2.5811217e+001 5.1562932e+001 -8.1531177e+000
Bias H1 H2	2.8152756e+001 2.1424013e-001 -5.1593572e-001 -1.6982473e+001 1.7902615e+001
Mathematical Equation	Y7 = -19,272381(y4) – 36,156994(y5) + 20,455303(y6) + 28,152756 Y8 = 4,8605148(y4) + 0,16417726(y50 – 4,7280249(y6) + 0,21424013 Y9 = 29,145204(y4) – 3,8219479(y5) – 28,155620(y6) – 0,51593572 Y10 = 15,003047(y4) + 61,187897(y5) + 4,7564503(y6) – 16,982473 Y11 = 25,811217(y4) – 51,562932(y5) – 8,1531177(y6) + 17,902615 Y12 = 1/(1+exp(-y7)) Y13 = 1/(1+exp(-y8)) Y14 = 1/(1+exp(-y9)) Y15 = 1/(1+exp(-y10)) Y16 = 1/(1+exp(-y11))

Thus, the mathematical equation obtained from the results of the weight and bias calculations in the Artificial Neural Network (ANN) model development process can be expressed as follows: Y18 = 1/(1+exp(-(- 3.6882068(y12) – 2.5679343(y13) + 20.001051(y14) + 3.6645803(y15) +3.3459301(y16) – 0.88365229). This equation represents the mathematical relationship resulting from the ANN model, where the weight and bias parameters play an important role in determining the model output. The value of this mathematical equation is then used as a computational basis that will be implemented on a microcontroller through Arduino programming, so that the model can be applied directly to hardware.

Integration of JST Model with Microcontroller

The implementation of the mathematical model equations generated by the Artificial Neural Network (ANN) is carried out through a microcontroller with the help of Arduino software. This process involves programming using the C language written in the Arduino development environment. The input values entered into the system are first denormalized by dividing the input value by the highest value of the input data. Next, the output results are converted back through a normalization process by multiplying the output value by the highest value of the output data. After the mathematical model is entered, a verification and upload process is carried out to ensure that the program code does not contain syntax errors. Errors that occur are displayed as yellow or red notifications that indicate the location of the error in the code. In addition, tool configuration checks in the Arduino software, such as port selection and microcontroller board, are carried out to ensure the hardware is properly connected to minimize failures during the upload process.

Table 3. Mathematical equations for the weight of H1H2 and the bias of H1H2

ANN result	Values
Weight H2-O	-3.6882068e+000 -2.5679343e+000 2.0001051e+001 3.6645803e+000 3.3459301e+000
Bias H2_O	-8.8365229e-001
Mathematical Equation	Y17 = - 3,6882068(y12) – 2,5679343(y13) + 20,001051(y14) + 3,6645803(y15) +3,3459301(y16) – 0,88365229 Y18 = 1/(1+exp(-y17))

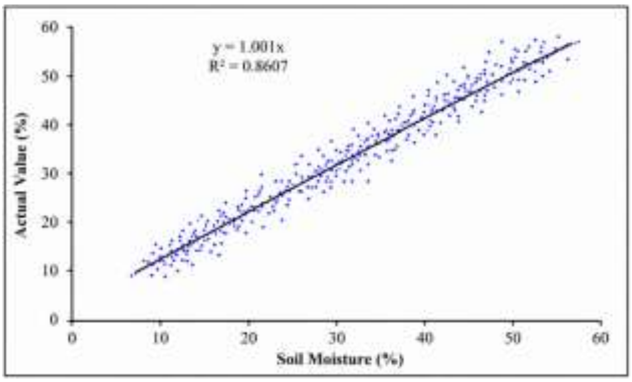

Figure 8. Validation of the mathematical model integration process testing

Results of the Modem Integration Process into the Microcontroller

The validation stage in the integration process is carried out using data patterns that have never been used in the training process or previous model testing. The new data is then tested with a model that has been built using an Artificial Neural Network (ANN). Integration validation aims to evaluate model performance by calculating the coefficient of determination (R^2) and Root Mean Square Error (RMSE) of the developed tool design. Statistical calculations are performed using Microsoft Excel 2010 software as an analysis tool. At this stage, the accuracy level of the ANN model can be measured to obtain an overview of the model's reliability in representing the relationship between input and output variables under different data conditions.

Figure 8 shows an R^2 value of 0.8607, which is close to 1. This indicates that the model's performance is accurate in predicting soil moisture values with the specified parameters, namely soil temperature 20°C, 24°C, and 28°C, resistance value, and probe depth 5 and 10 cm. Based on the very strong coefficient of determination, the resistance value, soil temperature, and probe depth are said to be suitable for use in developing an ANN model to predict soil moisture values. In addition to finding the coefficient of determination value in the process of integrating the mathematical model into the microcontroller, the Root Mean Square Error (RMSE) search process was carried out to determine whether the testing results match the estimate or not. After the calculation, the RMSE value was obtained at 7.61976044. This value compared to the RMSE value in the process of developing the artificial neural network model has a different value. A high coefficient of determination (R^2) value and a low RMSE value indicate an accurate mathematical model (Zhang et al., 2017). A higher RMSE value indicates that the resulting model estimation results are less accurate when compared to the observed results. This means that the RMSE value of the designed tool indicates that the ANN's predictive model values are accurate when compared to the observed output values.

Test Results Analysis

Test results showed that the developed Artificial Neural Network (ANN) model was capable of predicting soil moisture values with a high degree of accuracy. During the training phase, the coefficient of determination (R^2) was 0.995 with an RMSE of 1.0366. During the testing phase, the R^2 was 0.9923 with the same RMSE of 1.0366. An R^2 value close to 1 indicates a very strong relationship between observed and predicted values, while a low RMSE value indicates a low level of prediction error. These results indicate that the logsig-logsig-logsig activation function is capable of achieving the best performance in predicting soil moisture based on soil temperature, resistance, and probe depth. A high coefficient of determination indicates that the ANN model is capable of learning the nonlinear relationships between variables effectively, resulting in accurate data estimation (Abiodun et al., 2018; Hagan et al., 2017).

During the validation phase of the ANN model integration into the microcontroller, an R^2 value of 0.8607 was obtained with an RMSE value of 7.617. These values indicate that the system still has a good level of accuracy despite a decrease in performance compared to the training and testing phases. This decrease in accuracy is influenced by variations in soil conditions, changes in electrical resistance, soil temperature, and differences in field data that have not been used in the model training process. Variations in soil characteristics can affect the readings of electrical conductivity-based soil moisture sensors, so an adaptive approach such as ANN is needed to improve measurement accuracy (Zhao et al., 2024; Mane et al., 2024). However, the developed tool is still able to work in real time and shows good potential for application in precision agriculture-based soil moisture monitoring systems.

CONCLUSIONS

Based on the research that has been conducted, it was concluded that the design of the soil moisture measuring device works well according to the specified design criteria. The results of the ANN model training showed an RMSE value of 1.0366 and a coefficient of determination (R^2) of 0.995, while the results of the ANN model testing obtained the same RMSE value of 1.0366 with a coefficient of determination (R^2) of 0.9923, where the best activation function is logsig-logsig-logsig. The actual validation results produced a coefficient of determination (R^2) value of 0.8607 with an RMSE of 7.617. The results of the sensor calibration and validation using Artificial Neural Networks showed high values so that it was accurate in detecting and measuring soil moisture. However, this study is still limited by the variety of soil conditions used, which means that the influence of soil density and type can potentially lead to measurement errors. Therefore, further research is needed on a wider variety of soils and field conditions to improve the accuracy and development of an artificial intelligence-based soil moisture measurement system.

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REFERENCES

Abdelmoneim, A. A., Al Kalaany, C. M., Khadra, R., Derardja, B., & Dragonetti, G. (2025). Calibration of low-cost capacitive soil moisture sensors for irrigation management applications. Sensors, 25(2) 343. https://doi.org/10.3390/s25020343

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., Arshad, H., Kazaure, A. A., Gana, U., & Kiru, M. U. (2018). Comprehensive review of artificial neural network applications to pattern recognition. IEEE Access, 7, 142–158. https://doi/org/10.1109/ACCESS.2018.2883211

Al-Mattarneh, H., Ismail, R., Rawashdeh, A., Nimer, H., Khodier, M., Hatamleh, R., Telfah, D., & Jaradat, Y. (2025). Development of new dielectric models for soil moisture content using mixture theory, empirical methods, and artificial neural network. AIMS Environmental Science, 12(1), 137–164. https://doi.org/ 10.3934/environsci.2025007

Badan Pusat Statistik (BPS) Lampung Tengah. (2024). Statistik pertanian Lampung Tengah 2024. Lampung Tengah: BPS.

Badan Pusat Statistik (BPS) Tulang Bawang. (2023). Statistik pertanian Tulang Bawang 2023. Tulang Bawang: BPS.

Bogena, H. R., Huisman, J. A., Oberdörster, C., & Vereecken, H. (2007). Evaluation of a low-cost soil water content sensor for wireless network applications. Journal of Hydrology, 344(1–2), 32–42. https://doi.org/10.1016/j.jhydrol.2007.06.032

Fu, Z., Ciais, P., Wigneron, J.-P., Gentine, P., Feldman, A. F., Makowski, D., Viovy, N., Kemanian, A. R., Goll, D. S., Stoy, P. C., Prentice, I. C., Yakir, D., Liu, L., Ma, H., Li, X., Huang, Y., Yu, K., Zhu, P., Li, X., Zhu, Z., Lian, J., & Smith, W. K. (2024). Global critical soil moisture thresholds of plant water stress. Nature Communications, 15(1), 4826. https://doi.org/10.1038/s41467-024-49244-7

Hagan, M. T., Demuth, H. B., & Beale, M. H. (2017). Neural Network Design. 2nd ed. PWS Publishing.

Hardjowigeno, S. (2007). Ilmu Tanah. Akademika Pressindo, Jakarta.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(9), 770-778.

Hillel, D. (2004). Introduction to Environmental Soil Physics. Elsevier Academic Press, Amsterdam.

Jusoh, M. N. H., Syamsunur, D., Abd Rahman, N., Olisa, E., Rahim, A., & Md Yusoff, N. I. (2022). Soil parameters model prediction via resistivity value limit to shallow subsurface areas. Shock and Vibration, 6, 1-10. https://doi.org/10.1155/2022/3251250

Karsoliya, S., 2012. Approximating number of hidden layer neurons in multiple hidden layer BPNN architecture. Int. J. Eng. Trends Technol. 3, 714–717.

Kementerian Pertanian. (2022). Laporan tahunan Kementerian Pertanian 2022. Jakarta: Kementerian Pertanian Republik Indonesia.

Kivi, M., Vergopolan, N., & Dokoohaki, H. (2023). A comprehensive assessment of in situ and remote sensing soil moisture data assimilation in the APSIM model for improving agricultural forecasting across the US Midwest. HESS, 27(5), 1173-1199.

Kusumadewi, Sri. 2004. Membangun Jaringan Syaraf Tiruan Menggunakan MATLAB dan EXCEL link. Graha Ilmu,Yogjakarta.

Liu, Y., Xiao, J., Li, X., & Li, Y. (2025). Critical soil moisture detection and water–energy limit shift attribution using satellite-based water and carbon fluxes over China. Hydrology and Earth System Sciences, 29(3), 1241–1258. https://doi.org/10.5194/hess-29-1241-2025

M. Telaumbanua, E. Yana, S. Suharyatun, B. Lanya, F.K. Wisnu and W. Rahmawati. (2023). Rancang Bangun Sistem Pemanfaatan Parameter Lingkungan Berbasis Internet Of Things (IoT) di Gudang Penyimpanan Untuk Pabrik Gula, Jurnal Ilmiah Rekayasa Pertanian dan Biosistem, 11(1):135-145, https://doi.org/10.29303/jrpb.v11i1.481

Mane, S., Das, N., Singh, G., Cosh, M., & Dong, Y. (2024). Advancements in dielectric soil moisture sensor calibration: A comprehensive review of methods and techniques. Computers and Electronics in Agriculture, 218, 108686. https://doi.org/10.1016/j.compag.2024.108686

Munoth, P., Goyal, R., & Garg, A. (2016). Estimation of soil moisture and its application to irrigation water allocation: a review. 21st International Conference: Hydro 2016 International at central water & power research station, Pune, India.

Nasta, P., Franz, T.E., Gibson, J. and Romano, N. (2023). Revisiting the definition of field capacity as a functional parameter in a layered agronomic soil profile beneath irrigated maize. Agricultural Water Management, 284. 108368. https://doi.org/10.1016/j.agwat.2023.108368

Pane, M. A. S., & Saleh, K. (2025). Measuring soil moisture in real-time: Arduino Uno based tool innovation. Journal of Information Systems and Technology Research, 4(1), 37–43. https://doi.org/10.55537/jistr.v4i01.1035

Pusat Penelitian Sumber Daya Air. (2020). Kajian dampak kekeringan terhadap ketersediaan sumber daya air di Indonesia. Bandung: Puslit SDA.

Robinson, D. A., Jones, S. B., Wraith, J. M., Or, D., & Friedman, S. P. (2003). A review of advances in dielectric and electrical conductivity measurement in soils using time domain reflectometry. Vadose Zone Journal, 2(4), 444–475. https://doi.org/10.2136/vzj2003.4440

Songara, J. C., & Patel, J. N. (2022). Calibration and comparison of various sensors for soil moisture measurement. Measurement, 197, 111301. https://doi.org/10.1016/j.measurement.2022.111301

Visconti, F., de Paz, J. M., Martínez, D., & Molina, M. J. (2014). Laboratory and field assessment of the capacitance sensors Decagon EC-5, 5TE, and ECH2O-TE for estimating soil water content. Agricultural Water Management, 132, 111–119. https://doi.org/10.1016/j.agwat.2013.10.005

Wambua, N. L., & Shin, Y. (2025). Optimizing irrigation and water productivity for maize based on soil moisture deficit and crop water stress. Journal of the Korean Society of Agricultural Engineers, 67(1), 59–76. https://doi.org/10.5389/KSAE.2025.67.1.059

Zhang, J. (2017). Development of a Non-contact Infrared Thermometer, Proceedings of the 2017 International Conference Ad vanced Engineering and Technology Research (AETR 2017), Shenyang, China: Atlantis Press, 2018, https://doi.org/10.2991/aetr-17.2018.59

Zhao, Y., Zhang, X., & Wang, L. (2024). Advanced technologies of soil moisture monitoring in precision agriculture. Journal of Precision Agriculture, 25(3), 123–135. https://doi.org/10.3390/s25020343

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