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Internet of Things (IoT) for Soil Moisture Detection Using Time Series Model

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ABSTRACT

Technology in agriculture has been widely and massively applied. One of them is automation technology and the use of big data through the Internet of Things (IoT). The use of IoT allows a process to run automatically without human intervention. Extreme weather changes and narrow land use are one of the main problems in agriculture. The development of IoT devices has been widely developed regarding this subject. One of them is a soil moisture detection system. This study aims to build an IoT soil moisture detection system. The system will use a sensor as input which is then processed in a microcontroller device and the prediction results are sent to the IoT cloud platform. Prediction results are obtained using a time series model and then its performance is evaluated using RMSE. This model was chosen because the structure of the observed soil moisture data is based on time. The results of this study indicate that the soil moisture IoT system can work well. This is supported by the results of the prediction evaluation value of the RMSE = 1.175682×10^{-5} model which is very small.

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1. INTRODUCTION

Kevin Ashton, director of the Auto-ID Center at the Massachusetts Institute of Technology (MIT), was first used the term “Internet of things (IoT) in 1999. In the future, he predicts that IoT will be used in everyday life [1]. IoT means technology and environment that can exchange data in real time via internet communication with sensors mounted on different objects [2]. IoT can be used to perform data analysis that can be applied to various industries such as smart cities, smart homes, energy, and agriculture [2]. In agriculture, IoT is widely applied and is divided into four categories as follows: management systems, control systems, monitoring systems, and unmanned machines. Previous studies related to monitoring systems have been classified into field, disease, greenhouse, pest, livestock, and soil monitoring [1].

A soil moisture monitoring system is needed so that water resources can be used effectively, especially in extreme weather conditions. Not only on open agricultural land, the use of monitoring systems is massive enough to be used in greenhouse environments to keep the greenhouse environment at optimal soil moisture [1]. This study tries to present an intelligent agricultural field monitoring system that monitors soil moisture. After processing the sensing data, it takes the necessary actions without human intervention based on the data. Soil moisture data is measured and stored in the cloud for data analysis to make predictions. The benefit of the soil moisture detection system is to increase agricultural productivity and quality without continuous manual monitoring based on IoT to deal with adverse situations [3].

An IoT-based monitoring system can be developed through an automated prototyping system which is then upgraded to the next stage of a prototype system capable of communicating using the internet. In our previous research [4], we have succeeded in building a prototype of an automatic plant watering system using input soil moisture data stored in an external storage (memory card). Soil moisture data collected in this tool is data that is observed based on time. One of the modeling on time series data is autoregressive (AR) model. Before doing the AR modeling, it is necessary to do a stationarity test. If the test is not fulfilled, data transformation or alternative modeling can be performed. One alternative model that can accommodate the non-fulfillment of stationary assumptions is the time series regression model [5]. In our previous research related to time series regression modeling [6], time series regression modeling is able to predict the attacks number of pest and plant diseases.

Based on the problems stated above, it can be said that the main problem is how to build an IoT-based soil moisture detection and prediction system using the existing prototype in [4] and the prediction model in [5] which is the result of previous research. Unlike the related research in [7], [8] and [9] , this system uses a different prediction model and is applied to one sensor. The IoT system formed is a technology that can communicate with devices using time series data, while the time series model used is a technique for making predictions using time series data. The combination of these two things is expected to increase the quality and quantity of crop yields.

2. METHOD

2.1 Internet of things (IoT)

The concept of connecting between devices, applications and sensors via the internet is known as Internet of Things (IoT). All IoT devices can use cloud architecture platforms, software and infrastructure. They can be monitored and controlled remotely using IoT.

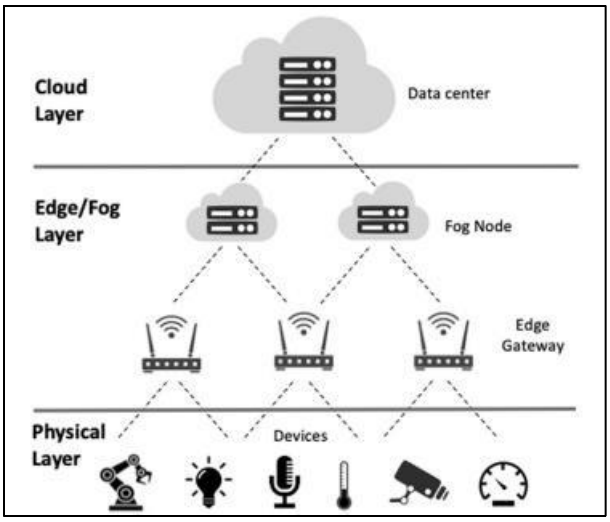

Figure 1. Activated 5G IoT architectures

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Figure 1 shows that one of the IoT environmental architectures. IoT is built on the idea of using cloud network platforms to communicate with each other. It enables users to build adaptable fast, connecting a large number of devices and efficient networks. [10]

2.2 Arduino

Microcontroller is a computer on a chip. It parades the output and input pins. The microcontroller includes a processor with a memory for storing program code.

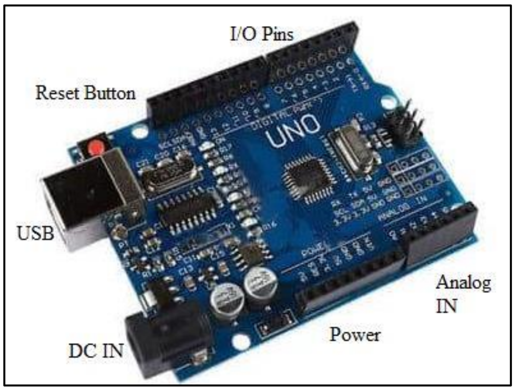

Figure 2. Aduino Uno Board

The Arduino Uno board, Figure 2, has an Atmega 328 on it as the main microcontroller. The sketch or code is done on an Integrated Development Environment (IDE) which makes it easy for engineers and electronics enthusiasts. The board has 14 I/O pins for input and output functions and 6 analog inputs (A0-A5) for handling analog signals. [11]

2.3 Autoregressive

Autoregressive (AR) is a model that uses the present value of observations depending on the value of observations at previous times. The p-order Autoregressive model written with AR(p) can be written in the form of an equation:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots . + \phi_p Z_{t-p} + \varepsilon_t \quad (1)$$

with $\varepsilon_t \sim N(0, \sigma^2)$ and ϕ is the p autoregressive parameter coefficient. [12]

In determining the order of p in the autoregressive model, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots can be used. For convenience, we can use pattern identification as follows: [5]

Table 1. ACF dan PACF Plot for AR orde

Correlation Function	**AR (p)**	**MA (q)**
ACF	Dies Down	Cut off after lag p
PACF	Cut off after lag p	Dies Down

2.3 Time Series Regression

The time series regression model is a model that is used to handle the regression model residuals that continue to increase from time to time. The time series regression model performs a time series model on the residual regression model. For example, given a linear regression model with the residual model following Autoregressive Order p=1.

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \quad (2)$$

$$\varepsilon_t = \phi \varepsilon_{t-1} + w_t \quad (3)$$

where ε_t is the error term in model at time period t, y_t is the response variable at time period t, x_t are the predictor variables at time period t, β_0 is an intercept, β_1 is a slope and w_t is an IIDN (0,σ_w^2). ϕ is parameter that defines the relationship between successive values of the model errors ε_t and ε_{t-1}. [13]

2.4 Root Mean Square Error (RMSE)

Root mean square error (RMSE) is one of the standard statistical metrics to measure model performance in research studies. RMSE is calculated using the error which is the difference between the actual and predicted values. we assume that we have *n* samples of model error calculated as (e_i , i = 1, 2, . . ., n).[14]

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} e_i^2} \quad (4)$$

2.5 Bartlett Test

Bartlett test is used to test whether k populations have homogeneous variance. Bartlett's test is based on a statistical chi-square distribution with k - 1 degrees of freedom. *k* is the number of groups in the independent variable. To investigate the differences between the variance of k normally distributed populations, independent samples were drawn from each population groups.

Hypothesis:

H_0: $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_k^2$

H_1: at at least two population variances are not equal

Test Statistics:

$$B = \frac{(N-k)ln\left(\frac{\sum_{i=1}^{k}(n_i-1)s_i^2}{N-k}\right) - \sum_{i=1}^{k}(n_i-1)ln(s_i^2)}{1+\frac{1}{3(k-1)}\left[\left(\sum_{i=1}^{k}\frac{1}{n_i-1}\right)-\frac{1}{N-k}\right]} \quad (5)$$

where s_i^2 is sample variance of n_i on population i = 1,2,…,k. N is the total number of data.

Test Criteria:

H_0 Rejected if $B > \chi^2_{(k-1)}$ or p-value < 0.05 [15]

2.6 Augmented Dickey Fuller (ADF) test

Augmented Dickey Fuller (ADF) is a unit root tester using the ARMA model. The model is defined as a process ARMA having Φ_1= 1 as a valid root of the characteristic equality polynomial. The ADF test steps are as follows

Hypothesis:
H_0: $\Phi_1 = 1$
H_1: $\Phi_1 \neq 1$
Test Statistics:

$$t_B = \frac{\hat{\beta}}{s.e.(\hat{\beta})} \tag{6}$$

Test Criteria:
H_0 Rejected if p-value < 0.05 [16]

2.7 Method and Data Analysis

The methods and steps of the data analysis process carried out in this research are:

1. Design and build a soil moisture detection system. The soil moisture detection system was built using Arduino, soil moisture sensor, SD Card Module and ESP-01. After the design is complete, the sensor is calibrated.
2. Taking and Visualizing Sample Data. Sample data was taken using a sensor and stored on the SD card memory for 2 hours.
3. Perform time series modeling using sample data. Modeling is carried out in stages:
   a. Stationary Test (ADF and Bartlett Test). ADF and Bartlett tests were carried out with the help of the R software package *tseries* [17] and *stats* [18]
   b. Identification of Order p autoregressive model using ACF and PACF. ACF and PACF plots were carried out with the help of the R software package *stats*[18].
   c. Time Series Modeling. There are two time series models used, namely autoregressive and time series regression models. Modeling is done with the help of packages in the R software package stats [18]
   d. Evaluation of the Goodness of the Model. Evaluation of the goodness of the model is done by calculating the RMSE value using R software package *Metrics* [19]
4. Build an IoT-based soil moisture detection system. IoT soil moisture detection system built using Blynk Cloud Platform.

3. RESULTS AND DISCUSSION

3.1 Soil Moisture Detection System

The series of soil moisture detection systems was made using Arduino Uno. The moisture detection system will collect data related to soil moisture using a soil moisture sensor. The data is then stored into memory for further analysis. The results of the series of soil moisture detection systems are as follows:

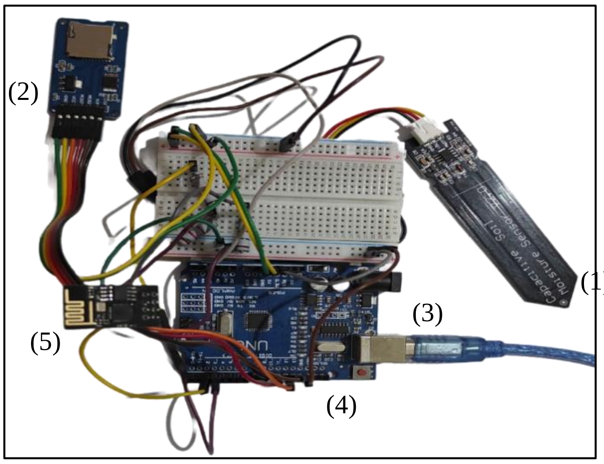

Figure 1. Soil Moisture Detection System

The moisture detection system is built using 1) Sensors to measure soil moisture, 2) SD Card module to store data, 3) Mini board to add the number of pins on Arduino uno, 4) Arduino Uno as the main processor and 5) ESP-01 as an intermediate connector. Arduino with cloud as shown in Figure 3. After obtaining the system circuit, the soil moisture sensor was calibrated. The result is that the maximum sensor value when wet is 600 and the minimum sensor value when dry is 260. To facilitate analysis, the sensor value is converted into percentage form in the range of 260 - 600.

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3.2 Data Visualization

The series of soil moisture detection systems, which have been calibrated with sensors, are then tested on a container containing soil media. Observations were made for 2 hours or 7200 seconds. Observation data will be stored in memory. The results of the data obtained are as follows:

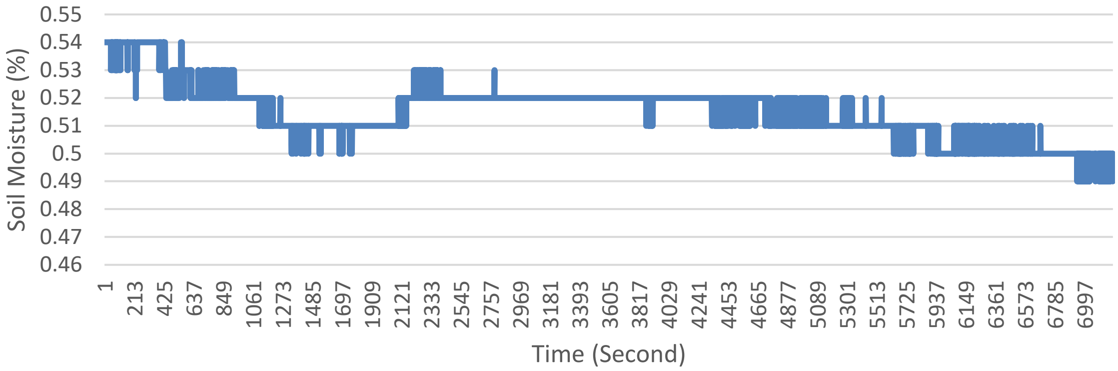


Figure 2. Soil moisture sensor data

Based on Figure 4, it is known that the value of soil moisture tends to constant at a value. This shows that the sensor is able to detect the state of soil moisture well. The soil moisture sensor value has an average of 0.51 with a standard deviation of 0.01. The small standard deviation value indicates the ability of the sensor or series of soil moisture detection systems to work well.

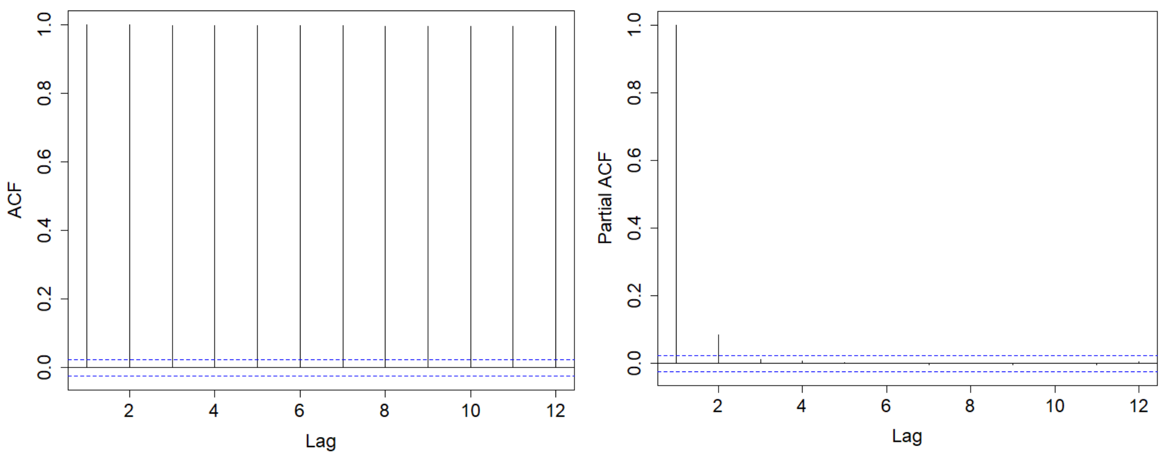
3.3 Time series model

The data that has been stored is then processed using a time series model. Before doing the modeling, the stationarity test was conducted using 2 tests. The ADF test is to test the stationary against the mean while the Bartlett test is to test the stationary against the variance. The test results are as follows:

Table 2. Bartlett and ADF Test Results

Model	Bartlett		ADF	
	Statistic	**P-value**	**Statistic**	**P-value**
Autoregressive	19.906	8.13×10^{-6}	-3.4668	0.04542
Time Series Regression Model	3.659	0.055	-3.4668	0.04542

Table 2 shows that the time series regression model can be used to model soil moisture data. The p-value > 0.05 in the Bartlett test and the p-value < 0.05 in the ADF test indicate that the assumption of stationarity is met. Therefore, further analysis will be carried out using a time series regression model. In the analysis of the time series regression model, the soil moisture data is first regressed with a dummy trend variable so that the residuals are obtained. This residue will be analyzed at a later stage. The p order of the time series regression model is then determined based on the ACF and PACF plots.



(a) (b)

Figure 3. Plot (a) ACF and (b) PACF Results

Figure 5 shows that the corresponding order of p is p=2. This can be seen from the PACF pattern in the form of a cut off at a certain lag. Even though p=2 is obtained, when modeling, the order of p=1 and p=2 is used. Then compare the AIC values of the two models.

Table 3. Comparison of model AIC values

Model	AIC
AR (1)	-61709.85
AR (2)	-63546.18

Based on Table 3, the best model is the AR(2) model with a smaller AIC. So that the remainder of the time series regression model will be modeled using AR(2). The equation for the best model can be written as follows:

$$y=0.0001063759T+0.5242629y_{t-1}+0.4756926y_{t-2}+e$$

where y is the prediction result, T is the dummy trend variable, y_{t-1} and y_{t-2} is the previous time soil moisture data and e is the error.

3.4 Evaluation of model goodness-of-fit

Based on the best model obtained, a prediction of the value of soil moisture is carried out. Evaluation of the goodness of the model is done by calculating the RMSE value. The plot of the prediction results against the actual value is as follows:

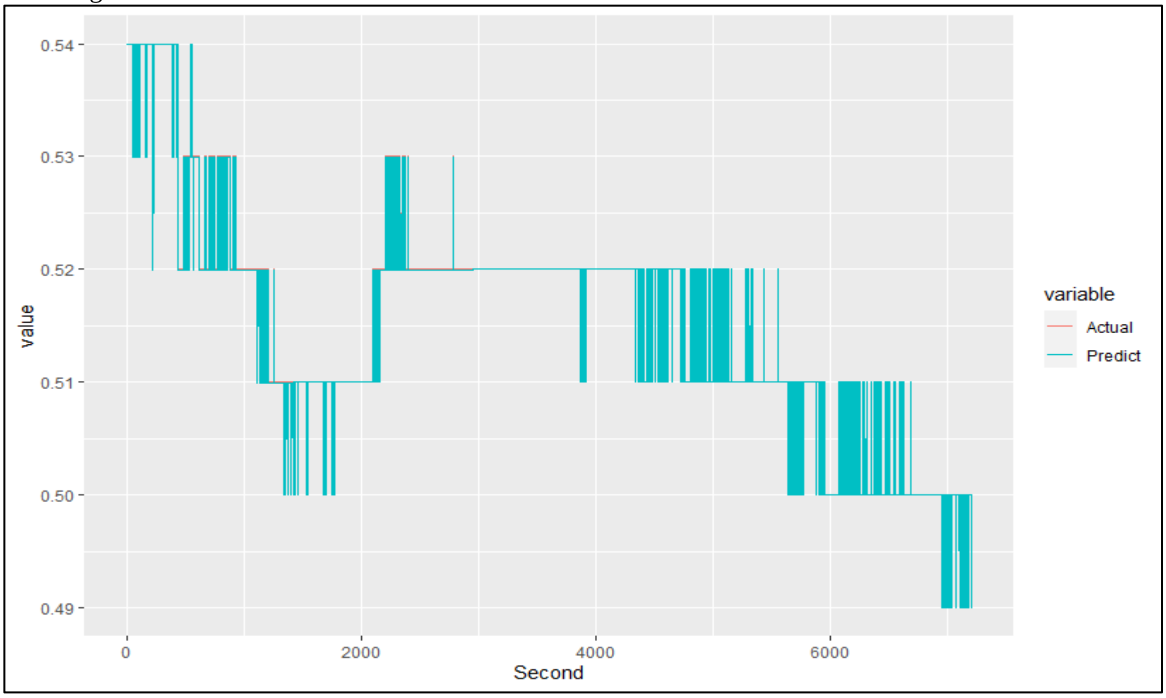


Figure 4. Plot the prediction results against the actual value

Based on Figure 6, it is known that the prediction results obtained using the time series regression model are very good. The prediction results also have a fairly small RMSE value of 1.175682×10^{-5}. The plot results and the small RMSE value indicate the model's ability to predict soil moisture data.

3.5 IoT Soil Moisture Detection System

Based on the best model that has been produced, an IoT soil moisture detection system is compiled. IoT is created using the blynk.cloud application. The ESP-01 device in Figure 3 will send the predicted data using the best model to the blynk.cloud application so that it can be displayed on the laptop or smartphone layer. The IoT implementation of soil moisture is carried out using soil placed in a 50 ml measuring cup for 10 seconds. The results of the IoT Dashboard display of the soil moisture detection system are as follows:

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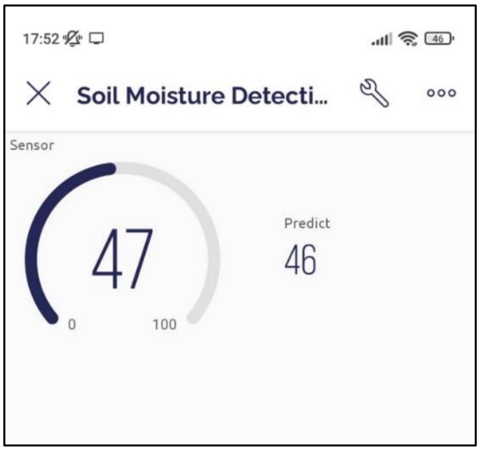

Figure 5. Display on smartphone IoT Soil Moisture Detection

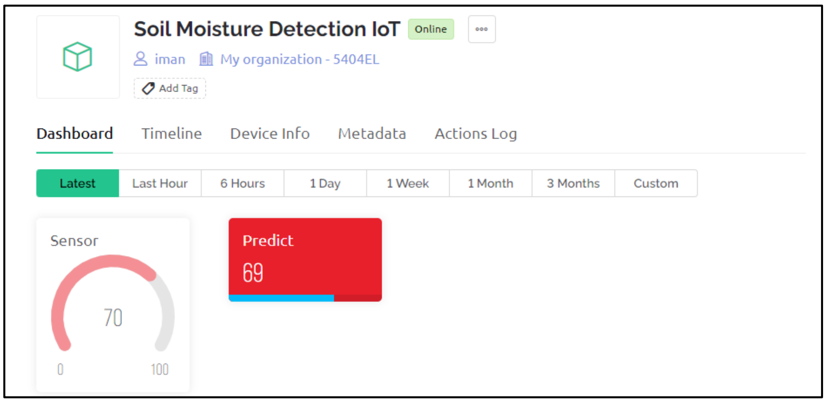

Figure 6. Display on IoT Soil Moisture Detection laptop

Figure 7 and Figure 8 show that IoT of soil moisture is going well. Soil moisture on the sensor is stored in the cloud which is then displayed as a percentage on the smartphone and web dashboard. IoT of soil moisture is also able to predict future soil moisture values using soil moisture values in the past. The simulation results on 50ml of soil in the measuring cup in Figure 7 show that IoT of soil moisture has successfully detected and predicted dry soil conditions of 47% and 46%. Figure 8 shows the IoT of soil moisture is also able to detect and predict wet soil conditions of 70% and 69%.

IoT of soil Moisture can run a monitoring system by utilizing the predictive feature of soil moisture values in the future. The soil moisture IoT system simulation was carried out on 50 ml of soil in a measuring cup for 10 seconds. The simulation results show that IoT of soil moisture can detect and predict soil conditions when dry or wet.

However, the model used in the prediction is not real time so that the prediction of soil moisture may not necessarily get the same results on the land. This is because the prediction results are very dependent on the type of soil and the depth of the sensor in the soil during the simulation. There is some improvement which can be implemented for further research. It is necessary to add several sensors so that you can use new predictive models such as regression, K-NN and so on.

4. CONCLUSION

IoT for soil moisture detection systems can be done using a time series regression model. The modeling is done using soil moisture data as a response variable and a dummy trend variable as an explanatory variable so as to produce model residual. The residual is then modeled again using the AR (2) model. The result of RMSE = 1.175682×10^{-5} shows that the modeling is able to predict soil moisture data well.

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