The Development of Precision Agriculture Design by Using a Smart Sensor for Time Series Forecasting Analysis on Relative Humidity

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Abstract. This research aims to design IoT effective and efficient tools for precision agriculture using NodemCu Board for measuring Temperature and Rh (Relative Humidity). The sensor for measuring Temperature and Rh uses DHT 11, a type of sensor DHT 11 using NTC (Negative Temperature Coefficient) as resistance based to measure temperature and Relative Humidity. The data from the sensor is sent to the Thingspeak website and compared with data from standard sensors. as a calibration process. The Rh data from DHT 11 used for time series forecasting for Rh with ANN models namely Feedforwardnet, Fitnet, Patternnet, and Cascade Forwardnet, the architecture of ANN using 468, 579, and 723. The Best result from ANN is best model Cascade Forwardnet with architecture 723 times 1.165, MSE train 1.4249 x 10^{-21}, MSE test 8.5620 x 10^{-22} with regression 1.

Keywords: DHT 11 · NodemCu · Soil Moisture 2.0 · Thinkspeak · Artificial Neural Networks

1 Introduction

Precision agriculture or precision farming is basically using the right agricultural inputs with the right technique, amount, place and time to produce maximum crop production [1]. Agricultural inputs in question are such as fertilizers, herbicides, insecticides, seeds, and others. Although to do farming accurately requires a lot of information, tends to be complex for most farmers, and requires collaboration from various multidisciplinary disciplines, precision farming systems can increase profits, reduce waste, reduce production costs, and maintain environmental quality [4].

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The concept of Precision agriculture or precision agriculture is actually not a new term in global agriculture. Precision agriculture was first coined at a workshop held in Minneapolis in 1992. Then in the late 1980s, it began to be applied to the fertilization process which was carried out based on soil fertility maps made at that time. However, the monitoring process has not yet been carried out because the existing technology is not yet qualified. In 1990, GPS began to be used and eventually became used in agricultural control.

The process of farming using satellites in its control is called Satellite Farming. The ever-developing technology has made precision agriculture increasingly known and used by many modern farmers in developed countries [2]. Before carrying out the agricultural process, a farmer must collect various information that can affect the agricultural process. The information needed includes soil structure and texture, types of plants to be planted, and harvest targets [3]. Soil structure and texture need to be known as information in selecting suitable plant species or nutrient application techniques to the soil. To determine the type of plant to be planted, farmers can also determine the desired target harvest from a plant [5]. Information in the form of land characteristics and prospective plants that are usually owned by the local government is taken into consideration in selecting plant species (Fig. 1).

If the type of plant and target harvest have been determined, then the farmer must determine the input such as the amount of nutrients needed for the plant to grow optimally. Again, farmers have to dig up information that influences the determination of agricultural inputs such as information on predecessor plants which will provide information on nutrients remaining in the soil, soil tests such as soil acidity, mineral content contained in the soil, ambient temperature, and other parameters. This information must be obtained so that farmers are able to carry out agricultural processes according to land conditions. Even though the land is in the same area, the nutritional needs cannot be generalized, so it is necessary to map the land. Thus, the need for nutrients such as fertilizer will be adjusted to the data obtained. The time of application is adjusted to the crops planted, and the use of herbicides is used based on pest data from previous crops [6].

After the information is collected, then the application of predetermined agricultural inputs can be carried out. In the application process, agricultural processes such as planting seeds, irrigation, fertilizing, and others are carried out using the right machine [7].

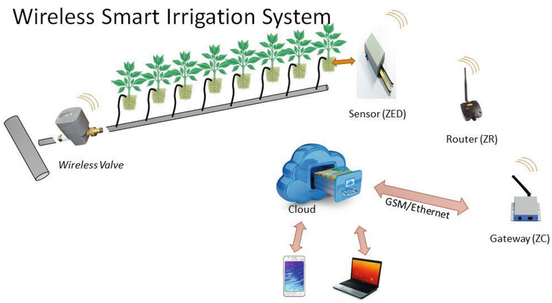

Fig. 1. Wireless Smart Irrigation System for Precision Agriculture

These machines are digital based so they can be set accurately and controlled remotely. This will save the human resources needed [8]. Detailed information will be processed and processed with the help of sophisticated agricultural tools. Even so, farmers must have the ability to adapt to advances in existing agricultural technology.

During the agricultural process, control is carried out with various tools, both special hardware and software. Examples of the tools used include the Global Positioning System (GPS), Grid soil sampling and variable-rate fertilizer (VRT), Geographic information system (GIS), and so on. The use of these tools will help farmers to manage their agricultural land specifically according to the information obtained. The process of farming using digital-based tools is called Digital Farming. Digital farming will be able to optimize production, quality, minimize risk and impact on the environment.

As mentioned above, examples of applying precision agriculture include using geographic information systems in sugarcane fertilization activities. Before fertilizing sugar cane, a yield map, soil map, plant growth map, land information map, application rate determination, yield sensor making, and variable rate applicator are made. The data is obtained from geographic information systems that use GPS technology, soil sensors, pest sensors, satellites, or aerial photography [9]. With this data, fertilization will be carried out more accurately according to the nutritional needs of plants. Farmers will provide fertilizer on each plot with varying amounts. Another example of the process of implementing precision agriculture is at the harvest stage. On date plantations in Saudi Arabia, each date palm is given an identity or ID which will be plotted onto a crop map digitally. Some of the quantities studied in agriculture include temperature, soil moisture. Air humidity, light intensity, wind speed, air pressure. This research will discuss the design/engineering of tools that support the field of Precision Agriculture using low costs, namely using NodemCu8266 board, Arduino, and DHT 11.

2 Method

A. NodemCu

NodemCu 8266 is the NodeMCU ESP8266 which is a derivative module developed from the IoT (Internet of Things) platform module of the ESP8266 family type ESP-12. The ESP8266 module can be studied from the previous article. Functionally, this module is almost similar to the Arduino module platform, but the difference is that it is specifically "Connected to the Internet"[12] (Fig. 2).

NODEMCU ESP8266 version, NodeMCU 0.9. This version (v0.9) is the first version to have 4MB of flash memory as the SoC (System on Chip) and the ESP8266 used is the ESP-12 [10]. The weakness of this version is that in terms of the size of the module

Fig. 2. NodemCu ESP8266 version

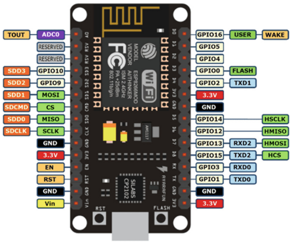

Fig. 3. NodemCu ESP 8266

board it is wide, so if you want to make a prototype using this module version on a breadboard, the pins are used up only for this module. NodeMCU 1.0 This version is a development of version 0.9. And in version 1.0, the ESP8266 used is the ESP-12E type, considered more stable than ESP-12. In addition, the size of the module board is reduced so that it is compatible with making project prototypes on breadboards as well as there are special pins for SPI (Serial Peripheral Interface) and PWM (Pulse Width Modulation) communication which are not available in version 0.9. NodeMCU 1.0 (unofficial board). It is said to be an unofficial board because this module product is produced unofficially due to approval from the Official NodeMCU Developer. The difference is not too significant with version 1.0 (official board), namely only the addition of V USB power output (Fig. 3).

B. DHT11

Air humidity describes the amount of water vapor content in the air which can be expressed as absolute humidity, relative (relative) humidity, or water vapor pressure deficit. The relative humidity is a comparison between the actual water vapor content/pressure and the saturated state or the air capacity to hold water vapor (Fig. 4).

We can get information about air humidity through measurements and sensors. One tool that we can use is a hygrometer. Apart from that, in the world of electricity, we also have smart sensors that are used to detect and measure the content of water vapor in the air, one of which is the smart sensor is DHT11 sensor. The DHT11 sensor is a digital sensor that can measure temperature and humidity levels simultaneously [11]. This sensor is very widely used because the price is cheap and easy to find on the market

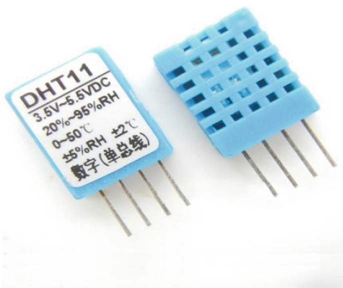

Fig. 4. DHT11 Sensors

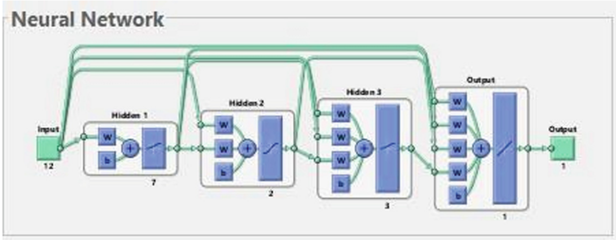

Fig. 5. Model and Architecture of ANN

and to use it is quite easy. Because there have been many tutorials shared by masters via the Internet, it cannot be denied that this sensor is quite in demand in the market. To measure the surrounding air, this sensor uses a thermistor and a capacitive humidity sensor. The voltage used to use this sensor is quite small because with a voltage of 5V we can already use this sensor.

C. Model and Architecture of ANN

There are 3 ANN models that we use, namely 4–6–8, 5–7–9, and 7–2–3. The model is obtained from artificial neural network training. We save this model in a file with the.mat extension. Later in the testing phase, we call this model and measure the resulting error. The model and architecture that we use can be seen in Fig. 5.

3 Results and Discussion

Soil Moisture value is sensed by two sensors. One is resistive and the other is a capacitive ground humidity sensor as shown in the figure. The soil moisture sensor measures the water content in the soil. This is an important parameter in research on the agricultural environment.

Measurement and monitoring of soil moisture are necessary to get an idea of when and how much to water the plants. Here soil moisture is calculated by the gravimetric method. Initially, the soil sample was dried in an oven to remove the moisture content of the sample and weighed. Then a certain amount of water was added to the dry sample and weighed. Then the water content is calculated based on the weight of the dried sample and the weight of the wet sample. Both soil moisture sensors are inserted into the dry soil of the soil sample and the corresponding voltage is recorded. This voltage is then fed to the ATMEGA328 microcontroller which converts this voltage into the respective humidity value. The DHT 11 sensor measures ambient air temperature and humidity and records them in the Thingspeak database. Figure 6 shows the sensors we used in this study.

Data from sensor observations are observed by monitoring through Thingspeak. Thingspeak.com is an Internet of Things platform in the cloud where we can send or receive data with the HTTP communication protocol and can also display data values through the free dashboard provided. Thingspeak.com functions as a data collector originating from node devices in the form of sensors that are connected to the internet and also allows data retrieval from the software for the purposes of visualization, notification,

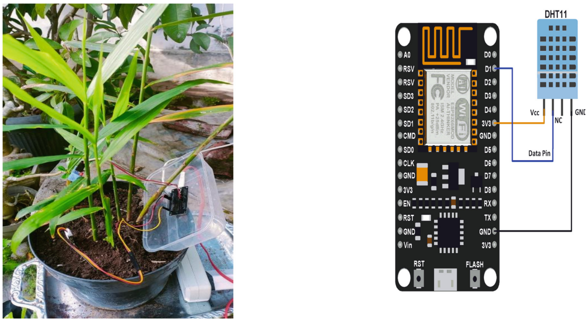

Fig. 6. The use of DHT11 in monitoring relative humidity

control, and analysis of historical data. Figure 7 shows observations of temperature, air humidity, and soil moisture at Thingspeak.

The time series forecasting using four types ANN Model namely Feedforwardnet, Fitnet, Patternet, Cascade forwardnet. The Architecture of each model using two types of three hidden layers 4–6–8, 5–7–9 and 7–2–3. The result of times series forecasting of relative humidity shown Table 1.

The data from the sensor is from 06.30 am until 06.30 pm, we divided the data into four segments each segment has an interval. First segment from 06.30 am to 09.30 am with an interval of time 15 min. The second segment from 09.30 am to 12.30 pm with an interval of time 15 min, The thirds segment from 12.30 pm to 03.30 pm with an interval of time 15 min, and The fourth segment from 03.30 pm to 06.30 pm with an interval of time 15 min. Total data from each segment is 83 data including data testing and data training. The results from model Feedforwardnet with ANN architecture 468 give regression value 1, Train time 17.2763, MSE Training 1322 $\times$ 10^{-16} and MSE test 6.9773 $\times$ 10^{-17}. The results from model Feedforwardnet with ANN architecture 579 give regression value 1, Train time 17.2763, MSE Training 4.3288 $\times$ 10^{-18} and MSE test 1.0014 $\times$ 10^{-18}. The

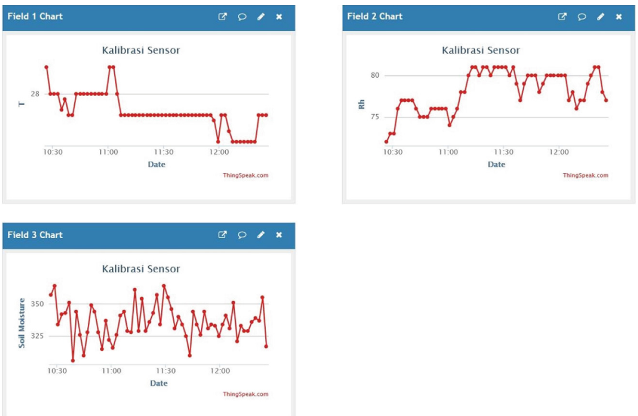

Fig. 7. Soil Moisture and DHT 11 sensor results using NodemCu

Table 1. Comparison of effectiveness between multiple models and network architectures

ANN Model	ANN Architecture	Regression Train	Time train (sec)	MSE Training	MSE Test
Feedforwardnet	ANN-(a)468	1	17.2763	2.1322 x 10^{-16}	6.9773 x 10^{-17}
	ANN-(a)579	1	1.8426	4.3288 x 10^{-18}	1.0014 x 10^{-18}
	ANN-(a)723	1	1.766	4.3516	8.2028 x 10^{-12}
Fitnet	ANN-(a)468	1	0.68545	3.1749 x 10^{-11}	3.0933 x 10^{-11}
	ANN-(a)579	1	1.9909	9.3651 x 10^{-12}	8.4265 x 10^{-12}
	ANN-(a)723	1	1.6674	1.4013 x 10^{-11}	5.2816 x 10^{-12}
Patternnet	ANN-(a)468	1	8.0009	2.4662 x 10^{-8}	2.5686 x 10^{-8}
	ANN-(a)579	1	6.2485	2.9187 x 10^{-9}	2.8407 x 10^{-9}
	ANN-(a)723	1	4.9387	0.0060458	0.0091
Cascade forwardnet	ANN-(a)468	1	1.3161	1.4411 x 10^{-23}	4.4377 x 10^{-16}
	ANN-(a)579	1	1.1718	1.3384 x 10^{-18}	7.1294 x 10^{-19}
	ANN-(a)723	**1**	**0.99902**	**4.5125 x 10^{-22}**	**3.4889 x 10^{-23}**

results from model Feedforwardnet with ANN architecture 723 give regression value 1, Train time 1.766, MSE Training 4.3516, and MSE test 8.2028×10^{-12}. The results from model Fitnet with ANN architecture 468 give regression value 1, Train time 0.68545, MSE Training 3.1749×10^{-11} and MSE test 3.0933×10^{-11}. The results from model Fitnet with ANN architecture 579 give regression value 1, Train time 1.9909, MSE Training 9.3651×10^{-12} and MSE test 8.4265×10^{-12}. The results from model Fitnet with ANN architecture 723 give regression value 1, Train time 1.6674, MSE Training 1.4013×10^{-11}, and MSE test 5.2816×10^{-12}.

The results from model Patternnet with ANN architecture 468 give regression value 1, Train time 8.0009, MSE Training 2.4662×10^{-8} and MSE test 2.5686×10^{-8}. The results from model Feedforwardnet with ANN architecture 579 give regression value 1, Train time 6.2485, MSE Training 2.9187×10^{-9} and MSE test 2.8407×10^{-9}. The results from model Feedforwardnet with ANN architecture 723 give regression value 1, Train time 4.9387, MSE Training 0.0060458, and MSE test 0.0091. The results from model Cascadeforwardnet with ANN architecture 468 give regression value 1, Train time 1.3161, MSE Training 1.4411×10^{-23} and MSE test 4.4377×10^{-16}. The results from model Feedforwardnet with ANN architecture 579 give regression value 1, Train time 1.1718, MSE Training 1.3384×10^{-18} and MSE test 7.1294×10^{-19}. The results from model Feedforwardnet with ANN architecture 723 give regression value 1, Train time 0.99902, MSE Training 4.5125×10^{-22}, and MSE test 3.4889×10^{-22}. The best result is shown from ANN model Cascadeforwardnet with architecture three hidden layers. The first hidden layer uses 7 neurons, the second hidden layer uses two neurons, and the last hidden layer uses 3 neurons. The time of data processing is 1.165 s with the MSE training score is 4.5125×10^{-22}, the score of the MSE test is 3.4889×10^{-23}. The architecture of casacade forwardnet is shown in Figs. 7 and 8.

The ANN separated two steps namely training and testing each step to give an output as plotting graphics performance shown in Fig. 9. In this figure, the best mean square error result is 4.512×10^{-22} which is obtained when the epoch equals 9. Meanwhile, the regression generated by the model we have trained can be seen in Fig. 10. In the figure it appears that the model we produced has reached a regression equal to one. The results obtained from this study can be seen in the training plots, testing, and forecasting. The row shown in Fig. 11, 12. 13. Based on the results of the training and testing that we have done, it shows that the ANN output is similar to the target. While the results of forecasting using the model, we have trained can be seen in Fig. 13. Based on the figure, we can see that the lowest humidity value is 62, while the highest humidity is 80.

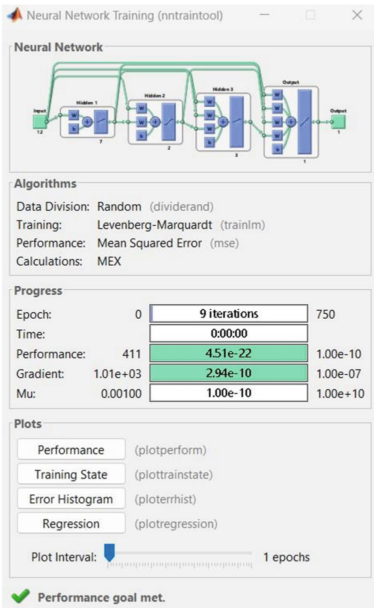

Fig. 8. The architecture of Cascade forwarnet

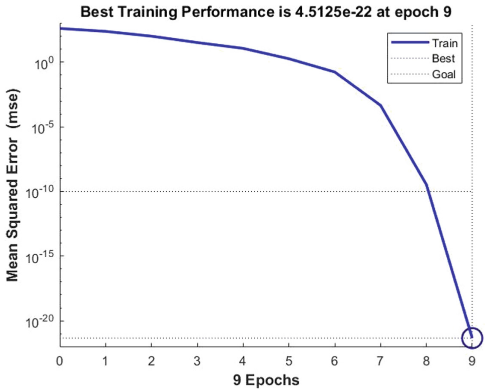

Fig. 9. Training Performance and Regression

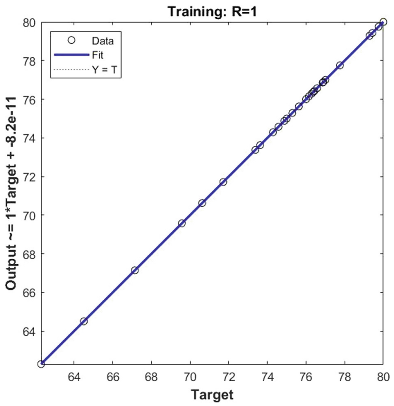

Fig. 10. Training Performance and Regression

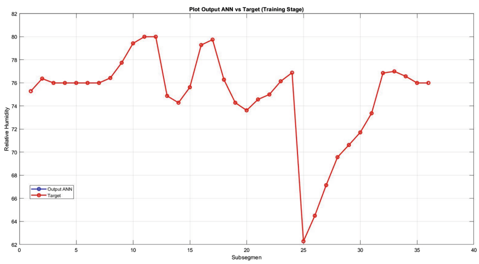

Fig. 11. Output in training stage

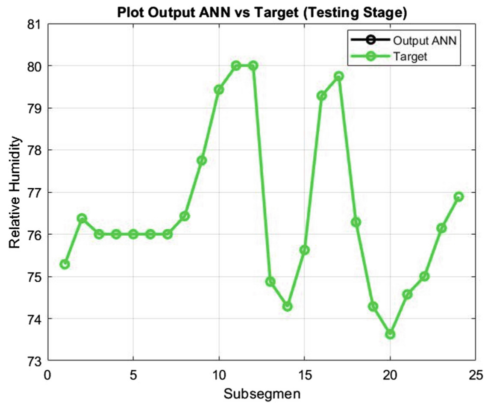

Fig. 12. Output in training stage

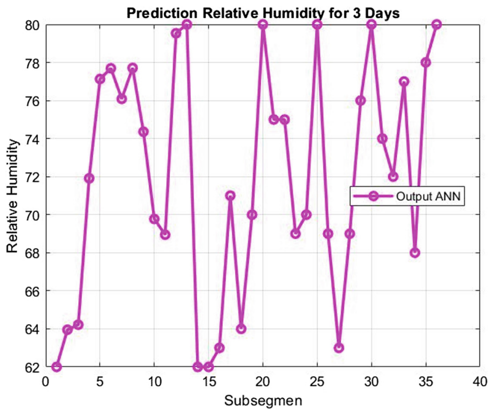

Fig. 13. Output in training stage

4 Conclusion

The designed system is used to measure temperature, relative humidity, and deep soil moisture in agriculture. The analysis was carried out to measure temperature and humidity using DHT11 over a certain period of time. Soil moisture is measured using a capacitive and resistive sensor. The analysis shows that capacitive sensors are more stable than resistive sensors, but resistive sensors are more sensitive than capacitive sensors. The capacitive sensor is more reliable because it doesn't corrode over time. We get the best ANN model by using cascadeforwardnet 7–2-3. The test MSE value generated by the model is 3.4489×10^{-23}.

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