IJSES

International Journal of Scientific Engineering and Science
Volume 6, Issue 10, pp. 1-6, 2022. ISSN (Online): 2456-7361

Internet of Things Based Rainfall Monitoring System in Smart Agriculture

Mahmud Mustapa[1], Ummiati Rahmah[1], Supriadi Sahibu[2], Afligandhi[3], Akbar Iskandar[3]
[1]Electronic Engineering Education, Universitas Negeri Makassar, Makassar, Indonesia
[2]Computer Systems, Universitas Handayani Makassar, Makassar, Indonesia
[3]Department of Informatics Engineering, Universitas Teknologi Akba Makassar, Makassar, Indonesia
Corresponding author: mahmud.mustapa@unm.ac.id

Abstract— *Changes in climatic conditions in an area have the potential to affect agricultural conditions. So that climate change and variability is a climate anomalous phenomenon that is a serious concern because it has a major impact, especially on the agricultural sector. The purpose of this study is to build an internet of things-based rainfall monitoring system on an intelligent agricultural system equipped with an effective monitoring system. This research resulted in an internet of things-based rainfall monitoring system that has been successfully designed with the help of raspberry devices, rainfall sensors, RTC, flashdisk and modems, so as to be able to present rainfall data and then process the prediction results using the moving average method, while the data grouping uses the oldeman classification. Based on the results of the analysis of the accuracy level of RMSE obtained 0.13 percent and MAPE 3.54 percent, then the results of the comparison of tools made by BMKG Indonesia for maros district obtained rmse accuracy rate of 0.04 percent and MAPE 3.71 percent, this shows very good results so that it can be a reference for farmers.*

Keywords— *Oldeman classification, IoT, Moving Average, RMSE, MAPE, Smart Farming.*

I. INTRODUCTION

Climate change has a very broad impact on people's lives. The increase in the earth's temperature not only has an impact on increasing the earth's temperature but also changes the climate system which affects various aspects of changes in nature and human life, such as the quality and quantity of water, habitats, forests, health, agricultural land and coastal ecosystems.[1],[2]. Climate change is a condition characterized by changes in global climate patterns that cause irregular weather phenomena. Climate change occurs due to changes in climate variables, especially air temperature and rainfall that occur continuously over a long period of time between 50 to 100 years (KLH 2004). Climate change is also influenced by unstable weather conditions such as irregular rains, frequent storms, extreme air temperatures, drastically changing wind directions.[3].

Climate change and variability is a climate anomaly phenomenon that is of concern because it has a major impact on the agricultural sector in particular[4]. Climate is closely related to climate change, where climate change and global warming can reduce agricultural production by up to 520 percent. Climate change is a condition characterized by changes in global climate patterns that result in irregular weather phenomena,[3].

Rainfall is the height of rainwater that collects in a rain gauge on a flat, non-absorbent, non-absorbent and non-flowing place[5]. Rain measurement is knowing the height of rainwater that floods a flat area or lands in an area[6]. The unit of measurement for rain is millimeters (mm), in one millimeter of rain it means that in an area of one square meter a flat area has accommodated one millimeter of rainwater or accommodated the volume of one liter of rainwater.[7].

Increasing food problems have now become a threat to food security, weather is one indicator of food problems. Climate change is something that is difficult to avoid and has an impact on various aspects of life. Climate change and anomalies affect the capacity and dynamics of agricultural production.

Climate change has a dominant influence on food security, namely changes in the rainy or dry season which have a strong influence on the pattern and timing of planting seasonal crops, which are generally food crops.[8]. The issue of the internet of things (IoT) is currently being focused on by many agencies, especially in the agricultural sector, for future developments[9],[10].

Climatic classifications can be mapped by collecting climatic element data over several decades. The occurrence of climate change due to global warming, the possibility of a change in climate type is very large, while information on decision making in the agricultural sector is needed because from climate and rainfall data it can be determined which plants are suitable for agricultural areas.[11].

The Oldeman climate classification system is a climate classification system that is relatively new compared to the research to be made and will produce an integrated crop calendar output, hereinafter referred to as the integrated planting calendar information system, providing spatial and tabular information about season predictions.

Technological developments are inseparable from human needs, especially in the development of an Internet of Things (IoT) based rainfall monitoring system.[12]. The developed system uses several software and hardware controller devices. On the information system website, part of the software is to display rainfall, while the hardware for building smart farming has several tools assembled including rainfall sensors, RTC, Raspberry, router (modem) and Flashdisk.

II. RESEARCH METHODS AND SYSTEM IMPLEMENTATION

A. *RTC (Real Time Clock)*

The stages in building smart farming begin with a series of tools consisting of input, process and output. The input data in question is rainfall data and then raspberries as a medium to process input data from the rainfall sensor, then send it to the IoT Server and the web application receives and monitors sensor data in real time through the RTC device.

The DS3231 real time clock (RTC) module is a type of module that functions as a digital timing interface. This module is accessed using the I2C (Inter Integrated Circuit) communication protocol. So when accessed using a microcontroller such as Arduino Uno, it requires 2 SDA and SCL pins and 2 power pins.[13]. The specifications of this RTC module are shown in Table 1.

TABLE 1. RTC (Real Time Clock)

Voltage	3.3 – 5.5 Volt
Time Calculation Error	+ 1 minute
clock chip	DS3231
Dimension	38 x 22 x 14 mm
Memory Chip	AT24C32

In making this block diagram aims as a reference for making hardware. Block diagrams are made to map the process of a job[14]. Block diagrams serve to facilitate reading in understanding the workings of the designed tool. So that in this design the authors design the system in blocks as an illustration to facilitate researchers in building the system.

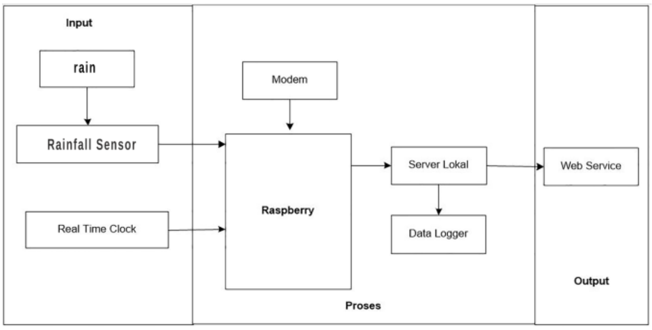

Fig. 1. Diagram of Blocks

The picture above is a block diagram of a smart farming circuit that will be built where there are inputs, processes and outputs to produce rainfall data information.

B. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is the magnitude of the prediction error rate, where the smaller (closer to 0) the RMSE value, the more accurate the prediction results will be. Root Mean Squared Error (RMSE) is one way to evaluate a linear regression model by measuring the level of accuracy of the estimated results of a model. RMSE is calculated by squaring the error (prediction "observation") divided by the amount of data (= average), then taking the root[15],[16]. The criteria for the method used to measure the goodness of a selected model is a root mean square error (RMSE) model.[17]. RMSE is a medium used to select the accuracy of a model based on estimation errors. The resulting error illustrates the difference between the estimation results and the value to be estimated. This value is used to determine which model is the best. The RMSE formula can be written as follows[15]:

$$RMSE = \frac{\sqrt{((At - Ft)/At)^2}}{n} \times 100\%$$

Information:
RMSE = Root Mean Square Error
n = Number of Samples
At= Actual Value
Ft = Predicted Value

C. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error is a statistical measurement of the accuracy of the forecast (prediction) in the forecasting method[18]. Furthermore, MAPE is calculated using the absolute error in each period divided by the actual observed value for that period. Then calculate the average absolute error percentage[19]. This approach is useful when the size of the forecast variable is important in assessing the accuracy of the forecast. MAPE shows how much error in the forecast is in relation to the true value.

Information:

At: Actual/Original Data
Ft: Prediction Data
n : Number of Cell Data

$$MAPE = \sum \left| \frac{\frac{At - Ft}{At}}{n} \right| x100\%$$

TABLE 2. Range Mean Absolute Percentage Error (MAPE)

MAPE Range	**Information**
<10%	Predictability is very good
10-20%	Good predictive ability
20-50%	Decent predictive ability
50%	Poor predictive ability

Mean Absolute Percent Error (MAPE) This is used when the size of the forecast variable is an important factor in assessing forecast accuracy. The mean absolute percentage error (MAPE) shows how much the forecast error is compared to the true value of the series.

D. Design of a Tool

The Internet of Things (IoT) has undergone many developments, such as the existence of wireless technology, sensor-based technology, and the application of Smart City in several developed countries.[20]. The design of an IoT-based rainfall monitoring system requires hardware, software and other supporting tools where all of these components must be integrated with each other so that they can carry out commands according to the instructions of each tool.

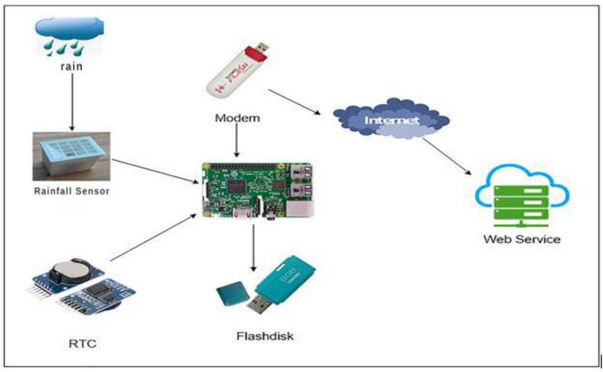

Fig. 2. Design Toolkit

Volume 6, Issue 10, pp. 1-6, 2022.

International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

E. Design of Software

In this study, the author describes how the appearance of the application that has been made and explains each tool contained in it. The following is a description of the application that is integrated with the tool:

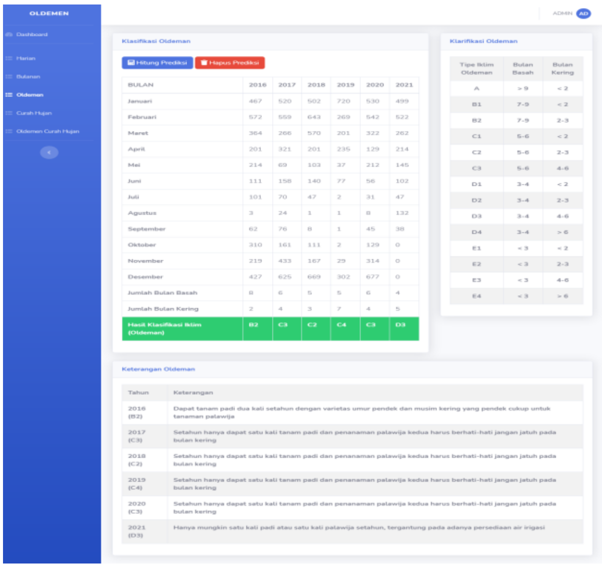

Fig. 3. Applications Design

III. TESTING AND RESULT OF APPLICATION DESIGN

A. Use case diagram design

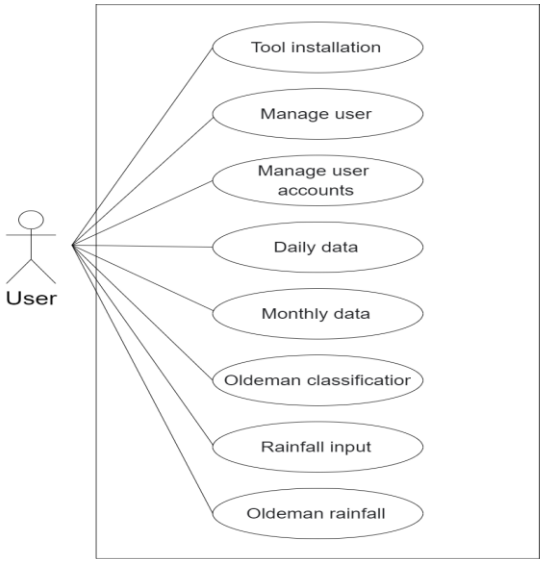

Fig.4. Use case diagrams

The picture above is a use case diagram that describes a workflow where users can assemble and install tools that will be connected to the application, in the application there is management of user or user accounts, besides that the application can display data, daily, monthly data and then display the classification results using Oldeman.

B. Sequence Diagram Design

The picture below is a sequence diagram for users who manage data in the form of daily data information, monthly data which is displayed in the form of a table list in the application and there is an Oldeman classification to display the output of the classification results.

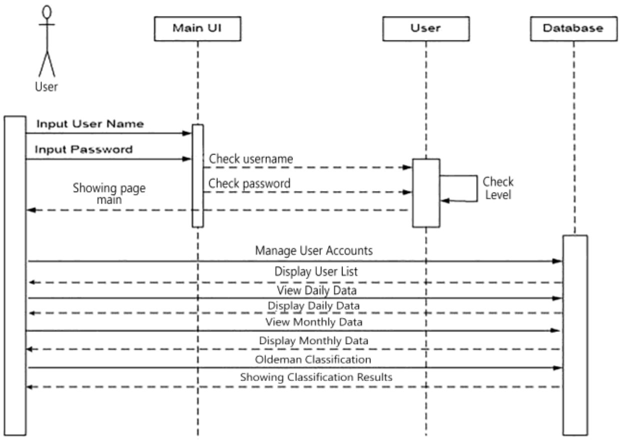

Fig. 5. Sequence Diagram Design

C. Activity Diagram Design

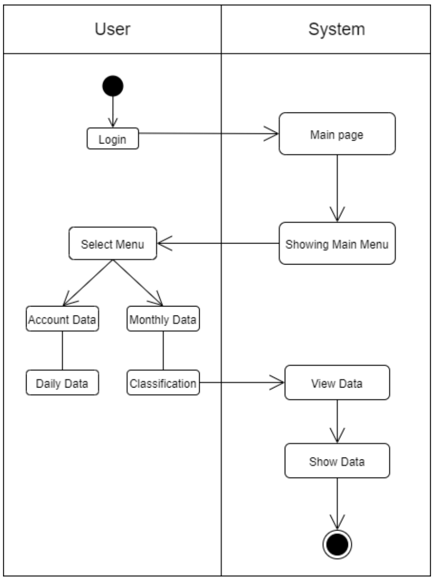

Fig. 6. Activity Diagram Design

Figure Above Activity diagram of users who manage data in the form of daily data information data, monthly data which is displayed in the form of a table list in the application and there is an Oldeman classification to display the output of the classification results. The picture above is a flowchart (Flowchart) of system work in the design where the process is designed as easy as possible to be understood by the user. The prototype of the IoT-based rainfall monitoring information system is a research that has been successfully created and has met the very good criteria based on the test results.

D. Local Server Network

Raspberry Pi 3 model B+ In the design of the tool, it functions as a local server that receives rain data from sensors, receives time data from RTC, as a data logger storage to flash.

International Journal of Scientific Engineering and Science
Volume 6, Issue 10, pp. 1-6, 2022. ISSN (Online): 2456-7361

Fig. 7. Local Server

E. Rainfall Sensor Circuit

The rainfall sensor uses a tipping bucket type with a tip value of 0.53 mm of rain. The physical form of the sensor is shown in Figure 8. The rainfall sensor in the final project uses a magnetic Hall sensor as a reader for each movement unit or every change that occurs in the bucket. This sensor has 3 pins, namely Vcc, Gnd and output.

TABLE 3. Raspberry pin with Rain sensor

Sensor Pins	**Raspberry Pi 3 Pins**	**Information**
	Rain Sensor	
Supply (5V)	Pin 2 (5V)	Supply Voltage
GND	Pin 6 (GND)	Ground
Output	Pin 17 (Output)	Output

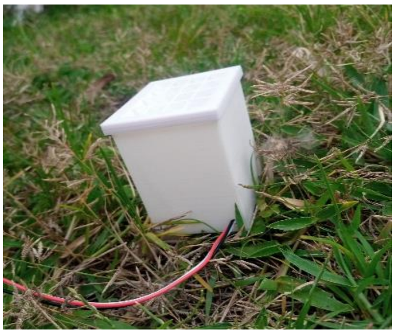

Fig.8. Rain sensor

F. Real Time Clock Circuit

The sensor or real time clock module is a series of tools that function to store and send time and date data that has been connected to a raspberry, shown in Figure 9.

Fig. 9. RTC circuit

G. Flashdisk

Figure 10 is a special device that will store data at a certain time. The measurement data of the tool is designed to be stored in a flash if it is not connected to the internet. The data format used to store the data logger is CSV format. The data stored in the flash can be seen in table 4.

Fig. 10. Data Logger (Flashdisk)

TABLE 4. Data storage structure

Date	**Time**	**Rainfall data**
dd / mm / yyyy	hh : mm : ss	000

H. Modem

The modem is part of a series of tools used as a connection that will connect to the internet so that it is connected to the application that has been developed, the modem model used can be seen in Figure 7.

Fig. 11. Modem Circuit

I. Overall Circuit

Previously, the functions of each tool that will be executed using raspberry have been explained, therefore the overall circuit results are shown in Figure 12.

Fig. 12. Overall Circuit

J. Data processing

The data obtained in this study are monthly rainfall data generated from rainfall monitoring tools from 2015 - 2020 in Maros district.

The data in the table below is used to refer to the classification of climate divisions based on the number of wet and dry months used by Oldeman as a reference to determine the division of agro-climatic zones and their relationship to agriculture, Oldeman revealed that the water requirement for rice plants is 150 mm per year. month, while for secondary crops it is 70mm/month, assuming that the same chance of rain

Volume 6, Issue 10, pp. 1-6, 2022.

International Journal of Scientific Engineering and Science
ISSN (Online): 2456-7361

is 75%, then to meet the water needs of 150 mm/month rice plants need 220 mm/month of rain, while for secondary crops, 120 mm of rain is needed. mm/month, so according to Oldeman it is said to be a wet month if the monthly rainfall is more than 200 mm/month,a humid month when the rainfall is 100 mm - 200 mm and is said to be a dry month if the rainfall is less than 100 mm / month.

TABLE 5. Rainfall data

Period	Rainfall (mm)						
	2015	2016	2017	2018	2019	2020	2021
January		467	520	502	720	530	499
February		572	559	643	269	542	522
March		364	266	570	201	322	262
April		201	321	201	235	129	214
May		214	69	103	37	212	145
June		111	158	140	77	56	102
July		101	70	47	2	31	47
August		3	24	1	1	8	132
September		62	76	8	1	45	
October	9	310	101	111	2	129	
November	67	219	433	167	29	314	
December	763	427	625	699	302	677	

K. Moving Average Analysis

The data that will be used in this study is rainfall data from the results of the study, to be able to make predictions/forecasting data from the previous period are needed as a guide for forecasting.

$$S'_{t(1)} = \frac{9 + 67 + 763}{3} = 280$$

$$S'_{t(2)} = \frac{67 + 763 + 467}{3} = 432$$

$$S'_{t(3)} = \frac{763 + 467 + 572}{3} = 601$$

The results of the next prediction calculation can be seen in table 6:

TABLE 6. Rainfall prediction calculation

Year	Month	Actual Data	Prediction	Error	Absolute	MAPE	RMSE
		At	Ft	At-Ft	l At-Ft l	l At-Ft/At l	(At-Ft/At)2
2016	Jan	491		491	491.00	1.00	1,000
	Feb	583		583	583.00	1.00	1,000
	Mar	379		379	379.00	1.00	1,000
	April	202	484	-282	282.33	1.40	1,954
	May	221	388	-167	167.00	0.76	0.571
	Jun	119	267	-148	148.33	1.25	1.554
	Jul	101	181	-80	79.67	0.79	0.622
	Aug	5	147	-142	142.00	28.40	806.560
	Sep	66	75	-9	9.00	0.14	0.019
	Oct	317	57	260	259.67	0.82	0.671
	Nov	222	129	93	92.67	0.42	0.174
	Des	436	202	234	234.33	0.54	0.289
2017	Jan	530	325	205	205.00	0.39	0.150
	Feb	587	396	191	191.00	0.33	0.106
	Mar	276	518	-242	241.67	0.88	0.767
	April	331	464	-133	133.33	0.40	0.162
	May	86	398	-312	312.00	3.63	13,162
	Jun	163	231	-68	68.00	0.42	0.174
	Jul	75	193	-118	118.33	1.58	2.489
	Aug	28	108	-80	80.00	2.86	8.163
	Sep	94	89	5	5.33	0.06	0.003
	Oct	101	66	35	35.33	0.35	0.122
	Nov	450	74	376	375.67	0.83	0.697
	Des	777	215	562	562.00	0.72	0.523
2018	Jan	523	443	80	80.33	0.15	0.024
	Feb	667	583	84	83.67	0.13	0.016
	Mar	594	656	-62	61.67	0.10	0.011
	April	213	595	-382	381.67	1.79	3.211
	May	109	491	-382	382.33	3.51	12.304
	Jun	150	305	-155	155.33	1.04	1.072
	Jul	51	157	-106	106.33	2.08	4.347
	Aug	1	103	-102	102.33	102.33	10472.111
	Sep	8	67	-59	59.33	7.42	55.007
	Oct	116	20	96	96.00	0.83	0.685
	Nov	184	42	142	142.33	0.77	0.598
	Des	798	103	695	695.33	0.87	0.759
2019	Jan	735	366	369	369.00	0.50	0.252
	Feb	282	572	-290	290.33	1.03	1.060
	Mar	217	605	-388	388.00	1.79	3.197
	April	247	411	-164	164.33	0.67	0.443
	May	47	249	-202	201.67	4.29	18,411
	Jun	95	170	-75	75.33	0.79	0.629
	Jul	5	130	-125	124.67	24.93	621,671
	Aug	0	49	-49	49.00	0.00	0.000
	Sep	0	33	-33	33.33	0.00	0.000
	Oct	0	2	-2	1.67	0.00	0.000
	Nov	33	0	33	33.00	1.00	1,000
	Des	308	11	297	297.00	0.96	0.930
2020	Jan	557	114	443	443.33	0.80	0.634
	Feb	564	299	265	264.67	0.47	0.220
	Mar	339	476	-137	137.33	0.41	0.164
	April	138	487	-349	348.67	2.53	6.384
	May	233	347	-114	114.00	0.49	0.239
	Jun	67	237	-170	169.67	2.53	6.413
	Jul	33	146	-113	113.00	3.42	11.725
	Aug	11	111	-100	100.00	9.09	82.645
	Sep	53	37	16	16.00	0.30	0.091
	Oct	136	32	104	103.67	0.76	0.581
	Nov	321	67	254	254.33	0.79	0.628
	Des	900	170	730	730.00	0.81	0.658
2021	Jan	820	452	368	367.67	0.45	0.201
	Feb	421	680	-259	259.33	0.62	0.379
	Mar	628	714	-86	85.67	0.14	0.019
	April	298	623	-325	325.00	1.09	1.189
	May	77	449	-372	372.00	4.83	23,340
	Jun	87	334	-247	247.33	2.84	8082
	Jul	79	154	-75	75.00	0.95	0.901
	Aug	104	81	23	23.00	0.22	0.049
	Sep	0					
	Oct	0			Total	240.46	12184.21
	Nov	0				MAPE	RMSE
	Des	0				3.54	0.13

L. Comparison Results

In this study, a comparison was made to measure the accuracy of the monitoring tool data made with data from the BMKG in August. The results of the comparison can be seen in table 7.

TABLE 7. Comparison results

Year	Month	BMKG	Monitoring Tool	*Error*	*Absolute*	MAPE	^2
2021	Aug	104	132	-28	28	3.71	13.8
	Sep	0	0			**MAPE**	**RMSE**
	Oct	0	0			3.71	0.04

Volume 6, Issue 10, pp. 1-6, 2022.
ISSN (Online): 2456-7361

Prediction Calculation

a. MAPE

$$= \frac{240.46}{68} = 5{,}4\%$$

b. RMSE

$$\text{RMSE} = \sqrt{\sum \frac{(At-Ft)^2}{n}} \times 100\%$$

$$\sqrt{\sum \frac{12184.21}{68}} \times 100\% = 0{,}13$$

Comparison Calculation

a. MAPE

$$= \frac{3.71}{1} = 3{,}71\%$$

b. RMSE

$$= \sqrt{\sum \frac{(At-Ft)^2}{n}} \times 100\%$$

$$= \sqrt{\sum \frac{13.796}{1}} \times 100\% = 0{,}04$$

Table 6 explains that to determine a certain level of accuracy from a given data set using the Mean Absolute Percentage Error (MAPE) method. The results of the prediction analysis using the moving average method obtained an accuracy rate of 0.13 RMSE and 3.54% MAPE. Then in table 7 shows the results of the comparison of data from the tool made with data from the BMKG, the accuracy rate of RMSE is 0.04 and MAPE is 3.71%.

IV. Conclusion and Suggestion

A. Conclusion

Based on the results of data analysis and testing of Internet of Things-based rainfall data monitoring tools in the application of the Oldeman classification, it is concluded that (1) the Internet of Things-based rainfall monitoring system has been successfully designed with the help of raspberry devices, rainfall sensors, RTC, flash drives, modems. , and has been able to perform its functions in accordance with the purpose of making smart farming tools, such as reading data from sensors and RTC, storing data (data logger), modem as a wifi connection, then displaying rainfall data to the web service and has been tested using testing tools and black box testing. (2) the internet of things-based rainfall monitoring system application has been able to present rainfall data.

B. Suggestion

Making this tool is still far from perfect, for the development of the tool at a later stage there are several suggestions, namely: (1) Further research can be developed with better sensors in detecting rainfall. (2) it is recommended to make a data backup program so that the measured daily rainfall data is regular and durable in the weather during implementation in the field.

References

[1] P. Cianconi, S. Betrò, and L. Janiri, “The impact of climate change on mental health: a systematic descriptive review,”*Front. psychiatry*, vol. 11, p. 74, 2020.

[2] NK Arora, “Impact of climate change on agriculture production and its sustainable solutions,” *Environmental Sustainability*, vol. 2, no. 2. Springer, pp. 95–96, 2019.

[3] C. Muslim, "Climate Change Mitigation in Maintaining Rice Paddy Soil Productivity (Case study in Indramayu Regency) Climate Change Mitigation In Maintaining Land Productivity Rice Rice Fields (Cases; Regency of Indramayu) Chairul Muslim Indonesian Cent," vol. 13, no. 3, pp. 211–222, 2013.

[4] S. Lu, X. Bai, X. Zhang, W. Li, and Y. Tang, “The impact of climate change on the sustainable development of regional economy,”*J. Clean. Prod.*, vol. 233, pp. 1387–1395, 2019.

[5] C. Lúcio, CM Silva, and V. Sousa, “A scale-adaptive method for urban rainwater harvesting simulation,” *environment. science. Pollut. res.*, vol. 27, no. 5, pp. 4557–4570, 2020.

[6] H. Waqas *et al.*, “Flash flood susceptibility assessment and zoning using an integrating analytic hierarchy process and frequency ratio model for the Chitral District, Khyber Pakhtunkhwa, Pakistan,” Water, vol. 13, no. 12, p. 1650, 2021.

[7] IA Nurdiyanto, “Internet of Things (IoT)-Based Rainfall Data Monitoring,” *Semin. Nas. Deen. information. 2020*, vol. Vol 4, No, pp. 46–50, 2020.

[8] HS Lestari, “Smart agriculture as an effort for Indonesia to be food independent,” vol. 2, no. 1, pp. 55–59, 2020.

[9] JPM Stočes, J. Vaněk, J. Masner, “Internet of Things (IoT) in Agriculture - Selected Aspects,”*AGRIS on-line Pap. econ. Informatics*, vol. 8, no. 1, pp. 83–88, 2016, doi:10.7160/aol.2016.080108.Introduction.

[10] M. Ayaz, M. Ammad-Uddin, Z. Sharif, A. Mansour, and E.-HM Aggoune, “Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk,” *IEEE access*, vol. 7, pp. 129551–129583, 2019.

[11] IS Harahap, IZ Matondang, and E. Kumala, “Mapping Climate Classification of Oldeman in Agricultural Resources Management in South Tapanuli District Mapping Climate Classification of Oldeman in Agricultural Resources Management in South Tapanuli District,” doi: 10.1088/1757-899X /1156/1/012002.

[12] F. Tamrin, A. Asrul, and others, “Integration of Wifi and Mobile Communications in Fire Early Warning Data Sending in Home Based on The Internet of Things,” *Ceddi J. Inf. syst. Technol.*, vol. 1, no. 1, pp. 1–6, 2022.

[13] BPG Ryan, “the Design and Development of an Inlet Volute,” no. 3, 2011.

[14] N. Alsbou, NM Thirunilath, and I. Ali, “Smart Home Automation IoT System for Disabled and Elderly,” in*2022 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)*, 2022, pp. 1–5.

[15] S. Ameer *et al.*, “Comparative analysis of machine learning techniques for predicting air quality in smart cities,” IEEE Access, vol. 7, pp. 128325–128338, 2019.

[16] Z. Hu, Y. Zhao, and M. Khushi, “A survey of forex and stock price prediction using deep learning,”*app. syst. Innov.*, vol. 4, no. 1, p. 9, 2021.

[17] N. Sustainable *et al.*, "Forecasting Tourist Visits with the SARIMA Model Approach (Case study: Kusuma Agrowisata)," vol. 1, no. 1, 2012.

[18] JW Koo, SW Wong, G. Selvachandran, HV Long, and LH Son, “Prediction of Air Pollution Index in Kuala Lumpur using fuzzy time series and statistical models,”*Air Quality. Atmos. \& Heal.*, vol. 13, no. 1, pp. 77–88, 2020.

[19] U. Sahin and T. Sahin, “Forecasting the cumulative number of confirmed cases of COVID-19 in Italy, UK and USA using fractional nonlinear gray Bernoulli model,” *Chaos, Solitons \& Fractals*, vol. 138, p. 109948, 2020.

[20] X. Shi *et al.*, “State-of-the-art internet of things in protected agriculture,” Sensors, vol. 19, no. 8, p. 1833, 2019.