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Rain Intensity Forecast with Microcontroller Based Pluviometer and Machine Learning

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HIGHLIGHTS

- Global warming manifests itself as an irregularity in rainfall.
- Correct measures should be taken to determine the rainfall irregularities.
- More efficient use of water resources can only be achieved through data analysis.
- In this research, a new mobile pluviometer was developed.
- The rainfall intensity was best determined by Random Forest algorithm.

Abstract: One of the most important problems today is global warming, which occurs because of negative changes in the ecosystem. Global warming manifests itself as an increase in temperature, also a decrease in the number of glaciers, additionally an increase in seawater level, and irregularities in the rainfall. Correct measures should be taken to get rid of the resulting rainfall irregularities with the least damage. More efficient use of water resources can only be achieved through data analysis. In agriculture, the amount of rain falling on the field per unit of time is critical. The research focused on the amount of rain falling per unit time and a new mobile pluviometer was developed for this aim. With the designed microcontroller-based pluviometer, the rainfall intensity was determined, and after that data analysis was made with machine learning. In the developed pluviometer, firstly, the calibration process was performed, and then the rainfall intensity measurements were taken successfully. When these studies are considered, usage opportunities arise in subjects such as measuring the intensity of rainfall, efficient use of water, and taking precautions against natural disasters. Using machine learning techniques, Decision Tree, Random Forests, and Naive Bayes, the rainfall intensity forecasted between 98.5 to 100 % accuracy within the area of the investigation.

Keywords: pluviometer; rainfall intensity; microcontroller-based control; ultrasonic sensor; machine learning.

INTRODUCTION

Rain is one of the most important atmospheric events, which is useful not only for the environment but also for all living things on Earth. Rain has a significant effect on the universal indicator of atmospheric circulation and affects local weather conditions. In recent years, rainfall rates have undergone unexpected changes, so rainfall measurements are made to understand rain problems and to classify the amount. It is very important to know what rain is for rainfall measurements. The small grains of water with a diameter of 0.001-0.040 mm, which form fog and clouds, come together to be larger than 0.5 mm and when aggravated, they begin to fall to the ground as they do not succumb to the vertical air movements present in the clouds. These grains, which fall to the ground following a path in the atmosphere, are called rain [1].

The distribution of rainfall in the world varies noticeably due to the different locations. The annual rainfall exceeds 2200 mm in some stations, while some stations fall below 300 mm per year. There is a close relationship between the annual rainfall distribution map and the ground shapes and elevation. In Turkey, the change of ground shapes at a short distance and the increase in elevation values suddenly affect the annual rain distribution [2].

According to the data obtained from the Turkish State Meteorological Service in Turkey, the average rain in 268 stations is 628 mm. Turkey is in the 'Semi-Arid Climate Zone' according to the average annual rainfall. However, the distribution of rainfall varies significantly from region to region. Also, according to the data of the Turkish State Meteorological Service, rainfall intensities are classified as the categories in Table 1, ignoring the topography between regions with quantity-based measurement in 12 hours [3].

Table 1. Classification of rain intensity [3].

Rain Intensity Classification		
1. Light Rainfall	:	1-5 mm
2. Moderate Rainfall	:	6-20 mm
3. Heavy Rainfall	:	21-50 mm
4. Very Heavy Rainfall	:	51-75 mm
5. Severe Rainfall	:	76-100 mm
6. Extreme Rainfall	:	Over 100 mm

Different applications have been adopted using different methods based on the prediction of phenomena such as rainfall and temperature for human life, which are mentioned in the literature. Some of the literature in the field of rain studies and analysis are as follows. Crane [2] investigated 100 years of rainfall data from 104 stations in the United States. He used the self-organizing maps (SOMs) method from applications of artificial neural networks. In this way, he used the rainfall records of the stations to combine them into the regional dataset. Partal [4] carried out the research by applying artificial neural networks and wavelength analysis together for the first time to realize Turkey's daily rainfall forecast with the rainfall data. It has been determined that wavelength analysis makes important contributions to artificial neural network models. Sahin and coauthors [5] used the Fuzzy C-averages method to determine the sub-rain regions of Turkey. In their studies, they analyzed rain and temperature data for the period 1974-2002 and created a total of 15 sub-rain regions scattered throughout the 7 main climate zones in Turkey. Ahmad and coauthors [6] used hierarchical clustering methods to examine 30 years of rainfall data collected from 59 stations in Malaysia. In their studies, they describe three homogeneous rain regions on the Malaysian Peninsula with different natural and rain characteristics: A, B, and C. İyigün and coauthors [7], in 1970-2010, reclassified the climate zones of Turkey with the total monthly rainfall, humidity, and temperature data collected in 244 stations using the 'Ward' method from hierarchical clustering methods. According to the results obtained, 14 different clusters were created in Turkey, and they determined that these clusters were realistic in reflecting the climate zones. Ruivo and coauthors [8] conducted research using classification methods of data mining to determine the causes of frequent 'Santa Catarina' rain and Amazon droughts. As a first stage, they identified a subset of climate variables. In the next stage, the subsets used decision trees to divide them into weak, medium, and heavy rainfall intensity classes. Uzunali [9] used the data of the Kandilli Observatory and Earthquake Research Institute Directorate to estimate the average rain value using 100 years of data from the Kandilli Region between January 1918 and December 2018. In their study, average monthly rainfall meteorological data provide appropriate resources for time series data analysis.

The fact that meteorology stations are established at wide intervals sometimes cannot provide healthy and sufficient decision-support information for farmers' private production areas. And today, machine learning (ML) algorithms are commonly used in classification and regression models. ML offers the solution through easy and rapid simulations and overcomes several problems [10, 11]. ML presents powerful, effective, and accurate results in the evaluation of some engineering cases. In addition, various ML algorithms for adapting input-output mapping strategies as well as choosing useful features could perform [12, 13]. So, it is aimed to avoid this decision-support information deficiency with the help of mobile system data and machine learning algorithms. To measure the number of water particles falling from the atmosphere to the earth as rainfall, which has a skill of record, and unrecord pluviometer systems are used. A pluviometer is a rainfall measurement system that directly measures the amount of rain by calculating the total rain height. The amount of daily rain is kg/m^2 and the annual rain amount (mm, cm, m) can be measured with a pluviometer [14]. Because of this reason, in this study, a new mobile pluviometer was developed, and rainfall intensity was measured under laboratory conditions. In the developed pluviometer, calibration was performed first and then rainfall intensity measurements were successfully taken. With the designed microcontroller-based pluviometer, rainfall intensity was determined, and machine learning-based data analysis was performed. The used machine learning algorithms in this research are Decision Tree, Random Decision Forests, and Naive Bayes, respectively. These three algorithms were studied with various test rates to achieve the optimum success value.

MATERIAL AND METHODS

The system established in this research includes electronic equipment, as well as the software used to control this hardware. In this context, it was mentioned that the use of the pluviometer consisting of this software and hardware in laboratory conditions, the aim of getting the data and evaluations with the three different machine learning algorithms.

Equipment used for system design

Many electronic components have been used in the development of a microcontroller-based rain intensity measurement system. Arduino microcontroller unit is one of the components that make up the prototype pluviometer. Arduino is a microcontroller unit that enables interaction and communication with physical parameters. Arduino is a microcontroller that provides the control mechanism and various applications can be made by programming its microcontroller [15]. As time goes on, different types of Arduino cards appear. So, the Arduino type can be selected for the purpose according to the project to be used. Arduino UNO R3 development card was used in this research.

Arduino Uno R3 uses an ATmega328P processor (Figure 1). There are 14 digital input and output pins, and 6 of the pins are PWM outputs. The Arduino Uno R3 development card has a 16 MHz crystal oscillator, USB connection, 6 analog input pins, 2.1mm power input, ICSP header, and reset button. Arduino Uno R3 has everything it takes to support the microprocessor, and it takes enough to connect it to a 7~12V DC power supply to work [16].

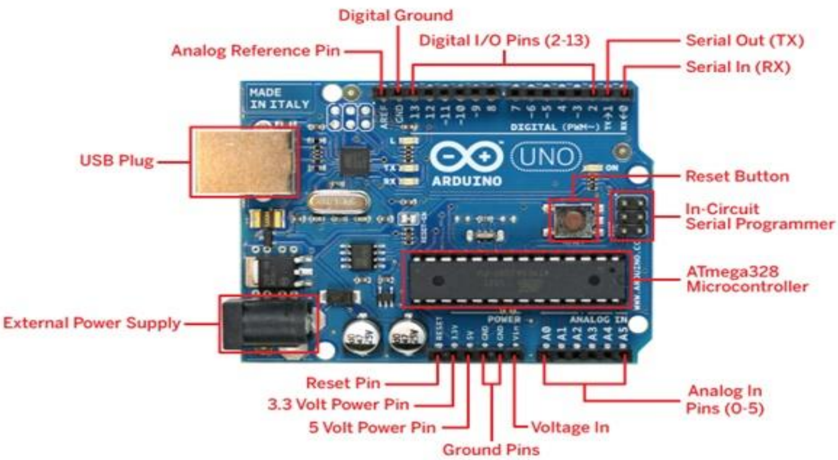

Figure 1. ATmega328P Ardunio [16]

Another piece of equipment used in the rain measurement system is the DS3231 RTC module. The output of the DS3231 RTC module can be retrieved from seconds to time intervals and from day to year data. The integrated internal oscillator and temperature measurement in the module can operate at a deviation rate of 1 minute per year [17].

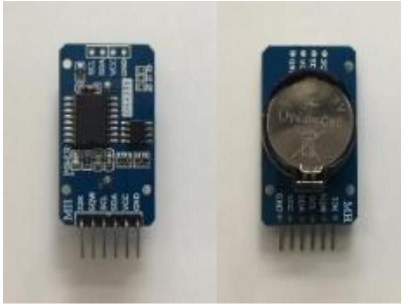

Figure 2. DS3231 RTC module.

The IRF520 MOSFET module was used to operate the water pump in the rain measurement system (Figure 3) [18].

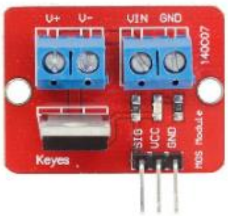

Figure 3. The IRF520 MOSFET module.

Also, in the system design, the HC05 Bluetooth-serial module card was used for Bluetooth SSP wireless serial communication. (Figure 4). In addition to supporting Bluetooth 2.0, the HC05 Bluetooth module provides communication at a frequency of 2.4 GHz and around 10 meters. In this study, it was used to monitor wireless data transmission and the operation of the device [19].

Figure 4. HC05 Bluetooth module.

Additionally, in the research, a digital water flow sensor compatible with Arduino was used. It is a plastic body product with a rotor and hall effect sensor. A conductor in contact with a magnetic field creates a voltage difference in the right direction to the current and magnetic field passing through it, and this voltage difference is defined as Hall Effect. When water starts flowing through the hall-operated flow absorber, the rotor begins to rotate, and the hall effect sensor generates a signal according to the rotor's rotational speed (Figure 5). Since it has a digital output, it can be used with Arduino and microcontroller platforms.

Figure 5. Digital water flow sensor.

The HC-SR04 ultrasonic sensor is used to calculate how high the rain comes from. HC-SR04 ultrasonic sensor calculates the distance to the object opposite (Figure 6). The ultrasonic system calculates the distance of the object with the help of sound waves. Since the speed at which the sound is emitted in the air is known, the distance between the trig pin can be calculated by measuring the amount of time the ECHO pin is active from the signal given to the TRIG pin.

Figure 6. HC-SR04 sensor.

In the study, a micro-SD card module was used to read and write rainfall data to SD cards via SPI protocol available with Arduino and many microcontroller platforms (Figure 7).

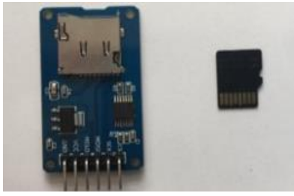

Figure 7. Micro SD card module.

Additionally, a submersible pump used in the research; is a pump type that works in the liquid. The connection locations are positioned separately so that they do not pass water. It can use the 5V mini submersible motor from a 5V USB port by connecting the plus and minus ends with a 5V source (Figure 8). The mini submersible water pump functions at a 3V to 6V DC voltage.

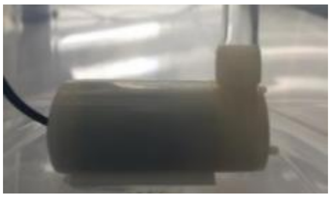

Figure 8. A mini submersible pump.

The most important factor in the systems developed to determine the amount of rainfall is the size of the surface area of the container to be used in the collection of rain to be measured. If the area of the container is small, problems arise in rainwater collection in windy weather conditions (Figure 9). In the rainfall collection, a container used within the scope of the prototype study, the size of the rainwater collection container was selected by optimizing the mobility of the pluviometer. During times of very heavy rainfall, the entire amount of rain that falls in the collection area can be measured.

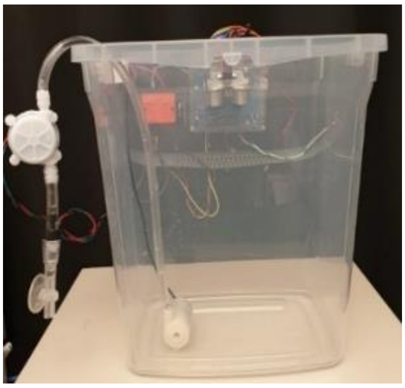

Figure 9. Rain collection container.

The liquid level measurement method, which operates with the developed electronic system can make measurements with high precision to determine the amount of water remaining in the measuring container. With the ultrasonic sensor HC-SR04, which detects the liquid surface in the electronic level measurement system, the movement of the liquid in the vertical direction can be measured quickly. The working time of the submersible pump can be determined by the microcontroller on the development card that controls the system. The distance taken afterward is calculated by the microcontroller and the water depth of the measuring container is determined.

Principle of operation of rain intensity measurement system

The schematic representation of the microcontroller-based pluviometer used in this research is shown in Figure 10. ATmega328P microcontroller, which is produced by ATMEL, was used to carry out all control, measurement, and data transmission operations of the automatic rain measurement system carried out within the scope of the study.

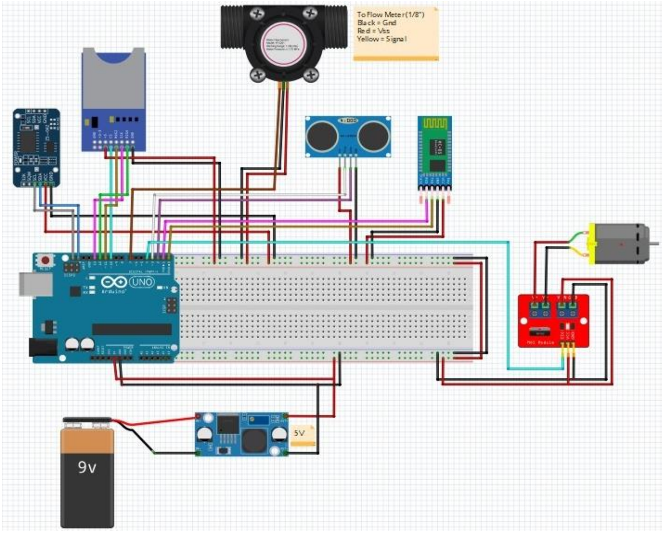

Figure 10. Circuit diagram of rainfall measurement system.

A ranked cup with a volume of 500 mL was used in the calibration of the rain measurement system. The calibration process of the rain measurement system can be seen in Figure 11 with the calibration of the rain measurement system.

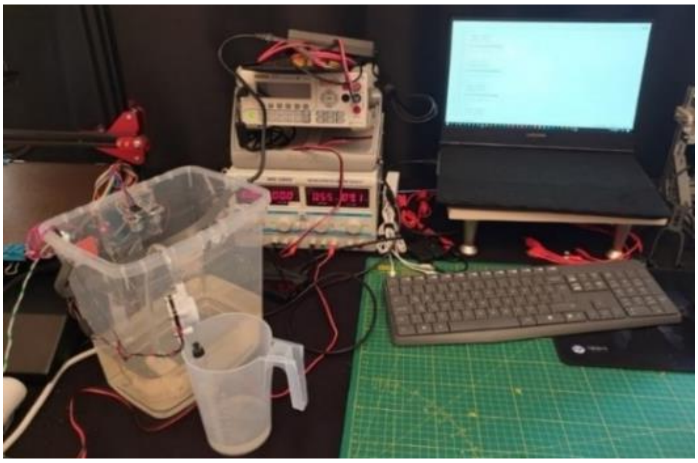

Figure 11. Calibration of rain measurement system.

In this study, three different classification algorithms based on machine learning were used for rain measurement. These are Decision Trees, Random Decision Forests, and Naive Bayes classification and forecasting algorithms. For the analysis, the data analysis algorithms with KNIME software were carried out successfully.

Decision tree

In machine learning, segmentation is classified to understand the relationship between target and input qualities. Decision trees and induction methods, in general, have arisen through the acquisition of knowledge for professional systems, and the development of machine learning to avoid time-consuming methods [20]. Decision trees are an efficient non-parametric method used for classification purposes. Hierarchical data structures for supervised training, where the input field is divided into local regions to predict the dependent variable. A single decision tree algorithm is being developed specifically prepared for datasets from each application area (homogeneous approach) [21]. The data left for machine learning creates a model for the classification algorithm and allows us to get an accurate analysis (Figure 12).

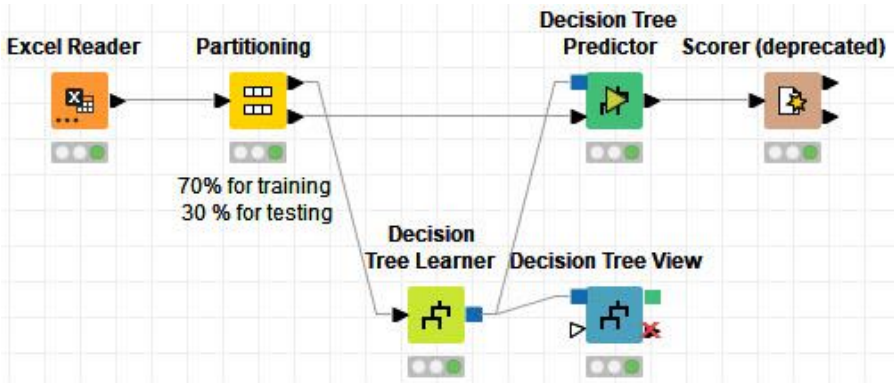

Figure 12. KNIME Decision Tree flow diagram.

Random Forest

Random Forests can be defined as versatile and intelligent machine learning algorithms. It is a method that can perform the classification task. In addition, dimension reduction methods may not detect outliers but can detect missing values and make data discovery steps possible with healthy results. It is an expert solution for most problems. This is known as a collective training path, as a group of weak models is combined to create a powerful model [21]. A random forest occurs with multiple decision trees. This is the opposite of the CART model. Each tree offers a classification for the classification of new object-based attributes (Figure 13). This presentation is also known as 'voting' for the class. It then offers the forest the option to choose the classification that receives the most votes and reflects the result in a branched form [21].

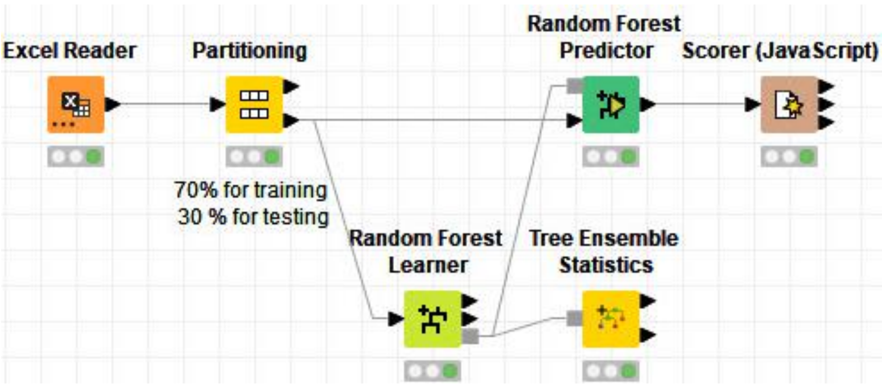

Figure 13. KNIME Random Decision Forests flow diagram.

Naive Bayes Classifier

This rule-based algorithm is often limited in use because common rules cannot be reduced in real life. Naive Bayes theorem, which is one of the probabilistic methods, can be explained. In other words, it questions the possibility of condition an if condition B occurs (Figure 14). This example also means condition change status. In this case, the possibilities of A and B can be answered separately when known [21].

$$\boldsymbol{P(A|B)} = \frac{\boldsymbol{P(B\backslash A)\,P(A)}}{\boldsymbol{P(B)}}$$

P(A| B): Last probability,
P(B| A): Similarity,
P(A): Pre-possibility.

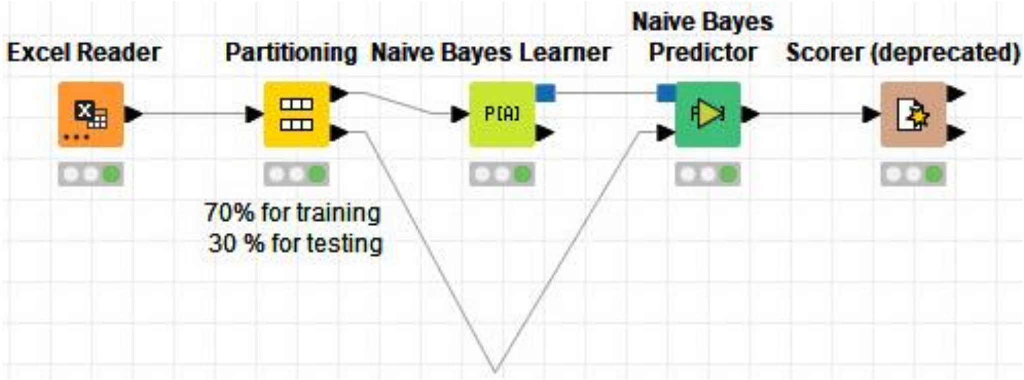

Figure 14. KNIME Naive Bayes flow diagram.

Validation Methodology

The data in the study were obtained in four different categories due to the low monthly rain average in the Central Anatolia Region in Turkey, especially the average monthly rain of 58 millimeters in Ankara province. These rain levels were light (1-5 mm), moderate (6-20 mm), heavy (21-50 mm), and very heavy (51-75 mm). A total of 400 measurement data, including 100 for each rain intensity, were evaluated. Decision Tree, Random Forests, and Naive Bayes machine learning algorithms were used respectively. For all three algorithms, the results of 50% and 50%, 60% and 40%, 70% and 30%, 80% and 20% training and test rates were used based on the random selection of training data and presented with Cohen's kappa (κ) coefficients.

RESULTS

The first step was the calibration of the pluviometer. The regression equation and regression coefficient of the calibration of the rain measurement system are seen in Figure 15.

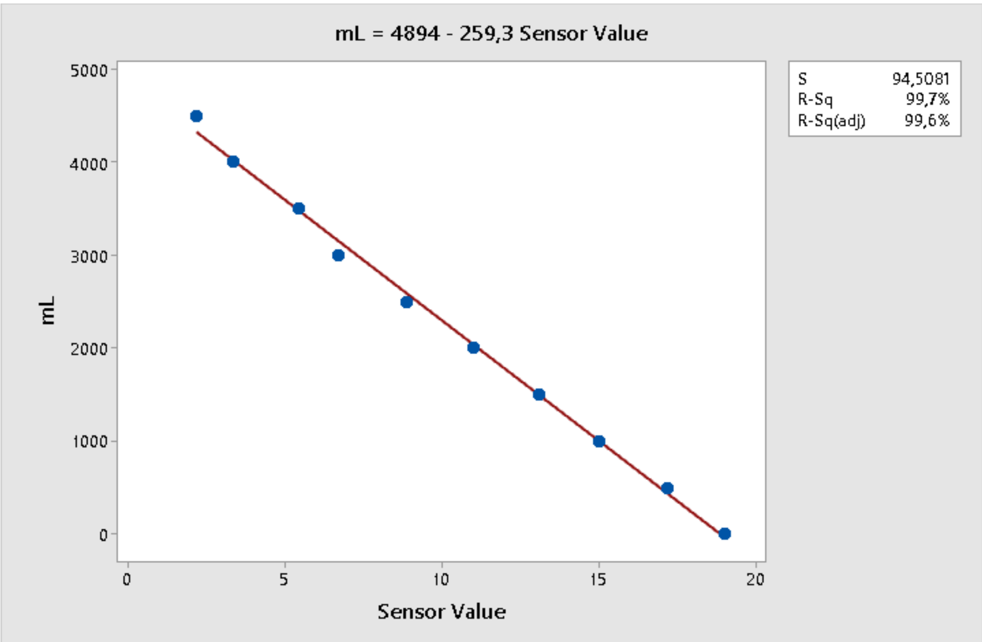

Figure 15. The regression equation and regression coefficient of calibration of rainfall measurement system.

In the research, KNIME data analysis software was used for machine learning. It allows data processing, visualization, and reporting by ensuring that it is in the stream with the nodes under KNIME. Three different machine learning algorithms were used. Algorithms are Decision Tree, Random Forests, and Naive Bayes, respectively. For all three algorithms, the results of 50% and 50%, 60% and 40%, 70% and 30%, 80% and 20% training and test rates were used based on the random selection of training data and presented with Cohen's kappa (κ) coefficients respectively. Cohen's kappa coefficient is a statistical method that measures the reliability of comparative agreement between two raters. As shown in Figure 16 for the 50% and 50%

training and test rate of the total data in the Decision Tree algorithm, the test data was determined as light rain with an accuracy value of 99.5% with Cohen's kappa (κ) coefficient 0.99, and the limit values of other rain classes were successfully categorized and classified.

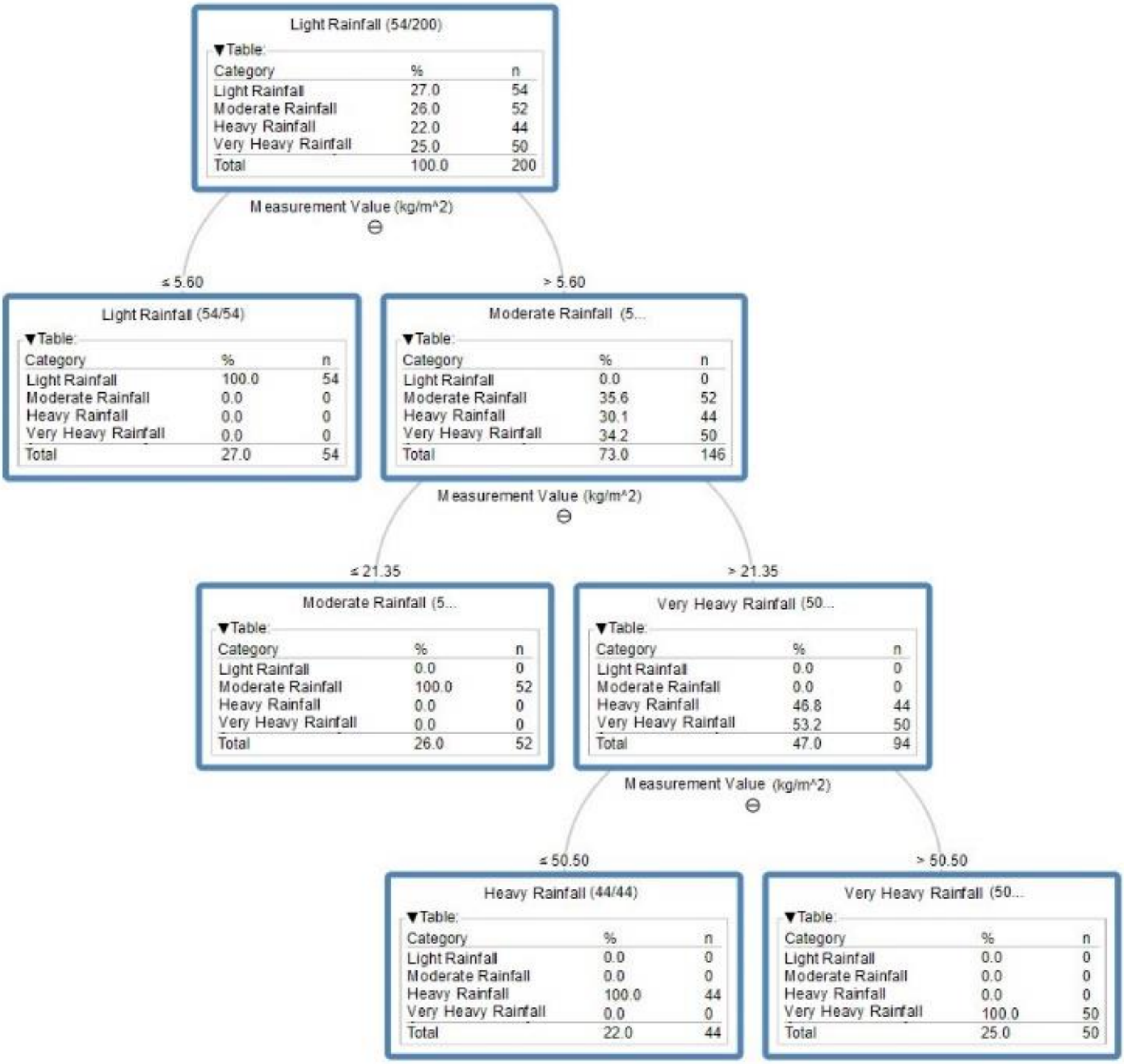

Figure 16. Decision Tree Analysis results in the 50% training / 50% test rates.

Figure 17 for the 60% and 40% training and testing rate of total data in the Decision Tree algorithm. The test data was determined as heavy rainfall with a 100% accuracy value with Cohen's kappa (κ) coefficient 1 as seen in Figure 17, and the limit values of other rain classes were successfully categorized and classified.

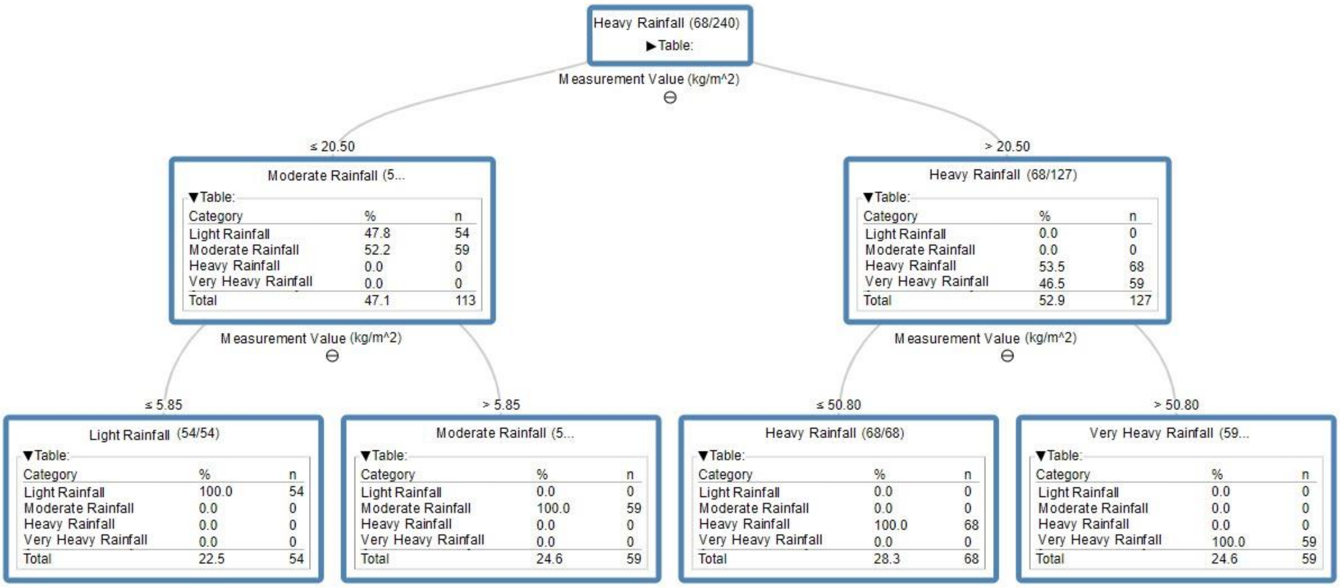

Figure 17. Decision Tree Analysis results in the 60% training / 40% test rates.

In addition, Figure 18 for 70% and 30% training and testing rate of total data in the Decision Tree algorithm. The test data was determined as moderate rain with a 100% accuracy value with Cohen's kappa (κ) coefficient 0,98 as seen in Figure 18. The boundary values of other rain classes are successfully categorized and classified.

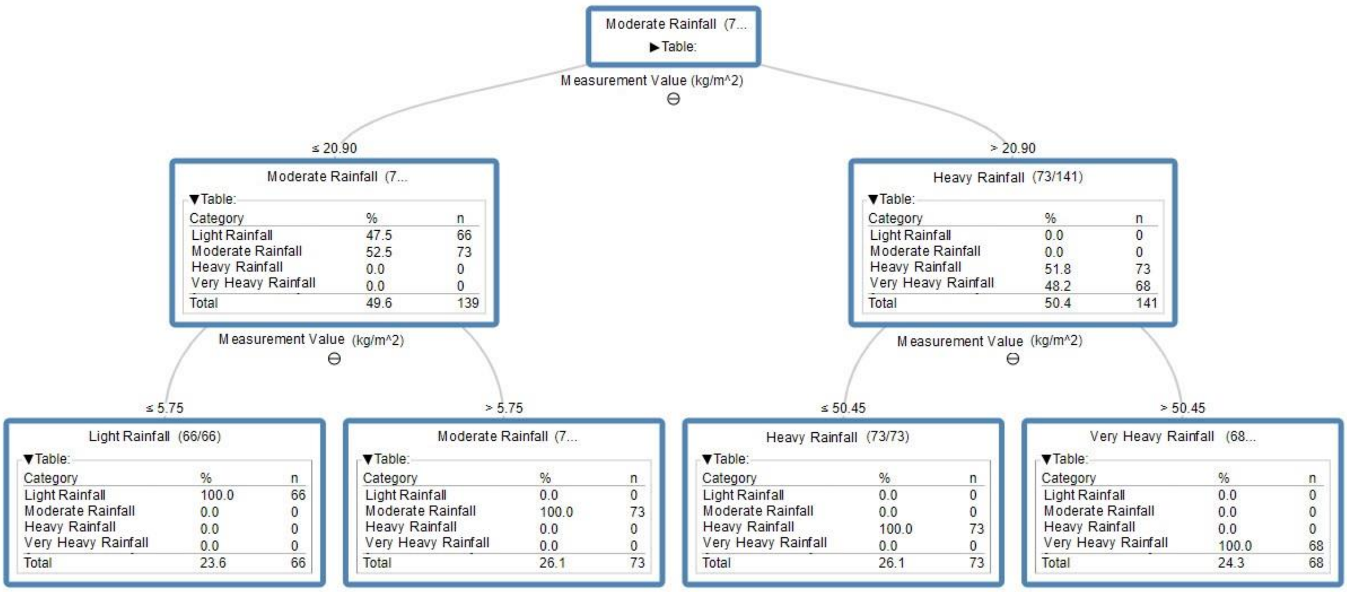

Figure 18. Decision Tree Analysis results in the 70% training / 30% test rates.

Finally, in the Decision Tree algorithm, Figure 19 for the 80% and 20% training and testing rate of the total data. The test data was determined as light rain with a 100% accuracy value with Cohen's kappa (κ) coefficient 1 as seen in Figure 19, and the limit values of other rain classes were successfully categorized and classified.

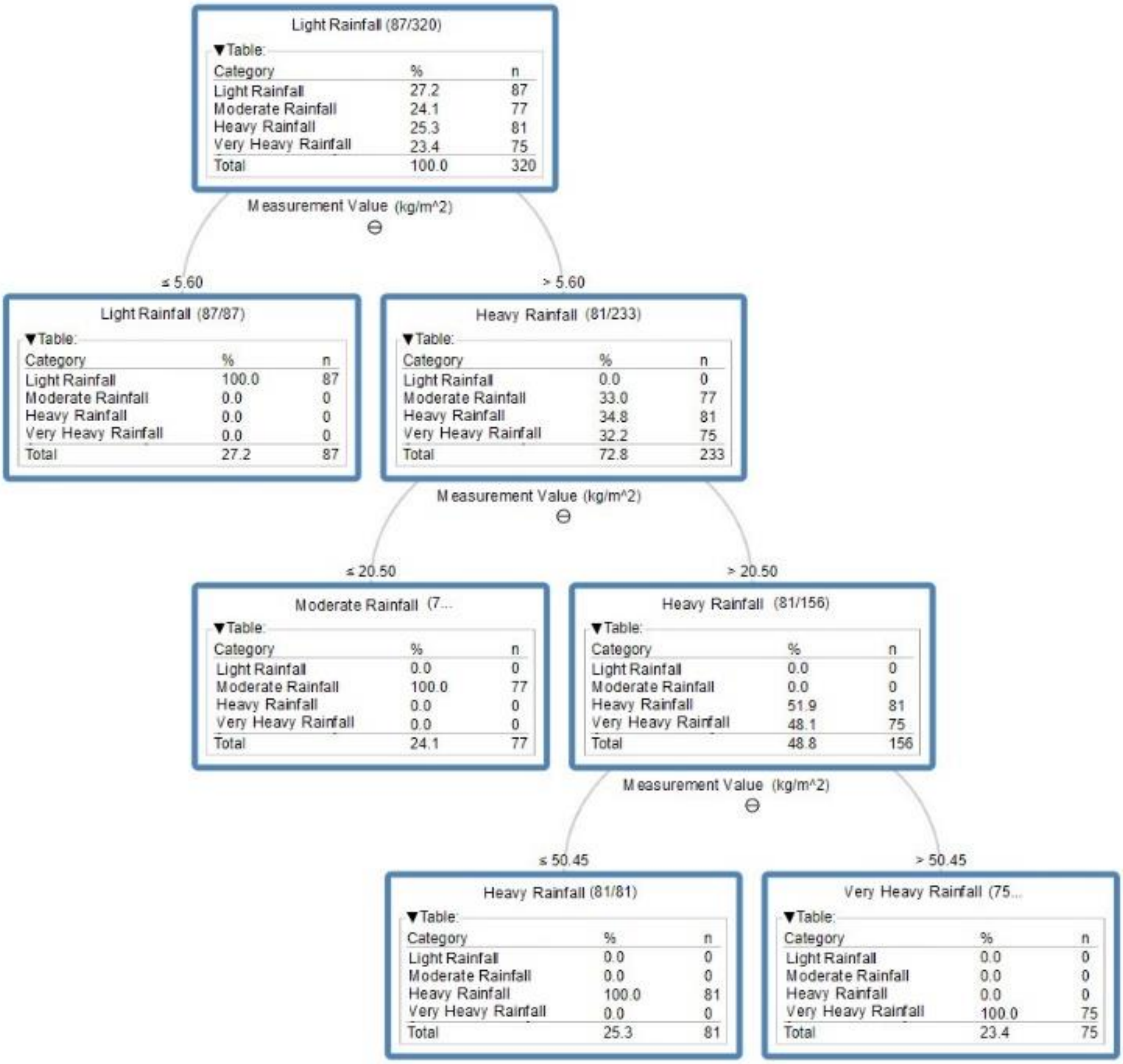

Figure 19. Decision Tree Analysis results in the 80% training / 20% test rates.

Figure 20 for a 50% and 50% training and testing rate of total data in the Random Forests algorithm. The test data was determined as moderate rain with a 100% accuracy value with Cohen's kappa (κ) coefficient 1 as seen in Figure 20, and the limit values of other rain classes were successfully categorized and classified.

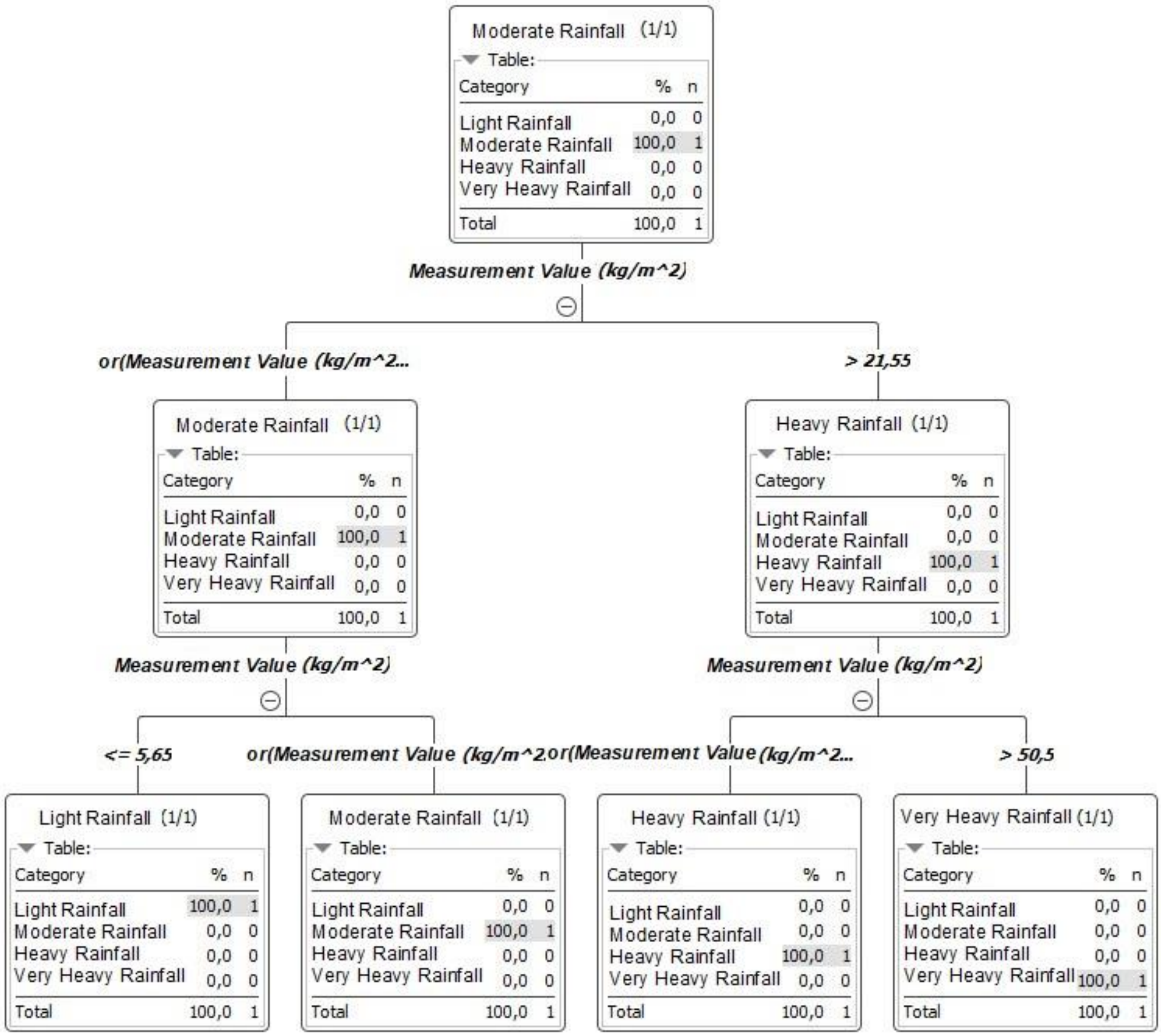

Figure 20. Random Forests analysis results for 50% Training / 50% test rates.

According to Figure 21 for a 60% and 40% training and testing rate of total data in the Random Forests algorithm, the test data was determined as moderate rain with a 100% accuracy value with Cohen's kappa (κ) coefficient 1 as seen in Figure 21, and the limit values of other rain classes were successfully categorized and classified.

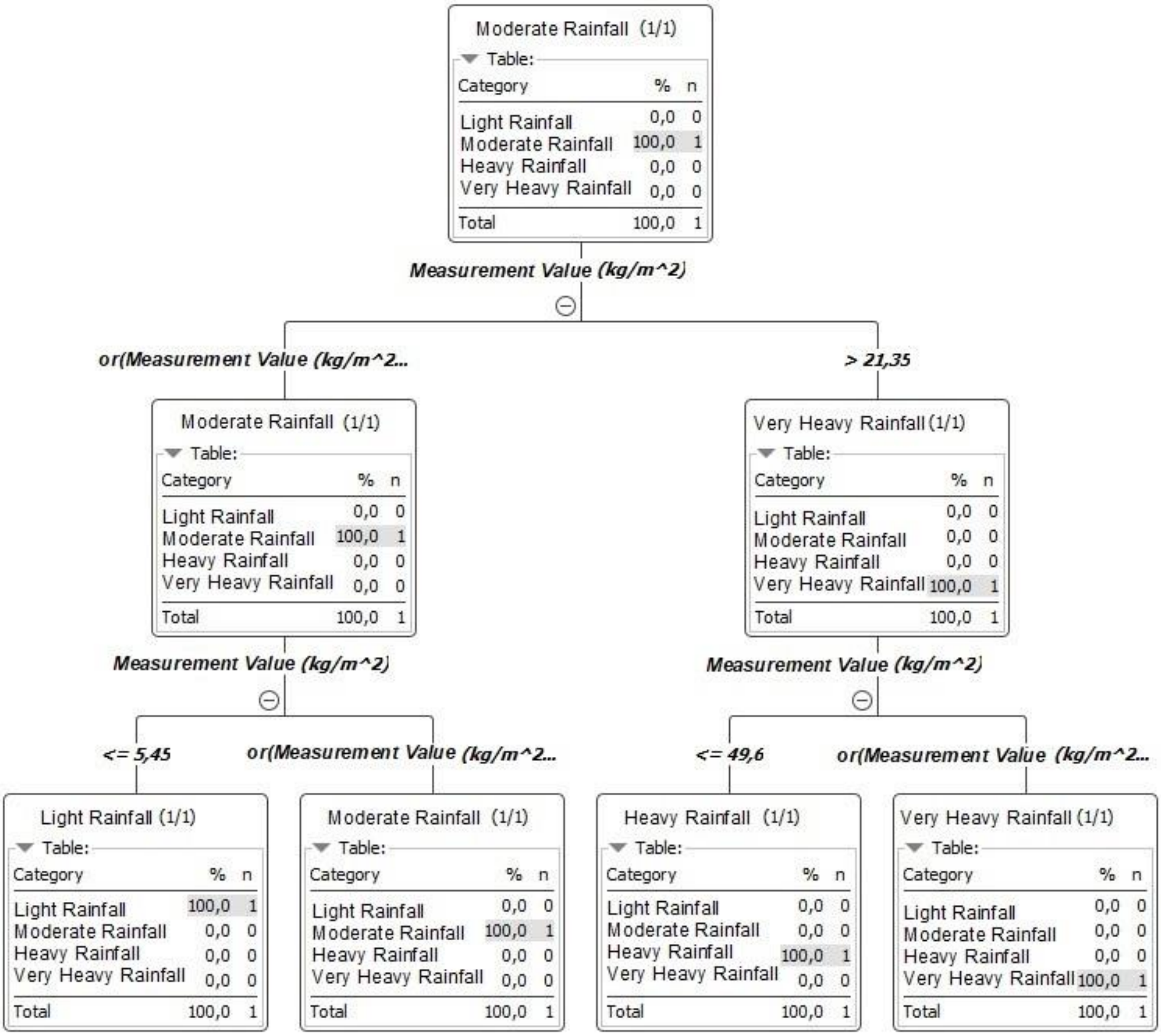

Figure 21. Random Forests analysis results for 60% Training / 40% test rates.

In addition, in the Random Forests algorithm, Figure 22 for 70% and 30% training and testing rate of total data, the test data was determined as moderate rain with a 100% accuracy value with Cohen's kappa (κ) coefficient 1 as seen in Figure 22, and the limit values of other rain classes were successfully categorized and classified.

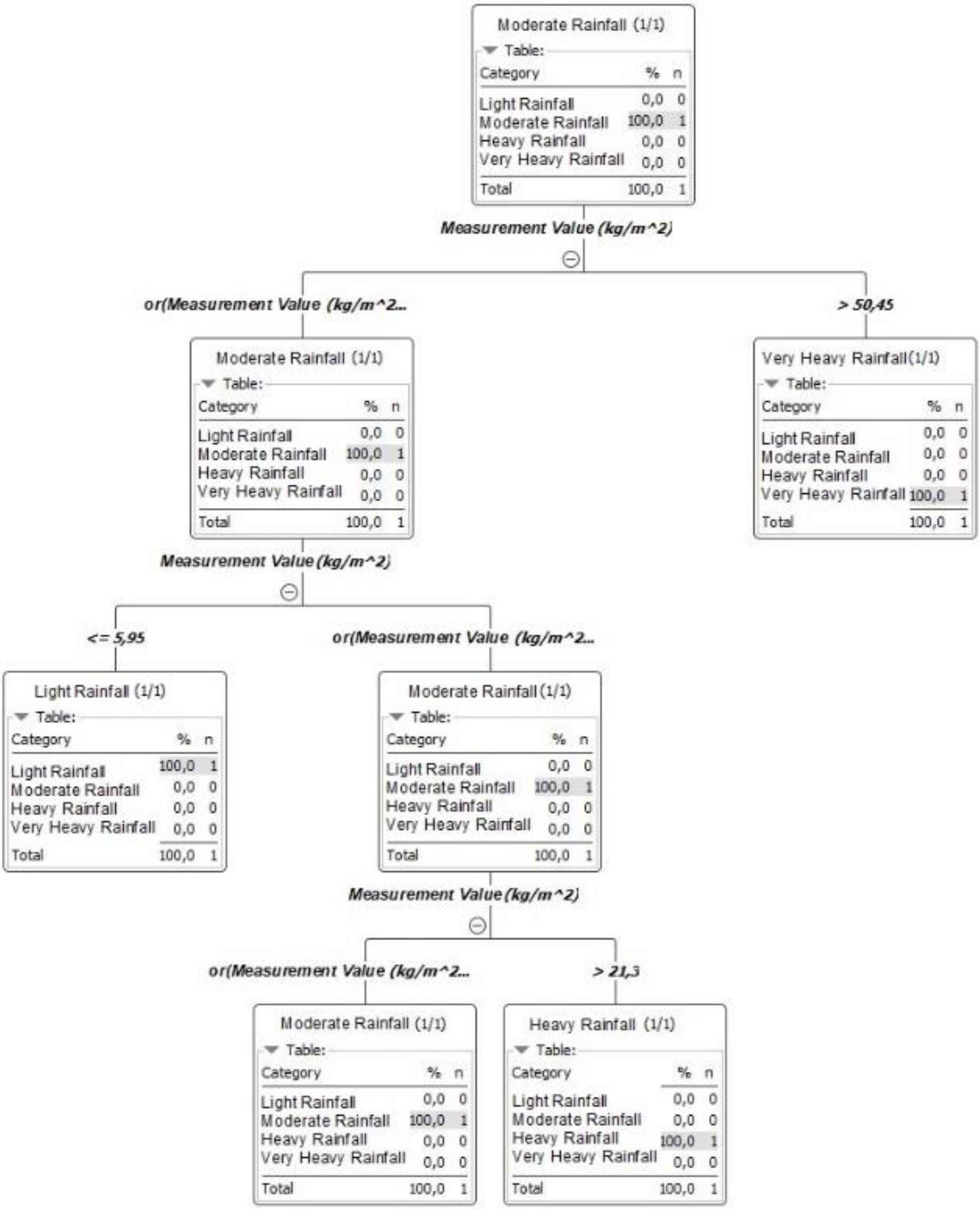

Figure 22. Random Forests analysis results for 70% Training / 30% test rates.

Finally, in the Random Forests algorithm, Figure 23 for the 80% and 20% training and testing rate of the total data, the test data was determined as moderate rain with a 100% accuracy value with Cohen's kappa (κ) coefficient 1 as seen in Figure 23, and the limit values of other rain classes were successfully categorized and classified.

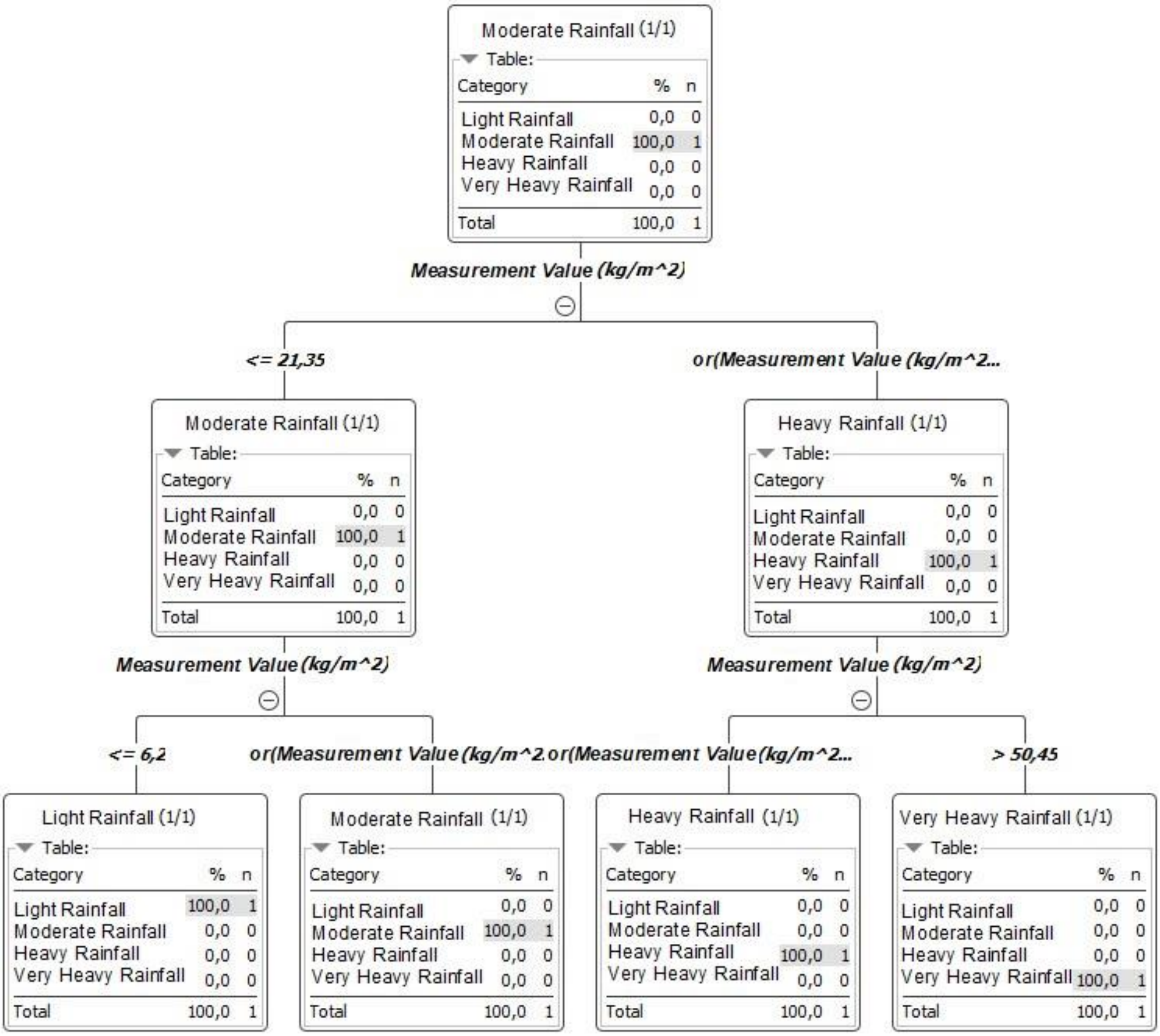

Figure 23. Random Forests analysis results for 80% Training / 20% test rates.

The 50% and 50% training and testing rate of total data in the Naive Bayes algorithm, the accuracy value of 99.25% with Cohen's kappa (κ) coefficient 0.99, and the limit values of other rain classes were successfully categorized and classified. Also, in the Naive Bayes algorithm, the limit values of other rain classes were successfully categorized with an accuracy value of 99.25% with Cohen's kappa (κ) coefficient 0.99, for the 60% and 40% training and testing rate of the total data. Additionally, in the Naive Bayes algorithm, the 98,50% accuracy value with Cohen's kappa (κ) coefficient 0.98 and the limit values of other rainfall classes were successfully categorized and classified for the 70% and 30% training and testing rate of the total data. Finally, in the Naive Bayes algorithm, the 80% and 20% training and testing rate of the total data is categorized successfully categorized with an accuracy value of 98.88% with Cohen's kappa (κ) coefficient 0.98 and the limit values of other rainfall classes.

The operation, obtaining of the data, interpreting, and evaluation of the microcontroller-based Pluviometer device used in the research was carried out in the laboratory environment. The results with high accuracy values obtained by the different machine learning algorithms used within the scope of the research were successfully determined and classified. With future field test studies, it will be possible to use the device outdoors where it is needed to predict rainfall by analyzing time series.

DISCUSSION

In addition to the efficient use of water resources, it is necessary to analyze the amount of rain falling in the unit area with the right methods, especially in agricultural areas. However, a lack of data due to many problems for the future can be addressed by rain forecasting methods [5]. Using artificial neural networks, Saplıoglu and Çim [22] created 11 YSA models using daily rain data in their studies on estimating the daily amount of rain and examined the results obtained from these models for both training data and test data. In their study, they estimated the daily amount of rain with 91% success using the 4-neuron YSA model. Ghada and coauthors [23] used the random decision forester machine training algorithm to estimate with 98% accuracy with a machine training approach to classifying rain type based on dysdrometers and cloud observations. Ingsrisawang and coauthors [24] in their work on machine learning techniques to realize short-term rain forecasting in Thailand's Northeast Region, artificial neural network and decision support machines techniques are used to divide the amount of rainfall into three classes with no rain, low rainfall, and moderate rainfall, respectively artificial neural network, and support vector machines 68.15%, and 69.10% respectively. Moon [25] worked on the application of machine training to the early warning system for very short periods of heavy rainfall, they have achieved accuracy values ranging from 99.90% to 99.93% of all techniques used in their squatting.

In this research, the results for rainfall intensity prediction using machine learning algorithms Decision Tree, Random Forests, and Naive Bayes methods change between 98.5% to 100% accuracy values, and the desired success rates were achieved within the scope of the research.

CONCLUSION

Rain, snow, or hail is the most important parameter of the hydrological cycle. To calculate the water budget in a basin that receives water with rain, this rainfall needs to be digitized. Based on the amount of rain information, it can be estimated how much of this water seeped into the soil or was added to the flow, these parameters are of great importance for the design of hydraulic structures. Agricultural activities are also planned according to rain data. Such information is still of great interest today to understand and predict the effects of a possible event worldwide.

As a result of the research, possibilities develop in areas such as assessing rainfall intensity, maximizing water use, and preventing natural catastrophes. Also, the fact that meteorological stations are spaced far apart does not always give farmers' private production regions healthy and appropriate decision-support information. So, in this research, the advantages of the pluviometer device, which was developed to predict rain intensity using a microcontroller-based pluviometer device and machine training algorithms, can be listed as follows compared to other pluviometers available on the market. The microcontroller-based pluviometer device has portable capability and is much more mobile than other pluviometers. The recording is possible thanks to the memory card. Allows data transfer via Bluetooth. It can be used outdoors for a long time. Suitable for agricultural use. High-accuracy data measurement can be made according to the results obtained by using the machine training algorithm. Compared to other pluviometer devices, it is seen to be much more economical. It is a practical, economical pluviometer device that can be created from materials that can be obtained from the market at an affordable price. At last, and the most important feature of this device is that it is mobile, and it can be used to increase irrigation efficiency.

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