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Precipitation and water discharge for internet of things based flood disaster prediction improvement

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ABSTRACT

Floods are a major global problem affect communities and businesses. For these effects to be mitigated and emergency measures to be improved, accurate prediction is essential. Conventional flood prediction models frequently fail because the models ignore important hydrological elements like water discharge and instead solely use rainfall data. This limitation was addressed by the combination of rainfall and water discharge data on internet of things (IoT)-based technologies. It focuses on analyzing historical records from flood-prone areas in Semarang using gated recurrent unit (GRU) models. The findings demonstrate how effectively the GRU model performs when rainfall and water discharge factors are taken into account, resulting in very accurate and dependable predictions of flood events. Precision, Recall, and F1-score are evaluation metrics that demonstrate the accuracy on which the model determines flood emergency statuses. This study advances flood prediction methods and highlights the value of integrating internet of things data to improve preparedness and resilience against flood disasters.

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1. INTRODUCTION

Globally, the devastation caused by floods is increasing, impacting people and businesses alike. Flood prediction significantly is able to lessen these effects. Flood events can be predicted, allowing for better emergency reaction times, the protection of sensitive areas, and more efficient resource allocation. This may result in lower financial losses, fewer fatalities, and improved readiness for subsequent floods, which would increase resilience to natural catastrophes. For the purpose of protecting communities and reducing the destructive effects of floods, accurate flood projections are crucial [1].

Flood disaster prediction is a crucial element in efforts to mitigate and manage the impacts of flood disasters. However, the accuracy and timeliness of flood predictions for many times pose significant challenges due to various factors that must be considered, for example: rainfall, river water levels, and the geographical conditions of the area. Modeling simulations have been conducted in various aspects of natural disasters such as floods, creating scenarios for flood disaster management [2]–[4] and even developing models [5], [6] to enhance safety during flood events.

Urbanization reduces infiltration rates, increasing flood risks for nearby residents. Accurate flood modeling aids in better watershed management and hazard mitigation [7]. Interval of lag time occurs between the rainfall starts and the peak runoff [8], [9], influenced by factors like slope, flow path length and roughness, basin size, soil type, and land use [10]. It can be estimated empirically or using hydrological data from upstream precipitation and downstream flow monitoring stations. For data-based intelligent models, this method predicts water levels by analyzing observed data. Research in data analysis and data mining technologies is ongoing across various fields and is advancing rapidly. Selection of inputs to build a rainfall-runoff model that uses data is an important task because this model will find the relationship between rainfall and runoff so that it is able to directly map input to output [11].

Deep learning techniques have shown promising results across various domains. These techniques have been effectively applied to disaster susceptibility prediction. Some techniques such as convolutional neural networks [11]–[14], recurrent neural networks (RNNs) [15] and deep neural networks (DNNs) [16], [17] have been utilized successfully in this field. Among these techniques, RNNs have garnered significant interest due to their ability to capture sequential data through specialized recurrent hidden units [18]. Gated recurrent unit (GRU) integrates several gating mechanisms that allow multiple selective updates of its hidden state using input data. In particular, GRU also uses an update gate that combines the functions of the forget gate and the input gate in long short-term memory (LSTM), simplifying the architectural form and reducing the number of parameters. This results in computational efficiency and faster training times. The GRU design combines cells and hidden states, improving information flow efficiently. This allows GRU to retain information and discard some unnecessary stuff, making it better for sequential data analysis purposes. In recent years, GRU models have been investigated for flood prediction. GRU has shown superior performance for short-term flood forecasting when compared with other algorithms especially LSTM [19], in addition the GRU model shows potential but requires improvement for long-term forecasting [20], [21]. Compared with other RNN models, the GRU architecture is simpler with fewer gate mechanisms, making it more computationally efficient. GRU is known to have comparable performance to LSTM in a variety of machine learning tasks, including sequence prediction [22]. GRU has shown promising results in applications for example speech recognition [19], location prediction [23], time series forecasting [24], and dynamic risk prediction in healthcare [25]. Additionally, GRU has been explored with other models, such as convolutional neural networks (CNN), to improve performance in tasks such as electrical load estimation [26]. The GRU model was chosen in this analysis because of its superiority in weather prediction. GRU has been widely used in various domains, for example landslide displacement prediction [27], traffic prediction [28], electricity load forecasting [29], solar radiation forecasting [30], precision agriculture [31], wind speed and temperature estimation [32] carbon dioxide concentration prediction [33], and solar radiation forecasting [34]. The GRU model has shown promising results in terms of accuracy, prediction performance, and efficiency in various weather prediction tasks, making it a good choice for this analysis. Therefore, this research aims to address this gap by investigating the utility of GRU networks for flood prediction in Semarang's East Flood Canal.

There are a lot of drawbacks when predicting floods only using rainfall data. Rainfall has a significant impact on floods, but it ignores other important hydrological factors like water discharge, which is essential for regulating water flow and buildup in rivers and downstream areas [35]–[37]. Because rainfall-only flood prediction models do not completely capture the dynamics of flood occurrences, they often produce forecasts that are less accurate. Water discharge data can improve flood prediction models' accuracy by giving a more thorough understanding of the processes that cause floods. The actual flow rate in rivers is reflected in water discharge, which has an immediate effect on water levels and the likelihood of flooding. Integrating data on water discharge allows the forecast model to more accurately. This research proposes the use of gated recurrent unit (GRU) as the main tool for predicting flood events. GRU was chosen because of its ability to handle sequential data, such as rainfall and water discharge data in this context, with high computational efficiency. This model is designed to integrate information from two main variables: downstream rainfall and downstream water levels (scenario 1), as well as additional water discharge data (scenario 2).

2. METHOD

This research develops a flood detection system model in flood-prone areas through a context-aware mechanism. In this study, the research location is in flood-susceptible areas in the city of Semarang, namely the East Flood Canal Watershed and at the Pucanggading Dam Water Gate. This dam is used as an indicator for flood control in parts of Semarang City area by considering the water level. Water level is used as the basis for decision-making for local officials to determine the water gate openings will be opened. The water level at the dam determines the amount of water discharge that will flow into the East Flood Canal River. The higher the water level at the Pucanggading Dam, the higher the water gates will be opened, resulting in a larger discharge of water flowing downstream, namely the East Flood Canal River in Semarang. This research method is represented in Figure 1.

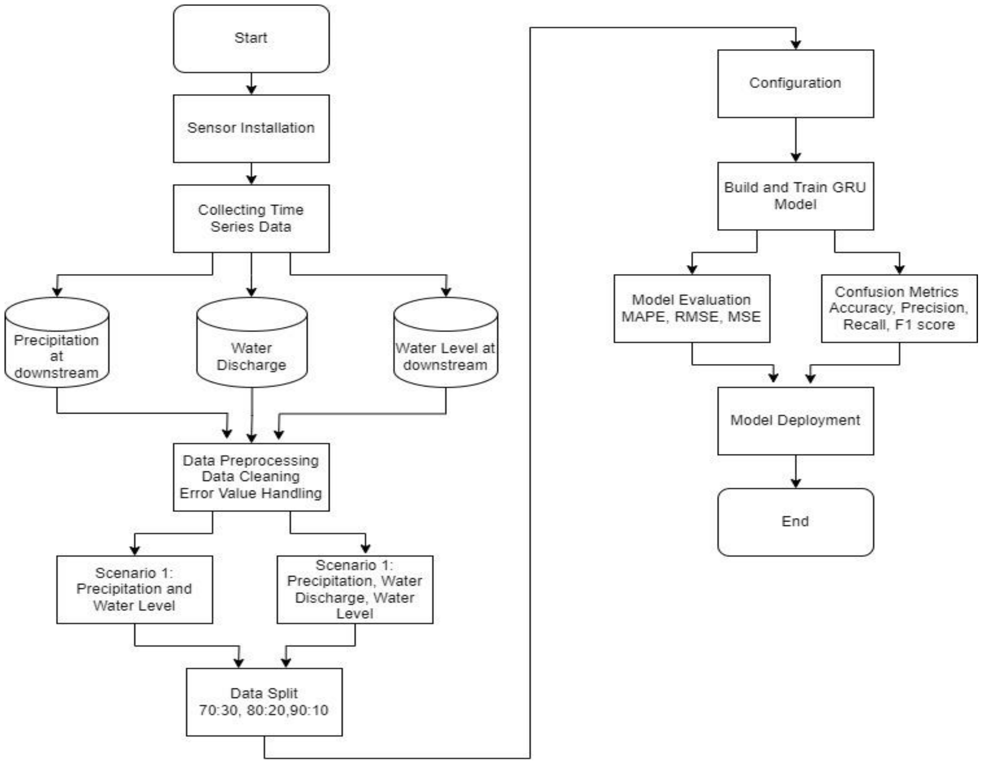


Figure 1. Flowchart of research process

2.1. Data collection

In this phase, the project conducts comprehensive measurements of various physical parameters crucial for flood detection and management. These parameters encompass precipitation, water discharge and water elevation level. Figure 2 represents how data was obtained. Some sensors are used as a tool for obtaining data was installed at points that had been previously surveyed, namely at the Pucanggading Semarang sluice gate at the upstream point and the East Flood Canal River at the downstream point. This system consists of two main parts, namely the remote site and the control center. Remote site means equipment located in the field/where the data is measured. In this case the remote site is at East Flood Canal Kaligawe and Pucanggading Dam, while the control center is on a web server that can be opened on any computer via the internet. The remote site section consists of remote sensors and data units, remote sensors have water level sensors and rainfall sensors. The data unit has parts for processing and sending data. The processing section uses an ATMega328 microcontroller (Arduino Nano) as the brain that processes all signals from the sensors. The signal from the processed sensor is then sent by the microcontroller to the data transmission section, namely the communication module. The data collection process utilizes a network of sensors strategically positioned in key locations prone to flooding. These sensors, including rainfall gauges and water elevation level sensors, continuously monitor environmental conditions like water discharge. The sensor installation spanned 17 days, with data recorded every 15 minutes, yielding a total of 1,772 records. Throughout this period, there were 32 instances of rainfall and 9 occurrences of flooding in several areas or roads known to be prone to floods. The collected data is critical for analyzing weather patterns and the correlation between rainfall and flooding in these vulnerable regions. By monitoring these parameters closely, it becomes possible to develop more effective flood prediction and management strategies.

The data also serves as a valuable resource for local authorities to improve infrastructure and implement timely preventive measures. Understanding the frequency and impact of such events is essential for enhancing community preparedness and minimizing damage caused by natural disasters. The continuous monitoring provided by the sensors helps in creating a robust database for future reference and action planning. Data from these sensors are transmitted in real-time to a central server for analysis and processing. The server integrates this contextual information, providing a comprehensive understanding of the hydrological dynamics in flood-prone areas like the East Flood Canal Watershed and the Pucanggading Dam Water Gate in Semarang. The table of sluice gate openings procedure at Pucanggading Dam is shown in Table 1. By monitoring these variables, local authorities can make informed decisions regarding flood control measures, such as adjusting dam sluice gate openings to manage water discharge effectively. This data-driven approach improves flood preparedness and response capabilities, which in turn reduces the impact of flooding on communities and infrastructure. In addition, the data collected facilitates research and analysis to improve flood prediction models, thereby supporting long-term flood risk management efforts.

After data was obtained from the sensors then the data was processed. Table 2 shows two scenarios for using the GRU model to predict downstream water levels. Scenario 1 used downstream precipitation data, while Scenario 2 adds water discharge.

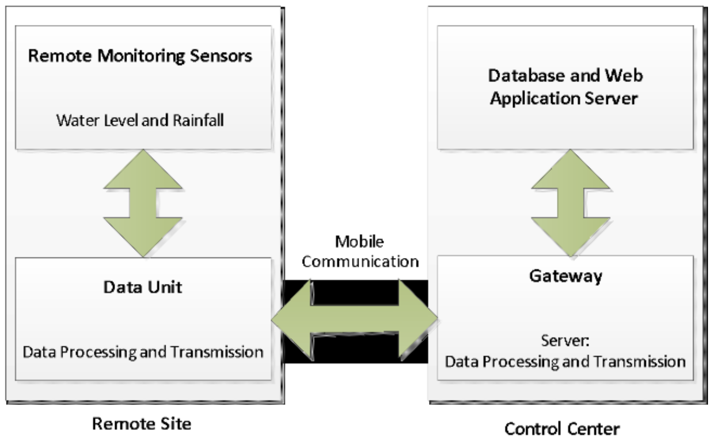


Figure 2. Flood monitoring system architecture

Tabel 1. Dam sluice gate opening procedure

Water level (m)	Water elevation level		Dam sluice gate opening procedure (m)						Q (m3/s)	Status
	H (m)	Q(m3/s)	A	B	C	D	E	F		
22.86	0.00	0	-	-	-	-	-	-		
23.16	0.30	5.56	-		0.50	0.50		-	12.28	
23.66	0.80	30.27	-	0.50	1.00	1.00	0.50	-	38.82	
23.86	1.00	43.64	-	1.00	1.00	1.00	1.00	-	52.64	
24.06	1.20	58.29	-	1.00	1.50	1.50	1.00	-	65.85	
24.16	1.30	66.11	-	1.50	1.50	1.50	1.50	-	76.72	Alert
24.36	1.50	82.7	-	2.00	2.00	2.00	2.00	-	102.96	Caution
24.56	1.70	106.59	1.00	1.50	2.00	2.00	1.50	1.00	134.88	Emergency

Tabel 2. Details of experiments

Scenario	Model	Data Set	Details of variable
Scenario 1	GRU	70:30	Downstream precipitation, downstrem water level
		80:20	Downstream precipitation, downstrem water level
		90:10	Downstream precipitation, downstrem water level
Scenario 2	GRU	70:30	Downstream precipitation, water discharge downstrem water level
		80:20	Downstream precipitation, water discharge downstrem water level
		90:10	Downstream precipitation, water discharge downstrem water level

This study explores two scenarios using the GRU model for flood prediction based on different ratios of training and validation data. Scenario 1 investigates the influence of rainfall and water levels downstream; each scenario was tested with training to test data ratios of 70:30, 80:20, and 90:10. Meanwhile, Scenario 2 includes water discharge data along with downstream rainfall, also divided in the same ratio. This scenario aims to evaluate the accuracy of model predictions under different training conditions, which is important for optimizing the flood prediction model in East Flood Canal Semarang.

2.2. Data cleaning

The data cleaning process involves several crucial steps. First, identify and remove duplicate data to prevent bias in the analysis. Next, missing values are handled by filling in the missing values using the interpolation method or average values based on available data. Validation of data consistency is very important, including ensuring uniform data formats and types for rainfall and water discharge variables. Searching for and handling outliers is also carried out to identify and treat extreme data that can affect prediction accuracy. Optionally, data transformations such as normalization can be applied to improve data distribution. Finally, filtering out irrelevant or unnecessary data helps simplify the dataset to focus on variables that are significant for flood prediction. By conducting these steps systematically, data cleanliness can be improved, ensuring that flood prediction models, including the use of GRU models, can operate optimally and provide more accurate predictions.

2.3. Data splitting

Data splitting is a method of dividing data into two or more parts that form a subset of data. Generally, data splitting separates two parts, the first part is used to evaluate or test data and the other data is used to train the model. In this study, the split data was divided into 3 parts, namely 70:30, 80:20, and 90:10.

2.4. Configuration

The GRU algorithm configuration requires the use of 50 epochs. Apart from that, the batch size is also determined as 32. The data will be processed into three parts for training and testing, namely 70:30, 80:20, 90:10 respectively. The algorithms will incorporate four layers. Additionally, data scaling will be performed using StandardScaler, and the "Adam" optimizer will be used. These configurations ensure robust training and testing processes, allowing for effective learning of patterns and relationships within the data while optimizing model performance and accuracy.

In this phase the GRU is used to overcome the gradient problem inherent in traditional RNNs. The vanishing gradient problem arises if the value decreases exponentially over time, thus making it ineffective for learning. GRU tackles this issue by employing two gates namely the update gate and the reset gate. The gates regulate the flow of information, determining which information should be retained and passed on to the output. Unlike traditional RNNs, GRU can selectively retain relevant past information without completely discarding irrelevant data, thus enhancing its ability to capture long-term dependencies and make accurate predictions.

Figure 3 shows the architecture of the GRU, which is a type of recurrent neural network (RNN) architecture used to process sequential data. GRU consists of two main gates: the reset gate rt and the update gate z_t which control the flow of information between the network units. The reset gate determines how much information from the previous state should be forgotten, while the update gate determines how much new information should be stored in the network state. With this architecture, GRU is able to capture long-term dependencies in sequential data without experiencing the gradient decay problem that often occurs in traditional RNNs.

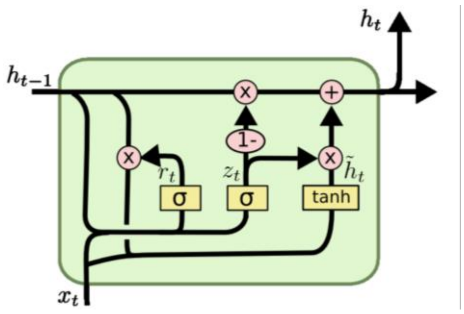


Figure 3. Gated recurrent unit

Reset gate

$$rt = \sigma\,(Wr\,[\,h_{t\,-\,1}, x_t] \,+\, b_r) \tag{1}$$

$$\tilde{h}_t \;=\; tanh\,(W_h[r_t \,*\, h_{t\,-\,1}, x_t] \,+\, b_h) \tag{2}$$

Update gate

$$z_t \;=\; \sigma\,(\,W_Z[\,h_{t\,-\,1}, x_t] \,+\, b_Z) \tag{3}$$

$$\tilde{h}_t \;=\; tanh(W_h[r_t \,*\, h_{t\,-\,1}, x_t] \,+\, b_h) \tag{4}$$

To explain how the GRU formulas relate to the inputs (precipitation, water discharge, water elevation level) and the output (downstream water level), the process is as follows:

a. Input and output
   - Input: Precipitation (P), water discharge (D), and water elevation level (E).
   - Output: Downstream water level (W_{down}).
b. Sequence input preparation
   - Create sequences of the input variables. For instance, for a given time t, the input might be [P_t, D_t, E_t].
   - These sequences span over several time steps. For example, a sequence length of 5 days would mean input sequences like [P_{t-4}, D_{t-4}, E_{t-4}], [P_{t-3}, D_{t-3}, E_{t-3}], ..., [P_t, D_t, E_t].
c. Reset gate ($r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$)
   - Here, x_t= [P_t, D_t, E_t] represents the current input at time t.
   - h_{t-1} is the hidden state from the previous time step.
   - r_t decides how much of the past information should be reset or forgotten when calculating the new candidate hidden state.
d. Update gate (z_t)
   - z_t determines the extent to which the hidden state must be updated with new information versus carrying forward the old information.
   - This gate helps in maintaining long-term dependencies by controlling information of the past hidden state is retained.
e. Candidate hidden state
   - The candidate hidden state combines the new input (x_t) and the reset-modified previous hidden state ($r_t * h_{t-1}$).
   - This allows the GRU to generate a potential new hidden state that integrates both current inputs and relevant past information.
f. Final hidden state (h_t)
   - The final hidden state is the previous hidden state ($\tilde{h}_{t-1}$) and the candidate hidden state ($\tilde{h}_t$) combination, which then weighted by the update gate (z_t)
   - This combination allows the GRU to selectively update its memory, retaining important information and discarding irrelevant information
g. Output layer
   - After the entire input sequence through the GRU layers is processed, the final hidden state is passed to a dense layer.
   - The dense layer produces the prediction for the downstream water level (W_{down})

In the context of predicting downstream water level with three input variables (precipitation, water discharge, and water level), GRU is used to capture the patterns and temporal relationships between these input variables over time. On input sequence, input data is fed as a time series. For instance, precipitation, water discharge, and water elevation level data from previous time points are processed to predict the downstream water elevation level at the next time point. Each GRU unit processes this input while retaining important information from previous sequences using mechanisms known as gates (reset gate and update gate).

2.5. Evaluation

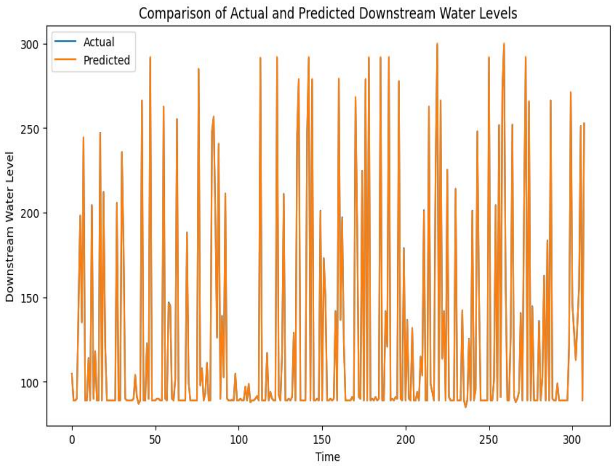
The purpose of evaluation in research is to assess the performance of a model or method, identify weaknesses and strengths, validate findings, increase trustworthiness, compare with standards, provide a basis for decision making, and increase transparency and replication. Evaluation ensures credible and useful results. In this research, the evaluation methods used are mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). Such methods help measure the accuracy with which a model can predict the correct values and provide a better understanding of the quality of model predictions. Apart from that, it also uses a confusion matrix to provide a clear understanding of the performance of the classification model by comparing model predictions with actual results. It helps identify the number of *True Positives*, *True Negatives*, *False Positives*, and *False Negatives*, which are further used to calculate evaluation metrics such as accuracy, precision, recall, and F1-score. Thus, the confusion matrix helps evaluate the reliability and validity of classification models and provides deep insight into their performance in classifying data.

3. RESULTS AND DISCUSSION

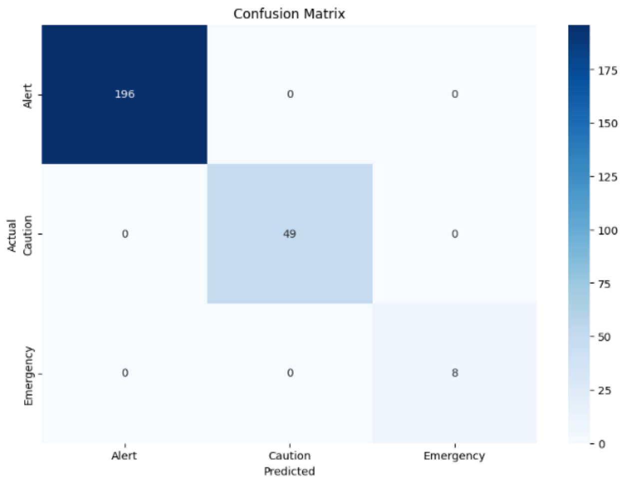
In this research, we evaluated the performance of the GRU model in flood prediction using various training and validation data compositions. In Scenario 1, we considered downstream rainfall variables and downstream water levels with data splits of 70:30, 80:20, and 90:10 between training and validation. The main focus is to measure how this combination affects the accuracy of flood predictions using the GRU model. Scenario 2 expands the analysis by adding water discharge data to a combination of downstream rainfall variables. We also performed equal data splits, 70:30, 80:20, and 90:10, to evaluate model performance in the face of the additional complexity of water discharge data integration. This research aims to provide insight into what is the optimal combination of variables and data sharing to improve flood predictions, especially in the context of using GRU models. Thus, it is expected that this research can provide a basis for the development of more accurate and reliable flood prediction techniques, which are relevant for mitigating disaster risk in areas prone to flooding in Semarang.

3.1. Downstream water level prediction analysis dataset 70:30

The dataset used for water level prediction analysis includes 3 attributes: dam water level, upstream rainfall, and water discharge. This dataset provides complete facts necessary for correct prediction modeling. The aim is to separate the data into two parts by dividing the dataset 70:30: training data (70%) and testing data (30%). Figure 4 shows the comprehensive results of the model performance using dataset of 70:30. It is divided into two sub-figures: Figures 4(a) and 4(b). Figure 4(a) provides the evaluation between the predicted and real downstream water level, utilizing a 70:30 split dataset and the GRU set of rules. Evaluation metrics, which include MAPE, RMSE, and MSE, to quantify the predictive performance version. It results a MAPE of 0.00187, RMSE of 0.368, and MSE of 0.135. The model demonstrates excessive accuracy and precision in its predictions. Despite minor deviations indicated by using RMSE, MSE, and MAPE. So that it shows near alignment among expected and real values. Overall, Figure 4 validates the model's efficacy in capturing underlying records styles with minimum mistakes.



(a)



(b)

Figure 4. Comparison of actual vs. predicted water levels using (a) GRU and (b) classification accuracy with a 70:30 dataset split

Figure 4(b) shows that in the alert column there are 196 samples that are correctly classified as "alerts" (true positives). This means the model correctly identified 196 samples that actually fell into the "alert" category. In this table there are also no samples of "alerts" that were incorrectly classified as "caution" or "emergency" (false negatives). This is indicated by the number 0 in the second and third columns. In the caution column there are 49 samples that were correctly classified as "cautions" (true positives). The model successfully recognized 49 samples that actually fell into the "caution" category. No "caution" samples were incorrectly classified as "alert" or "emergency" (false negatives). This is indicated by the number 0 in the first and third columns. In the emergency column, there are 8 samples that are correctly classified as "emergencies" (true positives). The model successfully recognized 8 samples that actually fell into the "emergency" category. No "emergency" samples were incorrectly classified as "alert" or "caution" (false negatives). This is indicated by the number 0 in other columns. So, the overall confusion matrix shows that the classification model has performed very well, no misclassifications were seen between the three classes.

Table 3 shows the model performance using GRU with a 70:30 data set with four categories: "alert," "caution," "emergency," and "errors." The model has perfect precision, recall, and F1-score (1.00) for "alert" and "caution", while "emergency" has an accuracy of 0.89 and F1-score of 0.94, it shows that some prediction error "error" class accuracy of 1.00, F1-score and 0.99. The overall accuracy of the 308 observations was 100%. The average precision, recall, and F1-scores were all 0.97, 1.00, and 0.98, respectively, while the weighted average of the three was 1.00. Although there is a slight drop in precision for the "emergency" category (89%), overall, the model shows very high performance with almost perfect metrics in all categories.

Table 3. Classification report dataset 70:30

Classification report:				
	Precision	Recall	F1-score	Support
Alert	1.00	1.00	1.00	196
Caution	1.00	1.00	1.00	49
Emergency	0.89	1.00	0.94	8
Error	1.00	0.98	0.99	55
accuracy			1.00	308
macro avg	0.97	1.00	0.98	308
weighted avg	1.00	1.00	1.00	308

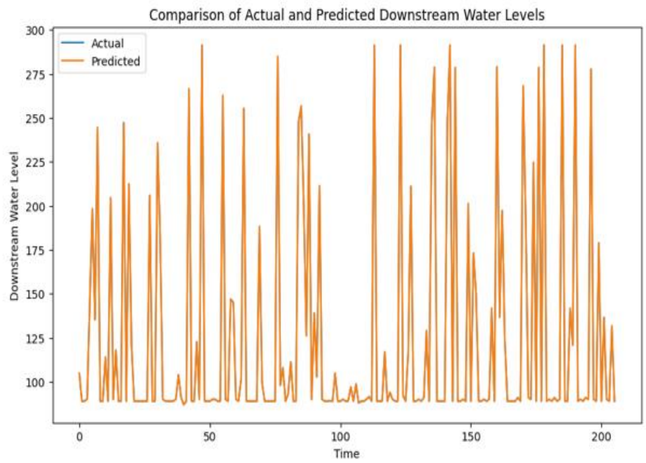
3.2. Downstream water level prediction analysis dataset 80:20

Three main characteristics are included in the dataset used for the water level prediction analysis: water level, downstream precipitation, and water discharge. These features provide a comprehensive view of factors affecting water levels, which is crucial for accurate forecasting models. The data is processed into training and test sets at a ratio of 8:2 which means that the model is trained on 80% of the data set, allowing the model to identify underlying patterns in the data. The remaining 20% is reserved for model testing, ensuring that its predictive performance is evaluated on unobserved data. Focusing on the water level on the dam, the model captures the state of instantaneous water storage. Precipitation data is important as this affects the water discharge and water level on the dam, while water discharge data help to understand the dynamics of the outflow. These factors can enable the model to account for both inputs and outputs affecting the watershed. This approach is helpful for the model performance is accurate, ensuring that it is well aligned with new information. Reliable forecasts of water levels are critical for the optimal utilization of water resources and for flood prevention and early warning systems. Studies using this dataset and methodology aim to improve the accuracy of water level forecasts.

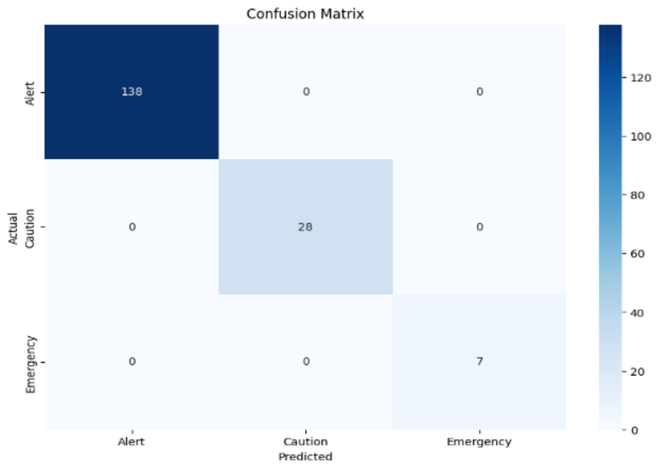
Figure 5 shows the comprehensive results of the model performance using dataset of 80:20. It is divided into two sub-figures: Figures 5(a) and 5(b). Figure 5(a) represents the comparison between predicted and actual downstream water levels, employing an 80:20 split dataset and the GRU algorithm. The model yields MAPE of 0.00144, RMSE of 0.304, and MSE of 0.093, the model demonstrates high precision in its predictions. Despite slight deviations denoted by RMSE and MSE, the low MAPE indicates close correspondence between predicted and actual result. Overall, the graph affirms the model's effectiveness in capturing underlying data patterns with minimal error, thus validating its predictive capability. Figure 5(b) shows that in 80:20 dataset there are 138 "alert" samples classified correctly, 28 "caution," and 7 "emergency." No misclassifications were noted. This shows excellent model performance, with no errors in the classification of the given data.

Table 4 shows the performance of a model using four categories: "Alert," "Caution," "Emergency," and "Error." For the "Alert" category, the precision is calculated 1.00, recall is 0.99, and

F1-score is 1.00, based on 138 samples. The “Caution” category shows a precision of 0.97, recall of 1.00, and F1-score of 0.98 from 28 samples. The “Emergency” category, with 7 samples, has a precision of 0.88, recall of 1.00, and F1-score of 0.93. The “Error” category, with 33 samples, has a precision of 1.00, recall of 0.97, and F1-score of 0.98. The overall accuracy of the model is 0.99 from 206 samples. The macro average for precision, recall, and F1-score is 0.96, 0.99, and 0.97, respectively, while the weighted average for these metrics is 0.99, indicating excellent model performance.



(a)



(b)

Figure 5. Comparison of actual vs. predicted water levels using (a) GRU and (b) classification accuracy with an 80:20 dataset split

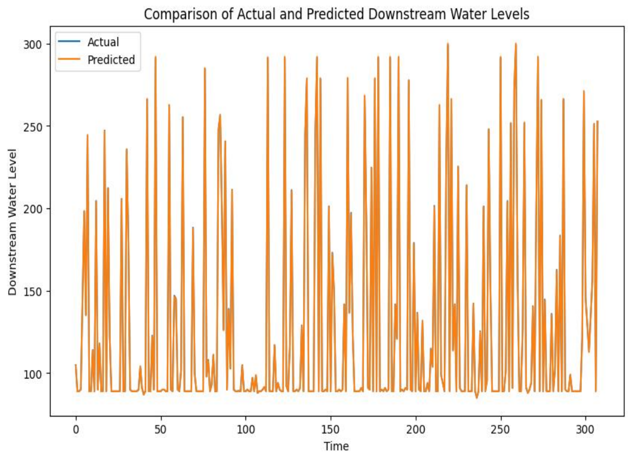
Table 4. Classification report dataset 80:20

Classification Report:	precision	recall	F1-score	support
Alert	1.00	0.99	1.00	138
Caution	0.97	1.00	0.98	28
Emergency	0.88	1.00	0.93	7
Error	1.00	0.97	0.98	33
(a) racy			0.99	206
macro avg	0.96	0.99	0.97	206
weighted avg	0.99	0.99	0.99	206

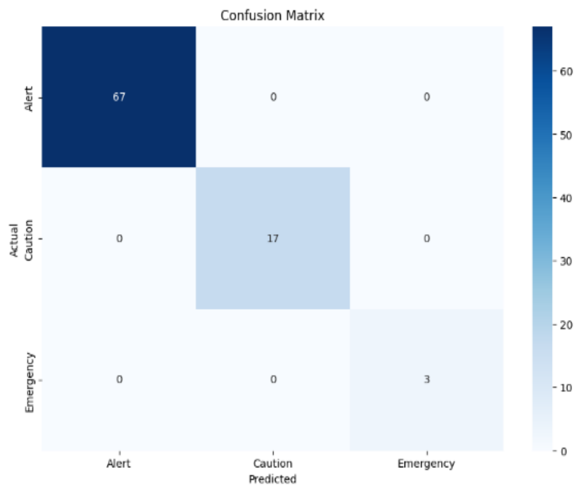
3.3. Downstream water level prediction analysis dataset 90:10

Splitting the dataset into 90:10 in research with three variables (precipitation, water discharge, and water level) aims to ensure the model can learn effectively and still provide accurate performance evaluations. In this scenario training data 90% is used to train the model. With a large proportion of data, the model can better understand the patterns and relationships between precipitation, water discharge and water levels, thereby increasing its accuracy and predictive capabilities. Test data (10%) is used to test the model after training.

Figure 6 shows the comprehensive results of the model performance using dataset of 90:10. It is divided into two sub-figures: Figures 6(a) and 6(b). Figure 6(a) represents a comparison between the actual downstream levels and the predicted values generated by the model. MAPE with a value of 0.00186 indicates the percentage of the mean deviation between the predicted and actual values. The predictions are more accurate and agree well with the actual values. The RMSE is calculated as 0.367, which represents the maximum error between the predicted and actual results. A lower RMSE indicates the model can perform better, which deviates from of the true value. The calculated MSE of 0.135 gives the difference in squared difference between predicted and actual values. Figure 6(b) shows an evaluation of the performance of the classification model with the confusion matrix on dataset 90:10. In this case, the model correctly classified 67 data as “alert” and 17 data as “caution.” However, only 3 data were correctly classified as “emergency.” No classification errors were recorded in this matrix, indicating high accuracy.



(a)



(b)

Figure 6. Comparison of actual vs. predicted water levels using (a) GRU and (b) classification accuracy with a 90:10 dataset split

Table 5 shows the performance of a model. For the “Alert” category, the precision yields 1.00, recall yields 1.00, and F1-score yields 1.00, based on 67 samples. The “Caution” category shows a precision of 1.00, recall of 1.00, and F1-score of 1.00 from 17 samples. The “Emergency” category, with 3 samples, has a precision of 0.75, recall of 1.00, and F1-score of 0.97. The “Error” category, with 16 samples, has a precision of 1.00, recall of 0.94, and F1-score of 0.97. The overall accuracy of the model is 0.99 from 103 samples. The macro average for precision, recall, and F1-score is 0.94, 0.98, and 0.96, respectively, while the weighted average for these metrics is 0.99 which indicates excellent model performance.

Table 5. Classification report dataset 90:10

Classification Report:				
	precision	recall	F1-score	support
Alert	1.00	1.00	1.00	67
Caution	1.00	1.00	1.00	17
Emergency	0.75	1.00	0.86	3
Error	1.00	0.94	0.97	16
accuracy			0.99	103
macro avg	0.94	0.98	0.96	103
weighted avg	0.99	0.99	0.99	103

3.4. Scenario 1 and 2 comparison results

Based on the analysis of the model performance on scenario 2, it can be concluded that the data set with 80:20 ratio is the best in supporting internet of things (IoT)-based flood risk prediction using GRU. If compared with the experiment that was conducted previously in scenario 1, the comparison results can be seen in Table 6.

This table compares two GRU model scenarios for predicting emergency status based on the variables “downstream precipitation” and “water discharge downstream water level” with training and testing data ratios of 70:30, 80:20, and 90:10. Scenario 1 only uses “downstream precipitation” and “downstream water level”, while scenario 2 adds “water discharge.” Scenario 2 with dataset of 80:20 shows better performance with MAPE as low as 0.001, MSE 0.134, and RMSE 0.093. The highest accuracy is 1,000 at a ratio of 70:30 for Scenario 2. Precision, recall, and F1-score are also higher in Scenario 2 compared to Scenario 1 which means adding water discharge as the variable is an important indicator of water dynamics in a system. Adding them can improve prediction accuracy because the model gets more comprehensive information about water flow conditions.

Table 6. GRU flood prediction performance comparison

Scenario	Model	Data set	Details of variable	Validation model			Confusion metrics (Emergency status)			
				MAPE	MSE	RMSE	Accuracy	Precision	Recall	F1 Score
Scenario 1	GRU	70:30	Downstream precipitation, Downstrem water level	0.235	0.212	0.460	0.976	0.882	0.990	0.912
		80:20	Downstream precipitation, Downstrem water level	0.145	0.313	0.559	0.891	0.875	0.940	0.931
		90:10	Downstream precipitation, Downstrem water level	0.230	0.342	0.585	0.910	0.730	0.915	0.831
Scenario 2	GRU	70:30	Downstream precipitation, Water discharge downstream water level	0.002	0.135	0.368	1.000	0.890	1.000	0.940
		80:20	Downstream precipitation, Water discharge downstream water level	0.001	0.304	0.093	0.990	0.880	1.000	0.930
		90:10	Downstream precipitation, Water discharge downstream water level	0.002	0.134	0.367	0.990	0.750	1.000	0.860

4. CONCLUSION

This study aims to improve flood disaster predictions by integrating rainfall and water discharge data using an IoT-based system. This research highlights the weaknesses in flood predictions using only rainfall data, which often produces less accurate predictions because it does not consider important hydrological factors such as water discharge. Water discharge is vital in regulating water flow in rivers and downstream areas, as well as directly influencing water levels and the possibility of flooding. Integration of water discharge data allows flood prediction models to more accurately predict flood events by considering actual river flow conditions. This research employed the GRU model to analyze historical rainfall and water discharge data, with the results showing that GRU is able to provide very good predictions, especially in scenarios with integration of rainfall and water discharge data. Experimental results show that in scenario 2 with an 80:20 data division for rainfall and water discharge variables, the GRU model succeeded in achieving a high level of accuracy (0.990), as well as optimal Precision, Recall and F1-score values, indicating the model's ability to identify status. flood emergency well.

Overall, this research contributes to the development of more accurate and timely flood prediction techniques, especially for flood-prone areas in Semarang. By considering the integration of IoT data to combine weather and water discharge information, it is hoped that this research can improve flood mitigation and prevention responses more effectively, as well as increase community preparedness in facing frequent natural disasters.

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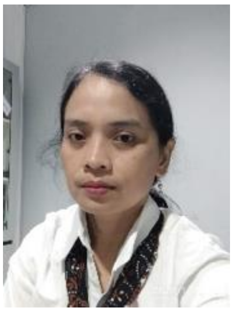

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