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Implementing IoT and Machine Learning for Disaster Mitigation

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Abstract: This prototype output research has the aim of creating a dashboard that is used to monitor river water levels. The dashboard created will display data in real-time and prediction results. The use of the dashboard is to minimize the risk in the event of flooding caused by river overflow. The way this prototype works is to take data from sensors that have been installed at several points. The recorded data will be stored in a database using the working principles of *the Internet of Things*. For predictions, *machine learning* is used to produce future river water level figures. The machine learning used is using *time series* regression with rainfall input and river water level output. Long-term output data is needed, therefore to forecast future rainfall the Hybrid method is used. Data generated from sensors as well as from prediction results are stored in one database. From the database, data visualization is displayed along with important figures used for *river overflow intelligence*. Therefore, the dashboard is very useful for people living around the river flow.

Keywords: Prototype; Disaster Management; Flood Prediction, Internet of Things, Machine Learning

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1. Introduction

Disasters are natural events that are not desired by everyone. Disasters can happen anytime and anywhere. Disasters can occur due to nature or can occur due to the consequences of human activities. One of the natural disasters that often occur in Indonesia is the flood disaster. Floods can occur due to several causes such as high rainfall, lack of water catchment areas, river overflow, and many others. One area that has a high risk of flooding is the riverside area. Call it a river that often contributes to flooding, namely the Bengawan Solo River. Bengawan Solo is the longest river on Java Island with two upstream rivers namely from Wonogiri and Ponorogo, then empties into the Gresik area. Almost every year the water of the Bengawan Solo River overflows and causes floods. Flood disasters caused by river overflow can be prevented by dredging shallow rivers, not throwing garbage in rivers, reducing the construction of houses or buildings around the river, and others. However, with this prevention, flood disasters can come if the rainfall at that time is very high. Risk management is an effort to avoid risk by monitoring the source of risk, tracking, and making a series of efforts so that the impact of risk can be minimized. The consequences of flooding can be reduced if we know early when the chance of flooding is very high.

Nowadays technology is growing rapidly. The combination of several technologies can provide benefits for everyday life. In the field of flood disaster management problems, some sensors can read river water levels. The sensor can read the current water level of the river. However, the censorship can only be accessed by certain agencies and people. In addition, the weakness of the sensor has not been able to predict the condition of river water levels for a long period in the future. In general, someone will be more comfortable if they know short-term risks and long-term risks. Therefore, *early flood warnings* need to be developed for a long period as well. The combination of short-term early warning can use current river level sensors while long-term *early warning* can use data from future predictions. Currently, many data visualization *tools* have been developed that can be used as *dashboards* for monitoring and can be accessed by anyone and anywhere. The ease of access is useful for the wider community to know the possibility of flooding in the near and long term.

Previous studies that have developed flood sensors are Andayani, Indrasari, and Iswanto (2016). In their research, a flood sensor was developed using ultrasonic sensor calibration HC-SR04. The censorship can be developed again by working with the *Internet of Things* (IoT), where an object can transfer data over the network without requiring human-to-human or human-to-computer interaction. River water level data can be recorded in the database in seconds. These sensors are installed and deployed at several points along the existing river to monitor the continuity of one region with another. To find out the long-term prediction of water levels, *machine learning* can be used. *The machine learning* used is *a time series* regression (Susila et al., 2022) with the output in the form of river water level data. As for the input to predict the level of river water, namely rainfall. Applications of *machine learning* have been developed in internal campus research to predict stock price indexes. The creation of *machine learning* is done by adjusting as many flood sensor points are installed. To get the results of river water level prediction, input that describes rainfall conditions is needed. One method that has high accuracy to predict a future event is the *hybrid* model (Susila, 2021). The way the hybrid method works is to combine several forecasting methods or models into one output of *forecast* results. The hybrid model has been developed in internal campus research to forecast the circulation of electronic money and obtained better accuracy than the non-hybrid model. Forecast data, as well as historical data on river water levels and rainfall, are integrated into one database, which then from the database can be made a visualization of the data. Where from the visualization can be used as *river height intelligence*. From the visualization data, users can filter based on place, time, and risk profile, and can also see historical data and *forecast* data.

The purpose of developing this prototype is to make it easier for the wider community to monitor flood risk in the area around the watershed in *real time* and picture the risk of flooding in the future. Very easily people can access it through *their smartphones* and computers. The public can get information on river water levels, rainfall, historical data, and *data from the results of forecas*ts. The display of the *dashboard* is in the form of numbers, tables, and graphs that make it easier for users to obtain information.

2. Literature Review

Disaster Management

The definition of disaster according to the WHO (World Health Organization) is 'any event that causes disruption to the environment, loss of human life, and loss of health services. This requires extraordinary intervention from anywhere within the affected community or area.' In other words, a disaster is an event or situation that involves serious disruption to the environment, has the potential to cause loss of human life, and requires an unusual emergency response or action from various parties in the affected community. This definition includes many different types of disasters, including natural disasters such as earthquakes, floods, and storms, as well as human disasters such as industrial accidents or pandemics. More deeply, Sharma et al., (2021) explained that disaster management is an approach or series of actions

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taken to reduce the negative impact of natural disasters or other emergency events. Disaster management aims to protect lives, property, the environment, and infrastructure, as well as to reduce risks and losses that may arise as a result of such disasters.

Disaster management involves planning, preparation, risk reduction, rapid response, and post-disaster recovery. This covers a wide range of aspects, including monitoring and early warning, evacuation, provision of first aid, coordination of assistance, and restoration of the environment and affected communities. The importance of disaster management is to minimize the losses incurred by disasters, both in terms of people and property and to ensure an efficient and effective response in the face of emergencies. The following are the phases of disaster management:

Figure 1: Phase of disaster management
Sources: researcher's 2023

From this figure, the phase of management according to Sharma et al., (2021) is as follows; **Preparedness:** This phase involves pre-disaster practices. It includes prior planning, implementation of preparedness plans, emergency exercises/training, and early warning systems. The goal is to prepare communities, authorities, and relevant institutions to face potential disasters. **Response**: This phase occurs during an ongoing disaster or emergency. It includes emergency operations, such as the use of public alert devices, emergency isolation, and search and rescue operations. The response involves quick actions to address the emergency and protect lives and property. **Recovery**: After the disaster has passed, the recovery phase begins. It includes post-disaster practices such as the construction of temporary shelters, claims collection and assistance, long-term medical care, and therapy. This phase aims to help communities and affected areas recover and rebuild. **Mitigation:** This phase involves efforts to reduce the risk and vulnerability to disasters. It includes the development of safe building codes, spatial planning, community education on prevention measures, and vulnerability identification. The goal is to reduce the impact of future disasters.

Flood Prediction

Flooding is a natural event that can occur in various locations that have water. It is a natural occurrence that involves the flow of excess water into a previously dry area. Flood management is very important in reducing the negative impact of this flood. Referring to the presentation of Bentivoglio et al., (2022) the types of floods are divided into several categories based on their causes and characteristics;

- **River Floods**: These floods are caused by extensive and prolonged rainfall, resulting in rivers overflowing their banks and flooding the surrounding area.

- **Flash Floods**: Flash floods occur due to intensive rain for a short period or the sudden melting of snow. They tend to be fast and intense.
- **Coastal Floods**: These floods are caused by extreme meteorological conditions that increase water levels in large bodies of water, such as due to a combination of low atmospheric pressure and strong winds.
- **Urban Floods**: These floods occur due to the failure of the drainage system of urban sewers, usually due to extreme rainfall.
- **Dam and Dike Breach Floods: This type of flooding occurs due to** the failure of flood protection structures, either due to extreme flooding or management problems.

Therefore, research related to flood management is still being developed following its causes and characteristics. The following is a summary of some previous studies that discuss flood mitigation.

Table 1. Previous Research

No.	Author	Article Title	Method	Key Findings
1	Chidthong et al., (2009)	Developing a hybrid multi-model for peak flood forecasting	"Soft computing" approach with the development of multi-model hybrid models. (Fuzzy logic, Artificial Neural Network (ANN), Genetic Algorithm (GA)	The hybrid multi-model approach used successfully predicts flood levels efficiently and accurately, with advantages, especially in estimating flood peaks.
2	Chang et al., (2010)	Clustering-based hybrid inundation model for forecasting flood inundation depths	CHIM (clustering-based hybrid inundation model)	The CHIM approach using a combination of linear regression models and artificial neural networks can predict flood inundation rates well and efficiently, by combining pre-processing data and model building in two stages. The result greatly reduces the computation time required.
3	Kaur et al., (2021)	Energy Efficient IoT Based Cloud Framework for Early Flood Prediction	1. Internet of Things (IoT). IoT sensors are used to collect environmental data such as temperature, humidity, and precipitation, as well as water parameters such as water flow and water height. 2. Artificial Neural Network (ANN) algorithm is used to predict floods.	The proposed architecture for IoT-based flood prediction systems enables efficient flood prediction by leveraging collected environmental data.
4	Munawar et al., (2021)	An Integrated Approach for Post-Disaster Flood Management via the Use of Cutting-Edge Technologies and UAVs: A Review	Descriptive qualitative	Use of Latest Technology, Importance of Integration, Identification of the next research direction
5	True et al., (2021)	Flood Disaster Mitigation Using the HEC-RAS	Nakayasu, Snyder, and HEC-RAS applications	In most of the upstream areas, there is no waterlogging during flooding with payback

		Application to Determine River Water Levels in the Old City Area of Jakarta		periods of 10 years and 25 years, but the upstream areas are more vulnerable to flooding compared to the middle downstream areas.
6	Puttinaovarat & Horkaew, (2020)	Flood Forecasting System based on Integrated Big and Crowdsource Data by using Machine Learning Techniques	The data used include meteorological, hydrological, geospatial, and data contributed by the community (crowdsourcing). Flood early warning systems use adaptive machine learning frameworks. The learning method used is MLP ANN (Multi-Layer Perceptron Artificial Neural Network).	System configuration using MLP ANN provides the most effective prediction, with a correctness level of 97.93%, a Kappa value of 0.89, a Mean Absolute Error (MAE) of 0.01, and a Root Mean Square Error (RMSE) of 0.10. That is, the developed flood early warning system is successful in forecasting flood incidents, including specific locations and specific periods.
7	Wong, (2020)	Flood Prediction using ARIMA Model in Sungai Melaka, Malaysia	• Box-Jenkins method for developing flood prediction models. • Real-time flood parameter data • The selection of the best ARIMA (AutoRegressive Integrated Moving Average) model is carried out based on the criteria of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).	The ARIMA model (2, 1, 2) is the best model for forecasting the water level of the Melaka River. This ARIMA model proved suitable for short-term flood prediction with lead times of up to 8 hours.
8	Chang et al., (2018)	Building an Intelligent Hydroinformatics IntegrationPlatform for Regional Flood Inundation Warning Systems	Development of an Intelligent Hydroinformatics Integration Platform (IHIP) platform that integrates machine learning, visualization, and system development techniques	IHIP's ability to provide real-time flood data and improve flood risk management in Tainan City, Taiwan.
9	Chitwatkulsiri et al., (2022)	Development and Application of a Real-Time Flood Forecasting System (RTFlood System) in a Tropical Urban Area: A Case Study of Ramkhamhaeng Polder, Bangkok, Thailand	using a system called "Real-Time Flood Forecasting System" (RTFlood System) which consists of three main modules.	The RTFlood System is effective in providing early warning of lightning floods in vulnerable areas such as Ramkhamhaeng polder in Bangkok.

10	Yang & Chang, (2020)	Regional Inundation Forecasting Using Machine Learning Techniques with the Internet of Things	IoT sensor data is used as an input factor into the Machine Learning model to continuously update the model and make more accurate predictions.	The incorporation of machine learning technology and IoT sensor data can improve flood prediction and its use in flood management.

3. Method

Software Development Methods

The prototype of the river overflow flood risk management system developed is a tool that can be used to monitor flood risk caused by river overflow. This prototype accommodates flood risk profiles in *real-time* and in the future. The public can get information easily from the *dashboard* display presented. The information presented is in the form of numbers, tables, and graphs. On the *dashboard*, there are several kinds of information such as river water levels from upstream and downstream in *real time*, river water levels from upstream and downstream prediction results, and rainfall at several location points for historical data and *forecast* results.

To develop the prototype, a sensor capable of reading river water levels is needed such as the HC-SR04 ultrasonic sensor. The sensor stored river water level data from various points of the region on databases such as Postgresql. These sensors and databases are used for risk in *real-time*. For risk files in the future of data, historical rainfall data and river water level data are needed as material for making models. To get the results of predicting river water levels, *machine learning* is used. The model used is *time series* regression and the software used is R *software*. The output of *machine learning* is in the form of prediction of river water levels and inputs using rainfall forecasted using the Hybrid method. River water level prediction data and *forecast* results are used for future risks. All existing data is stored in one database. From the database, a *dashboard* display is created that can be accessed by anyone and anywhere. To create the *dashboard*, you can use Power BI.

Data Collection Techniques

To develop the prototype, a sensor capable of reading river water levels is needed such as the HC-SR04 ultrasonic sensor. The sensor stored river water level data from various points of the region on databases such as Postgresql. These sensors and databases are used for risk in *real-time*. For rainfall data data secondary data is used. The data used is from January 2021 to November 10, 2022. The rainfall data used are rainfall data obtained from the East Java Climatology Station and the Central Java Climatology Station for the period January 2021 to November 10, 2022.

Dashboard Design

The design design of the *dashboard* used to analyze flood risk due to river overflow is as follows.

i. Main menu

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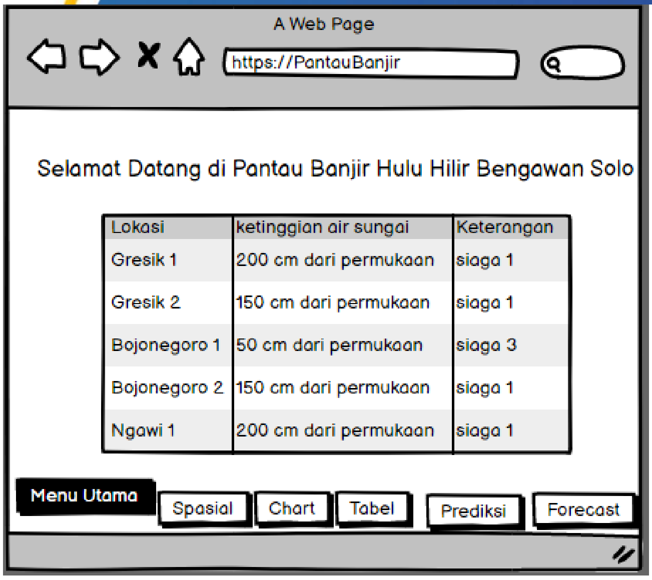

Figure 2: Main Menu
Sources: researcher's data (2022)

On the main menu, there is a welcome to users and *a real-time data display* of river water levels from all points.

ii. Spatial menu

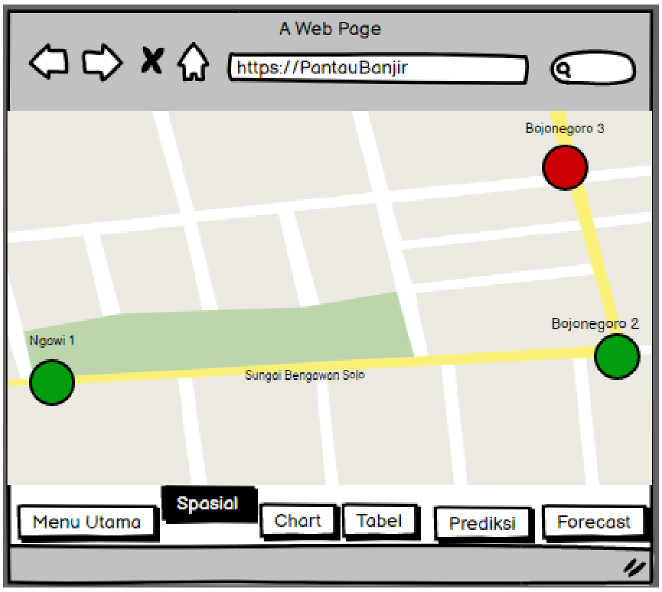

Figure 3: Spacial Menu
Sources: researcher's data (2022)

In the spatial menu, *a map* is displayed where sensor points are placed. Green indicates alert status 1, yellow indicates alert status 2, and red indicates alert status 3.

iii. Menu Chart

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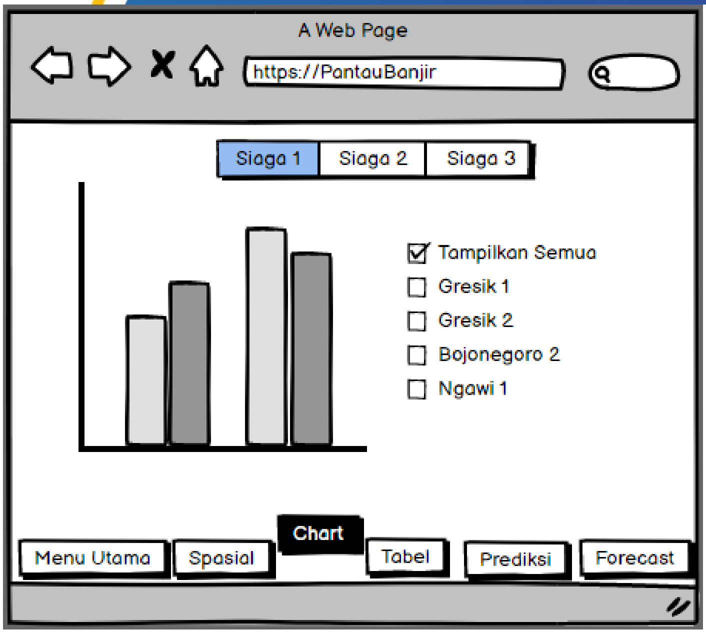

Figure 4: Chart Menu
Sources: researcher's data (2022)

In this menu users can filter by status and can be forwarded location filters, in this menu is a display of *real-time* status.

iv. Table Menu

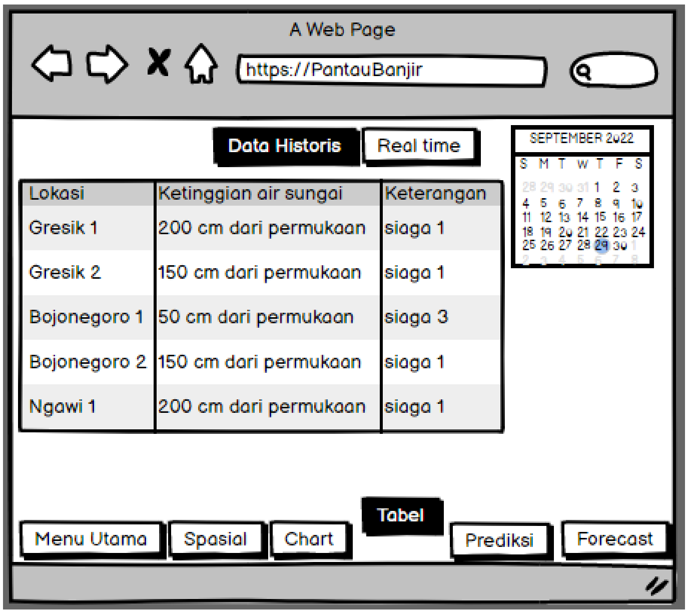

Figure 5: Table Menu
Sources: researcher's data (2022)

In this menu, historical data and real-time river water level data from all sensor points are displayed.

v. Prediction Menu

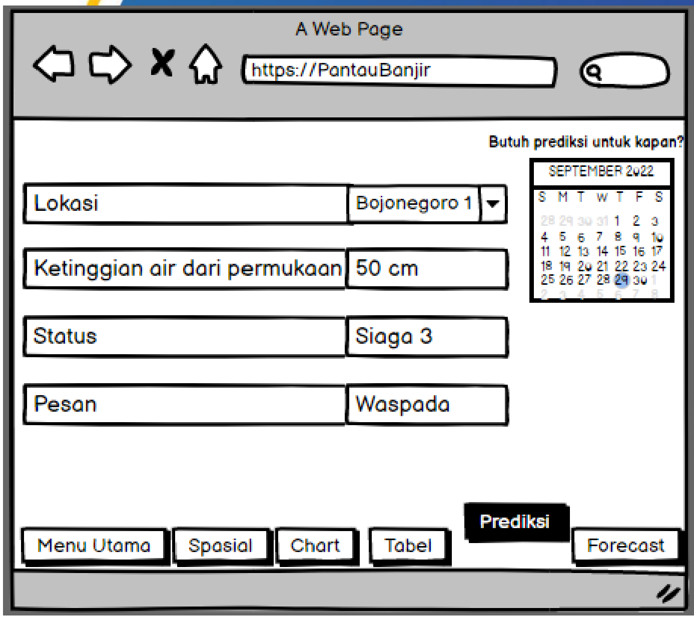

Figure 6: Prediction Menu

Sources: researcher's data (2022)

In this menu, the results of the prediction of river water levels for the future are displayed, and users can choose what date and location. On this menu, users will get a recommendation message to do.

vi. *Forecast Menu*

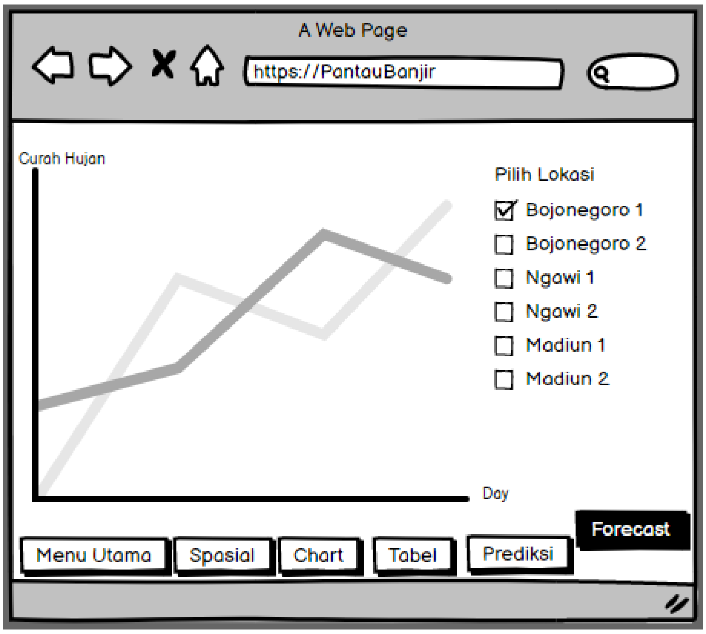

Figure 7: Forecast Menu

Sources: researcher's data (2022)

In this menu, the results of rainfall forecasting for the future are displayed. Users can choose the desired location.

4. Result and Discussion

The prototype of the river overflow flood risk management system is made in the form of a dashboard display that can be accessed on a computer or the user's smartphone. In general, the way this tool works is to get water level data using sensors, store the data in a database, and make the results of the analysis in the form of data and graphs that make it easier for users to get information. The dashboard display also presents the results of river height predictions along with rainfall forecasts. Given that the tool made is a prototype, the installation of the water sensor is carried out in a safe place. Water sensors are temporarily not placed in rivers, due to safety concerns and the lack of other facilities to support the work of the sensors (such as electrical energy sources and the internet). On the dashboard, three water level measurement points of the Bengawan Solo River are given, namely in Jurug, Sekayu, and Karanggeneng. For the data of the three measurement points and rainfall data, secondary data are used. The data used is from January 2021 to November 10, 2022.

To obtain water level data, an ultrasonic sensor HC-SR04 is used. With the sensor data is stored through the esp32 microcontroller. Water level data is stored in a database (Postgresql). By using the web API, the water level data is created tables and visualizations in Power BI. In making the dashboard, original data (secondary data) measurements from three points of the Bengawan Solo River are displayed, namely Jurug, Sekayu, and Karanggeneng. Sensor data is also displayed on the dashboard, secondary data is used because for making machine learning to predict river water levels, historical data is needed, namely river water level data of the three points and rainfall data. In the process of making machine learning, rainfall forecasts are also needed for the future. To forecast a hybrid model ARIMA-Artificial Neural Network. The rainfall data used are rainfall data obtained from the East Java Climatology Station and the Central Java Climatology Station for the period January 2021 to November 10, 2022. For code and results of hybrid and machine learning models can be seen in the appendix of this study.

The *results* of the river overflow flood risk management system dashboard are presented in the following capture figures:

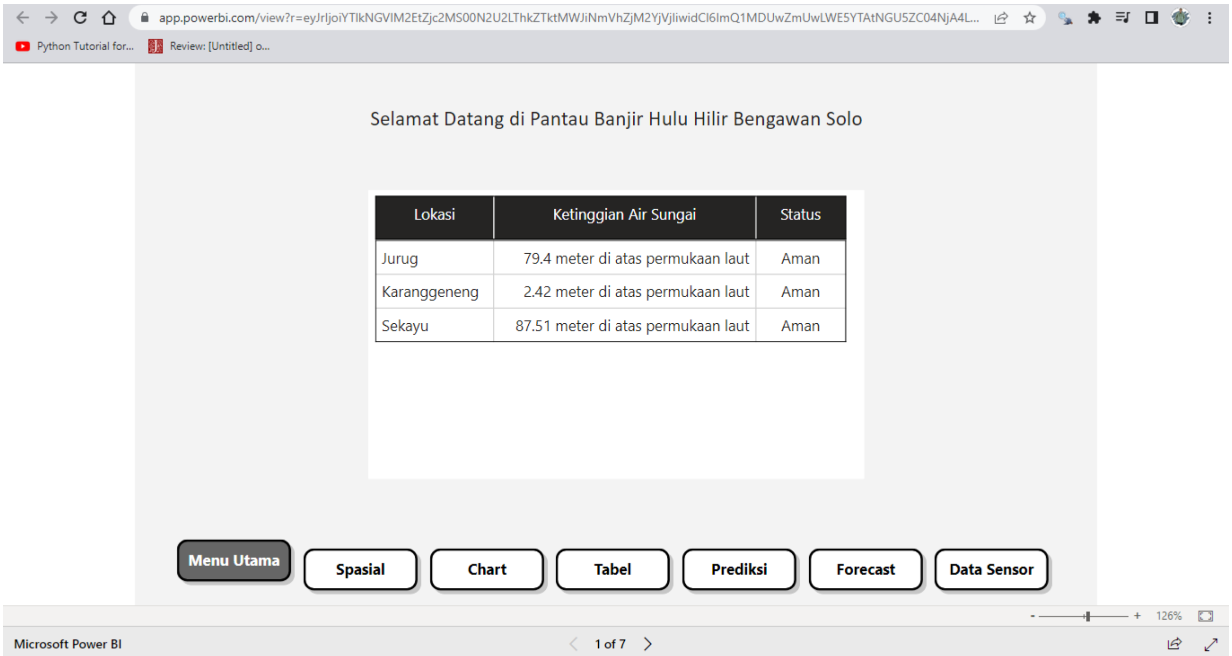

Figure 8: Main Menu of Power BI
Sources: researcher's data (2022)

In the "Main Menu", there is a display of water level data of the Bengawan Solo River which is measured at three points, namely in Jurug, Sekayu, and Karanggeneng. The main menu displays the measurement location, river water level, and status. For Jurug alert status 1 if the river water level is more than or equal to 82.98 to 83.97, alert 2 is more than or equal to

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83.98 to 84.97, and alert 3 is more than or equal to 84.98. For Sekayu alert status 1 if the river water level is more than or equal to 89.22 to 90.21, alert 2 is more than or equal to 90.22 to 91.21, and alert 3 is more than or equal to 91.22. For Karanggeneng alert status 1 if the river water level is more than or equal to 3.13 to 3.62, alert 2 is more than or equal to 3.63 to 4.12, and alert 3 is more than or equal to 4.13.

The second menu is "Spatial", in this menu is displayed the location of the river water level measurement point. The use of this menu is that users can analyze the potential for flooding caused by river overflow based on regional linkages. The spatial correlation that is used as an indicator is that if the upstream region has a standby status, the downstream region must be aware of it. Because there will be river water sent from the upstream area.

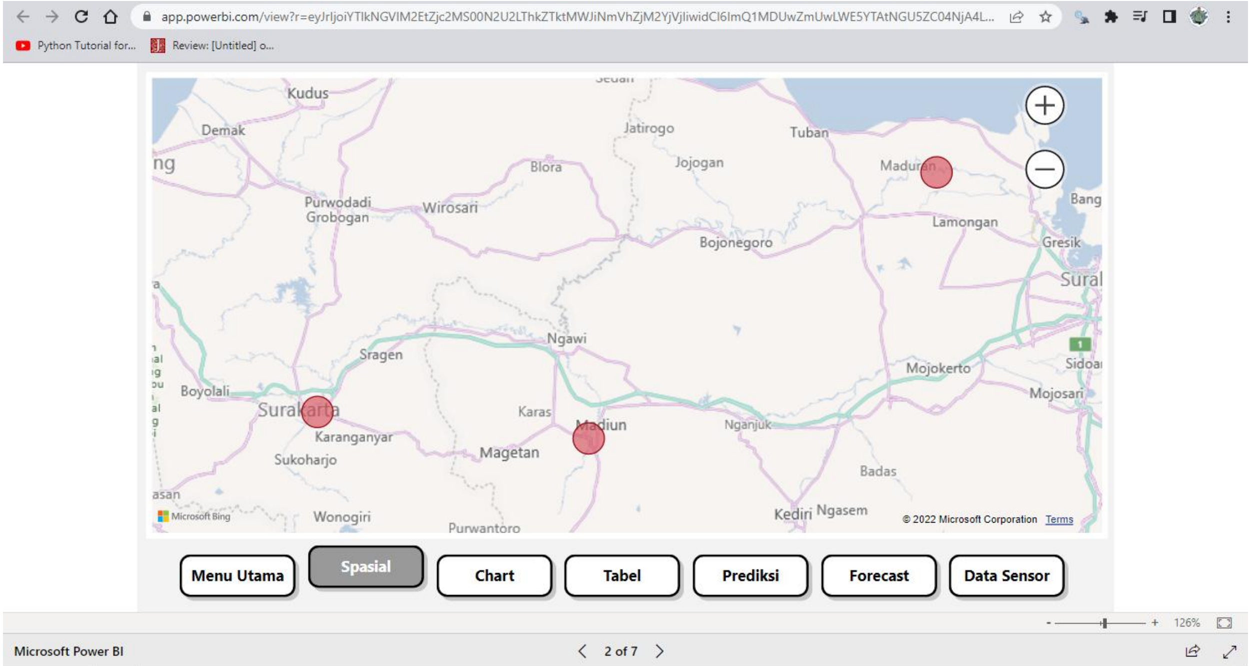

Figure 9: Spacial Menu of Power BI
Sources: researcher's data (2022)

On the menu, users can already see which points of river water level measurements are carried out spatially. Users can *zoom in* or *zoom out the map* that has been presented. If the status of Jurug and Sekayu is "alert 3", then downstream areas such as Karanggeneng must be careful, it is feared that there will be water sent from upstream. The same goes for other locations.

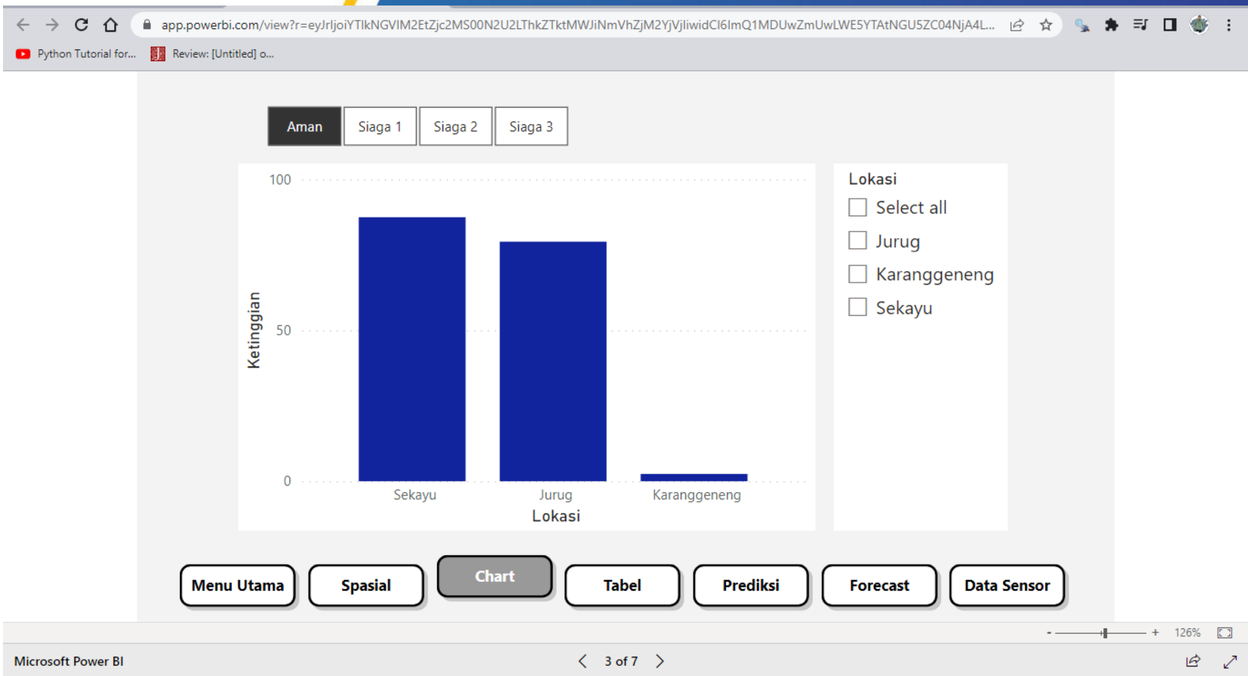

Figure 10: Chart Menu of Power BI
Sources: researcher's data (2022)

The next menu is "Chart", in this menu a visualization of the river water level from observation points is displayed. Users can choose the measurement location or status of the water level according to their needs. If the "Safe" status is selected, a location point with a safe status will be displayed, as well as for other statuses. Users can quickly filter which location points are safe, standby1, standby2, or standby3. If you select all locations, the dashboard will display all observation locations. Users can choose the location *of concern*. On this dashboard, only three dots are displayed. In the future, it can be developed again for observation points, because the more points that become observations, the more useful it will be for users of the flood monitoring application due to the overflow of this river.

The next menu is the "Table", this menu displays sub-menus of historical, *real-time*, and prediction data for river water levels. In the historical data sub-menu, users can only see backward data until January 1, 2021. For the *real-time* sub-menu, the user will be presented with the current data. Because the sensor cannot be installed directly on the river considering the constraints described in the previous discussion, *real-time* data is taken from forecast data and made predictions of river water levels for each location. For the prediction sub-menu, users can filter the prediction results until January 31, 2023.

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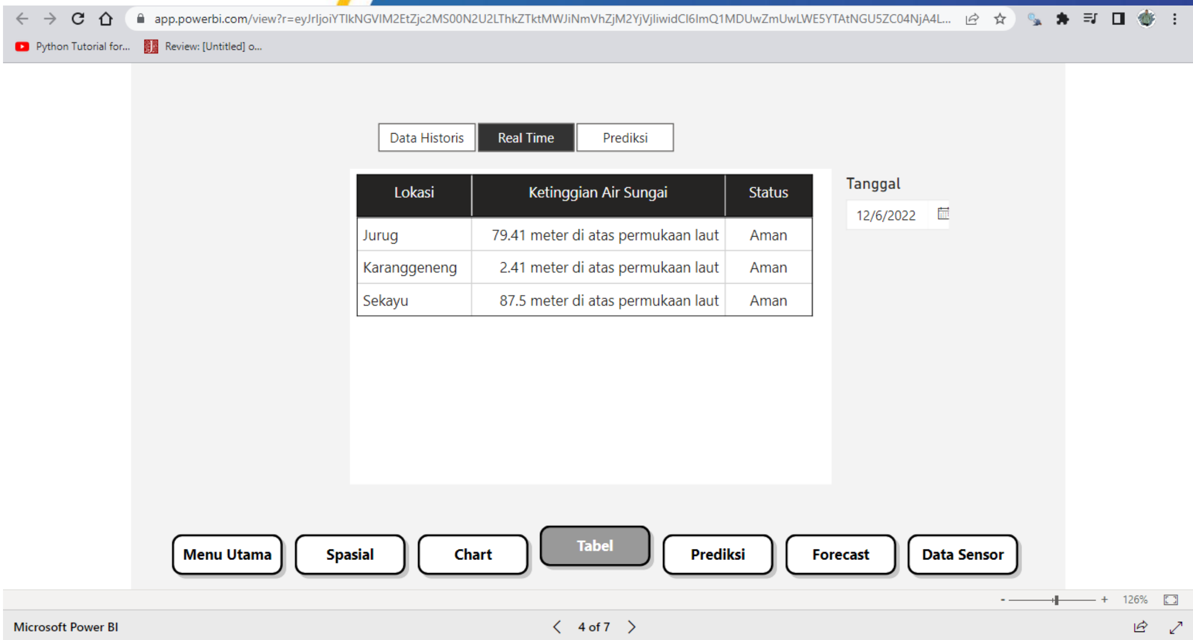

Figure 11: Table Menu of Power BI
Sources: researcher's data (2022)

Users can customize the date to see river level data from all measurement points, past, present, and future. The table will display the location, river water level, and status.

The next menu is "Prediction", in this menu users can choose the location of the measurement they want to see the river water level, status, and messages suggested by the application. Users can see the prediction of river water levels in the future in anticipation of floods caused by river overflow.

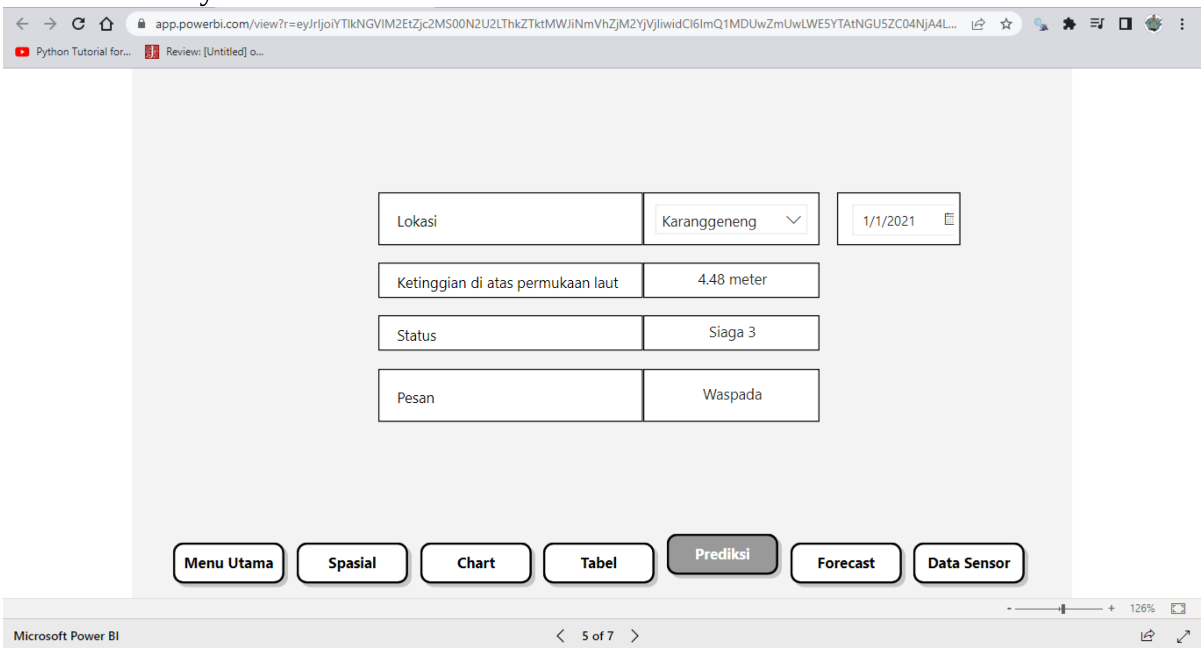

Figure 12: Prediction Menu of Power BI
Sources: researcher's data (2022)

The next menu is "*Forecast*", in this menu historical data and *rainfall data forecast* from each measurement location are displayed.

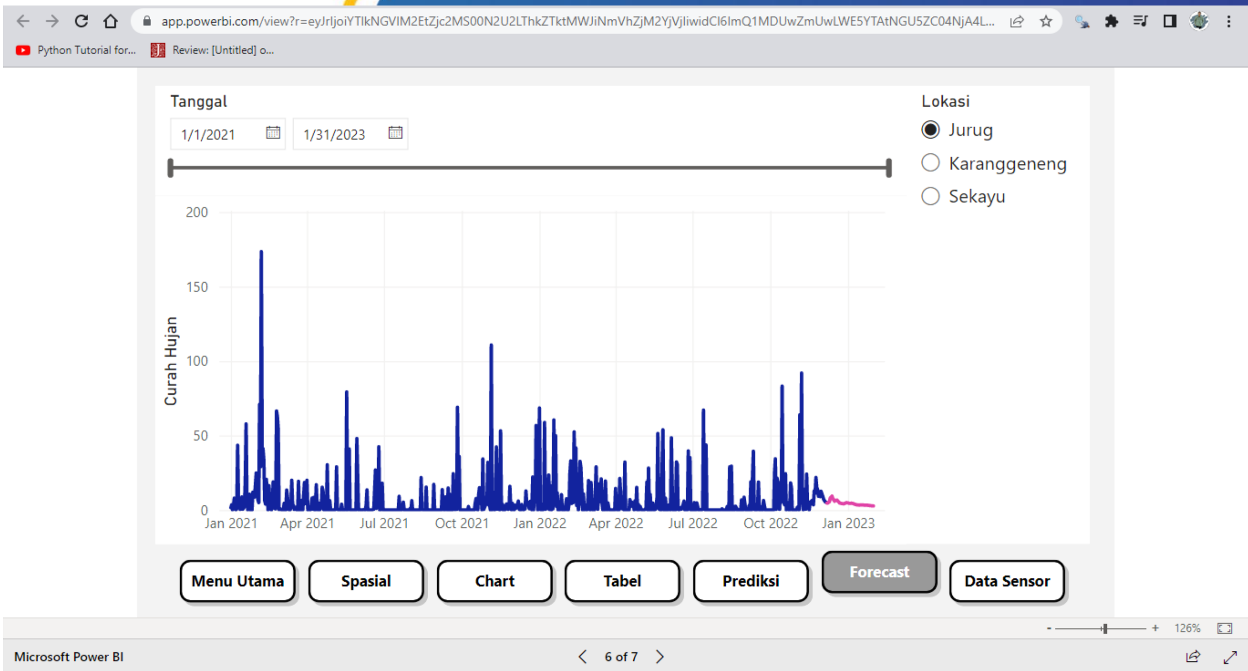

Figure 13: Forecast of Power BI
Sources: researcher's data (2022)

The data used are rainfall data from the East Java Climatology Station and Central Java Climatology Station for the period January 2021 to November 10, 2022. From this data, the forecast is made until January 31, 2023. The two stations were chosen because they are the most complete historical data stations compared to other climatological stations. Rainfall data from the Central Java Climatology Station is used to predict the water level of the Jurug River. For rainfall data from the East Java Climatology Station, it is used to predict the water level of the Sekayu and Karanggeneng rivers.

The last menu is the "Sensor Data", in this menu displays data produced from sensors. The sensor data menu, cannot be used to make *machine learning* because the data is not the original data measured from river water levels. In this menu, you just want to prove that the sensor used can be stored in the database and can be visualized. Sensor data is ready for use when the sensor has been installed in the river and continuously stored in the database. From the data generated by sensors installed in the river, the data can be used for analysis such as secondary data that has been created on the prototype including menus, namely the main menu, spatial, chart, table, prediction, and forecast.

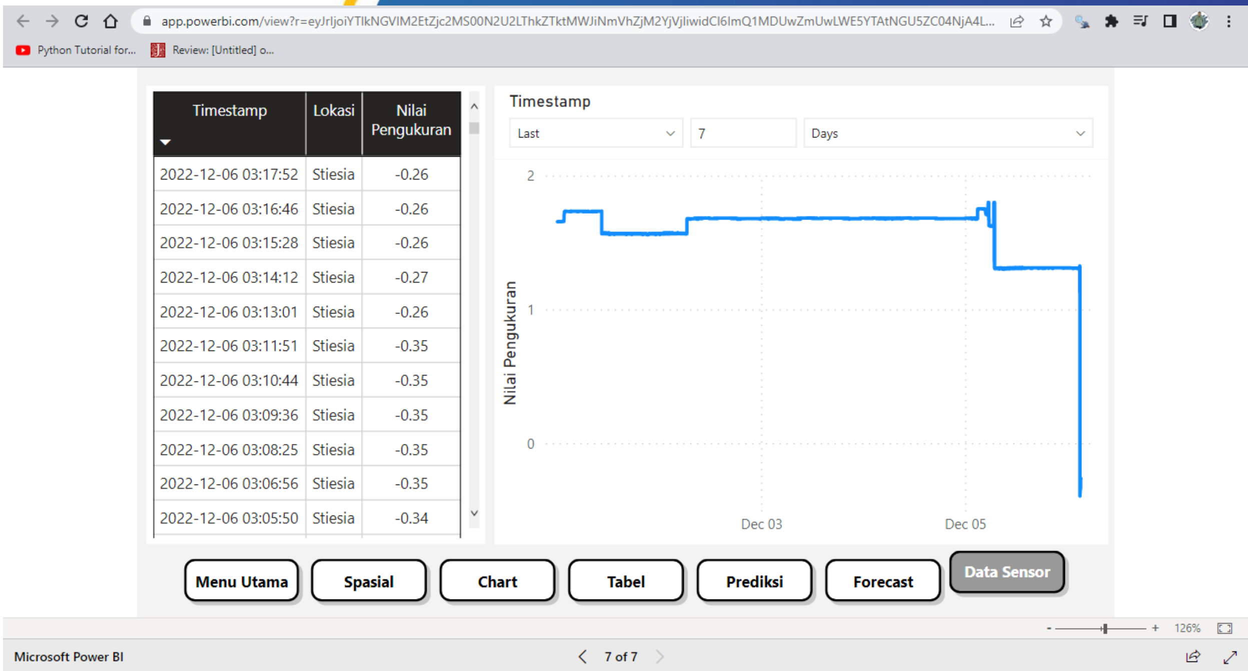

Figure 14: Sensor data of Power BI
Sources: researcher's data (2022)

5. Conclusions

The conclusion obtained from the results of the study is that the flood risk management system due to river overflow that has been made can be used. In this study, the sensor could not be installed on the river due to constraints such as the safety of the sensor, Wi-Fi, and energy sources. For making forecast and prediction menus, secondary data is used, because data from sensors still uses data from water placed in water containers. Sensor data can be used if the data is installed in the stream and there is historical data used to create machine learning.

The suggestion for the development of this prototype is that it is necessary to update the forecast results from the rainfall data used because rainfall data is difficult to forecast for the long term. Models from machine learning that are created are updated every certain period. The machine learning model created has not considered the correlation between river points, in theory, the water level of the upstream river will affect the level of river water below. This research has not been able to capture the phenomenon.

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