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Development of Drainage Status Prediction Model Based on Internet of Things and Long Short Term Memory Algorithm

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ABSTRACT

The capacity of drainage can overflow due to inadequate conditions and high rainfall intensity. Several incidents in Bekasi City due to poor drainage resulted in inundation of water on the roads which resulted in damaged roads and flooding in residential areas. Several previous studies have discussed the evaluation of the drainage system using the analytical method hydrology in modeling water discharge. In most cases, the minimum capacity of the drainage canal is caused by the high intensity of rain, so the research focuses on the volume of drainage and the intensity of the rain. However, based on observations and interviews with the cleaning service, it turns out that many drainage channels are in a non-optimal condition, where there is a lot of garbage and sedimentation that hinders the flow of water when it rains. This study combines hydrological analysis modeling with drainage channel conditions whose real time data is obtained by using sensors through the internet of things (IoT). IoT devices have been able to send data well in the cloud, by combining rainfall data and then predictive modeling using RNN LSTM with training model parameters used are two layers and 20 cells with each layer given a Dropout layer with a probability of 10%. In the metric evaluation, four functions are used, namely mean squared error, Mean absolute, Nash-Sutcliffe Efficiency and Coefficient of Determination. The model has been able to see the occurrence of an increase or decrease in height and discharge. However, if you look at the results of metric calculations, the predictions generated by the model are not very good.

1. Introduction

Rapid population growth has resulted in urban areas experiencing very significant development, causing the need for residential land to increase. This shift in land use function from open areas to residential areas causes rainwater catchment areas in residential areas to decrease, causing puddles and flooding [1]. Based on data from the Bekasi medium-term development plan (RPJMD) for 2018-2023, the population of Bekasi this year has reached 3.2 million, bringing the population density to 16,500 per kilometer out of a total area of 210 thousand kilometers. The National Development Planning Agency (BAPPENAS) said that Bekasi City is a metropolitan city with the highest population in Indonesia after DKI Jakarta and Surabaya City [2].

Every year there are cases of flooding on roads and flooding in residential areas. On January 21, 2020 there was a flood as high as 80cm in residential areas due to poor drainage [3]. This is because the water from the culverts comes from three directions, but the drain is narrow and full of mud. Based on field observations and interviews with officers at the Bekasi City cleaning service, every rainy season the streets are often flooded with water. Inundation points usually occur at the fork in the road and inundation occurs because the rainwater catchment area is not balanced with the rapid settlement area. In addition, drainage channels along the road are inadequate and cannot function properly to accommodate rainwater. So that puddles are inevitable. Therefore we need a means to drain rainwater, one of which is a drainage system.

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The drainage system is an important part in planning the development of an urban area. Judging from the decrease in existing land, the drainage system is one of the efforts to overcome and reduce the problem of waterlogging in residential areas. Generally, residential areas are unable to accommodate the runoff discharge because the drainage channels cannot function properly. Some channels that are not able to accommodate the runoff discharge optimally need to be repaired and some changes to the dimensions and shape of the channel [4]. Meanwhile, according to Evid Zulhaqi (2013), the channel has decreased storage capacity due to the absence of regular cleaning of sedimentation, garbage and plants in the drainage channel, resulting in obstacles for water to the outlet channel [5].

The development of sensor technology and the internet of things has been able to monitor and sending data in real time [6][7]. Hydrological analysis modeling has been quite good in measuring channel discharge and capacity. Research related to the prediction of water flow and rain discharge using a neural network produces a fairly good accuracy [8][9]. This study focuses on evaluating waterlogging based on the existing condition of drainage channels and the factors that influence the occurrence of inundation using hydrological modeling associated with monitoring data for internet of things devices. The combination of the two is expected to provide more updated information in creating an early warning system for preventing puddles and flooding.

2. Method

Figure 1 describes the stages of research in building an early warning system for drainage. The study began with observing the existence of the existing canal by checking the condition of the research location, in this case looking at the problems (inundation/flood) that occurred at the research location. The existing inundation problem is expected to be overcome by structuring the channel system in the form of changing the channel system, increasing the number of channels or adding channel capacity. The arrangement of the canal system has resulted in a new drainage network system that will be used as a benchmark for further analysis. Hydrological analysis was carried out to determine the value of the design discharge and capacity discharge. Hydrological analysis includes analysis of rainfall data and analysis of planned discharge. Rainfall data analysis aims to determine the rainfall data that will be used for calculations. The steps that must be taken are to identify rain gauge stations both within the research location and around the research location, then collect data from all selected stations and select the data to be analyzed. To find statistical data that deviates from the data set, an analysis of the quality of the data is carried out in the form of outlier analysis. Looking at the condition of the research location, the method used to calculate the average rainfall of the area was determined.

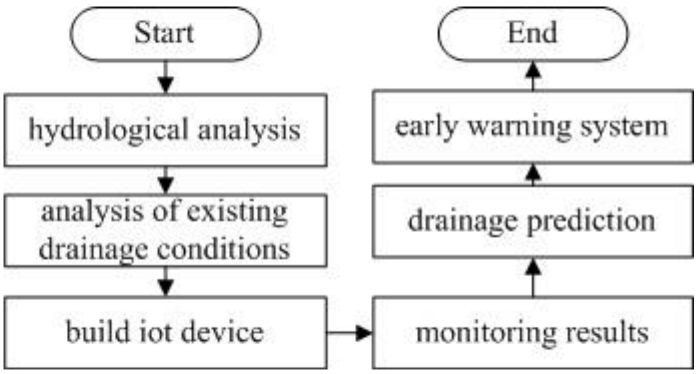

Fig. 1. Research Stages

The next stage is to build an internet of things device that requires system architecture design and sensor calibration. The device is built using an ultrasonic sensor HCSR-04, Humidity and Rain Drop Sensor, NodeMCU Lua ESP8266 and Powerbank 10000mah. The results of the hydrological analysis will be combined with data on the condition of the drainage channel and then predictive modeling will be made using the RNN LSTM algorithm so that an early warning system can be produced to prevent waterlogging and flooding.

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3. Result and Analysis

The development of an early warning system by making prediction models and recommendations for action on drainage channels begins with making Internet of Things (IoT) devices with the architecture and devices in Figure 2. Figure 3 describes the network architecture starting from the IoT devices that are built to capture water level data, humidity and raindrops and sends it to the cloud server. Rainfall data in the related area and data from IoT devices will be processed for predictive modeling. The results of the prediction modeling are then made an early warning system to notify the condition of the drainage system in preparation for the rainy season.

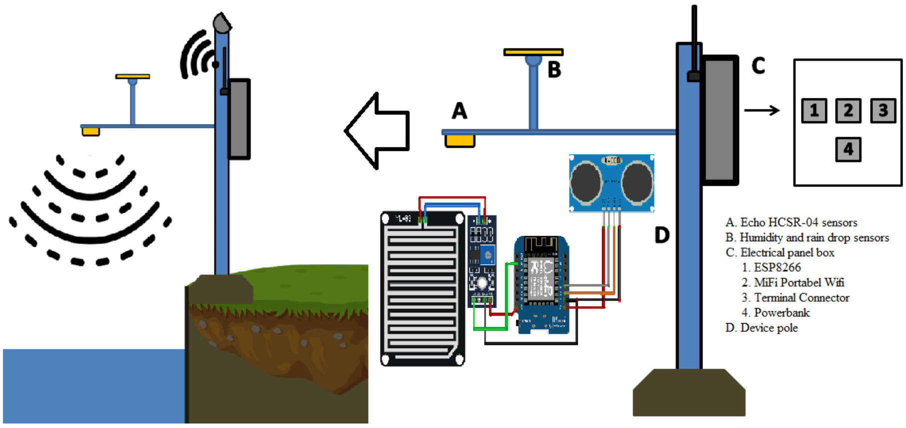

Fig 2. Internet of Things Device Drainage System

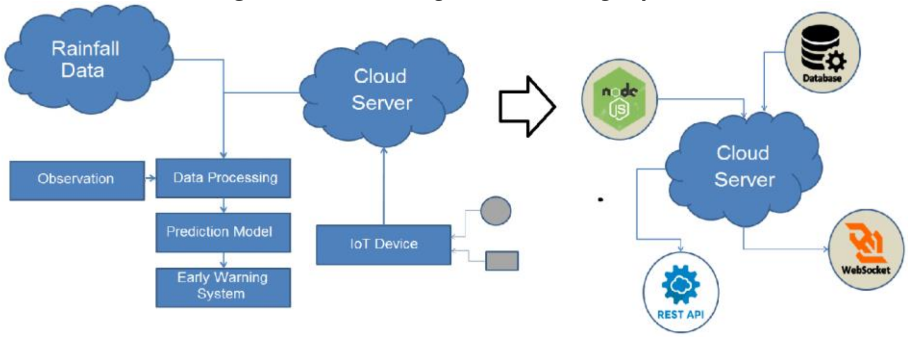

Fig 3. Drainage System Cloud Architecture

Prediction model development using Jupyter Notebook using the Recurrent Neural Networks (RNN) algorithm used is Long Short-Term Memory (LSTM), the RNN LSTM architecture model can be seen in Figure 4. LSTM is one of the developments of neural networks that are capable of storing long time series information, able to overcome the problem of gradient descent when processing long sequence data in conventional RNN [10][11]. The data in the cloud is then processed by checking the invalid data, data missing and then make corrections and adjustments to the completeness of the data.

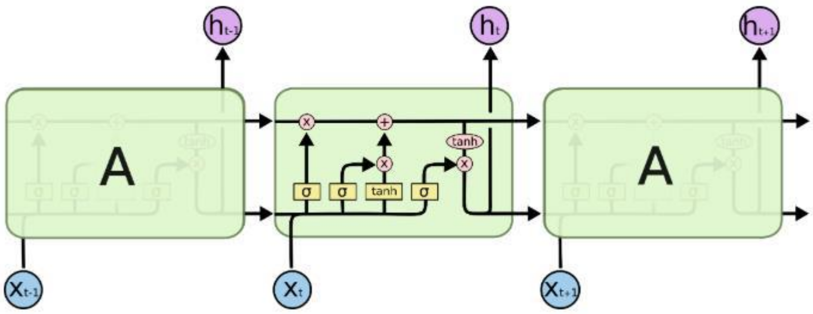

Fig 4. RNN LSTM Architecture

Next, divide the dataset into two parts, namely the train set and the test set. Then normalize the values on the dataset. In the training model the parameters used are two layers and 20 cells with each layer given a Dropout layer with a probability of 10% [12].

In the metric evaluation, four functions are used, namely the mean squared error (MSE) which is used as a loss function loss: 0 MSE , the smaller the better. Mean absolute error (MAE): 0 MAE , the smaller the better. Nash-Sutcliffe Efficiency (NSE): NSE < 1, the bigger the better. Coefficient of Determination (R2): 0 R2 1, with a value of 1 indicating perfectly correlated data (prediction data is exactly the same as the actual data) [13]. Since we want to evaluate the metrics for every epoch, a special function was created to be included when compiling the model[14].

TABLE 1
COMPARISON OF TRAIN SET AND TEST SET METRICS

Metrics	Train	Test
Mse	0.408920	0.836735
Mae	0.451762	0.585794
Nse	0.621280	0.339275
R2	0.697100	0.384172

The results of the flow discharge prediction using the test data set are still not good. It can be seen that there are some values that miss the observation data, but the model is able to predict the conditions of altitude and rain that occur in a certain month. Based on Table 1, the metric results show that the predictions from the test data set are not very good, so the model is arguably still under-trained.

4. Conclusion

The development of IoT devices has been successfully built and is able to send data to the cloud server well. In predictive modeling so far the model is still unsatisfactory. The model has been able to see the occurrence of an increase or decrease in height and discharge. However, if you look at the results of metric calculations, the predictions generated by the model are not good, none of the parameters are considered satisfactory.

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