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ROAD CONDITION DETECTION BASED ON ACCELEROMETER AND GYROSCOPE SENSORS USING DEEP LEARNING LSTM

Agus Susanto and Gede Putra Kusuma

Computer Science Department, BINUS Graduate Program – Master of Computer Science
Bina Nusantara University
Jl. K. H. Syahdan No. 9, Kemanggisan, Palmerah, Jakarta 11480, Indonesia
agus.susanto001@binus.ac.id; inegara@binus.edu

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Abstract. *The development of a system that can automatically detect road condition is quite required, particularly in megapolitan cities such as Jakarta that has large-scale road network. The system is very important for monitoring tool as a part of road maintenance. Several previous studies have developed the model using accelerometer and gyroscope sensors data, but it has not been mentioned that the data is segmented. In this study, we developed the model with segmented data using deep learning that can detect road conditions and classify them into three categories, namely Normal Road, Bad Road and Bad Road with Potholes. Input dataset was obtained from accelerometer and gyroscope on a smartphone placed in a car. This study also tested with other models that are Support Vector Machine (SVM) and Decision Tree. The results of accuracy using Long Short-Term Memory (LSTM) is 79.02%. The result is 8% higher than SVM and 19% higher than Decision Tree.*

Keywords: Road condition, Accelerometer sensor, Gyroscope sensor, Deep learning, LSTM model

1. **Introduction.** Roads are one of the important infrastructures for the people's economy movement. Damaged road conditions lengthen the travel duration; therefore, it affects economic activities. Based on the Law of the Republic of Indonesia Number 22 year 2009 concerning Road Traffic and Transportation article 24 paragraph (1) states that "The road operator obligates to repair the damaged road immediately and properly that may cause traffic accident" and paragraph (2) states that as the road maintenance cannot be done yet refers to paragraph (1) the road operator obligates to provide road signs or marks on the damaged road for traffic accident prevention [1].

The road condition detection system has been implemented by several researchers. These studies include using a stand-alone hardware sensor installed on a vehicle permanently [2]. Other researchers use laser imaging to detect potholes and crack roads [3]. These methods require specific devices; therefore, they are not economical. There is a study that utilizes the accelerometer sensor on a smartphone using Artificial Neural Network (ANN) algorithm to detect road anomalies [4]. Another study uses both of accelerometer and gyroscope sensors, and this study is to detect pothole and non-pothole roads using SVM classification method [5].

Based on previous studies, there are weaknesses from the impracticality of the tool, the use of special tools installed on the vehicle and of course its economic value. Other solutions with economical devices, for example, using accelerometer and gyroscope sensors on smartphones, currently have no research that uses deep learning methods that utilize time series datasets to detect road conditions.

In this study, an optimal model is developed to classify road conditions which results in road classification categories, namely Normal Road, Bad Road and Bad Road with

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Pothole. The input data uses data from the accelerometer and the gyroscope sensors that record vehicle vibrations while driving on the road. This study uses the LSTM method, which is one of the proven deep learning methods in processing time series dataset [6,7]. The results of this study can contribute to the government (the road operator) in developing a road maintenance system.

This paper is organized as follows. After the Introduction section, Section 2 discusses some literature review. Section 3 gives out the system architecture that is proposed for road condition detection. Section 4 discusses the experiments consisting of experimental design and experimental result. The last section concludes the study.

2. Literature Review.

2.1. Motion-based method. Research on the detection of road conditions has been carried out by several researchers using data from motion sensor and from camera sensor. The accelerometer and gyroscope sensors are motion sensor-hardware based [8]. The orientation of the accelerometer and gyroscope sensors can be seen in Figure 1. This figure shows three sensor orientations: x-axis, y-axis and z-axis.

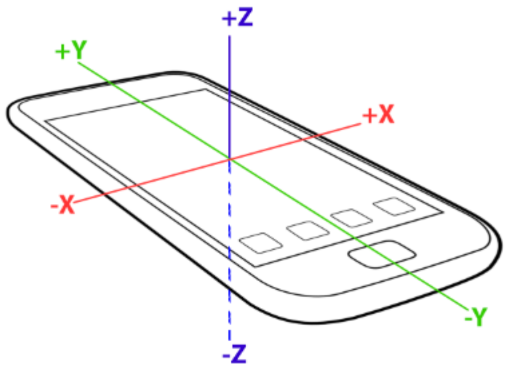

Figure 1. Sensor orientation

Study based on motion sensor that utilizes an accelerometer was conducted in 2008. The z-axis accelerometer signal from the sensor is processed using a high-pass filter. If there is a value above threshold, it is used as a marker that the road has anomalies [9,10].

Another study using accelerometer was conducted with the Power Spectral Density (PSD) method. This study result classifies the pavement roughness level into four: Excellent, Good, Qualified and Unqualified [2]. In addition, there are studies using with Gaussian model for abnormal event detection method which results in an error rate of 1.6%-5% [11].

In Indonesia, there is a study for road damage classification with accelerometer sensor. This study uses the ANN method to classify into 4 classes: Normal, Pothole, Speedbump and Expansion Joint [4]. Other studies using the ANN method have also been carried out, but apart from the accelerometer sensor it also uses a gyroscope sensor [12,13].

Research using accelerometer and gyroscope sensors from smartphones to detect road quality has also been conducted by researcher. This study uses the Mahalanobis-Taguchi System (MTS) algorithm. With data from these two sensors, the results of the study have an error rate of 2.45% [14]. Other researchers use SVM algorithm with polynomial kernel and also use Decision Tree that before being tested, the data is filtered using Correlation based Feature Selection (CFS) [15,16]. Another study using the Decision Tree method has also been conducted in India with the same sensor as the path detected only the pothole [17]. In addition to road detection, accelerometer and gyroscope sensors are also used for human motion anomaly detection [18].

2.2. **Image-based method.** Image data can be used to detect road conditions, on this study used to detect cracked roads. Images are taken using the camera facility from a smartphone instead of a professional DSLR camera with total 500 images collected. In this study, the detection method uses the deep learning Convolutional Neural Network (CNN) method with the Rectified Linear Unit (ReLU) activation function [19].

2.3. **Long short-term memory.** LSTM uses the concept of three gates: input gate, forget gate, and output gate. The function of these gates is to select and process data, which date is stored and used as input for the next activation or ignore unnecessary data. With this concept, data storage to memory is faster and more efficient than the traditional RNN model [20]. LSTM produces good output using large data input, but small data input is inaccurate output [21]. The use of gates in LSTM allows overcoming the vanishing gradient problems that usually arise in RNN [22]. Compared to other algorithms, LSTM has advantages in processing sequential data.

3. Proposed Method.

3.1. **Data collection.** The collection of sensor data is obtained by putting a smartphone between A-pillar and B-pillar of the car. The car has driven in the road at less than 40 km per hour of speed [11]. In this study, the data collection was carried out using the sensor of the Samsung Galaxy A50s smartphone in the car Mitsubishi Xpander Ultimate Model Year 2018. The data taken were labelled according to the classification, namely Normal Road, Bad Road and Bad Road with Pothole.

The accelerometer and gyroscope signal when the car passes through the road anomaly is shown in Figure 2. The marked signals are called anomaly signals. Meanwhile, others are signals when a car passes through normal or good condition road. Figure 2 shows examples when a car passes through potholes road. It can be seen that the signal is flat or constant, starting from $t0$ to tn with anomaly signal. It means that the car passes through potholes road.

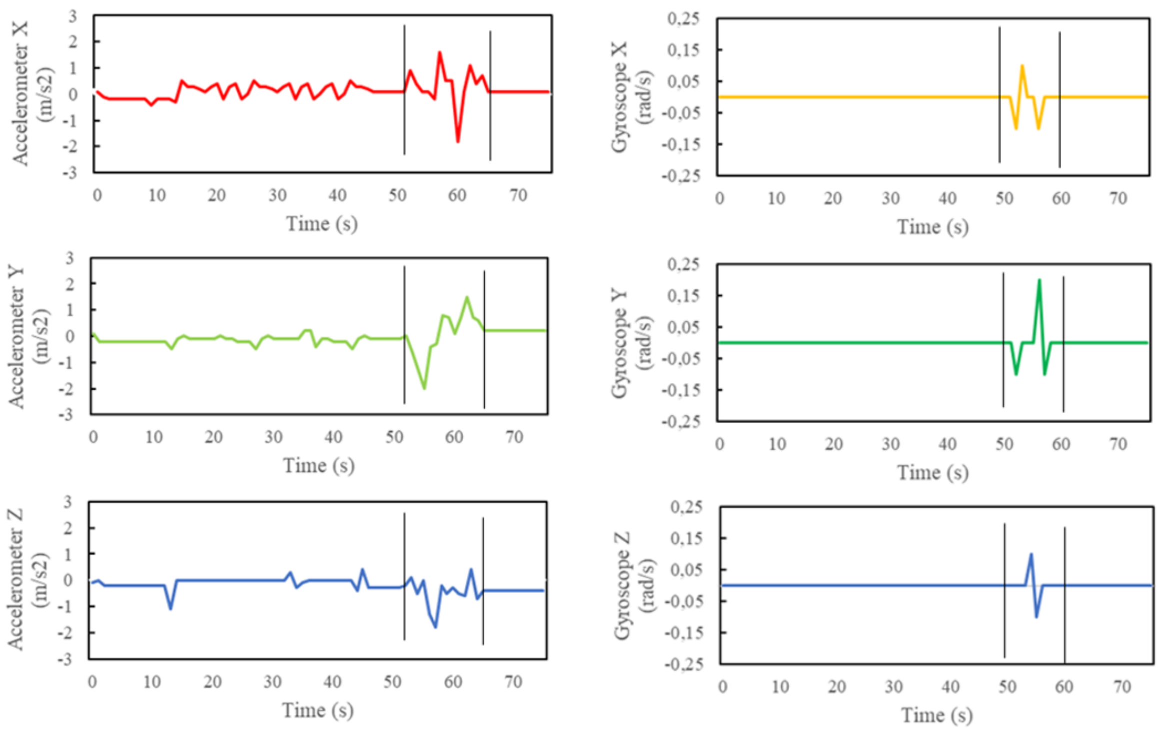

FIGURE 2. Accelerometer and gyroscope signal when vehicle through road anomalies

3.2. **Segmentation of time series data.** The recorded result data is in time series data form. As we know, when a car passes an anomaly road, a series of data is formed in the sensor that forms an anomaly signal. The anomaly signals appear sequentially starting from $t0$ second to tn second. Before the data is processed in the model, the data must be pre-processed first. The results of time series data cannot be directly processed. Time series data must be segmented for t seconds into inseparable one data frame. This one data frame is labeled based on the anomaly class. Figure 3 shows accelerometer and gyroscope data signal that has been segmented per 10 rows into one frame and labeled into one data.

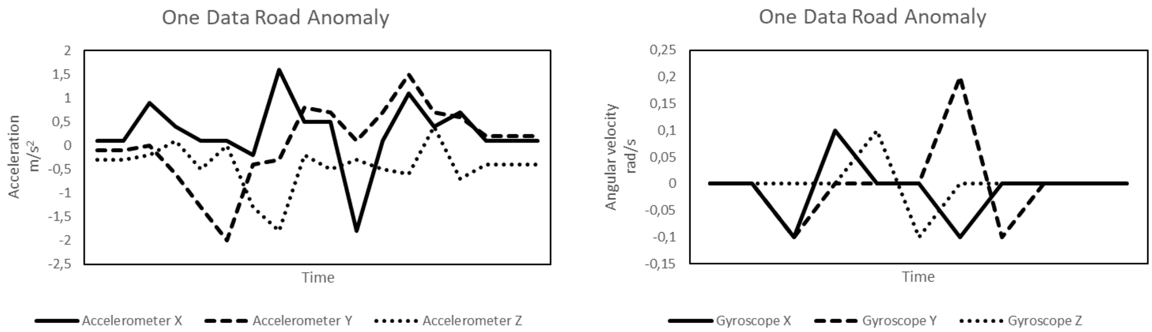

FIGURE 3. Segmented accelerometer and gyroscope signal

3.3. **Proposed model.** The proposed road detection system is shown in Figure 4.

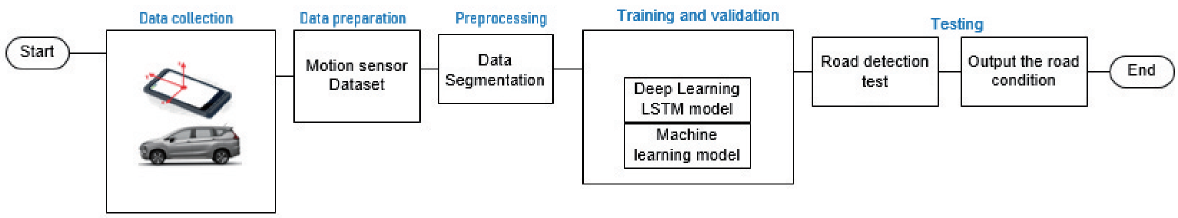

FIGURE 4. Proposed method

In Figure 4, the data collection was obtained by putting smartphone in the middle part of the car, in the boundary between pillar A and pillar B of the vehicle. The car was driven along the roads with its speed less than 40 km/hour [11]. Next, the data were pre-processed using time series data segmentation. Then, the data were trained and tested by deep learning LSTM. The LSTM model architecture is shown in Figure 5. The comparison model is trained and tested by setting the hyperparameter values and with segmented input data.

In Figure 5, there are 6 neurons in the input layer from accelerometer x, y, z and gyroscope x, y, z. Then process to the LSTM hidden layer. From the hidden layer, enter the dense layer which functions to add a fully connected layer. In the final process, there are 3 neurons as detection class for road condition classification.

LSTM hyperparameter tuning is very important in forming the best model. The correct hyperparameter setting will result in a high degree of accuracy. In this study, the LSTM hyperparameter settings are as shown in Table 1.

Besides deep learning model, the test was also conducted by using machine learning SVM and Decision Tree model. The SVM and Decision Tree hyperparameter values are determined from the default settings as shown in Table 2 and Table 3.

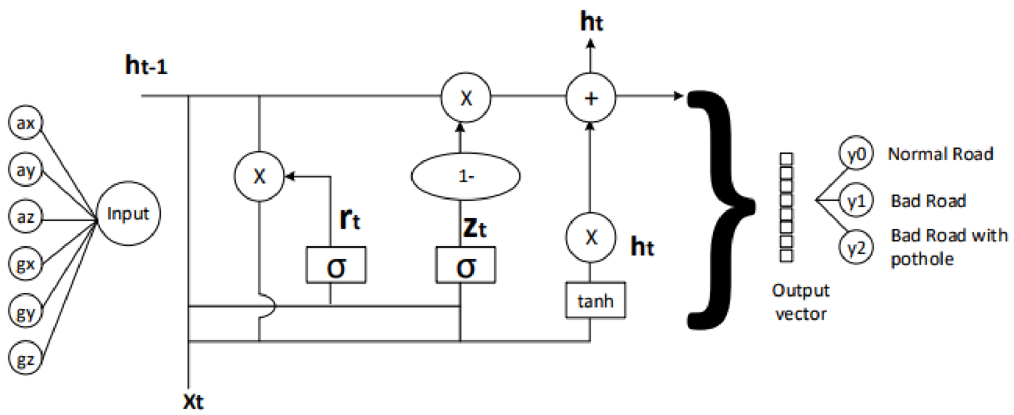

FIGURE 5. LSTM architecture for road detection

TABLE 1. LSTM hyperparameter

Hyperparameter	Value
Learning rate	0.01, 0.02
Optimizer	ADAM, SGD
LSTM hidden unit	8, 16, 32
Loss function	Categorical Cross Entropy
Max epoch	300

TABLE 2. SVM hyperparameter

Hyperparameter	Value
Kernel	Linear, RBF, Sigmoid
Splitter	0.001, 1, 100

TABLE 3. Decision Tree hyperparameter

Hyperparameter	Value
Criterion	Gini, Entropy
Splitter	Best, Random

4. **Experiments.**

4.1. **Experimental design.** At the time this study was conducted, the datasets were divided into 60% training data, 20% validation data and 20% testing data. In the training and validation phases, perform LSTM hyperparameter tuning as shown in Table 1. In Table 1 learning rate tuning is made to get the maximum training process. In this study, the learning rate was set from 0.01 and 0.02. The optimizer functions to measure the effectiveness of the model in making predictions for each epoch. The optimizer in this study uses Stochastic Gradient Descent (SGD) and Adaptive Moment Estimation (ADAM). The LSTM layer uses a variation of the number of hidden units 8, 16 and 32. After getting the best accuracy value and the best hyperparameters value in the validation phase, then the test phase is carried out with the best hyperparameters.

4.2. **Experimental result.** On the result of validation phase, the best accuracy of the LSTM model was 79.02%. This result is conducted with hyperparameter learning rate = 0.02, optimizer = SGD and hidden unit = 32. Meanwhile, in the SVM model, the best validation accuracy results are 71% with the hyperparameters kernel = RBF and

C = 1. In the Decision Tree model, the best validation accuracy is 60.27% with the hyperparameter criterion = Gini and splitter = best.

Testing is applied to getting confusion matrix as shown in Tables 4, 5, and 6. In those tables, there are prediction scores result of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). We can calculate precision (p) and recall (r) by using those scores with the following formula: $p = TP/(TP + FP)$, $r = TP/(TP + FN)$. We can calculate F1-Score from precision and recall. The best F1-Score is 1. On the contrary, the worst score is 0. F1-Score can be defined by $F1\text{-}Score = 2 \times p \times r/(p + r)$. The accuracy ($acc$) can be defined by using formula as follows: $acc = (TP + TN)/(TP + FP + TN + FN)$.

From the confusion matrix table and the formula that has been described, we can calculate the value of accuracy, precision, recall and F1-Score. Accuracy values at LSTM = 79.02%, SVM = 72.77% and Decision Tree = 63.84%. Details of the results can be seen in Table 7.

From the accuracy results of SVM and Decision Tree, the accuracy results are both lower than using LSTM. This could be due to the test data being segmented per frame. As we know this road anomaly data cannot be lined with sensor data but must be sequential data from sensors that make the signal. From this one frame sequential data, when tested

Table 4. LSTM confusion matrix using testing data

		Predicted		
		Normal	Bad Road	Bad Road with Pothole
Actual	Normal	51	13	20
	Bad Road	6	54	9
	Bad Road with Pothole	3	6	66

Table 5. SVM confusion matrix using testing data

		Predicted		
		Normal	Bad Road	Bad Road with Pothole
Actual	Normal	63	5	12
	Bad Road	8	45	16
	Bad Road with Pothole	12	8	55

Table 6. Decision Tree confusion matrix using testing data

		Predicted		
		Normal	Bad Road	Bad Road with Pothole
Actual	Normal	53	16	11
	Bad Road	10	41	18
	Bad Road with Pothole	10	16	49

Table 7. The result of testing phase with test data

Model	**Accuracy**	**Average precision**	**Average recall**	**Average F1-Score**
LSTM	79.02%	79%	79%	78.67%
SVM	72.77%	73.33%	72.33%	72.67%
Decision Tree	63.84%	64%	63.33%	63.66%

using LSTM, it can produce better results because LSTM has a memory cell that can overcome vanishing gradients when processing sequential data.

5. **Conclusion.** Sequential data processing needs to be segmented per frame so that data reading from the model made does not jump around but is ensured sequentially. In this study, the average sequential data when detecting each road anomaly is 10 lines of data. Based on the results and analysis of research to detect road conditions which are classified into three classes, namely normal, bad road, bad road with pothole, it can be concluded that the LSTM deep learning model has higher accuracy than other models, SVM and Decision Tree. The higher LSTM accuracy capability is due to the LSTM concept which has a memory cell so that it is better at processing sequential data than the other 2 models.

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