An Implementation of Artificial Neural Network based on IMU sensor for Train Detection

Anton Cahyo Saputro, 1), Amang Sudarsono 2) , Mike Yuliana 3)

[1,] Dept. of Electrical Engineering, Electronic Engineering Polytechnic Institute of Surabaya (PENS) Surabaya, INDONESIA
Email: [1,*]
[1)] Corresponding author: [1)]antoncahyosaputro@gmail.com [2)]amang@pens.ac.id [3)]mieke@pens.ac.id

A B S T R A C T

The purpose of train detection systems is to check the clearness-relation in track section of vehicles before a train passes through a route. A train detection system has an important role in ensuring the safety of train traffic. There are mainly 2 commercially used train detection systems. They consist of an axle counter and a track circuit. The problem with both systems is the high-cost installations and related equipment management. Several solutions have already been presented either on previous research with various methods, such as using Infrared and computer vision/image processing. Most of them want to make the system more effective and less cost maintenance than commercial use. To solve the issues, we propose a new method for train detection based on the usage of an Inertia Measurement Unit (IMU) with embedded artificial neural network module mounted on the sleeper's train in the following section. We utilize the method of train detection by involving an appropriate data acquisition method and a convolution operator as a time series processing algorithm. This idea equips the system to recognize the difference between train and gangway at the speed of 30 km/h. Several experiments conducted on actual rails demonstrate the method's dependability, suggesting its adoption in an automatic track warning system. So, in this proposed train detection system, we propose the train detection system using IMU with Artificial Neural Network Algorithm.

Keywords: Train, IMU, Convolution Operator, Artificial Neural Network

Corresponding Author:

Nuri Aslami
Faculty of Islamic Economics and Business , Univesitas Islam Negeri Sumatera Utara ,Medan, Indonesia
Email: nuriaslami@uinsu.ac.id

1. INTRODUCTION

The transportation system contributes significantly to national growth. As a component of the economic system, transportation is required to ensure the movement of people and things. The train, which is a popular mode of transportation, is one of them. Enhancement of service and passenger comfort is one of the primary factors influencing the community's selection of this mode of transportation[1].

The first reason why railways require train detection is that trains cannot generally stop within the visible distance of the driver. When a train conductor observes a green light, he is authorized to travel at the maximum speed permitted for his train at that location. Therefore, the signaling system must ensure that the line ahead is clear until the next signal and (at a minimum) the train's braking distance after that. To run at 200 kilometers per hour (125 miles per hour) on a level grade, it can take a train almost two kilometers to come to a stop, therefore "driving by sight" is clearly not an option for high-speed lines. Even at a relatively modest 80 km/h (50 mph), certain types of trains require up to 1 kilometer to stop[2].

Trains have unique characteristics, such as their ability to move on rails, and only one train is permitted to pass in each stretch of railway. There are numerous types of signaling equipment, including mechanical, electromechanical, and electrical signaling. Electrical signaling equipment employs electric power to control the signal's polarity and direction. Interlocking VPI (Vital Processor) signaling equipment is one sort of electrical signaling. On the railroad track, the train detection sensor transmits an electrical signal to the equipment. In Indonesia,[3] common train detection equipment includes:

1.1 Track circuit

This device detects trains by electrically isolating each rail and connecting them in a closed circuit. The train tracks are powered by direct current (VDC) from Cikampek to Madiun and alternating current (VAC) from Jabotabek to Cikampek. Using the potential difference when the section is passed, the track relay transmits a digital signal to the VPI for processing by the train dispatcher in place of de-energized (no train) and energized (no train) conditions. But track circuits can have problems like low-precision detection, right- and wrong-side failures caused by contaminants on railheads, rusting, leaves on the track, and wideband interference currents caused by traction[2].

1.2 Axle Counter

This tool's detection system consists of four components: a wheel sensor, a wheel sensor detector, a track side connection box, and an evaluator. In this method, the axles in one section are counted and compared with the incoming and leaving axles to confirm the train has passed the parameters and is safe for the following train to pass. The track circuit implementation demands a substantial amount of energy. On the axle detection sensor counter, sensor readings are still restricted to a maximum of 255 axles for trains passing the criterion. In addition, the use of detecting equipment with this axle counter is very expensive[2].

Several low-cost technology solutions have been proposed and developed in recent years to address the problem of precisely measuring the positions and speeds of trains on railways. Some studies have employed infrared (IR) transmitters and receivers to measure vehicle speed and cracks [4] [5]. However, the IR transmitter and receiver can only detect rail cracks. With the advancement of image processing technology, some train monitoring research use computer vision or image processing methods. They are effective with respect to railroad monitoring. To monitor trains and rails at night, however, high-performance cameras are required, which increases the system's cost and energy consumption, not to mention the impossibility of real-time monitoring over the long run[6].

The structural vibration of the wheel and rail, which is caused by a combination of small-scale undulations on the wheel and rail contact surfaces, is the main cause of railway rolling noise. One of the primary sources of vibration for cars and tracks is the irregularity of a railway's profile[7]. The vibration transmission process, comprising the track and the ground, can be defined as follows: The first step is the origin, as the interaction of the train with the track structure creates dynamic forces between the rail and wheels. These forces cause the track construction and the vehicles to move. The track structure's movements generate stress waves that propagate across the surrounding soil[8].

There are several prototype approaches to detect train like axle counter's technology [9] [10]. The Axle counter prototype can control up to eight sections and monitor up to twelve counting points. The most of available axle counters support smaller number of sections and counting points per one device than presented axle counter prototype. In this study, we try to be able to make a prototype with a different method, using a time series approach, so as to get better and more accurate counting results.

Prediction estimates future events using a specific scientific approach [11] of analyzing time-series data patterns [12] [13]. The basic principle of analyzing time series data patterns is to break time series data into distinct patterns, identify the distinct time series, and then uncover each pattern separately [14] [15]. One of the techniques is Artificial Neural Network (ANN). ANNs belong to the data-driven method, i.e., the analysis is dependent on the existing data, with minimal a priori justification of the correlations between variables and the models. Several general-purpose "learning" algorithms handle the procedure of creating the associations between the input and output variables [16]. For preprocessing data, there are convolution operators while fully connected layers have a memory to store information in time series data [17]. They are used in image processing in CNN, but the difference is that they are modelled as a 1D array for time series forecast [18]. The observation sequence can interpret the raw input data as a 1D array, which the CNN model can read and filter. Consequently, this principle is applicable to time-series analysis [19].

The state-of-the-art developments with neural networks, especially the Artificial Neural Network (ANN), demonstrate an end-to-end time series classification approach in preprocessing with raw data. In this research, we propose detecting train based on raw data vibration that through railway using IMU (Inertia Measurement Unit) that consist of accelerometer. We specialize in oil train, because oil train carry the same weight and have the same dimensions of carriage. The ANN algorithm is based on human brain neurons. The incoming data will be analysed in the same way as a human brain does until a decision is reached. The sensing device will be fastened in place on the sleeper train, and the accelerometer, gyroscope, and magnetometer on the accelerometer designated BNO055 will record the sensor's output value when the train passes.

2. RESEARCH METHODOLOGY

The ANN model will learn a function that maps a sequence of past observations as input to an output observation. Therefore, it is necessary to create several examples from which the model can learn from the series of observations. In this section is divided into two parts, they are:

1. Data Preparation
2. Training Methods
3. Performance comparison

This evaluation will be conducted using ANN Machine Learning by MLP (Multi-Layer Perceptron) models comparing with LSTM (Long Short-Term Memory) model as algorithms. Regarding the system architecture, this research can be found in Figure 1.

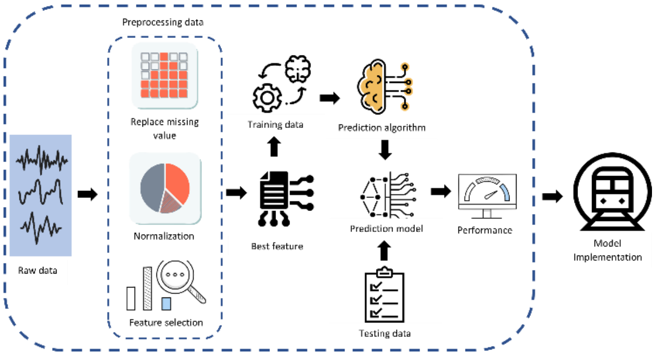

FIGURE 1. System design

Before entering the testing procedure, the raw data must complete data preprocessing. Before beginning the data training process, this step is very useful for data cleansing. In addition, there is a feature selection that helps identify future-important attributes for making predictions.

2.2 Data Preparation

A time series is a sequence of data points (measurements) whose temporal order is inherent. It is challenging to create a statistical model from time series data because these data may be non-stationary and exhibit changing statistical features over time. In contrast, data mining techniques degenerate due to the high dimensionality of the time series and noise. Classification of time series involves assigning a label to an interval of data points through time depending on their behaviour. Train detection from the acceleration data can be fulfilled through the time series classification approach[20].

The conventional time series classification approaches can be summarized in similarity-based and feature-based methods[21]. The similarity-based method is based on specific similarity measurements, such as Euclidian distance, in which the testing samples are assigned the class labels of the matching training samples whose similarity measurements are minimized. Research [22] suggests that a convolution layer can be viewed as a filter that is applied and dragged over a time series. The output of a convolution layer (one filter) on an input time series can be viewed as another time series that was filtered to provide discriminative features useful for classification problems. Like shows in Fig 1., the numerous filters are applied to an input time series, various discriminative features are automatically learnt. Pooling is like aggregating the time series across the entire time dimension, resulting in a single real value. Typically, a global aggregation reduces the number of parameters in a model, hence reducing the danger of overfitting. The final discriminative layer creates a probability distribution over the class labels for the input time series using the features from the convolution and pooling layers.

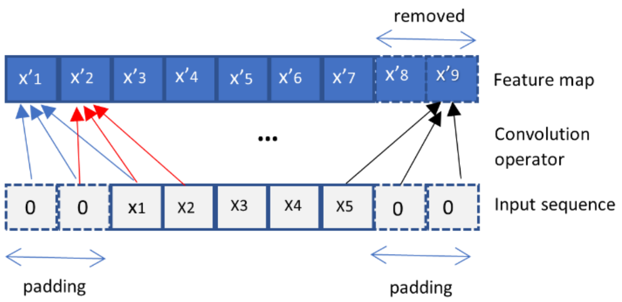

FIGURE 2. Convolution Operator

In this research, convolution layer is used to construct an end-to-end time series classification model that can detect a passing train using raw data from accelerometer. The input sequence will be divided into several input or output patterns called samples, with 516-time steps being used as input and 2 output for the one-step prediction being learned.

A dataset will be split into training and testing sets. The training set will be used for model training, while the testing set will be used for model validation. In general, it is expected that the training set and testing set are taken from the same population and have mean and standard deviation values that are comparable. The testing set represents data from railroad in future. The testing set is normalized by the mean and the standard deviation of the whole dataset is used. Future information will be introduced in model learning.

2.3 Training Methods

In recent years, Artificial Neural Networks (ANNs) have gained popularity as an alternative to time series forecasting. Although the availability of several time series models, the accuracy of time series forecasting is today crucial to numerous decision-making processes; as a result, research into enhancing the effectiveness of forecasting models has been abandoned[23]. Numerous research investigations on time series forecasting have asserted that the predictive ability of mixed models is enhanced[24].

We suppose to mix ANNs model with convolution layer and Min-Max process. Mixing models is motivated by the belief that it is impossible to identify the underlying data-generating process or that a single model may not adequately all the time series features.

Our ANN model consists of four hidden layers, each containing 64 filters of length 5, a max-pooling layer of length 5, and a hidden layer of size 100. ReLU was utilized as an activation function between layers prior to output. The second design was a long-short-term memory (LSTM) with one LSTM layer containing fifty hidden states, followed by a fully connected layer with a sigmoid activation function across layers till output.

The input size for both models was set to 516, and the output size was the number of classified, train or no train. The training was done in 200 epoch and data were forwarded through the model in batches of size 4. The learning rate of the models was used as a loss function. The number of trainable parameters and the number of layers for different neural network architectures are presented in table 4.

2.4 Algorithm test and scenario

As for the test scheme, there are two test scenarios: Multilayer Algorithm Perceptron (MLP) and Deep Learning (LSTM) are presented in table below:

Table 1. Algorithm test scenario

Parameter	MLP	LSTM
Activation	ReLu	Sigmoid
Epoch	200	200
Batch_size	64	64
Optimizer	Adam	Adam
Hidden Layer	4	50
Learning Rate	0,001	0,001

At this research, it will be focused on Multilayer Perceptron (MLP). The pseudocode for the neural network algorithm is displayed in the Table. 3

2.5 Performance Analysis

In this research, to indicate the feasibility of train detection using neural network from accelerometer, we use confusion matrix figure to show accurate identification of system.

The confusion matrix is a tool for measuring the performance of a model, especially in the case of classification (supervised learning). Basically, the confusion matrix provides information on the comparison of the classification results performed by the system (model) with the actual classification results. The confusion matrix is in the form of a matrix table that describes the performance of the classification model on a series of test data whose actual values are known.

Table 2. Pseudocode algorithm

Chronological	Process
Step-1	Call train dataset
Step-2	Data normalization
Step-3	Replace missing value
Step-4	Make sequence with 100
Step-5	Dataset validation method
Step-6	Windows size=seq-_len – 1
Step-7	Input parameter
Step-8	Model compilation with loss type = MAE, and optimizer=ADAM
Step-9	Data test prediction

3. RESEARCH RESULT

This The machine learning training process uses its function in Google Collab. Python with the Keras Library was chosen as the implementation. The dataset used is raw data from the accelerometer sensor. The first thing to do on the raw data is to determine the composition of the data to be used, and then proceed with the feature selection process that influences the determination of train detection conditions. Then the learning process is carried out using 2 types of algorithms, namely Multilayer perceptron (MLP) and long-short-term memory (LSTM), as a comparison.

The experimental procedures were reviewed and approved by the DAOPS VI Public Relation Section of Indonesian Railways Company (abbreviated PT.KAI) Administration, and the entire experiment was conducted by corporate employees.

3.1 Collecting Data

The collected data is generated by the accelerometer, gyroscope, and magnetometer on the BNO055 sensor. In the experiment, a CC 2040304 locomotive with 20 oil trains for gasoline was used. Each train measured 12.8 meters in length and was fully loaded. Fig. 3 shows sensor placement at the railroad. Sensing device at this research installed at the sleeper's train because it has a flat surface to smoothly contact with the side of the sensing device.

FIGURE 3. Sensor Placement

When the train crosses the sensor parameters, it takes between 11 and 12 seconds. Based on these parameters, 10 sensor data of each axis are collected every 1 second. In this test, we used the BNO055 sensor's accelerometer, gyro meter, and magnetometer features, each of which has three axes, x, y, and z. The value taken on the accelerometer gyro meter, and magnetometer features is set by taking 10 input data every second from the accelerometer sensor. The predictor results were obtained from 516 data samples. The following image shows the signal generated during the sampling process:

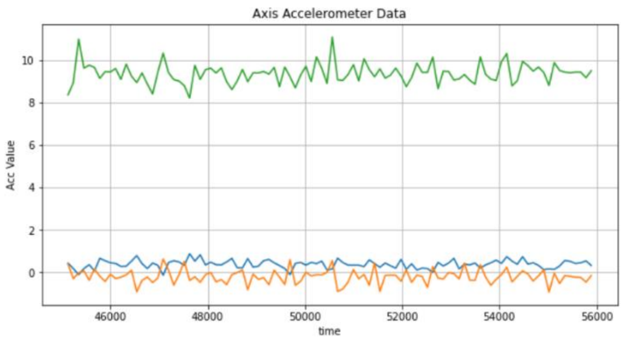

FIGURE 4. Sampling process from accelerometer axis

This raw data will be labelled and standardized by convolution operator in the next step.

3.2 Data segmentation

Acceleration data from the IMU sensor in this paper is used to detect train vibration. The whole dataset is ordered by acceleration continuously. 2 conditions are considered as class label consist of train, and no train. Train represented by “1”, and no train represented by “0”. 516 data was collected from the BNO055 sensor. Each class represents a fixed-length interval in a time series. In order to modify the acceleration dataset in the required format, time series data is divided using sliding windows, with each segmentation serving as a sample. The interval between the sliding windows is fixed.

	timestamp	gyro x	gyro y	gyro z	accel x	accel y	accel z	mag x	mag y	mag z	result
0	00:00:19	0.000000	-0.001091	0.001091	0.37	-0.19	9.43	33.0000	-22.0000	2.3750	0
1	00:00:19	0.000000	-0.001091	0.000000	0.37	-0.20	9.45	32.2500	-22.7500	0.6750	0
2	00:00:19	0.001091	0.004363	0.000000	0.36	-0.17	9.46	32.5625	-21.5625	1.1875	0
3	00:00:19	0.000000	0.001091	0.001091	0.35	-0.19	9.46	32.5625	-22.7500	0.7500	0
4	00:00:19	0.000000	0.001091	-0.001091	0.36	-0.18	9.43	33.0000	-22.3750	0.3750	0
...	...	...	...	...	...	...	...	...	...	...	...
510	00:01:15	-0.044724	-0.038179	0.002182	0.52	-0.19	9.42	33.5000	-22.7500	-0.5625	1
511	00:01:15	0.007636	0.000000	-0.002182	0.42	-0.23	9.45	33.0625	-23.1875	-0.5625	1
512	00:01:15	-0.001091	0.000000	-0.001091	0.45	-0.24	9.45	33.5000	-23.5625	-0.1875	1
513	00:01:15	-0.039270	-0.032725	0.001091	0.54	-0.46	9.19	32.6875	-23.2500	0.5625	1
514	00:01:15	0.016362	0.020726	-0.002182	0.32	-0.15	9.52	32.2500	-22.5625	-0.1875	1

FIGURE 5. Class label dataset

3.3 Data normalization

For raw data to have a consistent scale, it must be normalized first. Standardization is a common normalization technique when the data have a mean of zero and a variance of one. A data column is utilized to calculate the mean and standard deviation. Then, each column data point is subtracted from the mean and divided by the standard deviation. In the first step, signals were normalized in both the X- and Y- axes to prevent train misdetection. The number of samples in available train signals approximately 1.102. On the X-axis, signals were resampled to the input size which was chosen to 516. This amount of samples is enough since it keeps sufficient information with fewer samples than the original signal. On the Y-axis, the signal levels were standardized between 0 and 1.

3.4 Algorithm performance output

Our ANN model consists of four hidden layers, each containing 64 filters of length 5, a max-pooling layer of length 5, and a hidden layer of size 100. ReLU was utilized as an activation function between layers prior to output. The input size for each model was set to 516, and the output size was the number of train situations, "train" or "no train." For ANN, the training procedure generates an error/loss number that lowers with each epoch iteration, and data is passed through the model in batches of size 4. The models' learning rate was fixed at 0.001. Mean absolute error was employed as the loss function and the Adam optimizer was selected for automatic differentiation. The table presents the number of trainable parameters and the number of layers for various neural network topologies. Table 1.

The second design was a long-short-term memory (LSTM) with one LSTM layer containing fifty hidden layer, each hidden layer size was set to 100 neurons, followed by a fully connected layer with a sigmoid activation function across layers till output. We use sigmoid activation function to get robust results for binary classification in this system.

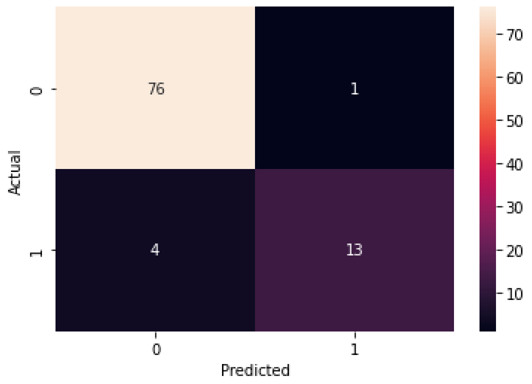

FIGURE. 6 Confusion Matrix ANN with MLP model

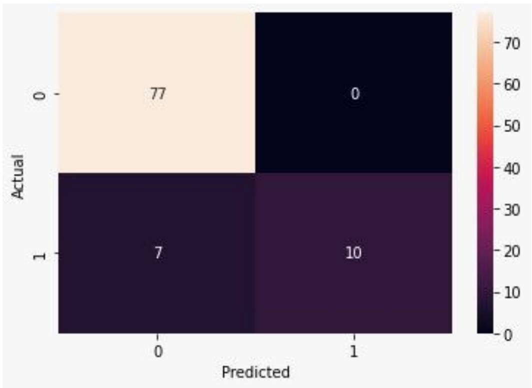

FIGURE. 7 Confusion Matrix ANN with LSTM model

Table III compares the precision and accuracy of the ANN and LSTM algorithms. The datasets they utilize are the same. Overall, as shown in table 3, the ANN algorithm is more accurate than the LSTM approach. We get the value from confusion matrix process in Fig.6 and Fig.7. The accuracy of the ANN is 94.7% whereas that of the LSTM is 89.0%. So, it can be stated that the ANN with MLP model is better than LSTM model in this study. Consequently, the ANN model has a lower error value.

Table 3. comparison algorithm performance

Model performance	MLP	LSTM
Accuracy	0,9468	0,8967
Precision	0,7647	0,5882

3.5 Applying Model

With embedded platform Raspberry Pi 4B with 2GB of RAM, we apply ANN's model to implement train detection. We placed the BNO055 sensor in embedded module on the sleeper's train. Then the result, module sensor can work like the algorithm scenario, and it can differentiate train between the gangway at the speed of 30 km/h. It is shown in Fig. 8.

FIGURE 8. Applying model in railway

4. CONCLUSION

The machine learning model studied in this research produces satisfactory results on the dataset of the vibration accelerometer in railways. Convolution operator has succeeded in constructing an end-to-end time series classification model that can detect a passing train using raw data from accelerometer. Therefore, it is necessary to normalize by Min-Max normalization. By utilizing min-max process, the calculated data will be generated more efficiently.

According to tests conducted by oil train, the accuracy of machine learning is 94%. Then, it is demonstrated that, when deployed on an embedded platform, the machine learning model can recognize train axles like an axle counter. This indicates that machine learning is designed to detect trains passing by a sensor with great precision. So that the train detection system can be utilized to monitor the location of trains on railroads.

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