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Railway Detection Of Axle Detection Patterns Using The KNN Method

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ABSTRACT (10 PT)

The track circuit is a device used to determine whether a vehicle is on the track. This device is installed on the track and needs to be monitored to ensure it functions properly. All objects detected in practice are considered railway vehicles, even though the detected objects may not be railway vehicles. Accurate and reliable detection technology is crucial for preventing accidents and keeping train traffic safe. This detection system uses metal sensors to identify objects as railway or non-railway assets. This is done based on two variables: the frequency of the object's metal and the object's speed. The test results show that this tool can classify objects according to their class. The class with no objects has an accuracy level of 100%, while the class of non-railway has an accuracy level of 86.67%. The railway class trials using the inspection train axle show an accuracy level of 93.33%.

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1. INTRODUCTION

The use of trains as a mode of transportation is a manifestation of their characteristics and advantages. Trains enable mass transportation of both passengers and goods, which significantly reduces road congestion and helps smooth traffic flow in urban areas. That there are two main aspects in the operation of trains, namely the rolling stock and railway infrastructure. Broadly speaking, rolling stock refers to vehicles that can move on tracks, including locomotives, carriages, and special equipment. Meanwhile, railway infrastructure encompasses everything that is a primary support for the operation of train journeys, including railway tracks, train stations, and railway operation facilities so that trains can be operated. [1]

The track circuit detector is a device that functions to detect the presence or absence of a train on the railway track. The track circuit detector is divided into two types: axle counter and track circuit. The track circuit functions to detect the presence of a train or railway vehicle on a section of the track and to detect the state of the track, while the axle counter functions to count the axles of the train or railway vehicle [2]. Axle counter has the advantage of not requiring rail joint isolation or rail connection isolation, but it has the disadvantage of being prone to sensor reading failures. Meanwhile, the track circuit operates by utilizing the short circuit that occurs when the train wheels pass over it or through the feeder current supplied to the relay coil. However, this method is susceptible to lightning interference. Both detection methods are installed on the train tracks and require proper maintenance to function optimally[3]. From the advantages and disadvantages of axle counters and track circuits, there is a similarity that neither of these devices possess, namely the ability to classify objects, whether the detected object is railway equipment or something else.[4]

To enhance the safety and security of railways, train detection systems play a crucial role in this matter. Detection of facilities on this railway line is required with a high level of accuracy regarding facility information[5]. The detection of the presence of facilities along the railway tracks becomes critical and important, so the use of accurate and reliable detection technology is essential to avoid potential collisions and ensure safe train traffic. With accurate and reliable railway facility detectors, it is expected that the detectors can classify the passing facilities, especially whether the passing object is a railway facility or something other than a railway facility. [6]

Classification is a type of data analysis that can help people determine the class label of a sample they want to classify. Classification is a supervised learning method that attempts to find the relationship between input attributes and target attributes. The goal of classification is to improve the reliability of the results obtained from the data.[7] In this study, the parameters used for clustering are the speed of the object and the output from the hall effect sensor, which are then processed in Google Colab using the K-Nearest Neighbors method. Google Colab itself is a modified version of Jupyter Notebook provided by Google, where this platform is often utilized for Machine Learning and Deep Learning[8]. And KNN is one of the most well-known classification algorithms used to predict the class of a record or (sample) with an undetermined class based on the class of its neighboring records.[9]

This research uses the metal detector sensor because the sensor can be used to detect magnetic fields. The sensor will generate a voltage proportional to the strength of the magnetic field received by the sensor. The metal detector sensor is often used as a sensor to detect proximity, positioning, speed, directional movement, and electrical current. (current sensing). The sensor can detect magnetic fields with detection results in the form of analog voltage.[10]

2. RESEARCH METHOD

2.1. Design Methods

In this research, two stages were conducted. First, grouping objects based on metal frequency and object speed. Second, determining the best K value. Then, the design of the object classification device was carried out and tested on objects crossing the tracks. If the device does not work well, corrective measures are taken. If the device works well, the results of object classification can be seen.

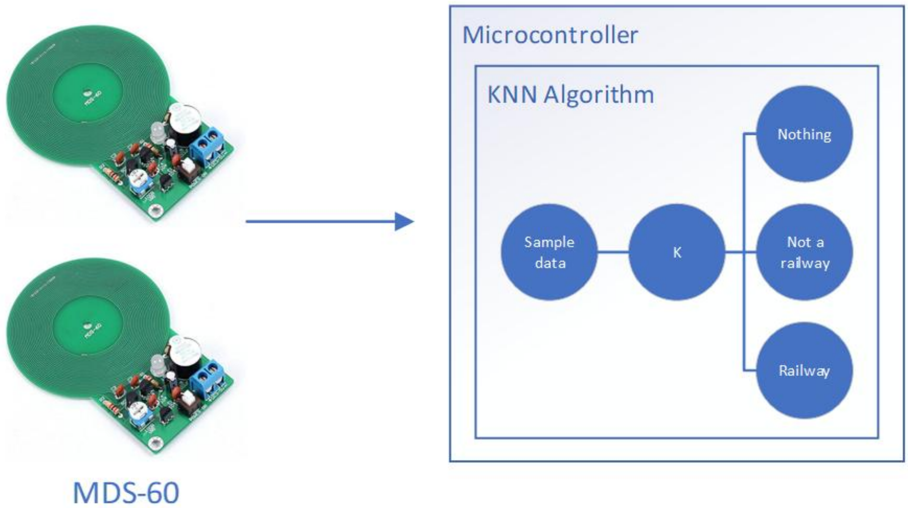

Figure 1. Block diagram device railway detection

The block diagram of the device represents the overall working process of the object classification device on the track. Figure 1 explains how the MDS-60 metal detector sensor is used to classify objects on the track. Starting with sensor 1 detecting the frequency generated by the object and sensor 2 detecting the frequency generated by the object. Then, the distance between the two sensors, which is 20 cm, is used as a variable to calculate the object's speed, while the time taken for the object to move from sensor 1 to sensor 2 is used as a time variable to calculate the object's speed. After both parameters for classifying the object have been obtained, these variables are then used as input and processed on the Arduino Uno, which has been enhanced with the KNN algorithm library.

2.2. Software Design

There are 3 stages in making device. The first stage is the creation of a data logger that will be used to take samples of speed data and object frequency levels or comparative data from the KNN algorithm. The second stage is a flowchart from Google Colab to find the most appropriate K value for the sample data. The third stage is a flowchart of the application of the KNN algorithm for object classification on the rails

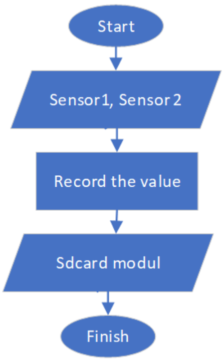

Figure 2. Flowchart of data logger

Figure 2 is a flowchart that explains the creation of a data logger. There are several components that will be used, namely 2 MDS-60 metal detector sensors that will serve as inputs to the microcontroller. The MDS-60 metal detector sensors are used to detect objects on the tracks. Microcontroller will be used to process all inputs and initialize ports, as well as process output results that will be uploaded to a microSD card. The data that has been uploaded to the microSD card will then be stored on a laptop. The data logger is used to store sample data from each class. Starting from sensor 1 detecting the frequency produced by the object and sensor 2 detecting the frequency produced by the object. Then, the distance between the two sensors, which is 20 cm, is used as a variable to calculate the object's speed, while the time taken for the object to move from sensor 1 to sensor 2 is used as a time variable to calculate the object's speed. Then, the output is saved to a microSD card.

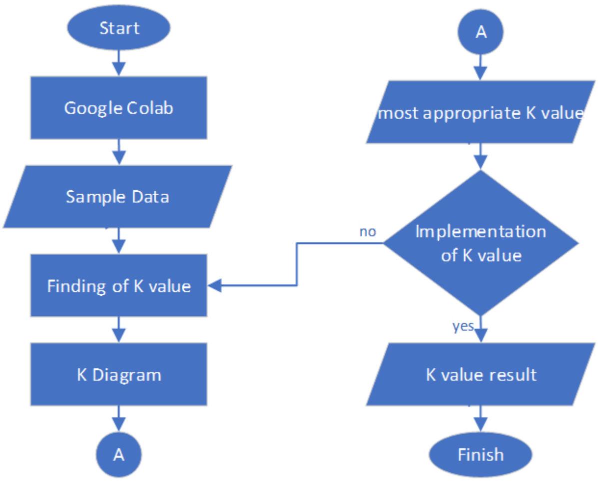

Figure 3. Flowchart finding K value

In the case of object classification on the rail. The value of K in the KNN algorithm is the number of nearest neighbors that will be used to make predictions or classifications on new data. In Figure 3, this research explains the use of a tool called Google Colab to find the most suitable K value for the sample data. The flowchart in the figure explains the process of selecting the optimal K value in an algorithm, starting from

Google Colab. First, the sample data is collected and then used to find the K value. A K value diagram is created to assist in selecting the most suitable K value. If the most suitable K value is found, it is implemented. The results of the K value implementation are then examined. If the K value is not suitable, the process returns to the K value search step. If the K value is suitable, the K value results are used, and the process ends.

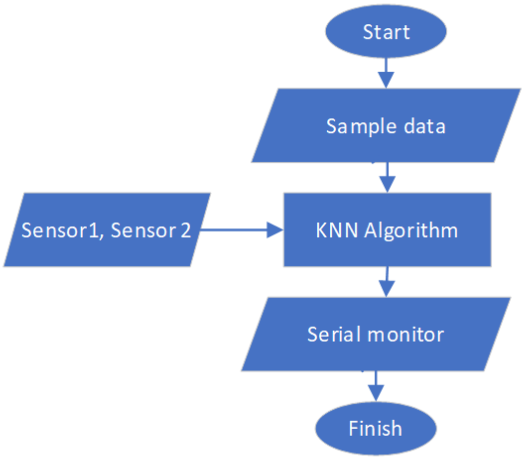

Figure 4. Flowchart of object classification on the rails

Figure 4 explains the process of classifying objects on the rail using the KNN algorithm. The first step of the KNN algorithm program is to classify new data by comparing it with sample data on the microcontroller. When the Arduino Uno receives new data from the MDS-60 metal detector sensor, the microcontroller will perform a comparison using the KNN algorithm. The result of the KNN algorithm will be displayed in the serial monitor as the class of the object that has similarities with the objects in the microcontroller's sample data.

2.3. Design and Placement Device

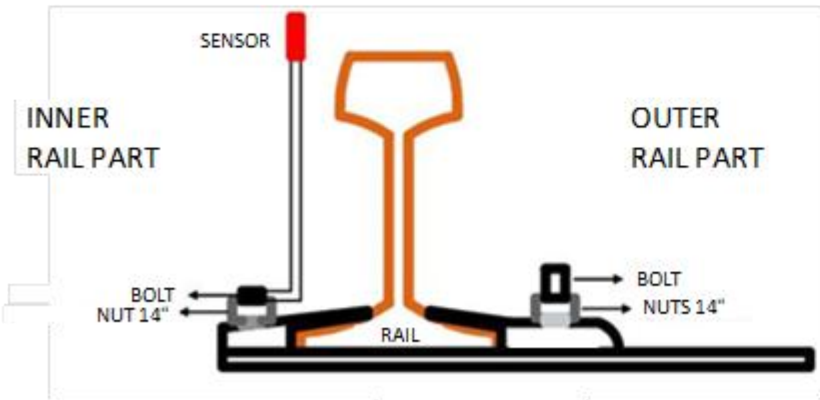

Figure 5. Device placement

The sensor mount will be placed on the railway track. The concept of this sensor mount is that it can be attached and locked to the rail foot by tightening its nuts and bolts. Then, the sensor support section can be used to place the sensor. Figure 3.10 is a design illustration for the sensor mount and support. The main material used in making the sensor mount and support is a 3 mm thick iron plate, but additional tools and materials are needed to support the construction of the sensor mount and support.

3. RESULTS AND DISCUSSION

3.1. Determination of Sample Data for the KNN Algorithm

Object sample data will be divided into 3 classes: no object sample data, railway sample data, and non-railway sample data. These classes are used to determine the results of object classification to be performed by the KNN algorithm. The object data logger tool uses 2 MDS-60 metal detector sensors for object detection and a microSD card reader to store the object detection results.

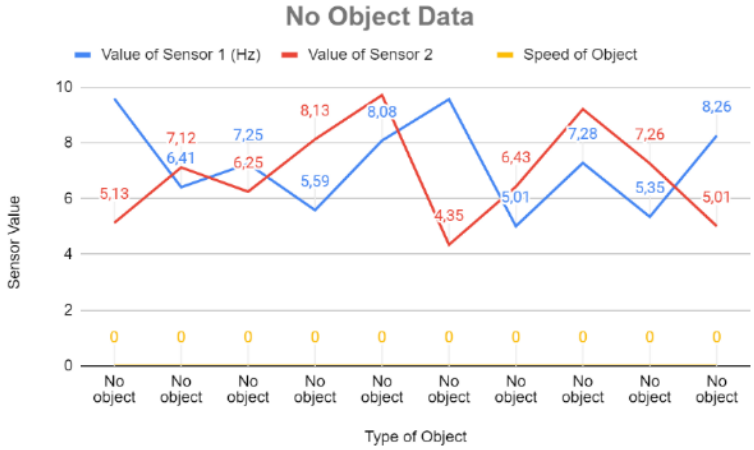

Figure 6. No object data collection

Figure 6 is the result of the sample data for the no object class that was successfully recorded by the sensor. Ten data examples for the no object class are displayed Figure 6. From the sample data results for the no object class that have been obtained, the range of values for the no object class varies. Therefore, to determine the no object class data, it can be taken from the obtained sample data to see the lowest and highest values under no object conditions. In the Figure 6 is a sample class data graph with no objects. The graph contains the value of sensor 1 shown in blue, the value of sensor 2 shown in red, and the speed shown in yellow.

Figure 7 is the result of the recorded sample data of the railway railway class. Five examples of data per object for the railway class are displayed in Figure 7. From the obtained sample data of the railway class, the range of values for the railway class varies because railway class are divided into four categories: Locomotives, Train Cars, and Non-revenue cars. Therefore, the determination of the railway class data can be taken from the obtained sample data to see the range of its values.

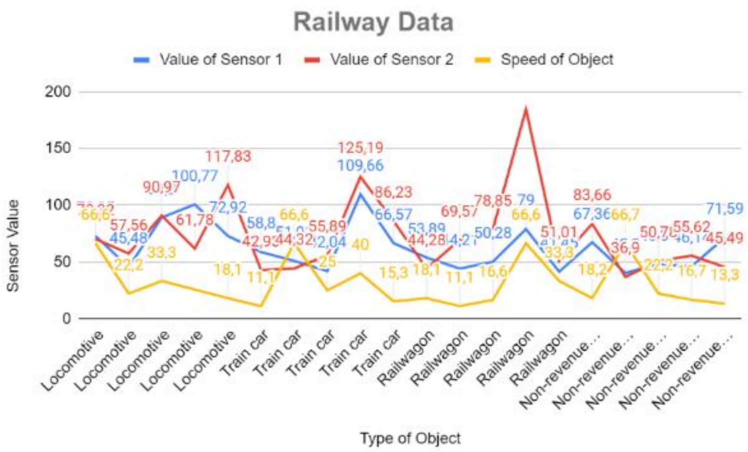

Figure 7. Railway class data collection

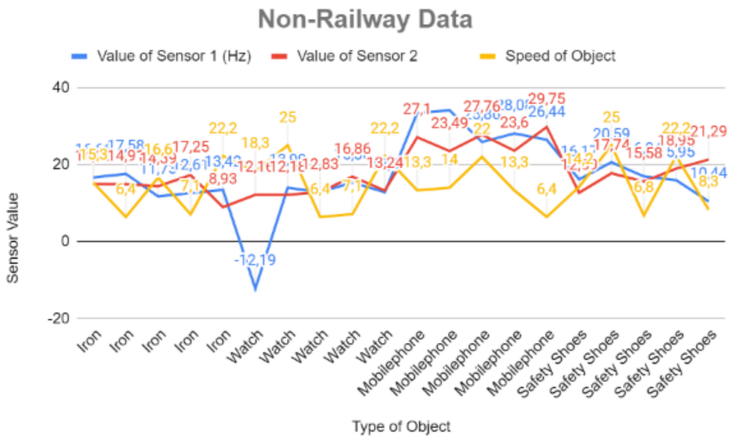

Figure 8. Non-railway class data collection

In the Figure 8 is the result of the recorded sample data for the non-railway class. Five examples of data per object for the non-railway facilities class are displayed in Figure 8. From the obtained sample data for the non-railway class, the range of values for the non-railway class varies because that can be detected by the sensor are divided into four categories: Iron (Bolt Key), Watch, Mobile Phone, and Safety Shoes. Therefore, the determination of the non-railway class data can be taken from the obtained sample data to see the range of its values.

3.2. Comparison of the Best K Value Results Through Google Colab and Algorithm Testing

Before conducting KNN algorithm testing, it is necessary to process the obtained sample data. That aims to achieve the best results. Google Colab is used to find the best K value, which is very influential in the KNN algorithm. The K value is the number of neighbors of the new data that will be classified with the previously obtained data. The results of the search for the best K value using Google Colab can be seen in Figure 9.

From Figure 9, the best K values are at 1, 2, and 3. Next, these K values are implemented in Arduino programming using the Arduino IDE software. To compare the best K values from Google Colab, the K values are directly implemented into Arduino. This is done to determine whether the obtained best K values can be patented and whether the KNN algorithm can classify objects based on the sample data obtained.

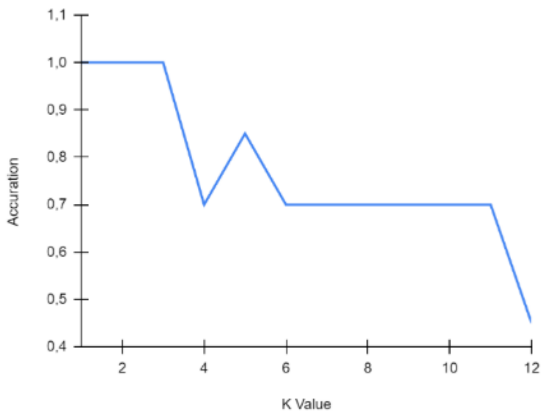

Figure 9. Best K Value Results Google Colab

3.3. Implementation of KNN Algorithm

The testing of the error rate and accuracy of the tool was conducted at the Indonesian Railway Polytechnic Station site. This testing was conducted using an inspection train axle. The testing was carried out 25 times to determine the error rate in the system.

Table 1 shows the success rate of the KNN algorithm in classifying objects from the non-railway vehicle class. From the table, the KNN algorithm can classify the non-railway vehicle class with an accuracy rate of

86.67%. This is because, in the experiment, the object in the form of a mobile phone was attached to the sensor. Ideally, the distance between the object and the sensor should be 1 cm.

Table 1. Results of Applying the KNN Algorithm for Non-Railway Class

No.	Type of Object	Value of Sensor 1 (Hz)	Value of Sensor 2 (Hz)	Speed of Object (m/s)	Result KNN
1.	Iron	15.41	18.07	5.0	Non-revenue cars
2.	Iron	16.84	17.03	2.9	Non-revenue cars
3.	Iron	15.86	18.45	4.1	Non-revenue cars
4.	Iron	17.75	14.86	5.3	Non-revenue cars
5.	Watch	16.34	14.78	6.5	Non-revenue cars
6.	Watch	17.02	18.05	6.1	Non-revenue cars
7.	Watch	17.25	17.04	7.7	Non-revenue cars
8.	Safety shoes	17.99	14.30	6.9	Non-revenue cars
9.	Safety shoes	15.15	17.06	6.1	Non-revenue cars
10.	Safety shoes	16.42	14.84	5.9	Non-revenue cars

Table 2 Results of KNN Algorithm Testing for Inspection Train Axle Detection

No.	Total axle	Detection of front axle	Detection of rear axle	Error	Accuration
1.	2	railway	railway	0%	100%
2.	2	railway	railway	0%	100%
3.	2	railway	railway	0%	100%
4.	2	railway	railway	0%	100%
5.	2	railway	railway	0%	100%
6.	2	railway	Non-revenue cars	0%	50%
7.	2	railway	railway	0%	100%
8.	2	railway	railway	0%	100%
9.	2	railway	railway	0%	100%
10.	2	railway	Non-revenue cars	0%	0%
		Total		6,67%	93,33%

The results of the KNN algorithm testing for inspection train axle detection are shown in Table 4.12. From the table, the KNN algorithm testing for inspection train axle detection has a total error rate of 28.33% and a total accuracy rate of 71.67%. These percentages were obtained from 25 trials. In this case, it was found that the system still has a high error rate in detection, due to natural disturbances such as temperature that affect the detection. And the speed of the moving train becomes an obstacle in detecting the axle due to the sensor having a low refresh rate in terms of detection.

4. CONCLUSION

The creation of the KNN algorithm in the form of an Arduino program involves calling the KNN library, adding sample data to each data point to be classified, and inputting class data to store the classification results performed by the KNN algorithm. For the class with no objects, the accuracy level is 100%, for the class that is not railway facilities, the accuracy level is 86.67%. For the class of railway facilities, testing was conducted using an inspection train with an accuracy level of 93.33%. These percentages were obtained from 25 trials for each class. The distance between the sensor and the railway track affects the object classification results. Therefore, the distance between the sensor and the railway track is set at 4 cm.

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