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REAL-TIME DETECTION OF RAIL DEFECTS BY MACHINE LEARNING

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ABSTRACT

In this study, real-time detection of defects that may occur in rail components will be investigated with machine learning algorithms. This research aims to detect the faults that will occur in the railway components early and to prevent accidents and losses in advance. The study was carried out by detecting the faults of basic parts such as rail fractures, lack of fastener, lack of rail fixing clamp, and lack of screws. Multiple images will be used in our application for training machine learning algorithms. Defective or non-defective images will be classified by a deep learning network. In other words, our deep learning network will detect incoming test images contactless and in real-time. In our study, appropriate methods and success metrics are given and the results are explained comparatively.

Keywords: Machine learning, Deep learning, Railway, Rail components

1. INTRODUCTION

Railways have been an indispensable means of transportation in passenger and freight transport from past to present. While providing comfortable, safe, and fast passenger transportation, it also provides economic gains with freight transportation. Recently, with the development of high-speed trains, the interest in railway transportation has increased considerably [1,2]. It is of vital importance to carry out planned and regular maintenance of railway vehicles and to detect and repair any errors that may occur in advance. Due to different reasons, problems such as rail surface cracks, breakage, and traverse cracks occur in the railway. 30% of rail accidents in the United States in the last decade are due to defects in railroad tracks [3].

Traditional methods of defects in train tracks are used. Defects in rail and rail components that may prevent transportation can be detected by visual inspection. Performing such checks by humans is a laborious task and increases errors. To detect defection much more efficiently, quickly, and safely, it is necessary to use advanced technologies. Non-contact, fast, low-cost detections can be made with methods such as image processing technologies, deep learning, and machine learning.

Machine learning is a method based on various algorithms and techniques for computers to learn like humans. Machine learning is a field that enables computers to develop through experiences [5].
Many studies and research have been carried out with the machine learning method, and research done in this field belongs to Thilagavathy et al. The research aims to determine whether the wheels traveling on the rail cause noise and vibration and this vibration is detected with the help of sensors and using machine learning algorithms in the system to determine whether it is defective. The sensor automatically detects the error on the rail and notifies the driver and the train station [6].

Another study in the same area was conducted by Krummenacher et al. Wheel defects are identified as one of the most important sources of damage to railway infrastructure and wagons. To reduce noise and vibration, they were able to detect the defects of all types of wheels measured by sensors. [7].
In the research of Zhang et al., while estimating broken rails; They developed a machine learning-based algorithm that includes records of railway track features, railway profile information, track laying information and traffic-related data, number of cars passing at a given time, maintenance records, and past track defects. This forecasting model enables the detection of broken rails and enables early maintenance planning [8].

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The machine learning method, which is the method that will be used in this study; gives accurate results by associating the input data with the output data [9]. The data defined for the training of the system can be trained through the algorithm and then processed with the algorithm and model prediction can be made [10].
In this study, determinations can be made about the health status of the rails by utilizing the machine learning methodology. Similar to the predictive maintenance activity, malfunctions that may occur in rail and rail components can be detected in advance and will enable rapid intervention.

2. METHOD

In this study, the SqueezeNet algorithm was used to process the data. SqueezeNet is a system of building blocks called fire modules with a compressed architecture using the CNN technological model. It works with fewer parameters compared to similar models. Its biggest advantage is that it can work faster by reducing the workload in the neural network thanks to its more efficient distributed layers [11]. This architecture requires less communication between servers, requires less bandwidth when transferring a new model from the cloud, and provides higher accuracy classification [12].
The dataset used in the study is the dataset titled "Railroad Track Fault Detection" on the Kaggle.com site. These data were trained using the SqueezeNet algorithm on MATLAB. These data were re-estimated by the trained network and the confusion matrix seen in table 1 and table 2 was created.

Table 1. Confusion matrix of 4-class prediction

	BrokenRail	MissingFastener	MissingScrews	NonDefective
BrokenRail	3	1	2	9
MissingFastener	0	48	0	21
MissingScrews	0	12	0	9
NonDefective	0	7	5	138

Figure 1. 4 class image samples

In the first analysis, 4 classes were used. The images in the dataset are labeled as 4 separate classes: BrokenRail, MissingFastener, MissingScrews, and NonDefective. these labeled images are shown in Figure 1. In the detection

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of broken rails in the analysis; only 3 of them got correct results. He analyzed 1 of them as missing terminal blocks, 2 of them missing screws, and 9 of them without error. Since there is more data than 69 missing terminals, 48 of them reached the correct result. From 21 missing screw data, 12 correct results were obtained. 138 correct results were obtained from 150 error-free image data.
The analysis was subjected to the algorithm again by reducing the number of classes. According to the new data set, the results in Table 2 were obtained.

Table 2. Confusion matrix of 2-class prediction

	Defective	**NonDefective**
Defective	119	15
NonDefective	7	143

In Table 2, unlike the first analysis, the number of classes was reduced to 2 and the images were labeled as defective and undefective as seen in Figure 2. 119 of 134 defective data were found to be defective. of the 150 non-defective data, 143 were found to be non-defective. It achieved a success rate of 88.80% in the analysis of defective images and 95.33% in the analysis of non-defective images.

Defective Nondefective

Figure 2. 2 class image samples

3. FINDINGS
In this study, the network was trained separately as 4 classes and 2 classes. 4 classes classification achieved less accurate results than the study with 2 classes. Class imbalance is the main reason for achieving lower results. Since the number of non-defective images is high in the data set, a deep learning algorithm can also detect some defective images as non-defective. When the data set is separated as defective and non-defective, each class was trained with more data than 4 class classification It was seen that more accurate results were found due to the presence of more data in the classes.

3. CONCLUSION
In this study, the working method is discussed to detect rail defects faster than traditional methods. Contact and contactless inspection methods are used to detect rail defects. In this study, the more preferred contactless method, which provides faster solutions and higher accuracy, has been examined. With the computer-aided intelligent detection method, damage detection is provided without requiring high costs and is error-free. The success of the data set in this study was determined by the deep learning algorithm. The effects of the amount of the data set on the study were presented in 2 tables, and it was seen in the study that the success rate increased as the amount of data set increased.

It is important to be prepared for the consequences that may be encountered by making quick and correct interventions in the transportation sector, such as the railways, where mistakes can have very serious consequences. In the study, it has been shown that defective images can be successfully detected by training the data set. Using this method allows the detection of defective rail and rail components successfully.

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