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Research Article

Prediction of Radio Signal Failures of Communication Based Train Operating Systems by Machine Learning Methods

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Abstract

The use of rail systems in urban public transportation has become a necessity for reasons such as time saving, travel comfort and operating costs, especially in cities with high population and road traffic. Communication based train operating systems (CBTC) are used for the safe use of urban rail systems and the maximum capacity of the railway line. In this study, in line with the data collected from the trains on a railway line operated with CBTC, the status of the radio signals that enable the wireless communication of the trains with the trackside signaling equipment was evaluated by machine learning methods, and the situations that may have negative effects on the train operations of the problems at the signal level were evaluate. The problems on the antennas which receives signals from trackside above trains, the poor connection related with fiber optical and LAN cables, the trackside transmitter antenna orientation problems causes decrease on signal levels. It is aimed that to take actions about the problematic signal levels without any negative impact on the passenger comfort and the operation yet. The radio signal losses cause unexpected trains stops and delays. A decision support model has been developed that will offer early solution suggestions to system maintainers in order to intervene first. In conclusion, since it is the first study related with failure prediction by using radio signal levels data on railway signaling system, this study presents an important innovation in terms of literature.

Keywords: Railway transportation, communication based train operating systems, machine learning methods, failure prediction, maintenance management

Makine Öğrenmesi Yöntemleri ile Haberleşme Tabanlı Tren İşletim Sistemlerinin Radyo Sinyal Hatalarının Tahmini

Öz

Kentsel toplu taşımada raylı sistemlerin kullanılması, özellikle nüfus ve karayolu trafiğinin yoğun olduğu şehirlerde zaman tasarrufu, seyahat konforu ve işletme maliyetleri gibi nedenlerle bir zorunluluk haline gelmiştir. Kent içi raylı sistemlerin güvenli kullanımı ve demiryolu hattının maksimum kapasiteyle kullanımı için haberleşme tabanlı tren işletim sistemleri (CBTC) kullanılmaktadır. Bu çalışmada, CBTC ile işletilen bir demiryolu hattındaki trenlerden toplanan veriler doğrultusunda, trenlerin yol kenarı sinyalizasyon ekipmanları ile kablosuz iletişimini sağlayan sinyallerinin durumu makine öğrenmesi yöntemleri ile değerlendirilmiş ve durumlar değerlendirilmiştir. Tren üzerinde radyo sinyallerini yakalayan antenlerin bağlantılarında, hat boyu verici radioların fiber optic ve LAN kablo sonlandırmalarında, hat boyu verici antenlerin oryantasyonlarındaki problemler sinyal seviyelerinde düşmelere sebep olmaktadır. Sinyal seviyesindeki problemlerin tren işletmesini olumsuz etkileyebileceği durumlar değerlendirilmiş, yolcu konforuna ve operasyonuna henüz olumsuz bir etkisi olmadan müdahale edilmesi amaçlanmıştır. Radyo sinyal seviyelerindeki kayıplar beklenmedik tren duruşlarına ve tehirlere sebep olmaktadır. Sistem yöneticilerine önceden müdahale etmeleri için erken çözüm önerileri sunacak bir karar destek modeli geliştirilmiştir. Sonuç olarak, demiryolu sinyalizasyon sistemindeki radio sinyal seviyeleri verileri kullanılarak arıza tahmini ile ilgili ilk çalışma olması nedeniyle bu çalışma literatür açısından önemli bir yenilik sunmaktadır.

Anahtar Kelimeler: Demiryolu ulaşımı, haberleşme tabanlı tren işletim sistemleri, makine öğrenmesi yöntemleri, hata tahmini, bakım yönetimi

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1. Introduction

Transportation and social life styles are significantly impacted by technological advancements. Due to improved connectivity and ties between far-flung places, the importance and speed of long-distance passenger and freight transportation is growing every day. Additionally, it has become crucial for logistics and transport to compete on the basis of moving people and goods as swiftly, safely, affordably, and sustainably as feasible. In recent years, rail transit has gained popularity in urban and intercity freight and passenger transportation because to its affordability, safety, and environmental friendliness.

The unexpected breakdowns of numerous pieces of railroad equipment, however, pose the biggest threat to the continuous and secure operation of rail transit. If appropriate action is not taken, these failures result in a loss of time, money, and confidence. To avoid breakdowns from happening in the first place, railway lines must undergo planned maintenance.

As it is known, CBTC are used for the safe use of urban rail systems and the maximum capacity of the railway line. Examining the failures of the aforementioned railway equipment reveals that CBTC radio signal failures have a direct impact on the railway operates [1]. By identifying and fixing the issue without interfering with train movement, continuous operation can be achieved. When a failure has already happened, the time it takes to fix it can be cut in half by learning what caused it, and the operation of the railway can resume normally with the least amount of disruption. Statistical analysis, classification, model-based methods are used in the literature to evaluate data related to failures and make predictions [2-4]. Particularly, for the detection of railway failures used classification methods [2].

Machine learning methods such as artificial neural networks (ANN) are widely used in the solution of many engineering and biomedical engineering problems by classification and prediction [5]. In recent years, a maintenance decision model has been established and successfully implemented in many areas. Grobellar S. and Visser J. K have combined a renewal theory and a decision analysis model to develop a model that predicts the frequency of equipment change [6]. O.F. Eker et al. have used the SVM method for detecting misalignment failures in the actuators connected to the railway switch motors [7]. J. Lee et al. have used sound sensors for the detection of switch motor failures and classified the data with the support vector machines (SVM) and performed a fault prediction study [1]. L.F. Molina et al. have used image processing to detect wear failures on railway tracks [8]. Arslan and Tiryaki have used various artificial intelligence methods for predicting switch point failures [9]. Cinus et al. have used ANN methods for production plan optimization through preventive maintenance management [10]. Amruthnath and Gupta have used vibration data which is collected from an exhoust fan and classified the data with machine learning methods to minimize maintenance costs [11]. Krenek et al. have used ANN methods for early fault detection and predictive maintance suggestions [12]. Sun et al. have used self-organizing map (SOM) For failure prediction and information interaction problems of multi-equipment health management, fault prediction technology of multi-equipment and multi-parameter was proposed based on the system network [13]. Jancikova et al. have used artificial neural networks for prediction of steel atmospheric corrosion by using various factors such as local temperature, relative humidity, amount of precipitation, pH of rainfall, concentration of main pollutants and exposition time [14].

In this study, in line with the data collected from the trains on a railway line operated with CBTC, the status of the radio signals that enable the wireless communication of the trains with the roadside signaling equipment was evaluated by machine learning methods, and the situations that may have negative effects on the train management of the problems at the signal level were evaluated, without any negative impact on the passenger comfort and the operation yet. A decision support model has been developed that will offer early solution suggestions to system maintainers in order to intervene first. A decision support model was created that can both forecast potential failures and provide details on the underlying causes of failures that have already happened. By ensuring that the data acquired about changes in radio signals is processed and that the maintenance staff is informed of the required corrective and preventive actions, this model seeks to ensure that failures are eliminated before they impair railway operations and that the time it takes to solve existing failures is shortened. In supervised learning, the intended and actual outputs were compared, error calculations were performed, and the process for producing predictions with higher accuracy was looked at. In conclusion, since it is the first study related with failure prediction by using radio signal levels data on railway signaling system, this study presents an important innovation in terms of literature.

In the second section of this study, the materials employed in the system - the radio signals of CBTC - as well as the parameters used as model inputs were initially explained. The model outputs that were produced as a consequence of the interpretations that were formed using these inputs were provided. An explanation was given of the machine learning techniques applied to the data processing. The established model's performance was assessed using specified criteria, which were explained. In the third section, tables containing the outcomes of the data processing using MATLAB Classification Learner Application were displayed, and it was discussed which machine learning techniques produce the best results in comparison. The results were interpreted in the fourth section.

2. Materials and Method

2.1. Communication based train operating systems

According to IEEE 1474.1, CBTC is a continuous and automatic train control system based on high-precision train positioning and high-capacity train-to-track communication [15]. In general, the CBTC system instantly receives information such as rail circuit occupancy, switch position, safe stopping distance, and allowed speed limits of the conventional trackside signaling system via the wireless communication equipment on the train. In line with this information, the train proceeds safely through the automatic train supervision (ATS) system. Likewise, the train sends information such as its instant precise location and speed to the center. Thus, it is ensured that the block processor in the center gives safe movement authorization to each train according to the situation of other trains in the region. Thanks to the block processor, which instantly monitors all trains in the region, the line is operated with maximum frequency and safety. All this communication flow is provided by 2.4 GHz wireless radio signals. In case of any interruption in this communication, the train that cuts off its communication is stopped by ATS with an emergency brake. Evaluating that there is an unsafe situation, and proceeds with a maximum speed of 25 km/h which is a safe and limited speed, by the driver, until it provides CBTC communication again. All trains in the operating cycle will be affected by this delay and there will be serious disruptions in train operation. In addition, emergency braking of the train will cause wear on the train wheels and rails, thus shortening their useful life. In this direction, it is of great importance that there is no loss in the CBTC signal when evaluated in terms of both passenger comfort, operational continuity and equipment life.

Figure 1 shows the communication structure of CBTC operation with classical signaling systems, traffic management center, line length radios and block processor.

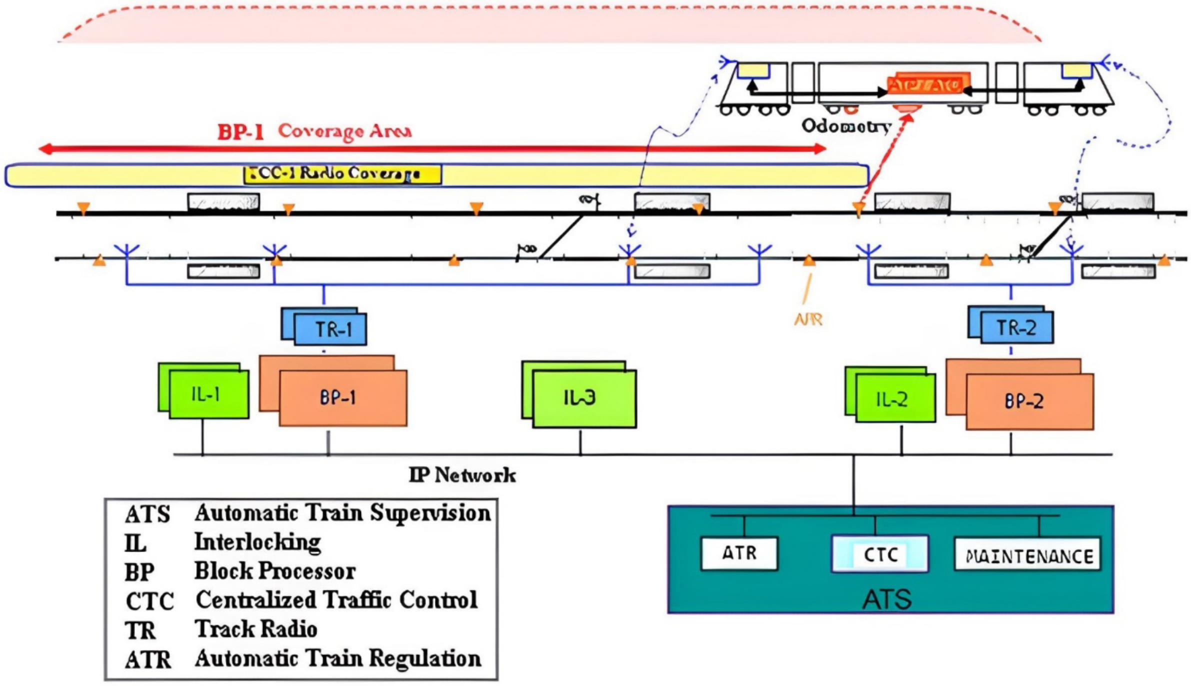

Figure 1. CBTC train communication general concept [15]

As it can be seen from the Figure 1, ATS monitorize the track conditions and train positions continously. Interlocking (IL) tells to BP track conitions (point machine position, next signal status etc), Block processor (BP) gives movement authority to trains accordingly. The communication between ATS, IL, BP and track radios provided by optical fiber and ethernet cables. The communication between trains and track hub radios is provided by wireless radio signals. In this study, the wireless signal values which are received by trains were evaluated.

2.2. Proposed method

In this study, it is aimed to evaluate the instant wireless communication signals during the course of the trains on a railway line operated by CBTC, to detect possible problems at the signal level and to determine solutions. It is aimed to eliminate these negativities in signal levels by warning the system maintainers before they reach the level that will affect the train operation.

In this context, the signal levels received by the trains from the radios along the line during the journey were interpreted with the industry experience and system requirements, and the problems were determined and solution suggestions were put forward. Considering the technical features of the system in which the study is carried out, the ideal working conditions are that the train receives a signal higher than -85db from at least one trackside radio and the packet loss rate is less than 1%. According to these conditions, the signals received instantly were evaluated and 6 different results/ recommendations in Table 1 were presented.

Table 1. Maintenance recommendations provided as system output

Recommendations	Maintenance Proposal
R1	Signal Level normal Level normal
R2	Low Packet Loss, F/O and LAN connections should be checked
R3	High Packet Loss, F/O and LAN connections should be checked
R4	Signal level is low, radio and antenna should be checked
R5	Zone without CBTC Signal
R6	Signals are received from more than one radio at the same level, radio output powers should be checked

Based on the results of this study, the Artificial Neural Networks structure, which was decided as the best method for all outputs, is explained in detail in below.

Artificial neural networks (ANNs) are the systems that can learn from samples by simulating the human brain's nerves, and then use that knowledge to make judgements about samples they have never seen [16]. The engineering equivalent of a biological neuron is an artificial neuron [17]. Inputs, weights, addition, activation, and output are the five elements that make up an ANN [18]. The artificial neuron is depicted in Figure 2.

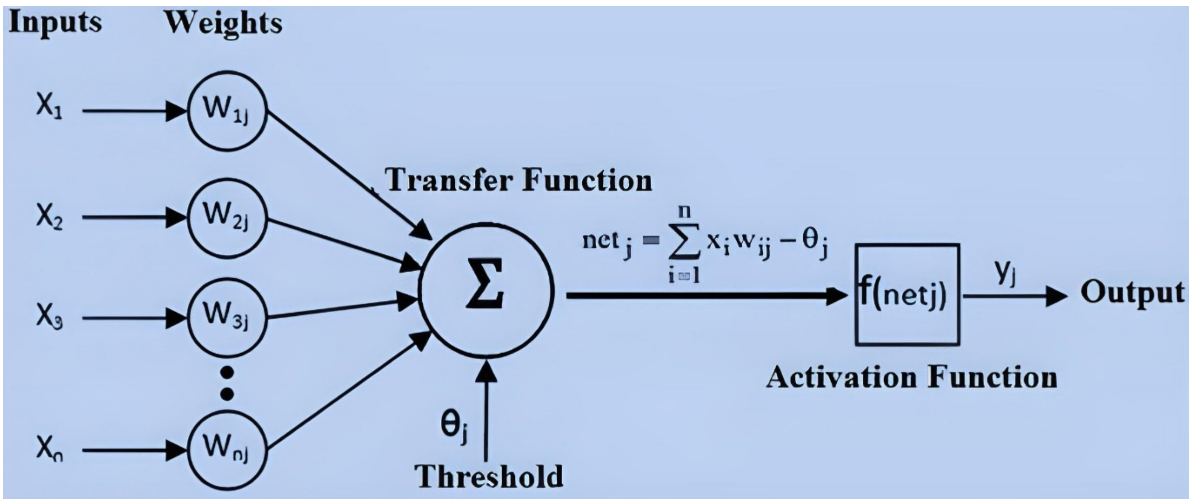

Figure 2. Artificial neuron [9]

The network incorporates the data from the input layer. These inputs are handled in the middle layers before being sent to the top layer. Each input is converted to an output using the network weight values in the intermediary layers. To get the right outputs, weight values must also be computed accurately. By correctly training the network, the correct weights can be found. At first, these weight values are assigned at random. The weights are then modified in accordance with the network's learning rule during training, when each sample is submitted to the network [19]. The network is then given a new sample, the weights are changed once more, and the best weight values are sought for. Until the right results are produced for each sample in the training set, these actions are repeated. The test set samples are presented to the network once all weights have been determined. The network is considered to have been effectively trained if it responds correctly to the test set samples [9].

$$V = \sum_{i=0}^{i=n} W_i x X_i \tag{1}$$

$$y = \varphi(V) \tag{2}$$

Here; W shows the weights matrix of the cell, X shows the input vector of the cell, V shows the net input of the cell, y shows the output of the cell and φ shows the activation function of the cell.

3. Results and Discussion

First of all, with the training data of the radio signals of CBTC training was carried out using 29 machine learning methods and the most successful method was determined.

3.1. Training and validation

During the training phase, 29 machine learning methods Decision Trees (Coarse Tree, Medium Tree, Fine Tree), Discriminant Analysis (Linear Discriminant), Naive Bayes (Kernel Naive Bayes), Support Vector Machines (Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM), Nearest Neighbor (Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN), Kernel Approximation (SVM Kernel, Logistic Regression Kernel), Ensembles (Boosted Trees, Bagged Trees, Subspace Discriminant, Subspace KNN, RUSBoost Trees) and Neural Networks (Narrow Neural Network, Medium Neural Network, Wide Neural Network, Bilayered Neural Network, Trilayered Neural Network) in the MATLAB R2022a Classification Learner application were used for 502 training data and the most successful method was determined.

In order to make an objective evaluation, all 502 training data were applied and compared with 10-k fold cross validation for the different machine learning methods mentioned above. In order for the match to be carried out in a healthy way, the Correlation Coefficient (R^2), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values were calculated as performance criteria. The formulae of these criteria are given below.

$$R^2 = 1 - \frac{\sum_{l=1}^{n}(y_i - \hat{y_l})^2}{\sum_{l=1}^{n}\left(y_i - \widehat{y_{avg}}\right)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_l})^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|(y_i - \hat{y_l})| \tag{5}$$

Here, y_i, $\hat{y_l}$, and $\widehat{y_{avg}}$ are the desired output *i*, the predicted output, and the average of the desired output, respectively. *n* represents each sample in the dataset [20, 21].

In Table 2, the training results of the most successful of the method families applied for the machine learning model are presented comparatively.

Table 2. Training results

Classification Methods Families	R^2 (Squared Correlation coefficient)	RMSE (Root Mean Squared Error)	MAE (Mean Absolute Error)
Neural Networks (Bilayered Neural Network)	0.972	0.0333	0.0238
Nearest Neighbor	0.960	0.0713	0.0437
Decision Trees	0.960	0.0738	0.0449
Support Vector Machines	0.958	0.0899	0.0644
Ensembles	0.954	0.1203	0.0795
Naive Bayes	0.916	0.1293	0.0879
Discriminant Analysis	0.871	0.1331	0.1008
Kernel Approximation	0.867	0.2308	0.1588

As can be seen in Table 2, the most successful machine learning method is the Bilayered Neural Network method for training. For this method, the actual training data and the prediction data obtained as a result of the training are presented in Figure 3 comparatively.

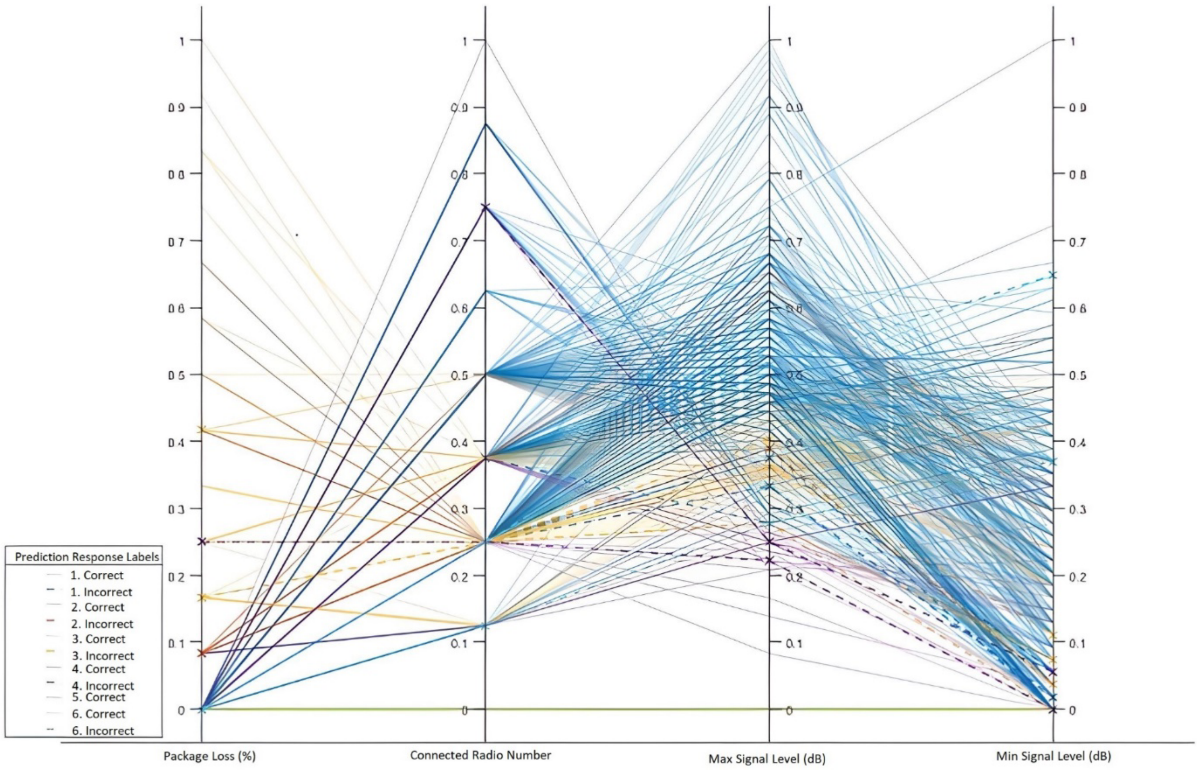

Figure 3. Real and predicted training data

As seen in Figure 3, the prediction data obtained as a result of the training is very close to the real training data. This situation demonstrates that the established decision support model is successful. Figure 4 shows the confusion matrix of validation for the Bilayered Neural Network method.

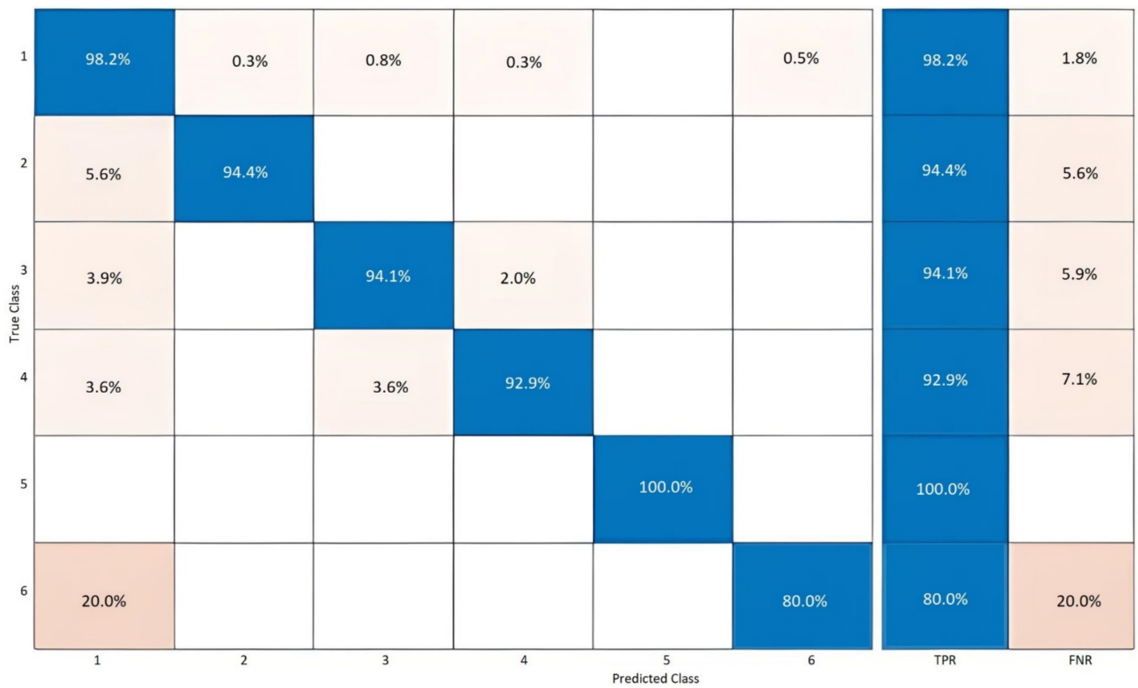

Figure 4. Confusion matrix of validation

As can be seen in Figure 4, True Positive Rates (TPR) higher than False Negative Rates (FNR). This situation shows that the Bilayered Neural Network method is successful for the CBTC system. Figure 5 shows the ROC curve of validation for the Bilayered Neural Network method.

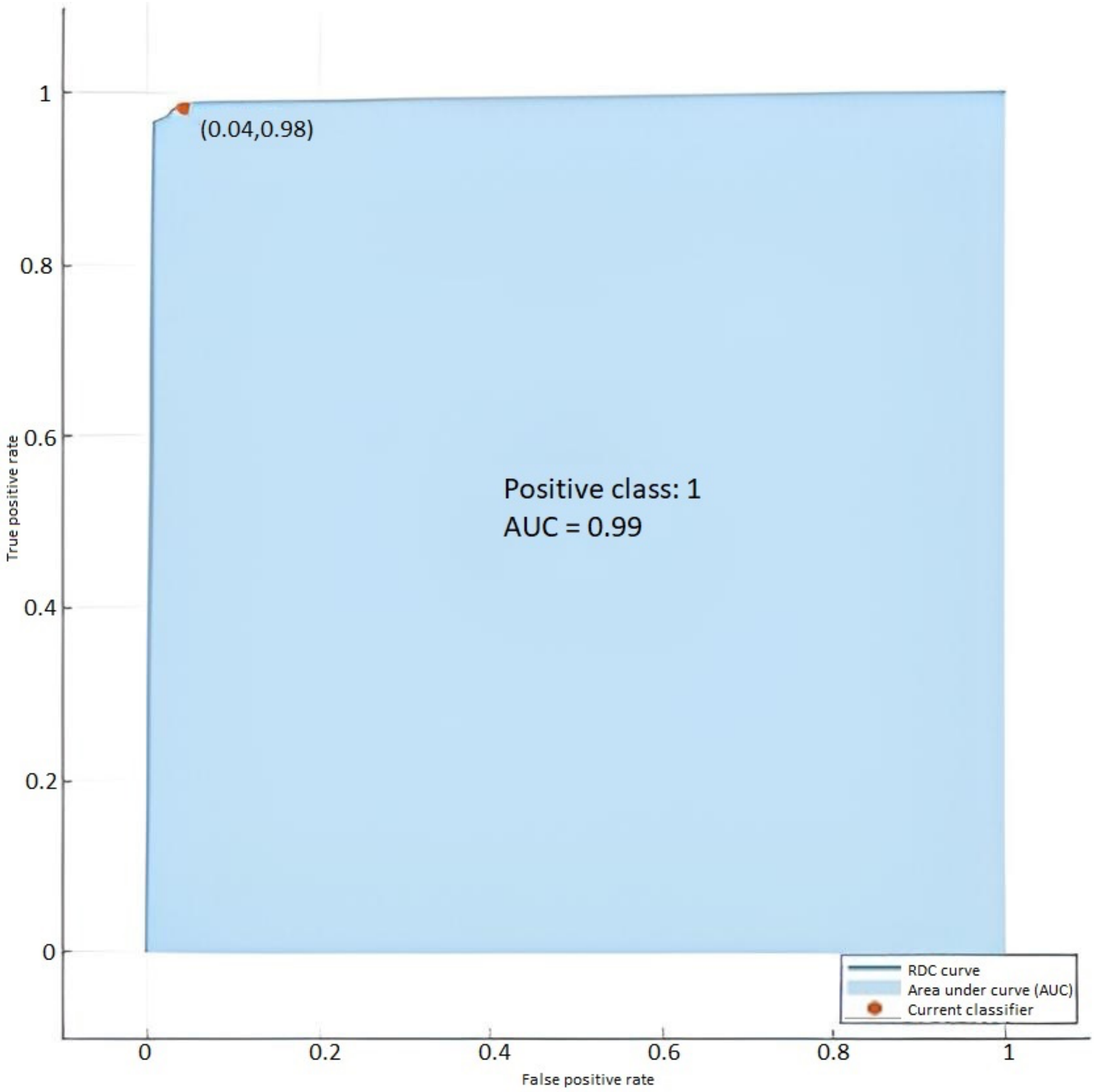

Figure 5. ROC curve of validation

As can be seen in Figure 5, area under curve (AUC) is very close to the 1. As known, this value is expected to be 1 is the most perfect result. Since the value obtained from the Bilayered Neural Network method used for the CBTC system is 0.99, it is quite successful.

3.2. Test

During the test phase, 29 machine learning methods mentioned training phase in the MATLAB R2022a Classification Learner application were used for 101 test data and the most successful method was determined. The Multi Layer Perceptron method, which is the equivalent of the Artificial Neural Networks method in WEKA 3.8.5 program, which was decided as the best method for all outputs based on the training results in the MATLAB R2022A Classification

Learner application, was used for show the artificial neural network architecture. Figure 6 show artificial neural network architecture for CBTC data.

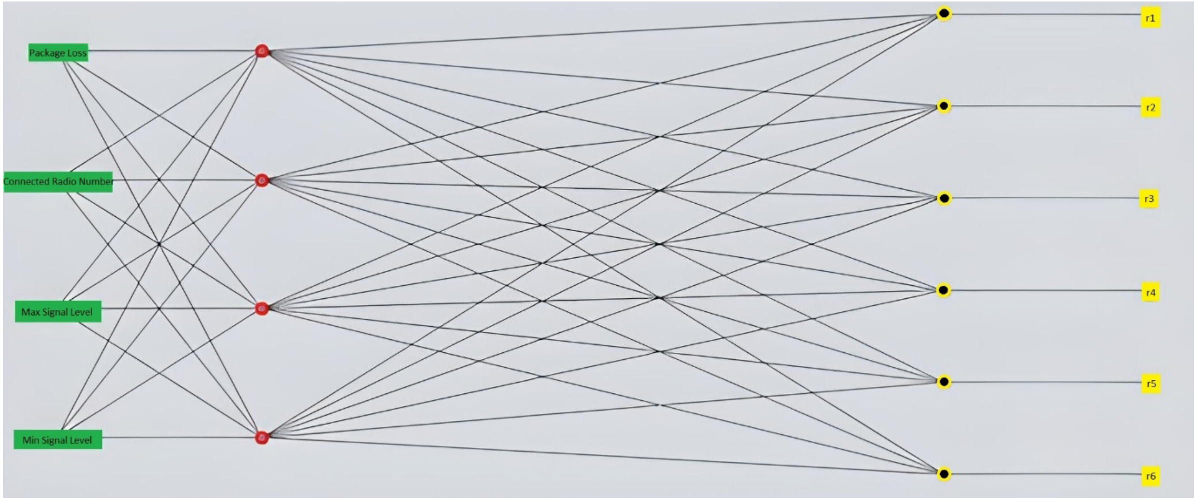

Figure 6. Neural network architecture for CBTC data

In this architecture, 4 neurons in a single hidden layer are used for inputs and 6 (for each recommendations) neuron is used for outputs. In Table 3, the test results of the most successful of the method families applied for the machine learning model are presented comparatively.

Table 3. Test results

Classification Methods Families	R^2 (Squared Correlation coefficient)	RMSE (Root Mean Squared Error)	MAE (Mean Absolute Error)
Neural Networks (Bilayered Neural Network)	0.980	0.0232	0.0137
Ensembles	0.970	0.0612	0.0336
Nearest Neighbor	0.950	0.0637	0.0348
Support Vector Machines	0.941	0.0798	0.0543
Decision Trees	0.931	0.1102	0.0694
Kernel Approximation	0.861	0.1192	0.0778
Naive Bayes	0.842	0.1230	0.0907
Discriminant Analysis	0.792	0.1307	0.1487

As can be seen in Table 3, the most successful machine learning method is the Bilayered Neural Network method for test. Figure 7 shows the confusion matrix of test for this method.

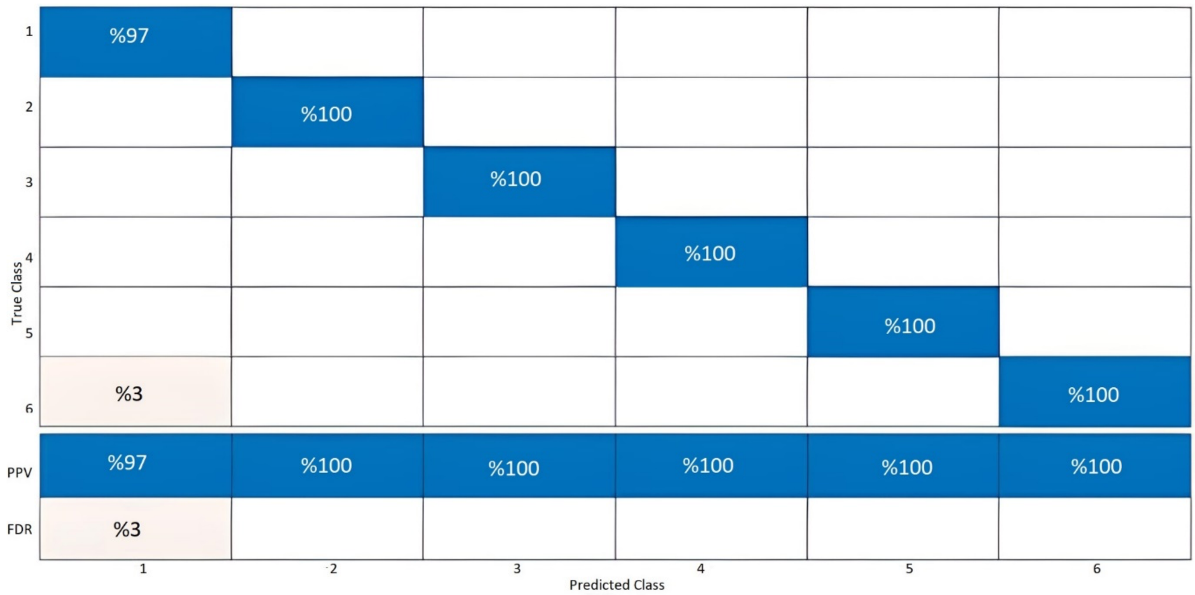

Figure 7. Confusion matrix of test

As can be seen in Figure 7, Positive Predictive Values (PPV) higher than False Discovery Rates (FDR). This situation shows that the Bilayered Neural Network method is successful for the CBTC system. Figure 8 shows the ROC curve of validation for the Bilayered Neural Network method.

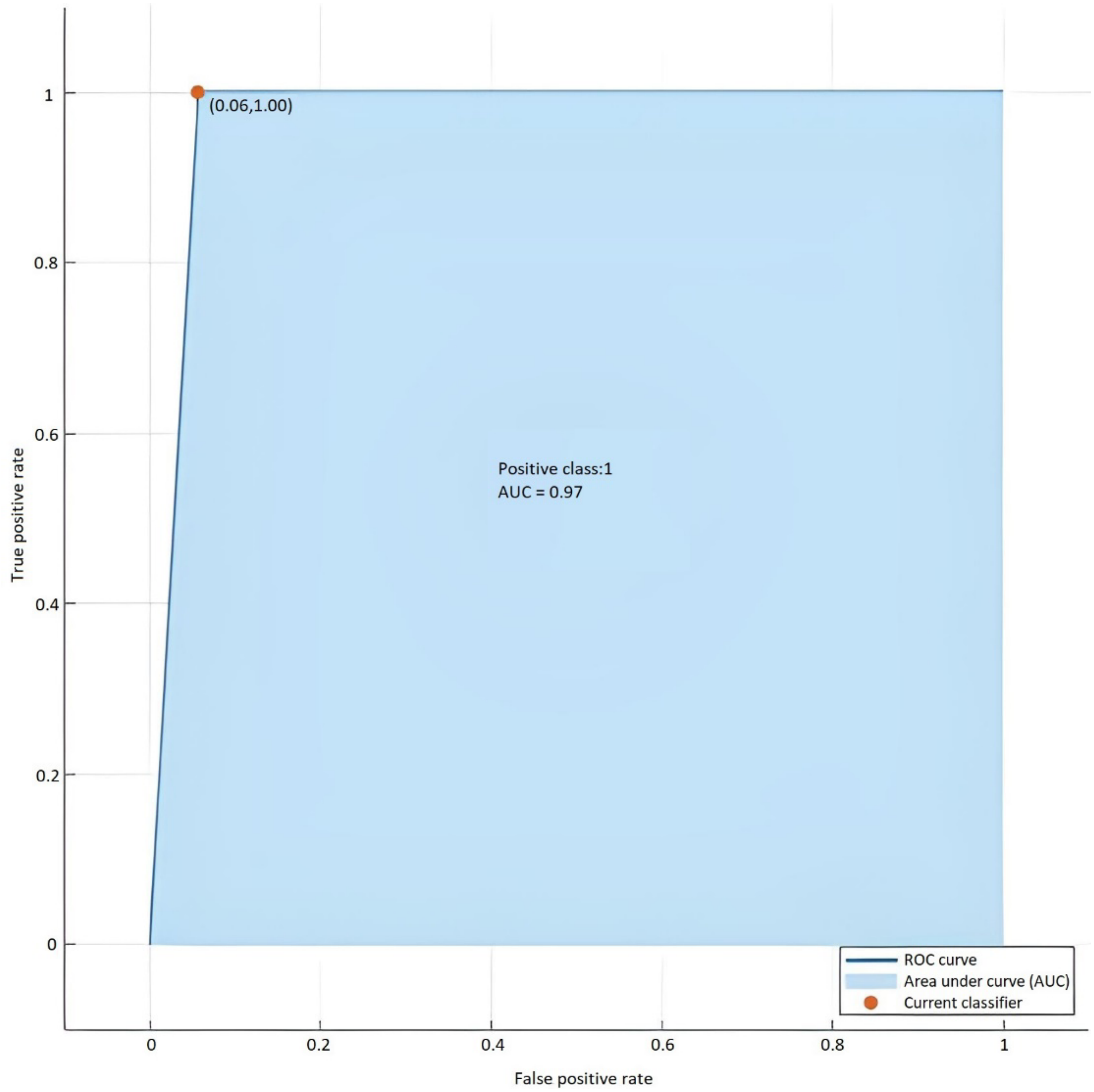

Figure 8. ROC curve of test

As can be seen in Figure 8, area under curve (AUC) is very close to the 1. As previously stated, this value is expected to be 1 is the most perfect result. Since the value obtained from the Bilayered Neural Network method used for the CBTC system is 0.97, it is quite successful.

4. Conclusion

This study aims to contribute to the planned maintenance operations on trains by using machine learning techniques to address radio signal failures of CBTC. Classification and failure prediction studies were conducted and the findings evaluated using the model that was built to expedite the process of resolving radio signal problems and to fix the faults before they grew big enough to affect operation.

Using MATLAB software, the data set was processed using different machine learning methods, and the outcomes were assessed. The assessments showed that the outcomes of the cross-validation model performance were quite similar to the conclusions drawn from the training and testing phases. These findings indicate that, as a result of the significantly optimal computation of the R-Squared, RMSE, and MAE values, the employment of artificial neural networks will be more effective in the implementation of the failure prediction model developed.

High success rates for machine learning methods demonstrate that the model was developed using relevant industry knowledge and the right strategy. Due to the established model's success, even if the system's inputs vary, the system will still accurately predict failures and decide its outputs.

In this approach, radio signal failures will be prevented, unscheduled train stops will be avoided, the resolution procedure for problems will be sped up, and the continuity of railway traffic will be guaranteed. Similar apps that help scheduled maintenance would enable high-level railway maintenance management, preventing the loss of time, money, energy, and manpower.

The aforementioned study will be expanded upon in the future to produce interface software that may be actively utilized in preventative maintenance operations and function as a failure operator decision support model.

Ethics in Publishing

There are no ethical issues regarding the publication of this study

Author Contributions

ARSLAN, B.: conceived and designed the study, scanned the literature, collected the material, determined and interpreted the results.

TIRYAKİ, H.: organized the study, implemented the method and wrote the study, analyzed and interpreted the study, evaluated and interpreted the results.

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