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Prediction of railway switch point failures by artificial intelligence methods

Burak ARSLAN, Hasan TİRYAKİ*
Department of Electrical and Electronics Engineering, Faculty of Engineering, İstanbul University-Cerrahpaşa, İstanbul, Turkey

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Abstract: In recent years, railway transport has been preferred intensively in local and intercity freight and passenger transport. For this reason, it is of utmost importance that railway lines are operated in an uninterrupted and safe manner. In order to carry out continuous operation, all systems must continue to operate with maximum availability. In this study, data were collected from switch motors, which are the important equipment of railways, and the related equipment and these data were evaluated with sector experience and the results related to the failure status of the switch points were revealed. The obtained results were processed with support vector machines and artificial neural networks, which are artificial intelligence methods, and machine learning was performed. In the light of this learning, a decision support model, which predicts possible failures and gives information about the root cause of the failures that have occurred, was developed. This model aims to ensure that the data obtained in each movement of the railway switch point are processed and the necessary corrective and preventive actions are communicated to the maintenance personnel; thus, failures are eliminated before they affect the railway operation and the solution process of the failures that have occurred is shortened. Considering the six switch points from which the data were collected, the experimental results were predicted with 24% RMSE error rates in the SVM method, while they were successfully predicted with RMSE error rates ranging from 2.4% to 6.6% in the ANN method. Therefore, it is observed that the ANN method is more appropriate in the implementation of the established model.

Key words: Railway switch point, artificial neural networks, support vector machines, failure prediction, maintenance management

1. Introduction

Technological innovations and developments have a profound effect on transportation and social life styles. The importance and speed of passenger and freight transportation between long distances increase day by day due to increased communication and relations between distant regions. In addition, transporting passengers and cargoes more quickly, safer, more economically, and as environmentally sensitive as possible has become important competitive conditions for transport and logistics. Due to its economic, safe, and environment-friendly nature, rail transportation has been preferred in urban and intercity freight and passenger transportation in recent years.

However, the biggest obstacle to the uninterrupted and safe operation of railway transportation is the failures of various railway equipment at unexpected times. These failures cause loss of time and money as well as a lack of confidence if adequate measures are not taken. For this reason, it is necessary to prevent failures before they occur and to perform planned maintenance on railway lines.

*Correspondence: hasan.tiryaki@istanbul.edu.tr

When the failures of the above mentioned railway equipment are examined, it is seen that the failures occurring in switch points directly affect the railway operation [1]. Switch points are controlled and monitored by signaling systems that manage railway traffic. It is possible to monitor all the movements of switch points and predict failures by collecting data from the points that may cause failure. Continuous operation can be achieved by detecting and resolving the failure without affecting the railway traffic. In the case of failures that have occurred, the solution time of the failure can be shortened by obtaining information about the root cause of the failure and the railway operation can be returned to its normal course with minimum interruption. Statistical analysis, classification, and model-based methods are used in the literature to evaluate data related to failures and to make predictions [2–4]. In particular, classification methods are frequently used in the detection of railway failures [2].

Machine learning methods such as artificial neural networks (ANN) and support vector machines (SVM) are widely used in the solution of many engineering and biomedical engineering problems by classification and prediction [5–7]. In recent years, a maintenance decision model has been established and successfully implemented in many areas. Grobellar and Visser combined a renewal theory and a decision analysis model to develop a model that predicts the frequency of equipment change [8]. Bin Zhao et al. developed a model that determines the most appropriate maintenance method with an optimal budget in petrochemical plants by the fuzzy neural network method [9]. Eker et al. used the SVM method for detecting misalignment failures in the actuators connected to the railway switch motors [10]. Lee et al. used sound sensors for the detection of switch motor failures and classified the data with the SVM and performed a fault prediction study [1]. Molina et al. used image processing to detect wear failures on railway tracks [11].

In this study, unlike the other studies, the data collected from the points that are important in the functioning of switch points were examined in machine learning by using the ANN and SVM methods. A decision support model, which predicts possible failures and gives information about the root cause of the failures that have occurred, was developed. This model aims to ensure that the data obtained in each movement of the railway switch point are processed and the necessary corrective and preventive actions are communicated to the maintenance personnel; thus, failures are eliminated before they affect the railway operation and the solution process of the failures that have occurred is shortened. In supervised learning, the desired and obtained outputs were compared and error calculations were made and the method by which more accurate prediction can be made was investigated.

A data set consisting of 7 inputs and 1 output from each of the 6 switch points and peripheral equipment currently operated in İstanbul subway lines was created. The collected data related to 6000 switch point movements are also very large compared to the training data used in other studies.

In this study, in the second part, the railway switch points and the parameters used as model inputs, which are the materials used in the system, were explained in the first place. The model outputs obtained as a result of the interpretations made in line with these inputs were given. The ANN and SVM methods used to process the collected data were explained. The criteria used to evaluate the performance of the established model were explained. In the third part, the results obtained by processing the data using Weka were presented in tables and it was discussed comparatively which of the ANN and SVM methods give better results. In the fourth part, the results obtained were interpreted and which method provided more successful results to the model was evaluated.

2. Materials and methods

2.1. Railway switch points

Switch points are the equipment that allows vehicles traveling on the railway line to be guided from one track to another. Switch points have two positions. The first is the normal position that allows the vehicle to continue on the track without changing directions, and the other is the diverted (reverse) position that allows the vehicle to be guided from one track to another through switch points.

The position change of switch points is done by electric motors or electrohydraulic systems. In electrohydraulic systems, the regulating motor transmits the applied force to the other points of the switch with hydraulic connections. In electric motor systems, the motor force is transmitted directly to the tie rods and switch direction change is provided [12]. The other end of the rods connected to the electric motor is connected to the movable tracks and thus, the power produced by the motor moves the tongue and the switch position is changed in the desired direction.

The switch tongue, which is the moving part of switch points, moves on flat surfaces called the sliding plate. In order for the switch tongue to move easily, the sliding plates must be clean and lubricated at regular intervals. The dirt and particles deposited on the sliding plates or lubricated parts will require more power from the electric motor during the movement of the switch points, so the electric motor driving the switch points will draw more current.

After the switch points are arranged in a position, they must not lose their position while the train passes over it, otherwise, there is a danger that the train will derail. Thus, so-called claw type lock systems are used to maintain the position of the switch points. This mechanism has a metal part called swallow tail which clamps the drive rod connected to the motor after completing the switch movement. Each switch motor has two swallow tails. One clamps the drive rod in the position in which the switch point is regulated, while the other enters the space inside the drive rod to provide locking. Figure 1 shows the positions of the swallow tail in the normal and sling positions of the switch point in the claw type lock system.

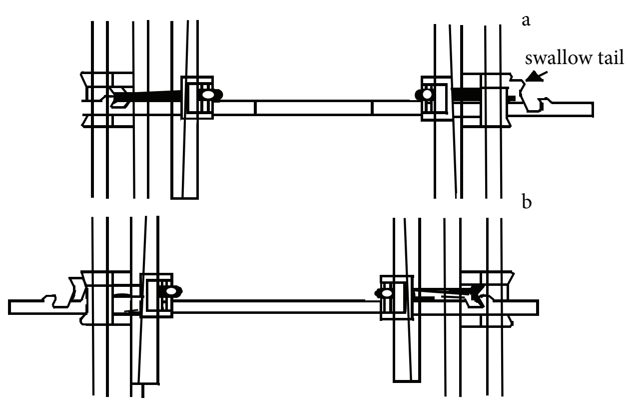

Figure 1. Swallow tail positions (a) Locked to normal position, (b) Locked to reverse position.

If we examine the movement of the switch point from the moment the drive command comes to the electric motor, it will first unlock from its position, then move on the sliding plates and finally lock to the other position. The electric motor will draw more current as it encounters a mechanical strain in any of these stages since the electric motor will use more power. If the power of the electric motor is not sufficient to overcome that obstacle where it encounters mechanical stress, the drive to which the motor is connected will drive the motor for 12,320 ms and then stop drawing power.

In this study, current-time graphs were generated for each movement of the switch points with the help of current sensors connected to the switch motor and the currents were given as an introduction to the model established for the 3 stages of the above-mentioned switch point movement. These 3 stages may require the motor to draw more power during the movement of the switch point due to possible failures such as the unlocking of switch point motor, moving on the sliding plates and locking to the other position. The current drawn by the switch points during unlocking is defined as A1, the current drawn during movement on the sliding plates is defined as A2 and the current drawn during locking is defined as A3. Thus, in which stage or stages the switch motor draws more current than normal, it is interpreted that there is mechanical strain in that stage. In this study, currents varying between 3 and 9 A were measured from the motors used. The motor travel time was given as millisecond input to the system input. Figure 2 shows the current-time graph of the switch point that normally completes its movement.

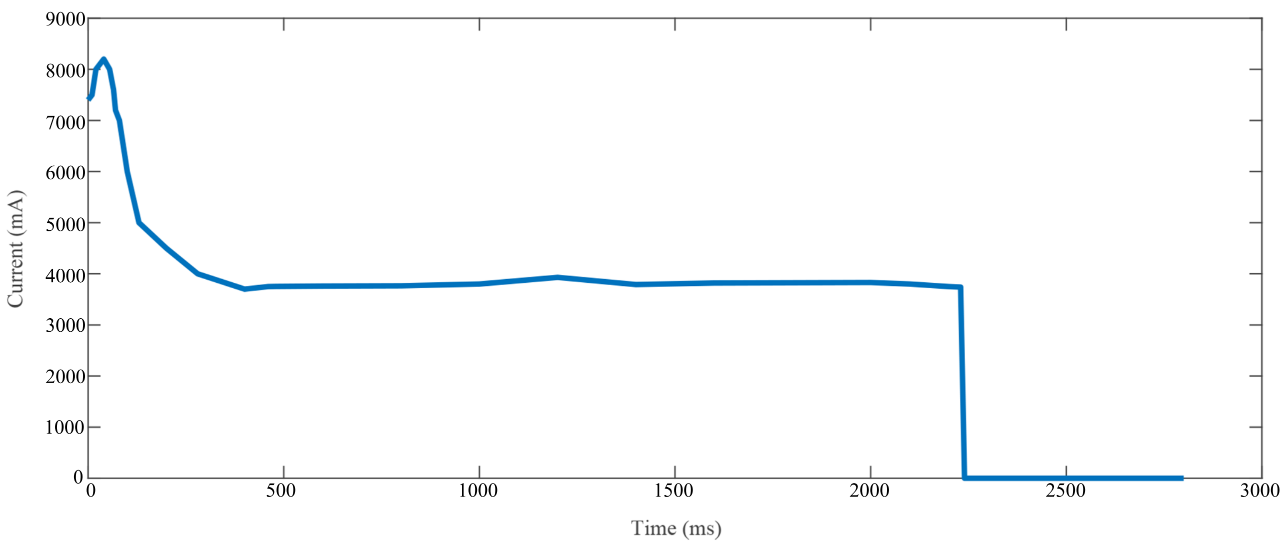

Figure 2. Current-time graph of a smooth switch point movement.

As can be seen from the graph in Figure 3, more power was used for the switch point movement during the unlocking, which is the first stage of the current-time graph, and then the power consumed decreased.

As can be seen from the graph in Figure 4, the switch point moved with normal current values in the first two stages, the current value increased due to mechanical strain during locking and the drive interrupted the movement as a result of 12,320 ms and could not complete the switch point movement. The current-time graphs recorded during all switch point movements were analyzed separately in this way and the data set was created.

The order of movement to the switch points is given by the signaling system. The signaling system sends a movement command to the switch points, but it is interpreted as a fault with the motor drive if the motor does not draw any current.

A movement command is sent to the switch points, the switch point completes its movement in normal current values and normal time, but if the position of the switch points cannot be detected in the signaling system, it is interpreted as a problem in the detector circuit. This value is taken from the signaling system logs. If the position is detected after switch point movement, "1" value is used as model input, and if not detected, "0" value is used as model input.

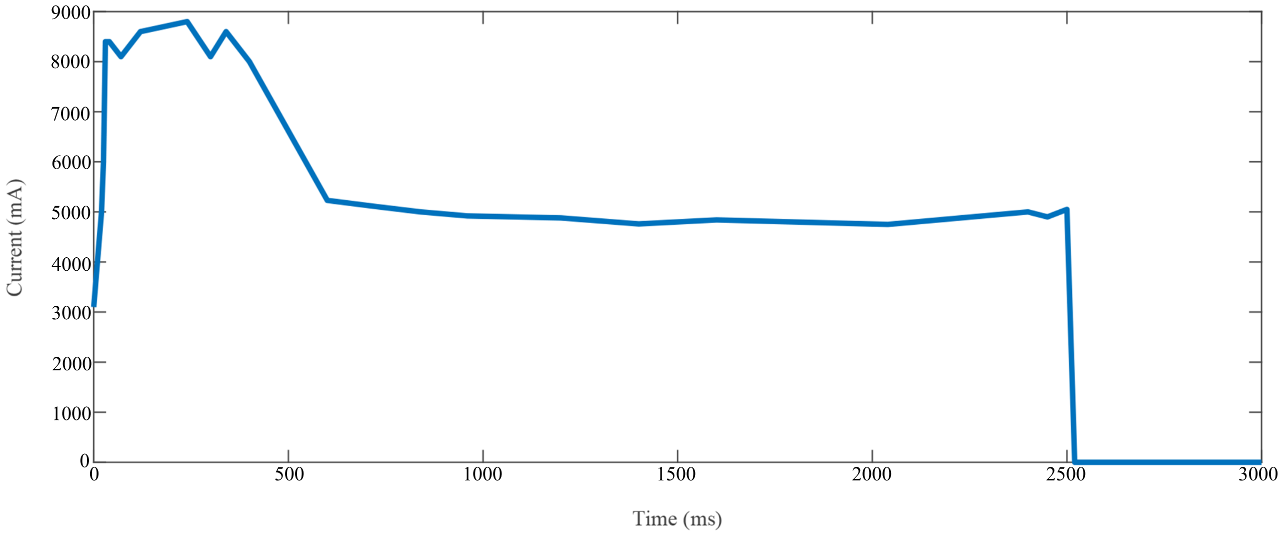

Figure 3. Current-time graph of a constrained switch point movement during unlocking.

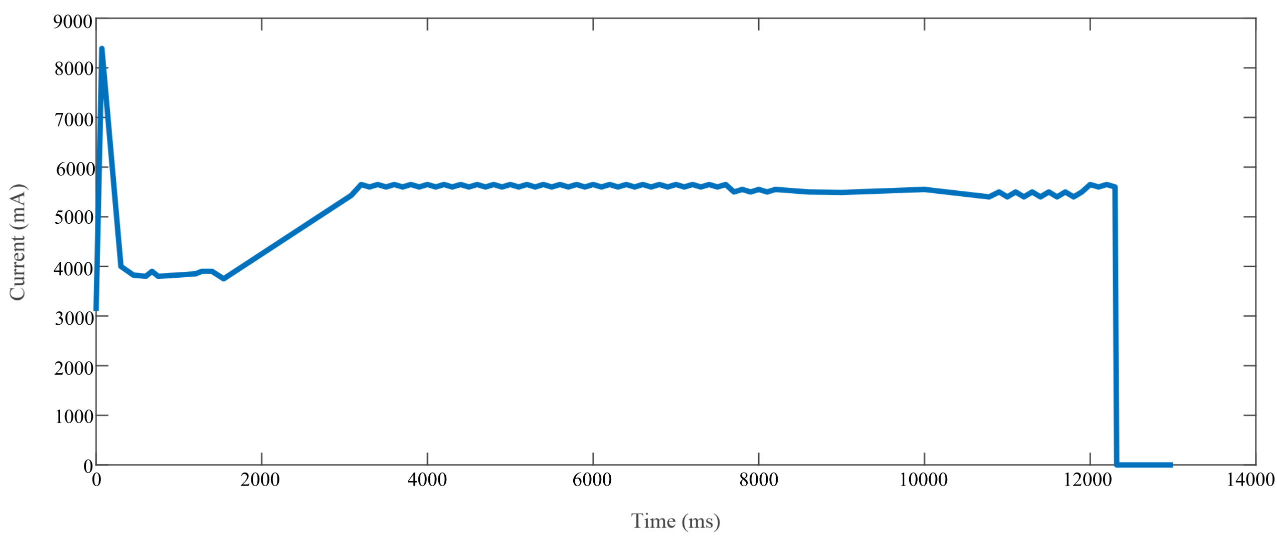

Figure 4. Current-time graph of a switch point movement that completed due to strain during locking.

After the switch points have moved in one direction, the gap between the movable track and the fixed track must be less than 1 mm for the train wheel to pass safely. Failure to do so could result in derailment of the train wheel. In this study, no sensor was used for rail gauge measurement and the values recorded by the maintenance team at regular intervals were used. If the measured value is less than 1 mm, “1” value was used as model input, and if it is higher than 1 mm, “0” value was used as model input.

It is important for which direction of the switch point movement the system inputs given above will be evaluated. It can move smoothly when moving in one direction and problematic when moving in the other direction. Therefore, it must be known for which direction of the switch point movement the current-time graph is analyzed. The direction of the switch point movement was taken from the signaling system logs. “1” value was used as model input for normal movement while “0” value was used as model input for sling movement. Table 1 shows the maintenance proposals provided as system output. System inputs are shown in Figure 5.

Table 1. Maintenance proposals provided as system output.

Identification	Maintenance proposal
R1	Motor movement is smooth
R2	Mechanical adjustments of switch point reverse unlocking function should be checked
R3	Mechanical adjustments of switch point normal unlocking function should be checked
R4	Mechanical adjustments of switch point reverse locking function should be checked
R5	Mechanical adjustments of switch point normal unlocking function should be checked
R6	Sliding plates should be checked
R7	Mechanical adjustments of switch point reverse unlocking function and sliding plates should be checked
R8	Mechanical adjustments of switch point normal unlocking function and sliding plates should be checked
R9	Mechanical adjustments of switch point reverse locking function and sliding plates should be checked
R10	Mechanical adjustments of switch point normal locking function and sliding plates should be checked
R11	Motor driver and power supply must be checked
R12	Detection circuit must be checked
R13	Rail gauge must be checked

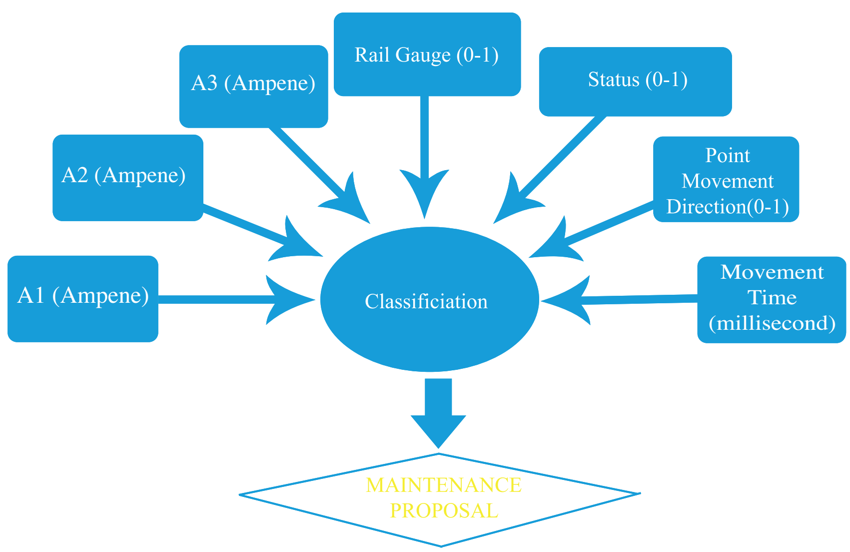

Figure 5. Model inputs.

2.2. Artificial neural networks

Artificial neural networks (ANNs) are the systems that have the ability to learn using the samples by modeling the nerves in the human brain and then make decisions by using the information they have learned about the samples they have never seen [13]. An artificial neuron is the engineering approach of a biological neuron [14]. ANNs are composed of five components: inputs, weights, addition function, activation function, and output [15]. Figure 6 shows the artificial neuron.

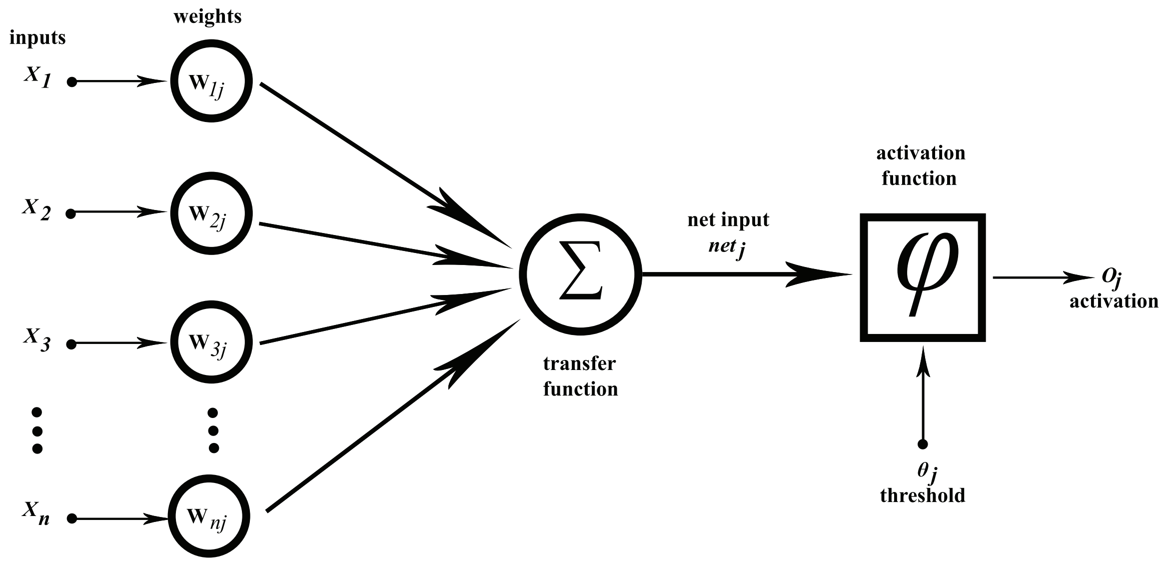

Figure 6. Artificial neuron.

The information is included in the network from the input layer. These inputs are processed in intermediate layers and transmitted to the output layer. The process done in the intermediate layers is to convert each input to output using the weight values of the network. Weight values must also be calculated correctly in order to obtain the correct outputs. Finding the right weights is achieved by training the network correctly. These weight values are initially assigned randomly. Then, during training, when each sample is introduced to the network, weights are changed according to the learning rule of the network. Then another sample is presented to the network and weights are updated again and the most appropriate weight values are tried to be found. These operations are repeated until the correct outputs are generated for all samples in the training data. After all weights have been calculated, the samples in the test set are shown to the network. If the network responds correctly to the samples in the test set, the network is considered to be properly trained [16].

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

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

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 $\varphi(V)$ shows the activation function of the cell.

2.3. Support vector machines

Support vector machine (SVM) is a classification algorithm based on statistical learning. SVM was first designed for the problem of classification of two-class linear data, then generalized for the classification of multiclass and nonlinear data. The basic principle of SVM is to find the most appropriate decision function that separates the two classes, in other words, to define the hyperplane that separates the two classes from each other in the most appropriate way [17].

It is one of the most appropriate methods for classification. A boundary is drawn between the two groups to be classified at the farthest point to the members of the two groups and the groups are separated. SVM determines how to draw this boundary. For this operation, two parallel lines are drawn at the closest point to both groups and a boundary line is drawn to the midpoint of these two lines as shown in Figure 7 so that new incoming inputs are classified according to their position with respect to this line.

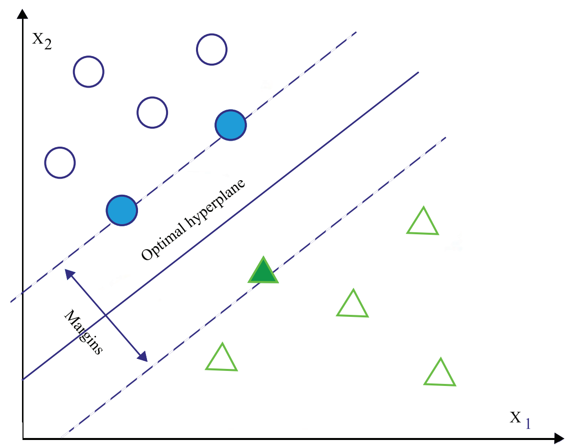

Figure 7. Optimum lines separating the two classes.

The vast majority of SVM data sets cannot be classified linearly. SVM is linearized by mapping nonlinear data in the feature space at high dimensions [18]. Thus, the complex data set is put into a form that can be easily separated as shown in Figure 8.

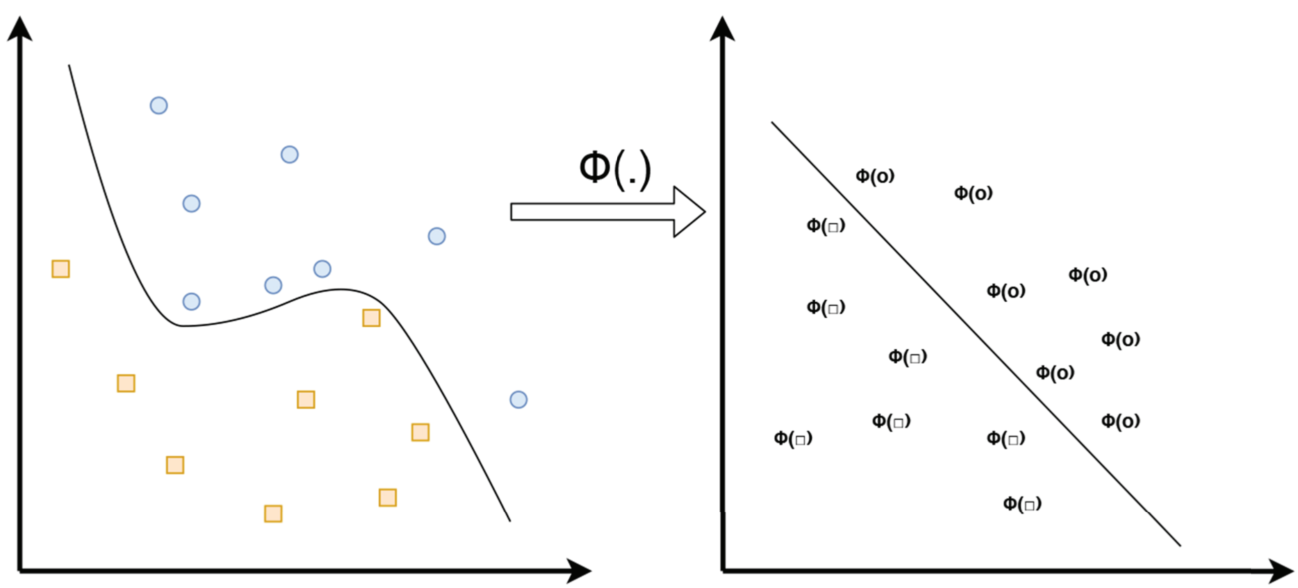

Figure 8. Mapping of data to feature space.

If the number of groups to be classified is more than two, one of the multiclass SVM methods is preferred. These include reducing the problem into binary groups (one-to-one approach), modeling the problem from a single group to all groups (one-to-many approach), and multiclass sorting SVMs. The most commonly used approach is the one-to-one approach. In this approach, classes are trained in binary groups and SVM multipliers are determined against each other. Whichever of the binary queries gets more answers, the input is included in that class [19]. Figure 9 shows the classification of multiclass SVM.

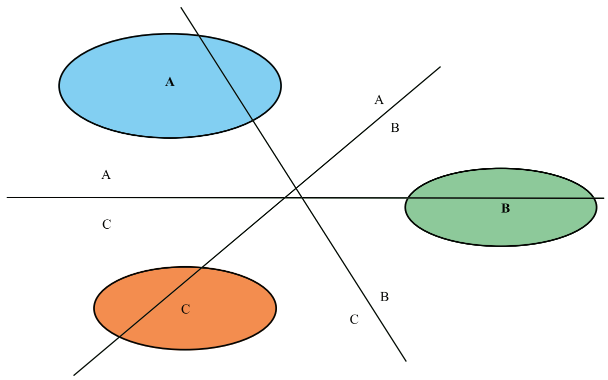

Figure 9. Classification of multiclass SVM.

2.4. Model performance evaluation criteria

The correlation coefficient is used to determine the relationship between two or more variables. While one variable changes, if the other variable also changes accordingly, it can be said that there is a correlation between them. The square of the correlation coefficient is expressed as the determination coefficient (R^2). Determination coefficient indicates the percentage of change in the dependent variables explained by the dependent variable or variables. It takes a positive value between 0 and 1 and as this value approaches 1, the correlation between the variables can be said to be stronger [20].

In order to evaluate the performance of the classification model used in machine learning, the complexity matrix is used to compare the targeted and actual values [21]. TP shown in Table 2 shows the rate of data that has a positive classification result when the actual state is positive. TN indicates the rate of data that has a negative classification result when the actual state is positive. FP shows the rate of data that has a positive classification result when the actual state is negative. FN shows the rate of data that has a negative classification result when the actual state is negative.

Precision, sensitivity, and F-measure values are calculated using the values specified in Table 2 [22].

Table 2. Complexity matrix.

Class recognized	as positive	as negative
Positive	TP	FN
Negative	FP	TN

Precision is the rate of the number of TP samples predicted to be class 1 to the total number of samples predicted to be class 1. The fact that the model is close to 1 shows that the performance of the established model is good [22]. It is shown by Equation 3.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

Sensitivity is the rate of the number of samples classified as true positive to the total number of positive samples. The fact that the model is close to 1 shows that the performance of the established model is good [23]. It is shown by Equation 4.

$$Sensitivity = \frac{TP}{TP + FN}. \tag{4}$$

F-measure is the harmonic mean of the precision and sensitivity values. The fact that the model is close to 1 shows that the performance of the established model is good [22]. It is shown by Equation 5.

$$F - Measure = \frac{2 \times Sensitivity \times Precision}{Sensitivity + Precision}. \tag{5}$$

Receiver Operating Characteristic (ROC) curve is generated by plotting the true positives as a function of the false negatives from the graded data. The area under this curve is indicated as the ROC-Area value. 1 indicates that the performance of the established model is good [24].

The absolute value of the difference between the measured values and the predicted values divided by the number of measurements is called the mean absolute error (MAE) and is calculated as shown in Equation 6.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y - y'| \tag{6}$$

The root mean square error (RMSE) is calculated by taking the square root of the sum of the squares of the true errors of a measure sequence divided by the number of measures. In this error calculation, since the squares of the errors are taken, the effect of large errors on the mean is greater and the effect on the whole measurement can be determined. It is shown by Equation 7.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y - y')^2} \tag{7}$$

In Equation 6 and Equation 7, y shows the measured value, y' shows the predicted value, and n shows the number of measurements. MAE calculation is easy but it calculates errors linearly. RMSE is more preferred as it defines the magnitude of errors [25].

3. Results and Discussion

In this study, the prediction was made by using Support Vector Machines and Artificial Neural Networks, which are artificial intelligence methods, and the results were evaluated. A total of 6000 data were collected including 1000 data from each of the 6 switch motors currently operated. Each data contains seven inputs and one output. Of the 1000 data collected for each switch point, 850 were used for training and 150 for testing.

Weka 3.8 software [26] was used for the ANN method application. In order to obtain the best results using Weka software, many trials were performed with different parameters and the most appropriate values were determined. Accordingly, “Multilayer Perceptron,” which is frequently used in ANN, was preferred as the algorithm [13]. The ANN architecture consists of one input layer, nine artificial neurons in one hidden layer, and one output layer. Momentum was selected as “m = 0.2” and learning rate was selected as “l = 0.3” as the values that give the optimum results and the data were normalized and the training with 1000 iterations was performed. The ANN model created is shown in Figure 10.

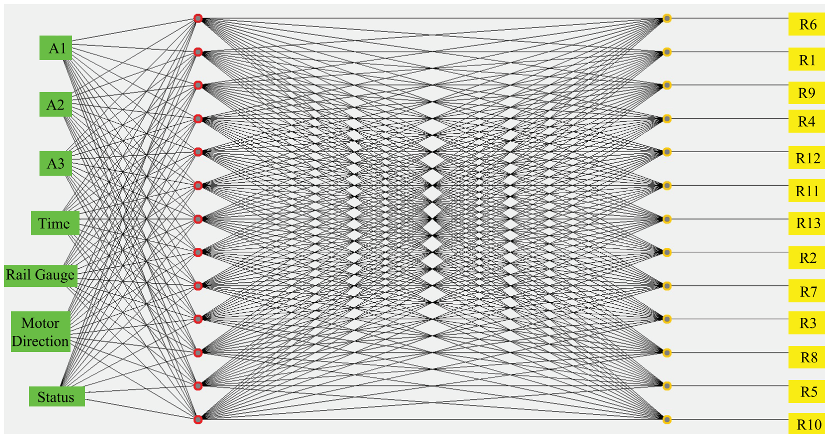

Figure 10. Created ANN model.

WEKA 3.8 [26] software was used for the SVM method application. Many attempts have been made to determine the parameters that will give the best result. Accordingly, SVM parameters with the highest performance are the complexity parameter ”c = 1”, the kernel function the polynomial kernel, the kernel's exponent value ”e = 1” were chosen as optimum values and the data normalized.

For the SVM method implementation, WEKA 3.8 [26] software was used. Many attempts have been made to determine the parameters that will work best. Accordingly, the SVM parameters with the best performance, including complexity parameter of “c=1”, kernel function polynomial kernel, exponential value of the kernel of “e=1”, were selected as the optimum values and the data were normalized.

Table 3 shows the results obtained during the training phase with the SVM and ANN methods, and Table 4 shows the results obtained during the test phase.

Table 3. Results obtained during the training phase.

Switch Points/Method	Precision	Sensitivity	F-Measure	ROC Area	R^2	MAE	RMSE
M1/SVM	0.998	0.998	0.998	0.999	0.9951	0.1311	0.2479
M1/ANN	0.993	0.995	0.996	1.000	0.9910	0.0048	0.0225
M2/SVM	0.995	0.994	0.994	0.999	0.9807	0.1302	0.2475
M2/ANN	0.979	0.987	0.961	0.999	0.9568	0.0036	0.0352
M3/SVM	0.998	0.998	0.998	1.000	0.9961	0.1389	0.2554
M3/ANN	0.999	0.995	0.999	1.000	0.9921	0.0039	0.0289
M4/SVM	0.999	0.999	0.999	1.000	0.9973	0.1324	0.2468
M4/ANN	0.985	0.959	0.968	0.973	0.9108	0.0085	0.0687
M5/SVM	0.986	0.984	0.984	0.998	0.9728	0.1322	0.2470
M5/ANN	0.998	0.993	0.999	1.000	0.9881	0.0037	0.0208
M6/SVM	0.996	0.982	0.880	0.990	0.9707	0.1337	0.2478
M6/ANN	0.997	0.979	0.900	0.998	0.9647	0.0068	0.0440

Table 4. Results obtained during the testing phase.

Switch points/method	Precision	Sensitivity	F-Measure	ROC Area	R^2	MAE	RMSE
M1/SVM	0.992	0.991	0.991	0.999	0.9954	0.1305	0.2479
M1/ANN	0.996	0.983	0.998	1.000	0.9693	0.0068	0.0369
M2/SVM	0.985	0.973	0.977	0.992	0.9535	0.1303	0.2468
M2/ANN	0.961	0.937	0.952	0.988	0.8895	0.0113	0.0786
M3/SVM	1.000	0.990	0.995	0.998	0.9826	0.1389	0.2556
M3/ANN	0.882	0.950	0.994	0.997	0.9091	0.0120	0.0869
M4/SVM	0.991	0.990	0.991	0.996	0.9837	0.1315	0.2478
M4/ANN	0.991	0.990	0.991	0.995	0.9837	0.0048	0.0393
M5/SVM	0.991	0.991	0.991	0.987	0.9838	0.1312	0.2464
M5/ANN	0.991	0.991	0.991	0.995	0.9838	0.0051	0.0392
M6/SVM	0.969	0.944	0.931	0.979	0.9152	0.1301	0.2481
M6/ANN	0.994	0.972	0.992	0.993	0.9582	0.0082	0.0565

When the results obtained in Tables 3 and 4 are compared, it is observed that similar results were obtained in 6 switch points. The accuracy, sensitivity, F-measure, ROC area, and R^2 values which are the criteria indicating that model performance is successful as they approach 1 were calculated close to 1 for all switch points during the training and testing phase. Similar values were calculated for the MAE and RMSE values of the 6 switch points during the training and testing phases, indicating that system success increases as it approaches 0. However, the values calculated in ANN are quite close to 0 and higher in SVM.

The data are divided into training and test data to understand how the model performs on data that it has not seen before. The results obtained above were obtained by using 850 of the data for training and 150 for testing. However, during the training and testing phases, some errors may occur due to distribution and the system may become based on memorization. To minimize these errors, the k-fold cross-validation method is applied [27]. In this method, the data set is divided into k equal parts, k-1 is used for training and the remaining part is used for testing. This process is repeated k times, and it is repeated by using a different part for the test each time, and the calculated system success and errors are added up and their mean is calculated each time. Thus, the success of the model is calculated more accurately. In the literature, the 10-fold cross-validation method is generally used [28].

In order to make a more objective evaluation at this stage, in addition to SVM and ANN methods, optimizable trees (fine tree, medium tree, coarse tree), optimizable naive Bayes (Gaussian naive Bayes, Kernel naive Bayes) and optimizable ensemble trees (boosted trees, bagged trees, RUSBoosted trees) classification methods were applied to the established model by 10-fold cross-validation and R^2 values were compared in Table 5.

As can be seen in Table 5, SVM and ANN methods were more successful than other methods. In Table 6, the results obtained from SVM and ANN methods by 10- fold cross-validation are presented in detail.

When the cross-validation results given in Table 6 were evaluated, similar results were obtained in the training and testing phases. Precision, sensitivity, F-measure, ROC area, and R^2 values were similar and very close to 1 in SVM and ANN. On the other hand, MAE and RMSE provided more successful results in the ANN method compared to SVM. In other words, ANN method produced 17.4% more successful results in RMSE error rate comparison and 12.2% more successful results in MAE error rate comparison than SVM method.

Table 5. Comparison of different methods.

Switch points	SVM	ANN	Optimizable trees	Optimizable naive Bayes	Optimizable ensemble trees
M1	0.9954	0.9693	0.9500	0.9590	0.9570
M2	0.9535	0.8895	0.8703	0.8490	0.8473
M3	0.9826	0.9091	0.9077	0.8600	0.7730
M4	0.9837	0.9837	0.9380	0.9210	0.9690
M5	0.9838	0.9838	0.9563	0.7150	0.8520
M6	0.9152	0.9582	0.9373	0.9370	0.9210

Table 6. Detailed results obtained by cross-validation.

Switch Points/Method	Precision	Sensitivity	F-Measure	ROC Area	R^2	MAE	RMSE
M1/SVM	0.995	0.995	0.995	0.998	0.9906	0.1302	0.2470
M1/ANN	0.985	0.992	0.988	1.000	0.9849	0.0034	0.0239
M2/SVM	0.993	0.992	0.992	0.999	0.9781	0.1306	0.2477
M2/ANN	0.970	0.986	0.963	0.999	0.9613	0.0040	0.0353
M3/SVM	0.995	0.996	0.997	0.998	0.9934	0.1298	0.2480
M3/ANN	0.940	0.980	0.893	0.991	0.9669	0.0049	0.0442
M4/SVM	0.998	0.998	0.998	0.999	0.9957	0.1303	0.2478
M4/ANN	0.984	0.964	0.971	0.977	0.9271	0.0080	0.0666
M5/SVM	0.986	0.984	0.984	0.997	0.9741	0.1312	0.2475
M5/ANN	0.960	0.983	0.905	0.997	0.9719	0.0055	0.0434
M6/SVM	0.993	0.979	0.960	0.988	0.9656	0.1316	0.2468
M6/ANN	0.978	0.977	0.972	0.992	0.9622	0.0066	0.0509

Therefore, it is observed that the ANN method is more appropriate in the implementation of the established model.

4. Conclusion

In this study, for the first time in the literature, it is aimed to predict railway switch point failures with the help of artificial intelligence and thus, it is aimed to contribute to the planned maintenance works on the railways. Classification and failure prediction study were carried out with the model which was created in order to shorten the solution process of railway switch point failures and to solve the failures before reaching the size that would affect the operation and the results were evaluated. The data set was processed by the ANN and SVM methods using Weka software and the results obtained were evaluated. According to the evaluations, the model performance results obtained by cross-validation were very close to the results obtained during the training and testing phases. According to these results, the use of artificial neural networks method will be more successful in the application of the failure prediction model established due to the much lower calculation of the MAE and RMSE values. Achieving high success in both artificial intelligence methods shows that the model was created with sector experience and a correct approach. Considering the success of the established model, even if the inputs to the system change, the system will correctly determine the outputs and make the correct prediction of failures. In this way, railway switch point failures will be prevented, the solution process of failures will be shortened, unplanned train stops will be prevented and the continuity of railway traffic will be ensured. Thanks to similar applications that will provide an advantage for planned maintenance, maintenance management of the railways will be carried out at high levels, thus preventing the loss of time, money, energy and manpower.

In the future, it is planned to take the above-mentioned study one step further to create interface software that can be actively used in preventive maintenance activities in the sector and to use it as a decision support model for the failure operators.

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