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Predictive Maintenance Based On Machine Learning In Public Transportation Vehicles

Toplu Taşıma Araçlarında Makine Öğrenmesine Dayalı Kestirimci Bakım

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ABSTRACT

Predictive maintenance is an approach to prevent failure in a system by estimating the time of failure before a mechanical component fails, so that the maintenance decision can be properly planned. Maintenance forecasting models are used to increase the productivity and efficiency of a hardware. In the public transport sector, whose efficiency is heavily dependent on equipment, forecasting of failures is vital. In this study, predictive maintenance work was carried out in order to minimize the problems such as stopping the voyage, delaying the journey and having an accident caused by unplanned breakdowns in public transport vehicles. Based on instant vehicle health data obtained from IoT sensors, classification techniques were run in machine learning. For maintenance planning, the probability of vehicles being normal and malfunctioning was examined with fuzzy logic and fuzzy outputs were obtained at maintenance speed. As a result of the study, almost all of the faults in the vehicles could be detected with the predictive maintenance approach applied.

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ÖZET

Kestirimci bakım, bir sistemin mekanik bir bileşeninde arıza oluşmadan önce arıza zamanını tahmin ederek bakım kararının doğru planlanabilmesi için arızanın önlenmesini sağlayan bir yaklaşımdır. Bir donanımın üretkenliğini ve verimliliğini artırmak için bakım tahmin modelleri kullanılmaktadır. Verimliliği büyük ölçüde donanıma bağlı olan toplu taşıma sektöründe de, arızaların önceden tahmin edilmesi hayati önem taşır. Bu çalışmada toplu taşıma araçlarında plansız arızalardan kaynaklanan seferin durdurulması, yolculuğun ertelenmesi ve kaza yapılması gibi sorunları en aza indirmek için kestirimci bakım çalışması yapılmıştır. IoT sensörlerinden elde edilen anlık araç sağlığı verilerine dayalı olarak makine öğrenmesinde sınıflandırma teknikleri çalıştırılmıştır. Bakım planlaması için araçların normal ve arızalı olma olasılığı bulanık mantıkla incelenmiş ve bakım hızında bulanık çıktılar elde edilmiştir. Çalışmanın sonucunda, uygulanan kestirimci bakım yaklaşımı ile araçlardaki arızaların neredeyse tümü tespit edilebilmiştir.

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1. INTRODUCTION

Maintenance is any corrective and preventive action to prevent any part of a system from failing or completely stopping the system from working. Predictive maintenance, on the other hand, minimizes the number and cost of unplanned outages caused by machine failures at the maximum interval between repairs by regularly monitoring the true mechanical health, operating efficiency, and other indicators of operating condition of any part of a machine or system [1]. Predictive maintenance works based on fault prediction. Such predictive technologies integrate intelligent algorithms with electronics and disconnected intelligence even more as more software and embedded intelligence are integrated into industrial products and systems. These technologies can also be used to predict performance degradation of a system or machine and to independently manage and optimize the needs of that system or machine [2]. Especially in hardware-dependent systems, using a predictive and intelligent maintenance strategy has advantages over maintenance strategies that are determined to be repaired when it breaks down or to maintain at standard specified periods. In order to prevent instant undesired breakdowns, delays and stoppages in a hardware-dependent system, a management where maintenance is planned and predicted is often preferred. Diagnostics, performance assessment of failure level, and maintenance forecasting models can be used to achieve near-zero failure performance and increase a company's productivity.

In this study, it is aimed to prevent unplanned breakdowns and increase driving safety in public transportation vehicles by establishing an intelligent, automatic and real-time maintenance forecasting model. As a result of the study, it is expected that the number of unfinished voyages due to breakdowns, voyage delays, disruptions while cruising, and the costs and the amount of labor spent due to malfunctions are expected to decrease. The data source and solution focus of the study is the "Kent Kart" company working on smart transportation systems. Kent Kart provides services in many cities both in the country and abroad with the smart solutions it brings to the public transportation sector and domestic production. Vehicle health data were obtained from a working vehicle in order to prevent negative situations such as disruptions and even stopping of voyages, waiting for passengers, experiencing accidents, loss of property and life due to malfunctions observed in public transportation for many years. By examining the health data of the vehicles taken from the IoT sensors, the data sources that cause the most serious malfunctions are considered as attributes in the study. Defective/healthy data labels were made on the collected data and the tagged data formed the training data set for machine learning. The data set, which generates the values of the same attributes randomly taken at any time, was also used for testing purposes in the application. For the maintenance prediction model of the study, classification methods such as support vector machines, random forest, naive bayes, k-nearest neighbor and logistic regression were created. As the output of these methods, the vehicle is classified as normal/defective, and thus, the system is warned as soon as the vehicle starts to produce data close to the first failure. The warnings made to the system were obtained according to the maintenance probabilities obtained from the normality of the vehicles. Fuzzy decision set is obtained by fuzzing these two variables.

In the first part of the study, predictive maintenance methodology is mentioned. Then, in the method part, classification models and performance measurement criteria used in machine learning and the fuzzy logic model used are defined. In the last section, the application and the results of the application were given and the study was concluded.

2. PREDICTIVE MAINTENANCE

According to the first comprehensive maintenance terminology published, predictive maintenance is a hardware maintenance strategy that relies on measuring the condition of the equipment to assess whether or predictably when it will fail in the future, and then taking appropriate action to avoid the consequences of that failure [3]. This strategy is based on regular monitoring of the data received on the hardware and the performance measurements of the hardware, and parameter optimization on these data. After performance and/or parameter monitoring, the system should plan the next precautionary actions. In this case, as the definitions for predictive maintenance say, the estimation of "Maintenance performed after an estimate derived from analysis and evaluation of key parameters of item condition" becomes the maintenance actions to be taken in subsequent actions. Planning and scheduling predictive maintenance actions can be run automatically or work in interaction with other systems and people. In this case, an advanced or complex condition-based maintenance system for a comprehensive system or hardware can also perform maintenance operations independently [4].

The advantages of predictive maintenance have been compiled in the literature as follows.

- Minimizes uncertain downtime and maintenance cost [5].
- Allows specific control of machines indicating the initiation of a fault [5].
- Increases the availability of industrial facilities [6].
- Both internal and subcontracted maintenance interventions have the capacity to perform quality checks [5].
- Increases factory safety [7].
- It facilitates certification and ensures the verification of the requirements of the ISO 9000 standard [5].
- It provides the best programming of maintenance actions [5].
- Provides efficient scheduling of consumables and personnel [5].

- Production quality is optimized by operating the machine uninterruptedly due to malfunctions [8].
- Provides support during the design phase of equipment, particularly through the application of modal analysis [9].
- Provides direct maintenance costs reduction by checking only defective equipment [10].
- Improves company image by adhering to delivery dates and meeting customers' quality demands [5].
- It reduces spare part and labor costs [11].
- By keeping industrial equipment operational while applying predictive tools, the measurement process does not directly affect equipment availability [5].
- As in-plant security increases, costs associated with insurance policies decrease [5].
- Provides complete historical information on each piece of equipment that helps determine reliability parameters and optimize maintenance planning. This information about machines and equipment is available to management for decision making [12].
- It ensures the reduction of energy consumption [5].

3. METHOD

Statistical (trend, regression, correlation, survival analysis) methods [13], machine learning-based (supervised-classification, unsupervised-clustering, semi-supervised) methods in predictive maintenance approach [14-19] model-based (simulation, mathematical, experimental) methods [20], knowledge and rule-based methods and hybrid methods [18] can establish a care model [21]. In this study, data were collected from vehicles with IoT sensors and a machine learning-based prediction system was established on the collected data. Although IoT-based predictive maintenance studies have become widespread in recent years [14], machine learning-based maintenance prediction studies with an intelligent system for vehicle health in the public transportation sector are relatively new [20]. For this reason, applying this method to the public transport sector provides an innovative contribution to the literature. The focus of the study is to provide a smart maintenance forecasting model with high performance, which can be applied to the literature in smart cities and smart municipality studies, provides fast results by making real-time calculations.

3.1. Classification in Machine Learning

All data in any dataset used for machine learning is represented using the same set of variables. This set of variables can consist of continuous, categorical or binary variables. If the target variable contains labeled data, this type of learning is supervised as opposed to unsupervised learning where the data is not labeled. This learning process is called classification [22]. In the prepared structure, random forest (RF), logistic regression (LR), support vector machines (SVM), naive bayes (NB) and k-nearest neighbor (kNN) supervised classification methods were used to classify IoT sensor data in machine learning.

- Support Vector Machines (SVM): The basis of the method is based on the division of data into optimal classes with the help of a hyperplane. There are many possible linear classifications here that can separate the data. But only one of these classifications maximizes the limit. This linear classifier is called the optimal separation hyperplane. This plane makes optimal discrimination by maximizing the distance between itself and the data point closest to each class [23].
- Random Forest (RF): According to the definition of Breiman [24], a random forest is a combination of tree estimators that depend on the random vector values of each tree in the forest with the same distribution and independent samples. Accordingly, the random forest classification algorithm works with the combination of each tree in the forest. When a new object is to be classified, each tree in the forest votes for a classification result or a class. The forest classifies the new object into the class with the most votes [25].
- Logistic regression (LR): Fits a separating hyperplane that is a linear function of input properties between two conditions or classes. In a given training data set, the goal is to predict the hyperplane that accurately predicts the class label of a new sample and to identify the subset of features that are most informative about class separation [26]. LR is useful for situations where you want to be able to predict the presence or absence of a feature or result based on the values of a set of prediction variables [27].
- Naive Bayes (NB): Naive Bayes (NB) classifier, which is widely used for classification, is provided by Bayes' theorem, which is a simple probability theorem. The classifier obtained using the set of discriminant functions and calculating the corresponding probabilities from the training set is generally called the Naive Bayesian classifier. Because if the "pure" assumption is made that the attributes are independent when considering the class, this classifier can easily be shown as optimal in terms of misclassification rate or minimizing zero-one loss [28].
- K-Nearest Neighbor (kNN): To classify a data record, its nearest neighbors are rearranged, forming a neighborhood of t. Among the neighboring data records, majority voting is often used to decide on the t classification, with or without the distance-based weighting [29]. The KNN rule classifies each unlabeled sample with the majority label among the k nearest neighbors in the training set.

3.2. Performance Measuring in Classification

For performance measures, a confusion matrix was drawn and the results of the matrix were evaluated using the area under the curve (AUC) and accuracy (ACC) metrics. A confusion matrix is a matrix that summarizes the classification performance of a classifier against some test data. For a two-class classification result, it is a two-dimensional matrix [30] indexed in one dimension by the actual class of the data and in the other by the class predicted by the classifier. The confusion matrix is suitable for traditional classification methods where it is assumed that cells at reference locations can be assigned to single classes, and accuracy measures based on the proportion of correctly classified area are then calculated from the correct pixel count [31]. The complexity matrix is plotted as in Table 1 below.

Table 1. Confusion matrix.

	Observed True	**Observed False**
Predicted True	TP	FP
Predicted False	FN	TN

- True Positive (TP): A case of incorrectly predicting and incorrect data
- False Positive (FP): The state of a data being predicted to be incorrect but not incorrect.
- True Negative (TN): A situation where a data is predicted to be non-erroneous and not erroneous.
- False Negative (FN): A situation where a data is incorrect even though it is predicted not to be incorrect.

The ratio between the number of faulty data correctly classified in the confusion matrix and the total number of samples gives the accuracy measurement. The higher the accuracy value, the better the performance output. It is calculated as follows in (1).

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

A two-dimensional graph, called ROC, is drawn on the vertical axis of the true positive rate and the false positive rate on the horizontal axis in the confusion matrix. The area under this curve is called the AUC. The AUC indicates the classifier's ability to prevent misclassification. The larger the area is calculated, the better the performance measurement.

3.3. Fuzzy Logic

Computers reveal certain facts such as "black and white", "true-false", "yes-no" with zero and one sequences, they cannot reason like the human brain can reason under uncertainty or with claims containing value judgments. However, instead of these real judgments, when these are partially correct, people, unlike computers, have common sense in situations where transition values such as "black-gray-white", "warm-warm-cold-freezing" are not clear. Fuzzy logic is a branch of machine intelligence that helps computers paint gray, common-sense pictures of an uncertain world by manipulating ambiguous concepts [32]. Fuzzy logic deals with the formal principles of precise reasoning and approximate reasoning, which limit decisions in situations where it cannot always be decided with certainty. Unlike classical exact logical systems, this method aims to model modes of reasoning that cannot be expressed precisely and play an important role in making rational decisions in an environment of uncertainty [33].

Fuzzy logic is based on fuzzy set operations that can take any degree of membership between 0 and 1. In this fuzzy set, real values are transformed into linguistic terms. The value that determines how much an input value belongs to any term of the transformed linguistic variable is called membership degree in fuzzy logic literature. The functions in which membership degrees are calculated are membership functions. There are different types of membership functions that are frequently used like triangle, trapezoid, Gaussian and sigmoid. In Figure 1, different type of membership representations are exemplified [34].

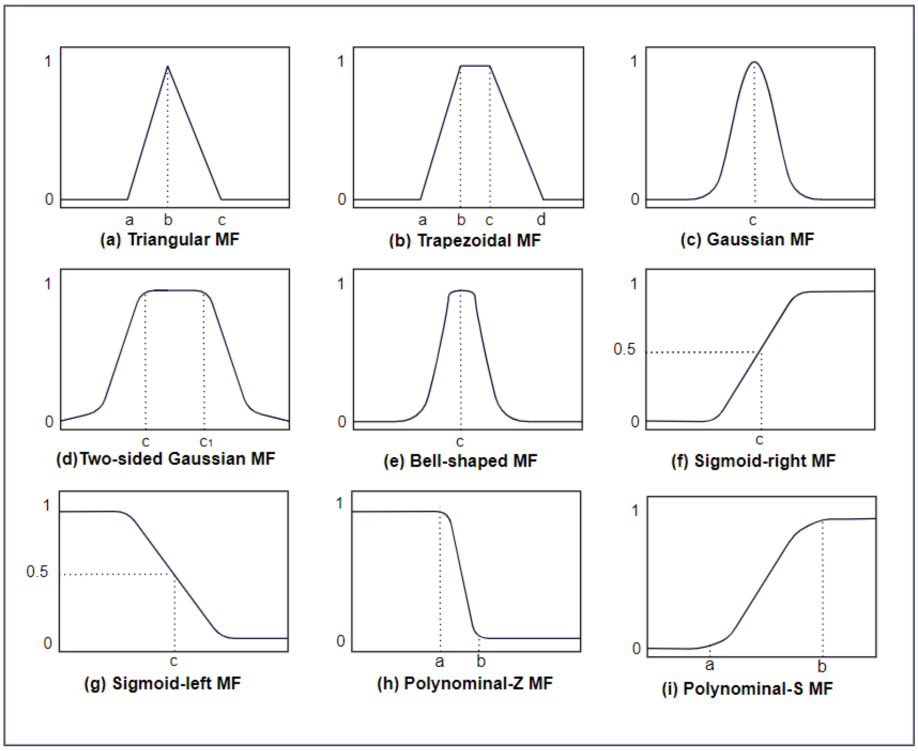

Figure 1. Different types of membership representations.

In this study, triangle type of membership function is used. As can be seen in the (a) chart of the Figure 1, this function has three parameters, a, b and c given by the following expression (2).

$$f(x,a,b,c)=\begin{cases}0, & x\le a\\ \dfrac{x-a}{b-a}, & a\le x\le b\\ \dfrac{c-x}{c-b}, & b\le x\le c\\ 0, & c\le x\end{cases} \tag{2}$$

Basically, in fuzzy logic flow, data input is blurred with membership function. Here real values are transformed into linguistic values. After the membership functions are determined according to the fuzzy set boundaries of the application, the fuzzy rules are defined and the rule-based fuzzy inference step is applied. Here, the rules are explained with "if", "then" conditions. Then, the clarification process is performed using the membership function. This is the process of converting the fuzzy result obtained as a result of fuzzy inference to the real value. After that, data output is provided.

4. APPLICATION

According to the method map followed, the appropriate features for the telemetry data received from the IoT sensors were selected and separated into test and training data sets. The training dataset was trained in classification algorithms in machine learning and prediction outputs were produced for the unlabeled data in the test dataset. Then, performance measurements and outputs were evaluated on the test data set. Whenever new telemetry data is generated in the system, it is transmitted to the center together with the time of occurrence of this data and the value of the relevant sensor. For this pilot predictive maintenance study, basic independent variables such as engine cooling degree, engine operating speed, engine oil pressure, engine intake manifold pressure, total distance traveled and total fuel consumed level are considered. The dependent variable is the machine status, which consists of the normal (0) label, which indicates that there is no fault in the vehicle, and the faulty (1) labels, indicating that there is a fault. Of the total 138733 data, approximately 92% (127733) are normal labeled data and the remaining 8% (11000) are defective label data. These data were randomly divided into two as 25% (34676) test and 75% (104057) training dataset. Then, the training data was run with the determined classification algorithms and then the predictions in the test data set were evaluated.
Figure 2 shows the confusion matrix according to the random forest classifier. According to the RF algorithm, only 3 of the measurements in the test dataset were labeled with deviation as normal while actually defective.

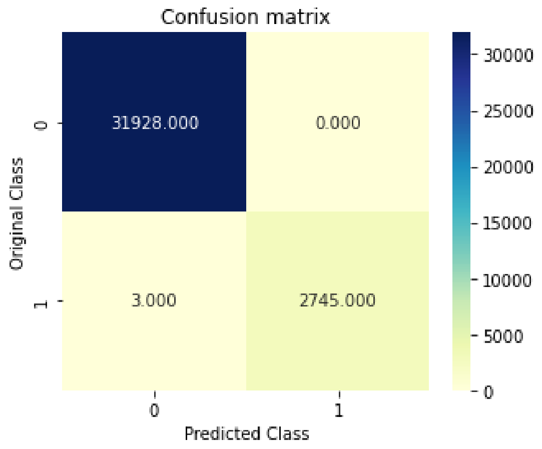

Figure 2. Confusion matrix of random forest classifier.

Figure 3 shows the confusion matrix according to the logistic regression classifier. According to the LR algorithm, a total of 128 of the measurements in the test data set were labeled with deviation as normal while actually defective.

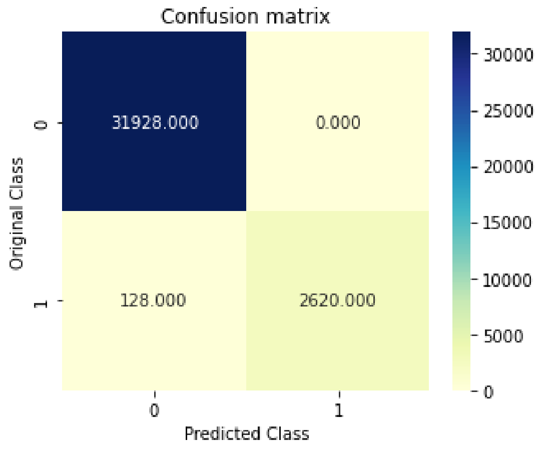

Figure 3. Confusion matrix of logistic regression classifier.

Figure 4 shows the confusion matrix according to the k nearest neighbor classifier. According to the kNN algorithm, only 5 of the measurements in the test data set were deviatedly labeled as normal while actually defective.

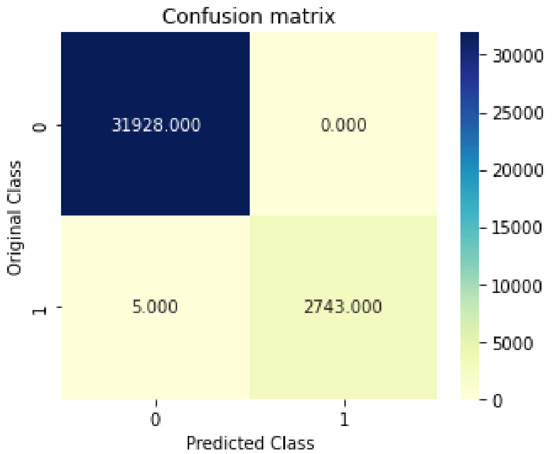

Figure 4. Confusion matrix of k nearest neighbor classifier.

Figure 5 shows the confusion matrix according to the support vector machines classifier. According to the SVM algorithm, 50 of the measurements in the test data set were labeled with deviation as normal while actually defective.

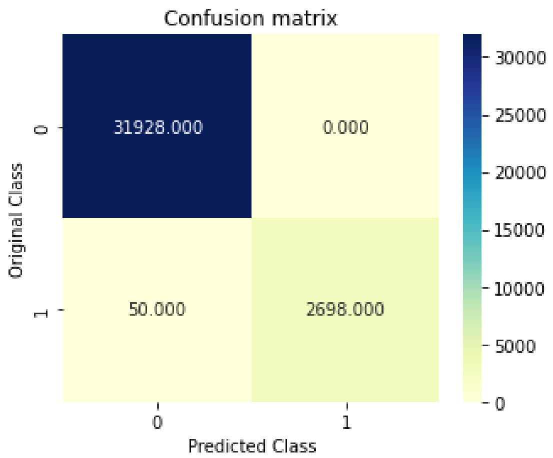

Figure 5. Confusion matrix of suport vector machines classifier.

Figure 6 shows the confusion matrix according to the naive bayes classifier. According to the NB algorithm, a total of 137 measurements in the test data set were labeled with deviation. 122 of these deviated labels were estimated as faulty when they were actually normal, and 15 of them were incorrectly estimated as normal when they were actually faulty.

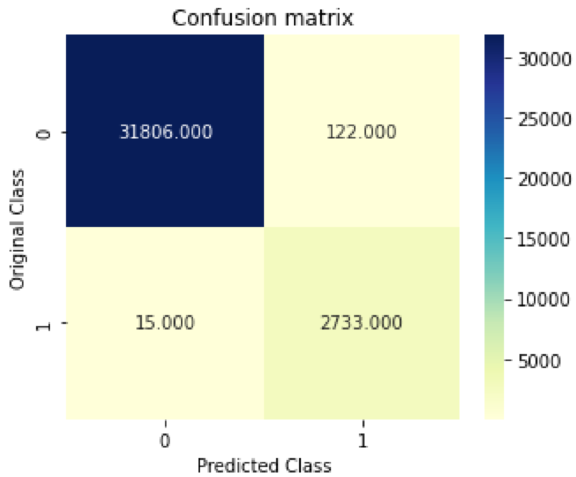

Figure 6. Confusion matrix of naive bayes classifier.

Table 2 compares the AUC and ACC values of all classifiers. When the results of Table 2 were evaluated, it was seen that all classifiers had a prediction success of close to 100%. The best result is the random forest classifier.

Table 2. Classification Performances.

	AUC	ACC
RF	0.99999984	0.99991348
LR	0.99896336	0.99630868
KNN	0.99981788	0.99985580
SVM	0.99994755	0.99855808
NB	0.99695318	0.99604914

The classification weights of the random forest, which is the best performance output of the classification results, were obtained. These weights show the probability that the vehicle is normal or healthy. The opposite values of the weights show the maintenance speed of the vehicle. These two new variables were evaluated with fuzzy logic and it was concluded that the maintenance speed should be done low (long term), medium (medium term) and high (urgent) according to the low, medium and high probability of the vehicles being normal.
The probability of being normal and the rate of care variables were represented by the triangular membership function. Figure 7 and Figure 8 show the triangular membership functions of normality probability and maintenance rates, respectively.

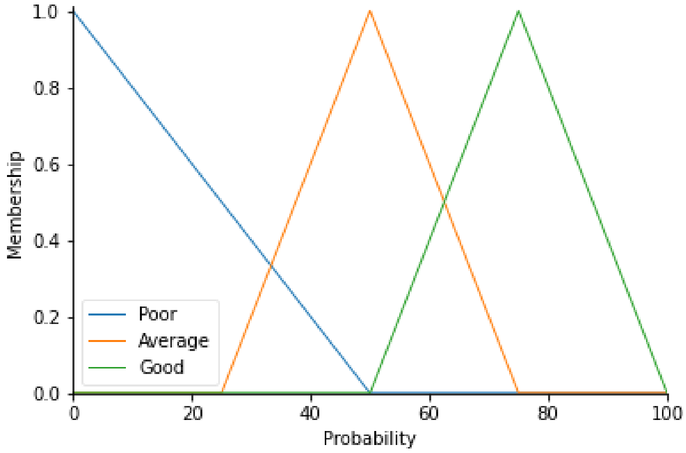

Figure 7. Membership function of probability of being normal.

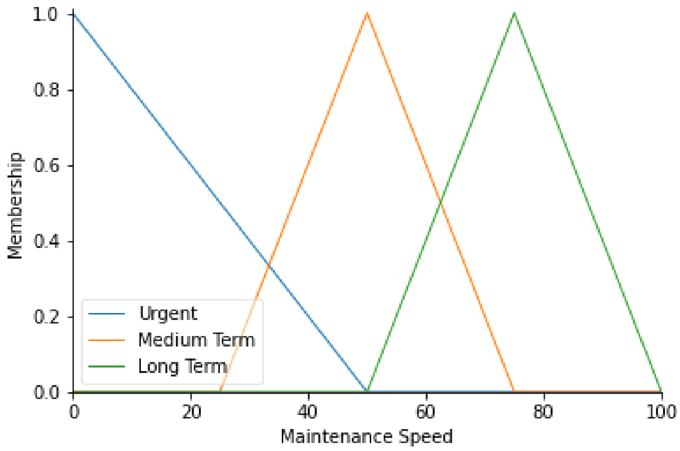

Figure 8. Membership function of maintenance speed.

Both membership functions have the same descriptive parameters. The parameters showing the descriptive points of the triangle membership function of the input and output variables are shown in Table 3.

Table 3. Descriptive Points of Memberships.

Memberships	Descriptive Points
Poor	0 ; 0 ; 50
Average	25 ; 50 ; 75
Good	50 ; 75 ; 100

After the membership functions, the rules of the relevant input and output variables are determined. The fuzzy rules can be expressed as follows.

- Rule 1: If the vehicle is unlikely to be normal, the maintenance speed is high.
- Rule 2: If the vehicle has a moderate probability of being normal, the maintenance speed is moderate.
- Rule 3: If the vehicle is likely to be normal, the maintenance speed is low.

According to these rules, inference was made in fuzzy logic and as a result, the prediction and probability inference made by machine learning were blurred and the estimated maintenance plan was obtained. For example, when the probability of vehicles not being defective is 30%, the example of Figure 9 below was obtained and it was suggested that the maintenance plan triangle function that should be applied should be done with 40% fast and approximately 20% normal maintenance speed. In this case, the medium-term maintenance covering the minimum action plan, namely 20% speed, will be carried out as per the fuzzy logic rule applied. Similarly, when the 90% normality probability is calculated, an alarm is given to the system for the long-term care plan or for the emergency care plan implementation when the 15% normality probability is calculated.

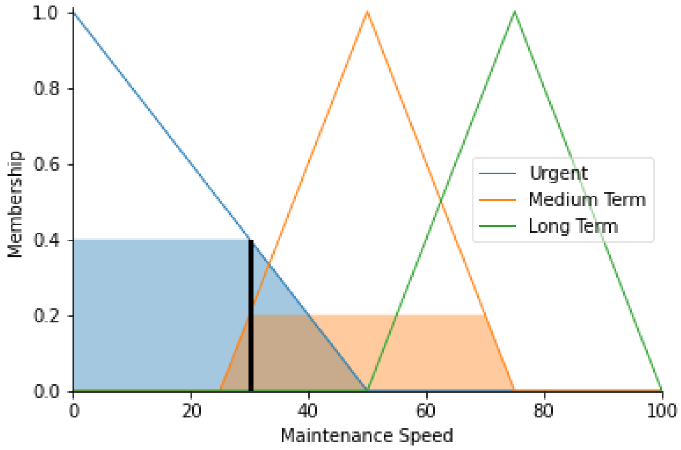

Figure 9. An example for fuzzy decision making.

5. CONCLUSION

The establishment of a predictive maintenance model based on machine learning in public transport has produced near-precise prediction results for the prediction of failures. The error state estimates of all estimators resulted in a negligible margin of error. In the study, the RF estimator, which has the highest result among all classifiers, was used as a result of the final machine learning in the fuzzy decision making step. With the established fuzzy logic model, it is possible to predict the maintenance times with linguistic time outputs. Thus, an application has been developed that will continuously measure the status of vehicles to be used in public transportation vehicles and notify the center of the maintenance time, that is, the remaining useful time of the vehicle. This pilot study showed that the failure prediction model can be used realistically in public transport. With this fault model, as soon as fault information starts to occur, alarms are generated in the system and measures can be taken before the fault causes serious damage. Thus, the study will have administrative effects such as customer satisfaction, prevention of accidents, death and injury, major material damage and increase in reputation. For this reason, practitioners can set up an intelligent estimating model by using this application for both the maintenance forecasts of vehicles in the transportation sector and for similar equipment that can receive instant health data.

In order not to cause loss of information and benefit, the results will be evaluated by making a generalization by establishing an ensemble model on the classifiers used in future studies without eliminating any estimators. In addition, choosing the right size of the data set is a challenging limitation for the study, since the application is based on instant data and instant changes in the health status of the vehicle are vital. For this reason, in future studies, both the data set and feature size will be increased, and the application will be re-evaluated for more vehicles and longer-term datasets, and instant calculation performance will be measured on the server side.

Author Contributions

The authors contributed equally to the study.

Conflict of Interest

The authors of the article declare that there is no conflict of interest between them.

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