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Application of machine learning methods for predicting hazardous failures of railway track assets

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Abstract. *The Aim of the paper is to reduce the number of hazardous events on railway tracks by developing a method of prediction of rare hazardous failures based on processing of large amounts of data on each kilometre of track obtained in real time from diagnostics systems. Hazardous failures are rare events; the set of variate values of the number of such events for an individual kilometre of track per year is: [0, 1]. However, for a railway network as a whole the yearly number of such events is in the dozens and efficient management requires the transition from the estimation of the probability of hazardous failure occurrence to the identification of the most probable location of failure.* **Methods.** *The problem of identification of rare, but hazardous possible events out of hundreds of thousands of records of non-critical railway track parameter divergences cannot be solved by conventional means of statistical processing. Hazardous events are predicted using the above statistics and artificial intelligence. Big Data and Data Science technology is used. Such technology includes methods of machine learning that enable item classification based on characteristics (features, predicates) and known cases of undesired event occurrence. The application of various algorithms of machine learning is demonstrated using the example of prediction of track superstructure failures using records collected between 2014 and 2019 on the Kuybyshevskaya Railway.* **Findings and conclusions.** *The result of facility ranking is the conclusion regarding the location of the most probable hazardous failure of railway track. That conclusion is based on the correspondence analysis between the actual characteristics of an item and conditions of its operation and the cases of adverse events and cases of their non-occurrence. The practical value of this paper consists in the fact that the proposed set of methods and means can be considered as an integral part of the track maintenance decision-making system. It can be easily adapted for online operation and integrated into the automated measurement system installed on a vehicle.*

Keywords: *machine learning, railway track facility failure, decision trees.*

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1. Introduction

The role of digital technology in the process management is on a steady rise. Automated management systems (AMS) enable much higher rate of business operations performance; autonomous control systems are deployed in trains and airplanes ensuring traffic safety at speeds beyond human reaction time. Today's diagnostics tools detect things the human eye is unable to capture and are used in healthcare, engineering, space exploration and other areas of science and industry. But the digital world is not limited to the automation of processes humans cannot perform, especially in case of major manufacturing facilities. Since 2016, JSC RZD has constructed an electronic document management system that connects over a thousand companies involved in freight transportation [1]. In the Lastochka EMUs diagnostic information is collected using 342 sensors and instruments. Together with the locomotive diagnostics systems, JSC RZD employs dozens of AMSs that provide the company with information on the condition of track [2, 3], power supply equipment [4], traffic safety systems [5], train graph [6] and a large number of other items and processes. Each of JSC RZD's AMSs is designed to solve individual problems, but in order to manage railway transportation in a holistic manner corporate-level systems were developed: EK ASU I (Single Corporate Automated Infrastructure Management System), EKP URRAN (Single Corporate Platform for Managing Resources, Risks and Dependability at Lifecycle Stages), EK ASU TR (Single Corporate Automated Workforce Management System), EK ASU FR (Single Corporate Automated Financial and Assets Management System). The existing data collection and storage systems, as well as the corporate systems that aggregate information from various sources, enable JSC RZD to successfully apply the Data Science technology (see. Fig. 1).

2. Relevance of track superstructure hazardous failure prediction

High train traffic and speed, environmental conditions, ageing cause tear and wear of railway infrastructure, primarily the track. Rail defects may cause derailments, accidents or crashes. Such hazardous events are associated with damage to the track, power supply systems, as well as cars and locomotive units with potential exclusion from the inventory rolling stock [7]. Derailed units of rolling stock may also intrude into the operational space of the adjacent track, which may cause a collision with an opposing train and, as the consequence, make damage catastrophic [8, 9]. A significant share of hazardous events attributed to the condition of track is typical not only to Russia's railways. Over the last decade, about one third of all railway incidents in the US were caused by track-related defects [10].

The analysis of derailments, accidents and crashes involving units of freight trains identified that such events caused by track malfunctions could occur on a kilometre of track rated, for instance, as "good". In this context, the aggregated estimate of a kilometre of track is not sufficient for predicting its condition, and it is required to take into consideration other parameters: number of widenings, realignments, etc. However, the collection of additional parameters alone will not suffice. According to [11], only a part of data on a controlled item is useful in terms of decision-making when managing specific events (see. Fig. 2).

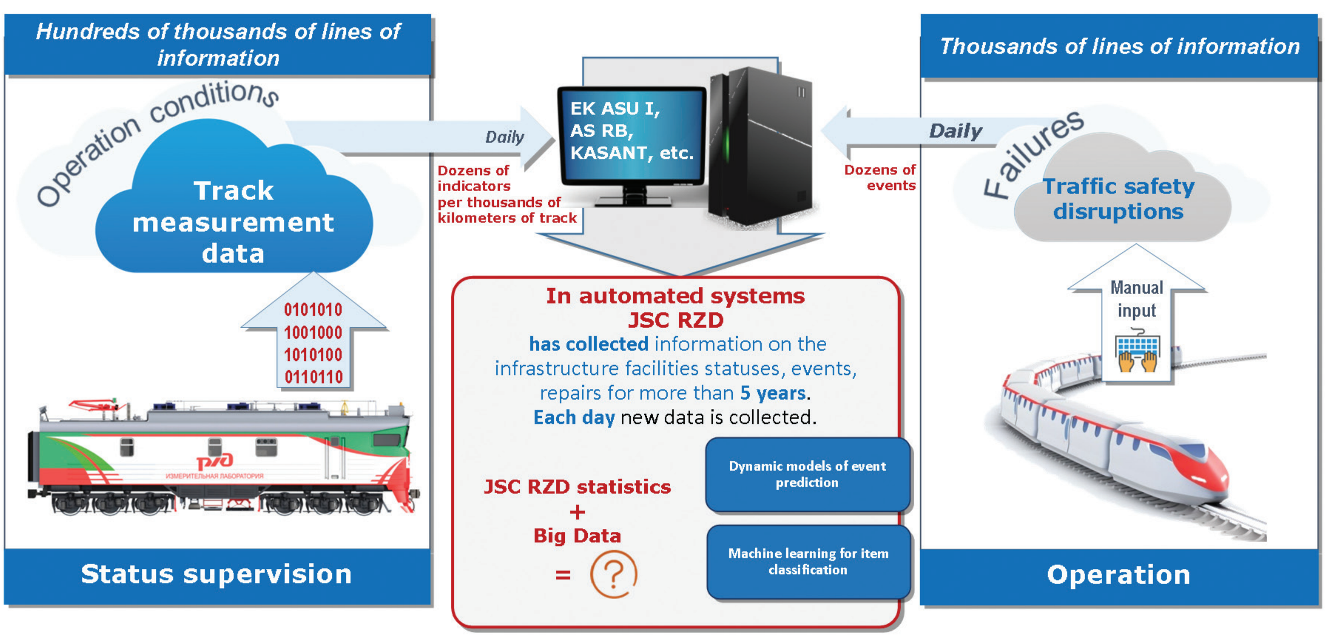

Fig. 1. JSC RZD AMSs as the foundation for Big Data application

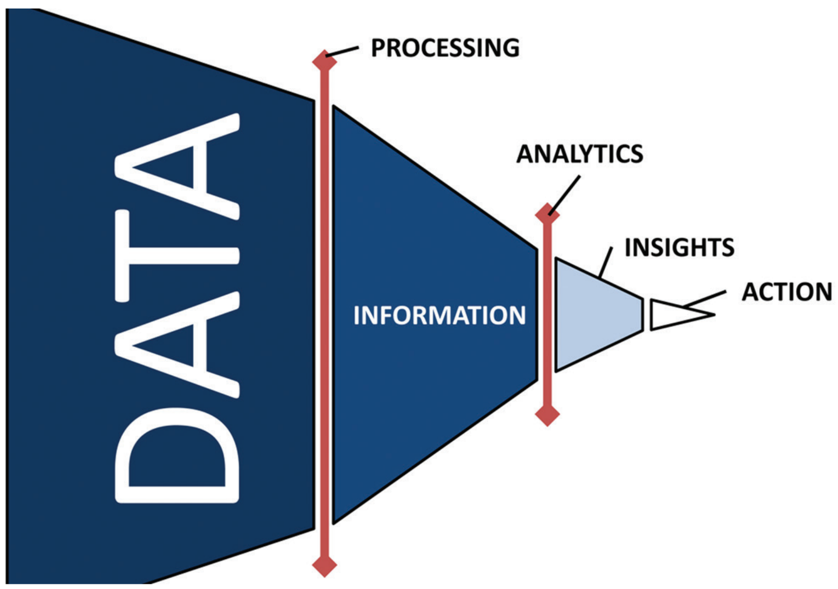

Fig. 2. Transformation of large volumes of raw data into actionable information

Modern methods of multiple factor data analysis and machine learning technology that allow including over 50 factors into models enable – based on existing knowledge of measured featured that characterize the condition of track – making conclusions regarding the need for urgent repairs in order to avoid track failures and derailments, accidents and crashes caused by an unsatisfactory condition of track. Conclusions regarding the efficiency of Big Data and Data Science can be made based on existing international practical experience, the analysis of which is set forth below.

3. Overview of the methods of machine learning and their application for the purpose of railway track defects analysis

With the growth of the amount of data collected by monitoring devices, such as wireless sensor networks or high-definition video cameras that are widely used for monitoring of critical railway infrastructure, machine learning also becomes increasingly popular in respect to improving the operational performance and dependability of railway systems [13].

Currently, due to the rapid technological advancements and widespread deployment of inexpensive sensors and wireless communications, the role of the Internet technology is increasing in the context of efficient implementation of maintenance strategies in a whole range of industries. In railway transportation, Data Science is also in active use [12]. Machine learning is increasingly popular as means of improving the dependability of railway systems. It also allows minimizing the daily cost of the maintenance [13].

Methods of machine learning can be subdivided into classical algorithms [14] and deep learning methods [15]. The main difference is the presentation level. The classical learning methods include the principal components method, support vectors method [16], solution trees [17], random forest [18, 19, 20], logistic regression [21] and nearest neighbours method [22].

In [23], the methodology of data classification for rail condition monitoring is presented. The authors put the emphasis on identifying the patterns of failure occurrence in sharp turns (horseshoe curves) using the principal components method and data obtained as the result of in situ inspections of the Swedish railway network.

In [24], the support vectors method is used for predicting a situation, when minor track defects deteriorate into major ones.

In [25], based on decision trees, a system is developed for preliminary automatic ranking of incidents that evaluates the probability of a pre-failure state based on the existing features.

Jiang and co-authors [26] proposed a hybrid approach to identifying contact fatigue based on ultrasound laser data.

In [10], the principal components method along with the support vectors method were applied to a set of data on 31 items collected on a US class I network for the purpose of detecting four types of surface defects.

As of late, the academic community has been making use of the advantages of the deep learning methods for studying rail defects. Researchers believe that deep learning may become an element of completely automatic railway monitoring systems [27].

Deep learning algorithms based on neural networks are employed as the primary tool for detecting structural defects in rails. The convolutional neural networks (CNN) are most widely used. That is due to the widespread use of video cameras that supply the research community with vast quantities of data and enable the application of more complex learning methods. However, CNN is a "black box" and practically cannot be interpreted. In other words, a researcher of machine learning cannot explain how a CNN model made its predictions or prove their reliability for the end user.

In [28], the CNN technology is used in examining the approaches to solving the problems of automated processing of images of track superstructure for the purpose of identifying the locations of potential defects. Images were used that had been collected by one of the trains of the Centre for Diagnostics and Monitoring of Infrastructure Facilities of the West Siberian Railway.

Lee and co-authors [29] used artificial neural networks and support vectors method for predicting the tear and wear of the ballast section based on such factors as the curvature, tonnage handled, etc. The authors however note that in order to obtain stable predictions, measurements must be taken over at least two years.

A more detailed overview of the application of various methods of machine learning in detecting track defects can be found in [30].

The diversity of the used models is evidence of the fact that the application of the machine learning technology currently represents a research process that includes the following stages:

- analysis of the sources of information on the track condition;
- data condition for machine learning;
- definition of machine learning objectives;
- training of models;
- selection of the best model;
- application of the model.

4. Algorithm of conditioning of railway track condition data as part of the JSC RZD machine learning application

Data received from JSC RZD AMSs are conditioned using an algorithm that includes 5 stages shown in Table 1.

Sample is one of the key concepts of machine learning. A sample is a finite set of cases (items, instances, events, test articles) and corresponding data (item characteristics) that form the description of the case. A sample that includes a full set of available data must include the target variable, i.e. an indicator, the prediction of whose value is the goal of machine learning. Additionally, a sample is subdivided into two parts: the learning sample and the test sample. The algorithm of conditioning of the data obtained from JSC RZD's AMSs for sampling as part of machine learning is shown in Fig. 3.

5. Algorithm of machine learning application for predicting hazardous failures of railway track

The problems of machine learning are normally described in terms of the ways a machine learning system is to process the learning sample. As the case of TSS learning sample, a kilometre of TSS was chosen, whose condition is characterized by 77 parameters, including the diagnostic results, operational conditions, qualitative estimates. The values of such parameters are represented in the form of vector $x \in R^n$, each element of which is the value of a feature.

Table 1. Stages of data conditioning

Name of stage	Aim	Conditions of stage performance	Relevance criterion of the stage
Data cleansing	Improvement of simulation through higher quality of data	Performed always	Performed always
Data conversion	Improvement of simulation through the capability to compare sequences with different physical units and/or value ranges	Performed if required for discrete sequences	1. Value variation ranges of various features differ more than 5 times. 2. Different physical units of features?
Data sampling	Extension of the scope of applicable models	Performed if required for continuous sequences	1. Target feature is a continuous value, but it is required to evaluate the probability of being within the range. 2. It is planned to employ a method that does not allow using continuous data.
Text cleansing	Improvement of simulation through higher quality of data	Performed if required for continuous sequences	It is planned to use information from the text in the simulation
Sampling	Quality verification of the developed models	Performed always	Performed always

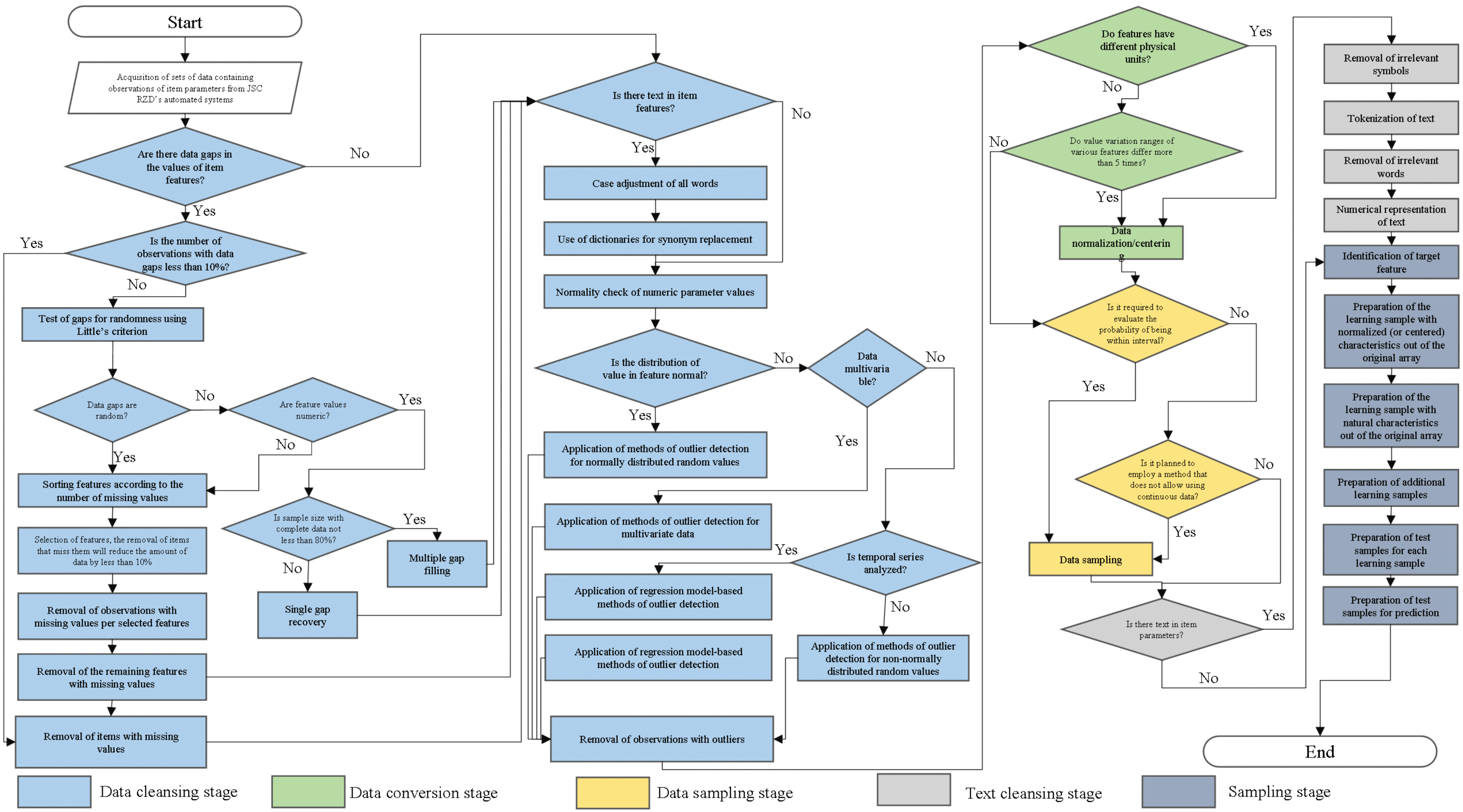

Fig. 3. Algorithm of AMS-generated data conditioning in sampling for machine learning

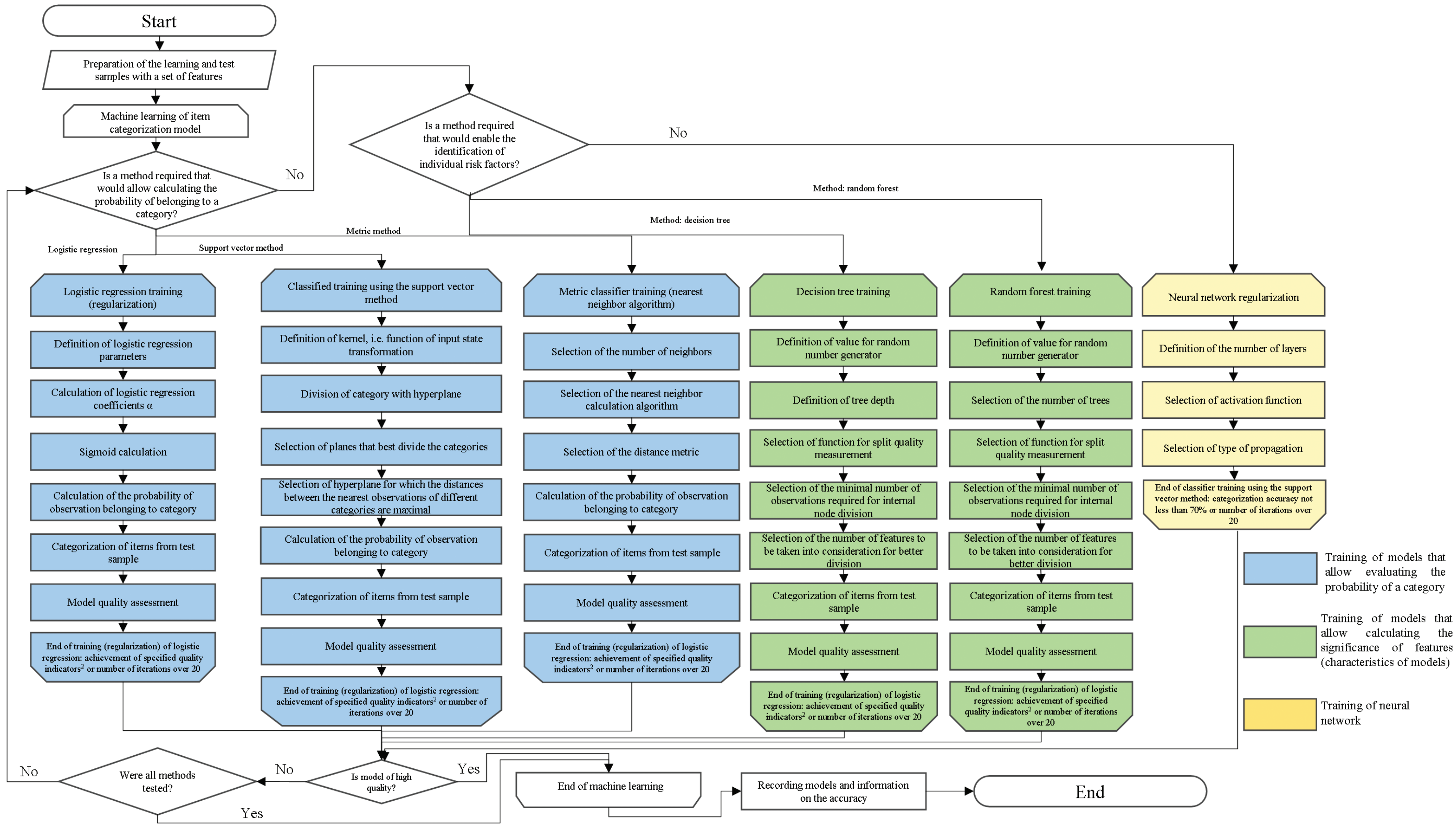

Fig. 4. Algorithm of machine learning methods application for classification of TSS condition

Classification, as the most common machine learning problem, consists in building models that serve to assign the examined item to one of the several known classes. With respect to that type of problems the classification algorithm is to answer the question as to which category the item belongs to. In terms of traffic safety (prevention of derailments, accidents and crashes) each item (kilometre of TSS) is divided into two classes: 0, a kilometre with no hazardous TSS failure; 1, a kilometre with a hazardous TSS failure.

From the learning sample we select the best parameters for the classification algorithm. On the test sample we calculate the classification error and in order to select the best algorithm.

Let X be an object space that is described by the set of features $X=\{X^1, ..., X^n\}^T$; $Y=\{0,1\}$ be the set of allowable responses; $y^*: X\rightarrow Y$ be the target dependence only known for the items of learning sample $Z^N=(x_i, y_i)_{i=1}^N$, where x_i is the vector of feature values, while $y_i=y^*(x_i)$ is the responses of the target variable, $i=1, ..., N$.

Let us denote $x=\{x_1, ..., x_n\}^T$, $y=\{y_1, ..., y_n\}^T$.

The learning problem consists in the requirement to re-establish the functional relationship between items and responses, i.e. to construct algorithm $a: X\rightarrow Y$ that approximates the target relationship y^* in the whole set X, not only the items of the learning sample Z^N.

Figure 4 shows the algorithm of application of six primary machine learning methods for kilometre of TSS classification.

6. Criteria of best model selection

A number of methods have been devised for the purpose of analysing the accuracy of the machine learning algorithm and comparing the accuracy of different algorithms.

For the purpose of problem binary classification, let us introduce the following designations:

TP, the number of correctly predicted category «1» items;

FN, the number of category «1» items with «0» prediction;

FP, the number of category «0» items with «1» prediction;

TN, the number of correctly predicted category «0» items.

Below are the primary measures of the quality of binary classification models.

1) General accuracy of the algorithm $AC=\frac{TP+TN}{TP+FP+FN+TN}$ that defines the overall efficiency of the classifier in terms of correct answers.

2) False alarm $FPR=\frac{FP}{FP+TN}$ that shows the efficiency of the classifier in terms of anomaly prediction.

3) Accuracy of the algorithm $PR=\frac{TP}{TP+FP}$ that shows the share of accurately predicted items identified as category «1».

4) Completeness of the algorithm $RE=\frac{TP}{TP+FN}$ that shows the share of items that are effectively category «1» and were predicted correctly.

5) *F*-measure of the algorithm, $F=\frac{2\cdot PR\cdot RE}{PR+RE}$ the harmonic average of accuracy and completeness.

6) Area under the curve of AUC errors, the global quality characteristic whose values are between 0 and 1. The value 0.5 corresponds to random guessing, while the value 1 implies correct recognition. AUC is the area under the ROC curve. The ROC curve shows the correlation between the share of false positive rate (FPR) and share of correct positive classifications (RE). The ROC curve is a sufficiently complex measure of algorithm accuracy; it is examined in more detail in [31].

7. Numerical experiment of line categorization based on failure prediction

Let us examine the problem of TSS failure classification. In order to prevent derailments, accidents and crashes, throughout the railway network, the condition

Table 2. Model quality indicators

Quality indicator	Logistic regression (sample 2)	Decision tree (sample 2)	Random forest (sample 2)	Support vectors method (sample 2)	Nearest neighbours method (sample 1)
1. AC	0.74	0.76	0.75	0.73	0.72
2. FPR	0.41	**0.28**	**0.28**	0.41	0.46
3. PR	0.78	0.94	0.94	0.94	0.89
4. RE	0.78	0.94	0.94	0.94	0.89
5. F-measure	0.78	0.86	0.86	0.94	0.88
6. AUC	0.68	0.83	0.83	0.76	0.71

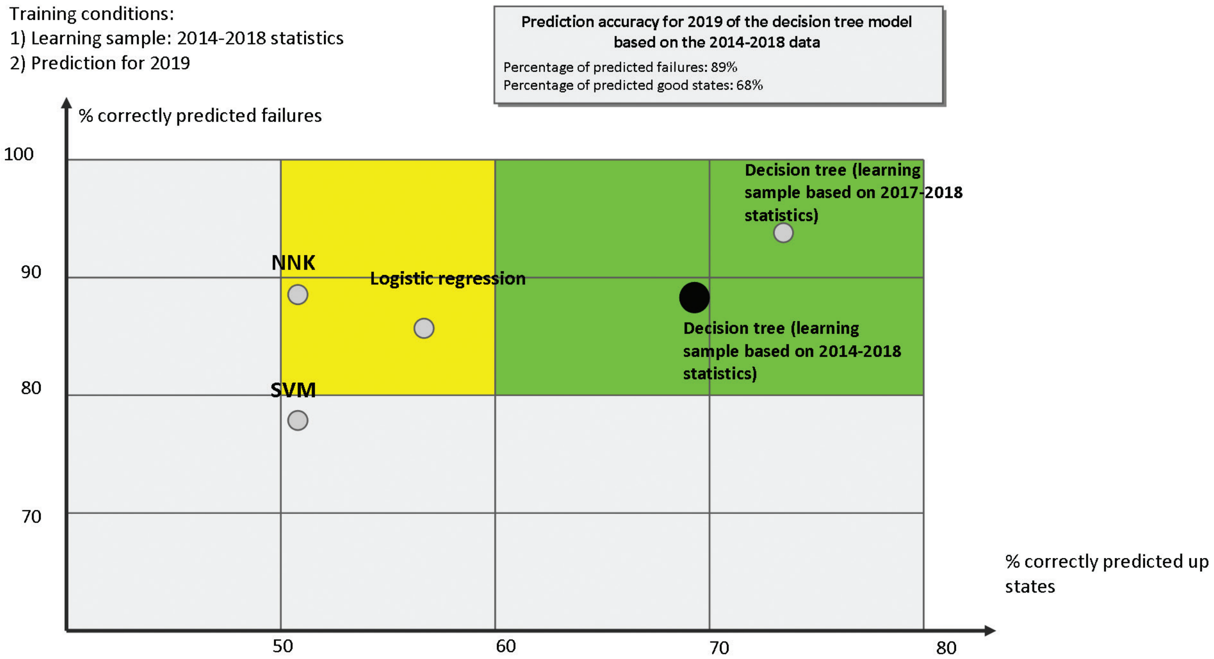

Fig. 5. Comparison of models in terms of quality

of track is checked for deviations from standard values using a geometry car. Based on the obtained data each kilometre of track is assigned a rating: "unsatisfactory", "satisfactory", "good" or "excellent" that is supposed to indicate the hazard of transportation incident caused by the condition of the track.

Between 2014 and 2019, TSS condition statistics were collected on the Kuybyshevskaya Railway. The following failures of railway infrastructure elements were registered: isolated joint, concrete tie, rail line as a whole, rail joint, geometrical parameters of the track, etc. Over a number of years, for each kilometre of track the following parameters were measured monthly: number of widenings, number of deviations, number of realignments, number of sags, traffic speed within the specific kilometre, etc.

If, within a kilometre of track, a failure is detected, the response is assigned the value of «1», otherwise, the value is «0», i.e. a set of category labels is of the form $Y=\{0,1\}$. It is required to solve the problem of binary classification based on the observations made in prior moments of time and verify the efficiency of the algorithm using the 2019 observations. Based on the performed classification, a hazardous failure is predicted.

194328 observations of various items (kilometres of track) were obtained. 267 items out of them were affected by hazardous failures. The data were subdivided

Table 3. List of test sample items within the zone of unacceptable risk

Date of check	Track maintenance department	Operational line	Track number	Kilometre	Probability of hazardous failure
29-JAN-19	9	2	1	979	0.55
29-JAN-19	9	1	1	969	0.51
14-JAN-19	9	2	1	979	0.48
14-JAN-19	9	1	1	969	0.48
29-JAN-19	9	2	1	1018	0.37
29-JAN-19	9	2	1	1003	0.28
14-JAN-19	9	2	1	1018	0.21
14-JAN-19	9	2	1	1003	0.17
23-JAN-19	20	1	1	36	0.003
25-JAN-19	20	2	1	36	0.0014

into the learning sample (192375 items, including 257 with hazardous failure, 2014 – 2018 data) and the test sample (1953 items, including 10 with hazardous failures, January 2019 data).

The classification problem was solved using several machine learning algorithms: logistic regression, solution tree-based algorithm, random forest method, methods of support vectors and nearest neighbours.

Learning samples were generated:

learning sample 1: 2014 – 2018 observations using standardized data;

learning sample 2: 2017 – 2018 observations using standardized data.

Additionally, data reduction was performed. The aim was to improve the quality of simulation through balanced learning samples, in which the number of observations with category «1» was at least 40% of the total number of observations.

Feature selection was done by means of recursive selection of the feature for each machine learning method.

Fig. 5 shows a comparison of the quality of models, Table 2 contains the indicators of model quality. The table shows models trained using the samples that demonstrated the best quality indicators for its type of model.

The results of model ranking: rank 1 is decision trees (trained using sample 6), rank 2 is random forest (trained using sample 6).

Table 3 shows a list of TSS elements with the highest probability of hazardous failure (corresponding to the highest levels of risk) in January 2019.

Upon an analysis of the data from Table 2 it can be concluded that the best possible results of item classification are ensured by using methods based on decision trees.

Shown in the last column of Table 3 are the values of frequency of trees classifying item category as “1”, i.e. the number of trees that identified an item as “kilometre with hazardous TSS failure”, in relation to the total number of constructed trees. Based on the results of the action of training sample classification algorithm, the threshold value of probability of failure is to be chosen depending on which classification error is the priority for us. The higher the threshold, the rarer the items will be classified as “kilometre with hazardous failure” (TP decreases, but TN grows). The lower the threshold, the lower will be the number of “kilometre with hazardous failure” items will be missed, but the higher the number of item with no hazardous failure (“0”) will be identified as having a hazardous failures (“1”) (TP and FP increase). In the context of TSS item classification, it is important not to miss an item with possible hazardous failure. Albeit at the cost of a larger number of items with no hazardous failure (“0”) that will be falsely identified as items with a hazardous failure (“1”).

Subject to the results of classification for the learning sample the threshold was chosen as $\overline{p}$=0,15. On the test sample that resulted in a situation, when out of 10 items with hazardous failures 8 were classified correctly and 5 items with no hazardous failure (marked “0”) were also classified as items with a hazardous failure. If the threshold was set at $\overline{p}$=0,10, the number of correctly identified items with a hazardous failure (“1”) would remain unchanged, while the number of incorrectly classified items with no hazardous failure (“0”) would have risen to 14. Under $\overline{p}$=0,001, all ten items with a hazardous failure (“1”) would have been classified correctly, but at the same time, the number of incorrectly identified items with no hazardous failure (“0”) would have risen to 251.

8. Conclusion

The paper presents the methodological foundations of prediction of rare hazardous events (failures) that can be used in the design of an automated system that performs real-time prediction of adverse events in railway transportation within a certain period of time by using and processing large amounts of information. The components of such system – mathematical models and methods, various metrics for model quality verification – should be defined subject to and based on the problem of prediction of railway track failures depending on various sets of factors. This problem was used in the process of optimization of the sequence of actions for taking the decision regarding the need for additional maintenance operations at any given railway line. For that purpose, models were compared using the proposed metrics. The ranking of facilities produced a conclusion regarding the presence of key indicators and their values of early warning of risk factors. That conclusion is based on the correspondence analysis between the actual characteristics of an item and conditions of its operation and the cases of adverse events and cases of their non-occurrence. The proposed set of methods and means can be easily integrated into an automated measurement system installed on a vehicle.

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The authors' contribution

Shubinsky I.B. Definition of the requirements for the content of the algorithm of data conditioning for sampling, objectives of each stage. Definition of the requirements for classification of machine learning methods based on the capabilities of simulation data interpretation.

Zamyshliaev A.M. Aim definition, analysis of the problem and applicability of machine learning for prediction of hazardous failures of track superstructure, conclusions.

Pronevich O.B. Development of the superstructure condition data conditioning algorithm for the purpose of machine learning application, algorithm of machine learning application for predicting hazardous failures of track.

Ignatov A.N. Preprocessing and analysis of data for computation.

Platonov E.N. Overview of the methods of machine learning and their application for the purpose of railway track defects analysis. Classification problem definition.