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APPLICATION OF ALGORITHMIC MODELS OF MACHINE LEARNING TO THE FREIGHT TRANSPORTATION PROCESS

Summary. *The results of the analysis of algorithmic models of machine learning application to the freight transportation process are given in this paper. Analysis of existing research allowed discovering a range of advantages in the application of computational intelligence in logistic systems, including increasing the accuracy of forecasting, reduction of transport costs, increasing the efficiency of cargo delivery, risks reduction, and search for key performance factors. In the research process, the main directions of application of algorithmic models of machine learning were determined. They are vehicle routing, choice of cargo type, transportation type and vehicle type; forecasting fuel consumption by vehicles, disruptions in transportation, transport costs, duration of the order fulfillment; evaluation of the rolling stock fleet and the efficiency of carrying out the transport task. Based on the researched publications, the most common algorithmic models of machine learning in freight transportation were identified, and their effectiveness was analyzed. Linear and logistic regression models are simple enough; however, they do not always provide high simulation results. Deep learning models are quite widely applied to all identified areas. Decision tree and random forest models often show the highest simulation performance. Models of k-nearest neighbors and support vectors should be used both in classification tasks, for example, in choosing the type of cargo and type of transportation, and for forecasting the fuel consumption and the duration of the transport process.*
Keywords: *intellectual approach, machine learning, algorithmic models of machine learning, freight transportation, cargo delivery.*

1. INTRODUCTION

Machine learning is seen as the science of computer algorithms that improve automatically due to their experience [1]. The first studies on the application of machine learning for the simulation of transport processes and for solving transportation problems can be traced to the works of foreign scientists published at the end of the 20th century. At that time, researchers [2] claimed the unlimited potential of computational intelligence in transport engineering. According to the authors [3], machine learning algorithms, as a component of artificial intelligence [4], make it possible to solve non-linear problems such as routing optimisation or planning freight vehicles` operation more effectively. Today, machine learning techniques are widely used as tools to understand the functionality and capabilities of freight transportation, supply chains, and logistics systems; they allow better forecasting of the evolution and future states of these systems, and they offer reliable support for the identification, planning, and decision-making [5].

2. RESEARCH STATEMENT

Researchers constantly face the problem of increasing the accuracy of modeling transport processes to reduce transport costs, increase the efficiency of cargo delivery, reduce risks, and find key efficiency factors. Along with this, using computational intelligence can become an effective tool for improving the effectiveness of such models.

3. RELEVANCE OF THE STUDY

Since the use of computational intelligence to improve the efficiency of cargo delivery is becoming more popular, the problem of systematizing research to identify common features, advantages and disadvantages, as well as borrowing foreign experience to improve the transport process, arises.

4. AIM AND THE TASKS OF THE RESEARCH

This study aims to analyze the application of algorithmic machine learning models to the cargo transportation process.

The following tasks have been formulated to achieve the goal:

– to justify the expediency of the application of algorithmic models of machine learning to the process of cargo transportation;
– to carry out the analysis of publications where algorithmic models of machine learning apply to the process of cargo transportation;
– to group the existing research by the main directions of application of algorithmic models of machine learning during the cargo delivery and establish the relationships between the algorithmic models of machine learning and directions of their application in the process of cargo transportation;
– to determine the most optimal algorithmic models of machine learning in the process of cargo transportation, to investigate their essence, advantages and disadvantages.

5. ANALYSIS OF RESENT RESEARCH AND PUBLICATIONS

O. Horiainov has analyzed the relevance of the application of machine learning algorithms as an instrument for modelling logistic and transport systems [6]. Among the advantages of using machine learning, the author singled out an increase in the accuracy of forecasting, a reduction in transport costs, an increase in the efficiency of cargo delivery, a reduction in risks, the search for crucial efficiency factors, etc.

We can meet the use of algorithmic models of machine learning with the aim of simulation of transport processes during the cargo delivery in papers of foreign [2; 7–9; 11;12;14–26] and native researchers [13]. Analysis of existing research shows that scientists focus on various machine-learning tools to achieve their goals. It is also worth noting that the frequency of publications in which we trace the use of algorithmic models of machine learning during cargo delivery increased significantly in 2020–2022 compared to previous years.

6. PRESENTATION OF BASIC MATERIAL

Application of algorithmic models of machine learning as a component of artificial intelligence, regardless of the problem they are solving (assessment, forecasting, classification), requires computational intelligence. The intelligent approach in algorithmic models of machine learning has a general pattern of application, which is implemented in several stages, shown in Fig. 1.

Based on the analysis of publications, the following priority areas of application of algorithmic models of machine learning were identified:

1. Forecasting disruptions in transportation. In research [7], authors developed and proposed an improved model of gray neural networks to solve the problem of market demand anomalies that arise after disruptions in transport processes. According to the researchers, this approach suggests that gray neural networks can provide better market demand forecasts compared to the GM(1,1) model, and the forecasting results can provide information for production and inventory management decisions.

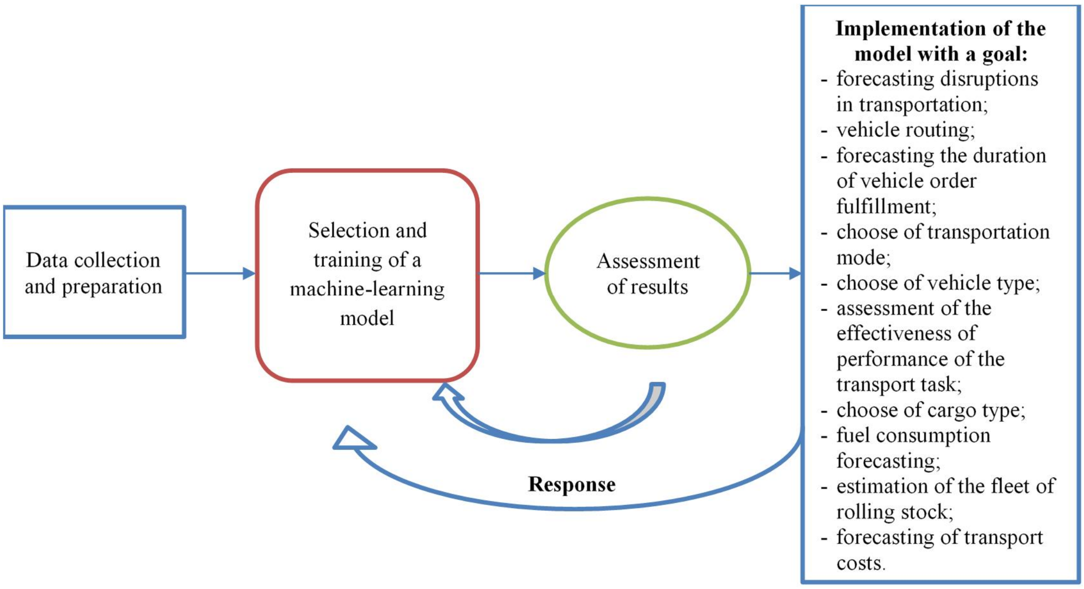

Fig.1. Stages of application of an intelligent approach in algorithmic models of machine learning during cargo delivery

2. Vehicles routing. Scientists [8] used the model of artificial neural networks to determine its effectiveness in solving routing problems compared to five heuristic algorithms. The experimental research carried out by the authors using a real simulation scenario of logistics processes in the automobile terminal of Hamburg showed that the application of the model of artificial neural networks increases the efficiency of simulation by 48 % in comparison with existing heuristic routing algorithms.

3. Forecasting the duration of vehicle order fulfillment. Scientists [9] advise applying an adaptive boosting method typically used as a booster in decision tree models [10] to forecast the arrival time of a vehicle during cargo delivery. In [9], an analysis of the forecasting accuracy of several machine learning models was carried out, including the random forest model, method of Support Vector Machines (SVM), method of k-Nearest Neighbours (k-NN), method of Recursive Partitioning (RPart), and adaptive boosting method (Adaboost.M1). At the same time, the highest performance of the models is achieved when the weather and traffic data are divided into categories.

Researchers Servos N, Liu X, Teucke M, and Freitag M. [11] compared the effectiveness of machine learning algorithms for forecasting cargo delivery duration. Scientists say machine learning is well suited to solve non-linear and complex relationships in existing transportation data. Three different algorithms were used for the simulation: ExtraTrees, AdaBoost, and SVR, which can handle small amounts of data at low runtimes. The data of the tracking system in trucks, including the beginning, end of transportation, cargo volume, geolocation at the time of information transmission, temperature and humidity of the environment, are determined as the main parameters of the models. The study showed the highest forecasting accuracy using the SVR algorithm with an absolute mean error of 17 h for 30-day transportation.

Yakushenko O., Shevchuk D. and Medynskyi D., in their research [12], use artificial neural networks to forecast the time to complete the transport task. Authors use data that every transport enterprise has: departure time, duration of the trip, identifiers of the driver and freight forwarder (loader) on the trip and the time of the route under favorable weather conditions. The proposed model allows considering the impact of seasonality (in particular icicles) and the day of the week when transport work is done. The authors also note that neural network models are widely used to solve logistical problems.

4. Choose of transportation mode. Abdelwahab, W., Sayed, T. [2] proposed to use the model of artificial neural networks to forecast the choice of a mode of transport for cargo delivery. At the beginning of its formation, the model included 27 variables that, according to the authors, had an impact on the choice of the type of transportation. However, the machine learning toolkit makes it possible to single out the most important predictors for the model, including: the volume of cargo, the need to freeze cargo (yes/no), the liquid state of cargo (yes/no), the need for interregional transportation, cost of transportation, percentage of cargo losses during a particular type of transportation and other. Simulation results showed the same or higher predictive accuracy of the choice of mode of transportation compared to conventional models.

The choice of the type of cargo transportation based on machine learning algorithms is reflected in the study of researchers [13]. Tortum A., Yayla N., and Gökdag M. compared the effectiveness of multiple regression, logistic regression, artificial neural networks (ANN) and adaptive neuro-fuzzy systems (ANFIS) models to predict the probability of choosing a rail or road mode of transport based on distance, cost and delivery time. According to the authors, using such approaches is highly adaptive and effective in studying nonlinear relationships between different variables. Approbation of models based on data on freight flows in the cities of Turkey, Germany, France and Austria showed a higher accuracy of machine learning models (ANN and ANFIS) compared to classical models.

In the paper [14], the authors use machine learning algorithms to forecast the choice of the mode of cargo delivery between road and rail. Scientists compare the effectiveness of forecasting such machine learning algorithms as SVM, ANN, and decision tree DT C5.0. The study analyzed the impact of weight, type, properties and type of cargo packaging, and transportation distance on the transportation mode choice. From the research results, the cost-adjusted support vector method is the best method for predicting the delivery method; DT C5.0 and ANN have slightly lower performance. Besides, scientists suggest considering the importance of the variables that determine the mode of transportation in the following order: weight, the distance between the point of origin and the point of destination, type of cargo, impedance coefficient of rail and freight transport, and the need for container transportation.

5. Choose of vehicle type. Researchers Ahmed U. and Roorda M.J. used machine learning algorithms to forecast the vehicle type choice by the enterprise, depending on the field of activity and the type of cargo delivered. In their paper [15], scientists compared the effectiveness of three models, which are the Random Forest model (RF), the Multinomial Logit Model (MNL), and the Mixed Logit Model (Mixed MNL). Forecasting of vehicle type is carried out based on such variables as a sphere of operation, number of employees, type of cargo, weight, point of departure and destination. A comparison of model results for the choice of vehicle types showed that the tractor-trailer and a pickup truck or van are most accurately predicted, followed by trucks without a trailer and cars. The most productive model among those used was the RF model, with a forecast accuracy of 94.5 %.

6. Assessment of the effectiveness of performance of the transport task. The ANN model was used by the authors [16] to analyze the efficiency of the transport tasks of the enterprise carrying out the transportation of bulk cargoes. The basis of the model is data on the performance of transport operations by selected specialized vehicles. The results of the study, highlighted in the paper, showed that the most critical factors that affect the company's income from a specific trip are the fuel consumption of individual vehicles, the driving style of a particular driver, and weather conditions.

7. Choose of cargo type. In the paper [17], researchers used machine learning algorithms to determine the type of cargo based on the information given in invoices of enterprises, about the transportation distances, cargo weight, and vehicle type. Scientists used the following machine learning algorithms in the modeling process: Averaged one-dependence estimators (AODE), Sequential minimal optimization (SMO), k-NN, LogitBoost, JRIP algorithm of repeated incremental reduction to reduce errors, Logistic Model Trees (LMT), and HyperPipes. Assessment of simulation results showed the highest efficiency for the k-NN algorithm compared to other algorithmic machine learning models. According to the authors' observations, forecasting the type of cargo can be used to form a decision-making system by carriers regarding the automation of the vehicle selection process at the stage of receiving an order from the client.

8. Fuel consumption forecasting. Scientists F. Perrotta, T. Parry and L. C. Neves [18] used three types of algorithmic machine learning models to forecast fuel consumption by heavy vehicles: RF model, deep learning model (ANN), and SVM. Researchers used data HAPMS from the Highways England Pavement Management System and telematics systems of freight vehicles for the formation of input values (average speed, road gradient, gross weight, vehicle acceleration, etc.) and the output parameter of the models (fuel consumption by the vehicle). Research results showed that all three models allow developing models with high accuracy. Still, the RF model is superior to the SVM and ANN models, providing larger R2 and minor errors.

In a paper [19], scientists use ANN to increase the accuracy of forecasting fuel consumption for both a fleet and an individual vehicle. Seven parameters that characterize a trip are used to obtain the forecasted value: the number of stops, duration of a stop, average speed of movement, characteristic acceleration, a square of the aerodynamic speed, change in kinetic energy and change in potential energy for a specific distance traveled. The model's effectiveness was estimated by the value of the root mean square error of forecasting the particular fuel consumption of 0,015 l/100 km.

The use of machine learning algorithms for forecasting fuel consumption by freight vehicles is observed in researchers' study [20]. Determining as the main predictors of models: a model of vehicle, average speed, speed deviation, type of the road, the total weight of the vehicle, and weather conditions in 10-minute intervals, authors compare the effectiveness of forecasting on different algorithms, among which are k-NN, ANN, Gradient boosting decision tree. Simulation results showed the slightest forecasting error when using the decision tree algorithm, then ANN, and the highest – k-NN.

In the paper [21], researchers improve the accuracy of the SVM model for forecasting fuel consumption by freight vehicles using a machine learning algorithm. Estimating fuel consumption is based on geographic coordinates, vehicle speed, engine rpm, and throttle position sensor values. The scientists also selected the input parameters of the model, which made it possible to achieve higher accuracy with the value R2 =0.97, compared to other studies where the SVM regression algorithm model was used.

The paper [22] presents the forecasting of fuel consumption by freight vehicles using algorithmic machine learning models. To perform the forecast, the researchers applied three types of machine learning regression models: an ANN model of back propagation (BP), a DT model, and an RF model. Modeling of fuel consumption by freight vehicles is carried out by taking into account the technical condition of the engine, road characteristics, and weather and temperature conditions. Results showed that the accuracy of forecasting of DT, ANN, and RF is 81,38 %, 83,98 %, and 86,58 %, respectively.

The application of machine learning algorithms for forecasting fuel consumption by freight vehicles is observed in research [23]. Scientists compared the effectiveness of different regression models, including the generalized linear regression (GLM) model, classical linear regression model, regression with variable selection, and Bayesian regressions. The simulation was carried out based on data from GPS vehicle trackers of a small transport company. Researchers established that for the specific data set Least-angle regression (LARS) model and a classical linear regression model are the most effective models.

Simulation of vehicle fuel consumption is met in researchers' study [24]. Authors use deep learning models (artificial neural networks) and linear regression models to forecast. Based on the input data: vehicle speed, acceleration and road gradient, the model was trained and the accuracy of the predictions was checked. The test results showed that the proposed neural network-based approach provides high forecasting accuracy and acceptable execution speed, which makes it suitable for various vehicle route optimization, driving cycle verification, fleet operation planning, etc.

9. Estimation of the fleet of rolling stock. The use of a model of artificial neural networks to assess the operational quality of vehicles used for freight transportation is found in the study of Świderski A., Jóźwiak A., Jachimowski R. [25]. The authors use parameterized estimates for the model's input variables: frequency of breakdowns, age, number of hours worked, the technical condition of vehicles and a weighted average rating of vehicle quality as output variables, to train the model.

Acording to scientists, artificial neural networks should be considered a helpful tool for a decision-making support system regarding the use of vehicles for the delivery of goods by motor transport companies, as well as for forecasting the quality and efficiency of transport operations.

10. Forecasting of transport costs. Authors [26] propose using the ANN model to solve the problem of forecasting the cost of the cargo delivery order. In the research process, using fuzzy logic, scientists determine the main parameters of the model: order volume for a specific delivery point and distance. At the same time, scientists note that the weather conditions and driving habits of a particular driver have a smaller effect on transportation, so they do not use these factors in their model. The model results showed a high correlation rate between the received and actual data of 99.92 %. The authors claim that modeling with the help of ANN allows forecasting the total cost of transportation, which depends not only on the unit cost of transportation. In addition, this approach can be used to solve more complex problems in supply chain management, including multi-item, multi-source problems where the supplier cannot fulfill all end-user requirements.

The analysis made it possible to identify the most common models of machine learning during cargo delivery, establish joint directions of use in freight transportation (Fig. 2), and their advantages and disadvantages (Table 1).

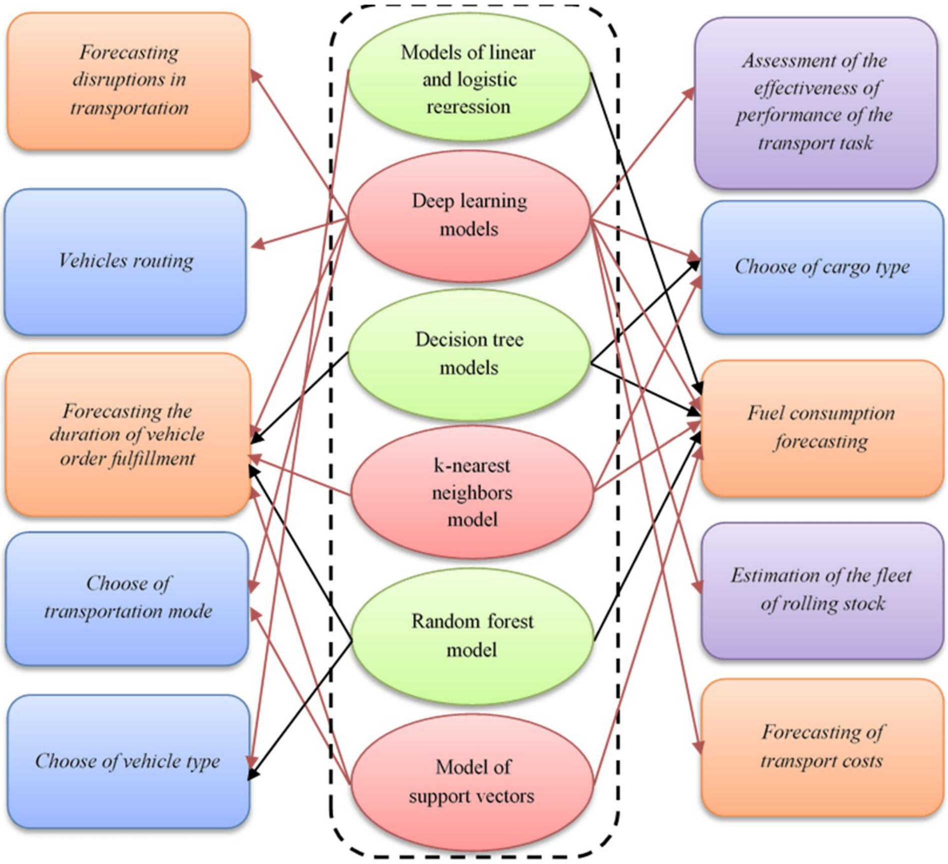

Fig. 2. Directions of algorithmic models of machine learning application during cargo delivery

Table 1

Advantages, disadvantages and areas of application of algorithmic models of machine learning

Group of machine learning models	Advantages	Disadvantages	Application
1	2	3	4
Models of linear and logistic regression	▪ ease of use; ▪ clarity of results; ▪ fast learning.	▪ forecast accuracy is not always high.	Linear regression models are used to forecast fuel consumption by vehicles [23], while logistic regression models due to their main task (classification) are used to choose the type of vehicle for cargo delivery [15].

Table continuation 1.

1	2	3	4
Artificial neural networks and deep learning models	▪ the ability to process a large amount of data, identify complex dependencies between input and output data, as well as the ability to perform generalizations [27]; ▪ the possibility of application both in forecasting and in classification; ▪ high efficiency of working with non-linear connections, simple learning rules and strong strength, memory capacity; ▪ ability of self-learning and to reverse error propagation [28].	▪ the need for a large amount of data, statistical observations; ▪ requires specialized knowledge from the researcher; ▪ nondeterminism, i.e. the trained model is a "black box", and it becomes difficult to establish cause-and-effect relationships between the components of the model [29].	Despite the complexity of building an effective ANN and the relatively long training of the model, this algorithmic model is the most common. Among the analyzed publications, ANN models are used for almost all tasks and at the same time show a high efficiency of forecasting and classification [2; 7; 8; 12; 13; 16; 18–20; 22; 24–26].
Decision tree models	▪ simple calculation, processing of samples with invalid attribute values; ▪ the ability to evaluate a subject with various features, modeling linear and non-linear relationships;	▪ poor training on small samples; ▪ high probability of retraining [30].	The models show sufficiently high indicators of forecasting delivery time [9; 11], fuel consumption both with [20] and without boosting [22], and cargo classification by type of transportation [14].
Random forest models	▪ high accuracy, especially when modeling nonlinear dependencies; ▪ insensitivity to missing data and outliers.	▪ tendency to retraining; ▪ the need to manually select the number of trees [30].	Application of the random forest model for forecasting fuel consumption by freight vehicles showed the highest forecast accuracy compared to other machine learning models [18; 22]. Also, this type of model demonstrates high efficiency indicators when forecasting the choice of the type of vehicle for cargo delivery [15]. In the case of forecasting the duration of cargo delivery, this model did not show sufficiently accurate results [9; 11].
k-nearest neighbors model	▪ ease of use for classification and regression, especially for non-linear classification; ▪ lack of reaction to data releases.	▪ the need to pre-set the value of k; ▪ does not work on large unbalanced datasets.	It shows high efficiency in the tasks of choosing the type of cargo based on classification features [17]; it can be used to forecast the time of cargo delivery [9] and fuel consumption by vehicles [20] with a slightly lower efficiency.
Model of support vectors	▪ possibility of application for non-linear classification and regression; ▪ are easily interpreted [31].	▪ not suitable for large datasets; ▪ performance degrades when the dataset contains more noise, i.e. the target classes overlap [32].	Although the main task of the models is the classification of objects, such as: choosing the type of transportation between road and rail [14], this algorithm shows quite good results in regression analysis, namely, forecasting the duration of cargo delivery [11] and predicting fuel consumption by vehicles [21].

1. Models of linear and logistic regression are the most well-known regression algorithms belonging to learning "with a teacher" models. They can forecast the output variable based on the input variables [30].
2. Artificial neural networks and deep learning models represent a group of computational and mathematical models built according to the principle of functioning of the biological nervous

system [33]. The weights in the neural network are determined by reducing the error between the actual value and the forecasting [34]. Deep ANNs are called deep learning models because of several hidden layers [28].

3. Decision tree models classify data into smaller subsets, where each subset contains (mainly) answers of the same class (“yes” or “no”) [35]. Decision tree ensembles are used using the boosting technique [36], which is often implemented by algorithms AdaBoost [9;12] and Gradient boosting [21] to increase classification accuracy.
4. Random forest models are ensemble algorithms of machine learning, which are one of the implementations of the Bagging technique [37].
5. The k-nearest neighbor model is a learning algorithm “with a teacher” used for regression and classification [38]. K-NN tries to predict the correct class for the test data by calculating the distance between the test data and all training points [39].
6. The support vector model is an algorithm whose main task is to identify multidimensional boundaries separating data points belonging to different classes [40].

The problem of choosing the optimal model of machine learning for a specific task is solved by implementing several models and then comparing them according to the efficiency criterion. The most common evaluation criteria among the analyzed models are the following:

– absolute error $MAE \rightarrow min$;
– relative error $RE \rightarrow min$;
– root mean square error $MSE \rightarrow min$;
– the square root of the root mean square error $RMSE \rightarrow min$;
– average absolute percentage error $MAPE \rightarrow max$;
– correlation coefficient $R \rightarrow max$;
– coefficient of determination $R^2 \rightarrow max$;
– forecast accuracy $Accuracy \rightarrow max$.

The analysis of the algorithmic models of machine learning (Table 2) according to efficiency criteria allowed identifying the most optimal models, among the studied publications, for their further application concerning the identified problem areas in the freight transportation process.

Table 2

Comparison of the results of the evaluation of algorithmic models of machine learning by areas of application during cargo delivery

Direction*	Name of the model	Assessment of accuracy	Group of models**
1	2	3	4
1	**Grey Neural Network (GNN) [7]**	**RE: 0.3592 %**	**2**
2	**Neural Network model (NNM) [8]**	**Model's performance is 48 % compare with heuristics algorithms**	**2**
3	Neural Network model (NNM) [12]	MSE: 0.5 h	2
3	RPart [9]	Accuracy: 72.5 %	3
3	**Adaboost.M1 [9]**	**Accuracy: 72.8 %**	**3**
3	AdaBoost [11]	MAE: 18.78 h; RMSE: 28.40 h	3
3	Random Forest (RF) [9]	Accuracy: 72.1 %	4
3	ExtraTrees (Randomized Trees) [11]	MAE: 43.66h; RMSE: 54.61h	4
3	k-Nearest neighbors (k-NN) [9]	Accuracy: 60.6 %	5
3	Support Vector Machine (SVM) [9]	Accuracy: 72.2 %	3
3	**Support Vector Regression (SVR) [11]**	**MAE: 16.91h; RMSE: 22.7 h**	**3**
4	Artificial Neural Network (ANN) [2]	Accuracy: 86.6 %	2
4	Artificial Neural Network (ANN) [13]	R: 0.724	2
4	**C5.0 DT [14]**	**Accuracy: 96.2 %**	**3**
4	Support Vector Machine (SVM) [14]	Accuracy: 95.2 %	3

Table continuation 2

1	2	3	4
5	Multinomial Logit Model (MNL) [15]	Accuracy: 41.7 %	1
5	Mixed Logit Model (Mixed MNL) [15]	Accuracy: 39.9 %	1
5	**Random Forest (RF) [15]**	**Accuracy: 49.5 %**	**4**
6	**Multilayer Perceptron (MLP) 24-25-4 [16]**	**R^2: 0.805**	**2**
7	**k-Nearest neighbors (IBk) [17]**	**Accuracy: 82.72%**	**5**
8	Least-angle regression (LARS) [23]	MSE: 563.33 l; RMSE: 23.73 l; R^2: 0.85	1
8	Linear Regression model (LRM) [23]	MSE: 560.67 l; RMSE: 23.68 l; R^2: 0.85	1
8	Artificial Neural Network (ANN) [18]	RMSE: 4.88 l/100km; MAE: 3.46 l/100 km; R^2: 0.85	2
8	Neural Network model (NNM) [19]	RMSE: 0.015 l/100 km; R^2: 0.91; MAE: < 4.0 %	2
8	Neural Network model (NNM) [20]	MAE: 3.63 l/100 km; RMSE: 4.81 l/100km; R^2: 0.916	2
8	Back propagation Neural Network (BP) [22]	Accuracy: 83.98 %	2
8	**Two-stages Neural Network model (NNM)[24]**	**R^2: 0.964**	**2**
8	**Gradient boost [20]**	**MAE: 3.34 l/100 km; RMSE: 4.65 l/100 km; R^2: 0.917**	**3**
8	CART DT [22]	Accuracy: 81.38 %	3
8	Random Forest (RF) [18]	RMSE: 4.64 l/100 km; MAE: 3.21 l/100 km; R^2: 0.87	4
8	**Random Forest (RF) [22]**	**Accuracy: 86.58 %**	**4**
8	k-Nearest neighbors (k-NN) [20]	MAE: 3.37 l/100 km; RMSE: 4.71 l/100 km; R^2: 0.915	5
8	Support Vector Machine (SVM) [18]	RMSE: 5.12 l/100 km; MAE: 3.56 l/100 km; R^2: 0.83	3
8	**Support Vector Machine (SVM) [21]**	**R^2: 0.96**	**3**
9	**Multilayer Perceptron (MLP) 6-3-1 [25]**	**R^2: 0.994**	**2**
10	**Multilayer Perceptron (MLP) 6-9-1 [26]**	**R: 0.9992; MSE: 0.000421; MAPE: 4.35 %**	**2**

* *No. of direction of application of the algorithmic model of machine learning according to the order given in the article*

** *No. of group of the algorithmic model of machine learning according to the order given in the article*

It should be noted that implementing the above-described algorithmic models of machine learning involves the use of such software packages as STATISTICA, MATLAB, and machine learning libraries (Scikit-learn, Keras, TensorFlow) for the programming language Python.

7. CONCLUSIONS AND FUTURE RESEARCH PERSPECTIVES

Based on the results of this study, the following general conclusions can be drawn:

1. Algorithmic models of machine learning are becoming more and more widespread in the processes of freight transportation modeling.
2. The analysis of the publications made it possible to identify the advantages, disadvantages and main areas of application of algorithmic models of machine learning. They include routing of vehicles, selection of the type of cargo, type of transportation and type of vehicles; forecasting fuel consumption by vehicles, disruptions in transportation, transportation costs, duration of order fulfillment; evaluation of the fleet of rolling stock and the efficiency of carrying out the transport task.
3. Among the groups of algorithmic models of machine learning, it was found that linear and logistic regression models are quite simple but do not always provide high indicators of forecasting accuracy; deep learning models are quite widely applied to all identified areas;

decision tree and random forest models often show the highest rates of modeling efficiency; models of k-nearest neighbors and support vectors are suitable to be used both in classification tasks, for example, choosing the type of cargo and type of transportation, and for predicting fuel consumption and the duration of the transportation process.

4. Based on the developed areas of application of algorithmic models of machine learning, it can be stated that the choice of the optimal model involves a comparative analysis of the results of the work of several models. Since the effectiveness of modeling primarily depends on the available data set for training the model, it is impossible to predict the results of the model without its implementation. The recommendations given in the article will further guide researchers in the process of selecting algorithmic models of machine learning for their effective implementation depending on the problem arising in freight transportation.

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ЗАСТОСУВАННЯ АЛГОРИТМІЧНИХ МОДЕЛЕЙ МАШИННОГО НАВЧАННЯ ДО ПРОЦЕСУ ПЕРЕВЕЗЕННЯ ВАНТАЖІВ

Анотація. *У роботі наведено результати аналізу застосування алгоритмічних моделей машинного навчання до процесу перевезення вантажів. Аналіз існуючих досліджень дозволив виявити ряд переваг застосування обчислювального інтелекту у логістичних системах, серед яких: підвищення точності прогнозування, зменшення транспортних витрат, підвищення ефективності доставки вантажів, зниження ризиків, пошук ключових факторів ефективності. У процесі дослідження було визначено основні напрями застосування алгоритмічних моделей машинного навчання, як-от: маршрутизація транспортних засобів, вибір виду вантажу, виду транспортування та типу транспортних засобів; прогнозування витрат палива транспортними засобами, збоїв у транспортуванні, транспортних витрат, тривалості виконання замовлення; оцінка парку рухомого складу та ефективності виконання транспортного завдання. На основі досліджуваних публікацій було виявлено найбільш поширені у вантажних перевезеннях алгоритмічні моделі машинного навчання та проаналізовано їхню ефективність. Моделі лінійної та логістичної регресії є достатньо простими, проте не завжди дають високі показники моделювання; моделі глибокого навчання досить широко застосовуються до всіх виявлених напрямів; моделі дерев рішень та випадкового лісу часто показують найвищі показники ефективності моделювання; моделі k-найближчих сусідів та опорних векторів доцільно застосовувати як у задачах класифікації, наприклад, вибору виду вантажу та виду транспортування, так і для прогнозування витрат палива та тривалості транспортного процесу.*

Ключові слова: *інтелектуальний підхід, машинне навчання, алгоритмічні моделі машинного навчання, вантажні перевезення, доставка вантажів.*