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–
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–
autonóm közlekedés előtt

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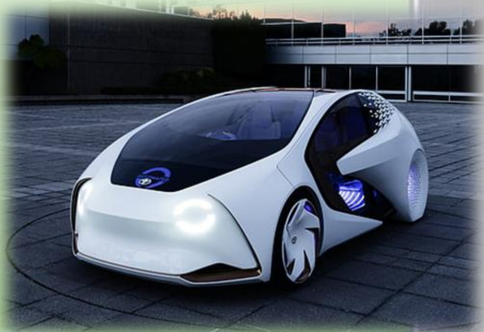

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Implementation Machine Learning Model into Web Application for Freight Price Prediction in Road Transport

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Abstract: The possibility of using machine learning to predict the price for road transport of goods is presented. The methodology of registering data about offers, useful in the analysis, was presented. Methods for the use of machine learning have been developed. The following models were compared: DecisionTreeRegressor, RandomForestRegressor, ExtraTreesRegressor, GradientBoostingRegressor according to the success metric mean squared error. The influence of particular features on the price was presented. Implementing the model in a web application was proposed to validate it with employees managing transport in future research. The project was made available for open access in the GitHub repository.

Keywords: transport management, transport modelling, logistic, machine learning

Introduction

Machine learning was defined in [1] by Tom Mitchel as the science of computer algorithms that improve automatically through experience. Applications range from data mining programmes that discover general principles in large data sets to information filtering systems that automatically learn about user interests. Alan Turing in [2] proposed to consider whether machines can think. This article considers the question of whether the machine can help road transport managers in their daily work that requires processing large amounts of data. In [3] describes the possibility of learning a machine to play checkers, which is an example of how a machine can perform certain tasks better than a human.

Machine learning can be used in many modes of transport. In [4] scientists presented the use of machine learning to predict greenhouse gas emissions from road transport in Canada. In [5], the relationship between sea imports and exports in Spain was modelled. In [6] smartphones and the OBD (On-Board Diagnostic) system in taxis is a source of data. The use of neural network models, backpropagation errors, support vector regression, and random forests were the methods presented. The fuel consumption of the condition of vehicles in an energy company was discussed in [7]. The prediction for passenger vehicles was presented in [8]. Methods used: Multiple linear regression, an artificial neural network, and a support vector machine were used. In [9] carrier vector regression and artificial neural networks were used. In [10] prediction for 40 tons of vehicles in international transportation was presented. 13 machine learning models were compared. The prediction of the volume of transported goods is described in [11] with methods: the seasonal Winter method, harmonic analysis and harmonic analysis supported by the artificial immune system and in [12] double Holt-Winters exponential smoothing, double Holt-Winters exponential smoothing supported by the artificial immune system, Bayesian networks and Bayesian networks with the unemployment rate. In [13] the prediction was based on data from the Central Statistics Office using an additive and multiplicative model. In [14] a prediction during a hurricane was presented and in [15] was based on data from the freight exchange transport barometer with 32 compared machine learning models.

The context is important to predict transportation [16]. Effective prediction requires, in addition to knowledge of technology, also understanding of data. The final price of the road transport service depends on many factors. The impact of the gross domestic product on transport was investigated in [17] on the number of tonnes of kilometres and in [18] and on the price. In [19] the influence of relationships is described. The [20] shows the dependence of the price on seasonality. In [21] the problems of pallet exchange are described. The price depends on the type of goods that will be transported. Different goods require different methods of securing [22]. In [23] the problems of food transport, in [24] temperature-controlled, and in [25] oversized ones are described. In [26] the method is presented to predict the risk and cost of cargo theft in road transport. It is important for an entrepreneur performing a transport service to know who is the payer, what the form and date of payment is. Payment terms can be long and the customer's financial situation can be a concern for the transport company. Effective cash flow management in transport companies is described in [27]. The issue of cash flow also affects container transport [28].

The Jupyter Notebook [29] is an editor for programming code. Pandas [30] is a data processing programming library. NumPy [31] is the programming library for calculation analysis, Scikit-Learn [32] is the machine learning programming library. Matplolib [33] and Seaborn [34] are visualisation programming libraries. GitHub [35] is a repository for programming projects. The summary of methods by number cited in the Scopus database is shown in Figure 1. Articles about Pandas and Seaborn are presented in conference papers. The data are current as of April 7, 2022.

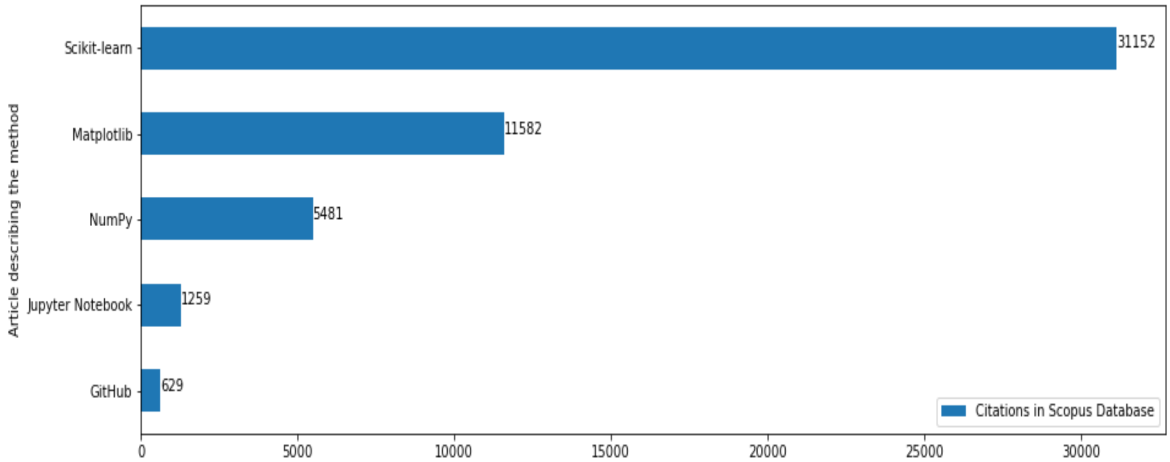

Figure 1. Summary of the number of citations of articles describing the methods

The main research goal is to find a method to train a machine learning model to predict the price of a road transport service and implement it in the application in order to be able to validate it in the future by evaluating it with experts. The thesis is that few process managers are familiar with machine learning and Python programming. To validate and evaluate the model with industry experts, it is proposed to programme a web application that will be available to everyone.

1. Methodology

The statistical method, including regression and correlation analysis, is used in the project. The experimental method is used in the project. The experiments consist of checking how the model behaves with various combinations of input data. Data processing and model training were performed in the Jupyter Notebook editor and the Python programming language. Programming libraries: Pandas for data processing, NumPy for calculation analysis, Scikit-Learn for machine learning, Matplolib, and Seaborn for visualisation are used to complete the project. The code for executing the project has been made available in open access on the GitHub repository. This project is available at [36]. The methods of using Python are described in [37] The import system, the Python code in one module, accesses the code in another module through the import process.

1.1 Pandas

The methods to work with data using the Pandas [38] library are presented below:

- pandas.read_csv - read a comma-separated csv file in DataFrame
- pandas.DataFrame.info - give information about a DataFrame
- pandas.DataFrame.agg - an aggregation method that uses at least one operation, for example: mean, median, minimum, maximum, standard deviation
- pandas.DatetimeIndex - method to get valuable date and time data
- pandas.DataFrame.corr - method to compute pairwise correlation of columns
- pandas.DataFrame.fillna - empty values fill method
- pandas.factorize - method to obtain a numeric representation

1.2 Numpy

The calculation methods that use Numpy [39] are shown below:

- numpy.mean - method for the arithmetic mean along the specified axis.
- numpy.median - method to compute the median along the specified axis.
- numpy.ndarray.max - method to return the maximum along a given axis.
- numpy.ndarray.min - method to return the minimum along a given axis.
- numpy.ndarray.std - method to return the standard deviation along a given axis.
- numpy.corrcoef - method to return Pearson product-moment correlation coefficients.

1.3 Scikit-Learn

Methods with the use of Scikit-Learn [40] are presented below:

- sklearn.tree.DecisionTreeRegressor - method based on decision tree regressor
- sklearn.ensemble.RandomForestRegressor - method based on random forest which is a metaestimator that fits a number of classification decision trees on various subsamples of the dataset and uses averaging to improve predictive accuracy and control overfitting
- sklearn.ensemble.ExtraTreesRegressor - method implements a meta-estimator that fits a number of randomised decision trees
- sklearn.ensemble.GradientBoostingRegressor - method of gradient boosting for regression
- sklearn.metrics.mean_squared_error - mean squared error regression loss.

2. Results

The dataset contains information on 262 free-market freight offers. All offers are for full truck loads (FTL). Each order is assigned a quantity with a price in euros. The most expensive price is 4300€ and the cheapest 20€. The average price is 811.98€ and the median is 690€. The standard deviation was 527.16 €. The prices are varied. Price is variable for prediction. The number of kilometres is assigned to each order. The longest route is 2045.4 km and the shortest is 20.7 km. The mean load would be transported over a distance of 817.66 km, and the median is 747 km. The standard deviation was 422.78 km. The distances are varied. Each load is assigned a weight in tons. The heaviest is 25.7t. and the lightest 1.52t. The average is 21.24t. and the median is 24t. It is common practise for transport seekers to expose a maximum weight of about 24 tons for the tautliner or curtain body type. The standard deviation is 5.13t. The Pearson correlation of distance and price is 0.77. The highest rate was 6.72 [€/km] and the lowest was 0.46 [€/km]. The average cost is 1.02 [€/km] and the median is 0.92[€/ km]. The standard deviation is 0.52 [€/km]. The price of [€/km] of the route is a feature that allows analysis to compare all offers with each other. The correlation between weight in tonnes and rate [€/km] is negative and is -0.04. This shows that it is better to choose the rate in [€/km] than in [€/tonne-kilometre]. This is a phenomenon that may seem illogical. This is because non-standard loads, which are more expensive to transport, are light. The price dependence on the loading and unloading place is shown in the figure 2. For transports in relation to and from Sweden, for better visualisation, prices are given after deducting the costs of ferries. Poland is a country in which all exports are higher than import prices. Sweden is a country where all exports are cheaper than imports.

The model presented in the article covers 9 countries of the European Union presented in the figure 3 in dark green color. This is because data is available to train a valuable model. Further coverage expansion is planned. The planned area of activity is marked in light green in the figure. It is an area of the European Union. The European Union is an area of free exchange of goods and services. Based on this, it can be concluded that modeling for such an area makes sense. Modeling transport with countries outside the European Union is more complicated for modelling because political and administration reasons. The target area of the European Union is argued because of the free flow of goods and services between countries. It is made with MapChart. A weak positive correlation is demonstrated with: the number of pallets for exchange 0.03, the number of loading places 0.01, and the payment term 0.04. A weak positive correlation of 0.1 was shown between the TimoID number and the price.

TimoID is assigned to the company in chronological order, which means that longer-running companies have a lower number. The correlation between the rate in [€/km] and the distance was -0.13, which means that longer routes have a lower rate.

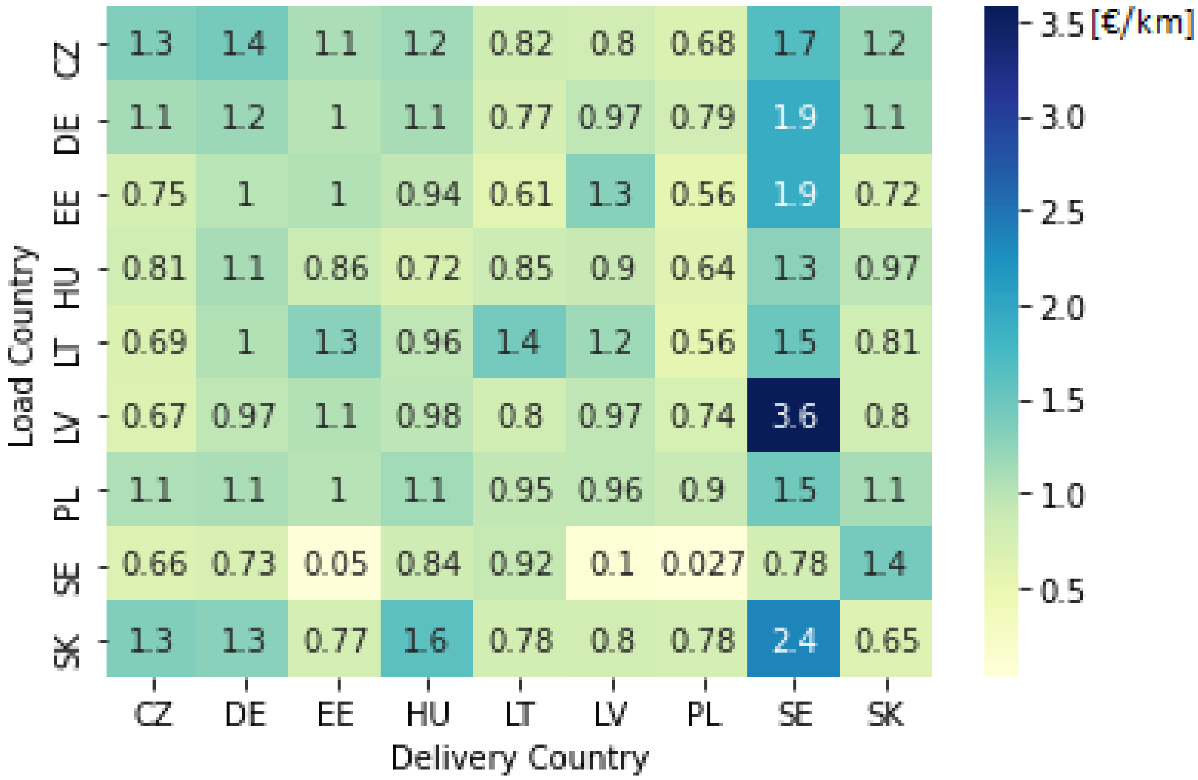

Figure 2. Average freight price in transporting goods between countries in [€/km]

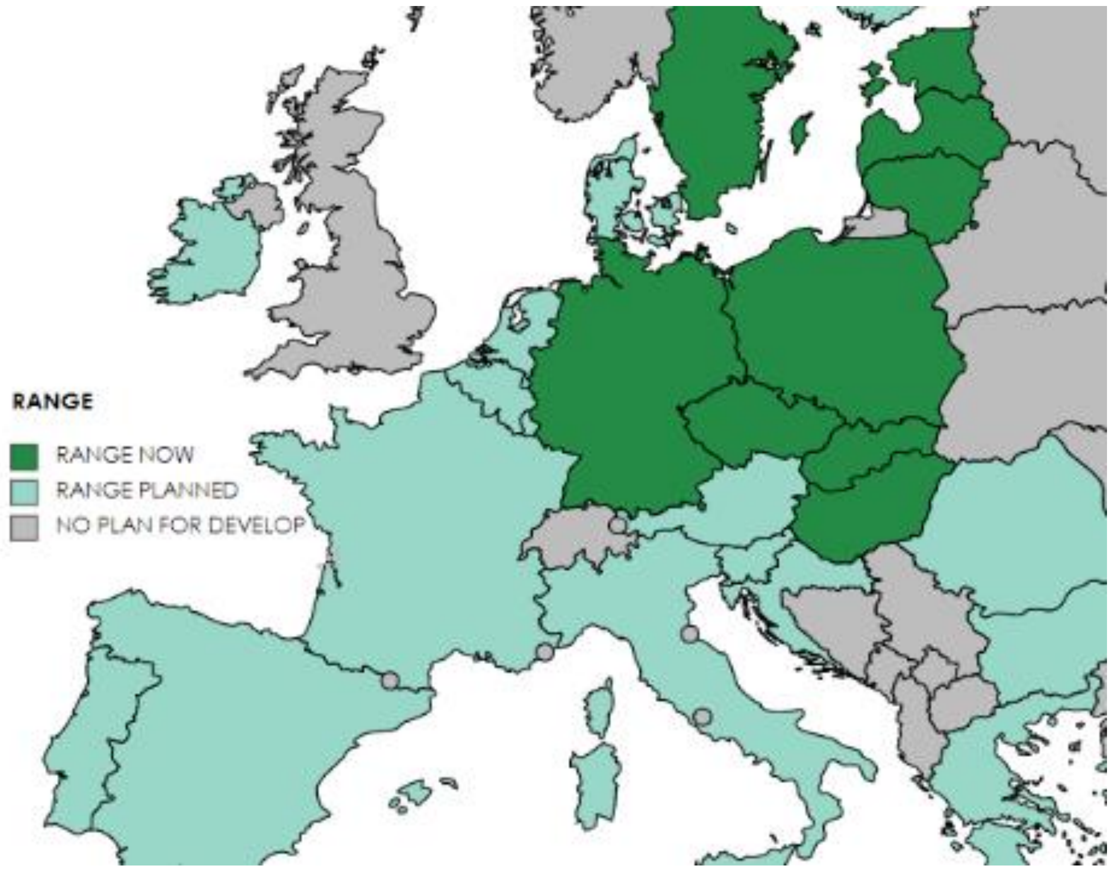

Figure 3. The operating range of the model

Four machine learning models were compared according to the MSE metric. The results are shown in the figure 4. The models are cross-validated. The best is ExtraTreesRegressor with MSE = 169.76. The best model will be analyzed and implemented into the application.

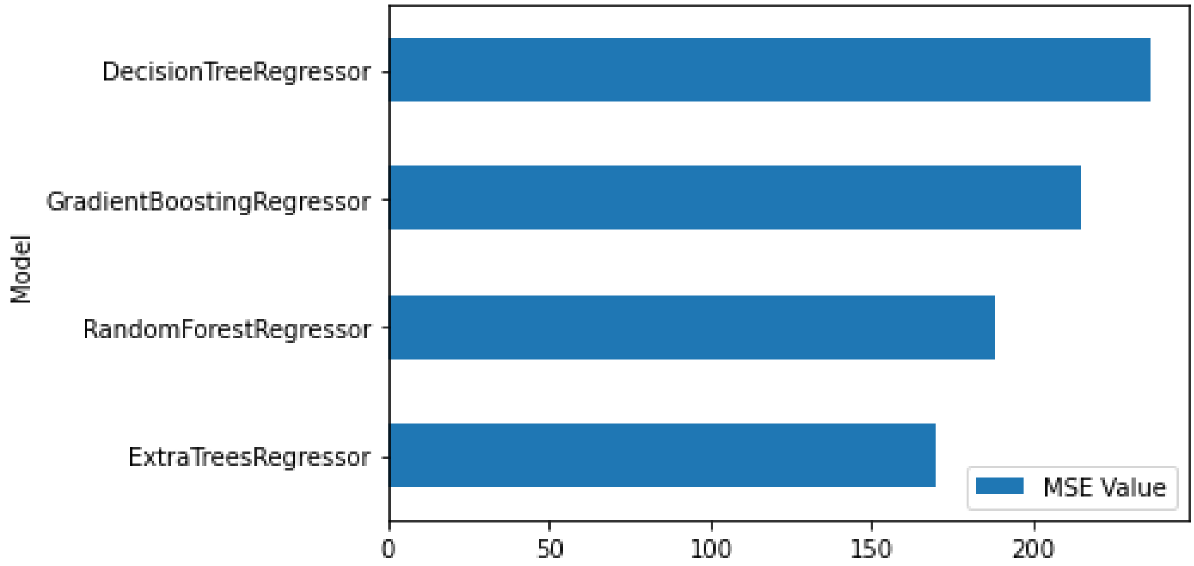

Figure 4. Compared models according to the MSE metric

The 20 most important features of the model are presented in the figure 5. The most important feature is KM, which means the sum of kilometers from the initial loading point to the last unloading point. This group includes more features that define the distance: SE_KM - the number of kilometers in Sweden, PL_KM - the number of kilometers in Poland, LT_KM - the number of kilometers in Lithuania, CZ_KM - the number of kilometers in the Czech Republic, EE_KM - the number of kilometers in Estonia. OTHER_COSTS is the amount of additional costs, such as tunnels or ferries, that the carrier has to pay extra. In this database, these costs represent the ferry costs for shipments to and from Sweden. COUNTRY_DELIVERY_PLACE is 1 of 9 countries of unloading, COUNTRY_LOAD_PLACE is 1 of 9 countries of loading, RELATION is 1 of 81 unique relationships between countries. The characteristics that describe the requirements are: VEHICLE_TYPE - vehicle type, BODY_TYPE - trailer body type, GOODS_TYPE - goods type, LOAD_UNLOAD_METHOD - loading and unloading method, REQUIREMENTS - special equipment requirements. END_LOAD_DATA_DAY - describes the day of the month in which the goods are to be finally loaded. The features that describe the company that requests transport are: TIMO_ID - chronological user number assigned to companies, CLIENT_VAT - unique number of the person offering transport.

Weight	Feature
0.4537 ± 0.2410	KM
0.0875 ± 0.1152	OTHER_COSTS
0.0840 ± 0.1561	COUNTRY_DELIVERY_PLACE
0.0614 ± 0.1255	SE_KM
0.0459 ± 0.1004	VEHICLE_TYPE
0.0233 ± 0.0800	DE_KM
0.0230 ± 0.0896	RELATION
0.0197 ± 0.0839	SOURCE
0.0191 ± 0.0634	PL_KM
0.0148 ± 0.0312	COUNTRY_LOAD_PLACE
0.0128 ± 0.0350	BODY_TYPE
0.0104 ± 0.0534	TIMO_ID
0.0097 ± 0.0519	GOODS_TYPE
0.0074 ± 0.0396	LT_KM
0.0072 ± 0.0198	CZ_KM
0.0067 ± 0.0383	CLIENT_VAT
0.0063 ± 0.0265	LOAD_UNLOAD_METHOD
0.0062 ± 0.0198	EE_KM
0.0058 ± 0.0238	REQUIREMENTS
0.0054 ± 0.0297	END_LOAD_DATA_DAY

Figure 5: Top 20 features for the ExtraTreesRegressor model

2.1 Implementation

The scheme of the application functioning is presented in a simplified version in figure 6. The data for the study are obtained from transport offers on the free market, such as freight exchanges. Raw data cannot be directly entered into the model. The most important thing is that user can communicate with the machine using numbers, not words. The data processing stage requires the data to be translated from text to numerical. The Pandas library is used for this. Prepared data is data in numerical form. In this form, model is trained using the Scikit-Learn library. A method has been proposed that will allow all potential users to access the application. The model, along with other files necessary for operation, is made available in the Git Hub repository. The Heroku server retrieves data from the data repository in real time. Then make it available on the server page. The user can enter the website, input the data regarding his query and in response, he will receive the predicted price from the server. Scheme is made at lucid.app. A simplified version of the application is available on the website [41]. Transport industry experts who are not machine learning specialists can assess the suitability of the system. Presentation of the results in this form allows authors to receive feedback from transport managers. An application evaluation survey may be conducted. This will allow searching for research gaps and planning further research.

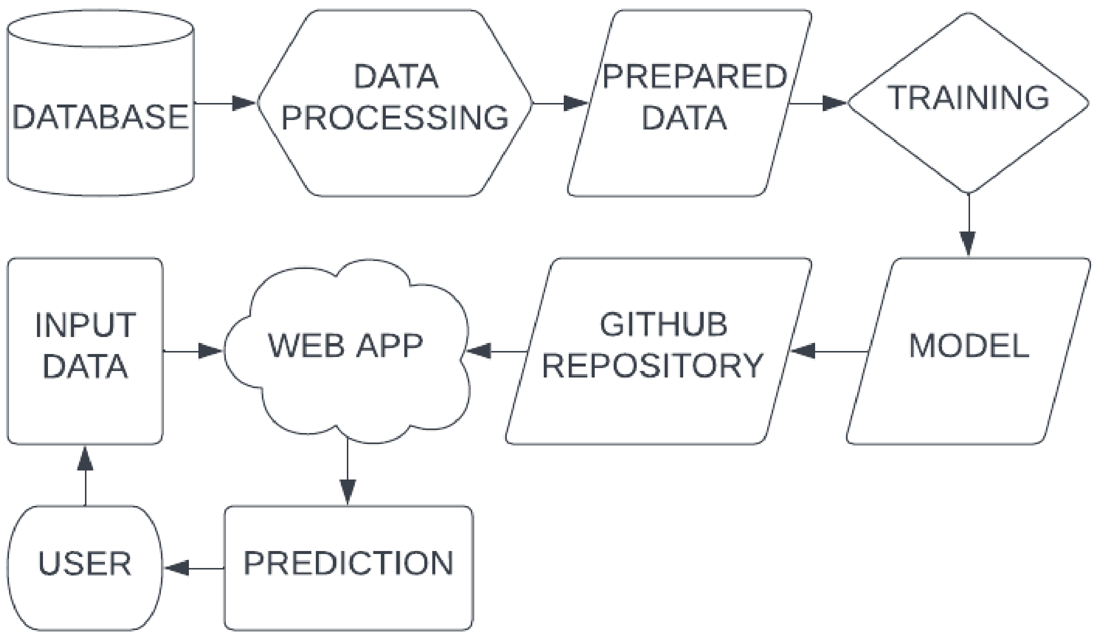

Figure 6: Scheme of the functioning of the application for price prediction

Conclusions

Machine learning methods can be used successfully to predict the price of road freight transport. The price of transporting goods by road depends on many factors. The most important factor is distance. The price is influenced by the relationship depending on the starting place of the loading and the final location of the unloading. Poland and Sweden are special cases. All export relations from Poland to other countries were more expensive than import relations. It may be influenced by a very large number of registered companies and vehicles for international transport in Poland. All Sweden export relations were cheaper than import relations. Firms operating on the market for longer pay less for their services. This may be due to the fact that companies operating for a shorter period of time are a risky payer. The type of vehicle, body, and method of loading and unloading affect the price. The more complex the requirements, the more expensive it will be. The more universal the load is in the selection of the means of transport, the cheaper it is. The best model in experiment was ExtraTreesRegressor. Implementing a machine learning model in a web application will allow non-Python programming and machine learning users to evaluate the application. The expected effect of the research is to reduce the amount of time that operational employees spend on tasks that require a lot of computing power. Employees can focus on tasks where natural intelligence is more effective. The use of the model allows managers to improve the efficiency of the organisation and make better decisions. Better decisions will translate into improved financial results and better company development. In future research, the software can be evaluated by employees who manage transport processes on a daily basis. The answer will be feedback that will allow researchers to plan future research more effectively.

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References

[1] Mitchell, T.: Machine learning. McGraw hill Burr Ridge, 1997
[2] Turing, A. M.: I – Computing machinery and intelligence. Mind 1950 Vol.LIX. No.236. 433–460
[3] Samuel, A. L.: Some studies in machine learning using the game of checkers. IBM Journal of Research and Development 1959 Vol.3 No.3. 210–229
[4] Khan M. – Awasthi A.: Machine learning model development for predicting road transport ghg emissions in canada. WSB Journal of Business and Finance 2019 Vol. 53 No. 2
[5] Coto-Millán, P. - Baños-Pino, P. – Castro, J. V.: Determinants of the demand for maritime imports and exports. Transportation Research Part E: Logistics and Transportation Review 2005 Vol.41. No.4. 357-372
[6] Yao, Y. - Zhao, X. – Liu, C. - Rong, J. – Zhang, Y. – Dong, Z. – Su, Y.: Vehicle Fuel Consumption Prediction Method Based on Driving Behavior Data Collected from Smartphones. Journal of Advanced Transportation 2020
[7] Zargarnezhad, S – Dashti, R. - Ahmadi R.: Predicting vehicle fuel consumption in energy distribution companies using ANNs. Transportation Research Part D: Transport and Environment 2019 Vol.74. 174-188
[8] Çapraz, A. – Özel, P. – Şevkli, M. - Beyca O. Fuel consumption models applied to automobiles using real-time data: A comparison of statistical models. Procedia Computer Science 2016 Vol.83. 774–781
[9] Moradi, E. - Miranda-Moreno, L.: Vehicular fuel consumption estimation using real world measures through cascaded machine learning modeling. Transportation Research Part D: Transport and Environment 2020 Vol.88.
[10] Budzyński, A. - Sładkowski, A. The use of machine learning to predict diesel fuel consumption in road vehicles, 19th European Transport Congress of the EPTS Foundation e.V. European Green Deal Challenges and Solutions for Mobility and Logistics in Cities, Maribor 2021. october 7-8.
[11] Mrowczyńska, B. - Lachacz, K. - Haniszewski, T. – Sladkowski, A. A comparison of forecasting the results of road transportation needs. Transport 2012 Vol.27. No.1. 73-78
[12] Mrówczyńska, B – Cieśla, M. - Król, A. – Sładkowski, A.: Application of artificial intelligence in prediction of road freight transportation. PROMET - Traffic&Transportation 2017 Vol.29. No.4.
[13] Macioszek, E. Kurek, A.: International road cargo transport in poland and other EU countries. Scientific Journal of Silesian University of Technology. Series Transport 2021 Vol.111. 99–108
[14] Kamol, C.R. – Samiul, H. – Aron, C. – Naveen, E.: Predicting traffic demand during hurricane evacuation using real-time data from transportation systems and social media. Transportation Research Part C: Emerging Technologies 2021 Vol.131.
[15] Budzyński , A. – Sładkowski, A.: Forecasting road transport demand with use machine learning, Proceedings of the International Conference on Problems of Logistics, Management and Operation in the East - West Transport Corridor (PLMO), Baku 2021, october 27-29
[16] Pereira, F. - Bazzan A. - Ben-Akiva, M.: The role of context in transport prediction. IEEE Intelligent Systems Magazine 2014 Vol.29. No.1. 76-80
[17] McKinnon, A.C. - Woodburn, A. Logistical restructuring and road freight traffic growth: An empirical assessment. Transportation 1996 Vol.23. 141–161
[18] Budzyński, A.: Use dependencies between freight prices and economic factor as a solution in improve efficiency work in road transport. Sładkowski, A. (ed.) XII Int. Sci. Conf. & IX Int. Symposium of Young Researches „Transport Problems'2020". Conference Proceedings, 2020. november 30 – december 2
[19] Poliak, M. – Poliaková, A. – Svabova, L. – Zhuravleva, N. - Nica, E.. Competitiveness of price in international road freight transport. Journal of Competitiveness 2021 Vol.13. No.2. 83–98

[20] Hammer J. - Poliak M. – Jaśkiewicz, M. – Ríha, Z. Identification of change seasonality of demand to transportation in road freight transport. Transportation Research Procedia TRANSCOM 2019 13th International Scientific Conference on Sustainable, Modern and Safe Transport. Novy Smokovec 2019. may 29-31
[21] Elbert, R. - Lehner R.: Influence of a reasonable allocation of pallets in the pallet exchange system, Advances in Production, Logistics and Traffic, Dortmund 2019. march
[22] Nieoczym, A. – Caban, J. - Vrabel, J.: The problem of proper cargo securing in road transport – case study. Transportation Research Procedia 2019 Vol.40. 1510-1517
[23] Ackerley, N. – Sertkaya, A. – Lange, R. Food transportation safety: Characterizing risks and controls by use of expert opinion. Food Protection Trends 2010 Vol.30. No.4.
[24] Gnap, J. - Rovňaníková, D. – Jaśkiewicz, M.. Temperature control for regional transport. LOGI – Scientific Journal on Transport and Logistics 2017 Vol.8. No.2. 81-89
[25] Macioszek, E.: Oversize cargo transport in road transport – problems and issues. Scientific Journal of Silesian University of Technology. Series Transport 2020 Vol.108. 133–140
[26] Lorenc, A. - Kuźnar M. An intelligent system to predict risk and costs of cargo thefts in road transport. International Journal of Engineering and Technology Innovation 2018 Vol.8. 284–293
[27] Naydenova, M – Bontsevich N. - Sidelnikova, V. Modern concept of the financial strategy of transport industry. International Journal of Engineering & Technology 2018 Vol.7. 617-622
[28] Holter, A. - Grant, D. - Ritchie, J. - Shaw, W. - Towers, N.: Long-range transport: Speeding up the cash-to-cash cycle. International Journal of Logistics: Research and Applications 2010 Vol.13. 339-347
[29] Kluyver, T. - Ragan-Kelley, B. - Perez, F. - Granger, B. - Bussonnier, M - Frederic, J. - Kelley, K. - Hamrick, J. - Grout, J. - Corlay, S. - Ivanov, P. - Avila, D. - Abdalla, S. - Willing, C, Jupyter Notebooks – a publishing format for reproducible computational workflows, Conference: 20th International Conference on Electronic Publishing. 2016
[30] Mckinney, W.: Data Structures for Statistical Computing in Python, Proceedings of the 9th Python in Science Conference, 2010
[31] van der Walt, S. - Colbert, S. - Varoquaux, G. The NumPy Array: A Structure for Efficient Numerical Computation. Computing in Science and Engineering 2011 Vol.13. No.2. 22-30
[32] Pedregosa, F. - Varoquaux, G. Gramfort, A. - Michel, V. - Thirion, B. - Grisel, O. - Blondel, M. - Prettenhofer, P. - Weiss, R. - Dubourg, V. - Vanderplas, J. - Passos, A. - Cournapeau, D. - Brucher, M. - Perrot, M. - Duchesnay, E. - Louppe, G.: Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 2012.
[33] Hunter, J.: Matplotlib: A 2D Graphics Environment. Computing in Science & Engineering 2007 90-95
[34] Waskom, M.: seaborn: statistical data visualization. Journal of Open Source Software 2021
[35] Dabbish, L. - Stuart, H. - Tsay, J. - Herbsleb, J.: Social Coding in GitHub: Transparency and Collaboration in an Open Software Repository. Proceedings of the ACM Conference on Computer Supported Cooperative Work, 2012
[36] https://github.com/BudzynskiA/RFPPS (2022.04.13)
[37] https://docs.python.org/3/ (2022.04.13)
[38] https://pandas.pydata.org/docs/reference/index.html
[39] https://numpy.org/doc/stable/reference/index.html
[40] Buitinck, L. - Louppe, G. - Blondel, M. - Pedregosa, F. - Mueller, A. - Grisel, O. - Niculae, V. - Prettenhofer, P. - Gramfort, A. - Grobler, J. - Layton, R. Vanderplas, J. - Joly, A. - Holt, B. - Varoquaux, G.: API design for machine learning software: Experiences from the scikit-learn project, European Conference on Machine Learning and Principles and Practices of Knowledge Discovery in Databases, 2013
[41] https://rfpps.herokuapp.com/ (2022.04.13)