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MACHINE LEARNING MODEL FOR FINANCIAL FORECASTING USING THE MILITARY HEALTHCARE AS AN EXAMPLE

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Abstract

Predicting future events through the analysis of historical data poses a challenge for decision makers. In this paper, the authors investigate the possibility of machine learning application by solving a regression problem for prediction from time series data of the military healthcare costs in the Republic of Serbia. The present research aims to determine the possibilities of using artificial intelligence in financial forecasting, as well as to select, based on the research results, the most reliable model which, taking into account the relationships between the historical data of the planning subject and the market economic conditions in the observed period, will provide relevant data for future decisions.

Key words: *Forecasting, management, defense, healthcare, machine learning.*

Introduction

In this paper, the authors explored a very important area intended for top management with a view to preparing actions using historical data. Anticipating future needs requires the use of modern tools to analyze and process available data from the past, to determine their relationship and build a tailored financial planning model. Viewed through the prism of limited resources and ever-increasing needs, the authors of this paper propose artificial intelligence, the application of machine learning, in predicting future expenditures in line with the economic position of the country.

Human perception is not able to foresee, through rational consideration of economic trends and current emotional cognitions, all the factors and to independently put them in the context of future events. Hence, statistical methods were developed that, based on historical data and by calculating the influence coefficients, can observe patterns of

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behavior which, with variable conditions, will further give a picture of possible future outcomes.

In the first part of the paper, the authors address the healthcare spending structure; in the second part, they discuss the theoretical basis for predicting future costs and present a review of the literature relevant to this area. The third part of the paper offers, through the machine learning model analysis, an answer as to which model will give the best prediction results. The analysis was conducted on the ten proposed machine learning models by solving the linear regression problem on the data pertaining to investments in the military healthcare in the Republic of Serbia and relative to the market economic conditions in the observed period.

Healthcare system challenges

The public healthcare system requires considerable financial resources to achieve effective protection of all citizens. Health care of the population is organized through public health system and private practice, with special social categories requiring a specially organized and financed health care. This paper will discuss public healthcare for military personnel.

Healthcare costs at the global level range from 5-12% of total GDP. Throughout history, since the creation of the first health insurance system, healthcare costs have been constantly on the rise. **Figure 1** illustrates the increase in total spending in the period from 1880 through 2021. Nowadays, healthcare is a constitutional category, not the willingness and ability to pay for it, thus the state is under obligation to provide sufficient funds for the successful functioning of the health system. (Ortiz-Ospina et al. 2017)

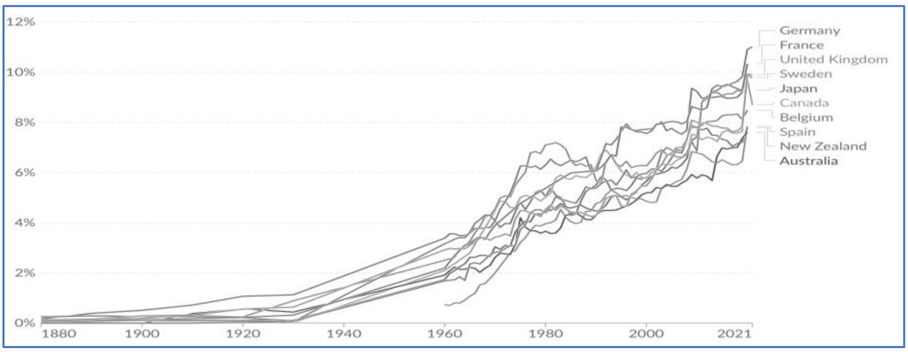

Figure 1. Total healthcare spending relative to GDP in the period from 1880 through 2021
Source: OECD Health Expenditure and Financing Database (2024)

In the Republic of Serbia, allocations for health spending, expressed as a percentage of GDP, are at the level of the European Union, but the amount is nominally much smaller in terms of the purchasing power of health services compared to the possibilities of individual European economies. (Gajić-Stevanović et al., 2010)

Public healthcare is often organized and financed for particularly sensitive categories of the population thus the members of the armed forces have a separately organized health system. It is primarily designed to provide support to military operations and exercises, as well as to assist the population in extraordinary circumstances, natural and environmental disasters.

The most developed economy in the world, the US, has a separate medical system, the so-called TRICARE program, for military personnel (active-duty service and reserve members), retirees, war veterans and their families. Depending on the location and the beneficiary categories, the program provides different levels of care by bringing together the healthcare resources of the military health system with private healthcare capacities. However, it is important to underline that the costs for all military operations are borne by the central administration. (McEvoy, 2018)

It should be noted that, on a global level, military health systems have been cooperating together. At the European level, military health systems have been uniting through the European Union, as part of the PESCO (Permanent Structured Cooperation) and NATO initiative, in the multinational program European Military Medical Service, where development and collaboration are being monitored. The health systems of the member states and candidate countries, i.e., the member countries of the Partnership for Peace, have been joining the said programs through joint exercises and joint training. This cooperation was particularly established at the time of the major global health crisis, during the Covid 19 pandemic.

Healthcare for the members of the armed forces is globally recognized as the responsibility of the executive branch. Each of these systems is regulated differently across countries. Military healthcare systems differ in terms of their organization, number and beneficiary structure, the facilities they employ for those purposes and the direct relationship, in the economic sense, with healthcare in general, as well as in terms of required operational capabilities of the military organization. (Leone, et al., 2021)

In the Republic of Serbia, the healthcare of military insurees is still governed by the Law on the Yugoslav Armed Forces. The military health system is part of the overall healthcare system, and it is organized in accordance with the needs of the defense system. The highest military health management authority is the Military Health Department, as a separate organizational unit of the Ministry of Defense. Responsibilities in the healthcare system, as a logistic support function, are divided according to the levels of care into primary, secondary and tertiary care.

The military health system is financed through making adjustments of revenues and expenditures from health insurance. The collection of revenues from military insurees is carried out by the Military Health Insurance Fund (FSOVO), which conducts a transfer from military service members to the population exercising the right to military health care services. Given that the number of active insurance beneficiaries and health service beneficiaries is not balanced, subsidizing costs that cover the total needs of the military health is required. The largest share, more than 85% of military health costs, is financed from the defense budget (FSOVO share in total costs: 13.9% for 2014; 12.4% for 2015; 12.9% for 2016). (Miladinović and Damnjanović, 2017)

Acknowledging the fact that there is a significant impact on the defense budget, proper planning of financial resources and efficient spending of limited funds for healthcare of military insurees, a need arises to pay special attention to those processes. **Figure 2** shows the level of healthcare spending in the Serbian Armed Forces and the Ministry of

Defense, where a constant increase in demand can be observed. In this regard, there is a need to determine the most expedient tool that will predict the future level of funds for that purpose, allowing at the same time the policy makers to define, as objectively as possible, the goals and requirements for reaching the necessary capabilities of the military organization.

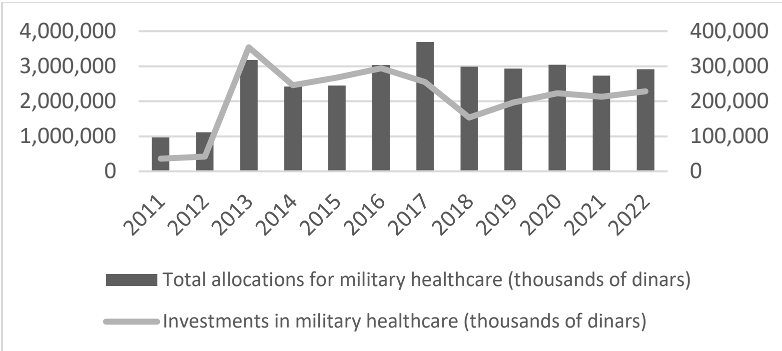

Figure 2. Total allocations for military healthcare in the 2011-2022 period
Source: Authors

Cost forecasting models

Forecasting the financing of public expenditure is essential for the proper allocation, budgeting and strategic planning of the limited resources of a society. The data obtained through the application of predictive techniques enable the public sector to predict future financial needs, ensure the sustainability of the system and the required efficiency, all within foreseeable market challenges.

In order for the forecast to respond to the task, it would have to fulfill the following conditions (Lipovina-Božović, 2014):

- it should capture the existence of rules in historical data,
- those rules should contain data on future trends,
- the data should be concisely presented in the model, and
- exclude unnecessary data (random, irregular).

A time interval over which predictions are made can be divided into short-term, for the next two years, mid-term, up to five years, and long-term forecast up to 10 years (in line with the rules on defense system development planning). The unit of measure that will be taken into focus will depend on the time horizon, all with a view to obtaining the most accurate projection. In the short term, the most reliable are the data on current costs and market conditions, i.e. inflation measures and purchasing power trends. In the medium term, using a real measure of per capita consumption adjusted for inflation and the expected population growth will provide the best picture of future spending, while in the long run inflation and real income per capita will create more uncertainty, thus the share of GDP will give the best result. (Getzen, 2000)

In professional literature, statistical methods such as regression analysis and time series analysis are most often used to forecast public service expenditures based on historical data.

Regression analysis is a statistical tool used to understand the relationship between consumption patterns and various factors it is affected by, such as growth in the number of beneficiaries, macroeconomic indicators, political changes, etc. The application of multiple regression analysis in examining the impact of GDP on public revenues and expenditures to forecast future values based on historical data gives good results. (Mihajlovic, et al,. 2023) The use of regression analysis as an instrument that will, through forecast, reduce the risk without using complicated systems is important for local authorities. (Wong, 1995)

For political authorities, it is very important to determine the cost flows of public institutions and to adjust them to the generated revenues, ensuring thereby the financial sustainability of the health system. (Gajić-Stevanović et al., 2010) Using the U.S. TRICARE healthcare program as an example, the historical data show that in the long run there is a high level of uncertainty of future expenditures in relation to GDP, while per capita income has a significant impact in the short run, through the analysis of time series. (Lee and Timothy, 2002)

The internal capacities of a health system itself play a special role in forecasting. By analyzing costs, without looking at the impact of macroeconomic factors, and by using historical operating cost data on the example of Greece, the regression models can be successful in the prediction of future costs for improving health care and the necessary financial resources for maintaining the health structure. (Zaza and Pantelis, 2022) A survey including U.S. contiguous states confirmed that regression models can be used to predict costs in real time. (Ghysels et al., 2022)

Forecasting in healthcare financing involves predicting the future financial needs and expenditures of healthcare facilities based on historical data, trends and expected changes in the healthcare environment. This process helps policy makers and decision makers to prepare for future financial scenarios and allocate resources appropriately. Further through the paper, the authors explore the possibility of applying machine learning in cost forecasting using the example of the military healthcare system of the Republic of Serbia, as well as identifying the machine learning model that would be best suited for data in the observed period.

Cost analysis of the military healthcare system with future cost projection

Healthcare costs account for a large share in total public expenditure and continue to rise. What is characteristic is the trend of higher health spending in developed countries compared to that of the economically disadvantaged ones, and that the public share in financing healthcare is much lower in low and medium developed countries than in wealthy ones. (Ortiz-Ospina and Max, 2017)

Bearing in mind the above, the authors point out the importance of rational management of public finances as well as that opportunity costs reduce the development possibilities of other branches in the economy, which calls for proper allocation of scarce resources. In order for an entity to make an economically justified and effective allocation of available funds for the purpose of achieving defined results, it is necessary to foresee possible scenarios within the planning process and provide policy makers with information for making the most expedient decisions.

Military healthcare of the Republic of Serbia constitutes an important segment of national security. Hence, forecasting the amount of financial resources needed for equipping military healthcare facilities, i.e. investments in military healthcare, is of crucial importance for proper planning. In the further analysis of the military health system costs, we used publicly available data from reports covering the period from 2011 through 2023.

In this paper, we will analyze the impact of economic and security factors on investments in the military healthcare system of the Republic of Serbia using machine learning. The main goal of the research is to explore the possibility of prediction through the analysis of known machine learning models and selection of those that will provide the most accurate data and offer the most accurate information with a view to helping decision makers in investment forecasting and optimization of the proper allocation of scarce resources in the process of allocation planning for the military health system.

This paper is based on the analysis of the gathered data regarding the implementation of the financial plan for the 2011-2023 period as well as on the analysis of the impact of macroeconomic indicators and safety factors on the financing of the military health needs in the Republic of Serbia. The dataset used in the analysis includes a set of variables with the greatest influence on the predicted value, to wit: gross domestic product (GDP), gross domestic product per capita (GDP per capita), GDP growth rate, inflation, allocations for the defense of the Republic of Serbia, allocations for healthcare in the Serbian Army, the presence of health crises and war events in Europe and the world.

All the data collected in the research are used to create models that can predict investments in the military healthcare of the Republic of Serbia. In accordance with the research task, the value to be predicted is investment financing for the needs of the military health system; it is a continuous value, hence it can be inferred therefrom that it is a regression problem.

Accordingly, it is necessary to choose a machine model that will produce the best results for the given problem. For this research, we used the Scikit-learn library of existing regression models. The dataset was divided into two sets, one for training and one for testing the obtained models. We used 70% of the data for training and 30% of the data for testing. Following the training and testing of the model, the mean squared error (MSE) and the mean absolute error (MAE) were taken as metrics for selecting the best model.

The data were prepared and saved (in the Baza.csv table) in a format suitable for loading and analysis using the Scikit-learn library. The paper will present only the key parts of the code and visualization, including diagrams and results relevant to the analysis.

The first step in the analysis of the mutual influence of the processed data is the correlation matrix which provides insights into the influence of all the attributes of the dataset on the dependent variable, the investments in the military health system. Based on the presented correlation matrix (**Figure 3**), it can be seen that there is a strong positive impact on investments in military health system, greater allocations from the defense budget for the needs of the health system and crisis situations, both health and war related. On the other hand, all other variables in the dataset show a slight negative impact on investments.

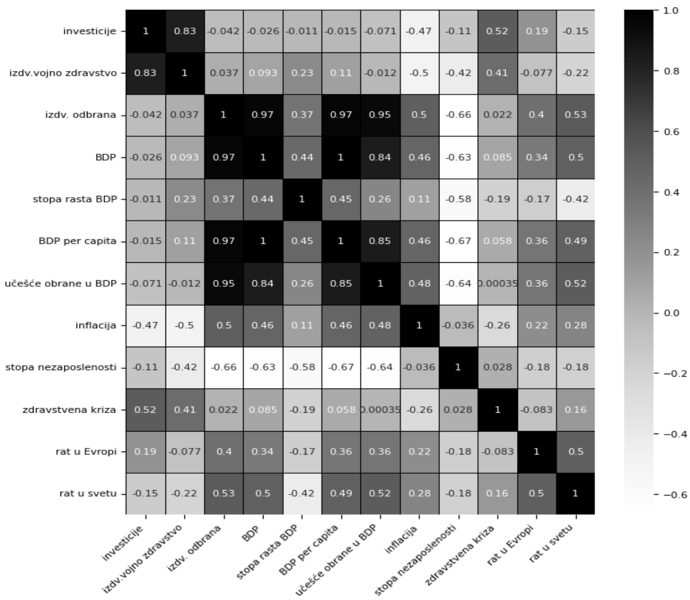

Figure 3. Correlation matrix
Source: Authors

Figure 4 illustrates the scatter diagrams with a regression line, where the impact of each of the variables on investments in the military healthcare system in the Republic of Serbia in the observed period can be viewed.

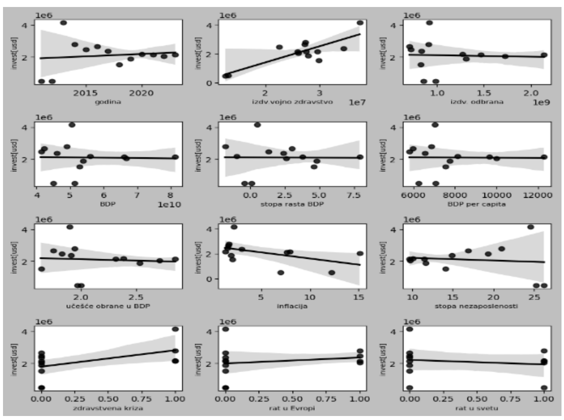

Figure 4. Diagram of the impact of the collected data on investments in military healthcare
Source: Authors

In the process of data preparation, a preliminary analysis was performed given that the data are of different order of magnitude. Data need to be scaled or normalized so that all attributes can have a similar effect on the model and improve the stability and efficiency of learning. In order to determine the optimal data preparation, by finding a model that provides data with the best metrics in the preparation process, data preparation was carried out in two ways. The data was treated using the built-in MinMaxScaler and StandardScaler data preprocessing functions.

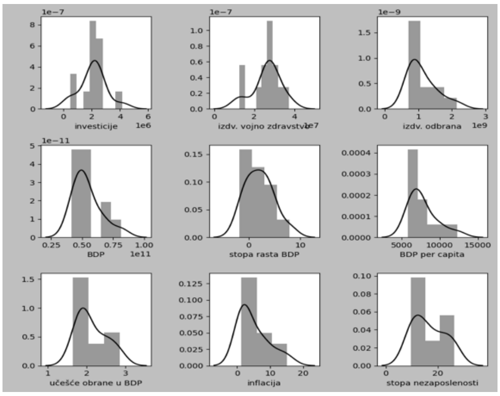

Figure 5. Visualization of input data distribution
Source: Authors

In the process of data preparation, we first drew histograms that demonstrate the distribution of the available data being observed in **Figure 5**.

Based on the presented diagrams, it can be inferred that all data have a normal distribution. Further, Shapiro-Wilk was also used to confirm the normal distribution of data. The test results are shown in **Table 1**. This test confirmed that all numerical data have a normal distribution, except for categorical data.

Table 1. Data distribution

Column	Shapiro-Wilk stat	p-value	Norm. distrib.
Year	0.96	0.83	YES
Investments	0.91	0.19	YES
Military healthcare allocations	0.88	0.09	YES
Defense allocations	0.85	0.05	YES
GDP	0.88	0.08	YES
GDP growth rate	0.96	0.87	YES
GDP per capita	0.86	0.04	NO
Share of military spending in GDP	0.90	0.17	YES
Inflation	0.78	0.01	NO
Unemployment	0.89	0.10	YES

Source: Authors

Further, the data were prepared for training the model using the MinMaxScaler function from the Scikit-learn library. The MinMaxScaler function performs normalization of data transforming thereby values into a predefined range [0,1] (**Figure 6**).

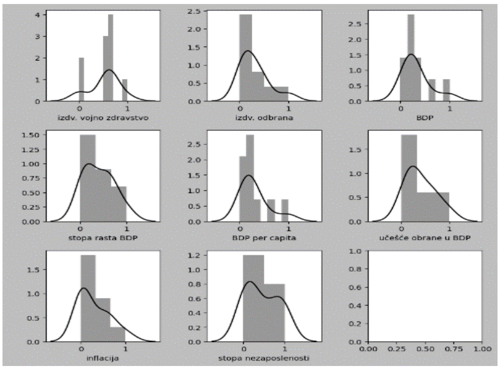

Figure 6. Visualization of data distribution following normalization (MinMaxScaler)
Source: Authors

Mathematical transformation formula:

X_scaled = (X - X_min) / (X_max - X_min)

The StandardScaler function from Scikit-learn library was used to standardize data transforming the value with a mean of 0 and a standard deviation of 1. This procedure enabled the data to be normalized, to be distributed around the mean value and to have a uniform variance (**Figure 7**).

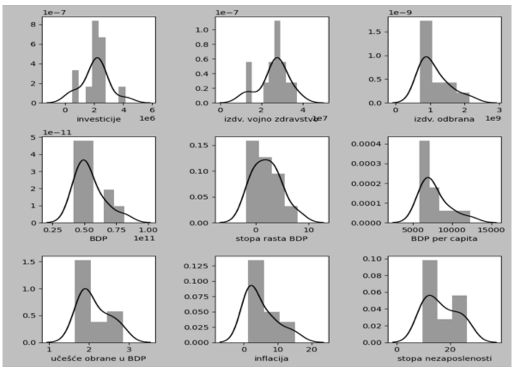

Figure 7. Visualization of the data distribution following standardization (StandardScaler)
Source: Authors

Mathematical transformation value:

X_scaled = (X - μ) / σ

- X – original value
- μ – mean of the dataset
- σ – standard deviation of the dataset
- Xscaled– transformed value

Training and evaluation of the model

Ten different regression models that are part of the standard machine learning libraries were tested. The evaluation goal was to identify the most accurate model to predict investments in the military healthcare of the Republic of Serbia. The mean absolute error (MAE) and mean square error (MSE) metrics were used to evaluate the performance.

Description of all ten tested regression models and their characteristics is given below:

1. LinearRegression() – classical regression analysis, uses least squares to fit a model;
2. SVR(C=1,kernel='linear') – Support Vector Regression with a linear kernel, works well on linear problems;
3. SVR() – uses the RBF default kernel, which allows the model to capture non-linear relationships in the data;
4. RandomForestRegression() – a model based on a set of decision trees, robust and good for complex data;
5. DecisionTreeRegressor() - a regression decision tree, prone to overfitting if not controlled;
6. ExtraTreeRegressor(random_state=0) – similar to DTR, but it uses a random strategy to select the split point which can improve generalization capability;
7. BaggingRegressor(estimator=ExtraTreeRegressor (random_state=0), random_state=0) – method based on ETR, improves model stability by reducing variance;
8. KNeighborsRegressor() – a model based on the nearest neighbor methodology, suitable for local patterns in data;
9. Ridge() – linear regression with L2 regularization, reduces model overfitting;
10. Lasso() – linear regression with L1 regularization, selects important features by reducing coefficients of less significant variables to zero.

The training of regression models in this research was carried out on the dataset in the time interval from 2011 through 2023. The models were treated with normalized, and then with standardized data. After training, model evaluation metrics including MAE (Mean Absolut Error) and MSE (Mean Squared Error) were calculated.

The results of model training with normalized data show the value of MAE and MSE for ten different models trained after standardization (**Figure 8**).

The best results were obtained in the analysis for the KNeighborsRegressor() model, with the following values:

MSE = 36,791,701,339.74

MAE = 174,230.06

The result shows that the prediction using this model will produce the most accurate data compared to other tested models when normalization is used to fit the data. When data are standardized, the best results are given by the SVR(C=1,kernel='linear') model.

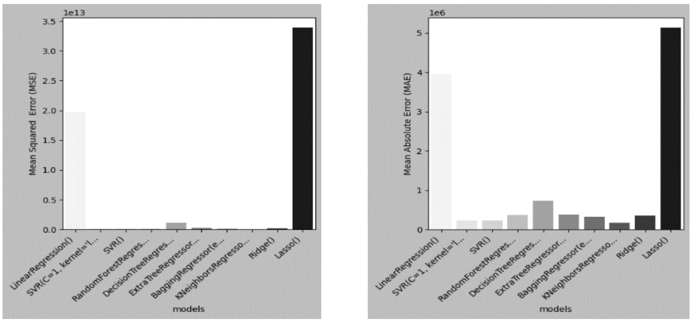

Figure 8. Visualization of the normalized MAE and MSE results
Source: Authors

Figure 9 shows the results of MAE and MSE analyses on ten different models with standardized data. The obtained values of the most accurate prediction model, SVR(C=1,kernel='linear'), are:

MSE = 56,933,668,392.38

MAE = 218,292.07

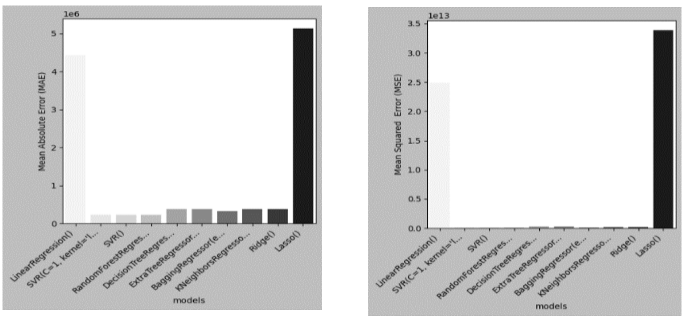

Figure 9. Visualization of the standardized MAE and MSE results
Source: Authors

The comparison of the obtained results achieved by the models by training with normalized and standardized data made it possible to compare the performance of ten models based on the obtained MSE and MAE values. The research results provide a clear assessment of different approaches to data preparation and, in this regard, single out the most acceptable prediction models.

Table 2. Comparative results of MSE and MAE analysis

Model	Data preparation	MSE (Mean Squared Error)	MAE (Mean Absolute Error)
KNeighborsRegressor()	Standardization	36,791,701,339.74	174,230.06
SVR(C=1,kernel='linear')	Normalization	56,933,668,392.38	218,292.07

Source: Authors

Analyzing the dataset used in this research, the two regression models KNeighbors Regressor() and SVR (C=1,kernel= 'linear') stand out in terms of the quality of prediction (**Table 2**).

Conclusion

In this paper, the authors observed that military expenditures, i.e., allocations for military healthcare of the Republic of Serbia, are strongly affected by factors indicating the level of economic development, GDP and GDP per capita. Events such as the occurrence of major crises or health threats like large-scale epidemics or pandemics similar to Covid 19 have a moderate impact on the costs of military healthcare in the Republic of Serbia. Unemployment has an inversely proportional impact on military spending, which implies a consequent impact on military healthcare costs which are strongly related to the allocations for the defense of the Republic of Serbia.

Risks thus defined can assist policy makers and decision makers in predicting scenarios from which to draw necessary information for defining future needs in health policy, i.e., in preparing certain financial and material reserves for intervening in crisis situations. By applying machine learning through defining the impact of macroeconomic factors, the future spending level can be predicted. In this paper, the research selected the KNeighbors Regressor() model as a model which will give the most accurate prediction compared to all other analyzed models.

The application of artificial intelligence and machine learning models in planning military spending and costs for military healthcare of the Republic of Serbia would raise the quality of business decision-making for decision makers. Based on the above, we can infer that the level of development of modern techniques and tools does not correspond to the level of use of artificial intelligence in the field of financing public expenditures in the Ministry of Defense of the Republic of Serbia, but the implementation thereof would offer a new dimension for more efficient management of limited resources.

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MODEL MAŠINSKOG UČENJA ZA FINANSIJSKO PROGNOZIRANJE NA PRIMERU VOJNOG ZDRAVSTVA

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Apstrakt

Predviđanje budućih događaja kroz analizu istorijskih podataka predstavlja izazov za donosioce odluka. U ovom radu autori istražuju mogućnost primene mašinskog učenja rešavanjem regresionog problema za predviđanje troškova vojnog zdravstva u Republici Srbiji iz vremenskih serija podataka. Cilj ovog istraživanja je da se utvrde mogućnosti korišćenja veštačke inteligencije u finansijskom prognoziranju, kao i da se na osnovu rezultata istraživanja odabere najpouzdaniji model koji će, uzimajući u obzir odnose između istorijskih podataka subjekta planiranja i tržišnih ekonomskih uslova u posmatranom periodu, pružiti relevantne podatke za buduće odluke.

Ključne reči: *Prognoziranje, upravljanje, odbrana, zdravstvo, mašinsko učenje.*

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