PROJECT RESARCH ARTICLES
Project: ORCA-LAB and COST CA 19130
Corporate Governance
Original paper

TOWARD STOCK PRICE FORECASTING ON NEWLY ACQUIRED BELEX DATASET

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Abstract:

Currently there is a lot of research with the aim of applying machine learning in stock price prediction as one of the challenging trends in fintech. Fintech helps to other stakeholders to make better/optimal financial decisions which will improve their wealth and satisfaction. In this paper, the first steps in examining the potential application of basic machine learning algorithms for the prediction of stock prices on the Belgrade Stock Exchange (BELEX) are presented. The results showed that future research is needed to increase dataset and improve quality of data in order to adapt modern and more advanced machine learning methods to achieve higher accuracy in forecasting stock prices. The additional value of this research is the database that combines data from the BELEX, indicators of the company's success and economic parameters of Serbia's growth in the period from 2010 to 2022 and is the basis not only for this but also for future research.

Keywords:

stock price forecasting, machine learning, linear regression, support vector regression, multi-layer perceptron.

1. INTRODUCTION

Contemporary, the fintech topic is on the high interest of different stakeholders including industry and academia. There are different definitions of fintech based on the different contexts and across countries, while the common point is the way of creating the term. The term comes from the first three letters of the words "financial" and "technology" (Schueffel, 2016). Moreover, fintech is defined by the Financial Stability Board FSB as "technology-enabled innovation in financial services that could result in new business models, applications, processes, or products with an associated material effect on the provision of financial services."(IMF, 2022) According to Kagan (2023) of fintech "refers to any application, software, or technology that allows people or businesses to digitally access, manage, or gain insights into their finances or make financial transactions." Jović et al. (2019) and Jourdan et al. (2023) fintech is the name used for companies or new financial industry that develop or use the latest information technology in order to improve financial services and activities or to introduce new one. Furthermore, the term mainly connects with companies that implement information technology (IT companies) services to banks and other financial institutions (IMF, 2022). Moreover, Alt et al. (2018) stressed that fintech is revolution that had evolved from offline, hierarchical, process-oriented organizations to digital, agile, customer-centric system and stated. Complementary development of fintech will require cooperation between academia and industry (Jović et al., 2019).

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DOI: 10.15308/finiz-2023-154-161

Fintech has been applied to many areas of finance. Some of them are (Jourdan et al.,2023; Kagan, 2023; Lagani &Ravishankar, 2022; IMF, 2022; Allen et al., 2021;):

1. Payments - execution of /instant/ payment orders, internet and mobile payments (or e-money), personal finance, online identification, other important innovations;
2. Deposit and lending - Peer-to-peer (P2P) lending platforms which allow individuals and small business owners to receive loans from an array of individuals who contribute microloans directly to them; credit scoring;
3. Insurtech - is an abbreviated term for insurance technology and refers to innovative technologies and new digital tools developed to optimize the performance of insurance companies (International Association of Insurance Supervisors 2017 in IMF, 2022).
4. Other financial services: capital raising, investment management, and market provisioning (do not require amendments in the statistical methodology); in addition, big tech companies may also be providing financial services enabled by technologies. Accordingly, applications robo-advisors and wealth management, investments (to buy and sell stocks and/or and crypto currency from mobile device, often with little or no commission); Crypto apps, including wallets, exchanges, and payment applications, allow you to hold and transact in crypto currencies and digital tokens (like Bitcoin and non-fungible tokens /NFTs/).

According to the World Bank (2022) and Lagani & Ravishankar (2022), most research considers different forms of financial intermediation between different parties. Also, it can be noticed that fintech helps other stakeholders to make better i.e., optimal financial decisions, which will improve their wealth and satisfaction. In accordance with the definition of fintech, it means that new technologies, such as machine learning/artificial intelligence, predictive behavioral analytics, and data-driven marketing, will take the guesswork and habit out of financial decisions (Kagan, 2023; Barjaktarović et al., 2020).

To investigate the potential use of machine learning as the new technology for supporting financial decision making, this research tries to test the existing appropriate model for financial market data forecasting. This research is in line with the common trend of using machine learning tools in fintech applications, but due to the aim to enhance local knowledge; in the focus is a model for predicting the prices of securities on the Serbian capital market. In this way, this research should contribute to the further development of the local financial market, especially in terms of capital market and trading with securities, as the Serbian Government recognized these tasks as highly important in future period.

The Serbian state is awarded that it should development of financial market should be improved with application of appropriate measures. Accordingly, Serbian Strategy of industrial policy from 2021-2030 is defined as one of key challenges development of alternative financing for SME's (Small and Medium Enterprises) and innovative start-ups (10th ranked). Moreover, as special answer to the implementation of the Strategy, it prescribes increasing the availability of financial instruments for digitization and innovation in industry (1.4). The adopted Serbian Program of Economic reforms from 2023-2025 in the area of structured reform identified as one of the three crucial challenges for competiveness and inclusion growth is improving environment favorable for investments. The capital market in the Republic of Serbia (RS) is not sufficiently developed and does not succeed into a good extent they fulfill their main function - efficient financial allocation resources of savings and investors towards the development of companies. It is widespread traditional financing through banking products (loans based on collected deposits), and the largest obstacles to the development of the capital market in RS are insufficient financial education of the population regarding the possibilities and risks of investing free funds into various financial instruments leading to a dominant orientation towards savings as the simplest form of investment, insufficiently developed economic awareness companies on the possibility of financing regular operations and research and development through the capital market, as well as an inadequate supply of domestic financial instruments available to investors. The Serbian Strategy for development of capital market from 2021-2025, the Action plan for the execution of the Strategy from 2021-2023, and new Law on Capital Market (2021) represent the basis for promotion of the Serbian capital market in the coming period, creating conditions for the use of a wider one spectrum of financial instruments by the private sector, while at the same time reducing the dependence of SME's on banks' financing and state subsidies, which makes a significant contribution to the acceleration of economic growth, increasing the number of jobs and additional support for investments in innovative industry.

This research is part of the ORCA-LAB project, funded by the Serbian Scientific Fund (ORCA-LAB, 2023). The project is about designing an all-Optical Reservoir Computing Architecture (ORCA). It includes one task in which, unlike standard synthetic tests for performance measurement of the optical neural network, real data should be used. As the implementation of neural network in photonic devices is out of the scope of this paper, only two fundamental characteristics of optical neural networks are stated here, the speed and very low power consumption, just to demonstrate their computational significance in the future.

For the testing, a financial dataset for BELEX was created, and in this paper, it will be described in brief as one of the contributions for the ORCA-LAB project, together with results obtained using the standard machine learning models. These results will be a starting point for future research and also a baseline for testing ORCA's models.

The research consists of 4 chapters. The Introduction is the first chapter. The Methodology is presented in the second chapter. The third chapter represents Research Results. The Conclusion is the last chapter.

2. METHODOLOGY

As it was stated in the introduction, this research is related to the following tasks of the ORCA-LAB project: 1) collecting of the data related to the: a) financial characteristics (first of all financial statements) of privately owned companies whose securities – shares are subject of the trade on BELEX, b) data related to the securities such as price of securities, volume of trading, BELEX, etc., c) macroeconomic indicators of RS (such as gross domestic product/GDP/inflation, unemployment, etc.) 2) fundamental and technical analyses for evaluation of securities (Jeremić & Terzić, 2019), 3) proposal of the model for predicting price of shares subject of trade, 4) training and testing of proposed model. The source of information is based on previously mentioned financial datasets, available open from International Monetary Fund (IMF) Data, BELEX, and Business Register Agency /BRA/ (financial reports) and received from business partner Cube Team Belgrade.

As starting point in the moment of preparing documentation for the project (06/30/20) was that:

(I) relevant period for training and testing would be the period of 2010-2022, with making the distinction between the period before 2021, and after 2021; After the collecting data it was concluded that there three different financial reporting standards: 1) 2010-2012, 2) 2013-2020, and 3) 2021-today. So the authors of the research decided to take into the consideration period from 2013 to 2020. Furthermore, it is decided that period 2012-2019 will be used for training, and year 2020 will be used for testing.

(II) Starting number of companies whose securities were subject of trade used to be 53; After the collecting data it was concluded that there is 24 companies (30 including different financial intermediaries which have specific reporting standards) which have all necessary data for comparison in defined period of time, especially in the terms of continuity in trading with securities.

Technical indicators which were taken into consideration are: 1) average (AVG) rate of change – due to the fact that there are not significant movements on daily level (AVG monthly price vs previous), 2) moving average (SMA) – on 50 (SMA 50) and 10 days (SMA10), 3) Bollinger bands (BB; BBLOW – indicating the lower band, and BBUP – indicating the upper band) – on 50 and 10 days. On the basis of existing data it was calculated Total Value Traded (TVT). It is supported with facts that: 1) Serbian capital market isn't sufficiently developed and it is exposed to high political risk, as component of country risk, which is evident in the weak (or zero) or dramatically high trading in particular periods of time; 2) insufficient amount of information for comparison between analysed companies or short time series comparing to the defined period of analysis.

Targeted value is average monthly change in price in January next year, due to facts that: 1) a) in RS first seven days of January are not working days; what more production companies usually do not work until 14th of January. So, many companies decide to invest available cash into short term investment alternatives on 31st of December, and withdraw (convert) it into the cash in the first half of January. b) currently collected and prepared data based is set for January (existing research of Ivanova et. al, 2018, confirmed that 80% of confident in stock price predicting is possible in January especially in the first seven days of the months in the case of oil trading on global market) and the researches' aim to test is it applicable at all and if so the data base will be expended to incorporate other months/periods of the year; 2) Existing research for Serbian capital market confirmed that applied machine learning models: a) LS-SVM and SVM are suitable for short term stock market trend prediction (Marković et al, 2014; Marković et al., 2014a), and b) neural networks can be useful for stock market trend prediction (Kalinić et al, 2012) especially if it is taken in consideration specific characteristics of emerging markets (Ralević et al., 2013).

So, on the tested databases consist of 4 set of information (further the dataset), which can be split into two groups in terms of:

1) comparable financial reporting standards implemented;

a) companies in real sector (24) with items from financial reports (expressed in form of AOP's item /automatic data processing/), calculated relevant performance and market value ratios, size of the company, number of employees, macroeconomic indicators, calculated mentioned technical indicators and their descriptive statistics (MIN and MAX values, AVG, CV – coefficient of variation; SD – standard deviation);

b) Additionally included financial intermediaries (in total 30) without AOP's items including macroeconomic indicators, and calculated mentioned technical indicators and their components;

2) Period of analysis which includes: a) last quarter of the year (Q4), b) whole /one/ year; in the terms of calculated change in AVG price between two months.

So, both groups of companies have sets which include Q4 and 1 year, resulting with numbers of features that are shown in Table 1.

As this is initial study and should establish basic pipeline and baseline results for future investigation of using some newer or more complex machine learning models for stock price prediction, it incorporates three standard and easy to implement algorithms, linear regression (LR), support vector regression (SVR) and multilayer perceptron (MLP). LR is linear and the simplest ML method to understand, yet sometimes sufficient for a lot of different prediction tasks. SVR and MLP were chosen as two very common and robust algorithms that can handle both linear and non-linear dependencies in the data. Also, while the choice of algorithm depends on the specific problem and data, still SVR and MLP are among the most common used standard machine learning algorithms for stock market forecasting (Kumbure et al., 2022).

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the observed data. It seeks to find the best-fitting line (or hyper plane in higher dimension space) that minimizes the difference between predicted values and actual data points. Linear regression is commonly used for predictive modelling (Maulud & Abdulazeez, 2020).

Support Vector Regression (SVR) is a machine learning technique used for regression tasks, which means predicting a continuous output variable based on input features. SVR extends the principles of Support Vector Machines (SVM) to regression problems. It works by finding a hyper plane (or multiple hyper planes) that best represents the relationship between the input variables and the target variable while minimizing the prediction error. SVR aims to fit the data within a specified margin of error, which is controlled by a parameter called the epsilon (Smola & Scholkopf, 2004). SVR can handle non-linearity in the data through the use of the kernel trick, which allows SVR to implicitly map the input data into a higher-dimensional feature space where a linear relationship can be established. In the new space, the data may become linearly separable or exhibit a more favourable linear relationship. To improve accuracy, SVR uses regularization parameter C to control the trade-off between achieving a smaller margin (which reduces model complexity) and minimizing the prediction error. A smaller C allows for a larger margin, potentially leading to a smoother, simpler model, while a larger C emphasizes fitting the training data more closely.

And MLP is a type of artificial neural network with multiple layers of interconnected neurons, including input, hidden, and output layers. Each neuron in an MLP is a mathematical function that takes weighted inputs, applies an activation function, and passes the result to the next layer. MLPs can be used for non-linear regression, where the input layer matches the number of input features and an output layer with a single neuron for single value prediction. To introduce non-linearity into the model activation function must be non-linear and the most common chose is Rectified Linear Unit (RELU) or sigmoid (Hornik et al., 2004).

The obtained dataset contains a high number of indicators and for robust prediction and to prevent over fitting as to improve accuracy reduction in number of parameters is the first step prior to train the algorithm. Usually, the most common algorithm for dimension reduction is Principal Component Analysis (PCA), but it projects original vector space to low dimension one finding the new set of basic vectors, which contains most variability in the data. Although, PCA is effective in reducing dimension of parameters, the new coordinates of feature vector are delivered for original ones, which means that it not easy to understand what they represent and how to explain them from the point of economic theories. As it is stated in previous paragraphs fintech should improve decision making, but the logic behind that theory should be explainable, and for that reason, dimension reduction is achieved using backward elimination algorithms, which keeps the original parameters that contains most of information, and ensure that the resulting model remains transparent and comprehensible to non ML experts. Backward elimination involves iteratively removing less significant features from a dataset to improve model performance and reduce computational complexity. The process typically starts with all available features and sequentially eliminates one feature at a time, assessing the impact on model performance using a chosen criterion (e.g., p-values or cross-validation scores). The process continues until no further improvement in performance is observed, resulting in a subset of the most relevant features (Pierna et al., 2009). All code was written using Python programming language and appropriate libraries like sklearn, seaborn, stats models and similar.

In this study, Root Mean Error Square (RMSE) was used as a metric for comparing three stated algorithms as one of the most common performance indicators for the regression model. Also, in the acquired data, the value zero is several times present as a target value, which means that the price will be the same on the 31st of December and 14th of January next year. When the target value is zero, it is impossible to calculate the relative error.

3. RESEARCH RESULTS

As was described in the previous section, the first step was parameters reduction. Of course, before the implementation of backward elimination algorithms, prediction using the complete set of indicators was performed to investigate how the prediction algorithm benefits from the parameters reduction process, Table 1.

Backward elimination was conducted on each dataset, and the resulting sets of features for each database are shown in Table 2.

Tables 1 and 2 show that the set of features that contains the most information depends on the data present in the dataset. As expected the inclusion of data from financial reports of 24 companies' results in a different list of important features. In accordance, with it for investors in shares of those companies are becoming more important items from financial reports (i.e. business success), such as long and short term financial investments, and paid and received advance payments. The smallest error is for the LR and with a reduced feature vector, but there is a very high RMSE with extended data set when LR is used. A possible reason for the very high RMSE with the extended database can be the small database and some outliers in the feature vector, which are much better handled by SVR or MLP. When the number of features is reduced to 10, improvement for LR is significant. Also, there is some improvement for SVR and MLP.

The next step in this experiment was to investigate further improvement as it was recognized that using differentiated data can significantly improve the RMSE for some ML algorithms (Schmid et al., 2023), and an additional tests were performed with the differentiated data. The differentiated data further reduce dataset, the data for starting year must be removed from dataset as each differentiated parameter represents difference between value of that parameter in that and previous years. Tests were conducted with both a full set of parameters and only 10

Table 1. RMSE for 3 ML algorithms trained with full feature vector (LR, SVR, MLP) and reduced feature vector (LR_10, SVR_10, MLP_10), where 10 represents the number of coordinates in the feature vector. Train and test were performed with four different dataset versions, with other feature vectors but the same target value.

MLmethod Dataset	No. of features	LR	LR_10	SVR	SVR_10	MLP	MLP_10
No_ratios_Q4	41	0.162	0.144	0.183	0.145	0.184	0.142
No_ratios_1Year	50	0.171	0.139	0.160	0.152	0.155	0.139
Ratios_Q4	313	19.77	0.171	0.117	0.108	0.188	0.128
Ratios_1Year	322	15.48	**0.103**	0.132	0.113	0.180	0.150

Source: Author's calculations on the basis of dataset described into the Methodology chapter.

Table 2. Set of features that contain most of the information for each database. The maximum number of features was set to 10.

Dataset Feature	No_ratios_Q4	No_ratios_1Year	Ratios_Q4	Ratios_1Year
Feature 1	Change in AVG price Dec-Nov	Change in AVG price Dec-Nov	Change in AVG price Dec-Nov	Change in AVG price Dec-Nov
Feature 2	CV SMA 50	Change in AVG price Apr-Mar	AOP0033	Change in AVG price Nov-Oct
Feature 3	MAX BBLOW 50	CV SMA 50	AOP0050	AOP0029
Feature 4	AVG BBUP 50	STDEV SMA 50	AOP0062	AOP0065
Feature 5	CV SMA 10	CV TVT	AOP0422	AOP0422
Feature 6	AVG SMA 10	CV BBUP 50	AOP0450	AOP0461
Feature 7	STDEV SMA 10	STDEV BBUP 50	AOP3028	AOP1026
Feature 8	CV BBLOW 10	CV SMA 10	MAX SMA 50	AOP3035
Feature 9	AVG BBLOW 10	AVG SMA 10	CV SMA 10	CV BBLOW 50
Feature 10	STDEV BBLOW 10	MIN BBUP 10	CV BBLOW 10	CV SMA 10

Source: Author's calculations on the basis of dataset described into the Methodology chapter.

with the most informative, which were selected with a backward elimination algorithm, Table 3.

Table 4 presents the most informative parameters for each dataset. It can be noticed that the data from financial reports is prevalent in the dataset of 24 companies in both period of times.

Tables 3 and 4 showed that with differentiated data, reducing the number of parameters can significantly improve RMSE, especially for LR in some cases. However, this variation in results demonstrates that this small dataset is insufficient for accurate forecasting of stock prices, especially for undeveloped stock markets like Serbian one. It might seem that a linear model is more appropriate for this dataset, but higher RMSE for SVR and MLP can be a consequence of the lack of data, as nonlinear models require more data for training. Next, number 10 is chosen as it was considered that ten features might be sufficient for improving accuracy, but this must be checked with hyper parameters tuning. To validate all stated, a bigger dataset is required.

4. CONCLUSION

This research, at the first, described a new dataset that was collected for analyzing the Serbian stock market and to investigate possible use of ML tools in forecasting of stock prices on BELEX. The benefit of this new dataset is not only for the ORCA-LAB project, but for others research that can provide some new inside of BELEX and to improve development level of Serbian Stock Market. In addition, it was shown that standard machine learning tools can provide forecast of stock prices with RMSE of 0.043 % in the best case. This must be taken with caution as small data can be insufficient for model training. Also, as it was mentioned in the introduction, with the development of Serbian Stock Market, it is expected that the stock price will be less influenced with some other factors, such as market sentiment. For future research additional data will be prepared as data for developed market such as United States of America and Germany, and then hyper parameter tuning will be undertaken together with use of some more advanced ML models for forecasting of stock prices.

Table 3. RMSE for full and reduced set of features.

MLmethod Dataset	No. of features	LR	LR_10	SVR	SVR_10	MLP	MLP_10
No_ratios_Q4	41	0.192	**0.043**	0.260	0.356	0.169	0.178
No_ratios_1Year	50	0.182	0.184	0.150	0.215	0.270	0.177
Ratios_Q4	313	0.172	0.077	0.064	0.074	0.158	0.138
Ratios_1Year	322	0.188	**0.081**	0.065	0.087	0.143	0.108

Source: Author's calculations on the basis of dataset described into the Methodology chapter.

Table 4. Set of features that contain most of the information for each database when differentiated values were calculated. The maximum number of features was set to 10.

Dataset Feature	No_ratios_Q4	No_ratios_1Year	Ratios_Q4	Ratios_1Year
Feature 1	Unemployment rate	Change in AVG price July-June	AOP0047	AOP0047
Feature 2	CV SMA 50	Change in AVG price Mar-Feb	AOP0056	AOP0056
Feature 3	STDEV SMA 50	Unemployment rate	AOP0068	AOP0068
Feature 4	CV TVT	CV SMA 50	AOP0417	AOP0417
Feature 5	MAX TVT	STDEV SMA 50	AOP0418	AOP0418
Feature 6	AVG TVT	CV TVT	AOP1020	AOP1020
Feature 7	MAX BBUP 50	MAX BBUP 50	AOP1021	AOP1021
Feature 8	CV SMA 10	CV SMA 10	AOP3004	AOP3004
Feature 9	STDEV SMA 10	STDEV SMA 10	AOP3033	AOP3033
Feature 10	MAX BBUP 10	MAX BBUP 10	AOP3034	AOP3034

Source: Author's calculations on the basis of dataset described into the Methodology chapter.

In additional conclusion is that further development of Serbian capital market should be supported by effective and efficient administrative procedures and accompanied activities in order to speed up process of issuing securities, in order to increase volume of trading. Furthermore, permanent financial education of all population should be implemented. Moreover, good business practices should be shared in order to attract new investors on Serbian stock market.

5. ACKNOWLEDGMENT

This research study: 1) has been supported by the Scientific Fund of the Republic of Serbia, Program Ideje 2022-2024 project no. 7750121. "All-Optical Research Computer Architecture based on Laser Bistability" (ORCA-LAB); 2) is part of the project COST CA19130 - Fintech and Artificial Intelligence in Finance - Towards a transparent financial industry.

6. LITERATURE

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