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Using Machine Learning for Short-term Capital Investment in the Polish Stock Market

ABSTRACT

Objective: The main purpose of this article is to assess the potential implications of machine learning in making investment decisions when investing capital in stock markets. The analysis carried out focuses on the so-called day-trading, i.e., investing for very short periods of time, covering only one stock market session. The hypothesis adopted by the authors is that the use of machine learning can, under certain conditions, effectively contribute to attractive rates of return for players making short-term investments.

Methodology: The study used Microsoft Machine Learning Studio's Azure tool to enable machine learning-based computing. Thanks to this publicly available computing platform, any potential interested investor can create a model and test it. An important assumption of the described study is the adoption of a short investment horizon for the calculation. The calculations used data from five stock market sessions, so that the most recent data is taken into account.

Findings: Based on the calculations, the authors observed that the methodology adopted for applying machine learning to investment decision-making can be a valuable tool to help make short-term investment decisions.

Value Added: The research made can be used in a practical way by investors when they transact in the stock market.

Recommendations: It should be noted that the presented method requires updating the data on which the predictions are made every time. Further in-depth research is also needed to determine the impact of the number of financial instruments on the effectiveness of the learning process.

Key words: stock market, investment strategies, machine learning, capital market, artificial intelligence.

JEL codes: E 22, E 44, G 11, G 31

Introduction

Modern technology is used in many areas and its influence on shaping human behavior seems to be increasing. One such area is the ability to make investment decisions that will result in the deployment of capital in selected financial instruments. Internet access and modern technology in the day-to-day activities of investors have changed the image of their work considerably from what we observed even 10–15 years ago. For example, stock exchange orders can be placed personally based on various types of brokerage investment accounts allowing the player to view real-time quotations with various technical indicators plotted on the chart, or the possibility to simultaneously view quotations at different time intervals (daily, hourly, or minute chart) and the option to view the order book.

The negative effects of an excess of information reaching the trader from the market can adversely affect objective assessment of market conditions and emotional composure during trading. The solution to this problem may be to use methods that remove the negative impact of information and emotions.

The so-called machine learning is an example of such tools, and their skilful use to support an investor's decision-making processes should help to eliminate the excess information impulses that arise when selecting assets for a portfolio.

This way a trader can obtain a valuable tool for managing cash and financial instruments that differs from the popular techniques used by many players on the market. The application of machine learning can be used for trading on short--time horizons, i.e., during the so-called day-trading.

Given these considerations, the main goal of this research is to explore and assess the applicability of machine learning to investment decisions in equity markets.

The study hypothesizes that the use of machine learning can contribute to a positive return for a stock market player investing within a single trading session.

The analysis undertaken in this way is justified by the fact that the research area of this article does not have an academic study that analyses the use of machine learning by short term investors.

Literature review

The markets for financial instruments have been analyzed many times in terms of their potential for profitable returns and decision-making strategies, but the scope of these studies was of a different nature to that of this paper.

Many of the studies in the area under discussion address the issue of the informational efficiency of equity markets. The first cited one concerned the feasibility of using averages and oscillators, the technical analysis tools commonly used by investors, and the results obtained suggested that these tools were incapable of providing the investor with statistically significant and above-market returns (Czekaj et al., 2001).

A further survey (Szyszka, 2003) comes to the conclusion that the stock market in Poland was not efficient in the first years of its existence. Subsequent years of the stock market, in turn, did not provide grounds to reject the hypothesis of low information efficiency of the market.

Understanding how prices move has been a point of interest for investors practically from the very beginning of the possibility of trading in the securities market. Many years of observing the markets have allowed investors to develop methods that they believe are 'rational'. It is worth paying particular attention to this because in economic sciences, economics and psychology, people try to act rationally, although taking into account the behavior of investors. Over the years, a number of methods have been developed to facilitate investment decisions, the most popular of which are fundamental, technical, and portfolio analysis (Tarczynski, 2001).

Dozens of pieces of information flow into investors every day, and an approach based on their ongoing analysis may prove inefficient (Elder, 1993).

The current market situation, the period adopted for the analyses, and the type of decision-making approach adopted affect the usefulness or uselessness of the study (Anghel, 2015).

Given that modern technology is developing at a rapid pace, there are new opportunities to deal with current difficulties in a number of areas. One of them is the ability to make more accurate predictions about the prices of the financial assets, which can be especially valuable for traders.

In various areas of study and everyday life, the term 'artificial intelligence' is becoming increasingly used, which is a very wide term that describes technology that allows intelligent reactions to external stimuli (Stephenson, 2020).

The term 'machine learning', which is used in research, can also refer to the technology by which a software improves its efficiency without the assistance of a human programmer. Machine learning algorithms can deal with very large numbers of learning data, and artificial neural networks are well used in this field (Stephenson, 2020).

Neural networks are tools for processing large and complex amounts of data. Their structure represents a kind of similarity of elements to the biological nervous system. Nowadays, neural networks are increasingly used in areas where the amount of data and their complexity would be difficult and time--consuming to process with classical data processing methods. Examples of use include the preparation of stock market forecasts, the analysis and evaluation of data from medical and biological research, or the analysis and forecasting of economic data (Rutkowski, 2005).

The terms artificial intelligence and machine learning are commonly used interchangeably, but their exact meaning differs. The first term describes a situation in which a system mimics human intelligence in solving complex problems. The system must, therefore, be able to recognize patterns, as well as analyze and evaluate them; moreover, it must also be able to create new solutions on its own. Machine learning, on the other hand, is a subset of artificial intelligence and its main characteristic is self-improvement based on the data and information it receives. Machine learning uses specially designed algorithms to make information acquisition and analysis processes work (Wodecki, 2018).

Analysis of the use of artificial intelligence in predicting the value of securities has been a topic of interest to researchers for some time. In an analysis of the feasibility of using machine learning algorithms for Bitcoin, in a 2019 publication, researchers identified the prospect of improving the efficiency of price prediction by around 10% compared to traditional methods. This indicates a growing commitment to using modern technology to understand and predict market behavior. However, with the increasing complexity of the cryptocurrency market, continuous improvement and adaptation of analysis methods

is needed to maintain their effectiveness in a dynamic financial environment (Fernandes & Mallqui, 2019).

Similar findings on the advantages of using artificial intelligence were also observed by researchers who limited their research to one company in the portfolio. Their analysis focused on the effectiveness of the monitored machine learning models. The aforementioned study suggests that, even for single assets, significant benefits can be achieved through the use of advanced data analytics techniques (Torres et al., 2019).

In each of the studies cited, machine learning provides an effective tool for solving the problem at hand. In light of previous considerations, the authors have attempted to fill the research gap by conducting the analysis identified in the purpose of this article. This approach demonstrates an understanding of the need to fill existing gaps in the academic literature through proactive research efforts. In addition, this study can further contribute to the body of knowledge on the potential of machine learning in finance.

Methodology adopted in the study

This paper uses the Azure Microsoft Machine Learning Studio tool to enable machine learning-based calculations. It is a widely available cloud computing platform that allows an investor interested in creating a model and testing it to do so. An important assumption of the research performed in the study is the adoption of a short-term investment horizon and, consequently, data from only five preceding trading sessions were deliberately used for the calculations. The rationale behind this approach was the desire to consider only the most recent data.

Assumptions made:

1. The values of the stock exchange indices were used for the calculations: WIG--Banki, WIG-Budownictwo, WIG-Chemia, WIG-Energia, WIG-Górnictwo,

WIG-Gry, WIG-Informatyka, WIG-Leki, WIG-Media, WIG-Motoryzacja, WIG-Nieruchomości, WIG-Odzież, WIG-Paliwa, WIG-Spożywczy.

2. The forecast was based on the closing price at the trading session on 31.10.2023.
3. The calculations used the opening, closing, maximum, and minimum values for the five sessions preceding the session for which the closing value forecast was made, and the opening value from that trading session.
4. Having the historical data indicated in section 3 and the opening value of the selected index from the current session, and having a forecast of the closing value for this session based on the machine learning model, the investor had the opportunity to buy shares of companies included in the selected index on the market after the start of trading at the opening price, or at a price lower than that, if the forecast assumes that the closing value of the index is higher than its opening value and price fluctuations allow it – for simplicity, the opening value was assumed in calculating the effectiveness of the strategy.
5. If the forecast was to close at a lower level than the opening, the investor did not take a position in the market, i.e., he or she did not buy shares that were part of the relevant index.
6. The investor, having bought the shares, sold them at the closing price by placing a corresponding order at the end of the session at the market price.
7. The calculations were made according to two schemes. The first scheme involved teaching the model by taking seven indices chosen randomly from all fourteen, while the second scheme involved teaching the model by taking ten indices chosen randomly from all fourteen.
8. For the sake of simplicity, the commission for orders placed has been omitted.
9. The study was based on a linear regression model.
10. In conclusion, rates of return were calculated for both schemes and forecast error rates: mean absolute error, root mean square error, approximation error, and the coefficient of determination R^2 were also calculated.

Results obtained

By performing calculations based on machine learning, the forecast values for the closing values of the indices for the analyzed session were obtained for a learning set of seven and ten out of a total of fourteen indices, as shown in Tables 1 and 2, respectively. In addition, the error values for the individual forecasts were determined, as shown in Table 3.

Analyzing the results presented in Tables 1 and 2, it is possible to come to a general conclusion that using forecasts allows an investor to take positions in the market and generate a profit, provided, of course, that the conditions for taking a position are met, i.e., according to the forecast the closing value of the index will be higher than the opening value. If this is not the case, the forecast will not be useful, as it indices declines in value, which will not generate a profit during using shares.

In Table 1 showing the results of the forecasts using the learning set of seven indices, positive returns were obtained for each concluded transaction – according to the assumptions for the other cases, the transaction should not be concluded, protecting the investor from loss. Based on the assumptions made, the investor can purchase companies included in the indices: WIG-Banks, WIG--Leki, WIG-Clothing, and WIG-Fuels. The actual daily returns for the indices were 1.21%, 0.30%, 0.03%, and 0.91%, respectively. In the case of the other indices in Table 1, the investor should refrain from purchasing shares of the companies constituting these indices due to the projected closing price at a lower level than the opening price, thus allowing the investor to avoid capital loss.

Table 1. Forecast and actual values for a learning set comprising seven of all fourteen indices

Index Name (1)	Opening Value (2)	Real Closing Value (3)	Forecasted Closing Value (4)	Real Index Change (5) = (3) – (2)	Theoretical Transaction Return (6) = (5) / (2)
WIG-Banki	9478.31	9592.59	9591.48	114.28	1.21%
WIG-Energia	2495.14	2488.92	2492.65	-6.22	-0.25%
WIG-Gry	12478.85	12433.7	12411.31	-45.15	-0.36%
WIG-Leki	2789.77	2798.12	2794.89	8.35	0.30%
WIG-Media	7467.71	7458.91	7457.13	-8.8	-0.12%
WIG-Odzież	7329.84	7331.8	7332.56	1.96	0.03%
WIG-Paliwa	6729.03	6790.42	6786.04	61.39	0.91%

Source: Azure Microsoft Machine Learning Studio.

Table 2. Predicted and actual values for a learning set comprising ten of all fourteen indices

Index Name (1)	Opening Value (2)	Real Closing Value (3)	Forecasted Closing Value (4)	Real Index Change (5) = (3) – (2)	Theoretical Transaction Return (6) = (5) / (2)
WIG-Budownictwo	6203.31	6219.35	6224.86	16.04	0.26%
WIG-Informatyka	4448.44	4458.71	4457.63	10.27	0.23%
WIG-Nieruchomości	3827.24	3803.25	3809.72	-23.99	-0.63%
WIG-Spożywczy	2129.31	2130.91	2131.12	1.6	0.08%

Source: as in Table 1.

Table 3. Forecast error values

Error Name	Error value for a learning set of 7 indices	Error value for a learning set of 10 indices
Average absolute error	0.632107	0.291277
Root mean square error	1.049521	0.475312
Approximation error	0.162752	0.015216
Determination coefficient R2	0.999576	0.999628

Source: as in Table 2.

In Table 2 showing the results of the forecasts using a learning set of ten indices, positive returns were also obtained for each transaction. The investor was able to choose the companies included in the indices: WIG-Construction, WIG--Informatics, and WIG-Food, and the obtained rates of return were, respectively: 0.26%, 0.23%, and 0.08%. In the case of the WIG-Real Estate index, the investor should refrain from purchasing companies included in it to protect the capital from losses.

Table 3 presents the values of selected forecasting and model fitting errors. As we can see, the use of a larger number of indices to teach the model results in lower error values, and the determination coefficient R2 indicates a better model fit.

Conclusions

The results of the calculations presented here indicate that an investor using machine learning-based forecasts of the closing value of selected indices could achieve positive returns by purchasing shares included in the index. This is only the case if the closing forecast indicates a closing value higher than the opening value. If the forecast indicates a closing value lower than the opening value, the investor, to preserve capital, should refrain from buying the shares included in the index in question.

Regarding the initial thesis of the article, it can be confirmed that it has been successfully validated. This confirmation suggests that a machine learning approach can be a valuable tool to support investment decisions over short periods of time. Additionally, these results may encourage further research into the use of advanced data analytics techniques to optimize investment strategies in financial markets.

The advantage of the proposed method is undoubtedly that it removes the investor's emotions and subjective view from the decision-making process, which can occur when using technical analysis tools.

The results obtained undoubtedly provide a basis for further research by the authors, who plan to include the exploration of a larger pool of past data and the modification of the periods of analysis (e.g., intraday, weekly data) in order to assess the effectiveness of the trading operations performed. Such a direction for further analysis may help to better understand the impact of different time frames and amounts of data on the effectiveness of investment strategies.

The Authors are aware that the demonstration of positive rates of return in selected cases does not constitute proof of the effectiveness of the proposed method under all market conditions. This is why the subject of further and extended research by the Authors will be the evaluation of returns in the case of upward, downward, and horizontal trends.

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