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Forecasting Prices of Shares Listed on the Warsaw Stock Exchange Using Machine Learning

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ABSTRACT

Objective: The technology developing before our eyes is entering many areas of life and has an increasing influence on shaping human behavior. Undoubtedly, it can be stated that one such area is trading on stock exchanges and other markets that offer investors the opportunity to allocate their capital. Thanks to widespread access to the Internet and the computing capabilities of computers used in the daily activities of investors, the nature of their working has changed significantly, compared to what we observed even 10–15 years ago. At present, stock exchange orders may be placed in person using various types of brokerage investment accounts, which allow the investor to view real-time quotations which opens up a whole new range of opportunities for investorsIts skillful application during the stock market game can positively influence a player's investment performance.Machine learning is a branch of artificial intelligence and computer science that focuses on using data and algorithms to solve decision-making problems based on large amounts of information. In machine learning, algorithms find patterns and relationships in large data sets and make the best decisions and predictions based on this analysis.

Methodology: The main objective of this paper is to investigate and evaluate the applicability of machine learning for investment decisions in equity markets. The analysis undertaken focuses on so-called day-trading, i.e. investing for very short periods of time, often involving only a single trading session. The hypothesis adopted is that the use of machine learning can contribute to a positive return for a stock market player making short-term investments.

Findings: 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 provides an investor interested in creating a model and testing it. The calculations were made according to two schemes. The first involves teaching the model by taking 50% of the companies randomly selected from all companies, while the second involves teaching the model by taking 80% of the companies randomly selected from all companies.

Value Added: The results from the study indicate that investors can use machine learning to earn returns that are attractive to them. Depending on the teaching model (50% or 80% companies), daily returns can range from 1.07% to even 4.23%.

Recommendations: The results obtained offer investors the prospect of using the method presented in the article in their capital management strategies, which of course requires them to adapt the techniques used so far to the specifics of machine learning. However, it is necessary to note that the presented method requires that each time the data on which the forecast was made be updated..Further research is needed to determine the impact of the number of companies on the effectiveness of the learning process.

Key words: stock market, investment strategies, machine learning

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

Introduction

The real-time quotations allow the player to view real-time stock quotes with various technical indicators plotted on the chart, or to view parallel quotes in different time frames (daily, hourly or in any minute intervals) and the option to view the order book. Another important aspect is the almost immediate access of investors to the news that may influence the course of quotations and stock exchange volatility. This can also have the negative effect of overloading these investors with market information, which in turn can have a negative impact on their cool heads and emotional composure when making transactions. The solution to these problems may turn out to be the use of such tools, which will eliminate the negative influence of large amounts of information and will remove, of course only to a limited extent, the negative influence of emotions on the decision-making process.

An example of such tools can be the use of so-called machine learning, which assists the investor in the analysis of information coming from the market, which will form the basis for assessing the possibility of taking a position in the market. Thanks to the use of this tool, the investor may receive a valuable instrument for managing money and financial instruments, which differs significantly from technical, fundamental or portfolio analysis. The idea of using machine learning in stock exchange trading may boil down to making transactions in very short time horizons covering the duration of a single stock exchange session.

Keeping the above considerations in mind, the purpose of this study is to investigate and evaluate the applicability of machine learning for making investment decisions on stock market. The study hypothesizes that the use of machine learning can contribute to a positive rate of return for a stock market player making short-term investments. The rationale behind the analysis undertaken in this way is that within the scope of this article it is difficult to find academic studies that examine this issue in a comprehensive manner and that consider the application of machine learning to short-term investment decisions.This article contributes to closing the research gap concerning the investigated topic.

Additionally, an important aspect that one should pay attention to is the so-called "market efficiency", i.e., the assumption that it is impossible to obtain a "better-than-market" rate of return by relying on historical information when making decisions to buy and sell financial instruments. In this paper, the authors undertake to evaluate the effectiveness of a machine learning-based investment method in the context of the possibility of obtaining positive rates of return, rather than comparing these rates with control strategies, as is done when studying market efficiency.

Literature review

Stock markets have been analyzed for their efficiency many times before, but the framing of these studies has been of a different nature than in this paper.

A number of studies are relevant to this issue. In terms of efficiency, the first one was related to the evaluation of the use of so-called technical tools (averages and oscillators), and the results obtained indicated that these methods do not give above-average and, importantly, statistically significant rates of return (Czekaj et al., 2001). The other study (Szyszka, 2003) noted that the stock market in Poland was not efficient in its initial phase of development. Also in the subsequent years of the functioning the stock market, there were no grounds to reject the low information efficiency on this market.

Investors, practically from the very beginning of trading on stock exchanges, have been trying to figure out the mechanism by which prices move in such and such a way. Over the years many methods, tools or techniques have been developed that allow taking investment decisions in a "rational" way. It is worth paying attention to this rationality, because on the grounds of economic sciences and psychology man tries to act rationally, although the reality shows unequivocally that not all behaviors meet this criterion.

Over the years many methods have been developed to facilitate investment decisions, among the most popular are fundamental, technical and portfolio analysis. Fundamental analysis seems to be a relatively good solution for investors prepared for quite a long-time horizon of their transactions. Fundamental analysis examines phenomena characterized by duration counted in months, quarters and even years (Tarczyński, 2001).

Technical analysis, another approach facilitating decision processes, is completely unable to keep track of the dozens or even hundreds of pieces of information that constantly flow in from the market, and that can have an impact on the quotes and focuses only on observation of quotation charts, which are supposed to be the basis for forecasting the direction of price changes. Although computer programs and literature provide investors with dozens of indicators, in general, they can be divided into three basic categories (Elder, 1993):

- Trend indicators – the most important of which are moving averages and Moving Average Convergence / Divergence (MACD),
- Oscillators – which include the Relative Strength Index (RSI), Momentum, and Stochastic Oscillator,

- Sentiment indicators – to gauge how optimistic or pessimistic the market crowd is.

Technical analysis is based on several important assumptions:

- the price of a financial instrument discounts everything, i.e., all relevant information about a given stock is contained in it, therefore there is no point in analyzing dozens of pieces of information about, for example, the company which is the subject of our investment,
- history likes to repeat itself, i.e., some characteristic mutual arrangements of prices have a feature of periodical appearance on the chart of the stock,
- the prices move in trends, which means that the price of the financial instrument that interests us may in a certain time horizon have an upward or downward trend or move within the so-called horizon (Murphy, 2019).

Portfolio analysis, the third method supporting decision processes, is a method based on determining risk based onhistorical data concerning quotations and rates of return in order to minimize the risk of transactions when building the portfolio.

The problem associated with the use of technical analysis boils down to the fact that it is not possible to obtain an accurate forecast of share prices. Depending on the research period, the market situation and the approach to decision-making used, the obtained results may indicate both the usefulness and uselessness of technical analysis (Anghel, 2015). In view of the foregoing, the development of modern technology has created new opportunities to solve existing problems in many areas. One of these is the ability to make more accurate forecasts of the prices of financial instruments, which can be particularly important for investors.

In many fields of science, as well as in everyday life, the term "artificial intelligence" is becoming more and more common, which is a very broad term describing technology that enables intelligent responses to external stimuli

(Stephenson, 2020). The term "machine learning", on the other hand, can refer to a technology by which a computer program can improve its performance, even without the input of a programmer. Machine learning algorithms can process very large amounts of training data, and artificial neural networks are already well understood and used in this area (Stephenson, 2020). Neural networks are information processing systems, in the structure of which one can find a kind of mapping of elements of the biological nervous system. Nowadays, the application of neural networks is very wide, and they are used, among others, in stock market forecasting, medical and biological research, data analysis and economic forecasting (Rutkowski, 2005).

Although the terms artificial intelligence and machine learning are often used interchangeably their meanings are slightly different. In the first case, we have a situation where the system will try to mimic human intelligence in solving complex problems. This involves the ability to recognize specific patterns, analyse and evaluate them, but it also means creating new solutions on its own. Machine learning, on the other hand, is a subset of artificial intelligence, so to speak, and its feature is self-improvement based on the data and information provided.Machine learning involves the use of special algorithms through which the processes of data ingestion and analysis occur. This can be done in three ways (Wodecki, 2018):

- supervised learning – which means constant human control by providing the system with data along with the solution to the problem. After introducing enough sample information, the system will be able to independently assess the new incoming data and evaluate it in an appropriate manner.
- unsupervised learning – like supervised learning with the difference that during training the system receives data without solving the problem and its role is to appropriately classify information into a given number of categories.
- reinforcement learning – which is a special case of supervised learning with the difference that the system learns based on feedback from the environment rather than by having prepared feedback from the training set.

The topic of using machine learning in share price forecasting has been an area of research interest for some time. In a study on the potential of using machine learning for the Bitcoin cryptocurrency in a 2019 paper, the authors observed the potential for a 10% increase in price prediction performance compared to other methods (Fernandes & Mallqui, 2019). Similar conclusions regarding the benefits of using machine learning have also been recognised by researchers who have focused on only one company in a portfolio. In particular, their study focused on the usefulness of supervised machine learning algorithms (Torres et al., 2019). In the 2020 study, on the other hand, the researchers focused on analysing three companies from the binding sectors of finance, IT and health sciences listed on the National Stock Exchange. The study took a long time period into account, as the training data covered a period of six years. The results also suggest the possibility of obtaining attractive returns based on machine learning (Mondal et al., 2020).

In all the studies cited, machine learning is an effective tool for forecasting the price of market-listed financial instruments. Given the considerations so far, the authors have attempted to fill the research gap by carrying out the research set out in the purpose of this article.

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 provides an investor interested in creating a model and testing it. An important assumption of the research performed in the study is the adoption of a short investment horizon, and consequently, data from only five preceding trading sessions were intentionally used for the calculations. This approach's rationale was to consider only the most recent data.

1. The companies used in the calculation were those that were part of the WIG20 index in September 2021. These companies are: Asseco

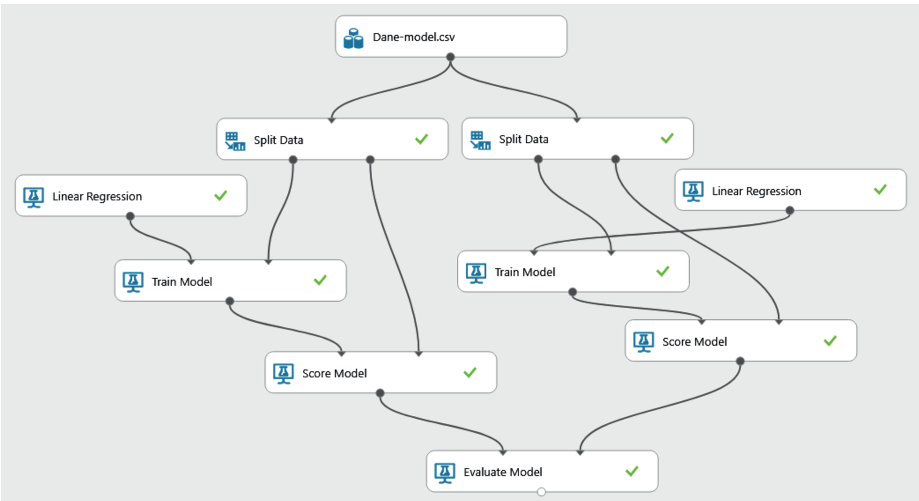
Poland SA (ACP), Allegro.eu SA (ALE), CCC SA (CCC), CD Projekt SA (CDR), Cyfrowy Polsat SA (CPS), Dino Polska SA (DNP), Jastrzębska Spółka Węglowa SA (JSW), KGHM Polska Miedź SA (KGH), LPP SA (LPP), Grupa Lotos SA (LTS), Mercator Medical SA (MRC), Orange Polska SA (OPL), Bank Polska Kasa Opieki SA (PEO), PGE Polska Grupa Energetyczna SA (PGE), Polskie Górnictwo Naftowe i Gazownictwo SA (PGN), Polski Koncern Naftowy ORLEN SA (PKN), Powszechna Kasa Oszczędności Bank Polski SA (PKO), Powszechny Zakład Ubezpieczeń SA (PZU), Santander Bank Polska SA (SPL) i Tauron Polska Energia SA (TPE).

2. The forecast includes the closing price for the trading session on 13.09.2021.
3. The calculations were based on the opening, closing, maximum and minimum prices for the five sessions preceding the one for which the closing price forecast was made, as well as on the opening price from that session.
4. Having historical data as mentioned in point 3 and the current session opening price, as well as having the closing price forecast for the current session based on the machine learning model, an investor is able to take a long position on the market after the opening at the opening price or at a price lower than the opening price, if the forecast assumes the closing price to be higher than the opening price and the price fluctuation allows it – for the sake of simplicity the opening price was used in calculating the strategy effectiveness.
5. If the forecast assumes closing at a level lower than the opening one, the trader does not take a position on the market.
6. After taking a long position, the investor closes it at the closing price by placing an appropriate order to close the session at the market price.
7. The calculations were made according to two schemes. The first assumes teaching the model using 50% of the companies selected randomly from all twenty, while the second uses 80% of the companies selected randomly from among all twenty.
8. The number of companies for which forecasts were made for the first scheme is ten, for the second four.

9. For simplicity, the commission for orders was omitted.
10. In conclusion, the rates of return for both schemes were calculated, and the level of forecasting error was calculated: mean absolute error, root mean square error, approximation error and the coefficient of determination R^2 was calculated.

Figure 1 shows an illustrative diagram of the machine learning model construction used in this study.

Figure 1. Illustrative diagram of the machine learning model construction used in the predictions



Source: Azure Microsoft Machine Learning Studio.

The individual modules shown in Figure 1 are:

- "Data-model.csv" – data covering historical quotations for WIG 20 companies in the analyzed period,
- "Split data" – a module that randomly selects from 20 companies those that will be used to "train" the model and those on which the model parameters will be applied,
- "Linear regression" – linear regression module,

- "Train model" – learning module based on test data selected by the "Split Data" module,
- "Score Model" – forecasting module,
- "Evaluate Model" – module calculating model fitting error and coefficient of determination.

Results obtained

Using calculations based on machine learning, the values of forecasted closing prices for the analyzed session were obtained for the teaching set comprising 50% and 80% of the total number of WIG 20 companies, which is presented in Tables 1 and 2. Additionally, error values for forecasts were determined and presented in Table 3.

Table 1. Forecasted and actual values for the learning set comprising 50% of the total number of WIG 20 companies

Company (1)	Opening (2)	Closing (3)	Forecasted closing (4)	Theoretical profitin PLN (5) = (3) – (2)	Theoritical transaction profitability (6) = (5) / (2)
CPS	33.96	34.34	34.32	0.38	1.12%
KGH	181	178.25	179.51	–	–
PZU	37.24	37.64	38.07	0.4	1.07%
JSW	52.02	54.22	53.06	2.2	4.23%
MRC	168.5	159	161.58	–	–
ACP	84.95	85.9	85.28	0.95	1.12%
CCC	119	118.6	119.56	–	–
TPE	3.53	3.65	3.61	0.12	3.40%
ALE	63.61	63.45	63.48	–	–
PKO	43.21	43.72	43.7	0.51	1.18%

Source: Calculations based on Azure Microsoft Machine Learning Studio and stock quotes of selected companies.

Table 2. Forecasted and actual values for the learning set comprising 80% of the total number of WIG 20 companies

Company (1)	Opening (2)	Closing (3)	Forecasted closing (4)	Theoretical profit in PLN (5) = (3) – (2)	Theoritical transaction profitability (6) = (5) / (2)
JSW	52.02	54.22	53.25	2.2	4.23%
PKO	43.21	43.72	43.22	–	–
TPE	3.53	3.65	3.59	0.12	3.40%
ALE	63.61	63.45	63.58	–	–

Source: Calculations based on Azure Microsoft Machine Learning Studio and stock quotes of selected companies.

Table 3. Forecast error values

Error name	Error value for learning setcovering 50% of companies	Error value for learning setcovering 80% of companies
Average absolute error	0.711202	0.331053
Root medium square error	1.053273	0.495408
Approximation error	0.15466	0.017604
Coefficient of determination R2	0.999622	0.999528

Source: Calculations based on Azure Microsoft Machine Learning Studio.

Analysing the results shown in Tables 1 and 2, we can come to the general conclusion that the use of forecasts allows an investor to take positions in the market and generate profit, provided that the conditions for taking a position are met, i.e. according to the forecast, the closing price will be higher than the opening price. In otherwords, the trader should not trade on that day when the forecast closing price is lower than the opening price.

Table 1, which shows the results of forecasts using a 50% learning set, presents positive returns for every deal made. Whenever the system indicates a potential loss on the transaction, investors should not make the deal. In fact, the results obtained in reality confirm that with both potential gains and potential losses the system based on machine learning indicated correctly. The exception was the result obtained in relation to one company, that is, CCC, but in this case the difference resulting from the system and the actual result were tiny, which could be offset by the cost of commissions. Table 2, which shows the results of forecasts using the 80% learning set, also shows positive returns for each deal. Table 3 shows the values of selected forecast and model fitting errors. As it can be observed, using more companies to teach the model makes the error values lower, with the increase in the number of companies introduced to the teaching set the coefficient of R2 determination indicates a better model fit. In Table 2, which shows the results of forecasts using the 80% teachinggroup of companies, positive returns were also obtained for each transaction. Table 3 shows the values of selected forecast and model fitting errors. As we can see, using a larger number of companies to teach the model, error values are lower and the coefficient of determination R2 indicates a better model fit.

Conclusions

The purpose of this study was to investigate and evaluate the applicability of machine learning to investment decision-making in stock markets. The results of the presented calculations indicate that an investor using machine learning based closing price forecasts could earn positive returns. Depending whether we use 50% or 80% teachingset of the companies, daily returns can range from 1.07% to even 4.23%.This applies only if the closing forecast indicates the value of this closing at a level higher than the opening price. Referring to the hypothesis formulated at the beginning of the article, if the use of machine learning can contribute to obtaining a positive rate of return by a stock market player making short-term investments, it can be stated that it has been verified positively.

The results obtained will undoubtedly be a reference point for further research conducted by the authors, including the use of instruments that allow to generate profits during price drops (futures contracts), a different interval of data (daily, weekly, monthly), or the use of more companies to improve the quality of forecasts.

The scientific contribution presented in this research consists mainly ofthe application of machine learning to short-term trading, which can be used by investors as an effective tool for making capital allocation decisions. In particular, this method can be helpful for investors trading for very short periods (daytrading).

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