Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 225 (2023) 941–950

Procedia Computer Science

www.elsevier.com/locate/procedia

27th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2023)

The potential of convolutional neural networks for the analysis of stock charts

Grzegorz Wojarnik*

Institute of Economics and Finance, University of Szczecin, Mickiewicza 64, 71-101 Szczecin, Poland

Abstract

Theoretical background: Undoubtedly, forecasting share prices is a non-trivial task. However, thanks to the rapid development of science, in recent years, more and more research work has been devoted to the prediction of stock market prices, thanks to which it is becoming more accessible and easier to forecast, among other things, share prices using a variety of methods, including machine learning and deep learning in particular. In the age of big data, deep learning used to predict prices and stock trends has become even more popular than before. At the same time, attempts are made to develop solutions similar to the method of analyzing stock market data by humans, i.e., data analysis presented in the form of charts. Therefore, it is worth taking a closer look at the possibilities of discovering patterns in stock charts by convolutional neural networks.
Purpose of the article: The adopted research hypothesis says that convolutional neural networks can potentially analyze stock data. The study aims to use a machine learning method, a convolutional neural network, to analyze stock market charts. For this purpose, a convolutional neural network will be built and programmed, which will be able to recognize relevant information based on previously prepared images constituting simplified stock charts.
Research methods: The study used the method of deep machine learning, including convolutional neural networks, which are characterized, among others, by the ability to process and analyze graphical data. In particular, the TensorFlow library was used with Keras functions, which have implemented algorithms of convolutional neural networks.
Main findings: The conducted research experiment showed high efficiency (close to 100%) of the adopted algorithm and the proposed convolutional neural network structure, thanks to which it can be assumed that convolutional neural networks contain a high potential for the analysis of stock data represented by charts showing the behavior of share prices or other financial instruments.

* Corresponding author. Tel.: +48 691 215 445
E-mail address: grzegorz.wojarnik@usz.edu.pl

10.1016/j.procs.2023.10.081

Keywords: convolutional neural networks; stock exchanges; data presentation; machine learning

1. Introduction

Stock market forecasting is a scorching topic in the financial world. Successfully predicting stock market traffic can promise high returns. However, accurately predicting stock movement is a complicated and challenging as many factors can affect the stock price, such as the global economy, politics, investor expectations, etc. Several nonlinear models, such as artificial neural networks, fuzzy systems, and hybrid models, are used to forecast the stock market. These models have limitations, such as slow convergence and the problem of overfitting.

Based on the literature review, the author is in favor of the view that machine learning methods, and in particular convolutional neural networks, have the potential to analyze stock market data aimed at using charts as a source of valuable information also on the behavior of stocks and financial instruments in the future. Hence, it is worth putting forward a research hypothesis that convolutional neural networks can discover regularities related to the data shown on the graphs. The primary research problem that should be posed is the legitimacy of using machine learning, in particular convolutional neural networks, which will be able to support the analyst (investor) in the analysis of stock market data (investment decisions) not based on dry data, but images generated on their basis. Of course, the solution to the problem posed in this way goes beyond the experiment's scope, but its positive result may deepen research in the selected research area. It is worth noting that machine learning has, for example, been widely used in image analysis in medicine [1], which shows the great potential of these methods in recognizing and discovering the regularities appearing in the analyzed images.

Stock market forecasts continue to be a problematic analytical issue as the stock price is influenced by factors such as company news and performance, industry performance, investor sentiment, social media sentiment, and economic factors.

Although computational intelligence techniques are widely used in trading systems in financial markets, almost all the models developed use time series data to predict prices or identify buy and sell points.

Stock charts are essential tools analysts or brokers use to analyze the prices of various instruments and stock exchange securities. The analysis of charts, among other things, gives the analyst an insight into the formation of technical analysis patterns, which are indications, he takes into account when making investment decisions (or issuing recommendations).

At the same time, the rapid development of artificial intelligence methods, including machine learning methods, also in the area of image analysis allows for the proposal of a working hypothesis that the use of convolutional neural networks (CNN) for the analysis of stock market charts can effectively support the activities of stock market analysts.

So, the experiment aims to verify the ability of the convolutional neural network to recognize the accuracy of the increase or decrease shown in the diagram. This goal will be achieved through the construction and software in Python of a convolutional neural network, the task of which will be to analyze two types of graphs: in the first variant, they would be upward and downward graphs plotted by straight lines, and in the second variant, upward and downward graphs will also be used, but plotted through curved lines.

2. Literature review

Predicting future stock price movements has been the subject of much research. On the one hand, we have supporters of the efficient market hypothesis who say that stock prices cannot be predicted; on the other hand, there are propositions that illustrate that, with appropriate models, stock prices can be predicted with high accuracy. There is also a substantial body of literature on stock price technical analysis aimed at identifying patterns in stock price movements and capitalizing on investment benefits. Machine learning and artificial intelligence methods have been used many times for these purposes.

Convolutional neural networks were used to investigate the problem of finding the starting and ending points of trends that are optimal entry and exit points, and the aim of the work was to explore long-term trends that last several months [2].

In the work [3] a model of stock price prediction based on a convolutional neural network has been proposed, which is characterized by the feature of self-adaptation, i.e. the ability to learn. The data was taken from the Thai stock exchange which was then trained and tested after pre-treatment. Three stocks (BBL, CAPLL & PTT) listed on the Thai stock exchange were used for the research, which were tested and compared with the actual share price. The results of the research showed that the CNN-based model can effectively identify and predict the shifting trend in stock prices, which can provide a valuable reference to the stock price forecast. The accuracy of predictions was assessed as high and worth using.

There have been many studies on predicting stock price trends, but most of them focused on public market data and did not use trading behaviour due to the unavailability of data from real transaction records. In fact, trading behaviour can better reflect market movements, and a combination of trading information and market information can further improve the accuracy of forecasts. In an article [4] they proposed a deep neural network model that uses desensitized transaction records and public market information to predict stock price trend. Given the correlation between the stocks, the proposed method uses the knowledge graph and chart embedding techniques to select the appropriate stocks. Given the large number of investors and the complexity of the trading data, investors are grouped to reduce the dimensions of the trading function matrix, and these matrices are then neutered to discover investment patterns. Ultimately, a two-way network can predict stock price trends to support financial decisions. The authors found that their experiments in determining the direction of price movement and predicting trends showed high performance compared to other forecasts.

The work [5] uses a hybrid approach to predicting stock prices through the use of machine learning and deep learning methods. The values of the NIFTY 50 index of the National Stock Exchange (NSE) of India in the period of four years: 2015-2018 were selected for the research. Based on 2015-2018 NIFTY data, various predictive models were built using machine learning methods and then used to predict the NIFTY 50 'Close' value for 2019, with a forecast horizon of one week (five trading days). A number of classification methods were used to predict the NIFTY index movement patterns, while various regression models were built to forecast the actual NIFTY closure values. The predictive power of the models was then increased by building a deep learning regression model using the Convolutional Neural Network (CNN) with walk-forward validation. The CNN model is fine-tuned for its parameters so that the loss of validation stabilizes as the number of iterations increases, and the learning and validation accuracy converge. CNN power was used to forecast future NIFTY index values using three approaches that differ in the number of variables used in forecasting, the number of sub-models used in general models, and the size of inputs for model training. Extensive results are presented on various metrics for all classification and regression models. The results clearly show that the multivariate forecasting model based on CNN is the most effective and accurate in predicting changes in the value of the NIFTY index over the weekly forecast horizon.

In the article [6], they proposed a deep learning method based on a convolutional neural network to predict stock price movements in the Chinese stock market. The open price, the highest price, the lowest price, the closing price, and the volume of the stock were set as inputs to the architecture. The results showed that the use of a deep learning-based method to predict stock price movements in China is quite (as indicated by the authors) credible.

The authors of the paper [7] collected 2-year data from the Chinese stock exchange and proposed a comprehensive adaptation of the function engineering and deep learning model to predict price trends on exchanges. They proposed a comprehensive solution that includes preprocessing a stock data set, the use of multiple function engineering techniques, combined with an adapted deep learning based system to predict price trends in the stock market. The authors conducted comprehensive evaluations of frequently used machine learning models and concluded that the proposed solution is better due to the complex functional engineering built. The authors showed that the system achieves an overall high accuracy in predicting stock market trends.

In an article [8], they proposed a recursive-convolutional neural kernel (RCNK) model that used complementary features from different data sources, namely historical price data and text data on the bulletin board to predict price movement. share. RCNK has integrated the advantages of technical analysis and sentiment analysis. Unlike previous studies, textual data was treated as sequence data and used the RCNK model to train sentiment embedding with temporal features. Besides, in the classification part of the model, the explicit kernel mapping layer was used to replace several fully interconnected kernels.

The paper [9] proposes a 3D Convolutional Neural Network approach to classifying directional stock price trends. For this purpose, five companies from a given sector are grouped, and the general trend in each of them is predicted simultaneously. This is done in order to analyse the impact of one company on another. Multiple technical indicators are selected for each company and stock prices are converted into a 15 × 15 × 5 3D image. To find the best features, they experimented with hierarchical clustering. To complement the 3D Convolutional Neural Network, the ideas of team learning were also analysed. The proposed method and several existing models were combined to improve system performance. The experiments were carried out on forty-five different companies of the National Stock Exchange. Compared to other similar techniques reported in the literature, their work achieved up to 35% annual returns for some stocks, with an average of 9.19%. Finally, they also tried to show that grouping companies and making sector forecasts can serve as a new benchmark for classifying stock market trends.

The study [10] proposes a stock trading system based on optimized technical analysis parameters to create buy and sell points using genetic algorithms. The model was developed using the Big Data Apache Spark platform. The optimized parameters are then passed to the deep neural network for buy-sell-hold forecasting. 30 items from the Dow Jones index were selected for model validation. Each stock is trained separately using daily closing prices in 1996-2016 and tested in 2007-2016. The results show that optimizing the parameters of technical indicators not only improves the performance of stock trading, but also provides a model that can be used as an alternative to Buy and Hold and other standard technical analysis models.

It should be noted that in the work on the analysis of stock market data, not only time series processed by machine learning algorithms were used, but also images were used for this, and so in his research [11] he took up the topic of researching information / patterns in stock market charts using convolutional neural networks. In the author's opinion, the results seem much better than random predictions, and he therefore considered this approach promising.

The authors of the paper [12] noted that traditional stock price forecasting involved a variety of linear or non-linear models, using standardized figures such as corporate financial data and stock price data. Due to the difficulties in securing sufficient data diversity, convolutional neural networks were also used with only stock price chart images. However, little is known about what features of stock charts affect the accuracy of forecasts and to what extent. The purpose of this study was to analyse the effect of stock chart characteristics on predicting stock prices via CNN. To this end, the characteristics of the stock chart image were defined and significant differences in forecast performance for each of the characteristics were identified. The results showed that the accuracy of the prediction is improved by using solid lines, colour and a single image without axis marks. Based on these findings, the implications of making predictions based on images only, which are unstructured data, without using a large amount of standard data.

The article [13] proposes a convolutional neural network-based stock price prediction model to test the applicability of new learning methods on stock exchanges. Using CNN, 9 technical indicators were selected as predictors of the prognostic model and the technical indicators were converted to images of the time series graph. To verify the suitability of deep learning for recognizing images on exchanges, the predictive accuracy of the proposed model was compared to a typical artificial neural network model and the Support Vector Machine model. Based on the experimental results, it has been noticed that CNN may be a desirable choice for building inventory forecasting models. In order to test the efficiency of the proposed method, an empirical study was carried out using the S & P500 index. This study addressed two critical issues in using CNN to predict stock prices: how to use CNN and how to optimize it. The authors found that CNN, which analyses time series data on charts, could be useful for predicting stock prices.

The study [14] used two-dimensional stock market bar charts without introducing any additional time series related to the underlying stocks. A new algorithmic commercial model CNN-BI (Convolutional Neural Network with Bar Images) using a two-dimensional convolutional neural network has been proposed. 2D images of the sliding window 30-day bar charts for 30 Dow Jones stocks were generated and the model was trained based on CNN. This model was tested separately for 2007-2012 and 2012-2017 to represent different market conditions. The results showed that the model was able to outperform the Buy and Hold strategy, especially in markets without a trend or bear market.

In the article [15], a model of stock trading was developed and implemented by integrating technical indicators and the convolutional neural network (TI-CNN). Ten technical indicators are extracted from historical data and treated as feature vectors. The feature vectors are then converted to an image using the Gramian Angular Field method and fed as input to CNN. The closing prices of the stock data are manually marked as selling, buying, or holding points by specifying the top and bottom points in the sliding window. Data from the period from January 2009 to December 2018 was used for the analysis. The prognostic ability of the developed TI-CNN model was tested on NASDAQ and NYSE data. Performance indicators such as accuracy and F1 score were calculated and compared to prove the effectiveness of the proposed stock trading model. The experimental results showed that the proposed TI-CNN achieves a higher accuracy of prediction than the models considered for comparison.

The paper [16] proposed a pattern-based deep learning neural network-based stock trading system that was used to analyse and forecast highly volatile stock price patterns. Three highly volatile price patterns have been defined that contain at least a record of the price reaching the daily ceiling in the last trading days. The implications of each pattern are analysed in the examples of charts. The training of the neural network was carried out with the stock data filtered according to three patterns, and the trading signals were generated using the prediction results of these neural networks. Using data from the markets of the South Korean stock exchange KOSPI and KOSDAQ, it was found that the proposed pattern-based trading system could outperform domestic and foreign indices. The importance of this study is to develop a model for predicting stock prices that exceeds the market index.

The paper [17] examines the predictability of the stock market using convolutional neural networks and candlestick charts. The result is used to design a decision support framework that can be used by traders to provide suggested clues about the future direction of stock prices. Historical stock data converted into candlestick charts. Finally, these candlestick charts will be introduced as input to training the convolutional model. This model supported the analysis of patterns on the candlestick chart and made it possible to predict future movements in the stock market. The effectiveness of the proposed method is assessed in stock market forecasts with promising results with an accuracy of 92.2% and 92.1% for the Taiwan and Indonesia stock data sets, respectively. The built model was implemented as a web-based system available free of charge at http://140.138.155.216/deepcandle/ for predicting the stock market using candlestick chart and deep learning neural networks.

The article [18] presents a novel algorithmic trading model CNN-TA using a 2-D convolutional neural network based on image processing properties. The authors use 15 different technical indicators each with different parameter selections to convert financial time series into 2-D images. Each image is then labeled as Buy, Sell or Hold depending on the hills and valleys of the original time series. The authors report that their model outperforms Buy & Hold Strategy and other common trading systems over a long out-of-sample period for stocks and ETFs. Next paper [19] introduces a new chart similarity measurement framework based on graph convolutional networks (GCNs). The authors construct a spatial graph from each chart image and use GCNs to learn the chart information. The authors apply their method to stock movement prediction and show that it can capture the complex patterns and relationships among charts better than existing methods.

As we can see, the available literature covering the use of convolutional neural networks, or more broadly machine learning, shows the wide possibilities of their use to analyse stock data, including charts, so it is worth taking a closer look and examining the potential of the algorithms behind convolutional neural networks for chart analysis.

3. Methodology of the research experiment

For the purpose of the research experiment, a convolutional neural network was created and programmed in Python. Convolutional neural networks are able to gradually filter different parts of the training data and sharpen important characteristics in the discrimination process used to recognize or classify patterns. The feature of such an approach to significant features is also important in the process of analyzing stock data, because the complex nature of the data often does not allow you to easily notice significant regularities, e.g. found and displayed on stock market charts..

As part of the experiment performed, the following steps were performed:

1. Creation of two data sets of images constituting the training data:

a. Segments where the left end is above or below the right end (Figure 1),

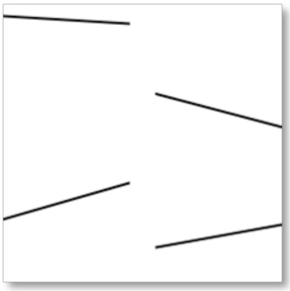

Fig. 1. Sample 4 images for a set of sections ("Minus" group above, "Plus" group below).

b. Curves where the left end is above or below the right end (Figure 2)

Fig. 2. Sample 4 images for a set of curves ("Minus" group above, "Plus" group below).

Each of the sets has been divided into two groups:
"Minus" - the left end above the right (rising curve) - 47 images for each set,
"Plus" - right end below the right (descending curve) - 49 images for each set.

2. Division of both data sets into training and validation data in a ratio of 0.2 (i.e. 80% of training data and 20% of validation data).
3. Creation of convolutional neural network models:

a. Model for a straight lines set:

```
model = Sequential([
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
  layers.Conv2D(16,3,padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32,3,padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 5, padding='same', activation='sigmoid'),
  layers.MaxPooling2D(),
  layers.Conv2D(16, 10, padding='same', activation='sigmoid'),
  layers.MaxPooling2D(),
  layers.Flatten(),
```

```
  layers.Dense(8, activation='relu'),
  layers.Dense(num_classes)
])
```

b. Model for a set of curves:

```
model = Sequential([
  layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),
  layers.Conv2D(16, 3, padding=padding, activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding=padding, activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding=padding, activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 5, padding=padding, activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(16,10, padding=padding, activation='sigmoid'),
  layers.MaxPooling2D(),
  layers.Conv2D(8, 4, padding=padding, activation='sigmoid'),
  layers.MaxPooling2D(),
  layers.Flatten(),
  layers.Dense(8, activation='relu'),
  layers.Dense(num_classes)
])
```

Where *num_classes* is the number of classes in each data set, i.e. 2 ("Minus" and "Plus" groups).

4. Compiling models with statements:
   a. `model.compile(optimizer='adam', loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), metrics=['accuracy'])`, for straight lines,
   b. `model.compile(optimizer='Nadam', loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), metrics=['accuracy'])`, for curves.
5. Training convolutional models (due to the greater complexity of the data set of curves, the model was trained for 200 generations of solutions, while for the sections - 100 generations, the *epochs* parameter):

```
model.fit(
  train_ds,
  validation_data=val_ds,
  epochs=epochs
)
```

6. Visualization of the results of trained convolutional models.

4. Results

The result of the test procedure are graphs for a set of sections (Figure 3) and curves (Figure 4), which show the accuracy and loss of training and validation of both created models.

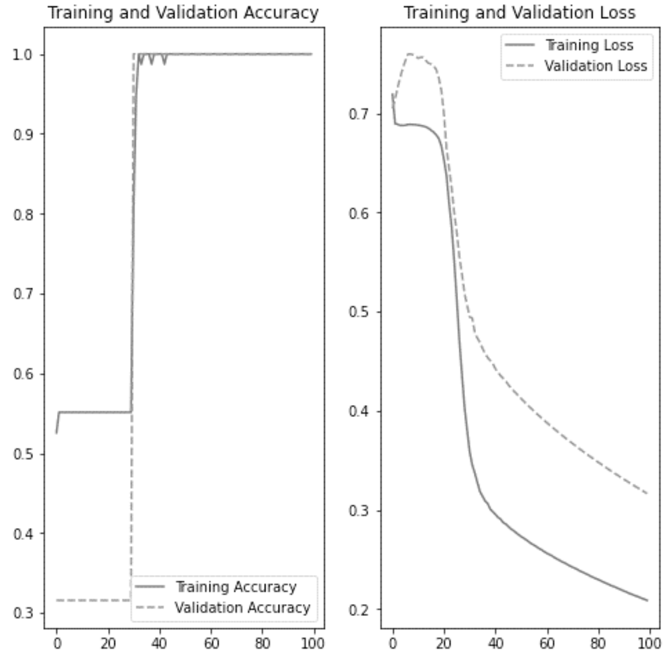

Fig. 3. Accuracy and loss charts in training and validation sets for a set of straight lines (next generations on the x axis).

As can be seen in the figure above, the predictive model obtained by using the convolutional neural network for images containing sections reached 100% accuracy for both training and validation data, which can be considered a very good and desirable result. At the same time, attention should be paid to the decreasing value of the validation loss parameter, which indicates whether the model requires further fine-tuning or adjustment. Of course, this is possible, because you can always create a model that does the job better.

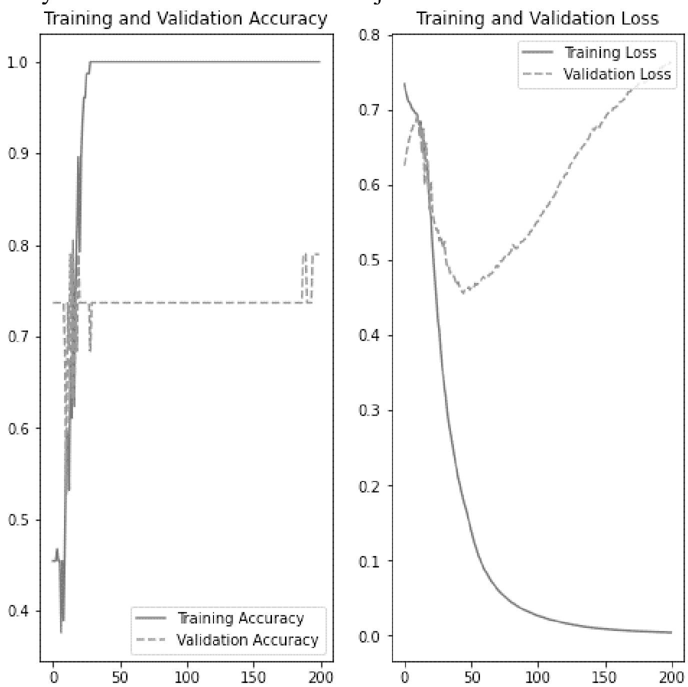

Fig. 4. Accuracy and loss plots in training and validation sets for a set of curves (on the x-axis consecutive generations).

The predictive model obtained by using the convolutional neural network for the images containing the curves achieved 100% accuracy for the training data and 78% for the validation data, which can be considered a good and desirable result. Its quality is lower than that of the segment model due to the greater complexity of the graph, which is represented by these curves. At the same time, attention should be paid to the variable value of the validation loss parameter (which has been increasing for the 60th generation, which may indicate an overtraining of the model), which says that this model can definitely be further improved to make it even better suited to the set of images representing the curves.

The research is part of a wide range of works using machine learning (including convolutional neural networks) to analyse stock market data.

In the author's opinion, the obtained results for pseudo-charts, which were images of sections and lines, used and generated for the purpose of the experiment, constitute a good basis for building a simplified model of operating conditions of a convolutional neural network analysing stock charts. The results of the experiment showed that convolutional neural networks, in accordance with the adopted assumptions, can be used to create solutions that allow for the processing of stock data. Admittedly, the approach to stock market data analysis proposed by the author has not been presented before in other studies, but it should definitely be stated that the use of an image in the form of a stock chart to analyse the behaviour of stock prices or other financial instruments in accordance with the principle that "one image is worth a thousand. words ”gives hope for the possibility of creating target predictive models based on convolutional neural networks enabling more accurate forecasts as to the behaviour of stock exchange rates.

As stock market charts may also consist mainly of curves depicting stock price fluctuations, the conducted experiment showed that convolutional neural networks, as indicated in the section devoted to the literature review, undoubtedly have the ability to pick up some nuances important from the point of view of the problem being solved. , depicted on the charts. Of course, the question arises whether there are artifacts (groups of pixels) there, which will signal the later behaviour of the share price.

5. Conclusion

The conducted research experiment showed high efficiency (even close to 100%) of the adopted algorithm and the proposed convolutional neural network structure, thanks to which it can be assumed that convolutional neural networks contain a high potential for the analysis of stock data represented by graphs showing the behavior of stock prices, or other financial instruments.

However, it should be noted that the conducted research is only an introduction to further analysis of stock market charts. It gives a chance to deepen the work aimed at choosing the type of chart and information that should appear on the chart so that the predictive ability of the convolutional neural network allows it to be learned well enough to add value to the process of making investment decisions or determining the time of seizure market positions (both long and short). For this, of course, further research will be needed to select the data and type of graph, as mentioned earlier, but also in-depth analysis and construction of the convolutional structure of the neural network. At the same time, it is worth looking at the possibility of using fundamental data available for selected stocks or financial instruments and in particular, the methods of presenting them on charts, which would allow their use during the process of learning a convolutional neural network, thanks to which this process would undoubtedly allow for even better results. It should also be noted that the presented experiment can be treated as related to technical analysis, which is sometimes treated more as an art than a science, but in the author's opinion, it is very important, for example, in behavioural analysis because the majority of active participants in financial markets follow it (TA) when undertaking their investment decisions.

In the course of subsequent studies, the computational capacity of the system within which the neural network will be learned may undoubtedly be a limitation. However, in the era of availability and high scalability of e.g., cloud solutions, it should be assumed that this will be a problem to overcome.

As this is a preliminary study and probably one of the first attempts to use such an unconventional approach, it can be assumed that there is room for improvement in the obtained results. Overall, the obtained results are so promising that, in the author's opinion, it is worth making an effort to deepen the topic and enter into broader research aimed at analyzing the possibility of using stock market charts as the basis for building a system, or a methodology that will allow supporting more right investment decisions.

References

[1] Korczak Karol. (2019) “Uczenie maszynowe w opiece zdrowotnej” *Collegium of Economic Analysis*, **56**: 305-316

[2] Zolotareva Ekaterina. (2021) “Applying Convolutional Neural Networks for Stock Market Trends Identification” *Arvix*, https://arxiv.org/ftp/arxiv/papers/2104/2104.13948.pdf. Access: 2022-07-14

[3] Sayavong, Lounnapha, Zhondong Wu and Sookasame Chalita. (2019) “Research on Stock Price Prediction Method Based on Convolutional Neural Network” *2019 International Conference on Virtual Reality and Intelligent Systems (ICVRIS)*: 173-176, doi: 10.1109/ICVRIS.2019.00050

[4] Long, Jiawei, Zhaopeng Chen, Weibing He, Taiyu Wu and Jiangtao Ren. (2020) “An integrated framework of deep learning and knowledge graph for prediction of stock price trend: An application in Chinese stock exchange market” *Applied Soft Computing*, **91**, June 2020, ISSN 1568-4946, doi: 10.1016/j.asoc.2020.106205

[5] Mehtab, Sidra and Jaydip Sen. (2020) “Stock Price Prediction Using Convolutional Neural Networks on a Multivariate Timeseries” *Arvix*, https://arxiv.org/ftp/arxiv/papers/2001/2001.09769.pdf. Access 2022-07-14

[6] Chen Sheng and Hongxiang He. (2018) “Stock Prediction Using Convolutional Neural Network.” *IOP Conf. Series: Materials Science and Engineering*: 435, doi:10.1088/1757-899X/435/1/012026

[7] Shen, Jingyi and Shafiq, M. Omair. (2020) “Short-term stock market price trend prediction using a comprehensive deep learning system.” *Journal of Big Data* **7**. doi: 10.1186/s40537-020-00333-6

[8] Liu Suhui, Zhang Xiaodong, Wang Ying and Feng Guoming. (2020) “Recurrent convolutional neural kernel model for stock price movement prediction.” *PLOS ONE* **15(6)**: e0234206. doi: 10.1371/journal.pone.0234206

[9] Sinha, Siddhant, Shambhavi Mishra, Vipul Mishra and Tanveer Ahmed. (2022) “Sector influence aware stock trend prediction using 3D convolutional neural network” *Journal of King Saud University - Computer and Information Science*, ISSN 1319-1578, doi: 10.1016/j.jksuci.2022.02.008

[10] chart, Omer Berat, Ozbayoglu Murat and Erdogan Dogdu. (2017) “A Deep Neural-Network Based Stock Trading System Based on Evolutionary Optimized Technical Analysis Parameters.” *Procedia Computer Science* **114**: 473-480. ISSN 1877-0509, doi: 10.1016/j.procs.2017.09.031

[11] Nayak Asutosh. (2020) “Stock Buy/Sell Prediction Using Convolutional Neural Network” https://towardsdatascience.com/stock-market-action-prediction-with-convnet-8689238feae3. Access 2022-07-14

[12] Jin, Guangxun and Ohbyung Kwon. (2021) “Impact of chart image characteristics on stock price prediction with a convolutional neural network.” *PLOS ONE* **16(6)**: e0253121. doi: 10.1371/journal.pone.0253121

[13] Sim, Hyun Sik, Hae In Kim and Jae Joon Ahn. (2019) “Is Deep Learning for Image Recognition Applicable to Stock Market Prediction?” *Hindawi journals, Complexity*, Article ID: 4324878. doi: 10.1155/2019/4324878

[14] Sezer, Omer and Ozbayoglu Murat. (2020) “Financial Trading Model with Stock Bar Chart Image Time Series with Deep Convolutional Neural Networks.” *Intelligent Automation and Soft Computing* **26 (2)**, doi: 10.31209/2018.100000065

[15] Chandar, S. Kumar. (2022) “Convolutional neural network for stock trading using technical indicators.” *Automated Software Engg.* **29, 1** (May 2022), doi: 10.1007/s10515-021-00303-z

[16] Oh, Jangmin. (2022) “Development of a stock trading system based on a neural network using highly volatile stock price patterns.” *PeerJ Computer Science* **8**:e915, doi: 10.7717/peerj-cs.915

[17] Mangir Irawan Kusuma, Rosdyana ; Ho, Trang-Thi ; Kao, Wei-Chun ; Ou, Yu-Yen ; Hua, Kai-Lung. (2019) “Using Deep Learning Neural Networks and Candlestick Chart Representation to Predict Stock Market” arXiv:1903.12258, https://ui.adsabs.harvard.edu/abs/2019arXiv190312258M. Access 2022-03-14

[18] Sezer, Omer Berat and Ozbayoglu , Ahmet Murat. (2018) “Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach.” *Applied Soft Computing* **70**: 525-538. ISSN 1568-4946, doi: 10.1016/j.asoc.2018.04.024

[19] Li, Shangzhe, Wu, Junran, Jiang Xin and Xu Ke (2022) “Chart GCN: Learning chart information with a graph convolutional network for stock movement prediction.” *Knowledge-Based Systems* **248**: 108842. ISSN 0950-7051, doi: 10.1016/j.knosys.2022.108842