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INVESTIGATION OF DECISION MAKING SUPPORT IN DIGITAL TRADING

Ilona Stalovinaitė[1], Nijolė Maknickienė[2], Raimonda Martinkutė-Kaulienė[3]

[1]Strategic Planning, Quality Management and Analysis Centre,
Vilnius Gediminas Technical University, Saulėtekio al. 11, Vilnius, Lithuania
[2, 3]Department of Financial Engineering, Faculty of Business Management,
Vilnius Gediminas Technical University, Saulėtekio al. 11, Vilnius, Lithuania
E-mails:[1]ilona.stalovinaite@vgtu.lt; [2]nijole.maknickiene@vgtu.lt;
[3]r.martinkute.kauliene@vgtu.lt (corresponding author)

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Abstract. In order to trade successfully investors are looking for the best method to determine possible directions of the price changes of financial means. The main objective of this paper is to evaluate the results of digital trading using different decision-making techniques. The paper examines deep learning technique known as Long Short – Term Memory (LSTM) neural network and parabolic stop and reverse (SAR) technical indicator as possible means for decision-making support. Based on an investigation of theoretical and practical aspects of digital trading and its support possibilities, investment portfolios in real-time "IQ Option" digital trading platform were created. Short-term results show that investment portfolios created using LSTM neural network performed better compared to the ones that were created using technical analysis. The study contributes to the development of new decision-making algorithms that can be used for forecasting of the results in the financial markets.

Keywords: deep learning, neural network, technical analysis, digital trading, investment portfolio.

JEL Classification: G10, G11, G17.

1. Introduction

Rapid digitalisation and increasing levels of Artificial Intelligence (further – AI) applications in all aspects of life bring many changes in how people and businesses operate and create value in everyday activities. At the same time, they bring many new opportunities, which have also been evident in the case of financial markets in all over the world. Digitalisation reshaped the way financial markets operate and made trading processes between the buyers and the sellers of various financial instruments not only faster and less costly, but also more efficient. Meanwhile, as financial markets are not as efficient as it is stated in Efficient Market Hypothesis, there is a high probability that various applications of AI may result in the recognition of unseen patterns in the behaviour of financial instruments and provide useful insights while making financial decisions. However, along with the opportunities many challenges are created. The possibility to access multiple digital trading platforms and trade in different financial instruments has never been so easy. This attracts not only professional investors, but also individual investors who may not necessarily have proper knowledge or necessary skills to apply either basic or more advanced methods and techniques, such as AI, to perform profitable trades. Therefore, in order to exploit the opportunities and combat the challenges created by digitalisation in financial markets, LSTM neural network and its possibilities will be adopted for specific trading decisions and compared against more traditional analytical methods, such as technical analysis, which can also be applied for supporting particular trading decisions.

So the aim of the research is to investigate whether digital trading with the application of LSTM neural network for decision-making processes is superior to technical analysis based trading.

In order to fulfil the aim of the article, the following steps are going to be implemented in the research: to investigate the scientific literature on the main aspects of digital trading and deep learning techniques' application for forecasting the behaviour of financial markets; to adopt deep learning based LSTM neural network for financial time series forecasting; to speculate in real-time selected digital trading platform and compare LSTM neural network based trading portfolios with technical analysis portfolios; to present final conclusions, research limitations and suggestions that would be based on the analysis of scientific literature and the implemented research.

Methods that are going to be used comprise systemization and analysis of scientific sources, including theoretical and experimental studies, also comparative analysis, graphical representation and systemization of data, programming using MatLab and its multiple functions, technical analysis using parabolic stop and reverse (further –SAR) technical indicator.

The conducted research on digital trading and application of deep learning techniques for forecasting the behaviour of financial markets helped to systemize already existing information and to create the basis for further investigation of these matters. The applications performed in the research serve as examples of how both selected strategies potentially behave and what results could be expected with their application. The findings should be useful for anyone who has professional or personal interest in digital trading, while at the same time give an idea whether it is worth dedicating time for more complex methods and their application for more successful trading in digitalized financial markets.

2. Theoretical aspects of decision making techniques in digital trading

2.1. Perspectives of digital trading and its influence for financial markets

In general, digitalisation could be simply understood as the usage and adoption of digital technologies in various aspects of life, or as transformative actions that tend to change formerly physical or analogue actions into digital data systems (T. Dufva & M. Dufva, 2019). There are no doubts that well implemented digitalisation can bring many new opportunities not only for businesses, but also for the society as a whole. It increases the cost efficiency, productivity, the level of innovativeness, as well as brings many other benefits by further increasing the importance of its role in today's world. It is obvious that digitalisation has brought many useful changes for all parties involved in various trades and it further tends to create new opportunities for better, more innovative and effective trading processes.

According "Asia-Pacific Trade and Investment Report 2016: Recent Trends and Developments" published by United Nations ESCAP (Economic and Social Commission for Asia and the Pacific) digital trading is referred to "the use of digital technologies to facilitate businesses without limiting it to just online sales or purchases" (Akhtar et al., 2016). In this report, digital trading is understood very widely since the whole essence is put on the general use of digital technologies. López-González and Jouanjean (2017) state that "digital trade encompasses digitally enabled transactions in trade in goods and services which can be either digitally or physically delivered involving consumers, firms and governments". A trade can be considered as digital when it is digitally enabled, but there is no difference whether a good or a service is delivered physically or digitally. Unlike the first definition, this one clarifies what parties could possibly be involved in the process of trading.

Fefer et al. (2018) identify digital trading as "the delivery of products and services over the Internet by firms in any industry sector, and of associated products such as smartphones and Internet-connected sensors. While it includes provision of e-commerce platforms and related services, it excludes the value of sales of physical goods ordered online, as well as physical goods that have a digital counterpart (such as books, movies, music, and software sold on CDs or DVDs)." It has been noticed that not all researchers use the term "digital trading". Other synonyms that are used instead include such terms as "online trading" (Zhong et al., 2012; Rüdiger & Rodríguez, 2013; Dayanand, 2016), "electronic commerce", or "e-commerce" (Zhong et al., 2012; Akhtar et al., 2016; Khan, 2016; López-González & Jouanjean, 2017; Fefer et al., 2018), "electronic trading", or "e-trading" (Bank for International Settlements [BIS], 2001; Orlowski, 2015; Dutta et al., 2017), and "paperless trading" (Fefer et al., 2018; Gao, 2018).

Despite the different terms all authors emphasize either the use of digital technologies, digital channels, or digital devices in the initiation of trades, but not all provide the same extent of detailing on the main players involved in the trades and what can be traded.

In this research, it was decided to focus on digital trading in financial services, particularly on trading that takes place in the financial markets, which play a significant role in both national and global financial systems.

According to Gomber et al. (2017) digital trading in the financial markets covers mobile trading, social trading, online brokerage, online trading, high- frequency and algorithmic trading in Business-to-Consumer (B2C) and Business-to-Business (B2B) areas. It supports both individuals and institutions in making investments decisions and arranging them by using digital devices and technologies from basically anywhere and at any time (Shukla & Nerlekar, 2019). This definition gives an idea that digital trading covers multiple possibilities how to engage in trading activities in a non-physical market, whereas each possibility has its own special features.

Digitalisation has changed the way trading takes place between the participants of the financial markets. In the scientific literature such benefits of digital trading as increased level of liquidity, also a better access to the financial markets due to increased digital connectivity, reduced costs of trading since fees of handling orders became smaller, removed geographic limitations as it became possible for the financial markets' participants to engage in trading activities while being in any place in the world that has an Internet connection, improved speed of execution of transactions since traders became more independent and able to place or cancel orders by themselves without the need of discussing it with a broker, as well as greater transparency of trades since traders have a better access to a wide range of relevant trading information. Digital trading also helps investors to avoid possible misjudgements made by brokers since they can become fully responsible for their decisions whether to buy or sell certain financial assets, or their combinations (Lee, 2009; Petric-Iancu, 2015; Orlowski, 2015; Rani & Srinivasan, 2015; Bech et al., 2016; Kumar, 2018; Shukla & Nerlekar, 2019). It is obvious that a lot of new possibilities became available for the participants of the financial markets after most of the trading activities were transferred to a digital marketplace.

But it must be emphasised that without proper means and knowledge most of the mentioned opportunities may become challenging. Increased trading speed may put slower market players at a disadvantage while benefiting the others (Rani & Srinivasan, 2015), whereas, being independent from a broker may not necessarily result in higher trading profits because traders are left alone with their knowledge, skills and they need to stay connected to their used digital trading platforms (Petric-Iancu, 2015). To do this all on your own may become a huge challenge for anyone who wants to start a successful trading path online. It becomes important to be aware and take actions against possible privacy and cyber security risks (Lee, 2009; Dandapani, 2017), also deal with interpretation, appropriate choice, quick search and data reliability difficulties while making investment and trading decisions due to increased data volumes (Maknickienė, 2015). Grall-Bronnec et al. (2017) have discovered that digital trading has many similar characteristics to gambling and may lead to an addictive-like behaviour.

Despite digitalisation has brought many changes into trading processes happening within the financial markets, not all of them are in the favour of investors and traders. Finding the ways to exploit the opportunities and combat the challenges arising from digitalisation become of paramount importance for all participants of the financial markets. One of such ways could be the application of AI, or more precisely deep learning techniques. As deep learning is considered to be more advanced than such traditional methods as technical analysis, it becomes important to see whether its application to financial trading could be superior in terms of achieved results.

2.2. Application of deep learning techniques in financial markets

Financial markets do not always perform in an efficient manner and this in turn may lead to poor trading decisions. However, there is a high possibility that traders and investors who apply complex strategies, models or even AI could potentially achieve a little bit higher than average returns. In recent years AI have gained special interest and was applied in many different areas, including finance, where it covers a wide range of possible applications from market analysis and data mining to portfolio management. Multiple techniques can be applied for predicting the direction of price movements of various assets in this way supporting specific trading decisions.

According to Tsantekidis et al. (2017), in many cases traders apply statistical models for making decisions about whether and when to enter and exit particular markets, but often these models are limited and fail to properly forecast how market participants should act due to naturally noisy and stochastic nature of the financial markets.

Sirignano and Cont (2019) find that with the use of deep learning better accuracy of forecasting of movements in stock prices is achieved.

According to Chatzis et al. (2018) deep learning is a subgroup of machine learning in AI, which constitutes of new generation of artificial neural networks and brings increased versatility in learning nonlinear dynamics in huge sets of data. These techniques have increased in the popularity due to their cutting-edge performance in a variety of scientific fields, including computer vision, natural language processing, and many more, and with the employment of statistical modelling arguments help beating vanishing gradients and over-fitting problems met in traditional methods. Several more ways to define deep learning are presented by Korczak and Hemes (2017). Authors state that it is "a set of machine learning algorithms that attempt to model high-level abstractions in data by using architectures composed of multiple nonlinear transformations", whereas Abe and Nakayama (2018) states that deep learning is "a representation-learning method with multiple levels of representation that passes data through many simple but nonlinear modules". It is visible that, despite different formulations, all definitions give similar information on what deep learning stands for.

Deep learning techniques are actively used as a research object for problem solving in the financial markets during the recent years. Roondiwala et al. (2015) proposed a LSTM neural network approach to model and predict the returns of stocks listed in NIFTY 50 Index and measured the efficiency of their approach by using Root Mean Square Error (further – RMSE). Authors performed multiple simulations by training the LSTM neural network with different historic price combinations and number of epochs, and found out that the best RMSE results were achieved by employing four features set that included high, low, open and close historic stock prices and 500 epochs, proving that the suggested approach was of good use for predicting future behaviour of stock market. Bao et al. (2017) suggested a novel deep learning approach referred as WSAEs-LSTM, which combined Wavelet Transforms (WT), Stacked Autoencoders (SAEs) and LSTM neural network, and was aimed at forecasting the prices of six stock market indices, including CSI 300 Index, NIFTY 50 Index, Hang Seng Index, Nikkei 225 Index, S&P Index and Dow Jones Industrial Average (further – DJIA). For model prediction authors used three different types of input variables: high, low, open and close historic stock prices and trading volume, multiple technical indicators as well as macroeconomic indicators. Also, to compare the performance of the suggested framework, authors evaluated the predictive accuracy and profitability of additional three models, including conventional Recurrent neural network (further – RNN), LSTM neural network and WLSTM. After evaluating and comparing all of the models, authors found out that their suggested approach outperformed other models in both predictability and profitability, suggesting that the combination of different techniques could give useful insights while making investment or trading decisions in the financial markets.

In addition to already overviewed researches, it has been seen that for financial time series forecasting several scientists (Press, 2018; S. Siami-Namin & A. Siami-Namin, 2018) have successfully employed the architecture of LSTM neural network and compared its performance with Autoregressive Integrated Moving Average (further – ARIMA) model. In both cases authors found out that LSTM neural network outperformed ARIMA in predicting and forecasting the financial time series data. In addition, Hiransha et al. (2018) for time series forecasting and price prediction have employed not only LSTM neural network, but also Multilayer Perceptron (MLP), RNN and Convolutional neural network (further – CNN), and found out that all deep learning based models performed better compared to ARIMA.

Continuing, LSTM neural network for financial time series prediction was also applied by Fischer and Krauss (2018), where authors used the network for a large-scale S&P 500 Index directional movements' prediction, and compared its performance with other memory-free benchmark methods, such as Random forest (further – RAF), Deep neural network (further – DNN), and a Logistic Regression classifier (further – LOG). Authors found that LSTM neural network surpassed other methods as it achieved statistically and economically significant daily returns of 0,46 per cent and a Sharpe ratio of 5.8 prior to transaction costs, while daily returns and Sharpe ratios for RAF, DNN and LOG were 0.43, 0.32, 0.26 per cent and 5.0, 2.4, 1.7, respectively. Shah et al. (2018) applied DNN and LSTM neural network, and compared their performance in making daily and weekly price predictions of Bombay Stock Exchange Index (further – BSE SENSEX) and daily predictions of Tech Mahindra stock.

To sum up, investigation of multiple researches focused on the application of deep learning techniques has shown that there are various different ways and deep learning based architectures that can be employed in order to forecast and predict potential behaviour of financial markets, whereas the received information can be used for supporting trading or investment decisions. It has been noticed that multiple scientists tried to achieve this purpose by employing LSTM neural network, or its combinations, as this network greatly performs at financial time series forecasting. Exactly this formed the basis for selecting LSTM neural network for the research.

3. Methodology of digital trading support applying deep learning based Long Short-Term Memory (LSTM) technique

In order to apply LSTM neural network for financial time series forecasting that would result in efficient decision-making while trading in digitalized financial markets, MatLab program and MathWorks (2019) suggested algorithm were used.

It is known that the RMSE serves as a measure that helps to evaluate the performance and accuracy of predictions (Chong et al., 2017), therefore it was chosen for the determination of the research accuracy.

At the same time, it is important to identify main external and internal parameters of the final LSTM neural network algorithm. Starting with external parameters, Dukascopy Bank's "Historical Data Feed" was used as the main source of historical hourly data of selected financial assets. It was decided to perform training on 90 per cent of the data and testing on the remaining 10 per cent. Continuing with internal parameters, the number of features and number of responses were set to 1, while number of LSTM neural network layer's hidden units was set to 200. Considering training options, the solver of network was set to Adam (adaptive moment estimation) optimizer, training was performed for 250 epochs, also, to prevent the gradients from exploding, the gradient threshold was set to 1, initial learn rate was set to 0.005, the learn rate was dropped after 125 epochs by multiplying by a factor of 0.2. Hardware resources, in MatLab referred as "ExecutionEnvironment", was set to central processing unit (CPU).

It is important to note that for every financial instrument the LSTM neural network algorithm had to be run separately, so that relevant forecasting results for each investigated instrument could be received. This means that the only parameter that was changed each time before running the LSTM neural network algorithm was the financial time series data collected for each selected financial instrument.

Since it was decided to investigate whether digital trading with the application of LSTM neural network for decision-making processes is superior to technical analysis based trading, it remains important to cover the main aspects of technical analysis. Generally, technical analysis involves choosing financial assets based on prior trading patterns (Azzam, 2015), or in other words, it examines past market actions and uses that data to predict the future. It is thought that markets tend to repeat themselves, therefore, previous trends in most areas of life are almost always good indicators of the future (Asefeso, 2011). In this research, it was decided to focus on parabolic SAR indicator, which was selected based on personal interest. This technical indicator may be used for determining stop points and estimating when it is best for the trader to reverse his current position and enter into an opposite one.

The position of dots of parabolic SAR shows the trader to buy the financial asset or to sell it (Prasetijo et al., 2017). Exactly these indicator's sings were used to support buy/sell decisions while implementing the technical analysis based trading strategy.

For the implementation of the previously indicated trading strategies, it was decided to select and use "IQ Option" digital trading platform. This was done in order to test how both of the strategies would perform under real-time market conditions, as well as to compare whether LSTM neural network based trading strategy would performed superior to the trading strategy based on the use of technical indicator.

The amount for either buying or selling each selected foreign exchange option in both LSTM neural network and technical analysis based strategies were based on 1/N investment strategy. This means that for each trading strategy total funds of 10000 USD were equally allocated and set to 2500 USD per instrument. The decisions whether to buy the options, or, in this case, bet that the price of foreign exchanges will go higher, or sell the options – bet that the price of foreign exchanges will get lower –, for both LSTM neural network and technical analysis based trading strategies were made in the same manner. This means that for LSTM neural network based trading strategy, if the forecasted price of analysed foreign exchange was going up, the decision to buy the option was made, whereas, if the forecasted price of foreign exchange was going down, the decision to sell the option was initiated. All of the decisions whether to buy or sell each option were made one by one without using any other additional tools or indicators. Whilst, for technical analysis based trading strategy, the decision whether to buy or sell a certain foreign exchange option was based on the indications from the parabolic SAR indicator, which was selected from the list of technical indicators provided by "IQ Option" trading platform. So, when the parabolic SAR indicator was turned on, a foreign exchange option was bought when a series of dots was be-low the price line, while, when a series of dots was above the price line then the selected option was sold. Each foreign exchange option based on parabolic SAR indications was bought or sold on the spot one by one without using any other additional tools.

All of the indicated LSTM neural network and technical analysis strategies' steps were performed numerous times in order to form multiple investment portfolios. This was done in order to see whether the application of both strategies gave consistent results. All LSTM neural network and technical analysis portfolios in "IQ Option" trading platform were formed within the period from 2019-11-11 to 2019-11-29. The final summary of all the criteria that were followed while creating all of the trading accounts and multiple LSTM neural network and technical analysis investment portfolios are presented in Table 1.

Table 1. Summary of criteria for LSTM neural network and technical analysis investment portfolios creation in "IQ Option" digital trading platform (source: compiled by the authors)

Portfolio creation criteria	LSTM neural network investment portfolio	Technical analysis investment portfolio
Financial instruments	Foreign exchange options	Foreign exchange options
Number of instruments	4	4
Total funds	10000 USD	10000 USD
Allocation of funds	1/*N*: 2500 USD per instrument	1/*N*: 2500 USD per instrument
Decision-making support	Forecasts received after running LSTM neural network algorithm	Parabolic SAR technical indicator
Trading time	≥1 hours	≥1 hours

After all the steps indicated in both trading strategies were implemented and results from multiple investment portfolios were received, it becomes possible to evaluate them individually as well as to compare whether the investment portfolios based on the application of LSTM neural network for particular decision-making processes actually performed superior to those investment portfolios based on single parabolic SAR technical indicator, or not.

4. Implementation of digital trading support applying Long Short-Term Memory (LSTM) network and evaluation of results

Based on the theoretical study and research, an integrated model was adopted to test how well the LSTM neural network works at forecasting the prices of selected foreign exchanges and whether these forecasts are suitable for supporting particular decision-making processes while trading in "IQ Option" real-time digital trading platform. The whole trading in digital marketplace that involves the use of complex algorithms, such as LSTM neural network algorithm, could be considered as algorithmic trading. This type of trading can be successfully used in several ways:

- **Recommendation system**. It works like assistant of specialist that takes information, but the trader makes particular trading decisions himself.
- **Robo-Advisor**. Automatically working Robo-Advisor can get data, analyse it and build an optimized portfolio for asset management by using risk models.

Although there are several ways how algorithmic trading could be performed, this research focuses on the use of LSTM neural network algorithm to form the basis of the recommendation system. It is important to notice that the algorithm itself does not make any particular decisions related with buying or selling selected financial assets, it only supports the trader to make decisions whether to buy or sell the assets based on the received forecasts.

Continuing, currency pairs that were selected for this research included EUR/JPY (Euro to Japanese Yen), USD/CAD (United States Dollar to Canadian Dollar), GBP/AUD (British Pound to Australian Dollar) and EUR/NZD (Euro to New Zealand Dollar), AUD/CHF (Australian Dollar to Swiss Franc), GBP/JPY (British Pound to Japanese Yen), NZD/USD (New Zealand Dollar to United States Dollar) and USD/CAD. Later the decision to present the visual outputs of exactly four currency pairs was made because four corresponding financial instruments, in this case, four matching foreign exchange options, were later on included in investment portfolios created in "IQ Option" digital trading platforms, while the investigation of other foreign exchanges was performed in the same manner.

The very first visual outputs that were received after running the LSTM neural network algorithm with EUR/JPY, USD/CAD, GBP/AUD and EUR/NZD historical close prices in MatLab, were the plots of these prices transformed into row vectors. Exactly this kind of data representation helped to realize how much the close prices of each selected instrument were fluctuating during the analysed period. In every case, the historical close prices of selected currency pairs were collected based on the date, which was selected for testing them in real-time digital trading platform. Therefore, as it was decided to form the very first LSTM neural network investment portfolios in "IQ Option" trading platforms on 2019-11-11, the period for collecting each currency pair's historical data was set from 2019-05-13 to 2019-11-11. The relevant data was not collected from 2019-05-11 because this date coincided with the weekend.

Later on, the training of networks with all of the predefined internal and external parameters were performed. After the training of the networks was finished the forecasting of the next time step were performed and the forecasted close prices of EUR/JPY, USD/CAD, GBP/AUD and EUR/NZD were received (see Figure 1). Once again, it is important to notice that all forecasted prices for each currency pair were not received at the same time and are represented together only for the sake of convenience and because they later formed the basis for the formation of investment portfolios.

After the forecasted closure prices of each currency pair were received they were compared with the corresponding test data. In these cases the following RMSE values for each currency pair were received: EUR/JPY – 1.4827, USD/CAD – 0.010788, GBP/AUD – 0.029451, and EUR/NZD – 0.014518. A smaller value of the RMSE indicates a better fit of the model to the data, which means that the smaller the RMSE, the better. However, in these particular cases the values of all received RMSE values could be interpreted as quite high, and since it is known that the predictions are more accurate when the network state is updated with the observed values instead of the predicted values, further corrections were implemented.

The implemented changes after updating the network state of the LSTM neural network are discussed further. It was seen that in these cases the received RMSE values for each currency pair were much smaller compared to the previous ones: EUR/JPY – 0.86882, USD/CAD – 0.00082057, GBP/AUD – 0.0018808, and EUR/NZD – 0.0014945. This indicates that the predicted values ended up being much closer to the observed ones, which in turn means that LSTM neural network is suitable for making predictions and, therefore, can be used for particular decision-making support while implementing the previously described LSTM neural network based trading strategy in "IQ Option" digital trading platform.

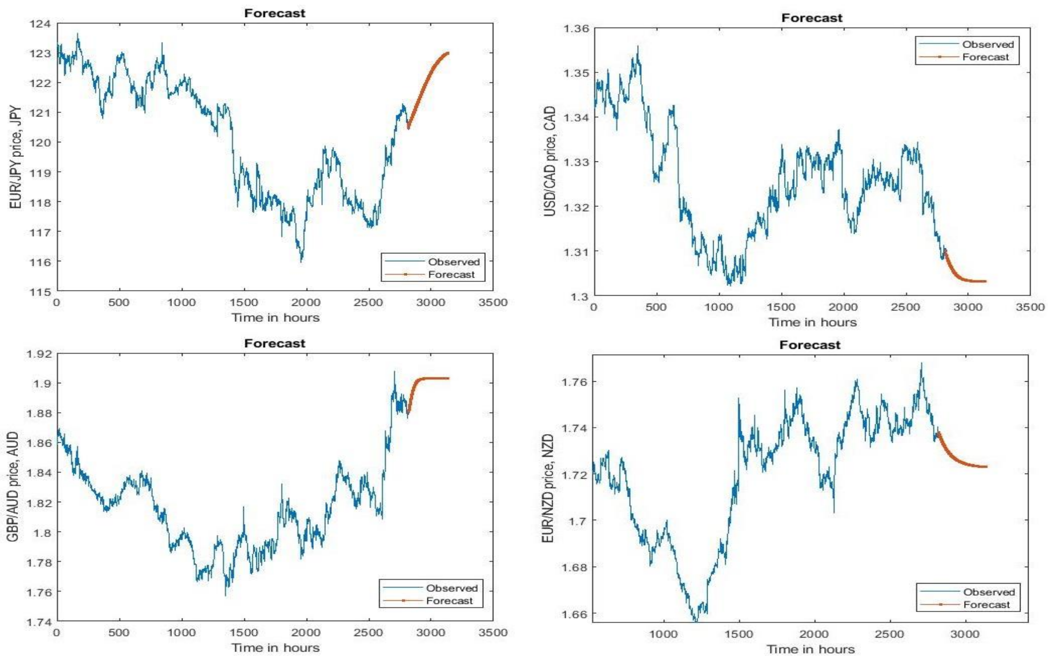

Figure 1. Forecasts of EUR/JPY, USD/CAD, GBP/AUD and EUR/NZD close prices
(source: compiled by the authors, based on data from Dukascopy, 2019)

Now, as the logic of application of LSTM neural network for forecasting the prices of selected foreign exchanges as well as its suitability for supporting further trading decisions have been discussed, it is possible to go further by covering how final investment portfolios, following previously identified steps of both LSTM neural network and technical analysis based trading strategies, were formed.

Eighteen investment portfolios were created in "IQ Option" digital trading platform between 2019-11-11 and 2019-11-29. Two investment portfolios were formed from EUR/JPY, USD/CAD, GBP/AUD and EUR/NZD options, whereas all other investment portfolio were formed from AUD/CHF, NZD/USD, GBP/JPY and USD/CAD options. Moreover, all foreign exchange options included in either LSTM neural network or technical analysis investment portfolios were traded for no longer than 1 hour, as it was the maximum time to the expiration of each option.

To begin with, for LSTM neural network based trading strategy particular decisions whether to buy or sell each foreign exchange option to form final investment portfolio were based on the forecasts received after running the LSTM neural network algorithm with each selected foreign exchange's historical six months data in MatLab. For instance, as EUR/JPY and GBP/AUD forecasts shown increasing trends of the close price, the decision to buy each option was made, whereas decreasing trends in USD/CAD and EUR/NZD supported the decisions to sell both of the foreign exchange options. Meanwhile, for technical analysis based trading strategy the decisions whether to buy or sell certain options to form a portfolio were taken after observing the signals of parabolic SAR technical indicator directly in "IQ Option" digital trading platform.

Certain amounts for buying or selling each foreign exchange option were set based on the same 1/N investment strategy for both of the strategies. Therefore, each selected option was either bought or sold for the amount of 2500 USD, resulting in total investment of 10000 USD.

Considering that decisions in all LSTM neural network and technical analysis investment portfolios were taken in the same manner, the final investment portfolios after implementing the steps of both trading strategies looked as follows (see Table 2).

Table 2. Created LSTM neural network and technical analysis investment portfolios in "IQ Option" digital trading platform (source: compiled by the authors)

Number of investment portfolio	Instrument	Direction (using LSTM neural network)	Direction (using technical analysis)	Amount invested (USD)	Total investment (USD)
1	EUR/JPY option	Buy	Sell	2500	10 000
	USD/CAD option	Sell	Sell	2500	
	GBP/AUD option	Buy	Sell	2500	
	EUR/NZD option	Sell	Sell	2500	
2	AUD/CHF option	Sell	Buy	2500	10 000
	NZD/USD option	Sell	Buy	2500	
	GBP/JPY option	Buy	Buy	2500	
	USD/CAD option	Sell	Buy	2500	
3	AUD/CHF option	Sell	Buy	2500	10 000
	NZD/USD option	Buy	Sell	2500	
	GBP/JPY option	Buy	Buy	2500	
	USD/CAD option	Buy	Sell	2500	
4	AUD/CHF option	Sell	Buy	2500	10 000
	NZD/USD option	Buy	Sell	2500	
	GBP/JPY option	Buy	Buy	2500	
	USD/CAD option	Sell	Sell	2500	
5	AUD/CHF option	Sell	Sell	2500	10 000
	NZD/USD option	Buy	Buy	2500	
	GBP/JPY option	Buy	Sell	2500	
	USD/CAD option	Buy	Sell	2500	

End of Table 2

Number of investment portfolio	Instrument	Direction (using LSTM neural network)	Direction (using technical analysis)	Amount invested (USD)	Total investment (USD)
6	AUD/CHF option	Buy	Sell	2500	10 000
	NZD/USD option	Sell	Buy	2500	
	GBP/JPY option	Buy	Sell	2500	
	USD/CAD option	Buy	Sell	2500	
7	AUD/CHF option	Sell	Sell	2500	10 000
	NZD/USD option	Buy	Buy	2500	
	GBP/JPY option	Sell	Sell	2500	
	USD/CAD option	Sell	Buy	2500	
8	AUD/CHF option	Sell	Buy	2500	10 000
	NZD/USD option	Sell	Buy	2500	
	GBP/JPY option	Buy	Buy	2500	
	USD/CAD option	Sell	Buy	2500	
9	AUD/CHF option	Sell	Sell	2500	10 000
	NZD/USD option	Sell	Sell	2500	
	GBP/JPY option	Sell	Buy	2500	
	USD/CAD option	Buy	Buy	2500	

After all active positions in "IQ Option" digital trading platform were automatically closed, separate results on the performance of nine LSTM neural network and nine technical analysis investment portfolios were received.

Table 3. LSTM neural network investment portfolios' results after trading in "IQ Option" digital trading platform (source: compiled by the authors)

Number of investment portfolio	Total profit or loss (USD)	Total balance (USD)	Profitability (%)
1	–191.87	9808.13	–1.9187
2	–3867.93	6132.08	–38.6793
3	1501.2	11501.2	15.012
4	–4820.21	5179.79	–48.2021
5	–5320.34	4679.66	–53.2034
6	–7381.02	2618.98	–73.8102
7	1377.04	11377.04	13.7704
8	–2066.42	7933.58	–20.6642
9	–1491.95	8508.05	–14.9195

Starting with the performance and results of LSTM neural network investment portfolios (see Table 3), it can be seen that each individual portfolio generated different results ranging from 1377.04–1501.2 USD profits to 191.87–5320.34 USD losses. These significant differences indicate that the application of LSTM neural network trading strategy did not give consistent results, as well as, in majority of cases, did not help to achieve the goals of avoiding losses and earning some amount of profits.

When talking about investment portfolios' results that were received after trading based on the technical analysis trading strategy (see Table 4), similar situation as with LSTM neural network investment portfolios has been seen in the context of results' consistency and achievement of goals. The received results ranged from 712.93–5014.4 USD profits to 1363.69–7700.29 USD losses, which shows that application of technical analysis trading strategy did not help to achieve consistent results among all investment portfolio and failed at fulfilling the goals to generate profits instead of losses.

Table 4. Technical analysis investment portfolios' results after trading in "IQ Option" digital trading platform (source: compiled by the authors)

Number of investment portfolio	Total profit or loss (USD)	Total balance (USD)	Profitability (%)
1	–4015.42	5984.58	–40.1542
2	–1363.69	8636.31	–13.6369
3	712.93	10712.93	7.1293
4	–4368.95	5631.05	–43.6895
5	–7133.23	2866.77	–71.3323
6	–7700.29	2299.71	–77.0029
7	5014.4	15014.4	50.144
8	–3321.47	6678.53	–33.2147
9	–5635.1	4364.9	–56.351

It was decided to compare the final performance of both LSTM neural network and technical analysis investment portfolios by reviewing the total number of profitable and unprofitable trades within all created portfolios as well as their average values. Moreover, it was decided to compare how many profitable and unprofitable investment portfolios, after following each of the trading strategy, were created and what were their average profits or losses and average profitabilities. Exactly these results are reflected in Table 5 and will be discussed further.

Table 5. Comparison of LSTM neural network and technical analysis investment portfolios and their results after trading in "IQ Option" digital trading platform (source: compiled by the author)

	LSTM neural network trading strategy	Technical analysis trading strategy
Profitable trades	14	12
Unprofitable trades	22	24
Average value of profitable trade (USD)	1761.39	1704.82
Average value of unprofitable trade (USD)	–2132.77	–2011.2
Profitable portfolios	2	2
Unprofitable portfolios	7	7
Average value of profits or losses (USD)	–2473.5	–3090.09
Average profitability of all portfolios (%)	–24.735	–30.9009

It was noticed that the exact number of profitable and unprofitable trades within all created portfolios, differed only by two trades in each strategy's case. To be more precise, the total number of profitable and unprofitable trades based on LSTM neural network trading strategy was equal to fourteen and twenty-two trades, whereas for technical analysis trading strategy it was equal to twelve and twenty-four trades, respectively. Nevertheless, despite the fact that the number of profitable trades following LSTM neural network trading strategy was higher, the average values of these trades for both LSTM neural network and technical analysis trading strategies were quite close to one another and equal to 1761.39 USD and 1704.82 USD, accordingly. In addition, despite the fact that the number of unprofitable trades, which were based on LSTM neural network trading strategy, was lower, their average value was higher and equal to 2132.77 USD, whereas for technical analysis based trading strategy the average unprofitable trade value was equal to 2011.2 USD.

Continuing, a little bit different results were seen in the overall number of profitable and unprofitable investment portfolios, as following each of the strategy two profitable and seven unprofitable portfolios were created. Average value of profits or losses as well as average profitability of all portfolios was calculated. From the received results it has been seen that LSTM neural network and technical analysis investment portfolios following both trading strategies gave average losses equal to 2473.5 USD and 3090.09 USD, while the rates of return from initial investments were negative and equal to 24.74% and 30.9%, accordingly. From these results it is possible to state that LSTM neural network investment portfolios performed superior compared to technical analysis investment portfolios, since average losses of all LSTM neural network portfolios were about 1.3 times lower compared to the average losses of technical analysis investment portfolios.

On the other hand, although LSTM neural network investment portfolios have demonstrated better average results than technical analysis investment portfolios, the overall performance of these portfolios could be considered as poor, as no traders or investors want to receive losses instead of profits. Moreover, the application of LSTM neural network trading strategy required much more time compared to technical analysis trading strategy and the fact that in majority of cases it gave largely unfavourable results, raises doubts whether this trading strategy is worthwhile.

5. Conclusions

Investigation of scientific literature made it clear that digital trading is a broad concept, which in terms of financial markets covers multiple possibilities, such as mobile trading, social trading, online brokerage, online trading, high- frequency and algorithmic trading and may serve as a facility that supports the provision of electronic order routing, automated trade execution, and electronic dissemination of pre-trade and post-trade information.

Adoption of deep learning based LSTM neural network algorithm using MatLab computing environment and its multiple functions allowed to forecast financial time series of selected financial instruments and in this way formed the basis of a recommendation system, which was aimed at supporting particular buy and sell decisions. Exactly the information received from the Forecasts helped to make particular decisions, which led to the creation of LSTM neural network investment portfolios. It is worth mentioning, that LSTM neural network algorithm did not have the ability to make any automated trading decisions in selected digital trading platform. Instead, it only supported the trader in making final decision whether to buy or sell each selected financial asset.

Speculation in “IQ Option” real-time digital trading platform following the steps of both LSTM neural network and technical analysis trading strategies resulted in the formation of eighteen investment portfolios. The comparison of the results that were received in the selected digital trading platform has shown that, in majority of cases, investment portfolios generated losses instead of profits, but, in average terms, LSTM neural network investment portfolios performed superior to technical analysis portfolios, as they achieved almost 1.3 times lower losses.

After performing the scientific analysis and implementing the final research, it is possible to conclude that digital trading with the application of LSTM neural network for decision-making processes performed better than technical analysis based trading. It has been noticed that in “IQ Options” digital trading platform, the experienced average losses of LSTM neural network investment portfolio was equal to 2473.5 USD, while technical analysis investment portfolios’ average losses were higher and equal to 3090.09 USD. On the other hand, it has been see that LSTM neural network portfolios in most of the cases generated losses, which did not match with the expectations to achieve higher than average returns, nor matched with the goals of avoiding losses and achieving some undefined amount of profits. This might have happened due to various limitations faced while implementing the LSTM neural network based trading strategy, such as limited time period, frequency and type of selected input data for the analysis, also constant input parameters of LSTM neural network algorithm.

Future research focusing on the fine-tuning of the LSTM neural network algorithm should be performed in order to investigate whether better and more profitable results while trading could be achieved.

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