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Застосування методів глибокого навчання до прогнозування зміни короткострокових трендів валютних курсів

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Анотація. Робота присвячена питанням короткострокового прогнозування валютних курсів за допомогою моделей глибокого навчання, що є актуальним як для наукової спільноти, так і для трейдерів та інвесторів. Метою роботи є побудова моделі прогнозу напряму зміни руху цін валютних котирувань на основі глибоких нейронних мереж. В основу розробленої архітектури було покладено модель вентильного рекурентного вузла, що є модифікацією моделі «довготривалої короткочасної пам'яті», але є більш простою за кількістю параметрів і часом навчання. Проведено прогнозні розрахунки динаміки котирувань валютної пари євро/долар і найбільш капіталізованої криптовалюти біткоїн/долар із використанням щоденних, чотиригодинних і щогодинних спостережень. Отримані результати бінарної класифікації (прогнозу напряму зміни тренду) під час застосування щоденних і годинних котирувань виявились загалом кращими, ніж дають моделі часових рядів, або моделі нейронних мереж іншої архітектури (зокрема, багатошарового персептрону, чи моделі на основі «довготривалої короткочасної пам'яті»). Згідно з одержаними результатами, найбільша точність класифікації виявилася для моделі щоденних котирувань як для євро/долар – близько 72 %, так і для біткоїн/долар – близько 69 %. Під час використання чотирьохгодинних і щогодинних часових рядів точність класифікації зменшувалась, що можна пояснити як збільшенням впливу «ринкового шуму», так і вірогідним перенавчанням моделей. Унаслідок комп'ютерних експериментів було з'ясовано, що моделі краще прогнозують зростаючий тренд, ніж спадаючий. Проведене дослідження підтвердило перспективність застосування моделей глибокого навчання для задач короткострокового прогнозування часових рядів валютних котирувань. Водночас використання розроблених моделей виявилось ефективним як для фіатних, так і для криптовалют. Запропоновану систему моделей на основі глибоких нейронних мереж можна покласти в основу під час розробки автоматизованої торгової системи на валютному ринку

Ключові слова: рекурентні нейронні мережі, короткострокове прогнозування, часові ряди валютних котирувань, криптовалюти

Application of Deep Learning Methods to Forecast Changes in Short-Term Exchange Rate Trends

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Abstract. This paper investigates the issues of short-term forecasting of exchange rates using deep learning models, which is relevant for both the academia and traders and investors. The purpose of this study is to build a model to forecast the direction of changes in the price movement of currency quotes based on deep neural networks. The developed architecture is based on the gated recurrent unit model, which is a modification of the "long short-term memory" model, but is simpler as to the number of parameters and learning time. Forecast calculations of the dynamics of quotations of the euro/dollar currency pair and the most capitalised cryptocurrency – bitcoin/dollar are carried out using daily, four-hour, and hourly observations. The obtained results of binary classification (forecasting the direction of trend change) when applying daily and hourly quotes turned out to be generally better than those given by time series models, or models of neural networks of other architecture (namely multilayer perceptron, or models based on "long short-term memory"). According to the results obtained, the highest classification accuracy was found for the model of daily quotes for both EUR/USD – about 72%, and for BTC/USD – about 69%. When using the four-hour and hourly time series, the classification accuracy decreased, which can be explained both by an increase in the impact of "market noise" and by the likely retraining of models. As a result of computer experiments, it was found that models better predict an upward trend than a downward one. The conducted research confirmed the prospects of using deep learning models for short-term forecasting of time series of currency quotes. At the same time, the use of the developed models proved to be effective for both fiat and cryptocurrencies. The proposed system of models based on deep neural networks can be used as a basis for the development of an automated trading system in the foreign exchange market

Keywords: recurrent neural networks, short-term forecasting, time series of currency quotes, cryptocurrencies

Introduction

In the current conditions of increasing instability and crisis phenomena both at the regional level and in the global economy in general, traders and investors, especially with short-term investment horizons, are forced to seek new efficient investment tools. If 20-30 years ago, both stock and FOREX currency market (FOReign EXchange – "foreign currency exchange") were mainly considered as traditional platforms for stock trading, then recently such innovative financial instruments as cryptocurrencies have become increasingly popular. Thus, after relatively stable 2018-2019, over the past year, the exchange rate value of leading cryptocurrencies has increased several times [1], which caused a new wave of interest in these instruments.

This necessitates a reliable identification of the optimal conditions of the currency market (both FOREX and crypto markets) for decision-making concerning trading operations, which should be based on adequate forecasts of currency quotes. For conventional assets, a considerable arsenal of effective methods and approaches to modelling and predicting their dynamics was developed and tested: causal econometric models,

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supply and demand balance models, adaptive forecasting methods, time series models of autoregression – integrated moving average (ARIMA) and their modifications, etc. [2-4].

Despite the wide variety of developed methods and models for forecasting exchange rates, work in this area is relevant. The dynamics of currency quotes are influenced both directly and indirectly by numerous factors. Due to the presence of complex causal chains, these influences are difficult to formalise within a certain theoretical concept or formalised model. The situation with cryptocurrency forecasting is even more complicated. Their dynamics are influenced by several latent factors, the vast majority of which remain understudied and unidentified [5-7]. Furthermore, cryptocurrencies are much more volatile and riskier than fiat currencies or securities. Many empirical studies indicate the limited practical value of applying classical statistical and econometric approaches to predicting the dynamics of cryptocurrencies [8-12].

Recently, machine and deep learning methods have been increasingly used to predict financial time series, which have proven effective both for analysing conventional assets (exchange rates, stocks, stock indices, commodity prices) and for cryptocurrencies [10-17]. In [12], models of recurrent neural networks (RNNs) and long short-term memory (LSTM) were used to predict changes in the price directions of bitcoin (BTC). The best result was obtained using an LSTM with a classification accuracy of 52%. At the same time, ARIMA time series models and recurrent RNN networks were less accurate.

The authors of the paper [15] tested four machine learning (ML) algorithms for predicting price trends in the cryptocurrency market: linear regression (LR), random forest (RF), support vector machine (SVM), and gradient boosting machine (GBM). According to the results obtained, the use of the ML algorithms applied for making a purchase/sale decision exceeded the results of applying the "*Buy and Hold*" investment strategy on the crypto market. The best result was obtained by voting ensembles (classification accuracy 59.3%).

In [16], several classifiers (RF, GBM, SVM, and LSTM) were also used for 5-minute BTC ticks and daily prices. The authors used a wide range of data, including both technological, market-based stock market factors, and those that consider preferences and interest in crypto assets (*sentiment analysis*). Somewhat unexpectedly, for daily prices, the best results were obtained using statistical methods (average accuracy 65%), as opposed to ML methods (average accuracy 55.3%). The article [17] also compares the effectiveness of various classifiers for predicting the direction of changes in cryptocurrency prices. The best classification result was achieved using multilayer perceptron (MLP) and random forest (RF) about 61%.

The authors of the study [18] applied ensembles of deep network models based on LSTM and convolutional neural networks (CNN) both to predict the price of cryptocurrencies (BTC, ETH, XRP) for the next hour (regression) and to predict changes in the price direction (classification). The best architectures developed by the authors demonstrated classification accuracy within the range of 52-55%. In [19], MLP and LSTM deep network models were used to predict the prices of the second-largest ETH cryptocurrency by capitalisation for daily, hourly, and minute data. The LSTM model demonstrated higher accuracy: on time data, the mean absolute percentage error (MAPE) was 1.38%, on daily data – 3.67%.

Over the past 5 years, there has been an increase in researchers' attention to applying deep neural networks to the tasks of studying both conventional exchange rates and those of cryptocurrencies. The authors of [20] published a detailed review on the use of deep learning (DL) approaches in the field of financial forecasting. The main conclusion of this review is that in general, the performance of DL algorithms is superior to time series models and often demonstrates higher accuracy than conventional ML algorithms.

The purpose of this study is to investigate the efficiency of using a deep neural network built based on a modified model of "long short-term memory" (LSTM) to predict changes in the direction BTC prices and compare the results with the exchange rate of the euro-dollar (EUR/USD) currency pair.

Materials and Methods

The problem of forecasting exchange rates should be solved using a systematic approach. At the first stage, it is advisable to decompose the problem into several interrelated tasks:

1) identification of the input set of factors (dataset), which must be considered when predicting based on a neural network. At the same time, the criteria, or requirements for selecting essential factors are to achieve the required forecast accuracy on a test or deferred sample, provided that the span of this data set is minimised;

2) identification of the required volume of training, test, and control samples. When solving this problem, there are also conflicting requirements related to the ability of neural networks to generalise (or vice versa, retrain);

3) selection of the type, basic structure, and composition of a neural network and its architecture;

4) optimisation of the underlying architecture by performing a series of computer experiments using different data sets;

5) application of the model to predict the dynamics of currency quotes;

6) evaluation of modelling results.

In this study, to better assess the predictive properties of the proposed models, the authors used only past (lagged) values of the target variable (currency quote) as explanatory variables (model factors). The time lag is 7 days: based on observations for the last 7 days (trading week), changes in the direction of quote movement for the next day are predicted using one-step forecast technology. Since the purpose of this paper is not to forecast the direct numerical value of the currency quote, but only a change in the direction of trend movement, that is, the problem of binary classification, there is no need for pre-processing of the time series under study, which usually entails filtering, smoothing, removing market noise and emissions, normalising or standardising time series. Therefore, all the time series under study were converted to binary variables: 1 – if the closing price of the quote of the day t is greater than or equal to the corresponding closing price of the day t -1, and 0 – in the opposite case.

Standard practice for building machine learning models is to break down the entire sample of data into training and testing data. The training data is designed to evaluate model parameters, while the test data – to check the quality of the model and fine-tune the hyperparameters. Therefore, in this paper, the authors did not use the last 10% of observations when training models, but used them to evaluate the accuracy and fine-tune the hyperparameters.

The most difficult stage of this study is the choice of network architecture. Notably, the process of choosing an architecture and building a network is still not formalised, but is based mainly on heuristic technologies, intuition, and experience of the researcher. For a long time, the most common network architecture was models based on multi-layer perceptron (MLP). Recently, however, due to the growth of computing power and the development of cloud services, deep networks of other architectures, namely CNNs and RNNs have become very popular. If CNNs are more adapted to image processing, then RNNs work better with time series.

Specific features of RNNs are that the connections between their elements form a directed sequence or chain (Fig. 1). At each time t, not only the input values (vector $x(t)$) but also the values of the parameters describing the internal state of the network at the previous time $h(t$-1) are fed to the network. This allows processing a series of events over time. The advantage of RNNs over MLPs is their ability to use their internal memory to process sequences of arbitrary length. Therefore, networks of this architecture are more suitable for processing and predicting time series than direct propagation networks, namely MLPs.

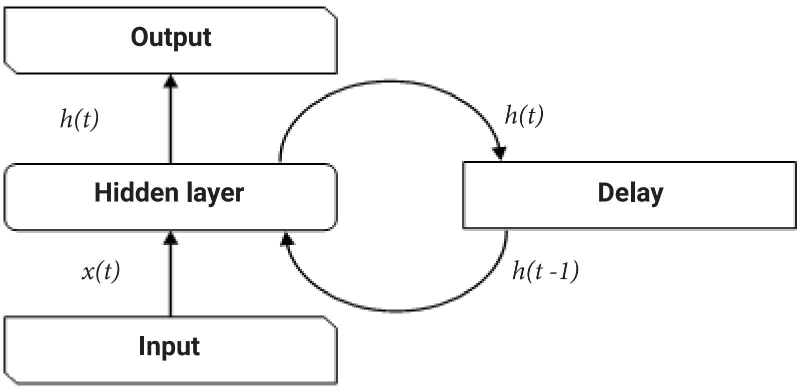

Figure 1. Simplified structure of a recurrent neural network

Source: compiled by the authors

One of the promising types of RNN architectures that can factor in long-term time dependencies is "long short-term memory" (LSTM) networks. Unlike conventional RNNs, LSTMs are more efficient at predicting time series in cases where important events are separated by time lags with indefinite duration or boundaries. The deep neural network architecture proposed by the authors of this study is based on the gated recurrent units (GRU) model [21], which is a modification of the LSTM model. The advantage of this model is that the performance of GRU-based networks is comparable to LSTM, but they have fewer parameters and therefore learn faster, requiring less data to train and configure.

For the software implementation of the models, the authors used data mining and machine learning methods using the Python and MQL5 programming languages, Google Colaboratory cloud services, Keras and Tensorflow libraries, and Pytorch.

Results and Discussion

For analysis, the authors took currency quotes of EUR/USD and BTC/USD for 01.02.2017-10.08.2020 according to the Yahoo Finance service [22]. This particular segment of the time series of quotes was chosen because analogous graphical patterns of behaviour of exchange rate quotes (similar patterns) are observed on the quote charts, marked with rectangles (Fig. 2).

The main purpose of the constructed graphical model (Fig. 2) lies in a short-term forecast of the direction of change in the quote of a financial instrument (growth or decline). The training window is seven days, the forecast horizon is one day, the number of training iterations (epochs) is 100, the training sample size is 90% of the total number of quotes, according to the test sample – 10%. Error (Fig. 3, 4(a)) and accuracy (Fig. 3, 4(b)) indicators of the models of daily (D1) EUR/USD (Fig. 2) and BTC/USD (Fig. 3) quotes have similar characteristics:

– the accuracy for the test sample remains at the same level all the time and increases after the 60th epoch;

– the error for the training sample decreases and the accuracy increases, which indicates that the models are retrained.

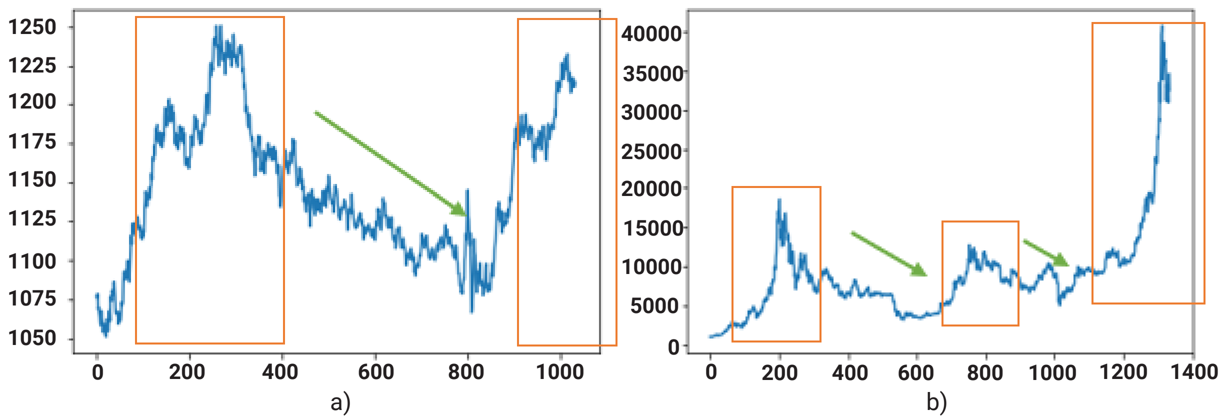

Figure 2. Charts of daily quotes of EUR/USD (a) and BTC/USD (b) for 01.02.2017-10.08.2020

Source: compiled by the authors based on [22]

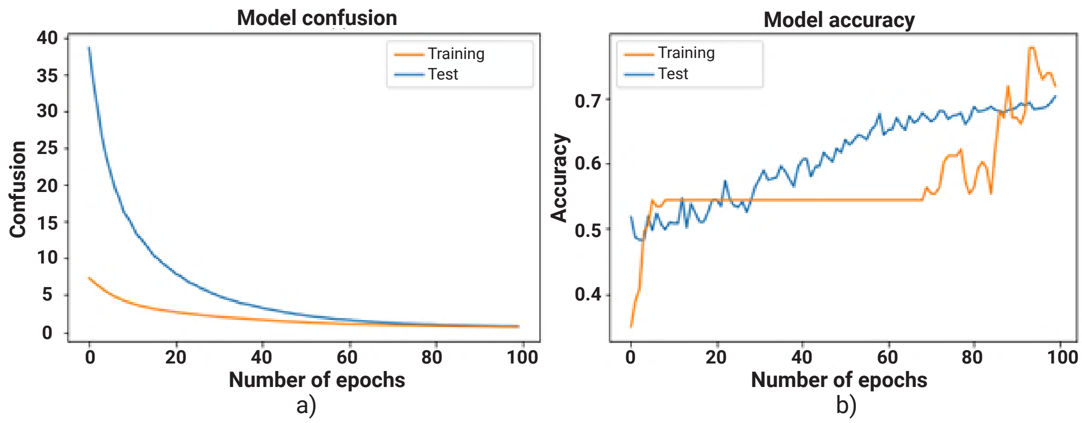

Figure 3. Model error and accuracy charts for daily EUR/USD quotes

Source: compiled by the authors based on testing of built models

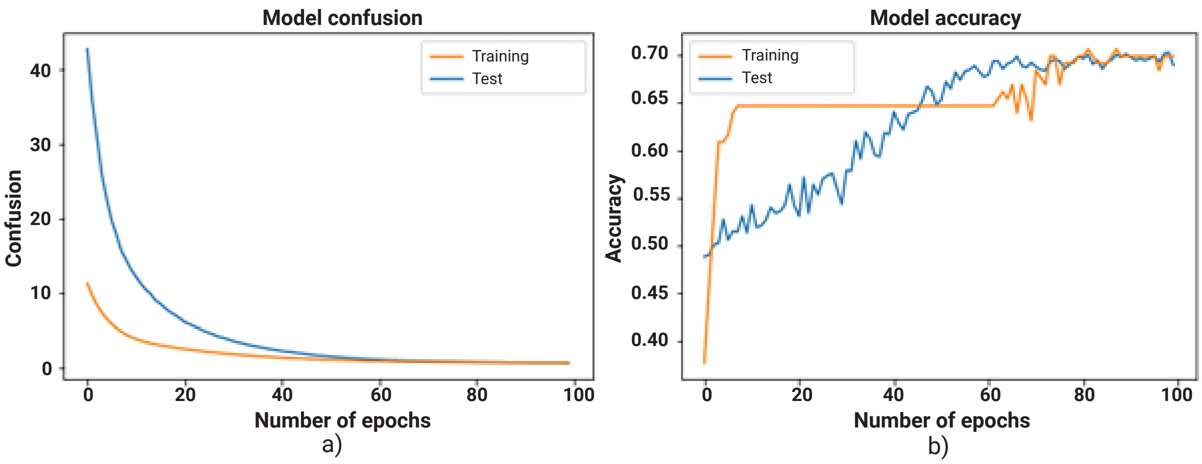

Figure 4. Model error and accuracy charts for daily BTC/USD quotes

Source: compiled by the authors based on testing of built models

Since the authors used the constructed model to solve the problem of binary classification (whether there will be a growth or decline in the studied indicator in the next period), the confusion matrix was used as a metric for evaluating the efficiency (accuracy) (Table 1). Table 1 presents: class *P* (*positive*) – growth of the indicator; class *N* (*negative*) – decline in the indicator; *TP* (*true positive*) – the model showed growth and there was also factual growth; *FP* (*false positive*) – the model showed growth, but there was a factual decline; *TN* (*true negative*) – the model showed a decline and there was also a factual decline; *FN* (*false negative*) – the model showed a decline, but there was a factual growth.

Table 1. General structure of the confusion matrix

		Output data	
		P	***N***
Projected data	***P***	***TP***	*FP*
	N	*FN*	***TN***

The following standard derived metrics were used for further analysis and comparison of forecasting models: accuracy (*ACC*) (1), the proportion of correctly classified positive objects (*TPR*) (2) and negative classes (*TPN*) (3), balanced accuracy (*BA*) (4):

$$ACC = \frac{TP + TN}{P + N} \tag{1}$$

$$TPR = \frac{TP}{P} \tag{2}$$

$$TPN = \frac{TN}{N} \tag{3}$$

$$BA = \frac{TPR + TPN}{2} \tag{4}$$

These confusion matrices allow quantifying the quality of the constructed model not only in general, but also depending on the type of confusion. Table 2 demonstrates the number of confirmed forecasts in the test sample of daily quotes EUR/USD (40 growth and 34 decline in quotes) and BTC/USD (65 growth and 28 decline in quotes).

Table 2. Confusion matrix of daily quotes of EUR/USD and BTC/USD

EUR/USD		**Output data**	
		Growth	*Decline*
Projected data	*Growth*	**40**	16
	Decline	13	**34**

BTC/USD		**Output data**	
		Growth	*Decline*
Projected data	*Growth*	**65**	21
	Decline	19	**28**

Source: compiled by the authors based on the results of using the built models

A graph was also used to evaluate the quality of the model (Fig. 5), which displays the initial data of the test sample and forecast data for a set of 50 time series samples. The number of matches allows evaluating the available opportunities for making decisions on conducting trading operations with a positive result.

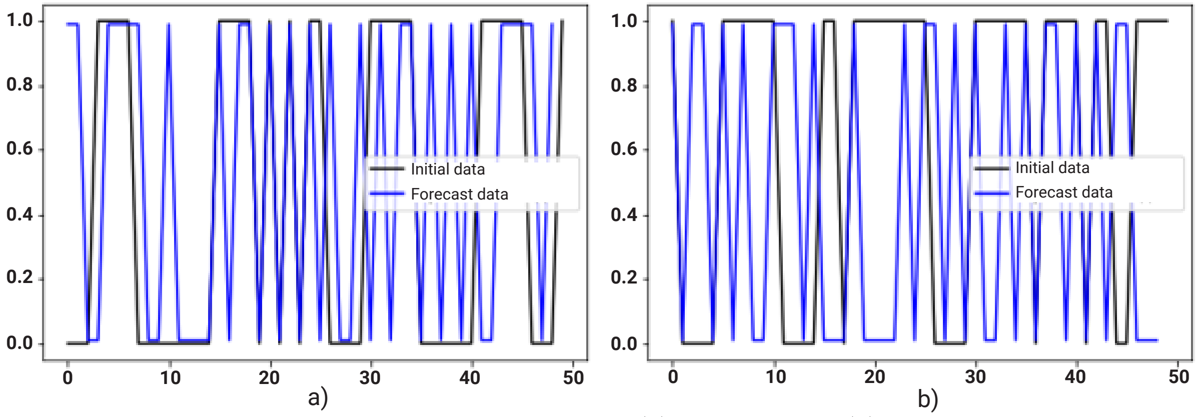

Figure 5. Factual and projected value of the EUR/USD (a) and BTC/USD (b) daily quote dataset
Source: compiled by the authors based on the results of using the built models

The next stage of analysing the quality of the constructed model was the transition from daily quotes to four-hour ones (H4 – 6 quotes per day). This increases the amount of data in the training and test samples, and the window for training the model is 42 periods (7 days), the forecast horizon is 6 periods (1 day). Decisions on trading operations are made every four hours for the next 24 hours. According to the results obtained, the accuracy indicators for four-hour EUR/USD quotes (Fig. 6) increase to the 20th epoch, which correlates with a decrease in confusion. From the 20th epoch onward, the accuracy is within the range of 58-62%, these data are confirmed by the values in the confusion matrix (Table 3). Accuracy for four-hour BTC/USD quotes (Fig. 7) is within the range of 60-64%. However, even though the accuracy is higher than that of the corresponding EUR/USD model, the number of true negative forecasts in the BTC/USD confusion matrix (Table 3) does not substantially differ from false positive and false negative forecasts (Fig. 8).

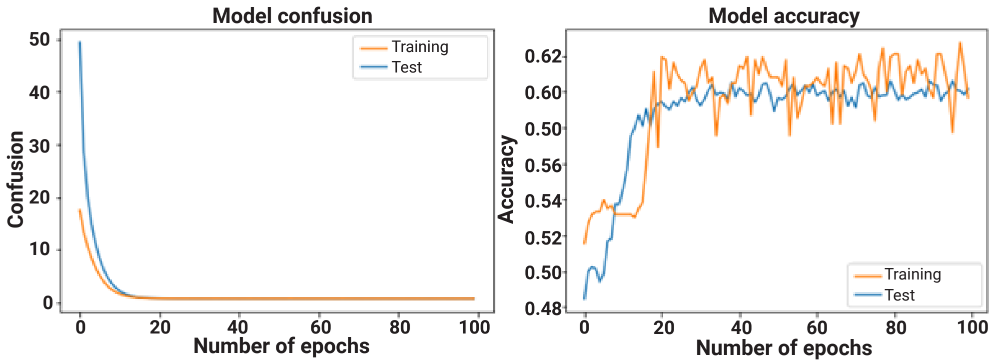

Figure 6. Charts of confusion and accuracy of the four-hour EUR/USD quote model
Source: compiled by the authors based on testing of built models

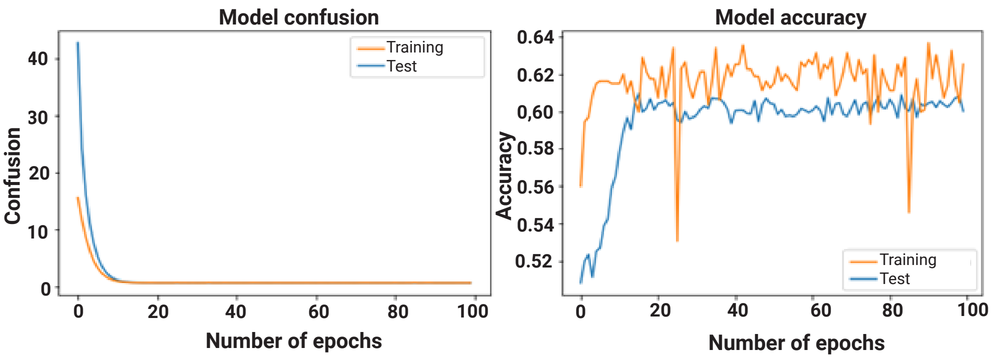

Figure 7. Charts of confusion and accuracy of the four-hour BTC/USD quote model
Source: compiled by the authors based on testing of built models

Table 3. Confusion matrix of the four-hour EUR/USD and BTC/USD quote models

EUR/USD		Output data		BTC/USD		Output data	
		Growth	*Decline*			*Growth*	*Decline*
Projected data	*Growth*	**191**	136	**Projected data**	*Growth*	**344**	138
	Decline	112	**176**		*Decline*	146	**156**

Source: compiled by the authors based on the results of using the built models

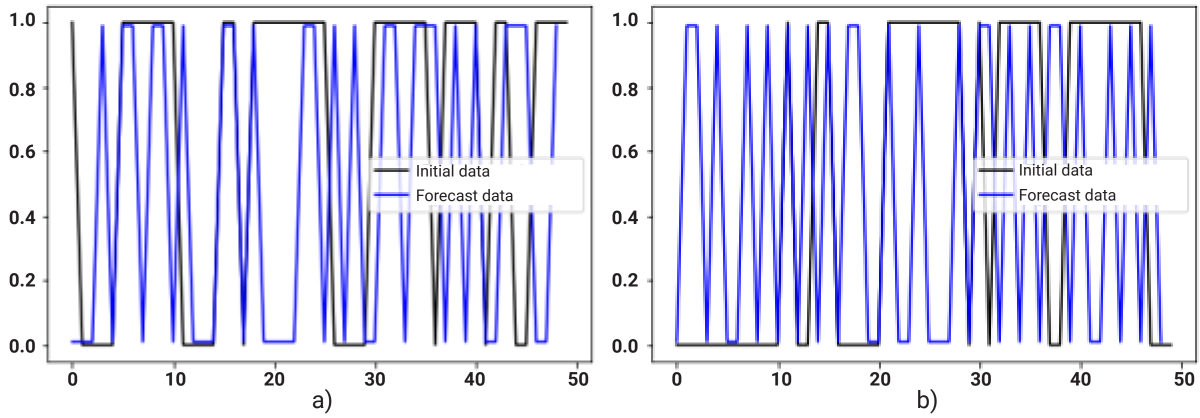

Figure 8. Factual and projected value of the EUR/USD (a) and BTC/USD (b) four-hour quote dataset
Source: compiled by the authors based on the results of using the built models

At the last stage of forecasting quality analysis, hourly quotes (H1 – 24 quotes per day) were selected using the GRU deep network model. At the same time, the amount of data in the training and test samples increased 24 times compared to the daily quotes, while the window for training the model was 168 periods (7 days), and the forecast horizon was 24 periods (1 day). Decisions on trading operations were made every hour on the horizon of 24 hours. Accuracy indicators of the hourly EUR/USD quote model (Fig. 9) for the entire range of training iterations was within the range of 50-55%, which is less than the corresponding indicators of the four-hour model. On the chart of the accuracy of hourly BTC/USD quotes (Fig. 10), there is a delta between the training and test samples, the accuracy of which is within the range of 53-55% for the training sample and 58-62% for the test sample, respectively. Furthermore, in the confusion matrices for EUR/USD and BTC/USD display a considerable number of false positive forecasts, which are 2 times higher than true negative forecasts. Figure 11 demonstrates this in the form of discrepancies between the original and forecast data. Table 4 presents the results of the confusion matrix for hourly quotes. Evidently, there was a decrease in classification accuracy for hourly quotes: the value of metric (1) was 0.53 and 0.6 for EUR/USD and BTC/USD, respectively.

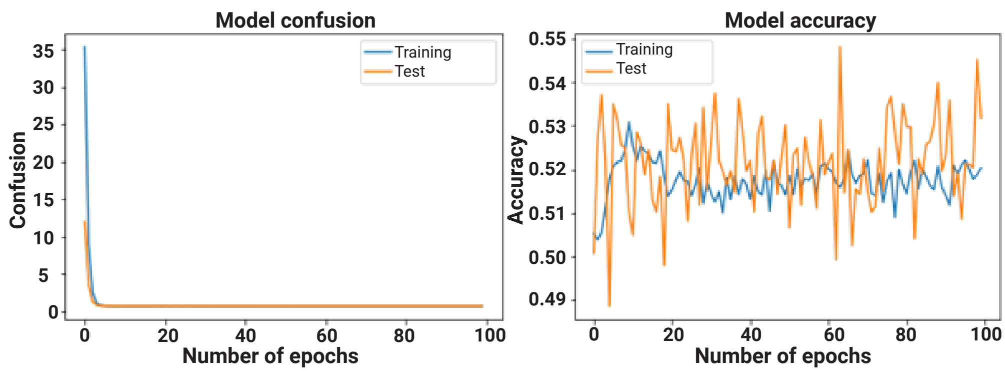

Figure 9. Charts of error and accuracy of the EUR/USD hourly quote model
Source: compiled by the authors based on testing of built models

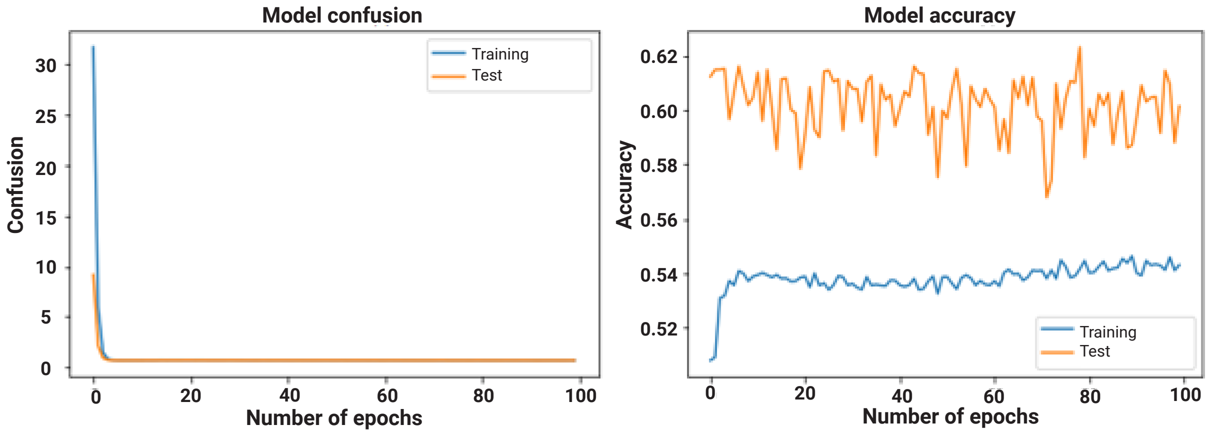

Figure 10. Charts of error and accuracy of the BTC/USD hourly quote model
Source: compiled by the authors based on testing of built models

Table 4. Confusion matrix of the EUR/USD and BTC/USD hourly quote models

EUR/USD		**Output data**		BTC/USD		**Output data**	
		Growth	*Decline*			*Growth*	*Decline*
Projected data	*Growth*	**922**	397	**Projected data**	*Growth*	**1526**	392
	Decline	753	**384**		*Decline*	851	**350**

Source: compiled by the authors based on the results of using the built models

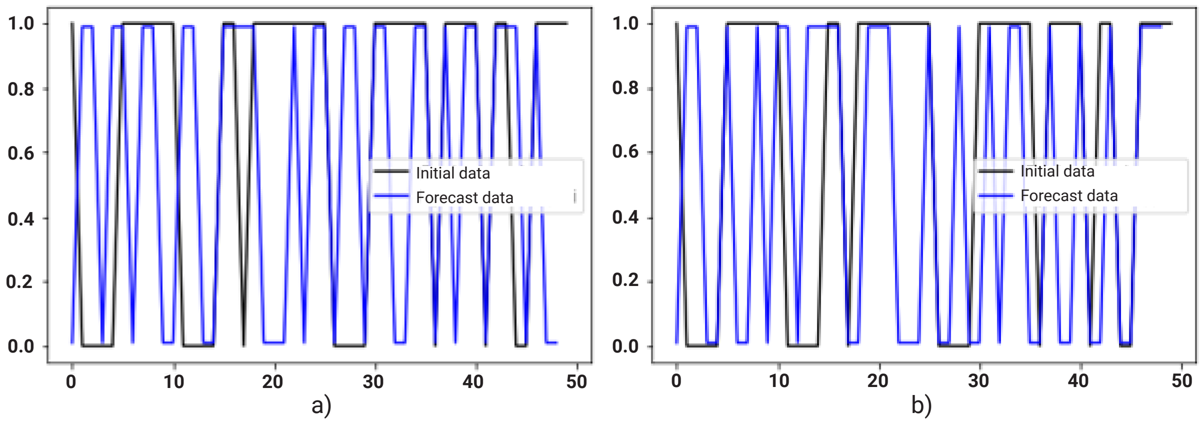

Figure 11. Factual and projected value of the EUR/USD (a) and BTC/USD (a) hourly quote dataset
Source: compiled by the authors based on the results of using the built models

The final results of applying the constructed GRU deep network model to predict the EUR/USD and BTC/USD exchange rates are presented in Table 5.

Table 5. Final results of the accuracy of the constructed models

	EUR/USD			BTC/USD		
Period	**D1**	**H4**	**H1**	**D1**	**H4**	**H1**
Total bars in the sample	1035	6195	24747	1335	7887	31374
Training sample	923	5531	22098	1193	7054	28062
Test sample	103	615	2456	133	784	3119
LSTM network metrics						
Training sampling confusion	0.7594	0.6862	0.7043	0.6629	0.6855	0.7001

Table 5, Continued

Period	EUR/USD D1	EUR/USD H4	EUR/USD H1	BTC/USD D1	BTC/USD H4	BTC/USD H1
Test sample confusion	0.6939	0.6901	0.6994	0.6328	0.6697	0.6900
Test sample accuracy	0.7184	0.5967	0.5318	0.6992	0.6250	0.6015
Training sample MSE	0.22322	0.23576	0.24905	0.20908	0.23442	0.24608
Training sample RMSE	0.47246	0.48555	0.49905	0.45725	0.48417	0.49606
Test sample MSE	0.21206	0.24075	0.24861	0.20454	0.23056	0.24130
Test sample RMSE	0.46050	0.49066	0.49861	0.45226	0.48017	0.49122
Confusion matrix						
Accuracy (ACC)	0.71844	0.59674	0.53175	0.69924	0.63775	0.60147
True positive rate (TPR)	0.75471	0.63036	0.55044	0.77380	0.70204	0.64198
True negative rate (TNR)	0.68000	0.56410	0.49167	0.57142	0.53061	0.47169
Balanced accuracy (BA)	0.71735	0.59723	0.52105	0.67261	0.61632	0.55683

Note: D1 – Daily models, H1 – 24 quotes per day, H4 – 6 quotes per day
Source: compiled by the authors based on the results of using the constructed models

Analysis of the data in Table 5 suggests as follows: in general, the models demonstrated higher accuracy when using the EUR/USD time series than for the BTC/USD. The best results were obtained when using daily quotes. When using four-hour and hourly data, the accuracy on the test sample was higher than on the training one. At the same time, no test data was used during model training. One explanation for this may be the effect of retraining the model. Models predict an uptrend (maximum value of the TPR metric=0.75 for daily EUR/USD quotes) better than a downtrend (maximum value of the TNR metric=0.68 for daily EUR/USD quotes).

In summary, the indisputable advantage of using deep networks is their ability to find hidden complex nonlinear patterns in data, as well as identify influential factors (*feature extraction*). Their disadvantage is that, theoretically, deep networks are essentially "event data recorders", and therefore it is quite difficult to analytically restore the functionality for which the forecast is made. Therefore, the result of their work is too "opaque".

Conclusions

The study proved the prospects of applying deep neural networks of the GRU type to predicting the directions of changes in exchange rates. According to the results of the analysis conducted by the authors of this study, such models were effective both in predicting the exchange rates of fiat and cryptocurrencies. The results of binary classification (forecasting the direction of trend changes) when applying daily and hourly quotes were generally better than time series models, or MLP-based models, or LSTM-based models. According to the findings of this study, the highest accuracy (in terms of the ACC metric) was observed in the model of daily quotes for both EUR/USD – about 72%, and for BTC/USD – about 69%.

When using four-hour and hourly data, the accuracy decreased. Notably, an increase in the training sample usually leads to an increase in the accuracy of forecasts. But if the time series consists of currency quotes, the so-called "noise" also increases at the same time, which leads to the opposite consequences – a decrease in the accuracy of forecasts. To prevent this, it may be efficient to use the Fourier transform, and the Wavelet transform of the original time series. Furthermore, an increase in the quality of classification can be achieved through fine-tuning of the hyperparameters. A promising area of further research may be the development of models based on the synthesis of convolutional neural networks and recurrent neural networks, as well as their further testing for classification tasks and to forecast future values of quotations for different time horizons of bias. Considering the above, the developed models can serve as a basis for creating an automated trading system in the currency market.

References

[1] Information resource: CoinMarketCap. (2020). Retrieved from https://coinmarketcap.com/.

[2] Mirkina, Ya.M. (Ed.) (2014). *International practice of forecasting world prices in financial markets (raw materials, stocks, exchange rates)*. Moscow: Magistr.

[3] Diebold, F.X. (1998). The past, present and future of macroeconomic forecasting. *Journal of Economic Perspectives*, 12, 175-192.
[4] Mills, T.C. (2011). Forecasting financial time series. *The Oxford Handbook of Economic Forecasting*. Retrieved from https://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780195398649.001.0001/oxfordhb-9780195398649-e-19?result=3&rskey=g04vJp#oxfordhb-9780195398649-div1-120.
[5] Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182-199.
[6] Datsenko, N.V., Derbentsev, V.D., & Ignatova, Yu.V. (2018). Cryptocurrencies for small and medium-sized businesses are the locomotive of the digital economy. In *Financial and credit support of innovation of small and medium business* (pp. 287-304). Kyiv: Kyiv National Economic University named after Vadym Hetman.
[7] Liuand, Yu., & Tsyvinski, A. (2018). *Risks and returns of cryptocurrency*. Cambridge: National Bureau of Economic Research.
[8] Catania, L., & Grassi, S. (2017). *Modelling crypto-currencies financial time-series*. Roma: Tor Vergata University.
[9] Bakar, N., & Rosbi, S. (2017). Autoregressive integrated moving average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: A new insight of bitcoin transaction. *International Journal of Advanced Engineering Research and Science (IJAERS)*, 4(11), 130-138.
[10] Derbentsev, V., Datsenko, N., Stepanenko, O., & Bezkorovainyi, V. (2019). Forecasting cryptocurrency prices time series using machine learning. *CEUR Workshop Proceedings*, 2422, 320-334.
[11] Saxena, A., & Sukumar, T. (2018). Predicting bitcoin price using LSTM and compare its predictability with ARIMA model. *International Journal of Pure and Applied Mathematics*, 119(17), 2591-2600.
[12] McNally, S., Roche, J., & Caton, S. (2018). Predicting the price of bitcoin using machine learning. In *26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP)* (pp. 339-343). Cambridge: IEEE.
[13] Derbentsev, V.D., Velikoivanenko, G.I., & Datsenko, N.V. (2019). Application of machine learning methods to predict time series of cryptocurrencies. *Neuro-Fuzzy Modeling Technologies in Economics*, 8, 66-93.
[14] Persio, L., & Honchar, O. (2018). Multitask machine learning for financial forecasting. *International Journal of Circuits, Systems and Signal Processing*, 12, 444-451.
[15] Borges, T.A., & Neves, R.N. (2020). Ensemble of machine learning algorithms for cryptocurrency investment with different data resampling methods. *Applied Soft Computing*, 90, 106-187.
[16] Chen, Z., Li, C., & Sun, W. (2020). Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics*, 365, article number 112395.
[17] Valencia, F., Gómez-Espinosa, A., & Valdés-Aguirre, B. (2019). Price movement prediction of cryptocurrencies using sentiment analysis and machine learning. *Entropy*, 21(6), article number 589.
[18] Livieris, I.E., Pintelas, E., Stavroyiannis, S., & Pintelas, P. (2020). Ensemble deep learning models for forecasting cryptocurrency time-series. *Algorithms*, 13(5), article number 121.
[19] Kumar, D., & Rath, S.K. (2020). Predicting the trends of price for Ethereum using deep learning technique. In *Artificial intelligence and evolutionary computations in engineering systems* (pp. 103-114). Singapore: Springer.
[20] Sezer, O.B., Gudelek, M.U., & Ozbayoglu, A.M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005-2019. *Applied Soft Computing*, 90, article number 106181.
[21] Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). *Empirical evaluation of gated recurrent neural networks on sequence modeling*. Retrieved from https://arxiv.org/abs/1412.3555.
[22] Information resource: Yahoo Finance. (n.d.). Retrieved from: https://finance.yahoo.com.

Список використаних джерел

[1] Інформаційній ресурс: CoinMarketCap. URL: https://coinmarketcap.com/ (дата звернення 05.08.2020).
[2] Международная практика прогнозирования мировых цен на финансовых рынках (сырье, акции, курсы валют) / под ред. Я.М. Миркина. Москва: Магистр, 2014. 456 с.
[3] Diebold F.X. The past, present and future of macroeconomic forecasting. *Journal of Economic Perspectives*. 1998. Vol. 12. P. 175–192.
[4] Mills T.C. Forecasting financial time series. *The Oxford Handbook of Economic Forecasting*. Oxford, 2011. URL: https://www.oxfordhandbooks.com/view/10.1093/oxfordhb/9780195398649.001.0001/oxfordhb-9780195398649-e-19?result=3&rskey=g04vJp#oxfordhb-9780195398649-div1-120 (accessed date: 05.07.2020).
[5] Corbet S., Lucey B., Urquhart A., Yarovaya L. Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*. 2019. Vol. 62. P. 182–199.

[6] Даценко Н.В., Дербенцев В.Д., Ігнатова Ю.В. Криптовалюти для малого та середнього бізнесу – локомотив цифрової економіки. *Фінансово-кредитне забезпечення інноваційної діяльності малого та середнього бізнесу* / за заг. ред. М.І. Диби. Київ: КНЕУ, 2018. С. 287–304.

[7] Liuand Yu., Tsyvinski A. Risks and returns of cryptocurrency. Cambridge: National Bureau of Economic Research, 2018. 68 p.

[8] Catania L., Grassi S. Modelling crypto-currencies financial time-series. Roma: Tor Vergata University, 2017. 39 p.

[9] Bakar N., Rosbi S. Autoregressive integrated moving average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: A new insight of bitcoin transaction. *International Journal of Advanced Engineering Research and Science (IJAERS)*. 2017. Vol. 4, No. 11. P. 130–138.

[10] Derbentsev V., Datsenko N., Stepanenko O., Bezkorovainyi V. Forecasting cryptocurrency prices time series using machine learning. *CEUR Workshop Proceedings*. 2019. Vol. 2422. P. 320–334.

[11] Saxena A., Sukumar T. Predicting bitcoin price using LSTM and compare its predictability with ARIMA model. *International Journal of Pure and Applied Mathematics*. 2018. Vol. 119, No. 17. P. 2591–2600.

[12] McNally S., Roche J., Caton S. Predicting the price of bitcoin using machine learning. *26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP)* (Cambridge, March, 21–23, 2018). Cambridge, 2018. P. 339–343.

[13] Дербенцев В.Д., Великоіваненко Г.І., Даценко Н.В. Застосування методів машинного навчання до прогнозування часових рядів криптовалют. *Нейро-нечіткі технології моделювання в економіці*. 2019. Вип. 8. С. 66–93.

[14] Persio L., Honchar O. Multitask machine learning for financial forecasting. *International Journal of Circuits, Systems and Signal Processing*. 2018. Vol. 12. P. 444–451.

[15] Borges T.A., Neves R.N. Ensemble of machine learning algorithms for cryptocurrency investment with different data resampling methods. *Applied Soft Computing*. 2020. Vol. 90. Article number 106187.

[16] Chen Z., Li C., Sun W. Bitcoin price prediction using machine learning: An approach to sample dimension engineering. *Journal of Computational and Applied Mathematics*. 2020. Vol. 365. Article number 112395.

[17] Valencia F., Gómez-Espinosa A., Valdés-Aguirre B. Price movement prediction of cryptocurrencies using sentiment analysis and machine learning. *Entropy*. 2019. Vol. 21, No. 6. Article number 589.

[18] Livieris I.E., Pintelas E., Stavroyiannis S., Pintelas P. Ensemble deep learning models for forecasting cryptocurrency time-series. *Algorithms*. 2020. Vol. 13, No. 5. Article number 121.

[19] Kumar D., Rath S.K. Predicting the trends of price for Ethereum using deep learning technique. *Artificial Intelligence and Evolutionary Computations in Engineering Systems* / Eds. by. S.S. Dash, C. Lakshmi, S. Das, B.K. Panigrahi. Singapore: Springer. 2020. P. 103–114.

[20] Sezer O.B., Gudelek M.U., Ozbayoglu A.M. Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing*. 2020. Vol. 90. Article number 106181.

[21] Chung J., Gulcehre C., Cho K., Bengio Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. URL: https://arxiv.org/abs/1412.3555 (accessed date: 10.07.2020).

[22] Інформаційний ресурс: Yahoo Finance. URL: https://finance.yahoo.com (дата звернення: 05.08.2020).