Przegląd Statystyczny. Statistical Review, 2022, vol. 69, 4, 41–60 https://doi.org/10.59139/ps.2022.04.4
Received: 31.01.2023, revised: 14.04.2023, accepted: 24.04.2023

Comparison of the accuracy of forecasts based on neural networks before and after the outbreak of the COVID-19 pandemic on the example of selected exchange rates

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Abstract. This article examines the impact of the COVID-19 pandemic on the accuracy of forecasts for three currency pairs before and after its outbreak based on neural networks (ELM, MLP and LSTM) in terms of three factors: the forecast horizon, hyper parameterisation and network type.

Keywords: neural network, currency market, forecasts, COVID-19 pandemic

JEL: C45, C53, E44

1. Introduction

The outbreak of the COVID-19 pandemic has been one of the most important events of recent years. It has had a significant impact on many aspects of life including demographics, through a recorded increase in mortality and a decrease in the birth rate (Balbo et al., 2020), the level of education, as schools were closed to prevent the spread of the virus (Daniel, 2020), and growing domestic violence (Boserup et al., 2020). Along with the increase in domestic crimes and the isolation of children from their peers, the pandemic has also had an impact on people's mental health (Cullen et al., 2020; Pfefferbaum & North, 2020; Usher et al., 2020). Cultural life also suffered since cultural events were either postponed or cancelled (Akser, 2020).

This article focuses on another aspect of the phenomenon, i.e. on the impact of the economic uncertainty on stock markets and the closure of specific industries and bankruptcies of companies.

The impact of COVID-19 was also very quickly and extensively recognised in the case of the broadly understood economy. On 24 February 2020, considerable drops were recorded on stock exchanges worldwide caused by an increasing number of infections (mainly in China). Prices of other assets, such as crude oil, gas, cryptocurrencies and corporate bonds also decreased. It is estimated that for the first

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nine days of March 2020, listed companies lost a total of USD 9 trillion in value (Raifu et al., 2021). Transport limitations caused further economic problems as did the frequent excessive purchases of necessities done by the population as they deregulated the logistics sector. The purpose of this study, however, is to check the impact of the pandemic on the accuracy of forecasts generated by neural networks.

The influence that COVID-19 has had on various aspects of economic life has been widely analysed in the latest scientific articles. The impact of the pandemic on the stock market on the example of indices such as IBEX35, FTSE100, DAX30, CAC40, and others are examined in Zeren & Hizarci (2020). The research in this article has been conducted over a short period, from January to March 2020, and indicated that investing in stocks after the COVID-19 outbreak was very risky and safer forms of investment should have been sought. After the virus appeared, information on the number of deaths and infections on a given day was provided frequently and on a regular basis. In the study by Ashraf (2020), where stock markets in as many as 64 countries were analysed, it was demonstrated that the information about the increase in the number of deaths was detrimental to stock markets and that their reaction was immediate. It should be emphasized that COVID-19 significantly affected other markets, e.g. those relating to oil: the impact of the pandemic on the volatility of the oil markets exceeded the consequences caused by the global financial crisis of 2008. The sharp drop in oil prices created an unprecedentedly high level of risk, causing investors to suffer from major losses in the short term (Zhang & Hamori, 2021). Countless articles also describe how the COVID-19 pandemic influenced currency markets. A vast linear relationship was observed between the number of confirmed deaths and the stability of the US and Chinese currencies (Li et al., 2022). A risk analysis of six currency pairs (USD/EUR, USD/GBP, USD/JPY, USD/CNY, USD/BRL, USD/TRY) shows that in the early months of the pandemic, the movements in the currency markets were not as intense as during the 2008 crisis. However, the Diebold-Yilmaz spillover index demonstrated that in the long run, the shock wave of the COVID-19 pandemic was about eight times greater than in 2008 (Gunay, 2021).

The second key element of this article is neural networks. The literature on forecasting based on neural networks states that the ones often used are ELM (Extreme Learning Machines), MLP (Multilayer Perceptrons) and LSTM (Long short-term memory) (Das et al., 2021; Sun et al., 2018; Wu & Gao, 2018). Therefore, the aforementioned networks were applied to make predictions in the empirical part of this article. The main objective of this study was to verify the accuracy of exchange rate forecasts generated using neural networks before and after the outbreak of the COVID-19 pandemic. The study is based on three neural networks with different hyperparameters. In their article, Abedin et al. (2021) indicated that the ensemble deep learning method based on the LSTM network achieved better results than the proposed benchmark regarding committed forecast errors for exchange rates. However, it was noted that the differences in the size of the prediction errors before and after the COVID-19 outbreak were substantial. When investing in currency markets, it is crucial to identify and measure the size of the error made in forecasting and to be aware of the correctly forecasted direction of change. Thus, this article also analyses neural networks which are less complex than LSTM, ELM and MLP. They were examined in terms of the accuracy obtained in forecasting the direction of change in the exchange rate.

The choice of exchange rates as the forecast asset was dictated by the fact that exchange rate fluctuations have a great impact on individual countries' economies. In the era of globalisation, exchange rates directly affect the operation of corporations, enterprises and individual investors (Markova, 2019). Many consider the exchange rate as a factor reflecting the current situation and condition of a given country's economy (Kartono et al., 2020). In this context, the most significant currency pairs are USD/EUR, GBP/EUR and CHF/EUR.

2. Methodology

Forecasting currency prices using neural networks is made at price levels. Three different neural networks were used in the study, namely:

- MLP (Rosenblatt, 1958);
- ELM (Rumelhart et al., 1986);
- LSTM (Hochreiter & Schmidhuber, 1997).

The MLP network is the simplest network used in the empirical studies presented in this article. It is built of at least three different layers, each performing its characteristic tasks:

- input layer – receives the signal for processing;
- hidden layers – responsible for processing signals from the input layer so as to generate auxiliary data. These data form the basis for determining the final solution through the output layers. Hidden layers mediate between the input and output layers, and their effect is visible indirectly through the output layer results;
- output layer – it returns the result of the calculations made in the hidden layers.

The way MLP networks operate is simple. Each neuron from each layer calculates a weighted sum of its inputs. The calculated activation level is an argument passed to the activation function which calculates the neuron's output. Each node, in addition to the input nodes, has a non-linear activation function which can take different forms. Examples include the sigmoidal function. MLP is a feedforward network, which means that the signal between the input layer and output layer runs only one way, i.e. from the input nodes, through the hidden nodes to the output nodes. Despite its simplicity, MLP networks can approximate any continuous function and solve problems that are not linear (Abirami & Chitra, 2020). An essential step in designing MLP networks is determining the appropriate number of layers and neurons in the layers.

ELM was initially developed for single hidden layer feedforward neural networks (SLFNs), i.e. as a single layer network. It uses a continuous and differentiable activation function to activate the hidden neurons, with sigmoidal and Gaussian functions used most often (Jastrzębski et al., 2015). Neural network learning occurs in two stages. The ELM network learning paradigm assumes the random generation of hidden layer parameters to map the input data into the feature space. These parameters remain constant (independent of the learning process). The second stage is based on minimising the squared error present in the first stage. As a result, the weights connecting the hidden layer and the output layer are determined. The output layer weights are obtained using the generalised inverse of the output matrix of the hidden layer.

LSTM belongs to the class of recurrent networks. A characteristic feature of LSTM networks is their structure designed to remember short patterns (hence 'short-term' in the name). LSTM was initially developed for sequence analysis and used in text sequence analysis. It contributed to the development of a number of applications, including Google Translate, Siri and Google's voice assistant. In the later stages of development, it was also adapted into time series (Smagulova & James, 2019). The LSTM network consists of connected multiple recurrent memory blocks. Each block includes three gates: an input, output and memory gate. What distinguishes LSTM from other recurrent networks are memory blocks. In classical recurrent networks, there is a data flow within the network. However, LSTM additionally has what is called a long memory: thanks to the gates, the LSTM network can store data for more than one period (Van Houdt et al., 2020). Another important difference between classical recurrent networks and LSTM worth mentioning here is the fact that the memory cell receives information from three input sources.

For each of the neural networks, 49 different combinations of hyperparameters describing the network were used. The assessed hyperparameters are the number of lags and the number of hidden nodes. Both hyperparameters can take seven different values. The number of hidden nodes took the values of 2, 5, 10, 15, 20, 25, 50, and the number of lags used in the neural network took the values of 1, 2, 3, 4, 5, 6, 7.

The number of hidden nodes did not take the form of consecutive natural numbers but at certain intervals so as to search for the optimal order of the magnitude of nodes and to examine the forecast results' dependence on this parameter. Other neural network settings, particularly the LSTM network are fine-tuned in the training process. The empirical part of the study considered three currency pairs: CHF/EUR, GBP/EUR and USD/EUR.

This paper describes the accuracy of individual neural networks. The forecast accuracy in this study is understood as the ratio of correctly forecasted directions of changes in relation to all of the produced forecasts. Each day, a forecast is made for 10 different horizons (from 1 to 10 days) using all combinations of two hyperparameters, which allows the determination of not only one relevance for a given network, but also the maximum, minimum and average relevance for a given network in each horizon. The study compares these values before and after the outbreak of the COVID-19 pandemic.

3. Data description

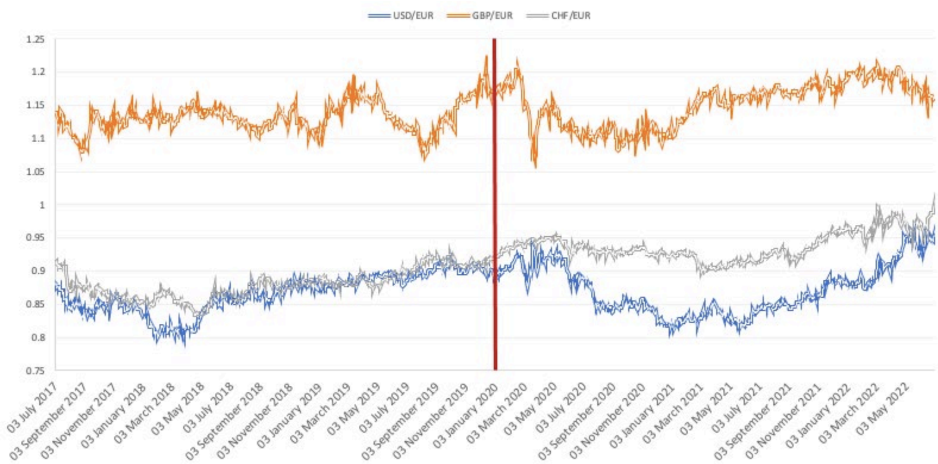
As previously mentioned, the currency pairs used in this study were USD/EUR, GBP/EUR and CHF/EUR. Forecasts with three neural networks for all currency pairs were made from 1 July 2017 to 30 June 2022, and the data were daily. It was assumed that the data before the COVID-19 outbreak included 10 quarters from 1 July 2017 to 31 December 2019; after the pandemic outbreak, we also considered 10 quarters: from 1 Jan 2020 to 30 June 2022. When generating forecasts, the data were divided into training and test sets. Therefore, the training data extended the data adopted in the study to 100 days before 1 July 2017. The study was carried out at price levels and the horizon length extended from 1 to 10 days. For forecasts more than one day ahead, a direct forecast was used. The training set was always composed of data one hundred days before the day the forecast was computed, which means that the training set always contained an equal number of observations, but their scope depended on the day of the forecast. Table 1 shows the descriptive statistics of the rates of return studied in two periods and Figure 1 shows the relevant exchange rates of the same period. The red line indicates the COVID-19 pandemic outbreak date adopted in the study, i.e. 1 January 2020.

Table 1. Descriptive statistics of the currency pairs

Currency pair	Period	Mean	Standard deviation	Skewness	Kurtosis
USD/EUR	01/07/2017–31/12/2019	0.00002	0.00401	0.16324	0.78288
	01/01/2020–30/06/2022	0.00011	0.00446	0.18710	1.61366
CHF/EUR	01/07/2017–31/12/2019	0.00007	0.00440	0.03802	1.82360
	01/01/2020–30/06/2022	−0.00002	0.00445	−0.65019	3.33893
GBP/EUR	01/07/2017–31/12/2019	0.00002	0.00301	−0.00539	0.89935
	01/01/2020–30/06/2022	0.00013	0.00302	0.30309	4.07684

Source: author's work based on stooq.com.

Figure 1. Currency rate chart – USD/EUR, CHF/EUR and GBP/EUR



Source: author's work based on stooq.com.

The information presented in Table 1 indicated little difference between the average rate of return, which for all currency pairs and regardless of the period studied was close to zero. Similar conclusions could be drawn from the standard deviation. However, the skewness and kurtosis show differences for all currency pairs. Particularly for the GBP/EUR pair, the skewness changed from positive for the 2.5 years before the pandemic outbreak to negative for the 2.5 years after the COVID-19 pandemic outbreak. There was also a change in skewness for the CHF/EUR pair, although in this case from negative to positive. Significant changes in kurtosis could also be seen for these pairs. The skewness change was small for the USD/EUR pair, while the kurtosis change was smaller than in the case of the other currency pairs. Figure 1 shows the price levels of the three currency pairs under study. Price levels are intended to illustrate the trends in the currency pairs during the period under study. Figure 1 indicates that just before the end of 2019, all the currencies studied were in an uptrend. After the pandemic outbreak, the largest losses were recorded for the GBP/EUR pair. For USD/EUR, there was also a decline at the same time as for GBP/EUR, but the change was less abrupt, and the exchange rate of this currency returned more quickly to the levels before the decline. The slightest fluctuations in the period after the outbreak of the COVID-19 pandemic were recorded for the CHF/EUR pair.

4. Research

The empirical study predicted three currency pairs using 49 different combinations of hyperparameters for three neural networks, making it a total of 147 models analysed. Many of the obtained forecasts were aggregated in search of answers on the impact of the COVID-19 pandemic on the accuracy of forecasts generated using neural networks. The first part of the empirical study focused on more general conclusions. Then a more in-depth analysis was performed to search for more detailed conclusions. As mentioned in Section 3, the data were divided into 20 quarters. Forecasts were made for individual days for each of the quarters. Accordingly, the data in Tables 2–7 refer to the accuracy of the forecasts for the days included in each quarter. Accuracy in this case describes the number of correctly forecasted directions of change in relation to all of the produced forecasts. If the table does not contain a division by neural network, it should be assumed that the data include accuracy across all neural networks.

Tables 2–4 present the average accuracy for all 147 models, broken down by quarter and forecast horizon but not by neural network types. These tables show that for the majority of forecast horizons and throughout most of the studied period, neural networks achieved accuracy exceeding 50%.

Table 2. The average prediction accuracy for all neural networks for the USD/EUR currency pair

Period	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
	%									
Q3 2017	**52.49**	44.89	45.72	46.06	**51.19**	46.72	45.39	47.53	47.70	43.90
Q4 2017	**58.41**	**54.21**	**54.52**	**55.31**	**55.57**	**55.73**	**55.47**	**63.91**	**66.43**	**67.32**
Q1 2018	49.52	**51.71**	**56.48**	**50.54**	**52.82**	49.17	**50.88**	48.33	46.09	47.38
Q2 2018	47.83	45.60	43.32	43.30	42.13	41.73	45.13	46.98	47.05	47.96
Q3 2018	**55.55**	**59.54**	**63.84**	**59.90**	**56.86**	**55.79**	**57.88**	**61.13**	**62.80**	**61.40**
Q4 2018	**52.63**	**54.89**	**53.19**	49.38	49.21	**61.22**	**59.85**	**55.11**	**53.90**	**50.28**
Q1 2019	**58.81**	**56.56**	**60.45**	**64.60**	**69.06**	**69.38**	**71.55**	**70.69**	**68.54**	**67.06**
Q2 2019	49.43	**51.12**	**53.21**	**59.86**	**56.05**	**56.16**	**58.04**	**54.27**	**52.25**	**50.80**
Q3 2019	48.61	**55.71**	**57.79**	**58.48**	**55.94**	**56.95**	**55.80**	**55.36**	**58.79**	**54.07**
Q4 2019	**51.91**	**51.91**	**55.81**	**60.00**	**63.70**	**66.95**	**63.08**	**67.56**	**64.13**	**62.00**
Q1 2020	47.49	44.90	46.18	**50.80**	**52.77**	**54.10**	**55.67**	**51.39**	**57.75**	**55.53**
Q2 2020	46.03	**50.62**	49.97	49.85	**52.30**	**51.42**	**55.91**	**55.72**	**57.94**	**54.25**
Q3 2020	43.65	49.29	45.80	48.44	46.85	47.39	48.49	43.93	45.81	41.99
Q4 2020	**51.26**	**54.64**	**51.97**	**53.49**	**51.65**	49.71	**53.20**	48.43	**54.89**	49.08
Q1 2021	**50.81**	**53.77**	**50.91**	**52.25**	**52.33**	**52.70**	**54.30**	**52.55**	**60.76**	**53.02**
Q2 2021	**58.84**	**58.76**	**59.55**	**59.68**	**60.74**	**65.82**	**62.17**	**57.58**	**62.79**	**62.85**
Q3 2021	47.20	**53.93**	48.29	44.67	46.17	49.34	48.52	47.44	**53.76**	**54.32**
Q4 2021	**56.35**	**54.19**	**50.02**	43.88	48.92	47.81	**50.80**	47.35	**53.30**	**50.01**
Q1 2022	**59.95**	**58.83**	**56.37**	**58.72**	**61.15**	**62.38**	**63.24**	**59.57**	**60.93**	**61.07**
Q2 2022	**57.14**	**53.13**	45.26	43.74	44.28	46.65	48.47	46.80	47.19	42.58

Note. *t*+1, *t*+2, ..., *t*+10 – forecast horizons. The numbers in bold indicate accuracy above 50%.
Source: author's work.

Table 3. The average accuracy of forecasts for all neural networks for the CHF/EUR currency pair

Period	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
	%									
Q3 2017	**54.71**	49.58	**58.42**	**59.93**	**61.12**	**66.69**	**64.72**	**64.31**	**63.10**	**62.18**
Q4 2017	**50.65**	44.66	42.67	44.83	42.64	40.13	36.80	32.87	35.66	34.52
Q1 2018	46.51	**50.98**	48.83	49.67	45.93	43.36	43.92	43.29	41.95	38.77
Q2 2018	46.18	40.66	38.83	41.55	39.35	38.17	36.23	37.80	35.20	37.08
Q3 2018	**54.42**	**55.46**	**53.60**	**55.68**	**57.06**	**56.18**	**55.68**	**58.22**	**58.53**	**54.88**
Q4 2018	**51.80**	**52.93**	48.94	**53.04**	**53.81**	**53.17**	**51.27**	**51.57**	**54.82**	**56.19**
Q1 2019	**50.66**	**54.83**	**55.85**	**54.55**	**55.41**	**57.95**	**53.70**	**55.47**	**57.02**	**54.45**
Q2 2019	48.22	**51.88**	47.34	45.54	46.71	46.04	46.12	46.01	43.29	38.76
Q3 2019	**50.59**	**54.95**	**57.75**	**58.29**	**56.35**	**57.96**	**59.61**	**61.85**	**68.08**	**63.92**
Q4 2019	**50.63**	**58.16**	**52.80**	**56.63**	**61.58**	**63.84**	**60.94**	**60.30**	**55.48**	**52.26**
Q1 2020	44.35	48.54	40.18	42.50	38.65	38.67	37.82	37.18	40.99	35.67
Q2 2020	**52.16**	**54.62**	48.24	**54.30**	**52.97**	**50.87**	48.45	47.83	45.59	43.01
Q3 2020	**52.21**	**52.88**	**51.52**	**55.94**	**51.11**	**51.75**	**51.77**	**51.72**	**53.82**	49.92
Q4 2020	**52.85**	**53.59**	**56.44**	**59.15**	**50.17**	49.51	**55.15**	**54.66**	**58.50**	**54.19**
Q1 2021	**54.78**	**56.42**	**55.71**	**54.85**	**53.31**	49.40	**58.51**	**57.22**	**60.94**	**56.36**
Q2 2021	**55.13**	**53.05**	**55.11**	**58.92**	**52.87**	49.48	**55.82**	**50.91**	**57.20**	49.39
Q3 2021	**54.14**	49.60	49.44	**52.15**	**51.56**	47.46	**51.98**	**54.25**	**54.81**	**54.23**
Q4 2021	**50.55**	45.73	43.32	38.72	36.98	33.20	38.61	38.06	41.49	35.97
Q1 2022	**52.62**	**50.29**	42.80	47.83	48.77	45.10	**52.98**	**51.65**	**56.36**	**52.61**
Q2 2022	**54.29**	**51.52**	48.05	**56.16**	**51.06**	**51.35**	**62.37**	**62.05**	**65.19**	**63.95**

Note. As in Table 2.
Source: author's work.

Table 4. The average prediction accuracy for all neural networks for the GBP/EUR currency pair

Period	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
	%									
Q3 2017	46.28	40.81	37.33	39.74	38.77	39.83	37.68	34.81	32.45	30.90
Q4 2017	**56.73**	**61.80**	**60.83**	**60.45**	**62.43**	**65.38**	**65.16**	**69.44**	**66.96**	**68.97**
Q1 2018	**61.69**	**62.58**	**64.34**	**70.04**	**66.51**	**69.16**	**69.48**	**70.04**	**69.67**	**72.06**
Q2 2018	**55.94**	**53.89**	**61.90**	**60.57**	**62.39**	**55.87**	**52.54**	**55.18**	**57.04**	**60.75**
Q3 2018	47.32	**51.82**	48.57	47.08	47.90	45.39	46.44	44.30	44.72	43.69
Q4 2018	48.23	48.39	**51.10**	**59.52**	**59.90**	**57.52**	**59.09**	**55.97**	**58.20**	**55.48**
Q1 2019	**50.63**	**51.51**	**52.71**	**53.81**	**53.09**	**54.82**	48.48	**52.09**	**56.04**	**54.28**
Q2 2019	46.91	43.08	43.03	46.01	45.39	46.65	45.87	48.86	**51.28**	46.99
Q3 2019	47.22	42.36	42.52	34.50	34.71	31.77	36.46	36.53	34.24	37.12
Q4 2019	49.67	**50.61**	**52.58**	48.17	49.64	**50.14**	49.15	48.45	49.26	49.21
Q1 2020	47.12	**51.27**	48.86	**52.43**	47.48	**50.86**	**50.80**	49.08	48.13	48.73
Q2 2020	49.23	**50.34**	**51.03**	49.85	44.21	**52.36**	**53.32**	**53.89**	**54.87**	**52.74**
Q3 2020	49.25	48.67	**57.02**	**57.06**	**52.03**	**58.03**	**59.61**	**59.08**	**59.38**	**61.23**
Q4 2020	**57.35**	**55.82**	**64.42**	**62.47**	**58.10**	**60.97**	**63.61**	**62.53**	**62.64**	**58.63**
Q1 2021	44.54	44.50	46.85	48.76	42.66	47.61	48.48	46.91	45.71	46.04
Q2 2021	**57.38**	**58.26**	**64.15**	**60.97**	**57.13**	**64.97**	**65.45**	**63.67**	**61.87**	**59.40**
Q3 2021	**56.47**	**61.80**	**65.16**	**62.77**	**57.39**	**63.19**	**62.05**	**64.97**	**62.27**	**59.72**
Q4 2021	**51.72**	**52.46**	**51.71**	**51.48**	45.40	**53.24**	49.93	**58.38**	**53.32**	**55.23**
Q1 2022	**53.08**	**59.86**	**61.80**	**58.62**	**56.03**	**62.50**	**63.70**	**65.57**	**57.93**	**59.55**
Q2 2022	**51.30**	49.84	**53.72**	**51.48**	44.09	49.31	45.27	**53.44**	47.52	49.16

Note. As in Table 2.
Source: author's work.

Tables 2–4 above indicate a situation in which the accuracy of forecasts grew as the forecast horizon increased. This situation can have two potential causes. The first is the characteristics of the LSTM network and the consistent flow of gradients through the network. The gradient in a recurrent neural network is responsible for remembering how many errors the network makes in the successive iterations. The second reason for higher accuracy over longer horizons may be the influence of trends. If the network correctly recognizes a trend, it makes fewer errors in multiple-day forecasts as it follows the trend.

To illustrate the results, Figure 2 presents the changes in the accuracy of forecasts in individual quarters for 1-, 2-, 3-, and 4-day-ahead forecasts for the USD/EUR currency pair.

Figure 2. The average accuracy of forecasts for the USD/EUR network in a 1- to 4-day forecast horizon

Source: author's work.

When comparing the last period before the pandemic (Q4 2019) and the first period of the pandemic (Q1 2020) shown in Figure 2, a decrease in the accuracy of forecasts was observed. However, it should be objectively noted that the decrease in the accuracy of forecasts at the beginning of 2020 was not considerably lower than the accuracy of forecasts for Q3 2017 with 1-, 2- or 3-day forecasts or with 1-, 2-, 3- and 4-day forecasts in Q2 2018.

Not all currency pairs showed significant drops compared to the period prior to the COVID-19 outbreak. The average accuracy of forecasts, despite a temporary decrease, very often returned to the levels recorded before the pandemic.

In the next stage of the study, only the accuracy of forecasts obtained in the quarter preceding the start of the pandemic and Q1 2020 were compared. In this case, however, the data were broken down into individual types of neural networks.

Table 5. Comparison of forecast accuracy in Q4 2019 and Q1 2020 for the USD/EUR currency pair

NN	Period	USD/EUR									
		t+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
		%									
ELM	Q4 2019	**53.85**	**52.72**	**58.05**	**62.61**	**67.06**	**68.57**	**64.33**	**68.10**	**63.39**	**62.92**
	Q1 2020	**50.64**	**50.13**	**52.20**	**58.26**	**61.32**	**63.52**	**67.67**	**58.77**	**66.74**	**63.74**
	Difference ...	–3.21	–2.59	–5.85	–4.35	–5.74	–5.05	3.33	–9.33	3.35	0.82
MLP	Q4 2019	**52.24**	**51.15**	**53.66**	**57.24**	**62.29**	**67.82**	**62.07**	**65.87**	**60.28**	**56.30**
	Q1 2020	44.96	36.93	41.36	42.35	43.94	46.43	**51.40**	45.63	49.11	49.36
	Difference ...	–7.28	–14.22	–12.30	–14.89	–18.35	–21.39	–10.67	–20.24	–11.18	–6.93
LSTM	Q4 2019	49.63	**51.87**	**55.71**	**60.15**	**61.76**	**64.47**	**62.82**	**68.72**	**68.72**	**66.78**
	Q1 2020	46.88	47.66	44.98	**51.79**	**53.03**	**52.34**	47.95	49.78	**57.41**	**53.48**
	Difference ...	–2.76	–4.21	–10.73	–8.36	–8.72	–12.13	–14.87	–18.94	–11.31	–13.30

Note. As in Table 2. The numbers are marked red (green) when the forecast accuracy for Q4 2019 is higher (lower) than that for Q1 2020.

Source: author's work.

Table 6. Comparison of forecast accuracy in Q4 2019 and Q1 2020 for the CHF/EUR currency pair

NN	Period	CHF/EUR									
		t+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
		%									
ELM	Q4 2019	**52.18**	**54.19**	49.80	49.61	**55.67**	**58.30**	**55.38**	**53.75**	**50.61**	**54.91**
	Q1 2020	36.26	40.21	31.31	29.08	25.16	23.95	21.17	19.61	19.36	15.27
	Difference ...	–15.93	–13.98	–18.48	–20.53	–30.51	–34.36	–34.21	–34.14	–31.26	–39.64
MLP	Q4 2019	48.63	**57.83**	**51.65**	**60.72**	**66.81**	**68.82**	**65.78**	**64.21**	**58.15**	**57.77**
	Q1 2020	43.97	**50.77**	41.14	47.90	44.83	47.19	43.27	44.39	45.18	44.87
	Difference ...	–4.66	–7.07	–10.51	–12.83	–21.98	–21.63	–22.51	–19.82	–12.96	–12.90
LSTM	Q4 2019	**51.06**	**62.45**	**56.96**	**59.56**	**62.27**	**64.40**	**61.65**	**62.93**	**57.69**	44.10
	Q1 2020	**52.83**	**54.65**	48.10	**50.52**	45.97	44.86	49.01	47.55	**58.43**	46.86
	Difference ...	1.77	–7.81	–8.86	–9.04	–16.30	–19.54	–12.64	–15.38	0.74	2.76

Note. As in Table 5.

Source: author's work.

Table 7. Comparison of forecast accuracy in Q4 2019 and Q1 2020 for the GBP/EUR currency pair

NN	Period	GBP/EUR									
		t+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
		%									
ELM	Q4 2019	47.03	45.90	43.80	34.07	36.04	31.65	30.80	28.76	25.71	25.49
	Q1 2020	43.27	46.88	45.25	44.90	46.91	46.08	48.05	44.04	40.88	37.85
	Difference ...	–3.76	0.97	1.45	10.83	10.86	14.43	17.25	15.28	15.17	12.36
MLP	Q4 2019	**52.94**	**53.59**	**53.78**	**53.03**	**52.18**	**55.23**	**51.15**	**52.09**	**54.79**	**52.28**
	Q1 2020	**55.93**	**52.61**	**50.73**	**54.72**	**53.95**	49.43	**51.72**	**51.88**	**51.02**	**55.01**
	Difference ...	3.00	–0.98	–3.05	1.69	1.77	–5.80	0.58	–0.21	–3.77	2.73
LSTM	Q4 2019	49.05	**52.34**	**60.15**	**57.40**	**60.70**	**63.55**	**65.49**	**64.51**	**67.29**	**69.85**
	Q1 2020	42.15	**54.31**	**50.59**	**57.66**	41.59	**57.07**	**52.64**	**51.32**	**52.49**	**53.33**
	Difference ...	–6.90	1.96	–9.56	0.26	–19.11	–6.49	–12.86	–13.19	–14.80	–16.53

Note. As in Table 5.
Source: author's work.

When summarising the values in the 'difference' rows, it can be observed that in 68 cases, a decrease in the accuracy of forecasts was recorded in Q1 2020 compared to Q4 2019. In 22 cases, on the other hand, an increase appeared in the accuracy of forecasts. However, two crucial features of the presented data should be noted. As many as 16 out of the 22 cases concern the GBP/EUR currency pair. For this pair, the lowest differences between the examined accuracy in the surveyed quarters were recorded. Therefore, only six times higher accuracy was noted in Q1 2020 than in Q4 2019 for the USD/EUR and CHF/EUR currency pairs (three each). For these two currency pairs, the differences between Q1 2020 and Q4 2019 in several cases oscillated within a dozen or so percentage points of difference. At this point, the conjecture about the negative impact of the outbreak of the COVID-19 pandemic on the accuracy of forecasts generated using neural networks has been confirmed.

In order to look for more complex relationships between the accuracy of individual neural network forecasts and currency pairs, tables were created to present the average accuracy of forecasts across all quarters of the studied period jointly with forecast horizons. In addition to the average accuracy, the tables also focused on the maximum and minimum forecasts within the forecasts of the same neural network but with different hyperparameters. Table 8 shows an example of such a table, with the average relevance for the ELM network and, in parentheses, the maximum relevance for this network forecasting the GBP/EUR currency pair.

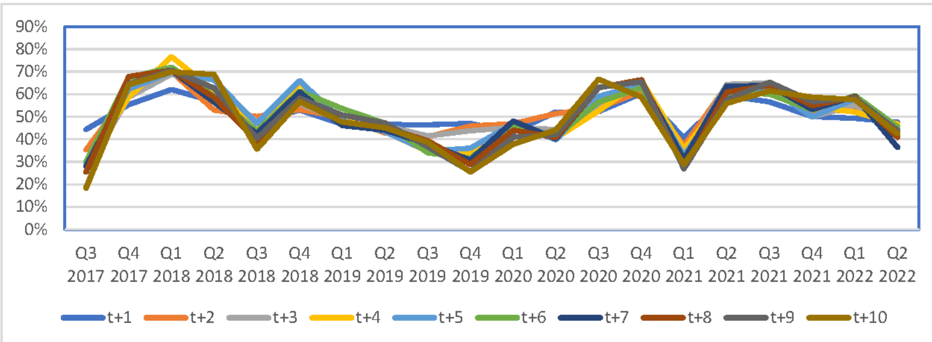
Table 8. The average accuracy of forecasts for the ELM network and the GBP/EUR currency pair

Period	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
	%									
Q3 2017	44.36	35.32	25.71	29.92	29.70	29.95	28.01	25.43	18.59	18.27
	(47.69)	(40.00)	(29.23)	(32.31)	(33.85)	(33.85)	(35.38)	(29.23)	(23.08)	(23.08)
Q4 2017	55.42	60.65	58.71	58.74	62.18	67.32	64.25	67.83	64.54	64.19
	(62.50)	(65.63)	(67.19)	(65.63)	(68.75)	(73.44)	(70.31)	(75.00)	(76.56)	(78.13)
Q1 2018	62.09	69.96	68.91	76.63	69.90	71.97	70.44	70.66	70.63	69.93
	(65.63)	(71.88)	(71.88)	(79.69)	(73.44)	(73.44)	(73.44)	(73.44)	(73.44)	(71.88)
Q2 2018	56.70	52.97	62.76	61.48	66.31	59.03	56.51	58.62	62.70	68.73
	(60.00)	(56.92)	(67.69)	(63.08)	(70.77)	(61.54)	(58.46)	(61.54)	(64.62)	(70.77)
Q3 2018	47.94	50.05	47.82	46.28	46.97	43.64	42.48	39.06	40.53	35.60
	(53.85)	(55.38)	(53.85)	(49.23)	(52.31)	(46.15)	(46.15)	(44.62)	(43.08)	(40.00)
Q4 2018	52.90	53.12	55.79	64.71	65.93	61.35	60.85	57.46	58.27	56.73
	(61.54)	(63.08)	(61.54)	(69.23)	(69.23)	(64.62)	(64.62)	(63.08)	(61.54)	(64.62)
Q1 2019	46.61	49.76	48.07	48.62	48.20	53.61	46.10	47.68	50.79	47.62
	(52.38)	(53.97)	(50.79)	(52.38)	(49.21)	(53.97)	(47.62)	(49.21)	(50.79)	(47.62)
Q2 2019	46.59	42.83	46.01	43.40	43.37	47.13	44.04	45.31	47.26	45.15
	(51.56)	(48.44)	(51.56)	(46.88)	(48.44)	(53.13)	(48.44)	(46.88)	(50.00)	(46.88)
Q3 2019	46.39	41.15	41.46	34.48	34.69	34.02	37.95	39.23	36.58	38.59
	(53.73)	(49.25)	(50.75)	(43.28)	(41.79)	(35.82)	(44.78)	(44.78)	(40.30)	(41.79)
Q4 2019	47.03	45.90	43.80	34.07	36.04	31.65	30.80	28.76	25.71	25.49
	(49.23)	(49.23)	(46.15)	(35.38)	(36.92)	(33.85)	(32.31)	(30.77)	(26.15)	(26.15)
Q1 2020	43.27	46.88	45.25	44.90	46.91	46.08	48.05	44.04	40.88	37.85
	(46.88)	(51.56)	(50.00)	(50.00)	(54.69)	(51.56)	(53.13)	(50.00)	(46.88)	(43.75)
Q2 2020	52.01	51.43	44.32	40.53	39.83	41.20	40.21	40.82	42.06	44.10
	(60.94)	(56.25)	(50.00)	(45.31)	(45.31)	(46.88)	(43.75)	(48.44)	(46.88)	(45.31)
Q3 2020	52.29	53.99	54.64	52.63	58.97	56.52	62.96	62.83	62.96	66.57
	(54.55)	(57.58)	(57.58)	(54.55)	(62.12)	(60.61)	(65.15)	(65.15)	(66.67)	(68.18)
Q4 2020	60.31	61.22	66.22	66.00	64.46	62.89	65.53	66.41	65.49	58.71
	(67.69)	(66.15)	(67.69)	(67.69)	(66.15)	(64.62)	(66.15)	(67.69)	(66.15)	(61.54)
Q1 2021	40.56	37.16	32.56	35.67	32.82	31.55	31.10	27.05	26.92	28.93
	(46.03)	(44.44)	(41.27)	(44.44)	(41.27)	(39.68)	(39.68)	(38.10)	(36.51)	(38.10)
Q2 2021	59.38	63.62	64.35	59.66	59.60	61.00	63.49	60.87	57.53	55.93
	(65.63)	(70.31)	(67.19)	(65.63)	(68.75)	(68.75)	(73.44)	(68.75)	(65.63)	(62.50)
Q3 2021	56.62	63.30	64.94	63.30	62.52	60.02	63.88	63.98	65.28	61.41
	(60.61)	(68.18)	(66.67)	(68.18)	(68.18)	(66.67)	(69.70)	(68.18)	(69.70)	(65.15)
Q4 2021	50.06	51.95	49.88	54.48	50.00	53.09	53.18	54.89	56.74	58.72
	(54.55)	(56.06)	(53.03)	(57.58)	(53.03)	(54.55)	(54.55)	(56.06)	(59.09)	(62.12)
Q1 2022	49.27	53.28	55.19	52.10	57.82	59.34	59.06	58.72	58.29	57.61
	(51.56)	(56.06)	(59.09)	(56.06)	(60.61)	(63.64)	(63.64)	(63.64)	(62.12)	(60.61)
Q2 2022	47.51	45.79	45.45	46.82	42.52	45.45	36.36	40.88	43.94	42.42
	(50.00)	(46.97)	(46.97)	(46.97)	(43.94)	(45.45)	(36.36)	(40.91)	(43.94)	(42.42)

Note. as in Table 2.
Source: author's work.

A graphic representation of the table above for the average accuracy of forecasts is shown in Figure 3.

Figure 3. The average forecasted accuracy for the ELM network and the GBP/EUR currency pair



Note. *t*+1, *t*+2, ..., *t*+10 – forecast horizons.
Source: authors' work.

Figure 3 shows three quarters for which the forecasts were considerably lower: Q3 2017 (the first period covered by the study), Q4 2019 (just at the start of the pandemic) and Q1 2021. The figure also shows slight differences between the accuracy of forecasts depending on the forecast horizon. For different quarters, different forecast horizons demonstrated the highest accuracy. It is difficult to determine for which horizons the forecasts were most accurate due to the fluctuations in accuracy occurring in different quarters. It should be noted that the most negligible differences in accuracy between various quarters can be observed in the forecast for the following day.

Table 9 shows the aggregate results for the period before and after the COVID-19 outbreak for the GBP/EUR currency pair predicted by the ELM network. The average accuracy of the period preceding the outbreak of COVID-19 (from Q3 2017 to Q4 2019) was lower than that observed in the period following the outbreak of the pandemic (from Q1 2020 to Q2 2022).

Table 9. The average accuracy for the period before and after the COVID-19 outbreak for the GBP/EUR currency pair predicted by the ELM network

Period in relation to COVID-19 outbreak	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
	%									
Before	**50.60**	**50.17**	49.90	49.83	**50.33**	49.97	48.14	48.00	47.56	47.03
After	**51.13**	**52.86**	**52.28**	**51.61**	**51.54**	**51.71**	**52.38**	**52.05**	**52.01**	**51.23**

Note. As in Table 2.
Source: author's work.

However, when making such a comparison for all neural networks and currency pairs, this situation is not a dominant one. The average accuracy for individual neural networks and currency pairs broken down into periods before and after the COVID-19 outbreak is presented in Table 10.

Table 10. Average accuracy for the period before and after the COVID-19 outbreak for all currency pairs and types of neural networks

Currency pair	NN	Period in relation to COVID-19 outbreak	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
			%									
USD/EUR	ELM	Before	**52.89**	**50.63**	**52.97**	**52.00**	**53.08**	**53.47**	**53.04**	**53.09**	**53.06**	**50.48**
		After	48.41	49.11	48.29	48.49	48.79	48.64	**50.18**	47.50	49.13	47.98
	MLP	Before	**54.15**	**53.92**	**54.65**	**54.87**	**55.49**	**56.38**	**57.06**	**56.89**	**56.42**	**54.51**
		After	49.83	**51.29**	**50.29**	**51.48**	**52.71**	**53.03**	**53.68**	**52.76**	**52.58**	**52.27**
	LSTM	Before	**50.52**	**53.30**	**55.67**	**57.35**	**57.19**	**58.08**	**58.83**	**61.28**	**60.82**	**60.66**
		After	**57.38**	**59.23**	**52.72**	**51.69**	**53.64**	**56.52**	**58.38**	**52.97**	**64.83**	**57.17**
CHF/EUR	ELM	Before	**51.68**	**51.49**	**51.95**	**52.13**	**52.76**	**53.30**	**51.79**	**51.23**	**50.70**	49.74
		After	47.96	48.67	46.12	46.51	45.90	45.76	44.38	45.12	45.52	44.92
	MLP	Before	49.74	48.99	45.91	48.81	47.84	47.22	46.43	45.65	46.72	44.98
		After	**50.45**	49.34	48.78	**50.76**	49.97	**51.54**	48.85	**50.17**	48.45	48.82
	LSTM	Before	49.89	**53.74**	**53.65**	**54.97**	**55.40**	**56.52**	**54.47**	**56.62**	**56.53**	**53.19**
		After	**58.52**	**56.86**	**52.34**	**58.89**	**50.35**	42.74	**60.81**	**56.37**	**66.50**	**54.85**
GBP/EUR	ELM	Before	**50.60**	**50.17**	49.90	49.83	**50.33**	49.97	48.14	48.00	47.56	47.03
		After	**51.13**	**52.86**	**52.28**	**51.61**	**51.54**	**51.71**	**52.38**	**52.05**	**52.01**	**51.23**
	MLP	Before	**50.83**	49.90	**50.51**	**51.21**	**50.50**	49.25	48.63	49.10	49.93	48.76
		After	**51.90**	**52.75**	**54.11**	**55.21**	**55.24**	**55.51**	**56.27**	**56.93**	**57.12**	**56.77**
	LSTM	Before	**51.75**	**51.99**	**54.05**	**54.92**	**55.39**	**55.74**	**56.33**	**57.60**	**58.47**	**60.05**
		After	**52.21**	**54.23**	**63.03**	**59.95**	44.57	**61.69**	**60.02**	**64.28**	**56.97**	**57.13**

Note. As in Table 2.
Source: author's work.

When comparing the average accuracy before and after the COVID-19 outbreak, the following conclusions can be drawn:

- higher accuracy was obtained before the COVID-19 outbreak period for the USD/EUR currency pair forecasted by the ELM and MLP networks and for CHF/EUR forecasted by ELM networks;
- higher accuracy was obtained after the COVID-19 outbreak for the GBP/EUR currency pair forecasted by the ELM and MLP networks, and CHF/EUR forecasted by MLP networks;
- the results for the LSTM network vary across all of the tested currency pairs.

After having compared the average accuracy of forecasts obtained by all neural networks with 49 different hyper-parameterisations, the next step was to conduct a study comparing the highest and the lowest accuracy of forecasts. The difference between these validities was obtained within the same neural network but using different combinations of hyperparameters. The results are presented in Table 11.

Table 11. Differences between the minimum and maximum forecast accuracy

Currency	NN	Period in relation to COVID-19 outbreak	*t*+1	*t*+2	*t*+3	*t*+4	*t*+5	*t*+6	*t*+7	*t*+8	*t*+9	*t*+10
			%									
USD/EUR	ELM	Before	8.82	8.83	7.90	7.90	7.90	9.30	9.46	9.45	9.44	8.97
		After	10.22	9.38	8.62	8.73	9.18	8.73	8.89	9.64	8.74	8.57
	MLP	Before	12.37	12.85	12.84	10.99	11.28	10.04	11.28	10.19	9.90	9.74
		After	15.45	13.21	14.45	14.28	14.76	14.75	14.77	15.03	14.59	15.50
	LSTM	Before	15.48	20.99	20.69	22.68	23.26	25.44	26.69	27.75	29.97	29.46
		After	32.50	31.43	27.69	23.59	26.61	21.59	23.85	26.92	22.06	25.08
CHF/EUR	ELM	Before	10.82	10.83	10.07	10.54	10.86	12.40	12.24	13.04	12.41	13.95
		After	9.44	11.19	10.47	10.78	9.69	8.93	8.62	9.08	8.02	8.94
	MLP	Before	9.73	9.27	10.20	10.36	11.91	11.44	13.14	12.67	12.22	12.53
		After	15.01	17.21	16.12	17.21	18.14	16.89	17.35	16.59	17.37	16.47
	LSTM	Before	16.56	17.62	23.62	22.87	32.33	22.92	21.97	26.94	32.48	29.07
		After	26.09	29.52	26.92	19.06	38.55	28.89	21.54	22.15	15.40	29.21
GBP/EUR	ELM	Before	9.88	10.32	9.39	7.72	8.64	7.41	8.48	7.37	7.55	8.47
		After	8.53	8.81	8.51	8.98	9.91	10.23	9.91	10.71	10.24	7.91
	MLP	Before	14.51	14.34	16.52	19.01	19.15	19.15	19.49	18.07	19.94	19.48
		After	12.11	14.48	13.26	14.61	12.00	15.22	13.07	15.06	13.82	16.30
	LSTM	Before	15.94	20.58	25.65	25.95	27.17	27.83	29.99	30.75	31.15	32.43
		After	26.72	26.98	20.31	20.78	31.13	16.98	18.46	20.77	23.97	29.05

Source: author's work.

The numbers in the table indicate by how many percentage points the most practical combination of hyperparameters achieved higher accuracy than the least effective one.

When comparing the obtained results with descriptive statistics, the following conclusions can be drawn:

- the USD/EUR exchange rate (which fell after the pandemic outbreak and began to rise in about the middle of the studied period – see Figure 1) influenced the low accuracy for the ELM and MLP in the period after the outbreak of the pandemic; the vast majority achieved a level of accuracy below 50% (which they often exceeded before the pandemic began);

- as regards the pairs with minor exchange rate fluctuations, i.e. CHF/USD for the ELM and LSTM networks, the accuracy of forecasts after the COVID-19 outbreak in most cases was higher than before the pandemic began.

Table 11 shows that there were more instances when the difference between the highest and lowest relevance within a given network was higher after the COVID-19 outbreak than before it. The abovementioned situation occurred 50 times, and the reverse only 40 times, which means that the uncertainties related to the situation in the global economy resulted in more significant differences in the accuracy of forecasts generated by neural networks. If only the USD/EUR and CHF/EUR currency pairs were to be compared, in 40 out of 60 cases the difference was higher in the years 2020–2022 than before the outbreak of COVID-19. However, for the GBP/EUR pair, such a relationship cannot be indicated. As regards the ELM network forecasting of the GBP/EUR exchange rate, higher values were obtained in the period preceding the outbreak of COVID-19 rather than in the period after in individual forecast horizons in a 6 to 4 ratio. In contrast, these relationships were reversed for the MLP and LSTM networks, where the ratio was 1 to 9 and 3 to 7, respectively. A particular analogy may be observed here to Table 7, where the only currency pair achieving higher forecast accuracy in Q1 2020 than in Q4 2019 was the GBP/EUR pair.

5. Discussion and conclusions

The literature indicates a significant impact of the COVID-19 pandemic on various aspects of social and economic life. The research presented in this article aimed to examine the impact of the pandemic on the accuracy of forecasts generated by neural networks. This examination was carried out both on a broader scope (by comparing the accuracy of forecasts from the 10 quarters preceding 2020 and the 10 quarters following it) and in a narrower scope, by comparing the accuracy of forecasts generated in the quarters at the turn of the pandemic, i.e. the last quarter of 2019 and the first quarter of 2020.

Sciences dealing with economic and market phenomena seek forecasting methods resistant to various fluctuations. The comparison of the accuracy of forecasts on a broader scope indicates slight differences between them before and after the outbreak of the pandemic. The tables with average relevance shown in this article prove the above. For some neural networks, a decrease in accuracy was noticeable after the COVID-19 outbreak, while for others an increase in accuracy was achieved. This may suggest that these results were influenced not only by the COVID-19 pandemic. In conclusion, based only on a broader scope, it can be indicated that neural networks are an appropriate tool for making forecasts in periods of uncertainty. The study showed no significant differences between the two studied periods. The neural networks achieved satisfactory levels of accuracy compared to the period before the outbreak of the COVID-19 pandemic.

However, the conclusions differ when only extreme periods are analysed, i.e. Q4 2019 and Q1 2020. Except for the ELM network forecasting CHF/EUR, where the accuracy was very low for all horizons (below 40% and for horizons from 8 to 10 days below 20%), the network's accuracy in Q1 2020 was not very low. An accuracy below 40% can be considered very low accuracy, while above 50% satisfactory. For most results, the accuracy oscillated around 40–50%. When comparing the accuracy with Q1 2020, it should be noted that the accuracy of 40–50% in many cases is the accuracy by about 5 to a dozen or so percentage points lower than the accuracy noted in Q4 2019.

In conclusion, the research results show that neural networks are a useful tool for forecasting exchange rates. However, like many other tools, neural networks have not been immune to the impact of COVID-19. Due to fluctuations in the markets, exchange rate quotations were more challenging to forecast, resulting in decreased accuracy of forecasts in the short term (less than 5 days). Nevertheless, this impact was reduced in the longer term (more than 5 days).

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