Impact of COVID-19 pandemic virus on G8 countries' financial indices based on artificial neural network

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Abstract

Purpose – The COVID-19 pandemic virus has affected the largest economies around the world, especially Group 8 and Group 20. The increasing numbers of confirmed and deceased cases of the COVID-19 pandemic worldwide are causing instability in stock indices every day. These changes resulted in the G8 suffering major losses due to the spread of the pandemic. This paper aims to study the impact of COVID-19 events using country lockdown announcement on the most important stock indices in G8 by using seven lockdown variables. To find the impact of the COVID-19 virus on G8, a correlation analysis and an artificial neural network model are adopted.

Design/methodology/approach – In this study, a Pearson correlation is used to study the strength of lockdown variables on international indices, where neural network is used to build a prediction model that can estimate the movement of stock markets independently. The neural network used two performance metrics including R^2 and mean square error (MSE).

Findings – The results of stock indices prediction showed that R^2 values of all G8 are between 0.979 and 0.990, where MSE values are between 54 and 604. The results showed that the COVID-19 events had a strong negative impact on stock movement, with the lowest point on the March of all G8 indices. Besides, the US lockdown and interest rate changes are the most affected by the G8 stock trading, followed by Germany, France and the UK.

Originality/value – The study has used artificial intelligent neural network to study the impact of US lockdown, decrease the interest rate in the USA and the announce of lockdown in different G8 countries.

Keywords Artificial neural network, Stock market, Lockdown, Group eight

Paper type Research paper

1. Introduction

World Health Organization (WHO) officially declared coronavirus (COVID-19) outbreak as a global pandemic on March 11th, 2020 after 40 days of considering it as global emergency (Al-Najjar and Al-Rousan, 2020). As of May 31st, 2020, the number of confirmed cases surpassed six million and deceased cases exceeded 350,000.

Accordingly, lockdown is considered the crucial consequence accompanied with COVID-19 which affected all economic sectors: technology adaption, teaching, financial market and

Journal of Chinese Economic and Foreign Trade Studies
Vol. 14 No. 1, 2021
pp. 89-103

1754-4408
DOI 10.1108/JCEFTS-06-2020-0025

tourism (Shenoy *et al.*, 2020; Padmavathi and Murthy, 2020). Many researchers studied many lockdown variables and link them with other dimensions. For instance, technology side Mandel and Veetil (2020) studied how the price flexibility and minor technological adaptions help in reducing the time it takes for the economy to recover. They found that the world economy takes about one quarter to move towards the new equilibrium at the end of all lockdown, while the recovery time is likely to be significantly greater if partial lockdown persists.

Regarding air pollution dimension; lockdown added a benefit in minimizing the air pollution, as Saadat *et al.* (2020) mentioned that lock down improved both the air quality in many cities and drop in water pollution in some parts of the world. Paital *et al.* (2020) found that CO_2 pollution decreased in lockdown period and Shehzad *et al.* (2020) found that there is a significant decline in nitrogen dioxide in reputed states of India which will good for India and its neighbor. In reference to the political dimension, lockdown has made a strong effect on political support (Bol *et al.*, 2020), they study the political effect of the enforcement of a strict confinement policy on response to the COVID-19 pandemic. They found lockdown have increased vote intentions for the party of the president and trust in government and satisfaction with democracy. Moreover, Alon *et al.* (2020) predicted that the blanket lock down are generally less effective using costs of the pandemic saving fewer lives per unit of lost GDP, while age specific lock down policies are more powerful in developing countries and save more lives.

Also, COVID-19 crisis made robust shocks for all macroeconomic factors like unemployment rate, consumer spending, debt and so forth. Few scholars study this effect and concluded that, the imposition of lockdown made a decline in both employment rate and household expectation (Coibion *et al.*, 2020; Blanchard *et al.*, 2020; buheji *et al.*, 2020). According to Coibion *et al.* (2020) and Goolsbee and Syverson (2020), lockdown decrease the consumer spending and has significantly change consumer activity away from nonessential to essential business. Regarding debt crisis, Arellano *et al.* (2020) found that lockdown policies are useful for alleviating the health crises, but they carry large economic cost and that social value of debt relief can be substantial because it can prevent the debt crisis and can save lives.

Although lockdown is very important to decrease the spread of COVID-19 but has an important disadvantage on damage the population well-being. Brodeur *et al.* (2020) study Google trends in lockdown period and found a significant increase in searching for loneliness, worry and stress. They found that people's mental health will be severely affected by lockdown. Finally, the challenging point is that no one even scientist could predict when COVID-19 will diminish. According to Taskinsoy (2020) if there are second and third wave of COVID-19, all economies as well as world's biggest economy will be in deep coma. In this research, we aim to investigate the effect of COVID-19 on developed countries stock indices; mainly G8 stock markets' indices. Starting from January 2020, many cases in the whole world were confirmed as COVID-19, these numbers were increasing rapidly in G8 countries and worldwide. Accordingly, countries decided to announce for lockdown period in way to control the situation and flatten the curve of confirmed cases. In this study, researchers used G8 countries to study COVID-19 effect on stock market indices using lockdown variable.

2. COVID-19 and G8 stock market's indices

Financial market's index is one of the vital indictors for any country, and it is important to understand index fluctuation as it is resulted from the interaction between multi factors (economic and non-economic factors) that walk-in line and across each other in challenging way (Assous *et al.*, 2020).

Many researches were interested in investigating stock market efficiency under lockdown circumstances (Capelle-Blancard and Desroziers, 2020), while other scholars investigated the difference between developed and developing countries in facing COVID-19 pandemic. Few researchers study how COVID-19 hit emerging and developing economies (Çakmaklı *et al.*, 2020; Hevia and Neumeyer, 2020), they found that developing countries through COVID-19 pandemic suffer from collapsing export, dwindling remittances and tightening international credit conditions. According to Hevia and Neumeyer (2020), it is worth mentioning that economist and epidemiologists in developing countries should work together to respond effectively and efficiently to COVID-19.

Recently, COVID-19 statistics for G8 countries till 29 May showed that USA reached the maximum number of total cases with around 1.7 million cases among G8 countries, then Russia with more than 379,000. The highest number of deceased cases were in USA with around 101,000 (which represents around 6% of total cases) then UK with 37.8 thousand. While France has the highest ratio of total deceased cases to total cases with around 15.6% then UK with 14.1%. It is important to mention that Canada has the lowest number of total and deceased cases with around 90,000 and 185, respectively.

Zhang *et al.* (2020) analyzed COVID-19 effect on financial markets using volatility analysis, correlation analysis and minimum spanning tree and found that investors face losses because of COVID-19 and financial markets have seen dramatic changes on an unprecedented scale. Moving to correlation, they found a high correlation between US and EU financial markets before and after the formal announcement of the COVID-19 pandemic; meanwhile, minimum spanning trees (MST) showed separation between US and Chinese markets. Ali *et al.* (2020) studied the impact of COVID pandemic on the volatility of the financial markets. The concerned markets covered both equities and fixed income plus oil and gold datasets, and findings expect a more deteriorating situation in the markets as COVID-19 moved on. Liu *et al.* (2020) evaluated the short run effect of COVID-19 pandemic on financial markets. They used an event study approach and found that COVID-19 has a significant negative impact on equities returns. Çıtak *et al.* (2020) applied quantile on quantile regression (QQR) to study the stock markets' reaction to COVID-19 outbreak. They found a heterogeneous effect of COVID-19 cases on the stock markets, and they exhibited that the number of cases has a substantial negative effect at lower quantiles.

Narayan *et al.* (2020) mentioned that lockdown has positive effect on G8 countries stock market and are most effective in cushioning the effects of COVID-19. Clemens and Heinemann (2020) presented that German economy cause of limited access to financial markets and less stable government budget position, will suffer higher welfare losses and increases inequality.

According to Lau *et al.* (2020), who found positive impact of lockdown on China as the growth rate of COVID-19 curves decreased was observed. However, Huo and Qiu (2020) studied how China's stock market reacts to the announcement of the pandemic lockdown. They observed reversals at industry and firm levels because of investors overreaction to the lockdown and found that overreactions are stronger for stocks with lower institutional ownership. Moreover, Phan and Narayan (2020) found that markets overreact for any unexpected news and as more information becomes available and people understand the ramifications more broadly; the market will correct itself.

Baig *et al.* (2020) investigate the impact of COVID-19 on the microstructure of US equity market, they found increases in confirmed cases and deaths due to coronavirus are associated with significant increase in market liquidity and volatility. Also, they mentioned that declining the implications of lockdown contribute in the deterioration of liquidity and market stability.

3. Financial market estimation, COVID-19 and artificial neural network

Financial markets estimation known as one of the most challenging estimation as there are many aspects that interfere together on linear and non-linear relations (Qiu *et al.*, 2016; Gurjar *et al.*, 2018; Assous *et al.*, 2020) Nowadays, artificial neural networks (ANN) became a well-known estimation technique in all fields and can be applied to many financial problems such as macroeconomic forecasts (Kemal *et al.*, 2016; Chung and Shin, 2020).

Several researchers used ANN to estimate stock market return for many international stock markets (Kemal *et al.*, 2016; Qiu *et al.*, 2016; Sahoo and Mohanty, 2020). D'Ecclesia and Clementi (2019) used daily equity prices and stock market indices traded on major international exchanges and found ANN approach results the most accurate to track the equity returns implied volatility over E-GARCH approach, the Heston model. Mallikarjuna and Rao (2019) found that ANN is better over ARIMA model in forecasting stock return. And Kalyoncu *et al.* (2020) and Lee and Seok (2020) presented that ANN is one of best models in predicting stock market estimation. Finally, Tabar *et al.* (2020) mentioned that the results show that the algorithm is capable in predicting stock market crashes in advance by issuing STOP labels.

Few researchers have used ANN to study the effect of COVID-19, which is one of the important researches in the field. According to Mollalo *et al.* (2020), they examined the performance of multilayer perceptron (MLP) neural network in predicting the cumulative COVID-19 incidence rates across the continental USA. The results indicated that a single-hidden-layer MLP could explain almost 65% of the correlation with ground truth for the holdout samples the findings may provide useful insights for public health decision makers regarding the influence of potential risk factors associated with the COVID-19 incidence at the county level.

Tamang *et al.* (2020) studied COVID-19 confirmed cases in India, the USA, France, the UK, China and South Korea, they showed that ANN can efficiently forecast the future cases of COVID-19 outbreak of any of these countries. Moreover, Asogwa *et al.* (2020) applied multilayer perception algorithm-based model in this research. The result showed that the established ANN model was able to correctly predict and classify the effects of COVID-19 outbreak on the well-being of Nigerian citizens.

4. Data analysis and neural network setup

To study the impact of lockdown on G8 countries' indices, researchers collected stock market indices data from investing.com. All COVID-19-related data are from John Hopkins Coronavirus Resource Center. Also, data were collected on daily basis, covering the period from January 1st, 2020 till May 7th, 2020. Statistical analysis is used to understand the behavior of the first death, the first 100 cases in the country and to select appropriate independent variables in constructing the neural network prediction. The results of our analysis showed that country lockdown variables are the most effective variables across all the selected variables. Therefore, lockdown variables are being used in building an ANN model to show their impact on stock market indices in the G8 countries. For brevity, only analysis of lockdown variables is discussed in this article.

The collected data is analyzed by employing different statistical parameters (i.e. mean, sum, standard deviation, frequency and variance) as show in Table 1. The aim of this step is to find the most suitable model in building a predictor that can be used to study the behavior of stock markets' indices of G8 countries in the lockdown periods. The analysis shows that the number of international index days that used in the analysis is between 80 and 89 days. The lockdown variables are USA, UK, Russian, Italy, France, Japan and Germany. The analysis showed variation in lockdown variables from one country to another, due to the

Index		N	Sum	Mean	Std. Dev.	Var	Index	N	Sum	Mean	Std. Dev	Var
DAX	USA	88	45	0.511	0.503	0.253	NIKKEI	80	42	0.525	0.503	0.253
	UK	88	31	0.352	0.480	0.231		80	29	0.363	0.484	0.234
	Russian	88	26	0.295	0.459	0.211		80	24	0.300	0.461	0.213
	Italy	88	37	0.420	0.496	0.246		80	38	0.475	0.503	0.253
	France	88	35	0.398	0.492	0.242		80	32	0.400	0.493	0.243
	Japan	88	17	0.193	0.397	0.158		80	17	0.213	0.412	0.169
	Germany	88	31	0.352	0.480	0.231		80	29	0.363	0.484	0.234
Dow Jones	USA	88	47	0.534	0.502	0.252	S&P_TSX 60	89	47	0.528	0.502	0.252
	UK	88	33	0.375	0.487	0.237		89	33	0.371	0.486	0.236
	Russian	88	28	0.318	0.468	0.219		89	28	0.315	0.467	0.218
	Italy	88	39	0.443	0.500	0.250		89	39	0.438	0.499	0.249
	France	88	37	0.420	0.496	0.246		89	37	0.416	0.496	0.246
	Japan	88	19	0.216	0.414	0.171		89	19	0.213	0.412	0.170
	Germany	88	33	0.375	0.487	0.237		89	33	0.371	0.486	0.236
FCHI	USA	88	47	0.534	0.502	0.252	S&P500	88	47	0.534	0.502	0.252
	UK	88	33	0.375	0.487	0.237		88	33	0.375	0.487	0.237
	Russian	88	28	0.318	0.468	0.219		88	28	0.318	0.468	0.219
	Italy	88	39	0.443	0.500	0.250		88	39	0.443	0.500	0.250
	France	88	37	0.420	0.496	0.246		88	37	0.420	0.496	0.246
	Japan	88	19	0.216	0.414	0.171		88	19	0.216	0.414	0.171
	Germany	88	33	0.375	0.487	0.237		88	33	0.375	0.487	0.237
FTSE 100	USA	89	46	0.517	0.503	0.253	MOEX	86	46	0.535	0.502	0.252
	UK	89	32	0.360	0.483	0.233		86	33	0.384	0.489	0.239
	Russian	89	27	0.303	0.462	0.214		86	28	0.326	0.471	0.222
	Italy	89	38	0.427	0.497	0.247		86	38	0.442	0.500	0.250
	France	89	36	0.404	0.494	0.244		86	37	0.430	0.498	0.248
	Japan	89	18	0.202	0.404	0.163		86	19	0.221	0.417	0.174
	Germany	89	32	0.360	0.483	0.233		86	33	0.384	0.489	0.239
FTSEMIB	USA	88	45	0.511	0.503	0.253	NASDAQ	88	47	0.534	0.502	0.252
	UK	88	31	0.352	0.480	0.231		88	33	0.375	0.487	0.237
	Russian	88	26	0.295	0.459	0.211		88	28	0.318	0.468	0.219
	Italy	88	37	0.420	0.496	0.246		88	39	0.443	0.500	0.250
	France	88	35	0.398	0.492	0.242		88	37	0.420	0.496	0.246
	Japan	88	17	0.193	0.397	0.158		88	19	0.216	0.414	0.171
	Germany	88	31	0.352	0.480	0.231		88	33	0.375	0.487	0.237

Table 1. Statistical description of G8 stock indices

difference in stock trading dates for the G8 countries. All lockdown variables showed a variance between 0.1 and 0.3 with a standard deviation between 0.4 and 0.6 as shown in Table 1.

Moreover, according to Jarrah and Salim (2019) and Sahoo and Mohanty (2020), ANN is the most used and affected model in predicting the movement of financial markets using different inputs. To create an artificial neural network predictor, different parameters should be tuned to achieve the highest performance. The performance parameters are initial bias values, weight values, number of hidden layers and nodes, learning rate, momentum, local and global optimization algorithm for error correction, and the type of transfer function of hidden and output layers. To create an ANN predictor, the simulation parameters are 70, 30, 1000, 0.4 and 0.9% for training, testing, number of epochs, initial learning rate and momentum, respectively. Activation function is set as Hyperbolic Tangent to accept the nonlinear output and improve the performance of the output layer, where gradient descent is adopted as optimization algorithm to find the sub optimal solution of the prediction model as shown in Dhenuvakonda *et al.* (2020) and Patel and Yalamalle (2014).

The neural network predictor achieved high performance parameters including high prediction rate and low mean square error, after considering the performance parameter in Table 2. The adopted parameters are set based on experimental tests and previous research articles in the field of artificial neural network as shown by Al-Rousan *et al.* (2020) and Al-Najjar and Al-Rousan (2020). To validate the capability of the neural network model in predicting the stock market index using lockdown variables, the training and testing data are combined together to find the accuracy of the proposed model. All the results are built based on the overall dataset to remove the repetition.

5. Research methodology

Few numbers of researches used different parameters (i.e. number of confirmed and deceased cases) to study the impact of COVID-19 variables on financial markets indices (Zhang *et al.*, 2020). In this research, the lockdown parameters will be used to reflect the COVID-19 variable and to show the worst situation reached by each of the G8 countries, as these countries made the decision to close when the number of cases increased at rates higher than expected.

As previously mentioned, lockdown variables are used to study the impact of COVID-19 on G8 countries stock markets indices, through building an artificial neural network model. Lockdown variables are lockdown announcement date of Germany, USA, UK, France, Russia, Italy, besides the emergency announcement (instead of Lockdown) date of Japan. While Canada was excluded from the study as there was no formal declaration of any lockdown or emergence situation for the period under study. Finally, all variables are

Parameter	Value
Number of epochs	1000
Initial learning rate	0.4
Momentum	0.9
Total number of parameters	Based on data set
Training ratio	70%
Testing ratio	30%
Number of hidden layers	1–50
Training type	Batch
Activation function	Hyperbolic tangent
Optimization algorithm	Gradient descent

Table 2.
Neural network performance parameters

denoted based on the country name, where Time variable consider the day, month and year under study. To create a neural network predictor, different architecture can be used. In this study, a feed forward backpropagation neural network is adopted as shown in Figure 1.

The neural network prediction output of the j-th node in the hidden layer is calculated using equation below.

$$O_j = f\left(\sum_{i=1}^{I} x_i w_{ij+} b_j\right) \tag{1}$$

where $f(.)$ is the transfer function, i is the number of nodes in the input layer, x_i and w_{ij} are inputs and weight from i-th node in the input layer to the j-th node in the hidden layer, and b_j is the bias for j-th hidden node. The output of k-th node in the output layer can be calculated using equation (2)

$$y_k = f\left(\sum_{j=1}^{J} O_j \quad w_{jk} + b_k\right) \tag{2}$$

where y_k is the output of k-th node in the output layer, K is the number of nodes in the output layer, w_{jk} is the weight from the j-th node in the hidden layer to the k-th hidden node in the output layer, and b_k is the bias for the k-th output node. Hyperbolic tangent activation functions $f(.)$ is used. The hyperbolic tangent transfer function normally used to calculate the output of the hidden layer nodes using equation below.

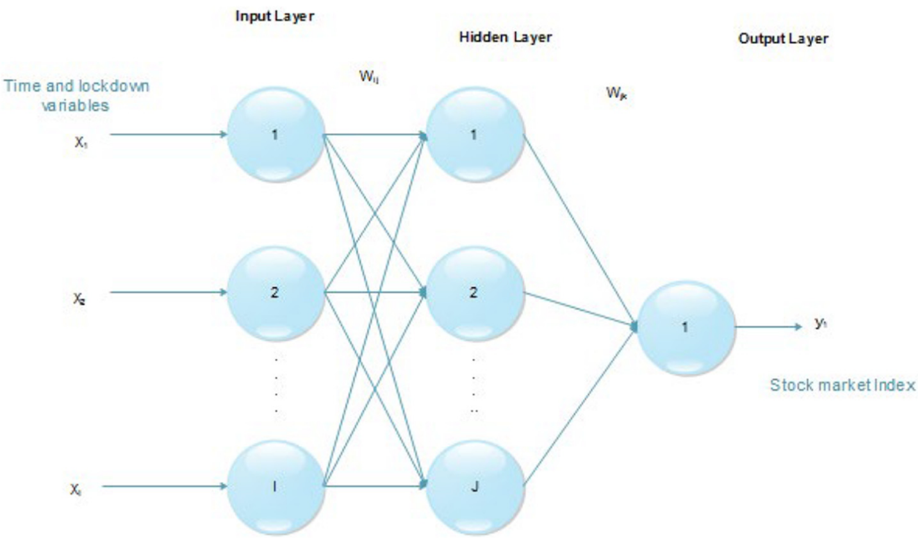

Figure 1.
The architecture of neural network for one hidden layer

$$f(z) = \frac{2}{1+e^{-2z}} - 1 \tag{3}$$

where z is the inputs of the node. Hyperbolic tangent function has been selected experimentally as the optimum activation functions that commonly used in researches. Several studies have been published to discuss the optimal number of hidden nodes in neural network. Panchal *et al.* (2011) proved that the best method to find the optimum number of hidden layers and hidden nodes is by trial. This can be done by) hanging the number of hidden nodes and layers until obtain a network needs less training time and can obtain better accuracy. Thus, the number of hidden nodes can be determined based on trial and error. Trial and error are the optimum method to find an efficient network that can be employed to achieve high performance error, and less training time. In addition, it should be simple, therefore, fast processing time (Nadia *et al.*, 2020).

To validate and support the research study, ten stock indices are used; four US indices which are Dow Jones, NASDAQ, S&P_TSX 60 and S&P500, the rest are DAX, FCHI, FTSE 100, FTSEMIB, MOEX and NIKKEI. To authenticate the effect of lockdown variable on stock market indices, two performance metrices are considered including root mean square error (RMSE) and R^2. The target of the study is to maximize R^2 and minimize the RMSE of the artificial neural network results to find the most accurate results. R^2 and RMSE can be calculated by using the following equations.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{4}$$

$$MSE = \frac{1}{N}\sum_{i=0}^{N}(y_i - \hat{y}_i)^2 \tag{5}$$

where y_i, $\hat{y}_i$ and $\bar{y}$ are the real value of stock index, the predicted stock index value, and the mean of the real value of stock index, respectively. While N and i are the number of observations and the ID of the stored data in the dataset, respectively.

6. Results and discussion

To examine the impact of countries' lockdown on stock market indices, a correlation analysis is first adopted then ANN model is built. According to correlation matrix, the correlation direction between lockdown variables (for all countries) and stock market indices are negative. For brevity, the correlation tables are removed, and results are reported without citing the table.

The correlation analysis of DAX, Dow Jones, FCHI, FTSE 100, FTSEMIB, MOEX, NIKKEI and S&P500 indices showed that each index is negatively correlated with its country lockdown and strongly affected by other countries' lockdown. The correlation coefficients are ranged from medium to strong with negative direction. Also, it's important mentioning that all stock market indices; American and Non- American are strongly influenced by US lockdown.

After dividing the data sets into training and testing datasets, neural network prediction was adopted with different lockdown variables. To report the results of COVID-19 models, the overall dataset (training and testing) is used to test and validate the capability of the model in improving the stock market prediction. The impact of COVID-19 models is shown in Figures 2 and 3. The results showed that COVID-19 variables enhanced the prediction power of G8 countries stock market indices, but with a different ratio. To show the most among all COVID-19 variables, the R^2 and root mean square error of all models (i.e. USA, UK, Russia, Italy, France, Japan, Germany) are calculated as shown in Table 3.

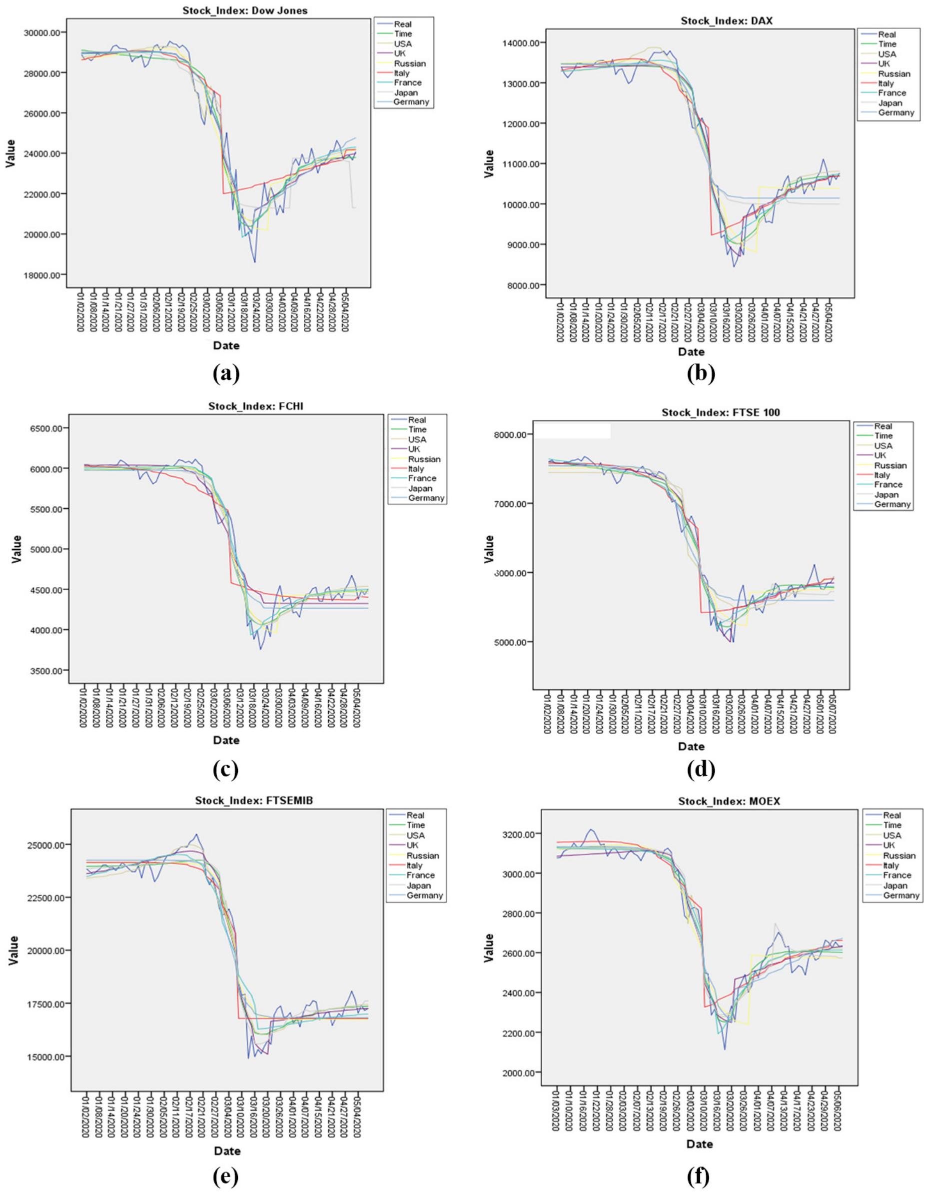

Figure 2.
The results of applying neural network model using different lockdown variables in different countries and its relationship on stock indices namely (a) Dow Jones, (b) DAX, (c) FCHI, (d) FTSE 100, (e) FTSEMIB, (f) MOEX

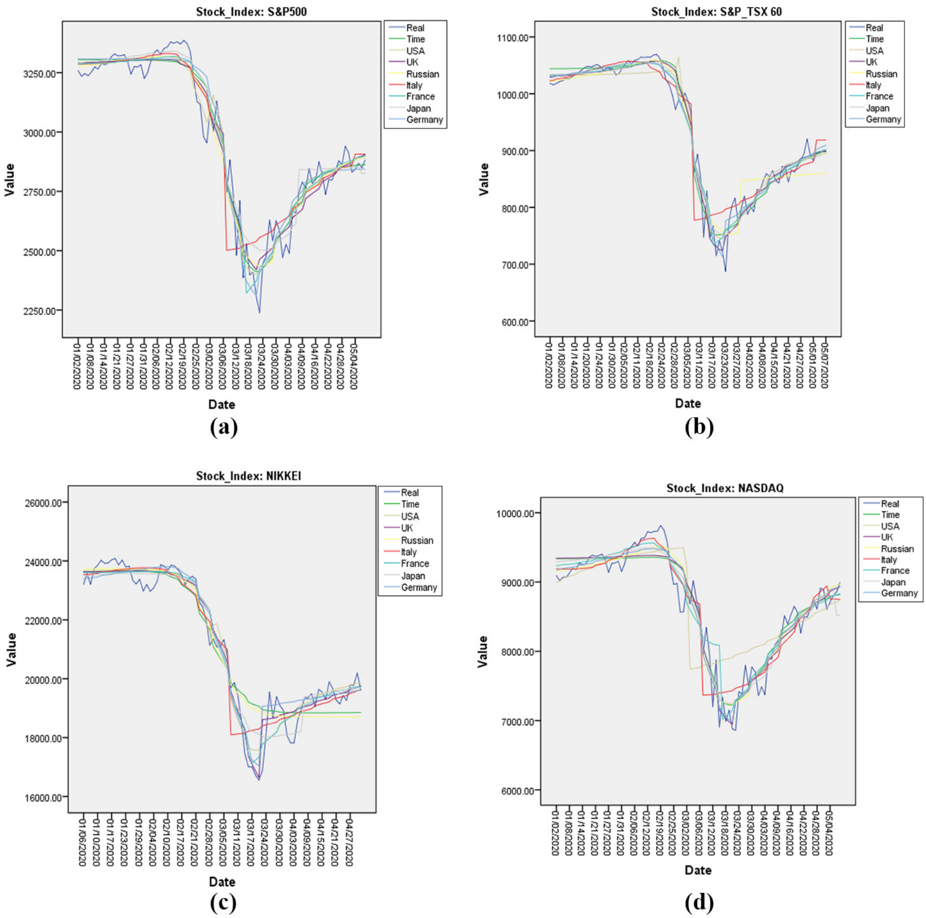

Figure 3.
The results of applying neural network model using different lockdown variables in different countries and its relationship on stock indices, namely, (a) S&P500, (b) S&P TSX 60, (c)NIKKEI and (d) NASDAQ

As shown in Table 3, UK lockdown variable has the highest impact on DAX, NIKKEI and FTSE 100 compared to lockdown variables of other countries. The R^2 values for the DAX and NIKKEI models are 0.986 and 0.982, respectively, while RMSE values are 285 and 453 for DAX and NIKKEI models, respectively. The range of R^2 for DAX varies from 0.950 to 0.986, where, the range of R^2 for NIKKEI is from 0.942 to 0.982. On the other hand, the range of RMSE varies from 285 to 538, and from 285 to 538 for DAX and NIKKEI, respectively. These variations indicate that neural network model can efficiently predict UK stock index. It is also found that FTSE 100 index and UK lockdown performed better compared with other lockdown variables. The R^2 and RMSE values are 0.989 and 134, respectively.

Dow Jones, MOEX and S&P500 indices showed that US lockdown along with changing the interest rate as a result highly affected on the movement of these three indices compared to other models with R^2 values equal to 0.982, 0.984 and 0.979, and RMSE values equal to 604, 54 and 65, respectively.

Table 3. The overall results of R^2 and RMSE using different stock indices

Stock index	Models	R^2	RMSE	Stock Index	Models	*R*2	RMSE
DAX	Time	*0.985*	*297*	MOEX	Time	0.984	55
	USA	0.984	308		USA	*0.984*	*54*
	UK	0.986	285		UK	0.977	66
	Russia	0.970	413		Russia	0.970	77
	Italy	0.972	402		Italy	0.972	74
	France	0.985	297		France	0.984	56
	Japan	0.950	530		Japan	0.980	62
	Germany	0.950	538		Germany	0.975	68
Dow Jones	Time	0.974	733	NASDAQ	Time	0.956	235
	USA	*0.982*	*604*		USA	0.845	430
	UK	0.976	694		UK	0.957	231
	Russia	0.970	777		Russia	0.959	225
	Italy	0.948	1048		Italy	0.950	248
	France	0.977	675		France	0.951	248
	Japan	0.962	868		Japan	0.961	221
	Germany	0.975	707		Germany	*0.963*	*213*
FCHI	Time	0.986	134	NIKKEI	Time	0.942	792
	USA	0.986	135		USA	0.978	492
	UK	0.971	195		UK	*0.982*	*453*
	Russia	0.986	137		Russia	0.944	780
	Italy	0.960	229		Italy	0.964	627
	France	*0.988*	*127*		France	0.979	480
	Japan	0.986	135		Japan	0.971	567
	Germany	0.973	191		Germany	0.977	523
FTSE 100	Time	0.988	141	S&P_TSX 60	Time	0.979	23
	USA	0.970	225		USA	0.978	23
	UK	*0.989*	*134*		UK	0.983	20
	Russia	0.981	175		Russia	0.970	27
	Italy	0.983	169		Italy	0.965	29
	France	0.989	136		France	0.983	21
	Japan	0.985	162		Japan	0.982	21
	Germany	0.970	222		Germany	*0.984*	*20*
FTSEMIB	Time	0.986	592	S&P500	Time	0.973	74
	USA	*0.990*	*514*		USA	*0.979*	*65*
	UK	0.990	517		UK	0.973	75
	Russia	0.978	748		Russia	0.972	75
	Italy	0.979	723		Italy	0.955	96
	France	0.978	743		France	0.972	77
	Japan	0.988	558		Japan	0.971	81
	Germany	0.977	763		Germany	0.970	81

Also, US lockdown has the greatest impact on FTSEMIB movement compared to other models with R^2 and RMSE equal to 0.990 and 514, respectively. The FTSEMIB index R^2 range is between 0.990 and 0.977, while the RMSE range is between 514 and 763. France lockdown, Japan Emergency announcement and Germany lockdown are the highest variables that affected FCHI, NASDAQ and S&P_TSX 60 indices, respectively. These three models have R^2 and RMSE ranges from 0.961 to 0.988, and from 65 to 221, respectively.

The Russian and Italian lockdown variables showed more improvement in some international indices than the other variables without reaching the best results compared to the other models (other lockdown variables). Besides, the period between March 1, 2020 and April 1, 2020 was the worst trading for all international indices all over the group G8 countries.

Finally, although the results showed a negative effect of G8 countries' lockdown, but this does not mean that lockdown is the only variable that affect the trading of stocks, as there are other combined events of COVID-19 influence the movement of stocks market indices of these countries. COVID-19 combined events include increasing the number of deceased cases and the number of confirmed cases, number of recovery cases, announcement of new COVID-19 treatment, and so forth. As a result, COVID-19 events in general and lockdown variable in specific, have a strong correlation and effect on stock market indices' movements in G8 countries. Finally, as shown in Figures 2 and 3, the impact of the COVID-19 pandemic is decreasing, and the growth rate of stock market indices has started to improve.

However, although artificial neural networks are better than conventional intelligent models, but these systems suffer from many problems may occur while running the model including high complexity, slow convergence to reach the desired goal, high cost and outlier cases when a variation in data is used. It was proved that using an artificial neural network predictor can improve the efficiency of the overall predictors and can reduce time response, where increasing the number of neurons in the hidden layers and the number of hidden layers themselves will obtain highly non-linear neural network. This can improve the generalization of the forecaster and reduce the overfitting problems in several cases. Increasing the complexity of the network by increasing the number of hidden layers and neurons to unaccepted level would increase the number of parameters that used to learn the network and would increase the chances of overfitting.

Besides, increasing the size of dataset that used to train and test neural network models would increase the complexity of input data, therefore, low performance output can be produced because neural network would not well explain the relationships between data and this would increase the chances of overfitting as well.

7. Conclusion

The aim of this study is to investigate the impact of COVID-19 pandemic events on stock market indices of G8 countries. To show the effect of COVID-19 on the group eight countries, lockdown variables are used. Lockdown variables are lockdown announcement date of Germany, USA, UK, France, Russia, Italy and the emergency announcement of Japan. Canada was excluded as there was no formal declaration of lockdown in the country within the period of study. The stock indices are DAX, Dow Jones, FCHI, FTSE 100, FTSEMIB, MOEX, NASDAQ, NIKKEI, S and P_TSX 60 and S and P500.

To achieve the aim of the study, the artificial neural network approach and the correlation between financial market indices and lockdown variable are used, where to find the performance of artificial neural network, R^2 and RMSE are adopted. The results showed that all financial markets were negatively correlated with lockdown variables in different G8 countries, which indicate COVID-19 events had a negative impact on stock market indices. Not only because of the lockdown period but also because of other consequences factors; just like increasing numbers of confirmed and deceased cases, the decreasing of interest rate and the deterioration of oil prices in the first quarter of 2020. This lead to decrease the stock market indices figures strongly.

The results revealed that COVID-19 lockdown has a strong impact on financial trading on G8 countries, besides the prediction of stock movement of G8 countries is enhanced when the lockdown variables are considered in all the studied cases. This gives an evidence that anomaly events can change the movement of stock markets within a short period.

But an interesting and optimistic result came to the surface, our ANN charts revealed that the impact of the pandemic is declining in G8 countries, as growth rate of stock market indices started to improve. This is highly expected especially with new circumstances of increasing number of recovered cases and announcements of some trials for new COVID-19 treatment and Vaccination. Also, public awareness and understanding of COVID-19 worldwide is the core point that could truly make things come back to normal soon, as people became mature and educated enough on how to behave correctly in the coming period; through avoiding the crowded places, maintaining the social distance, washing hands frequently for adequate time.

As a future work, Group 20 will be discussed to show the impact of COVID-19 on the largest economies around the world. Besides, various artificial intelligence techniques will be used to improve predictability such as fuzzy logic which uses logical rules and the fuzzification model.

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