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Stock price prediction using deep learning and frequency decomposition

Hadi Rezaei *, Hamidreza Faaljou, Gholamreza Mansourfar

Economic and Management Department, Urmia University, Urmia, West Azerbaijan, Iran

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ABSTRACT

Nonlinearity and high volatility of financial time series have made it difficult to predict stock price. However, thanks to recent developments in deep learning and methods such as long short-term memory (LSTM) and convolutional neural network (CNN) models, significant improvements have been obtained in the analysis of this type of data. Further, empirical mode decomposition (EMD) and complete ensemble empirical mode decomposition (CEEMD) algorithms decomposing time series to different frequency spectra are among the methods that could be effective in analyzing financial time series. Based on these theoretical frameworks, we propose novel hybrid algorithms, i.e., CEEMD-CNN-LSTM and EMD-CNN-LSTM, which could extract deep features and time sequences, which are finally applied to one-step-ahead prediction. The concept of the suggested algorithm is that when combining these models, some collaboration is established between them that could enhance the analytical power of the model. The practical findings confirm this claim and indicate that CNN alongside LSTM and CEEMD or EMD could enhance the prediction accuracy and outperform other counterparts. Further, the suggested algorithm with CEEMD provides better performance compared to EMD.

1. Introduction

One of the main concerns of stock market investors is to gain a view of the future and predict the trend of data as well as graphs to make the proper decisions and the right plans for the future. Although precise forecast of markets is impossible, some researchers in this field try to tackle this problem by proposing different methods, ideas, and analyses. Nevertheless, some characteristics of financial time series data such as non-stationary, nonlinearity, and high volatility (Polanco-Martínez, 2019) have imposed some challenges and made researchers continuously seek to find better and more precise models for analysis. As the efficient market hypothesis states, the prediction of stock markets is impossible (Fama, 1970). But, with the latest progress in computing technology, it is quite possible (Hoseinzade et al., 2019). Hence, Stock market prediction has become a subject in the intersection of finance and computer science (Jiang, 2020). In this regard, artificial intelligence and its application in the financial field have become much popular. In recent years, scholars have focused on the role of artificial intelligence in the financial markets and topics such as application of machine learning and deep learning in this field (Wall, 2018). The advance of computer technology and learning methods have been the solution to traditional challenges in the areas of finance, and potent deep learning has made an effective approach in theory and applications (Gan et al., 2020).

Machine learning methods have drawn the attention of some researchers in the last two decades and have tried to solve some challenges of time series analysis (Lippi et al., 2013; Qin & Chiang, 2019). Some methods of machine learning, such as support vector regression (SVR) and decision tree regression (DTR) have been applied for the prediction of time series. Vapnik (1999) firstly utilized the support vector machine (SVM) and then improved it to SVR. Due to its handling of nonlinear relationship, this supervised machine learning algorithm is applied for learning and prediction (Chen & Tan, 2017). Levis and Papageorgiou (2005) clarified the numerous advantages of SVR. They compared it with other forecasting methodologies and then used it for nonlinear times series forecasting. Hao and Yu (2006) utilized SVR to analyze non-stationary financial time series and concluded that SVR had better results than traditional forecasting models. Decision Trees regression (DTR) is also a popular supervised learning method used for classification and regression. It can forecast target value by detecting data features and learning easy decision rules (Nabipour et al., 2020). Rathan et al. (2019) predicted Crypto-Currency's price using DTR and admitted the accuracy of this method. Ongsritrakul and Soonthornphisaj (2003) also applied DTR and SVR for gold price movement prediction and concluded that the combination of these methods had acceptable performance.

In the case of financial time series, the data is extremely nonlinear

* Corresponding author.
E-mail addresses: rezaei.hadi82@gmail.com (H. Rezaei), h.faaljou@urmia.ac.ir (H. Faaljou), g.mansourfar@urmia.ac.ir (G. Mansourfar).

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and fluctuated. To analyze such dynamical series, we need the algorithms that can catch the hidden patterns of data and underlying dynamics. Although machine learning has been helpful recently and applied in various research, there is also the need for more advanced methods than machine learning, which can handle time series analysis (Chen & He, 2018). To deal with such challenges, neural networks have been employed in this field. Their advantages have been extensively considered for the prediction of the stock market. Despite the advantages of the neural networks, they may also fall through and be incapable to predict the financial markets accurately (Pang et al., 2018). In other words, the traditional neural networks have shallow neural networks that cannot learn effective data feature representation appropriately. Consequently, it reduces the analysis accuracy. To deal with this issue, it demands a deep network that can analyze the features and dependencies in data and grasp the long trend and the fluctuations (Cao & Wang, 2019). In other words, to overcome these difficulties, computing technology has been developed based on neural networks. Moreover, such technology has allowed machines to learn deeply for themselves (Wall, 2018). Thus, Deep learning algorithms can recognize and utilize the patterns and relationships in data through a self-learning process (Selvin et al., 2017).

The application of deep learning in the capital market has significantly increased due to high analytical power, with a growing number of articles applying it in recent studies (Bao et al., 2017; Hiransha et al., 2018). LSTM and CNN are among the deep learning models that have been used in financial research and yielded good results (Nelson et al., 2017; Sezer & Ozbayoglu, 2018). Although using these methods have been very helpful in data analysis, some time series are so volatile and stochastic that their analysis and predictions are still challenging. To tackle this issue, the frequency decomposition methods are offered to facilitate the data analysis process. The frequency decomposition methods such as EMD and CEEMD can act as a useful tool in reducing the complexity of data series. These methods can easily isolate the high fluctuating data into respective smaller frequency components (Mumtaz et al., 2019). The EMD has the power to reduce the influence of nonlinear characteristics of the stock series (Xuan et al., 2020). Furthermore, CEEMD and EMD algorithms have recently entered this field with the advantage of sequential data decomposition into different frequency spectra. These algorithms could play a useful role in financial time series analysis coupled with deep learning models such as LSTM (Chen et al., 2019; Niu et al., 2020). The combination of LSTM with frequency decomposition algorithms conveys that LSTM is capable of analyzing decomposed time-series better than the integrated time series. The reason is that a stationary time series with low volatility would be analyzed more easily than a non-stationary time series with high volatility. It means that the hybrid deep learning models are able to overcome the drawbacks of a single models (Wang et al., 2018). Hybrid models, combining the benefits of some models, are suggested to achieve better prediction and the decomposition approaches such as CEEMD enhance the performance of hybrid models (Mo et al., 2020). Thus, some studies approve the relative superiority of these models by investigating EMD-LSTM and CEEMD-LSTM hybrid models and comparing them with deep learning and machine learning models. In this regard, in addition to investigating the LSTM as a state-of-the-art method and the above-mentioned models, the present study seeks to improve these types of hybrid models. Hence, this article intends to answer this question whether it is possible to improve the performance of the LSTM model, and the mentioned hybrid algorithms and obtain more accurate results by introducing the CNN models to them. In other words, given the characteristics of the CNN model, whether the convolutional and Max pooling layers can develop CEEMD-LSTM or EMD-LSTM models. If yes, the model must be discussed and examined practically. To this end, we use four international stock price indices for practical evaluation, and compare the proposed model with other models, including hybrid and non-hybrid models, as well as with undecomposed models.

The rest of the paper is organized as follows. Section 2 deals with the literature review. The methodology is explained in the third section. Section 4 analyzes the experimental results. The final section concludes the paper.

2. Review of literature

This part of the article deals with a review of related literature and confirms the application of deep learning models, especially LSTM and CNN models in stock market as well as frequency decomposition algorithms.

Recurrent neural networks (RNNs), introduced before LSTM models, are capable of keeping information of previous periods and applying it in analyzing the present period (Hochreiter & Schmidhuber, 1997). In other words, RNN models have been proposed for sequential series. These models benefit from particular flexibility and capability in analyzing time series in spite of their nonlinearity and non-stationary features (Zhang et al., 2019). Zhang et al. (2019) studied deep learning and how to analyze the complex and irregular behavior of economic data and claimed that RNNs are among those neural networks that are distinct in realizing the trend and behavior of time series. These models could store information of time series for a while and function better in realizing their behavior, while this characteristic does not exist in traditional neural networks and mostly fail in the analysis of series (Abdel-Nasser & Mahmoud, 2019). Despite these characteristics, these models have some problems such as vanishing gradient preventing them from detecting long-term effects. Nevertheless, as long-term time series and analysis of long-term effects are of particular importance, more developed models of RNN are required. Thus, long short-term memory (LSTM) models have been considered as an improved version of the RNN model for time series analysis (Kamal et al., 2020). In addition to possessing short-term memory, LSTM models could catch the long-term effects and succeed in predicting financial data (Zhang, Xiong, et al., 2018). The research findings in this field support this assertion. Nelson et al. (2017) stated that LSTM is an appropriate model for time series, while providing more precise results than other machine learning models such as random forest, multilayer perceptron, and pseudo-random models. Nikou et al. (2019) studied some methods such as ANN, SVR, Random Forest, and LSTM concerning the nonlinearity and difficult prediction of financial time series, and finally introduced LSTM as the method with high precision in prediction. Kaushik and Giri (2020) compared LSTM with traditional econometrics, vector auto-regression, and support vector machine to forecast exchange rate changes. They found that in analysis and prediction, the LSTM model outperformed SVM and VAR methods. Namini et al. (2018) confirmed the superiority of LSTM over ARIMA in forecasting various indices such as S&P500 and Nikkei225. To decrease the impact of the data fluctuation on analysis performance, Trana et al. (2018) applied the fuzzy techniques. They also used LSTM to increase prediction accuracy. The findings showed the efficiency and feasibility of their proposed multivariate fuzzy LSTM (MF-LSTM) model. Thus, concerning the above points and similar studies, it can be concluded that LSTM models are one of the accepted models of deep learning in the financial area.

In addition to LSTM, the CNN model has also attracted the attention of some researchers in this area. Feature extraction, pattern recognition, and dependencies in data (Lai et al., 2018) are among the main characteristics of the CNN model, and they are mostly used in machine vision (Raj et al., 2016). These characteristics made this model and its applications enter the financial area. CNN model treats the financial data as image data, and tries to analyze and forecast them by identifying the data patterns (Kim & Kim, 2019). Recognition of some features such as ascending or descending trend of data as the existing patterns in data and their dependencies could be considered as the principal step in data analysis and used in financial studies. Emphasizing the feature extraction characteristic of CNN networks, Hoseinzade and Haratizadeh (2019) forecasted the price movements of some stock indices such as S&500, NASDAQ, and the Dow Jones. Despite confirming noisy data and nonlinear behavior of prices, they evaluated the proposed CNN model as more accurate than CNN-Cor, Technical, as well as the PCA-ANN. Chen and He (2018) believed that CNN models could succeed in time series analysis; further, they consider them as equal to the LSTM model and compare them with each other. Sim et al. (2019) believe that the CNN model is more accurate than ANN and SVM models for investigating and predicting stock market time series.

Some studies have gone beyond the use of individual LSTM model and examined the combination of LSTM and CNN models, which can provide an effective method in its kind. The integration of these two models as a hybrid model offers a better performance and can improve the prediction accuracy, since individually these models have some limits which could be improved when combined (Zhang, Yuan, & Shao, 2018). Some researchers, such as Ma et al. (2015), Donahue et al. (2015), and Wang et al. (2016) have studied the CNN-RNN method for sequential data and confirmed the advantage of combining these models in investigating sequential data. Using the sliding window, Selvin et al. (2017) predicted time series with CNN-LSTM model and promoted the accuracy of data training. Authenticating the feature extraction of the CNN model and time series analysis of LSTM, Eapen et al. (2019) combined these two models and predicted S&P500 stock price. The results of the hybrid model were better than SVR regression findings. Also, it was more accurate in prediction than LSTM and CNN models. Vidal and Kristjanpoller (2020) considered the prediction of price volatility of different types of financial assets as a complex issue because of non-stationary and noisy data, and studied it through LSTM, GARCH, and ANN-GARCH methods as well as LSTM-CNN hybrid model. The findings indicated that the MSE obtained from the hybrid model was lower than that of other models and had higher precision in prediction. Livieris et al. (2020) compared the CNN-LSTM hybrid model with SVR, FFNN, and LSTM models in the prediction of gold price time series. They evaluated hybrid method as being relatively superior over other models because of utilizing the characteristics of CNN and LSTM models.

On the other hand, some algorithms such as empirical mode decomposition (EMD) and complete empirical ensemble mode decomposition (CEEMD) are effective for dealing with non-linear and nonstationary time series (Xian et al., 2020). In other words, these algorithms facilitate analysis of complex and high frequency time series through decomposing them to stationary and low frequency time series (Ali et al., 2020). These characteristics have attracted some attention to these algorithms.

Using the frequency decomposition algorithm, Chen and Pan (2016), Jothimani and Yadav (2019), and Jin et al. (2020) verified the predictive power of hybrid models, and recognized that when combined with other machine learning and deep learning models, CEEMD could provide more accurate results than EMD. The significance of oil price prediction persuaded Wu et al. (2019) to apply the LSTM model based on improved EEMD as a more accurate model for predicting Texas crude oil price. According to the results, EEMD-LSTM had lower RMSE and MAPE compared with the hybrid model of EEMD alongside ELM, KRR, and LSSVR. For improving the stock price prediction, Cao et al. (2019) proposed the CEEMDAN-LSTM hybrid model and examined it with other hybrid models for S&P500 and HIS indices. The findings confirmed that CEEMD-LSTM outperformed CEEMD-SVR and CEEMD-MLP and even individual LSTM and SVR models. Also, the predictive power of CEEMD-LSTM was greater than that of EMD-LSTM. For managing risk in international trade, Lin et al. (2020) predicted exchange rate fluctuations (USD–AUD) using CEEMD-LSTM and compared it with other models. They confirmed that the proposed model had higher accuracy compared to SVM, RNN, MRNN, SRIMA, and Bayesian models. Wei et al. (2019) a hybrid model that could take advantage of the CEEMD algorithm, the fuzzy time analysis technique, and the LSTM model. They stated that each part of the hybrid algorithm could enhance the forecasting ability to a great extent. Vlasenko et al. (2020) evaluated the nonlinear dynamics of financial time series using the combination of EMD and multidimensional Gaussian neuro-fuzzy model. The proposed hybrid model achieved a high prediction accuracy. Zhanga et al. (2020) constructed the LSTM based hybrid prediction model by combining the CEEMD, PCA, and LSTM to predict daily stock prices. They applied the CEEMD as sequence smoothing module, and LSTM and PCA as prediction models, and finally, their hybrid model outperformed the LSTM as a benchmark model.

This review of literature suggests that the hybrid methods of deep learning models with frequency decomposition algorithms, compared to other reviewed models, yield more accurate financial time series analysis. Thus, this article tries not only to use the knowledge of these types of models but also to improve them by proposing CEEMD-CNN-LSTM and EMD-CNN-LSTM hybrid algorithms, and then practically evaluate them and finally compare them with other models.

3. Methodology

The main methodology of this article involves deep learning methods and frequency decomposition algorithms. Meanwhile, in order to understand the proposed method, first, it is crucial to understand what constituting models are, as well as how they learn or perform. Then, the architecture of hybrid algorithm will be presented and investigated. The constituting models include CNN, LSTM, CNN-LSTM, EMD, and CEEMD.

3.1. Convolutional neural network model (CNN)

CNN models are mostly recognized for the training of two-dimensional data images. They are capable of extracting the features of images using convolutional and max-pooling layers. The convolutional layers, the number of kernels of these layers, max-pooling layers, activation function, the number of forward-looking steps, as well as fully connected layers are the main components of CNNs and affect the accuracy of these models (Cao & Wang, 2019). Due to efficiency and nonlinearity, sigmoid, Hyperbolic Tangent, and the rectifier linear unit (Relu) are usually used as activation functions in CNN models (Hoseinzade & Haratizadeh, CNNpred: CNN-based stock market prediction using a diverse set of variables, 2019). This study utilizes the Relu to solve the vanishing gradient problem (Maas et al., 2013). Since the data applied in this article are financial time series, one-dimensional convolutional neural networks are used. In other words, the CNN model includes one-dimensional convolutional hidden layers of 512 filters of size two and one-dimensional max-pooling of size two. The output of these two layers transfer to the next stage, i.e., LSTM model, which can play the role of fully connected layers (Tsantekidis et al., 2020).

3.2. Long short-term memory (LSTM) model

Recurrent neural networks (RNNs) are the developed model of feed-forward traditional neural networks which can manage the sequence of input data. RNN models have some gates that store previous inputs and can manage sequential data (Chung, Gulcehre, Cho, & Bengio, 2014). Although RNNs theoretically could manage the past sequential data, they have some problems practically in terms of long-term memory; i.e., they can look back to few steps and are not qualified to process long sequential data (Le et al., 2019). The gradient vanishing and exploding gradient are among the problems that RNNs confront (Bengio et al., 1994). In vanishing gradient, standard RNNs have problems with retraining information for long-term intervals (Hochreiter, 1998). In the exploding gradient, the training algorithm allocates higher values to matrix weights without any reason or justification. In order to avoid such problems, RNN models have been developed, and the LSTM model with long and short-term maintenance power has been presented (Hochreiter & Schmidhuber, 1997).

LSTM models could have a better performance by adding three gates to RNN models (Fig. 1). These gates enable LSTM model to learn long-term dependencies in a sequence: a forget gate f_t to control what information requires to be cut from the LSTM memory; an input gate i_t to

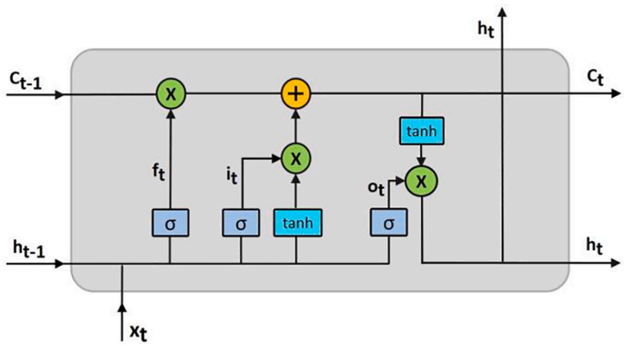

Fig. 1. Structure of the LSTM.

indicate if new information will be added into the LSTM memory; an output gate o_t to control whether to output the state (Namini et al., 2019).

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{3}$$

$$h_t = o_t \, tanh(C_t) \tag{4}$$

where, W_i, W_f, W_o are weight matrices, b_i, b_f and b_o represent bias vectors, h_t is the value of the memory cell at time t, f_t denotes the value of the forget gate layer, C_t indicates the current cell state, i_t shows the values of the input gate, and o_t is the output gate layer (Press, 2018).

3.3. Empirical mode decomposition (EMD)

EMD, proposed by Huang et al. (1998), is a model for analyzing nonlinear and non-stationary data at different time intervals and frequencies. This algorithm decomposes data into some intrinsic mode functions with two conditions: first, the number of extremums and zero-crossing points shall be equal or at most with one difference; second, the mean value of the upper envelope ($x_{up,\,t}$) and lower envelope ($x_{low,\,t}$) at any point should be zero.

$$x_t = \sum_{j=1}^{n} c_{j,t} + r_{n,t} \tag{5}$$

where, n is the number of intrinsic mode functions (IMF), $c_{j,\,t}$ is jth IMF of data, and $r_{n,\,t}$ denotes the residual error. The mean value of upper and lower envelopes is calculated as Eq. (6):

$$m_t = (x_{up,t} + x_{low,t})/2 \tag{6}$$

The difference between the mean of envelope and data (in this study, time series) x_t is shown by c_t:

$$c_t = x_t - m_t \tag{7}$$

If c_t meets the above conditions, we extract the next IMF, replace r_t with x_t, obtain a new c_t, and examine the above conditions again. If the conditions are not met, there would be no IMF. What remains is residual. Meanwhile, we iterate these steps until the above conditions satisfy the obtained c_t and these iterations create new IMF. Otherwise, the final component will be residual, and the frequency decomposition will end (Zhou et al., 2018).

Note that EMD suffers from a drawback called mode mixing (Huang et al., 1998). Thus, to solve such a problem, the CEEMD algorithm, which is a developed version of EMD, will be studied in the following section.

3.4. Complete empirical ensemble mode decomposition (CEEMD)

Torres et al. (2011) proposed CEEMD by expanding previous models of frequency decomposition. CEEMD algorithm has been derived from the development of the EMD original model (Yeh et al., 2010) with the capability of providing a reconstructed noise-free time series. For a better understanding of this algorithm, we explain the steps of its creation.

Before explaining the algorithm, the definitions are as follows: $E_h(.)$ Operator is the jth intrinsic mode calculated through the EMD method. ω^i denotes the white noise, x(t) is time series, ε_0 represents a constant coefficient, and $\overline{IMF_k}$ is IMF of CEEMD model.

First, we calculate IMF_1^i for τ times by EMD model, while the IMF of CEEMD is calculated as follows:

$$\overline{IMF_1} = \frac{1}{\tau}\sum_{i=1}^{\tau} IMF_1^i \tag{8}$$

Then, the first residual value is obtained from Eq. (9):

$$r_1 = x(t) - IMF_1 \tag{9}$$

By obtaining r_1, again we calculate $r_1 + \varepsilon_1 E_1(\omega^i)$ for τ times and then obtain the IMF through the following equation:

$$\overline{IMF_2} = \frac{1}{\tau}\sum_{i=1}^{\tau} E_1\left(r_1 + \varepsilon_1 E_1\left(\omega^i\right)\right) \tag{10}$$

In the same way, we continue up to step k and then calculate the residual value in step k as follows:

$$r_k = r_{k-1} - IMF_k \tag{11}$$

Then, again, we calculate $r_k + \varepsilon_k E_k(\omega^i)$ for τ times and next obtain k + 1th of IMF.

$$\overline{IMF_{k+1}} = \frac{1}{\tau}\sum_{i=1}^{\tau} E_1\left(r_k + \varepsilon_k E_k\left(\omega^i\right)\right) \tag{12}$$

We iterate these steps until the calculated series remains a trend and indecomposable. The general relation of intrinsic and residual mode functions with the main time series is shown as Eq. (13):

$$x(t) = \sum_{1}^{k} \overline{IMF_k} + R \tag{13}$$

where, R is the residual component.

3.5. CNN-LSTM model

CNN-LSTM hybrid model is a combination of CNN, which is mostly specialized in data pattern extraction and LSTM models, which are known for sequential data analysis. CNN network can play an effective role in training the network by extracting the features in the data, and recording the dynamics of time series. Then, CNN transfers processed information to the LSTM model. LSTM model can enhance the accuracy of prediction by maintaining long-term and short-term time sequences (Donahue et al., 2015). Thus, integrating these models can improve their performance over the individual mode (He et al., 2019). It means that there is a collaboration between them (Mathapati et al., 2018). Data in the CNN-LSTM model are first processed through convolutional layers followed by max-pooling layers. After extraction of patterns and data dynamics, the LSTM model is used instead of a fully connected CNN layer, which can analyze the processed data of two previous layers with a high ability to maintain the time sequence (Tsantekidis et al., 2020).

3.6. The hybrid algorithm of frequency decomposition and CNN-LSTM

The model proposed in this study is a combination of frequency decomposition algorithm and CNN-LSTM model. The examination of the above models indicates that each CEEMD and EMD algorithm could play a considerable role in the analysis through decomposing time series to various frequency spectra. On the other hand, the CNN-LSTM model has a relative advantage over individual CNN and LSTM models. It could offer a better performance and high-accuracy prediction in the analysis of IMFs and the residual. Fig. 2 presents the algorithm proposed in this paper.

As seen in Fig. 2, financial time series is first decomposed by CEEMD or EMD to IMFs and the residual. Their arrangement is from high to low frequency, and at the end, the residual component only shows the trend in time series. In the second step, the CNN model processes the patterns and features of decomposed components separately and then transfers them to LSTM. The LSTM model with the property of maintaining data time sequences examines the information of the previous step, and conducts the final analysis. In the fourth step, we sum up the analyzed IMFs and the residual. Thus, the trained algorithm is ready to be evaluated by the out-of-sample data (test data).

3.7. Assessment metric

In deep learning models, loss error is usually used to evaluate the prediction, which refers to the difference between the actual observed value and the predicted value. In order to evaluate the loss error, different tools can be used. The standard metrics in this type of models include root-mean-square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The formula for their calculation is as follows:

$$MSE = \frac{1}{n}\sum_{i}^{n}\left(y_i - \widehat{y}_i\right)^2 \tag{14}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \widehat{y}_i\right| \tag{15}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y}_i}{y_i}\right| \tag{16}$$

Obviously, the lower the number of the above metrics, the more reliable and accurate will be the predictions (Ahmed et al., 2020).

4. Analysis of experiments

This study aims to introduce CEEMD-CNN-LSTM and EMD-CNN-LSTM hybrid algorithms evaluated with data of various stock price indices. Comparing these proposed algorithms with CEEMD-LSTM and EMD-LSTM algorithms as well as with CNN-LSTM and LSTM undecomposed models allows assessing their accuracy and performance. Before discussing the models, the following is the description of data.

4.1. Data preprocessing and description

To study the proposed algorithm, we extract the historical daily financial time series from January 2010 to September 2019 from the Yahoo Finance Website. The daily data includes the close price of S&P500, Dow Jones, DAX, and Nikkei225. To better visualize these indices, we briefly describe the data in Table 1 and then present their graphs in the Fig. 3.

4.2. EMD and CEEMD

As previously mentioned, the frequency decomposition algorithms decompose data into various frequency spectra. In other words, the time series of price indices is decomposed into several IMFs and one residual. The arrangement of IMFs is from high to low frequency, with the residual component occurring at the end. It is evident that training the networks on IMFs with low volatility is easier than IMFs with high volatility.

For the sample, the Dow Jones price index is presented in Fig. 4 using CEEMD and EMD algorithms.

After decomposition of indices into various frequency spectra, it is required to convert the original data to normal data before training. Normalization leads to the adjustment of the data noise effect and implementation of neural networks with high efficiency and speed (Diehl et al., 2015; Makridakis, 1993). To this end, we use the following equation.

$$x_{in}(t) = \frac{x_i(t) - min\,x_i(t)}{max\,x_i(t) - min\,x_i(t)} \tag{17}$$

where, $x_i(t)$ is ith data of IMF and $x_{in}(t)$ denotes its normalized data. It is possible to calculate predicted values at level after predicting each IMF by reversing Eq. (17).

Table 1
The statistical analysis results of price of indices.

Index	Count	Mean	Min	Max	Standard deviation
S&P500	2516	1962.608	1022.580	3240.020	588.910
Dow Jones	2516	17,606.741	9686.480	28,645.259	5147.050
DAX	2531	9530.664	5072.330	13,559.599	2384.721
Nikkei225	2449	15,786.655	8160.009	24,270.619	4933.656

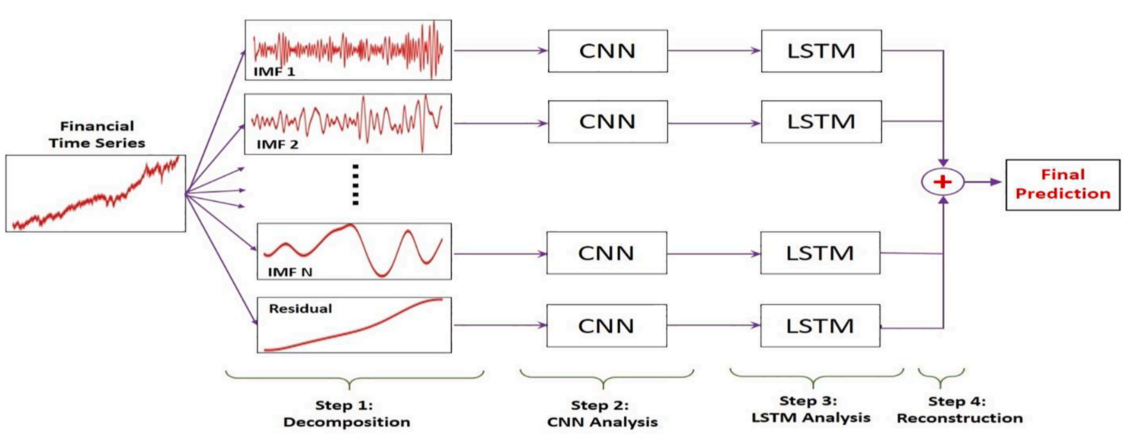

Fig. 2. Structure of the CEEMD-CNN-LSTM algorithm.

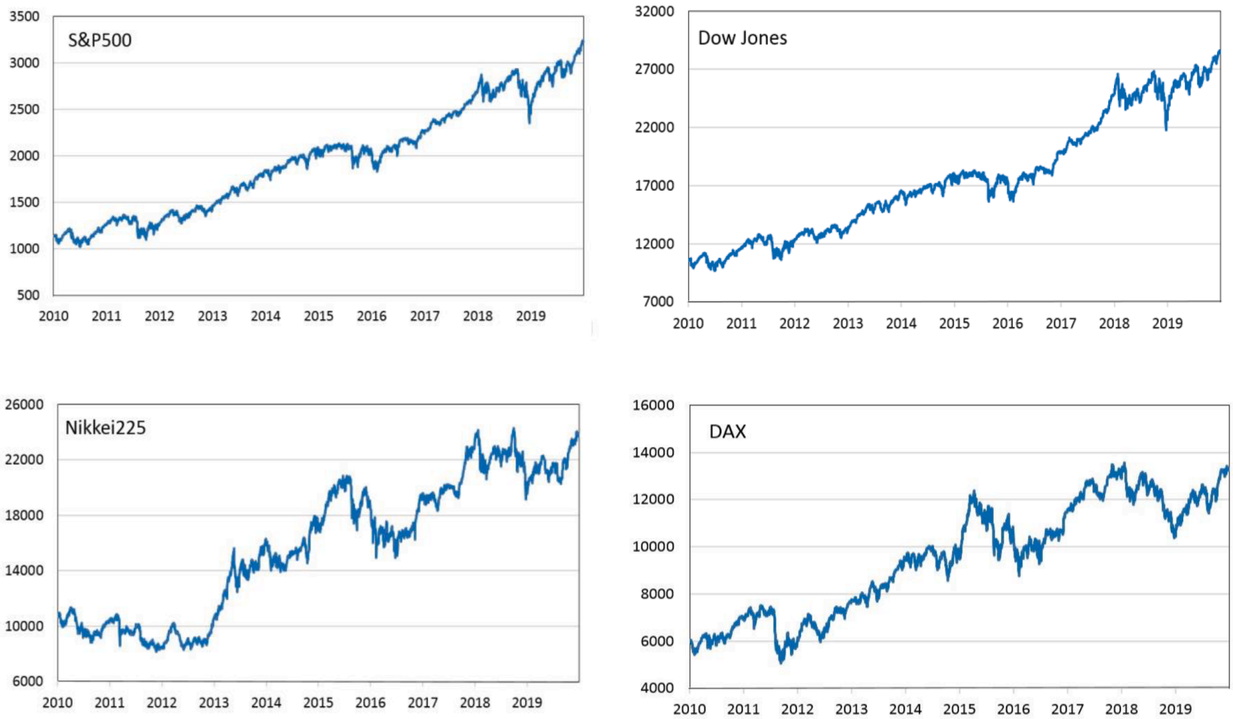

Fig. 3. Price index for S&P 500, Dow Jones, Nikkei225, and DAX.

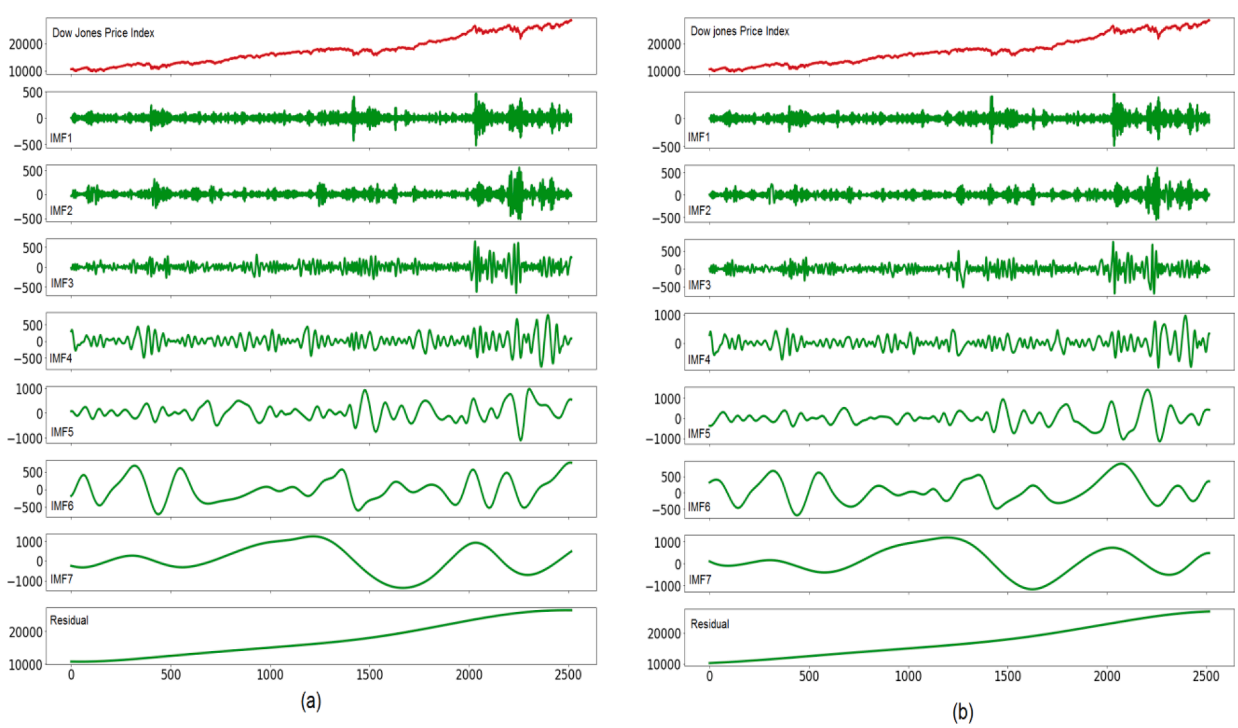

Fig. 4. The IMF components of Dow Jones price index.

4.3. The training process and prediction results

For better prediction of long-term time series, one of the methods applied before the training algorithm is the sliding window where data are divided into various intervals for training (Zivot & Wang, 2003). In this study, as seen in Fig. 5, the windows of the constant length of 250 steps have been used, with these windows moving forward by unit steps. Generally, $x_i(t)$ to $x_{i+250}(t)$ constitute the input data of ith sliding window, $w_i(t)$, while $x_{i+251}(t)$ indicates the output data. For the next sliding window, $w_{i+1}(t)$, the input data are $x_{i+1}(t)$ to $x_{i+251}(t)$ and output is $x_{i+252}(t)$. This sequence moves forward as one step and continues to the end of the time series (Wu et al., 2020). Since the number of data in the time series is different, we select 150 data for testing (out-of-sample data), and split the remaining data into training set (80%) and validation set (20%).

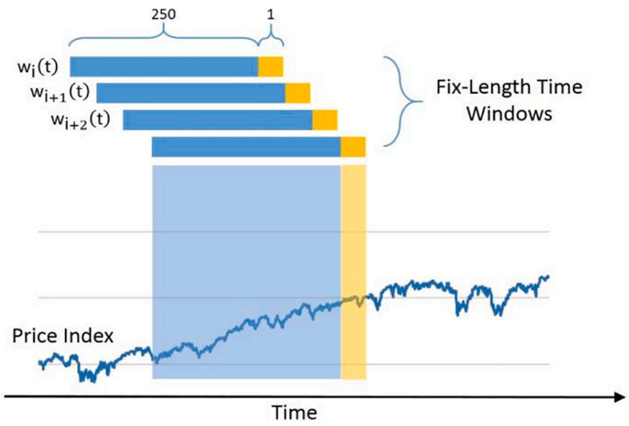

Fig. 5. Structure of one-step-ahead sliding windows.

4.3.1. *Undecomposed model results*

Before investigating the suggested algorithm, the results of the SVR, DTR, LSTM, and CNN-LSTM models without frequency decomposition are presented in Tables 2 & 3. In this state, instead of predicting decomposed indices, the undecomposed indices are just predicted. Accordingly, we discuss the results of the undecomposed models in this section. Then, in the next sections, we compare them with the decomposed algorithms and assess the impact of the decomposition algorithms on the prediction. The prediction accuracy is also evaluated through RMSE, MAE, and MAPE metrics.

According to Tables 2 & 3, it is observed that the RMSE values of the LSTM model are 22.985, 198.320, 144.303 and 240.907 for S&P500, Dow Jones, DAX, and Nikkei225, respectively which are lower than 23.904, 198.468, 147.854 and 245.869 for SVR model and 24.352, 209.193, 153.041 and 271.569 for DTR model. On the other hand, the RMSE values of the CNN-LSTM model are 21.362, 185.655, 141.415, and 221.989 for S&P500, Dow Jones, DAX, and Nikkei225, respectively, which are lower than the RMSE values of the LSTM model. This state also applies to MAE and MAPE, suggesting that the accuracy of the LSTM model is better than the SVR and DTR models. It also indicates that the CNN-LSTM model reaches the minimum values of MSE, MAE, and MAPE for all indices, which means that adding the CNN network to the LSTM model enhances the prediction accuracy.

Table 2
Prediction results based on undecomposed data (deep learning methods).

Index	Method	Number of epochs & hidden units		RMSE	MAE	MAPE
		LSTM	Epochs			
S&P 500	CNN-LSTM (CNN layer = 512)	260	420	21.362	16.597	0.829
		250	350	23.523	17.500	0.869
		200	300	33.568	25.599	1.254
	LSTM	260	420	22.985	17.274	0.858
		250	350	25.424	19.441	0.958
		200	300	35.661	27.131	1.331
Dow Jones	CNN-LSTM (CNN layer = 512)	280	420	185.655	138.086	0.765
		250	350	186.219	142.138	0.790
		200	300	281.357	217.429	1.199
	LSTM	280	420	198.320	146.394	0.810
		255	370	200.751	148.631	0.820
		200	300	297.636	229.727	1.258
DAX	CNN-LSTM (CNN layer = 512)	280	390	141.415	103.368	1.113
		250	350	156.551	119.276	1.277
		200	300	178.780	134.653	1.437
	LSTM	280	390	144.303	106.246	1.153
		250	350	165.065	124.258	1.341
		200	300	191.970	143.612	1.5621
Nikkei 225	CNN-LSTM (CNN layer = 512)	260	420	240.287	179.003	1.179
		280	390	221.989	170.892	1.092
		200	300	321.419	239.808	1.580
	LSTM	260	420	258.412	207.129	1.281
		280	390	240.907	183.844	1.222
		200	300	328.073	246.669	1.662

Table 3
Prediction results based on undecomposed data (machine learning methods).

Index	Method	Number of gamma & epsilon		RMSE	MAE	MAPE
		Gamma	Epsilon			
S&P 500	SVR	0.01	0.01	23.904	17.867	0.893
		0.05	0.05	58.003	49.969	2.555
		0.005	0.005	26.238	18.819	0.924
	DTR	–	–	24.352	17.974	0.861
Dow Jones	SVR	0.01	0.01	198.468	150.400	0.831
		0.05	0.05	467.166	395.025	2.254
		0.005	0.005	212.458	156.000	0.848
	DTR	–	–	209.193	152.432	0.843
DAX	SVR	0.01	0.01	147.854	107.022	1.166
		0.05	0.05	226.584	186.451	2.017
		0.005	0.005	154.813	110.698	1.194
	DTR	–	–	153.041	111.614	1.175
Nikkei 225	SVR	0.01	0.01	245.869	186.995	1.240
		0.05	0.05	418.967	347.511	2.405
		0.005	0.005	249.222	187.698	1.241
	DTR	–	–	271.569	193.544	1.234

4.3.2. *Proposed algorithm results*

In this section, the suggested algorithm will be presented and investigated in terms of the mentioned price indices and then used for one step ahead prediction. The proposed model is a novel hybrid algorithm of frequency decomposition with LSTM and CNN, thoroughly explained in the previous section. Initially, we decompose the time series of indices to various frequency spectra using EMD or CEEMD algorithm and analyze IMFs as well as residual components with the CNN-LSTM model separately. Finally, the sum of these analyzed IMFs and residual constitutes the primary time series analysis which can do the prediction based on sample data. The model prediction accuracy is determined by comparing prediction values with original values through the three metrics. For further examination, first, we have the model properties in Table 4.

The number of epochs is the number of times the entire data are executed for fitting the model. Tables 5 and 6 indicate the number of epochs for IMFs and residual in both models based on EMD and CEEMD.

As seen in Tables 5 and 6, in IMFs of high frequency, a high number of epochs is required for training network in both CEEMD and EMD models, while in IMFs of lower volatility, fewer epochs are required. The reason is that at high frequencies, the model requires more iterations to train the network to learn high volatility and complexities of data. However, at low frequencies, there are fewer complexities in the data and less volatility. So, there is no need for more iterations.

The results of the CEEMD-CNN-LSTM algorithm are presented in Table 7.

The RMSE of the proposed CEEMD-CNN-LSTM algorithm for four price indices, including S&P500, Dow Jones, DAX, and Nikkei225 are 13.76, 155.52, 84.88, and 177.43 respectively which are lower in comparison with 15.05, 165.61, 88.78, and 187.56 for CEEMD-LSTM algorithm. The MAE values of CEEMD-CNN-LSTM compared to

Table 4
Characteristics of CEEMD and EMD based algorithms.

	CEEMD-LSTM	CEEMD-CNN-LSTM	
	Number of hidden units	Number of hidden units (LSTM)	Number of hidden units (CNN)
S&P500	200	200	512
Dow Jones	200	200	512
DAX	200	200	512
Nikkei225	200	200	512

Table 5
Hyper-parameters of CEEMD based algorithmsTable 5: Hyper-parameters of CEEMD based algorithms.

	S&P500		Dow Jones		DAX		Nikkei225	
	LSTM	CNN-LSTM	LSTM	CNN-LSTM	LSTM	CNN-LSTM	LSTM	CNN-LSTM
IMF1	270	270	300	300	300	300	290	290
IMF2	270	270	280	280	300	290	280	280
IMF3	260	260	260	260	270	270	250	250
IMF4	230	230	230	230	240	240	230	230
IMF5	190	190	200	200	220	220	190	190
IMF6	170	170	140	140	160	160	160	160
IMF7	120	120	130	130	130	130	130	130
Residual	100	100	100	100	100	100	100	100

Table 6
Hyper-parameters of EMD based algorithms.

	S&P500		Dow Jones		DAX		Nikkei225	
	LSTM	CNN-LSTM	LSTM	CNN-LSTM	LSTM	CNN-LSTM	LSTM	CNN-LSTM
IMF1	270	270	300	300	300	290	290	280
IMF2	270	270	280	280	300	290	280	280
IMF3	260	260	260	260	270	270	250	250
IMF4	230	230	230	230	240	240	230	230
IMF5	190	190	200	200	220	220	190	190
IMF6	170	170	140	140	160	160	160	160
IMF7	120	120	130	130	130	130	130	130
Residual	100	100	100	100	100	100	100	100

Table 7
Prediction based on CEEMD based algorithm.

		Number of hidden units		RMSE	MAE	MAPE
		LSTM	CNN			
S&P500	CEEMD-CNN-LSTM	200	512	13.76	10.58	0.536
	CEEMD-LSTM	200	–	15.05	11.81	0.597
Dow Jones	CEEMD-CNN-LSTM	200	512	155.52	118.02	0.6515
	CEEMD-LSTM	200	–	165.61	123.03	0.6840
DAX	CEEMD-CNN-LSTM	200	512	84.88	65.03	0.702
	CEEMD-LSTM	200	–	88.78	70.12	0.772
Nikkei225	CEEMD-CNN-LSTM	200	512	177.43	136.45	0.9324
	CEEMD-LSTM	200	–	187.56	145.90	0.9993

CEEMD-LSTM have decreased by 10.41, 4.07, 7.25 and 6.47%, respectively. This also applies to MAPE, which indicates that adding CNN to the hybrid algorithm extracts more effective features from original data and reduces the loss error. In the end, it demonstrates that CEEMD-CNN-LSTM algorithm outperforms the CEEMD-LSTM in RMSE, MAE, and MAPE.

Furthermore, EMD-CNN-LSTM is also presented in Table 8.

Table 8
Prediction based on EMD based algorithm.

		Number of hidden units		RMSE	MAE	MAPE
		LSTM	CNN			
S&P500	EMD-CNN-LSTM	200	512	14.88	12.04	0.611
	EMD-LSTM	200	–	15.51	12.60	0.639
Dow Jones	EMD-CNN-LSTM	200	512	163.56	120.97	0.6729
	EMD-LSTM	200	–	171.40	128.55	0.7184
DAX	EMD-CNN-LSTM	200	512	108.56	86.05	0.907
	EMD-LSTM	200	–	109.97	86.75	0.920
Nikkei225	EMD-CNN-LSTM	200	512	194.17	147.18	0.9413
	EMD-LSTM	200	–	213.45	164.08	1.0513

The EMD-CNN-LSTM algorithm's RMSEs for price indices of S&P500, Dow Jones, DAX, and Nikkei225 are 14.88, 163.56, 108.56, and 194.17 respectively which are lower than EMD-LSTM model's RMSE with the values of 15.51, 171.40, 109.97, and 213.45. According to MAE, there is a reduction of 4.44, 5.89, 0.80, and 10.29% for the EMD-CNN-LSTM model as compared to the EMD-LSTM model. The same descending trend is also true for MAPE. Such results indicate that the EMD-CNN-LSTM algorithm has a better performance and higher capability in prediction as compared to the EMD-LSTM model.

Based on the results of Tables 7 and 8, it is inferred that the idea of introducing CNN in the hybrid algorithm has been effective, and the fluctuation recognition of time series has been better than the model without CNN. In other words, CNN could be effective in the data training alongside LSTM to improve the model performance. It could be perceived as the concept of collaboration between these three models of CEEMD, LSTM, and CNN. First, the frequency decomposition reduces the complexity of volatilities by decomposing time series into different IMFs and the residual. Evidently, analysis of stationary and low volatile IMFs is far easier than that of non-stationary and high volatile time series. Then, the data of each decomposed component will be transferred to the CNN model separately. According to the feature extraction of the CNN model, it is possible to process patterns and dependencies in IMFs or residuals; thus, the information processed by the CNN model will enter the LSTM model. The LSTM with high analytical power in the context of the time analyzes the relationship between the extracted properties and their dependencies in long-term and short-term periods and provides the results with high accuracy.

Furthermore, the comparison of two recent tables indicates that adding the CNN to CEEMD-LSTM model could first enhance the model performance. Also, in training deep neural networks, CEEMD can be more effective than the EMD algorithm. It is due to the improvement made in CEEMD compared to the EMD algorithm. In other words, solving the problem of mode mixing in CEEMD could help it improve the analysis of the IMFs. Thus, the CEEMD-CNN-LSTM hybrid algorithm is relatively superior to EMD-CNN-LSTM and yields more accurate results. Fig. 6 presents the values of RMSE for four stock price indices.

Also, the comparison between the two recent tables and Tables 2 & 3 demonstrates that in undecomposed time series, the tree metrics for CNN-LSTM model are lower than for LSTM, SVR and DTS models and the

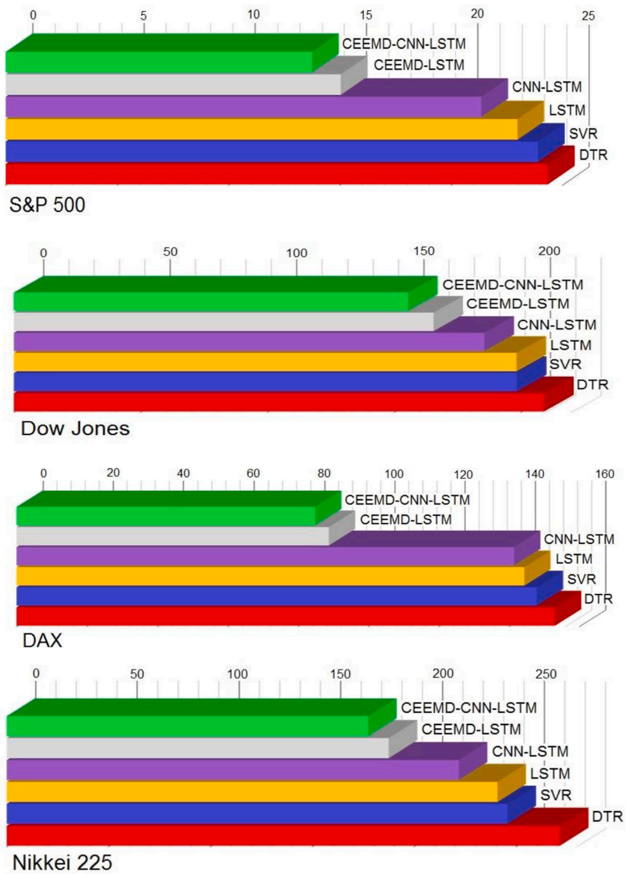

Fig. 6. RMSE comparison of different models for stock price indices.

accuracy of CNN-LSTM is higher than that of them. Nevertheless, the notable point is that the comparison of metrics indicates the decomposed time series models is more accurate than undecomposed time series models. This means that, by decomposing time series, CEEMD and EMD algorithms play a significant role in the analysis of nonlinear and non-stationary time series.

Accordingly, this study indicates that the proposed CEEMD-CNN-LSTM algorithm outperformed all models in this study and it was more effective in predicting S&P500, Dow Jones, DAX, and Nikkei225 price indices. The following figures illustrate the brief picture of the results for a better comparison (Figs. 7–10).

5. Conclusion

Concerning the significance of stock market prediction and its challenges, researchers always try to introduce modern methods in the analysis of these markets. LSTM as a state-of-the-art model and CNN which are deep learning models yield good results in the analysis of stock market. EMD and CEEMD are among the effective algorithms that have recently been considered in this research area. Thus, this article sought to introduce the proposed algorithm of CEEMD-CNN-LSTM by studying each of these models and evaluate them based on data of different stock price indices. The major concept of the suggested algorithm was to create a collaboration between CEEMD, CNN, and LSTM models by joining them together, which could extract deep features and time sequences. Then, we applied the trained algorithm for one-step-ahead stock price forecasting. In this regard, first, we decomposed the financial time series to different IMFs and the residual by CEEMD and EMD algorithms. The IMFs and the residual were separately analyzed by CNN-LSTM model. Facilitation of their analysis with CEEMD and EMD, as well as extracting features and patterns in data with CNN and further analysis in the context of the time plus analysis of the dependencies with LSTM enhanced the predictive capabilities of this model. The practical results of this article also support this claim. Note that the assessment metrics used in this study were RMSE, MAE, and MAPE.

The practical findings indicated that according to assessment metrics, the CEEMD-CNN-LSTM algorithm had more accurate results than CEEMD-LSTM and LSTM, and it was also true for EMD-CNN-LSTM compared to EMD-LSTM, and LSTM. It suggests that the idea of introducing CNN in the suggested model has been effective, and the CNN model could improve the model performance in the data training alongside LSTM. Furthermore, the decomposed algorithms had a better performance than undecomposed models, and demonstrating the advantages of CEEMD and EMD models. Further, CEEMD-CNN-LSTM had relative superiority over the EMD-CNN-LSTM algorithm and provided more accurate results. In other words, the proposed CEEMD-CNN-LSTM algorithm evidently outperformed the other counterparts discussed in this article.

Recommendations for further research

In this article, we only studied the simple form of proposed algorithm; however, there is still room for future studies to consider multi-layer CNN and LSTM models with various hidden units and investigate the possible improvement of the algorithm.

CRediT authorship contribution statement

Hadi Rezaei: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Hamidreza Faaljou:** Supervision.

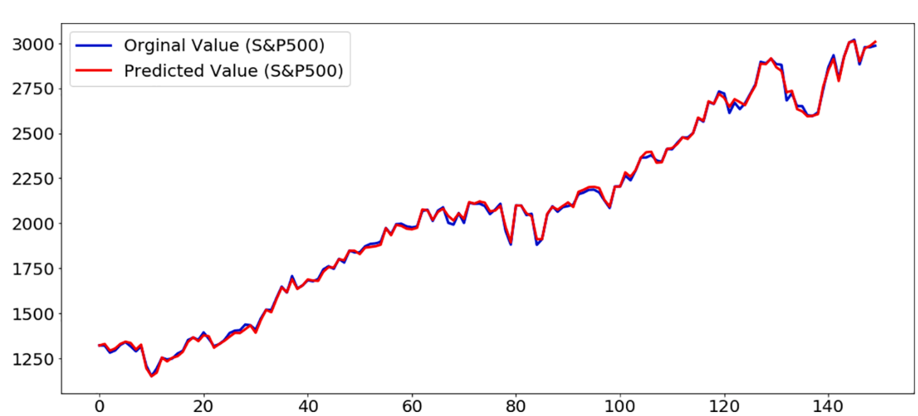

Fig. 7. S&P500 price index and prediction of CEEMD-CNN-LSTM algorithm.

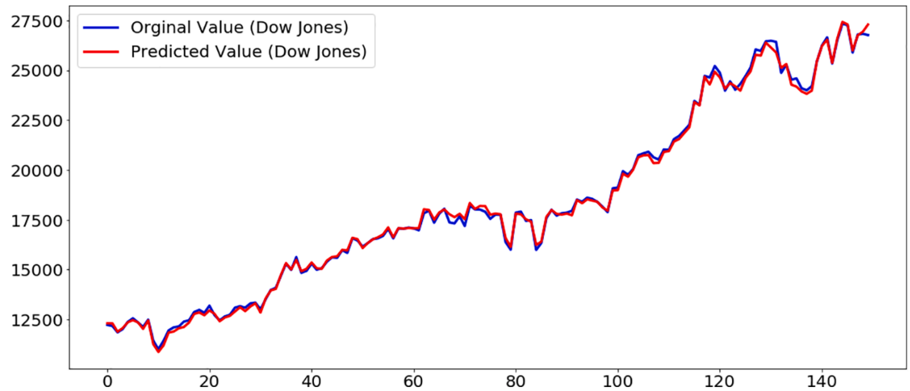

Fig. 8. Dow Jones price index and prediction of CEEMD-CNN-LSTM algorithm.

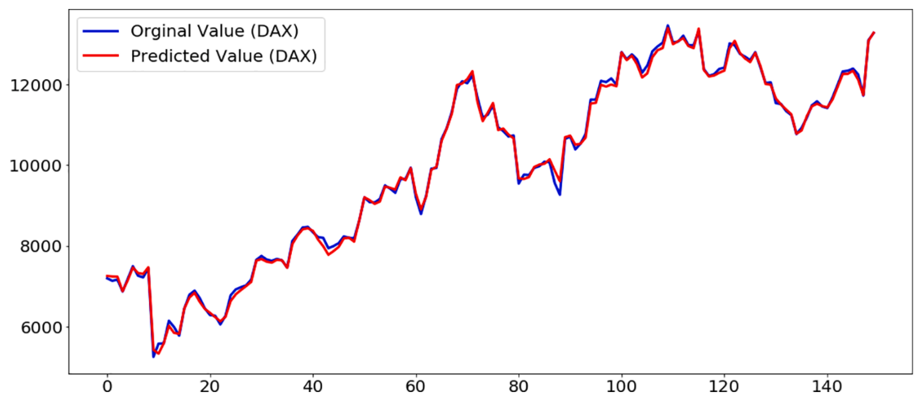

Fig. 9. DAX price index and prediction of CEEMD-CNN-LSTM algorithm.

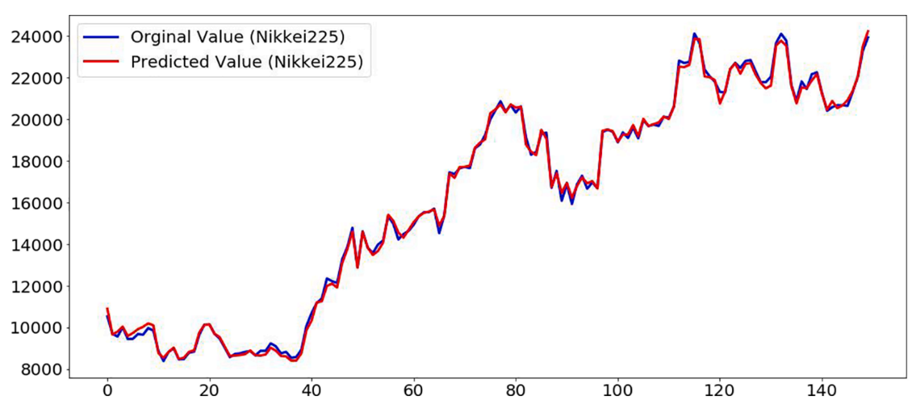

Fig. 10. Nikkei225 price index and prediction of CEEMD-CNN-LSTM algorithm.

Gholamreza Mansourfar: Supervision.

Declaration of competing interest

None.

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