IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 1, March 2024, pp. 475~486
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i1.pp475-486

Parallel multivariate deep learning models for time-series prediction: A comparative analysis in Asian stock markets

Harya Widiputra[1], Edhi Juwono[2]
[1]Faculty of Information Technology, Perbanas Institute, Jakarta, Indonesia
[2]Faculty of Economics and Business, Perbanas Institute, Jakarta, Indonesia

Article Info

Article history:

Received Dec 25, 2022
Revised Apr 13, 2023
Accepted Jul 7, 2023

Keywords:

Chaotic data
Deep learning
Financial prediction
Multivariate model
Time-series

ABSTRACT

This study investigates deep learning models for financial data prediction and examines whether the architecture of a deep learning model and time-series data properties affect prediction accuracy. Comparing the performance of convolutional neural network (CNN), long short-term memory (LSTM), Stacked-LSTM, CNN-LSTM, and convolutional LSTM (ConvLSTM) when used as a prediction approach to a collection of financial time-series data is the main methodology of this study. In this instance, only those deep learning architectures that can predict multivariate time-series data sets in parallel are considered. This research uses the daily movements of 4 (four) Asian stock market indices from 1 January 2020 to 31 December 2020. Using data from the early phase of the spread of the Covid-19 pandemic that has created worldwide economic turmoil is intended to validate the performance of the analyzed deep learning models. Experiment results and analytical findings indicate that there is no superior deep learning model that consistently makes the most accurate predictions for all states' financial data. In addition, a single deep learning model tends to provide more accurate predictions for more stable time-series data, but the hybrid model is preferred for more chaotic time-series data.

Corresponding Author:

Harya Widiputra
Faculty of Information Technology, Perbanas Institute
Jakarta, Indonesia
Email: harya@perbanas.id

1. INTRODUCTION

A type of data that is gathered the most frequently is time-series data. This is also one of the forms of data that is used to construct a model, which is done through a number of different methods that have been widely researched and also applied in real-world settings, that may reflect the behaviour of a dynamic system [1], [2]. However, one of the greatest challenges in time-series analysis, which occurs in many industries such as banking, statistics, and computing, is selecting the ideal prediction model that is derived from historical data and has the capacity to improve forecast accuracy [1]–[3].

In regard to the explanation that was given in the first paragraph above, numerous strategies and algorithms have been devised so that time-series data can be used to construct prediction models that can further be utilized in forecasting their future movements such as in [4], [5], and [6]. One very successful approach for time-series prediction is the use of deep learning. Deep learning models are a powerful tool for time-series prediction because they can automatically learn complex patterns in the data, which can be difficult to identify using traditional statistical methods [7]. In particular, recurrent neural networks (RNNs) and their variants, such as long short-term memory (LSTM) networks, have proven to be highly effective for time-series prediction. RNNs are designed to process sequential data, such as time-series data, by maintaining a hidden state that summarizes the information seen so far. LSTM networks is a variant of RNNs that are specifically designed to address the problem of vanishing gradients, which can occur when training deep networks on sequential data [8], [9]. In addition to RNNs, other deep learning models have also been used for time-series prediction, including convolutional neural networks (CNN) and transformer networks [10]. CNN can be used to extract temporal features from time-series data, while transformer networks can learn to model long-range dependencies between time steps. Despite the fact that it is well-known that the selection of a deep learning model for time-series prediction should be based on the characteristics of the investigated data, the large number of proposed deep learning models that have been evaluated has sparked debates about the best deep learning architecture or model for time-series data prediction. It has been found that time-series periodicity matters. If the time-series has a clear and continuous periodicity, seasonal autoregressive integrated moving average (ARIMA) and seasonal decomposition may work. If the time-series has cycles or irregular patterns, more complex model such as different deep networks may work better. Data availability, complexity, and necessary interpretability may also affect the choice. So, the model must match the facts and research goals.

This study compares deep learning models for financial time-series data prediction. This research seeks to identify the best deep learning model for financial time-series data prediction. This study will use a multivariate deep learning model that can process multivariable input and output. Findings from previous studies by [9] and [10] indicating prediction accuracy in a dynamic system with many interralted variables i.e., a financial system, are better when multivariate rather than univariate model is applied are the main reason why this approach was chosen in this research. In addition, the deep learning models being assessed will undergo simultaneous learning and prediction processes, with all variables being predicted together at once. A trained deep learning network will record the association between variables and use it to make predictions in parallel, which may improve accuracy [9], [10]. The deep learning model's "parallel multivariate" technique combines these two approaches. Moreover, this research also seeks to determine if the architecture of a deep learning model and time-series data properties affect prediction accuracy.

The next section of the paper provides review of literatures followed by description of research stages that were carried out to conduct a comparative analysis of the observed deep learning models' performance. In section 4, findings from the experiments that were carried out are presented, along with an analysis and exploration of the assessment results to determine the deep learning model that is most effective for predicting multivariate financial data in parallel. Finally, in section 5 we will summarize our findings and draw some conclusions, as well as provide a general overview of how we plan to continue our research in the future.

2. DEEP LEARNING FOR FINANCIAL TIME-SERIES PREDICTION

Over the course of the past ten years, many architectures or models that belong to the family of deep learning have emerged as one of the approaches that has been demonstrated to have good performance in predicting time-series data [7]–[9]. For instance, the long short-term memory (LSTM) architecture is a popular choice for use in deep learning applications that involve the prediction of time-series data. The results of research carried out by [10] and [11] indicate that LSTM achieves a high level of accuracy when it is applied to the task of predicting the movement of financial data. In addition to the LSTM, the convolutional neural network (CNN) is another fundamental architecture of deep learning that has the capacity to forecast the development of time-series data [12]. CNN was developed primarily for the purpose of extracting features from data, so that they can then be used in the process of classification [13]. However, a number of studies, including those that were carried out by [14] and [15], confirm that CNN is capable of being used as a method for the prediction of time-series data with satisfactory results as well.

Additionally, other deep learning models that are a combination of the LSTM and CNN models have also been widely developed e.g., Stacked-LSTM [16], CNN-LSTM [17], and convolutional LSTM (ConvLSTM) by [18]. The integration of advantages offered by CNN in terms of feature extraction, and the capabilities offered by LSTM regarding the storage of data motion patterns is the goal of combining the two models; as a result, it is expected that the integration of these two models will be of help to improve time-series prediction accuracy. Another study in the area of time-series prediction with the combined deep learning approach was conducted by [19] who has also found that the approach is effective for predicting the air quality as well. In addition, [20] and [21] suggested in their work that the usage of CNN and LSTM is also successful when it comes to making predictions about Covid-19 cases. In their work with wind speed data, [22] was investigating the use of mixed deep learning models and confirmed that the integration of different models is a promising solution for complex wind speed forecasting. Another study on forecasting of electricity load data conducted by [23] also suggests similar results as they have surveyed and experimentally tested the most applicable deep learning models when being applied on the short-term load forecasting problem.

Five deep learning models i.e., CNN, LSTM, Stacked-LSTM, CNN-LSTM, and ConvLSTM, that are commonly used as time-series data prediction techniques and can be employed on multivariate data sets are analyzed in this study. This selection is based on the characteristics of the models and by referring to some previous studies as well. Figure 1 shows a comparison of the structures in terms of input and output flows in the five deep learning models studied in this study. As can be seen in Figure 1, there are 2 (two) groups of deep learning models, namely single (CNN, LSTM and Stacked LSTM) and hybrid (CNN-LSTM and ConvLSTM).

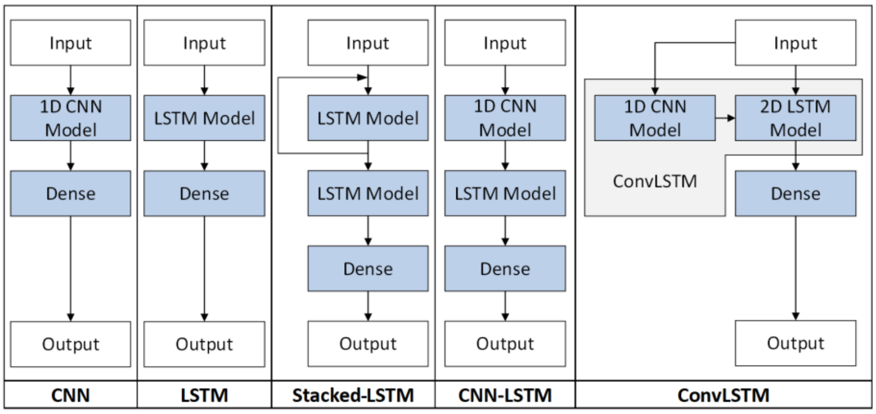

Figure 1. Architecture of CNN, LSTM, stacked-LSTM, CNN-LSTM and ConvLSTM

2.1. Convolutional neural network (CNN) model

CNN are a type of artificial neural network that have quickly become the go-to solution for a wide range of computer vision problems, as well as for time-series pre-diction. CNN is designed to learn spatial hierarchies of information automatically and adaptively through the process of backpropagation [12], [14]. This is accomplished through the utilization of several building pieces, including convolution layers, pooling layers, and fully connected layers. Nevertheless, using CNN to time-series prediction problems presents several challenges, particularly when we are working with a small datasets and over fitting the model [13]. Several studies have proved the usefulness of CNN for predicting financial time-series. In a 2018 study, for instance, CNN was used to forecast the direction of the S&P 500 index where the model outperformed other methods such as logistic regression and random forests [9]. Additionally, a 2020 study utilized a 1D CNN to predict the closing prices of many equities. They discovered that CNN could recognize complex data patterns and make accurate predictions [7].

2.2. Long short-term memory (LSTM) model

LSTM is developed by Hochreiter and Schmidhuber based on a Recurrent Neural Network (RNN) architecture [24]. LSTM addresses the issue of the RNN's long-term dependencies, in which the RNN is unable to forecast the upcoming condition that is kept in the long-term memory but is abl e to make more accurate predictions based on more recent information. In this case, by nature RNN does not deliver an efficient performance when the gap length between data is increased. By design LSTM has the capability to remember the information for a significant amount of time as an improvement to RNN. On the basis of time-series data, it is then can be employed for the purposes of processing, making predictions, and classifying [25]. Several studies have demonstrated that LSTM outperforms standard time-series forecasting models, such as ARIMA and GARCH, in terms of accuracy of prediction. In a 2019 study, for instance, LSTM was used to predict the stock values of 5 (five) technological businesses. They discovered that the LSTM model outperformed a number of other models, such as random forests and conventional time-series models [4]. In another 2019 study, researchers predicted the Bitcoin exchange rate using LSTM. They discovered that the LSTM model could capture nonlinear relationships between various input characteristics and generate good predictions [3].

2.3. Stacked-LSTM model

Stacked-LSTM is an evolution of LSTM architecture that is consist of multiple hidden LSTM layers with numerous memory cells per layer and therefore widely known as the extension of the initial LSTM model [26]. The stacked LSTM hidden layers increase the model's depth, more properly qualifying it as a deep learning method. It is the depth of neural networks that is credited with the method's performance on a variety of difficult prediction challenges and why it is expected to perform better that the basic LSTM [27]. Many studies have demonstrated that Stacked-LSTM could outperform single-layer LSTM in terms of prediction accuracy for tasks involving financial time-series data. For instance, researchers employed Stacked-LSTM to forecast the values of four distinct equities in a 2019 study and found that the model outperformed conventional machine learning models, such as single-layer LSTM and random forests [27]. In another study, researchers predicted human-activities using Stacked-LSTM [16]. They discovered that the Stacked-LSTM model could capture the intricate correlations between various input characteristics and generate reliable predictions.

2.4. CNN-LSTM model

CNN-LSTM is a hybrid model, which is the combination of a CNN and LSTM models. Within the context of this concept, CNN is a viable candidate for the encoding step of an encoder-decoder architecture [14]. In this scenario, the CNN does not provide direct support for sequence input; rather, a one-dimensional CNN is able to read through sequence input and automatically learn the important characteristics of the data. After that, an LSTM decoder will be able to understand these as it would normally. As a consequence, the CNN layer anticipates that the input data will have the same structure as the LSTM model, despite of the fact that numerous features are read as distinct channels that eventually provide the same result. Thereafter, these combined layers of CNN and LSTM can then be applied to forecast the movement of multivariate time-series data [28], [29]. Additionally, [17] did a study using CNN-LSTM for financial time-series prediction. The authors trained a CNN-LSTM model using a datasets of daily stock prices for publicly traded businesses to forecast the closing prices for the following day. According to the findings of the study, the CNN-LSTM model beat a number of other models, including standard time series models and other deep learning models such as feed-forward neural networks and LSTM networks. Another study using CNN-LSTM was carried out by [29] using individual household load data and find similar facts. The researchers then came to the conclusion that CNN-LSTM architecture is a good strategy for predicting financial time series.

2.5. Convolutional LSTM (ConvLSTM) model

ConvLSTM is an extension of the CNN-LSTM method that conducts the convolutions of the CNN i.e., how the CNN reads the input sequence data as a component of the LSTM for each time step [30]. Convolutions are a way that the CNN interprets the data that is input to it. A Convolutional LSTM, or ConvLSTM for short, is a combination of CNN and LSTM model originally designed for processing spatio temporal data where in this architecture, convolutions are read directly into the LSTM units them-selves and used as a component of the reading input [31]. Consequently, ConvLSTM is different to LSTM, which reads the data in directly in order to calculate its internal state and state transitions, as well as to CNN-LSTM, which LSTM layer interprets the output from CNN models as input. A study using the ConvLSTM model for sentiment analysis in social media demonstrated the model's superiority in forecasting the sentiment trend of social media users [30]. The researchers also discovered that ConvLSTM performed better than the CNN or LSTM model on its own. In addition, a study by [18], in which ConvLSTM was used to forecast the movement of a stock market index, demonstrated that the model can be effectively applied to super-high dimensional time-series data. Hence, it can be stated that ConvLSTM is a trustworthy deep learning model to consider when working with financial time-series data prediction.

3. METHODOLOGY AND DATA SET

As shown in Figure 2, the research began with a literature review to find a number of well-performing deep learning architectures that are often used for modelling and predicting time-series data. After getting a variety of deep learning architectures whose performance will be evaluated, the following step is to collect time-series data that is originating from a real-world setting. The third stage of this research is the pre-processing of the collected data set, which is the process of normalizing their values according to the various ranges of existing stock market index values. The data is then separated into two groups i.e., training data and test data. Next is the development and tuning of the identified deep learning architectures so that these models can be applied to multivariate time-series data. Adjustments were made to the structure and configuration of the 5 (five) models in exploration i.e., convolutional neural network (CNN), long short-term memory (LSTM), stacked-LSTM, CNN-LSTM, and convolutional LSTM (ConvLSTM). Afterwards, the 5 (five) models undergo the training procedure, followed by a performance evaluation. Based on the results of the performance test, analysis to recognize the existence of relationship between the properties of the processed data and the tested models was conducted. The final phase of this methodology is the identification of deep learning models and their structure with the highest prediction accuracy.

As previously stated, the learning process in the five deep learning models will use a parallel-multivariate approach, which means that the entire models will receive multi-variable inputs and produce multi-variable outputs as well and the prediction process is carried out simultaneously (parallel) for all variables. This is different from the non-parallel prediction approach where predictions for each variable of interest will be made individually. The main difference between making predictions on multivariate data in parallel and non-parallel is the process that occurs. In parallel prediction, the prediction process is conducted once for all variables, whereas in non-parallel prediction, the prediction process is conducted individually for each variable of concern. Making predictions in parallel has an advantage because a trained model will record the relationship between variables and utilize it in the prediction process so that it has the potential to provide better accuracy.

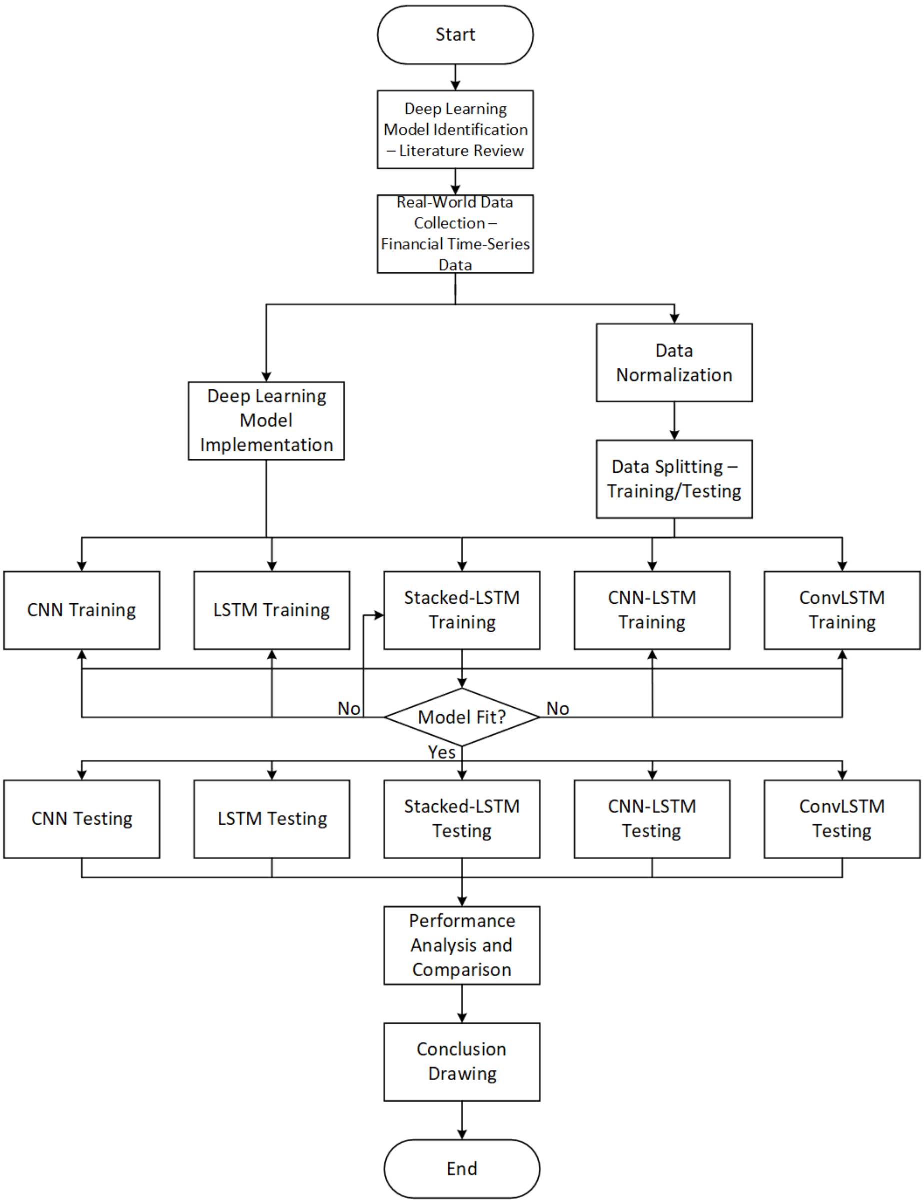

Figure 2. Research methodology applied in the study for comparative analysis of deep learning models

3.1. Data Set

The time-series data set used in this study is data from the financial field as previously described. In this study, data from the 4 (four) stock markets is combined into one multivariate data set on the basis of findings from several previous studies which confirmed that the movement of stock market indexes influences one another [10], [14]. Therefore, using a multivariate modeling approach gives better results as it takes into account the correlation and influence between one stock market and another. In detail, the data used in this study is the daily stock market indexes movement from Indonesia as shown in Figure 3(a), Hong Kong as shown in Figure 3(b), Japan as shown in Figure 3(c), and Singapore as shown in Figure 3(d) for the period of 1 January 2020 until 31 December 2020. This selection of period is based on fact that throughout the year 2020 there were turbulences in the movement of stock market indices due to the spread of Covid-19 pandemic. Using data from the early period of the spread of Covid-19 pandemic that has caused global economic instability can confirm the performance of the deep learning model being analysed. The financial data used in this experimentation consists of 242 data points that represent the total number of trading day for the year 2020 and is plotted in Figures 3(a)-3(d).

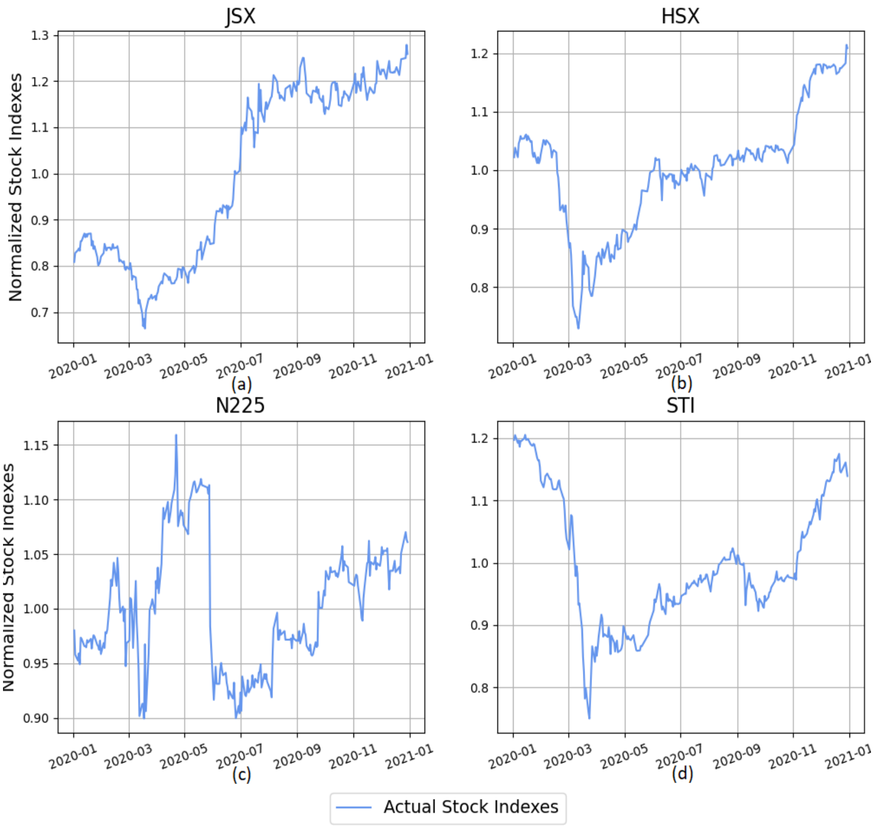

Figure 3. Normalized stock market indexes in the period of 1 January 2020 to 31 December 2020: (a) Indonesia (JSX), (b) Hong Kong (HSX), (c) Japan (N225), and (d) Singapore (STI)

3.2. Training and Testing

Out of 242 data points that represent daily stock market index values movement from 1 January 2020 to 31 December 2020, 223 data points that are corresponding to stock market index values from 1 January 2020 to 30 November 2020 are used as input for training. Predictions are then made for the movement of the stock market index values during the month of December 2020 or as many as 19 daily data points. All 5 (five) deep learning models that are considered in this work i.e., CNN, LSTM, Stacked-LSTM, CNN-LSTM, and ConvLSTM are implemented using the Python artificial intelligence framework. Additionally, the trials in this study were conducted using a computer with a Windows 10 platform, Intel Core i7 processor, 8 GB RAM. In addition, complete setting of parameters for all deep learning models analyzed in this research is given in Table 1. Selection of paremeter values refer to the structure and configuration of parameter values used by [17] in their CNN-LSTM ensemble model for stock prices prediction in the Shanghai Composite Index, as well as the work of [14] and [28] when using CNN, LSTM, and CNN-LSTM model for prediction of stock market indexes in Asia and human mobility during the spread of COVID-19. Additionally, for every model, single layer of CNN and LSTM is used except for the Stacked-LSTM, where 2 (two) LSTM layers with the same number of hidden units are applied.

All 5 (five) models are also trained on a subset of the collected financial time-series data set. After that, predictions for each stock market index are generated and compared to their actual values. In this study, the root mean squared error (RMSE) and mean absolute percentage error (MAPE) is used to measure the performance of each model's prediction error [32], [33]. In this study, the performance of all observed deep learning models is evaluated on the basis of accuracy for one-step prediction and not multi-steps prediction. This selection of one-step prediction is based on practical considerations that investment on stock markets is more inclined towards short-term investments, thus requiring more accurate short-term predictions.

Table 1. Parameter configuration for the 5 (five) deep learning model under investigation

No.	Parameter	Values				
		CNN	LSTM	Stacked-LSTM	CNN-LSTM	ConvLSTM
1	Convolutional layer filters	64	n/a	n/a	64	64
2	Convolutional layer kernel size	2	n/a	n/a	2	2
3	Convolutional layer activation function	Relu	n/a	n/a	Relu	n/a
4	LSTM layer hidden unit	n/a	100	100	100	100
5	LSTM Activation Function	n/a	Relu	Relu	Relu	Relu
6	Optimizer	Adam	Adam	Adam	Adam	Adam
7	Loss function	MAE	MAE	MAE	MAE	MAE
8	Epochs	1,000	1,000	1,000	1,000	1,000

4. RESULTS AND DISCUSSION

Figure 4 shows a comparison of the prediction results provided by CNN, LSTM, Stacked-LSTM, CNN-LSTM, and ConvLSTM for each stock market throughout December 2020. Generally, we can see that the 5 (five) deep learning models analysed were able to reconstruct the movement patterns of the index values in the 4 (four) observed stock markets. However, we can also see that there is quite a variable distance between the predicted yield curve and the original value curve. In particular, Figure 4(a) shows that the LSTM model generates the closest prediction curve for the JSX and Figure 4(b) shows that for the HSX index, the curve produced by the Stacked-LSTM model has the farthest distance from the original value curve compared to the other models We can also see different conditions on the N225 (Japan) stock market chart in Figure 4(c) whereas on the N225 graph, the prediction curve generated by CNN has the farthest distance from the original value compared to other models. Another fact is that for the HSX the closest prediction curve is generated by the CNN model as shown in Figure 4(d). In addition, for N225, the best prediction curve was produced by the ConvLSTM model whilst for STI the CNN model again showed the best performance. These findings indicate that among the 5 (five) deep learning models compared, there is no such single model that consistently provides the best predictive results.

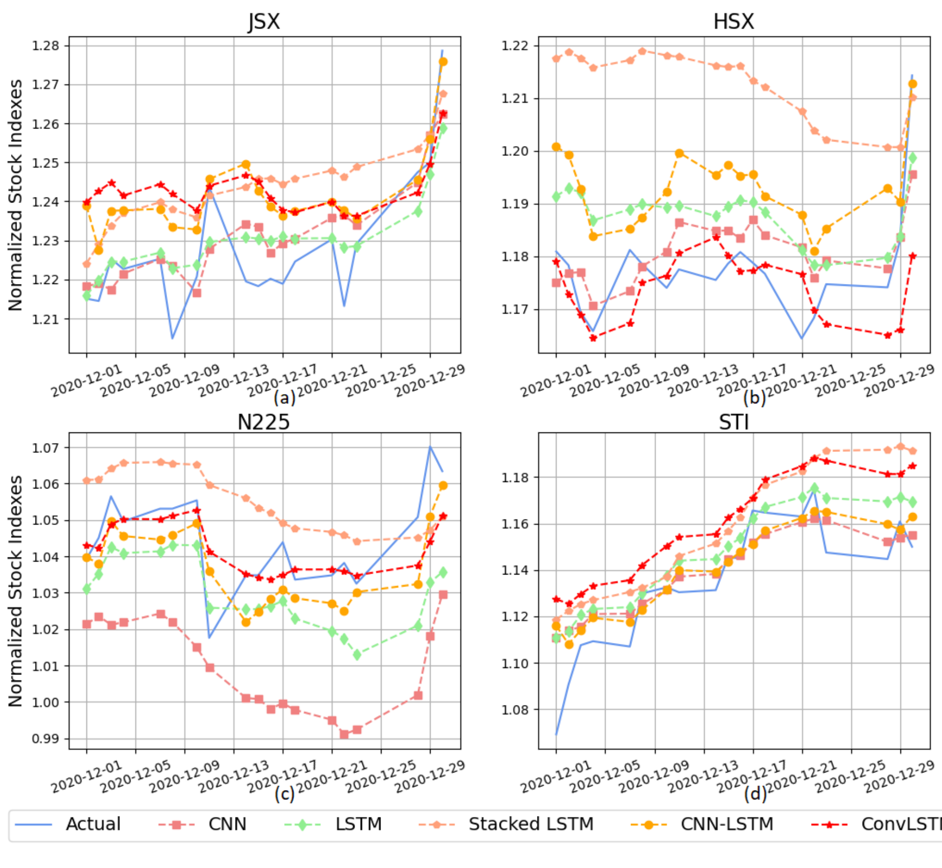

Figure 4. Comparison between actual (solid line) and predicted (dashed lines) stock indexes for the last month of 2020: (a) Indonesia (JSX), (b) Hong Kong (HSX), (c) Japan (N225), and (d) Singapore (STI)

Prediction errors in RMSE and MAPE are outlined in Table 2. In general, Table 2 indicates that the error rates are consistent between RMSE and MAPE and it can be observed that the single models could outperform combined models. Table 2 also shows comparison of error between training and testing phase. Here, we can also see that error rates are increasing in training phase which is a normal condition in time-series prediction setting. As we sum up RMSE values of the 5 (five) deep learning models in testing phase, total error for CNN is 0.0782, LSTM is 0.0686, Stacked-LSTM is 0.1009, CNN-LSTM is 0.0679, and ConvLSTM is 0.0752. Therefore, the two models with the lowest total RMSE values are LSTM and CNN-LSTM. Thus, we can draw an initial conclusion that these two models are deep learning models that have the best general performance when used to predict multivariate financial time-series data in parallel.

Table 2. Comparison of error for prediction of JSX, HSX, N225 and STI indexes

Stock Market	Root mean squared error (RMSE)									
	CNN		LSTM		Stacked-LSTM		CNN-LSTM		ConvLSTM	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Training
JSX	0.0146	0.0160	0.0138	0.0157	0.0182	0.0205	0.0177	0.0197	0.0190	0.0213
HSX	0.0100	0.0107	0.0132	0.0147	0.0340	0.0366	0.0158	0.0179	0.0126	0.0143
N225	0.0335	0.0372	0.0188	0.0204	0.0162	0.0180	0.0126	0.0146	0.0115	0.0128
STI	0.0127	0.0143	0.0157	0.0178	0.0224	0.0258	0.0143	0.0157	0.0233	0.0268
	Mean absolute percentage error (MAPE)									
JSX	2.24%	2.46%	2.12%	2.41%	2.79%	3.15%	2.72%	3.02%	2.92%	3.27%
HSX	1.53%	1.64%	2.03%	2.26%	5.22%	5.62%	2.43%	2.75%	1.93%	2.19%
N225	5.14%	5.71%	2.89%	3.13%	2.49%	2.76%	1.93%	2.24%	1.77%	1.96%
STI	1.95%	2.19%	2.41%	2.73%	3.44%	3.96%	2.19%	2.41%	3.58%	4.11%

Figure 5 shows the comparison of the reduction in loss among the 5 (five) deep learning models assessed during training. The loss reduction during the training process for CNN, LSTM, Stacked-LSTM, CNN-LSTM and ConvLSTM is shown in Figures 5(a)-5(e) respectively. In this instance, the 5 (five) deep learning models were trained using data collected between 1 January 2020 to 30 November 2020. From closer inspection on Figure 5, it can be seen that the loss value stabilizes around the 800th iteration (epoch) on average (epoch is set to 1,000 for all models as given in Table 1). In addition, the CNN model achieves the fastest loss reduction stability as shown in Figure 5(a), whereas the ConvLSTM model achieves the slowest as shown in Figure 5(e). This is consistent with the structure of the two models, with CNN's structure being the simplest and ConvLSTM's structure being the most complex. Whereas for the other three models, the stability of the loss values tends to be reached at the same time as they can be seen in Figures 5(b)-5(d). Figure 5(e) also demonstrates that the ConvLSTM model, which is the most complex deep learning model with the longest learning time to achieve loss stability (relative to the other four), does not necessarily provide the best accurate prediction, as discussed before based on Figure 4's results.

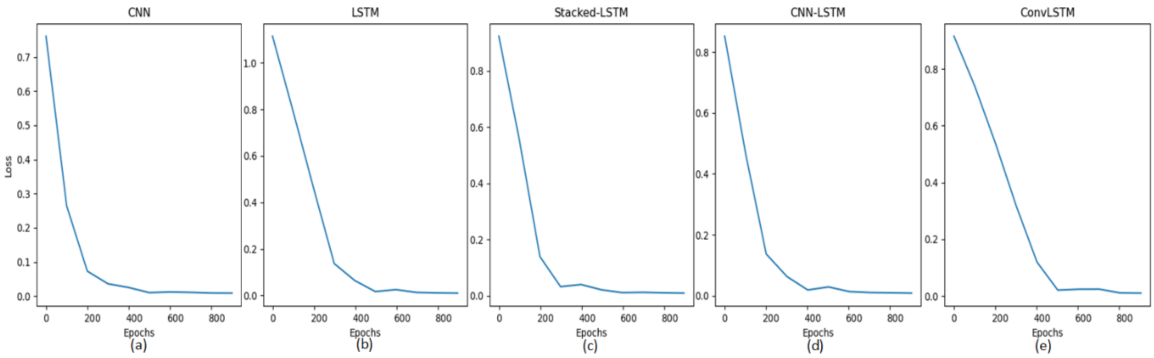

Figure 5. Comparison of loss reduction during training for each deep learning model: (a) CNN, (b) LSTM, (c) Stacked-LSTM, (d) CNN-LSTM, and (e) ConvLSTM

Accordingly, Figure 6 shows a comparison of the prediction results of the two models (LSTM and CNN-LSTM) which are also accompanied by a plot of the prediction error area. Here, Figures 6(a)-6(d) shows the plot of prediction and its error for JSX, HSX, N225, and STI correspondingly. In general, we can see that the error area of CNN-LSTM (yellow color) dominates for JSX and HSX predictions as shown in Figures 6(a) and 6(b). Whereas for N225 and STI, the error area of the LSTM (red color) is wider as it can be observed in Figures 6(c) and 6(d). In this regards, another understanding that we can get is that apart from LSTM and CNN-LSTM being the two deep learning models with the best performance, it turns out that LSTM has better performance for predicting JSX and HSX data while CNN-LSTM is more accurate for N225 and STI. Consequently, further analysis to answer the question of the relationship between LSTM and the predicted results of JSX and HSX, as well as between CNN-LSTM and the predicted results of N225 and STI needs to be carried out. However, an initial conclusion can be drawn which indicates that there is a certain performance pattern in the deep learning model tested against the characteristics of the processed time-series data as shown in Figure 6. Additionally, from Figure 3 we can observe that JSX and HSX share different patterns with N225 and STI where movement of the JSX and HSX indexes seem more stable when compared to that of the N225 and STI indexes.

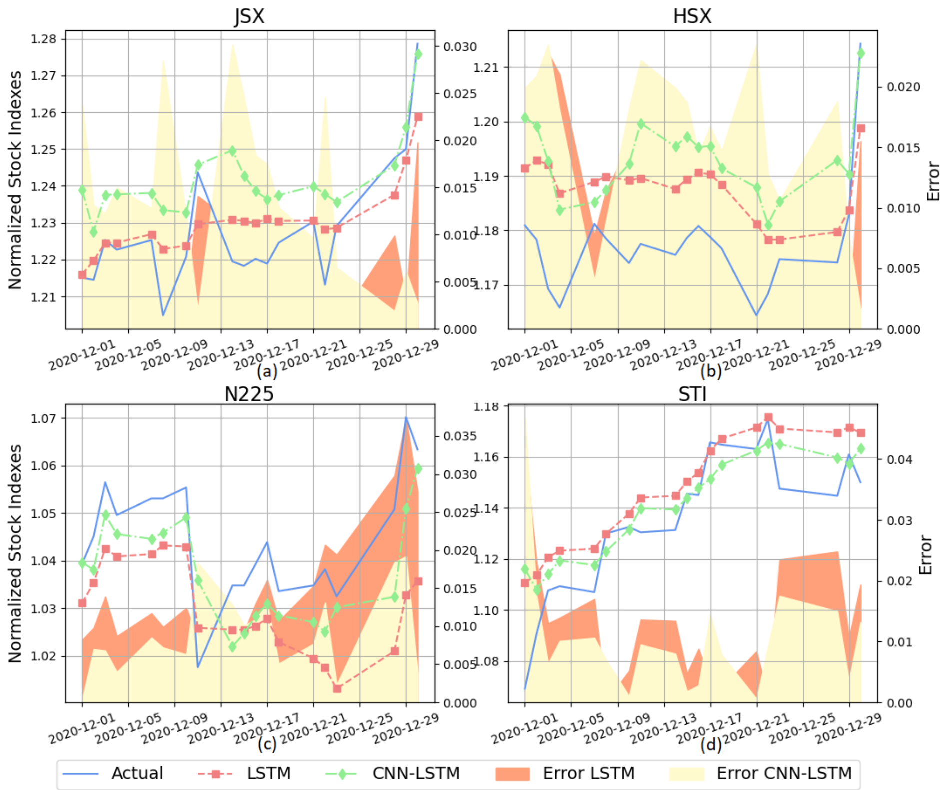

Figure 6. Plots of actual (solid line) against prediction (dashed lines) produced by LSTM dan CNN-LSTM with error: (a) Indonesia (JSX), (b) Hong Kong (HSX), (c) Japan (N225), and (d) Singapore (STI)

To confirm chaoticity level variation between the 4 (four) stock markets, difference in daily movement of the stock market indices is calculated and showed in Figure 7. Here, Figure 7 shows a comparison of the level of volatility between the four stock market index values analyzed. The level of volatility is measured by the difference in the daily movements of the index values. Figure 7(a) describes the volatility states of the JSX during the year 2020, while Figure 7(b). shows the volatility of the HSX, Figure 7(c) for the N225, and Figure 7(d) for the STI. As can be observed, the graphics in Figures 7(a) and 7(b) show that the JSX and HSX have daily index movement volatility with a smaller magnitude in comparison to N225 and STI as depicted in Figures 7(c) and 7(d). This indicates that the movement of the N225 and STI stock market indices is more chaotic compared to that of JSX and HSX. Table 3 outlines the descriptive statistics of the data set also exhibit consistent conditions. Here we can see that in general standard deviations and variances of JSX and HSX is smaller than the ones belong to N225 and STI. Hence, based on the standard deviation and variance values, it can be learned that indexes of JSX and HSX are more stable compared to those of N225 and STI. This descriptive statistic confirms the characteristics of data set as discussed based on the graphics in Figure 7 previously.

Referring to the facts found from the experimental results that have been carried out, there is a fairly strong initial indication that LSTM provides the best predictive results for financial time-series data that has more stable volatility. Meanwhile, for the prediction of stock market indices with a higher level of volatility or more chaotic, CNN-LSTM provides better accuracy. Furthermore, in general it can be said that single deep learning models are more effective for predicting less-chaotic financial time-series data. Nevertheless, for chaotic time-series, combined deep learning models perform better.

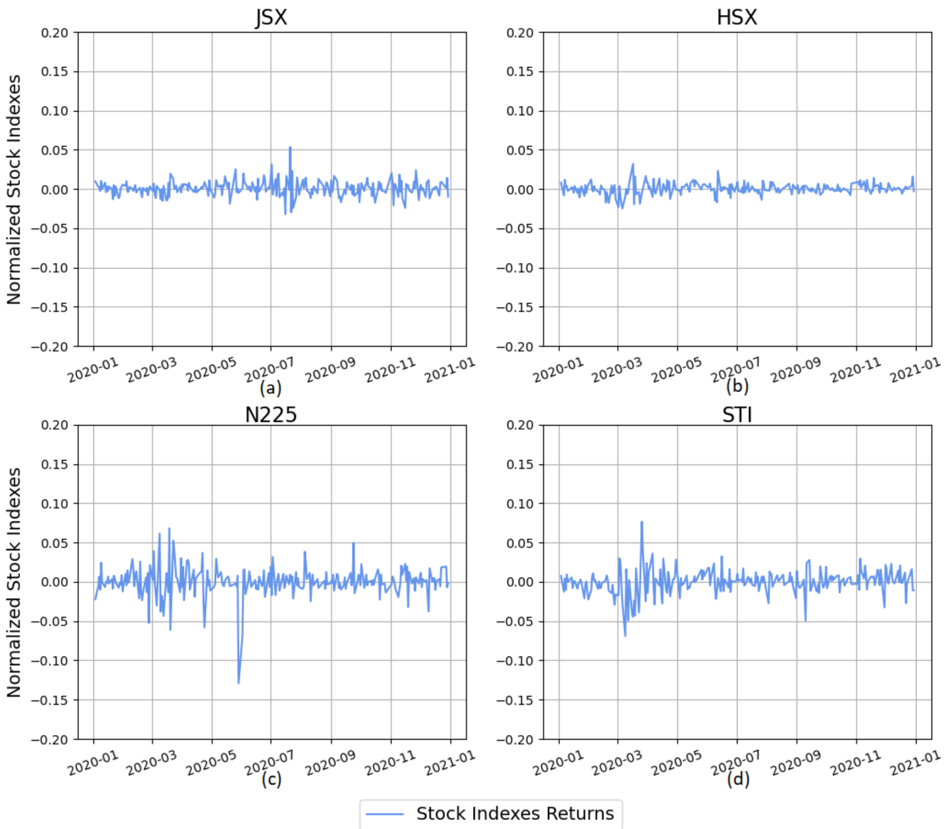

Figure 7. Comparison of the chaotic characteristics between (a) JSX, (b) HSX, (c) N225, and (d) STI based on the movement of the daily index value differential

Table 3. Descriptive statistics of the data set in the period of 1 January 2020 to 31 December 2020

Stock Market	Median	Standard Deviation	Variance	Kurtosis	Skewness
JSX	1.0213	0.0188	0.0035	-1.7015	-0.1193
HSX	1.0161	0.0102	0.0020	0.1085	-0.2911
N225	0.9901	0.1571	0.0113	-0.5949	0.3756
STI	0.9746	0.1490	0.0130	-0.7253	0.3094

The findings of conducted experiments also reveal that more complicated deep learning architectures, such as ConvLSTM, may not always produce the greatest results, particularly in terms of financial time-series data forecasting. Therefore, it is not totally accurate to assert that combining multiple models is the greatest strategy to increase the forecasting accuracy of time-series data. In certain circumstances, a more simple and single structure can produce better results; in this example, LSTM has a lower RMSE value than Stacked-LSTM and ConvLSTM. This newly extracted knowledge is crucial, particularly in the application of data analysis methodologies for decision making, where it is common to believe that a more complex approach is the best model for answering all. This study indicates that for financial time-series data, a simpler model is more effective when applied to data with a low level of chaoticity. This new knowledge is the main contribution of the research being conducted, where this understanding can provide benefits to the world of investment, especially when choosing a predictive model to be used in building an investment decision support system.

However, one important limitation of this research is the scope of the financial data used. In this case, the data tested is limited to stock market index data in 4 (four) Asian countries, while the types of financial data are very diverse. Therefore, further exploration using more complete and cross-sectoral financial data is necessary to confirm the results obtained from this study. In addition, another limitation is that in this study the results obtained have not been compared with conventional machine learning techniques that are commonly used for time-series predictions such as KNN and SVM. This is because the focus of this research is indeed to identify the best deep learning models for predicting multivariate time-series in parallel. Nevertheless, in the future it is planned to carry out performance test comparisons between the deep learning models that have been discussed with other conventional techniques as well as with other deep learning models that are commonly used for predicting cuber attacks and short-term traffic loads such as the GRU network [34].

5. CONCLUSION

According to testing and research, no deep learning model consistently makes the best accurate predictions for all states of multivariate time-series data. CNN, LSTM, Stacked-LSTM, CNN-LSTM, and ConvLSTM can be used to predict time-series data movement in general, but the prediction results show that each data set performs differently. The study also found a substantial association between time-series data chaoticity and the structure of the best deep learning model for prediction. With stable time-series data, a single deep learning model makes more accurate predictions, whereas for chaotic data, a collection of models is better. For future research, it is planned to develop an intelligent deep learning system that has the ability to recognize the chaoticity characteristics of input data and then can autonomously determine a suitable deep learning model to use. The use of financial data that is more complete and cross-sectoral also needs to be carried out so that it can confirm the findings of this study and in order to produce a generic parallel multivariate deep learning model for financial time-series prediction.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the Ministry of Education, Culture, Research and Technology of the Republic of Indonesia for the research grant No. 448/LL3/AK.04/2022 and also Perbanas Institute for their support in this work.

REFERENCES

[1] S. Siami-Namini, N. Tavakoli, and A. Siami Namin, “A comparison of ARIMA and LSTM in Forecasting time series,” in *2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA)*, Dec. 2018, pp. 1394–1401, doi: 10.1109/ICMLA.2018.00227.

[2] H. A. Dau *et al.*, “The UCR time series archive,” *IEEE/CAA Journal of Automatica Sinica*, vol. 6, no. 6, pp. 1293–1305, 2019, doi: 10.1109/JAS.2019.1911747.

[3] J. Cao, Z. Li, and J. Li, “Financial time series forecasting model based on CEEMDAN and LSTM,” *Physica A: Statistical Mechanics and its Applications*, vol. 519, pp. 127–139, 2019, doi: 10.1016/j.physa.2018.11.061.

[4] A. R. S. Parmezan, V. M. A. Souza, and G. E. A. P. A. Batista, “Evaluation of statistical and machine learning models for time series prediction: Identifying the state-of-the-art and the best conditions for the use of each model,” *Information Sciences*, vol. 484, pp. 302–337, 2019, doi: 10.1016/j.ins.2019.01.076.

[5] H. He, S. Gao, T. Jin, S. Sato, and X. Zhang, “A seasonal-trend decomposition-based dendritic neuron model for financial time series prediction,” *Applied Soft Computing*, vol. 108, 2021, doi: 10.1016/j.asoc.2021.107488.

[6] X. Chen and L. Sun, “Bayesian temporal factorization for multidimensional time series prediction,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 9, pp. 4659–4673, 2022, doi: 10.1109/TPAMI.2021.3066551.

[7] B. Lim and S. Zohren, “Time-series forecasting with deep learning: A survey,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 379, no. 2194, 2021, doi: 10.1098/rsta.2020.0209.

[8] O. B. Sezer, M. U. Gudelek, and A. M. Ozbayoglu, “Financial time series forecasting with deep learning: A systematic literature review: 2005–2019,” *Applied Soft Computing Journal*, vol. 90, 2020, doi: 10.1016/j.asoc.2020.106181.

[9] H. Yan and H. Ouyang, “Financial time series prediction based on deep learning,” *Wireless Personal Communications*, vol. 102, no. 2, pp. 683–700, 2018, doi: 10.1007/s11277-017-5086-2.

[10] A. Moghar and M. Hamiche, “Stock market prediction using LSTM recurrent neural network,” *Procedia Computer Science*, vol. 170, pp. 1168–1173, 2020, doi: 10.1016/j.procs.2020.03.049.

[11] X. Yan, W. Weihan, and M. Chang, “Research on financial assets transaction prediction model based on LSTM neural network,” *Neural Computing and Applications*, vol. 33, no. 1, pp. 257–270, Jan. 2021, doi: 10.1007/s00521-020-04992-7.

[12] H. Weytjens and J. De Weerdt, “Process outcome prediction: CNN vs. LSTM (with attention),” Apr. 2021, doi: 10.1007/978-3-030-66498-5_24.

[13] F. Sultana, A. Sufian, and P. Dutta, “Advancements in image classification using convolutional neural network,” *Proceedings - 2018 4th IEEE International Conference on Research in Computational Intelligence and Communication Networks, ICRCICN 2018*, pp. 122–129, 2018, doi: 10.1109/ICRCICN.2018.8718718.

[14] H. Widiputra, A. Mailangkay, and E. Gautama, “Multivariate CNN-LSTM model for multiple parallel financial time-series prediction,” *Complexity*, vol. 2021, 2021, doi: 10.1155/2021/9903518.

[15] K. Wang *et al.*, “Multiple convolutional neural networks for multivariate time series prediction,” *Neurocomputing*, vol. 360, pp. 107–119, 2019, doi: 10.1016/j.neucom.2019.05.023.

[16] M. Ullah, H. Ullah, S. D. Khan, and F. A. Cheikh, “Stacked LSTM network for human activity recognition using smartphone data,” *Proceedings - European Workshop on Visual Information Processing, EUVIP*, vol. 2019-Octob, pp. 175–180, 2019, doi: 10.1109/EUVIP47703.2019.8946180.

[17] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-based model to forecast stock prices," *Complexity*, vol. 2020, 2020, doi: 10.1155/2020/6622927.
[18] S. W. Lee and H. Y. Kim, "Stock market forecasting with super-high dimensional time-series data using ConvLSTM, trend sampling, and specialized data augmentation," *Expert Systems with Applications*, vol. 161, 2020, doi: 10.1016/j.eswa.2020.113704.
[19] N. Zaini, L. W. Ean, A. N. Ahmed, and M. A. Malek, "A systematic literature review of deep learning neural network for time series air quality forecasting," *Environmental Science and Pollution Research*, vol. 29, no. 4, pp. 4958–4990, 2022, doi: 10.1007/s11356-021-17442-1.
[20] H. Abbasimehr, R. Paki, and A. Bahrini, "A novel approach based on combining deep learning models with statistical methods for COVID-19 time series forecasting," *Neural Computing and Applications*, vol. 34, no. 4, pp. 3135–3149, 2022, doi: 10.1007/s00521-021-06548-9.
[21] M. O. Alassafi, M. Jarrah, and R. Alotaibi, "Time series predicting of COVID-19 based on deep learning," *Neurocomputing*, vol. 468, pp. 335–344, 2022, doi: 10.1016/j.neucom.2021.10.035.
[22] S. X. Lv and L. Wang, "Deep learning combined wind speed forecasting with hybrid time series decomposition and multi-objective parameter optimization," *Applied Energy*, vol. 311, 2022, doi: 10.1016/j.apenergy.2022.118674.
[23] A. Gasparin, S. Lukovic, and C. Alippi, "Deep learning for time series forecasting: The electric load case," *CAAI Transactions on Intelligence Technology*, vol. 7, no. 1, pp. 1–25, 2022, doi: 10.1049/cit2.12060.
[24] G. Van Houdt, C. Mosquera, and G. Nápoles, "A review on the long short-term memory model," *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5929–5955, 2020, doi: 10.1007/s10462-020-09838-1.
[25] A. Sherstinsky, "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network," *Physica D: Nonlinear Phenomena*, vol. 404, 2020, doi: 10.1016/j.physd.2019.132306.
[26] Y. Li, T. Bao, J. Gong, X. Shu, and K. Zhang, "The prediction of dam displacement time series using STL, extra-trees, and stacked LSTM neural network," *IEEE Access*, vol. 8, pp. 94440–94452, 2020, doi: 10.1109/ACCESS.2020.2995592.
[27] S. O. Ojo, P. A. Owolawi, M. Mphahlele, and J. A. Adisa, "Stock market behaviour prediction using stacked LSTM networks," *Proceedings - 2019 International Multidisciplinary Information Technology and Engineering Conference, IMITEC 2019*, 2019, doi: 10.1109/IMITEC45504.2019.9015840.
[28] H. Widiputra, "GA-optimized multivariate CNN-LSTM model for predicting multi-channel mobility in the COVID-19 pandemic," *Emerging Science Journal*, vol. 5, no. 5, pp. 619–635, 2021, doi: 10.28991/esj-2021-01300.
[29] M. Alhussein, K. Aurangzeb, and S. I. Haider, "Hybrid CNN-LSTM model for short-term individual household load forecasting," *IEEE Access*, vol. 8, pp. 180544–180557, 2020, doi: 10.1109/ACCESS.2020.3028281.
[30] R. K. Behera, M. Jena, S. K. Rath, and S. Misra, "Co-LSTM: Convolutional LSTM model for sentiment analysis in social big data," *Information Processing and Management*, vol. 58, no. 1, 2021, doi: 10.1016/j.ipm.2020.102435.
[31] M. Rahman, D. Islam, R. J. Mukti, and I. Saha, "A deep learning approach based on convolutional LSTM for detecting diabetes," *Computational Biology and Chemistry*, vol. 88, 2020, doi: 10.1016/j.compbiolchem.2020.107329.
[32] Y. Liu *et al.*, "Wind power short-term prediction based on LSTM and discrete wavelet transform," *Applied Sciences (Switzerland)*, vol. 9, no. 6, 2019, doi: 10.3390/app9061108.
[33] J. Xie and Q. Wang, "Benchmarking machine learning algorithms on blood glucose prediction for type i diabetes in comparison with classical time-series models," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 11, pp. 3101–3124, 2020, doi: 10.1109/TBME.2020.2975959.
[34] M. S. Ansari, V. Bartoš, and B. Lee, "GRU-based deep learning approach for network intrusion alert prediction," *Future Generation Computer Systems*, vol. 128, pp. 235–247, 2022, doi: 10.1016/j.future.2021.09.040.

BIOGRAPHIES OF AUTHORS

Harya Widiputra is a permanent lecturer and researcher at the Faculty of Information Technology, Perbanas Institute, Indonesia. Harya completed his doctoral studies in 2011 from Auckland University of Technology, New Zealand, majoring in time-series data analysis and modeling research. Some research areas that are of his expertise are machine learning and computational algorithms that are related to analysis and modeling of financial time-series data. He is also affiliated with IEEE as a member and has served as invited reviewer in a number of computer science journals. Besides, he is also involved in some ministries of the Republic of Indonesia as a technical expert. He can be contacted at email: harya@perbanas.id.

Edhi Juwono earned his Ph.D. in 2018 from Binus University in Indonesia, with an emphasis on study on the use and application of information systems to support firm performance, particularly in banks. His PhD dissertation investigated the alignment of IT and business strategy to improve corporate business performance. He is currently a permanent lecturer at Perbanas Institute's Faculty of Economics and Business, as well as an active researcher with expertise in information systems, strategic management, organizational behavior, and strategic planning. He has also served as a reviewer for various international journals in the field of management and is a member of Indonesian lecturer associations. He can be contacted at email: edhi.juwono@perbanas.id.