TRADE VALUE PREDICTION USING HYBRID GRAPH CONVOLUTIONAL RECURRENT NEURAL NETWORK WITH LION OPTIMIZATION MODEL

by

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Trade value prediction (TVP) is major for understanding financial dynamics and directing policy decisions in the perspective of complex systems science. The study emphases on an analytical model intended to predict future trade values by evaluating financial indicators, past trade data, and geopolitical powers. By using advanced statistical models and machine learning techniques, the model explores relationships and patterns in trade flows among countries. The perceptions increased from this technique offer beneficial support for policymakers and businesses, guiding them to forecast the effects of financial and policy changes on global trade. Also, the study emphasizes the importance of a complicated method to enhance the accuracy of trade predictions and aid tactical decision-making in a worldwide interconnected economy. This study proposes trade value prediction using hybrid graph convolutional recurrent neural network with Lion optimizer algorithm (TVP-HGCRNNLOA) methodology. The objective function of the TVP-HGCRNNLOA methodology is to develop an accurate predictive model for trade values between countries. Primarily, the TVP-HGCRNNLOA approach undergoes the data normalization by employing linear scaling normalization technique. Then, the hybrid graph convolutional recurrent neural network (HGCRNN) method is used for forecasting process. At last, the TVP-HGCRNNLOA model performs the hyperparameter tuning by utilizing the Lion optimization algorithm model. The experimental analysis of the TVP-HGCRNNLOA methodology is investigated in terms of various measures under mean squared error, mean absolute error, and mean absolute percentage error. The performance validation portrayed the superior performance of the TVP-HGCRNNLOA methodology over other existing approaches.

Key words: *trade value prediction, convolutional recurrent neural network, lion optimizer algorithm, economic forecasting, machine learning*

Introduction

In a global economy, financial markets becoming a significant part in playing a significant role in prosperity and the development of several countries globally, Guan *et al.* [1].

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These markets offer stockholders open and free platforms for interchanging various securities and commodities from a kind of areas, including banking, financial, manufacturing healthcare services, *etc.,* Ibrahim [2]. Financial markets can mostly exchange stocks, which are known to provide high investment profits compared to other kinds of investments and it creates attention for hedge funds and several investors and offers them an extensive variety of opportunities and tools to create investments and develop their wealth, Zhang *et al*. [3]. But, one of the challenges is that spending in stock markets is a difficult and time-consuming task and it needs stock market traders and investors to always monitor the market activities and Kottou *et al*. [4], regularly examine the stock price movements, seeking possible successful trade which upsurges their probabilities of making investment returns and decreases the loss risk, Vijh *et al*. [5].

Forecasting the stock market was a hot topic to sparked the curiosity among many professionals who come from diverse fields, Xu *et al*. [6]. To keep an eye on the stock market movement, many methods and processes are utilized, like deep neural networks (DNN) and support vector machines (SVM). By evaluating the historical data, these methods have been utilized to define the stock market trends, Vidal and Kristjanpoller [7]. With the growth in trading, several professionals have aimed to improve techniques and approaches to evaluate and predict upcoming stock prices. There are several efforts to forecast the market movement by utilizing several methods, Chen *et al*. [8]. In recent times, there have been several studies that utilize machine learning (ML) methods for financial market forecasting. They attained the best performance relating to the ML benchmarks, but, have no similar outcomes from the economic perspective. Artificial intelligence (AI) is at the core of these endeavors, Hoseinzade and Haratizadeh [9]. Machine and deep learning (DL)-based AI has changed various features of our everyday activities. The usage of machines and DL in the financial sector is the most profitable task. For, in the financial sector, predicting depends on the past data which can be beneficial for the stockholders in increasing return and decreasing risk on investments, Picasso *et al*. [10].

This study proposes trade value prediction using a hybrid graph convolutional recurrent neural network with Lion optimizer algorithm (TVP-HGCRNNLOA) methodology. Primarily, the TVP-HGCRNNLOA approach undergoes data normalization by employing the linear scaling normalization (LSN) technique. Then, the hybrid graph convolutional recurrent neural network (HGCRNN) method is used for the forecasting process. At last, the TVP-HGCRNNLOA model performs the hyperparameter tuning by utilizing the Lion optimization algorithm (LOA) model. The performance validation portrayed the superior performance of the TVP-HGCRNNLOA methodology over other existing approaches.

Related works

Friday *et al*. [11] presents a DL-based fusion model integrating neural network such as CNN, GRU, and attention mechanism models to anticipate market trending across diverse stock indices. The technique dynamically evaluates the input sequence with the AM method, comprehends local structure via CNN, and effectually methods long-term reliabilities with GRU thus focusing on accurate classification of the Zhu *et al*. [12], a clustering-enhanced DL method is presented to anticipate stock prices with three DL techniques, namely GRU, RNN, and LSTM methods. The technique introduces a resemblance quantity, namely the weighted dynamic time warping (WDTW) technique, by encompassing logistic WDTW (LWDTW). Furthermore, the methodology additionally employs the clustering-assisted anticipating model with the aforementioned three DL methodologies. Mohamed *et al*. [13] introduce a fusion DL technique, the CNN-LSTM, incorporating the 2-D-CNN to process the imaging with the LSTM model to manage classification and image sequences. The method altered the technical pointers from economic time sequence into 15 × 15 imaging for diverse day periods. Every image is later classified depending on the trading information.

Singh *et al.* [14] presented a technique depending on dual diverse learning models: incremental and offline-online. In the initial method, the technique is upgraded uninterruptedly upon getting the stock's subsequent instance from the live data, whereas in the second model, the methodology is reinstructed afterwards each trading period to confirm that it integrates the latest data difficulties. These techniques were utilized for uni variate and multivariate time series (recognized from past stock prices and technical indicators). Alzakari *et al*. [15] propose an LSTM-RNN method for anticipating potato costs. The method accumulated a past potato price dataset and other financial parameters, performing normalization by the *Z*-score technique to confirm that the overall data was consistent and credible. The efficiency of the technique was compared with five conventional ML techniques: kNN, RF, SVM, LR, and GB utilized for classifying remote households and determine their socio-financial status. Shilpa and Shumlhavi [16], an anticipation model is proposed via sentiment evaluation. The news information is processed for determining the sentiments by specific procedures such as: pre-processing, extraction of keywords, in which WordNet and sentiment classification procedure are executed, feature extraction, in that extraction of holo-entropy-based factors is accomplished, and a DNN model is employed to classify, which returns the output. The neural network training is accomplished by a SIWOA. Lastly, an improved DNN is utilized.

Methodology

In this study, we have presented a novel TVP-HGCRNNLOA methodology. The objective function of the TVP-HGCRNNLOA methodology is to develop an accurate predictive model for trade values between countries. Figure 1 depicts the entire flow of the TVP-HGCRNNLOA methodology.

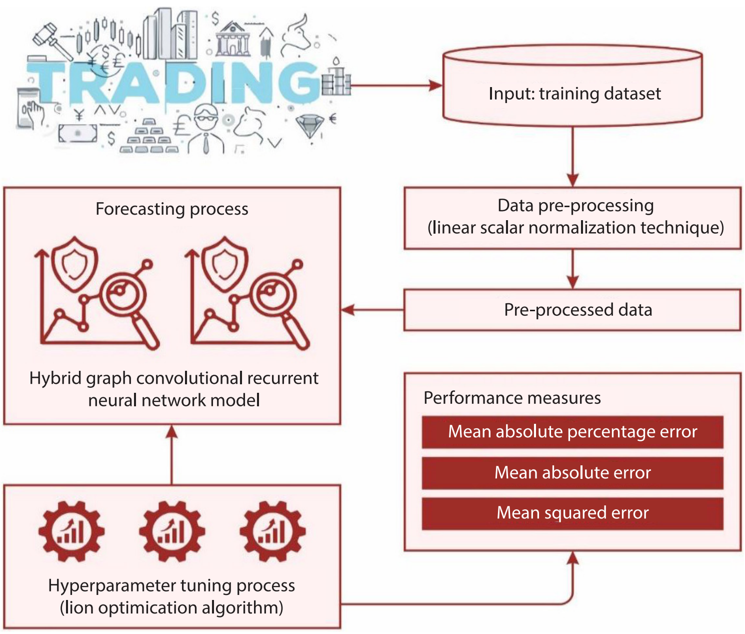

Figure 1. Overall flow of TVP-HGCRNNLOA methodology

Data normalization

Primarily, the TVP-HGCRNNLOA approach undergoes data normalization by employing the LSN technique. The LSN is a technique that is employed to alter trade value data to an exact range, regularly between 0 and 1. This method converts every value of trade by subtracting the trade value of the minimum and dividing by the range (maximum minus minimum). The procedure aids in alleviating the impacts of outliers and fluctuating scales, making the data more appropriate for analytical modelling. By normalizing the trade value, the technique can emphasize the relationships and patterns in the data instead of being inclined by the extent of the values. This is vital for enhancing the performance and accuracy of trade value prediction methods.

Prediction process

Then, the HGCRNN method is used for the forecasting process. The convolution operation is extensively utilized for the development of data-driven and ML techniques, and it can be widely described as a process of splitting weights among nearby regions in space or time to calculate various transformations and operations [17]. Relating to DL, a traditional CNN utilizes convolution operations on multi-dimensional arrays taking a temporal meaning. The CNN was generally utilized for classification intentions like image detection; meanwhile, images could be regarded as matrices in Euclidean space. The CNN displayed a strong performance in signal handling and graphic study owing to the inherent ability to resolve the structure type, extract important features that could be united with the data, and utilize a huge variety of various analyses. Common GCN are qualified to handle graph data with a related zone standard than the CNN afterward the description of appropriate operations and data transformation.

It presented to utilize the convolution operation over the GCN structure that goals for extracting the node features from the graph structure. In this research, the goal of GCN is to offer a node representation by utilizing not only the related node features it also neighboring node features. The GCN method output can be usually ◦ D calculated:

$$Y = \tilde{A}XW \tag{1}$$

where X is the input data, Y – the output, and W – the signifies the matrix with the parameters. In addition, $\tilde{A}$ is the normalized adjacency matrix:

$$\tilde{A} = \left(\hat{D}^{-1/2}\hat{A}\hat{D}^{-1/2}\right) \tag{2}$$

The RNN consist of a specific structure, which creates a prediction by utilizing not just the input data it utilizes the neighboring unit output also. Presented the initial form of this class of system, especially provided to seizure data in time and handle time-based data. The outcome is a system model among neurons, intentionally created to offer data from the previous. The intelligence of this structure kind lies in the association among hidden layers that are together in time and among layers. In this demonstration, the vector $x = (x_1,..., x_t)$ signifies the input sequence, the vector $y = (y_1, ..., y_t)$ is the output sequence and $h^n = (h_1^n, ..., h_t^n)$ is the hidden vector sequences in the nth layer. Based on the presented model of the RNN developed, the common hidden state ht of the 1st layer could be computed:

$$h_t^1 = \tanh\left(W_{xh^1}x_t + W_{h^1h^1}h_{t-1}^1 + b_h^1\right) \tag{3}$$

where W is the weight matrices, W_{xh^1} – the weight among the 1st hidden layer and the input, $W_{h^1h^1}$ – the recurrent weight in the 1st hidden layer, and b^1_n – the the bias. In common, the hidden state of the n^{th} layer could be computed:

$$h_t^n = \tanh\left(W_{h^n h^n} h_t^{n-1} + W_{h^n h^n} h_{t-1}^n + b_h^n\right) \tag{4}$$

where $W_{h^{n-1}h^n}$ is the weight allocated among the n layer and the $n-1$ layer. The weight $W_{h^n h^n}$ denotes the weight given to the recurrent of the n^{th} layer, and $b_{h_t}^n$ is the bias. Therefore, the temporal representation, and significance of the output, provided by the presented RNN could be expressed:

$$y_t = W_{h^n y} h_t^n + b_y \tag{5}$$

The earlier presented structure is created by utilizing simple recurrent units. This type of structure can undergo vanishing gradient problems, which indicates RNN could have difficulties while studying long-time dependency data. As a result, various recurrent units are presented to resolve this problem such as the gated recurrent unit or the LSTM. Specified the comparison among these dual structures, this research implements the LSTM as recurrent units:

$$f_t = \sigma\left(W_f h_{t-1}^n + w_f h_t^{n-1} + b_f\right) \tag{6}$$

$$i_t = \sigma\left(W_i h_{t-1}^n + w_j h_t^{n-1} + b_i\right) \tag{7}$$

$$C_t = f_t C_{t-1} + i_t \tanh\left(W_c h_{t-1}^n + w_c h_t^{n-1} + b_c\right) \tag{8}$$

$$o_t = \sigma\left(W_o h_{t-1}^n + w_o h_t^{n-1} + b_o\right) \tag{9}$$

$$h_t = o_t \tanh\left(C_t\right) \tag{10}$$

The forget states of the input and output gates are denoted by f_t, i_t, C_t, and o_t, correspondingly, In addition, the weights and biases allocated to these gates are b_f, w_f and W_j, b_c, w_c, and W_c and b_o, w_o, and W_o.

The basic concept of the spatiotemporal GCRNN is to combine various data representations provided by the recurrent and GCN layers. The RNN are intended to capture time-based data, whereas GCN denote spatial associations through graph forms. The integration of these dual structures can produce the GCRNN: integration of this dual architecture, RNN, and GCN, to make use of their potencies in temporal and spatial representation, correspondingly A GCRNN can be formed in various methods, it denotes the various probable forms that combine the GCN spatial representation with the RNN temporal representation. Specifically, the graph data have been initially served during the GCN layers that handle the inputs and give an initial output spatial consciousness with various sizes. In such an instance, the GCN creates a novel input for the next recurrent layers which are the outcomes of the GCN layer spatial feature extraction. After that, the novel input undergoes the LSTM layers that seize the data temporal features and offer a novel temporal representation. The final dense layer obtains the data spatio-temporal representation produce the concluding prediction. Figure 2 depicts the structure of GCRNN.

Hyperparameter tuning

At last, the TVP-HGCRNNLOA model performs the hyperparameter tuning by utilizing the LOA model. The LOA aids as a metaheuristic model where a group of produced solutions at random recognized as lions begins a preliminary population [18]. The N solutions establish the population and every solution covers features α and β that want to be enhanced. Its mathematical expression:

$$\text{Solution}(\text{Lion}) = [\alpha,\ \beta] \tag{11}$$

Some lions in the novel population, N, create the nomads and the residual is chosen as Prides, P, randomly. Between nomad lions, S% of those are female, and the remaining are male. The solutions are covered and select dissimilar combinations of contrast and brightness.

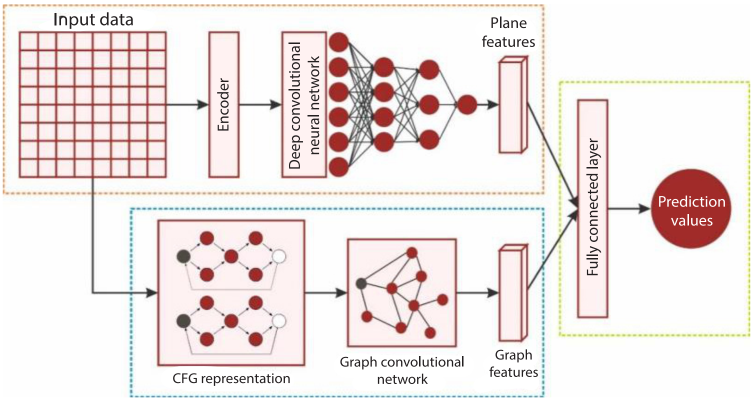

Figure 2. Structure of GCRNN

From every pride, some female lions search for the victim in clusters to help their pride. The predators typically have their specific exact heuristic for catching and encircling the victim. Generally, the lioness tracks a similar pattern for searching their victim. Throughout hunting, every lioness alters its location by utilizing its existing site and the places of its cluster members. Usually, predator's attacks their victims from opposed directions for precise targets and so Opposition-based learning was employed to solve optimization issues.

The finest solution in the preceding iteration is denoted as the finest-visited position and upgraded as the optimizer method grows. Territorial takeover is the procedure of holding the finest female and male solutions, which are proficient in surpassing novel solutions to an assumed quantity while eliminating present solutions from the pride. A predator will be refining his fitness constantly and simultaneously, PREY generally efforts to escape from the predator and acquire its novel location as expressed:

$$\text{PREY}' = \text{PREY} + \text{rand}(0,1) \times \text{PI} \times (\text{PREY} - \text{Hunter}) \tag{12}$$

where PREY is the prey's present position, Hunter – the novel location employed by the predator to violent the victim, and PI – the specifies percentage of predator's fitness development.

The prey surrounding by predator clusters for right and left wings are assumed:

$$\text{Hunter}' = \begin{cases} \text{rand}\big((2\times\text{PREY}-\text{Hunter}),\text{PREY}\big) \\ (2\times\text{PREY}-\text{Hunter}) < \text{PREY} \\ \text{rand}\big(\text{PREY},(2\times\text{PREY}-\text{Hunter})\big) \\ (2\times\text{PREY}-\text{Hunter}) > \text{PREY} \end{cases} \tag{13}$$

whereas Hunter states the hunter's present location and Hunter' specifies the novel location. The upgraded locations of center hunters are signified by utilizing:

$$\text{Hunter}' = \begin{cases} \text{rand}(\text{Hunter},\text{PREY}), \text{Hunter} < \text{PREY} \\ \text{rand}(\text{PREY},\text{Hunter}), \text{Hunter} > \text{PREY} \end{cases} \tag{14}$$

The lands of every pride cover the finest solution and aid in keeping the finest solution for technique. Over the iteration, it is employed to enhance the solution of LOA. The calculation of novel locations for female lions is denoted:

$$\text{Female Lion}' = \text{Female Lion} + 2\times \text{D}\times \text{rand}(0,1)\{\text{R1}\} + \text{U}(-1,1)\times \tan()\times \text{D}\times\{\text{R2}\}$$
$$\{\text{R1}\}\{\text{R2}\} = 0 \tag{15}$$
$$\|\{R2\}\| = 1$$

where female lion signifies the lion's present location, D is the means the location of the lion that recognized utilizing contest range in the pride's land. The $\{\text{R1}\}$ denotes the initial place and the preceding location is signified by $\{\text{R2}\}$. Both $\{\text{R1}\}$and $\{\text{R2}\}$ are vertical to one another. Also, the local male lion travels to a few nominated positions at random and if the recognized novel locations are superior to the preceding ones, then it directly upgrades its local finest solution.

Next, mating is completed to generate novel young's. In each pride, pre-defined $c\%$ of female lions traversed over with single or many local males at random. However, nomad lions will mate with only a single male at random. Once a set for mating is chosen, the dual offspring are produced using:

$$\text{Offspring}_j 1 = \beta\times \text{Female Lion}_j + \sum \frac{1-\beta}{\sum\limits_{i=1}^{NR} S_i}\times \text{MaleLion}_j^i \times S_i \tag{16}$$

$$\text{Offspring}_j 2 = (1-\beta)\times\ \text{Female Lion}_j + \sum \frac{\beta}{\sum\limits_{i=1}^{NR} S_i}\times \text{MaleLion}_j^i \times S_i \tag{17}$$

In this case, the LOA is employed to define the parameter tangled in the GCRNN method. The MSE is measured the main function and is expressed:

$$\text{MSE} = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \tag{18}$$

where M and L are the resulting value of layer and data, respectively, and y_j^i and d_j^i – the achieved and proper extents for j^{th} unit from the resulting layer of system in time, t, respectively.

Performance validation

The performance analysis of the TVP-HGCRNNLOA technique is examined utilizing its own real financial data.

Figure 3 offers a complete set of prediction outcomes of the TVP-HGCRNNLOA system under different epochs. The outcomes demonstrated that the TVP-HGCRNNLOA method has improved prediction results. The figure means the actual vs. prediction outcomes of the TVP-HGCRNNLOA technique under distinct epochs. The results showed that the TVP-HGCRNNLOA approach has exposed heightened predicted outcomes. Also, it is defined that the change between the predicted and actual values is dignified at the smallest.

Figure 4 distributes a complete set of cumulative outcomes of the TVP-HGCRNNLOA system. The figure illustrates the actual vs. prediction results of the TVP-HGCRNNLOA model under timesteps. It is also determined that the difference between the predicted and actual values is calculated at the lowest.

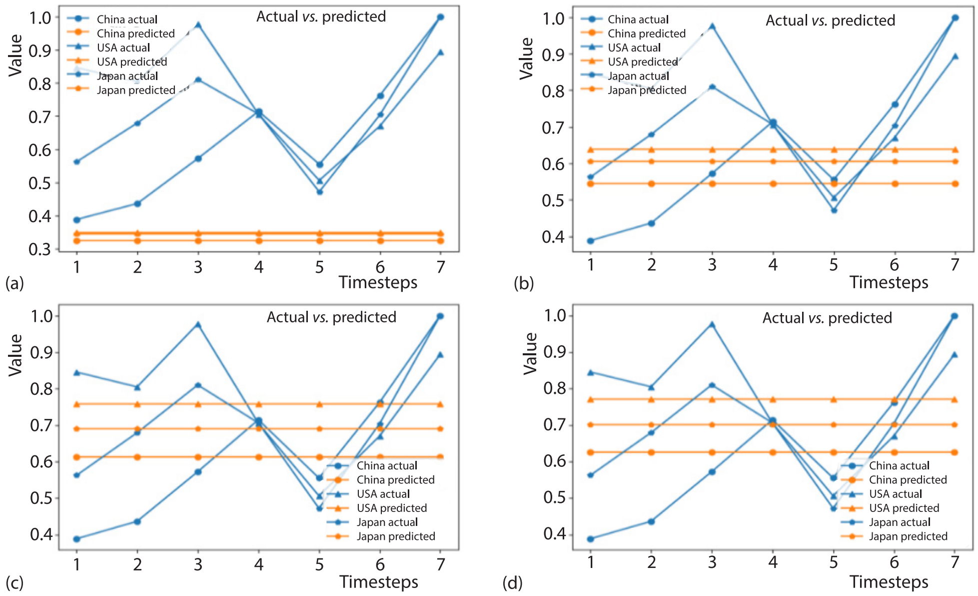

Figure 3. Actual *vs.* predicted values in number of epochs; (a) 50, (b) 100, (c) 150 and (d) 200

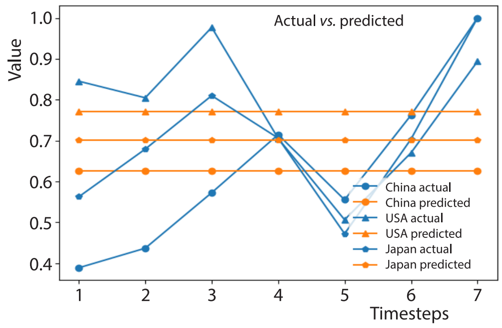

Figure 4. Cumulative results on applied dataset actual *vs.* predicted

Table 1. Classifier outcome of TVP-HGCRNNLOA technique under different metrics

Metrics	China	USA	Japan
MSE	0.0380	0.0212	0.0248
MAE	0.1643	0.1239	0.1150
MAPE	0.2623	0.1607	0.1641

Table 1 and fig. 5 display the classification results of the TVP-HGCRNNLOA approach under various metrics. The figure specifies that the TVP-HGCRNNLOA system precisely predicted the outcomes. It is also observed that the predicted values by the TVP-HGCRNNLOA approach are nearer to the actual values. Based on China, the TVP-HGCRNNLOA method reaches an MSE of 0.0380, MAE of 0.1643, and MAPE of 0.2623. Likewise, based on the U.S.A, the TVP-HGCRNNLOA process attained MSE of 0.0212, MAE of 0.1239, and MAPE of 0.1607. Finally, based on JAPAN, the TVP-HGCRNNLOA model achieved an MSE of 0.0248, MAE of 0.1150, and MAPE of 0.1641.

Table 2 and fig. 6 establish the MSE result of the TVP-HGCRNNLOA system with recent approaches. The results pointed out that the TVP-HGCRNNLOA model attains improved results with the lowermost values of MSE. While, RF, GB, CNN, and LSTM techniques got the highest values of MSE. Based on China, the USA, and JAPAN, the TVP-HGCRNNLOA process obtained MSE values of 0.038, 0.021, and 0.025, respectively.

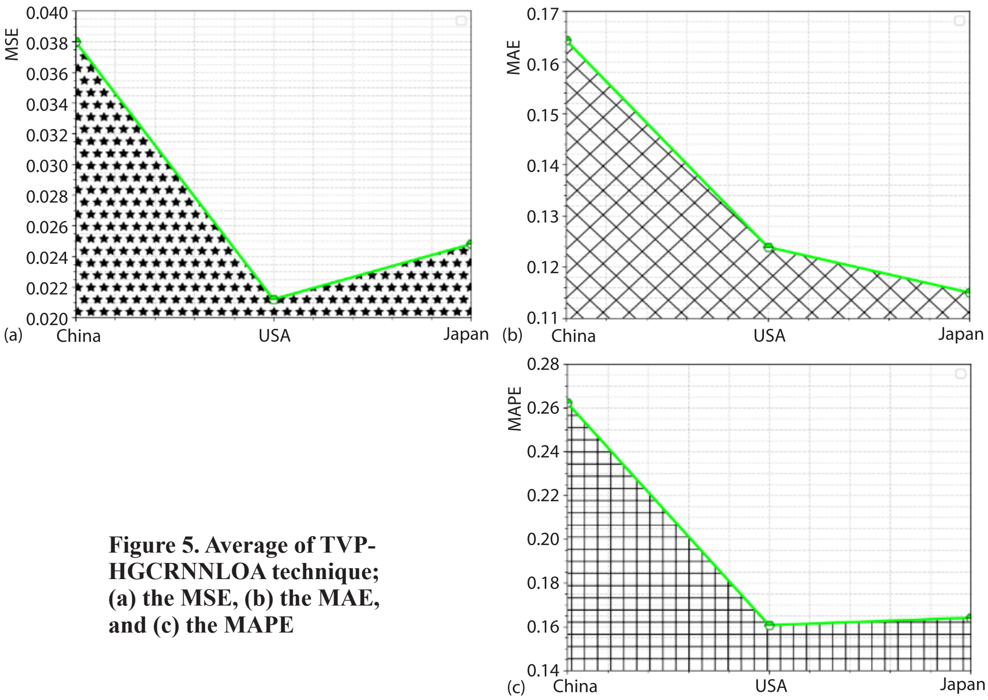

Figure 5. Average of TVP-HGCRNNLOA technique; (a) the MSE, (b) the MAE, and (c) the MAPE

Table 2. The MSE outcome of TVP-HGCRNNLOA technique with recent models

MSE			
Methods	China	USA	Japan
TVP-HGCRNNLOA	0.038	0.021	0.025
Random forest	0.190	0.176	0.199
Gradient boosted	0.365	0.350	0.357
CNN classifier	0.518	0.510	0.536
LSTM model	0.674	0.675	0.697

Conclusion

In this research, we have proposed a new TVP-HGCRNNLOA methodology. The objective function of the TVP-HGCRNNLOA methodology is to develop an accurate predictive model for trade values between countries. Primarily, the TVP-HGCRNNLOA approach undergoes data normalization by employing the LSN technique. Then, the HGCRNN method is used for the forecasting process. At last, the TVP-HGCRNNLOA model performs the hyperparameter tuning by utilizing the LOA model. The experimental analysis of the TVP-HGCRNNLOA methodology is investigated in terms of various measures under MSE, MAE,

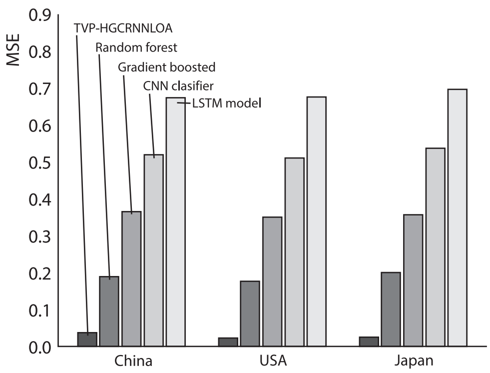

Figure 6. The MSE outcome of TVP-HGCRNNLOA technique with recent models

and MAPE. The performance validation portrayed the superior performance of the TVP-HG-CRNNLOA methodology over other existing approaches.

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