ATTENTION RECURRENT NEURAL NETWORK WITH EARTHWORM OPTIMIZATION ON GROSS DOMESTIC PRODUCT PREDICTION USING MAIN ECONOMIC ACTIVITIES

by

Hanan T. HALAWANI[a*], Halima Younis A. MOHAMED[b], Sarah A. ALZAKARI[c], Khalil A. ALRUWAITEE[d,e], Thikraa M. ALHARETHI[f], Rahntalla Y. YAGOUB[g], and Alnour OSMAN[h]

[a] College of Computer Science and Information Systems, Najran University, Najran, Saudi Arabia
[b] Department of Mathematics, Turabah University College, Taif University, Taif, Saudi Arabia
[c] Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia
[d] Department of Economics and Finance, Taif University, Taif, Saudi Arabia
[e] Applied College, Taif University, Taif, Saudi Arabia
[f] E-Learning Manager,Deanship of Digital Transformation and Knowledge Resources, Najran University, Najran, Saudi Arabia
[g] Department of Statistics, College of Science, Tabuk University, Tabuk, Saudi Arabia
[h] Business Education Building, Mississippi Valley State University, USA

Original scientific paper
https://doi.org/10.2298/TSCI2406087H

Gross domestic product (GDP) is a vital metric for evaluating the financial strength and development of a nation. It extends the complete value of services and goods produced within an exact time, presenting critical perceptions into the complete financial performance and health. This study focuses on enhancing GDP prediction by examining key economic activities such as non-oil, oil, and government sectors. Understanding these modules is important for accurately predicting economic trials, which impact tax revenue, living standards, and economic stability. By incorporating these foremost financial activities, the research emphasizes improving the exactness of GDP prediction and provides actionable perceptions for strategic economic policy and planning growth. Besides, the study inspects how variations in these areas affect GDP, giving a more complete view of trade trends and helping shareholders make informed decisions to raise steady growth. This study proposes GDP prediction by utilizing an attention recurrent neural network with earthworm optimization algorithm (GDPP-ARNNEOA). The main objective of the GDPP-ARNNEOA technique is to improve GDP prediction accuracy by analyzing key economic activities to inform economic planning and policy-making. To accomplish that, the GDPP-ARNNEOA approach performs normalization by utilizing a min-max scaler. Then, the ARNN approach is employed for prediction process. Subsequently, the GDPP-ARNNEOA model accomplishes the hyperparameter tuning by implementing the EOA model. The performance validation of the GDPP-ARNNEOA technique is examined in terms of various measures namely Mean squared error, mean absolute error, and mean absolute percentage error. The experimental results revealed the superior performance of the GDPP-ARNNEOA technique over other recent models.

Key words: *ARNN, GDP, EOA, economic activities, deep learning*

[*] Corresponding author, e-mail: hthalawani@nu.edu.sa

Introduction

One of the major conclusions of current economics is that finance is good for improvement. The concept that an economy requires mediation match lenders and borrowers, controlling resources to their well-organized applications, is important to our intelligence [1]. The innovative work has been capable of pointing in proof to support the opinion that financial development is beneficial for progression [2]. The finance area generally plays a vital role in the economic improvement process and plays an important part across the country thus, banks as financial mediators have an abundant impact on transferring payments into financial properties [3]. They transmit funds from entities with additional liquidity to those requiring it thus enabling capital trade and formation. The GDP is the standard price of all services and products that the region entity made within the country's national limits during the year [4]. The GDP can be a gauge to evaluate the complete economic performance of a country, which contains all services and products prepared by the economy along with individual consumption, government purchases, non-public records, paid-in building values, and then the foreign trade break. The GDP subject has become of great position between the pointers of economic variables [5].

The GDP Information has been believed to be a critical sign for estimating the national economic growth and development of a complete macro-economy [6]. The GDP mostly lies on the final services and goods that were made inside the city or country at a particular time. The GDP can be openly available on a quarterly and annual basis, but the divisional GDP for the various areas has been calculated only once a year, and no official amount can be provided for cities or provinces [7]. Besides, provincial estimations for every quarter might be computed only after different months at the end of the quarter, after the essential economic information has been issued [8]. The developments in machine learning (ML) algorithms, and more precisely in deep learning (DL), have carried with them the best tool by which to solve several difficulties in various fields, including economics. Primarily, this technique can be dealing with and learning from sequential or unstructured information, such as time series or text strings [9]. To start with, ML techniques are found to increase estimating accuracy compared with standard statistical methods. The two features are mainly exciting regarding increasing the outcomes achieved with conventional models. Various works have applied ML and knowledge-based economy indicators to predict macroeconomic levels, like the unemployment rate or the GDP [10]. This study proposes GDP prediction by utilizing attention recurrent neural network with earthworm optimization algorithm (GDPP-ARNNEOA). The main objective of the GDPP-ARNNEOA model is to improve GDP prediction accuracy by analyzing key economic activities to inform economic planning and policy-making. To accomplish that, the GDPP-ARNNEOA approach performs normalization by utilizing min-max scaler. Then, the ARNN approach is employed for prediction process. Subsequently, the GDPP-ARNNEOA model accomplishes the hyperparameter tuning by implementing the EOA method. The performance validation of the GDPP-ARNNEOA technique is examined in terms of various measures namely mean squared error, mean absolute error, and mean absolute percentage error.

Literature review

Gangwar *et al.* [11] introduce a distributed sailfish optimized hybrid improved ANN (DSO-HIANN) method to handle problems in economic development. The study accumulated economic data. The logistics information is accumulated and pre-processed by utilizing z-score normalizing technique. The technique utilized principal component analysis methodology for feature extraction. Administrations, economic organizations, stockholders, and a politician needs a precise economic development anticipation. Yang *et al*. [12] present an ensemble learning (EL) model to enhance anticipation accomplishment by fusing the structural associations between trade and DL methods. This technique initially presents an association between exporting and importing and their operational parameters. The incorporated techniques are later employed for anticipating the trade future, which is implemented as a standard technique for comparison. A fusion DL model utilizes the incorporated parameters as input to anticipate trade information, and later are associated with time-series anticipation and financial operational methods. Sun *et al*. [13] employ ANN and Shapley additive explanations for evaluation. Initially, the impact of the digital economy and several features on energy yield shows a *U*-shaped form. Specifically, digital inclusive finance is gradually growing as the main aspect. Then, the lagging result of digital structure and economics stands as a significant driver without showing a growing trend. As a promising persuader, digital economy efficiently disturbs growth activity, crucially taking part in the growth of energy efficiency. Third, the effect clarifies as a gradual strengthening, also considered by a non-equilibrium dispersal form spatially.

Wang *et al*. [14], a DL method is presented to anticipate the GDP growth rate. The methodology examines various DL methodologies, LSTM, BD-LSTM, ED-LSTM, and CNN, and relates their outcomes with the conventional time series technique (ARIMA, VAR). The technique proposes a recursive DL methodology for anticipating the GDP growth rate in the subsequent few years. Shi [15], the Lasso back propagation neural networking technique is implemented for conducting financial evaluation and anticipation for key global economies, concentrating on overall GDP, integrated GDP growth rate, and consumer price index (CPI). This classification, together with the consumption of neural network various hidden layer variable evaluation, eases the evaluation and anticipation of national financial drifts. Furthermore, implementing a single time series method efficiently anticipates GDP and CPI growth rates, together with other macroeconomic factors. Song *et al*. [16] integrate low frequency macro-financial variables dependent on a fusion method combining the DL technique with generalized autoregressive conditional heteroskedasticity and mixed data sampling (GARCH-MIDAS) methodology. The macroeconomic variables are initially taken as exogenous then the presented method to handle various frequencies amid the macro-economic variables and volatility of stock market and lastly the anticipated short-term volatility as the input factor into ML and DL methods to anticipate the realized volatility.

Proposed methodology

This study presents a novel GDPP-ARNNEOA technique. The major aim of the GDPP-ARNNEOA technique is to improve GDP prediction accuracy by analyzing key economic activities to inform economic planning and policy-making. The GDPP-ARNNEOA approach performs min-max scaler-based normalization, ARNN-based prediction, and EOA-based hyperparameter tuning process are demonstrated in fig. 1.

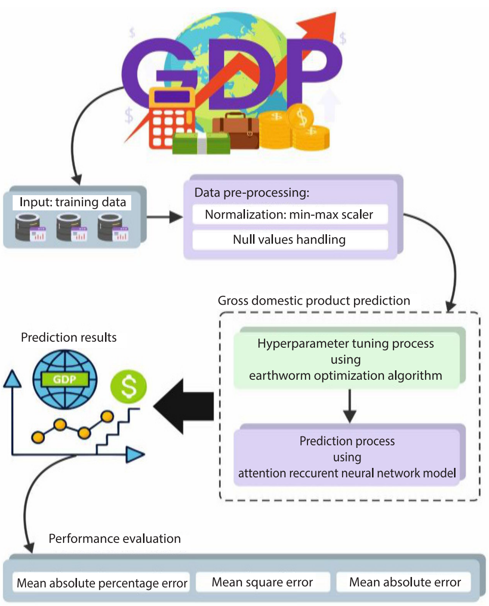

Figure 1. Overall process of GDPP-ARNNEOA model

Pre-Processing

The GDPP-ARNNEOA model performs normalization by utilizing min-max scaler method. This technique is employed to rescale data to a fixed interval, normally between 0 and 1. When used to GDP data, it aids in normalizing the values, making them similar across dissimilar timeframes and countries. By subtracting the least GDP value and dividing by the interval (maximum minus minimum), every value of GDP is changed to fit in the preferred scale. This method protects the proportions and relationships among the original values. It's mainly beneficial in ML and data analysis to certify that features correspondingly to the method.

The ARNN-based prediction

The ARNN technique is implemented for the prediction process of the GDPP-ARNNEOA model [17]. An recurent neural network (RNN) is a variation on a traditional neural network, expanding to challenge data sequences. However, various neural network behaviors are retained namely connections and neurons, an RNN can be able to repeat a particular operation for sequential inputs over the usage of the recurrent connection.

These efficiently allow RNN to retain processed values memories, which are utilized next to upcoming inputs. An assumed sequence of input $I = i_1, i_2, i_3,..., i_T$, for every stage t the networks repeat the operation is defined:

$$\begin{bmatrix} \hat{o}_t \\ h_t \end{bmatrix} = \phi_W \left(i_t,\ h_{t-1} \right) \tag{1}$$

where $\hat{o}$ and h_t are the signif hidden layer (HL) and output at time, t, correspondingly. Additionally, ϕ_W is the neural network considered in a weighted network, W. Assumed networks consider the t^{th} input i_t along with the preceding HL h_{t-1}within input. The RNN structure can be fairly flexible and remains, then appropriate for addressing several composite problems. The attention mechanism's introduction in RNN architectures aids the networks in maintaining memory. These increase memory retention over lengthier sequences and improve performance. Whereas there exist various dissimilar techniques of applying attention, in that study, a Luong attention mechanism has been applied.

On every time phase, t, the Luong attention mechanism is responsible for encoded weights, w_t, with encoded source sequences:

$$\sum_s w_t(s) = 1 \ \text{ and } \ \forall s w_t(s) \geq 0 \tag{2}$$

The value of outputs forecast in assumed timestep denotes a function of the RNN hidden state, h_t, and the weights of the encoded HL is based:

$$\sum_s w_t(s) = \hat{h}_s \tag{3}$$

The main variances among attention methods are in the manner that w_t values are defined. The Luong attention method uses the softmax function calculate sequence scores previously a complete sequence as defined:

$$w_t\left(s\right) \leftarrow \frac{\exp\left[\beta_t \text{score}\left(h_t, \hat{h}_\text{s}\right)\right]}{\sum_\text{s}\left[\beta_t \text{score}\left(h_t, \hat{h}_{s'}\right)\right]} \tag{4}$$

where β characterizes a scaling-controlled parameter of the attention methods. Score values for every sequence have been established utilizing the dot product of every RNN hidden state h_t

and an encoder HL $\hat{h}$ transferred by matrix W_α as exposed:

$$\text{score}\left(h_t, \hat{h}_s\right) \leftarrow h_t^T W_\alpha \hat{h}_s \tag{5}$$

where T means the maximum iteration counts. Figure 2 illustrates the infrastructure of ARNN.

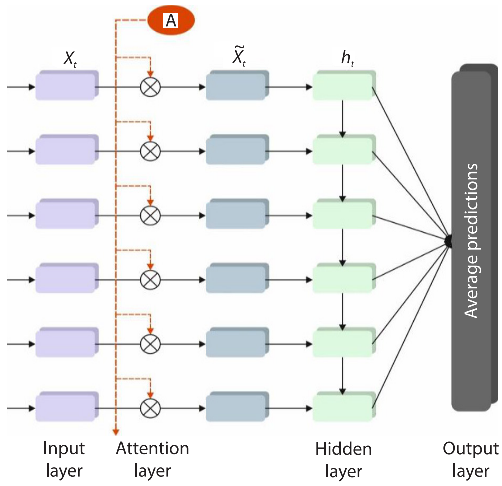

Figure 2. The ARNN structure

Earthworm optimization algorithm-based Hyperparameter Tuning

Finally, the GDPP-ARNNEOA approach performs hyperparameter tuning process by utilizing earthworm optimization (EWO) model [18]. The EWO algorithm has been applied, which is simulated in the EW reproductive process to resolve optimized problems. The EW is a hermaphrodite type and performs at all of them utilizing male and female sexual organs. Hence, the single-parent EW breeds a child EW on their own. The Reproduction 1 can be defined:

$$u_{i1,k} = u_{\max,k} + u_{\min,k} - \alpha u_{i,k} \tag{6}$$

The aforementioned equations explain the generating procedure k^{th} element of the child's EW$i1$ in parent EW $iu_{i1,k}$ and $u_{i,k}$ denotes the k^{th} element of EW $i1$ and $iu_{\max,k}$ and $u_{\min,k}$ signifies the operational limitation of k^{th} element of all EW. The α means the similarity feature that relies on between 1 and 0, and that decides the movements in parents to child EW.

The Reproduction 2 uses a better crossover operator type. Let, M exist as the number of child EW, and it's 2, or 3 in most possessions. This count of parent EW (N) means any number that can be greater than 1. The uniform crossover is used by $N = 2$ and $M = 1$. During 2 parent EW P_1 and P_2 were selected to use the roulette wheel picked. That is explained:

$$P = \begin{bmatrix} \rho_1 \\ \rho_2 \end{bmatrix} \tag{7}$$

Mainly, two offspring U_{12} and U_{22} are produced in two parents. rand arbitrary integer ranges from 0 to 1 has been done and K^{th} element of U_{12} and U_{22} are made:

If rand > 0.5:

$$u_{12,k} = P_{1,k} \quad u_{22,k} = P_{2,k} \tag{8}$$

then

$$u_{12,k} = P_{2,k} \quad u_{22,k} = P_{1,k} \tag{9}$$

Finally, the produced EW U_{i2} in Reproduction 2 are represented as eq. (10). Estimate which rand 1 is another arbitrary number produced between 0 and 1:

$$u_{i2} = \begin{cases} u_{12} & \text{forrand } 1 < 0.5 \\ u_{22} & \text{else} \end{cases} \tag{10}$$

then the producing EW U_{i1} and U_{i2}, the EW U_i for the group measures:

$$u_i' = \beta u_{i1} + !(1-\beta) u_{i2} \tag{11}$$

where β can be named as a *proportional factor*. That has been utilized to operate the proportion of U_{i1} and U_{i2} that local and global searching efficacy was recalled from balancing. It can be presented:

$$\beta^{t+1} = \gamma\beta^{t} \tag{12}$$

where t involves the present generation. Mainly at $t = 0$, $\beta = 1$. The γ denotes the parameters that are the result of the cooling factor. This solution requires a run-away in a local optimum. Hence, the *Cauchy Mutation* (CM) can be performed. This increased the searching ability of EWO. The operator of CM can be described:

$$W_k = \frac{\left(\sum_{i=1}^{N_{\text{pop}}} u_{i,k}\right)}{N_{\text{pop}}} \tag{13}$$

where W_k is the signifies the weighted vector for K_{th} element of population i and N_{pop} infers the dimension of the population. The K^{th} element for last EW growths:

$$u_i'' = u_i' + W_k^* Cd \tag{14}$$

Now, Cd denotes the arbitrary amount that is depicted in the *Cauchy distribution* regarding = 1. Nowadays, r represents the *scale parameter*.

In this paper, the EOA has been deployed for determining the parameter contianed in the ARNN technique. The MSE is assumed that the main function and is determined:

$$\text{MSE} = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \tag{15}$$

where M and L are the signifies the outcome rate of layer and data correspondingly and y_j^i and d_j^i – the achieved and suitable magnitudes for j^{th} unit from the outcome layer of network in time, t, correspondingly.

Result analysis and discussion

This section examines the performance analysis of the GDPP-ARNNEOA technique using own KSA Finance dataset. Figure 3 distributes a complete set of prediction outcomes of GDPP-ARNNEOA technique under distinct epochs. The figure means the actual vs. prediction outcomes of the GDPP-ARNNEOA method under distinct epochs. It is also well-known that the variance between the predicted and actual values is measured at the least.

Figure 4 allocates an entire collection of cumulative results of GDPP-ARNNEOA methods. This figure signifies the actual vs. prediction results of the GDPP-ARNNEOA model under diverse timesteps. It is also well-known that the difference between the actual and predicted values can be calculated at a minimum.

Table 1 and fig. 5 show the classifier outcomes of the GDPP-ARNNEOA approach under different metrics. The figure specifies that the GDPP-ARNNEOA method accurately predicted the outcomes. It is also observed that the predicted values by the GDPP-ARNNEOA technique are nearer to the actual values. Based on oil activities, the GDPP-ARNNEOA method achieved MSE of 0.047, MAE of 0.197, and MAPE of 0.284. Likewise, based on Non-Oil Activities, the GDPP-ARNNEOA method achieved MSE of 0.018, MAE of 0.098, and MAPE of 0.136. Finally, based on Government Activities, the GDPP-ARNNEOA method achieved MSE of 0.031, MAE of 0.152, and MAPE of 0.197.

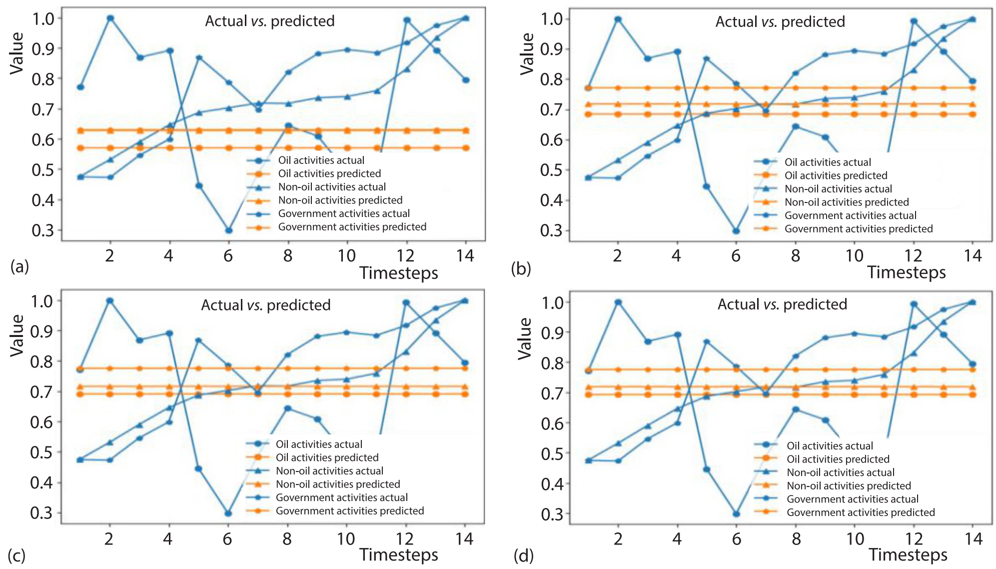

Figure 3. Result analysis of different number of epochs; (a) 50, (b), 100, (c) 150, and (d) 200

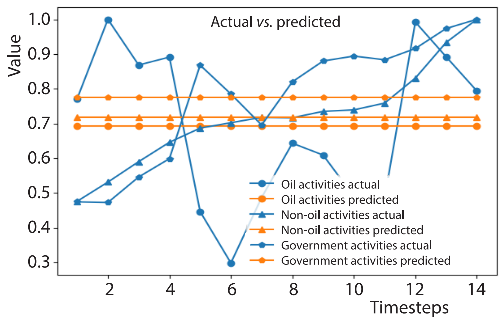

Figure 4. Cumulative results on applied dataset actual *vs.* predicted

Table 1. Classifier outcome of GDPP-ARNNEOA technique under different metrics

Metrics	Oil activities	Non-oil activities	Government activities
MSE	0.047	0.018	0.031
MAE	0.197	0.098	0.152
MAPE	0.284	0.136	0.197

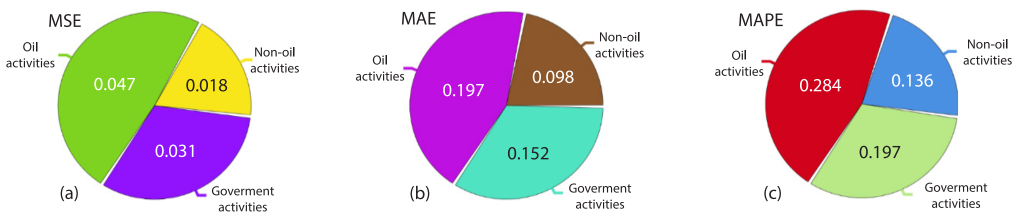

Figure 5. Average of GDPP-ARNNEOA technique; (a) MSE, (b) MAE, and (c) MAPE

Table 2 and fig. 6 establish the MSE outcome of GDPP-ARNNEOA technique with recent approaches. The results pointed out that the GDPP-ARNNEOA technique obtains better performance with the lowermost values of MSE. Whereas, logistic regression, decision tree, deep belief network (DBN), and neural network based learning for prediction (NLP) methods got highest values of MSE. Based on oil activities, non-oil activities, and government activities, the GDPP-ARNNEOA method achieved MSE values of 0.047, 0.018 and 0.031, respectively.

Table 2. The MSE outcome of GDPP-ARNNEOA technique with existing models

MSE			
Metrics	Oil activities	Non-oil activities	Government activities
GDPP-ARNNEOA	0.047	0.018	0.031
Logistic regression	0.211	0.193	0.201
Decision tree	0.392	0.372	0.383
DBN algorithm	0.551	0.551	0.545
NLP classifier	0.712	0.708	0.702

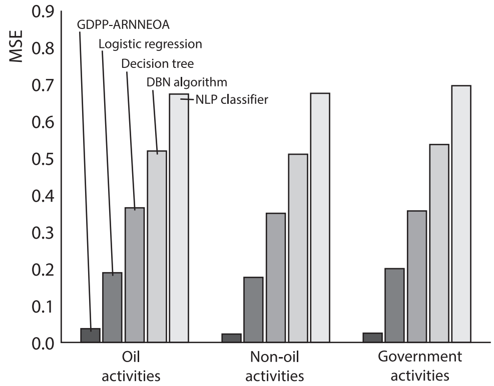

Figure 6. The MSE outcome of GDPP-ARNNEOA technique with existing models

Conclusion

This study presents a novel GDPP-ARNNEOA technique. The main objective of the GDPP-ARNNEOA technique is to improve GDP prediction accuracy by analyzing key economic activities to inform economic planning and policy-making. To accomplish that, the GDPP-ARNNEOA approach performs normalization by utilizing min-max scaler. Then, the ARNN approach is employed for prediction process. Subsequently, the GDPP-ARNNEOA model accomplishes the hyperparameter tuning by implementing the EOA method. The performance validation of the GDPP-ARNNEOA technique is examined in terms of various measures namely mean squared error, mean absolute error, and mean absolute percentage error. The experimental results revealed the superior performance of the GDPP-ARNNEOA technique over other recent models.

Acknowledgment

The authors are thankful to the Deanship of Graduate Studies and Scientific Research at Najran University for funding this work under the Easy Fuding Program grant code (NU/EFP/2024/12/14).

Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2024R716), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia

References

[1] Naeem, M., *et al.*, A Novel Approach for Reconstruction of IMF of Decomposition and Ensemble Model for Forecasting of Crude-oil Prices, *IEEE Access*, *12* (2024), Feb., pp. 34192-34207

[2] Daori, H.K., et al., Stock Price Predictions in the Saudi Market Using LSTM + SVM and Weighting Twitter Sentiments, Sc. M. thesis, Tabuk University, Tabuk, KSA, 2023
[3] Chen, L., *et al*., Geopolitical Risk and Crude-Oil Price Predictability: Novel Decomposition Ensemble Approach Based Ternary Interval Number Series, *Resources Policy*, *92* (2024), 104966
[4] Ali, Khan, M., Prediction of Complex Stock Market Data Using an Improved Hybrid EMD-LSTM Model, *Applied Sciences*, *13* (2023), 1429
[5] Kute, D.V., *et al*., Explainable Deep Learning Model for Predicting Money Laundering Transactions, *International Journal on Smart Sensing and Intelligent Systems*, *17* (2024), 1
[6] Zhao, G., *et al*., A New Hybrid Model for Multi-Step WTI Futures Price Forecasting Based on Self-Attention Mechanism And Spatial-Temporal Graph Neural Network, *Resources Policy*, *85* (2023), 103956
[7] Ionascu, A. E., *et al*., Analyzing Primary Sector Selection for Economic Activity in Romania: An Interval-Valued Fuzzy Multi-Criteria Approach, *Mathematics*, *12* (2024), 8, 1157
[8] Zhao, Y., *et al.*, Early Warning of Exchange Rate Risk Based on Structural Shocks in International Oil Prices Using the LSTM Neural Network Model, *Energy Economics*, *126* (2023), 106921
[9] Patel, M., *et al.*, Deep Learning Techniques for Stock Market Forecasting: Recent Trends and Challenges, *Proceedings*, 6th International Conf., on Software Engineering and Information Management, Palmerston North, New Zealend, 2023, pp. 1-11
[10] Maccarrone, G., *et al.*, The GDP Forecasting: Machine Learning, Linear or Autoregression, *Frontiers in Artificial Intelligence*, *4* (2021), 757864
[11] Gangwar, J., *et al*., Deep Learning Models for tthe Forecasting and Regulation of Global Financial Growth, *Multidisciplinary Science Journal*, *6* (2023), e2024ss0409
[12] Yang, C. H., *et al*., Export-and Import-Based Economic Models for Predicting Global Trade Using Deep Learning, *Expert Systems with Applications*, *218* (2023), 119590
[13] Sun, C., *et al*., Deep Learning: Spatiotemporal Impact of Digital Economy on Energy Productivity, *Renewable and Sustainable Energy Reviews*, *199* (2024), 114501
[14] Wang, T., *et al*., Recursive Deep Learning Framework for Forecasting the Decadal World Economic Outlook, *IEEE Access*, *12* (2024), Oct., pp. 152921-152944
[15] Shi, J., Establishment of Economic Analysis Model Based on Artificial Intelligence Technology, *International Journal of Advanced Computer Science and Applications*, *15* (2024), 5
[16] Song, Y., *et al.*, Volatility forecasting for Stock Market Incorporating Macroeconomic Variables Based on GARCH-MIDAS and Deep Learning Models, *Journal of Forecasting*, *42* (2023), 1, pp. 51-59
[17] Predić, B., *et al*., Cloud-Load Forecasting Via Decomposition-Aided Attention Recurrent Neural Network Tuned by Modified Particle Swarm Optimization, *Complex and Intelligent Systems*, *10* (2023), Nov., pp. 2249-2269
[18] Rajalakshmi, J., *et al*., Artificial Intelligence with Earthworm Optimization Assisted Waste Management System for Smart Cities, *Glob. NEST J*., *25* (2023), 4, pp. 190-197

Paper submitted: June 21, 2024
Paper revised: October 10, 2024
Paper accepted: October 29, 2024