International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V70I2P2235

Volume 70 Issue 2, 294-304, February, 2022

Original Article

An Efficient Multi-Objective Optimization-Based Framework for Stock Market Prediction

Jyothi R[1], Dr Krishnamurthy G. N.[2]

[1]Assistant Professor: Principal, Department of Computer Science and Engineering, BNMInstitute of Technology, PES University, 100 feet Ring Road, BSK 3rd Stage, Bangalore, BSK 2nd Stage, Bangalore,

[1]jyothir@pes.edu. [2] bnmitprinciple@gmail.com

Abstract — *Stock prediction is an important parameter for all business applications to improve business deals. To analyze the reason for the available stocks, the stocks should be estimated in the primary section. Several statistical and neural models were implemented to meet these issues, but the data's complexity can still reduce the prediction outcomes. So, Long Short term memory (LSTM) has been introduced. However, the LSTM model has observed the worst results in some cases by consuming more time and less prediction accuracy. The current work has focused on designing a novel Artificial Bee and Buffalo-based Recurrent LSTM (AB-BRL) for the stock prediction framework to enhance the stock forecasting exactness score up to the desired level. In addition, to analyze the stability of the designed model, different error statistics were measured and compared with other models. Besides, the planned design is executed in the python environment. Finally, the novel AB-BRL has gained a good outcome by reducing the error percentage and maximizing the forecasting accuracy.*

Keywords — *Stock Prediction, Mean Square Error, Big Data, Hybrid Optimization, Stock Prediction Accuracy***.**

I. INTRODUCTION

Nowadays, many people are ready to invest money in the stock market to gain a profit in a short duration [1]. The stock market consists of many corporate shares, and their prices fluctuate on a minute-by-minute basis, based on the firm's surroundings and country's economic boundary condition [2]. Numerous brokers in the stock market handle the selling and buying of the stocks between companies and clients [3]. It was difficult to forecast the stock market in the past years due to a lack of advanced technologies [4]. Still, the technology has become advanced that can help forecast the stock market more readily than in the previous years [5]. The predictive stock system is illustrated in fig.1.

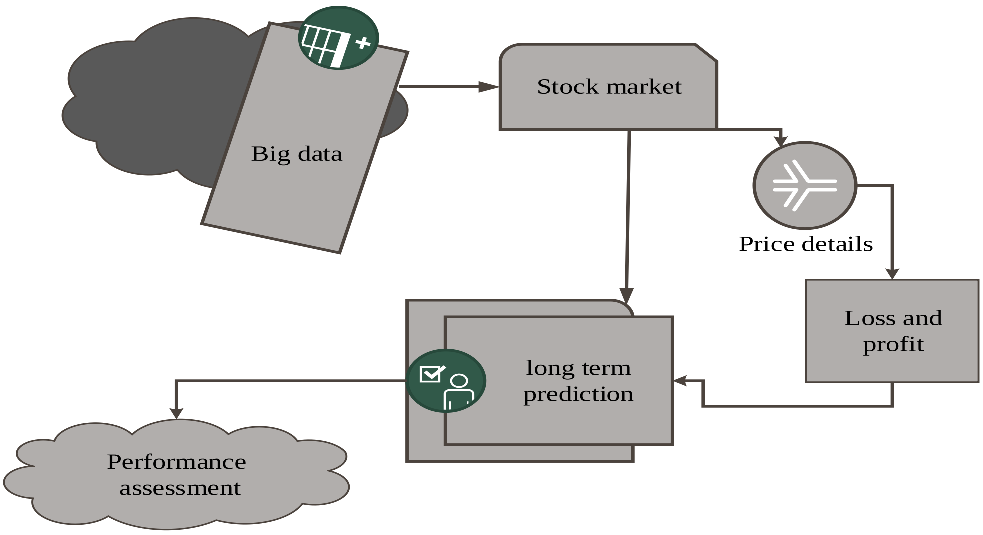


Fig.1 Stock market prediction system

In addition, the neural approaches and optimization models are effectively applied in stock-market prediction systems to forecast stock prices by evaluating historical data [6]. Moreover, Machine Learning (ML) is a trending and efficient technique because it combines statistics functions for their prediction function [7]. In general, ML has a high capacity for finding patterns and prediction info from the trained database [8]. Moreover, In the ML domain, prediction problems such as boosting and bagging are effective and usual calculations amongst prediction methods [9]. Besides, statistical techniques such as exponential smoothing [13], state-space analysis [10], filtering models [11], and regression methods [12] are frequently utilized for stock market prediction. Furthermore, the prediction results differ based on the trained datasets; the collected raw datasets are structured [14] or unstructured [15]. In the case of the structured dataset, the best outcome has been earned in a short duration by all numerical and intelligent models [16]. However, the unstructured stock data has created challenges during the pre-processing and feature extraction steps [17]. For this reason, it has taken more time than the structure data for execution [18].

To forecast the stock market, powerful and dependable technologies are required. Numerous models, like LSTM [23], the fully connected long short-term model [21], and others, have been used before forecasting individual product stock details. Still, the challenges have been remained due to the complexity and unstructured nature of the data. Thus, the current effort aimed to optimize the deep neural model in order to obtain the best prediction outcomes. In addition, to tune the recurrent LSTM parameters, hybrid optimization was used that is artificial been and African buffalo procedures. In the past, numerous optimization models such as ant colony [26], particle swarm [27], firefly [28], genetic [29], grey wolf algorithm [30], etc., have been executed in the LSTM to improve the prediction parameter. Still, this solution is not suitable for all datasets; if the dataset parameters differed, the forecasting rate became very low. So, the present research has shown interest in the multi-objective models to tune the dense layer parameters to gain the expected results.

The current article contents are aligned as follows; section.2 has demonstrated the recent related cellular communication research works with merits and demerits. Then RFC channel and its problem are explained in section.3. the novelty of the work is elaborated in section.4. The outcome of the designed approach is discussed in section.5, and the research arguments are concluded in section.6

II. RELATED WORKS

A few recent works related to stock prediction system is described below,

The stock prediction systems can be used in a variety of ways, including data methods, text analytics, and human interest. Xiaodong Li et al. [21] developed a framework for stock discovery based on analytical tools and news sentiment. As a result, a completely integrated LSTM with all characteristics was developed to examine the market's stock items. At last, the results are compared to that of other established models. However, it took a longer duration to implement.

Weiwei Jiang [22] conducted a study to ascertain the neural approach's performance. As a result, the primary goal of this investigation is to assist subsequent researchers in developing fresh optimum approaches to forecast the stock prediction for all applications. In addition, this study was based on 30 years of stocks prediction techniques.

Xiongwen Pang et al. [23] established an LSTM strategy to improve the stock market system's prediction ratio. This scheme has improved online business applications. Moreover, the reason for developing this novel neural model is that existing neural systems have consistently forecasted the influencers incorrectly. So, the LSTM method was implemented. It achieved the best prediction outcome, but if the data is large, it requires additional time to execute.

Although Convolutional neural networks have been used to forecast stocks previously, their accuracy has been limited due to their inability to use the previous layer's output to the following layer. So, Krishna Kumar and Md. TanwirUddinHaider [24] were developed the Recurrent Neural scheme to assess the stock of each commodity. As of last, the highest accuracy is achieved; but it is complex in design.

Rasha Abdel Kawy et al. [25] developed a multi-stock predictive model using a deep network model. Furthermore, this approach can be used in conjunction with public goods to evaluate the profitability of any product in both positive and negative scenarios. Finally, the suggested model's consecutive rate was evaluated against various datasets. Although the created technique is capable of analyzing large amounts of market data, it has needed more resources to accomplish. The summary of the discussed literature is described in table.1.

Table.1 Summary of literature review

Authors	methods	merits	Demerits
Xiaodong Li et al. [21]	analytical tools with LSTM	Here, the sentiment of the customer review is predicted with maximum accuracy	But, it has taken more time to execute
Weiwei Jiang [22]	Estimation of optimization performance	Several optimization methods were surveyed to estimate the function of the optimum parameter in predicting the stock scores	30 years of literature were reviewed but, only optimum parameters were considered

Xiongwen Pang et al. [23]	LSTM strategy	Achieve a better prediction score than other conventional models	If the size of the dataset is too vast, then it has required more duration to complete one run
Krishna Kumar and Md. TanwirUddinHaider [24]	Recurrent Neural scheme	Best forecasting accuracy was recorded	While designing this method, a high range of complexity was reported
Rasha Abdel Kawy et al. [25]	a multi-stock predictive model using a deep network	This model is sufficient to validate the large quantity of data	More resources were needed to gain the highest forecasting value.

Key steps of the proposed model are described as follows,

- Initially, the bank stock data is collected from the social site and imported into the python system
- Consequently, a novel AB-BRL has been designed with required layers with desired statistical evaluation metrics
- Initially, after the data training preprocessing function has been performed by activating the primary layer of AB-BRL, hereafter, the error-free data is imported in the following process.
- Here, incorporation of the hybrid optimization fitness in the recurrent model has helped to gain the best results
- Finally, the robustness of the intended model has been evaluated in terms of Root-Mean-Square-Percentage-Error (RMSPE), Root-Mean-Square-error (RMSE), Mean-Absolute-Error (MAE), Mean-Square-error (MSE), and accuracy.

III. SYSTEM MODEL AND PROBLEM STATEMENT

The stock market is usual in all business items including online business, so predicting the stock and validating the reason of stock is very important to improve the market business [19] For that several research works were already made, few kinds of literature are mentioned in the present related work section. Several problems were discussed in the previous section, like more resources, high execution time, and design complexity. Hence, the key reason for gaining such problems is because of the vast data [20]. So, to deal with big data for different purposes and applications, the optimizing parameter is more important to earn the desired results.

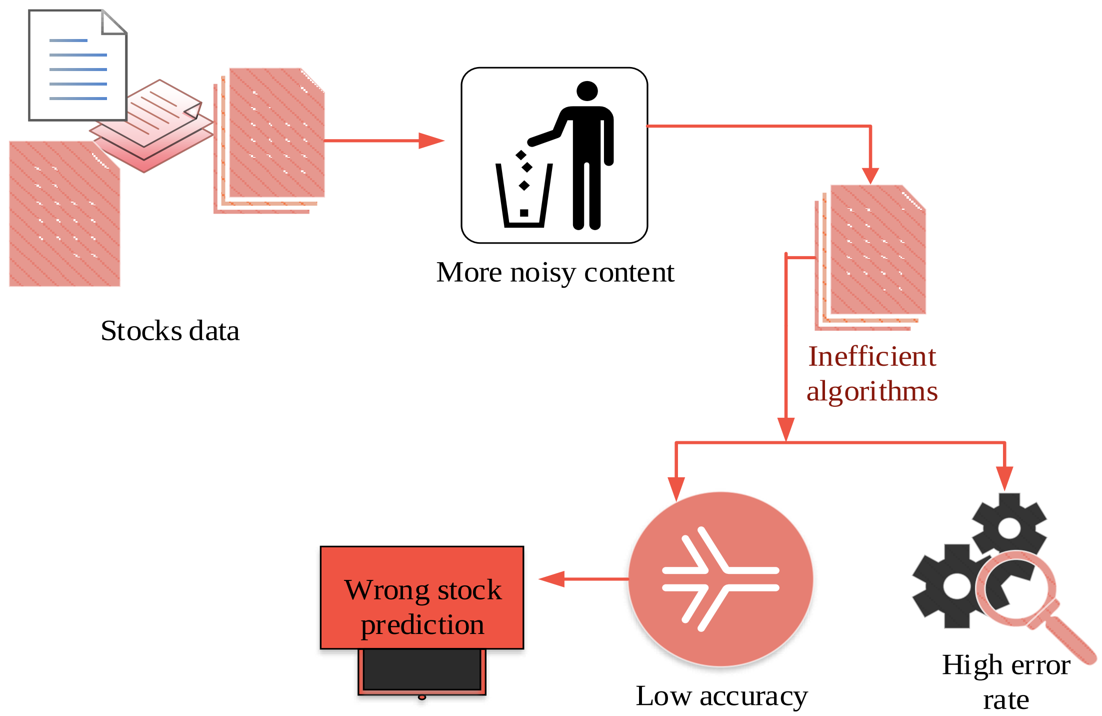


Fig.2 System model with problem

The usual process of stock prediction system and common difficulties are described in fig.2. This system architecture has clearly defined that the less prediction score has been attained because of the inefficient models.

IV. PROPOSED AB-BRL METHOD FOR STOCK FORECASTING SYSTEM

The current research work has aimed to design a novel Artificial Bee and Buffalo-based Recurrent LSTM (AB-BRL) for stock prediction systems to gain the finest prediction results. Hence, the planned model contains a few layers: input, pre-processing, feature extraction, prediction, and output. In this input layer, the collected datasets are trained to the system. Hereafter, the training errors are removed in the pre-processing layer then the error-free data is imported from the feature extraction layer for the feature selection process.

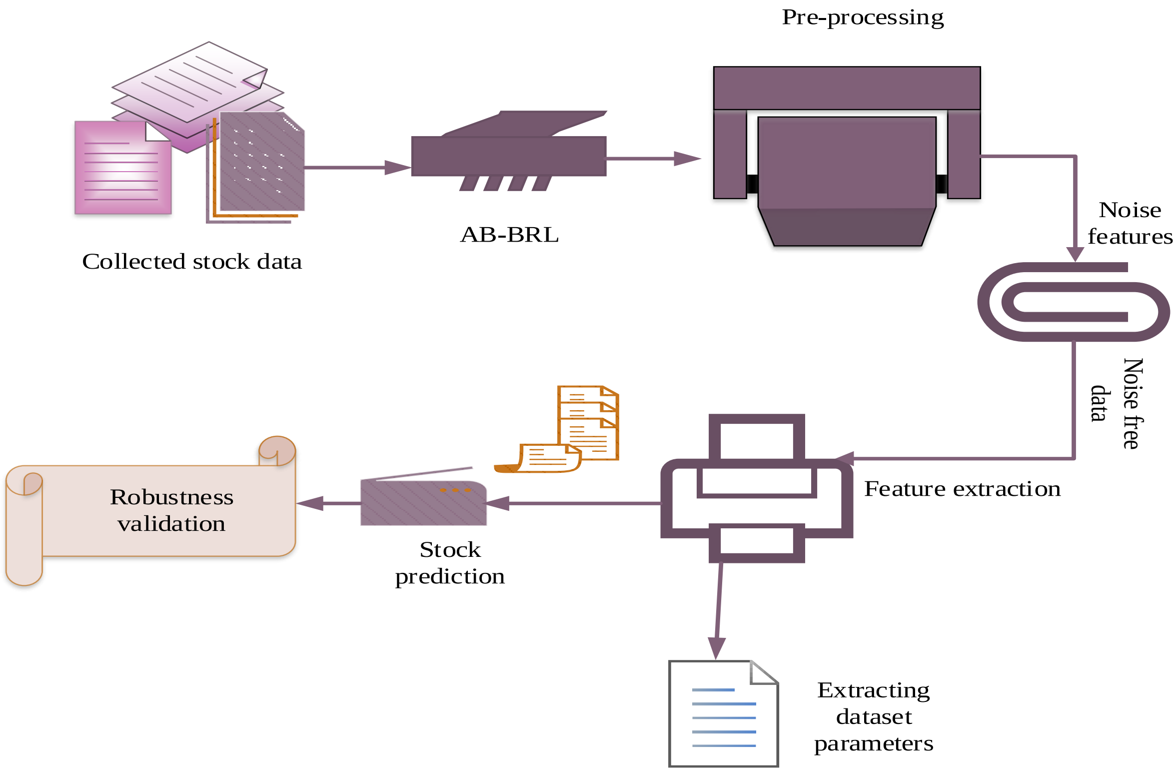


Fig.3 Proposed AB-BRL architecture

Then the prediction of stocks was calculated in the prediction layer. Finally, the prediction output for the long-term model was obtained and compared with other models to validate the robustness of the designed model.

A. Design of AB-BRL

In this present work, the AB-BRL is designed by incorporating the three models that are recurrent neural scheme [32], African buffalo [33], and artificial bee [34] procedure. In addition, a hybrid algorithm is created by combining the performance of artificial bees and African buffalo. Consequently, the designed hybrid optimization is utilized in the recurrent classification layer to tune the prediction parameter.

The desired stock data were primarily collected from the Kaggle site and trained to the system using Eqn. (1)

$$f(R) = D \ \ (1,2....n)\forall nD \tag{1}$$

After the training process, the trained information or database is stored in the recurrent memory called LSTM, using Eqn. (2).

$$\begin{pmatrix} q \\ r \\ s \end{pmatrix} = L_{t^*}^{t^*-1} \begin{pmatrix} D_{p1} \\ D_{p2} \\ D_{p3} \end{pmatrix} (i,j) \tag{2}$$

Where, $p_1, p2, p3$ are the dataset parameters p and the present stock features in the trained data is denoted as i, j.

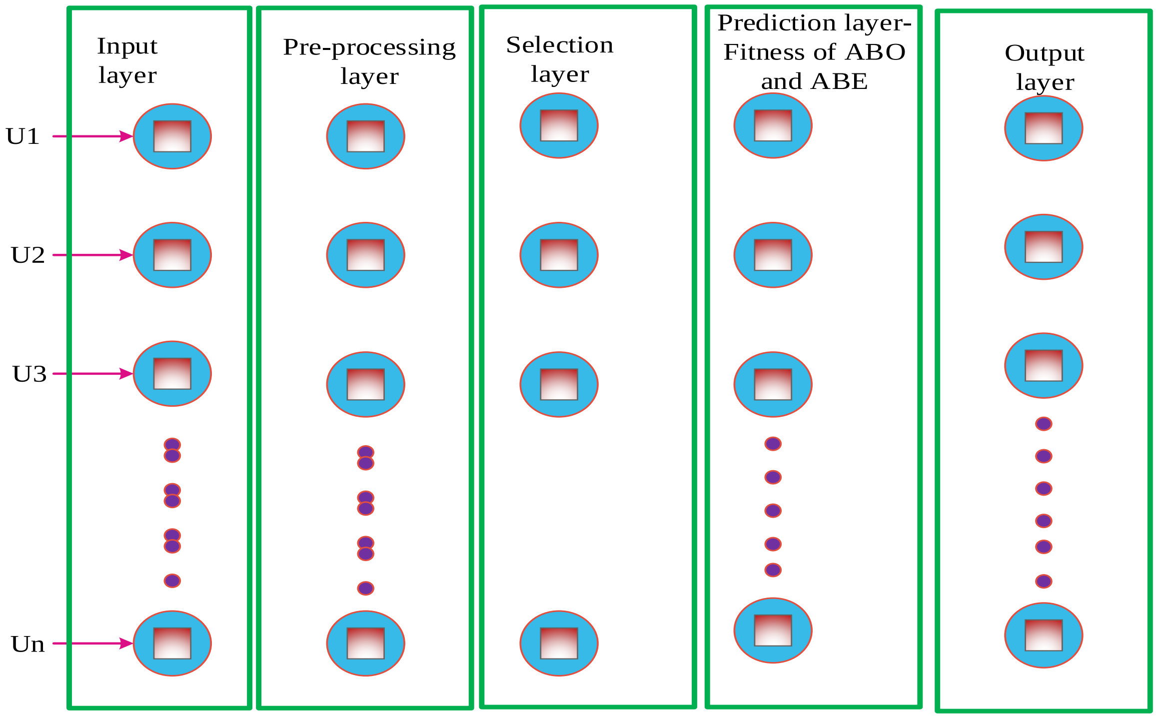


Fig.3 proposed AB-BRL layers

In this input layer, the collected datasets are trained to the system. Hereafter, the training errors are removed in the pre-processing layer then the error-free data is imported from the feature extraction layer for the feature selection process. Then the prediction of stocks was calculated in the prediction layer. Finally, the prediction output for the long-term model was obtained. The proposed AB-BRL layers are detailed in fig.3.

a) Pre-processing

In ML, pre-processing is the fundamental step to gain the finest evaluation accuracy. Moreover, training flaws were removed in the pre-processing steps, and the input data became refined. The noise removal is performed using Eqn. (3)

$$fl = r(D - r_{ij}) = D^{*} \qquad (3)$$

Here r is the noise tracking parameter, r_{ij} is the noise features, and D^{*} is the cleaned data; for further process, the error cleared data is used.

b) Feature extraction and stock prediction

Initially, the prediction parameters were initialized and formulated in the classification module of AB-BRL. Hence, the dataset parameter setting is processed by Eqn. (4).

$$p = \frac{h_p}{\sum_{m=1}^{D^*} h_n} \qquad (4)$$

The prediction function was initiated using Eqn. (4), here, p is the dataset parameter, feature tracing parameter is denoted as h and D^* is the total dataset. Before predicting the stocks, the features of stocks should be analysed using Eqn. (5)

$$S_{i,j} = D^{*}_{ij} + \alpha_{i,j}(D^{*}_{i,j} - D^{*}_{n,j}) \qquad (5)$$

Where, $S_{i,j}$ is the feature analyzing parameter $D^{*}_{i,j}$ represents the present features in the dataset, n denotes the n number of features and α is the feature tracking parameter. In this present research, the stock prediction is made for the long-term data, so the maximum objective function is adopted from the hybrid optimization.

$$D^{*i}_{j} = bk(D^{*j}_{\max}) + rand(0,1)(p^{i}_{g\max} - p^{i}_{g\min})ck \qquad (6)$$

Here, bk is the profit estimating parameter and loss prediction parameter is denoted as ck. The maximum profit of the year is denoted as $D^{*j}_{\max}$ and the minimum stock price is denoted as $p^{i}{g\,min}$ and $p^{i}{g\,max}$ represents the long year data. The loss and profit analysing parameters are detailed in eqn. (6).

$$bk + 1 = \frac{bk(D^{*j}_{\max} - ck(p^{i}_{g\min})}{total \quad product} \qquad (7)$$

Finally, using Eqn. (7), the details of stocks were obtained. Moreover, this Eqn. (7) is obtained by the hybridization process. Here the fitness of artificial bee and African buffalo has been considered.

Algorithm:1 AB-BRL

start

{

int $D = 1,2,3...n;$

// dataset initialization and training

$LSTM = q, r, s(D)$

// storing the trained dataset on the LSTM layer

Training flaw removal()

{

$fl = v(D) = D^{*}$

// Here fl *is the pre-processing parameter and* D^{*} *is the error removed data,* v *is the error tracking parameter*

$fl \rightarrow D - v(ij)$

// Here $v(ij)$ *is the error features*

}

Feature extraction ()

{

int $h, p;$

// initializing feature extraction variables

$p \rightarrow h_{ij}(D^{*})$

// here, the present features were extracted

}

Stock prediction()

{

$Stocks \rightarrow bk, ck$

// loss and profit calculating module, hereafter the stock is predicted using eqn. ()

}

}

stop

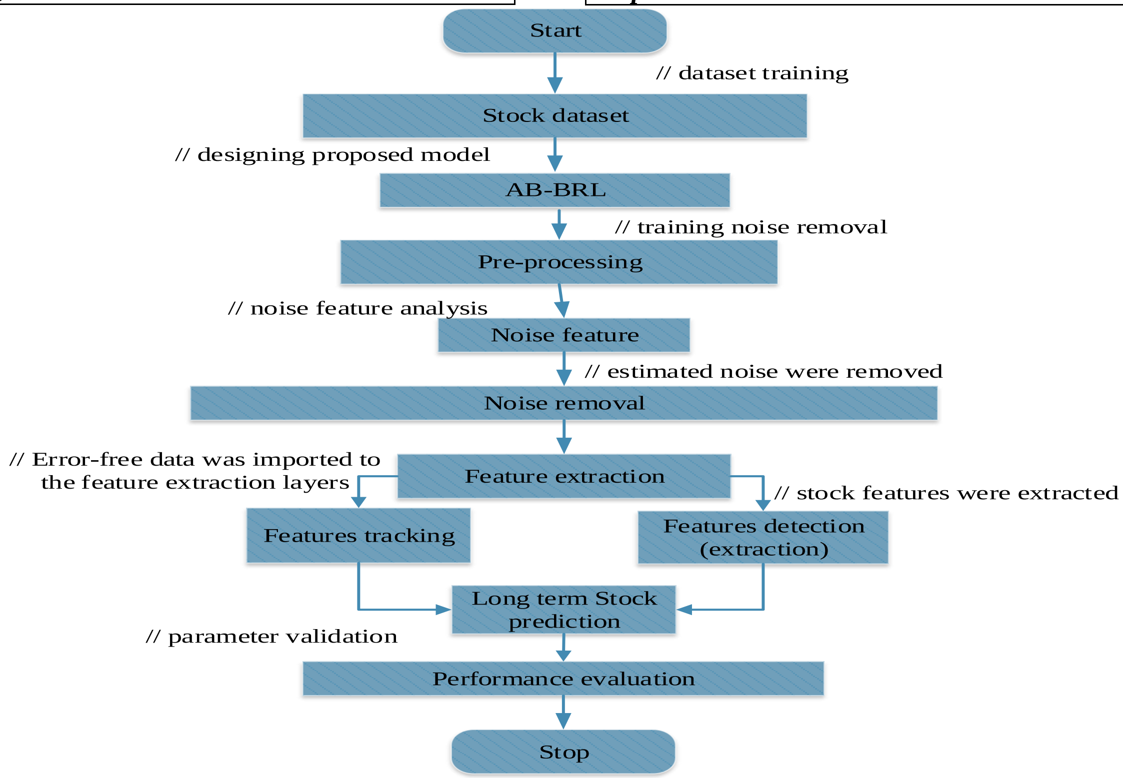


Fig.4 AB-BRL flow model

The steps given in fig. 4 are used to execute the model in the python environment. By validating this flow model, algorithm.1 has been designed, and then the python code has been developed for the specific algorithm.

V. RESULTS AND DISCUSSIONS

The planned model is executed in the Python platform running in the windows 10 platform. Here, the dataset known as bank stock estimation data has been taken to estimate the scalability of the designed AB-BRL model. The bank stock data is initially gathered from the Kaggle site; it includes various parameters like high, low, timestamp, loss, and profit. Then the gathered data is trained to the python system. Hereafter, the pre-processing function was performed to eliminate the present noise in the imported datasets. After the error elimination process, the refined data is entered into the classification layer. Here, the feature extraction and prediction have been performed.

A. Case study

To check the finest outcome of the designed model, long-term data is adopted from the year 2017 to 2021. Hence, the dataset parameters have been included profit, loss, timestamp, high and close. These parameters are updated in place of i, j Eqn. (5) to Eqn. (7).

Finally, by estimating the loss and profit of the trained stock dataset, the 4 years' stocks have been predicted successfully. Hence, the timestamp versus close price is detailed in fig. 5. p) and q)

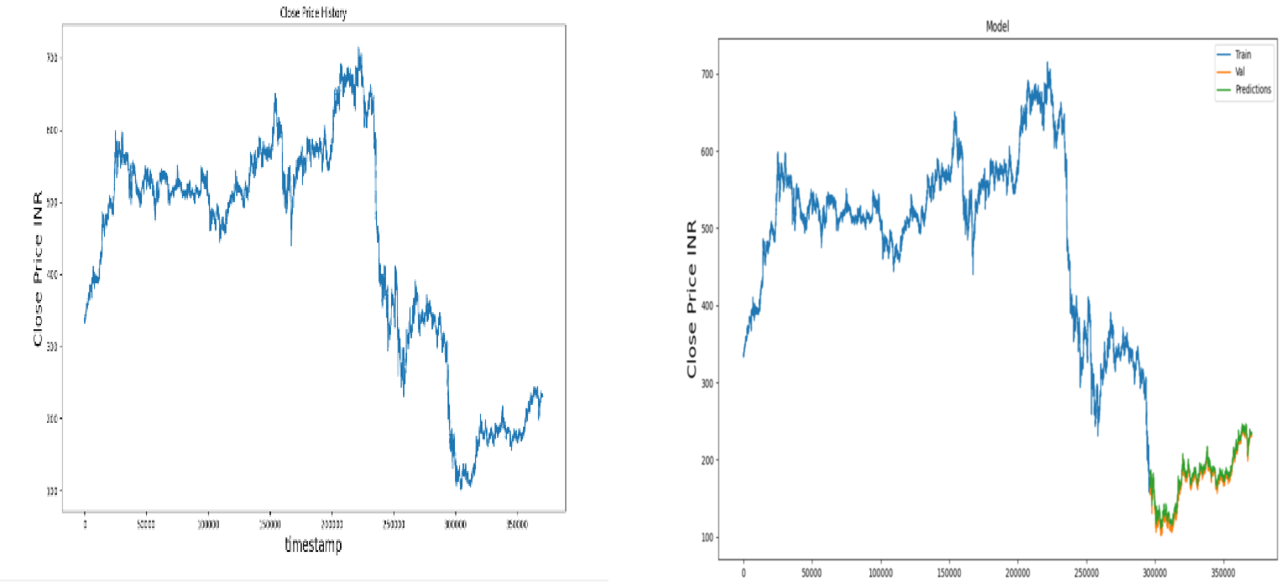
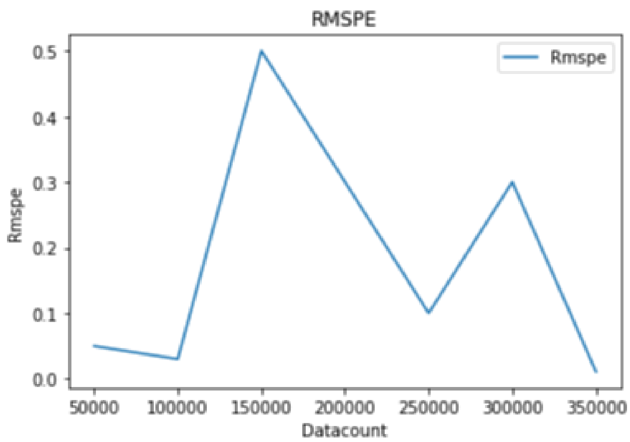
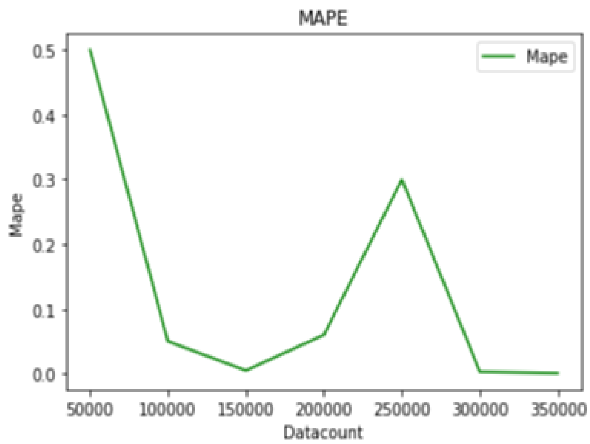


Fig.5 Prediction results: p) stock history, q) Stock validation

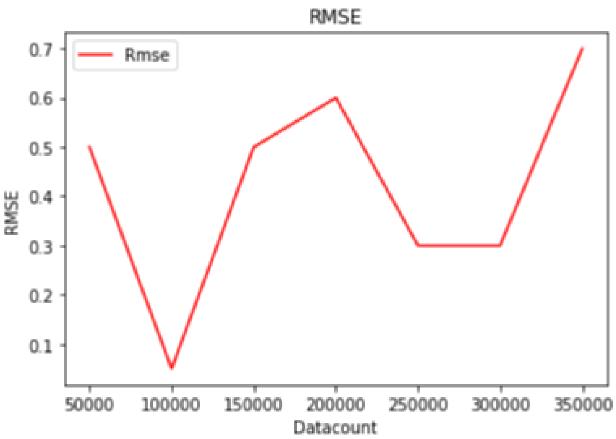
The utilized data contains the total file count as 350000, in that 80% is used for train the system and 20% data is worn to estimate the proposed model robustness. Here, the stock is predicted by measuring the difference between profit and loss then the attained outcome is divided by total files.



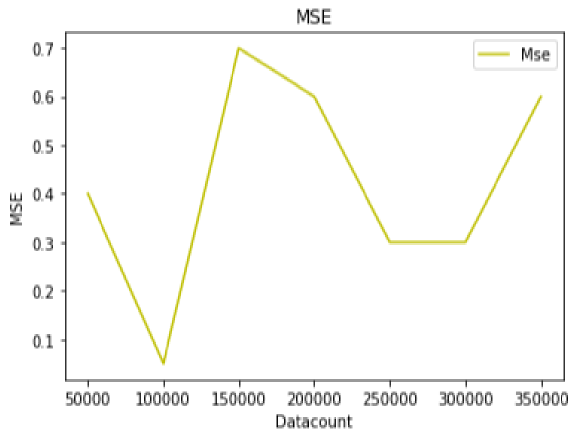
r)



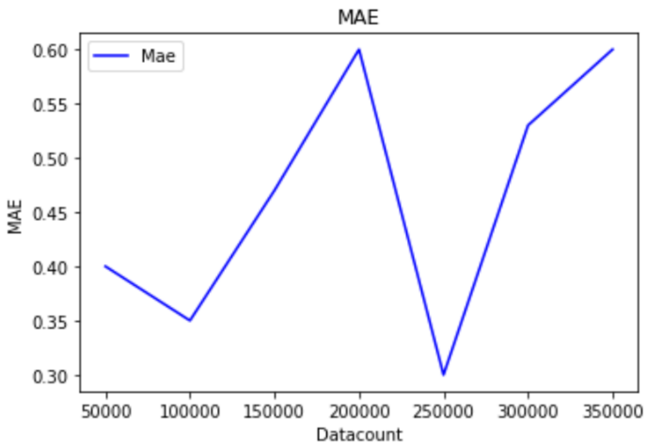
s)



t)



u)



v)

Fig. 6 Validation r) RMSPE, s)MAPE, t) RMSE, u) MSE, v) MAE

The statistics of the training and testing score is 80:20 is described as training 80% and testing 20%. This graph has illustrated the results of training samples, loss validation, and prediction scores. The parameter calculation for the long-term bank data is described in fig.6.

B. Comparison

To value the successful score of the designed model, a comparison assessment has been performed. Few recent old models were adopted: Bayesian and neural networks (NN) [31].

a) MAE and MAE

All statistical analyses obtained the error values between the true and false prediction range. In addition, in this calculation, the negative symbol

should be ignored. Hence, the MAE statistics are valued using eqn. (8)

$$MAE = t_v - p_s \tag{8}$$

Here, the true score is denoted as t_v and p_s represents the predicted score. Evaluating the estimated and actual scores' square root value is described as MSE. Moreover, it is formulated by eqn. (9)

$$MSE = \frac{1}{D}\sum_{m=1}^{n} a_s - p_s \tag{9}$$

Here, the dataset is denoted as D, m is the ranging value that is 1 to m value and the actual score is determined as a_s. Also, $\sum$ denote the different estimation

Table. 2 Assessment of statistical value

Statistical analysis					
Methods	**RMSPE**	**MAPE**	**RMSE**	**MSE**	**MAE**
Bayesian	0.0141	0.01108	0.89317	0.79775	0.70382
ML (neural network)	0.01407	0.01109	0.89153	0.79574	0.70438
proposed	0.011	0.001	0.732	0.694	0.653

The error statistics were calculated to measure the training and testing performance of the specific model. The model, which has gained very little error value, will gain the finest prediction results that are accurate. Hence, to value the successive score accurately, different statistics were calculated. Consequently, the estimated value is compared with other models to check the improvement score. Hence, the statistics were tabulated in table.2.

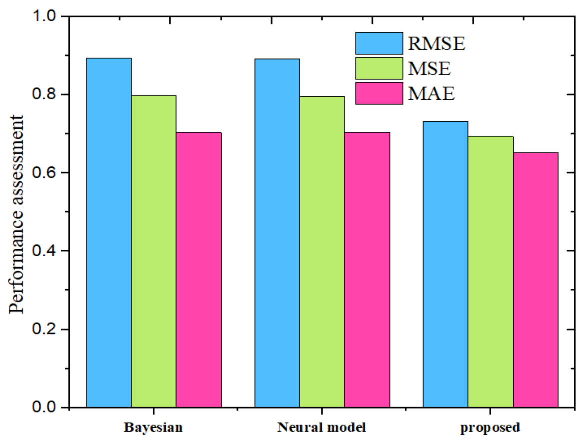


Fig.7 assessment of MAE, MSE and RMSE

RMSE is similar to the MSE; it is the standard deviation of observed and forecasted scores. Consequently, analyzing the average score of MSE and RMSE is termed as RMSPE. The approach NN has recorded the RMSE score as 0.8915, MSE value as 0.79574, MAE score as 0.70438. Also, the old Bayesian scheme has reported the RMSE score as 0.89317, MSE 0.79775, and MAE as 0,70382. Finally, the designed novel AB-BRL has recorded the statistics score as MAE 0.653, MSE 0.694, and RMSE value as 0.732. These values are displayed in fig.7.

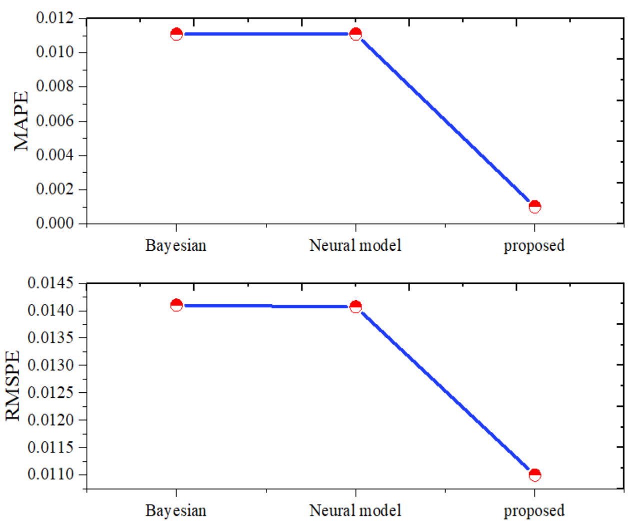


Fig.8 RMSPE and MAPE validation

The subject stock prediction is evaluated for a large number of stocks, so the average prediction results have been attained by estimating the average score of RMS and MAE. Here, the model Bayesian has earned the RMSPE value as 0.0141, a neural network has gained the RMSPE as 0.01407, and the designed AB-BRL has obtained the reduced RMSPE as 0.011. In addition, the technique Bayesian has gained the MAPE value as 0.01108, the neural network has obtained the MAPE is 0.01109, and the executed AB-BRL has obtained the MAPE as 0.001. This score was estimated in fig.8.

b) Validation of accuracy

To measure the stability of the designed model in predicting function, accuracy was calculated. Hence, the accuracy formula is defined by Eqn. (10). To check the prediction capability of the proposed AB-BRL model, some recent techniques were taken, such as Convolutional LSTM [24], LSTM [22], and recurrent optimized LSTM [25]. The stock forecasting rate is described in table.3.

Table.3 Estimation of prediction rate

Accuracy calculation	
Techniques	**Accuracy (%)**
LSTM [22]	82.5
Convolutional LSTM (C-LSTM) [24]	53.2
Recurrent Optimized-LSTM (RO-LSTM) [25]	86
proposed	98

$$Accuracy = \frac{tp^* + tn^*}{tn^* + tp^* + fp^* + fn^*} \tag{10}$$

Here, the conventional LSTM has earned 82.5% accuracy, C-LSTM has gained 53.2% accuracy, optimized recurrent has earned 86% accuracy, and the proposed AB-BRL has attained the highest prediction rate as 98%. This verified the robustness of the proposed model. Here, tp^* is truly positive, true negative is determined as tn^*, fp^* has represented false positive and fn^* denoted false negative.

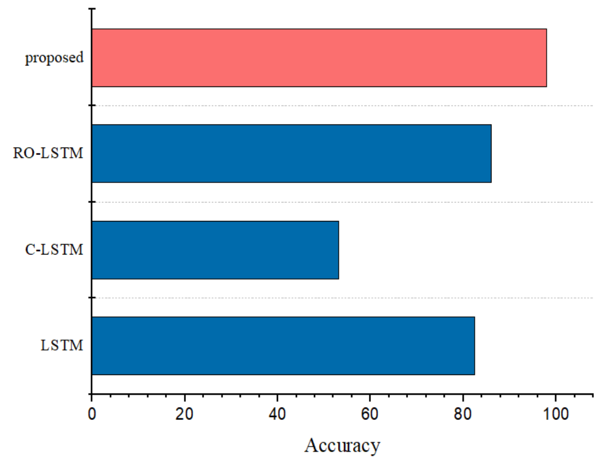


Fig.9 Accuracy comparison

The comparison validation of accuracy is graphically shown in fig. 9, in that proposed AB-BRL has reported the high prediction results. It shows the need for the proposed scheme for the stock prediction application.

C. Discussion

From all the validated results, the proposed model has earned the finest outcome; it has proved the effectiveness of the presented model in the stock prediction system. In this research, to estimate the stability score of the proposed system, different error values were calculated. Finally, the average error score was also measured and compared with other models. As shown in

Table.4 overall performance of AB-BRL

Performance of AB-BRL	
Parameters	**Attained score**
RMSPE	0.011
MAPE	0.001
RMSE	0.732
MSE	0.694
MAE	0.653
Accuracy	98

Hence, the designed scheme is suitable for the stock market application to predict the stocks for the long term data with less error rate. The novel AB-BRL isn't supported for all stock market data because of differing dataset parameters. So, another multi-objective optimization has to be incorporated in the LATM Recurrent model for the finest outcome and flexibility rate in the future.

VI. CONCLUSION

To improve the Stock prediction system, the present work has proposed a novel AB-BRL strategy based on a hybrid optimized intelligent model. The dataset that is used for this research is long-term bank stock data. In the initial stage, the data was pre-processed thoroughly then the clean data was imported to the following layers for the stock prediction process. Finally, the proposed AB-BRL has earned the finest stock prediction exactness measure as 98%, while compared to other models, it has improved the prediction score up to 10%. Simultaneously, it has obtained a less error statistics as 0.694 for MSE 0.653 for MAE. When estimated this results with other models, it has reduced the error statistics up to 0.5%. Hence, the presented model became successful in predicting the bank stocks. However, the designed model is not applicable for other datasets. So in the future, validating the other optimization model with recurrent LSTM might improve the automatic stock prediction system.

REFERENCES

[1] Haq, Anwar Ul, et al., Forecasting daily stock trend using multi-filter feature selection and deep learning, Expert Systems with Applications 168 (2021) 114444.

[2] Mondal, Saikat, A. Dutta, and P. Chatterjee. Application of Deep Learning Techniques for Precise Stock Market Prediction." National Conference on Machine Learning and Artificial Intelligence, (2020).

[3] Ye, Zhengxin Joseph, and Björn W. Schuller. Capturing dynamics of post-earnings-announcement drift using a genetic algorithm-optimized XGBoost. Expert Systems with Applications , 177 (2021) 114892.

[4] Samadi, Ali Hussein, SakineOwjimehr, and ZohoorNezhadHalafi., The cross-impact between financial markets, Covid-19 pandemic, and economic sanctions: The case of Iran., Journal of policy modelling 43(1) (2021): 34-55.

[5] Lin, Mei-Chen, and Yu-Ling Lin., Idiosyncratic skewness and cross-section of stock returns: Evidence from Taiwan, International Review of Financial Analysis (2021) 101816.

[6] Dai, Zhifeng, Huan Zhu, and Jie Kang. "New technical indicators and stock return predictability, International Review of Economics & Finance 71 (2021) 127-142.

[7] Dogan, Eyup, Mara Madaleno, and BuketAltinoz. "Revisiting the nexus of financialization and natural resource abundance in resource-rich countries: New empirical evidence from nine indices of financial development, Resources Policy 69 (2020): 101839.

[8] Mensi, Walid, et al., Oil, natural gas and BRICS stock markets: Evidence of systemic risks and co-movements in the time-frequency domain, Resources Policy ., 72 (2021) 102062.

[9] Liu, Hui, and Zhihao Long., An improved deep learning model for predicting stock market price time series., Digital Signal Processing 102 (2020) 102741.

[10] Thakkar, Ankit, and KinjalChaudhari. "Fusion in stock market prediction: a decade survey on the necessity, recent developments, and potential future directions., Information Fusion 65 (2021) 95-107.

[11] Moghar, Adil, and MhamedHamiche. "Stock market prediction using LSTM recurrent neural network., Procedia Computer Science 170 (2020) 1168-1173.

[12] de Pauli, Suellen Teixeira Zavadzki, Mariana Kleina, and Wagner Hugo Bonat.,Comparing artificial neural network architectures for Brazilian stock market prediction.., Annals of Data Science 7(4) (2020) 613-628.

[13] Kumar, Deepak, Pradeepta Kumar Sarangi, and RajitVerma., A systematic review of stock market prediction using machine learning and statistical techniques, Materials Today: Proceedings (2021).

[14] Saura, Jose Ramon., Using data sciences in digital marketing: Framework, methods, and performance metrics,. Journal of Innovation & Knowledge 6(2) (2021) 92-102.

[15] Ren, Qiubing, et al., A novel deep learning prediction model for concrete dam displacements using an interpretable mixed attention mechanism, Advanced Engineering Informatics 50 (2021) 101407.

[16] Salam, Roquia, and Abu Reza MdTowfiqul Islam. Potential of RT, Bagging and RS ensemble learning algorithms for reference evapotranspiration prediction using climatic data-limited humid region in Bangladesh., Journal of Hydrology ., 590 (2020): 125241.

[17] Seong, Byeongchan..,Smoothing and forecasting mixed-frequency time series with vector exponential smoothing models., Economic Modelling, 91 (2020) 463-468.

[18] Zareef, Muhammad, et al., An overview on the applications of typical non-linear algorithms coupled with NIR spectroscopy in food analysis., Food Engineering Reviews., (2020) 1-18.

[19] Alhnaity, Bashar, and MaysamAbbod.., A new hybrid financial time series prediction model., Engineering Applications of Artificial Intelligence., 95 (2020) 103873.

[20] Lee, Si Woon, and Ha Young Kim., Stock market forecasting with super-high dimensional time-series data using ConvLSTM, trend sampling, and specialized data augmentation, Expert Systems with Applications 161 (2020) 113704.

[21] Li, Xiaodong, Pangjing Wu, and WenpengWang, Incorporating stock prices and news sentiments for stock market prediction: A case of Hong Kong., Information Processing & Management ., 57(5) (2020) 102212.

[22] Jiang, Weiwei., Applications of deep learning in stock market prediction: recent progress., , Expert Systems with Applications., (2021) 115537.

[23] Pang, Xiongwen, et al. An innovative neural network approach for stock market prediction. The Journal of Supercomputing 76(3) (2020) 2098-2118.

[24] Kumar, Krishna, and MdTanwirUddinHaider. Enhanced Prediction of Intra-day Stock Market Using Metaheuristic Optimization on RNN–LSTM Network, New Generation Computing., 39(1) (2021) 231-272.
[25] AbdelKawy, Rasha, Walid M. Abdelmoez, and Amin Shoukry., Asynchronous deep reinforcement learning model for automated multi-stock trading., Progress in Artificial Intelligence ., 10(1) (2021) 83-97.
[26] Rokhsatyazdi, Ehsan, et al. Optimizing LSTM Based Network For Forecasting Stock Market." 2020 IEEE Congress on Evolutionary Computation (CEC). IEEE, (2020).
[27] Liu, Hui, and Zhihao Long., An improved deep learning model for predicting stock market price time series., Digital Signal Processing ., 102 (2020) 102741.
[28] Das, SmrutiRekha, Debahuti Mishra, and Minakhi Rout., Stock market prediction using Firefly algorithm with evolutionary framework optimized feature reduction for OSELM method, Expert Systems with Applications: X 4 (2019) 100016.
[29] Wu, Jimmy Ming-Tai, et al., A graph-based CNN-LSTM stock price prediction algorithm with leading indicators, Multimedia Systems., (2021) 1-20.
[30] Chandar, S. Kumar., Grey Wolf Optimization-Elman neural network model for stock price prediction." Soft Computing., 25(1) (2021) 649-658.
[31] Leng, Na, and Jiang-Cheng Li., Forecasting the crude oil prices based on Econophysics and Bayesian approach, Physica A: Statistical Mechanics and its Applications ., 554 (2020) 124663.
[32] Veerasamy, Veerapandiyan, et al. , LSTM recurrent neural network classifier for high impedance fault detection in solar PV integrated power system., IEEE Access., 9 (2021) 32672-32687.
[33] Khan, RahatUllah, Biplab Bhattacharyya, and Gajendra Singh., A novel African buffalo optimization for the minimization of cogging torque in modified permanent magnet DC motor., Sustainable Energy Technologies and Assessments ., 46 (2021) 101240.
[34] Parsajoo, Maryam, DanialJahedArmaghani, and Panagiotis G. Asteris., A precise neuro-fuzzy model enhanced by artificial bee colony techniques for assessment of rock brittleness index., Neural Computing and Applications., (2021) 1-19.