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A Business Intelligence Expert System for Predicting Market Price in Stock Trading using Data Analysis: Deep Learning Model With Feature Selection Mechanism

D. Syinthiya[1], Dr. K. Sujith[2]
[1]Research Scholar in Computer Science
PG & Research Department of Computer Science
Annai College of Arts and Science
(Affiliated to Bharathidasan University, Tiruchirappalli)
Kovilacheri, Kumbakonam, Thanjavur – 612503
Tamilnadu, India
syinthiyad86@gmail.com
[2]Associate Professor of MCA,
Research Advisor in PG & Research Department of Computer Science,
Annai College of Arts & Science
(Affiliated to Bharathidasan University, Tiruchirappalli),
Kovilacheri, Kumbakonam, Thanjavur - 612503
Tamilnadu, India.
mailme.sujith@gmail.com

Abstract: Because of the availability of data and reasonable processing capability, business intelligence methods are rapidly being used in finance, such as managing assets, trading using algorithms, credit financing, and blockchain-based financing. Machine learning (ML) algorithms use enormous amounts of data to automatically understand and enhance predictability and performance via knowledge and data without being programmed by someone. Due to the stock data's dynamic, high-noise, non-parametric, non-linear, and chaotic qualities, the stock market prediction has been a challenge and has received much interest from scholars over the last decade. Some studies seek a method for accurately predicting stock prices; however, due to the high correlation between stock prices, stock market analysis is more complex. So, this paper proposes an improved stock price prediction (SPP) model using a novel optimal parameter tuned with cross entropy included bidirectional long short-term memory (OPCBLSTM) with efficient feature extraction and selection schemes. It starts with missing values imputation, and data standardization on the collected dataset. From the preprocessed dataset, the features are extracted using modified rectifier linear unit activation based residual network (MRResNet50). Then the optimal features are selected using the improved whale optimization algorithm (IWOA). Finally, the SPP is done using the OPCBLSTM. The experimental results proved that the proposed method achieves more high-level outcomes than the traditional methods.

Keywords*:* Stock Prediction, National Stock Exchange, Nifty-50, Feature Selection, and Deep Learning.

1. INTRODUCTION

Global economies are becoming more digital and interconnected. Big data has become increasingly critical in developing a broad range of endeavors. Businesses have widely employed it to regularize essential business understandings and intelligence. The finance and banking sectors have newly used big data to follow financial market movements. Big data analytics and network analytics were utilized to detect illegal economic trading. Similarly, vendors, large banks, monetary organizations, and firms employed big data to develop trade analytics for high-frequency trading. A multinational corporation influences many firms. Furthermore, big data analytics aided in the discovery of criminal activities such as money laundering and financial fraud. Stock price movements in these companies may impact the financial situation of many stakeholders. As a result, forecasting the value of stocks is becoming increasingly important [1]. The stock market is an internet market where buyers and sellers discuss business and exchange opinions [2]. It allows businesses to benefit by allowing them to be traded openly, which increases their resources for growth by purchasing firm shares on the stock exchange. Stock market investment aims to generate income by buying and keeping various stocks, mutual funds, bonds, and other assets [3]. The stock exchange is a pool of buyers and sellers of assets separated into three exchanges: private, open, and mixed ownership. A private exchange sells private company shares, whereas an open exchange sells publicly traded firm shares in a public market for securities. Firms with mixed proprietorship stock have shares that can only be partly sold on the public exchange of stocks [4]. Stock market forecasting has been a research topic over the past decades, even though its activity, complexities, and chaos are complicated. Forecasting the future performance of stock markets is difficult because of the enormous variables, examined data sources, and low signal-to-noise ratio.

One well-known technique to tackle the difficulty is to use machine learning (ML) algorithms to detect the future stock prices according to the stock's price history [5, 6]. k-nearest neighbor (KNN), decision trees, support vector machines (SVM), as well as other ML techniques are employed to predict stock prices. In practice, these techniques only succeed if data is collected over a long period of time and storage capacity is limited (dealing with data at once is unfeasible) [7]. Because of the ever-increasing abundance of incoming data, many academics have recently used deep learning (DL) algorithms to forecast the stock [8]. On stock market prediction, DL approaches say restricted boltzmann machine (RBM), recurrent neural network (RNN) [9], long short-term memory (LSTM) network, and convolutional neural network (CNN) outperformed both linear and ML models [10, 11]. However, the limitation of using DL models is they depend on the given data representation module. Because the behaviour of the stock market is complex, unpredictable, and noisy, choosing the proper characteristics becomes increasingly tricky. In addition, when the feature space expands, the model's training time increases, making its results more challenging to understand [25] [26] [27] [28]. Efficient attention-based feature extraction and the optimal feature selection mechanism are introduced to address the issues with the DL model for SPP. The paper's major contributions are listed as follows:

- This study aims to examine the significance of business intelligence expert systems with the help of deep learning for predicting stock market prices over big data analysis.
- Incorporate business intelligence into various areas of stock trading in order to enable business functions for organizational success.
- To improve the accuracy of stock trading prediction by incorporating deep learning algorithm namely OPCBLSTM with an effective feature selection mechanism.
- We employ MRResnet50 to extract the features from the pre-processed dataset to improve the system's prediction performance and avoid overfitting issues.
- Utilizing IWOA to select the optimal features increases the prediction accuracy and decreases the classification system's computational complexity.

The upcoming sections of the maniscript is enlisted as follows: the recent methods of SPP are surveyed in section 2. Section 3 presents the overview of the suggested research model. The outcomes of the proposed and existing works for SPP are discussed in section 4, and finally, conclusion and future works of the suggested system is provided in section 5.

2. RELATED WORK

Here, a survey of current methods developed to detect stock market prices are presented. The limitations of the surveyed methods and the solutions offered by the proposed system to overcome those limitations are also discussed at the end of the section.

Theyazn H. H. Aldhyani and Ali Alzahrani [12] presented a hybrid DL approach called CNN with LSTM (CNN-LSTM) for SPP. The two years' stock market data of Tesla and Apple were collected. Then normalization of the collected data was done for enhancing the forecast accuracy of the classification. Then CNN was utilized to extract the more relevant features from the normalized dataset. Finally, SPPs were made using the LSTM model. The results showed that the system achieved slightly better results than the existing schemes by providing the R-squared of 98.37% for Tesla and 99.48% for Apple. **Jingyi Shen and M. Omair Shafq [13]** presented a long short-term memory framework for SPP. Initially the stock market data was collected from the Chinese stock market, and then data pre-processing was done by performing min-max normalization, polarization, and fluctuation percentage estimation. Then recursive feature elimination was utilized to perform feature selection. Finally, LSTM was utilized to predict the stock prices of the financial markets. The method achieved an accuracy, mean square error (MSE), and mean absolute error (MAE) of 0.9325%, 0.0669, and 0.0702, better than the previous approaches. **Gourav Kumar *et al.* [14]** presented a hybrid DL system for SPP using LSTM and particle swarm optimization (PSO). Initially, the data was collected from publicly available datasets such as Sensex, Nifty 50, and S&P 500. Then the collected data was pre-processed by performing min-max normalization to improve the prediction accuracy. After pre-processing, the LSTM model was utilized to predict the SPP, in which tuning of the LSTM was done using PSO. The method achieved a symmetric mean absolute percentage error (SMAPE) of 0.92% for Sensex, 1.19% for Nifty 50, and 0.94% for S&P500 datasets, which were lower than the existing schemes.

Isaac Kof Nti *et al.* [15] suggested a CNN-LSTM-based SPP system. Initially, the data was collected from publicly available sources such as macroeconomic data (MD), the Google trends index (GTI), and Historical stock data (HSD). Then preprocessing was done on the collected data by performing min-max normalization. Then CNN was utilized to perform feature extraction, and finally, LSTM was utilized for SPP. The method attained a sensitivity, specificity, f-measure and accuracy of 89.39%, 99.75%, 96.72%, and 98.31%, which were better than the existing schemes. **KS Rekha and MK Sabu [16]** introduced a hybrid deep-learning model for SPP. The data was collected from Kaggle, and a deep autoencoder was applied to the collected dataset to remove the noise. The sentiment scores were combined with the preprocessed data and fed into the LSTM/gated recurrent unit (GRU) classification scheme for SPP. The method attained an RMSE of 7.46, superior to the conventional stock prediction schemes.

The surveys mentioned above provide efficient results, but they have their shortcomings. Most of the work uses a DL approach to predict the stock model, and it efficiently produces the results. However, these are used by CNN to extract the most relevant features from the dataset. CNN is great for feature extraction from the dataset. However, it faces numerous obstacles, including overfitting, explosive gradients, class imbalance, and the requirement for large datasets. They require a lot of computer power and considerable time to train the data. This paper proposes an attention mechanism, ResNet50, to extract the features efficiently to solve these issues. Also, only a few studies have been done on feature selection for stock prediction. Feature selection is essential because the system extracts more features from the dataset. Training with more features improves the training time and needs more computational power. So, the proposed system uses IWOA to select the features optimally. Thus, the prediction was accurate and had minimal error values. This makes our proposed DL model, OPCBLSTM, efficient and robust.

3. PROPOSED METHODOLOGY

In this paper, the system proposes an improved stock prediction model using a novel OPCBLSTM DL approach with attention mechanism-based feature extraction and optimal feature selection. Four phases are involved in the proposed work: preprocessing, feature extraction, feature selection, and stock prediction. First, the stock data is collected from the publicly available source, and the missing value imputation and data standardization preprocessing are applied to the dataset. Then the essential features are extracted from the MRResNet50 model. After that, the most relevant features are optimally selected using IWOA, and finally, the prediction of future stock is made using the OPCBLSTM approach. The proposed work's flow diagram is shown in Figure 1.

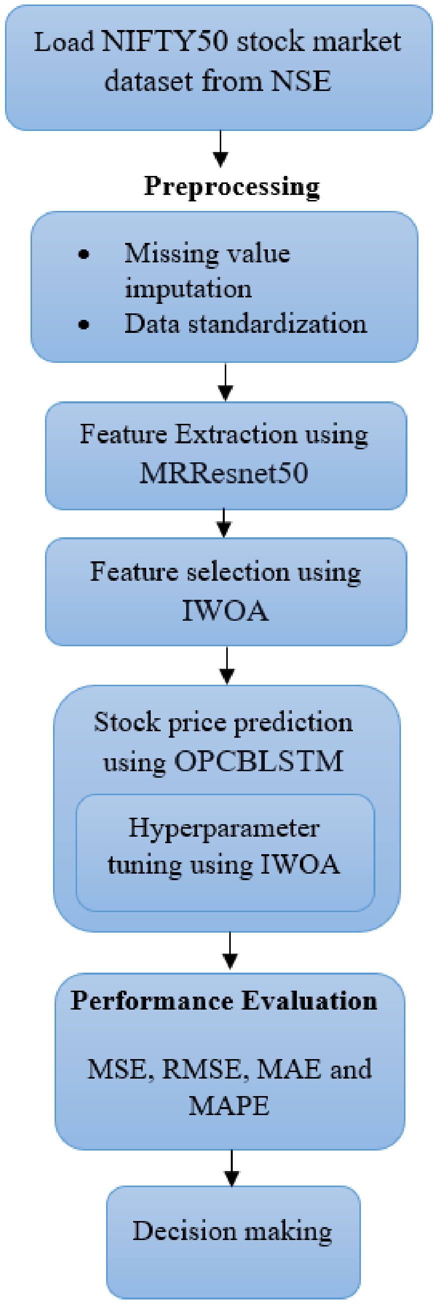

Figure 1: Workflow of the proposed methodology

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3.1 Preprocessing

First, the stock market data was collected from the Nifty 50 index of India's National Stock Exchange (NSE), which provides ten years of historical stock price data from December 2011 to December 2021. After that, the preprocessing is performed on the collected dataset. Preprocessing involves transforming raw data into a more coherent format to improve the prediction rate. First, the missing value imputation is performed to supplement missing values. In this case, missing values can be addressed by removing the columns or rows with null values. If over fifty per cent of the rows in a column are null, the column can be eliminated. After that, data standardization is performed to train the model better. The proposed system performs the z-score standardization method to standardize the input data. The z-score indicates how far a data point is from the mean in a distribution, which is superior to the standardization process. Mathematically, it is expressed as follows:

$$\underline{\underline{SV}}_n^{''} = \left(\frac{\underline{\underline{ID}}_n^{''} - Avg\left(\underline{\underline{ID}}^{''}\right)}{\sigma} \right) \tag{1}$$

Where, $\underline{\underline{SV}}_n^{''}$ refers to the standardized value, $\underline{\underline{ID}}_n^{''}$ indicates the input data, $Avg\left(\underline{\underline{ID}}^{''}\right)$ and σ signifies the input data's average value and standard deviation.

3.2 Feature Extraction

Price fluctuations in the stock market are impacted by various factors, including historical data on the stock market, fundamental reasons, and investors' psychological behaviour. The variety of features makes it challenging to achieve higher accuracy in forecasting. A feature extraction method should be undertaken to extract the necessary features from the preprocessed dataset. Henceforth, the proposed system uses MRResNet50 with an attention mechanism for feature extraction. ResNet-50 includes 50-layer CNN with 48 Convolution layers, one maximum poling layer, as well as one average pool layer. The primary concept is to use connections with shortcuts to skip the blocks of convolutional layers. It decreases the number of variables and matrix multiplications, allowing for substantially faster layer training. However, the traditional usage of ReLU activation in ResNet-50 has a vanishing gradient problem which decreases the prediction rate of the classifier by increasing the classification errors. So, to address these issues, the proposed system uses the Modified ReLU activation function in ResNet-50 to avoid the vanishing saturation problem in the network. This modification in conventional ResNet50 is termed MRResNet50. The process involved in the MRResNet50 is explained as follows:

Initially, the convolutional layer extracts feature maps from the preprocessed dataset using a fixed number of filters. ResNet50 chooses the following filter sizes: (7x7), (1x1), and (3x3). During the training phase, each filter acquires the capacity to identify low-level features in the stock data. The suggested approach employs the modified ReLU activation mechanism. The ReLU activation function discards any negative values and replaces them with zero, although it suffers from gradient vanishing. So, the proposed system uses parametric leaky ReLU, which generalizes the traditional rectified unit with a slope for negative values. It has a learning parameter function that fine-tunes the activation function based on its learning rate. This incorporation into traditional ReLU is termed the modified ReLU activation function, which is expressed as follows:

$$\xi^*\left(DP_z\right) = \begin{cases} DP_z\,, & if\;\; DP_z > 0 \\ \lambda_z\, DP_z\,, & if\;\; DP_z \le 0 \end{cases} \tag{2}$$

Where, DP_z refers to the input preprocessed dataset from the Z^{-th} layer input to the activation function and λ_z indicates the slope parameter. The convolution layer's output is given into the pooling layer for reducing the data dimensions. The max-pooling function prevents overfitting and saves computing costs by reducing the number of variables. The reduced feature maps from the polling layer are inputted to the batch normalization layer, which normalizes the data into the ranges of 0 and 1. It improves the training of the system via superior learning and prevents the system from gradient saturation and overfitting. Finally, the feature map is given into the fully connected layer, which maps the feature maps obtained from the previous layers and provides the feature representation for further process.

3.3 Feature Selection

The feature selection procedure also aids in the reduction of irrelevant variables, computational cost, and the overfitting problem, as well as the improvement of stock forecasting model accuracy. The feature selection method in this paper is carried out using an IWOA. The WOA is a newly developed swarm-based optimization method influenced by humpback whale hunting behavior. Exploring global solutions is a basic concept that is successful. Nevertheless, the conventional WOA suffers from premature convergence or loss of diversity, stagnation in local optima, and the skipping of true solutions. So, the proposed system uses oppositional-based learning (OBL) to enhance the diversity of the population and Cauchy function to enhance the

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exploration capability of WOA and help search agents jump out the local optimal. These two improvisations in conventional WOA are termed as IWOA. The steps are deeply explained as follows:

Step 1: Population initialization

Initially, the position of the whales is initialized by using the OBL strategy to increase the diversity and avoid the premature convergence problem. Here, the population and its opposite population are taken as input. It is mathematically formulated as follows:

$$\underline{\underline{ZX}}_m = a + b - \upsilon_{rw} \tag{3}$$

Where, every randomly chosen weight υ_{rw} has a unique opposite $\underline{\underline{ZX}}_m$ at m^{-th} whale, and $a, b \in R$, R represents a real number.

Step 2: Evaluate the fitness $\left(FF^{"}_{fn}\right)$ of each whale in $\underline{\underline{ZX}}_m$ according to the MSE in the classification scheme.

$$FF^{"}_{fn}\left(\underline{\underline{ZX}}_m\right) = \min\left(MSE\right) \tag{4}$$

$$MSE = 1/Q_N \sum_{k=1}^{Q_N}\left(OV_k - GV_k\right) \tag{5}$$

Where, OV_k and GV_k refers to the actual value and predicted value, and Q_N refers to the number of instances in the training dataset. The whale obtaining the lowest MSE is chosen as the best individual in the current iteration.

Step 3: The individuals encircle the prey and their positions are updated until the maximum count of iterations in the population. This behavior is expressed as:

$$\underline{\underline{ZX}}_m\left(\kappa+1\right) = \underline{\underline{ZX}}^*_m\left(\kappa\right) - \breve{A}\,.\,\breve{B} \tag{6}$$

$$\breve{B} = \left|\breve{P}\,.\,\underline{\underline{ZX}}^*_m\left(\kappa\right) - \underline{\underline{ZX}}_m\left(\kappa\right)\right| \tag{7}$$

$$\breve{A} = 2\,.\,\hat{l}\,.\,\hat{r}_n - \hat{l} \tag{8}$$

$$\breve{P} = 2\,.\,\hat{r}_n \tag{9}$$

Where, $\underline{\underline{ZX}}^*_m$ indicates the historically best position, $\underline{\underline{ZX}}_m\left(\kappa\right)$ refers to the position of m^{-th} whale at κ iteration, $\breve{B}$ indicates the distance between the random and current individual of the population, $\breve{A}$ and $\breve{P}$ refers to the coefficients, $\hat{l}$ is decreased linearly from 2 to 0, and $\hat{r}_n$ represents an arbitrary number between [0, 1]. Next, compute the distance betwixt the current whale and the optimal individual, as well as then simulate the agent for capturing the food in a spiral. It is expressed as follows:

$$\underline{\underline{ZX}}_m\left(\kappa+1\right) = \breve{B}^{"}\,.\,e^{\alpha\beta}\,.\,\cos\left(2\pi\beta\right) + \underline{\underline{ZX}}^*_m\left(\kappa\right) \tag{10}$$

$$\breve{B}^{"} = \left|\underline{\underline{ZX}}^*_m\left(\kappa\right) - \underline{\underline{ZX}}_m\left(\kappa\right)\right| \tag{11}$$

Where, $\breve{B}^{"}$ refers to the distance between the current optimal position and the m^{-th} whale, α refers to the constant value which defines the logarithmic spiral form, and β is an arbitrary number ranges between [− 1, 1]. Then, $1 < \breve{A} < -1$ is utilized in the exploration phase, which forces the whale to move away from the current location. The exploration process of the algorithm is mathematically derived using equations (12) and (13):

$$\underline{\underline{ZX}}_m\left(\kappa+1\right) = \underline{\underline{ZX}}_{rand}\left(\kappa\right) - \breve{A}\,.\,\breve{B} + Cauchy\left(\underline{\underline{ZX}}_m\,;0,1\right) \tag{12}$$

$$\breve{B} = \left|\breve{P}\,.\,\underline{\underline{ZX}}_{rand}\left(\kappa\right) - \underline{\underline{ZX}}_m\left(\kappa\right)\right| \tag{13}$$

Where, $\underline{\underline{ZX}}_{rand}$ refers to the whale's arbitrarily selected position vector, and $Cauchy\left(\underline{\underline{ZX}}_m\,;0,1\right)$ represents the Cauchy mutation function, which updates the whale's position based on its optimal position in the population. This can be computed as follows;

$$Cauchy\left(\underline{\underline{ZX}}_m\,;0,1\right) = 2/\pi\,\arctan\left(\underline{\underline{ZX}}_m\right), \quad \underline{\underline{ZX}}_m \in \left(0,+\infty\right) \tag{14}$$

This process continues until the optimum solution (optimal features) is obtained.

3.3 Stock Prediction

After getting the optimal features from the extracted features, the stock prediction is made in this phase using OPCBLSTM. Bidirectional LSTM (BLSTM) is a type of RNN that connects two hidden layers of opposite directions to the same output. It includes forward and backward LSTM, in which a forward LSTM contains the past knowledge and the backward LSTM obtains the future knowledge about the data. The BLSTM has high robustness in predicting future stock events; however, the random initialization of parameters (weight and bias) in conventional BLSTM exposes the vanishing gradient problem. So, the proposed system uses IWOA to optimally select the weight and bias to solve the vanishing gradient problem. Also, the BLSTM suffers from overfitting issues, which decrease the prediction rate and increases the training time. So, the proposed system uses cross-entropy loss (CEL) value to solve the overfitting issues. Thus, the optimal parameter selection, modified activation function, and modified loss function incorporations in conventional BLSTM are termed OPMRBLSTM. The LSTM's structure comprises three gates, namely, input $\left(\underline{\underline{INP}}^{''}\right)$, forget $\left(\underline{\underline{FOR}}^{''}\right)$, and output gates $\left(\underline{\underline{OUT}}^{''}\right)$ at the time step ε. The mathematical formulations performed in LSTM are given as follows:

$$\underline{\underline{FOR}}^{''}_{\varepsilon} = \xi^{*}\left(\tilde{\omega}_{\underline{\underline{FOR}}^{''}} \cdot \left[\hat{s}_{\varepsilon-1}, \underline{\underline{SF}}_{\varepsilon}\right] + \tilde{\varphi}_{\underline{\underline{FOR}}^{''}}\right) \tag{15}$$

$$\underline{\underline{INP}}^{''}_{\varepsilon} = \xi^{*}\left(\tilde{\omega}_{\underline{\underline{INP}}^{''}} \cdot \left[\hat{s}_{\varepsilon-1}, \underline{\underline{SF}}_{\varepsilon}\right] + \tilde{\varphi}_{\underline{\underline{INP}}^{''}}\right) \tag{16}$$

$$\underline{\underline{OUT}}^{''}_{\varepsilon} = \xi^{*}\left(\tilde{\omega}_{\underline{\underline{OUT}}^{''}} \cdot \left[\hat{s}_{\varepsilon-1}, \underline{\underline{SF}}_{\varepsilon}\right] + \tilde{\varphi}_{\underline{\underline{OUT}}^{''}}\right) \tag{17}$$

$$\underline{\underline{CES}}^{''}_{\varepsilon} = \xi^{*}\left(\tilde{\omega}_{\underline{\underline{CES}}^{''}} \cdot \left[\hat{s}_{\varepsilon-1}, \underline{\underline{SF}}_{\varepsilon}\right] + \tilde{\varphi}_{\underline{\underline{CES}}^{''}}\right) \tag{18}$$

$$\hat{R}\hat{S}_{\varepsilon} = \underline{\underline{FOR}}^{''}_{\varepsilon} \cdot \hat{R}\hat{S}_{\varepsilon-1} + \underline{\underline{INP}}^{''}_{\varepsilon} \cdot \underline{\underline{CES}}^{''}_{\varepsilon} \tag{19}$$

$$\hat{s} = \underline{\underline{OUT}}^{''}_{\varepsilon} \cdot \xi^{*}\left(\hat{R}\hat{S}_{\varepsilon}\right) \tag{20}$$

Where, $\tilde{\omega}_{\underline{\underline{FOR}}^{''}}, \tilde{\omega}_{\underline{\underline{INP}}^{''}}, \tilde{\omega}_{\underline{\underline{OUT}}^{''}}, and\ \tilde{\omega}_{\underline{\underline{CES}}^{''}}$ and $\tilde{\varphi}_{\underline{\underline{FOR}}^{''}}, \tilde{\varphi}_{\underline{\underline{INP}}^{''}}, \tilde{\varphi}_{\underline{\underline{OUT}}^{''}}, and\ \tilde{\varphi}_{\underline{\underline{CES}}^{''}}$ represents the optimal weight values and bias of forget gate, input gate, output gate, and cell state, respectively, which is optimally selected using IWOA and the procedure of the IWOA is given in section 3.3, $\underline{\underline{SF}}_{\varepsilon}$ refers to the selected feature input set, and $\hat{s}_{\varepsilon-1}$ indicates the memory unit's output in the previous time interval $\varepsilon-1$. In addition, the term ξ^{*} refers to the modified ReLU activation function, which is calculated using equation (2). Next, BLSTM's hidden state at time ε includes forward, and reverse processes are computed as shown below:

$$\overrightarrow{\hat{s}_{\varepsilon}} = \overrightarrow{LSTM}\left(\hat{s}_{\varepsilon-1}, \underline{\underline{SF}}_{\varepsilon}, \hat{R}\hat{S}_{\varepsilon-1}\right) \tag{21}$$

$$\overleftarrow{\hat{s}_{\varepsilon}} = \overleftarrow{LSTM}\left(\hat{s}_{\varepsilon-1}, \underline{\underline{SF}}_{\varepsilon}, \hat{R}\hat{S}_{\varepsilon+1}\right) \tag{22}$$

$$\hat{S}_{\varepsilon} = \left[\overrightarrow{\hat{s}_{\varepsilon}}, \overleftarrow{\hat{s}_{\varepsilon}}\right] \tag{23}$$

Finally, the classifier utilizes the CEL function to avoid the neuron's slower learning capability in the output layer and to solve the overfitting issues. This is expressed as follows:

$$CEL = -\sum_{x=1}^{y} \vec{p}_{x} \log\left(p_{x}\right) \tag{24}$$

Where, $x-$denotes the total count of classes, p_x denotes the x^{-th} prediction class of classifier, and $\vec{p}_x$ is the x^{-th} true class of training samples.

4. RESULTS AND DISCUSSION

Here the outcomes of the proposed scheme are proved in SPP over conventional classification schemes. The proposed system is executed in Python Keras with the back end of the TensorFlow library. The programming simulation uses the GPU with 12.72 GB RAM and 107.77 GB disc offered by googles cloud. The system collected the data from the Nifty 50 index of India's NSE, which offers ten years of historical stock price data from 10 December 2011 to 10 December 2021. This dataset was partitioned into optimum splitting ratios of 60-80 with optimum window sizes of 30, 60, and 90 to test the proposed system.

4.1 Performance Analysis

This section first analyzes the outcomes of the proposed OPCBLSTM model at various optimal window sizes and splitting ratios regarding MSE, root mean square error (RMSE), MAE, and mean absolute percentage error (MAPE). Then a comparative analysis of the proposed and existing works is done regarding the same performance metrics.

Table 1: Results of the proposed model for optimum window sizes and splitting ratios

Proposed approach		MSE	RMSE	MAE	MAPE
Window 30	Split 60	0.0004662	0.0226497	0.0049531	109.25
	Split 65	0.0000048	0.0042031	0.0028445	54.142
	Split 70	0.0000085	0.0046392	0.0032203	23.124
	Split 75	0.0000096	0.0047835	0.0032791	19.241
	Split 80	0.0000102	0.0049515	0.0033351	13.241
	Split 60	0.0004466	0.0222138	0.0045428	106.87

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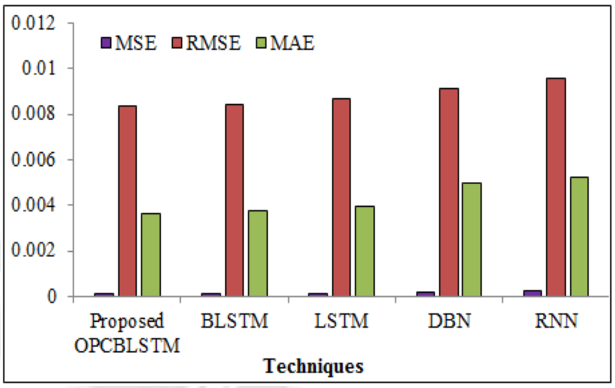
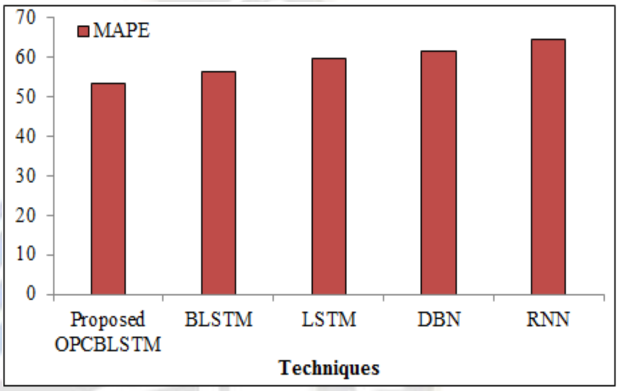
Window 60	Split 65	0.0000046	0.0041913	0.0028411	50.021
	Split 70	0.0000079	0.0045871	0.0031573	21.147
	Split 75	0.0000098	0.0048093	0.0033047	18.471
	Split 80	0.0000141	0.0052931	0.0036016	7.258
Window 90	Split 60	0.0004846	0.0230499	0.0057825	101.021
	Split 65	0.0000074	0.0045719	0.0031171	48.145
	Split 70	0.0000069	0.0045553	0.0031235	19.854
	Split 75	0.0000116	0.0048981	0.0033446	17.241
	Split 80	0.0000138	0.0052081	0.0035116	6.141

Table 1 indicates the efficiency of the proposed work with varying optimum window sizes of 30, 60, and 90 and splitting ratios of 60 to 80. For the optimum window sizes of 30, 60, and 90 and the optimum splitting ratio of 60, the proposed method attains the MSE of 0.0004662, 0.0004466, and 0.0004846, RMSE of 0.226497, 0.0222138, and 0.0230499, MAE of 0.0049531, 0.0045428, and 0.0057825, and the MAPE of 109.25, 106.87, and 101.021, which shows the performance effectiveness of the suggested scheme. Similarly, when the splitting ratios vary from 65 to 80, the proposed method achieves better results for the exact ideal window sizes of 30, 60, and 90. Overall, it was observed that the proposed method attains the minimal values of MSE (0.0000046), RMSE (0.0041913), MAE (0.0028411), and MAPE (6.141). Thus, the proposed one achieves superior performance for varying window sizes and optimum splitting ratios. Then the comparative results of the proposed and existing models, say BLSTM, LSTM, deep belief network (DBN), and RNN, are discussed, shown in Figure 2. The proposed work offers a higher performance level than the existing SPP methods. For example, the existing BLSTM attains the MSE, RMSE, MAE, and MAPE of 0.0001132, 0.0084469, 0.0037754, and 56.231, the existing LSTM attains 0.0001355 of MSE, 0.0086452 of RMSE, 0.0039462 of MAE, and 59.418 of MAPE, the existing DBN achieves 0.0001854 of MSE, 0.0091129 of RMSE, 0.0049769 of MAE, and 61.457 of MAPE, and the existing RNN attains 0.0002263 of MSE, 0.0095385 of RMSE, 0.0052315 of MAE, and 64.258 of MAPE. However, the proposed one attains an MSE, RMSE, MAE, and MAPE of 0.0001007, 0.0083354, 0.0036255, and 53.214, which are lower than the existing schemes. These better results are because of using cross-entropy loss function in the prediction layer, so the error probability is relatively low compared to the existing methods. The proposed method also uses an efficient feature extraction and selection approach, which reduces training time and minimizes prediction error by avoiding overfitting and saturation issues.



(a)



(b)

Figure 2: Results of the classifiers regarding (a) MSE, RMSE, and MAE and (b) MAPE

5. CONCLUSION

This paper suggests a novel DL-based SPP system with a practical feature extraction and selection scheme. The proposed system mainly consists of four phases: preprocessing, feature extraction, feature selection, and stock prediction. The data was collected from the Nifty 50 index dataset to implement the proposed system. The outcomes of the proposed research framework are discussed by varying the optimum window sizes and optimum splitting ratios. The proposed work achieves superior performance by providing the minimal values of MSE (0.0000046), RMSE (0.0041913), MAE (0.0028411), and MAPE (6.141). Next, the proposed work's outcomes are investigated against the traditional BLSTM, LSTM, DBN, and RNN approaches. The results showed that the proposed one attains the lowest MSE, RMSE, MAE, and MAPE of 0.0001007, 0.0083354, 0.0036255, and 53.214, which are lower than the conventional methods. So, from the results, we can conclude that the proposed method predicts future stock prices more accurately than previous algorithms.

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