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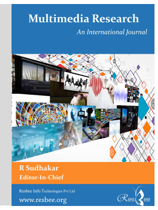

Dynamic Learning and Instant Feature Fusion-Based Stock Market Prediction Using a Fractional Hybrid Optimization Algorithm

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Abstract: In recent days, access to the future price of the stock market has been an active domain in the financial world. The prices of stock alter due to several variables. Hence, a precise prediction of stock price is employed as a complicated task. This paper devises a novel technique for dynamic learning in stock market prediction. At first, the stock data and review-based data are fed as input to feature extraction. For stock data, technical indicators like absolute price oscillator (APO), directional movement indicators (DMI), simple moving average (SMA), WILLIAMS's % R (WILLR), triangular moving average (TRIMA), and percent price oscillator (PPO) are extracted as features and from review-based data, the Senti WordNet based features are extracted. The features are fed to the feature fusion module, which is done using K-Nearest Neighbour (KNN) and holoentropy. Thereafter, the fused features are fed to Deep Convolutional Long Short-Term Memory (Deep-ConvLSTM) wherein the training of Deep-Conv LSTM is done using the proposed Fractional Rider-Elephant herd Optimization (Fractional REHO) algorithm. The proposed Fractional REHO is devised by combining Fractional Calculus (FC) and the Rider-Elephant herd Optimization (REHO) algorithm. Here, the Deep-ConvLSTM is learned dynamically for stock market prediction. The proposed Fractional REHO-based deep-convLSTM offered enhanced performance with the smallest MSE of 0.003 and RMSE of 0.057.

Keywords: Stock Market Prediction, Deep Convolutional Long Short-Term Memory, Feature Fusion, KNN, Fuzzy Bounding

Nomenclature

Abbreviation	Expansion
ANN	Artificial Neural Networks
RNN	Recurrent Neural Networks
LSTM	Long-Short Term Memory model
ML	Machine Learning
ENN	Elman Neural Network
MAPE	Mean Absolute Percentage Error
TSRM	Time Series Relational Model
GCN	Graph Convolution Networks
DL	Deep Learning
FC	Fractional Calculus
MSE	Mean Square Error

1. Introduction

The stock market is a network that offers an infrastructure for providing transactions in the world at a dynamic rate known as stock value which is devised based on market equilibrium. Forecasting the value of stock provides huge profit skills that are considered a large inspiration for research in this domain. The acquaintance in stock value prior can lead to elevated profits. Likewise, a probabilistically precise prediction is profitable in an amortized scenario. This benefit of determining the solution has acquired the attention of researchers in both academia and organizations to find ways for issues such as seasonality, time dependence, volatility, and economies [14]. Forecasting in finance for predicting the stock market is an emerging domain in research due to industrial applications that own elevated stakes and huge benefits. However, the stock market is imperatively non-linear, complex, dynamic, nonparametric, and chaotic data. The time series tends to be noisy, multi-stationary, and arbitrary which has recurrent structural ruptures. Moreover, the movements of the stock market are influenced by

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several macroeconomic aspects like policies, commodity price indexes, political events, firms, and economic conditions [15]. Moreover, the prediction of stock prices or economic markets is considered a major issue for AI-based communities. Several fundamental, technical, and arithmetical indicators are devised with altered outcomes. However, none of the strategies are successful in accurate prediction [16].

The forecasting of stock prices for the future is a complex process based on various internal and external aspects. Despite a huge number of researchers analyzing the stock prices, but still, there are huge alterations in forecasting the original data. The procedure for producing high yield in the stock market depends on effectual prediction regarding the asset prices. The stock index is employed as an unreal portfolio and is a general measure used to analyze the performance of each sector. Meanwhile, the market trading technique is ensured to be effective if and only if accurate prediction is ensured in that particular market [27]. The forecasting of the stock market is complex in science both in methodology and prediction. The prediction of stock precisely is impossible considering the notions and techniques of classical scenarios. The Efficient Market Hypothesis describes that present data is inherited in stock prices and the occurrence of current data cases is devised based on impetuous stock prices. The reports produced arbitrarily readapted for predicting the stock prices but are not precisely predicted with past values and hence pose the issue that prediction of the stock market is a complex task [28].

In recent days, the analysis of the stock market has been done based on historical market prices using certain techniques that involve Neural Networks [20], Case-based reasoning [22], Autoregressive, moving average [18], Support Vector Machines [21], Genetic Algorithm [19], and other strategies for assessing the behavior of the stock market. The issue with an accurate prediction of these techniques is formulating the arbitrary behavior of the market, but there is no explanation for it. The major solution for examining the arbitrary behavior of the market is adapting the influence of un-quantifiable events on the market. In recent days, researchers have discovered that influential sources are essential for attaining precise predictions [17]. ANN has been extensively utilized in predicting the stock market in the last decades. In [23], an ANN is utilized for predicting the stock index of Tokyo. In [24], ANN is used for predicting the buying and selling patterns for computing the overall rate of prediction. In [25], a technique is devised for predicting the stock market wherein the momentum is utilized. Here, the learning of arbitrary points can address the issues that may happen in the process of training. In [26], a neural network with a genetic algorithm is devised for exchanging stock and predicting the market direction considering the accuracy. Hence, ANN is extensively utilized in forecasting financial malfunctions.

The goal is to devise a stock market prediction system to ensure the effective prediction of the stock market. Thus, an approach is developed to predict the future market based on the past and the current status of the market. Initially, the input data are given for the extraction of features that arebased on technical indicators like APO, DMI, WILLR, SMA, TRIMA, and PPO. The technical indicators ensure the information of the data that significantly contributes to predicting the stock market. These technical indicators represent the features and are used for the stock market prediction using the predictor. The highly significant features of the data are fed to the sentiment feature extraction module where the sentiment feature extraction is done considering the Senti Word Net features. The output generated by the feature extraction and the sentiment feature extraction are passed to the feature fusion module, which is carried out using KNN and holoentropy. Finally, the Deep-Conv LSTM is learned dynamically based on the fuzzy bounding theory and the Fractional REHO algorithm. The proposed Fractional Rider-EHO is the integration of FC and REHO, wherein the REHO is the combination of ROA and EHO.

The major contribution of the paper is

- Proposed Fractional REHO-based Deep-ConvLSTM for dynamic learning in predicting the stock market: The proposed Fractional REHO is employed for training Deep-ConvLSTM wherein the proposed Fractional REHO is devised by combining REHO and FC.

The paper is organized in the following manner. Section 1 presents the introductory part based on stock market prediction. Section 2 discusses the existing techniques devised based on stock market prediction. Section 3 describes the proposed Fractional REHO-based Deep-ConvLSTM for predicting the stock market. Section 4 describes the efficiency of the proposed model and section 5 presents the conclusion.

2. Motivations

The eight existing papers are briefly examined along with their challenges. These issues are considered as a motivation to develop a novel stock market prediction model.

2.1. Literature Review

The classical techniques devised based on stock market prediction are illustrated along with its issues. Moghar, A. and Hamiche, M [2] utilized RNN and LSTM for predicting the future values of the stock. The goal was to predict the precision of ML models in predicting the stock index. However, the technique failed to elevate the prediction accuracy.

Chandar, S.K *et al.* [3] devised an effective technique for forecasting the future price of stock data considering technical indicators devised from historical data. The method employed the ENN to learn the previous data that are apposite for addressing stock issues. Here, the trial and error technique was extensively utilized for determining the attributes of ENN. However, this technique was a time-consuming task.

Xi Zhang *et al.* [5] developed a method to predict the stock market considering the trends of the composite index. In this model, the consistencies among different data sources are used and multi-source multiple instance models were considered for incorporating events, quantitative data, and sentiments. However, the technique failed to improve the performance.

Xiongwen Pang, *et al.* [8] devised a neural network for acquiring the prediction of the stock market. Here, the data was acquired using the live stock market in real-time and analysis was adapted to analyze the stocks. Here, the deep LSTM was employed for predicting the stock. However, the technique failed to employ other datasets for predicting the stock movement.

In 2023, Majiid *et al.* [7] have used an ML algorithm for stock price prediction. Initially, data were gathered from various websites. The exert features from the images like open and closed prices, the volume of low and high prices, and other relevant information. After that ensemble learning techniques such as ET-GRU/ET-LSTM were used to predict the stock results. Then the results were optimized to obtain accurate results through model training. Finally, the results were evaluated based on the performance metrics depending upon the use case they want to solve through this approach. This method was effective compared to other DL methods. However, this method didn't consider external factors that impact the market trends.

In 2023, Aburto *et al.* [6] implemented a mathematical model with two ratios used for stock prediction. Initially, this method contained investors with a finite budget used as the input value. Then Treynor and Sharpe ratio was used to measure the ROI relative to its level of risk. After that, the returns were predicted through the LSTM neural network and compared with MAPE. The GARCH model was used to predict the Volatility of the market using heteroscedastic risk and incorporated into the Sharpe ratio for calculation. The mathematical model optimizes the portfolio and predicts the exert combination to get maximum results with the minimum risk. Finally, the result was displayed on the screen. This method was effective with ML and GARCH techniques with only historical data.

In 2023, Zhao *et al.* [4] applied TSRM to predict related images and time in stock prices. Initially, Stock market data was collected. Then the stocks were classified based on their transaction data through the K-means clustering algorithm. The classified data was then extracted from the time-series pattern through LSTM. They also collect trends from historical price movements of individual stocks over some time. From the collected information the related features were extracted through GCN. The relationship features were then integrated into a single framework where the expected output was obtained.

In 2023, Li *et al.* [1] experimented clustering-enhanced DL framework to identify stock prices. Initially, the data were grouped with similar stocks using logistic-weighted dynamic similarity warping (LWDTW). The three DL models were used for training each cluster to obtain the fine-tuned parameters for the prediction of every stock price. The DL model also predicted future stocks accurately by comparing the previous clustered datasets. Finally, the expected results were obtained through evaluation. The stock prices were more accurate than other methods but it didn't work well with certain financial time series data.

2.2. Challenges

The major issues confronted by the stock market prediction techniques are given below.

- The forecasting of stock groups is complex for shareholders because of certain aspects that involve a multifaceted nature, non-linearity, and intrinsic dynamics.
- The researchers assume that the prediction of the stock price is a complex issue because of the non-stationary and noisy features of data.
- Various techniques are devised based on ML techniques for effective prediction of the stock market. However, this technique doesn't rely on one long-term memory-passed sequence of data [2].
- The prices of stock vary due to several variables. Hence, precise forecasting of stock prices is adapted as a complicated task. These dynamic, non-linear, volatile, and chaotic stock data make it complex to devise a reliable model [3].

- The prediction of the stock market has huge benefits in industries and the academic world. Here, precise prediction assists the investors in making decisions and gaining profit while exchanging stock. However, this prediction task is complicated due to the financial data nature ahigh degree of uncertainty, noise, and chaotic characteristics [9].

3. Proposed Fractional REHO-based Deep-ConvLSTM for Predicting Stock Market

The prediction of the stock market is a promising domain that reveals that the market is extremely stochastic and there exist temporally-dependent predictions using messy data. In addition, several models are utilized in predicting the stock market, but these models are not able to offer precise predictions. The aim is to devise an optimization-driven DL technique for predicting the stock data. This technique is devised for predicting the future market based on the current and past status of the market. At first, the input stock data is fed to the feature extraction phase, wherein the stock data features and review-based features are extracted. The stock data features are obtained by extracting the technical indicators like APO, DMI, SMA, WILLR, TRIMA, and PPO. The review-based features are extracted considering the reviews which initially undergo stemming and stop word removal and then the Senti WordNet features are extracted. These features are fed to the feature fusion module wherein KNN and holoentropy are considered. Once the fusion is done, the feature vector is passed to Deep-ConvLSTM wherein the training of Deep-ConvLSTM is done using the proposed Fractional REHO algorithm. The proposed Fractional REHO algorithm is devised by incorporating FC [34] in REHO wherein the REHO is obtained by combining EHO [31] and ROA [30]. Here, the proposed Fractional REHO-based Deep-Conv LSTM is adapted for dynamic learning based on fuzzy bound theory in stock market prediction. Fig. 1 presents a schematic view of the stock market prediction model using the proposed Fractional REHO-based Deep-ConvLSTM.

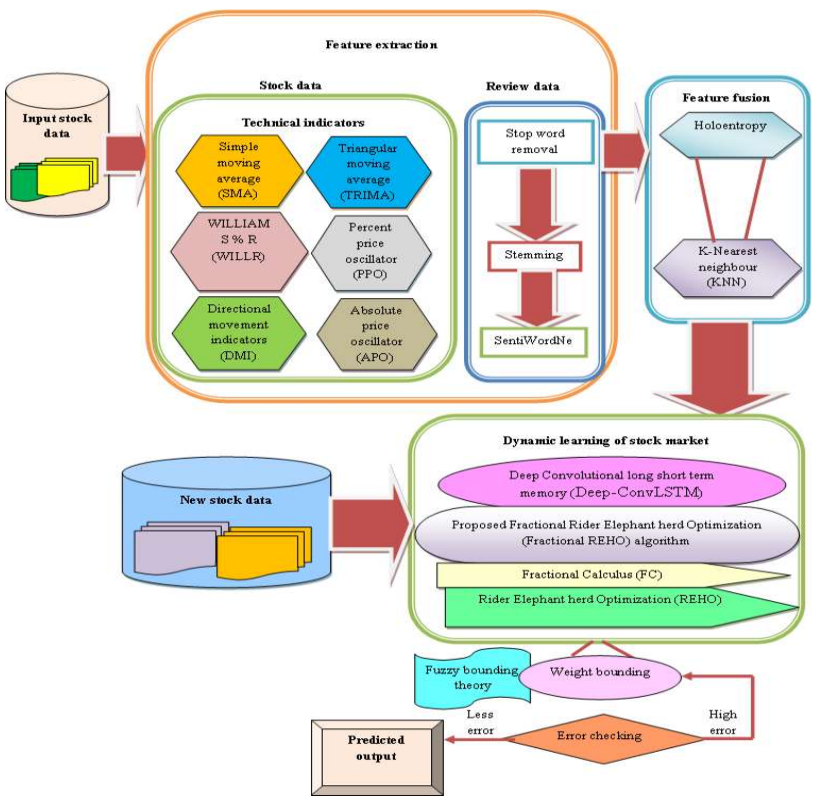


Fig. 1. *The architecture of the stock market prediction model using the proposed Fractional REHO-based Deep-ConvLSTM*

3.1. Time Series Data Acquisition Process

The time-series data is considered an important class of temporal objects and it is produced with monetary and scientific applications. In addition, it is built by accumulating the contents of past data. In this model, the time series data of the stock market and user review is employed, which assists in predicting the trends in the market concerning time.

3.1.1. Obtain input stock market data

The forecasting of the stock market is done by employing inputted stock data. In this model, the prices of stocks are analyzed for each day considering the time-series data, which helps to make an accurate prediction of the stock market. Consider the stock data as S collected with the stock market dataset Y. The stock market data S is used for attaining the prediction by mining the intellectual features with technical indicators.

3.1.2. Obtain Input Review Data

Assume an input review data denoted as M considering different attributes and is formulated as

$$M = \{M_{d,e}\};(1 \le d \le b)(1 \le e \le a) \tag{1}$$

where, $M_{d,e}$ signifies the user reviews data present in the dataset M with d^{th} attributes in e^{th} data. Here, a symbolizes total data points and b is the total count of attributes. Each data is subjected to the feature extraction phase, wherein stop word removal, stemming, and Senti Word Net are employed for mining the review-based features.

3.2. Extraction of Features Using Inputted Stock Market Data and Reviews

After the acquisition of time-series data, the features are mined using the time-series data. The mining of features facilitates effective prediction of the stock market. For mining features from stock data, the technical indicators are employed whereas review-based features are obtained using Senti WordNet.

3.2.1. Stock Market Features by Extracting Technical Indicator

The technical indicators are employed as an important component in extracting features with data that provides effective prediction. The technique employs six technical indicators for mining stock features. Here, the stock market data S is adapted for mining the technical indicator features that include APO, DMI, SMA, WILLR, TRIMA, and PPO. The technical indicators represent a series of data points that are extracted by employing the function using the price data at the study period and time. The technical indicators are obtained with the input stock market data S and are given as,

a) WILLIAMS % R (WILLR):

It is chiefly termed as Williams Percent Range (Williams %R) that assists in determining the closing price of the day based on the past ten day's transaction. The WILLR is expressed as,

$$W = \frac{x}{y} * 100 \tag{2}$$

where, x signifies highest closed, and y indicates highest lowest. The WILLR feature is expressed by T_1.

b) Simple Moving Average (SMA):

It indicates an arithmetic moving average evaluated by summing the present prices and then dividing the fig. by the period's count. It is computed based on the average price at a specific time q. SMA is evaluated as,

$$G = \frac{1}{x}\sum_{j=0}^{x-1} W_{t-j} \tag{3}$$

where, W_t express closing price on the day t, and x symbolize input window length. The SMA feature is expressed as T_2.

c) Triangular Moving Average (TRIMA)

The TRIMA represents an average of prices and places weight on the middle price of the time. The indicator assists in filtering fluctuations in the market by averaging the price values concerning time. The TRIMA is expressed as,

$$TRIMA = \frac{SMA_1 + SMA_2 + \ldots + SMA_N}{P} \tag{4}$$

where, P signifies the count of stocks. The TRIMA feature is denoted as T_3.

d) Directional Movement Indicators (DMI)

It discovers the track wherein the asset's price is moving. The indicator performs this process by analyzing the highs and lows by drawing two lines a positive directional movement line (+DMt) and a negative directional movement line (-DMt). When +DMt is above -DMt, there is more upward price pressure, and if –DMt is above +DMt, then there is more downward pressure in price. This indicator assists traders in accessing the direction of the trend and DMI is formulated as,

$$+DMt = [+DMt - 1 - (+DMt - 1/n)] \tag{5}$$

$$-DMt = [-DMt - 1 - (-DMt - 1/n)] \tag{6}$$

Where, $+DMt$ signifies $+DM$ at a provided time, t and $+DMt-1$ represents $+DM$ at a provided time $t-1$, $-DMt$ refers $-DM$ at a provided time, t and $-DMt-1$ signifies $-DM$ at a provided time $t-1$. The DMI feature is formulated as T_4.

e) Absolute Price Oscillator (APO)

It represents the difference between two exponential moving averages and is formulated as an absolute value. The APO is obtained based on absolute differences amongst two moving averages of altering lengths fast and slow-moving averages. Thus, the APO is expressed as,

$$APO = Fast\ Exponential\ Moving\ Average - Slow\ Exponential\ Moving\ Average \tag{7}$$

In this model, the APO feature is expressed as $T_{5.}$

f) Percent Price Oscillator (PPO)

It refers to the differences amongst two moving averages of altering lengths fast and slow-moving averages. The PPO evaluates the difference between two averages divided by the slower of two moving averages and it seems to normalize values. The PPO is considered as a nine-day exponential moving average, reduced and then divided by a 26-day exponential moving average, which is expressed as,

$$PPO = \frac{EMA_{9\_day} - EMA_{26\_day}}{EMA_{26\_day}} \tag{8}$$

where, EMA signifies an exponential moving average of stock closing price. The PPO feature is denoted as T_6.

3.2.2. Extraction of Review-Based Features

Prior to the extraction of review-based features, the review data must be pre-processed by adapting stemming and stop word removal for offering effectual features. The review dataset comprises inadequate words or phrases that influence the feature extraction procedure. Hence, the removal of stop words and stemming is carried out to remove the incompatible words by extracting the reviews. In this process, the input user review data M is adapted for carrying out stop word removal and stemming and is briefly examined below.

i) Stop word removal:

The stop words represent the word that does not uphold any data. The removal of stop words is a process for removing stop words from huge text reviews. In this process, the non-informative words are eliminated to reduce the noise contained in the data. The removal of stop words can be used to savea large space and make the processing faster by acquiring effective results. Here, the stop words such as verbs and nouns are eliminated from the review data.

ii) Stemming:

The stemming process is used to transform the words into its stem. In a huge review, various words are utilized that convey the same concept. The important technique used for reducing the words to their roots is termed stemming.

Here, the extraction of the feature is done considering the user review data, which is performed with Senti Word Net. In this process, the opinion-based features are generated from the opinions of users based on the product. Then, the Senti WordNet is employed on keywords of user review data.

Senti WordNet [29] is employed as a lexical resource for mining user opinions. Senti WordNet allocates each synset of WordNet by adapting two sentiment numerical words, like positive Pos(s), and negative Neg(s). Here, Senti WordNet is employed to discover the positivity and negativity of words present in review data. Hence, the Senti WordNet is formulated as,

$$S(\varpi) = \{p, n\} \tag{9}$$

After applying Senti Word Net, two kinds of review-based features are obtained that include positive word set and negative word set and expressed as T_7 and T_8 is formulated as,

$$T_7 = \sum_{l=1}^{m} p_l \tag{10}$$

where, m symbolizes the count of words in a review in such a way that $1 \le l \le m$, P_l the express l^{th} word is positive.

$$T_8 = \sum_{l=1}^{m} n_l \tag{11}$$

where, m express count of words in a review in such a way that $1 \le l \le m$, n_l the expressed l^{th} word is negative. Hence, the stock data features and review-based features are fed to the feature fusion

3.3. Feature Fusion Using Holoentropy and KNN

Feature fusion T is a procedure for combining different data sources to produce precise, dependable, and useful information from the data sources. The advantage of feature-level fusion is that different features can be extracted using a similar pattern and return the features. By combining and optimizing these features, it only acquires effectual information, but also remove sun necessary data to a prescribed degree. This is effective for discovery. Here, the feature fusion can increase the rate of recognition. In this method, the feature fusion is performed in two steps in which feature sorting and feature grouping are performed.

3.3.1. Feature Sorting by Holoentropy

In feature sorting, the features are arranged based on the holoentropy values. The holoentropy is a standard measure used for discovering the uncertainty in any data and is used for increasing the mutual information in various operations. Holoentropy is computed by comparing the entropy [35] of the dataset before transformation and after transformation. The huge accessibility of Holoentropy variations inspired suitability preference for a scrupulous operation. Hence, the Holoentropy of input data is used to target the difference between data in a group. In addition, the Holoentropy is described as corresponding states of intensity level. The holoentropy can be used in quantitative assessment for evaluating details of input data and provides enhanced comparison amongst input data. The holoentropy is expressed as,

$$H_e(a_i) = \omega \circ \varepsilon(a_i) \tag{12}$$

$$\omega = 2\left(1 - \frac{1}{1+\exp(-\varepsilon(a_i))}\right) \tag{13}$$

$$\varepsilon(a_i) = -\sum_{i=1}^{u(a_i)} P_i \log(P_i) \tag{14}$$

where a_i denote attribute vector, u_i refers count of unique values in the attribute vector a_i, and P expresses the probability distribution of input data.

3.3.2. Grouping of Features for Feature Fusion

The FC is employed to group the features in which the fractional idea is utilized for fusing features. The FC [34] is adapted for computing the best outcomes from previous iterations and is determined for acquiring the chronological features. In addition, the performance is improved with consecutive features. The FC is adapted for fusing the features. In addition, the performance is improved with the fusing process considering individual features. Here, the feature fusion is carried out with the equation generated by the FC, and the groups are formed using the chosen features.

$$T = \sum_{\substack{i=1 \\ i=1+N/k}}^{a} \frac{\alpha}{g} T_i \tag{15}$$

where n signifies the count of features to be selected N represents the total count of features and $k = N/n$, α signifies fractional coefficient, which is determined using KNN. Here, the value of α is discovered with KNN theory [36]. The KNN is considered the simplest similarity-assisted artificial learning technique that could offer improved performance in some milieu. While categorizing the provided instances, the fundamental notion is to formulate the nearest neighbor instances at a predefined distance to vote on. Here, the class of novel instances is described based on the most general class amongst k-nearest neighbors. The selection of the k-value is done beforehand. These values should not be a multiple of classes count to avoid tie votes. Hence, in the case of classification, it is essential to take the value as odd. The efficiency of KNN relies on the measure utilized to compute the distances amongst instances. The KNN is non-parametric and thus the technique is liable to categorize without making any suppositions regarding the function $Y = f(x_1, x_2, \ldots, x_n)$ that links class Y to the attributes $x_j (1 \le j \le n)$. Thus, the fused features are expressed as,

$$T = \left\{T_1^{fused}, T_2^{fused}, \ldots, T_f^{fused}, \ldots, T_g^{fused}\right\} \tag{16}$$

3.4. Dynamic Learning with Proposed Fractional REHO-Based Deep-Convlstm and Fuzzy Bound Theory For Stock Market Prediction

The forecasting of the stock market is performed with the proposed Fractional REHO-based Deep-ConvLSTM. For effectual prediction, the Deep-ConvLSTM is used that assist in determining optimal weights–biases with the proposed REHO algorithm. Thus, the prediction of the stock market is carried out with a Deep-ConvLSTM classifier that acquires effective features as input. The training of the Deep-ConvLSTM classifier is performed by the proposed Fractional REHO algorithm, which is generated by combining the Fractional idea [34] with REHO, wherein REHO is obtained by combining EHO [31] and ROA [30]. The Deep-ConvLSTM is capable of forecasting the future considering dynamic time-series data. The Deep-ConvLSTM provides effective feature patterns considering a huge transitional kernel. The brief illustration of Deep-ConvLSTM architecture and training of Deep-ConvLSTM using proposed fractional-REHO are given below.

3.4.1. Architecture of Deep-ConvLSTM

The generated fused features T are subjected to the Deep-ConvLSTM for attaining the forecasting of the stock market. The Deep-ConvLSTM [32] attains extra advantages in contrast to other classifiers in such a way that Deep-ConvLSTM is highly effective for attaining the forecasting of the stock market using the memory cell of the classifier. Deep-ConvLSTM uses previous states and input linked to its neighbours for predicting future states using the Hadamard product $\circ$ and Convolutional operator. The Deep-ConvLSTM provides effective stock forecasting by employing a huge transitional kernel, and the Deep-ConvLSTM structure is formed with forecasting and encoding layers. Fig. 2 describes the structural design of the Deep-ConvLSTM classifier.

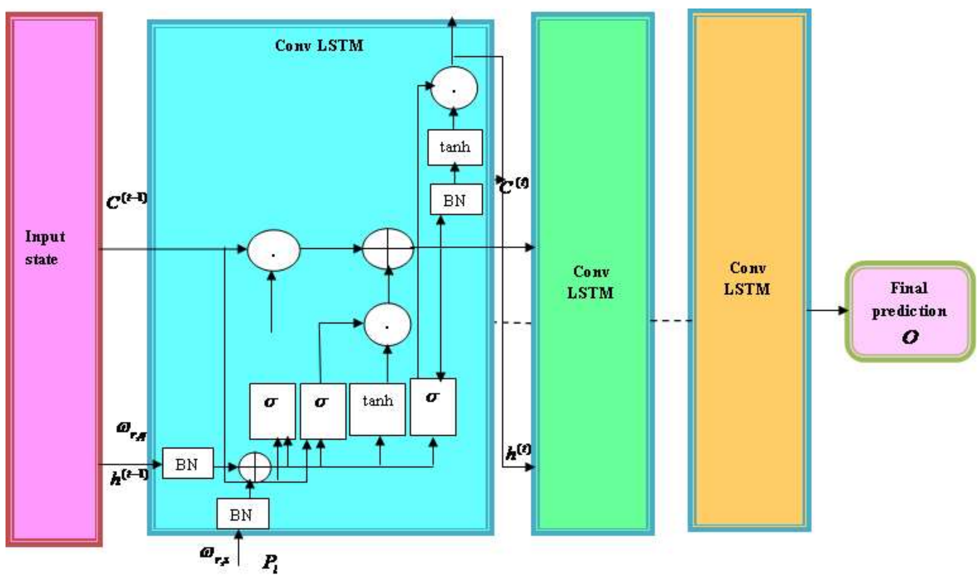


Fig. 2. *Structural design of Deep-Conv LSTM classifier*

The Deep-ConvLSTM consists of input F_h, cell G_h, and output U_h, weight $\omega_{i,j}$ that is fully associated to F_h. In this model, the input F_h and working memory U_{h-1} are combined to learn the forget gate. In ConvLSTM, each attribute in the forget gate tensor determines to which extent the long-term memory attributes in [0, 1] exist. Here, the highest value 1 indicates completely saved, and the minimal value 0 refers to completely forgotten. The mathematical modeling of Deep-ConvLSTM is expressed below. At first, the CNN is adapted to learn the forget gate K_j which is expressed as,

$$K_j = \sigma\left(\omega_{i,j} * F_h + \omega_{t,j} * U_{h-1}\right) + u_j \tag{17}$$

where, σ express sigmoid function, $\omega_{i,j}$ and $\omega_{t,j}$ represent weights linked between conv layers, U_{h-1} signifies working memory, and F_h represents input.

Secondly, the mining of data can be learned using F_h which is the candidate memory K of long-term memory, which is formulated as,

$$K_j = \tanh(\omega_i * F_h + \omega_t * U_{h-1} + u) \tag{18}$$

The third step is the integration of the aforementioned two steps. The goal is to forget the memory that is not received and save the constructive part of the input. Then, the update of long-term memory L_h is produced, which is stated as,

$$K_o = \sigma(\omega_{v,o} * F_h + \omega_{t,o} * U_{h-1} + u_o) \quad (19)$$

$$L_h = K_j \circ L_{h-1} \circ K_o \circ K \quad (20)$$

The fourth step is a working memory update. The network needs the learner to spotlight the long-term memory and make more sense in the present step. Thus the learning of focus vector K_w is modelled as,

$$K_w = \sigma\left(\omega_{v,w} \times F_h + \omega_{t,w} * U_{h-1} + u_w\right) \quad (21)$$

Fifth, the working memory is examined. Thus, the network concentrates on an element in which the attention vector is 1 and ignores the element, whose attention vector is 0 and is formulated as,

$$U_h = K_\ell \circ \tanh(L_o) \quad (22)$$

Thus, the output produced by the Deep-ConvLSTM is denoted as U.

3.4.2. Training of Deep-ConvLSTM using proposed Fractional REHO-based Deep-ConvLSTM

The prediction of the stock market is attained using the Deep-ConvLSTM classifier, whose training is performed by the proposed Fractional REHO algorithm. Here, the proposed Fractional REHO algorithm is the integration of FC in REHO wherein REHO is the combination of ROA and EHO. Here, the properties of REHO are inherited by the FC algorithm to enhance the efficiency of predicting the stock market. The FC [34] is adapted for computing optimal solutions with previous iterations and is determined for updating solutions from the present iteration. In addition, the performance is enhanced with an update of records. Thus, the combination of fractional ideas in REHO leads to a globally optimal solution with combined benefits and assists in attaining improved performance. The proposed Fractional REHO is highly effective for performing stock prediction with limited memory. Thus, the combination of REHO and FC can help to generate global optimal solutions. The steps of the proposed Fractional REHO-based Deep-ConvLSTM are illustrated as follows:

Step 1) Initialization: The preliminary step is solution initiation, which is mathematically stated as,

$$Q = \{Q_1, Q_2, \cdots, Q_\kappa, \cdots Q_\ell\}; 1 \le \kappa \le \ell \quad (23)$$

where, ℓ express the total count of solutions and Q_κ symbolize κ^{th} the solution

Step2) Evaluation of the Error: The optimal solution is discovered with error, which is modeled as a minimization issue and thus, a solution with less MSE is selected as an optimum solution and MSE is represented as,

$$MS_{err} = \frac{1}{g}\sum_{f=1}^{g}\left[O_f - U\right]^2 \quad (24)$$

where O_f express expected output and U symbolize predicted output, g is the count of data, where $1 < f \le g$.

Step3) Determination of weights:

To solve all the optimization issues, the REHO is employed. As per REHO, the update is given by,

$$Q_{r,s}^{o+1} = \frac{\delta\beta_s}{\delta\beta_s - (1-\alpha n)}\left[\frac{-\delta Q_{\sum s}^{o}(1-\beta_s)}{\delta\beta_s}(1-\alpha n) + \alpha n Q_r^{best}\right] \quad (25)$$

Where, $Q_{r,s}^{o+1}$ and $Q_{r,s}^{o}$ represents the new and old position of elephant s in the clan r, α signifies constant ranging between 0 and 1, n is an arbitrary number between 0 and 1, Q_r^{best} is fittest elephant individual in the clan r, and δ is a random number ranging between 0 and 1, β is an arbitrary number ranging between 1 and R.

Subtract $Q_{r,s}^{o}$ on both sides,

$$Q_{r,s}^{o+1} - Q_{r,s}^{o} = \frac{\delta\beta_s}{\delta\beta_s - (1-\alpha n)}\left[\frac{-\delta Q_{\sum s}^{o}(1-\beta_s)}{\delta\beta_s}(1-\alpha n) + \alpha n Q_r^{best}\right] - Q_{r,s}^{o} \quad (26)$$

From FC [34], the differential term D^{λ} is obtained which is incorporated on the update position of REHO for computing the final update position of proposed Fractional REHO and is mathematically represented as,

$$D^{\lambda}\left[Q_{r,s}^{o+1}\right]=\frac{\delta\beta_s}{\delta\beta_s-(1-\alpha n)}\left[\frac{-\delta Q_{\sum s}^{o}(1-\beta_s)}{\delta\beta_s}(1-\alpha n)+\alpha n Q_r^{best}\right]-Q_{r,s}^{o} \tag{27}$$

where, λ signifies fractional coefficient.

$$Q_{r,s}^{o+1}-\lambda Q_{r,s}^{o}-\frac{1}{2}\lambda Q_{r,s}^{o-1}-\frac{1}{6}(1-\lambda)Q_{r,s}^{o-2}+\frac{1}{24}\lambda(1-\lambda)(2-\lambda)Q_{r,s}^{o-3}=$$
$$\frac{\delta\beta_s}{\delta\beta_s-(1-\alpha n)}\left[\frac{-\delta Q_{\sum s}^{o}(1-\beta_s)}{\delta\beta_s}(1-\alpha n)+\alpha n Q_r^{best}\right]-Q_{r,s}^{o} \tag{28}$$

$$Q_{r,s}^{o+1}=\lambda Q_{r,s}^{o}+\frac{1}{2}\lambda Q_{r,s}^{o-1}+\frac{1}{6}(1-\lambda)Q_{r,s}^{o-2}-\frac{1}{24}\lambda(1-\lambda)(2-\lambda)Q_{r,s}^{o-3}+$$
$$\frac{\delta\beta_s}{\delta\beta_s-(1-\alpha n)}\left[\frac{-\delta Q_{\sum s}^{o}(1-\beta_s)}{\delta\beta_s}(1-\alpha n)+\alpha n Q_r^{best}\right]-Q_{r,s}^{o} \tag{29}$$

The final update equation of Fractional REHO is given as,

$$Q_{r,s}^{o+1}=Q_{r,s}^{o}(\lambda-1)+\frac{1}{2}\lambda Q_{r,s}^{o-1}+\frac{1}{6}(1-\lambda)Q_{r,s}^{o-2}-\frac{1}{24}\lambda(1-\lambda)(2-\lambda)Q_{r,s}^{o-3}+$$
$$\frac{\delta\beta_s}{\delta\beta_s-(1-\alpha n)}\left[\frac{-\delta Q_{\sum s}^{o}(1-\beta_s)}{\delta\beta_s}(1-\alpha n)+\alpha n Q_r^{best}\right] \tag{30}$$

Step 4) Re-evaluation of update solutions: The error of solution update is re-evaluated, wherein the weights linked to the highest fitness are adapted for Deep-ConvLSTM training.
Step 5) Stopping criterion: The optimum weights are produced frequently until the utmost iteration is attained.

3.4.3. Fuzzy bounding theory

Whenever incremental data is added to the model, the error is computed and weights are updated without considering the weights of the previous instance. If the error computed by the current instance is less than the error of the previous instance then, the weights are updated based on the proposed Fractional REHO algorithm else if the error computed by the current instance is more than the error of the previous instance, then the classifiers are remodeled by setting a boundary for weight using fuzzy theory [33] and then, choose optimal weight using proposed Fractional REHO algorithm. On arrival of data d_{i+1}, the error e_{i+1} will be computed and that will be compared with that of previous data d_i. If $e_i < e_{i+1}$, then prediction with training based on Fractional REHO is done else the fuzzy bounding-based learning will be done by bounding the weights which is given as,

$$\omega^{B}=\omega^{t}\pm F^{s} \tag{31}$$

where, ω^{t} is weight at current iteration, and F^{s} signifies fuzzy score. For the dynamic data, extract the features $\{F\}$. Here, the membership degree is given as,

$$Membership\ Degree=\|\omega^{t-2}-\omega^{t-1}\| \tag{32}$$

where ω^{t-2} represent weights at iteration $t-2$, and ω^{t-1} signifies weights at iteration $t-1$. After updating the weight, the error is recomputed to ensure that the bounded weight is optimal. The process is iterated repeatedly until new data is added to confirm that the feasible weights are selected for prediction. Finally, when maximum iteration is attained, the procedure is terminated.

4. Results and Discussion

The effectiveness of developed Fractional REHO + Deep-ConvLSTM is evaluated using MSE and RMSE. The assessment is carried out by varying the training data from 50% to 90%.

4.1 Experimental Setup

The implementation of the proposed model is performed in MATLAB considering Windows 10 OS, i3 processor, and 2GB RAM.

4.2 Dataset Description

The stock market dataset [13] is used to carry out prediction of the stock market that consists of stock data of various companies, which are taken from the years 2000-2020. Here, two different datasets are used for performing stock market prediction, which are Reliance Communications, and Relaxo Footwear.

Dataset 1: Dataset-1 comprises stock data using Reliance communications daily considering the start date of 1 January 2019 to 1 December 2020.
Dataset-2: Dataset-2 consists of stock data using Reliance communications monthly considering the start date of 1 January 2000 to 1 December 2020.
Dataset-3: Dataset-3 consists of stock data using Reliance communications yearly considering the start date of 2000 to 2020.
Dataset 4: Dataset-1 consists of stock data using Relaxo Footwear daily considering the start date of 1 January 2019 to 1 December 2020.
Dataset-5: Dataset-2 consists of stock data using Relaxo Footwear monthly considering the start date of 1 January 2000 to 1 December 2020.
Dataset-6: Dataset-3 consists of stock data using Relaxo Footwear yearly considering the start date of 2000 to 2020.

4.3 Performance Measures

The performance metrics used for evaluating the efficiency of the proposed model concerning other models are briefed below.
MSE: It describes the difference between estimated value and actual classifier output, and is expressed as,

$$M = \left(K_n - e^{\tau}\right)^2 \tag{33}$$

where, K_n signifies classifier output, and e^{τ} denote estimated output.

RMSE: It indicates the square root difference between actual and estimated value, and is expressed as,

$$R = \sqrt{K_n - e^{\tau}} \tag{34}$$

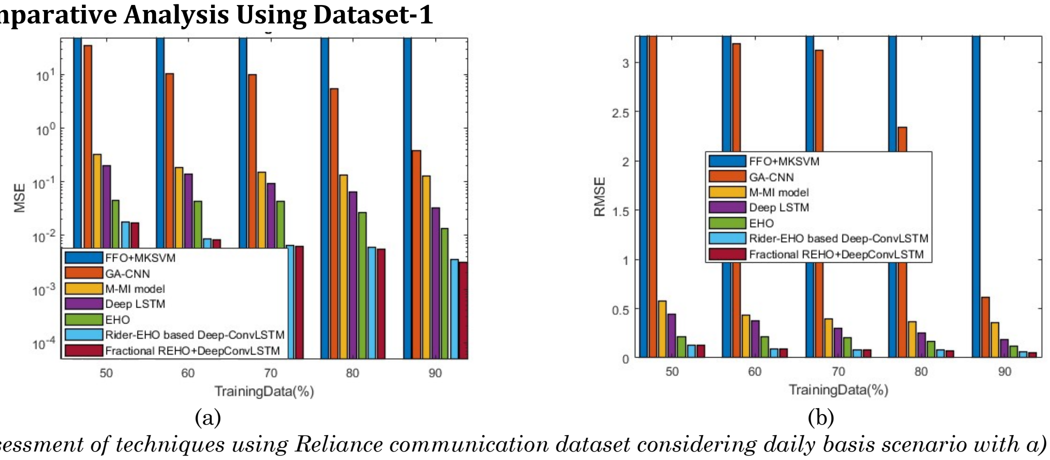
4.4. Comparative Methods

The methods employed for comparison include FFO+MKSVM [10], GA-CNN (Applied GA [11] on CNN), M-MI model [5], Deep LSTM [8], EHO [12], Rider-EHO based Deep-ConvLSTM and proposed Fractional REHO + Deep-ConvLSTM.

4.5 Comparative Analysis

The assessment of strategies is done using Reliance communications and Relaxo Footwear data considering daily, monthly, and yearly basis are evaluated. The analysis is performed by varying training data from 50% to 90%.

4.5.1 Comparative Analysis Using Dataset-1

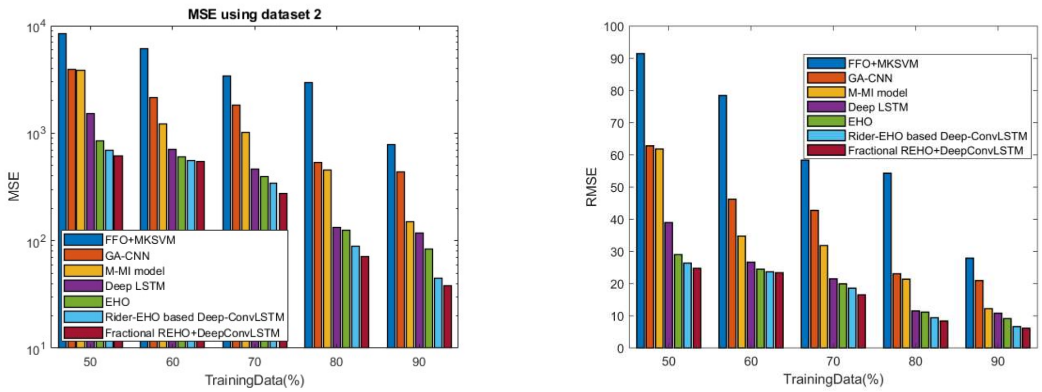


(a) (b)

Fig. 3. *Assessment of techniques using Reliance communication dataset considering daily basis scenario with a) MSE b) RMSE*

Fig. 3 presents the assessment of techniques using the Reliance communication dataset considering daily basis scenarios with MSE and RMSE. The assessment of techniques with MSE is depicted in Fig. 3a). For 50% training data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO+Deep-ConvLSTM are 427.076, 34.185, 0.328, 0.197, 0.044, 0.018, and 0.017. Likewise, for 90% of data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 86.386, 0.377, 0.129, 0.033, 0.013, 0.003, and 0.003. The assessment of techniques with RMSE is depicted in Fig. 3b). For 50% training data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 20.666, 5.847, 0.573, 0.444, 0.211, 0.133, and 0.132. Likewise, for 90% of data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 9.294, 0.614, 0.360, 0.182, 0.116, 0.059, and 0.057.

4.5.2 Comparative Analysis Using Dataset-2

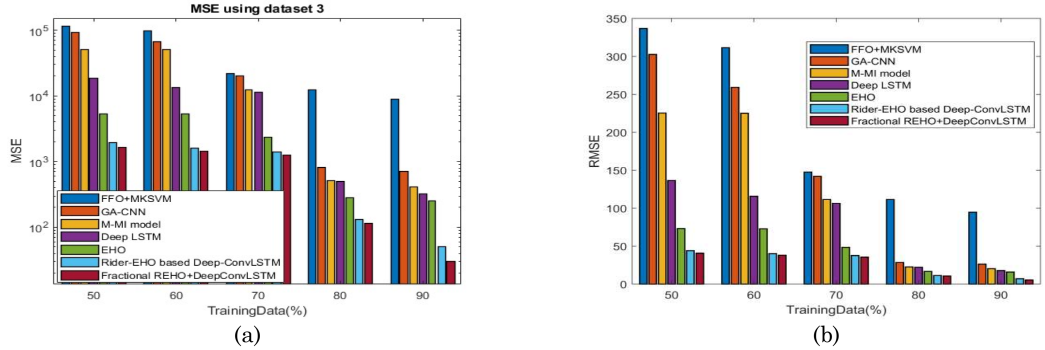


(a) (b)

Fig. 4. *Assessment of techniques using Reliance communication dataset considering monthly basis scenario with a) MSE b) RMSE*

Fig. 4 presents the assessment of techniques using the Reliance communication dataset considering monthly basis scenarios with MSE and RMSE. The assessment of techniques with MSE is depicted in Fig. 4a). For 50% training data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 8363.030, 3947.858, 3821.064, 1518.829, 840.559, 695.458, and 612.797. Likewise, for 90% of data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 779.248, 440.134, 150.028, 117.319, 83.308, 44.435, and 37.957. The assessment of techniques with RMSE is depicted in Fig. 4b). For 50% training data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 91.450, 62.832, 61.815, 38.972, 28.992, 26.372, and 24.755. Likewise, for 90% data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 27.915, 20.979, 12.249, 10.831, 9.127, 6.666, and 6.161.

4.5.3 Comparative Analysis Using Dataset-3

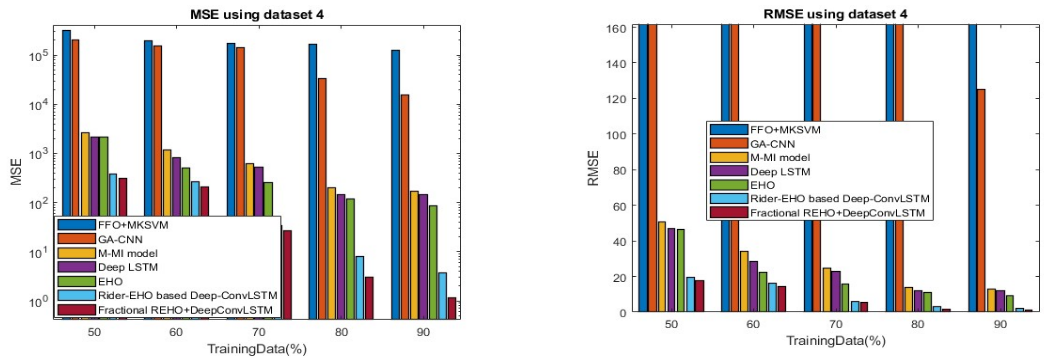


(a) (b)

Fig. 5. *Assessment of techniques using Reliance communication dataset considering yearly basis scenario with a) MSE b) RMSE*

Fig. 5 presents the assessment of techniques using the Reliance communication dataset considering a yearly basis scenario with MSE and RMSE. The assessment of techniques with MSE is depicted in Fig. 5a). For 50% training data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 113473.704, 91563.270, 50805.488, 18651.930, 5352.844, 1943.666, and 1662.114. Likewise for 90% data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 8997.309, 699.406, 413.183, 322.455, 253.156, 50.396, and 30.301. The assessment of techniques with RMSE is depicted in Fig. 5b). For 50% training data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 336.859, 302.594, 225.401, 136.572, 73.163, 44.087, and 40.769. Likewise, for 90% of data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 94.854, 26.446, 20.327, 17.957, 15.911, 7.099, and 5.505.

4.5.4 Comparative Analysis Using Dataset-4

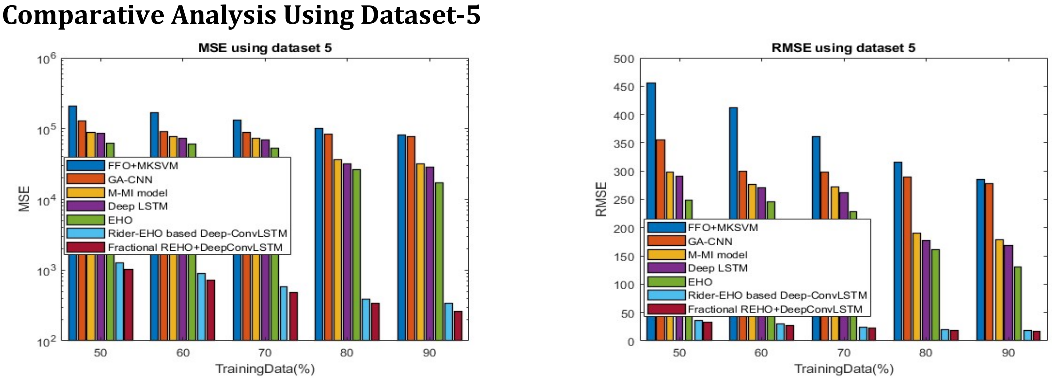


(a) (b)

Fig. 6. *Assessment of techniques using Relaxo Footwear dataset considering daily basis scenario with a) MSE b) RMSE*

Fig. 6 presents the assessment of techniques using the Relaxo Footwear dataset considering daily basis scenarios with MSE and RMSE. The assessment of techniques with MSE is depicted in Fig. 6a). For 50% training data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 311887.521, 206725.754, 2588.969, 2186.087, 2148.638, 386.354, and 305.506. Likewise, for 90% of data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 127871.562, 15644.667, 170.773, 142.793, 86.504, 3.731, and 1.172. The assessment of techniques with RMSE is depicted in Fig. 6b). For 50% training data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 558.469, 454.671, 50.882, 46.756, 46.353, 19.656, and 17.479. Likewise, for 90% of data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 357.591, 125.079, 13.068, 11.950, 9.301, 1.931, and 1.083.

4.5.5 Comparative Analysis Using Dataset-5

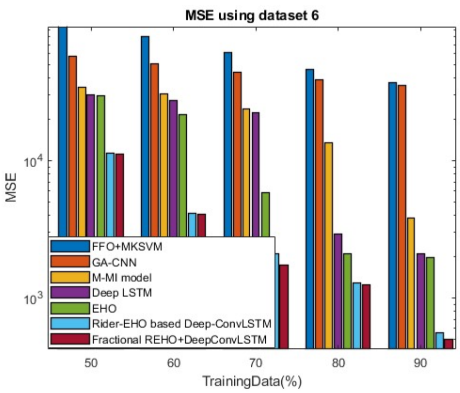


(a) (b)

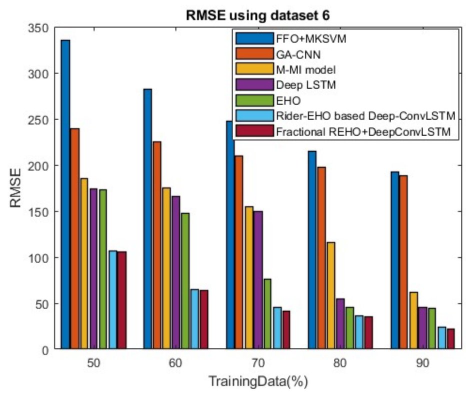
Fig. 7. *Assessment of techniques using Relaxo Footwear dataset considering monthly basis scenario with a) MSE b) RMSE*

Fig. 7 presents the assessment of techniques using the Relaxo Footwear dataset considering monthly basis scenarios with MSE and RMSE. The assessment of techniques with MSE is depicted in Fig. 7a). For 50% training data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 207972.264, 126494.828, 89025.129, 84931.522, 61506.676, 1274.588, and 1032.508. Likewise, for 90% data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 81332.992, 77380.833, 31816.548, 28424.865, 16968.819, 336.285, and 261.355. The assessment of techniques with RMSE is depicted in Fig. 7b). For 50% training data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 456.040, 355.661, 298.371, 291.430, 248.005, 35.701, and 32.133. Likewise for 90% data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 285.189, 278.174, 178.372, 168.597, 130.264, 18.338, and 16.166.

4.5.6 Comparative Analysis Using Dataset-6



(a)



(b)

Fig. 8. *Assessment of techniques using Relaxo Footwear dataset considering yearly basis scenario with a) MSE b) RMSE*

Fig. 8 presents the assessment of techniques using the Relaxo Footwear dataset considering a yearly basis scenario with MSE and RMSE. The assessment of techniques with MSE is depicted in Fig. 8a). For 50% training data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 112696.409, 57425.375, 34279.311, 30410.691, 29921.674, 11268.124, and 11096.675. Likewise for 90% data, the MSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 37075.898, 35269.354, 3800.855, 2105.128, 1968.611, 554.895, and 502.742. The assessment of techniques with RMSE is depicted in Fig. 8b). For 50% training data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are335.703, 239.636, 185.147, 174.387, 172.979, 106.151, and 105.341. Likewise, for 90% of data, the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, Rider-EHO based Deep-ConvLSTM, and proposed Fractional REHO + Deep-ConvLSTM are 192.551, 187.801, 61.651, 45.882, 44.369, 23.556, and 22.422.

4.6. Comparative Discussion

Table 1 elaborates on the assessment of strategies considering MSE and RMSE using Reliance communication and Relaxo Footwear dataset by employing daily, monthly, and yearly basis. Using dataset-1, the minimal MSE of 0.003 is computed by the proposed Fractional REHO + Deep-ConvLSTM while the MSE of the remaining FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, and Rider-EHO-based Deep-ConvLSTM are 86.386, 0.377, 0.129, 0.033, and 0.013 and 0.003. The minimal RMSE of 0.057 is evaluated by the proposed Fractional REHO + Deep-ConvLSTM whereas the RMSE measured by FFO+MKSVM, GA-CNN, M-MI model, Deep LSTM, EHO, and Rider-EHO based Deep-ConvLSTM are 9.294, 0.614, 0.360, 0.182, 0.116 and 0.059. Using dataset-2, the minimal MSE of 37.957 is computed by the proposed Fractional REHO + Deep-ConvLSTM while the minimal RMSE of 6.161. Using dataset-3, the minimal MSE of 30.301 and minimal RMSE of 5.505 is computed by the proposed Fractional REHO + Deep-ConvLSTM. With dataset-4, the proposed Fractional REHO + Deep-ConvLSTM measured a minimal MSE of 1.172 and minimal RMSE of 1.083. Using dataset-5, the proposed Fractional REHO + Deep-ConvLSTM measured a minimal MSE of 261.355 and a minimal RMSE of 16.166. With dataset-6, the proposed Fractional REHO + Deep-ConvLSTM measured a minimal MSE of 502.742 and a minimal RMSE of 22.422.

Table 1. *Comparative analysis*

Dataset	Metric	FFO+ MKSVM	GA-CNN	M-MI model	Deep LSTM	EHO	Rider-EHO based Deep-ConvLSTM	Proposed Fractional Rider-EHO based Deep-ConvLSTM
Dataset-1	**MSE**	86.386	0.377	0.129	0.033	0.013	0.003	0.003
	RMSE	9.294	0.614	0.360	0.182	0.116	0.059	0.057
Dataset-2	**MSE**	779.248	440.134	150.028	117.319	83.308	44.435	37.957
	RMSE	27.915	20.979	12.249	10.831	9.127	6.666	6.161
Dataset-3	**MSE**	8997.309	699.406	413.183	322.455	253.156	50.396	30.301
	RMSE	94.854	26.446	20.327	17.957	15.911	7.099	5.505
Dataset-4	**MSE**	127871.562	15644.667	170.773	142.793	86.504	3.731	1.172
	RMSE	357.591	125.079	13.068	11.950	9.301	1.931	1.083
Dataset-5	**MSE**	81332.992	77380.833	31816.548	28424.865	16968.819	336.285	261.355
	RMSE	285.189	278.174	178.372	168.597	130.264	18.338	16.166
Dataset-6	**MSE**	37075.898	35269.354	3800.855	2105.128	1968.611	554.895	502.742
	RMSE	192.551	187.801	61.651	45.882	44.369	23.556	22.422

5. Conclusion

This paper presents a novel strategy for dynamic learning in predicting the stock market. The purpose is to devise a stock market prediction system to ensure the effective prediction of the stock market. Initially, the stock data and review-based data are subjected as input to feature extraction. These technical indicators represent the features and are used for the stock market prediction using the predictor. For stock data, the technical indicators like APO, DMI, WILLR, SMA, TRIMA, and PPO are extracted as features, and from review-based data, the SentiWordNet-based features are extracted. Here, the reviews undergo a stemming and stop word removal process to make the review suitable for extraction. Thus, the extracted features are subjected to a feature fusion module, which is performed with KNN and holoentropy. Then, the fused features are subjected to Deep-ConvLSTM wherein the training of Deep-ConvLSTM is done using the proposed Fractional REHO algorithm. The proposed Fractional REHO is devised by combining FC and REHO algorithms. Here, the Deep-ConvLSTM is learned dynamically for stock market prediction. The proposed Fractional REHO-based Deep-ConvLSTM offered enhanced performance with the smallest MSE of 0.003 and RMSE of 0.057.

Compliance with Ethical Standards

Conflicts of Interest: Authors declared that they have no conflict of interest.

Human Participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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