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Original Article

Stock Market Price Trend Prediction Using Modified Recurrent Neural Network and Energised Chimp Optimization Algorithm (ECOA)

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Abstract - *Vast data is available for the Stock market, which gets instantly updated and corrected. The stock market is always forecasted as a non-linear time series due to its volatility characteristics. There are many variables that affect the Stock price. Using a simple model to predict is difficult. To overcome this gap, a new deep learning-based stock market price prediction model is used to predict the best time to buy/sell shares. Refinement, extraction of features, feature selection, and stock price prediction are the four fundamental steps of the predictive paradigm. The new Energised Chimp Optimization Algorithm (ECOA) is designed to choose the best extracted features from the processed dataset. This ECOA model is an extended version of the standard Chimp Optimization Algorithm (COA). The new Modified Recurrent Neural Network is used to forecast stock market price trends (M-RNN). The M-RNN makes accurate predictions about stock price value. To improve the RNN's detection precision. The proposed model is then tested against the current models*.

Keywords - *Energised Chimp Optimization Algorithm (ECOA), Feature Extractions, Indicators, Modified Recurrent Neural Network (M-RNN), Stock Market Prediction.*

1. Introduction

A significant practical issue in the field of economics is Stock Market Prediction (SMP) [1]. Expert analysts and investors show interest and a strategic development process in predicting stock prices [2]. Due to the inherent noise in the environment and the unpredictable nature of market trends, SMP for trend analysis is complex [3]. The famous Efficient Market Hypothesis (EMH) expresses a pessimistic viewpoint and suggests that the financial market is effective for solving this issue by maintaining that technical analysis or fundamental analysis [4] would not consistently produce above-average profits for investors. A large number of researchers have resisted EMH. While other studies work to create accurate stock market prediction models, some studies attempt to scale the various efficiency levels for already evolved markets [5]. When it comes to stock market behaviour, a ton of historical data is available. Machine learning is important for the forecasting and evaluation of the movements of stocks using historical information. Several machine learning algorithms can be used to predict stock market movement [6]. However, there is no method that can correctly forecast changes in the stock market. Performance evaluation of various machine learning algorithms is required in order to identify the suitable algorithm that will result in the most precise and ideal stock movement predictions and, as a result, minimise financial losses for stock market investors. Recurrent Neural Networks (RNNs) are employed because the stock data needs to take into account long-term data dependencies. The following exhibits the research's main contribution and is presented in the paper as the main novel approach to identify the best forecasting technique that can be implemented in the paper in order to find the best predictive method for forecasting the stock market:

- To extract the improved statistical feature-based features to improve the suggested model's predictive performance.
- To use the energised chimp optimization algorithm to select the best features from the features extracted.
- A modified Recurrent Neural Network (M-RNN) is used to predict the price volatility of the stock market's cost.

2. Literature Survey

In 2020, Reddy et al. [16] examined the effectiveness of techniques for stock market forecasting in light of the development of deep learning architectures and sophisticated computational processors. A comparison is made between the efficacy of standard Long Short-Term Memory (LSTM), stacked LSTMs, Auto-Regressive Integrated Moving Average (ARIMA), and exponential smoothing models. Portfolio optimization technique was suggested to determine returns and keep profits while investing in the stock market.

In 2019, Pathak et al. [17] researched creating a much more accurate forecast by combining multiple methods, and it should be capable of dealing with a variety of situations where investing may be helpful.

The application of current methods, like sentiment classification or neural methods, may be too restricted, resulting in erroneous results in a variety of conditions. By utilizing both methods, this forecasting model can provide suggestions that are more precise and adaptable. Investors can lower risk and boost returns by using technical indicators.

In 2020, Qiu et al. [18] proposed the RNN model, which is a hybridised model with the best work on stock market timing to produce results using the LSTM and Gated Recurrent Unit/GRU. Performance was increased by developing a novel model with a 3-layer LSTM, 3-layer GRU, and 1-layer ReLU.

In 2019, Jarrah et al. [19] used the Saudi stock price trends to predict using an RNN and a Discrete Wavelet Transform (DWT) based on price history. The DWT method helped reduce the noise surrounding the data taken from the Saudi stock market based on a small number of carefully chosen samples of companies.

In 2018, Liu et al. [20] suggested a method of predicting stock prices using Numerical-Based Attention (NBA). With the help of encoding, that method chooses the numerical data from the news. This transformation removed noise and utilised relevant stock trend information.

In 2019, Wen et al. [21] presented the rebuilding of time series using high-order structures, which is a novel approach for predicting financial time series trends. CNN or Convolutional Neural Networks, work in learning patterns in the reconstructed series, which yields information that can be used to predict ups and downs. Here, the approach was remarkably less computationally complex when compared to earlier work that makes use of sequential models like recurrent neural networks.

In 2018, Chung et al. [22] developed a Recurrent-based stock forecasting model using LSTM units, one of the common deep learning techniques. Then, the Genetic Algorithm (GA) and LSTM networks were combined with the model's customised architectural components to consider the stock market's temporal characteristics. In 2022, Leippold et al. [23] worked on different Machine learning methods to predict the best trends of the stock market in China. Then, discovered that liquidation in trading was the most important factor. A stock's shares must mature over a span of many years before it possesses the characteristics that enable and promote fundamental investments. However, findings reveal that factors affecting stocks are the second most important factor category, despite the fact that the Chinese stock market was moving in that direction.

In 2018, author Zhang et al. [24] shared a novel share price trend forecast model that can predict all share prices and their period of growth within already scheduled durations. After using an unsupervised heuristic algorithm to split each stock's raw payment information into several frames of a predetermined fixed length, it categorizes those clips into four primary categories according to the trends of their costs.

In 2019, Zhou et al. [25] integrated a strategy for price prediction in trading, which is presented using NN factorization machines and Empirical Mode Decomposition (EMD). IMFs, which can be observed as quasi-stationary through EMD, are created from the original non-stationary and non-linear time series.

3. Problem Statement

The behavior of a company and other unforeseen international, national, and societal occurrences are generally brought to the attention of investors while making a decision on whether or not to buy or sell a stock. Although such occurrences are bound to instantly affect stock prices, either in a positive or a negative way, in most instances, the effects do not last long. Thus, applying FA to predict stock prices and trends is not feasible. Consequently, an automation process or design is proposed to assess the share market and forthcoming stock movements using historical costs and STI. Based on previous price data, determining strongly correlated STIs is laborious and could result in inaccurate predictions.

Therefore, identifying highly correlated STIs is a challenge that is addressed as a problem. The share price moves in a chaotic way, and traditional machine learning and deep learning techniques yield unimpressive results [7]. App of the Optimum LSTM Deep learning framework and adaptive STI is essential for creating an accurate estimation. An approach was applied where the ideas were integrated, and the outcomes were better. The majority of earlier works, which are overfitted, did not examine the algorithm's prediction accuracy. A company's stock value changes every day in reaction to market shifts, which is still the biggest issue in forecasting. Numerous regression and classification techniques are already available for stock forecasting. The main agenda is to discover the best methods offered to improve stock forecasting outcomes and provide precise patterns or forecasting units, weekly or monthly, for the best-suited trading time. Additionally, to deliver enhanced performance with high precision and a low error rate, new kernel functions should be considered.

4. Proposed Stock Market Price Prediction Model

4.1. Proposed Model: An Architectural Description

The stock price forecast makes an effort to predict possible changes in the stock value on the financial exchange. The accuracy of the share price movement prediction would increase investor returns [8]. The new stock market prediction model presented in this paper has four main phases. Pre-processing, feature extraction, best feature choice, and price prediction.

4.1.1. Step 1: Pre-processing

The stock market data S_i^{in} $(i = 1,2, \dots N)$that has been collected is first pre-processed using Min-Max data scaling and data cleaning. Here, N denotes the number of data points. Initially, this $S_i^{in}$is subjected to data cleaning, wherein the missing values and null values in S_i^{in} are removed. The data acquired after the data cleaning approach is pointed out as S_i^{clean}which is also known as MinMax data scaling.

4.1.2. Step 2: Feature Extraction

The enhanced statistical features are then extracted from S_i^{norm}, including Mean, Correlated Skewness, Standard Deviation, Median, and regression Moments. Additionally, S_i^{norm} is used to extract the common indicator-based features such as Exponential Moving Average or EMA, Relative Strength Index or RSI, Average True Range or ATR, and Rate of Change or ROC [9]. The extracted statistical and standard indicator-based features are indicated as $S_i^{stat}$and S_i^{ind}, respectively. These S_i^{stat} and S_i^{ind} are fused together, and they are represented using the symbol F_i^{feat}.

4.1.3. Step 3: Feature Selection

Among the features extracted F_i^{feat}, the optimum features are chosen using the new Energized Chimp Optimization Algorithm (ECOA). The isolated optimal features are pointed out as F_i^{opt}.

4.1.4. Step 4: Stock Market Price Prediction

Using the new Modified Recurrent Neural Network (M-RNN), stock market price trends are projected. The stock price value is predicted accurately by the M-RNN, as its loss function has been modified from the cross-entropy function to the Root Mean Square function. This M-RNN is trained using. F_i^{opt}. The final outcome regarding the price volatility will be forecasted accurately by M-RNN as shown in Figure 1.

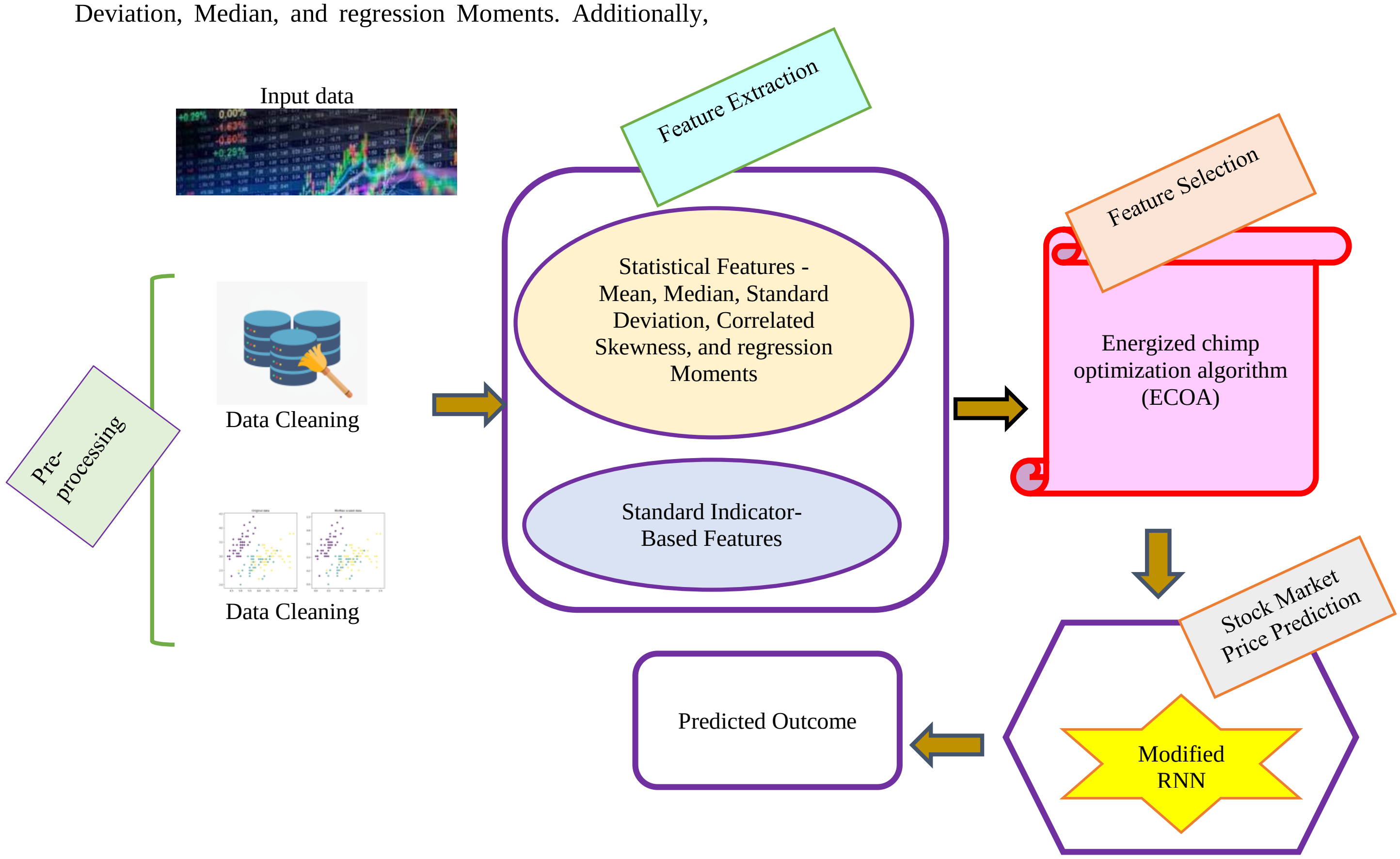


Fig. 1 Proposed architecture

4.2. PreProcessing

The stock market data S_i^{in} $(i = 1,2, \dots N)$ that has been collected is first pre-processed using Min-Max data scaling and data cleaning. Missing values and null values in this $S_i^{in}$are first removed during the data cleaning process. The acquired data is designated as S_i^{clean}, after the data cleaning method. This $S_i^{clean}$is scaled using MinMax data [10]. "The so-called Min-Max scaling is an alternative method to Z-score normalisation (or standardisation). It is also frequently referred to as "normalisation". This method scales the data to a fixed range, typically 0 to 1. $S_i^{norm}$is the abbreviation for the data obtained after Min-Max data scaling. The statistical and standard indicator-based features were extracted from S_i^{norm}.

4.2.1. Data Cleaning

The input to data cleaning is S_i^{in}. The goal of data cleaning is accomplished by filling the null, locating and eradicating isolated data, smoothing noisy data, and resolving discrepancies. The different ways to deal with missing values include handling uncleaned data, modifying incorrect data, and removing unnecessary information. Through data cleansing, errors are reduced and data quality is increased, but correcting data and removing false information is time-consuming. The final outputS_i^{clean}.

4.2.2. Min-Max Data Scaling

$S_i^{clean}$is subjected to Min-Max data scaling. Feature scaling is a method that minimised the independent variables or attributes present in information. The source dataset is transformed linearly using min-max normalisation, also known as scaling of features. This methodology obtains all the scaled data within the range of [0, 1]. This can be done using Equation (1)

$$a_{scaling} = \frac{a - a_{min}}{a_{max} - a_{min}} \tag{1}$$

Where, a_{min} defines the minimum value and a_{max} is the maximum value. The data acquired after Min-Max data scaling is denoted as is S_i^{norm}. From S_i^{norm}, the statistical and standard indicator-based features extracted [11].

4.3. Feature Extraction

From the pre-processed data S_i^{norm}, improved statistical features and standard indicator features are extracted.

4.3.1. Statistical Features

The extracted statistical and standard indicator-based features are indicated as $S_i^{stat}$and S_i^{ind}, respectively.

4.3.2. Mean

The sum of all items divided by the number of elements in a collection is referred to as the mean. Through Mean calculation, one can gather a complete set of knowledge of the whole data. Consequently, the mean formula is calculated as per Equations (2) and (3)

$$Mean = \frac{Sum\ of\ all\ the\ elements}{Number\ of\ elements} \tag{2}$$

$$\bar{x} = \frac{\sum S_i^{norm}}{N} \tag{3}$$

Where, $\bar{x}$ = mean value, S_i^{norm}= Pre-processed data, N = Total number of elements.

The usefulness of the mean is in its ability to represent the entire dataset as a single value.

4.3.3. Median

The midpoint of the data after the rankings have been arranged in ascending order is known as the median [12]. The number of numbers above and below the median is equal.

If n is even, the median is defined as per Equation (4)

$$M = \frac{\left(\frac{S_i^{norm}}{2}\right) + \left(\frac{S_i^{norm}}{2} + 1\right)}{2} \tag{4}$$

If n is odd, the median is defined as per Equation (5)

$$M = \frac{S_i^{norm} + 1}{2} \tag{5}$$

4.3.4. Standard Deviation

A measurement that depicts the degree of variance from the Mean is the standard deviation. The amount of variance from the Mean is maintained by the standard deviation. The standard deviation has a unique origin and size, but it is also helpful.

$$SD\ (\sigma) = \sqrt{\frac{\sum (S_i^{norm} - \mu)^2}{N}} \tag{6}$$

4.3.5. Correlated Skewness

The skewness of a distribution serves as a gauge of its symmetry. The major disadvantage of the skewness is that it is unpredictable.

To solve this issue, the Correlation Coefficient is newly introduced within the standard skewness.

According to Equation (7), a normal distribution shows no skewness and is completely symmetrical.

$$skewness = \frac{3(HM - Median)}{StandardDeviation} * Cov(A, B) * \varepsilon \tag{7}$$

Here, Cov(A, B) is the covariance between the variables A and B of S_i^{norm}. Mathematically, the correlation coefficient ε is given as per Equation (8).

$$\varepsilon = \frac{N * \sum(A,B) - (\sum(A) * \sum(B))}{\sqrt{(N * \sum(A^2) - \sum(B^2)) * (N * \sum(B^2) - \sum(B^2))}} \tag{8}$$

4.3.6. Regression Moments

A random variable's variance and expected value are specific instances of the quantities known as this variable's moments. "The regression analysis is a powerful tool for uncovering the associations between variables observed in data. A regression model is able to show whether changes observed in the dependent variable are associated with changes in one or more of the explanatory variables". The extracted statistical features are indicated as S_i^{stat}.

4.4. Standard Indicator Feature

4.4.1. Average True Value (ATR)

The first step is finding a series of true range values for a security in the ATR calculation process. An asset's price range for a specific trading day is equal to its high minus its low [13]. However, the true range is broader and is defined as per Equations (9) and (10)

$$TR = MAX\left[(L-H), Abs\left(L-A_p\right), Abs\left(H-A_p\right)\right] \quad (9)$$

$$ATR = \left(\frac{1}{m}\right)\sum_{n=1}^{i} TR_n \quad (10)$$

Where, $TR_n$is the particular true range, and i is the employed time period.

4.4.2. Exponential Moving Average (EMA)

The price of a financial instrument is tracked over time using the widely used technical chart indicator known as the Exponential Moving Average (EMA). EMA is calculated as per Equation (11)

$$EMA = Closed\ price \times Multiplier + EMA(last\ day) \times (1 - Multiplier) \quad (11)$$

4.4.3. RSI-Relative Strength Index

The measurement of the change in price momentum is the goal of the RSI indicator. As per Equations (12) and (13), RSI is calculated.

$$RSI = 100 - \frac{100}{1+RS} \quad (12)$$

$$RS = \frac{Avg\ gain}{Avg\ loss} \quad (13)$$

4.4.4. ROC-Rate of Change

ROC is a mathematical model that represents the percentage value change over a predetermined amount of time and measures a variable's movement. Formula for rate of change according to Equation (14).

$$Roc = \frac{(E_2 - E_1)}{T} \quad (14)$$

Where, Roc is the rate of change, E defines the distance estimated at the start and end of the time frame, and T is the duration during which that change occurred [14]. The extracted standard indicator-based features are indicated as S_i^{ind}.

The resultant features F_i^{feat} and the favourable features are selected using the new ECOA model or Energised chimp optimization algorithm.

5. Energised Chimp Optimization Algorithm (ECOA)

The ECOA model is a conceptual enhancement for the standard COA model. The chimps in each group develop a distinct search strategy, and thus they search the space independently. In any group, chimps have different levels of intelligence and abilities and play different roles in work. Although they are colonists, every chimpanzee has a definite role. The grouping involves four major categories, namely: drivers, barriers, chasers, and attackers.

Drivers stick very close to the prey without attempting to overtake it. The barriers place themselves in the way of the prey in order to hinder their way. Chasers pursue the prey on foot in an attempt to shorten the gap. Predators anticipate the escape direction of the prey in the lower canopy and intersect. All the roles contribute to the group's hunting strategy. With this division of labor, they are better able to capture the target efficiently. For chimpanzees, "there are two processes with which hunting is done in a distinct way: Drive, block, and chase are part of the expedition group.

Prey attacked by an attacker constitutes the misuse phase. To stop the exploitation and prevent it from becoming trapped in the local optima, the random position $Y_{Rand}(t)$and the mean position of the search agent $Y_{m\_pr}(t)$ is considered. In addition, the lower bound lb and upper bound ub [15] of the solutions are also considered". This consideration of ub and lb prevents the solutions from going beyond the search space. This is mathematically given in Equations (15) to (20), respectively.

$$c = \left|\left(d.Y_{m_{pr}}(t)\right) - n.\left(Y_{Rand}(t) - 2.ra_1.Y_{Ch}(t)\right)\right| * ra_1(lb + ra_2.(ub - lb) \quad (15)$$

$$Y_{ch}(t+1) = Y_{pr}(t) - b.c \quad (16)$$

$$b = 2.f.ra_1 - f \quad (17)$$

$$d = 2.ra_2 \quad (18)$$

$$n = Chaotic\_value \quad (19)$$

$$f = 2 - \frac{2t}{T} \quad (20)$$

Equations (15) and (16) represent "the driver and chaser". Here, t represents the number of reiterations, $b, n, and\ d$ depict the variant vectors, and $Y_{m_pr}(t)$and Y_{Ch}, discretely, depicts the Mean positions of the group of prey and the chimps. Equations (17) to (19) calculate $b, n, and\ d$ variables [16]. With every count, f trends decreases asynchronously from 2.5 to 0. $ra_1$and ra_2 represents random vectors within the range of [0,1]. Also, n is a vector which is disorganized and can be calculated through various Chaotic maps while T represent the number of maximum iterations. t is the current iteration".

5.1. Exploration and Exploitation Transformation (Proposed)

A key element in the transitional phase is the prey's escape energy E, which is assessed and shown in Equations (21) and (22), respectively.

$$E = 2.\left(1 - \frac{t}{T}\right) \tag{21}$$

$$E = E^0.E^1 \tag{22}$$

Here, t, T denotes the current and maximal iteration, respectively. In addition, $E^0$is the initial energy of the prey.

5.2. Weighted Exploration phase (Proposed)

The prey's position is considered to be the same as that of the attacker in the model proposed. With this information, the attacker will be able to vary the positions of the barrier, the driver and the catcher accordingly. It is part of the coordination that aids in perfecting the hunting strategy. It makes sure that all roles are aligned depending on the position of the attacker.. The 4 excellent choices were kept, while the other chimps updated their location to match the best chimp location. Equation. (23) to Equation. (28) explained as follows:

$$d_{att} = |b_1 Y_{attack} - n_1 Y| \tag{23}$$

$$d_{bar} = |b_2 Y_{barr} - n_2 Y| \tag{24}$$

$$d_{cha} = |b_3 Y_{chas} - n_3 Y| \tag{25}$$

$$d_{dri} = |b_4 Y_{driv} - n_4 Y| \tag{26}$$

$$\bar{y}_1 = Y_{att} - b_1(\bar{d}_{attack}), \bar{y}_2 = Y_{barr} - b_2(\bar{d}_{barr}), \bar{y}_3 = Y_{cha} - b_3(\bar{d}_{chas}), \bar{y}_4 = Y_{dri} - b_4(\bar{d}_{driv}) \tag{27}$$

$$y(t+1) = \frac{\omega_1 y_1 + \omega_2 y_2 + \omega_3 y_3 + \omega_4 y_4}{4} \tag{28}$$

Here, weight $\omega_1, \omega_{2,}\omega_3, \omega_4$are the weights of the Drivers, barriers, chasers, and attackers [17]. This weight function is newly introduced within the standard COA model. First of all, all of the weights should be varied and limited to 1.0. This weight function can be mathematically given as per Equation (29).

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1 \tag{29}$$

5.3. Phases of Exploitation (Proposed)

Another parameter, b and d, was added and used in the exploration phase to avoid a hurdle in the local minima of the exploitation phase. If the absolute value of a is larger than 1 (|a| > 1), the chimpanzees are instructed to move out of the way to escape local optima. On the other hand, when |a| < 1, they are directed to move towards the location of the prey, in the effort to achieve the global optimum. Random vector represented as d lies within the range of [0, 2], which ensures that random weights to prey can increase $(c > 1)$ or may decrease $(c < 1)$. The prey's position affects the concept of distance in Equations (27) and (28). When $\mu < 0.5$, the new position of the solution was updated using the $\lfloor \Delta Y_{ch}(t) \rfloor$ (energy of escape) and δ (escape potential) function. Also, when $\mu > 0.5$, the solutions computed position was updated using a chaotic map, but, in ECOA, the new positions of the solution will be updated based on the energy function, potential of escape parameter and the Levy function $LF(d)$. These parameters help in finding the global solutions rapidly [18]. The chaotic maps that COA employs perform optimally. In the model as suggested, $E\lfloor \Delta Y_{ch}(t) \rfloor$ (energy of escape) and δ (escape potential) is introduced first Time, for efficient capture of the prey". Equation (30) is utilized in the method as a model of the updating process:

$$Y_{ch}(t+1) = \begin{cases} Y_{pr}(t) - b.c.E\lfloor \Delta Y_{ch}(t) \rfloor.\delta & \mu < 0.5 \\ \Delta Y_{ch}(t) - E\lfloor \delta.Y_{pr}(t) - Y_{ch} \rfloor.LF(d) & \mu > 0.5 \end{cases}$$

$$\Delta Y_{ch}(t) = Y_{pr}(t) - Y_{ch}(t) \tag{30}$$

Here, μ is the random number in [0,1]

6. Modified Recurrent Neural Network (M-RNN)

A common artificial neural network type used in natural language processing and speech recognition is the RNN. The following most likely scenario can be predicted using an RNN by identifying patterns in the data. The main reason is that all can transmit data at each time step thanks to the RNN's structure.

$$c_k^{(i)} = \sigma\left(B_g^{(i)}.\left[c_{k-1}^{(i)}, x_k^{(i)}\right] + M_r^{(i)} c_{k-1}^{(i)} + d_g^{(i)}\right) \tag{31}$$

LSTM, "which uses a gate mechanism to control information flow and information loss, was developed to address the long-term stability issue [19]. Important parts of the LSTM include the input, output, and forgotten gates. The forward propagation procedure has an expression in Equations (32) to(37). In reality, the LSTM's cell state is made up of two parts: the first is long-term memory from a previous moment multiplied by the forgotten gate, and the second is newly learned information from this moment multiplied by the input gate".

$$j_k^{(i)} = \sigma\left(b_j^{(i)}.\left[a_{k-1}^{(i)}, x_l^{(i)}\right] + d_j^{(i)}\right) \tag{32}$$

$$g_k^{(i)} = \sigma\left(B_g^{(i)}.\left[a_{k-1}^{(i)}, x_l^{(i)}\right] + d_g^{(i)}\right) \tag{33}$$

$$o_k^{(i)} = \sigma\left(b_o^{(i)}.\left[a_{k-1}^{(i)}, x_l^{(i)}\right] + d_o^{(i)}\right) \tag{34}$$

$$a_k^{(i)} = o_k^{(i)}.tanh(L_l) \tag{35}$$

$$\tilde{L}_k{}^{(i)} = tanh\left(b_c^{(i)}.\left[a_{k-1}^{(i)}, x_l^{(i)}\right] + d_c^{(i)}\right) \tag{36}$$

$$L_k^{(i)} = g_k^{(i)}.L_{k-1}^{(i)} + j_k^{(i)}.\widetilde{L_k}^{(i)} \tag{37}$$

Here, $j_k^{(i)}$, $g_k^{(i)}$, $o_k^{(i)}$ and $L_k^{(i)}$ are the ith LSTM layer's input, forgotten, output gate, and cell state at time k ; $B_j^{(i)}$, $B_g^{(i)}$, $B_o^{(i)}$, $B_c^{(i)}$are coefficient matrices, weight, and $d_j^{(i)}$, $d_g^{(i)}$, $d_o^{(i)}$and $d_c^{(i)}$are vectors of bias [20]. The loss subsidiary appraises the disparity between the forecasted output and the actual output. Binary classification problems helped calculate the binary cross-entropy. Although it can add some sparsity to the dual (but not necessarily), it does not help in an effective way for probability estimation. It, instead, penalizes misclassifications, which makes it useful in computing the decision margin, since the hinge loss reduces when there are fewer violations of the margin [21]. In order to overcome this shortcoming, an alternative to cross-entropy, named RMSE (Root Mean Squared Error), is presented. RMSE is commonly used to find the performance of a model in predicting continuous values, and it is especially efficient since it gives a greater penalty to larger errors [22]. The loss function is mathematically given as per Equation (38).

$$loss = RMSE \tag{38}$$

The minimization of this loss function is the objective of this study. The objective function obj can be mathematically given as per Equation (39).

$$obj = \min(RMSE) \tag{39}$$

7. Proposed Algorithm

Here, the algorithm worked on a large span of data input from the stock market. Detailed steps followed, along with pseudocode explained below:

Input: Raw dataset S_i^{in}
Output: Predicted output $Y_i^{\wedge}$
1. Begin
2. Data Cleaning
   2.1. Consider the Raw input data of the stock market in S_i^{in}
   2.2. Detect and remove isolated or noisy data
   2.3. Resolve discrepancies to obtain cleaned data S_i^{clean}

3. Data Normalization
   3.1. Apply Min-Max scaling on S_i^{clean} using:
   $a_{scaling} = \frac{a - a_{min}}{a_{max} - a_{min}}$
   3.2. Obtain normalized data S_i^{norm}

4. Feature Extraction
   4.1. Extract Statistical Features considering the native neural network from S_i^{norm}:
   - Mean, Median, Standard Deviation, Correlated Skewness, Regression Moments→ S_i^{stat}
   4.2. Extract Standard Indicator Features using the best market indicators, like:
   - ATR, EMA, RSI, ROC→ S_i^{ind}
   4.3. Combine features from the output of Statistical features & Standard indicator feature:
   $F_i^{feat} = S_i^{stat} \cup S_i^{ind}$

5. Feature Selection using ECOA
   5.1. Initialize famous chimp population with roles: driver, barrier, chaser, attacker
   5.2. Execute exploration using driver, barrier, and chaser logic in order to find the best time and method.
   5.3. Execute exploitation using attacker and energy-based position updates
   5.4. Evaluate and select optimal features F_i^{opt}

6. Classification using Modified RNN (M-RNN)
   6.1. Input optimal features F_i^{opt} into M-RNN
   6.2. Apply forward propagation using LSTM-based gates (input, forget, output)
   6.3. Update hidden state and memory using equations based on gates (input, forget, output)
   6.4. Calculate RMSE loss:
   $loss = RMSE$
   6.5. Minimize loss:
   $obj = \min(RMSE)$

7. Return predicted output $Y_i^{\wedge}$
End

It gives a detailed explanation about the algorithm used in this paper, along with the code explaining the input series and the expected outcome.

8. Result and Discussion

8.1. Research Framework

The resultant model was formulated using MATLAB. The acquired dataset helps in evaluating the required collected data [26]. Comparison and evaluation of the proposed method's performance with the current set of framework such as LSTM, Bi-LSTM, RNN, and GRU or Gated recurrent unit for the prediction of the stock market price and Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), COA (Chimp Optimization Algorithm), and GA (Genetic algorithm) for feature selection [23]. Effectiveness of the proposed model was evaluated in terms of "Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Tables 1, 2, and 3 show the outcomes acquired for the proposed work for varying the open/close, high/low/close, and high/low/open/close cases, respectively", for the prediction [24]. Tables 4, 5, and 6 show the outcomes acquired for the proposed work for feature selection. Tables 7 and 8 explain the extracted and selected features.

8.2. Performance Analysis

8.2.1. Predictive analysis case1-open/close

The proposed model recorded by MAE=0.0552, MAPE=11.72133, RMSE=0.065558, NMSE=0.0139, and Cross entropy loss=0.632104. Among these methods, the proposed model has recorded the lowest values. The proposed method is recommended as the most accurate stock price predictor. Table 1 displays the obtained results.

8.2.2. Predictive analysis case2-low/high/close

At the high/low/close case, "MRNN, RNN, Bi-LSTM, LSTM, and GRU are evaluated in terms of MAE, MAPE, RMSE, NMSE and cross-entropy loss [25]. The acquired results are shown in Table 2. As per the acquired result, the proposed model, MRNN, has recorded the lowest error value compared to the existing model. Thus, MRNN is suggested as the best method for prediction purposes".

8.2.3. Predictive Analysis case3-high/low/open/close

The findings obtained are presented in Table 3. The RMSE recorded by the proposed model is 0.65161, which is better than existing models [26]. When compared to the results obtained, the suggested technique has the smallest error value, making it the best option for the prediction of stock prices.

Table 1. Prediction analysis case 1: open/close

Models	MAE (3-decimal)	MAPE (3-decimal)	RMSE (3-decimal)	NMSE (3-decimal)	Cross Entropy Loss (3-decimal)
MRNN	0.055	11.721	0.066	0.014	0.632
RNN	0.064	13.398	0.077	0.019	0.637
Bi-LSTM	0.197	41.190	0.229	0.136	0.754
LSTM	0.166	35.105	0.191	0.099	0.701
GRU	0.340	72.291	0.389	0.329	0.937

Table 2. Prediction analysis case 2: low/high/close

Models	MAE (3-decimal)	MAPE (3-decimal)	RMSE (3-decimal)	NMSE (3-decimal)	Cross Entropy Loss (3-decimal)
MRNN	0.056	12.008	0.067	0.014	0.630
RNN	0.065	13.585	0.078	0.019	0.634
Bi-LSTM	0.200	41.144	0.230	0.137	0.736
LSTM	0.167	35.316	0.192	0.100	0.701
GRU	0.338	71.336	0.387	0.327	0.865

Table 3. Prediction analysis case 3: high/low/open/close

Models	MAE (3-decimal)	MAPE (3-decimal)	RMSE (3-decimal)	NMSE (3-decimal)	Cross Entropy Loss (3-decimal)
MRNN	0.055	11.616	0.065	0.014	0.631
RNN	0.064	13.659	0.079	0.020	0.637
Bi-LSTM	0.213	45.148	0.241	0.147	0.772
LSTM	0.168	34.703	0.194	0.102	0.713
GRU	0.318	67.243	0.370	0.305	0.876

Table 4. Feature selection case 1: open/close

Models	MAE (3-decimal)	MAPE (3-decimal)	RMSE (3-decimal)	NMSE (3-decimal)	Cross Entropy Loss (3-decimal)
SI-COA	0.059	12.226	0.072	0.016	0.633
COA	0.062	12.967	0.074	0.017	0.635
GWO	0.063	13.449	0.075	0.018	0.635
PSO	0.065	13.844	0.077	0.019	0.635
GA	0.065	13.714	0.077	0.019	0.636

Table 5. Feature selection case 2: high/low/close

Models	MAE (3-decimal)	MAPE (3-decimal)	RMSE (3-decimal)	NMSE (3-decimal)	Cross Entropy Loss (3-decimal)
SI-COA	0.062	12.920	0.073	0.017	0.633
COA	0.061	13.010	0.073	0.017	0.635
GWO	0.063	13.077	0.073	0.017	0.634
PSO	0.061	13.000	0.072	0.017	0.633
GA	0.064	13.732	0.076	0.019	0.634

Table 6. Feature selection case 3: high/low/open/close

Models	MAE (3-decimal)	MAPE (3-decimal)	RMSE (3-decimal)	NMSE (3-decimal)	Cross Entropy Loss (3-decimal)
SI-COA	0.059	12.540	0.070	0.016	0.633
COA	0.064	13.575	0.076	0.018	0.635
GWO	0.066	13.891	0.077	0.019	0.636
PSO	0.064	13.421	0.074	0.018	0.635
GA	0.060	12.960	0.072	0.016	0.633

Table 7. Extracted features

Models	Mean (3-decimal)	Standard Deviation (3-decimal)	Median (3-decimal)	Skewness (3-decimal)	Moment (3-decimal)	ATR (3-decimal)	EMA (3-decimal)	RSI (3-decimal)	ROC (3-decimal)
Extracted Feature	0.869	0.017	0.867	-0.291	0.000	0.020	0.869	0.002	0.003
	0.873	0.016	0.881	-0.909	0.000	0.018	0.873	0.040	0.023
	0.873	0.017	0.881	-0.888	0.000	0.018	0.873	0.019	0.040

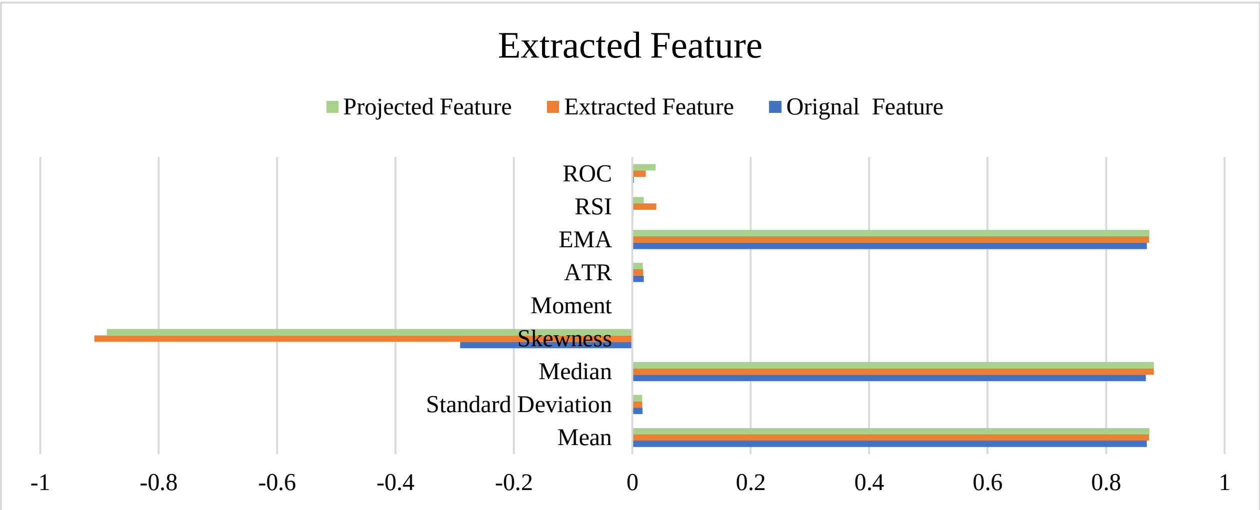
Table 8. Selected features

Models	Mean (3-decimal)	Skewness (3-decimal)	ATR (3-decimal)	EMA (3-decimal)	ROC(3-decimal)
Selected Feature	0.869	-0.291	0.020	0.869	0.003
	0.873	-0.909	0.018	0.873	0.023
	0.873	-0.888	0.018	0.873	0.040

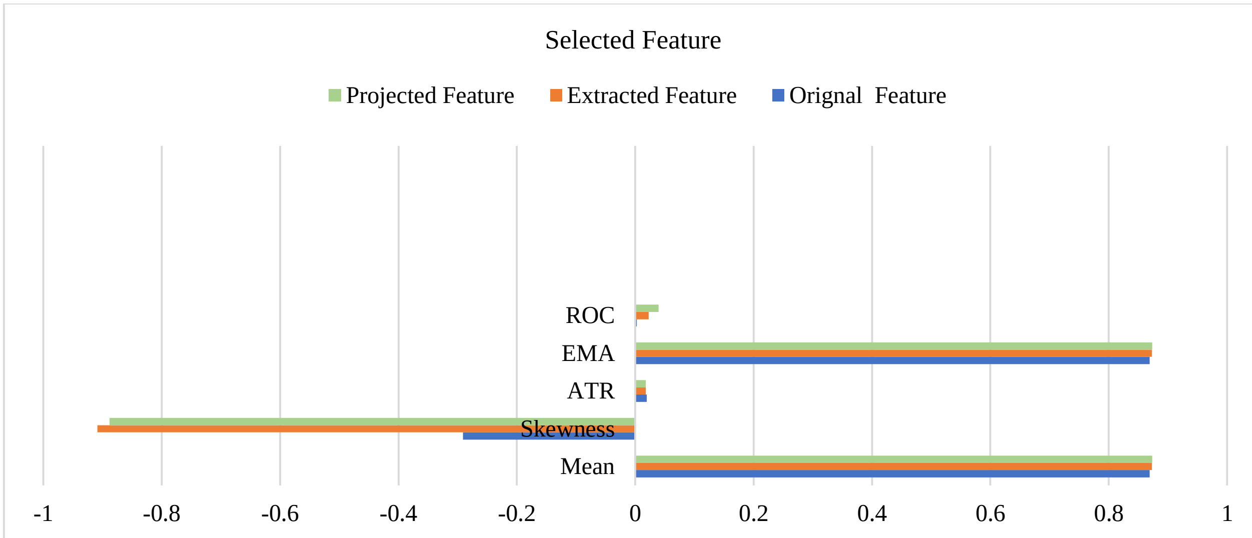
8.3. Overall Performance of the Analysis Work

8.3.1. Extracted Feature Vs Selected Feature

The original feature was already present in Table 8, but the feature was projected after correcting it and using only the selected one for further evaluation.



(a)



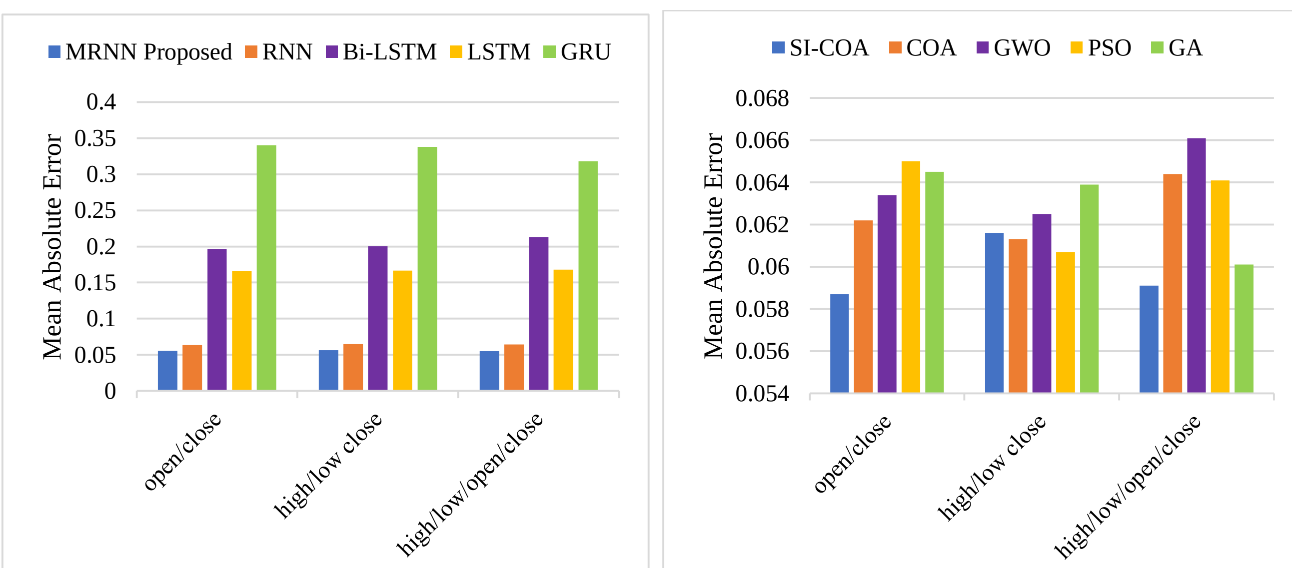
(b)

Fig. 2 Evaluation and selection of features: (a) Extracted, and (b) Selected.

8.3.2. MAE

Mean Absolute Error, or MAE, is known as the average of all error values. The formula to calculate MAE as per Equation (33) and illustrated in Figure 3,

$$MAE = \frac{1}{i}\sum_{n=1}^{i}|y_n - y|$$



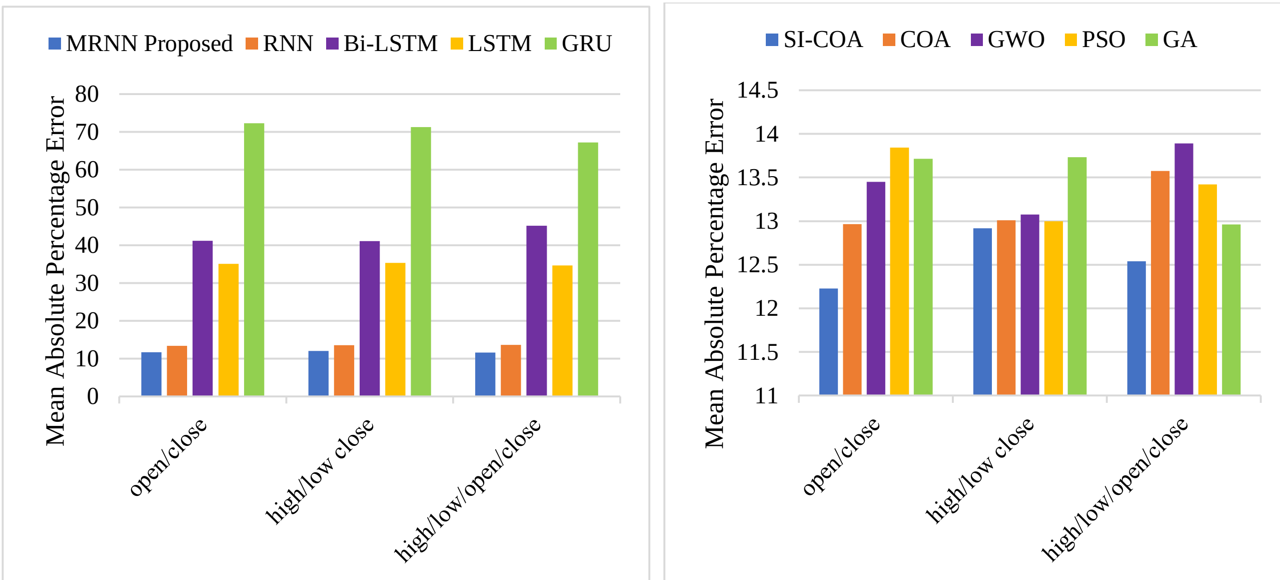
(a) **(b)**

Fig. 3 MAE overall performance: (a) Prediction, and (b) Feature selection.

8.3.3. MAPE

MAPE shows the average absolute error frequency. It is not influenced by the measurement scale but is affected by the data transformation. There is no information about the direction of the error. Acute deviations in MAPE are not panellized. Errors with opposite signs are not reflected by the measure. The error evolution of MSE is checked with the respective learning rate, as explained in Figure 4.

$$MAPE = \frac{1}{i}\sum_{n=1}^{i}\left|\frac{y_i}{e_i}\right| \times 100$$

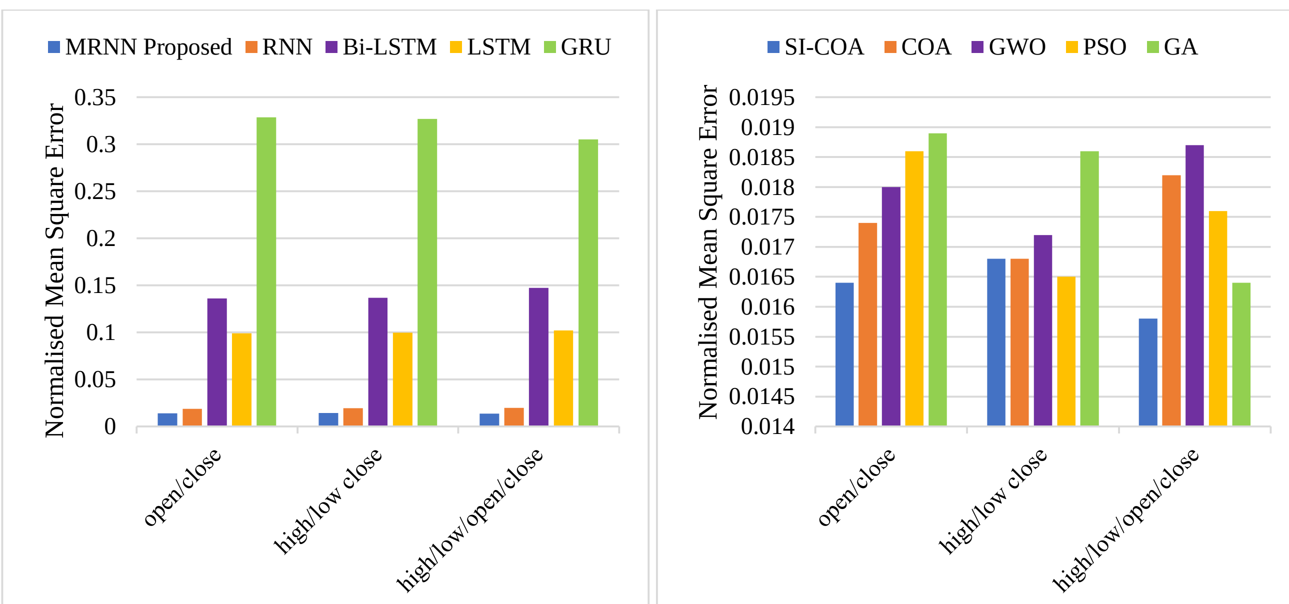


(a) (b)

Fig. 4 MAPE overall performance: (a) Prediction, and (b) Feature selection.

8.3.4. NMSE

Figure 5 shows the error evolution of NMSE, which is evaluated with the respective prediction and feature selection



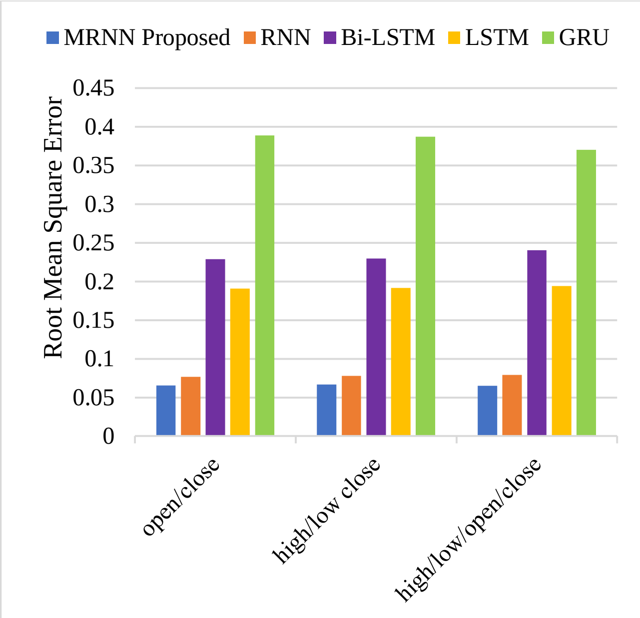
(a) (b)

Fig. 5 NMSE overall performance: (a) Prediction, and (b) Feature selection.

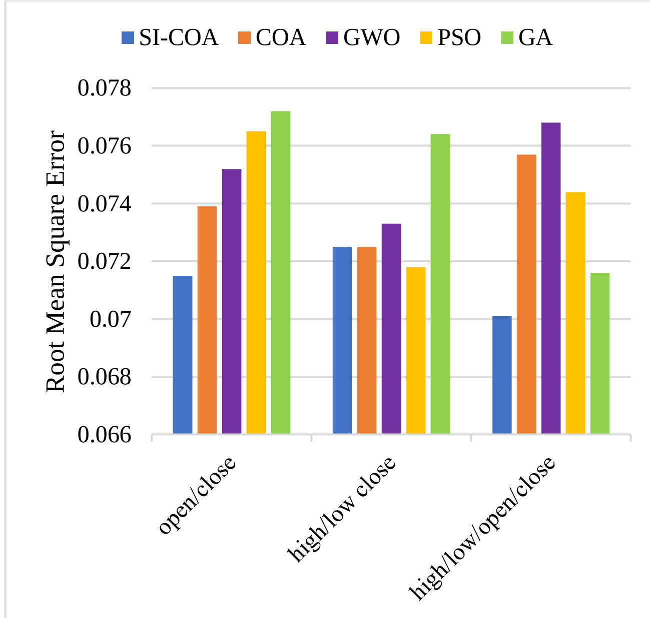
8.3.5. RMSE

This metric is represented by the mean square error's square root. It performs the role of a squared mean error. The root mean square error is another error measurement method commonly used to test differences between a value estimated by an estimator and an actual received value. The evolution of the error of MSE is tested with the corresponding learning rate, as explained in Figure 6.

$$RMSE = \sqrt{\frac{1}{i}\sum_{n=1}^{i} e_n^2}$$



(a)

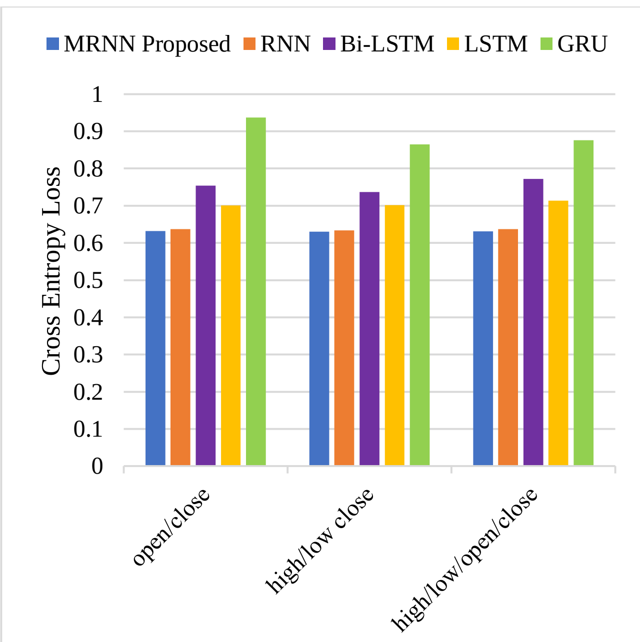


(b)

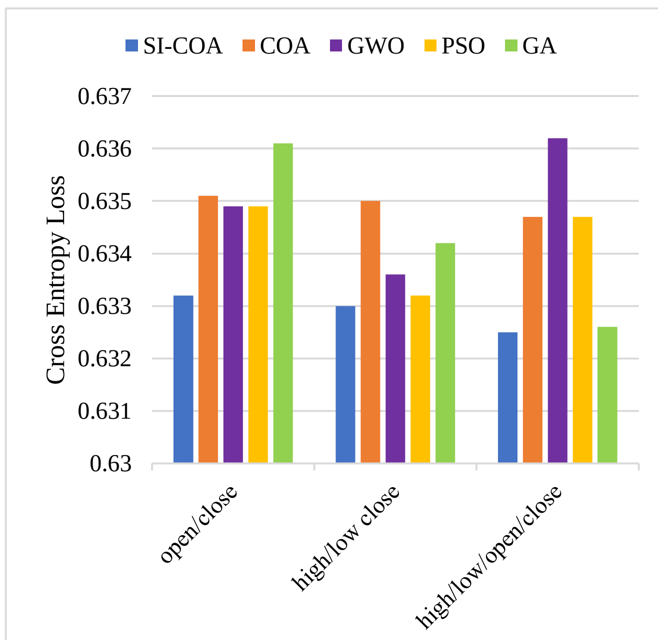
Fig. 6 RMSE overall performance: (a) Prediction, and (b) Feature Selection.

8.3.6. Cross-Entropy Loss

Machine learning performance of a classification model is measured by cross-entropy loss. The loss is indicated by a number between 0 and 1, with 0 indicating the ideal form as shown in Figure 7.



(a)



(b)

Fig. 7 Cross-entropy loss overall performance: (a) Prediction, and (b)Feature Selection.

9. Conclusion

The proposed predicted stock market model works on Deep learning as explained in this study. Pre-processing, extraction of features, selection of features, and stock price prediction are the four fundamental steps of the predictive paradigm. The pre-processing of gathered raw data starts with data cleaning and min-max data scaling. The characteristics, including statistical features and typical indicator-based features, were extracted from the cleaned data. The optimum features are derived from the returned features using an Energised Chimp Optimization Algorithm (ECOA). As a result, the predicted price of the stock market is calculated using a Modified Recurrent Neural Network (M-RNN). Experimental analysis shows that the modified RNN model can reduce prediction lag times while improving prediction accuracy. Experimental findings show that the proposed model was trustworthy and efficient when benchmarked against the most recent state-of-the-art methods. The study proposes to create a classifier by classifying 7 gestures that are insensitive to forearm orientation variations. Accuracy of CNN here outperformed others in comparison with different classifiers (SVM, KNN, LDA, and DT) ($p<0.05$) as per the achieved resultant. There was a decrease in CNN accuracy (<5%), which resulted from the difference between scheme 4 (combination of all orientations) and schemes 1, 2, and 3. Furthermore, multiple comparisons using various methods revealed that 4 out of 6 groups result in no significant difference in accuracy (p-value> 0.05). Hence, the execution time of the proposed CNN method was still within the recommended permissible range (<200ms). In conclusion, further studies related to the implementation of CNN in embedded systems should be proposed to develop a prosthetic hand that is robust against orientation.

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