J. Electrical Systems 20-3s (2024): 341-354

[1]Li Han

[1]Guili Huo

[2]Ying Lou

Forecasting Model of Sustainable Financial Market Trend Based on Neural Network Algorithm

Abstract: - Recent advances in computer technology have resulted in the ongoing gathering of massive amounts of data and information. Because the financial market creates so much real-time data, including transaction records, we have a great potential to get important insights from analysing that data, especially in the banking industry. As a result, the goal of this work is to use the financial data that is now accessible to create a unique stock market prediction model. We employ the deep learning approach because of its exceptional capacity to learn from large datasets. This study proposes a hybrid approach that integrates the Archimedes optimisation algorithm (AOA) with a long short-term memory (LSTM) network. So far, heuristic-based trial and error has been extensively used to estimate the temporal window size and architectural components of long short-term memory networks. This paper investigates the temporal properties of financial market data by providing a systematic way to selecting the topology and time window size for the LSTM network. The experimental results demonstrate that the hybrid LSTM network and AOA model outperform the benchmark model.

Keywords: Financial Market, ensemble model, long short-term memory, Archimedes optimisation algorithm, prediction.

I. INTRODUCTION:

In today's modern world, having access to well-established financial markets is very necessary in order to achieve economic growth that is both sustainable and rapid. These markets have caught the attention of economic enthusiasts and professors on a constant basis due to the fact that they serve as an essential reservoir of financial capital, economic development, and advancement in every given nation. As a result of the opportunity for investors with a short-term perspective to make a profit, there has been a discernible increase in the number of traders operating in the financial markets during the last few years. In light of this, one of the most significant areas of study in recent years has been the quest for reliable methods that may aid traders in making decisions on the financial markets [1]. Due to the unpredictable and ever-changing nature of financial markets, as well as the many variables that might potentially impact price variations, forecasting in the financial markets is a process that is fraught with difficulty [2]. These uncertainties are influenced by a number of different variables, including changes in the political and economic spheres as well as the attitude of investors. In spite of this, it is not quite evident how the majority of these variables contribute to the rise in prices [3]. In the financial markets, predicting prices with any degree of accuracy is difficult and requires a combination of inventive and trustworthy tactics. This is a result of the previously described factor. This motivation led to the proposal of unique hybrid neural network-based metaheuristics in this research to address the massive uncertainty in the precious metals and financial markets. The study's conclusions indicate that the prediction models now available on the market are unable to satisfy the demands of the modern, intricate financial markets. Some standard techniques, like the regression model for time series predictions, are not very good at identifying upward and downward trends in the series charts by looking at the direction of price movement. This is due to the fact that identifying these patterns requires the analysis of other markets, including the energy market [4]. Technical analysis indicators, which are often used with the aim of making short-term gains, may be used to manage complicated data with non-linear correlations. Adhering to these recommendations does not need expert financial knowledge or exploring other marketplaces [5]. There are supplemental charts and mathematical functions known as indicators, which are used to offer indications for buying and selling prices. They do this by collecting data from time charts and price charts, and then feeding that data into specialised mathematical procedures. The results of this technique make it possible for analysts to make decisions in a timely manner [6]. The advancement of science and technology, in conjunction with the utilisation of artificial intelligence in the process of analysing data derived from technical analysis indicators, has the potential to play a significant part in addressing

[1]School of Management, Qufu Normal University, Rizhao, Shandong, 276827, China

2Rizhao Donggang District Local Financial Development Service Center, Rizhao, Shandong 262399, China

*Corresponding author email: hanli@qfnu.edu.cn

challenges associated with the prediction of prices on the financial market and in enhancing the profitability of individuals, organisations, and nations [7,8].

DL approaches are extensively used in the area of artificial intelligence and machine learning. DL is a powerful method that mimics the learning process of the human mind, specifically in relation to ANNs. This methodology allows for quicker and easier analysis of findings and subjects [9]. Despite the abundance of literature on the advancement of deep learning techniques and ANNs, there are still inherent limitations and drawbacks connected with these approaches. Researchers have extensively studied the issue that NN hyperparameters are chosen by random search and grid search, which is considered a weakness of neural networks [10]. These operations are laborious and need more complex mathematical computations. Therefore, this research suggests a hybrid neural network-based metaheuristic approach to address this challenge by leveraging the advantages of several techniques.

The proposed method integrates the Archimedes optimisation algorithm (AOA) with Long Short-Term Memory Networks (LSTM). Employing this metaheuristic approach reduces the computational time while simultaneously improving the level of accuracy. In order to assess the accuracy, precision, and validity of the proposed model, we compared it to existing single and hybrid DL and machine learning techniques. The moth-flame optimisation (MFO) method, a very effective metaheuristic technique, has been used for feature selection due to the potential decrease in accuracy that might come from using all variables in modelling.

Ultimately, the main achievement of this research is the ability to forecast signals obtained from technical analysis indicators in the worldwide gold market via the use of hybrid neural network-based metaheuristics. Investors may experience substantial financial losses when indicators provide inaccurate indications. Given its ability to enhance signal accuracy, this strategy may be very advantageous for gold market participants throughout the globe. Put simply, using this approach to invest in this market has the potential to provide rewards for consumers and function as a tool for making informed decisions. Indeed, this method has the potential to mitigate investment losses and provide gains. The algorithm may also be used to identify misleading signals that tell investors when precisely to join and leave the financial markets because of its high degree of accuracy.

The remainder of this article is structured to achieve the above specified goals in the following manner: The literature on the subject is examined in Section 2. We examine at the issue description and provide our prediction model in Section 3. In Section 4, results and discussion are discussed. Section 5 presents managerial techniques and findings.

II. RELATED WORKS:

This research adds to the corpus of knowledge in a number of ways. First, we examine relevant research on technical analysis and widely used indicators in the field. Next, we address DL and forecasts related to this topic. In conclusion, we examine the function of metaheuristics in financial markets while analysing pertinent research. This study [11] enhances stock market prediction using neural networks, tackling their interpretability challenge. Inspired by technical analysis, it selects diverse neural network models and extracts effective features from short-term stock data. Incorporating an attention mechanism boosts interpretability without sacrificing accuracy. This experimental results show an 85% classification accuracy, offering precise insights into investor sentiment.

This study [12] develops a novel stock market prediction model by integrating a long short-term memory (LSTM) network with a genetic algorithm (GA). We systematically determine LSTM parameters using GA, improving upon heuristic-based methods. This evaluations on daily Korea Stock Price Index (KOSPI) data show that our hybrid approach outperforms benchmarks. EMD2FNN, a hybrid technique for stock market trend prediction, is proposed in this study [13]. It combines a neural network based on a factorization machine with empirical mode decomposition. When used on indexes such as the S&P 500, NASDAQ, and SSEC, EMD2FNN performs better than other approaches in terms of MAE, RMSE, and MAPE. Even after accounting for transaction expenses, profitability analysis shows encouraging outcomes. This study [14] investigates the role of deep neural networks (DNNs) in stock market prediction, highlighting their significance and applicability to temporal data. We explore various DNN variations and conduct experiments to evaluate their performance in forecasting stock market trends. The survey also discusses potential limitations, challenges, and future research directions in this domain.

This paper [15] addresses the challenge of forecasting currency exchange rates, a crucial financial problem with practical applications. It discusses the limitations of traditional linear approaches and highlights the effectiveness of nonlinear models, particularly neural networks. For the purpose of predicting exchange rates, the research offers enhanced neural network and fuzzy models, such as multi-layer perceptions, radial basis functions, dynamic neural networks, and neuro-fuzzy systems.

In the precious metals market, this research [16] presents novel techniques for spotting bogus signals using technical analysis indicators. To improve signal accuracy, it combines bidirectional gated recurrent units and convolutional neural networks optimised using metaheuristic techniques. Moth-flame optimization algorithm is utilized to select influential variables. Results show that these hybrid neural network-based metaheuristics outperform other methods, offering investors a valuable decision support tool for navigating financial uncertainties. This research [17] combines wavelet transformations and recurrent neural networks (RNN) optimised using the artificial bee colony (ABC) method to offer an integrated system, ABC-RNN, for stock price forecasting. The system comprises three stages: wavelet transform for noise elimination, RNN construction using fundamental and technical indicators, and ABC optimization of RNN weights and biases. Simulation results from various international stock markets demonstrate the system's effectiveness, suggesting its potential for real-time trading applications to forecast stock prices and maximize profits.

This paper [18] presents a hybrid forecasting model, HTBP Neural Network, for stock prices. It transforms historical data into fluctuation trend time series (FTTS), then into fuzzy time series (FFTS), before employing HTBP neural network to capture nonlinear relationships. The model combines fuzzy set theory and neural network algorithms to address overfitting, yielding promising results in predicting stock market trends. Neural networks—more especially, the Backpropagation (BP) algorithm—are used in this research [19] to forecast trends in stock prices. The BP algorithm neural network outperforms deep learning fuzzy algorithms with a prediction accuracy of 73.29% using transaction data over five consecutive days. This provides valuable insights for investors and may assist government in macroeconomic regulation. This study [20] introduces an ARIMA-ANN hybrid forecasting approach for the Colombo Stock Exchange (CSE), Sri Lanka, aiming to address high volatility. Comparative analysis indicates its superiority over traditional ARIMA models, particularly in forecasting accuracy, thus offering valuable insights for financial decision-making in volatile markets. This study [21] presents a novel model addressing key challenges in fuzzy time series (FTS) forecasting, including interval determination, repeated fuzzy sets, trend handling, and defuzzification. It introduces an artificial neural network (ANN) algorithm for interval determination and assigns weights to fuzzy sets based on occurrence frequency. Fuzzified data are used to establish fuzzy logical relations (FLRs), with trends identified using three conditions. Validation with real-world data demonstrates the model's efficiency and superiority over conventional statistical methods. Table 2 shows the comparison of the related works.

Table 1. Comparison of related works

Ref No	Methods	Advantages
11	Diverse neural network models, attention mechanism	Improved interpretability, precise insights into investor sentiment
12	Integration of LSTM with genetic algorithm, systematic parameter determination	Enhanced predictive performance, effective in handling high volatility
13	EMD with Factorization Machine based NN,	Outperforms other methods in prediction accuracy, promising profitability results
14	Exploration of various DNN variations,	Insightful discussion on DNN significance, identification of limitations
15	Improved neural network and fuzzy models for exchange rate prediction	Highlights effectiveness of nonlinear models
16	CNNs and bidirectional GRUs with metaheuristic algorithms, Moth-flame optimization algorithm for variable selection, comparative evaluation	Enhanced accuracy in identifying fake signals
17	Integration of wavelet transforms and RNNs with ABC algorithm	Effective noise reduction, potential for real-time trading applications
18	Combination of FFTS and HTBP neural network	Efficient prediction, robust forecasting model
19	Utilization of BP algorithm for stock price patterns	High prediction accuracy, valuable insights for investors
20	Introduction of ARIMA-ANN hybrid approach	Superior accuracy
21	Introduction of ANN algorithm for interval determination	demonstrates superiority over traditional methods

III. PROPOSED AOA-LSTM METHOD:

The financial crisis of SMEs has been identified by the effective AOA-SVM approach proposed in this study. The block design for the suggested AOA-SVM is shown schematically in Figure 1.

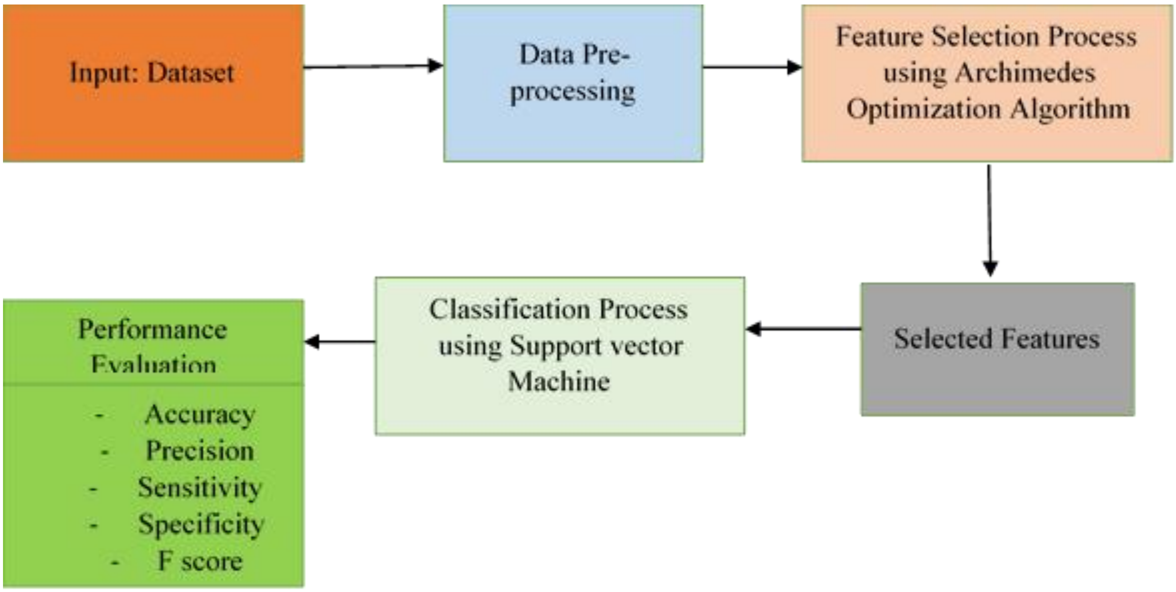

Figure 1. Block Diagram for proposed AOA-SVM

The AOA-SVM technique consists of three main sub-processes: pre-processing, feature selection using the Archimedes optimization algorithm (AOA), and classification using Support Vector Machines (SVM). The use of AOA for the appropriate selection of features contributes to increased classification performance. Figure 1 shows the overall block diagram of the proposed AOA-SVM approach.

3.1 Pre-processing

The financial data is comprised of fundamental signals with a multitude of distinct characteristics and is very intricate. However, a reliable assessment of the transformation performance from cellular networks is helpful in developing networks data prediction tools. The data is adjusted so that load packets from the network with larger numerical values don't dominate individuals with lower numerical values. Scaling the data also speeds up the modelling process while maintaining optimum accuracy. To normalise the data inside the range of [0, 1], a min-max approach is used, which is shown in fig 2. To improve the model's predictive accuracy for network traffic, the data must be scaled.

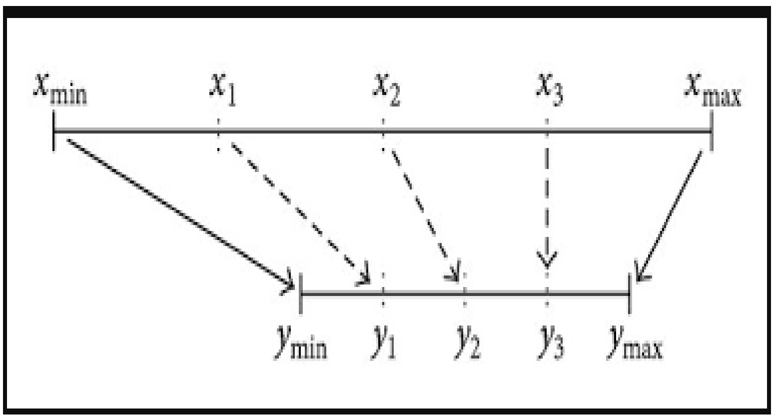

Figure 2. Min – Max Technique

Scaling has two main advantages: it reduces numerical challenges under the prediction and avoids samples with larger numeric ranges by regulating individuals with smaller numeric ranges. The following is:

$$Z_n = \frac{x - x_{min}}{x_{max} - x_{min}} \left(New_{max_x} - New_{min_x} \right) + New_{min_x}$$

where x_{min} represents the smallest value in the dataset, while x_{max} represents the maximum value in the dataset. The term "New_{min_x}" represents the minimum value, which is 0, and "New_{min_x}" also suggests the maximum value, which is 1.

3.2 Feature selection by MFO metaheuristic algorithm

The MFO algorithm, a powerful feature selection metaheuristic, finds solutions by mimicking the movements of moths around a flame. The only animals that have night vision are moths. Through the use of moonlight, they have developed to fly at night. They move by the application of a transverse orientation system. This technique allows a moth to fly in reference to the moon at a set angle. Butterflies often fly in a deadly spiral pattern around artificial lights, despite their transverse orientation. According to this theory, flames represent the highest moth position ever seen, and moths themselves are the real search agents that scour the search space. Here is the pseudo-code for Algorithm 1.

Algorithm: Moth Flame Optimization Algorithm

$The\ initialization\ of\ solutions\ and\ the\ required\ parameters\ of\ the\ algorithm$

$Set\ it = 1;$

$Evaluate\ the\ fitness\ of\ solutions$

$While\ iteration\ it \leq it_{max}$

$If\ it == 1\ then$

$F \leftarrow Sorted\ (M)$

$OF \leftarrow Sorted\ (OM)$

$else$

$F \leftarrow Sorted\ (F_{t-1,}M_t)$

$OF \leftarrow Sorted\ (OF_{t-1,}OM_t)$

End

$For\ i\ th$

$Determine\ D\ for\ the\ Moth\ and\ Flame$

$Update\ Moth(i)$

End

$It\ =\ it + 1$

End

$F \leftarrow Sorted\ (F_{t-1,}M_t)$

$Return\ the\ most\ optimal\ solution$

IV. PROPOSED NN BASED METAHEURISTICS:

4.1 Archimedes Optimization Algorithm:

The AOA approach and NR mathematical technique were employed to solve the provided optimal issue. The AOA approach is a meta-heuristic strategy used to solve various mathematical optimization problems. It has been proven to be effective in quickly reaching a global solution. The fundamental requirement of the AOA relies on Archimedes' principle of buoyancy. The AOA encompasses multiple stages that establish a nearly comprehensive solution, and these stages are illustrated as:

Phase 1 In the 'Initialised' stage, the volume, density, and acceleration of the populations containing the submerged item (solution) are assessed. Equation (2) specifies that a random point from the fluid is used to initialise all solutions. Next, each solution's fitness value is determined,

$$o_i = lb_i + rand(0,1) \times (ub_i - lb_i), \forall i \in \{1,2,3, \ldots., N\} \quad (1)$$

$$Den_i = rand(0,1) \quad (2)$$

$$Vol_i = rand(0,1) \quad (3)$$

$$Acc_i = lb_i + rand(0,1) \times \ (ub_i - lb_i), \forall i \in \{1,2,3, \ldots., N\} \quad (4)$$

In this case, N denotes the population sizes, and o_i stands for the i-th answer from the populations. The terms ub_i and lb_i denote the upper and lower limits of the ith solution, respectively. where the i-th solutions' density, volume, and acceleration are denoted, respectively, by the symbols Den_i; Vol_i and Acc_i. The function rand(0,1) represents a random scalar that can take on values between zero and one.

Phase 2 'During this phase, the density and volume of all the solutions were increased using the following formulae:

$$Den_i^{(t+1)} = Den_i^{(t)} + rand(0,1) \times (Den_{best} - Den_i^{(t)}) \quad (5)$$

$$Vol_i^{(t+1)} = Vol_i^{(t)} + rand(0,1) \times (Vol_{best} - Vol_i^{(t)}) \quad (6)$$

where $Den_i^{(t)}$, and $Vol_i^{(t)}$indicate the density and volume, respectively, of the i-th solution at the t-th iteration. The terms Den_{best}, and Vol_{best} represent the ideal densities and volumes of optimal solutions that have the highest fitness value.

Phase 3 'The transfer operator and density factor pertain to the phase in which the interactions between solutions reach a state of equilibrium. The mathematical mechanics of the collision were shown:

$$TF = \exp\left\{\frac{t-t_{max}}{t_{max}}\right\} \quad (7)$$

where TF refers to the transfer operators that are capable of facilitating the transmission of the search process during the transition from exploration to exploitation phase. t_{max} represents the maximum number of iterations, which is set at 20. In addition, the presence of a decreasing density factor (d) enables the AOA to identify solutions that are close to being globally optimal.

$$d^{t+1} = \exp\left\{\frac{t-t_{max}}{t_{max}}\right\} - \left\{\frac{t}{t_{max}}\right\} \quad (8)$$

Phase 4 'Exploration': During this phase, the collision between solutions happens. Thus, when the value of TF is less than or equal to 0.5, a material is selected randomly (mr) in which the acceleration of the solution has been enhanced as:

$$ACC_i^{(t+1)} = \frac{Den_{mr} + Vol_{mr} \times ACC_{mr}}{Den_i^{(t+1)} \times Vol_i^{(t+1)}} \quad (9)$$

where Den_{mr}; Vol_{mr}, and ACC_{mr} indicate the densities, volumes, and accelerations of random material.

Phase 5 'Exploitation': In this phase, there are no collisions between solutions. Thus, when the time frame was 0:5, the solution's acceleration was enhanced:

$$ACC_i^{(t+1)} = \frac{Den_{best} + Vol_{best} \times ACC_{best}}{Den_i^{(t+1)} \times Vol_i^{(t+1)}} \quad (10)$$

where ACC_{best} is the acceleration of the most fitness-maximizing option.

Phase 6 ‘Normalize acceleration’: The acceleration was normalised to estimate the proportion of change in the following manner:

$$ACC_{i-norm}^{(t+1)} = g \times \frac{ACC_i^{(t+1)} - \min\{ACC\}}{\max\{ACC\} - \min\{ACC\}} + z \quad (11)$$

Where g, and z indicate the normalised range. The term "$ACC_{i-norm}^{(t+1)}$" is used to measure the proportion of agents that are in a certain phase.

Phase 7 ‘Evaluation’: The fitness value of all solutions was evaluated during this phase, and the best solutions, such as x_{best}; Den_{best}; Vol_{best}, and ACC_{best}, were stored.

The searching space was represented as an n-dimensional Boolean lattice, in contrast to the standard AOA, where the answer was improved by exploring the space surrounding the continuous valued spot from the BAOA. The hypercube's vertex was also improved in the solution. Furthermore, binary solution vectors and a set of parameters were used to tackle the dilemma of electing or not. In this approach, a value of 1 indicates that a parameter is selected to be included in the new datasets, while a value of 0 indicates otherwise. During binary approaches, the step vector is used to assess the potential for changing position, and the transfer function has a substantial impact on the balance between exploitation and exploration. During the feature selection approach, as the size of the feature vector reaches N, the number of different feature combinations increases to 2^N. This results in a large search space to be explored. The hybrid approach used in the study was IASC, 2023, vol.35, no.1 525. It was employed to effectively search the feature space and accurately choose the appropriate set of features. The FS algorithm is used in multi-objective applications where it aims to achieve many objectives simultaneously. It seeks to find solutions that minimise the subset of FS while maximising the accuracy of output for classification purposes.

Based on the information provided before, the fitness function (FF) is used to calculate the solution in order to achieve a balance between the two objectives:

$$fitness = \alpha \Delta_R(D) + \beta \frac{|Y|}{|T|} \quad (12)$$

The term $\Delta_R(D)$ denotes the rate at which the classifier makes errors. The symbol |Y| denotes the size of the subsets that the technique selects, while |T| indicates the total number of features included in the current datasets. The parameter α is a weight assigned to the error rate of classifiers, with α ∈ [0, 1]. Similarly, β, which is equal to 1-α, represents the relevance of decreasing features. The importance of the classifier's efficiency was given priority over the quantity of selected features. If the evaluation function simply considers classifier accuracy, it fails to take into account the impact of a solution that may have the same accuracy but utilises a minimal set of selected features, which is crucial for addressing the problem of high dimensionality.

Algorithm 1. Initial AOA pseudo-code Setting the Arithmetic Optimisation Algorithm's initialization parameters, α and μ

$Random\ initialization\ of\ the\ positions\ of\ the\ solutions.\ (Solutions: i = 1, \dots, N)$

$while\ CIter < MIter\ do$

$Calculation\ of\ the\ Fitness\ Function\ (F\ F\ )\ for\ the\ given\ solutions$

$Finding\ the\ best\ solution\ (Determined\ best\ so\ far).$

$Updating\ the\ MOA\ value\ by\ the\ Eq. 7.$

$Updating\ the\ MOP\ value\ by\ the\ Eq. 9.$

$for\ i = 1\ to\ Solutions\ do$

$for\ j = 1\ to\ P\ ositions\ do$

$Generation\ of\ random\ values\ between\ [0, 1] (r1, r2, andr3)$

$if\ r1\ >\ MOA\ then$

$Exploration\ phase$

$if\ r2\ >\ 0.5\ then$

(1) $Application\ of\ the\ Division\ math\ operator\ (D"\div")$.

$Updating\ of\ the\ i-th\ solutions'\ positions\ using\ the\ first\ rule\ in\ Eq.8$

$else$

(2) $Application\ of\ the\ Multiplication\ math\ operator\ (M"\times")$.

$Updating\ of\ the\ i-th\ solutions'\ positions\ using\ the\ second\ rule\ in\ Eq.8$

$end\ if$

$else$

$Exploitation\ phase$

$if\ r3\ >\ 0.5\ then$

(1) $Application\ of\ the\ Subtraction\ math\ operator\ (S"-")$.

$Updating\ the\ i-th\ solutions'\ positions\ using\ the\ first\ rule\ in\ Eq.10$

$else$

(2) $Application\ of\ the\ Addition\ math\ operator\ (A"+")$.

$Updating\ the\ i-th\ solutions'\ positions\ using\ the\ second\ rule\ in\ Eq.10$

$end\ if$

$end\ if$

$end\ for$

$end\ for$

$CIter\ =\ CIter\ +\ 1$

$end\ while$

$Return\ the\ best\ solution\ (x)$

4.2 LSTM:

The human brain and its learning process had the most impact on the development of artificial neural networks (ANNs). Neural networks execute their signal transmission and interpretation functions as an algorithm. This kind of network uses deep learning and is capable of example-based learning. RNNs are ANNs that store data within the network and provide two-way data flow. The results of the previously acquired input have an impact on future results. The RNNs are appropriate for time series prediction issues because of this property. Memory cells from hidden layers replace the cells in a typical network to realise the memory mechanism. Three gates comprise the construction of the memory cells: input, output, and forget which is shown in fig 3. This makes it possible to store and disclose data selectively.

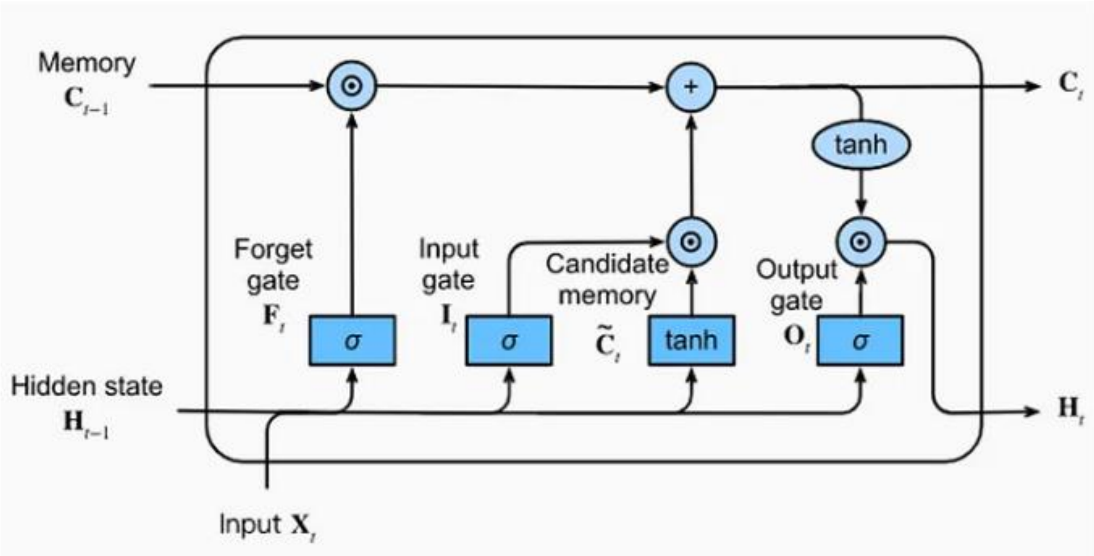

Figure 3. Structure of LSTM

The data is initially filtered by the forget gate (f_t), which determines whether or not the data should be deleted. Remember gate f_t is described by equation (1).

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

W_f and U_f are the variable matrices; b_f is the bias vector; σ is the sigmoid function; and f_c, with a range of values from 0 to 1, is utilised for the forget gate.

The data that is to be stored in memory cells is selected using the following stem. By using Equation (2) the sigmoid function determines the values for renewal for a given input gate i_t,

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

While the b_i (W_i, U_i are learnable parameters, the range for the i_t is the same as with the previously mentioned f_t,

The possible vectors for updating $C_t$from the Eq. (3) are given by the function tanh,

$$C_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

wherein b_c, W_c U_c are the learnable parameters.

Following the data selection process for storing the specified cell state, C_t is determined using Eq. (4).

$$C_t = F_t \odot C_{t-1} + i_t \odot C_t$$

where the date to be erased is C_{t-1}, the element-wise multiplication and meaning are ⊙, the chosen data is represented by F_t C_t, and the data to be saved in a memory cell C_t is indicated by i_t C_t. Equation (5) defines the hidden state h_T as the output gate o_t,

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

where b_o, W_o and U_o are the input gate's learnable parameters, and the range for o_t is the same as for the two gates before it. Lastly, the product of o_t and the tanh value of C_t, as shown in Eq. (6), represents the output value ht.

$$h_t = o_t \odot \tanh(C_t)$$

V. DATASET:

This research makes use of the data set that was given by the Economic Statistics Branch of the United Nations Statistics Division (UNSD) and consists of Pakistan's gross domestic product (GDP) broken down by category of expenditure at current prices in national currency from 1970 to 2016.

5.1 Hyper parameter optimization:

In order to determine the hyperparameters of the network, this research used the alternative optimisation approach (AOA). The parameters that have been hyperoptimized include the activation function type that is used in the LSTM layers, the number of neurons, the number of filters, and the activation function type that is utilised in the LSTM component. [40, 80, 100, 120, 140, 160, 180, 200, 220, 240, 260] is the range of numbers that make up the search space. These values are for the number of neurons and filters. All of the following activation functions are available to choose from: relu, selu, tanh, sigmoid, and linear. In Table 2, all of the hyperparameters that are used in the structure of the network are listed.

Table 2. Description of Hyper parameters

Hyperparameter	**Values**
Number of LSTM units	128
Number of layers	2
Input shape	num_features
Activation function	Tanh,
Dropout	0.5
Recurrent dropout	0.5
Optimizer	Adam
Learning rate	0.01
Batch size	32
Epochs	200
Loss function	Cross-Entropy

Here are the formulas for accuracy, sensitivity, specificity, and F1 score:

1. **Accuracy**:

Accuracy is a metric that quantifies the proportion of correct predictions, including both true positives and true negatives, made by the classifier out of all its predictions. The metric measures the overall precision of the model.

Accuracy = $\frac{TP+TN}{FP+FN+TP+TN}$

2. Precison: Precision is a quantitative measure used to assess the effectiveness of a classification model. The metric quantifies the ratio of accurate positive predictions (properly identified positive instances) to all positive predictions produced by the model, irrespective of the actual class labels.

Precision = $\frac{TP}{TP+FP}$

3. **Sensitivity:**

Recall, or sensitivity, is computed by dividing the number of true positive cases by the classifier's correctly recognised positive instances. "It indicates the model's ability to correctly identify positive instances" means it can distinguish positive events.

Sensitivity=$\frac{TP}{TP+FN}$

4. **F1 Score**:

The F1 Score is calculated as the reciprocal of the arithmetic mean of the reciprocals of accuracy and recall. It offers a harmonious combination of accuracy and completeness, particularly in situations when there is an uneven distribution of classes.

$$\text{F1 Score}=2\times\frac{Precision\times Recall}{Precision+Recall}$$

5.2 Results Analysis of proposed model with Existing models

In order to validate the effectiveness of our AOA-LSTM model in signal prediction, we conducted experiments using several deep learning and machine learning methods. Trial and error is used to optimise the hyperparameters of these algorithms, aiming to minimise their potential inaccuracy. In order to assess the effectiveness of the developed model, we conducted a comparative analysis of its performance against other deep learning (DL) and machine learning techniques, including CDS_CNN, Resnet_CNN, RNN_LSTM. The algorithms' performance has been evaluated using metrics such as precision, accuracy, recall, F1-score. This study introduces an MFO method as a solution to the crucial problem of feature selection in training machine learning models. The programme aims to identify variables that exhibit a fair and optimum relationship with the response variable. The results shows the efficacy of DL and ML learning models in forecasting using the MFO method. The feature selection process for the MFO indicates that AOA-SVM achieves the highest accuracy of 92%.

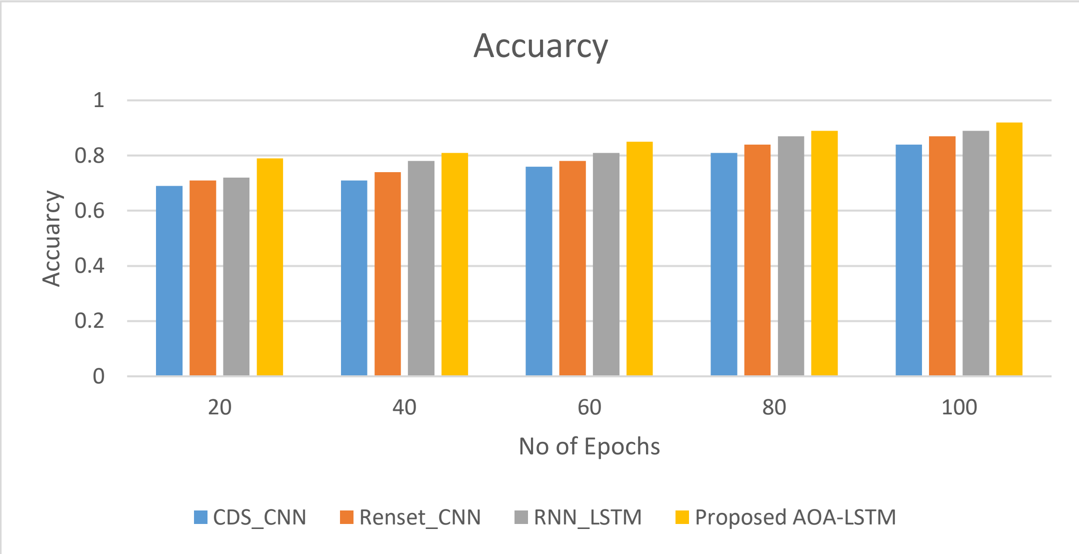

Figure 4: Performance of the Accuracy analysis

The Figure 4 provides the accuracy scores of existing CDS_CNN, Resnet_CNN, RNN_LSTM, and Proposed AOA-LSTM models. The Proposed AOA-LSTM model achieves the highest accuracy score of 0.92, indicating its superior performance in correctly classifying instances across all classes. Then, the RNN_LSTM model demonstrates robust performance with an accuracy score of 0.89, signifying its effectiveness in accurately classifying instances. The Resnet_CNN model follows suit with a respectable accuracy score of 0.87, while the CDS_CNN model achieves a slightly lower accuracy score of 0.84. These results underscore the efficacy of the Proposed AOA-LSTM and RNN_LSTM, in achieving high accuracy in classification tasks.

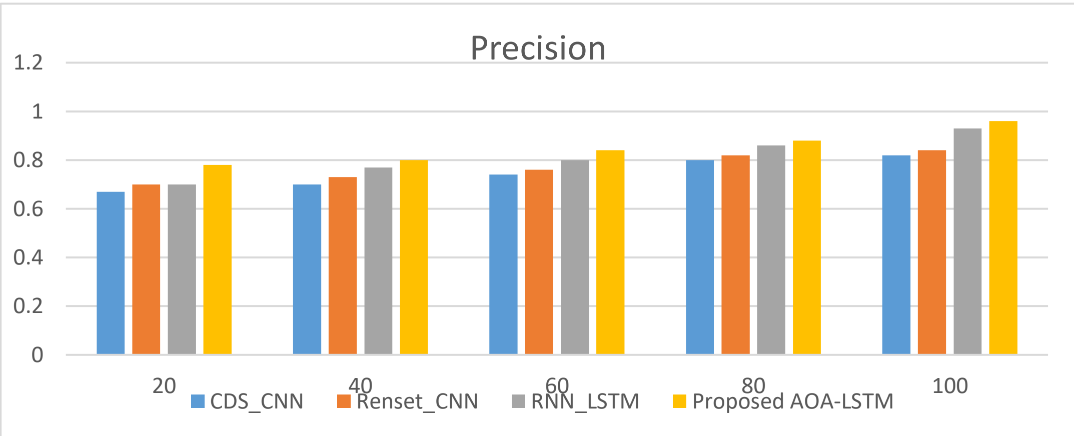

Figure 5: Performance of the Precision analysis

The Figure 5 shows the precision scores for existing models CDS_CNN, Resnet_CNN, RNN_LSTM, and Proposed AOA-LSTM models. The Proposed AOA-LSTM model achieves the highest precision score of 0.96, denoting its outstanding capability in making accurate positive predictions. Then, the RNN_LSTM model demonstrates robust performance with a precision score of 0.93. The Resnet_CNN model follows suit with a respectable precision score of 0.84, while the CDS_CNN model achieves a slightly lower precision score of 0.82. These results emphasize the effectiveness of the Proposed AOA-LSTM and RNN_LSTM, in achieving high precision, underscoring their suitability for classification tasks.

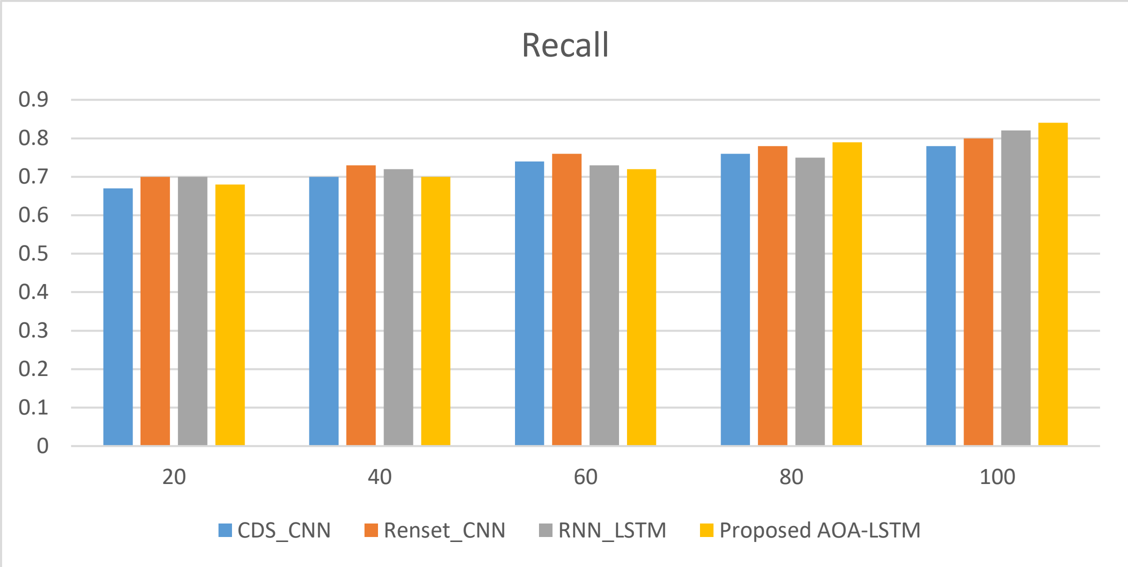

Figure 6 : Performance of the Recall analysis

The Figure 6 shows the recall scores for existing models CDS_CNN, Resnet_CNN, RNN_LSTM, and Proposed AOA-LSTM model. Among them, the Proposed AOA-LSTM model achieves the highest recall score of 0.84. Then the RNN_LSTM model demonstrates strong performance with a recall score of 0.82. The Resnet_CNN model follows suit with a recall score of 0.80, while the CDS_CNN model achieves a slightly lower recall score of 0.78. These findings underscore the effectiveness of Proposed AOA-LSTM, in accurately identifying positive instances, thus emphasizing the significance of model selection in achieving superior recall performance.

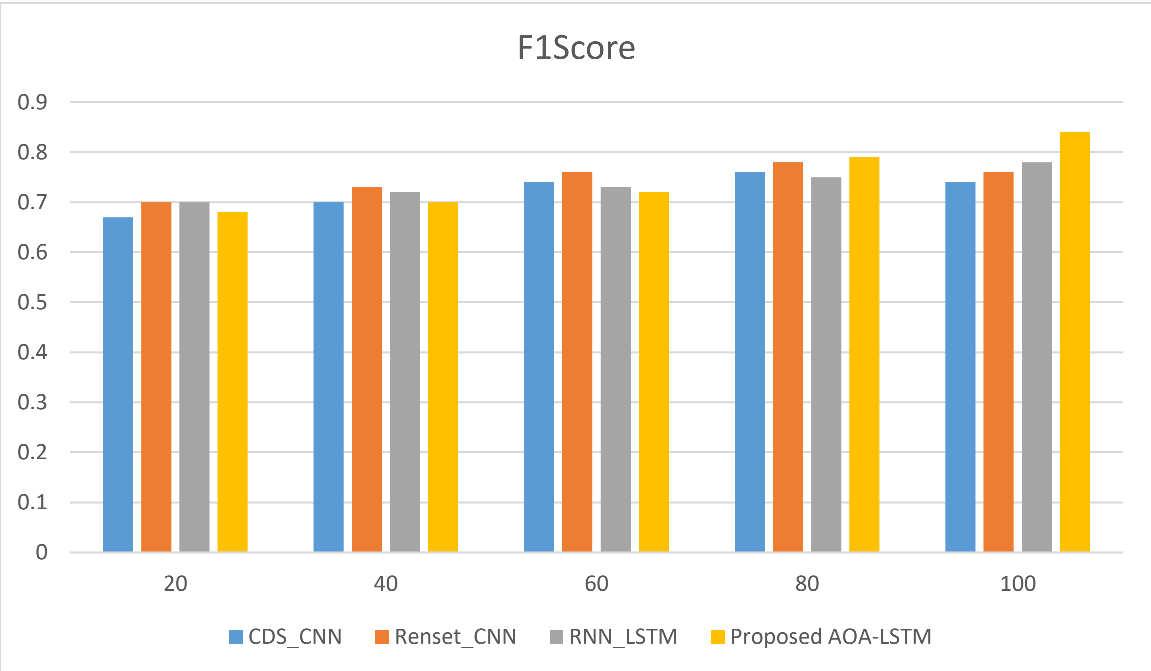

Figure 7: Performance of the F-score analysis

The figure 7 provides the F1 Score for existing models CDS_CNN, Resnet_CNN, RNN_LSTM, and Proposed AOA-LSTM. The Proposed AOA-LSTM model exhibits the highest F1 score of 0.84, showing its effectiveness in accurately predicting positive instances. Then the RNN_LSTM model achieves a F1 score of 0.78. However, both the CDS_CNN and Resnet_CNN models fall slightly behind with F1 scores of 0.74 and 0.76, respectively. These findings highlight the superiority of LSTM-based architectures, particularly the Proposed AOA-LSTM, in achieving high F score for the given task.

VI. CONCLUSION:

For economic authorities, precise forecasting of the financial and precious metals markets is essential because it improves social and economic stability. Nevertheless, predicting the behaviour of these markets is very challenging because of their unpredictable and intricate characteristics. Consequently, the field of literature has seen several techniques aimed at enhancing the precision of predicting models. This research introduced an AOA-LSTM model that has a 92% accuracy in properly predicting forecasts. Initially, in order to identify the most impactful factors on the target variable, we devised a very effective metaheuristic algorithm known as MFO. The selected technique after choosing the features is AOA-LSTM. The hyperparameters of this method are optimised using a technique called AOA. The primary objective of this study is to develop a hybrid model of optimised neural networks for classification. The accuracy and validity of the proposed strategy are assessed by comparing it with several ML and DL approaches. Although our research has helped investors and scholars create new indicators, there are a number of ways that future studies might broaden our technical indicators. If we have the capability to use data at several time intervals such as hourly, minute, and second. We may use different selection algorithms based on multi-criteria decision-making theories by adding further functions. One other important piece of advice is to employ different time series algorithms. Future researchers are encouraged to look at the role of fuzzy techniques and fuzzy data since financial markets are so unpredictable and difficult to predict.

Acknowledgement: Shandong social science planning Youth Project: "Research on the mechanism and path of green finance supporting the realization of ecological product value in the Yellow River Delta"（No.22DGLJO10）

REFERENCES:

[1] Nabipour, M., Nayyeri, P., Jabani, H., Shahab, S., & Mosavi, A. (2020). Predicting stock market trends using machine learning and deep learning algorithms via continuous and binary data; a comparative analysis. *Ieee Access*, *8*, 150199-150212.

[2] Selvamuthu, D., Kumar, V., & Mishra, A. (2019). Indian stock market prediction using artificial neural networks on tick data. *Financial Innovation*, *5*(1), 1-12.

[3] Ghasemiyeh, R., Moghdani, R., & Sana, S. S. (2017). A hybrid artificial neural network with metaheuristic algorithms for predicting stock price. *Cybernetics and systems*, *48*(4), 365-392.

[4] Di Persio, L., & Honchar, O. (2016). Artificial neural networks architectures for stock price prediction: Comparisons and applications. *International journal of circuits, systems and signal processing*, *10*, 403-413.

[5] Ahmed, M. K., Wajiga, G. M., Blamah, N. V., & Modi, B. (2019). Stock market forecasting using ant colony optimization based algorithm. *Am J Math Comput Model*, *4*(3), 52-57.

[6] Yu, L., Wang, S., Lai, K. K., & Wen, F. (2010). A multiscale neural network learning paradigm for financial crisis forecasting. *Neurocomputing*, *73*(4-6), 716-725.

[7] Wilson, I. D., Paris, S. D., Ware, J. A., & Jenkins, D. H. (2002). Residential property price time series forecasting with neural networks. In *Applications and Innovations in Intelligent Systems IX: Proceedings of ES2001, the Twenty-first SGES International Conference on Knowledge Based Systems and Applied Artificial Intelligence, Cambridge, December 2001* (pp. 17-28). Springer London.

[8] Wang, J., & Wang, J. (2017). Forecasting stochastic neural network based on financial empirical mode decomposition. *Neural Networks*, *90*, 8-20.

[9] Benzschawel, T. L., Dzeng, C., & Berman, G. A. (2009). *U.S. Patent No. 7,529,703*. Washington, DC: U.S. Patent and Trademark Office.

[10] Katarya, R., & Mahajan, A. (2017, December). A survey of neural network techniques in market trend analysis. In *2017 International Conference on Intelligent Sustainable Systems (ICISS)* (pp. 873-877). IEEE.

[11] Lu, R., & Lu, M. (2021). Stock trend prediction algorithm based on deep recurrent neural network. *Wireless Communications and Mobile Computing*, *2021*, 1-10.

[12] Chung, H., & Shin, K. S. (2018). Genetic algorithm-optimized long short-term memory network for stock market prediction. *Sustainability*, *10*(10), 3765.

[13] Zhou, F., Zhou, H. M., Yang, Z., & Yang, L. (2019). EMD2FNN: A strategy combining empirical mode decomposition and factorization machine based neural network for stock market trend prediction. *Expert Systems with Applications*, *115*, 136-151.

[14] Thakkar, A., & Chaudhari, K. (2021). A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions. *Expert Systems with Applications*, *177*, 114800.

[15] Kodogiannis, V., & Lolis, A. (2002). Forecasting financial time series using neural network and fuzzy system-based techniques. *Neural computing & applications*, *11*, 90-102.

[16] Mousapour Mamoudan, M., Ostadi, A., Pourkhodabakhsh, N., Fathollahi-Fard, A. M., & Soleimani, F. (2023). Hybrid neural network-based metaheuristics for prediction of financial markets: a case study on global gold market. *Journal of computational design and engineering*, *10*(3), 1110-1125.

[17] Qiu, J., Wang, B., & Zhou, C. (2020). Forecasting stock prices with long-short term memory neural network based on attention mechanism. *PloS one*, *15*(1), e0227222.

[18] Guan, H., Dai, Z., Zhao, A., & He, J. (2018). A novel stock forecasting model based on High-order-fuzzy-fluctuation Trends and Back Propagation Neural Network. *PloS one*, *13*(2), e0192366.

[19] Zhang, D., & Lou, S. (2021). The application research of neural network and BP algorithm in stock price pattern classification and prediction. *Future Generation Computer Systems*, *115*, 872-879.

[20] Rathnayaka, R. K. T., Seneviratna, D. M. K. N., Jianguo, W., & Arumawadu, H. I. (2015, October). A hybrid statistical approach for stock market forecasting based on artificial neural network and ARIMA time series models. In *2015 International Conference on Behavioral, Economic and Socio-cultural Computing (BESC)* (pp. 54-60). IEEE.

[21] Singh, P. (2018). Rainfall and financial forecasting using fuzzy time series and neural networks based model. *International Journal of Machine Learning and Cybernetics*, *9*(3), 491-506.