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A FRAME WORK ON ADVANCED ELEMATRIX HARMONY OPTIMIZATION (EHO) USING MACHINE LEARNING ALGORITHM FOR STOCK MARKET PREDICTIONS

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ABSTRACT

Using statistical and machine learning techniques, stock market prediction is the activity of projecting an individual stock's or the market's overall performance. The purpose of stock market forecasting is to better inform investors about the potential risks and rewards associated with buying or selling a particular stock. Machine learning algorithms are being used more and more in stock market forecasting because of their capacity to analyze massive amounts of data and identify patterns that human analysts would not immediately detect. These algorithms use historical market data together with other relevant variables to develop predictive models that can forecast future stock prices or market patterns. This method uses a preprocessed supervised technique known as Depth Adjacent Surrounding (DSA) to fill in any missing data. Elematrix Harmony Optimization (EHO), a unique optimization technique, is then applied to optimize the necessary features that were taken out of the data. This procedure helps to improve the prediction model's efficacy and reduce the amount of input data required to provide accurate forecasts. A Probabilistic Multi-Model Neural Network (PMNN) makes predictions about whether or not to purchase stocks based on the input data. This neural network creates a single, more accurate, and trustworthy forecast by combining the output of multiple different models. The primary goal of this process is to develop a tool that will help investors make better decisions about whether or not to purchase a particular stock by using data-driven analysis of relevant market and company information. By using machine learning algorithms to analyze and comprehend vast amounts of data, this strategy can provide a more reliable and accurate prediction of stock performance than more traditional methods.

Index Terms—Stock Market Prediction, Depth Adjacent Surrounding (DAS), Preprocessing, Elematrix Harmony Optimization (EHO), Machine Learning, and Probabilistic Multi-Model Neural Network (PMNN).

I. INTRODUCTION

The stock market provides an indication of the economy's and businesses' anticipated future growth[1]. Stock price fluctuations are produced by a range of factors, including socioeconomic conditions, investor expectations, and trust in the company's leadership and operations, among others. Because of technology improvements, the general population now has access to more information faster. Stock analysis has gotten more challenging due to the necessity to quickly analyze large amounts of data[2]. People expect that advances in big data, particularly in the field of machine learning, will allow them to comprehend stock data. Foreign exchange (Forex) is one of the world's major financial markets. The exchange rate projection can provide key decision-making instructions for investors seeking to increase returns while reducing risk. Forecasting and predicting the forex market has proven to be a difficult research topic because the exchange rate is constantly influenced by a variety of factors, including the economies, government, and social circumstances of numerous nations, as well as the overall state of the world[3, 4].As a result of continual advances in artificial intelligence, machine learning techniques are widely applied in a variety of academic disciplines and real-world scenarios. The applications include machine learning for image recognition, medical forecasting, and other usage. Because of the growing popularity of artificial intelligence (AI), neural networks used in various applications have grown and improved [5-7]. Due to technical advancements, stock prediction models now have a solid foundation and greater room to grow. Stock prices are long-term uncertain, making it impossible to predict them. According to the outdated market theory, it is impossible to foresee stock values since stocks fluctuate indiscriminately. However, modern technical evaluation has indicated that a great deal of stock prices have been documented in prior data; hence, movement patterns are critical for accurately forecasting values. Stock market prediction is a method of using statistical and machine learning approaches to predict the potential growth of a certain stock or the market as a whole [8-10]. The purpose of forecasting the stock market is to help buyers understand the possible hazards and benefits of buying or selling a particular stock. Algorithms[11] based on machine learning are becoming more utilized in stock market prediction because they can analyze enormous amounts of data and detect trends that human beings may not see right away. The aforementioned algorithms employ past market data and other pertinent parameters for developing predictive models capable of estimating prospective stock prices or market patterns. The primary contributions of the planned work are as follows:

- Data is preprocessed using Depth Adjacent Surrounding (DAS) approach to regulate irregular values before stock prediction.
- The preprocessed information is examined using the Elematrix Harmony Optimization (EHO) algorithm to obtain optimized features.
- A probabilistic multi-model neural network (PMNN) classification algorithm is employed to predict stock based on selected features.
- The proposed EHO-PMNN mechanism is validated and contrasted based on metrics such as training and testing accuracy, f1-score, and others.

The rest of the paper has been divided into the following categories. Section 2 presents significant scholarly works on stock market forecasting. Section 3 provides a block diagram and algorithmic details for the proposed EHO-PMNN based stock market prediction system. Section 4 further compares and validates the results of the proposed EHO-PMNN model across a variety of parameters. Section 5 concludes and discusses the overall research findings.

II. RELATED WORKS

Shen et al [12]established an extensive artificial intelligence approach to predict short-term stock market prices. Stock market research is a prominent topic among scholars in both economic and technological disciplines because it is one of the key businesses that investors give their complete attention. The authors of this work seek to develop a cutting-edge price trend prediction model that focuses on timely price pattern estimation. Sim et al [13] proposed a Convolutional Neural Network (CNN) classification system for stock market prediction. This study proposes a stock price forecasting algorithm based on CNN and technical analysis to demonstrate the usefulness of new learning approaches in the financial sector. The CNN is a deep learning-based framework that duplicates biological creatures' visual recognition capabilities. The CNN framework combines a fully connected layer with a few convolutional and pooling layers to form an artificial neural network (ANN) structure. A Multi-Filter Neural Network (MFNN) classification method has been developed by Long et al. [14] for the purpose of predicting stock movement. For scholars and traders, predicting financial time series—particularly stock price—has proven to be one of the most difficult tasks. It is crucial to trade strategies in order to identify opportunities for stock trading. The primary sources of difficulty are the samples' noise and ambiguity. In addition to historical market patterns, the macroeconomic environment and investor sentiment have an impact on sample production. Nikou et al. [15] developed a stock price prediction system using deep learning and machine learning algorithms. Security indexes are the primary tools used to analyze the status of financial markets. Furthermore, making investments in stock markets contributes significantly to a country's GDP. As a consequence, if it can be done to predict the future trajectory of the stock market using appropriate processes, investors may be able to maximize their return on investment. The process of deep learning entails doing a thorough investigation of the subject matter while employing iteration and the development of progressively greater depths in order to impart systems specific strategies. Nti et al. [16] did a thorough examination of methods to anticipate stock market prices. Because the stock market acts as a critical pivot for any thriving and rising economy, every investment is undertaken with the goal of maximizing profit while minimizing risk. As a result, numerous studies on stock market forecasting utilizing fundamental or technical analysis have been conducted, employing a wide range of soft computing methodologies and techniques.

For the purpose of stock market prediction, Moghar et al. [17] combined the RNN and LSTM classification models to create a hybrid learning method. Numerous studies on the subject have shown that machine learning algorithms can be used to anticipate prices for managing and controlling an entire asset portfolio, as well as for the investment process and many other operations. All algorithmic methods that use computers to find patterns based just on data and without the need of programming codes are collectively referred to as machine learning. Because it is one of the main businesses that investors focus their entire attention on, stock market research is a popular topic for academics in both the economic and technical sectors. A state-of-the-art price trend prediction model with an emphasis on real-time price trend prediction is what the study's authors hope to create. The proposed price forecasting system incorporates a novel feature called feature extension. The authors of this work employ heuristic processing techniques gleaned from investor feedback in conjunction with technical indices to close the knowledge gap between the financial and technical research domains. Nabipour et al. [18] used AI algorithms to do research on current stock market trends. Investors have long been confused about the nature of stock market movement due to a multitude of determining factors. This approach significantly lowers the risk associated with trend predictions by utilizing deep learning and machine learning techniques. Stock prediction[19] is a challenging task that has long been recognized by finance and statistics experts. Buying equities with a high likelihood of price increase and selling stocks with a high likelihood of price decrease constitute the main methodology utilized in this forecast. In the past, stock market predictions were frequently made by financial specialists. But as learning methods have improved, data scientists have started to work on prediction problems.

A machine learning system was used by Vijh, et al. [15] to forecast the closing price of equities. The stock market is notorious for its volatility, unpredictability, and unexpectedness. Since stock values are dependent on a wide range of factors, including the state of the global economy, the political climate, the company's financial performance, and more, it can be challenging to predict stock values. As a result, techniques to estimate stock value by looking at trends over the previous several years may prove to be highly helpful in predicting movements in the stock market, boosting profits, and decreasing losses[20]. In this work, new variables are added to each decision tree's training set, which influences the choices made at the nodes of the tree. The noise in stock market data is usually rather severe due to its large magnitude, which might lead to the trees developing quite differently than anticipated. It attempts to lower forecasting error by treating stock market analysis as a classification issue and using training factors to estimate the closing price of a given firm's shares the following day.

III. PROPOSED METHODOLOGY

The goal of the present study is to provide an innovative structure for stock market prediction using a newly designed machine learning classification method. In our procedure, we use a supervised technique called Depth Adjacent Surrounding to fill in any missing variables. The following phase is to use the Elematrix Harmony Optimization (EHO) technique to extract the necessary features from the data. This process reduces the number of input features required to create an effective forecast, hence improving the prediction model's performance. A probabilistic multi-model neural network is used to predict whether a stock should be purchased or not depending on the input data. This neural network integrates the findings of multiple models to produce a final prediction with higher accuracy and dependability. The primary objective of this method is to give a tool that allows investors to make more informed decisions about whether or not to invest in a specific stock, based on a data-driven examination of pertinent market and company information. The method, which uses machine learning algorithms to analyze and understand massive amounts of data, can produce a more accurate and dependable prediction of stock performance than traditional methods does. Fig. 1 depicts the structure and diagram of the proposed stock market prediction system, which includes the actions listed below.

- Depth Adjacent Surrounding (DAS) based data preprocessing
- Elematrix Harmony Optimization (EHO)
- Stock prediction using Probabilistic Multi-Model Neural Network (PMNN)

Step 1: Input the data;

Step 2: Preprocess the data to fill the missing value by Depth Adjacent Surrounding supervised algorithm;

Step 3: Optimized the need feature from Elematrix Harmony Optimization algorithm;

Step 4: Predict the stock buy or not buy using the Use Probabilistic Multi-Model Neural Network to predict the data;

Step 5: Analysis the process;

The DAS algorithm is used to preprocess the provided dataset by filling in the missing fields once the input data has been obtained. Next, the features from the preprocessed dataset are selected using the EHO method. The PMNN classifier forecasts the stock market with high accuracy and performance results based on the features that have been chosen.

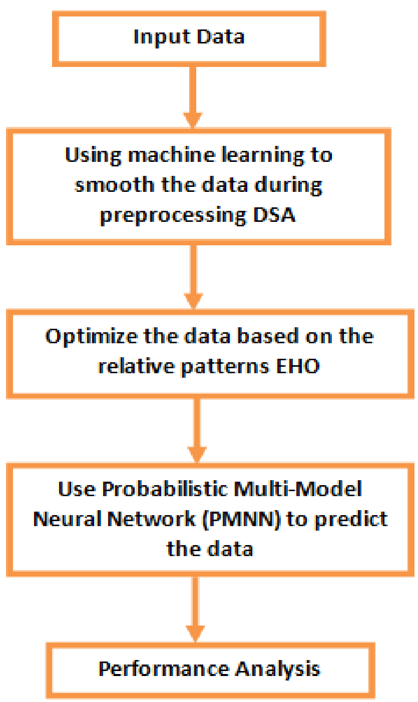

Fig. 1 Overview of the proposed stock market prediction framework

A. Data Preprocessing using Depth Adjacent Surrounding (DAS) Model

Information mining and machine learning programs have to cope with the practical issue of imputation. Missing values can cause bias and reduce the mining process's efficacy. However, most machine learning techniques are not well suited to some application domains due to the problem of missing information[21, 22]. The assumption that datasets include no missing values forms the foundation of the great majority of algorithms in use today. But in practical applications, a reliable method for managing those omitted details is needed. Class attributes (the target attribute) and dependent attributes both contain missing values. Missing values can be handled in a variety of ways, such as (a) ignoring items with empty values, (b) manually filling in the missing value, (c) substituting a global constant or the average of the objects for the absent values, and (d) figuring out the least likely value to fill in the gaps. The second approach usually loses too little important data and requires too much time and money, making it unworkable in many situations. Absence of attribute values: A few attribute values might not exist for instances in the training set or for objects that need to be classified. The reason for missing data could be that the value was not captured at the time the data was collected, or it was unrelated to a particular situation.

B. Elematrix Harmony Optimization (EHO)

An EHO algorithm is used to choose the features from the input samples following preprocessing. The optimization algorithm is typically used to find potential solutions for complicated issues[23]. A set of features is chosen from the stock dataset based on the best optimal solution in order to raise the classifier's prediction rate.

Algorithm 1 - Optimization algorithm

Input: Input Data samplesD_T

Output: Selected Feature sets$F_s(x)$.

For$i$ = 1 to N //Iteration from 1 to N

Initialize attributes 'ar'and the weight value 'wv'

$ar(N) = \{ar_0, ar, \dots, ar_n\} \ \ \forall N = 1, 2, \dots, n$

//'n' represents the number of attributes

If (mod(length(ar)) = 0)

$C = P_1^{e1} \times P_2^{e2} \times \dots\dots\dots \times P_k^{ek}$ [0 e^i]

Else

$ar(N) = \{ar_0, ar, \dots, ar_n, 0\} \ \ \forall N = 1, 2, \dots, n$

//'n' represents the number of attributes

$C = P_1^{e1} \times P_2^{e2} \times \dots\dots\dots \times P_k^{ek}$ [0 e^i]

End

$Mat_r = C[i]$

$Mat_c = C[i+1]$

$Mat_{ar} = ar \rightarrow (Mat_r \ X \ Mat_c)$

Where C is factorization index of making Matrix

Where update element gathering

$EG\{i, c+1\} = OE\{i, c\} + \alpha 1 \gamma 1(\rho\{i, c\} - C\{i, c) + \alpha 2 \gamma 2(\sigma\{i, c\} - ar\{i, c)$

$C\{i, c+1\} = C\{i, c\} + EG\{i, c\}$

Estimate the similarity index by

$S_{1:i}^j = S_{1:i-1}^j \times S_i^j$

Where, $S_i^j = \frac{1}{K}\sum_{i=1}^{K} P_i^k\big(C(k)\big) + \frac{1}{K}\sum_{i=1}^{K} EG_i^k\big(C(k)\big)$

Update ω_i for every change in 'i',

$\omega_i(n+1) = \sum_{i=1}^{N} \omega_i(n)\, \delta(x_n)$

Update particles by, $x(n+1) = \frac{1}{N}\sum_{i=1}^{N} \delta(x)$

Find likelihood from overall samples, $m_i^* = max(L_{1:i}^{m})$

Find the similarity index and the value of maximum in it by,

$\omega_i^*(n) = max\left(P_i^n\left(x(n)\right)\omega_i(n)\right)$

If$(m_i^* > m_{i-1}^*)$, then

Update weight value corresponding to C

If $(L_{1:i}^{m}) > 0$, then

$s_v = \{s_{v-1}, i\}$

End if

Else

Continue for loop 'i'.

End If

$F_s(x) = D_T(s_v)$

End '*i*' Loop

C. Probabilistic Multi-Modal Neural Network (PMNN) based Stock Prediction

Following feature optimization, the PMNN classifier is used to predict whether or not to buy a stock based on the input data's attributes. The PMNN is a type of machine learning method that was built using the standard neural network paradigm[24]. Compared to previous classification algorithms, the benefits of utilizing this technique include lesser training complexity, shorter processing time, and higher accuracy. In addition, this strategy combines the procedures of traditional probabilistic and multi-model neural network approaches to provide better classification results[25]. This technique takes the optimized data parameters as input and outputs the anticipated class label. In the beginning, the network is set up with m number of nodes, and the parameters such as weight value, material parameter, and amount of data interpreted. The sample time is used to estimate the data flow function based on the number of optimization particles and the degree of rotation.

Initially, the network formation is done with *m* number of nodes, where the parameters such as weight value, material parameter, and amount of data transformed are initialized at the beginning. According to the number of optimization particles and rotation angle in degree, the data flow function is estimated with the sample time *t*, and the initial weight value is updated by using the following equation:

$$\gamma_{i,j}^{t} = \gamma_{i,j}\left(f_{i,j}^{t}\right), \forall (i,j) \in L \qquad (1)$$

Then, the probability of maximum data transfer to the material in $\{y_{i,j}^{k}\}$ is computed as shown in the following model:

$$\{y_{i,j}^{k}\} = \sum_{s,r}\sum_{t} h_{s,r} \times P(r|C_n)\left(v_{s,r}\left(f_{i,j}^{t}\right)\right) \times a_{i,j}^{r} \qquad (2)$$

Where, (s, r) represent the starting point to resultant end pair, $v_{s,r}$ – Speed of data transformation from 's' to 'r' point, $a_{i,j}^{r}$ – weight value of particles update at each time samples with respect to their point distance of the material. Consequently, the flow pattern is updated by using the following equation:

$$f_{i,j}^{t+1} = f_{i,j}^{t} + \alpha_n \times \left(y_{i,j}^{t} - f_{i,j}^{t}\right) \qquad (3)$$

Moreover, the highest possible point is computed for identifying path length at the time 't' as shown in below:

$G(y) = max(y_{i,j}^{t})$ (4)

Furthermore, the distance vector between the particles is estimated by using the following equation:

$L(j) = \frac{1}{n}\sum_{x=1}^{n}\left\|N\left(f_{i,j}^{k}\right) - G(y)\right\|$ (5)

Moreover, find the optimal model of transfer function material difference at each time instant as shown in below:

$\Delta_{(t)} = \Delta_{j-1} + \mu \times \partial L/\partial t_{i}^{j}$ (6)

Then, the rotation angle is updated for each time instant with respect to data flow function as shown in below:

$\emptyset = f_{i,j}^{t+1} + \Delta_{(t)}$ (7)

Based on the function, the maximum data energy is updated from the table '$y_{i,j}^{k}$', and also the weight value and rotation angle are update for predicting the final classified label.

Algorithm 2: PMNN Classification

Input: Optimized Data Parameters $\{M_i\}$

Output: Estimated data transform with respect to class label

For t = 1 to m //Loop run for 'm' number of network formation.

Initialize γbe the weight value of the particles which can be represent as

$\gamma = \{M, L\}$ // where, 'M' denotes the material parameter and 'L' denotes the amount of data transformed at the time of 't'.

For i = 1 to n //'n' is number of optimization particles

For j = 1 to *l* // '*l*' rotation angle in degree.

Estimate data flow function $\{f_{i,j}^{t}\}$ for 't' samples f time

Update $\gamma_{i,j}^{t}$ using equ (11);

Compute probabilities of maximum data transfer to the material in $\{y_{i,j}^{k}\}$ that can represent in equ (12);

Update flow pattern, $f_{i,j}^{t+1}$ using equ (13);

Check convergence for each t+1 value

Calculate $G(y)$ using equ (14);

Calculate $L(j)$using equ (15);

//Find the distance vector between the particles.

If $\lambda < L$, then // λ defines the threshold value for contour check

Calculate $\Delta_{(t)}$using equ (16); // Find optimal model of transfer function material difference at each time instant.

Calculate $\emptyset$using equ (17); // Update the rotation angle for each time instant with respect to data flow function.

Continue.

Else

Replace previous data value of $\Delta_{(t)}$ and update $\emptyset$ as $\emptyset = \emptyset + 1$.

Continue loop.

End If

End For '*j*'

End For '*i*'

Sort the maximum data energy from the updated table '$y_{i,j}^{k}$'

Update weight and rotation angle.

End For

IV. RESULTS AND DISCUSSION

The proposed EHO-PMNN method's findings are evaluated and contrasted using a variety of factors to demonstrate its performance. Fig. 2 and Fig. 3 demonstrate the training input stock market data used in this study, with the open, low, and high stock data depicted by date. Furthermore, Fig. 4 and Fig. 5 depict the input class and its associated class ID, which are generated throughout the training process. Fig. 6 to Fig. 8 exhibits the test class, actual class and predicted class data, respectively. This study employs a number of metrics to evaluate the effectiveness of existing and proposed categorization systems for stock market prediction. It covers accuracy, area under curve (AUC), sensitivity, specificity, and so on, which are determined using the following models.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (9)$$

$$Specificity = \frac{TN}{TN + FP} \quad (10)$$

$$\Pr ecision = \frac{TP}{TP + FP} \quad (11)$$

$$\operatorname{Re} call = \frac{TP}{TP + FN} \quad (12)$$

$$Error\_Rate = 1 - Accuracy \quad (13)$$

$$Kappa\_Coeff = \frac{P_o - P_e}{1 - P_e} \quad (14)$$

$$F1\_Score = \frac{2 \times \Pr ecision \times \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \quad (15)$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (16)$$

Where, TP – True Positive, TN – True Negative, FP – False Positive, FN – False Negative.

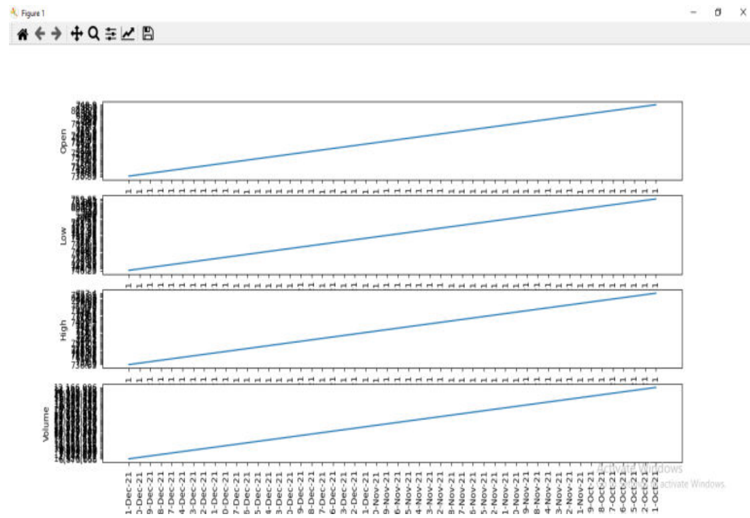

Fig. 2 Training data

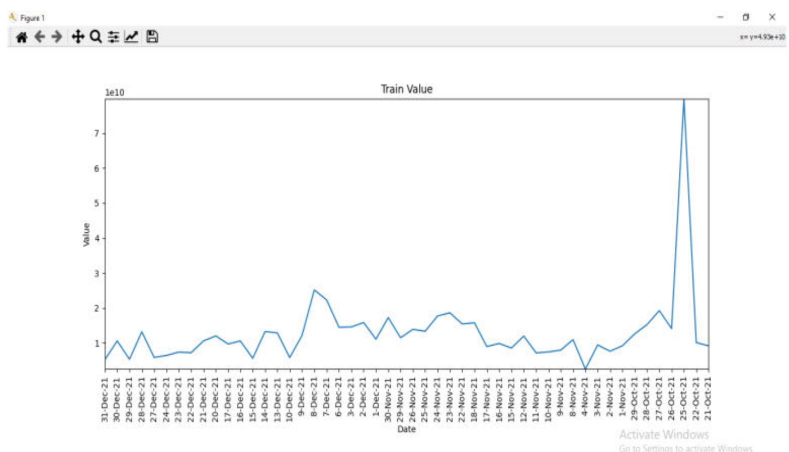

Fig. 3 Volume of training stock data

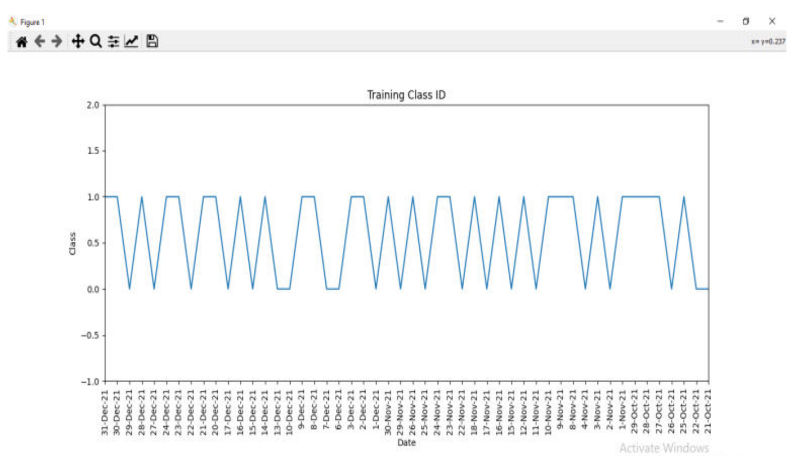

Fig. 4 Class of input data

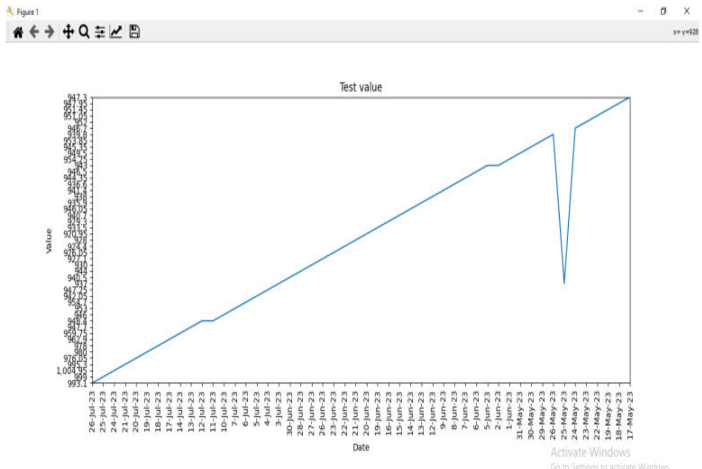

Fig. 5 Test value

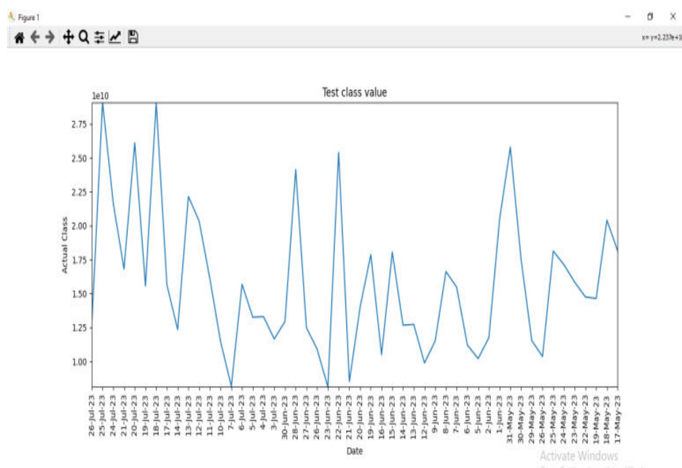

Fig. 6 Test class value

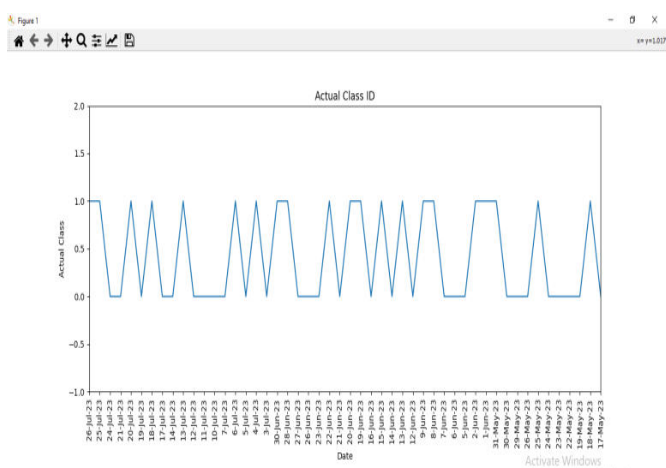

Fig. 7 Actual class

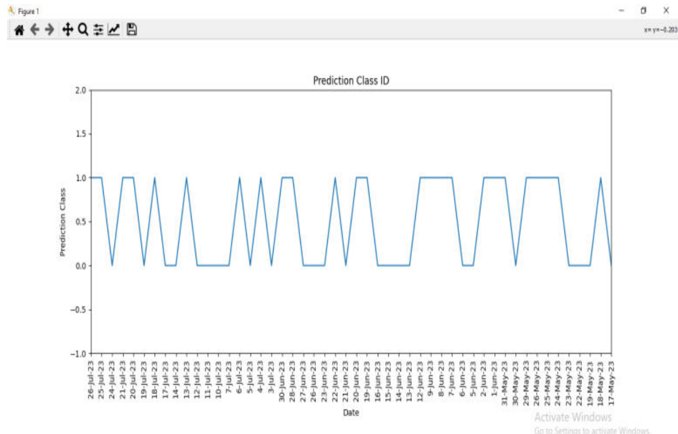

Fig. 8 Predicted class

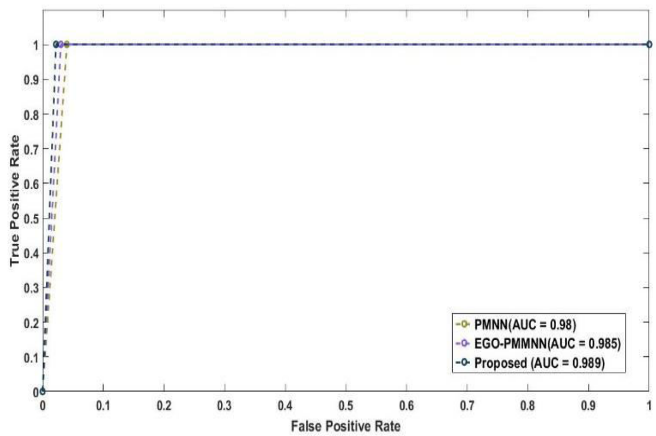

Fig. 9 ROC

The suggested model's ROC is displayed in Fig. 9 along with the true positive and false positive rates. As a consequence, the comparative study of the PMNN and suggested EHO-PMNN models utilizing a range of parameters is shown in Fig. 10 to Fig. 12, and its tabular values are displayed in Table 1. The enhanced performance of the suggested EHO-PMNN is examined in this work by a thorough comparison analysis. The findings indicate that, in comparison to the other models, the suggested EHO-PMNN produces superior outcomes.

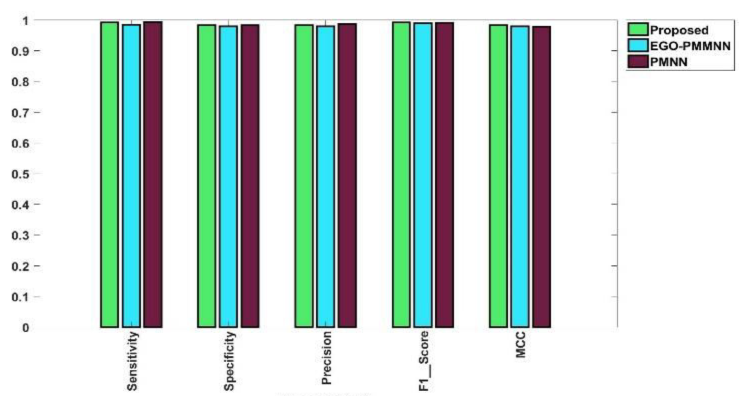

Fig. 10 Overall comparative analysis

Table 1 Overall performance comparative study

Parameters	Proposed (EHO-PMNN)	EGO-PMNN	PMNN
Sensitivity	0.992	0.985	0.9938
Specificity	0.9841	0.98	0.984
Precision	0.9840	0.98	0.9876
F1_Score	0.993	0.99	0.9907
MCC	0.9840	0.98	0.9786
Accuracy	0.992	0.985	0.98
Kappa Coefficient	0.9840	0.98	0.975
Error rate	0.0080	0.015	0.02
FPR	0.0080	0.012	0.02

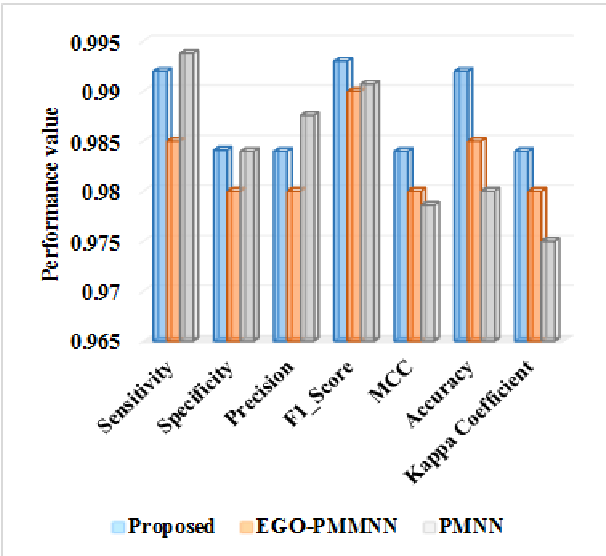

Fig. 11 Performance analysis of existing and proposed stock market prediction approaches

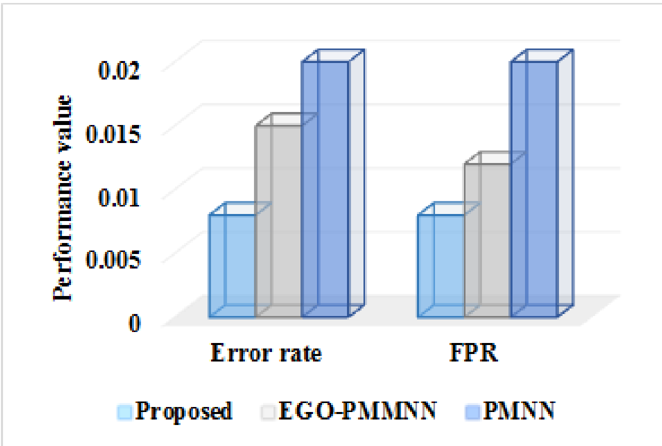

Fig. 12 Comparison based on error rate and FPR

Additionally, Table 2 and Table 3 compare the accuracy and AUC values of the suggested and standard stock market forecast approaches; related graphical representations are provided in Fig. 13 and Fig. 14. When compared to the other methods, the suggested model offers an enhanced AUC and accuracy values, as demonstrated by the entire study.

Table 2 AUC comparison

Methods	AUC
MCC	0.6
CSM	0.57
MDC	0.86
Bayes	0.73
CS	0.92
SoGF-FV	0.92
PMNN	0.96
EGO-PMNN	0.975
Proposed (EHO-PMNN)	0.981

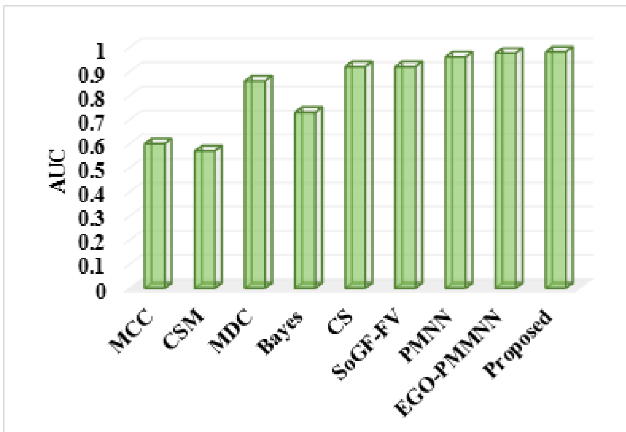

Fig. 13 Comparison based on AUC

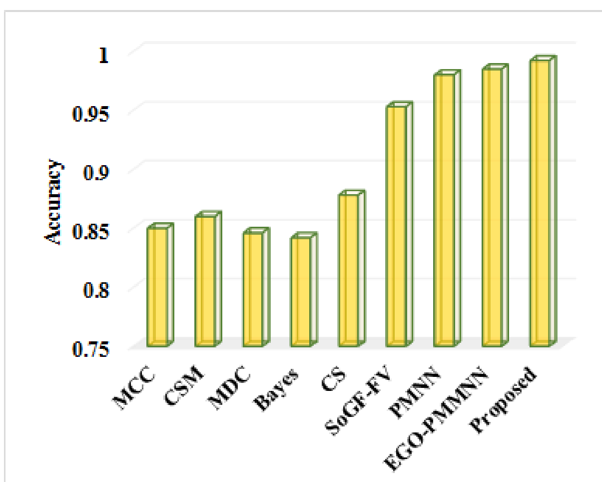

Fig. 14 Comparison based on accuracy

Table 3 Accuracy comparison

Methods	Accuracy
MCC	0.85
CSM	0.86
MDC	0.846
Bayes	0.842
CS	0.878
SoGF-FV	0.953
PMNN	0.98
EGO-PMNN	0.985
Proposed (EHO-PMNN)	0.992

V. CONCLUSION

Future stock price movement predicting has been the subject of numerous research initiatives. Stock market prediction is the process of estimating the performance of a specific stock or the market as a whole using statistical and machine learning approaches. The goal of stock market forecasting is to give investors a clearer picture of the benefits and drawbacks of purchasing or disposing of a specific stock. Because machine learning algorithms can analyze large volumes of data and spot patterns that human analysts might miss at first glance, its application in stock market forecasting is expanding. These algorithms create predictive models that forecast future stock prices or market trends based on historical market data and other pertinent factors. This method uses the preprocessed supervised technique called DSA to fill in the missing data. Then, a state-of-the-art EHO algorithm is used to optimize the required features that were extracted from the data. By following this process, the prediction model performs better and requires less input data to produce forecasts that are correct. Based on the input data, a PMNN predicts whether or not to purchase a stock. This neural network combines the information from multiple separate models to generate a single, more precise forecast. The main objective of this approach is to create a tool that will assist investors in making decisions about whether or not to purchase a specific stock.

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