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Financial Market Sentiment Analysis and Investment Strategy Formulation of Social Network Data using Epistemic Neural Networks

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Abstract: - Financial market sentiment analysis using social network data involves extracting and analysing relevant information from social media platforms to gauge the overall sentiment of investors and traders towards specific financial assets or markets. The task involves utilizing social network data to perform sentiment analysis on financial markets. This manuscript present the Epistemic Neural Networks (ENN) optimized with Elk Herd Optimizer (EHO) for financial market sentiment analysis and investment strategy formulation (FMSA-ENN-EHO). Initially data is taken from Stock Marketdataset. Afterward the data is fed to Multi-window Savitzky-Golay Filter (MWSGF) based pre-processing process. After that the pre-processed data is fed into Synchro Spline-Kernelled Chirplet Extracting Transform (SSCET) extracting attributes such as raw data, stock quotes then textual data. The output of SKCT is fed into Epistemic Neural Networks (ENN) is to predicts the probability value, adaptability, robustness and interpretability. The weight limits of the ENN are enhanced using Elk Herd Optimizer (EHO). The suggested technique is applied in Python and the efficiency of the suggested technique FMSA-ENN-EHO is assessed with the help of several presentations evaluating measures in terms of accuracy is 98%, F1-score is 95%, Mean absolute percentage Error (MAPE) is 0.05%, precision is 95% and the recall is 97%,while comparing other existing methods such as stock price forecast procedure with leading pointers by Convolution Neural Network (CNN)then Long Short Term Memory (SPI-CNN-LSTM), BP Procedure in Stock Price Design Classification and Forecast (SPC-BPNN) and Forecast of stock price way utilized by hybrid GA-XGBoost algorithm (PSD-GAXA) respectively.

Keywords: Financial Market, Investment, Social Media, Epistemic Neural Networks (ENN), Stock price, Savitzky-Golay Filter, Investment Strategy Formulation.

I. INTRODUCTION

Financial market sentiment analysis with social network data entails extracting insights from the massive amounts of information shared on social media stageslike, Twitter, Facebook, and then Reddit [1]. These platforms offer a wealth of real-time information, including opinions, emotions, and news about various financial instruments such as stocks, currencies, and commodities [2]. Natural language processing (NLP) methods are utilized to examine text data and determine the overall sentiment expressed by users towards specific financial assets [3].Emotion can be positive, negative, or neutral, and it can provide valuable visions into market sentiment trends and potential market movements [4]. After conducting sentiment analysis, investors can use the results to develop investment strategies [5]. For example, if sentiment analysis shows that investors are generally positive about a particular stock, they may consider buying or holding it in anticipation of a price increase [6].

In contrast, if sentiment is negative, investors may decide to sell or avoid investing in that asset [7]. Financial market sentiment analysis with social network data is a practice that takes advantage of the vast and real-time nature of social media platforms to assess investor sentiment toward various financial assets [8-9]. This approach acknowledges the impact of social media on market dynamics, as opinions, news, and emotions are shared instantly among users [10, 11].Textual data from social media posts can be analysed using sophisticated natural language processing (NLP) algorithms to determine prevailing sentiments about specific stocks, currencies, or commodities, whether bullish, bearish, or neutral [12]. The importance of such sentiment analysis stems from its ability to provide insights into broader market trends and potential price movements [13]. For example, a surge in positive sentiment toward a specific stock may indicate increased investor confidence and signal a market bullish trend [14].

A spike in negative sentiment, on the other hand, may indicate apprehension, potentially signalling a downturn or correction in asset prices [15]. These insights can be used to inform investment strategies, allowing investors

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to make timely decisions to capitalize on market trends or mitigate risk [16]. However, it should be noted that sentiment analysis alone may not be sufficient for making investment decisions [17]. It should be combined with other fundamental and technical analyses to help you make informed asset choices [18].

Furthermore, the reliability and accuracy of sentiment analysis are determined by the excellence of the data and effectiveness of the NLP procedures [19]. Integrating social network data into financial market analysis provides a useful tool for determining investor sentiment and identifying potential market opportunities or risks [20].

The existing techniques of financial market sentiment and investment strategy formulation based methods affected from various issues of stock market. This paper purposes to address the shortcomings of existing models by proposing an innovative technique for financial market sentiment and investment strategy formulation that employs an Epistemic Neural Networks (ENN) optimized with Elk Herd Optimizer (EHO).

A. Contribution Statement

The key role of this work is,

- The study utilizes statistics from the Stock Market Dataset, which is a benchmark dataset commonly used for financial market sentiment analysis and investment strategy formulation.
- The manuscript employs pre-processing techniques as Multi-window Savitzky-Golay Filter (MWSGF) to reduce noise and cleaning the data. Then the feature extraction is performed using the SSCET.
- The prediction task is carried out using an Epistemic Neural Networks (ENN) to predict theprobability value, adaptability, robustness and interpretability.
- The manuscript introduces the Elk Herd Optimizer (EHO) for optimizing the ENN model. EHO is engaged to fine-tune method limits and improve accuracy of financial market sentiment analysis.

B. Organization

The organization of this paper is, section 2 defines the literature survey, section 3 defines suggested methodology, section 4 defines result and debate and section 5 describes conclusion.

II. LITERATURE SURVEY

Here we review some paper based on financial market sentiment and investment strategy formulation using deep learning as follows;

Wu et al. [21] has presented the goal of growing and sustaining worth in order to hurry asset development. Between, the investment also financial management, people's preferred investment creation is frequently stocks, since the stock market has many rewards and charms, particularly when compared to other asset approaches. More and more scholars are developing methods for predicting the stock market from multiple perspectives. Based on the characteristics of monetary time series and mission of value forecast, this clause suggests new construction that syndicates CNN and LSTM to attain a more precise forecast of stock price. This new technique was appropriately named stock system array convolutional LSTM (SACLSTM).

Zhang and Lou [22] has suggested using Back Propagation Neural Network (BPNN) to classify and forecast stock price designs. The method involved using the BP procedure NN as input samples for 5 consecutive days of transaction data, resulting in 20 response layer nodes. The output sample was the next day's final value, with one node in the production layer. The goal of system training was to catch 20 spline purposes. Following the preparation of the BP procedureNN, the test information (stock price data for 5 successive days) was used as the neural network's input, and the network's target output was next day's closing rate. The error between the actual and target outputs was used to assess the network model's stock price prediction ability.

Yun et al. [23] has introduced a hybrid GA-XGBoost guess system with improved feature work, comprising data preparation, attribute set extension, and hybrid GA-XGBoost algorithm-based feature set selection. The significance of feature work method in stock rate direction forecast is empirically validated in this work by comparing the produced attribute collections with the original data collection and improving forecast performance to surpass benchmark models. Feature enhancement improves 67 technical pointers to unique historical stock rate information, providing the greatest precision boost. Additionally, this work uses the GA-XGBoost technique to generate a sparing optimum attribute set, which can achieve the necessary act with a substantially less number of features.

Huang et al. [24] has presented the financial market sentiment analysis and investment strategy formulation. This paper introduces a method for predicting stock price changes that syndicates social media feeling, genetic algorithms (GA), and DL. Initially, it uses hybrid genetic algorithm (HGA) in conjunction by machine learning

(ML) to classify chip-based pointers intimately connected with stock price variations, which are then used as input for LSTM to create a forecast method. Next, this study presents five feeling attributes to examine the impact of PTT social networks on TSMC stock price fluctuations, followed by grey relational analysis (GRA) to classify the feeling factors greatest carefully linked to rate variations.

Al Ridhawi, [25] has presented the financial market sentiment analysis and investment strategy development. This paper describes a method for forecasting the stock market by financial stock data and sentiment research. An ensemble-based approach is utilized to assess sentiment in social media messages that incorporates Multi-Layer Perception (MLP), LSTM, and CNN methods. For financial stock predictions, we use an LSTM model. The method were qualified on the stocks AAPL, CSCO, IBM, and Microsoft, using financial stock data and sentiment removed from Twitter posts.

Issam et al. [26] has presented the financial market sentiment analysis and investment strategy development. The online and digitization of information and works have occasioned in a significant increase in the capacity of unstructured text in current years. This flood of data will only rise, and It will originate from fresh and unexpected places.. To practice and make sense of this statistics, new and innovative approaches and tools will be required. The CNN and LDA procedures were employed.

Jing et al. [27] has presented the financial market sentiment analysis and investment strategy development. It introduces a hybrid method for stock price forecast that syndicates DL with feeling study. We use a CNN method to classify investors' hidden sentiments removed from significant stock discussion board. We present hybrid study method that uses the LSTM Neural Network method to analyse technical indications for the stock market.

III. PROPOSED METHODOLOGY

In this segment describe the suggested methodology FMSA-ENN-EHO. This study leverages the Stock Market Dataset and implements advanced techniques to improve financial market sentiment and investment strategy formulation. Pre-processing involves Multi-window Savitzky-Golay Filter (MWSGF) for cleaning data and noise reduction. Feature selection is conducted using the SSCET for extracting attributes such as raw data, stock quotes and textual data. After that, prediction using Epistemic Neural Networks (ENN) for predicts the probability value, adaptability, robustness and interpretability. Additionally, the Elk Herd Optimizer (EHO) is introduced to optimize the ENN for financial market sentiment and investment strategy formulation. The block diagram of suggested methodology is shown in the figure 1.

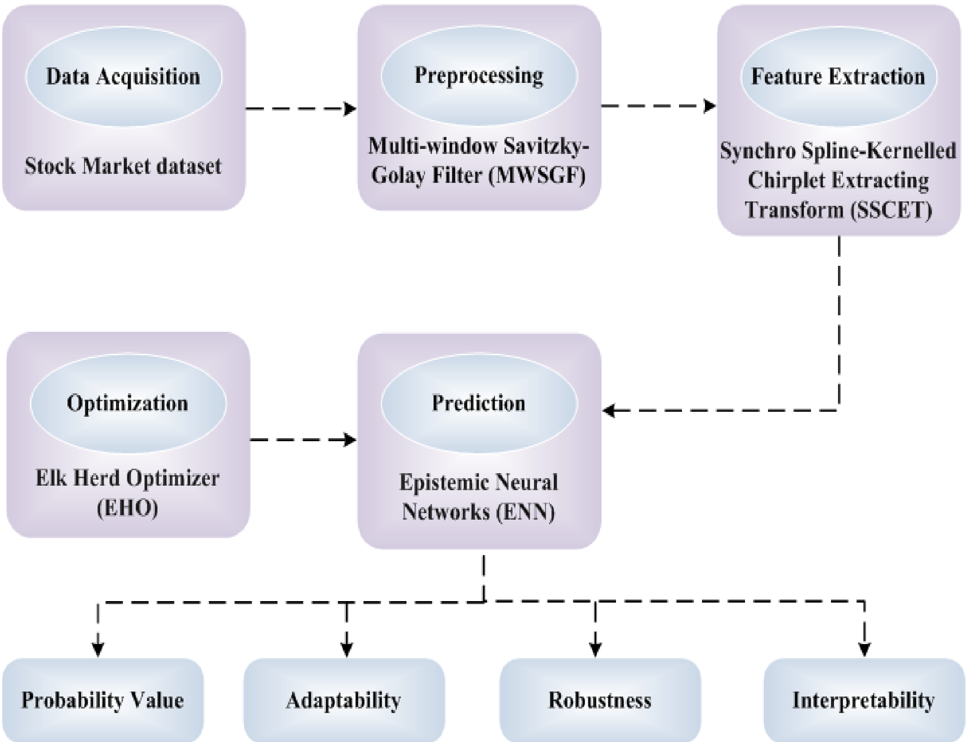

Figure 1: Block diagram of proposed methodology

A. Data Acquisition

The data is composed through share Marketplace dataset [28]. The facts for this study were gained from Yahoo Finance. It measured the NASDAQ-100 index, which is one of the greatest popular guides in United States (US). More specifically, it is an altered capitalization-weighted index comprised of 103 fairness safeties allotted by 100 of the biggest non-financial firms registered on the Nasdaq. Yahoo! Finance. The statistics collection is updated on a daily basis and covers the period since October 21, 2020 to March 17, 2021. We used the short-term historical stock rates (seven days earlier) as an input data collection.

B. Pre-processing using Multi-window Savitzky-Golay Filter (MWSGF)

To reduce noise and cleaning the data, pre-processing can be done using Multi-window Savitzky-Golay Filter (MWSGF) [29]. The SG strainer smoothed data while retaining most of its unique assets. Despite its extensive use and excellent structures, it has received little attention in the geophysical society and has yet to be documented in MT data handling. It begins with a brief theoretic impression of 1D SG filter before introducing our preparation for multi-window SG (MWSG) filtering method.

Simplified least-squares fitting convolution is what the SG filter. That is used to compute the derivatives of a series of successive values after smoothing them out. Difficulty can be compared to a biased moving normal filter, where weights are defined as degree-specific polynomials. Examine a series of data points representing seeming resistance (or stage). $x[i]$ Derivative through the fresh capacities.

$$P(i) = \sum_{k=0}^{n} a_k i^k \tag{1}$$

Wherever, a_k indicates the k^{th} weight constant of polynomial $P(i)$. In every window, the following remaining purpose reduced.

$$\delta_n = \sum_{i=-M}^{M} (P(i) - x[i])^2 = \sum_{i=-M}^{M} \left(\sum_{k=0}^{n} a_k i^k - x[i] \right)^2 \tag{2}$$

The worth of polynomial $P(i)$ at the center point $(i = 0)$ is the filter productivity. The gap moves detail by detail while calculating the filtration production. This procedure is equal to combining input facts points within openings and applying a fixed impulse reply. As a result, the productivity of a filter can expressed as follows:

$$y(k) = \sum_{i=-M}^{M} \omega_i x[k-i] = \sum_{i=-M}^{M} \omega_{k-i} x[i] \tag{3}$$

Where, $\{\omega_i\}$ represents the fixed instinctre sponse of the SG filters. This means that in a given window, the SG filter result is the weighted regular input data points in that window.

To get the weight coefficients vector $a = [a_0, a_1, \dots a_n]^T$ of the polynomial, it achieves difference on δ_n notation with respect to and let the off shoots equivalent is zero, ensuing in equations in $n+1$ unknowns as follows,

$$\sum_{k=0}^{n} \left[\sum_{i=-M}^{M} i^{j+k} a_k \right] = \sum_{i=-M}^{M} i^j x[i] \tag{4}$$

The data point'spath $X = [x_{-M}, \dots x_{-1}, x_0, x_1, \dots, x_M]^T$, the above eqn can be carved in medium form as follows,

$$(A^T A) a = A^T X \tag{5}$$

Then, weight constantspath can be derivative as follows,

$$a = (A^T A)^{-1} A^T X = A^* X \tag{6}$$

The matrix A^* is unaffected by the input information facts in the space and is only dependent on the opening size and grade of the polynomial. After pre-processing the pre-processed data's are transferred in to feature extraction phase.

C. Feature Extraction using Synchro Spline-Kernelled Chirplet Extracting Transform (SSCET)

To extract features of financial sentiment analysis using SSCET [30]. The SSCET technique is based on adapted Synchro extracting worker that is enriched over the occurrence-rotating and frequency-shifting operators of SCT. The Gaussian window is described as:

$$g_\sigma(t) = \frac{1}{\sqrt{2\pi\sigma}} \cdot e^{-\frac{1}{2}\left(\frac{t}{\sigma}\right)^2} \tag{7}$$

Where, $g_\sigma(t)$ is a Gaussian window, σ is the determination parameter of the window purpose. The stage-shifted procedure of SCT is stated by:

$$SCT = \int_{-\infty}^{\infty} g_\sigma(\tau - t_0) \cdot s(\tau) \cdot \Phi^R(\tau)\Phi^S(\tau) \cdot e^{-i\omega(\tau - t)} dt \tag{8}$$

The original estimated IF trajectory ω_0 is defined by:

$$\omega_0^{\sim} = -i \cdot \frac{\partial_t SCT_e(t,\omega)}{SCT_e(t,\omega)} \tag{9}$$

Founded on fresh two-dimensional (2D) IF route $\omega_0^{\sim}$, represents the SEO is swapped by an adapted Synchro extracting operator, which is stated as:

$$\delta\left(\omega - \omega_0^{\sim}\right) = \begin{cases} 1, & \omega = \omega_0^{\sim} \\ 0, & \omega \neq \omega_0^{\sim} \end{cases} \tag{10}$$

With the modified synchro extracting operator, the SSCET technique is well-defined as:

$$SSCET(t,\omega) = SCT_e \cdot \delta\left(\omega - \omega_0^{\sim}\right) \tag{11}$$

Where, ω_0 is a rajectory, SCT is the synchro chirplet transform. The extracted features such as raw data, stock quotes and textual data are fed into prediction phase.

D. Prediction using Epistemic Neural Networks (ENN)

In this section, prediction of financial sentiment analysis using ENN is discussed[31].The ENN is a sophisticated deep learning architecture used for prediction tasks, especially in context of financial sentiment analysis. This type of network is well-suited for handling data, making it particularly effective for predicting financial sentiment types such as probability value, adaptability, robustness and interpretability.

The output of a traditional neural network is vector-valued and is defined by a parameterized function class. f, $f_\theta(x)$ given limits θ and an input x. The output $f_\theta(x)$ allocates an agreeing chance $\hat{P}(y) = \exp\left(\left(f_\theta(x)\right)_y\right) / \sum_{y'} \exp\left(\left(f_\theta(x)\right)_{y'}\right)$ to every class y .For shorthand, we write such class chances as,

$$\hat{P}(y) = soft\max\left(f_\theta(x)\right)_y \tag{12}$$

We refer to a predictive class delivery $\hat{P}$ created in this way as a marginal guess, as it pertains to a single input x .

A parameterized function class and a reference distribution, on the other hand, define the ENN architecture. Additionally, the vector-valued output of an ENN is dependent on an epistemic index that accepts values as arguments. A standard Gaussian over a vector space or a uniform distribution over a finite set are common options for the reference distribution. Epistemic uncertainty is expressed by the index. Specifically, the network output fluctuation with denotes uncertainty that may be addressed by more data. As we shall show, we can characterize the type of uncertainty necessary to produce good joint predictions by introducing an epistemic index. Given inputs $x_1,\ldots,x_\tau$, a joint guess assigns a chance $\hat{P}_{1:\tau} = \left(y_{1:\tau}\right)$ to each class grouping $y_1,\ldots,y_\tau$. While CNN are not planned to offer joint forecasts, joint predictions can be produced by increasing marginal calculations:

$$\hat{P}_{1:\tau}^{NN}\left(y_{1:\tau}\right) = \prod_{t=1}^{\tau} soft\max\left(f_\theta(x_t)\right)_{yt} \tag{13}$$

However, this demonstration method each result $y_{1:\tau}$ as autonomous and so fails to distinguish uncertainty from deficiency of data. ENN addresses this by allowing more expressive joint forecasts through mixing over epistemic catalogues:

$$\hat{P}_{1:\tau}^{ENN}\left(y_{1:\tau}\right)=\int_{z} P_Z\left(dz\right)\prod_{t=1}^{\tau} soft\max\left(f_\theta\left(x_t, z\right)\right)_{yt} \tag{14}$$

This integration presents needs, so joint guesses are not always the result of peripheral. ENN represents a sophisticated neural network architecture that leverages advanced techniques in temporal data processing, graph convolution, and gated mechanisms to address the challenges inherent in financial sentiments prediction such as such as probability value, adaptability, robustness and interpretability. In this work, Elk Herd Optimizer (EHO) for accurate financial sentiments prediction in deep learning, this method optimizes the ENN optimum parameter as P . Here, EHO is applied for tuning the weight parameter of ENN.

E. Elk Herd Optimizer (EHO)

The EHO is used to optimize the weight parameter of the ENN as P [32].The EHO is stimulated by the upbringing process of an elk herd. Elk have dual primary propagation periods: rutting and calving. The elk, also known as the wapiti, is a deer species that is second only to the moose deer in size. Elks live in woods and forest edges throughout Central East Asia then North America, They desire earnest climate over cold climate. Elks are not killers, and eat bark, leaves, plants, then grasses. EHO efficiently converges to optimal solutions by mimicking EHO behaviour, resulting in faster convergence and less training time for ENN. The flow chart of EHO is shown in the figure 2.

Step 1: Initialization

Initially in ENN, a solution covariance matrix representing the starting positional vectors of the search is identified. This matrix is originally established as random values inside a search space. Additionally, each position vector has a value for the initial fitness function. The steps of the suggested EHO initialization are mathematically expression is given as,

$$E=\begin{bmatrix} E_{11} & E_{12} & E_{13} & \dots & E_{1n} \\ E_{21} & E_{22} & E_{23} & \dots & E_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ E_{n1} & E_{n2} & E_{n3} & \dots & E_{nn} \end{bmatrix} \tag{15}$$

Where, E signifies the elk herd that are created randomly, n is the number of size of the function.

Step 2: Random Generation

Input parameters generated at random after initialization. Therefore, optimization process of EHO and it transfer from exploration to exploitation steps utilizing various behaviours depend on this condition.

Step 3: Fitness Function

The outcome is determined by initialized judgments and random responses. The fitness is then computed using,

$$F = Optimize\left(P\right) \tag{16}$$

Step 4: Exploration Phase

In exploration phase,Families are created using the EHO model depending on the instruction rate. First, the entire quantity of families is determined by $B = B\left|B_r \times EHS\right|$. The elks of shocking with the greatest fitness ratings at the top of EH are then designated as bulls. The bulls are then chosen from EH based on their fitness standards. This is to represent the combat domination challenges, when more harems are awarded to the stronger elks.

$$P_j = \frac{f\left(x_i\right)}{\sum_{k=1}^{B} f\left(x^k\right)} \tag{17}$$

Where, $f(x_i)$ is the absolute fitness value, B is the selection probability, P_j is the summation of absolute fitness.

Step 5: Exploitation Phase for Optimize P

In exploitation phase,the calve $\left(x_i^j(t+1)\right)$ of every family are repeated founded on the attributes typically removed from their father bull $\left(x^{hj}\right)$ and mother harem $\left(x_i^j(t)\right)$.In case the calf $\left(x_i\,(t+1)\right)$ has the similar index i as its bull dad in the domestic, the calf is describes as,

$$x_i^j(t+1) = x_i^j(t) + \alpha \cdot \left(x_i^k(t) - x_i^j(t)\right) \tag{18}$$

Where, α is a chance worth within the variety of [0, 1] that regulates the rate of the genetic qualities from the arbitrarily selected elk in the herd $x^k(t)$ wherever, $k \in (1,2,\ldots,EHS)$.

Step 6: Update Best Solution

An elk herd iteration ends when every elk herd position based on the fitness factor has been updated using the data from the exploration and exploitation phases.

Step 7: Termination Condition

The function values P of generator from ENN is optimized with the help of EHO, repeat step 3 until fulfill halting criteria $N = N+1$ is met. Then ENN has accurately predicted the financial market of social network with high accuracy.

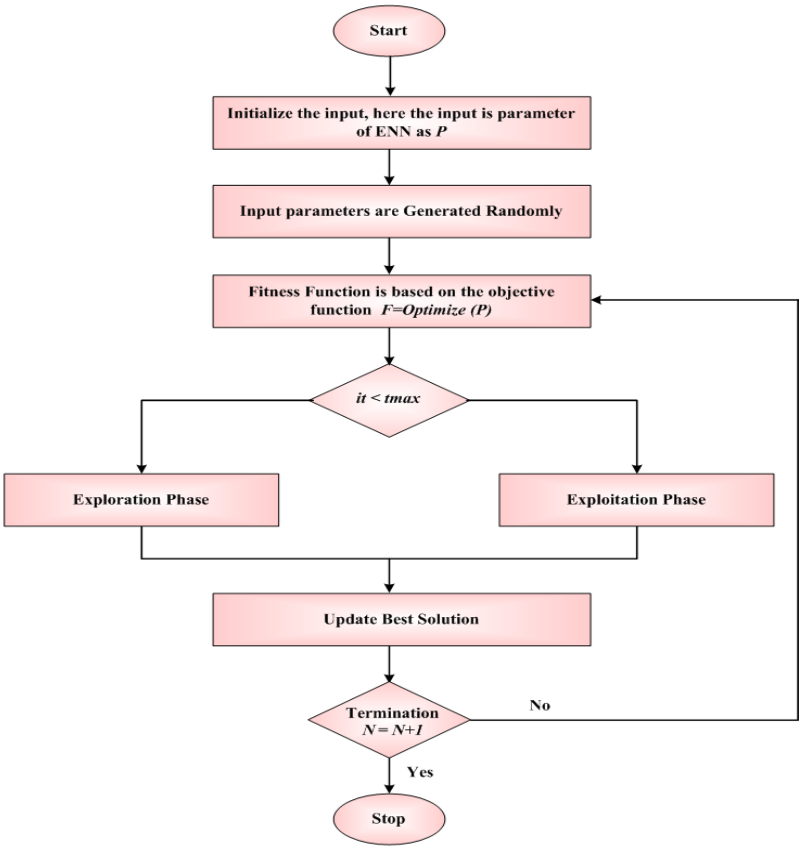

Fig 2: Flow chart of EHO

IV. RESULT & DISCUSSION

The proposed method FMSA-ENN-EHO is implemented in python and analysed performance metrics likes accuracy, F1-score, MAPE, precision and recall. The proposed method FMSA-ENN-EHO is comparing with existing methods like SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA respectively.

A. Performance Measures

To study the performance, measures like accuracy, F1-score, precision, MAPE and recall are determined.

1) Accuracy

Accuracy is the relation of exact forecast to overall amount of records in the data collection. Accuracy is dignified as the following equation (19),

$$Accuracy = \frac{(T_P + T_N)}{(T_P + F_P + T_N + F_N)} \tag{19}$$

2) F1-Score

It evaluates the precision of the model on the dataset. It is determined by equation (20),

$$F1Score = \frac{T_P}{\left(T_P + \frac{1}{2}\left[F_P + F_N\right]\right)} \tag{20}$$

3) Mean Absolute Percentage Error (MAPE)

The MAPE is measured by the following equation (21),

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{21}$$

Where, $\hat{y}_t$ and y_t denote the forecast and actual values, and n represents the entire number of guesses.

4) Precision

Precision is the positive predict value. Precision is compute by following equation (22),

$$\Pr ecison = \frac{T_P}{T_P + F_P} \tag{22}$$

5) Recall

Recall is the relation of true positive guesses to the total amount of actual positive samples (both properly and in accurately forecast by positive). The formulation of recall is exposed in equation (23),

$$\mathrm{Re}call = \frac{T_P}{T_P + F_N} \tag{23}$$

B. Performance Analysis

The simulation results of proposed FMSA-ENN-EHO method shows in fig: 3 to 7. Then the proposed method FMSA-ENN-EHO is likened with existing systems like SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA respectively. In order to show the efficiency of the suggested ENN predictor with optimization EHO algorithm, evaluation experiment was carried and the results.

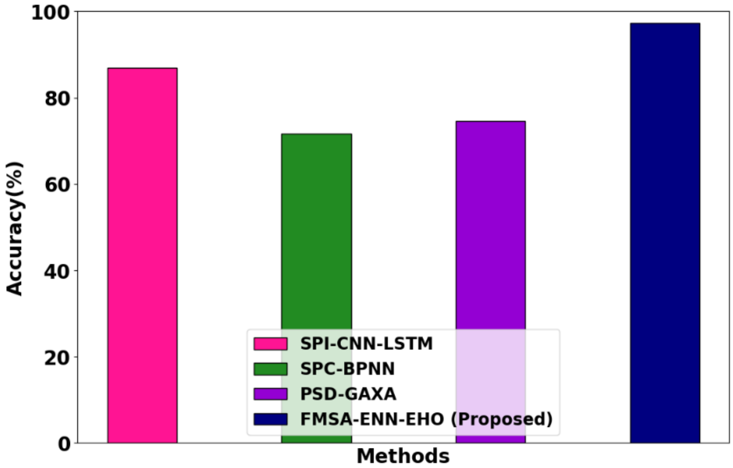

Fig 3: Analysis of accuracy

Figure 3 shows analysis of accuracy. The performance of suggested EMSA-ENN-EHO technique results in accuracy that is 98% and then the existing methods such as SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA accuracy are 85%, 70% and 75%. The proposed EMSA-ENN-EHO method accuracy is higher compared with the existing methods.

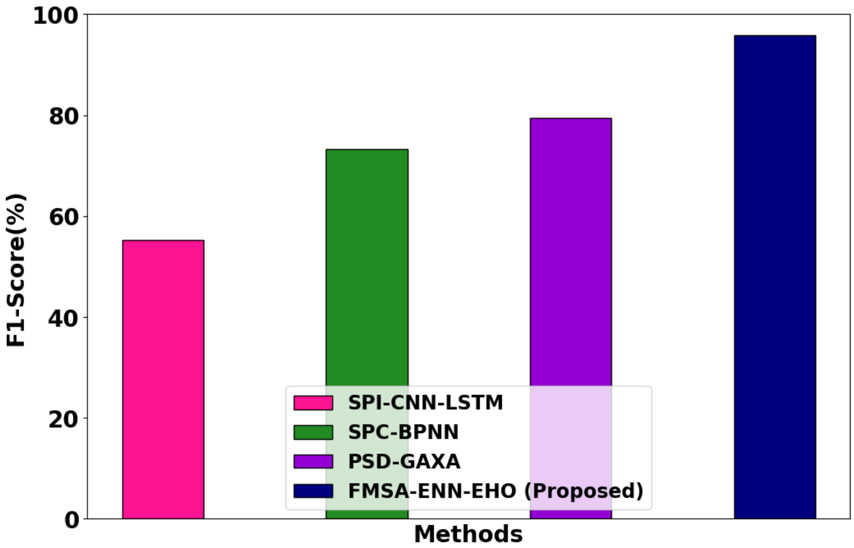

Fig 4: Analysis of F1-score

Figure 4 shows the study of F1-score. The performance of suggested EMSA-ENN-EHO method results in F1-score achieves 95% and then the existing SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA methods F1-score is 55%, 75% and 80% lower F1-score. The proposed EMSA-ENN-EHO method shows higher F1-score compared with other existing methods.

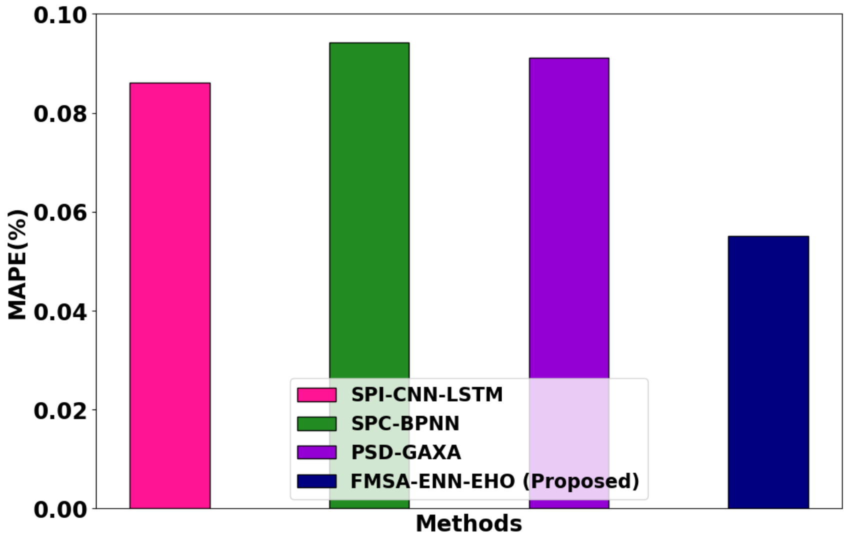

Fig 5: Analysis of Mean Absolute Percentage Error (MAPE)

The analysis of MAPE is shown in fig 5. The act of the suggested EMSA-ENN-EHO method results in MAPE achieves 0.05% and then the existing methods such as SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA achieves MAPE are 0.09%, 0.095% and 0.093%. The proposed EMSA-ENN-EHO method shows less MAPE compared with other existing methods.

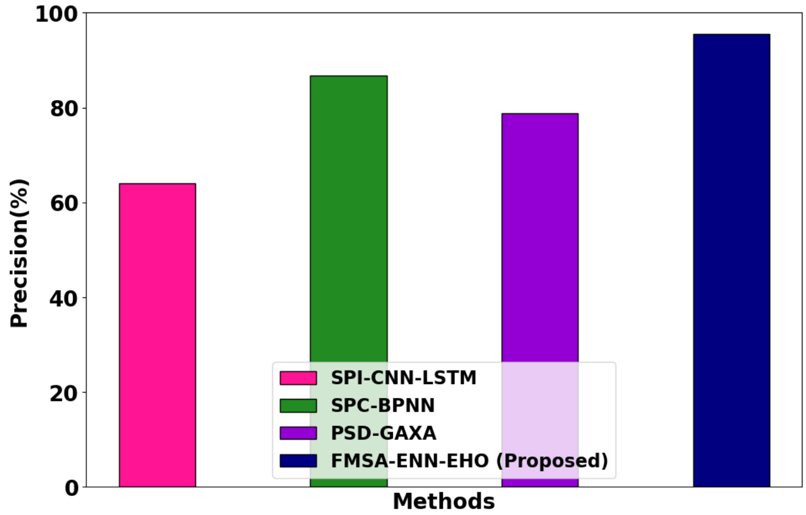

Fig 6: Analysis of precision

The analysis of precision is shown in fig 6. The act of the suggested EMSA-ENN-EHO technique results in precision achieves 95% and the existing methods such as SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA achieve precision are 65%, 85% and 75%. The proposed EMSA-ENN-EHO method shows higher precision compared with other existing methods.

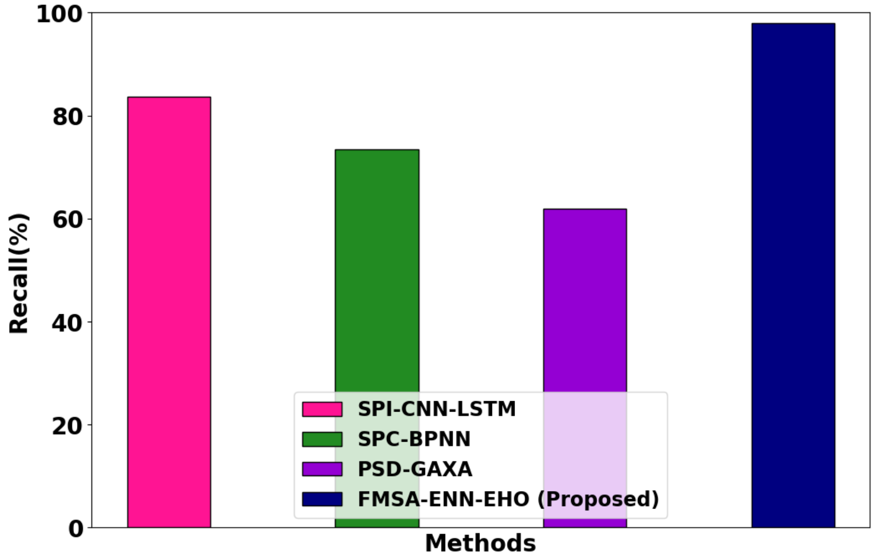

Fig 7: Analysis of recall

The analysis of recall is shown in fig 7. The act of the suggested EMSA-ENN-EHO method results in recall attains 97% and then the existing methods such as SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA achieve recall are 85%, 70% and 65%. The proposed method shows higher recall compared with other existing methods.

C. Discussion

In the discussion section, the study of FMSA-ENN-EHO method in financial market sentiment analysis and investment strategy formulation, shows its high accuracy, F1-score, low MAPE, precision, and recall compared to existing systems like SPI-CNN-LSTM, SPC-BPNN, and PSD-GAXA. The discussion emphasizes the advantages of using ENN optimized with EHO for sentiment analysis, the effectiveness of feature extraction through SSKCET, and the impact of MWSGF for pre-processing on data quality. Additionally, the optimization techniques contribution to model robustness and interpretability is explored, positioning the FMSA-ENN-EHO method as a reliable tool for making informed investment decisions and predicting market trends accurately.

V. CONCLUSION

In conclusion, the study on financial market sentiment analysis and investment strategy formulation using epistemic neural networks optimized with elk herd optimizer highlights the importance of leveraging advanced deep learning techniques for accurate and efficient prediction of financial market emotion study. Through the optimization of ENN and utilization of information, significant improvements in prediction performance have been achieved. The proposed FMSA-ENN-EHO method is executed in the python platform utilizing the dataset of stock market dataset. The performance of the FMSA-ENN-EHO method contains accuracy, precision, recall, F1-score and MAPE. The suggested FMSA-ENN-EHO method attains 98% higher accuracy for financial market sentiment analysis, respectively. The FMSA-ENN-EHO method attains 95% higher F1-score of financial market emotion study. The proposed FMSA-ENN-EHO method attains 0.05% lower MAPE of financial market emotion study. The FMSA-ENN-EHO method attains 95% higher precision of financial market emotion study. The FMSA-ENN-EHO method attains 97% higher recall of financial market sentiment analysis. The recital of the suggested FMSA-ENN-EHO technique is better related with the current approaches such as SPI-CNN-LSTM, SPC-BPNN and PSD-GAXA.

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