International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 1817-1829

http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Hyper Capsule LSTM-Gated GAN with Bayesian Optimized SVM for Cloud-based Stock Market Price Prediction in Big Data Environments

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Article Info:

DOI: 10.22399/ijcesen.1418
Received : 21 January 2025
Accepted : 13 March 2025

Keywords :

Big Data,
Hybrid Cloud Model,
Non-Relational Databases,
Stock Market Prices,
Preliminary Data,
HCG-GAN,
LSTM-Gated GAN.

Abstract:

In the modern era, big data is a brand-new and developing buzzword. With a significant expansion of finance and business growth and forecast, the stock market is a dynamic, ever-evolving, unpredictable, and fascinatingly promising specialty. This study presents a novel approach for enhancing forecast accuracy through optimal feature selection combined with deep learning techniques. By employing an Artificial intelligence method to identify and select the most significant features influencing stock prices, we mitigate the risks of overfitting and improve model interpretability. To propose an advanced methodology called Hyper Capsule LSTM Gated Generative Adverbial Network (HCG-GAN) with Bayesian Optimized Support Vector Machine (BOSVM) for stock market price prediction, which is well-suited for time-series data. A comparative analysis is conducted to evaluate the performance of our model against traditional prediction methods. The preliminary process takes place in stock market pricing data log normalization using a Min-max z-score normalizer. Then Active stock distinction impact rate (ASDIR) is estimated to find the scaling factor of stock market mean changes. The prediction performance of the proposed model is compared with that of the benchmark models CNN-LSTM, DLSTMNN, and ANN-RF using evaluation metrics of accuracy, precision, recall, F1-score, AUC-ROC, PR-AUC, and MCC. Results indicate that the integration of optimal feature selection not only boosts prediction accuracy but also ensures robustness against market volatility. This work contributes to the growing body of literature on artificial intelligence applications in finance, offering insights that can significantly enhance trading strategies and investment decisions.

1. Introduction

The stock market is a competitive playing field dependent on a range of aspects of the economy, such as fiscal, political, and quantity. Modern analytical techniques in the wake of big data have changed traditional methods of prediction for the stock market, which have become more precise and meaningful. Big Data is defined as a deal that comprises structured, semi-structured, and unstructured information that is accessed at an enormous scale and at a substantial rate. Big Data here consists of all manner of information from historical stock market prices and volumes and other financial releases to social media sentiment and macroeconomic data [1]. The stock market is recognized as a very competitive and multinational field that significantly impacts the economic situation of countries and business investments. Forecasting the stock market is a very complex affair because of its random nature, non-linearity, and interactions between multiple variables, including economic data, politics, and market perception [2,3]. Such intricate patterns, however, are beyond the understanding of traditional models such as the linear regression equation and simple statistical models, so their prediction capacity is usually relatively low.

Despite the apparent growth of the line of machine learning and deep learning, many existing approaches meet certain limitations. For example, although LSTM networks are capable of offering a good representation of the temporal structure, their representation of spatial relationships is not efficient enough. Like AC-GANs, Generative Adversarial Networks (GANs) are adequate to generate synthetic data that look nearly real but are still problematic during the training process, where their modes can collapse and become unstable [4]. However, SVMs, which are computationally powerful and accurate, may need a proper selection of hyperparameters; it may also be time-consuming and sometimes non-optimal when conventional optimization techniques are employed [5,6]. Forecasting market movements can help businesses and individuals avoid significant losses and make wise decisions. This research study will explore how machine learning algorithms and cloud computing capacity may be used to forecast stock closing prices, a difficult task for conventional methods. As seen earlier, these disadvantages show that there is a place for developing an improved, compound approach for higher accuracy and effectiveness of the stock market forecast. Based on these challenges, this paper presents an Enhanced Stock Market Prediction Framework that comprises a Hyper Capsule LSTM Gated GAN model together with a BOSVM Bayes-SVM. The Hyper Capsule LSTM integrates capsule networks to capture contextualized hierarchical spatial-temporal features compared to standard Conv-LSTM networks, and the Gated GAN improves data realism and reduces noise through gated operations. Last, the hyperparameters of the Bayes-SVM are optimized using the distinctive feature of Bayesian optimization to reduce computational cost while achieving better predictive capability. This construction methodology combines the features of two primary disciplines that strengthen the system's precision and efficiency in stock market prediction.

2. Literature Survey

According to the author [7], using DL to forecast stock market prices and trends has grown even more common. The author suggested a thorough modification of the DL-based model and feature engineering for stock market price trend prediction. The suggested approach is all-inclusive since it incorporates a customized DL-based system for stock market price trend prediction, pre-processing of the stock market dataset, and the application of several feature engineering techniques. It needs a lot of historical, high-quality market data. Biassed, noisy, or incomplete datasets can make predictions less accurate. Because of its intrinsic dynamism, non-linearity, and complexity, stock group value projection has always been both appealing and challenging for shareholders, according to the author [8]. A Long-Short Term Memory (LSTM) technique was used to fix the problem. Poor generalization of unknown data may result from overfitting training data, mainly if the model is overly sophisticated or the dataset is small. A Comprehensive Ensemble Empirical Mode Decomposition with Convolutional Neural Network and LSTM (CEEMD-CNN-LSTM) approach was used to address the problem. Deep features and time sequences could be extracted and used for one-step-ahead prediction. However, historical data might not adequately capture the suggested approach [9].

The author [10] discussed how several businesses spend billions and millions of dollars in foreign nations in the hopes of turning a profit. Predicting market movement can help companies or individuals make wise judgments and avoid significant losses in such a volatile industry. Cloud and ML methods were used to anticipate the closing values in order to achieve the goal. However, the primary disadvantages of this approach are security and privacy issues. In order to address the problem, the author [11] employed big data analysis to aid in forecasting and making precise business decisions and lucrative investments. According to the author [12], predicting the development trends of financial data is a very challenging task since it contains complicated, ambiguous, and incomplete information. Deep Neural Networks (DNNs) were used to fix the problem. It can be applied to address nonlinear problems more satisfactorily. It can be challenging to determine whether features or indications have a significant influence on market patterns, and this can affect the accuracy of the model. A Deep LSTM Neural Network (DLSTMNN) with embedded layer methodology was used to fix the problem. The random selection problem's starting weight in this approach may be readily subject to inaccurate forecasts [13].

Future stock prediction is one of the most well-liked and intricate DL in finance, according to the author [14]. There are too many variables that influence the frequency and magnitude of stock rises and falls, which makes forecasting future stock prices challenging. A Recurrent Neural

Networks (RNN) approach was used to address the problem. Because they are frequently viewed as "black boxes," it is challenging to understand the logic underlying their forecasts, which erodes credibility and usefulness when making delicate financial decisions. An LSTM, Bi-directional LSTM, and Attention Mechanism (LSTM-Bi-LSTM-AM) methodology were used to address the problem. It was employed to record how feature states affected the closing price of the stock at various points in time. It may not be able to produce predictions fast enough, though, and it can be computationally demanding [15]. Because financial stock markets are volatile and non-linear, it is tough to estimate stock market returns accurately, as the author [16] stated. The Artificial Neural Network and Random Forest (ANN-RF) technology was used to fix the problem. It was used to forecast the closing price of five businesses from various industries for the following day. Although it can spot connections, it might not comprehend the market's causal links, which could result in inaccurate forecasts. A Deep RNN (DRNN) methodology was used to fix the problem. It can simultaneously forecast a stock's starting price, lowest price, and highest price. Smaller businesses or individuals, however, may find it less accessible due to its high computational resource requirements [17].

According to the author [18], investing in a collection of assets has never been simple since the financial market's anomalies prevent basic models from making more accurate predictions about future asset values. Therefore, future stock market values were predicted using an LSTM-RNN technique. Although it mostly depends on historical data, unanticipated events like wars, pandemics, and changes in the economy can cause market trends to alter. A GA-XGBoost methodology was used to fix the problem. Contrasting the acquired feature sets with the original dataset confirms the significance of the feature engineering process on stock price direction prediction. It might be difficult for the suggested approach to distinguish between relevant signals and noise [19]. The author [20] discussed how stock price data resembles time series. A CNN-LSTM algorithm was used to classify the time series appropriately. Because of the market's inherent unpredictability and volatility, the CNN-LSTM performs better at short-term forecasting but struggles with long-term projections. A Decision Tree (DT) approach was used to address the problem. It necessitates careful hyperparameter adjustment, which takes time and cannot provide the best outcomes [21].

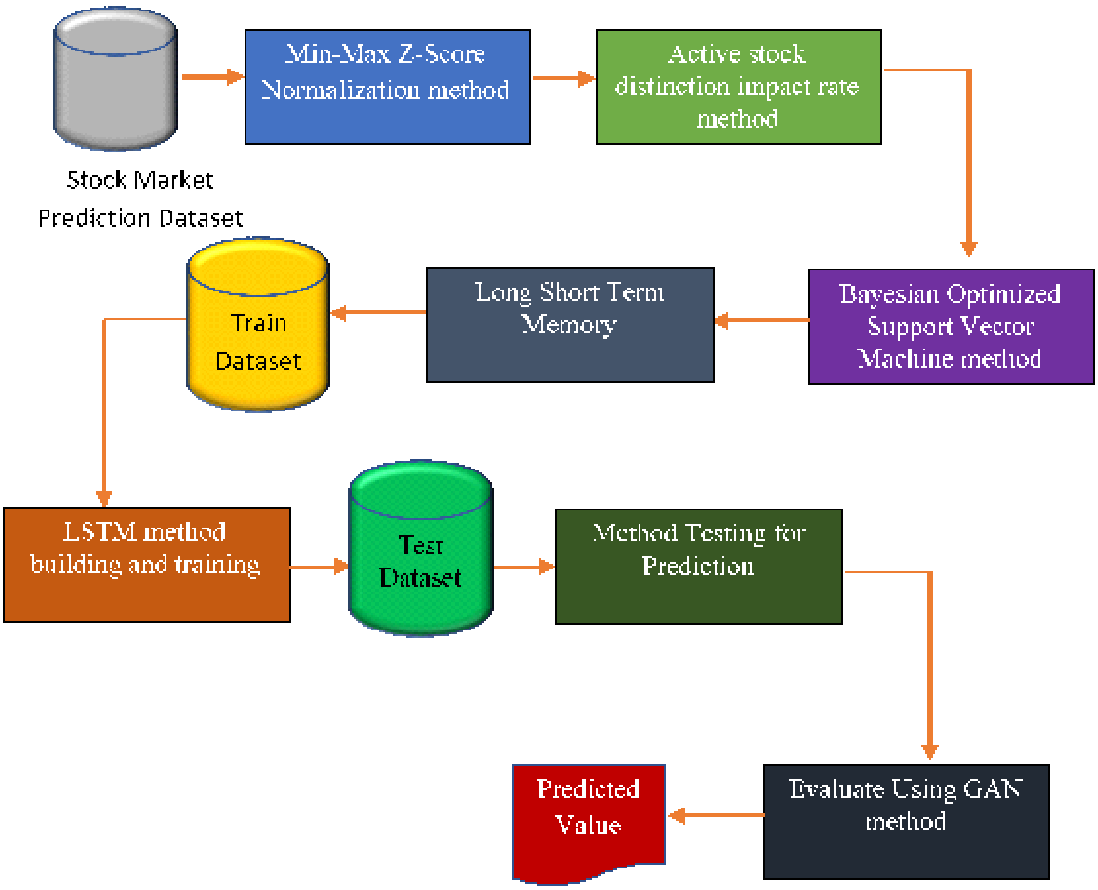

Figure 1. *Architecture Diagram of the Proposed Method*

Table 1. *Analysis of various DL methods based on Stock market prediction*

Author/Year	Used Methodology	Dataset	Accuracy	Limitations
Lawi, A et al, (2022) [22]	LSTM/GRU	Company stock prices	95.95%	In this proposed method missing values, noisy data, and incorrect labels can degrade model performance.
Chhajer P, et al., (2022) [23]	ANN, SVM, LSTM	DJIA dataset	95.6%	It is sensitive to outliers, and detecting and handling them in a used dataset can be complex.
Xiao J et al, (2020) [24]	SVM	CSMAR	95.63%	However, the deployed method for stock market prediction may be limited in size, causing the model to overfit.
Ingle V et al, (2021) [25]	Term Frequency-Inverse Document Frequency (TF-IDF)	online news data	85%	This can be expensive and time-consuming, particularly with limited access to high-performance hardware.
Tashakkori et al, (2024) [26]	Long Short-Term Memory (LSTM)	CAC40	78%	In financial contexts like stock market prediction, it is critical to understand the reasoning behind decisions

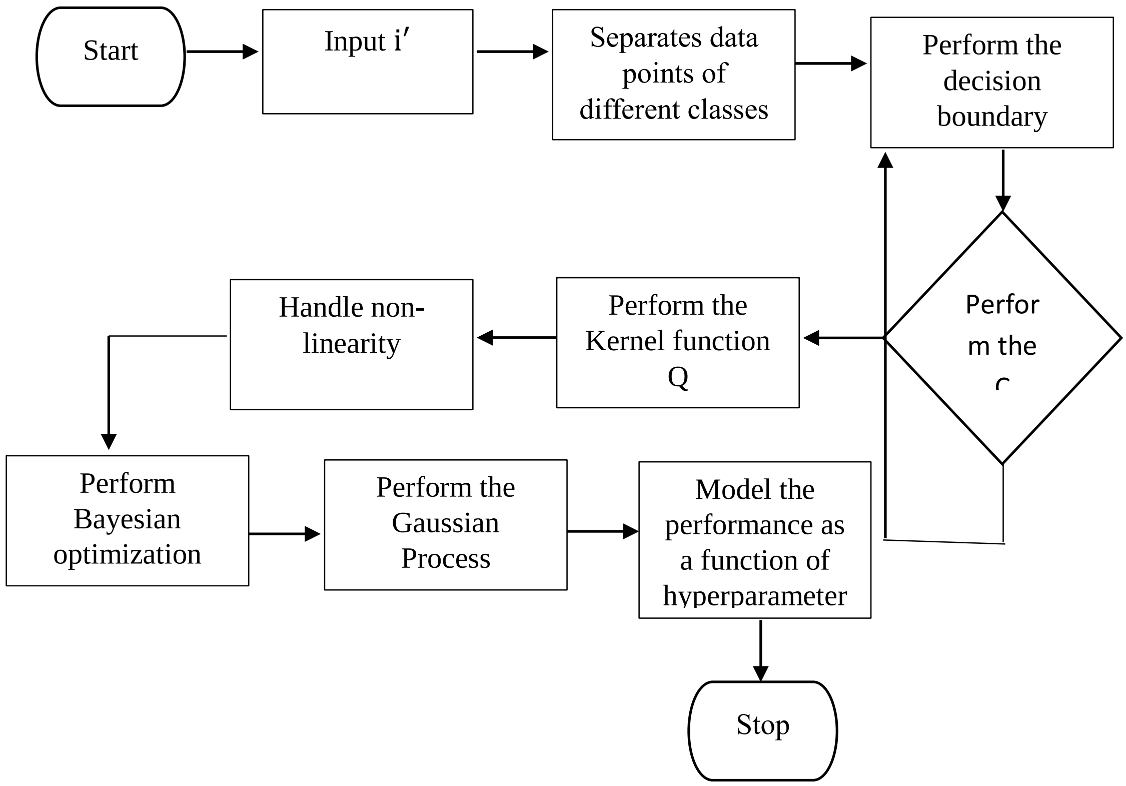

Figure 2. *Flowchart Diagram of the BO-SVM method*

A Multi-DQN methodology was used to achieve the goal. However, as market behavior depends on a number of external factors, training Multi-DQN classifiers in this manner may suffer from over-fitting. A Genetic Algorithm and CNN (GA-CNN) methodology were used to address the problem. GA-CNN can efficiently learn the data patterns. Table 1 shows analysis of various DL methods based on Stock market prediction.In order to minimize such issues, the author [27] suggests a collection of reinforcement learning techniques that learn how to maximize a return function during the training phase rather than using annotations. To create an ideal model, however, a number of hyper-parameters must be changed [28].

3. Implementation of Proposed Method

In this section we briefly described about the deployed methodology to predict the stock market price. In this proposed method we perform four stages like dataset preprocessing, impact rate analyzing, feature selection, and classification. In this paper we use stock prediction dataset which is collected from Kaggle website. We use Min max Z-Score normalization method for dataset preprocessing, for analyze the impact rate we use ASDIR method, a BOSVM method is used for feature selection, and in last phase we use LSTM-Gated GAN for dataset classification.

In Figure 1 we illustrate the architecture diagram of the proposed method. Min-max normalization is classified as one of the data normalization methods that are used to scale the feature ranges of the data set to a specific fixed range, commonly 1 or -1. In the case of features like stock prices, trading volumes, and financial ratios in the stock market prediction datasets, the kind of features may vary in terms of ranges. These variables are then normalized using min-max normalization in order to bring the ranges of these variables within a more manageable scale. ASDIR is a technique used in stock market analysis to determine the scaling factor that reflects the average impact of active stock movements on the mean changes of the overall stock market. This method focuses on identifying the subset of active stocks those with significant trading volume, price volatility, or momentum and quantifying their collective influence on the stock market's mean performance. BOSVM method for feature selection in stock market prediction for the dataset is the integration of Bayesian optimization of kernel parameters in SVM algorithm. The deployed method searches for a hyperplane in a high dimensional space, which can maximize the separation between data points. The LSTM-Gated GAN is used to sort stock market prediction data sets into different categories according to the patterns, trends, or anomalies that have been extracted from them. It can predict market movement categories, including bullish, bearish, or neutral trends, or categorize stocks by risk levels.

3.1` Min-Max Normalization method

Min-max normalization is classified as one of the data normalization methods that are used to scale the feature ranges of the data set to a specific fixed range, commonly 1 or -1. This method is suitable for datasets that contain data with fairly different ranges, such as stock market prediction. It ensures that all features canvass their contributions because the contribution of features that have large numerical values will outweigh the rest. The information below standardizes all features by bringing all predictors to the exact measurement level, which helps achieve faster convergence during the training process. A unique feature of the proposed method is that the features are not predisposed to the side with an enormous scope. In the case of features like stock prices, trading volumes, and financial ratios in the stock market prediction datasets, the kind of features may vary in terms of ranges. These variables are then normalized using min-max normalization in order to bring the ranges of these variables within a more manageable scale for Deep Learning (DL) feature learning and final prediction.

$$i' = \frac{i - \min(i)}{\max(i) - \min(i)} \tag{1}$$

Let assume, i as original value, $\min(i)$ as minimum value in dataset, $\max(i)$ as maximum value in dataset, and i' as normalized value. In this equation 1 we normalized the original value by subtract the maximum and minimum values in the dataset through divide by the difference between original and minimum value in the dataset. By the equation 2 we modify the equation 1 for custom range,

$$i' = x + \frac{(i - \min(i)).(y - x)}{\max(i) - \min(i)} \tag{2}$$

Let assume, x as lower bound of the desired range, and y as upper bound of the desired image. This equation is used to scale data to a specific range. It determines the $\max(i)$ and $\min(i)$ values in the dataset. For each data point, subtract the minimum value. Multiply by the desired range and then, if normalizing to a range (add the lower bound value before rounding). Unlike other similar methods, the proposed method attempts to ensure that all the features contribute to the classification in proportion to the features' importance scale. Continuity in the relative distribution of data points is achieved. This normalization helps make the stock prices range between 0 and 1, as it is beneficial for scaling for the predictive model.

3.2 Active stock distinction impact rate (ASDIR) method

ASDIR is a technique used in stock market analysis to determine the scaling factor that reflects the average impact of active stock movements on the mean changes of the overall stock market. This method focuses on identifying the subset of active stocks those with significant trading volume, price volatility, or momentum and quantifying their collective influence on the stock market's mean performance. In this method stocks are categorized as "active" based on criteria like trading volume, price changes, or frequency of transactions over a defined time period. The impact rate is derived by analyzing the proportionate effect of these stocks on the mean change in the market. The scaling factor is a measure that adjusts for the relative weight of active stocks in relation to the total market. This factor can be expressed as a ratio or multiplier that represents how much active stocks drive mean changes in the stock market compared to the rest of the market. The ASDIR helps in distinguishing the impact of high-momentum stocks versus stable stocks. In equation 3 we evaluate the impact rate,

$$R_x = \frac{(Q_{x,p} - \mu_p)}{\sigma_p} \quad (3)$$

Let assume, R as impact rate, x as stock, p as time, Q as price of stock, μ as mean market price and σ as standard deviation of market price. This equation evaluates how a specific stock affects the overall stock market's mean behaviour. By the equation 4 we compute the weighting factor,

$$U_x = \frac{|R_x|}{\sum_{y=1}^{N} |R_x|} \quad (4)$$

Let assume, U as weighting factor, N as total number of stocks, and $|R_x|$ as absolute value of impact rate of stock. This equation emphasizes the role of stocks with significant deviations. After calculating the weight we perform scaling factor for market mean changes through the equation 5,

$$S = \frac{\sum_{x=1}^{N} U_x \cdot (Q_{x,p} - \mu_p)}{\mu_p} \quad (5)$$

This equation is used to quantify how much the stock market mean changes due to stock distinctions. By following in equation 6 we adjusted the μ of stock market,

$$\mu_{adj} = \mu_p + (\mu_p . S) \quad (6)$$

Let assume, μ_{adj} as adjusted market mean, μ_p as initial mean market price, and S as scaling factor. The equation reflects the stock market's new average after considering the scaling factor. Then we perform an active stock distinction index through the equation 7,

$$A = \frac{1}{N} \sum_{x=1}^{N} |R_x| . U_x \quad (7)$$

This equation is used to evaluate the overall impact of active stocks on market fluctuations. ASDIR method provides valuable insights into stock market behavior, offering tools to calculate how individual stocks' fluctuations impact the broader market and how these can be quantified into meaningful scaling factors. This analysis can enhance decision-making for investors and market analysts by highlighting which stocks are driving market shifts and how these changes influence the broader economic landscape.

3.3 Bayesian Optimized Support Vector Machine (BOSVM) method

After preprocessed the stock market prediction dataset we select the appropriate features through the BOSVM method. BOSVM method for feature selection in stock market prediction for the dataset is the integration of Bayesian optimization of kernel parameters in SVM algorithm. The deployed method searches for a hyperplane in a high dimensional space, which can maximize the separation between data points. A good approach ought to quickly search through the hyperparameter space for the best values of the parameters through a delicate balance between exploration and exploitation. It has a model of the objective function (Although it could be any model, popular choices include Gaussian Processes). Bayesian optimization is used in the selection of features by combining them in such a way that the SVM model provides maximum accuracy. Employ the model used in the analysis of stock market trends or the prediction of price changes. BOSVM also guarantees that the most relevant features are taken to minimize overfitting. This comes in handy more so when working with high dimensional stock market data whereby the selection of appropriate features and setting other tunable parameters to enhance predictive models' performance are essential. In the equation 8 we perform the SVM objective function,

$$\min_{u,b\xi} \frac{1}{2} \|u\|^2 + P \sum_{x=1}^{N} \xi_x \quad (8)$$

Let assume, u as weight vector, b as bias term, ξ_x as slack variables to allow misclassifications, N as number of data points, and P as regularization parameter, it is used to balances margin size and classification error. This equation is used to find a hyperplane that separates data points of different classes with the maximum margin. After find the hyperplane we perform the decision boundary for SVM in equation 9,

$$f(i) = u\, i + b \quad (9)$$

Let assume, i as the feature vector of the dataset, and $f(i)$ as the decision function value. By the equation 10 we illustrate the Class Label C,

$$C = \begin{cases} +1 \; if \; f(i) \geq 0 \\ -1 \; if \; f(i) \leq 0 \end{cases} \quad (10)$$

We perform the Kernel function Q for Non-linear SVM through the below equation 11,

$$Q(i_x, i_y) = \emptyset(i_x)^{\top} \emptyset(i_y) \quad (11)$$

Let assume, $\emptyset$ as mapping function, it is used to transform input data into a higher-dimensional space. This equation is used to handle non-linearity, SVM uses kernel functions to transform the input space. After then we perform bayesian optimization for hyperparameter tuning by equation 12,

$$i_{next} = arg\max_{i} \alpha(i \backslash H) \quad (12)$$

Let assume, H as observed dataset of hyperparameter-performance pairs, and $\alpha(i \backslash H)$ as acquisition function that guides the search for the next set of hyperparameters. This equation is used to optimize the SVM hyperparameters. By following we perform the Gaussian Process (GP) through equation 13,

$$Z(j|i) \sim \mathcal{N}\big(\mu(i), \sigma^2(i)\big) \quad (13)$$

Let assume, $\mu(i)$ as mean function predicting the expected performance, and $\sigma^2(i)$ as variance indicating uncertainty in predictions. This equation is used to model the performance as a function of hyperparameters. The importance of each feature in the dataset used in BO-SVM is determined by analyzing the contribution of the feature in the classification performance of SVM. Using BO, the hyperparameters of the SVM are well-tuned because Bayesian optimization enables a highly accurate predictive model rather than relying on pure trial-and-error approaches such as grid search. The method assigns significance values to the features based on the effects they have on the model's accuracy. This helps to control the number of features that are escalated so that only the more essential ones are contained, thus adding to the interpretability of the workflow. Similarly, Bayesian enhancement of the regularization parameter, P, insulates BO-SVM against noisy stock market data due to a balance between model complexity and noise sensitivity. In Figure 2 we illustrate the flow work of the BO-SVM method for feature selection. In this method we input the preprocessed data to perform the feature selection method. After input the data we separate the data point from different classes, next perform the decision boundary. Perform the class label to check the condition, if it’s true perform the kernel function, if it false again goes to the separate class. In kernel function handle non-linearity, next we perform Bayesian optimization, then perform the Gaussian Process to model the performance as a function of hyperparameters.

3.4 Long Short-Term Memory-Gated Generative Adversarial Network (LSTM-GGAN) method

The LSTM-Gated GAN approach of the presented stock market prediction dataset classification is based on the synergism of LSTM networks and GANs to handle time-series financial data and classify them. However, it is advantageous when working with a time series, like stock price fluctuations, because of its long-term memory characteristic. Temporal patterns and features are learned using historical stock market data from an LSTM-GGAN. GAN is formed of two neural networks – a generator and a discriminator – that work against each other. The generator can generate a synthetic data sample similar to the real data set, while the discriminator measures the extent of the authenticity of the said data. In stock market prediction, LSTM-GGAN is used to create more realistic profiles of stock distribution that can be useful in increasing the training data set’s variability and classification effectiveness. The gating mechanism combines LSTM and GAN components that are exclusively used to manage the flow of patterns and transmit only valuable data. By so doing, it manages the flow of information while passing only the temporal features that are important to the training of GAN or classification from the LSTM. The combined model is used to sort stock market prediction data sets into different categories according to the patterns, trends, or anomalies that have been extracted from them. It can predict market movement categories, including bullish, bearish, or neutral trends, or categorize stocks by risk levels. Though the equation 14, 15, 16 we perform the LSTM network equations, in these equations we perform forget gate f, input gate i, and output gate o. By the following in equation 14 we perform forget gate f,

$$f_t = \sigma\big(U_f . [g_{t-1}, a_t] + b_f\big) \quad (14)$$

Let assume, f_t as forget gate activation vector, σ as sigmoid activation function, U as weight matrix, b as bias term, g_{t-1} as hidden state, and a_t as current input. This equation is used to decides what information to discard from the cell state. Then we perform the input gate i through the equation 15,

$$\begin{aligned} i_t &= \sigma(U_i . [g_{t-1}, a_t] + b_i) \\ \widetilde{D}_t &= \tanh(U_D . [g_{t-1}, a_t] + b_D) \\ D_t &= f_t . D_{t-1} + i_t . \widetilde{D}_t \end{aligned} \quad (15)$$

Let assume, i_t as input gate activation vector, $\widetilde{D}_t$ as the candidate values for the cell state, and D_t as updated cell state. This equation decides what new information to store in the cell state. We perform the output gate o through the equation 16,

$$\begin{aligned} o_t &= \sigma(U_o . [g_{t-1}, a_t] + b_o) \\ h_t &= o_t . \tanh(D_t) \end{aligned} \quad (16)$$

Let assume, o_t as output gate activation vector, h_t as output and also known as hidden state. This equation is used to decides the output based on the cell state. By following in equation 17 and 18 we perform the GAN equations, it consists two main components: generator and discriminator. In the equation 12 we perform the G generator,

$$G(k) = \tanh\left(U_g . k + b_g\right) \quad (17)$$

Let assume, $G(k)$ as output of the generator, z as random noise, U_g as generator weights, and b_g as biases of generator. Next, we perform the discriminator D through equation 18,

$$D(i) = \sigma(U_d . i + b_d) \quad (18)$$

Let assume, i as input, $D(i)$ as output of the discriminator, U_d as weight of discriminator, and b_d as biases of discriminator. This equation determines whether the i is real or synthetic. After perform the objective of G, D then we perform the loss function of G, D. Through the equation 19 we perform generator loss,

$$\mathcal{L}_G = \mathbb{E}_{k \sim q_k(k)}\left[\log\left(D\left(G(k)\right)\right)\right] \quad (19)$$

In equation 20 we perform discriminator loss,

$$\mathcal{L}_D = -\mathbb{E}_{i \sim pdata\,(i)}\left[\log\left(D(i)\right)\right] - \mathbb{E}_{k \sim q_k(k)}\left[\log\left(1 - D\left(G(k)\right)\right)\right] \quad (20)$$

In these equations the G tries to minimize $\mathcal{L}_G$ while the D tries to minimize $\mathcal{L}_D$. In equation 21 and 22 we combine temporal features of the stock data with GAN's data generation capabilities. In equation 21 we perform GAN with LSTM Z Generator,

$$G_{\mathcal{L}}(k) = Z(k) \quad (21)$$

In this equation the generator is enhanced with an LSTM network to capture temporal dependencies in stock market data. Next, we perform GAN with LSTM Discriminator through equation 22,

$$D_{\mathcal{L}}(i) = \sigma\left(Z(i)\right) \quad (22)$$

In this equation the discriminator uses an LSTM network to distinguish between real and synthetic sequences. After training, the synthetic data and real data are used to train a classification model for stock market trends.

$$j = Softmax\ (U.h + b) \quad (23)$$

In this equation, Softmax is applied to the LSTM's h to classify stock trends. The proposed LSTM-gated GAN guarantees the generated data will adhere to the temporal relation. The integration of LSTM-GAN produces better classification results by utilizing both real and fake data. This mixed approach enables the model to perform better during market volatility than under the pure strong form market efficiency hypothesis. LSTM-Gated GAN is shown to be a viable framework for stock market prediction and dataset classification by leveraging the temporal learning capabilities of LSTMs as well as the abilities of GANs to generate synthetic data. In figure 3 we illustrated the flow diagram of the LSTM-Gated GAN method to classify the stock prediction dataset. In this we use the feature selected data as input, first we perform forget gate to discard unwanted data from cell sate, then we perform input gate to store the new data in cell state, after store the data we perform the output gate to decides the output based on the cell state. After perform the D and G to check the data as real or synthetic, then perform the loss function of D and G. To capture temporal dependencies in stock market data Perform GAN with LSTM Z, after we perform GAN with LSTM Discriminator to classify the stock trends. Then we train the classification model to distinguish among real and synthetic.

4. Results and Discussions

The performance of the deployed approach is being evaluated for inquiry through the use of accuracy, precision, recall, F1 score, AUC-ROC, PR-AUC, and MCC. The goal of this assessment is to predict a stock price (investing) by utilising the CNN-LSTM, DLSTMNN, and ANN-RF deployment method. The parameters and simulations are displayed in Table 2. Contains 7782 values, the stock market prediction dataset is used to find the price for the next day, and only for that stock. With Python and the Anaconda Tool, the implementation method is executed. The accuracy performance of the CNN-LSTM is 77.5%, the DLSTMNN is 83.4%, the ANN-RF is 89.5%, and the LSTM-GGAN is 96.4%, as illustrated in Figure 4. The adopted methodology is more accuracy than the one that was used previously. High accuracy ensures that predictions align closely with actual stock price movements, enabling informed investment strategies.

Table 2. *Simulation Parameters*

Parameters	Values
Name of the Dataset	Stock Market Prediction
No of Values	7782
Used Language	Python
Used Tool	Juypter

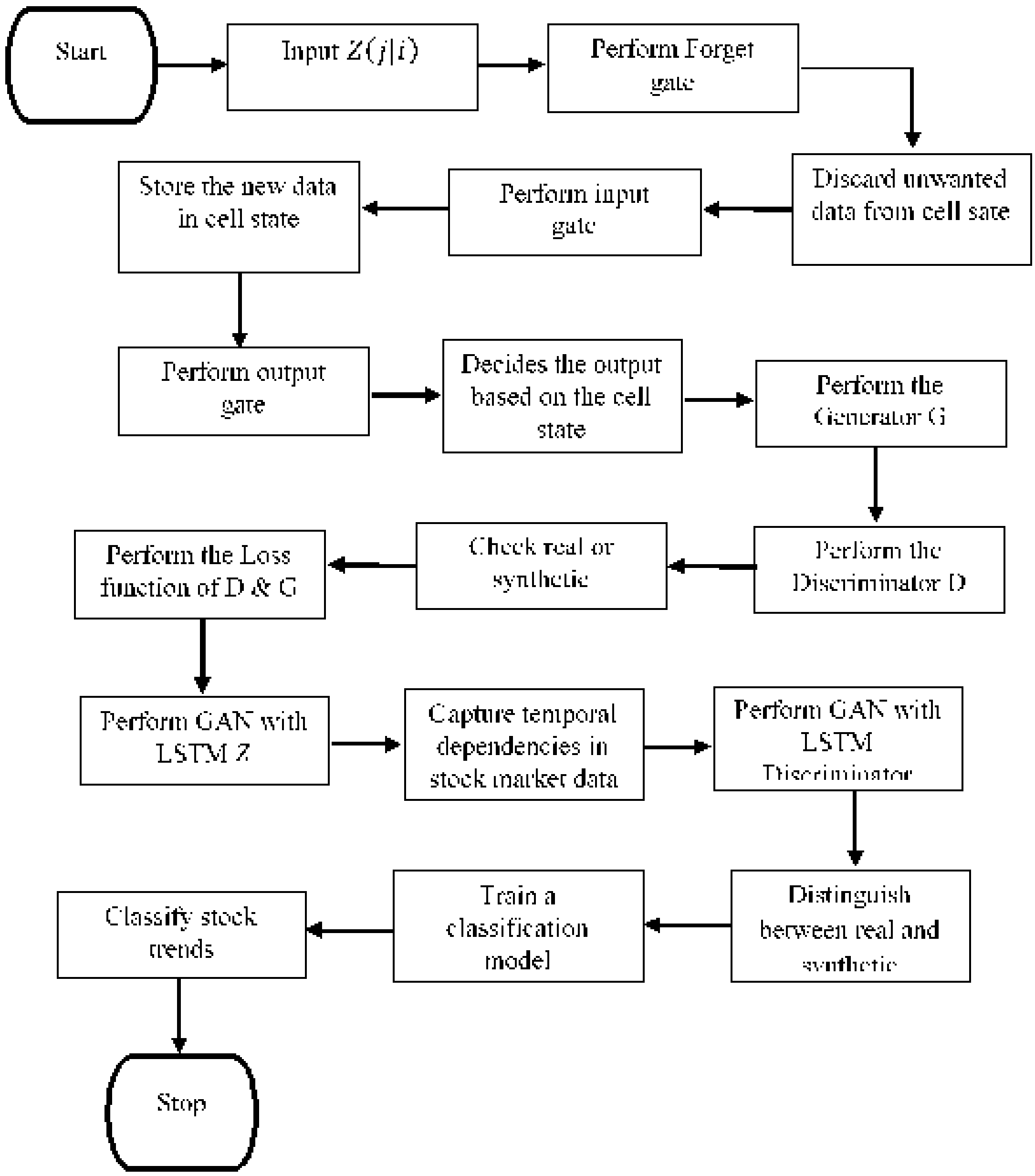

Figure 3. *Flowchart Diagram of the LSTM-Gated GAN method*

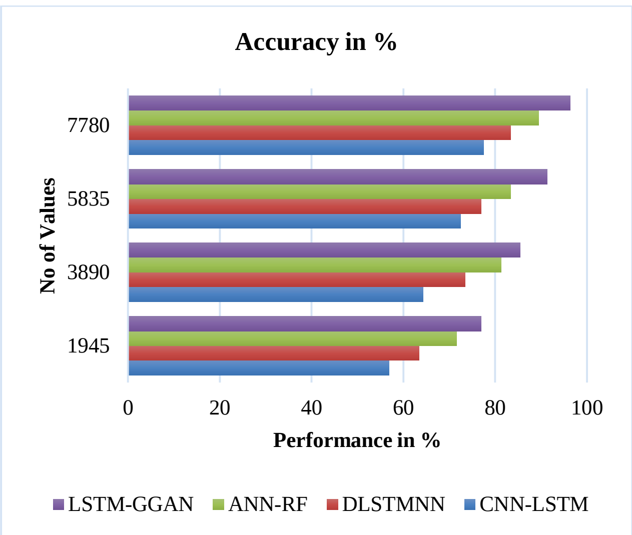

Figure 4. *Accuracy performance in %*

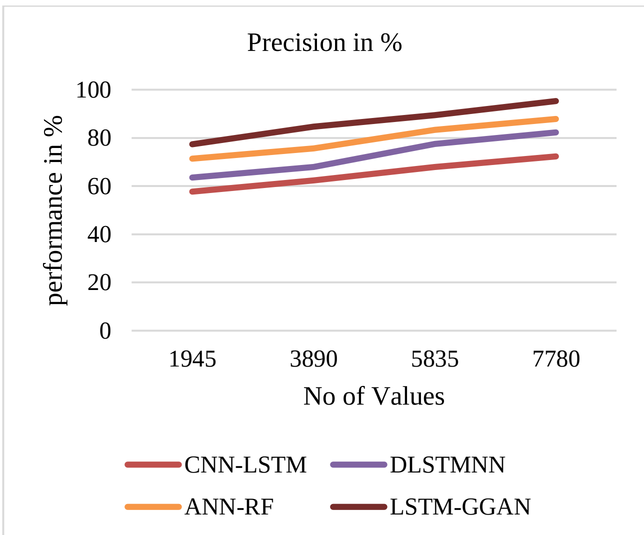

Figure 5. *Precision performance in %*

Reliable predictions help investors and traders maximize returns by correctly timing their market entries and exits. It reduces losses from incorrect predictions, improving the overall return on investment. The high value ensures efficient use of computational and financial resources. As can be shown in Figure 5, the CNN-LSTM has a precision performance of 72.3%, the DLSTMNN 82.3%, the ANN-RF 87.9%, and the LSTM-GGAN 95.3%. Compared to the prior approach, the deployed methodology has a higher precision value. High precision minimizes false positives, ensuring that buy/sell signals are more reliable. With high precision, models can better identify potential market downturns or risks, allowing investors to hedge their portfolios effectively. Accurate predictions reduce exposure to volatile market conditions. High accuracy and precision reduce the need for frequent manual interventions and re-analysis of strategies.

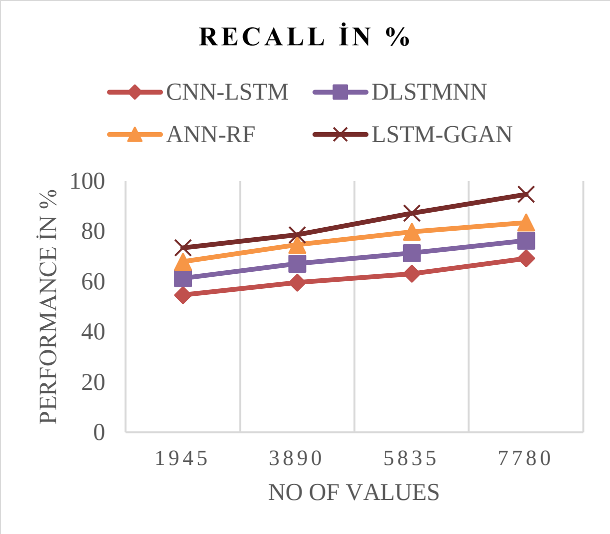

Figure 6. Recall performance in %

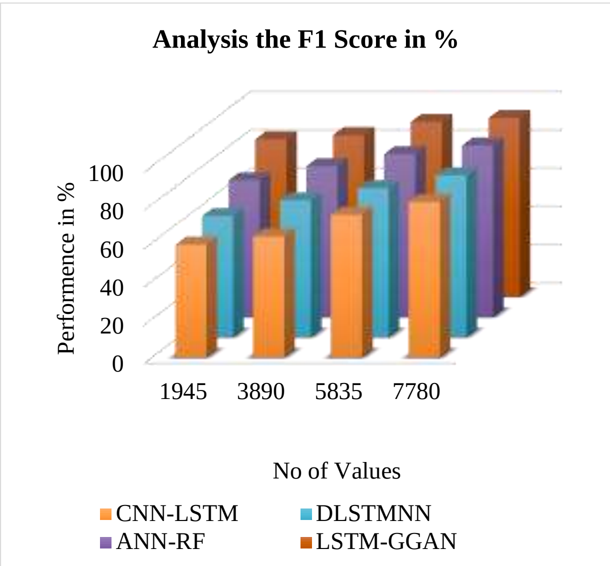

Figure 7. F1-Score performance in %

The recall performance of the CNN-LSTM is 69.2%, that of the DLSTMNN is 76.3%, that of the ANN-RF is 83.5%, and that of the LSTM-GGAN is 94.7%, as shown in Figure 6. Compared to the old technique, the deployed methodology has higher recall value. High recall ensures that all critical movements are captured, avoiding missed opportunities. High-performance metrics ensure trading algorithms make better real-time decisions, increasing efficiency and profitability in high-frequency trading scenarios. It minimizes trading errors, saving costs on erroneous tradesThe F1-Score performance of the CNN-LSTM is 81.3%, that of the DLSTMNN is 84.6%, that of the ANN-RF is 89.7%, and that of the LSTM-GGAN is 93.6%, as can be shown in Figure 7. Compared to the previous technique, the deployed methodology has a higher F1 score value. High recall value balances precision and recall, optimizing decision-making for both risk and reward. Accurate and reliable predictions build trust among investors, encouraging adoption of predictive tools. Consistency in high-performance metrics leads to long-term confidence in the predictive model.

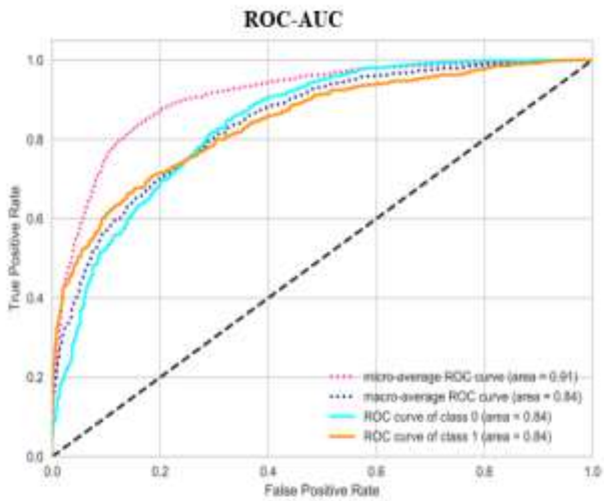

Figure 8. *Analysis Diagram of LSTM-GGRN AUC-ROC Curve*

In figure 8 we depicted the analysis diagram of proposed method AUC-ROC Curve In this the proposed method achieve 0.91 micro average ROC curve. Using classification, AUC-ROC also measures how one class does against the other where cases are being forced between two classes like increase and decrease of the price. It is easily effective in rendering a complete view on performance for every defined classification limit. It enables to understand the trade-off between True Positive Rate (TPR), False Positive Rate (FPR). Since the stock market depends on various factors and there are significant differences between the

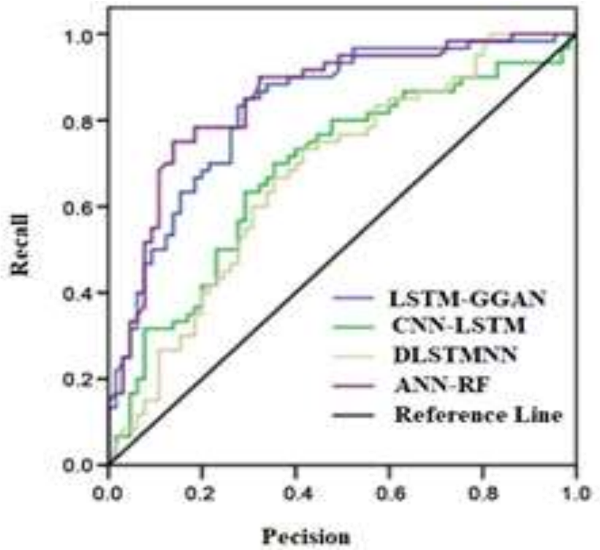

Figure 9. *Analysis Diagram of PR-AUC Curve*

indicators when a price goes up or down, AUC forecast the model using AUC-ROC to consider various thresholds.Specifically, for imbalanced data such as the case of price increase as illustrated in Figure 9 the PR-AUC Curve is more informative. This is in a bid to avoid high rates of wrong outcomes which may have negative influence to decisions made. But the proposed LSTM-GGAN guarantees precision whereby there are minimal misrepresentation, which may often affect decisions. In stock exchange prediction, false alarms result to monetary losses. PR-AUC stands for precision-recall curve for area under curve where a classifier is more important when it does not misclassify important but infrequent events.

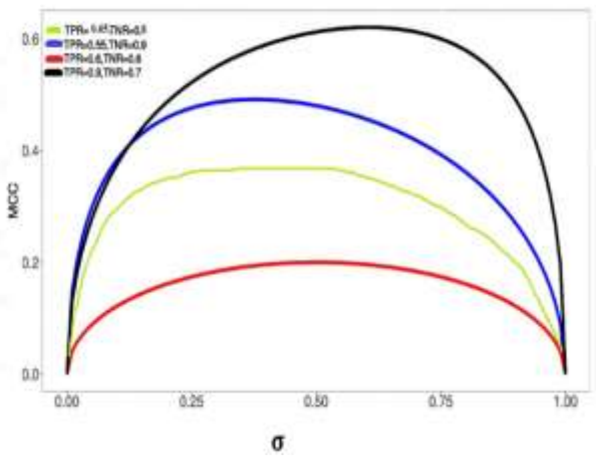

Figure 10. *Analysis Diagram of the MCC*

As figure 10 depicted the MCC integration all of the confusion matrix attributes which include: true positive, true negative, false positive and false negative values offering a more stable marker. Unlike accuracy, MCC does not reduce for datasets with misclassified classes while being imbalanced. Coefficient values vary from -1 to +1 in which 0 imply no predictive ability at all. There are usually distortions in trends of stocks price movements; therefore, MCC is useful to consider the general performance of a predictive model.

4. Conclusions

The LSTM-Gated GAN method proposed for stock market prediction has proven to be accurate with 96.4%, as revealed in the study. The only measure of pre-processing the data was to apply the Min-Max Z-score normalization to the collected data in an effort to normalize the data for the lessons learned betterment for the model. To enhance the prediction accuracy, a more excellent stock identification impact rate method was used on the Active Stock Distinction Impact Rate. In feature selection, the BOSVM method was used to eliminate noise and improve the efficiency of the model. LSTM Gated GAN stands out as an effective classification technology due to its combination of LSTM's sequential learning capacity and GANs' ability to generate; the high level of accuracy and reliability it offered in informing the classification was impressive. This scheme is, therefore, very effective in handling the buffer and noise characteristics of stock market data, leading to the provision of a robust tool for stock market analysis and decision-making. By striking a balance between accuracy, scalability, and adaptability in big data contexts, the LSTM-Gated GAN is utilized to predict stock market prices, opening the door for developments in financial analytics. LSTM is used for different application in the literature [29-36].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] G. Sismanoglu, M. A. Onde, F. Kocer and O. K. Sahingoz, (2019). Deep Learning Based Forecasting in Stock Market with Big Data Analytics, *Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), Istanbul, Turkey*, 2019, pp. 1-4, doi: 10.1109/EBBT.2019.8741818.

[2] Zhou, Y., et al. (2020). Deep Learning-Based Stock Market Prediction: A Comprehensive Survey. *Expert Systems with Applications*.

[3] Chen, L., et al. (2021). Time-Series Analysis of Stock Market Data Using LSTM Networks. *Information Sciences*.

[4] Khoshnood, A., & Sadri, J. (2022). Improving GAN Stability for Financial Applications. *Applied Soft Computing*.

[5] Babu, S., & Ramesh, S. (2023). Optimization Techniques for Machine Learning in Financial Predictions. *Engineering Applications of Artificial Intelligence*.

[6] Wang, Q., et al. (2024). Bayesian Optimization for Enhancing SVM Performance in Predictive Analytics. *Journal of Machine Learning Research*.

[7] Shen, J., Shafiq, M.O. (2020) Short-term stock market price trend prediction using a comprehensive deep learning system. *J Big Data* 7, 66. https://doi.org/10.1186/s40537-020-00333-6

[8] Nabipour, M., Nayyeri, P., Jabani, H., Mosavi, A., & Salwana, E. (2020). Deep Learning for Stock Market Prediction. *Entropy*, 22(8), 840. https://doi.org/10.3390/e22080840

[9] Rezaei, H., Faaljou, H., & Mansourfar, G. (2021). Stock price prediction using deep learning and frequency decomposition. *Expert Systems With Applications*, 169, 114332. https://doi.org/10.1016/j.eswa.2020.114332

[10] Narkhede, Nirbhay. (2019). Stock Market Prediction using Machine Learning and Cloud Computing. *International Journal of Engineering and Computer Science.* 8. 24847-24850. 10.18535/ijecs/v8i09.4361.

[11] Gomathy, C K. (2023). STOCK MARKET PREDICTION USING BIG DATA.

[12] Yu, P., Yan, X. (2020). Stock price prediction based on deep neural networks. *Neural Comput & Applic* 32, 1609–1628. https://doi.org/10.1007/s00521-019-04212-x

[13] Pang, X., Zhou, Y., Wang, P. et al.(2020) An innovative neural network approach for stock market prediction. J Supercomput 76, 2098–2118. https://doi.org/10.1007/s11227-017-2228-y

[14] Li, Y., Pan, Y. (2022) A novel ensemble deep learning model for stock prediction based on stock prices and news. Int J Data Sci Anal 13, 139–149. https://doi.org/10.1007/s41060-021-00279-9

[15] Lu, W., Li, J., Wang, J. et al. (2021) A CNN-BiLSTM-AM method for stock price prediction. Neural Comput & Applic 33, 4741–4753. https://doi.org/10.1007/s00521-020-05532-z

[16] Vijh, M., Chandola, D., Tikkiwal, V. A., & Kumar, A. (2019). Stock Closing Price Prediction using Machine Learning Techniques. *Procedia Computer Science*, 167, 599-606. https://doi.org/10.1016/j.procs.2020.03.326

[17] Ding, G., Qin, L. (2020). Study on the prediction of stock price based on the associated network model of LSTM. *Int. J. Mach. Learn. & Cyber*. 11, 1307–1317. https://doi.org/10.1007/s13042-019-01041-1

[18] Moghar, A., & Hamiche, M. (2019). Stock Market Prediction Using LSTM Recurrent Neural Network. *Procedia Computer Science*, 170, 1168-1173. https://doi.org/10.1016/j.procs.2020.03.049

[19] Yun, K. K., Yoon, S. W., & Won, D. (2021). Prediction of stock price direction using a hybrid GA-XGBoost algorithm with a three-stage feature engineering process. *Expert Systems with Applications*, 186, 115716. https://doi.org/10.1016/j.eswa.2021.115716

[20] Lu, W., Li, J., Li, Y., Sun, A., & Wang, J. (2019). A CNN-LSTM-Based Model to Forecast Stock Prices. *Complexity*, 2020(1), 6622927. https://doi.org/10.1155/2020/6622927

[21] Nti, I.K., Adekoya, A.F. & Weyori, B.A. (2020) A comprehensive evaluation of ensemble learning for stock-market prediction. *J Big Data* 7, 20. https://doi.org/10.1186/s40537-020-00299-5.

[22] Lawi, A., Mesra, H. & Amir, S. (2022) Implementation of Long Short-Term Memory and Gated Recurrent Units on grouped time-series data to predict stock prices accurately. *J Big Data* 9, 89. https://doi.org/10.1186/s40537-022-00597-0.

[23] Chhajer P, Shah M, Kshirsagar A. (2021) The applications of artificial neural networks, support vector machines, and long-short term memory for stock market prediction. *Decis Anal J.* 2021; 2:100015. https://doi.org/10.1016/j.dajour.2021.100 015.

[24] Xiao J, Zhu X, Huang C, Yang X, Wen F, Zhong M. (2020) A new approach for stock price analysis and prediction based on SSA and SVM. *Int J Inf Technol Decis Mak.* 2020;18(1):287–310. https://doi.org/10.1142/S021962201841002X.

[25] Ingle V, Deshmukh S. (2021). Ensemble deep learning framework for stock market data prediction (EDLF-DP). In: *Paper presented at the Global Transitions Proceedings* 2(1);47–66. https://doi.org/10.1016/j.gltp.2021.01.008.

[26] Tashakkori, Arash, et al. (2024). Enhancing stock market prediction accuracy with recurrent deep learning models: A case study on the CAC40 index. *World Journal of Advanced Research and Reviews* 23(1); 2309-1.

[27] Carta, S., Ferreira, A., Podda, A. S., Reforgiato Recupero, D., & Sanna, A. (2021). Multi-DQN: An ensemble of Deep Q-learning agents for stock market forecasting. *Expert Systems with Applications*, 164, 113820. https://doi.org/10.1016/j.eswa.2020.113820

[28] Chung, H., Shin, Ks. (2020). Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction. *Neural*

Comput & Applic 32, 7897–7914. https://doi.org/10.1007/s00521-019-04236-3

[29] Venkata Simhadri Naidu Surapu, Kanusu Srinivasa Rao, & Ratnakumari Challa. (2025). Aerobic Stress Detection in Aquatic Environments with Water Quality Data Using Hybrid Deep Learning Based ConvRec Model. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.793

[30] B.Vaidehi, & K. Arunesh. (2025). Deep Learning Fusion for Student Academic Prediction Using ARLMN Ensemble Model. *International Journal of Computational and Experimental Science and Engineering,* 11(2). https://doi.org/10.22399/ijcesen.734

[31] Ponugoti Kalpana, Shaik Abdul Nabi, Panjagari Kavitha, K. Naresh, Maddala Vijayalakshmi, & P. Vinayasree. (2024). A Hybrid Deep Learning Approach for Efficient Cross-Language Detection. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.808

[32] Rajani Kumari Inapagolla, & K . Kalyan Babu. (2025). Audio Fingerprinting to Achieve Greater Accuracy and Maximum Speed with Multi-Model CNN-RNN-LSTM in Speaker Identification: Speed with Multi-Model CNN-RNN-LSTM in Speaker Identification. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.1138

[33] Boddupally JANAIAH, & Suresh PABBOJU. (2024). HARGAN: Generative Adversarial Network BasedDeep Learning Framework for Efficient Recognition of Human Actions from Surveillance Videos. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.587

[34] Vaidhya Govindharajalu Kaliyaperumal, & Paavai Anand Gopalan. (2025). A Machine Learning Approach For Indian Sign Language Recognition Utilizing Bert And Lstm Models: Indian Sign Language Recognition Utilizing Bert And Lstm Models. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.1276

[35] Ibeh, C. V., & Adegbola, A. (2025). AI and Machine Learning for Sustainable Energy: Predictive Modelling, Optimization and Socioeconomic Impact In The USA. *International Journal of Applied Sciences and Radiation Research,* 2(1). https://doi.org/10.22399/ijasrar.19

[36] Olola, T. M., & Olatunde, T. I. (2025). Artificial Intelligence in Financial and Supply Chain Optimization: Predictive Analytics for Business Growth and Market Stability in The USA. *International Journal of Applied Sciences and Radiation Research,* 2(1). https://doi.org/10.22399/ijasrar.18