



Enhancing Stock Price Prediction Accuracy Using Deep Learning and Hierarchical Frequency Decomposition Technique

S. S. Akhila^{1*}, Naveena A Priyadharsini²

¹Post Graduate, Student of Communication system, Arunachala college of Engineering, Manavilai, Nagercoil, Tamil Nadu - 629203

³Associate professor, Department of Electronics and Communication Engineering, Arunachala College of Engineering, Manavilai, Nagercoil, Tamil Nadu 629203

Corresponding Author E-mail: akhilass8673@gmail.com

ABSTRACT: Accurate stock price prediction is essential for investors and financial analysts to make informed decisions in volatile markets. Traditional models struggle with nonlinear patterns, necessitating advanced Deep Learning (DL) techniques to improve forecasting accuracy. Stock price prediction is a crucial yet challenging task due to the highly volatile and nonlinear nature of financial markets. This paper presents an advanced DL approach to enhance stock price prediction accuracy by leveraging a hybrid Bidirectional Long Short-Term Memory (BiLSTM) - Gated Recurrent Unit (GRU) model integrated with hierarchical frequency decomposition techniques. The proposed framework begins with historical stock data preprocessing, including handling missing values and data cleaning, followed by feature engineering to extract relevant market indicators. The dataset is then split into training and testing sets, ensuring standardized scaling and normalization to prevent model bias and outdated data issues. The classification model, based on a hybrid BiLSTM-GRU architecture, is employed to capture temporal dependencies and complex stock market patterns effectively. By incorporating hierarchical frequency decomposition, the model further enhances feature extraction, leading to improved predictive performance. Overall, this work is implemented using Python Jupyter software and achieves the predicted error value, such as the Root Mean Square Error (RMSE) of 6.1175 and the Mean Absolute Error (MAE) of 2.8093. This work significantly improves accuracy with the investor and customer behavior analysis of stock performance.

Keywords: Stock Price Prediction, Preprocessing, Feature Engineering, Hybrid BiLSTM-GRU, RMSE, MAE.

1. Introduction

In today's dynamic and competitive business environment, the integration of marketing, financial analysis, and investment planning plays a critical role in achieving organizational success and sustainability. Marketing is the process of identifying customer needs and delivering value through products and services. It involves market research, advertising, branding, and strategic communication to attract and retain customers. Effective marketing not only drives sales but also builds long-term relationships with consumers and

strengthens a company's position in the market [1]. Financial analysis is the evaluation of a company's financial performance through its financial statements, ratios, and historical data. Financial analysis is essential for assessing the health of a business and making informed decisions regarding budgeting, funding, and resource allocation. Investment planning is the strategic process of allocating funds to various assets or ventures to achieve specific financial goals over time [2-3]. It involves assessing risk tolerance, time horizon, and expected returns.

Proper investment planning enables individuals and organizations to grow wealth, secure their financial future, and make sound decisions in line with their financial objectives. Together, these three areas form a foundation for effective decision-making and long-term financial success, whether at the individual, corporate, or institutional level. Stock price prediction is the process of estimating the future value of a company's stock or other financial instruments traded on an exchange [4-5]. It plays a crucial role in financial markets, where investors and traders aim to make informed decisions to maximize profits and minimize risks. Better predictions lead to more stable markets by reducing panic-driven decisions and promoting data-backed trading behavior [6-7]. Due to this complexity, predicting stock prices is a challenging task that has attracted interest from economists, data scientists, and financial analysts alike. Despite advancements in data analysis and Machine Learning (ML), predicting stock prices remains a complex task due to several challenges. So, effective prediction model is required.

With the rise of machine learning and data-driven techniques, stock price prediction has evolved from traditional statistical methods to more advanced approaches involving algorithms such as Linear Regression (LR), Support Vector Machines (SVM), Decision Trees (DT), and Neural Networks (NN). However, these models are complex and learn patterns that only exist in historical data, leading to poor performance on new, unseen data. This makes them unreliable for real-time predictions [8-9]. So, DL technology is needed to be used in order to attain high accuracy in the analysis of the stock price prediction. DL technology's explosive growth in recent years has transformed a number of industries, including signal analysis, data analysis, and speech recognition. DL is the predictable nature of financial markets; accurate predictions, even with a small edge, led to significant financial gains

[10]. Therefore, the hybrid BiLSTM-GRU is proposed in this work for the prediction of stock prices. This work achieves the following objectives:

- To handle the missing data and to enhance data quality, data preprocessing is utilized.
- To improve the performance and enhance a model's ability, feature engineering is applied.
- To predict the stock price ranges accurately, the hybrid BiLSTM-GRU algorithm is developed.
- To calculate the MAE and RMSE error values, hybrid BiLSTM-GRU classification is utilized.

This paper proposes a DL technique for stock price prediction. The order in which the paper is given is indicated in the list below: Section II covers the most recent work. Section III provides a detailed description of the proposed work. The results are shown in Section IV. Section V provides a conclusion.

2. Recent Works

Babak Amiri *et al* (2025) [11] have proposed a hybrid model that integrates a Graph Convolutional Network (GCN) with an attention-enhanced LSTM architecture. It helps the model focus on the most relevant time steps and key relationships across the graph, improving predictive performance. With attention, the model learns which past time steps are most influential for a specific stock prediction. However, it requires GPU acceleration and optimized batch processing for real-time use.

Kun Huang *et al* (2022) [12] have developed a Multilevel Graph Attention Network (ML-GAT) for predicting the stock market trends. Attention allows the model to dynamically focus on relevant time steps and key neighboring stocks, rather than treating all inputs equally. Further, it helps reduce over-reliance on a single stock's history, making predictions more robust across various market

conditions. Moreover, this hybrid model is resource-intensive, especially with many stocks and long historical windows.

Fatemeh Moodi et al (2024) [13] have presented a hybrid framework of DL models for stock price movement prediction. The Convolutional Neural Networks (CNN) -LSTM model is well-suited for handling complex financial time-series data, especially when multiple indicators or assets are involved. Further, CNNs are excellent at extracting local patterns and features from raw stock data or technical indicators. Nevertheless, this model is computationally expensive, especially with large datasets or long-time sequences. One significant disadvantage is that it is difficult to explain how exactly node-level embeddings affect predictions.

Yi Li et al (2024) [14] have proposed a new hybrid model termed, the Hierarchical Decomposition-based Forecasting Model (HDFM), to decompose and forecast stock prices in a hierarchical fashion. By forecasting decomposed components separately, models focus on simpler sub-problems, leading to better overall prediction accuracy. Further, it helps financial analysts understand what part of the signal is driving predictions. However, improper decomposition or incorrect selection of components may lead to loss of important information, affecting prediction accuracy and leading to poor final predictions.

Thendo Sidogi et al (2023) [15] have presented a signature transform of limit order book data for stock price prediction. It handles large datasets and high-dimensional data, making them suitable for multi-asset, multi-indicator models. It offers a range of powerful advantages that make them well-suited for complex tasks like stock price prediction, where traditional models often fall short. However, it is prone to overfitting, especially with noisy and volatile financial data. Furthermore, this work is insufficient for huge data, which is considered a major limitation.

3. Proposed Work Explanation

The five components that make up the proposed structure are stock data, data preprocessing, feature engineering, scaling and normalization, and classification. In Figure 1, the proposed block diagram is presented.

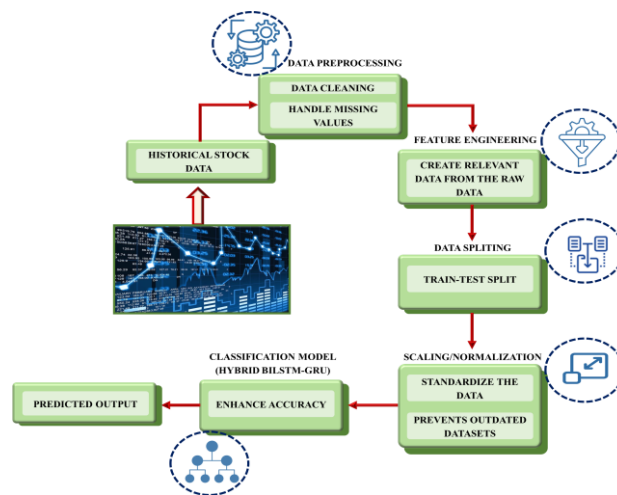


Figure 1: Block Diagram for Proposed System

First, the input data for the stock price prediction is the first step in the data preprocessing procedure. Preprocessing is done on the dataset to take care of missing values, handle the data, and filter it. The process of data analysis and cleaning further involves preprocessed data. Using feature engineering helps by extracting meaningful signals that a model uses to predict future trends more effectively. Further, the data train-test split is used to divide the datasets into training and testing sets. Test data is used to evaluate the performance of the model. After that, the scaling and normalization process used helps models converge faster during training and reduces the risk of such errors. Then, the hybrid BiLSTM-GRU is used to classify the features of stock price, which improves its prediction. Ultimately, R2 score values are predicted with accuracy based on the categorization of RMSE and MAE.

3.1 Pre-processing

Data preprocessing is the act of collecting, altering, and transforming electronically stored information and data from a particular set of values. For the purpose of obtaining as much

information as possible, the observer notices altered data. Generally speaking, the dataset's minimum and maximum values differ significantly from one another. The normalizing procedure lowers algorithm and data complexity, which is beneficial for the classification of neural network-related algorithms.

3.1.1 Data Cleaning

The most crucial preprocessing stage is data cleaning, which guarantees that your data is prepared for your downstream requirements. All of the inconsistent data you found during the data quality evaluation will be fixed via data cleaning. Check for unanswered survey questions, blank spaces in text, and missing data fields. This is the result of missing data or human mistake. To address missing data in order to carry out data cleansing. By removing duplicates and anomalies, normalizing the data for comparison, and increasing the quality of the findings, preprocessing aids in the consistency of the data.

3.2 Feature Engineering

Feature engineering is the process of selecting, transforming, and creating relevant input features from raw data to improve the performance of ML/DL models. By using these insights from the data, feature engineering involves automatically choosing the best features for algorithmic frameworks and models without the requirement for expert knowledge or other types of external information. Automatically refers to the employment of an algorithm or process that retains just the most crucial features for this model and its application area, as compared with identifying the features. In stock price prediction, effective feature engineering significantly enhances a model's ability to understand market patterns and make accurate forecasts.

3.3 Train Test Split

Train-test split is a fundamental step in building and evaluating a classification model. It involves

dividing the dataset into two parts Training set and Testing set. In training set is used to train the machine learning model. Further, the testing set is used to evaluate the model's performance on unseen data. This split helps ensure that the model is generalize well and is memorizing patterns from the training data. By training a model on past data and testing it on more recent data, it simulates real-world conditions and ensure the model makes accurate predictions in practice.

3.4 Scaling / Normalization

Scaling typically refers to methods like Min-Max scaling, which transforms data into a fixed range, while normalization often refers to standardization, where data is adjusted to have a mean of zero and a standard deviation of one.

3.4.1 Min-Max Scaling

Scaling refers to transforming data so that it falls within a specific range usually [0, 1] or [-1, 1]. It ensures that no single feature dominates the learning process due to its larger value range. Data scaling, which is comprised of minimum and maximum methods, is the fundamental technique of normalization. Data conversion to current range usually occurs in the intervals of (-1, 1) and (0, 1). Rescales data to a fixed range, usually [0, 1] can explained as,

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Scales data between [-1, 1] by dividing by the maximum absolute value.

3.4.2 Normalization

Normalisation converts a data into a regularised range, allowing for more accurate comparison. These techniques help ensure that all input features are on a similar scale, which improves the efficiency and accuracy of the learning algorithms. This method helps to center the data around zero, making it easier for DL algorithms to learn and converge more efficiently. Standardization is especially useful when features have varying

scales or when the data may contain outliers, as it reduces the impact of extreme values. It reduces the risk of overfitting, and ensures that no single feature dominates the prediction.

3.5.2 GRU

GRU classifiers are a type of RNN architecture commonly used for sequence classification tasks. The issue of vanishing or raising gradients is what the GRU is intended to address. GRUs possess merely two gates: updating and resetting gates, currently the LSTM combines the input and forget gates. Figure 3 depicted the GRU structure.

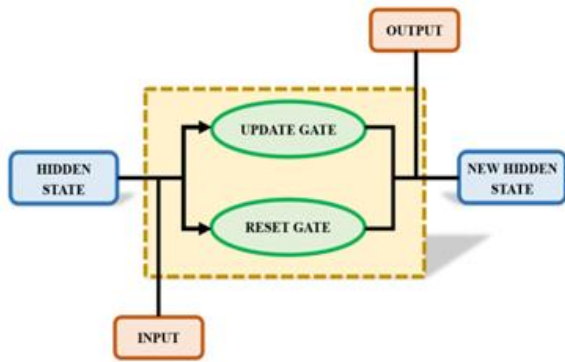


Figure 3: The GRU Structure

Because of their more straightforward nature, GRUs perform better and require fewer parameters. The following equations illustrate GRU resetting and updating stages.

$$m_s = \sigma([W_m h_{(s-1)}, x_s] U_m h_{(s-1)} + b_m) \quad (4)$$

$$n_s = \sigma([W_n h_{(s-1)}, x_s] U_n h_{(s-1)} + b_n) \quad (5)$$

Here, x_s is the value provided at period s , m_s and n_s are the restored and updating gates, and, subsequently, $h_{(s-1)}$ is the state that is concealed that exists at period phase $s - 1$. The value grids for the refreshing and cleared gates are W_m and W_n , respectively. The biases that are utilized for the refreshing and restored gates are b_m and b_n and the active sigmoid function that operates is σ .

The concealed state at the period s , h_s , is then found by interpolating between the proposed concealed state and the preceding concealed state.

$$h_s = (1 - n_s) * h_{(s-1)} + n_s * \tilde{h}_s \quad (6)$$

The location of the transfer gate ($1 - n_s$) establishes the distance to which the target's concealed state is utilized for updating the prior concealed state and the point to which the previously concealed state is transmitted ahead.

3.5.3 Hybrid BiLSTM-GRU

A hybrid BiLSTM - GRU refers to a neural network architecture that combines elements of both GRUs and LSTM units. GRUs and LSTMs are both types of RNNs that are commonly used for sequence modeling tasks, such as regression and recognition.

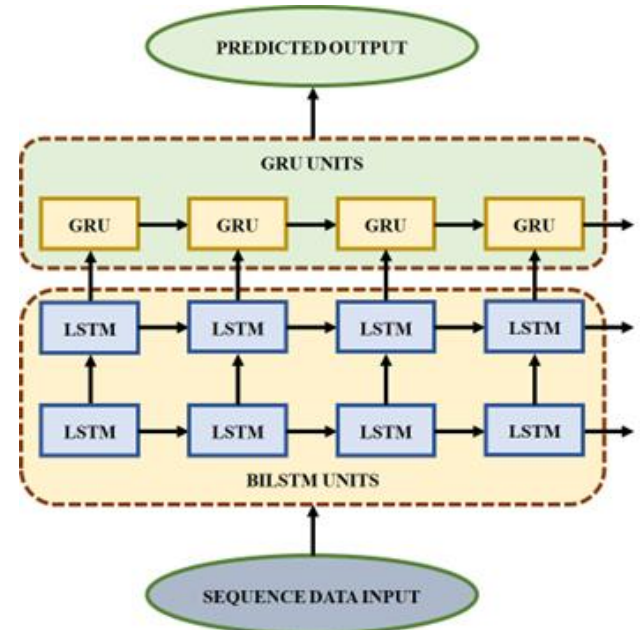


Figure 4: Hybrid BiLSTM-GRU for the proposed model

As shown in Figure 4, this work uses a predictive analytics technique that combines BiLSTM - GRU. Six hidden levels, each with 256 hidden units, make up the suggested architecture. LSTM units make up three of these hidden layers, whereas GRU units make up the remaining three. The activation functions a well-liked non-linear activation function in neural networks, is used as a trigger function in each of these concealed layers. A single element and one density layer with a linear function of activation are used in the layer of output. The values produced lack precisely limited to a certain region because of the result

layer's linear stimulation function, which is advantageous in some situations.

4. Results and Discussion

In this work, the hybrid BiLSTM-GRU model integrated with hierarchical frequency decomposition technique is developed for stock price prediction and implemented using Python software and the obtained outcomes are discussed below with the comparative analysis.

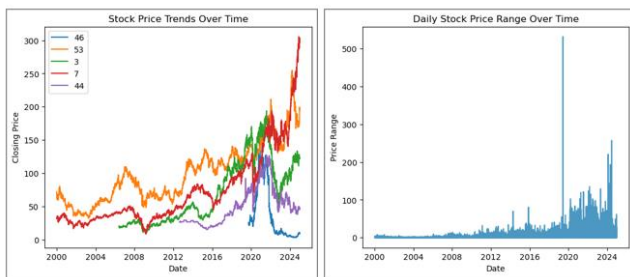


Figure 5: Stock Price Trends Over Time

Figure 5 displays the distributions of stock price trends over time. In the first graph, the stock price trends over time between closing time and date are noted. In the second plot, the daily updated stock price over time shows the relationship between the date and price range, and 2020 achieved a high range of stock prices.

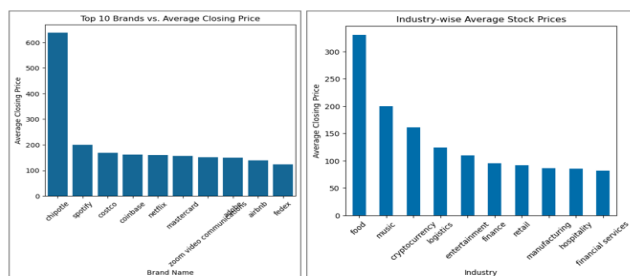


Figure 6: Histogram plot of closing price and stock price

Figure 6 demonstrates the histogram plot of closing price and stock price. In the first histogram plot, the top 10 brands in average closing price are analyzed, and the Chipotle brand attained the highest closing price. In the second histogram, the average stock price-wise industry and the food industry achieved the highest range of stock prices.

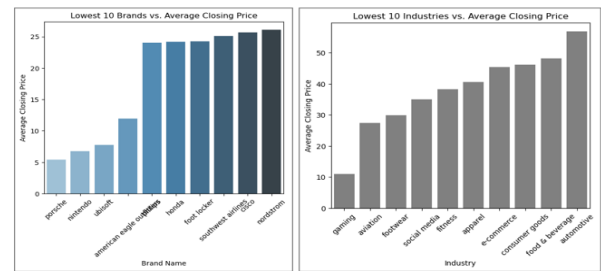


Figure 7: Histogram plot of lowest brands and industries of closing price

In Figure 7, it illustrates a histogram plot of the lowest brands and industries of closing price. In the lowest brand plot, the Porsche brand has attained the lowest value of average closing price. Similarly, the second plot is analyzed to determine the closing price of the 10 lowest industries, and the gaming industry achieved the lowest range of closing prices.

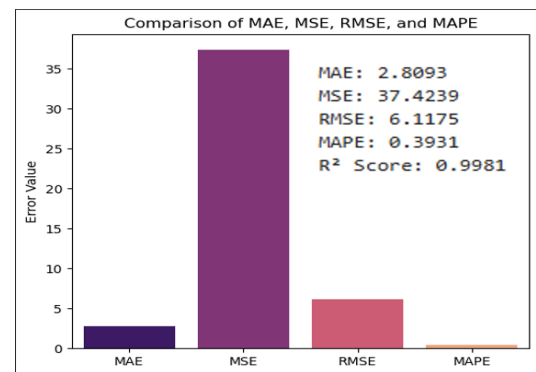


Figure 8: Comparison of error values.

The comparison of error values is clearly seen in Figure 8. In the chart, the MAE is 2.8093, the MSE is 37.4239, the RMSE is 6.1175, and the MAPE is 0.3931.

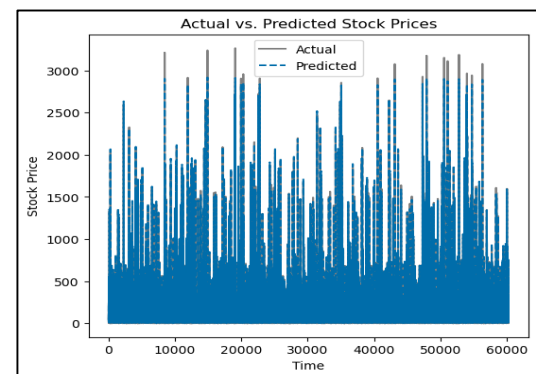


Figure 9: Actual vs. Predicted Range of Stock Prices.

Figure 9 illustrates the actual vs. predicted range of stock prices. In the plot drawn between stock price and time, the actual and predicted values are identified. These two predicted and actual ranges, which are occupied above 3000, readily demonstrate the predicted stock price.

Table 1: Performance of Comparative Analysis

Classifications	RMSE %	MAE %
Deep Neural Networks (DNN)[15]	18.93	15.64
CNN-LSTM [13]	13.76	10.58
GCN-LSTM [11]	9.20	7.83
Proposed BiLSTM-GRU	6.11	2.80

The of the various classifications and proposed work are indicated in Table 1. When compared to other algorithms, the proposed BiLSTM-GRU classification outperforms in terms of classification.

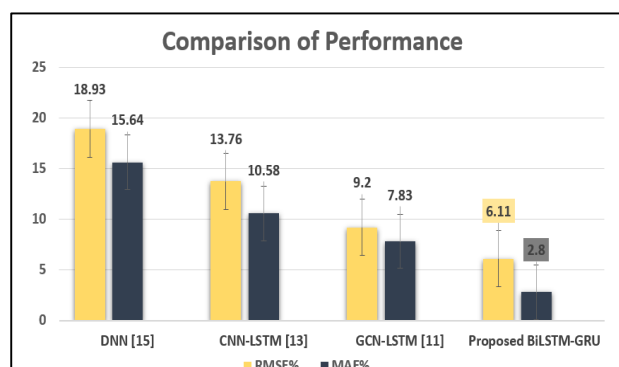


Figure 10: Comparison of the Model's Performance

Figure 10 illustrates a comparison of different classifications of RMSE and MAE values. In the graph, the proposed classification is RMSE of 6.11% and MAE of 2.80%. Previous classifications of DNN provide a highest RMSE value of 18.93% and an MSE value of 15.64%, respectively. The second classification RMSE value, CNN-LSTM of 13.76%, and MAE value of 10.58% are attained. The third classification of CNN-LSTM, RMSE value of 9.20%, and MAE value of 7.83 % are achieved.

5. Conclusion

This paper develops the hybrid BiLSTM-GRU model integrated with the hierarchical frequency

decomposition technique for stock price prediction. In this work, the advanced DL architecture of the hybrid BiLSTM-GRU model yielded significantly more accurate and robust predictive results compared to conventional approaches. Further, the results demonstrate that hierarchical frequency decomposition enhances the model's ability to capture non-linear and non-stationary patterns in financial time-series data, and it also reduces overfitting by simplifying complex signals. Then, the RMSE and MAE errors are calculated by using model predictions. Following that, the MAE of 2.8093, the MSE of 37.4239, the RMSE of 6.1175, and the MAPE of 0.393 are achieved. Overall, this system helps identify high-value customer segments based on market behavior, enabling marketers to personalize offers or communications more effectively.

References

1. Shuzhen Wang, 2023, "A Stock Price Prediction Method Based on BiLSTM and Improved Transformer", in IEEE Access, Vol: 11, pp. 104211-104223.
2. Jisoo You, Haryeom Jang, Minsuk Kang, Sung-Byung Yang, Sang-Hyeak Yoon, 2024, "Leveraging Stock Discussion Forum Posts for Stock Price Predictions: Focusing on the Secondary Battery Sector", in IEEE Access, Vol: 12, pp. 153537-153549.
3. Guangyu Mu, Nan Gao, Yuhan Wang, Li Dai, Year: 2023, "A Stock Price Prediction Model Based on Investor Sentiment and Optimized Deep Learning", in IEEE Access, Vol: 11, pp. 51353-51367.
4. Khorshed Alam, Mahbulul Haq Bhuiyan, Injamam ul Haque, Md Fahad Monir, Tarem Ahmed, 2024, "Enhancing Stock Market Prediction: A Robust LSTM-DNN Model Analysis on 26 Real-Life Datasets", in IEEE Access, Vol: 12, pp. 122757-122768.

5. Yu Sun, Sofianita Mutalib, Nasiroh Omar, Liwei Tian, 2024, "A Novel Integrated Approach for Stock Prediction Based on Modal Decomposition Technology and Machine Learning", in IEEE Access, Vol: 12, pp. 95209-95222.
6. Yasmeen Ansari, 2024, "Multi-Cluster Graph (MCG): A Novel Clustering-Based Multi-Relation Graph Neural Networks for Stock Price Forecasting", in IEEE Access, Vol: 12, pp. 154482-154502.
7. Arindam Kishor Biswas, 2025, "A Dual Output Temporal Convolutional Network with Attention Architecture for Stock Price Prediction and Risk Assessment", in IEEE Access, Vol: 13, pp. 53621-53639.
8. Rui Zhang, Vladimir Y. Mariano, 2024, "Integration of Emotional Factors with GAN Algorithm in Stock Price Prediction Method Research", in IEEE Access, Vol: 12, pp. 77368-77378.
9. Babak Amiri, Amirali Haddadi, Kosar Farajpour Mojdehi, 2025, "A Novel Hybrid GCN-LSTM Algorithm for Energy Stock Price Prediction: Leveraging Temporal Dynamics and Inter-Stock Relationships", in IEEE Access, Vol: 13, pp. 24815-24832.
10. Kun Huang, Xiaoming Li, Fangyuan Liu, Xiaoping Yang, Wei Yu. 2022, "ML-GAT: A Multilevel Graph Attention Model for Stock Prediction", in IEEE Access, Vol: 10, pp. 86408-86422.
11. Fatemeh FMoodi, Amir Jahangard Rafsanjani, Sajad Zarifzadeh, Mohammad Ali Zare Chahooki, 2024, "Fusion of Technical Indicators and Sentiment Analysis in a Hybrid Framework of Deep Learning Models for Stock Price Movement Prediction", in IEEE Access, Vol: 12, pp. 195696-195709.
12. Alsheebah, Fikry Mansour M., Belal Al-Fuhaidi, 2024, "Emerging Stock Market Prediction Using GRU Algorithm: Incorporating Endogenous and Exogenous Variables", in IEEE Access, Vol: 12, pp. 132964-132971.
13. Le Yu, Yaoquan Chen, Yanting Zheng, 2025, "A Multi-Market Data-Driven Stock Price Prediction System: Model Optimization and Empirical Study", in IEEE Access, Vol: 13, pp. 65884-65899.
14. Yi Li, Lei Chen, Cuiping Sun, Guoxu Liu, Chunlei Chen, Yonghui Zhang Zhang, 2024, "Accurate Stock Price Forecasting Based on Deep Learning and Hierarchical Frequency Decomposition", in IEEE Access, Vol: 12, pp. 49878-49894.
15. Thendo Sidogi, Wilson Tsakane Mongwe, Rendani Mbuva, Peter Olukanmi, Tshilidzi Marwala, 2023, "A Signature Transform of Limit Order Book Data for Stock Price Prediction", in IEEE Access, Vol: 11, pp. 70598-70609.