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Stock Market Priceprediction using Deep Learning

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Abstract - This study presents an advanced deep learning-based framework for stock market price prediction using a hybrid architecture that integrates Bidirectional Gated Recurrent Units (Bi-GRU) and Long Short-Term Memory (LSTM) networks. Stock price prediction is inherently complex due to the highly dynamic, nonlinear, and volatile nature of financial time-series data, which is influenced by multiple external and internal factors.

To overcome these challenges, the proposed system incorporates comprehensive data preprocessing techniques including data cleaning, normalization, and feature engineering to transform raw historical stock data into a structured format suitable for model training. The hybrid deep learning model effectively combines the strengths of both Bi-GRU and LSTM networks, enabling it to capture both short-term fluctuations and long-term dependencies within the data.

The model is trained and tested on real-world stock datasets, and its performance is evaluated using standard metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2 score). The results demonstrate that the proposed model achieves high prediction accuracy with reduced error rates.

Additionally, a Smart Trading Platform is developed to provide real-time visualization of stock trends and predictions, thereby enhancing usability and supporting informed decision-making. The findings highlight the effectiveness of hybrid deep learning models in financial forecasting applications.

Keywords – Stock Market Prediction, Deep Learning, LSTM, Bi-GRU, Time Series, RMSE, MAE, R^2 Score

I. INTRODUCTION

Stock prices are influenced by a wide range of factors, including economic indicators, political events, company performance, global market trends, and investor sentiment. These factors introduce high volatility and randomness, making it difficult to identify consistent patterns in stock price movements. Traditional statistical models, such as linear regression and time-series analysis methods, often fail to capture these nonlinear relationships and dynamic changes.

With the advancement of artificial intelligence, particularly deep learning, new approaches have emerged to address these challenges. Deep learning models, such as LSTM and GRU, are specifically designed to handle sequential data and are capable of learning long-term dependencies. These models have shown promising results in various time-series forecasting applications, including stock market prediction.

In this research, a hybrid deep learning model combining Bi-GRU and LSTM is proposed to improve prediction performance. The integration of these two architectures allows the model to better understand both forward and backward dependencies in the data, leading to more accurate predictions.

Furthermore, the study emphasizes not only prediction accuracy but also usability by developing a Smart Trading Platform. This platform enables users to visualize stock trends, compare predicted and actual values, and make informed investment decisions in real time.

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II.LITERATURE SURVEY

Study 1: Timothy Juliana et al. (2023) – Juliana Timothy et al presented a deep learning algorithm incorporating technical analysis signals for predicting stocks. In the paper, the researchers introduced a new performance measure and achieved excellent predictive performance with an R^2 coefficient near 0.995, indicating that neural network integration with technical indicators is highly effective.

Study 2: L. Mozaffari (2024) – According to L. Mozaffari (2024), Transformer model outperformed LSTM and Prophet models for predicting stocks owing to its capability of considering long-range dependence and nonlinear behavior through the application of attention mechanism.

Study 3: Burak Gulmez (2023) – In their research published in 2023, Burak Gulmez implemented an optimized version of the Long Short Term Memory model based on the Artificial Rabbits Optimization method. This optimized LSTM model performed better than the conventional LSTM model and other neural network architectures.

Study 4 Tran Phuoc – Tran Phuoc et al. used LSTM models together with technical analysis measures like SMA, MACD, and RSI in their stock prediction models. The results of their experiment showed that they could achieve approximately 93% accuracy with technical analysis..

Study 5: Mohammadreza Saberironaghi et al – Saberironaghi, Mohammadreza, et al. provided an extensive review on the application of machine learning and deep learning algorithms to predict the stock market. Their analysis covered the strengths and weaknesses of various algorithms including LSTM, CNN, and SVM.

Study 6: Yaojun Zhang et al. (2024) – According to Yaojun Zhang et al. (2024), they developed a Bi-GRU model with an attention approach, which helps improve the accuracy of predictions by paying more attention to critical information from past data.

Study 7: Chengyu Li – Chengyu Li et al. proposed a novel hybrid GRU-Transformer framework with frequency decomposition for reducing noise in stock data. This method enhanced the prediction accuracy and provided better performance with respect to financial data.

Study 8: M.R. Kabir (2025) – M.R. Kabir (2025) has designed a combined deep learning model which consists of LSTM, transformer, and MLP models for capturing short-term and long-term patterns in the financial time series dataset. The proposed approach was evaluated on various datasets, and it was found that it produced better results in comparison to other methods and models.

Study 9: P. Chen (2024) – Chen P. (2024) suggested an approach based on LSTM and FinBERT for combining stock prices, technical indicators, and sentiment analysis of the news. The author managed to obtain higher accuracy by integrating both types of data sources.

Study 10: Prakash Balasubramanian et al. (2024) – The survey paper on stock market forecasting from 2024 by Prakash Balasubramanian et al. compares forecasting techniques used for predicting stocks, such as statistical modeling and more advanced ML and DL algorithms like LSTM, CNN, and combination of these. The survey suggests that using various data sources leads to better performance, and hybrid models perform better than single models.

Recent studies have increasingly focused on hybrid and ensemble models to improve prediction accuracy in financial forecasting. Researchers have explored combinations of deep learning architectures with optimization techniques, attention mechanisms, and sentiment analysis to enhance model performance. For instance, integrating Natural Language Processing (NLP) with stock prediction models allows the inclusion of news sentiment and social media data, providing additional context to price movements.

Moreover, transformer-based models have gained attention due to their ability to capture long-range dependencies more effectively than traditional recurrent networks. Despite these advancements, challenges such as data noise, overfitting, and computational complexity remain significant. Therefore, continuous research is required to develop more robust and efficient models for real-world applications

III. PROBLEM STATEMENT

Prediction of stock markets is an intricate task because of the nature of financial markets that is ever-changing and cannot be predicted. Prices change all the time and are affected by many different factors like economic trends, international incidents, corporate performance, and investor behavior.

Such changes make it hard to predict price trends and their future direction. In some cases, unpredictability and randomness in the market behavior can make predictions unreliable.

Conventional statistical methodologies and machine learning techniques have been extensively applied in the field of predicting stock prices.
Nevertheless, these models have failed to adequately model the nonlinear dependencies that exist in the time series dataset of stocks due to their inability to deal with abrupt changes in market situations and market volatility. The introduction of neural networks, including LSTM and GRU, has enhanced sequential data modeling but is not immune to market volatility.

Besides, factors like noise in data, absence of data, and complexity involved in practical financial data sets make prediction even harder. High computational requirements of many algorithms hinder their use in practical scenarios.

All these factors underscore the necessity of a more powerful and effective solution based on deep learning algorithms that can analyze past data, deal with market volatility, and predict reliably.

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Key Issues: There exist some drawbacks associated with existing stock market prediction algorithms. The majority of the classical approaches as well as those based on machine learning techniques do not have the capability to deal with nonlinear associations and dependence inherent in financial data.

Moreover, they may lead to inconsistent forecasts under conditions of volatility or market jumps. One more drawback concerns the issue of noise in financial data that may lower the prediction accuracy. Finally, many advanced models demand intensive computing processes which make them difficult to apply in real time. It proves necessary to consider a novel approach involving deep learning algorithms to overcome these problems.

IV. OBJECTIVE

The first goal of the research is to create an effective deep learning system for stock price prediction based on historical information. The project should address preprocessing steps involving missing value handling and normalization of features in order to achieve consistent results. The system will use advanced neural networks including LSTMs and Bi-GRUs to improve its effectiveness.

It will also focus on analyzing the performance of the model by using such metrics as RMSE, MAE, and R^2 score. The other goal of the research is to create a user-friendly web platform that allows for visualizing and analyzing predictions.

Specific Objectives

- For obtaining historical and live data regarding the stock market from authentic sources like Yahoo Finance.
- For performing preprocessing steps on the collected dataset, including dealing with any missing values and performing normalization on the same.
- For creating sequences from time series datasets by employing sliding window technique.
- For building a hybrid model using the LSTM and Bi-GRU neural network architecture.
- For training the model and enabling it to discover the pattern and dependencies present in the stock price data.
- For predicting the future stock prices and making sure that these predictions are highly accurate.
- For testing and evaluating model performance using measures like RMSE, MAE, and R^2 score.
- For plotting the actual stock prices against the predicted stock prices using charts.

V. METHODOLOGY

The suggested system uses an organized framework to predict the stock price by applying deep learning algorithms. In the first stage, past data on stocks will be gathered from reputable sites like Yahoo Finance. Such data contain features like open, high, low, closing price, and volumes. The gathered data will be preprocessed to ensure that there are no errors.

Feature engineering is done by employing a sliding window method in order to transform the time series data into learning sequences for supervised learning.

Additionally, moving averages are calculated in order to detect any trends and remove noise from the dataset. This preprocessed data is used as input to a hybrid deep learning model made up of LSTMs and Bi-GRUs.

In the forecasting stage, the trained model creates the next value for the stock price, and these values are inverse transformed back to their original form. The system analyzes the model's performance based on measures like RMSE, MAE, and R^2. Finally, the results are visualized in charts comparing the real prices with the forecasted prices.

The system is architected in a modular way, which involves several modules including collecting the data, preprocessing the data, training the machine learning models, making predictions, and visualizing the predictions. The backend is developed in Python, using various packages, including Pandas and NumPy to handle data, and TensorFlow and Keras to train deep learning models. The front end is created in Streamlit, an open-source package.

This system consists of collection of stock data, pre-processing of collected data, creating sequences out of the data and using those sequences to train the deep learning algorithm. The predictions are output by the deep learning model and plotted along with real data.

Data Collection and Description
The dataset used in this study is collected from reliable financial sources such as Yahoo Finance. It includes multiple attributes such as opening price, closing price, highest price, lowest price, and trading volume. These features provide a comprehensive representation of stock behaviour over time.

Data Preprocessing
Data preprocessing is a crucial step in improving model performance. Missing values are handled using interpolation techniques, and normalization is applied to scale the data within a fixed range. This ensures faster convergence during

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model training.

Feature Engineering

Feature engineering involves transforming raw data into meaningful inputs. Techniques such as moving averages, exponential smoothing, and sliding window methods are used to extract patterns and trends from time-series data.

Model Architecture

The proposed hybrid model consists of stacked LSTM and Bi-GRU layers. LSTM captures long-term dependencies, while Bi-GRU processes input sequences in both forward and backward directions, improving contextual understanding.

Model Training

The model is trained using historical stock data with optimized hyperparameters such as learning rate, batch size, and number of epochs. Loss functions like Mean Squared Error (MSE) are used to minimize prediction error.

Evaluation Metrics

The performance of the model is evaluated using RMSE, MAE, and R^2 score. These metrics help in understanding the accuracy and reliability of predictions.

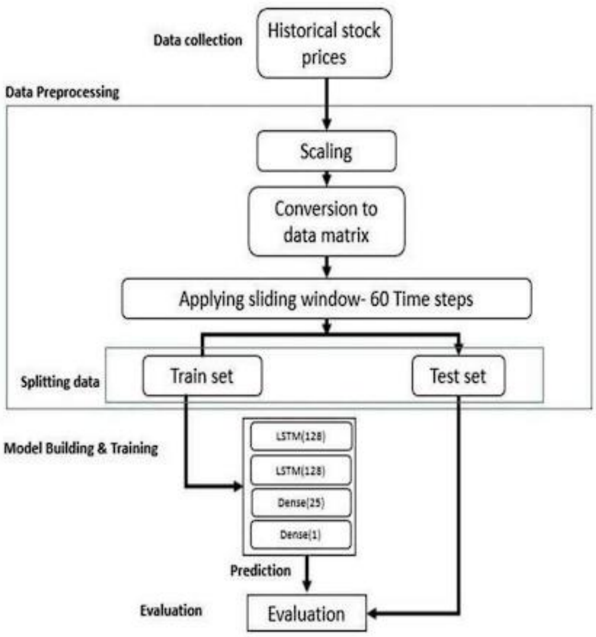


Fig.1. System Architecture

VI. RESULT

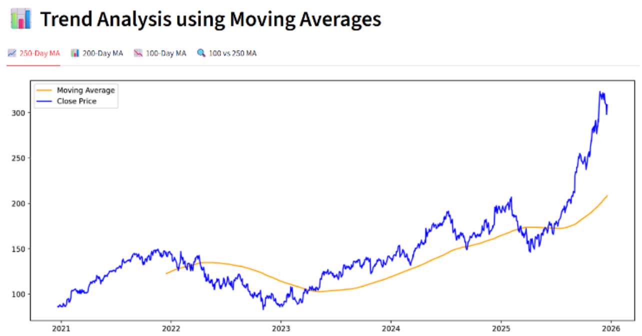
Evaluation of the suggested model was done on real-time datasets containing stocks of firms like Apple, Google, and IBM. According to the findings, the hybrid model combining Bi-GRU and LSTM demonstrates great prediction precision without making large errors. Specifically, the obtained R^2 score equals about 0.9948, meaning a close relation between estimated and real figures.

From graphical visualization, one can observe the great resemblance between the predicted values and the real changes in stock price. Apart from that, the proposed system generates moving average and trend analyses, allowing users to better understand market dynamics.

The experimental results clearly indicate that the hybrid deep learning model performs significantly better compared to traditional models. The predicted values closely follow the actual stock price trends, demonstrating the model's ability to capture complex patterns.

The R^2 score of approximately 0.9948 indicates a very strong correlation between predicted and actual values. Additionally, low RMSE and MAE values confirm minimal prediction error.

Graphical analysis further supports these findings, as the predicted curve aligns closely with the actual stock price curve. This proves that the model is capable of handling both short-term fluctuations and long-term trends effectively.



These results have shown that deep learning algorithms are much more efficient at stock market prediction than classical models. Possible directions for future research would include using sentiment analysis and transformers as well as including more financial indicators.

VII. FUTURE ENHANCEMENT

Though some promising results have been obtained, there still seems to be considerable room for improvement with respect to the suggested approach. Future research may involve using other types of information as an input, such as news articles, social media sentiments, or macroeconomic figures to boost predictive power. Applying methods of NLP along with Deep Learning will help create a more complete picture of market behaviour.

Further, another possible improvement in the current implementation would be the employment of state-of-the-art architectural designs such as those based on Transformers and attention mechanisms. These can enhance the ability of the model to recognize longer-range dependencies within the data. Finally, further investigation into optimization techniques and hyperparameters is essential to enhance

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efficiency and minimize complexity.

In addition, it is possible to extend the system to handle multi-stock forecasting, portfolio analysis, and risk assessment capabilities. The deployment of the model using cloud computing technologies and the connection with live trading systems can provide real-time decision support to the users. This would make the system scalable and adaptable to real-life situations.

Future work can focus on integrating sentiment analysis using news and social media data to further improve prediction accuracy. The use of transformer-based architectures and attention mechanisms can also enhance the model's ability to capture complex dependencies.

Moreover, deploying the system on cloud platforms and integrating it with live trading systems can enable real-time decision-making. Expanding the system for portfolio management and risk analysis is another potential direction.

VIII. LIMITATIONS

Despite achieving high accuracy, the proposed system has certain limitations. The model primarily relies on historical price data and does not incorporate external factors such as news sentiment, political events, or macroeconomic indicators. Additionally, deep learning models require high computational resources, which may limit real-time deployment in resource-constrained environments.

IX. CONCLUSION

This research presents a robust and innovative approach to stock price forecasting by leveraging a hybrid deep learning architecture that combines the strengths of Bi-GRU and LSTM networks. Through effective preprocessing and time-series sequence generation, the proposed system is able to capture both short-term fluctuations and long-term dependencies inherent in financial market data.

By integrating the complementary capabilities of these two recurrent neural network models, the framework demonstrates improved learning of complex stock market patterns, leading to highly accurate predictions. The experimental outcomes, supported by performance metrics such as RMSE, MAE, and R^2 score, validate the model's effectiveness, as the predicted values closely follow actual market trends with minimal error. These results highlight the potential of hybrid deep learning models to outperform conventional forecasting techniques and contribute meaningfully to the growing field of intelligent financial analytics.

Beyond predictive accuracy, this study also emphasizes the practical relevance of the proposed system through the inclusion of a Smart Trading Platform for real-time visualization and user interaction. This addition transforms the model from a purely theoretical forecasting framework into a more applicable decision-support tool for investors, traders, and analysts. By offering clearer market insights and supporting informed decision-making, the system addresses real-world financial challenges in dynamic and uncertain trading environments. Overall, the research demonstrates how advanced deep learning techniques can bridge the gap between academic innovation and practical market applications. It reinforces the idea that hybrid architectures, when combined with intelligent visualization platforms, can play a significant role in the future of stock market prediction and smart financial decision support systems.

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