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Real-Time Stock Market Prediction Using Deep Learning

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Abstract: -There is no one approach that appears to anticipate stock price both precisely and long-term at the same time, despite years of research on the subject by academics and financial experts. This is brought on by the unpredictable pattern of stock movement and numerous factors that affect market performance. The real-time stock market prediction uses real-time market data to forecast stock price movements and provide buy/sell signals to investors, lowering risk of loss while boosting profit. To anticipate the stock price, the proposed paper employs an ensemble of approaches, including the Rainbow Deep Q Network, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Moving Average Convergence Divergence (MACD).

Index Terms - Real-time stock, LSTM, GRU, MACD.

I. INTRODUCTION

The stock market can be described as unpredictable, non-linear, and dynamic. It is difficult to predict stock values since they depend on several variables, such as the state of the world's politics, the performance of the company's finances, and more. By examining the pattern over the last few years, strategies to estimate stock values in advance could therefore prove to be very helpful for making stock market movements, maximizing profit and minimizing losses. For estimating an organization's stock price, there have historically been two basic approaches put forth. The closing and opening prices of stocks, volume traded, adjacent close values, and other historical stock price data are all used by technical analysis methods to forecast future stock prices.

The second sort of analysis is qualitative, and it is carried out based on outside variables such as the firm profile, the market environment, political and economic issues, textual data in the form of financial news stories, social media, and even blogs written by economic analysts. Modern predictive methods involve sophisticated intelligence procedures based on technical or fundamental analyses. An effective model that can find the hidden patterns and intricate relationships in this vast data collection is required to handle this diversity of data. Compared to previous methodologies, machine learning techniques in this field have been shown to increase efficiencyby 60–86%.

However, with the aid of the ensemble, AI has enabled us to analyze both technical and fundamental data. For the purpose of predicting stock prices, a number of machine learning and deep learning algorithms have been separately implemented. They only appear to function effectively for a brief period of time, and the crucial aspect of generalization—the ability to function well on previously unknown data—is lost. A martingale impact on the stock price is to blame for this. This has made these methods ideal for achieving quick results. Better models with state of the-art performance are the product of recent advancements and concepts in the field of artificial intelligence, and they have the potential to provide outcomes that have never been seen before.

II. Literature Survey

[1] This study by Tian Ye, presented at the 3rd International Conference on Information Management (ICIM), 2021, employed wavelet decomposition and reconstruction to split stock prices into reconstructed and error components. ARIMA predicted the reconstructed component, while SVR modeled the error component. The model, tested on Shanghai Pudong Development Bank's closing prices (Jan 5, 2019–Jan 29, 2021), achieved a satisfactory MSE of 0.57.

[2] At the International Joint Conference on Neural Networks (IJCNN), 2021, Rafael Ramos et al. proposed using Restricted Boltzmann Machines (RBMs) for stock price prediction. The method involved five steps: historical data extraction, transformation, dimensionality reduction, feature extraction, and classification. Applied to time series from BM&F BOVESPA, the combined accuracy of RBM and SVM models ranged from 54% to 66%.

[3] Xinxin Jiang et al., at IJCNN 2020, utilized a cross-domain deep learning approach to predict financial markets. Attention mechanisms were applied to stock and currency domains across markets in the USA, China, and India, both pre- and post-financial crisis. The model's performance was assessed using F1 Score and Area Under the Curve (AUC).

[4] Chen, Zhou, and Dan presented their study at ICCEAI 2021, focusing on predicting Chinese stock market prices. They improved LSTM and GRU model performance by standardizing data, reducing noise from trend reversals, and employing ICA. Sampling training data from diverse intervals further enhanced model accuracy.

III. Scope and Methodology

3.1 Scope

The scope of this study extends to the development of an advanced stock market prediction and trading system that combines historical price analysis with real-time sentiment evaluation. This system aims to bridge the gap between traditional quantitative approaches and the qualitative factors influencing market movements by incorporating data-driven insights from multiple sources. Historical price and volume data are obtained from the National Stock Exchange of India, providing structured daily information, and Alpha Vantage, which offers detailed intraday market data at intervals of 1 minute, 5 minutes, and 15 minutes. In parallel, sentiment data is derived from real-time business news headlines gathered every minute from various financial websites. By combining these datasets, the system ensures that both the long-term trends and immediate market sentiments are captured, offering a holistic view of stock price behavior.

The study further explores the role of advanced deep learning models in processing and analyzing these datasets to achieve high prediction accuracy. The integration of Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) enables the system to capture intricate temporal patterns and immediate sentiment-driven price fluctuations. The inclusion of sentiment scores, derived through a pretrained encoder-decoder network, provides an additional dimension to the analysis, enhancing the system's ability to anticipate market movements influenced by real-world events. Beyond prediction, the study also focuses on practical applications by employing Rainbow DQN, a state-of-the-art reinforcement learning algorithm, to generate actionable buy/sell signals based on the predicted trends. This comprehensive approach not only supports more informed decision-making for traders and investors but also establishes a scalable framework for integrating diverse financial data streams into predictive and decision-making systems.

3.2 Methodology

The methodology involves a multi-layered approach to data collection, preprocessing, model training, and prediction. Initially, two primary data types are gathered: stock market data, including closing prices and trading volumes, and sentiment data derived from real-time news headlines. Sentiment scores are calculated using a pretrained encoder-decoder network that processes the textual content of headlines to determine their emotional tone. These scores are then aligned with their corresponding stock prices based on precise timestamps, ensuring that the sentiment data accurately reflects market conditions at the time of price movement.

To forecast stock trends, two advanced deep learning models are employed: Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU). LSTMs are trained on historical data containing closing prices and volumes, focusing on capturing long-term dependencies and trends inherent in sequential data. GRUs, on the other hand, incorporate additional features such as sentiment scores, allowing the model to factor in real-time market dynamics alongside price and volume data. Both models use a structured training approach where input-output batches are prepared with a time step size of four intervals. This ensures that the models can learn temporal patterns effectively. Each model employs a layer size of 128 units, balancing the capacity to capture complex patterns with computational efficiency.

The ensemble technique plays a crucial role in enhancing prediction accuracy and robustness. Predictions from the LSTM and GRU models are averaged, combining the strengths of both architectures to produce a unified and more reliable forecast. This ensemble output is then inverse transformed to its original scale for interpretation.

To translate these predictions into actionable trading strategies, the study employs Rainbow DQN, an advanced reinforcement learning algorithm. Rainbow DQN interprets the predicted stock prices from the ensemble model to generate buy/sell signals. The algorithm incorporates multiple enhancements, including prioritized experience replay and double Q-learning, making it a cutting-edge approach in reinforcement learning applications for financial markets. By combining these methodologies, the system not only predicts stock prices but also offers practical trading guidance, making it a comprehensive tool for market analysis and decision-making.

IV. System Architecture

The system architecture begins with data input from stock market sources and sentiment extraction mechanisms. The preprocessing module normalizes the data and aligns sentiment scores with price data for integration into the predictive models. The LSTM network processes historical data to identify long-term price trends, while the GRU network integrates sentiment scores to account for real-time market dynamics. The ensemble layer combines predictions from both models to produce a unified forecast. These forecasts are then processed by a reinforcement learning module using Rainbow DQN, which interprets the predicted prices to generate optimal buy or sell signals. Rainbow DQN, known for its advanced capabilities in reinforcement learning, utilizes features such as prioritized experience replay and double Q-learning to enhance decision-making accuracy. The output layer delivers both predicted closing prices and actionable trading signals, offering a comprehensive tool for market analysis and decision-making. The system’s design ensures seamless integration of historical and real-time data, deep learning for prediction, and reinforcement learning for trading signal generation.

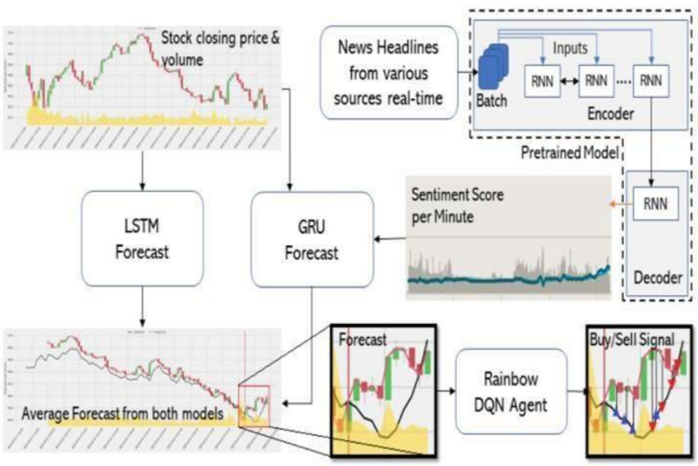

Figure 4.1:System Architecture

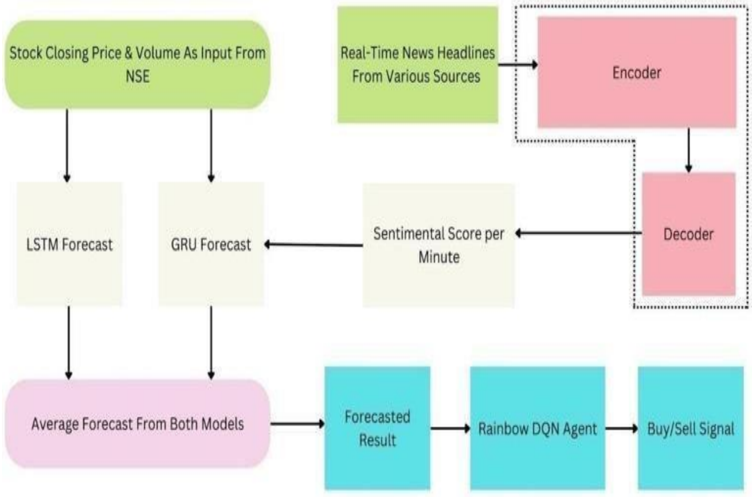

Figure 4.2:Complete Working Architecture

V. Conclusion

In this study, we trained 2 separate models (LSTM and GRU) using the ensemble approach on deep learning algorithms, considering technical and fundamental characteristics, and combined and obtained the features from both models for real-time stock market prediction. When compared to long-term price prediction, the short-term price prediction performed admirably with respectable directional accuracy. We also suggested using a cutting-edge method called Rainbow DQN to forecast buy/sell signals because it surpassed all other systems in terms of Return on Investment. In spite of these findings, the model did not perform well with high volatility and consequently value accuracy. For more accurate findings, multiple models can be combined or more parameters can be considered. Fast Fourier Transform and Decomposition are examples of mathematical models [23]. The final architecture that is being presented can also be utilized to create trading bots. The ability to predict the stock market has been constantly increasing, and upcoming technological breakthroughs may produce more accurate outcomes than were previously possible. In comparison to a standard Artificial Neural Network with Rainbow DQN algorithm, an LSTM [24] base model may perform better. We did not include distributional RL in our implementation, even though it could greatly enhance our agent's current performance.

References

[1] "Predictive stock market using natural language processing" by Karlo Puh and Marina Bagic Babac,Faculty of Electrical Engineering and Computing , University of Zagreb, Zagreb ,Croatia,13 March 2023.

[2] "A comprehensive review on multiple hybrid deep learning approaches for stock prediction" by Jaimin Shah , Darsh Vaidya, Manan Shah,14 August 2022.

[3] "A Study of Stock Market Prediction through Sentiment Analysis " by Sandipan Biswas , Sandip Roy, Rajesh Bose,ISSN 0975-3303 , 26 April 2023.

[4] Benjamin M. S. Hegde, G. Krishna, and R. Srinath "An Ensemble Stock Predictor and Recommender System" IEEE, dated 03 December 2021.

[5] "Cross-Domain Deep Learning Approach for Multiple Financial Market Prediction" IEEE, dated October 15, 2021, by X. Jiang, S. Pan, J. Jiang, and G. Long.