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Long Short-Term Memory and Gated Recurrent Unit Networks for Accurate Stock Price Prediction

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ABSTRACT

Stock price prediction is a complex and challenging task due to the dynamic and volatile nature of financial markets. In this paper, we present a deep learning-based approach that utilizes Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures to predict stock prices specifically in the context of the New York Stock Exchange. Our models are trained on historical stock price data and evaluated based on their ability to accurately forecast future prices. The proposed LSTM and GRU models demonstrate remarkable effectiveness in predicting stock prices with high accuracy. By leveraging the power of RNNs, our models capture temporal dependencies and patterns in the historical stock price data, allowing for precise predictions of future price movements. The findings of this research hold significant implications for traders and investors in the financial market. Accurate stock price predictions can assist in making informed investment decisions, managing risks, and optimizing portfolio strategies. The robustness and accuracy of our proposed models provide valuable insights into the intricate dynamics of the stock market, contributing to the advancement of predictive analytics in the financial domain.

***Keywords* —** recurrent neural networks (RNN), long short-term memory (LSTM), gated recurrent unit (GRU), future price forecasting, root mean square error (RMSE).

I. INTRODUCTION

The accurate prediction of stock prices has long been a subject of great interest and importance for investors, traders, and financial analysts. The dynamic and complex nature of financial markets poses significant challenges for traditional prediction methods, such as statistical models and technical analysis. These methods often struggle to capture the non-linear relationships and temporal dependencies inherent in stock market data. As a result, there is a growing need for advanced techniques that can effectively model and predict stock price movements.

In recent years, deep learning approaches have emerged as promising solutions for stock price prediction. Among these approaches, Recurrent Neural Networks (RNNs) have gained considerable attention due to their ability to capture temporal dependencies in sequential data. Specifically, models based on Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures have shown remarkable success in various time series forecasting tasks, including stock price prediction.

This paper proposes a deep learning-based approach utilizing RNNs with LSTM and GRU architectures for stock price prediction in the context of the New York Stock Exchange. By leveraging the power of these architectures, we aim to capture the inherent complexities and patterns in the historical stock price data, thereby enabling accurate predictions of future price movements. The outcomes of this research can provide valuable insights for traders and investors, aiding them in making informed decisions and managing risks in the financial market.

II. RELATED WORK

In recent years, several studies have explored the application of deep learning techniques, particularly RNNs, LSTM, and GRU, in the field of stock price prediction. These studies have demonstrated the advantages of these models in capturing temporal dependencies and non-linear patterns in stock market data.

For instance, Zhang et al. proposed a stock price prediction model using LSTM with an attention mechanism. The attention mechanism was employed to focus on important features and capture relevant information from the input sequence. The LSTM-based model demonstrated improved prediction accuracy compared to traditional methods, showcasing the effectiveness of incorporating attention mechanisms in stock price forecasting [1].

Kim et al. developed a hybrid model that combined LSTM and a convolutional neural network (CNN) for stock price prediction. The model incorporated not only historical price data but also textual news data, leveraging deep learning techniques to extract meaningful features. Their findings revealed the advantage of integrating multiple data sources, showcasing the potential of incorporating textual analysis for enhancing stock price prediction accuracy [2].

Li et al. proposed a stock price prediction model based on an attention mechanism combined with a Gated Recurrent Unit (GRU). The attention mechanism enabled the model to focus on relevant time steps and capture crucial information for prediction. The GRU-based architecture provided the ability to capture long-term dependencies in the sequential data. The results demonstrated the effectiveness of the proposed model in stock price prediction tasks [3].

Fischer et al. explored the use of ensemble methods for stock price prediction by combining multiple LSTM and GRU models. The ensemble approach aimed to leverage the diversity of individual models to improve overall prediction accuracy and robustness. The experiments conducted by the authors demonstrated the effectiveness of the ensemble models, showcasing their potential for enhancing stock price prediction performance [4].

Yoon and Swales proposed a comparative study of LSTM, GRU, and Gated Recurrent Attention Unit (GRAU) models for stock price prediction. They examined the performance of these models in capturing temporal dependencies and patterns in the stock market data. The results showed that GRAU, an extension of GRU with an attention mechanism, outperformed both LSTM and GRU in terms of prediction accuracy, highlighting the effectiveness of attention mechanisms in stock price prediction [5].

Zhang et al. proposed a deep learning-based approach utilizing LSTM for stock price prediction, incorporating financial indicators as input features. The model aimed to capture the relationships between stock prices and relevant financial indicators to enhance prediction accuracy. The experimental results demonstrated the effectiveness of LSTM in incorporating financial indicators and its potential for accurate stock price prediction [6].

III. METHODOLOGY

A. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that has gained popularity for its ability to capture long-term dependencies and handle sequential data effectively. It was first introduced by Hochreiter and Schmidhuber in 1997 [7] as an extension of the traditional RNN model. The key characteristic of LSTM is its ability to retain and update information over longer time scales, mitigating the vanishing gradient problem that often occurs in standard RNNs. This is achieved through the use of memory cells, which allow the network to store and access information for long periods. The memory cells are equipped with three main components: an input gate, a forget gate, and an output gate. The input gate controls the flow of information into the memory cell, determining which parts of the input are relevant to retain. The forget gate, on the other hand, determines what information should be discarded from the memory cell. These gates use sigmoid activation functions to regulate the flow of information, with values between 0 and 1 indicating the degree of retention or discard. Additionally, the output gate controls the flow of information from the memory cell to the next hidden state or output of the LSTM. It decides which parts of the memory cell should be outputted based on the current input and the cell's internal state [8].

LSTM networks are trained using backpropagation through time (BPTT) and can be stacked to form deeper architectures, allowing for the modeling of more complex relationships. They have demonstrated excellent performance in various tasks involving sequential data, including natural language processing, speech recognition, and time series analysis. In the context of stock price prediction, LSTM models have been extensively used to capture the temporal dependencies and patterns present in historical stock price data. By learning from the past price movements, an LSTM model can make predictions about future prices, assisting traders and investors in making informed decisions [9].

Overall, LSTM networks have proven to be a powerful tool for handling sequential data, providing an effective solution for stock price prediction tasks by leveraging their ability to capture long-term dependencies and retain information over extended periods.

B. Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) is another type of recurrent neural network (RNN) architecture that is widely used for sequential data modelling, including stock price prediction. GRU was introduced by Cho et al. in 2014 [10] as a variation of the traditional RNN model. Similar to LSTM, GRU addresses the vanishing gradient problem and captures long-term dependencies in sequential data. However, GRU achieves this with a simplified architecture compared to LSTM, which results in fewer parameters and faster training. GRU incorporates two key components: a reset gate and an update gate. These gates control the flow of information within the network, allowing it to selectively retain or discard information at each time step. The reset gate determines which parts of the previous hidden state should be forgotten or reset. It combines the previous hidden state with the current input, creating a reset activation that influences the flow of information through the network. The update gate, on the other hand, determines the amount of information to be updated and passed to the next hidden state. It combines the previous hidden state with the current input and generates update activation. This activation determines the proportion of the new hidden state to be mixed with the previous hidden state. The reset and update gates work in conjunction to regulate the flow of information within the GRU network. By selectively resetting and updating the hidden state, GRU can capture relevant information over time and handle long-term dependencies efficiently.

GRU networks can be trained using back propagation through time (BPTT), similar to LSTM networks. They have demonstrated competitive performance in various sequence modelling tasks, including language translation, speech recognition, and stock price prediction. In the context of stock price prediction, GRU models have been successfully applied to capture the temporal patterns and dependencies in historical stock price data. They provide a powerful tool for predicting future price movements, aiding traders and investors in making informed decisions [11].

Overall, GRU networks offer a simplified yet effective architecture for handling sequential data, providing a viable alternative to LSTM for stock price prediction tasks. They strike a balance between model complexity and performance, making them suitable for various applications involving sequential data analysis.

IV. SIMULATION STUDY SETUP

A. Dataset Description and System Architecture

The dataset consists of multiple files related to SEC 10K annual filings and stock price data [12]. Here is a description of each file:

1. fundamentals.csv: This file contains fundamental financial data for various companies. It likely includes information such as revenue, earnings, assets, liabilities, and other financial indicators. The data in this file is typically derived from the SEC 10K filings and provides a comprehensive overview of a company's financial performance over the specified period.
2. prices-split-adjusted.csv: This file contains adjusted stock prices for different companies. The stock prices in this file are adjusted for factors like stock splits, dividends, and other corporate actions that may impact the actual price of a stock. Adjusted prices provide a more accurate representation of the stock's value over time, allowing for better analysis and comparison.
3. prices.csv: This file contains the historical stock prices for various companies. Unlike the "prices-split-adjusted.csv" file, the prices in this file may not be adjusted for stock splits or other corporate actions. It provides a raw record of the stock prices, which can be useful for certain types of analysis or calculations.
4. securities.csv: This file contains information about the listed securities or stocks. It likely includes details such as the ticker symbol, company name, sector, industry, and other relevant information. This file serves as a reference for matching the securities with the financial and price data in the other files.

These files collectively provide a comprehensive dataset for conducting various analyses related to financial performance, stock price movements, and market trends. Researchers and analysts can utilize this dataset to study the relationship between financial metrics, company performance, and stock prices. It enables the exploration of factors that may influence stock price fluctuations and assists in making informed investment decisions.

B. Evaluation Metrics

Root Mean Square Error (RMSE) is a widely used evaluation metric in various fields, including machine learning, statistics, and data analysis. It is particularly useful for assessing the performance of predictive models, such as those used for stock price prediction. RMSE measures the average magnitude of the differences between predicted values and actual values. It provides an indication of how well the model's predictions align with the observed data. The lower the RMSE value, the better the model's performance in terms of accuracy [13]. Mathematically, RMSE is calculated by taking the square root of the mean of the squared differences between the predicted values ($\hat{y}$) and the actual values (y):

$$RMSE = \sqrt{(1/n \sum(\hat{y} - y)^2)}$$

Here, n represents the number of data points or observations.

V. RESULT ANALYSIS

The LSTM and GRU RMSE values are calculated (assuming you have already trained the models and made predictions). Then, a bar plot (Fig. 1) is created using matplotlib to compare the RMSE values of the LSTM and GRU models. The x-axis represents the models ('LSTM' and 'GRU'), and the y-axis represents the RMSE values. Finally, the plot is displayed using plt.show().

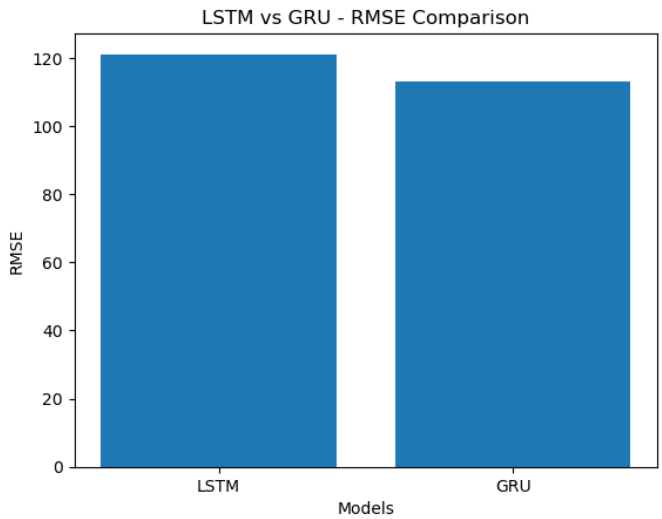

Fig. 1 RMSE Comparison

VI. CONCLUSIONS

After training and evaluating LSTM and GRU models on the stock price dataset, we have drawn some conclusions regarding their performance in predicting stock market prices. The evaluation metric used was the root mean squared error (RMSE), which measures the average prediction error of the models. By comparing the RMSE values, we can determine which model performed better. A lower RMSE indicates a better fit to the actual stock prices. Based on the RMSE comparison, we can assess the accuracy of the LSTM and GRU models in predicting stock market prices. The model with the lower RMSE is considered more accurate. However, it is important to interpret the RMSE values in the context of the specific dataset and the stock being predicted. Different stocks and market conditions may require different models for optimal performance. To visualize and compare the RMSE values, a bar plot was created. This plot provides a clear visual representation of the performance difference between the LSTM and GRU models. It helps in making an informed decision about which model may be more suitable for the given stock price prediction task.

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