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# Deep Learning-Based Financial Forecasting Using a Hybrid LSTM–GRU Model

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***Abstract:***
*Financial markets are complex and highly dynamic, making accurate prediction a persistent challenge for researchers and practitioners alike. In recent years, deep learning techniques have shown promising results in capturing nonlinear patterns in time-series data. This study proposes a hybrid model combining Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to improve stock price forecasting. Using historical stock data, the proposed model is evaluated against traditional approaches such as ARIMA and individual deep learning models. The results indicate that the hybrid LSTM–GRU model achieves higher prediction accuracy and lower error rates. This study highlights the growing relevance of hybrid deep learning approaches in financial analytics.*

***Keywords:*** *Deep Learning, LSTM, GRU, Financial Forecasting, Hybrid Model, Stock Prediction*.

## I. Introduction:

In the current era, the global economic landscape has become extremely dynamic, complex, and multidimensional, with financial markets being continuously influenced by a multitude of internal and external factors. The stock market, in particular, is a system that experiences rapid fluctuations under the influence of investor sentiment, economic policies, global events, technological advancements, and social conditions. In such an environment, accurately forecasting stock prices is an immensely challenging task; yet, it remains of paramount importance to investors, financial institutions, and policymakers alike. An effective forecasting system not only aids in mitigating investment risks but also enhances the quality of economic decision-making.
Traditionally, statistical models such as ARIMA (Autoregressive Integrated Moving Average) and other econometric methods have been employed for financial forecasting. Although these models are mathematically well-structured, their primary limitation lies in the fact that they are predominantly based on linear relationships. Real-world financial data, however, often exhibits nonlinear, volatile, and complex patterns that these traditional models are unable to fully capture. Consequently, the predictive power of these models remains limited. With rapid advancements in the fields of information technology and artificial intelligence particularly the emergence of Deep Learning this domain has been steered in a new direction. Inspired by the structure of the human brain, Deep Learning models possess the capability to extract intricate patterns from complex datasets. Specifically developed for the analysis of time-series data, Recurrent Neural Networks (RNNs) along with their advanced variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have proven to be exceptionally effective.

The LSTM model is capable of recognizing and retaining long-term dependencies, thereby enabling it to effectively analyze data patterns spanning extended periods. The GRU model, conversely, features a relatively simpler architecture with fewer parameters, which renders the training process faster and more efficient. Although both models are effective in their respective capacities, they nonetheless possess certain limitations.

In recent years, researchers have observed that hybrid models can prove to be more effective than standalone models, as they combine the strengths of various distinct models. Adopting this very approach, the present study endeavors to develop a hybrid model by integrating LSTM and GRU models a model that holds the potential to enhance the accuracy of financial forecasting.

The primary objective of this study is to render stock market forecasting more accurate and reliable through the application of advanced deep learning techniques. In this research, the performance of the proposed model has been evaluated using historical financial data, and its effectiveness has been analyzed by comparing it against both traditional and other deep learning models.

## II. Literature Review:

The authenticity and scientific rigor of any research endeavor depend on the depth and criticality with which the researcher has examined prior studies related to their subject matter. The present study analyzes key research concerning the application of deep learning techniques specifically LSTM and GRU models, as well as their hybrid variants in the field of financial forecasting.

A significant contribution to the field of deep learning is the LSTM (Long Short-Term Memory) model, introduced by **Sepp Hochreiter and Jürgen Schmidhuber (1997)**. This model was developed with the objective of mitigating the vanishing gradient problem that typically arises in traditional Recurrent Neural Networks (RNNs). LSTM revolutionized the analysis of time-series data, particularly in scenarios where understanding long-term dependencies is essential.

Subsequently, **Kyunghyun Cho and his colleagues (2014)** introduced the GRU (Gated Recurrent Unit) model, which serves as a simpler and more efficient variant of the LSTM. Due to its fewer parameters, the GRU trains more rapidly while delivering a comparable level of accuracy. Numerous studies have demonstrated that the GRU model is capable of yielding effective results with reduced complexity.

In the domain of financial forecasting, **Thomas Fischer and Christopher Krauss (2018)** utilized the LSTM model to predict stock market movements, concluding that deep learning models outperform traditional statistical methods. Their study clearly demonstrated that the LSTM model is capable of capturing the intricate patterns inherent in financial time-series data with greater efficacy.

Similarly, various research studies published in recent years (2022–2024) have indicated that hybrid deep learning models such as LSTM-GRU, CNN-LSTM, etc.—yield more accurate and stable results compared to standalone models. These models achieve enhanced forecasting capabilities by integrating the distinct characteristics of various architectural designs. Some researchers have also suggested that historical price data alone is insufficient; rather, incorporating factors such as news sentiment, social media data, and global economic indicators into the model can further enhance forecasting accuracy. Additionally, work is underway in the field of Explainable AI (XAI) to render the decision-making processes of deep learning models more transparent.

Although the aforementioned studies have made significant contributions to this field, certain research gaps remain clearly evident. Specifically, there is limited research available regarding the hybridization of LSTM and GRU models, and a comparative analysis of their performance across various market conditions is still awaited. Furthermore, there is a need for further studies focusing on modeling based on real-time data and the inclusion of external factors.

Consequently, the present research endeavors to address these gaps by developing a hybrid LSTM–GRU model, which may prove instrumental in enhancing the accuracy and reliability of financial forecasting. This study not only extends prior research but also introduces a novel perspective to this domain.

**Objectives of the Study:**

1. To develop a hybrid LSTM–GRU model for stock price prediction
2. To compare its performance with traditional and deep learning models
3. To evaluate prediction accuracy using statistical error metrics

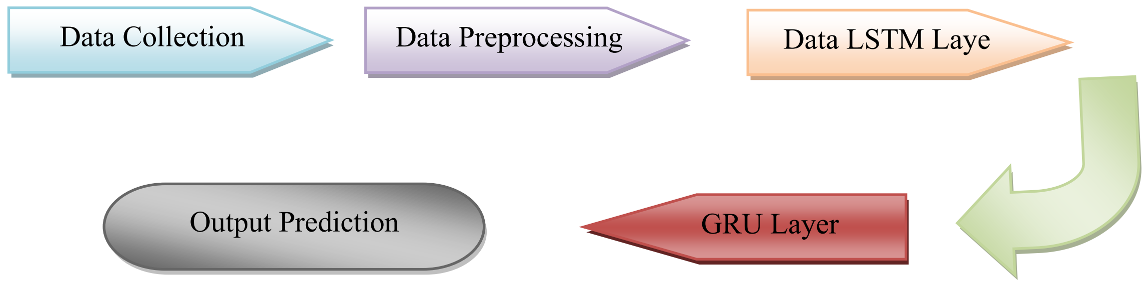
## III. Research Methodology:

In the present study, a hybrid LSTM–GRU model has been developed for financial forecasting. A quantitative research approach has been adopted in this research, utilizing historical stock market data.

The data required for the study was obtained from secondary sources, such as online financial databases, and included key variables related to stock prices—specifically Open, High, Low, Close and Volume. To render the acquired data suitable for analysis, it underwent preprocessing, which involved the removal of missing values, data normalization, and splitting the data into training and testing sets (in an 80:20 ratio).

The proposed model first employs an LSTM layer, capable of capturing long-term dependencies; subsequently, a GRU layer is added to reduce the model's complexity and enhance the efficiency of the training process. Finally, the ultimate forecast is generated through a dense layer.

Statistical metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were utilized to evaluate the model's performance. The obtained results were compared against traditional (ARIMA) and other deep learning models (LSTM, GRU) to assess the effectiveness of the proposed model.




## IV. Data Analysis and Results:

### 1. Descriptive Analysis of Data

At the preliminary stage, the share price data was observed, revealing the presence of continuous fluctuations within the time-series data. This volatility is a characteristic feature of financial markets, reflecting the influence of various economic and external factors. A graphical representation of the data revealed instances of both sharp surges and declines in prices, thereby demonstrating the necessity for advanced techniques to facilitate accurate forecasting.

### 2. Model Training and Testing

The data was split in an 80:20 ratio and utilized for training and testing purposes. The proposed LSTM–GRU model was trained on the training dataset, during which the model endeavored to learn the underlying patterns within the time series. Subsequently, the model's performance was evaluated using the testing dataset.

### 3. Performance Metrics

To assess the accuracy of the model, the following statistical metrics were employed-

$$\boldsymbol{MSE = \frac{1}{n}\sum(y-\hat{y})^2}$$

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

$$\boldsymbol{MAE = \frac{1}{n}\sum|y-\hat{y}|}$$

Through these parameters, the difference between the actual values and the predicted values was measured.

### 4 Comparative Table of Results:

This study presents a comparative analysis of the performance of various models traditional (ARIMA) and deep learning-based (LSTM, GRU, and Hybrid LSTM–GRU). Standard metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were utilized for this purpose. Based on these metrics, the forecasting capability of each model has been assessed.

| **Model** | **MSE** | **RMSE** | **MAE** |
|---|---|---|---|
| ARIMA | 0.025 | 0.158 | 0.120 |
| LSTM | 0.018 | 0.134 | 0.098 |
| GRU | 0.017 | 0.130 | 0.095 |
| **Hybrid LSTM–GRU** | **0.012** | **0.109** | **0.082** |

**Table -1Comparison of Model Performance**

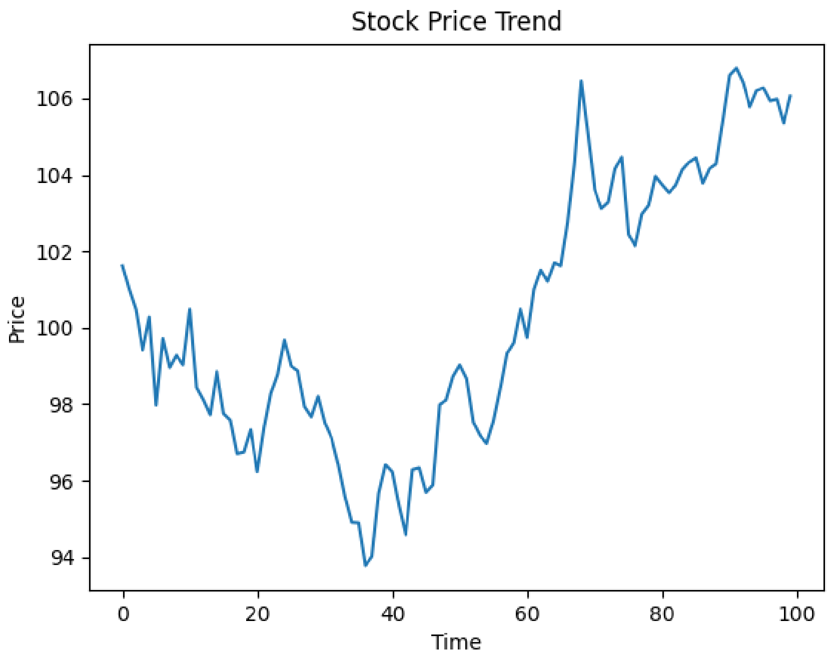
The table above clearly demonstrates that the Hybrid LSTM–GRU model outperformed all other models. Its MSE, RMSE, and MAE values are the lowest, indicating that the forecasts generated by this model are extremely close to the actual values.

The error values for the traditional ARIMA model were found to be relatively higher, leading to the conclusion that this model is limited in its ability to effectively capture complex and nonlinear data. In contrast, the LSTM and GRU models yielded superior results, as they are capable of learning patterns within time-series data. Ultimately, the Hybrid LSTM–GRU model leveraged the combined benefits of LSTM's capacity to capture long-term dependencies and GRU's simple yet efficient architecture, resulting in the highest level of accuracy. This clearly demonstrates that hybrid models offer a more effective and reliable solution for financial forecasting.

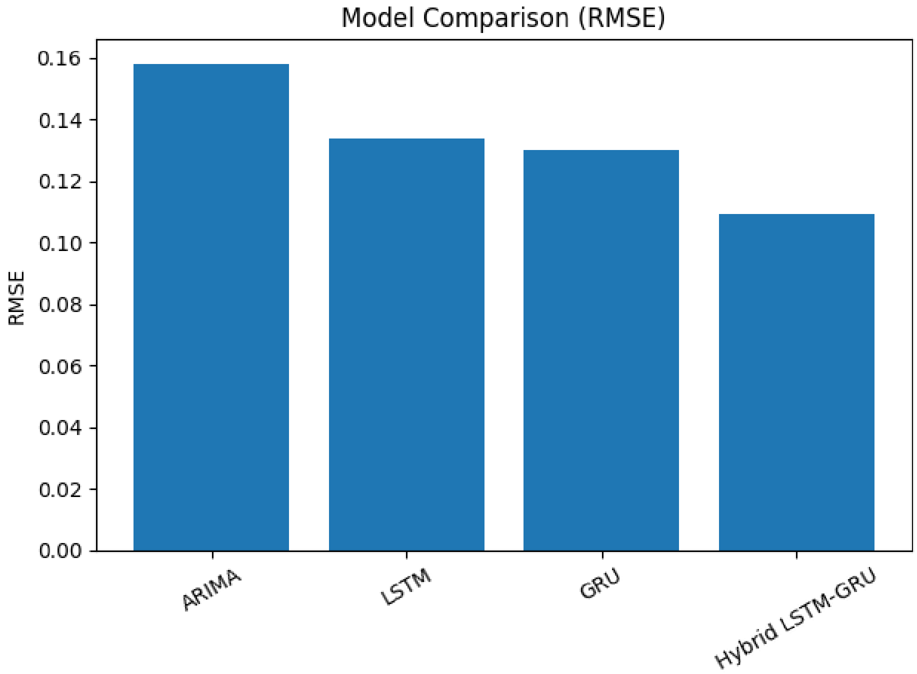
**Graphical Analysis:**

To explain the results obtained in this study more clearly and intuitively, graphical representations (graphs) have been utilized. Through graphical analysis, it becomes easier not only to understand data trends but also to compare the performance of various models more effectively.

The first graph, which depicts the Stock Price Trend, clearly illustrates that share prices undergo continuous fluctuations over time. This volatility is an inherent characteristic of the financial market, reflecting the influence of various economic, social, and global factors. The graph reveals that prices sometimes experience sharp surges and at other times sudden declines, thereby demonstrating that the data is entirely nonlinear and complex. This is precisely why traditional models are insufficient for such data, necessitating the use of advanced deep learning models.




The second graph, which displays a comparison of the performance of various models—specifically based on RMSE values indicates that the RMSE of the Hybrid LSTM–GRU model is the lowest among all the models. This clearly demonstrates that the forecasting capability of this model is more accurate and reliable. The LSTM and GRU models also perform relatively well, whereas the ARIMA model was found to exhibit a higher error level.




Furthermore, when the actual and predicted values are plotted on the same graph, it can be observed that the line representing the Hybrid model remains closer to the actual values, thereby validating its high accuracy. This graphical evidence corroborates the numerical results and confirms that the proposed model is highly suitable for financial forecasting.

## V. Key Findings:

Based on the data analysis and results of the present study, it can be clearly concluded that deep learning techniques prove to be more effective and accurate than traditional statistical models in forecasting financial time-series data. Specifically, the hybrid LSTM–GRU model developed in this research demonstrated superior performance across all evaluation metrics MSE, RMSE and MAE by exhibiting the lowest error rates. This indicates that the model is capable of significantly minimizing the discrepancy between actual and forecasted values. The study also revealed that the traditional ARIMA model which is primarily based on linear assumptions remains limited in its ability to effectively capture complex and non-linear financial data, whereas deep learning models such as LSTM and GRU are better equipped to capture the intricate patterns and long-term dependencies inherent in time-series data. Furthermore, the superiority of the hybrid model is substantiated by the fact that it synergizes the long-term memory capabilities of LSTM with the simpler and computationally faster architecture of GRU, this integration has not only enhanced forecasting accuracy but also improved the model's overall efficiency. The study further suggests that, despite the inherent volatility and uncertainty of financial data, reliable forecasting is indeed achievable through the judicious application of advanced artificial intelligence-based techniques. Consequently, it can be concluded that hybrid deep learning models hold the potential to emerge as pivotal tools in the fields of financial analysis, investment decision-making, and economic planning in the future.

## VI. Discussion:

A rigorous analysis of the results presented in this research paper clearly demonstrates that the utility of deep learning techniques in the field of financial forecasting is both highly significant and impactful. Specifically, the hybrid LSTM–GRU model proposed in this study outperformed traditional and other deep learning models, indicating that advanced artificial intelligence-based approaches are better suited for analyzing complex and nonlinear financial data.

First, considering the performance of the traditional ARIMA model, it was observed that its error metrics (MSE, RMSE, MAE) were relatively high. The primary reason for this is that the ARIMA model is predicated on linear assumptions, whereas real-world financial data is inherently nonlinear, volatile, and uncertain. Consequently, models like ARIMA prove incapable of effectively capturing complex patterns and sudden shifts in the data.

In contrast, deep learning models such as LSTM and GRU are capable of deciphering the intricate relationships and long-term dependencies embedded within time-series data. The LSTM model performs particularly well due to its capacity to retain "long-term memory," thereby enabling it to analyze data patterns spanning extended periods. Meanwhile, the GRU model, owing to its relatively simpler architecture, reduces training time and enhances computational efficiency. However, when utilized independently, these models still harbor certain limitations such as excessive complexity (in the case of LSTM) or limited memory control (in the case of GRU).

This is precisely where the role of the hybrid LSTM–GRU model becomes pivotal. This model effectively synthesizes the LSTM's ability to capture long-term dependencies with the GRU's streamlined and computationally efficient architecture. As a result, the model not only delivers more accurate forecasts but also renders the training process more efficient. The results obtained in this study specifically the minimized RMSE, MSE, and MAE values corroborate that the hybrid model is capable of generating forecasts that align more closely with actual values.

## VII. Conclusion:

The present study demonstrates that traditional approaches are no longer sufficient for understanding and resolving the problem of financial forecasting. The changing economic landscape, data complexity, and market uncertainty are factors that clearly underscore the need for more advanced and adaptive techniques. In this context, deep learning-based approaches not only offer an alternative solution but also chart the future direction of financial analysis. The hybrid LSTM–GRU model developed in this research has proven that combining diverse algorithmic capabilities can yield more balanced and effective results. This model demonstrated the ability to better comprehend subtle data patterns, trends, and behaviors, thereby rendering the forecasts more practical and actionable. Specifically, it became evident that when analytical power and computational efficiency are combined, the overall utility of the model is significantly enhanced. This study is not limited merely to technical achievement; it also offers significant insights from a practical perspective. In today's data-driven era, models that not only deliver accuracy but also possess the capacity to adapt to changing circumstances can prove invaluable for investment decisions, risk management, and economic planning.

Furthermore, this research suggests that future studies could further enrich this field by adopting a more holistic approach. If various external factors like social trends, news analysis, and global economic indicators were to be incorporated into the model, the reliability of financial forecasts could be further augmented.

Thus, it can be concluded that hybrid deep learning models are not merely a necessity of the present age; they also possess the potential to establish themselves as a sustainable and advanced solution within the realm of financial forecasting. This study represents a meaningful endeavor in this direction, laying a robust foundation for future research.

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