Integrating Deep Learning Techniques for Enhanced Stock Price Prediction

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Abstract. The volatility and complicated structure of financial markets makes it difficult to precisely predict stock prices. The multifaceted patterns and non-linear correlations seen in stock market data are sometimes difficult to capture using conventional methods like Linear Regression (LR) and time-series analysis. Therefore, there is an increasing need for investigation into innovative approaches that can get beyond these limitations and boost accuracy in predictions. Previous studies was primarily focused on single neural network employed Deep Learning (DL) model in the field of stock price prediction. These models have the potential to recognize both the immediate as well as long-term dependencies in time-series data, but often fall short when tackling the intricate dynamics of the stock market. The field of hybrid DL models offers a big chance of resolving the challenges that individual models suffer from when predicting stock values. Merging models provides ability to use of the advantages of each architecture to build a more reliable and thorough prediction framework. These hybrid models are capable of accurately capturing patterns, allowing for a better comprehension of underlying market trends and a quicker identification of significant discoveries. The integrated networks in the proposed architecture provide a powerful ensemble of models. These models could be used to provide a comprehensive analysis of the time-series dataset that captures the nonlinear patterns and multiple temporal dependencies included in the stock market data. When compared to conventional and single-model approaches, the hybrid DL technique has a number of benefits. The suggested technique provides reliable prediction even in the face of noisy and erratic market behavior by using the combined power of models. By using this approach, hidden patterns may be explored in more detail, allowing financial analysts and investors to make better judgments.

Keywords: Stock Price Prediction · Time Series · Deep Learning · Neural Networks · CNN · LSTM · GRU · BiLSTM · BiGRU

1 Introduction

The stock market is a dynamic and complicated space where prices are influenced by a broad spectrum of variables, such as business performance, geopolitical developments, and stakeholders sentiments. Predicting stock prices accurately has been a perennial challenge for researchers and financial analysts due to the inherent fluctuations and non-linear nature of financial markets [1]. Traditional approaches, relying on conventional Machine Learning (ML) algorithms and single-layer neural networks, have shown limited efficacy in capturing the intricate patterns and dependencies in time-series stock price data [2,3]. In order to overcome these challenges and enhance prediction confidence, it is essential to investigate innovative methodologies.

Previously, researchers have employed Linear Regression (LR), auto-regressive models, and Moving Averages (MA) to forecast stock prices. While these approaches offer transparency, they often fail to adequately reflect the complexities of market dynamics and the interplay of various underlying factors [4,5]. Also, they are inadequately prepared to handle the non-linear relationships and temporal dependencies inherent in financial time-series data.

Additionally, traditional ML algorithms, such as Support Vector Machines (SVM) and Random Forests (RF), may not fully capitalize on the rich features present in the data, leading to sub-optimal performance, especially in highly competitive markets [11]. Single-layer neural networks, though more capable of capturing non-linear patterns, may still have trouble with long-term dependencies and tend to under-perform when faced with varying fluctuations in markets [6]. The lack of sophisticated feature extraction and the inability to learn hierarchical representations limit their effectiveness in capturing the subtle intricacies that dictate stock price movements.

In response to the limitations of traditional techniques and single-model approaches, this research paper describes a novel and comprehensive solution for stock price prediction using hybrid Deep Learning (DL) models [7]. The central idea behind this approach is to harness the strengths of multiple neural network architectures by combining models, such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Gated Recurrent Unit (GRU), and Bidirectional GRU (BiGRU). To evaluate the effectiveness of the suggested approach, a comparison with established techniques was performed. The experimental findings indicated that the combined model improves the overall performance in forecasting the stock market.

1.1 Motivation and Contribution

The motivation behind this research stems from the ongoing difficulties faced in accurately predicting stock prices using traditional approaches and single-model DL techniques [2]. The stock market's highly dynamic and non-linear nature makes it a complex domain where numerous factors influence the trajectory of prices [4]. Inaccurate predictions can lead to substantial monetary losses for investors, while precise projections can provide valuable insights for making informed decisions. As the financial markets continue to evolve with increasing volumes of data and rapidly changing conditions, there is an urgent need for more sophisticated and robust predictive models.

The primary contributions of this study can be summarized below:

- To understand previous circumstances and evaluate their influence on forecasting the stock opening price for the upcoming trading day, it investigates various MA [8].
- The study suggests and evaluates Hybrid DL models like CNN-LSTM, CNN-BiLSTM, CNN-GRU, CNN-BiGRU, BiLSTM-BiGRU, and BiGRU-BiLSTM for predicting stock price.
- The study highlights the efficacy of the BiGRU-BiLSTM, CNN-BiLSTM, and CNN-BiGRU models for accurate stock market forecasting by demonstrating their higher performance and effectiveness in comparison to the others.

This study advances stock market price prediction using DL approaches, providing shareholders and monetary institutions with accurate prediction models.

The organization of the paper is as follow: Related work on DL in stock market research is included in Section 2. An introduction of important concepts and models, together with their structures, is provided in Section 3. With the use of graphs, Section 4 evaluates model accuracy through training and adjustment. Section 5 concludes by summarizing the research results and any possible ramifications.

2 Literature Review

The field of stock market prediction has seen extensive research efforts, with a wide array of approaches aimed at addressing its intricate nature. This section provides an overview of the studies conducted in stock market prediction, encompassing a variety of hybrid DL models.

A novel DL approach, CNN-LSTM, which leverages both CNN and LSTM networks introduces significant contributions in stock price prediction [9]. CNN extracts temporal features, while LSTM performs data forecasting. This hybrid model effectively captures stock price trends using time sequences. Through comprehensive comparisons with MLP, CNN, RNN, LSTM, and CNN-RNN models, [9] demonstrates that CNN-LSTM achieves superior forecasting accuracy, making it a more suitable choice for stock price prediction.

One-dimensional CNN enhancing stock price feature extraction is introduced. By leveraging local connections, weight sharing, and down-sampling, the model effectively captures intricate data features, leading to improved prediction accuracy for stock closing prices. The proposal of BiSLSTM, an enhancement of BiLSTM, incorporates a modified output gate. This modification widens the output gate's value range, enhancing learning capacity and yielding superior fitting outcomes during model training. Consequently, BiSLSTM is adept at exploring time series data relationships [10].

CNN-BiLSTM-AM, a DL model, was created to forecast the closing prices of stocks the next day by examining the temporal correlation and order of stock price data. The model integrates Adaptive Memory (AM), which employs weighted calculations of past characteristic states based on their impact on the upcoming day's stock closing price. This inclusion aims to enhance prediction accuracy. Comparative analysis against seven alternative ML methods validates CNN-BiLSTM-AM's exceptional accuracy and efficacy, underscoring its suitability for robust stock price prediction [11].

A CNN-Attention-GRU-Attention, is introduced through the analysis of stock data, recognizing its time series nature. To address the temporal aspect, the GRU model is employed, addressing issues like vanishing and exploding gradients inherent in RNNs. Additionally, the model integrates Attention to measure the impact of data at various temporal stages, improving prediction accuracy. CNN-Attention-GRU-Attention outperforms six competing stock price prediction models in an experimental evaluation utilizing data from the Shanghai Composite Index, proving its applicability for stock price forecasting. [12].

3 Methodology

In this study, we use the capabilities of hybrid DL models for enhanced stock market prediction. This section explains a step-by-step procedure used for stock market prediction. Additionally, Fig. 1 shows the graphic representation of the suggested approach.

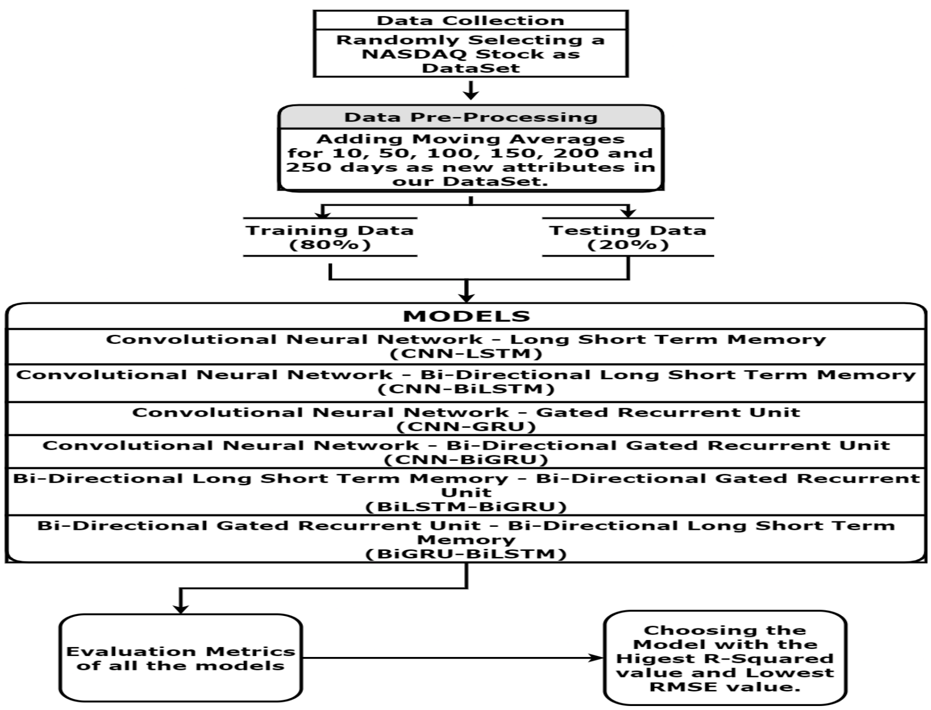

Fig. 1. Flowchart for our Proposed Methodology

3.1 Data Collection

The objective of the research is to strengthen stock price prediction while taking into account the level of detail in the data. A randomly selected organization currently trading on NASDAQ[3] is considered in the historical daily prices utilized in this study's data set. Important elements of its structure are the date, opening price, highest price, lowest price, closing price, modified closing price, and volume information.

3.2 Data Pre-processing

The forecast of stock prices heavily relies on data preparation. It deals with a number of problems, including missing data, noise, outliers, feature scaling, normalization, and time series dependencies [8]. Additionally, it makes it possible for efficient feature engineering to uncover significant patterns while removing duplication. Together, these methods make the data appropriate for prediction models, increasing the accuracy and predictive strength of the models used. MA's are a noteworthy statistical technique in the field of prediction of stock prices. Since they may mitigate the impacts of short-term fluctuations in the market, they are particularly beneficial. MA creates a cleaned trend-line by computing the mean across predetermined duration, which helps researchers find underlying patterns within surface-level noise. This makes it easier to predict the trajectory of the market as a whole and possible stock price changes. MA additionally assists with the identification of chart patterns that reveal insights about anticipated movements in the future.

- **Fundamentals of Moving Averages (MA):** MA are statistical techniques for averaging a set number of successive data points in order to smooth out data [8].

$$MA_n = \frac{x_1 + x_2 + \ldots + x_n}{n} \tag{1}$$

  In equation (1), the symbol MA_n denotes the moving average calculated for the given set of data points. The values $x_1 + x_2 + \ldots + x_n$ represent the specific data points that are being subjected to averaging. The variable n corresponds to the total count of data points taken into account when computing this average.

Over a range of duration, spanning 10, 50, 100, 150, 200, and 250 days, moving averages (MA) were calculated. Each independent data point was then given the properties derived from these computed averages. To maintain uniformity throughout the NASDAQ datasets, these intervals of time were carefully chosen and standardized. This method produced patterns that could potentially be applied to the most important equities traded on US exchanges throughout the

[3] https://www.kaggle.com/code/jacksoncrow/download-nasdaq-historical-data/input?select=stocks

short, medium, and long terms. While longer-term views offered insights into momentum and important support/resistance levels, shorter intervals (10 and 50 days) were useful in catching transitory variations. These smoothed trend features enhanced the accuracy of prediction models when compared to utilizing raw data values, albeit they are not universally appropriate for all datasets.

Fig. 2 displays stock prices with their corresponding MA.

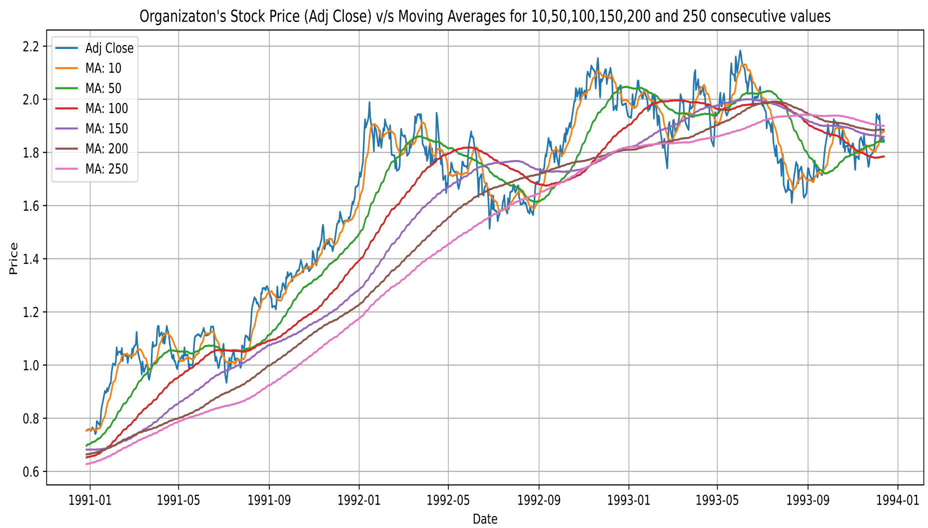

Fig. 2. Moving Averages for better Pattern Recognition.

3.3 Hybrid Deep Learning (DL) Models

- **Convolutional Neural Network - Long Short Term Memory (CNN-LSTM)**: In order to identify spatial and temporal patterns in stock data, a CNN-LSTM model for predicting the stock prices combines CNN with LSTM networks. By taking into account their spatial relationships, the CNN component identifies relevant details from historical stock price data [9]. Once the LSTM component, which is intended to record sequential dependencies and patterns through time, receives these characteristics, it begins to process them. The integrated model seeks to increase the precision of stock market predictions through employing both local patterns (learned by CNN) and long-term trends (recorded by LSTM) [11].

- **Convolutional Neural Network - Bi-Directional Long Short Term Memory (CNN-BiLSTM)**: BiLSTM networks and CNN are incorporated in a CNN-BiLSTM model for the prediction of stock prices [10]. In the

CNN component, relevant spatial characteristics are extracted from historical stock data to identify trends over short time frames. The BiLSTM component receives these characteristics then utilizes them to represent sequential dependencies in both forward and backward directions, therefore capturing long-term temporal patterns in the data. The model tries to improve accuracy in stock market prediction by integrating spatial and bidirectional temporal insights.

- **Convolutional Neural Network - Gated Recurrent Unit (CNN-GRU)**: For stock market forecasting, CNN and GRU are integrated [12]. From historical stock data, the CNN segment extracts pertinent information and highlights trends within localized windows. The GRU component receives these characteristics and uses gated strategies to record sequential dependencies across time. The model aims to increase the accuracy of stock market behavior prediction through the inclusion of spatial and temporal insights.

- **Convolutional Neural Network - Bi-Directional Gated Recurrent Unit (CNN-BiGRU)**: A stock market prediction model, known as CNN-BiGRU, merges CNN with BiGRU. The CNN portion identifies crucial spatial features within historical stock data, detecting patterns in shorter sections. These features are then fed into the BiGRU segment, which captures temporal relationships from both the past and the future by utilizing bidirectional information flow. By combining spatial and bidirectional temporal perspectives, this model strives to improve the precision of predicting shifts in the stock market [13].

- **Bi-Directional Long Short Term Memory - Bi-Directional Gated Recurrent Unit (BiLSTM-BiGRU)**: Bidirectional Long Short-Term Memory and Bidirectional Gated Recurrent Units are combined in the BiLSTM-BiGRU model for stock market forecasting. The BiLSTM component records both forward- and backward-moving sequential patterns [11]. This is improved even further by the BiGRU component, which takes into account bidirectional temporal relationships [13]. By successfully utilizing both forward and backward temporal information, this integrated strategy strives to increase the accuracy of stock market trend predictions.

- **Bi-Directional Gated Recurrent Unit - Bi-Directional Long Short Term Memory (BiGRU-BiLSTM)**: BiLSTM and BiGRU are combined in the BiGRU-BiLSTM stock market prediction model. The data's bidirectional temporal patterns are captured by the BiGRU component [13]. The BiLSTM, which additionally takes into account bidirectional sequences, refines this information after that [11]. Through the effective use of bidirectional temporal insights, this combination model seeks to improve predicting accuracy for stock market movements.

Table 1. Parameters for CNN-LSTM, CNN-BiLSTM, CNN-GRU, CNN-BiGRU, BiLSTM-BiGRU, BiGRU-BiLSTM Models

PARAMETERS	MODELS					
	CNN-LSTM	CNN-BiLSTM	CNN-GRU	CNN-BiGRU	BiLSTM-BiGRU	BiGRU-BiLSTM
Dense Layers	3	3	5	5	3	3
Units used in Dense Layers	64, 1, 1	64, 1, 1	64, 1, 256, 512, 1	64, 1, 256, 512, 1	256, 512, 1	256, 512, 1
LSTM Layers	4	-	-	-	4	4
BiLSTM Layers	-	4	-	-	-	-
GRU Layers	-	-	2	2	-	-
BiGRU Layers	-	-	-	-	2	2
Units used in LSTM Layers	96, 96, 96, 1	-	-	-	-	-
Units used in BiLSTM Layers	-	96, 96, 96, 1	-	-	96, 96, 96, 96	96, 96, 96, 96
Units used in GRU Layers	-	-	64, 128, 256, 512, 1	-	-	-
Units used in BiGRU Layers	-	-		64, 128, 256, 512, 1	64, 128	64, 128
Convolutional Two-Dimensional	1	1	1	1	-	-
Window Size	10	10	10	10	-	-
Number of Filters used	32	32	32	32	-	-
MaxPooling size	(2, 1)	(2, 1)	(2, 1)	(2, 1)	-	-
Filter/Kernel Size	(3, 1)	(3, 1)	(3, 1)	(3, 1)	-	-
Flatten	1	1	2	2	1	1
Activation Function	Rectified linear unit	Rectified linear unit	Hyperbolic tangent	Hyperbolic tangent	Hyperbolic tangent	Hyperbolic tangent
Dropout Value	0.2	0.2	0.3	0.3	0.2, 0.3	0.2, 0.3
Loss Function	Mean Squared Error	Mean Squared Error	Mean Squared Error	Mean Squared Error	Mean Squared Error	Mean Squared Error
Optimizer	Adam	Adam	Adam	Adam	Adam	Adam
Batch Size	32	32	32	32	32	32
Epochs	50	50	20	20	50	50

The parameters selected for hybrid CNN-LSTM and CNN-BiLSTM DL models are presented in Table 1. The CNN-LSTM model starts with a 2-dimensional CNN layer with filter size of 32 and a kernel size of (3, 1) to extract features from the input sequences. MaxPooling with a pool size of (2, 1) is applied to sub-sampling the feature maps. The extracted features are then flattened and passed through two dense layers with 64 units each, followed by a final dense layer. The model includes a total of four LSTM layers with 96 units each, followed by dropout layers. It uses the Adam optimization technique, Mean Squared Error loss function, and a batch size of 32. CNN-BiLSTM model also follows the same architecture as CNN-LSTM with a 2D CNN layer and a subsequent Dense layer setup. The key difference is that it includes four BiLSTM layers with 96 units each, followed by dropout layers. It uses the same optimizer, loss function, and batch size as CNN-LSTM.

The parameters selected for hybrid CNN-GRU and CNN-BiGRU DL models are presented in Table 1. CNN-GRU follows a similar CNN architecture as the previous models, including a 2D CNN layer with 32 filters and max-pooling. It doesn't use LSTM layers but proceeds with three GRU layers: two with 64 and 128 units, respectively, followed by dropout. The model further includes dense layers with 256 and 512 units, followed by flattening and a final dense layer with a single output. It uses the Hyperbolic Tangent activation function for GRU layers and the Adam optimizer. Like the previous models, CNN-BiGRU has the same CNN architecture as the others, followed by two BiGRU layers with 64 and 128 units respectively, along with dropout layers. The architecture also comprises dense layers having 256 and 512 units each. These are succeeded by a flattening step and a concluding dense layer. The activation function and optimizer are unchanged throughout.

The parameters selected for hybrid BiLSTM-BiGRU and BiGRU-BiLSTM DL models are presented in Table 1. BiLSTM-BiGRU has separate input paths for the BiLSTM and BiGRU components. The BiLSTM path includes four BiLSTM layers with 96 units each and dropout layers. TThe BiGRU section involves a pair of BiGRU layers with 64 and 128 units correspondingly. This is succeeded by dense layers and flattening. The results from both pathways are combined and directed through a dense layer with a solitary output. The model employs the Adam optimization method and the Mean Squared Error loss function. Much like in the case of BiLSTM-BiGRU, the BiGRU-BiLSTM approach also adopts the concept of distinct input pathways for each network type. Within the BiGRU route, there are two BiGRU layers with 64 and 128 units, in addition to dense layers and flattening. The BiLSTM route consists of four BiLSTM layers, each having 96 units, accompanied by dropout layers. The results from both pathways are joined together and directed through a dense layer with a sole output. Just like the preceding models, it employs the Adam optimizer and employs the Mean Squared Error loss function.

4 Experiment Result Analysis

Table 2. Experiment Result Analysis

Models	RMSE Value	R^2 Score
CNN [9]	42.967	0.9585
LSTM [9]	41.003	0.9622
BiLSTM [11]	33.579	0.9780
GRU [12]	39.875	0.9642
BiGRU [14]	5.410	0.820
CNN-LSTM	0.012354	0.974957
CNN-BiLSTM	0.008575	0.911205
CNN-GRU	0.012663	0.973688
CNN-BiGRU	0.012212	0.975531
BiLSTM-BiGRU	0.019878	0.994695
BiGRU-BiLSTM	0.009001	0.9989122

To showcase the effectiveness of the hybrid Deep Learning models used, the assessment of their performance relies on metrics such as Root Mean Square Error (RMSE) and R-square (R^2). These metrics serve as criteria to gauge the accuracy and efficiency of prediction methods. The subsequent section presents a comparative examination of diverse hybrid DL models applied in the study as shown in Table 2.

When evaluating the models across different categories, their performances reveal varying degrees of improvement or alteration. While comparing CNN, LSTM, and CNN-LSTM models, the baseline CNN [9] establishes initial reference points with an RMSE of 42.967 and an R^2 score of 0.9585. Slightly advancing from this, the LSTM [9] exhibits an RMSE of 41.003 and an R^2 score of 0.9622. However, the CNN-LSTM model, showcases a remarkable leap in performance. With a low RMSE of 0.012354 and a high R^2 score of 0.974957, it significantly enhances predictive accuracy and data fitting compared to both CNN [9] and LSTM [9].

In the context of BiLSTM and CNN-BiLSTM models, the BiLSTM [11] model demonstrates notable progress, recording an RMSE of 33.579 and an R^2 score of 0.9780 indicating substantial predictive accuracy compared to baseline models. However, the proposed CNN-BiLSTM model takes this further by achieving an RMSE of 0.008575 and an R^2 score of 0.911205. These values underscore the substantial boost in predictive accuracy and data fitting compared to the reference BiLSTM [11] model, with a significant decrease in RMSE and a concurrent increase in R^2 score.

The GRU and CNN-GRU models offer intriguing insights as well. The GRU [12] model registers an RMSE of 39.875 and an R^2 score of 0.9642. However, the proposed CNN-GRU model introduces a considerable enhancement, with an RMSE of 0.012663 and an R^2 score of 0.973688. These figures spotlight a substantial improvement in predictive accuracy and data fitting compared to the baseline GRU [12].

The BiGRU [14] model reports an RMSE of 5.410 and an R^2 score of 0.820. While showcasing a notable RMSE value, the R^2 score indicates a scope for improvement. Conversely, the CNN-BiGRU model stands out with an RMSE of 0.012212 and an R^2 score of 0.975531. This reflects a remarkable advancement in predictive accuracy and data fitting compared to the reference BiGRU [14], highlighted by a significant decrease in RMSE and an increase in R^2 score.

The BiLSTM-BiGRU and BiGRU-BiLSTM models, the former emerges as a top performer. The BiLSTM-BiGRU model achieves an RMSE of 0.019878 and an impressive R^2 score of 0.994695, positioning itself as a leader in predictive accuracy and data fit. Simultaneously, the BiGRU-BiLSTM model takes this performance to astonishing heights with an RMSE of 0.009001 and a remarkably high R^2 score of 0.9989122. These values emphasize its exceptional predictive prowess and superiority among the models.

In conclusion, the hybrid DL models consistently surpass their respective single DL baseline models in terms of predictive accuracy and data fitting. With significant decreases in RMSE values and substantial increases in R^2 scores, these hybrid models demonstrate an enhanced ability to capture intricate data patterns and relationships. This outcome solidifies the effectiveness of hybrid approaches in enhancing stock price prediction accuracy compared to conventional single-model strategies.

Fig. 3, 4, 5, 6, 7, 8 aid with comprehension of the effectiveness and precision of the different model employed.

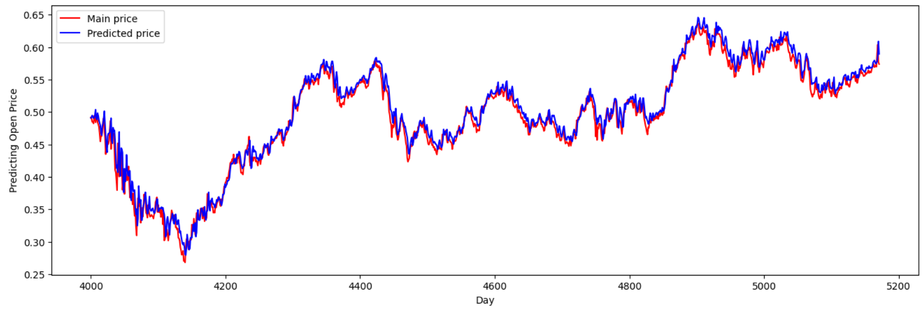

Fig. 3. Predicted Vs. Actual Price for CNN-LSTM Model.

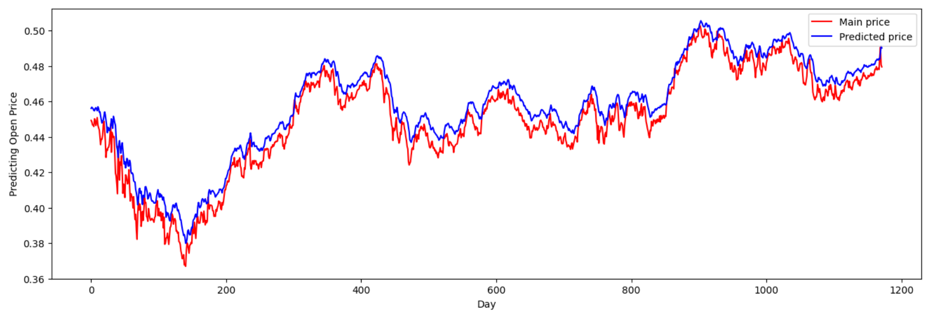

Fig. 4. Predicted Vs. Actual Price for CNN-BiLSTM Model.

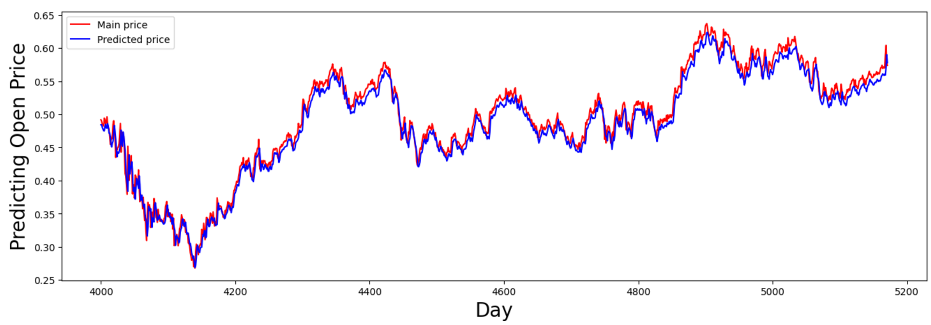

Fig. 5. Predicted Vs. Actual Price for CNN-GRU Model.

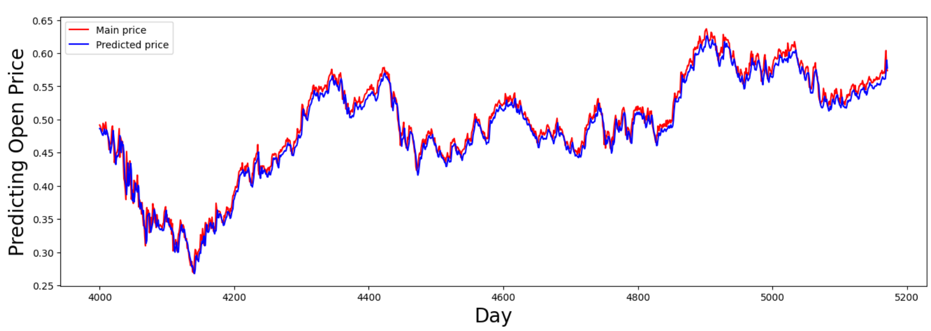

Fig. 6. Predicted Vs. Actual Price for CNN-BiGRU Model.

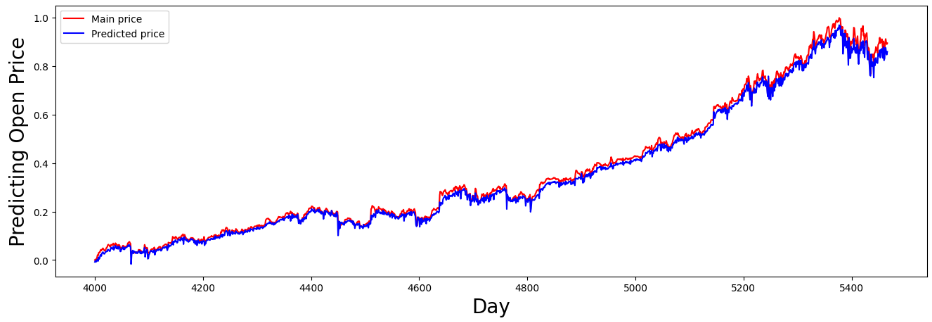

Fig. 7. Predicted Vs. Actual Price for BiLSTM-BiGRU Model.

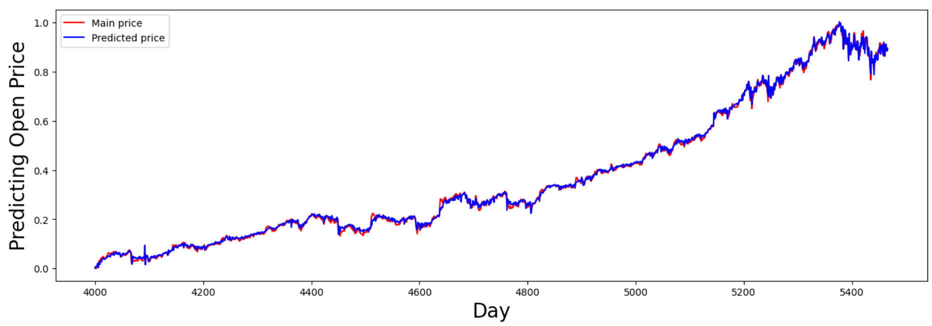

Fig. 8. Predicted Vs. Actual Price for BiGRU-BiLSTM Model.

5 Conclusion

Navigating the complex landscape of stock market prediction demands innovative solutions capable of addressing the volatility and intricate dynamics inherent in financial markets. The limitations of single-model DL methods have prompted the exploration of more sophisticated techniques. The hybrid DL models presented in this research paper offer a compelling strategy to tackle these challenges.

In the realm of stock price prediction, where patterns can be multifaceted and correlations non-linear, single neural network-based models have often struggled to deliver consistent accuracy. The hybrid models proposed in this study leverage the strengths of different architectures, creating a synergistic framework that excels in capturing both immediate and long-term dependencies within stock price data. This methodology allows for a deeper understanding of underlying market trends and facilitates the identification of crucial insights.

Notably, in this study, BiGRU-BiLSTM and BiLSTM-BiGRU hybrid models emerge as the best performers, exhibiting outstanding predictive prowess with minimal RMSE values and impressive R^2 scores. These models not only outperform their individual counterparts but also showcase remarkable performance when compared to other hybrid models. The comprehensive comparison and analysis of the hybrid models against their individual counterparts underscore the clear advantage of the hybrid models.

This research reveals the potential of hybrid DL models in revolutionizing stock market prediction. The ability to synergize different architectures and leverage their strengths results in enhanced accuracy and a deeper understanding of market behavior. These findings have implications for investors, financial analysts, and institutions, offering them a more reliable tool for making informed decisions in the ever-evolving landscape of financial markets. The hybrid models' consistent out-performance over single-model approaches underscores their pivotal role in driving accurate stock price forecasting and shaping the future of financial analysis.

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