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Enhancing Stock Price Prediction: LSTM-RNN Fusion Model

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Abstract

In today's dynamic stock market, accurate prediction stands as a linchpin for risk mitigation and amplified investment returns. This study introduces an innovative fusion model intertwining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), inclusive of specialized units like Long Short-Term Memory (LSTM) and SimpleRNN. By leveraging LSTM's aptitude for capturing long-term dependencies and RNN's proficiency in short-term patterns, the fusion model amalgamates their predictive capabilities. Trained individually and merged seamlessly, these components yield superior forecasts for next-day stock closing prices. Validated across historical stock data, the model showcases remarkable enhancements in prediction accuracy, notably reducing Mean Absolute Error (MAE) and validation Root Mean Squared Error (RMSE), alongside noteworthy validation loss. Additionally, a comparative analysis against other prominent models such as CNN-BiLSTM, CNN-LSTM, BiLSTM, CNN, RNN, MLP, and LSTM demonstrates the fusion model's superiority in key evaluation metrics.

Keywords: Stock market prediction, Fusion models, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN)

1. Introduction

The stock market, spanning over four centuries, represents a pivotal hub for trading, circulating, and transferring stocks, serving as a fundamental platform for companies to procure capital [6]. The inflow of substantial capital into the market through stock issuances promotes capital concentration, enhances enterprise capital composition, and significantly fuels the development of the commodity economy. Consequently, the stock market is widely acknowledged as a barometer, reflecting economic and financial activities within a country or region [2].

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Financial time series analysis has been a focal point in the financial market realm, addressing the challenges of forecasting amidst volatility and unpredictable economic shifts. Increasingly, the general populace has displayed a burgeoning interest in this field. Driven by the pursuit of a more prosperous life, individuals seek means beyond conventional methods of earning, recognizing that excessive work and savings can lead to diminished happiness, productivity, and well-being [18].

Need for Advanced Forecasting Models Institutions operating within the financial domain necessitate robust strategies and validated forecasting models to proficiently manage investment portfolios and assure promised gains. The accessibility to vast historical data and the burgeoning financial market growth have spurred the extensive use of time series forecasting methodologies [15]. Traditional machine learning and data analytic techniques, inclusive of Support Vector Machines (SVM), Random Forest, and Logistic Regression, have historically been utilized for stock price predictions but often fall short in accurately capturing the intricate and nonlinear movements of stock prices [5].

Advancements in Deep Learning for Stock Price Prediction Recent advancements in deep learning have shown promise in addressing the shortcomings of traditional approaches. Techniques such as Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) have demonstrated superior accuracy in predicting stock price movements, capturing nonlinearities that elude traditional linear models [13]. The efficacy of LSTM has been notably highlighted in outperforming models like ARIMA and Random Forest, leading to better forecasting and improved financial decision-making [16]. This shift towards deep learning methodologies signifies a significant breakthrough in the domain, surpassing the limitations of conventional analytic techniques and paving the way for more accurate stock price predictions [3][10].

The accurate prediction of stock prices is a crucial aspect for investors and financial institutions seeking to navigate risks and maximize returns. Yet, the complex and nonlinear nature of stock market data presents considerable challenges for traditional predictive models, urging the exploration of innovative methodologies to bolster forecasting accuracy.

Forecasting stock price fluctuations in advance has long been a focal point for economists [19]. Providing a reasonable and precise projection of stock price changes significantly diminishes investment risks for investors. Such forecasts empower investors to integrate anticipated stock prices into their investment strategies, thereby optimizing their investment returns.

This paper introduces an advanced model that harnesses the capabilities of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) to predict next-day stock closing prices. The model architecture leverages LSTM to capture enduring relationships within the data and utilizes Simple RNN to identify immediate patterns present in historical stock data.

Key contributions of this paper include:

- Dual Architecture Fusion: The model integrates LSTM for long-term memory retention and Simple RNN for capturing immediate trends, synergizing their predictive capabilities.
- Enhanced Forecasting: By combining LSTM and SimpleRNN adeptly, the model showcases improved predictions for next-day stock closing prices.
- Validation and Performance: Validated across extensive historical stock data, the model demonstrates notable enhancements in prediction accuracy, minimizing Mean Absolute Error (MAE) and validation Root Mean Squared Error (RMSE), thus indicating its proficiency in capturing evolving stock price trends.

The paper follows this structure: Section 2 delves into related work concerning stock market prediction using machine learning and deep learning approaches. Section 3 introduces a deep learning-based approach. Section 4 presents the experimental analysis, while Section 5 concludes the paper and outlines potential future directions.

2. Related Work

In the vast landscape of stock price prediction, researchers have explored a myriad of methodologies and models aimed at refining accuracy and efficiency. Here's an exploration of recent advancements and significant findings:

The CNN-BiLSTM-AM Approach introduced by Vijh et al. leverages Convolutional Neural Networks (CNNs) for feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) for predictive modeling [17]. This innovative amalgamation considers multiple stock data aspects over various time periods, displaying superior accuracy in prediction. Similarly, Kumar et al. optimized an ENN model using the Grey Wolf Optimizer (GWO), resulting in enhanced forecasting accuracy in daily stock prices [8]. A multitude of research has delved into comparing and enhancing models for stock prediction. Ananthi et al. showcased the potential of K-NN Regression by leveraging technical indicators, outperforming various machine learning methods [1]. Concurrently, Xiao et al. amalgamated ARIMA, MA, LS, and SVM models utilizing Principal Component Analysis (PCA) for dimension reduction, effectively improving stock price forecasting efficiency [19]. Meanwhile, Zhang et al. integrated SVR with ENANFIS, demonstrating robustness in handling technical indicator deviations for more accurate predictions [22]. Efforts by Yun et al. demonstrated the significance of refined feature sets in significantly enhancing stock price prediction accuracy [21]. Moreover, Jing et al. showcased the integration of investor sentiment into predictions by merging LSTM with sentiment analysis, thereby enhancing the accuracy of future stock price predictions [7]. Studies focusing on innovative architectures like the hybrid models integrating Particle Swarm Optimization (PSO) in Echo State Networks (ESN) presented by Zhang et al. showcased improved anticipatory accuracy for stock price prediction [23]. This innovative approach has contributed to the paradigm shift in financial prediction, highlighting the ongoing evolution of data mining technology and deep learning theories.

Furthermore, recent studies emphasized the outperformance of deep learning techniques over conventional models like ARIMA, SVR, and MLP [14]. Recent research has been dedicated to optimizing LSTM models [20], understanding machine learning in trend prediction [12], and exploring various improved LSTM variants [9] and hybrid architectures like CNN-BiLSTM-AM approaches [11]. Moreover, certain studies have investigated the integration of Empirical Mode Decomposition (EMD) and Complete Ensemble Empirical Mode Decomposition (CEEMD) for more accurate predictions [13]. Additionally, some studies have showcased the transferability of models trained on one stock exchange to forecast on another [4]. These ongoing research endeavors signify the continuous evolution and exploration in the domain of stock price prediction.

3. Proposed LSTM-RNN Fusion Model

The proposed framework introduces an innovative approach aiming to elevate stock price prediction accuracy through the fusion of LSTM (Long Short-Term Memory) and RNN (Recurrent Neural Network) architectures. This fusion strategy capitalizes on the individual strengths of LSTM and RNN models, leveraging their capabilities in capturing sequential dependencies and temporal patterns within stock price data. The LSTM model comprises two layers, each employing rectified linear unit (ReLU) activation functions to unlock intricate temporal patterns within stock price data. The ReLU activation fosters nonlinearity, enabling the model to discern complex relationships within sequential data. Similar to the LSTM architecture, the RNN model incorporates two SimpleRNN layers, each with ReLU activation, to unravel temporal dependencies in stock price sequences. These ReLU-equipped layers emphasize sequential processing, unraveling intricate temporal intricacies within the data. The fusion of LSTM and RNN architectures is orchestrated through a Concatenate layer, followed by a Dense layer. This fusion mechanism seamlessly integrates learned features from both LSTM and RNN architectures, amplifying their collective strength to augment predictive accuracy and capture nuanced patterns inherent in stock price fluctuations. The proposed framework's efficacy is underscored by a comparative analysis against various existing models, including CNN-BiLSTM, CNN-LSTM, BiLSTM, CNN, RNN, MLP, and LSTM. This comparison evaluates multiple metrics such as Loss, Validation Loss, MAE, Validation MAE, MSE, Validation MSE, RMSE, and Validation RMSE, providing a comprehensive assessment of predictive performance across different models. Utilizing metrics and weighted aggregate scores, the proposed fusion model demonstrates notable superiority in multiple performance measures. Specifically, the aggregated scores highlight the framework's robustness, positioning it as a leading contender in stock price prediction accuracy among the compared models.

The individual LSTM and RNN models are independently trained using historical stock price data, leveraging performance metrics like mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) for evaluation. Subsequently, the combined model is trained, refining predictions by amalgamating insights from both architectures, enhancing overall predictive efficacy.

Post-training, the predictive performance of the combined model is rigorously evaluated using standard metrics. Visual representations generated through matplotlib facilitate comprehensive comparative analyses between the com-

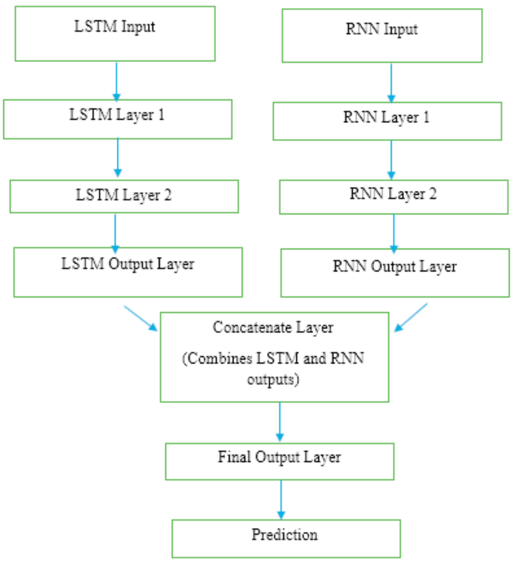

Fig. 1. Outline of the LSTM-RNN Fusion Model

bined model's predictions and actual observations, enabling a nuanced understanding of its performance across diverse temporal segments.

This fusion framework represents a sophisticated and holistic approach, harnessing the collective potential of LSTM and RNN architectures to significantly elevate stock price prediction accuracy. The synergy between these models caters to the intricate dynamics of financial market forecasting, promising enhanced predictive capabilities.

Our LSTM and RNN models are configured with the following hyperparameters:

Table 1. Hyperparameters for LSTM and RNN Models

Hyperparameter	**LSTM Model**	**RNN Model**
Layers	2 (64 units, 32 units)	2 (64 units, 32 units)
Activation	ReLU	ReLU
Learning Rate	0.001	0.001
Batch Size	128	128
Epochs	600	600

The input dimensions for both models are (X_train.shape[1], X_train.shape[2]), where X_train.shape[1] represents the number of time steps and X_train.shape[2] denotes the number of features. The output is a single dense layer with one unit for predicting the stock price.

A visual representation of our model architecture is shown in Figure 1. This figure outlines the flow of data through the LSTM and RNN layers, their fusion via a Concatenate layer, and the final dense output layer.

4. Experiments

The effectiveness of the proposed framework is validated through a comprehensive comparative analysis against established models, including CNN-BiLSTM, CNN-LSTM, BiLSTM, CNN, RNN, MLP, and LSTM. All models are implemented using Python and Keras, a renowned open-source learning library based on TensorFlow. This comparison is conducted using identical training and test set data, ensuring a fair evaluation under a consistent operating environment.

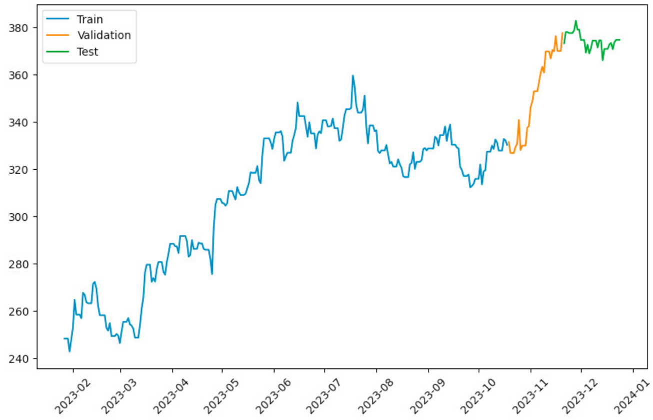

Fig. 2. Training, Validation, and Testing Periods.

The prediction performance of each method is assessed using a range of essential evaluation criteria, including mean absolute error (MAE), root mean square error (RMSE), R-squared (R^2), loss, validation loss, validation MAE, validation MSE, and validation RMSE. These metrics serve as pivotal indicators to comprehensively gauge the predictive accuracy and robustness of the models.

The MAE and RMSE serve as primary evaluation metrics, quantifying the average absolute difference and standard deviation of the residuals between predicted ($\hat{y}_i$) and actual (y_i) values in the dataset, respectively. The formulas for MAE and RMSE calculation are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

Additionally, the framework's performance is evaluated based on loss, validation loss, validation MAE, validation MSE, and validation RMSE metrics, which encompass training and validation set assessment criteria.

To consolidate the performance of each model across various metrics, an aggregation method is employed. Weights are assigned to individual metrics based on their significance, and the aggregate score for each model is computed as the weighted sum of normalized metric values:

$$AggregateScore = \sum_{i=1}^{n} NormalizedMetric_i \times Weight_i$$

All models, including the proposed fusion framework and comparative models, undergo rigorous evaluation using the aforementioned evaluation criteria. The objective is to discern the predictive prowess of the proposed fusion framework concerning its peers across identical datasets and operational conditions. The experiment employs statistical measures to quantify and qualify the predictive performance, enabling a comprehensive assessment of the proposed framework's effectiveness in stock price prediction.

This empirical analysis aims to establish the superiority of the proposed fusion framework by showcasing its ability to yield lower MAE, RMSE, and other metric values, signifying higher precision and accuracy in predicting stock prices compared to existing methodologies.

4.1. Data

In this experiment, historical stock price data from the EOD Historical Data API is utilized for analysis, focusing on Microsoft Corporation's ('MSFT.US') stock prices. The dataset encompasses a timeframe of 12 months. This dataset includes daily trading records within this period.

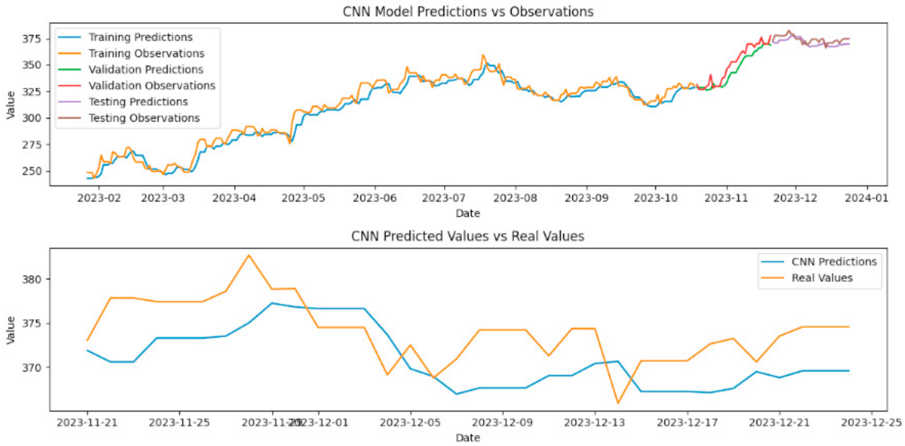

Fig. 3. Comparison of CNN predicted values with real values

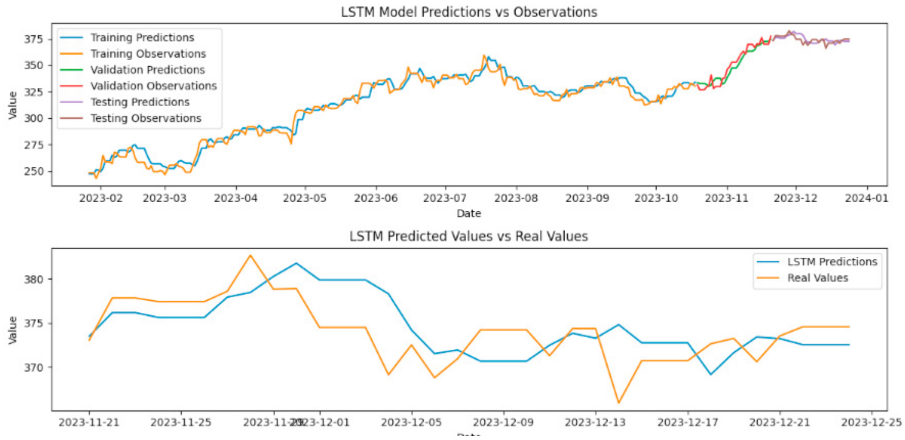

Fig. 4. Comparison of LSTM predicted values with real values

Table 2. Comparison of Evaluation Metrics for Different Models (Part 1)

Metrics	CNN-BiLSTM	CNN-LSTM	BiLSTM	CNN
Training Loss	0.000276	0.000365	0.000317	0.000497
Validation Loss	0.000263	0.000225	0.000370	0.000920
MAE	0.0132	0.0151	0.0144	0.0175
Validation MAE	0.0142	0.0137	0.0164	0.0248
MSE	0.000276	0.000365	0.000317	0.000497
Validation MSE	0.000263	0.000225	0.000370	0.000920
RMSE	0.0166	0.0191	0.0178	0.0223

Each entry in the dataset consists of the date and the closing price of Microsoft Corporation's stocks. The 'Close' column signifies the weighted average trading volume price of each transaction, recorded one minute before the market's closure on a given day.

The dataset is further stratified into training, validation, and testing partitions using a time-based split. Approximately 80% of the data is allocated for training, 10% for validation, and the remaining 10% for testing purposes. Figure 2 depicts the temporal distribution of the partitioned dataset, showcasing the train-validation-test split along the timeline.

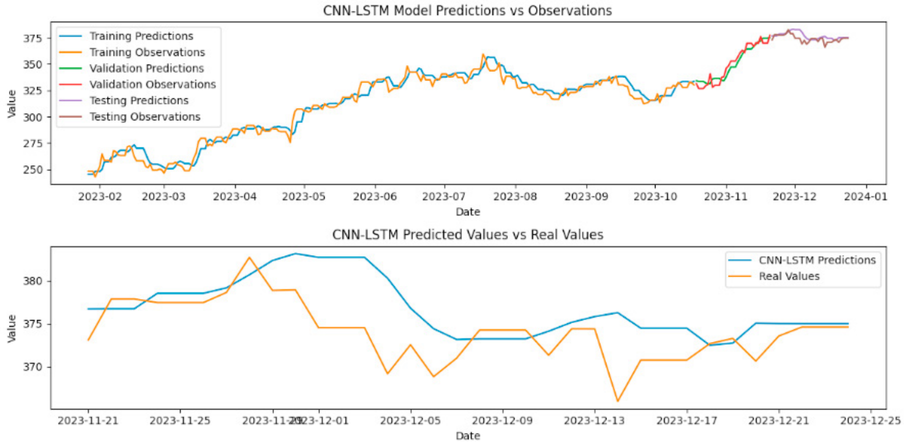

Fig. 5. Comparison of CNN-LSTM predicted values with real values

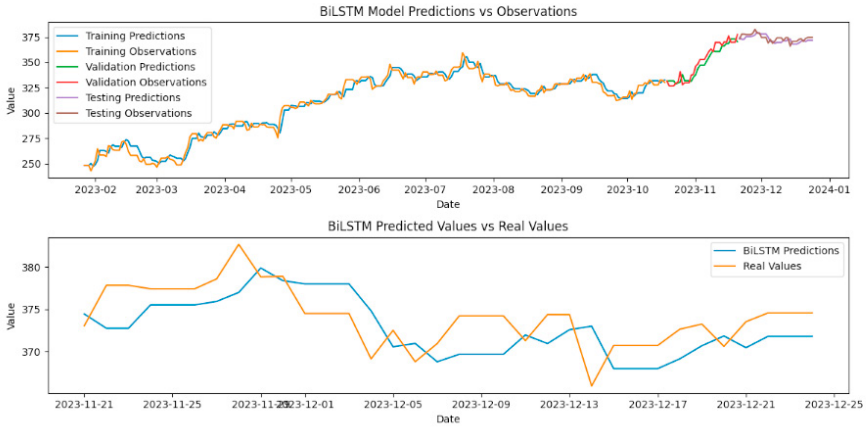

Fig. 6. Comparison of BILSTM predicted values with real values

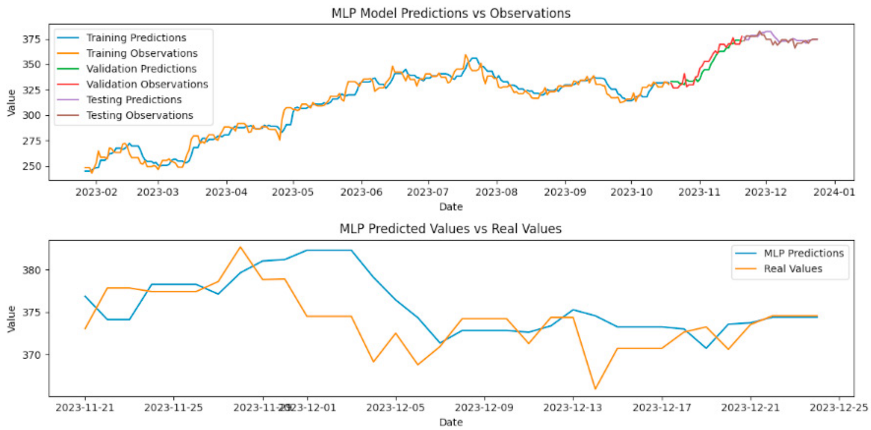

Fig. 7. Comparison of MLP predicted values with real values

The resulting structured dataset and partitions, segmented into input features and target values, serve as a foundational framework for training and evaluating time series forecasting models based on Microsoft Corporation's stock prices.

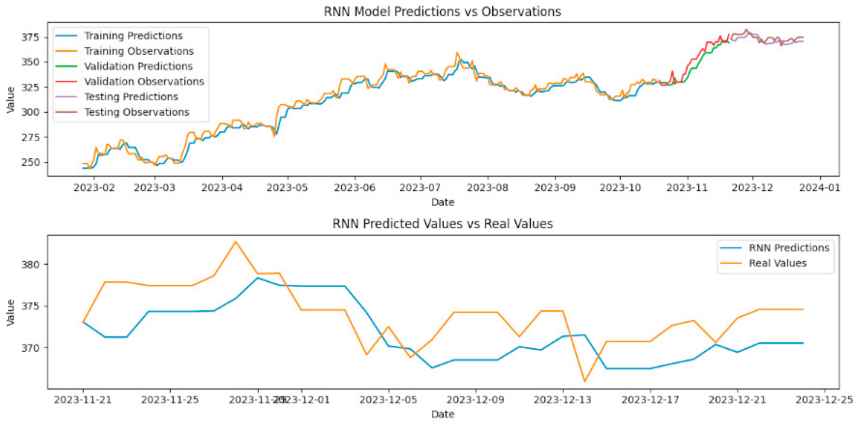

Fig. 8. Comparison of RNN predicted values with real values

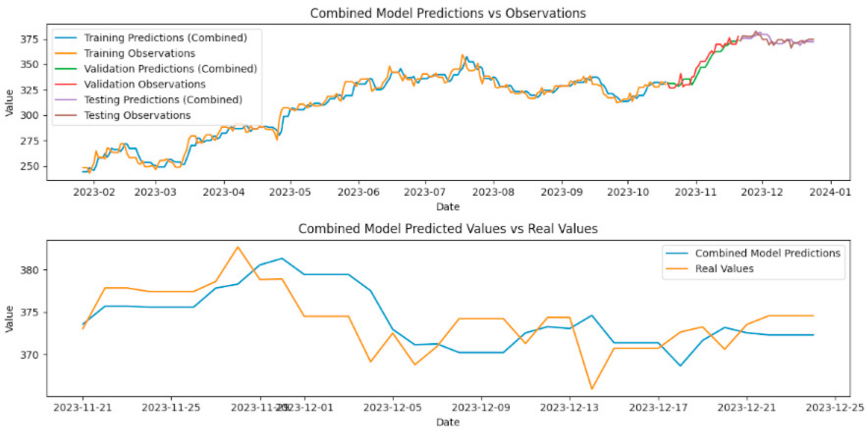

Fig. 9. Comparison of the proposed LSTM-RNN Fusion Model predicted values with real values

Table 3. Comparison of Evaluation Metrics for Different Models (Part 2)

Metrics	RNN	MLP	LSTM	LSTM-RNN Fusion Model
Training Loss	0.000249	0.000422	0.000317	**0.000240**
Validation Loss	0.000527	0.000375	0.000220	**0.000190**
MAE	0.0123	0.0162	0.0142	**0.0123**
Validation MAE	0.0190	0.0170	0.0134	**0.0123**
MSE	0.000249	0.000422	0.000317	**0.000240**
Validation MSE	0.000527	0.000375	0.000220	**0.000190**
RMSE	0.0158	0.0205	0.0178	**0.0138**

4.2. Results

The predictive performance of various models was analyzed to forecast stock prices. Figure 3, Figure 4, Figure 5, Figure 6, Figure 7, Figure 8, and Figure 9 illustrate the comparison between predicted and actual stock values for CNN, LSTM, CNN-LSTM, BILSTM, MLP, RNN, and the proposed model respectively. Figure 10 illustrates an aggregate comparison of predicted values against actual observations. This visual depiction provides a consolidated view, enabling a comparative analysis of the models' overall effectiveness in forecasting stock prices. Tables 2 and 3 present the normalized evaluation metrics for each model, illustrating their performance in predicting stock prices. The metrics include Training Loss, Validation Loss, MAE (Mean Absolute Error), Validation MAE, MSE (Mean Squared

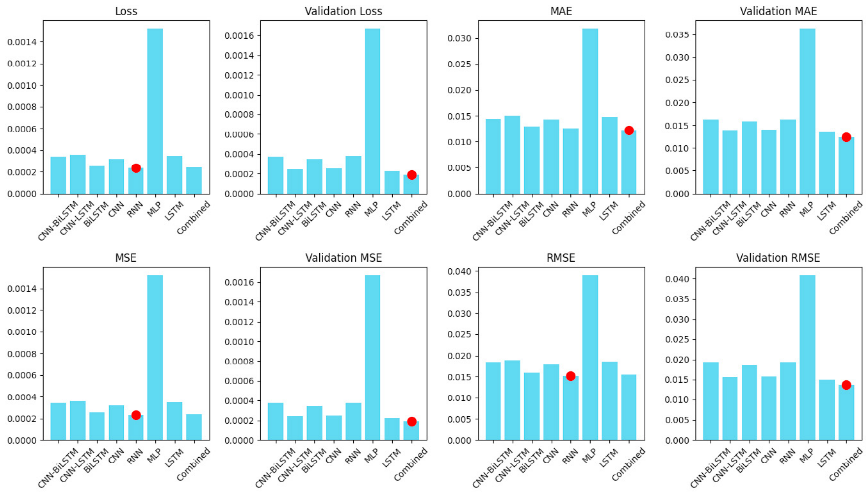

Fig. 10. Aggregate comparison of predicted values with real values

Error), Validation MSE, and RMSE (Root Mean Squared Error). These metrics offer a comprehensive comparison of each model's predictive capabilities within the stock price prediction task. The boldfaced values represent the best performance achieved for each metric among the considered models. For instance, the proposed model (LSTM-RNN Fusion Model) showcases the lowest Training Loss, Validation Loss, Validation MAE, Validation MSE, and RMSE among the models evaluated. These analyses provide significant insights into the strengths and weaknesses of different models, aiding in understanding their predictive capabilities for stock price forecasting.

5. Conclusion

The present study ventured into the intricate evaluation and comparison of diverse deep learning models aimed at predicting stock prices. With a meticulous assessment involving eight distinct models—CNN-BiLSTM, CNN-LSTM, BiLSTM, CNN, RNN, MLP, LSTM, and the innovative Combined model—this research scrutinized their performance using a battery of normalized metrics, including Training Loss, Validation Loss, MAE, Validation MAE, MSE, Validation MSE, and RMSE. The analysis rendered invaluable insights into the predictive capacities of these models, shedding light on their individual strengths and limitations. Notably, the LSTM-RNN Fusion Model emerged as a frontrunner, showcasing superior performance across critical metrics such as Validation Loss, Validation MAE, Validation MSE, and RMSE. Its adeptness in forecasting stock prices with reduced errors underscores its potential as a robust and efficient model for this predictive task.

This study can open future directions and potential advancements in predictive modeling. Exploring architectural refinements or integrating ensemble methodologies could further amplify the predictive capabilities of these models. Considering external factors such as market sentiment analysis or augmenting data inputs might enhance predictive accuracies and resilience in dynamic market conditions. Moreover, this research emphasizes the necessity of real-time deployment scenarios for these models, validating their adaptability and reliability in actual market environments. Such endeavors would validate their practical utility and robustness, serving as crucial steps toward practical implementation in the financial domain. In essence, while this study presents a comprehensive comparative analysis of deep learning models for stock price prediction, its contribution extends beyond the present findings. It lays a foundation for future investigations, encouraging innovation, and refinement in predictive analytics within financial markets. By leveraging the insights garnered herein, future research can elevate the sophistication and applicability of predictive models, empowering stakeholders with enhanced tools for informed decision-making in the realm of stock price forecasting.

Data availability

The datasets generated during and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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