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| RESEARCH ARTICLE

Deep Learning in Stock Market Forecasting: Comparative Analysis of Neural Network Architectures Across NSE and NYSE

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| ABSTRACT

This research explores the application of four deep learning architectures—Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN)—in predicting stock prices using historical data. Focusing on day-wise closing prices from the National Stock Exchange (NSE) of India and the New York Stock Exchange (NYSE), the study trains the neural network on NSE data and tests it on both NSE and NYSE stocks. Surprisingly, the CNN model outperforms the others, successfully predicting NYSE stock prices despite being trained on NSE data. Comparative analysis against the ARIMA model underscores the superior performance of neural networks, emphasizing their potential in forecasting stock market trends. This research sheds light on the shared underlying dynamics between distinct markets and demonstrates the efficacy of deep learning architectures in stock price prediction.

| KEYWORDS

Deep Learning, Stock Market Forecasting, Neural Network Architectures

| ARTICLE INFORMATION

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1. Introduction

In the ever-evolving landscape of financial markets, the accurate prediction of stock prices remains a complex and critical challenge: the inherent nonlinearity and high volatility of time series data in the stock market demand sophisticated forecasting tools. Over the past decade, researchers have increasingly turned to advanced data mining techniques, with a notable emphasis on neural networks, to unravel the intricate patterns hidden within financial data.

This study delves into the realm of stock market prediction by employing four powerful deep learning architectures: Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN). The focus is on predicting stock prices based on historical data from two major stock markets: India's National Stock Exchange (NSE) and the New York Stock Exchange (NYSE). The exploration encompasses a diverse set of sectors, including Automobile, Banking, and IT, providing a comprehensive analysis of the models' capabilities. Traditional linear models, such as AR, ARMA, and ARIMA, have historically been used for stock market forecasting. However, their limitations in capturing the nonlinear and

fluctuating nature of market data have paved the way for the application of deep learning models. The neural networks in this study outshine the traditional linear model, ARIMA, showcasing their ability to discern intricate nonlinear trends that elude conventional methods.
The research methodology involves training the neural networks with data from Tata Motors on the NSE and testing on a diverse set of companies from both the NSE and NYSE. The chosen window size and prediction period are carefully considered, and comparative analyses with the ARIMA model reveal the superior performance of neural networks in capturing the complexities of financial time series data.

As the financial landscape continues to evolve, the integration of deep learning models into stock market forecasting holds significant promise. Despite challenges associated with computational resources and potential overfitting, the adaptability and pattern recognition capabilities of neural networks offer a more comprehensive framework for modeling complex relationships within financial data. This interdisciplinary research, merging finance and machine learning, not only contributes to advancing stock market prediction methodologies but also opens avenues for further exploration. Continuous refinement and adaptation of deep learning techniques will be crucial in enhancing their performance and reliability in forecasting market trends.

In the dynamic landscape of financial markets, predicting stock prices remains a formidable challenge due to the inherent nonlinearity and high volatility of time series data. Over the last decade, researchers have increasingly turned to advanced data mining techniques, particularly neural networks, to tackle this complex task. This study focuses on employing four powerful deep learning architectures—Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN)—to predict stock prices based on historical data. The analysis spans two major stock markets, the National Stock Exchange (NSE) of India and the New York Stock Exchange (NYSE), offering a comprehensive exploration of the model's capabilities.

The primary market serves as the platform for introducing new securities through Initial Public Offerings (IPOs), while the secondary market facilitates the trading of already-owned securities by investors. The stock market, characterized by highly fluctuating and non-linear time series data, poses challenges for accurate forecasting. A time series, defined as a dataset measured over time to capture the evolution of a particular activity, is integral to understanding market dynamics. Traditional linear models like AR, ARMA, and ARIMA have historically been employed for stock market forecasting; however, their limitation lies in their specificity to time series data. These models tailored for one company might not generalize well to others. The unpredictable nature of the stock market introduces significant risk, making accurate forecasting a formidable task. This challenge is where the application of deep learning models in financial forecasting becomes crucial. Deep neural networks, named for their utilization of neural network architecture in deep learning models, offer a promising approach to addressing the intricacies of stock market prediction.

2. Literature Review

Khan et al. (2023) explore the application of deep reinforcement learning (DRL) as a novel method for predicting stock market movements. Traditional approaches to stock price prediction often rely on statistical models or technical indicators, which may struggle to capture the non-linear patterns and sudden shifts in stock prices. In contrast, deep reinforcement learning has gained prominence for its ability to learn intricate patterns from raw data and make sequential decisions. The proposed framework for stock price prediction incorporates a deep neural network as a function approximator. This neural network is trained using the Q-learning algorithm, allowing it to learn optimal actions for buying, selling, or holding stocks based on historical stock price data. The neural network outputs Q-values, representing expected rewards for different actions at each time step. The decision-making process involves selecting the best course of action in each market state based on these Q-values.

A sensitivity analysis was conducted to explore the impact of various network designs and hyperparameters on the effectiveness of the DRL-based strategy. The findings highlighted the significant influence of hyperparameters, such as learning rate and exploration rate, on performance. Fine-tuning these hyperparameters proved to be crucial in further improving prediction accuracy.

Sako et al. (2022) predicts the closing prices of eight stock market indexes and six currency exchange rates linked to the USD, utilizing the Recurrent Neural Networks (RNNs) model and its variations, namely the Long Short-Term Memory (LSTM) and the Gated Recurrent Unit (GRU). The findings indicate that GRU consistently yields the most favorable outcomes, particularly excelling in univariate out-of-sample forecasting for currency exchange rates and multivariate out-of-sample forecasting for stock market indexes.

Shen et al. (2020) demonstrate a thorough approach, encompassing the preprocessing of stock market datasets, the application of various feature engineering techniques, and the implementation of a tailored deep learning system for predicting stock market price trends. Through extensive evaluations of commonly used machine learning models, it is concluded that the proposed solution outperforms others, attributing its success to the comprehensive feature engineering incorporated. The system consistently achieves high accuracy in predicting stock market trends. This work, with its detailed design and assessment of prediction term lengths, feature engineering, and data preprocessing methods, constitutes a valuable contribution to both the financial and technical domains within the stock analysis research community.

Singh et al. (2023) In this study, a novel stock price forecasting strategy is proposed, employing two distinct learning approaches: incremental learning and Offline–Online learning. In incremental learning, the model is continually updated as it receives each successive instance from the live market stream, while in Offline-Online learning, the model undergoes retraining after each trading session to incorporate the latest data complexities. These approaches were applied to both univariate time-series, derived from historical stock prices, and multivariate time-series, considering historical stock prices along with technical indicators. Rigorous experiments were conducted on the eight most liquid stocks listed on the American NASDAQ and Indian NSE stock exchanges. The Offline–Online models demonstrated superior performance in terms of minimizing forecasting errors when compared to incremental models.

3. Methodology

The research methodology involves training the neural networks with data from Tata Motors on the NSE, followed by testing on a diverse set of companies from both the NSE and NYSE. The dataset encompasses highly traded stocks from the Automobile, Banking, and IT sectors. Notably, the chosen neural network architectures outshine the traditional linear model, ARIMA, showcasing their prowess in capturing the nonlinear patterns inherent in financial time series data. The training process involves careful consideration of window sizes, with a window size of 200 identified as optimal for a 10-day prediction period. Comparative analysis against ARIMA reveals the superior performance of neural networks, emphasizing their ability to discern intricate nonlinear trends that elude traditional linear models.

3.1. Artificial Neural Network and Feed Forward Network

Artificial Neural Network (ANN), as referenced in, operates in a manner analogous to biological neurons. Its primary function is to discern underlying patterns within data and derive generalizations from them. ANNs are recognized as non-linear statistical tools, adept at modeling the intricate relationships between inputs and outputs. One of the key advantages of ANNs lies in their capacity to learn underlying data patterns, a capability often lacking in traditional methods [Haque, 2023]. Typically, ANNs consist of three layers: the input layer, the hidden layer, and the output layer. Non-linear activation functions are employed in all nodes within the hidden and output layers, excluding the input layer. Each node in the input layer establishes connections with every neuron in the subsequent hidden layer, followed by the output layer. The feed-forward network, as illustrated in [Khan et al. 2023], is synonymous with the Multilayer Perceptron (MLP) and represents a straightforward example of a neural network. The linkage between input neurons and the subsequently hidden layer neurons is established through a weighted matrix denoted as A_1B_2. The network comprises three layers: the input layer, the hidden layer, and the output layer [Haque et al 2023]. Artificial neurons also referred to in [Haque et al 2023], are present in both the hidden and output layers [Haque et al 2023]. These neurons in the network receive inputs from the preceding layer, and it's important to note that neurons within the same layer are not interconnected; rather, they form connections with neurons in the subsequent layer.

3.2 Dataset

The dataset used in this study is sourced from highly traded stocks representing three distinct sectors: Automobile, Banking, and IT, specifically Maruti, Axis Bank, and Hcltech from the NSE. Each dataset includes details such as stock symbol, stock series, stock date, and various price metrics like previous closing, opening, high, low, last closing, and average prices, along with total traded quantity, turnover, and the number of trades. For the analysis, we focus on extracting the day-wise closing prices of each stock since investors typically base their decisions on buying or selling stocks on the market's closing prices. The training dataset chosen is TATA MOTORS, originating from the Automobile sector. This dataset spans from January 1, 1996, to June 30, 2015, encompassing the closing prices over 4,861 days. The closing prices in the training data range from 58.79 to 1365.15. Normalization is applied to ensure uniformity in the data range between 0 and 1. Normalizing the data is crucial when dealing with stock data from different markets, aiming to bring the data into a standardized range. This normalization process is executed using the equation.

Y norm = (Y− Y min) / (Y max −Y min--------(1)

In the given context, Y_{norm} represents the normalized value, while Y_{min} and Y_{max} correspond to the minimum and maximum values within the training dataset. This normalized data, obtained by applying the normalization equation, serves as the input to the network, with a fixed window size of 200 days, aiming to predict the stock values for the subsequent 10 days. The output generated by the network undergoes a de-normalization process to obtain the original predicted values. The training of the network involves 1000 epochs. The determination of the window size involves an error calculation for various window sizes ranging from 50 to 250. Among these, a window size of 200 is identified as optimal, resulting in the minimum error compared to other window sizes.

Determining the Optimal Window Size: Table 1 displays the Mean Absolute Percentage Error (MAPE) for various window sizes and prediction days. The initial row, featuring values 50, 100, 150, 200, and 250, denotes different window sizes, while the first column, with values 10, 20, 30, and 40, represents the prediction days. Upon examination, it is evident that the minimum MAPE occurs with a window size of 200 for a 10-day prediction period. Consequently, we establish our window size as 200 for the prediction of 10 days.

Table 1 provides details on the window size and the range of days for which predictions are made.

PREDICTION DAYS	50	100	150	200	250
10	4.5 6.	4.34	4.62	4.17	4.18
20	6.53	6.05	5.88	5.61	5.16
30	6.49	7.84	6.97	5.11	5.86
40	9.65	9.34	6.84	5.86	7.06

Testing Phase: For the testing phase, we selected data from three primary sectors - Automobile, Banking, and IT, with corresponding stocks being Maruti, Axis Bank, and HCL Technologies, respectively. Like the training phase, we extracted the day-wise closing prices for each stock, subjected them to data normalization, and applied the de-normalization process to the predicted outputs, mirroring the procedures employed in the training dataset. The test datasets spanned from October 5, 2007, to June 30, 2017. The input window size for stock data fed into the network during testing was determined as 200 through error calculations across various window sizes. To assess the accuracy of the predicted output, mean absolute percentage error (MAPE) was employed with the calculation.

3.3 verifying Dataset.

To assess whether the models can recognize shared dynamics across different stock exchanges, we conducted predictions using NYSE stock data sourced from Yahoo Finance. Specifically, we focused on the top two active stocks on the New York Stock Exchange: Bank of America (BAC) and Chesapeake Energy (CHK). The dataset spans from January 3, 2011, to December 30, 2016, and the values are expressed in US dollars. Solely, the day-wise closing prices were extracted from this dataset. For the testing phase, we selected the day-wise closing prices for each company within the timeframe of January 3, 2011, to December 30, 2016. Subsequently, we normalized the extracted data using equation (1) to standardize the data before presenting it as input to the network.

4. Result and Discussion

The study encompasses an analysis of data from two distinct stock markets: NSE (National Stock Exchange) and NYSE (New York Stock Exchange). Four types of deep neural networks, namely MLP, RNN, LSTM, and CNN, were employed for this analysis. All these networks underwent training with NSE data, specifically from Tata Motors, a company in the automobile sector. Subsequently, the networks were tested using data from both NSE and NYSE. For NSE, data from the automobile, financial, and IT sectors were chosen, while data from the NYSE and financial and petroleum sectors were selected. To draw a comparison between linear and non-linear models, the study incorporated the ARIMA model as a linear benchmark. A 400-day prediction period was considered for both ARIMA and neural network models to evaluate their performance over a specific timeframe. The obtained results are presented in Tables 2 and 3.

Table 2 displays the Mean Absolute Percentage Error (MAPE) incurred in forecasting NSE values for MARUTI, HCL, and AXIS BANK using the ARIMA model over 400 days.

COMPANY	MAPE
MARUTI	21.56
HCL	22.70
MARUTI	18.89

Table 2 shows the MAPE obtained for predicting closing price for 400 days using ARIMA model.

COMPANY	RNN	LSTM	CNN	MLP
MARUTI	5.63	6.33	4.30	4.71
HCL	5.45	5.50	4.33	3.74
MARUTI	11.45	4.90	5.32	5.45

Table 3 illustrates the Mean Absolute Percentage Error (MAPE) derived from the neural network for a 400-day prediction period. Upon comparing the results in Table 2 and Table 3, it is evident that the neural network architecture outperforms ARIMA. This difference in performance may be attributed to the fact that ARIMA struggles to discern the nonlinearities inherent in the data, while neural network architectures excel in identifying and capturing these nonlinear trends within the dataset.

Table 4 illustrates the Mean Absolute Percentage Error (MAPE) generated in predicting NSE values for MARUTI, HCL, and AXIS BANK using a Deep Learning (DL) network.

COMPANY	RNN	LSTM	CNN	MLP
MARUTI	7.63	6.36	5.30	6.71
HCL	8.45	6.88	6.33	7.74
MARUTI	9.45	8.16	7.32	8.45

Table 4 presents the Mean Absolute Percentage Error (MAPE) values acquired during the testing of MARUTI, HCL, and AXIS BANK for the period spanning from October 5, 2007, to June 30, 2017.

In Figure 1b and Figure 2a, during the timeframe of 1500 to 2300 days, both RNN and LSTM encounter challenges in recognizing the seasonal pattern, indicating a shift in the system's behavior. Contrarily, Figure 2b illustrates that CNN adeptly captures the pattern, attributing this success to its focus on the data within a specific window.

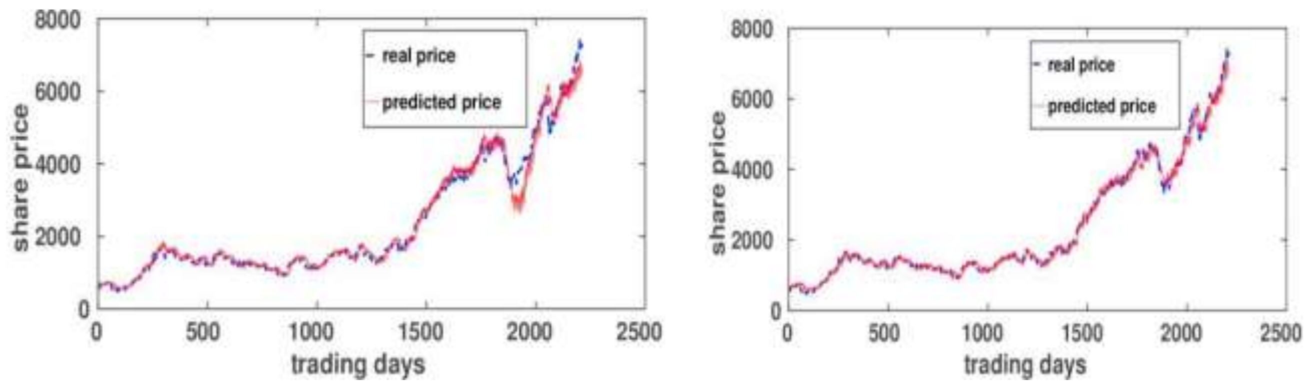

Fig 1 exhibits two sub-figures: (a) showcases the actual and predicted values of MARUTI stock using LSTM, and (b) illustrates the real and predicted values of MARUTI stock using CNN.

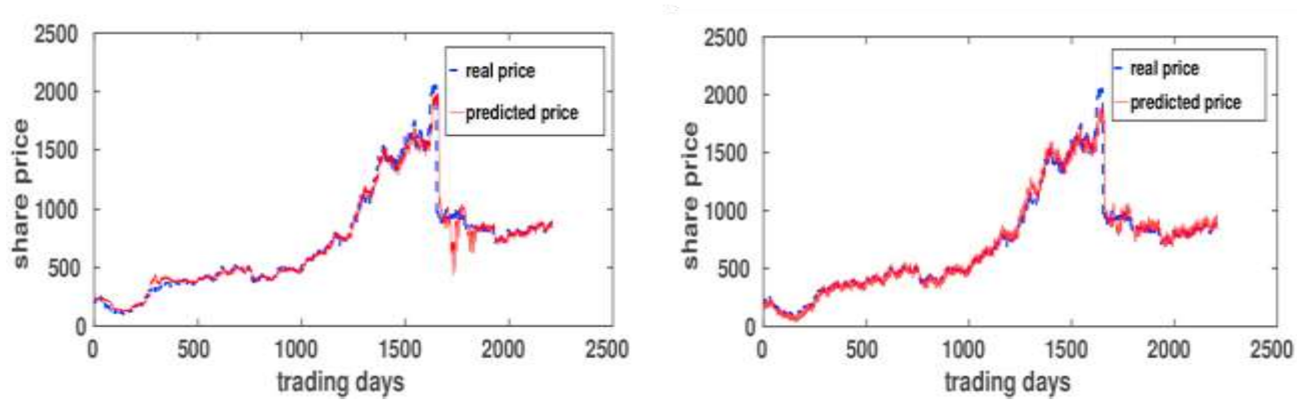

Fig 2 displays two sub-figures: (a) presents the actual and predicted values of HCLTECH stock using MLP, and (b) depicts the real and predicted values of HCLTECH stock using RNN.

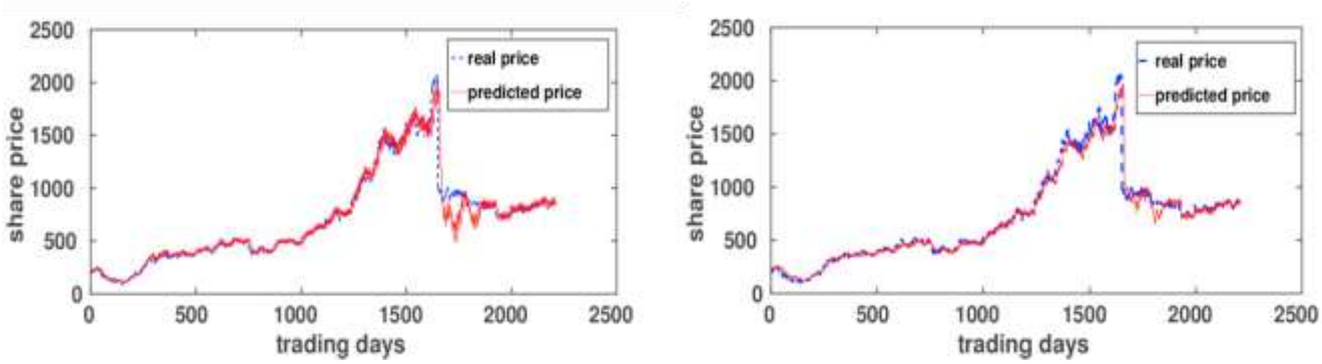

Fig. 3. (a) Real and Predicted values of HCLTECH stock using LSTM; (b) Real and Predicted values of HCLTECH stock using CNN.

For HCLTECH, as depicted in Figure 2a, the MLP network effectively captures the seasonal pattern, but it encounters difficulty in capturing the pattern between days 1600 and 1900. In Figure 2b, the RNN demonstrates considerable success in recognizing the pattern, whereas Figures 3a and 3b reveal that both LSTM and CNN struggle to capture the system's changes within the period of 1400 to 1800 days.

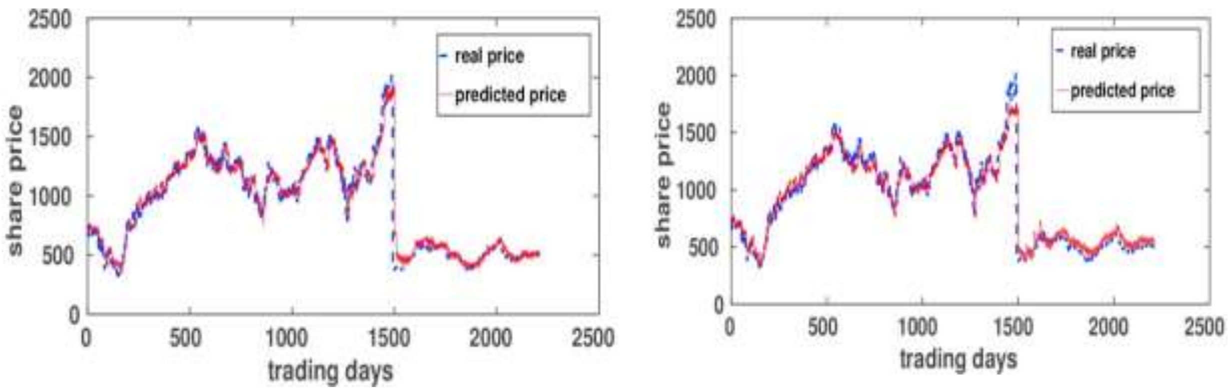

Fig. 4. (a) Real and Predicted values of AXISBANK stock using MLP; (b) Real and Predicted values of AXISBANK stock using RNN.

Regarding AXIS BANK, as evident from Figure 8a, the MLP network successfully recognizes the pattern initially but encounters difficulty in capturing it between days 1400 and 1700. A similar trend is observed in Figure 3b, where the RNN identifies the pattern initially but struggles to do so between days 1300 and 1600. Figures 4a and 4b depict that both LSTM and CNN face challenges in identifying the pattern during the periods between 200 and 500 days, while CNN performs relatively well, capturing the pattern except for the period between 1600 and 1800 days.

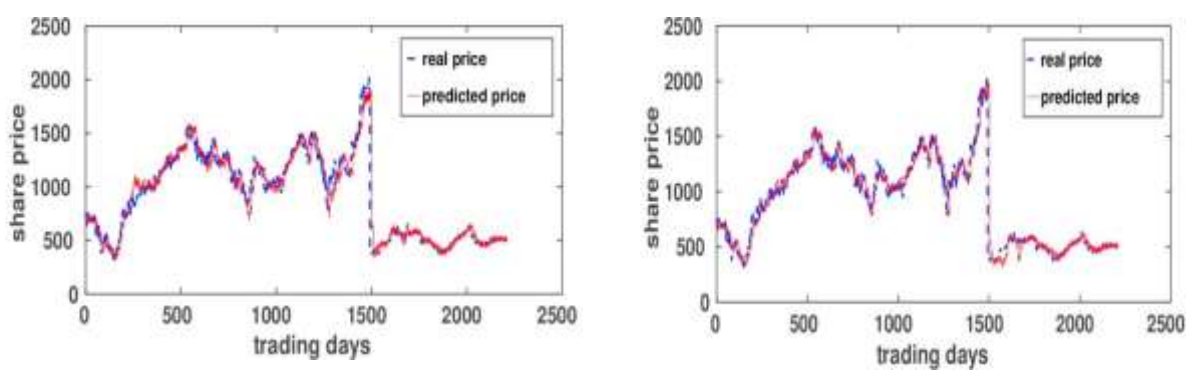

Fig 5 depicts the actual and predicted values of AXISBANK stock using LSTM in sub-figure (a) and the real and predicted values of AXISBANK stock using CNN in sub-figure (b).

5. Conclusion

In conclusion, the stock market, with its dynamic and unpredictable nature, presents substantial challenges for accurate forecasting. Traditional linear models such as AR, ARMA, and ARIMA, while historically used, face limitations due to their specificity to time series data. The stock market's non-linear and fluctuating time series data demands more sophisticated approaches for effective forecasting.

The emergence of deep learning models in financial forecasting, particularly deep neural networks, marks a significant advancement in addressing the complexities of stock market prediction. The primary and secondary markets, serving as pivotal arenas for securities introduction and trading, underscore the need for robust forecasting tools to navigate the inherent risks.

Deep neural networks offer a promising avenue for overcoming the limitations of linear models. Their adaptability and ability to capture intricate patterns in time series data make them well-suited for the unpredictable dynamics of the stock market. The utilization of neural network architecture in deep learning models provides a more comprehensive and flexible framework for modeling complex relationships within financial data.

However, it is essential to acknowledge the challenges associated with implementing deep learning models, including the need for substantial computational resources and potential overfitting. The effectiveness of these models also depends on the quality and quantity of the available data. As the financial landscape evolves, continuous refinement and adaptation of deep learning techniques will be crucial to enhancing their performance in stock market forecasting.

Furthermore, the interdisciplinary nature of this research, combining finance and machine learning, opens avenues for further exploration. Continuous advancements in deep learning architectures, coupled with a deeper understanding of financial market dynamics, will contribute to refining forecasting models and mitigating risks associated with stock market predictions.

In summary, the fusion of deep learning models with financial forecasting signifies a promising frontier in navigating the challenges posed by the stock market. As these models continue to evolve, their integration into real-world financial decision-making processes holds the potential to enhance accuracy and efficiency in predicting market trends, thereby aiding investors and financial institutions in making more informed decisions amidst the ever-changing dynamics of the financial world.

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