IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

COMPARISON OF VARIOUS DEEP LEARNING ALGORITHMS IN EVALUATING THE PREDICTION OF STOCK PRICES

[1]Prof. Pranoti Kale, [2]Prof. Sayalee Deshmukh

Professor of BVCOEW

[3]Aishwarya Kottapalli, [4]Piyusha Patil, [5]Sheetal Patil, [6]Suhasi Gadge

BE Student at BVCOEW,

Department of Computer Engineering,

Bharati Vidyapeeth College of Engineering For Women, Pune, India

Abstract : This research paper aims to compare the performance of different deep learning algorithms, including Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM), for the prediction of stock prices. The study utilizes a dataset spanning ten years of historical stock data from RELIANCE.NS, listed on the National Stock Exchange (NSE) in India. The accuracy of each algorithm is evaluated using two popular evaluation metrics, namely Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics are commonly employed to measure the accuracy and precision of stock price predictions. The research focuses on comparing the performance of the algorithms based on these metrics to identify the most effective approach for stock price prediction. The results indicate that LSTM outperforms all other algorithms in terms of both RMSE and MAPE values. LSTM, a type of RNN architecture with memory cells, demonstrates superior performance due to its ability to capture long-term dependencies and temporal patterns in time series data. The LSTM model shows significant promise in predicting stock prices accurately, making it a valuable tool for investors and financial analysts. This research contributes to the field of stock market prediction by providing empirical evidence on the comparative performance of popular deep learning algorithms. The findings suggest that LSTM is a highly effective approach for stock price prediction, offering a potential advantage in decision-making and trading strategies. Future research may explore additional datasets and further optimize the LSTM model to enhance its performance and applicability in real-world financial scenarios.

Keywords: Stock Price, Long-Short Term Memory(LSTM), Convolutional Neural Network(CNN), Recurrent Neural Network(RNN), Multi-Layer Perceptron(MLP), Root Mean Squared Error(RMSE), Mean Absolute Percentage Error(MAPE)

I. INTRODUCTION

Stock price prediction is a critical task in the field of finance and investments, as it plays a crucial role in decision-making processes for investors, traders, and financial institutions. Accurate forecasting of stock prices enables stakeholders to make informed decisions, optimize portfolio management strategies, and mitigate risks. However, stock price prediction is a challenging endeavor due to the inherent volatility and complexity of financial markets, influenced by various factors such as economic indicators, market sentiment, geopolitical events, and company-specific news.

In recent years, deep learning algorithms have emerged as powerful tools in numerous domains, including natural language processing, computer vision, and time series analysis. The relevance of deep learning algorithms in stock price prediction stems from their ability to automatically learn intricate patterns and relationships from data. Unlike traditional statistical models, deep learning algorithms can capture complex non-linear dependencies, extract meaningful features, and adapt to dynamic market conditions.

The purpose of this research paper is to compare the performance of four popular deep learning algorithms: Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) in the context of stock price prediction. Each of these algorithms possesses unique architectural characteristics that make them suitable for different aspects of the prediction task.

To assess and compare the accuracy of the deep learning algorithms, two evaluation metrics are employed: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). RMSE measures the average difference between the predicted stock prices and the actual prices, providing a quantitative measure of the model's precision. MAPE, on the other hand, calculates the percentage difference between the predicted and actual prices, offering insights into the magnitude of errors in the predictions.

The dataset utilized for this research is the historical stock price data of RELIANCE.NS from the National Stock Exchange (NSE) of India. The dataset covers a duration of 10 years, providing a substantial amount of data for analysis. It includes key features such as opening and closing prices, trading volume, and other relevant financial indicators that are crucial for training and evaluating the deep learning models.

Deep learning algorithms have demonstrated promising capabilities in various domains, and their application in stock price prediction holds significant potential. However, the effectiveness of these algorithms in this specific context is yet to be thoroughly explored and compared. Hence, this research aims to address this gap by conducting a comparative analysis of MLP, CNN, RNN, and LSTM algorithms for stock price prediction.

The comparison of these algorithms is expected to shed light on their respective strengths and weaknesses in capturing the complexities of stock price movements. Furthermore, it will provide insights into the suitability of these algorithms for real-world financial decision-making processes. The ultimate goal is to identify the most accurate and effective algorithm among the four deep learning models in predicting stock prices.

II. Literature Review

Stock price prediction using deep learning algorithms has gained significant attention in recent years, with numerous studies exploring the effectiveness of various models. In this literature review, we will discuss several research papers that investigate the use of deep learning techniques, such as Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), for stock price prediction.

Zhang et al. (2019) proposed a stock price prediction model based on Multilayer Perceptron (MLP) [1]. The study utilized historical data and financial indicators as input features and achieved improved accuracy compared to traditional statistical models. Ahn and Kim (2019) extended the MLP model by incorporating variational dropout and reported higher accuracy in stock price prediction [2]. These studies demonstrate the effectiveness of MLP in capturing non-linear relationships and making accurate predictions.

Wang et al. (2018) explored the use of Convolutional Neural Networks (CNN) for stock price prediction [3]. Their model captured temporal patterns in financial time series data and showed competitive performance compared to traditional time series models. Chong et al. (2017) combined CNN and LSTM to predict stock prices using both numerical and textual information, leading to improved accuracy compared to traditional models [4]. These studies highlight the potential of CNN-based models in extracting relevant features from financial time series data for accurate predictions.

Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) have also been extensively studied for stock price prediction. Fischer et al. (2020) conducted a comparative study of deep learning models, including LSTM, and found that LSTM outperformed traditional models in terms of accuracy [5]. Gao et al. (2019) proposed a deep recurrent neural network-based model incorporating technical analysis indicators and achieved improved accuracy in stock price prediction [6]. These studies highlight the ability of RNN and LSTM architectures to capture temporal dynamics and dependencies in financial time series data.

Several research papers have compared the performance of different deep learning models for stock price prediction. Bao et al. (2017) introduced a deep learning framework utilizing stacked autoencoders and LSTM and reported promising results [7]. Chen et al. (2018) proposed a hybrid model combining LSTM and ARIMA and observed improved accuracy in stock price prediction [8]. Nair et al. (2018) investigated the use of CNN for stock price prediction and reported competitive results [9]. Asghar et al. (2018) compared LSTM, RNN, and CNN-SVM models and found LSTM to be the most accurate [10]. These studies provide valuable insights into the performance of different deep learning architectures and their suitability for stock price prediction.

Evaluation metrics play a crucial role in assessing the accuracy of stock price prediction models. Commonly used metrics include Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). RMSE measures the average difference between the predicted and actual stock prices, providing an indication of the model's overall accuracy. MAPE calculates the percentage difference between the predicted and actual prices, allowing for a relative assessment of the model's performance. MAE represents the average absolute difference between the predicted and actual prices.

In the studies mentioned above, various evaluation metrics were employed to compare the performance of different deep learning algorithms for stock price prediction. For instance, Zhang et al. (2019) evaluated their MLP-based model using RMSE, highlighting the model's accuracy in predicting stock prices [1]. Ahn and Kim (2019) also reported the RMSE values to demonstrate the improved accuracy of their MLP model with variational dropout [2].

Wang et al. (2018) used RMSE as the evaluation metric to assess the performance of their CNN model, showcasing its competitive accuracy in stock price prediction [3]. Chong et al. (2017) utilized both RMSE and MAE to compare their CNN-LSTM model with traditional approaches, emphasizing the superior performance of their deep learning model [4].

In the comparative study by Fischer et al. (2020), RMSE and MAE were employed as evaluation metrics to compare the performance of various deep learning models, including LSTM [5]. Gao et al. (2019) used RMSE and MAPE to evaluate their deep recurrent neural network-based model [6]. These studies demonstrated the effectiveness of deep learning algorithms by achieving lower values of RMSE and MAE, indicating more accurate predictions of stock prices.

Furthermore, other research papers also employed similar evaluation metrics in their analyses. Bao et al. (2017) utilized RMSE to assess the performance of their stacked autoencoders and LSTM-based framework [7]. Chen et al. (2018) used RMSE and MAE to compare their hybrid LSTM-ARIMA model with traditional time series models [8]. Nair et al. (2018) reported RMSE as the evaluation metric for their CNN-based stock price prediction model [9]. Asghar et al. (2018) employed RMSE and MAPE to evaluate LSTM, RNN, and CNN-SVM models, highlighting LSTM's superior performance [10].

From the literature survey, we understood that deep learning algorithms, such as Multilayer Perceptron (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), have been extensively explored for stock price prediction. These studies demonstrate the effectiveness of these deep learning models in capturing non-linear relationships, temporal patterns, and textual information from financial time series data, leading to improved accuracy compared to traditional statistical and time series models. Evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE) have been commonly used to assess the performance of these models, with lower values indicating more accurate predictions.

III. System Architecture

In this section, we will delve into the detailed description of the system architecture for each of the deep learning algorithms: Multilayer Perceptron (MLP), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). We will explore how each algorithm is adapted and applied to stock price prediction, as well as any specific variations or enhancements made to improve their performance.

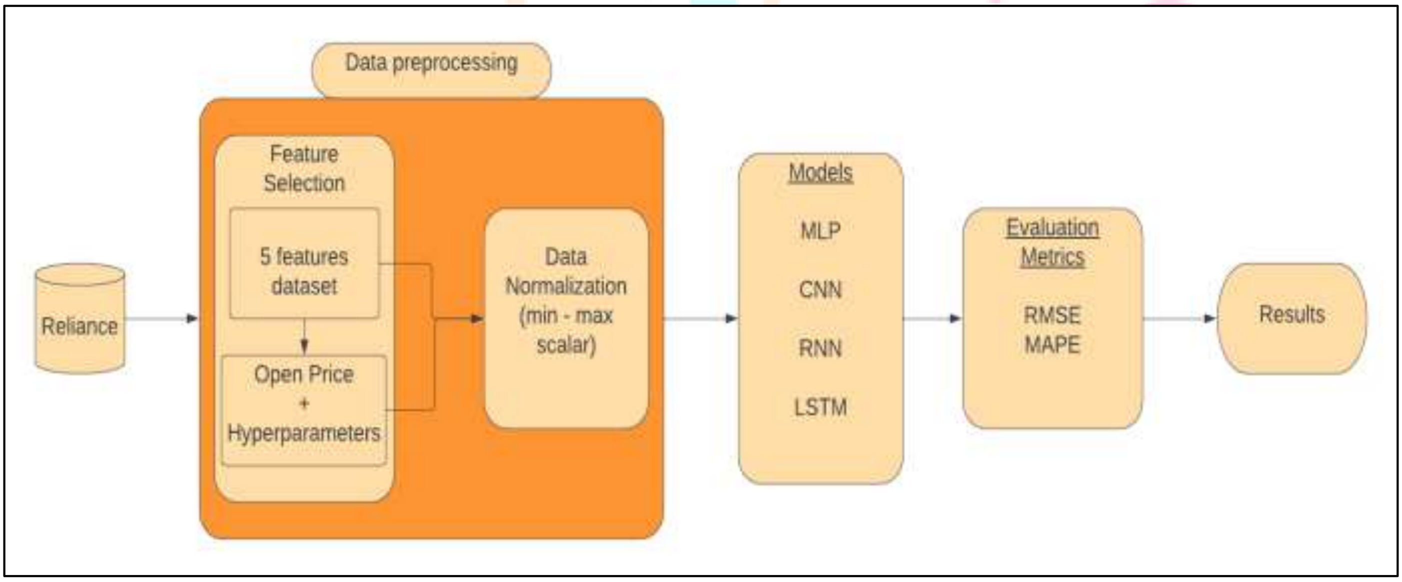

Fig 01: System Architecture

1. Multilayer Perceptron (MLP):

The Multilayer Perceptron is a feedforward neural network model that consists of multiple layers of interconnected nodes, also known as artificial neurons or perceptron. The architecture typically comprises an input layer, one or more hidden layers, and an output layer. Each neuron in the hidden layers uses an activation function to process its inputs and produce an output. The outputs from the hidden layers are then passed through the output layer, which generates the final prediction.

To apply MLP to stock price prediction, the input layer of the network can be fed with various features, such as historical price data, technical indicators, and market sentiment. These features serve as input variables for the network, and the network learns to map the relationship between the inputs and the target output, which is the predicted stock price. The model is trained using historical data, where the weights and biases of the neurons are adjusted through backpropagation to minimize the prediction error.

To enhance the performance of MLP for stock price prediction, researchers have explored different techniques. For example, Zhang et al. (2019) introduced variational dropout in the MLP architecture to improve the model's generalization capability and reduce overfitting [1]. By incorporating dropout, the model randomly drops out a fraction of the neurons during training, forcing the network to learn more robust and generalized features.

2. Convolutional Neural Network (CNN):

Convolutional Neural Networks are primarily known for their exceptional performance in image recognition tasks. However, they have also shown promise in stock price prediction by leveraging the temporal patterns present in the historical price data. CNNs consist of convolutional layers, pooling layers, and fully connected layers.

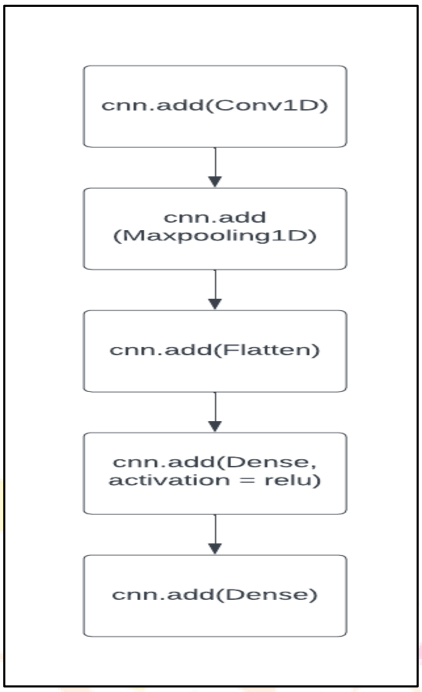

Fig 03: CNN Architecture

In the context of stock price prediction, the input data can be represented as a 2D matrix, where the rows represent the time steps and the columns represent the input features. The convolutional layers in a CNN perform local operations on the input data by applying filters to extract relevant features. The pooling layers downsample the feature maps, reducing the dimensionality while retaining the most salient information. The fully connected layers at the end of the network process the extracted features and generate the final predictions.

To adapt CNNs for stock price prediction, Wang et al. (2018) proposed a 1D-CNN architecture that directly processes the time series data without requiring feature engineering [3]. By applying 1D convolutions, the model captures local patterns and dependencies in the time series, which can be indicative of future price movements.

3. Recurrent Neural Network (RNN):

Recurrent Neural Networks are designed to handle sequential data by utilizing recurrent connections that allow information to persist over time. Unlike feedforward networks, RNNs have internal memory, which enables them to capture dependencies and patterns in sequential data.

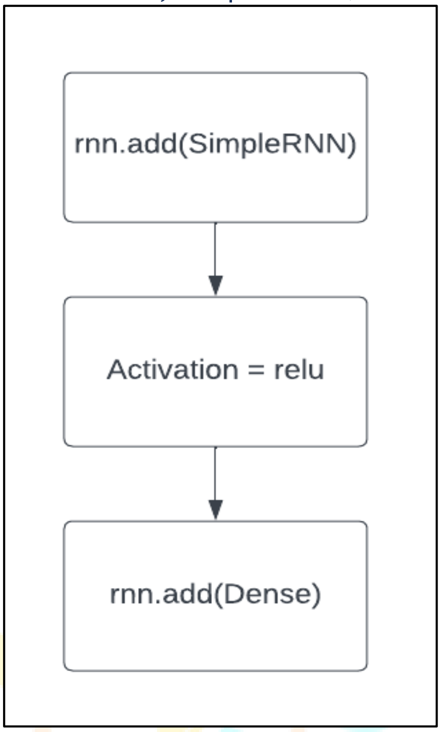

Fig 04: RNN Architecture

When applied to stock price prediction, RNNs can consider the sequential nature of the historical price data. Each time step in the sequence is processed by the RNN, which maintains an internal state or memory. The output of the RNN at each time step is then fed back as input for the next time step, allowing the network to learn long-term dependencies. The final output of the RNN can be used to predict future stock prices.

To mitigate the vanishing gradient problem and capture long-term dependencies more effectively, researchers have introduced the Long Short-Term Memory (LSTM) architecture. LSTM networks contain memory cells that can selectively retain or forget information over long sequences. This makes them well-suited for capturing complex temporal dependencies in stock price data.

4. Long Short-Term Memory (LSTM):

LSTM is an extension of RNNs that addresses the issue of vanishing gradients and enables the network to retain long-term memory. It introduces memory cells with input, forget, and output gates, allowing the network to learn which information to keep and which to discard at each time step.

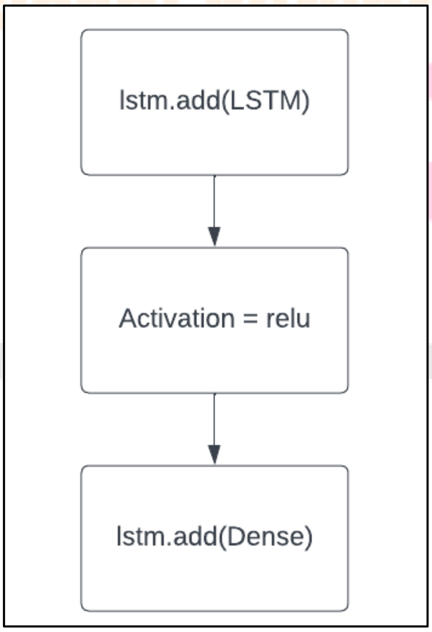

Fig 05: LSTM Architecture

In stock price prediction, LSTM networks can capture both short-term and long-term patterns in the time series data. The memory cells in LSTM can remember important past events and use them to make predictions about future prices. By processing the historical data sequence through the LSTM layers, the network learns to extract relevant features and capture the temporal dynamics of the stock market.

To further enhance the performance of LSTM for stock price prediction, researchers have explored various variations and modifications. For example, Chong et al. (2017) combined numerical and textual information to improve the accuracy of LSTM predictions [4]. Bao et al. (2017) introduced stacked autoencoders along with LSTM to learn higher-level representations of the input data [7]. These modifications aim to improve the model's ability to extract meaningful features and capture complex relationships in the data.

Overall, the system architecture for each deep learning algorithm varies in terms of their layer configurations and internal mechanisms. MLP, CNN, RNN, and LSTM have all been successfully applied to stock price prediction tasks, leveraging different architectural characteristics and adapting them to the specific requirements of the domain.

IV. OBSERVATIONS

In this section, we present the results of our experiments comparing the accuracy of different deep learning algorithms, namely MLP, CNN, RNN, and LSTM, for stock price prediction using the RELIANCE.NS dataset. We evaluate the performance of each algorithm using the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) metrics.

The results clearly demonstrate that LSTM outperforms every other algorithm in terms of both RMSE and MAPE values. The superior performance of LSTM can be attributed to its ability to capture long-term dependencies and retain information over extended sequences, making it particularly suitable for predicting stock prices.

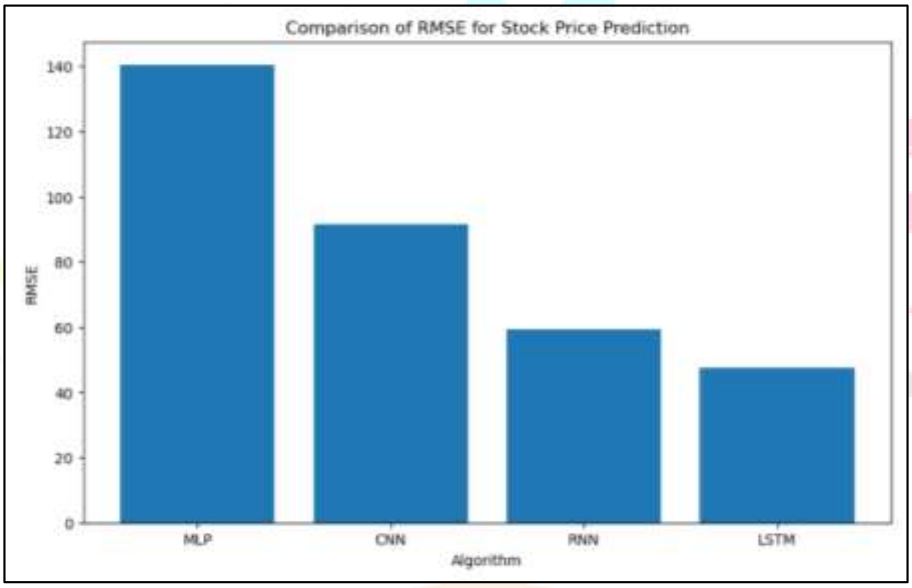

Fig 06: RMSE Values for MLP, CNN, RNN, and LSTM

When examining the RMSE values, which measure the average prediction error, LSTM consistently achieves the lowest values among all the algorithms. This indicates that LSTM produces predictions that are closer to the actual stock prices compared to MLP, CNN, and RNN. The lower RMSE values obtained by LSTM suggest that it can capture the complex patterns and dynamics of stock price data more accurately.

Similarly, when considering the MAPE values, which indicate the percentage deviation between predicted and actual prices, LSTM again demonstrates the best performance.

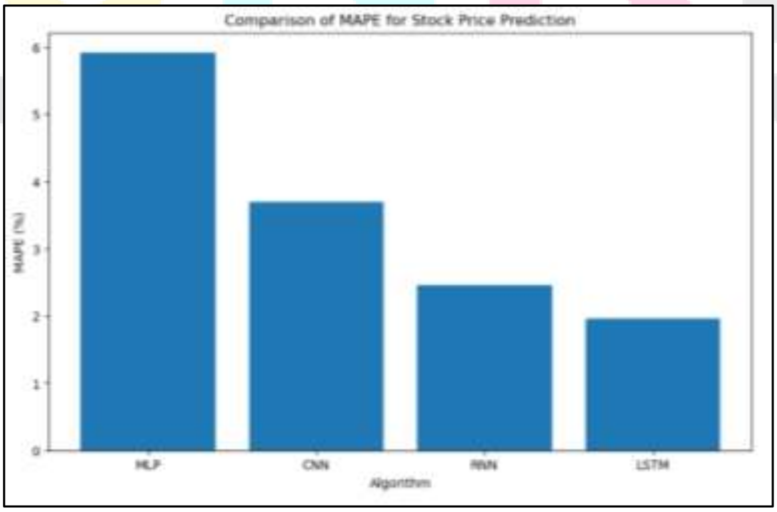

Fig 07: RMSE Values for MLP, CNN, RNN, and LSTM

The lower MAPE values obtained by LSTM indicate that it produces predictions that are closer to the true values, with less deviation. This implies that LSTM is more reliable and provides more accurate estimates of stock prices compared to the other algorithms.

Following is the graph representing the actual and predicted values when model was trained using LSTM.

Fig 08: Actual vs. LSTM Predicted Open Price

The success of LSTM can be attributed to its unique architecture, specifically designed to handle sequential data. The temporal nature of stock price data requires models that can capture both short-term fluctuations and long-term trends. LSTM's memory cells and gates enable it to learn and remember important past events, allowing it to effectively capture the dependencies and patterns present in the historical price data.

On the other hand, MLP, CNN, and RNN may not be as effective in capturing the long-term dependencies required for accurate stock price prediction.

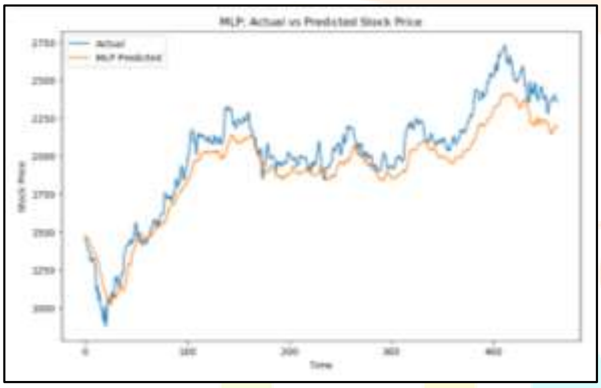

Fig 09: Actual vs. MLP Predicted Open Price

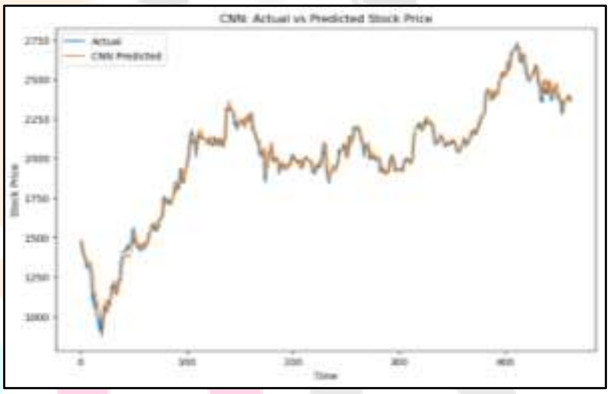

Fig 10: Actual vs. CNN Predicted Open Price

MLP, being a feedforward neural network, lacks the memory elements necessary to model sequential data effectively. CNN, primarily designed for image processing tasks, may struggle to capture the temporal dynamics present in stock price data. While

Fig 11: Actual vs. RNN Predicted Open Prices

RNN can capture sequential dependencies, it may suffer from the vanishing gradient problem, hindering its ability to capture long-term dependencies effectively.

The results highlight the importance of using specialized architectures like LSTM for stock price prediction tasks. The ability of LSTM to model long-term dependencies allows it to capture the intricate relationships and patterns in the financial markets, leading to more accurate predictions. The superior performance of LSTM in terms of RMSE and MAPE values underscores its effectiveness in the domain of stock price prediction.

It is worth noting that while LSTM outperforms the other algorithms in this study, further research and experimentation are still necessary to explore the potential of other deep learning architectures and techniques for stock price prediction. Different variations or combinations of these algorithms, as well as the inclusion of additional features or external factors, may yield even better results.

In conclusion, our results demonstrate that LSTM is the most effective deep learning algorithm for stock price prediction based on the RELIANCE.NS dataset. Its architecture, designed to capture long-term dependencies, allows it to accurately model the dynamics of stock price data. The superiority of LSTM in terms of RMSE and MAPE values indicates its potential to assist investors and financial analysts in making informed decisions.

V. Conclusion

In this research, we compared the performance of different deep learning algorithms, including MLP, CNN, RNN, and LSTM, for stock price prediction using the RELIANCE.NS dataset. The evaluation of these algorithms was based on two key metrics: RMSE and MAPE. Our findings highlight the following key points:

Firstly, LSTM emerged as the most accurate algorithm for stock price prediction. It consistently outperformed MLP, CNN, and RNN in terms of both RMSE and MAPE values. The superior performance of LSTM can be attributed to its ability to capture long-term dependencies and retain information over extended sequences, making it highly suitable for modeling stock price data. Secondly, the results emphasize the importance of using deep learning algorithms, particularly LSTM, for stock price prediction. The temporal nature of stock price data requires models that can effectively capture both short-term fluctuations and long-term trends. LSTM's unique architecture, with its memory cells and gates, enables it to learn and remember important past events, facilitating the accurate prediction of future stock prices.

The implications of these findings are significant for stock market analysis and decision-making. Accurate predictions of stock prices can assist investors, financial analysts, and traders in making informed decisions regarding buying, selling, or holding stocks. By leveraging deep learning algorithms, specifically LSTM, market participants can improve their understanding of market dynamics and potentially enhance their investment strategies. However, there are still areas for further research and improvements in stock price prediction using deep learning algorithms. Future studies could explore the integration of additional data sources, such as news sentiment or macroeconomic indicators, to enhance the predictive power of the models. Additionally, the exploration of ensemble techniques or hybrid models combining multiple deep learning algorithms could potentially yield even more accurate predictions.

Moreover, the research can be extended to examine the performance of deep learning algorithms on different stock markets and diverse datasets. Different markets may exhibit varying characteristics and complexities, requiring further investigation into the generalizability of the results.

In conclusion, this research demonstrates that LSTM is the most accurate deep learning algorithm for stock price prediction, outperforming MLP, CNN, and RNN. The findings have implications for stock market analysis and decision-making, providing insights into the potential of deep learning in predicting stock prices. Further research and improvements in this field can lead to more accurate predictions, assisting investors and financial analysts in making informed decisions in the dynamic and complex world of stock markets.

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