Conference Paper

Contemporary Global Perspectives in Management Environment and Technology (CGPMET-2025)

How to Cite:
Harini, J., Jayasree, J., & Aparna, R. (2025). Analysis of stock market trends prediction models with machine learning algorithms. *International Journal of Economic Perspectives*, *19*(S1), 121–135. Retrieved from https://ijeponline.org/index.php/journal/article/view/921

Analysis of stock market trends prediction models with machine learning algorithms

Harini J.
Student, Data Science, M.O.P. Vaishnav College for Women, India
Email: 2213721102012@mopvaishnav.ac.in

Jayasree
Student, Data Science, M.O.P. Vaishnav College for Women, India
Email: 2213721102051@mopvaishnav.ac.in

Aparna R.
Assistant Professor, Data Science, M.O.P. Vaishnav College for Women, India
Email: aparnar.csc@mopvaishnav.ac.in

***Abstract*---**Stock market trading is a major and predominant activity when one talks about the financial markets. With the inevitable uncertainty and volatility in the prices of the stocks, an investor keeps looking for ways to predict future trends to dodge losses and make the maximum possible profits. However, it cannot be denied that as of yet there is no such technique to predict the upcoming trends in the markets with complete accuracy, while multiple methods are being explored to improve the predictive performance of models to an extent as large as possible. With the advancement in Machine Learning (ML) over the past few years, many algorithms are being deployed for stock price prediction. This paper researches 3 algorithms namely Linear Regression, CNN, and Long Short-Term Memory for predicting stock prices of 10 leading companies of the Indian stock market. After exhaustive research of the various aspects related to the application of ML in the stock market, data implementation has been carried out as a part of this research work wherein the stock price dataset of 12 companies over the last 7 years was collected and used. The paper also highlights some more efficient and robust techniques that are used to forecast trends in the stock market. In detail, the methodology

Corresponding author: *Aparna, R., Email: aparnar.csc@mopvaishnav.ac.in*
Submitted: 15 November 2024, Revised: 04 March 2025, Accepted: 12 March 2025

followed, to acquire the results, has been talked about step-wise. Furthermore, a detailed comparative analysis of the performances of the aforementioned algorithms for stock price prediction has been carried out with the results displayed in a legible tabulated and graphical form to analyse them better. The conclusions from this novel, data comprehensive research work have been presented and it has been inferred that the ML algorithm outperforms all the other algorithms for stock price or time series prediction and provides results with extensive accuracy.

***Keywords*---**Machine Learning, Stock Market Prediction, Predictive Analysis, Linear Regression, CNN.

1. Introduction

Who doesn't want to be wealthy? We spend our entire lives in the bread-winning competition and sacrifice numerous things to provide our family with a good life. The stock market can become a paramount way to earn money quickly but the majority of the people in different countries are still hesitant to invest their money in this game of legal gambling. This is due to many reasons such as a large quantity thinking that the stock market is very complicated and far out of their understanding or they don't trust the market to yield them good results and are probably scared of losing their money or many of them do not even know where to start. To answer all of this, we need machine learning techniques that provide unerring results and are extremely trustworthy so that even common men and women can make their lives easier by using them.

The stock market is a crucial platform for investing in various stock exchanges such as the NYSE, BSE, NSE, and NASDAQ, and the investors get a high return. The stock market gives an important arc for both investors and sellers to interact and execute stock market transactions. It provides a centralized platform for investors to buy and sell traded corporate shares publicly while stabilizing the market. Moreover, the stock exchange offers investors critical market information such as stock prices, trade volumes, and corporate finances. Whereas, predicting and evaluating the stock market can be difficult due to various reasons like volatility in the market and numerous independent and dependent factors that influence the value of a stock. This makes it difficult for specialists to precisely forecast the market's ups and downs. However, with the arrival of artificial intelligence and machine learning, there has been a rise in interest in applying these approaches to forecast stock values. Before investing in a stock, investors usually perform two types of research: fundamental analysis and technical analysis. Fundamental analysis includes determining the underlying value of equities as well as the state of the market, economy, and political environment. Technical analysis, on the other hand, studies statistical information generated by market behaviour, such as previous prices and volumes. In our study, we used technical analysis to forecast the stock's closing price. By finding trends and patterns in market data, this strategy can help investors make better-educated decisions and potentially generate higher profits. However, it's vital to remember that no evaluation method can ensure success in the stock market because it's a complicated and uncertain system influenced by a variety of factors. These approaches involve generating approximate rough estimates using diverse datasets, including news headlines, historical data, and sentiment data. In predicting the Share market, a fascinating and innovative method has emerged, using advanced technology to its fullest potential. This new approach relies on complex algorithms and models to understand the intricacies of the market, providing valuable insights for investors and analysts. It focuses on finding patterns and uncovering hidden trends within a large amount of historical data. By examining the intricate network of Share market dynamics, this method reveals valuable insights that may not be easily noticed by humans alone. Using statistical analysis and models, it identifies previously unknown signals, leading to highly accurate predictions.

Through this process, the Share market becomes like a puzzle waiting to be solved. With each piece of data, the algorithm adjusts and improves, continuously refining its understanding of market behaviour. It carefully analyses market trends and sentiments, examining vast information to identify indications of future opportunities. This approach goes beyond guesswork or intuitive judgments by utilizing technology and data to generate reliable predictions. Over time, the model evolves and becomes more sophisticated, learning from both successful and unsuccessful outcomes and adapting to the ever-changing nature of the stock market. By adopting this unique and transformative methodology, investors gain a valuable advantage in an uncertain world. It provides a glimpse into the future, acting as a guiding light amidst the market's unpredictable fluctuations. Although imperfect, it enables investors to make better-informed decisions, improve their investment strategies, and maximize returns. Stock market forecasting and assessment are challenging tasks influenced by various factors, including dependent factors like average value and stock news and independent factors like market sentiments. These factors contribute to fluctuations in stock prices, making it difficult for traders and investors to identify the stock's trend accurately.

2. Literature review

Greff K et al. (2018) proposed a model that developed three different deep learning algorithms—CNN, LSTM, and RNN—to predict the stock returns of the NIFTY 50 index. These methods are particularly effective for scenarios involving sequential data, outperforming traditional deep learning techniques. The model utilizes time-varying prediction algorithms that depend solely on historical data to forecast stock prices. The final steps of the process involve generating results and evaluating them using various assessment measures. After conducting multiple trials with different attributes and epochs, the LSTM model emerged as the most effective option.

Reddy VKS (2018) explored the use of Support Vector Machines (SVM) and Back Propagation (BP) neural networks for predicting futures prices in the Indian stock market. The study found that SVM demonstrated superior performance with lower error rates compared to BP, highlighting the importance of model selection in achieving accurate stock market forecasts. The authors emphasized that SVM's ability to handle high-dimensional data makes it a strong candidate for financial predictions.

Wang H (2020) employed a hybrid model combining LSTM and CNN-LSTM to predict the closing price of stocks for the day. The results indicated that the CNN-LSTM model significantly outperformed the standalone LSTM model. This study demonstrated that the integration of CNN with LSTM enhances the predictive accuracy for stock prices, establishing a more reliable benchmark for investors looking to make informed decisions based on closing price forecasts.

Adhikar AJ et al. (2020) utilized LSTM networks for short-term stock price predictions, showcasing the model's ability to capture temporal dependencies in stock price movements. The study reported improved accuracy over traditional time series models, reinforcing the effectiveness of LSTM in financial forecasting. The authors concluded that LSTM is a powerful tool for predicting stock prices, particularly in volatile markets.

Kadam MY et al. (2022) integrated sentiment analysis with SVM to predict stock movements. The study found that incorporating sentiment data significantly improved prediction accuracy, achieving an accuracy of 89.93%. The authors highlighted the importance of external factors, such as public sentiment, in stock market forecasting, suggesting that sentiment analysis can serve as a valuable complement to traditional financial indicators.

Torres PEP et al. (2019) proposed a hybrid model that combined Artificial Neural Networks (ANN) with Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to predict stock market indices. The study demonstrated significant improvements in prediction accuracy compared to traditional methods, emphasizing the effectiveness of hybrid approaches in capturing both linear and nonlinear patterns in financial data.

Nikou M et al. (2019) conducted a comparative study of Linear Regression and SVM for stock price prediction. The findings indicated that SVM outperformed Linear Regression, achieving an average accuracy of 80%. The authors stressed the need for selecting appropriate machine learning techniques based on the specific characteristics of the dataset, underscoring the importance of model evaluation in financial forecasting.

Rezaei H et al. (2021) evaluated the effectiveness of ANN in predicting stock market indices in Shanghai. The results showed an accuracy of 75.74%, indicating that ANN can be a useful tool for stock market forecasting. However, the study also noted that the performance of ANN varies significantly with different market conditions, suggesting the need for further research to enhance its robustness.

Karim ME et al. (2022) explored the application of hybrid models combining LSTM and CNN for stock price forecasting. The study demonstrated that the hybrid approach outperformed traditional models, achieving higher accuracy in predicting stock prices. The authors concluded that leveraging the strengths of both LSTM and CNN can lead to more reliable predictions, making it a promising avenue for future research in stock market forecasting.

Thakkar A and Chaudhari K (2021) investigated the use of Recurrent Neural Networks (RNN) for predicting stock prices based on historical data. The study demonstrated that RNNs are particularly effective in capturing temporal dependencies in time series data, leading to improved prediction accuracy. The authors highlighted the importance of tuning hyperparameters and using appropriate training techniques to enhance the model's performance in financial forecasting.

Hossain MA et al. (2018) applied a hybrid approach combining Convolutional Neural Networks (CNN) and LSTM to predict stock market trends. The study utilized historical price data and technical indicators as input features, achieving a notable increase in prediction accuracy compared to traditional models. The authors concluded that the CNN-LSTM hybrid model effectively captures both spatial and temporal patterns in stock price movements.

Babu CN and Reddy BE (2014) explored the effectiveness of using Genetic Algorithms (GA) for optimizing the parameters of machine learning models in stock price prediction. The study found that GA significantly improved the performance of various models, including SVM and ANN, by optimizing hyperparameters. The authors emphasized the potential of evolutionary algorithms in enhancing the predictive capabilities of machine learning techniques in finance.

Vanipriya CH and Thammi Reddy K (2014) focused on the application of Long Short-Term Memory (LSTM) networks for predicting stock market volatility. The study demonstrated that LSTM could effectively model the volatility clustering phenomenon observed in financial markets. The authors reported that their LSTM-based model outperformed traditional GARCH models, providing more accurate forecasts of market volatility.

Bukhari AH et al. (2020) examined the role of macroeconomic indicators in stock price prediction using machine learning techniques. The study integrated various economic factors, such as interest rates and inflation, into predictive models, finding that these indicators significantly enhance forecasting accuracy. The authors concluded that incorporating macroeconomic variables is crucial for developing robust stock market prediction models.

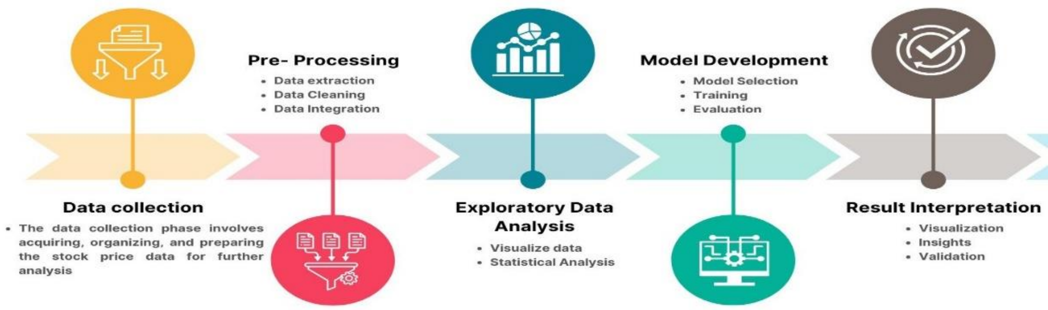
Gao Y et al. (2021) utilized a hybrid model combining LSTM and attention mechanisms to improve stock price prediction accuracy. The study highlighted that attention mechanisms allow the model to focus on relevant parts of the input data, leading to better performance in forecasting stock prices. The authors reported significant improvements in prediction accuracy compared to standard LSTM models.

R. Akshaya et al. (2023) examined, due to the surging competition in the business world, a single inaccurate decision can lead to radical setbacks. Data needs to be analysed in order to arrive at better decisions, thus improving the organization’s performance and standards. This is achieved through Big Data which makes use of the process of business intelligence to elevate strategic and operational decision-making.

3. Data Analysis and Visualization

When predicting stock prices, some common features or variables are typically included in datasets. The first is the date, which refers to the day the stock price was recorded. This variable is essential for organizing the data in chronological order and tracking changes in stock prices over time. The opening price, or the value of a stock at the start of the trading day, is another important consideration. This variable aids in determining the stock's beginning value and monitoring daily price fluctuations. The high price of a stock is crucial since it represents the stock's peak value and potential gains during that trading day. On the other hand, the low price, or the stock's lowest point throughout the trading day, is crucial for comprehending the lowest possible price and risk of losses. The cost of a stock after the trading day is referred to as the closing price, which gives information about the total value and tracks price fluctuations over time. The dataset is often broken down into two phases: training and testing, to train and test a model for forecasting stock prices. During training, the model is trained using 80 percent of the data to recognize patterns and provide predictions. The training model's performance is then assessed by contrasting its forecasts on brand-new, unobserved information with the experimental data, which makes up the final 20 percent of the dataset.

4. Research Methodology



4.1 Dataset Collection:

A dataset is a collection of historical data on a company's stock prices. The dataset usually includes several attributes, such as the date, high, low, open, close, adjusted close, and volume, for each trading day over a specified period. The dataset contains comprehensive stock price data for 50 companies, likely from the Indian stock exchange. Each company's data is stored in a separate CSV file, capturing daily trading details such as the opening price, highest and lowest prices, closing price, and trading volume. This time-series data is crucial for financial analysis and modelling stock price trends, enabling researchers to identify patterns and forecast future prices.

In addition to individual company files, the dataset includes a metadata file named stock_metadata.csv. This file provides descriptive details about the companies, such as their names, sectors, industries, and exchange symbols. This supplementary information allows for sectoral comparisons and a deeper understanding of market dynamics.

The companies represented span diverse industries, from banking and technology to manufacturing and pharmaceuticals. Notable names include Reliance Industries, Tata Consultancy Services, HDFC Bank, and Infosys. This variety offers the potential for cross-sectoral analysis and insights into the performance of specific industries over time.

	Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close	VWAP	Volume	Turnover	Trades	Deliverable Volume	%Deliverble
0	2000-01-03	TELCO	EQ	201.60	207.4	217.25	207.4	217.0	216.75	214.28	676126	1.448775e+13	NaN	NaN	NaN
1	2000-01-04	TELCO	EQ	216.75	217.0	219.00	206.0	211.9	208.20	209.50	679215	1.422962e+13	NaN	NaN	NaN
2	2000-01-05	TELCO	EQ	208.20	194.0	217.80	194.0	213.1	213.25	210.33	1120951	2.357684e+13	NaN	NaN	NaN
3	2000-01-06	TELCO	EQ	213.25	215.0	229.90	215.0	222.0	222.10	225.29	1968998	4.435932e+13	NaN	NaN	NaN
4	2000-01-07	TELCO	EQ	222.10	224.0	239.90	223.1	239.9	239.90	236.32	2199431	5.197636e+13	NaN	NaN	NaN

Figure 1. Sample dataset

4.2 Pre-Processing

After conducting some analysis, we decided to switch from a time series dataset to a sequential one. To achieve this, we eliminated characteristics like volume, date, and adjacent close from our dataset that were not necessary for our analysis of the final price prediction. The four features—Open, High, Low, and Close—are what we used to predict the final feature space. Next, we used these features to compare how well different machine learning models performed. For evaluation, we split the entire set into 90% learning data and 10% testing data.

4.3 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is a crucial step in understanding the dataset and preparing it for modeling. It involves summarizing the main characteristics of the data, visualizing trends, and identifying anomalies. EDA ensures that the data is understood and prepared for further predictive modelling. This step also highlights potential challenges, such as handling missing data or capturing volatility, which are crucial for building accurate and reliable stock prediction models.

5. Model Development

The development of a stock price prediction model involves several systematic steps, from choosing a suitable model to training and evaluating its performance. This methodology ensures a robust and accurate stock price prediction model that adapts well to complex, volatile financial data.

5.1 Long Short-Term Memory (LSTM)

Stock prices can be influenced by events that happened months or even years ago. LSTMs can learn these long-term dependencies by selectively retaining information through the memory cell and gates. For example, an LSTM might remember a significant economic policy change that could have a long-term impact on a company's stock price.

In essence, LSTMs provide a powerful tool for building predictive models for time series data like stock prices by overcoming the limitations of traditional methods and standard RNNs. They can capture complex patterns and long-term dependencies within the data, making them a valuable approach for stock forecast, although with inherent limitations and the ever-present volatility of the market. LSTMs address this issue with their core component – the memory cell. This cell contains gates that control the flow of information:

- **Forget Gate:** Decides what information to forget from the previous cell state.
- **Input Gate:** Determines what new information to store in the current cell state.
- **Output Gate:** Controls what information from the current cell state to output.

LSTM is a Recurrent Neural Network (RNN) utilized to obtain information relevant to a particular context from extensive datasets to make predictions. A LSTM unit has a unique structure that consists of an input gate, an output gate, a forget gate, and a cell state. The LSTM network can be likened to a cell that has gates because it decides whether to retain or discard information based on its perceived significance. The function of the gates in an LSTM is to regulate the information that enters and exits the cell state, while the cell state itself preserves data from previous time steps. The distinguishing characteristic of LSTM lies in its capacity to act as a memory cell, which is achieved through its multiple gating mechanisms. These gates control the input and output of information into and out of the cell, allowing it to store information over arbitrary periods. We employed LSTM networks instead of conventional recurrent neural networks because they can effectively handle complete sequences of data and overcome the problem of vanishing gradients. Two LSTM network layers make up our sequential model:
1. The first LSTM layer consists of 64 units.
2. The second LSTM layer consists of 32 units.
3. The output layer consists of one neuron within a dense layer.

Fig 2. Actual vs. predicted for open price

Fig 3 Actual vs. predicted for close price

From Fig. 2 and Fig. 3, The predicted values closely follow the actual values, indicating that the model effectively captures the overall trend of the stock price.

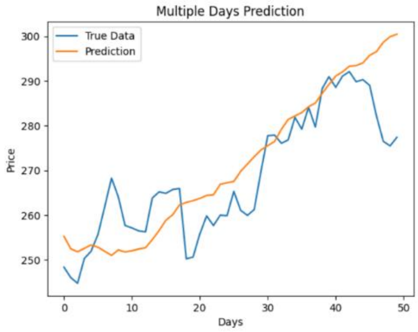


Figure 4. LSTM based on Sequence length 15

In Fig.4 the predicted prices generally follow the upward trend of the true prices, indicating that the model captures the overall direction of price movement.

5.2 Convolutional Neural Networks (CNNS):

Convolutional Neural Networks (CNNs) use convolutional layers instead of general matrix multiplication. CNNs are efficient and effective at automatically learning features from raw input data. The number of hidden layers in a CNN varies depending on the architecture and task; generally, CNNs have more hidden layers, which demonstrates their capacity to extract and classify features from the input. The number of hidden layers in CNNs affects their ability to extract features, with more layers leading to more complex features. The dropout rate of 0.2 has been set, which implies that during each training iteration, 20% of the neurons in the previous layer will be randomly eliminated. This random elimination of neurons helps the model to depend on different sets of neurons for various input patterns, making it more resilient and reducing the possibility of overfitting the training data. An advantage of CNNs over general feedforward networks is that the input is maintained in its original shape to reduce the complexity of the network

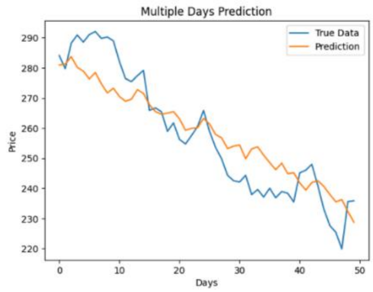


Figure 5. CNN based on Sequence length 5

5.3 Linear Regression

The dataset at hand can be analyzed using a fundamental machine learning technique— linear regression, which provides an equation indicating the relation between the dependent and independent variables. However, linear regression alone cannot be used to train sequential datasets. Therefore, we experimented with various sequential lengths to process each training example. A test set consisting of 50 features can be utilized to evaluate a linear regression model, which is generated by aggregating 5 features over 10 days. We used Multilayer Linear Regression, which includes 2 layers:

1. The first layer captures the core attributes of each day by utilizing the Open, High, Low, and Close features.
2. Using the sequential length from the first layer as a base, the second layer forecasts the closing price of the stock by utilizing the essence of prior days.

The sole disadvantage of employing linear regression is its elevated testing loss because it cannot effectively incorporate the past day's data for forecasting.

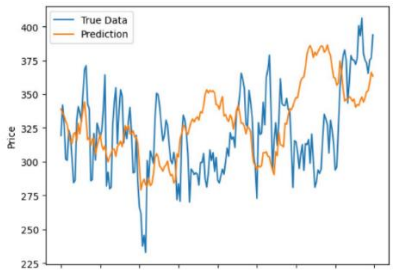


Figure 6. Linear Regression based on Sequence length 25

6. Results and Discussion

6.1 Sequence Length and ITS Impact

Based on the comparison of different sequence lengths in various models, we found that the sequence length is a crucial factor that impacts the accuracy of the prediction results. The term "sequence length" refers to the number of previous days' data needed to forecast the current day's closing price. To clarify, if the sequence length is set to 10, then the OHLC features from the last 10 days would be necessary to predict the closing price for the 11th day. We considered various sequence lengths, including 5, 10, 15, 25, and 60 to achieve higher accuracy and better results. The graph compares the RMSE values for multiple-day predictions for various sequence lengths. The graph shows that the RMSE values increase as the sequence length and prediction period increase. However, there may be some fluctuations or exceptions to this trend for certain sequence lengths or prediction periods. In our analysis, we included companies that operate in different sectors to ensure better transparency and robustness of our results.

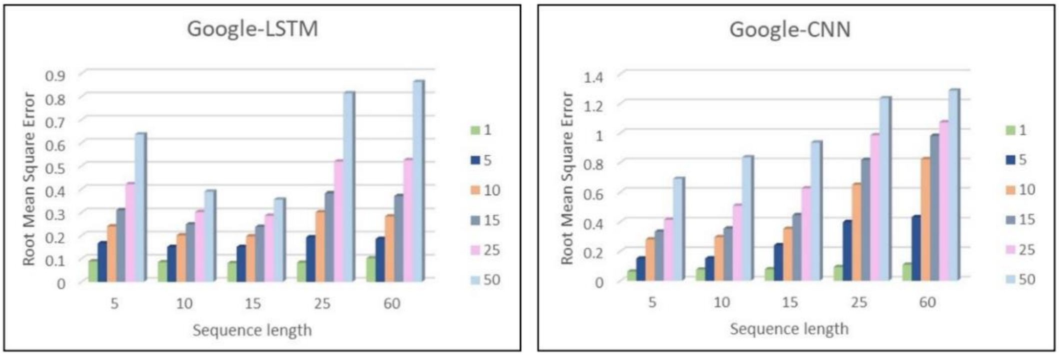


Figure 7. Comparing LSTM and CNN model performance on Google dataset across multiple days with varying sequence lengths

From Fig.7, the CNN model exhibits higher RMSE compared to the LSTM model, especially at larger sequence lengths, indicating that the CNN model may struggle more with capturing dependencies in longer sequences.

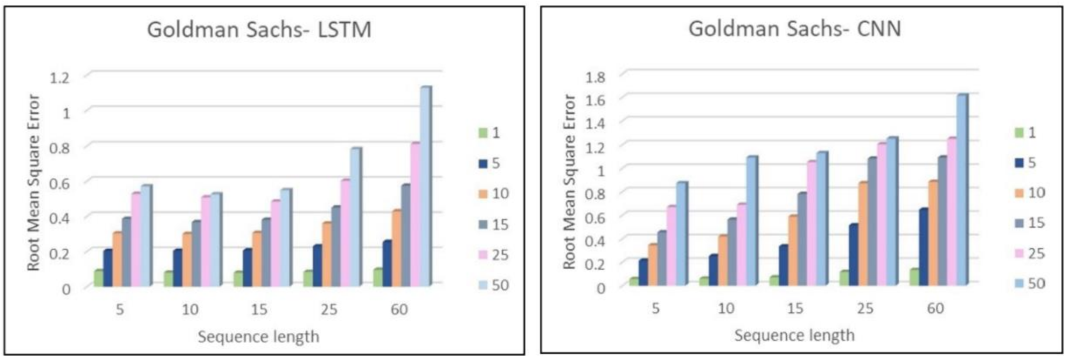


Fig. 8

Comparing LSTM, and CNN model performance on the Goldman Sachs dataset across multiple days with varying sequence lengths

From Fig.8, the shorter sequence lengths (e.g., 5 and 10), the performance gap between LSTM and CNN is smaller. However, as the sequence length grows, the CNN model's RMSE becomes notably higher compared to the LSTM model.

Table 1 MSE of each model based on Goldman Sachs Dataset across Multiple days

MODEL	1	5	10	15	20	25
LSTM	0.009	0.042	0.089	0.137	0.337	0.357
CNN	0.004	0.074	0.174	0.317	0.484	0.857
LR	0.085	0.115	0.914	0.349	0.511	1.057

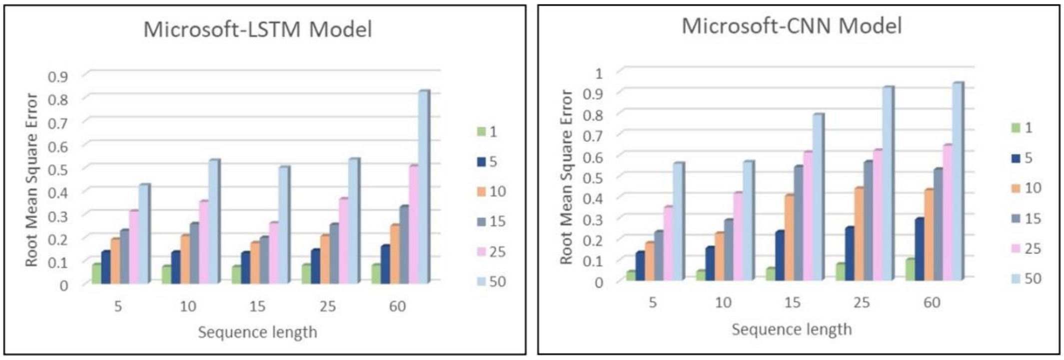


Figure 9. Comparing LSTM, and CNN model performance on Microsoft dataset across multiple days with varying sequence length

From Fig.9, the CNN model consistently shows higher RMSE than the LSTM model, particularly for sequence lengths beyond 25. Among all the models we tested, the LSTM model consistently provided the best results. Our analysis suggests that the choice of sequence length and model algorithms is crucial when predicting financial data. While the CNN model works best for shorter sequences, the LSTM model is more suitable for longer sequences. Finally, the LSTM model consistently outperformed all other models for the sequence lengths we considered.

6.2 Limitation

In this analysis we chose OLHC features (Open, High, Low, Close), that may not capture all the relevant factors that affect stock prices. Market sentiments, news, economic indicators, and external events can significantly impact stock prices, and including them may improve model accuracy. Stock price data can exhibit non-stationary, which makes it challenging for linear models. More data pre-processing to ensure stationarity, such as differencing or using log returns, to make it more suitable for the chosen algorithms. Also, trading based on frequent predictions can incur significant transaction costs, which may impact the overall profitability of the strategy.

7. Economic Impact

Accurate stock market predictions contribute to broader economic stability by enhancing investor confidence. As more businesses and individuals make informed decisions, market volatility decreases, leading to a more predictable financial ecosystem. These models encourage participation by fostering market trust and promoting economic growth and resilience. The widespread adoption of machine learning models in stock market prediction has the potential to transform the economy. By increasing the accuracy of market forecasts, these models reduce the overall volatility of the financial system, fostering a more stable economic environment. Investors, armed with reliable predictions, are more likely to participate in stock markets, increasing liquidity and driving capital toward businesses. This increased participation benefits not only individual companies but also the economy at large, as the efficient allocation of capital spurs innovation, job creation, and economic growth.

8. Implications

8.1 Customization for Industries

Machine learning models can be tailored to address the unique dynamics of specific industries. For instance, the technology sector may require algorithms that factor in rapid innovation cycles, while the banking industry may prioritize stability and risk metrics. Such customization ensures that predictions are accurate and relevant to each sector's unique challenges and opportunities. Different industries exhibit unique financial behaviours and challenges, making customization critical for effective stock market predictions. Machine learning models can be tailored to account for these sector-specific nuances. For example, in the technology sector, where innovation cycles are rapid and market sentiment shifts quickly, models can be trained to prioritize short-term trends and sentiment analysis. Conversely, in industries like manufacturing or energy, where changes occur over longer periods, models can focus on macroeconomic indicators and supply chain data. This flexibility ensures that predictions are not only accurate but also contextually relevant, giving businesses actionable insights that align with their strategic goals.

8.2 Integration with Business Tools

The integration of machine learning models with existing business systems amplifies their utility. For financial institutions, these models can be embedded into trading platforms, automating the analysis of market data and executing trades based on predictive insights. Businesses can also link these models with customer relationship management (CRM) systems to gain a holistic view of client behavior and tailor investment products accordingly. Integration with enterprise resource planning (ERP) systems further allows businesses to align financial forecasting with operational planning, creating a cohesive strategy that enhances overall efficiency and profitability.

9. Conclusion and Future Scope

Stock markets offer opportunities for businesses to grow and provide individuals with a source of additional income through investments. As the popularity of stocks continues to increase, investors are able to make significant profits. To evaluate the efficiency of the method, we performed experiments using various machine learning models under the same environment and configurations to compare their performance across different sequence lengths. In brief, the LSTM model can be utilized for longer sequence lengths for higher precision in the outcomes of prediction. Sequence length is a crucial feature to consider when predicting financial data. Future study endeavours could investigate the integration of real-time situations and further constraints to enhance the precision of price forecasts. Implementing algorithms using deep learning that use financial news stories to improve stock price forecasting precision is one possible approach. Optimizing the choice of hyperparameters such as changing the number and the amounts of epochs, can also improve the performance of the model. Future studies might also examine how well alternate data sources, like sentiment analysis on social media or market movement metrics, could be used to improve the precision of predictions. Lastly, to further increase prediction accuracy, the application of ensemble techniques—such as merging the outputs from multiple models—could also be examined.

Reference

Adhikar AJ, Jadhav AK, KH CG, HS MS. Literature survey on stock price prediction using machine learning. Int J Eng Appl Sci Technol. 2020;5(8):2143–455. https://www.ijeast.com/papers/258-262,Tesma508,IJEAST.pdf

Babu CN, Reddy BE. Selected Indian stock predictions using a hybrid ARIMA-GARCH model. In: 2014 international conference on advances in electronics computers and communications. IEEE; 2014. p. 1–6. https://www.shs-conferences.org/articles/shsconf/pdf/2024/16/shsconf_edma2024_02008.pdf

Bukhari AH, Raja MAZ, Sulaiman M, Islam S, Shoaib M, Kumam P. Fractional neuro-sequential ARFIMA-LSTM for financial market forecasting. IEEE Access. 2020; 8:71326–38. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9057460

Gao Y, Wang R, Zhou E. Stock prediction based on optimized LSTM and GRU models. Sci Progress. 2021; 2021:1–8. https://www.scirp.org/reference/referencespapers?referenceid=3800742

Greff K, Srivastava RK, Koutník J, Steunebrink BR, Schmidhuber J. LSTM: a search space odyssey. IEEE Trans Neural Network Learn System. 2016;28(10):2222–32. https://ieeexplore.ieee.org/document/7508408

Hossain MA, Karim R, Thulasiram R, Bruce ND, Wang Y. Hybrid deep learning model for stock price prediction. In: 2018 IEEE symposium series on computational intelligence. IEEE; 2018. p. 1837–44. https://www.scirp.org/%28S%28351jmbntvnsjt1aadkposzje%29%29/reference/referencespapers?referenceid=3448122

Kadam MY, Kulkarni MS, Lonsane, MS, Khandagale AS. A survey on stock market price prediction system using machine learning techniques. 2022. https://www.ijraset.com/research-paper/stock-market-price-prediction-system-using-machine-learning-techniques

Karim ME, Foysal M, Das S. Stock price prediction using BiLSTM and GRU-based hybrid deep learning approach. In: Proceedings of third doctoral symposium on computational intelligence: DoSCI 2022. Singapore: Springer Nature Singapore; 2022. p. 701–11. https://ijritcc.org/index.php/ijritcc/article/view/6985

Nikou M, Mansourfar G, Bagherzadeh J. Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms.

Intelligent System Account Finance Manag. 2019;26(4):164–74. https://www.scirp.org/reference/referencespapers?referenceid=3800749

R. Akshaya, Varsha Ravi, S. Raja Lakshmi, and R. Aparna, Big Data to Big Impact: Effect of Big Data in Modern Decision Making. Proceedings of the International Conference on Emerging Trends in Business & Management (ICETBM 2023) 978-94-6463-162-3, https://www.atlantis-press.com/proceedings/icetbm-23/125986548

Reddy VKS. Stock market prediction using machine learning. Int Res J Eng Technology (IRJET). 2018;5(10):1033–5. https://www.irjet.net/archives/V5/i10/IRJET-V5I10193.pdf

Rezaei H, Faaljou H, Mansourfar G. Stock price prediction using deep learning and frequency decomposition. Expert System Appl. 2021;169: 114332. https://www.scirp.org/reference/referencespapers?referenceid=3800749

Thakkar A, Chaudhari K. A comprehensive survey on deep neural networks for stock market: the need, challenges, and future directions. Expert System Appl. 2021;177: 114800. https://www.scirp.org/reference/referencespapers?referenceid=3856374

Torres PEP, Hernández-Álvarez M, Torres Hernández EA, Yoo SG. Stock market data prediction using machine learning techniques. In: Information technology and systems: proceedings of ICITS 2019. Springer International Publishing; 2019. p. 539–47. https://ouci.dntb.gov.ua/en/works/4M0LdmN7/

Vanipriya CH, Thammi Reddy K. Indian stock market predictor system. In: ICT and critical infrastructure: proceedings of the 48th annual convention of Computer Society of India-Vol II: hosted by CSI Vishakapatanam Chapter. Springer International Publishing; 2014. p. 17–26. https://link.springer.com/chapter/10.1007/978-3-319-03095-1_3

Wang H. Stock price prediction based on machine learning approaches. In: Proceedings of the 3rd international conference on data science and information technology. 2020. p. 1–5. https://dl.acm.org/doi/10.1145/3414274.3414275