Time Series Forecasting

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***Abstract*—This project tackles the complex task of predicting stock market prices using advanced techniques like LSTM neural networks, historical data, and technical indicators, with a specific focus on the technology sector. It recognizes the ongoing challenge of achieving accurate predictions in the dynamic world of finance and aims to develop a robust LSTM model for this purpose. The study's scope is confined to historical price data and technical indicators, while being mindful of potential limitations. The project's significance lies in its potential to empower investors and financial institutions with more informed decision-making tools, contributing to a better understanding of financial market dynamics. The project structure includes a comprehensive literature review, a detailed research methodology encompassing data collection and preprocessing, model development, and experimental setup. The results and discussion section assesses the model's performance and discusses its limitations and future research possibilities. Ultimately, this project seeks to bridge the gap between predictive analytics and financial markets, offering a practical contribution to the field of stock price forecasting, benefiting both individual investors and financial professionals.**

***Index Terms*—Deep Learning, LSTM, Machine Learning, time series analysis and Historical stock data.**

I. INTRODUCTION

In statistics, data analysis, and machine learning, time series forecasting is a method for predicting future values from previous data points grouped chronologically. When examining and predicting trends, patterns, and behaviors in time-ordered data, it is an invaluable tool. A time series is made up of data that is gathered or recorded at regular intervals, like monthly, annual, or daily. Time series data encompasses various variables such as energy usage, population growth, stock prices, weather measurements, and website traffic.

Making forecasts or guesses about future values based on historical observations and trends in time-ordered data is also known as time series forecasting. Numerous industries, including banking, economics, sales, weather forecasting, and more, heavily rely on this approach. The components of time series are: Trend: The data's long-term movement or orientation. Seasonality: The data's recurring, regular variations. Cycle: More extensive, wavy patterns that aren't always regular Noise in data refers to sporadic changes or anomalies. The techniques which can be used to predict the time series data are: Statistical techniques: These include exponential smoothing and ARIMA (Auto Regressive Integrated Moving Average). Machine learning techniques: Utilize algorithms such as GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory), and others. Hybrid Methods: For increased accuracy, combine machine learning and statistical techniques.

Coming to its advantages, there are lots of advantages they are Making Well-Informed Decisions: aids in making well- informed judgments based on projections for the future helps companies to more effectively plan their operations, production, and resource allocation. Identification of Patterns: finds trends and patterns in data from the past. allows companies to react to changing circumstances in a proactive manner. optimization of Resources: predicts future needs to optimize resource allocation. helps to optimize the supply chain and manage inventories. Measuring the Uncertainty gives a prediction's degree of uncertainty. aids in emergency preparation and risk mitigation. Monitoring Performance: makes it possible to track performance in relation to projections. allows for strategy modifications and enhancements.

Not only advantages but there are some limitations, they are: Many approaches make the assumption that the time series' underlying statistical characteristics remain constant across time, which may not always be the case. Sensitivity to Disparities Extreme values, outliers, or sudden changes in the data can all affect how sensitively time series models perform. Seasonality and Trend Complexity: Complex patterns, erratic trends, and seasonality can be difficult to handle and call for more sophisticated models. Missing values and the quality of data: The quality of the data is crucial for time series fore-casting. Prediction accuracy may be impacted by inaccurate or missing data. Restricted Range: Predictions made with a longer forecasting horizon are less accurate as predicting is by its very nature unpredictable.

The Future Developments and Trends are Machine Learning Progress continuous incorporation of machine learning methods to create forecasting models that are more precise and adaptable. Integration of Big Data with IoT: expanded and real-time data with the use of big data analytics and Internet of Things (IoT) connectivity. AI that can be explained: To improve trust and decision-making, concentrate on improving the interpretability and explainability of AI models. Integration and Automation: improved connection with corporate operations and complete automation of the forecasting process.

Here we are forecasting the price of stock market shares in this study. Here, we are utilizing well-known machine learning techniques to forecast stock prices through the use of machine learning. Because financial markets are inherently volatile and unpredictable, accurately predicting stock market prices is a difficult challenge for any algorithm to guarantee. Here, the algorithm we employed is Long Short-Term Memory (LSTM) Networks, here Long-term dependencies in time series data can be effectively captured by recurrent neural networks (RNNs), such as LSTM. For sequence prediction applications, such as stock price forecasting, it is commonly employed.

II. RELATED WORK

Ayitey et al. [1] contributes to a deeper understanding of the applicability and potential of machine learning techniques in forecasting forex price movements, offering valuable insights for the financial industry and beyond.

Zhao et al. [2] offers a fresh perspective on the application of data mining techniques in the realm of stock market forecasting. By exploring the relationship between outlier patterns and price trends, the research provides valuable insights that can empower market participants with more informed decision-making capabilities. This paper contributes to the ongoing exploration of innovative methods for predicting stock market movements, offering potential benefits to traders and investors alike.

Lindsay et al [3] contributes to the ongoing discourse on responsible and informed investment strategies. Transparent models have the potential to bridge the gap between advanced machine learning techniques and the need for transparency and trust in financial market predictions, offering a promising avenue for improving forecasting practices.

Selvin et al. [4] showcases the potential of LSTM, RNN, and CNN in capturing complex patterns in stock price data, with the sliding window model providing a structured framework for temporal analysis. This paper offers valuable insights for those seeking to harness the power of deep learning in the domain of stock price forecasting, with practical applications in investment and risk management.

J. Taylor et al. [5] showcasing the capabilities of LSTM networks in capturing intricate patterns, the research opens doors for more sophisticated and accurate financial predictions. This paper serves as a valuable resource for financial professionals seeking to leverage deep learning techniques in their market analysis and decision-making processes, offering a promising avenue for enhancing financial forecasting practices.

Z. Zhang et al,[6] provides a promising avenue for enhancing predictive accuracy in the financial domain. This paper serves as a valu- able resource for individuals and institutions seeking to refine their strategies for short-term trading and investment decisions in the stock market.

A.Rupavathi et al. [7] delves into the cap- tivating domain of stock market prediction and its intersection with machine learning. It represents an insightful exploration into the application of machine learning algorithms to forecast stock market prices. Recognizing the complexity and volatility of financial markets, the study evaluates the effectiveness of a wide array of machine learning techniques, including the Long Short-Term Memory (LSTM) neural network, to provide a comprehensive understanding of their capabilities in this challenging field.

A.Yadav et al. [8] contributes to the ongoing exploration of innovative methods for predicting stock prices. This paper serves as a valuable resource for those seeking to leverage attention-based neural networks to enhance their trading and investment strategies in the dynamic world of financial markets.

P. Sandhya et al. [9] showcases the potential of RNN and LSTM models in capturing temporal dependencies and intricate patterns in stock price data. This paper serves as a valuable resource for those interested in using deep learning techniques for stock price forecasting, with practical applications in investment and risk management.

Sisodia et al. [10] showcases the potential of LSTM networks in capturing temporal dependencies and forecasting trends in the Nifty50 index. This paper serves as a valuable resource for those interested in using deep learning approaches for analyzing and predicting stock market movements, particularly in the context of the Indian equity market.

W. Waheeb et al. [11] conducted a one-step forecasting comparison using simulated nonlinear autoregressive moving- average (NARMA) time series. They divided the neural net- work models into two groups: Group I, which uses only autoregressive inputs, and Group II, which incorporates au- toregressive and moving-average (error feedback) inputs.The simulation results revealed that the models in Group II, utiliz- ing error feedback inputs, generated more accurate forecasts compared to the models in Group I. This indicates that integrating error feedback into neural networks improves their forecasting ability for NARMA time series.

Islam et al. [12] focuses on stock price forecasting using the popular Recurrent Neural Network (RNN) model, specifically the Long Short-Term Memory (LSTM) variant. The study demonstrates that with appropriate hyper-parameter tuning, these RNN models, particularly LSTM, can accurately predict future stock market prices. The evaluation involved calculating Root Mean Square Error (RMSE) for LSTM models by varying epochs and measuring the difference between predicted and actual stock prices. The research utilized accessible stock market datasets containing various price and volume-related information. The primary objective was to assess the accuracy of Machine Learning algorithms, specifically LSTM, in predicting stock market prices.

Bharti et al. [13] focuses on leveraging news headlines to incorporate sentiment data alongside daily stock information for improved stock market trend and price pre- diction. Traditional approaches often use only daily stock data or standard machine learning algorithms. However, this study proposes utilizing an ensemble technique, XGBoost, for market trend prediction, and Long Short-Term Memory (LSTM) cells for price prediction using time series data. The results demonstrate that combining both data sources using these advanced techniques yields significantly more accurate outputs compared to conventional methods.

Sayavong et al. [14] proposed a stock price prediction model using Convolu- tional Neural Network (CNN) to enhance returns and mitigate market risks in the financial industry. The CNN model, known for its adaptability and self-learning capability, is tailored to the Thai stock market's characteristics. The model is trained and tested using preprocessed data, focusing on three stocks listed on the Thai Stock Exchange (BBL, CAPLL and PTT). The results demonstrate the CNN-based model's effectiveness in identifying stock price trends and making accurate predic- tions, showcasing its potential as a valuable tool for stock price forecasting with high accuracy. Further promotion of this approach in the financial sector is recommended.

Liu et al. [15] addresses the ongoing volatility in China's stock market due to the growth of emerging industries and the necessity for accurate stock market predictions. The study introduces an improved support vector machine (SVM) algorithm-based network model to enhance the precision of stock price trend prediction. The objective is to achieve accurate stock price prediction while maintaining model efficiency. Through ex- periments, the proposed model proves effective in approx- imating short-term stock price trends, providing a reliable foundation for accurate stock price predictions. Ultimately, this contributes to advancements in high-tech development and the progress of the stock market amidst China's advancing economic landscape.

Zhang et al [16] addresses the challenge of predicting stock market fluctuations due to its complex and nonlinear nature, making traditional machine learning methods impractical. The focus is on utilizing deep learning, particularly Long Short- Term Memory (LSTM) recurrent neural networks, to enhance prediction accuracy and efficiency. The study centers on stock price trend prediction for China's leading new energy vehicle company, Build Your Dreams (BYD). The paper constructs a stock price prediction index system and employs LSTM to predict BYD's stock price, overcoming issues related to long sequence dependence. Data preprocessing involves interpola- tion and wavelet denoising, followed by training and testing in LSTM models with varying hidden neurons to determine the appropriate setup for improved prediction accuracy.

Gunturu et al. [17] aims to enhance stock market investment decisions by comparing a range of Machine Learning and Deep Learning techniques for predicting stock trends. It evaluates models like LSTM, Prophet, Random Decision Forest, Auto-ARIMA, KNN, Linear Regression, and Moving Average (SMA and EMA). Additionally, the research introduces a superior hy- brid model and assesses performance on a historical dataset across various industrial sectors. The findings provide valuable insights into model accuracy, aiding investors, traders, and analysts in making informed investment choices. Moreover, this research sets a benchmark for future studies in stock market prediction.

Faraz et al. [18] proposed a strategy for the stock market closing price prediction-by-prediction using the autoencoder long short-term memory (AE-LSTM) networks. To integrate technical analysis with deep learning methods, technical indicators and oscillators are added to the raw dataset as features. The wavelet transformation is used as a noise-removal technique in the stock index. Anomaly detection in dataset is also performed through the z-score method. First, the autoencoder is trained to represent the data. Then, the encoder extracts feature and puts them into the LSTM network for predicting the closing price of the stock index. Afterwards, the system predicts subsequently based on the previous predictions. To evaluate the theoretical results, the proposed method is experimented on the standard and poor's 500 (SP 500) stock market index through several simulation studies. To analyze the results, several performance criteria are used to compare the results with the generative adversarial network (GAN). The simulation studies are conducted to show the effectiveness of the proposed method in the Python envi- ronment, and the results show that the proposed prediction- by-prediction method outperforms GAN in terms of daily adjusted closing price prediction.

Fengxia et al. [19] introduces an ensemble forecasting model that combines autoregressive integrated moving average (ARIMA) with artificial neural networks (ANN) based on multiple objectives. The model utilizes the Golden section criteria to determine the weights for these two objectives. The study evaluates this approach using Canadian Lynx data series and finds that the combined model significantly enhances forecasting accuracy compared to using either of the individual models separately.

M. Samin-Al-Wasee et al. [20] focuses on developing an accurate price prediction model for the cryptocurrency Ethereum (ETH), known for its price volatility due to its role in decentralized applications and the Ethereum network. The study employs Long Short-Term Memory (LSTM) networks to forecast Ether's price by analyzing historical time-series data. Various LSTM network variants, both basic and hybrid, are utilized for this purpose. The research includes univariate and multivariate time-series analysis to predict future prices. A comparative analysis is conducted to assess the performance of these models against established forecasting methods like Autoregressive Integrated Moving Average (ARIMA), serving as a baseline for evaluating LSTM network effectiveness in predicting Ethereum's future market behavior.

III. PROPOSED METHODOLOGY

Predicting stock market prices has long been a challenging and crucial task in the world of finance. Accurate forecasts can empower investors with valuable insights, aid in risk management, and potentially lead to more informed financial decisions. Traditional financial models often struggle to capture the intricate dynamics of stock markets, which are influenced by a multitude of factors, including economic conditions, investor sentiment, and news events. This project delves into the exciting realm of stock market price prediction using machine learning, with a particular focus on the LSTM model. By harnessing historical stock price data, technical indicators, and the capabilities of LSTM networks, this re- search aims to provide enhanced and more precise predictions of daily stock prices. The stock market's dynamic nature presents an ongoing challenge, where even small changes in information can lead to significant price fluctuations. Despite advancements in technology and data availability, consistently accurate predictions have remained elusive. However, machine learning, especially deep learning models like LSTM, offers a promising approach to tackle this problem. LSTM networks are well-suited for handling sequential data, making them particularly effective for time series forecasting, such as stock prices, where the order and timing of data points are crucial. This study's primary objectives are twofold: first, to develop a robust LSTM-based model tailored specifically to stock price prediction, and second, to comprehensively evaluate its performance. Through a meticulous exploration of historical price data and relevant technical indicators, this research seeks to bridge the gap between predictive analytics and the complex world of financial markets. In the following sections, we will delve into the background of financial markets, emphasizing the need for improved prediction accuracy. We will also define the problem statement, highlighting the persistent challenges in achieving consistent accuracy in stock price predictions.

The project's objective is to forecast the stock prices of businesses that are listed on the NASDAQ and DowJones.To anticipate the price, this system will make use of a variety of machine learning approaches and algorithms. In this case, the recurrent models' memory is increased by the use of the long short-term memory (LSTM) model. Recurrent neural networks are superior than short-term memory networks because they enable the use of previously determined information in the present neural networks. The earlier data is used for immediate tasks. It's possible that we don't have a whole history of the neural node. The vanishing gradient problem, which arises from the repetitive use of the same parameters in RNN blocks, is one of the primary problems with RNN. We must try to use different parameters to overcome this problem at each time step. We try to find a balance in such a situation. We bring novel parameters at each step while generalizing variable-length sequences and keeping the overall amount of learnable parameters constant. We introduce gated RNN cells like LSTM and GRU. LSTMs are a common choice for time series data, such as stock market values, because they are especially well-suited for modeling and predicting sequences. It is made up of memory cells and different gates (for example, input, forget, and output gates) that regulate the information passing through the cell. There are commonly 3 gates, they are input gate, output gate and Forget gate.

INPUT GATE: It regulates how fresh data enters the mem- ory cell. The input gate aids the long short-term memory (LSTM) in determining which fresh information is pertinent and ought to be stored in the memory cell when it comes to prediction. In order to create an update vector that is utilized to update the cell state, it combines the current input with the prior concealed state.

Input Gate (i_t)

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi})$$

$$\tilde{C}_t = \tanh(W_{ic}x_t + b_{ic} + W_{hc}h_{t-1} + b_{hc})$$

FORGET GATE:it determines which data from the memory cell's prior state should be ignored. It generates a forget vector based on the input, which is currently, and the prior concealed state.As per our forecast, the forget gate can play a pivotal role in eliminating extraneous prior data that might not exert a substantial influence on forthcoming price fluctuations. The LSTM can concentrate on the most current and pertinent market conditions thanks to this gate.

Forget Gate (f_t)

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf})$$

OUTPUT GATE:The output gate controls which memory cell information is sent to the next time step or used as a prediction. It aids in the control of information flow from the LSTM to the final forecast. The output gate in our model ensures that the LSTM outputs the most relevant information stored in the memory cell. It might be a stock price prediction or another financial statistic.

Output Gate (o_t)

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \; h_t = o_t \odot \tanh(C_t)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \qquad (1)$$

These equations show how the LSTM gates control in- formation flow through the network, allowing the model to capture long-term relationships and make predictions based on learnt patterns in the input data. During the training phase, the weights and biases (W and b) are learned.

IV. EXPERIMENTAL RESULTS

A. Dataset Description

The dataset for analysis that we used in the work is a collection of historical stock price data for four important technological companies: Apple Inc. (AAPL), Alphabet Inc. - the parent company of Google (GOOG), Microsoft Corporation (MSFT), and Amazon.com Inc. (AMZN). The data spans a one-year period before the present day, including each stock's opening and closing values, as well as its daily high and low prices. The dataset also includes information on the volume of shares exchanged. Here we have grabbed live stock data from the last few years. This stock data was obtained using the Yahoo Finance API.To improve the identification of the corresponding firm, we added an additional column called" column name" to the all four stocks dataset. This dataset is adaptable and may be used for a variety of analytics and visualizations, providing insights on stock market patterns and volatility for these renowned tech titans throughout the selected time period.

B. Evaluation Technique

The Root Mean Squared Error (RMSE) is the evaluation approach used to analyze the effectiveness of our LSTM (Long Short-Term Memory) model in stock price prediction. Fol- lowing the training phase on historical stock data, the testing phase entails making predictions on a separate dataset. The RMSE is derived after comparing the anticipated stock prices to the actual stock prices. The root mean square error (RMSE) is a popular metric for quantifying the average amount of errors between expected and observed values. It calculates the square root of the mean of the squared discrepancies between expected and actual values. Using RMSE as the assessment metric, the code intends to provide a quantifiable measure of the LSTM model's accuracy in predicting stock prices, providing insights into the model's ability in capturing the underlying patterns and trends in financial data. The mathematical equation of RMSE matric is fig 4:

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

where n is the number of predictions, $\hat{y}_i$ is the predicted value, and y_i is the corresponding actual value.

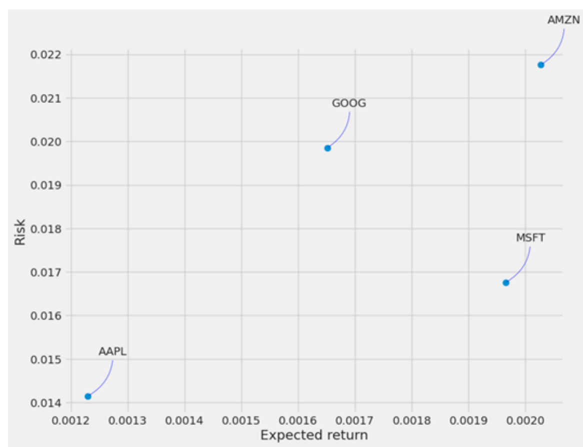

Fig. 1. predicted price of apple for next one year

The study's results highlight the effectiveness of the sug- gested system in predicting stock prices with increased ac- curacy, establishing it as a useful resource for both traders and investors. Using a variety of algorithms on all four stocks produced positive outcomes, but the attention to Apple stock stood out as being especially productive because of its risk- profit ratio.its risk-profit ratio is better than remaining 3 stocks as we can see in Fig 1. Predictions made with 9, 44, and 200-day moving averages were significantly more successful than those made with other indicators. The fact that these moving averages are so good at making forecasts supports not only their importance in technical analysis but also the fact that many traders and investors use them extensively. The financial community's approval of this technique highlights its usefulness, implying that the insights of the suggested system may impact trading strategies and decision-making processes in actual market situations. All things considered, the study offers insightful information on the field of stock price prediction, highlighting a methodology that has proven to be accurate and in line with industry standards.

We obtained a Root Mean Squared Error of 8.81, as table 1 demonstrates. It is the model's average prediction error; smaller values are better. Mean Squared Error (MSE) calculates the average squared difference between the actual good. In the end, we also used the R-squared error metric, and the result was a poor -0.28. Consequently, we may conclude that while R squared error is inappropriate for these kinds of models, RMSE, MSE, and MAE metrics can be employed in our model to evaluate the model.

TABLE I MODEL EVALUATION METRICS

Metric	Outcome
RMSE	8.81
MSE	7.76
MAE	7.84
R^2	-0.28

The average squared difference between the expected and actual values is measured by MSE (Mean Squared Error), which is comparable to RMSE. For you, it is 7.76.

Fig. 2. closing price of apple from past 1 year

The above image shows a graph which shows the actual closing price of apple stock from 11-2022 to 11-2023.

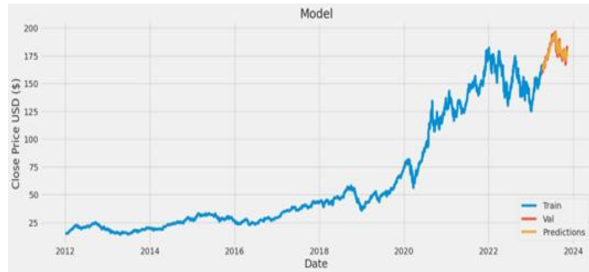

Fig. 3. predicted price of apple for next one year

The above image shows a line which is combination of blue and orange colour.the blue colour part of graph shows the past closing price of the apple share from 11-2022 to 11-2023, the orange part of the graph shows the predicted price of apple share price for the next one-year form 11- 2023 to 11-2024 using 3 moving averages, they are 9,44 and 200 moving averages. we used many techniques like SMA, stochastic rise and pivot points etc. but moving averages showed more accuracy by comparing all the techniques.

The system will prioritize user-friendliness, accuracy, and efficiency in predicting the price. Accomplishing these objectives will enable users to take decision before investing or trading in stocks.

V. CONCLUSION

Time series analysis is a tough and demanding task. Because there is still much work to be done to predict the future outcome of any organization, this study will be helpful for future research. The primary goal is for the estimated stock values to be as precise as possible without deviating from human behavior. Two LSTM layers and two Dense layers make up the four-layer LSTM model that we presented in this work. Here, we are using the RMSE and R squared error accuracy metrices to validate the model, and the results show a 3.57 rmse and 79 percent accuracy. As such, this is a useful paradigm to utilize.

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