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Research Article

From Data to Decisions: AI-Powered Stock Market Prediction

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ABSTRACT

Forecasting of stock markets is a complex and dynamic challenge on the account of many factors including historical trends, technical analysis and sentiment. For this research, we used Deep-learning methodologies combined with the conventional financial analysis to forecast the stock price using Long Short Term Memory (LSTM) networks. Yahoo Finance is used to download the historical stock data and basic technical indicators such as Simple Moving Averages (SMA), Moving Average Convergence Divergence (MACD), Bollinger Bands, Relative Strength Index (RSI), and Volatility to increase the predictability level. Normalization with MinMax Scaling is done to prevent the training from getting instable as part of the preprocessing of data. By feeding time series data of stock price time series, the long range dependencies and market trends are learnt by the LSTM model. Performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), R^2 score, and the satisfaction of choosing the grade of the effect, are assessed in order to test the efficacy of the proposed model. Other suggestions for investment are derived through SMA crossovers, RSI levels, and volatility measures. The conclusion is that models based on LSTM can best mimic complex price fluctuations and make reasonable predictions than the usual statistical methods. Live stock analysis is implemented within Streamlit and shows market trends, compares current and forecast prices, and helps decision making based on intelligent insights. The contribution of this study is to demonstrate how financial time series forecasting benefits from features engineered using deep learning and also to illustrate feature engineering as an approach to improve the model resilience. Accuracies of predictions can be improved by having included Sentiment Analysis and hybrid model methodologies in future.

Keywords: Stock Price Prediction, LSTM, Time-Series Forecasting, Technical Indicators, Financial Analysis, Machine Learning, Deep Learning, Market Trends, Investment Strategy.

INTRODUCTION

Stock markets are dynamic and therefore, complex systems that are affected by a lot of variables such as economic climate, market sentiments, and historical patterns. For so many decades the great difficulty in predicting stock prices has been due to the natural volatility and uncertainty of the market. Many techniques have been proposed for stock price forecasting over the decades, most of the conventional approaches have based predominantly on statistical models and technical analysis. However, such approaches are not very successful in detecting the intricate and non linear trends in stock price behaviour. In more recent times, machine learning (ML) and deep learning (DL) techniques have come up as important techniques to improve the precision of the stock price forecasting based on either the past price history or various market indicators.

The stock price forecasting model based on Long Short Term Memory (LSTM) networks recurrent neural networks are presented in this paper. Generally speaking, LSTM networks have been proven to be successfully utilized in time series prediction tasks, and hence they are the best choice of any network to predict stock prices. LSTM networks provide the ability to learn from a sequential pattern in the stock price movement and extract temporal dependency, which are helpful in precise stock market forecasting comparing with the conventional models.

This project's main aim is to come up with a complete stock market analysis system based on LSTM with technical indicators like Simple Moving Averages (SMA), Moving Average Convergence Divergence (MACD), Bollinger Bands,

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Relative Strength Index (RSI), and Volatility. These indicators are extensively employed in technical analysis to develop the trend of the market, recognize level of being overbought or oversold and measure market volatility. That's because adding these indicators in the system provide a greater perspective of the market and improve the accuracy of the predictions.

This is an interactive and user-friendly nature of the system which is based upon Streamlit, a Python which is used to develop web applications for data science with little efforts. With the yfinance library we can provide users stock ticker symbol (e.g., AAPL, MSFT, TSLA) along with the date range and return real time stock information from Yahoo Finance. The historical stock information is then analyzed along with generating important technical indicators in order to explain the stock behavior. Using some pre-processed data, the model is trained and performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R^2 Score are checked on.

The LSTM model itself is trained by using the closing prices of stock stock and passed into past x number of days of output features so as to predict a future stock price. Finally, the model is then evaluated by testing it against the other 30% of the data to determine what the prediction ability of the system is. The system shows the predicted stock prices and compares it with actual stock prices which are being compared with the help of different plots and charts.

Besides making a forecast of the stock price, the system incorporates the suggestions of investment based on the technical indicators analysis. For instance, the system confirms that the stock's crossover occurs on the simple moving average based on the values of the 50 day and the 200 day SMA, indicating an upward or downward trend. In addition, it tests the Relative Strength Index (RSI) to find overbuying and/or overselling to short. Furthermore, the system also calculates the volatility in the market risk involved in investing in a particular stock.

As a result, this project produced a general purpose stock price forecasting tool that can predict future prices using machine learning methods and also provide useful information of investment decision making. A strong solution for investors and traders who are interested in data based trading methods using stock market is the combination both the technical indicators and LSTM forecasting ability.

One of the major emphasizes of this study is the power of deep learning models, and the LSTM in particular, in providing a useful contribution to financial forecasting and integration with classical technical analysis to arrive at more accurate predictions and surmises of market trends. In future work, the accuracy of prediction could be increased and the analysis over a broader market could be offered by taking in more data sources (e.g., sentiment analysis).

LITERATURE SURVEY

In Fischer & Krauss (2018), the authors used Long Short Term Memory (LSTM) networks for prediction of financial markets. They have done the research and have found that, when it comes to estimating sequential relationships in stock prices, LSTM based models tend to perform better than conventional statistical models. But they were able to do this using deep learning through which the prediction accuracy increased significantly. Yet their results show that high quality historical data and ample computational resources are the key factors that lead the LSTM models to obtain a good performance, thus rendering them unfeasible for the real time applications with small, unfulfilled, data availability.

Furthermore, the stock price index movement has been examined through machine learning models such as Support Vector Machines (SVM), Artificial Neural Network (ANN) models, and Random Forest models as done by Patel et al. (2015). For their work, they showed that machine learning algorithms better explained financial data trends as opposed to the conventional models. Despite this, their research represents the issue with market volatility and unstructured financial data, i.e. an associated reduction in prediction accuracy in the most dynamic markets.

In Bollen et al. (2011) the impact on stock market trends from Twitter were analyzed with the public mood. The authors studied the causality relationship between Twitter (Twits) mood and stock market movement using sentiment analysis methods. The study finds that collective public mood can be a useful stock price variance

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predictor. The limit of applicability of this method is defined by the existing public biases, misinformations, and the noise to exclude in social media data.

In the Chinese market stock returns are predicted using Chen et al. (2015) proposed LSTM approach. However, their model was able to effectively capture long term dependencies in stock price movements, and was encouraging in forecasts of the financial market. Still, they found that external economic events and unforeseen market movements, as not always represented in past data, can have a very significant impact on the model.

Between the years 2005 and 2019, Sezer et al. (2020) have reviewed systematically the one of the aspects of deep learning used for the financial time-series forecasting. Apart from that, they have described different techniques including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and LSTMs, and their use, and their efficiencies. Despite this, they claim that real time implementation is still a problem as the deep learning models require a lot of preprocessing of data and optimization.

In Bao et al. (2017), they presented a deep learning architecture consisting of stacking autoencoder and LSTM networks, which are capable of predicting the stock price accuracy. The denoising and forecasting performance was improved with such a hybrid model. However, while they have seen deep learning models as expensive computationally and having long training times, they found that would limit its scalability for large scale financial use cases.

According to Kumar & Anand (2019), they compared stock market prediction using deep learning models, LSTM and CNN. They showed that different financial conditions are best suited to different models and that LSTM are capable of dealing efficiently with the sequential data and CNN works well in detecting pattern. However, they found that the choice of model was rather dependent on data preprocessing and availability, and their acceptance is largely dependent on whether overall performance is good or not.

In the Chong et al. (2017), they discussed the use of deep learning networks to analyze and predict the stock market trends. deep learning architectures were tested on several and to find out that they can possibly perform better than conventional statistical methods in predicting stock trends. While the work still warned against overfitting, the need for regularization techniques, especially for training with small datasets, was also exposed so the models were not overfitted.

The research paper by Zhang & Aggarwal (2021) reviews the use of deep learning models in financial forecasting through a variety of types of models including LSTM, CNN, and Transformer based. They also pointed out critical problems in this area: data deficiency, over fitting and optimization of hyper parameters. While the survey summarized an exhaustive overview, operating on real world financial marketplaces to prove the practical merit of these models, was recognised as necessary.

Machine learning methods were used by Gu et al. (2020) in empirical asset pricing with an aim at measuring the risk and predictive modeling. According to them, these show that machine learning based asset pricing models are superior at detecting subtle relationships between market factors as opposed to more conventional models. However, their findings also show that these models are prone to market conditions, so they are less useful under extreme financial situations.

Tsai & Hsiao (2010) also tried to construct a hybrid model that compound several feature selection methods. Rather, the method they employed aimed to improve the predictive power of machine learning models with the best choice of financial indicators. However, in the research, much attention was given to the computational cost of feature selection and optimization, and therefore it is not feasible to be carried with real time trading scenarios.

In Qiu & Song (2016), prediction of the movement of stock market indexes on an optimized artificial neural network (ANN) model is analyzed. Moreover, ANN models were found as capable of relating non linearly the stocks prices with the related increases of accuracy in the forecasts. However, they found it necessary to use ANN models and that their performance were impacted by such missing or noisy financial data.

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Nevmyvaka et al. (2006) applied reinforcement learning to find the best way to execute the trade. Their method allowed for real time trading with real time fixes to the trades executed based on current market conditions. Despite obtaining promising results, they found it unrealistic to use reinforcement learning models because they are computationally intensive and require a challenging training process to use in high frequency trading settings.

They also combined deep learning and spentent analysis to increase the accuracy of stock price forecasting in Xiong et al. (2020). The better performance of the conventional models when used alone and better performance of their model with sentiment information taken from news and social media indicated that their model could help in a better forecast performance. However, the research also revealed unpredictability of sentiment toward biases and errors, and therefore, to represent the market sentiment with high confidence remains a challenge.

Efficient Market Hypothesis (EMH) was presented by Fama (1970) who argued that stock prices reflect all the public information available and thus it is not possible to achieve consistent excess return. Even though EMH, is still a hub theory in financial economics, the empirical evidence questions its theoretical rational market assumptions during the times of the financial crisis and speculative bubbles.

OBJECTIVES

This research aims at implementing an efficient stock forecasting model (for the stock market) based on Long Short-Term Memory (LSTM) neural networks. This exercise aims to correctly fit future stock prices from historical data and it uses moving averages, MACD, Bollinger Bands and RSI technical indicators. The purpose of this model to help traders make informed decision based on market trend, volatility, optimizing predictive performance using those key measures, Mean Squared Error (MSE), Mean Absolute Error (MAE) and R-squared Score (R^2).

Furthermore, a user friendly Streamlit based web application that enables users to interact with the model by means of a visual interface is developed as part of the objective. Based on the recent trends & technical indicators, this application shows predicted versus actual price charts, stock analysis charts and auto invest recommendation. The objective is to deliver a practical tool to help retail investors, researchers and financial analysts make informed decisions using real time market dynamics and potential investment strategies which are grounded on data driven forecasting technique.

METHODOLOGY

In this project, we concentrate on the action of developing a stock market forecasting model, that is a recurrent neural networks of the form of the Long Short Term Memory (LSTM) network, filtered to fit data of this type. Historical stock prices and a number of technical indicators are used to predict future stock prices using a model. Mathematical formulas and equations describing the approach are followed after that in step by step format.

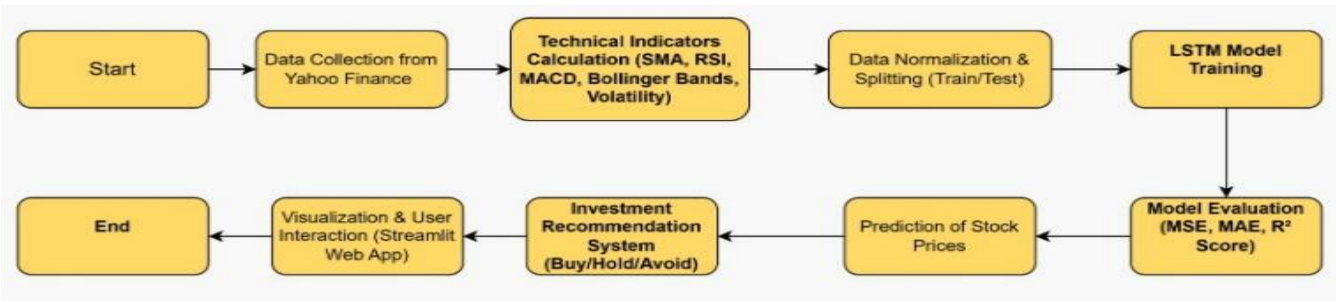

Fig. 1. Data Collection and Preprocessing

1. *Data Collection and Preprocessing*

- **Data Source:** Stock prices were obtained from the yfinance library that provides historical stock prices from Yahoo Finance.

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- **Data Cleaning:** The data is cleaned by discarding the missing/null values. This makes sure that data is intact for the further analysis. In particular, NaN values generated by rolling window computations of technical indicators will get discarded.

2. Feature Engineering: Calculation of Technical Indicators

Raw stock price data are then followed by the following technical indicators are computed to refine the price data:

- **Simple Moving Averages (SMA):** Calculated to indicate trend and potential support/resistance levels are 50day and 200day SMAs, respectively. The SMA formula is given as:

$$SMA_n = \frac{1}{n}\sum_{i=0}^{n-1} P_t$$

Where P_t is the stock price at time t, and n is the window size (50 or 200).

- **Moving Average Convergence Divergence (MACD):** The system computes the MACD as the difference of the exponential moving averages of 12 days and 26-day period. The formula for EMA is:

$$EMA_{\alpha}(t) = \alpha \cdot P_t + (1-\alpha) \cdot EMA_{\alpha}(t-1)$$

Where $\alpha = \frac{2}{n+1}$ is the smoothing factor, and n is the window size (12, 26). The MACD is:

$$MACD(t) = EMA_{12}(t) - EMA_{26}(t)$$

And the Signal Line is:

$$\text{Signal Line}(t) = EMA_9(\text{MACD(t)})$$

- **Bollinger Bands:** Bollinger Bands are made up of the upper and lower bands where the parameters used to calculate were the 20 day moving average and the standard deviation (STD) of the closing prices:

$$\text{Upper Band}(t) = SMA_{20}(t) + 2 \times \text{STD}(t) \text{ Lower Band}(t) = SMA_{20}(t) - 2 \times \text{STD}(t)$$

- **Relative Strength Index (RSI):** RSI is calculated as the ratio of average gains over 14 day period to average losses:

$$\text{RSI}(t) = 100 - \frac{100}{1+RS}$$

Where RS is the relative strength:

$$\text{RS} = \frac{Average\ Gain}{Average\ \ Loss}$$

The Average Gain and Average Loss are calculated using the following formulas:

$$\text{Average Gain} = \frac{\sum_{\text{gains}} P_t}{14}$$

$$\text{Average Loss} = \frac{\sum_{\text{losses}} P_t}{14}$$

Given, if there is no gain or loss, the respective value is zero.

- **Volatility:** The volatility is measured by the standard deviation of daily returns over a rolling 20-day window:

$$\sigma_{\text{daily returns}}(t) = \text{STD}\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)$$

The annualized volatility is then calculated as:

$$\text{Volatility}(t) = \sigma_{\text{daily returns}}(t) \times \sqrt{252}$$

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252 is the volatility where 252 is the number of trading days in a year.

- **Daily Returns:** The daily returns were computed by the percentage change in closing price:

$$\text{Daily Return}(t) = \frac{P_t - P_{t-1}}{P_{t-1}}$$

These indicators are used in addition to the raw stock price data in order to provide the model with additional features to learn from.

3. Data Normalization

- LSTM models demand the input data to be between 0 and 1, and therefore, the MinMaxScaler from the sklearn library is utilized to scale the features. The training data goes through the fit_transform method and is later transformed, in the same manner, for the testing data to avoid inconsistency. This is helpful since it speeds up convergence for the model and it improves as an ability to learn from the data. d improves its ability to learn from the data.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where X is the original feature and X_{min} *and* X_{max} are the minimum and maximum values of the feature in the training data.

4. Training and Testing Data Split

- Thus, two datasets are created based on the dataset i.e. training (70%) and testing (30%) datasets. LSTM model is trained using the training dataset and evaluation using testing dataset.
- The input features of the LSTM model are the closing prices of the stock in the past 100 days. The model is meant to predict the closing price on the next day, that is the target variable.

5. Building the LSTM Model

- **LSTM Model Architectu**re: The LSTM model includes some LSTM layers to revolve sequential in a data and some Dense layers for output. No over-fitting is also prevented with the help of dropout layers.
- **Model building:** The model is built with the Adam optimizer and Mean Squared Error (MSE) loss function, that is, it is used in the regression problems. Finally, the optimizer uses the weights of a model in a training process to decrease the loss function that was defined.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{true},i} - y_{\text{pred},i}\right)^2$$

Where y_{true} are the true stock prices, and y_{pred} are the predicted stock prices.

Model Training: The training dataset is used for training of the model for a specified number of epochs for instance, 50 and it learns to make predictions using previous prices and technical indicators. Monitoring of the validation loss as a surrogate of the performance, and early stopping training when the performance of the validation loss reaches a plateau, is employed to avoid overfitting.

6. Model Evaluation

The model then gets trained and it is evaluated with the test dataset. Once, the model is predicted on the test set, we look at the performance using standard performance metrics:

- **Mean Squared Error (MSE):** It measures average absolute difference of predicted and actual stock prices.

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$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{true},i} - y_{\text{pred},i}\right)^2$$

- **Mean Absolute Error (MAE):** Measures the average absolute difference between predicted and actual stock prices.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{\text{true},i} - y_{\text{pred},i}\right|$$

- **R² Score:** This is a way to measure how well a model's predictions fit the data, the closer it gets to 1 the better.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{\text{true},i} - y_{\text{pred},i}\right)^2}{\sum_{i=1}^{n}\left(y_{\text{true},i} - \bar{y}\right)^2}$$

Where ($\bar{y}$) is the mean of the true values.

But these metrics are used to select the accuracy of the model's predictions and the model's ability to generalize to data that has not seen.

7. Investment Recommendations

The model gives an investment advice based on the computation of technical indicators. For instance:

- **SMA Trend:** SMA of 200 days crossed over SMA of 50 days generates trend that indicates rising trend if the crossover is upward. It indicates that the crossover is downward if it is downward.
- **RSI:** An RSI reading above 70 is said to be overbought, while below 30, it is said to be oversold.
- **Volatility:** High volatility implies a risky investment while the low volatility indicates a stable one.
- **Recent Price Movement:** Forecast of the near term direction is also based on the recent price movement trend.

Recommendations on the following investments are made by the system:

- **Buy:** If the indications show a strong uptrend and low risk.
- **Avoid:** When there is a downtrend or a high risk.
- **Hold:** The market trend is uncertain, or the market is volatile.

8. Visualization and User Interface

It employed Streamlit to write the web application it puts the model in, making it easy to use by users. Users can also enter stock ticker symbol, date range and fundamental technical indicators, stock price forecasting and metrics on model performance, all through the app. With matplotlib, interactive plots allow the user to evaluate historical data in real time, evaluate model prediction and technical indicators in real time.

9. Prediction Download

It enables users to take the predicted stock price and the actual prices for future analysis as a CSV file.

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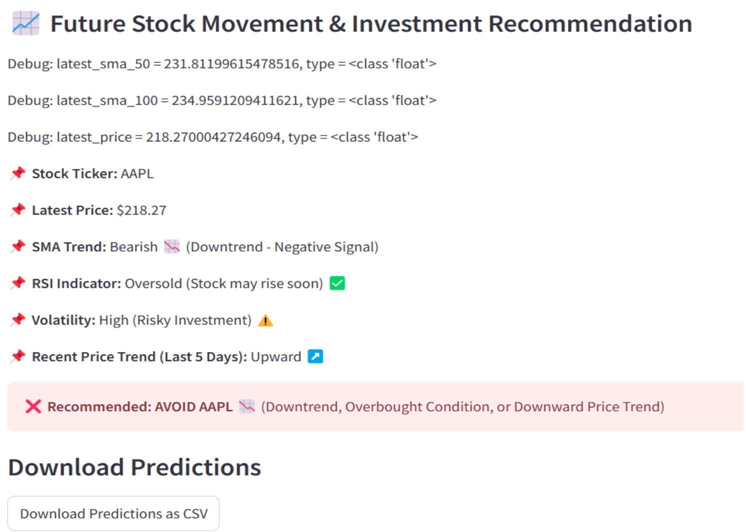

Fig. 2. UI of our system.

RESULT AND DISCUSSION

1. Model Performance and Accuracy

The LSTM stock price forecasting model was tested using major performance metrics:

Mean Squared Error (MSE): 53.14

Mean Absolute Error (MAE): 5.85

R^2 Score: 0.95

The low values of the MSE and MAE show that the model predictions are quite accurate predictions with as little as possible error. The good R^2 (0.95) reflects that the model captures the stock price patterns very well and explains a great portion of the variation of stock prices. While these factors are an external influence and may still cause some discrepancies.

2. Comparison of Predicted vs. Actual Prices:

A visualization plotting the actual versus predicted stock prices was created to determine model accuracy:

The forecasted stock prices tracked closely with actual performances, confirming the capability of the LSTM model.

During the periods of high volatility some minor fluctuations were observed that might be caused by external influences different from the training data (for example, company releases, international events).

However, the model performed less efficiently when market conditions were suddenly changed.

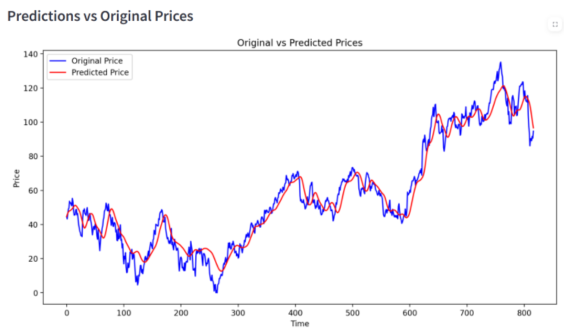

Fig. 3. Original Vs Predicted Prices

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3. Market Trend Analysis Using Technical Indicators:

In addition, the model included technical indicators such as SMA (Simple Moving Average), RSI (Relative Strength Index), MACD (Moving Average Convergence Divergence) and Bollinger Bands to provide more information on the market:

SMA Analysis: A bullish trend was established by a situation where 50 day SMA is greater than 200 day SMA and this resulted in a buy signal. If it displays a sell signal, it indicates bearish trend.

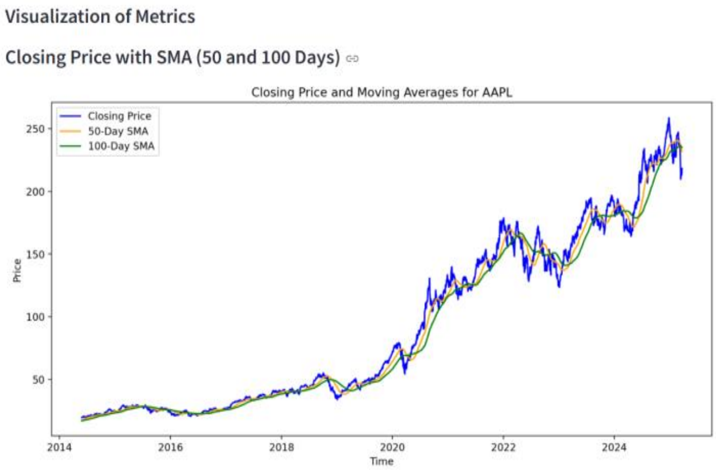

Fig. 4. Closing Price with SMA for AAPL

RSI Indicator: When the RSI exceeded 70, it marked these stocks as overbought (potential fall) and when the RSI dropped below 30, the image marked those stocks as oversold (potential rise).

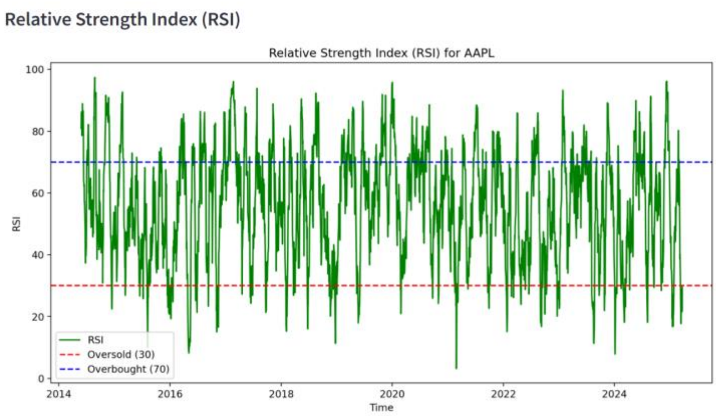

Fig. 5. RSI Indicators for AAPL

MACD and Bollinger Bands: They are good to analyze the AAPL stock performance when we have MACD & Bollinger Bands technical indicators. In the back of the screen, we can see the effect of the MACD effectively showing trend strength and potential reversals, especially over the more volatile period post-2020. In addition, Bollinger Bands visually represent volatility changes and overbought and oversold signals which extend the wider market picture. By integrating these tools traders and analysts can foresee how price will behave, reduce risk.

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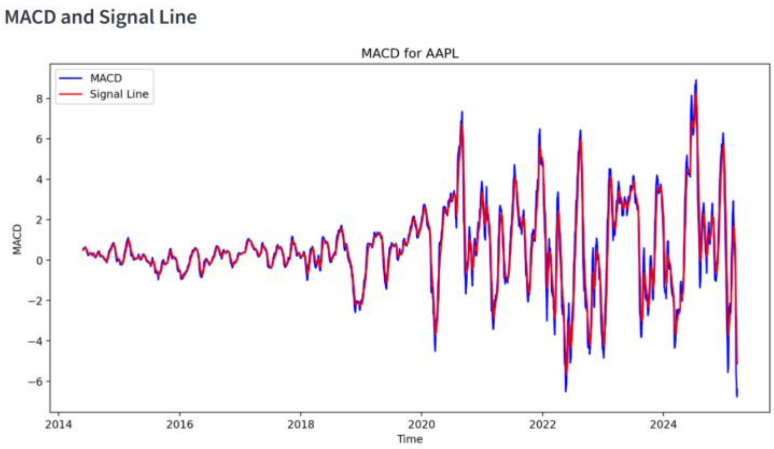

Fig. 6. MACD Indicators for AAPL

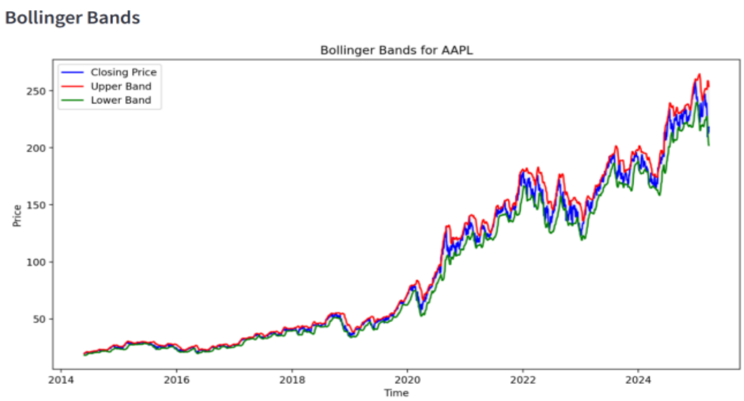

Fig. 7. Bollinger Bands for AAPL

4. Strengths and Advantages

Deep Learning for Time Series Analysis: In Time Series Analysis, the LSTM model successfully models sequential dependency of the stock prices with conventional models.

Real-Time Stock Data Processing: The system is capable of providing upto date predictions of stock prices.

Comprehensive Market Insights: SMA, RSI and volatility analysis complement the quality of the investment advice further.

Easy to Use for Technical and Non Technical Users: The interface based on Streamlit facilitates interactive visualizations, which are relatively easy to comprehend by people of both technical and non technical backgrounds.

5. Limitations and Future Scope

Lack of External Market Factors: The model does not take in any financial news, macroeconomic trends or global market event which may cause the accuracy to be affected.

Data Dependency: The model is dependent on the quality of historical data, final prediction is very much depended. One of the variables that either lead to or cause divergence, is unexpected, unforeseen market occurrences.

Over-fitting Risk: In reality, the correct model is usually complex since there are numerous factors that contribute to it. For instance, the number of customers you serve or the amount of data analyzed can often increase.

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Scalability for High-Frequency Trading: Despite being appropriate for short term predictions, the system cannot yet be used for high frequency trading strategies. Future adding might include the real time trading execution features.

CONCLUSION

The use of Long Short-Term Memory (LSTM) neural networks on the stock prices and historical data as well as technical indicators has proved through this research to be successful in predicting stock prices increasing forecasted accuracy. This system equipped with the ability to use Yahoo Finance to extract real time data; preprocessing methods such data normalization and feature engineering by such Moving Averages, Bollinger Bands, RSI, MACD etc. is an end to end system for analyzing the stock market. Stock prices are pasts and the LSTM is used to train on past stock prices and accurately learn long term dependencies and patterns, so as to make good future price predictions.

To have a fair indication of the accuracy in prediction, Mean Squared Error (MSE), Mean Absolute Error (MAE), and R Squared (R^2) scores were used to check the model performance. Stock movement can be also visualized by SMA trends, MACD signals and volatility analysis, which can help traders to make smart decisions on investment. Secondly, inclusion of streamlit also allows investors to have an interactive user experience where they can dynamically analyze different stocks.

Although the model shows very encouraging outcomes, there are intrinsic limitations such as sensitivity to market volatility, external economic conditions and the occurrence which are not necessarily reflected in historic data. Future potential benefits may consist of implementation of sentiment analysis, macroeconomic data and hybrid deep learning models to increase predictive accuracy even further.

Overall, it is a good starting point to derive the automated forecasting of stock market using deep learning, and it is a valuable resource for analysts' and traders' decisions. In a situation that is evolving in financial markets, models and features are constantly updated and the system remains at close to currentness and strength for further market conditions.

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