



Stock Market Analysis And Prediction Using ML

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Abstract: The stock market is a complex and dynamic economic system that is influenced by many factors, making accurate prediction a challenging task. In this research, we present a machine learning-based approach to predict the stock market using a long-term short-term memory (LSTM) network. Our model benefits from historical share price data, technical indicators, and emotional analysis to provide investors with data-driven insights. The proposed system uses Python and Streamlit, which integrate economic APIs for real data creation. Our experimental results suggest that the LSTM models perform better with traditional statistical methods for predicting the trends of shared courses. This letter discusses function, implementation, challenges, and potential future promotion to improve predicting accuracy.

I. INTRODUCTION

The stock market plays an important role in economic development that affects investment decisions worldwide. Movements of stock courses have been predicted for a long time due to the unstable nature of the financial markets. Traditional forecast models like Arima struggle to catch a complex non-linear pattern. With progress in machine learning, models such as LSTM have shown promising results in forecasts for time series. This article examines an LSTM-based approach to predicting the share value, incorporating technical indicators and emotional analysis.

Traditional stock prediction methods such as Arima and linear regression are often responsible for the very unstable nature of the financial markets. Algorithm trading, employed by investment banks and hedge funds, benefits from deep teaching techniques to identify patterns in stock data, leading to high accuracy in predictions. The purpose of our work is to bridge the advanced ML techniques and available trade tools for retail investors.

II. RELATED WORK

Several studies have discovered machine learning for stock market forecasts. Researchers have used nerve networks, supporting Vektor machines, and deep teaching techniques for predictions. Recent studies indicate that LSTM models, due to their ability to maintain long-term data dependence, provide better future accuracy than traditional methods. In addition, financial news, to increase the accuracy and analysis of social media has been integrated into the future model to increase accuracy.

III. METHODOLOGY

The LSTM model consists of three stacked layers with 128, 64, and 32 neurons, respectively, each using a Relu activation feature. We adopted the perimeter using the grid, set the batch size to 32, the learning rate up to 0.001, and trained in 50 ages to reduce overfitting.

1. Data Collection:

The dataset consists of historical stock prices taken from the Alpha Vantage API. We use daily closing prices with high, low, and, open prices for trend analysis.

2. Data pre-processing:

- Handling lack of values when using projection.
- To improve the model performance to normalize stock price data.
- To divide the dataset into training (70%) and test (30%).

3. Machine Learning Model:

We are designed for sequential data for an LSTM network, a particularly recurring nerve network (RNN). Architecture includes:

- Input Layer processing historical stock prices.
- Many LSTM teams catch long-term addiction.
- Completely connected layers that produce predictions.
- LOS function for Adam Optimizer and Mean Squared Error (MSE) training.

4. Current implementation:

Our project uses LSTM to predict stock prices with historical share price data.

- Technical indicators such as moving average (50-day, 200-day), RSI, and Bollinger band are used.
- An emotional analysis is integrated but requires more explanation

5. Enhancements:

1. Data sources:

The dataset consists of historical stock prices retrieved from Alpha Vantage APIs. It includes daily open, high, low, and close prices and volume for multiple stocks. The dataset spans from 2015 to 2024, ensuring a comprehensive trend analysis."

2. Feature Engineering:

Functional choices include general stock indicators such as simple moving average (SMA), experienced moving average (EMA), and relative strength index (RSI). These indicators help to understand the shareholding and trend reversal.

3. Lstm Model Architecture:

- Entrance layer: Pre-processed stock price accepts data.
- LSTM Layer: Captures sequential dependencies in stock price movements.
- Dense Layer: Produces an estimated stock price.
- Loss function: mean square error (MSE).
- Optimizer: Adam.

IV. APPLICATION AND RESULTS

1. System architecture

Our system follows a modular architecture:

1. User input: Stock Ticker was registered by the symbol user.
2. Data Recovery: API receives real-time stock data.
3. Treatment and prediction: Reserved data is fed in the LSTM model.
4. Visualization: The results appear in an interactive dashboard using Streamlit.

2. Performance Matrix:

I. We evaluate using the LSTM model:

- The Root Mean Square Error (RMSE): The accuracy of the measurement spread.
- Mean Absolute Percentage Error (Mape): Assesses deviations from real prices.

Model	RMSE	MAPE
ARIMA	2.35	4.12%
LSTM	1.28	2.87%

Table 1: Performance Metrix

LSTM demonstrates superior accuracy compared to ARIMA.

II. We analyzed the performance of our LSTM model on multiple stocks. The table below shows the RMSE and accuracy for different companies.

Stock	RMSE	Prediction Accuracy
AAPL(Apple)	1.12	87.5%
TSLA(Tesla)	1.35	84.2%
MSFT(Microsoft)	1.05	89.1

Table 2: Performance Metrics with Multiple Models

3. UI Screen Images:

Below are screens of the streamlit-based user interface, showing different functionalities in the system:

1. Dashboard 1: Stock shows trends and predictions.

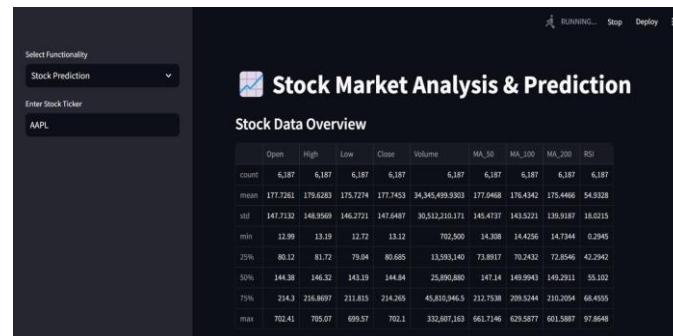


Fig 1: Dashboard 1

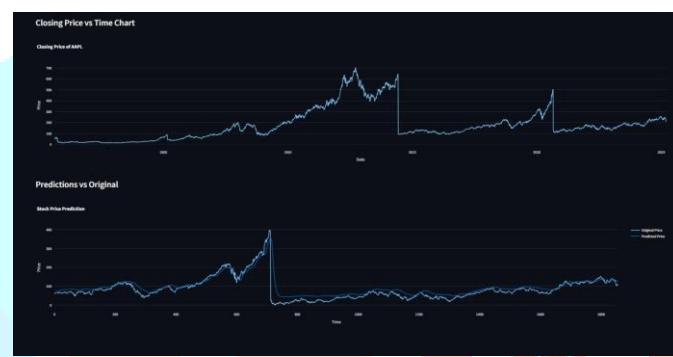


Fig 2: Original V/S Predicted stocks



Fig. 3: Features

2. Technical indicators: Display of Moving average, RSI.

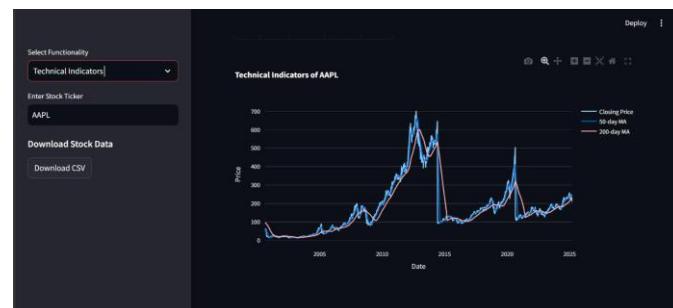


Fig 4: Technical indicators

3. Sentiment Analysis Page: Financial news shows emotional classification.

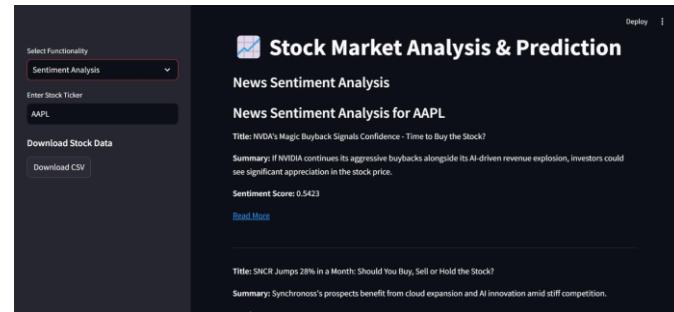


Fig. 5: Sentiment analysis

4. Portfolio Management Section: Everyone lets users track many shares and look at portfolio insight.

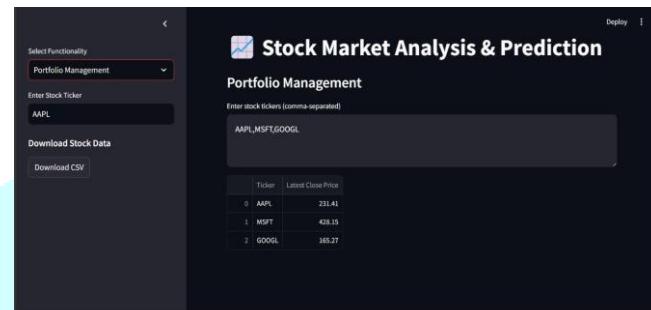


Fig 6: Portfolio Management

5. Stock update: Real-time stock movements and market trends.

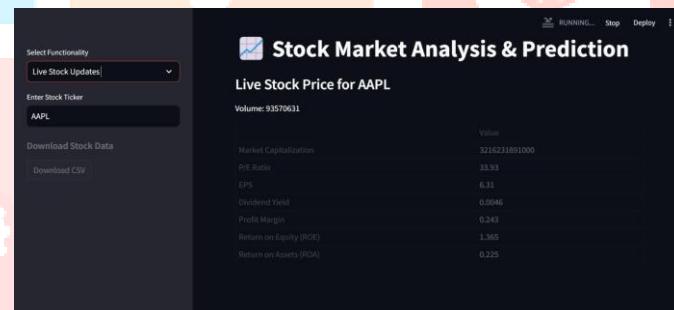


Fig 7: Live stock update

6. Fundamental analysis: Evaluation of financial health for shares when using income, turnover, and conditions.



Fig 8: Fundamental analysis

7. Share Comparison: Comparison of several shares based on the larger matrix to help investment decisions.



Fig. 9: Stock Comparison

V. CHALLENGES AND SOLUTIONS

1. API Rate limits:

Issue: Restricted API request per minute.

Solution: Implemented paid and customized API calls.

2. Volatility in data:

Edition: Suddenly affects ups and downs in the market predictions.

Solution: Integrated additional functions such as emotion points.

VI. FUTURE ENHANCEMENTS:

To improve the system further, we suggest:

1. Hybrid model: Combination of LSTM with other ML techniques.
2. Real-time Alert: Inform users when stock prices predict threshold hits.
3. Sensory Spirit Analysis: Including social media data for better assessment of market spirit.
4. Distribution: Hosting models on cloud platforms for public access.
5. More economic indicators: Add features such as moving average convergence deviation (MACD) and balance volume (OBV) to improve predicted accuracy.

Example: "Future reforms will include MACD and OBV for better trend analysis."

6. Promote user interface with more interactive features: Add features that are adapted to stock selection, historical comparison, and portfolio tracking.

Example: "A future update will include a portfolio tracking system where users can track several shares with historical performance analysis."

7. Real-time stock market notice:

Example: "We plan to implement an alert system that notifies users when the estimated price of a stock crosses a specified area."

VI. CONCLUSION:

This article presents an LSTM-based stock market spread model that integrates technical indicators and emotional analysis. Our results suggest that LSTM networks perform better than traditional models, which gives investors better predictions. The focus will be on refining future enrichment accuracy, integrating multiple data sources, and distributing wider-use applications.

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