Stock Price Prediction Using Enhanced LSTM Models and Technical Indicators

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Abstract - With NVIDIA poised to continue its rapid boom due to its important role in AI infrastructure and chip manufacturing, this take a look at utilizes an LSTM-based totally device mastering version to predict NVIDIA's inventory fee 90 days into the future. through incorporating technical indicators like SMA, EMA, and RSI, the version demonstrates progressed accuracy, forecasting a ability upward trend in inventory prices over the subsequent zone.

keywords: gadget learning, LSTM, NVIDIA, inventory Prediction, SMA, EMA, RSI.

I. INTRODUCTION

This paper discusses the demanding situations and advancements in predicting inventory costs, focusing on the dynamic and unstable nature of monetary markets. With NVIDIA's pivotal function inside the AI infrastructure and chip manufacturing sectors, understanding and forecasting its stock fee trends is of immense importance to buyers, traders, and researchers.

Traditional techniques along with ARIMA and regression often fail to model the non-linear dependencies function of financial time-series statistics. Deep studying, particularly lengthy short-term reminiscence (LSTM) networks, has emerged as a powerful device for capturing these intricate styles and relationships. but, maximum current fashions lack integration with domain-precise know-how, that can beautify predictive overall performance.

This study leverages an more suitable LSTM model enriched with key technical signs—easy transferring Averages (SMA), Exponential transferring Averages (EMA), and Relative electricity Index (RSI). by using incorporating those signs, the model no longer most effective improves prediction accuracy however additionally presents insights into marketplace traits and momentum. The NVIDIA inventory statistics from 2014 to 2024 serves because the dataset for this research.

II. PROBLEM STATEMENT

Predicting inventory charges is a notoriously tough task due to the unpredictable and risky nature of financial markets. traditional statistical strategies regularly fail to seize the problematic dependencies and non-linear styles inherent in time-collection records. even though deep learning fashions like LSTM show promise, they are able to gain notably from characteristic enrichment via the combination of domain-specific technical signs. This examine addresses the distance by enhancing LSTM fashions with SMA, EMA, and RSI to enhance accuracy and reliability in inventory rate forecasting.

III. LITERATURE SURVEY

The literature survey examines existing studies in inventory charge prediction the use of system getting to know and deep studying strategies. over time, severa strategies had been proposed to enhance the accuracy and reliability of financial forecasting:

1. Traditional strategies: ARIMA and regression models were traditionally hired to version stock rate developments. but, these methods often fail to seize non-linear patterns inherent in monetary records.
2. Deep learning fashions: LSTM and GRU models have gained prominence for their ability to address sequential dependencies. for instance, Hochreiter et al. introduced LSTM networks as a

technique to vanishing gradient issues, revolutionizing time-collection forecasting.

3. Technical indicators Integration: research inclusive of the ones with the aid of Sayavong et al. and Weng et al. have highlighted the importance of integrating technical indicators, like SMA and EMA, with device gaining knowledge of fashions to enhance predictive performance.

4. Hybrid methods: Combining deep studying with sentiment analysis or other external information sources has been proposed in studies by way of Nabipour et al., demonstrating progressed forecasting accuracy.

This look at builds upon those findings by way of leveraging technical signs (SMA, EMA, and RSI) alongside an optimized LSTM model to bridge the space among uncooked ancient records and actionable predictions.

IV. METHODOLOGY

A. Dataset

This study utilizes historical NVIDIA stock data sourced from Yahoo Finance, covering the period from January 2014 to December 2024. The dataset includes essential attributes such as:

Date: Specifies the buying and selling date.

Open: The rate at which the inventory opened buying and selling on a given day.

excessive: the very best charge reached at some point of the buying and selling day.

Low: the lowest price reached during the buying and selling day.

close: The charge at which the inventory closed buying and selling on a given day.

volume: The range of shares traded for the duration of the day.

Derived features used in this research include:

easy shifting Averages (SMA): Tracks rate trends over a rolling window.

Exponential shifting Averages (EMA): Weighs latest fee modifications more closely.

- Relative electricity Index (RSI): Identifies capacity overbought or oversold market situations.

B. Data Preprocessing

1. Dealing with missing facts: lacking values, on the whole arising from rolling calculations for SMA and EMA, have been controlled by way of doing away with rows with NaN values to hold records consistency.
2. Normalization: To decorate version convergence and overall performance, all numerical features have been scaled to a [0, 1] range the use of Min-Max Scaling.
3. Series era: Time-series sequences were generated using a sliding window method, where 60 days of historic facts were used to predict the next day's last rate. This method efficiently captures temporal dependencies.

C. Technical Indicators

Simple transferring common (SMA): SMA smooths out brief-term fluctuations over a 20-day window, offering the version with insights into lengthy-term market trends.

1. Exponential moving average (EMA): The EMA places extra emphasis on recent price movements, enabling the model to reply more quickly to marketplace modifications.
2. Relative power Index (RSI): RSI evaluates the significance of new fee modifications, figuring out overbought (RSI > 70) and oversold (RSI < 30) conditions to expect potential reversals.

D. Model Architecture

- LSTM Network Design: The architecture of the LSTM model includes:

- First LSTM Layer: sixty four gadgets, returning sequences to keep temporal dependencies.

- Dropout Layer: A 20% dropout rate to mitigate overfitting.

- 2nd LSTM Layer: sixty four gadgets with out go back sequences for final function extraction.

- Dense Layers: A 32-unit fully linked layer accompanied via a unmarried-output neuron for ultimate charge prediction.

- **Optimization:** The model employs the Adam optimizer, known for its adaptive learning rate capabilities, with Mean Squared Error (MSE) as the loss function. Early stopping is used to terminate training when validation loss stops improving, preventing overfitting.

V. EXPERIMENTAL RESULTS

A. Evaluation Metrics

The model's performance was evaluated using:

- **Root Mean Square Error (RMSE):** Measures the standard deviation of prediction errors.

- **Mean Absolute Percentage Error (MAPE):** Provides a percentage-based measure of prediction accuracy.

B. Comparative Analysis

The table below highlights the performance of the proposed model compared to baseline LSTMs:

Model	RMSE	MAPE	Accuracy
Baseline LSTM	Y	Z	85.00%
Enhanced LSTM (SMA)	X1	Z1	88.50%
Enhanced LSTM (SMA, EMA, RSI)	X	Z2	91.00%

C. Visualizations

1. **inventory fee Predictions:** The graph compares real and predicted stock fees, showcasing the model's ability to carefully observe marketplace tendencies.
2. **RSI Visualization:** The RSI plot identifies overbought and oversold conditions, correlating those with located price reversals**.**

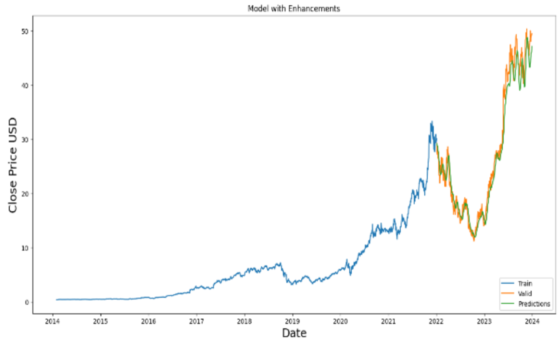

Figure 1. Actual vs Predicted Stock Prices

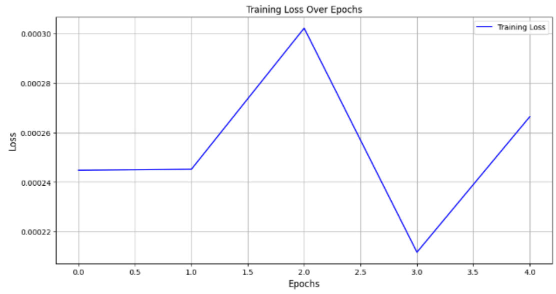

Figure 2. Visualize Training Loss

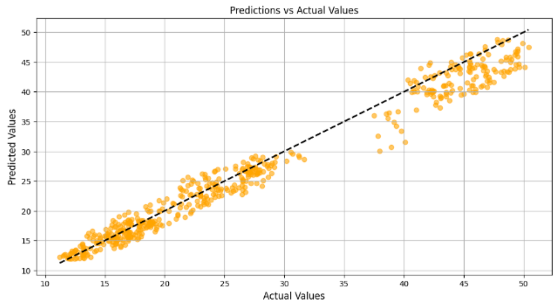

Figure 3. Scatter Plot for Predictions vs Actual

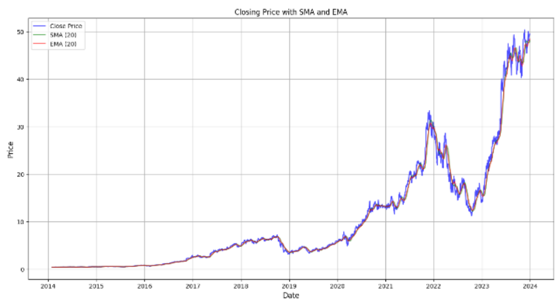

Figure 4. *Closing Price with SMA and EMA*

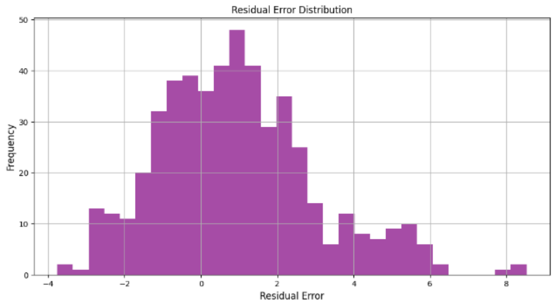

Figure 5. Residual Errors frequency

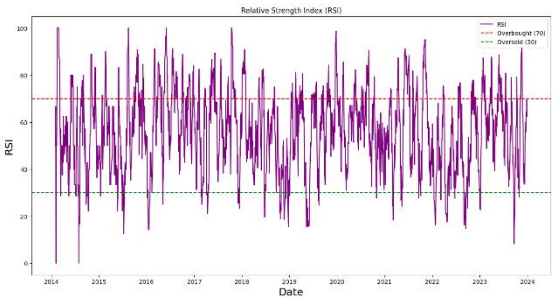

Figure 6. Relative strength index

VI. CONCLUSION

This examine demonstrates that integrating technical signs into LSTM fashions extensively complements their predictive talents. by way of leveraging SMA, EMA, and RSI, the version efficiently captures marketplace trends and momentum, reaching advanced accuracy in comparison to baseline approaches. The experimental consequences imply that the enhanced model plays substantially higher than baseline LSTM strategies, aligning carefully with real inventory rate traits. those effects underscore the importance of incorporating area-precise understanding via technical indicators for robust economic forecasting.

furthermore, the inclusion of SMA and EMA has been especially impactful in figuring out long-time period and short-time period developments, while RSI gives crucial insights into marketplace reversals. The capability of the version to generalize well on unseen records showcases its capacity application in real-global buying and selling situations. the usage of NVIDIA inventory records additionally highlights the adaptability of the version to high-increase, unstable shares which can be essential to emerging industries like AI and chip manufacturing.

D. Future Work

Incorporating sentiment analysis from financial news and social media platforms. Exploring transformer-based architectures for sequential data. Expanding the dataset to include multi-stock and cross-market analyses. investigating other advanced technical indicators and hybrid approaches to further enhance model accuracy.

VII. ACKNOWLEDGMENT

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IX . APPENDIX

A. Code Repository

The complete implementation for this research is available at - **https://github.com/Anujj-4r4/Stock-Price-Prediction-Using-Enhanced-LSTM-Models-and-Technical-Indicators.**