STOCK PRICE PREDICTION AND DIRECTION CLASSIFICATION FOR APPLE INC. USING LSTM

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Introduction

- Stock market prediction is one of the most complicated challenges in the financial area. Traditional statistical models struggle with capturing the non-linear dependencies and chaotic behavior exhibited by stock prices.
- This project explores the application of Long Short-Term Memory (LSTM) neural networks — a type of Recurrent Neural Network (RNN) — to predict the stock price movement of Apple Inc (AAPL).
- Long Short Term Memory networks are known for their capability to understand long term dependencies, making them perfect for time-series forecasting tasks like stock prediction.

By training on historical stock data and technical indicators, the aim is two fold:

- Predict the future stock prices.
- Classify the future price movement as "Up" or "Down" (binary classification).

Problem Statement and Proposed Solution

- Investors and analysts constantly continuously search for reliable and robust models for stock price prediction and movement direction to enhance trading strategies and for risk management.
- Traditional approaches often fail to adapt the non-stationarity, noise, and external influences that characterize financial time series.

  Our proposed solution was to use a hybrid deep learning model based on LSTM networks.

  We designed our model to:

  - Predicts the next-day closing prices of Apple Inc. based on past data.
  - Labels the movement direction as Up or Down based on predicted and previous prices.
  - It uses the Relative Strength Index (RSI) as a technical feature to improve directional trading signals.

Architecture Used

Our architecture consists of the following:

- **Data Source:** We used Yahoo Finance to collect Apple's daily stock closing prices and calculated the RSI as a feature.
- **Data Range:** Data from 2015 till the present.
- **Model Design:**
  - The input layer receives a sequence of past stock prices.
  - Three stacked LSTM layers, each having 50 units, process the sequential data.
  - Dropout layers can be optionally added to prevent overfitting.
  - Output consists of a Dense layer: predicts continuous prices.
- **Hyperparameters:** We used Mean Squared Error(average squared difference between predicted and actual values) as the loss function, Adam as the optimizer, and trained the model for 100 epochs with a batch size of 64.
- **Visualization Tools:** Matplotlib was used for plotting graphs, and Confusion Matrix Display from Scikit-learn for classification results.

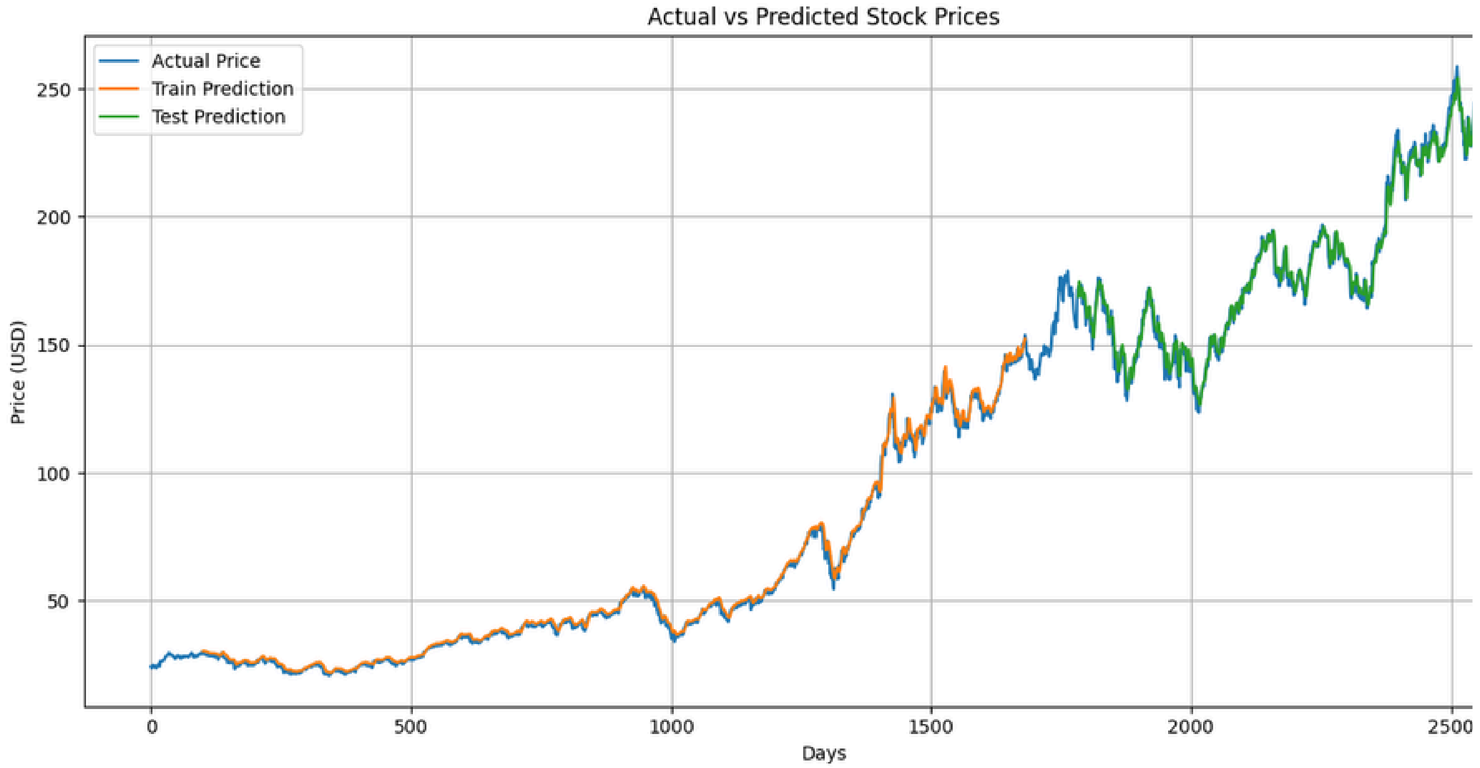
Result

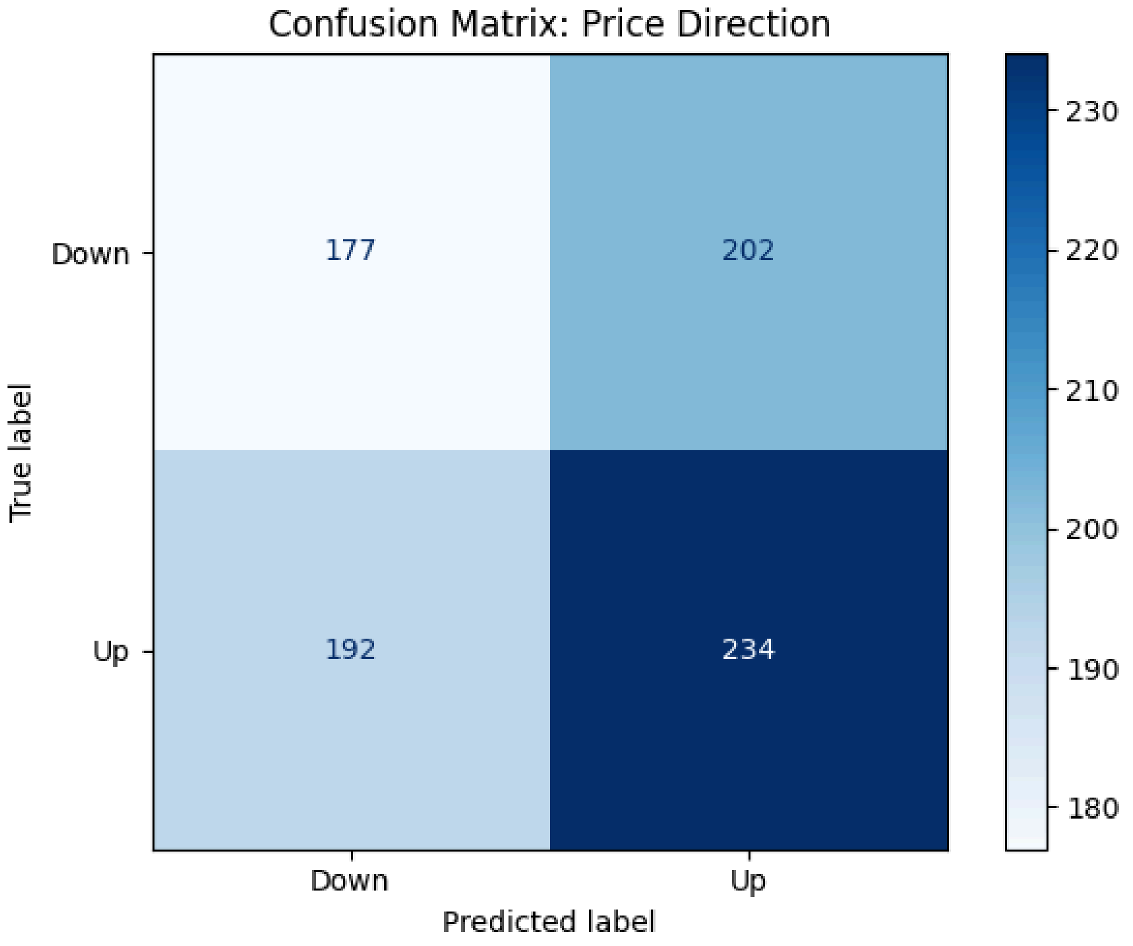
Our model performed well on price prediction:

- RMSE: 4.14 - lower RMSE value indicates a better fit.
- MAE: 3.07 - It measures the average magnitude of the errors in predictions, without considering their direction
- R^2 Score: 0.98 - The model fits the data very well.

For classification:

- Accuracy (51.06%): The prediction of the model is slightly better than random guessing.
- Precision (53.67%): About 54% of the predicted movements were correct.
- Recall (54.93%): The model correctly identifies 55% of actual movements.
- F1-Score (54.29%): There is a balanced measure of precision and recall that showing moderate performance.





Overall Analysis

- The LSTM-based model shows excellent ability in forecasting stock prices (high R^2, low error metrics).
- Classification of price direction still remains challenging because of the volatility in natural stock, market noise, and external factors like news which are not a part of the model.
- Including technical indicators like RSI helped improve the decision making even if classification metrics are average.
- Overall, the model shows promise, but more work is needed especially for directional classification.

Future Work

- Use sentiment analysis of news headlines related to Apple Inc.
- Use hybrid models like a combination of LSTM and XGBoost to utilise strengths of different algorithms.
- Hyperparameter tuning using techniques like Bayesian Optimization.
- Exploring transformer-based models for better temporal awareness.

Conclusion

- Deep learning models specifically the LSTM models, exhibit strong potential in the stock market prediction.
- While predicting the direction of stock movement correctly remains difficult, a combination of forecasting models along with technical indicators presents a tool that has better-informed trading decisions.
- Continuously enhancing and incorporating of bigger data sources will further boost model accuracy and robustness.
- Future improvements like hybrid models, sentiment analysis, and advanced architectures can enhance model performance and reliability.

THANK YOU

For your attention