Stock Price Prediction and Direction Classification for Apple Inc. Using LSTM

Submitted for
CBCA216: Intelligent Model Design using AI

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1.Introduction

Stock market prediction remains one of the most complex and dynamic challenges in the financial domain. 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)**. LSTM networks are known for their ability to learn long-term dependencies, making them particularly suited for time-series forecasting tasks like stock prediction.

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

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

This dual-objective approach enhances the model's practical applicability for traders and investors.

2. Problem Statement & Proposed Solution

Problem Statement

Investors and analysts constantly seek accurate and robust models for stock price prediction and movement direction to optimize trading strategies and manage risks. Traditional approaches often fail to accommodate the non-stationarity, noise, and external influences that characterize financial time series.

Proposed Solution

We propose a **hybrid deep learning approach** using LSTM networks that:

- Predicts the next-day closing prices of Apple Inc. based on historical data.
- Classifies the movement direction (Up/Down) based on predicted and previous prices.
- Utilizes the **Relative Strength Index (RSI)** as a technical feature to improve directional trading signals.

Evaluation Strategy

- **Regression Metrics:**
    - Mean Absolute Error (MAE)
    - Root Mean Squared Error (RMSE)
    - R^2 Score (Coefficient of Determination)
- **Classification Metrics:**
    - Accuracy
    - Precision
    - Recall
    - F1-Score

Incorporating both regression and classification evaluation gives a **comprehensive view** of model performance

3.Architecture Used

Data Pipeline

- **Data Source:** Yahoo Finance via `yfinance` API
- **Features Used:**
    - Closing Prices (daily)
    - Relative Strength Index (RSI) — a momentum indicator for trading signals
- **Data Range:**
    - From 2015 to Present (latest available data)

Model Architecture

- **Input Layer:** Sequence of past stock prices (look-back window)
- **Hidden Layers:**
    - 3 stacked LSTM layers (each with 50 units)
    - Dropout layers (to prevent overfitting) — [Recommended but optional in future]
- **Output Layer:**
    - Dense layer for price prediction (continuous)
    - Dense layer (with Sigmoid activation) for direction classification (binary)
- **Hyperparameters:**
    - Loss Function: Mean Squared Error (MSE) for price prediction
    - Optimizer: Adam
    - Epochs: 100
    - Batch Size: 64
    - Learning Rate: Default Adam settings

Visualization and Evaluation Tools

- **Matplotlib:** For plotting actual vs predicted graphs.
- **ConfusionMatrixDisplay (Scikit-learn):** For classification evaluation.

4.Results

Model Evaluation:

- **RMSE**: 4.14
- **MAE**: 3.07
- **R^2 Score**: 0.98

Interpretation:

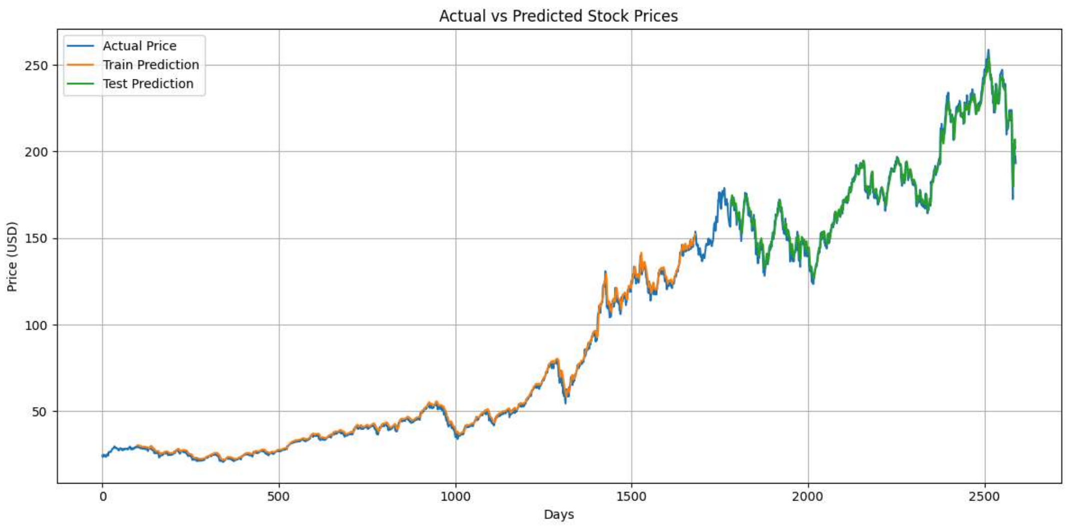
The very high R^2 score (0.98) combined with low RMSE and MAE indicates strong model ability to fit the data, capturing trends accurately.

Classification Metrics:

- **Accuracy**: 51.06%
- **Precision**: 53.67%
- **Recall**: 54.93%
- **F1 Score**: 54.29%

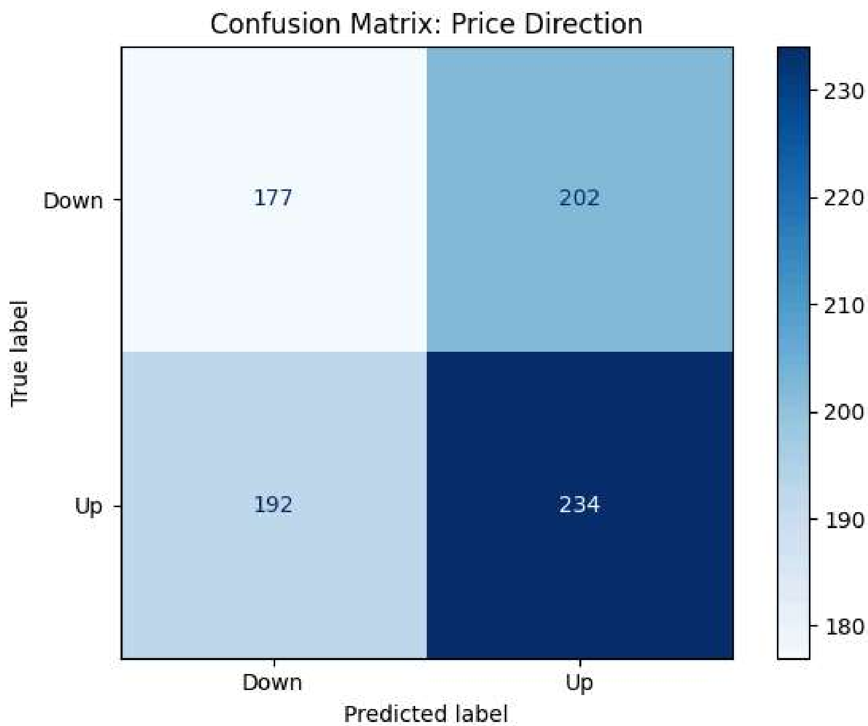
Interpretation:
Classification metrics show moderate performance. Although slightly better than random guessing (~50%), further improvements (e.g., feature engineering, ensemble methods) could be explored.

Actual vs Predicted Prices Graph



30-day Future Forecast

Confusion Matrix (Up/Down direction)



What this means:

- The model correctly predicted "Down" 177 times.
- It correctly predicted "Up" 234 times.
- It wrongly predicted "Up" instead of "Down" 202 times.
- It wrongly predicted "Down" instead of "Up" 192 times.

Performance:

- Accuracy (overall correct predictions) is about 51%.
- Precision for Up (how often it was correct when it said "Up") is about 54%.
- Recall for Up (how often it caught actual "Up" movements) is about 55%.
- Precision for Down is about 48%.
- Recall for Down is about 47%.

Summary:

- The model is only slightly better than guessing randomly.
- It is a little better at predicting "Up" than "Down".

- There are many wrong predictions, showing that the model needs to improve.

5.Overall Analysis, Limitations & Conclusion

Analysis

- The LSTM-based model demonstrates excellent capabilities in forecasting stock prices (high R^2, low error metrics).
- Classification of price direction remains challenging due to natural stock volatility, market noise, and external factors (news, geopolitical events) which are not included in the model.
- Integrating technical indicators like RSI improves practical decision-making even if classification metrics are moderate.

Limitations

- **Limited Features:** Only closing price and RSI used. Including volume, MACD, moving averages could enhance results.
- **External Factors Ignored:** Real-world events, earnings reports, or macroeconomic indicators significantly influence stock prices.
- **Risk of Overfitting:** Deep learning models risk memorizing noise instead of general patterns if not tuned carefully.
- **Lag in RSI:** RSI itself is a lagging indicator; combining it with predictive indicators could improve strategies.

Future Work

- Integrate **sentiment analysis** of news headlines related to Apple Inc.
- Use **hybrid models** (e.g., LSTM + XGBoost) to leverage strengths of multiple algorithms.
- Tune hyperparameters using techniques like **Bayesian Optimization**.
- Explore **attention mechanisms** or **transformer-based models** for better temporal understanding.

Conclusion

Deep learning models, particularly LSTM networks, show promising potential in stock market prediction tasks. While predicting the exact direction of stock movement remains inherently difficult, combining predictive modeling with technical indicators offers a practical tool for better-informed trading decisions. Continued enhancements and incorporation of broader data sources will further boost model accuracy and robustness.