PORTFOLIO OPTIMIZATION USING DEEP LEARNING TECHNIQUES

FINAL PROJECT REPORT

IST 691 :- DEEP LEARNING IN PRACTICE

M002 - GROUP 05

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1. Project Overview

Portfolio optimization is the process of selecting the right mix of assets to maximize returns while minimizing risk. Traditional methods, though widely used, often struggle to account for the complex relationships and changing conditions of financial markets. This project explores a new approach to portfolio optimization using a CNN-LSTM model.

Convolutional Neural Networks (CNNs) are used to identify relationships between different assets, while Long Short-Term Memory (LSTM) networks focus on understanding patterns and trends over time. Together, these techniques offer a better way to analyze financial data, predict market movements, and create more effective portfolios. By applying these deep learning methods, this project aims to provide a fresh perspective on portfolio optimization, helping investors make smarter decisions in a fast-changing market.

Portfolio Optimization Using Deep Learning Techniques leverages CNN-LSTM architecture to optimize investment portfolios by predicting asset price movements. It focuses on addressing the limitations of traditional methods, such as Markowitz's Mean-Variance Optimization, by incorporating deep learning techniques that model non-linear dependencies and process financial data. By utilizing Yahoo Finance API data, the project aims to help investors make more informed decisions through enhanced predictions of asset prices and market trends.

2. Goals

The primary goals of the project are:

1. Prediction Goals:
    - Utilize a CNN-LSTM model to accurately forecast the next-day stock prices for different stocks.
    - Specifically, focus on predicting adjusted closing prices, as they reflect the most reliable value by accounting for corporate actions like stock splits and dividends.

2. Inference Goals:
    - Identify significant patterns and dependencies among price-related features (e.g., Open, High, Low, Close) that influence stock price behavior.
    - Analyze stock-specific characteristics, such as volatility and trading volume, to understand their impact on prediction accuracy.

3. Visualization Goals:
    - Generate intuitive and informative visualizations, including: Line graphs showing actual vs. predicted stock prices to evaluate model performance.

- Candlestick charts to highlight stock trends and trading activity. Use these visualizations to support insights into data trends, model behavior, and prediction accuracy.

4. Portfolio Optimization Goals:
   - Create a way to build a better investment portfolio using deep learning.
   - The goal is to balance risk and returns while overcoming the limits of traditional methods like Markowitz's approach, which struggles with complex patterns.

3. Data Exploration

Dataset Summary:

Source: Yahoo Finance

Stock Ticker: AAPL (Apple Inc.), XLC (Communication Services Select Sector SPDR Fund)

Date Range: [2023-10-31] to [2024-10-31]

Features:

- Date: Serves as the index for the time series dataset.

- Open: The starting price of the stock for each trading day.

- High: The highest price during the trading day, indicative of price spikes and volatility.

- Low: The lowest price during the trading day, complementing High to show the daily trading range.

- Close: The final price of the stock at the end of each trading day.

- Adj Close: Adjusted closing price accounting for corporate actions like splits and dividends, offering the most reliable price.

- Volume: Total number of shares traded during the day, reflecting market activity and liquidity.

Preprocessing:

1. Preprocessing Missing Data:
   Missing values were primarily caused by non-trading days (e.g., weekends and holidays). These gaps were handled using the forward-fill method to ensure continuity in the time series.

2. Normalization: The features were scaled using MinMaxScaler to normalize the data between 0 and 1, ensuring all features had equal weight in the deep learning model.

3. Look Back Period: A 60-day look back period was applied to create feature sequences, capturing historical trends and patterns for input into the CNN-LSTM model. This window length balances short-term variability with long-term trends.

4. Summary of Methods

Model Architecture:

The predictive model combines Convolutional Neural Networks (CNN) for feature extraction and Bidirectional Long Short-Term Memory (LSTM) layers to capture temporal dependencies in stock price movements. To further enhance the model's performance, an Attention mechanism is incorporated to refine the prediction process. The architecture concludes with dense layers for regression tasks, predicting the future day adjusted closing prices.

Technical Details:

- Optimizer: Adam
- Loss Function: Mean Squared Error (MSE)
- Training Epochs: 100
- Batch Size: 32

Workflow:

The dataset was preprocessed by normalizing individual stock symbols using MinMaxScaler, ensuring all features have equal weight. A 60-day look-back window was applied to create input sequences, capturing historical trends for model training. Separate models were dynamically created for each stock symbol. For training, the dataset was split into 80% training and 20% testing sets. Model performance was measured using MSE to evaluate prediction accuracy. Line graphs and candlestick charts were used to compare actual and predicted stock prices, showing the model's ability to follow trends.

➢ Comparison of MSE with different models:-

Models	**Average MSE**
CNN-Bidirectional LSTM with Attention	6.42
CNN-LSTM Based Model	9.74
Combined SARIMA CNN-LSTM	38.53

The comparison table shows the performance of three models based on their average Mean Squared Error (MSE). The CNN-Bidirectional LSTM with Attention achieved the lowest average MSE of 6.4268, showcasing its superior ability to capture both past and future dependencies while focusing on the most relevant patterns through the attention mechanism. This made it the most accurate and reliable choice for our predictions. The CNN-LSTM Based Model followed with an average MSE of 9.7413, performing well but lacking the added benefits of bidirectionality and attention. In contrast, the Combined SARIMA CNN-LSTM model had a significantly higher MSE of 38.53, reflecting its limitations in handling the dataset's complexity.

5. Results

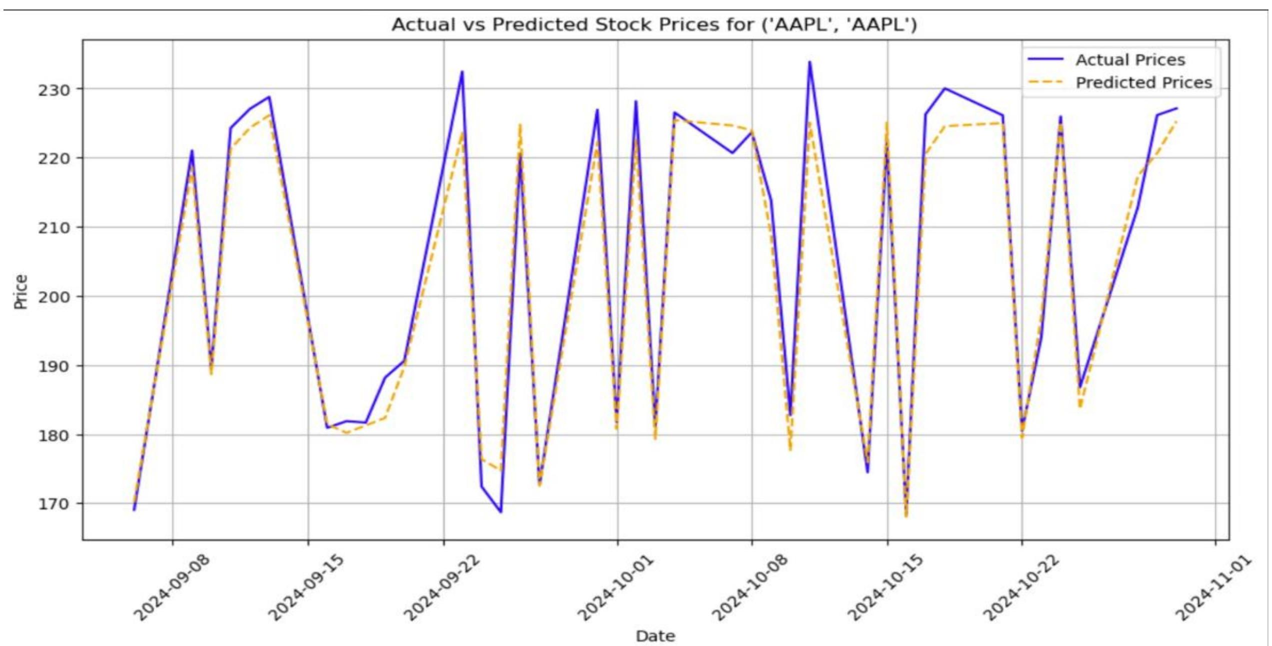

Figure 1: This chart compares the actual and predicted stock prices for AAPL over time. The actual prices (blue solid line) exhibit frequent and sharp fluctuations, which the predicted prices (orange dashed line) generally follow closely, indicating the model's ability to track trends.

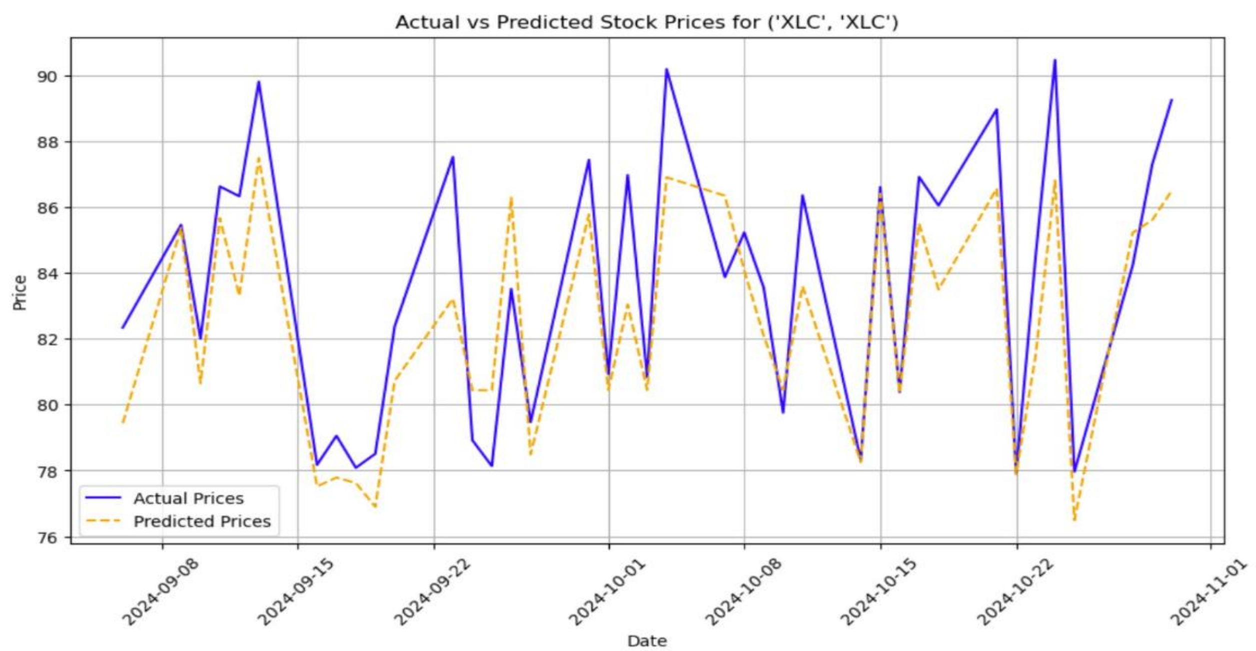

Figure 2: Actual vs. Predicted Stock Prices for XLC. This chart highlights the model's ability to track stock price trends effectively while exposing its limitations in accurately predicting rapid price spikes or drops.

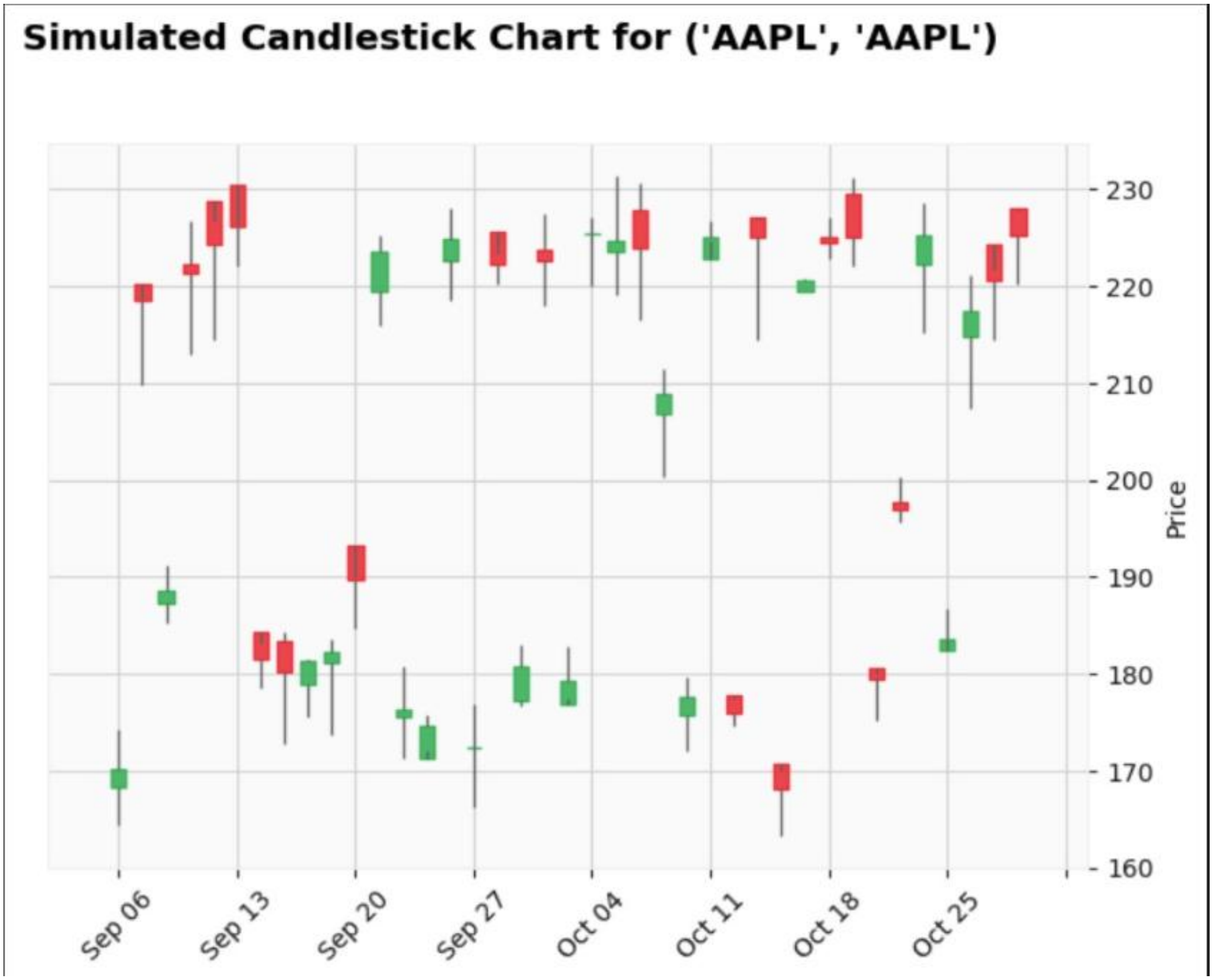

Figure 3: Simulated Candlestick Chart for AAPL. This chart visually captures the stock's daily price behavior, showing upward trends and periods of high volatility. The presence of green and red candles highlights alternating bullish and bearish days, while the wick lengths point to significant intraday fluctuations.

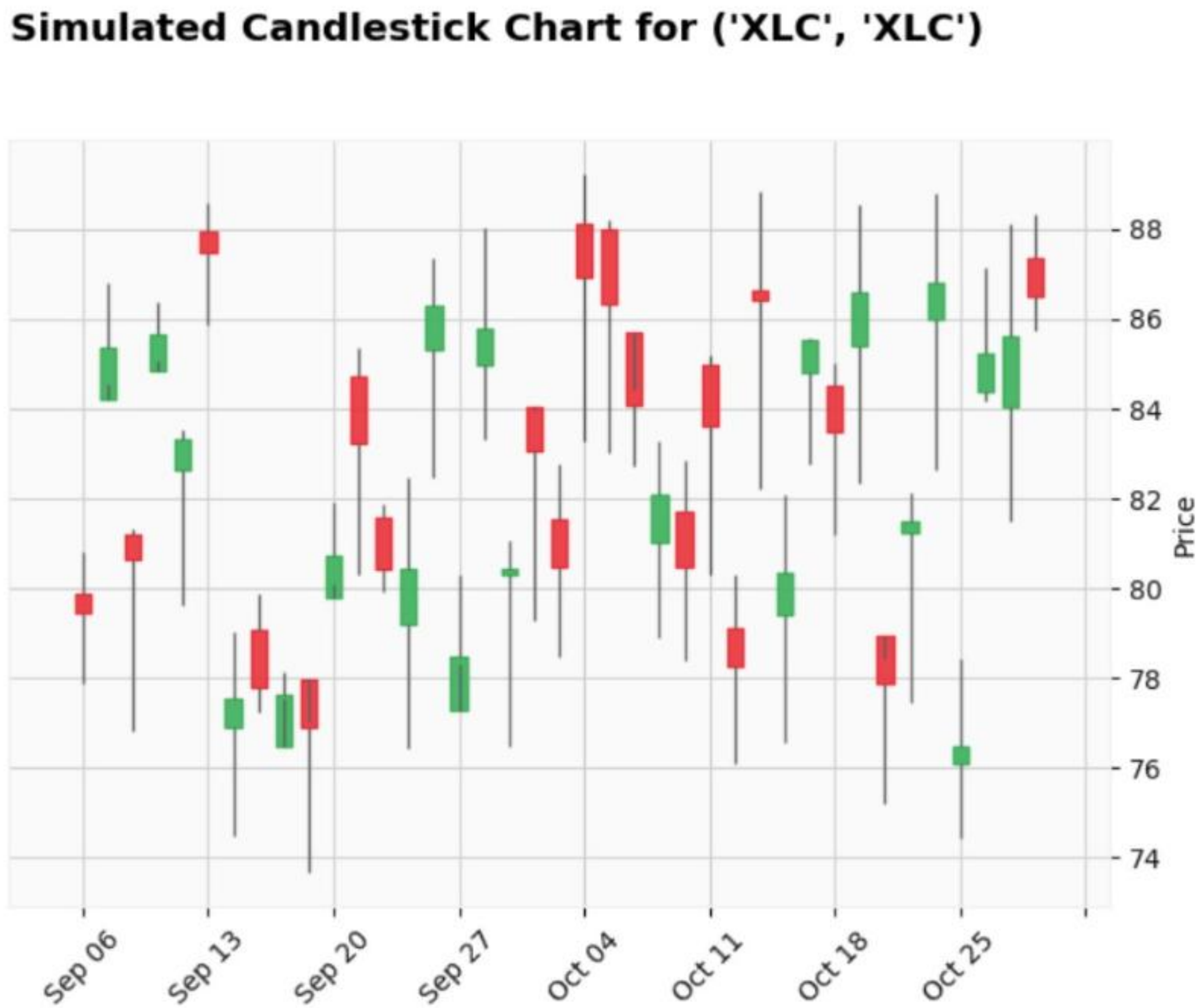

Figure 4: This chart captures XLC's daily stock price movements, showing opening, closing, high, and low prices. Green candles indicate bullish days where prices closed higher than they opened, while red candles signify bearish days with a lower close. The distribution of green and red candles showcases alternating trends, with periods of upward and downward momentum shaping the stock's performance.

6. Challenges Encountered

We encountered the following problems during our project:

1. Data Gaps:
   Financial data from Yahoo Finance sometimes includes missing or NaN values for certain dates or specific stock tickers. This can occur due to market holidays, incomplete data

updates, or API limitations. For example, during weekends or public holidays, the stock market is closed, resulting in missing data points.

2. High Market Volatility Problem:
   Financial markets are highly volatile, making it challenging for the model to generalize. Sudden price spikes or drops caused by specific events or announcements introduce noise in the data.

3. API Limitation:
   Initially, data was sourced from the Alpha Vantage API, but it lacked the "Adjusted Close" column essential for accurate stock price predictions. As a result, we switched to the Yahoo Finance API, which provided more comprehensive data.

7. Discussion and Conclusion

This project utilized a CNN-LSTM bi-directional model with an attention mechanism to predict stock prices by analyzing historical data. The combination of convolutional layers and LSTM layers with attention allowed the model to identify patterns in the data and learn trends over time. Preprocessing techniques, such as normalization and feature scaling, ensured the data was prepared effectively for modeling. Metrics like moving averages and daily returns were used to extract meaningful insights from the data, aiding in the model's understanding of trends.

This work demonstrates the effectiveness of deep learning models for stock price prediction by uncovering patterns that traditional methods may not detect. Future improvements could involve experimenting with different look-back periods to identify the optimal amount of historical data required for accurate predictions. Additionally, expanding the data range and testing advanced techniques could further enhance predictions.

8. Citations

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