**PORTFOLIO OPTIMIZATION USING DEEP LEARNING TECHNIQUES**

**FINAL PROJECT REPORT**

**IST**

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**:- DEEP LEARNING IN PRACTICE**

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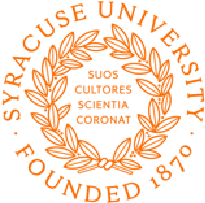
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1. **Project Overview**

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 Alpha Vantage API data, the project aims to help investors make more informed decisions through enhanced predictions of asset prices and market trends.

1. **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.

1. 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.

1. 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.

1. 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.

1. **Data Exploration**

Dataset Summary:

Source: Yahoo Finance

Stock Ticker: AAPL (Apple Inc.), TSLA (Tesla Inc)

Date Range: [2024-01-01] to [2024-11-30]

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.

1. 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.
2. 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.
3. **Summary of Methods**

**Model Architecture:**

CNN-LSTM:

* CNN: Captures relationships and correlations between assets.
* LSTM: Models temporal dependencies in stock price movements.
* Input: Preprocessed historical stock prices normalized between 0 and 1.
* Output: Predicted adjacent closing prices for the next days.

Technical Details:

* Optimizer: RMSprop
* Loss Function: Mean Squared Error (MSE)
* Training Epochs: 40
* Batch Size: 64

Workflow:

* Historical stock prices were fetched using yfinance.
* Features were normalized using MinMaxScaler to ensure uniform scaling.
* Data was split into training (80%) and testing (20%) sets.
* The CNN-LSTM model was trained on the data to predict adjacent closing prices.

1. **Results**

A graph showing the difference between stock prices

Description automatically generated

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.

A graph showing the price of a stock price

Description automatically generated

Figure 2: Actual vs. Predicted Stock Prices for TSLA. 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.

A chart with red and green candlesticks

Description automatically generated

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.

A graph of candlesticks on a white background

Description automatically generated

Figure 4: This chart captures TSLA'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.

1. **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.

1. 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.

1. Overfitting Problem:

Due to the limited size of the dataset (e.g., daily prices for less than a year), the model risked overfitting, particularly with complex architectures like CNN-LSTM. Overfitting was evident when the model performed well on the training data but poorly on the test set.

1. **Discussion and Conclusion**

This project utilized a CNN-LSTM model to predict stock prices by analyzing historical data. The combination of convolutional layers and LSTM layers 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.

The model performed well in capturing general trends, but challenges were observed with sudden price changes and limited data coverage. These challenges highlight the importance of using larger datasets and incorporating additional factors, such as market news or broader economic conditions, to improve accuracy.

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.

1. **Citations**

Aadhitya, A., et al. "Predicting Stock Market Time-Series Data Using CNN-LSTM Neural Network Model." *arXiv*, 21 May 2023, arxiv.org/abs/2305.14378v1.

Eapen, Jithin, et al. "Novel Deep Learning Model with CNN and Bi-Directional LSTM for Improved Stock Market Index Prediction." *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, IEEE, 2019, pp. 264–270, doi:10.1109/CCWC.2019.8666592.

Mehtab, Sidra, et al. "Robust Analysis of Stock Price Time Series Using CNN and LSTM-Based Deep Learning Models." *arXiv*, 7 Nov. 2020, arxiv.org/abs/2011.08011.

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