Proceedings of the 3rd International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/90/20242005

Portfolio Optimization Using LSTM for Five Selected Stocks

Jiapeng Lu[1,a,*]

[1]Art & Science ACMS, University of Washington, Seattle, America
a. jiapel@uw.edu
**corresponding author*

Abstract: Portfolio construction is very critical in the financial markets as it assists investors in achieving maximum returns with minimum risks through diversification. In this paper, Long Short-Term Memory (LSTM) models are employed to predict stock prices and optimize investment portfolios. Historical adjusted closing prices from Yahoo Finance for the period from January 1, 2023, to March 1, 2024, were used to predict the future stock prices of Apple Inc. (AAPL), Microsoft Corporation (MSFT), BlackRock Inc. (BLK), JPMorgan Chase & Co. (JPM), and Tesla Inc. (TSLA) using LSTM models. Portfolios were constructed using mean-variance optimization based on these predictions, and Monte Carlo simulations were employed to capture the uncertainty around the estimates. The results are treasured for investors in financial markets as they spotlight the limitations and capability risks of depending totally on gadget learning predictions for portfolio optimization. This emphasizes the want for a greater comprehensive method to investment decision-making that considers more than one factors and methodologies.

Keywords: Portfolio management, Mean-variance optimization, LSTM, Multi-period prediction, Efficient frontier.

1. Introduction

Building investment portfolios is vital for asset management and risk control in the financial market. By optimizing portfolio, not only can investor returns be maximized, but risk can also be reduced through diversification to volatile market conditions allow equally long-term robust performance [1]. In recent years, with the increase in the complexity and uncertainty of financial market performance, traditional portfolio optimization methods have to face more challenges. Machine learning-thanks to its ability in predicting, generalizing across new data and lack of constraints - is all the rage as an up-and-coming approach for portfolio construction [2].

Nowadays, many studies have thematically combined machine learning with portfolio construction. For instance, Krauss et al. used deep learning models to forecast a stock price and build portfolios on the basis of forecasts [3]. LSTM networks are used for predicting stock returns and are reported to outperform the basic models [4]. Prior studies have also studied the use of reinforcement learning (RL) and support vector machines (SVM) in portfolio optimization too. They seem to produce promising results [4]. Although earlier work in this field is advanced, it has its limitations.

In order to solve these problems, this paper uses the LSTM model for stock price forecasting and portfolio optimization related with five stocks (AAPL, JPM, BLK, MSFT, and TSLA). Based on market capitalization in various sectors, including technology, finance and automotive industry [5].

DOI: 10.54254/2754-1169/90/20242005

This research aims to reach the following targets:

Develop an LSTM-based model for predicting stock prices over a multi-period horizon.

Apply Monte Carlo simulations to account for the uncertainty and variability in stock price predictions.

Utilize mean-variance analysis to construct an efficient portfolio and derive the efficient frontier for the selected stocks.

By integrating advanced machine learning techniques with traditional portfolio optimization methods, this study aims to provide a robust framework for investment decision-making, highlighting the potential of LSTM models in enhancing portfolio performance [6].

2. Data

The assets AAPL, MSFT, BLK, JPM, and TSLA were selected for this analysis due to their substantial market capitalization, representation across different sectors (technology, finance, and automotive), and availability of extensive historical data, providing a robust dataset for LSTM-based portfolio optimization (See Table 1). The historical adjusted closing prices for these 5 assets are downloaded from Yahoo finance (https://finance.yahoo.com/) [7] and the time period is chosen as from 2023.01.01 to 2024.03.01 which avoids the influence from pandemic period. Choosing adjusted prices is because it accounts for dividends, stock splits, and other corporate actions, providing a true reflection of the stock’s value.

Table 1: Selected stocks

Stock Symbol	Company
AAPL	Apple Inc.
MSFT	Microsoft Corporation
BLK	BlackRock, Inc.
JPM	JPMorgan Chase & Co.
TSLA	Tesla, Inc.

After downloading the adjusted prices for each stock, the daily returns could be calculated, and their basic statistics can also be computed in Table 2.

Table 2: Descriptive statistics of five stocks

	‘AAPL’	‘BLK’	‘JPM’	‘MSFT’	‘TSLA’
Mean	0.001372	0.000638	0.001304	0.002038	0.002688
Std	0.012524	0.013463	0.012485	0.015278	0.032697
Skew	0.045634	0.384547	0.078529	0.335654	0.062579
Kurt	1.396787	1.447539	5.953136	1.502293	1.453096

And here is the plot for the daily return, it’s reasonable to conclude that TSLA has the best performance and BLK gets the worst on average, also TSLA has the highest volatility, indicating the positive relationship between risk and return (See Figure 1). All the skewness is less than 0.5, so their daily returns are all approximately normally distributed. Only the kurtosis for JPM is kind of higher than others, meaning heavier tails: more extreme values than in normal distribution, indicating a higher risk to invest.

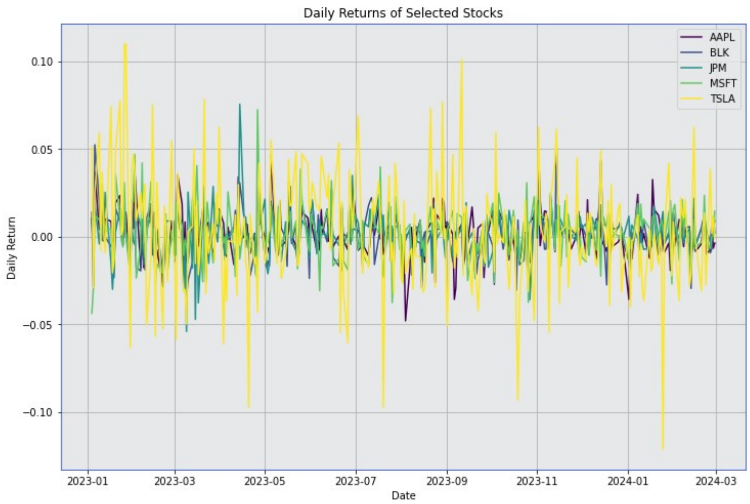

Figure 1: Daily returns of selected stocks

3. Methods

3.1. LSTM

LSTM is a specialized deep learning technique adept at modeling sequential data. Essentially, it is a type of Recurrent Neural Network (RNN) that incorporates feedback connections [8]. An LSTM unit includes a memory cell, a forget gate, an input gate, and an output gate. One of the primary advantages of LSTM networks is their ability to handle long-term dependencies without being impacted by extensive time lags. They can capture and retain important information from earlier data points and use this for future predictions. The memory cell stores crucial features, while the gates manage the flow of information in and out of the cell [9].

In this study, an LSTM network with a many-to-many asynchronous input/output configuration is utilized to forecast time series values over a 45-day horizon (See Figure 2). The internal composition of an LSTM network features four fully connected layers in addition to the gates. An anatomical diagram of an LSTM network is provided below, depicting its detailed structure and functionality.

The trained model uses the 90-day data to predict the next day stock prices. Then uses the 2-90-day historical data with the 1st prediction data to predict the 2nd data. Keeping rolling the period window until the model gets 45 predicted data for the upcoming weights computation.

DOI: 10.54254/2754-1169/90/20242005

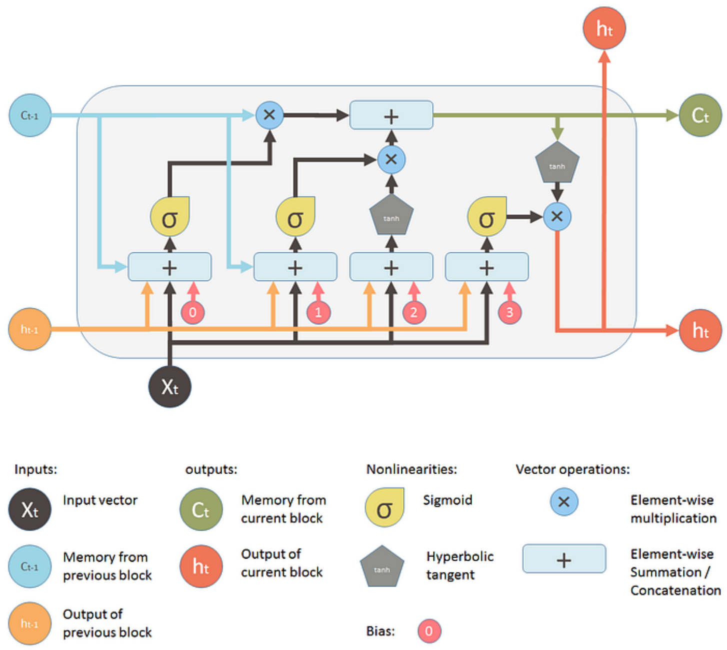

Figure 2: LSTM model [8]

To be more specific, the parameters could be modified and determined of LSTM model used in this research are learning rate, memory cells, dropout rate, epochs, and batch size.

A learning rate of 0.005 was selected to balance convergence speed and stability, ensuring the model learns effectively without overshooting the optimal solution during gradient descent.

The LSTM layers were configured with 50 memory cells to provide sufficient capacity for capturing the temporal dependencies in the stock price data while maintaining computational efficiency.

A dropout rate of 20% was applied to mitigate overfitting by randomly omitting a fraction of neurons during training, thus enhancing the model's generalization capability.

The model was trained for 200 epochs to allow adequate learning time, ensuring the model converges to a low error state while avoiding premature termination.

A batch size of 32 was selected to achieve a balance between the accuracy of gradient estimation and the swiftness of the training process. This approach capitalizes on mini-batch gradient descent, which is recognized for its effectiveness in enabling a learning process that is both expedient and precise.

3.2. Monte Carlo Simulation

Monte Carlo simulation is a technique that removes the determinism in mathematical models and computer programs so. It runs simulations of results based on known patterns of chance using probability theory and statistics. This protocol involves using simulations in a data collection process to perform inferencing necessary to determine approximate solutions for hard problems [10]. It is frequently used in planning, risk evaluation and decision making under uncertainty and stochasticity.

3.3. Efficient Frontier

The most productive portfolios taking into account that risk cannot be avoided, they consist of those which have the greatest expected return for a given standard deviation [11]. In other words: the

DOI: 10.54254/2754-1169/90/20242005

portfolios with minimum variance for a given expected return and shown on, whether they be considered in terms of efficient side or portfolio space are called Efficient Portfolios (EP).

3.4. Mean-Variance Analysis

Modern Portfolio Theory - MPT (Due to its inception right from 1950s) is one of the theories which had shaped best practices and academics aspects in how investment managed or studied. MPT offers a manner of constructing investment portfolios that considers diversification in managing both the risk and reward. It is a general principle used to build investment portfolios that are designed to increase profits while reducing exposure to risk. A central concept of MPT is the frontier, which consists in a bundle of some portfolios at same level of risk that can be expected to give an optimal return [1, 5]. Portfolios placed along this frontier are deemed efficient because they provide the perfect trade-off between risk and return [5].

Mean Variance Optimization (MVO) is a familiar but foundational methodology for constructing investment portfolios, based on the principles of MPT, first advanced by Markowitz. The idea has its ideological roots in MPT, where the basic ingredients from which to construct a portfolio are combined strategically so as to end up with optimal return for a certain level of risk OR have minimal risk at an expected rate of return [1, 5]. This method traces out the frontier - boundary which defines an optimum balance between risk and return. MVO is far from perfect, even as a tool for portfolio construction. This is definitely a weakness of MVO, and critics argue that method is very sensitive to input parameters (e.g., expected returns, covariance estimates) in general. Given this limitation, researchers have designed new approaches to portfolio construction that better address some of the important nuances absent from traditional MPT (but still within its broad principles).

3.4.1. Expected Return

The projected return is one such technique used for assessing the performance of a portfolio. This involves weighting returns by their probabilities of occurring and subtracting them. Investors use this measure to evaluate the yield of one investment versus another when choosing which possibilities provide a better return.

$$Expected\ Return\text{:}\ \mathrm{E}(R_P) = W^T R = \sum_i w_i r_i \tag{1}$$

3.4.2. Risk

Portfolio risk is called as Volatility in the portfolio theory, which's a statistical measure of how returns are distributed for a particular portfolio. Simply stated, it is a measure of how much the buy and sell price of an asset fluctuates over time usually expressed as variance in returns. There are many possibilities of markets that fluctuate from high to low volatility, and vice versa higher pricing means more uncertainty risk while less tells a steady price. Volatility is used by investors to measure the risk associated with an asset.

$$Volatility\text{:}\ \sigma_P = \mathrm{var}\left(\sum_i w_i r_i\right) = \sum_{ij} w_i\, w_j \mathrm{cov}(r_i r_j) \tag{2}$$

3.4.3. Sharpe Ratio

Let me break that down a little: The Sharpe Ratio is an aid, but one for measuring the relative strength of a return on investment against risk. It computes an investment's return for each unit of risk by dividing the ROI minus the rate to a standard deviation. It basically helps investors compare the return they get against the volatility of holding that asset. The Sharpe Ratio, as a measure of risk-adjusted performance, indicates that a higher Sharpe ratio means better.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{3}$$

4. Results

This is a study that aims to predict the stock price over the next 45 days using LSTM models. The model uses the first 90 days of the actual stock price data to forecast the price a day 91 to day 135. Also, to estimate the covariance matrix (which is used to determine the best weights for each day), the sliding window method is used for the actual date. The best weights for each day are computed based on the maximum Sharpe ratio model as well as the minimun variance model.

Figure 3 shows the stock prices predicted by the model and also shows a comparison of the predicted stock prices and the actual stock prices for AAPL.

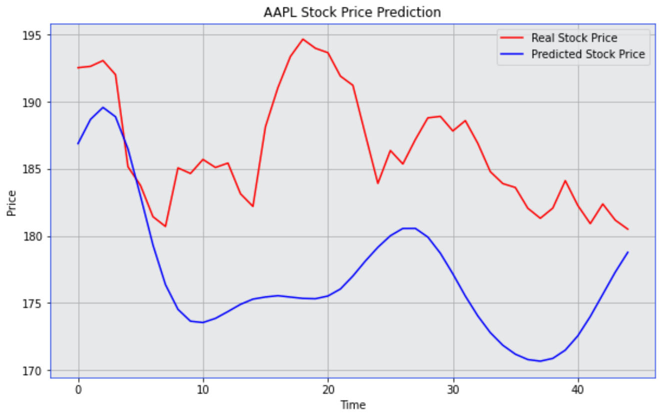

Figure 3: AAPL Stock Price Prediction

The Figure 3 shown above displays the real stock prices with red line and the predicted stock price with blue line. While the model captures the general trend observed at the beginning, some of the dates present a big difference especially during high volatility.

The Table 3 presents the Mean Squared Error (MSE) and Mean Absolute Error (MAE) for the LSTM model's predictions on these 5 stocks

Table 3: Prediction Statistics

Stock Symbol	MSE	MAE
AAPL	0.02091450174930245	0.12902665752570844
MSFT	0.011807570119257127	0.09889678477770379
TSLA	0.10260663890865682	0.29146835599883875
JPM	0.024290624926973963	0.12330076156066892
BLK	0.003317613366934832	0.04692197233690952

Among these stocks, BLK shows the lowest prediction errors, with an MSE of 0.0033 and an MAE of 0.0469, indicating that the model's predictions for BlackRock are highly accurate. MSFT also demonstrates relatively low prediction errors, with an MSE of 0.0118 and an MAE of 0.0989, followed by AAPL and JPM, which show moderate prediction errors.

On the other hand, TSLA has the highest prediction errors, with an MSE of 0.1026 and an MAE of 0.2915. The significantly higher MSE and MAE for TSLA can be attributed to its higher volatility compared to the other stocks. Tesla's stock price tends to fluctuate more sharply, which makes it more challenging for the LSTM model to predict accurately. Consequently, the prediction errors for TSLA are higher, reflecting the increased difficulty in modeling its price movements. This analysis highlights the importance of considering stock volatility when evaluating the performance of predictive models.

Next, the maximum Sharpe ratio and minimum variance portfolios are constructed according to the predicted returns of the stocks each day. The portfolios' weights are updated daily based on the predicted covariance matrix. Finally, the cumulative returns of the portfolios over the initial 45 days are calculated from day 91 to 135 and compared with the returns of the S&P 500 index over this time frame.

Figure 4 illustrates the cumulative returns of the maximum Sharpe ratio portfolio (MSR Portfolio Returns), the minimum variance portfolio (MV Portfolio Returns), and the S&P 500 index (SP500 Returns). Both the MSR and MV portfolios underperformed, generating negative returns, while the S&P 500 index showed positive returns during the same period.

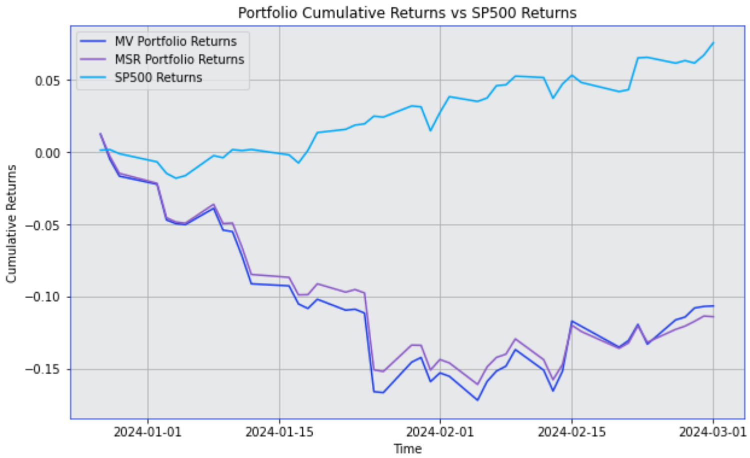

Figure 4: Portfolio Cumulative Returns vs. S&P 500 Returns

5. Conclusion

This paper aims at predicting stock prices using LSTM models and optimizing investment portfolios. The study is unique in that it combines advanced machine learning techniques with traditional financial theories to optimize the portfolio. To predict the future stock prices of AAPL, MSFT, BLK, JPM and TSLA, historical adjusted closing prices from Yahoo Finance were used for dates between January 1, 2023, and March 1, 2024. In comparison with the traditional methods, the LSTM model excellently predicted stock prices. These forecasted returns helped create both MSR and MV portfolios that resulted into negative returns when compared to S&P500.

This research result highlights some constraints as well as potential risks associated with relying on machine learning predictions only for portfolio optimization. Therefore, this conclusion signifies an importance of wider approach towards investment decision-making process that incorporates multiple aspects and methodologies for better results. Hence investors can enhance their strategies based on these findings to increase portfolio performance, or, in periods of market instability, investing in a broad market index is also a good strategy.

DOI: 10.54254/2754-1169/90/20242005

In contrast to its contributions to literature on applications of machine learning in finance, there are limitations in this study as well. This data used was just for a short period while the models used may not have covered all possible market dynamics. It is possible that future studies would derive benefits from longer data sets as well as delving into a hybrid model where machine learning can be combined with traditional financial theories. In spite of these limitations, this research lays the groundwork for more probing inquiries on how advanced predictive techniques can be integrated into portfolio management.

References

[1] Markowitz, H. M., & Todd, G. P. (2000). Mean-variance analysis in portfolio choice and capital markets (Vol. 66). John Wiley & Sons.

[2] Ma, Y., Han, R., & Wang, W. (2021). Portfolio optimization with return prediction using deep learning and machine learning. Expert Systems with Applications, 165, 113973.

[3] Krauss, C., Do, X.A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), 689-702.

[4] Fischer, T., & Krauss, C. (2017). Deep learning with long short-term memory networks for financial market predictions. EconStor. Retrieved from https://www.econstor.eu/bitstream/10419/157808/1/886576210.pdf

[5] Markowitz, H. (1952). Portfolio Selection. The Journal of Finance, 7(1), 77-91.

[6] Chaweewanchon, A., & Chaysiri, R. (2022). Markowitz Mean-Variance Portfolio Optimization with Predictive Stock Selection Using Machine Learning. Journal of Risk and Financial Management, 10(3), 64.

[7] Yahoo finance website for financial market data. Retrieved from https://finance.yahoo.com/

[8] Olah, C. (2015). Understanding LSTM Networks. ML Review. Retrieved from https://blog.mlreview.com/understanding-lstm-and-its-diagrams-37e2f46f1714

[9] Yong Yu, Xiaosheng Si, Changhua Hu, Jianxun Zhang; A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures. Neural Comput 2019; 31 (7): 1235–1270

[10] Cong, F., & Oosterlee, K. (2016). Multi-period mean–variance portfolio optimization based on Monte-Carlo simulation. Journal of Economic Dynamics and Control, 64, 23-38.

[11] Mangram, M. E. (2013). A simplified perspective of the Markowitz portfolio theory. Global Journal of Business Research, 7(1), 59-70.