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Leveraging LSTM Predictions for Enhanced Portfolio Allocation with Markowitz Mean-Variance Optimization

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Abstract

This research investigates the application of Long Short-Term Memory (LSTM) networks for predicting expected returns and integrating these predictions into the Markowitz Mean-Variance Optimization (MVO) framework. The study utilized historical data from eight Indonesian stocks: BBCA, BBRI, TLKM, EXCL, UNVR, ICBP, ASII, and SMGR. The dataset covered the period from 2018 to 2024. The LSTM model was employed to predict cumulative returns over a 90-day horizon, and its performance was compared to the Exponentially Weighted Moving Average (EWMA) method. The findings indicate that LSTM achieved lower Root Mean Squared Error (RMSE) than EWMA for four stocks (BBCA, BBRI, UNVR, ICBP), while EWMA demonstrated better performance for the remaining four stocks. MVO results revealed that LSTM-based predictions achieved an average return of 4.285%, surpassing EWMA's 1.856% but falling short of the 12.298% obtained using actual returns. These results highlight the potential of LSTM models to enhance portfolio allocation strategies.

A. Introduction

Indonesia has been experiencing a significant increase in the number of stock investors. The Indonesia Stock Exchange recently set a new record, surpassing six million single investor identifications (SID) [1]. This figure represents an annual growth of approximately 744,000 investors, reflecting the growing level of trust and confidence in the stock market as a viable investment avenue. According to JakPat survey, 15% of respondents reported owning stocks as a form of investment [2]. This percentage may serve as a proxy for understanding the proportion of Indonesians choosing stock investments. The stock market is considered one of the most attractive investment instruments due to its potential to generate high returns, contributing to its rising popularity among investors.

High-return investment instruments are inherently associated with high risks, making effective risk management essential for investors [3]. One approach to managing risk is through portfolio management frameworks. Among these, the Markowitz Mean-Variance Optimization (MVO) framework is one of the most widely utilized tools in portfolio management. The MVO framework provides a systematic approach to asset allocation by optimizing the balance between risk and expected returns [4]. This approach has been applied in various studies to optimize stock allocations, such as the FTSE 100 index [3]. Other studies have utilized MVO to optimize portfolios involving Bitcoin [5], equity funds like the S&P 500 ETF [6], and gold [7].

MVO is a mathematical framework for constructing efficient portfolio that balances risk and return. The goal is to minimize portfolio variance for a given level of expected return or maximize returns for a specified level of risk [6]. The expected return of a portfolio is given by:

$$E(R_p) = \sum_{i=1}^{n} w_i E(R_i) \quad \text{.....(1)}$$

Where $E(R_p)$ is the expected portfolio return, w is the weight of asset, and $E(R_i)$ is the expected return of asset *i.* Next, the portfolio variancem which measures risk, is calculated as:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \quad \text{.....(2)}$$

Where σ_p^2 is the portfolio variance, and σ_{ij} is the covariance between the returns of asset *i* and asset *j*, finally the w is the portfolio weights.

A key component of the MVO framework is the expected return, which serves as a critical parameter directly influencing portfolio allocation outcomes. There are various methods to calculate expected returns. The initial approach proposed by Sharpe utilized the Capital Asset Pricing Model (CAPM) [8]. More recently, Navoneel et al. applied logarithmic returns to calculate expected returns in optimizing stock portfolios from eight companies using MVO [9]. In other research, Thavaneswaran applied exponentially weighted moving average (EWMA) to optimize 444 stocks using MVO [10]. Another research employed the autoregressive integrated moving average (ARIMA) model to estimate expected returns for Bitcoin assets [5]. Advances in machine learning have introduced robust models capable of addressing the complexities and dependencies inherent in sequence modeling. Some researchers have leveraged these methods to calculate expected returns. For instance, neural network models have been used to estimate Bitcoin returns, demonstrating superior performance compared to ARIMA [5].

Long Short-Term Memory (LSTM) networks is a specialized class of Recurrent Neural Networks (RNNs) that are particularly well-suited for capturing temporal dependencies and patterns in time-series data [6]. There are three gate of LSTM, forget gate, input gate, and output gate. These gates regulate the flow of information within the network, enabling it to learn and retain relevant sequences over time. In the context of regression or forecasting, LSTM excels in modeling temporal dependencies, making it particularly suitable for predicting stock prices by capturing the critical relationships between features and labels [11]. The architecture of LSTM is shown in Figure 1 [11].

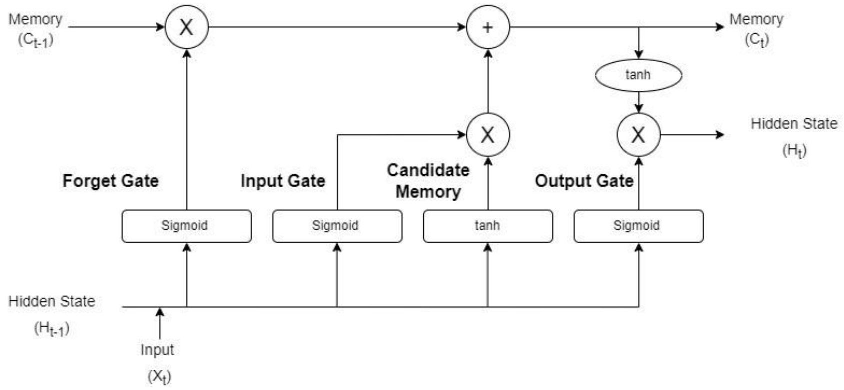

Figure 1. LSTM Architecture

Numerous studies have highlighted the superiority of LSTM models for predicting time-series data. For example, Sarika et al. used LSTM to predict stock prices, achieving an accuracy of 94% [12]. Another research combined LSTM with Bidirectional Encoder Representations from Transformers (BERT) to predict stock prices of Chinese-listed companies [13]. Bathla et al. conducted experiments comparing LSTM with Support Vector Regression (SVR) for forecasting various stock indices, including the S&P 500, NYSE, NSE, BSE, Dow Jones Industrial Average, and NASDAQ. Their results showed that LSTM outperformed SVR in terms of prediction accuracy [14].

Integrating LSTM-based predictions into the MVO framework has the potential to improve portfolio weighting strategies. This approach has been explored in several studies. Sabharwal and Aggarwal stated that LSTM is the most commonly used machine learning model for predicting stock returns, while MVO has emerged as the most popular approach for calculating stock allocation [15]. Ye et al. utilized a combination of MVO and LSTM to determine optimal portfolio allocations among Bitcoin, gold, and cash [16]. Another research predicted the closing prices of the FTSE 100 index using LSTM and adjusted the weightings through the MVO framework [3]. Chaweewanchon and Chaysiri incorporated two variants of LSTM, namely Bidirectional LSTM (BiLSTM) and CNN-LSTM, to predict stock returns, which were then used as inputs for the MVO model. Their experiments demonstrated that incorporating LSTM predictions improved portfolio returns [17].

Lastly, Xiong et al. compared the performance of an LSTM-MVO model with three other strategies, finding that the LSTM-MVO model achieved higher returns than the alternatives [6]. These research underscore the advantages of utilizing LSTM to predict returns, which can then be integrated into the MVO framework for portfolio optimization.

This paper investigates the application of LSTM models for predicting expected returns and their integration into the MVO framework for Indonesian stock prices. This research contributes to the field of portfolio optimization by exploring the applicability and effectiveness of machine learning models within the MVO framework in the context of Indonesia's stock market.

B. Research Method

This research employs a research methodology to integrate predictive modeling with portfolio optimization, focusing on the application of Long Short-Term Memory (LSTM) networks for estimating expected returns. The research framework includes several stages: data extraction, preprocessing, model training, evaluation, prediction, and portfolio optimization.

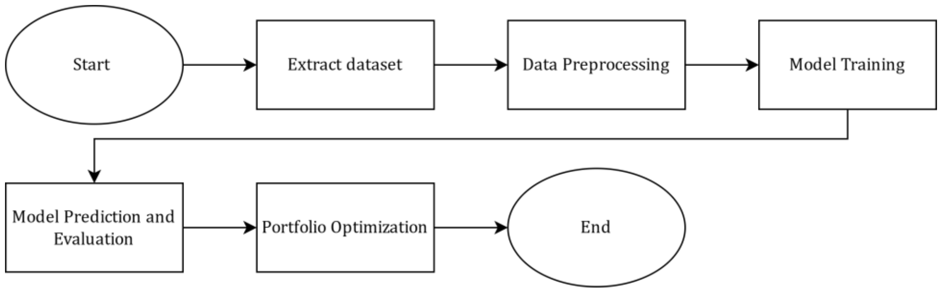

Figure 2. Research Flow

These stages are designed to examine how LSTM-based predictions can contribute to improving portfolio allocation strategies within the Markowitz Mean-Variance Optimization (MVO) framework. The research flow is shown in Fig 2.

1. **Extract Dataset**
   The dataset used in this research consists of historical stock prices obtained from yahoo finance library. Daily Adjusted Closing Prices from 2018 to 2024 were extracted. The stocks included in the dataset were selected based on their liquidity and inclusion in the LQ45 index, These stocks are Bank Central Asia (BBCA,JK), Bank Rakyat Indonesia (BBRI.JK), Telkom Indonesia (TLKM.JL), XL Axiata (EXCL.JK), Unilever (UNVR.JK), Indofood CBP (ICBP.JK), Astra International (ASII.JK), and Semen Indonesia (SMGR.JK).
2. **Data Preprocessing**
   The data preprocessing stage comprised several steps to prepare the dataset for analysis and modeling. First, the dataset underwent a cleaning process where missing values were addressed using linear interpolation, and outliers were identified and removed through statistical techniques. Next, the dataset was split into training and testing sets, with the training dataset spanning the period from 2018 to 2023 and the testing dataset covering data from 2024. Both training and testing datasets were further divided into input features

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(X) and label data (Y). The X data consisted of sequences representing 365 consecutive days (lookback period), capturing historical stock price patterns and trends. The Y labels were calculated as the cumulative percentage return between the closing price on the initial day (D) and the closing price at the end of a 90-day period (D+90) after the training period. This process was repeated with a sliding window approach, shifting one day at a time. In total, 1,000 training samples and 196 testing samples were generated. An illustration of these processes is provided in Table 1, where r denotes return and p denotes the adjusted closing price. To ensure consistency and enhance the performance of machine learning models, all features in X were normalized to a range of [0, 1]. Finally, the dataset was split into 80% for training and 20% for testing.

Table 1. Input and label processing

X	*y*
r1,r2 ... r365	(p455 – p366) / p366
r2, r3 … r366	(p456 – p367) / p367
r3, r4 … r367	(p457 – p368) / p368

3. **Model Training**
   The LSTM model was trained to predict expected returns for individual stocks based on historical price data. The model architecture consisted of an input layer, two LSTM layers with 32 and 8 units, respectively, and an output layer. Dropout techniques were applied to the LSTM layers to prevent overfitting. The model utilized the Adam optimizer and mean squared error (MSE) as the loss function.
4. **Model Prediction and Evaluation**
   The performance of the LSTM model was evaluated using the test dataset. The LSTM predicted the 196 data from test dataset, then root mean squared error (RMSE) was employed to assess prediction accuracy. Additionally, the performance of the LSTM model was compared to EWMA model to assess accuracy and determine whether the difference is significant. EWMA was used as a benchmark for standard performance.
5. **Portfolio Optimization**
   The final stage of this research involved portfolio optimization. The Markowitz Mean-Variance Optimization (MVO) framework was employed to optimize portfolio allocation based on the LSTM-predicted expected returns. For benchmarking purposes, portfolio allocation was also optimized using the EWMA model and actual returns. Lastly, the average returns of the portfolios were calculated and compared.

C. Result and Discussion

The LSTM was trained using 1,000 samples from the training dataset, where each sample consisted of input features (X) and corresponding labels (Y). The dataset was further divided into training and validation sets. In total, eight models were trained, with each stock having its own dedicated model. These models were then used to predict 196 samples from the test dataset, and the Root Mean Squared Error (RMSE) was calculated for each. The RMSE results for these models are presented in Table 2. It can be observed that for 4 out of 8 stocks, specifically BBCA, BBRI, UNVR, and ICBP, the LSTM model achieved a lower RMSE compared to EWMA. However, for the remaining 4 stocks, specifically TLKM, EXCL, ASII, and SMGR, EWMA demonstrated a lower RMSE than the LSTM model.

Table 2. Comparison of LSTM and EWMA RMSE

Model	LSTM - RMSE	EWMA - RMSE	Interpretation
BBCA	0.061	0.073	LSTM is lower
BBRI	0.129	0.140	LSTM is lower
TLKM	0.074	0.072	EWMA is lower
EXCL	0.188	0.173	EWMA is lower
UNVR	0.105	0.144	LSTM is lower
ICBP	0.093	0.096	LSTM is lower
ASII	0.151	0.145	EWMA is lower
SMGR	0.115	0.108	EWMA is lower

Examples of the prediction results from LSTM and EWMA compared to the actual cumulative returns are presented in Table 3. This table displays the cumulative returns predicted by LSTM and EWMA, alongside the actual values, for the BBCA stock.

Table 3. Examples of Predictions and Actual Values

LSTM Prediction	EWMA Prediction	Actual Cumulative Return
5.179%	0.015%	16.691%
4.597%	0.004%	17.728%
5.321%	0.072%	5.485%

Next, the Kolmogorov-Smirnov (KS) test was conducted to evaluate the differences between the predictions of the LSTM model and EWMA. The results are presented in Table 4.

Table 4. KS-Test Result Between LSTM and EWMA Predictions

Stock	KS-Test P value	Interpretation
BBCA	4.904e-110	Significantly Different (Reject H0)
BBRI	1.607e-82	Significantly Different (Reject H0)
TLKM	2.710e-81	Significantly Different (Reject H0)
EXCL	3.10e-49	Significantly Different (Reject H0)
UNVR	4.923e-117	Significantly Different (Reject H0)
ICBP	1.913e-52	Significantly Different (Reject H0)
ASII	5.363e-89	Significantly Different (Reject H0)
SMGR	1.35e-25	Significantly Different (Reject H0)

From Table 4, it can be observed that the interpretation for all stock predictions is significantly different, indicating that the predictions made by LSTM and EWMA were drawn from different distributions.

The final stage of the research involved performing Markowitz Mean-Variance Optimization (MVO) using the expected returns predicted by the LSTM model. These results were then compared to the expected returns calculated using EWMA and the actual returns. For this analysis, the test data was reused, meaning that MVO was performed 196 times, once for each sample. Finally, the average return across these calculations was determined. The average return results are presented in Table 5.

Table 5. Average Return Comparison

Method	Average Return (%)
LSTM	4.285%
EWMA	1.856%
Actual	12.298%

From Table 5, it can be observed that when stock allocation was determined using actual returns, the average return reached 12.298%. In comparison, the average return achieved using LSTM predictions was 4.285%. Although this is lower than the actual return, it is higher than the average return calculated using EWMA, which was 1.856%.

D. Conclusion

This research examined the use of LSTM for predicting expected returns and integrating these predictions into the Markowitz Mean-Variance Optimization (MVO) framework for portfolio allocation. The evaluation on eight stocks demonstrated that LSTM outperformed the traditional Exponentially Weighted Moving Average (EWMA) method in four cases (BBCA, BBRI, UNVR, and ICBP) in terms of lower Root Mean Squared Error (RMSE). However, EWMA showed better predictive performance for the other four stocks (TLKM, EXCL, ASII, and SMGR). A Kolmogorov-Smirnov (KS) test confirmed significant differences between the distributions of predictions made by LSTM and EWMA.

In the portfolio optimization stage, MVO using LSTM predictions achieved an average return of 4.285%, outperforming EWMA's 1.856% but falling short of the 12.298% achieved using actual returns. These results highlight the potential of LSTM models to provide more effective expected return estimates than traditional methods, making them a valuable tool for portfolio allocation in dynamic markets. Future work could explore enhancing LSTM architectures, incorporating additional market features, and applying this approach to other asset classes or global markets to further validate and generalize the findings.

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