

**Enhanced Mean-Variance Optimization
Using Multi-Branch LSTM**

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Table of contents

Introduction.....	3
Methodology	3
Research and Model Selection	3
Multi-Branch LSTM Architecture	3
Data Preprocessing and Model Training	3
Scalability and Liquidity	3
Results and Performance	4
Enhanced MVO Performance	4
Standard MVO Performance	4
Key Takeaways	4
Future Work.....	4
Conclusion	5

Introduction

This report outlines the development and implementation of a stock price prediction model using a Multi-Branch Long Short-Term Memory (LSTM) network, integrated with a mean-variance optimization framework for portfolio management. The project aimed to improve upon previous models and standard Mean-Variance Optimization (MVO) techniques, resulting in significantly enhanced risk-adjusted returns.

Methodology

Research and Model Selection:

After reviewing various stock price prediction models from research papers, including Recurrent Neural Networks (RNNs), Random Forests, and XGBoost, LSTM was chosen due to its ability to handle univariate time series data and capture long-term dependencies in stock price movements.

Multi-Branch LSTM Architecture:

A multi-branch LSTM architecture was implemented to capture interdependencies between ETFs in the portfolio, reducing complexity and computational costs compared to developing separate models for each ETF. This approach allowed for a more holistic view of the market and improved scalability.

Data Preprocessing and Model Training:

Challenges and Solutions:

- **Data Preprocessing:** Non-stationary raw price data was stabilized using differencing techniques.
- **Model Training:** High initial training loss was mitigated by adjusting weight initialization and implementing learning rate scheduling.
- **Hyperparameter Tuning:** Manual fine-tuning was performed to balance training efficiency and model performance, avoiding time-consuming grid or random search methods.

Scalability and Liquidity

The model utilizes sector ETFs, which offer high liquidity and diversification, ensuring scalability while effectively managing risk.

Results and Performance

The integration of the Multi-Branch LSTM predictions with a mean-variance optimization framework yielded impressive results:



Figure 2: Investment Growth Comparison

Enhanced MVO Performance:

- Annualized Return (after 0.1% transaction costs): 33.27%
- Annualized Log Return: 28.88%
- Current Expected Sharpe Ratio: 2.10

This represents a substantial improvement over the previous model (13% annualized returns) and significantly outperforms standard MVO.

Standard MVO Performance:

- Annualized Return (after 0.1% transaction costs): 11.34%
- Annualized Log Return: 10.80%
- Expected Sharpe Ratio: 0.95

Key Takeaways:

- Nearly 3x increase in annualized returns compared to standard MVO.
- More than 2x improvement in risk-adjusted performance.
- Scalable long/short strategy with potential for further optimization.
- Robust performance across various market conditions.

Future Work

While the current Sharpe ratio of 2.1 demonstrates strong performance, it may not fully capture the strategy's risk-return profile. Future work will focus on:

- Exploring more robust risk calculation methods.
- Testing on live data to obtain a more accurate risk profile.
- Further optimizing the Multi-Branch LSTM architecture.
- Investigating the integration of additional technical indicators and fundamental data to enhance prediction accuracy.

Conclusion

The Multi-Branch LSTM approach, combined with mean-variance optimization, has demonstrated significant improvements in both returns and risk-adjusted performance compared to standard methods. This project showcases the potential of combining advanced machine learning techniques with traditional portfolio optimization strategies to achieve superior investment outcomes.