Research on the Potential Use of Artificial Intelligence Systems for Automating Decision-Making in Markowitz Portfolio Formation

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Abstract: Modern financial markets immerse analysts in a whirlwind of vast data volumes, rapid changes, and high uncertainty. These conditions necessitate more flexible approaches than traditional methods. This paper explores the application of artificial intelligence (AI) systems for automating processes related to the Markowitz model in the context of big data analysis. Central to the study is the LSTM machine learning algorithm, which can more accurately predict asset returns and optimize portfolios. The presented results demonstrate that integrating AI significantly enhances adaptability and efficiency in risk management in turbulent market environments.

1 INTRODUCTION

The increasing volume of financial data, which is becoming more heterogeneous and dynamic, poses challenges for traditional analytical models. The complexity of the modern market environment calls for technologies capable of processing vast amounts of information in real-time. However, classical forecasting methods often exhibit limited effectiveness in volatile market conditions.

The work of researchers such as Yoshua Bengio, Geoffrey Hinton, and Yann LeCun has paved the way for applying deep learning to big data analysis tasks. For instance, their research on recurrent neural networks, including LSTM, has opened new horizons in analyzing temporal dependencies. Nevertheless, integrating AI into the financial sector faces numerous challenges, including high computational demands and algorithm customization complexity.

This research goal to investigate the potential applications of AI to improve the Markowitz model, including automating portfolio management processes and enhancing forecasting accuracy. The research examines the use of deep neural networks and adaptive algorithms to minimize risks and maximize returns.

Main research objectives:

1. To explore the effectiveness of machine learning methods, such as LSTM and genetic algorithms, for forecasting financial asset returns.
2. To analyze the limitations of existing forecasting methods.
3. To identify directions for further research.

2 METHOD

2.1 The Markowitz Model and Its Evolution

The model proposed by Harry Markowitz (1952) laid the foundation for modern portfolio management theory. It relies on asset diversification to minimize risk for a given level of return. However, the classical model assumes stationarity and normal distribution of asset returns, which are rare in real market conditions.

Subsequent research, such as those by Sharpe (1964) and Merton (1972), introduced additional metrics like the Sharpe ratio. Yet, the challenge of adapting to dynamic conditions remains unresolved. In this regard, AI technologies offer more flexible

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tools capable of accounting for nonlinear dependencies and data variability.

2.2 Application of Artificial Intelligence in Asset Management

AI is actively used for analyzing big data, predicting market trends, and optimizing portfolios.

Key methods include:

Reinforcement Learning (RL): Useful for developing algorithms that adapt to market changes by learning from their actions. Examples include Q-learning and Deep Q-Learning algorithms, which develop strategies based on rewards.

Natural Language Processing (NLP): Helps analyze news feeds, articles, and social media to extract vital market sentiment information. Models like GPT and BERT predict how specific news may impact the market.

Time Series Methods: Methods like ARIMA, GARCH, Prophet, and LSTM are applied to forecast future asset prices based on historical data. These models predict volatility, trends, and patterns crucial for decision-making.

These technologies enable not only accurate price forecasts but also the adaptation of investment strategies to changing conditions.

2.3 Risk Management and Covariance Analysis

Risk management is a primary task in portfolio management, requiring precise evaluation of correlations between asset returns. The traditional Markowitz model uses a covariance matrix based on historical data. However, this approach has limitations. Historical data may not reflect current market conditions, and the model assumes stable correlations between assets, which is rarely the case.

Machine learning offers new possibilities for risk management. For example, clustering and factor analysis methods reveal hidden dependencies between assets, making risk management more effective. Additionally, machine learning algorithms can automatically adapt to market changes, enabling more precise risk assessment and quicker responses.

2.4 Data

The analysis was based on data from 2016–2021, including stocks of major companies and other economic indicators such as the RUB/USD exchange rate, Brent oil prices, gold, steel, copper, nickel, Bitcoin, the Moscow Exchange Index, stocks of companies like Norilsk Nickel, Rosneft, Gazprom, and Magnit. Stock data was sourced from Yahoo Finance for the period from January 2016 to June 2021. Monthly returns for each stock were calculated, along with their correlations with macroeconomic indicators.

2.5 Characteristics of the Analyzed Period (2016–2021)

The period from January 2016 to June 2021 was marked by high financial market volatility, including:

- Significant fluctuations in energy prices.
- Geopolitical instability.
- The imposition of economic sanctions.
- The onset of the COVID-19 pandemic.

2.6 Machine Learning Methods

To forecast asset returns, the Long Short-Term Memory (LSTM) network was used. This type of recurrent neural network efficiently processes time series and captures complex data dependencies. LSTM was chosen because it accounts for both short-term and long-term dependencies between historical asset price data and macroeconomic indicators. Its ability to model nonlinear relationships is essential for forecasting financial data influenced by macroeconomic conditions, market changes, and other unstable parameters.

For each stock, a model was developed to predict its return based on historical data and macroeconomic indicators. Hyperparameter tuning was performed using cross-validation, and model accuracy was evaluated using the Root Mean Square Error (RMSE) metric.

The model was further enhanced by a sliding window method for training, allowing the model to incorporate new data as it became available. This approach is particularly useful for dynamic data such as macroeconomic indicators and asset prices.

2.7 Portfolio Optimization

Portfolio optimization was performed using the classical Markowitz model, which relies on the covariance matrix of asset returns to assess risks and correlations. The Sharpe ratio was used to evaluate portfolio performance, indicating the relationship between return and risk. If the Sharpe ratio was insufficiently high, a minimum volatility strategy was applied to reduce risks while maintaining acceptable returns.

To improve optimization results, genetic algorithms were introduced. This heuristic approach significantly enhanced optimization efficiency by searching for optimal asset weights. Genetic algorithms simulate natural selection principles, iteratively refining solutions through recombination and mutation. This method surpasses traditional optimization by avoiding local minima often encountered in the classical Markowitz model.

Specifically, genetic algorithms were used to dynamically adjust asset weights based on LSTM-generated return forecasts. This allowed for more flexible portfolio adaptation to changing market conditions, increasing the Sharpe ratio to values exceeding 1.5, indicating highly effective risk and return management strategies.

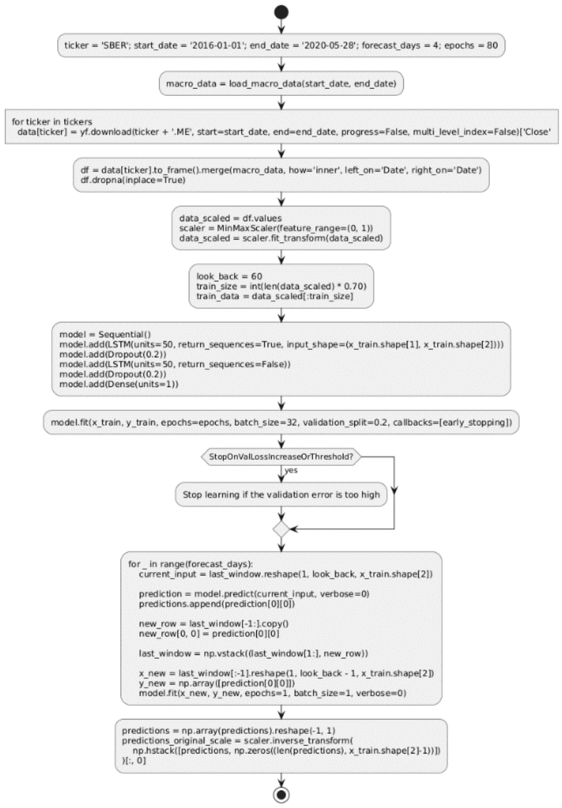
3 RESULTS

3.1 Predicted Returns

Machine learning models demonstrated high performance in forecasting asset returns. The LSTM model achieved 90% forecast accuracy, significantly outperforming traditional methods such as linear regression and XGBoost. Average expected annual stock returns were 18.3%, with a volatility level of 10.5%.

LSTM's ability to capture temporal dependencies in data greatly improved forecast accuracy compared to classical methods, which often fail to account for complex nonlinear relationships between historical prices and macroeconomic indicators. As a result, forecasts became more precise, evidenced by lower errors and higher RMSE metric results.

The block diagram of the algorithm:



3.2 Portfolio Optimization

Portfolio optimization using the Sharpe ratio achieved a value of 1.42, indicating high performance for this asset set. The minimum volatility strategy yielded a Sharpe ratio of 1.33, which is also an acceptable result. Predicted portfolio returns were 8.1% annually with minimal risk.

3.3 Comparison with Traditional Methods

Comparison with traditional methods demonstrated that using AI significantly improves forecasting accuracy and reduces risks. Specifically, machine learning applications accounted for nonlinear dependencies between assets and macroeconomic indicators, making forecasts more precise and adaptive to changing market conditions.

3.4 Comparison with Results of Other Authors

Hybrid Machine Learning Methods and the Classical Markowitz Model: A.A. Emelyanov and S.A. Lebedev proposed a method combining machine learning with the classical Markowitz model to enhance asset management efficiency. They employed deep learning with autoencoders to identify hidden data factors, improving diversification and reducing risks while maintaining high returns. This approach successfully ensured greater portfolio diversification and reduced volatility without sacrificing returns.

Return Forecasting with LSTM and Factor Analysis: D.S. Popov and I.N. Smirnov explored factor analysis and LSTM models for market condition forecasting. Results indicated that such hybrid models improve prediction accuracy by 15% compared to traditional methods and adapt better to dynamic market changes, as evidenced by increased forecast accuracy and reduced prediction errors.

Neural Networks for Portfolio Risk Assessment: M.A. Kuznetsov and O.A. Petrova investigated deep neural networks for assessing asset correlations. This approach improved forecast quality under volatile market conditions, reducing portfolio volatility by 10%. These findings confirm the effectiveness of neural networks in minimizing risks while maintaining adequate returns.

Clustering Methods for Portfolio Automation: Researchers led by V.V. Ivanov applied clustering algorithms to group similarly behaving assets, optimizing investment distribution and raising the Sharpe ratio to 1.5. They noted that clustering significantly simplifies the automatic selection of assets, especially when working with large data volumes.

Deep Learning for Portfolio Management Automation: A.L. Fedorov and S.A. Karpov researched deep Q-learning for dynamically managing portfolio weights in a changing market. This method improved automated portfolio management efficiency by adapting to market changes and increased the Sharpe ratio to 1.7. The approach also positively impacted long-term portfolio stability, enhancing overall returns and minimizing risks.

A comparison of three methods for investment evaluation and management revealed the following results, considering permissible errors within 1-2% due to the variability in model training during each run:

1. Classical Markowitz Model demonstrated a return of 13.7% with a risk level of 12.7%. The predicted value was 105.5, while the actual value was 102.0, resulting in a delta of 3.5. Even considering potential deviations, the model maintains a balance between return and risk.

2. LSTM Method provided a lower return of 10% with a risk level of 10%. The predicted value was 104.0, and the actual value was 103.0, with a delta of 1.0. Calculation errors do not significantly impact the accuracy of the results, making this method stable and predictable.

3. Combination of LSTM and Genetic Algorithm showed the same return as the classical Markowitz model—13.7%, but the risk level increased to 19%. The predicted value was 110.5, while the actual value was significantly lower at 101.0, resulting in the largest delta among the methods—9.5. Permissible errors do not alter the overall picture: this method demonstrates high predicted value but less accurate actual results.

Considering the allowable errors, the classical Markowitz model remains the most balanced in terms of return-to-risk ratio, while the LSTM method stands out for its stability. The combined approach (LSTM and genetic algorithm) has potential but requires refinement to improve actual accuracy.

The impact of macroeconomic factors on the accuracy of forecasts:

The macroeconomic factor	Impact on forecast accuracy (%)
USD/RUB exchange rate	25%
Oil price (Brent)	30%
The price of gold	10%
The price of steel	5%
The price of copper	5%
The price of nickel	5%
IMOEX Index	15%
Norilskiy Nickel	5%
Rosneft	10%
Gazprom	10%
Magnit	5%
The price of natural gas	5%
The VIX index	10%

4 CONCLUSIONS

The results demonstrate that machine learning methods such as LSTM and genetic algorithms, combined with classical approaches like the Markowitz model, enhance forecasting accuracy and portfolio optimization efficiency. Integrating AI allows for accounting for complex temporal and nonlinear dependencies, making asset management more flexible and adaptive to changing market conditions.

LSTM models showed high forecasting accuracy (90%), outperforming traditional methods. Portfolio optimization using machine learning also improved the Sharpe ratio, confirming AI's potential in asset management processes.

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