Optimal Portfolio Prediction Using Advanced Deep Learning and Monte Carlo Simulation Techniques

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***Abstract*—To make the effective allocation of investment or portfolio management, we require sophisticated tools for managing financial markets that have become more complex. In dynamic, non-linear market environments, traditional methods, such as mean variance optimization, frequently fail. A framework based on deep learning to optimize portfolio prediction using historical stock prices, portfolio values, and Monte Carlo simulations with antithetic variates for reduction in prediction variance and enhancing reliability is presented in this study. We integrate bidirectional LSTM and GRU layers for processing sequential data, and use them to generate future portfolio value predictions as well as stock allocation percentages for 49 stocks on 49 future days. The custom loss functions make the priority the prediction of the portfolio value, thus increasing the model precision and applicability to real world financial situation.**

Our approach involves multiple innovations: data normalization and target generation with advanced preprocessing, a multibranch neural network model with sequence processing, mixed precision training for computational efficiency using dense layers with residual connections. We evaluate model performance with RMSE, NRMSE, MAPE, R^2, and provide visualizations to explore how antithetic variates impact prediction accuracy.

The results show that the framework can predict accurately the portfolio, and optimize the stock portfolio. By providing a structured, scalable solution to the dynamic portfolio optimization problem, this research contributes to the field of financial prediction.

***Index Terms*—Hindi handwriting, RNN, GAN, Encoder-Decoder, Sequence-to-sequence, Transformers, Handwriting Generation.**

I. INTRODUCTION

The interest in recent years for portfolio management and stock prediction has been enormous as it brings huge returns as well as increasing complexities of the global financial markets. In search of the strategies that can lead to promising returns, investors keep seeking the strategies that will genuinely mitigate risk. Therefore, portfolio prediction has become a function of study, advanced computational models are applied to historical data to predict future outcomes and to suggest optimum investment allocation.

Traditionally, mean variance optimization and the Capital Asset Pricing Model, to name a few, on which portfolio management is built. However, these approaches certainly facilitate value; however, their linear relationships and stable market behavior may limit their functionality in dynamic and volatile markets. A paradigm shift has emerged, thanks to machine learning and deep learning methodologies, which permit the use of techniques able to capture complex, non linear relationships between various financial indicators. The development of these methods has led to development of more robust, data driven prediction models allowing for improved decision making capabilities.

Specifically, our research builds a portfolio prediction system that can precisely suggest investment allocation across different stocks so that optimal portfolio performance is achieved. This framework is built to predict future portfolio values, and portfolio holdings for individual stocks, using deep learning techniques. A major part of our approach consists of complementing the model with Monte Carlo simulations with antithetic variates, for further improving the robustness and reducing the variance of the model, for more realistic future predictions.

The framework outlined in this paper includes several innovative components: I explore from data preprocessing techniques which can enhance the model accuracy, to my custom model architecture based on Bidirectional LSTM and GRU layers and a custom loss function that aims to predict portfolio value. We further perform mixed precision training to improve efficiency and provide rigorous validation of the system's predictive accuracy using evaluation metrics. We make another contribution to a nascent area of predictive finance, by providing a detailed methodological framework to both value and allocation prediction in portfolio management.

II. RELATED WORK

A large number of methodologies for Portfolio optimization have been already explored from a wide range, with the most prominent ones based on Monte Carlo simulations to model all the possible market situations. In this section we give an overview on important research in portfolio optimization based on Monte Carlo methods and in other related approaches.

In this way, portfolio optimization has been previously explored through Monte Carlo simulations to minimize tradeoffs between risk and return. In [1], Shadabfar and Cheng suggested an hybrid method to solve portfolio selection probalistically by combining Monte Carlo simulations with Markowitz model, the model is applied to Shanghai stock portfolios. However, the portfolio built using this approach was restricted by the fact that the Markowitz model's underlying assumptions may not necessarily hold true in non normal market conditions.

In US equity markets, Mukherjee et al. [2] had used Monte Carlo simulations to portfolio optimization in order to maximize the returns based on modern portfolio theory. By applying this method to specific portfolios, it was effective, but computational complexity grows as datasets become larger.

Monte Carlo simulation with resampled data from history has been used by Pedersen [3] to estimate future values for the equity and optimize a portfolio. The study shows that mean-variance optimization may not capture most of investment risk, and thus alternative approaches like the Kelly method are more suitable for risk control in portfolio management.

First, in a companion work [4], Detemple et al. present a dynamic, simulation-based method for portfolio optimization that accounts for complex state variables more closely tracking market dynamics. It improved portfolio allocation, but to undertake this used advanced modeling techniques for large scale financial problems.

An overview of Monte Carlo simulation as a statistical tool for financial analysis, focusing on its future potential and limitations when computational complexity arises, especially in high dimensional financial models, was provided in [5].

Desai et al. [6] present a Monte Carlo method for portfolio optimization under partially observed stochastic volatility, using market volatility as a benchmark to show improvement in optimization. This model, however, was very resource intensive and required detailed modeling.

Cong and Oosterlee [7] developed in a final success a multi-period mean variance optimization approach through Monte Carlo simulation coupled with a recursive programming technique to accomplish allocation through the time. Although this approach was effective, its use was limited by restrictions imposed by mean variance optimization on the complexity of risk.

We present a new framework that takes these foundational studies as a starting point, and incorporate Monte Carlo simulations with antithetic variates for variance reduction, and a deep learning based architecture for better portfolio value and stock allocation prediction. This combination improves on several limitations of previous models, especially in terms of computational efficiency and scalability.

III. Proposed Methodology

We propose an AI based architecture in this section for optimal portfolio prediction. It is a deep learning based framework that leverages prepared historical stock data and recommends future portfolio allocation. Below, we describe our architecture as consisting of several different components.

A. Data Acquisition and Preprocessing

1) Data Collection: To predict accurately, we collect stock prices, portfolio values and portfolios allocations of 49 stocks in historical data. The model is trained and validated using this data set.

2) Data Normalization: The data itself is normalized so that we have consistent scaling across input features and we are able to improve model convergence and performance. The network is then made more flexible by scaling each feature to a standard range, so that each type of financial data is represented within the same standard range.

3) Target Generation: The basis of the model's portfolio value and stock allocation predictions is selected from 253 to 365 days ahead of a target future day. This intermediary enables model accuracy to be precise benchmarked against with any other process.

4) Variance Reduction Using Antithetic Variates: We perform Monte Carlo simulations using antithetic variates in order to improve robustness and increase the predictive power of the model. By generating paired, negatively correlated samples with a realistic future market condition, this technique reduces the prediction variance. Figure shows the effectiveness of this method in variance reduction. 1.

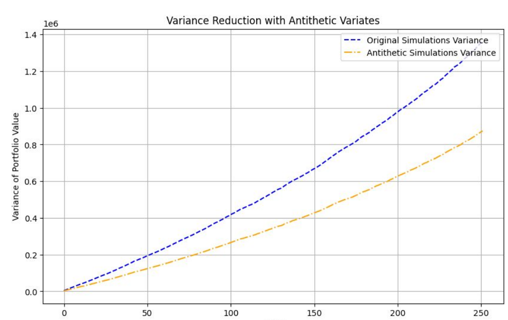

Fig. 1: Variance Reduction with Antithetic Variates

TABLE I: Summary of Related Work on Portfolio Optimization Using Monte Carlo Simulation

Study	Objective	Methodology	Key Findings and Limitations
[1]	Probabilistic approach for optimal portfolio selection	Hybrid Monte Carlo simulation with Markowitz model	Optimized portfolio selection, with robustness checks; limited by assumptions of Markowitz model in non-normal market conditions.
[2]	Portfolio optimization for US equity instruments	Monte Carlo simulation based on modern portfolio theory	Optimized US-based portfolios with Monte Carlo, highlighting computational challenges for large-scale datasets.
[3]	Portfolio optimization and risk modeling	Monte Carlo simulations with historical data resampling	Showed benefits in risk reduction, yet noted limitations in mean-variance optimization as a risk measure.
[4]	Optimal portfolio allocation under complex dynamics	Simulation-based approach with dynamic state variables	Achieved improved portfolio allocations but required complex modeling for large-scale applications.
[5]	Status and future potential of Monte Carlo simulation	Summary of advancements in Monte Carlo applications	Addressed future directions in financial modeling, with a focus on limitations in computational complexity.
[6]	Portfolio optimization under stochastic volatility	Monte Carlo simulation under partially observed stochastic volatility	Enhanced optimization for volatile assets, though complex modeling increases computational requirements.
[7]	Multi-period mean-variance portfolio optimization	Dynamic Monte Carlo simulation approach with constrained optimization	Developed a recursive programming approach for improved allocation, though limited by constraints of mean-variance optimization.

5) Monte Carlo Simulation for Portfolio Forecasting: A Monte Carlo simulation is conducted to establish what the potential range of future portfolio value might be. The output of this simulation is a plot of portfolio performance in response to different hypothetical market scenarios over the life of a 250 day period to gain an understanding of what outcomes might be and the associated risks.

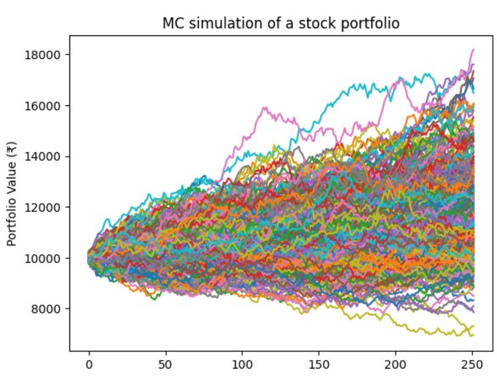

Fig. 2: MC Simulation of a Stock Portfolio: The simulated portfolio values over 250 days with different growth trajectories across broad market conditions. Each line corresponds to a single simulation path.

Figure 2 The Monte Carlo simulation results of the stock portfolio over 250 days are illustrated with each line representing a different simulation path. Seeing this visualization offers a glimpse of how much portfolio growth could shake out depending on historical data and simulated market conditions.

B. Model Input Structure

1) Portfolio Sequence: The model takes in a sequence of values from past 252 days of the portfolio's value and captures how the portfolio behaved historically in terms of trends and volatility in the performance of the portfolio.

2) Stock Sequence: Each of the 49 stocks is given a parallel sequence of stock allocation over the past 252 days which supplies the model with a detailed breakdown of stock specific behavior and the pattern of their allocation trends.

3) Target Day Input: Actually, it gives another input to the target prediction day for directing to the model the prediction of a specific future date. The key for this input is to ensure that the model's predictions line up with what their future will entail.

C. Model Architecture Overview

1) Sequence Processing Layers: The portfolio and stock sequence processing branches of the model have bidirectional LSTM and GRU layers and process sequences separately. These layers also have Batch normalization and dropout functions added in them so that it helps with the improved generalization and it also prevents one of the most important issues which is overfitting.

2) Concatenation and Dense Layers: The outputs of the portfolio and stock sequences, together with the day we wish to predict for, are concatenated after sequence processing. Such representative features have been processed by dense layers of ReLU activation, batch normalization, dropout, and residual connections in order to learn stable and efficient features.

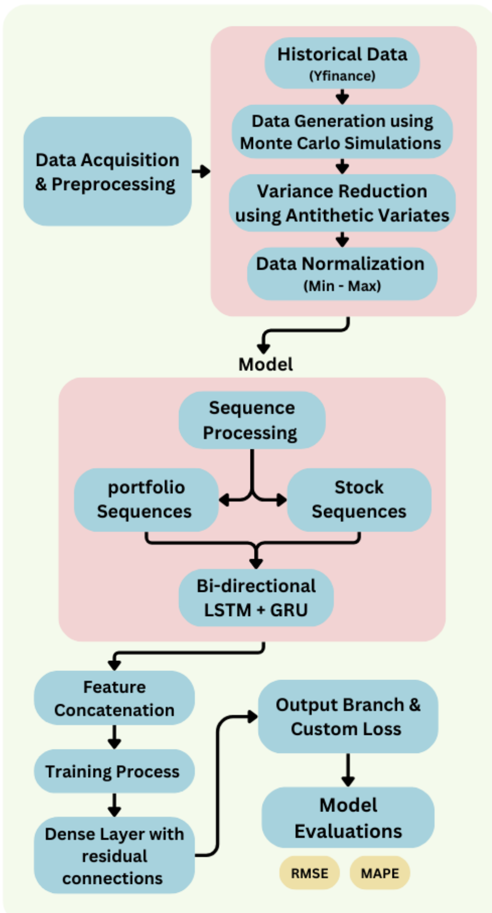

Fig. 3: Proposed Methodology Flow Diagram

D. Output Branches and Custom Loss Function

1) Future Portfolio Value Prediction: First output branch of the model predicts the continuous value of future portfolio. Its branches consist of dense layers specialising in value prediction, with custom loss weighting applied to give priority to portfolio value accuracy.

2) Stock Allocation Prediction: Second output generate predicted allocation percentages for each stock. These allocation, which sum to unity, is then standardized by a softmax activation function, so that portfolio composition predictions are realistically and balanced.

3) Custom Loss Function: Portfolio value prediction is assigned higher weight compared to loss function used. Using this approach improves the quality of the value predictions while meeting the dual goals of value and allocation prediction for the model.

E. Training Process

1) Mixed Precision Training: In order to ensure computational efficiency, mixed precision training is used. Using reduced-precision arithmetic wherever possible, training is sped up without sacrificing accuracy in this technique.

2) Data Generators and Callbacks: Training, validation and test data handling is done with batch data generators. Early stopping, learning rate reduction and save model checkpoint key callbacks are used to optimize training to prevent overfitting and to avoid stall of some or all of the parameters during training.

F. Evaluation and Metrics Calculation

Once trained, the model's performance is assessed through several metrics: These are Root Mean Square Error (RMSE) Normalized RMSE (NRMSE), Mean Absolute Percentage Error (MAPE), and R^2. Portfolio value and allocation predictions are captured in these metrics of model predictive accuracy.

IV. Results

The performance of the proposed portfolio prediction model was assessed on a test dataset using key performance metrics, RMSE, NRMSE, MAPE, and R^2 score of 0.0944, 0.1218, 17.85%, and 0.4721, respectively. The low RMSE suggests that the minimization of large prediction errors achieves an effective portfolio value approximation that is reasonably accurate in future values. Moreover, the NRMSE of 0.1218 shows that the model performs well at various portfolio sizes. In fact, however, a MAPE of 17.85% implies some error in percentage terms, which might be due to market movements, but also to the inherent volatility of stock allocation. This leaves a R^2 score of 0.4721, which, although relatively low, endows moderate explanatory power, accounting for about a 47% of the variance in portfolio inherent return. This is a good first evidence that the model has learned correct patterns, but there is still some room for improvement through the use of architectural refinement or additions to the data features.

However, the results imply that the model does not sufficiently exploit portfolio sensitivity to predict extreme market conditions and/or rapid changes in asset allocation. Adding more data sources like economic indicators or sentiment analysis could increase this performance as it may capture macroeconomied impacts on stock prices. In addition, prediction accuracy may be improved by adjusting weighting in the custom loss function, or by experimenting deeper architectures. The results verify the framework's potential and this is a promising tool for investors wishing for data driven automated portfolio management.

V. Conclusion

Modeling portfolio prediction using deep learning to take advantage of historical stock prices, portfolio values, and Monte Carlo simulations with antithetic variates and minimize variance is done in this paper. The model was evaluated on a 49 stock dataset, attaining RMSE of 0.0944, NRMSE of 0.1218, MAPE of 17.85%, and R^2 score of 0.4721. However, the results indicate that model has the potential for forecasting portfolio values and their allocations.

Reduced variability in model robustness resulted from the application of antithetic variates to Monte Carlo simulations. The model is a promising starting point for future development of automated portfolio management, despite the limitations of the R^2 score that do not capture the complexity of portfolio dynamics.

Additional market indicators can be added in future research and other deep learning architectures tried, as well as more sophisticated variance reduction techniques. On the other hand, advances of these may enhance predictive accuracy increasing a very useful tool for investors and financial institutions that want to maximise portfolio allocation and control risk excellently.

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