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AI-Driven Financial Portfolio Management

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Abstract

Artificial intelligence (AI) is reshaping portfolio management by augmenting classical mean–variance optimization with machine learning (ML) for prediction, risk modelling and decision automation. This project surveys state-of-the-art methods (supervised learning, deep learning and reinforcement learning) and implements a compact, reproducible workflow for equity portfolios under realistic frictions (transaction costs, turnover constraints, risk budgets). Preliminary results indicate that ML models can improve risk-adjusted returns relative to equal-weight and mean–variance methods when rigorously regularized and combined with robust risk controls. However, performance remains sensitive to feature design, transaction costs, and overfitting risks.

Introduction & Motivation

Classical portfolio theory (Markowitz, 1952) provides the foundation of risk–return optimization, while Sharpe (1964) and Black–Litterman (1992) extended evaluation and integration with investor views. In today's environment, AI and ML offer non-linear modelling power, regime detection, and adaptive decision policies. This research asks: Can AI methods deliver robust improvements in real-world risk-adjusted performance after costs, compared with traditional baselines?

Methods

I benchmark several approaches: (1) Equal■Weight (EW) and Mean–Variance (MV); (2) supervised ML (Gradient Boosted Models, Random Forests) combined with MV; (3) Deep Learning (LSTM/Transformers) for temporal dependencies; (4) Reinforcement Learning (policy optimization with PPO/DDPG). All models integrate realistic constraints (turnover, costs, exposure limits).

Results

Illustrative backtest results suggest that AI-enhanced methods can increase Sharpe ratios compared to EW and MV. Supervised ML and deep models provided better risk-adjusted returns but at the cost of higher turnover, which reduces net performance once realistic transaction costs are applied. Reinforcement Learning achieved the highest raw Sharpe but was very cost-sensitive.

Key conclusions

• AI methods can add value, but gains are modest after frictions.
• Robust covariance estimation plus modest alpha forecasts often outperform aggressive RL strategies in small universes.
• Simpler models with proper regularization, turnover control, and risk constraints tend to be more robust across regimes.
• Ethical, compliance, and explainability considerations are essential when deploying AI in financial decision-making.
• Future work should focus on hybrid approaches (ML forecasting + conservative risk control) and robustness under market regime shifts.

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