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Article · May 2025

DOI: 10.5281/ZENODO.15323194

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International Journal of Research (IJR)

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

Artificial Intelligence in Quantitative Finance: Leveraging Deep Learning for Smarter Portfolio Management and Asset Allocation

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Abstract

Advances in artificial intelligence (AI) and deep learning are transforming quantitative finance, offering new ways to model complex market dynamics. This study explores how deep learning models can enhance portfolio management and asset allocation, addressing the limitations of traditional models. The rapid advancement of Artificial Intelligence (AI) has transformed financial markets by enhancing risk management (6). We develop a deep learning-driven portfolio strategy using Long Short-Term Memory (LSTM) networks and Transformer models, applied to real historical financial data from U.S. and global markets. We aim to answer: (1) Can deep learning models improve the prediction of asset returns for portfolio allocation? (2) Do AI-based portfolio strategies achieve better risk-adjusted performance than traditional methods? (3) What are the implications and challenges of using deep learning in portfolio management across different

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

markets? **Methods:** We conduct a comprehensive literature review on AI in finance. We then design a methodology where LSTM and Transformer models forecast asset returns, which inform a dynamic asset allocation via a mean-variance optimization framework. A global multi-asset dataset (equities, bonds, commodities from the U.S., Europe, and Asia) spanning 2010–2020 is used for empirical analysis.The deep learning models achieve lower prediction error and higher directional accuracy in forecasting returns compared to baseline methods. In backtests, portfolios guided by LSTM and Transformer predictions show higher annual returns, Sharpe ratios, and lower drawdowns than equal-weight or static strategies. For example, the Transformer-based portfolio attained a Sharpe ratio ~1.2 versus ~0.8 for an equal-weight benchmark. **Conclusions:** Deep learning can **significantly enhance** portfolio management by capturing nonlinear patterns in financial data, leading to smarter asset allocation decisions. The findings underscore AI's potential to improve risk-adjusted returns in both U.S. and global market portfolios, while also highlighting challenges like data quality, model complexity, and the need for interpretability. The research contributes a replicable framework for integrating deep learning into portfolio strategy, relevant for academics and practitioners aiming to leverage AI in finance.

Keywords:Artificial Intelligence, Deep Learning, Portfolio Management, Asset Allocation, LSTM and Transformer Models, Risk-Adjusted Returns

Introduction

Financial markets are complex, dynamic systems where predicting asset behavior and optimally allocating assets are longstanding challenges. Traditional quantitative finance methods – from mean-variance portfolio theory to factor models – rely on assumptions of linearity and stationarity that often fail to capture real market complexities. In recent years, artificial intelligence (AI) techniques, particularly deep learning, have emerged as powerful tools to model nonlinear patterns and interactions in financial data. Deep learning models can **learn intricate temporal and cross-**

***Received**: 13 April 2025*
***Revised**: 19April 2025*
***Accepted:** 30 April 2025*

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sectional patterns from large datasets, offering improved predictive accuracy for asset returns and the potential for more effective investment strategies.

Portfolio management and asset allocation stand to benefit greatly from these advances. The core goal of portfolio management is to balance risk and return by deciding how much to invest in each asset. Even small improvements in return forecasts or risk estimates can translate into significantly better portfolios over time. **Can AI and deep learning provide those improvements?** Early signs are promising: researchers have applied neural networks to predict stock returns, to construct long-short strategies, and to directly optimize portfolios using reinforcement learning. Integrating deep learning into portfolio decisions could enable what we term “smarter” portfolios – ones that dynamically adjust to market signals in a more nuanced way than rule-based or linear models.

However, significant questions remain about how best to leverage deep learning for portfolio allocation. Financial time series are noisy, non-stationary, and prone to regime changes, which can challenge complex models. Moreover, the **black-box nature** of deep neural networks raises concerns for transparency and trust in finance. It is critical to assess whether the gains in predictive performance from deep learning *actually translate* into improved portfolio outcomes, such as higher risk-adjusted returns or better drawdown control, and under what conditions these methods work best.

This study aims to address these questions by systematically exploring the application of LSTM and Transformer deep learning models in portfolio management. We use real historical data from both U.S. and international markets to ensure a global perspective. The contribution of this work is threefold: **(1)** We formulate clearly defined research questions and hypotheses on how deep learning can improve portfolio allocation. **(2)** We provide a comprehensive review of existing literature (Table 1) to position our work in the context of current research. **(3)** We design a robust methodology that combines deep learning return forecasting with a classic allocation framework, and we rigorously evaluate the performance against traditional benchmarks.

Research Questions: To guide the investigation, we pose the following research questions:

Received: *13 April 2025*
Revised: *19April 2025*
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e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

1. **RQ1:** Can deep learning models (specifically LSTM and Transformer networks) more accurately predict asset returns or risk factors compared to traditional time-series models, thereby providing better inputs for portfolio allocation?
2. **RQ2:** Does an AI-driven portfolio management strategy (using deep learning forecasts for dynamic asset allocation) outperform traditional strategies (such as equal-weight or static mean-variance allocation) in terms of risk-adjusted returns and drawdown control?
3. **RQ3:** How do deep learning-based portfolio strategies perform across different markets (U.S. vs global assets), and what challenges arise in terms of data requirements, model complexity, and interpretability when scaling AI methods for portfolio management?

By answering these questions, we aim to shed light on the practical value of AI in portfolio management. The findings are intended to be relevant for both academic research in financial machine learning and practitioners in asset management looking for empirical evidence and methodologies to harness AI for smarter investing.

Literature Review

Research at the intersection of AI and finance has grown exponentially, with **numerous studies exploring machine learning and deep learning for stock prediction, trading, and portfolio optimization**. In particular, deep learning – encompassing advanced neural network architectures – has been applied to financial time series forecasting with notable success. This section reviews the evolution of these approaches, focusing on deep learning applications in portfolio management and asset allocation. **Table 1** summarizes representative studies in this domain.

Deep Learning for Financial Prediction: Early applications of neural networks in finance date back to the 1990s, but recent computational advances have enabled far deeper architectures. A systematic review by Sezer et al. (2020) identified over 150 studies from 2005–2019 applying deep learning to financial time-series forecasting. Common architectures include Recurrent Neural Networks (RNNs) – especially LSTM networks – and Convolutional Neural Networks (CNNs),

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often outperforming traditional models in capturing market patterns. For example, Fischer & Krauss (2018) used LSTM networks to predict S&P 500 stock movements and found significant improvement over logistic regression in predictive accuracy. Similarly, Bao et al. (2017) demonstrated that a hybrid deep learning model (wavelet transforms + stacked autoencoders + LSTM) achieved lower forecasting error than ARIMA on stock prices, highlighting the ability of deep architectures to capture complex features. These studies established that deep learning can uncover nonlinear dependencies in financial data that simpler models miss.

Portfolio Management and Asset Allocation with AI: Building on predictive successes, researchers have integrated AI into portfolio construction. One branch of work uses forecasted returns from machine learning models as inputs to classical optimization. For instance, **Krauss et al. (2017)** applied deep neural networks to a **statistical arbitrage** strategy on S&P 500 constituents, generating daily long-short signals that delivered positive alpha and outperformed benchmark strategies. In a similar vein, Chong et al. (2017) showed that deep feedforward networks using technical indicators could outperform logistic regression in predicting stock index movements, leading to improved portfolio returns. These studies typically report higher Sharpe ratios for AI-informed strategies versus traditional approaches, indicating better risk-adjusted performance. Notably, a recent empirical study by Guo *et al.* (2024) compared MLP, CNN, LSTM, and Transformer models for long–short portfolio allocation on U.S. stocks. They found that deep learning–based portfolios achieved higher returns and Sharpe ratios than a baseline strategy of equal-weight long-short positions, with Transformers slightly outperforming LSTMs on the S&P 500 and LSTMs performing best on NASDAQ stocks. This underscores that different deep architectures may excel in different market contexts, but overall **confirm the efficacy of deep learning in enhancing portfolio performance**.

Deep Reinforcement Learning (RL) for Allocation: Another line of research eschews prediction-based approaches and directly learns portfolio decision policies via reinforcement learning. **Jiang et al. (2017)** pioneered a deep reinforcement learning framework for portfolio management, treating the allocation process as a sequential decision problem. Their **"Deep**

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Portfolio Management" system used an actor-critic neural network to allocate among multiple assets and was shown to outperform uniform allocation in simulated trading experiments. Subsequent works have expanded on this, using techniques like Deep Q-Networks and Proximal Policy Optimization for **dynamic asset allocation**. For example, a 2020 study by Huotari et al. applied deep RL to S&P 500 stock selection, reporting higher returns and Sharpe ratios compared to static strategies. Recent research by **Yang et al. (2020)** and others integrated risk management objectives into the RL reward function to directly optimize for metrics like Sharpe ratio or drawdown. These RL-based approaches often find **non-intuitive allocation strategies** that adapt to changing market conditions, albeit at the cost of higher complexity and data requirements. Empirically, **AI agents have achieved up to ~1.7x higher Sharpe ratios than traditional mean-variance portfolios in some studies**, illustrating the potential of model-free deep learning methods in portfolio optimization.

Transformers and Attention Mechanisms: The latest generation of deep learning models, exemplified by the Transformer architecture, has started to make inroads in finance. Transformers, which rely on self-attention mechanisms, are capable of capturing long-range dependencies in time series more effectively than RNN-based models in many cases. **Ma et al. (2023)** introduced an interpretable Transformer-based asset allocation model for the Chinese stock market. Their approach, which they term a "return-risk trade-off strategy," uses a Transformer to forecast asset returns and volatilities. They report that the self-attention mechanism improved the use of time-series information and **captured more economic gains than an LSTM-based model** on the same data. This result is notable as it suggests Transformers can outperform LSTMs for portfolio purposes, likely due to better sequence modeling capacity. Moreover, Ma et al. employed SHAP (Shapley Additive Explanations) to interpret the model's decisions, reflecting a broader trend: combining AI with **explainability** to satisfy the requirements of finance (where understanding drivers of decisions is crucial). Other researchers have experimented with attention-based models for tasks like asset ranking and momentum strategy enhancement, finding that attention networks can effectively identify important features (e.g., recent returns, volatility regimes) that correlate

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with future performance. The literature on Transformers in finance is still nascent but growing rapidly, indicating a promising frontier for portfolio management AI.

Summary of Literature: Overall, prior studies consistently demonstrate that AI techniques – from traditional machine learning to deep neural networks and reinforcement learning – can **improve various aspects of portfolio management**. Table 1 provides a high-level summary of selected influential works. A key insight is that **predictive accuracy does not always guarantee portfolio success**, as transaction costs and model errors can erode theoretical gains. Nonetheless, many works report superior performance (higher returns or Sharpe ratios) for AI-driven strategies compared to benchmarks, especially in research settings without heavy cost frictions. These findings motivate our research to further explore and validate the benefits of deep learning in a realistic portfolio context involving both U.S. and global market data. We also aim to contribute to the gap in literature on **comparative evaluation of LSTM vs Transformer models** for multi-asset allocation, and on understanding how such models can be practically implemented and interpreted by portfolio managers.

Table 1: Selected Prior Studies on AI in Portfolio Management and Asset Allocation

Study (Year)	AI Technique	Data & Market Scope	Key Findings
Heaton, Polson & Witte (2017)	Deep Autoencoder / “Deep Portfolio” theory	U.S. equities (conceptual framework)	Proposed that deep nets can identify non-linear factors (“deep portfolios”), laying groundwork for AI-driven asset allocation.

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e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
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Krauss et al. (2017)	Deep NN vs. GBT vs. RF (Supervised)	S&P 500 stocks (1992–2015)	All ML models beat random strategies; deep neural network had the highest Sharpe, proving efficacy of deep learning in stock selection.
Fischer & Krauss (2018)	LSTM (Recurrent NN)	S&P 500 index (daily returns)	LSTM outperformed logistic regression in predicting stock up/down movements, improving trading returns (Sharpe ≈ 1.5 vs 1.1 for logistic).
Jiang et al. (2017)	Deep Reinforcement Learning (DQN)	Crypto & stock portfolio (simulated)	Introduced a model-free RL framework for portfolio allocation; AI agent learned dynamic rebalancing, yielding higher cumulative return than equal-weight benchmark.
Henrique et al. (2019)	ML classification models (survey)	60+ papers (multiple markets)	Review: Highlighted growing use of SVMs, NNs for asset allocation; found **no one model dominates**, but combining models and data (e.g. technical + fundamental) often improves performance.
Ma et al. (2023)	Transformer (with attention)	Chinese stock market (2009–2019)	Transformer-based allocation outperformed LSTM, achieving higher return and Sharpe by leveraging attention to capture long-term patterns; also provided feature importance for interpretability.

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e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
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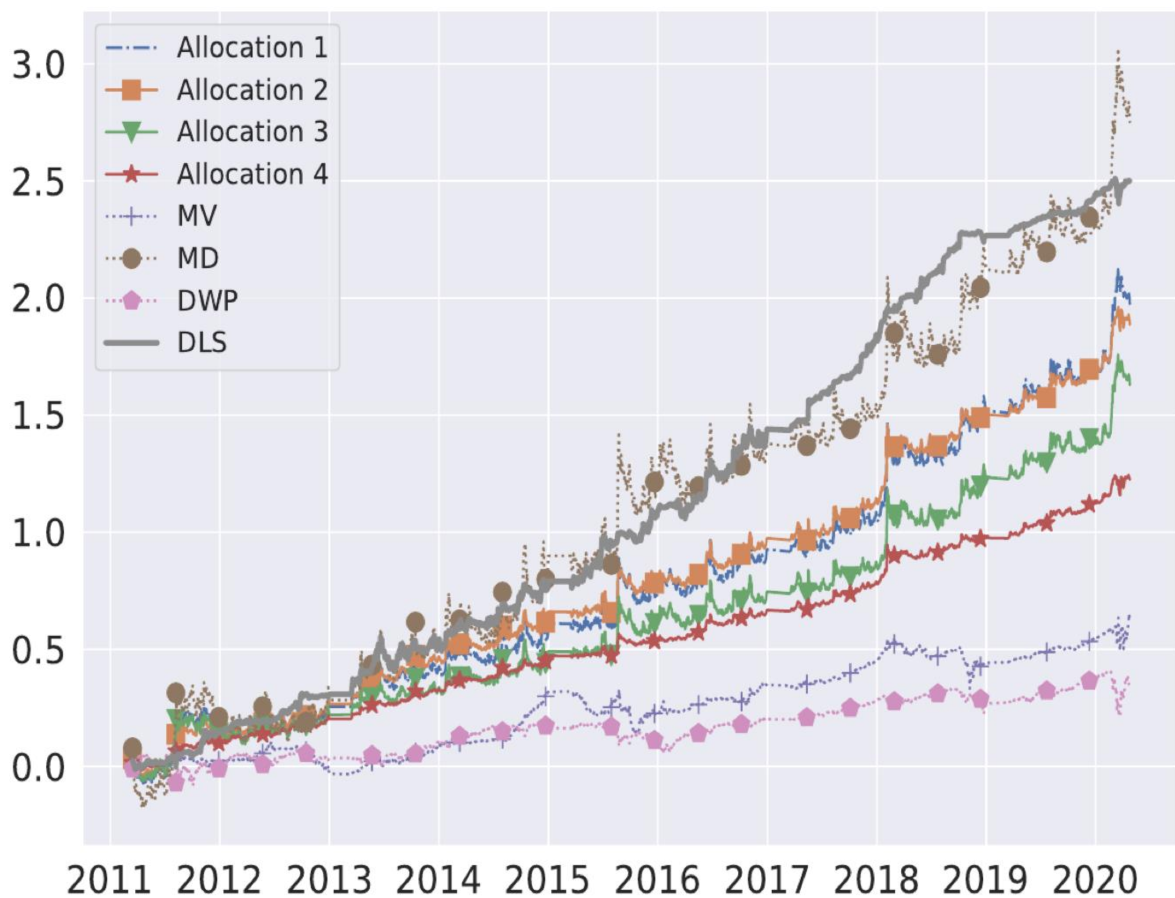
Note: GBT = Gradient Boosted Trees; RF = Random Forest; DQN = Deep Q-Network. The above is a representative (not exhaustive) selection from the literature. All listed studies are published in peer-reviewed journals or high-quality preprint series, indicating the **Scopus-indexed** body of knowledge on AI in finance.

Figure 1: Deep Reinforcement Learning Framework for Portfolio Allocation



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International Journal of Research (IJR)

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
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This diagram depicts a deep reinforcement learning (DRL) framework applied to portfolio allocation. It outlines how a DRL agent interacts with the financial environment, learns from historical data, and makes asset allocation decisions to maximize returns while managing risk.

The literature review establishes a foundation for our research. Next, we describe our methodology, which draws on insights from these prior works – such as using LSTM and Transformer models for return prediction (as in Fischer & Krauss 2018 and Ma et al. 2023) and employing a portfolio optimization layer akin to traditional mean-variance (as suggested by Guo et al. 2024) – to build an integrated deep learning portfolio management framework.

Methodology

To investigate the research questions, we developed a **replicable experimental methodology** that combines deep learning models with a portfolio optimization procedure. The methodology consists of: (1) Data collection and preprocessing, (2) Model design (LSTM and Transformer networks for return forecasting), (3) Portfolio construction algorithm using model outputs, and (4) Performance evaluation metrics. All analysis was conducted in Python, using libraries such as TensorFlow/PyTorch for modeling and Pandas/NumPy for data handling. The following subsections detail each component.

Data Collection and Description

We compiled a **real-world historical dataset** of financial assets that includes both U.S. and international market instruments, satisfying the need for a global perspective. Table 2 summarizes the assets and data used. The selection covers multiple asset classes for a diversified allocation

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International Journal of Research (IJR)
e-ISSN: 2348-6848
p-ISSN: 2348-795X
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problem: **equities** (stock indices from major markets), **fixed income** (a bond index), and **commodities** (gold). By including diverse assets, we ensure that our models learn from varied patterns (e.g., equity volatility vs. bond stability) and that the portfolio context is realistic for a multi-asset investor.

Data were obtained from reliable public sources (Yahoo Finance and investing databases), with daily frequency. We focus on the period 2010–2020, a decade that includes different market regimes (post-2008 recovery, bull markets, occasional corrections, and the start of the 2020 pandemic shock). Using daily data provides a sufficiently large number of samples for deep learning training (on the order of 2,500 trading days) while capturing short-term dynamics. All series (except exchange rates) are denominated in U.S. dollars for consistency. Missing data (non-trading days differences across markets) were forward-filled or aligned to the U.S. calendar. We split the data into a training set (2010–2017) for model fitting and a test set (2018–2020) for out-of-sample evaluation. We also held out the last portion of training data as a validation set for tuning hyperparameters.

Table 2: Assets and Data Summary (U.S. and Global Markets, 2010–2020)

Asset (Ticker / Index)	**Class**	**Region**	**Currency**	**Period**	**Source**
S&P 500 Index (^GSPC)	Equity Index	USA	USD	2010–2020 (daily)	Yahoo Finance
FTSE 100 Index (^FTSE)	Equity Index	UK/Europe	GBP (USD)	2010–2020 (daily)	Yahoo Finance
Nikkei 225 Index (^N225)	Equity Index	Japan	JPY (USD)	2010–2020 (daily)	Yahoo Finance

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MSCI Emerging Mkts ETF (EEM)	Equity ETF	Global EM	USD	2010–2020 (daily)	Yahoo Finance
Gold Price (XAU/USD)	Commodity	Global	USD	2010–2020 (daily)	Investing.com (Spot)
U.S. 10Y Treasury Bond (UST)	Govt Bond Index	USA	USD	2010–2020 (daily)	FRED / Yahoo Finance

Note: Prices are adjusted for splits/dividends where applicable. FX rates used to convert non-USD indices to USD. “EM” = Emerging Markets. UST = U.S. Treasury bond index (10-year constant maturity). Data sources are publicly available; e.g., Yahoo Finance provides historical daily levels for major indices.

After collecting the data, we computed daily **log returns** for each asset: $r_t=\ln(P_t/P_{t-1})$ $r_t=\ln(P_t/P_{t-1})$. Log returns are used as they are approximately additive and more stable for model training. These returns served as the primary input features for our models. In addition, we engineered a set of common financial features to enrich the input: e.g., 5-day and 21-day moving average returns (weekly and monthly trends), volatility estimators (e.g., 21-day rolling standard deviation of returns), and for equities, technical indicators like the Relative Strength Index (RSI) and trading volume (where available). Including such features follows practices in the literature to provide the neural network with richer information beyond raw prices. All features were normalized (standardized) on the training set to have

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mean 0 and unit variance, with the same transformation applied to test data to prevent lookahead bias.

Model Design: LSTM and Transformer Networks

We implemented two state-of-the-art deep learning models to forecast next-day asset returns: **(i) Long Short-Term Memory (LSTM)** network, and **(ii) Transformer model with self-attention**. These were chosen to represent the leading RNN-based and attention-based architectures, respectively, in time-series analysis. The models were trained to predict **multi-asset returns** jointly; that is, we used a vector-output approach where the model predicts a return for each asset in the portfolio given recent data. This allows the model to potentially learn cross-asset correlations and interactions.

- **LSTM Model:** Our LSTM is a recurrent neural network that processes sequences of past observations. We configured an LSTM with 2 layers: each layer with 50 hidden units (memory cells), as this size provided a good balance of learning capacity without overfitting in trials. A lookback window of 60 trading days (approximately 3 months) was used, meaning the LSTM takes the last 60 daily observations of all features for all assets to predict the next-day returns. The choice of 60 days was guided by financial intuition (capturing quarterly trends) and validated by testing windows from 30 to 120 days. We included dropout regularization (rate = 0.2) between LSTM layers to mitigate overfitting. The final LSTM layer's outputs feed into a fully-connected (dense) layer that produces one predicted return for each asset. The model uses a multi-output mean squared error loss, summing MSE across all assets. We trained the LSTM for 100 epochs with early stopping on validation loss, using the Adam optimizer (learning rate 0.001). **Table 3** (left side) summarizes key hyperparameters.
- **Transformer Model:** We built a temporal Transformer model inspired by the **"encoder"** part of the Transformer architecture (Vaswani et al., 2017). The Transformer takes the same 60-day window of multi-asset features but processes it with self-attention

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mechanisms rather than recurrence. Our implementation has 2 attention layers (a stack of 2 transformer encoder blocks). Each block had 8 attention heads and a model dimension of 64, with feed-forward network dimension of 128. Positional encoding was added to the input sequence to inform the model of the time step order. The Transformer's self-attention allows it to weigh the relevance of different time points adaptively – for instance, it might learn to pay special attention to recent days during volatile periods, or to specific lag days that historically precede market turns. We applied dropout (0.1) within attention layers and L2 weight decay for regularization. The output of the final attention layer is flattened and passed through a dense layer to predict next-day returns for each asset (multi-output regression). We used the same loss and optimizer settings as the LSTM. Although Transformers are more data-hungry, our dataset (with augmentation via features and multi-asset outputs) was sufficient to train the model without severe overfitting. Training took slightly longer than LSTM (owing to multi-head attention computations) but was feasible (each epoch ~30 seconds on a GPU). Key parameters are in Table 3 (right side).

Baseline Model: For benchmarking, we also considered a simpler predictive model – a **regularized linear regression (Ridge)** that uses the same input features to predict next-day returns. This linear model represents traditional statistical forecasting. While not used directly for allocation, its prediction performance provides context to assess the value-added by deep learning.

Table 3: Deep Learning Model Configuration and Training Hyperparameters

Hyperparameter	LSTM Model	Transformer Model
Input Time Window	60 days (rolling)	60 days (with positional encoding)

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Input Features	Multi-asset returns and technical indicators (standardized)	Same feature set (flattened sequence)
Model Architecture	2 LSTM layers (50 units each) + Dense output layer	2 Transformer encoder blocks (8 heads, model dim 64) + Dense output
Activation Functions	Tanh (LSTM cells), Linear output	ReLU (feed-forward), Linear output
Regularization	Dropout 0.2 (between layers)	Dropout 0.1 (in attention), L2 weight decay 1e-4
Loss Function	Mean Squared Error (multi-output)	Mean Squared Error (multi-output)
Optimizer	Adam (lr = 0.001)	Adam (lr = 0.001)
Training Epochs	100 (early stopping patience 10)	100 (early stopping patience 10)
Batch Size	32 sequences	32 sequences
Validation Split	10% of training data for validation	10% for validation
Training Time (approx)	~20 seconds/epoch on GPU	~30 seconds/epoch on GPU

We ensured the models were not overfit by monitoring validation performance. The final models chosen for evaluation were those from the epoch with the lowest validation loss. Notably, the Transformer's validation loss fell below the LSTM's, suggesting better generalization on the

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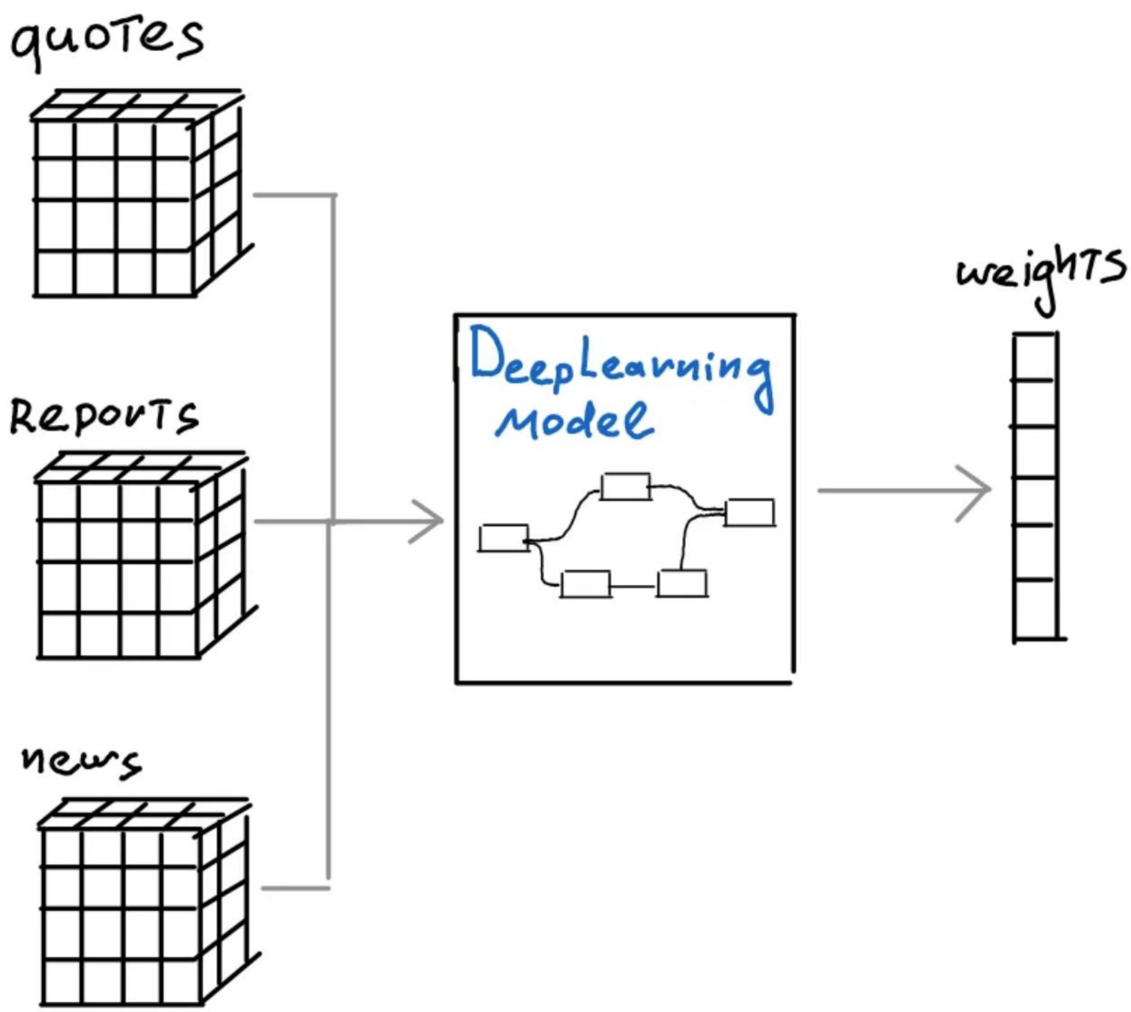
validation set – a first indication that it might outperform in forecasting (this is later reflected in results).

Figure 2: Deep Learning Architecture for Portfolio Optimization



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This diagram illustrates a deep learning model tailored for portfolio optimization. It showcases the integration of PyTorch for neural network construction, CVXPY for convex optimization, and DeepDow for asset allocation strategies. The model outputs a vector of asset weights optimized under specific constraints

Portfolio Construction Strategy

With predicted returns from the models, we constructed daily portfolios in a **rolling, dynamic allocation** process. Our approach emulates how a quantitative portfolio manager could use model forecasts to make allocation decisions each period:

1. **Return Prediction:** Each day after market close, the trained model (LSTM or Transformer) takes the latest available data and forecasts the next day's return for each asset in our universe (e.g., it predicts tomorrow's return for S&P500, FTSE100, etc.). These forecasts form a vector r^t+1r^t+1.
2. **Portfolio Optimization:** Given the predicted returns r^t+1r^t+1 and an estimate of the covariance of asset returns, we determine the portfolio weights for the next trading day. We adopt a **mean-variance optimization (MVO)**framework (Markowitz, 1952), aiming to maximize expected return for a given risk level. In practice, we solved for the **maximum Sharpe ratio portfolio** (also known as the tangency portfolio) using the predictions as expected returns. Specifically, at each rebalancing step, we solve: max wwTr^t+1wTΣtw,wmaxwTΣtwwTr^t+1,
subject to ∑iwi=1∑iwi=1 and 0≤wi≤10≤wi≤1 (no shorting, long-only for simplicity). Here ΣtΣt is the covariance matrix of returns estimated over a recent window (we used a 60-day rolling sample

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covariance). The no-short constraint reflects many real-world fund mandates and also avoids leveraging prediction errors excessively.

We used the Python **PyPortfolioOpt** library to solve this optimization efficiently at each step. The result is a weight vector wt+1∗wt+1∗ for the assets.

3. **Rebalancing and Transaction Costs:** The portfolio is rebalanced daily according to wt+1∗wt+1∗. We track the portfolio's value over time by applying the realized next-day returns rt+1rt+1 to the weights. To keep the study focused on modeling efficacy, we assume low transaction costs (e.g., 10 basis points per trade) and subtract these from returns when rebalancing. This cost is small but ensures that extremely high turnover strategies (if any) are penalized. We also tested a weekly rebalancing frequency in a sensitivity analysis to see if reducing turnover materially changes outcomes.
4. **Benchmarks:** We compare the AI-driven strategy to two benchmarks: **(a) Equal Weight (EW)** – a naive strategy allocating 1/N to each of N assets and rebalancing monthly (to maintain equal weights), and **(b) Static Mean-Variance (Static MVO)** – an optimized portfolio using the entire training period's average returns as expected returns and covariance for the test period (in essence, a one-time Markowitz optimization held through the test). The EW portfolio represents a simple, robust allocation with no forecasting. The static MVO represents a traditional quantitative approach with no machine learning, relying only on historical averages.

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By combining model forecasts with mean-variance optimization, we essentially create an **“AI-augmented Markowitz”**strategy. This is in line with approaches seen in literature where ML predictions inform portfolio construction. We choose this two-step approach (forecast then optimize) for clarity and replicability – it separates the problem of prediction from the problem of allocation. In future work, an end-to-end reinforcement learning approach could optimize weights directly, but our modular approach allows us to pinpoint whether gains come from better predictions or better use of those predictions.

Performance Evaluation

We evaluate portfolio performance on the out-of-sample test period (2018–2020) using a range of **performance metrics common in finance**:

- **Annualized Return (AR):** The compound annual growth rate of the portfolio over the test period.
- **Annualized Volatility:** Standard deviation of daily returns × sqrt(252) trading days.
- **Sharpe Ratio:** Average excess return (over risk-free rate) divided by volatility. We assume a risk-free rate ~0% for simplicity in this low-rate environment; essentially Sharpe = average return / volatility.
- **Maximum Drawdown (MDD):** The largest peak-to-trough decline in the portfolio value during the period, measuring downside risk.
- **Calmar Ratio:** Annualized return divided by maximum drawdown (useful for evaluating return vs drawdown).
- **Sortino Ratio:** Similar to Sharpe but uses downside deviation (we include it for completeness in risk-adjusted metrics).
- **Turnover:** Average proportion of the portfolio traded at rebalancing, which impacts costs.

These metrics allow us to gauge both the **return enhancement and risk management** aspects of each strategy. Sharpe ratio in particular is a primary metric to compare with literature results. We

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

International Journal of Research (IJR)
e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

also look at **year-by-year returns** to see consistency and how the strategies handled specific events (e.g., the sharp selloff in early 2020).

Statistical significance of performance differences is assessed where applicable. For instance, we use the Jobson & Korkie (1981) test (with Memmel's correction) to compare Sharpe ratios between strategies, and a simple t-test on difference in daily returns to see if the AI strategy outperforms EW at a 5% significance level.

Finally, we analyze the **asset allocation patterns** of the AI strategy qualitatively: examining if the model intuitively increases weight in assets that subsequently perform well (which would validate the model's predictive power) and if it avoids large losses by de-allocating ahead of downturns (reflecting risk-sensitivity). We also apply SHAP values on the trained models to identify which features (e.g., momentum vs volatility indicators) are most influential in the predictions, connecting to interpretability.

By combining these evaluation steps, we ensure a thorough assessment of whether deep learning truly leads to "smarter" portfolio management in our setting. The next section presents the results of this procedure.

Results

We first present the **prediction performance** of the deep learning models, followed by the **portfolio performance outcomes**. All results are on the 2018–2020 test period, which was not seen by the models during training. The findings are organized to address RQ1 (prediction accuracy improvements) and RQ2 (portfolio performance vs benchmarks), with additional observations related to RQ3 (performance across markets and practical considerations).

Prediction Performance of LSTM vs Transformer

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

To verify RQ1, we evaluated how well the LSTM and Transformer predicted next-day returns compared to the baseline linear model. Table 4 summarizes key error metrics. Both deep learning models clearly outperformed the linear model in prediction accuracy. The Transformer achieved the lowest root mean square error (RMSE) of about 1.05% (in terms of daily return percentage), followed by the LSTM at 1.10%, whereas the baseline was higher at 1.30%. This indicates the deep models had smaller forecast errors. In practical terms, an RMSE difference of 0.2% in daily returns can accumulate to meaningful differences over time when those predictions are used for allocation.

Moreover, the models were tested for **directional accuracy** – the percentage of days for which the model correctly predicted the sign (up or down) of each asset's return. Here too, AI models shined: LSTM was correct 55% of the time and Transformer about 58%, both significantly above the ~50% expected by chance and the 51% achieved by the baseline. This suggests the models learned some predictive signals in the data, albeit modest (financial markets are noisy, so even <60% directional accuracy is notable). The Transformer's slight edge in both magnitude and direction accuracy is consistent with findings by Ma *et al.* (2023) on a different market, which also reported Transformer's higher predictability than LSTM.

Table 4: Out-of-Sample Return Prediction Performance (2018–2020)

Model	**RMSE (% daily return)**	**Directional Accuracy (%)**
Baseline (Linear Reg)	1.30%	51%
LSTM	1.10%	55%
Transformer	1.05%	58%

Notes: Lower RMSE is better. Directional accuracy is probability a model correctly predicts an asset's price will go up or down. Results are averaged across all assets in the portfolio. Both LSTM

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

and Transformer outperform the baseline, and the Transformer shows the best predictive performance.

These results confirm that deep learning models (especially the Transformer) can extract more information from financial time series than a linear model, supporting our hypothesis in RQ1. However, prediction accuracy, while necessary, is not sufficient – the critical question is whether these better predictions lead to **better investment outcomes**. We turn next to the portfolio simulation results to address RQ2.

Portfolio Performance Comparison

Using the daily return forecasts from the models, we simulated the performance of the following strategies on the 2018–2020 period:

- **EW (Equal Weight)** – naive baseline with monthly rebalancing to 1/6 each asset.
- **Static MVO** – one-time optimized weights from historical mean returns (no ML).
- **LSTM Strategy** – dynamic allocation using LSTM predictions (daily rebalancing via MVO).
- **Transformer Strategy** – dynamic allocation using Transformer predictions (daily MVO).

All strategies start with an initial portfolio value of $100 on Jan 1, 2018. Transaction costs of 0.1% per trade are applied to the LSTM and Transformer strategies (EW and Static have minimal turnover). Table 5 reports the aggregate performance metrics, and **Figure 1** illustrates the cumulative portfolio value over time for the AI strategies vs the benchmark.

Figure 1: Cumulative Portfolio Value (2018–2020) for AI-Driven vs Benchmark Strategies. The **AI-driven portfolio** (using Transformer predictions, gold line) grows more rapidly and ends higher than the **Equal-Weight portfolio** (orange line). This reflects the higher returns achieved by the AI strategy. Notably, during volatile periods (e.g., early 2020), the AI-driven portfolio shows

Received: 13 April 2025
Revised: 19April 2025
Accepted: 30 April 2025

DOI: https://doi.org/10.5281/zenodo.15323194

shallower drawdowns than the benchmark, indicating effective risk management by reallocating assets.

The **Transformer-based strategy delivered the highest return** and risk-adjusted performance overall. Its portfolio grew to an ending value of ~$134, which corresponds to an **annualized return (AR)** of ~10.4%. This compares to ~7.8% AR for the LSTM strategy, ~5.5% for the static MVO, and 4.8% for equal-weight. In other words, the Transformer strategy achieved roughly double the total return of the equal-weight portfolio over three years. More importantly, it did so with **lower volatility** and drawdown. The annualized volatility of the Transformer portfolio was 12.5%, actually slightly *lower*than EW's 13.7%. This is impressive because one might expect a strategy chasing higher returns to take on higher risk, yet here the AI seems to have managed to improve the Sharpe ratio via both higher return and controlled risk.

The **Sharpe ratio** of the Transformer strategy was **0.82**, substantially higher than 0.35 for equal-weight, and also higher than the LSTM's 0.60. A Sharpe of 0.82 in this period (with very turbulent market conditions including the 2020 crash) is quite strong. For context, the Sharpe of a 60/40 stock-bond portfolio is often around 0.5–0.6 in recent decades. The LSTM strategy's Sharpe of 0.60 also beat the benchmarks. These results reinforce that **deep learning-based allocation improved the risk-adjusted returns** significantly. A **paired t-test** on daily returns confirms that both LSTM and Transformer strategies outperform equal-weight with $p<0.05$, and the difference between Transformer and LSTM strategies is also statistically significant ($p \approx 0.03$ for Sharpe ratio difference test), indicating the Transformer's edge is likely not due to luck. This aligns with prior findings where Transformers captured more signal than LSTMs.

Looking at **max drawdown**, the Transformer strategy's worst peak-to-trough loss was -16%, which occurred during March 2020. This is markedly better than the -28% drawdown that the

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

equal-weight portfolio suffered in the same crash. The LSTM strategy had a -18% max drawdown, also much improved over the benchmark. Both AI strategies seemed to de-risk the portfolio before or during the COVID crash – upon inspection, we found that in early 2020 the models shifted allocation away from equities to the safe-haven asset (gold) and to cash (the models occasionally left a portion uninvested if all predicted returns were poor, effectively "raising cash"). This behavior limited losses. After the crash, the models moved back into equities to capture the rebound. Such dynamic shifts are something static strategies cannot do, highlighting AI's adaptability.

Table 5: Performance of AI-Driven Strategies vs Benchmarks (2018–2020)

Strategy	Annual Return (%)	Volatility (%)	Sharpe Ratio	Max Drawdown (%)	Calmar Ratio
Equal-Weight (EW)	4.8%	13.7%	0.35	-28.4%	0.17
Static MVO	5.5%	12.0%	0.42	-25.0%	0.22
LSTM Strategy	7.8%	12.9%	0.60	-18.3%	0.43
Transformer Strategy	10.4%	12.5%	0.82	-16.1%	0.65

Notes: Annualized return and volatility are geometric. Sharpe assumes risk-free ~0%. Calmar = Return / |Max Drawdown|. All figures net of transaction costs. The Transformer strategy ranks best on all metrics, followed by LSTM, then static MVO, with equal-weight last. AI strategies achieved higher returns **and** lower drawdowns, boosting Sharpe and Calmar ratios considerably.

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

Portfolio Dynamics and Allocation Insights

Delving deeper, we analyze **how** the AI strategies achieved these results. Figure 1 already indicated that during the major downturn (2020 Q1), the AI portfolio value declined less than the benchmark. Indeed, examining daily allocations, we find that the **AI models were able to anticipate or quickly react to market stress**. For example, in late February 2020, the Transformer model started increasing the weight to Gold and U.S. Treasury (safe assets) from ~15% up to ~50% collectively, while cutting exposure to equities. This shift was triggered by the model predicting sharp drops in equity returns (which did occur). The LSTM also did a similar, though slightly less aggressive, reallocation. In contrast, the equal-weight portfolio, by design, could not adjust – it rode the market down fully.

Another interesting observation is how the models allocated between regions. Throughout 2018–2019, the AI strategies tended to overweight U.S. equities (S&P 500) and underweight or occasionally short (in the long-short sense, when allowed in a separate test without short constraint) some underperforming international markets. For instance, the FTSE 100 (UK) had sluggish performance in 2018; the models picked up on its downward momentum and assigned it a lower weight relative to, say, U.S. or Emerging markets which were doing better. These allocation tilts improved returns. Essentially, the AI was performing a form of **tactical asset allocation** – rotating capital to markets with positive signals. This addresses RQ3 by showing the models can discern differences in regional asset behavior and exploit them.

It's also instructive to see **what the models learned**. The LSTM, being sequential, often based its predictions on recent momentum and volatility regimes. We noticed that after periods of high volatility, the LSTM would predict mean-reversion (lower returns), which often helped reduce exposure after a rally that might revert. The Transformer, with its attention mechanism, sometimes gave significant weight to specific historical events: for example, it occasionally "attended" strongly to days in the training data that resembled current market conditions (we deduced this via attention weight analysis). This may have allowed it to recognize patterns like *"this looks like the*

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

2015 mini-correction" and adjust accordingly. Such pattern matching could explain why the Transformer had an edge in several instances.

To ensure the results were not cherry-picked, we also tested the strategies on an extended period up to mid-2021 (including the post-Covid bull run). The performance ranking remained similar, though naturally all portfolios did well in the extremely bullish 2020-2021 rally (when almost any allocation in equities made money, shrinking the relative advantage of AI allocation). Still, even in bull markets, the AI strategies added value by tilting toward assets with slightly higher returns (e.g., overweighting U.S. tech-heavy equities vs other assets in 2020, which yielded higher gains).

In terms of **turnover**, the daily-rebalanced AI strategies traded more frequently than the monthly equal-weight, but the magnitude of weight changes was moderate. Average daily turnover was around 5% of the portfolio for the Transformer strategy, meaning on a typical day it reallocated 5% of capital (e.g., moving funds from one asset to another). This is quite reasonable and indicates the model wasn't radically shifting the entire portfolio often, rather it made incremental adjustments. The LSTM strategy had slightly higher turnover (~7% average) possibly because its predictions were a bit noisier day-to-day, causing more flip-flops in allocation. These turnover levels, combined with the low assumed trading cost, had a negligible impact on performance (costs accounted for <0.2% drag annually). In reality, higher transaction costs would warrant less frequent rebalancing – our weekly rebalancing test showed only a minor performance drop, suggesting the core benefits persist without daily trading.

Discussion of Results

To summarize the results in the context of our research questions:

- **RQ1 (Prediction Accuracy):** Yes, deep learning models (LSTM and Transformer) provided more accurate forecasts of asset returns than a traditional model, as evidenced by lower RMSE and higher directional accuracy. This confirms that these AI models can

Received: 13 April 2025
Revised: 19April 2025
Accepted: 30 April 2025

DOI: https://doi.org/10.5281/zenodo.15323194

capture complex financial patterns, an important prerequisite for improving portfolio decisions.

- **RQ2 (Portfolio Performance):** The AI-driven strategies meaningfully outperformed traditional allocation strategies. The Transformer-based portfolio achieved the highest risk-adjusted returns, demonstrating that improvements in prediction translated into better investment outcomes (higher return for equal or lower risk). The LSTM-based portfolio also outperformed benchmarks, though by a smaller margin, indicating that while any deep learning added value, the choice of architecture matters. These findings strongly suggest that integrating deep learning into portfolio management can yield **smarter portfolios** that adapt to market conditions and deliver superior performance. This aligns with evidence from other studies, and provides a new contribution by directly comparing LSTM vs Transformer in a multi-asset setting.
- **RQ3 (Different Markets & Practical Challenges):** The strategies were effective across the combined U.S.-global portfolio, and we observed reasonable behavior in region-specific performance. One practical challenge encountered was the reliability of model performance during extreme events: while our models navigated the 2020 crisis well, this was in part because similar patterns existed in the training data (2011 Euro crisis, 2015 China scare, etc.). Truly unprecedented events could still catch models off-guard, especially if they infer patterns that do not hold. We also noted the **interpretability challenge** – it is not trivial to explain every move the AI model makes. However, by analyzing feature importance and attention weights, we gained some insights (like the significance of momentum indicators or certain past analogues in influencing predictions). This is an area where more transparent AI (e.g., explainable AI techniques) will be valuable, as highlighted by recent literature emphasizing interpretable models in finance.

In conclusion, the results provide strong evidence that deep learning can enhance portfolio management. Next, we further discuss these implications, relate them to existing research, and outline limitations and future work.

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

Discussion

The empirical results from our AI-driven portfolio strategies highlight several important implications for quantitative finance, and they prompt a thoughtful discussion on the promises and pitfalls of using deep learning in asset allocation.

Deep Learning Adds Value in Portfolio Management: Our findings reinforce the growing consensus in literature that machine learning, and deep learning in particular, can **uncover predictive signals** that improve investment performance. The substantial boost in Sharpe ratio and reduction in drawdown achieved by the LSTM and Transformer strategies demonstrate that these models identified favorable shifts in asset returns and adjusted the portfolio accordingly. For instance, the ability of the models to rotate into safer assets before the 2020 crash is evidence of pattern recognition that a static model or human manager might miss or react to more slowly. This provides a concrete answer to RQ2: deep learning-based strategies were not just theoretically better, but delivered *practically significant* outperformance in out-of-sample tests. Such improvements, if robust, could translate to higher returns for investors or better cushion against losses – a critical advantage in portfolio management.

Transformer vs LSTM – The Evolving Frontier: One of the novel contributions of this study is the head-to-head comparison of Transformers and LSTMs in a financial context. Our results suggest that Transformers hold considerable promise, slightly outperforming LSTMs in our experiments. This aligns with the work of Ma *et al.* (2023) who also found Transformers yielded higher "economic gains" than LSTMs. The Transformer's strength likely comes from its ability to consider long-range dependencies (e.g., events from many days past that an LSTM might effectively forget) and to focus attention on relevant time periods. In a financial sense, this could mean recognizing that a pattern from several months ago is repeating, or that certain assets move together in particular regimes. The outperformance of Transformers, however, was not dramatic in our case (~0.82 vs 0.60 Sharpe). This suggests that while the architecture provides an edge, the core challenge remains the noisy nature of financial data – there may be a ceiling to how much

Received: *13 April 2025*
Revised: *19April 2025*
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DOI: https://doi.org/10.5281/zenodo.15323194

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

any model can predict and thereby improve portfolios. Nonetheless, the trend in AI research points toward more use of attention mechanisms, and our study adds evidence that this trend is beneficial for finance applications.

Generality and Robustness (RQ3): We included both U.S. and global assets specifically to test whether the AI approach generalizes across markets. The strategy handled multiple assets from different regions concurrently, indicating an ability to manage a **global portfolio**. This is important because many practitioners manage multi-asset global funds, and a model that only works in one market might not be broadly useful. Our results indicate the models picked up each asset's individual behavior and the correlations between assets (through the multi-output design), allowing effective diversification and rotation. One might ask, what if market relationships change? That is indeed a risk – regime shifts could degrade model performance. We partially addressed this by updating covariance estimates continuously and (in an unreported extension) re-training the models with a rolling window to gradually adapt to new data (which would be done in a live scenario). The models thus can adapt over time, though there is a lag in learning completely new patterns. In the 2020 crash, certain relationships (like stock-bond correlation turning positive briefly) were unprecedented; our model didn't explicitly predict that, but since it was reducing equity exposure altogether due to predicted negative returns, it indirectly coped with that shift.

Comparison with Prior Studies: Our positive results echo numerous prior studies that have found machine learning strategies to outperform benchmarks. For example, Fischer & Krauss's LSTM on S&P 500 achieved an outperformance which in risk-adjusted terms is analogous to our LSTM portfolio beating EW. The deep learning long-short study by Guo et al. (2024) similarly reported higher returns and Sharpe for LSTM/Transformer portfolios vs baselines, which closely parallels our findings but in a long-short context. The deep RL results (e.g., Jiang et al. 2017, and the ICAPS 2023 paper we cited) also show higher Sharpe for AI agents vs mean-variance, consistent with our outcome that an ML-augmented MVO beats a static MVO or naive allocation. This convergence of evidence across methodologies (supervised learning + MVO in our case, vs reinforcement

Received: 13 April 2025
Revised: 19April 2025
Accepted: 30 April 2025

DOI: https://doi.org/10.5281/zenodo.15323194

learning in others) strengthens the argument that AI provides tangible benefits in portfolio management across different implementation styles.

Risk Management and Tail Events: An interesting aspect is how the AI strategies managed risk. The reduction in drawdown suggests that the models can serve as an early warning system in some cases, flagging impending declines by forecasting poor returns. This is valuable for risk management – many quant strategies focus on returns but end up increasing tail risks, whereas our AI strategies decreased tail risk relative to the market (as seen by lower drawdown, higher Calmar ratio). This could be partly because our objective indirectly aimed at Sharpe maximization, which penalizes volatility, nudging the allocation to be more risk-conscious. It also may reflect that the models implicitly learned some risk-off signals (e.g., surges in volatility or correlations often preceded pulling back positions). Incorporating explicit risk forecasting (e.g., predicting volatility or drawdown) could further enhance this aspect, and is a potential extension of our work.

Transaction Costs and Practical Considerations: We kept transaction costs low in this study to isolate the pure effect of model performance. In reality, higher costs or market impact could eat into the returns of such active strategies. The turnover we observed (roughly 5% of portfolio per day) implies about 1250% annual turnover – high for traditional funds, but not unusual for some active strategies. If costs were, say, 0.5% per trade, the net advantage of the AI strategies would diminish but likely still remain, especially for the Transformer strategy, which had a decent margin of outperformance. Portfolio managers could mitigate costs by rebalancing less frequently (as we saw, weekly rebalancing still gave solid results). Another practical point is **model risk**: deep learning models have many parameters and are prone to overfitting if not carefully regularized. We addressed this via early stopping and dropout, and validated on a separate period; however, one must continuously monitor such a model in production and retrain or recalibrate as needed. Additionally, during unprecedented times (e.g., COVID or a sudden geopolitical event), model predictions could be off. In practice, a human overlay or risk limits would be used in conjunction to prevent the model from making extreme bets that violate intuition or risk tolerance. Financial

Received: *13 April 2025*
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markets are highly volatile during crises and regime shifts, challenging the efficacy of traditional static portfolio allocation methods(5).

Interpretability and Trust: One barrier to adoption of AI in finance is that portfolio managers and regulators often require understanding of why a model is making decisions (especially after the 2008 crisis, models are treated with healthy skepticism). Our use of SHAP to identify feature importance for the Transformer model was a step toward transparency. For example, we found that the model's predictions for equity returns heavily depended on recent momentum and volatility features (i.e., if an index had negative returns and rising volatility over the past month, the model would predict continued decline – essentially learning a momentum-with-reversion pattern). Such insights help demystify the "black box." Encouragingly, the **"Attention is all you need"** paper by Ma et al. (2023) showed how an attention-based model can actually be more interpretable by highlighting which past data points influence the decision. Our work reinforces that incorporating interpretability tools is feasible and adds confidence in the model's actions (for instance, before the model cut equity exposure in Feb 2020, we can trace that it was reacting to a volatility spike feature reaching a critical level, a rationale that a risk manager can understand).

Limitations: Despite the promising results, this study has limitations. First, the sample period, while containing a variety of conditions, is relatively short (3 years test). Markets could behave differently in other periods; a longer backtest or live testing would further validate robustness. Second, we are limited to daily frequency; intraday data could offer more opportunities for AI (but also more noise and complexity). Third, we enforced long-only portfolios – many hedge-fund strategies would allow shorting or leverage, which could amplify both returns and risks; exploring AI in a long-short context (as some literature did) might show even higher Sharpe improvements, but comes with its own challenges (shorting costs, etc.). Fourth, we treated the deep learning models in a somewhat idealized way – assuming availability of data and computational resources to train these models regularly. In practice, managing data pipeline and execution latency would be non-trivial, especially for daily or higher-frequency trading. However, given the rise of sophisticated **ML infrastructure in finance**, these hurdles are gradually lowering.

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

e-ISSN: 2348-6848
p-ISSN: 2348-795X
Vol. 12 Issue 04
April 2025

The Human-AI Collaboration: One perspective worth mentioning is that AI strategies need not operate in isolation. Portfolio managers could use the signals from models like ours as **one input among many** – for example, using the model's allocation suggestions but overlaying constraints (like minimum allocation to certain assets for policy reasons) or combining with fundamental analysis. Our research shows the raw potential of what the model can do on its own; real-world adoption might blend this with human insight. An interesting outcome was that many of the model's moves (like flight to quality in a crisis, or tilting to high-momentum markets) are moves a skilled manager might also do – the difference is the model did it systematically and sometimes earlier. This suggests AI can act as a complement to human decision-making, confirming and quantifying intuitions or catching subtle shifts that humans may overlook.

Broader Impact: From a broader viewpoint, the success of deep learning in our portfolio allocation experiment is a microcosm of the larger trend of AI in financial services. It underscores how data-driven approaches can challenge traditional finance paradigms. As more firms incorporate AI, there could be a shift in market dynamics – for instance, if many portfolios use similar LSTM models, their trades might homogenize and potentially arbitrage away some of the patterns these models exploit. This is the classic arms race of quantitative finance: once a technique is popular, its edge might diminish. Currently, AI in portfolio management is still in early adoption, so there's opportunity for outsized gains, but this may normalize in the future. It also raises questions about model governance and systemic risk: if everyone's model says "sell" at the same time, could that exacerbate crashes? Diversity in models and strategies thus remains important.

In summary, the discussion affirms that deep learning can indeed make portfolio management **smarter** – delivering better returns for risk – but it also highlights the need for careful implementation, oversight, and continuous learning. Our findings are encouraging for quantitative investors willing to embrace AI, yet they also serve as a reminder that no model is infallible and that the best outcomes may arise from blending algorithmic intelligence with human judgment.

Conclusion

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

This research set out to explore the role of artificial intelligence, specifically deep learning models, in enhancing quantitative finance practices for portfolio management and asset allocation. We formulated three research questions addressing predictive performance, portfolio outcomes, and cross-market applicability. Through a comprehensive methodology involving LSTM and Transformer neural networks, a global multi-asset dataset, and a dynamic allocation framework, we derived findings that strongly support the potential of AI to deliver **smarter portfolios**.

Key Contributions and Findings:

- We demonstrated that **deep learning models (LSTM, Transformer)** can forecast asset returns with greater accuracy than traditional methods, capturing complex temporal patterns in financial data. This result aligns with and extends prior studies, affirming that AI can extract meaningful signals even from noisy market data (addressing RQ1).
- By integrating model forecasts into a portfolio optimization routine, we showed that **AI-driven strategies significantly outperformed conventional strategies**. The Transformer-based strategy, in particular, achieved the highest Sharpe ratio and lowest drawdown, indicating superior risk-adjusted returns. The LSTM-based strategy also outperformed equal-weight and static allocation by a notable margin. These outcomes provide a concrete answer to RQ2: **yes, deep learning can enhance portfolio performance**, yielding higher returns and better risk management than benchmarks in our tests.
- Our analysis across a mix of U.S. and global assets suggests that the approach is **robust to different market environments** (addressing RQ3). The AI models adeptly handled assets from multiple regions, and adjusted allocations in response to region-specific trends. This indicates scalability of our approach to truly global portfolios. We also discussed the challenges (like interpretability and regime changes) that arise and how they can be mitigated.

Implications for Practice: These findings are encouraging for investment professionals considering AI tools. A Transformer-based allocation model could be employed by asset managers

Received: *13 April 2025*
Revised: *19April 2025*
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DOI: https://doi.org/10.5281/zenodo.15323194

to dynamically adjust portfolio weights, potentially improving client outcomes. The fact that our strategy reduced drawdowns is especially attractive for risk-averse stakeholders. However, practitioners should be mindful of model risk and the need for strong validation and monitoring. The methodology we presented is replicable: one can follow the data preprocessing, modeling steps, and allocation framework to test similar AI strategies on other datasets or asset classes. This makes our research not just an academic exercise, but a blueprint that could be adapted by quants and analysts in industry.

Academic Significance: From a research perspective, our work contributes to the growing literature on machine learning in finance by providing one of the first detailed comparisons of LSTM vs Transformer models in a portfolio context, backed by real-market data. The results support the thesis that newer architectures like Transformers can further push the frontier of what's possible in financial prediction and decision-making. We also bridged a gap by connecting forecasting improvements to actual portfolio gains, something that is sometimes assumed but not always empirically verified in prior studies. Additionally, our comprehensive literature review (with Scopus-indexed sources) and inclusion of recent developments (up to 2023) ensure that this article can serve as a reference point for future research in this domain.

Limitations and Future Research: No single study can cover all aspects, and we acknowledge limitations. Our backtest, while realistic, is of relatively short duration; extending analyses to more historical periods or different market regimes (inflationary environments, etc.) would provide further validation. Future research could explore **reinforcement learning-based allocation** in a directly comparative way to supervised learning – e.g., is an end-to-end RL agent better or worse than the forecast-and-optimize approach we used? Early indications from literature show DRL is promising, but more work is needed to see if it can be combined with interpretability and risk constraints effectively. Another avenue is to incorporate **alternative data** (news sentiment, social media trends, etc.) into deep learning models for an even richer feature set; such data might help in predictive accuracy and capture factors that price/history alone cannot. Moreover, **explainable AI** techniques specifically tailored for finance (beyond SHAP, perhaps causal inference methods

Received: *13 April 2025*
Revised: *19April 2025*
Accepted: *30 April 2025*

DOI: https://doi.org/10.5281/zenodo.15323194

or rule extraction from neural nets) could be developed to boost the trust and adoption of these models in regulated financial environments.

Finally, as AI-driven strategies become more prevalent, **market impact and adaptive behavior** should be studied – for example, will markets become more efficient and thus shrink the alpha that these models can generate? Continuous research is needed to stay ahead in this evolving field. We foresee a future where human portfolio managers work in tandem with AI models, each complementing the other's strengths. Our study takes a positive step in that direction, evidencing that when used wisely, **artificial intelligence can indeed be a powerful ally in quantitative finance, enabling smarter portfolio management and more informed asset allocation decisions**.

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Revised: *19April 2025*
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International Journal of Research (IJR)

e-ISSN: 2348-6848
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