From Headlines to Holdings: Deep Learning for Smarter Portfolio Decisions

Yun Lin [1] Jiawei Lou [1] Jinghe Zhang [2]

[1]Barnard College of Columbia University [2]Columbia University in the City of New York

Introduction

Most existing approaches in Machine Learning and Deep Learning to forecast stock returns and inform investment decisions [2][3] adopt a two-step process: first predicting individual stock returns, then applying separate portfolio optimization techniques [1]. This pipeline is often unstable due to compounding prediction errors and typically ignores the interdependencies between assets.

Our research project propose a novel **end-to-end deep learning model** that directly outputs portfolio weights for nine major stocks spanning six sectors: Apple and Nvidia (Information Technology), Johnson & Johnson and Thermo Fisher Scientific (Health Care), Tesla and Amazon (Consumer Discretionary), Boeing (Industrials), Costco (Consumer Staples), and Valero Energy (Energy). Our architecture combines:

- **LSTM (Long Short-Term Memory)** to capture temporal patterns in historical stock features
- **GAT (Graph Attention Network)** to model the dynamic relationships between stocks—enabling each stock representation to be informed by its most relevant peers.

In addition, we further integrate data from **sentiment analysis of financial news** to our model, capturing market sentiment signals that are often overlooked in purely price-based models.

Our model significantly outperforms both the equal-weighted portfolio and the traditional CAPM-based mean-variance optimization, achieving an annualized Sharpe ratio of up to **1.15** and annualized returns of up to **31.23%**.

Research Questions

Our research questions include:

1. To what extent can an end-to-end LSTM-GAT model—leveraging dynamic Graph Neural Networks to model inter-stock relationships—generate portfolio allocations that outperform equal-weight and baseline models?
2. How significantly does the integration of sentiment data from financial news enhance portfolio performance, particularly during periods of elevated market uncertainty or volatility?

Data Collection and Cleaning

We collected stock price and financial news data using public APIs and processed them to construct our feature set.

- **Price Data:** Retrieved from the **AlphaVantage API**. For each stock, we obtained daily open, high, low, close, and volume data from January 2021 to May 2025.
- **Sentiment Data:** Retrieved from the **Marketaux API**. For each stock, we downloaded timestamped news articles including titles, snippets, keywords, and entity metadata. Each entity record contains a match score and a sentiment score indicating the relevance and tone toward the mentioned stock. Sentiment scores range from **-1 to 1**, where negative values indicate negative sentiment, 0 indicates neutral sentiment, and positive values indicate positive sentiment. We aggregated this information to compute daily sentiment metrics for each stock.

Model Architecture

Figure 1 shows our end-to-end model. Historical stock features are processed by an LSTM to capture temporal patterns. The output embeddings are passed through a GAT, which captures inter-stock relationships using return correlation, sector info, and sentiment similarity. A linear layer with tanh activation generates raw portfolio weights, which are normalized and optimized via a Sharpe ratio-based loss. The entire model is trained jointly using backpropagation with the Adam optimizer.

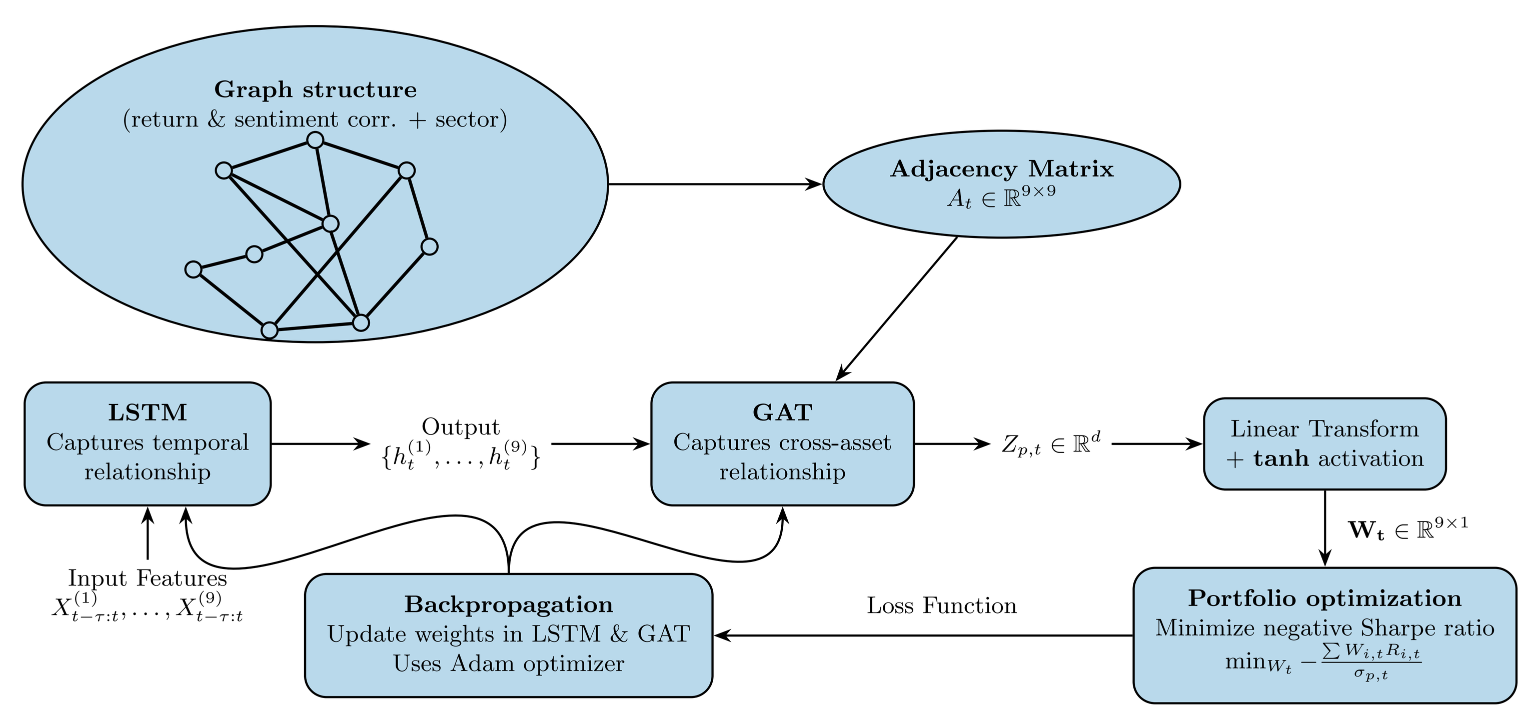

Figure 1. Model Architecture

Features and Graph Structure

Our model incorporates both market and news sentiment-based features:

Price-Based Features:

1. **Close/Volume:** End-of-day stock price / total daily trading volume.
2. **Log Return:** Logarithmic change in closing price from one day to the next.
3. **Annualized Returns (1W/2W/1M):** 1W/2W/1M returns scaled to yearly rate.
4. **5D Rolling Volatility:** Standard deviation of log returns (5-day rolling window).
5. **MACD (1W–1M):** Moving Average Convergence Divergence computed using short-term (1 week) minus long-term (1 month) moving averages (measures momentum).

Sentiment-Based Features:

6. **News Count:** Total number of articles related to the stock on a given day.
7. **Average Sentiment:** Mean sentiment score across all articles for the day.
8. **Sentiment Variance:** Variability of sentiment scores in the day.
9. **News Frequency:** Proportion of news about a stock over all stocks that day.
10. **Weighted Sentiment:** Average sentiment score multiplied by news frequency.

We use two approaches of **graph** structures to model stock relationships:

- **Static Graph:** Built using the full-period correlation matrix of log returns. Edge weights are raw correlation values. This graph remains fixed during training.
- **Dynamic Graph:** Edges are binary (|corr| > 0.5) and updated weekly using the union of:
  1. 5-trading-day rolling correlation of log returns
  2. 5-trading-day rolling correlation of daily average sentiment score
  3. Sector membership (edge if in same sector)

Models & Result

Table 1. Summary of Model Variants and Feature/Graph Configurations

Model Version	Features Used	Graph Type
Model v1	Features 1–2	Static
Model v2	Features 1–5	Static
Model v3	Features 1–5 + 8 + 10	Static
Model v4	Features 1–5 + 8 + 10	Dynamic
Model v5	PCA on Features 1-6 + 7-8 + 10 → first 6 components	Dynamic

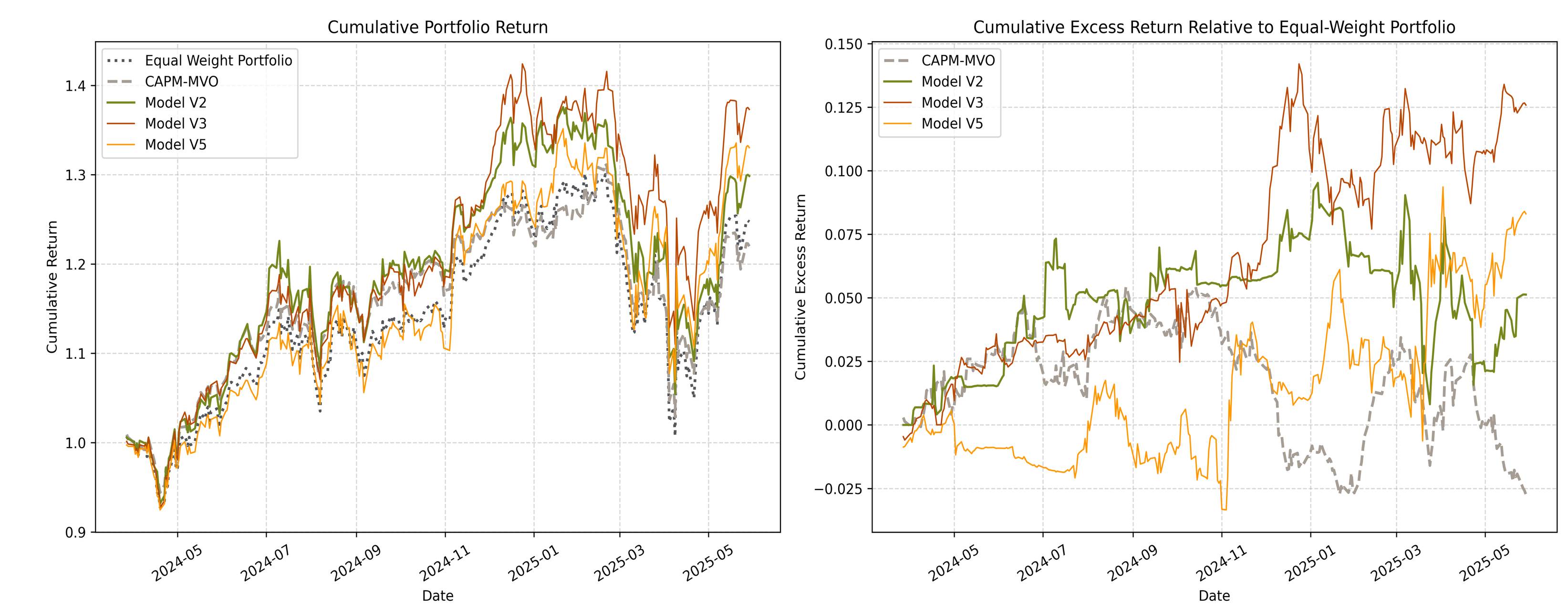

Figure 2. Comparison of the results from four models

Table 2. Performance Comparison (Test Period)

Metric	Model V1	Model V2	Model V3	Model V4	Model V5	Equal-Weight	CAPM-MVO
Total Return	28.11%	29.86%	37.32%	33.50%	33.04%	24.73%	21.99%
Annualized Return	23.65%	25.10%	31.23%	28.10%	27.72%	20.85%	18.58%
Volatility	26.02%	26.29%	27.19%	26.60%	28.45%	24.89%	22.03%
Sharpe Ratio	0.91	0.95	1.15	1.06	0.98	0.83	0.84
VaR (95%)	-2.62%	-2.57%	-2.5%	-2.68%	-2.64%	-2.53%	-2.04%
Max Drawdown	-23.38%	-23.35%	-22.05%	-21.70%	-20.99%	-22.60%	-21.59%

Conclusion & Significance

- **Model v3** significantly outperformed both the equal-weight and CAPM-MVO portfolios, as well as the baseline model (v2), in terms of **annualized return** and **Sharpe ratio**—achieving improvements of **49.87%** and **37.09%** over the equal-weight portfolio, respectively. It also achieved the lowest Value at Risk **(VaR)** at **-2.50%**, indicating stronger downside protection.
- **Model v5** demonstrated the best drawdown performance, limiting the maximum drawdown to just **-20.99%** during the April 2025 tariff-induced market shock. This represents a reduction of approximately **6.6%** compared to the drawdown of the equal-weight portfolio, highlighting the benefits of incorporating sentiment-based features, using a dynamic graph structure, and applying PCA for dimensionality reduction. These design elements contribute to improved portfolio stability during turbulent market conditions.
- Overall, the results confirm that integrating **sentiment analysis** and **dynamic graph structures** can substantially reduce losses and enhance risk-adjusted returns.

References

[1] Lu, X., Poon, J., Khushi, M. (2025). *Leveraging BiLSTM-GAT for enhanced stock market prediction: a dual-graph approach to portfolio optimization*. *Applied Intelligence*, 55, 601. doi:10.1007/s10489-025-06462-w

[2] Pacreau, G., Lezmi, E., Xu, J. (2021). *Graph neural networks for asset management*. SSRN preprint. ssrn.com/abstract=3976168

[3] Zhang, Z., Zohren, S., Roberts, S. (2020). *Deep learning for portfolio optimization*. arXiv preprint arXiv:2005.13665

yl5852@barnard.edu jl6685@barnard.edu jz3893@columbia.edu