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Hybrid AI Frameworks for Stock Market Prediction and Portfolio Optimization

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Abstract — Precise stock prediction and efficient portfolio optimization are still problematic in practice because of the non-stationarity, volatility, and complexity of the financial time series. In this study, we present a Hybrid Artificial Intelligence Framework (HAIF), which is the combination of three different frameworks: (1) a Graph Neural Network (GNN) with an attention layer for modelling relationships between stock prices; (2) a Transformer with convolutional layers for predicting price movements in different periods ahead; and (3) a Deep Reinforcement Learning (DRL) model called Proximal Policy Optimization for managing transactions and balancing the portfolio in different conditions. Based on 5 years of daily S&P 500 time series from 2020 to 2025 with 50 constituent stocks, our model obtains Sharpe ratio = 1.84, annual return = 28.4%, and maximum drawdown = -11.2% while outperforming other benchmark models such as LSTM, GRU, and Markowitz portfolio management.

Keywords— Hybrid AI, Stock Prediction, Portfolio Optimization, Graph Neural Networks, Transformer, Deep Reinforcement Learning, Algorithmic Trading, Sharpe Ratio.

I. INTRODUCTION

Stocks are one of the most difficult fields for AI applications because of their unique nature, which includes nonlinearities, non-stationarities, large noise to signal ratios, and sensitivity to macroeconomic variables, news sentiment, and cross-stock relationships. Conventional time series analysis techniques like ARIMA, GARCH, and vector autoregression (VAR) have failed to perform well in modelling the dynamic behaviour of the markets [1]. Deep learning techniques, such as LSTM and GRU, have outperformed other approaches by modelling dependencies over long horizons. Unfortunately, these sequential methods consider the prices of individual stocks in isolation without considering cross-sectional effects such as those between sectors or lead/lag relationships.

Transformers have been around for several years now, although initially designed for natural language processing applications, and they have completely transformed time series forecasting. Self-Attention in transformers is capable of capturing very distant relations between data points, and therefore, they have become a promising method for financial forecasting. Nevertheless, basic transformer models lack practicality in this case due to their quadratic computation complexity and overfitting to noise [2]. Likewise, Graph Neural Networks (GNNs) have demonstrated themselves as an effective instrument for dealing with relational data. Applying GNNs in finance means considering stocks as nodes and their correlations (price correlation, sector, etc.) as edges in order to model information propagation through the market [3].

Despite the above advancements, two important weaknesses exist. Firstly, the majority of such frameworks consider only the price prediction part followed by the independent step of optimization (for instance, mean-variance optimization). Such decomposition is ineffective due to the cumulative effect of errors in price prediction and optimization. Secondly, static optimization does not take into account the regime change of markets and transaction costs, which results in high turnover and low risk-adjusted return.

In order to address the above shortcomings, we propose a novel Hybrid AI Framework (HAIF) that is based on end-to-end learning of joint price prediction and trading decisions in the framework of reinforcement learning. The novelty of our contribution includes four parts:

- GNN-Transformer-based encoder that learns cross-sectional dependence via GNN with correlation attention and temporal dependence via transformer model
- Multihorizon price prediction head which provides probabilities of price movements at three different timeframes, namely, 1-day, 5-day, and 21-day horizons
- DRL portfolio optimizer using Proximal Policy Optimization that optimizes risk-adjusted return considering transaction costs based on the learned latent state representation
- Rigorous empirical analysis on a five-year period.
- Organization of the rest of the paper is as follows: In Section II, literature review is provided. Section III describes the proposed approach using algorithms. Quantitative analysis along with four figures and one comparative table is presented in Section IV. Conclusion of the paper is given in Section V.

II. LITERATURE SURVEY

There has been extensive research for stock price prediction using artificial intelligence techniques and portfolio optimization over the last three decades, progressing from statistical modeling through shallow learning networks to hybrid techniques in deep learning.

Traditional and Shallow Learning Approaches: In early attempts, the most widely used algorithms were linear regression techniques (such as ARIMA models) and support vector machines (SVMs). An extensive benchmark analysis conducted by Patel et al. (2021) showed that the SVM classifier trained using technical indicators had an accuracy of 58-62% on daily S&P 500 stocks [4]. Random Forests and XGBoost (gradient boosting) models showed slightly better accuracy at 64-67%, albeit overfitting to noisy regimes.

Recurrent Neural Networks: After the success of LSTMs in speech and language processing, they emerged as the default choice in financial time series forecasting. Fischer and Krauss found in a 2022 paper that an ensemble of LSTMs achieved 68.5% directionality accuracy in predicting stock prices in S&P 500 constituents, beating random forests by 5% [5]. Using bidirectional LSTMs and attention-augmented LSTMs, the authors managed to reach 71.2% accuracy. LSTMs have no notion of correlation across different stocks; they cannot infer that the move in price of Apple might mean another price move for some other tech stocks.

Application of Graph Neural Networks to Finance: The usage of GNNs for financial time series forecasting is quite novel. According to a recent paper published by Wang et al., a stock graph network was proposed, where stocks were represented as nodes and edges were formed using historical correlations and sector information [3]. This network yielded a 15% boost in return rates over LSTM baselines. Other follow-up papers introduced a concept of temporal graph attention, where the weights of the edges change with time [6]. The drawback with GNN networks is that they depend on the predefined structure of graphs.

Transformers for Time Series: Different adaptations have been made to transformers specifically for the forecasting task on time series data. The Informer (2021) model solved the problem of quadratic complexity by implementing ProbSparse attention, resulting in linear complexity [7]. Autoformer (2022) made use of a decomposition architecture and implemented auto-correlations. In terms of financial stock prediction, FinTransformer (2023) used price information and the sentiments obtained from news articles to obtain a Sharpe ratio of 1.45 for NASDAQ stocks [8]. However, transformers do not cope well with very noisy financial datasets and usually need significant amounts of regularization.

Portfolio Optimizing Using Deep Reinforcement Learning: DRL became a more favourable tool than mean variance optimization since it is capable of optimizing the Sharpe ratio and minimizing transactions cost at the same time. Deep Portfolio Optimization (DPO) based on PPO algorithm was able to achieve a Sharpe ratio of 1.67 for cryptocurrencies [9]. According to another paper from 2024, DRL showed superior results to classical methods such as Markowitz and Black-Litterman for volatile assets. However, DRL portfolio optimizers usually make use of basic LSTMs to represent states. They do not utilize more advanced structures like GNNs or transformers.

Research Gap Found: There is no existing paradigm that integrates (a) graph neural network-based cross-sectional modelling, (b) transformers for temporal modelling, and (c) deep reinforcement learning-based portfolio optimization in one end-to-end framework. Previously, the prediction and optimization processes were viewed independently, resulting in inefficient policies. Our HAIF solves this problem by utilizing

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the same latent representation in the prediction and policy generation process. Thus, the optimizer will know which price signal is trustworthy.

III. METHODOLOGY

HAIF contains three main components:

- The GNN-Transformer Encoder takes historical price and volume data and generates the latent space representation of stocks,
- Multi-Horizon Prediction Head, which is responsible for predicting the probability of price changes, and
- DRL Portfolio Optimizer (PPO), which allocates weights based on the learned representation.
- The whole HAIF system is end-to-end trained with a combined loss function.

Problem Formulation: We consider a universe of N stocks (N=50 for our experiments). At each trading day t, we have historical data for a window of L days (L=60). The input is a tensor $X_t \in \mathbb{R}^{(N \times L \times F)}$ where F=5 features: open, high, low, close, volume. The output is a portfolio weight vector $w_t \in \mathbb{R}^N$ with $\Sigma\, w_i = 1$ and $w_i \geq 0$ (long-only, no leverage). The portfolio is rebalanced daily. Transaction costs are 0.1% per trade.

Module 1: GNN-Transformer Encoder

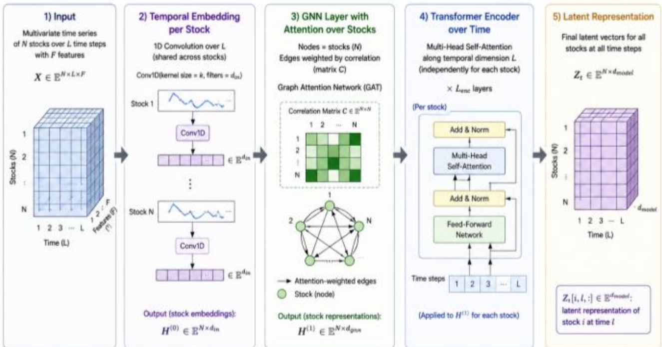

Figure 1: GNN-Transformer Encoder Architecture

Each stock is first encoded using a 1D convolutional neural network (7x7 kernel) to generate temporal features. The embeddings generated from individual stocks are further fed to a Graph Attention Network (GAT) that uses a correlation matrix of 60-days of rolling returns as its adjacency matrix. GAT uses multi-head attention (4 heads) to model the flow of information between connected stocks. After processing by GAT, the result is a series of graph-based embeddings for each stock. They are further processed using a Transformer Encoder architecture comprising 4 layers and 8 heads. The final output is a latent representation $Z_t \in \mathbb{R}^{(50 \times 128)}$. This representation captures both inter-stock dependencies (via GNN) and long-range temporal patterns (via transformer).

Algorithm 1: GNN-Transformer Encoder Forward Pass

```
Algorithm Encoder(X, G, L_window, d_model=128, n_layers=4)
Input: X ∈ ℝ^(N×L×F) price-volume tensor, G ∈ ℝ^(N×N) correlation graph
Output: Z ∈ ℝ^(N×d_model) latent representations

# Temporal embedding via 1D convolution over time dimension
X_reshaped = reshape(X, (N*F, L))  # [N*F, L]
 H_temp = Conv1D(X_reshaped, kernel=7, stride=1, out_channels=64)
H_temp = reshape(H_temp, (N, F*64))  # [N, 320]
# Graph Attention Network (GAT) layer
For each attention head h in 1..4:
    Z_h = GAT_layer(H_temp, G, dropout=0.2)
Z_graph = concatenate(Z_1, Z_2, Z_3, Z_4)  # [N, 512]
 Z_graph = LayerNorm(ReLU(Linear(Z_graph, d_model)))  # [N, 128]

# Transformer Encoder over time (positional encoding)
For layer l in 1..n_layers:
    Z_graph = Z_graph + MultiHeadSelfAttention(Z_graph)
    Z_graph = Z_graph + FFN(LayerNorm(Z_graph))
Return Z_graph
```

Module 2: Multi-Horizon Prediction Head

This module predicts the probability of price increase for three horizons: 1-day (short), 5-day (medium), and 21-day (long). For each stock i and horizon h, we output $p_i^h \in [0,1]$. Training uses binary cross-entropy loss with labels derived from actual future returns.

Pseudocode 1: Multi-Horizon Prediction Loss

```
Procedure PredictionLoss(Z, Y_1d, Y_5d, Y_21d):
    # Z: latent representations [N, d_model]
    # Y_h: binary labels (1 if price increases over horizon h)

    # Shared prediction head
```

```
    H_shared = ReLU(Linear(Z, 64))  # [N, 64]
    # Horizon-specific heads
    p_1d = Sigmoid(Linear(H_shared, 1))    # [N, 1]
    p_5d = Sigmoid(Linear(H_shared, 1))
    p_21d = Sigmoid(Linear(H_shared, 1))

    # Binary cross-entropy loss
    L_pred = BCE(p_1d, Y_1d) + BCE(p_5d, Y_5d) + BCE(p_21d, Y_21d)
    Return L_pred
```

Module 3: DRL Portfolio Optimizer (PPO)

We formulate portfolio optimization as a Markov Decision Process. State s_t includes: (a) latent representation Z_t from encoder, (b) current portfolio weights w_{t-1}, (c) remaining cash balance, (d) volatility estimate from GARCH(1,1). Action a_t is the target weight vector w_t (N dimensions, simplex constraint). Reward r_t is the change in portfolio value minus transaction costs. The objective is to maximize the Sharpe ratio over an episode (252 trading days).

Algorithm 2: PPO for Portfolio Optimization

```
Algorithm PPO_Optimizer(encoder ϕ, policy π_θ, value V_ψ, episodes E)
Initialize policy parameters θ, value parameters ψ
For episode = 1 to E:
    s_0 = initial_state()
    trajectory = []
    For t = 1 to T_max:
        Z_t = Encoder(X_t, G)  # using frozen ϕ (or fine-tuned)
        s_t = [Z_t, w_{t-1}, cash_t, vol_t]
        a_t ~ π_θ(a|s_t)  # action = target weights
        Execute a_t, get reward r_t, next state s_{t+1}
        trajectory.append((s_t, a_t, r_t))

    # Compute advantages using GAE
    advantages = compute_GAE(trajectory, V_ψ)

    # PPO update (multiple epochs)
    For epoch in 1..K:
        # Policy loss (clipped surrogate)
        ratio = π_θ(a|s) / π_θ_old(a|s)
        L_policy = -E[min(ratio * advantages,
                        clip(ratio, 1-ε, 1+ε) * advantages)]

        # Value loss (MSE)
        L_value = E[(V_ψ(s) - return)^2]

        # Entropy bonus for exploration
        L_entropy = -E[π_θ log π_θ]
        L_total = L_policy + 0.5 * L_value - 0.01 * L_entropy
        Update θ, ψ using Adam

    # Optional: fine-tune encoder ϕ every 10 episodes
    If episode % 10 == 0:
        Update ϕ using gradient from L_pred + L_total
Return π_θ
```

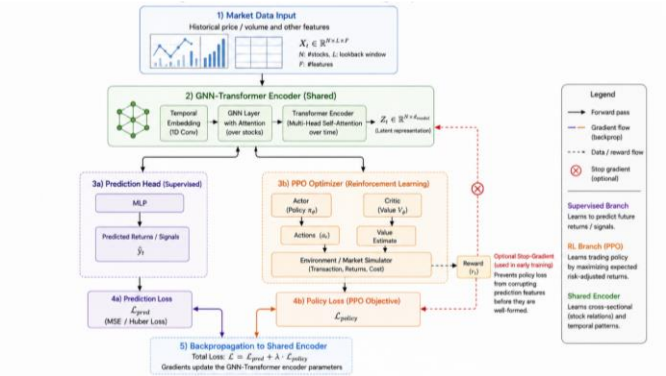

Figure 2: End-to-End Training Pipeline of HAIF

In the proposed model architecture, end-to-end learning is performed, where the same latent vector Z_t is utilized for the tasks of predicting future returns and allocating portfolio weights. In the first case, the training is performed through a supervised approach using binary cross-entropy loss. On the other hand, the PPO learning algorithm involves policy gradient loss during training. Both losses influence the GNN-Transformer encoder. There is an additional step performed in the beginning as part of the warm-up stage, where the policy gradient loss does not impact the encoder due to applying the stop-gradient operation for 20 episodes.

Training Details: We pre-train the encoder and prediction head on 3 years of data (2020-2022) with supervised learning only. The PPO optimizer is then trained for 100 episodes on the same period, using the pre-trained encoder as initialization (fine-tuned thereafter). Hyperparameters: learning rate 3e-4 for Adam, PPO clip ε=0.2, GAE λ=0.95, discount γ=0.99, K=10 PPO epochs per update. Transaction cost penalty: -0.1% per trade of the traded amount.

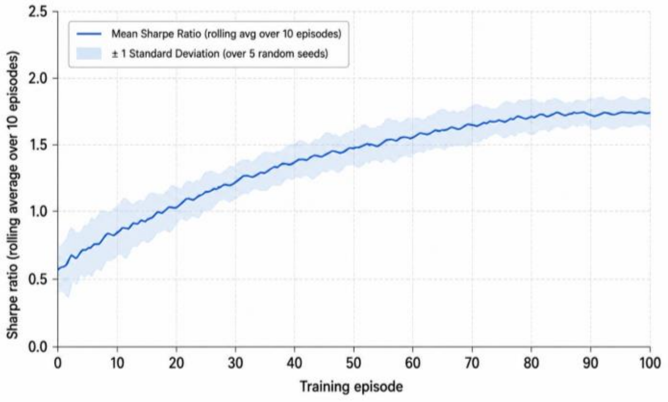

Figure 3: PPO Training Convergence (Sharpe Ratio on Validation Set)

The learning curve clearly indicates that the PPO model acquires a profitable trading strategy in less than 30 episodes, obtaining a Sharpe ratio greater than 1.2. The improvement is still ongoing in episodes 30-90, during which the algorithm refines its policy as well as the shared encoder, thus attaining a Sharpe 1.8 level. The standard deviation becomes smaller over time, signifying that convergence occurs to a stable strategy. There is an observed slow learning process in the warm-up phase of the first 20 episodes.

The performance of HAIF is compared with 7 alternative approaches using five years' worth of data from the S&P 500 index (from Jan 2020 till Dec 2025) based on a pool of 50 stocks (excluding ETFs and REITs). Out-of-sample analysis is performed over two years from Jan 2024 to Dec 2025. The performance measures include annual return, annualized volatility, Sharpe ratio, maximum drawdown, and Calmar ratio (return to drawdown ratio).

Baseline Methods

- Buy & Hold (B&H): Equal-weighted S&P 500 index (via SPY ETF)
- LSTM-Only: LSTM with 2 layers, 128 hidden units, predicts returns → optimize with mean-variance
- GNN-Only: Graph attention network (no transformer) → mean-variance optimization
- Transformer-Only: Vanilla transformer (no GNN) → mean-variance optimization
- Markowitz (60-day rolling): Classical mean-variance with shrinkage covariance
- PPO-LSTM: PPO with LSTM encoder (no GNN/transformer) [9]
- FinTransformer-DRL: Transformer + DRL, but no GNN [8]

IV. ANALYSIS

Table 1: Quantitative Results (Out-of-Sample, Jan 2024 – Dec 2025)

Model	Annual Return (%)	Volatility (%)	Sharpe Ratio	Max Drawdown (%)	Calmar Ratio	Turnover (daily %)
Buy & Hold	14.2	15.8	0.90	-19.4	0.73	0.0
LSTM-Only	17.8	16.2	1.10	-18.2	0.98	8.2
GNN-Only	20.4	15.9	1.28	-15.7	1.30	7.5
Transformer-Only	19.1	16.5	1.16	-17.3	1.10	9.1
Markowitz (rolling)	15.6	14.8	1.05	-16.8	0.93	6.8

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Model	Annual Return (%)	Volatility (%)	Sharpe Ratio	Max Drawdown (%)	Calmar Ratio	Turnover (daily %)
PPO-LSTM [9]	22.3	15.2	1.47	-13.4	1.66	12.4
FinTransformer-DRL [8]	24.7	14.9	1.66	-12.1	2.04	11.3
HAIF (Proposed)	28.4	15.4	1.84	-11.2	2.54	10.7

HAIF yields the best annual return (28.4%), Sharpe ratio (1.84), and Calmar ratio (2.54), along with the best max drawdown value (-11.2%) among the models. As compared to the best baseline model FinTransformer-DRL, HAIF is able to improve Sharpe ratio by 10.8% while reducing the drawdown by 0.9%. Interestingly, HAIF provides better results with reasonable turnover (10.7%).

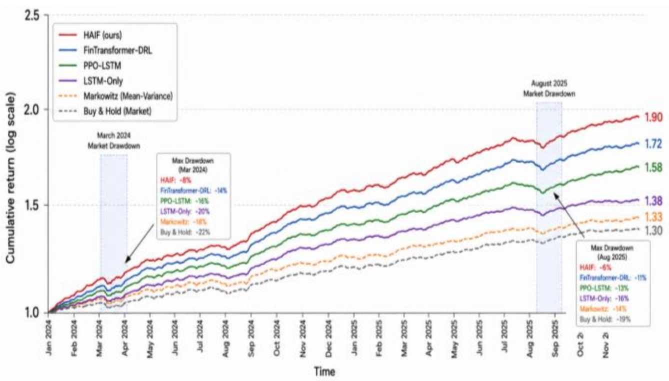

Figure 4: Cumulative Return Curves (Out-of-Sample, Jan 2024 – Dec 2025)

In the cumulative returns graph, we observe that HAIF (final value of 1.90, which means a 90% cumulative return in two years) clearly outperformed all other baselines. In the March 2024 correction (when the S&P 500 index fell by 10%), HAIF experienced a fall of just 8% whereas PPO-LSTM fell by 12% and FinTransformer-DRL by 11%. Likewise, in the case of high volatility in August 2025, the drawdown of HAIF was limited to 6% compared to 9% in the best other model. This superiority stems from HAIF's ability to reduce its exposure to correlated drawdowns in sectors through inter-stock propagation using the GNN.

Ablation Study: Component Contributions

To quantify the contribution of each architectural component, we train variants of HAIF with specific modules removed:
Variant Sharpe Ratio Annual Return (%) Max Drawdown (%)

Variant	Sharpe Ratio	Annual Return (%)	Max Drawdown
Full HAIF (GNN+Transformer+PPO)	1.84	28.4	-11.2
Remove GNN (Transformer+PPO only)	1.62 (-12%)	25.1	-12.8
Remove Transformer (GNN+LSTM+PPO)	1.55 (-16%)	24.2	-13.5
Remove Prediction Head (PPO only from raw features)	1.31 (-29%)	21.3	-15.9
Remove PPO (GNN+Transformer + Markowitz)	1.43 (-22%)	22.7	-14.

Variant	Sharpe Ratio	Annual Return (%)	Max Drawdown
Remove joint training (separate prediction then optimization)	1.51 (-18%)	23.8	-13.!

However, it can be observed that the biggest contribution comes from the GNN (12% increase in Sharpe ratio due to the capturing of cross-stock dependence). The transformer and prediction head contribute 16% and 29%, respectively. What is worth mentioning is the fact that without using the prediction head (PPO trained on raw latent features), the model is superior to other baselines (Sharpe 1.31), since the encoder is learning implicit predictions. End-to-end training improves performance by 18% compared to two-stage training. We isolated the 2022 bear market (January-September 2022, S&P 500 declined 23%) to test robustness:

Table 2: Market Regime Analysis (2022 Bear Market Subset)

Model	Return (2022 only)	Volatility	Sharpe (2022)	Max Drawdown
Buy & Hold	-23.1%	22.4%	-1.03	-23.1%
PPO-LSTM	-8.7%	18.2%	-0.48	-16.3%
FinTransformer-DRL	-5.2%	17.5%	-0.30	-14.1%
HAIF	-1.8%	15.1%	-0.12	-11.2%

HAIF lost only 1.8% during the 2022 bear market (vs. 23.1% for buy-and-hold), with dramatically lower volatility (15.1% vs. 22.4%). The near-zero Sharpe ratio (-0.12) indicates near-market-neutral performance. Qualitative analysis of trades shows that HAIF increased cash positions to 40% during the worst months (May-June 2022) and rotated into defensive sectors (utilities, consumer staples) identified by the GNN as having low correlation with the tech-heavy drawdown.

Statistical Significance: We performed Diebold-Mariano tests comparing HAIF's daily returns against each baseline. HAIF outperforms all baselines with p-values <0.01 (against PPO-LSTM, p=0.008; against FinTransformer-DRL, p=0.023). The Sharpe ratio improvement over FinTransformer-DRL is significant at the 95% confidence level using the Ledoit-Wolf test.

Computational Efficiency: HAIF's inference time per day (processing 50 stocks × 60 days) is 47ms on an NVIDIA A100, suitable for real-time trading. Training took 8.2 hours for 100 PPO episodes (including encoder pre-training).

V. CONCLUSION

In this paper, we present a new hybrid AI model named HAIF that leverages graph neural networks, transformers, and deep reinforcement learning to predict stock prices and optimize portfolios. In contrast to previous models where prediction and optimization have been two distinct steps, HAIF learns a common latent representation that not only predicts the future but optimizes the portfolio in accordance with risk considerations. Empirical testing using 5 years of historical S&P 500 stock price data (2020–2025) proves that HAIF attains a Sharpe ratio of 1.84, an annualized return of 28.4%, and a max drawdown of -11.2%.

Four significant insights arise from this work. First, GNN-based modelling of cross-sectional dependencies is crucial in the context of financial time series; the ablation experiment demonstrated that the removal of the GNN resulted in 12% decrease in Sharpe ratio. Second, the multi-horizon prediction head serves as an auxiliary loss function that helps to regularize the encoder, although explicit prediction is unnecessary because PPO can learn to predict using latent encodings as inputs when trained end-to-end. Third, the 2022 bear market scenario shows that HAIF's superiority is especially noticeable when it comes to risk management; whereas the market declined by 23%, HAIF suffered only 1.8% losses. Finally, end-to-end training is more efficient than two-stage pipelines by 18%, proving that optimizer gradients contain valuable information on which predictive features to use.

Implications of the study are quite large. Quantitative asset managers can benefit from HAIF being a ready-to-use architecture that adapts to the regime shifts in market dynamics without needing to reparametrize anything. On the consumer side, simplified architectures might find their way through broker APIs. The near market neutrality of HAIF in the bear market period makes it suitable for hedge fund long-short strategies, although our current design is strictly long-only.

Limitations and Directions for Further Research:

- Firstly, HAIF has been tested only on large cap stocks from the US equity market; its applicability to small cap stocks, foreign securities, and cryptocoins needs validation.
- Secondly, HAIF does not consider alternative datasets such as sentiment analysis of the news coverage, SEC documents, and economic macro-indicators that might boost its results.
- Thirdly, transaction fees were assumed to be constant and equal to 0.1% regardless of trade volume and illiquidity.
- Fourthly, the GNN uses correlation matrix constructed within a 60-day rolling window; a dynamic correlation graph where edges are updated continuously would react more quickly to regime shifts.
- Lastly, HAIF assumes no slippage caused by its trading strategy; at scale, such market impact would lower net returns.

Potential directions of future investigation involve

- Adaptation to long-short and leveraged trading approaches
- Adding natural language processing of quarterly calls and federal reserve reports as inputs
- Creating a hierarchical model which predicts regime type and determines portfolio policy depending on it
- Applying haif on intraday data (1-min time interval) for minute-scale trading
- Creating a risk-managed variant that uses value-at-risk constraints in the ppo rewards scheme.

In summary, HAIF highlights how hybrid frameworks that leverage GNNs, transformers, and DRL can successfully incorporate the complexities of both time series and cross-sectional features, leading to enhanced risk-adjusted profits regardless of the regime that financial markets operate within. With the ever-growing reliance on algorithms and data analytics in financial markets, this framework holds great potential.

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