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PERFORMANCE OPTIMIZATION OF DEEPSEEK MOE ARCHITECTURE IN MULTI-SCALE PREDICTION OF STOCK RETURNS

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Abstract: Stock market data has significant multi-scale characteristics. High-frequency data (such as minute-level price fluctuations) contains rich but noise-intensive short-term information, while low-frequency data (such as daily trend) reflects long-term market dynamics but has response delays. Traditional time-series models (such as LSTM or Transformer) have inherent limitations in processing multi-scale features: the recursive structure of LSTM is difficult to efficiently process high-frequency noise, and the self-attention mechanism of Transformer is insufficient in capturing local features and has a large number of parameters. This study proposes a dynamic routing optimization framework based on DeepSeek MoE (Mixture of Experts), which realizes effective decoupling and fusion of multi-scale features through a hierarchical processing architecture, intelligent routing mechanism, and efficient parallel computing technology. Experimental results show that on the Shanghai-Shenzhen 300 constituent stocks (2018-2024) dataset, the high-frequency prediction error of the model is reduced by 32.7% compared with traditional methods, and the maximum drawdown rate under extreme market conditions is reduced by 41%. Gradient attribution analysis reveals the dominant role of liquidity factors (such as turnover rate) in the prediction results, providing an interpretable intelligent decision-making framework for quantitative investment.

Keywords: DeepSeek; Mixture of Experts (MoE); Dynamic routing mechanism; Stock return prediction; Multi-scale feature decoupling; Financial time-series analysis; VIX volatility index; Gradient attribution analysis; Shanghai-Shenzhen 300 index

1 INTRODUCTION

1.1 Research Background and Significance

DeepSeek large model [1] has recently received extensive attention. DeepSeek MoE is an innovative Mixture-of-Experts (MoE) architecture designed to achieve higher expert specialization and computational efficiency through fine-grained expert segmentation and shared expert isolation strategies [2].

Stock return prediction is a core challenge in the field of quantitative investment, and its complexity stems from the multi-scale characteristics of financial time series. High-frequency data (such as 5-minute K-lines) contains market microstructure information but is easily disturbed by short-term noise; low-frequency data (such as daily closing prices) reflects macro trends but has significant time-lag effects. Traditional models face dual dilemmas when processing such data:

LSTM Model: It captures long-term dependencies through a gating mechanism, but its recursive calculation results in a time complexity of O(T), making it difficult to efficiently process high-frequency data. At the same time, due to the problem of gradient disappearance, the modeling ability of deep LSTM networks for long-distance dependencies is limited (Hochreiter & Schmidhuber, 1997) [3].

Transformer Model: It achieves O(1) time complexity for long-range dependency modeling based on the self-attention mechanism but lacks the hierarchical extraction ability of local features. Moreover, its quadratic complexity ($O(N^2)$) leads to a sharp increase in computational resource consumption in high-frequency data scenarios (Vaswani et al., 2017) [4].

The Mixture of Experts (MoE) model provides a new paradigm for multi-scale modeling by dynamically routing mechanisms to allocate specialized computing resources for different subtasks. The DeepSeek-V3 model has shown significant advantages in processing high-frequency financial data through the collaborative scheduling of 256 expert networks.

However, the application of existing MoE models in the financial field still faces three major challenges [5]:

1) Scale Conflict Problem: The mixed input of high-frequency noise and low-frequency trends leads to functional redundancy of expert networks.
2) Insufficient Dynamic Adaptability: Traditional static routing strategies (such as Top-k) cannot respond to changes in market conditions in real-time.
3) Lack of Interpretability: The black-box decision-making process is difficult to meet the requirements of financial supervision.

1.2 Technical Challenges

This study focuses on the following key technical bottlenecks:

1) Multi-scale Feature Decoupling: How to design a hierarchical feature extraction module to effectively separate high-frequency noise and low-frequency trends.
2) Dynamic Routing Optimization: How to introduce a market state perception mechanism to improve the model's adaptability to extreme market conditions.
3) Enhanced Interpretability: How to quantify the decision-making logic of expert networks to provide a theoretical support for investment strategies.

1.3 Research Contributions

This study proposes a systematic solution with the following innovations:

1) Hierarchical Routing Architecture: Construct a dual-channel processing module for high-frequency CNN and low-frequency LSTM-Transformer, and dynamically allocate data based on the Hurst index.
2) Market State Perception: Introduce the VIX volatility index as a routing weight adjustment factor to enhance the model's response to market mutations.
3) Interpretability Framework: Combine gradient attribution analysis with routing heatmap visualization to reveal factor contribution and expert decision-making logic.

2 RELATED WORK

2.1 Financial Applications of Mixture of Experts Models

Research on MoE models in the financial field mainly focuses on the following directions:

1) High-Frequency Trading Optimization: DeepSeek-V3 processes data from different time windows in parallel through expert networks to generate microsecond-level trading signals (Shazeer et al., 2017) [6].
2) Multi-Asset Portfolio Management: DeepSeek-V3 proposes a fine-segmented expert strategy to reduce redundant calculations for cross-asset modeling through shared expert networks [7].
3) Risk Prediction: Andrew M. Dai et al. combined MoE with Copula theory to propose a model for predicting the risk dependence of multiple assets [8].

Limitations of existing research:

1) Static routing strategies are difficult to adapt to dynamic market changes.
2) Lack of targeted design for multi-scale features.
3) Relatively scarce interpretability research.

2.2 Multi-Scale Time-Series Analysis Methods

Traditional multi-scale analysis methods can be divided into two categories:

Frequency Domain Decomposition Methods: Such as wavelet transform (Wavelet Transform) and empirical mode decomposition (EMD), which realize multi-scale feature separation through fixed basis functions. However, the non-stationarity of financial data limits their decomposition accuracy (Mallat, 1999) [9].

Deep Learning Methods:

1) LSTM-Transformer Hybrid Architecture: Uses LSTM to capture local dependencies and Transformer to model global correlations but does not solve the problem of high-frequency noise interference (Zhang et al., 2021) [10].
2) Dilated CNN: Expands the receptive field through dilated convolutions but lacks coherent modeling of low-frequency trends (Yu & Koltun, 2015) [11].

Compares the Performance Differences of Mainstream Methods can be seen in table 1.

Table 1 Compares the Performance Differences of Mainstream Methods

Method	High-Frequency Processing	Low-Frequency Processing	Interpretability	Computational Efficiency
LSTM	Poor	Excellent	Medium	Low
Transformer	Medium	Excellent	Poor	Medium
XGBoost	Poor	Medium	Excellent	High
DeepSeek-V3	Excellent	Medium	Medium	High
Our Model	Excellent	Excellent	Excellent	High

3 METHODOLOGY

3.1 Model Architecture Design

3.1.1 Hierarchical Routing Mechanism

This study proposes a two-layer routing strategy:

1. Primary Routing: Allocates data channels based on the Hurst index. The Hurst index H ∈ [0,1] is used to measure the long-term memory of the time series. When H > 0.65, it is determined to be dominated by low-frequency trends, and the data enters the low-frequency channel; otherwise, it enters the high-frequency channel. This threshold is optimized on the training set using the Bootstrap method.
2. Secondary Routing: Adopts a competitive gating mechanism within the expert layer, with the formula:

$$g_j(x) = \frac{\exp(f_j(x))}{\sum_{k=1}^{K} \exp(f_k(x))} \cdot (1 + \lambda \cdot \mathrm{Entropy}(g))$$

where fj (x) is the output of the expert network, and λ=0.01 is the regularization coefficient used to balance the expert load.

3.1.2 Multi-Scale Processing Module

1. High-Frequency Expert Group: Composed of 10 lightweight CNNs, each containing 3 dilated convolution layers (dilation rates = 1, 3, 5), with group normalization (GroupNorm) to suppress noise. The number of parameters per expert is controlled within 0.5M.
2. Low-Frequency Expert Group: Adopts an LSTM-Transformer hybrid structure, where the LSTM module (hidden layer dimension 128) extracts time-series features, and the multi-head latent attention (MLA) mechanism models cross-cycle dependencies.

3.1.3 Dynamic Fusion Strategy

Introduce the VIX index as a market volatility indicator to dynamically adjust the weights of high-frequency and low-frequency outputs: Wfusion=σ (α· VIX+β)
where σ is the Sigmoid function, and α and β are optimized through reinforcement learning.

3.2 Computational Optimization Strategies

3.2.1 Dual Pipe Parallel Technology

1. Data Parallelism: Divide the Shanghai-Shenzhen 300 constituent stocks into 32 sub-batches by industry and update gradients asynchronously on 4 NVIDIA A100 GPUs.
2. Model parallelization: High-frequency layers of CNN in channel dimension split, low-frequency layers of LSTM in time step dimension split, memory allocated down to 18 GB.
3. Mixed-Precision Training: Uses a mixture of FP16 and FP32 calculations, increasing the training speed by 1.8 times.

Table 2 shows the optimization effects:

Table 2 Optimization Effects

Optimization Item	Processing Speed (samples/s)	Memory usage in gigabytes (GB)	Training Cycle (hours)
Traditional Model	412	32	78
Our Model	1,280	18	53
Improvement Rate	210%	44%↓	32%↓

3.2.2 Expert Preloading Technology

Preload expert network weights into shared memory to reduce PCIe (Peripheral Component Interconnect Express) transmission latency, shortening the critical path calculation time to 3.2ms.

3.3 Interpretability Enhancement Methods

3.3.1 Gradient Attribution Analysis

Use the integrated gradient method to quantify feature contribution:

$$\mathrm{Attribution}(x_i) = \int_{\alpha=0}^{1} \frac{\partial F(x_0+\alpha(x-x_0))}{\partial x_i} d\alpha$$

Where x_0 is the baseline input (e.g., zero vector), and F is the model output.

3.3.2 Routing Heatmap

Visualize the distribution of expert weights during market state transitions. For example, when VIX > 40 in extreme market conditions, the weight of low-frequency experts increases from 45% to 65%.

4 EXPERIMENTS AND RESULTS

4.1 Dataset and Preprocessing

4.1.1 Data Sources

1) High-Frequency Data: Shanghai-Shenzhen 300 constituent stocks (2018-01-01 to 2024-06-30), including:
5-minute K-line data (open, high, low, close, volume);
26 technical indicators (e.g., MACD, RSI, OBV, turnover rate, order book slope, etc.).
Total of 120 million records covering 28 Shenwan first-level industries.
2) 2. Low-Frequency Data:
Daily macroeconomic indicators (8 dimensions such as year-on-year CPI, M2 growth rate, social financing increment);
Industry capital flow data (northbound capital inflow, main capital trends).

4.1.2 Data Cleaning

1) Outlier Handling:
Filter extreme values using the 3σ principle (e.g., daily price change exceeding 15% is considered an outlier);
Exclude ST stocks and samples with more than 5 trading days of suspension.
2) Downsampling Strategy:
Aggregate original 1-minute data into 5-minute granularity using OHLC (Open-High-Low-Close) aggregation.
3) Missing Value Filling:
High-frequency data: Use forward fill for short-term missing values;
Low-frequency data: Complement missing macro indicators using linear interpolation.

4.2 Experimental Setup

4.2.1 Comparison Models

Comparison models can be seen in table 3.

Table 3 Comparison Models

Model Name	Core Architecture	Parameter Configuration
LSTM-Transformer	LSTM + Transformer	3 LSTM layers, hidden dimension 256; 6 Transformer layers, 8 heads, FFN dimension 512
DeepSeek-V3	MoE architecture (64 experts)	Expert networks: CNN-LSTM hybrid; Routing strategy: Top-2 static routing
XGBoost	Gradient Boosting Tree	1000 trees, learning rate 0.01, maximum depth 6, subsample 0.8
TFT	Temporal Fusion Transformer	4 encoder layers, 2 decoder layers, 4 attention heads, learning rate 1e-4
LightGBM	Gradient Boosting Tree	2000 trees, learning rate 0.005, maximum depth 8, feature subsampling 0.7

4.2.2 Parameter Settings

Optimizer: AdamW (weight decay 0.01)
Learning Rate Scheduling: Cosine annealing (initial LR = 1e-4, minimum LR = 1e-6)
Batch Size: 512 (high-frequency)/256 (low-frequency)
Training Epochs: 100 epochs (early stopping patience = 10)
Loss Function:
Regression task: Huber Loss (δ = 1.0)
Routing regularization: KL divergence constraint for expert load balancing

4.2.3 Evaluation Metrics

Evaluation metrics can be seen in table 4.

Table 4 Evaluation Metrics

Metric Type	Specific Metric	Calculation Method
Prediction Accuracy	RMSE (Root Mean Squared Error)	$SQRT(\Sigma(y_i - \hat{y}_i)^2 / N)$
	MAE (Mean Absolute Error)	Σ（$y_i - \hat{y}_i$）$/ N$
	R^2 (Coefficient of Determination)	$1 - \Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2$
Risk-Return	Maximum Drawdown (MDD)	max(1 - min(portfolio_value))
	Adjusted Sharpe Ratio (ASR)	(Annualized Return - Risk-Free Rate) / Downside Standard Deviation
Statistical Significance	Two-Tailed t-Test (p-value)	Compare the significance of differences between models

4.3 Performance Comparison Analysis

4.3.1 Full Sample Results

Full sample results can be seen in table 5.

Table 5 Full Sample Results

Model	RMSE (High-Frequency)↓	MAE (Low-Frequency)↓	R^2↑	Maximum Drawdown↓	ASR↑	p-value (vs DeepSeek-V3)
LSTM-Transformer	0.47	0.32	0.61	15.8%	1.92	-
DeepSeek-V3	0.39	0.28	0.72	12.1%	2.41	-
XGBoost	0.53	0.35	0.58	18.4%	1.67	-
TFT	0.42	0.30	0.68	13.7%	2.15	-
LightGBM	0.51	0.33	0.60	16.9%	1.89	-
Our Model	0.31	0.23	0.81	7.2%	2.87	<0.001

Key Findings:

1) High-frequency prediction: Our model's RMSE is 20.5% lower than DeepSeek-V3 ($p < 0.001$), verifying the noise filtering ability of the CNN module.
2) Low-frequency trends: R^2 of 0.81, better than second place in DeepSeek-V3's 0.72.
3) Extreme risk management: Maximum drawdown rate of 7.2%, better than second place in DeepSeek-V3's maximum drawdown rate of 12.1%.

4.3.2 Performance in Different Market States

Performance in different market states can be seen in table 6.

Table 6 Performance in Different Market States

Market State	Metric	LSTM-Transformer	DeepSeek-V3	Our Model
Bull Market	RMSE (High-Frequency)	0.42	0.35	0.28
(VIX < 20)	Maximum Drawdown	12.3%	9.8%	5.1%
Bear Market	RMSE (High-Frequency)	0.51	0.44	0.34
(VIX > 30)	Maximum Drawdown	21.5%	16.7%	9.3%
Volatile Market	RMSE (High-Frequency)	0.45	0.37	0.30
(20 ≤ VIX ≤ 30)	Maximum Drawdown	14.8%	11.2%	6.8%

4.4 Ablation Experiments

4.4.1 Validation of Key Components

Validation of key components can be seen in table 7.

Table 7 Validation of Key Components

Model Variant	RMSE (High-Frequency) ↓	MAE (Low-Frequency) ↓	Maximum Drawdown ↓	ASR ↑	Expert Load Variance↓
Full Model	0.31	0.23	7.2%	2.87	0.12
-Hierarchical Routing (Ours-w/o Routing)	0.44	0.29	10.5%	2.12	0.38
-VIX Dynamic Adjustment (Ours-w/o VIX)	0.34	0.25	9.8%	2.53	0.15
-Expert Preloading Technology	0.32	0.24	7.8%	2.76	0.13

Conclusions:

1. Hierarchical routing reduces expert load variance by 68.4%.
2. The VIX adjustment strategy increases ASR by 13.4% in bear markets.
3. Preloading technology reduces critical path latency by 47.8%.

4.5 Interpretability Validation

4.5.1 Feature Contribution (Integrated Gradient Method)

Feature contribution (integrated gradient method) can be seen in table 8.

Table 8 Feature Contribution (Integrated Gradient Method)

Feature Category	High-Frequency Prediction Contribution	Low-Frequency Prediction Contribution
Turnover Rate	23.7%	8.2%

Feature Category	High-Frequency Prediction Contribution	Low-Frequency Prediction Contribution
Order Book Slope	18.4%	-
M2 Year-on-Year Growth Rate	-	31.2%
Industry Capital Flow	9.8%	27.9%
Bollinger Band Width	15.2%	6.5%
VIX Volatility	7.3%	12.1%

4.5.2 Routing Strategy Statistics

Routing Strategy Statistics can be seen in table 9.

Table 9 Routing Strategy Statistics

VIX Range	Average High-Frequency Expert Activation Rate	Average Low-Frequency Expert Activation Rate	Routing Response Delay (ms)
[10, 20)	78.2%	21.8%	3.2
[20, 30)	55.4%	44.6%	3.5
[30, 40)	32.1%	67.9%	3.8
[40, 50)	18.7%	81.3%	4.1

4.6 Computational Resource Consumption

Computational Resource Consumption can be seen in table 10.

Table 10 Computational Resource Consumption

Model	GPU Memory Usage (GB)	Single-Sample Inference Time (ms)	Training Throughput (samples/s)
LSTM-Transformer	22.4	12.3	412
DeepSeek-V3	28.7	15.8	685
Our Model	18.2	8.7	1280

4.7 Statistical Significance Test

Two-tailed t-tests ($\alpha = 0.05$) were conducted between our model and DeepSeek-V3:

1) RMSE difference: $t = 8.32$, $p = 2.1e\text{-}15$
2) MAE difference: $t = 6.17$, $p = 4.3e\text{-}9$
3) Maximum drawdown difference: $t = 7.91$, $p = 5.8e\text{-}14$
4) ASR difference: $t = 5.29$, $p = 1.7e\text{-}7$

5 DISCUSSION AND OUTLOOK

5.1 Application Value

1) Intelligent Investment Advisor System: Real-time display of model decision-making logic through routing heatmaps, such as dynamically increasing the weight of low-frequency experts during central bank interest rate cuts.
2) Risk Early Warning Tool: Combine the VIX index to build an early warning system. Before the stock market crash in Q2 2024, the model reduced high-risk asset allocations 5 trading days in advance.

5.2 Limitations

1) Hurst Index Sensitivity: During periods of policy intervention (such as the 2020 circuit breaker mechanism), the calculation accuracy of the Hurst index decreases, leading to routing deviations.
2) Cross-Market Generalization: Testing in the U.S. stock market showed that the Sharpe ratio decreased from 2.87 to 2.15, requiring further optimization of parameter sharing mechanisms.

5.3 Future Research Directions

1) Multi-Modal Fusion: Integrate news sentiment (NLP) and capital flow graphs (graph networks) to build a joint representation space.
2) Online Learning Framework: Use reinforcement learning strategies to achieve dynamic evolution of expert networks and improve the model's time-varying adaptability.
3) Optimization of edge computing techniques, including Fixed-point arithmetic, quantization to compress memory usage down to 10GB below, supports mobile deployment across a distributed edge computing network.

6 CONCLUSION

The DeepSeek MoE framework proposed in this study effectively solves key challenges in multi-scale financial time-series prediction through a hierarchical processing architecture, dynamic routing mechanism, and efficient parallel technology. Experimental results show that the model has made breakthroughs in prediction accuracy, risk control, and interpretability. Future research will focus on multi-modal fusion and online optimization to promote the practical application of intelligent financial analysis systems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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EXPLANATION OF PROFESSIONAL TERMS

1. **Hurst Index:** A statistical indicator measuring the long-term memory of a time series, proposed by British hydrologist Harold Edwin Hurst in 1951. It quantifies the rate at which autocorrelation decays over time to determine whether the data has trend continuity or periodicity. Calculated through R/S analysis, it reflects the long-term memory of the time series. $H = 0.5$: The sequence is a random walk (no long-term memory); $H > 0.5$: Positive correlation (trend continuity); $H < 0.5$: Negative correlation (trend reversal). In finance, it is used for market state recognition: Bull market: $H \approx 0.7\sim0.9$ (strong trend persistence); Bear market: $H \approx 0.6\sim0.7$ (weak trend persistence); Volatile market: $H \approx 0.4\sim0.5$ (mean reversion dominant).
2. **VIX Volatility Index:** A key indicator measuring the market's expected volatility over the next 30 days, introduced by the Chicago Board Options Exchange (CBOE) in 1993 and known as the "fear index." It is calculated using the implied volatility of S&P 500 index options and reflects market expectations of potential risks. In this paper, the VIX index is used for: (1) Dynamic routing mechanism: Real-time adjustment of high-frequency and low-frequency module weights: $wfusion = \sigma(\alpha \cdot VIX+\beta)$. When VIX > 40 (extreme market conditions), the weight of low-frequency experts increases from 45% to 65%; (2) Risk early warning: Before the stock market crash in Q2 2024, the model reduced high-risk asset allocations in advance due to an abnormal increase in VIX (average 43.2).
3. **Dilated Convolution:** Exponentially expands the receptive field through the dilation rate while maintaining the number of parameters. The receptive field is a core concept in convolutional neural networks (CNNs), referring to the range of the original input data corresponding to a neuron (or a point in the feature map) in the neural network. Specifically, in image tasks, the receptive field is the size of the pixel region in the original image corresponding to a pixel in the feature map. In natural language processing, it may refer to the context range of a position in the word vector sequence.
4. **Integrated Gradient Method:** A path-integral-based attribution method that quantifies the contribution of input features to the output by calculating the cumulative impact of the input features on the output.