MM-DREX: Multimodal-Driven Dynamic Routing of LLM Experts for Financial Trading

Yang Chen[1], Yueheng Jiang[1], Zhaozhao Ma[1], Yuchen Cao[2+],
Jacky Keung[2], Kun Kuang[1], Leilei Gan[1], Yiquan Wu[1], Fei Wu[1]

[1]Zhejiang University, China [2]City University of Hong Kong, Hong Kong SAR, China
{ychen2014, yuehengj, zhaozhaoma, kunkuang, leileigan, wuyiquan, wufei}@zju.edu.cn
cynthcao2-c@my.cityu.edu.hk, jacky.keung@cityu.edu.hk [+]Corresponding

Abstract

The inherent non-stationarity of financial markets and the complexity of multi-modal information pose significant challenges to existing quantitative trading models. Traditional methods relying on fixed structures and unimodal data struggle to adapt to market regime shifts, while large language model (LLM)-driven solutions—despite their multi-modal comprehension—suffer from static strategies and homogeneous expert designs, lacking dynamic adjustment and fine-grained decision mechanisms. To address these limitations, we propose MM-DREX: a Multimodal-driven, Dynamically-Routed EXpert framework based on large language models. MM-DREX explicitly decouples market state perception from strategy execution to enable adaptive sequential decision-making in non-stationary environments. Specifically, it: (1) Introduces a vision-language model (VLM)-powered dynamic router that jointly analyzes candlestick chart patterns and long-term temporal features to allocate real-time expert weights; (2) Designs four heterogeneous trading experts (trend, reversal, breakout, positioning) generating specialized fine-grained sub-strategies; and (3) Proposes an SFT-RL hybrid training paradigm to synergistically optimize the router's market classification capability and experts' risk-adjusted decision-making. Extensive experiments on multi-modal datasets spanning stocks, futures, and cryptocurrencies demonstrate that MM-DREX significantly outperforms 15 baselines (including state-of-the-art financial LLMs and deep reinforcement learning models) across key metrics: total return, Sharpe ratio, and maximum drawdown, validating its robustness and generalization. Additionally, an interpretability module traces routing logic and expert behavior in real-time, providing an audit trail for strategy transparency.

Introduction

Automated financial trading systems serve as essential tools for efficient capital allocation and risk management in financial markets. However, financial markets are inherently non-stationary, frequently shifting due to policy changes, macroeconomic cycles, and black-swan events. This dynamic complexity poses fundamental challenges to traditional trading models like ARIMA and GARCH (Sezer, Gudelek, and Ozbayoglu 2020; Tian et al. 2024), whose fixed structures and preset parameters struggle to adapt to rapidly changing environments, often leading to catastrophic drawdowns—for instance, during the 2020 COVID-19 crisis, many quantitative funds experienced single-day losses exceeding 15%. Deep Learning approaches such as Deep Reinforcement Learning (DRL) (Yang 2023; Charpentier, Elie, and Remlinger 2021) and Transformers have improved feature learning by processing large-scale time-series data, but remain constrained by static strategy logic and parameters upon deployment, limiting real-time adaptation. Furthermore, their reliance on structured, unimodal numerical data overlooks critical visual patterns in candlestick charts—such as head-and-shoulders formations and support/resistance levels—weakening sensitivity to subtle market movements. Many existing models also employ binary "all-in" or "all-out" strategies, leading to excessive trading costs and heightened volatility exposure.

Recent breakthroughs in large language models (LLMs) offer promising solutions. Financially specialized LLMs—including FinGPT, PIXIU, BloombergGPT—and multi-modal agents such as FinAgent have expanded textual and visual understanding in financial applications (Yang, Liu, and Wang 2023; Xie et al. 2023; Wu et al. 2023; Zhang et al. 2024). The Time-LLM framework (Jin et al. 2024) has reprogrammed frozen LLMs as autoregressive forecasters for financial time-series analysis. However, these LLM-based frameworks remain largely limited to question-answering-style signal detection, falling short of enabling autonomous sequential decision-making. Mixture-of-experts (MoE) architectures such as TradExpert (Ding et al. 2024) and memory-augmented frameworks (e.g., FinMem, TradingAgents) (Yu et al. 2024; Xiao et al. 2024) have explored enhanced strategy diversity and reasoning capabilities. However, these approaches suffer from homogeneous expert designs and static routing mechanisms, making effective differentiation and response to diverse market scenarios difficult, particularly during sector rotations or extreme market conditions.

To address these challenges, we propose **MM-DREX**: **M**ulti**m**odal-Driven **D**ynamic **R**outing of LLM **Ex**perts for Financial Trading, an adaptive multi-modal trading framework powered by LLMs. The core innovation lies in its decoupled architecture: a dynamic router processes historical time-series data and visual patterns to infer market conditions and generate real-time capital allocation across expert agents. Each expert independently generates fine-grained

trading strategies based on its specialization, and the final portfolio aggregates weighted expert outputs for diversified, risk-resilient investment. By separating market-state perception from strategy generation, MM-DREX enhances adaptability under rapidly shifting market conditions. To summarize, our main contributions are as follows:

- **Adaptive Multimodal Trading Architecture**: MM-DREX explicitly decouples routing and expert modules. The router dynamically assigns expert weights through joint visual-temporal encoding, while experts generate composable, fine-grained sub-strategies, introducing a generalizable paradigm for sequential decision-making under non-stationary environments.

- **Collaborative Optimization Training Paradigm**: We introduce a hybrid scheme addressing end-to-end training challenges: supervised fine-tuning(SFT) optimizes the router's market-state classification, while reinforcement learning optimizes expert policy heads for maximizing returns. This paradigm handles joint training of heterogeneous modules with different objectives, mitigating gradient interference.

- **Cross-Market Verification System**: We construct the first multi-modal financial trading dataset tailored for LLM training, covering U.S. and Chinese equity markets, futures, ETFs, and cryptocurrencies, integrating price data, candlestick charts, and technical indicators. This dataset demonstrates MM-DREX's adaptability across diverse markets, serving as a strong benchmark for evaluating trading models.

- **Enhanced Explainability and Decision Auditing**: We develop a real-time strategy interpretation module that interpret expert selection and routing weights, revealing causal links between market states and system behavior, addressing the "black-box" nature of LLM-based trading systems for regulatory auditing and strategy refinement.

Problem Formulation

We cast the trading task as a *Partially Observable Markov Decision Process* (POMDP) described by the sextuple $(\mathcal{S}, \mathcal{A}, T, R, \Omega, O)$:

- **State space** $\mathcal{S}$: the latent, partially-observable market state $s_t \in \mathcal{S}$ at time t.

- **Action space** $\mathcal{A} = \{a_1, a_2, \ldots, a_N\}$: each action denotes a *trading strategy*, rather than a primitive buy/sell command.

- **Transition kernel** T : $T(s_{t+1} \mid s_t, a_t)$ gives the probability of moving to state s_{t+1} after executing a_t in s_t.

- **Reward function** R : $R(s_t, a_t)$ returns the immediate payoff obtained at t.

- **Observation space** Ω: the agent receives an observation $\omega_t \in \Omega$ that partially reveals s_t.

- **Observation kernel** O : $O(\omega_t \mid s_t)$ is the likelihood of observing ω_t given the underlying state s_t.

The agent seeks a policy $\pi(a_t \mid o_t)$ that maximises the expected cumulative *discounted* reward

$$G_t = \mathbb{E}\Big[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \Big],$$

where the discount factor satisfies $\gamma \in (0, 1)$, K is an index variable representing future time steps starting from the current time step.

Effective trading demands synthesising diverse market evidence—candlestick images, high-quality numerical streams, and structured textual reports—into a coherent situational picture.

MM-DREX

Building on the formal definition above, we next describe how MM-DREX operationalises adaptive trading through a dynamic-router $\rightarrow$ heterogeneous-experts $\rightarrow$ aggregation-optimisation *pipeline.*

An overview of MM-DREX is depicted in Figure 1. It consists of three decoupled stages. (i) A **shared VLM encoder** fuses candlestick images with aligned time–series features to obtain a unified market representation. (ii) A **dynamic router**, initialised by SFT(Doimo et al. 2024) and subsequently refined via reinforcement learning, learns to allocate portfolio weights to downstream experts according to the current market regime. (iii) Four **heterogeneous domain-specialised experts** run in parallel, each optimising a single trading archetype. Their weighted outputs are finally aggregated into an executable portfolio. This separation of *macro regime perception* from *micro strategy execution* balances diversity, interpretability, and adaptability to heterogeneous market conditions.

(i)Multimodal Observation Encoding

To obtain a comprehensive market view, we model each observation ω_t as a *multi-modal tuple* that fuse three complementary information sources within the lookback window:

$$\omega_t = (V_t, T_t, L_t) \tag{1}$$

where V_t denotes the *visual modality*—Klines and technical-indicator images, T_t the *temporal modality*—historical price and indicator time series, and L_t the *text modality*—prompt instructions and high-level summaries of market trends.

(ii)Dynamic Router

We propose a dynamic router based on vision-language large models (VLLM) for real-time allocation of portfolio weights among four complementary trading experts. For each target asset, the router receives multi-modal market view ω_t that summarizes both structured and visual information within the lookback window. Leveraging VLLM's advanced capabilities in image understanding and causal reasoning, the router identifies critical technical patterns from chart images—such as head-and-shoulders formations, double bottoms, moving average crossovers, and volume breakouts—and integrates these visual cues with structured time-series features. This joint representation enables the
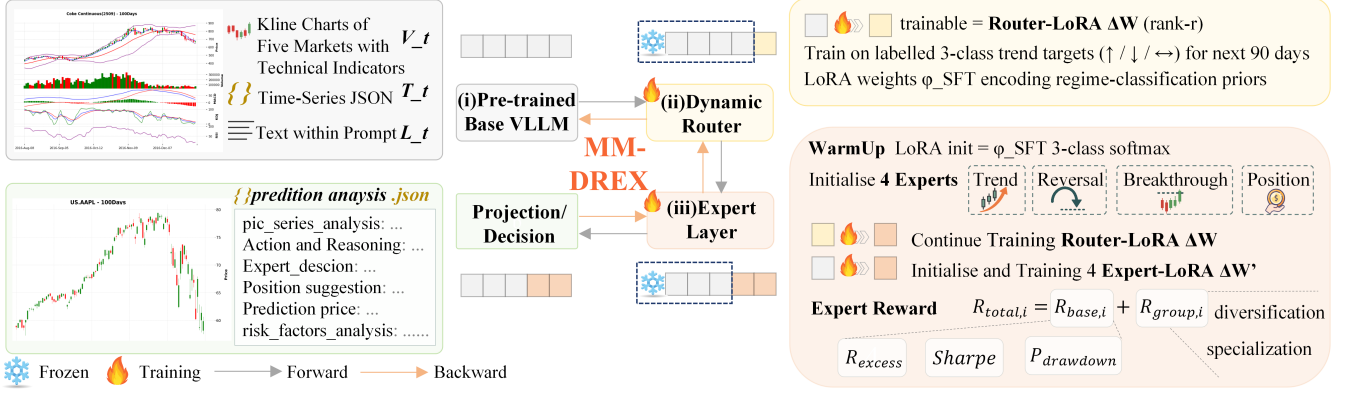
Figure 1: Schematic of the MM-DREX framework. The system processes multimodal market inputs via a pre-trained VLLM, routes representations through a dynamic Router with LoRA adaptation, and outputs expert-driven decisions from four trading specialists. Gray arrows indicate standard forward/backward propagation; red arrows represent feedback loops for continuous optimization based on expert performance.

router to interpret complex market conditions, detect regime transitions, and generate expert allocation decisions that reflect both quantitative indicators and visual trend signals predictive of future price movements.

Based on the given multi-modal information, the router computes an expert allocation vector:

$$\mathbf{w} = (w_{\text{trend}}, w_{\text{reversal}}, w_{\text{breakout}}, w_{\text{static}}) \in \mathbb{R}^4 \qquad (2)$$

subject to the constraints:

$$\sum_i w_i = 1, \quad w_i \geq 0 \qquad (3)$$

The vector $\mathbf{w}$ represents the portfolio weights allocated to four distinct trading experts over the next trading window: the trend expert executes trades based on momentum signals, the reversal expert specializes in mean-reversion strategies using contrarian signals, the breakout expert capitalizes on event-driven breakout signals, and the static expert maintains fixed positions throughout the period.

(iii)Heterogeneous Expert Layer

To cope with heterogeneous market regimes we instantiate *four* mutually–independent trading experts. All experts receive the *same* multimodal observation s_t, yet their parameters are optimised separately so that their decision logics remain diverse.

• **Trend Expert** looks for clear upward or downward movements and tries to "ride the wave." Its action space $\mathcal{A}_{\text{trend}} = \{a_1, a_2, a_3\}$ comprises a_1 *moving–average crossover* (MACROSS), a_2 *momentum following* (MOMENTUM), and a_3 the classical *Turtle* breakout rule;

• **Reversal Expert** tries to catch turning points. It excels at trading against the trend when prices are overvalued or undervalued. Its space $\mathcal{A}_{\text{revert}} = \{a_4, a_5, a_6\}$ covers a_4 BOLLinger-band reversion, a_5 RSI swing reversal, and a_6 KDJ oscillator reversal;

• **Breakthrough Expert** watches for moments when prices suddenly jump out of a quiet period. Such breakouts are often accompanied by surges in trading volume and typically signal the beginning of a new trend. Its repertoire $\mathcal{A}_{\text{break}} = \{a_7, a_8\}$ includes a_7 VOLUME breakout and a_8 ATR range breakout;

• **Position Expert** sets the baseline stance for an entire horizon (e.g. 90 days). Its minimalist space $\mathcal{A}_{\text{passive}} = \{a_9, a_{10}, a_{11}\}$ specifies a_9 LONGONLY, a_{10} SHORTONLY, and a_{11} CASH.

By keeping the four experts disjoint yet complementary, MM-DREX supplies the router with a rich, specialised policy pool from which to synthesise a diversified portfolio. Full action details in policy pool are reported in Appendix A.

Hybrid Collaborative Optimisation

To address the conflicting objectives between routers and experts, we design a "supervised fine-tuning - reinforcement learning" hybrid training process, which consists of two main implementation stages:

Stage 1 Direct training of routers starting from random weights in complex financial environments may lead to inefficient exploration. To enable routers to acquire basic market trend prediction capabilities during the early training phase, we introduce a knowledge injection mechanism. Specifically, we first train the base VLM on an independent SFT task. The objective of this task is to predict market ternary classification trends (Uptrend/Downrend/Consolidation) for the next trading window.

Stage 2 The LoRA adapter weights obtained from the SFT stage are used to initialize the router strategy network for the reinforcement learning stage. This knowledge transfer initialization strategy encodes the historical trend classification knowledge from the financial domain as the starting parameters for the router, significantly reducing random exploration in the RL stage and accelerating convergence.

Under the RL framework, the system performs end-to-end training. The router receives fused multi-modal representations and outputs expert weights w_t:

$$w_t = \text{softmax}(f_{\text{router}}(\omega_t; \phi)) \qquad (4)$$

where ϕ represents the parameters of the router f_{router} initialized by SFT prediction.

Strategy Loss Function The router strategy loss function is:

$$L_{\text{router}}(\phi) = -E_t[(R_t - b(\omega_t)) \log \pi_{\text{router}}(w_t|\omega_t) \\ + c_3 S[\pi_{\text{router}}](\omega_t)] \qquad (5)$$

where $R_t = \sum_{i=1}^{N_{\text{experts}}} w_{t,i} R_{t,i}$, $b(\omega_t)$ is the baseline, $S[\cdot]$ is the regularization term, and π_{router} is the router weight output distribution.

In the expert network, each expert receives ω_t, outputs strategy distribution and state value estimation:

$$\pi_i(a_t|\omega_t) = \text{softmax}(l_{i,t}) \qquad (6)$$
$$(l_{i,t}, V_i(\omega_t)) = f_{\text{expert}_i}(\mathcal{H}_{\text{fused}}; \theta_i) \qquad (7)$$

where $l_{i,t}$ is the action logits, and θ_i represents the expert's parameters.

Expert Training Objective The expert training objective function is:

$$L_{\text{expert}_i}(\theta_i) = E_t[L_i^{\text{CLIP}}(\theta_i) - c_1 L_i^{\text{VF}}(\theta_i) + c_2 S[\pi_{\theta_i}](\omega_t)] \qquad (8)$$

$$L_i^{\text{CLIP}}(\theta_i) \\ = E_t\left[\min\left(r_t^{(i)} A_{t,i}, \text{clip}\left(r_t^{(i)}, 1-\epsilon, 1+\epsilon\right) A_{t,i}\right)\right] \qquad (9)$$

where $r_t^{(i)} = \frac{\pi_{\theta_i}(a_t|\omega_t)}{\pi_{\theta_{\text{old}}}(a_t|\omega_t)}$, $A_{t,i}$ is the advantage function.

Value function loss: $L_i^{\text{VF}}(\theta_i) = (V_{\theta_i}(\omega_t) - G_t)^2$, where G_t is the return.

Regularization term:

$$S[\pi_{\theta_i}](\omega_t) = -\sum_{a \in \mathcal{A}} \pi_{\theta_i}(a|\omega_t) \log \pi_{\theta_i}(a|\omega_t) \qquad (10)$$

Reward Function The unified reward function consists of base reward and group reward components for each expert:

$$R_{\text{total},i}(\omega_t, a_t) = R_{\text{base},i}(\omega_t, a_t) + R_{\text{group},i}(\omega_t, a_t) \qquad (11)$$

The base reward measures the absolute performance of the strategy, incorporating dual evaluation of return and risk:

$$R_{\text{base},i} = \alpha_R \cdot f(R_{\text{excess}}) + \alpha_S \cdot g(\text{Sharpe}) - P_{\text{drawdown}} \qquad (12)$$

where R_{excess} is the excess return, Sharpe is the Sharpe ratio, P_{drawdown} is the maximum drawdown, and $f(\cdot), g(\cdot)$ are non-linear smoothing functions.

The group relative reward promotes expert differentiation and specialization:

$$R_{\text{group},i}(a_t) = \beta \cdot (\log \pi_i(a_t|\omega_t) - \log \pi_{-i}(a_t|\omega_t)) \qquad (13)$$

where $\pi_{-i}(a_t|\omega_t) = \frac{1}{N_{\text{experts}}-1} \sum_{j \neq i} \pi_j(a_t|\omega_t)$. This encourages expert i to choose actions different from the group average, avoiding all experts converging to the same strategy and promoting mutual complementarity.

Experiments

Our research aims to comprehensively evaluate MM-DREX's trading effectiveness and highlight its unique advantage mechanisms through addressing the following research questions (RQs). **RQ1:** Can MM-DREX significantly outperform existing state-of-the-art financial trading models (including LLM-based and deep reinforcement learning methods) in non-stationary market environments? **RQ2:** Does the dynamic router's real-time weight allocation capture market regime transitions more effectively than static routing approaches (such as uniform weighting or single expert selection)? **RQ3:** Do visual modalities provide critical incremental information, and what performance degradation occurs when visual features are omitted? **RQ4:** How does MM-DREX respond to severe market volatility (such as black swan events), and does it successfully avoid catastrophic drawdowns?

Dataset Construction To comprehensively evaluate the performance of MM-DREX under non-stationary and cross-market conditions, we construct a multimodal, long-horizon financial dataset specifically designed for training large trading models (shown in Table 1). The dataset spans five major markets—U.S. equities, Chinese A-shares, ETFs, cryptocurrencies, and futures (Lee and Yoo 2019; Chang, Hsieh, and McAleer 2018)—covering a wide range of market regimes, including bull and bear markets, sideways consolidations, and extreme events such as the COVID-19 crash in 2020 (Mazur, Dang, and Vega 2021; Ramelli and Wagner 2020) and the cryptocurrency collapse in 2022 (Özdemir 2022; Sui, Chang et al. 2022). To highlight the dataset's breadth and representativeness, we compare it against those used in recent state-of-the-art trading models—including FinAgent (Zhang et al. 2024), FinMem (Yu et al. 2024), and PIXIU (Xie et al. 2023)—across five dimensions (Figure 2). This dataset is designed to demonstrate MM-DREX's robustness and generalization ability across diverse financial markets, providing a solid foundation for benchmarking the adaptability of MM-DREX and other trading agents. For detailed dataset specifications, please refer to Appendix B.

Given **the absence of systematic research on optimal input-output window configurations for large language models in financial time series prediction** within current publications, we conduct a comprehensive evaluation of multimodal LLMs' financial forecasting capabilities . Our assessment encompasses 12 vision-temporal fusion capable LLMs from 5 mainstream providers, including GPT-o3,Grok-4, and other state-of-the-art models, with detailed testing protocols provided in Appendix C. The evaluation results demonstrate that within the testing range of [30, 250] trading days, models achieve approximately 60% accuracy in directional movement prediction when configured with an input window of $T_{in} = 100$ and prediction window of $T_{pred} = 90$ trading days. MM-DREX adopts this configuration as the standard window setting, balancing computational feasibility with predictive performance.

To generate high-quality market regime labels for the router's SFT pre-training, we employ a dual annotation mechanism that combines quantitative technical indicator
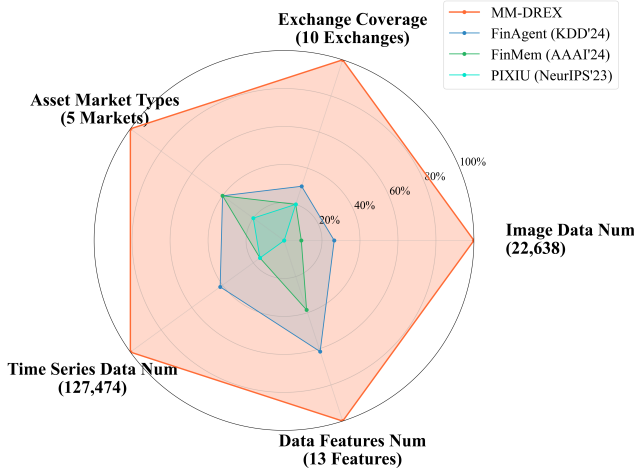
Figure 2: Multi-dimensional Dataset Comparison

Table 1: MM-DREX Multimodal Financial Dataset Specifications

Component	Description
Asset Classes(Num)	
US Stocks(15)	NASDAQ 100 constituents; 2017-01-01 to 2025-05-01
A-Shares(10)	Leading Chinese companies across sectors; 2017-01-01 to 2025-05-16
ETFs(15)	US & Hong Kong ETFs covering equity market, bonds, commodities; 2017-01-01 to 2025-06-26
Crypto(2)	Bitcoin (BTC) and Ethereum (ETH); 2021-01-01 to 2025-03-23
Futures(20)	3 equity indices, 1 bond, 16 commodity contracts; 2017-01-01 to 2025-06-26
Temporal Mode	
OHLCV Data	Open, high, low, close, volume
Indicators	MA, MACD, RSI, KDJ, Bollinger Bands
Visual Mode	
Candlestick	Charts with OHLCV data
Indicator Plots	MA, MACD, RSI, KDJ, Bollinger Bands
Textual Mode	
Analysis	Technical analysis including trend consistency, pattern recognition (head-and-shoulders, double bottom), support&resistance levels, volume analysis, market sentiment

analysis with financial expert validation. We design three market regime labels: uptrend, downtrend, and consolidation. All datasets undergo initial classification through technical indicators, followed by independent review from three institutional traders with over 5 years of professional experience. For the comprehensive dataset covering 62 assets, temporal partitioning remains consistent across all markets, with the first 60% of data allocated for training, 20% for validation, and the remaining 20% reserved for testing.

Evaluation Metrics and Baselines Our evaluation employs three standard financial metrics for assessing MM-DREX and baseline performance: total return (TR), Sharpe ratio (SR), and maximum drawdown (MDD).

To demonstrate the effectiveness of our proposed framework, we compare MM-DREX against 15 diverse trading strategies spanning traditional technical analysis, machine learning, and deep reinforcement learning paradigms. The traditional technical indicators include **Buy-and-Hold (B&H)** (Dichtl 2020), **MACD** (Anghel 2015), **KDJ-RSI** (Wu and Diao 2015), **CR** (Dai et al. 2020), **BBI** (Forero-Laverde 2018), **WR** (Paik, Choi, and Vaquero 2024), and **BIAS** (Deep et al. 2024). Machine learning approaches encompass **LightGBM** (Ke et al. 2017), **LSTM** (Fischer and Krauss 2018), and **Transformer** (Vaswani et al. 2017). Deep reinforcement learning baselines include **SAC** (Haarnoja et al. 2018), **PPO** (Schulman et al. 2017), and **DQN** (Mnih et al. 2015). LLM baseline include **FinAgent** (Zhang et al. 2024), and **FinMem** (Yu et al. 2024). Comprehensive mathematical formulations of evaluation metrics, baseline implementations, and hyperparameter configurations are provided in Appendix D.

Implementation Details All MM–DREX training and inference runs were executed on **eight NVIDIA A800** GPUs. The vision–language backbone was the **Qwen 2.5 72B** foundation model. Unless explicitly stated otherwise, every baseline system was trained and evaluated in the *same* environment to ensure a fair comparison. Full implementation details and hyper-parameter settings are reported in Appendix E.

Primary Results

Comparison with Baselines & LLM-based (RQ1). In our comprehensive multi-market empirical evaluation, MM-DREX demonstrates superior generalization capabilities and exceptional risk-return balance characteristics across diverse market conditions. In the US equity bull market environment, while all strategies underperformed the Buy-and-Hold (B&H) benchmark, MM-DREX achieved a remarkable total return of 47.5%, significantly outperforming the best-performing baseline FinAgent (39.34%), with its Sharpe ratio of 1.83 also exceeding that of the top deep reinforcement learning model PPO (1.73), validating its efficiency in capturing growth stock momentum trends. In the policy-sensitive A-shares market, MM-DREX further established its dominance with a 24.36% return, leading FinAgent (21.77%) by 11.9%, while achieving the highest Sharpe ratio of 2.15 across all methods, highlighting its exceptional adaptability to high-volatility environments. For the high-noise futures market, MM-DREX delivered a substantial 27.31% return, surpassing the best baseline CR (20.63%) and second-best PPO (18.53%) by 32.3% and 47.4% respectively, demonstrating robust performance in low-liquidity, high-volatility scenarios. Notably, MM-DREX achieved the highest Sharpe ratio across all markets while maintaining excellent drawdown control, with its success attributed to

Table 2: Comprehensive Trading Performance Comparison Across Asset Classes

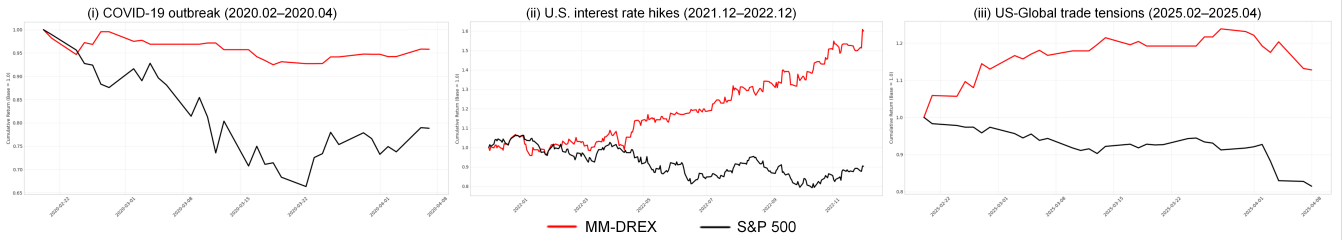| Category	Model	A-shares			US Equities			ETFs			Futures			Crypto		
		TR%	SR	MDD%	TR%	SR	MDD%	TR%	SR	MDD%	TR%	SR	MDD%	TR%	SR	MDD%
Traditional	B&H	10.94	0.75	**17.5**	**60.56**	1.76	22.8	10.93	0.97	**19.88**	18.2	0.84	**24.53**	11.5	0.98	8.92
Traditional	MACD	4.32	0.58	9.2	18.13	1.07	**6.06**	7.21	1.22	4.65	11.46	0.64	15.71	**-4.57**	**-0.31**	8.66
Traditional	KDJ-RSI	8.46	1.01	5.11	16.74	0.87	10.54	4.79	0.43	**2.69**	2.25	0.35	9.08	3.59	0.68	**2.91**
Traditional	CR	7.25	0.77	10.51	19.29	0.9	9.34	15.78	**1.57**	6.49	20.63	0.69	19.36	8.23	0.55	13.71
Traditional	BBI	9.81	0.82	8.73	24.83	1.06	17.79	4.19	0.58	5.9	**-5.7**	**-0.27**	9.82	14.74	1.35	8.5
Traditional	WR	-1.53	-0.12	**4.16**	17.4	1.13	6.76	10.7	1.26	5.11	9.83	0.92	**7.38**	9.43	0.74	13.61
Traditional	BIAS	**-3.85**	**-0.44**	10.22	**15.77**	0.86	9.51	**-2.5**	**-0.45**	5.24	18.3	1.08	14.67	-1.26	-0.14	**14.67**
DL-based	LGBM	19.62	1.57	11.64	38.08	1.69	10.51	12.74	1.17	8.41	21.67	1.37	15.54	9.41	0.51	13.55
DL-based	LSTM	7.63	0.97	8.79	17.85	1.11	7.12	7.93	0.83	6.48	11.78	0.83	8.78	2.58	0.24	10.83
DL-based	Transformer	-3.43	**-0.51**	10.75	25.54	1.21	9.28	8.17	0.91	5.87	8.63	0.65	9.21	-3.1	**-1.19**	13.09
RL-based	SAC	10.65	1.13	8.78	20.29	**0.84**	15.04	9.32	1.05	7.24	15.32	0.45	18.3	2.01	-0.43	10.29
RL-based	PPO	13.2	1.25	8.42	29.34	1.73	8.73	11.37	1.36	6.13	18.53	1.25	12.54	**16.58**	**1.69**	9.07
RL-based	DQN	7.14	0.45	10.13	16.17	1.24	9.15	7.84	0.59	8.82	9.92	0.34	13.65	9.52	1.01	8.82
LLM-based	FinAgent	21.77	1.82	12.36	39.34	1.61	20.37	12.84	1.21	10.43	5.38	0.56	13.2	3.41	0.54	12.53
LLM-based	FinMem	15.7	1.15	14.37	35.26	1.43	**24.83**	10.25	1.11	7.86	-2.6	**-0.42**	8.83	8.26	0.88	10.98
Ours	**MM-DREX**	**24.36**	**2.15**	11.42	47.5	**1.83**	14.5	**15.7**	1.44	9.34	**27.31**	**1.61**	14.24	13.58	1.37	5.56

Figure 3: Performance comparison between MM-DREX and the S&P 500 index under extreme market conditions. From left to right: (i) COVID-19 outbreak (2020.02–2020.04), (ii) U.S. interest rate hikes (2021.12–2022.12), and (iii) U.S.–Global trade tensions (2025.02–2025.04). MM-DREX demonstrates stronger resilience and downside protection across all stress periods.

the synergistic combination of returns from heterogeneous expert ensembles and dynamic risk hedging mechanisms. In contrast, existing LLM-based approaches (FinAgent/Fin-Mem), while achieving competitive performance in certain markets (A-shares, US equities, ETFs), suffered significant failures in cryptocurrency and futures markets, with FinAgent's returns plummeting to merely 5.38% and 3.41% in futures and cryptocurrency scenarios respectively, while Fin-Mem even recorded negative returns in the futures market, exposing critical cross-market adaptability deficiencies when confronting vastly different market characteristics. These comprehensive results in Table 2 conclusively demonstrate that MM-DREX, through its dynamic routing and expert collaboration mechanisms, successfully addresses the risk accumulation problems inherent in traditional models' reliance on single-strategy approaches, achieving dual optimization of profitability and stability in non-stationary financial environments.

Ablation Studies

Effectiveness of Dynamic Weight Routing (RQ2). To validate the core value of the dynamic router, we fix the expert modules and conduct comparative testing of four routing mechanisms on a test set of 62 assets: dynamic routing (MM-DREX original design), uniform weighting (25% allocation to each of the four experts), best-expert-only selection (exclusive decision-making by the historically best-performing expert), and random routing (randomly generated weights). We average the test results across all assets for each mechanism, yielding the results presented in Table 3.

The results demonstrate that dynamic routing significantly outperforms all static strategies with a total return of 25.75% and Sharpe ratio of 1.63. Specifically, uniform weighting, unable to adapt to market regime shifts, results in a maximum drawdown of 21.45%, representing a 45.3% increase compared to dynamic routing, thereby validating the non-stationary fragility of static routing approaches. The best-expert-only strategy, while superior to random routing, still suffers from single-strategy failure with an MDD of 19.82%, a 34.1% increase over dynamic routing. Random routing experiences comprehensive performance collapse due to disordered weight allocation. This experiment confirms the necessity of multi-expert collaboration for risk diversification, establishing dynamic routing as the core mechanism of MM-DREX that enables the system to achieve sustained adaptability in non-stationary environments.

Effectiveness of Visual Modality Integration (RQ3). The incorporation of candlestick chart patterns provides critical incremental information that substantially enhances

Table 3: Dynamic Routing Mechanism Comparison

Routing Strategy	TR%	SR	MDD%
Dynamic Routing (Original)	**25.75**	**1.63**	**14.76**
Uniform Weighting	15.94	0.96	21.45
Best-Expert-Only	20.11	1.12	19.82
Random Routing	9.3	0.52	31.55

Table 4: Multimodal Input Ablation Study Results

Input Modality	Accuracy%	TR%	SR	MDD%
Complete (V+T+L)	**60.21**	**25.75**	**1.63**	**14.76**
T+L (w/o Visual)	53.72	20.11	1.21	19.37
V+L (w/o Temporal)	48.13	18.37	1.01	22.48

trading performance beyond traditional numerical features alone. To quantify the incremental value of visual modality, we conduct multimodal input ablation experiments on a test set of 62 assets, comparing three configurations: complete modality (V+T+L), vision-absent (T+L), and temporal-absent (V+L). The statistical results demonstrate that removing visual features leads to significant performance degradation: total return decreases by 21.9% (25.75%→20.11%), Sharpe ratio declines by 25.8% (1.63→1.21), and maximum drawdown surges by 31.2% (14.76%→19.37%). Furthermore, relying solely on visual and textual inputs (V+L) further deteriorates performance (TR=18.37%, MDD=22.48%). Importantly, the prediction accuracy for directional movement (bullish/bearish forecasting) drops substantially from 60.21% with complete modality to 53.72% without visual features and further to 48.13% without temporal data, as shown in Table 4.

These consistent results indicate that candlestick chart patterns and temporal features are not merely redundant but complementary: visual modality provides critical pattern signals (such as candlestick combinations) that require quantitative validation from temporal data in the price-volume dimension, with their synergistic integration enabling robust decision-making. The substantial accuracy degradation when removing either modality underscores the necessity of multimodal fusion for effective market regime identification and directional prediction in non-stationary financial environments.

Risk Studies

Effectiveness of Crisis Resilience and Drawdown Control (RQ4). MM-DREX exhibits exceptional robustness during extreme market volatility events, successfully avoiding catastrophic drawdowns through its multi-expert risk diversification and dynamic hedging mechanisms. To evaluate the model's defensive capabilities under systemic risk, we select the S&P 500 index as our benchmark—this index represents the world's most resilient developed market with strong long-term bullish momentum and exceptional risk resistance capacity. Over the past decade, it has achieved an annualized return of 13%, making strategies that consistently outperform this index extremely rare.

We conducted testing during six black-swan events or market downturn periods over the past five years, with MM-DREX consistently and significantly outperforming the S&P 500, validating its robustness and excess return generation capability under extreme market conditions as demonstrated in Table 5. To further illustrate MM-DREX's performance intuitively, we visualize the results through net asset value curves for comparison, as shown in Figure 3, with complete net value curve comparisons provided in the Appendix F for supplementary .

Table 5: Crisis Performance Comparison Against S&P 500 Benchmark

Crisis Event	MM-DREX TR%	S&P 500 TR%
2020 Q1 COVID-19 Outbreak (2020-02-20 to 2020-04-07)	**-4.2**	-21.16
2020 Q3 COVID-19 Second Wave (2020-07-01 to 2020-10-01)	**17.82**	8.5
2022 Interest Rate Hiking Cycle (2021-12-01 to 2022-12-01)	**60.04**	-9.67
2022 Russia-Ukraine Conflict (2022-02-24 to 2022-05-25)	**7.51**	-7.23
2024 Q3 Economic Recession (2024-07-01 to 2024-10-01)	**4.54**	4.27
2025 Q1 Trade War Escalation (2025-02-20 to 2025-04-08)	**12.77**	-18.55

Conclusion and Future Work

Conclusion We proposed MM-DREX, a novel multimodal, LLM-driven trading framework that decouples market regime perception from strategy execution via dynamic routing and expert specialization. By integrating visual, temporal, and textual signals, and optimizing the system through a hybrid supervised fine-tuning and reinforcement learning (SFT-RL) paradigm, MM-DREX achieves superior performance, robustness, and adaptability across diverse asset classes, market structures, and extreme economic events. Our extensive experiments demonstrate its consistent outperformance of state-of-the-art baselines in terms of return, Sharpe ratio, and drawdown control, validating its effectiveness in real-world financial environments.

Future Work While MM-DREX shows strong adaptability in non-stationary markets, several directions remain for exploration. First, we plan to extend the framework to real-time multi-asset portfolio optimization, incorporating transaction costs, liquidity constraints, and latency for practical deployment. Second, instead of fixed expert archetypes, future work may explore meta-learning-based expert evolution, allowing experts to adapt to changing regimes. Third, we aim to integrate long-term memory modules (e.g., retrieval-augmented or episodic memory) to capture cross-cycle dependencies and rare events, enhancing long-horizon forecasting. Lastly, we seek to improve transparency and control through human-in-the-loop feedback—such as interactive routing or expert overrides—to support collaborative trading and regulatory compliance.

References

Anghel, G. D. I. 2015. Stock market efficiency and the MACD. Evidence from countries around the world. *Procedia economics and finance*, 32: 1414–1431.

Chang, C.-L.; Hsieh, T.-L.; and McAleer, M. 2018. An Econometric Analysis of ETF and ETF Futures in Financial and Energy Markets Using Generated Regressors. *Econometrics*, 6(1): 2.

Charpentier, A.; Elie, R.; and Remlinger, C. 2021. Reinforcement Learning in Economics and Finance. *Computational Economics*, 62(1): 425–462.

Dai, Z.; Dong, X.; Kang, J.; and Hong, L. 2020. Forecasting stock market returns: New technical indicators and two-step economic constraint method. *The North American Journal of Economics and Finance*, 53: 101216.

Deep, A.; Monico, C.; Shirvani, A.; Rachev, S.; and Fabozzi, F. J. 2024. Assessing the Impact of Technical Indicators on Machine Learning Models for Stock Price Prediction. *arXiv preprint arXiv:2412.15448*.

Dichtl, H. 2020. Investing in the S&P 500 index: Can anything beat the buy-and-hold strategy? *Review of Financial Economics*, 38(2): 352–378.

Ding, Q.; Shi, H.; Guo, J.; and Liu, B. 2024. Tradexpert: Revolutionizing trading with mixture of expert llms. *arXiv preprint arXiv:2411.00782*.

Doimo, D.; Serra, A.; Ansuini, A.; and Cazzaniga, A. 2024. The representation landscape of few-shot learning and fine-tuning in large language models. *Advances in Neural Information Processing Systems*, 37: 18122–18165.

Fischer, T.; and Krauss, C. 2018. Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, 270(2): 654–669.

Forero-Laverde, G. 2018. A New Indicator for Describing Bull and Bear Markets. Working Paper in Economic History 129, European Historical Economics Society (EHES).

Haarnoja, T.; Zhou, A.; Abbeel, P.; and Levine, S. 2018. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *International conference on machine learning*, 1861–1870. PMLR.

Jin, M.; Wang, S.; Ma, L.; Chu, Z.; Zhang, J.; Shi, X.; Chen, P.-Y.; Liang, Y.; Li, Y.-f.; Pan, S.; et al. 2024. Time-LLM: Time Series Forecasting by Reprogramming Large Language Models. In *International Conference on Learning Representations (ICLR)*.

Ke, G.; Meng, Q.; Finley, T.; Wang, T.; Chen, W.; Ma, W.; Ye, Q.; and Liu, T.-Y. 2017. Lightgbm: A highly efficient gradient boosting decision tree. In *Advances in neural information processing systems*, 3146–3154.

Lee, S. I.; and Yoo, S. J. 2019. Multimodal Deep Learning for Finance: Integrating and Forecasting International Stock Markets. *arXiv preprint arXiv:1903.06478*.

Mazur, M.; Dang, M.; and Vega, M. 2021. COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, 38: 101690.

Mnih, V.; Kavukcuoglu, K.; Silver, D.; Rusu, A. A.; Veness, J.; Bellemare, M. G.; Graves, A.; Riedmiller, M.; Fidjeland, A. K.; Ostrovski, G.; et al. 2015. Human-level control through deep reinforcement learning. *nature*, 518(7540): 529–533.

Özdemir, O. 2022. Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. *Financial Innovation*, 8(1): 1–19.

Paik, C. K.; Choi, J.; and Vaquero, I. U. 2024. Identifying oversold levels and developing low-frequency trading algorithms for the S&P 500: An analysis using stochastic oscillator, Williams% R, and trading volume.

Ramelli, S.; and Wagner, A. F. 2020. Feverish stock price reactions to COVID-19. *The Review of Corporate Finance Studies*, 9(3): 622–655.

Schulman, J.; Wolski, F.; Dhariwal, P.; Radford, A.; and Klimov, O. 2017. Proximal policy optimization algorithms. In *arXiv preprint arXiv:1707.06347*.

Sezer, O. B.; Gudelek, M. U.; and Ozbayoglu, A. M. 2020. Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied soft computing*, 90: 106181.

Sui, B.; Chang, H.-L.; et al. 2022. Impacts of COVID-19 on the Return and Volatility Nexus among Cryptocurrency Market. *Complexity*, 2022: 5346080.

Tian, Y.; Gao, M.; Gao, Q.; and Peng, X. 2024. Trading in Fast-Changing Markets with Meta-Reinforcement Learning. *Intelligent Automation and Soft Computing*, 39(2): 175–188.

Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A. N.; Kaiser, Ł.; and Polosukhin, I. 2017. Attention is all you need. In *Advances in neural information processing systems*, 5998–6008.

Wu, M.; and Diao, X. 2015. Technical analysis of three stock oscillators testing MACD, RSI and KDJ rules in SH & SZ stock markets. In *2015 4th International Conference on Computer Science and Network Technology (ICCSNT)*, volume 1, 320–323. IEEE.

Wu, S.; Irsoy, O.; Lu, S.; Dabravolski, V.; Dredze, M.; Gehrmann, S.; Kambadur, P.; Rosenberg, D.; and Mann, G. 2023. BloombergGPT: A Large Language Model for Finance. *arXiv preprint arXiv:2303.17564*.

Xiao, Y.; Sun, E.; Luo, D.; and Wang, W. 2024. TradingAgents: Multi-agents LLM financial trading framework. *arXiv preprint arXiv:2412.20138*.

Xie, Q.; Han, W.; Zhang, X.; Lai, Y.; Peng, M.; Lopez-Lira, A.; and Huang, J. 2023. Pixiu: A large language model, instruction data and evaluation benchmark for finance. *arXiv preprint arXiv:2306.05443*.

Yang, H.; Liu, X.-Y.; and Wang, C. 2023. FinGPT: Open-Source Financial Large Language Models. *arXiv preprint arXiv:2306.06031*.

Yang, S. 2023. Deep reinforcement learning for portfolio management. *Knowledge-Based Systems*, 278: 110905.

Yu, Y.; Li, H.; Chen, Z.; Jiang, Y.; Li, Y.; and Zhang, D. 2024. FinMem: A Performance-Enhanced LLM Trading

Agent with Layered Memory and Character Design. *Proceedings of the AAAI Spring Symposium on AI in FinTech.*

Zhang, W.; Zhao, L.; Xia, H.; Sun, S.; Qin, M.; and Li, X. 2024. A Multimodal Foundation Agent for Financial Trading: Tool-Augmented, Diversified, and Generalist. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), to appear.*

Appendix A   Details of Actions in Policy Pool

In order to cope with heterogeneous market regimes, we create four experts with different trading preference. Trend Expert detects and rides sustained directional moves in clearly bullish or bearish markets. Its action space $\mathcal{A}_{\text{trend}} = \{a_1, a_2, a_3\}$ comprises a_1 *moving–average crossover* , a_2 *momentum following* , and a_3 the classical *Turtle* breakout rule; Reversal Expert exploits *mean–reversion* by spotting "overbought" or "oversold" deviations. Its space $\mathcal{A}_{\text{revert}} = \{a_4, a_5, a_6\}$ covers a_4 BOLLinger-band reversion, a_5 RSI swing reversal, and a_6 KDJ oscillator reversal; Breakthrough Expert specializes in identifying critical moments when an asset's price breaks out of a consolidation trading range. Its repertoire $\mathcal{A}_{\text{break}} = \{a_7, a_8\}$ includes a_7 VOLUME breakout and a_8 ATR range breakout; Position Expert sets the baseline stance for an entire horizon (e.g. 90 days). Its minimalist space $\mathcal{A}_{\text{passive}} = \{a_9, a_{10}, a_{11}\}$ specifies a_9 LONGONLY, a_{10} SHORTONLY, and a_{11} CASH.

Moving Average Crossover

The Moving Average Crossover strategy is a classic trend-following approach that uses two moving averages of different periods to identify trend changes and generate trading signals.

Algorithm 1 MA Cross Adaptive Strategy

1: **Input:** Price data; fast period $f = 5$; slow period $s = 20$; ATR period $a = 14$; ATR multiplier $m = 1.5$; max layers $L = 4$; trend strength threshold $\gamma = 0.02$
2: **Initialize:** position $= 0$; layers $= 0$; entry price list; position size list
3: **for** each trading day t **do**
4:     Compute $MA_{fast}(t)$, $MA_{slow}(t)$, ATR(t), trend strength $\tau_t = (P_t - P_{t-5})/P_{t-5}$
5:     **if** position $= 0$ **then**
6:         **if** $(MA_{fast}(t-1) \leq MA_{slow}(t-1)$ AND $MA_{fast}(t) > MA_{slow}(t))$ **OR** $(|MA_{fast}(t) - MA_{slow}(t)|/MA_{slow}(t) > 0.02$ OR $\tau_t > 0.03)$ **then**
7:             BUY, set position $= 1$, record entry, layers $= 1$
8:         **else if** $(MA_{fast}(t-1) \geq MA_{slow}(t-1)$ AND $MA_{fast}(t) < MA_{slow}(t))$ AND $\tau_t < -0.02$ **then**
9:             SELL, set position $= -1$, record entry, layers $= 1$
10:        **end if**
11:    **else if** position $= 1$ **then**
12:        $stop = $ avg entry price $-m \times ATR(t)$; (if $\tau_t > 0.05$, $m \leftarrow m \times 1.5$; if $0.02 < \tau_t \leq 0.05$, $m \leftarrow m \times 1.2$)
13:        **if** price $<$ stop **AND** $\tau_t < -0.02$ **then**
14:            CLOSE long, reset position/layers
15:        **else if** layers $< L$ **AND** (recent breakout, MA divergence, pullback) **then**
16:            Add long layer, $layers \leftarrow layers + 1$, record entry
17:        **end if**
18:        **if** $(MA_{fast}(t-1) \geq MA_{slow}(t-1)$ AND $MA_{fast}(t) < MA_{slow}(t))$ **AND** $\tau_t < -0.02$ **then**
19:            CLOSE long
20:        **end if**
21:    **end if**
22: **end for**
23: Close any open positions at end

Momentum Strategy

The Momentum Strategy capitalizes on price momentum by entering positions when price movements exceed certain thresholds and exiting when momentum weakens.

Algorithm 2 Momentum Adaptive Strategy

1: **Input:** Price data; lookback $l = 10$; entry threshold $\theta_e = 0.02$; exit threshold $\theta_x = 0.005$; ATR period $a = 14$; ATR multiplier $m = 1.5$; max layers $L = 3$; RSI threshold $= 40$

2: **Initialize:** position $= 0$; layers $= 0$; entry price $= 0$

3: **for** each trading day t **do**

4:     Compute $momentum_{short}$, $momentum_{mid}$, $momentum_{long}$; combine $momentum = 0.5 \times momentum_{mid} + 0.3 \times momentum_{short} + 0.2 \times momentum_{long}$

5:     Compute momentum acceleration (last 5 days), ATR, RSI, volume ratio

6:     **if** position $= 0$ **then**

7:         **if** $momentum > \theta_e$ AND (momentum acceleration > 0, RSI > 50, volume ratio > 1.2) **then**

8:             BUY, set position $= 1$, record entry, layers $= 1$

9:         **else if** $momentum < -\theta_e$ AND momentum acceleration < 0 AND RSI < 40 **then**

10:            SELL, set position $= -1$, record entry, layers $= 1$

11:        **end if**

12:    **else if** position $= 1$ **then**

13:        $stop =$ entry price $-m \times ATR(t)$

14:        **if** price $<$ stop **OR** $momentum < \theta_x$ **then**

15:            CLOSE long, reset position/layers

16:        **else if** layers $< L$ **AND** ($momentum > \theta_e \times (1 + 0.5 \times layers)$, price $>$ entry price $\times (1 + 0.01 \times layers)$, momentum acceleration $> 0.5 \times \theta_e$, volume ratio > 1.3, at least 2 met) **then**

17:            Add long layer, $layers \leftarrow layers + 1$, record entry

18:        **end if**

19:    **end if**

20: **end for**

21: Close any open positions at end

Turtle Trading

The Turtle Trading Strategy is based on the famous Turtle Trading system, using Donchian channels to identify breakouts and trend following opportunities.

Algorithm 3 Turtle Trading Adaptive

1: **Input:** Price data, entry period ($n_{\text{entry}} = 20$), exit period ($n_{\text{exit}} = 10$), ATR period ($n_{\text{ATR}} = 20$), ATR multiplier ($m = 2.0$), max units ($U = 5$)
2: **Initialize:** Donchian entry/exit channels, ATR, position = 0, entry_price = 0, units = 0
3: **for** each trading day t **do**
4:     Calculate entry high/low (max/min of past n_{entry}), exit high/low (past n_{exit}), ATR
5:     **if** position = 0 **then**
6:       **if** price > entry high **then**
7:         Compute position size based on volatility, volume, etc.
8:         **BUY** (open long, $units = 1$)
9:       **else if** price < entry low **then**
10:         **SELL** (open short, $units = 1$)
11:       **end if**
12:     **else**
13:       stop_price = entry_price $\pm$ (dynamic $m \times$ ATR)
14:       **if** long position **then**
15:         **if** profit > 10% AND $units > 1$ **then**
16:           Partially take profit
17:         **end if**
18:         **if** price < exit low OR price < stop_price **then**
19:           **CLOSE** (exit long, reset units)
20:         **else if** units < U **and** pyramid/add signal **then**
21:           Add to long position ($units + 1$)
22:         **end if**
23:       **end if**
24:     **end if**
25: **end for**
26: Close any open position at end

Bollinger Bands Reversion

The Bollinger Bands Reversion strategy exploits price mean reversion by entering positions when prices reach extreme levels relative to the moving average.

Algorithm 4 Bollinger Bands Reversion Adaptive

1: **Input:** Price data, MA period ($n = 20$), std multiplier ($k = 1.8$), ATR period ($n_{\text{ATR}} = 14$), ATR multiplier ($m = 1.8$), max layers ($L = 3$)
2: **Initialize:** Calculate Bollinger Bands (upper, middle, lower), ATR, position $= 0$, entry_price $= 0$, layers $= 0$
3: **for** each trading day t **do**
4:     Calculate Bollinger Bands for window n with k std, ATR
5:     **if** position $= 0$ **then**
6:         **if** price $<$ lower band **and** oversold signals (RSI, momentum, volume) **then**
7:             **BUY** (open long, size by oversold score)
8:         **else if** price $>$ upper band **and** overbought signals **then**
9:             **SELL** (open short)
10:         **end if**
11:     **else**
12:         stop_price $=$ entry_price $-m\times$ ATR
13:         **if** long position **then**
14:             **if** price $\geq$ middle band **and** momentum negative **then**
15:                 **CLOSE** (target reached)
16:             **else if** price $<$ stop_price **then**
17:                 **CLOSE** (stop loss)
18:             **else if** layers $<$ L **and** add-signal (e.g., more extreme, time, false break) **then**
19:                 Add to position ($layers + 1$)
20:             **end if**
21:         **end if**
22:     **end if**
23: **end for**
24: Close any open position at end

RSI Reversion

The RSI Reversion strategy uses the Relative Strength Index to identify overbought and oversold conditions for mean reversion trading opportunities.

Algorithm 5 RSI Reversion Adaptive

1: **Input:** Price data, RSI period ($n_{\text{RSI}} = 14$), oversold ($\theta_{\text{os}} = 35$), overbought ($\theta_{\text{ob}} = 65$), neutral ($\theta_{\text{neu}} = 50$), ATR period ($n_{\text{ATR}} = 14$), ATR multiplier ($m = 1.8$), max layers ($L = 3$)
2: **Initialize:** Position $= 0$, Entry price $= 0$, Layers $= 0$
3: **for** each trading day t **do**
4:     Calculate $\text{RSI}(t)$, $\text{ATR}(t)$, RSI momentum, short-term trend, volume spike, bullish divergence
5:     **if** Position $= 0$ **then**
6:       **if** RSI $< \theta_{\text{os}}$ **and** strong oversold signals **then**
7:         **BUY** (open long, position size based on oversold score)
8:       **else if** RSI $> \theta_{\text{ob}}$ **and** flat or negative trend **then**
9:         **SELL** (open short)
10:       **end if**
11:     **else**
12:       stop_price $=$ entry_price $- m \times$ ATR
13:       **if** long position **then**
14:         **if** RSI $> \theta_{\text{neu}}$ **and** RSI momentum < 0 **then**
15:           **CLOSE** (mean reversion)
16:         **else if** price $<$ stop_price **then**
17:           **CLOSE** (stop loss)
18:         **else if** profit $> 8\%$ **and** RSI > 60 **then**
19:           **CLOSE** (profit target)
20:         **else if** layers $< L$ **and** add signal (e.g., RSI even more extreme, new divergence, price drop) **then**
21:           Add to position (layers $+ 1$)
22:         **end if**
23:       **else if** short position **then**
24:         (Symmetric short-side logic)
25:       **end if**
26:     **end if**
27: **end for**
28: Close any open position at the end

KDJ Reversion

The KDJ Reversion strategy combines the stochastic oscillator with crossover signals to identify overbought/oversold conditions and trend reversals.

Algorithm 6 KDJ Reversion Adaptive

1: **Input:** Price data, KDJ period ($n = 9$), J buy ($\theta_{Jb} = 10$), K buy ($\theta_{Kb} = 20$), J sell ($\theta_{Js} = 90$), K sell ($\theta_{Ks} = 80$), ATR period ($n_{\text{ATR}} = 14$), ATR multiplier ($m = 1.8$), max layers ($L = 3$)
2: **Initialize:** K, D, J, position = 0, entry price = 0, layers = 0
3: **for** each trading day t **do**
4:     Calculate K, D, J, check golden/death cross, ATR, recent momentum, volume
5:     **if** Position = 0 **then**
6:         **if** J < θ_{Jb} **or** K < θ_{Kb} **and** strong buy signals (e.g., golden cross, volume, momentum) **then**
7:             **BUY** (open long, position size based on buy score)
8:         **else if** J > θ_{Js} **and** K > θ_{Ks} **and** (death cross or strong negative momentum/volume) **then**
9:             **SELL** (open short)
10:         **end if**
11:     **else**
12:         stop_price = entry_price $-m\times$ ATR
13:         **if** long position **then**
14:             **if** K crosses below D **and** K > 70 **then**
15:                 **CLOSE** (death cross)
16:             **else if** J > 80 **and** J momentum < -10 **then**
17:                 **CLOSE** (J reversion)
18:             **else if** price < stop_price **then**
19:                 **CLOSE** (stop loss)
20:             **else if** profit > 8% **and** (J > 70 or K > 70) **then**
21:                 **CLOSE** (profit target)
22:             **else if** layers < L **and** add signal (e.g., J even lower, new golden cross, KDJ divergence) **then**
23:                 Add to position (layers + 1)
24:             **end if**
25:         **else if** short position **then**
26:             (Symmetric short-side logic)
27:         **end if**
28:     **end if**
29: **end for**
30: Close any open position at the end

Volume Breakout

The Volume Breakout strategy combines price breakouts with volume confirmation to identify high-probability trading opportunities with strong market participation.

Algorithm 7 Volume Breakout

1: **Input:** Price data, price window ($n_p = 20$), volume window ($n_v = 5$), moving average period ($n_{\mathrm{ma}} = 10$), volume multiplier ($\lambda = 1.5$), ATR period ($n_{\mathrm{ATR}} = 14$), ATR multiplier ($m = 1.8$)
2: **Initialize:** High/low of last n_p bars, average volume of last n_v bars, position $= 0$, entry price $= 0$, position layers $= 0$
3: **for** each trading day t **do**
4:     Calculate recent high/low, short/long average volume, volume ratios, moving average, ATR
5:     **if** no position **then**
6:         **if** price $>$ recent high **and** volume ratio $> \lambda$ **then**
7:             **BUY** (open long, position size based on breakout score)
8:         **else if** price $<$ recent low **and** volume ratio $> \lambda$ **then**
9:             **SELL** (open short)
10:         **end if**
11:     Set stop price: $stop\_price = entry\_price - m \times ATR$
12:     **else**
13:         **if** long position **then**
14:             **if** price $<$ stop_price **or** volume exhaustion detected **then**
15:                 **CLOSE** (stop loss or exhaustion)
16:             **else if** breakout extends and volume stays high **and** layers < 3 **then**
17:                 Add to position (pyramiding)
18:             **end if**
19:         **else if** short position **then**
20:             (Symmetric logic)
21:         **end if**
22:     **end if**
23: **end for**
24: Close any open position at the end

ATR Breakout

The ATR Breakout strategy uses Average True Range to create dynamic entry channels based on market volatility, ensuring entries occur at significant breakout levels.

Algorithm 8 ATR Breakout

1: **Input:** Price data, MA period ($n_{\mathrm{ma}} = 20$), ATR period ($n_{\mathrm{ATR}} = 20$), entry multiplier ($m_e = 1.5$), exit multiplier ($m_x = 0.75$), stop multiplier ($m_s = 1.2$)
2: **Initialize:** Moving average, ATR, upper/lower entry channel, position = 0, entry price = 0, position layers = 0
3: **for** each trading day t **do**
4:    Calculate MA, ATR, upper channel = $MA + m_e \times ATR$, lower channel = $MA - m_e \times ATR$
5:    **if** no position **then**
6:      **if** price > upper channel **then**
7:        **BUY** (open long, position size based on quality score)
8:      **else if** price < lower channel **then**
9:        **SELL** (open short)
10:      **end if**
11:     Set stop price: $stop\_price = entry\_price - m_s \times ATR$
12:     Set exit price: $exit\_price = MA + m_x \times ATR$ (for long)
13:    **else**
14:      **if** long position **then**
15:        **if** price < stop_price **or** price < exit_price **then**
16:          **CLOSE** (stop loss or exit)
17:        **else if** breakout continues and layers < 3 **then**
18:          Add to position (pyramiding)
19:        **end if**
20:      **else if** short position **then**
21:        (Symmetric logic)
22:      **end if**
23:    **end if**
24: **end for**
25: Close any open position at the end

Always Long Strategy

The Always Long strategy serves as a benchmark by maintaining a continuous long position throughout the entire trading period, representing a simple buy-and-hold approach.

Algorithm 9 Always Long

1: **Input:** Price data
2: **Initialize:** entry_price = None
3: **for** each trading day **do**
4:    **if** no position **then**
5:      **BUY**
6:    **end if**
7:    Hold long position (no exit conditions)
8: **end for**

Always Short Strategy

The Always Short strategy maintains a continuous short position, serving as a benchmark for bearish market exposure and inverse performance measurement.

Algorithm 10 Always Short

1: **Input:** Price data
2: **Initialize:** entry_price = None
3: **for** each trading day **do**
4:    **if** no position **then**
5:        **SELL**
6:    **else**
7:        **SELL** (maintain short position)
8:    **end if**
9: **end for**

Always Cash Strategy

The Always Cash strategy maintains a cash position throughout the trading period, serving as a neutral benchmark and risk-free reference point.

Algorithm 11 Always Cash

1: **Input:** Price data
2: **Initialize:** No trading variables needed
3: **for** each trading day **do**
4:    Do nothing (stay in cash)
5: **end for**

Appendix B   Dataset Specifications and Radar-Chart Comparison

We construct a five–market, multi–modal dataset that spans about eight years. Table 1 in our main body summarises the asset coverage and the features of our dataset, while Fig. 2 in our main body benchmarks it against recent public collections.

The raw OHLCV series for securities are obtained from *Yahoo Finance* and other partnering brokerage firms. Due to space constraints and data licensing agreements, we provide only representative samples of the original CSV datasets, generated visualizations, and related files in our supplementary materials. All prices are forward-adjusted for splits and dividends.

Asset Class	#	Description	Constituents / Contracts
U.S. Stocks	15	NASDAQ-100 components	AAPL, ADBE, AMAT, AMD, AMGN, AMZN, AVGO, COST, CSCO, GOOGL, INTC, META, MSFT, NVDA, TSLA
China A-Shares	10	Leading mainland listed companies	ZGTJ (601186), ZGLY (601600), ZXGJ (688981), NDSD (300750), ZSYH (600036), HKWS (002415), MDJT (000333), GZMT (600519), ZGSY (601857).etc
U.S. & HK ETFs	15	Diversified exchange-traded funds	**U.S.:** SPY, QQQ, AGG, BSV, GLD, IWF, IWY, USD **HK:** 2820.HK, 2822.HK, 2828.HK, 2836.HK, 3010.HK
Cryptocurrencies	2	Large-cap digital assets	BTC, ETH
Futures	20	Equity, commodity and rates contracts	*Equity index:* CSI-300, SSE-50, CSI-500; *Metals:* Gold, Silver, Copper, Iron Ore, Rebar; *Energy:* Crude Oil, Coke; *Agricultural:* Corn, Cotton, Sugar, Soybean No. 1, Apple; *Chemicals:* PTA, LLDPE, Glass; *Rates/Other:* 10-Y T-Bond, EA Container Freight

Table 6: Detail of our multimarket dataset used in this study.

Our MM-DREX system demonstrates comprehensive coverage across five key dimensions as illustrated in the radar chart in the main body with all metrics derived from rigorous statistical analysis of our actual dataset:

Image Data Volume (22,638 images) This metric represents the total count of high-quality financial chart images in our comprehensive multimodal dataset. The calculation methodology involves 62 trading assets spanning five major markets (U.S. equities, Chinese A-shares, ETFs, futures, and cryptocurrencies), multiplied by an average of 122 valid trading time points per asset, and further multiplied by 3 core chart types (candlestick charts, technical indicator charts, and trend analysis charts), yielding a total of 22,638 financial image instances.

Exchange Coverage (10 exchanges) Our dataset achieves extensive global exchange coverage, encompassing major U.S. exchanges including the New York Stock Exchange (NYSE) and NASDAQ, the Hong Kong Stock Exchange (HKEX), mainland Chinese exchanges including the Shanghai Stock Exchange and Shenzhen Stock Exchange, five major Chinese futures exchanges (Shanghai Futures Exchange SHFE, Dalian Commodity Exchange DCE, Zhengzhou Commodity Exchange CZCE, China Financial Futures Exchange CFFEX, and Shanghai International Energy Exchange INE), and leading global cryptocurrency exchanges, establishing a truly comprehensive global financial market coverage network.

Asset Market Categories (5 major markets) Our dataset spans five core financial market domains: U.S. equity markets (including technology stocks and traditional blue-chip stocks), Chinese A-share markets (covering main board and ChiNext), Exchange-Traded Fund (ETF) markets (including U.S. and Hong Kong ETFs), futures markets (encompassing commodity futures, financial futures, and energy futures), and cryptocurrency markets (featuring Bitcoin, Ethereum, and other mainstream digital assets), achieving comprehensive coverage of both traditional and emerging financial markets.

Time Series Data Points (127,474 time series points) This statistic represents the cumulative total of all valid trading day OHLCV (Open, High, Low, Close, Volume) time series data points in our dataset, spanning from August 15, 2016, to the dataset cutoff date. This extensive temporal coverage ensures sufficient historical depth and data continuity, providing rich temporal features for model training and validation.

Feature Engineering Dimensions (13 core features) We construct a comprehensive technical analysis feature system comprising: 3 moving average indicators (MA10, MA20, MA100) capturing multi-timeframe trend information; 1 Relative Strength Index (RSI14) measuring overbought/oversold conditions; 3 Bollinger Band indicators (upper band, middle band MA20, lower band) analyzing price volatility ranges; 3 stochastic oscillators (K, D, J values) determining optimal entry/exit timing; and 3 MACD indicators (DIF, DEA, MACD histogram) analyzing momentum changes. This multi-dimensional, multi-timeframe comprehensive technical feature matrix significantly exceeds the basic OHLC raw data utilized by competing approaches.

All five dimensional metrics utilize our actual statistical data as the 100% baseline reference. Competing systems (FinAgent, FinMem, PIXIU(Zhang et al. 2024; Yu et al. 2024; Xie et al. 2023)) are evaluated using official data published in their respective papers from top-tier conferences including KDD'24, AAAI'24, and NeurIPS'23, ensuring objective and scientifically rigorous comparative assessment.

Appendix C Multimodal LLMs' Financial Forecasting Capabilities

In this section, we conduct a comprehensive evaluation of state-of-the-art multimodal large language models on financial forecasting tasks. Our assessment focuses on their ability to interpret financial chart images and generate accurate price movement predictions across different time horizons and precision thresholds.The workflow of our test is in the Fig 4.

(i) Test 5 Vendors 12 Modelsto Find the Best Model and Time Span	(ii) Time Span_100DAYS Pic ,90days Prediction and GPT-o3 are Best as the Highest Predictication Accurcy	(iii) Using GPT-o3 to analyze the trends of technical indicators over the past 100 trading days and predict the price movement over the next 90 days.

Figure 4: Workflow of our Test.

Experimental Setup

We design a systematic evaluation framework to assess multimodal LLMs' capabilities in financial chart analysis and prediction. The evaluation process involves three key components: standardized input prompts, structured output format, and comprehensive visual inputs.We randomly selected 37 assets as test phase dataset from our comprehensive dataset of 62 financial instruments. For each selected asset, we partitioned the time series into ten equal segments and randomly chose one temporal window to generate corresponding technical indicator charts and sequential data for evaluation. Our evaluation process handled a total of 5,164 data files, resulting in 25,001 valid predictions across all tested models.
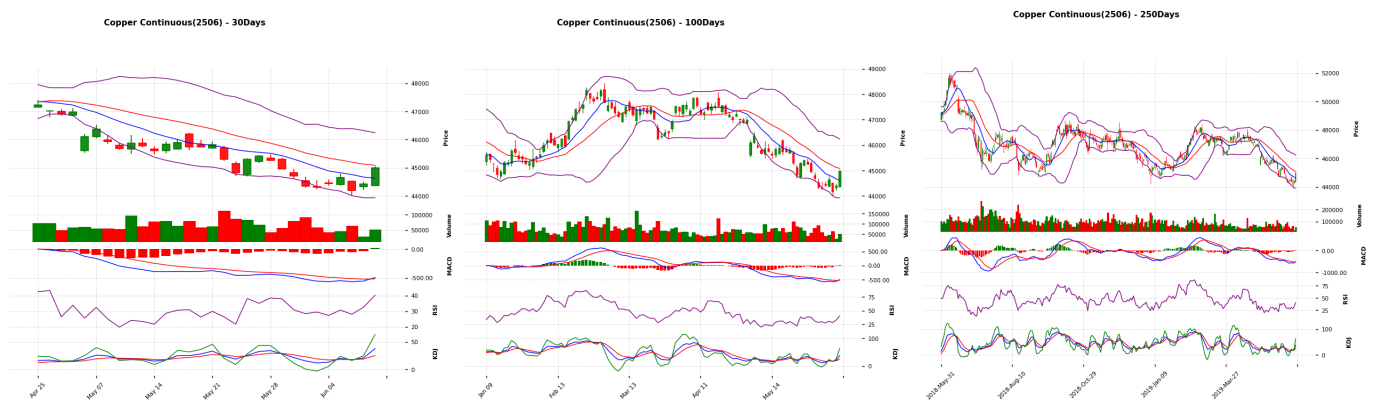
Figure 5: Copper continuous futures — multi-horizon K-line charts (30/100/250 days).

Visual Input Specifications The evaluation utilizes three types of financial chart visualizations: (1) candlestick charts showing OHLCV data with technical indicators, (2) multi-timeframe comparative charts displaying short-term and long-term patterns. For the time span[30,250], we choose 30Days,100Days, 250Days to generate charts to find the best time span for large lannguage model to detect best time span. Each chart type provides different perspectives on market dynamics and technical signals.Eg:Fig 5

Input Prompt Design Our evaluation employs carefully crafted prompts that provide context about the financial analysis task, specify the required output format, and guide the models toward making structured predictions. The prompts include market context, historical performance indicators, and clear instructions for generating directional forecasts with confidence levels.

Listing 1: Prompt template that fuses visual-chart and numerical time-series information for supervised fine-tuning

```
def extract_period_and_days(filename):
    m = re.search(r'_(\d+)Days?_mrkab', filename, re.IGNORECASE)
    if m:
        period = int(m.group(1))
        if period == 30:
            prediction_days = [1, 3, 5, 7, 15]
        else:
            prediction_days = [1, 3, 5, 7, 15, 30, 60, 90]
        return period, prediction_days
    return None, []

def build_prompt(period, prediction_days, time_series_data=None):
    time_series_text = ""
    if time_series_data:
        time_series_text = f"""

the corresponding time series data for this chart:
{json.dumps(time_series_data, indent=2)}

Please use BOTH the visual chart analysis AND the precise numerical data from the time series
 to make your predictions. The time series data provides exact prices, volumes, and dates
that complement the visual patterns you see in the chart."""

    prompt = f"""Please analyze and predict based on the candlestick chart and time series
     data:

Currently analyzing {period}-day chart, need to predict prices for the following time points:
 {', '.join([f'{d} days' for d in prediction_days])} ahead.
{time_series_text}

Please consider:
1. Trend consistency across different time periods
2. Technical patterns (e.g., head and shoulders, double bottom)
```

```
30   3. Support and resistance levels
31   4. Volume characteristics
32   5. Market sentiment
33   6. Precise numerical values from the time series data
34   7. Focus solely on technical indicators; Exclude fundamental analysis
35
36   Please return in JSON format with the following fields:
37   {{
38       "period": {period},
39       "current_closing_price": "closing price of the last candlestick",
40       "predictions": {{
41           "1 day": {{
42               "predicted_price": "predicted closing price",
43               "price_range": {{
44                   "high": "highest price",
45                   "low": "lowest price"
46               }},
47               "confidence": "prediction confidence (between 0-1)",
48               "return": "percentage return calculated as (predicted_price/current_closing_price -
                 1)",
49               "reasoning": "detailed reasoning for the prediction"
50           }},
51           "3 days": {{
52               "predicted_price": "predicted closing price",
53               "price_range": {{
54                   "high": "highest price",
55                   "low": "lowest price"
56               }},
57               "confidence": "prediction confidence (between 0-1)",
58               "return": "percentage return calculated as (predicted_price/current_closing_price -
                 1)",
59               "reasoning": "detailed reasoning for the prediction"
60           }},
61           ...
62       }},
63       "analysis": "detailed analysis including trend judgment and technical pattern
         interpretation",
64       "risk_factors": "list of potential risk factors affecting the prediction"
65   }}
66
67   Key requirements:
68   1. Add return field showing percentage change from current_closing_price to predicted_price
69   2. Include current_closing_price from the last available candlestick
70   3. Return value should show 4 decimal places for prices and 2 decimal places for return (e.g
     ., 0.0523 for 5.23%)
71   4. Include confidence score (0-1) for each prediction
72   5. Provide detailed reasoning for each prediction that combines both visual chart patterns
     and numerical time series analysis
73   6. Maintain all original analysis dimensions
74   7. If time series data is provided, reference specific data points, trends, and numerical
     patterns in your analysis
75
76   Please ensure the response is in valid JSON format with proper numeric formatting."""
```

Testing Results

We conducted comprehensive evaluations across 12 state-of-the-art multimodal large language models. The results are presented across five complementary tables: overall performance metrics, temporal accuracy summary, and detailed analyses for 30-day, 100-day, and 250-day analytical periods.

The comprehensive evaluation encompassed 25,001 individual forecasting tests across all 12 models, revealing critical insights into the temporal dynamics and analytical context dependencies of multimodal LLMs in financial forecasting.

From the overall performance analysis (Table 7), while o1 achieved the highest directional accuracy at 58.9%, o3 demonstrated superior performance in volatility-constrained scenarios with 92.1% accuracy within $\pm 10\%$ price deviation and 74.7%

Table 7: Overall Performance Evaluation of Multimodal LLMs on Financial Forecasting

Rank	Model	Tests	Direction Accuracy	Stricter ±10%	Very Strict ±5%	Best Period	Best Accuracy
1	o3	3,975	54.5%	92.1%	74.7%	100D	57.6%
2	o1	2,635	58.9%	88.4%	65.7%	100D	59.1%
3	claude_3_5_sonnet	2,137	48.7%	94.4%	80.0%	100D	50.1%
4	gpt4o	2,065	52.1%	93.8%	79.9%	100D	54.2%
5	grok4	2,057	53.1%	94.3%	80.2%	100D	55.9%
6	gemini_2_5_flash	2,050	50.7%	92.5%	77.7%	100D	51.7%
7	gemini_2_0_flash_thinking	2,030	51.4%	92.7%	78.8%	30D	51.7%
8	claude_3_7_sonnet	1,996	50.7%	93.9%	80.4%	100D	51.9%
9	gemini_2_5_pro	1,990	50.9%	93.2%	78.9%	250D	51.2%
10	claude_sonnet_4	1,680	48.0%	91.3%	73.0%	100D	54.0%
11	doubao_vision_pro	1,415	51.9%	94.1%	83.5%	30D	55.6%
12	doubao_seed_thinking	971	48.2%	94.7%	80.6%	250D	48.9%

Table 8: Temporal Analysis Summary: Average Accuracy Across Different Forecasting Horizons

Rank	Model	1D	3D	5D	7D	15D	30D	60D	90D
1	o3	53.5%	54.6%	53.8%	48.6%	61.9%	59.7%	56.3%	63.5%
2	o1	53.3%	61.9%	57.5%	52.8%	69.1%	68.0%	71.1%	69.7%
3	claude_3_5_sonnet	42.3%	49.1%	44.2%	50.5%	57.5%	59.6%	57.3%	65.6%
4	grok4	49.1%	52.8%	52.1%	55.2%	55.9%	56.4%	52.9%	59.3%
5	gpt4o	48.4%	54.5%	47.2%	51.3%	58.8%	61.5%	58.5%	64.0%
6	gemini_2_5_flash	46.8%	53.2%	49.3%	49.8%	54.6%	50.4%	49.6%	59.6%
7	gemini_2_0_flash_thinking	47.3%	51.7%	48.8%	52.2%	56.9%	54.1%	52.6%	59.4%
8	gemini_2_5_pro	47.0%	49.7%	49.5%	53.3%	54.8%	54.3%	52.8%	59.6%
9	claude_3_7_sonnet	45.2%	50.1%	49.1%	50.9%	58.1%	56.1%	59.5%	63.7%
10	claude_sonnet_4	48.5%	47.3%	42.6%	44.0%	57.7%	54.4%	59.8%	63.6%
11	doubao_vision_pro	47.3%	52.7%	49.1%	51.6%	59.0%	54.9%	54.9%	56.3%
12	doubao_seed_thinking	42.4%	54.0%	42.1%	43.5%	57.9%	56.9%	60.8%	67.7%

Table 9: 30-Day Analysis Period: Short-term Forecasting Performance (1, 3, 5, 7, 15 Days)

Rank	Model	1D	3D	5D	7D	15D
1	o3	51.1%	53.8%	50.8%	46.6%	57.9%
2	o1	53.7%	61.6%	58.2%	52.0%	68.4%
3	claude_3_5_sonnet	40.6%	49.0%	42.0%	51.7%	57.3%
4	grok4	44.4%	49.3%	48.6%	58.5%	50.0%
5	doubao_vision_pro	51.1%	54.6%	53.9%	55.3%	63.1%
6	gemini_2_0_flash_thinking	46.4%	53.6%	45.7%	52.9%	60.0%
7	gemini_2_5_flash	47.9%	51.4%	50.0%	51.4%	54.3%
8	gpt4o	47.8%	52.2%	44.9%	48.6%	54.3%
9	claude_3_7_sonnet	43.8%	48.9%	47.4%	54.0%	56.9%
10	gemini_2_5_pro	42.9%	46.6%	47.4%	56.4%	59.4%
11	doubao_seed_thinking	41.7%	55.6%	41.7%	40.3%	55.6%

Verified 5 Vendors × 5 Asset Categories
Best Direction Accuracy Heatmap
(Range: 30%-90%)

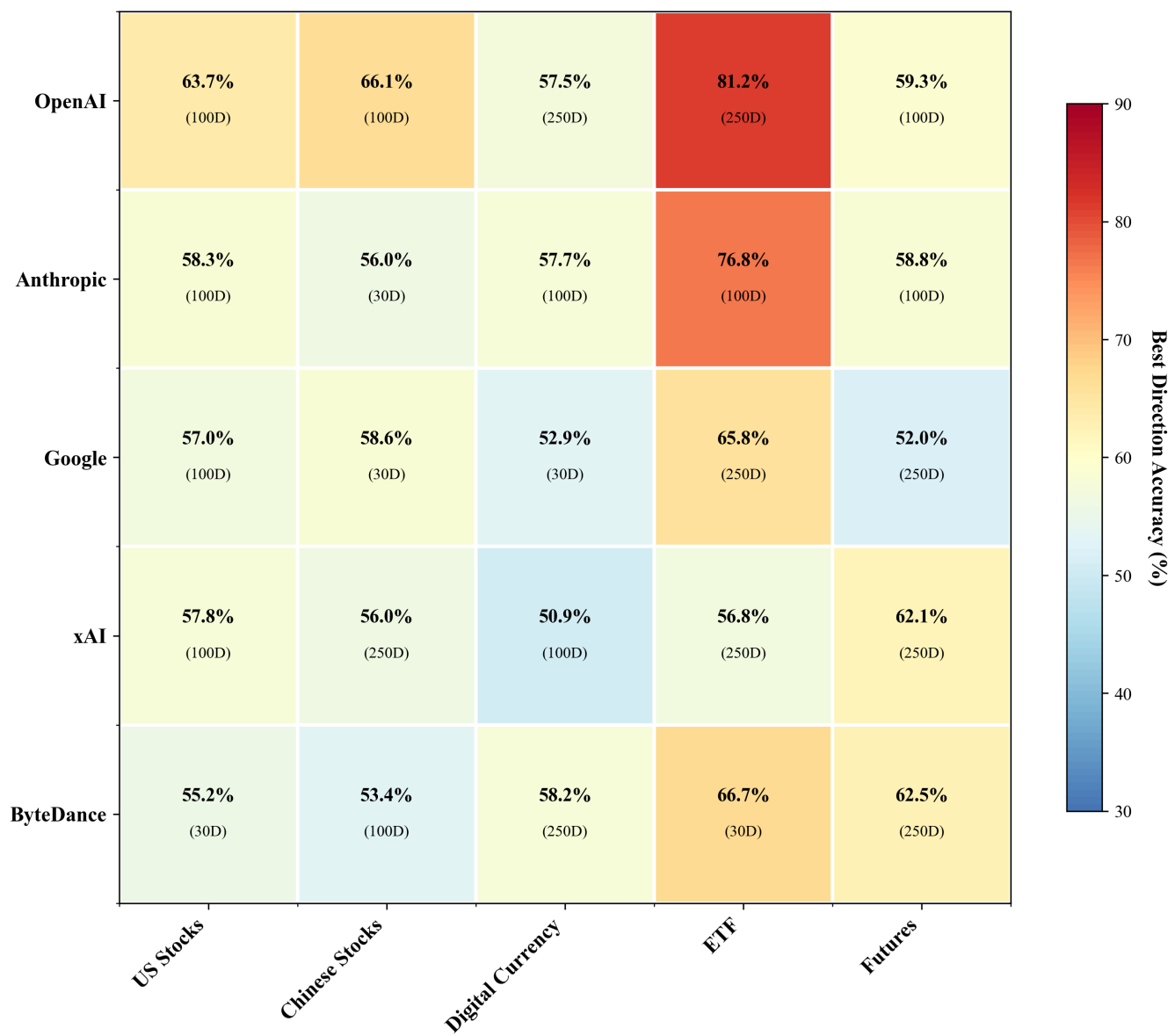|	US Stocks	Chinese Stocks	Digital Currency	ETF	Futures
OpenAI	63.7% (100D)	66.1% (100D)	57.5% (250D)	81.2% (250D)	59.3% (100D)
Anthropic	58.3% (100D)	56.0% (30D)	57.7% (100D)	76.8% (100D)	58.8% (100D)
Google	57.0% (100D)	58.6% (30D)	52.9% (30D)	65.8% (250D)	52.0% (250D)
xAI	57.8% (100D)	56.0% (250D)	50.9% (100D)	56.8% (250D)	62.1% (250D)
ByteDance	55.2% (30D)	53.4% (100D)	58.2% (250D)	66.7% (30D)	62.5% (250D)

Figure 6: Vendor Asset Heatmap

Table 10: 100-Day Analysis Period: Comprehensive Forecasting Performance Across All Horizons

Rank	Model	1D	3D	5D	7D	15D	30D	60D	90D
1	o3	57.7%	56.6%	58.8%	51.7%	63.3%	57.3%	56.2%	63.3%
2	o1	53.7%	62.7%	56.5%	54.8%	67.8%	67.8%	71.2%	67.8%
3	doubao_vision_pro	43.7%	50.7%	44.4%	47.9%	54.9%	54.9%	54.9%	56.3%
4	claude_3_5_sonnet	43.1%	49.3%	48.9%	48.6%	60.4%	61.8%	53.7%	63.2%
5	grok4	49.6%	54.9%	54.2%	57.7%	62.0%	54.9%	47.2%	57.0%
6	gpt4o	52.5%	55.4%	49.6%	54.0%	59.7%	61.2%	59.0%	63.3%
7	gemini_2_5_flash	49.6%	53.3%	49.6%	51.1%	54.7%	51.8%	53.3%	62.8%
8	claude_3_7_sonnet	46.3%	54.8%	52.6%	47.4%	58.5%	58.5%	63.7%	67.4%
9	gemini_2_0_flash_thinking	44.8%	47.0%	52.2%	53.7%	56.0%	53.7%	53.0%	57.5%
10	gemini_2_5_pro	46.5%	50.4%	51.2%	53.5%	52.7%	51.9%	51.2%	57.4%
11	claude_sonnet_4	59.8%	54.6%	42.3%	49.5%	63.9%	53.6%	63.9%	64.9%
12	doubao_seed_thinking	39.5%	53.7%	44.4%	42.6%	59.3%	59.3%	61.1%	72.2%

Table 11: 250-Day Analysis Period: Long-term Forecasting Performance Across Multiple Horizons

Rank	Model	1D	3D	5D	7D	15D	30D	60D	90D
1	o3	51.5%	53.4%	51.9%	47.3%	64.5%	62.2%	56.5%	63.7%
2	o1	52.6%	61.3%	57.8%	51.4%	71.1%	68.2%	71.1%	71.7%
3	claude_sonnet_4	46.5%	43.0%	40.8%	39.4%	52.1%	54.9%	57.0%	62.7%
4	gemini_2_5_pro	51.5%	52.2%	50.0%	50.0%	52.2%	56.6%	54.4%	61.8%
5	gpt4o	44.9%	55.9%	47.1%	51.5%	62.5%	61.8%	58.1%	64.7%
6	claude_3_5_sonnet	43.3%	48.9%	41.8%	51.1%	54.6%	57.4%	61.5%	68.4%
7	grok4	54.8%	54.3%	53.6%	49.3%	55.8%	58.0%	58.7%	61.6%
8	gemini_2_5_flash	42.9%	54.9%	48.1%	46.6%	54.9%	48.9%	45.9%	56.4%
9	gemini_2_0_flash_thinking	50.8%	54.5%	48.5%	50.0%	54.5%	54.5%	52.3%	61.4%
10	claude_3_7_sonnet	45.7%	46.5%	47.2%	51.2%	59.1%	53.5%	55.1%	59.8%
11	doubao_seed_thinking	44.6%	52.6%	40.8%	47.3%	59.2%	55.3%	60.5%	64.5%

accuracy within ±5% deviation. This contrast becomes crucial when considering practical trading applications where both directional accuracy and price precision matter.

The multi-period analysis (Tables 9, 10, and 11,Fig 6) reveals distinct analytical context dependencies. The 100-day analysis period consistently produced the most reliable results across models, with o3 achieving peak performance in the 90-day forecasting horizon (63.3% accuracy). This finding suggests that 100-day analytical windows provide optimal market context for price movement prediction.

The temporal analysis summary (Table 8) demonstrates that longer forecasting horizons (60-90 days) generally outperform shorter-term predictions across all models. Most notably, o1 excelled in 60-day predictions (71.1%), while o3 showed consistent performance across multiple horizons with peak accuracy in 90-day forecasts.

Cross-period comparisons reveal interesting stability patterns: o3 maintained consistent performance across all analytical periods (30D: 57.9%, 100D: 63.3%, 250D: 64.5% in their respective optimal horizons), while o1 showed greater variability but higher peak performance in specific contexts.

Based on these comprehensive results, we selected o3's 100-day analytical period with 90-day forecasting horizon as the foundation for our supervised fine-tuning (SFT) training dataset. This strategic decision was motivated by several key factors: while o3's long-term directional performance (54.5%) is marginally lower than o1's (58.9%), o3 demonstrates significantly superior performance in volatility-constrained scenarios with stricter accuracy requirements (92.1% within ±10% vs. 88.4% for o1, and 74.7% within ±5% vs. 65.7% for o1). This enhanced precision in price deviation control, combined with the largest test volume (3,975 tests) ensuring robust statistical significance and consistent performance across multiple analytical contexts, makes o3's predictions ideal for training a reliable financial forecasting system that balances directional accuracy with price precision requirements.

Using GPT-o3 to make Further training base

We selected GPT-o3 to generate the training dataset. Specifically, we designed prompts to elicit model responses across three key aspects: (1) analyzing the trends of technical indicators over the past 100 trading days; (2) forecasting the price movement over the next 90 days; and (3) providing detailed reasoning to support the prediction.

Listing 2: JSON prompt template used for supervised fine-tuning data generation.

```
1  {
2  """Please predict the stock trend for the next 90 trading days based on the candlestick chart
    and price analysis data.
3
4  OUR CRITERIA:
5  MA5+MA20+ADX Combined Strategy:
6  - UPTREND: MA5 > MA20 AND ADX > 15 AND +DI > -DI
7  - DOWNTREND: MA5 < MA20 AND ADX > 15 AND -DI > +DI
8  - CONSOLIDATION: ADX ≤15 OR other combinations
9
10 TREND STANDARDS:
11 - Uptrend ≥50% of next 90 days →"Uptrend"
12 - Downtrend ≥50% of next 90 days →"Downtrend"
13 - Otherwise →"Consolidation"
14
15 Price Analysis Data:
16 {price_analysis}
17
18 Analyze the chart and predict based on:
19 1. Technical Indicators: MA10/MA20, ADX/+DI/-DI, MACD, RSI, KDJ, Bollinger Bands, Volume
20 2. Chart Patterns: Candlestick patterns, support/resistance, trend signals
21 3. Price Prediction: 90-day target price, price range, key levels
22 4. Trend Assessment: 90-day trend evolution, risk factors
23
24 Return JSON format:
25 {{
26     "current_market_state": {{
27         "ma5_vs_ma20": "MA5 vs MA20 relationship (above/below/close)",
28         "estimated_adx_strength": "ADX strength (strong/medium/weak)",
29         "estimated_di_direction": "+DI vs -DI relationship",
30         "current_trend_assessment": "Current trend (uptrend/downtrend/consolidation)"
31     }},
32     "technical_indicators_analysis": {{
33         "moving_averages": {{
34             "ma5_trend": "MA5 trend direction",
```

```
            "ma20_trend": "MA20 trend direction",
            "ma_crossover_signals": "MA crossover signals"
        }},
        "adx_analysis": {{
            "adx_strength": "ADX strength assessment",
            "di_relationship": "+DI vs -DI status",
            "trend_momentum": "Trend momentum"
        }},
        "macd_analysis": {{
            "macd_signal": "MACD vs signal line",
            "histogram_trend": "MACD histogram pattern",
            "momentum_assessment": "MACD momentum"
        }},
        "rsi_analysis": {{
            "rsi_level": "RSI level and interpretation",
            "overbought_oversold": "RSI conditions",
            "divergence_signals": "RSI divergence patterns"
        }},
        "kdj_analysis": {{
            "kdj_position": "KDJ position and signals",
            "crossover_signals": "%K/%D crossover analysis",
            "momentum_indication": "KDJ momentum"
        }},
        "bollinger_bands_analysis": {{
            "price_position": "Price vs Bollinger Bands",
            "band_width": "Band width and volatility",
            "squeeze_expansion": "Band patterns"
        }},
        "volume_analysis": {{
            "volume_trend": "Volume patterns",
            "volume_price_relationship": "Volume-price confirmation",
            "accumulation_distribution": "Volume signals"
        }}
    }},
    "price_prediction": {{
        "target_price_90_days_prediction": 150.25,
        "price_range_90_days": {{
            "high_estimate": 165.00,
            "low_estimate": 135.50
        }},
        "key_levels": {{
            "resistance_levels": [160.00, 170.00, 180.00],
            "support_levels": [140.00, 130.00, 120.00]
        }},
        "price_confidence": 0.75
    }},
    "prediction_90_days": {{
        "trend_conclusion": "90-day trend (uptrend/downtrend/consolidation)",
        "confidence_level": 0.75,
        "expected_trend_days": {{
            "up_days": 45,
            "down_days": 30,
            "consolidation_days": 15
        }},
        "trend_reasoning": "Reasoning based on MA5+MA20+ADX criteria"
    }},
    "risk_assessment": {{
        "trend_reversal_risk": "Risk level (high/medium/low)",
        "volatility_expectation": "Expected volatility (high/medium/low)",
        "key_risk_factors": ["List of risk factors"],
        "confidence_factors": "Confidence support factors"
    }},
    "detailed_analysis": "Comprehensive analysis of how indicators align with MA5+MA20+ADX
    criteria"
}}
```

```
 99
100   Requirements:
101   - Analyze ALL visible indicators (MA, ADX, MACD, RSI, KDJ, Bollinger Bands, Volume)
102   - Provide specific numeric price predictions
103   - Use numeric values for confidence_level (0-1) and trend_days
104   - Base analysis on MA5+MA20+ADX criteria
105   - Focus on technical alignment with uptrend/downtrend rules"""
106     ]
107   }
```

This training data allows the model to internalize structured reasoning patterns specific to financial contexts, enabling it to capture the logical dependencies between market variables and technical signals. Through iterative training, the model refines its parameters to produce coherent, step-by-step reasoning traces and generate accurate, contextually grounded responses to complex financial queries.

Appendix D   Evaluation Metrics and Baseline Details

Evaluation Metrics

To compare MM-DREX with a broad set of baselines, we employ three standard performance indicators in quantitative finance: total return (TR), Sharpe ratio (SR), and maximum drawdown (MDD).

Total Return (TR)   Total return measures the overall appreciation (or depreciation) of the portfolio over the evaluation horizon $[0, T]$:

$$\text{TR} = \frac{V_T - V_0}{V_0}, \tag{Appendix D.1}$$

where V_0 and V_T denote the initial and terminal net-asset values.

Sharpe Ratio (SR)   Sharpe ratio quantifies risk-adjusted performance by normalising the mean of the excess return series r_t with its volatility:

$$\text{SR} = \frac{\mathbb{E}[r_t]}{\sigma[r_t]}, \tag{Appendix D.2}$$

with $\mathbb{E}[\cdot]$ and $\sigma[\cdot]$ denoting expectation and standard deviation, respectively.

Maximum Drawdown (MDD)   Maximum drawdown captures the most severe peak-to-trough loss:

$$\text{MDD} = \max_{t \in [0,T]} \frac{\max_{s \in [0,t]} P_s - P_t}{\max_{s \in [0,t]} P_s}, \tag{Appendix D.3}$$

where P_t is the portfolio value at time t.

Baseline Details

Buy-and-Hold (B&H)   Buy-and-hold represents the simplest passive investment strategy where investors purchase securities and hold them for the long term regardless of market fluctuations. This strategy assumes that markets generally trend upward over time:

$$h_{\text{B\&H}} = \text{sign}(P_{t+1} - P_t), \tag{Appendix D.4}$$

where P_t denotes the asset price at time t, and the sign function determines the position direction based on expected price movement.

Moving Average Convergence Divergence (MACD)   MACD is a momentum oscillator that identifies trend changes by analyzing the relationship between two exponential moving averages of different periods. It generates buy and sell signals when the fast moving average crosses above or below the slow moving average:

$$h_{\text{MACD}} = \text{sign}(\text{EMA}_{12}(P_t) - \text{EMA}_{26}(P_t)), \tag{Appendix D.5}$$

where $\text{EMA}_n(P_t)$ represents the n-period exponential moving average of price P_t. A positive signal indicates a bullish trend, while a negative signal suggests a bearish trend.

KDJ-Relative Strength Index (KDJ-RSI)   KDJ-RSI combines the KDJ stochastic oscillator with the Relative Strength Index to identify overbought and oversold conditions. This composite indicator provides more robust signals by requiring both momentum indicators to align:

$$h_{\text{KDJ-RSI}} = \begin{cases} +1, & K_t < 20 \ \wedge \ \text{RSI}_t < 30, \\ -1, & K_t > 80 \ \wedge \ \text{RSI}_t > 70, \\ 0, & \text{otherwise}, \end{cases} \tag{Appendix D.6}$$

where K_t is the KDJ indicator value and RSI_t is the RSI value at time t. The strategy generates buy signals when both indicators suggest oversold conditions and sell signals when both indicate overbought conditions.

Commodity Channel Index (CR Channel)   CR Channel uses the typical price (average of high, low, open, and close) as a reference level for generating trading signals. It assumes that prices tend to revert to their typical values over time:

$$\mathrm{CR}_t = \tfrac{1}{4}\big(P_t^H + P_t^L + P_t^O + P_t^C\big), \qquad h_{\mathrm{CR}} = \mathrm{sign}(P_t - \mathrm{CR}_t), \tag{Appendix D.7}$$

where P_t^H, P_t^L, P_t^O, and P_t^C represent the high, low, open, and close prices at time t, respectively. The strategy takes long positions when the current price exceeds the typical price.

Bull-Bear Index (BBI)   BBI is a comprehensive trend-following indicator that combines multiple moving averages of different periods to smooth out short-term price noise and identify the underlying trend direction:

$$\mathrm{BBI}_t = \tfrac{1}{4}\big(\mathrm{MA}_3 + \mathrm{MA}_6 + \mathrm{MA}_{12} + \mathrm{MA}_{24}\big), \qquad h_{\mathrm{BBI}} = \mathrm{sign}(P_t - \mathrm{BBI}_t), \tag{Appendix D.8}$$

where MA_n denotes the n-period simple moving average. By averaging multiple timeframes, BBI provides more stable signals compared to single moving average strategies.

Williams Percent Range (WR)   Williams relative to the highest high for a given period. It oscillates between 0 and -100, identifying overbought and oversold market conditions:

$$\mathrm{WR}_t = -100 \, \frac{P_N^H - P_t}{P_N^H - P_N^L}, \qquad h_{\mathrm{WR}} = \begin{cases} +1, & \mathrm{WR}_t < -80, \\ -1, & \mathrm{WR}_t > -20, \\ 0, & \text{otherwise,} \end{cases} \tag{Appendix D.9}$$

where P_N^H and P_N^L are the highest high and lowest low over the past N periods. Values below -80 indicate oversold conditions (buy signal), while values above -20 suggest overbought conditions (sell signal).

Bias Ratio (BIAS)   BIAS measures the percentage deviation of the current price from its moving average, indicating whether the asset is overvalued or undervalued relative to its recent average price:

$$\mathrm{BIAS}_t = \frac{P_t - \mathrm{MA}_n(P)}{\mathrm{MA}_n(P)}, \qquad h_{\mathrm{BIAS}} = \mathrm{sign}\big(-\mathrm{BIAS}_t\big), \tag{Appendix D.10}$$

where $\mathrm{MA}_n(P)$ is the n-period moving average of price. The strategy assumes mean reversion, taking positions opposite to the current bias direction.

Light Gradient Boosting Machine (LGBM)   LGBM is a gradient boosting framework that uses tree-based learning algorithms optimized for speed and memory efficiency. It processes engineered features to predict future price movements:

$$h_{\mathrm{LGBM}} = f_{\mathrm{GBDT}}(\mathbf{x}_t), \tag{Appendix D.11}$$

where f_{GBDT} represents the gradient boosted decision tree model and $\mathbf{x}_t$ is the feature vector at time t containing technical indicators, price patterns, and market microstructure variables.

Long Short-Term Memory (LSTM)   LSTM is a recurrent neural network architecture designed to capture long-term dependencies in sequential data. It processes historical price sequences to predict future market movements:

$$h_{\mathrm{LSTM}} = f_{\mathrm{LSTM}}\big(P_{t-k:t}\big), \tag{Appendix D.12}$$

where f_{LSTM} denotes the LSTM network function and $P_{t-k:t}$ represents the price sequence from time $t - k$ to t. The model learns temporal patterns and relationships in price movements.

Transformer (Trans)   Transformer architecture uses self-attention mechanisms to process sequential data without recurrence, enabling parallel computation and better capture of long-range dependencies in financial time series:

$$h_{\mathrm{Trans}} = f_{\mathrm{SA}}\big(P_{t-k:t}\big), \tag{Appendix D.13}$$

where f_{SA} represents the self-attention based transformer model that processes the input price sequence $P_{t-k:t}$ to generate trading decisions.

Soft Actor-Critic (SAC)   SAC is an off-policy reinforcement learning algorithm that maximizes both expected return and policy entropy. It learns optimal trading policies through continuous action spaces while maintaining exploration:

$$h_{\mathrm{SAC}} = \pi_\theta^\star(\mathbf{s}_t), \qquad \pi_\theta^\star = \arg\max_\pi \mathbb{E}\big[R - \alpha\mathcal{H}(\pi)\big], \tag{Appendix D.14}$$

where $\pi_\theta^\star$ is the optimal policy parameterized by θ, $\mathbf{s}_t$ is the state at time t, R represents the expected return, α is the temperature parameter, and $\mathcal{H}(\pi)$ is the policy entropy.

Proximal Policy Optimization (PPO) PPO is a policy gradient method that constrains policy updates to prevent large, destabilizing changes. It uses a clipped objective function to maintain training stability:

$$L^{\text{CLIP}}(\theta) = \mathbb{E}\Big[\min\big(r_t A_t,\ \text{clip}(r_t, 1\pm\epsilon)A_t\big)\Big], \tag{Appendix D.15}$$

where r_t is the probability ratio between new and old policies, A_t is the advantage function, and ϵ is the clipping parameter that limits the policy update magnitude.

Deep Q-Network (DQN) DQN combines Q-learning with deep neural networks to approximate the action-value function in high-dimensional state spaces. It uses experience replay and target networks for stable learning:

$$\mathcal{L}_{\text{DQN}} = \Big(R_t + \gamma \max_{a'} Q_{\theta^-}(s_{t+1}, a') - Q_\theta(s_t, a_t)\Big)^2, \tag{Appendix D.16}$$

where $Q_\theta(s_t, a_t)$ is the Q-value function, Q_{θ^-} is the target network, R_t is the immediate reward, γ is the discount factor, and a' represents possible future actions.

Appendix E Implementation Details and hyper-parameter settings

Model Architecture

Backbone Model MMD-DREX adopts Qwen2.5-VL-72B-Instruct as the shared backbone network. This large-scale VLM serves as the core of the MoE decision-making framework, responsible for processing and understanding multimodal inputs. To manage memory consumption during inference and training, the model is loaded in bfloat16 half-precision format.

Router and Expert Heads To enable multi-strategy integration and adaptive decision-making under dynamic market conditions, we design an expert routing architecture, which consists of a learnable router and $K = 4$ expert heads. Given an input state s, we first utilize the frozen large-scale vision-language model to extract a feature representation $h_{[CLS]} \in R^d$ from the [CLS] token, $d = 4096$. This global representation serves as a shared input to all downstream policy modules.

Learnable Router. The router module dynamically computes a weight distribution over the K experts, based on the input representation, thereby enabling context-aware fusion of expert outputs. The computation is defined as:

$$w = \text{softmax}(W_r \cdot \text{LN}(h_{[CLS]}) + b_r), \quad w \in \Delta^{K-1} \tag{Appendix E.1}$$

where $\text{LN}(\cdot)$ denotes Layer Normalization, $W_r \in R^{K \times d}$ and $b_r \in R^K$ are learnable parameters. The resulting w is a categorical distribution over the K experts, used to modulate their influence on the final decision.

Expert Heads. Each expert $k \in \{1, \ldots, K\}$ consists of two components: a policy head and a value head. The final policy and value outputs are computed as weighted averages over all experts, using the router-generated weights w_k:

$$\pi(a \mid s) = \sum_{k=1}^{K} w_k \cdot \pi^{(k)}(a \mid s), \quad V(s) = \sum_{k=1}^{K} w_k \cdot V^{(k)}(s) \tag{Appendix E.2}$$

This architecture enables the model to dynamically integrate decisions from multiple experts during inference, thereby enhancing policy adaptiveness and robustness, particularly in response to varying market regimes and volatility conditions.

Parameter-Efficient Fine-Tuning. To fine-tune the 72B-parameter backbone model under constrained computational resources, we introduce independent and trainable LoRA adapters for the router as well as for each of the four expert heads. This modular design enables each component to be specialized and fine-tuned independently, without interfering with the others. The LoRA configuration follows standard settings, with a rank of $r = 16$ and a scaling factor of $\alpha = 32$.

Input Feature Construction

Image Features $\mathbf{x}_t^{\text{img}}$ Raw Market Chart. For each trading day t, the corresponding candlestick chart is denoted as $I_t \in R^{H \times W \times 3}$. The entire chart is resized to a fixed shape: $I_t^G = \text{Resize}(I_t, H_G, W_G)$. to provide a global view, the rightmost window with width proportion α is cropped to provide local detail: $I_t^L = \text{Resize}(\text{Crop}[(1-\alpha)W, W](I_t), H_L, W_L)$.

The image encoder φ_{img} (from Qwen2.5-VL) maps each image to a vector:

$$v_t^G = \varphi_{\text{img}}(I_t^G), \quad v_t^L = \varphi_{\text{img}}(I_t^L), \quad v_t^G, v_t^L \in R^{d_{\text{img}}}. \tag{Appendix E.3}$$

The final image feature is their concatenation:

$$x_t^{\text{img}} = [v_t^G; v_t^L] \in R^{2d_{\text{img}}}. \tag{Appendix E.4}$$

Time Series Features $\mathbf{X}_t^{\text{ts}}$. Given a fixed window length K (100 days), we collect the past K days' price and indicators:

$$z_{t-i} = [\text{Open}, \text{High}, \text{Low}, \text{Close}, \text{Volume}, \ldots]_{t-i} \in R^m, \quad i = 0, \ldots, K-1. \tag{Appendix E.5}$$

Based on z_{t-i}, we compute common technical indicators (MA, RSI, BOLL, MACD, KDJ, etc.), resulting in an m-dimensional feature vector. Stacking the past K days, we form the raw feature matrix:

$$X_t^{\text{raw}} = \begin{bmatrix} z_{t-K+1}^\top \\ \vdots \\ z_t^\top \end{bmatrix} \in R^{K \times m}. \tag{Appendix E.6}$$

We standardize each column (feature) to zero mean and unit variance:

$$X_t^{\text{ts}} = (X_t^{\text{raw}} - \mu) \oslash \sigma, \tag{Appendix E.7}$$

where $\mu, \sigma \in R^m$ are the mean and standard deviation for each feature, estimated from the training set.

No.	Feature	No.	Feature	No.	Feature
1	Closing Price	7	Price Amplitude	13	BOLL Middle
2	High Price	8	MA10	14	BOLL Lower
3	Low Price	9	MA20	15	KDJ_K
4	Open Price	10	MA100	16	KDJ_D
5	Normalized Volume	11	RSI	17	KDJ_J
6	Price Change	12	BOLL Upper		

Table 12: List of time series features.

The summary T_t is converted to a natural language prompt:

$$\tau_t = \text{concat}(\text{The Last return over the past 100 days is } \delta_t; \ldots). \tag{Appendix E.8}$$

Taking τ_t as the prompt, we use the language encoder φ_{txt} to obtain:

$$x_t^{\text{txt}} = \varphi_{\text{txt}}(\tau_t) \in R^{\text{txt}}. \tag{Appendix E.9}$$

No.	Summary Indicator	Symbol / Description
1	Latest return	$\delta_t = \dfrac{\text{Close}_t - \text{Close}_{t-1}}{\text{Close}_{t-1}}$
2	Price amplitude	$\text{amp}_t = \dfrac{\text{High}_t - \text{Low}_t}{\text{Close}_{t-1}}$
3	Volume ratio	$\text{vol\_ratio}_t = \dfrac{\text{Volume}_t}{\frac{1}{n}\sum_{i=1}^n \text{Volume}_{t-i}}$
4	Historical volatility	Standard deviation of past 100-day log-returns
5	Average True Range	$\text{ATR}_t = \frac{1}{14}\sum_{i=0}^{13}\left[\max\{H_{t-i}, C_{t-i-1}\} - \min\{L_{t-i}, C_{t-i-1}\}\right]$
6	Moving average ordering	Relative order of MA10, MA20, MA100 (e.g., "bullish order")
7	Relative Strength Index	14-day RSI
8	Bollinger band width ratio	$\dfrac{\text{BOLL}_{\text{upper}} - \text{BOLL}_{\text{lower}}}{\text{BOLL}_{\text{middle}}}$
9	Market summary	Textual conclusion on the day's trend (based on MA, momentum, volatility, etc.)

Table 13: Key summary indicators.

For a given input, our framework employs a router to dynamically assign decision weights to each expert. Each expert receives the input and outputs its own strategy decision. The final decision return is then obtained by aggregating the experts' outputs according to their respective decision weights assigned by the router

Hyper-parameter Settings

We apply LoRA to the Qwen2.5-VL model via PEFT by inserting adapters into the key attention projection layers (q_proj, k_proj, v_proj, o_proj). We use a rank of $r = 16$, a scaling factor of $\alpha = 32$, and a dropout probability of $p = 0.05$ to mitigate overfitting, while keeping all bias terms frozen. We set the random seed to 42 and the base learning rate to 3×10^{-5}. The core RL hyperparameters are the discount factor $\gamma = 0.99$ and the clipping threshold $\epsilon = 0.15$. During training, we use a batch size of 16, train for a maximum of 2500 episodes, perform a gradient update every 4 steps, and clip the gradient norm to 0.5 to stabilize training.

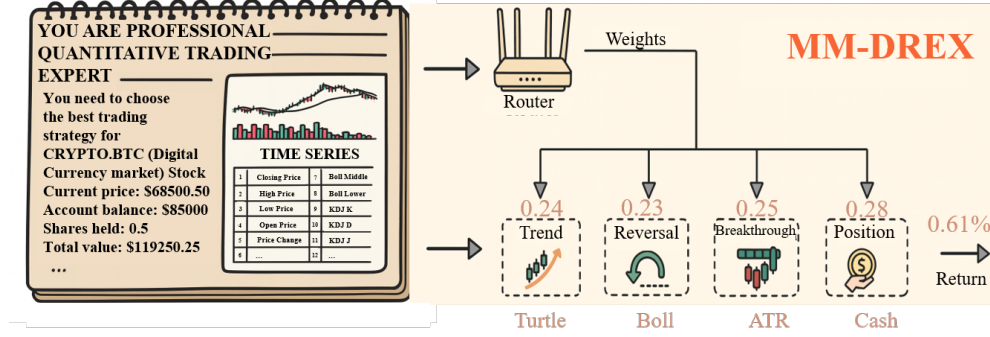| Sub-item	Indicator	Value / Description
1. Moving Average State	Relative order of MA10, 20, 100	"Bullish order" / "Bearish order" / "Mixed"
2. Momentum Strength	RSI (14)	< 30: "Oversold"; $30 \leq RSI \leq 70$: "Neutral"; > 70: "Overbought"
3. Volatility Change	ATR(14) vs. its past 14-day mean	"Increasing volatility" / "Decreasing volatility" / "Stable volatility"

Table 14: Market summary descriptions.

Figure 7: Model Architecture

Appendix F   Experiment Supplementary Materials

In this section, we provide additional experimental materials to supplement the main paper, including detailed input prompt example and additional risk analysis figures that were not presented in the main body due to space constraints. This example clearly demonstrates how MM-DREX constructs textual input features.Fig 3 contains the the remaining three images that have not be placed in the **Risk Studies**section at the time in our main body.

Listing 3: MM-DREX Input Prompt Example for Bitcoin Trading

```
1  You are a professional quantitative trading expert, you need to choose the best trading
   strategy for CRYPTO.BTC (Digital Currency market) stock.
2  Current price: $68500.50
3  Account balance: $85000.00, Shares held: 0.5, Total value: $119250.25
4
5  Available trading strategies:
6  [Trend Following Strategies]
7  - MACross : Moving-average crossover strategy (5-day/20-day MA golden-cross / death-cross)
8  - Momentum: Momentum strategy (10-day return > 5 % buy, < -5 % sell)
9  - Turtle : Turtle trading strategy (20-day high/low breakout)
10
11 [Breakout Strategies]
12 - Volume : Volume-breakout strategy (price breakout + volume 2×)
13 - ATR : ATR-breakout strategy (price breaks MA ±2 ×ATR)
14
15 [Reversal Strategies]
16 - Boll : Bollinger-band reversal strategy (touch upper/lower band, reverse trade)
17 - RSI : RSI reversal strategy (RSI < 30 buy, > 70 sell)
18 - KDJ : KDJ reversal strategy (J < 10 or K < 20 buy, J > 90 or K > 80 sell)
19
20 [Position Strategies]
21 - LongOnly : Always hold long
22 - ShortOnly : Always hold short
23 - Cash : Always hold cash
24
25 Market condition analysis:
26 Price data (last 10 days): [67100, 67300, 67250, 67800, 68100, 67900, 68300, 68200, 68450,
```

```
    68500.5]
27  Moving-average system: MA10 = 67800.00, MA20 = 67500.00, MA100 = 65000.00
28  RSI(14): 68.50 (neutral zone)
29  Bollinger bands: Upper = 69500.00, Middle = 67500.00, Lower = 65500.00
30  Price at Bollinger-band 50.0 % position
31  KDJ: K = 75.0, D = 70.0, J = 85.0
32  Volume: Current = 1 500, 5-day avg = 1 100, Volume ratio = 1.36
33  Price change: 1.50 %, Amplitude: 2.50 %
34
35  Market judgment:
36  - Moving averages in bullish alignment, up-trend clear
37  - 10-day momentum: 2.09 %
38  - 20-day price-volatility range: 9.06 %
39
40  Based on the above complete historical data and technical analysis,
41  please select the trading strategy most suitable for the current market conditions.
```


Figure 8: Performance comparison between MM-DREX and the S&P 500 index under extreme market conditions. From left to right: (i) COVID-19 Second Wave (2020.07–2021.01), (ii) Russia-Ukraine Conflict (2022.02–2022.05), and (iii) Economic Recession (2024.07–2024.10). MM-DREX demonstrates stronger resilience and downside protection across all stress periods.