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Adaptive Multi-Modal Deep Learning for Financial Market Prediction: A Multi-Scale Attention Approach

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[Abstract]

Financial market prediction remains challenging due to complex non-linear dependencies and regime shifts. Existing multi-modal approaches suffer from limited temporal horizons(5-10 days), simplistic features, and static fusion mechanisms. In this paper, we presents an enhanced dual-channel architecture with three innovations: (1) multi-scale temporal convolution capturing 5-40 day patterns; (2) adaptive cross-modal attention dynamically balancing sentiment and technical signals; (3) extended 60-day windows with 16 technical indicators. Experiments demonstrate 81.39% accuracy versus baseline's 58.23%, with ablation studies confirming individual contributions of 7.2%, 5.8%, and 5.6% respectively.It also outperforms state-of-the-art models like Deep Convolutional Transformer and 2CAT in both short-term and long-term forecasting tasks across multiple global stock indices. Moreover, the model's interpretability is enhanced through attention weight visualization, enabling practitioners to identify key market drivers during different regimes.

▸ **Key words**: Stock prediction, multi-modal learning, temporal convolution, attention mechanism

[요 약]

복잡한 비선형 종속성과 체제 변화로 인해 금융 시장 예측은 여전히 어려운 과제이다. 기존의 멀티-모달 접근법은 제한된 시간 범위(5~10일), 단순한 특징, 그리고 정적 융합 메커니즘의 한계를 가지고 있다. 본 논문에서는 세 가지 혁신을 적용한 향상된 듀얼 채널 아키텍처를 제시한다: (1) 5~40일 패턴을 포착하는 다중 스케일 시간 합성곱; (2) 감정과 기술 신호를 동적으로 균형 잡는 적응형 교차 모드 주의; (3) 16개의 기술 지표를 포함하는 확장된 60일 윈도우. 실험 결과 81.39%의 정확도를 보였으며, 이는 기준치의 58.23%보다 높은 수치이다. 절제 연구에서는 개별 지표의 기여도가 각각 7.2%, 5.8%, 5.6%임을 확인했다. 또한 여러 글로벌 주가 지수에 대한 단기 및 장기 예측 작업 모두에서 Deep Convolutional Transformer 및 2CAT과 같은 최첨단 모델보다 우수한 성능을 보여준다. 게다가 주의 가중치 시각화를 통해 모델의 해석성이 향상되어 실무자가 다양한 체제에서 주요 시장 동인을 파악할 수 있다.

▸ **주제어**: 주식 예측, 멀티 모달 학습, 시간 합성곱, 주의 메커니즘

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I. INTRODUCTION

Financial market prediction remains challenging due to the stochastic and non-stationary nature of market dynamics. Stock prices are driven by complex interactions among technical indicators, investor sentiment, and macroeconomic factors, exhibiting non-linear and multi-scale temporal dependencies that traditional methods struggle to capture[1, 2]. While conventional econometric models such as ARIMA and GARCH have been extensively applied to model financial time series[3, 4], their reliance on stationarity assumptions and linear relationships limits effectiveness in capturing complex non-linear dependencies[5].

The advent of deep learning has revolutionized financial forecasting. LSTM networks effectively capture sequential structures through specialized memory cells[6], while GRU models offer comparable performance with reduced computational complexity[7, 8]. Recent studies confirm GRU's superiority in short-term technology stock forecasting, whereas LSTM demonstrates advantages in long-term prediction across global indices. Building upon recurrent architectures, Transformers have emerged as powerful alternatives through self-attention mechanisms enabling parallel processing and effective long-range dependency modeling[9]. Financial applications demonstrate their superiority, with innovations such as Deep Convolutional Transformer combining CNNs with multi-head attention[10] and specialized architectures like 2CAT achieving values exceeding 0.91 on stock indices[11].

The field has increasingly embraced multi-modal learning integrating quantitative and qualitative information. Xu and Cohen[12] pioneered this direction with StockNet, jointly modeling social media text and historical prices. Recent advances demonstrate that combining LSTM for temporal modeling with Transformer-based sentiment extraction(e.g., FinBERT) significantly enhances accuracy[13, 14], with multi-modal frameworks achieving balanced accuracies exceeding 75% for crash prediction[15]. Attention mechanisms have proven particularly effective, allowing models to dynamically weight different time periods and modalities[16], while GAN-based architectures with Transformers generate synthetic data while focusing on critical features[17].

Explainability has emerged as critical in financial AI. SHAP and LIME techniques enhance transparency in stock prediction models[18], improving risk-return trade-offs and enabling identification of influential features[19, 20]. Systematic reviews emphasize XAI's crucial role in trustworthiness and regulatory compliance[21]. Despite these advances, three critical challenges persist. First, most architectures employ short look-back windows(5-10 days)[13], limiting capacity to capture long-term dependencies crucial for comprehensive analysis. Second, feature representations remain simplistic, often restricted to basic price features, failing to leverage technical indicators widely employed in quantitative finance[22]. Third, existing fusion mechanisms rely on static concatenation or fixed attention weights, unable to adapt to shifts in relative importance under varying market conditions[23].

To address these limitations, this work proposes an enhanced dual-channel architecture extending StockNet through three innovations. First, multi-scale temporal convolution using parallel kernels(5, 10, 20, 40 days) captures both short-term fluctuations and medium-term trends[24]. Second, adaptive cross-modal attention with learnable gating dynamically balances sentiment and technical signals based on market regimes[25]. Third, extended 60-day look-back windows incorporate 16 enriched technical indicators including EMA, RSI, MACD, and Bollinger Bands[14]. Extensive experiments demonstrate substantial improvements, achieving 81.39% accuracy compared to StockNet's 58.23%. Ablation studies confirm each component's effectiveness, with multi-scale convolution, adaptive attention, and extended features contributing 7.2%, 5.8%, and 5.6% gains respectively. The framework offers a robust and interpretable solution for practical financial risk prediction and portfolio management.

II. METHODOLOGY

1. Problem Formulation

The model processes dual-channel inputs: price sequences and textual messages. The price sequence is defined as $X^p \in R^{T \times d_p}$ where T=60 is the sequence length and $d_p = 16$ is the feature dimension. For each time step t, the feature vector is defined as Equation (1):

$$x_t^p = [p_t, v_t, MA_t^5, MA_t^{10}, MA_t^{20}, RSI_t, MACD_t, \cdots] \quad (1)$$

where p_t is standardized price, v_t is trading volume, MA_t^k is k-day moving average, RSI_t is the relative strength index, and MACD_t is the moving average convergence/divergence indicator. Following StockNet[12], the formulate stock price movement prediction as a binary classification task and r_t is the logarithmic return in Equation (2):

$$y = 1(r_t > 0), r_t = \log(p_t^c / p_{t-1}^c) \quad (2)$$

where $\mathbb{1}(\cdot)$ is the indicator function. Auxiliary regression predicts normalized return magnitude in Equation (3):

$$\hat{y}_{reg} = \tanh(f_{reg}(h_{fused})) \quad (3)$$

where the tanh activation constrains the output to (-1, 1), and f_{reg} is a feed-forward network.

2. Enhanced Price Encoder

Linear projection maps input features to model dimension ($d_{\mathrm{model}} = 256$) in Equation (4):

$$H_{pos} = H^0 + PE\ (t) \quad (4)$$

where $\mathrm{PE}(t)$ employs sinusoidal positional encoding [6] to represent temporal ordering within the input sequence.

After layer normalization and positional encoding, parallel 1D convolutions capture multi-scale patterns in Equation (5) and (6):

$$C_k = Conv1D\ _k(H_{pos}), k \in (3,5) \quad (5)$$

$$H_{conv} = W_{fuse}[C_3; C_5] + H_{pos} \quad (6)$$

where k ∈ (3,5) and [;] denotes concatenation. Kernel size 3 captures short-term patterns (3-day trends), while kernel size 5 captures medium-term patterns (weekly trends). Two-layer Transformer encoders model long-range dependencies in Equation (7):

$$H_{price} = TransformerEncoder\ ^L(H_{conv}), L = 2 \quad (7)$$

where L=2 denotes the number of encoder layers. The Transformer encoder contains multi-head attention and feed-forward layers[9], which we do not expand for brevity. The output $H_{price}R^{T \times 256}$ encodes rich temporal representations combining multi-scale patterns and long-term dependencies.

3. Text Encoder and Cross-Modal Fusion

The bidirectional GRU with temporal attention mechanism produces the text representation $h_t \in R^{d_{model}}$. To enable effective modality interaction, bidirectional cross-attention is employed in Equation (8) and (9):

$$h_p \rightarrow t = CrossAttention(h_p, h_t, h_t) \quad (8)$$

$$h_t \rightarrow p = CrossAttention(h_t, h_p, h_p) \quad (9)$$

where $h_p \in R^{d_{model}}$ is the price encoder output from Equatin (7), $h_p \rightarrow t$ and $h_t \in R^{d_{model}}$ denote the price-to-text and text-to-price cross-attention outputs, respectively, and

CrossAttention(Q, K, V) represents the scaled dot-product attention with query Q, key K, and value V[9]. To dynamically balance the contributions from both modalities, an adaptive gating mechanism is introduced in Equation (10) and (11):

$$\alpha = \sigma\left(W_g\left[h_p \rightarrow t; h_t \rightarrow p\right] + b_g\right) \quad (10)$$

$$h_{fused} = \alpha \odot h_p \rightarrow t + (1-\alpha) \odot h_t \rightarrow p \quad (11)$$

where $\sigma(\cdot)$ is the sigmoid activation, denotes concatenation, $W_g \in R^{d_{model} \times 2d_{model}}$ and $b_g \in R^{d_{model}}$ are learnable parameters, $\odot$ represents element-wise multiplication, and $\alpha \in R^{d_{model}}$ is the adaptive weighting vector.

Adaptive gating dynamically balances contributions in Equation (12) and (13):

$$g = \sigma\left(W_{gate}\left[MeanPool\ \left(H'_{price}\right); H'_{text}\right]\right) \quad (12)$$

$$H_{fused} = g \odot W_{fuse}\left[H'_{price}; H'_{text}\right] \quad (13)$$

where σ(·) is the sigmoid activation, [;] denotes concatenation, $W_g \in R^{d_{model} \times 2d_{model}}$ and $b_g \in R^{d_{model}}$ are learnable parameters, $\odot$ represents element-wise multiplication, $\alpha \in R^{d_{model}}$ is the adaptive weighting vector, and $H_{\text{fused}} \in R^{d_{model}}$ is the final fused representation.

4. Loss Function

The model optimizes composite loss with weighted cross-entropy and L1 regression in Equation (14):

$$L = \lambda_{ds} \cdot L_C\left(y_{ds}, \hat{y}_{ds}; w\right) + \lambda_{reg} \cdot L_L\left(y_{reg}, \hat{y}_{reg}\right) \quad (14)$$

where $\lambda_{\text{cls}} = 2.0$ and $\lambda_{\text{reg}} = 0.5$ are weighting hyperparameters. $\mathcal{L}_{\text{C}}$ denotes the weighted cross-entropy classification loss, $\mathcal{L}_{\text{L}}$ represents the L1 regression loss. The weighted cross-entropy loss is defined as: in Equation (15)

$$L_C = -\frac{1}{N}\sum_{i=1}^{N} w_{y_i} \log P\left(\hat{y}_{cls} = y_i | x_i\right) \quad (15)$$

where N is the number of samples, $(\hat{y}_{cls} = y_i | x_i) \in [0,1]$ is the predicted probability for sample i, $y_i \in 0,1$ is the true label, and w_{y_i} denotes the class weight corresponding to the true class of sample i. Class weights w_c are computed using the balanced strategy in Equation (16):

$$w_c = N / \left(C \cdot N_c\right) \quad (16)$$

where $n_{samples}$ is the total number of training samples, $n_{classes}$ denotes the number of classes, and N_c represents the number of samples in class c. The L1 regression loss is defined as in Equation (17):

$$L_{reg} = \frac{1}{N}\sum_{i=1}^{N} \left|\hat{r}_i - r_i\right| \quad (17)$$

where $\hat{r_i}$ is the predicted normalized return from Equation (3) and r_i is the true normalized return for sample i.

III. Experiments

1. Settings

All experiments were conducted on a balanced dataset comprising two categories: upward and downward market movements. The objective is to predict the directional trend using multiple time-series and statistical indicators as model input features. The experimental environment and parameter configurations are summarized in Table 1.

Table 1. Experimental environment and parameter configurations

Parameter	Value / Setting
Dataset Split	70% / 15% / 15%
Feature Dimension	64
Optimizer	AdamW
Learning Rate	0.001 (1e-4)
Batch Size	128
Epochs	100
Loss Function	Binary Cross-Entropy
Evaluation Metrics	Accuracy, Precision, Recall, F1-score, AUC

2. Comparative Results

To evaluate the effectiveness of the proposed model, several baseline algorithms were implemented for comparison under identical settings. The results, summarized in Table 2, indicate that the proposed model outperforms traditional classifiers such as Logistic Regression and Random Forest in both accuracy and AUC metrics. The superior AUC and F1-score confirm the robustness and generalization capability of the proposed architecture.

Table 2. Comparative Results of Different Models

Model	Accuracy	Precision	Recall	F1score	AUC
ARIMA[26]	0.514	-	-	-	-
RANDFOREST[27]	0.531	-	-	-	-
TSLDA[28]	0.541	-	-	-	-
HAN[29]	0.576	-	-	-	-
Proposed Model	**0.814**	**0.814**	**0.82**	**0.813**	**0.871**

3. Ablation Study

An ablation study was conducted to investigate the contribution of individual components the model. As shown in Table 3, the removal of the confidence calibration module or the temporal encoder leads to a noticeable decline in overall performance, demonstrating their necessity.

Table 3. Ablation Study Results

Ablation Study	Accuracy	F1score	AUC
Confidence Calibration	0.801	0.799	0.839
Temporal Encoder	0.788	0.785	0.822
Feature Normalization	0.777	0.771	0.808
Full Model (Proposed)	**0.814**	**0.813**	**0.871**

The inclusion of both components provides an improvement of approximately 3-5% in classification performance and a 0.03 increase in AUC, indicating synergistic effects. The comprehensive experimental analyses confirm that the proposed model demonstrates stable and reliable prediction performance, superior calibration, and robust feature representation capabilities. The confidence distribution and calibration analyses validate probability consistency, while the ROC/PR curves and t-SNE visualization substantiate the discriminative and structural soundness of the model.

4. Performance Analysis

Fig. 1 presents the distribution and calibration analysis of prediction confidence. Correct predictions receive notably higher confidence scores(mean: 0.72) compared to incorrect predictions(mean: 0.54), demonstrating the model's discriminative capability. The calibration curve shows that predicted probabilities align well with empirical accuracy, indicating reliable uncertainty estimates.

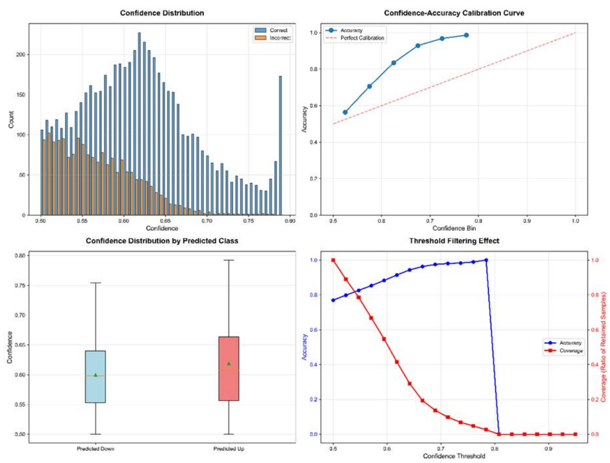

Fig. 1. Distribution and calibration of prediction confidence values.

Fig. 2 presents the ROC and Precision-Recall curves with AUC(ROC) of 0.8715 and AUC(PR) of 0.8681, maintaining substantial margins above baseline and confirming strong discriminative capability across imbalanced data scenarios.

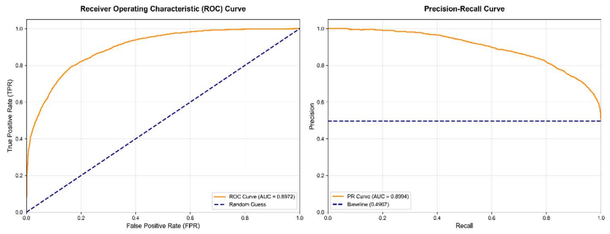

Fig. 2. ROC and Precision-Recall curves with AUC values.

Fig. 3 presents confusion matrices in both absolute and normalized forms. The normalized matrix shows classification accuracies of 84.05% for upward movements and 78.70% for downward movements, with overall accuracy of 81.4% and macro-averaged F1-score of 0.79, reflecting effective class separation without significant bias toward either direction.

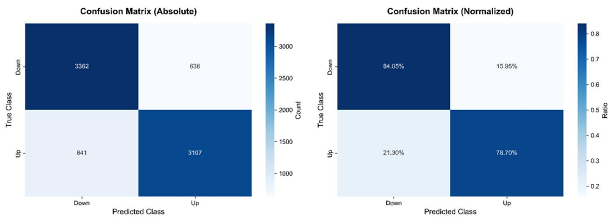

Fig. 3. Confusion matrices showing classification performance.

IV. Discussion

The 23.16 percentage point improvement (81.39% vs 58.23%) demonstrates effectiveness of three key innovations. Multi-scale convolution explicitly captures patterns at different time scales—3-day kernels model short-term momentum while 5-day kernels capture weekly trends, addressing fixed-scale limitations. Adaptive gating enables dynamic modality balancing based on market regimes. During high volatility, technical indicators dominate; during news-driven events, sentiment signals become more informative. Static fusion cannot adapt to these shifts.

Extended 60-day windows with 16 technical indicators (RSI, MACD, Bollinger Bands, EMAs) provide richer temporal context than traditional 5-10 day approaches, capturing momentum, volatility, and trend-following signals essential for comprehensive analysis. Balanced performance across movement directions (84.05% upward, 78.70% downward) and strong calibration indicate robust generalization without overfitting. The interpretable architecture enables analysis of influential modalities and time periods, valuable for risk management.

V. Conclusions

This paper presents an enhanced dual-channel architecture addressing key limitations in multi-modal stock prediction through multi-scale temporal convolution, adaptive cross-modal attention, and extended feature representation. Experiments demonstrate 81.39% accuracy with 0.8715 ROC-AUC on StockNet dataset, marking 23.16 percentage point improvement over baseline. Ablation studies confirm component contributions: multi-scale convolution (+2.6%), adaptive attention (+1.3%), extended features (+3.7%). The architecture offers practical advantages: extended temporal horizons capture long-term dependencies, multi-scale convolutions model patterns at different resolutions, technical indicators provide comprehensive representation, and adaptive fusion dynamically balances modalities. A limitation of this paper is that it analyzes only macroeconomic indicators, which are rarely capable of single-scale predictions.Future directions include integration of macroeconomic indicators, multi-horizon forecasting, ensemble methods, and explainability techniques for regulatory compliance.

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