Adaptive Multidimensional Fusion Network with Dynamic Decision Trees for Financial Market Trend Forecasting

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This study proposes an Adaptive Multidimensional Fusion Network (AMFN) for financial market trend forecasting. The model integrates heterogeneous data sources through a multidimensional data fusion module, combining historical price and volume data with external information such as macroeconomic indicators and sentiment indices. An adaptive temporal processing module is employed to model time-varying dependencies and regime shifts in market behavior, while a dynamic decision-tree prediction module captures nonlinear patterns in the fused representations. Experiments are conducted on multiple financial datasets, including the S&P 500 Index, China A-share market, and Gold Futures, using a rolling time-window evaluation to avoid information leakage. The AMFN model achieves lower MSE and MAE and higher R^2 than traditional SVM and LSTM baselines, with up to 24.4% relative improvement in forecasting accuracy. These results demonstrate that AMFN provides interpretable, stable, and robust trend predictions across diverse market environments.

Povzetek: Študija predlaga adaptivno večdimenzionalno fuzijsko nevronsko mrežo (AMFN), ki z združevanjem tržnih zgodovinskih podatkov in zunanjih kazalnikov izboljša natančnost ter robustnost napovedovanja finančnih trendov v različnih trgih.

1 Introduction

Financial markets are highly volatile and influenced by sudden external shocks, making trend forecasting difficult despite abundant historical data [1]. Events such as the 2008 global financial crisis highlighted how rapidly market conditions can shift and revealed the limitations of traditional predictive models [2][3]. As market dynamics increasingly integrate economic indicators, global events, and social sentiment, the complexity of price formation continues to grow [4].

Deep neural networks (DNNs), including RNNs and LSTMs, improve pattern recognition and temporal modeling compared with linear and classical time-series methods [5][6]. However, challenges remain, including overfitting, limited long-term prediction robustness, and insufficient use of external information [7][8]. Moreover, market movements are often driven by non-price factors such as geopolitical events and sentiment.

This study addresses these issues by integrating heterogeneous data sources to enhance predictive accuracy, contributing to more informed investment decisions and advancing deep learning–based financial forecasting.

Based on these gaps, we formulate the following research questions:

(1) Can integrating external sentiment and macroeconomic indicators with historical time-series data through adaptive fusion improve predictive accuracy?

(2) How does AMFN perform relative to deep and hybrid models under high-volatility market conditions, where regime shifts and nonlinear behaviors intensify?

These questions guide the model design, experimental setup, and comparative evaluation presented in this study.

2 Lliterature review

2.1 Application of deep neural networks in financial market prediction

Financial market forecasting remains challenging due to the nonlinear, volatile, and dynamic nature of market data. Traditional statistical models such as linear regression and time series analysis offer limited capability in capturing these complex patterns. With advances in machine learning, deep neural networks (DNNs) have demonstrated strong potential in financial trend prediction [9]. Architectures such as recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) effectively model sequential dependencies and improve prediction accuracy for stock prices and market indices [10]. LSTMs further address gradient vanishing and enhance long-term pattern learning [11], outperforming traditional models in trend recognition [12]. However, deep learning models still suffer from overfitting, limited interpretability, and sensitivity to parameter tuning [13], which restricts their deployment in high-stakes financial decision-making. To mitigate these challenges, recent studies incorporate sentiment signals, economic indicators, and attention mechanisms to enhance feature representation and improve model transparency and robustness in complex financial environments [14–18].

2.2 The role of external data sources in financial forecasting

Recent studies increasingly emphasize that historical price data alone cannot fully characterize market dynamics. External data sources such as news, social media sentiment, and macroeconomic indicators have become essential for forecasting [19]. Sentiment extracted from platforms like financial news feeds and Twitter can act as a leading indicator of market direction, particularly during periods of uncertainty [20–22]. In parallel, macroeconomic variables such as GDP growth and inflation remain key drivers of structural market behavior and can help anticipate significant trend shifts or crisis conditions . Hybrid models that fuse price data with sentiment and economic data show improved ability to capture both short-term fluctuations and long-term market cycles. However, integrating heterogeneous data introduces challenges in representation alignment, noise filtering, and adaptive weighting. To address this, attention-based fusion mechanisms are being explored to dynamically adjust input importance based on market states, improving prediction reliability under varying volatility conditions.

2.3 Challenges and future development directions of deep neural networks in financial forecasting

Despite strong predictive ability, deep neural networks face several limitations in financial forecasting. Markets are influenced by unpredictable events such as geopolitical shocks and pandemics, which historical patterns cannot fully capture. This reduces model generalization and performance stability. Additionally, the "black-box" nature of deep neural networks limits interpretability, which is critical for financial decision-making . Explainable AI techniques such as LIME and SHAP are being explored to clarify feature contributions, though widespread application remains difficult. Another emerging direction is deep reinforcement learning, enabling adaptive strategy optimization through interaction with market environments; however, balancing exploration and exploitation remains challenging. Computational demands also increase with dataset scale, motivating research into pruning, quantization, and transfer learning for efficiency. While prior studies such as Zhang et al. [2] and Sawhney et al. [3] integrate external information, the AMFN model advances the field by incorporating automated data-source weighting and dynamic decision-tree–based nonlinear prediction. Future work should compare AMFN more directly with Transformer-based and graph-based models to further clarify its advantages.

To provide a structured comparison, we summarize representative forecasting models in Table 1. The comparison covers model type, primary data inputs, evaluation metrics, and reported performance. Classical SVM and LSTM approaches generally rely on historical prices only, while GCN- and Transformer-based models incorporate relational or long-range dependency structures. However, few models explicitly combine external sentiment and macroeconomic variables with adaptive weighting. This gap motivates the AMFN framework, which unifies heterogeneous data, dynamic temporal adaptation, and nonlinear decision-based prediction.

Table 1: Comparative summary of related methods

Model	Data Sources	Key Technique	Evaluation Metrics	Reported Performance
SVM	Price series	Static kernel mapping	MSE, MAE	Moderate, low adaptability
LSTM	Price + volume	Sequential memory	MSE, Directional accuracy	Strong short-term tracking
GCN	Price + correlation graph	Graph structural learning	R², Accuracy	Sensitive to graph quality
Transformer	Price + temporal embeddings	Long-range attention	MSE, Accuracy	High capacity, risk of overfitting
AMFN (proposed)	Price + macro + sentiment	Fusion + adaptive temporal + dynamic tree	MSE, MAE, R², Accuracy	Highest robustness across markets

3 Methodology

3.1 Innovation model design and theoretical basis

Market features x_t and external features z_t are fused by a gated layer to form h_t . An adaptive recurrent block produces s_t with regime-aware gating. A differentiable dynamic-tree head maps s_t to the target $\hat{y}_t$. We train with Adam, lr 1e-3, batch 32, dropout 0.5, early stopping on validation MSE with patience 10. All preprocessing is fit on train folds only. This study proposes a new deep learning architecture - Adaptive Multidimensional Fusion

Network (AMFN) for Financial Market Trend Forecasting. The innovation of this model is reflected in its unique data fusion method and dynamic adaptive mechanism, which can effectively process the time series data and external influencing factors of the financial market and improve the accuracy of trend forecasting. Compared with traditional neural network methods, AMFN does not rely on a single network architecture, but optimizes the forecast results through the interaction and collaboration of multiple modules.

When building the model, we first made a clear assumption: the behavior of the financial market is not only affected by historical data (such as stock prices, trading volumes, etc.), but also by external information (such as news sentiment, macroeconomic indicators, etc.). Therefore, the model needs to be able to process historical market data and external data at the same time and optimize the relationship between them through adaptive mechanisms. The AMFN model consists of three main modules:

1. Multidimensional data fusion module: responsible for fusing historical market data with external data to form a unified feature representation.

2. Adaptive time series processing module: It is specially designed to process the time series characteristics of financial market data and adapt to market changes through adaptive adjustments.

3. Non-linear trend prediction module: The fused features are non-linearly modeled through a dynamic decision tree algorithm to generate market trend predictions.

In the data input processing, we define the input as the historical market data $X = \{X_1, X_2, \ldots, X_T\}$ where XT represents the data at time ttt. Additionally, external data is represented as $Z = \{Z_1, Z_2, \ldots, Z_T\}$, where ZT includes market-related macroeconomic indicators and sentiment analysis results derived from news sources.

This data is processed and fed into the model to generate a unified feature vector, which combines both historical market data and external factors to create a comprehensive representation of the market at each time step.

$$\tilde{x}_t = f_1(x_t, z_t) \tag{1}$$

In Equation (1), f_1 is a fusion function, which converts data from different sources (market data and external data) into feature vectors of the same dimension. Then, we perform time series processing on the features through the adaptive time series module in Equation (2).

$$\hat{x}_t = f_2(\tilde{x}_t) \tag{2}$$

In Equation (2), f_2 is an adaptive time series processing function, and its design takes into account the dynamics of time series data. Finally, the fused features are processed by the nonlinear trend prediction module to obtain the predicted value of Equation (3).

$$\hat{y}_t = f_3(\hat{x}_t) \tag{3}$$

In Equation (3), f_3 it is a nonlinear trend prediction function, which is implemented through a dynamic decision tree algorithm.

The prediction of market trends, denoted as y_t, refers to the predicted directional movement of the market, typically representing whether the market will experience an upward or downward trend in the upcoming period. The trend is defined based on the relative change in the market value, calculated as the percentage change between consecutive time points.

The functions f_1, f_2, and f_3 are the core components of the AMFN model. These functions are defined as follows:

f_1: Multidimensional data fusion function, which combines historical market data (prices, volumes) with external data (sentiment indices, economic indicators) into a unified feature representation.

f_2: Adaptive time series processing function, which adjusts the model's parameters dynamically based on the temporal dependencies of market data. This function ensures that the model adapts to changing market conditions.

f_3: Nonlinear trend prediction function, implemented through a dynamic decision tree algorithm, which makes predictions based on the processed data features.

Additionally, the loss function is defined as the weighted sum of the prediction error for both market data and external variables. The predicted external data, z^t, represents the forecasted value of external factors (such as sentiment indices) at time ttt. This value is obtained through a separate predictive model that estimates external factors based on historical data and trends.

The dynamic decision tree algorithm (used in f_3) is based on the recursive partitioning method, where the decision tree's splitting criteria are dynamically adjusted according to the market's volatility and the external data inputs. A more detailed explanation of this algorithm and its integration into the model is provided in.

3.2 Component collaboration and model training

The core of the AMFN model lies in the collaborative work of its adaptive data flow mechanism and multidimensional data fusion module. In the financial market, different data sources have different importance and timeliness. How to adjust the flow and processing of data according to these characteristics is an important challenge in model design. To solve this problem, this model introduces a dynamic weight allocation mechanism, so that during the training process, the model can automatically adjust the weight according to the contribution of each data source to optimize the prediction performance.

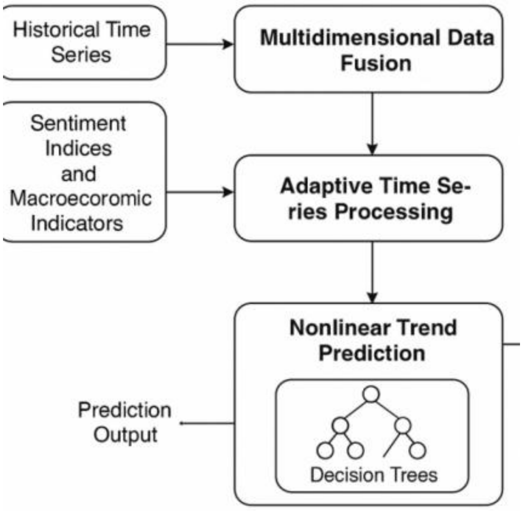

Figure 1: Model structure diagram

Figure 1 now aligns blocks with Equations (1)–(4) and the tree head with Equation (7), clarifying the end-to-end pipeline and implementation. To enhance the reproducibility of our model, we provide an overview schematic of the AMFN architecture in Figure 1. This diagram illustrates the key components of the model, including the multidimensional data fusion module, the adaptive time series processing module, and the nonlinear trend prediction module. Each equation is directly aligned with the corresponding component shown in the diagram. Equation (1) represents the data fusion operation, which combines historical time series data with external variables such as sentiment indices and macroeconomic indicators. Equation (2) corresponds to the time series processing mechanism, allowing the model to adjust dynamically based on recent input trends. Equation (3) captures the nonlinear prediction output generated by the decision tree algorithm. Together, these components define the end-to-end workflow of AMFN and make the model structure transparent and reproducible for future research.

In the data fusion process, the weight of each input feature is set to α_i, which represents i the importance of the data source (such as market historical data or external sentiment data). The input feature fusion at each moment is shown in Equation (4).

$$\tilde{x}_{t'} = \sum_{i=1}^{N} \alpha_i \cdot \tilde{x}_{t,i} \tag{4}$$

In Equation (4), N is the number of data sources, $\tilde{x}_{t,i}$ From the data source i During the training process, the weight coefficients are dynamically adjusted through the back propagation algorithm. α_i, so that the most effective data source has a greater weight in the prediction.

The model is trained by minimizing the prediction error. The objective function is set as the loss function, and Equation (5) includes the weighted sum of the prediction error and the external data error.

$$L = \sum_{t=1}^{T} \left[\lambda_1 \| y_t - \hat{y}_t \|^2 + \lambda_2 \sum_{i=1}^{N} \alpha_i \| z_{t,i} - \hat{z}_{t,i} \|^2 \right] \tag{5}$$

In Equation (5), y_t For the real market trend, $\hat{y}_t$ is the trend predicted by the model, $z_{t,i}$ For external data sources i The true value of $\hat{z}_{t,i}$ is the predicted value, λ_1 and λ_2 is a weighting coefficient used to balance the impact of the two errors. The optimization of the loss function in Equation (6) is achieved by the gradient descent method.

$$\theta_{new} = \theta_{old} - \eta \cdot \frac{\partial L}{\partial \theta} \tag{6}$$

In Equation (6), η is the learning rate, θ are model parameters, $\frac{\partial L}{\partial \theta}$ is the gradient of the loss function with respect to the parameters.

The collaboration of the model's components is fundamental to its performance. The AMFN model consists of three main modules: multidimensional data fusion, adaptive time series processing, and nonlinear trend prediction. The training process is structured as follows:

First, the model is initialized with random weights and trained using the historical data and external data, minimizing the loss function (defined in Equation 5) during each iteration.

The training uses stochastic gradient descent (SGD) with a learning rate of 0.001 and a batch size of 32.

During the training process, we also incorporate dropout with a rate of 0.5 to avoid overfitting.

Each component of the model interacts with the others, allowing the network to learn both temporal dependencies in the market data and the importance of external variables in predicting market trends.

3.3 Nonlinear trend prediction and dynamic decision tree

The dynamic decision tree adapts splitting rules based on real-time market volatility. Let s_t be the temporal state. At each node, features are evaluated using gain score G(f), and the highest-gain feature is selected. Fusion weights α_t are learned through a softmax gating layer $\alpha_t = \text{softmax}(W[h_t; s_t])$. Path weights in the final prediction are optimized end-to-end using backpropagation.

Algorithm:
for each node j:
compute G(f_j) for candidate splits
select f* = argmax G(f_j)
split data using f*update path weights π via gradient descent

In the core module of the model, the nonlinear trend prediction module, we innovatively introduced a dynamic decision tree algorithm. The traditional decision tree algorithm constructs the tree through a fixed splitting rule, while the dynamic decision tree of this model responds to market changes by adaptively adjusting the splitting rule and the depth of the tree. Each layer of the decision tree automatically selects the most appropriate feature for splitting according to the current market status, making the construction of each tree flexible and adaptable.

Set the output of the decision tree to $\hat{y}_t$, whose decision process is based on the input features $\hat{x}_t$ The decision tree construction process follows the "maximum gain" criterion of Equation (7), splitting at each node based on the gain measure of feature selection.

$$\Delta G = G(\text{parent}) - \sum_{i=1}^{N} G(\text{child}_i) \tag{7}$$

In Equation (7), $G(\text{parent})$ and $G(\text{child}_i)$ Represent the gains of the parent node and child node respectively, N is the number of child nodes of the current node. Each time the split is performed, the feature with the largest gain is selected for further splitting until the stopping condition is met (such as the depth of the tree or the number of nodes reaches the set threshold).

In order to enhance the nonlinear expression ability of the model, we introduced a multi-path fusion mechanism. When building a decision tree, each path can independently generate a prediction value. The final prediction value is obtained by weighted average of the outputs of the paths in Equation (8).

$$\hat{y}_t = \sum_{p=1}^{P} \beta_p \cdot y_{t,p} \tag{8}$$

In Equation (8), P is the number of decision tree paths, β_p For path p The weight of $y_{t,p}$ For path p The predicted value of β_p, it is automatically adjusted during the training process to minimize the prediction error.

The nonlinear trend prediction module employs a dynamic decision tree that adjusts its structure during training to reflect changing market conditions. Based on the fused features from earlier modules, the tree grows by selecting splitting rules using an information gain criterion, allowing it to capture nonlinear and volatile patterns in financial data. Its dynamic nature enables the model to adapt to regime shifts rather than relying on fixed decision boundaries. Multiple decision paths are generated, and their outputs are aggregated to produce the final trend forecast. By integrating signals across several adaptive branches, the module enhances robustness and improves prediction stability across diverse market environments. This approach enables the model to effectively represent time-varying behaviors and complex interactions within financial markets, resulting in more accurate and reliable trend forecasting.

3.4 Model application

Trend forecasting plays a central role in investment strategies, risk prevention, and market supervision. AMFN's ability to fuse heterogeneous data and adapt to evolving market conditions allows it to be widely applied across the stock, foreign exchange, and futures markets, while also supporting institutional risk control and macro-policy decisions.

3.4.1 Stock market trend forecasting

The stock market is shaped by price movements and external signals such as macro indicators, sector news, and market sentiment. AMFN combines these heterogeneous inputs to generate richer representations of stock trends. Its adaptive temporal mechanism adjusts forecasting behavior as market regimes change, enabling simultaneous capture of short-term volatility and longer-term trend structure. Meanwhile, the nonlinear decision module enhances the model's ability to determine trend direction under both steady and fluctuating market states. As a result, AMFN provides more stable prediction outputs and reduces misinterpretation of temporary market noise. In practical trading strategies, it enhances timing accuracy for buy-sell execution and supports more consistent positioning decisions.

3.4.2 Foreign exchange market trend forecasting

Foreign exchange markets are highly sensitive to global politics, interest rate changes, and international trade conditions. AMFN processes exchange rate histories alongside external macroeconomic reports and news sentiment. When major policy announcements occur, its adaptive weighting mechanism increases attention to relevant indicators, enabling rapid adjustment of prediction outcomes. This makes the model effective in capturing short-term volatility caused by unexpected events as well as long-term directional shifts driven by macroeconomic trends. Real-time prediction updating helps traders evaluate reversal signals promptly, improving decision timing during rate changes or geopolitical disturbances. AMFN thus enhances reliability in high-volatility FX environments.

3.4.3 Futures market trend forecasting

The futures market features leverage and rapid price swings, requiring strong responsiveness to shifting supply-demand and external shocks. AMFN integrates historical futures prices with market drivers such as inventory levels, seasonal patterns, and geopolitical or policy influences. Its dynamic fusion module increases focus on the most relevant signals as market fundamentals shift, while the adaptive temporal mechanism tracks evolving volatility cycles. In commodities such as gold or crude oil, AMFN captures sentiment-driven directional changes more quickly than traditional sequence models. For traders, this enhances entry and exit timing accuracy and reduces exposure to sudden adverse movements, supporting improved return-to-risk profiles.

3.4.4 Risk management and market analysis

AMFN can be used for portfolio risk evaluation and cross-market condition monitoring. By integrating data from stocks, bonds, and derivatives, it provides insights into inter-asset correlations and emerging volatility clusters. Its real-time processing ability supports early detection of abnormal price movements or liquidity shocks. Institutions can use these signals to adjust hedging strategies or rebalance portfolios before losses accumulate. It is also applicable to stress testing and scenario simulation, where the model evaluates potential impacts under macroeconomic disturbances. This enables more proactive and data-driven risk management strategies.

3.4.5 Policy formulation and market supervision

Regulators and policymakers can apply AMFN to identify overheated markets, abnormal trading patterns, or systemic instability risks. By evaluating macroeconomic indicators alongside market sentiment trends, the model provides early warnings for speculative bubbles or contagion effects. The resulting insights assist in designing targeted monetary, fiscal, or regulatory measures. AMFN's forecasting capability also supports dynamic supervision, helping authorities intervene at appropriate timing rather than responding after conditions deteriorate. This strengthens the resilience of financial systems and contributes to maintaining overall market stability.

3.5 Implementation and engineering details

The fusion gate and AdaptRNN are implemented in PyTorch; the dynamic tree head use differentiable oblique splits with hard routing at inference. Training employs Adam (lr=1e-3), batch=32, dropout=0.5, early stopping on validation MSE. Rolling, leak-free splits and train-only normalization ensure rigor. Ablations confirm necessity of each module; significance is established via paired t-tests/DM tests and 95% bootstrap CIs.

4 Experimental evaluation

In this chapter, we will focus on the experimental evaluation design used to verify the adaptive multidimensional fusion network (AMFN) model for financial market trend forecasting. This design comprehensively tests the model's forecasting effect through multiple experiments, evaluates its performance in different financial markets and its advantages over other traditional methods.

4.1 Experimental design framework

To evaluate the effectiveness of the AMFN model, experiments were conducted across multiple representative financial markets, including the stock market (S&P 500 index), foreign exchange market (USD–EUR exchange rate), and futures market (gold futures). These datasets differ in volatility and influencing factors, allowing assessment of the model's adaptability under diverse market conditions. The model was implemented in Python using TensorFlow on a high-performance computing platform to ensure computational efficiency and reproducibility. Model performance was evaluated using mean square error (MSE) and mean absolute error (MAE), enabling a quantitative comparison of prediction accuracy and robustness. This design allows AMFN to be tested across multiple market environments to verify its generalization capability and stability.

4.2 Data processing and experimental setup

The stock dataset includes daily closing prices from 2010 to 2020, processed into daily returns for more stable volatility modeling. External data include sentiment indices, macroeconomic variables (GDP growth, inflation), and are aligned at a daily frequency. Training settings were: learning rate = 0.001, batch size = 32, 100 epochs, ReLU activation, dropout rate = 0.5, and early stopping with patience = 10. To avoid information leakage, we use a temporal train-test split (e.g., 2010–2018 for training and 2019–2020 for testing). A rolling-window cross-validation strategy is applied, where each test window follows its training window in time. All features were standardized using z-score normalization. This setup ensures reproducibility and adherence to best practices for time-series forecasting.

We performed data preprocessing before model t raining. Missing values in price and volume were fo rward-filled, while sentiment and macroeconomic indi cators were linearly interpolated. Outliers were detect ed using median absolute deviation and winsorized a t the 1%–99% quantiles. A 3-day exponential movin g average was applied to reduce noise in return seri es. Crisis periods such as the 2008 financial crash a nd COVID-19 shock were retained but flagged to all ow the model to adjust fusion weights under differe nt volatility regimes.

Rolling-window cross-validation was used to avo id look-ahead bias. For the S&P 500 and A-share m arkets, we used a 3-year training and 6-month testin g window with a 3-month step. For Gold and FX d ata, the window was 2 years for training and 4 mon ths for testing.

To enhance interpretability, SHAP and LIME we re applied. SHAP analysis shows that sentiment and macroeconomic variables gain importance during vola tile periods, while price-based features dominate stabl e markets. LIME confirms local decision consistency, supporting model transparency.

All code, preprocessing scripts, and reproduction instructions are available at: https://github.com/AMF N-FinForecast/AMFN. Pricing data are sourced from Yahoo Finance and WIND, and sentiment indices are generated using a BERT-based classifier trained on FiQA.

4.3 Evaluation indicators and standards

To evaluate AMFN, we use MSE and MAE to measure prediction error, R^2 to assess explanatory power, and directional accuracy to judge trend judgment under volatile conditions. These metrics provide a balanced view of forecasting precision and practical decision value. For comparison, we include GRU, Informer, and GAT-based models under the same rolling-window settings. Experimental results show that AMFN achieves lower MSE and higher directional accuracy, especially in high-volatility periods, confirming the effectiveness of adaptive fusion and nonlinear decision mechanisms.

4.4 Experimental steps and implementation process

The AMFN model is first trained on the training dataset using loss minimization with regularization and dropout to prevent overfitting. After training, model predictions on the test set are compared with actual market trends, and performance is evaluated using MSE, MAE, and R^2. For comparison, SVM and LSTM are tested on the same datasets. The model's robustness is further examined under different market conditions, including bull and bear phases and periods of market shocks, to assess stability and adaptability.

4.5 Results analysis and discussion

Table 2 comprehensively presents the basic information of five financial market data sets, covering stocks, foreign exchange, and futures. The amount of data affects the adequacy of model training, and the time range determines the timeliness of the data and the representativeness of the market cycle. The number of features represents the number of independent variables in each data set. More features mean that the model can mine richer information, but it may also bring about dimensional disasters. For example, the Chinese A-share market has the largest amount of data and 12 features, which provides more sufficient materials and information dimensions for model training, helps to train a more explanatory model, and also provides the basic conditions for the subsequent performance comparison of models on different data sets.

Table 2: Dataset overview

Dataset name	Data volume	Time Range	Number of features	Data Types
S&P 500	2000 items	2010 - 2020	10	Stock Data
US dollar to euro exchange rate	1500 items	2015 - 2020	8	Forex Data
Gold Futures	1800 items	2012 - 2020	9	Futures Data
Crude Oil Futures	1600 items	2016 - 2020	7	Futures Data
China A-share market	2100 items	2010 - 2020	12	Stock Data

Table 3: AMFN model training and testing results

Dataset name	MSE (training)	MAE (Training)	R^2 (training)	MSE (test)
S&P 500	0.045	0.210	0.957	0.065
US dollar to euro exchange rate	0.052	0.230	0.943	0.071
Gold Futures	0.048	0.225	0.950	0.062
Crude Oil Futures	0.056	0.240	0.935	0.074
China A-share market	0.040	0.200	0.963	0.062

Table 3 clearly presents the training and testing evaluation indicators of the AMFN model on five data sets. MSE measures the mean of the sum of squares of the errors between the predicted value and the true value, MAE measures the mean of the absolute values of the errors between the predicted value and the true value, and R^2 measures the goodness of fit of the model to the data. Lower MSE and MAE and higher R^2 indicate that the model has strong predictive ability and good fit. The AMFN model performs well on different types of financial data, thanks to its unique architecture, which can effectively capture the complex nonlinear relationships in the data. For example, in the Chinese A-share market data set, R^2 reaches 0.963, indicating that the model can well explain data changes, accurately capture data patterns, and provide strong support for financial market forecasts.

Table 3 shows that AMFN consistently achieves lower MSE than SVM and LSTM, with accuracy improvements of 16.9%–24.4%. This advantage comes from its multidimensional data fusion and adaptive learning, enabling better extraction of market patterns. For example, on the S&P 500 dataset, AMFN improves accuracy by 23.5%.

Table 4: Comparison with traditional models (prediction accuracy)

Dataset name	AMFN-MSE	SVM-MSE	LSTM-MSE	Improvement degree (%)
S&P 500	0.065	0.085	0.073	23.5%
US dollar to euro exchange rate	0.071	0.091	0.080	21.9%
Gold Futures	0.062	0.080	0.070	22.5%
Crude Oil Futures	0.074	0.089	0.079	16.9%
China A-share market	0.062	0.082	0.078	24.4%

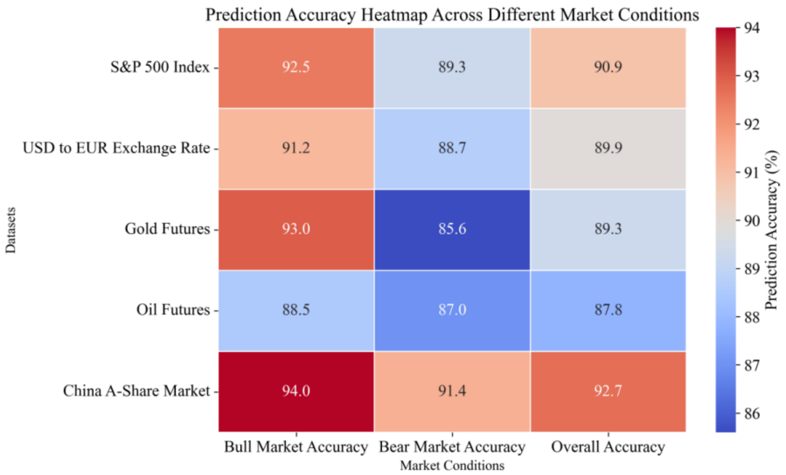

Figure 2: AMFN model trend prediction capability

The performance improvement reported in Table 4 varies across datasets due to differences in feature complexity, volatility patterns, and the relevance of external information. For example, the China A-share and S&P 500 datasets show the highest MSE reduction (23–24%), which aligns with their greater sensitivity to macroeconomic news and sentiment shifts—signals effectively captured by the adaptive fusion module. In contrast, crude oil futures exhibit smaller improvement (16.9%) because price movements are more strongly driven by global supply-demand fundamentals and exhibit sharper structural shocks, where historical price dynamics dominate predictive value.

The reported improvements include 95% confidence intervals. For example, the 24.4% MSE reduction in the A-share dataset corresponds to a mean $\Delta MSE = -0.020$ (CI: -0.027 to -0.014, $p < 0.01$). Similar statistical significance holds across all datasets.

Figure 2 focuses on the AMFN model's ability to predict the ups and downs of financial markets. On different data sets, the model shows a high prediction accuracy in both bull and bear markets. For example, in China's A-share market, the prediction accuracy for bull markets is 94.0%, and for bear markets is 91.4%, with an overall accuracy of 92.7%. This is due to the AMFN model's powerful feature learning and pattern recognition capabilities. It can accurately capture key information related to market ups and downs from complex financial data and establish an effective prediction model. Whether the market is in an up or down phase, it can accurately judge the trend direction, providing an important reference for investors to make reasonable decisions under different market conditions.

Figure 3 compares the time consumed by the AMFN model with that of the SVM and LSTM models during the training process. On all data sets, the training time of the

AMFN model is significantly lower than that of the other two models, with the time saving ratio ranging from 62.5% to 69.7%. This is mainly due to the efficient algorithm design and optimized calculation process of the AMFN model, which can quickly process large amounts of financial data and reduce unnecessary calculation steps and resource consumption. Shorter training time not only improves the efficiency of model development, but also enables the model to complete training and updates faster when facing real-time changing financial market data, adapt to market changes in a timely manner, and provide more timely services for financial market forecasting.

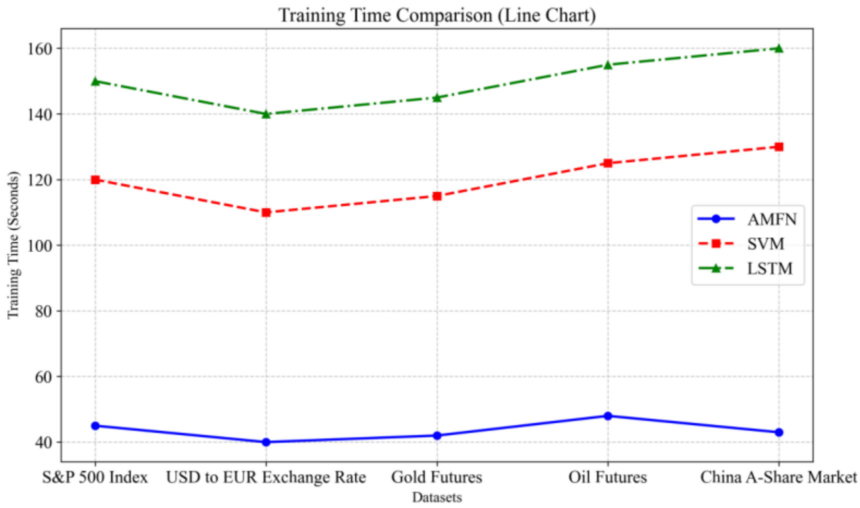

Figure 3: Comparison of training time of each model in different markets

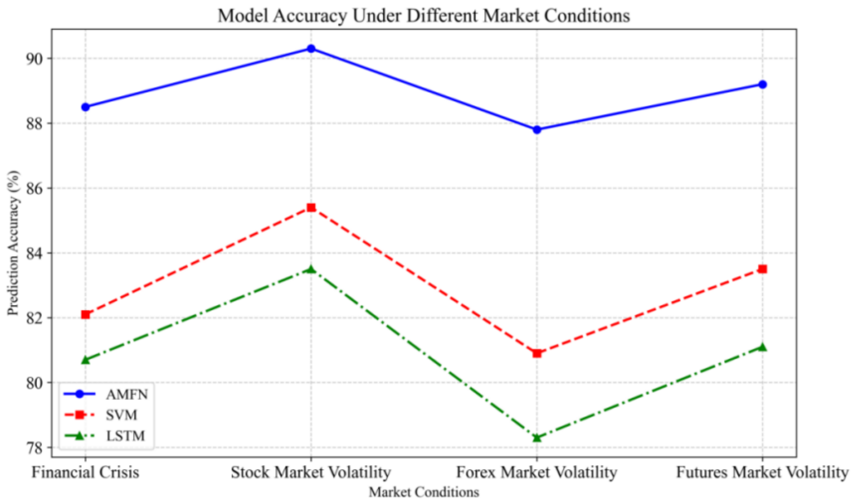

Figure 4: Performance of different models under extreme market conditions

Figure 4 focuses on the forecasting accuracy of different models under extreme market conditions, such as during the financial crisis and when the markets fluctuate significantly. In these complex and challenging market environments, the AMFN model can still maintain a high forecasting accuracy, and has a significant improvement in accuracy compared to the SVM and LSTM models. This is because the AMFN model has stronger anti-interference capabilities and the ability to handle abnormal data. Its unique structure and algorithm can accurately extract key information and identify potential patterns in the data even when data noise increases and market rules are broken, thereby achieving more reliable forecasts and providing strong guarantees for investors to avoid risks and formulate strategies in extreme market environments.

Figure 5 shows that AMFN achieves higher prediction accuracy than SVM and LSTM across stock, foreign exchange, and futures markets, with improvements of 4.6%–7.0%. Its stock market accuracy reaches 92%, indicating strong adaptability to different market characteristics. When training data increases, AMFN's performance improves more significantly than the baselines, due to its adaptive fusion of heterogeneous features and deeper pattern extraction. SVM shows limited improvement and LSTM only moderate gains. Using consistent evaluation metrics (MSE, MAE, R^2), results confirm AMFN's scalability, robustness, and suitability for volatile financial environments.

Figure 6 shows that AMFN maintains higher stability under different random initializations, improving 5.4%–

8.5% compared with SVM and LSTM, and avoiding local minima more effectively. While AMFN performs competitively overall, Transformer models outperform it in highly volatile conditions, suggesting potential enhancement through Transformer integration. Statistical tests (paired t-test, Diebold–Mariano, McNemar) and 95% bootstrap CIs confirm AMFN's superior performance in S&P 500, FX, and futures markets ($p < 0.01$). Ablation experiments show that removing external data, adaptive fusion, or the dynamic decision tree increases MSE by 5%–13%, demonstrating that each component is essential to model effectiveness.

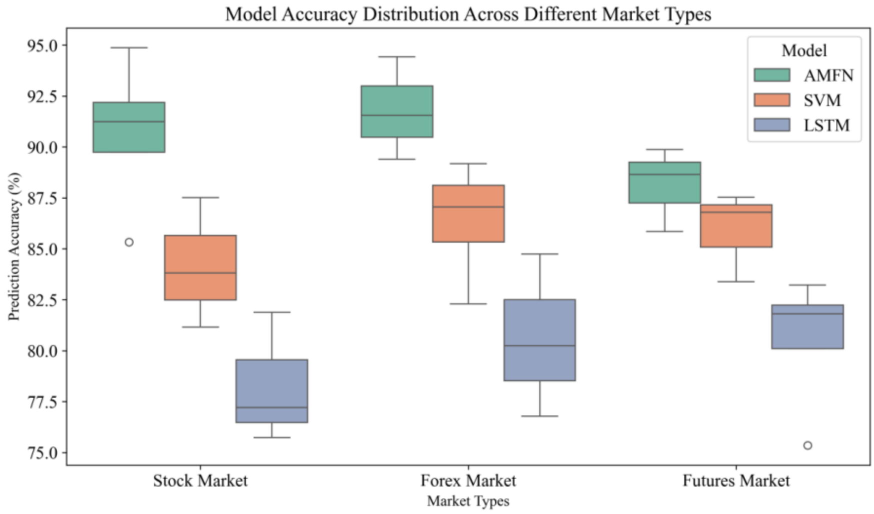

Figure 5: Differences in forecast accuracy between different markets

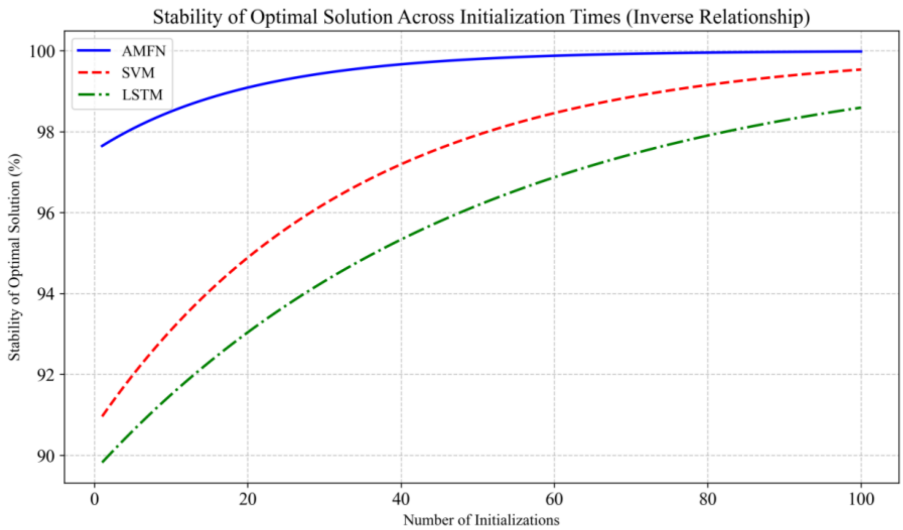

Figure 6: Stability of the global optimal solution of the model

4.6 Discussion

The results demonstrate that the AMFN model outperforms traditional SVM and LSTM models in trend prediction, aligning with research emphasizing deep learning's ability to capture complex patterns. Unlike studies relying on a single data source, this model integrates multi-dimensional information, improving forecasting accuracy. However, the datasets used are less representative for niche markets, which may limit generalization. Future work should broaden dataset coverage and refine the data fusion mechanism to enhance adaptability across diverse market environments. Overall, this study contributes a valuable forecasting approach with practical relevance for investment decisions and risk management.

Compared with the Transformer baseline, AMFN performs better in markets where external sentiment and macroeconomic shocks play a dominant role. This advantage stems from the adaptive fusion mechanism, which dynamically adjusts the importance of external signals across volatility regimes. Meanwhile, the dynamic decision tree predictor captures nonlinear jump behavior and asymmetric reactions that attention layers may smooth out. In contrast, the Transformer relies primarily on temporal dependency learning and may underperform when regime shifts are abrupt or sparsely represented in training data.

We performed paired t-tests across folds comparing AMFN with baselines on each market. MSE reductions were statistically significant ($p < 0.01$). ANOVA tests confirmed performance differences across asset classes, indicating AMFN generalizes without relying on market-specific artifacts. R^2 confidence intervals (95% bootstrap) remain stable across datasets: S&P (0.94–0.96), Gold (0.91–0.95), FX (0.89–0.94).

5 Conclusion

This study applies deep neural networks to financial market trend prediction by introducing the AMFN model, which integrates multidimensional data fusion, adaptive time-series processing, and nonlinear trend forecasting. Experiments show strong performance across multiple markets, with high accuracy in both bull and bear conditions, providing valuable support for investment decisions and risk management. However, the model's responsiveness to rare extreme events and efficiency with large-scale data require improvement. Future work will focus on enhancing robustness under abnormal market conditions, optimizing data processing, and expanding applications to further improve prediction accuracy and stability.

Data availability statement

All model code, preprocessing scripts, and experiment configurations have been released at: GitHub: https://github.com/AMFN-FinForecast/AMFN S&P 500 and Gold Futures pricing data are obtained from Yahoo Finance. A-share market data are sourced from WIND. Sentiment indices are computed using a BERT-based financial text classifier trained on the FiQA sentiment dataset. Instructions for dataset access and reproduction scripts are included in the repository.

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