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# Real-Time Monitoring and Image Recognition System for Abnormal Activities in Financial Markets Based on Deep Learning

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**ABSTRACT**

As the complexity and dynamic changes in financial markets continue to increase, real-time monitoring of abnormal activities has become a critical task in financial regulation and risk management. Traditional monitoring methods, which rely on rules and experience, struggle to handle the nonlinear and highly volatile nature of financial markets, especially when dealing with large-scale and multidimensional data. In recent years, the rapid development of deep learning technology has provided new solutions for real-time monitoring of abnormal activities in financial markets. By transforming time-series data into images and leveraging the pattern recognition capabilities of deep learning, abnormal market fluctuations can be more accurately detected, enabling efficient early-warning systems. However, existing research still faces challenges such as inadequate data adaptability, difficulties in integrating multidimensional information, lack of real-time performance, and poor interpretability of warning systems. This paper proposes a deep learning-based real-time monitoring and early-warning system for abnormal activities in financial markets, which consists of two main components: first, a real-time monitoring model for financial market time-series curve patterns based on information block recognition, aimed at extracting key features from time-series data for precise market fluctuation monitoring; second, an early-warning method for abnormal activities based on the changes in time-series curve trends, designed to identify potential abnormal activities in real time and issue early-warning signals. The core value of this study lies in the proposed innovative monitoring model and warning mechanism, which overcome the limitations of traditional methods and provide a more accurate and real-time tool for abnormal activity monitoring and early warning, with significant theoretical and practical value.

## 1. INTRODUCTION

With the high complexity and volatility of global financial markets, abnormal activities in the market have increasingly become an important issue in financial regulation and risk management [1-4]. Abnormal activities in financial markets are usually manifested by sharp price fluctuations, unusual trading volumes, etc. These activities often signal potential systemic risks or manipulative behaviors in the market, which can have a serious impact on investors and market stability [5-8]. Therefore, real-time monitoring and identification of abnormal activities in financial markets have become one of the key tasks of financial regulation. Traditional monitoring methods often rely on rules and experience, which are difficult to effectively handle the complexity and nonlinearity of financial markets. Deep learning-based automated analysis methods, with their strong data processing and pattern recognition capabilities, can more accurately capture subtle changes in market fluctuations. As a result, deep learning-based financial market abnormal activity monitoring systems have gradually become a hot topic of research.

Real-time monitoring of abnormal activities in financial markets not only helps improve market transparency and prevent systemic risks but also provides investors with more timely early warning information, thus enhancing the efficiency and fairness of the market [9-11]. Currently, deep learning-based image recognition technology has made significant progress in multiple fields, and it also shows great potential in the analysis of financial market time-series data [12, 13]. By converting time-series data into images and using advanced algorithms such as deep convolutional neural networks for image recognition, potential abnormal activities can be rapidly detected within massive amounts of financial data [14-17]. Moreover, deep learning-based models can improve recognition accuracy and early warning sensitivity through self-learning, providing more scientific and efficient tools for risk management in financial markets.

However, existing research methods often have certain limitations. Firstly, many deep learning-based monitoring models are overly dependent on historical data and lack the ability to quickly adapt to dynamic market changes [18-20]. Secondly, existing methods tend to focus on analyzing a single data source, failing to effectively combine multidimensional market information, which limits the ability to monitor and warn about abnormal activities. Furthermore, most research is concentrated on offline analysis, which cannot meet the demands of real-time monitoring, posing a significant shortcoming in fast-changing financial markets. In addition, the interpretability of existing abnormal activity early warning systems is poor, making it difficult for financial regulators to accurately understand the specific reasons for market changes based on the model results, thus hindering effective decision-making.

This paper primarily studies a deep learning-based real-time monitoring and early warning system for abnormal activities in financial markets, proposing an innovative real-time monitoring model for financial market time-series curve patterns based on information block recognition, and constructing an abnormal activity early warning mechanism based on this. Specifically, this paper first extracts key features from market time-series curves using information block recognition technology, and then constructs a deep learning model capable of real-time monitoring of financial market dynamics. Secondly, based on the changes in the market time-series curve patterns, an intelligent early warning method for abnormal activities is designed to promptly issue early warning signals when abnormal market fluctuations occur. The core value of this research lies in breaking through the limitations of traditional methods by introducing deep learning and image recognition technologies, achieving more accurate and real-time monitoring and early warning of market abnormal activities, which has important theoretical significance and practical application value.

## 2. REAL-TIME MONITORING MODEL FOR FINANCIAL MARKET TIME-SERIES CURVE PATTERNS BASED ON INFORMATION BLOCK RECOGNITION

In the recognition of time-series curve patterns in financial markets, traditional heuristic information block recognition methods often rely on spatial proximity and structural similarity to extract feature elements from market curves. However, this approach has limitations when dealing with complex financial time-series data. Especially when financial market data is highly volatile and multidimensional, relying solely on the spatial or structural relationships between elements often fails to accurately reflect the true changing trends of the curve. To address this issue, this paper proposes an information block recognition model based on scene graphs. This model not only considers the spatial proximity and structural similarity in time-series data but also enhances the modeling ability of the elements' features in financial market time-series curves by introducing color similarity. Financial market time-series curves are typically composed of multiple fluctuation cycles and trading nodes, and the color similarity between these nodes, such as trend color, color changes in the rise and fall amplitude, etc., can effectively complement spatial and structural information, helping to more accurately capture the market's fluctuation trends.

To further enhance the real-time monitoring ability of financial market time-series curves, the model views financial time-series curves as a financial market time-series graph and models it as a scene graph. As a graphical data structure, a scene graph represents various elements in the time-series data and their relationships through nodes and edges. In the model, different financial information blocks, such as market fluctuations, rise and fall cycles, etc., are treated as nodes in the scene graph, and the structural similarity between nodes serves as the training objective to guide the model in identifying abnormal activities in time-series data. Through this approach, the model can not only identify and monitor regular market fluctuations but also precisely capture potential abnormal activities.

Figure 1 shows the real-time monitoring model of financial market time-series curve patterns. The model includes a Gestalt feature extractor, a relationship proposal network module, an attention map convolution network module, and an information block narrative sequence recognition module. The following sections provide a detailed introduction to each module.

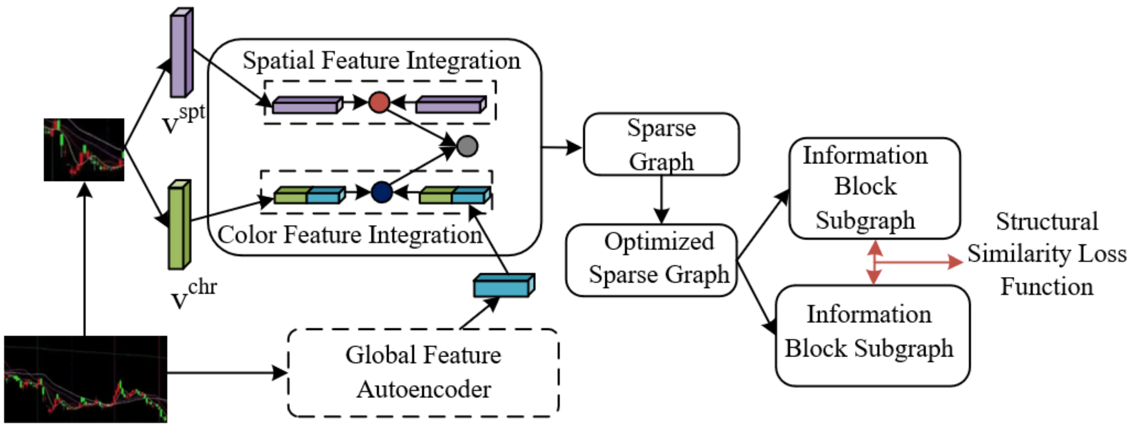



**Figure 1.** Real-time monitoring model of financial market time-series curve patterns

(1) Gestalt Feature Extractor

The time-series curves of financial markets contain a large amount of time-series data and market fluctuation information. Elements such as price points, trading volume, and trend reversals in the time-series charts can reflect different dynamic characteristics of the market based on their spatial distribution and color changes. The Gestalt feature extractor, through local feature extractors and global feature autoencoders, can extract these key features from financial market time-series graphs. The local feature extractor focuses on capturing micro-level trend information from the local changes in market fluctuations, helping to identify short-term fluctuation patterns and the emergence of abnormal activities. The global feature autoencoder, from a more macro perspective, integrates the fluctuation trends of the entire time-series curve and captures long-term market behavior patterns. This process transforms the financial time-series curve into a scene graph that integrates spatial and color features, providing more accurate and comprehensive inputs for subsequent recognition tasks.

The Gestalt feature extractor, based on the Gestalt organizational principles of color similarity and spatial proximity, provides an effective way to identify information blocks in financial time-series curves. These information blocks not only represent key fluctuation intervals in the market but may also correspond to potential abnormal market behaviors. By learning these features, the model can automatically capture the main factors influencing market trends, providing important support for real-time monitoring of financial markets.

First, the Gestalt feature extractor helps the model identify elements that may belong to the same information block by calculating the color similarity between each pair of elements in the financial time-series curve. Although financial time-series curves are usually composed of a series of numerical points, these fluctuations often present different colors or grayscale values, especially in visualized charts. For example, when the trend rises, the curve may be represented in green, while a decline may be shown in red or other colors. Based on Gestalt principles, color similarity can help the model judge whether adjacent elements share similar behavioral patterns, thus grouping them into the same information block. In the scene graph modeling of financial market time-series curves, color similarity can not only help identify similar fluctuation intervals but also provide important clues for abnormal activity detection. To ensure the effectiveness of this feature extraction, the model uses ResNet50 to extract the color features of each time-series point, $n^{zge}=ResNet(n_u)$, and calculates the color feature vector similarity between different elements $n_u$ and $n_k$. Assuming the projection functions of elements $n_u$ and $n_k$ are represented by $\Gamma(\cdot)$ and $\Omega(\cdot)$, where $\Gamma(\cdot)$ and $\Omega(\cdot)$ are multilayer perceptrons with the same architecture but different parameters, the following calculation formula holds:

$$d_{YS}\left(n_u,n_k\right)=\left\langle\Gamma\left(n_u^{zge}\right),\Omega\left(n_k^{zge}\right)\right\rangle,u\neq k \quad (1)$$

Furthermore, the principle of spatial proximity is also fully applied in the Gestalt feature extractor. The fluctuations in financial market time-series curves are often continuous, and price changes and trends at different time points tend to influence each other within a certain range. Therefore, spatial proximity not only refers to the physical closeness of elements in the image but also indicates that adjacent elements in the financial time-series curve may have temporal correlations. The Gestalt feature extractor models the spatial positions of each element in the financial market time-series graph and calculates the spatial proximity between every two elements. This can help the model identify market fluctuations occurring over a short period and determine whether these fluctuations belong to the same information block. Specifically, the model determines the relative relationship of each time-series element based on its positional information, helping to identify instantaneous trend changes or pullback phenomena in the market. Suppose the coordinates of the top-left vertex of the current element's bounding box are $a$ and $b$, and the coordinates of the bottom-right vertex are $a_e$ and $b_y$, denoted as $[a_m,b_s,a_e,b_y]$. Given a single element's spatial region $e^p{}_u=[a_u,b_s,a_e,b_y]$, the representation of this position box can be obtained as $n^{tos}$:

$$n^{tos}=\left[\frac{a_m}{q_o},\frac{b_s}{g_o},\frac{a_e}{q_o},\frac{b_y}{g_o},\frac{AR}{q_o\times g_o},\frac{b_y-b_s}{a_e-a_m}\right] \quad (2)$$

Assuming that MLPs with the same architecture are represented by $\Phi(\cdot)$ and $\Pi(\cdot)$, and matrix multiplication is denoted by <·>, the spatial proximity between each pair of elements can be characterized by the following formula:

$$d_{tos}\left(n_u,n_k\right)=\left\langle\Phi\left(n_u^{tos}\right),\Pi\left(n_k^{tos}\right)\right\rangle,u\neq k \quad (3)$$

To further enhance feature extraction, the model also introduces an adaptive adjustment mechanism for global color features. Visualized financial market time-series charts may present various different color patterns, especially in black-and-white or single-color charts, where color features often lack intuitive differentiation. Therefore, the model needs to adaptively adjust according to the global color features of the current financial market time-series graph, avoiding over-reliance on color features. To achieve this, the model introduces a deconvolution network module after the Gestalt feature extractor, using an autoencoder structure to recover the global color features of the current financial market time-series chart from the image features extracted by the feature pyramid network. Guided by the autoencoder, the model can adjust the usage of color feature vectors according to the overall color pattern of the current chart, ensuring that valuable features can be effectively extracted from different types of charts. Figure 2 shows the architecture of the global feature autoencoder.

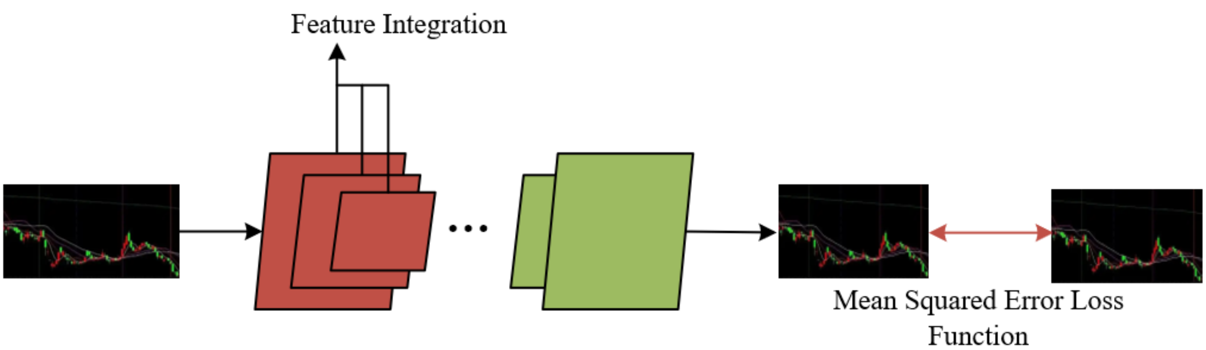
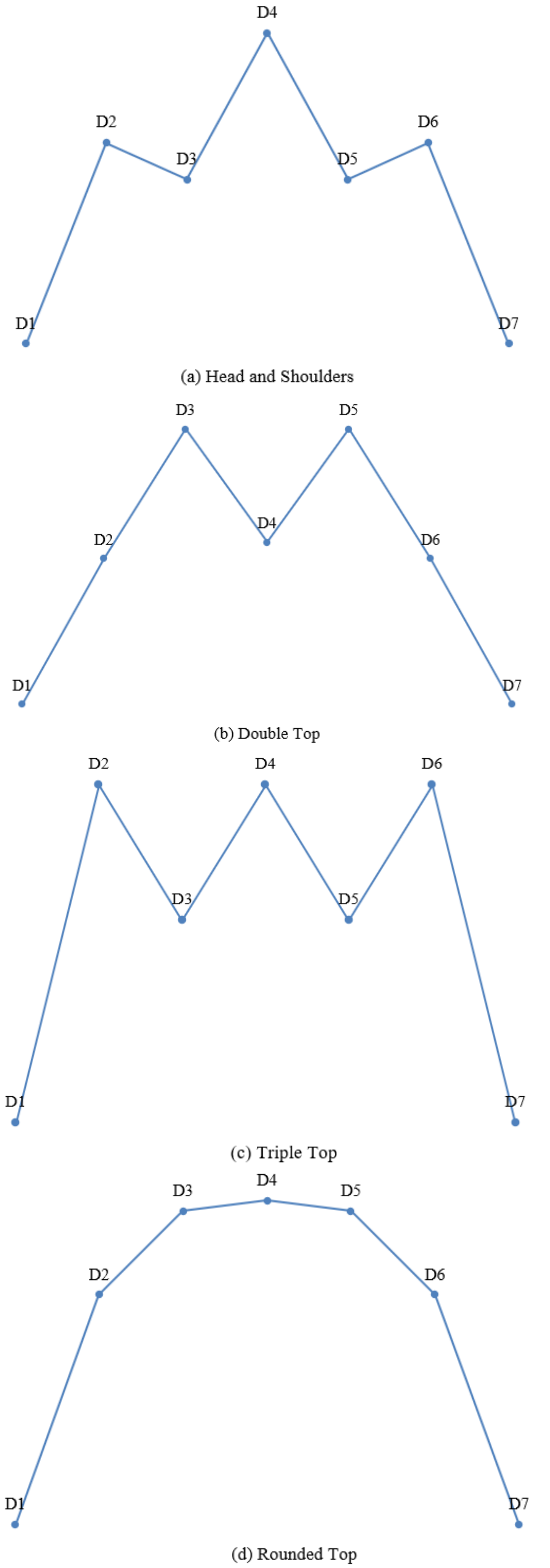



**Figure 2.** Architecture of the global feature autoencoder

(2) Relationship Proposal Network



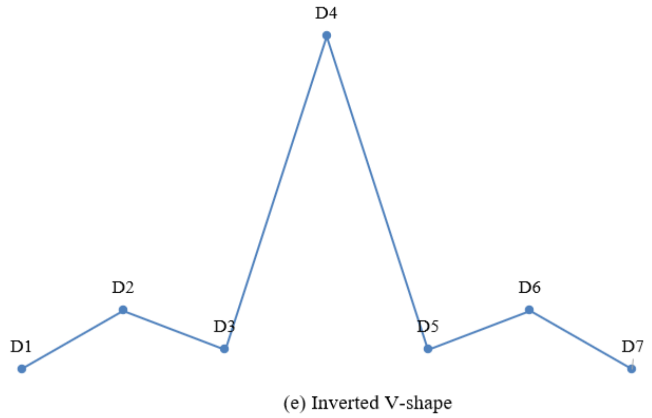




**Figure 3.** Schematic diagram of five financial market time-series curve feature structures

In financial market time-series data, the relationships between elements cannot be fully covered by spatial proximity and structural similarity alone. The volatility of the market means that different time nodes often have complex nonlinear relationships, so in a fully connected scene graph, many connections do not have practical computational significance. The role of the relationship proposal network module is to trim this complex graph structure and filter out relationships with actual significance, thereby generating a sparse graph structure. With such a graph structure, the model can focus on efficient computation and reduce unnecessary computational burden. Figure 3 shows the schematic diagram of five financial market time-series curve feature structures.

Specifically, the relationship proposal network calculates the probability score that each pair of elements in the scene graph belongs to the same information block. Based on multidimensional factors such as color similarity, spatial proximity, and major color features, it filters out irrelevant elements in the graph, ultimately obtaining a sparse graph.

Let the global color feature vector of the financial market time-series graph be denoted as $d_U$, the color similarity function between elements $n_u$ and $n_k$ be denoted as $d_{YS}$, and the spatial proximity function between elements $n_u$ and $n_k$ be denoted as $d_{tos}$. The submodules in the Gestalt feature extractor are denoted as $d_{YS}$ and $d_{tos}$. Finally, the sparse graph $H_{SP}$ can be represented by the following formula:

$$DF_{uk} = d_U * d_{YS}\left(n_u, n_k\right) + d_{tos}\left(n_u, n_k\right) \tag{4}$$

By calculating the probability score between each pair of elements, the module can evaluate which elements belong to the same information block at the same moment or trend, and which belong to different patterns or events. The score calculation is based on color similarity and spatial proximity, with these two factors combined with the weighted major color features to help the model determine which information blocks have higher relevance, thereby deciding whether to retain the edge connections between them. By sparsifying the scene graph, the module can help the model exclude elements that are unlikely to form abnormal patterns or trends in the current market environment. For example, certain price fluctuations may just be short-term market noise, while others may reflect long-term market trends or potential abnormal activities.

(3) Attention Graph Convolutional Network (aGCN)

Financial market time-series data often contain complex dynamic fluctuations, where some fluctuations may have significant impacts on market trends, while others may just be short-term noise. The introduction of this module enables the model to assign different levels of importance to the edges between each pair of nodes in the graph, further refining the flow of information. For example, certain nodes may have a very tight relationship, meaning they exhibit similar market trends or fluctuations at the same time, while other nodes may have a looser relationship. In such cases, the aGCN module, by introducing attention weights, enables the model to automatically focus on critical connections during the information propagation process and ignore irrelevant information, thereby increasing its sensitivity to important fluctuations. In financial market time-series curves, price fluctuations at different time points often exhibit some correlation. Some fluctuations may trigger subsequent trend reversals or intensify trends. The aGCN module helps the model better identify these potential associations by constructing a graph with relations and elements as nodes, and adding connecting edges between these nodes, facilitating interaction between information blocks and providing more contextual information to the model, which helps capture market behaviors across time nodes. For instance, when a sudden price fluctuation occurs at a specific time point, related fluctuations at other time points may be influenced by this change. By establishing corresponding connections in the graph, aGCN can help the model better recognize these potential links, enhancing its ability to predict market anomalies. Let the learnable weight matrices be represented by $Q^{SK}$ and $Q^e$. The representation matrix of elements adjacent to the element node $u$ is denoted as $C^p$, and the representation matrix of relation nodes adjacent to the relation node $k$ is denoted as $C^e$. For element nodes, their representations are updated using the following formula:

$$c_u^e = \delta\left(Q^{SK} C^p \beta^{SK} + Q^e C^e \beta^e\right) \tag{5}$$

For relation nodes, their representation $c^e_k$ can be updated using the following formula:

$$c_k^e = \delta\left(c_k^e + Q^e C^p \beta^e\right) \tag{6}$$

The learnable parameters $\beta_{SK}$ and $\beta_e$ can be computed using the following formula:

$$\beta = SOFTMAX\left(i\right) \tag{7}$$

The value of each element $i_{uk}$ of $i$ in the above equation can be obtained using the following formula:

$$i_{uk} = q_g^T \delta\left(Q_x\left[c_u, c_k\right]\right) \tag{8}$$

(4) Information Block Narrative Sequence Recognition

The financial market time-series curve is not a simple time series but rather a complex graphical structure composed of multiple information blocks, such as fluctuation cycles, trend changes, and price breakouts. These information blocks not only have explicit spatial and structural similarities but may also contain implicit temporal order and causal relationships. For instance, a rapid decline after a price peak may be a precursor to a market bubble burst, and this change may exhibit a certain narrative order between different time nodes in the financial market time-series graph. Therefore, directly using heuristic rules for information block recognition may ignore the sequence and causal relationships between information blocks, affecting the accuracy of anomaly prediction in financial markets. To address this shortcoming, this paper proposes an information block narrative sequence recognition module based on the information block scene graph, which captures the implicit relationships between information blocks by constructing an information block scene graph, enabling more precise information block narrative sequence recognition. Figure 4 illustrates the information block narrative sequence construction process.

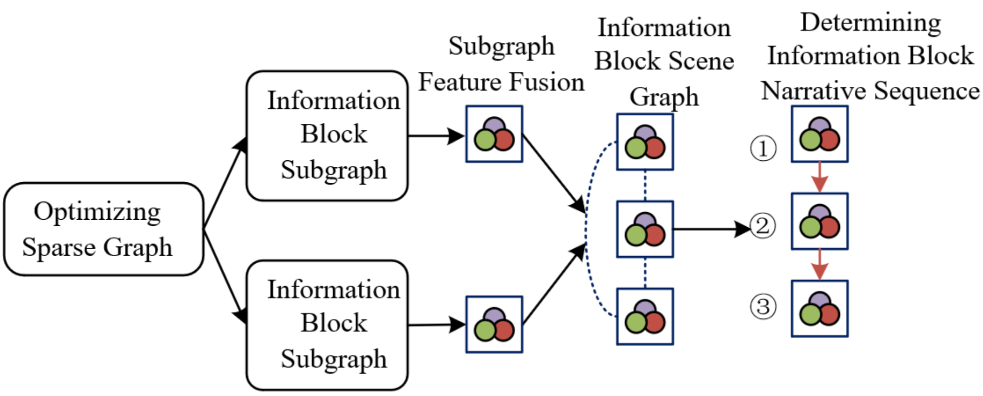



**Figure 4.** Information block narrative sequence construction flowchart

When processing financial market time-series graphs, the model extracts $v$ subgraphs $H_{tiy}=\{h_1,...,h_v\}$ to form different sub-scene graphs. These sub-scene graphs correspond to local trends at different times or periods in the financial market. In each sub-scene graph, seed elements, such as key indicators or price change points in the market, are considered the core of the information block, while other non-seed elements are evaluated based on their relationships with the seed elements to determine whether they belong to the same information block. This relationship is measured by a possibility score $DF_{tl}$, where the relationship score between each pair of elements reflects whether they belong to the same information block. Possible relational factors include temporal synchronization, similarity in market behavior characteristics, etc.

In constructing the scene graph, the feature fusion process within the information block is critical. In each information block, the model processes all element features within the scene graph and performs feature fusion using the seed element's features $d_{SE}$ via an attention mechanism. This process enhances the model's attention to key elements when recognizing information blocks by computing correlation weights between elements. For example, factors like price fluctuations, trading volume, and technical indicators may exhibit different relationships across various time windows. The attention mechanism can dynamically adjust the importance of elements within the information block based on their correlations, further strengthening the model's understanding of the financial market time-series graph. Let the features of all elements within the scene graph be denoted by $d$, and the features of the seed element in the information block by $d_{SE}$. The trainable parameters are represented by $q_0$, $Q_0$, and $y_0$, and the feature concatenation of two element nodes is denoted as $[d_u;d_k]$. The attention mechanism feature fusion of $d$ and $d_{SE}$ results in the correlation weight between two element nodes:

$$q_{uk} = q_0^T \delta\left(Q_0\left[d_u; d_k\right] + y_0\right) \tag{9}$$

The attention weight formula is:

$$\beta_{uk} = \frac{\exp\left(q_{uk}\right)}{\sum_{k \in h_t} \exp\left(q_{uk}\right)} \tag{10}$$

Assuming the trainable parameters are $Q_1$ and $y_1$, the overall representation of the current information block can be expressed as:

$$d_{BL} = \delta\left(d_{SE} + \sum_{k \in h_t} \beta_{uk}\left(Q_1 d_k + y_1\right)\right) \tag{11}$$

Through this process, the model generates a graph structure $H_{BL}=\{N_{BL},R_{BL}\}$ containing information block features, where nodes $N_{BL}$ represent different information blocks, with each node corresponding to a fused feature representation $d_{BL}$, and edges $R_{BL}$ represent the relationships between information blocks, which may include causal relationships, temporal dependencies, etc. This graph structure not only captures local interactions between information blocks but also reflects the development trends and patterns of information blocks in the time series. To further improve the accuracy and real-time performance of the model, a multi-layer perceptron (MLP) is introduced to predict the features of the information blocks. For each fused feature $d_{BL}$ of the information block, MLP can predict the likelihood of its starting block, i.e., whether this information block marks the beginning of a new anomaly activity.

$$t'_{NE} = MLP\left(d_{BL}\right) \tag{12}$$

Using MLP to predict the "next" relationship $e'_{NE}$ between the $u$-th information block and the $k$-th information block:

$$e'_{NE} = MLP\left(\left[d_u, d_k\right]\right) \tag{13}$$

Using $t'_{HE}$ and $e'_{NE}$, the information sequence $T^{\rightarrow}=\{t_1{:}p_1,\ldots,t_j{:}p_j\}$ of the financial market time-series graph can be directly determined.

(5) Loss Function

In the context of financial market time-series data, there may be various complex correlation patterns between information blocks. The accurate identification of these patterns is critical for monitoring anomalous activities. Therefore, in the task of detecting relationships between paired elements in information blocks, this paper selects binary cross-entropy as the training loss function. This loss function is primarily used to measure the difference between the model's predicted result $o$ and the true label $b$. By using binary cross-entropy, the model can optimize predictions for the presence or absence of relationships during training, thereby improving its sensitivity to market anomalous activities. For example, if a significant fluctuation occurs at a certain time point, the binary cross-entropy loss function helps determine whether it should be classified as part of an anomalous activity.

$$M_{zmt} = -\left(b\log\left(o\right) + \left(1-b\right)\log\left(1-o\right)\right) \tag{14}$$

Additionally, to obtain the global color features of the information chart, this paper designs a deconvolution network and uses pixel-level mean squared error as the training loss function. The information chart in this study refers to the time-series curves of the financial market, which contain a large number of temporal features closely related to their spatial distribution and image features. By introducing the deconvolution network, the model can recover finer temporal features from the image, and the mean squared error loss function can optimize the pixel-level difference between the predicted and true images:

$$M_{RE} = \frac{1}{v}\sum_{u}^{v}\left(b_u - \hat{b}_u\right)^2 \tag{15}$$

Fluctuations in financial market time-series data often appear in similar patterns. During different time periods or market states, price, trading volume, and other indicators may exhibit similar trends. In this case, by measuring the structural similarity between information blocks, the model can learn the relationships between similar information blocks, thus improving the model’s ability to model time-series data. This paper uses cosine similarity to measure the similarity between the element distribution vectors $g_u$ and $g_k$ of information blocks. Specifically, by calculating the structural similarity of each pair of information blocks and including it in the total loss, the model can maintain the structural consistency between different information blocks during training, preventing overfitting and enhancing the model’s generalization ability.

$$M_{ST} = \sum_{u,k \in v} COS\left(\overrightarrow{g_u}, \overrightarrow{g_k}\right), u \neq k \tag{16}$$

Furthermore, the model also needs to discriminate the "next" relationship and the starting points between information blocks. In the financial market time-series curve, fluctuations at certain moments may indicate the reversal of future trends or the beginning of anomalous activities, and identifying these key points is crucial for real-time monitoring systems. To achieve this, this paper once again uses the binary cross-entropy loss function to train the "next" relationship and the starting point identification in the Block-Graph module. This design allows the model to identify key points in the time-series curve and predict the occurrence of anomalous activities in advance. For example, when an unexpected market fluctuation occurs, the model can not only identify the fluctuation itself but also predict whether it marks the beginning of an anomalous activity and issue a corresponding early warning. Let the fused feature of all elements in the information block containing a specific seed element be denoted as $d_{BL}$, and the fused feature in the standard answer of the information block containing the same seed element be denoted as $d^{hs}_{BL}$. The feature similarity between each information block and the standard answer block is computed as:

$$M_{B\_S} = 1 - COS\_SIM\left(d_{BL}, d_{BL}^{hs}\right) \tag{17}$$

Let the "next" relationship between each pair of information blocks in the standard answer be denoted as $e_{NE}$. The loss function for determining the "next" relationship in the Block-Graph module is:

$$M_{NE} = -\left(e_{NE}\log\left(e'_{NE}\right) + \left(1-e_{NE}\right)\log\left(1-e'_{NE}\right)\right) \tag{18}$$

Let the information blocks that belong to the starting point in the standard answer be denoted as $t_{HE}$. The loss function for identifying the starting point of the information block narrative sequence in the Block-Graph module is:

$$M_{HE} = -\left(t_{HE}\log\left(t'_{HE}\right) + \left(1-t_{HE}\right)\log\left(1-t'_{HE}\right)\right) \tag{19}$$

The total objective function of the model is:

$$\begin{aligned} M &= \beta M_{zmt} + \alpha M_{RE} + \varepsilon M_{ST} \\ &+ \varsigma M_{B\_S} + \sigma M_{NE} + \psi M_{HE} \end{aligned} \tag{20}$$

## 3. ANOMALOUS ACTIVITY EARLY WARNING BASED ON FINANCIAL MARKET TIME-SERIES CURVE PATTERNS

In this paper, the anomalous activity early warning strategy based on financial market time-series curve patterns is one of the core tasks. The goal is to use deep learning models to identify abnormal fluctuations and potential risks in the market in real-time and issue early warnings in advance. To effectively monitor and warn against these anomalous activities, the strategy must integrate the changing trends of the time-series data, market behavior patterns, and the features of abnormal fluctuations. Figure 5 shows the principle of anomalous activity early warning based on financial market time-series curve patterns.

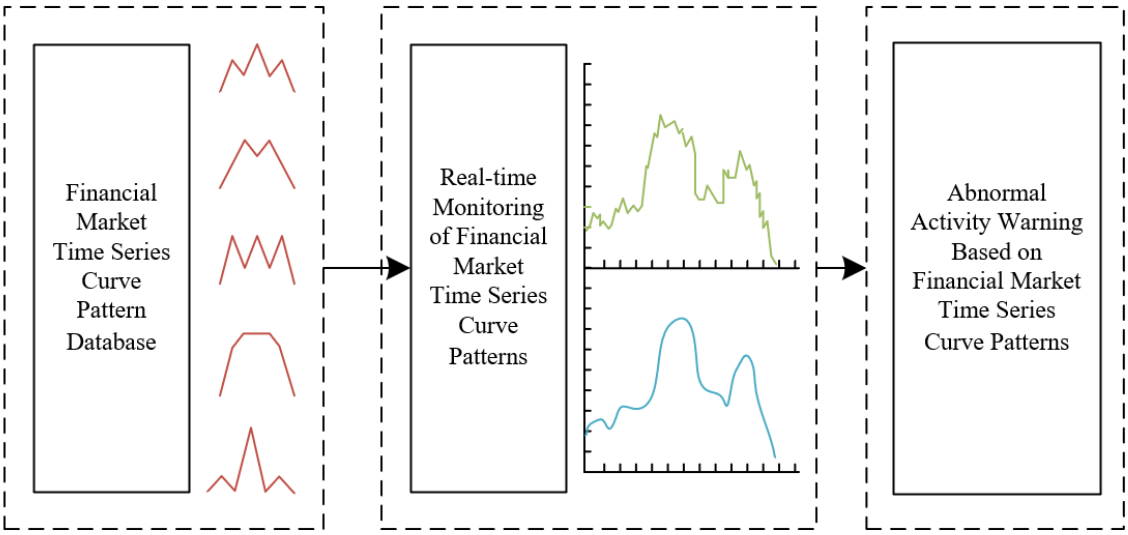



**Figure 5.** Anomalous activity early warning principle based on financial market time-series curve patterns

Once the scene graph modeling is completed, anomalous activity identification becomes the next key step. Using deep learning-based anomalous activity detection algorithms, the model analyzes the relationships between each information block in the graph and captures potential risk signals in the market. In practical applications, anomalous activities in financial markets often manifest as significant price fluctuations, abnormal increases in trading volume, or breakouts of specific technical indicators. By learning and predicting these indicators, the model can identify the presence of anomalous activities in real-time and determine whether these anomalies are temporary market fluctuations or signals that could trigger more significant market changes.

In the model output, the following types of information are typically included: 1) Time location of anomaly points: identifies the specific time when abnormal activity occurs in the market; 2) Anomaly type: determines whether the anomaly is triggered by sudden events, market sentiment changes, capital flows, or other factors; 3) Intensity of the abnormal activity: measures the degree of the anomaly, helping to assess its potential impact on the market.

In order to respond to abnormal activities in the financial market in real-time, the design of the warning mechanism is crucial. Based on the output of the deep learning model, the warning mechanism automatically issues market anomaly warning signals by setting certain thresholds or probability models. These warning signals can be classified and processed according to specific needs, such as:

- **High-Risk Warning**: When the model detects significant market fluctuations that exceed a certain threshold, the system will issue a high-risk warning, signaling to investors or decision-makers that the market is about to experience major changes.
- **Medium-Risk Warning**: When the market experiences large fluctuations but not at a high-risk level, the system

will issue a medium-risk warning, reminding investors to pay attention to market dynamics.

- **Low-Risk Reminder**: When market fluctuations are small or the predicted anomalous activity is not significant, the system will provide a general market reminder, urging investors to stay observant.

Additionally, the model can integrate external factors (such as policy changes, global economic conditions, etc.) for multimodal data fusion, further improving the accuracy of the early warning. With an automated early warning system, decision-makers can take timely action when anomalous activities occur in the market, avoiding excessive losses.

In practice, financial market anomalous activities are often uncertain and complex. Therefore, a feedback and adjustment mechanism for the strategy is key to ensuring the system's stability. Based on the performance of the model's predictions and actual market conditions, the system needs to undergo continuous feedback and optimization. For example, if the early warning system repeatedly generates false positives (i.e., predicted anomalous activities do not occur), the threshold may need to be adjusted, or the model's prediction strategy may need improvement. If false negatives occur (i.e., genuine anomalous activities are not predicted in time), the model's sensitivity should be increased, or additional features should be incorporated for supplementary training.

## 4. EXPERIMENT RESULTS AND ANALYSIS

According to the experimental results in Table 1, the real-time monitoring model based on information block recognition for financial market time-series curves proposed in this paper shows certain advantages under different experimental configurations. Specifically, the traditional information block recognition algorithm performs relatively poorly in terms of the integrity of a single information block, the accuracy of information block detection, and the integrity of narrative sequence recognition, with scores of 0.7866, 0.5589, and 0.4125, respectively. The model using the full proposed method outperforms in all metrics, especially in terms of the integrity of a single information block (0.8452) and information block detection accuracy (0.6554), achieving the best experimental results, indicating that the proposed method outperforms traditional methods in terms of overall performance. In contrast, when different modules (such as the Gestalt feature extractor, relationship proposal network, and attention mechanism) are excluded, the proposed model shows a decrease in these metrics to varying degrees.

**Table 1.** Information block recognition experiment results for real-time monitoring of financial market time-series curve patterns

| Model | Integrity of a Single Information Block | Information Block Detection Accuracy | Narrative Sequence Recognition Integrity |
|---|---|---|---|
| Traditional Information Block Recognition Algorithm | 0.7866 | 0.5589 | 0.4125 |
| Proposed Method (Excluding Gestalt Feature Extractor) | 0.8125 | 0.6123 | 0.4236 |
| Proposed Method (Excluding Relationship Proposal Network) | 0.8125 | 0.6235 | 0.4325 |
| Proposed Method (Excluding Attention Mechanism) | 0.8265 | 0.6358 | 0.4458 |
| Proposed Method (Without Narrative Sequence Recognition) | 0.8365 | 0.6359 | 0.4562 |
| Proposed Method | 0.8452 | 0.6554 | 0.4512 |

**Table 2.** Ablation experiment results for information block recognition model

| Experiment Item | Model | Traditional Information Block Recognition Algorithm | Proposed Method (Excluding Gestalt Feature Extractor) | Proposed Method (Excluding Relationship Proposal Network) | Proposed Method (Excluding Attention Mechanism) | Proposed Method (Without Narrative Sequence Recognition) | Proposed Method |
|---|---|---|---|---|---|---|---|
| Two Elements Belong to the Same Information Block | $P$ | 0.8852 | 0.8652 | 0.9123 | 0.9354 | 0.9125 | 0.9123 |
| | $R$ | 0.8564 | 0.8623 | 0.8794 | 0.8652 | 0.8865 | 0.8612 |
| | $F1$ | 0.8516 | 0.8852 | 0.8962 | 0.8741 | 0.8762 | 0.8795 |
| Two Elements Do Not Belong to the Same Information Block | $P$ | 0.9852 | 0.9632 | 0.9642 | 0.9652 | 0.9682 | 0.9631 |
| | $R$ | 0.9721 | 0.9653 | 0.9874 | 0.9785 | 0.9862 | 0.9685 |
| | $F1$ | 0.9655 | 0.9784 | 0.9623 | 0.9845 | 0.9712 | 0.9862 |
| Information Block Recognition Performance | Integrity of a Single Information Block | 0.8152 | 0.8124 | 0.8236 | 0.8365 | 0.8248 | 0.8233 |
| | Information Block Detection Accuracy | 0.6125 | 0.6257 | 0.6248 | 0.6548 | 0.6325 | 0.6584 |
| | Narrative Sequence Recognition Integrity | 0.4215 | 0.4685 | 0.4525 | 0.4512 | 0.4563 | 0.4879 |

Based on the ablation experiment results in Table 2, the proposed information block recognition-based model demonstrates significant improvement and optimization under different experimental configurations. First, for the experiment item "Two elements belong to the same information block," the model's Precision (P), Recall (R), and F1 scores fluctuate after removing each module but show an overall improvement trend. For example, when the Gestalt feature extractor is removed, the Precision and Recall are 0.8652 and 0.8623, respectively, and the F1 score is 0.8852. These results are slightly lower than the full model, but still maintain high performance. When the Relationship Proposal Network is removed, Precision reaches 0.9123, and the F1 score is 0.8962, demonstrating the significant role of this module in enhancing information block recognition capabilities. In other configurations, removing the attention mechanism and not performing information block narrative sequence recognition still show good performance for the model, with F1 scores stable between 0.8741 and 0.8762. For the "Two elements do not belong to the same information block" experiment item, the model's performance remains good after removing modules, especially when the Relationship Proposal Network is removed, where Recall and F1 scores reach 0.9874 and 0.9623, respectively, indicating that this module significantly improves the model's ability to handle complex relationships between information blocks. From the ablation experiment results, it can be concluded that the proposed model maintains a high level of overall information block recognition performance even after removing different modules. The removal of the Gestalt feature extractor and the attention mechanism has relatively small effects on the model, indicating that these modules are less important for improving information block recognition accuracy compared to the Relationship Proposal Network and information block narrative sequence recognition. Particularly, the removal of the Relationship Proposal Network, while improving Precision, has a significant negative impact on Recall and F1, highlighting its crucial role in capturing complex relationships between information blocks. Ultimately, the overall performance of the model achieves a high level of integrity in single information block detection, recognition accuracy, and narrative sequence recognition, proving the effectiveness and feasibility of the proposed method in anomaly activity monitoring of financial market time-series curves.

**Table 3.** Number of narrative sequence recognition samples for the model under different curve feature structure types

| Financial Market Time-Series Curve Feature Structure | Head and Shoulders | Double Top | Triple Top | Round Top | Inverted V-shape |
|---|---|---|---|---|---|
| Traditional Information Block Recognition Algorithm | 6 | 4 | 28 | 13 | 2 |
| Proposed Method (Excluding Gestalt Feature Extractor) | 6 | 2 | 41 | 9 | 1 |
| Proposed Method (Excluding Relationship Proposal Network) | 5 | 1 | 52 | 8 | 0 |
| Proposed Method (Excluding Attention Mechanism) | 6 | 3 | 53 | 5 | 0 |
| Proposed Method (Without Narrative Sequence Recognition) | 6 | 3 | 52 | 6 | 0 |
| Proposed Method | 5 | 2 | 44 | 14 | 0 |

According to the experimental results in Table 3, it can be seen that the proposed information block recognition-based model shows varying narrative sequence recognition abilities across different financial market time-series curve feature structures. From the number of recognition samples for each curve feature structure, the traditional information block recognition algorithm recognized 6 samples in the "Head and Shoulders" pattern, while it recognized only 2 samples in the "Inverted V-shape" pattern. In contrast, the proposed model performed similarly in the "Head and Shoulders" pattern (5 samples), but its performance varied in other patterns. For example, after excluding the Gestalt feature extractor, the number of recognized samples in the "Triple Top" pattern increased to 41, which is significantly higher than the traditional method (28 samples), but decreased in the "Round Top" pattern (9 samples). When the Relationship Proposal Network was excluded, the number of recognized samples in the "Triple Top" pattern increased to 52, while other patterns, such as "Inverted V-shape", had zero samples. After excluding the Attention Mechanism, the model performed particularly well in the "Triple Top" and "Round Top" patterns, with 53 and 5 samples, respectively. Overall, after removing the narrative sequence recognition function, the model's recognition performance decreased in most curve feature types, while in the complete method, the recognition sample count for the "Triple Top" pattern was 44, showing strong recognition ability. From these results, it can be concluded that the proposed method significantly improves narrative sequence recognition ability under different curve feature structures compared to the traditional information block recognition algorithm, especially in complex patterns such as "Triple Top" and "Round Top", where the model shows better adaptability. After removing different modules, although the recognition ability slightly decreased for some curve structures, overall, removing the Gestalt feature extractor and Relationship Proposal Network had a significant impact on the model, especially the Relationship Proposal Network, which played a key role in recognizing complex structural patterns. For instance, the number of recognized samples in the "Triple Top" pattern significantly increased, indicating that this network module is crucial for capturing market trend shape changes. At the same time, removing the Attention Mechanism or not performing narrative sequence recognition did not lead to significant improvements in the model's performance across most patterns. Therefore, maintaining the complete model provides higher accuracy and robustness for real-time monitoring of financial market time-series anomalies.

From the data in Figure 6, it can be observed that the error rates of real-time monitoring models for financial market time-series curves at different network depths change during both training and testing processes. For the training iterations, the 6-layer network model starts with an error rate of 20 at iteration 0, gradually decreasing and fluctuating to 9.5, indicating that the model is progressively converging and improving during training. Notably, after the 5th iteration, the error rate fluctuates less and stabilizes at a lower value in the later iterations (such as 7.5, 7, 6, etc.). In contrast, the 20-layer network starts with an error rate of 20 at the beginning of training, and although the error rate decreases gradually as training progresses, the overall decline is relatively small. A noticeable decrease occurs around the 20th iteration, eventually stabilizing between 3.5 and 1.8, showing a more gradual convergence trend. For the testing iterations, the 6-layer network starts with a test error rate of 20, gradually decreasing and stabilizing around 13. Although some fluctuations occur (such as 13.7, 14, etc.), it maintains a relatively high level of accuracy. The 20-layer network's test error rate decreases gradually from 20 to around 10.2, showing a more stable performance, and after the 20th iteration, the error rate stabilizes around 10%. From the analysis of the experimental data above, it can be concluded that the number of layers in the model has a significant impact on the error rate of real-time monitoring for financial market time-series curve patterns. The 6-layer model converges earlier during training and maintains a lower error rate, but its stability is relatively poor, especially in the testing phase, where the error rate fluctuates significantly. This suggests that it may lack sufficient modeling capability for the complexity of market dynamics. On the other hand, the 20-layer model shows slower convergence during training but eventually achieves more stable test performance, with the error rate stabilizing around 10%. This indicates that a deeper network (20 layers), although requiring more iterations to converge during training, has stronger expressive power when handling complex market dynamics and can stably make predictions and monitor market trends.

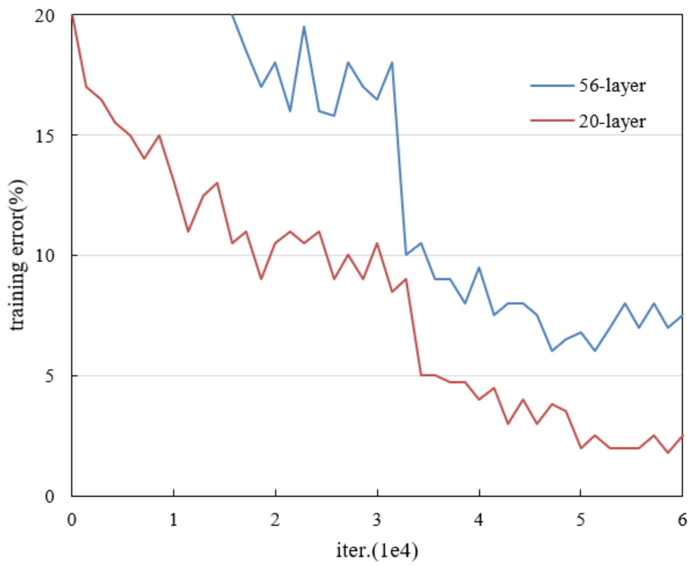



**Figure 6.** Error rate comparison of real-time monitoring models for financial market time-series curves at different network depths

Therefore, despite the 20-layer network converging more slowly in the initial stages of training and not controlling the initial error rate as well as the 6-layer network, it demonstrates higher precision and more stable testing performance after prolonged training. This suggests that deeper networks in deep learning models are better equipped to capture the nonlinear features of financial market time-series data, thus improving the reliability and accuracy of the model in real-time monitoring. While the 6-layer network performs better during training, to address the abnormal fluctuations and complex patterns in financial markets, the 20-layer deep network model undoubtedly offers a more promising solution.

**Table 4.** Model performance for narrative sequence recognition across different curve feature structures

| Financial Market Time-Series Curve Feature Structure | *R* | *P* | *F1* |
|---|---|---|---|
| Head-Shoulder Top | 0.8124 | 0.9256 | 0.8651 |
| Double Top | 0.8562 | 0.8847 | 0.8741 |
| Triple Top | 0.8623 | 0.8896 | 0.8623 |
| Rounded Top | 0.9124 | 0.8892 | 0.8741 |
| Inverted V-shape | 0.9128 | 0.8652 | 0.8952 |
| Total | 0.8851 | 0.8954 | 0.8741 |

Based on the data in Table 4, the information-block recognition-based model proposed in this paper demonstrates excellent performance across different curve feature structures of financial market time-series data. Specifically, for each curve feature structure (e.g., Head-Shoulder Top, Double Top, Triple Top, Rounded Top, and Inverted V-shape), the model exhibits strong performance in terms of Precision (P), Recall (R), and F1 score. For example, for the Head-Shoulder Top pattern, the model achieves a Recall of 0.8124, Precision of 0.9256, and an F1 score of 0.8651, showing strong recognition capability. Similarly, for the Inverted V-shape pattern, the model achieves a high Recall of 0.9128 and an F1 score of 0.8952, with a Precision of 0.8652, indicating high accuracy in recognizing this pattern. Overall, the total values for all patterns are: Precision (0.8851), Recall (0.8954), and F1 score (0.8741), demonstrating stable and excellent performance across various types of financial market time-series curves.

Analysis of the experimental results reveals that the information-block recognition-based model proposed in this paper exhibits strong adaptability and efficiency in recognizing financial market time-series patterns. Particularly, it performs well in recognizing different patterns, such as Head-Shoulder Top and Inverted V-shape, achieving high Recall and Precision values. A high Recall indicates that the model is capable of correctly identifying market patterns, while high Precision suggests its ability to avoid false positives. Therefore, the overall high F1 score demonstrates the good balance of the model in recognition tasks. Especially when handling more complex patterns such as the Inverted V-shape, the model shows high accuracy and effectively captures key market features, adapting well to the complex variations of different patterns.

## 5. CONCLUSION

This paper presented a deep learning-based real-time monitoring and early warning system for abnormal activities in financial markets, combining information-block recognition technology. The system aims to provide accurate monitoring and early warning support for market dynamics by recognizing key features in financial market time-series curves. The core innovation of the research lies in proposing a method for time-series curve pattern recognition based on information-block recognition, which can effectively extract and utilize latent patterns in market data through deep learning models for real-time dynamic monitoring. Experimental results show that the proposed model exhibits high accuracy and stability in recognizing financial market time-series curves, especially for common market patterns such as Head-Shoulder Top and Inverted V-shape, with strong recognition ability. Furthermore, through an intelligent abnormal activity early warning mechanism, the model can promptly issue alerts when market fluctuations occur, providing effective technical support for financial market risk management.

However, despite the achievements of this research in financial market monitoring and early warning, there are still some limitations. First, the model primarily relies on historical market data for training and prediction, which may be affected by external sudden events in the market, limiting the model's generalization ability. Second, although deep learning models have high complexity and can handle complex time-series data, in real-time applications, the computational resources and time costs are relatively high, which may affect their use in fast-changing markets such as high-frequency trading. Moreover, this study focuses on the recognition and early warning of time-series curve patterns, lacking a more in-depth exploration of the mechanisms behind abnormal activities under different patterns and their multidimensional influencing factors. Future research could expand in the following directions: First, more market factors could be incorporated into the model to further improve prediction accuracy and generalization ability. Second, to address the computational demands of real-time monitoring, the model's computational efficiency could be optimized by adopting lightweight deep learning architectures or hardware acceleration technologies to enhance the system's responsiveness and adaptability. Additionally, future research could combine reinforcement learning and other techniques to explore methods for dynamically adjusting the early warning mechanism, leading to smarter and more precise financial market abnormal activity alerts. Furthermore, with the continued development of quantitative trading and intelligent decision-making systems, this system could be integrated with trading strategies and risk management systems to further enhance the automation of decision-making in financial markets.

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