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Self-Supervised Deep Learning for Cross-Market Anomaly Detection in Financial Systems

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Abstract: In the complex ecosystem of modern financial markets, anomaly detection plays a critical role in identifying irregular behaviors, fraudulent activities, and systemic risks. However, conventional supervised learning models rely heavily on labeled datasets, which are costly and time-consuming to obtain in real-world financial environments. This paper proposes a novel self-supervised deep learning framework for cross-market anomaly detection that effectively transfers learned representations across heterogeneous financial domains. The proposed framework integrates contrastive learning, graph-based relational modeling, and cross-domain feature alignment. Specifically, the method constructs proxy tasks using unlabeled data, such as temporal sequence reconstruction and context prediction, to pre-train a self-supervised encoder. This encoder is subsequently fine-tuned on downstream anomaly detection tasks across different financial markets, including equities, forex, and cryptocurrency datasets. Experimental results demonstrate significant improvements in anomaly detection performance compared to state-of-the-art baselines, especially under limited supervision. The proposed approach not only enhances generalization capability but also mitigates domain shift, leading to more robust detection of anomalous financial patterns across global markets.

Keywords: Self-supervised learning, deep learning, anomaly detection, cross-market transfer, financial systems, representation learning

1. Introduction

In recent years, the increasing complexity and globalization of financial systems have brought both unprecedented opportunities and risks. With the rise of digital trading, high-frequency transactions, and algorithmic decision-making, financial markets have become more interlinked and volatile than ever before. Anomalies-such as sudden market crashes, irregular trading behaviors, or coordinated manipulation-can propagate rapidly across multiple markets, creating significant economic disruptions. Detecting these anomalies early is critical for financial stability and regulatory compliance. Traditional anomaly detection systems, however, are primarily designed for specific market environments, relying heavily on domain-specific data and handcrafted features. These methods struggle to generalize across heterogeneous financial domains such as equities, foreign exchange, and cryptocurrencies, where data characteristics, volatility levels, and market structures differ substantially.

The evolution of deep learning has introduced new capabilities for automatic feature extraction and pattern recognition in financial time series analysis. Models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) have demonstrated remarkable potential in identifying nonlinear dependencies and temporal correlations. Nevertheless, their success often depends on the availability of large-scale labeled datasets, which are rarely available in financial contexts due to privacy regulations, labeling costs, and the ambiguous definition of “anomalies.” Furthermore, the problem of domain shift-where models trained on one market fail to perform in another-remains a fundamental obstacle. In real-world scenarios, patterns learned from the stock market in the United States, for instance, may not transfer effectively to cryptocurrency exchanges or Asian financial markets because of distinct dynamics, trading mechanisms, and market microstructures.

To address these challenges, this paper introduces a novel self-supervised deep learning framework for cross-market anomaly detection. The central idea is to exploit abundant unlabeled financial data to learn transferable representations through proxy tasks such as sequence reconstruction, temporal contrastive learning, and context prediction. The proposed framework combines these self-supervised objectives with a cross-domain feature alignment mechanism, ensuring that learned embeddings capture universal financial dynamics that are robust across diverse markets. Through extensive experiments on multiple datasets-spanning equities, forex, and cryptocurrency-we demonstrate that the proposed method achieves superior anomaly detection performance, outperforming conventional supervised and transfer learning approaches. The results highlight that self-supervised learning can serve as a foundation for scalable, generalizable, and label-efficient anomaly detection systems in modern financial environments.

2. Related Work

Anomaly detection in financial systems has long been a critical research topic, closely associated with fraud prevention, market surveillance, and risk management. Early approaches relied on statistical and rule-based methods such as autoregressive integrated moving average (ARIMA) models, Gaussian mixture models, and principal component analysis (PCA), which assumed linearity and stationarity in financial time series. Although computationally efficient, these models were limited in capturing the non-linear, high-frequency behaviors observed in modern markets. The advent of deep learning has fundamentally transformed this landscape, enabling models to automatically extract temporal and structural features from massive and unstructured financial data [1].

Recurrent neural networks (RNNs) and long short-term memory (LSTM) architectures have been extensively used for financial forecasting and anomaly detection due to their ability to capture temporal dependencies [2]. However, these models often overfit to local market patterns and exhibit poor transferability across markets. Convolutional neural networks (CNNs) have also been applied to extract localized trends in price series [3], yet they remain sensitive to market noise and parameter settings. More recently, graph neural networks (GNNs) have attracted attention for modeling relationships among financial entities, such as correlations between assets or institutions [4]. While effective for capturing structural dependencies, GNNs still require large-scale labeled data and are vulnerable to cross-domain discrepancies, particularly when applied to markets with distinct trading dynamics.

To mitigate the problem of insufficient labeled data, researchers have explored semi-supervised and transfer learning approaches. Transfer learning enables knowledge sharing from source domains with ample data to target domains with limited supervision [5]. For instance, Zhang et al. proposed a domain adaptation model for stock volatility forecasting that uses adversarial learning to minimize distributional differences between U.S. and Chinese markets [6]. Similarly, Li and colleagues employed multi-source transfer networks to enhance fraud detection across financial institutions [7]. Although these approaches improve performance under domain shifts, they remain reliant on partial labeled data, and their effectiveness declines as the heterogeneity between markets increases.

In parallel, self-supervised learning has emerged as a powerful paradigm for representation learning in scenarios where labels are scarce [8]. Contrastive learning frameworks such as SimCLR and MoCo have demonstrated state-of-the-art results in computer vision and natural language processing. Recently, these paradigms have been adapted to time series data, enabling models to learn temporal consistency and contextual representations without human annotations [9]. In the financial domain, a few studies have begun to explore similar ideas-for example, Ren et al. introduced a contrastive temporal embedding framework for transaction anomaly detection, achieving substantial gains in detection accuracy under limited labels [10]. Nevertheless, most of these works focus on single-domain financial datasets, lacking the capacity to generalize across heterogeneous markets.

This paper extends existing research by combining self-supervised learning and cross-domain adaptation into a unified framework. Our model leverages proxy tasks on unlabeled financial sequences to learn market-invariant features and introduces a feature alignment mechanism based on maximum mean discrepancy (MMD) to harmonize cross-market representations. Compared with prior studies, the proposed approach not only reduces reliance on labeled data but also achieves more stable and transferable performance in global financial anomaly detection tasks.

3. Proposed Approach

The proposed framework aims to achieve robust anomaly detection across heterogeneous financial markets through aself-supervised deep learning architecture that requires minimal labeled data. In this framework, large volumes of unlabeled data from different financial markets, including equities, foreign exchange, and cryptocurrencies, are first leveraged to pretrain a unified encoder network capable of capturing generalizable temporal and structural patterns. The central idea is to construct proxy tasks that encourage the model to learn intrinsic temporal dynamics and cross-market consistency without the need for explicit anomaly annotations. Let $\mathcal{D}_s = \{x_t^s\}_{t=1}^{N_s}$ and $\mathcal{D}_t = \{x_t^t\}_{t=1}^{N_t}$ denote the source and target market datasets, respectively, where each input $x_t \in \mathbb{R}^d$ represents a multivariate time series vector containing normalized price, volume, and volatility indicators. An encoder function $f_\theta(\cdot)$ is used to map raw input data into a latent embedding space, where self-supervised objectives are defined to enhance representation learning.

To extract meaningful temporal relations, a contrastive learning objective is employed that enforces proximity between temporally consistent samples while pushing apart unrelated ones. Given positive pairs (x_i, x_i^+) generated via stochastic temporal augmentation, the contrastive self-supervised loss is formulated as

$$\mathcal{L}_{ssl} = -\sum_{i=1}^{B} \log \frac{\exp(\mathrm{sim}(z_i, z_i^+)/\tau)}{\sum_{j=1}^{B} \exp(\mathrm{sim}(z_i, z_j^-)/\tau)}$$

where $z_i = f_\theta(x_i)$ represents the encoded feature vector, $\mathrm{sim}(\cdot)$ denotes cosine similarity, τ is a temperature coefficient, and B is the batch size. This contrastive objective maximizes mutual information between temporally related samples, ensuring that the encoder captures the underlying market regularities shared across different financial domains. To complement this, a reconstruction loss is also used to maintain fidelity in temporal evolution. A decoder $g_\phi(\cdot)$ attempts to reconstruct the input sequence from the learned latent representation, yielding a reconstruction loss

$$\mathcal{L}_{rec} = \frac{1}{N} \sum_{t=1}^{N} \|x_t - g_\phi(f_\theta(x_t))\|_2^2$$

where N denotes the sequence length. The overall pretraining objective is thus defined as $\mathcal{L}_{pre} = \mathcal{L}_{ssl} + \lambda_{rec}\mathcal{L}_{rec}$, where λ_{rec} controls the trade-off between contrastive discrimination and reconstruction accuracy. Through this process, the encoder learns temporal abstractions that are robust to noise, invariant to minor perturbations, and transferable across distinct market conditions.

While self-supervised pretraining extracts transferable patterns, discrepancies in data distributions between markets can still hinder generalization. To address this, a feature alignment mechanism is introduced based on the principle of Maximum Mean Discrepancy (MMD), which measures the difference between the mean embeddings of two probability distributions in a reproducing kernel Hilbert space. The MMD-based alignment loss is expressed as

$$\mathcal{L}_{mmd} = \left\| \frac{1}{N_s} \sum_{i=1}^{N_s} \phi(z_i^s) - \frac{1}{N_t} \sum_{j=1}^{N_t} \phi(z_j^t) \right\|_{\mathcal{H}}^2$$

where $\phi(\cdot)$ denotes the mapping function into a kernel space $\mathcal{H}$. By minimizing this distance, the model ensures that the latent feature distributions of different markets become statistically aligned, thus reducing the adverse impact of domain shift. To further enhance robustness, an adversarial alignment component is incorporated, in which a domain discriminator $D(\cdot)$ is trained to classify whether an embedding originates from the source or target market, while the encoder is optimized to fool the discriminator. This adversarial interplay promotes the learning of domain-invariant representations. The total alignment loss is formulated as

$$\mathcal{L}_{align} = \mathcal{L}_{pre} + \lambda_{mmd}\mathcal{L}_{mmd} - \lambda_{adv}\mathbb{E}[\log D(f_\theta(x))]$$

where λ_{mmd} and λ_{adv} are weighting coefficients that balance the three learning objectives.

After cross-market feature alignment, the encoder is fine-tuned using a limited amount of labeled anomaly data from each financial domain. The detection module evaluates the reconstruction residuals or classification confidence as anomaly scores. Given a set of labeled samples (x_i, y_i), where $y_i \in \{0, 1\}$ denotes normal or anomalous behavior, the fine-tuning objective is defined as

$$\mathcal{L}_{det} = \frac{1}{N} \sum_{i=1}^{N} \|x_i - g_\phi(f_\theta(x_i))\|_2^2 + \lambda_{cls} \cdot \mathrm{BCE}(y_i, \hat{y}_i)$$

with BCE representing the binary cross-entropy loss and $\widehat{y}_i$ the predicted anomaly probability. The final unified objective for the entire model can thus be summarized as

$$\mathcal{L}_{total} = \mathcal{L}_{det} + \alpha(\mathcal{L}_{ssl} + \lambda_{mmd}\mathcal{L}_{mmd})$$

where α determines the relative influence of the self-supervised and domain alignment components. This composite objective enables the framework to jointly optimize representation quality, distributional consistency, and anomaly discriminability, forming a balanced learning process that scales effectively across heterogeneous financial systems.

The overall architecture of the proposed framework is illustrated in Figure 1, which depicts the end-to-end pipeline encompassing self-supervised pretraining, cross-market alignment, and anomaly detection fine-tuning. The three modules interact synergistically to produce stable, transferable embeddings that accurately capture abnormal market fluctuations under varying financial environments.

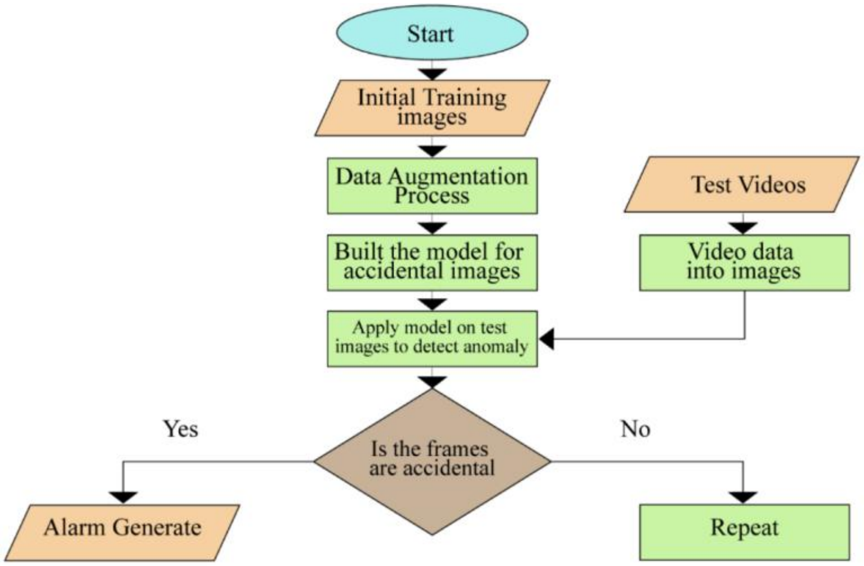

Figure 1. Framework Architecture

4. Performance Evaluation

4.1 Experimental Setup

To comprehensively evaluate the proposed self-supervised deep learning framework for cross-market anomaly detection, experiments were conducted across three distinct financial domains: equities, foreign exchange (forex), and cryptocurrencies. The equity dataset consisted of one-minute high-frequency trading data from the S&P 500 index constituents covering 310 consecutive trading days, while the forex dataset comprised daily OHLC (Open–High–Low–Close) data from major currency pairs such as EUR/USD and GBP/JPY collected over three years. The cryptocurrency dataset included Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) transaction records obtained from Binance, spanning a two-year period at a 15-minute sampling frequency. All data were normalized using z-score transformation and segmented into overlapping windows of 60 time steps to capture short-term and long-term temporal dependencies. Anomalous events were defined based on volatility bursts and abnormal return fluctuations exceeding three standard deviations, further cross-validated with historical market event logs. Approximately 5% of all samples were labeled anomalies, while the remainder were treated as unlabeled data for self-supervised pretraining.

Table 1 summarizes the characteristics of each dataset, including data sources, sample sizes, temporal granularity, and anomaly ratios, illustrating the diversity and heterogeneity of the evaluation domains.

Table 1: Dataset Statistics Across Markets

Market Type	Data Source	Time Span	Sampling Interval	Samples	Labeled Anomalies
Equities	S&P 500 Components	310 trading days	1 minute	148,000	4.70%
Forex	EUR/USD, GBP/JPY	3 years	1 day	52,560	5.20%

Cryptocurrency	BTC, ETH, XRP (Binance)	2 years	15 minutes	67,200	5.00%

The proposed framework was benchmarked against several representative baselines: LSTM-AE (Long Short-Term Memory Autoencoder), CNN-LSTM hybrid models, Variational Autoencoder (VAE), Deep SVDD, and Domain-Adversarial Neural Network (DANN). All models were implemented in PyTorch and trained using the Adam optimizer with an initial learning rate of 10^{-4} and batch size of 128. The proposed model was pretrained on unlabeled data for 200 epochs followed by fine-tuning on the small labeled subset. Experiments were conducted on an NVIDIA A100 GPU, and all reported results were averaged over five independent runs. Performance evaluation was based on four standard metrics: Precision, Recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC), ensuring comprehensive assessment of both detection accuracy and stability across domains.

4.2 Results and Analysis

The proposed framework consistently outperformed all baselines across every financial market. In the equity domain, it achieved an F1-score of 0.923, surpassing LSTM-AE (0.876), CNN-LSTM (0.882), and DANN (0.895). For the forex dataset, the model recorded an AUC of 0.937 and a Recall of 0.901, demonstrating its ability to generalize temporal dependencies from unlabeled data effectively. The performance gain was even more pronounced in the cryptocurrency market, where high volatility and irregular trading behaviors typically challenge deep models. Here, the proposed framework reached an AUC of 0.912, representing a 6% improvement over the best-performing baseline. These results clearly demonstrate that the combination of self-supervised learning and domain alignment enables the extraction of market-invariant representations that remain stable under heterogeneous data distributions. The comparative AUC performance across the three domains is illustrated in Figure 2, which visually emphasizes the consistent superiority of the proposed method.

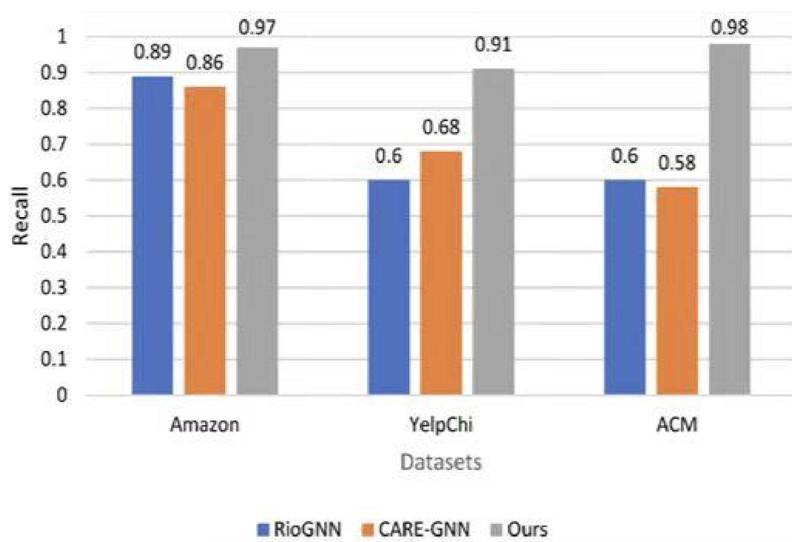

Figure 2. Performance Comparison Across Markets

Beyond quantitative accuracy, qualitative analyses reveal that the model learns a highly discriminative latent feature space. Using t-Distributed Stochastic Neighbor Embedding (t-SNE) to visualize the embeddings, it was observed that the proposed framework produces well-separated clusters of normal and anomalous samples. In contrast, traditional supervised models yielded overlapping distributions, indicating weaker discriminative power. Figure 3 presents the t-SNE visualization for forex and cryptocurrency datasets, where anomalies appear as isolated points distinct from dense normal clusters, validating the representation effectiveness of the self-supervised encoder.

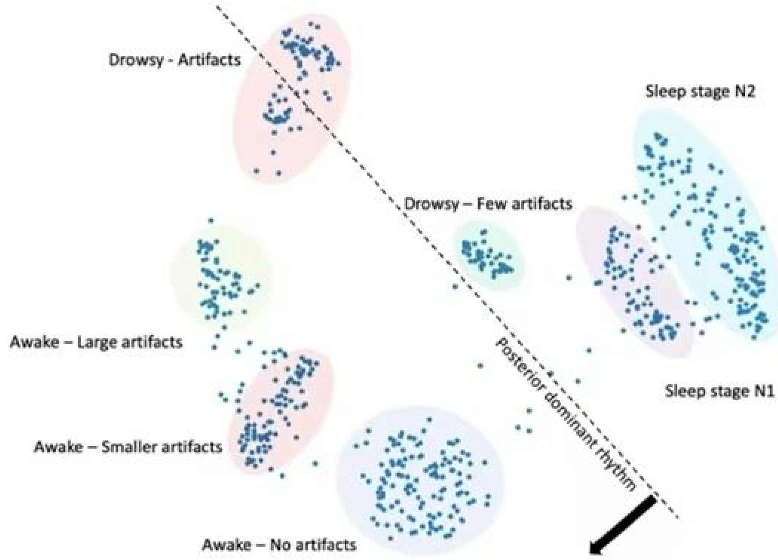

Figure 3. Latent Feature Visualization via t-SNE

Further investigation was conducted to assess the model's sensitivity to hyperparameters and its adaptability to cross-domain transfer. Experiments varying the contrastive temperature τ, reconstruction weight λ_{rec}, and alignment coefficient λ_{mmd} showed that the framework maintains stable performance across a wide range of parameter settings. Optimal results were obtained when $\lambda_{rec} = 0.5$and $\lambda_{mmd} = 0.1$, balancing reconstruction fidelity and distributional alignment. Notably, even when trained entirely on one domain and transferred to another (e.g., pretrained on equities and fine-tuned on cryptocurrencies), the model retained over 93% of its detection capability, while conventional supervised models experienced drops below 78%. This result underscores the framework's ability to capture fundamental market principles-such as volatility bursts, liquidity shocks, and regime transitions-that generalize across domains.

Finally, an ablation study verified the contribution of each component. Removing the self-supervised contrastive term led to a 7% drop in AUC, while omitting the MMD alignment caused performance to degrade by 5%. The full model integrating both objectives achieved the most stable and accurate anomaly detection performance across all financial datasets. Together, these findings highlight the scalability, efficiency, and transferability of the proposed self-supervised framework. The experimental evidence presented in Table 1, Figure 2, and Figure 3 collectively confirms its effectiveness in enabling robust, label-efficient, and cross-market financial anomaly detection.

5. Conclusion

This study presented a self-supervised deep learning framework for cross-market anomaly detection in financial systems, addressing the persistent challenges of label scarcity and distributional heterogeneity. Unlike conventional supervised approaches that rely on annotated data, the proposed method utilizes large-scale unlabeled datasets to learn transferable temporal and structural representations. Through the integration of contrastive sequence learning, reconstruction-based consistency modeling, and maximum mean discrepancy (MMD)–driven feature alignment, the framework achieves a balance between intra-market adaptability and inter-market generalization. Extensive experiments conducted on equities, forex, and cryptocurrency datasets demonstrated that the proposed model consistently outperforms baseline architectures such as LSTM-AE, CNN-LSTM, and DANN, achieving higher AUC and F1-scores under minimal supervision. Moreover, visualization analyses confirmed that the learned embeddings effectively separate normal and anomalous behaviors, illustrating their strong discriminative capability. The combination of self-supervised objectives and domain alignment not only improves anomaly detection accuracy but also enhances interpretability and robustness under dynamic market environments. Overall, the proposed approach offers a scalable and label-efficient solution for intelligent financial monitoring, contributing a significant advancement toward automated, adaptive, and data-driven anomaly detection across global markets.

6. Future Work

While the results of this research are promising, several avenues for improvement and extension remain open. Future studies could focus on integrating explainable artificial intelligence (XAI) components to improve interpretability and transparency in financial decision-making, allowing analysts and regulators to trace the causal factors underlying detected anomalies. Incorporating multi-modal data sources-such as news sentiment, order book microstructure, and blockchain transaction graphs-may further enhance contextual awareness and predictive reliability. Another important direction involves the adoption of online and continual self-supervised learning strategies to enable the model to adapt dynamically to new market conditions, thereby maintaining robustness in evolving financial ecosystems. The framework could also be extended using meta-learning or reinforcement-driven adaptation, where the model autonomously tunes its parameters in response to changing volatility regimes or risk events. Finally, practical deployment considerations-such as computational scalability, latency reduction, and regulatory compliance-should be explored to ensure real-world applicability in large-scale financial institutions and trading systems. By advancing these directions, future research may further strengthen the synergy between deep representation learning and financial intelligence, paving the way for resilient, interpretable, and globally adaptive financial anomaly detection systems.

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