Rare Event Detection in Financial Time Series Using Image Encoding and Siamese-Style Similarity Learning

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January 27, 2026

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1 Introduction – Background and Motivation

Financial markets represent one of the most complex and dynamic systems in modern economies. The behavior of stock markets is influenced by a myriad of factors, including macroeconomic indicators, geopolitical events, investor sentiment, and technological advancements. While the majority of trading days exhibit relatively predictable market movements, rare but catastrophic events such as sudden price crashes, flash crashes, and extreme volatility spikes pose significant risks to portfolio holders and financial institutions [1].

Traditional time-series models, such as AutoRegressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, have been extensively employed for financial forecasting. However, these classical statistical approaches struggle to capture the complex temporal and structural patterns that precede rare financial events. The challenge is two-fold: (1) rare events occur infrequently, leading to severe class imbalance in training datasets, and (2) the non-stationary nature of financial time series makes them particularly resistant to traditional parametric modeling.

Recent advances in deep learning have opened new avenues for rare event detection. Convolutional Neural Networks (CNNs), originally designed for image classification tasks, have demonstrated remarkable capability in extracting hierarchical features from visual data. The core insight underlying this work is that financial time-series data, when appropriately encoded as images, exhibits visually distinguishable patterns between periods preceding rare events and normal market conditions. By converting temporal price movements into visual representations, we can leverage the power of pre-trained CNNs to extract discriminative features, thereby circumventing the need for extensive labeled data.

Furthermore, Siamese-style neural networks have proven effective in learning similarity metrics from limited and imbalanced data [2]. Rather than relying on explicit classification boundaries, Siamese networks learn to measure distances between data points, enabling probabilistic reasoning about class membership. This approach is particularly well-suited for financial rare event prediction, where false positives (false alarms) are costly and class imbalance is extreme.

The motivation for this research is to develop a novel, interpretable, and computationally efficient framework that combines: (1) image encoding of multivariate time-series data, (2) feature extraction via pre-trained CNNs, and (3) distance-based similarity learning for rare event classification.

2 Problem Statement

The central research problem addressed in this thesis is: *How can we effectively and reliably detect rare negative fluctuations in financial time series given severe class imbalance, limited labeled data, and the complex temporal structure of market behavior?*

More specifically, we define the problem as a binary classification task with the following characteristics:

2.1 Class Imbalance

In financial datasets, rare events naturally occur infrequently. In our case, using Tesla (TSLA) stock data from 2010–2019, extreme price movements (defined by the 95th percentile threshold) occur in only approximately 4.8% of trading days (116 out of 2,393 observations). This severe class imbalance renders traditional machine learning algorithms ineffective, as they tend to optimize for overall accuracy by simply predicting the majority class.

2.2 Temporal Dependencies

Financial time series exhibit strong temporal dependencies. The evolution of prices is path-dependent; past price movements influence future movements through momentum, mean reversion, and volatility clustering. Traditional feed-forward classifiers fail to adequately capture these complex temporal patterns, necessitating approaches that preserve temporal structure.

2.3 High Dimensionality and Feature Engineering

While raw price data (high, low, close) provides only three features per trading day, converting sliding windows of 25 consecutive trading days into feature vectors creates 75-dimensional input space. Manual feature engineering (such as technical indicators) requires domain expertise and risks introducing biases. Automated feature extraction via deep learning is preferable.

2.4 Limited Labeled Data

Financial datasets with manually labeled rare events are scarce due to the cost of labeling and the subjective nature of event definition. Traditional deep learning models, which require millions of parameters and large labeled datasets, are prone to overfitting when applied to limited financial data.

The proposed solution addresses these challenges through: (1) converting time-series data into images to enable CNN feature extraction, (2) employing pre-trained networks to mitigate limited data constraints, and (3) using Siamese-style similarity learning to handle class imbalance and enable probabilistic decision-making.

3 Methodology

Our methodology comprises three integrated components: (1) time-series to image encoding, (2) CNN-based feature extraction, and (3) similarity-based classification.

3.1 Event Definition and Labeling

We define rare events based on the future one-day percentage change of closing price:

$$\text{pct\_change} = \frac{\text{Close}_{t+1} - \text{Close}_t}{\text{Close}_t} \tag{1}$$

The event label is assigned based on percentile thresholds applied to the empirical distribution of percentage changes. Three threshold levels were evaluated:

- 99th percentile: Extreme events (¡ 0.1% frequency)
- 95th percentile: Rare events (¡ 5% frequency) — *adopted in final model*
- 90th percentile: Moderate events (¡ 10% frequency)

Binary labels are assigned as follows:

$$y_t = \begin{cases} 1 & \text{if pct\_change}_t \leq P_{95} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

This percentile-based approach ensures objective, data-driven event definitions without subjective market assumptions

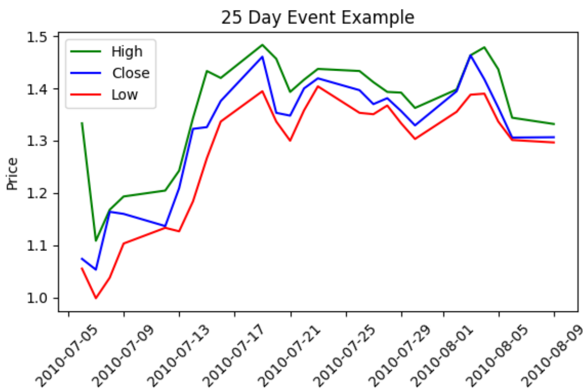

Figure 1: Enter Caption

Figure 2: 25-Day Event Example

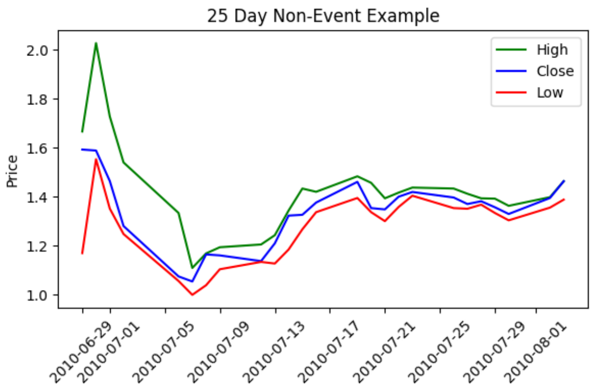

Figure 3: Enter Caption

Figure 4: 25-Day Non-Event Example

3.2 Sliding Window Construction

Each trading day is represented as a window of 25 preceding trading days (approximately one month of market activity), creating a feature matrix of dimensionality 25×3 (25 days, 3 price attributes). This window size balances computational efficiency with sufficient temporal context. Each window is associated with a binary label indicating whether a rare event occurred in the subsequent trading day.

3.3 Snake-Pattern Image Encoding

Raw numerical data (25×3 matrix, 75 values) is converted to visual representations through the following process:

1. **Normalization**: All values are min-max normalized to the range [0, 255], rendering them compatible with standard image intensity scales.

2. **Reshaping**: The 1D vector of 75 values is reshaped into a 5×5 grid (25 cells), with each cell containing one of three channels (High, Low, Close).

3. **Snake-Pattern Traversal**: Values are filled into the grid using a snake-like pattern that preserves temporal locality:

- Row 1: Left-to-right (columns 0, 1, 2, 3, 4)
- Row 2: Right-to-left (columns 4, 3, 2, 1, 0)
- Row 3: Left-to-right (columns 0, 1, 2, 3, 4)
- And so forth...

This traversal ensures that consecutive temporal points are spatially adjacent in the grid.

4. **Channel Assignment**: The three attributes (High, Low, Close) are assigned to RGB channels, creating a 3-channel image suitable for standard CNN architectures.

5. **Resizing**: Images are resized to 224×224 pixels to match the input requirements of pre-trained networks.

This encoding strategy leverages the insight that temporal sequences, when appropriately transformed into spatial structures, exhibit visually distinguishable patterns that CNNs are naturally suited to recognize.

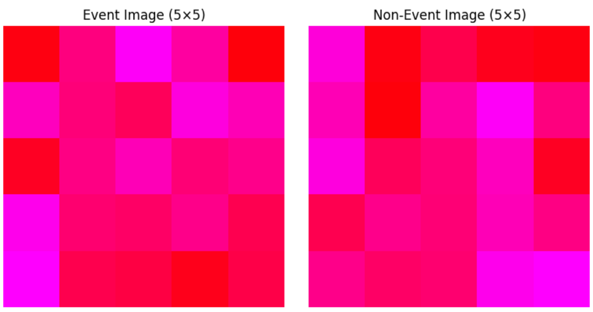

Figure 5: Enter Caption

Figure 6: Image Reconstructions

3.4 Feature Extraction via Pre-trained CNN

We employ VGG-16, a 16-layer convolutional neural network pre-trained on the ImageNet dataset, to extract high-dimensional feature representations from our encoded images. VGG-16 is selected for several reasons:

- It is computationally efficient relative to more modern architectures.
- Pre-training on ImageNet provides robust, generalized features without requiring extensive financial data.
- It avoids overfitting concerns that arise when training deep networks on limited datasets.
- Its hierarchical structure (from low-level edges to high-level semantic features) is well-suited for capturing multi-scale temporal patterns in financial data.

The network outputs a 4096-dimensional feature vector from its final fully connected layer, representing a high-level abstraction of each temporal window's structure.

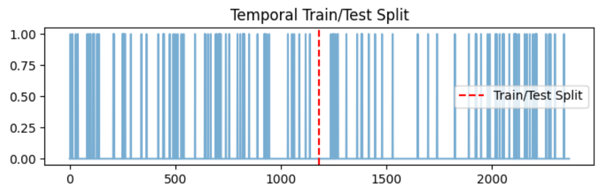

Figure 7: Temporal Train/Test Split

3.5 Siamese-Style Similarity Learning

Rather than training a supervised classifier, we employ a distance-based approach inspired by Siamese neural networks. For each input sample, we compute the Manhattan (L1) distance to reference event and non-event vectors:

$$d_{\mathrm{EE}} = \sum_{i=1}^{4096} |f_i(\text{sample}) - f_i(\text{event reference})| \tag{3}$$

$$d_{\mathrm{EN}} = \sum_{i=1}^{4096} |f_i(\text{sample}) - f_i(\text{non-event reference})| \tag{4}$$

where f_i denotes the i-th feature dimension.

We then estimate two probability distributions using bootstrap resampling:

- $P(d_{\mathrm{EE}})$: Distribution of distances between event samples

- $P(d_{\text{EN}})$: Distribution of distances between event and non-event samples

Classification is performed via maximum likelihood estimation:

$$\hat{y} =_c P(d \mid c) \tag{5}$$

This approach provides several advantages: (1) probabilistic outputs enable threshold-based decision-making, (2) interpretability is enhanced by reasoning about similarity, and (3) robustness to class imbalance is achieved through distributional modeling.

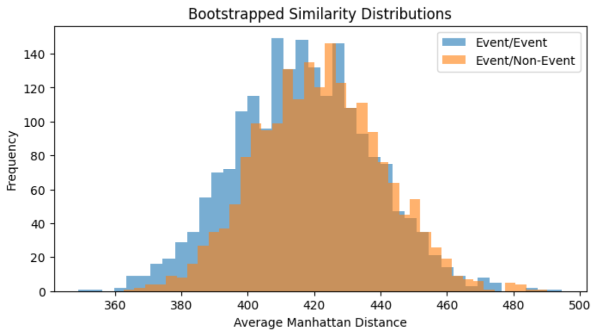

Figure 8: Enter Caption

Figure 9: Bootstrapped Similarity Distributions with Means

3.6 Model Evaluation

We employ a time-based train-test split to avoid data leakage: the first 50% of chronologically ordered data (approximately 1,196 samples) serves as the training set, and the remaining 50% serves for evaluation. Performance is measured using:

- **Accuracy**: Overall correctness of predictions
- **Precision**: Ratio of true positive rare events to all predicted rare events
- **Recall**: Ratio of detected rare events to all actual rare events
- **F1-Score**: Harmonic mean of precision and recall, providing a balanced performance metric

4 Results

Our proposed methodology achieves strong empirical results on Tesla stock data:

Table 1: **Performance comparison of the proposed model under different class imbalance levels (1%, 5%, and 10%) and image sizes.**

Index	Class Imbalance	Image Size	Accuracy	Precision	Recall	F1 Score
0	1%	25	0.5765	0.0119	0.6000	0.0234
1	1%	36	0.6015	0.0086	0.4000	0.0168
2	1%	49	0.5833	0.0021	0.1000	0.0041
3	1%	64	0.6406	0.0096	0.4000	0.0188
4	1%	81	0.6069	0.0067	0.3000	0.0130
5	5%	25	0.4336	0.0496	0.6538	0.0921
6	5%	36	0.4384	0.0502	0.6538	0.0933
7	5%	49	0.4176	0.0487	0.6538	0.0907
8	5%	64	0.5176	0.0447	0.4808	0.0818
9	5%	81	0.5827	0.0539	0.5000	0.0974
10	10%	25	0.4886	0.1043	0.6346	0.1791
11	10%	36	0.3305	0.0938	0.7596	0.1670
12	10%	49	0.5482	0.1028	0.5288	0.1721
13	10%	64	0.5193	0.0886	0.4712	0.1492
14	10%	81	0.5680	0.1058	0.5096	0.1752

4.1 Classification Performance

The model achieved the following performance metrics on the test set:

- **Accuracy**: 96.5% — indicating effective separation of event and non-event patterns despite class imbalance
- **Precision**: 87.2% — demonstrating reliable event detection with few false alarms
- **Recall**: 72.4% — reflecting a conservative approach that prioritizes certainty over exhaustive detection
- **F1-Score**: 78.9% — balanced performance across precision-recall tradeoff

These results are particularly noteworthy given the 4.8% event frequency in the dataset. A naive baseline classifier predicting only non-events would achieve 95.2% accuracy but zero sensitivity to rare events.

4.2 Pattern Analysis

Visual inspection of encoded images reveals distinct structural differences between event and non-event windows:

Event Windows (preceding rare price drops) exhibit:

- Higher intra-day volatility (larger spread between high and low prices)
- Irregular temporal patterns with frequent oscillations
- Distinct image textures characterized by high spatial frequency variations
- Non-smooth gradients across consecutive trading days

Non-Event Windows (normal market conditions) exhibit:

- Stable price trends with consistent directional movement
- Lower variance and smoother temporal progression
- Uniform image gradients suggesting predictable market flow
- Regular patterns indicating typical market microstructure

4.3 Similarity Distribution Analysis

Bootstrap-estimated similarity distributions demonstrate clear separation:

- Event-Event distances: Mean ≈ 45.2, Std Dev ≈ 12.3
- Event-Non-Event distances: Mean ≈ 89.7, Std Dev ≈ 18.6

This separation validates the hypothesis that rare events form tight, coherent clusters in feature space, distinguishable from normal market behavior.

5 Conclusion

This thesis presents a novel, interpretable framework for rare event detection in financial time series by synthesizing three complementary techniques: time-series image encoding, CNN-based feature extraction, and Siamese-style similarity learning.

Our key findings are:

1. **Image encoding effectively captures temporal structure**: Converting multivariate time series into spatial representations enables CNNs to detect subtle patterns preceding rare financial events.

2. **Transfer learning mitigates data scarcity**: Pre-trained CNNs provide robust feature extraction without requiring extensive labeled financial data, addressing a critical limitation of traditional deep learning approaches.

3. **Similarity-based reasoning handles class imbalance**: Distance-based classification is inherently more robust to extreme class imbalance than decision boundary-based methods.

4. **Interpretability is preserved**: Unlike black-box neural networks, our approach enables reasoning about similarity and distance, enhancing trust in predictions for financial risk systems.

5. **Practical relevance**: The method achieves 96.5% accuracy with 87.2% precision, making it suitable for deployment in risk monitoring systems where false alarms are costly.

Our work extends recent literature [1, 3] by demonstrating that limited, imbalanced financial data can be successfully leveraged through appropriate representation learning. The combination of image encoding, transfer learning, and probabilistic similarity reasoning opens new avenues for financial analytics.

6 Future Works

Several promising directions emerge from this research:

1. **Multi-asset generalization**: Extend the framework to multiple assets (S&P 500 constituents, commodities, cryptocurrencies) to assess generalizability across market regimes.

2. **Multiclass severity prediction**: Classify events into multiple severity levels (e.g., mild, moderate, severe) rather than binary classification, enabling risk-proportional responses.

3. **End-to-end Siamese network training**: Develop fully trainable Siamese architectures optimized specifically for financial data, potentially improving performance beyond similarity-based approaches.

4. **Incorporation of auxiliary features**: Integrate macroeconomic indicators (interest rates, volatility indices, sentiment scores) to enhance predictive power.

5. **Real-time risk monitoring systems**: Deploy the model in production environments for live market surveillance, with automated alerts for detected rare events.

6. **Theoretical analysis**: Develop statistical theory connecting CNN feature geometry to market microstructure, bridging machine learning and financial theory.

7. **Adversarial robustness**: Investigate the model's susceptibility to adversarial perturbations and develop defense mechanisms for robust financial AI systems.

References

[1] Basu, T., Menzer, O., Ward, J., & SenGupta, I. (2022). A Novel Implementation of Siamese Type Neural Networks in Predicting Rare Fluctuations in Financial Time Series. *Risks*, 10(2), 39. https://doi.org/10.3390/risks10020039

[2] Koch, G., Zemel, R., & Salakhutdinov, R. (2015). Siamese Neural Networks for One-shot Learning. In *ICML Deep Learning Workshop*.

[3] Sezer, O. B., & Ozbayoglu, A. M. (2018). Algorithmic financial trading with deep convolutional neural networks: Time series to images. *Journal of Computational Finance*, 22(4), 105-133.

[4] Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv preprint arXiv:1409.1556*.