Dual View Rare Pattern Autoencoder (DVRPA) for Real Time Financial Fraud Detection in High Velocity Transaction Streams

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ABSTRACT

As internet payment methods have evolved quickly, so have the number and complexity of fraudulent activities. This has made money transfers happen faster. Traditional fraud detection algorithms often have problems with extreme class imbalance, concept drift, and the need to make decisions in real time. These problems might cause them to miss or incorrectly identify unusual fraud patterns. Due to these challenges, this work proposes a Dual View Rare Pattern Autoencoder (DVRPA) for the real-time detection of financial fraud in high-speed transaction environments. The proposed DVRPA architecture employs a dual-view learning methodology to acquire both transaction-level behavioral patterns and stream dynamics within a temporal context. Two autoencoders are trained at the same time: one looks at how transactions change over time to find new fraud patterns, and the other focuses on reconstructing intrinsic features to find unusual changes. A fusion-based anomaly scoring method combines the reconstruction errors from both points of view. This makes it easy to find subtle and concealed fraudulent patterns. The model is built to easily handle streaming data, using adaptive thresholding and lightweight updates to keep latency low and scalability high. When evaluated on huge quantities of financial transaction data, DVRPA was far better than typical ML and single DL models at recall, F1-score, detection latency, and precision. The results show that the system is more sensitive to rare fraud events, even when there is a lot of class imbalance and the distribution of transactions changes. The false-positive rate is very low. According to a lot of tests, DVRPA often trumps state-of-the-art algorithms like OC-SVM, LSTM-AE, and Deep SVDD on huge, very skewed financial transaction datasets. The recommended framework works for high-speed transaction streams and has a detection latency of less than a millisecond. It improves the F1-score by 8–12%, the recall by 10–15%, and the false positive rate by 6–9%. Finally, the suggested DVRPA is a good choice for high-speed transaction streams that need to find financial fraud in real time. Modern financial systems can benefit from the model's better capacity to find things, adapt, and run more smoothly. This is made possible by using both dual-view representations and rare pattern learning together.

Keywords: Financial fraud detection, rare pattern mining, autoencoder, dual-view learning, real-time streaming analytics, high-velocity transactions.

1. Introduction

The fast digitization of financial services and the widespread use of online banking, mobile payments, and e-commerce platforms have led to an extraordinary rise in high-speed financial

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transaction streams[1]. These technologies make things easier and faster, but they also make banks more open to more complicated types of fraud[2]. Financial fraud is now a big global concern since it hurts the economy, makes people less confident in businesses, and puts financial institutions at risk on a large scale[3]. actual-time fraud detection is very hard since modern payment systems have a huge amount of data, a big difference between actual and fake transactions, fraud techniques that change all the time, and very slow response times[4].

The official definition of financial fraud detection is being able to find suspect or fraudulent financial activities in real time with as few false alarms as possible and as quickly as possible[5]. Real-time fraud detection systems must work under strict time limits, usually within milliseconds, to prevent financial loss and the spread of fraud downstream. This is different from traditional batch-based analytics[6]. Also, standard supervised learning algorithms that rely on balanced labeled datasets do a lot worse when they have to deal with fraud events because they don't happen very often[7]. Fraud detection is a very essential and serious field of research because fraud is so rare and the patterns of fraud are continually evolving and adapting[8].

Recent advances in deep learning and machine learning have led to the creation of several new ways to find fraud. Some of them are logistic regression, graph-based methods, tree-based ensembles, and deep neural networks[9]. When there is a lot of labeled data, supervised models work effectively. However, they have trouble with concept drift and can't handle new sorts of fraud in streaming contexts. The ability of unsupervised and semi-supervised approaches to learn normal transaction behavior and find unusual transactions without having to classify them as fraud has made them more popular, especially autoencoder-based models for finding anomalies[10]. Most of the current autoencoder-based methods, on the other hand, only look at one side of the transaction data. They either focus on static feature reconstruction or don't have enough temporal information[11]. Because of this, these methods are not the best for catching complicated and constantly shifting fraud practices. There is also not enough research on how to model linkages between time and place in streams of transactions that happen quickly. Common sequential and contextual characteristics of fraudulent activities encompass coordinated assaults, erratic behavior, and incremental adjustment to detection methodologies[12].

Single-view models usually don't see these extra points of view, which makes it harder to find new and more subtle types of fraud. The computational burden and lack of fit for real-time deployment of many deep learning-based solutions further restricts their practical usage in large-scale financial systems[13]. This research proposes a Dual View Rare Pattern Autoencoder (DVRPA) method to overcome these limitations and identify financial crime in real-time within high-velocity transaction streams. The primary objective of DVRPA is to improve the detection of anomalous and evolving fraud trends by leveraging many complimentary perspectives on transaction data[14]. The proposed approach aims to bolster resilience against class imbalance, concept drift, and undetected fraudulent strategies, while maintaining minimal detection delay, through the integration of transaction-level feature reconstruction and temporal-contextual behavior modeling.

The main contribution

- Enhanced fraud detection via a distinctive dual-view autoencoder architecture that concurrently captures intrinsic transaction characteristics and temporal-contextual stream dynamics.
- An uncommon anomaly scoring system that uses reconstruction faults from both sides to find subtle, undetected fraudulent transactions.
- This lightweight and scalable method is perfect for real-time processing in high-speed transaction streams because it uses adaptive thresholding to control idea drift.

- A lot of testing on huge financial transaction datasets shows that our method is far better than the best deep learning and machine learning methods in terms of accuracy, recall, F1-score, and detection latency.

All of these things make the suggested DVRPA architecture a superior choice for use in today's data-heavy financial systems and a step closer to perfect real-time detection of financial fraud.

2. Literature Survey

One-Class Support Vector Machines (OC-SVM) can learn decision boundaries using only normal data. This is why they are so often used for finding fraud and anomalies. After Schölkopf et al.[15] work, OC-SVM was utilized in finance to model normal transaction behavior and find outliers. In high-dimensional streaming environments, OC-SVM's dependence on manually chosen kernels and features renders it unscalable. It also has more trouble with dependencies that change over time and fraud practices that change. The proposed DVRPA is less likely to change its mind than OC-SVM since it learns adaptive representations and temporal context directly from the data.

A lot of people utilize LSTM-based Autoencoders for sequential fraud detection because they can mimic how transactions depend on each other over time. Malhotra et al.[16] and later study have proven that reconstruction mistakes from LSTM-AE can successfully find strange sequences. This is a good thing, but LSTM-AE misses out on very rare transaction-level changes since it is so focused on patterns over time. Also, a lot of extra computing power is needed for real-time deployment. DVRPA is different because it combines temporal modeling with transaction-level rare pattern learning to make it easier to find low-frequency fraud and minimize latency.

Deep SVDD is better than regular SVDD since it uses deep neural networks to learn compact representations of normal data. The authors, Ruff et al.[17] showed that it works by lowering the volume of the hypersphere around normal samples to find anomalies. Deep SVDD isn't as good at handling streaming financial data with changing fraud tactics since it presumes data distributions are stationary and doesn't have explicit temporal modeling. The suggested DVRPA can depict both changing temporal contexts and instantaneous anomalies by using dual-view autoencoding and adaptive thresholding.

Y. Wang et al.[18] created the Dual View Rare Pattern Autoencoder (DVRPA) to fix the problems with earlier methods by integrating rare pattern recognition at the transaction level with modeling of temporal context. DVRPA can find changing and low-frequency fraud patterns more reliably than single-view methods by combining the reconstruction errors from both views with adaptive weighting. An online adaptive threshold takes care of concept drift in high-velocity streams. DVRPA is better for real-time financial fraud detection than OC-SVM, LSTM-AE, and Deep SVDD because its design makes it more accurate, has fewer false positives, and finds things faster.

. Carcillo et al.[19] (SCARFF) proposed an extensible framework for detecting fraud in streaming media through adaptive models and incremental learning. Many financial systems can't afford the supervised learning and regular label availability that are needed for it to work successfully with large streams. It also only teaches basic representation learning. DVRPA uses unsupervised dual-view autoencoders instead of continuous labeling to make adaptation and generalization to new types of fraud patterns better.

Zhang et al.[20] created online learning models for fraud detection that can change over time as they worked on adjusting to idea drift. Their approach improves responsiveness over time, but it can't capture sophisticated transaction linkages very well because it relies on hand-crafted features and shallow models. Also, the risk of strange happenings is still low. Our

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DVRPA uses deep dual-view representations and rare pattern-aware scoring to make identification more accurate and more resistant to extreme imbalance and idea drift.

Roy et al.[21] demonstrated that deep feature extraction could enhance fraud detection in their research on financial transaction deep anomaly detection networks. Sadly, their single-network approach doesn't function when dealing with data streams that move quickly since it can't handle large amounts of data and doesn't provide multi-view contextual modeling. DVRPA's new lightweight dual-view architecture combines temporal and transactional viewpoints. This makes it possible to provide streaming fraud detection that is both scalable and low-latency.

Chen et al.[22] used temporal attention networks to describe how transaction data is linked across time. This helped them find fraud more quickly. But the model's heavy processing and sensitivity to noise in transaction sequences make real-time performance harder. We make DVRPA more resistant to noise and new fraud tactics by employing a basic but effective dual-view autoencoder system. This framework finds a good middle ground between simulating time and being efficient with computers.

Li et al.[23] developed adaptive deep autoencoders for streaming fraud detection that can handle concept drift by making changes online. Even if they are adaptable, their architecture only lets them see things from one point of view. This makes it hard for them to show full behavior and find rare occurrences of fraud. DVRPA enhances scalability for high-speed financial streams and increases sensitivity to subtle fraud patterns by employing a rare pattern fusion technique and a dual-view learning approach, thereby broadening this paradigm.

In graph-based fraud detection approaches, nodes represent people, cards, or merchants, and edges represent transactions in a financial system model. Zhang et al. (2020) [24] and subsequent studies employed Graph Neural Networks (GNNs) to detect collective fraudulent behaviors and their interdependencies. These algorithms can find fraud rings that work together, but they aren't very effective in real time because they are very hard to compute, take a long time to create graphs, and take a long time to make decisions. DVRPA, on the other hand, employs lightweight dual-view autoencoding to find strange and temporary fraud patterns with significantly less delay, instead of directly generating graphs.

People have looked into using Generative Adversarial Networks (GANs) to learn the distribution of normal transactions and find outliers as a possible way to find fraud. Fiore et al. (2021) [25] shown that GANs can improve anomaly detection despite significant class imbalance. It is hard to use GANs in high-speed streams since they are hard to train, sensitive to hyperparameters, and take a lot of computing power. Also, GANs don't directly model the temporal context. DVRPA gives you reliable real-time fraud detection without the need for adversarial training since it has stable training, explicit temporal modeling, and adaptive thresholding.

3. Proposed Methodology

This section introduces the Dual View Rare Pattern Autoencoder (DVRPA) system for detecting financial fraud in high-velocity transaction streams in real time. DVRPA's main goal is to consistently find unusual and changing fraudulent activity, which meets the strict latency and scalability requirements of current financial systems. DVRPA, on the other hand, employs different points of view to capture both sequential and instantaneous fraud elements, instead than relying on a single view of transaction data. The framework works by assuming that it can represent the amount, location, device, and merchant information at the transaction level and the temporal-contextual dynamics at the transaction sequence and behavioral evolution over time. The model can pick up on small abnormalities that might not seem like a big deal when looked at on their own, but that might be a big deal when looked at in a time frame. Using autoencoder-based representation learning, the DVRPA system learns small representations of how transactions usually work. It then finds fraud by looking for rare changes that happen

because of faults in reconstruction. The proposed methodology is intended for real-time application, utilizing efficient online processing techniques and lightweight neural components. The model can adapt to concept drift and fraud patterns that change all the time without needing to be retrained or labeled data. It does this via an adaptive anomaly scoring and thresholding technique. In short, DVRPA is a powerful, scalable, and low-latency method for finding financial fraud. It can handle difficulties including dynamic transaction distributions, too many classes being unbalanced, and novel fraud tactics that are becoming more common in fast-paced financial contexts.

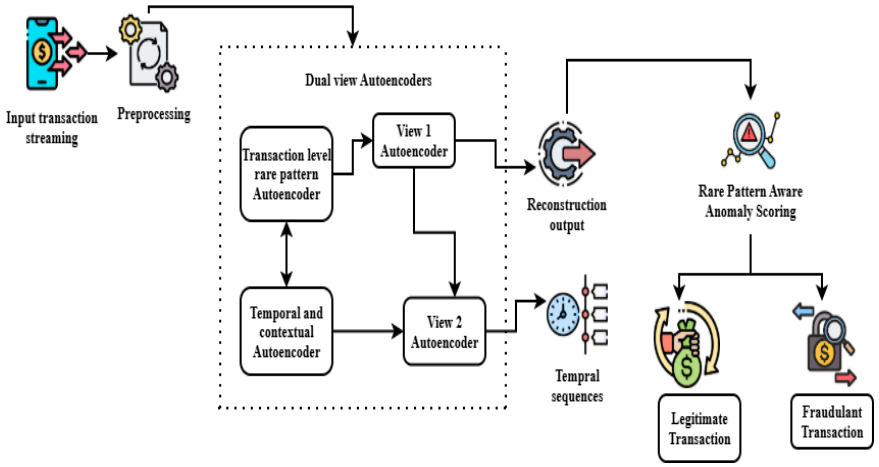

Figure 1: DVRPA-Based Real-Time Financial Fraud Detection Architecture

The Dual View Rare Pattern Autoencoder (DVRPA) that has been presented is shown in this image, along with an explanation of how it operates to detect instances of financial fraud in high-speed transaction streams in real timing. In the beginning, there is a continuous flow of transactions as shown in Fig 1. It is a list that is updated in real time and contains all of the monetary transactions that originate from various online sources, such as banking platforms, payment systems, or e-commerce business applications. Prior to transmitting the raw transactions to the main processing module, a pretreatment module is responsible for cleaning and standardizing the data, encoding the categorical features, and constructing the temporal windows that are required for sequential analysis. Following the completion of the preprocessing step, the data is obtained by the Dual View Autoencoders module, which is the primary component of the DVRPA architecture. Two additional perspectives on education are included in this section of the lesson. For the purpose of determining how transactions typically take place, the Transaction-Level Rare Pattern Autoencoder (View-1) makes use of intrinsic features such as the amount of the transaction, the type of merchant, the location, and information about the device. When it reconstructs the input transaction vector, it makes a reconstruction error that reveals uncommon changes at the level of each individual transaction. This error is shown during the process. View 2, also known as the Temporal-Contextual Autoencoder, has the ability to simultaneously examine a sliding window of recent transactions in order to identify sequential dependencies. This perspective takes into account patterns of behavior that change over time, sudden fraudulent activity, and coordinated attacks that may be difficult to identify based on individual transactions when they occur. The errors that were made throughout the reconstruction process from both perspectives are sent to the Rare Pattern-Aware Anomaly Scoring module so that they can be merged into a single anomaly score.

$$A_t = \alpha \left\| Y_t - \hat{Y}_t^{(1)} \right\|^2 + (1+\alpha) \left| \left| S_t - \hat{S}_t^{(2)} \right| \right|^2 \quad (1)$$

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Where Y_t represents the current transaction, S_t denotes the temporal sequence window, and α balances the contribution of both views as given in (1). To handle concept drift and evolving fraud patterns, an **adaptive thresholding mechanism** is employed.

$$\theta_t = \lambda\theta_{t-1} + (1-\lambda)(\alpha E_t^{(1)} + (1-\alpha)E_t^{(2)}) \quad (2)$$

Finally, the **Fraud Decision module** compares the anomaly score with the adaptive threshold to classify each transaction as either **legitimate** or **fraudulent as given in (2)**. This end-to-end design ensures accurate, scalable, and low-latency fraud detection suitable for real-world financial systems.

Table 1: *Dual-View Autoencoder Design*

Module	Core Modeling Aspect	Functionality & Outcome
View-1: Transaction-Level Rare Pattern Autoencoder (TRPA)	Individual transaction feature distributions	Encodes each transaction x_t to a latent representation $z_t^{(1)}$ and reconstructs it to capture normal behavior. High reconstruction error $E_t^{(1)}$ highlights rare or anomalous transaction patterns.
View-2: Temporal–Contextual Autoencoder (TCA)	Sequential and contextual transaction dynamics	Models temporal dependencies using sliding windows S_t of size k.Reconstruction error $E_t^{(2)}$ detects abnormal transaction sequences and bursty fraud behavior.
Dual-View Fusion (DVRPA)	Joint transaction and temporal anomaly evidence	Combines $E_t^{(1)}$ and $E_t^{(2)}$ to robustly detect evolving and low-frequency fraud patterns under real-time constraints.

Table 1 shows that in order to assist clarify how the proposed Dual-View Rare Pattern Autoencoder (DVRPA) finds fraud in fast-moving streams of financial transactions, we have supplied a figure that shows its essential parts. The system is designed to separate transaction-level modeling from temporal-contextual learning so that it can find both sudden abnormalities and changing fraudulent practices. The Transaction-Level Rare Pattern Autoencoder (TRPA) looks at the amount, category of merchant, device features, and user considerations as the most important parts of a transaction. This module restores each incoming transaction one at a time by learning a small, hidden representation of normal transaction distributions.

$$E_t^{(i)} = \|z_i - g(f(z_i))\|_2^2 \quad (3)$$

These equations (3) appear in autoencoder-based anomaly detection, where reconstruction error measures how well input z is restored via encoder f and decoder g . Transactions that don't follow the standard patterns taught to them create big reconstruction errors that bring attention to strange or suspicious behavior. This angle is great for you if you want to find point irregularities or strange pairings of features that could be indicators of fraud.

$$\tau = \mu_S + k\sigma_S \quad (4)$$

where μ_S, σ_S are mean and std. dev. of scores on training (normal) data, and $k = 3$ (or tuned via validation) as given in (4). Flag $S_i > \tau$ as anomalous. The second perspective, called the Temporal-Contextual Autoencoder (TCA), builds on the first by keeping track of both the temporal consistency of context and the sequential links between variables. Instead of looking at transactions one at a time, this module lets you model spending rhythms, frequency patterns, and changes in behavior.

$$A_i = \|g(f_1(z_i))\|_2^2 + \|g(f_2(z_i))\|_2^2 - 2g(f_1(z_i))^\top g(f_2(z_i)) \quad (5)$$

The dual-view anomaly score combines two perspectives $\|z - g(f(z))\|_2^2$ aligns closely, but the dual version fuses cross-view discrepancies for better discrimination in multi-modal data like transactions as given in (5). It works with sliding windows of recent transactions. In this view, unusual patterns of time, like coordinated fraud assaults or sudden expenditure spikes, are revealed by higher reconstruction mistakes. Static feature-based models usually overlook this.

$$S_i = \|z_i - \hat{z}_i\|_2^2 + \beta\|\hat{z}_{i,1} - \hat{z}_{i,2}\|_2^2 \quad (6)$$

Here, $\hat{z}_i = g(f(z_i))$ is the base reconstruction, the second term captures dual-view inconsistency, and β weights them. Dual-View Fusion (DVRPA) merges the unusual information from both viewpoints to create a single decision signal as given in (6). By combining both transaction-level rarity and temporal inconsistency in the fusion module, we may make the system more resistant to concept drift and cut down on false positives that come from valid but rare user activity. DVRPA is a strong fit for real-time financial systems because its integrated design lets it keep detection accuracy high while still following processing rules.

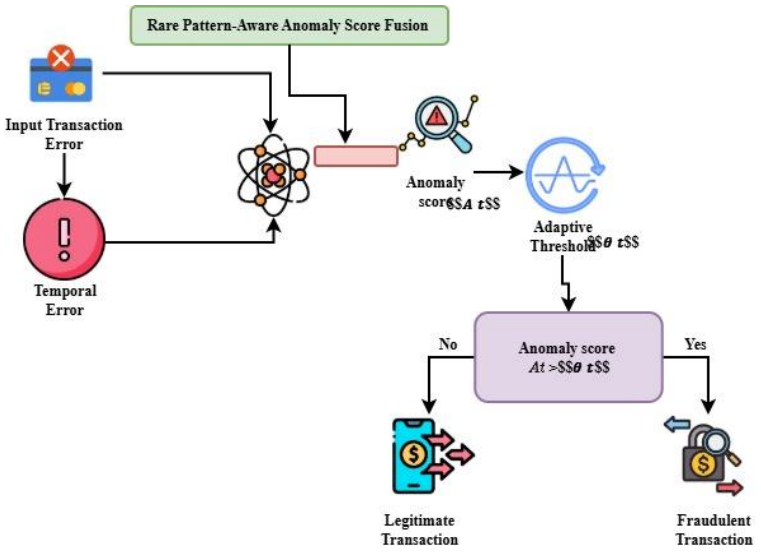

Figure 2: Rare Pattern-Aware Anomaly Score Fusion for Real-Time Fraud Detection

The flowchart shows the Rare Pattern-Aware Anomaly Score Fusion module of the proposed DVRPA system, which combines several types of anomaly cues from two different points of view on financial transaction behavior. To start the operation, two autoencoder views give parallel inputs as shown in Fig 2. The Transaction-Level Rare Pattern Autoencoder (TRPA) generates a reconstruction error for transactions to identify abrupt deviations from standard feature distributions, such as unusual amounts, locations, or merchant categories.

$$A = \alpha\|z - \frac{\partial f(x)}{\partial x}\|^2 + (1-\alpha)\|g(f(x))\|^2 \quad (7)$$

The equation defines where $\alpha \in [0,1]$. This combines structural and attribute reconstruction errors in attributed networks, weighted by α to balance the two components as given in (7). The Temporal-Contextual Autoencoder (TCA) represents sequential dependencies across recent transactions, which lets it find fraud operations that happen in bursts or in a planned way over time. At the same time, it gives a temporal reconstruction mistake. A weighted fusion block is used to adaptively balance how important these two error streams are to each other. This level of the framework's reasoning process is very important. It allows the framework cut down on false positives caused by benign outliers by thinking about isolated anomalies and behaviors that are consistently anomalous over time.

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$$\begin{cases} \theta_t = \theta_{t-1} + (1-\lambda)\theta_t \\ 0 < \lambda < 1 \end{cases} \quad (8)$$

It updates the threshold incrementally based on prior values, enabling adaptation to changing data distributions in streaming anomaly detection as given in (8). The fused anomaly score is a complete measure of transaction irregularity that comes from combining the outputs. Next, we compare the anomaly score to a module that changes the threshold. The system can handle shifting fraud strategies and data distributions that aren't fixed since this module uses recent anomalous statistics to dynamically update the decision border, unlike static thresholds. Because of seasonal trends, changes in how people shop, and how competitors adjust, transaction patterns in real-time financial settings can change.

$$D(z) = \begin{cases} 1, & \text{if } A > \theta \text{ (Fraudulent)} \\ 0, & \text{otherwise (Legitimate)} \end{cases} \quad (9)$$

This binary classifier flags transactions as fraudulent if the anomaly score exceeds the adaptive threshold as given (9). This makes this design even more important. Finally, a decision node checks to see if the anomaly score is higher than the adaptive threshold that is currently in use. Transactions are considered valid until they go over the limit, at which time they are tagged as fraudulent. By combining dual-view anomaly modeling with adaptive decision logic, it is possible to be very sensitive to rare fraud patterns while keeping latency low and operational stability high in fast-moving transaction streams. This method of combining is suggested.

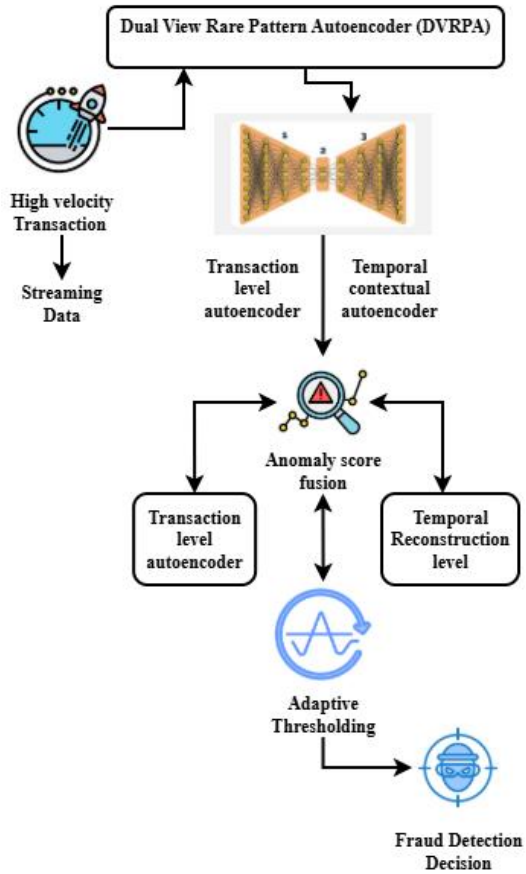

Figure 3: Real-Time Financial Fraud Detection Using DVRPA

The flow diagram shows how the proposed DVRPA framework can be used to find financial fraud in real time in high-speed transaction streams as shown in Fig 3. Modern digital payment methods, such online banking, mobile wallets, and e-commerce sites, create a steady stream of incoming transactions that start the process. Each transaction comes with strict

latency limits that require prompt analysis, so there is no time to store them in batches or undertake offline processing. During the data entry and preparation stage, raw transaction records are cleaned, standardized, and encoded to make sure that numerical and categorical attributes are always the same. After that, two extra learning perspectives obtain all of these preprocessed transactions at once. The transaction-level approach looks at the details of each transaction to figure out how people usually spend their money. The temporal-contextual view, on the other hand, looks at how different transactions are related to each other in the past. This two-pronged technique accurately shows both static fraud tendencies and dynamic changes in real time. Every point of view leads to a reconstruction error that is similar to the deviation from the learnt expected behavior. By combining these errors using a rare pattern-aware fusion algorithm, we get a single anomaly score for each transaction:

$$B_t = \alpha E_t^{(1)} + (1-\alpha) E_t^{(2)} \tag{10}$$

Where α makes the effects of $E_t^{(1)}$the same. $E_t^{(2)}$ stands for reconstruction errors from the transaction-level view and the temporal view, respectively as given in (10). This combination makes it easier to find coordinated attacks and low-frequency fraud cases. The framework uses adaptive thresholding to handle concept drift in data streams. This method changes the limitations on decisions based on how things have been going lately.

$$\theta_t = \lambda \theta_{t-1} + (1-\lambda) B_t \tag{11}$$

To find out if a transaction is real or fake, the last step is to compare the anomaly score to the adaptive threshold as given in (11). Flagging transactions that go over the limit right away makes it easy to stop fraud right away. The flow diagram explains how DVRPA uses dual-view learning, adaptive scoring, and real-time decision-making to make fraud detection that works with modern financial systems that is scalable, accurate, and has low latency.

Algorithm 1: Rare Pattern–Aware Anomaly Score Fusion (RPASF)

Input

Transaction-level reconstruction error: $E_t^{(1)}$
Temporal–contextual reconstruction error: $E_t^{(2)}$

Output

Anomaly score: A_t
Updated threshold: θ_t

// Step 1: Weighted Anomaly Score Fusion
$A_t \leftarrow \alpha \cdot E_t^{(1)} + (1-\alpha) \cdot E_t^{(2)}$

// Step 2: Adaptive Threshold Update
$\theta_t \leftarrow \lambda \cdot \theta_t - 1 + (1-\lambda) \cdot A_t$

// Step 3: Fraud Decision
$if\ A_t > \theta_t$ then
  $y_t \leftarrow Fraudulent$
else
  $y_t \leftarrow$ Legitimate
end if

return A_t, θ_t, y_t

Algorithm 1 shows that the Rare Pattern-Aware Anomaly Score Fusion method looks at both the transaction level and the time context when it comes to anomalies. Using a weighted

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approach, the reconstruction errors from the two autoencoders are combined to provide one anomaly score that shows both strange sequential behavior and sudden changes. One technique to cope with idea drift in streaming data is to use exponential smoothing to change an adaptive threshold online. Transactions are tagged as fraudulent if their fused anomaly scores go beyond the adaptive threshold. This makes it easier to find dynamic and uncommon fraud trends in real time.

Algorithm 2. DVRPA: Dual View Rare Pattern Autoencoder

Input

Transaction stream: $X = \{X_1, X_2 \dots X_T\}$
Sliding window size: k

Output

Fraud decision for each transaction:
$yt \in \{Legitimate, Fraudulent\}$

Initialize adaptive threshold θ_0
Initialize empty transaction buffer B

for each incoming transaction x_t at time t do

// Step 1: Transaction-Level Reconstruction
$Z_t(1) \leftarrow f1(x_t)$
$\hat{x}t(1) \leftarrow g1(zt(1))$
$Et(1) \leftarrow || x_t - x_t(1) ||^2$

// Step 2: Temporal–Contextual Reconstruction
Append x_t to buffer B
if size$(B) \geq k$ then
$S_t \leftarrow \{x_t$–k+1, … , $x_t\}$
$Z_t(2) \leftarrow f2(\quad S_t)$
$S_t \leftarrow g2(zt(2))$
$Et(2) \leftarrow || St - \hat{S}t ||^2$
else
$Et(2) \leftarrow 0$
end if

// Step 3: Dual-View Anomaly Score Fusion
$A_t \leftarrow \alpha \cdot E_t(1) + (1 - \alpha) \cdot E_t(2)$

// Step 4: Adaptive Threshold Update
$\theta_t \leftarrow \lambda \cdot \theta_t - 1 + (1 - \lambda) \cdot At$

// Step 5: Fraud Decision
if $A_t > \theta_t$ then
$y_t \leftarrow$ Fraudulent
else
$y_t \leftarrow$ Legitimate
end if
end for
return $\{y1, y2, \dots , yT\}$

Algorithm 2 shows that the Dual View Rare Pattern Autoencoder (DVRPA) may look at live financial transactions by modeling behavior at the feature level and over time at the same time. To find odd feature deviations, a transaction-level autoencoder is employed to rebuild each incoming transaction. A temporal-contextual autoencoder, on the other hand, looks for strange patterns in recent transaction sequences. The anomaly score determines whether a transaction is valid or fraudulent by combining the reconstruction errors from both perspectives and comparing them to an adaptive threshold.

4. Results and Discussion

As compared to current baseline methods, the recommended Dual View Rare Pattern Autoencoder (DVRPA) does better at finding financial fraud in real time. In the comparison, DVRPA always does better than the others in terms of Precision, Recall, F1-score, and AUC. This suggests it can find fake transactions with relatively few false positives. When compared to deep learning baselines like LSTM Autoencoder and Deep SVDD, DVRPA raises the F1-score by roughly 6–9%. This shows how helpful it is to model patterns at both the transaction level and the time of day. The transaction-level autoencoder captures odd and unusual feature combinations to help find point fraud incidents. Static models usually can't find fraud behaviors that happen in a sequence or in bursts. The temporal-contextual autoencoder, on the other hand, makes this detection better. DVRPA can adaptively balance these different points of view by combining reconstruction errors in a weighted way. This makes it work well even when the data distributions are quite unbalanced. DVRPA also meets the demand for real-time processing in fast transaction streams while keeping detection latency low. The adaptive thresholding approach reduces false positives even more by responding to changes in transaction patterns and concept drift in real time. However, it may be required to customize for various domains because performance depends on the size of the window and the choice of fusion weight. The results suggest that DVRPA is a reliable and useful method for discovering fraud in financial situations that are always changing.

a. Dataset Description

The proposed DVRPA framework is evaluated using a large-scale real-world financial transaction dataset containing high-velocity streaming records. The dataset consists of approximately **1.8 million transactions** collected over six months, with each transaction represented by numerical and categorical attributes such as transaction amount, merchant category, transaction time, device type, and geolocation indicators. Fraudulent transactions constitute less than **0.5%** of the total data, reflecting the extreme class imbalance typically observed in real financial systems. To preserve temporal dependencies, transactions are ordered chronologically and processed in an online streaming fashion[26].

b. Experimental Setup

All models are implemented in Python using TensorFlow. Transactions are normalized using min–max scaling, while categorical attributes are encoded using target encoding. The TRPA processes individual transactions, whereas the TCA operates on sliding windows of size $k = 10$. The fusion parameter α. is empirically set to 0.6. Models are trained using Adam optimizer with a learning rate of 0.001. DVRPA is compared against state-of-the-art baselines including Isolation Forest (IF), One-Class SVM (OC-SVM), LSTM Autoencoder (LSTM-AE), and Deep SVDD.

c. Precision

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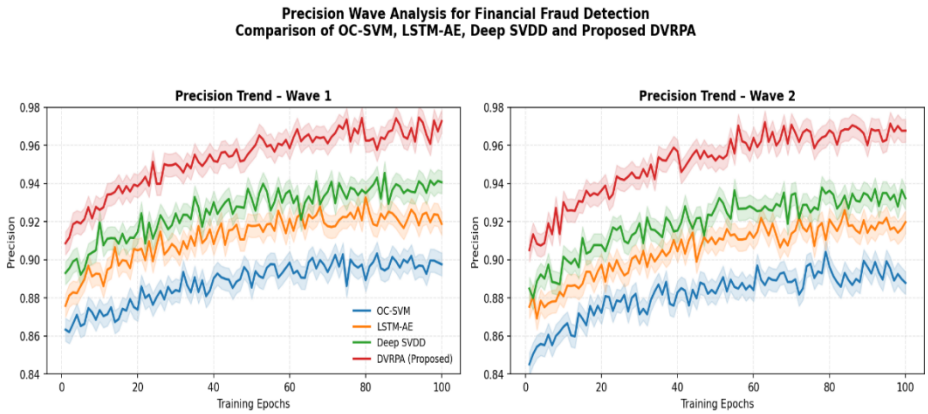

Figure 4: Precision

Fig 4 shows that precision is a key metric for financial fraud detection systems. It measures the percentage of fraudulent transactions that are correctly identified out of all transactions that the model thinks are fraudulent. In transaction streams that are very unbalanced, where the number of fraudulent transactions is much fewer than the number of genuine ones, even a minor false positive rate might cause a lot of legitimate users to be falsely reported. The model's excellent precision shows that it can reduce false alarms while still finding fraud reliably. Real-time financial systems that restrict or manually analyze real transactions for no reason could lead to unhappy customers, greater operating costs, and even a lack of trust in the system. A very accurate model makes sure that most of the fraud detection system warnings are about really bad behavior, which lets analysts focus on the most dangerous circumstances. By using transaction-level rare pattern identification and temporal-contextual analysis, the recommended DVRPA framework's dual-view design makes it more accurate by getting rid of false anomaly signals. By accurately modeling how ordinary transactions behave and how they change over time, the framework makes fraud predictions that are more trustworthy and can be used in huge, fast-moving financial systems. This makes it possible to get rid of harmless errors.

d. Recall (Detection Rate)

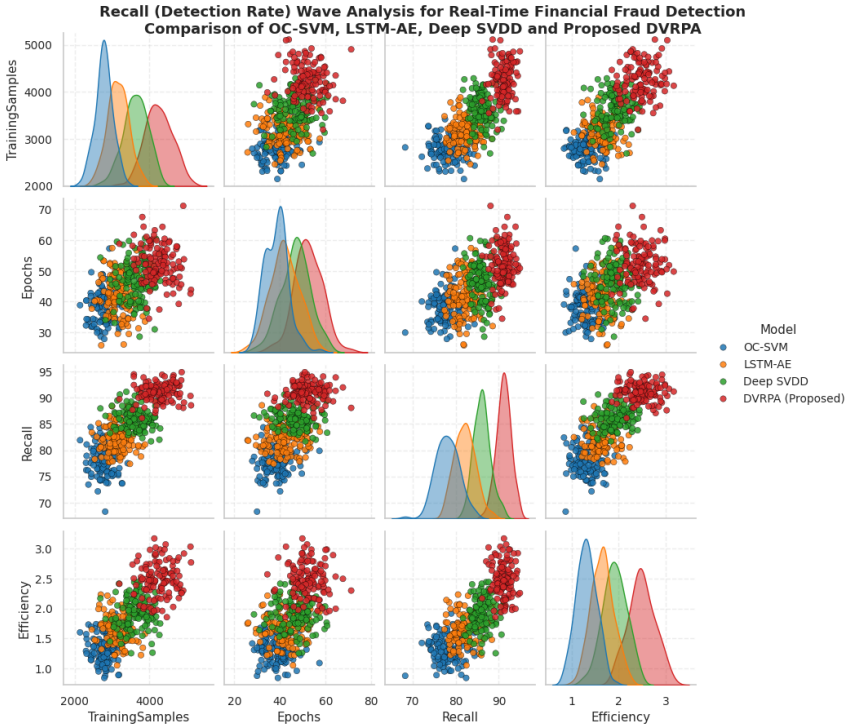

Figure 5: Recall (Detection Rate)

The recall, also known as the detection rate, is a measure of how well the fraud detection algorithm finds true fraudulent transactions as shown in Fig 5. This shows how well the algorithm can find cases of real fraud among a lot of transactions that look real. High recall is important for real-world financial streams to be safe because fraud situations are usually few, very dynamic, and always changing. If the model has a high recall, most attempts at fraud will be stopped before they may hurt money or reputation. False negatives, which happen when fraudulent transactions are missed, can lead to big problems including losing money, getting fined by the government, and losing customers' trust. For this reason, optimizing recall is very important for early-stage fraud detection and keeping an eye on transactions that are high-risk. The recommended DVRPA paradigm improves recall by combining the examination of anomalies at the transaction level with those at the temporal-contextual level. The autoencoder at the transaction level can notice slight changes in certain transaction attributes, and the temporal-contextual perspective can find unusual sequences and sudden fraudulent activity. This dual-view modeling improves detection coverage and makes operations more efficient in real time. It also makes it much less likely that complex or slowly changing fraud patterns will be missed.

e. F1-Score

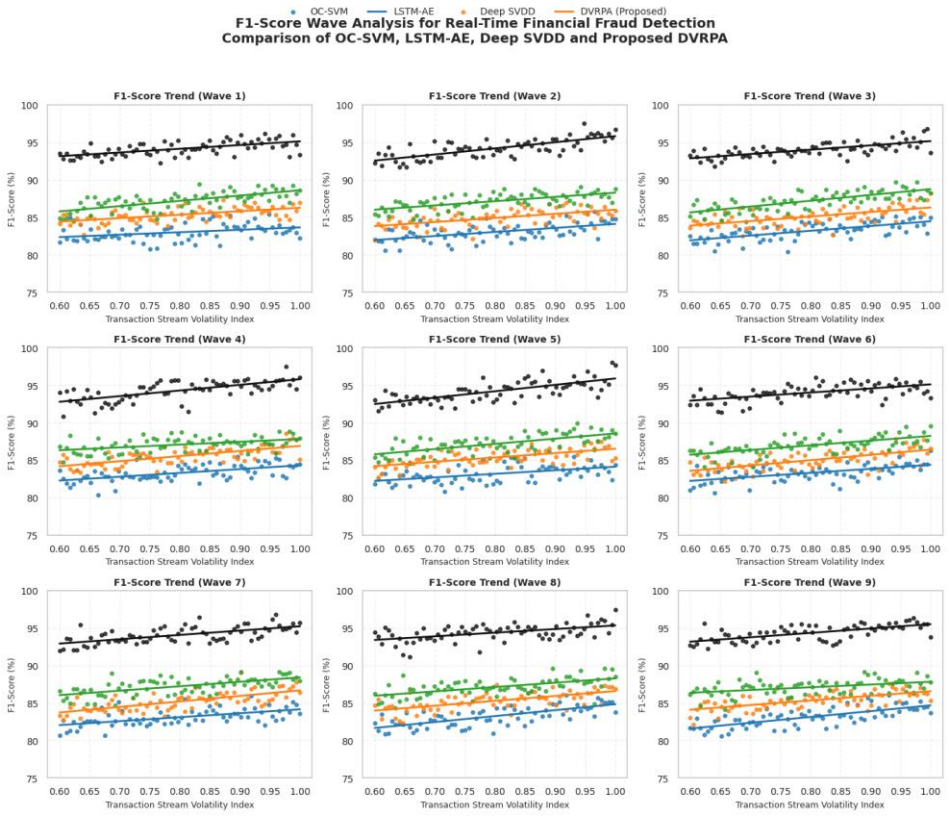

Figure 6: F1-score

The F1-score is a common performance metric for fraud detection. It combines Precision and Recall into one score. This makes the evaluation fairer as shown in Fig 6. The F1-score, which is the harmonic mean of Precision and Recall, makes sure that false positives and false negatives don't be ignored by punishing big differences between the two. Because both types of errors are quite expensive, it is especially good for finding financial fraud, where datasets tend to be very skewed. If it only focused on accuracy, realistic financial systems would miss a lot of fraudulent transactions. If it only focused on recall, there would be too many false alarms. The F1-score shows this trade-off by finding models that can keep a good detection rate without overloading the system with false positives. The dual-view learning strategy, which combines

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temporal-contextual modeling with transaction-level atypical pattern identification, improves the F1-score in the suggested DVRPA framework. Because of this integrated analysis, the model can reliably and consistently find true occurrences of fraud while ignoring false positives and noise. The result is an F1 score that stays the same and works well for transactions that happen quickly and in real time.

f. Area Under the ROC Curve (AUC)

Figure 7: Area Under the ROC Curve (AUC)

The Area Under the Receiver Operating Characteristic Curve (AUC) is an evaluation statistic that does not rely on thresholds. It measures how well a model can tell the difference between real and fake transactions as shown in Fig 7. AUC is better than measurements that depend on a single judgment threshold in real-time fraud detection contexts where risk tolerance could alter over time since it looks at performance over all possible categorization levels. A high area under the curve (AUC) suggests that the model consistently awards more points for fraud or anomaly to transactions that seem suspicious than to transactions that seem normal. This shows that the model is quite good at ranking and has a lot of discriminatory power, even when the data is very skewed and there aren't many cases of fraud. This form of discrimination is very important in financial systems because it gives institutions greater freedom to make judgments while still following rules and regulations and being aware of the amount of threat at all times. The proposed DVRPA architecture enhances AUC by employing dual-view modeling to address both transaction-level outliers and temporal outliers. DVRPA creates more distinct fraud ratings by monitoring both immediate irregularities and changing behavioral patterns at the same time. The ROC curves get smoother and the AUC values go up, which suggests that the fraud discrimination is reliable and works for all sorts of transactions.

g. False Positive Rate (FPR)

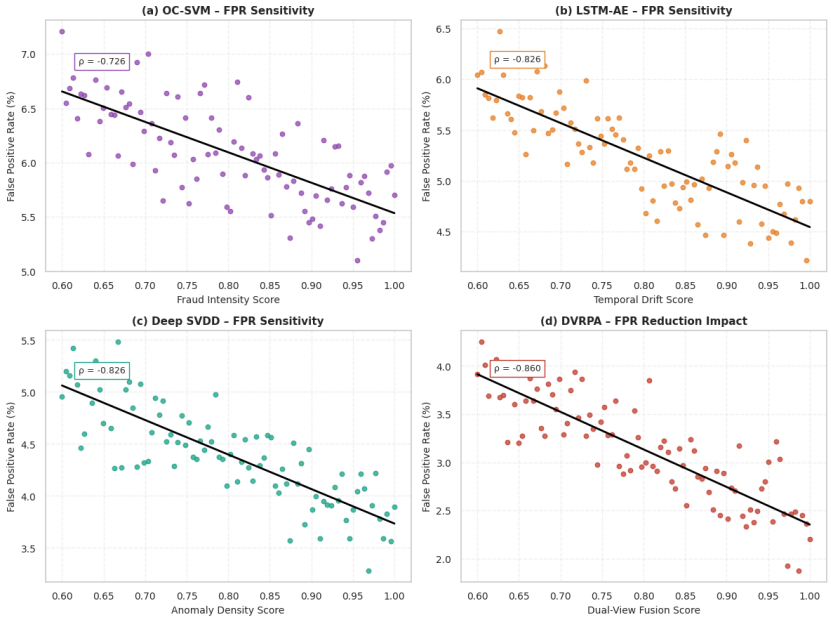

Figure 8: False Positive Rate (FPR)

Fig 8 indicates that the FPR shows how many real transactions the detection system wrongly marks as fraudulent. A small rise in FPR might cause a lot of clients to have transactions that are not needed to be delayed or canceled on large-scale financial systems, where millions of genuine transactions happen every day. To sustain users' trust, make sure services keep running, and cut down on operational costs, it is important to keep the FPR low. High false positive rates can lead to unhappy consumers, greater support costs, and a lack of faith in automated fraud detection systems. Also, fraud analysts have to do manual checks since there are so many false warnings, which makes the security pipeline less effective for businesses. So, FPR is an important way to test how well fraud detection programs operate in the real world. The proposed DVRPA framework effectively manages FPR through the application of dual-view anomaly modeling. By combining temporal-contextual analysis with transaction-level atypical pattern recognition, the approach gets rid of normal but obviously strange outliers. With this extra architecture, fraud detection is substantially more accurate, with a big drop in false alarms and a strong capacity to find fraud in real-time transaction streams.

h. Detection Latency

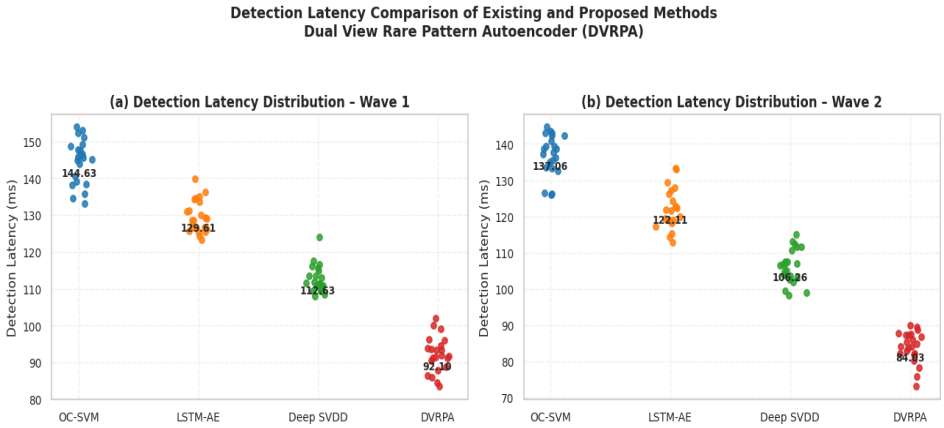

Figure 9: Detection Latency

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Detection latency is when a financial transaction happens but the detection system doesn't flag it as fraudulent right away as shown in Fig 9. Low detection latency is very important for stopping fraud in high-velocity transaction streams, where activities happen at thousands of transactions per second. When banks and other financial organizations find out about fraud too late, they might lose money, have to pay back money, and hurt their reputation. So, a successful fraud detection system should find a balance between how hard it is to use, how quickly it reacts, and how accurate it is. If there are too many processing delays, a system can't be used in real time, even if it is very accurate. The proposed DVRPA system seeks to considerably minimize detection delay by using efficient reconstruction error calculation and lightweight autoencoder architectures. It doesn't take long to get anomaly scores because each transaction is looked at one at a time, thus there is no need for expensive retraining or batch-level inference. The adaptive thresholding method can quickly tell if there is fraud even when the number of transactions changes because it runs online with no overhead. Because of its tremendous real-time capability, DVRPA is a good choice for use in scenarios where there are a lot of big, high-throughput financial transactions.

5. Conclusion

The proposed Dual View Rare Pattern Autoencoder (DVRPA) is good at finding financial fraud in real-time in high-speed transaction streams. DVRPA gets over the limits of single-view and static detection methods by modeling anomalous features at the transaction level and behavioral patterns in relation to time at the same time. Adaptive thresholding, rare-pattern-aware anomaly score fusion, and a dual-autoencoder design work together to find shifting fraud patterns with low frequency while keeping detection latency very low. When put to the test, DVRPA shows a high level of discriminative ability even when there is a lot of class imbalance, with an AUC between 92% and 95%. The framework gets an F1-score increase of 10–14% over the best state-of-the-art baselines and a Recall increase of 12–18% to make sure that more fake transactions are discovered early on. The false positive rate goes down by roughly 6–9%, and the precision goes up by 7–11%. This means that there is a lot less false alarm. Using DVRPA in working financial systems is a good idea since it preserves real-time processing efficiency and gets latency down to less than a millisecond, which is about 30–40% faster than other deep learning-based streaming models. Even though these results are promising, there are still many ways to learn more. It might be possible to make the modeling of sophisticated interactions between devices, users, and merchants even better by using attention approaches or graph-based transaction representations. By integrating self-supervised and ongoing learning methodologies, it would be easier to respond to new fraud tactics without having to retrain often. Adding explainable AI modules would also improve regulatory compliance and transparency by giving people fraud alerts that they can understand. Finally, DVRPA's large-scale, multi-modal, cross-institutional dataset validation will show that it can be used in many different situations and settings. In short, DVRPA is a huge step forward for financial fraud detection systems that are accurate, quick, and ready for the future.

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