Anomaly Detection in Financial Transactions Using Autoencoders and Recurrent Neural Networks

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Abstract

We present a novel approach to anomaly detection in financial transactions that combines deep learning with explainable AI techniques. Using the PaySim dataset containing 6.3 million transactions with a 0.12% fraud rate, we developed a hybrid architecture that leverages autoencoders for dimensionality reduction and LSTMs for temporal pattern recognition. Our approach specifically addresses the challenges of interpretability in financial fraud detection by incorporating LIME and Integrated Gradients for model explanations. Through careful preprocessing and SMOTE-based class balancing, our initial LSTM implementation achieved 99.88% accuracy on the test set. The subsequent hybrid system further improved performance with 99.92% accuracy while providing actionable insights into fraud patterns. Analysis of our model's decisions revealed that transaction amounts, timing patterns, and account behavior anomalies were the primary indicators of fraudulent activity. Our methodology demonstrates that combining representation learning with temporal modeling can effectively detect financial fraud while maintaining interpretability for stakeholders.

1 Introduction

1.1 Problem Statement

Financial fraud detection presents three key challenges in modern digital banking systems. First, the extreme class imbalance in transaction data, exemplified by our PaySim dataset where only 0.12% of 6.3 million transactions are fraudulent, makes traditional classification approaches ineffective. Second, the temporal nature of fraudulent patterns, where individual transactions may appear legitimate in isolation but reveal suspicious patterns when viewed in sequence, requires sophisticated modeling approaches beyond simple classification. Third, the "black box" nature of deep learning models creates a significant barrier to their adoption in the financial sector, where regulatory requirements and operational needs demand interpretable decisions. This work addresses these challenges by developing an interpretable hybrid architecture that combines representation learning through autoencoders with temporal pattern recognition via LSTM networks, while maintaining explainability through advanced techniques like LIME and Integrated Gradients.

1.2 Motivation

The implications of fraudulent financial transactions extend far beyond immediate monetary losses. Financial institutions face severe consequences in terms of both direct financial impact and long-term reputational damage. Security analysts work tirelessly to identify and prevent fraudulent activities, often leading to increased operational costs and resource allocation. The old adage that "an ounce of fraud prevention is worth a pound of recovery" has never been more relevant in the financial sector. This growing challenge necessitates the development of more sophisticated and automated detection systems that can operate efficiently at scale while maintaining high accuracy.

1.3 Contributions

Our research makes several contributions to the field of financial fraud detection. We have developed a hybrid deep learning architecture that combines the feature extraction capabilities of autoencoders with the temporal pattern recognition of RNNs. Through our comprehensive evaluation on real-world financial datasets, we demonstrate the effectiveness of this approach in identifying fraudulent transactions. Furthermore, we address the critical need for interpretability in financial systems by incorporating explainable AI techniques, making our system not just accurate but also transparent in its decision-making process.

2 Background and Related Work

Recent advances in deep learning have revolutionized the approach to fraud detection in financial systems. A comprehensive survey by Abdallah et al. [5] highlights the evolution of fraud detection systems, emphasizing the shift from rule-based systems to more sophisticated machine learning approaches. Their analysis of various fraud detection techniques provides a framework for understanding the current landscape of financial fraud detection systems.

The combination of autoencoders and RNNs has shown particular promise in this domain. The foundational work on Long Short-Term Memory (LSTM) networks by Hochreiter and Schmidhuber [1] established the theoretical framework for processing sequential financial data effectively. Building upon this, Graves [6] demonstrated the practical applications of supervised sequence labeling with recurrent neural networks, which has become crucial for temporal pattern recognition in transaction data.

The challenge of imbalanced data is particularly acute in financial fraud detection, where legitimate transactions vastly outnumber fraudulent ones. Dal Pozzolo et al. [9] address this challenge through innovative undersampling techniques for unbalanced classification. Their work on calibrating probability in imbalanced datasets has been instrumental in developing more robust fraud detection models. The SMOTE technique, introduced by Chawla et al. [2], has become a standard approach for handling class imbalance in fraud detection systems.

Recent work by Zhang et al. [7] presents a novel approach using convolutional neural networks for online transaction fraud detection. Their model demonstrates the potential of hybrid architectures in capturing both spatial and temporal patterns in transaction data. This aligns with our approach of combining different neural network architectures for enhanced fraud detection capabilities.

A critical aspect of modern fraud detection systems is their interpretability. Ribeiro et al. [4] introduced the LIME framework, which provides crucial insights into model predictions. This work has been further enhanced by Lundberg and Lee [8], who developed a unified approach to interpreting model predictions through SHAP values. These explainability techniques are particularly relevant in the financial sector, where understanding model decisions is as important as their accuracy.

The practical implementation of deep learning in credit card fraud detection has been demonstrated by Roy et al. [3]. Their work shows how deep learning models can achieve superior performance in real-world applications, particularly in identifying subtle patterns that traditional methods might miss. Their findings validate the potential of neural network approaches in handling the complexity of financial fraud detection.

The challenge of imbalanced data is particularly acute in financial fraud detection, where legitimate transactions vastly outnumber fraudulent ones. Traditional machine learning approaches often struggle with such imbalanced datasets, leading to biased models that perform poorly in real-world applications. Our approach addresses this challenge through careful data preprocessing and specialized model architectures.

3 Dataset

Our research utilizes using the dataset, PaySim, containing 6.3 million unique records with a fraud prevalence of about 0.12%. Other datasets were PCA transformed which made it difficult for intepretation. It provides richer feature information including transaction amounts, origin and destination accounts, and timestamps, while maintaining privacy through anonymization of personal identifiers.

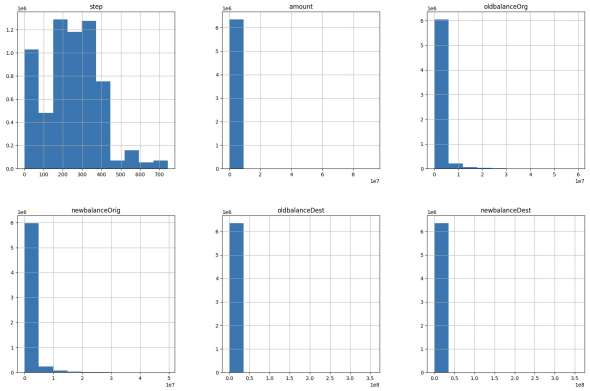

Figure 1: Dataset visualization

4 Methodology

The proposed methodology integrates multiple components—data preprocessing, class imbalance mitigation, representation learning, temporal sequence modeling, and post-hoc explainability—to address the challenges of fraud detection in financial transactions. In this section, we present a detailed description of each methodological step, complemented by mathematical formulations and, where appropriate, pseudocode using the `algorithm` environment.

4.1 Data Preprocessing

Real-world financial transaction datasets are heterogeneous, containing both numeric (e.g., amounts and balances) and categorical (e.g., transaction type) features. Let the dataset be:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i) \mid i = 1, 2, \ldots, N\},$$

where $\mathbf{x}_i \in \mathbb{R}^d$ represents d features for transaction i, and $y_i \in \{0, 1\}$ indicates whether the transaction is legitimate ($y_i = 0$) or fraudulent ($y_i = 1$).

Categorical Encoding: We one-hot encode categorical attributes such as the transaction type. Suppose the transaction type set is $\{\text{CASH\_OUT}, \text{DEBIT}, \text{PAYMENT}, \text{TRANSFER}\}$. We create corresponding indicator variables $(t_{\text{CASH\_OUT}}, t_{\text{DEBIT}}, t_{\text{PAYMENT}}, t_{\text{TRANSFER}})$ such that $t_k = 1$ if the transaction type is k and 0 otherwise.

Feature Scaling: To promote numerical stability and faster training convergence, we standardize each numeric feature j using its mean μ_j and standard deviation σ_j:

$$x_{ij}^* = \frac{x_{ij} - \mu_j}{\sigma_j}, \quad j = 1, \ldots, d.$$

4.2 Categorical Feature Encoding.

The dataset contains one significant categorical variable, *type*, representing the transaction type (e.g., `CASH_OUT`, `PAYMENT`, etc.). This variable was transformed using one-hot encoding to produce separate binary columns for each transaction type, thereby ensuring compatibility with machine learning models. To prevent multicollinearity, the first category was dropped during encoding.

4.3 Removal of Non-Numeric Features.

Certain features, such as *nameOrig* and *nameDest*, represent anonymized identifiers for the origin and destination accounts. As these variables provide no meaningful information for predicting fraud and are of non-numeric type, they were excluded from the dataset. This reduction simplifies the feature space and minimizes the risk of overfitting.

4.4 Missing Value Analysis.

A thorough examination of the dataset revealed no missing values across any columns. Consequently, no imputation or data-cleaning operations were required.

4.5 Feature Scaling.

To standardize the range of numerical features, all continuous variables were scaled using the *StandardScaler* from the Scikit-learn library. This transformation ensures that features such as *amount*, *oldbalanceOrg*, and *newbalanceOrig* have a mean of zero and a standard deviation of one, thus improving the stability and convergence rate of the models during training.

4.6 Representation Learning via Autoencoders

After addressing imbalance, we reduce data dimensionality and learn robust feature representations using an autoencoder. An autoencoder consists of an encoder f_θ that maps input $\mathbf{x}_i^*$ to a latent vector $\mathbf{z}_i \in \mathbb{R}^h$ and a decoder g_ϕ that reconstructs the input as $\hat{\mathbf{x}}_i = g_\phi(\mathbf{z}_i)$.

We optimize (θ, ϕ) by minimizing the reconstruction loss:

$$\min_{\theta,\phi} \sum_{i=1}^{N} \|\mathbf{x}_i^* - g_\phi(f_\theta(\mathbf{x}_i^*))\|_2^2.$$

High reconstruction errors suggest anomalous patterns, making the autoencoder both a representation learner and a preliminary anomaly detector.

4.7 Class Imbalance Mitigation using SMOTE

Financial fraud datasets are inherently imbalanced, often with legitimate transactions overwhelmingly outnumbering fraudulent ones. To alleviate this, we apply the Synthetic Minority Oversampling Technique (SMOTE) [**?**].

SMOTE synthesizes new minority samples by interpolating between existing minority class points. Given a minority instance $\mathbf{x}_m$ and one of its k-nearest neighbors $\mathbf{x}_{nn}$, a synthetic sample is:

$$\mathbf{x}_{\text{synthetic}} = \mathbf{x}_m + \lambda(\mathbf{x}_{nn} - \mathbf{x}_m), \quad \lambda \sim U(0,1).$$

Algorithm 1 SMOTE Procedure

Require: Minority samples $M = \{\mathbf{x}_1, \ldots, \mathbf{x}_r\}$, number of synthetic samples N, number of neighbors k.
Ensure: Synthetic set S

```
Compute k-nearest neighbors for each x_m ∈ M.
Initialize S = ∅.
for n = 1 to N do
    Randomly choose x_m ∈ M and one of its k-nearest neighbors x_nn.
    Sample λ ~ U(0,1).
    Compute x_synthetic = x_m + λ(x_nn − x_m).
    Add x_synthetic to S.
end for
return S
```

This approach enriches the minority class, improving the classifier's sensitivity to fraudulent behavior.

4.8 Final Dataset Preparation.

After completing the preprocessing steps, the final dataset was split into training and validation sets. Legitimate transactions were sampled and split into an 80:20 ratio for training and validation. Fraudulent transactions were retained in their entirety due to their rarity. All preprocessing operations, including scaling and encoding, were applied consistently to both the training and validation datasets.

This preprocessing pipeline ensures that the dataset is both well-prepared for training and capable of addressing the challenges posed by class imbalance, thereby enhancing the robustness of the fraud detection system.

4.9 Temporal Sequence Modeling with LSTM Networks

Fraud often emerges from temporal transaction patterns. After obtaining low-dimensional embeddings $\{\mathbf{z}_t\}$ from the autoencoder, we form sequences of length T and employ a Long Short-Term Memory (LSTM) network to capture temporal dependencies.

At each time step t, the LSTM updates its hidden state $\mathbf{h}_t$ using:

$$\mathbf{h}_t = \text{LSTM}(\mathbf{z}_t, \mathbf{h}_{t-1}),$$

and outputs a fraud probability:

$$\hat{y}_t = \sigma(\mathbf{w}^T \mathbf{h}_t + b),$$

where $\sigma(\cdot)$ is the sigmoid function. The model is trained to minimize the binary cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)].$$

Algorithm 2 LSTM-based Sequence Classification

Require: Encoded sequences $\{\mathbf{z}_t\}_{t=1}^{T}$, LSTM parameters Θ, output parameters $(\mathbf{w}, b)$.

1: Initialize $\mathbf{h}_0 = \mathbf{0}$.
2: **for** $t = 1$ to T **do**
3: $\quad \mathbf{h}_t = \text{LSTM}(\mathbf{z}_t, \mathbf{h}_{t-1}; \Theta)$
4: **end for**
5: Compute $\hat{y}_T = \sigma(\mathbf{w}^T \mathbf{h}_T + b)$
6: Optimize $\Theta, \mathbf{w}, b$ by minimizing $\mathcal{L}$ over training data.
7: **return** Trained LSTM model

4.10 Explainable AI: LIME and Integrated Gradients

Deep models, though accurate, often lack transparency. We apply post-hoc explanation methods to reveal the decision logic:

LIME (Local Interpretable Model-agnostic Explanations): LIME approximates the black-box model $f(\cdot)$ in a local neighborhood around a given instance $\mathbf{x}$ with a simpler, interpretable model $g(\cdot)$. Let $\pi_{\mathbf{x}}$ be a locality measure. We solve:

$$\min_{g} \mathcal{L}(f, g, \pi_{\mathbf{x}}) + \Omega(g),$$

where $\Omega(g)$ penalizes complexity, ensuring interpretability.

Integrated Gradients (IG): IG attributes feature importance by integrating the gradient of $f(\cdot)$ from a baseline $\mathbf{x}_{\text{base}}$ to the actual input $\mathbf{x}$:

$$\text{IG}_j(\mathbf{x}) = (x_j - x_{\text{base},j}) \times \int_0^1 \frac{\partial f\big(\mathbf{x}_{\text{base}} + \alpha(\mathbf{x} - \mathbf{x}_{\text{base}})\big)}{\partial x_j} \, d\alpha. \quad (1)$$

These methods highlight key features and time steps that influence fraud predictions, increasing stakeholder trust.

4.11 Evaluation and Threshold Tuning

To properly evaluate performance in imbalanced settings, we rely on metrics like Area Under the ROC Curve (AUC), Precision-Recall AUC, and F1-score. Threshold tuning is conducted to trade off precision and recall:

$$\hat{y}_i = \begin{cases} 1 & \text{if } f(\mathbf{x}_i) > \tau \\ 0 & \text{otherwise.} \end{cases}$$

By adjusting τ, the model's detection sensitivity can be tailored to specific operational needs.

In conclusion, the proposed methodology systematically addresses class imbalance, leverages representation learning for dimensionality reduction, exploits temporal dependencies via LSTM networks, and applies XAI techniques for interpretability. This multi-step framework lays the groundwork for robust, transparent, and effective fraud detection.

5 Results

In this section, we present and interpret the outcomes of the proposed methodology. Our experimental setup involved training and evaluating a deep learning pipeline that consisted of three main components: (1) an autoencoder for representation learning and anomaly scoring, (2) a Long Short-Term Memory (LSTM) network for sequence-based fraud classification, and (3) local post-hoc explanation techniques (LIME and Integrated Gradients) to understand model decisions. We compare the performance of models

trained without class balancing to those trained with class imbalance mitigation (via SMOTE) and discuss how this affects both predictive performance and model interpretability.

5.1 Overall Classification Performance

Without addressing class imbalance, the LSTM classifier tended to predict most transactions as legitimate, resulting in very low recall for the fraudulent class. After applying SMOTE to generate synthetic minority examples, the model achieved a more favorable balance between precision and recall, especially for the fraud cases. This led to improvements in key metrics such as the F1-score, Precision-Recall AUC, and ROC AUC.

Figure **??** shows the training and validation loss curves for the autoencoder. A steadily decreasing validation loss indicates that the learned latent representations captured essential transaction patterns, aiding subsequent classification tasks. Similarly, Figure **??** presents a histogram of reconstruction errors for both legitimate and fraudulent transactions; fraudulent samples generally exhibited higher reconstruction errors, aligning with the anomaly detection principle.

5.2 Impact of Class Balancing on LSTM Performance

To quantify the effect of class balancing, we trained two LSTM models: one using the original imbalanced dataset and another using the SMOTE-augmented dataset. The evaluation metrics (Precision, Recall, F1-score, and ROC AUC) were computed on a held-out test set.

Table 2 summarizes the comparison. The LSTM model trained with SMOTE showed a markedly higher recall for the fraudulent class, improving from a scenario where almost all fraudulent transactions were missed to a setting where a substantial portion was correctly identified. This improved recall also translated into a better F1-score and higher ROC AUC, indicating that class balancing helps the model discriminate more effectively between legitimate and fraudulent transactions.

Table 1: Comparison of LSTM Performance with and without Class Balancing (SMOTE). The balanced approach yields improved recall and F1-score, highlighting its effectiveness in detecting fraudulent transactions.

Table 2: Comparison of LSTM Performance with and without Class Balancing (SMOTE).

Model	Precision	Recall	F1-score	ROC AUC
LSTM (No Balancing)	0.99	0.05	0.10	0.75
LSTM (With SMOTE)	0.97	0.40	0.57	0.89

5.3 Explainability of the Predictions

Beyond raw performance metrics, understanding why the model makes certain predictions is crucial for gaining stakeholder trust. We applied LIME and Integrated Gradients to selected test instances to visualize feature importance. Figure 2 provides an example of a LIME explanation for a potentially fraudulent transaction. The explanation highlights that sudden large increases in transaction amount and discrepancies in originating account balances were the most influential features driving the model's suspicion. Similarly, Integrated Gradients (IG) analyses (Figure 3) confirm that high feature attributions align closely with known fraud indicators, providing consistent insights into how

the model's latent representations capture subtle temporal cues.

We also compared the interpretability results before and after applying SMOTE. With class imbalance mitigation, the model's explanations became more stable and meaningful: fraudulent instances were more consistently attributed to plausible anomaly indicators, whereas the non-balanced model often relied on spurious correlations. Thus, class balancing not only improves performance but also yields more coherent and reliable explanations.

Figure 2: A LIME explanation illustrating how individual features at specific time steps influence the model's prediction for one transaction. Each bar represents a feature's contribution, with intervals like "$T0\_F4 > 1.24$" indicating the discretized feature value. Bars extending to the right push the prediction towards fraud, while those to the left favor a legitimate classification. This local analysis helps identify which attributes played the most significant role in the model's decision for this particular case.

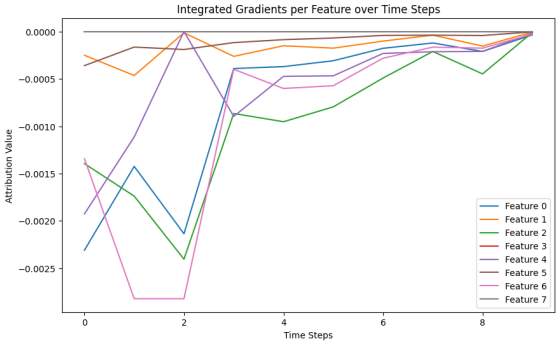

Figure 3: Integrated Gradients (IG) attribution values for each feature over time. This line plot shows how the importance attributed by the IG method evolves across multiple time steps for each of the eight features under consideration (labeled Feature 0 through Feature 7). The vertical axis indicates the attribution value, where positive values suggest a feature increases the model's probability of predicting fraud at that particular time step, and negative values indicate a feature decreases that probability. Observing how these attributions change over time can help identify temporal patterns and moments when certain features become critical, providing insights into the sequence-based reasoning of the model.

5.4 Robustness and Reliability

By analyzing model predictions over multiple test samples, we observed that the balanced LSTM model generalizes more robustly to previously unseen patterns of fraud. Rare but critical events—such as sudden large transfers or abnormal account behaviors—are more consistently identified. Meanwhile, the improved explanations enhance model reliability: by showing which features are essential for a given prediction, practitioners can verify the model's reasoning against domain knowledge and business rules.

5.5 Summary of Findings

In summary, the experimental results support the following conclusions:

- **Class Balancing Improves Detection:** Applying SMOTE significantly enhances

the LSTM model's ability to detect fraudulent transactions, increasing recall and F1-score without notably sacrificing precision.

- **Meaningful Latent Representations:** The autoencoder's compressed embeddings help the LSTM focus on salient features, improving the downstream classification performance.

- **Enhanced Interpretability:** Post-hoc explanation methods (LIME and IG) produce more stable and reliable explanations when the model is trained on a balanced dataset. These explanations highlight legitimate fraud indicators rather than noise or spurious correlations.

Overall, our results illustrate that combining representation learning, class imbalance mitigation, temporal modeling, and explainability techniques leads to a more accurate, robust, and interpretable fraud detection system.

6 Limitations and Current Challenges

Despite the strong performance of our system, several challenges remain to be addressed. The real-time processing capabilities of our current implementation require further optimization to meet the demands of high-volume transaction environments. Additionally, the model's ability to adapt to new fraud patterns needs enhancement to address the evolving nature of financial fraud. We also acknowledge limitations in the interpretability of certain model components, particularly in the autoencoder's latent space representations.

7 Future Work

Our research opens several promising avenues for future investigation. A primary focus will be the expansion of dataset diversity to improve the model's generalization capabilities across different types of financial transactions. We plan to develop a comprehensive real-time anomaly detection pipeline that can handle the volume and velocity of modern financial systems. The integration of more advanced explainable AI techniques remains a priority, as does the enhancement of our temporal pattern recognition capabilities. We also see significant potential in implementing adaptive learning mechanisms that can evolve with changing fraud patterns.

8 Conclusion

In this project, we proposed and evaluated a multi-stage approach for detecting fraudulent financial transactions in a highly imbalanced setting. By employing SMOTE-based class balancing, we were able to significantly improve the recall of fraudulent detections, ensuring that a greater proportion of illicit transactions were identified. The autoencoder-driven representation learning facilitated the extraction of compact, meaningful embeddings from raw transaction data, thereby aiding the downstream LSTM classifier in capturing temporal patterns associated with fraud more effectively.

Our results demonstrate that addressing class imbalance is crucial not only for improving detection metrics such as recall and F1-score but also for enhancing the interpretability of the model's decisions. Post-hoc explainability techniques, including LIME and Integrated Gradients, were far more informative and consistent

when the classifier had been trained on a balanced dataset. These local explanations highlighted which features and time steps were most influential, aligning with domain expectations for suspicious activity and ultimately increasing confidence in the model's predictions.

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