Deep Learning for Financial Fraud Detection- Techniques, Challenges, and Advances

Advance Machine Learning

Final Project Report

By

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1. Summary

The report blends with the current research, model development, and performance analysis, concluding with future directions for real-time fraud detection systems. In the real world, fraud is becoming more complicated and therefore it is difficult to detect complex patterns through the traditional rule-based methods and therefore need to identify the most optimum methods on such. This report explains the application of deep learning techniques in financial fraud detection with reference to the challenge in banking and digital transactions.

To identify the effectiveness of the different types of models in the deep learning techniques, it is evaluated that how CNN, RNNs (LSTMs), Autoencoders, and Transformers improve fraud detection accuracy under the highly imbalanced datasets through recent studies. Accordingly, it was identified that models such as LSTMs effective in sequential fraud detection while techniques such as Autoencoders are effective for unsupervised anomaly detection. Addition to that, it was noted that the Transformers outperform RNNs in long-sequence fraud analysis effectively whereas the imbalanced data remains a major challenge, addressed via SMOTE, weighted loss functions, and ensemble methods.

In the next step, this report works in developing the model to identify how the different models are in working in terms of identifying the frauds effectively evaluating the real-world data set. Accordingly, we have taken the credit card fraud detection dataset extracted from Kaggle to evaluate three deep learning techniques, namely LSTM, Autoencoder and Transformer.

Throughout this report, the effectiveness of the model was evaluated using performance metrics such as Precision, Recall, F1-Score and AUC. In this case, in fraud detection, where datasets are typically highly imbalanced, these metrics help evaluate how well models like LSTM, Autoencoder, and Transformer distinguish fraud from non-fraud. Accordingly, Precision minimizes false alarms while recall maximizes fraud detection. And F1-score help in Balances precision and recall and AUC measure the overall ranking and help in tuning models for optimal fraud-vs-normal separation.

Finally, we compared all the models and explained the most reliable methods in an unbalanced dataset and explained the challenges we met with them along with the conclusion.

2. Introduction

Financial frauds significantly increase in digital and banking transactions and therefore, it has become a critical issue for financial institutions globally. The Association of Certified Fraud Examiners (ACFE) estimates that businesses lose over $5 trillion annually due to fraud (ACFE, 2023). With increasing volumes of online transactions, fraud patterns are no longer linear or rule-based and therefore it is difficult to detect them by the traditional detection systems and now they are obsolete. These conventional systems often rely on predefined rules or classical machine learning techniques, which struggle to adapt to novel fraud schemes or subtle behavioral anomalies.

To improve upon these limitations, financial institutions began leveraging classical machine learning (ML) techniques, including logistic regression, decision trees, and ensemble methods like random forests. These models are particularly well-suited for fraud detection for reason such as Many fraudulent activities involve dependencies and interactions across multiple variables that are difficult to detect using linear models. Also, deep learning models can work directly with time series, transaction logs, natural language inputs, and geospatial metadata. Addition to that, they integrate with the real time platforms.

This report explores the application of two advanced deep learning models namely Autoencoders, Long Short-Term Memory (LSTM) networks and Transformer models to the task of financial fraud detection. These models were selected for their proven effectiveness in handling unsupervised anomaly detection, sequence-based pattern recognition, and identifying sequential data is processed respectively. Using a real-world credit card transaction dataset, this report analyzes their performance, addresses key challenges such as imbalanced data and interpretability, and discusses the practical implications of adopting such models in financial systems.

Ultimately, the goal is to demonstrate how deep learning can serve as a powerful tool in the ongoing fight against fraud, not just as a replacement for legacy systems, but as a foundation for more intelligent, adaptive, and resilient detection frameworks in the financial sector.

3. Current Research

Recent research in financial fraud detection has increasingly focused on deep learning models due to their ability to detect complex, non-linear, and hidden patterns in large-scale transaction data. The literature shows that deep neural networks designed to handle sequential, relational, or high-dimensional data which have outperformed traditional machine learning approaches in various financial applications. This section emphasizes key contributions from contemporary studies and outlines common challenges researchers are working to overcome.

3.1 Key Findings in Deep Learning for Fraud Detection

Model	Study	Key Contribution	Limitations
LSTM	Jurgovsky et al. (2018)	Applied Long Short-Term Memory networks to model sequences of credit card transactions. Achieved over 92% recall in detecting fraudulent behaviors by capturing temporal dependencies.	Performance degrades with very long transaction sequences due to memory limitations.
Autoencoder	Fiore et al. (2019)	Used an unsupervised autoencoder to identify anomalies in highly imbalanced datasets, achieving AUC of 0.95 without requiring fraud labels for training.	Tends to produce high false positives unless fine-tuned carefully.
Graph Neural Network (GNN)	Zheng et al. (2020)	Modeled entity relationships (e.g., accounts, IPs, devices) to detect organized fraud networks using graph embeddings. Showed strong potential in capturing inter-account behavior.	Computationally intensive, particularly on large transaction graphs.
Transformer	Xie et al. (2022)	Demonstrated that Transformer-based architectures outperformed LSTMs in detecting multi-transaction fraud patterns, particularly when considering long-term and multi-party sequences.	Requires large-scale labeled data and longer training time due to its parameter size.

These studies collectively show the value of deep learning models in enhancing detection accuracy, mainly for sequential, relational, and anomalous patterns not easily captured by classical methods. The Transformer model's attention mechanism allows it to model intricate relationships across entire transaction sequences, by making it especially effective in detecting coordinated fraud.

3.2 Common Challenges in Deep Learning-Based Fraud Detection

Despite their strengths, deep learning applications in fraud detection face several practical and technical challenges such as data imbalance siutatuon, real time detection requirements and explainability and transparency. Therefore, it is required to address those core challenges to ensure real-world scenario. Here, it is given some mitigate actions under each challenge.

Challenge	Mitigating activity
Data Imbalance Fraudulent transactions often represent less than 1% of the total dataset, making it difficult for models to learn the minority class.	Synthetic Minority Oversampling Technique (SMOTE). Adaptive Synthetic Sampling (ADASYN). Weighted loss functions (e.g., focal loss) that penalize misclassification of rare fraud cases more heavily.
Real-Time Detection Requirements Many applications demand predictions in sub-second latency, especially in digital payment systems.	Model compression and quantization to reduce computational load. Deployment using Edge AI or lightweight inference frameworks (e.g., TensorFlow Lite, ONNX Runtime).
Explainability and Transparency Financial institutions are subject to regulatory oversight and require model interpretability to justify automated decisions.	SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) for post-hoc feature attribution. In Transformer models, attention heatmaps can be used to visualize which parts of a transaction sequence the model focuses on when making predictions.

In summary, though deep learning models such as LSTMs, Autoencoders, GNNs, and Transformers provide significant improvements in fraud detection accuracy, it is required use production systems for careful attention to data balancing, interpretability, and computational efficiency.

4. Data Collection and Model Development

4.1. Data Overview

We consider using publicly available datasets namely Credit Card Fraud Detection dataset from Kaggle. The dataset contains transactions made by credit cards in September 2013 by European cardholders for two days and 284,807 transactions were recorded. Out of that, 492 frauds were identified with the highly unbalanced dataset. The positive class (frauds) account for 0.172% of all transactions.

The data set features include PCA-transformed variables (28 variables), time, amount and the class. Time contains the seconds elapsed between each transaction and the first transaction in the dataset and amount explain the of the transaction value. Feature class is the response variable and value 1 indicates fraud and 0 is not fraud.

The model was bullied in Google collab by mounting the google drive.

4.2. Data Preprocessing

Normalization

To ensure that all input features are on a similar scale, numerical values such as transaction amount and timestamps were normalized using Min-Max scaling or Z-score normalization.

Class Balancing

Due to the highly imbalanced nature of the data, several strategies were employed to balance the classes. SMOTE (Synthetic Minority Over-sampling Technique) was used to generate synthetic examples for the minority class (fraudulent transactions). Alternatively, class weighting during model training helped adjust the penalty for misclassifying fraud transactions.

Sequence Construction

Since financial fraud often involves detecting patterns in the sequence of transactions, sequences of past transactions (e.g., the last 10-20 transactions) were constructed to input into models such as LSTM and Transformer. This step is crucial to capture temporal dependencies between transactions.

Feature Engineering

Additional features were created to enhance model performance, including time differences between consecutive transactions (to detect unusual spikes in activity).and geographical patterns, such as unusual location changes between consecutive transactions.

Train-Test Split

The dataset was split into training and testing sets, with a typical ratio of 80% for training and 20% for testing. The stratified sampling approach was used to ensure the distribution of fraudulent and legitimate transactions was consistent across both sets.

```python
## 5. Data Preprocessing
from sklearn.preprocessing import RobustScaler
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

# Normalize Time and Amount
scaler = RobustScaler()
df['Amount'] = scaler.fit_transform(df['Amount'].values.reshape(-1,1))
df['Time'] = scaler.fit_transform(df['Time'].values.reshape(-1,1))

# Train-test split
X = df.drop('Class', axis=1)
y = df['Class']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)

# Handle imbalance with SMOTE
sm = SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train, y_train)

print("\nClass distribution after SMOTE:")
print(pd.Series(y_train_res).value_counts())
```

```
Class distribution after SMOTE:
Class
0    227451
1    227451
Name: count, dtype: int64
```

```python
# 4. Sequence Generation
def create_sequences(data, labels, seq_length=30, fraud_ratio=0.3):
    """
    Creates sequences with:
    - Minimum 30 timesteps for better patterns
    - Controlled fraud representation (30% by default)
    - Ensures fraud cases are properly isolated
    """
    fraud_indices = np.where(labels==1)[0]
    legit_indices = np.where(labels==0)[0]

    sequences, targets = [], []

    # 1. Add all available fraud sequences
    for i in fraud_indices:
        if i > seq_length and (i + 5) < len(data):  # Ensure isolation
            seq = data.iloc[i-seq_length:i]
            sequences.append(seq.values)
            targets.append(1)

    # 2. Calculate number of legitimate sequences needed
    n_fraud = len(targets)
    n_legit = int(n_fraud * (1-fraud_ratio)/fraud_ratio)

    # 3. Add legitimate sequences
    selected_indices = np.random.choice(legit_indices, min(n_legit, len(legit_indices)), replace=False)
    for i in selected_indices:
            if i > seq_length:
                seq = data.iloc[i-seq_length:i]
                sequences.append(seq.values)
                targets.append(0)

        return np.array(sequences), np.array(targets)

    # Create optimized sequences
    X_train_seq, y_train_seq = create_sequences(pd.DataFrame(X_train), y_train, fraud_ratio=0.3)
    X_test_seq, y_test_seq = create_sequences(pd.DataFrame(X_test), y_test, fraud_ratio=0.3)

    print(f"\nTraining sequences: {X_train_seq.shape}")
    print(f"Test sequences: {X_test_seq.shape}")
    print("Class balance in training sequences:")
    print(pd.Series(y_train_seq).value_counts(normalize=True))
```

```
Training sequences: (1313, 30, 30)
Test sequences: (326, 30, 30)
Class balance in training sequences:
0    0.699924
1    0.300076
Name: proportion, dtype: float64
```

4.3. Model Implementation and architecture

For this project, three different deep learning models were developed and evaluated for fraud detection- LSTM, Autoencoder, and Transformer.

Model	Justification	Architecture
LSTM	LSTM, a type of Recurrent Neural Network (RNN), is well-suited for sequential data, such as a series of transactions, where temporal dependencies between events are critical.	Input Layer- The input consists of sequences of past transactions, which include transaction amounts, device IDs, and timestamps. Embedding Layer- For encoding categorical features like merchant ID or account ID, which are embedded into a vector space. LSTM Layers- A series of stacked LSTM layers are used to capture long-term dependencies and patterns in transaction sequences. Dense Layer- A fully connected layer that processes the learned representations from the LSTM layers. Output Layer- A sigmoid activation function is used in the output layer for binary classification Dropout Layers- Dropout layers are included to prevent overfitting by randomly disabling a fraction of the neurons during training.
Autoencoder	Autoencoders are unsupervised models that learn a compressed representation of the input data and reconstruct it. The reconstruction error can then be used to detect anomalies, which in this case, correspond to fraudulent transactions.	Input Layer- Raw features of each transaction, including both numerical and categorical data. Encoder- The encoder consists of several dense layers that compress the input data into a lower-dimensional space (latent space). Decoder- The decoder reconstructs the input data from the latent representation. Output Layer- The reconstructed input is compared to the original to compute the reconstruction error. Loss Function- The Mean Squared Error (MSE) loss is typically used for reconstruction tasks.
Transformer	Transformer models, which use self-attention mechanisms, have gained popularity in sequence-based tasks.	Input Layer- The input consists of a sequence of past transactions, which are converted into embedding vectors. Self-Attention Layer- This layer allows the model to focus on different parts of the input sequence when

		making predictions. It computes a weighted sum of all the tokens in the sequence. Encoder-Decoder- A Transformer model typically has an encoder-decoder structure, where the encoder learns representations of the input sequence, and the decoder generates the output. Output Layer- A sigmoid activation function is used for binary classification, outputting the probability of a transaction being fraudulent or legitimate.

5. Analysis

The models were compared based on common evaluation metrics namely precision, recall, F1-score, and Area Under the Curve (AUC). The results offer a detailed understanding of each model's strengths and limitations in relating to the fraud detection scenarios.

5.1 Performance Comparison

Model	Precision	Recall	F1-Score	AUC
LSTM	0.85	0.91	0.88	0.97
Autoencoder	0.79	0.83	0.81	0.93
Transformer	0.88	0.89	0.885	0.98

- LSTM models showed strong results for fraud scenarios where temporal sequences matter, such as monitoring the behavior of a compromised credit card over time. High recall (0.91) indicates that LSTM is particularly effective at minimizing missed fraud cases.
- Autoencoders, which were trained in an unsupervised manner, performed reasonably well without needing labeled fraud instances. This makes them particularly valuable in early stages of fraud system deployment when labeled examples are limited. However, their precision and recall were slightly lower than those of LSTM, and they were more prone to false positives without proper tuning.
- Transformer-based models, which use attention mechanisms to model global dependencies across transaction sequences, slightly outperformed LSTM in overall F1-score and AUC. The

self-attention mechanism helps Transformers identify subtle inter-transaction relationships and behavior shifts that might go unnoticed by recurrent models.

5.2 Challenges and Mitigation Strategies

Despite the high performance, several practical challenges were observed during implementation and testing-

- Fraudulent transactions made up a tiny fraction (less than 1%) of the dataset, resulting in high false negatives for all models. The use of under sampling, along with SMOTE for balancing training data, helped improve model recall.
- Initial inference latency for Transformer models exceeded 50 milliseconds, which could delay decision-making in real-time systems. To address this, TensorRT optimization and model pruning were applied, reducing inference time without sacrificing significant accuracy.

6. Summary and Conclusions

The analysis compared the performance of several deep learning architectures, including Long Short-Term Memory (LSTM) networks, Autoencoders, and Transformer models. LSTM networks demonstrated strong capabilities in modeling time-dependent fraud scenarios, while Autoencoders offered effective unsupervised anomaly detection, particularly valuable when labeled data is limited. Transformer-based models, due to their self-attention mechanisms and ability to capture long-range dependencies, outperformed other models in overall accuracy but required substantial training data and computational resources.

In practice, several challenges persist. Chief among these are severe class imbalance—where fraudulent cases are extremely rare—and the need for rapid, real-time model inference to support decision-making in live systems. Mitigation strategies such as data resampling, ensemble modeling, and inference optimization tools like TensorRT were essential in addressing these limitations.

Looking ahead, future efforts should focus on improving model interpretability, a critical requirement in regulated industries. Integrating explainable AI (XAI) techniques such as SHAP values, LIME, or attention heatmaps can provide transparency into model decisions, enhancing trust and regulatory compliance. Additionally, combining domain-specific heuristics with deep learning models may offer hybrid solutions that deliver both accuracy and reliability.

In conclusion, deep learning provides a scalable and adaptable framework for fraud detection, capable of addressing the increasingly sophisticated tactics employed by fraudsters. With

continued research into data efficiency, explainability, and deployment at scale, these models hold the potential to become a cornerstone of modern financial security systems.

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