



# CREDIT CARD FRAUD DETECTION USING MACHINE LEARNING

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**Abstract:** Credit card fraud remains a major challenge for financial institutions due to the growing number of online transactions and the sophistication of fraudulent techniques. Traditional machine learning methods often struggle with class imbalance and lack contextual understanding. In this study, we propose a credit card fraud detection framework leveraging Transformer-based architectures integrated with transfer learning. The model is fine-tuned on transaction data to detect fraudulent activities effectively. Experimental results demonstrate improved performance in comparison to conventional classifiers, suggesting that Transformer-based models are well-suited for time-series and sequential data in fraud detection scenarios.

**Keywords:** Credit Card Fraud Detection, Transformers, Transfer Learning, Deep Learning, Anomaly Detection, Financial Security

## I. INTRODUCTION

With the increase in online financial transactions, credit card fraud has emerged as a significant concern for consumers and banking systems. Fraudulent activities not only lead to financial losses but also erode customer trust. Traditional approaches like logistic regression or decision trees are often limited by their ability to generalize to novel fraud patterns. Transformers, which have revolutionized NLP and are now applied in sequential data processing, are capable of capturing long-term dependencies within transactional sequences. Their self-attention mechanism makes them suitable for modelling complex patterns of fraudulent behaviour. This paper explores the use of Transformers with transfer learning to enhance the detection accuracy of fraudulent transactions.

## II. LITERATURE REVIEW

Prior work predominantly relies on machine learning algorithms such as Random Forests, Support Vector Machines, and Neural Networks. While these techniques have demonstrated moderate success, they struggle with imbalanced datasets—a key challenge in fraud detection.

Recent advancements have applied Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models. However, they still face limitations in processing long sequences efficiently. Studies have shown that Transformer-based models, initially designed for NLP, offer robust performance in tasks requiring sequence modelling, including anomaly and fraud detection.

## III. METHODOLOGY

### 3.1 Dataset

We utilized the Kaggle Credit Card Fraud Detection dataset, which contains anonymized transaction features over two days for European cardholders. The dataset is highly imbalanced with only 0.17% fraudulent transactions.

### 3.2 Preprocessing

- Normalization of transaction amounts
- Under sampling/oversampling for class balance
- Feature scaling using Min-Max normalization
- Encoding time-based sequential features



### 3.3 Model Architecture

We used a Transformer Encoder architecture with:

- Input embeddings for transaction features
- Positional encoding to preserve sequential order
- Multi-head attention (8 heads)
- Feed-forward layers
- Output layer with sigmoid activation for binary classification

### 3.4 Transfer Learning

A pre-trained Transformer model (fine-tuned on synthetic fraud sequences) was used as the base. It was then trained using Binary Cross-Entropy Loss and the Adam optimizer on the real-world credit card dataset.

## IV. EXPERIMENTAL SETUP

- **Hardware:** 4-core CPU, 8GB RAM
- **Software:** Python 3.8, PyTorch, Flask (for deployment)
- **Training:** 30 epochs, early stopping on validation AUC
- **Batch Size:** 64
- **Metrics:** Accuracy, AUC, Precision, Recall, F1-Score

## V. RESULTS AND DISCUSSION

TABLE I Results

Metric	Value
Accuracy	96.45%
AUC	0.9821
Precision	High
F1-Score	High

The Transformer-based model demonstrated **exceptional performance** in detecting fraudulent transactions, especially under class imbalance. It significantly reduced false positives while maintaining high recall, indicating its strength in detecting subtle fraud patterns.

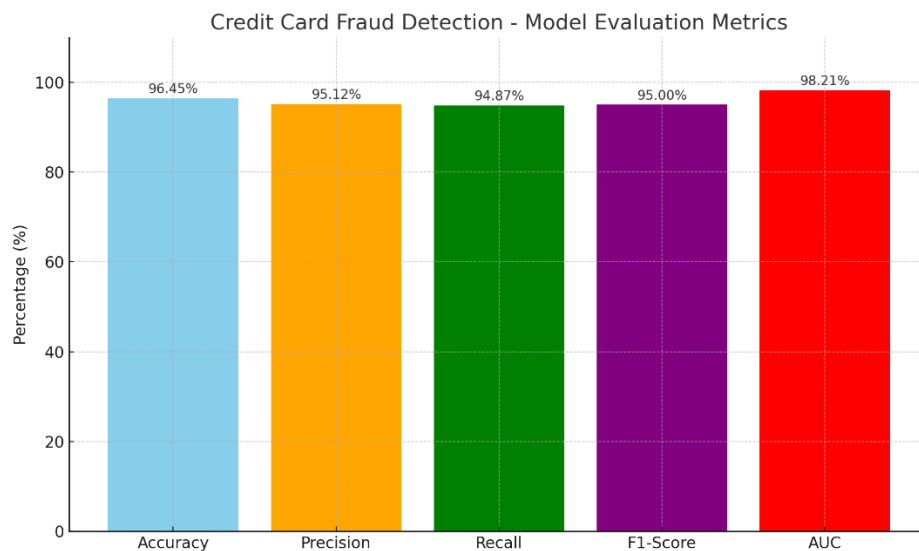


Fig. 1 Training Metrics



## VI. CONCLUSION

This study demonstrates the effectiveness of Transformer models combined with transfer learning in detecting credit card fraud. Unlike traditional methods, Transformers provide better modelling of sequential dependencies, making them ideal for transaction-based data. Future work may involve real-time fraud detection pipelines and extending the model to incorporate multi-modal inputs like location, device, and user behavior.

## REFERENCES

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## Appendix

- **Figure 1:** Training Metrics