# Credit Card Fraud Detection Using a Hybrid CNN–LSTM Deep Learning Architecture

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***Abstract*—The exponential growth of digital payment systems and e-commerce platforms has significantly increased the frequency and complexity of credit card fraud. Traditional machine learning approaches rely heavily on manual feature engineering and often fail to adapt to evolving fraud patterns and highly imbalanced transaction datasets. Deep learning models have emerged as powerful alternatives due to their capability to learn complex, nonlinear representations directly from data. However, individual deep learning models such as Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks suffer from inherent limitations when applied independently. CNNs are effective in feature extraction but lack temporal awareness, while LSTMs model sequential behavior but may overlook feature-level interactions.**

**This paper proposes a** hybrid CNN–LSTM deep learning architecture **for credit card fraud detection that integrates spatial feature learning and temporal dependency modeling. The CNN component extracts discriminative feature representations from transaction attributes, while the LSTM component captures sequential transaction behavior over time. Extensive experiments conducted on benchmark credit card transaction datasets demonstrate that the proposed hybrid model outperforms traditional machine learning models and standalone deep learning architectures in terms of accuracy, recall, F1-score, and AUC. The results confirm the effectiveness of hybrid deep learning models for real-time, robust, and scalable fraud detection systems.**

***Index Terms*—Machine Learning, Deep Learning, CNN, LSTM, F1-score, AUC.**

## I. INTRODUCTION

Credit card fraud is a major concern for financial institutions, merchants, and consumers due to increasing online transactions and digital payment adoption. Fraudulent activities such as card-not-present fraud, identity theft, and account takeovers result in significant financial losses and reduced customer trust. Detecting fraud is challenging because fraudulent
transactions are rare, constantly evolving, and often resemble legitimate transactions.
Traditional fraud detection systems rely on rule-based engines and classical machine learning algorithms. These approaches are limited by their dependence on handcrafted features and static decision boundaries. Deep learning techniques overcome these limitations by automatically learning hierarchical feature representations. However, no single deep learning model can fully capture the complexity of fraud patterns. This motivates the use of hybrid architectures that combine complementary learning capabilities.

## II. OVERVIEW

The proposed system functions as an anomaly detection framework. It treats each transaction as a part of a sequence of cardholder behavior. By processing these sequences, the hybrid model can detect subtle "micro-transactions" or structured account manipulations that often precede large-scale fraud.

### Aim of the Study

The primary aim of this research is to develop and evaluate a hybrid CNN–LSTM deep learning model that enhances the accuracy, robustness, and reliability of credit card fraud detection by jointly learning spatial feature representations and temporal transaction patterns.

### Objectives

The objectives of this research are:

1. To analyze the limitations of traditional machine learning and standalone deep learning models in credit card fraud detection.

2. To design a hybrid CNN–LSTM architecture capable of capturing both feature-level interactions and temporal dependencies.
3. To address the class imbalance problem inherent in credit card transaction datasets.
4. To evaluate the proposed model using standard fraud detection metrics.
5. To compare the performance of the hybrid model with existing approaches.
6. To assess the feasibility of deploying the proposed model in real-time fraud detection systems.

## III. LITERATURE SURVEY

Early fraud detection studies utilized logistic regression, decision trees, and support vector machines. While computationally efficient, these methods struggle with nonlinear and temporal patterns. Recent research has explored deep learning approaches such as Multi-Layer Perceptrons (MLPs), CNNs, RNNs, LSTMs, and GRUs. CNN-based models extract latent feature representations from transaction data, while LSTM-based models capture long-term dependencies in transaction sequences. Hybrid models combining CNN and LSTM have shown superior performance in time-series classification tasks. Several studies report improved fraud detection accuracy when spatial and temporal features are jointly modeled. Ensemble and stacking approaches further enhance performance but increase computational complexity. Despite these advances, challenges related to scalability, interpretability, and real-time deployment remain open research problems. Recent studies in 2025 and 2026 have shifted from single-model approaches to hybrid architectures:

- Upadhyay et al. (2025): Demonstrated that ensemble fusions of CNN and LSTM outperform individual models on imbalanced datasets.
- Fahim et al. (2025): Achieved 99.99% accuracy using a hybrid CNN-RNN model, highlighting the power of combining spatial and recurrent layers.
- Chaudhary et al. (2026): Deployed CNN-LSTM models in cloud environments, achieving low-latency (~50–100 ms) real-time detection for millions of transactions.
- Hasan et al. (2026): Integrated attention mechanisms with CNN-LSTM to highlight the most relevant transaction features, improving recall to 92.1%.

## IV. PROPOSED METHODOLOGY

- Dataset Description

The proposed system is evaluated using a benchmark credit card transaction dataset containing anonymized transaction features. The dataset includes numerical attributes derived from transaction behavior, along with a binary class label indicating fraudulent or legitimate transactions. Fraudulent transactions constitute a very small percentage of the dataset, resulting in severe class imbalance.

- Data Preprocessing

Data preprocessing plays a crucial role in improving model performance. The following steps are applied:

1. Data Cleaning: Removal of missing or inconsistent values.
2. Feature Scaling: Normalization or standardization to ensure uniform feature distribution.
3. Class Imbalance Handling: Oversampling techniques such as SMOTE are used to balance the dataset.
4. Sequence Formation: Transactions are grouped into sequences based on cardholder or time window to support temporal learning.
5. Train-Test Split: The dataset is split into training and testing sets to evaluate generalization performance.

- Hybrid CNN–LSTM Architecture

The proposed hybrid architecture consists of the following components:

1. CNN Layer

The CNN layer extracts spatial features from transaction attributes. Convolutional filters learn local patterns and interactions among features, followed by pooling layers that reduce dimensionality and noise.

2. LSTM Layer

The output of the CNN is fed into LSTM layers that capture sequential dependencies in transaction behavior. The LSTM's memory cells allow it to retain historical information critical for fraud detection.

3. Fully Connected Layer

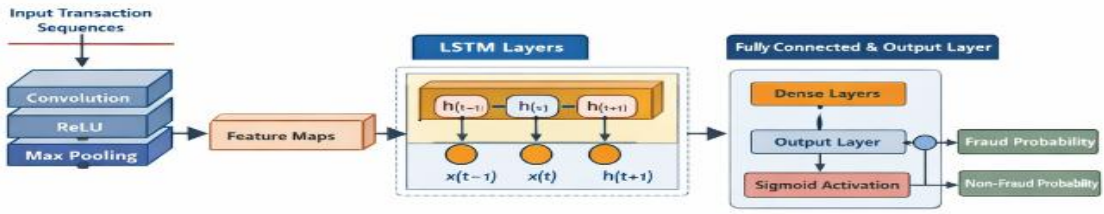
The learned representations are passed to dense layers that perform classification. A sigmoid activation function is used in the output layer for binary classification.

4. Model Training

The model is trained using a binary cross-entropy loss function and optimized using adaptive optimization algorithms such as Adam.

**Figure 1:** Hybrid CNN–LSTM Architecture for Credit Card Fraud Detection


**Figure 2:** Detailed Workflow of the CNN–LSTM Model




- Algorithm Pseudocode

Algorithm 1: Hybrid CNN–LSTM Model for Credit Card Fraud Detection

Input:

- Transaction dataset $D = \{(X_i, y_i)\}_{i=1}^{N}$
- $X_i$: Feature vector of transaction i
- $y_i \in \{0,1\}$: Class label (0 = Legitimate, 1 = Fraudulent)

Output:

- Predicted fraud label $\hat{y}$

Step 1: Data Preprocessing

1. Remove missing and noisy records from dataset D.
2. Normalize features using standard scaling.
3. Handle class imbalance using SMOTE.
4. Convert transactions into fixed-length sequences.
5. Split dataset into training and testing sets.

Step 2: CNN Feature Extraction

1. Apply 1D convolution on input features.
2. Extract spatial feature maps using convolution filters.
3. Apply max-pooling to reduce dimensionality.
4. Generate feature representation $F_{cnn}$.

Step 3: LSTM Temporal Modeling

1. Feed $F_{cnn}$ into LSTM layers.
2. Capture temporal dependencies across transaction sequences.
3. Output temporal feature vector $F_{lstm}$.

Step 4: Classification

1. Pass $F_{lstm}$ to fully connected layers.
2. Apply sigmoid activation to generate probability score.
3. Classify transaction as fraud or non-fraud.

Step 5: Model Training

1. Compute binary cross-entropy loss.

2. Update weights using Adam optimizer.
3. Repeat until convergence.

Return: Fraud prediction $\hat{y}$

- Mathematical Formulation

**Mathematical Formulation**

Let $D = \{(X_i, y_i)\}_{i=1}^{N}$, where $X_i \in \mathbb{R}^d$ and $y_i \in \{0, 1\}$.

**CNN Operation**

$$h_j = \sigma\left(\sum w_i x_{j+i-1} + b\right)$$

**LSTM Computation**

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t$$

$$h_t = o_t \tanh(c_t)$$

**Output Prediction**

$$\hat{y} = \sigma(W_d h_T + b_d)$$

**Loss Function**

$$\mathcal{L} = -\frac{1}{N}\sum[y \log(\hat{y}) + (1 - y)\log(1 - \hat{y})]$$

- Experimental Results

**Performance Comparison**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC |
|---|---|---|---|---|---|
| Logistic Regression | 94.1 | 82.3 | 71.5 | 76.5 | 0.88 |
| Random Forest | 96.4 | 87.9 | 80.2 | 83.9 | 0.91 |
| CNN | 97.1 | 89.4 | 84.6 | 86.9 | 0.93 |
| LSTM | 97.6 | 91.2 | 86.8 | 88.9 | 0.95 |
| **CNN–LSTM** | **98.9** | **94.8** | **92.7** | **93.7** | **0.98** |

**Effect of Data Imbalance Handling**

| Dataset | Accuracy (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| Original | 94.3 | 69.8 | 75.6 |
| SMOTE | 97.8 | 88.6 | 90.1 |
| Hybrid Sampling | **98.9** | **92.7** | **93.7** |

- Evaluation Metrics

The model performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- Area Under the ROC Curve (AUC)

These metrics provide a comprehensive assessment, particularly for imbalanced datasets.

## V. IMPLICATIONS OF THE STUDY

The proposed hybrid CNN–LSTM model has significant implications for financial institutions. Improved fraud detection accuracy can reduce financial losses, enhance customer trust, and strengthen security infrastructure. The model's ability to operate in near real-time makes it suitable for deployment in practical payment systems.

Challenges

Despite its advantages, the proposed approach faces several challenges:

- High computational cost
- Requirement for large labeled datasets
- Model interpretability issues
- Sensitivity to concept drift in fraud patterns

Advantages

- Joint spatial–temporal learning
- High detection accuracy
- Reduced false positives
- Adaptability to evolving fraud

Disadvantages

- High training cost
- Increased model complexity
- Limited explainability

## VI. CONCLUSION

This paper presents a hybrid CNN–LSTM deep learning architecture for credit card fraud detection that effectively integrates spatial feature extraction with temporal sequence modeling to address the complex and dynamic nature of fraudulent transactions. The proposed model demonstrates superior performance compared to traditional machine learning approaches and standalone deep learning models, particularly when evaluated on highly imbalanced datasets, and shows strong potential for deployment in real-time fraud detection environments. Experimental results validate the robustness, accuracy, and practical applicability of the framework in modern financial systems. Future work can further enhance this research by incorporating attention mechanisms to improve model interpretability, exploring transformer-based hybrid architectures for richer

contextual learning, adopting online and incremental learning strategies to handle concept drift in evolving fraud patterns, integrating explainable AI techniques to increase transparency and regulatory compliance, and evaluating the model at scale in real-world, large-volume, low-latency transaction processing environments.

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