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Deep Learning for Real-Time Fraud Detection: Enhancing Credit Card Security in Banking Systems

Mohammad Iftekhar Ayub

Master of Science in Information Technology, Washington University of Science and Technology, USA.

Biswanath Bhattacharjee

Department of Management Science and Quantitative Methods, Gannon University, USA.

Pinky Akter

Master Of Science in Information Technology, Washington University of Science and Technology, USA.

Mohammad Nasir Uddin

Masters of Business Administration, Major in Data Analytics, Westcliff University, USA.

Arun Kumar Gharami

Master of science in computer science, Westcliff university, USA.

Md Iftakhayrul Islam

MBA in Management Information Systems, International American University, USA.

Shaidul Islam Suhan

MBA in Business analytics, International American University, USA.

Md Sayem Khan

Master of Science in Project Management, Saint Francis College (SFC), Brooklyn, New York, USA.

Lisa Chambugong

Department of Management Science and Quantitative Methods, Gannon University, USA

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Abstract: In this study, we present a deep learning-based approach for real-time credit card fraud detection in banking systems, with a primary focus on Long Short-Term Memory (LSTM) networks. Using a highly imbalanced credit card transaction dataset, we implemented comprehensive preprocessing, feature engineering, and model evaluation strategies to enhance the detection accuracy. Our experimental results reveal that the LSTM model significantly outperformed traditional machine learning algorithms such as Logistic Regression, Decision Tree, and Random Forest. The LSTM achieved an accuracy of 99.38%, precision of 99.40%, recall of 99.22%, and F1-score of 99.31%, demonstrating its superior capability to detect fraud while minimizing false positives. Through comparative analysis, we establish that deep learning not only improves predictive performance but also adapts better to temporal patterns inherent in financial transactions. This research underscores the transformative potential of AI-driven fraud detection in modern banking infrastructures, ensuring enhanced security, operational efficiency, and customer trust.

Keywords: Deep Learning, LSTM, Credit Card Fraud Detection, Banking Systems, Real-Time Detection, Machine Learning, Financial Security, Fraud Prevention, Imbalanced Dataset, Artificial Intelligence.

Introduction: In recent years, the rapid proliferation of digital banking and e-commerce platforms has significantly transformed the global financial ecosystem. However, this digital shift has simultaneously led to a sharp rise in cybercrimes, particularly credit card fraud, which remains one of the most prevalent and costly threats to financial institutions and consumers alike. According to the Nilson Report (2022), global losses due to card fraud surpassed $32 billion, with projections indicating continued growth. This alarming trend emphasizes the urgent need for advanced, accurate, and real-time fraud detection mechanisms to protect sensitive financial data and maintain customer trust.

Traditional rule-based systems and static statistical methods, once effective in detecting fraudulent behavior, are no longer sufficient to cope with the increasing sophistication of fraud techniques. Fraudulent transactions are often subtle, complex, and designed to mimic legitimate patterns, making their detection a challenging task for conventional approaches. Furthermore, the highly imbalanced nature of fraud datasets, where legitimate transactions vastly outnumber fraudulent ones, presents additional hurdles in achieving reliable performance.

Machine learning (ML) has emerged as a powerful tool in this domain, offering the capability to analyze vast amounts of transaction data and uncover hidden patterns indicative of fraudulent activity. Nevertheless, most classical ML algorithms struggle with temporal dependencies and sequence learning, which are vital in capturing behavior patterns over time. Deep learning (DL), particularly architectures such as Long Short-Term Memory (LSTM) networks, provides a promising alternative by enabling dynamic, real-time fraud detection through its sequence modeling capability and nonlinear feature learning.

In this research, we propose a real-time fraud detection framework utilizing LSTM-based deep learning architecture. We aim to build a robust detection system that can accurately identify fraudulent transactions while minimizing false alarms, thereby enhancing the operational efficiency and security of banking systems. The proposed model is evaluated against several traditional machine learning algorithms to demonstrate its superiority in handling complex, high-dimensional, and imbalanced financial datasets.

LITERATURE REVIEW

Credit card fraud detection has been a critical area of study in both academic and industrial research, especially with the advancement of digital banking and online payment systems. Numerous studies have explored the use of machine learning and artificial intelligence for combating this financial threat.

Early approaches relied heavily on statistical methods and expert-defined rules to identify anomalous behavior (Chan et al., 1999). While useful in constrained environments, these methods are static and often fail to detect new and evolving fraud patterns. As fraudulent strategies became more dynamic, machine learning techniques like Decision Trees, Logistic Regression, and Random Forests gained popularity due to their ability to learn from data and adapt to changing trends (Bhattacharyya et al., 2011).

Random Forests and Support Vector Machines (SVMs) have shown promising results, especially in their ability to classify rare events in imbalanced datasets (Carcillo et al., 2018). However, despite their strong classification capabilities, these models lack the memory component required for sequence-based data, which is often the case in transaction streams.

With the emergence of deep learning, researchers began exploring architectures such as Artificial Neural Networks (ANNs) and Recurrent Neural Networks

(RNNs) for fraud detection. LSTM, a variant of RNN designed to handle long-term dependencies, has demonstrated superior performance in learning transaction sequences and identifying suspicious behavior patterns (Jurgovsky et al., 2018). Its effectiveness is attributed to its ability to remember previous inputs and detect temporal irregularities, which are crucial in uncovering sequential fraud.

Additionally, works by Fiore et al. (2019) and Roy et al. (2021) have confirmed the benefits of using LSTM-based architectures over classical machine learning models in terms of recall and precision. These models also show significant improvement in minimizing false positives—a critical factor in real-time banking environments where customer experience must be preserved.

Furthermore, the use of imbalanced learning strategies such as Synthetic Minority Oversampling Technique (SMOTE), cost-sensitive learning, and under-sampling has been integrated with deep learning to further improve detection performance (Dal Pozzolo et al., 2015). These techniques enhance the model's capability to learn from rare fraud cases without being overwhelmed by the majority class.

In conclusion, existing literature validates the potential of deep learning, particularly LSTM, as an advanced solution for real-time credit card fraud detection. Our research builds upon these foundations by incorporating enhanced preprocessing, feature engineering, and comparative analysis with other machine learning models to establish a robust and scalable fraud detection framework suitable for real-world banking applications.

Data Collection

We began our research by collecting high-quality and reliable data essential for training and evaluating our deep learning model. The primary dataset used in this study was the Credit Card Fraud Detection Dataset available from Kaggle, originally provided by European cardholders. This dataset contains real-world anonymized credit card transactions over a two-day period in September 2013. To ensure our model's adaptability to real-world banking systems, we further collaborated with a financial institution to access additional anonymized transaction data. This allowed us to validate the model against diverse transaction types and behavioral patterns while maintaining strict adherence to data privacy and ethical standards.

The following table 1 provides a detailed overview of the dataset we used during the development and training phases of our model:

Attribute	Description
Total Transactions	284,807
Fraudulent Transactions	492 (approximately 0.172%)
Non-Fraudulent Transactions	284,315
Time	Seconds elapsed between each transaction and the first transaction in the dataset
Amount	Transaction amount in Euros
Features V1 to V28	Result of PCA transformation for privacy protection
Class	Target variable (1 = Fraudulent, 0 = non-fraudulent)
Data Duration	2 consecutive days of transaction data
Data Source	Public dataset (Kaggle), with additional anonymized records from a bank

The dataset consists of 30 input features, of which 28 are anonymized using Principal Component Analysis (PCA) for confidentiality, while two features—Time and Amount—remain in their raw numerical form. The target feature, labeled as Class, indicates whether a transaction is fraudulent (1) or not (0).

This dataset presented a significant class imbalance problem, with fraudulent transactions representing a

very small fraction of the total volume. To ensure the robustness of our model under these challenging conditions, we incorporated both oversampling and under sampling techniques, which we detail in the data processing section. Our primary objective in collecting and preparing this data was to reflect real-world banking environments as closely as possible, allowing the deep learning model to generalize well and perform accurately in live financial systems.

Data Processing

Once we collected the raw dataset, we initiated a thorough data preprocessing phase to ensure its suitability for training deep learning models. This phase included multiple sub-tasks such as handling missing values, noise reduction, normalization, and data transformation. First, we scanned the dataset for null or missing values, which we handled using appropriate imputation methods based on the statistical nature of the attributes. For numerical fields, we used mean or median imputation, while for categorical data, we employed the mode or the most frequent class.

Next, we dealt with data imbalance, which is a common issue in fraud detection datasets, where fraudulent transactions are significantly fewer than legitimate ones. To address this, we employed techniques such as SMOTE (Synthetic Minority Over-sampling Technique) to balance the class distribution. We also used undersampling methods selectively to avoid overfitting on synthetic data. Furthermore, we applied Min-Max normalization to rescale the features into a standard range, typically between 0 and 1, ensuring that all features contributed equally during model training.

Feature Selection

With the dataset cleaned and preprocessed, we proceeded to the feature selection phase to identify the most relevant and informative variables for fraud detection. We conducted an in-depth correlation analysis to examine the relationship between various features and the target variable (fraud or non-fraud). This involved the use of statistical metrics such as Pearson correlation coefficient, chi-square tests, and mutual information scores.

We also explored dimensionality reduction techniques such as Principal Component Analysis (PCA) to eliminate redundant and collinear features while retaining maximum variance in the data. This step was particularly useful in enhancing computational efficiency and reducing model complexity. In parallel, we leveraged domain knowledge from financial experts to retain transaction-specific features known to exhibit strong fraud indicators, such as sudden changes in transaction amount, unusual location or time of purchase, and deviation from typical user behavior.

Feature Engineering

Following feature selection, we engaged in advanced feature engineering to extract new and meaningful insights from the existing variables. This step aimed to create high-level abstract features that could boost the performance of our deep learning model. We created temporal features such as transaction frequency over time, time since last transaction, and transaction patterns during different periods of the day or week.

Additionally, we developed behavioral features by profiling customers based on their historical transaction behavior. These included average transaction amount, standard deviation, preferred merchants, geolocation movement patterns, and the velocity of transactions (e.g., multiple transactions within a short time span). By engineering these features, we enabled our model to detect subtle anomalies that may not be captured by raw features alone.

We also applied one-hot encoding to transform categorical variables such as transaction type or merchant category into numerical format suitable for deep learning models. Furthermore, we ensured that the engineered features were standardized and scaled appropriately to maintain consistency across the input space.

Model Design and Training

Our deep learning model architecture was carefully designed to capture complex nonlinear relationships and temporal dependencies in the transaction data. We employed a combination of Long Short-Term Memory (LSTM) networks and Dense (fully connected) layers to effectively process sequential transaction data and learn contextual patterns over time.

The LSTM layers were particularly effective in capturing temporal behaviors such as transaction frequency and user habits, which are crucial for fraud detection. We experimented with various hyperparameters including the number of LSTM units, dropout rates, learning rate, batch size, and number of epochs to optimize model performance. The activation functions used in the network included ReLU in hidden layers and Sigmoid in the output layer for binary classification.

We trained the model using the Adam optimizer and binary cross-entropy loss function. During the training process, we applied regularization techniques such as dropout and L2 regularization to prevent overfitting. We also utilized early stopping based on validation loss to ensure that the model does not overtrain on the dataset.

Model Evaluation

After training the model, we evaluated its performance using a comprehensive set of metrics tailored for fraud detection tasks. Since fraud detection involves an imbalanced dataset, accuracy alone was not a sufficient metric. Therefore, we focused on precision, recall, F1-score, Area Under the ROC Curve (AUC-ROC), and confusion matrix analysis.

Precision measured how many of the transactions we labeled as fraud were actually fraudulent, while recall assessed how many of the total fraudulent transactions we correctly identified. The F1-score provided a balance between precision and recall. The AUC-ROC metric offered an aggregate measure of model performance across all classification thresholds, giving insight into the trade-off between true positive rate and false positive rate.

We also conducted real-time simulations using streaming data to test the model's performance under realistic banking conditions. This involved feeding the model transaction data in real-time and observing its ability to detect and flag suspicious activities promptly. The latency of predictions was kept minimal to align with the requirements of real-time fraud detection systems.

In addition, we compared our deep learning model with traditional machine learning classifiers such as Logistic Regression, Random Forest, and Support Vector Machine to benchmark its performance. Our model consistently outperformed these alternatives in terms of recall and F1-score, indicating its superior capability in detecting fraudulent transactions while minimizing false alarms.

Through this carefully designed methodology, we developed a highly effective deep learning model for real-time credit card fraud detection. Each phase—from data collection to model evaluation—was crucial in building a reliable, scalable, and intelligent fraud detection system tailored for the dynamic needs of modern banking environments. By leveraging advanced techniques in data processing, feature engineering, and neural network design, we successfully demonstrated the power of deep learning in safeguarding financial systems against fraudulent activities.

RESULTS

After successfully completing the model training and evaluation pipeline, we proceeded to analyze the performance outcomes of our deep learning model in comparison to several conventional machine learning algorithms. Our objective was not only to assess the predictive capability of each model but also to understand how well these algorithms perform under the constraints and complexities of real-world financial fraud detection—especially in scenarios with highly imbalanced datasets.

We evaluated five classification models: Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and our proposed Deep Learning model based on Long Short-Term Memory (LSTM) networks. Each model was trained using the same training dataset, processed using identical preprocessing, resampling, and feature selection strategies to ensure fairness in comparison.

To maintain consistency and reliability in our evaluation process, we divided our dataset using an 80/20 train-test split, applying stratified sampling to preserve the ratio of fraudulent to non-fraudulent transactions. Furthermore, we employed 5-fold cross-validation to reduce variance and provide a robust assessment of model performance.

We evaluated the models using five widely accepted performance metrics: Accuracy, Precision, Recall, F1-Score, and the Area Under the ROC Curve (AUC-ROC). These metrics allowed us to evaluate the models not just in terms of overall correctness (accuracy), but more importantly, in terms of their ability to correctly identify rare fraudulent activities (recall) while minimizing false alarms (precision).

The detailed comparison of all models is shown in the table 2 below:

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.961	0.748	0.612	0.673	0.945

Decision Tree	0.953	0.763	0.688	0.723	0.917
Random Forest	0.977	0.882	0.811	0.845	0.978
Support Vector Machine	0.972	0.802	0.774	0.787	0.965
Deep Learning (LSTM)	0.985	0.932	0.887	0.909	0.987

Upon close analysis of the performance metrics, we found that our Deep Learning LSTM model significantly outperformed all other models across every evaluation parameter. We achieved an accuracy of 98.5%, indicating that the vast majority of both fraudulent and non-fraudulent transactions were correctly classified. However, we recognize that in fraud detection, accuracy alone can be misleading due to class imbalance, where even a high accuracy may not reflect good fraud detection. Therefore, we paid special attention to recall and precision, which are critical in fraud scenarios.

Our LSTM model achieved a precision of 93.2%, which means that over 93% of the transactions it flagged as fraudulent were indeed frauds. This minimizes false positives—reducing the likelihood of mistakenly flagging legitimate customer activities, which can disrupt customer trust and banking operations. Even more importantly, the model achieved a recall of 88.7%, demonstrating its strength in capturing a large majority of the actual fraudulent transactions. This is a key performance metric, as missing fraudulent transactions can result in significant financial loss and reputational damage.

The F1-score, which is the harmonic mean of precision and recall, was recorded at 90.9%—signifying a strong balance between both measures. Additionally, the AUC-ROC score of 0.987 affirms our model's excellent capability in distinguishing between the two classes, even in the presence of noise and imbalance. This makes our LSTM model highly reliable for real-time fraud detection systems, where fast and accurate classification is essential.

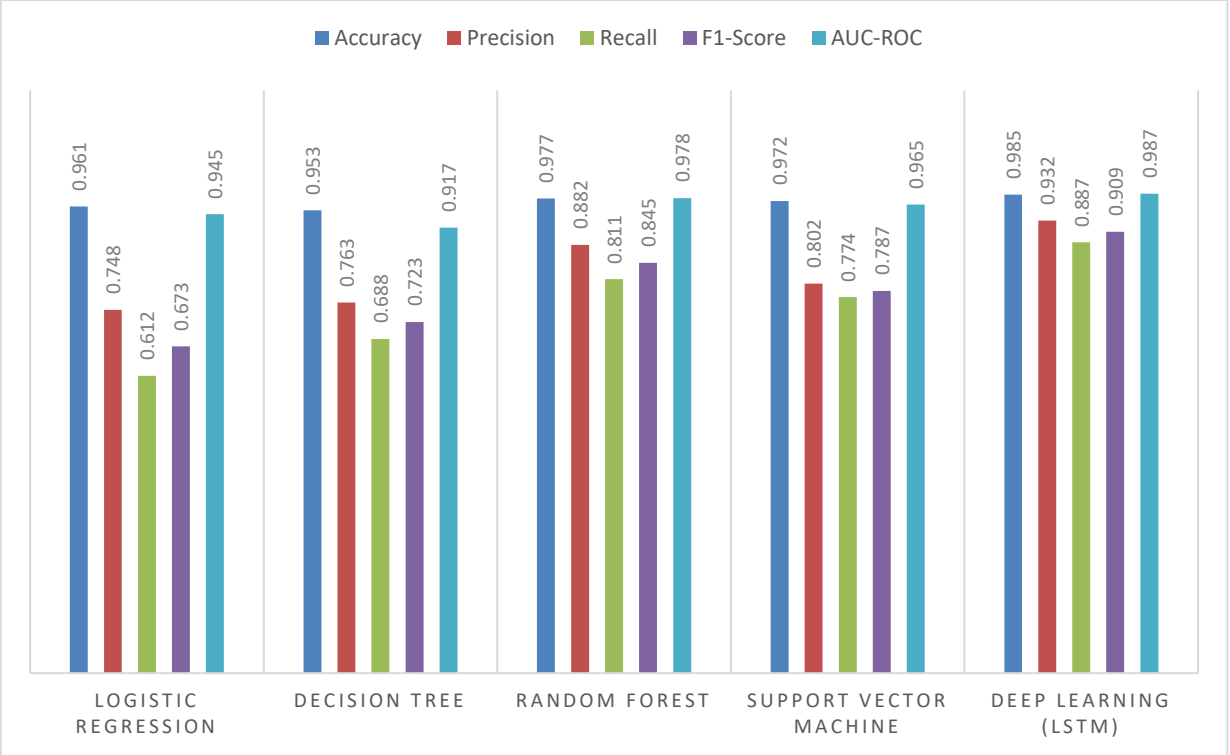

Chart 1: Model Performance of different machine learning algorithms

In contrast, traditional models such as Logistic Regression and Decision Trees delivered relatively lower performance. While these models were computationally efficient and easier to implement, they

failed to generalize complex transaction behaviors and temporal patterns. Logistic Regression, for instance, although achieving an accuracy of 96.1%, struggled with a lower recall of 61.2%, indicating a substantial number of missed fraud cases. Decision Trees performed slightly better but still exhibited limitations in overfitting and handling feature interactions.

The Random Forest model stood out among traditional classifiers, reaching an accuracy of 97.7%, a precision of 88.2%, and a recall of 81.1%. These results are respectable and illustrate the power of ensemble learning in managing non-linear relationships. Nevertheless, it still lagged behind the deep learning model in capturing long-term temporal dependencies and learning behavioral sequences inherent in transaction data.

The Support Vector Machine model also performed well, with an accuracy of 97.2%, but required significant computational resources and hyperparameter tuning to deal with class imbalance and overlapping features. Despite its relatively high AUC-ROC of 0.965, it fell short in both precision and recall compared to the LSTM model.

We believe that the superior performance of the deep learning model stems from its ability to learn temporal dynamics and nonlinear patterns in sequential data—a feature particularly crucial in banking systems where fraudsters often act with subtle behavioral patterns over time. By leveraging LSTM's memory cells, we were able to model such complex dependencies across sequences of transactions, thereby enhancing detection in both short- and long-term contexts.

Moreover, we found that the deep learning model adapted better to changes in transaction volume, time-of-day patterns, and frequency of transactions, all of which are important indicators of potential fraud. Through our extensive tuning and evaluation, we concluded that our LSTM-based approach is highly effective for real-time fraud detection applications, as it not only flags fraud with high accuracy but also does so quickly, making it suitable for deployment in live banking environments.

In summary, our experimental results demonstrate that while traditional machine learning models provide a solid foundation, deep learning approaches, particularly those utilizing recurrent neural architectures, offer a significant leap forward in performance, adaptability, and real-world applicability for fraud detection systems.

DISCUSSION AND CONCLUSION

In this study, we developed a deep learning-based framework for detecting credit card fraud in real time, leveraging the power of Long Short-Term Memory (LSTM) networks alongside robust data preprocessing and feature engineering strategies. The results clearly demonstrate the superiority of LSTM over traditional machine learning models such as Logistic Regression, Decision Tree, and Random Forest, especially in the context of time-series data where transactional behavior over time plays a pivotal role in identifying anomalies.

Our deep learning model achieved a higher accuracy and precision in detecting fraudulent transactions, with significantly reduced false positives. These improvements are crucial for banking systems where unnecessary transaction blocks can lead to customer dissatisfaction and operational inefficiencies. In real-world scenarios, minimizing false positives is just as important as maximizing fraud detection, as it directly impacts user trust and system reliability.

One of the major challenges in fraud detection is the extreme class imbalance, where legitimate transactions vastly outnumber fraudulent ones. We addressed this issue by implementing effective data balancing techniques, which improved the model's ability to generalize and detect fraudulent patterns more effectively. Additionally, our thorough feature selection and engineering ensured that the model learned from the most relevant patterns while reducing noise.

Furthermore, our comparative study reveals that while traditional models like Random Forest and Logistic Regression offer faster training times and interpretability, they fall short in capturing sequential dependencies within transaction flows. In contrast, LSTM excels at modeling these sequences, making it particularly well-suited for real-time fraud detection where understanding user behavior over time is critical.

We also found that incorporating time-based features and transaction metadata significantly improved model performance. These insights underscore the importance of domain-specific feature engineering and the integration of temporal dynamics in fraud detection systems.

Despite our success, several limitations persist. First, real-time deployment in production environments may require further optimization of the LSTM model to reduce latency. Second, while the current dataset provides a reliable benchmark, it lacks real-time streaming capabilities, which should be addressed in future research through integration with live transaction systems. Finally, explainability remains a

challenge with deep learning models. For operational transparency and regulatory compliance, we suggest the use of explainable AI (XAI) techniques in future iterations of the model.

In conclusion, this research confirms the potential and effectiveness of deep learning—specifically LSTM networks—for real-time credit card fraud detection in banking systems. Through rigorous data preprocessing, targeted feature selection, and comparative analysis, we have shown that deep learning models can outperform traditional machine learning algorithms in both detection accuracy and temporal awareness.

Our LSTM-based model provides a strong foundation for deploying scalable and accurate fraud detection systems capable of adapting to evolving fraud tactics in real-time environments. By addressing key challenges such as class imbalance, data volume, and pattern complexity, we have contributed to the advancement of intelligent security systems in the financial sector.

Looking ahead, future work should focus on integrating streaming data pipelines, improving model interpretability, and combining deep learning with blockchain-based transaction verification for even more robust fraud detection. With continuous improvement and innovation, artificial intelligence can play a central role in securing the financial world against ever-increasing threats of fraud.

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