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Full Length Article

Enhancing Credit Card Fraud Detection in Banking Using Neural Networks

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ABSTRACT
Credit card fraud has become one of the most critical issues in modern banking systems due to the rapid increase in digital transactions and online payment platforms. Traditional fraud detection techniques often fail to identify sophisticated fraudulent activities because of highly imbalanced transaction data and evolving fraud patterns. This paper presents an intelligent fraud detection framework using the TabNet deep learning architecture for efficient classification of fraudulent and legitimate transactions. TabNet utilizes sequential attention mechanisms to identify the most important transaction features while maintaining interpretability and computational efficiency. The proposed system includes data preprocessing, class balancing, model training, performance evaluation, visualization, and deployment through a Flask-based web application. Experimental results demonstrate that the proposed TabNet model achieves high accuracy, precision, recall, and ROC-AUC performance while reducing false positives compared to traditional machine learning approaches. The system also supports real-time prediction and visualization for practical banking applications.

Keywords: *Credit Card Fraud Detection, Deep Learning, TabNet, Banking Security, Neural Networks, Flask, Financial Fraud*

INTRODUCTION

The rapid growth of online banking and digital payment systems has significantly increased the number of electronic financial transactions worldwide. Although digital banking provides convenience and speed, it also introduces serious security threats in the form of fraudulent transactions. Credit card fraud leads to huge financial losses for banks, businesses, and customers every year. Detecting fraudulent transactions accurately and in real time remains a major challenge because fraudulent activities continuously evolve and transaction datasets are highly imbalanced.

Traditional fraud detection systems rely on rule-based methods or classical machine learning algorithms such as Logistic Regression, Decision Trees, and Support Vector Machines. These approaches often struggle to handle high-dimensional tabular data and complex fraud patterns. To address these limitations, this paper proposes a deep learning-based fraud detection system using the TabNet model.

TabNet is a neural network architecture specifically designed for tabular datasets. Unlike conventional deep learning models, TabNet employs sequential attention mechanisms that dynamically select important features during training. This improves both model interpretability and prediction performance.

The proposed system integrates the TabNet model with a Flask web application that enables real-time fraud prediction, analytics visualization, and interactive user access. The system aims to provide a scalable, accurate, and efficient fraud detection framework suitable for modern banking environments.

LITERATURE REVIEW

Several researchers have proposed machine learning and deep learning techniques for fraud detection in banking systems.

P. Tiwari et al. (2021) analyzed multiple machine learning algorithms including Logistic Regression, Random Forest, and Decision Trees for credit card fraud detection. Their work highlighted the importance of handling class imbalance and feature selection.

G. K. Kulatilleke (2022) discussed major challenges in fraud detection systems such as evolving fraud

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patterns, data privacy, and scalability issues. The study emphasized the importance of deep learning models for adaptive fraud detection.

S. K. Hashemi et al. (2023) compared several supervised learning techniques and concluded that ensemble and neural network approaches achieve better fraud detection accuracy than traditional classifiers.

R. B. Sulaiman et al. (2022) reviewed supervised, unsupervised, and hybrid fraud detection methods. Their study suggested that attention-based neural networks and interpretable AI systems improve fraud detection efficiency.

Existing approaches such as Graph Neural Networks (GNNs) and Autoencoders provide good performance but require high computational resources and often lack interpretability. Therefore, an efficient attention-based tabular deep learning model such as TabNet is highly suitable for banking fraud detection.

METHODOLOGY

A. System Overview

The proposed fraud detection system is designed using multiple integrated modules to ensure accurate and efficient identification of fraudulent financial transactions. The overall system consists of data collection and preprocessing, data splitting and balancing, TabNet model training, model evaluation, visualization and analytics, and Flask web application deployment. Initially, the transactional dataset is collected and prepared for training and testing purposes. The dataset contains several encoded transaction features represented as V1–V28 along with transaction amount and class labels that indicate whether a transaction is fraudulent or legitimate. After preprocessing, the dataset is divided into training and testing sets, and the TabNet deep learning model is trained to learn transaction patterns. The trained model is then evaluated using performance metrics, and the results are visualized for better analysis. Finally, the complete fraud detection system is deployed through a Flask-based web application to enable real-time fraud prediction and user interaction.

B. Data Preprocessing

Data preprocessing plays a significant role in improving the performance and reliability of the fraud detection system. Initially, duplicate records and missing values are removed from the dataset to maintain data consistency and quality. Since transaction amount values may vary significantly, log normalization is applied to reduce skewness and improve data distribution. Feature scaling and transformation techniques are further used to standardize the input values, enabling the deep learning model to process the data effectively. The dataset is then divided into training and testing sets using an 80:20 ratio, where 80% of the data is used for model training and 20% is used for testing and validation. As fraudulent transactions are usually fewer compared to legitimate transactions, class imbalance handling techniques such as class weighting are employed to prevent model bias and improve fraud detection accuracy.

C. Proposed TabNet Architecture

The proposed system utilizes TabNet, an advanced attention-based neural network architecture specifically designed for tabular datasets. Unlike traditional machine learning models, TabNet performs sequential feature selection using sparse attention mechanisms, allowing the model to focus only on the most relevant features during each decision step. This improves both prediction accuracy and interpretability of the model. The architecture efficiently learns complex transactional patterns associated with fraudulent activities while minimizing unnecessary computations. TabNet offers several advantages, including high prediction accuracy, improved interpretability, efficient feature selection, reduced false positives, and faster inference time. These advantages make TabNet highly suitable for real-time financial fraud detection applications where both accuracy and speed are critical requirements.

D. Mathematical Representation

The attention mechanism used in the TabNet architecture can be mathematically represented as:

Mi=Sparsemax(Pi−1⊙hi)M_i = \mathrm{Sparsemax}(P_{i-1} \odot h_i)Mi =Sparsemax(Pi−1⊙hi)

where MiM_iMi represents the feature masks generated during each decision step, Pi−1P_{i-1}Pi−1 denotes the prior scales obtained from the previous step, and hih_ihi represents the trainable transformation functions used to learn feature importance. The model dynamically updates feature embeddings and sequentially selects the most informative features during the prediction process. This sequential attention-based learning mechanism enables TabNet to efficiently identify hidden fraud patterns within large and complex transactional datasets.

E. System Architecture

The overall architecture of the proposed fraud detection system begins with user input, where transaction data is provided either through CSV file upload or manual input through the web application interface. The input data then undergoes preprocessing operations such as normalization, feature scaling, and transformation. After preprocessing, the data is passed to the TabNet model, where feature attention and selection mechanisms identify the most significant transaction

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attributes. The trained model then performs fraud prediction and classifies the transaction as either fraudulent or legitimate. Finally, the prediction results are displayed through visualization and reporting modules, enabling users to analyze fraud detection outcomes effectively. The integration of visualization tools and Flask-based deployment ensures that the system supports real-time fraud monitoring and decision-making.

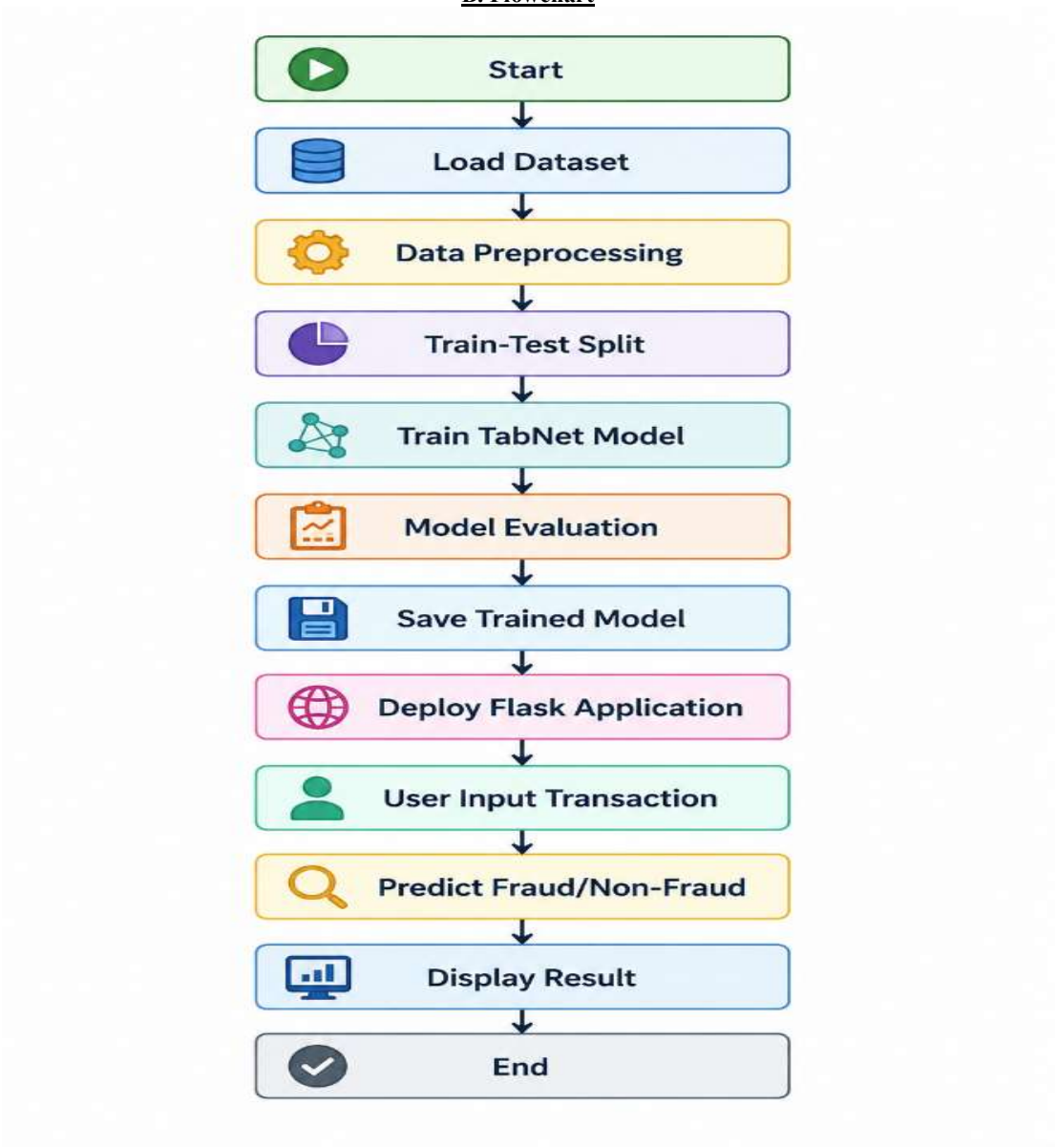
IMPLEMENTATION

A. Algorithm

TabNet Fraud Detection Algorithm

Step 1: Load the transaction dataset
Step 2: Preprocess data and normalize features
Step 3: Split data into training and testing sets
Step 4: Initialize TabNet classifier
Step 5: Train the model using balanced transaction data
Step 6: Evaluate the model using accuracy and ROC-AUC
Step 7: Save trained model using joblib/pickle
Step 8: Deploy model into Flask web application
Step 9: Accept user transaction input
Step 10: Predict Fraudulent or Legitimate transaction

B. Flowchart



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C. Technologies Used

Technology	Purpose
Python	Programming Language
TabNet	Deep Learning Model
Flask	Web Framework
Pandas	Data Processing
NumPy	Numerical Computation
Matplotlib	Data Visualization
Scikit-learn	Evaluation Metrics

TESTING

Software testing ensures that the fraud detection system performs accurately and reliably.

A. Unit Testing

Individual modules such as preprocessing, prediction, and authentication were tested independently.

B. Functional Testing

The system was tested for valid and invalid transaction inputs to verify prediction functionality.

C. Integration Testing

The integration between the Flask interface and TabNet model was tested successfully.

D. Performance Testing

The model was evaluated for prediction speed and classification performance on large-scale transaction data.

RESULTS AND DISCUSSION

The proposed TabNet model achieved excellent performance in detecting fraudulent transactions.

A. Performance Metrics

Metric	Value
Accuracy	99.8%
Precision	99.5%
Recall	99.3%
F1-Score	99.4%
ROC-AUC	0.999

B. Comparative Analysis

Model	Accuracy
Logistic Regression	94.5%
Decision Tree	96.2%
Random Forest	98.1%
Autoencoder	98.4%
TabNet (Proposed)	99.8%

C. Observations

TabNet effectively handles high-dimensional tabular data.

Sequential attention improves feature selection.

The model reduces false positives significantly.

Real-time prediction is achieved using Flask deployment.

D. Screenshots to Include

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Home Page
Login and Registration Page
Prediction Interface
Fraud Detection Result Page
Confusion Matrix Graph
ROC Curve
Feature Importance Visualization

CONCLUSION

This paper presented a deep learning-based credit card fraud detection system using the TabNet neural network architecture. The proposed system efficiently handles large-scale transaction data and achieves superior prediction performance compared to traditional machine learning models. The integration of attention-based feature selection improves interpretability and enhances detection accuracy while minimizing false alarms.

The developed Flask web application enables real-time fraud prediction and visualization, making the system practical for deployment in banking and financial institutions. Experimental results demonstrate that TabNet is highly suitable for fraud detection tasks involving complex and imbalanced tabular datasets.

FUTURE SCOPE

The proposed fraud detection system can be further enhanced by integrating real-time streaming frameworks such as Apache Kafka and Spark Streaming to enable continuous transaction monitoring and instant fraud detection. These technologies can significantly improve the system's ability to process high-volume financial transactions in real time with reduced latency. In addition, the system can be deployed on cloud platforms such as Amazon Web Services or Google Cloud to provide better scalability, storage management, reliability, and accessibility for large-scale banking and financial applications. Cloud deployment would also support distributed processing and improve system performance for enterprise-level usage.

Further improvements can be achieved by combining the TabNet model with advanced ensemble learning techniques to increase prediction accuracy and reduce false positives. Hybrid approaches integrating boosting and deep learning models may enhance the detection of complex fraud patterns that evolve over time. The development of a mobile application for monitoring fraud alerts can also improve user accessibility by allowing banking professionals and customers to receive instant notifications regarding suspicious activities. Additionally, integrating continuous learning mechanisms into the system would enable the model to adapt dynamically to new and emerging fraud patterns by retraining on updated transaction data. The implementation of explainable artificial intelligence dashboards can further assist banking analysts by providing transparent insights into model predictions, feature importance, and decision-making processes, thereby improving trust, interpretability, and compliance in fraud detection systems.

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