ABSTRACT

With the rapid rise in mobile payment adoption, ensuring secure and reliable digital transactions has become a critical concern. Fraudulent activities such as unauthorized transactions, phishing, and identity theft pose significant challenges to financial institutions and users. Traditional rule-based fraud detection systems struggle to adapt to evolving fraud patterns and address the imbalance in transaction data, where fraudulent cases are a minority.

This project focuses on developing a robust fraud detection system using Machine Learning (ML). It employs advanced algorithms such as **Random Forest**, **XGBoost**, and **Deep Neural Networks (DNN)** to classify transactions as fraudulent or legitimate. These models are selected for their ability to handle large datasets, manage class imbalance, and detect complex patterns in transaction data. The DNN, with fully connected layers for numerical inputs and embedding layers for categorical data, helps capture intricate relationships and improves classification accuracy. To address the issue of data imbalance, the project applies **SMOTE (Synthetic Minority Oversampling Technique)**, which generates synthetic fraudulent samples to ensure a balanced training dataset, improving the model's ability to detect rare fraudulent instances.

Future work involves integrating **Blockchain Technology** to improve data security and transparency.
Blockchain's decentralized ledger ensures tamper-proof data sharing and model updates among entities like banks and e-commerce platforms, without compromising transaction privacy. Smart contracts will further enable secure, automated collaboration across stakeholders, aligning with privacy regulations like
GDPR.

Model evaluation is conducted using metrics such as accuracy, precision, recall, F1-score, and ROCAUC. **Random Forest** and **XGBoost** demonstrate high accuracy and resilience to data imbalance, while the **DNN** and **LSTM** excel in detecting complex patterns and sequential fraud behavior in transaction data.

This project demonstrates the potential of machine learning in real-time fraud detection for mobile payments and lays the groundwork for future improvements through blockchain integration, ensuring scalability, security, and collaborative fraud mitigation

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1. INTRODUCTION

What?

Fraud detection in mobile payment systems is becoming increasingly critical as the volume of digital transactions continues to grow. Fraudulent activities such as unauthorized transactions, phishing, and identity theft pose significant risks to financial institutions and users. Traditional rule-based fraud detection methods often fail to address the complexity and dynamic nature of modern fraud patterns effectively.

This project provides an **application-based solution** leveraging **Deep Neural Networks (DNN)** to build a robust fraud detection system. By analyzing transaction data, DNN models can predict fraudulent transactions with high accuracy, even in the presence of challenges like imbalanced datasets. While the focus is currently on utilizing machine learning, the system aims to integrate **Blockchain Technology** in future iterations to enhance data security and privacy.

Why?

The increasing reliance on mobile payment systems highlights the need for advanced fraud detection mechanisms to address the following challenges:

- **Dynamic Fraud Patterns:** Fraudsters continuously adapt their techniques, rendering traditional static rule-based systems inadequate.
- **Data Imbalance:** Fraudulent transactions constitute a small fraction of all transactions, often causing models to favor legitimate transactions and overlook rare fraud cases.
- **Scalability and Real-Time Detection:** Fraud detection systems must scale with the growing volume of transactions while delivering real-time predictions.

Machine learning provides solutions to these challenges by:

- **Adapting to new fraud patterns** through continuous learning from fresh data.
- **Handling data imbalance** using oversampling techniques like SMOTE to improve model performance on minority classes.
- **Improving detection accuracy** with advanced techniques, including DNNs with embedding layers for categorical data and fully connected layers for numerical features.

Future work will incorporate **Blockchain Technology** to ensure tamper-proof data storage, enhanced transparency, and privacy-preserving collaboration among financial entities.

How?

The project is implemented in the following stages:

1. Data Preprocessing and Feature Engineering:

- Transaction data is collected, cleaned, and normalized.
- SMOTE is applied to balance the dataset by generating synthetic samples for fraudulent transactions.
- Features such as transaction amount, frequency, and intervals between transactions are engineered to enhance model performance.

2. Machine Learning Models:

- A **Deep Neural Network (DNN)** is employed for classification, combining:
  ○ Fully connected layers for numerical inputs.

○ Embedding layers to handle high-cardinality categorical features like nameDest.

- The model is evaluated using metrics such as **accuracy, precision, recall, F1-score, and AUC** to ensure robust and reliable performance.

3. Future Integration of Blockchain:

- **Blockchain** will be introduced in subsequent iterations to ensure data security, transparency, and privacy.
- **Smart Contracts** will automate data-sharing agreements, allowing secure collaboration between entities while maintaining compliance with privacy regulations like GDPR.

This phased approach ensures the development of a scalable, adaptive, and privacy-preserving fraud detection system, ready to evolve with the integration of blockchain for enhanced security and collaboration.

2. OBJECTIVE

2.1. Develop a Fraud Detection System Using Deep Neural Networks

The primary objective is to build a highly effective and adaptive fraud detection system tailored for mobile payment platforms. The system will utilize Deep Neural Networks (DNN), with fully connected layers for numerical features and embedding layers for high-cardinality categorical data like nameDest. These advanced techniques are designed to detect subtle patterns indicative of fraud and handle the complexities of transactional data. Additionally, the system will incorporate incremental learning capabilities, enabling it to adapt continuously to emerging fraud strategies. This adaptability is critical in maintaining high accuracy and minimizing both false positives and false negatives as fraud tactics evolve

2.2. Address Class Imbalance in Fraudulent Transactions

Fraudulent transactions often represent only a small fraction of total transactions, leading to a severe class imbalance. This imbalance can cause traditional machine learning models to favor the majority class (legitimate transactions), reducing their ability to identify fraud effectively. To address this, the project will implement the Synthetic Minority Oversampling Technique (SMOTE) to generate synthetic samples for the minority class, ensuring the model learns effectively from fraudulent cases. The system will also prioritize minimizing false negatives, enhancing its ability to detect rare fraudulent activities without compromising overall accuracy.

2.3. Deploy a Scalable and Secure Fraud Detection System

The trained DNN model will be deployed through a web-based application capable of providing real-time predictions of transaction legitimacy. The application will be designed to scale efficiently, ensuring quick response times even with increasing transaction volumes. Furthermore, strong data security measures will be implemented to protect sensitive transaction information.

2.4. Future Scope: Integrate Blockchain for Privacy-Preserving Collaboration

In the future, the fraud detection system will incorporate Blockchain Technology to enhance security, transparency, and privacy in collaborative environments. Blockchain's decentralized and immutable ledger will ensure that fraud detection data remains tamper-proof, fostering trust among stakeholders such as banks, payment platforms, and financial institutions.

Smart contracts will automate the secure sharing of model metrics, updates, and fraud detection insights between stakeholders without exposing sensitive raw transaction data. This integration will facilitate privacy-preserving collaboration while aligning with global data privacy regulations like GDPR. The adoption of blockchain will also enable stakeholders to collaborate transparently and securely, creating a scalable and trustworthy ecosystem for fraud detection. This future enhancement will significantly strengthen the system's capabilities, ensuring it remains resilient and compliant in the face of evolving fraud scenarios.

3. LITERATURE SURVEY AND TECHNOLOGIES

Paper Title	Purpose	Strengths	Limitations
Blockchain-Enabled Collaborative Fraud Detection	Proposes a privacypreserving collaborative approach using blockchain and ML for fraud detection.	High accuracy (93.64%); privacy preserving collaboration between organizations.	High computational cost of integrating blockchain.
Hybrid Mobile Payment Fraud Detection	Enhances real-time fraud detection using adversarial training and LSTM models.	Provides robust defense against adversarial attacks; effective real-time detection.	High computational demand; complexity in adversarial model training.
Bitcoin Fraud Detection	Detects fraudulent Bitcoin transactions by combining ML models (XGBoost, RF) and blockchain.	High AUC (0.90 for XGBoost, 0.92 for RF); effective at detecting doublespending and Sybil attacks.	Limited dataset; scalability issues in larger systems.
Bi-3DQRNN for Fraud Detection	Uses Bi-3DQRNN to improve fraud detection performance on imbalanced datasets.	Improves accuracy by 12.09%; effective for detecting fraud in imbalanced data.	High resource requirements; complex model architecture.
Adversarial Training for Mobile Payments	Focuses on improving fraud detection resilience against adversarial attacks.	Improved adversarial robustness; better performance in adversarial settings.	Increased computational cost; model complexity
Robust ML for Credit Card Fraud	Applies Random Forest and SMOTE to detect credit card fraud in imbalanced datasets.	Achieved 98.72% accuracy with balanced data; efficient with synthetic data.	Relies on synthetic datasets for fraud representation.

Real-Time Fraud Detection with Blockchain	Introduces real-time fraud detection with blockchain and smart contracts for secure transactions.	Improved transaction security with real-time detection.	Challenges in scalability and response time.

Explanation of Technology Used:

- **Deep Neural Networks (DNN):** A machine learning model used for predicting fraudulent transactions. The DNN is designed with fully connected layers to handle numerical data and embedding layers for categorical features like nameDest. It is highly effective at capturing complex patterns in data, but it requires significant computational resources and careful tuning to prevent overfitting.

- **SMOTE (Synthetic Minority Oversampling Technique):** Used to address class imbalance by generating synthetic samples for the minority class (fraudulent transactions). This ensures better representation of rare events during model training, although excessive use of SMOTE can introduce noise and lead to overfitting.

- **TensorFlow:** The framework used to implement and train the DNN model. TensorFlow provides flexibility and scalability, allowing for the development of complex neural networks. However, it requires expertise to handle properly and can be computationally intensive for large datasets.

- **Normalization and One-Hot Encoding:** Numerical features are normalized to ensure consistency in scale, improving model performance. One-hot encoding is applied to categorical variables, allowing the model to process non-numerical data effectively. While powerful, these preprocessing techniques can increase memory usage with high-dimensional data.

- **Embedding Layer:** An embedding layer is used in the DNN to represent high-cardinality categorical features like nameDest. It reduces the dimensionality of such features and captures semantic relationships, making the model more efficient and accurate. However, embeddings require sufficient data to learn effectively.

- **Performance Metrics:** Metrics like accuracy, precision, recall, F1-score, and AUC are used to evaluate the model. These metrics provide a comprehensive understanding of how well the model detects fraudulent transactions, though optimizing for all metrics simultaneously can be challenging.

- **Web Application Deployment:** The trained DNN model is deployed via a web application for real-time fraud detection. The application enables users to input transaction details and receive predictions instantly. However, ensuring the app's security and scalability requires robust backend support.

4. PLANNING OF WORK

4.1 Requirement Engineering (SRS) / Research Methodology

Functional Requirements:

The fraud detection system must meet the following key functional requirements:

- **Real-Time Fraud Detection:** Detect real-time fraudulent transactions as they occur on mobile payment platforms.
- **Scalability:** Handle a high volume of transactions efficiently and scale seamlessly with growing transaction data over time.
- **Adaptability:** Continuously learn and improve detection accuracy as new data becomes available, adapting to evolving fraud patterns.
- **Privacy Preservation:** Protect user and transaction data privacy, ensuring compliance with global data protection regulations like GDPR.
- **Model Evaluation:** To ensure reliability, regularly assess model performance using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

Non-Functional Requirements:

- **Performance:** Operate with low latency to enable real-time fraud detection.
- **Usability:** Be easy to integrate with existing mobile payment platforms, requiring minimal effort for adoption.
- **Robustness:** Resist adversarial attacks and maintain a low rate of false positives and false negatives.
- **Data Security:** Ensure the security of sensitive data using robust encryption and secure storage mechanisms.
- **Compliance:** Adhere to international data privacy regulations, including GDPR, to guarantee lawful operation.

4.2 Design

System Architecture Overview:
The architecture of the fraud detection system is divided into the following key stages:

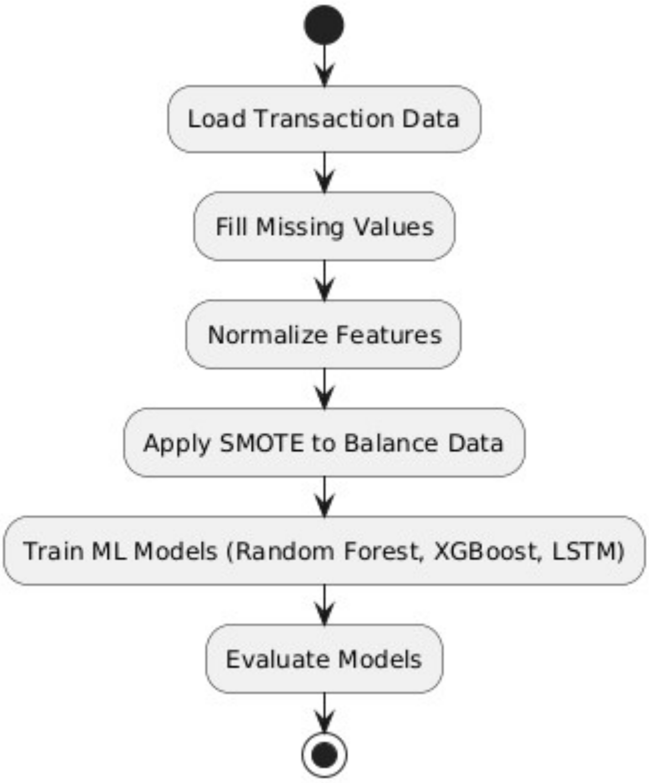
- **Data Collection:**
  - Transaction data is gathered from mobile payment platforms, including features such as transaction amounts, timestamps, transaction types, and user details.
- **Data Preprocessing:**
  - **Handling Missing Values:** Missing values are filled with appropriate substitutes (e.g., mean or zeros).
  - **Normalization:** Numerical features are normalized to ensure uniformity in scale across the dataset.
  - **SMOTE Application:** SMOTE is applied to balance the dataset by creating synthetic samples for the minority class (fraudulent transactions).
- **Model Training:**
  - A **Deep Neural Network (DNN)** is used for fraud detection, incorporating:
    - ■ Fully connected layers for numerical data.

■ Embedding layers for high-cardinality categorical features like nameDest.

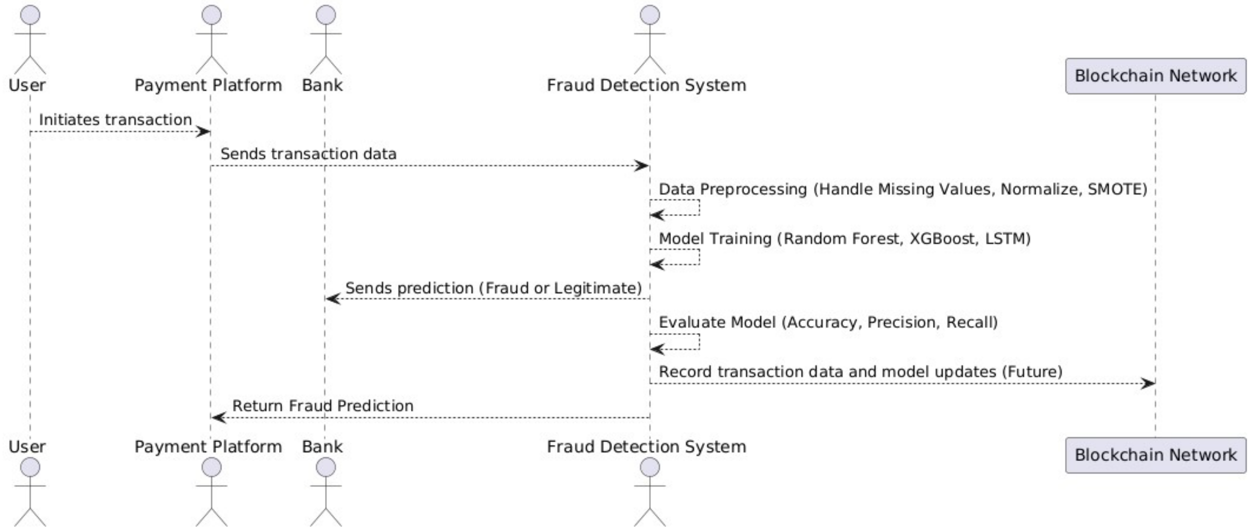
  - The model is trained using preprocessed data to classify transactions as fraudulent or legitimate.
- **Model Evaluation:**
  - The model is evaluated on metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to ensure reliable and effective performance.
- **Deployment:**
  - The trained model is deployed via a web application to provide real-time fraud detection capabilities.
- **Blockchain Integration (Future Scope):**
  - Blockchain technology will be integrated to ensure data privacy and security.
  - An immutable ledger will maintain tamper-proof transaction histories and enable transparent sharing of model updates.
  - **Smart Contracts** will automate the sharing of insights and updates, ensuring

data integrity and compliance with privacy regulations.

System Diagram (Flowchart for Data Preprocessing)


Load Transaction Data
Fill Missing Values
Normalize Features
Apply SMOTE to Balance Data
Train ML Models (Random Forest, XGBoost, LSTM)
Evaluate Models

System Architecture Diagram


User
Payment Platform
Bank
Fraud Detection System
Blockchain Network
Initiates transaction
Sends transaction data
Data Preprocessing (Handle Missing Values, Normalize, SMOTE)
Model Training (Random Forest, XGBoost, LSTM)
Sends prediction (Fraud or Legitimate)
Evaluate Model (Accuracy, Precision, Recall)
Record transaction data and model updates (Future)
Return Fraud Prediction
User
Payment Platform
Bank
Fraud Detection System
Blockchain Network

5. CODES AND IMPLEMENTATION OF PROPOSED SYSTEM

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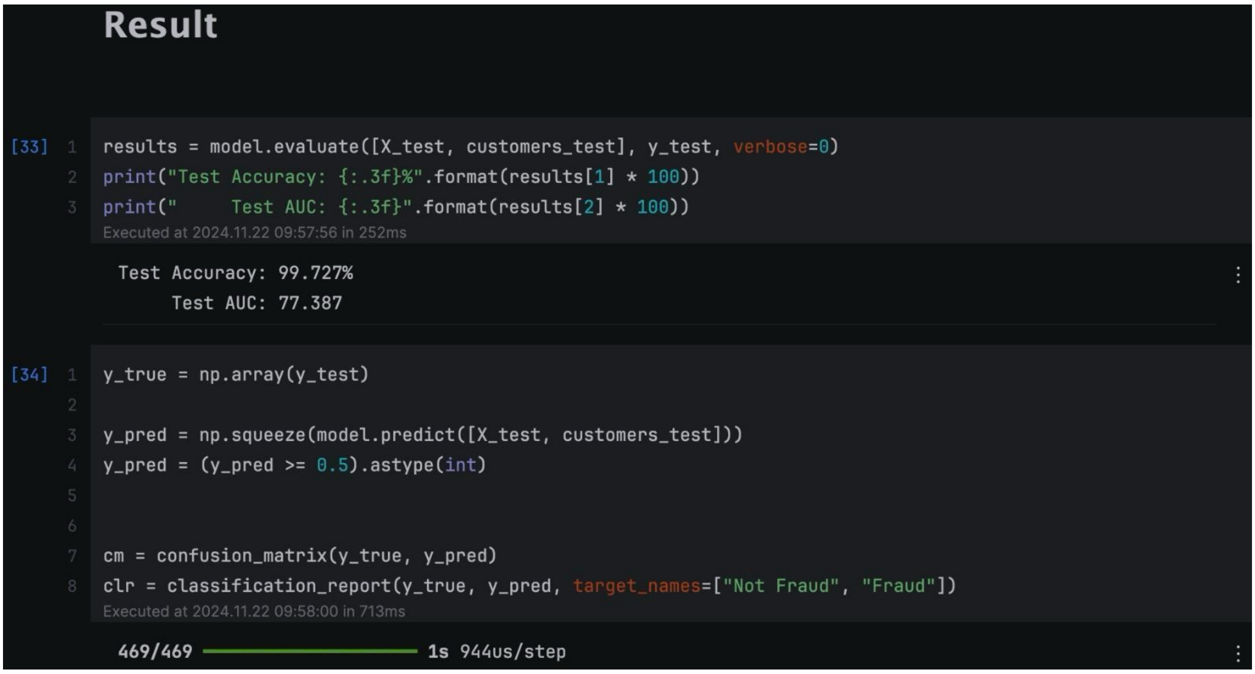
1. Implementation and Result



Result

[33]

```
results = model.evaluate([X_test, customers_test], y_test, verbose=0)
print("Test Accuracy: {:.3f}%".format(results[1] * 100))
print("     Test AUC: {:.3f}".format(results[2] * 100))
```

Executed at 2024.11.22 09:57:56 in 252ms

```
Test Accuracy: 99.727%
     Test AUC: 77.387
```

[34]

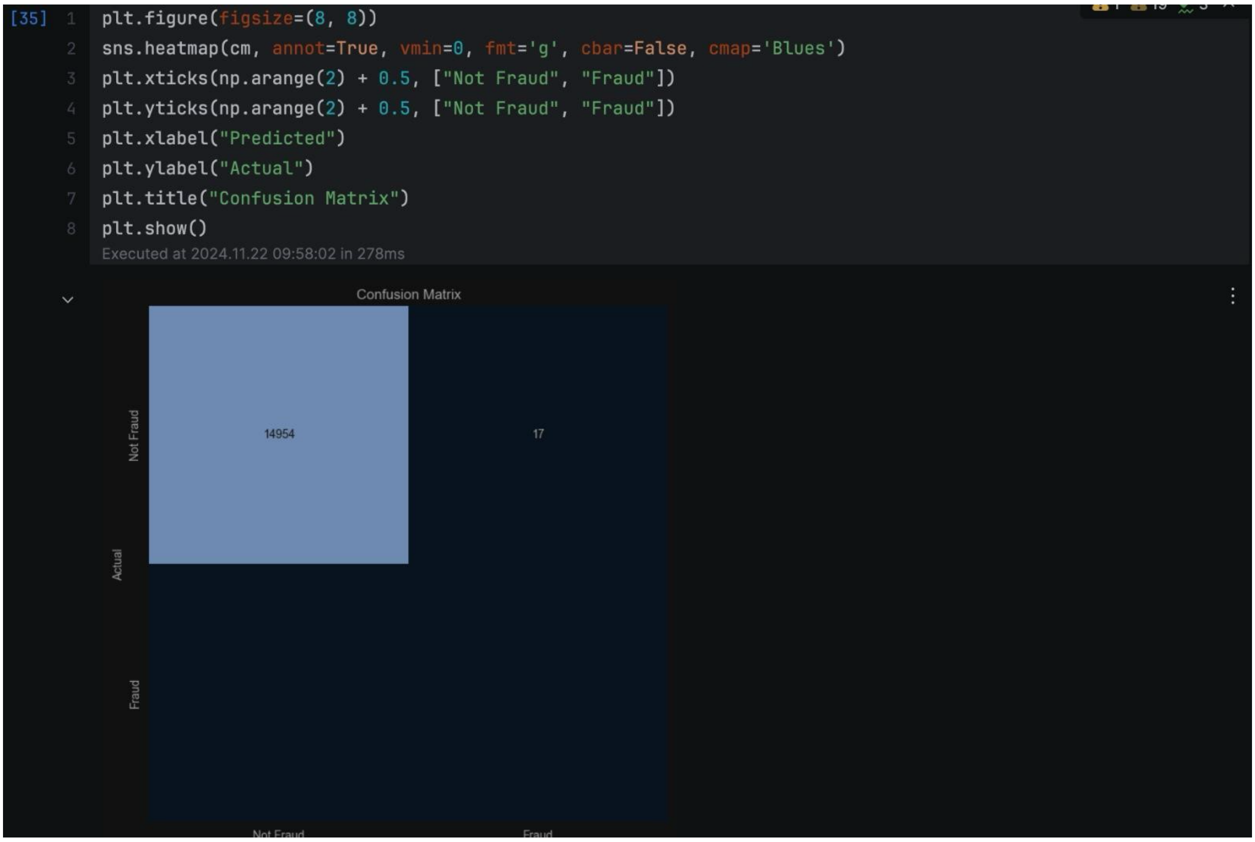
```
y_true = np.array(y_test)

y_pred = np.squeeze(model.predict([X_test, customers_test]))
y_pred = (y_pred >= 0.5).astype(int)


cm = confusion_matrix(y_true, y_pred)
clr = classification_report(y_true, y_pred, target_names=["Not Fraud", "Fraud"])
```

Executed at 2024.11.22 09:58:00 in 713ms

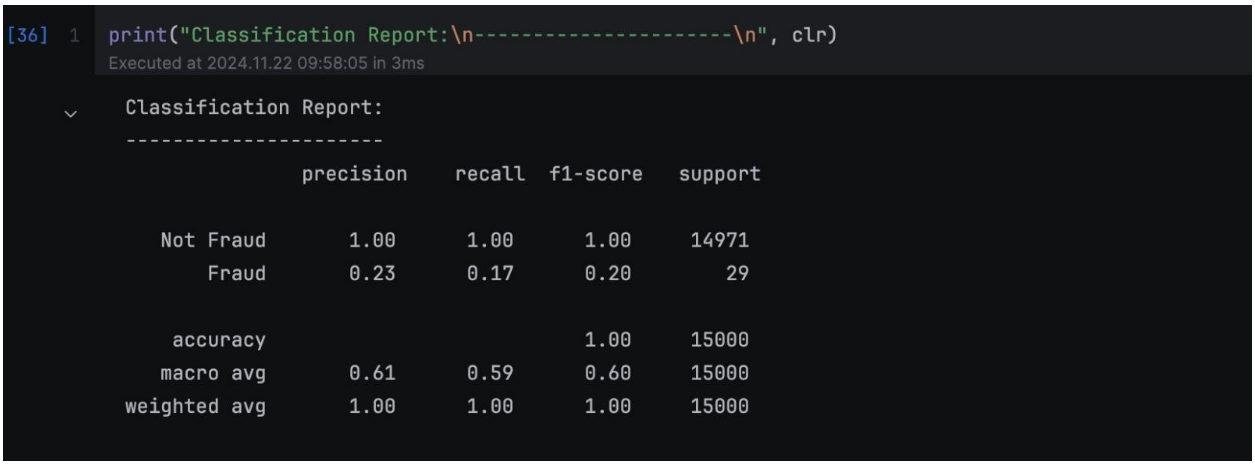
```
469/469 ━━━━━━━━━━━━━━━━━━━━ 1s 944us/step
```



[35]

```
plt.figure(figsize=(8, 8))
sns.heatmap(cm, annot=True, vmin=0, fmt='g', cbar=False, cmap='Blues')
plt.xticks(np.arange(2) + 0.5, ["Not Fraud", "Fraud"])
plt.yticks(np.arange(2) + 0.5, ["Not Fraud", "Fraud"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

Executed at 2024.11.22 09:58:02 in 278ms



[36]

```
print("Classification Report:\n----------------------\n", clr)
```

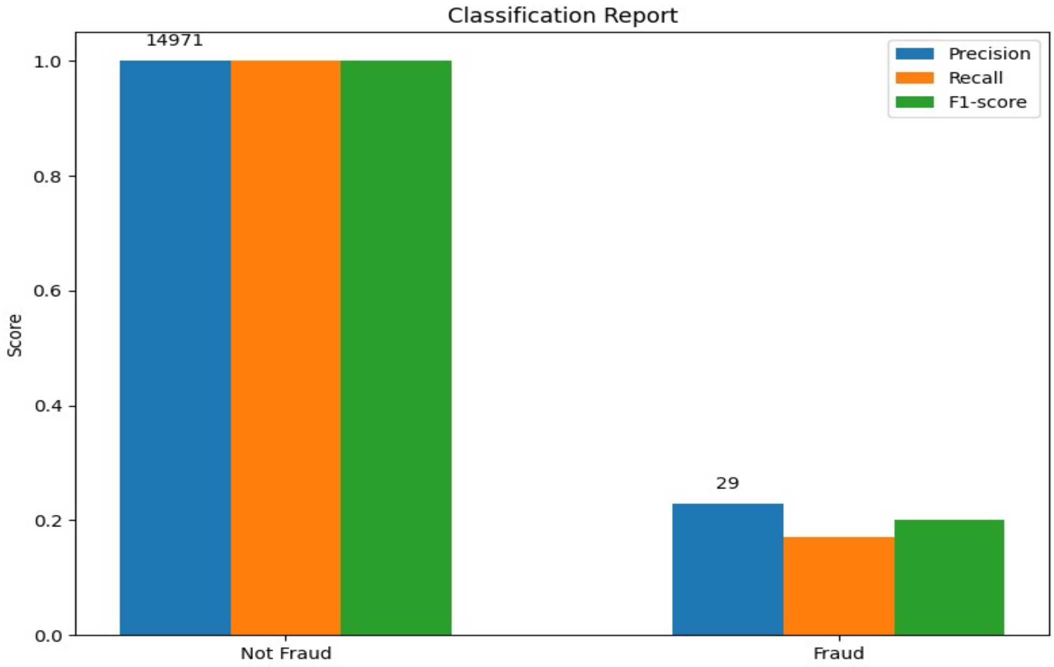
Executed at 2024.11.22 09:58:05 in 3ms

```
Classification Report:
----------------------
               precision    recall  f1-score   support

   Not Fraud       1.00      1.00      1.00     14971
       Fraud       0.23      0.17      0.20        29

    accuracy                           1.00     15000
   macro avg       0.61      0.59      0.60     15000
weighted avg       1.00      1.00      1.00     15000
```

2.Classification Report



Blockchain Integration (Future Scope)

In the future, integration of **Blockchain Technology** into the fraud detection system will enhance security, transparency, and collaboration while maintaining data privacy.

1. **Private Blockchain Setup**: A **private blockchain network** will be established to securely store fraud detection metrics (accuracy, precision, recall) and model updates, ensuring that only authorized parties (e.g., banks, payment platforms) have access to the data.
2. **Smart Contracts**: **Smart contracts** will automate the sharing of model updates and fraud detection results between stakeholders without revealing sensitive data. This will ensure privacy while fostering collaboration and transparency.
3. **Benefits**:
   - **Transparency**: All model updates and performance metrics will be visible to authorized parties, ensuring trust.

○ **Security**: Blockchain's encryption prevents tampering with data and updates.

   - **Collaboration**: Stakeholders can collaborate securely without sharing raw sensitive data.
   - **Data Integrity**: Blockchain's immutable nature ensures the accuracy and accountability of all updates.

6. CONCLUSION

Shortcomings of the Current Deep Neural Network (DNN) Approach and How Blockchain Integration Can Overcome Them Shortcomings of the DNN Approach:

- **Lack of Interpretability:**
  While DNNs excel at capturing complex patterns in data, they are often considered "black-box" models. This lack of interpretability can make it challenging for stakeholders (e.g., banks, regulators) to understand and trust the reasoning behind the model's predictions.
- **Computational Complexity:**
  Training and deploying DNNs, especially for large-scale, real-time fraud detection, can be computationally expensive. The requirement for high computational resources may lead to delays in processing, affecting the system's real-time performance.
- **Data Privacy Concerns:**
  Collaboration between institutions, such as banks and payment platforms, often requires sharing sensitive user transaction data. This raises privacy concerns, as exposing raw data to unauthorized entities could lead to potential misuse or security breaches.

How Blockchain Integration Can Overcome These Shortcomings:

Enhanced Transparency:

- Blockchain's immutable ledger provides a secure and auditable record of model updates, performance metrics, and decision logs. Stakeholders can verify the system's operations without needing access to the model's internal workings.
- Smart contracts enable automated sharing of model updates and predictions, ensuring consistency and trust among all parties using the system.

Optimized Computational Load:

- By enabling decentralized collaboration, blockchain reduces the burden on a single organization's computational resources. Institutions can share fraud detection insights, distributing the workload and enhancing system scalability.
- Off-chain storage solutions can be integrated to handle data processing and storage, while only critical results (e.g., detected fraud events) are recorded on the blockchain.
  This reduces on-chain computational and storage requirements.

Improved Data Privacy:

- Blockchain's encryption mechanisms ensure that sensitive transaction data is not directly shared. Instead, institutions exchange anonymized fraud detection results (e.g., fraud probabilities) or encrypted insights, maintaining user privacy.
- Smart contracts enforce strict data-sharing rules, allowing only authorized entities to access specific information. This ensures compliance with privacy regulations like GDPR and builds a secure framework for collaboration.

By addressing the shortcomings of traditional DNN-based approaches with blockchain integration, the fraud detection system can achieve greater transparency, scalability, and privacy. This forward-thinking approach ensures that the system is not only effective in detecting fraudulent transactions but also trustworthy and compliant with evolving global data protection standards. The combination of advanced machine learning models and blockchain technology creates a robust framework, ready to adapt to the ever-changing landscape of financial fraud.

7.REFERNECES

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8.

Dataset Used:
Fraud Detection in Mobile Transactions-Kaggle
https://www.kaggle.com/code/tomaszurban/fraud-detection-in-mobile-transactions/data