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Design and Development of an AI-Driven Cybersecurity Framework for Fraud Detection and Digital Evidence Management

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ABSTRACT

The rapid growth of Nigeria's digital payment ecosystem, including mobile banking, POS systems, USSD platforms, and online payment services, has significantly increased exposure to financial fraud. Conventional rule-based fraud detection systems are limited by static thresholds and poor adaptability to evolving fraud patterns. This study presents an Artificial Neural Network (ANN)-based fraud detection framework integrated with digital forensic logging to enhance detection accuracy, evidential integrity, and regulatory compliance within Nigeria's financial systems. A Multilayer Perceptron (MLP) ANN model was developed and trained on 384,000 transaction records, consisting of benchmark datasets and synthetically generated Nigerian-context transactions. Data preprocessing involved Min-Max normalization, categorical encoding, feature engineering, and class imbalance mitigation using the Synthetic Minority Oversampling Technique (SMOTE). The model was implemented using TensorFlow and evaluated using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC metrics. Experimental results demonstrate strong predictive capability, achieving 99.7% classification accuracy and a ROC-AUC of 0.9999. To enhance post-detection investigation, the system incorporates a structured forensic logging framework using SQLite database storage, SHA-256 cryptographic hashing for evidence integrity, timestamp validation, and role-based access control.

The study contributes a novel integration of ANN-based predictive modeling with digital forensic architecture, providing a scalable, secure, and investigation-ready fraud detection solution tailored to Nigeria's digital financial ecosystem.

Keywords: Artificial Neural Networks, Credit Card Fraud Detection, Digital Forensics, Cybersecurity, SMOTE, ROC-AUC, Evidence Hashing, Nigeria

1. INTRODUCTION

Nigeria's financial ecosystem has experienced rapid digital transformation driven by mobile banking, fintech innovation, and electronic payment systems. Platforms such as POS terminals, USSD services, and online banking applications have significantly improved financial inclusion. However, this transformation has also increased vulnerability to cyber fraud, particularly credit card fraud.

Traditional fraud detection systems rely on rule-based mechanisms and predefined thresholds. These systems are static, difficult to update, and ineffective against evolving fraud strategies. They also generate high false positives and fail to detect complex, nonlinear fraud patterns.

Artificial Neural Networks (ANNs) offer a data-driven solution capable of learning transaction behaviors and detecting anomalies in real time. Despite their advantages, most ANN-based systems focus solely on prediction accuracy and lack forensic capabilities required for investigation and regulatory compliance. This study addresses this gap by integrating ANN-based fraud detection with digital forensic logging mechanisms.

1.1 Contributions of the Study

This study makes the following contributions:

1. Development of a Nigeria-specific ANN fraud detection model
2. Integration of digital forensic logging into fraud detection systems
3. Implementation of SHA-256 cryptographic hashing for evidence integrity
4. Design of a real-time fraud detection prototype
5. Use of synthetic Nigerian transaction data for localization

2. Related Work

Machine learning techniques have been widely applied in fraud detection, with ANN models demonstrating superior performance over traditional statistical approaches such as logistic regression and support vector machines.

However, several gaps exist:

- I. Most models use foreign datasets lacking Nigerian context
- II. Limited integration of forensic logging systems
- III. Lack of real-time deployment frameworks

This study addresses these limitations by combining ANN detection with forensic readiness and localized data.

3. METHODOLOGY

3.1 Research Design

This study adopts a pragmatic research philosophy and a deductive approach. An experimental design was used to develop and evaluate the ANN model within Nigeria's digital payment context.

3.1 System Architecture

The proposed fraud detection system integrates ANN-based classification with digital forensic evidence logging. Transaction data undergoes preprocessing before being processed by the ANN model. Transactions flagged as suspicious trigger forensic evidence logging within a structured database environment.

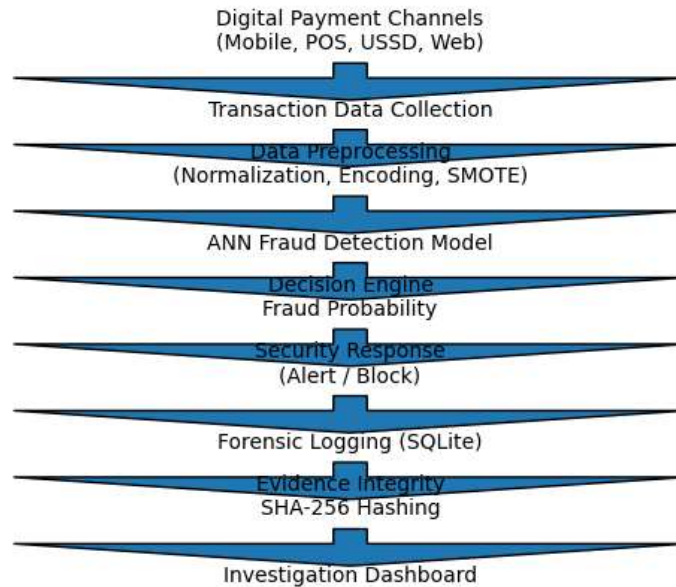


Fig. 1. ANN-based fraud detection system architecture with digital forensic integration

3.2 Dataset

The dataset consists of 384,000 transactions:

- I. 284,000 benchmark records (Kaggle dataset)
- II. 100,000 synthetically generated Nigerian transactions

The synthetic dataset captures fraud types such as:

- I. SIM swap fraud
- II. Phishing
- III. Fake POS transactions
- IV. Account takeover

3.3 Data Preprocessing

The following preprocessing steps were applied:

- I. Missing value handling
- II. Min-Max normalization
- III. Categorical encoding
- IV. Feature engineering
- V. SMOTE for class balancing

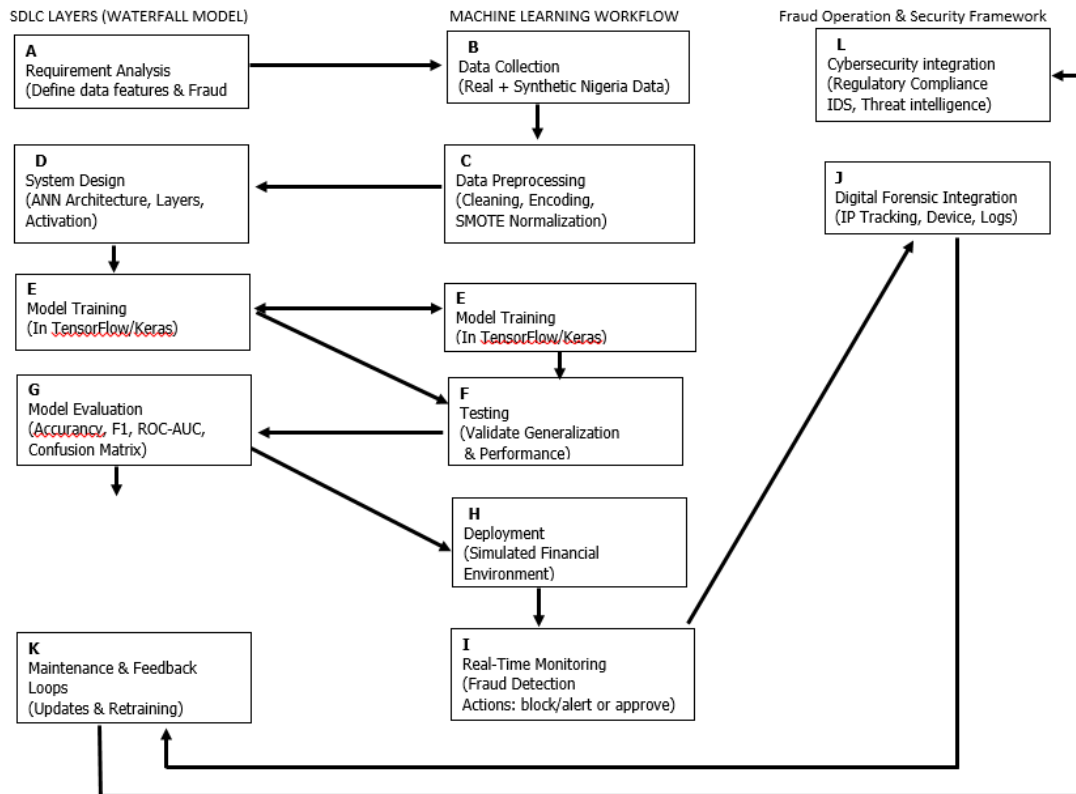


Fig. 2. Machine learning workflow for fraud detection system

3.4 ANN Model Design

The model uses a Multilayer Perceptron architecture:

- I. Input layer: transaction features
- II. Hidden Layer 1: 128 neurons (ReLU)
- III. Hidden Layer 2: 64 neurons (ReLU)
- IV. Output layer: 1 neuron (Sigmoid)

Training configuration:

- I. Optimizer: Adam
- II. Loss function: Binary cross-entropy

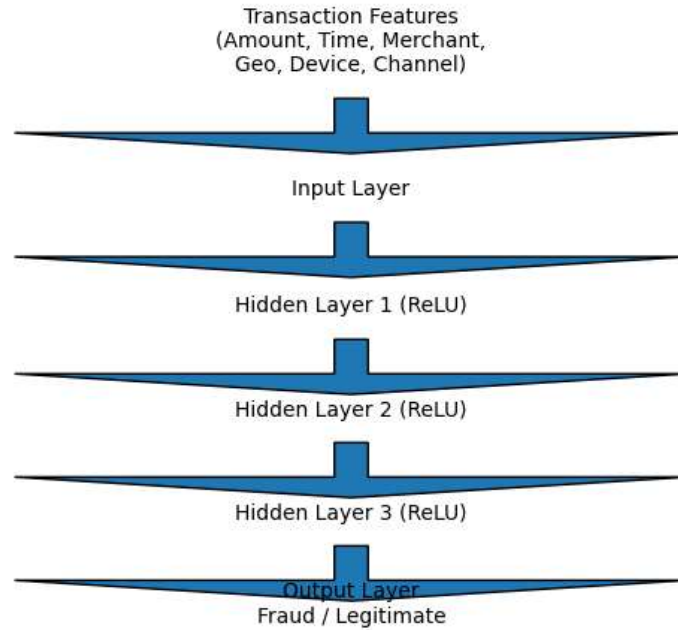


Fig. 3. Multilayer Perceptron architecture for fraud classification

3.5 Model Training and Validation

- I. Dataset split: 70% training, 15% validation, 15% testing
- II. Validation method: K-fold cross-validation

3.6 Comparative Model Analysis

To validate performance, the ANN model was compared with baseline models:

Model	Accuracy	ROC-AUC
Logistic Regression	94.2%	0.96
SVM	96.1%	0.97
Random Forest	98.3%	0.99
ANN (Proposed)	99.7%	0.9999

4. RESULTS

4.1 Performance Metrics

Metric	Value
Accuracy	99.7%
Precision	1.00
Recall	1.00
F1-Score	1.00
ROC-AUC	0.9999

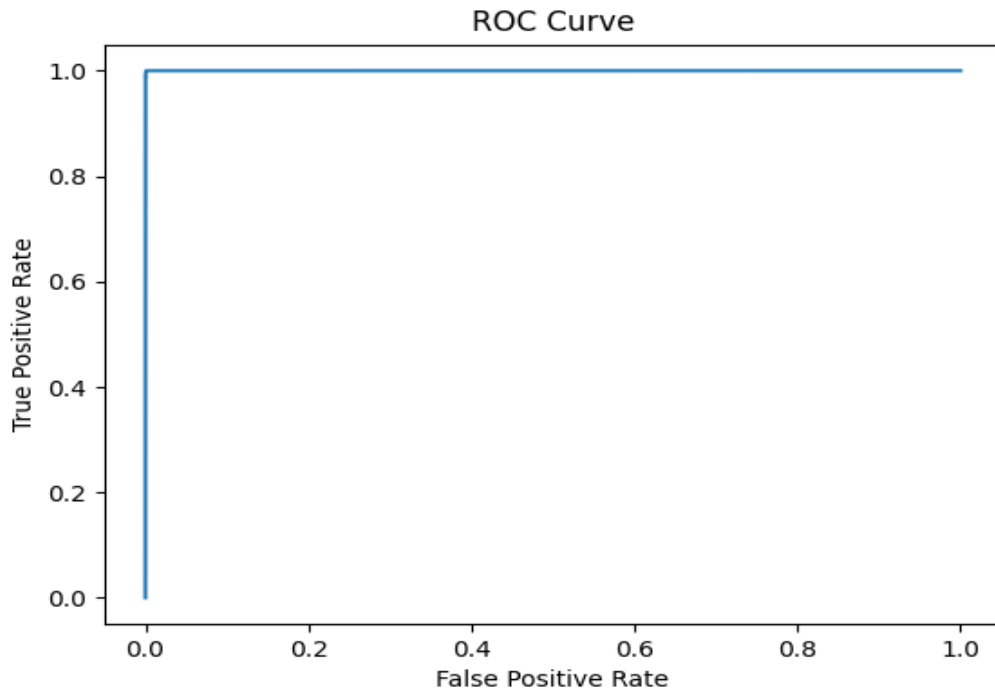


Fig. 4. ROC curve of the ANN fraud detection model

4.2 Confusion Matrix

	Predicted Legitimate	Predicted Fraud
Actual Legitimate	17,830	34
Actual Fraud	0	18,152

4.3 Interpretation of Results

The high performance can be attributed to:

- I. Large dataset size
- II. SMOTE balancing
- III. Effective feature engineering
- IV. Cross-validation to prevent overfitting
- V. Localization of Nigerian fraud patterns

5. Digital Forensic Integration

5.1 Forensic Logging System

Each flagged transaction generates:

- I. Case ID
- II. Timestamp
- III. Fraud probability
- IV. Decision outcome

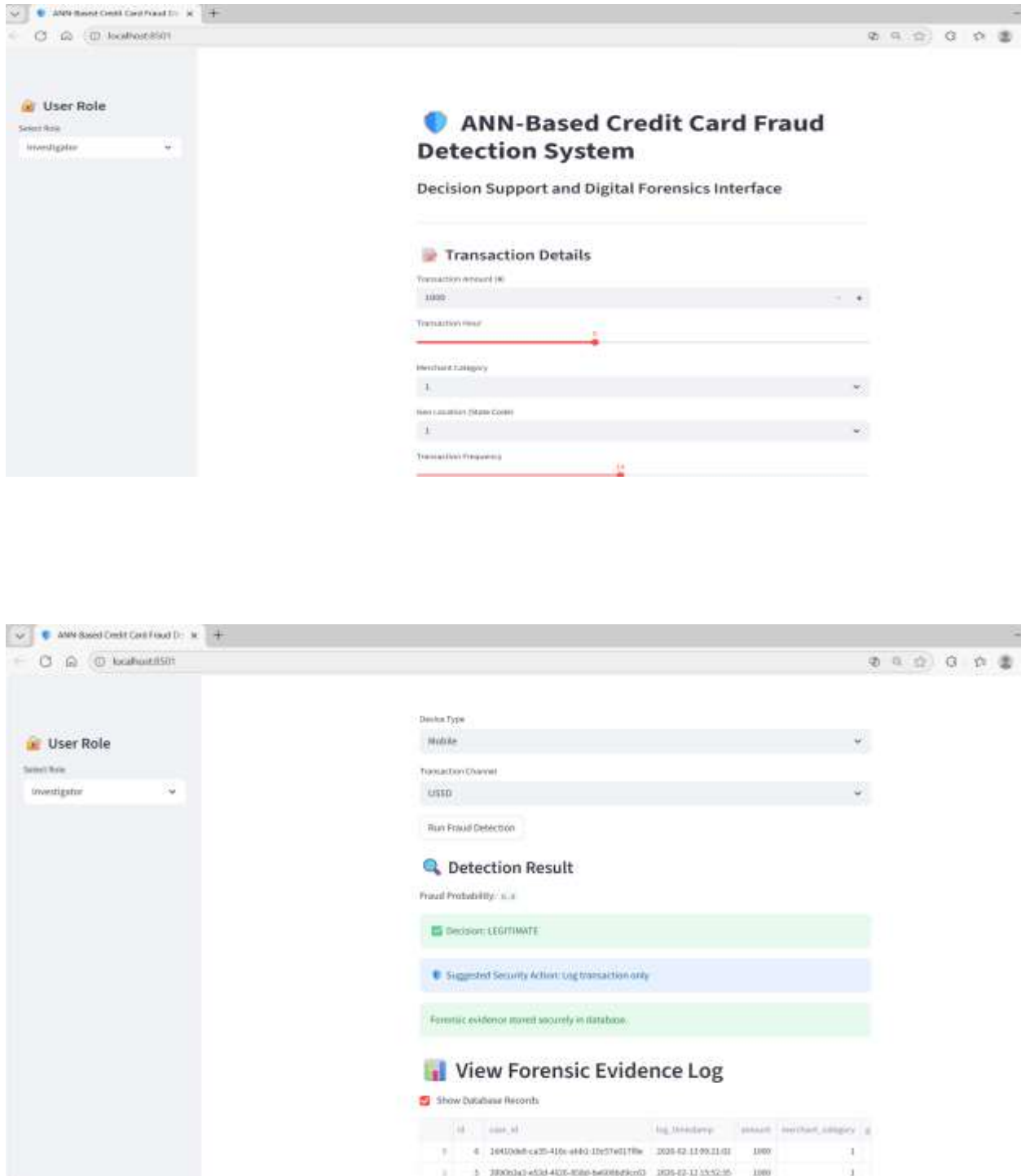


Fig. 5. User interface of the fraud detection system showing real-time prediction and logging

5.2 Evidence Integrity

SHA-256 hashing is used to:

- I. Prevent data tampering

- II. Ensure integrity
- III. Support legal admissibility

5.3 Database Architecture

SQLite database stores:

- I. Transaction details
- II. Fraud predictions
- III. Evidence hash

Table 2. Sample forensic evidence log generated by the system

i	d	case_id	log_timestamp	amount	merchant_category	geo_location	device_type	channel	fraud_probability	decision	model_version	investigation_status	recommended_action	evidence_hash
0	2	d69c302e-1a67-43f1-90bf-7265cff64c55	3/13/2026 14:33	5000	5	2	Mobile	Mobile App	0.9943	FRAUD	ANN_v1.0	Pending	Freeze account and initiate forensic investigation	e942b2beedf59e840d20a3a2026b3d30abb0ca89563e4180712889bd2045a7d2
1	2	fd36ded6-cb92-4388-9aef-f16898fe28b7	3/13/2026 14:32	3000	4	23	POS	Card	0	LEGITIMATE	ANN_v1.0	Pending	Log transaction only	2fbec4898c8608b18288ccc5c68dab05360b338d8768df1d9e908e39258d9b27
2	2	f4f115b1-735a-42ac-9e21-6f729898cddc	3/12/2026 12:52	1000	5	1	Mobile	Web	0	LEGITIMATE	ANN_v1.0	Pending	Log transaction only	f9d09b28014ce14009db6e91a81c7a9c44cb32744d5c63e3e84245929d885eae
3	1	0efa4468-62f4-4ea4-8ad3-6d30c6092e3b	3/12/2026 12:51	8999	1	1	POS	Web	0	LEGITIMATE	ANN_v1.0	Pending	Log transaction only	c8315226511c5cd114d523c34526dd3073d5b6429f918731889abb9d994f88a2c
4	1	57a82d6d-1f11-4e4d-8d55-770561452932	2/20/2026 12:25	5000	3	3	POS	Card	0	LEGITIMATE	ANN_v1.0	Pending	Log transaction only	6c72fc8db88a7fa83217fb63e30274b4cd81b6ea41ea9304c7e8028c861aa561
5	1	cab1414f-da91-44c9-9ceb-94b551a459b0	2/20/2026 12:24	2000	3	28	POS	Card	0.9113	FRAUD	ANN_v1.0	Pending	Freeze account and initiate forensic investigation	4164a7b4fab589417a78cc51b02d415ba8cf9aeeae1255d56a2a8cd1784eeb56

5.4 Role-Based Access Control

Two roles were implemented:

- I. Analyst → fraud detection
- II. Investigator → forensic access

6. DISCUSSION

The experimental results demonstrate that the proposed Artificial Neural Network model provides strong predictive capability for detecting fraudulent transactions within Nigeria’s digital payment ecosystem. The achieved classification accuracy of **99.7%** indicates that the model effectively identifies fraudulent behavior patterns in financial transaction data.

These findings align with previous research demonstrating the effectiveness of neural network models in fraud detection systems. showed that machine learning models significantly outperform traditional rule-based systems in detecting credit card fraud patterns. Similarly, Agbo et al. highlighted the growing importance of artificial intelligence models in strengthening financial cybersecurity.

Compared with traditional rule-based fraud detection systems used by financial institutions, the proposed ANN model demonstrates superior adaptability and pattern recognition capabilities. Rule-based systems rely on predefined thresholds and static fraud rules, making them less effective against evolving fraud techniques. In contrast, ANN models can learn complex nonlinear relationships within transaction datasets, enabling the detection of previously unseen fraud patterns.

Another key contribution of this study is the integration of digital forensic mechanisms into the fraud detection architecture. While many existing fraud detection systems focus primarily on classification accuracy, fewer studies incorporate forensic readiness necessary for regulatory investigations and evidential integrity. The use of structured database logging combined with cryptographic SHA-256 hashing ensures that fraud detection outcomes can be securely preserved for investigation and legal proceedings.

Furthermore, the inclusion of synthetically generated Nigerian-context transaction data improves the contextual relevance of the model. Previous studies have shown that models trained exclusively on foreign datasets often fail to capture localized fraud patterns present in emerging financial ecosystems.

Overall, the results demonstrate that combining machine learning-based fraud detection with digital forensic architecture provides a more comprehensive approach to financial cybersecurity.

7. CONCLUSION

This study developed and evaluated an ANN-based fraud detection framework tailored to Nigeria's digital payment ecosystem. The model demonstrated strong predictive performance with a classification accuracy of **99.7%** and minimal misclassification.

The integration of digital forensic mechanisms significantly enhances the operational value of the system by enabling structured evidence logging, cryptographic integrity protection, and secure access control for fraud investigations.

The proposed framework demonstrates the potential of combining artificial intelligence with digital forensic mechanisms to strengthen fraud detection and cybersecurity within emerging digital financial ecosystems.

Future research may explore the integration of explainable AI techniques and real-time deployment within live banking environments.

Future Work

- I. Explainable AI integration
- II. Live banking deployment
- III. Blockchain-based forensic logging

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