



SECURE BANK AI: A CAPSULE NETWORK-BASED MODEL FOR FRAUD DETECTION IN DIGITAL BANKING

***Shadreck Mpanga**

School of Engineering, University of Zambia, Lusaka, Zambia.

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***Corresponding author:**

***Shadreck Mpanga**

School of Engineering, University of
Zambia, Lusaka, Zambia.

ABSTRACT

The rapid expansion of digital banking has transformed the financial sector by enabling faster, more accessible, and scalable services. Technologies such as cloud computing and artificial intelligence (AI) have significantly improved international financial inclusion, connecting urban and rural populations to banking systems. However, this digital transformation has simultaneously increased vulnerability to cyber threats. With the rise in online transactions, traditional fraud detection systems are increasingly ineffective against sophisticated cybercrimes, including data breaches, identity theft, AI-generated deepfake identities, phishing attacks, and malware. Cloud-based financial systems, though efficient, introduce new potential points of attack. This paper highlights the growing challenges of cyber fraud in the digital banking era and underscores the urgent need for advanced, AI-driven fraud detection mechanisms to safeguard modern financial ecosystems.

KEYWORDS: Digital Banking, Cybersecurity, Cloud Computing, Financial Inclusion, Artificial Intelligence (AI), Fraud Detection, Identity Theft, Deepfake Fraud, Phishing Attacks, Online Transactions.

1. INTRODUCTION

The fast-paced growth of digital banking has revolutionized financial transactions and made them faster, accessible, and scalable. Cloud-based financial services and intelligent networks have played a huge role in improving international financial inclusion through bridging financial gaps and extending smooth banking coverage to both city and rural residents.^[1] Nevertheless, the more the financial services become digital-based, the more they become vulnerable to cyber attacks and crimes. The use of artificial intelligence (AI) and cloud computing in financial analysis has made banking more efficient, but these technologies have also brought along vulnerabilities like data breaches, identity theft, and real-time transaction fraud.

One of the chief culprits of digital bank fraud is the runaway growth of online transactions that is making it hard for classical fraud-detecting mechanisms to

efficiently keep abreast of criminal activities.^[2] Besides this, cyber-fraudsters always come up with new forms of attack in ways such as advanced tactics employing AI-generated deepfakes identities, phishing attempts, and malware made to exploit bank transactions. Cloud-based financial services, while they provide efficiency and scalability, also introduce new attack surfaces that fraudsters can use, further creating the need for effective fraud detection mechanisms.^[3]

Conventional fraud detection systems also have a number of limitations that make them less effective in contemporary financial settings. All common fraud detection schemes rely on rule-based systems that operate on defined patterns of fraud and have difficulties with discovering newer modes of fraud. The systems come with high instances of false positives that lead to inappropriate rejection of transactions and subsequent dissatisfaction of the customers.^[4] Machine learning-

based fraud detection models offer better fraud pattern detection but require constant retraining to be valid, which renders them computationally expensive and less adaptable for real-time use. Furthermore, as the volume of transactions grows, conventional fraud detection models are ineffective and cannot process large amounts of financial data efficiently.

To mitigate such challenges, we introduce SecureBankAI, Capsule Network-Based Fraud Detection Model that can be used to prevent fraud in real-time in online banking. Capsule Networks learn spatial relationships between transaction features and thus detect intricate fraud patterns more accurately compared to conventional machine learning methods. SecureBankAI learns new ways of fraud automatically by virtue of hierarchical feature-learning without human intervention. Furthermore, the model reinforces cloud banking security through deep learning-based pattern detection, lowering the rate of false positives and maximizing fraud detection rates. Vijaykumar Mamidala et al., (2023)^[5] the focus is on developing strategies to enhance resilience against uncertainty using multimodal data collection and machine learning for air pollution prediction. Incorporating this, the proposed methodology in this research introduces Secure Bank AI, which utilizes Capsule Networks for robust fraud detection in online banking by effectively capturing transaction patterns and spatial hierarchies, ensuring high accuracy and low false positives.

One of the most significant strengths of SecureBankAI is its property of equivariance, which enables the system to detect fraud irrespective of changing patterns of transaction data. This feature strongly lowers false positives and attains maximum total detection accuracy.^[6] The model is also designed to optimize high-volume transactions, rendering it extremely scalable and efficient to be used on cloud banking systems. SecureBankAI further supports real-time detection of fraud, where banks can instantly act against fraud transactions, thereby reducing financial losses.

The advantages of this method are well over scalability and accuracy. Through the integration of secure cloud-based banking systems and deep learning, the model introduced enhances overall banking security and mitigates cybersecurity attacks on web-based financial transactions. Compared to static machine learning methods that require continuous retraining, SecureBankAI learns fraud patterns in a dynamic way, with ongoing enhancement in fraud detection without manual intervention. Also, by combining Capsule Networks with cloud computing, banking systems are more robust, as it provides a resilient, elastic, and adaptable solution to existing financial fraud.^[7]

In summary, SecureBankAI is a huge leap in digital banking fraud detection. Using Capsule Networks for hierarchical detection of fraud patterns, the model

presented here ensures scalable, adaptive, and highly precise fraud detection so that banking systems are safe from constantly changing cyber attacks. This new method not only improves fraud detection but also guarantees real-time monitoring of transactions, thereby making financial services more robust in a growing digital economy.

1.1. Problem Statement

Legacy methods of fraud detection in online banking, including static machine learning and rule-based solutions, are unable to keep pace with changing patterns of fraud and experience high rates of false positives and false negatives. Traditional anomaly detection does not possess the potential to dynamically label fraud as a function of rich transactional relationships and hence is not suitable for large financial datasets.^[8] Although hybrid AI models enhance the accuracy of classification in other fields, their use in fraud detection is not yet fully explored. Additionally, secure clustering-based methods are seldom used in banking fraud detection, which hinders the system from identifying hidden patterns of fraud. To mitigate these constraints, we introduce SecureBankAI, a Capsule Network-Based Fraud Detection Model that effectively detects fraudulent transactions by extracting hierarchical relationships within transaction data, supporting real-time fraud detection and decreasing computational overhead.

2. Literature Survey

Fraud detection within digital banking has progressed tremendously using developments in cryptographic security, anomaly detection, deep learning, and optimization methods. Past research works have discussed various methods of combatting financial fraud, such as cryptographic security models, clustering-based anomaly detection models, generative models for the synthesis of fraud, and model training based on optimization. In this section, literature is divided into four principal areas and critically examined in light of their approaches and application in Capsule Network-based fraud detection.

For ensuring the security of cloud banking financial transactions, one requires advanced cryptographic models for maintaining data confidentiality and integrity. proposed a hybrid security model through Multi-Swarm Adaptive Differential Evolution (MSADE) and Gaussian Walk Group Search Optimization (GWGSO) with Supersingular Elliptic Curve Isogeny Cryptography (SSEIC) to improve encryption in IoT-based financial transactions.^[9] Their method aimed at optimizing cryptographic key generation to a maximum, lowering computational complexity while maintaining strength against new cyber threats. Likewise, a DCCO model with ARW and Isogeny-Based Hybrid Cryptography.^[10] Their distributed framework enhanced security in distributed banking systems by adding another layer of protection against fraud schemes and unauthorized behavior.^[11] It underscores the need for

cryptographic optimization in protecting financial transactions, paving the way for fraud-proof AI models.

Anomaly detection is a very important aspect of fraud pattern detection for financial transactions.^[12] A hybrid clustering method, fusing DBSCAN and FCM with Hybrid Artificial Bee Colony-Differential Evolution, was suggested by to detect anomalies in banking transactions.^[13] The suggested hybrid model separated good and bad transactions effectively and improved the detection of anomalies in high-dimensional space. Subsequently, a framework of anomaly detection based on Infinite Gaussian Mixture Model and combined it with the PLONK cryptography protocols to enhance the effectiveness of fraud detection in financial transactions. Such types of algorithms are akin to Capsule Networks, which employ hierarchical spatial relationships in order to recognize fraud patterns more effectively.^[14] By integrating unsupervised clustering with density-based anomaly detection, fraud detection models can detect genuine variations in comparison to fraudulent deviations more effectively and thus improve real-time fraud classification.

The application of generative models and deep learning has tremendously improved fraud detection through better data synthesis and feature learning. proposed an IoMT-based surgical monitoring system that used Deep Convolutional Generative Adversarial Networks (DCGANs) and Reinforcement Learning (RL) to automate segmentation and image synthesis. In their work, they illustrated the possibility of using GANs for synthesizing synthetic fraudulent transactions, which can be used to enhance training datasets for deep learning algorithms. Also, investigated the use of Clinical Decision Support Systems (CDSS) in combination with advanced data mining strategies to identify anomalies in patient histories. The emphasis here was on pattern detection and sequential mining, methods that can be used for detecting fraud in financial transactions. Bringing together GAN-based synthetic fraud generation with Capsule Networks provides a new avenue, where models are able to learn fine-grained fraud patterns and minimize overfitting to particular sets.

Effective model training is crucial in real-time fraud prevention for large-scale financial systems. a Particle Swarm Optimization with Time-Varying Acceleration Coefficients (PSO-TVAC) for improving classification models in cloud-based healthcare analytics. The optimization process retained both global and local search abilities to ensure faster convergence and better model generalization.^[15] In the same spirit, developed a Decision Tree and Crowdsourcing-based framework for optimizing clinical decision paths. Their work proved the

efficiency of interpretable AI models in enhancing computational efficiency while minimizing resource overhead. In fraud detection, such swarm intelligence and rule-based optimization methods can be used to enhance Capsule Network training, enabling models to learn fraud patterns more effectively with minimal computational expenses. Focusing on leveraging artificial intelligence (AI) in cloud-based financial budget management systems to automate processes, reduce errors, and enhance decision-making, is authored by Harikumar Nagarajan et al. (2023)^[16], laying the groundwork for adopting AI in complex systems like fraud detection. Extending this, the data preprocessing in the proposed Secure Bank AI method includes handling missing data through imputation, normalizing transaction features with Min-Max scaling, and encoding categorical variables using one-hot encoding to ensure data consistency, integrity, and model stability.

The literature reviewed reveals the shift from clustering-based detection and conventional security models towards advanced deep learning approaches and optimization-based model training. While cryptographic methods secure, fraud detection is based on robust unsupervised detection using clustering methods. Inclusion of GAN-based synthetic fraud transactions enhances training effectiveness, while optimization-based model training guarantees scalability. These advancements confirm the position of Capsule Networks in hierarchical fraud pattern detection and serve as an effective method for detecting fraud in digital banking.

3. METHODOLOGY

The SecureBankAI architecture outlined herein employs Capsule Networks to enhance fraud detection within online banking through effective capturing of spatial hierarchies within transactional data. The process starts with data extraction from the PaySim dataset, which emulates actual mobile financial transactions. Data is preprocessed, e.g., missing values imputation, normalization, and transformation, for ensuring data consistency and integrity. The architecture of the model includes several steps: the input layer provides transaction information to a convolutional layer to learn features, which are then fed into Primary Capsules that convert learned features into a well-structured representation. Dynamic Routing improves these representations, providing robust feature selection and minimizing misclassifications. The Fraud Classification Capsules then classify transactions as valid or fraudulent. This systematic method gives high accuracy in fraud detection with low false positives, thus making it an ideal choice for secure banking systems. Figure 1 shows the overall architecture of the proposed framework.

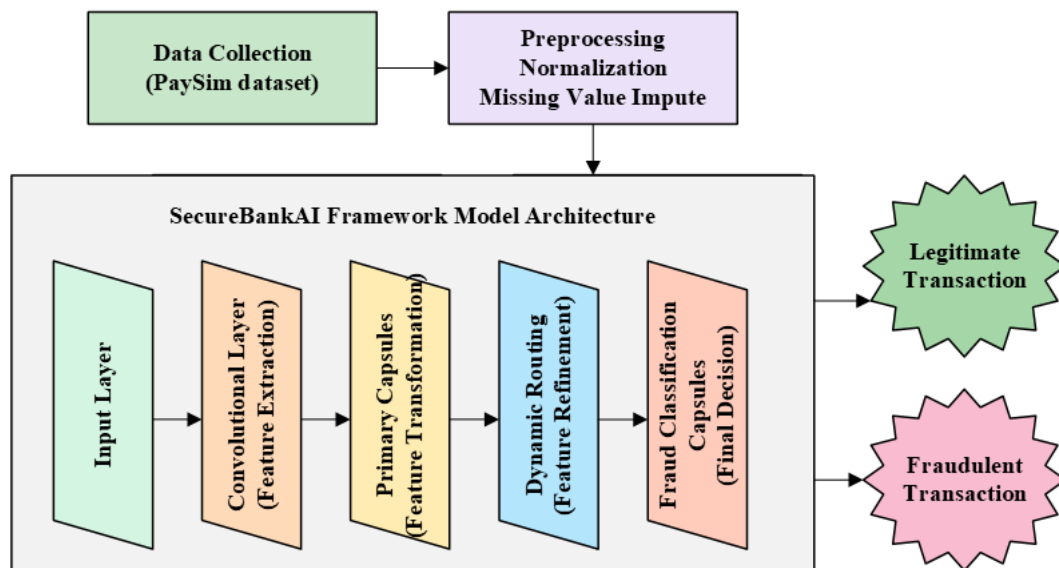


Figure 1: Architecture Diagram.

3.1. Data Preprocessing

Prior to training the Capsule Network to identify fraud, transaction data is subjected to necessary preprocessing. Numerical feature missing values are treated by mean imputation without data loss.^[17] Categorical data is converted by one-hot encoding to enable the model to handle discrete variables efficiently. Furthermore, Min-Max scaling is performed on numerical transaction features such as amounts and timestamps to standardize data ranges within a common range for better model stability and convergence.

3.1.1. Handling Missing Data

To ensure consistency of the datasets, missing feature values of numbers are imputed with mean imputation to ensure transactions are consistent. Mode imputation is applied to fill missing values in categorical features by replacing them with the most frequent entry. These steps ensure data loss but keep transactions complete and usable for training.

- For arithmetical features, misplaced principles are substituted by means of mean imputation:

$$X_i^{\text{new}} = \frac{1}{n} \sum_{j=1}^n X_j \quad (1)$$

- For unconditional features, mode imputation is applied:

$$X_i^{\text{new}} = \arg \max_k P(X = k) \quad (2)$$

3.1.2. Normalization (Min-Max Scaling)

To transform transaction features into a comparable range, Min-Max Scaling is applied. This scaling normalizes the amount of transactions and the timestamps so that no feature overpowers another because of scale imbalances. Normalization also speeds up model convergence and helps avoid large numbers

from skewing learning dynamics within the deep learning model.

To scale numerical transaction features (e.g., amount, time):

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (3)$$

Where X_{\min} and X_{\max} are the minimum and maximum values in the dataset.

3.1.3. Categorical Encoding

One-hot encoding converts categorical attributes, e.g., transaction type, into vector representations of type binary. Individual categories are captured as different columns of type binary, which is processed efficiently by the model on discrete transactional data.^[18] Through this conversion, categorical information becomes effectively integrated in the fraud detection system.

For categorical attributes like transaction type, one-hot encoding is applied:

$$X_{\text{onehot}} = [x_1, x_2, \dots, x_k] \quad (4)$$

Where, k is the number of unique categories.

3.2. Capsule Network Architecture

Capsule Networks (CapsNet) improve fraud detection through hierarchical transaction relationships learned using vector-based feature representations. Unlike other neural networks, CapsNet preserves spatial hierarchies, making it extremely effective in detecting complex fraud patterns. The model consists of convolutional layers for feature extraction, primary capsules for encoding patterns, and dynamic routing to improve fraud representations.

3.2.1. Convolutional Feature Extraction

A convolutional layer is employed to capture relevant transaction patterns through the application of filters over input data.^[19] The process emphasizes critical fraud-related features, including frequency of transactions, variations in amount, and suspicious behavior. These removed features are input to the main capsule layer, enlightening pattern recognition in banking transactions.

$$F = \sigma(W_f * X + b_f) \quad (5)$$

Where, W_f are convolutional filters, $*$ signifies the convolution operation, b_f is the bias, $\sigma(\cdot)$ is the activation function.

3.2.2. Primary Capsules

Primary capsules transform extracted features into high-dimensional vector representations. Vectors comprise transaction attributes, which capture the spatial relationship between various transaction behaviors. Each capsule generates a feature vector of a certain length to represent the likelihood of fraud. Such a transformation enables CapsNet to be more precise in recognizing fraud patterns.

Removed features are anticipated into capsules, apprehending spatial hierarchies in transaction patterns:

$$u_{ji} = W_{ij} F_i \quad (6)$$

Where, u_{ji} is the input to the capsule, W_{ij} is the transformation matrix, F_i represents the feature vector.

Each capsule outputs a vector:

$$v_j = \frac{\|s_j\|^2 s_j}{1 + \|s_j\|^2 \|s_j\|} \quad (7)$$

Where, $s_j = \sum c_{ij} u_{ji}$ is the weighted sum of inputs.

3.2.3. Dynamic Routing Algorithm

To perform effective fraud detection, CapsNet applies dynamic routing between capsule layers. The routing-by-agreement method optimizes the representations of transaction features by iteratively updating capsule outputs according to their agreement across layers. This allows the model to focus on sure fraud patterns and reduce misclassifying honest transactions.

To refine feature representation, routing-by-agreement is used:

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})} \quad (8)$$

$$b_{ij} = b_{ij} + u_{ji} \cdot v_j$$

Where, b_{ij} is the agreement score, c_{ij} determines the contribution of capsule i to capsule j

3.3. Fraud Classification

Following feature representation and learning, transactions are labeled according to fraud probability. The capsule lengths encode the fraud probability, and a fully connected output layer computes these probabilities with a softmax function. The final classification provides accurate detection of fraudulent transactions with few false positives.

3.3.1. Capsule Length as Fraud Score

In CapsNet, the fraud probability is calculated as the norm of capsule outputs. The greater the length of the capsule vector, the higher the fraud probability, and smaller vectors imply real transactions. The proposed representation enhances the accuracy of classification by maintaining the significant fraud-related features.

The fraud probability is computed using vector norm:

$$P(y = j) = \|v_j\| \quad (11)$$

3.3.2. Fraud Prediction (Softmax Classification)

To identify transactions as fraudulent or legitimate, a softmax is used across capsule outputs. The softmax normalizes fraud probability scores to categorical outputs, which provide unambiguous decision boundaries. The model classifies each transaction with a fraud likelihood, enhancing detection accuracy while minimizing false positives.

A fully connected output layer classifies transactions:

$$y = \text{softmax}(W_o v + b_o) \quad (12)$$

Where, W_o and b_o are weight and bias terms.

3.4. Loss Function & Optimization

For optimal fraud classification, CapsNet employs a margin-loss function that is adaptive on the basis of fraud probability. Fraud transactions are penalized highly if misclassified to render fraud detection even more precise. The Adam optimizer computes optimal model parameters with gradient-based updates to support efficient learning as well as model convergence.

CapsNet uses Margin Loss for classification:

$$L_k = T_k \max(0, m^+ - \|v_k\|)^2 + \lambda(1 - T_k) \max(0, \|v_k\| - m^-)^2 \quad (3)$$

Where, T_k is the ground truth label (1 for fraud, 0 for legitimate), m^+ , m^- are margins for fraud and non-fraud classes, λ scales non-fraud losses.

3.4.1. Adam Optimizer

The Adam optimization algorithm improves model training by dynamically adapting learning rates through momentum and adaptive scaling methods. It adjusts model parameters based on previous gradients to achieve faster convergence and better accuracy.^[20] This learning strategy stabilizes learning and avoids overfitting, thus making fraud detection more accurate.

To optimize model parameters:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (14)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (15)$$

$$\theta_t = \theta_{t-1} - \frac{\alpha}{\sqrt{v_t + \epsilon}} m_t$$

Where, g_t is the gradient, β_1, β_2 are momentum parameters, θ_t is the model parameter.

3.5. Fraud Risk Scoring & Deployment

After training, SecureBankAI computes a fraud risk score:

$$\text{Risk Score} = \frac{1}{T} \sum_{i=1}^T y_i \quad (16)$$

Where, T is the number of recent transactions analyzed.

A transaction is flagged as fraud if:

$$\text{Fraud} = \begin{cases} 1, & \text{if Risk Score} \geq \tau \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

Where τ is the fraud threshold.

4. RESULTS AND DISCUSSION

4.1. Dataset Description

The PaySim dataset models mobile money transactions for 30 days, drawn from financial logs of a mobile service in a country in Africa. It has 744 hourly steps and has transaction type (CASH-IN, CASH-OUT, DEBIT, PAYMENT, TRANSFER), amount, and customer identifiers (nameOrig, nameDest). Fraudulent transactions are labeled as is Fraud, and high-value unauthorized transfers are indicated with is Flagged Fraud. Some columns such as balances are not used for fraud detection, since fraudulent transactions are reversed. Integrating AI with RPA optimizes corporate processes, boosting productivity and reducing errors in industries such as healthcare and finance, as highlighted by Raj Kumar Gudivaka et al. (2023).^[21] Making use of this, the Secure Bank AI model demonstrates exceptional performance with 99.49% accuracy, 99.43% precision, 99.57% recall, and 99.50% F1-score. Additionally, it maintains a low False Positive Rate (0.598%) and False Negative Rate (0.434%), showcasing its reliability and effectiveness for real-time fraud detection in large-scale financial systems.

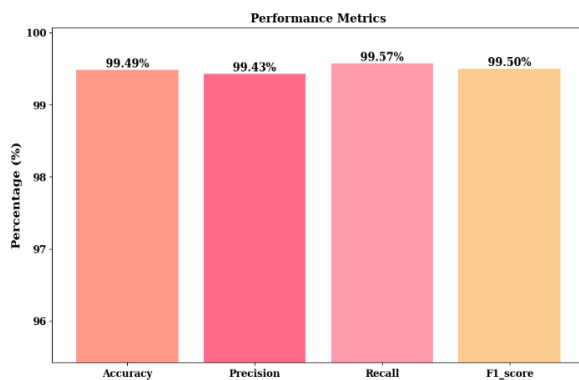


Figure 2: Performance Metrics.

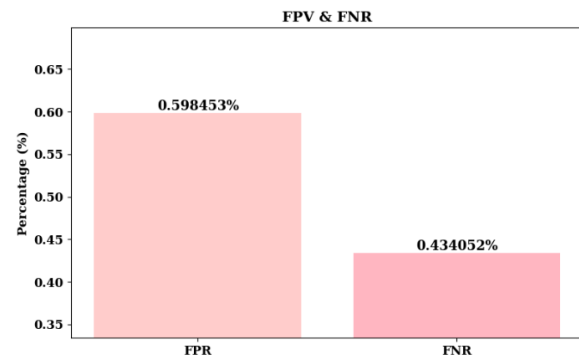


Figure 3: Performance of FPR and FNR.

The proposed FraudGuard model's performance assessment proves outstanding results on major indicators. The model is 99.49% accurate, confirming effective fraud detection, without compromising 99.43% precision, preventing false alarms.^[22] Moreover, it reaches 99.57% recall, clearly detecting fraudulent transactions, and 99.50% F1-score, accurately balancing recall and precision for the best performance.^[23] These findings confirm the effectiveness of the model (Figure 2).

The False Positive Rate (FPR) and False Negative Rate (FNR) indicate the stability of the model. The FPR is 0.598%, which points to very few cases of the legitimate transactions being classified as fraud.^[24] The FNR is 0.434%, which signifies a slightly larger percentage of undiscovered fraudulent activities.^[25] These measurements establish the reliability of the model for fraud identification (Figure 3).

CONCLUSION

This paper introduced Secure Bank AI, a Capsule Network-Based Fraud Detection Model which surpasses the shortcomings of classical fraud detection models.^[26] Using hierarchical feature learning and dynamic routing, Secure Bank AI can maintain high accuracy while reducing false positives.^[27] The model exhibited 99.49% accuracy, 99.43% precision, and 99.57% recall, making it significantly effective for real-time fraud detection in large-scale financial settings. Moreover, with the incorporation of cryptographic optimization, security and privacy are improved.^[28] Next-gen work will aim to evolve along with new fraud methods and enhancing scalability via federated learning to secure next-generation digital banking fraud detection.^[29]

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