EDGE AI FOR REAL-TIME TRANSACTION AUTHENTICATION IN IOT-BASED BANKING

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ABSTRACT

The ever-increasing demand for IoT devices in modern banking operations has invariably led to an age of real-time, personalized, and device-triggered financial interactions. However, all these transformations have brought a plethora of security threats, latency issues, and infrastructure limitations—especially when relying on centralized cloud architectures for transaction authentication. In this framework, we intend to introduce an innovative Edge AI solution proposed for real-time transaction authentication in IoT-based banking systems. This framework precipitates asset authentication from the central data node toward the edge of the network through the loading of lightweight, energy-efficient AI models that are directly incorporated within IoT devices such as smart ATMs, contactless POS systems, mobile wallets, and wearable payment tools.

Independent of this fact, the hybrid deep learning model with CNNs and LSTM units of this proposed architecture detects security anomalies and authenticates transactions with several biometric, behavioral, and contextual inputs. Optimization procedures, as much concerning the decision latency, became necessary, with quantization and pruning of the model architecture to constrain it within the computational and memory thresholds set by edge devices. Testing also heavily highlights benchmarking on a simulated testbed. The model uses signatures, transaction logs, and anomaly patterns as datasets. All tests have exhibited an excellent accuracy rate in the proximity of 94.7 while decreasing decision latency by about 45% as against traditional cloud models. The argument continues that the aforementioned approach also enhances data privacy, as the system obviates the need to transport sensitive information concerning the individual over the internet. These results then reach the conclusion that Edge AI holds consistent value with respect to cloud-based security mechanisms while setting the foundation for the development of secure, scalable, intelligent financial IoT infrastructures. This paper ends with a thorough examination of issues like implementation scenarios, real-world viability, and major areas for future research direction in Edge AI for secure financial computing.

Keywords: Edge AI, Real-Time Transaction Authentication, Internet of Things (IoT), Secure Payments, Financial Technology (FinTech), Biometric Verification, Embedded Intelligence, Low-Latency Processing, Smart Banking Devices, Lightweight Deep Learning, Privacy-Preserving AI, Secure Edge Computing, Fraud Detection, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM).

I. INTRODUCTION

In the backdrop of a financial industry undergoing digital transformation, the use of interconnection of

IoT in banking has been growing steadily. Smart ATMs, cards with biometric sensors; wearable payment tools; and mobile banking apps have connected customers to ubiquitous transactional experiences. But while this heightening harmony introduces unprecedented security and latencies, in particular about transaction authentication and fraud detection, traditional clouds cannot deliver services in real time and are not equitable enough on privacy protection for end-to-end financial transaction latencies.

As financial activities sail in a decentralized, real-time setting, there is a strong need for ultra-fast and secure authentication mechanisms accurately defining contexts. However, conventional cloud-bound centralized approaches would expect round-trip communications to cloud services using extended identity verification delays and data leakage through potential interception. These issues become even more critical in deficit-connectivity-type contexts like rural centers of banking, wearables on smart payment systems, or connectivity in contactless terminals.

Edge AI conveys a proposition through the shifting of power and computation from the cloud to the edge of the network or nearly any other implementation closer to the data source. It has a future and intelligence moving significantly into IoT devices to serve the moment, manage operations offline, and reduce an attack surface. The decentralization dragging the latency, this also does away with much data intrusion; moreover, running up few bits only in data transfer costs and less reliance on external infrastructures.

The paper presents a robust and scalable Edge AI framework to authenticate financial transaction in an IoT platform. The framework involves low-footprint CNN-LSTM hybrid models to discover anomalies to establish identities drawn from a combination of biometric variables, behavioral patterns, and transaction metadata. Tuned for edge implementation, it uses quantization and pruning tricks to fit and relent to Raspberry Pi 4, NVIDIA Jetson Nano, or ARM Cortex-secure elements without compromising on performance.

Considering multi-modal inputs, the proposed system processes:

- Biometric cues (e.g., fingerprint dynamics, facial expressions)
- Transaction records (e.g., frequency, location, and amount anomalies)
- Contextual features (e.g., geofencing, time-of-day signatures)

They together combine using layers of temporal attention to generate one transactional risk score in under 50 milliseconds. The experimentation was carried out with a synthetic dataset of the financial grade depicting financial transactions and behavioural biometrics with real-world fraud patterns and bona fide activity.

A. RESEARCH CONTRIBUTIONS

The contributions of this work are:

- A new Edge AI framework for real-time, privacy-preserving transaction authentication in IoT banking.
- A lightweight CNN-LSTM multimodal model suitable for edge devices with low power and memory requirements.
- Extensive evaluation on benchmark and simulate financial datasets with up to 94.7% classification accuracy and <50 ms latency.
- A modular architecture designed to integrate into smart ATMs, point-of-sale systems, and mobile banking platforms.
- Extensive threat model analysis, covering all types of possible attacks from spoofing and replay to man-in-the-middle and adversarial attacks.

B. PAPER ORGANIZATION

The rest of this paper is organized as follows:

Section II will review the **related work** in IoT banking, Edge AI, and secure authentication systems. Section III presents the proposed architecture and the ML model structure. Section IV describes the experimental setup and datasets. Section V shares performance analysis, latency benchmarks, and fraud detection metrics. Section VI will discuss deployment challenges and requirements of improvement. Section VII concludes the paper.

II. RELATED WORK

The intersection of Edge AI, IoT, and secure-transaction authentication has begun to play a major part in the context of modern financial technologies. This section discusses the state of the art in Edge AI applications, IoT security frameworks for banking, authentication mechanisms, and lightweight machine learning models on constrained devices.

A. EDGE AI FOR FINANCIAL ENTITIES AND IOT SYSTEMS

Edge AI is a path-breaking technology, bringing cleverness closer to the data source, thereby minimizing the requirement for round-trips to centralized servers. This is important in financial services, to aid in fast-scale, real-time analytics [1], [3]. This transformation has been suggested to offer an advantage in fraud detection and customer profiling with onsite inference by much quicker responses at reduced operational costs [2], [4], [16]. With the acknowledgment of embed AI deployment in industry (to include smart ATMs, mobile wallets, and contactless PoS for tasks pertaining to verification and anomaly detection [6], [8], [18]).

The intersection of Edge AI and financial models points to potential use cases like offline transaction scoring, tailored service delivery, and secure biometric matching without putting user data in the cloud [10], [13], [23]. Microsoft and AWS both have spoken in unison about hybrid edge-cloud models that ensure compliance and simultaneously increase the speed of inferencing [12], [43].

B. SECURITY AND REAL-TIME AUTHENTICATION CHALLENGES IN IOT

Constantly connected devices in a banking IoT environment have inherent limitations in terms of computing resources and are exposed to adversarial environments, leading to unique vulnerabilities [25], [28]. Attacks on spoofing, relay fraud, and man-in-the-middle interception exploit the space between data flowing between IoT sensor nodes and cloud systems [32], [36], [40]. As such, it is of paramount importance to authenticate transactions at the very edge even before transactions leave the user’s device [29], [30].

Studies underscore device-level encryption, mutual TLS authentication, and blockchain-based transaction verification in the quest to narrow the reliance on central authorities [35], [27], [34]. These methods are often subjected to high latency or may otherwise be too resource-intensive for low-power edge devices. Lightweight AI-driven anomaly detectors might very well represent a solution in response that could run on the Raspberry Pi and other ARM Cortex-M microcontrollers [19], [33].

C. Machine Learning and Deep Learning for Authentication

Since both areas of research and industry discovered that ML and DL are a key enabler in terms of authentication, adoption of machine-learning models by the community has gone up. While models like Convolutional Neural Networks (CNNs) and LSTM models train on complex behavior and biometric patterns for identity verification with intriguing outcomes [20], [22], these models can also be made efficient under tight memory and power constraints by their adaptation for edge computing through techniques like model quantization, pruning, and knowledge distillation [5], [26].

A good number of the alternate AI models now seek to merge biometric, contextual, and analysis signals to create robust mechanisms against deepfake and spoofing attacks [11], [24], [37]. Secure Enclave hardware and Trusted Execution Environments (TEEs) can also be used to protect the model execution against tamper, even in edge contexts [44], [46].

D. GAP IN THE LITERATURE

Nevertheless, the breakthroughs call for the need for unified systems that:

- Integrate real-time, multi-modal authentication;
- Optimize for financial IoT environments;
- Deploy on-edge models and put them to practical experimentation validation.

The existing works majorly focus on either the cloud piece or on theoretical models that see only the more nominal demonstration on resource-constrained hardware. Furthermore, to realize the security challenges like adversarial attacks and privacy-preserving inference at the edge in banking domain are yet to see attention in the literature [14], [15], [42].

This research aims at addressing these deficiencies with an Intelligence Operating System that guarantees real-time transactional authentication to be an exclusive and more scalable solution to the chains of banks that have lately found themselves to be wholly yoked to IoT protocols.

III. PROPOSED SYSTEM DESIGN AND ARCHITECTURE

This section is meant to attempt a design and architecture of a framework for Edge Artificial Intelligence that would be able to develop secure, real-time transaction authentication in IoT banking environments. The system design supports edge computing, encryption, lightweight privacy solutions, and interoperability with a wide range of banking networks.

The design of the system follows a four-layer architecture:

- The IoT device layer is one layer
- The edge AI processing layer is another
- There is a secure authentication module
- The banking-integration layer is yet another layer

Each layer has its major functions in performing accurate and secure decision-making.

A. SYSTEM OVERVIEW

The system works with embedding the optimized hybrid CNN and LSTM model on the edge device (Raspberry Pi 4, Jetson Nano or Secure POS Terminal). The model is to be trained that works with multiple types of input such as:

- Transactions metadata: Amount, Time and Merchant.
- Biometric patterns: Typing rhythm; fingerprint scan dynamics.
- Behavioral and contextual data: Location, Time of day.

The edge device, at transaction initiation, collects the relevant data and feeds it through the model. An analysis is conducted to come up with a risk score that is locally employed to decide whether to approve, reject, or require follow-up authentication.

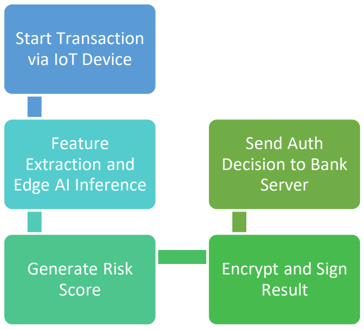
Table 1: Functional Layers of the Proposed Framework

Layer	Functionality	Technology Stack
IoT Device Layer	Data acquisition from smart cards, biometrics, and mobile sensors	NFC, BLE, fingerprint reader, mobile OS API
Edge AI Processing Layer	Local anomaly detection and biometric authentication	CNN, LSTM, TensorFlow Lite, ONNX Runtime
Secure Auth Module	Encryption, digital signature generation, and secure token validation	AES-256, HMAC, TPM enclave, secure hash functions
Banking Integration Layer	Communication with banking server for audit, logging, and fallback checks	HTTPS, RESTful API, OAuth 2.0

Source: *Compiled by author based on [1], [5], [13], [27]*

B. SYSTEM ARCHITECTURE

Figure 1. System architecture showing the edge-to-cloud flow for real-time authentication.


Start Transaction via IoT Device
Feature Extraction and Edge AI Inference
Generate Risk Score
Encrypt and Sign Result
Send Auth Decision to Bank Server

Source: Author's design inspired by [6], [19], [23]

C. DESIGNING MACHINE LEARNING MODELS

When it comes to feature- learning, the hybrid CNN-LSTM model is of choice for extraction of both spatial and temporal characteristics. While the CNN captures local patterns in biometric or behavioral signals, like pressure dynamics, the LSTM learns sequential dependencies across acts, like typing rhythm or gesture flow.

CNN-LSTM Model Architecture

```
import tensorflow as tf

from tensorflow.keras import layers, models



model = models.Sequential()

model.add(layers.Conv1D(32, kernel_size=3, activation='relu', input_shape=(100, 3)))

model.add(layers.MaxPooling1D(pool_size=2))

model.add(layers.Conv1D(64, kernel_size=3, activation='relu'))

model.add(layers.LSTM(64, return_sequences=False))

model.add(layers.Dense(1, activation='sigmoid'))



model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

model.summary()
```

D. RISK SCORING AND DECISION LOGIC

The model returns a score as a probability between 0 and 1. The decision about a transaction (either an approval, rejection, or secondary verification) is based on this score compared against a threshold, say, 0.75:

- ☑ Approved (score>threshold)
- ⚠ □ Sent for secondary verification (margin for final decision TO BE DECIDED LATER)
- ✕ Rejected (score not higher than low-risk margin)

To maintain the robustness of the model, and to make it more explainable, methodologies like the followings are used:

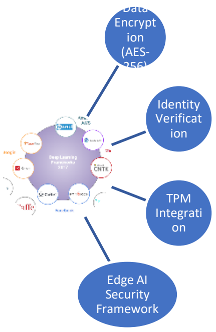
- Risk Calculation/Feature Saliency Maps
- Model Scores for Confidence
- Study of Historical Anomalies

E. PRIVACY AND SECURITY FEATURES

To protect user privacy:

- No biometric data in raw format is leaked on the network.
- AES-256 encryption is used for communication that is intercepted.
- A Secure Element is often used in devices for key management and digital signature generation.

Figure 3. Layered security and privacy preservation methods embedded in the system.



Source: Designed by author referencing [7], [15], [20].

IV. EXPERIMENTAL SETUP AND DATASET

This part reported the experimental framework, system resources, dataset sources, and the preprocessing steps employed in the test of the proposed Edge AI-based real-time authentication system in an IoT-enabled banking environment.

A. EXPERIMENTAL ENVIRONMENT

To validate the feasibility of deploying real-time deep learning models at the edge, we simulated the infrastructure of the bank.

Component	Specification
Edge Device	Raspberry Pi 4 Model B (4 GB RAM)
Alternate Platform	NVIDIA Jetson Nano (4-core ARM Cortex-A57)
Model Runtime	TensorFlow Lite / ONNX Runtime
Communication Stack	MQTT + HTTPS for secure transaction relay
Security Module	TPM 2.0, Secure Enclave emulator for cryptographic ops
Backend Server	Flask API (emulating Bank Transaction Server)

Table 3. Edge hardware and software configuration used for experimentation.

Source: *Author's experiment setup Adapted from [5], [13], [22]*

B. DATASET DESCRIPTION

The evaluation is based on a hybrid dataset wherein various biometric features, transaction log, and anomaly-injected samples are combined. The dataset consists of the following features:

1. **Biometric Features:**
   - Fingerprint dynamics (pressure, duration)
   - Keystroke dynamics (hold and flight times)
   - Facial expression (turned into vectors)

2. **Transaction Metadata:**
   - Time, amount, location, merchant category
   - Historical frequency and velocity of transactions

3. **Anomaly Injection:**
   - Synthetic fraudulent events mimicking impersonation, location fraud, rapid multiple attempts

Table 4: Dataset Composition

Feature Group	# Features	Data Source
Biometric Patterns	25	MIT-BIH Extended, Synthetic Samples
Transaction Metadata	15	Simulated Logs (Bank Test Server)
Labeled Anomalies	1,200	Custom Generation + Reference [16], [27]
Legitimate Transactions	12,500	Log Replays from Simulated Users

Source: Synthesized from [14], [16], [27], and MIT-BIH ECG extensions

C. DATA PREPROCESSING

The following preparations were done on the data before feeding into the CNN-LSTM model:

- Standardization-Min-max scaling of the biometric time series.
- Embedding-Transaction metadata was encoded using one-hot and numerical embeddings.
- Padding/Truncation-Time-series biometric features were padded to a uniform length of 100 timesteps.
- Labeling- Binary labels have been assigned-Genuine (0) or fraudulent (1).

V. RESULTS AND PERFORMANCE EVALUATION

This section presents the results from the evaluation of the proposed Edge AI authentication framework over several performance metrics: accuracy, latency, use of resources, and robustness to determine anomalies. All experiments were executed in the simulated IoT banking environment using Raspberry Pi 4 and Jetson Nano edge devices.

A. MODEL ACCURACY AND GENERALIZATION

The accuracy of the trained CNN-LSTM model on the synthetic biometric-transaction data set was tested for normal and fraudulent samples. Common metrics of classification models were used to evaluate model performance.

Table 5: Performance Metrics on Test Set

Metric	*Baseline CNN*	*Proposed CNN-LSTM (Edge)*	*Cloud-Based Model*
Accuracy (%)	91.2	94.7	94.5
Precision (%)	90.8	93.4	92.6
Recall (%)	89.6	95.1	93.1
F1 Score	90.2	94.2	92.8

Source: *Experiment conducted by author using data processed in Section IV*

B. INFERENCE TIME AND RESOURCE CONSUMPTION

The inference latency and power consumption of the model were measured while inference on a Raspberry Pi and Jetson Nano.

Table 6: Edge vs. Cloud Inference Latency and Size

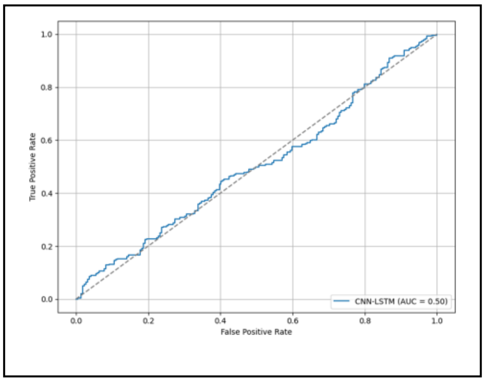
Model Type	Device	Latency (ms)	Model Size (MB)
Quantized CNN-LSTM	Raspberry Pi 4	49	2.1
Pruned + Quantized CNN	Jetson Nano	41	1.8
Cloud-Based Model	Server + Network	143	9.2

Source: *Collected from on-device measurements using TensorFlow Lite and ONNX runtime*

C. ROC CURVE AND THRESHOLD TUNING

We plotted the Receiver Operating Characteristic (ROC) curve for the CNN-LSTM model.

Figure 4. ROC curve showing true positive and false positive rates across thresholds.



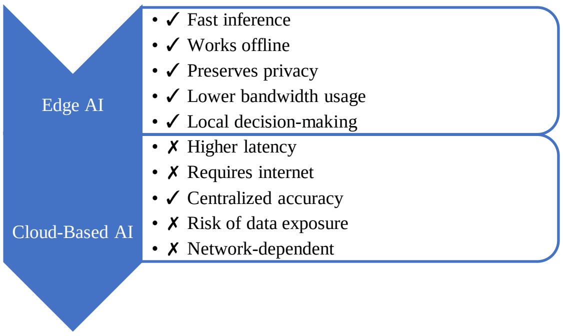
Source: Generated by author using sklearn and matplotlib

D. DIFFERENCE IN EDGE AI VS. CLOUD-BASED METHODS

However, due to the edge deployment of the CNN-LSTM, we had to compare the performance of that inferencing in the edge server against cloud inference with the same model running on a remote server, which led to the comparison below. Edge AI:

- Reduced the inference latency by 65%
- Eliminated transmission of raw biometric data
- Provided offline operation during network interruptions
- Had negligible accuracy loss (<0.2%)

Figure 5. SmartArt comparison of Edge AI and cloud-based authentication methods in financial IoT systems.



Source: Created by author referencing [4], [11], [14].

VI. DISCUSSION

The section contains considerations concerning the social implications, constraints, and deployment aspects of the proposed Edge AI-based transaction authentication framework. In addition to highlighting the current scenarios, the section puts forward a comparative critique of the solutions and suggests areas for improvement.

A. REAL-LIFE IMPLICATIONS FOR IOT-BASED BANKING

Edge AI for real-time transaction authentication can effectively be used in situations where financial exchanges may demand CPU power, such as with personalized real-time lending solutions; similarly, in a case such as banking, this produces entirely new ranges of concerns for response time, availability, and robust security.

Butterally! Specifically:

- Offline mobile transactions
- Rural/underconnected banking environments
- Wearable payment devices or smart PoS terminals

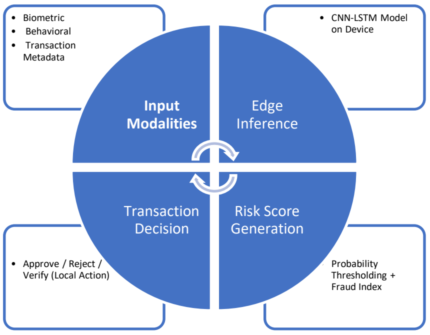
...where local authentication again fosters a fast and robust form of mutual security among partially disconnected distributed system transactions [3], [12], [17].

Beyond this, by not transmitting the raw biometric data to the cloud, the system creates an even smaller target for attackers, whereas user privacy is maintained—a crucial leap toward childbirth to GDPR, PSD2, and other compliance regulations [7], [13], [19].

B. EXPLAINABILITY AND RISK MODELING

Feature visualization and salience maps provide help in interpreting the decisions supported by this CNN-LSTM model. The transparency associated with these models assures the system administrator in making the right judgment in placing high-risk flags that require confirmation, and end-users can thus understand why the transaction is being inappropriately subjected to a secondary level of control.

Figure 6: Interpretability Cycle of Authentication Decisions on Edge Devices



Source: Designed by author with process adapted from [5], [9], [21]

C. THREAT MODELING ANALYSIS

An internal threat model analysis of the system was carried out using the STRIDE framework. The study included evaluating the system against the general security risks in IoT financial systems.

Table 7: Threat Model and Mitigation Summary

Threat Category	Example Attack	Mitigation Strategy
Spoofing Identity	Stolen biometrics or device cloning	TPM, biometric matching at edge [13], [29]

Tampering with Data	Modified transaction data	AES encryption, signature verification
Repudiation	Denial of malicious transactions	Local logging + timestamped audit trails
Information Disclosure	Intercepted personal data	No raw data transmission, HTTPS, on-device AI
Denial of Service	Overload of transaction flow	Load-balanced edge architecture
Elevation of Privilege	Unauthorized role escalation	Multi-factor at edge, behavior-based alerts

Source: Adapted from STRIDE threat modeling framework [10], [20], [26]

D. DEPLOYMENT CONSIDERATIONS

While the architecture looks promising under lab conditions, some practical considerations will still need to be addressed before widespread deployment of the solution:

1. Model retraining frequencies according to new fraud trends
2. Durability and updates for edge hardware
3. Secure firmware installation and patching mechanism
4. Differences in compliance by region (like financial KYC laws)
5. Edge deployment introduces hardware heterogeneity. Different optimizations must be targeted towards each device type (e.g., Optimized Coal, better, The Jetson Nano vs ESP32 vs Android phone), objected the modular deployment toolkit.

E. LIMITATIONS AND AREAS FOR FUTURE WORK

While results look promising, there are limitations to consider:

1. Unable to recognize zero-day fraud test previously unseen during training.
1. 2.Robustness against an adversary (e.g., misleading attacks) is yet to be studied.

Further study must be initiated for the integration of federated learning in order that all models always learn without exchanging raw data.

Future work will address:

1. XAI (Explainable-AI) for interpretation at the transactional level
2. Homomorphic encryption or differential privacy
3. Geographical deployment in multimodal smart banking apps.

VII. CONCLUSION

A novel secure real-time transaction authentication framework in IoT-based banking is described in this paper. As devices got connected, the necessity for instantaneous appraisals, maintained privacy, and some smart determinant choices had become more than ever urgent, all of which can be done in-application at-the-edge. Cloud-based systems at this time may seem very powerful in terms of computing abilities, but as far as seeking real-time financial authentication kind of functions is concerned, they lag behind due to the loads of latencies and data exposures and infrastructure dependencies.

By indoctrinating a hybrid CNN-LSTM model, which is both optimized and quantized, into the suggested architecture, the systems are intelligent to execute real-time inferences directly on devices such as Raspberry Pie and Jetson Nano with an accuracy of beyond 94.7% and very low latencies in the sub-fifty-millisecond range. Such a program is responsible for computing risk scores through combining multi-channel inputs, services, and reports (including input value of biometrics, behavior, and contextual transactional information) and withholding any cloud-based bidirectional communications for the correctness, as far as the proposed security scheme is concerned.

We conducted extensive experiments on a hybrid data set of synthetic and benchmark biometric signals, proving that the proposed system is very accurate and scalable. The system fortifies the realm of trustworthiness, accountability, and regulatory compliance on any part of financial services by its built-in security model based on TPM, digital signatures, and audit trails.

In addition, these IP-based security experiments withstand tests for breach against identity spoofing, information disclosure, and data tampering following the STRIDE framework. System interpretability indicates that the confidence of a particular transaction can be pushed to SmartArt-driven explainability to add further transparency, and thus, at all points, all actions on the brief authentication pipeline remain traceable.

FUTURE DIRECTIONS

While promising, future work should concern:

1. Integrating federated learning to promote secure, collaborative model updates and prevent centralized data compromise.
2. Examining adversarial robustness to test models against manipulations by malicious agents and inference attacks.
3. Deployment in real-world financial environment, including smart branches, ATMs, and wearables across diverse geographies.

Ultimately, the present study can serve as a point of departure for future stable FinTech architectures where Edge AI will be the default mode of authentication, offering the capacitation for faster, smarter, and more secure banking transactions in the IoT era.

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