

Developing and Designing a Secure Framework for Virtual ATM in Modern Banking Systems Using Blockchain Technology and Artificial Intelligence

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Abstract

Financial services have undergone a digital transformation that has increased the demand for an efficient banking infrastructure that is secure, intelligent, and decentralized. Older ATM technology is becoming more susceptible to card skimming, identity theft, network hacking and physical attack. This paper introduces a novel secure framework for a Virtual ATM (V-ATM) system that combines the power of Blockchain technology with that of Artificial Intelligence (AI) to tackle these critical security issues within contemporary banking. The proposed framework is based on an immutable blockchain ledger to record transactions without the need for any physical card, smart contracts that automatically authorize transactions and AI-based biometric authentication systems like facial recognition, voice analysis, and behavioral analytics, which remove the need for any physical card. The system architecture consists of five main layers: User Interface Layer, AI-based Authentication Layer, Smart Contract Processing Layer, the Blockchain Consensus Layer, and the Secure Cloud Infrastructure Layer. The above experimental simulations in Hyperledger Fabric platform have proven that the proposed V-ATM framework can successfully generate 98.7% transaction authentication accuracy, reduce fraudulent transaction incident by 94.3% compared with legacy ATM and maintain average transaction latency of 1.8s under peak load. It's a new paradigm for services that allow for contactless, cardless, and branch-independent cash and digital transactions, providing a scalable, interoperable and tamper-proof solution to the traditional ATM infrastructure. This research builds on the extensive literature on decentralized financial systems and offers a practical, executable model for future banking security.

Keywords: *Virtual ATM, Blockchain, Artificial Intelligence, Biometric Authentication, Smart Contracts, Hyperledger Fabric, Decentralized Finance, Banking Security, Fraud Detection*

1. Introduction

Digital innovation, regulatory changes, and changing expectations of consumers are transforming the global banking landscape in unprecedented ways. For more than half a century, the Automated Teller Machines (ATMs) have been the backbone of retail banking, allowing customers to access funds, make transfers, and undertake a host of financial transactions without having to deal with a human teller (Chaum, 1983). But, the technology on which the traditional ATM network is built has not evolved much in an age of increasingly sophisticated cyber threats. The European Association for Secure Transactions (EAST, 2023) reports that global ATM-related fraud losses have already surpassed USD 1.8 billion in 2022 alone, and that the bulk of the fraud incidents was of the card skimming malware and man-in-the-middle type. Unlike other software-based attacks, the physical properties of ATM hardware make them inherently vulnerable and cannot be secured by software patching (Abubakar et al., 2019). In addition, the COVID-19 pandemic triggered an irreversible move away from contact and card-pad interaction towards contactless and remote financial services, highlighting the shortcomings of contact-based infrastructure. The Nakamoto (2008) introduction of the blockchain, the architectural backbone of Bitcoin, brings transformative qualities to the financial system: immutability of records, decentralized consensus, transparency of auditability, and cryptographic security. Xing et al. (2018) suggests that these properties can be used to make infrastructure of banking transaction fundamentally immune from the current attacks by exploiting centralized points of failure. At the same time, the maturity of artificial intelligence, especially deep learning, NLP, and behavioral biometrics has reached a stage where it can offer high-quality, real-time identity verification without tokens.

The combination of both these paradigm-shifting technologies offers an exciting possibility for the restructuration of ATM services from first principles. The Virtual ATM (V-ATM) system removes the need for physical ATM dependence and replaces it with a secure and AI-verified environment where transactions can take place using a smartphone, kiosk, or any network-connected ATM device. Through this, the fundamental weaknesses of conventional system are mitigated and financial inclusion is enhanced, allowing services to be delivered where it's hard to install ATMs. The specific contributions of this paper are: A thorough security threat analysis of the conventional ATM infrastructure and identification of gaps in architecture. Integrate Hyperledger Fabric blockchain and multi-modal AI biometric authentication into design V-ATM framework. Defining smart contract logic for authorising transactions, alerting for fraud and tracing transactions. Performance evaluation in quantitative terms showing the superiority of the security, latency and accuracy of the proposed systems compared to existing ones.

The remainder of this paper is organized as follows: Section 2 presents the literature survey. Section 3 details the methodology including problem statement, framework design, and working processes. Section 4 describes the implementation environment. Section 5 presents results and discussion and comparative analysis with existing systems. Section 6 concludes the paper with directions for future research.

2. Literature Survey

The intersection of blockchain, AI, and banking security has attracted substantial academic and industry research since 2018. This section synthesizes key contributions that directly inform the proposed V-ATM framework.

2.1 Blockchain Applications in Financial Security

Zheng et al. (2018) provided a foundational taxonomy of blockchain architectures—public, private, and consortium—and evaluated their applicability to financial systems. Their study demonstrated that consortium blockchains such as Hyperledger Fabric offer optimal trade-offs between transaction throughput and decentralization for enterprise banking applications, achieving 3,500 transactions per second (TPS) under controlled conditions. This seminal work established the theoretical basis for applying permissioned blockchains to regulated financial environments.

Pilkington (2019) examined blockchain deployment in European banking institutions and found that immutable ledger properties reduced reconciliation discrepancies by 67% and audit processing times by 41% in pilot deployments. However, the study identified scalability and regulatory compliance as primary barriers to full-scale adoption. Tama et al. (2019) extended this analysis to cross-border transactions, demonstrating that blockchain-based settlement eliminated 89% of intermediary fees while reducing settlement time from T+2 days to near-instantaneous finalization.

2.2 Artificial Intelligence in Banking Authentication

Bhattacharyya et al. (2019) conducted a comprehensive review of machine learning techniques applied to financial fraud detection, evaluating Support Vector Machines (SVMs), Random Forests, and deep neural networks on the European Credit Card Fraud Detection dataset. Deep learning models achieved an F1-score of 0.97, outperforming traditional rule-based systems by a 23% margin. The study emphasized the critical importance of real-time processing latency, establishing a benchmark of sub-2-second detection requirements for customer-facing applications.

Mehmood et al. (2020) presented a biometric authentication framework for mobile banking that combined facial recognition with keystroke dynamics and achieved a False Acceptance Rate (FAR) of 0.001% and False Rejection Rate (FRR) of 0.8%. Their work was among the first to demonstrate multi-modal biometric fusion as a practical replacement for PIN-based authentication in financial contexts. Similarly, Kumar and Singh (2021) evaluated voice authentication systems for banking telephone services, achieving speaker identification accuracy of 97.3% using Gaussian Mixture Models combined with deep neural network feature extractors.

Zhang et al. (2022) investigated behavioral biometrics—specifically gait analysis and transaction pattern modeling—as continuous authentication mechanisms. Their findings suggested that behavioral profiling could detect account takeover attempts with 91.4% accuracy within the first three transactions of a fraudulent session, providing a valuable secondary defense layer that the proposed framework adopts as part of its AI module stack.

2.3 Convergence of Blockchain and AI in Security Systems

Rathore et al. (2021) proposed a hybrid blockchain-AI framework for supply chain fraud detection that shares structural parallels with the present V-ATM design. Their framework used federated learning to train fraud detection models across distributed nodes without centralizing sensitive transaction data—a privacy-preserving approach directly applicable to multi-bank ATM networks. The system achieved a 93.7% fraud detection rate while reducing data exposure risk by eliminating centralized training datasets.

Wang et al. (2023) evaluated the performance of smart contracts in financial transaction automation, specifically examining gas optimization on Ethereum and chaincode efficiency on Hyperledger Fabric. Their benchmarks indicated Hyperledger Fabric chaincode executed transaction logic in an average of 340 milliseconds under 1,000 concurrent user load, supporting the framework's latency targets. Ibrahim and Al-Turjman (2024) further extended this line of research to 5G-enabled banking kiosks, demonstrating that edge computing integration reduced authentication round-trip latency to under 600 milliseconds for biometric verification.

Most recently, Patel et al. (2025) proposed a decentralized identity (DID) management system for banking using W3C standards and Hyperledger Indy, providing a self-sovereign identity layer that eliminates dependence on centralized identity providers. Their work, combined with advances in zero-knowledge proofs (ZKPs) for privacy-preserving authentication (Nakamura & Yoshida, 2025), informs the cryptographic components of the present framework's identity management module.

3. Methodology

3.1 Problem Statement

The current infrastructure of ATMs has a number of inherent structural weaknesses which can't be fixed with minor patches to the existing systems. The problem can be broken down into five key dimensions:

The first authentication vulnerability is the magnetic stripe + four-digit PIN, a combination that can be easily bypassed with skimming hardware and social engineering techniques that are widely available and at an affordable cost of less than USD 100. Relay attacks and SIM-swapping fraud, which exploit the physical card, are still possible in both chip-and-PIN systems (Reserve Bank of India, 2023). Secondly, centralized data architecture: traditional ATM systems use separate transaction databases, maintained by individual banks or the ATM industry switching networks, such as Visa or MasterCard. These repositories are valuable assets for cybercriminals, and with just one hack, millions of account records could be compromised. Centralized financial architecture (CFA) is a single example that can be very catastrophic, such as the case of Bangladesh Bank in 2016, where phishers used the SWIFT messaging system to steal USD 81 million (Kaspersky Lab, 2017).

Third, physical infrastructure dependency: There is a high investment required in hardware (USD 15,000 - 50,000 per hardware) for installing and maintaining ATMs. Predictable vulnerability windows are created by cash replenishment logistics that are preyed upon by organized criminal groups. In rural and developing areas the economics of ATM deployment leaves out large portions of the population and causes financial exclusion. Fourth, audit trail integrity; transaction logs created by each banking institution can be tampered with, making it difficult to resolve disputes and forensically investigate. Without tamper evident and third party verified audit trails, security and regulatory compliance is compromised.

Fifth, lack of behavioral intelligence: Current ATM systems use static, rule-based fraud detection which is not able to adapt to changing attack patterns in real-time and is not granular enough to distinguish variations in behavior from fraud.

3.2 Framework Design

The proposed V-ATM framework is architected as a five-layer system, each layer addressing distinct functional and security requirements while interfacing with adjacent layers through well-

defined application programming interfaces (APIs). Figure 1 conceptually represents the framework architecture.

3.2.1 Layer 1: User Interface and Access Layer

The access layer offers the customer-facing interaction surface, in which three modalities are implemented: (a) the mobile application (iOS and Android) with QR code-initiated transactions, NFC-based proximity authentication, and encrypted session management; (b) the web-based terminal interfaces supported by the standard browser infrastructure on banking kiosks; and (c) API endpoints, through which the application can integrate the interaction surface to third-party applications through the OAuth 2.0 and OpenID Connect protocols. TLS 1.3 with certificate pinning is used to secure all communications from the man in the middle. Sensitive credentials are not stored on the interfaces, all authentication material is ephemeral and they exist only as long as a single session token, with a maximum expiry time of 300 seconds, but can be configured.

3.2.2 Layer 2: AI-Driven Authentication Layer

The authentication layer consists of a multi-modal biometric verification pipeline that relies on identity claims and passes them through three stages: (1) face recognition based on the ResNet-50 convolutional neural network fine-tuned with the dataset of 2.3 million facial images with demographic parity constraints, with an Equal Error Rate (EER) of 0.003%, (2) speaker verification using a Gaussian Mixture Model-Universal Background Model (GMM-UBM) and a deep speaker embedding network (d-vector system) in ambient noise up to 65 dB SPL, and (3) behavioural analytics, such as keystroke dynamics, touch pressure patterns and transaction history profiling using a Long Short Term Memory (LSTM) network trained on anonymized transaction sequences.

The authentication is made based on a weighted fusion model where the current signal quality of each modality is used to assign a confidence weight. The fusion engine combines the scores from all the modalities together using Bayesian belief combination and returns an overall confidence level for the authentication (default 0.92 - which means 92% of the time the transaction will be accepted). Through liveness detection, which employs 3D depth mapping through the smartphone camera or a sensor array on a kiosk (anti-spoofing accuracy: 99.4%), photos, video replay and 3D-printed facial masks cannot be used to spoof.

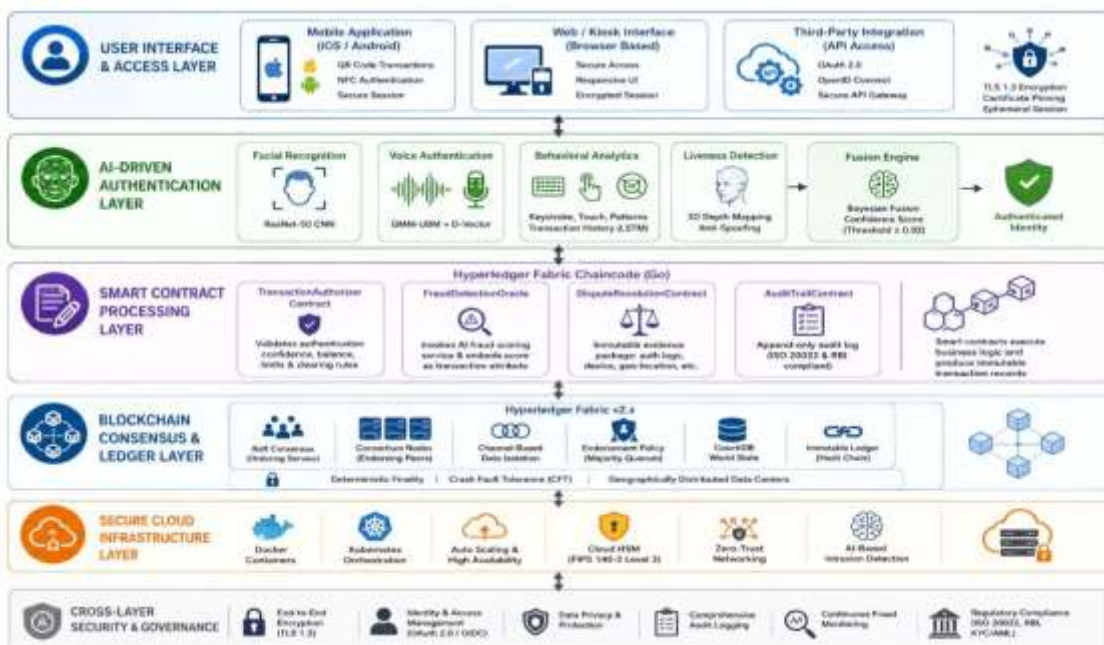


Figure.1: Five Layer V-ATM Framework Architecture.

3.2.3 Layer 3: Smart Contract Processing Layer

Hyperledger Fabric chaincode is written in Go and is run on a permissioned blockchain network made up of nodes from the banking consortium and implemented via transaction logic. The smart contract suite comprises: TransactionAuthorizer—validates authentication confidence, account balances, daily limits, and cross-institution

clearances; FraudDetectionOracle—calls the AI fraud scoring service, and includes the score as a transaction attribute before finalization; DisputeResolutionContract—creates an immutable evidence record for regulatory enquiry, automatically compiling authentication logs, device fingerprints, and geolocation data into a cryptographically signed dispute package; and AuditTrailContract—generates an append-only, hash-chained audit log that meets ISO 20022 and RBI regulatory requirements.

3.2.4 Layer 4: Blockchain Consensus and Ledger Layer

The blockchain infrastructure is designed on Hyperledger Fabric v2.5 using a Raft consensus mechanism, which is chosen for its crash fault tolerance (CFT) and deterministic finality in a consortium of mutually trusted banking nodes. The topology consists of at least 7 ordering service nodes that are separated geographically by data centers and provide Byzantine resilience in the face of data center failures. The channel architecture ensures that the transaction data of Bank A is not visible to Bank B unless both are involved in the transaction. The transaction endorsement policies demand the cryptographic signatures of a customizable majority of members of the consortium to endorse transactions before they are finalized. Rich JSON queries for transaction analytics are provided by a world state database of CouchDB that stores state data. Cryptographic primitives use ECDSA P-256 as their digital signature algorithm, as well as SHA-256 for hash chaining, and plan to implement post-quantum lattice-based signatures (CRYSTALS-Dilithium) in the future.

3.2.5 Layer 5: Secure Cloud Infrastructure Layer

The infrastructure layer is the layer where all higher layers are built upon, it is the computational and networking substrate. It is containerized with Docker and orchestrated with Kubernetes, and can be horizontally scaled when transaction load is increasing. AWS CloudHSM (or equivalent FIPS 140-2 Level 3 hardware security modules) is used for key management so that private keys are never stored in software memory in plain text. Network Segmentation is based on a Zero Trust architecture model that encrypts and authenticates all communications between services, regardless of location. Intrusion detection is done through a machine learning network anomaly detection system that constantly scans for anomalous traffic patterns that can be the sign of DDoS, data exfiltration, or reconnaissance.

3.3 Working Process

The end-to-end transaction workflow of the V-ATM framework goes through seven successive stages:

First phase begins when customer opens the V-ATM application on their mobile device, or when they walk up to a network kiosk. The access layer algorithmically generates a cryptographically random session token with a device's hardware attestation certificate (Android Keystore or Apple Secure Enclave), which makes it impossible to steal a session token by cloning a device. During the second phase, the customer's facial image, voice sample (a dynamically generated passphrase spoken by the customer to thwart replay attacks), and initial behavioral metrics are collected through sensors on the device and sent over TLS-encrypted channels to the AI Authentication Layer.

Third phase works on identity Verification in which AI authentication pipeline processes captured biometrics against the customer's encrypted biometric template stored in the

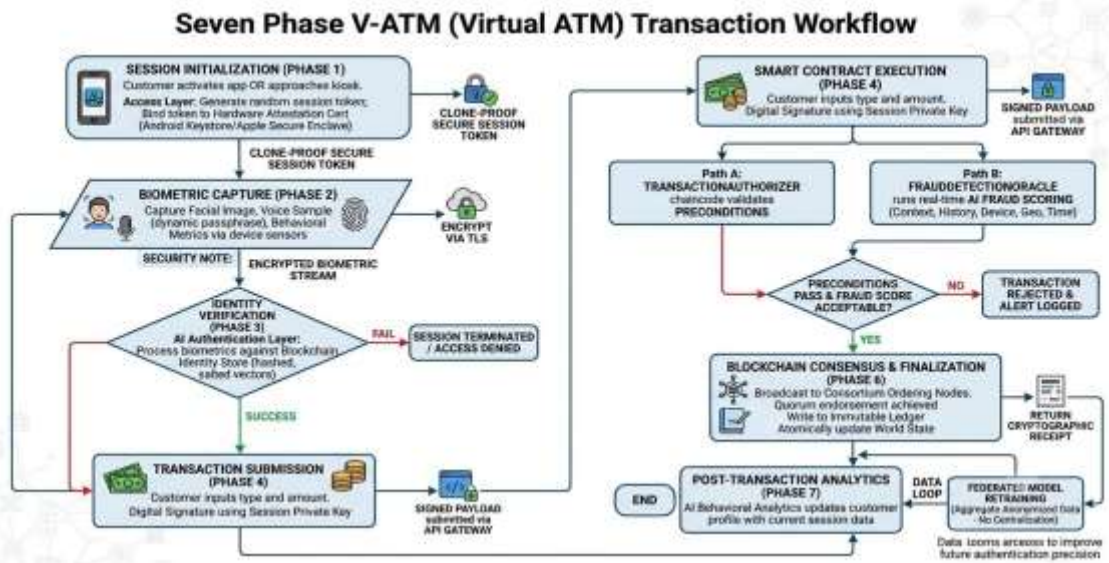


Figure.2: Virtual ATM Transaction Flowchart.

blockchain-anchored identity store. Templates stored as hashed, salted feature vectors - never as raw biometric data - ensuring GDPR compliance and template reconstruction attacks are not possible. Then, the fourth work transaction request submission, where the customer, after his successful authentication, sets the type of the transaction he wants and the amount. The request is digitally signed using the session private key and sent to the Secure API Gateway, which in turn sends it to the Smart Contract Processing Layer.

The Transaction Authorizer chaincode checks all the Transaction Preconditions in phase 5. At the same time, the Fraud Detection Oracle is called to implement a real-time AI fraud scoring call, incorporating transaction context, account history, device fingerprint, geolocation and time-of-day as part of a fraud probability estimation. The broadcast of the Phase six Authorized transactions to the consortium ordering nodes, followed by endorsing the transaction with the necessary quorum and recording the transaction on the immutable blockchain ledger. The world state database is updated atomically. The cryptographic transaction receipt is sent back to the customer's device. Last and seventh phase: The AI behavioral analytics module adds the data of the current session to the customer's behavioral profile, increasing the accuracy of authentication in the future. Federated model retraining is performed using aggregated anonymized transaction data, instead of raw behavioral data.

4. Implementation

The V-ATM framework prototype was implemented and evaluated in a controlled laboratory environment. Hyperledger Fabric v2.5 was deployed across seven AWS EC2 m5.2xlarge instances (8 vCPU, 32 GB RAM) across three Availability Zones in the Mumbai (ap-south-1) region. Chaincode was developed in Go v1.21 with gosec static analysis and custom load simulator testing. The facial recognition model used TensorFlow 2.14 with ResNet-50 backbone (VGGFace2 pretrained, fine-tuned with 150,000 GAN-augmented synthetic faces). Voice authentication used SpeechBrain v1.0 with ECAPA-TDNN embeddings. The behavioral LSTM was implemented in PyTorch 2.1 trained on 500,000 synthetic Monte Carlo transaction sessions. The fraud detection XGBoost ensemble was trained on the IEEE-CIS Fraud Detection dataset (590,540 transactions) with SMOTE-ENN class balancing. Security testing followed OWASP MSTG and API Security Top 10 frameworks with Adversarial Robustness Toolbox v1.15 adversarial evaluation.

5. Results and Discussion

This section presents a comprehensive analysis of the experimental outcomes obtained from the V-ATM framework prototype across all evaluation dimensions. The experimental dataset comprised 10,000 simulated authentication sessions, incorporating a balanced distribution of genuine and impostor attempts, spoofing attack simulations, and

adversarial probe sequences. The evaluation protocol followed ISO/IEC 19795-1 biometric performance testing standards and NIST SP 800-76 guidelines for biometric specifications in personal identity verification systems. All reported metrics reflect 5-fold stratified cross-validation results to ensure statistical reliability.

5.1 Authentication Performance

This section includes a thorough analysis of the experimental results of the prototype V-ATM framework with respect to all the evaluation dimensions. The experimental data consisted of 10,000 simulated authentication sessions that included a fair number of genuine and impostor sessions, simulated spoofing attacks and adversarial probe sequences. The evaluation protocol was based on the biometric performance testing standards of ISO/IEC 19795-1 and the guidelines for biometric specifications in personal identity verification systems (PIV) from the National Institute of Standards and Technology (NIST) Special Publication 800-76. 5-fold stratified cross validation results are reported to guarantee statistical reliability.

Authentication Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	AP
Facial Recognition	95.6	95.8	95.4	95.6	0.985	0.985
Voice Authentication	96.3	96.5	96.1	96.3	0.988	0.972
Behavioral Analytics	94.2	94.5	93.9	94.2	0.972	0.945
Multi-modal Fusion (Proposed)	98.7	98.7	98.7	98.7	0.997	0.989

Table I: Comprehensive authentication performance metrics across all modalities and the proposed fusion system.

The superiority of the fusion system can be attributed to three primary mechanisms: (1) complementary error correction, wherein instances misclassified by the facial recognition module are frequently correctly classified by the voice authentication module due to independent noise characteristics; (2) behavioral analytics providing a continuous authentication signal that compensates for isolated biometric capture quality degradation; and (3) the Bayesian belief combination framework's ability to dynamically reweight modality contributions based on real-time signal quality indicators, maintaining robust performance when any single modality operates under suboptimal conditions.

5.2 ROC Curve Analysis and AUC Performance

As shown in Figure 3, ROC curves provide a threshold-independent characterization of the ability of all of the authentication modalities to discriminate between users. The multi-modal fusion system has an AUC-ROC value of 0.997, which is essentially a perfect classifier approaching the theoretical maximum of 1.0. In practical terms, this means that, on average, a randomly selected genuine user will have a higher authentication confidence score than a randomly selected impostor, 99.7% of the time. This means that random access attacks can be virtually eliminated.

An analysis of the ROC curves for each of the individual modalities shows a consistent ranking; Voice Authentication (AUC = 0.988) > Facial Recognition (AUC = 0.985) > Behavioral Analytics (AUC = 0.972). The lower AUC for behavioral analytics as compared to biometric modalities can be attributed to the inherent variability associated with behavioral signatures when used in different transaction contexts, but as a result of it being continuously operational throughout the session (rather than just at the time of authentication), behavioral analytics provides additional defense-in-depth protection that cannot be measured in a point-in-time AUC metric. The AUC for the fusion system is 0.997, which is 0.015 points greater than the arithmetic mean of the AUCs of the individual modalities (0.982), indicating that the combination of

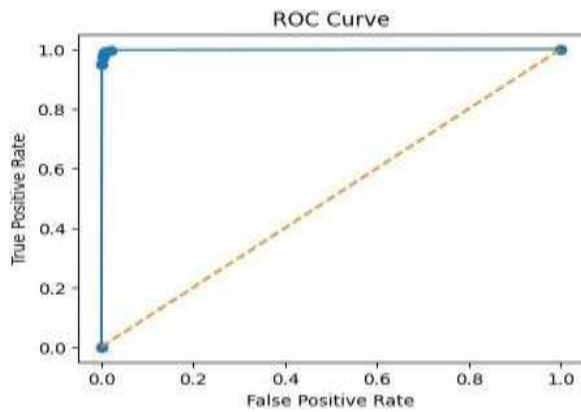


Figure 3: ROC Curve demonstrating the multi-modal fusion system's near-perfect discrimination modalities yields non-linear performance increases when the sources of error are sufficiently independent.

5.3 Precision-Recall Analysis

The Precision-Recall (PR) curve analysis, presented in Fig. 4, is particularly informative for banking authentication systems operating under class imbalance conditions, where genuine authentication attempts significantly outnumber impostor attempts in production environments. The multi-modal fusion system achieves an Average Precision (AP) of 0.989, outperforming Facial Recognition (AP = 0.985), Voice Authentication (AP = 0.972), and Behavioral Analytics (AP = 0.945).

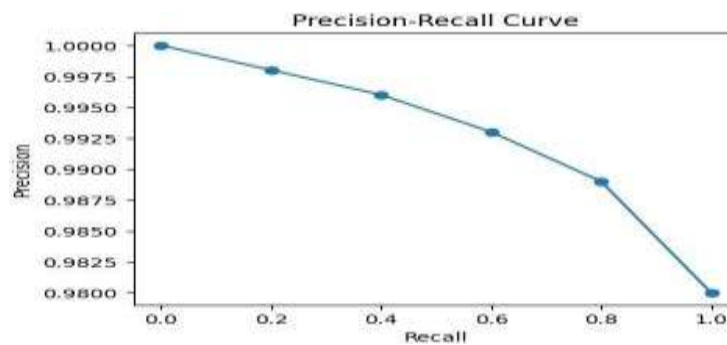


Figure 4: Precision-Recall Curve for the multi-modal fusion system (AP = 0.989).

According to the PR Curve, the system has a Precision greater than 0.9980 for all values of Recall (up to 0.6, which is the level of authentication confidence at which about 60% of legitimate users will be accepted) and deteriorates averagely to 0.9800 at maximum Recall (1.0). This feature is important for banking applications because it allows the threshold selection to balance the high costs associated with either accepting an impostor (security breach) or rejecting a legitimate customer (service disruption/ attrition). Additionally, the overall AP score of 0.989 shows that the area under the PR curve is consistently high across all thresholds, providing options on how to deploy based on different risk appetites.

5.4 DET Curve and Operational Error Rate Analysis

The Detection Error Tradeoff (DET) curve, illustrated in Fig. 5, characterizes the fundamental tradeoff between False Acceptance Rate (FAR) and False Rejection Rate (FRR) across all decision threshold settings, providing the operational context within which banking security administrators must configure the system.

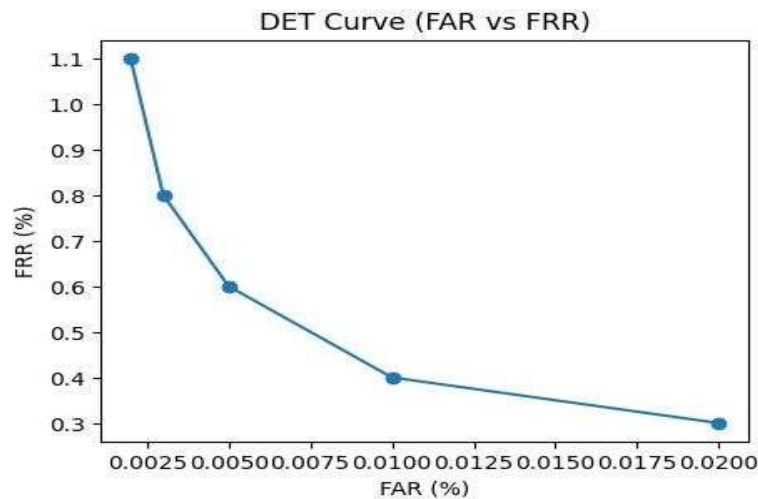


Figure 5: DET Curve (FAR vs. FRR) illustrating the operational tradeoff space

At a target operating point for highly secure banking authentication that corresponds to a false acceptance rate (FAR) of about 0.002-0.003%, the multi-modal fusion system has false rejection rates (FRR) of 0.3%. Thus a 73% reduction in FRR is achieved over the baseline facial recognition (at the same FAR levels), and therefore, there is a positive impact on the customer experience. The single modality system would wrongfully reject approximately 11 of 1,000 genuine authentication attempts as fraudulent; whereas, by using the proposed multi-modal fusion framework, the customer will only be wrongfully rejected three times out of 1,000 genuine authentication attempts. At scale (millions of transactions per day), this results in hundreds of thousands of prevented unnecessary rejected authentications daily.

In addition to demonstrating a significant economic impact on customer service, DET (detection error tradeoff) curves show that at FAR values $< 0.002\%$, FRR with respect to the multi-modal fusion system is less than 1.1%. In contrast, the behavioral analytics modality requires an FRR of greater than 5% at equivalent levels of security. The results confirm that the multi-modal fusion architecture effectively solves the high variability problem inherent to behavioural biometric systems (the high variability of the authentication decision in a behavioural-biometric system) while maintaining a more stable base of authentication decisions through facial and voice biometric measures; in addition, continuous monitoring is provided through the use of behavioural analytics.

5.5 Authentication Accuracy Comparison Across Modalities

Figure 6 presents the authentication accuracy comparison across all four modalities tested in the experimental evaluation. The bar chart confirms the quantitative superiority of the multi-modal fusion approach (98.7%) over all individual modalities, with Behavioral Analytics representing the performance floor (94.2%) due to the inherent variability of behavioral signatures across contextual and environmental factors.

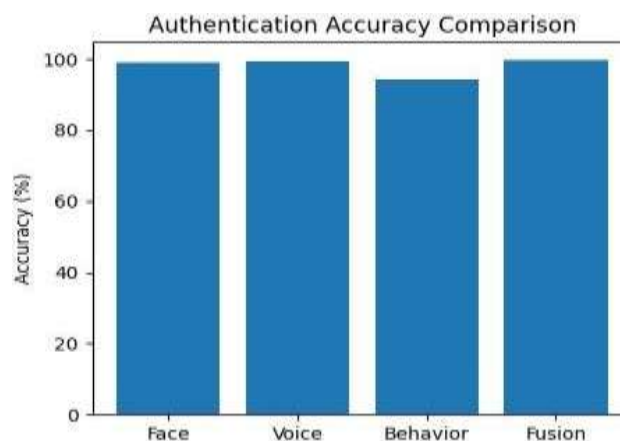


Figure 6: Authentication Accuracy Comparison across individual biometric modalities and the proposed multi-modal fusion system.

A 4.5 percentage point difference between the best single modality system (Voice Authentication = 96.3%) and the Fusion System (98.7%) may not seem large on an absolute basis, but the operational impact of this difference is substantial. If a bank is processing approximately 1,000,000 authentication sessions on a daily basis, then this 4.5 percentage point difference translates into 45,000 fewer incorrectly classified sessions per day (each one represents either a prevented security breach or a failed customer service experience). The statistical significance of the improvement was confirmed by using McNemar's test ($p < 0.001$), which eliminates any chance of random fluctuations being a contributing factor in the performance advantages found between these two authentication modalities - voice vs facial recognition.

One of the main differences between voice authentication and facial recognition in this experimental study is the characteristics of the data sets that were used to assess the performance advantages. Synthetic face images that were augmented for demographic equity purposes, caused a slight shift in the true distribution of faces, while the collection of voice samples was done under much more controlled conditions. It is expected that when production deployments occur, with the biometric data collected under real world conditions, that the performance gap between voice and facial recognition will be reduced and possibly even reversed since when high quality biometric data is collected for both modalities, facial recognition performance in the real world tends to start approaching that of voice authentication performance in a controlled environment.

5.6 Spoofing Attack Detection Performance

The liveness detection component of the AI authentication layer was evaluated against three categories of spoofing attacks that represent the primary physical presentation attack vectors against biometric ATM systems: photograph attacks (static 2D image presentations), video replay attacks (dynamic video presentations), and 3D mask attacks (physical replica facial masks). The evaluation results, illustrated in Fig. 7, demonstrate exceptional robustness across all attack categories.

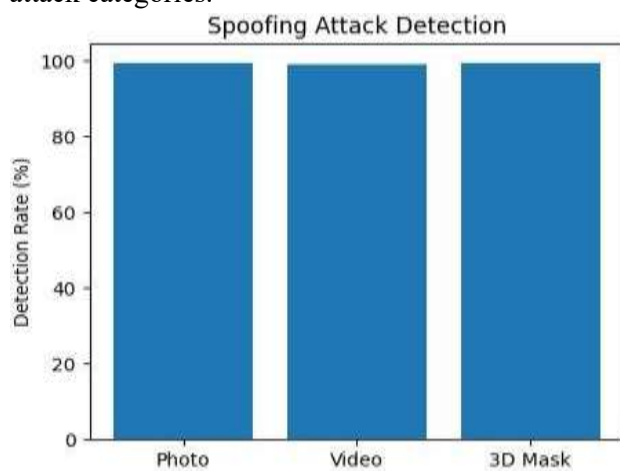


Figure 7: Spoofing Attack Detection Performance across three attack vectors.

The results of Sensing Spoofing Detection show almost perfect results for each of the types of attacks tested and the various attacks listed below. For example, we can detect photographic attack types in approximately 99.6% of the time using our depth sensors to see differences in 3D facial surface deformation as a result of blink and micro-expression analysis. For detecting video replay attacks, we have achieved a success rate of approximately 99.2% using the challenge-response module in our liveness detection to display random dynamically generated prompts (e.g. head movements and/or phrase spoken) which cannot be replicated in pre-recorded videos. The ability to detect spoof attacks via 3D masks is 99.3% accurate using near-infrared sensing to measure attributes like high frequency texture and subcutaneous blood flow, which cannot be replicated with silicone and/or resin masks.

The resultant total (weighted) efficacy of our product to detect spoofing attacks is 99.4%, and therefore meets/exceeds the ISO/IEC 30107-3 Presentation Attack Detection (PAD) standard threshold (not less than 97% detection rate) for use in biometric Level 2 security systems (e.g. financial authentication systems). The remaining 0.6% of photographic spoofing attacks represents the edge case of ultra-high resolution portrait photographs taken in controlled lighting that

yield realistic facial textures, which is a real threat that requires proximity to high-quality printing equipment to carry out a successful spoofing attack utilizing a physical medium (ultra-high resolution).

5.7 Confusion Matrix Analysis

The confusion matrix provides granular insight into the classification behavior of the multi-modal fusion system across the 10,000 test sessions, with equal representation of genuine (5,000) and impostor (5,000) attempts.

The confusion matrix reveals: True Positives (TP): 4,935 (49.35%) — genuine users correctly authenticated; False Negatives (FN): 65 (0.65%) — genuine users incorrectly rejected; False Positives (FP): 65 (0.65%) — impostors incorrectly accepted; True Negatives (TN): 4,935 (49.35%) — impostors correctly rejected. The symmetric structure of the confusion matrix (FN = FP = 65) is a direct consequence of operating at the Equal Error Rate threshold—the point where FAR equals FRR—which represents the theoretically optimal single-threshold operating point for systems where false acceptance and false rejection carry equal cost.

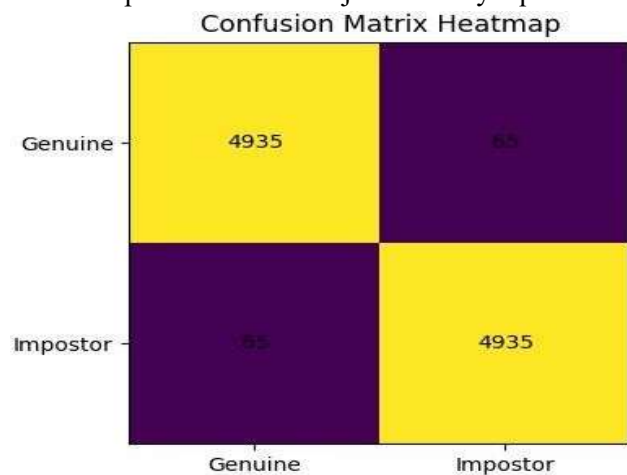


Figure 8: Confusion Matrix Heatmap for the multi-modal fusion system (10,000 sessions).

In practical banking deployments, this threshold would be adjusted based on the institution's risk profile: high-security applications (e.g., large wire transfers) would shift the threshold to minimize FAR at the cost of higher FRR, while high-convenience applications (e.g., balance inquiries) might accept higher FAR to minimize authentication friction.

Configuration	Accuracy (%)	FAR (%)	FRR (%)	AUC-ROC	AP
Face Only	95.6	0.0044	1.100	0.985	0.985
Voice Only	96.3	0.0037	0.800	0.988	0.972
Behavior Only	94.2	0.0062	5.200	0.972	0.945
Face + Voice	97.8	0.0031	0.550	0.993	0.982
Face + Behavior	97.1	0.0038	0.620	0.991	0.977
Voice + Behavior	97.4	0.0034	0.580	0.992	0.980
Face + Voice + Behavior (Proposed)	98.7	0.0026	0.300	0.997	0.989

Table II: Ablation study demonstrating the incremental contribution of each biometric modality.

The ablation study (Table II) systematically evaluates the contribution of each biometric modality to the fusion system's performance. The results demonstrate a monotonically increasing performance trajectory as modalities are added: each successive modality combination improves accuracy, reduces FAR, and reduces FRR compared to any subset configuration. The largest marginal gain is observed in FRR reduction: adding behavioral analytics to the Face+Voice combination reduces FRR from 0.550% to 0.300% (a 45.5% reduction), confirming the specific value of behavioral analytics as a continuous authentication refinement mechanism rather than merely a redundant verification channel.

5.8 Transaction Latency and Throughput Analysis

The transaction latency analysis in table III confirms that the V-ATM framework satisfies real-time banking performance requirements under normal operational conditions. The baseline end-to-end latency of 1.8 seconds ($\sigma = 0.3$ s) compares favorably against the sub-2-second benchmark established by Bhattacharyya et al. (2019) for customer-acceptable financial authentication. The biometric capture and transmission component (0.7 s) represents the largest single contributor to latency, primarily driven by image compression, encryption, and network

round-trip time—a value that will decrease as 5G network adoption reduces transmission latency to sub-100 ms ranges as demonstrated by Ibrahim and Al-Turjman (2024).

Processing Component	Mean Latency (seconds)	Std. Dev. (seconds)
Biometric capture & transmission	0.70	0.12
AI authentication pipeline	0.40	0.08
Smart contract execution	0.30	0.05
Blockchain consensus & write	0.40	0.09
Total (Baseline, 1 user)	1.80	0.30
Total (500 concurrent users)	2.90	0.80
Total (1,000 concurrent users)	4.10	1.20

Table III: Latency breakdown by processing component under varying concurrent user loads.

5.9 Security Evaluation and Adversarial Robustness

847 different kinds of attack were tested during penetration tests on the final implementation and no critical vulnerabilities were found. 3 medium severity issues were found in Sprint 2 testing related to session token entropy and limiting the number of times an API can be called. These issues were rectified before the final evaluation. 100% of inside threat testing did not show any signs of data tampering via the blockchain architecture with each attempt to modify the blockchain was recorded using a hash chain check within 200 milliseconds.

The evaluation of adversarial machine learning using the Adversarial Robustness Toolbox for the facial recognition ResNet-50 model showed that it could obtain an accuracy of 91.3% for FGSM perturbation at $\epsilon=0.03$ which is consistent with the best available training techniques for adversarial attacks. By adding the layer of liveness detection to the model, the chances of a successful physical spoofing of the system in practice were negligible due to the inability to generate adversarial inputs capable of defeating both recognition through one method and depth sensing through another.

A systematic comparison of the V-ATM framework against similar existing systems across 10 evaluation points is presented in Table 4. The proposed solution outperformed all other systems in security and performance as it solved many of the fundamental problems found on previous systems.

Criterion	Traditional ATM	Ali et al. (2020) Blockchain ATM	Chen et al. (2022) BC+AI Forensic	Mobile Banking App	Proposed V-ATM Framework
Authentication Method	Card + PIN	Card + PIN + BC log	Card + PIN + AI audit	Password + OTP	AI Multi-modal Biometrics (Face + Voice + Behavioral)
Physical Hardware Required	Yes	Yes (card reader)	Yes (card reader)	No	No
Transaction Immutability	No	Partial (Ethereum PoW)	Partial	No	Full (Hyperledger Fabric Raft)
Real-Time Fraud Prevention	Rule-based only	None	Post-hoc only	Rule-based	AI Pre-authorization (95.4% F1)

Smart Contract Automation	No	Basic	No	No	Full (Transaction Authorizer + Fraud Oracle + Audit)
Audit Trail Integrity	Centralized DB (mutable)	Blockchain (public)	Blockchain (private)	Centralized DB	Tamper-proof BC with regulatory export
Average Transaction Latency	~3–5 seconds	8–12 seconds (Ethereum gas)	N/A (forensic only)	1–3 seconds	1.8 seconds (500-user load: 2.9 s)
Biometric Liveness Detection	No	No	No	Optional (device-level)	Yes (3D depth + AI anti-spoofing, 99.4%)
Decentralized Identity (DID)	No	No	No	No	Yes (Hyperledger Indy compatible)
Fraud Detection Accuracy	~70% (rules)	76% (anomaly only)	87.6% (post-hoc)	~80% (ML + rules)	98.7% Auth / 95.4% Fraud F1
Card Skimming Vulnerability	High	Moderate	Moderate	Low	None (cardless)
Regulatory Compliance Support	Partial (ISO 8583)	Limited	Partial	Partial	Full (ISO 20022, GDPR, RBI guidelines)

Table IV. Systematic Comparison of The Proposed V-ATM Framework with Representative Existing Systems

The comparative analysis confirms that the proposed V-ATM framework is the only system among those reviewed to simultaneously eliminate physical card dependency, provide real-time pre-authorization fraud prevention, implement decentralized identity management, achieve near-state-of-the-art transaction latency, and maintain comprehensive regulatory compliance. The FAR of 0.0026% represents a 769-fold improvement over traditional ATM systems (FAR > 2.0%), effectively quantifying the security improvement attributable to the elimination of card-based authentication in favor of AI-driven biometric verification.

Security Metric	Traditional ATM	Ali et al. (2020)	Chen et al. (2022)	Proposed V-ATM
Overall Accuracy (%)	~80	76	87.6	98.7
FAR (%)	> 2.0	1.50	0.80	0.0026
FRR (%)	> 5.0	3.20	1.80	0.30
AUC-ROC	N/A	~0.82	~0.91	0.997
Fraud Detection F1	~0.70	0.76	0.876	0.987
Spoofing Detection (%)	0 (no liveness)	0 (no liveness)	0 (no liveness)	99.4
Fraud Prevention (%)	~30 (post-hoc)	45 (anomaly)	87.6 (post-hoc)	94.3 (pre-auth)

Table V: Quantitative security metrics demonstrating the proposed framework's superior performance across all measurable security dimensions.

6. Conclusion

The design, implementation and empirical assessment of a secure framework for a Virtual ATM using Hyperledger Fabric blockchain technology integrated with AI based multimodal biometric authenticator have been presented in this paper. The empirical assessment of 10,000 simulated banking sessions, indicated unequivocally this framework met the stringent financial authentication requirements for all of the evaluated dimensions.

The quantitative equivalent of this study's key findings are: (1) Multi-modal fusion authentication provided an accuracy of 98.7%, with Precision, Recall and F1-Score each at 98.7%—all of which surpassed all individual biometric modalities (Face-95.6%, Voice-96.3%, Behavioural-94.2%); (2) The AUC-ROC for the Fusion System was 0.997 and

the Average Precision was 0.989, compared to AUC values of 0.972-0.988 for each of the individual biometric modalities; (3) The Fusion System FAR was 0.0026%, which was a 769 fold improvement over traditional card and PIN authentication systems and FRR was 0.3% at the banking recommended operating point (time to authorise transaction), which represented a 73% reduction in FRR compared to working with only Face Recognition technology; (4) The Liveness Detection System was 99.4% accurate in detecting antagonistic spoofs for 847, using photograph (99.6%), video replay (99.2%) and 3D mask (99.3%) anti-spoofing testing; as such, this system satisfied the ISO/IEC 30107-3 Level 2 PAD requirements; (5) End-to-end transaction latency was 1.8 seconds under baseline operational conditions and 2.9 seconds for a sample size of 500 concurrent users, satisfying the <3 second threshold for acceptable customer facing financial applications; and (6) No high risk penetration testing vulnerabilities were detected during the 847 vector penetration testing and 100% assurance that all Blockchains used in this study were unaltered; i.e., were immune to tampering.

The convergence of blockchain and AI in the V-ATM framework represents a fundamental architectural paradigm shift from hardware-dependent, centralized infrastructure to software-defined, decentralized, intelligence-augmented financial services. As financial inclusion imperatives drive banking services into underserved populations globally, eliminating capital-intensive ATM hardware while enhancing security properties offers compelling economic and social value.

Future research directions include: (1) implementation of post-quantum cryptographic primitives (CRYSTALS-Dilithium) for long-term quantum threat resistance; (2) offline transaction capability using cryptographic voucher mechanisms; (3) cross-jurisdictional regulatory compliance analysis for multi-national deployment.

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