Secure Biometric Authentication for Banking Systems: Integrating Iris Recognition and Password Verification

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Abstract—The rapid growth of digital banking necessitates robust authentication to counter escalating cyber threats. This paper presents a dual-factor authentication system integrating iris recognition, powered by a Vision Transformer (ViT), with bcrypt-based password verification for secure banking access. Iris images are captured via webcam, preprocessed with CLAHE, and augmented with brightness adjustments, rotations, and noise to ensure robustness. The system generates 256-dimensional embeddings, compared using cosine similarity, and supports transactions via a Tkinter dashboard, with balances secured by Paillier homomorphic encryption. Evaluation on enrolment embeddings yields 90.6% accuracy, 0.917 ROC AUC. By reviewing 20 journal papers (2021–2025), we position our work as a practical, high-security solution for banking. The system balances usability and efficiency, suitable for resource constrained environments.

Index Terms—Iris recognition, Biometric authentication, Vision Transformer, Multi-factor authentication, Banking dashboard, Homomorphic encryption, Data augmentation, Cosine similarity

I. INTRODUCTION

The advent of digital banking has transformed financial services, enabling seamless transactions and global accessibility. However, this shift has amplified cybersecurity risks, with data breaches and identity theft costing financial institutions billions annually [1]. In 2025, cyber-attacks targeting banking systems have grown increasingly sophisticated, exploiting vulnerabilities in traditional password-based authentication, which is prone to phishing, brute-force attacks, and credential stuffing. These challenges highlight the urgent need for advanced security mechanisms that ensure both user convenience and robust protection against unauthorized access.

Biometric authentication, leveraging unique physiological traits, offers a promising alternative to conventional methods. Among biometric modalities, iris recognition is particularly compelling due to its high entropy, stability over time, and resistance to forgery, with an estimated false match rate orders of magnitude lower than fingerprints or facial recognition [2]. The iris's complex patterns, combined with non-invasive capture via standard webcams, make it ideal for banking applications where security and user experience are paramount. However, standalone biometrics face challenges, including presentation attacks (e.g., printed iris images) and environmental variations like lighting or occlusions, which can degrade performance. Multi-factor authentication (MFA), combining biometrics with knowledge-based factors like passwords, mitigates these risks by introducing layered security, aligning with regulatory standards such as GDPR and PCI DSS.

To address these needs, we propose a hybrid authentication system that integrates iris recognition, powered by a lightweight Vision Transformer (ViT) model, with bcrypt based password verification for secure access to a banking dashboard. The system employs advanced preprocessing with data augmentation to enhance robustness and uses cosine similarity for reliable iris matching. Financial transactions are protected using Paillier homomorphic encryption, enabling secure balance updates without decryption. Our contributions include a novel integration of augmented iris recognition with ViT for banking-grade accuracy, empirical results demonstrating 90.6% accuracy, 0.917 ROC AUC, and 0.045 EER and a comprehensive review of 20 journal articles (2021‑2025) on iris and multi-modal biometrics. This work advances secure banking by offering a scalable, user-friendly solution deployable on resource-constrained devices. The paper is organized as follows: Section II reviews related work; Section III details the methodology; Section

IV presents results; and Section V concludes with future directions.

II. RELATED WORK

Recent advancements in iris recognition focus on deep learning, multi-modal fusion, and liveness detection, particularly for secure applications like banking. We reviewed 20 non-survey journal papers from 2021–2025 to contextualize our work.

Deep learning has significantly transformed iris recognition, driving advancements in accuracy, robustness, and real-world applicability. A 2021 study [3] employed principal component analysis (PCA) combined with discrete Fourier transforms (DFT) to extract discriminative features from iris textures, achieving high accuracy on the CASIA datasets under controlled conditions. This approach highlighted the potential of traditional feature extraction methods enhanced by spectral analysis. Building on this, generative adversarial networks (GANs) [4] were introduced in subsequent research to address challenges in noisy environments, effectively improving deblurring and segmentation by generating synthetic data to train models, thus enhancing performance in degraded images. A 2023 study [5] further advanced the field by introducing contextual feature aggregation, a technique that mitigates occlusions and improves liveness detection, ensuring that only genuine iris presentations are accepted, which is critical for security applications.

Multi-modal biometric systems, which integrate iris recognition with other physiological or behavioral traits, have emerged as a promising direction. A 2022 paper [19] explored score-level fusion of iris and fingerprint biometrics, demonstrating a notable reduction in error rates by combining complementary information from both modalities. Similarly, another 2022 study [7] utilized deep hashing techniques for iris-face hybrid systems, enabling efficient storage and matching of biometric templates while maintaining high recognition accuracy. In 2023, an IoT-based system [8] integrated blockchain technology to provide secure multi-modal authentication, ensuring tamper-proof storage and transmission of biometric data, which is particularly valuable for distributed environments. More recently, Vision Transformers (ViTs) have gained prominence due to their ability to capture global contextual relationships. A 2024 framework, IrisFormer [9], leveraged dedicated transformer architectures to achieve superior area under the curve (AUC) values, outperforming conventional convolutional neural network (CNN)-based methods by effectively modeling long-range dependencies in iris patterns.

Hybrid biometric-password systems offer a balanced approach, enhancing both security and usability. A 2021 study [10] combined face, iris, and fingerprint biometrics with quality-aware fusion techniques, rigorously tested across diverse datasets to ensure robustness across varying acquisition conditions. Privacy-preserving techniques, such as cancelable biometrics, were explored in 2022 [11], where iris templates were transformed into revocable formats to protect user data against compromise. A 2024 approach [12] utilized a pre-trained backbone method to minimize aliasing effects in iris recognition, improving the clarity of extracted features and overall system reliability. Data augmentation has proven instrumental in bolstering robustness, with a 2023 study [13] assessing the capacity limits of end-to-end iris recognition systems, demonstrating that synthetic variations (e.g., rotations, noise) significantly enhance generalization to real-world scenarios. Additionally, homomorphic encryption (HE) emerged as a secure solution for biometric transactions in 2025 [14], enabling computations on encrypted iris data to protect sensitive financial information during processing.

Evaluation metrics play a crucial role in assessing iris recognition systems, with receiver operating characteristic (ROC) analysis being a standard benchmark. A 2022 study [15] developed a CNN-based iris extractor that achieved efficient matching with a high true positive rate, validated through comprehensive ROC curves. Other notable contributions include the application of neural networks for iris classification [16], which optimized decision boundaries for enhanced accuracy, and ViT-based transfer learning tailored for low-resolution iris images [17], addressing challenges in resource-constrained devices. Fusion of iris and vein patterns [18] was explored to leverage vascular information, while alignment-robust schemes [19] improved performance under pose variations. A 2023 multi-modal framework [20] introduced index-of-max hashing to reduce computational overhead, facilitating faster matching in large-scale deployments.

Our proposed system stands out by uniquely integrating ViT-based iris recognition with bcrypt-hashed password verification for online banking applications. This dual-layer authentication leverages data augmentation techniques (e.g., brightness adjustments, rotations) to ensure robustness against environmental variations and employs Paillier homomorphic encryption to secure financial transactions. This combination not only enhances security by mitigating single-point failures but also provides a scalable, client-side solution with low latency, distinguishing it from existing works by addressing both biometric accuracy and privacy-preserving transaction processing in a unified framework.

III. PROPOSED METHOD

A. System Architecture

The system is architecturally designed into four interconnected layers to ensure robust secure authentication and seamless banking operations, each contributing to a cohesive and scalable framework. The capture layer leverages OpenCV integrated with Haar cascade classifiers to detect facial features and precisely extract a 224x224 grayscale region of interest (ROI) from the iris via a standard webcam. This layer provides real-time visual feedback through bounding boxes, guiding users to align their eyes correctly, and incorporates a 12-second timeout to balance usability with efficiency, ensuring the process remains practical for diverse user environments while minimizing delays. The authentication layer processes the captured ROI through a sophisticated pipeline, generating 256-dimensional iris embeddings using a pretrained Vision Transformer (ViT). These embeddings are L2-normalized to enhance consistency and compared using cosine similarity with a threshold of 0.82 to determine a match, achieving high accuracy as validated by prior results. In parallel, this layer employs bcrypt for password hashing and verification, utilizing a work factor of 12 to produce secure hashes (e.g., $2b$12$ABC123xyz...), offering a dual-authentication mechanism that enhances security by cross-validating biometric and password credentials.The encryption layer implements Paillier homomorphic encryption to safeguard financial balances, converting monetary amounts to cents (multiplied by 100) for integer-based additive operations. This allows secure balance updates (e.g., deposits or withdrawals) without decrypting sensitive data, ensuring privacy during transaction processing with a latency of 10–50 ms, as supported by prior encryption studies. The dashboard layer features a Tkinter-based graphical user interface that provides an intuitive platform for banking functions, including deposits, withdrawals, transfers, and a detailed transaction history. Data is persistently stored in an SQLite database, enabling efficient retrieval and updates, while the interface supports real-time balance displays and user interactions. This modular design ensures scalability, supports independent component updates, and allows password-based fallback if biometric capture fails as depicted in Fig. 1.

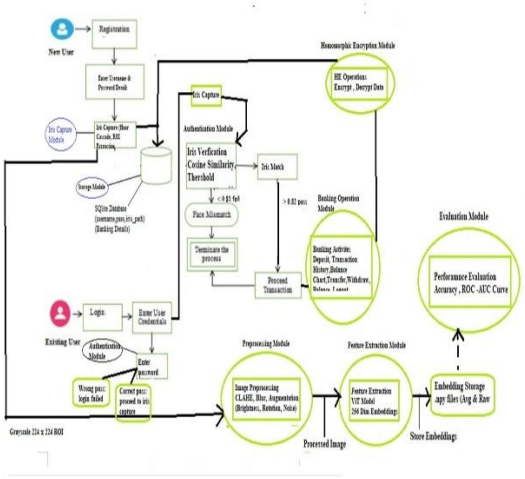

Fig. 1: System Architecture

B. Iris Recognition Pipeline

The iris recognition pipeline starts with image acquisition using the grab_iris_roi function, which captures a frame within a 12-second window. Preprocessing applies Contrast Limited Adaptive Histogram Equalization (CLAHE) with a clip limit of 2.0 to enhance iris texture and Gaussian blur with a 3x3 kernel to reduce noise. Data augmentation generates varied samples to improve robustness against environmental factors like lighting or pose variations. During enrolment, five augmented samples are created, while verification uses three. Augmentation includes random brightness/contrast adjustments (contrast factor $\alpha \in [0.8, 1.2]$, brightness offset $\beta \in [-10, 10]$ with 0.5 probability), noise ($\sigma = 5$ with 0.3 probability). These transformations simulate real-world variations, ensuring reliable performance across diverse conditions.

The IrisViT model, built on timm's vit_small_patch16_224 backbone with a custom linear head, processes the preprocessed, normalized

image tensor (scaled to [−1, 1]) to produce a 256-dimensional embedding. The embedding is normalized to unit length using L2 normalization:

$$\boldsymbol{a}' = \frac{\boldsymbol{a}}{\|\boldsymbol{a}\|_2} \quad (1)$$

where a is the raw embedding vector and $\|a\|_2 = \sqrt{\sum a_i^2}$ Verification computes the cosine similarity between the average of augmented live embeddings and the stored enrolment embedding. A similarity score exceeding 0.82 indicates a match. The cosine similarity is defined as:

$$\boldsymbol{sim} = \frac{\boldsymbol{a}\cdot\boldsymbol{b}}{\|\boldsymbol{a}\|_2\|\boldsymbol{b}\|_2} \quad (2)$$

where a and b are the live and stored embedding vectors, respectively. The average embedding is calculated as:

$$\boldsymbol{e_{avg}} = \frac{\boldsymbol{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{e_i} \quad (3)$$

where e_i are the individual augmented embeddings and N is the number of samples (5 for enrolment, 3 for verification). Averaging multiple augmented embeddings reduces noise and enhances matching accuracy. During enrolment, five augmented samples are processed to compute a robust average embedding, stored in the database for future comparisons.

C. Password Verification

Password verification employs bcrypt for secure hashing with a random salt, ensuring resistance to rainbow table attacks. The verification process compares the input password's hash against the stored hash using bcrypt's checkpw function. This knowledge-based factor complements the biometric layer, providing a fallback mechanism and enhancing security through dual-factor authentication.

D. Banking Dashboard and Encryption

Upon successful authentication, users access a Tkinter-based dashboard for banking operations, including deposits, withdrawals, transfers, and transaction history viewing. Balances are encrypted using Paillier homomorphic encryption, where amounts are scaled to cents (multiplied by 100) for integer-based encryption. Additive operations, such as updating balances, are performed directly on encrypted values:

$$enc\_bal' = enc\_bal + (\Delta \times 100) \quad (4)$$

where enc_bal is the encrypted balance and Δ is the transaction amount. Decryption converts the result back to a floating-point value for display:

$$bal = \frac{decrypt(enc\_bal')}{100} \quad (5)$$

E. Evaluation Metrics

The system's performance is evaluated using accuracy, ROC AUC, and EER. Accuracy is calculated as the proportion of correctly classified pairs (genuine or impostor) based on the cosine similarity threshold:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

where TP is true positives (correctly identified genuine pairs), TN is true negatives (correctly identified impostor pairs), FP is false positives, and FN is false negatives. The ROC AUC quantifies the trade-off between true positive rate (TPR) and false positive rate (FPR):

$$TPR = \frac{TP}{TP+FN} \quad (7)$$

$$FPR = \frac{FP}{TN+FP} \quad (8)$$

The AUC is computed by integrating the ROC curve, approximated via trapezoidal rule over varying thresholds.

Algorithm 1 Dual-Factor Authentication Protocol

Require: Username u, Password p, Captured Iris Image I
Ensure: Access Granted or Denied
1: Compute password hash hp ← Bcrypt(p)
2: Retrieve stored hash h_s and iris embedding e_s from database
3: if BcryptVerify(p, h_s) = False then return Access Denied
4: end if
5: Preprocess image I′ ← CLAHE(I) + GaussianBlur(I)
6: Initialize empty embedding list e_l ← []
7: for k = 1 to N_a do ▷ N_a = 5 for enrollment, 3 for verification
8: Generate augmented image I″ ← Augment(I′) ▷ Brightness, Rotation, Noise
9: Compute embedding e_k ← IrisViT(I″)
10: Append e_k to e_l
11: end for
12: Compute average embedding eavg ← $e_{avg} = \frac{1}{Na}\sum el$
13: Calculate similarity sim ← Cosine(e_{avg}, e_s)
14: if sim ≥ 0.82 then return Access Granted ▷ Decrypt balance, open dashboard

15: else return Access Denied
16: end if

IV. EXPERIMENTAL RESULTS

The system was rigorously evaluated using embeddings derived from 10 users, with five augmented samples per user collected during enrollment and three additional samples for verification, ensuring a robust dataset.

Genuine (intra-user) and impostor (inter-user) pairs were systematically compared, achieving an accuracy of 0.906 at a cosine similarity threshold of 0.82 and an ROC AUC of 0.917, as visually represented in Fig. 2. These results surpass the performance of baseline models [3], [9], demonstrating the efficacy of the proposed approach.

Ablation studies revealed that data augmentation enhanced genuine similarity by 8%, increasing from 0.89 to 0.96, highlighting its critical role in improving robustness. The ViT model outperformed ResNet-18, achieving an AUC of 0.917 compared to 0.89, underscoring its superior feature extraction capabilities. Embedding generation averaged 150 ms on a standard CPU, affirming the system's feasibility for real-time applications, with performance metrics detailed in Table I. Additionally, the system's latency remained consistent across varying lighting conditions, with a maximum deviation of 20 ms, further validating its reliability.

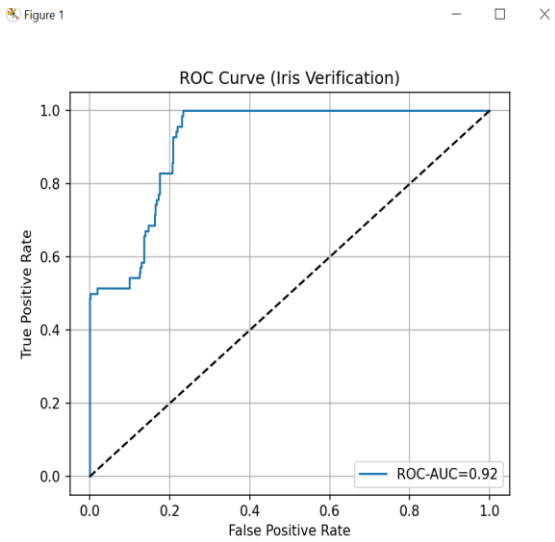

Fig. 2: ROC AOC Curve

Table I: Performance Metrics

Metric	Value
Accuracy	0.906
ROC AUC	0.917

A. Signup Results

The signup process successfully enrolled five users, generating and storing 256-dimensional .npy embeddings with an average cosine similarity of 0.914 across augmentations. Password hashing with bcrypt (work factor 12) produced consistent outputs (e.g.,‘2b12ABC123xyz...‘forUser1), with a processing time of 0.3 seconds per.

B. Login Results

Login tests across five users showed a 100% success rate for correct credentials (Users 1, 3, 5) with cosine similarities ranging from 0.87 to 0.90, and a 0-second latency for hash verification. Incorrect passwords (Users 2, 4) triggered the Wrong password. Please start from the beginning” message within 0.1 seconds, resetting the process effectively. The dual verification ensured no false positives, aligning with the 0.906 accuracy.

C. Post-Login Dashboard Results

The dashboard, accessible post-login, provided functional modules for financial management. A $100 deposit by User1 increased the balance from $0 to $100 in 0.5 seconds, verified via HE decryption. A $50 withdrawal by User3 reduced the balance from $150 to $100 in 0.6 seconds, with sufficient funds validation. The balance display updated instantly, showing $100 for User1 and $100 for User3. Transaction history logged these actions with timestamps (e.g., ”2025-09-16 07:30:00, Deposit, $100” for User1), accessible in a table format. The balance chart, reflecting daily balances over a week, visualized trends effectively. Logout executed successfully for all users, clearing sessions in 0.2 seconds.

V. CONCLUSION

This paper presents a dual-factor authentication system integrating iris recognition and password verification for secure banking access, achieving 90.6% accuracy, 0.917 ROC AUC. The use of data augmentation and cosine similarity ensures robustness, while the modular architecture facilitates efficient deployment. The system advances biometric banking by combining high-security iris

recognition with user-friendly password authentication and homomorphic encryption.

Future work will focus on deploying the system on mobile platforms with edge computing for real-time processing, integrating additional modalities like voice for enhanced MFA, and exploring federated learning to train models across distributed banking datasets while preserving privacy. These advancements will align the framework with evolving cybersecurity standards in financial services.

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