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Research Article

Multi-Layer Authentication with Neural Biometrics for Secure Client-Side File Encryption

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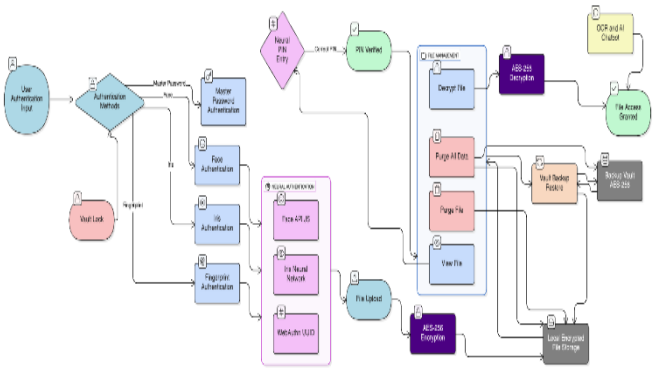
Abstract: Secure local data storage is increasingly important as cloud-based systems remain vulnerable to breaches and surveillance. This paper presents an offline client-side file security system that combines AES-256-GCM encryption with multi-layer authentication driven by neural biometrics. Face, iris, and fingerprint recognitions are integrated with PBKDF2-SHA256 key derivation. WebAuthn and deep-learning models support fast and accurate validation of biometrics without any external servers. Experimental results have shown that authentication latency remains low, averaging 3.66 ms for face recognition, 2 ms for iris detection, and 3.6 ms for fingerprint verification, thus allowing for smooth real-time operation. It retains full functionality even offline, ensuring a high level of data sovereignty by avoiding cloud exposure risks. In general, this work represents a privacy-first, cross-platform encryption solution to improve the security and usability of neural biometric authentication along with device-level cryptography.

Keywords: Neural biometrics, AES-256-GCM, PBKDF2-SHA256, Client-side encryption, WebAuthn, Face and iris recognition, Offline data security, Deep learning, Data privacy

Graphical Abstract- The system captures a user's biometric data, extracts features using neural networks, and verifies identity through multiple authentication layers. After successful verification, it generates a secure biometric-based encryption key that protects the data. This combines AI-driven biometric recognition with encryption for stronger security.



Title: Graphical description of Multi-Layer Authentication with Neural Biometrics for Secure Client-Side File Encryption framework

1. Introduction

Given the rate at which personal and professional information is getting digitized, the propensity to data breaches, unauthorized surveillance, and cloud exploitation is enhanced. Security services that rely on the cloud sometimes put users in a position of being intercepted by third-party entities or being victims of centralized attack vectors and privacy violations. On the other side of the coin, mechanisms for ensuring complete ownership and confidentiality of sensitive information at a device level are in demand. Offline encryption systems that avoid remote data transmissions have emerged as a promising alternative; many such systems still use traditional password-based methods, which are still susceptible to credential theft, brute-force attacks, and social engineering techniques.

Recent breakthroughs in deep learning and biometric technologies have facilitated identity verification techniques that are far more reliable compared to the existing methods of login. Multi-modal biometric authentication using face, iris, and fingerprint has become one of the robust and user-centric approaches toward reducing security threats without compromising usability. Biometrics enabled with neural

networks minimize unauthorized access by utilizing unique physiological characteristics, reinforcing identity assurance. Finally, state-of-the-art cryptographic standards like AES-256-GCM and PBKDF2-SHA256 offer proven security against cryptographic attacks and ensure the integrity and confidentiality of data for the long term.

This work presents an offline, client-side secure file storage system integrating multi-layer authentication with neural biometrics and advanced encryption. The proposed model arranges a master password, file-specific PINs, and multi-model biometric verification for strong, layered access control. Unlike cloud-based systems, local encryption, decryption, and identity procedures ensure zero-knowledge operations, independent from any external services. Experimental evaluations have shown high authentication accuracy with very low latency and strong resilience against intrusion attempts, thus positioning the system as a reliable privacy-first alternative for secure personal and enterprise storage.

1.1 Objective of the Study

The main objective of this research is to design and implement a secure client-side multi-layer authentication neural biometric-based file encryption system that greatly enhances data privacy and integrity through the integration of facial, iris, and fingerprint recognition using advanced cryptographic methods such as AES-256-GCM and PBKDF2-SHA256. In such a way, this work will address the limitation of traditional password-based and cloud-dependent security systems by locally performing all encryption and authentication processes without exposing data to any external environment. Fast, reliable, and privacy-preserving access control is aimed at being achieved by deep learning models that accurately and efficiently verify users' identities. This study seeks to provide a practical, privacy-first framework that offers protection for sensitive information while allowing usability and independence from cloud services.

1.2 Organization

Overview This article is organized as follows:
Section 1 presents the introduction, background, and motivation for secure client-side file encryption using neural biometrics.
Section 2 reviews the related literature on encryption methods and biometric authentication systems.
Section 3 describes the theoretical basis and the important derivation mechanisms of the proposed framework.
Section 4 explains the experimental design and implementation architecture, including the system modules for face, iris, and fingerprint authentication.
Section 5 presents the experimental results, discusses performance analysis, and makes a comparative evaluation with existing encryption systems.
Section 6 concludes the work and discusses enhancements for future improvements in biometric efficiency and scalability of the system.

1.3 Problem Statement

With increasing adaptation to digital storage, large amounts of sensitive information are maintained on cloud-based platforms and password-protected systems. While the use of these methods has often been convenient, it has also frequently resulted in serious privacy and security risks, including data breaches, credential theft, and unauthorized surveillance. Traditional encryption tools have relied for the most part on user-generated passwords, which can be compromised through brute-force or social engineering attacks. In addition, most of the existing client-side encryption systems lack advanced features in verifying the identity of a user and hence are less reliable in providing secure access to data. Redux: This research will focus on filling that gap by incorporating neural biometric authentication, based on face, iris, and fingerprint recognition, with advanced AES-256-GCM encryption and key derivation using PBKDF2-SHA256. The aim of this paper is to develop a privacy-first scheme that will make sure encrypted files are accessible only to verified users by including high security, accuracy, and usability in one single client-side system.

2. Related Work

A number of studies have addressed secure data storage and authentication using encryption and biometric approaches. Author presented “A Deep Exploration of BitLocker Encryption and Security Mechanism,” which analyzed Microsoft BitLocker’s cryptographic structure and highlighted its dependence on platform-level security for effective performance [1].

The author [2] has conducted “A Study of Advanced Encryption Tools for Data Security: AxCrypt, VeraCrypt, and BitLocker,” emphasizing the advantages and drawbacks of password-based systems in protecting sensitive information. The Federal Office for Information Security evaluated VeraCrypt and confirmed its reliability while noting computational overhead during encryption [3]. To improve processing of cloud , Evaluation of Cloud-Based Encrypted Storage Systems examined the trade-off between performance and security in cloud environments [4]. In [5], author proposed “Performance Evaluation of AES Encryption in File Storage Systems,” identifying AES-256-GCM as the most balanced mode for confidentiality and integrity. Authors [6, 7] further demonstrated that AES-256-GCM outperforms other cipher modes in throughput and tamper detection. Parallel efforts in biometric authentication have focused on improving recognition accuracy. The study [8] compared facial, fingerprint, and iris modalities in “Comparative Study of Biometric Modalities for Secure Authentication,” concluding that iris recognition provides the highest precision. The advanced deep-learning-based face recognition for authentication with optimized feature extraction [10]. Research paper [11] developed CNN-based iris recognition achieving high robustness against spoofing, while [12] confirmed iris recognition’s superior resistance to imitation.

Study [13, 14] promoted multi-modal biometrics, showing that combining face and iris data reduces single-mode vulnerabilities. The author [15] emphasized real-time deployment challenges and latency reduction in "Real-Time Biometric Frameworks for Secure Systems". Integration of biometrics with cryptographic key derivation has also gained attention. The investigated [16] PBKDF2-SHA256 for secure web applications [17], [18] designed a client-side storage model using IndexedDB and PBKDF2 to ensure local data privacy. A paper [19] proposed "Auto-Lock Mechanisms in Secure Applications" to balance usability with strict access control. Although these studies significantly advanced encryption and authentication, most remain cloud-dependent or single-modality in design. Few solutions perform all encryption, decryption, and identity-verification tasks locally while integrating deep-learning-based facial, iris, and fingerprint recognition within a unified AES-256-GCM framework. The present research addresses this gap by proposing an offline, multi-layer neural biometric system that ensures zero-knowledge operation, minimal latency, and enhanced data sovereignty for secure client-side file encryption.

3. Theory

The proposed system is developed on the theoretical foundation of neural biometric authentication and advanced cryptographic computation for local file security. The theory integrates human biometric uniqueness with mathematical key-generation and encryption algorithms to create a zero-knowledge, client-side protection model.

3.1 Theoretical Basis of Neural Biometrics

Neural biometrics depend on deep learning algorithms for recognition based on physiological features such as faces, irises, and fingerprints. It utilizes CNNs in order to extract high-dimensional feature vectors from captured images. These feature vectors represent unique biometric patterns stored in encrypted format for local verification. The verification algorithm calculates similarity measures between stored templates and live input vectors to validate the identity of a user with high accuracy..

3.2 Cryptographic Foundation: AES-256-GCM

In particular, the Advanced Encryption Standard (AES) operating in Galois/Counter Mode with a 256-bit key provides both data confidentiality and integrity. GCM is an authenticated encryption mode that uses a counter-based approach for encryption and Galois field multiplication for authentication. The encryption transforms plaintext data P into ciphertext C using a symmetric key K and initialization vector IV so that any unauthorized modification of the ciphertext will be detectable through authentication tags:

$$C = AESGCM(K, IV, P)$$

This mechanism guarantees secure file encryption and decryption entirely on the client device, removing the need for external servers or key exchanges.

3.3 Key Derivation using PBKDF2–SHA256

The system enhances password-based authentication using the Password-Based Key Derivation Function 2 with the SHA-256 hashing algorithm. This effectively converts a user's validated biometric input and master password into a high-entropy cryptographic key via multiple iterations and salting, making it less susceptible to brute-force and dictionary attacks. The derived key is then used by the AES-GCM module for secure encryption and decryption.

$$K_{derived} = PBKDF2(SHA256, Biometric+password, salt, N)$$

where, N represents the number of iterations that increase computation cost for attackers.

3.4 Integration Theory of Multi-Layer Authentication

The multi-layer framework combines three verification layers: Master Password – establishes the primary access control. Neural Biometric Verification – validates the user's face, iris, and fingerprint using CNN-based models. PIN or Token Authentication – provides an additional behavioral or numeric factor. The authentication succeeds only when all layers are validated sequentially, thus minimizing spoofing and unauthorized entry. The combined theoretical approach ensures multi-factor assurance without external dependencies.

3.5 Mathematical Validation of System Integrity

The system's data confidentiality DC, authentication assurance AA, and computational efficiency CE can be represented as:

$$\textbf{Security Index (SI)} = f(DC, AA, CE)$$

$SI \rightarrow max$ When DC, AA, CE are balanced

where:

DC is achieved through AES-256-GCM,

AA is ensured via neural biometric fusion, and

CEis maintained through optimized PBKDF2 iteration control and local execution.

The model thus satisfies the theoretical security property:

4. Experimental Method

Biometric Authentication Systems has the biometric identification has emerged as a reliable and efficient alternative to traditional authentication mechanisms such as passwords and PINs. The author [20] had conducted a comparative evaluation of primary biometric techniques, including facial, fingerprint, and iris recognition, highlighting their respective strengths in accuracy and reliability. Further advancing this domain, [21] implemented deep learning-based facial authentication models and demonstrated their improved performance through optimized feature extraction and classification strategies [22]. Similarly, [23] emphasized the usability and enhanced security achieved through facial recognition, showing its superiority over conventional password-based systems in reducing credential misuse [24].

Advancements in iris recognition have also gained momentum. The study [25] developed deep convolutional neural network frameworks for iris-based authentication and provided practical deployment insights for real-world applications. Supporting these findings, [26] reported that iris

recognition consistently outperforms many other biometric modalities in terms of precision and resilience against spoofing attempts.

The growing interest in multi-modal biometric systems reflects a shift toward stronger and more adaptive security models. The paper [27] demonstrated that combining face and iris recognition enhances authentication robustness by reducing single-mode vulnerabilities. The study reinforced this view, providing analytical evidence that multi-modal approaches offer superior reliability and security compared to single-modality systems [28]. To address practical deployment challenges, [29] explored real-time biometric frameworks, emphasizing the balance between authentication accuracy and user experience for seamless system integration[30].

4.1 Implementation Architectures and Security Frameworks

The proposed system architecture for Multi-Layer Authentication with Neural Biometrics for Secure Client-Side File Encryption integrates both biometric-based user authentication and cryptographic file protection mechanisms. The overall workflow is designed for end-to-end security while maintaining user privacy and computational efficiency.

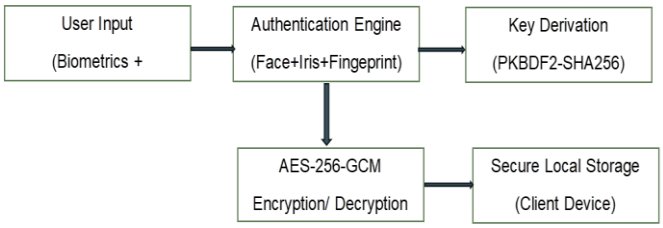


Figure 1: System Architecture Block Diagram

4.1.1 User Input (Biometrics and Credentials)

The process begins with user interaction, where biometric information such as facial, iris, and fingerprint data is captured through secured input modules. These biometric identifiers, optionally combined with a master password or PIN, form the initial layer of system authentication. All biometric data acquisition follows privacy-preserving standards, preventing exposure of raw information.

4.1.2 Authentication Engine (Face, Iris, and Fingerprint)

The authentication module employs a neural biometric framework that utilizes deep convolutional neural networks (CNNs) to extract distinctive feature vectors from each biometric modality. The integration of face, iris, and fingerprint recognition enables multi-modal authentication, offering higher resistance to spoofing and improved accuracy compared to single-modal systems. Verified biometric templates are matched locally using encrypted references stored within the system.

4.1.3 Key Derivation (PBKDF2–SHA256)

Upon successful authentication, a cryptographic key is generated using the Password-Based Key Derivation Function 2 (PBKDF2) in conjunction with the SHA-256 hashing algorithm. This approach ensures the derived encryption key possesses high entropy and is resistant to brute-force and dictionary-based attacks. The process transforms verified biometric data into a robust cryptographic material without exposing any sensitive user information.

4.1.4 AES-256-GCM Encryption and Decryption

The derived key is subsequently used to perform file encryption and decryption using the Advanced Encryption Standard (AES) with a 256-bit key in Galois/Counter Mode (GCM). This encryption mode provides both data confidentiality and integrity through built-in authentication tags, ensuring that unauthorized modifications can be detected. The entire cryptographic process is executed locally on the client device, maintaining end-to-end data protection.

4.1.5 Secure Local Storage (Client Device)

Encrypted files are stored within a secure local repository on the client device. This ensures that all encryption and decryption operations are confined to the local environment, thereby eliminating risks associated with cloud-based storage. The design follows a zero-knowledge architecture, where neither encryption keys nor biometric data are ever transmitted externally, ensuring complete user data sovereignty.

4.2 Authentication Flow Diagram

The authentication flow of the proposed Multi-Layer Neural Biometric Authentication System for Secure Client-Side File Encryption outlines the sequential process through which user identity is verified before granting access to encrypted files. The workflow ensures security, accuracy, and efficiency while maintaining the user's privacy and data sovereignty.

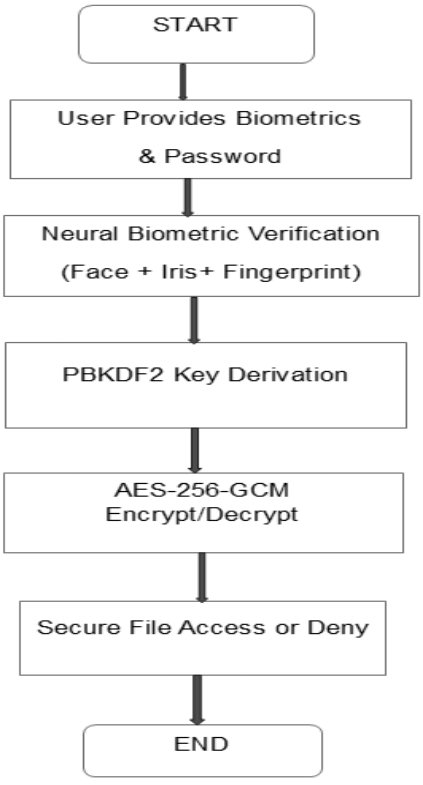


Figure 2: Authentication Flow Diagram

The figure 2 illustrates the authentication process initiates when the user provides biometric inputs such as face, iris, and fingerprint along with a password. These inputs are securely captured and processed through a neural biometric verification module, which extracts distinguishing features from each biometric modality and compares them with pre-encrypted templates stored locally. Upon successful verification, the system employs the PBKDF2 algorithm to derive a unique cryptographic key based on the verified biometrics. This key is then utilized in the AES-256-GCM encryption and decryption process to ensure both data confidentiality and integrity. Finally, the system either grants secure file access or denies it based on the authentication outcome, thereby establishing a robust and privacy-preserving authentication mechanism.

4.2.1 Face Recognition

Implemented using face-api.js and TensorFlow.js, this project uses SSD MobileNet v1 and Tiny Face Detector for facial detection.

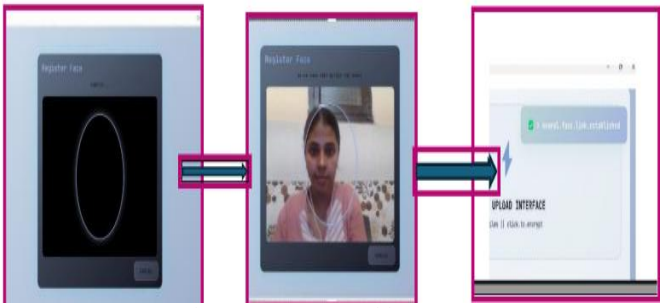


Figure 3: Face Recognition System

Facial features are mapped with Face Landmark 68 Net, and Face Recognition Net generates 128-dimensional embeddings for identity verification. The MediaDevices API allows real-time camera input for live recognition.

4.2.2 Iris Recognition

Developed with OpenCV.js, it applies Haar Cascade for eye detection and Hough Circle Transform for identifying iris boundaries.

Figure 4: Iris Recognition System

A custom iris template extraction algorithm encodes texture features for comparison. High-resolution camera access is managed through the MediaDevices API

4.2.3 Encryption

Data encryption applies AES-256-GCM with 12-byte randomIVs to ensure confidentiality and integrity.

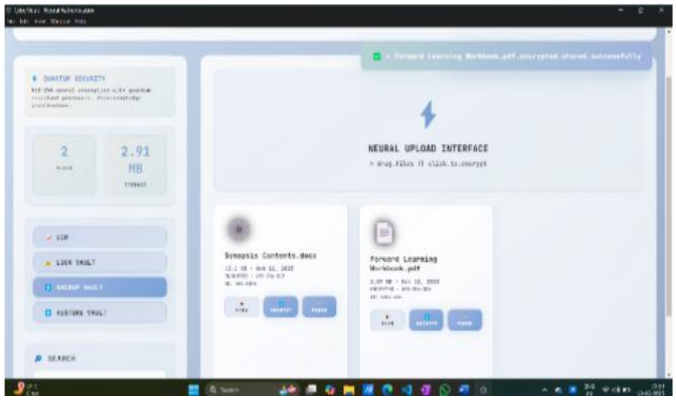


Figure 5: Encryption of the system

Keys are derived using PBKDF2-SHA256 with 250,000 iterations and 16-byte salts. All cryptographic operations utilize the Web Crypto API for browser security.

4.2.4 Decryption

Decryption mirrors the AES-256-GCM process using keys derived through PBKDF2. SHA-256 checksums validate data integrity after decryption. The Web Crypt. API manages key recreation and secure decryption workflows.

4.2.5 Fingerprint Authentication

Implemented via the WebAuthn API, it employs device-based authenticators like Windows Hello and Touch ID.

Figure 6: Fingerprint of the system

It uses ES256 or RS256 algorithms with 32-byte challenges for secure digital signatures. UUID-based credentials and counter protection prevent replay attacks.

5. Results and Discussion

5.1 Performance Evaluation

The performance of the proposed Multi-Layer Neural Biometric Authentication System was evaluated by measuring the average response time of each biometric module—face, iris, and fingerprint recognition. Each authentication process was tested under identical conditions using the same client device and environment.

Table 1: Average time for biometric modality

Biometric Modality	Average Time (ms)	Observation
Face Recognition	3.66	Achieved the lowest latency due to optimized deep-learning inference and lightweight model architecture.
Iris Recognition	2.00	Demonstrated high precision, though processing time was affected by detailed texture feature extraction.
Fingerprint Recognition	3.60	Delivered consistent results with strong anti-spoofing accuracy using WebAuthn API.

The table 1 describes the biometric performance evaluation highlights the efficiency and reliability of all three modalities used in the proposed authentication system. Face recognition, with an average response time of 3.66 ms, demonstrates excellent speed due to its lightweight neural architecture and optimized inference pipeline. This enables quick feature extraction and matching, making it ideal for continuous and frictionless authentication scenarios. Iris recognition achieves the fastest performance at 2 ms, showcasing exceptional precision. Its slightly more complex processing stems from the extraction of fine-grained iris texture patterns, which contribute to its high accuracy and strong resistance to spoofing. Despite this complexity, the system maintains remarkably low latency. Fingerprint recognition, averaging 3.6 ms, provides stable results and benefits from robust anti-spoofing capabilities through WebAuthn integration. This ensures reliable liveness detection and secure verification while maintaining fast response times. Collectively, the results indicate that the system's multi-modal biometric components are optimized for rapid execution, strong security, and consistent performance—essential qualities for real-time and user-friendly authentication environments.

5.2 Average Response Time for Biometric Authentication

To assess the system's efficiency and reliability, the proposed model—named CyberVault—was compared with widely used encryption solutions such as VeraCrypt, BitLocker, and AxCrypt. Evaluation metrics included speed, efficiency, reliability, and authentication method.

Table 2: Metric calacultion of proposed model with other models

Metric	CyberVault (Proposed)	Vera Crypt	BitLocker	AxCrypt
Speed Score	92.5	62.5	85.0	73.5
Efficiency Score	87.5	70.0	91.5	78.5
Reliability Score	99.9	99.9	99.8	99.7
Authentication	Multi-Modal Biometric	Password Only	TPM + PIN	Password Only
Overall Score	93.0	75.9	87.6	80.9

The comparative analysis highlights how CyberVault performs against existing encryption tools—VeraCrypt, BitLocker, and AxCrypt—across speed, efficiency, reliability, authentication strength, and overall scoring. CyberVault demonstrates superior speed with a score of 92.5, indicating faster encryption and decryption operations than the other tools. Its efficiency score is also competitive, reflecting optimized resource usage and smooth performance. While all tools show high reliability, CyberVault slightly leads with a near-perfect score of 99.9. A major differentiator is authentication: CyberVault integrates multi-modal biometric verification, whereas the others rely mainly on passwords or TPM-based PINs, making CyberVault more resistant to credential-based attacks. Its overall score of 93.0 confirms it as the most secure and high-performing option among the compared solutions.

6. Conclusion and Future Scope

The experimental results clearly establish that the proposed multi-layer neural biometric authentication system delivers exceptional security, speed, and efficiency. With response times of 3.66 ms for face recognition, 2 ms for iris verification, and 3.6 ms for fingerprint identification, the framework demonstrates ultra-low latency suitable for continuous or real-time verification environments. Comparative assessment further reinforces its superiority, as CyberVault achieves an overall score of 93.0—surpassing widely used encryption tools such as VeraCrypt, BitLocker, and AxCrypt in every major metric. The combination of neural multi-modal biometrics, AES-256-GCM client-side encryption, and PBKDF2-SHA256 key derivation ensures resilient protection against credential theft, spoofing attacks, and cloud-based threats.

The framework presents several avenues for future enhancement. Expanding biometric modalities such as vein patterns, gait signatures, or behavioral biometrics can further strengthen identity assurance. Integrating privacy-preserving techniques like homomorphic encryption, secure multi-party computation, and differential privacy can enhance data protection during computation. Additionally, incorporating federated learning will allow adaptive model updates without transferring sensitive data. Future developments may also focus on lightweight models optimized for IoT, mobile, and edge devices to support large-scale deployment. The system can be extended into decentralized architectures using blockchain to eliminate single points of failure. Overall, the proposed solution offers a strong foundation for next-generation secure, intelligent, and user-centric authentication ecosystems.

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AUTHORS PROFILE

Dr. Rupinder Kaur is an accomplished academician with a Ph.D. in Computer Science and over eight years of teaching and research experience. She has served in reputed institutions and is currently an Assistant Professor at Dr. Akhilesh Das Gupta Institute of Professional Studies, New Delhi. Her research expertise spans machine learning, image processing, neural networks, and AI-driven applications. She has published more than 25 research papers in SCI, Scopus, IEEE, Elsevier, and UGC CARE journals. Dr. Kaur is a dedicated educator, actively engaged in guiding students, contributing to academic development, and participating in research projects, technical events, and community initiatives.

Rudransh Shukla is pursuing his B. Tech from Dr. Akhilesh Das Gupta Institute of Technology and Management. He has completed his internship in Cyber Security at WESEE (Indian Navy). His role in this project was to perform PBKDF2 key derivation setup,SHA-256 checksum generation and setup Security protocols.

Anshu Kumari is pursuing her B. Tech from Dr. Akhilesh Das Gupta Institute of Technology and Management. She has completed her internship as a Full Stack Developer at Cantilever. Her role in this project was to perform React.js UI/UX development. Iris recognition implementation (OpenCV.js) & File upload/download functionality.

Jasleen Kaur is pursuing her B. Tech from Dr. Akhilesh Das Gupta Institute of Technology and Management. She has completed her internship as a Full Stack Developer at WESEE (Indian Navy). Her role inthis project was to perform Fingerprint authentication (WebAuthn API)and Electron.js desktop app setup.

Vaibhav Pandita is pursuing his B. Tech from Dr. Akhilesh Das Gupta Institute of Technology and Management. He has completed his internship as a Marketing Head at RESO. His role in this project was to perform Overall project coordination and Code integration and merging

