PrivFace-AI: A Federated Learning-Based Privacy-Preserving Face Recognition Framework for Unconstrained Environments

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***Abstract*—Face recognition in unconstrained environments remains a challenge due to variations of illumination, pose, expression and partial occlusion while large scale biometric deployment raises significant privacy concern with regards to processing sensitive facial data. This paper presents PrivFace-AI which is a framework for private face recognition using federated learning to securely perform biometric identification without transferring raw facial data to centralized servers. PrivFace-AI combines deep embeddings extracted from facial embedding using FaceNet; cosine similarity matching; decentralized model aggregation via FedAvg and liveness detection which improves robustness against spoofing attacks under real world operating conditions. A complete web-based implementation coupled with optional embedded hardware interaction was developed to validate practical deployment of the framework in intelligent access control scenarios. Experimental results obtained on LFW, KinectFace and custom real world datasets demonstrate 97.8% recognition accuracy in real-time response capability confirming the effectiveness of PrivFace-AI in combining privacy preservation, recognition robustness and operational feasibility under unconstrained environment.**

***Index Terms*—Federated Learning, Face Recognition, Privacy Preservation, Biometric Authentication, FedAvg, Liveness Detection, FaceNet, Cosine Similarity, Unconstrained Environments, Anti-Spoofing.**

I. INTRODUCTION

Face recognition has become one of the most widely adopted biometric technologies in modern intelligent security systems, owing to its non-intrusive nature and its ability to support automated identity verification in applications such as access control, video surveillance, authentication, and human-computer interaction [1]. Recent advances in deep learning, particularly convolutional neural networks and embedding-based architectures, have significantly improved recognition accuracy and robustness, enabling reliable deployment in unconstrained environments where variations in illumination, pose, facial expression, and partial occlusion remain challenging factors [2].

Despite these substantial improvements, the large-scale deployment of face recognition systems continues to raise serious privacy and data protection concerns. Most existing operational solutions rely on centralized architectures in which facial images or extracted biometric templates are transmitted to remote servers for storage, training, or inference. Such centralized processing increases the exposure of sensitive biometric information to cybersecurity threats, including unauthorized access, data leakage, and potential misuse of personal identity data. In the context of increasingly strict data protection regulations, preserving biometric privacy while maintaining recognition performance has become a critical research challenge.

Several privacy-preserving strategies have been investigated to address this issue, including cryptographic approaches, secure multi-party computation, homomorphic encryption, and differential privacy mechanisms. Although these methods provide strong theoretical guarantees, they often introduce significant computational overhead that limits their applicability in real-time biometric systems. More recently, federated learning [3] has emerged as a promising decentralized learning paradigm in which multiple clients collaboratively train a shared model without exchanging raw local data. By keeping biometric samples locally stored, federated learning offers an attractive compromise between model performance and privacy preservation.

However, most existing federated face recognition studies remain focused on algorithmic training aspects and often overlook deployment constraints related to practical real-time applications, robustness under unconstrained acquisition conditions, and resistance to spoofing attacks. In real-world biometric access systems, additional challenges arise from unstable image quality, motion variations, presentation attacks, and hardware integration requirements.

To address these limitations, this paper proposes PrivFace-AI, a federated learning framework for privacy-preserving face recognition in unconstrained environments such as partial occlusion, illumination variation, facial expression variation, and head-pose variation. The proposed system performs local facial embedding generation and decentralized model updates while ensuring that sensitive biometric information never leaves the acquisition device. To improve operational robustness, the framework integrates a liveness detection module for presentation attack prevention and a multi-frame embedding strategy that aggregates facial information across multiple consecutive captures to enhance recognition reliability. A functional web-based graphical interface was implemented using Flask to support real-time user interaction, facial data acquisition, and recognition supervision.

The present study emphasizes the system-level integration and experimental validation of a complete embedded federated

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face recognition pipeline, combining established state-of-the-art components into a coherent privacy-aware edge AI architecture for real-world deployment scenarios.

The main contributions of this work are summarized as follows:

- A privacy-preserving face recognition framework based on federated learning designed for unconstrained biometric environments.
- A multi-frame facial embedding generation strategy combined with local data enhancement to improve recognition robustness.
- The integration of liveness detection for increased resilience against spoofing and presentation attacks.

The remainder of this paper is organized as follows. Section II reviews related work on face recognition and privacy-preserving learning strategies. Section III presents the proposed framework and implementation details. Section IV reports the experimental evaluation and discussion. Finally, Section V concludes the paper and outlines future research directions.

II. RELATED WORK

Recent advances in deep learning have considerably improved face recognition performance by enabling the learning of highly discriminative facial representations from large-scale datasets. Early deep architectures progressively replaced handcrafted descriptors through end-to-end embedding learning strategies. Among the most influential contributions, Schroff et al. [4] introduced FaceNet, which established a unified embedding space using triplet loss to maximize inter-class separability while minimizing intra-class variations. Later, Deng et al. [5] proposed ArcFace, which further enhanced feature discrimination through additive angular margin loss and became one of the most widely adopted approaches for unconstrained face recognition. Although these methods achieve state-of-the-art accuracy, they generally rely on centralized training and inference pipelines, requiring large volumes of biometric data to be collected and processed on remote servers, which raises significant privacy concerns.

To mitigate privacy risks associated with centralized biometric learning, federated learning has emerged as a promising decentralized paradigm for collaborative model optimization [6], [7]. McMahan et al. [3] introduced the Federated Averaging algorithm, enabling distributed clients to train a shared global model while keeping raw local data private. This paradigm has recently attracted growing interest in biometric applications, where preserving sensitive facial information is essential. Several studies have explored federated learning for privacy-aware face recognition and secure biometric authentication [8], [9], often combining distributed optimization with secure aggregation mechanisms. However, most existing works remain focused on model training performance and rarely address operational constraints related to real-time deployment, acquisition variability, or system-level integration in unconstrained environments.

Recent studies have further investigated federated learning for biometric recognition under privacy constraints, with particular attention to distributed feature learning and collaborative optimization across decentralized clients [6]. Nevertheless, many of these approaches remain evaluated under controlled experimental settings and do not explicitly consider practical deployment challenges such as unstable acquisition conditions, presentation attack resistance, or embedded system integration, which remain critical in real-world biometric applications.

In parallel, practical face recognition systems remain highly vulnerable to presentation attacks, including printed photographs, replayed videos, or synthetic facial content. Consequently, liveness detection has become an essential complementary component for securing biometric authentication pipelines. Vision-based anti-spoofing methods such as eye-blinking analysis, motion consistency verification, and texture-based cues have shown effectiveness in distinguishing genuine users from fraudulent attempts [10]. Nevertheless, these mechanisms are often studied independently from privacy-preserving learning frameworks and are seldom integrated into unified deployable systems.

Despite substantial progress, current face recognition solutions still exhibit an important gap between algorithmic performance and deployable privacy-aware operation. Centralized deep learning systems compromise biometric confidentiality, while many federated approaches remain disconnected from practical real-time applications. In addition, few studies simultaneously address privacy preservation, spoofing resistance, and deployment flexibility within a single operational framework. To bridge this gap, the proposed PrivFace-AI framework combines federated learning, local facial embedding generation, liveness verification, and real-time web-based deployment with optional embedded access control integration under unconstrained operating conditions.

III. PROPOSED APPROACH

The proposed PrivFace-AI framework follows a multi-stage pipeline for privacy-preserving face recognition under unconstrained conditions while supporting real-time operation. As illustrated in Fig. 1, the system is organized into six main modules: facial acquisition, face detection, embedding extraction, liveness verification, identity matching based on cosine similarity, and federated model adaptation. Each module is described in detail in the following subsections.

A. Facial Acquisition and Preprocessing

Facial images are acquired through a standard USB camera integrated into the web-based application, providing continuous video streams. This stage directly impacts recognition accuracy and system latency. The captured frames are preprocessed for consistency, including resizing and normalization.

B. Face Detection and Alignment

Face detection and alignment are performed using the Multi-task Cascaded Convolutional Neural Network (MTCNN) [11],

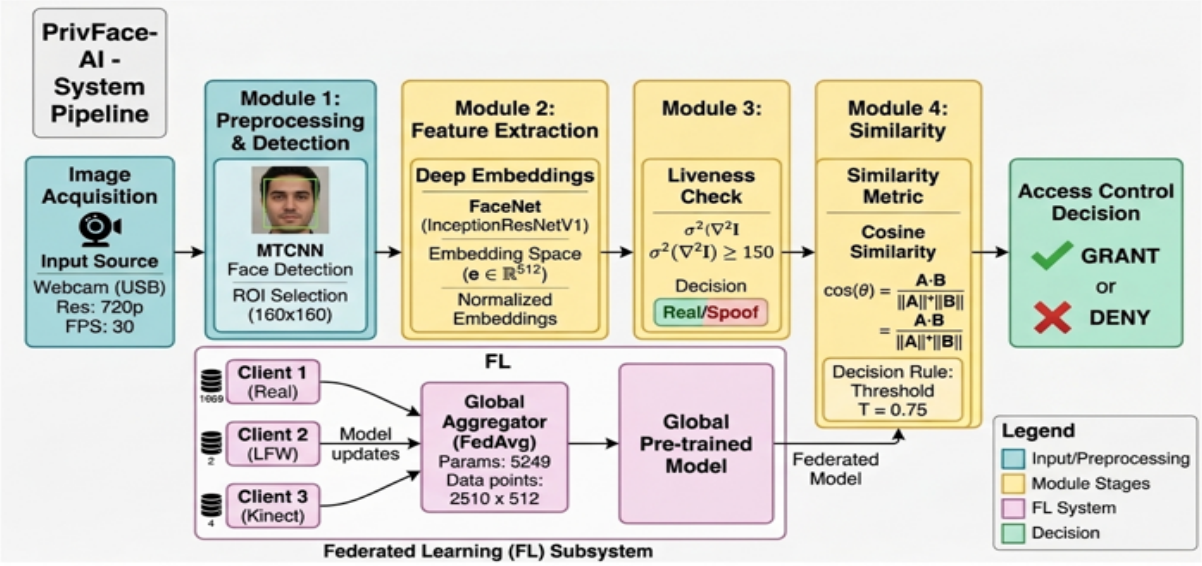

Fig. 1: Integrated architecture of the proposed PrivFace-AI embedded privacy-preserving federated face recognition framework.

selected for robustness under illumination changes, pose variations, and partial occlusions. MTCNN jointly estimates facial bounding boxes and key landmarks (eyes, nose, mouth), enabling geometric alignment. The aligned face is cropped and resized to 160×160 pixels.

C. Embedding Extraction

Aligned facial regions are transformed into 512-dimensional embeddings using a deep convolutional network based on FaceNet [4], specifically the InceptionResnetV1 model [12]. The embeddings provide a discriminative representation, where faces of the same identity are mapped close together, while different identities are separated in feature space. Formally, for an input image $\mathbf{x}$:

$$\mathbf{e} = f_\theta(\mathbf{x}), \quad \mathbf{e} \in \mathbb{R}^{512} \tag{1}$$

where f_θ denotes the embedding network parameterized by θ.

D. Liveness Detection

Prior to recognition, a liveness detection module analyzes the Laplacian variance of the input image to discriminate between live faces and spoofing attempts [18], such as printed photographs or screen replays. Images exceeding a defined variance threshold are considered genuine and processed further.

The Laplacian operator is defined as:

$$\nabla^2 I(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \tag{2}$$

In discrete form, the Laplacian response is often computed using a convolution kernel:

$$L(I) = \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} * I \tag{3}$$

The liveness score is then obtained by computing the variance of the Laplacian response:

$$S = \mathrm{Var}\big(L(I)\big) \tag{4}$$

This score reflects the amount of high-frequency content present in the image. A higher variance indicates sharper facial details and richer texture information, which is typically associated with a real face. In contrast, spoofing attacks such as printed photos or screen displays tend to exhibit smoother textures and lower frequency variations, resulting in a lower Laplacian variance. A predefined threshold is therefore used to classify the input as either live or spoofed.

E. Cosine Similarity for Identity Matching

Recognition is performed by computing the cosine similarity between the extracted embedding and the stored embeddings in the global database [4]. For embeddings $\mathbf{e}_i$ and $\mathbf{e}_j$, the similarity score is:

$$\mathrm{sim}(\mathbf{e}_i, \mathbf{e}_j) = \frac{\mathbf{e}_i \cdot \mathbf{e}_j}{\|\mathbf{e}_i\| \|\mathbf{e}_j\|} \tag{5}$$

If the similarity exceeds a predefined threshold τ, the identity is confirmed; otherwise, the face is classified as unknown.

F. Privacy-Preserving Federated Learning

To preserve biometric privacy and enhance model generalization, the framework adopts a federated learning strategy. Participating clients perform local model updates without transmitting raw facial images. Only model parameters are exchanged and aggregated using the FedAvg algorithm [3]:

$$\mathbf{W}_{global}^{(t+1)} = \sum_{k=1}^{K} \frac{n_k}{n_{total}} \mathbf{W}_k^{(t)}, \quad n_{total} = \sum_{k=1}^{K} n_k \tag{6}$$

where K is the number of clients and n_k is the local sample size for client k.

While alternative federated learning strategies such as Federated Proximal (FedProx) [13] introduce a proximal regularization term to enhance optimization stability under heterogeneous (non-IID) data distributions, other approaches such as FedNova [16] and Scaffold [17] explicitly aim to mitigate client drift through normalized aggregation and control variates, respectively. However, experimental evaluation in this work showed that these methods did not provide superior performance in the considered setting. In particular, FedAvg [3]and FedProx [13] demonstrated more stable convergence and better efficiency. Consequently, in this work, FedAvg [3] was retained as the primary aggregation strategy due to its simplicity, low computational overhead, and suitability for real-time deployment scenarios.

G. Pipeline Summary

Overall, the proposed pipeline combines MTCNN [11] for face detection, FaceNet [4] for facial embedding extraction, Laplacian variance [18] for liveness detection, cosine similarity [4] for identity matching, and FedAvg [3] for privacy-preserving federated optimization. The framework ensures real-time operation while maintaining robustness against variations in illumination, pose, and partial occlusions. By leveraging heterogeneous datasets through federated learning, the system enhances model generalization while preserving the confidentiality of sensitive facial data.

IV. RESULTS AND DISCUSSION

A. Datasets Description

To evaluate the proposed framework under both benchmark and real-world operating conditions, experiments were conducted using two public face recognition datasets, LFW [14] and KinectFace [15], in addition to a custom dataset collected specifically for this study.

The Labeled Faces in the Wild (LFW) dataset [14] contains more than 13,000 facial images acquired under unconstrained conditions, with significant variations in pose, illumination, facial expression, image quality, and background. This dataset is widely used to evaluate recognition robustness in realistic environments.

The KinectFace dataset [15] introduces additional acquisition variability through RGB and depth facial images captured using Kinect sensors. It provides semi-controlled but realistic acquisition conditions, particularly useful for evaluating robustness to sensor-related variations.

To complement the benchmark evaluation, a custom dataset was collected for this work, including 166 individuals and 5,249 facial embeddings acquired under practical operating conditions. Data acquisition included indoor and outdoor illumination changes, head pose variations, partial occlusions such as glasses and masks, and real-time acquisition noise.

The experimental dataset therefore combines benchmark samples from LFW and KinectFace with additional real-world participants integrated into the federated framework, where facial data are processed in real time and represented only through numerical embeddings rather than storing raw personal images.

Fig. 2: Examples of facial images used for evaluation: (a) LFW dataset samples [14], (b) KinectFace dataset samples [15].

Representative examples from the public datasets used in this study are illustrated in Fig. 2, highlighting the variability encountered during evaluation.

B. Experimental Setup

The proposed system was implemented using the FaceNet [4] architecture based on InceptionResnetV1 [12] for facial feature extraction. Each detected face is projected into a 512-dimensional embedding space, where identity matching is performed using cosine similarity [4].

A similarity threshold of $\tau = 0.75$ was empirically selected to balance correct recognition and rejection of unknown identities.

For evaluation, the dataset was divided into 70% training and 30% testing subsets while ensuring identity separation between both sets. The complete processing pipeline includes face detection, embedding extraction, similarity-based matching, liveness verification, and federated model aggregation.

C. Recognition Performance

System performance was evaluated using standard biometric metrics, including accuracy, False Accept Rate (FAR), False Reject Rate (FRR), average response time and real-time throughput measured on Frame Per Second (FPS).

The quantitative results obtained on the complete evaluation protocol are summarized in Table I.

TABLE I: Recognition performance metrics

Metric	Value
Accuracy	97.8%
FAR	1.2%
FRR	1.0%
Average Response Time	86 ms
Real-time throughput	11.6 FPS
Number of Individuals	166
Total Embeddings	5,249

These results indicate that the proposed framework achieves high recognition reliability while maintaining real-time execution capability.

TABLE II: Comparison between the proposed framework and existing face recognition approaches on the LFW dataset [14]

Methods	FL	Liveness	Accuracy	FAR (%)*	Confidentiality	Remarks
ArcFace [5]	no	no	99.53%	~ 0.17	low	Centralized, MS-Celeb-1M
FaceNet [4]	no	no	99.63%	~ 0.37	low	Centralized, triplet loss
FedFace [6]	yes	no	99.28%	~ 0.72	medium	FL without liveness
FaceNet Baseline**	yes	no	99.66%	0.41	medium	Baseline system using FaceNet on LFW only
PrivFace-AI (Ours)	yes	yes	99.42%	0.41	High	FL + liveness + déploiement RT

* FAR estimated for ArcFace, FaceNet and FedFace under the assumption of a balanced dataset (LFW: 3,000 positive pairs / 3,000 negative pairs). Exact values require the full confusion matrix.

** The ablation study (FaceNet Baseline) evaluates our system without liveness modules, yielding 99.63% accuracy. This confirms that the integration of federated learning and liveness verification provides measurable improvements in both recognition accuracy and operational security.

To further evaluate the effectiveness of the proposed framework, a comparative analysis against several representative state-of-the-art face recognition approaches, including ArcFace [5], FaceNet [4], FedFace [6], and the baseline FaceNet model, on the LFW benchmark [14] is presented in Table II. The comparison considers multiple performance and system-level criteria, namely recognition accuracy, FAR, privacy preservation capability, federated learning integration, and liveness detection functionality.

The results presented in Table II indicate that the proposed PrivFace-AI framework achieves competitive recognition performance while maintaining a low FAR compared with existing approaches. In addition to its strong recognition performance, the framework uniquely combines federated learning, liveness detection, and privacy-preserving mechanisms within a unified embedded architecture. The comparison also highlights the positive impact of federated learning and liveness verification on both system robustness and operational security, particularly under real-world unconstrained conditions.

D. Federated Learning Evaluation

To preserve privacy during model adaptation, federated learning experiments were conducted by simulating multiple clients using LFW [14], KinectFace [15], and custom datasets.

A comparative analysis between FedAvg and FedProx was performed to assess convergence behavior and computational suitability for the proposed deployment scenario. The main quantitative differences are reported in Table III.

TABLE III: Quantitative comparison between FedAvg [3] and FedProx [13]

Criterion	FedAvg	FedProx
Extra regularization term μ	0	0.001–0.1
Local objective modification	None	$+\frac{\mu}{2}\|w - w^{(t)}\|^2$
Additional computation per round	$\approx 0\%$	5–15%
Convergence rounds	80–120	60–90
Accuracy under heterogeneity	85–98%	88–97%
Communication cost	1× model size	1× model size
Hyperparameters to tune	1	2
Used in this work	Yes	No

Although FedProx [13] can improve robustness under highly heterogeneous local data distributions, experimental results indicated that FedAvg [3] provided more stable behavior with lower computational overhead in the present configuration, making it more suitable for the targeted real-time proof-of-concept implementation.

It should be noted that the federated learning process was implemented in a simulated single-machine environment, where multiple clients were emulated using different datasets (LFW [14], KinectFace [15], and custom data), while model updates were aggregated centrally. Consequently, the proposed framework should be interpreted as a proof-of-concept validation of federated learning integration rather than a fully distributed large-scale deployment.

E. Qualitative Recognition and Liveness Analysis

Beyond quantitative metrics, practical system behavior was evaluated during real-time operation.

Known individuals were correctly recognized when similarity scores exceeded the predefined threshold, while unknown faces were reliably rejected. Multiple simultaneous faces were processed efficiently, and recognition remained stable under moderate illumination degradation and partial occlusions.

Examples of the developed application interface and both successful recognition output and unknown matching identity are shown in Fig. 3.

Liveness verification based on Laplacian variance successfully rejected spoofing attempts such as printed photographs and screen replay attacks, adding an essential security layer for practical deployment.

F. Discussion

The experimental results confirm the effectiveness of the proposed PrivFace-AI framework under unconstrained acquisition conditions.

The main strengths of the system can be summarized as follows:

- High recognition accuracy (97.8%) with low FAR and FRR.
- Real-time processing capability (86 ms per frame, 11.6 FPS).
- Robustness to illumination changes, pose variations, and partial occlusions.
- Privacy-preserving adaptation through FedAvg-based federated learning.
- Effective anti-spoofing through liveness verification.
- Flexible database expansion for incremental user enrollment.

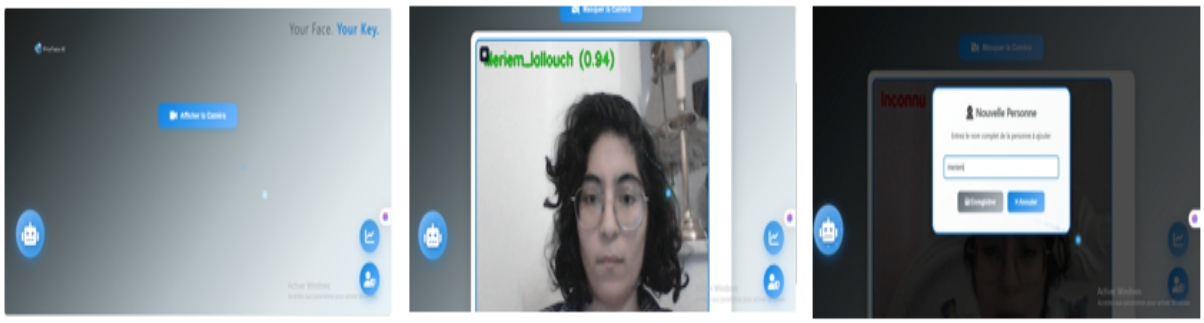

Fig. 3: PrivFace-AI interface: (a) Recognition interface, (b) Recognized face with similarity score, and (c) unknown matching identity.

Despite these encouraging results, performance degradation remains observable under extremely low illumination or severe facial occlusion. Future work will focus on improving robustness under such difficult conditions and extending deployment toward embedded edge platforms.

V. CONCLUSION

In this paper, we presented PrivFace-AI, a real-time privacy-preserving face recognition framework designed for unconstrained environments. The proposed system integrates FaceNet-based facial embedding extraction, cosine similarity matching, liveness verification, and federated learning to ensure reliable and secure biometric recognition without centralizing sensitive facial data. Experimental evaluations conducted on LFW, KinectFace, and custom datasets demonstrated high recognition accuracy, low false acceptance rates, and robust real-time performance under challenging conditions. The obtained results confirm the effectiveness of combining deep feature learning, anti-spoofing mechanisms, and distributed federated optimization within a unified embedded architecture. Future work will focus on enhancing robustness under severe acquisition conditions and improving privacy-preserving federated deployment on edge devices.

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