Privacy-Preserving Face Recognition System for Smart Campuses Using Federated Learning

Mr. Manivannan J [1], Dhayadevi R[2], Saujanya B[3], Pinninti Sai Kumari[4], Kumaran V[5]
[1,2,3,4,5] *Department of Artificial Intelligence and Data Science, Dhanalakshmi Srinivasan University, Trichy, India*

***Abstract*—Smart campus environments increasingly rely on face recognition systems for attendance monitoring and access control. However, conventional centralized systems raise serious privacy and security concerns because sensitive biometric data is stored and processed on a central server. To address these challenges, this paper presents a Privacy-Preserving Face Recog- nition System using Federated Learning (FL). The proposed system utilizes the Flower framework and PyTorch to enable distributed model training without sharing raw biometric data among clients. A lightweight GhostFaceNetV2 model is employed for efficient face recognition on edge-compatible devices. The system is trained on the AT&T face dataset across multiple clients using the FedProx optimization algorithm to handle non-IID data distribution. Experimental results demonstrate that the proposed federated model achieves an average evaluation accuracy of approximately 75% while preserving user privacy through local data processing. The architecture also supports low-bandwidth communication and future deployment on resource-constrained devices such as Raspberry Pi.**

***Index Terms*—Federated Learning, Face Recognition, Smart Campus, Privacy Preservation, GhostFaceNetV2, FedProx, Edge Computing**

I. INTRODUCTION

Smart campus environments are increasingly adopting in- telligent technologies to improve academic administration, student monitoring, and institutional security. Among these technologies, automated attendance management systems play a significant role in reducing manual effort and improving operational efficiency. Traditional attendance systems based on manual entry, RFID cards, or QR codes often suffer from limitations such as proxy attendance, device dependency, and administrative overhead. Consequently, biometric-based attendance systems, particularly face recognition systems, have gained considerable attention due to their contactless opera- tion, reliability, and ability to uniquely identify individuals.

Face recognition technology utilizes computer vision and deep learning techniques to identify or verify individuals based on facial features. Modern deep learning models have significantly improved the accuracy and robustness of facial recognition systems, enabling their deployment in educational institutions, corporate environments, and smart surveillance applications. In smart campuses, face recognition systems can automate attendance monitoring, access control, and security management while minimizing human intervention. However, most conventional face recognition systems rely on central- ized machine learning architectures where biometric data is collected and processed on a central server. Such centralized approaches introduce major privacy and security concerns be- cause sensitive facial data becomes vulnerable to unauthorized access, data leakage, and cyber-attacks.

The increasing concern regarding biometric data privacy has led governments and organizations to adopt stricter data protection regulations. Storing facial images in centralized databases may violate privacy policies and expose institu- tions to legal and ethical challenges. Furthermore, centralized systems often require continuous transmission of sensitive user data over networks, increasing communication overhead and security risks. These challenges highlight the need for privacy-preserving artificial intelligence solutions capable of maintaining high recognition performance without directly sharing sensitive biometric information.

Federated Learning (FL) has emerged as an effective dis- tributed machine learning paradigm for addressing privacy concerns in data-driven applications. Unlike centralized learn- ing approaches, Federated Learning enables multiple clients to collaboratively train a global model while keeping raw data localized on individual devices. In this framework, only model parameters or gradients are shared with the central aggregation server, thereby reducing direct exposure of sensitive user information. This decentralized learning strategy is particularly suitable for biometric systems where privacy preservation is a critical requirement. Additionally, FL supports scalability and distributed computation, making it suitable for smart campus infrastructures involving multiple departments or edge devices. In this work, a Privacy-Preserving Face Recognition System for smart campus applications is proposed using Federated Learning. The proposed system is implemented using the Flower framework and PyTorch deep learning library to facilitate distributed training across multiple clients. The system utilizes the lightweight GhostFaceNetV2 model for efficient facial feature extraction and recognition. GhostFaceNetV2 is specifically designed for edge-compatible deep learning applications, offering reduced computational complexity and lower memory consumption compared to conventional deep neural networks. This characteristic makes the model suitable for deployment in resource-constrained environments such as
smart classrooms and embedded edge devices.

To improve federated optimization performance under heterogeneous data distributions, the proposed system employs the FedProx optimization algorithm. FedProx extends traditional federated optimization by introducing a proximal regularization mechanism that stabilizes local client training in non-IID environments. Since biometric datasets across clients may differ in terms of facial variations, illumination conditions, and image distributions, the use of FedProx enhances model convergence and improves global model stability. The system is evaluated using the AT&T Face Dataset distributed across two clients to simulate decentralized training condi- tions.

The proposed architecture ensures that facial images remain on local client devices while only model updates are communicated to the aggregation server through low-bandwidth communication channels. Experimental evaluation demonstrates that the federated model achieves an average accuracy of approximately 0.75 across distributed clients. Although the achieved accuracy is lower than large-scale centralized systems, the proposed approach provides a practical balance between recognition performance and privacy preservation. Furthermore, the modular design supports future deployment on edge devices such as Raspberry Pi and other low-power embedded systems.

The major contributions of this work are summarized as follows:

- Development of a privacy-preserving face recognition attendance system using Federated Learning.
- Integration of the lightweight GhostFaceNetV2 model for edge-compatible biometric recognition.
- Implementation of the FedProx optimization algorithm to address heterogeneous client data distributions.
- Design of a scalable client-server architecture using the Flower framework and PyTorch.
- Experimental validation of distributed facial recognition using the AT&T Face Dataset with an average federated accuracy of 0.75.

The proposed system demonstrates the feasibility of integrating Federated Learning with biometric attendance systems to support secure, scalable, and privacy-aware smart campus applications.

II. LITERATURE SURVEY

The rapid advancemnt of artificial intelligence, computer vision, and distributed computing technologies has significantly transformed attendance management systems in educational institutions and smart campus environments. Automated attendance systems are increasingly replacing traditional manual methods to improve operational efficiency, reduce administrative workload, and enhance monitoring ac-curacy. Several technologies including centralized face recog- nition systems, RFID-based attendance mechanisms, QR- code attendance systems, IoT-enabled biometric platforms, and Federated Learning-based frameworks have been explored in recent years. Although these systems offer considerable advantages, they also introduce challenges related to

privacy preservation, scalability, computational overhead, and security vulnerabilities.

Traditional attendance systems based on manual record maintenance are time-consuming and highly susceptible to hu- man errors and proxy attendance. To address these limitations, RFID-based attendance systems were introduced as one of the earliest automated solutions. In RFID systems, users carry RFID-enabled identity cards that are scanned through RFID readers installed at classroom entrances or institutional check- points. These systems provide fast attendance recording and reduce manual administrative effort. However, RFID systems are vulnerable to card sharing and proxy attendance because authentication relies solely on possession of RFID cards rather than biometric identity verification. Furthermore, large- scale deployment requires dedicated hardware infrastructure, increasing maintenance and operational costs.

QR-code attendance systems later emerged as a lightweight and low-cost alternative for attendance automation. In these systems, students scan dynamically generated QR codes using smartphones or institutional devices to register attendance records. QR-based attendance systems are easy to deploy and support cloud-based attendance monitoring platforms. However, these systems remain dependent on user devices and internet connectivity. Security vulnerabilities such as QR-code sharing, duplication, and spoofing attacks reduce their reliability in sensitive institutional environments. Additionally, QR- code systems do not provide biometric verification, limiting their capability to prevent unauthorized attendance registration. Biometric attendance systems based on facial recognition have become increasingly popular due to their contactless operation, user convenience, and higher authentication reliability. Modern face recognition systems utilize deep learning architectures such as convolutional neural networks to extract facial features and perform identity verification. Several studies have demonstrated that centralized deep learning-based facial recognition systems can achieve high recognition accuracy under varying illumination conditions and facial expressions. Centralized architectures simplify data management because all biometric information is stored and processed on a central server. However, centralized systems introduce major privacy concerns since sensitive facial images are continuously trans- mitted and stored in centralized databases. Unauthorized access, data leakage, and cyber-attacks may expose confidential biometric information, creating significant ethical and legal challenges.

IoT-enabled smart attendance systems further extended automation capabilities by integrating cameras, sensors, cloud platforms, and embedded devices. These systems support real- time attendance monitoring and remote administrative access through interconnected network infrastructures. IoT-based biometric systems improve operational flexibility and enable intelligent campus management applications. Nevertheless, the large number of interconnected devices increases the attack surface for cyber threats and unauthorized access attempts. In addition, continuous communication between IoT devices and centralized cloud servers may increase network bandwidth consumption and latency during large-scale deployment.

To address the growing privacy concerns associated with centralized machine learning systems, Federated Learning (FL) has emerged as a promising distributed learning paradigm. Federated Learning enables multiple clients to collaboratively train a shared global model while keeping raw data localized on individual devices. Instead of sharing sensitive data, clients transmit only model parameters or gra- dients to the aggregation server. This decentralized approach significantly reduces direct exposure of sensitive information and improves privacy preservation in biometric applications.

The FedAvg algorithm introduced communication-efficient distributed optimization for Federated Learning environments by averaging local client updates to generate a global model. FedAvg demonstrated effective performance in distributed deep learning applications; however, its convergence perfor- mance often degrades under heterogeneous and non-IID client data distributions. In practical biometric systems, different clients may contain facial images with varying characteristics, image quality, and sample availability, which may negatively affect global model stability.

To improve optimization stability in heterogeneous environments, the FedProx algorithm was proposed as an extension of FedAvg. FedProx incorporates a

proximal regularization mechanism during local training to constrain excessive deviation between local and global model parameters. This approach improves convergence consistency and training robustness under decentralized non-IID data conditions. Consequently, FedProx has become increasingly suitable for privacy- preserving biometric recognition systems involving distributed client datasets.

Several privacy-preserving machine learning techniques such as secure aggregation and differential privacy have also been integrated with Federated Learning frameworks to enhance security protection. Secure aggregation prevents servers from directly inspecting individual client updates, while differential privacy introduces controlled noise to reduce information leakage risks. Although these methods strengthen privacy guarantees, they may also increase computational overhead and reduce model accuracy in resource-constrained environments.

Table I presents a comparative analysis of various atten- dance management approaches discussed in the literature.

TABLE I COMPARATIVE ANALYSIS OF EXISTING ATTENDANCE SYSTEMS

System Type	Technology Used	Advantages	Limitations	Privacy Level
Manual Attendance	Paper-based records	Simple implementation	Time-consuming and error-prone	Low
RFID Attendance System	RFID tags and read-ers	Fast attendance recording	Proxy attendance possible	Medium
QR-Code Attendance Sys-tem	Mobile QR scanning	Low-cost imple-mentation	QR sharing and spoofing	Medium
Centralized Face Recogni-tion	Deep learning and CNN models	High recognition accuracy	Centralized bio-metric storage	Low
IoT-Based Biometric Sys-tem	Sensors and cloud platforms	Real-time moni-toring	High network de-pendency	Medium
Federated Learning-Based System	Distributed deep learning	Privacy preserva-tion and scalabil-ity	Training complexity	High

Although existing attendance systems improve automation and monitoring efficiency, many approaches continue to face challenges related to centralized data storage, biometric pri- vacy, scalability, and communication overhead. Motivated by these limitations, the proposed work introduces a Privacy- Preserving Face Recognition System using Federated Learn- ing, GhostFaceNetV2, and FedProx optimization to support secure, scalable, and decentralized biometric attendance mon- itoring for smart campus environments.

III. PROPOSED METHODOLOGY

The proposed Privacy-Preserving Face Recognition System employs a Federated Learning (FL) framework to enable secure and decentralized biometric attendance monitoring for smart campus environments. The methodology integrates distributed deep learning, lightweight facial recognition, and privacy-aware model aggregation to minimize exposure of sensitive biometric data. The overall workflow consists of multiple federated clients performing local model training independently while a centralized server coordinates global model aggregation. The proposed system is implemented using the Flower Federated Learning framework and the PyTorch deep learning library.

A. System Architecture

The proposed architecture consists of a centralized federated server and multiple distributed client nodes connected through a communication network. Each client locally stores facial image datasets and independently performs model training without sharing raw biometric data with the central server. The overall architecture of the proposed system is illustrated in Figure 1.

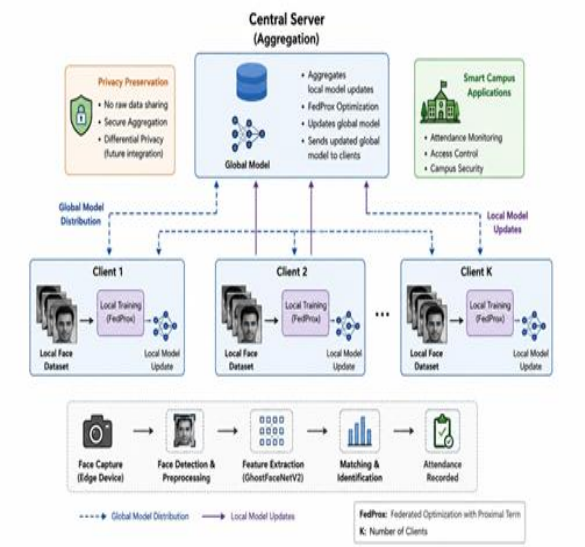

Fig. 1. Proposed Federated Face Recognition Architecture

Initially, the federated server initializes the global Ghost- FaceNetV2 facial recognition model and distributes the model parameters to all participating clients. Each client performs local training using its own facial image dataset and updates the local model parameters through multiple training epochs. After local optimization, only the learned model weights are transmitted back to the central server for aggregation. Since raw facial images remain on client devices throughout the training process, the proposed framework significantly reduces privacy risks associated with centralized biometric storage.

The federated server aggregates the local client updates using the FedProx optimization algorithm to generate an im- proved global model. The updated model parameters are then redistributed to all clients for the next federated learning round. This iterative communication process continues until stable model convergence is achieved. The decentralized training mechanism improves privacy preservation while supporting scalable deployment across distributed smart campus infras- tructures.

B. Federated Learning Workflow

The Federated Learning workflow consists of model ini- tialization, local client training, parameter aggregation, and iterative global optimization. The operational workflow of the proposed system is shown in Figure 3.

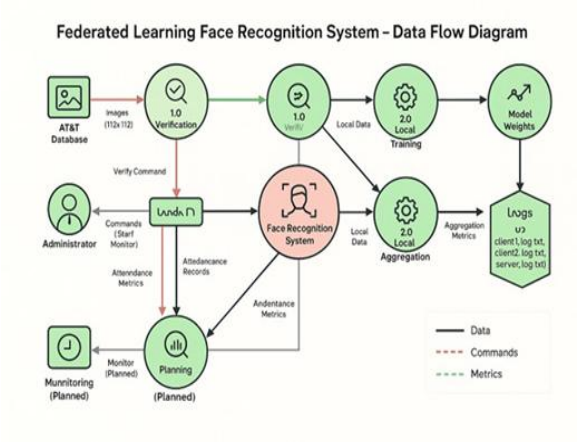

Fig. 2. Data Flow of the Proposed System

During the initial stage, the server initializes the global GhostFaceNetV2 model and distributes the parameters to all connected clients through the Flower framework. Each client independently trains the received model using locally available facial image data. Local optimization is performed using the PyTorch deep learning library with predefined training hyperparameters.

To improve convergence stability under heterogeneous client data distributions, the proposed framework employs the Fed- Prox optimization algorithm. FedProx introduces a proximal regularization term that restricts excessive deviation between local client models and the global model during optimization. This mechanism improves training robustness in non-IID distributed learning environments where clients may contain varying facial image distributions and feature characteristics. After completing local training, each client transmits only model updates to the federated server instead of sharing raw biometric data. The server aggregates the received parameters to produce an updated global model. This process is re- peated over multiple federated communication rounds until the global model achieves satisfactory performance. The proposed decentralized workflow improves data confidentiality while maintaining collaborative model learning across distributed clients.

C. Dataset Description

The experimental evaluation of the proposed system utilizes the AT&T Face Dataset, which contains grayscale facial im- ages collected under varying facial expressions and illumina- tion conditions. To

simulate decentralized learning conditions, the dataset is partitioned across two federated clients. Each client contains approximately 100 facial images representing localized biometric datasets.

Prior to model training, all facial images undergo prepro- cessing using OpenCV-based image processing operations. The preprocessing stage includes grayscale normalization, facial image alignment, and resizing to a fixed resolution of 112 × 112 pixels. The resized grayscale images reduce computational complexity while preserving essential facial feature information required for recognition tasks.

The dataset distribution across clients introduces non-IID characteristics because the image samples may differ in terms of facial appearance, illumination, and feature variation. Such heterogeneous distributions represent realistic smart campus scenarios where client devices may contain different student populations and environmental conditions. The use of the Fed- Prox optimization algorithm improves convergence stability under these distributed learning conditions.

The dataset configuration used for the proposed system is summarized in Table II.

TABLE II DATASET DESCRIPTION

Attribute	Value
Dataset Name	AT&T Face Database
Images per Client	Approximately 100
Image Size	112 × 112 pixels
Image Format	JPG
Image Type	Grayscale
Preprocessing Tool	OpenCV
Clients Used	2

D. Experimental Configuration

The proposed Federated Learning system is implemented using the Flower framework (flwr==1.18.0) and the Py- Torch deep learning library (torch==2.5.0). The Flower framework manages communication between the federated server and distributed clients, while PyTorch supports deep neural network training and optimization.

The GhostFaceNetV2 model is selected as the primary facial recognition architecture due to its lightweight compu- tational design and reduced memory requirements. Compared to conventional deep convolutional neural networks, Ghost-FaceNetV2 provides efficient facial feature extraction suitable for edge-compatible environments and low-power embedded systems.

Local client training is performed using a learning rate of 0.0001 and batch size of 8 for 15 training epochs. The federated optimization process is executed over five communication rounds using the FedProx optimization al- gorithm. Client-server communication is established through localhost:8080 to simulate distributed federated interac- tions.

The complete experimental configuration is presented in Table III.

TABLE III EXPERIMENTAL CONFIGURATION

Parameter	Value
Framework	Flower (flwr==1.18.0)
Deep Learning Library	PyTorch (torch==2.5.0)
Model	GhostFaceNetV2
Learning Rate	0.0001
Batch Size	8
Epochs	15
FL Rounds	5
Optimization Algorithm	FedProx
Communication Port	localhost:8080

The proposed methodology demonstrates the feasibility of integrating Federated Learning, lightweight deep learning models, and distributed biometric processing to support scal- able and privacy-aware smart campus attendance systems.

IV. RESULTS AND DISCUSSION

The proposed Privacy-Preserving Face Recognition System was experimentally evaluated using a distributed Federated Learning (FL) environment consisting of one centralized ag- gregation server and two decentralized clients. The evalu- ation focused on analyzing the effectiveness of distributed biometric learning, recognition performance, privacy preser- vation, and the suitability of lightweight facial recognition models for smart campus applications. The experiments were conducted using the Flower Federated Learning framework integrated with the PyTorch deep learning library and the

GhostFaceNetV2 facial recognition architecture.

The overall operational workflow of the proposed system is illustrated in Figure 3. The workflow consists of image prepro- cessing, local client training, federated parameter aggregation, and attendance prediction. Each client independently trains the facial recognition model using locally available facial image datasets. Instead of transferring sensitive biometric data to a centralized server, only model updates are communicated dur- ing each federated learning round. This decentralized approach significantly improves privacy preservation and reduces the risks associated with centralized biometric storage.

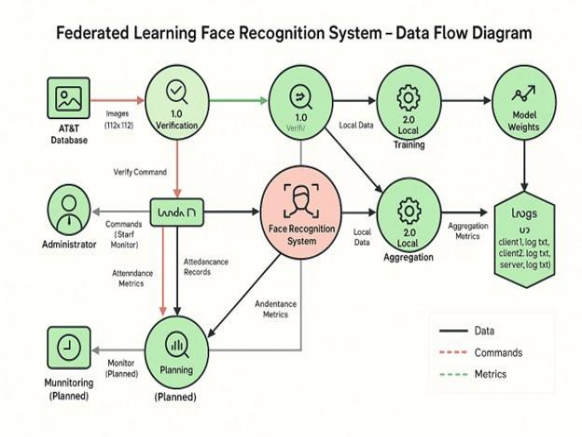

Fig. 3. Data Flow of the Proposed Federated Learning System

The performance evaluation results obtained during experi- mental testing are summarized in Table IV. The experimental observations indicate that Client 1 achieved a facial recogni- tion accuracy of 0.76, while Client 2 achieved an accuracy of 0.74. The aggregated global federated model achieved an aver- age accuracy of approximately 0.75 after five communication rounds.

TABLE IV PERFORMANCE EVALUATION RESULTS

Client	Accuracy
Client 1	0.76
Client 2	0.74
Average Federated Accuracy	0.75

The obtained results demonstrate that the proposed Feder- ated Learning framework can effectively train a distributed fa- cial recognition model without centralized biometric data col- lection. Although the achieved federated accuracy is slightly lower than the performance typically reported by fully cen- tralized deep learning systems, the proposed architecture pro- vides an important balance between recognition capability and privacy preservation. Centralized face recognition systems generally achieve higher accuracy because all training data is directly accessible to the server during optimization. In con- trast, Federated Learning environments rely on decentralized local updates, which may introduce convergence challenges under heterogeneous data distributions.

The effectiveness of Federated Learning in the proposed system is primarily influenced by the distributed nature of the client datasets. Since the AT&T facial image dataset was partitioned across multiple clients, the local datasets exhibited non-IID characteristics with variations in image distribution, facial expressions, and local training samples. Such heterogeneous conditions commonly occur in real- world smart campus deployments where users and devices maintain independent biometric datasets. To address these challenges, the FedProx optimization algorithm was incorporated into the training process. FedProx improved the stability of local model updates by introducing proximal regularization during optimization, thereby reducing divergence between local and global model parameters.

Another important contribution of the proposed system is its privacy-preserving capability. Conventional biometric at- tendance systems often rely on centralized databases that store sensitive facial images collected from users. Such centralized architectures increase the risk of unauthorized access, data leakage, and privacy violations. In the proposed Federated Learning framework, facial images remain stored locally on client devices throughout the entire training process. Only model parameters and learned updates are exchanged with the server during aggregation. This decentralized training mecha- nism significantly reduces direct exposure of biometric infor- mation over communication networks and supports privacy- aware attendance management in educational institutions.

The use of the lightweight GhostFaceNetV2 model also contributed to the computational efficiency of the proposed framework. GhostFaceNetV2 is

specifically designed for low- resource environments and requires reduced memory and com- putational overhead compared to conventional deep convolu- tional neural networks. The lightweight architecture improves compatibility with resource-constrained systems and supports future deployment on edge devices such as Raspberry Pi and smart classroom infrastructure. Furthermore, the communica- tion process operating through localhost:8080 demon- strated the feasibility of low-bandwidth distributed learning environments.

Scalability is another important advantage of the proposed architecture. The decentralized client-server framework can potentially support multiple distributed clients across class- rooms, laboratories, and institutional departments. Since each client performs independent local training, the computational burden on the central server is significantly reduced compared to fully centralized deep learning systems. The modular imple- mentation provided by the Flower framework also simplifies future expansion to larger Federated Learning environments involving multiple edge devices and geographically distributed clients.

Despite the successful implementation and evaluation, sev- eral technical challenges were encountered during system development and experimentation. One major issue involved software dependency conflicts between different versions of PyTorch, Torchvision, and Federated Learning libraries. Com- patibility issues affected package integration, model exe- cution, and environment configuration during implementa- tion. Additional complexity was introduced while integrating OpenCV preprocessing modules and GhostFaceNetV2 archi- tecture components into the federated training workflow.

Another significant challenge was associated with non-IID client data distribution. Since each client contained different subsets of facial images, variations in image quality and local sample diversity affected convergence consistency during distributed optimization. Although the FedProx optimization algorithm improved training stability, heterogeneous data dis- tributions still influenced the final global model accuracy.

The current work also contains several limitations. The experimental evaluation utilized only two federated clients and a relatively small facial image dataset. Larger and more diverse datasets may improve global model generalization and facial recognition performance. Additionally, the current implementation remains limited to experimental desktop-based deployment and does not include real-time attendance monitor- ing or large-scale distributed infrastructure. Advanced privacy-preserving mechanisms such as secure aggregation and differ- ential privacy were not integrated into the current framework and remain potential directions for future enhancement.

Overall, the experimental findings demonstrate that Feder- ated Learning provides a feasible and privacy-aware solution for biometric attendance systems in smart campus environ- ments. The proposed framework successfully combines decen- tralized machine learning, lightweight facial recognition, and privacy-preserving biometric processing to support scalable and secure attendance monitoring applications.

V. CONCLUSION AND FUTURE WORK

This paper presented a Privacy-Preserving Face Recognition System for smart campus applications using Federated Learn- ing. The proposed system was designed to address privacy and security challenges associated with conventional centralized biometric attendance systems. By utilizing a decentralized learning framework, the system enabled collaborative model training across distributed clients without requiring the transfer of raw facial image data to a centralized server. This approach significantly reduced direct exposure of sensitive biometric in- formation while supporting scalable and distributed attendance management.

The proposed implementation integrated the Flower Fed- erated Learning framework with the PyTorch deep learn- ing library to facilitate efficient client-server communication and distributed model optimization. The lightweight Ghost- FaceNetV2 model was employed for facial recognition due to its reduced computational complexity and suitability for edge- oriented environments. In addition, the FedProx optimization algorithm was incorporated to improve training stability under heterogeneous and non-IID client data distributions. The use of FedProx enhanced convergence consistency across distributed clients while maintaining effective federated

optimization per- formance.

Experimental evaluation was conducted using the AT&T Face Dataset distributed across two federated clients. The ob- tained results demonstrated that the proposed system achieved an average federated accuracy of approximately 0.75, with Client 1 and Client 2 achieving accuracies of 0.76 and 0.74 respectively. Although the achieved performance remains lower than some large-scale centralized systems, the pro- posed framework successfully demonstrated the feasibility of privacy-preserving biometric recognition using distributed machine learning techniques. The decentralized training pro- cess effectively maintained local data privacy while enabling collaborative global model improvement.

The proposed architecture also demonstrated compatibility with lightweight and resource-constrained environments. The reduced computational requirements of GhostFaceNetV2 make the system suitable for future deployment on edge devices such as Raspberry Pi and embedded smart classroom systems. Furthermore, the modular client-server architecture supports scalability across multiple classrooms, departments, and cam- pus infrastructures, making it appropriate for smart campus applications requiring distributed attendance management and biometric authentication.

Despite the successful implementation, several limitations remain in the current work. The experimental evaluation was conducted using a relatively small facial image dataset with only two federated clients. Larger and more diverse datasets may improve model generalization and recognition performance. In addition, real-time deployment and large- scale distributed evaluation were not fully implemented in the present study. Advanced privacy-preserving mechanisms such as differential privacy and secure aggregation were also not integrated into the current framework.

Future work will focus on extending the proposed system using larger facial recognition datasets and increasing the number of participating federated clients to improve scalability evaluation. Deployment on Raspberry Pi devices and other edge-computing platforms will also be explored to support low-power smart campus environments. Furthermore, the de- velopment of a real-time attendance dashboard with web-based monitoring capabilities may improve administrative usability and operational management. Additional privacy-preserving techniques such as secure aggregation and differential privacy mechanisms can also be incorporated to strengthen biometric data protection during federated communication. Increasing the number of federated learning rounds and optimizing com- munication efficiency may further improve model convergence and recognition accuracy. Finally, integration of the proposed framework with broader smart city infrastructures may enable future applications in distributed access control, intelligent surveillance, and secure urban monitoring systems.

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