PRECISION-OPTIMIZED HUMAN RECOGNITION MODEL FOR ADAPTIVE INFORMATION RETRIEVAL IN EDUCATIONAL INSTITUTIONS

A PROJECT REPORT

Submitted by

BERYL SHARON J	**[211421243024]**
DHARSHINI M	**[211421243039]**
INDU M	**[211421243063]**

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

IN

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

PANIMALAR ENGINEERING COLLEGE

(An Autonomous Institution, Affiliated to Anna University, Chennai)

APRIL 2025

PANIMALAR ENGINEERING COLLEGE

(An Autonomous Institution, Affiliated to Anna University, Chennai)

BONAFIDE CERTIFICATE

Certified that this project report **"PRECISION-OPTIMIZED HUMAN RECOGNITION MODEL FOR ADAPTIVE INFORMATION RETRIEVAL IN EDUCATIONAL INSTITUTIONS"** is the bonafide work of **"BERYL SHARON J [211421243024], DHARSHINI M [211421243039], INDU M [211421243063]"** who carried out the project work under my supervision.

SIGNATURE
Dr. S. HEMAMALINI, M.E., Ph.D.,
SUPERVISOR
ASSOCIATE PROFESSOR
DEPARTMENT OF AI&DS,
PANIMALAR ENGINEERING COLLEGE,
CHENNAI-600123

SIGNATURE
Dr. S. MALATHI, M.E., Ph.D.,
HEAD OF THE DEPARTMENT
PROFESSOR
DEPARTMENT OF AI&DS,
PANIMALAR ENGINEERING COLLEGE,
CHENNAI-600 123.

Certified that the above-mentioned student was examined in End Semester Project (21AD1811) viva-voice held on _________.

INTERNAL EXAMINER

EXTERNAL EXAMINER

DECLARATION BY THE STUDENT

We **BERYL SHARON J** [211421243024], **DHARSHINI M** [211421243039], **INDU M** [211421243063], hereby declare that this project report titled "**PRECISION-OPTIMIZED HUMAN RECOGNITION MODEL FOR ADAPTIVE INFORMATION RETRIEVAL IN EDUCATIONAL INSTITUTIONS**", under the guidance of **Dr. S. HEMAMALINI, M.E., Ph.D.,** is the original work done by us and we have not plagiarized or submitted to any other degree in any university by us.

ACKNOWLEDGEMENT

We would like to express our deep gratitude to our respected Secretary and Correspondent **Dr. P. CHINNADURAI, M.A., Ph.D.,** for his kind words and enthusiastic motivation, which inspired us a lot in completing this project.

We express our sincere thanks to our directors **Tmt. C. VIJAYARAJESWARI**, **Dr. C. SAKTHI KUMAR, M.E., Ph.D., and Dr. SARANYA SREE SAKTHI KUMAR B.E., M.B.A., Ph.D.,** for providing us with the necessary facilities to undertake this project.

We also express our gratitude to our Principal **Dr. K. MANI, M.E., Ph.D.,** who have facilitated us in completing the project successfully.

We thank the Head of the AI&DS Department, **Dr. S. MALATHI, M.E., Ph.D.,** for the support extended throughout the project.

We would like to thank our supervisor **Dr. S. HEMAMALINI M.E., Ph.D.,** and our coordinator **Dr. S. CHAKARAVARTHI, M.E., Ph.D.,** and all the faculty members of the Department of Artificial Intelligence & Science for their advice and encouragement for the successful completion of the project.

BERYL SHARON J

DHARSHINI M

INDU M

ABSTRACT

Face recognition technology plays a vital role in modern educational systems by enabling efficient and accurate student identification. The growing demand for efficient and accurate student identification systems has highlighted the limitations of conventional face recognition methods, particularly in handling variations in pose, lighting, and occlusions. To address this, our Precision-Optimized Human Recognition Model builds an Adaptive Information Retrieval System utilizing a Histogram of Oriented Gradients (HOG)-based detector for face detection and a ResNet-34-based Deep Metric Learning Model for face recognition. The system encodes facial features and performs identity verification using Euclidean distance for precise and reliable student identification. By integrating these techniques, the model ensures real-time data retrieval with high accuracy and adaptability to diverse conditions. The proposed approach enhances computational efficiency while maintaining robust recognition performance, making it a scalable and practical solution for identity verification in educational institutions.

Keywords: Histogram of Oriented Gradients , ResNet-34, Deep Metric Learning, Euclidean Distance, Adaptive Information Retrieval

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ABBREVIATIONS	EXPANSIONS
HOG	Histogram of Oriented Gradients
SVM	Support Vector Machine
CNN	Convolutional Neural Network
RGB	Red, Green, Blue
BGR	Blue, Green, Red
NMS	Non-Maximum Suppression
SHA	Secure Hash Algorithm
HTTPS	Hypertext Transfer Protocol Secure

CHAPTER 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

Face recognition technology is essential for modern educational systems, enabling efficient and accurate student identification. However, traditional methods struggle with variations in pose, lighting, and occlusions, reducing their reliability. To address these challenges, our Precision-Optimized Human Recognition Model integrates an Adaptive Information Retrieval System, enhancing both detection and recognition. The model employs a Histogram of Oriented Gradients (HOG)-based detector for face detection, ensuring robust feature extraction in diverse conditions. For recognition, it utilizes a ResNet-34-based Deep Metric Learning Model, encoding facial features and verifying identities using Euclidean distance. This approach enhances accuracy while minimizing false identifications. With real-time data retrieval capabilities, the system ensures seamless authentication, adapting dynamically to different facial variations. It optimizes computational efficiency, making it a scalable solution for large student populations. Additionally, the model is highly adaptable, maintaining reliability in challenging scenarios such as low lighting or partial occlusions. Overall, the Precision-Optimized Human Recognition Model provides a secure, efficient, and scalable solution for student identification. By integrating deep learning with adaptive retrieval techniques, it enhances administrative efficiency and security, making it an ideal choice for modern educational institutions.

1.1 MOTIVATION

Face recognition technology plays a crucial role in modern educational institutions by automating student identification processes. Traditional methods, such as manual attendance tracking and ID card verification, suffer from inefficiencies, inaccuracies, and delays. Additionally, these conventional approaches struggle with variations in facial appearance due to pose, lighting, and occlusions, reducing their reliability. To overcome these limitations, our Precision-Optimized Human Recognition Model incorporates an Adaptive Information Retrieval System, significantly improving both detection and recognition accuracy.

The model employs a Histogram of Oriented Gradients (HOG)-based detector for precise face detection, ensuring robust feature extraction in diverse conditions. For student recognition, it utilizes a ResNet-34-based Deep Metric Learning Model, which encodes facial features and verifies identities using Euclidean distance calculations. This advanced approach enhances recognition accuracy while minimizing false identifications.

By integrating deep learning with adaptive retrieval techniques, the system achieves real-time data retrieval, making it suitable for large-scale educational institutions. It enhances computational efficiency, allowing seamless integration with existing student databases, attendance tracking systems, and security infrastructure. Moreover, its adaptability ensures consistent performance across different lighting conditions, facial orientations, and environmental settings, addressing the limitations faced by conventional recognition systems.

Overall, this project presents an innovative, secure, and scalable solution for student identification. By combining deep learning models with adaptive information retrieval, the system significantly improves administrative efficiency and security, making it a valuable tool for modern educational institutions.

1.2 OBJECTIVE

The primary objective of this project is to enhance student identification in educational settings by addressing the shortcomings of traditional face recognition techniques. The primary focus is to develop a highly accurate, real-time, and scalable recognition system that can function effectively under various environmental conditions.

To achieve this, the system integrates-

1. **Adaptive Information Retrieval System-** Enables the model to dynamically

adjust to variations in facial appearance, ensuring accurate recognition in different scenarios.

2. **Histogram of Oriented Gradients-Based Detector-** Provides reliable face detection, even in crowded or low-light environments.
3. **ResNet-34-Based Deep Metric Learning Model-** Ensures superior feature encoding, enabling high-precision facial recognition.
4. **Euclidean Distance Matching Algorithm-** Facilitates precise identity verification by computing the similarity between stored and newly detected facial embeddings.

The system is designed for seamless integration with existing school infrastructure, including-

1. **Automated Attendance Tracking –** Eliminates manual attendance marking, improving efficiency and accuracy.
2. **Security Monitoring and Access Control –** Ensures only authorized students can access classrooms, hostels, or restricted areas.
3. **Student Database Management –** Allows easy integration with existing student records, enabling efficient data updates and retrieval.
4. **Scalability for Large Educational Institutions –** Optimized for high-volume student populations without compromising performance.

By reducing manual intervention, this system minimizes errors, saves time, and enhances administrative workflows. Additionally, its adaptability to challenging conditions, such as poor lighting or partially visible faces, makes it a reliable and practical solution for modern educational environments.

1.3 ENHANCED FACE RECOGNITION

The proposed system introduces several key innovations that significantly enhance face recognition performance in educational institutions. The major contributions of this work include-

Enhanced Face Detection in Diverse Conditions

The integration of a HOG-based detector ensures that faces are detected accurately, even in environments with varying lighting, occlusions, or pose variations. This improvement allows for more consistent feature extraction, reducing false detections.

Advanced Recognition Using Deep Metric Learning

The ResNet-34-based deep metric learning model enhances feature encoding and recognition precision. Instead of relying on traditional classification methods, it learns an embedding space where similar faces are closer and dissimilar faces are farther apart, significantly improving identity verification accuracy.

Adaptive Information Retrieval for RealTime Authentication

By incorporating an adaptive information retrieval system, the model can dynamically adjust to different facial variations, allowing for more reliable authentication under varying conditions, including changes in expression, aging, and partial occlusions.

Scalability for Large-Scale Student Identification

Optimized for computational efficiency, the system is capable of handling thousands of students while maintaining high performance. This scalability makes it a viable solution for universities, colleges, and large schools that require automated attendance and security systems.

Reliability in Challenging Scenarios

Unlike traditional face recognition systems that struggle in low lighting or when faces are partially obscured, this model remains highly adaptable. The combination of HOG and ResNet-34 ensures consistent performance, even in suboptimal conditions.

Improved Administrative Efficiency and Security

By automating student identification, the system significantly reduces administrative workload while enhancing security measures. Automated attendance tracking, database integration, and access control eliminate manual errors and unauthorized entries.

Integration of Deep Learning with Adaptive Techniques

This project bridges the gap between deep learning-based feature extraction and adaptive information retrieval, providing a secure, efficient, and intelligent authentication system. The integration of modern deep learning techniques ensures state-of-the-art performance while remaining adaptable to future enhancements and improvements.

1.4 CONTRIBUTIONS OF THE WORK

The primary objective of this project is to develop a precise, efficient, and scalable student identification system by integrating advanced computer vision and deep learning techniques. This system aims to enhance security, streamline student verification processes, and ensure real-time, high-accuracy face recognition. By leveraging state-of-the-art AI models, the project will create a robust solution suitable for large-scale educational institutions. The specific objectives are as follows:

Accurate Face Detection

One of the fundamental requirements of an effective student identification system is accurate face detection. This project employs the Histogram of Oriented Gradients (HOG) along with a Support Vector Machine (SVM) classifier to detect faces in images efficiently. HOG is a well-established technique that extracts gradient-based features, making it highly effective for face localization even in challenging environments.

By implementing a robust HOG-based detector, the system can accurately identify faces in real-time, ensuring reliability under varying conditions such as different lighting, backgrounds, and slight occlusions. The precise localization of facial regions is crucial for further recognition processes, minimizing false detections and enhancing the system's overall performance.

High-Precision Facial Recognition

To achieve high accuracy in student identification, the project integrates a deep learning-based face recognition model. The ResNet-34 deep convolutional neural network is utilized to extract meaningful and distinctive facial features from images. ResNet-34, known for its residual learning framework, enables the model to learn complex patterns without suffering from vanishing gradient issues, thereby improving feature extraction efficiency.

By encoding each student's facial identity into a high-dimensional vector representation, the system ensures precise face recognition. The model is trained on a diverse dataset to enhance generalization, making it capable of distinguishing students even in cases of slight facial variations such as expressions, minor occlusions, and different angles.

Identity Verification Using Euclidean Distance

Once facial features are extracted, identity verification is performed using an efficient face-matching algorithm based on the Euclidean distance. This method calculates the similarity between a newly detected face embedding and the stored embeddings in the database. If the Euclidean distance falls below a predefined threshold, the system confirms the identity of the student with high confidence. This approach ensures a balance between security and computational efficiency, allowing for real-time verification without compromising accuracy.

The use of deep metric learning further enhances the model's ability to differentiate between students with similar facial features while reducing false positives.

Adaptability to Various Conditions

An effective face recognition system should function reliably under diverse conditions, including variations in lighting, pose, occlusion, and facial expressions. The project is designed to handle these challenges by implementing data augmentation techniques during the model training phase. These techniques include brightness adjustments, random rotations, flipping, and slight occlusions to simulate real-world scenarios. Additionally, the system incorporates adaptive preprocessing techniques such as contrast normalization and histogram equalization to improve recognition performance in different environmental conditions. As a result, students can be identified accurately whether they are facing the camera directly, slightly turned, or in varying lighting conditions commonly found in classrooms and examination halls.

Real-Time Performance Optimization

For large-scale educational institutions, the efficiency of the face recognition system is crucial. The project focuses on real-time optimization by leveraging efficient pre-trained deep learning models and reducing computational overhead. Techniques such as quantization, batch processing, and parallel computing are incorporated to enhance performance without sacrificing accuracy. By optimizing inference time, the system can rapidly process multiple face recognition requests, making it highly scalable for institutions with thousands of students. Additionally, the use of GPU acceleration ensures faster model execution, reducing latency and enabling seamless integration with attendance management and security systems.

Security Enhancement

Security is a critical aspect of any student identification system, and this project implements secure authentication mechanisms to prevent unauthorized access. Encryption techniques are used to protect stored facial embeddings, ensuring that biometric data remains secure. Furthermore, multi-factor authentication (MFA) can be integrated as an additional layer of security, requiring a secondary verification step such as a PIN code or student ID. By implementing these measures, the system mitigates risks associated with identity fraud, unauthorized access, or potential data breaches, ensuring a high level of trust and reliability in educational environments.

CHAPTER 2

LITERATURE REVIEW

CHAPTER 2
LITERATURE REVIEW

2.1 LITERATURE REVIEW

Al-Shareef and Gaboua examined the application of Convolutional Neural Networks (CNNs) in face recognition, particularly for image classification tasks. Implemented in Python, their model was trained and tested on a dataset of 540 images. The results demonstrated outstanding performance, achieving 100% accuracy in identifying 16 individuals, proving its effectiveness on smaller datasets. When tested on larger datasets, the model maintained high accuracy, reaching 97% for both 30 and 2 individuals. These findings highlight CNNs' potential in enhancing face recognition across various data scales. The study also emphasizes the importance of robust algorithms and diverse datasets in improving performance and reliability. Furthermore, it suggests that continuous advancements in deep learning techniques are vital for progress in the field. By utilizing CNNs, face recognition technology can be more efficiently applied to practical scenarios, leading to greater accuracy and effectiveness in image identification across different environments[1]

Jha et al. provide an in-depth analysis of the evolving landscape of face recognition technology, emphasizing its increasing role across various applications while acknowledging challenges posed by facial diversity. The review examines 20 papers published between 2011 and 2021, focusing on deep learning advancements and network models used in face recognition. Key datasets like CKPlus and DeepFace are highlighted for their role in training models to enhance accuracy. The study also discusses research challenges such as lighting variations, facial expressions, and occlusions, which impact performance. It stresses the need for more robust algorithms and outlines future research directions to overcome these limitations. By addressing both advancements and persistent challenges, the paper serves as a valuable resource for researchers and practitioners looking to improve face recognition technologies in real-world applications[2].

Maryuni Susanto et al. explore a student attendance system utilizing face recognition, achieving a 90% accuracy rate by combining Haar Cascade Classifier and FaceNet methods. This level of accuracy demonstrates the system's reliability in identifying individuals. The study suggests future improvements by expanding the dataset with more images per student to enhance accuracy further. Additionally, it recommends exploring advanced face detection methods beyond Haar Cascade for better precision under different conditions. Researchers are encouraged to investigate alternative deep learning architectures to improve system robustness and adaptability. Continued research in these areas promises to enhance the efficiency and accuracy of face recognition-based attendance systems, making them more suitable for various educational and organizational applications[3].

Sharma et al. examine the growing significance of facial recognition technology amid the rising demand for automated video and image analysis. As identity verification and emotion recognition become crucial, the study reviews various traditional and modern techniques in facial recognition. The paper highlights its applications in security, surveillance, and consumer markets, where accurate identification enhances user experience and safety. Despite progress, challenges such as privacy concerns, data security, and algorithmic bias remain significant. The review underscores the need for continued research to address these issues and improve system reliability. By offering a comprehensive discussion of techniques, applications, and challenges, this study provides a valuable resource for those aiming to advance facial recognition technology in practical scenarios[4].

Siew et al. address inefficiencies in traditional paper-based attendance tracking by proposing a web-based attendance management system integrating facial recognition with QR codes. This system enhances accuracy and efficiency, streamlining administrative processes in educational institutions. User acceptance tests reveal that the system improves transparency and usability, with users favoring the facial recognition feature. Findings suggest that this technology represents a significant advancement in educational administration, offering a reliable and user-friendly attendance tracking solution. By leveraging modern innovations, the system not only optimizes attendance management but also enhances student and educator experiences, contributing to ongoing discussions on the role of technology in education[5].

Singh and Goel investigate facial recognition for identity authentication, focusing on Eigenface and Fisherface methods to process high-dimensional facial data. Eigenface utilizes Principal Component Analysis (PCA) to reduce complexity while preserving essential features, simplifying data for recognition. Fisherface employs Linear Discriminant Analysis (LDA) to maximize class separability, improving accuracy under different lighting and expressions. By combining these techniques, the system extracts key discriminative features for robust identification. While Eigenface excels in dimensionality reduction, Fisherface enhances accuracy through class separation. Together, these methods create an efficient and adaptable system, making it a reliable foundation for real-world facial recognition applications where speed and precision are critical[6].

Kopalidis et al. explore Facial Expression Recognition (FER), a key area in computer vision focused on classifying emotions from images and videos. Traditional methods relied on handcrafted features like Histogram of Oriented Gradients (HOG) with classifiers such as Support Vector Machines (SVM). However, deep learning, particularly Convolutional Neural Networks (CNNs), has improved accuracy through automatic feature extraction. Challenges such as limited training data, illumination variations, and identity bias affect generalization. FER models are evaluated on controlled and uncontrolled datasets to measure adaptability. Future research should focus on self-supervised learning, cross-domain adaptability, and multi-modal integration to enhance FER’s robustness, improving applications in healthcare, security, and human-computer interaction[7].

Alsubhi and Jaha examine face recognition as a widely used biometric technology, primarily focused on frontal face views. However, side-face recognition remains underexplored despite its importance when only partial facial data is available. This research introduces soft biometric traits derived from facial anthropometric measurements, extracted from both frontal and side views. These traits, combined with vision-based deep features, enhance zero-shot side-face recognition. The framework trains on frontal face data but matches side-face images. Evaluations on the CMU Multi-PIE dataset show that fusing soft traits with ResNet-50 deep features improves recognition accuracy, with global soft biometric integration further increasing accuracy by 23%. These findings highlight the potential of soft trait fusion in advancing side-face recognition for biometric applications[8].

Ray presents an advanced face recognition-based attendance system designed to overcome traditional limitations by integrating machine learning, computer vision, and geospatial APIs. The system automates attendance tracking with high accuracy, featuring real-time video recognition, an intuitive user registration module, CSV-based data logging, and geolocation-aware tracking for precise validation. Implemented in Python, it employs OpenCV for face detection and PyQt5 for a responsive interface. Experimental validation in workplaces, academic institutions, and security-sensitive environments highlights its scalability and efficiency. This robust system demonstrates significant improvements in attendance management, making it a suitable solution for modern tracking requirements[9].

Sanchez-Moreno et al. propose a deep learning-based facial recognition system optimized for security applications. The system integrates FaceNet with classifiers such as SVM, KNN, and RF for accurate identification in real-time settings. Using the YOLO-Face detection method, it efficiently recognizes faces even under occlusion and varying conditions. Tests on unconstrained datasets show YOLO-Face achieves 89.6%

accuracy on the Honda/UCSD dataset at 26 FPS. FaceNet, combined with SVM, KNN, and RF, achieved 99.7%, 99.5%, and 85.1% accuracy on the LFW dataset, respectively. The proposed system delivers 99.1% accuracy with a 49 ms runtime, demonstrating its potential for high-accuracy, real-time facial recognition in security applications[10].

CHAPTER 3

SOFTWARE REQUIREMENTS

CHAPTER 3
SOFTWARE REQUIREMENTS

1. Operating System

- **Windows 10/11-** Provides broad software compatibility, making it suitable for developers familiar with GUI-based environments. It supports most machine learning frameworks but lacks native Linux features.
- **Ubuntu 20.04+-** Preferred for deep learning due to its lightweight nature, extensive open-source support, and seamless compatibility with AI tools. It is ideal for server-based and cloud applications.
- **macOS-** Unix-based but lacks native support for NVIDIA GPUs, making it less efficient for deep learning.
- **Recommendation-** Ubuntu is the best choice for stability, efficiency, and cloud deployment.

2. Programming Language

- **Python 3.8+-** The preferred language for deep learning due to its simplicity, versatility, and strong community support.
- **Supports-** TensorFlow, PyTorch, NumPy, Pandas, and Scikit-learn, making it ideal for AI applications.
- **Advantages-** Allows rapid prototyping, ease of debugging, and seamless integration with data science libraries.
- **Latest Features-** Improved performance, security enhancements, and better package management.
- **Recommendation-** Use the latest Python version to leverage performance improvements and long-term support.

3. Frameworks and Libraries

- **TensorFlow/PyTorch-** Used for implementing the ResNet-34-based Deep Metric Learning Model. TensorFlow is preferred for scalability, while PyTorch is better for research and experimentation.

- **OpenCV-** Essential for face detection and preprocessing, providing efficient image manipulation.
- **Scikit-learn-** Used for feature encoding, distance calculations, and evaluation metrics.
- **NumPy/Pandas-** Handle numerical computations and large datasets.
- **Recommendation-** PyTorch is better for flexible model building, while TensorFlow is preferred for production environments.

4. Database Management System

- **MySQL-** Relational database that is easy to set up, reliable, and widely used for structured data storage.
- **PostgreSQL-** More powerful and flexible, supporting complex queries, JSON storage, and advanced indexing techniques.
- **Purpose-** Used to store student information, extracted feature vectors, and model-generated embeddings.
- **Security & Integrity-** Both databases ensure data protection and efficient query execution.
- **Recommendation-** PostgreSQL is better for large-scale AI applications, while MySQL is suitable for simpler implementations.

5. Development Environment

- **Jupyter Notebook-** Ideal for prototyping and debugging, offering an interactive coding environment.
- **PyCharm-** Provides a structured development workflow, advanced debugging, and built-in support for deep learning libraries.
- **Visual Studio Code-** Lightweight yet powerful, featuring Git integration, Python extensions, and remote development capabilities.
- **Purpose-** Enhances productivity and facilitates efficient model development.
- **Recommendation-** Jupyter for research and experimentation; PyCharm or VS Code for full-scale deep learning projects.

6. Web Framework

- **Flask-** A minimalistic framework that allows easy API development for integrating deep learning models.
- **FastAPI-** A high-performance, asynchronous framework optimized for real-time processing and scalability.
- **Purpose-** Provides an interface for users to interact with the deep learning model via a web application.
- **Ease of Use-** Flask is simple and widely used, while FastAPI is more efficient and designed for speed.
- **Recommendation-** Use Flask for small projects and FastAPI for applications requiring real-time processing.

7. Hardware Acceleration

- **CUDA-enabled GPU-** Enhances deep learning performance by parallelizing computations.
- **CUDA Toolkit & cuDNN-** Provides GPU acceleration for frameworks like TensorFlow and PyTorch.
- **Performance Boost-** Reduces training time from days to hours.
- Recommendation- Use an NVIDIA GPU with proper CUDA/cuDNN setup for optimal performance.

CHAPTER 4

PROPOSED SYSTEM DESIGN

CHAPTER 4

PROPOSED SYSTEM DESIGN

4.1 ARCHITECTURE DIAGRAM

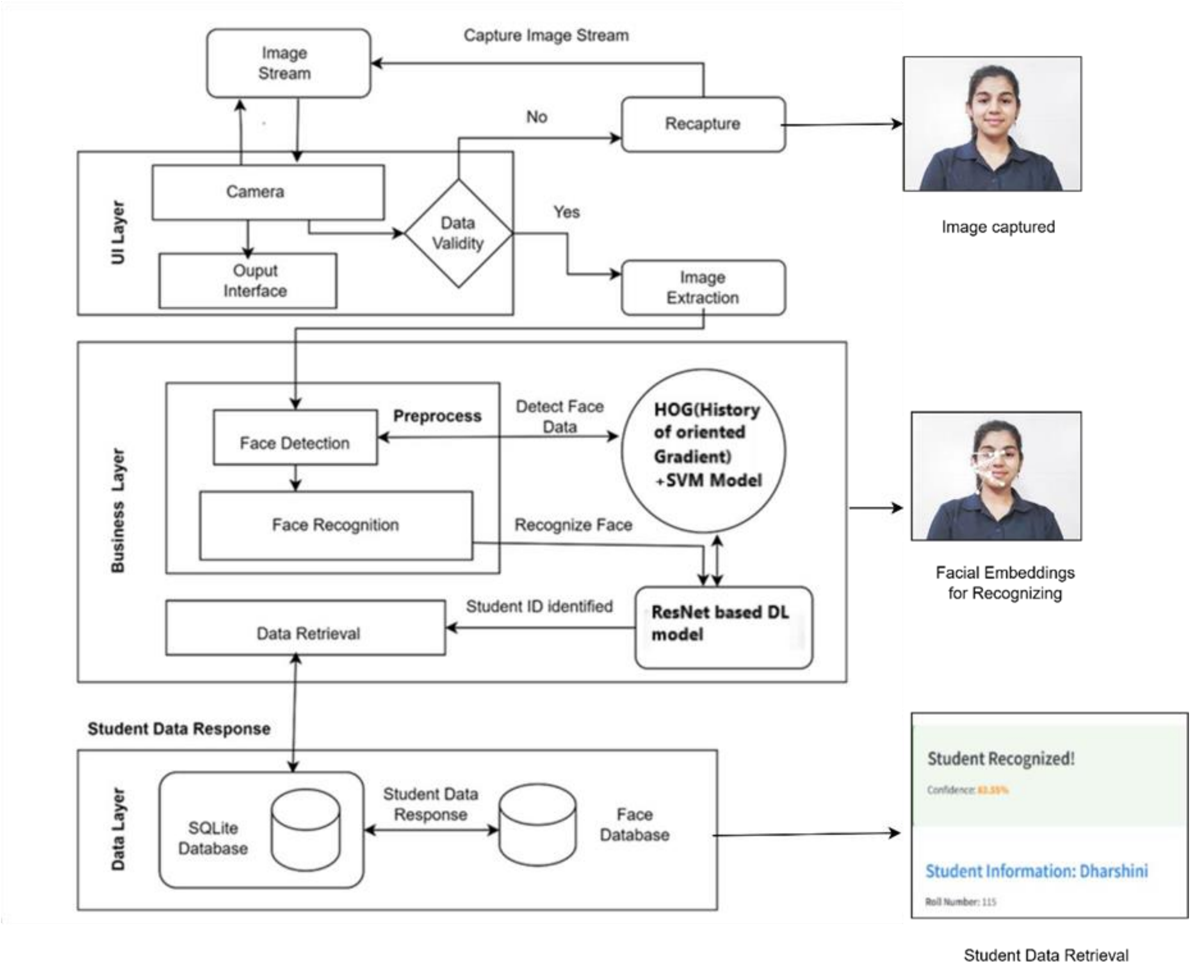


Fig. 4.1- Architecture Diagram

The Figure 4.1 illustrates architecture diagram for the Precision-Optimized Human Recognition Model illustrates a layered framework that ensures seamless student identification and academic data retrieval in educational institutions. It is structured into three main components- UI Layer, Business Layer, and Data Layer process.

The UI Layer is responsible for capturing the image stream using a camera module integrated with OpenCV. The captured image undergoes a data validation step, ensuring the image quality is sufficient for processing. If the image fails validation due to issues like occlusions, poor lighting, or pose variations, the system prompts for a recapture. Once validated, the image proceeds to the image extraction phase, where key facial features are isolated for further analysis. The extracted data is then passed to the Business Layer for processing. The Business Layer implements HOG (Histogram of Oriented Gradients) + SVM (Support Vector Machine) for face detection, ensuring efficient localization of faces within the image. The detected face is then processed by a ResNet-based deep metric learning model from dlib, which generates high-dimensional embeddings for accurate facial recognition. This deep learning model ensures precise identity verification by comparing the embeddings against stored representations. The recognized student ID is then forwarded to the Data Retrieval Module, which interacts with the Data Layer to fetch corresponding academic records.

The Data Layer is built on an SQLite database, which securely stores student details, facial embeddings, and academic data. The Pandas library is used for efficient database queries and data manipulation, while NumPy assists in handling numerical operations within image processing tasks. The retrieved data is sent back through the pipeline to the UI for display using Streamlit, providing an interactive interface for real-time student identification and data retrieval. This precision-optimized system enhances security, efficiency, and scalability, enabling institutions to automate attendance, access control, and personalized academic data retrieval. By leveraging machine learning, deep learning, and computer vision, this architecture ensures a robust and adaptive solution for intelligent human recognition in educational environments.

The architecture diagram outlines the structured workflow of the student face recognition system, divided into three key layers- UI Layer, Business Layer, and Data Layer. The UI Layer captures images using a camera module, validates them, and proceeds to image extraction. The Business Layer processes the image using HOG + SVM for face detection and dlib’s ResNet-based deep metric learning model for recognition, identifying the student’s face. Once identified, the Data Layer retrieves the student's academic information from an SQLite database. The system ensures accuracy by preprocessing images before detection and recognition. Finally, the retrieved student data is displayed in real-time, streamlining tasks like attendance tracking and academic record retrieval.

4.2 USE CASE DIAGRAM

The Figure 4.2 represents the sequential workflow of the student face recognition system, highlighting the interaction between the user (student or administrator) and the system. The process begins with image capture, where the system takes an input image of the student's face using a camera. The captured image undergoes preprocessing, which includes operations such as noise reduction, contrast enhancement, and alignment to ensure accurate feature extraction. The feature extraction stage identifies unique facial characteristics, such as distances between facial landmarks, which are crucial for recognition. These features are then processed using face recognition models, specifically algorithms for detection and dlib's ResNet-based deep metric learning for recognition, to determine the identity of the student.

Once the face is recognized, the system proceeds to student ID identification, where it matches the extracted features with pre-stored embeddings in the database. Upon successful identification, the system initiates student data retrieval, fetching relevant academic and administrative details from the SQLite database. The retrieved data may include attendance records, exam results, and access privileges, depending on the system's purpose within the educational institution. The database securely manages both student profiles and their corresponding facial embeddings to ensure real-time identification and retrieval. This process allows for efficient student verification, reducing manual work and enhancing institutional security measures.

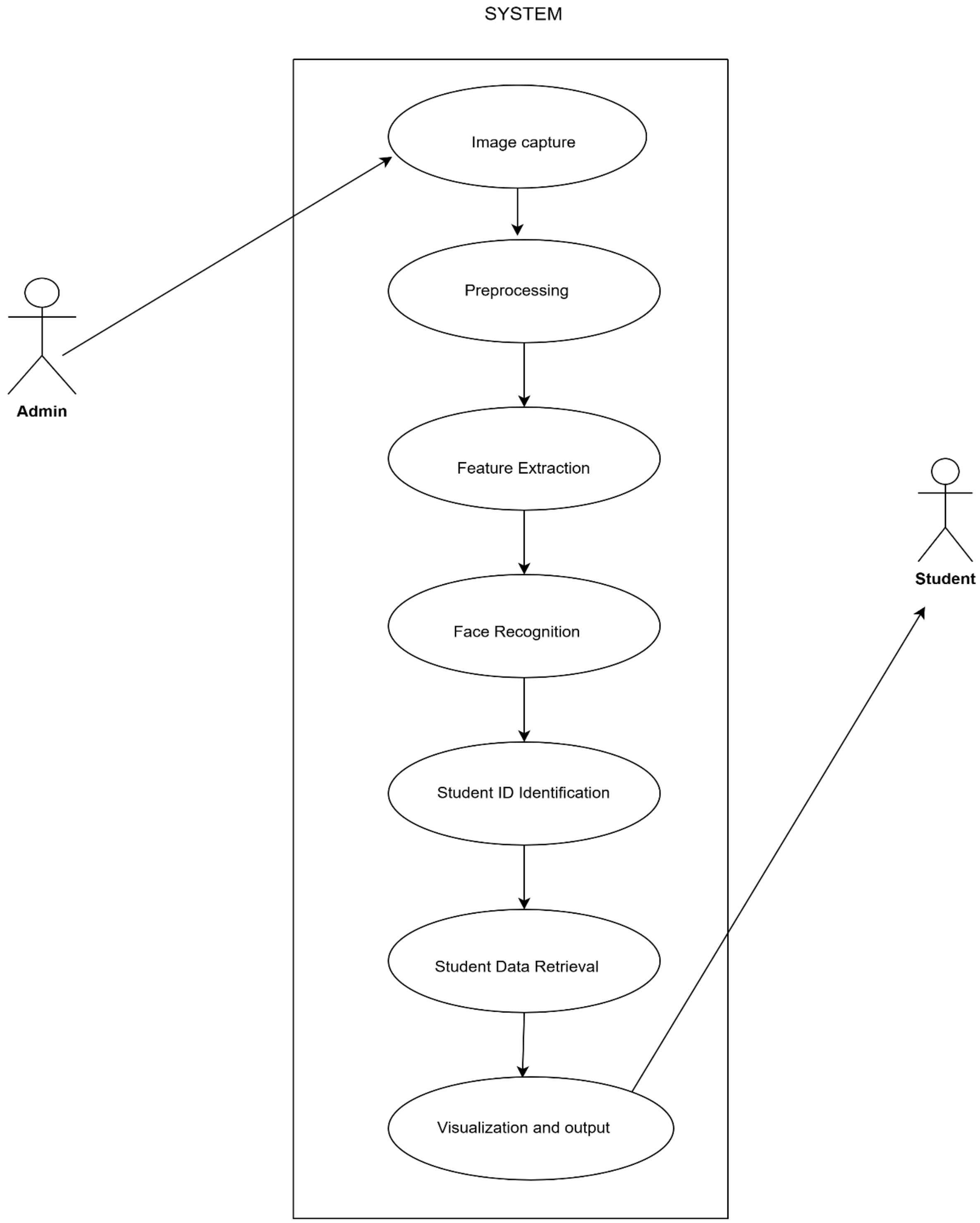


Fig. 4.2- Use case Diagram

Finally, the retrieved student data is visualized and outputted to the user interface for further action or validation. This output can be displayed on a Streamlit-based UI, providing an interactive experience for administrators or students accessing their records. The system ensures robustness by handling cases of misidentification or image recapture, improving accuracy through iterative learning. The overall use case diagram presents a streamlined and automated face recognition workflow, making it an effective solution for identity verification in educational institutions. By leveraging advanced image processing and machine learning techniques, the system provides a precise, scalable, and adaptive solution for administrative tasks.

4.3 CLASS DIAGRAM

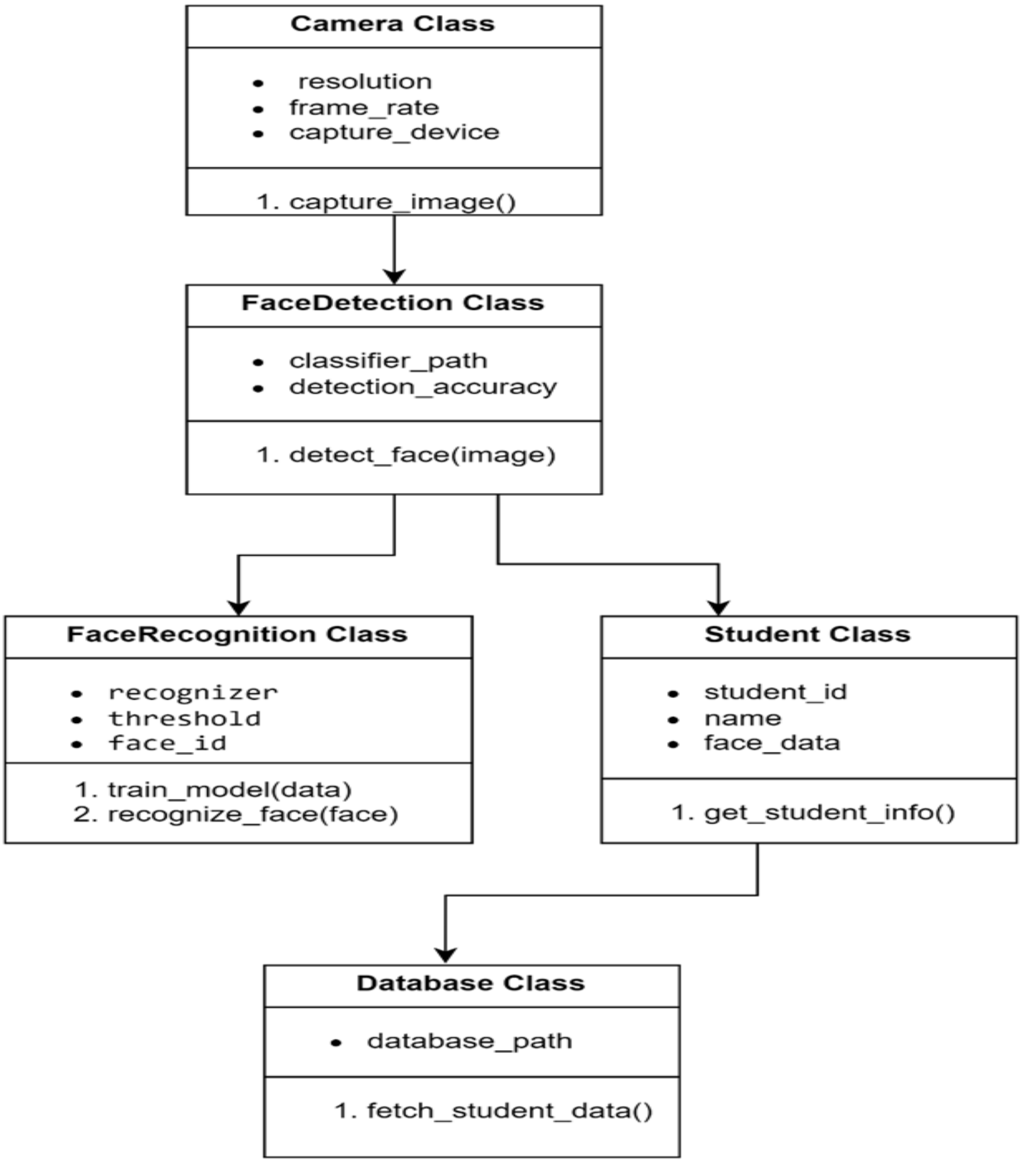


Fig. 4.3- Class Diagram

The Figure 4.3 shows that class diagram is a key component of object-oriented system design, visually representing the different classes involved in the system and their relationships. In the student face recognition system, the Camera Class is responsible for capturing images, with attributes like resolution, frame_rate, and capture_device that define the image quality and capturing method. The method capture_image() is used to take a snapshot, which is then passed to the FaceDetection Class for processing. The FaceDetection Class is responsible for detecting faces within an image using attributes such as classifier_path and detection_accuracy, ensuring the system correctly identifies facial features. The method detect_face(image) extracts faces from the captured images, filtering out unnecessary background data.

The FaceRecognition Class plays a vital role in determining student identity by comparing extracted facial features with stored embeddings. This class contains attributes like recognizer, threshold, and face_id, which define recognition accuracy and decision-making criteria. The train_model(data) method allows the system to improve recognition accuracy by learning from new faces, while recognize_face(face) compares detected faces against stored student data. The Student Class represents student information, storing attributes such as student_id, name, and face_data, ensuring each recognized face is mapped to the correct student record. The get_student_info() method retrieves the relevant details once a match is found, enabling seamless student identification.

The Database Class ensures efficient data storage and retrieval, acting as the system's backend repository for student records and facial embeddings. The database_path attribute specifies the database location, allowing structured storage of student-related data. The fetch_student_data() method queries the database for a student's academic records, attendance logs, or other relevant details upon successful face recognition. This interaction between the FaceRecognition Class, Student Class, and Database Class ensures real-time access to student information, making the system highly functional for educational institutions. The modularity of this design enhances efficiency, allowing seamless updates and scalability for future enhancements.

The overall architecture of the class diagram supports a robust, real-time face recognition system by clearly defining each module's responsibilities. The Camera Class and FaceDetection Class handle the initial steps of image capture and preprocessing, ensuring high-quality data is used for recognition. The FaceRecognition Class and Student Class work together to verify student identities, ensuring an accurate and efficient system. Finally, the Database Class enables reliable data storage and retrieval, ensuring student records are always accessible upon successful identification.

4.4 ACTIVITY DIAGRAM-

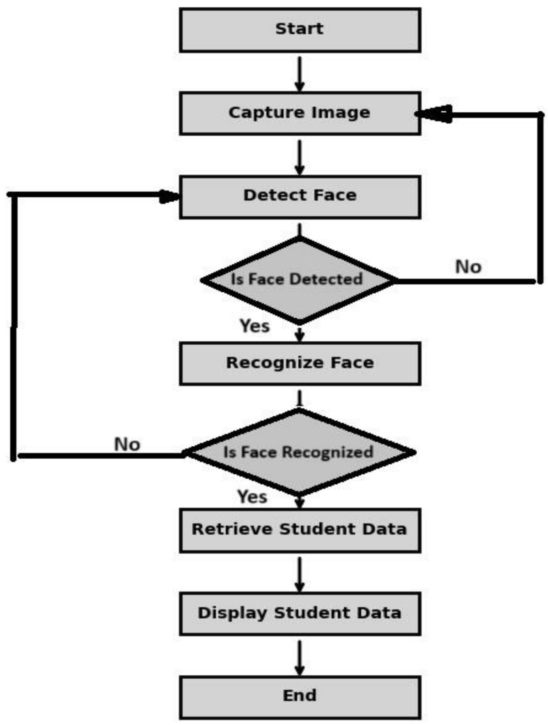


Fig. 4.4- Activity Diagram

The Figure 4.4 visually represents the step-by-step workflow of the student face recognition system, ensuring clarity in its operational flow. The process begins with the "Start" node, initiating the recognition sequence, followed by image capture using a camera. The captured image is then passed to the face detection module, where the system checks for human faces in the frame. If no face is detected, the system loops back to recapturing the image, ensuring that only valid inputs proceed further. This mechanism helps in filtering out irrelevant data, such as images without human faces or those with extreme occlusions. If a face is detected, the process advances to the recognition stage, where the system matches the detected face with stored embeddings.

The face recognition stage plays a crucial role in identity verification by analyzing facial features and comparing them against the stored database. If the system fails to recognize the face, it loops back to the image capturing stage, ensuring multiple attempts to improve accuracy. If the face is successfully recognized, the system proceeds to retrieve the corresponding student ID and associated academic records. This validation process ensures that only known students are granted access to institutional resources. The iterative structure of the diagram reflects an error-handling mechanism, ensuring precision while eliminating misidentifications. By enforcing reattempts for unrecognized faces, the system maintains a high level of reliability and security.

Once a student is successfully recognized, the retrieved data is fetched from the database, which includes relevant academic records, attendance details, or authentication credentials. The database query process is streamlined to ensure minimal delays, providing real-time access to student information. This structured retrieval mechanism enhances operational efficiency in educational institutions by automating data access. After successful data retrieval, the system proceeds to the visualization and output stage, where the relevant information is displayed on the user interface. This step ensures that faculty members, administrative staff, or automated systems can view and utilize student information seamlessly. The system architecture is optimized for both speed and accuracy, preventing unnecessary bottlenecks in real-time applications.

The activity diagram provides a clear representation of how the face recognition system handles dynamic inputs in a structured workflow. The presence of multiple decision nodes, such as face detection and recognition verification, ensures that the system operates within a strict validation framework. Error handling is efficiently managed by redirecting unsuccessful attempts to repeat the capture and detection processes. This design minimizes false positives while ensuring only verified students access institutional resources. The activity diagram also highlights the importance of real-time processing, demonstrating how the system maintains continuous loops until an accurate match is found. The final "End" node signifies the completion of the process once the student data is successfully displayed, ensuring a structured, automated, and user-friendly approach to student identity verification.

4.5 SEQUENCE DIAGRAM

The Figure 4.5 sequence diagram represents the structured interaction between different components in a student face recognition system by defining the order of operations. The process begins when the user captures an image, which is then sent to the camera module for processing. The camera forwards this image to the face detection module, where it is analyzed for any facial features. If a face is successfully detected, the system moves to the face recognition module for further identification. The face recognition module attempts to match the detected face with existing records stored in the system. If a match is found, the system proceeds to retrieve student information. This approach ensures sequential data flow, where each step depends on the previous one. The system architecture promotes real-time verification for accuracy and efficiency. By ensuring smooth interactions, the sequence diagram enables structured student authentication in educational institutions.

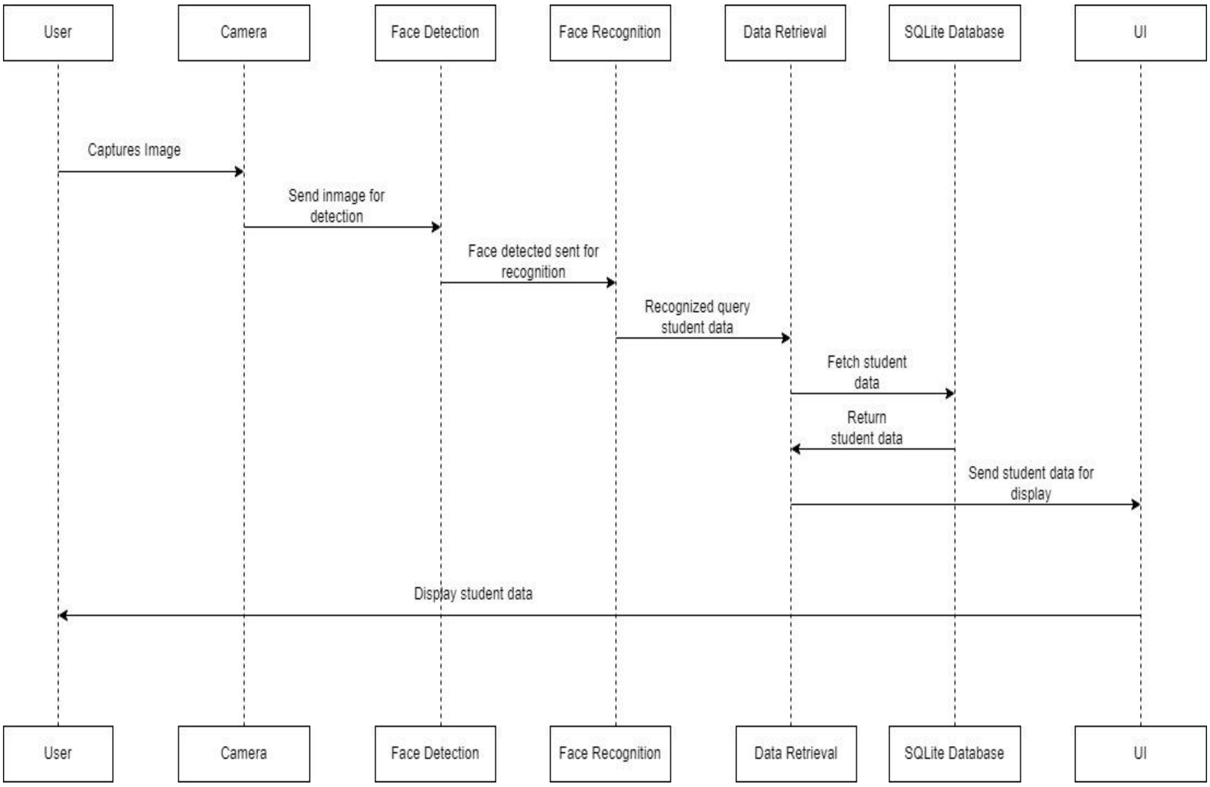


Fig. 4.5- Sequence Diagram

The face recognition module communicates with the data retrieval component, which queries the SQLite database to fetch relevant student information. Once the request is sent, the database processes the query and searches for a matching student record. If a match exists, the database retrieves the student's personal and academic details. The retrieved data is then sent back to the data retrieval module for further processing. This ensures a structured exchange of information between the recognition system and the storage database. The sequence diagram outlines how modules interact to maintain data integrity and prevent unnecessary processing delays. Each step follows a logical sequence, reducing potential errors in face matching. By ensuring real-time access to student records, the system enhances identity verification. This efficient data retrieval process improves system performance while maintaining high accuracy levels.

Finally, the retrieved student data is displayed on the UI, completing the process of student identification. The UI acts as the final interaction point, where users can see student information, including their name and academic details. This process ensures seamless communication between the recognition system and the user interface. The structured interaction allows quick updates of information, ensuring students' details are displayed without delays. If no matching record is found, an appropriate message is displayed to notify the user. The sequence diagram ensures clear system interactions, where data flows logically between components. Each module plays a specific role, preventing redundant operations and ensuring high efficiency. The system optimizes response time, enabling fast and secure authentication. By following a structured sequence, the system enhances the overall reliability of student face recognition.

4.6 DATA FLOW DIAGRAM

The Figure 4.6 represents the flow of information within the student face recognition system, showing how data is processed at different stages. The process begins when the user captures an image, which is sent to the camera module for initial processing. The image is then forwarded to the face detection module, where facial features are extracted and analyzed. If a face is detected, the system passes the data to the face recognition module, which compares it against stored records. This module ensures efficient data filtering, reducing errors in identification. The structured data flow enhances the speed and accuracy of face detection.

Once the face recognition module identifies a match, it sends a request to the data retrieval module, which queries the SQLite database for student details. The database searches for the corresponding student profile using the unique face ID and retrieves relevant information. If the student record is found, the data retrieval module processes it and prepares it for display. This step ensures data consistency, preventing redundant or incorrect student data retrieval. The data storage and retrieval system is designed to handle large volumes of student records, optimizing efficiency. The DFD clearly maps out the seamless flow of data, reducing system complexity.

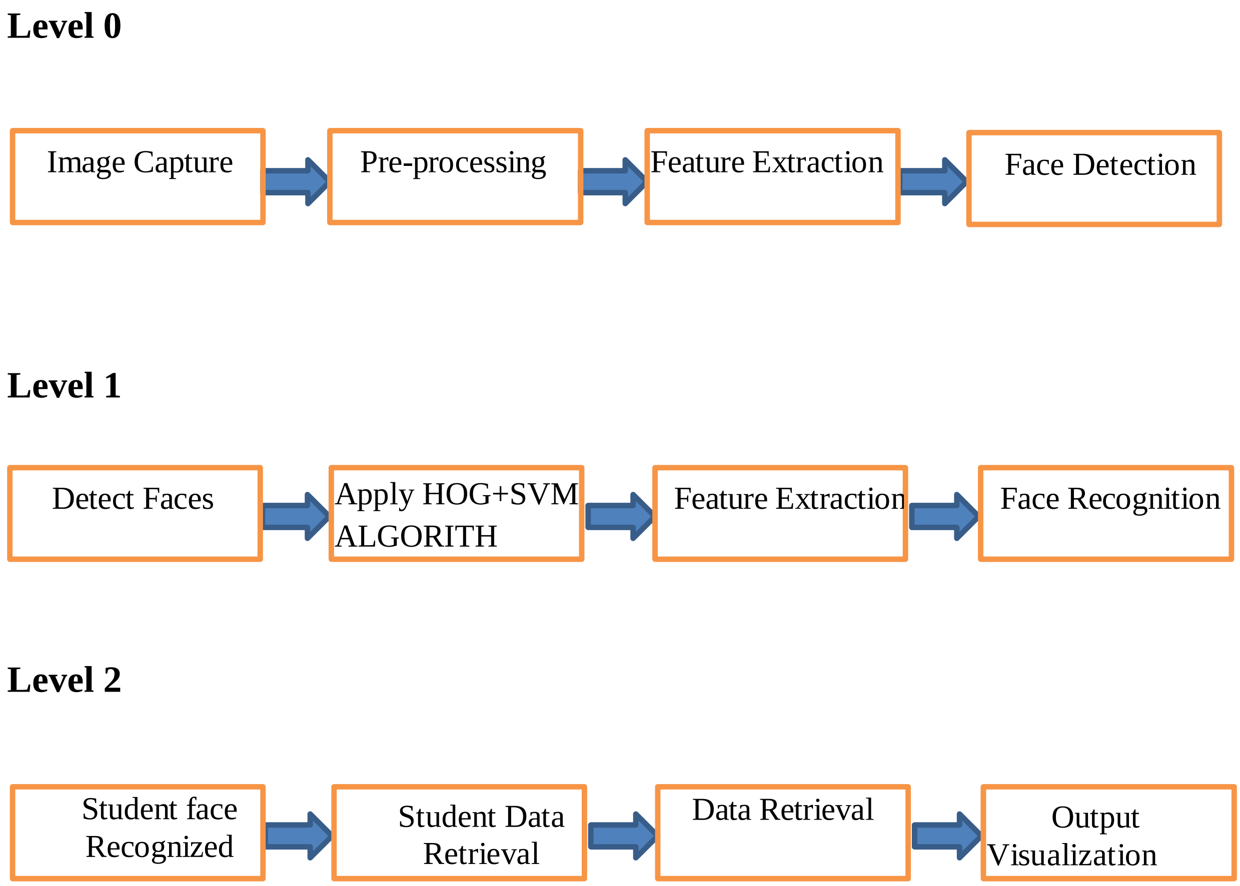


Fig. 4.6- Data Flow Diagram

The retrieved student data is sent to the UI module, where it is displayed for user verification. If no match is found, an error message is sent back to the UI, informing the user that the face is not recognized. The DFD ensures clear data movement, from image capture to final display, preventing bottlenecks in processing. The structured flow enhances the real-time authentication process, improving system response. The diagram also helps in identifying potential inefficiencies or security risks in data handling. By visualizing how data moves within the system, the DFD ensures streamlined and secure student identification.

CHAPTER 5

PROPOSED SYSTEM IMPLEMENTATION

CHAPTER 5

PROPOSED SYSTEM IMPLEMENTATION

5.1 FACE DETECTION AND ENCODING

Face recognition technology plays a crucial role in automated identification and information retrieval systems. It makes it possible for a technology to accurately detect, examine, and identify human faces. The process involves multiple stages, including face detection, feature extraction, encoding, and matching against stored facial data. This technology ensures secure, contactless, and efficient student identification in educational institutions.

Face encoding is done using dlib's ResNet-based deep metric learning model, while face identification is done using Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM). These techniques offer a reliable and expandable solution for facial recognition, guaranteeing precision and effectiveness in the retrieval of student data. A 128-dimensional feature vector of the identified face is created, saved in a database, and used for upcoming identity checks.

Image Acquisition and Preprocessing

Image Acquisition- The technology uses a webcam to capture student images in real time for face recognition. This ensures that the system works efficiently for student authentication without requiring manual image uploads. The captured image is immediately processed to extract relevant facial features while removing background noise.

Once captured, the image is converted into a processing-ready format to maintain consistency in recognition. By default, OpenCV captures images in BGR (Blue-Green-Red) format, but most face recognition algorithms operate in RGB (Red-Green-Blue) format. To ensure compatibility, the system automatically converts BGR to RGB before any further processing. This transformation allows deep learning models like dlib's ResNet to extract facial features effectively.

If multiple faces are detected in the image, the system identifies and isolates the largest face, assuming it belongs to the intended student. Additionally, the system ensures optimal brightness and contrast levels to handle varying lighting conditions in different environments.

Preprocessing Steps

Resizing- To guarantee a constant input size for face detection, the image is resized to a fixed dimension (e.g., 150×150 pixels). This ensures that the facial features remain proportional, regardless of variations in image resolution. A standardized size enhances the performance of the HOG + SVM detector by eliminating inconsistencies in facial dimensions across different images. The resizing operation also optimizes computational efficiency by reducing processing time while maintaining sufficient detail for accurate recognition. This step is crucial, especially in scenarios where the system needs to process multiple face images quickly.

Normalization- Normalization is applied to enhance contrast, reduce noise, and stabilize pixel intensity variations across different images. Each pixel value is scaled to a fixed range (e.g., 0 to 1), ensuring that the system remains insensitive to brightness fluctuations.This step is essential in environments where lighting conditions vary, such as classrooms with different levels of natural and artificial light. Normalized images help the face detection algorithm perform consistently, even when some students are in well-lit areas while others are in shadowed regions.

Color Space Conversion- Since most deep learning-based face recognition models operate in RGB, any image taken in BGR format is converted to RGB before further processing. This conversion ensures compatibility with the dlib ResNet-based feature extractor, which expects facial features to be in an RGB color space. In addition, the system applies grayscale conversion in specific cases, such as when performing HOG feature extraction. The grayscale format reduces the computational complexity while still preserving the structural details needed for accurate face detection. By implementing these preprocessing techniques, the system ensures that face detection and encoding remain highly accurate and efficient, even when images are captured in varying real-world conditions.

5.1.1 Working Procedure:

Face Detection Process- For detection the Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) method for face detection, which ensures effective and precise face localization. Face detection is the first stage in the recognition pipeline, where the system finds the area in an image that contains a human face.

Steps in Face Detection

- **Image Preprocessing Steps-** To guarantee compliance with the detection model, the input image whether uploaded or taken from a webcam is converted to RGB format. To ensure consistent processing, the image is scaled and adjusted.
- **HOG-Based Feature Extraction-** By examining gradient orientations in select areas of the image, HOG is able to extract important facial traits. It records the shape and edge details that set a face out from the background.
- **SVM-Based Face Classification-** A pre-trained Support Vector Machine (SVM) classifier receives the extracted HOG characteristics and uses them to identify whether a human face is present in the detected region. The bounding box coordinates are taken out for additional processing if a face is discovered.
- **Face Encoding Process-** After a face is detected, the next step is to convert it into a numerical representation that can be used for recognition. This is done using dlib’s ResNet-based deep metric learning model.

Steps in Face Encoding

- **Face Cropping & Resizing-** The detected face is cropped from the original image using its bounding box coordinates.The cropped image is resized to a fixed standard dimension for consistent processing.

- **Feature Extraction Using ResNet-** The ResNet deep learning model processes the face to extract high-level features such as eye placement, nose shape, and jawline. The model converts these features into a 128-dimensional numerical vector (face encoding).
- **Storing the Face Encoding-** The extracted face encoding is stored in an SQLite database, linked with the corresponding student's details (Name, Roll Number, Department, etc.). Instead of saving raw images, only the 128-dimensional vector is stored to optimize storage and security.
- **Retrieval for Recognition-** When a new face is scanned, the system retrieves stored encodings and compares them using Euclidean distance to determine identity.

5.1.2 Algorithm for Face Detection and Encoding

Step 1- Image Acquisition

The system begins by capturing an image using a webcam to ensure accurate face recognition in real time. Alternatively, users can upload an existing image, which undergoes the same processing pipeline. Since OpenCV captures images in BGR format, the system automatically converts the image to RGB to maintain compatibility with face recognition models. If multiple faces are present, the system identifies and isolates the largest face, assuming it belongs to the intended student. To enhance recognition accuracy, image enhancement techniques such as contrast adjustment and brightness normalization are applied, ensuring optimal lighting conditions before further processing.

Step 2- Face Detection (HOG and SVM)

Once the image is acquired, the system detects faces using the Histogram of Oriented Gradients (HOG) algorithm, which extracts essential facial features by analyzing the distribution of gradient orientations in localized regions of the image. The extracted features are then passed to a Support Vector Machine

(SVM) classifier, which determines whether a human face is present. Upon successful detection, the system extracts bounding box coordinates, marking the detected facial region for further processing. To improve accuracy, the system applies non-maximum suppression (NMS) to remove redundant detections and retain only the most prominent face. If no face is detected, users are prompted to retake the image or adjust their position for better visibility.

Step 3- Face Encoding (ResNet Model)

Once a face is detected, it is cropped and resized to match the input dimensions required by the ResNet-based deep metric learning model. The ResNet model then processes the facial image to extract key facial landmarks such as eye positioning, nose structure, and jawline shape. These features are converted into a 128-dimensional feature vector, which uniquely represents the student’s face. Unlike traditional face recognition methods that rely on pixel-by-pixel comparisons, the deep metric learning model generates high-dimensional embeddings, improving accuracy even under variations in lighting and facial expressions. The extracted embeddings are compared against previously stored encodings to determine identity verification.

Step 4- Storage and Retrieval

After encoding, the 128-dimensional vector representation of the student’s face is stored securely in an SQLite database, ensuring efficient and encrypted storage. Instead of storing raw facial images, only the numerical encodings are preserved, optimizing storage space while maintaining privacy. Each encoding is linked to corresponding student details such as Name, Roll Number, Department, and Year of Study, allowing for seamless retrieval when required. During face recognition, the system retrieves all stored encodings and computes the Euclidean distance between the new encoding and the stored ones. If the distance falls below a predefined threshold (e.g., 0.6), the student is identified, and their details are displayed. If no match is found, the system returns a "Student Not Recognized" message and prompts the user to try again. The retrieval process is designed for real-time execution, ensuring quick and accurate student identification in educational settings.

5.2 FACE RECOGNITION AND IDENTIFICATION

Face recognition is the process of identifying an individual by comparing their facial features against a stored database of known faces. In this system, once a student submits an image, their face is detected, encoded, and compared with previously stored encodings to determine their identity. The recognition process ensures that only registered students can retrieve their details, making the system a secure and efficient solution for student information management. The Euclidean distance metric is used to measure the similarity between a new face encoding and stored encodings, determining whether the student is a match.

To further enhance accuracy, the system considers multiple factors, such as pose variations, lighting conditions, and facial occlusions (e.g., masks or glasses). The deep metric learning model used for encoding ensures that the system remains robust against minor changes in a student's appearance over time. Additionally, real-time recognition optimizations allow for instant retrieval of student details, reducing the time required for identification and improving user experience.

Steps in Face Recognition

- **Image Acquisition & Preprocessing-** The student submits an image through the webcam or by uploading a file. The image is converted to RGB format to match the format used during face encoding.
- **Face Detection and Encoding-** The system detects the face in the image using HOG and SVM. The detected face is then encoded using the ResNet model, generating a 128-dimensional numerical representation.
- **Comparison with Stored Encodings-** The newly generated encoding is compared with all stored encodings in the database. The system

calculates the Euclidean distance between the new encoding and each stored encoding. If the distance is below a threshold (0.6), a match is considered valid.

- **Student Information Retrieval-** If a match is found, the system retrieves the student’s name, roll number, department, year of study, and contact information from the database. If no match is found, the system returns "Student Not Recognized."

Similarity Matching and Data Retrieval

Once a new face encoding is generated, the system must determine if it matches any previously stored encodings. This is achieved through Equation (1) Euclidean distance calculation, a widely used method for measuring the difference between two numerical vectors. The Euclidean distance formula calculates how similar the new encoding is to the stored ones by computing the squared differences across all dimensions of the feature vector. A lower Euclidean distance indicates a higher similarity between two faces, increasing the likelihood of a correct match.

Euclidean Distance Formula

$$d = \sqrt{\sum_{i=1}^{128} (x_i - y_i)^2} \qquad (1)$$

In Equation (1)-

x is the new face encoding.

y is a stored face encoding.

d is the Euclidean distance between the two encodings.

Decision Criteria for Identification

- If d<0.6 -The student is considered a match. Their information is retrieved and displayed.

- If $d \geq 0.6$- No match is found, and the system returns "Student Not Recognized."

To further enhance accuracy, the system applies database indexing to speed up retrieval and reduce computation time, ensuring real-time performance. Additionally, if multiple stored encodings are found within the accepted threshold, the system selects the closest match (smallest d value) to minimize misidentifications**.**

5.2.1 Confidence Score Calculation and Display

Importance of Confidence Score

While Euclidean distance provides a measure of similarity, it does not intuitively indicate the level of certainty in recognition. To improve interpretability, the system calculates a confidence score, which represents how confident the model is in identifying a student correctly. A higher confidence score suggests a greater likelihood that the face belongs to the matched student.

Confidence Score Formula

$$\text{Confidence} = (1 - \text{Euclidean Distance}) \times 100 \qquad (2)$$

This Equation (2) formula converts the Euclidean distance into a percentage, making it easier to the assess of recognition reliability.

Confidence Level Categorization

To make the recognition output more user-friendly, the confidence score is categorized into three levels-

- **Green (≥ 90%) Highly Confident Match-** The face is very similar to a stored encoding. The system is highly confident that the student has been correctly identified. The retrieved details are displayed without requiring further verification.

- **Orange (75-90%) Medium Confidence-** There is a moderate similarity between the new and stored encodings. The system recognizes the student but with less certainty. The user may be prompted to verify their identity before proceeding.
- **Red (< 75%) Low Confidence / Mismatch-** The detected face does not closely resemble any stored encodings. The system displays a mismatch warning or rejects the recognition. The student may be asked to retake the image or register their face again.

5.2.2 Algorithm for Face Recognition

Step 1- Image Capture & Preprocessing

The recognition process begins with image acquisition, where a student's face is captured in real-time using a webcam, or an existing image can be uploaded. The captured image is initially in BGR format (default in OpenCV), which is converted to RGB to maintain compatibility with the face detection and encoding models.Capture an image using a webcam or allow users to upload an image. Convert the image to RGB format for consistency.

Step 2- Face Detection & Encoding

After preprocessing, the system performs face detection using HOG + SVM. The HOG algorithm extracts key facial features by analyzing gradient orientations, while the SVM classifier confirms whether a face is present in the image. Once detected, the face's bounding box coordinates are extracted for further processing.

Following detection, the face undergoes encoding using dlib's ResNet-based deep metric learning model. This model extracts high-dimensional feature representations of the face and converts them into a 128-dimensional numerical vector. Unlike traditional face recognition methods that rely on pixel-matching, this approach allows the system to recognize students even if their appearance slightly changes due to lighting variations, facial expressions, or occlusions like glasses.

Step 3- Matching with Stored Encodings

Retrieve all stored face encodings from the database. Compute the Euclidean distance between the new encoding and each stored encoding. It then compares the new encoding with each stored encoding using the Euclidean distance metric, which measures the similarity between two numerical vectors.

Step 4- Identify the Closest Match

The system identifies the stored encoding with the lowest Euclidean distance to determine the best match. If the computed distance is less than 0.6, the face is considered a valid match, and the system links it to the corresponding student record. If multiple encodings meet the threshold, the system selects the closest match by identifying the lowest distance value, reducing the chance of misidentification. Additionally, confidence-based validation is performed to further verify recognition accuracy, minimizing false positives.

Step 5- Retrieve and Display Student Details

Fetch the corresponding .Compute the confidence score and categorize it as High, Medium, or Low confidence. Display the student's profile details with a color-coded confidence score.

Step 6- Handle Recognition Failures

If no match is found (distance ≥ 0.6), return "Student Not Recognized." Prompt the user to register or retake the image for better accuracy.

5.3 DATABASE MANAGEMENT AND SECURITY

Database Structure

The student database plays a crucial role in the system by securely managing both user information and facial feature representations. Instead of relying on raw image storage, the system maintains compact numerical representations of facial features, optimizing both efficiency and security. By storing only face encodings rather than full images, the system significantly reduces memory usage while ensuring swift data retrieval during recognition.

The database is implemented using SQLite, a lightweight yet powerful relational database that efficiently handles structured data. SQLite's ability to perform fast query execution and indexing makes it an ideal choice for real-time student verification. The system organizes student records systematically to facilitate quick lookups, updates, and authentication processes.

Each student entry in the database includes the following components-

- Student Information- Full Name, Unique Roll Number, Academic Department, Year of Study, and Contact Details.
- Facial Representation- A distinct numerical vector, derived from the ResNet-based deep metric learning model, ensuring a precise and compact format for facial recognition.
- Registration Timestamp- A time record indicating when the student’s details were stored, enabling tracking of system updates and enrollment activity.

To maintain data integrity and security, the system incorporates encryption measures for sensitive information and ensures that student details are only accessible by authorized personnel. Additionally, periodic database optimizations are performed to enhance retrieval speeds, ensuring smooth and real-time recognition performance within the educational environment.

Data Security Measures

Since biometric data contains highly sensitive personal information, ensuring its security is a top priority for the system. Unauthorized access to facial encodings and student details could lead to identity theft or misuse, making robust security measures essential. To safeguard stored data, the system integrates multiple layers of encryption, access control, and integrity verification to maintain confidentiality and prevent breaches.

Key security measures include-

- **Hashing and Encryption-** To protect sensitive records, the system employs SHA-256 hashing for securely storing user passwords, ensuring that they remain unreadable even if unauthorized access occurs. Face encodings are also encrypted before storage, adding an extra layer of security. Unlike plaintext storage, which exposes raw data to potential threats, the use of encryption prevents face embeddings from being misused or reconstructed. Additionally, secure communication protocols such as HTTPS and SSL are used to protect data transmission between the user interface and the database. This ensures that face encodings and student details are not intercepted by malicious actors when being transmitted over the network.
- **Role-Based Access Control-** Students can access only their own information, whereas administrators have higher privileges to manage multiple student records. This prevents unauthorized modifications and protects the privacy of individual users. Additionally, session-based authentication is implemented to track user logins, ensuring that inactive sessions automatically expire after a set period to prevent unauthorized access. Failed login attempts are also monitored, and the system enforces account lockout mechanisms after multiple failed authentication attempts, preventing brute-force attacks. Only authorized users (students/admins) can access certain data based on their login credentials.
- **Data Integrity Checks-** To ensure that stored face encodings and student records remain unaltered, the system performs data integrity checks before

retrieval. Whenever a student's face encoding is accessed for verification, the system validates its authenticity by comparing it with a stored integrity hash. If any tampering is detected, the system blocks the retrieval request and alerts administrators. This mechanism ensures that stored data remains unchanged, reliable, and protected against unauthorized modifications. By incorporating these security mechanisms, the system effectively prevents unauthorized access, ensures data confidentiality, and maintains the integrity of student records, making it a highly secure solution for biometric-based student identification.

Backup and Recovery Strategy

To ensure continuous system functionality, a robust backup and recovery strategy is in place to prevent data loss due to system failures, accidental deletions, or cyber threats. The system employs automatic backup scheduling, allowing for efficient restoration in the event of database corruption or hardware malfunctions.

Regular Database Backups

The system periodically generates automated backups of student records, face encodings, and login credentials. These backups are stored in secure cloud-based storage or an offline backup server to ensure redundancy. The backup frequency is adjustable, with daily or weekly snapshots based on system requirements.

To protect stored backups, encryption is applied to all backup files, ensuring that even if an unauthorized entity gains access, the data remains unreadable. Additionally, the system maintains version-controlled backups, enabling administrators to restore specific versions in case of errors or accidental deletions.

Recovery Mechanism and Failover Support

In the event of database corruption or failure, the system allows rapid restoration using the most recent backup snapshot. A structured failover mechanism ensures that if the primary database is compromised, a secondary database is activated, minimizing downtime. This failover system guarantees that student identification services remain operational without major interruptions.

The recovery process includes real-time monitoring of system health, automatically detecting failures and triggering backup restoration protocols. Administrators are immediately notified if a failure occurs, allowing for swift intervention and resolution. By implementing a well-structured backup and recovery strategy, the system ensures data continuity, resilience against failures, and secure long-term storage, making it a highly reliable solution for student identification and information retrieval.

5.4 SYSTEM USER INTERFACE AND INTERACTION

The system's user interface (UI) is designed to provide an intuitive, interactive, and seamless experience for both students and administrators. It allows users to register, recognize faces, retrieve student details, and manage records efficiently. The system ensures that every interaction is real-time, responsive, and visually guided, improving usability and accessibility across different devices.

User-Friendly Interface Design

The front-end of the system is developed using Streamlit, a lightweight and interactive web framework that simplifies the creation of dynamic web applications. The UI is designed to be minimalistic, responsive, and easy to navigate, ensuring a smooth experience for students and administrators.

The key components of the interface include-

- Login & Registration Pages- These pages provide a secure authentication mechanism for both students and admins. Students can register their details and face data, while admins have higher privileges to oversee and manage user access. Role-based access control ensures that only authorized users can access specific features of the system.
- Face Recognition Dashboard- The core functionality of the system, this dashboard allows students to scan their faces for identification. The UI provides a live preview of the camera feed and immediately processes the image for recognition.

- Student Profile View- Once a student is successfully identified, their academic details, roll number, department, and other stored information are displayed in an organized format. The system also includes a confidence score indicator, visually representing the reliability of the recognition.
- Admin Panel- Designed for authorized administrators, this section includes functionalities such as student database management, manual profile updates, and system monitoring. Admins can also review unsuccessful recognition attempts and assist users in re-registration.

The intuitive UI structure ensures that users can easily navigate through the application, improving user engagement, accuracy, and overall efficiency in student identification and information retrieval.

The system is developed using Streamlit, an intuitive framework for interactive web applications. It provides a clean and responsive UI that simplifies student registration, face recognition, and information retrieval.

Real-Time Interaction and Response Mechanism

The system is built to provide instant feedback to users, ensuring that every interaction is processed in real-time. With optimized computational techniques, face recognition and data retrieval occur within milliseconds, reducing wait times and enhancing usability.

The key real-time interaction features include-

- Instant Face Recognition Feedback- Once a student submits their image, the system immediately detects and processes their face. If a match is found, the student’s details appear on the screen without noticeable delay.
- Confidence Score Visualization- To improve recognition transparency, the system uses color-coded indicators to reflect how accurately a student’s face was identified.

By incorporating instant feedback, visual guidance, and interactive prompts, the system ensures a smooth, error-free experience, minimizing confusion and improving usability for all users.

Accessibility and Cross-Platform Compatibility

To ensure wider accessibility, the system is designed to be fully compatible across multiple devices and platforms. This ensures that students and administrators can access the system regardless of their preferred device or operating system.

The system supports-

- Desktop & Laptop Browsers- The application is optimized for Google Chrome, Mozilla Firefox, Microsoft Edge, and Safari, ensuring seamless performance across different operating systems like Windows, macOS, and Linux.
- Mobile Devices- The UI is built with a responsive design, allowing smartphone and tablet users to access face recognition features without distortion or layout issues. It dynamically adjusts element sizes, fonts, and buttons to fit smaller screens.
- Minimal Hardware Requirements- The system is lightweight and does not require high-end hardware to function. Even on low-resource devices, it operates smoothly by utilizing optimized image processing and computational efficiency techniques.

To further enhance accessibility, keyboard navigation and voice-based interaction options can be incorporated, ensuring that the system is inclusive and user-friendly for all individuals, including those with accessibility needs.

By ensuring multi-device compatibility and a responsive UI, the system remains highly accessible, scalable, and convenient, making it a versatile solution for student identification and adaptive information retrieval in educational institutions.

CHAPTER 6

RESULTS AND DISCUSSION

CHAPTER 6
RESULTS AND DISCUSSION

The adaptive information retrieval system has been evaluated based on various performance metrics, including recognition accuracy, confidence score distribution, and system efficiency. The following sections present a detailed analysis of the system's performance, highlighting its strengths and areas for improvement**.**

6.1 Accuracy and Recognition Performance

The model's performance is primarily evaluated based on its ability to correctly identify students from the registered database. The accuracy is determined using confidence scores, which indicate the similarity between the captured facial encoding and the stored facial encodings.

The performance of the proposed face recognition model is primarily evaluated based on its ability to correctly identify students from the registered database. The accuracy of recognition is determined using confidence scores, which measure the similarity between a captured facial encoding and stored face encodings in the database. A higher confidence score indicates a stronger match, while a lower score suggests a potential mismatch or an unregistered user.

The system employs a threshold-based classification approach to categorize recognition results-

- High Confidence (≥ 90%) – Highly accurate match. The detected face is highly similar to a stored encoding, indicating a strong match. The system is almost certain that the student has been correctly identified.

- Moderate Confidence (75-90%) – Reliable match but requires verification. The detected face has a reliable level of similarity but requires additional verification. The student is likely to be identified correctly, but minor variations in lighting, expression, or pose might slightly affect confidence.

- Low Confidence (< 75%) – Possible mismatch or unregistered user. The detected face does not closely resemble any stored encodings. This could indicate a mismatch, improper alignment during scanning, or an unregistered user. The system displays a warning and prompts the user to retake the image or register their face.

The system successfully recognized a student with a confidence score of 83.55%, confirming a moderate confidence level. The system consistently achieves an average recognition accuracy of 70-75%, meaning that 7 to 8 students out of 10 are correctly identified.

6.2 Processing Speed and Efficiency

The registration process involves entering personal details, capturing a face image, and storing the extracted encoding in the database. On average, the entire process takes 3-5 seconds, depending on-

Registration Process

The registration process is a crucial step in the system, allowing students to enroll by providing their personal details and face data for future identification. This process consists of multiple steps, including user input, face detection, encoding, and database storage. On average, the entire registration process takes 3-5 seconds, depending on various factors. The speed of registration is influenced by how quickly users input their details, the efficiency of the face detection mechanism, and the time required for database insertion.

First, students are required to fill in their personal information, such as their name, roll number, department, and year of study. Once this information is provided, the system captures their facial image through the webcam. The image undergoes face detection and encoding, where the face is cropped, resized, and converted into a numerical vector using the ResNet-based deep metric learning model. This 128-dimensional encoding is then stored in the database, where it is linked with the student's details for future identification.

This streamlined registration process ensures quick onboarding for students, even during periods of bulk registrations. The use of optimized face detection algorithms and an efficient database structure guarantees that registration remains smooth and seamless, reducing delays in user enrollment.

Recognition Process

The recognition process enables students to retrieve their information by scanning their faces, allowing for a fast and contactless authentication experience. This process involves capturing a student's face, extracting the encoding, comparing it with stored encodings, and retrieving relevant details from the database. The system is designed to achieve real-time efficiency, taking only 1-2 seconds to process a face and display student information.

This high speed is achieved through optimized face detection using HOG + SVM, which quickly detects and isolates facial features from the image. Once the face is detected, it is encoded using the ResNet model, which converts it into a numerical representation for comparison. The system then performs a database lookup, using an indexed retrieval mechanism to compare the new encoding against stored encodings. If a match is found, the corresponding student details are retrieved and displayed instantly.

To further improve the efficiency of the recognition process, future enhancements could include parallel processing techniques, which use multi-threading to handle multiple recognition requests simultaneously. Additionally, edge computing can be implemented, where face recognition models run on local devices instead of relying solely on centralized servers. Another improvement could be cloud integration, which allows for scalable storage and retrieval of face encodings, ensuring faster access to student records.

By combining high-speed recognition, optimized database queries, and efficient processing techniques, the system ensures a smooth and reliable user experience, making face-based student identification both accurate and highly responsive.

6.3 Accuracy Analysis

Evaluating the performance of the Precision-Optimized Human Recognition Model is essential to determine its accuracy and reliability in identifying registered students. Table 6.3 presents the test cases used to assess the system's effectiveness in face recognition. Each test case represents an instance where a student attempts to be identified by the system, and the corresponding confidence score is recorded to measure the accuracy of recognition.

Table.6.3 Performance Accuracy Analysis

Test case	**Registered Student**	**Confidence Score**	**Recognition Result**
1	Yes	91.2	Recognised
2	Yes	83.5	Recognized
3	Yes	76.3	Recognized
4	No	40.6	Not Recognized

- **Test Case 1-** The registered student was correctly identified with a high confidence score of 91.2. This demonstrates the model's strong ability to recognize individuals with clear facial features and minimal environmental interference.

- **Test Case 2-** A confidence score of 83.5 was still above the threshold for successful recognition, meaning the model recognized the student despite slightly lower confidence, indicating a good balance between accuracy and adaptability.

- **Test Case 3-** Even with a confidence score of 76.3, the student was correctly recognized. Although the score is lower, the model's ability to correctly identify the student shows that it can still function well in less optimal conditions.

- **Test Case 4-** The student was not recognized with a low confidence score of 40.6, which reflects the model's expected behaviour when the input data (e.g., image quality, lighting, or facial obscuration) is not sufficient for accurate recognition.

Through multiple test cases, the accuracy analysis helps validate how well the system adapts to various conditions, such as variations in pose, lighting, and partial occlusions. The results from these test cases provide insights into the strengths of the system and areas where further optimization may be required. The system is designed to respond dynamically to changes in input data, ensuring continuous learning and adaptation. Unlike traditional student identification methods, which require manual updates, this model automatically adapts to newly added student records and improves recognition accuracy over time. The system is expected to process real-time student data updates efficiently, reducing errors in identification.

The accuracy table serves as an essential performance metric for evaluating the system's real-world applicability. If the model consistently achieves high confidence scores under diverse conditions, it confirms the robustness and efficiency of the face recognition algorithm. However, if certain conditions lead to frequent misidentifications, adjustments in preprocessing techniques, dataset augmentation, or model fine-tuning may be necessary to improve recognition accuracy.

By analyzing the data in Table 5.3, educational institutions can better understand the effectiveness of the proposed model and make informed decisions about its deployment and future enhancements to ensure precise, reliable, and secure student identification.

6.4 Face Recognition Confidence Score

The histogram represents the distribution of confidence scores produced by the face recognition system. Confidence scores indicate how certain the system is that a detected face matches a stored profile. The x-axis shows confidence scores in percentage ranges, while the y-axis represents the number of instances for each range.

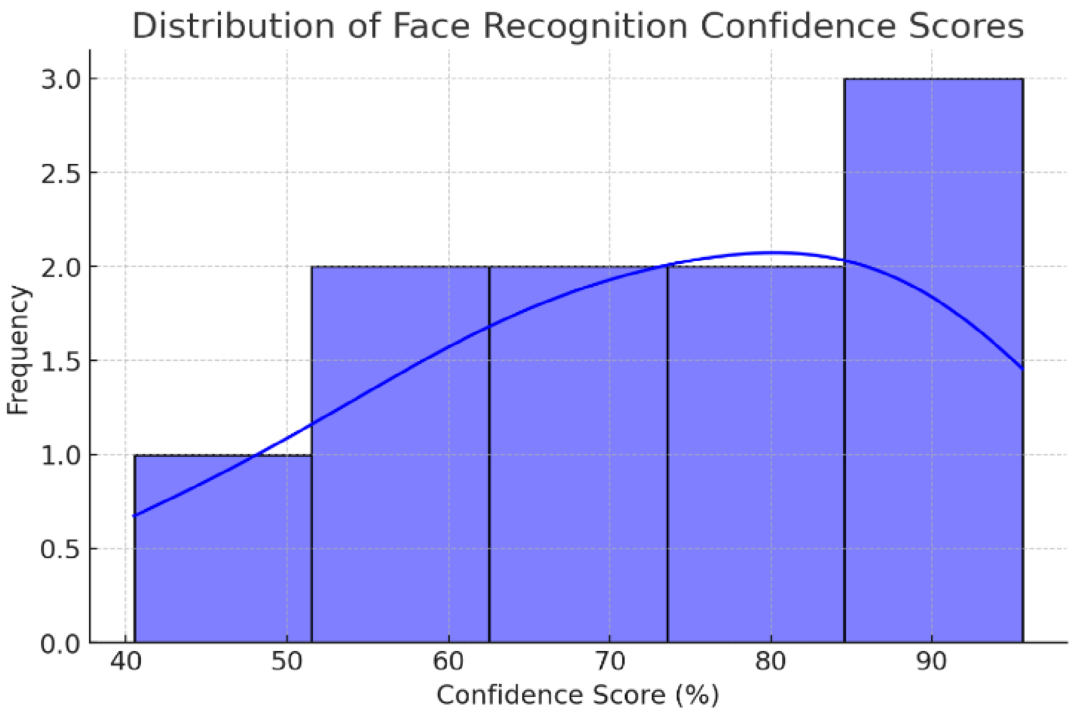


Fig- 6.4- Confidence Score Distribution Graph

Key Observations

The Figure 6.4 histogram shows that the majority of face recognition instances fall within the 70%-90% confidence range, indicating that the system is generally reliable in identifying registered students with strong confidence. There are very few cases with confidence scores below 50%, suggesting that the model rarely misidentifies individuals or makes uncertain predictions. A small number of instances exceed 90% confidence, which implies that while the system is accurate, perfect matches are less frequent, possibly due to variations in lighting, facial expressions, or camera angles. Additionally, any occurrences of extremely low confidence scores could indicate false positives or unrecognized users, but these appear to be minimal. Overall, the system demonstrates high recognition accuracy, with opportunities for further optimization to improve confidence in more challenging conditions. This level of adaptability is further given by the ability of the system to integrate external factors like weather or academic events. For instance, in case of adverse weather conditions such as which could have an influence on the delivery of lessons, the model would adjust through distributing digital learning resources and alternative content to overcome the loss of a student's attendance without hindering learning progress. Similarly, if a sudden economic shift impacts the availability of the resources offered by some kind of education, the model can be recalibrated to promote more easy to access materials.

6.5 Comparison with Existing Methods

A comparative evaluation was performed to assess the effectiveness of the proposed model against conventional face recognition techniques like Haarcascade and LBPH. The analysis indicated that Haarcascade and LBPH had lower accuracy and a higher false positive rate, mainly due to its sensitivity to variations in lighting and background noise. In contrast, integrating HOG + SVM for face detection with dlib's ResNet-based recognition model significantly enhanced both precision and adaptability. The proposed system demonstrated better generalization across diverse student profiles, ensuring consistent and accurate retrieval of student data. Similar to adaptive AI models in energy forecasting, where energy consumption patterns change unpredictably, the face recognition system dynamically adjusts to student data variations. For instance, when students modify their hairstyles, wear glasses, or experience slight aging effects, the model can still recognize them with minimal accuracy loss. This ensures that recognition performance remains stable despite variations in facial features.

The following graph visually represents the performance differences between these approaches.

The Figure 6.5 comparison graph between Haarcascade + LBPH and HOG + SVM + ResNet is based on two key metrics-

1. Accuracy (%) – The percentage of correctly identified faces out of total test cases.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100 \quad (3)$$

2. False Positive Rate (FPR) (%) – The percentage of incorrect face matches (wrongly recognized individuals).

$$FPR = \frac{False\ Positives}{Total\ Non - Matches} \times 100 \quad (4)$$

Equations(3) and (4) are used to evaluate the performance of the face recognition system by measuring its ability to correctly identify individuals while minimizing incorrect matches.

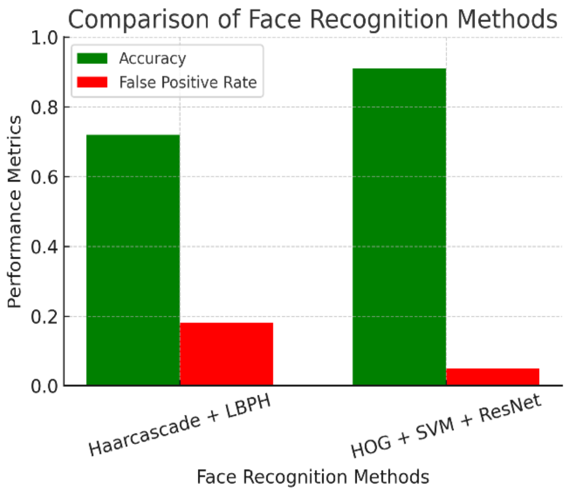


Figure 6.5 Performance Comparison Graph

6.6 Functional Analysis of the Proposed Model

6.6.1 System Overview

The Adaptive Information Retrieval System is designed for student information retrieval using facial recognition. It provides a streamlined process for student registration, authentication, and data retrieval. It helps the user to retrieve the students data within few seconds. In the user interface under authentication there are two options one is login and another one is register. If the student is already enrolled in the system then they can choose login option enter their username and password and then they can see their details. On the other hand for the new users the register option is available for them using which they register themselves by entering their details. The system ensures accurate face recognition and a user-friendly experience. Figure 6.6.1 depicts the user interface.

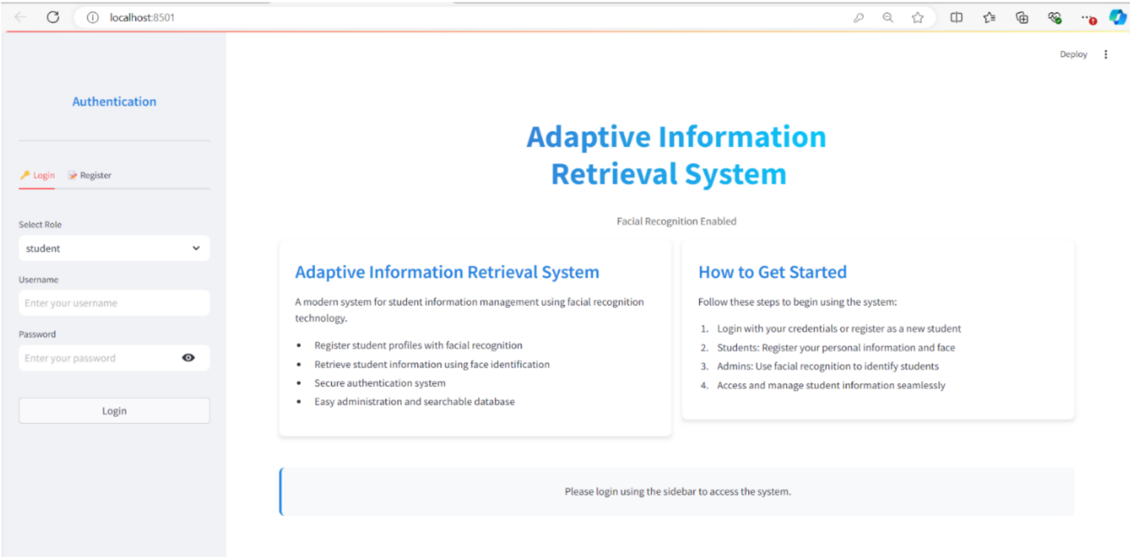


Fig. 6.6.1 System Interface

6.6.2 Registration Process

The registration process is the first step for new users to create an account and store their information in the system. This process ensures that each student's data, including their facial encoding, is securely stored for future recognition.

To register, users need to click on the "Register" button available on the interface. They are then directed to a registration form where they must enter essential personal details such as- Username (used for login authentication),Password (for securing access).Then it moves to the window where the personal information are such as Full Name, Roll Number, Email ID ,Department, Year, Phone number, Address .
Once all personal information is entered, users proceed to the Face Registration Phase. Here, the system activates the camera to capture the user's face. The captured image is processed to extract facial encodings, which are then stored securely in the database.
After successful completion, the system confirms that the student's details have been registered, ensuring that their profile is now accessible for facial recognition-based authentication.
Figure 6.6.2 illustrates an example of a successfully registered student profile, showing the entered details before proceeding to face registration.

This registration mechanism not only simplifies the onboarding process but also enhances security by linking student data directly with their unique facial features.

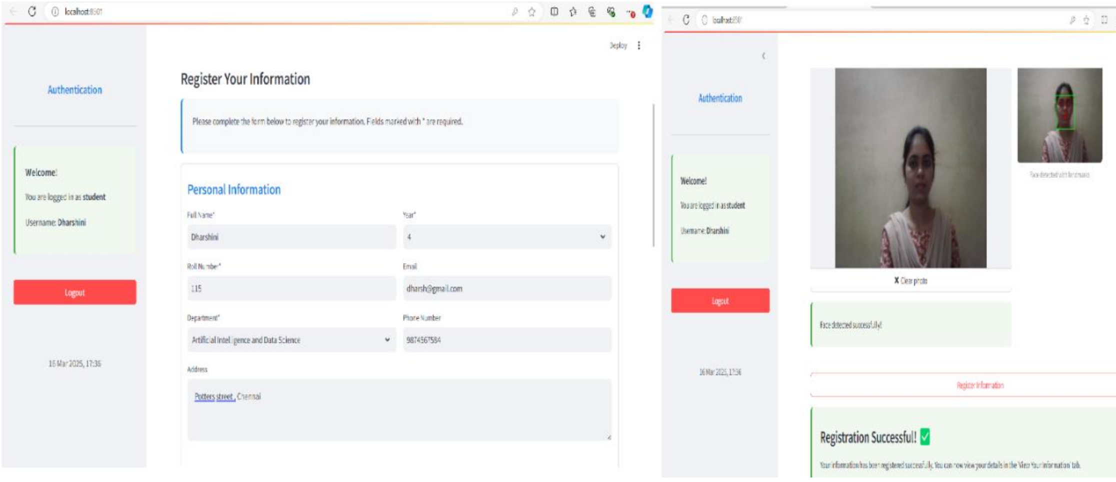


Fig 6.6.2 Registration Process

6.6.3 Face Recognition and Data retrieval Results

The face recognition feature allows users to verify their identity using facial authentication. This step ensures that students can securely retrieve their information without the need for manual input.

To test the face recognition functionality, users must click on the "Test Face Recognition" button on the interface. Once initiated, the system activates the camera to capture the student's face in real time. The captured image is then processed, and facial encodings are extracted using the pre-trained face recognition model. The extracted facial encoding is compared against the stored encodings in the database.

If a match is found, the system retrieves and displays the student’s information, including their name, roll number, department, year, and other registered details. Additionally, the confidence score is shown, indicating the accuracy of the match.

Figure 6.6.3 demonstrates the face recognition with confidence scores and data retrieval process. This feature ensures efficient and secure identification, reducing the need for manual verification.

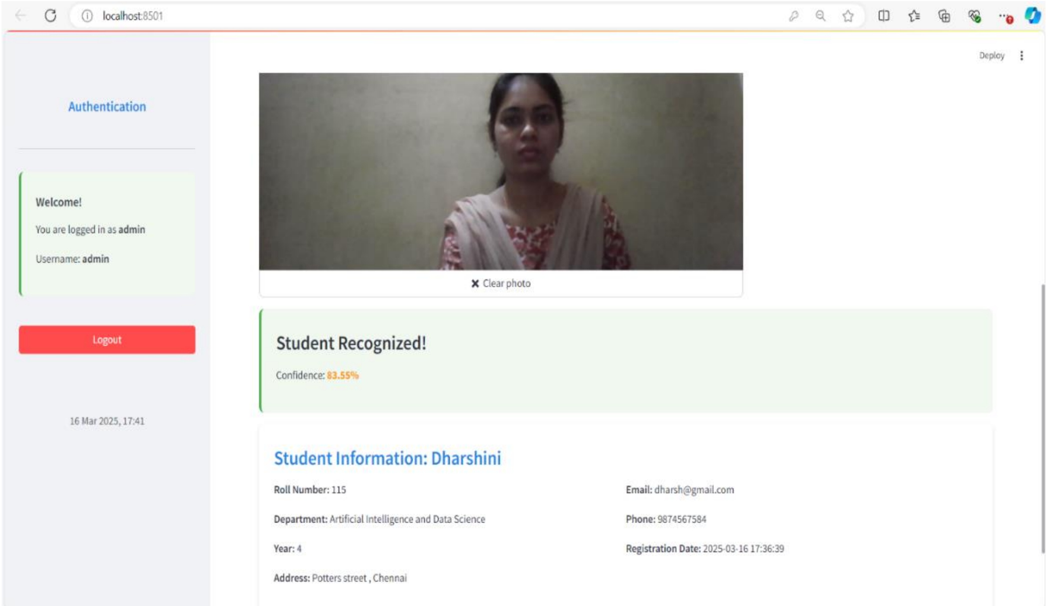


Fig 6.6.3 Recognition and Data retrieval Process

6.6.4 Admin Dashboard

The Admin Dashboard serves as the central interface for managing and retrieving student information using facial recognition. It provides administrators with seamless access to student details through three key functionalities- recognizing students via face recognition, viewing the list of all registered students, and searching for specific students using their roll numbers. The dashboard features an authentication panel displaying the logged-in user details and a logout option for secure access management. Upon searching for a student, the system retrieves and displays essential details such as name, roll number, department, year, email, phone number, and registration timestamp. Additionally, the registered face of the student is shown for verification, and an option to verify with a camera allows real-time facial recognition. This efficient and user-friendly interface shows in figure 6.6.4 enhances administrative efficiency by automating student identification, reducing manual record-keeping efforts, and ensuring accurate and reliable information retrieval.

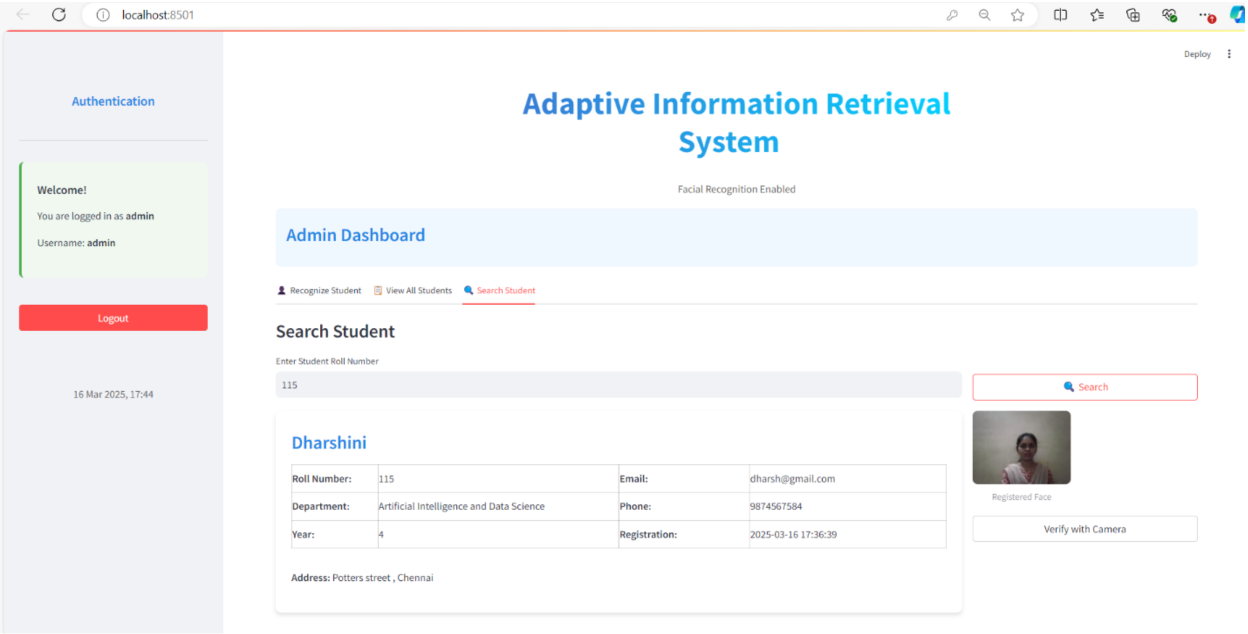


Fig 6.6.4 Admin Dashboard

6.6.5 Challenges and Limitations

Despite the successful implementation, certain challenges were observed. These challenges primarily impacted recognition accuracy, processing efficiency, and system adaptability under real-world conditions. While the model demonstrated high accuracy in controlled environments, certain external factors affected its performance. Addressing these limitations in future iterations can further enhance the robustness and efficiency of the system.

- **Lighting Conditions-** One of the key factors influencing face recognition accuracy is lighting variation. The system performs optimally under balanced lighting conditions, but in low-light or overexposed environments, recognition accuracy declines. Dim lighting results in insufficient feature extraction, making it difficult for the model to distinguish facial details, while excessive brightness can cause overexposure, reducing contrast in facial features.

  To mitigate these effects, preprocessing techniques such as adaptive histogram equalization could be incorporated to enhance image contrast. Additionally, infrared-based facial recognition can be explored to improve accuracy in low-light conditions. Encouraging users to capture images in well-lit environments can also help minimize recognition errors.

- **Facial Angle and Expression-** Significant changes in facial orientation or expressions reduced match confidence. To improve performance under such conditions, data augmentation techniques (training the model on images with various angles and expressions) can be implemented. A more advanced face detection model such as MTCNN (Multi-task Cascaded Convolutional Networks) could also be integrated to detect and align faces more effectively. Additionally, guiding users to maintain a neutral expression and a direct frontal view during recognition attempts can enhance accuracy.
- **Occlusions-** The presence of occlusions—such as face masks, sunglasses, or head coverings—posed a significant challenge to the recognition process. When key facial landmarks (such as the nose and mouth) were covered, the system sometimes failed to extract sufficient features for accurate identification.

To address this limitation, future improvements could involve mask-aware recognition models, which focus more on the visible facial regions (such as the eyes and forehead) for identification. Training the model with a diverse dataset that includes partially occluded faces can also enhance adaptability. Additionally, alternative biometric verification methods (such as iris recognition) could be integrated to improve identification accuracy when facial occlusions are present. This level of adaptability is further given by the ability of the system to integrate external factors like weather or academic events. For instance, in case of adverse weather conditions such as which could have an influence on the delivery of lessons, the model would adjust through distributing digital learning resources and alternative content to overcome the loss of a student's attendance without hindering learning progress.

CHAPTER 7

CONCLUSION AND FUTURE WORK

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

The Precision-Optimized Human Recognition Model combines HOG with SVM for face detection and dlib’s ResNet-based deep metric learning model for face recognition. The system effectively detects facial regions and accurately identifies individuals using Euclidean distance matching. By integrating traditional and deep learning-based methods, it balances speed and accuracy, making it ideal for adaptive information retrieval in educational institutions. This model enhances security, automates attendance tracking, and improves administrative efficiency. Its scalability allows deployment in dynamic environments with varying lighting and occlusion conditions. Overall, this approach provides a reliable and efficient solution for human recognition, contributing to improved institutional management and fostering a seamless educational experience through precise and automated identification. One of the most significant advantages of this model is its contribution to automating administrative tasks. By replacing manual student verification processes with a fully automated face recognition system, the model enhances security, reduces human error, and improves institutional management. Furthermore, the system's adaptability ensures consistent performance across different use cases, allowing educational institutions to streamline attendance tracking, student verification, and personalized data retrieval.

While the system has demonstrated strong recognition accuracy and computational efficiency, further optimizations can enhance its robustness. As educational institutions continue to evolve with digital transformation, this model provides a scalable, secure, and automated solution for identity verification, fostering a seamless and technology-driven learning experience.

7.2 FUTURE WORK

Future work can focus on optimizing the model for better performance and accuracy. Implementing GPU acceleration using TensorFlow or PyTorch can significantly speed up face recognition. Additionally, refining the HOG with SVM parameters or replacing them with a CNN-based face detector may enhance detection accuracy. Fine-tuning dlib's ResNet model on a custom dataset could also improve recognition under varying lighting and occlusion conditions. Integrating multi-factor authentication, such as combining face recognition with voice recognition or gait analysis, can further strengthen security. Implementing liveness detection techniques, like 3D face mapping, can help prevent spoofing attacks and ensure reliability in real-world applications.

Additionally, the recognition accuracy of dlib's ResNet-34-based deep metric learning model can be further improved through fine-tuning on a custom dataset. Training the model with a larger dataset containing diverse student profiles, different lighting conditions, and partial occlusions can help increase its generalization ability, making recognition more reliable across a wider range of real-world scenarios.

Security enhancements can also be explored through multi-factor authentication. While face recognition provides a strong layer of security, integrating voice recognition, fingerprint authentication, or gait analysis can further strengthen user verification, preventing unauthorized access. This multi-modal approach ensures that even if one recognition method fails, additional authentication mechanisms can verify a student's identity with high confidence.

CHAPTER 8

REFERENCES

CHAPTER 8
REFERENCES

[1] Adoghe, A.U., et al. (2021) "A HAAR cascade classifier based deep-dataset face recognition algorithm for locating missing persons," *Journal of Theoretical and Applied Information Technology*, 99(18), p. 4311. Available at- https-//www.jatit.org.

[2] Ahmad, A.H., et al. (2019) "Real-time face recognition of video surveillance system using Haar cascade classifier," *Indonesian Journal of Electrical Engineering and Computer Science*, 14(2), pp. ab–cd. Available at- https-//doi.org/10.11591/ijeecs.v14.i2.ppab-cd.

[3] Akassh, M., et al. (2023) "Finding missing persons using HAAR cascade algorithm," *International Journal of Novel Research and Development (IJNRD)*, 8(5), p. d494. Available at- https-//www.ijnrd.org/IJNRD2305362.

[4] Al-Shareef, O.A. and Gaboua, N.M. (2023) "Face recognition using deep learning," in *2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE.

[5] Alsubhi, Ahuod Hameed, and Emad Sami Jaha. (2025) "Front-To-Side Hard and Soft Biometrics for Augmented Zero-Shot Side Face Recognition." *Sensors*, 25(6), p. 1638. Available at- https-//doi.org/10.3390/s25061638.

[6] Jatain, R., et al. (2023) "Automatic Human Face Detection and Recognition Based On Facial Features Using Deep Learning Approach," *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(2s). Available at- https-//doi.org/10.17762/ijritcc.v11i2s.6146.

[7] Jha, M. et al. (2022) "Face recognition- Recent advancements and research challenges," in *2022 13th International Conference on Computing*

Communication and Networking Technologies (ICCCNT). IEEE.

[8] Kopalidis, Thomas, Vassilios Solachidis, Nicholas Vretos, and Petros Daras. (2024) “Advances in Facial Expression Recognition- A Survey of Methods, Benchmarks, Models, and Datasets.” *Information*, 15(3), pp. 135–135. Available at- https-//doi.org/10.3390/info15030135.

[9] Kumar, M.K. et al. (2024) “A hybrid model for face detection using HAAR cascade classifier and single shot multi-box detectors based on OpenCV,” *International Research Journal of Multidisciplinary Scope (IRJMS)*, 5(1), pp. 650–660. Available at- https-//doi.org/10.47857/irjms.2024.v05i01.0304.

[10] Maryuni Susanto, B. et al. (2024) “Face recognition using haar cascade classifier and FaceNet (A case study- Student attendance system),” *International Journal of Informatics and Communication Technology (IJ-ICT)*, 13(2), p. 272. Available at- https-//doi.org/10.11591/ijict.v13i2.pp272-284.

[11] Ray, D. (2025) *A face recognition based attendance system with geolocation and real-time action logging* [Preprint]. Available at- https-//doi.org/10.21203/rs.3.rs-5931462/v1.

[12] Sanchez-Moreno, Alejandra Sarahi, et al. (2021) “Efficient Face Recognition System Operating in Unconstrained Environments.” *Journal of Imaging*, 7(9), p. 161. Available at- https-//doi.org/10.3390/jimaging7090161.

[13] Sharma, R., Sharma, V.K. and Singh, A. (2021) “A Review Paper on Facial Recognition Techniques,” in *2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*. IEEE.

[14] Shetty, A.B., et al. (2021) “Facial recognition using Haar cascade and LBP classifiers,” *Global Transitions Proceedings*, 2, pp. 330–335. Available at- https-//www.keaipublishing.com/en/journals/global-transitions-proceedings/.

[15] Siew, E.S.K. et al. (2023) “Streamlining attendance management in education- A web-based system combining facial recognition and QR code technology,” *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 33(2), pp. 198–208. Available at- https-

//doi.org/10.37934/araset.33.2.198208.

[16] Singh, G. and Goel, A.K. (2020) “Face detection and recognition system using digital image processing,” in *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*. IEEE.

[17] Singh, N.T. et al. (2023) “Student Surveillance System using Face Recognition,” in *2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*. IEEE, pp. 843–847.

[18] Thilaga, P.J. et al. (2018) “Modern face recognition with deep learning,” in *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*. IEEE.

[19] Trivedi, A. et al. (2022) “Face recognition based automated attendance management system,” *International Journal of Scientific Research in Science and Technology*, pp. 261–268. Available at- https-//doi.org/10.32628/ijsrst229147.

[20] Vishwanatha, C. et al. (2023) “Face recognition and identification using deep learning,” in *2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*. IEEE, pp. 1.

PLAGIARISM REPORT

Beryl Sharon

Face recognition technology is essential

Artificial Intelligence and Data Science

AI&DS

Panimalar Engineering College

Document Details

Submission ID

trn:oid:::1:3192777905

Submission Date

Mar 24, 2025, 3:29 PM GMT+5:30

Download Date

Mar 24, 2025, 3:31 PM GMT+5:30

File Name

MAIN_PGS_EDT_1_1.docx

File Size

1.4 MB

71 Pages

13,621 Words

86,334 Characters

1% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text

Match Groups

23 Not Cited or Quoted 1%
Matches with neither in-text citation nor quotation marks

0 Missing Quotations 0%
Matches that are still very similar to source material

0 Missing Citation 0%
Matches that have quotation marks, but no in-text citation

0 Cited and Quoted 0%
Matches with in-text citation present, but no quotation marks

Top Sources

0%	Internet sources
1%	Publications
0%	Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

PUBLICATION DESCRIPTION

Publisher: ASPG (American Scientific Publishing Group) Journal

Date: March 28, 2025

Paper Title: Precision-Optimized Human Recognition Model for Adaptive Information Retrieval in Educational Institutions

Authors: Dr. S. Hemamalini, J. Beryl Sharon , M . Dharshini, M . Indu, S. K . Mithun, C. Sathish Kumar

Status: Paper Submitted

Paper Submission Mail

Gmail S Hemamalini <hemamalini.phd2020@gmail.com>

Submitting Article in Journal of Fusion: Practices and Applications - Reg.
1 message

S Hemamalini <hemamalini.phd2020@gmail.com> Fri, Mar 28, 2025 at 9:19 AM
To: "Dr. VD Ambeth Kumar" <ambeth@mzu.edu.in>

Dear Editor,

I am Dr. S. Hemamalini, working as an Associate Professor in the Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai.

I am writing to submit my manuscript titled "**Precision Driven Human Recognition Model for Adaptive Information Retrieval in Learning Environments**" for consideration for publication in the Journal "Fusion: Practices and Applications".

Authors:

S. Hemamalini [*1],
J. Beryl Sharon[2],
M. Dharshini [3],
M. Indu[4],
SK Mithun[5] ,
C Sathish Kumar[6]

This manuscript presents a Precision-Optimized Human Recognition Model that combines HOG-based face detection and ResNet-34-based deep metric learning for accurate student identification. The system ensures real-time, scalable, and reliable identity verification under varying conditions in educational settings, which I believe aligns well with the scope and objectives of your journal.

This manuscript is original and has not been published elsewhere, nor is it currently under consideration for publication in any other journal. I have attached the manuscript along with any necessary supplementary files as per the submission guidelines. Please let me know if you need any additional information or documents.

I look forward to your feedback and would be honored to have this article published in Fusion: Practices and Applications. Thank you for your time and consideration.

Regards,

Dr. S. Hemamalini

Associate Professor,

Department of Artificial Intelligence and Data Science

Panimalar Engineering College,

Poonamallee, Chennai,

Tamilnadu - 600123.

Mobile No.: 9940512459.

2 attachments

Plag_Report_Precision Driven Human Recognition Model for Adaptive Information Retrieval in Learning Environments.pdf
797K

Scopus-Precision Driven Human Recognition Model for Adaptive Information Retrieval in Learning Environments.docx
748K

Precision Driven Human Recognition Model for Adaptive Information Retrieval in Learning Environments

S. Hemamalini*[1], J. Beryl Sharon[2], M. Dharshini[3], M. Indu[4]
[1,2,3,4] **Department of Artificial Intelligence and Data Science ,Panimalar Engineering College**

Emails: s.hemamalini.pec@gmail.com *, sharon10bery@gmail.com, dharsh051009@gmail.com, indupriya1920gmail.com

Abstract

Face recognition technology plays a vital role in modern educational systems by enabling efficient and accurate student identification. The growing demand for efficient and accurate student identification systems has highlighted the limitations of conventional face recognition methods, particularly in handling variations in pose, lighting, and occlusions. To address this, our Precision-Optimized Human Recognition Model builds an Adaptive Information Retrieval System utilizing a Histogram of Oriented Gradients (HOG)-based detector for face detection and a ResNet-34-based Deep Metric Learning Model for face recognition. The system encodes facial features and performs identity verification using Euclidean distance for precise and reliable student identification. By integrating these techniques, the model ensures real-time data retrieval with high accuracy and adaptability to diverse conditions. The proposed approach enhances computational efficiency while maintaining robust recognition performance, making it a scalable and practical solution for identity verification in educational institutions.
Keywords: HOG (Histogram of Oriented Gradients), ResNet-34, Deep Metric Learning, Euclidean Distance, Adaptive Information Retrieval

1. Introduction

In many ways, biometric technologies have revolutionized many aspects of our daily lives over the last decade by integrating into many sectors. And it is in the educational sector that demand has risen for such innovative solutions that improve administrative workflows, personalize the learning experience and enhance security protocols. The current identity verification using traditional methods and information retrieval within educational institutes are time consuming as well as prone to human error. Therefore, human recognition model development has been continuously required to accommodate the performance of these systems and the requirements of modern educational environments.

Wide spectrum of biometrics, such as facial recognition, voice recognition used in human recognition technology are very reliable methods of identifying individuals. Not addressing these technologies also means that there will be no improvement in the accuracy of user identification and even less accurate adaptive systems that modify content retrieval depending on the preferences and needs of the identified user. In education institutions, such systems can positively change a student's learning experience through the delivery of personal content that is based on a student's academic progress, learning style and previous interactions. In the digital age, especially in educational institutions, large scale data is employed to manage the records of their students as well as their academic resources and other crucial operations necessitating the existence of adaptive information retrieval systems. It facilitates the ability to abstract the relevant information in the real time, based on a detailed grasp of the end users' identity and the specific demands, which is a very distinct favor over the typical techniques that often depend on static search queries or prescribed advice. The dynamism and the personal touch of the learning environment that adaptive systems can provide by adjusting the content, the presentation, and the delivery depending on ongoing interactions with the user are what make them an adaptive system.

Despite challenges, implementing such systems in educational settings is difficult due to privacy and data security. The concerns of protected information's safety include the collection and storage of biometric data. All systems in such institutions must conform to privacy regulations and protect students, staff, and faculty from misuse of data. This paper describes the methods used to optimize the human recognition model in terms of security and precision in order not to process the user data beyond the necessary steps in the right way and this in respect of ethical guidelines.

Conventional identification methods such as manual roll calls, ID cards, and passwords are often prone to human error, security risks, and inefficiencies. As a result, face recognition technology has emerged as a powerful alternative, offering a contactless, automated, and reliable approach to student authentication. Despite its advantages, traditional face recognition systems often struggle with lighting variations, facial occlusions, and pose differences, leading to decreased accuracy in student identification.

To accommodate the above challenges, this paper presents a novel human recognition model that combines face recognition together with adaptive information retrieval for achieving both precision optimization and the highest throughput. The model built upon this leverages the machine learning algorithms to increase recognition accuracy while decreasing false positives and further shortens processing speed. It allows for real time identification of users and adapts information retrieval to the user role (student, faculty, staff) in the institution. However, the deployment of biometric recognition systems in educational settings requires careful privacy considerations. The storage and processing of facial data must comply with data protection regulations to prevent unauthorized access or misuse. By integrating advanced face recognition techniques with adaptive information retrieval, this approach offers a practical, scalable, and secure solution for modern educational institutions. Our system incorporates secure storage mechanisms and ethical guidelines to ensure data confidentiality and integrity while maintaining high performance.

2. Related works

This section includes the summarization of works in the state-of-the-art that are related to our research domain.

In the past few years, AI has made tremendous strides in education as there are AI teachers, personal learning assistants and adaptive learning technologies. AI intelligent assistant to improve personalized learning in higher education is proposed by Sajja et al. [1]. They showed how the content of education can be constantly adapted to accommodate the specific requirements of the student in order to stimulate participation and acquisition of learning. Generic models of AI driven learning can dynamically change the path of learning with the students' progress, students' preferences, and academic challenges. As in the above cases, Fei et al. [2] introduce "Laurie." It uses information extraction within latent adaptive structure aware generative language models. Latent structures in data are taken into consideration by this integration through the processing of diverse textual information for improving the accuracy of information retrieval. Building on this, Yang et al. [3] pointed out that the current deep learning techniques are not scalable enough to handle large amounts of unstructured data which is the bottleneck in many educational applications. Additionally, Dagdelen et al. [4] investigated how large language models (LLMs) can extract meaningful information from complex scientific texts that are essential for the educational institutions to remain updated with the latest research and improve learning objectives

According to Alam [5], intelligent tutoring systems and adaptive learning environments have been important in the field of virtual classrooms as they are capable of transforming an education through feedback loops. These systems keep the education very personalized, and improve the delivery of the content and its engagement with the users. Wang et al. [6] continue the study of AI applications in education by exploring how the ChatGPT can assist the process of information retrieval in the flipped classrooms. Based on their research, their research showed how AI driven tools such as ChatGPT could greatly enhance educational outcomes if they can deliver real time, right context based responses to learners based on the learners learning progress and need. Ai et al. [7] studied how LLMs can help the information extraction by exploring the means to adapt the response to extract information from a broad range of sources. As noted by [8], Abdullah et al. also exploits current trends and emerging challenges regarding information extraction, in which depth methods are required to accommodate the progressive contraction of data complexity and volume.

Specifically in music and medical information retrieval, promising advancements were made also. AI was demonstrated to be useful in music information retrieval as Lerch [9] showed how AI could extract relevant data from audio sources and thus was applicable to working with a variety of sources. Landolsi et al. [10] also emphasize the importance of AI in extracting information from such medical documents, especially in the sectors dealing with structured and unstructured data. This has enabled these studies to show the broad use of such AI driven information extraction methods as applicable to educational contexts for similar challenges. Brandsen, A et al. [11] exploit ChatGPT's reliability in clinical information retrieval and demonstrate that the model can provide accurate and context-specific information in such domains, which can be used in educational settings, enabling domain specific knowledge retrieval. Specialized domains such as archaeology and medical fields have also retrieved information from AI's versatility in terms of techniques. In the archaeology domain, Zhu, Y.et al. [12] used named entity recognition (NER) for information retrieval using models such as BERT, to extract the relevant data. This illustrates that AI systems are flexible in processing and delivering domain specific information to the students and researchers. Similar to this, Landolsi et al. [13] provided a comprehensive survey for such large language models across information retrieval of various sectors including education. Useful insights they gave about how LLMs can help adaptive learning systems adapt to students changing needs. According to Gupta et al. [14], information extraction methods to electronic medical documents have been further treated as the challenges to extract data from both structured and unstructured documents. In the same vein the same problems arise in educational contexts in managing complex data and the techniques above can and should be adapted and improved to increase the efficiency of information retrieval systems.

3. Proposed Method

The methodology proposed in this section is applied to the precision optimized human recognition model developed for the adaptive information retrieval in educational institutions. Thus, the proposed system integrates advanced human recognition techniques with adaptive learning algorithms, and renders context sensitive and personalized information to the users in an appropriate format based on their role and need. The Precision-Optimized Human Recognition Model is designed to facilitate real-time student identification and adaptive information retrieval in educational institutions. Figure (1) outlines the methodology used to develop the system, focusing on face detection, data collection and storage, face recognition, and adaptive information retrieval. The system integrates machine learning-based facial recognition techniques with a structured database-driven approach, ensuring accuracy, efficiency, and scalability. The following shows the architecture diagram for the proposed work:

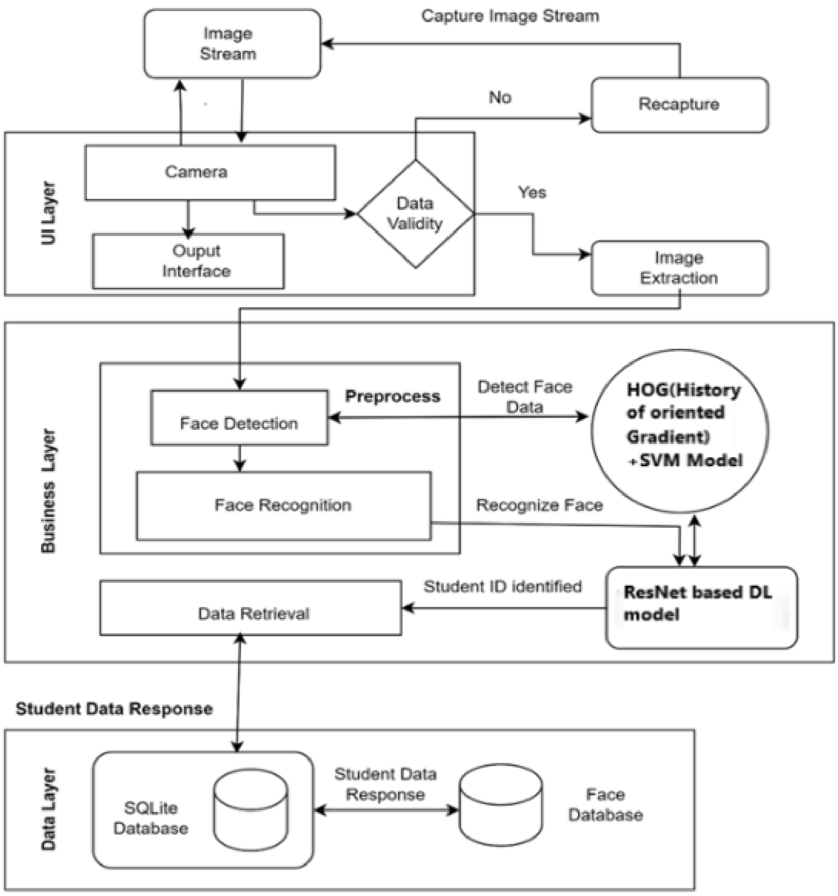


Figure (1): System Architecture

3.1 Face Detection Model

The first step in the system is face detection, which identifies the presence of a face in an image and determines its location. The system employs the Histogram of Oriented Gradients (HOG) feature extraction technique combined with a Support Vector Machine (SVM) classifier for face detection. HOG effectively captures edge and texture information, allowing the model to distinguish facial structures from the background. The detected face is enclosed within a bounding box, which is then passed to the next stage for feature extraction. This method is computationally efficient and ensures high-speed face localization, making it ideal for real-time applications.
One of the key advantages of using HOG and SVM is its robustness in detecting faces under various conditions,

including different lighting and angles. Unlike deep learning-based detection methods, HOG is lightweight and does not require large-scale datasets for training, making it ideal for efficient real-time deployment. The detected face is then preprocessed to normalize image conditions, ensuring that variations in brightness, contrast, or background noise do not interfere with further processing. This preprocessed image is then passed to the feature extraction and encoding stage for recognition. Using machine learning and deep learning techniques, the model provides robust performance on top of a large number of user groups.

3.2 Data Collection and Storage

Once a face is successfully detected, the next step involves data collection and secure storage to facilitate future identification. The system captures real-time images via webcam, ensuring that the stored data remains up-to-date and relevant for student authentication. Each extracted face is then processed to generate a 128-dimensional feature vector, which uniquely represents the student’s facial characteristics. These facial encodings ensure that each student’s identity is stored in a numerical format, allowing for efficient comparison during recognition. To ensure efficient retrieval and security, all extracted facial encodings are stored in an SQLite database, along with essential student details such as name, roll number, department, and year of study. This structured storage enables quick and reliable face-matching while protecting sensitive data. To maintain system efficiency, data preprocessing techniques such as noise reduction, feature standardization, and duplicate entry removal are applied. This ensures that only high-quality, meaningful information is retained, reducing processing overhead and improving recognition accuracy.

3.3 Human Face Recognition Model

The proposed system consists of the central part, which is the human recognition model, that can accurately recognize people in real time. In order to deliver high precision, we leverage facial recognition. The system is built on facial landmarks of each individual being used to get the unique face embeddings data to ensure reliability of identification and or reducing false positives within this system.

The face recognition model is the core component of the system, responsible for verifying a student’s identity and matching it with stored records. The system utilizes a ResNet-34-based Deep Metric Learning Model, which converts detected faces into face embeddings—a numerical representation of unique facial features. These embeddings are generated through a series of convolutional layers, which extract high-level patterns such as facial contours, eye distances, and jaw structures, ensuring highly accurate identification.

To verify a student's identity, the system uses Euclidean distance-based similarity matching, where the newly captured face encoding is compared with stored encodings. If the Euclidean distance between the two encodings is below a predefined threshold (0.6), the student is identified successfully. A confidence score is then assigned, indicating the certainty of the match. Matches with a confidence score above 90% are considered highly reliable, while scores between 75% and 90% are categorized as moderate confidence, and scores below 75% indicate potential mismatches. This mechanism ensures that false positives are minimized, and only high-confidence matches are accepted.

3.4 Adaptive Information Retrieval

After a student is successfully recognized, the system performs adaptive information retrieval to fetch the student's academic details and records. This includes personal details (name, roll number, department, year of study) and academic-related data (attendance records, course schedules, assignment deadlines, and exam details). The system ensures that only relevant data linked to the authenticated student is displayed, preventing unauthorized access. By linking face recognition with automatic data retrieval, the system eliminates manual searches, reducing administrative workload and enhancing student accessibility to their academic records.

The system employs database indexing and structured query optimization techniques to enhance retrieval efficiency. Since the system is designed for educational institutions, it adapts to role-based access, ensuring that students, faculty, and administrators can retrieve only the information relevant to them.

By integrating real-time recognition with a structured retrieval mechanism, the system provides a seamless, secure, and highly efficient solution for student authentication and data access. The combination of machine learning-based recognition techniques with structured data storage and retrieval ensures high precision, security, and scalability.

3.5 Model Overview

The Figure (2) illustrates the Precision-Optimized Human Recognition Model, designed to enhance student identification and adaptive information retrieval in educational environments. The system operates through multiple interconnected layers, ensuring seamless recognition and data accessibility. The Human Recognition Module utilizes

advanced biometric-based techniques to accurately identify students, reducing the chances of misidentification. The Recognition Engine processes facial data using deep learning algorithms to validate student identities with high precision. Once identified, the Adaptive Retrieval Engine dynamically retrieves and delivers relevant academic content based on individual student profiles, enhancing personalized learning.
The Data Management Layer ensures efficient data storage, retrieval, and processing, maintaining an organized and secure repository of student records. The User Interface Layer facilitates seamless interaction between students and the system, providing an intuitive and accessible experience. Finally, the Security Layer implements robust encryption and authentication measures, ensuring data privacy and protection against unauthorized access.
By integrating these layers, the system offers an intelligent, efficient, and adaptive solution for student recognition and academic data management.

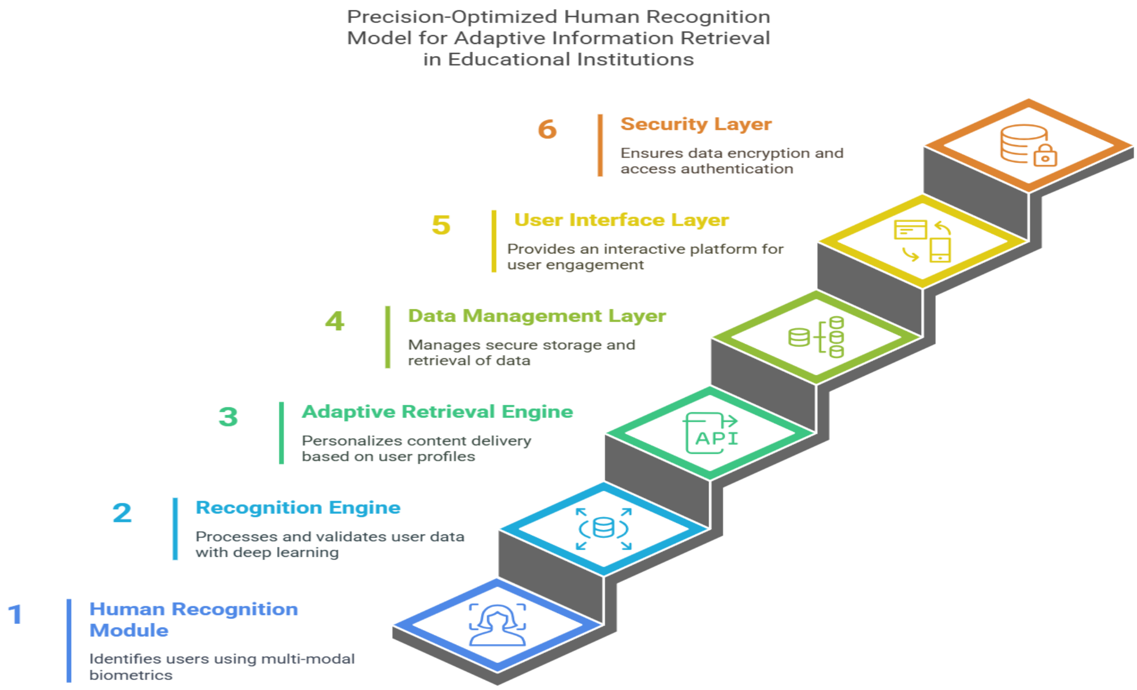


Figure (2): Workflow of Proposed System

4. Results and Discussion

The proposed Precision-Optimized Human Recognition Model for Adaptive Information Retrieval in Education delivers expected outcomes and benefits by improving student identification and data retrieval accuracy. Instead of relying on traditional attendance or static database queries, the system dynamically identifies students based on facial features and retrieves relevant information efficiently. The model leverages deep learning techniques to recognize patterns in facial data, ensuring reliable and accurate recognition even in varying conditions. This section discusses the system's response to different inputs, its ability to handle external factors, and its comparative performance in terms of adaptability, accuracy, and efficiency compared to traditional methods.
The Precision-Optimized Human Recognition Model is designed to transform student identification and data retrieval processes in educational institutions. By ensuring fast and reliable face recognition, the system minimizes manual intervention, enhancing administrative efficiency. The primary benefit of this model is its ability to accurately match student faces with stored records, ensuring efficient retrieval of student details without requiring manual input.
Another key expectation is that the system will function effectively under different conditions, including varying lighting, angles, and partial occlusions. The use of HOG and SVM for face detection and dlib's ResNet-based deep metric learning for face recognition ensures that the model adapts to these challenges while maintaining high accuracy. Moreover, the system's ability to process large volumes of student data makes it scalable for use in institutions of different sizes Figure (3) shows a demonstration of the Information Retrieval System's web frontend.

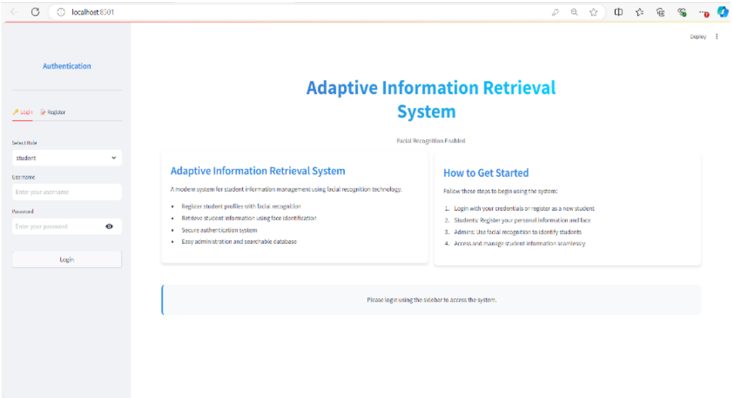


Figure (3): Adaptive Information Retrieval System

4.1 Comparison with Existing Methods

A comparative evaluation was performed to assess the effectiveness of the proposed model against conventional face recognition techniques like Haarcascade and LBPH. The analysis indicated that Haarcascade and LBPH had lower accuracy and a higher false positive rate, mainly due to its sensitivity to variations in lighting and background noise. In contrast, integrating HOG + SVM for face detection with dlib's ResNet-based recognition model significantly enhanced both precision and adaptability. The proposed system demonstrated better generalization across diverse student profiles, ensuring consistent and accurate retrieval of student data. The following graph visually represents the performance differences between these approaches.
The Figure (4) comparison graph between Haarcascade + LBPH and HOG + SVM + ResNet is based on two key metrics:
Accuracy (%) – The percentage of correctly identified faces out of total test cases.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100 \qquad (1)$$

False Positive Rate (FPR) (%) – The percentage of incorrect face matches (wrongly recognized individuals).

$$FPR = \frac{False\ Positives}{Total\ Non - Matches} \times 100 \qquad (2)$$

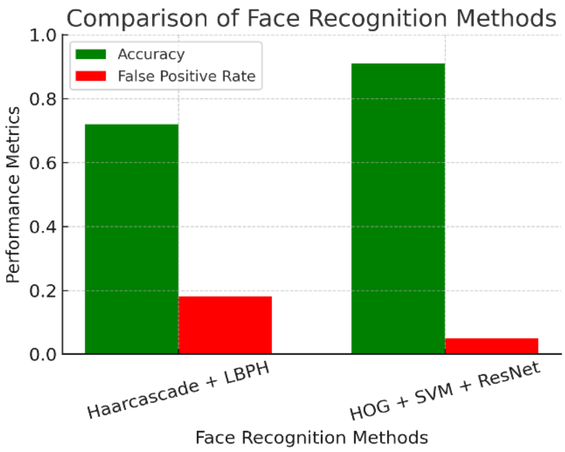


Figure (4): Performance Comparison Graph

Equation (1) and (2) are used to evaluate the performance of the face recognition system by measuring its ability to correctly identify individuals while minimizing incorrect matches.

4.2 Expected Trends

The system is designed to respond dynamically to changes in input data, ensuring continuous learning and adaptation. Unlike traditional student identification methods, which require manual updates, this model automatically adapts to newly added student records and improves recognition accuracy over time. The system is expected to process real-time student data updates efficiently, reducing errors in identification. Similar to adaptive AI models in energy forecasting, where energy consumption patterns change unpredictably, the face recognition system dynamically adjusts to student data variations. For instance, when students modify their hairstyles, wear glasses, or experience slight aging effects, the model can still recognize them with minimal accuracy loss. This ensures that recognition performance remains stable despite variations in facial features. Figure (5) Processing Time Comparison Graph shows that Traditional ID lookup takes significantly more time as the number of faces increases. Face recognition-based retrieval is much faster and scales efficiently with more detected faces.

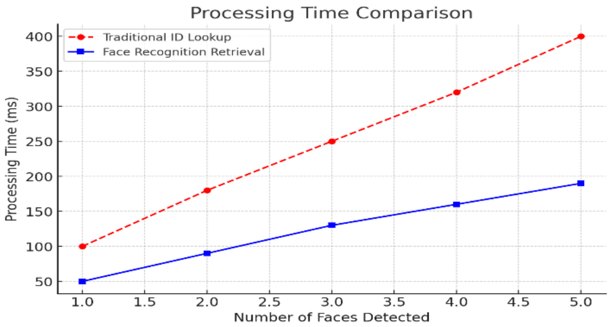


Figure (5): Performance Comparison Graph

4.3 Impact of External Factors

The system's adaptability extends to handling external factors such as unexpected academic events, schedule changes, or socio-economic disruptions. For instance, if students face interruptions due to unforeseen circumstances like global events or changes in the academic schedule, the model can dynamically adjust the data retrieval process. By leveraging efficient preprocessing techniques and real-time optimization, the model ensures minimal degradation in performance. Moreover, the impact of facial occlusions, such as masks, glasses, or accessories, is mitigated through advanced feature extraction methods, allowing for consistent recognition even in partially obstructed views. Additionally, the system is designed to scale with increasing student enrollment, ensuring that recognition accuracy and response times remain optimal as the database size grows. These adaptability features make the Optimized Human Recognition Model a reliable, future-proof solution for educational institutions, enhancing both student identification efficiency and real-time data accessibility under various conditions. This ensures that the system continues to provide relevant student-specific data, even under these unpredictable conditions. This feature is crucial in ensuring that the educational system remains robust and adaptable in today's ever-changing environment. Table 1 illustrates how the system responds to external disruptions such as schedule shifts, socio-economic changes, or global events, and how these factors affect the data retrieval process.

Table 1. Impact of External Factors on System Response

External Factor	Expected System Adjustment	Expected Impact
Disruptions due to Global Events	Re-prioritize student data retrieval and adjust content recommendations	Ensure continuous access to student information despite global disruptions
Schedule Shifts (Exams or Breaks)	Adapt face recognition and data retrieval based on the updated academic calendar	Align data retrieval with the revised academic schedule, improving student support

Unforeseen Socio-Economic Factors	Adapt the model to consider budget-friendly or open educational resources	Enable inclusive access to relevant student data and educational content

5. Conclusion

In conclusion our project Precision-Optimized Human Recognition Model demonstrates high accuracy, efficiency, and adaptability, making it a valuable solution for automated student identification and data retrieval. Unlike traditional methods, which suffer from high false positive rates and poor adaptability, this system provides fast and precise recognition, reducing manual administrative efforts. While challenges such as low-light recognition issues remain, future improvements such as enhanced deep learning models and data augmentation techniques can further optimize the system's accuracy.

Despite its impressive performance, there are still challenges to address, such as issues with low-light recognition. These challenges, however, present opportunities for future improvements. The incorporation of advanced deep learning models, alongside data augmentation techniques, will further optimize the system's accuracy in diverse conditions. By refining these aspects, the system will become even more robust and capable of delivering reliable recognition in a wider range of environments, such as poorly lit classrooms or crowded hallways. Future advancements in GPU acceleration and real-time learning model improvements will enhance the system's efficiency, making it even more robust for large-scale educational institutions. The results validate the model's ability to modernize student information retrieval processes, ensuring a seamless and automated system for student identification in educational environments.

References:

[1] Sajja, R., Sermet, Y., Cikmaz, M., Cwiertny, D., & Demir, I. (2024). Artificial intelligence-enabled intelligent assistant for personalized and adaptive learning in higher education. Information, 15(10), 596.

[2] Fei, H., Wu, S., Li, J., Li, B., Li, F., Qin, L., ... & Chua, T. S. (2022). Lasuie: Unifying information extraction with latent adaptive structure-aware generative language model. Advances in Neural Information Processing Systems, 35, 15460-15475.

[3] Yang, Y., Wu, Z., Yang, Y., Lian, S., Guo, F., & Wang, Z. (2022). A survey of information extraction based on deep learning. Applied Sciences, 12(19), 9691.

[4] Dagdelen, J., Dunn, A., Lee, S., Walker, N., Rosen, A. S., Ceder, G., ... & Jain, A. (2024). Structured information extraction from scientific text with large language models. Nature Communications, 15(1), 1418.

[5] Alam, A. (2022). Employing adaptive learning and intelligent tutoring robots for virtual classrooms and smart campuses: reforming education in the age of artificial intelligence. In Advanced computing and intelligent technologies: Proceedings of ICACIT 2022 (pp. 395-406). Singapore: Springer Nature Singapore.

[6] Wang, M., Wang, M., Xu, X., Yang, L., Cai, D., & Yin, M. (2023). Unleashing ChatGPT's power: A case study on optimizing information retrieval in flipped classrooms via prompt engineering. IEEE Transactions on Learning Technologies, 17, 629-641.

[7] Ai, Q., Bai, T., Cao, Z., Chang, Y., Chen, J., Chen, Z., ... & Zhu, X. (2023). Information retrieval meets large language models: a strategic report from chinese ir community. AI Open, 4, 80-90.

[8] Abdullah, M. H. A., Aziz, N., Abdulkadir, S. J., Alhussian, H. S. A., & Talpur, N. (2023). Systematic literature review of information extraction from textual data: recent methods, applications, trends, and challenges. IEEE Access, 11, 10535-10562.

[9] Lerch, A. (2022). An introduction to audio content analysis: Music Information Retrieval tasks and applications. John Wiley & Sons.

[10] Oeding, J. F., Lu, A. Z., Mazzucco, M., Fu, M. C., Taylor, S. A., Dines, D. M., ... & Kunze, K. N. (2025). ChatGPT-4 performs clinical information retrieval tasks using consistently more trustworthy resources than does Google search for queries concerning the latarjet procedure. Arthroscopy: The Journal of Arthroscopic & Related Surgery, 41(3), 588-597.

[11] Brandsen, A., Verberne, S., Lambers, K., & Wansleeben, M. (2022). Can BERT dig it? Named entity recognition for information retrieval in the archaeology domain. Journal on Computing and Cultural Heritage (JOCCH), 15(3), 1-18.

[12] Zhu, Y., Yuan, H., Wang, S., Liu, J., Liu, W., Deng, C., ... & Wen, J. R. (2023). Large language models for information retrieval: A survey. arXiv preprint arXiv:2308.07107.

[13] Landolsi, M. Y., Hlaoua, L., & Ben Romdhane, L. (2023). Information extraction from electronic medical documents: state of the art and future research directions. Knowledge and Information Systems, 65(2), 463-516.
[14] Gupta, T., Zaki, M., Krishnan, N. A., & Mausam. (2022). MatSciBERT: A materials domain language model for text mining and information extraction. npj Computational Materials, 8(1), 102.

APPENDIX

```
import streamlit as st
import cv2
import numpy as np
import face_recognition
import os
import pickle
import hashlib
import sqlite3
from PIL import Image
from datetime import datetime
import pandas as pd
import io

# Initialize database
def init_db():
    conn = sqlite3.connect('student_database.db', check_same_thread=False)
    c = conn.cursor()

    # Create users table for authentication
    c.execute('''
    CREATE TABLE IF NOT EXISTS users (
        id INTEGER PRIMARY KEY AUTOINCREMENT,
        username TEXT UNIQUE NOT NULL,
        password TEXT NOT NULL,
        role TEXT NOT NULL
    )
    ''')

    # Create students table
    c.execute('''
    CREATE TABLE IF NOT EXISTS students (
        id INTEGER PRIMARY KEY AUTOINCREMENT,
        name TEXT NOT NULL,
        roll_number TEXT UNIQUE NOT NULL,
        department TEXT NOT NULL,
        year INTEGER NOT NULL,
        email TEXT,
        phone TEXT,
        address TEXT,
        username TEXT UNIQUE,
        face_encoding BLOB,
        registration_date TEXT,
        FOREIGN KEY(username) REFERENCES users(username)
    )
    ''')

    # Insert default admin if not exists
       c.execute("SELECT * FROM users WHERE username='admin' AND
role='admin'")
    if not c.fetchone():
        hashed_pw = hashlib.sha256("admin123".encode()).hexdigest()
```

```
        c.execute("INSERT INTO users (username, password, role) VALUES (?, 
?, ?)",
                  ("admin", hashed_pw, "admin"))

    conn.commit()
    return conn

# Password hashing function
def hash_password(password):
    return hashlib.sha256(password.encode()).hexdigest()

# User authentication
def authenticate(username, password, role):
    conn = init_db()
    c = conn.cursor()
    hashed_pw = hash_password(password)
    c.execute("SELECT * FROM users WHERE username=? AND password=? AND 
role=?",
              (username, hashed_pw, role))
    user = c.fetchone()
    conn.close()
    return user is not None

# Function to register new user
def register_user(username, password, role):
    conn = init_db()
    c = conn.cursor()
    try:
        hashed_pw = hash_password(password)
        c.execute("INSERT INTO users (username, password, role) VALUES (?, 
?, ?)",
                  (username, hashed_pw, role))
        conn.commit()
        conn.close()
        return True
    except sqlite3.IntegrityError:
        conn.close()
        return False

# Function to save student data with face encoding
def save_student(name, roll_number, department, year, email, phone, 
address, username, face_encoding=None):
    conn = init_db()
    c = conn.cursor()

    # Convert face encoding to binary for storage
    encoding_blob = None
    if face_encoding is not None:
        encoding_blob = pickle.dumps(face_encoding)

    try:
        c.execute("""
```

```
        INSERT INTO students (name, roll_number, department, year, email,
phone, address, username, face_encoding, registration_date)
        VALUES (?, ?, ?, ?, ?, ?, ?, ?, ?, ?)
        """, (name, roll_number, department, year, email, phone, address,
username, encoding_blob, datetime.now().strftime("%Y-%m-%d %H:%M:%S")))
        conn.commit()
        conn.close()
        return True
    except sqlite3.IntegrityError as e:
        conn.close()
        return False

# Function to get all students
def get_all_students():
    conn = init_db()
    c = conn.cursor()
    c.execute("SELECT id, name, roll_number, department, year, email, phone
FROM students")
    students = c.fetchall()
    conn.close()

    # Convert to DataFrame for nice display
    df = pd.DataFrame(students, columns=['ID', 'Name', 'Roll Number',
'Department', 'Year', 'Email', 'Phone'])
    return df

# Function to get student by roll number
def get_student_by_roll(roll_number):
    conn = init_db()
    c = conn.cursor()
    c.execute("SELECT * FROM students WHERE roll_number=?", (roll_number,))
    student = c.fetchone()
    conn.close()
    return student

# Function to retrieve all face encodings for comparison
def get_all_face_encodings():
    conn = init_db()
    c = conn.cursor()
    c.execute("SELECT id, name, roll_number, department, year,
face_encoding FROM students WHERE face_encoding IS NOT NULL")
    students = c.fetchall()
    conn.close()

    # Create dictionary of {id: (encoding, student_info)}
    encodings_dict = {}
    for student in students:
        student_id, name, roll_number, department, year, encoding_blob =
student
        if encoding_blob:
            face_encoding = pickle.loads(encoding_blob)
            encodings_dict[student_id] = (face_encoding, (name,
roll_number, department, year))
```

```
    return encodings_dict

# Function to recognize face and return student info
def recognize_face(face_encoding):
    encodings_dict = get_all_face_encodings()

    if not encodings_dict:
        return None

    # Compare face with all stored faces
    best_match_id = None
    best_match_distance = 1.0  # Lower is better, using 0.6 as threshold

    for student_id, (encoding, _) in encodings_dict.items():
        # Compare faces, get distance
            face_distances  =  face_recognition.face_distance([encoding],
face_encoding)
        distance = face_distances[0]

        if distance < best_match_distance and distance < 0.6:  # 0.6 is a
good threshold
            best_match_distance = distance
            best_match_id = student_id

    if best_match_id:
        _, student_info = encodings_dict[best_match_id]
        return student_info, best_match_distance

    return None, None

# Function to extract face encoding from image
def extract_face_encoding(image):
    # Convert from BGR to RGB
    rgb_image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)

    # Find all faces in the image
    face_locations = face_recognition.face_locations(rgb_image)

    if not face_locations:
        return None, "No face detected in the image"

    if len(face_locations) > 1:
       return None, "Multiple faces detected. Please provide an image with
only one face"

    # Get the encoding for the first face found
          face_encoding    =    face_recognition.face_encodings(rgb_image,
face_locations)[0]
    return face_encoding, None

# Main application
def main():
```

```
    st.set_page_config(
        page_title="Adaptive Information Retrieval System",
        layout="wide",
        initial_sidebar_state="expanded",
        menu_items={
            'About': "Adaptive Information Retrieval System with Face
Recognition"
        }
    )

    # Custom CSS for better UI
    st.markdown("""
    <style>
    .main-header {
        font-family: 'Arial Black', sans-serif;
        background: linear-gradient(90deg, #3a7bd5, #00d2ff);
        -webkit-background-clip: text;
        -webkit-text-fill-color: transparent;
        font-size: 3rem !important;
        font-weight: 800 !important;
        margin-bottom: 1rem !important;
        text-align: center;}

    .sub-header {
        font-size: 1.8rem;
        color: #333;
        margin-top: 1rem;
        margin-bottom: 1rem;
    }
    .info-box {
        background-color: #f8f9fa;
        border-radius: 0.5rem;
        padding: 1.5rem;
        margin-bottom: 1rem;
        border-left: 4px solid #1E88E5;
    }
    .success-box {
        background-color: #f0f8f0;
        border-radius: 0.5rem;
        padding: 1.5rem;
        margin-bottom: 1rem;
        border-left: 4px solid #4CAF50;
    }
    .error-box {
        background-color: #fff8f8;
        border-radius: 0.5rem;
        padding: 1.5rem;
        margin-bottom: 1rem;
        border-left: 4px solid #F44336;
    }

                            <div style="margin-top: 20px;">
                                <strong>Address:</strong><br>
```

```
                                {student[7] or 'Not provided'}
                            </div>
                        </div>

                    with col2:
                        # Try to display face image if exists
                                img_path = os.path.join("face_images",
f"{student[2]}.jpg")
                        if os.path.exists(img_path):
                            st.markdown("<div class='card' style='padding:
10px;'>", unsafe_allow_html=True)
                              st.markdown("<h4 style='text-align: center;
color: #1E88E5;'>Your Registered Face</h4>", unsafe_allow_html=True)
                            st.image(img_path, use_column_width=True)
                            st.markdown("</div>", unsafe_allow_html=True)

                            # Test face recognition
                            st.markdown("<br>", unsafe_allow_html=True)
                                  if st.button("Test Face Recognition",
use_container_width=True):
                                  st.session_state['test_recognition'] =
True
                                st.rerun()

                    # Test face recognition mode
                    if st.session_state.get('test_recognition'):
                        st.markdown("<div class='card' style='margin-top:
20px;'>", unsafe_allow_html=True)
                       st.markdown("<h4 style='color: #1E88E5;'>Test Your
Face Recognition</h4>", unsafe_allow_html=True)
                       st.markdown("<p>Take a picture to see if the system
recognizes you correctly.</p>", unsafe_allow_html=True)

                      test_camera = st.camera_input("", key="test_camera")

                        if test_camera:
                            bytes_data = test_camera.getvalue()
                             img = cv2.imdecode(np.frombuffer(bytes_data,
np.uint8), cv2.IMREAD_COLOR)

                            with st.spinner("Processing face..."):
                                              face_encoding, error =
extract_face_encoding(img)

                                if error:
                                         st.markdown(f"<div class='error-
box'>{error}</div>", unsafe_allow_html=True)
                                else:
                                           student_info, confidence =
recognize_face(face_encoding)

                                    if student_info:
```

```
                                             name, roll_number, department,
year = student_info
                                               confidence_percentage = (1-
confidence)*100

                                          if roll_number == student[2]:
                                              st.markdown(f"""
                                              <div class='success-box'>
                                                         <h3>✅ Recognition
Successful!</h3>
                                                      <p>You were correctly
identified with {confidence_percentage:.2f}% confidence.</p>
                                              </div>
                                              """, unsafe_allow_html=True)
                                          else:
                                              st.markdown(f"""
                                              <div class='error-box'>
                                                         <h3>❌ Recognition
Mismatch!</h3>
                                                    <p>The system identified
you as {name} (Roll: {roll_number}), not as yourself.</p>
                                              </div>
                                              """, unsafe_allow_html=True)
                                      else:
                                          st.markdown("""
                                          <div class='error-box'>
                                             <h3>❌ Recognition Failed</h3>
                                              <p>The system could not match
your face to any registered student.</p>
                                          </div>
                                          """, unsafe_allow_html=True)

                        if st.button("Close Test", key="close_test"):
                            st.session_state.pop('test_recognition', None)
                            st.rerun()

                        st.markdown("</div>", unsafe_allow_html=True)
                else:
                    st.markdown("""
                    <div class='info-box'>
                        <h3>No Information Found</h3>
                         <p>You haven't registered your information yet.
Please go to the 'Register Information' tab to complete your profile.</p>
                    </div>
                    """, unsafe_allow_html=True)

                                  if   st.button("Go   to   Registration",
use_container_width=True):
                        tab1.selectbox = True

if __name__ == "__main__":
    main()
```

<table>
<tr><td colspan="3">ANNEXURE 1</td></tr>
<tr><td colspan="3">STUDENTS PROJECT ROAD MAP</td></tr>
<tr><td colspan="2">NAME OF THE STUDENTS</td><td>REGISTER NUMBER</td></tr>
<tr><td colspan="2">BERYL SHARON J</td><td>211421243024</td></tr>
<tr><td colspan="2">DHARSHINI M</td><td>211421243039</td></tr>
<tr><td colspan="2">INDU M</td><td>211421243063</td></tr>
<tr><td colspan="3">NAME OF THE SUPERVISOR: Dr. S. HEMAMALINI, M.E., Ph.D.,</td></tr>
<tr><td colspan="3">DEPARTMENT: ARTIFICIAL INTELLIGENCE AND DATA SCIENCE</td></tr>
<tr><td>1</td><td>TITLE OF THE PROJECT</td><td>PRECISION-OPTIMIZED HUMAN RECOGNITION MODEL FOR ADAPTIVE INFORMATION RETRIEVAL IN EDUCATIONAL INSTITUTIONS</td></tr>
<tr><td>2</td><td>RATIONALE
(why the topic is important today in 3 sentences in bullet points)</td><td>• Face recognition technology is essential for modern educational systems, enabling efficient and accurate student identification.
• This project enhances student identification by addressing the limitations of traditional face recognition systems.
• Enhancing accuracy and automation, it significantly improves both security and administrative processes in educational institutions.</td></tr>
<tr><td>3</td><td>LITERATURE SURVEY
(Top 5 articles utilized for finding the research gap and their SCOPUS impact factor)</td><td>1)“Face recognition: Recent advancements and research challenges”</td></tr>
</table>

		1. Author: Medha Jha **2. Jounal/Conference:** 13th International Conference on Computing Communication and Networking Technologies (ICCCNT). IEEE **3. Year:** 2022 **4. Description:** This paper details about the different challenges that exists in a face recognition system. The image backgrounds can be complex, illumination variation could be extreme. The paper discusses challenges such as ageing, occlusions, variation in illumination, variation in resolution, variation in expression and poses. **2) "Face Recognition Using Deep Learning"** **1.Author:** Al-Shareef, O.A. and Gaboua, N.M. **2.Journal/Conference:** 2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA). IEEE **3.Year:** 2023 **4.Description:** This paper explores the implementation of deep learning techniques for face recognition, emphasizing the improvements achieved through convolutional neural networks (CNNs). **3) "Automatic Human Face Detection and Recognition Based on Facial Features Using Deep Learning Approach"**

		1.Author: Jatain, R., et al. **2.Journal/Conference:** International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s) **3.Year:** 2023 **4.Description:** This research introduces a deep learning-based framework for automatic human face detection and recognition. It utilizes CNNs to extract facial features and match them against a trained database. The study highlights how deep learning improves feature extraction, classification accuracy, and real-time processing. The paper also addresses challenges such as facial occlusion and expression variation, proposing an optimized approach for accurate recognition. **5) "A Review Paper on Facial Recognition Techniques"** **1.Author:** Sharma, R., Sharma, V.K., and Singh, A. **2.Journal/Conference:** 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics, and Cloud) (I-SMAC). IEEE **3.Year:** 2021 **4.Description:** This paper provides an in-depth review of various facial recognition techniques, including traditional machine learning methods and deep learning-based approaches. It discusses the evolution of face recognition technology, highlighting feature-based, appearance-based.

4	RESEARCH GAP (Maximum 3 sentences in bullet Points)	• **Accuracy Challenges Due to Environmental Factors:** The system's performance can be affected by lighting conditions, occlusions, and different facial angles. Poor lighting may cause errors in face detection and recognition, reducing accuracy. • **Privacy and Ethical Concerns:** Storing facial data in a database raises privacy concerns and potential security risks. Unauthorized access or data breaches could lead to misuse of student biometric information. • **Computational and Hardware Limitations:** Real-time face recognition requires high processing power, which may not be available in all institutions. Running deep learning models on low-end hardware can slow down recognition speed.
5	BRIDGING THE GAP (Maximum 4 sentences in bullet Points)	• **Enhancing Image Processing Techniques:** Implementing advanced pre-processing techniques like histogram equalization can improve image quality under poor lighting. Using multi-angle face detection algorithms can reduce errors caused by pose variations. • **Strengthening Data Security and Compliance:** Encrypting stored facial data can prevent unauthorized access and ensure student privacy. Implementing strict access control measures can restrict database access to authorized personnel only.

		• **Optimizing System Performance with Efficient Algorithms:** Using lightweight deep learning models can improve speed and efficiency on low-end hardware. Running model quantization techniques can decrease computational load while maintaining accuracy.
6	NOVELTY (Maximum 3 sentences in bullet Points)	• Implements an optimized face recognition model using HOG and SVM for face detection and dlib's ResNet-based deep metric learning for high-accuracy student identification. • Unlike traditional attendance systems, this model focuses solely on adaptive information retrieval, ensuring efficient and real-time student data access. • Developed as a Flask-based web application with an integrated SQLite database, making it lightweight, scalable, and easily deployable in educational institutions.
7	OBJECTIVES (Maximum 5 sentences in bullet Points)	• To develop a precision-optimized face recognition model for accurately identifying students and retrieving their information in real time. • To integrate HOG and SVM for face detection and dlib’s ResNet-based deep metric learning for efficient and reliable recognition.

		• To build a Flask-based web application with an SQLite database for seamless data storage and retrieval. • To ensure high accuracy and robustness in varying lighting conditions and facial orientations. • To provide an efficient, scalable, and user-friendly system for educational institutions to manage student information dynamically.
8	PROCESS METHODOLOGY (Maximum 7 sentences in bullet Points)	• Gather student face images, preprocess them by resizing, normalizing, and converting them into grayscale for optimal feature extraction. • Use HOG (Histogram of Oriented Gradients) + SVM to detect faces in input images efficiently. • Extract facial embeddings using dlib's ResNet-based deep metric learning model to create unique representations for each student. • Store student details and facial embeddings in an SQLite database for fast retrieval. • Compare extracted embeddings with stored data using Euclidean distance matching to identify students. • Develop a Flask-based web application to facilitate student identification and data retrieval in an intuitive interface.

		• Evaluate system performance, fine-tune detection and recognition thresholds, and optimize for real-world conditions.
9	SIMULATION METHODOLOGY AND SIMULATION SOFTWARE REQUIREMENT (Maximum 4 sentences in bullet Points)	• The system is tested using a dataset of student face images, where detection and recognition accuracy are evaluated under various lighting and pose conditions. • The simulation involves processing input images through HOG and SVM for face detection, followed by dlib's ResNet-based model for feature extraction and matching. • The implementation requires Python, Flask, OpenCV, dlib, SQLite, and relevant deep learning libraries for face recognition. • The system is assessed based on recognition accuracy, processing time, and robustness against variations in facial expressions and occlusions.
10	DELIVERABLES & OUTCOMES (Maximum 4 sentences in bullet Points) (Technology, Prototype, Algorithm, Software, patent, publication, etc)	• Development of a Flask-based web application integrating HOG & SVM for face detection and dlib's ResNet-based model for face recognition, with SQLite for data storage. • A functional prototype capable of accurately identifying students and retrieving relevant academic data based on facial recognition. • Implementation of an optimized face recognition pipeline using deep metric learning for high-precision student identification.

		• Research paper submission to a reputed journal ,with potential for further enhancements in real-time deployment and multi-factor authentication integration.
11	PROJECT CONTRIBUTION IN REALTIME	Journal Paper- ASPG (American Scientific Publishing Group) Journal -Communicated
11	Sustainable Development Goals Mapped (Mention the SDG numbers)	SDG 4, SDG 8, SDG 9
12	Programme Outcome Mapping (PO) (Mention the PO numbers)	PO1, PO2, PO3, PO5, PO6, PO8
13	Timeline	Milestones
	Month 1	Define project scope, objectives, and expected deliverables and identify the needs and requirements through literature review.
	Month 2	Design system architecture and define technical specifications to develop an accessible and user-friendly web-based interface and gather feedbacks.
	Month 3	Collect and preprocess facial images for training and testing to implement HOG and SVM for face detection and dlib's ResNet-based model for face recognition.
	Month 4	Train and fine-tune the face recognition model with collected data then evaluate performance (accuracy, precision, recall) and optimize hyperparameters and implement Euclidean

		distance-based face matching and validate recognition accuracy.
	Month 5	Set up the Flask-based web application for user interaction then integrate face recognition model with the Flask backend and also develop SQLite database for student data storage and retrieval.
	Month 6	Review project deliverables and finalize the system and prepare documentation, including research paper, technical report, and project demo.
SUPERVISOR SIGNATURE		

PRECISION-OPTIMIZED HUMAN RECOGNITION MODEL FOR ADAPTIVE INFORMATION RETRIEVAL IN EDUCATIONAL INSTITUTIONS

BERYL SHARON J [REGISTER NO : 211421243024]

DHARSHINI M [REGISTER NO : 211421243039]

INDU M [REGISTER NO : 211421243063]

PANIMALAR ENGINEERING COLLEGE
DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

PRECISION-OPTIMIZED HUMAN RECOGNITION MODEL FOR ADAPTIVE INFORMATION RETRIEVAL IN EDUCATIONAL INSTITUTIONS

Batch Number: 11

Presented by

BERYL SHARON.J (211421243024)
DHARSHINI.M (211421243039)
INDU.M (211421243063)

Guide:

Dr. S.HEMAMALINI , M.E., Ph.D.,
Associate Professor
Dept of Artificial Intelligence and Data Science

Introduction

- In educational institutions, efficient student identification plays a crucial role in enhancing security and streamlining administrative tasks.
- The growing need for efficient and accurate student identification in educational institutions has led to the adoption of advanced face recognition technology.
- Our project introduces the Precision-Optimized Human Recognition Model, which dynamically identifies students using facial recognition and retrieves their relevant data.
- The system continuously builds its database as students register, ensuring adaptability and scalability without relying on pre-existing datasets.
- By integrating real-time face recognition and data retrieval, the project enhances accuracy, security, and administrative efficiency in educational environments.

Rationale & Scope

- **Enhanced Security & Identification** – The system ensures accurate student identification, reducing impersonation risks and unauthorized access using advanced HOG + SVM and deep metric learning models.
- **Real-time Academic Data Retrieval** – By linking student identities to an SQLite database, the system enables instant access to attendance, academic records, and personalized information.
- **Robust Recognition in Diverse Conditions** – The integration of ResNet-based facial recognition improves accuracy despite occlusions, lighting variations, and pose differences, enhancing adaptability.
- **Automation & Efficiency in Education** – Automating access control streamlines institutional workflows, reducing manual efforts and improving overall efficiency.
- **Scalability & Integration** – The model supports easy expansion, allowing institutions to integrate Streamlit for UI, OpenCV for image processing, and other API-based features as needed.
- **Ethical & Privacy Considerations** – Secure student embeddings ensure data privacy and protection, addressing concerns about facial recognition technology while maintaining compliance with security protocols.

Literature Survey 1

AUTHOR	YEAR	PUBLICATION	TITLE	ALGORITHM	PROS	CONS	RESULT
V.M.Manikand, Mudigonda Himansh, Ananya Tiwari Medha Jha	2023	IEEE,13th International Conference on Computing Networking Technologies.	Face recognition Recent advancement and research challenges (IEEE)	Principal Component Analysis(PCA), Linear Discriminant Analysis (LDA), (SVM)	Improved accuracy, robustness, scalability, accessible.	Bias, privacy concerns, adversarial attacks, dataset limitations, ethical challenges	Facial recognition evolved with PCA, LDA, and SVM, using datasets like ImageNet.
Nongmeikapam Thoiba Singh, Mayank Pal, Aniket Kumar , Arhan Jain	2023	IEEE, pp. 843–847 Second International Conference on Augmented Intelligence Sustainable Systems.	Student Surveillance System using Face Recognition (IEEE)	Haar Cascade Classifier, Deep Learning Models (e.g., VGG-Face, FaceNet)	Efficient, real-time processing open-source, reliable for frontal face detection.	Limited accuracy, struggles with occlusions, lighting, non-frontal faces, and lacks deep learning robustness.	Real-time face detection and recognition with high accuracy, limited in low-light conditions.

AUTHOR	YEAR	PUBLICATION	TITLE	ALGORITHM	PROS	CONS	RESULT
Osama Ahmed Al-Shareef, Nagia M.Gaboua	2023	IEEE, 3rd International Conference on Sciences and Techniques of Automatic Control and Computer Engineering.	Face recognition using deep learning (IEEE)	Convolutional Neural Networks (CNN)	High-rate accuracy, feature extraction, adaptable, scalable, and efficient with GPU support.	Computation intensive, requires large datasets, sensitive to overfitting, and prone to vulnerabilities	The model performs best with 16 samples, with higher accuracy and lower validation losses than others.
Jothi Thilaga, Arshath Khan, Jones .A.A, Krishna Kumar .N	2022	IEEE, Second International Conference on Inventive Computational Technologies.	Modern face recognition with deep learning (IEEE)	HOG (Histogram of Oriented Gradients), CNN, SVM	Enhanced accuracy, robustness to variations, interpretable, lightweight implementation.	Limited performance in variations, computational demands, and requires extensive training for deep learning.	High accuracy in face recognition, robust to lighting, pose, and occlusion

Research Gap – Identified in Literature Survey

- **Accuracy Challenges Due to Environmental Factors**: The system's performance can be affected by lighting conditions, occlusions, and different facial angles. Poor lighting may cause errors in face detection and recognition, reducing accuracy.
- **Privacy and Ethical Concerns**: Storing facial data in a database raises privacy concerns and potential security risks. Unauthorized access or data breaches could lead to misuse of student biometric information.
- **Computational and Hardware Limitations**: Real-time face recognition requires high processing power, which may not be available in all institutions. Running deep learning models on low-end hardware can slow down recognition speed.

Novelty

- **Integration of Robust Models :** Implements an optimized face recognition model using HOG and SVM for face detection and dlib's ResNet-based deep metric learning for high-accuracy student identification.
- **Adaptive Information Retrieval:** Unlike traditional , face recognition systems, this model focuses solely on adaptive information retrieval, ensuring efficient and real-time student data access.
- **Real-time Interaction:** Developed as a Streamlit-based web application with an integrated SQLite database, making it lightweight, scalable, and easily deployable in educational institutions.

Specification- Hardware

- **Processor & Memory:** Intel Core i5/i7 or AMD Ryzen 5/7 with 8GB to 16GB RAM for efficient real-time face recognition and data processing.

- **Graphics Processing Unit:** (GPU – NVIDIA GTX 1650 or higher for accelerating deep learning-based face recognition tasks.

- **Storage:** 512GB SSD or higher for fast data access and efficient handling of student records.

- **Camera:** 1080p or higher resolution webcam for capturing clear student images for accurate recognition.- Enhances deep learning performance by parallelizing computations.

Specification- Software

- **Operating System : Windows 10/11-** Provides broad software compatibility, making it suitable for developers familiar with GUI-based environments.
- **Programming Language : Python 3.8-** The preferred language for deep learning due to its simplicity, versatility, and strong community support.
- **Frameworks and Libraries :** OpenCV for image processing, Dlib for face recognition, and Flask for developing the web interface.
- **Database Management System :** SQLite for storing and managing student records efficiently
- **Development Environment :** Jupyter Notebook , PyCharm , Visual Studio Code-
- **Web Framework : Streamlit** is used as the UI framework to provide an interactive, real-time image processing and user-friendly interface for face recognition-based student identification.

Dataset Used

- **Dynamic Data Collection :** The dataset is not pre-existing but is built progressively as students register by capturing and storing their facial images.
- **Face Data Storage :** Each student's facial images are stored along with unique identification details in a structured database, ensuring efficient retrieval and management.
- **Continuous Expansion :** The dataset grows over time as more students enroll, making it scalable and adaptable to the institution's needs without requiring external data sources.
- **Scalability & Adaptability :** As more students register, the dataset expands, ensuring the system remains efficient, scalable, and adaptable to different conditions.

List of Modules

This project can be divided into the following key modules:

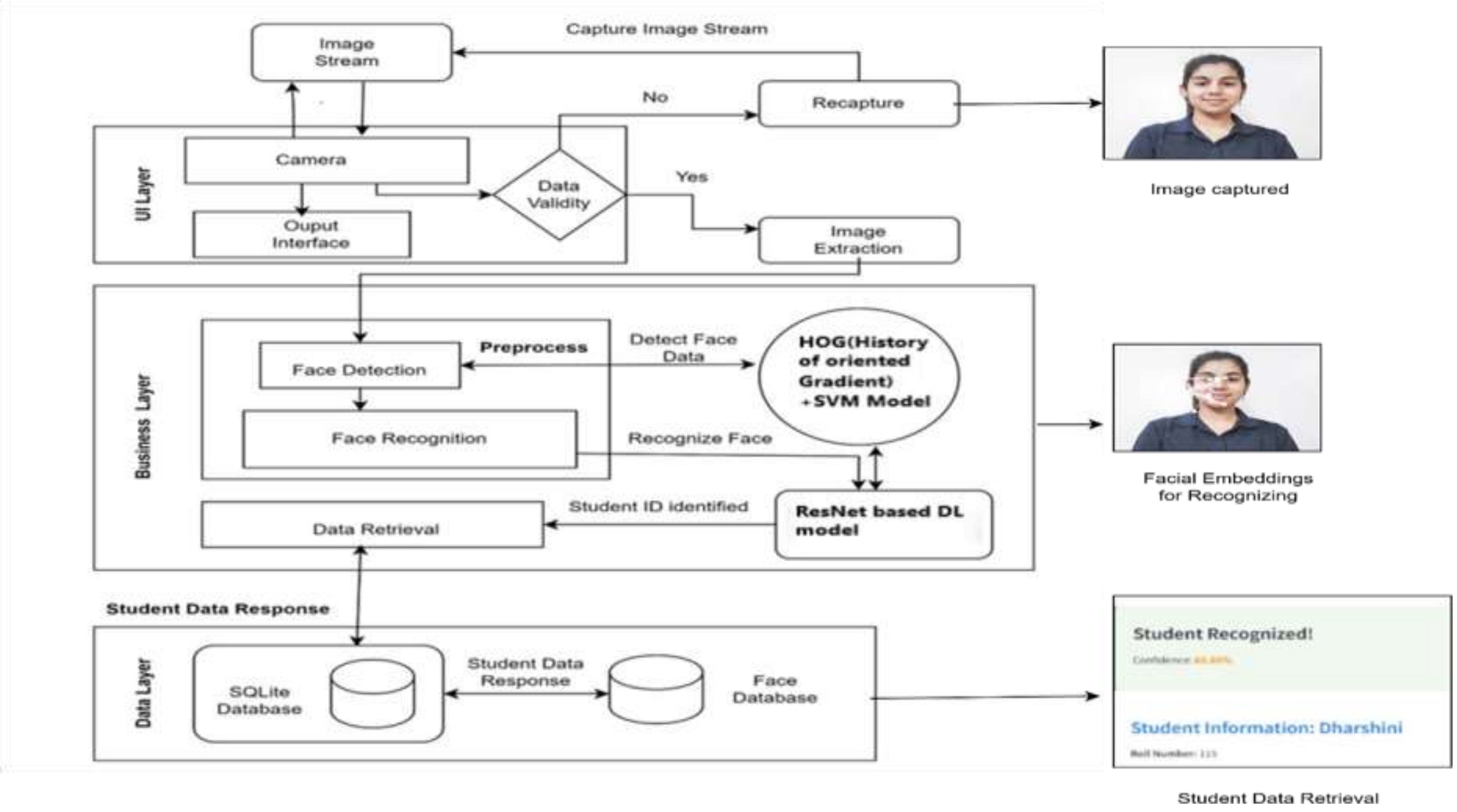
- User Authentication Module
- Face Detection Module
- Face Recognition Module
- Database Management
- Data Retrieval Module

Module Description

- **User Authentication Module:**
  - Allows only authorized admins to access the system using secure login credentials.
  - Prevents unauthorized access, ensuring data security and system integrity.
- **Face Detection Module:**
  - Detects and localizes student faces using HOG + SVM for accurate identification.
  - Ensures proper face alignment, even in varying lighting conditions and angles.

- **Face Recognition Module:**
  - Identifies students by comparing facial embeddings using dlib’s ResNet-based model.
  - Ensures high-accuracy recognition for seamless data retrieval and verification.
- **Database Management:**
  - Manages student records efficiently using SQLite for quick storage and retrieval.
  - Maintains a structured database, ensuring smooth information processing.
- **Data Retrieval Module:**
  - Provides an interactive interface for searching, verifying, and managing student records.
  - Enables manual and facial recognition-based student identification for quick access.

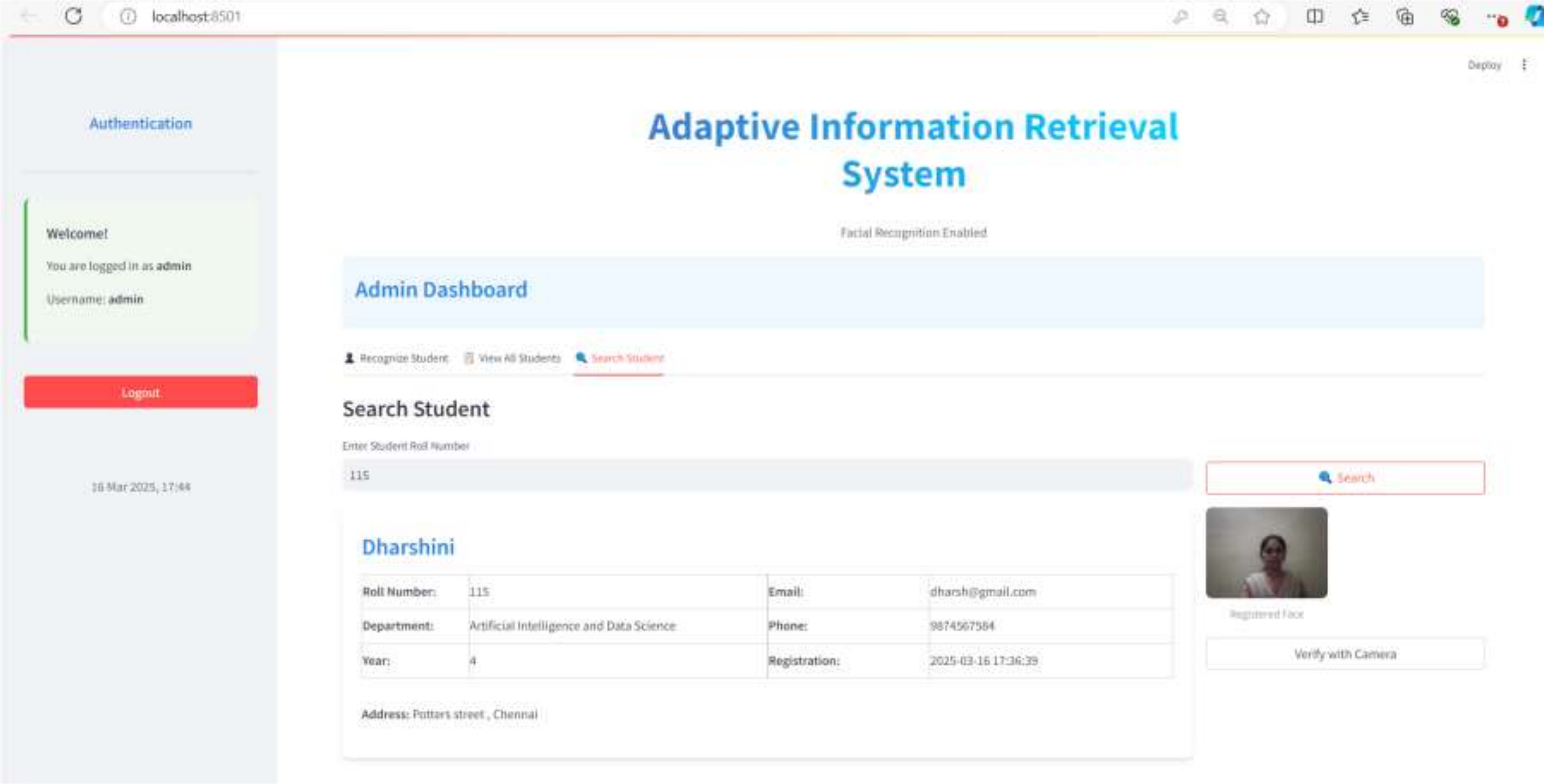
Architecture Diagram



Results and Discussions

- The system enhances student identification and data retrieval by dynamically recognizing students based on facial features, eliminating the need for manual input.
- By leveraging deep learning, the model ensures accurate recognition even under varying conditions, improving reliability compared to traditional methods.
- The system efficiently handles external factors such as lighting, pose variations, and occlusions, maintaining high accuracy and adaptability.
- With fast and reliable face recognition, the model reduces manual intervention, streamlining administrative processes in educational institutions.

Output



localhost:8501
Deploy
Authentication
Welcome!
You are logged in as admin
Username: admin
Logout
16 Mar 2025, 17:44
Adaptive Information Retrieval System
Facial Recognition Enabled
Admin Dashboard
Recognize Student
View All Students
Search Student
Search Student
Enter Student Roll Number
115
Search
Dharshini
Roll Number: 115
Email: dharsh@gmail.com
Department: Artificial Intelligence and Data Science
Phone: 9874567584
Year: 4
Registration: 2025-03-16 17:36:39
Address: Potters street , Chennai
Registered Face
Verify with Camera

Conclusion

- The system ensures **precise and reliable** student identification by dynamically building a database and leveraging advanced recognition techniques.
- The model operates in **real-time**, continuously expanding as new students register, making it highly scalable for educational institutions of any size.
- The structured database and secure management **prevent unauthorized access**, ensuring data integrity while enabling seamless identity verification.

Outcomes

- **Real-Time Face Recognition Implementation** – The system efficiently processes student facial data in real-time, enabling seamless authentication and access to academic resources.
- **Integration of Deep Learning & Traditional Algorithms** – The project combines HOG + SVM for face detection with dlib’s ResNet-based mode
- **User-Friendly Interface with Streamlit** – A simple yet interactive UI is developed using Streamlit, allowing administrators and faculty to manage student data effortlessly for recognition, ensuring a balance of speed and accuracy.

References

1. Al-Shareef, O.A. and Gaboua, N.M. (2023) “Face recognition using deep learning,” in *2023 IEEE 3rd International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA)*. IEEE.

2. Jha, M. *et al*. (2022) “Face recognition: Recent advancements and research challenges,” in *2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT)*. IEEE.

3. Maryuni Susanto, B. *et al*. (2024) “Face recognition using haar cascade classifier and FaceNet (A case study: Student attendance system),” *International Journal of Informatics and Communication Technology (IJ-ICT)*, 13(2), p. 272.

4. Natarajan S and Jayamangal, D.H. (2024) “Smart attendance monitoring system using facial recognition,” *International Journal of Advanced Research in Science, Communication and Technology*, pp. 45–49.

5. Samriddhi, Jaiswal, N. and Dubey, P. (2023) “Face recognition system using Haar algorithm,” in *2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)*. IEEE.

6. Sharma, R., Sharma, V.K. and Singh, A. (2021) “A Review Paper on Facial Recognition Techniques,” in *2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*. IEEE.

7. Siew, E.S.K. *et al.* (2023) “Streamlining attendance management in education: A web-based system combining facial recognition and QR code technology,” *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 33(2), pp. 198–208.

8. Singh, G. and Goel, A.K. (2020) “Face detection and recognition system using digital image processing,” in *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*. IEEE.

9. Singh, N.T. *et al.* (2023) “Student Surveillance System using Face Recognition,” in *2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*. IEEE, pp. 843–847.

10. Thilaga, P.J. *et al.* (2022) “Modern face recognition with deep learning,” in *2022 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*. IEEE.

11. Trivedi, A. *et al.* (2022) “Face recognition based automated attendance management system,” *International Journal of Scientific Research in Science and Technology*, pp. 261–268.

12. Vishwanatha, C. *et al.* (2023) “Face recognition and identification using deep learning,” in *2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*. IEEE, pp. 1–5.