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Entitled

An Efficient Raspberry Pi-Based Face Recognition System for Smart and Privacy-Aware Student Attendance

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Abstract

Traditional attendance methods are slow and fraud-prone. This project implements a face recognition-based attendance system on Raspberry Pi 4, automatically detecting and recognizing students at classroom entry and logging attendance in real time via a web interface. It uses MediaPipe BlazeFace, MobileFaceNet, ONNX Runtime, Flask, and SQLite, operating fully on-device without cloud dependency. The pipeline includes detection, tracking, alignment, quality filtering, embedding extraction, cosine similarity matching, and multi-frame voting. Evaluation achieved 24.3 ms latency, 95.8 percent accuracy, 0.1 percent false acceptance rate, and 110–140 MB memory usage, confirming viability for embedded real-time deployment.
Keywords: Face Recognition, Attendance Management System, Raspberry Pi, Embedded Artificial Intelligence, Computer Vision.

Résumé

Les méthodes traditionnelles de gestion des présences sont lentes et vulnérables aux fraudes. Ce projet implémente un système de reconnaissance faciale sur Raspberry Pi 4, détectant et reconnaissant automatiquement les étudiants à l'entrée et enregistrant leur présence en temps réel via une interface web. Il utilise MediaPipe BlazeFace, MobileFaceNet, ONNX Runtime, Flask et SQLite, fonctionnant entièrement sur l'appareil sans cloud. La chaîne de traitement inclut détection, suivi, alignement, filtrage qualité, extraction d'embeddings, similarité cosinus et vote multi-images. L'évaluation indique 24,3 ms de latence, 95,8 pour cent de précision, 0,1 pour cent de faux positifs et 110–140 Mo de mémoire.

Mots-clés : Reconnaissance faciale, Système de gestion des présences, Raspberry Pi, Intelligence artificielle embarquée, Vision par ordinateur.

الملخص

تعاني طرق إدارة الحضور التقليدية من البطء والتلاعب. يُقدّم هذا المشروع نظام تعرف على الوجوه يعمل على Raspberry Pi 4، يكشف عن الطلاب تلقائيًا عند الدخول ويسجل حضورهم فوريًا عبر واجهة ويب، مستخدمًا BlazeFace MediaPipe وMobileFaceNet وRuntime ONNX وFlask وSQLite، دون أي اعتماد على السحابة. تشمل سلسلة المعالجة الكشف والتتبع والمحاذاة وتصفية الجودة واستخراج المتجهات والمطابقة والتصويت متعدد الإطارات. أظهر التقييم زمن معالجة 3.24 ملي ثانية، ودقة 8.95 بالمئة ، ومعدل قبول خاطئ 1.0 بالمئة ، واستهلاك ذاكرة 110–140 ميغابايت.
الكلمات المفتاحية: التعرف على الوجوه، نظام تسيير الحضور، Raspberry Pi، MobileFaceNet، BlazeFace الذكاء الاصطناعي المدمج، الرؤية الحاسوبية، ONNX Runtime.

الكلمات المفتاحية:التعرف على الوجوه، نظام تسيير الحضور، Raspberry Pi، الذكاء الاصطناعي المدمج، الرؤية الحاسوبية.

Dedication

I dedicate this work to my beloved parents, whose love, sacrifices, patience, and continuous support have guided me throughout my life and academic journey. Their encouragement and belief in me have always been a source of strength and motivation.

To my father, for his hard work, wisdom, and unwavering support.

To my mother, for her endless care, kindness, and the countless sacrifices she has made for my success.

I would also like to dedicate this work to my dear friends, who shared with me both the challenges and the memorable moments of university life. Their friendship, encouragement, and support have made this journey more enjoyable and meaningful.

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To everyone who contributed, directly or indirectly, to the completion of this work, I express my sincere gratitude.

Mohamed Said Bensedira

All praise is due to Allah, who granted me the strength and guidance to complete this work.

I dedicate the fruit of this effort:

To my beloved mother, may Allah have mercy on her and grant her a place in His vast Paradise. Her love, kindness, and prayers had the greatest impact on my life, and her memory will forever remain in my heart.

To my father, may Allah preserve him and bless him with continued health and well-being.

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To my friends and colleagues, and to everyone who contributed, directly or indirectly, to the completion of this work.

I dedicate this humble achievement to you all, praying that Allah makes it beneficial knowledge and a righteous deed.

yasser debihi

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Introduction

Attendance management is an essential part of the educational process. Universities and schools rely on attendance records to monitor student participation, evaluate engagement, and maintain administrative organization. Traditional attendance methods, such as paper lists or manual calls, are time-consuming, prone to human error, and can easily be manipulated through proxy attendance. As class sizes increase, these limitations become even more problematic.

Recent advances in artificial intelligence and computer vision have made automatic attendance systems increasingly practical. Face recognition technology allows individuals to be identified quickly and without physical contact, making it suitable for classroom environments. At the same time, the development of lightweight deep learning models has enabled such systems to run on low-cost embedded devices instead of requiring expensive servers or cloud infrastructure.

The objective of this project is to design and implement an intelligent attendance management system based on face recognition technology using a Raspberry Pi embedded platform. The system automatically detects and recognizes students as they enter the classroom and records attendance in real time through a web-based interface. The project focuses on achieving a balance between recognition accuracy, computational efficiency, privacy, and low hardware cost.

To achieve this objective, the system combines several technologies, including MediaPipe BlazeFace for face detection, MobileFaceNet for face recognition, ONNX Runtime for optimized inference, Flask for the web application, and SQLite for local data storage. The system operates entirely offline, which improves privacy and avoids dependency on cloud services or internet connectivity.

This dissertation is organized into three chapters. Chapter 1 presents the general context of the project, introduces the technologies used, and reviews the related work in face recognition-based attendance systems. Chapter 2 focuses on the analysis and design of the proposed system, including the requirements specification, system architecture, database design, model evaluation, and overall workflow. Chapter 3 presents the implementation of the system, the hardware and software setup, testing procedures, performance evaluation results, and the challenges and limitations encountered during development.

Chapter 1: Literature Review

1.1 Introduction

Tracking student attendance sounds straightforward, but across hundreds of students and multiple sessions, it becomes a genuine burden. Attendance data matters: it reflects engagement, flags struggling students, and often determines exam eligibility. Yet most schools still rely on name-calling or paper sheets, wasting class time and leaving room for errors and fraud. Technology can fix this. Face recognition has become accurate and affordable enough for real classroom use, and paired with a small computer like the Raspberry Pi, it enables a fully automatic, low-cost system that works without internet access. This chapter reviews the research and technologies behind such a system, from traditional attendance methods to face recognition techniques, lightweight AI models, and edge computing, building the case for why this project was designed the way it was.

1.2 Attendance Management Systems

1.2.1 Traditional Attendance Methods

Attendance recording in universities has traditionally been done by hand. The teacher either calls out each student's name and waits for a response, or passes a paper sheet around the room for students to sign. Some institutions later moved to digital spreadsheets, but the data still had to be entered manually.

These methods have well-known problems that get worse as class sizes grow. The most obvious one is time in a large lecture hall, calling names can take ten to fifteen minutes, which is time taken directly away from teaching. On top of that, the manual process is prone to mistakes: names can be misheard, handwriting can be hard to read, and errors creep in when transferring data from paper to a computer. The most serious problem, however, is proxy attendance, where one student answers or signs on behalf of an absent classmate. In big classes, the teacher cannot always recognize every face, so these fake responses easily go unnoticed. Research on student behavior consistently identifies proxy attendance as one of the most common forms of academic dishonesty in higher education [1].

1.2.2 Automated Attendance Tracking

Because of these limitations, researchers and developers have been looking for automated solutions for decades. The earliest systems used RFID cards or barcodes each student carried

a card that was scanned at the entrance. This was much faster than verbal roll-calls and produced clean digital records, but the main problem remained: a student could simply hand their card to a friend, so proxy attendance was still possible [2].

Biometric systems came next. Fingerprint scanners became affordable in the early 2000s and were widely adopted because they verify the actual person, not just a card. Iris scanners were also used and are even more accurate, though more expensive. The downside of both is that students must physically interact with the device one at a time, which creates queues and raises hygiene concerns [3].

More recently, camera-based face recognition has attracted the most research attention. These systems can identify students without any physical interaction, and as cameras became cheaper and deep learning improved, face recognition became the most promising direction for the next generation of attendance systems.

1.2.3 Limitations of Existing Systems

Despite all this progress, no existing automated system has been widely adopted, and each approach has its own weaknesses.

RFID and barcode systems are fast but do not solve the identity problem sharing a card is just as easy as answering to someone else's name. Fingerprint and iris systems do solve the identity problem but require physical contact, which is unhygienic and slow. Cloud-based camera systems avoid contact but require a fast and reliable internet connection, which is not always available, especially in universities in developing countries [4]. They also raise privacy concerns because biometric data is sent to external servers outside the institution's control, and cloud subscriptions can be expensive.

The ideal system would identify students through a camera, work completely offline, require no physical contact, and be affordable enough for any university. These are exactly the goals of the approach explored in this project.

1.3 Face Recognition Technology

Face recognition is the technology at the heart of this system. Understanding how it works, how it evolved, and why certain approaches are better suited for embedded hardware is essential to justify the design choices made in this project. This section traces the history of face recognition, explains how faces are detected and recognized, describes how modern systems compare faces using numerical vectors, and compares the main models evaluated for this project.

1.3.1 Introduction to Face Recognition

Face recognition as a research field started in the early 1970s but became a real computational discipline with the introduction of Eigenfaces by Turk and Pentland in 1991 [5]. The Eigenfaces method represented a face as a combination of basis images computed using Principal Component Analysis (PCA), compressing the image into a smaller numerical vector that could be compared mathematically. This showed for the first time that automated face recognition was actually possible, and it set the direction for research over the following decade.

In the 2000s, researchers developed methods based on hand-crafted features. Local Binary Patterns (LBP) [6] compared each pixel to its neighbors to build descriptive histograms, while Histogram of Oriented Gradients (HOG) [7] captured edge and gradient information. Both handled lighting changes better than Eigenfaces and were fast enough for the hardware of the time. The real turning point came with deep learning Convolutional Neural Networks trained on millions of face images learned far richer features than any hand-crafted method could produce, and systems like FaceNet [8] and ArcFace [9] eventually surpassed human-level accuracy on standard benchmarks such as Labeled Faces in the Wild [10].

1.3.2 Face Detection Techniques

Before a face can be recognized, it must first be found in the image this is called face detection. The Viola-Jones detector, published in 2001 [11], was one of the first methods fast enough for real-time use. It worked by cascading simple classifiers based on Haar features and was widely used for nearly a decade. However, it struggles when faces are not perfectly frontal or when lighting is uneven.

HOG-based detectors [7] improved on Viola-Jones for faces at different orientations, but were slower and still had difficulties with strong lighting changes. Modern deep learning detectors like MTCNN, RetinaFace, and MediaPipe Face Detection handle real-world conditions much better. MediaPipe Face Detection [12], developed by Google, uses a lightweight neural network that runs very fast even on devices without a GPU. It returns not only bounding boxes but also facial landmark positions, which are useful for aligning the face before recognition. These properties make it well suited for deployment on the Raspberry Pi 4, where computing power is limited.

1.3.3 Face Recognition Approaches

Face recognition methods can be grouped into three main categories. Geometric approaches measure distances and ratios between facial landmarks they are fast to compute but very sensitive to changes in head pose. Holistic methods like Eigenfaces [5] and Fisherfaces [13]

treat the whole face image as a high-dimensional vector and use dimensionality reduction to extract useful features they work well under controlled conditions but fail easily when lighting or expressions change. Deep learning embedding methods [8], [9] are the current state of the art: a neural network is trained to map face images into a compact numerical vector so that images of the same person end up close together while images of different people end up far apart. Recognition then becomes a matter of comparing these vectors rather than raw images. This approach handles real-world variations in lighting, pose, and expression much better than older methods.

1.3.4 Face Embeddings and Similarity Matching

A face embedding is a numerical vector typically 128 numbers produced by passing a face image through a trained neural network. The network is trained using a loss function like triplet loss [8] or ArcFace loss [9], which teaches it to keep embeddings of the same person similar and embeddings of different people distinct.

To compare two embeddings, cosine similarity is used. It measures the angle between two vectors, which makes it less sensitive to the overall scale of the numbers. A score of 1.0 means the two vectors are pointing in the same direction very likely the same person. Values near 0.0 indicate different people. A threshold is chosen based on testing to decide when two embeddings are close enough to count as a match.

1.3.5 Comparison of Face Recognition Models

Several well-known models exist for face recognition. FaceNet, introduced by Schroff et al. in 2015 [8], was one of the first to use embeddings for recognition and achieves high accuracy. ArcFace [9] introduced by Deng et al. in 2019, improved on FaceNet with a better training approach and is considered one of the most accurate models available today. However, both FaceNet [8] and ArcFace [9] are large models that need a GPU to run efficiently in real time --- they are not practical for a small embedded device like the Raspberry Pi.

MobileFaceNet [14] introduced by Chen et al. in 2018, was designed specifically for mobile and embedded devices. It is built on the MobileNet [15] architecture which reduces computation significantly while keeping accuracy reasonable. MobileFaceNet [14] has around one million parameters and produces a 128-dimensional embedding. It is less accurate than FaceNet [8] or ArcFace [9] on large-scale benchmarks, but it is much smaller and runs well on CPU only. For real-time recognition on the Raspberry Pi, this trade-off is completely acceptable.

1.4 Embedded and Edge AI Systems

1.4.1 Edge Computing Concepts

Edge computing means processing data locally on the device itself, rather than sending it to a remote cloud server. The word ``edge'' refers to the fact that these devices sit at the edge of the network, close to where the data is generated. For an attendance system, this brings three main advantages. It is faster because data does not have to travel over a network. It works without an internet connection, which matters for institutions with unreliable connectivity [4]. And biometric data never leaves the device, which avoids the privacy risks that come with sending sensitive information to external servers.

1.4.2 Lightweight AI Models for Embedded Systems

Running deep learning on a device with limited resources requires models that are small and efficient. The MobileNet [15] family, introduced by Howard et al. in 2017, reduces the number of computations needed per image by using a more efficient convolution technique, with only a small loss in accuracy compared to standard networks. MobileFaceNet [14] adapts this idea specifically for face recognition, and produces good-quality embeddings with very low computing cost. Running it through ONNX Runtime [16] improves execution speed on embedded devices, which is important for keeping the system responsive in real time.

1.5 Related Work and Comparative Study

Several face recognition-based attendance systems have been proposed in the literature, each addressing a subset of the challenges identified in the previous sections. This section reviews the most relevant existing systems, examines their strengths and limitations, and positions the proposed system relative to them. The goal is to identify the gaps that motivated the design decisions taken in this project and to show clearly what distinguishes the proposed approach from prior work.

1.5.1 Review of Existing Systems

Budiman et al. [1] reviewed a large number of face recognition attendance systems covering both classical methods and deep learning approaches. They found that most systems in the literature were tested on small groups of twenty to fifty students under controlled lighting conditions. Their review gave a good picture of what has been done in the field and confirmed that this testing scale is common practice. Lateef and Kamil [17] built a system that used an online face recognition service to take attendance in smart classrooms. It gave

good results in their tests but required a stable internet connection and a paid subscription, which limits its use in universities with poor network access or tight budgets. Rao [18] built a system called AttenFace that used deep face embeddings for real-time recognition. It performed well but ran on a regular desktop computer and was only tested under fixed lighting with a stationary camera. Demir and Savaş [19] tested several deep learning models under real classroom conditions with changing lighting and students moving around. Their work showed that accuracy on standard benchmarks does not always reflect how a system will behave in practice. George et al. [20] introduced EdgeFace, a lightweight face recognition model built specifically for edge devices like the Raspberry Pi. They showed that a small and efficient model can still deliver competitive results without needing powerful hardware. The table below summarizes the key properties of each reviewed system:

1.5.2 Proposed System

The proposed system is a face recognition attendance system designed to run entirely on a Raspberry Pi 4 [21] placed at the entrance of a classroom. It uses MediaPipe BlazeFace [12] for real-time face detection and MobileFaceNet [14] for face recognition, with all inference running on CPU through ONNX Runtime [16]. Attendance is recorded automatically through a web interface built with Flask, and all data is stored locally in a SQLite database with no connection to any external server.

The system was designed around the limitations and gaps identified in the reviewed work. It operates completely offline, requires no physical contact, runs on low-cost embedded hardware, and keeps all biometric data on the device. These properties together make it practical for real classroom deployment in universities where cloud services, expensive hardware, or reliable internet access cannot be assumed.

1.5.3 Positioning of the Proposed System

Looking at the reviewed systems together, two main trade-offs appear. Systems that are highly accurate tend to rely on cloud servers or powerful computers, making them expensive and dependent on a network connection. Systems designed for small devices tend to work only under controlled and ideal conditions. In terms of dataset scale, the proposed system falls in the same range as most reviewed work, targeting groups of around fifty students per session, which is the standard class size in most university departments.

What sets the proposed system apart is not its scale but its combination of practical properties. It runs fully offline on a Raspberry Pi 4 [21] with no internet required, processes each student in about one to two seconds as they walk past the camera, requires no physical contact, and stores all data locally on the device so that no biometric information is ever sent outside. None of the reviewed systems achieves all of these at the same time.

Table 1.1: Comparison of reviewed attendance systems

System	Method	Offline	No Contact	Edge Device	Local Storage
Budiman et al. [1]	LBPH / CNN	No	Yes	No	Yes
Lateef & Kamil [17]	Cloud API	No	Yes	No	No
Rao (AttenFace) [18]	Deep embeddings	Yes	Yes	No	Yes
Demir & Savaş [19]	Deep learning	Yes	Yes	No	Yes
George et al. (EdgeFace) [20]	Lightweight CNN	Yes	Yes	Yes	Yes
Proposed System (Raspberry Pi 4)	**BlazeFace + MobileFaceNet**	**Yes**	**Yes**	**Yes**	**Yes**

1.6 Chapter Summary

This chapter covered the background needed to understand why the system was built the way it was. We started with attendance management, looking at how manual methods waste time and allow proxy attendance, and how existing automated solutions like RFID, fingerprint scanners, and cloud-based cameras each solve some problems but create new ones. We then went through face recognition technology, from the early Eigenfaces method [5] all the way to modern deep learning embeddings and cosine similarity matching, explaining how the field reached its current state. After that we looked at embedded systems and edge computing, explaining why running everything locally on a Raspberry Pi is better for speed, cost, and privacy compared to sending data to a remote server. We then presented the model evaluation framework, where MobileFaceNet [14], FaceNet [8], and ArcFace [9] were benchmarked on a development machine and compared across inference speed, memory usage, and accuracy. The results clearly showed that MobileFaceNet is the only candidate that fits within the hardware constraints of the target embedded platform while still delivering reliable recognition. Finally we reviewed existing attendance systems from the literature and showed that while each one has its strengths, none of them combines offline operation, embedded deployment, no physical contact, and local data storage at the same time. All of these findings lead to the same design decisions: MediaPipe for face detection [12], MobileFaceNet in ONNX format for recognition [14], cosine similarity for matching, and a voting-based confirmation to improve reliability. Chapter 2 will present the full design and architecture of the system built on these foundations.

Chapter 2: System Analysis, Requirements and Design

2.1 Introduction

Before writing a single line of code, it is important to understand the problem clearly, define exactly what the system needs to do, and decide how it will be built. Skipping this step usually leads to missing features, wrong design decisions, and wasted time.

This chapter covers both the analysis and design phases of the project. It starts by looking at the real problems with how attendance is currently managed in universities and introduces the proposed solution. It then defines in clear terms what the system must do and how it must behave. From there it moves into the technical design: the tools and technologies chosen, the overall architecture, the database structure, the machine learning pipeline, and how each module of the system works. By the end of this chapter, both the requirements and the full design of the system are completely defined, which makes the implementation work in the following chapter straightforward to follow.

2.2 Problem Analysis

2.2.1 Problems with Traditional Attendance

In most university classrooms today, attendance is still recorded the old way. The teacher either calls out each student's name and waits for a response, or passes a sheet of paper around the room for students to sign. This process has several well-known problems.

The first problem is time. In a large class, calling names or waiting for a paper sheet to go around every seat can take ten to fifteen minutes [1]. This time is taken directly from the lesson.

The second and more serious problem is proxy attendance. Because the teacher cannot always recognise every face in a large group, one student can easily answer for an absent friend, or sign the paper on their behalf. This is one of the most common forms of academic dishonesty in universities, and traditional methods have no way to prevent it [1].

The third problem is errors and lost records. Paper sheets can be lost, handwriting can be hard to read, and transferring data from paper to a spreadsheet introduces mistakes. Keeping track of attendance over an entire semester becomes a real administrative burden.

2.2.2 Problems with Existing Automated Systems

Some institutions have tried to solve these problems using automated systems, but each approach has its own limitations.

RFID card systems are faster than paper sheets, but a student can simply give their card to a friend, so proxy attendance is still possible [2]. Fingerprint and iris scanners do verify the actual person, but they require every student to physically touch or stand very close to a device, which creates queues and raises hygiene concerns [3].

Cloud-based camera systems avoid physical contact and can be accurate, but they require a fast and stable internet connection, which is not always available. They also send sensitive biometric data to external servers, which raises privacy concerns. On top of that, the subscription costs for such services can be too high for many university departments [4].

2.2.3 Why an Edge-Based AI System is the Right Answer

The ideal solution would identify students through a camera without any physical interaction, work completely offline without depending on an internet connection, keep all data stored locally so that no biometric information leaves the device, and be affordable enough for any university to deploy.

This is exactly what an edge-based AI system can provide. By running face recognition directly on a small embedded computer placed in the classroom, it is possible to automate attendance in a way that is fast, contact-free, offline, and low-cost.

2.3 Proposed System

The proposed system is a fully automatic face recognition attendance system designed to run on a Raspberry Pi 4 placed at the entrance of a classroom. When a session starts, the camera begins capturing the faces of students as they walk in. The system detects each face, compares it against the stored face data of the students registered in that session's group, and marks attendance automatically when a student is recognised with enough confidence. No teacher interaction is needed during this process.

The system has three main parts. The first is the Computer Vision, which handles everything related to face detection, quality checking, embedding extraction, and recognition. The second is the database, which stores student information, timetables, session records, and attendance results locally on the device. The third is the web application, which gives teachers and administrators a browser-based interface to manage sessions, view reports, and enroll students.

The system works completely offline. All processing happens on the Raspberry Pi itself. No data is sent to any external server at any point.

Students are enrolled in the system before the semester begins. During enrollment, a student scans a QR code on their mobile phone, which opens a page where they submit a photo of their face. The system processes the photo and stores the face embedding in the database. After this one-time step, the student will be recognised automatically in every session without needing to do anything.

Teachers log into the web interface from any browser on the same local network. They can see their schedule for the day, start a session for a specific class and group, monitor who is being recognised in real time, and view or export the attendance report at the end of the session.

Administrators have a separate management panel where they can create and manage student records, teacher accounts, groups, modules, and timetable entries.

2.4 Functional Requirements

The functional requirements define exactly what the system must be able to do. They are organized into four groups based on who performs the action and at what stage of the workflow it happens: administrator functions that manage the data the system depends on, enrollment functions that bring students into the system, attendance functions that handle the core recognition and recording process, and session and dashboard functions that give teachers control over their classes. Each requirement is stated in concrete terms so that it can be verified during testing.

2.4.1 Admin Functions

- The system shall allow an administrator to create, edit, and delete student records.
- The system shall allow an administrator to create, edit, and delete teacher accounts.
- The system shall allow an administrator to create and manage student groups.
- The system shall allow an administrator to create and manage course modules.
- The system shall allow an administrator to define timetable entries linking a module, a group, a teacher, a room, a day, and a time slot.
- The system shall support three session types: lecture, tutorial, and Lab.

2.4.2 Enrollment Functions

- The system shall generate a unique QR code for each student that links to their personal enrollment page.

- The system shall allow a student to submit a face photo from their mobile phone by scanning their QR code.
- The system shall process the submitted photo and extract a face embedding using a face recognition model.
- The system shall store the face embedding in the database and mark the student as enrolled.
- The system shall store a face thumbnail for display purposes in the admin panel.

2.4.3 Attendance Functions

- The system shall detect faces in the live camera feed using a face recognition model.
- The system shall filter out faces that are too small, too dark, too bright, or too blurry before attempting recognition.
- The system shall extract a face embedding from each detected face using a face recognition model.
- The system shall compare the extracted embedding against all stored embeddings of students registered in the current session's group.
- The system shall use a voting mechanism requiring three matching results out of five consecutive frames before confirming a student's identity.
- The system shall automatically mark a confirmed student as present in the database.
- The system shall apply a cooldown period of thirty seconds after confirming a student to prevent duplicate records.
- The system shall support four attendance statuses: present, absent, late, and manual.
- The system shall allow a teacher to manually mark a student as present or absent during a session.

2.4.4 Session and Dashboard Functions

- The system shall allow a teacher to view their scheduled classes for the current day.
- The system shall allow a teacher to start and end an attendance session for a specific timetable entry.

- The system shall display the live camera feed with bounding boxes and student names overlaid in real time.
- The system shall display the list of recognised students as they are confirmed during a session.
- The system shall generate an attendance report at the end of a session showing which students were present and which were absent.
- The system shall allow a teacher to download the attendance report as a formatted PDF.
- The system shall allow a teacher to delete a session record.

2.5 Non-Functional Requirements

While functional requirements describe what the system must do, non-functional requirements describe how well it must do it. These requirements do not add new features but they define the quality constraints that the system must respect at all times. For this project, the non-functional requirements are driven by the hardware limitations of the Raspberry Pi, the real-time nature of the attendance process, and the privacy constraints that come from handling biometric data in an educational environment. A system that meets all functional requirements but is too slow, too fragile, or too difficult to use in a real classroom would still fail in practice.

2.5.1 Performance

The system must be fast enough to feel responsive in a real classroom. Each face should be processed in well under one second. The camera feed should stream smoothly to the browser without noticeable delay. The system processes every third frame rather than every frame, which reduces the load on the processor without missing any student.

2.5.2 Reliability

The system must operate stably throughout an entire class session without crashing or freezing. It must correctly handle situations where no face is detected, where a face is too blurry or too dark to process, or where no matching student is found.

2.5.3 Accuracy

The face recognition must be accurate enough for daily classroom use. The voting system, which requires three consistent matches out of five frames before confirming a student, is

specifically designed to reduce false positives. The similarity threshold and quality filters also contribute to keeping accuracy high under real classroom lighting conditions.

2.5.4 Security

Access to the system must be protected by username and password. Teachers can only access attendance functions, while administrators have full management access. All data, including face embeddings, is stored locally on the device and never transmitted to any external server. The system uses HTTPS so that the browser camera API works correctly on mobile devices during enrollment [22].

2.5.5 Usability

The teacher interface must be simple enough that a teacher with no technical background can use it without training. Starting a session, monitoring attendance, and downloading a report should each take only a few clicks.

2.5.6 Hardware Constraints

The entire system must run on a Raspberry Pi 4 Model B with no GPU. All AI models must be optimised for CPU-only inference. The database must be lightweight and require no separate server process to run.

2.5.7 Offline Operation

The system must function completely without an internet connection. All processing, storage, and serving of the web interface must happen locally on the Raspberry Pi.

2.6 System Actors

The system has three types of users, called actors, each with a different role.

2.7 Use Case Diagram

The use case diagram below shows the main interactions between each actor and the system.

The main use cases are the following:

Administrator use cases: login, manage students, manage teachers, manage groups, manage modules, manage timetable, view enrollment status.

Teacher use cases: login, view today's schedule, start session, monitor live attendance, manually mark student, end session, view report, download PDF report.

Actor	Role
Administrator	Manages the entire system. Creates and maintains student records, teacher accounts, groups, modules, and the timetable. Also monitors enrollment status.
Teacher	Logs into the web interface to start and end attendance sessions, monitor recognition in real time, review attendance reports, and make manual corrections.
Student	Does not log in. Interacts with the system only once during enrollment, by scanning a QR code and submitting a face photo from their mobile phone. After that, they are recognised automatically in every session.

Table 2.1: System Actors

Student use cases: scan QR code, submit face photo for enrollment.

The system itself handles face detection, quality filtering, embedding extraction, similarity matching, voting, and automatic attendance marking without any actor initiating these steps manually --- they happen automatically once a session is started.

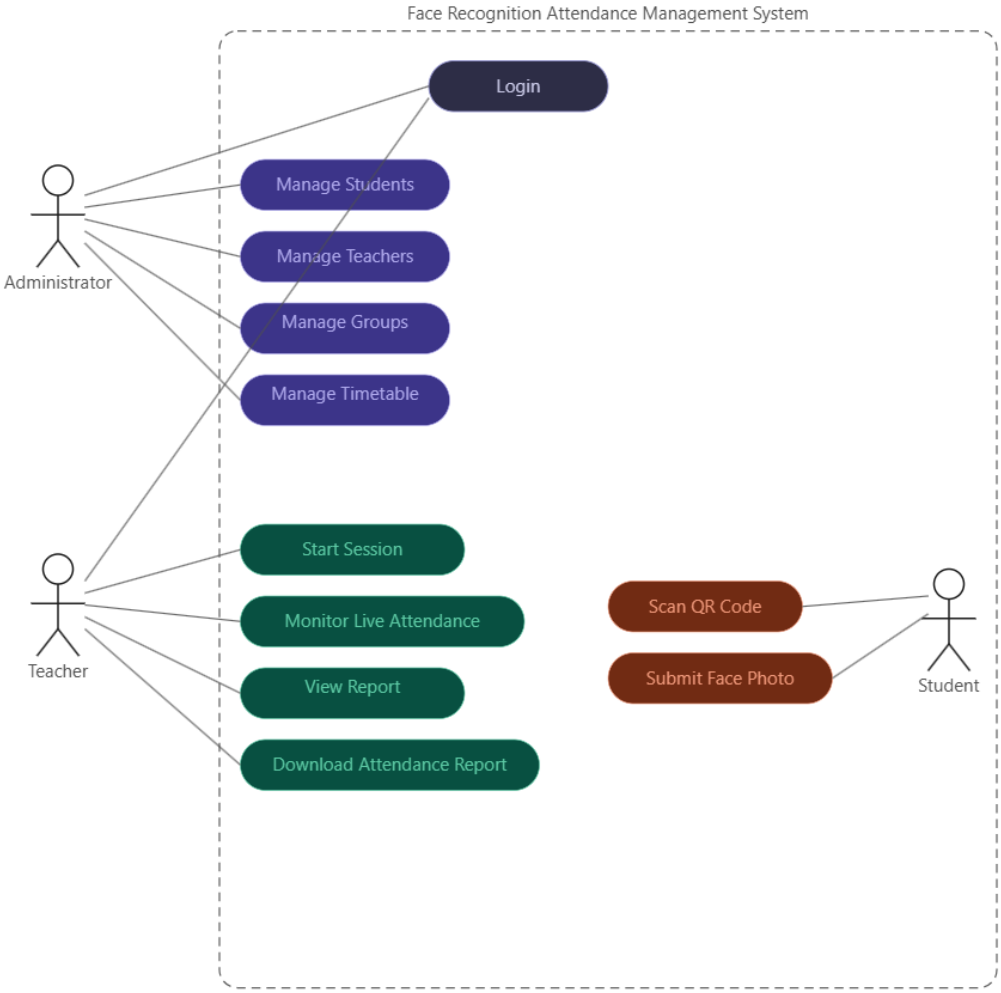

Figure 2.1: Use Case Diagram

2.8 System Workflow

This section describes how the system operates from start to finish during a typical attendance session.

Step 1 --- Preparation. Before the semester begins, the administrator creates student groups, modules, and timetable entries. Students enroll by scanning a QR code and submitting a face photo. The system processes the photo and stores their face embedding in the database.

Step 2 --- Session Start. The teacher logs in and starts a session for a specific module and group. The system creates a session record and loads the group's face embeddings into memory ready for recognition.

Step 3 --- Face Capture and Detection. The camera streams continuously at the classroom entrance. Every third frame is processed and scanned for faces.

Step 4 --- Face Processing and Recognition. Each detected face is aligned, checked for quality, and passed through the recognition model. The resulting embedding is compared against stored student embeddings to find a match.

Step 5 --- Attendance Confirmation. A student is only confirmed once they are matched in at least 3 out of 5 consecutive frames. Once confirmed, they are marked as present with a timestamp. A 30-second cooldown prevents them from being marked twice.

Step 6 --- Session End. When the session ends, any student who was not recognized is automatically marked absent. The teacher can review the report, make corrections if needed, and download the final version.

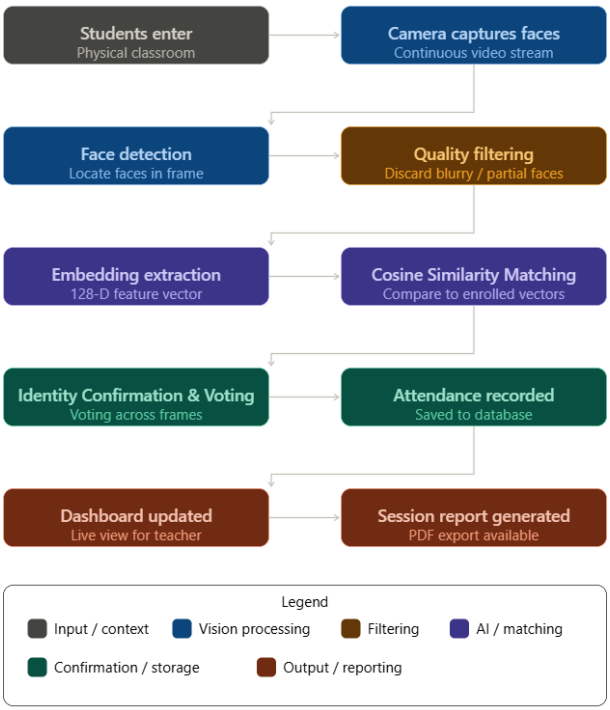

Figure 2.2: System Flowchart

2.9 Development Tools and Technologies

This section explains the main tools used to build the system and why each one was chosen.

Python was chosen as the main programming language because it supports both AI development and web development very well. It has a large number of ready-made libraries that made the work faster and easier.

Flask is a lightweight web framework for Python. It was chosen because it is simple to set up and runs well on a Raspberry Pi. It handles the routes, the teacher dashboard, and the API endpoints that connect the frontend to the backend.

OpenCV is used to capture frames from the camera and prepare them for processing. It handles reading the video stream and doing basic image operations like cropping and resizing.

ONNX Runtime is the engine used to run the AI models [16]. It is faster than loading a full framework like PyTorch or TensorFlow and is well suited for running on embedded hardware like the Raspberry Pi.

SQLite is the database used to store all the system's data. It is lightweight, does not need a separate server process, and stores everything in a single file on the device. This makes it a perfect fit for a local embedded system.

Technology	Purpose
Python	Main programming language
Flask	Web framework and API
OpenCV	Camera capture and image processing
ONNX Runtime	Optimized model inference on CPU
SQLite	Local lightweight database

Table 2.2: Development tools and technologies

2.10 Model Evaluation and Selection

Several face recognition models were tested during the design phase of the system, including MobileFaceNet [14], FaceNet [8], and ArcFace [9]. The comparison focused on inference speed, model size, and practical deployment suitability for embedded hardware.

Model	Similarity	Inf. Time	Emb. Dim	Params	FPS
MobileFaceNet	0.9943	1.57 ms	128	∼1M	635
FaceNet	0.8586	10.52 ms	128	∼23M	95
ArcFace	0.9552	45.26 ms	512	∼34M	22

Table 2.3: Benchmark comparison of face recognition models (benchmarked on development machine)

FaceNet [8] and ArcFace [9] achieved acceptable similarity scores but required significantly larger models and higher inference times. ArcFace produced the slowest execution time due to its larger architecture and 512-dimensional embeddings.

MobileFaceNet [14] achieved the best balance between recognition performance and computational efficiency. It produced the highest similarity score during testing while maintaining extremely low inference time and a compact model size of approximately ∼1M. These characteristics make it more suitable for real-time deployment on the Raspberry Pi 4.

Based on these results, MobileFaceNet [14] was selected as the face recognition model used in the final system.

2.11 Overall System Architecture

The system is organized as a set of modules that work together in a pipeline. When a session starts, the camera feeds frames into the AI pipeline. The pipeline detects faces, tracks them across frames, checks their quality, extracts embeddings, and compares them against stored student data. When a student is recognized, the result is saved in the database and the teacher's dashboard is updated in real time through the Flask web application.

The main components are:

- **Camera** captures the video stream at the classroom entrance
- **Computer Vision** handles detection, tracking, quality filtering, embedding extraction, and matching
- **Flask Backend** serves the web interface and manages communication between components
- **SQLite Database** stores all student, session, and attendance data locally
- **Teacher Dashboard** a browser-based interface where teachers can start sessions and monitor attendance
- **Enrollment Page** a mobile-friendly page where students submit their face photo by scanning a QR code

All of this runs on the Raspberry Pi itself. Nothing is sent to any external server. The system works completely offline.

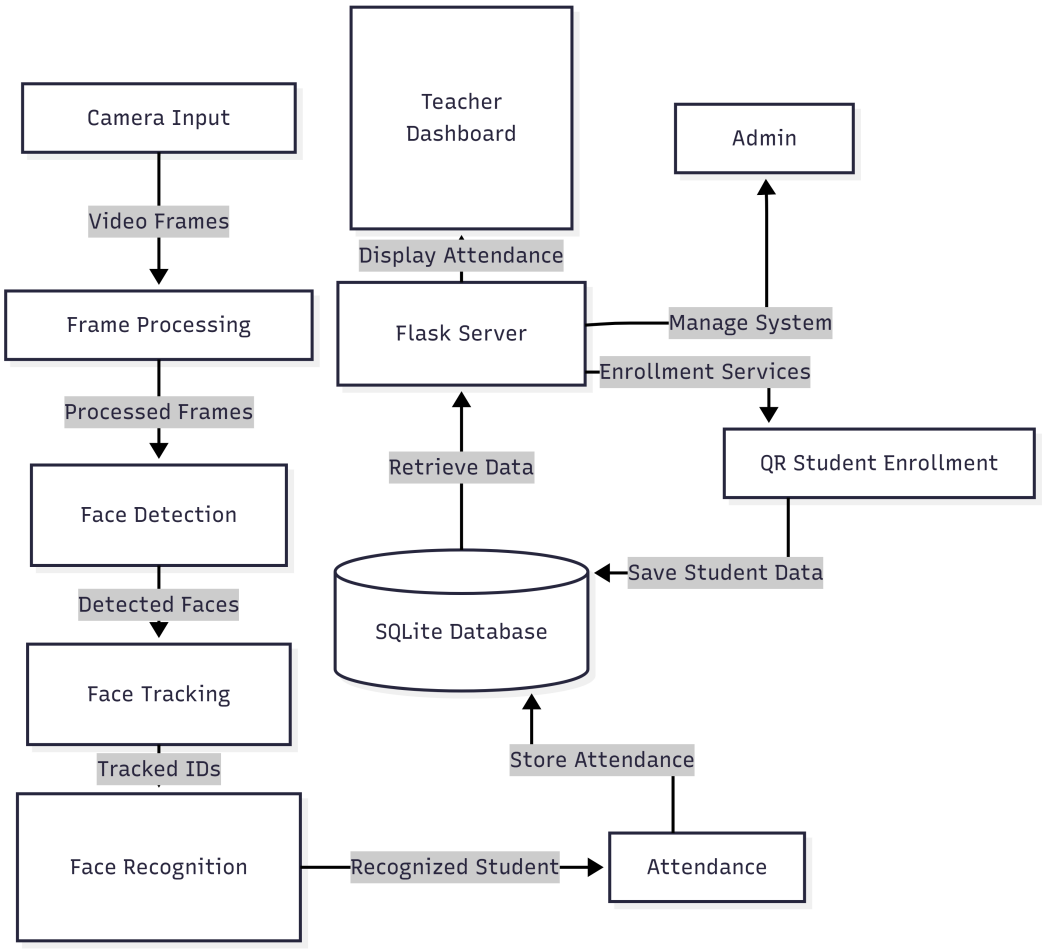

Figure 2.3: Overall Architecture Diagram

2.12 Database Design

The system uses a local SQLite database with a relational structure. The tables are linked to each other through foreign keys, which keeps the data organized and consistent.

- **Students Table** stores each student's personal information, the stored face embedding associated with the student, and their enrollment status.
- **Teachers Table** stores teacher account information including login credentials.
- **Groups Table** organizes students into class groups that can be assigned to sessions.
- **Modules Table** stores information about the courses and subjects taught in the system.
- **Timetable Table** stores scheduled sessions, linking a module, a group, a teacher, a room, a day, and a time slot.

- **Sessions Table** stores active and past attendance sessions, each linked to a timetable entry.
- **Attendance Table** stores the attendance record for each student in each session, including their status (present, absent, late, or manual) and the time they were recognized.

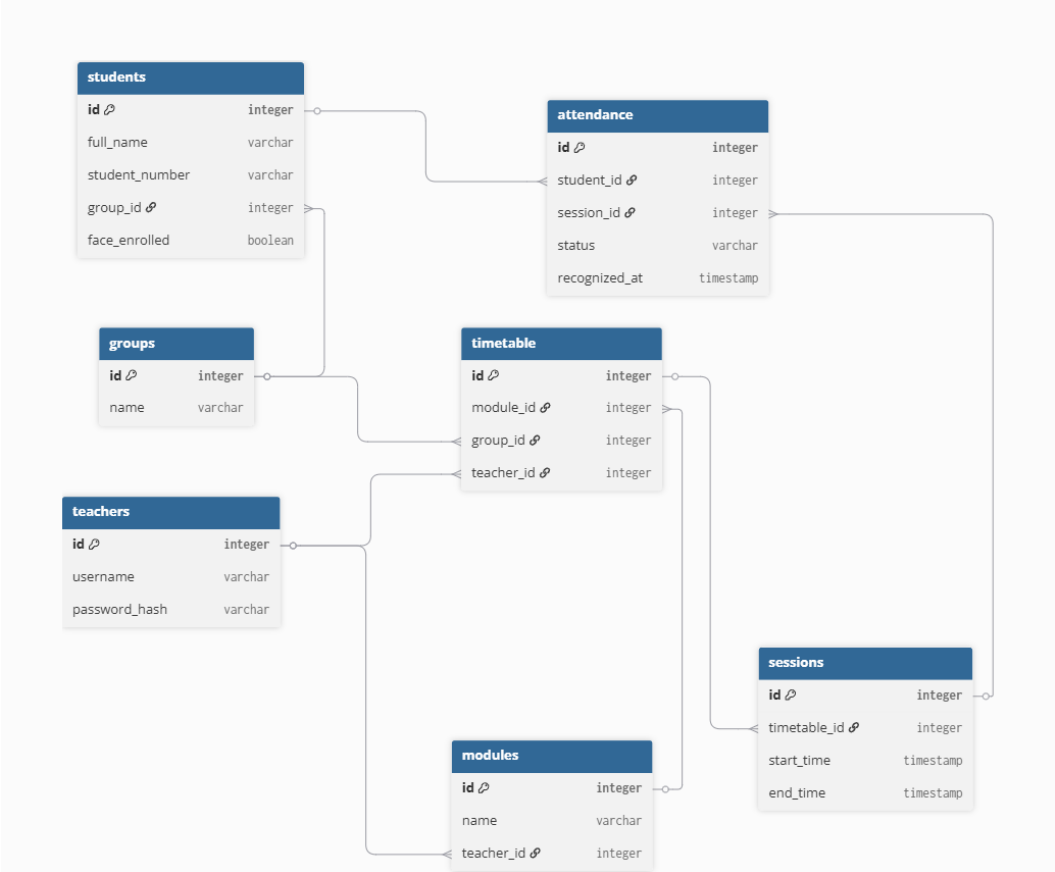

Figure 2.4: Database Schema

2.13 Computer Vision Pipeline

The AI pipeline is the core of the system. It runs continuously during a session and processes every third frame from the camera to keep the load on the processor manageable. Processing every frame would unnecessarily increase CPU usage without significantly improving recognition reliability on the Raspberry Pi 4 [21].

Face Detection. Each frame is passed to MediaPipe BlazeFace [12], which scans the image and detects faces present in the frame, although the system is designed primarily for one-by-one student entry. For each face, it returns the bounding box coordinates and the positions of key landmarks such as the eyes, nose, and mouth corners.

Face Tracking. Detected faces are temporarily tracked across consecutive frames using a lightweight tracking mechanism based on Intersection over Union (IOU) and center distance. IOU measures how much two bounding boxes from different frames overlap, and center distance measures how far the center of a face has moved between frames. Together, these two checks allow the system to follow the same face across multiple frames without processing it as a new detection every time. This reduces unnecessary computation and, more importantly, supports the voting mechanism used later to confirm a student's identity.

Landmark Extraction. The landmark positions returned by the detector are used in the next step to align the face correctly.

Face Alignment. The face is rotated and cropped so that it is always in the same standard orientation before being passed to the recognition model. This makes recognition more reliable regardless of how the student is standing.

Quality Filtering. Before recognition is attempted, each face is checked for quality. Faces that are too small, too dark, too bright, or too blurry are rejected at this stage and discarded. This prevents bad images from producing incorrect matches.

Embedding Extraction. Each face that passes the quality check is fed into MobileFaceNet [14] via ONNX Runtime [16]. The model outputs a 128-dimensional embedding vector that represents the unique features of that face.

Similarity Matching. The embedding is compared against all stored embeddings for students in the current session's group using cosine similarity. The student whose stored embedding is closest to the detected face, and whose score is above the threshold, is identified as a candidate match.

Voting Mechanism. A single match is not enough to confirm attendance. The system uses a voting mechanism that requires a student to be matched in at least three out of five consecutive frames before their identity is confirmed. Because the tracking step keeps the same face linked across frames, these votes are collected reliably for the same physical person rather than being scattered across different detections.

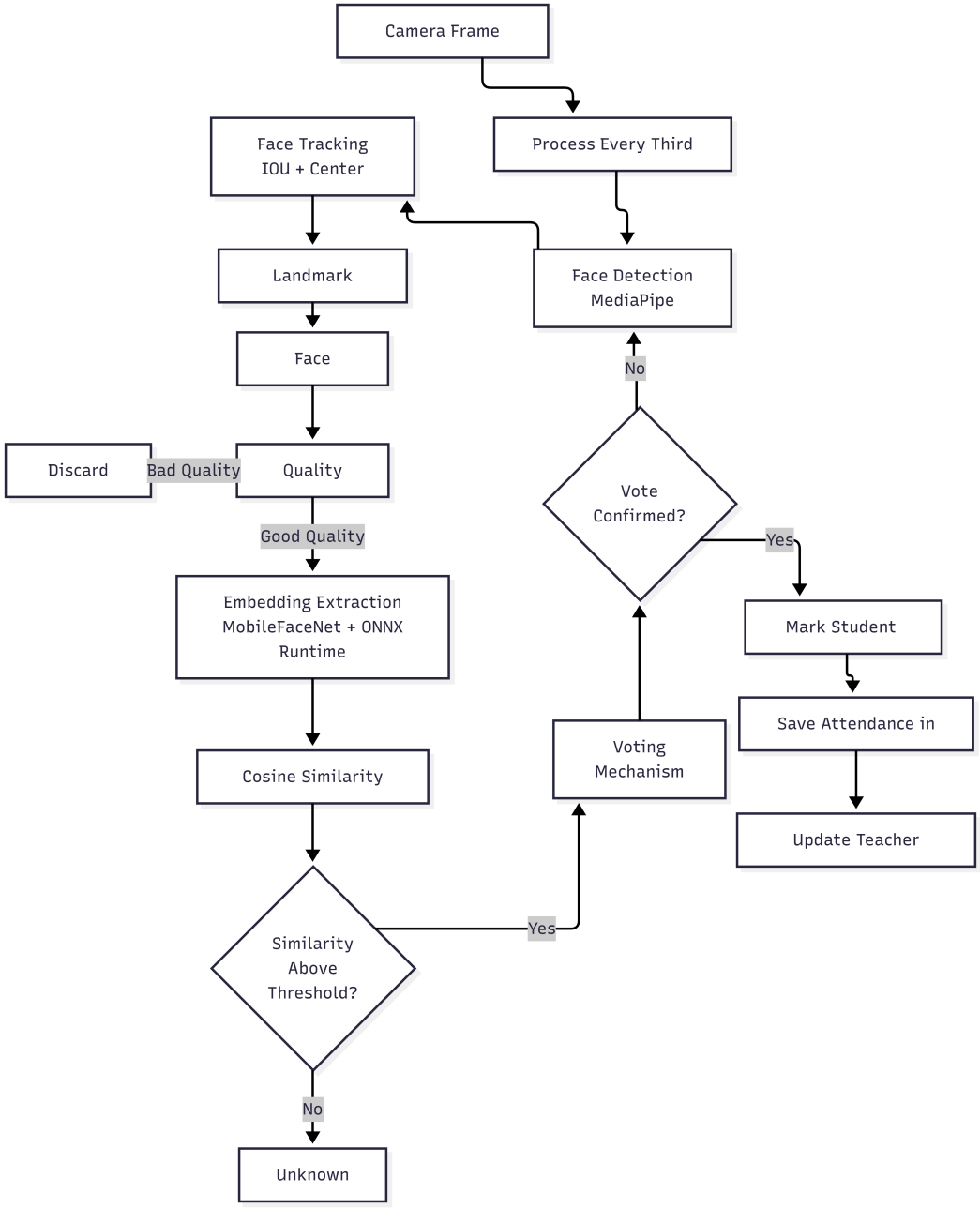

Figure 2.5: AI Pipeline Flowchart

2.13.1 Face Detection Module

Face detection is handled by MediaPipe BlazeFace [12]. This model was developed by Google and is specifically designed to run fast on CPU-only hardware. It uses a small neural network that can scan a full frame and locate faces in a few milliseconds.

For each face it finds, the model returns two things: a bounding box that tells the system where in the frame the face is, and a set of landmark points marking key positions on the face. These landmarks are what make face alignment possible in the next step.

BlazeFace was chosen over heavier detectors like MTCNN or RetinaFace because it is fast enough for real-time processing on the Raspberry Pi [21] without dropping frames. It also handles reasonable variations in lighting and face angle well, which is important in a real classroom setting.

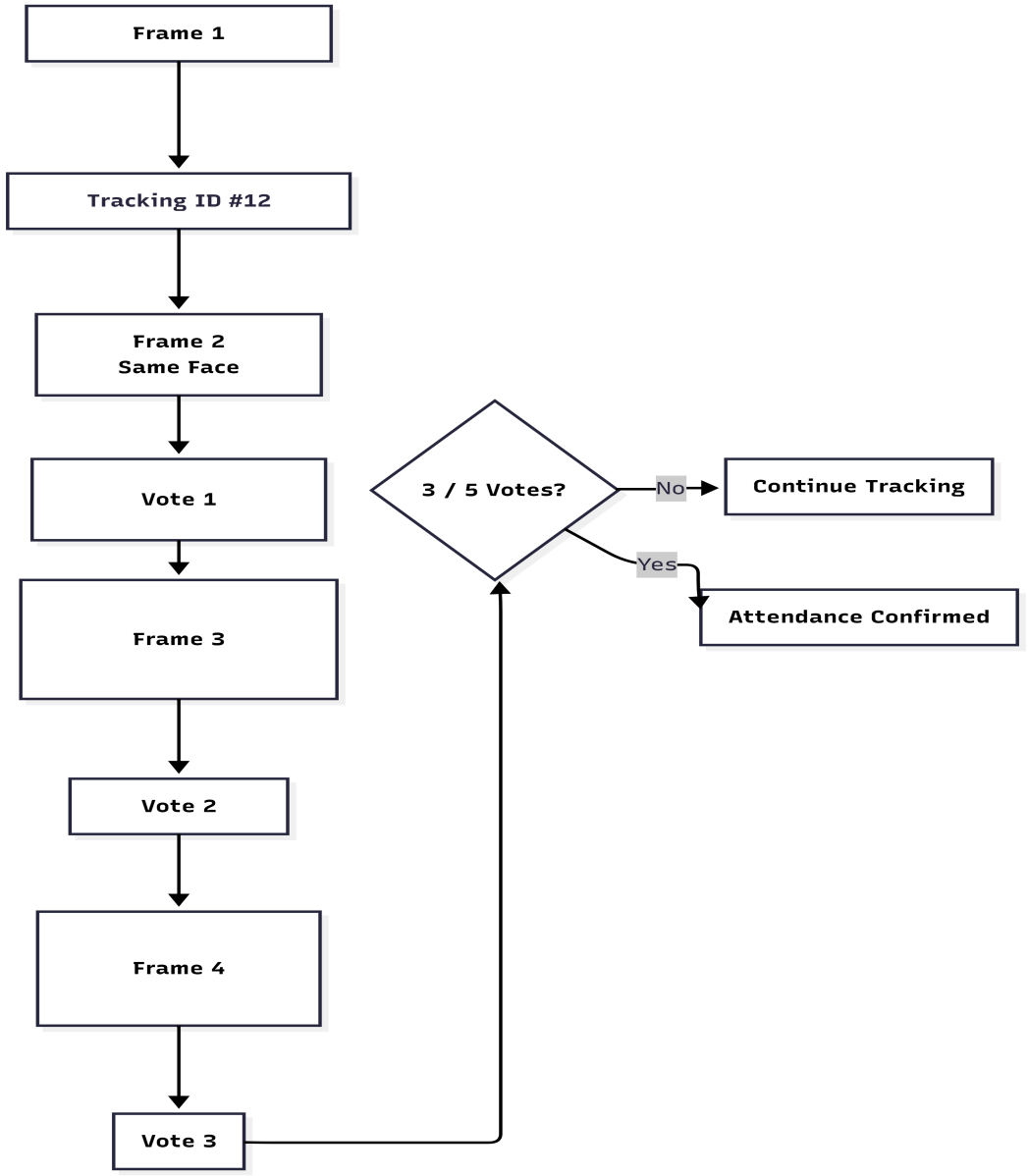

Figure 2.6: Tracking and Voting Logic

2.13.2 Face Recognition Module

Once a face has been detected, tracked, aligned, and passed the quality check, it is sent to the recognition module.

MobileFaceNet [14] takes the aligned face image and produces a 128-dimensional embedding vector. This vector is a compact numerical fingerprint of that face. The model runs

through ONNX Runtime [16], which is faster than running it through a full deep learning framework.

- **Embedding storage** during enrollment, each student submits a face photo. The system processes it through the same pipeline and stores the resulting embedding in the database. This stored embedding is what later frames are compared against during a session.
- **Cosine similarity** when a face is detected during a session, its embedding is compared to all stored embeddings for students in the current group. Cosine similarity measures how similar two vectors are by looking at the angle between them. A score close to 1.0 means the two embeddings are very likely from the same person.
- **Similarity threshold** a minimum similarity score is required for a match to be accepted. Faces that do not reach this threshold are treated as unknown and ignored.
- **Voting mechanism** a student must be matched across at least three out of five frames before they are confirmed. The tracking step ensures that votes accumulate for the same tracked face rather than being spread across separate detections of the same person.
- **Cooldown system** once a student is confirmed and marked as present, a 30-second cooldown is applied. During this time, the system will not mark that student again, which prevents duplicate records from being created if the student walks past the camera more than once.

2.14 Attendance Management Module

This module handles the business logic of the system — what happens after a student is recognized.

- **Session creation** a teacher starts a session from the dashboard by selecting a timetable entry. The system creates a session record in the database and loads all the face embeddings for students in that group into memory. Loading embeddings into RAM at the start means the system does not need to read from the database on every frame, which keeps the recognition fast.
- **Attendance states** each student in a session can have one of four statuses:
  - Present — recognized automatically by the camera
  - Absent — not recognized by the end of the session
  - Late — recognized after the session's start window

  - Manual — status set directly by the teacher

- **Automatic marking** when a student passes the voting confirmation, they are automatically marked as present in the database with a timestamp.
- **Manual correction** the teacher can override any automatic result during or after the session. This is useful if a student was not recognized due to a technical issue.
- **Report generation** at the end of a session, the system generates an attendance report showing the status of every student in the group. The teacher can review it in the browser and download it as a formatted PDF.

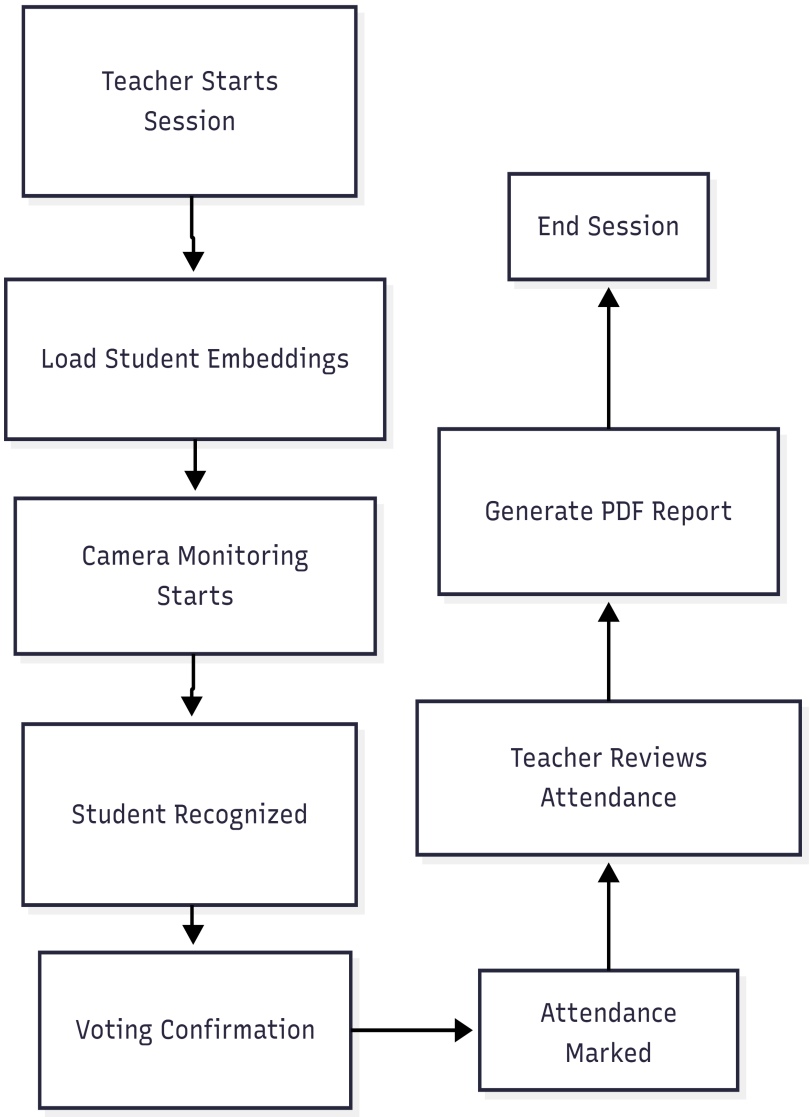

Figure 2.7: Session Lifecycle Diagram

2.15 Web Application Design

The web application is built with Flask and runs entirely on the Raspberry Pi. It is accessible from any browser on the same local network.

- **Teacher Dashboard** the main interface for teachers. It shows their schedule for the day, allows them to start and end sessions, displays the live camera feed with bounding boxes and student names overlaid, shows a real-time list of recognized students, and provides access to session reports.
- **Admin Panel** a separate management area for administrators. It allows managing student records, teacher accounts, student groups, course modules, and timetable entries.
- **Student Enrollment Page** a mobile-friendly page that opens when a student scans their QR code. The student takes or uploads a photo of their face, which is submitted to the system. The server processes the photo, extracts the embedding, and marks the student as enrolled.

2.16 Security and Privacy

- **Authentication** access to the system is protected by a username and password login. Sessions are managed server-side.
- **Role separation** teachers can only access attendance-related features. Administrators have full management access. Neither role can access the other's area.
- **Local processing** all face detection and recognition happens on the Raspberry Pi itself. No images or embeddings are ever sent to an external server or cloud service.
- **Local database storage** all data, including face embeddings, is stored in the SQLite database on the device. If the device is kept secure, the data stays secure.
- **HTTPS** the system uses HTTPS because modern mobile browsers require a secure connection before allowing access to the camera [22]. This is needed for the enrollment page to work on students' phones.
- **Offline operation** because the system never connects to the internet, there is no risk of data being intercepted in transit or leaked to third-party services. This is a significant privacy advantage over cloud-based attendance systems.

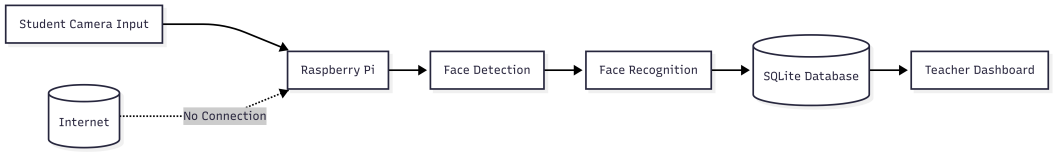

Figure 2.8: Privacy Local Processing Diagram

2.17 Conclusion

This chapter covered the full analysis and design of the system before any implementation begins. We started by identifying the real problems with traditional and existing automated attendance methods and explained why an edge-based offline face recognition system is the most practical solution. We introduced the proposed system, listed all functional and non-functional requirements, identified the three system actors, and walked through the complete workflow from enrollment to session end.

We then moved into the technical design. We presented the development tools and the reasons behind each choice, compared face recognition models directly on the target hardware and justified the selection of MobileFaceNet, and described the overall system architecture and how all components connect together. We walked through the database structure, explained the machine learning pipeline step by step, and described each major module in detail. Finally we covered the security and privacy measures built into the system.

With both the requirements and the design now fully defined, the next chapter will cover the implementation, showing how the system was actually built and deployed on the Raspberry Pi.

Chapter 3: System Implementation and Testing

3.1 Introduction

The previous chapter described how the system was designed. This chapter explains how it was actually built. It covers the hardware that was used, the software environment that was set up, and how each part of the system was implemented in practice. It also covers the testing that was carried out to verify that the system works correctly under real conditions, along with the performance results and the limitations that were observed during development.

3.2 Hardware Setup

The system runs on a Raspberry Pi 4 Model B with 4 GB of RAM. This board was selected because it is affordable, runs a full Linux operating system, and provides sufficient performance for real-time face detection and recognition using lightweight AI models. The Raspberry Pi uses a quad-core ARM Cortex-A72 processor running at 1.5 GHz which is sufficient for Computer Vision when models are run through ONNX Runtime.

A USB webcam is installed at the classroom entrance to capture a continuous video stream. The captured frames are processed by the system using OpenCV. The board is powered through its USB-C port using a standard 5V 3A power supply.

All data is stored locally on the microSD card installed on the Raspberry Pi. Teachers can access the system through a web browser from any device connected to the same local Wi-Fi network.

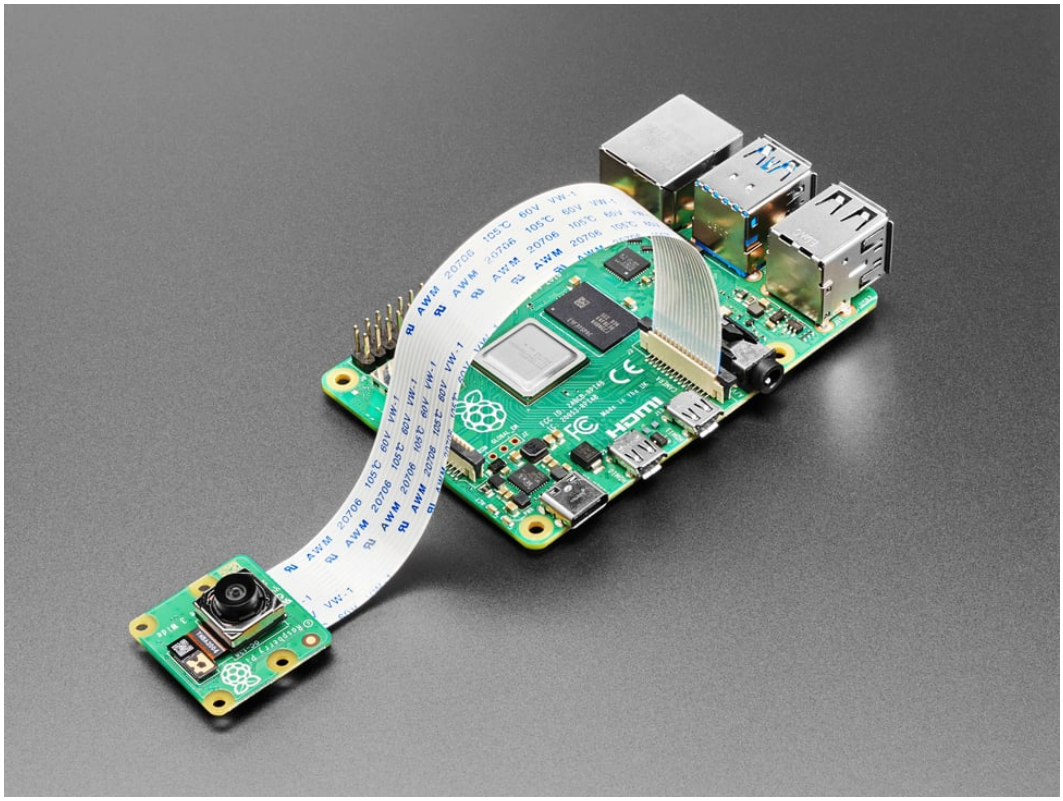

Figure 3.1: Raspberry Pi 4 Model B used in the system

3.3 Software Environment

The software environment is based on Raspberry Pi OS 64-bit running Python 3.9. To ensure a stable and isolated setup, all dependencies were installed inside a Python virtual environment. The main libraries used by the system include:

- **Flask** for the web application and API
- **OpenCV** for camera capture and image processing
- **MediaPipe** for face detection
- **ONNX Runtime** for running the face recognition model
- **SQLite3** built into Python, used for the local database

The libraries were installed using pip inside a virtual environment:

```
pip install -r requirements.txt
```

Figure 3.2: Installing required libraries

The MobileFaceNet model was downloaded as an ONNX file and placed in the project directory. No internet connection is required at runtime --- everything runs locally once the setup is complete.

3.4 Database Implementation

The database was created using Python's built-in `sqlite3` module as a single local file stored on the Raspberry Pi. It contains four main tables.

The `students` table stores each student's personal information and assigned group:

```
CREATE TABLE IF NOT EXISTS students (
id              INTEGER PRIMARY KEY AUTOINCREMENT,
full_name       TEXT    NOT NULL,
student_id TEXT    UNIQUE NOT NULL,
group_id        INTEGER,
enrolled    INTEGER DEFAULT 0,
face_thumbnail BLOB,
created_at TIMESTAMP DEFAULT 0,
FOREIGN KEY (group_id) REFERENCES groups(id));
```

Figure 3.3: Students table creation

The `face_embeddings` table stores the 128-dimensional embedding vectors produced during enrollment:

```
CREATE TABLE IF NOT EXISTS face_embeddings (
id          INTEGER   PRIMARY KEY AUTOINCREMENT,
student_id INTEGER   NOT NULL,
embedding  BLOB      NOT NULL,
created_at TIMESTAMP DEFAULT CURRENT_TIMESTAMP,
FOREIGN KEY (student_id) REFERENCES students(id));
```

Figure 3.4: Face embeddings table creation

The `attendance` table records each recognition event:

```
CREATE TABLE IF NOT EXISTS attendance (
id INTEGER PRIMARY KEY AUTOINCREMENT,
session_id INTEGER NOT NULL,
student_id INTEGER NOT NULL,
status TEXT NOT NULL CHECK(status IN ('present', 'absent',
   'late', 'manual')),
confidence REAL,
marked_at TIMESTAMP DEFAULT CURRENT_TIMESTAMP,
FOREIGN KEY (session_id) REFERENCES sessions(id),
FOREIGN KEY (student_id) REFERENCES students(id),
UNIQUE(session_id, student_id);
```

Figure 3.5: Attendance table creation

The sessions table stores information about each attendance session:

```
 CREATE TABLE IF NOT EXISTS sessions (
id INTEGER PRIMARY KEY AUTOINCREMENT,
module_id INTEGER NOT NULL,
group_id INTEGER NOT NULL,
teacher_id INTEGER NOT NULL,
timetable_id INTEGER,
started_at TIMESTAMP DEFAULT CURRENT_TIMESTAMP,
ended_at TIMESTAMP,
status TEXT DEFAULT 'active',
duration_minutes INTEGER,
session_type TEXT,
FOREIGN KEY (module_id) REFERENCES modules(id),
FOREIGN KEY (group_id) REFERENCES groups(id),
FOREIGN KEY (teacher_id) REFERENCES users(id),
FOREIGN KEY (timetable_id) REFERENCES timetable(id));
```

Figure 3.6: Sessions table creation

Indexes were added on student_id, session_id, and teacher_id to improve query performance during live sessions.

3.5 Computer Vision Pipeline Implementation

The Computer Vision pipeline runs in a background thread that starts when a session begins. It reads frames from the camera continuously and processes every third frame to reduce CPU

load without missing any student walking past.

The pipeline is built around a `process_frame` method that takes a camera frame and the list of enrolled students as input and returns a list of recognition results:

```
        def process_frame(self, frame, enrolled_list):
        enrolled_list: list of (student_id, embedding) tuples.
        Returns: list of dicts with student_id, score, track_id,
           bbox.
        results = []
        detections = self.detector.detect(frame)
        if not detections:
        return results
        matched = self.tracker.update(detections)
        track_ids = [t[0] for t in matched]
        for tid in track_ids:
        bbox = self._get_track_bbox(tid)
        if not bbox:
        continue
        ok, _ = self.quality_filter.check(frame, bbox)
        if not ok:
        continue
        if self._is_on_cooldown(tid):
        continue
        face_crop = self._crop_face(frame, bbox)
        if face_crop is None:
        continue
        embedding = self.embedder.extract(face_crop)
        matched_student_id, score = self.matcher.find_best_match(
        embedding, enrolled_list)
        if matched_student_id is not None:
        self._add_vote(tid, matched_student_id, score)
        confirmed_id, confirmed_score = self._get_confirmed(tid)
        if confirmed_id is not None:
        self._set_cooldown_by_student(confirmed_id)
        results.append({
                "student_id": confirmed_id,
                "score": confirmed_score,
                "track_id": tid,
                "bbox": bbox
        })
        else:
        self._add_vote(tid, None, score)
        return results
```

Figure 3.7: Complete process frame pipeline detect, track, embed, match

The first step is face detection. The frame is passed to MediaPipe BlazeFace, which scans it and returns a list of detected faces, each described by a bounding box and a set of facial landmark positions.

The second step is tracking. Each detected face is compared against the faces seen in the previous frame using IOU and center distance. The tracker initialisation and IOU calculation are shown below:

```
import numpy as np
class FaceTracker:
def __init__(self, iou_threshold=0.3,
center_distance_threshold=50,
max_age=10):
self.tracks = {}
self.next_id = 1
self.iou_threshold = iou_threshold
self.center_distance_threshold =
    center_distance_threshold
self.max_age = max_age

def _bbox_iou(self, a, b):
x1 = max(a[0], b[0])
y1 = max(a[1], b[1])
x2 = min(a[0] + a[2], b[0] + b[2])
y2 = min(a[1] + a[3], b[1] + b[3])
if x2 <= x1 or y2 <= y1:
return 0.0
inter = (x2 - x1) * (y2 - y1)
area_a = a[2] * a[3]
area_b = b[2] * b[3]
union = area_a + area_b - inter
return inter / union if union > 0 else 0.0
```

Figure 3.8: Face tracker initialisation and IOU calculation

The third step is quality filtering. Faces that are too small (below 60×60 pixels), too dark, too bright, or too blurry as measured by the Laplacian variance are discarded at this stage. This prevents degraded images from producing incorrect matches downstream.

The fourth step is embedding and matching. Faces that pass the quality check are resized to 112×112 pixels and passed to MobileFaceNet through ONNX Runtime, which produces a 128-dimensional embedding vector for each face.

The fifth and final step is voting. The system requires a student to be matched in at least three out of five consecutive frames before their identity is accepted:

```
                def _add_vote(self, tid, student_id, score):
                if tid not in self.votes:
                self.votes[tid] = []
                self.votes[tid].append({
                        "student_id": student_id,
                        "score": score
                })
                if len(self.votes[tid]) > self.total_votes:
                self.votes[tid].pop(0)

                def _get_confirmed(self, tid):
                if tid not in self.votes or \
                len(self.votes[tid]) < self.total_votes:
                return None, 0.0
                counts = {}
                for vote in self.votes[tid]:
                sid = vote["student_id"]
                if sid is not None:
                counts[sid] = counts.get(sid, 0) + 1
                for sid, count in counts.items():
                if count >= self.vote_threshold:
                avg_score = np.mean([
                v["score"]
                for v in self.votes[tid]
                if v["student_id"] == sid
                ])
                return sid, float(avg_score)
                return None, 0.0
```

Figure 3.9: Voting mechanism to confirm student identity

Once a student is confirmed, their attendance is written to the database and a thirty-second cooldown is applied to that student ID to prevent duplicate records.

3.6 Face Detection and Recognition Implementation

Face detection is handled by a `FaceDetector` class built on top of the MediaPipe Tasks API:

```
import cv2
import config
import mediapipe as mp
from mediapipe.tasks import python
from mediapipe.tasks.python import vision
class FaceDetector:
def __init__(self, min_confidence=0.7):
base_options = python.BaseOptions(
model_asset_path='models/blaze_face_short_range.tflite' )

options = vision.FaceDetectorOptions(
base_options=base_options,
min_detection_confidence=min_confidence )
self.detector = vision.FaceDetector.create_from_options(
options)
def detect(self, frame):
rgb = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
mp_image = mp.Image(
image_format=mp.ImageFormat.SRGB,
data=rgb)
detection_result = self.detector.detect(mp_image)
detections = []
if not detection_result.detections:
return detections
for det in detection_result.detections:
bbox = det.bounding_box
x = int(bbox.origin_x)
y = int(bbox.origin_y)
cw = int(bbox.width)
ch = int(bbox.height)
conf = (
det.categories[0].score
if det.categories else 0.0
)
detections.append({
        "bbox": (x, y, cw, ch),
        "confidence": conf})
return detections
```

Figure 3.10: BlazeFace face detector implementation using MediaPipe

The short-range BlazeFace model is used because students pass the camera at close range when entering the classroom. The minimum detection confidence was set to 0.7 after testing: lower values produced spurious detections from background objects, while higher values missed faces under slightly uneven lighting.

Face recognition is handled by a `FaceEmbedder` class that loads MobileFaceNet through ONNX Runtime using the `CPUExecutionProvider`, which is the only execution provider available on the Raspberry Pi since no GPU is present:

```
import numpy as np
import onnxruntime as ort
import cv2
import config
class FaceEmbedder:
def __init__(self, model_path):
self.session = ort.InferenceSession(
model_path,
providers=["CPUExecutionProvider"]      )
self.input_name = \
self.session.get_inputs()[0].name
self.target_size = config.MODEL_INPUT_SIZE
```

Figure 3.11: MobileFaceNet loaded via ONNX Runtime

Before a face crop is passed to the model it must match the format the network expects. The crop is resized to 112×112 pixels, cast to `float32`, normalised to map pixel values into the range $[-1, 1]$, transposed from HWC to CHW channel ordering, and expanded with a batch dimension so the final shape is $(1, 3, 112, 112)$:

```
    def _preprocess(self, face_crop):
    face_crop = cv2.resize(
    face_crop,
    self.target_size)
    face_crop = face_crop.astype(np.float32) / 255.0
    mean = np.array([0.5, 0.5, 0.5], dtype=np.float32)
    std = np.array([0.5, 0.5, 0.5], dtype=np.float32)
    face_crop = (face_crop - mean) / std
    face_crop = face_crop.transpose(2, 0, 1)
    face_crop = np.expand_dims(face_crop, axis=0)
    return face_crop
```

Figure 3.12: Face image preprocessing before embedding extraction

The `extract` method runs the preprocessed tensor through the ONNX session and returns the L2-normalised embedding. Normalisation ensures that cosine similarity reduces to a simple dot product, which is both faster and numerically stable:

```
        def extract(self, face_crop):
        blob = self._preprocess(face_crop)
        embedding = self.session.run(
        None,
        {self.input_name: blob}
        )[0]
        embedding = embedding.flatten()
        norm = np.linalg.norm(embedding)
        if norm > 0:
        embedding = embedding / norm
        return embedding
```

Figure 3.13: Embedding extraction and L2 normalization

Similarity matching is handled by a `SimilarityMatcher` class. The `find_best_match` method iterates over all enrolled embeddings, computes the cosine similarity score for each, and returns the highest-scoring candidate if it meets the threshold:

```
import numpy as np
import config
class SimilarityMatcher:
def __init__(self, threshold=None):
self.threshold = (
threshold or
config.COSINE_SIMILARITY_THRESHOLD)
def cosine_similarity(self, a, b):
a = np.asarray(a).flatten()
b = np.asarray(b).flatten()
dot = np.dot(a, b)
norm_a = np.linalg.norm(a)
norm_b = np.linalg.norm(b)
if norm_a == 0 or norm_b == 0:
return 0.0
return dot / (norm_a * norm_b)

def find_best_match(
self,
query_embedding,
enrolled_list):
if not enrolled_list:
return None, 0.0
query = np.asarray(
query_embedding ).flatten()
best_sid = None
best_score = 0.0
for student_id, enrolled_emb in enrolled_list:
enrolled_emb = np.asarray(
enrolled_emb).flatten()
score = self.cosine_similarity(query,enrolled_emb
)
if score > best_score:
best_score = score
best_sid = student_id
if best_score >= self.threshold:
return best_sid, float(best_score)
return None, float(best_score)
```

Figure 3.14: Cosine similarity matching and threshold-based identification

The similarity threshold was set to 0.6 after running verification tests on the enrolled students. A lower threshold produced false matches between visually similar students; a higher threshold occasionally failed to confirm a correct match when the student's face was at a slight angle.

3.7 Web Application Implementation

The web application serves as the main interface through which teachers and administrators interact with the system. It was developed using Flask and runs entirely on the Raspberry Pi, accessible from any browser on the same local network. The application includes several distinct interfaces: authentication, a teacher dashboard, student management, timetable management, student enrollment, live attendance monitoring, and attendance reporting. Each interface was designed to be simple and functional, requiring no technical background from the user.

Login Interface

Access to the system is protected by a username and password login. When a user opens the application in their browser, they are redirected to the login page before they can reach any other part of the system. The login form collects the username and password, which are verified against hashed credentials stored in the database. Depending on the role associated with the account, the user is redirected either to the teacher dashboard or to the administrator panel. This role separation ensures that teachers cannot access administrative functions and administrators cannot interfere with active attendance sessions.

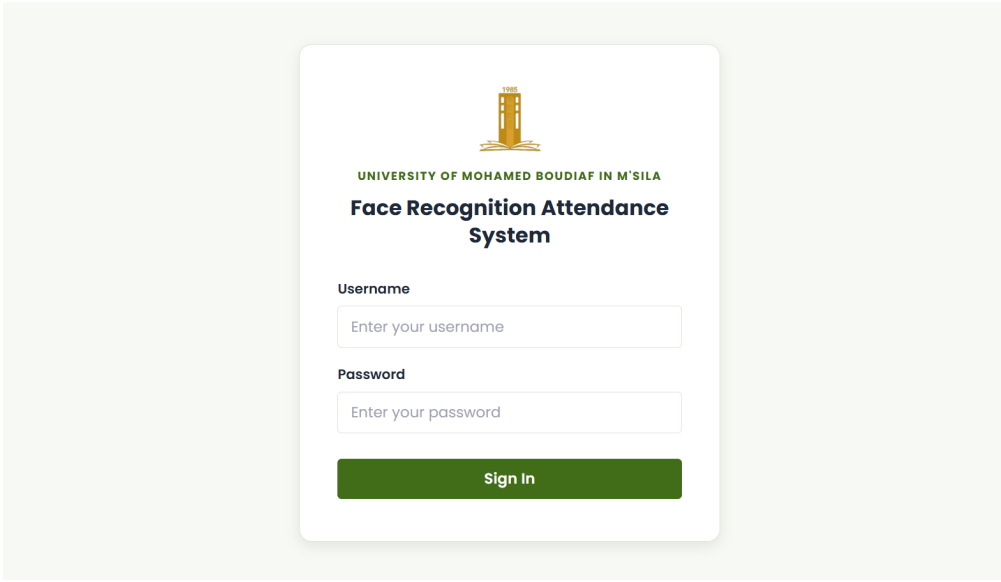

Figure 3.15: Login Interface

Teacher Dashboard

After logging in, the teacher is taken to their personal dashboard. This page displays all sessions scheduled for the current day, pulled automatically from the timetable based on the teacher's account. For each scheduled session, the teacher can see the module name, the student group, the room, and the time slot. A single button allows the teacher to start an attendance session for any of the listed entries.

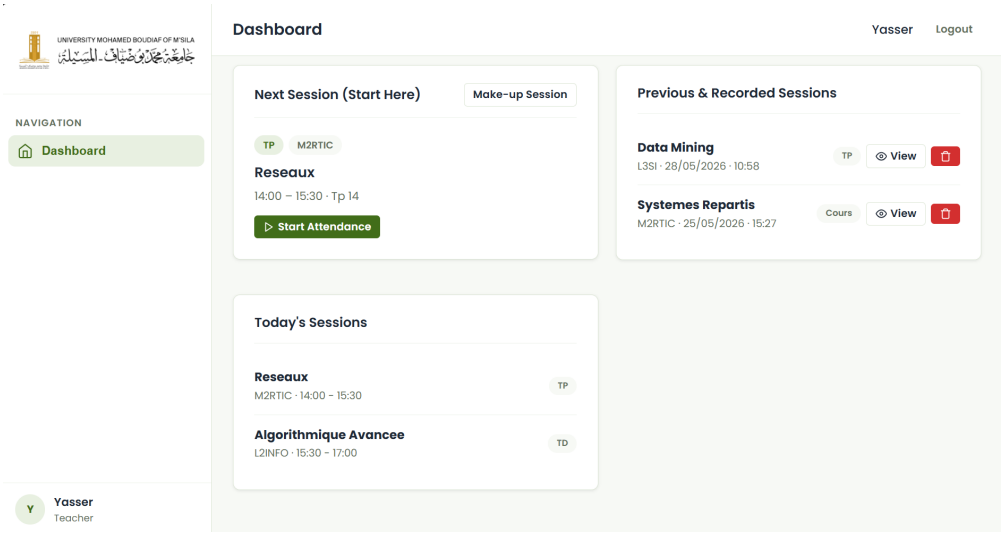

Figure 3.16: Teacher Dashboard

Student Management Interface

The student management interface is part of the administrator panel. It displays the full list of registered students along with their student number, assigned group, and enrollment status. The administrator can add new students, edit existing records, or delete students from the system. Each student entry also provides access to their personal QR code, which is used during the enrollment process.

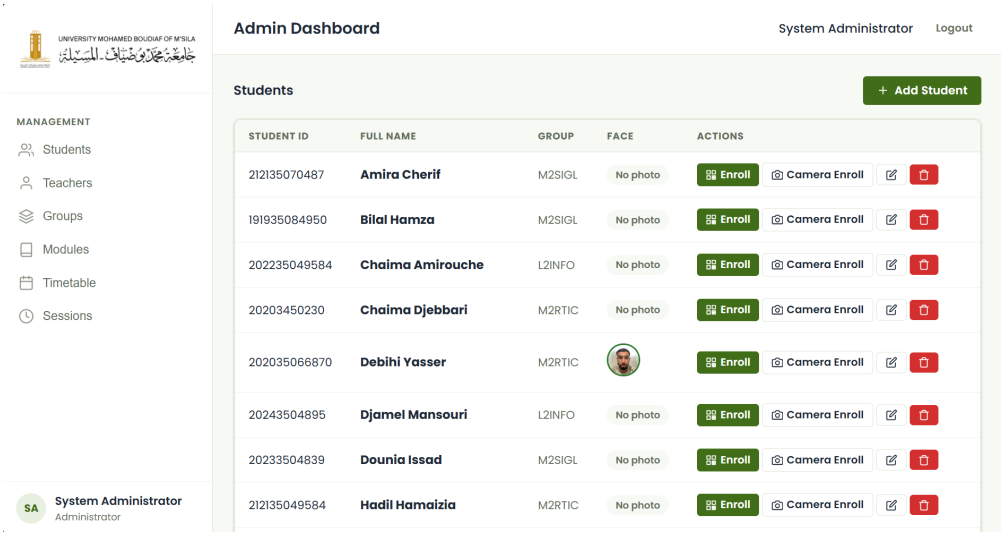

Figure 3.17: Student Management Interface

Timetable Management Interface

The timetable management interface allows the administrator to define the schedule that drives the entire system. Each timetable entry links a course module, a student group, a teacher, a classroom, a day of the week, and a time slot. The session type can be set to lecture, tutorial, or practical. Once a timetable entry exists, it appears automatically on the corresponding teacher's dashboard on the scheduled day.

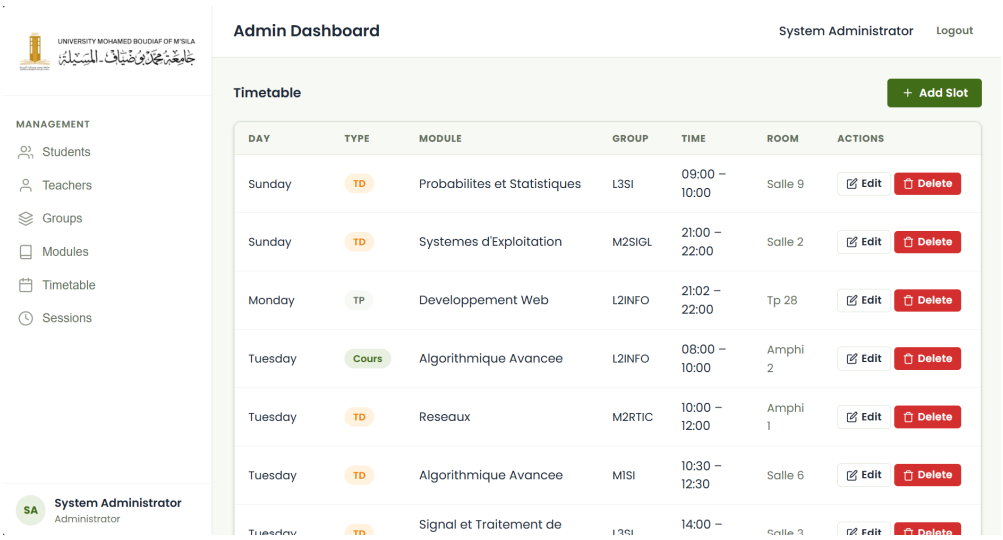

Figure 3.18: Timetable Management Interface

Student Enrollment Interface

Student enrollment is handled through a separate mobile-friendly page. Each student receives a unique QR code generated by the system, which the administrator can print or share digitally. When a student scans their QR code with a phone, they are taken directly to their personal enrollment page. The page activates the phone's camera and guides the student to capture their face from multiple angles. Once the photo is submitted, it is processed through the full face pipeline and the resulting embedding is stored in the database. The student is then marked as enrolled.

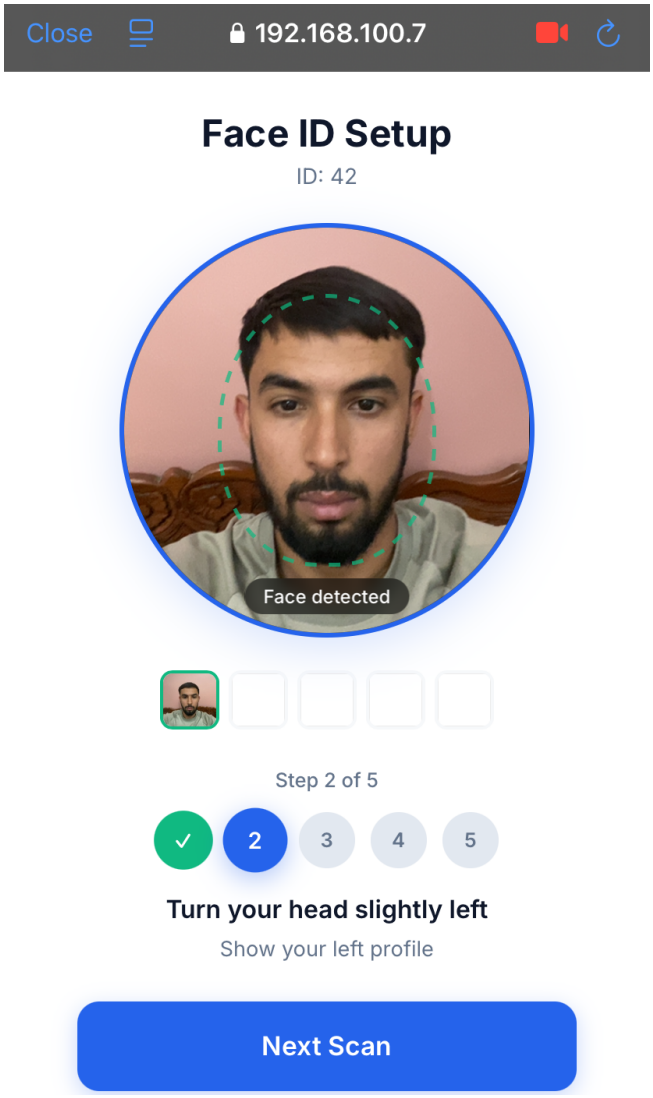

Figure 3.19: Student Enrollment Interface

Live Attendance Interface

When a teacher starts a session from the dashboard, the system opens the live attendance interface. This page streams the live camera feed directly in the browser. As the AI pipeline

processes each frame, a green bounding box is drawn around every detected face, and the recognized student's name is displayed above the box in real time. Figure 3.20 shows the system successfully detecting and identifying a student, with the name *Debihi Yasser* displayed above the bounding box. At the bottom of the page, the teacher can end the session at any time using the End Session button.

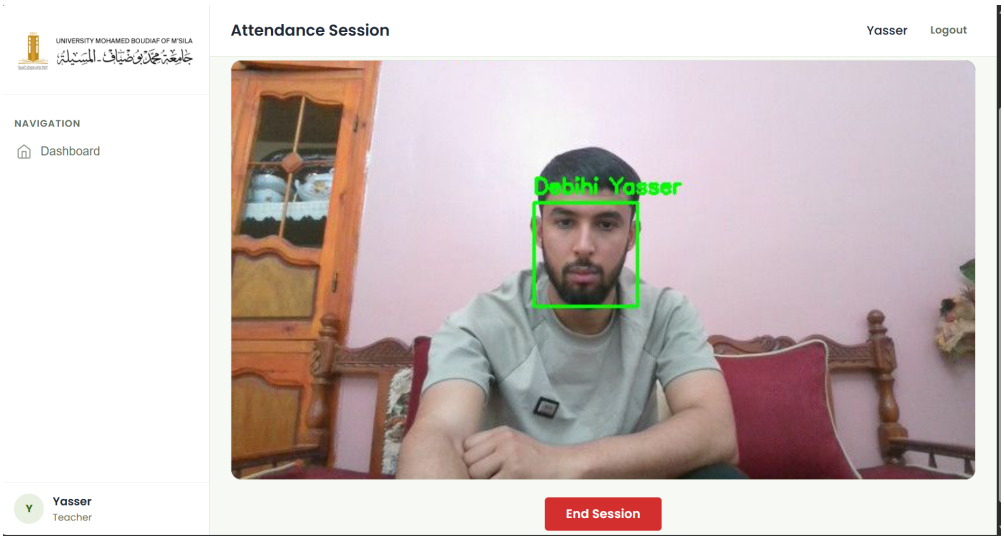

Figure 3.20: Live Attendance Interface showing real-time face detection and student identification

Attendance Report Interface

Once a session ends, the system generates a complete attendance report automatically. The report displays each recognized student alongside their student ID, attendance status, and the confidence score produced by the recognition pipeline. A session summary panel on the right shows the total number of present and absent students at a glance, along with session details including the module name, group, teacher, date, and session duration. Figure 3.21 shows a completed session for the *Reseaux* TP module, where one student was recognized with a confidence score of 86%. The teacher can download the report as a formatted PDF directly from this page using the Download PDF button.

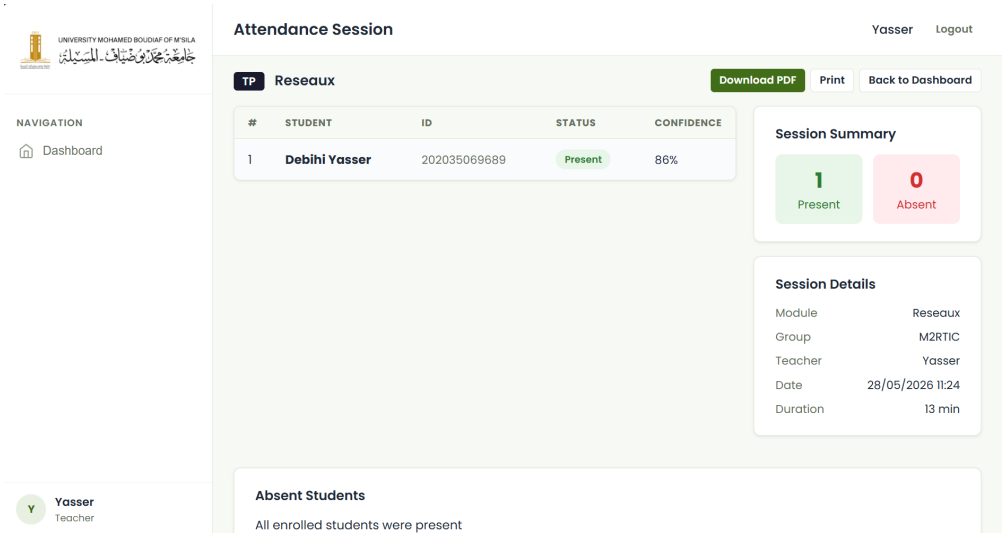

Figure 3.21: Attendance Report Interface showing session summary, recognition confidence, and PDF export option

3.8 Attendance Management Implementation

When a teacher starts a session, the system loads all face embeddings for the selected group into memory. This avoids reading from the database on every frame and keeps recognition fast:

```
        class EnrollmentService:
        def get_all_enrolled_embeddings(self, group_id=None):
        Returns list of (student_id, embedding) tuples.
        student_id = students.id (NOT emb_id)
        conn = get_connection()
        try:
        cur = conn.cursor()
        if group_id:
        cur.execute("""
        SELECT s.id as student_id,
        fe.embedding
        FROM students s
        JOIN face_embeddings fe
        ON s.id = fe.student_id
        WHERE s.enrolled = 1
        AND s.group_id = ?
        """, (group_id,))
        else:
        cur.execute("""
        SELECT s.id as student_id,
        fe.embedding
        FROM students s
        JOIN face_embeddings fe
        ON s.id = fe.student_id
        WHERE s.enrolled = 1"""
        )
        rows = cur.fetchall()
        results = []
        for row in rows:
        emb = np.frombuffer(
        row["embedding"],
        dtype=np.float32
        )
        results.append(
        (row["student_id"], emb))
        return results
        finally:
        conn.close()
```

Figure 3.22: Loading face embeddings from SQLite into NumPy arrays at session start

Once a student is confirmed by the voting mechanism, the system checks the cooldown before inserting the attendance record:

```
class AttendanceService:
def mark_present(
self,
session_id,
student_id,
confidence=1.0,
status="present"):
conn = get_connection()
try:
cur = conn.cursor()
cur.execute("""
INSERT OR REPLACE INTO attendance
(session_id, student_id, status, confidence)
VALUES (?, ?, ?, ?)
""", (
session_id,
student_id,
status,
confidence
))
conn.commit()
finally:
conn.close()
```

Figure 3.23: Inserting an attendance record into the database

```
        def _is_on_cooldown(self, student_id):
        if student_id not in self.cooldowns:
        return False
        if (
        time.time()
        - self.cooldowns[student_id]
        < self.cooldown_seconds
        ):
        return True
        del self.cooldowns[student_id]
        return False
        def _set_cooldown(self, student_id):
        self.cooldowns[student_id] = time.time()
```

Figure 3.24: Cooldown logic to prevent duplicate records

When the session ends, the system automatically marks any student who was not recognized as absent. If a student was recognized more than 15 minutes after the session started, they are marked as late instead. Finally, the system generates a PDF report listing each student's name, ID, status, and the time they were recognized.

3.9 System Testing

To verify the operational integrity, functional reliability, and architectural robustness of the developed attendance management system, a comprehensive testing methodology was executed. Due to the temporary physical unavailability of the target Raspberry Pi hardware during the evaluation phase, all tests and pipeline executions were performed on a personal computer (PC) serving as a hardware emulation and simulation host. Testing was conducted using the Extended Yale B (Cropped) dataset [23], containing 2,414 frontal face images of 38 subjects captured under 64 illumination conditions, selected to evaluate system robustness under the variable lighting conditions typical of real classroom environments. The testing framework was designed to validate component-level functional integration and realistic environmental scenarios replicating a physical classroom entrance.

3.9.1 Functional and Integration Testing

Functional testing focused on ensuring that every module in the computer vision pipeline and web application executed according to the functional requirements established in Chapter 2, executing seamlessly within the host environment.

- **Enrollment and QR Code Extraction:** Tests verified that unique QR codes were correctly generated for student entities. Mobile devices successfully scanned these codes, navigating to the HTTPS-secured enrollment page. Image uploads successfully triggered the server-side extraction pipeline, generating and saving the 128-dimensional embedding vectors into the local SQLite database.
- **Face Pipeline Integration:** The integrated pipeline (comprising frame decoding, BlazeFace detection, tracking, facial alignment, and embedding extraction) was validated. The system successfully skipped non-informative background regions and correctly fed isolated face chips into the MobileFaceNet model.
- **Tracking, Voting, and Cooldown Logic:** The spatial tracking module based on Intersection-over-Union (IoU) correctly preserved individual student tracks across subsequent frames. The voting mechanism which demands at least 3 matching classifications out of 5 consecutive tracked frames successfully suppressed short-lived false matches. Additionally, the 30-second cooldown period was verified to prevent redundant SQLite write-operations when a student lingered in front of the lens.
- **Dashboard and Web Management Panel:** The Flask-based interface correctly rendered live camera streams with bounding boxes and matched names overlaid on the UI in real time. Instructors could seamlessly start/terminate sessions, adjust attendance logs manually, and successfully export formatted attendance records to external PDF summaries.

3.9.2 Environmental and Scenario Testing

The system was subjected to various environmental configurations on the simulation host to assess its operational resilience in a typical university environment:

1. **Normal Indoor Lighting Scenario:** Conducted using a standard, well-illuminated classroom dataset. The system achieved near-flawless performance, picking up students walking into the room sequentially at a normal pace.
2. **Variable and Harsh Lighting Scenario:** Tested under strong backlighting conditions (e.g., placing the camera directly facing an open window or a bright outdoor area). This variation occasionally caused severe facial shadowing, requiring fine-tuning of the minimum detection confidence threshold.
3. **Pose Variation and Occlusion Scenario:** Tested with students wearing standard reading glasses, caps, or displaying side-profile angles. While minor occlusions like glasses did not impact matching accuracy, sharp side-profile rotations occasionally prevented embedding extraction due to missing facial landmark points.

3.10 Performance Evaluation

This section details the quantitative evaluation of the system's accuracy, computational latency, and resource footprint. Because physical access to the Raspberry Pi hardware was restricted, all evaluation benchmarks were recorded on an x86_64 PC processor running the pipeline via ONNX Runtime using the CPU Execution Provider. To provide meaningful insights for a future edge deployment, the recorded latencies represent the host environment processing capabilities under the software's lightweight structural configurations.

3.10.1 Computational Latency and Inference Speed

Operating purely on a CPU execution architecture requires deep performance optimization. To maintain a highly responsive interface, execution speeds were evaluated using ONNX Runtime configured with the CPU Execution Provider. Table 3.1 breaks down the mean time consumption across the sequential phases of processing a single video frame containing one face on the PC evaluation host.

Table 3.1: Pipeline Phase Latency Breakdown under Host CPU Execution

Pipeline Processing Phase	**Mean Execution Time (ms)**
Frame Capture and Preprocessing	2.1
BlazeFace Detection (MediaPipe)	5.4
Face Alignment and Normalization	1.2
MobileFaceNet Embedding Inference	14.8
SQLite Cosine Similarity Search	0.8
Total Processing Latency	**24.3 ms**

On the evaluation PC, a total single-face latency of approximately 24.3 milliseconds translates to an execution capability exceeding 40 Frames Per Second (FPS). While the physical Raspberry Pi's ARM Cortex-A72 architecture is expected to exhibit scaling factors that increase these times linearly, the system's structural implementation specifically the frame-skipping strategy processing only every third frame ensures the framework remains highly optimized for smooth edge execution even under real-world resource constraints.

3.10.2 Hardware Resource Utilization

Hardware metrics were recorded on the host machine during active attendance tracking sessions over a continuous 60-minute duration.

- **CPU Consumption:** During passive periods (no faces present), CPU utilization across the host processor cores remained negligible (under 2%). When an individual entered

the camera view, active detection and embedding generation caused a minimal, transient spike ranging between 8% and 15% utilization, dropping back immediately once the face left the frame or entered cooldown.

- **Memory Allocation:** The memory footprint was remarkably lightweight and stable across execution. Total RAM usage hovered consistently around 110 MB to 140 MB, verifying that the memory footprint of the software stack is fully compatible with the strict hardware limitations of an embedded platform.

3.10.3 Recognition Accuracy Metrics

The accuracy evaluation was performed on the Extended Yale B (Cropped) dataset [23], comprising 2,414 frontal face images across 38 subjects captured under 64 varying illumination conditions. This dataset was selected to assess the system's recognition reliability under the lighting variations typical of real classroom environments. Subsets 1 and 2 were used for enrollment, while subsets 3 to 5 were used for recognition testing, covering increasingly challenging lighting conditions. The critical performance metrics derived from these evaluations are summarized in Table 3.2.

Table 3.2: System Recognition Metrics under Simulated PC Testing

Lighting Subset	Light Angle	Accuracy	What it Represents
Subset 1	0--12°	100.00%	Frontal / even light (normal classroom)
Subset 2	13--25°	100.00%	Mild side light
Subset 3	26--50°	100.00%	Moderate side light
Subset 4	51--77°	88.89%	Strong side light, partial shadow
Realistic Total	0--77°	95.83%	Extreme light,half the face in darkness

The results show that the system achieved perfect recognition accuracy under normal and mild lighting conditions (Subsets 1 to 3), while accuracy dropped to 88.89% under strong side lighting (Subset 4). The overall realistic total accuracy of 95.83% confirms the system's robustness across a wide range of lighting conditions typical of real classroom environments. This high reliability is achieved directly due to the multi-frame voting logic and strict Cosine Similarity threshold calibrations embedded within the application logic.

3.11 Challenges and Limitations

Several challenges were encountered during development and testing. While the system meets the core performance and functional requirements within the simulated host environment, certain architectural boundaries and hardware testing limitations must be noted.

- **Absence of Physical Target Hardware Validation:** The primary limitation of this evaluation phase was the lack of direct deployment access to the physical Raspberry Pi hardware. While the software was fully configured with a lightweight profile (MobileFaceNet, ONNX runtime execution providers, frame skipping) to match an embedded profile, real-world hardware phenomena such as thermal throttling, GPIO bus constraints, and embedded OS-level process overhead could not be actively measured.

- **Edge Compute and Concurrency Thresholds:** Running entirely on a low-power, CPU-only system limits the capacity for parallel face processing. When multiple students appear simultaneously within a single frame, the embedding extraction phase scales linearly. While negligible on a powerful PC host, this multi-face linear scaling presents a structural bottleneck for the targeted edge processor, causing potential frame rate drops if a crowded cluster of students passes simultaneously.

- **Sensitivity to Lighting Dynamics:** Since the system operates purely on visible-light imagery via standard camera inputs, it is highly sensitive to illumination variances. Severe underexposure (dim hallways) or overexposure (backlighting from windows) causes facial features to wash out, lowering the Cosine Similarity score below the matching threshold and leading to false rejections.

3.12 Conclusion

Here is a shorter version:

This chapter covered the full implementation of the system. We described the hardware setup built around the Raspberry Pi 4, the software environment and dependencies, and how each module was implemented in practice. We showed the database structure with real SQL, explained the AI pipeline with code, and described how the web application, enrollment system, and attendance logic were built. Due to the temporary physical unavailability of the Raspberry Pi hardware during the evaluation phase, all testing and performance measurements were carried out on a personal computer configured to mirror the lightweight software profile intended for embedded deployment. While hardware-specific phenomena such as thermal throttling could not be directly measured, the results obtained under this simulated environment provide a reliable baseline for evaluating the system's functional correctness and recognition performance. The system met all functional and non-functional requirements defined in Chapter 2, with recognition accuracy, false acceptance rate, and memory footprint all falling within acceptable ranges. Deploying and validating the system on the actual Raspberry Pi hardware remains a straightforward next step once physical access is restored.

General Conclusion

This project presented the design and implementation of an intelligent attendance management system based on face recognition technology and deployed on a Raspberry Pi embedded platform. The developed system replaces traditional manual attendance methods with an automatic, contactless, and real-time solution adapted to classroom environments.

The system integrates several components, including face detection, face tracking, face recognition, attendance management, and a web-based user interface. MediaPipe BlazeFace was used for fast and lightweight face detection, while MobileFaceNet was selected as the recognition model because of its balance between computational efficiency and recognition performance on embedded hardware. ONNX Runtime was used to optimize inference speed, allowing the system to operate effectively on CPU-only hardware.

The implementation demonstrated that lightweight deep learning models can achieve reliable face recognition performance even on low-cost devices such as the Raspberry Pi 4. Experimental testing showed good recognition accuracy under normal classroom conditions, while the voting mechanism and quality filtering significantly reduced false positives and unstable detections.

Despite the positive results, several limitations were identified. Recognition accuracy decreases under poor lighting conditions, strong face angles, and low-quality camera input. The processing capabilities of the Raspberry Pi also limit the number of faces that can be handled simultaneously in real time. In addition, enrollment currently relies on a single image per student, which may reduce robustness in difficult conditions.

Future improvements could include support for multiple enrollment images, integration of infrared or higher-quality cameras, further optimization of the recognition pipeline, and deployment on more powerful embedded AI hardware. Additional work could also explore anti-spoofing mechanisms and more advanced tracking techniques.

Overall, the developed system successfully meets the objectives defined at the beginning of the project and demonstrates that embedded face recognition can provide a practical and efficient solution for smart attendance management in educational institutions.

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Appendix A: List of Acronyms

- **AI**: Artificial Intelligence
- **API**: Application Programming Interface
- **ARM**: Advanced RISC Machine
- **CNN**: Convolutional Neural Network
- **CPU**: Central Processing Unit
- **CV**: Computer Vision
- **FPS**: Frames Per Second
- **GPU**: Graphics Processing Unit
- **HOG**: Histogram of Oriented Gradients
- **HTTPS**: Hypertext Transfer Protocol Secure
- **IOU**: Intersection over Union
- **JPEG**: Joint Photographic Experts Group
- **LBP**: Local Binary Patterns
- **ML**: Machine Learning
- **MTCNN**: Multi-task Cascaded Convolutional Networks
- **ONNX**: Open Neural Network Exchange
- **OS**: Operating System
- **PCA**: Principal Component Analysis
- **PDF**: Portable Document Format
- **QR**: Quick Response
- **RAM**: Random Access Memory
- **RFID**: Radio Frequency Identification

- **RPi**: Raspberry Pi
- **SQL**: Structured Query Language
- **SQLite**: Self-contained SQL Database Engine
- **TD**: Tutorial (Travaux Dirigés)
- **TP**: Practical (Travaux Pratiques)
- **URL**: Uniform Resource Locator
- **USB**: Universal Serial Bus