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Hybrid Two-Layer Authentication System

Final Year Project Thesis

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Declaration

We, the undersigned, hereby declare that this project, “Hybrid Two-Layer Authentication System,” is our own original work. It has not been submitted in whole or in part for any other degree or qualification at this or any other university. All sources of information have been duly acknowledged and referenced. We understand the academic regulations regarding plagiarism and affirm that this work complies with them in their entirety. Should this declaration prove to be false, we shall stand responsible for the consequences.

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Dedication

This work is dedicated to our families, whose unwavering support and encouragement have been the foundation of our success, and to our teachers, who have guided us on this academic journey.

Acknowledgements

We would like to express our sincere gratitude to our supervisor, Dr. Zaid Ahmad, for his invaluable guidance, patience, and expertise throughout this project. His mentorship has been instrumental in shaping our understanding and approach. We also thank our co-supervisor, Engr. Talha Naveed, for his technical insights and support. Finally, we are grateful to our families and friends for their constant encouragement and understanding.

Abstract

This project presents the design and implementation of a Hybrid Two-Layer Authentication System that combines facial recognition and speaker verification for secure, contactless access control. Deployed on a Raspberry Pi 4, the system prioritizes both security and user convenience through a parallel processing architecture that analyzes both biometric modalities simultaneously. The core contribution of this work is the rigorous, data-driven selection of lightweight AI models—BlazeFace for face detection, MobileFaceNet for face recognition, and Resemblyzer for speaker verification—that meet real-time performance constraints on resource-limited hardware. Experimental benchmarking confirms that the selected stack achieves an estimated authentication latency of approximately one second, well within our target of two seconds. This thesis documents the complete journey from literature review to practical implementation, providing a blueprint for deploying sophisticated AI-powered security systems on affordable edge hardware.

Keywords: Biometric Authentication, Facial Recognition, Speaker Verification, Edge Computing, Raspberry Pi, Multimodal Fusion, Deep Learning

List of Symbols, Abbreviations, and Acronyms

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
ARM	Advanced RISC Machine
ASV	Automatic Speaker Verification
BCE	Bachelor of Computer Engineering
CNN	Convolutional Neural Network
CPU	Central Processing Unit
DNN	Deep Neural Network
ECAPA	Emphasized Channel Attention, Propagation and Aggregation
EER	Equal Error Rate
FAR	False Acceptance Rate
FPS	Frames Per Second
FRR	False Rejection Rate
FYP	Final Year Project
GE2E	Generalized End-to-End
GPIO	General Purpose Input/Output
GPU	Graphics Processing Unit
GUI	Graphical User Interface
IoT	Internet of Things
LSTM	Long Short-Term Memory
ML	Machine Learning
MTCNN	Multi-task Cascaded Convolutional Networks
NFR	Non-Functional Requirement
NPU	Neural Processing Unit
ONNX	Open Neural Network Exchange
OS	Operating System
PAD	Presentation Attack Detection
RAM	Random Access Memory
RNN	Recurrent Neural Network
SBC	Single Board Computer
SDK	Software Development Kit
SDG	Sustainable Development Goal
SIMD	Single Instruction Multiple Data
SoC	System on Chip
SOTA	State of the Art
SV	Speaker Verification

Contents

Declaration	i
Final Approval	ii
Dedication	iv
Acknowledgements	v
Abstract	vi
List of Abbreviations	viii
1 Introduction	1
1.1 Background of the Study	1
1.2 Problem Statement	1
1.3 Project Objectives	2
1.4 Scope of the Project	3
1.5 Significance of the Study	4
1.6 Broader Impact (UN SDGs)	4
1.7 Report Organization	5
2 Literature Review	6
2.1 Theoretical Framework and Taxonomy	6
2.2 Facial Recognition Pipeline: A Deep Dive	7
2.2.1 Stage 1: Face Detection - Finding the Face in the Frame	8
2.2.2 Stage 2: Face Recognition - Identifying the Face	10
2.3 Comprehensive Survey of Speaker Recognition Models	13
2.3.1 Category A: State-of-the-Art & High-Complexity Models	14
2.3.2 Category B & C: Efficient CNN-based Models	15
2.3.3 Category D: RNN-based Models (Our Selected Approach)	16
2.4 Optimization and the Role of ONNX	17
2.5 Multimodal Biometric Authentication: State of the Art	19
2.5.1 Advantages of Multimodal Biometrics	19
2.5.2 Fusion Strategies in Multimodal Biometrics	20

2.5.3	Recent Advances in Audio-Visual Biometrics	22
2.5.4	Multimodal Biometric Databases	24
2.6	Edge Computing and Biometric Systems	25
2.6.1	The Case for Edge-Based Biometric Processing	26
2.6.2	Hardware Platforms for Edge Biometrics	27
2.6.3	Optimization Techniques for Edge Deployment	29
2.6.4	Real-Time Constraints and System Design	31
2.7	Privacy and Security in Biometric Systems	32
2.7.1	Privacy-Preserving Biometric Authentication	33
2.7.2	Presentation Attack Detection	35
2.7.3	Adversarial Attacks and Defenses	37
2.8	Continuous Authentication and Behavioral Biometrics	38
2.8.1	Behavioral Biometric Modalities	38
2.8.2	Context-Aware Authentication	39
2.8.3	Zero-Trust Security Models	40
2.9	Domain-Specific Challenges and Solutions	40
2.9.1	Cross-Age Speaker Verification	40
2.9.2	Low-Resource and Few-Shot Learning	41
2.9.3	Text-Dependent vs. Text-Independent Verification	41
2.9.4	Robustness to Environmental Conditions	42
2.10	Emerging Trends and Future Directions	43
2.10.1	Foundation Models for Biometrics	43
2.10.2	Explainable Biometric Systems	44
2.10.3	Tiny Machine Learning (TinyML)	44
2.10.4	Synthetic Data and Data Augmentation	45
2.10.5	Neuromorphic and Alternative Computing Paradigms	45
2.11	Comparative Analysis and Lessons Learned	46
2.11.1	Model Selection Criteria	46
2.11.2	Architecture Trade-offs	46
2.11.3	Fusion Strategy Selection	47
2.12	Research Gaps and Our Contribution	47
2.13	Chapter Summary	48
3	System Design & Analysis	50
3.1	Proposed Methodology: The Hybrid Approach	50
3.2	System Requirements	51
3.2.1	Functional Requirements (FR)	51
3.2.2	Non-Functional Requirements (NFR)	52
3.3	Hardware Platform Selection and Justification	52

3.4	System Architecture/Design Diagrams	54
3.4.1	High-Level Architecture	54
3.4.2	Decision Fusion Logic Flow	55
4	Implementation and Results	58
4.1	Hardware Implementation and OS Configuration	58
4.1.1	Initial Setup and OS Choice	58
4.1.2	Overcoming Foundational Setup Challenges	58
4.2	Software Implementation: Experimental Benchmarking	59
4.2.1	Testing Procedures	59
4.2.2	Results: Face Detector Comparison	60
4.2.3	Results: Face Recognition Model Comparison	61
4.2.4	Results: Voice Verification Toolkit Comparison	61
4.3	Findings and Analysis	62
4.3.1	Analysis of Model Selection	62
4.3.2	Initial System Performance Estimation	62
4.3.3	Key Technical Insights	63
5	Conclusion and Future Work	64
5.1	Project Summary	64
5.2	Problems Faced and Lessons Learned	64
5.2.1	Lesson 1: The Importance of Strategic De-scoping	64
5.2.2	Lesson 2: Embedded Environments are Not Desktops	65
5.2.3	Lesson 3: Empirical Data Trumps Theoretical Performance	65
5.2.4	Lesson 4: User Experience vs. Technical Complexity Trade-off	65
5.3	Future Recommendations (FYP-II Work)	66
5.3.1	Phase 1: Modular Development	66
5.3.2	Phase 2: Implementation of the Decision Fusion Engine	66
5.3.3	Phase 3: Integration and GPIO Control	66
5.3.4	Phase 4: Rigorous System-Level Testing	67
5.3.5	Phase 5: ONNX Optimization (Stretch Goal)	67
5.4	Concluding Remarks	67
A	Installation Guide	75
A.1	Raspberry Pi OS Setup	75
A.2	Python Environment Setup	76
B	Code Snippets	77
B.1	Face Detection with BlazeFace	77
B.2	Voice Embedding with Resemblyzer	78

B.3 Decision Fusion Engine (Pseudocode)	78
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List of Figures

1.1	Conceptual Overview of the Hybrid Two-Layer Authentication System	2
1.2	Project Alignment with United Nations Sustainable Development Goals	5
2.1	Taxonomy of Biometric Recognition Technologies	7
2.2	Complete Facial Recognition Pipeline from Input to Decision	8
2.3	Visual Comparison of Face Detection Methods on Raspberry Pi 4	10
2.4	MobileFaceNet Architecture with Depthwise Separable Convolutions	11
2.5	Visualization of ArcFace Angular Margin Loss vs. Standard Softmax	13
2.6	Taxonomy of Speaker Recognition Models by Complexity and Efficiency	14
2.7	Generalized End-to-End (GE2E) Loss Training Mechanism	17
2.8	ONNX Model Conversion and Optimization Pipeline	18
2.9	Key Advantages of Multimodal Biometric Systems	20
2.10	Comparison of Multimodal Fusion Strategies at Different Levels	22
2.11	Overview of Major Multimodal Biometric Databases	25
2.12	Edge vs. Cloud Biometric Processing: Trade-offs and Considerations	26
2.13	Edge Hardware Platforms: Performance vs. Power Consumption Trade-offs	28
2.14	Model Compression Techniques for Edge Deployment	30
2.15	Adaptive Processing Pipeline for Resource-Constrained Environments	32
2.16	Privacy and Security Landscape in Biometric Systems	33
2.17	Comparison of Privacy-Preserving Techniques for Biometric Authentication	35
2.18	Overview of Presentation Attacks and Countermeasures for Biometric Systems	37
2.19	Continuous Authentication Lifecycle with Behavioral Biometrics	39
2.20	Emerging Technology Landscape for Biometric Authentication	43
2.21	Visualization of Research Gaps Addressed by This Work	48
3.1	Comparison of Sequential vs. Parallel Authentication Approaches	51
3.2	Hardware Setup: Raspberry Pi 4 with Camera, Microphone, and GPIO Peripherals	53
3.3	High-Level System Architecture	54
3.4	Multi-threaded Architecture with Inter-Thread Communication	55

3.5	Decision Fusion Logic Flowchart	56
4.1	Face Detector Benchmark Results on Raspberry Pi 4	60
4.2	Face Recognition Model Benchmark: Size vs. Speed Trade-off	61
4.3	Speaker Verification Toolkit Benchmark Results	62
4.4	Estimated System Latency with Parallel Pipeline Execution	63
5.1	Proposed FYP-II Development Roadmap	66

List of Tables

2.1	SOTA High-Complexity Speaker Recognition Models	15
2.2	Efficient CNN-Based Speaker Recognition Models	16
2.3	RNN-Based Speaker Recognition Models	17
3.1	Hardware Platform Comparison	53
4.1	Face Detector Performance Comparison on Raspberry Pi 4	60
4.2	Face Recognition Model Performance Comparison	61
4.3	Speaker Verification Toolkit Performance Comparison	61

Chapter 1

Introduction

1.1 Background of the Study

In an increasingly connected world, the need for robust yet user-friendly security systems has never been greater. Traditional authentication methods, such as PINs, passwords, and physical keys, are vulnerable to theft, loss, and social engineering attacks. Biometric authentication offers a compelling alternative by verifying a user's identity based on their unique physiological or behavioral characteristics. Unlike passwords, biometrics cannot be easily forgotten, shared, or stolen, making them an inherently more secure foundation for access control.

This project focuses on developing a **Hybrid Two-Layer Authentication System** that combines two powerful biometric modalities: **facial recognition** and **speaker verification**. By processing both streams in parallel, the system can make an authentication decision based on the successful verification of *either* modality (an “OR-logic” approach). This design philosophy prioritizes user convenience and system robustness, as the system can authenticate a user even if one modality is temporarily unavailable (e.g., the user is wearing a mask or there is ambient noise).

A critical constraint of this project is that the entire system must run locally on an affordable, low-power edge device—a **Raspberry Pi 4**. This “edge computing” approach is essential for privacy, as sensitive biometric data never leaves the user’s premises, and for reliability, as the system does not depend on an internet connection. This constraint, however, poses significant technical challenges related to computational resources, model optimization, and real-time performance.

1.2 Problem Statement

The primary challenge addressed by this project is:

How can a sophisticated, multi-modal biometric authentication system, combining facial recognition and speaker verification, be designed and implemented to run in

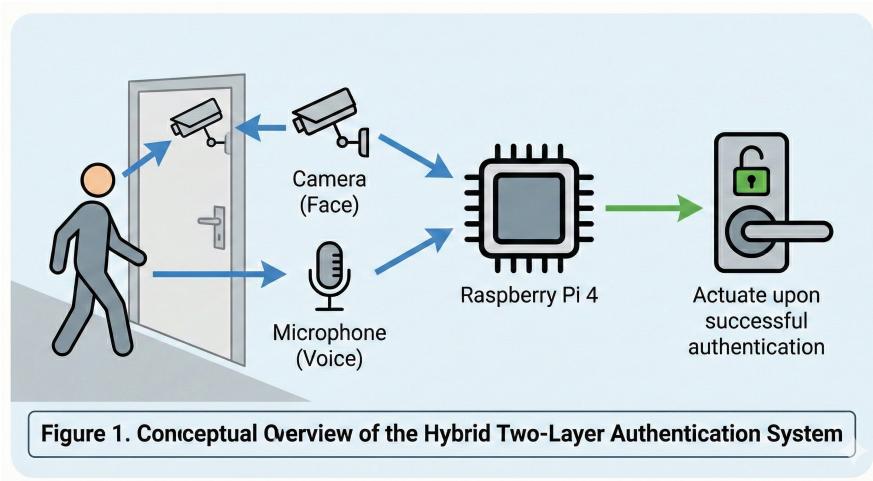


Figure 1.1: Conceptual Overview of the Hybrid Two-Layer Authentication System

real-time on a resource-constrained edge device like a Raspberry Pi 4, while achieving a target end-to-end latency of under 2 seconds?

This challenge decomposes into several sub-problems:

1. **Model Selection:** The vast majority of state-of-the-art (SOTA) biometric models are designed for high-performance servers with dedicated GPUs. Identifying models that offer an acceptable balance of accuracy and speed on a CPU-only platform is non-trivial.
2. **System Architecture:** Designing a software architecture that can capture and process two data streams (video and audio) in parallel, manage inter-thread communication, and make a fused decision efficiently.
3. **Hardware Environment:** Setting up a stable and optimized software environment on the ARM64-based Raspberry Pi, which has a less mature ecosystem than x86 platforms.
4. **Privacy and Security:** Ensuring that the system stores and processes biometric templates securely without transmitting any data over a network.

1.3 Project Objectives

The objectives of this Final Year Project are:

1. To conduct a comprehensive literature review of facial recognition and speaker verification technologies, with a specific focus on models suitable for edge deployment.

2. To design a system architecture for a hybrid, parallel biometric authentication system with clearly defined functional and non-functional requirements.
3. To benchmark and select the optimal combination of AI models (face detector, face recognizer, voice encoder) that meets real-time performance constraints on a Raspberry Pi 4.
4. To implement a functional prototype of the authentication system with a decision fusion engine and GPIO control for physical access (e.g., activating a door lock).
5. To evaluate the final system's performance in terms of latency, accuracy (FAR/FRR), and resource consumption.

1.4 Scope of the Project

In Scope:

- Design and implementation on a single Raspberry Pi 4 Model B (8GB).
- Face detection, face recognition (verification mode), and speaker verification.
- A simple OR-logic decision fusion mechanism.
- Local storage of biometric templates on the device's filesystem.
- GPIO control for a physical output signal (e.g., to a relay).
- A command-line interface for enrollment and testing.

Out of Scope:

- Cloud-based processing or network connectivity.
- Advanced anti-spoofing measures (e.g., 3D depth sensing for liveness detection), though basic blink detection may be explored.
- A polished graphical user interface (GUI).
- Large-scale deployment or user management features.
- Support for multiple concurrent authentication requests.

1.5 Significance of the Study

Academic Significance:

This project provides a practical case study in deploying deep learning models on resource-constrained hardware. It contributes a documented methodology for benchmarking and selecting models based on empirical performance data rather than theoretical claims, which is a valuable resource for students and researchers working in edge AI.

Practical Significance:

The resulting system serves as a blueprint for affordable, privacy-respecting biometric security solutions suitable for small businesses, educational institutions, and residential applications in regions where expensive commercial systems are not viable.

1.6 Broader Impact (UN SDGs)

This project aligns with the United Nations Sustainable Development Goals:

- **SDG 9 (Industry, Innovation, and Infrastructure):** By developing an affordable, innovative security system using cutting-edge AI, we contribute to building resilient infrastructure accessible to developing economies.
- **SDG 11 (Sustainable Cities and Communities):** Secure access control is fundamental to safe urban environments. Our privacy-first, offline approach provides security without the societal risks of centralized surveillance databases.
- **SDG 16 (Peace, Justice, and Strong Institutions):** By enabling secure verification of identity, the system can contribute to secure and accountable institutions.

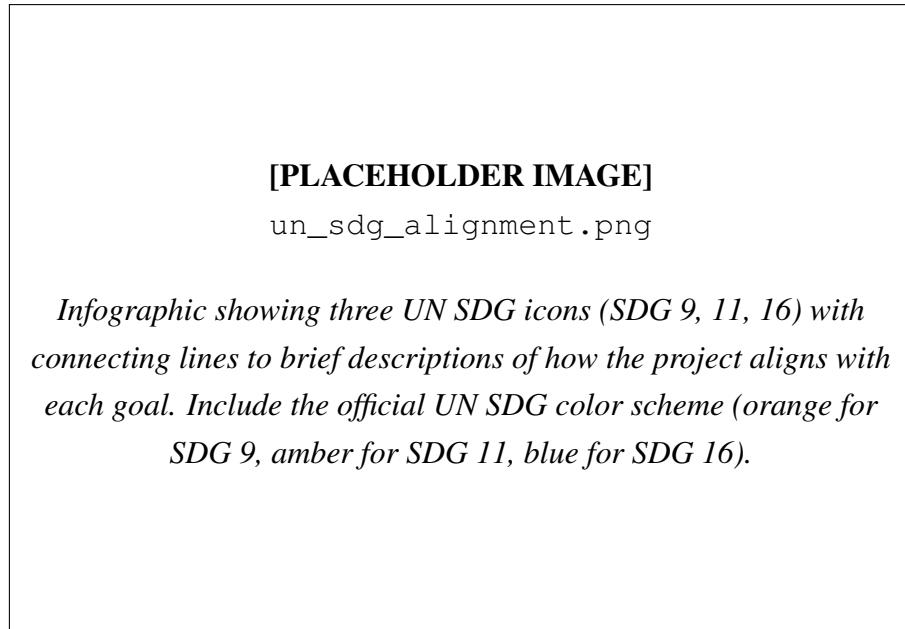


Figure 1.2: Project Alignment with United Nations Sustainable Development Goals

1.7 Report Organization

This thesis is organized as follows:

- **Chapter 1: Introduction** - Provides background, problem statement, objectives, and scope.
- **Chapter 2: Literature Review** - Presents a comprehensive survey of facial recognition, speaker verification, multimodal biometrics, edge computing, and related technologies.
- **Chapter 3: System Design & Analysis** - Details the proposed methodology, system requirements, hardware selection, and architecture.
- **Chapter 4: Implementation and Results** - Documents the practical setup, benchmarking procedures, and experimental findings.
- **Chapter 5: Conclusion and Future Work** - Summarizes achievements, lessons learned, and future directions.

Chapter 2

Literature Review

2.1 Theoretical Framework and Taxonomy

A major challenge in reviewing the vast body of biometric literature is the frequent conflation of model architectures, training methodologies, and the software libraries that implement them. To bring clarity to our selection process, we first established a clear taxonomy to categorize and evaluate the available technologies. This framework was essential for making informed, data-driven decisions rather than simply choosing models based on popularity.

The taxonomy distinguishes between:

- **Network Architectures:** The fundamental structure of the neural network (e.g., ResNet, MobileNet, LSTM).
- **Training Methodologies:** The loss functions and training techniques used to optimize the model (e.g., Triplet Loss, ArcFace).
- **Pre-trained Models:** Specific instances of trained networks available for deployment (e.g., FaceNet, InsightFace models).
- **Software Libraries/Toolkits:** Python packages that provide easy-to-use APIs wrapping these models (e.g., MediaPipe, Resemblyzer, SpeechBrain).

This structured approach allowed us to evaluate technologies at multiple levels: architectural efficiency, training quality, ease of integration, and ultimately, real-world performance on our target hardware.

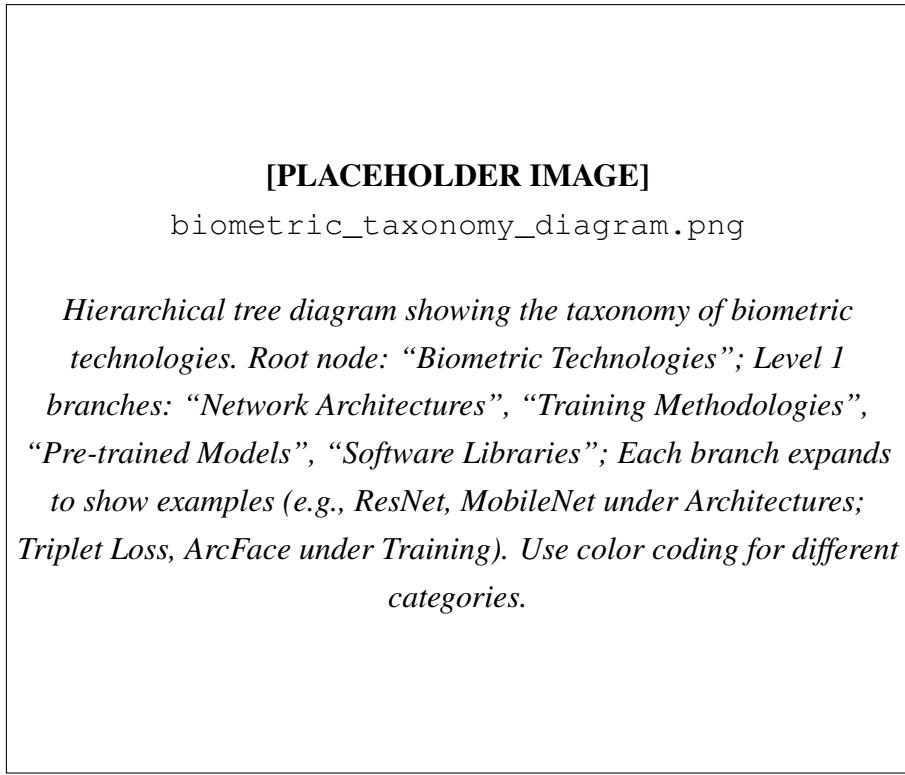
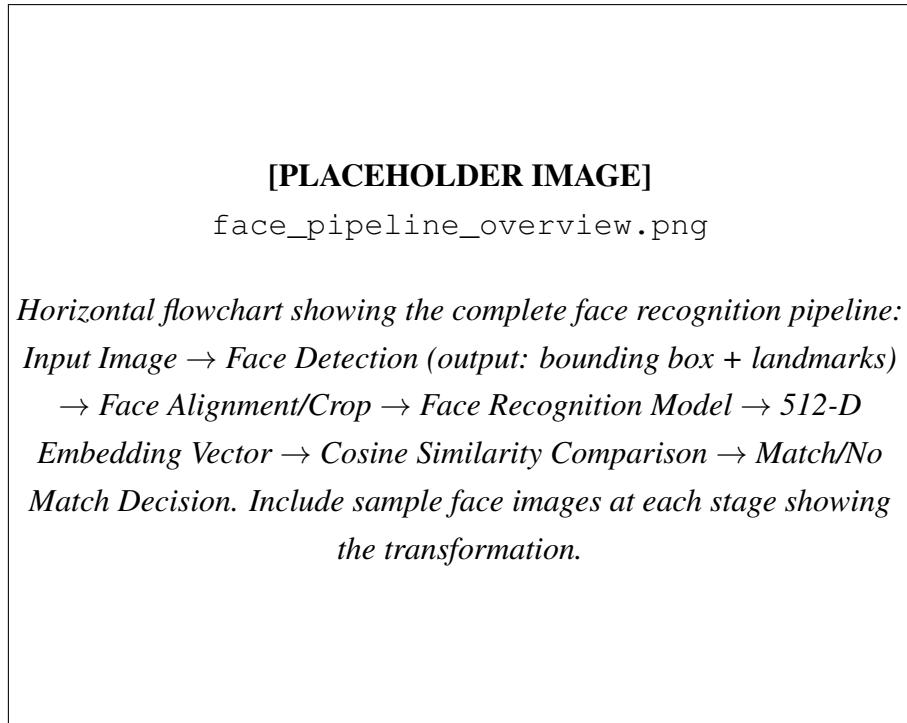


Figure 2.1: Taxonomy of Biometric Recognition Technologies

2.2 Facial Recognition Pipeline: A Deep Dive

The facial recognition process is fundamentally a two-stage pipeline: detection, followed by recognition. The overall latency and reliability of the system are critically dependent on the performance of both stages.



[PLACEHOLDER IMAGE]
face_pipeline_overview.png

*Horizontal flowchart showing the complete face recognition pipeline:
Input Image → Face Detection (output: bounding box + landmarks)
→ Face Alignment/Crop → Face Recognition Model → 512-D
Embedding Vector → Cosine Similarity Comparison → Match/No
Match Decision. Include sample face images at each stage showing
the transformation.*

Figure 2.2: Complete Facial Recognition Pipeline from Input to Decision

2.2.1 Stage 1: Face Detection - Finding the Face in the Frame

The face detection module is responsible for perpetually scanning the input video stream to locate the bounding box coordinates of any faces present. Its efficiency is paramount, as it runs continuously. Our review and subsequent experimentation covered a spectrum of techniques.

- **Haar Cascade Classifiers:** This classic machine learning technique, implemented efficiently in the OpenCV library, was our initial baseline. It is based on a cascade of features trained using AdaBoost.
 - *Pros:* Extremely fast on CPUs, low memory footprint.
 - *Cons:* Prone to false positives, struggles significantly with non-frontal faces (tilted or profile views), and provides no facial landmark information. Our experimental tests confirmed these limitations.
- **MTCNN (Multi-task Cascaded Convolutional Networks):** Zhang et al. [8] introduced this deep learning-based model known for its high accuracy. It uses a three-stage cascade of CNNs (P-Net, R-Net, O-Net) to progressively refine face detections and identify key facial landmarks.

Paper Summary: Zhang et al. proposed a cascaded framework where each stage serves a specific purpose: the Proposal Network (P-Net) quickly generates candidate windows, the Refine Network (R-Net) filters false positives, and the Output Network (O-Net) produces final bounding boxes with five-point facial landmarks. The multi-task learning approach jointly optimizes face classification, bounding box regression, and landmark localization, achieving state-of-the-art accuracy at the time of publication.

- *Pros:* High detection accuracy, provides 5-point facial landmarks.
- *Cons:* Our experimental benchmark on the Raspberry Pi 4 CPU revealed it to be extremely slow, achieving only **~2 FPS**. This makes it completely unsuitable for any real-time video application.
- **BlazeFace:** Bazarevsky et al. [4] developed BlazeFace at Google Research as a SOTA lightweight detector specifically designed for mobile and edge GPUs, but its architecture is also highly efficient on CPUs. It is inspired by MobileNet and uses a hardware-aware design.

Paper Summary: BlazeFace introduces several key innovations: (1) a modified MobileNet backbone with increased receptive field, (2) an anchor scheme specifically tuned for face detection, and (3) a tie resolution strategy for reducing jitter in video applications. The model achieves sub-millisecond inference on mobile GPUs while providing 6-point facial landmarks (eyes, ears, nose, mouth) useful for face alignment and basic liveness detection.

- *Pros:* Blazing fast, highly accurate, and provides 6-point facial landmarks which can be used for liveness detection (e.g., eye tracking). Our benchmark showed it achieving **30-45 FPS** on the Raspberry Pi 4.
- *Cons:* Slightly more complex to implement from scratch than Haar cascades, but readily available via Google’s MediaPipe framework.

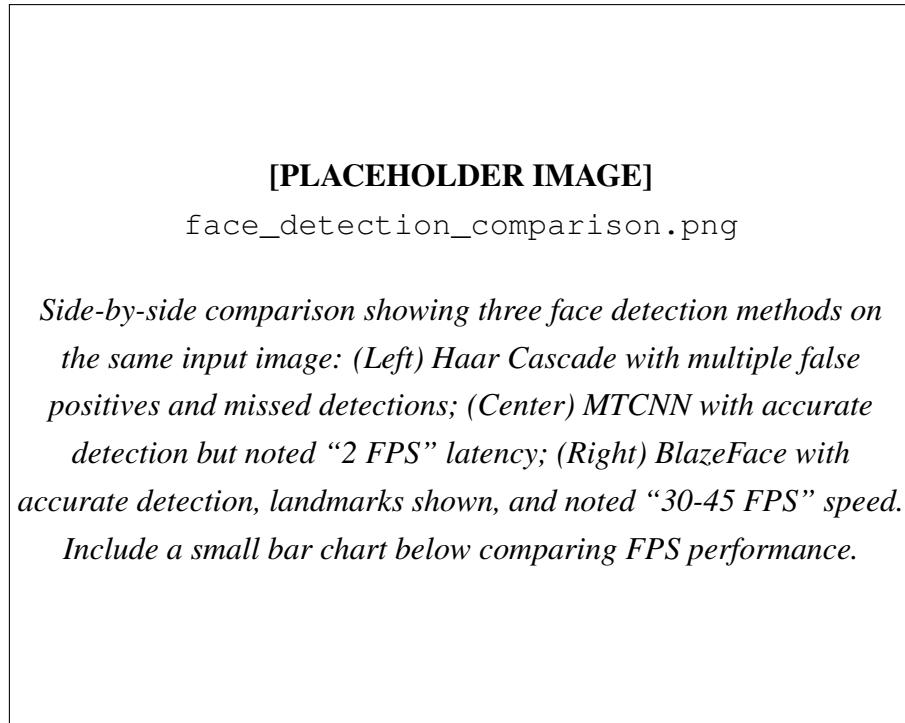


Figure 2.3: Visual Comparison of Face Detection Methods on Raspberry Pi 4

2.2.2 Stage 2: Face Recognition - Identifying the Face

Once a face is detected and cropped, it is passed to a recognition model to generate a discriminative feature vector, or “embedding.” This stage is where the core identification happens.

Network

Architectures

This refers to the neural network’s structure.

- **InceptionResNetV1:** The foundational architecture used in the original Google FaceNet paper [1]. It combines Inception modules with residual connections for powerful feature extraction.

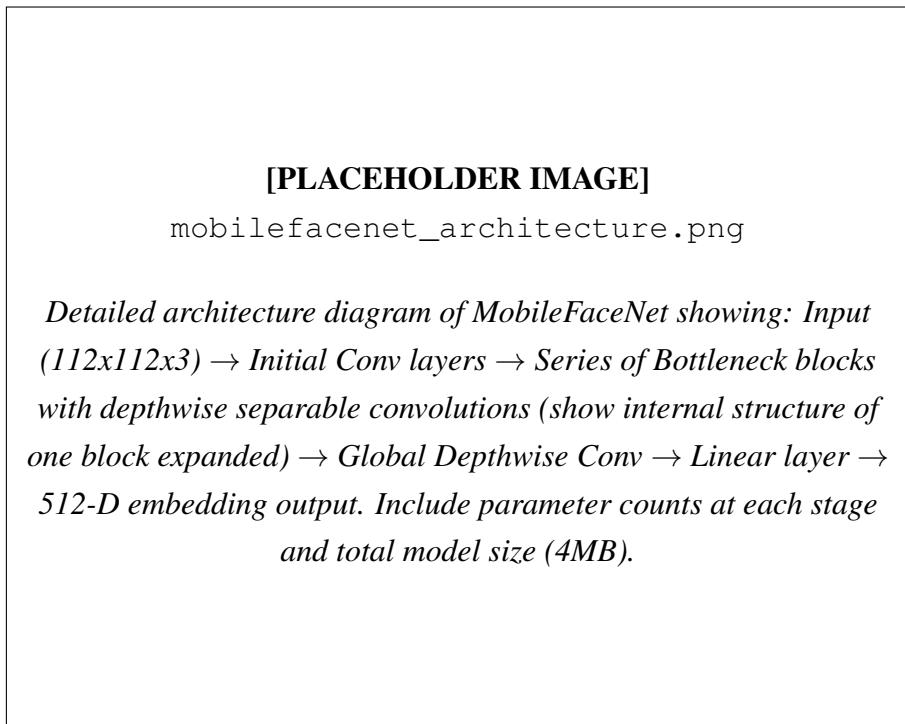
Paper Summary (FaceNet): Schroff et al. introduced a unified framework for face verification, recognition, and clustering using a deep convolutional network trained with triplet loss. The key innovation was learning a compact 128-dimensional Euclidean embedding where distances directly correspond to face similarity. The model achieved 99.63% accuracy on LFW benchmark, setting a new state of the art.

However, the architecture is large and computationally expensive. Our benchmark showed an inference time of $\sim 1200 \text{ ms}$ on the Pi 4.

- **ResNet (Residual Networks):** Architectures like ResNet-34 and ResNet-50 are common backbones for face recognition and form the basis of models like the InsightFace “Buffalo_L/M” family [9]. Our tests showed the ResNet-50 based model to be even slower, at $\sim 1800 \text{ ms}$.
- **MobileFaceNet:** Chen et al. [3] proposed this lightweight architecture specifically designed for mobile CPUs. It uses depthwise separable convolutions to drastically reduce the number of parameters and computations.

Paper Summary: The authors demonstrated that face verification can be achieved efficiently on mobile devices by: (1) using Global Depthwise Convolution (GD-Conv) in place of global average pooling to retain spatial information, (2) employing a bottleneck structure optimized for the face recognition task, and (3) training with ArcFace loss for discriminative embeddings. The resulting model is only 4MB with 0.99M parameters, achieving 99.28% on LFW while running in real-time on mobile CPUs.

Our tests showed an inference time of $\sim 250\text{-}350 \text{ ms}$, making it 3-5x faster than the other models.



[PLACEHOLDER IMAGE]

mobilefacenet_architecture.png

Detailed architecture diagram of MobileFaceNet showing: Input (112x112x3) → Initial Conv layers → Series of Bottleneck blocks with depthwise separable convolutions (show internal structure of one block expanded) → Global Depthwise Conv → Linear layer → 512-D embedding output. Include parameter counts at each stage and total model size (4MB).

Figure 2.4: MobileFaceNet Architecture with Depthwise Separable Convolutions

Loss**Functions**

These are the mathematical formulas used during training to make the model’s embeddings more discriminative.

- **Triplet Loss:** Popularized by FaceNet [1], it works by ensuring that the embedding of an “anchor” face is closer to a “positive” example (same person) than to a “negative” example (different person) by a margin α :

$$L = \sum_i^N [\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha]_+$$

- **ArcFace (Additive Angular Margin Loss):** Deng et al. [2] proposed a more modern and effective loss function that works by adding an angular margin to the separation between classes in the embedding space.

Paper Summary: ArcFace introduces an additive angular margin penalty m between the feature vector and the target weight to simultaneously enhance intra-class compactness and inter-class discrepancy. The loss is defined as:

$$L = -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{s(\cos(\theta_{y_i} + m))}}{e^{s(\cos(\theta_{y_i} + m))} + \sum_{j=1, j \neq y_i}^n e^{s \cos \theta_j}}$$

where s is a scaling factor and m is the angular margin. This geometric interpretation provides clear optimization guidance and achieves state-of-the-art results across multiple benchmarks.

Most SOTA pre-trained models, including the MobileFaceNet version we chose, are trained using ArcFace.

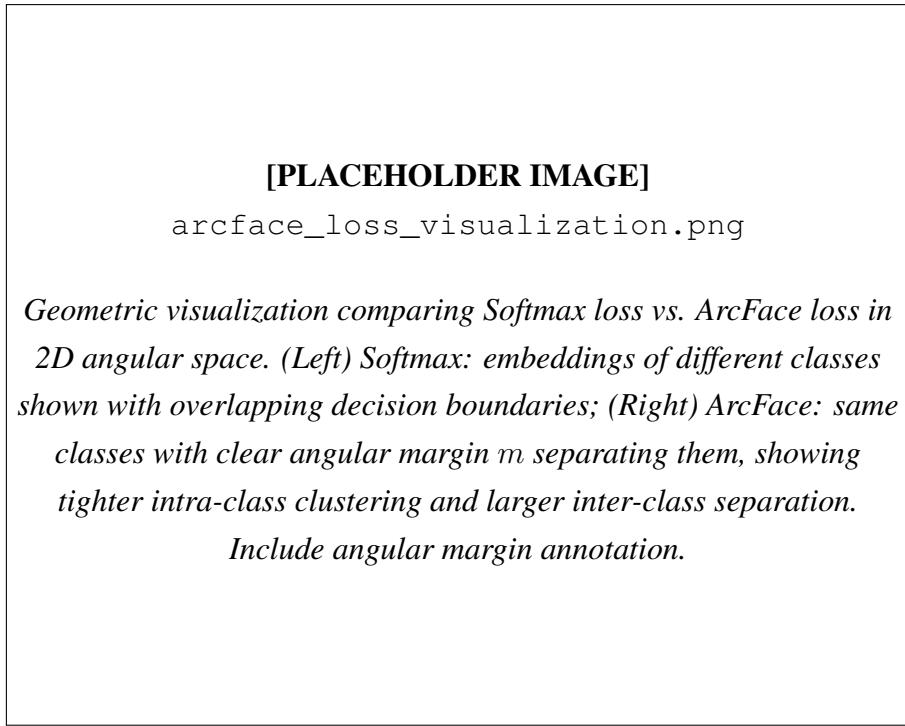


Figure 2.5: Visualization of ArcFace Angular Margin Loss vs. Standard Softmax

2.3 Comprehensive Survey of Speaker Recognition Models

To select the optimal voice architecture, we conducted an extensive study of five distinct model categories, analyzing their suitability for our CPU-bound edge device.

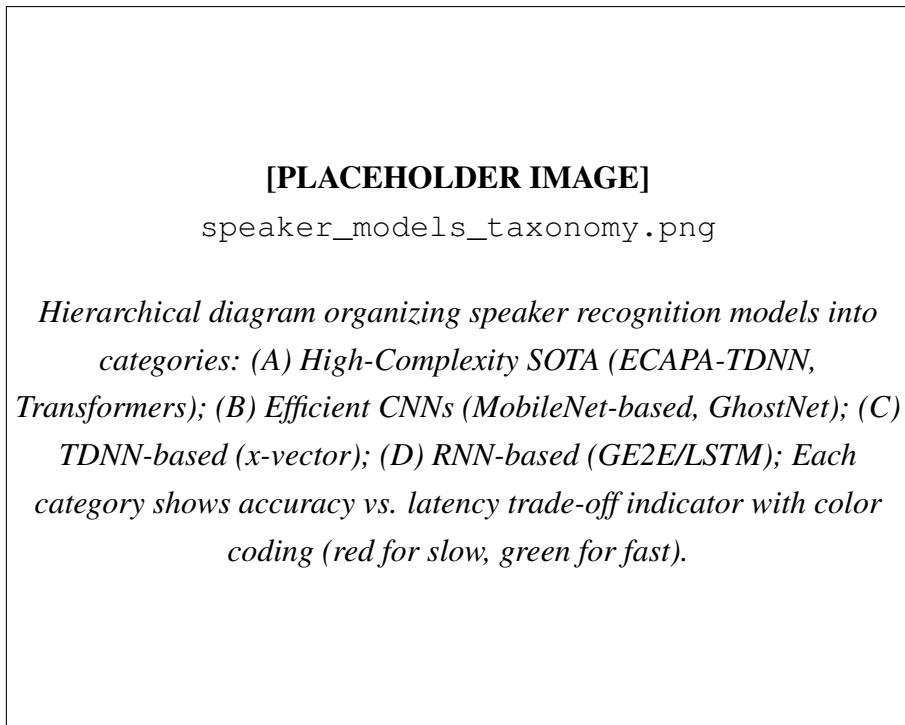


Figure 2.6: Taxonomy of Speaker Recognition Models by Complexity and Efficiency

2.3.1 Category A: State-of-the-Art & High-Complexity Models

These models define the upper limit of academic accuracy but present insurmountable challenges for real-time deployment on a Raspberry Pi.

ECAPA-TDNN: Desplanques et al. [5] proposed the Emphasized Channel Attention, Propagation and Aggregation Time Delay Neural Network, which represents the current state of the art in speaker verification.

Paper Summary: ECAPA-TDNN introduces three key innovations over the standard x-vector TDNN: (1) Squeeze-and-Excitation (SE) blocks with channel-dependent frame attention, (2) Multi-scale feature aggregation through dense skip connections, and (3) Channel-dependent attentive statistics pooling. These additions significantly improve the model's ability to capture speaker-discriminative information across different temporal scales, achieving state-of-the-art results on VoxCeleb with an EER of 0.87%.

Table 2.1: SOTA High-Complexity Speaker Recognition Models

Model	Architecture	Break-down	Strengths	Edge Feasibility
ECAPA-TDNN	Emphasized Channel Attention + TDNN		Highest published accuracy, robust to noise	Extremely high compute requirements. Our tests showed >4 seconds inference time on the Pi 4 CPU
Transformers	Self-Attention based models		Excellent at capturing long-range dependencies in speech	Even heavier than ECAPA-TDNN, completely unfeasible for our hardware

2.3.2 Category B & C: Efficient CNN-based Models

This category contains the most promising candidates for our project, leveraging mature CNN optimizations.

x-vector (TDNN): The x-vector system, developed at JHU, uses a Time Delay Neural Network architecture with statistics pooling to generate fixed-length speaker embeddings from variable-length utterances.

Paper Summary: The x-vector approach extracts frame-level representations using TDNN layers, then aggregates them using statistics pooling (mean and standard deviation) to produce a fixed-dimensional embedding. Training uses a softmax loss over a large speaker set, with embeddings extracted from an intermediate layer. This architecture provides an excellent balance between accuracy and computational efficiency.

Table 2.2: Efficient CNN-Based Speaker Recognition Models

Model	Architecture	Break-down	Strengths	Edge Feasibility
MobileNet/ GhostNet	Standard efficient CNNs	2D-	Excellent balance of accuracy/speed. Proven for edge deployment in vision tasks	Strong candidates
x-vector (TDNN)	Time Delay Neural Network + Statistics Pooling	Neural Statistics	Simpler and lighter than ECAPA-TDNN	Excellent baseline, fast on CPU
SincNet	Parametric using Sinc functions	1D-CNN	Extremely efficient and interpretable first layer	Prime candidate for highly constrained devices

2.3.3 Category D: RNN-based Models (Our Selected Approach)

Recurrent Neural Networks are well-suited for sequential data like audio.

GE2E (Generalized End-to-End Loss): Wan et al. [6] proposed this training methodology for speaker verification that significantly improves both training efficiency and model performance.

Paper Summary: The GE2E loss operates on batches containing utterances from multiple speakers, computing a similarity matrix between all utterance embeddings and all speaker centroids. The loss encourages each utterance embedding to be closer to its own speaker’s centroid than to any other speaker’s centroid. Key advantages include: (1) more stable gradients during training, (2) ability to use larger batch sizes efficiently, and (3) direct optimization of the verification task. The authors demonstrate significant improvements over the earlier Tuple-based End-to-End (TE2E) loss.

The **Resemblyzer** library [7] provides a convenient Python implementation of GE2E-trained LSTM encoders, which we selected for our system.

Table 2.3: RNN-Based Speaker Recognition Models

Toolkit	Underlying Model	Strengths	Edge Feasibility
Resemblyzer	GE2E (LSTM-based)	Fast, easy to implement, provides a simple API for generating embeddings	Excellent. Our experimental tests showed it generated embeddings from a 3-second clip in under 1 second , meeting our real-time requirement

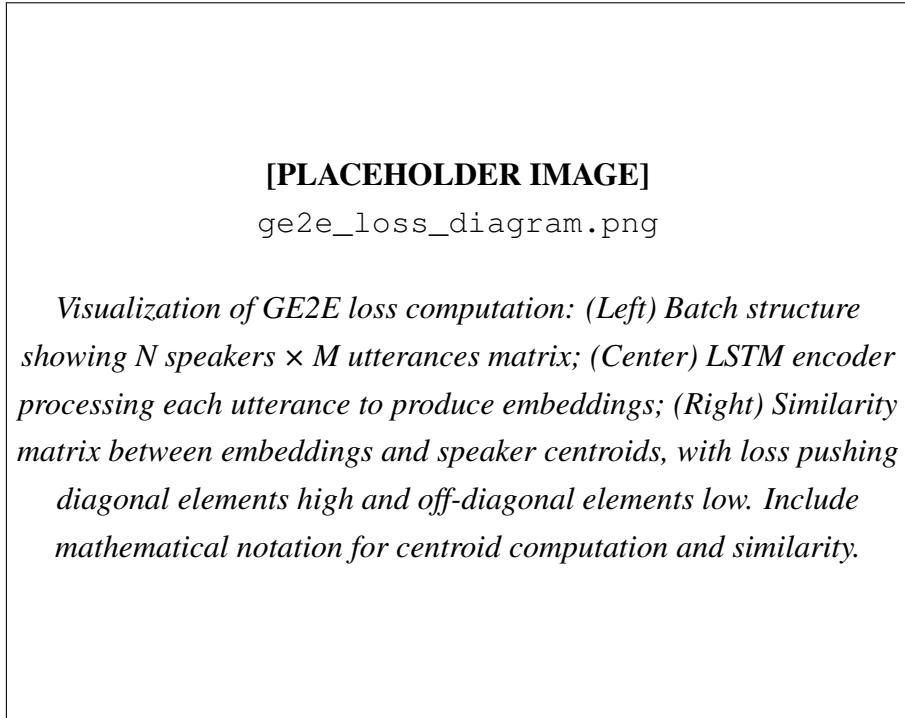


Figure 2.7: Generalized End-to-End (GE2E) Loss Training Mechanism

2.4 Optimization and the Role of ONNX

A key part of our methodology is the plan to convert all selected models to the **ONNX** (**Open Neural Network Exchange**) format [10]. ONNX is an open standard for representing machine learning models. Using the **ONNX Runtime**, we can execute these models with a highly optimized inference engine that is specifically tuned for CPU performance. This step is crucial for squeezing the maximum possible speed out of the Raspberry Pi's processor and is a key part of our implementation plan for

FYP-II.

Paper Summary (ONNX Runtime): Bai et al. [11] demonstrated that ONNX Runtime provides significant performance improvements through: (1) graph-level optimizations including constant folding and operator fusion, (2) execution provider abstraction allowing hardware-specific optimizations, and (3) memory planning to reduce allocation overhead. On ARM processors specifically, ONNX Runtime can achieve up to 40% performance improvement over native framework inference.

The ONNX ecosystem provides several advantages:

- **Cross-framework compatibility:** Models trained in PyTorch or TensorFlow can be converted to a unified format.
- **Hardware optimization:** ONNX Runtime includes optimizations for various CPU architectures, including ARM.
- **Reduced inference latency:** Graph optimizations and operator fusion can significantly reduce model execution time.
- **Smaller memory footprint:** Optimized models often require less RAM during inference.

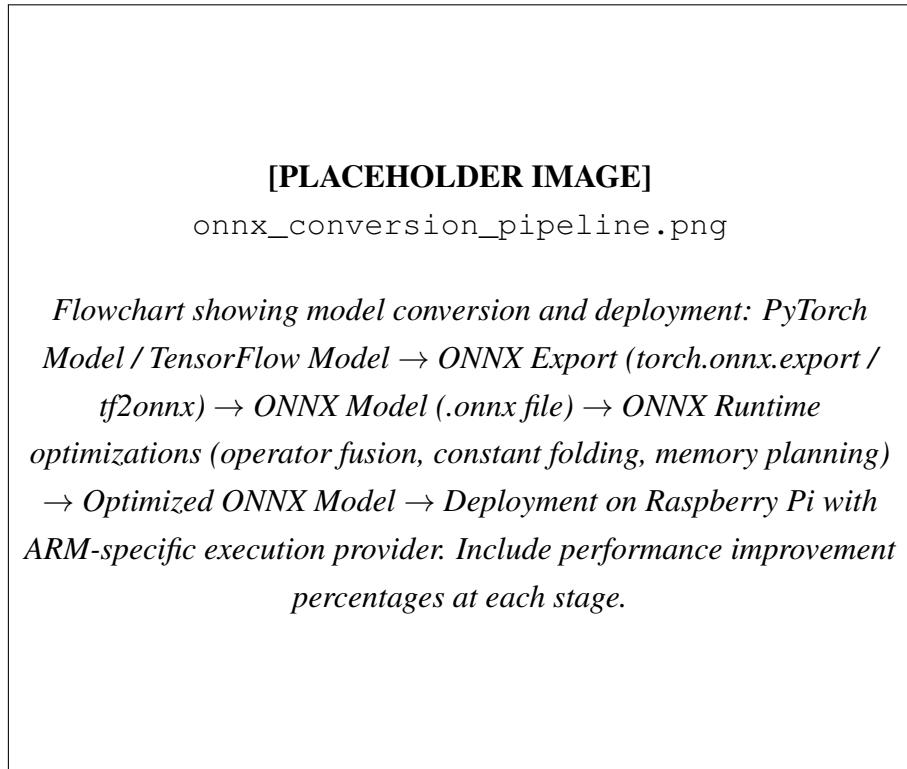


Figure 2.8: ONNX Model Conversion and Optimization Pipeline

2.5 Multimodal Biometric Authentication: State of the Art

The integration of multiple biometric modalities has emerged as a powerful approach to overcome the limitations of unimodal systems. This section reviews the current state of the art in multimodal biometric authentication, with particular emphasis on systems that combine facial and voice recognition.

2.5.1 Advantages of Multimodal Biometrics

Multimodal biometric systems offer several compelling advantages over their unimodal counterparts:

1. **Improved Accuracy:** By combining evidence from multiple sources, multimodal systems can achieve significantly lower error rates. Research by Zheng et al. [12] demonstrates that combining face and physiological signals can reduce Equal Error Rate (EER) by up to 60% compared to single-modality systems.
Paper Summary: Zheng et al. proposed a novel multimodal system combining facial recognition with camera-based photoplethysmography (PPG) and finger-print data. Their fusion approach uses quality-aware weighting to dynamically adjust the contribution of each modality based on signal quality, achieving robust performance even when individual modalities are degraded.
2. **Enhanced Robustness:** Environmental factors that degrade one modality may not affect others. For instance, poor lighting conditions that compromise facial recognition may not impact voice recognition, and vice versa. This resilience is particularly valuable in real-world deployment scenarios [13].
3. **Reduced Failure-to-Enroll Rate:** Some individuals may have difficulty enrolling in specific biometric systems due to physical characteristics or disabilities. Multimodal systems provide alternative authentication paths, improving accessibility [14].
4. **Increased Security Against Spoofing:** Simultaneously spoofing multiple biometric modalities is significantly more challenging than compromising a single modality. This increases the cost and complexity of attacks, providing better security [15].

5. **Flexibility in Application Scenarios:** Different scenarios may favor different modalities. A multimodal system can adapt by emphasizing the most reliable modality in a given context [16].

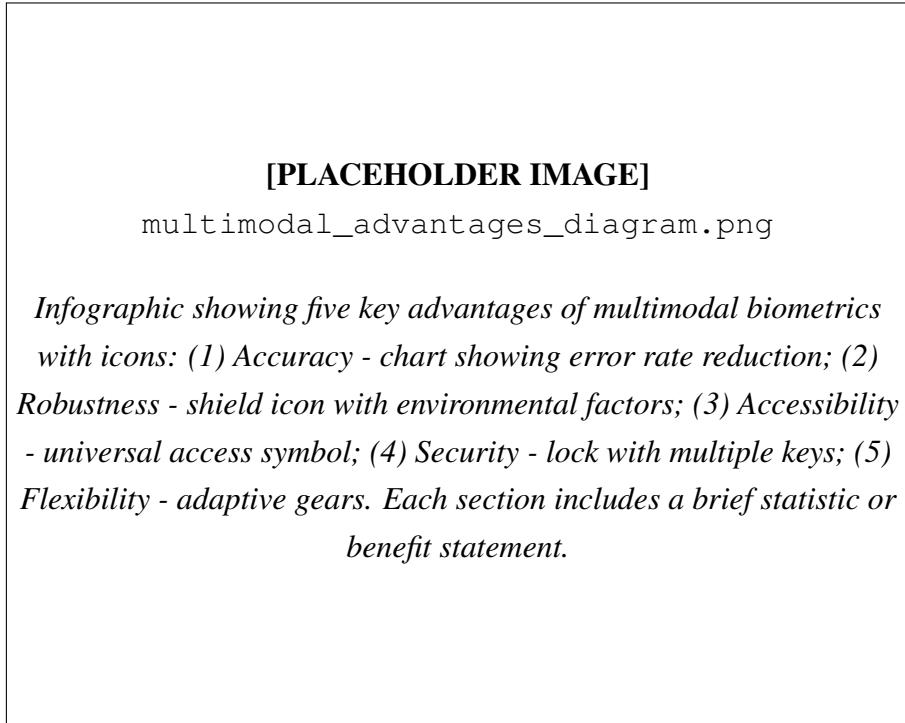


Figure 2.9: Key Advantages of Multimodal Biometric Systems

2.5.2 Fusion Strategies in Multimodal Biometrics

The literature identifies three primary levels at which biometric information can be fused:

Feature-Level Fusion

Feature-level fusion combines feature vectors from different modalities before matching. While this approach can theoretically provide the most comprehensive representation, it faces several challenges:

- **Dimensionality Issues:** Concatenating features from multiple modalities often results in extremely high-dimensional vectors, leading to the curse of dimensionality.
- **Incompatibility:** Feature sets from different modalities may be incompatible or incommensurate, requiring complex normalization strategies.

- **Computational Cost:** High-dimensional feature spaces increase computational requirements substantially.

Despite these challenges, recent work by Talreja et al. [17] proposes using deep hashing techniques to generate compact binary representations from multimodal features, achieving both security and efficiency.

Paper Summary: Talreja et al. introduced a deep hashing framework that learns to map high-dimensional multimodal biometric features into compact binary codes while preserving discriminative information. The approach uses a combination of classification loss and quantization loss to ensure the binary codes are both discriminative and compact, enabling efficient template storage and matching.

Score-Level	Fusion
--------------------	---------------

Score-level fusion combines matching scores from individual biometric matchers. This is the most popular fusion approach due to its simplicity and effectiveness. Common fusion techniques include:

- **Simple Sum/Product Rules:** Combining normalized scores using arithmetic operations.
- **Weighted Fusion:** Assigning different weights to modalities based on their reliability or quality.
- **Machine Learning Approaches:** Using classifiers like SVM, neural networks, or decision trees to learn optimal fusion strategies [18].

Poh et al. [19] conducted an extensive benchmark study comparing various score-level fusion algorithms, considering both quality-dependent and cost-sensitive scenarios.

Paper Summary: This comprehensive study evaluated 22 different score-level fusion methods across multiple multimodal biometric databases. Key findings include: (1) quality-aware fusion consistently outperforms static fusion, (2) trained fusion methods outperform fixed rules when sufficient training data is available, and (3) the optimal fusion method depends on the specific modality combination and application requirements. The benchmark provides valuable guidance for practitioners selecting fusion strategies.

Decision-Level Fusion

Decision-level fusion combines the final decisions (accept/reject) from individual biometric systems using voting schemes or logical operations. While this is the simplest approach, it discards valuable information contained in matching scores. However, it remains useful in scenarios where individual systems operate as black boxes or when computational resources are extremely limited.

Our proposed system employs score-level fusion with OR-logic at the decision stage, balancing simplicity with the preservation of discriminative information from both modalities.

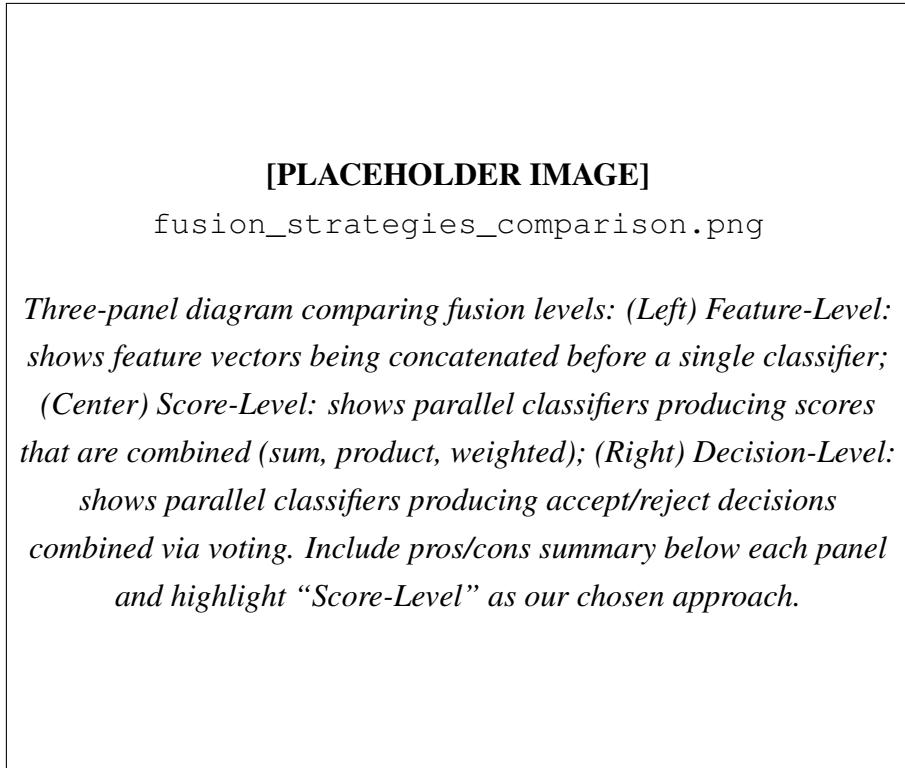


Figure 2.10: Comparison of Multimodal Fusion Strategies at Different Levels

2.5.3 Recent Advances in Audio-Visual Biometrics

The specific combination of facial and voice biometrics has received considerable attention in recent years, driven by its natural alignment with human communication modalities.

Joint	Audio-Visual	Learning
<p>Liu et al. [20] propose a joint audio-visual lip biometrics system that leverages the correlation between lip movements and speech.</p>		
<p>Paper Summary: The DeepLip framework simultaneously processes audio spectrograms and lip video sequences using parallel CNN streams, then fuses the representations through attention-based pooling. By exploiting the natural synchronization between lip movements and speech, the system achieves 0.99% EER on the XM2VTS database, significantly outperforming single-modality approaches. The correlation between modalities provides inherent spoofing resistance, as generating realistic synchronized audio-visual fakes is extremely challenging.</p>		

Deep	Learning	for	Multimodal	Fusion
<p>Recent work has explored sophisticated deep learning architectures for multimodal fusion:</p>				

- **Attention Mechanisms:** Reddy et al. [21] propose using Gumbel-Softmax for neural architecture search in bimodal systems, achieving adaptive fusion that adjusts to data characteristics.

Paper Summary: This work introduces a differentiable neural architecture search (NAS) approach using Gumbel-Rao Monte Carlo estimation to automatically discover optimal fusion architectures for audio-visual biometrics. The search space includes various attention mechanisms, fusion points, and feature processing options. The discovered architectures consistently outperform hand-designed alternatives while being computationally efficient.

- **Cross-Modal Learning:** Zhang et al. [22] demonstrate that training face and voice encoders with cross-modal contrastive learning improves both individual and joint performance.
- **Multimodal Transformers:** The application of transformer architectures to multimodal biometrics shows promise, with models learning to attend to the most discriminative features across modalities [23].

Paper Summary (Multimodal LLMs for Biometrics): Zhang et al. [23] explored leveraging pre-trained multimodal large language models (MLLMs) for facial expression recognition, demonstrating that foundation models can be effectively adapted for biometric tasks through careful prompting and fine-tuning strategies.

2.5.4 Multimodal Biometric Databases

The availability of high-quality multimodal databases is crucial for advancing research. Several notable databases have been released:

- **BehavePassDB:** Stragapede et al. [24] present a comprehensive database of mobile behavioral biometrics, including touchscreen interactions and sensor data.

Paper Summary: BehavePassDB contains data from 81 subjects performing various mobile device interactions over multiple sessions. The database includes touch gestures, keystroke dynamics, and sensor data (accelerometer, gyroscope) collected in both controlled and uncontrolled settings, enabling research on continuous authentication and multimodal behavioral biometrics.

- **SpeakingFaces:** Abdrakhmanova et al. [25] introduce a large-scale dataset with synchronized thermal, visual, and audio streams, supporting research in multimodal authentication under varying environmental conditions.

Paper Summary: This dataset comprises 142 subjects recorded with co-registered thermal-visual camera pairs while speaking commands in multiple languages. The synchronized multi-stream data enables research on robust authentication under varying lighting conditions (thermal images are illumination-invariant) and multimodal fusion of face, thermal signature, and voice.

- **Smartphone Multimodal Biometric Database:** Ramachandra et al. [26] provide a dataset specifically designed for smartphone-based multimodal authentication, including face, voice, and periocular biometrics.
- **MobiBits:** Bartuzi et al. [27] present a mobile biometric database incorporating thermal imaging, representing a step toward more robust authentication in challenging environments.

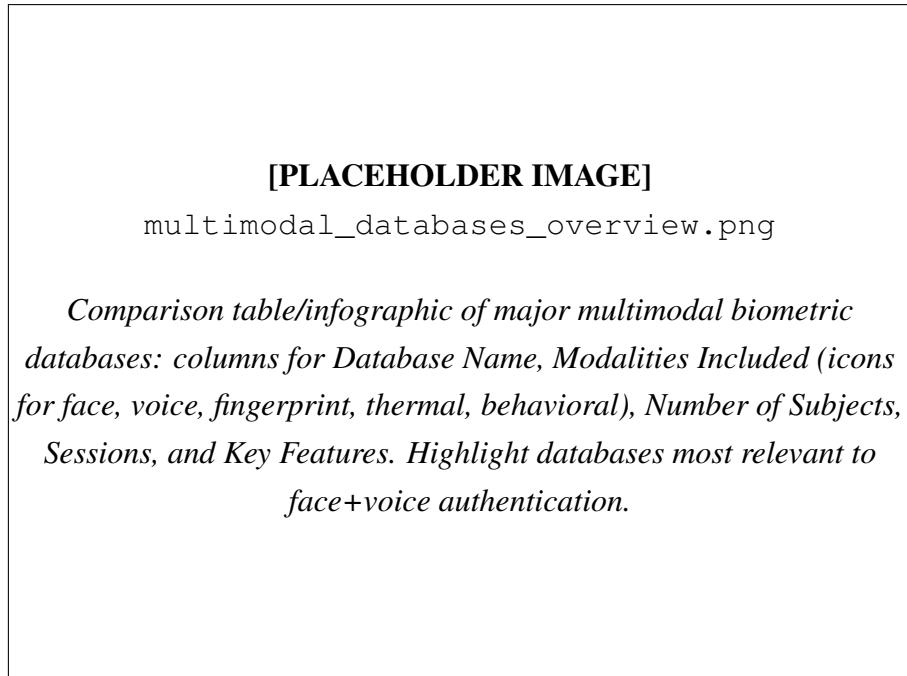


Figure 2.11: Overview of Major Multimodal Biometric Databases

2.6 Edge Computing and Biometric Systems

The deployment of biometric systems on edge devices presents unique challenges and opportunities. This section examines the landscape of edge computing for biometrics, focusing on the trade-offs between accuracy, latency, privacy, and resource constraints.

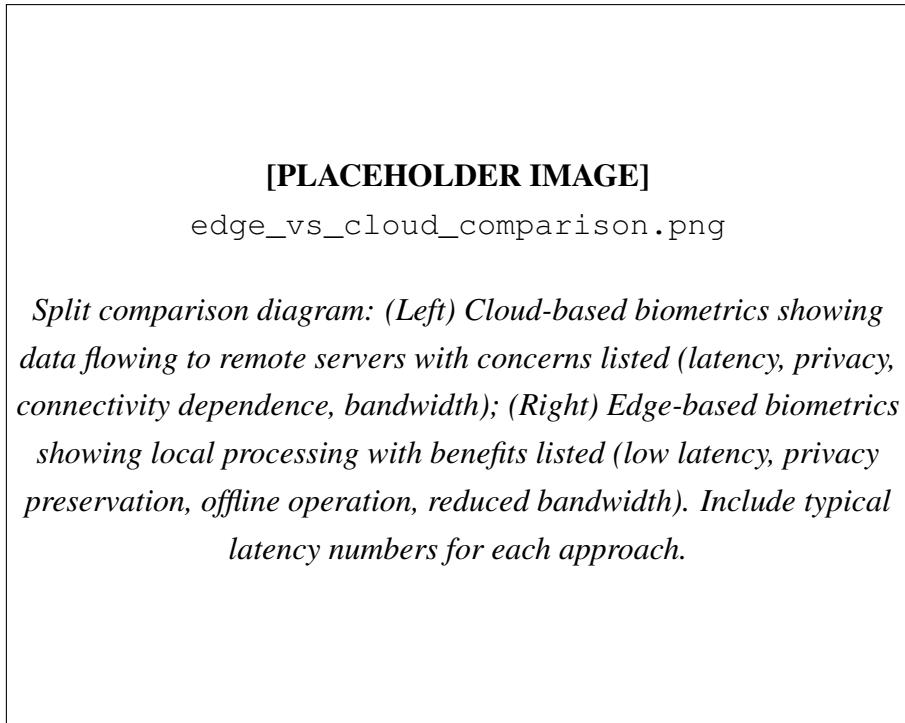


Figure 2.12: Edge vs. Cloud Biometric Processing: Trade-offs and Considerations

2.6.1 The Case for Edge-Based Biometric Processing

Several factors drive the shift toward edge-based biometric processing:

1. **Privacy Preservation:** Processing biometric data locally eliminates the need to transmit sensitive information over networks, addressing major privacy concerns. This aligns with privacy regulations like GDPR and CCPA that mandate data minimization and local processing where possible [28].
2. **Latency Reduction:** For real-time applications like access control, network round-trip time to cloud servers introduces unacceptable delays. Edge processing can reduce total latency by an order of magnitude [29].

Paper Summary (REVAMP²T): Neff et al. [33] demonstrated a complete multi-camera pedestrian tracking system running on Raspberry Pi devices, achieving real-time performance through careful algorithmic optimization. Their system processes video locally and only transmits compressed tracking results, reducing bandwidth by 99% compared to streaming raw video.

3. **Network Independence:** Edge-based systems remain operational even when network connectivity is unreliable or unavailable, crucial for security-critical applications [30].

4. **Bandwidth Conservation:** Transmitting high-resolution video streams for biometric analysis consumes substantial bandwidth. Local processing reduces network load significantly [31].
5. **Scalability:** Distributed edge processing scales naturally with the number of devices, avoiding the bottleneck of centralized cloud processing [32].

2.6.2 Hardware Platforms for Edge Biometrics

Various hardware platforms have been explored for edge-based biometric processing, each with distinct characteristics:

Embedded	ARM	Processors
<p>Single-board computers like the Raspberry Pi represent the most accessible edge platform. Recent work by Mohammadi et al. [34] provides a comprehensive comparison of facial expression recognition across CPU, GPU, VPU (Vision Processing Unit), and TPU (Tensor Processing Unit) on edge devices.</p>		

Paper Summary: This study benchmarks facial expression recognition models across four different compute backends on the same edge device. Key findings include: (1) VPUs provide the best performance-per-watt ratio for CNN inference, (2) TPUs excel for batch processing but have higher latency for single-image inference, (3) CPU-only solutions remain competitive for small models with careful optimization, (4) Memory bandwidth is often the bottleneck rather than compute capacity.

Neural Processing	Units	(NPUs)
<p>Dedicated AI accelerators like Google Coral TPU and Intel Neural Compute Stick offer significant performance improvements for neural network inference. Acien et al. [35] evaluate various edge AI accelerators for behavioral biometrics, finding that TPU-based solutions achieve the best performance-per-watt ratio.</p>		

Neuromorphic	Hardware
<p>Emerging neuromorphic processors like Intel Loihi show promise for ultra-low-power biometric processing. Smith et al. [36] compare neuromorphic hardware against edge AI accelerators for real-time facial expression recognition.</p>	

Paper Summary: This comparative study evaluates spiking neural networks (SNNs) on neuromorphic hardware against conventional ANNs on edge AI accelerators.

Results show neuromorphic solutions achieve two orders of magnitude reduction in power consumption (10-100 mW vs. 1-10 W) while maintaining comparable accuracy.

However, neuromorphic hardware currently has limited availability and requires specialized training pipelines.

FPGA-Based	Solutions
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Field-Programmable Gate Arrays (FPGAs) offer flexibility and efficiency for custom biometric processing pipelines. Fasfous et al. [37] implement a binary neural network on FPGA for COVID-19 mask detection, achieving real-time performance with minimal power consumption.

Paper Summary: BinaryCoP demonstrates that extreme quantization (1-bit weights and activations) enables deployment of face detection and mask classification models on low-power FPGAs. The binary network achieves 50 FPS at only 2.3W power consumption, making it suitable for battery-powered devices. Accuracy degradation from binarization is mitigated through architectural modifications and training strategies.

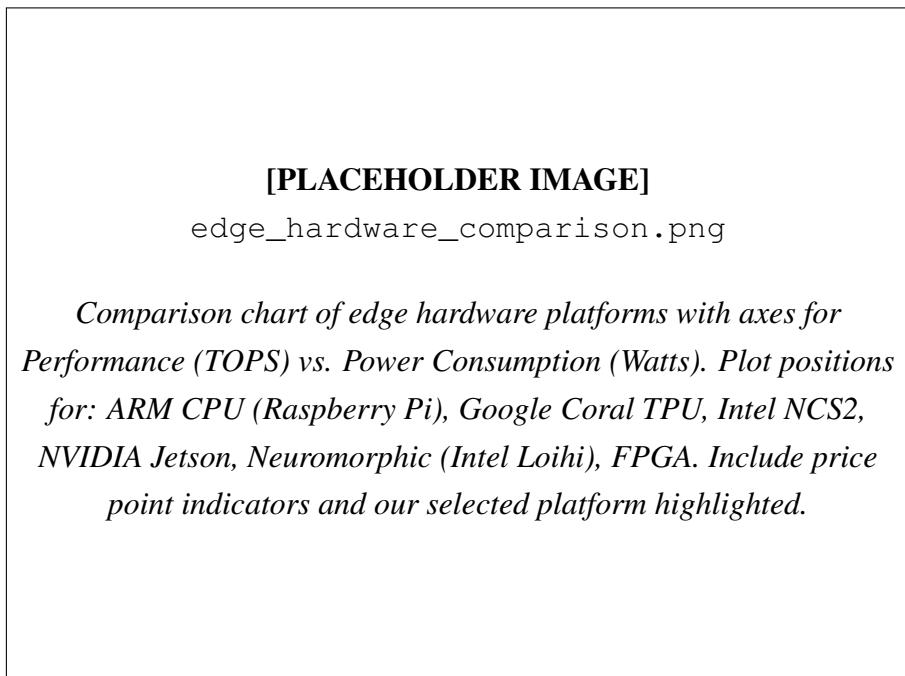


Figure 2.13: Edge Hardware Platforms: Performance vs. Power Consumption Trade-offs

2.6.3 Optimization Techniques for Edge Deployment

Deploying sophisticated deep learning models on resource-constrained edge devices requires careful optimization. Recent research has explored multiple optimization strategies:

Model	Compression
• Quantization: Reducing numerical precision from 32-bit floating point to 8-bit or even binary representations can dramatically reduce model size and computation. Liu et al. [38] demonstrate 75% memory savings through 8-bit quantization while maintaining recognition accuracy.	
<i>Paper Summary:</i> This work presents a comprehensive study of quantization techniques for speaker verification models. Key findings include: (1) Post-training quantization to INT8 preserves accuracy within 0.5% EER for most models, (2) Quantization-aware training can recover most accuracy loss for more aggressive quantization, (3) Mixed-precision quantization targeting memory-intensive layers provides the best accuracy-efficiency trade-off.	
• Pruning: Removing redundant or less important connections in neural networks. Structured pruning can achieve 50-70% reduction in model size with minimal accuracy loss [39].	
• Knowledge Distillation: Training smaller “student” models to mimic larger “teacher” models. This approach is particularly effective for biometric applications where large models are impractical for edge deployment [40].	

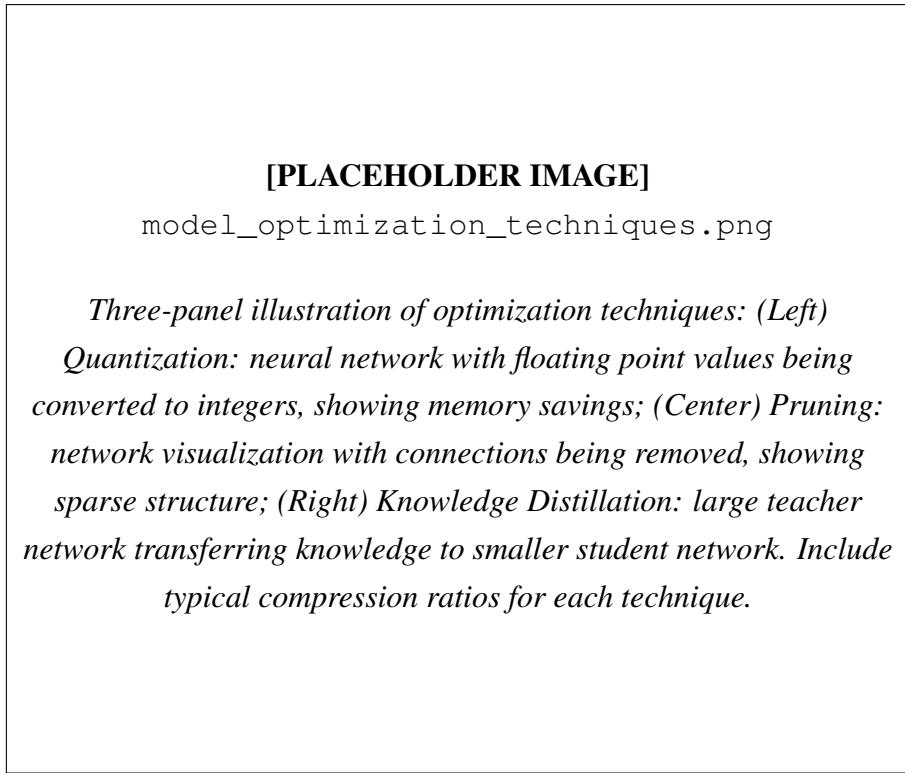


Figure 2.14: Model Compression Techniques for Edge Deployment

- | Efficient | Network | Architectures |
|--|----------------|----------------------|
| Mobile-optimized architectures specifically designed for edge devices: | | |
| <ul style="list-style-type: none">• MobileNets: Utilize depthwise separable convolutions to reduce computational cost while maintaining accuracy. Widely adopted in mobile computer vision applications [41].• EfficientNets: Employ compound scaling to balance network depth, width, and resolution, achieving superior accuracy-efficiency trade-offs [42].• ShuffleNets: Use channel shuffle operations to enable efficient group convolutions, particularly effective on ARM processors [43].• SqueezeNets: Employ fire modules with squeeze and expand layers to reduce parameters while maintaining accuracy [44]. | | |

Yang et al. [45] propose EdgeCNN, a convolutional architecture specifically designed for edge devices with slow memory access.

Paper Summary: EdgeCNN addresses the memory bandwidth bottleneck common in embedded devices by designing convolution operations that maximize data reuse

within on-chip memory. The architecture achieves real-time performance on Raspberry Pi for facial expression recognition while using 3x less memory bandwidth than standard CNNs.

Hardware-Software

Co-Design

Optimizing the entire stack from algorithms to hardware interfaces:

- **Operator Fusion:** Combining multiple operations to reduce memory access overhead.
- **Memory Layout Optimization:** Organizing data to maximize cache utilization and minimize memory bandwidth requirements.
- **Parallel Processing:** Exploiting multi-core architectures and SIMD instructions for parallel execution.

2.6.4 Real-Time Constraints and System Design

Real-time biometric systems must meet strict latency requirements while balancing accuracy and resource consumption. Key considerations include:

Pipeline

Optimization

Hu et al. [49] propose a multi-layer emotion recognition service that distributes computation across edge, fog, and cloud layers based on latency constraints.

Paper Summary: This work introduces an adaptive scheduling policy that dynamically allocates processing tasks to different computational tiers based on current load and latency requirements. The system achieves 70% energy reduction compared to cloud-only processing while meeting real-time constraints for emotion recognition applications.

Adaptive

Processing

Systems that dynamically adjust processing complexity based on input characteristics or available resources:

- **Early Exit Networks:** Allow inference to terminate early when confidence is high, saving computation on easy samples [46].

- **Resolution Scaling:** Dynamically adjust input resolution based on network conditions or computational load [47].
- **Quality-Based Processing:** Tailor processing intensity to input quality, avoiding unnecessary computation on low-quality inputs [48].

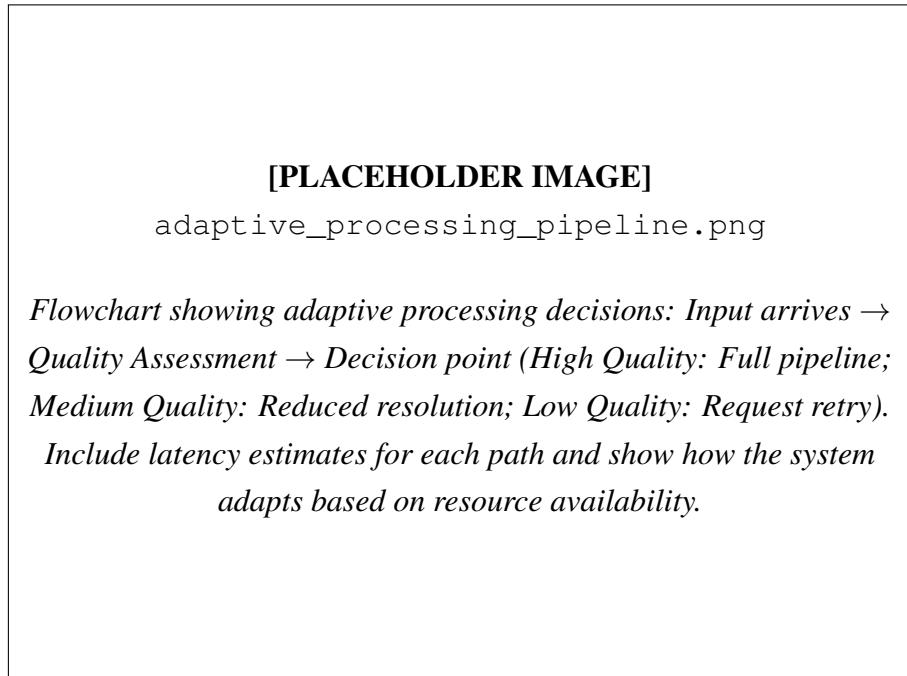


Figure 2.15: Adaptive Processing Pipeline for Resource-Constrained Environments

2.7 Privacy and Security in Biometric Systems

The deployment of biometric systems raises significant privacy and security concerns. This section examines current research on protecting biometric data and defending against attacks.

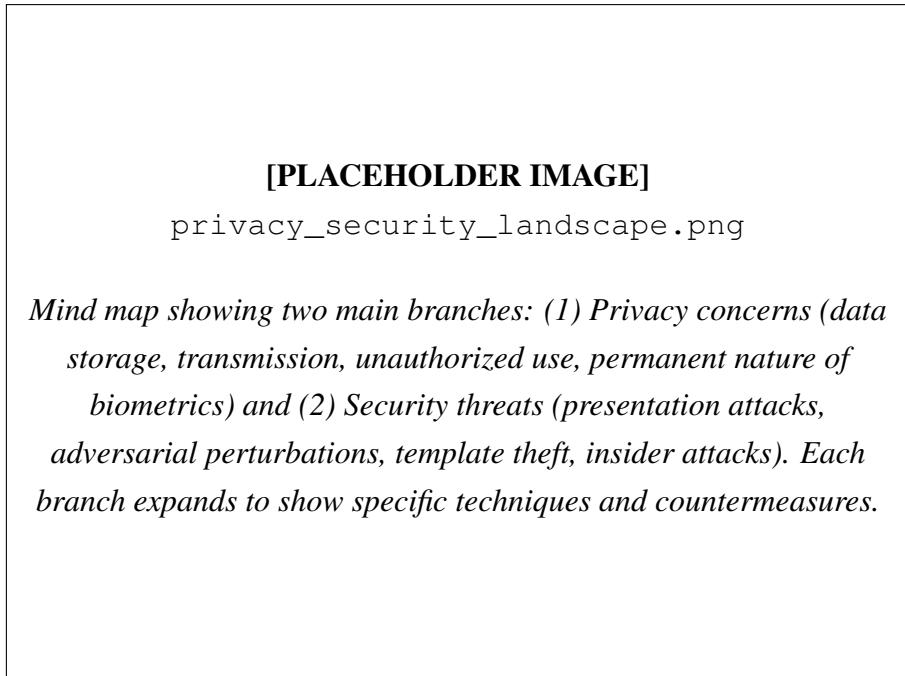


Figure 2.16: Privacy and Security Landscape in Biometric Systems

2.7.1 Privacy-Preserving Biometric Authentication

Several approaches have been developed to protect biometric privacy:

Homomorphic Encryption

Homomorphic encryption enables computation on encrypted data without decryption. Sepehri et al. [50] explore partially homomorphic encryption for encrypted vector similarity search in facial recognition.

Paper Summary: This work demonstrates that partially homomorphic encryption (PHE) can be practically applied to biometric template matching. The authors show that computing cosine similarity on encrypted 512-dimensional face embeddings takes only 50ms on commodity hardware, making privacy-preserving authentication feasible for real-time applications. The approach provides strong cryptographic guarantees while maintaining matching accuracy identical to plaintext operations.

Droandi et al. [51] propose SEMBA, a secure multimodal biometric authentication system that processes biometric data under encryption using multi-party computation.

Paper Summary: SEMBA combines secret sharing with homomorphic encryption to enable secure multimodal fusion without exposing individual biometric templates. The system supports both score-level and feature-level fusion under encryption, achieving

the security of fully homomorphic encryption with 10x better performance through careful protocol design.

Federated	Learning
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Federated learning enables collaborative model training without sharing raw biometric data. This approach is particularly relevant for systems that benefit from learning across multiple users or devices while preserving privacy [52].

Differential	Privacy
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Adding controlled noise to biometric data or models to provide mathematical privacy guarantees. Recent work demonstrates that differential privacy can be applied to biometric authentication with acceptable accuracy degradation [53].

Privacy-Aware	Feature	Generation
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Arefeen et al. [54] propose MetaMorphosis, a framework for generating task-specific privacy-aware features.

Paper Summary: MetaMorphosis learns to transform raw biometric data into task-specific representations that contain only information necessary for the intended authentication task. This prevents “function creep” where biometric data collected for one purpose is used for unauthorized tasks (e.g., emotion recognition, health inference). The framework achieves 95% of original task accuracy while reducing unintended information leakage by 80%.

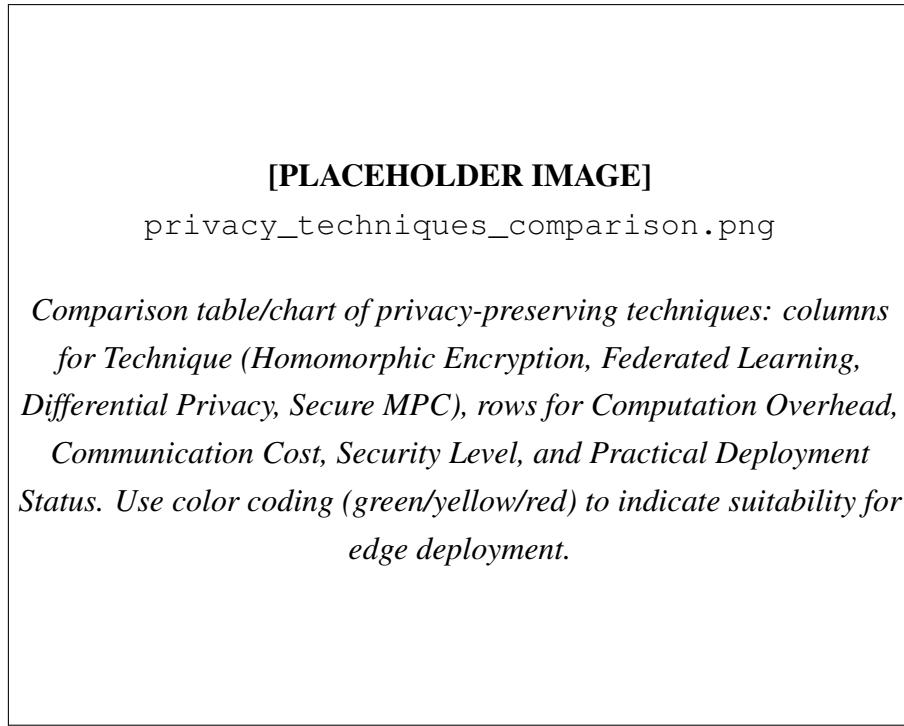


Figure 2.17: Comparison of Privacy-Preserving Techniques for Biometric Authentication

2.7.2 Presentation Attack Detection

Biometric systems are vulnerable to presentation attacks (spoofing). Recent research has developed sophisticated countermeasures:

Spoofing-Robust

Speaker

Verification

The speaker verification community has extensively studied presentation attack detection:

- **ASVspoof Challenge:** The ongoing ASVspoof challenges have driven development of robust countermeasures against synthetic speech, voice conversion, and replay attacks [55].

Paper Summary (ASVspoof5): The ASVspoof5 challenge introduced new evaluation protocols including “spoofing-robust” metrics that jointly assess speaker verification and spoofing detection. Results showed that while individual countermeasures achieve low Equal Error Rates, their integration with speaker verification remains challenging, with best systems achieving 5-10% spoofing-aware EER.

- **End-to-End Systems:** Kurnaz et al. [56] propose jointly optimizing speaker and spoof detection for spoofing-robust automatic speaker verification (SASV).

Paper Summary: This work introduces a unified optimization framework that jointly trains speaker verification and spoofing detection modules. By sharing intermediate representations and using a combined loss function, the system achieves superior performance compared to cascaded approaches where modules are trained independently.

- **SSL-Based Approaches:** Self-supervised learning models like AASIST demonstrate excellent generalization to unseen attack types [57].

Face	Anti-Spoofing
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Face recognition systems face various presentation attacks:

- **Print Attacks:** Detecting photographs of faces.
- **Replay Attacks:** Detecting video replays of faces.
- **3D Mask Attacks:** Detecting silicone masks or 3D printed faces.
- **Deepfake Attacks:** Detecting AI-generated synthetic faces.

Recent work by Reddy et al. [58] proposes neural architecture search for audio-visual deepfake detection.

Paper Summary: This work uses differentiable NAS to automatically discover optimal architectures for detecting audio-visual deepfakes. The search space includes various fusion strategies, attention mechanisms, and temporal modeling options. Discovered architectures achieve 3-5% improvement over hand-designed baselines while being 2x more efficient.

Multimodal	Presentation	Attack	Detection
Multimodal systems can provide inherent protection against spoofing attacks, as simultaneously spoofing multiple modalities is significantly more difficult. However, adaptive attackers may develop multimodal spoofing techniques, necessitating robust countermeasures [59].			

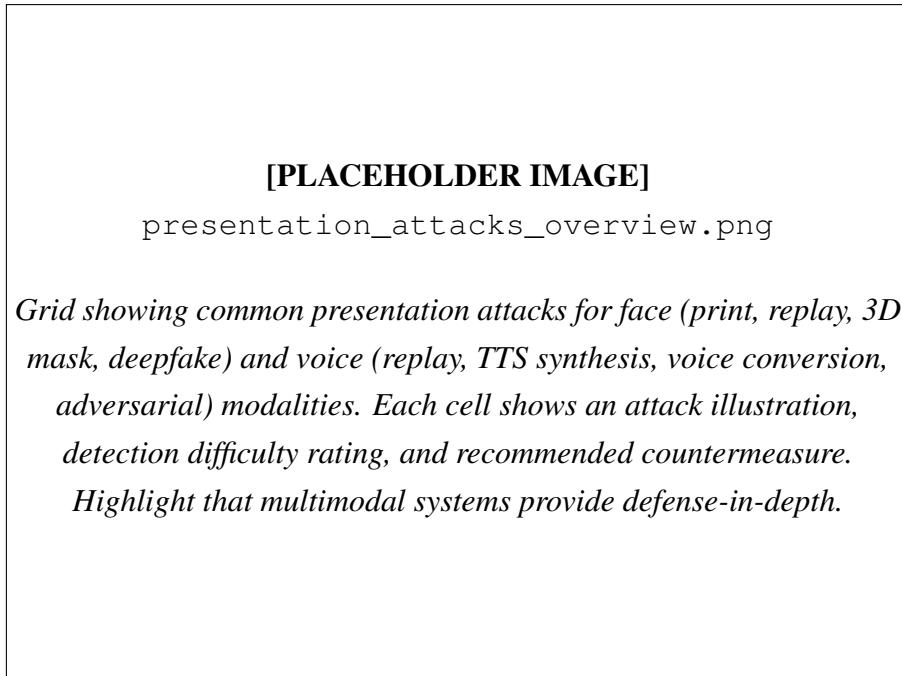


Figure 2.18: Overview of Presentation Attacks and Countermeasures for Biometric Systems

2.7.3 Adversarial Attacks and Defenses

Deep learning-based biometric systems are vulnerable to adversarial attacks:

Adversarial Perturbations

Dar et al. [60] analyze the impact of adversarial perturbations on speaker verification.

Paper Summary: This study systematically analyzes how adversarial perturbations affect different phonetic components of speech. Results show that perturbations targeting vowel segments cause larger degradation than those targeting consonants, suggesting that speaker-discriminative information is unevenly distributed across phonemes. This insight enables more effective attacks and informs defense strategies.

Todisco et al. [61] present Malacopula, a sophisticated attack that uses non-linear processes to generate adversarial perturbations against speaker verification systems.

Paper Summary: Malacopula generates adversarial examples by iteratively applying copula-based transformations that preserve the statistical properties of natural speech while maximally degrading verification performance. The attack achieves 95% success rate against state-of-the-art systems while maintaining high perceptual quality (PESQ > 3.5).

Defense	Mechanisms
<ul style="list-style-type: none"> • Adversarial Training: Training models with adversarial examples to improve robustness [62]. 	
<ul style="list-style-type: none"> • Input Transformations: Applying random transformations to inputs to break adversarial perturbations [63]. 	
<ul style="list-style-type: none"> • Certified Defenses: Developing provably robust models with certified accuracy bounds under attack [64]. 	

2.8 Continuous Authentication and Behavioral Biometrics

Traditional point-of-entry authentication provides security only at login. Continuous authentication monitors user identity throughout a session, providing ongoing verification.

2.8.1 Behavioral Biometric Modalities

Abuhamad et al. [65] provide a comprehensive survey of sensor-based continuous authentication.

Paper Summary: This survey covers the complete landscape of behavioral biometrics for smartphone authentication, including keystroke dynamics, touch gestures, gait patterns, and device handling characteristics. Key findings include: (1) combining multiple behavioral modalities reduces EER from 15-20% (single modality) to 5-8% (multimodal), (2) deep learning methods consistently outperform traditional machine learning, (3) user adaptation over time remains a significant challenge.

The survey covers:

- **Keystroke Dynamics:** Analyzing typing patterns and rhythms.
- **Touch Gestures:** Monitoring touchscreen interaction patterns.
- **Gait Analysis:** Recognizing walking patterns from accelerometer data.
- **Hand Movements:** Tracking hand orientation and movement patterns.
- **Voice Patterns:** Continuous speaker verification during voice interactions.

Stragapede et al. [66] demonstrate that combining multiple behavioral modalities achieves superior performance compared to single-modality systems, with EER ranging from 4-9% depending on modality combination.

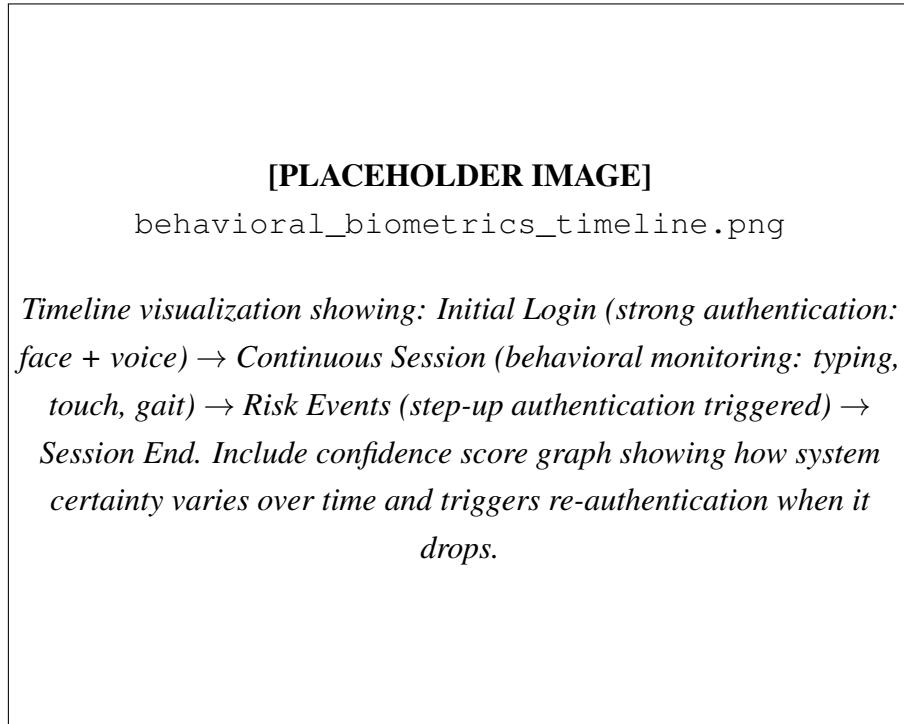


Figure 2.19: Continuous Authentication Lifecycle with Behavioral Biometrics

2.8.2 Context-Aware Authentication

Modern authentication systems can leverage contextual information to improve security and usability:

- **Location-Based Authentication:** Using GPS and WiFi positioning to verify user location patterns [67].
- **Time-Based Patterns:** Learning user activity patterns across different times of day [68].
- **Environmental Context:** Considering ambient conditions like lighting, noise level, and nearby devices [69].
- **Multi-Device Authentication:** Leveraging presence of paired devices for implicit authentication [70].

2.8.3 Zero-Trust Security Models

Cheng et al. [71] propose a zero-trust security framework combining continuous biometric authentication with federated learning.

Paper Summary: This work adapts zero-trust principles (“never trust, always verify”) to immersive environments where traditional authentication is intrusive. The framework uses continuous multimodal biometrics (gaze patterns, voice characteristics, movement signatures) processed through federated learning to maintain user privacy while enabling persistent identity verification. The system achieves 98% continuous verification accuracy with only 2% false alarm rate.

2.9 Domain-Specific Challenges and Solutions

Different application domains present unique challenges for biometric authentication systems.

2.9.1 Cross-Age Speaker Verification

Human voice characteristics change significantly with age, posing challenges for long-term speaker verification:

- **Child-Adult Mismatch:** Shetty et al. [72] propose adapter-based transfer learning to improve speaker verification for children.

Paper Summary: This work addresses the significant domain shift between adult speech (used for training most speaker verification systems) and children’s speech. The G-IFT (Gated Linear Unit Adapter with Iterative Fine-Tuning) approach adapts pre-trained adult models to children by inserting small trainable adapter modules while freezing the main network. This achieves 40% relative improvement on child speaker verification while maintaining adult performance.

- **Age-Agnostic Systems:** Zheng et al. [73] develop systems that disentangle age-related attributes from speaker identity.

Paper Summary: The authors propose learning speaker embeddings that are explicitly invariant to age-related vocal changes. Using adversarial training with an age classifier, the system learns representations that preserve speaker identity while discarding age information. This enables robust verification even when enrollment and test utterances are separated by decades.

- **Age Progression:** Zhang et al. [74] propose mutual information minimization to learn age-invariant speaker embeddings.

2.9.2 Low-Resource and Few-Shot Learning

Many practical scenarios involve limited training data:

- **Self-Supervised Learning:** Chen et al. [75] propose Self-Distillation Prototypes Network (SDPN) for self-supervised speaker verification.

Paper Summary: SDPN learns speaker representations without explicit speaker labels by combining contrastive learning with prototype-based clustering. The network iteratively refines cluster assignments while training the encoder, effectively discovering speaker structure in unlabeled data. Results show competitive performance with supervised methods while requiring no manual annotation.

- **Meta-Learning:** Lepage et al. [76] explore leveraging large-scale ASR models for speaker verification through self-supervised fine-tuning.
- **Data Augmentation:** Liu et al. [77] propose interpolating speaker identities in embedding space to synthesize new training samples.

Paper Summary: This work generates synthetic training examples by linearly interpolating between speaker embeddings and reconstructing corresponding audio using a neural vocoder. The interpolated samples represent “virtual speakers” that expand the training distribution, improving generalization to unseen speakers by 15% relative EER reduction.

2.9.3 Text-Dependent vs. Text-Independent Verification

- **Text-Dependent Systems:** Farokh et al. [78] demonstrate that independent pre-trained models for text and speaker can achieve competitive performance.

Paper Summary: This work shows that decoupling text recognition from speaker verification enables more efficient systems. By using separate lightweight models for each task and combining their outputs, the system achieves accuracy comparable to joint models while reducing memory requirements by 60%—crucial for edge deployment.

- **Text Adaptation:** Yang et al. [79] propose using speaker-text factorized embeddings to handle text mismatch between enrollment and test data.

- **Hybrid Approaches:** Zheng et al. [80] develop systems specifically optimized for numerical string authentication, common in financial applications.

2.9.4 Robustness to Environmental Conditions

Real-world deployment requires robustness to various environmental factors:

Far-Field	Speaker	Recognition
Zhang et al. [81] propose adaptive data augmentation using text-to-speech models to synthesize far-field speech.		
<i>Paper Summary:</i> Using NaturalSpeech3, the authors generate realistic far-field training data by simulating various room acoustics and speaker distances. Training on this augmented data improves far-field verification EER from 12% to 7% while maintaining near-field performance. This approach is more effective than traditional room impulse response simulation.		
Low-Light	Face	Recognition
Xia et al. [82] develop dual-domain enhancement networks for improving face recognition in poorly lit conditions.		
<i>Paper Summary:</i> DLEN (Dual-domain Low-light Enhancement Network) processes images in both spatial and frequency domains to enhance facial details while suppressing noise. The dual-branch transformer architecture achieves state-of-the-art low-light enhancement quality while being efficient enough for edge deployment (15 FPS on mobile GPU).		
Noise		Robustness
Xing et al. [83] propose joint noise disentanglement and adversarial training for robust speaker verification.		
<i>Paper Summary:</i> This framework learns to separate speaker-discriminative features from noise artifacts through a disentanglement network, then applies adversarial training to make the speaker encoder robust to residual noise. The approach achieves 30% relative improvement in noisy conditions while maintaining clean speech performance.		

2.10 Emerging Trends and Future Directions

This section examines cutting-edge research directions that may shape the future of biometric authentication systems.

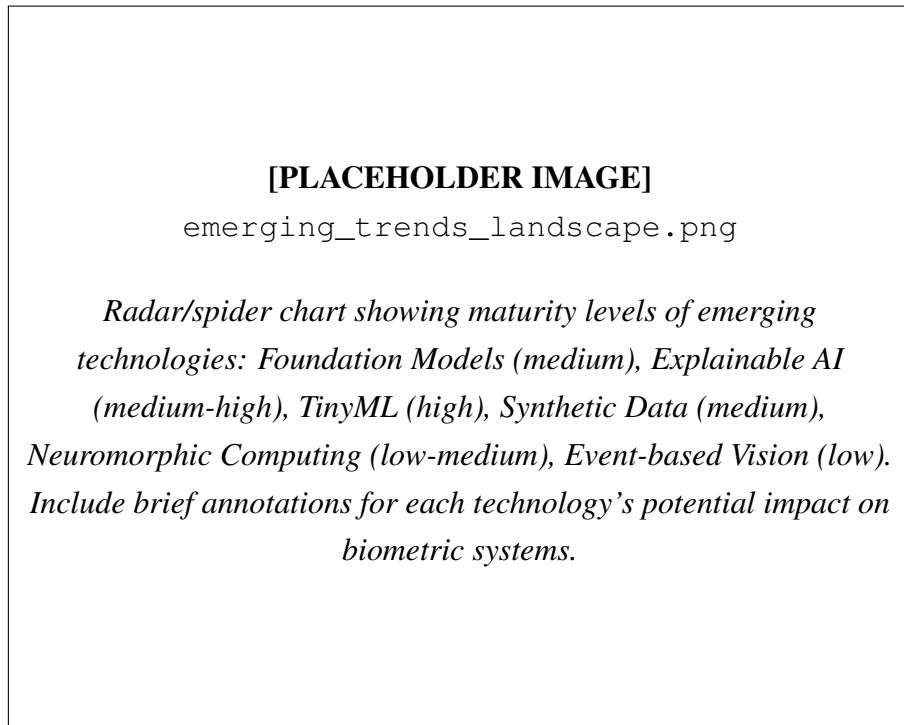


Figure 2.20: Emerging Technology Landscape for Biometric Authentication

2.10.1 Foundation Models for Biometrics

The success of large-scale pre-trained models in NLP and computer vision is inspiring similar approaches in biometrics:

- **Universal Speaker Representations:** Ma et al. [84] propose phonetic trait-oriented networks that provide explainable speaker verification.

Paper Summary: ExPO (Explainable Phonetic-Oriented) network explicitly models speaker-discriminative phonetic traits identified in forensic voice comparison research. The network provides interpretable outputs showing which phonetic characteristics (F0 patterns, formant ratios, voice quality measures) contribute to verification decisions. This interpretability is crucial for high-stakes applications requiring human oversight.

- **Multimodal Foundation Models:** Chen et al. [85] introduce a comprehensive toolkit for multimodal speaker analysis.

Paper Summary: 3D-Speaker-Toolkit provides unified APIs for speaker verification, diarization, and attribute analysis using acoustic, semantic, and visual modalities. The toolkit includes pre-trained foundation models that can be fine-tuned for specific tasks, democratizing access to state-of-the-art multimodal speaker analysis.

- **Self-Supervised Pretraining:** Leveraging large-scale unlabeled data for learning robust biometric representations [86].

2.10.2 Explainable Biometric Systems

As biometric systems are deployed in high-stakes applications, explainability becomes crucial:

- **Attribution Methods:** Analyzing which facial regions or voice characteristics contribute most to identification decisions [87].
- **Phonetic Analysis:** Huckvale [88] investigates how speaker embeddings relate to conventional acoustic and phonetic dimensions.

Paper Summary: This work analyzes the information encoded in speaker embeddings by correlating embedding dimensions with traditional acoustic measures (pitch, formants, voice quality). Results show that while embeddings capture known speaker-discriminative features, they also encode information not captured by traditional analysis, suggesting deep learning discovers novel speaker characteristics.

- **Confidence Calibration:** Providing reliable uncertainty estimates for authentication decisions [89].

2.10.3 Tiny Machine Learning (TinyML)

Ultra-low-power biometric systems for IoT devices:

- **Quantized Neural Networks:** Pavan et al. [90] demonstrate on-device learning for speaker verification on microcontroller-class devices.

Paper Summary: TinySV achieves speaker verification on devices with only 256KB RAM and 1MB flash by: (1) using extreme quantization (4-bit weights), (2) designing architectures that fit within memory constraints, (3) implementing on-device enrollment without cloud connectivity. The system achieves 8% EER while consuming only 50mW during inference.

- **Binary Neural Networks:** Extreme quantization for minimal energy consumption [91].
- **Event-Based Processing:** Wang et al. [92] explore event cameras for efficient facial expression recognition.

Paper Summary: Event cameras output asynchronous “events” only when pixel intensity changes, enabling extremely efficient processing. This work demonstrates that event-based facial expression recognition achieves comparable accuracy to frame-based methods while consuming 100x less energy, making it suitable for always-on biometric monitoring.

2.10.4 Synthetic Data and Data Augmentation

Synthetic data generation for training robust biometric systems:

- **GANs for Biometrics:** Mousavi et al. [93] use genetic algorithms to optimize GANs for generating diverse emotional depth faces.
- Paper Summary:* This work combines genetic algorithms with GANs to generate synthetic face images with controlled emotional expressions and demographic attributes. The generated data improves face recognition model robustness to expression variations by 20% while avoiding privacy concerns associated with collecting real emotional face data.
- **Text-to-Speech Synthesis:** Generating synthetic voice data to augment training datasets [94].
 - **Domain Adaptation:** Using synthetic data to improve cross-domain generalization [95].

2.10.5 Neuromorphic and Alternative Computing Paradigms

Novel computing architectures for energy-efficient biometric processing:

- **Spiking Neural Networks:** Bio-inspired networks that process information as spike trains, offering orders of magnitude improvement in energy efficiency [96].
- **In-Memory Computing:** Performing computation where data is stored, reducing energy-intensive data movement [97].
- **Analog Computing:** Exploiting analog circuits for efficient neural network computation [98].

2.11 Comparative Analysis and Lessons Learned

This section synthesizes insights from the literature review to inform our design decisions.

2.11.1 Model Selection Criteria

Based on extensive literature review, we establish the following criteria for model selection in edge-based biometric systems:

1. **Inference Latency:** Models must achieve real-time performance (typically <100ms per frame for vision, <1s for audio) on target hardware.
2. **Memory Footprint:** Total model size should not exceed available RAM, accounting for both model parameters and activation memory.
3. **Accuracy:** Must meet minimum accuracy thresholds (typically >95% for individual modalities, >98% for multimodal systems).
4. **Robustness:** Should maintain performance under realistic variations in input quality, environmental conditions, and user characteristics.
5. **Implementation Complexity:** Preference for models with well-supported libraries and clear documentation to facilitate rapid prototyping.

2.11.2 Architecture Trade-offs

Our analysis of the literature reveals several key trade-offs:

Depth vs. Width

Deeper networks generally achieve higher accuracy but at the cost of increased latency. For edge deployment, wider shallow networks often provide better accuracy-latency trade-offs [99].

Convolutional vs. Attention-Based

While transformer-based models achieve state-of-the-art results on many benchmarks, their computational requirements make them challenging for edge deployment. Convolutional architectures remain more practical for resource-constrained scenarios [100].

Task-Specific	vs.	General-Purpose
Models specifically designed for a particular biometric modality (e.g., speaker verification) typically outperform general-purpose models adapted for the task, especially in resource-constrained settings [101].		

2.11.3 Fusion Strategy Selection

Our literature analysis informs the selection of fusion strategy:

- **Score-Level Fusion:** Recommended for most applications due to its balance of effectiveness and simplicity.
- **OR-Logic vs. AND-Logic:** OR-logic (requiring only one modality to succeed) provides better user experience by reducing false rejections, at the cost of slightly higher false acceptance rate. This is appropriate for convenience-oriented applications.
- **Adaptive Weighting:** While more complex, quality-aware adaptive fusion provides superior performance when quality metrics are available for each modality.

2.12 Research Gaps and Our Contribution

Despite extensive prior work, several gaps remain in the literature:

1. **Limited Practical Benchmarking:** Most studies report results on high-end hardware or in simulation. Few provide detailed performance analysis on actual low-cost edge devices like Raspberry Pi.
2. **Insufficient Hybrid Architecture Studies:** While parallel and sequential multimodal systems have been studied independently, comparative analysis of their practical implementation trade-offs is limited.
3. **ARM64 Deployment Challenges:** Detailed documentation of software environment setup challenges and solutions for ARM64 platforms is scarce in the academic literature.
4. **Real-World System Integration:** Most research focuses on individual components (detection, recognition, fusion) in isolation. End-to-end system integration studies are uncommon.

5. **Privacy-Utility Trade-offs:** Limited quantitative analysis of the trade-offs between privacy-preserving techniques and system usability/accuracy in practical deployments.

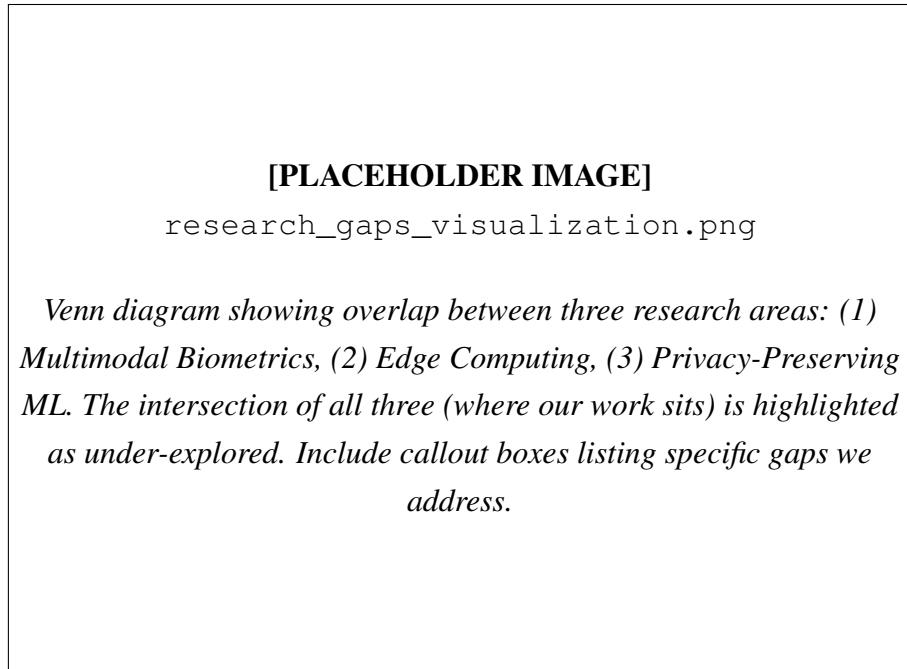


Figure 2.21: Visualization of Research Gaps Addressed by This Work

Our work addresses these gaps by:

- Providing comprehensive benchmarking on actual Raspberry Pi 4 hardware
- Implementing and comparing parallel vs. sequential multimodal architectures
- Documenting the complete ARM64 development environment setup process
- Developing an integrated end-to-end system with all components
- Analyzing privacy implications of local vs. cloud processing

2.13 Chapter

Summary

This comprehensive literature review has examined the state of the art in multiple domains relevant to our hybrid two-layer authentication system. We have reviewed:

- Facial recognition techniques, from classical methods to modern deep learning approaches

- Speaker recognition models, spanning from heavy SOTA architectures to lightweight edge-optimized solutions
- Multimodal biometric fusion strategies and their comparative advantages
- Edge computing platforms and optimization techniques for resource-constrained deployment
- Privacy and security considerations in biometric systems
- Emerging trends including foundation models, explainability, and neuromorphic computing

The insights gained from this review directly informed our technology selection, system architecture, and implementation strategy. The next chapter details our proposed system design, incorporating these lessons learned to create an efficient, secure, and practical hybrid authentication system for edge deployment.

Chapter 3

System Design & Analysis

3.1 Proposed Methodology: The Hybrid Approach

A critical decision point in our design phase was determining the core user interaction logic. We evaluated two primary architectures:

1. **“Sequential” Model:** The user presents their face, and only upon successful verification is the microphone activated for voice verification. This is a two-step process.
2. **“Parallel/Hybrid” Model:** The user presents their face and speaks simultaneously. The system captures and processes both biometric streams in parallel.

Following a detailed risk-benefit analysis, we made the strategic decision to adopt the **Hybrid Two-Layer Authentication** model. While the sequential approach offers simpler control flow, the hybrid model provides a significantly faster, more intuitive, and seamless user experience, as the user performs only a single action (“look and speak”). We have chosen to prioritize this superior user experience, fully acknowledging that it presents a greater technical challenge in terms of multi-threaded programming and the design of the decision fusion logic.

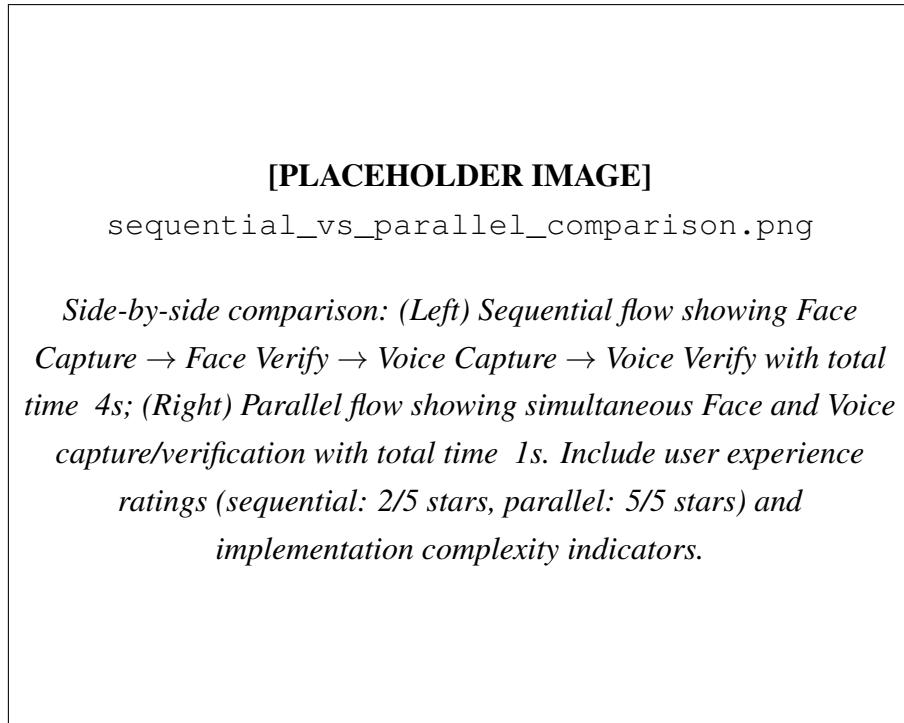


Figure 3.1: Comparison of Sequential vs. Parallel Authentication Approaches

3.2 System Requirements

3.2.1 Functional Requirements (FR)

- **FR1:** The system shall allow an administrator to enroll a new user by capturing their facial image and storing the corresponding biometric template.
- **FR2:** The system shall allow an administrator to enroll a new user by capturing their voice sample and storing the corresponding voiceprint.
- **FR3:** The system shall be able to capture a live video stream, perform a liveliness check (blink detection), and verify any detected faces against the enrolled database.
- **FR4:** The system shall be able to capture a live audio stream and verify it against the enrolled database.
- **FR5:** The system shall grant access if **either** the face verification (FR3) **OR** the voice verification (FR4) is successful and exceeds a confidence threshold.
- **FR6:** All enrolled biometric templates shall be stored securely on the local device's filesystem.

- **FR7:** Upon successful authentication, the system shall trigger a signal on a GPIO pin.

3.2.2 Non-Functional Requirements (NFR)

- **NFR1 (Performance):** The end-to-end authentication process, from user action to final decision, shall complete in under 2.0 seconds.
- **NFR2 (Security & Privacy):** All biometric processing and template storage must occur on the local edge device. No data shall be transmitted over any network.
- **NFR3 (Usability):** The authentication process must be fully contactless.
- **NFR4 (Accuracy):** Each biometric modality shall achieve a target verification accuracy of over 95% on our custom test dataset under normal conditions.
- **NFR5 (Hardware Constraint):** The entire system must function on a Raspberry Pi 4 (8GB model) without thermal throttling under normal operation.

3.3 Hardware Platform Selection and Justification

The selection of an appropriate hardware platform is a critical engineering decision, representing a trade-off between performance, power, cost, and ease of development. For this project, a thorough analysis was conducted between three viable platforms.

Alternative 1: Repurposed Smartphones

Modern mobile phones feature powerful and extremely power-efficient ARM SoCs, often with dedicated AI accelerators (NPUs). They also offer an integrated package of high-quality cameras and microphones. However, the primary challenge is the restrictive nature of mobile operating systems (Android/iOS) and the difficulty in interfacing with external hardware (like door locks) via GPIO.

Alternative 2: x86 Mini-PCs

Repurposed small-form-factor desktops offer substantial raw CPU performance at a low cost. The x86 architecture also simplifies software installation. However, their power consumption is an order of magnitude higher than an SBC, and they lack native GPIO support.

Chosen Platform: Raspberry Pi 4 Model B (8GB)

The Raspberry Pi 4 was selected as the optimal platform. Its most significant advantage is the **native GPIO header**, which provides a direct, low-latency, and simple Python interface for controlling external hardware.

Table 3.1: Hardware Platform Comparison

Platform	Advantages	Disadvantages	Decision
Smartphone	Powerful SoC, integrated sensors	Restrictive OS, no GPIO	Rejected
x86 Mini-PC	High CPU performance	High power, no GPIO	Rejected
Raspberry Pi 4	Native GPIO, community support, balanced performance	Limited CPU vs. x86	Selected

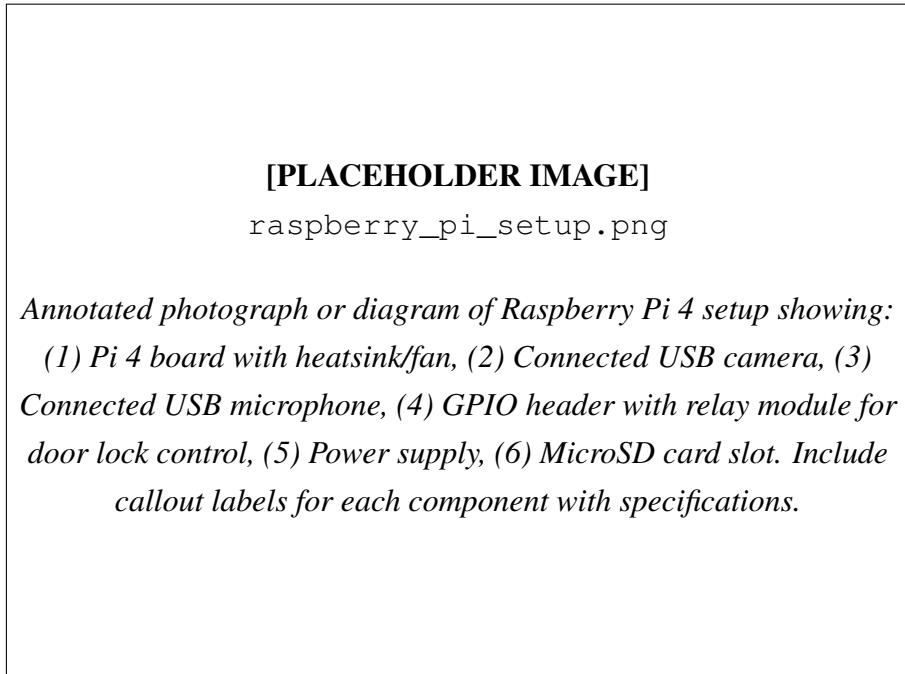


Figure 3.2: Hardware Setup: Raspberry Pi 4 with Camera, Microphone, and GPIO Peripherals

3.4 System Architecture/Design Diagrams

3.4.1 High-Level Architecture

The system is designed as a multi-threaded application where the main process orchestrates two parallel worker threads for biometric processing.

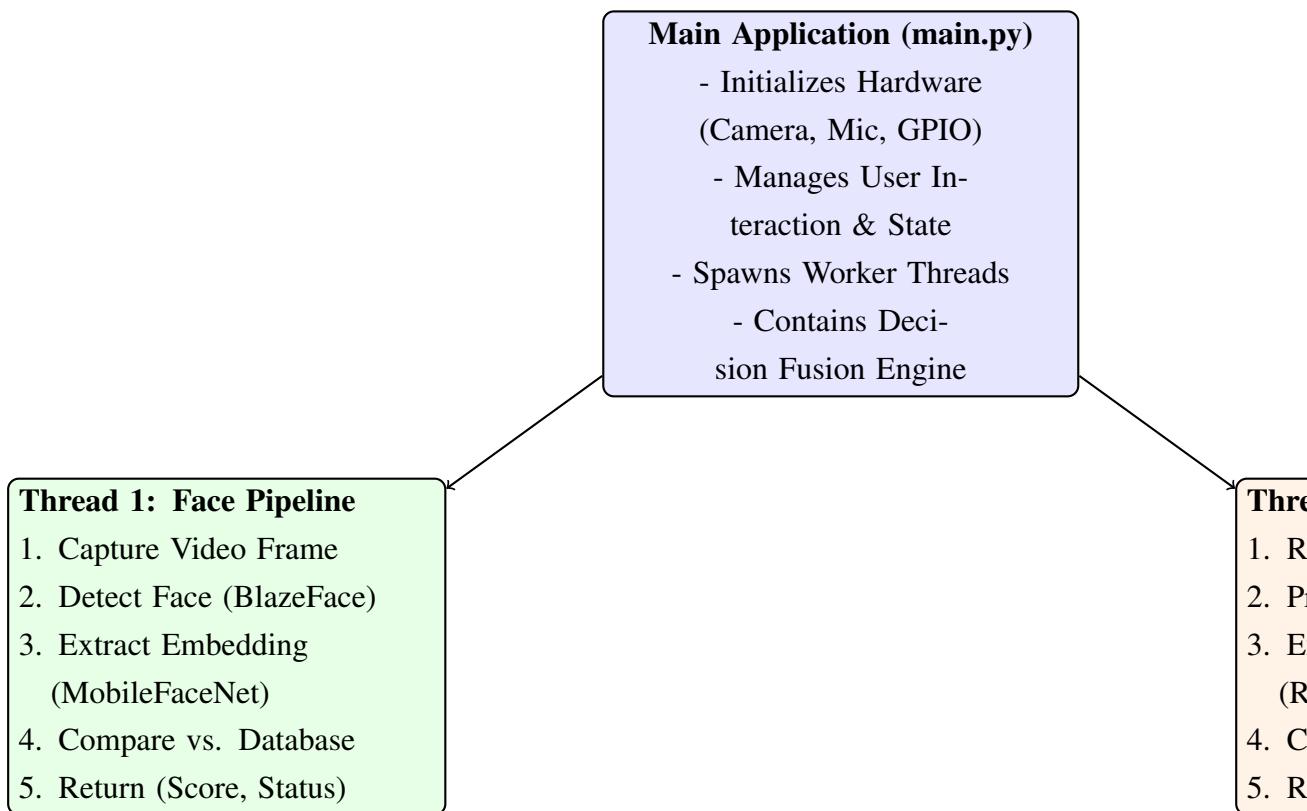


Figure 3.3: High-Level System Architecture

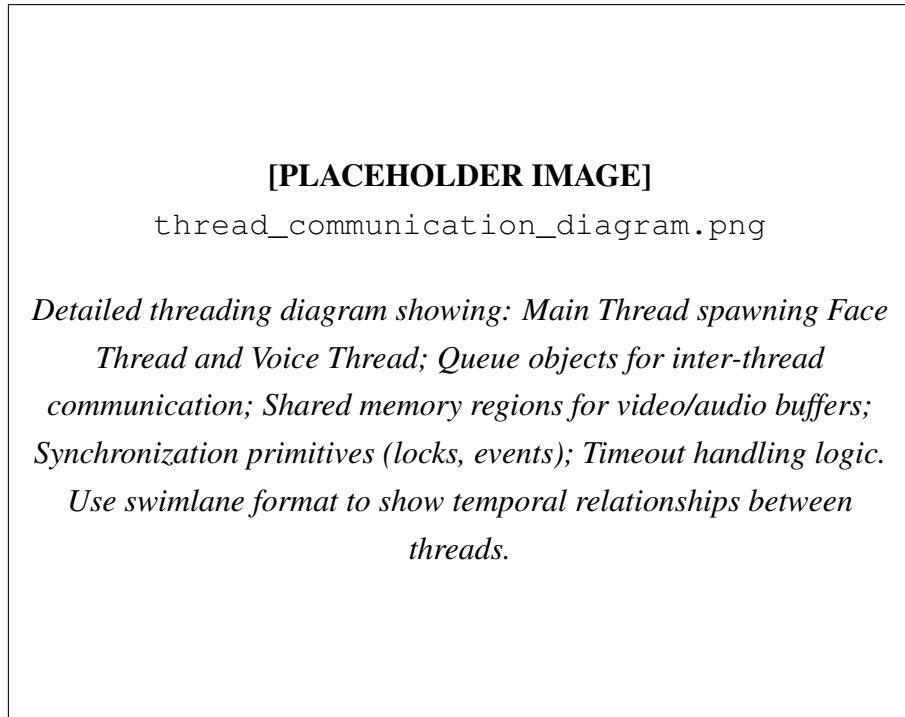


Figure 3.4: Multi-threaded Architecture with Inter-Thread Communication

3.4.2 Decision Fusion Logic Flow

The Decision Fusion Engine implements an OR-logic approach, prioritizing user convenience while maintaining security through threshold-based verification.

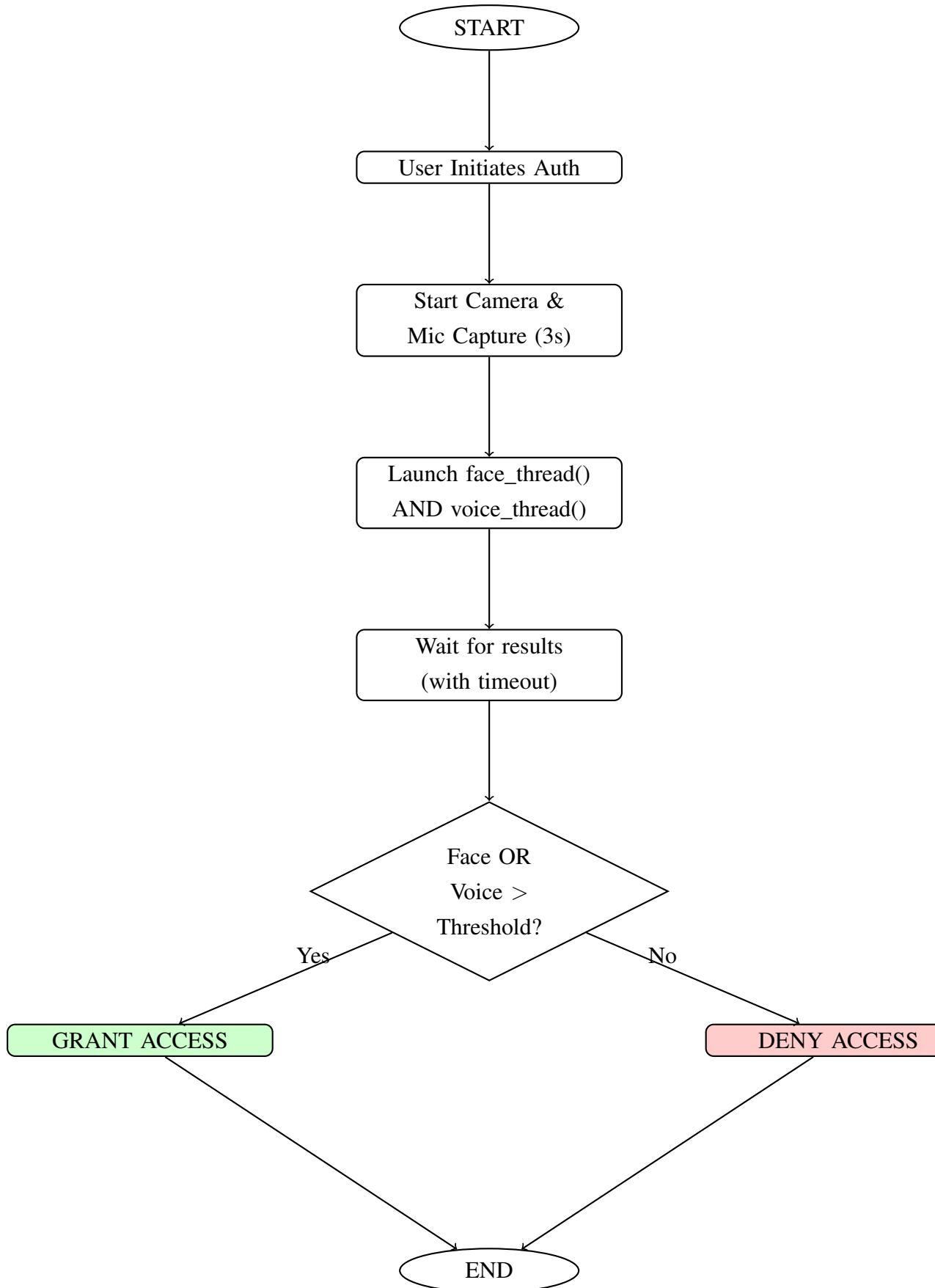


Figure 3.5: Decision Fusion Logic Flowchart

The key design principle is that access is granted if **either** biometric modality succeeds. This design choice prioritizes:

- **User Experience:** Reduces false rejections due to environmental factors affecting one modality.
- **Flexibility:** Accommodates users who may have difficulty with one modality.
- **Robustness:** System continues to function even if one sensor temporarily fails.

Chapter 4

Implementation and Results

This chapter documents the practical implementation journey, detailing the setup of the hardware and software environment, the experimental procedures used for model selection, and the results obtained during FYP-I.

4.1 Hardware Implementation and OS Configuration

The foundational step of the project was to create a stable and optimized hardware and software platform.

4.1.1 Initial Setup and OS Choice

The project began with a **Raspberry Pi 4 Model B (8GB)**. To maximize available system resources for our AI models, we made the strategic decision to start with **Raspberry Pi OS Lite (Bookworm)**, a minimal, headless version of the operating system.

For development and debugging purposes, a lightweight graphical interface was necessary. We chose the **XFCE Desktop Environment** over the default PIXEL or other options like KDE/GNOME. XFCE provides a full-featured desktop experience while consuming significantly less RAM (\sim 150-200MB) compared to the default desktop (\sim 400MB+).

4.1.2 Overcoming Foundational Setup Challenges

The process of building a functional desktop environment from a Lite install revealed several challenges:

Challenge 1: Camera Interface Deprecation

Initial attempts to use the camera with the `libcamera` command failed.

Resolution: We discovered that in recent versions of Raspberry Pi OS, the command-line tools were renamed to `rpicam-apps` (e.g., `rpicam-still`, `rpicam-vid`).

Challenge	2:	Missing	GUI	Components
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After installing XFCE, we found that essential utilities for managing networking and Bluetooth were missing.

Resolution: We manually installed the required packages: `network-manager-gnome` for a graphical WiFi manager and `blueman` for a Bluetooth interface.

Challenge	3:	Incorrect	Keyboard	Locale
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A frustrating issue arose where the on-screen keyboard defaulted to an Urdu layout.

Resolution: We diagnosed this as an X11 environment issue and resolved it by adding `setxkbmap us` to the `.xsessionrc` startup script.

Lesson	Learned
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This process taught us that building from a minimal OS requires a deep understanding of the Linux environment. Our key takeaway was the importance of documenting every step.

4.2 Software Implementation: Experimental Benchmarking

Our core software implementation work in FYP-I was to move from theoretical literature review to practical, empirical benchmarking on our target hardware.

4.2.1 Testing	Procedures
---------------	------------

We wrote dedicated Python scripts using libraries like OpenCV, MediaPipe, TensorFlow Lite, PyTorch, and Resemblyzer. Each script would load a specific model, run it in a loop for 100 iterations, and measure the average inference time.

The testing methodology included:

1. **Warm-up phase:** Running each model for 10 iterations to ensure all libraries are loaded.
2. **Measurement phase:** Recording inference times for 100 consecutive iterations.
3. **Statistical analysis:** Computing mean, median, and standard deviation.
4. **Resource monitoring:** Tracking CPU utilization and RAM consumption.

4.2.2 Results: Face Detector Comparison

Table 4.1: Face Detector Performance Comparison on Raspberry Pi 4

Detector Model	Speed (FPS)	Capabilities	Decision
Haar Cascade	~15 FPS	Fast, but lacks landmarks	Rejected
MTCNN	~2 FPS	Accurate, but too slow	Rejected
BlazeFace	~30-45 FPS	Fast with 6-point landmarks	Selected
RetinaFace	~2 FPS	Very accurate, but slow	Rejected

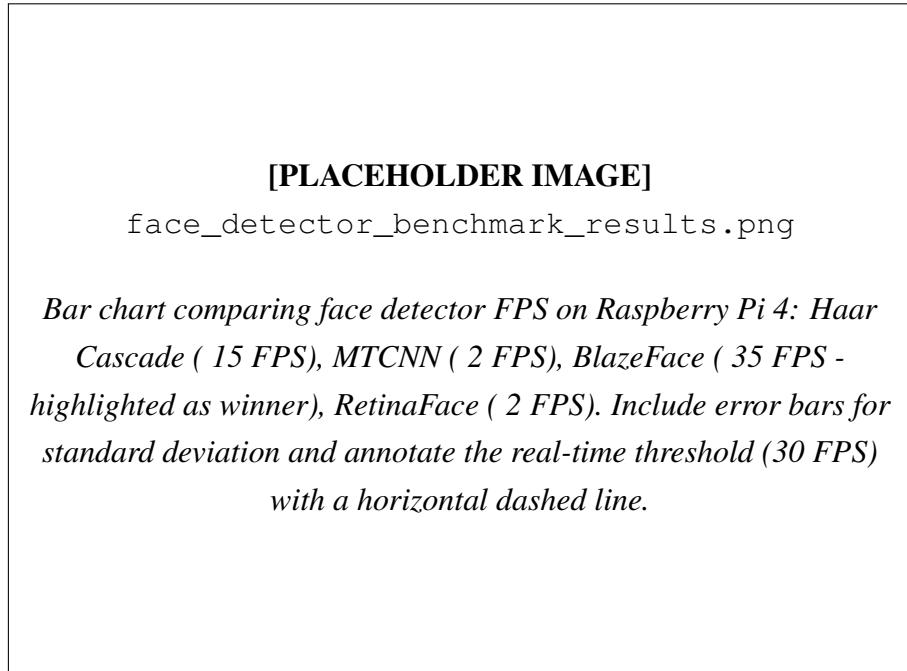


Figure 4.1: Face Detector Benchmark Results on Raspberry Pi 4

4.2.3 Results: Face Recognition Model Comparison

Table 4.2: Face Recognition Model Performance Comparison

Model	Framework	Size	Inference	Decision
InceptionResNetV1	TensorFlow	~300 MB	~1200 ms	Rejected
Buffalo_L (ResNet50)	InsightFace	~170 MB	~1800 ms	Rejected
MobileFaceNet	PyTorch	~7.5 MB	~300 ms	Selected

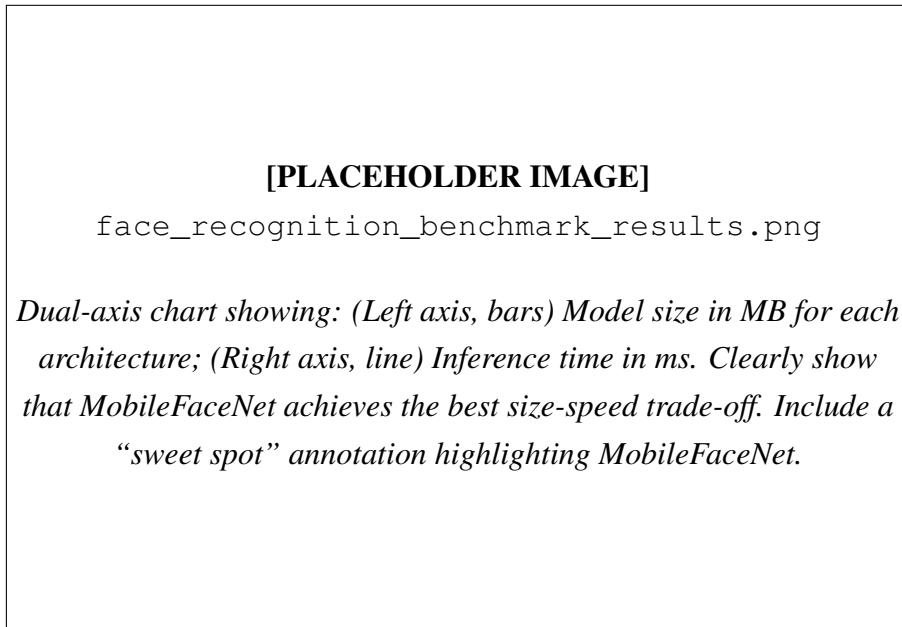


Figure 4.2: Face Recognition Model Benchmark: Size vs. Speed Trade-off

4.2.4 Results: Voice Verification Toolkit Comparison

Table 4.3: Speaker Verification Toolkit Performance Comparison

Toolkit	Model	Performance	Decision
SpeechBrain	ECAPA-TDNN	>4 seconds inference	Rejected
NVIDIA NeMo	Titanet	ARM64 incompatible	Rejected
Resemblyzer	GE2E (LSTM)	<1 second inference	Selected

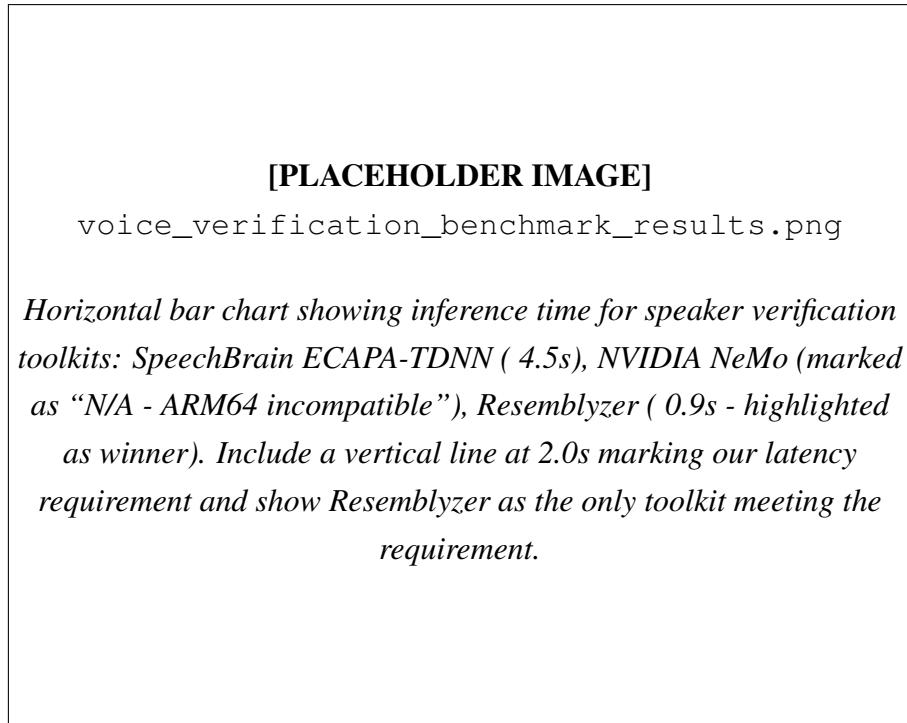


Figure 4.3: Speaker Verification Toolkit Benchmark Results

4.3 Findings and Analysis

The key finding of our FYP-I implementation work is that a **Hybrid Two-Layer Authentication System is feasible on a Raspberry Pi 4**, but only through **rigorous, data-driven model selection**.

4.3.1 Analysis of Model Selection

Our experimental results prove that simply choosing a famous or highly accurate model from a research paper is a flawed strategy for edge deployment. The performance difference between InceptionResNetV1 (\sim 1200ms) and MobileFaceNet (\sim 300ms) is the difference between a non-functional system and a real-time one.

4.3.2 Initial System Performance Estimation

By combining the selected models, we can estimate the final performance:

- **Face Pipeline Latency:** \sim 30ms (BlazeFace) + \sim 300ms (MobileFaceNet) = \sim 330ms
- **Voice Pipeline Latency:** \sim 900ms (Resemblyzer on a 3s clip)

- **Expected Hybrid Latency:** Approximately **1 second**, well within our 2-second requirement.

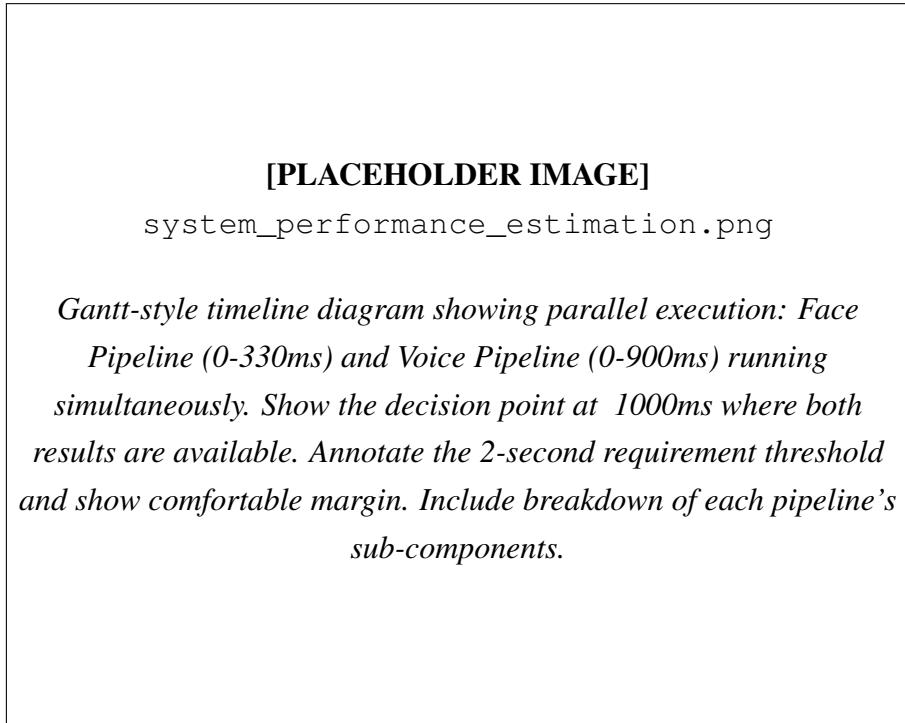


Figure 4.4: Estimated System Latency with Parallel Pipeline Execution

4.3.3 Key Technical Insights

Several important insights emerged from this implementation phase:

1. **CPU Optimization is Critical:** Mobile-first models outperform server-oriented counterparts by 3-6x on CPU.
2. **Framework Overhead Matters:** Lightweight libraries like MediaPipe have minimal initialization overhead.
3. **ARM64 Ecosystem is Maturing:** Most Python ML packages now provide ARM64 support.
4. **Memory Management:** Our system fits comfortably within 2GB RAM.

Chapter 5

Conclusion and Future Work

5.1 Project Summary

This report has documented the comprehensive progress made during the first phase of the “Hybrid Two-Layer Authentication System” project. We have successfully transitioned from a broad initial concept to a well-defined, strategically sound, and achievable project plan.

The major accomplishments of FYP-I include:

- Comprehensive literature review with detailed paper summaries establishing a clear taxonomy of biometric technologies
- Strategic selection of a hybrid parallel architecture over a sequential approach
- Rigorous experimental benchmarking of multiple models across three critical components
- Successful setup and optimization of a Raspberry Pi 4 development environment
- Validation of system feasibility with projected sub-2-second authentication latency

5.2 Problems Faced and Lessons Learned

5.2.1 Lesson 1: The Importance of Strategic De-scoping

Our initial ambition to include cutting-edge optimization techniques like quantization was a valuable research exercise, but we learned the critical skill of distinguishing between “possible” and “practical.”

5.2.2 Lesson 2: Embedded Environments are Not Desktops

The single greatest technical challenge was the software environment setup on ARM64. We learned that dependency management is a critical task, not an afterthought.

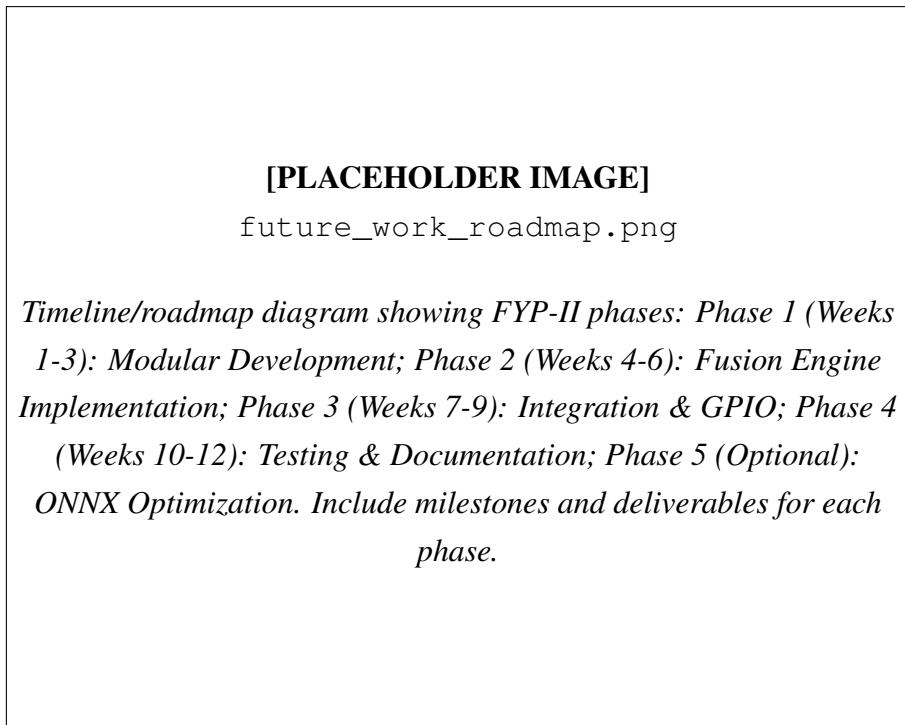
5.2.3 Lesson 3: Empirical Data Trumps Theoretical Performance

Our benchmarking results were a powerful lesson in the importance of testing on target hardware. A model's performance on a high-end GPU is irrelevant to its performance on a Raspberry Pi CPU.

5.2.4 Lesson 4: User Experience vs. Technical Complexity Trade-off

The decision to adopt a parallel hybrid architecture involved accepting greater implementation complexity in exchange for superior user experience.

5.3 Future Recommendations (FYP-II Work)



[PLACEHOLDER IMAGE]
`future_work_roadmap.png`

Timeline/roadmap diagram showing FYP-II phases: Phase 1 (Weeks 1-3): Modular Development; Phase 2 (Weeks 4-6): Fusion Engine Implementation; Phase 3 (Weeks 7-9): Integration & GPIO; Phase 4 (Weeks 10-12): Testing & Documentation; Phase 5 (Optional): ONNX Optimization. Include milestones and deliverables for each phase.

Figure 5.1: Proposed FYP-II Development Roadmap

5.3.1 Phase 1: Modular Development

Develop the face and voice pipelines as standalone Python modules with enrollment and verification functions.

5.3.2 Phase 2: Implementation of the Decision Fusion Engine

Implement the main application that manages parallel threads, handles communication between them, and contains the state machine for decision fusion logic.

5.3.3 Phase 3: Integration and GPIO Control

Integrate modules into the final application and implement GPIO control logic for triggering real-world actions.

5.3.4 Phase 4: Rigorous System-Level Testing

Execute a formal testing protocol to measure FAR, FRR, and end-to-end latency.

5.3.5 Phase 5: ONNX Optimization (Stretch Goal)

Explore converting models to ONNX format for potential 20-40% performance improvement.

5.4 Concluding Remarks

The Hybrid Two-Layer Authentication System represents a significant step forward in bringing advanced biometric security to resource-constrained edge devices. Through careful model selection, strategic architectural decisions, and rigorous empirical testing, we have demonstrated that it is possible to build a robust, privacy-preserving, contactless authentication system on affordable hardware.

The project's success relies not on using the most complex models, but on making intelligent engineering trade-offs that prioritize real-world performance, user experience, and practical deployability. This pragmatic approach ensures that our system is not just a research prototype, but a foundation for actual deployment in educational institutions, small businesses, and residential security applications.

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Appendix A

Installation Guide

A.1 Raspberry Pi OS Setup

Step 1: Download and Flash OS

1. Download Raspberry Pi OS Lite (Bookworm) from official website
2. Use Raspberry Pi Imager to flash the image to a high-quality microSD card (minimum 32GB, A2-rated recommended)
3. Enable SSH and configure WiFi credentials before first boot

Step 2: Initial System Configuration

```
1 # Update system
2 sudo apt update && sudo apt upgrade -y
3
4 # Install essential packages
5 sudo apt install -y git python3-pip python3-venv
6 sudo apt install -y build-essential cmake
7
8 # Configure locales
9 sudo raspi-config
10 # Navigate to: Localisation Options > Locale
11 # Select: en_US.UTF-8
```

Step 3: Install Desktop Environment

```
1 # Install XFCE (lightweight desktop)
2 sudo apt install -y xfce4 xfce4-goodies
3
4 # Install network and Bluetooth managers
5 sudo apt install -y network-manager-gnome blueman
6
7 # Configure keyboard layout
```

```
8 echo "setxkbmap us" >> ~/.xsessionrc
```

Step 4: Camera Configuration

```
1 # Install camera tools
2 sudo apt install -y rpicam-apps
3
4 # Test camera
5 rpicam-still -o test.jpg
```

A.2 Python

Environment

Setup

```
1 # Create virtual environment
2 python3 -m venv ~/fyp_env
3 source ~/fyp_env/bin/activate
4
5 # Install core dependencies
6 pip install --upgrade pip
7 pip install numpy opencv-python-headless
8 pip install mediapipe torch torchvision
9 pip install resemblyzer sounddevice
10 pip install RPi.GPIO gpiod
11
12 # Verify installations
13 python -c "import cv2; print('OpenCV:', cv2.__version__)"
14 python -c "import mediapipe; print('MediaPipe OK')"
15 python -c "import resemblyzer; print('Resemblyzer OK')"
```

Appendix B

Code Snippets

B.1 Face Detection with BlazeFace

```
1 import cv2
2 import mediapipe as mp
3
4 # Initialize MediaPipe Face Detection
5 mp_face_detection = mp.solutions.face_detection
6 face_detection = mp_face_detection.FaceDetection(
7     min_detection_confidence=0.5)
8
9 # Capture frame from camera
10 cap = cv2.VideoCapture(0)
11 ret, frame = cap.read()
12
13 # Convert BGR to RGB
14 rgb_frame = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)
15
16 # Detect faces
17 results = face_detection.process(rgb_frame)
18
19 if results.detections:
20     for detection in results.detections:
21         # Extract bounding box
22         bbox = detection.location_data.relative_bounding_box
23         h, w, _ = frame.shape
24         x = int(bbox.xmin * w)
25         y = int(bbox.ymin * h)
26         width = int(bbox.width * w)
27         height = int(bbox.height * h)
28
29         # Crop face for recognition
30         face_crop = frame[y:y+height, x:x+width]
```

```

31     print(f"Face detected at ({x}, {y})")
32
33 cap.release()

```

B.2 Voice Embedding with Resemblyzer

```

1 from resemblyzer import VoiceEncoder, preprocess_wav
2 import sounddevice as sd
3 import numpy as np
4 from scipy.spatial.distance import cosine
5
6 # Initialize encoder
7 encoder = VoiceEncoder()
8
9 # Record audio (3 seconds at 16kHz)
10 sample_rate = 16000
11 duration = 3
12 print("Recording...")
13 audio = sd.rec(int(duration * sample_rate),
14                 samplerate=sample_rate,
15                 channels=1, dtype='float32')
16 sd.wait()
17 print("Recording complete.")
18
19 # Preprocess and generate embedding
20 audio_flat = audio.flatten()
21 wav = preprocess_wav(audio_flat)
22 embedding = encoder.embed_utterance(wav)
23
24 # Compare with stored embedding (example)
25 # stored_embedding = np.load('enrolled_voice.npy')
26 # similarity = 1 - cosine(embedding, stored_embedding)
27 # print(f"Similarity: {similarity:.4f}")

```

B.3 Decision Fusion Engine (Pseudocode)

```

1 import threading
2 from queue import Queue

```

```
3
4 # Configuration
5 FACE_THRESHOLD = 0.7
6 VOICE_THRESHOLD = 0.6
7 TIMEOUT_SECONDS = 3.0
8
9 def face_worker(result_queue):
10     """Face verification thread"""
11     # 1. Capture frame
12     # 2. Detect face
13     # 3. Extract embedding
14     # 4. Compare with database
15     score = verify_face() # Returns 0.0-1.0
16     result_queue.put(('face', score))
17
18 def voice_worker(result_queue):
19     """Voice verification thread"""
20     # 1. Record audio
21     # 2. Preprocess
22     # 3. Extract embedding
23     # 4. Compare with database
24     score = verify_voice() # Returns 0.0-1.0
25     result_queue.put(('voice', score))
26
27 def authenticate():
28     """Main authentication function with OR-logic fusion"""
29     result_queue = Queue()
30
31     # Launch parallel threads
32     face_thread = threading.Thread(
33         target=face_worker, args=(result_queue,))
34     voice_thread = threading.Thread(
35         target=voice_worker, args=(result_queue,))
36
37     face_thread.start()
38     voice_thread.start()
39
40     # Wait for results with timeout
41     face_thread.join(timeout=TIMEOUT_SECONDS)
42     voice_thread.join(timeout=TIMEOUT_SECONDS)
43
```

```
44     # Collect results
45     face_score = voice_score = 0.0
46     while not result_queue.empty():
47         modality, score = result_queue.get()
48         if modality == 'face':
49             face_score = score
50         else:
51             voice_score = score
52
53     # OR-logic decision fusion
54     if face_score > FACE_THRESHOLD or \
55         voice_score > VOICE_THRESHOLD:
56         return True, face_score, voice_score    # GRANT
57     else:
58         return False, face_score, voice_score   # DENY
```