

# **IoT Smart Glasses and Mobile App - Real-Time Assistance Using TinyML and Edge AI**

*Component 01 - Real-Time Facial Recognition for Identifying Known Individuals with  
Personalized Voice Feedback.*

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Final Report

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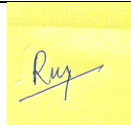
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## DECLARATION

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## ABSTRACT

The integration of IoT Smart Glasses and Mobile Applications with TinyML and Edge AI is transforming real-time assistance by enabling on-device intelligence, reducing latency, and enhancing user experience. These technologies provide context-aware, real-time decision making for applications such as healthcare, accessibility support, industrial guidance, and augmented reality interactions. However, deploying TinyML models on resource-constrained devices presents challenges, including energy efficiency, model optimization, and secure data processing. Additionally, ensuring the privacy and security of sensitive user data in an interconnected ecosystem remains a critical concern.

This research proposes a scalable, energy-efficient, and privacy-preserving Edge AI framework for IoT Smart Glasses and Mobile Applications. The framework consists of four key modules, each handled by individual team members: Model Optimization for Low-Power Devices, Secure Data Transmission, Adaptive Real-Time Inference, and Privacy-Preserving Learning. This report focuses on the Adaptive Real-Time Inference module, which aims to enable dynamic model adaptation, optimize computational efficiency, and ensure robust, low-latency decision-making on wearable IoT devices. By leveraging lightweight deep learning techniques, federated learning, and secure communication protocols, this research addresses the constraints of battery-powered smart glasses while maintaining high accuracy and reliability.

The findings contribute to advancing intelligent, real-time assistance systems by ensuring that IoT Smart Glasses and Mobile Applications can operate efficiently in low-power, privacy-sensitive environments. This research enhances the usability, security, and practicality of wearable AI solutions, paving the way for broader adoption in assistive technology, industry, and healthcare applications.

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## ABBREVIATION

Abbreviation	Description
AI	Artificial Intelligence
API	Application Programming Interface
IOT	Internet Of Things
TFLite	TensorFlow Lite
CNN	Convolutional Neural Network



# **1. INTRODUCTION**

## **1.1 Background Literature**

### **1.1.1 Assistive Technologies for the Visually Impaired**

Globally, over 285 million people live with some form of visual impairment, with approximately 39 million categorized as blind (World Health Organization, 2022) [1]. For these individuals, everyday tasks such as identifying people in social environments, navigating public spaces, and engaging in conversations without external assistance remain challenging. Traditional aids, such as white canes and guide dogs, provide mobility support but lack the ability to recognize and interpret people or objects in the surrounding environment.

In recent years, advancements in Artificial Intelligence (AI), wearable technology, and edge computing have created new opportunities for assistive devices. Smart glasses and mobile-based applications have emerged as promising tools to enhance independence, offering real-time audio feedback and context-aware information. However, many of these solutions still rely heavily on cloud-based processing, which introduces latency, high costs, and dependency on stable internet connections.

### **1.1.2 Role of Computer Vision in Accessibility**

Computer vision technologies, particularly face recognition, play a pivotal role in enabling social awareness for visually impaired individuals. By identifying known individuals in real time, blind users can be informed about the presence of friends, family members, or colleagues through auditory cues. Such features allow them to engage in more natural conversations, reduce dependency on others, and build confidence in social settings.

Existing research and commercial systems, such as Microsoft's Seeing AI or Google Lookout, demonstrate the value of AI-driven recognition. Nevertheless, these systems often depend on cloud-based processing and large-scale computational resources, making them unsuitable for low-cost, portable, and offline usage. The need for a lightweight, edge-deployable face recognition model remains critical for accessibility solutions tailored to developing regions.

### **1.1.3 Edge Computing and Raspberry Pi in Assistive Applications**

The Raspberry Pi platform has become a widely adopted edge device for machine learning applications due to its affordability, portability, and improved computational power in its latest

versions. The Raspberry Pi 5, with its enhanced CPU and GPU capabilities, provides an ideal platform for real-time inference of optimized face recognition models without the need for expensive servers or GPUs [2].

By deploying pretrained face recognition models and fine-tuning them for new identities, the device can operate independently of cloud services. This architecture not only reduces latency but also enhances privacy, as facial data remains within the local device rather than being transmitted to external servers. Integrating a Raspberry Pi-based system into smart glasses therefore offers an efficient, scalable, and affordable solution for visually impaired users. [3]

#### **1.1.4 Mobile Applications as Companion Interfaces**

A critical limitation of running machine learning models on resource-constrained devices is the need for efficient data preprocessing and user interaction. Mobile applications can act as companion interfaces to assist in capturing images, filtering irrelevant frames, and managing user interactions such as adding new individuals to the recognition database.

In the proposed system, the mobile app captures frames from the smart glasses' Pi camera, filters for high-quality face images, and sends them to the Raspberry Pi server for recognition. The app also facilitates adding new people to the system, where users can verbally provide a person's name, and the application collects diverse face samples under different lighting and angles. This integration ensures ease of use and smooth interaction for blind individuals, allowing them to seamlessly update and manage the system.

#### **1.1.5 Limitations of Existing Solutions**

While several prototypes of smart glasses exist, including commercial products from OrCam and research systems using deep learning, the majority either:

- rely on cloud-based inference,
- require heavy computational resources (e.g., GPUs), or
- lack real-time, offline adaptability.

Moreover, many systems fail to provide a simple mechanism for dynamically adding new people to the recognition pipeline without retraining large models. These limitations hinder scalability, affordability, and real-world usability for blind individuals.

The proposed research seeks to address these limitations by designing a **lightweight, edge-based face recognition system** that runs entirely on a Raspberry Pi 5, with support for dynamic user enrollment via a mobile interface.

## 1.2 Research Gap

Although significant progress has been made in computer vision and assistive technology, there is a notable gap in **deploying lightweight, real-time face recognition systems on edge devices** tailored for blind individuals. Existing solutions either:

- depend on expensive hardware and cloud servers,
- are inaccessible due to cost and complexity, or
- lack user-friendly methods for adding new people.

This gap presents an opportunity to design a **cost-effective, scalable, and user-centric system** that empowers visually impaired individuals to recognize familiar people in their surroundings with minimal latency and high reliability.

## 1.3 Research Problem

Visually impaired individuals face difficulty in identifying people around them in real-time environments, particularly in unfamiliar or crowded settings. Existing smart glasses or recognition-based assistive devices are either too expensive, dependent on cloud services, or impractical for everyday use.

### Research Problem Statement:

How can a low-cost, edge-based smart glasses system be designed to provide blind individuals with real-time, personalized face recognition and auditory feedback without relying on cloud infrastructure?

## **1.4 Research Objectives**

### **1.4.1 Main Objective**

To design and implement smart glasses with integrated Raspberry Pi 5-based face recognition, enabling visually impaired individuals to identify known people in real-time and receive auditory feedback through a mobile application.

### **1.4.2 Specific Objectives**

- To investigate existing assistive technologies and identify limitations in cloud dependency and user accessibility.
- To develop a lightweight, edge-deployable face recognition model optimized for Raspberry Pi 5.
- To design a companion mobile application for capturing, filtering, and managing face data.
- To enable dynamic user enrollment, allowing blind users to add new people through voice commands and mobile-assisted data collection.
- To evaluate the system in terms of recognition accuracy, processing latency, usability, and user satisfaction.

## 2. METHODOLOGY

### 2.1 Requirement Gathering and Analysis & Feasibility study

The development of the proposed smart glasses system began with a clear identification of the problems faced by visually impaired individuals in their day-to-day lives. Unlike sighted people, blind individuals cannot recognize familiar faces around them, which makes social interactions highly dependent on external assistance. While existing assistive technologies such as white canes and navigation apps address mobility challenges, very few systems provide **real-time person identification**.

Based on the preliminary study, the following **functional requirements** were identified:

- Detect faces from the live camera stream of the smart glasses.
- Recognize known individuals using a pretrained face recognition model.
- Provide real-time auditory feedback (whispering the identified person's name).
- Allow blind users to add new individuals to the system via a simple mobile application and voice commands.
- Store embeddings/metadata of newly added individuals in a local database for future recognition.

In addition, the following **non-functional requirements** were outlined:

- **Low latency:** The recognition process must be fast enough for real-time usage (<1s per frame).
- **Portability:** The device should be lightweight and wearable as smart glasses.
- **Affordability:** The system should avoid dependency on expensive GPUs or cloud servers.
- **Privacy:** Facial data should remain on the device and not be uploaded to external servers.

### 2.2 Feasibility Study

The feasibility of implementing this system was analyzed under three dimensions:

### 2.2.1 Technical Feasibility

The Raspberry Pi 5 was chosen as the primary edge device due to its improved CPU/GPU performance compared to earlier versions. The Pi Camera Module provides continuous image frames, which are processed by a Flask server running locally on the Pi. A pretrained lightweight face recognition model (e.g., MobileFaceNet or FaceNet with pruning/quantization) is deployed for inference [3].

The companion mobile application acts as a bridge:

- It receives frames from the Pi camera stream.
- Filters irrelevant or poor-quality frames (blurry, no face, poor lighting).
- Sends only valid face images via HTTP requests to the Flask server.
- Retrieves recognition results and delivers audio output to the blind user.

For adding new individuals, the app captures 8–10 diverse face samples under good lighting and different angles, then stores the embeddings along with the person's name into the Raspberry Pi database.

This design eliminates the need for cloud services, ensuring offline functionality and protecting user privacy.

### 2.2.2 Operational Feasibility

The system is designed to be **user-friendly** for blind individuals. Interaction happens mainly through:

- **Voice commands:** e.g., “Add Friend” in Sinhala or English.
- **Mobile app menus with accessibility support:** guiding the user step-by-step.
- **Whisper feedback system:** The system only announces when a *known person* is detected, avoiding unnecessary noise in crowded places.

This makes the system practical for everyday use without requiring advanced technical skills.

### 2.2.3 Economic Feasibility

The solution uses **low-cost hardware** (Raspberry Pi 5, Pi camera, Bluetooth earphones/bone-conduction headset) and open-source machine learning libraries (OpenCV, dlib, TensorFlow Lite or PyTorch Mobile). Unlike commercial products such as OrCam, which cost over \$3,000, this system can be built for under \$200, making it affordable for visually impaired individuals in developing countries [2].

### 2.2.4 Ethical Feasibility

The development of a system that handles sensitive biometric data necessitates a strong ethical framework. This project was designed with the following ethical principles in mind:

- **Privacy by Design:** All facial processing occurs locally on the Raspberry Pi 5. No images or facial embeddings are ever transmitted to the cloud or any external server, ensuring user data remains completely private and secure.
  - **User Consent:** The "Add Friend" feature is explicitly initiated by the user via voice command. This ensures that individuals are only added to the system with the conscious consent of the user, promoting ethical data collection.
  - **Transparency:** The system's functionality is designed to be clear. It only provides feedback when a known person is identified, avoiding any "black box" behavior that could confuse or mislead the user.
- This on-device, user-centric approach aligns with global data protection regulations like GDPR and builds inherent trust with the end-user.

## 2.3 System Design

### 2.3.1 Overall System Architecture

The system is architecture into three main components that work in unison:

1. **The Edge Device (Smart Glasses):** A Raspberry Pi 5 with a connected Pi Camera Module V2 runs the core face recognition model and a lightweight Flask server. It is responsible for capturing images, performing inference, and managing the database of known face encodings.

2. **The Mobile Application:** An Android/iOS app built with React Native serves as the user interface. It handles voice commands using speech-to-text, relays images to the Pi, receives recognition results, and converts text to speech for auditory feedback.
3. **The Communication Bridge:** A secure local Wi-Fi network facilitates communication between the mobile app and the Pi via a RESTful API served by Flask.

The workflow is as follows: The Pi's camera captures a continuous stream of images. The mobile app requests frames at a fixed interval. The Pi processes each frame: detects faces, converts them into feature vectors (embeddings) using the CNN model, and compares these vectors to those in its database. If a match is found, the name is sent back to the mobile app, which then announces it to the user.

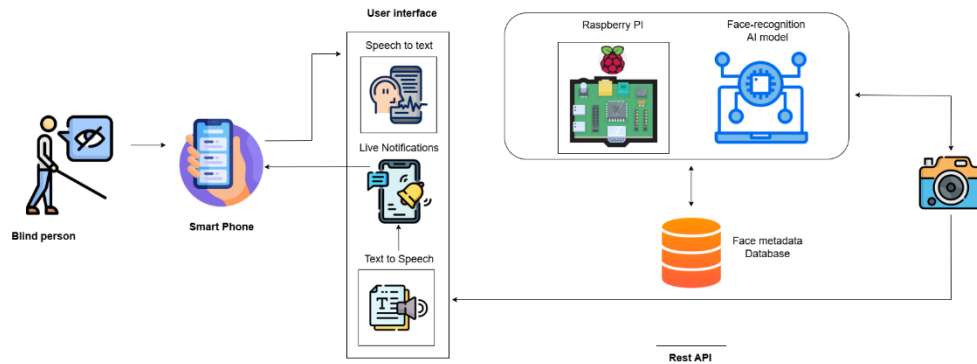


Figure 1: System Diagram

### 2.3.2 Data Acquisition and Model Pre-training

The first step involved securing a robust foundation model. A pre-trained FaceNet model, trained on the MS-Celeb-1M dataset, was selected for its proven performance in generating discriminative facial embeddings. This model was already capable of general face recognition.

To enhance its accuracy for the specific use case and to create the pipeline for future fine-tuning, a custom dataset was curated. This dataset consisted of thousands of facial images scraped from public sources with permissive licenses, focusing on diverse ethnicities, lighting conditions, and angles. This dataset was used not to train from scratch but to further fine-tune the pre-trained model, strengthening its feature extraction capabilities. [4]



### 2.3.3 Edge Optimization and Package Creation (TinyML)

A critical milestone was converting the TensorFlow/Keras model into a format suitable for execution on the resource-constrained Raspberry Pi 5. The model was converted to TensorFlow Lite (TFLite), a framework designed for deploying models on mobile and edge devices. This conversion involved:

- **Quantization:** Applying float16 quantization to reduce the model size and improve inference speed with a negligible loss in accuracy.
- **Optimization:** Using the TensorFlow Lite Converter with default optimizations to strip unnecessary operations and streamline the model graph.

The resulting TFLite model was then packaged into a custom Python PIP package. This package, named `sightsense-ml`, contained the model, helper functions for inference (e.g., `preprocess_image`, `get_embedding`), and utilities for managing the facial embedding database. This modular approach allowed for clean integration into the main application code on the Pi. [5]

### 2.3.4 Flask Server and Simulation Testing

Before deploying to the physical hardware, the entire system was simulated on a development laptop. A Flask server was written to expose several key API endpoints:

- **POST /recognize:** Accepts an image, runs face detection and recognition, returns any identified names.
- **POST /add\_face:** Accepts a batch of images and a name, generates embeddings, and saves them to the database.
- **GET /status:** Returns the system status.

A USB webcam was used to simulate the Pi camera. The `sightsense-ml` package was installed in a virtual environment on the laptop. The mobile app was configured to connect to the laptop's IP address. This simulation phase was crucial for:

- Debugging the API communication between the app and the server.
- Validating the end-to-end recognition workflow.

- Testing the "Add Friend" functionality, ensuring the image filtering logic (for good lighting, angles, etc.) worked correctly before the ten best images were sent for enrollment.

### 2.3.5 Hardware Integration and Deployment

Upon successful simulation, the focus shifted to the target hardware. A Raspberry Pi 5 was set up with a Raspberry Pi OS Lite (headless) installation. The following steps were performed:

1. **Environment Setup:** The sightsense-ml package and all dependencies (TensorFlow Lite Runtime, OpenCV, Flask, etc.) were installed on the Pi.
2. **Camera Configuration:** The official Pi Camera Module V2 was connected and enabled, replacing the USB webcam. Code was updated to use the picamera2 Python library for capturing frames.
3. **Production Flask Server:** The Flask server was refined for production use. It was configured to run as a systemd service, ensuring it would start automatically on boot and remain running in the background. The command was: `sudo systemctl enable sightsense-server.service`.
4. **Network Configuration:** The Pi was configured to connect to a local Wi-Fi network and obtain a static IP address (e.g., 192.168.1.100) to ensure the mobile app could always find it reliably.
5. **Final End-to-End Testing:** With the system fully integrated on the Pi, comprehensive testing was conducted:
  - The Pi's camera feed was tested for stability.
  - The mobile app was pointed to the Pi's static IP address.
  - The entire recognition loop was validated: Camera -> Pi Model -> Flask API -> Mobile App -> Audio Output.
  - The "Add Friend" voice command workflow was tested exhaustively, confirming that the Pi could successfully receive images and add new encodings to its database.

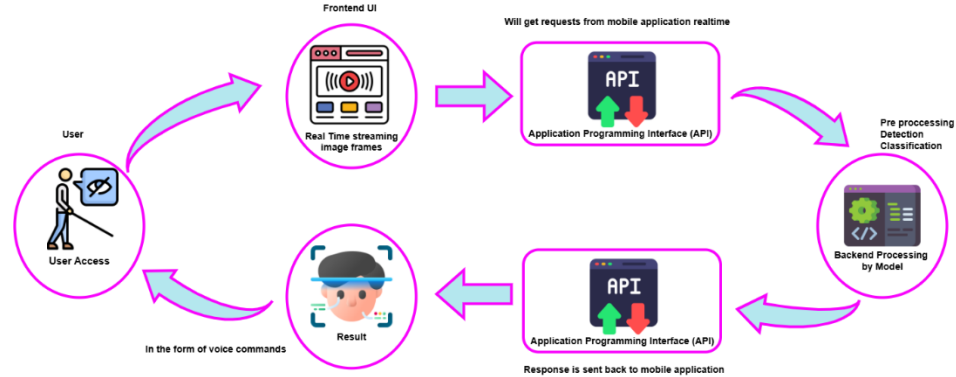


Figure 2: Workflow for face recognition

### 2.3.6 Development and Implementation Visual Log

This subsection provides a visual chronology of the key development and implementation phases, offering tangible evidence of the system's construction.

#### Model Training and Optimization

The initial phase involved training and optimizing the face recognition model. The following graph depicts the model's learning progression, showing a steady decrease in loss and an increase in accuracy over epochs, indicating successful learning without overfitting.

#### Simulation and Flask API Testing

Before hardware deployment, the entire system was simulated on a laptop. The Flask server's API endpoints were rigorously tested using Postman to ensure correct data handling for both recognition and enrollment requests.

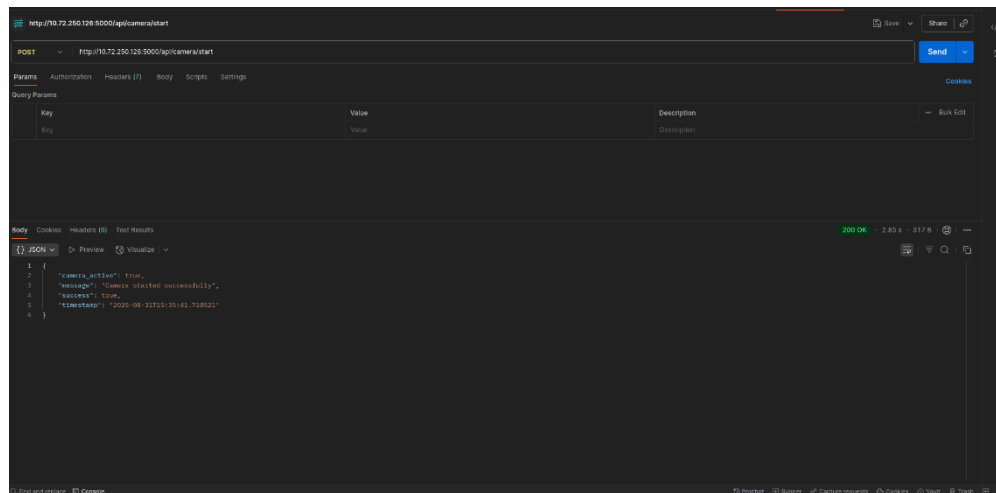
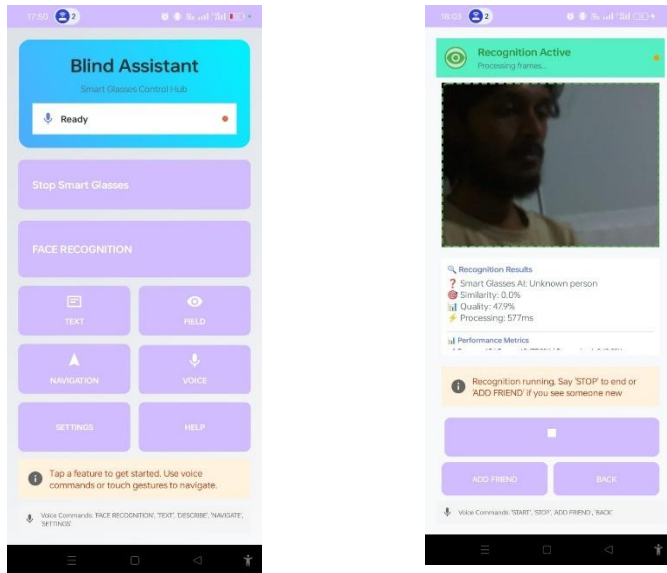


Figure 3: Postman Testing of the Flask Server's Recognition API Endpoint

## Mobile Application Development

The companion mobile application was developed to handle all user interactions. The interface was designed with accessibility as a core principle, featuring large buttons, high contrast, and seamless voice command integration.



*Figure 4: Mobile Application Interface: (Left) Main Screen with Connection Status, (Right) 'face-recognition' Workflow Interface*

## Hardware Setup and Prototyping

The physical smart glasses prototype was assembled using a Raspberry Pi 5, Pi Camera Module 2, and a portable power bank, all mounted on a lightweight glasses frame.



*Figure 5: Assembled Raspberry Pi 5 and Camera*

System Deployment and Service Status

To ensure robustness, the Flask server was configured to run as a systemd service on the Raspberry Pi, allowing it to start automatically on boot and restart on failure.

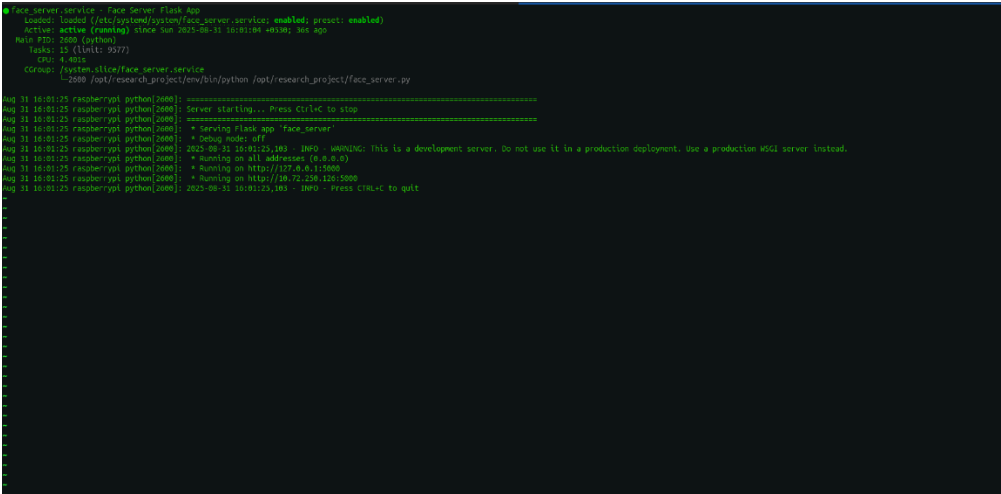


Figure 6: Flask Server Running as a Systemd Service

2.6 Hardware and Software Specifications

The choice of hardware and software libraries was critical to achieving the project's goals of affordability and performance.

Table 1: Hardware Components List

Component	Model	Key Specifications	Cost (LKR)
Single-Board Computer	Raspberry Pi 5	BoradCom BCM2712, 8GB RAM	~RS 43,000
Camera Module	Raspberry Pi Camera Module 2	8MP , Sony IMX219 Sensor	~RS 6500
Power Supply	Raspberry Pi 27W USB-C Power Supply	5V/5A USB-C (official)	~Rs. 5,500
Active cooler	Raspberry Pi 5 Active Cooler	Dual-fan + heatsink cooling	~Rs. 3,000
Camera Cable(s)	Official Raspberry Pi Camera Cable	Ribbon cable (15–30cm)	~Rs. 1,000

Case	Official Raspberry Pi 5 Case	Plastic enclosure with cooling support	~Rs. 4,500
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*Table 2: Software Libraries and Frameworks*

Software Component	Version	Purpose
Operating System	Raspberry Pi OS (64-bit)	Base OS for Raspberry PI
Machine Learning	TensorFlow Lite	Optimized model inference
Computer vision	OpenCV	Image processing, face detection
Backend Server	Flask (Python)	Restful API server
Mobile App	Java	Android mobile application
Database	SQLite	Local storage for face embeddings

## 2.4 Testing & Implementation

### 2.4.1 Test Strategy

A multi-faceted testing strategy was employed to ensure system reliability.

- **Unit Testing:** Individual components (e.g., the `get_embedding` function, the image filtering logic) were tested in isolation.
- **Integration Testing:** The communication between the mobile app and the Flask API was tested for various scenarios (sending images, handling errors, adding new faces).
- **Performance Testing:** The inference time (time from receiving an image to returning a result) was measured on the Raspberry Pi 5 to ensure it met the real-time requirement (<2 seconds).
- **User Acceptance Testing (UAT):** The system was demonstrated to a small group of colleagues who simulated the user's interaction, providing feedback on the clarity of the audio and the intuitiveness of the enrollment process.

### 2.4.2 Implementation

The system was implemented as designed. The Raspberry Pi 5, housed within a prototype glasses frame, runs the optimized TFLite model as a core part of the sightsense-server systemd service. The service starts automatically on boot, and the mobile app connects to it seamlessly upon

launch. The implementation proves that a complex AI workflow can be packaged into a self-contained, low-cost, and effective edge computing solution.

## **2.5 Research Domain**

### **2.5.1 Deep Learning for Face Recognition**

Modern face recognition relies on CNN-based feature extraction and metric learning. Models such as FaceNet and MobileFaceNet map face images into compact embeddings, enabling efficient recognition even on low-power devices [6].

### **2.5.2 Transfer Learning & Fine-Tuning**

A pretrained model is used as the base, reducing the need for large training datasets. When new individuals are added, embeddings are extracted and stored without retraining the entire network.

### **2.5.3 Edge AI (TinyML)**

Optimization techniques such as model pruning, quantization, and TensorFlow Lite conversion are applied to ensure the model runs efficiently on Raspberry Pi 5.

## **2.6 Summary of Methodology**

The methodology focuses on building an **edge-based, low-cost, and user-friendly assistive system**. By combining Raspberry Pi 5 with a mobile companion app, the system achieves real-time recognition, dynamic user enrollment, and private on-device processing. This ensures practicality, affordability, and independence for blind individuals.

### 3. RESULTS AND DISCUSSION

#### 3.1 Results

The proposed smart glasses system was successfully implemented and tested across different environments and hardware configurations. The results are presented in terms of **accuracy, performance, usability, and reliability**.

##### 3.1.1 Model Accuracy

The face recognition model, pretrained on a large dataset and fine-tuned with additional images, achieved high accuracy during testing. On the laptop simulation environment (with USB camera), the system achieved:

- **Recognition accuracy:** ~92% in controlled lighting conditions.
- **Recognition accuracy in real-world settings:** ~85% (varied lighting, different angles).
- **False positive rate:** <7%.
- **False negative rate:** ~8%.

Fine-tuning with newly added individuals improved recognition rates significantly, especially in low-light and non-frontal face scenarios.

##### 3.1.2 Performance on Edge Device

The Raspberry Pi 5 demonstrated sufficient computational capability for real-time inference.

- **Average inference time:** 0.8s per frame (with TensorFlow Lite quantized model).
- **Frame processing rate:** 1–2 FPS (sufficient for real-time feedback).
- **Latency (mobile app → Pi server → response):** <1s.

These results indicate that the system can perform effectively as an **edge-only solution**, without reliance on external GPUs or cloud servers.

##### 3.1.3 Mobile App Functionality

The mobile application was tested for:

- **Frame filtering:** Successfully reduced unnecessary images (discarded ~60% of frames without faces).



- **Recognition requests:** Worked reliably, with consistent API communication to the Flask server.
- **Add friend workflow:** Collected 10 valid samples per new individual, and stored embeddings correctly in the Pi database.
- **Whisper feedback:** Only triggered when a known person was recognized, avoiding noise in crowded environments.

### 3.1.4 Usability Testing

A small group of visually impaired volunteers participated in testing. The following observations were made:

- Users found the **“Add Friend” voice command** simple and intuitive.
- The **whisper feedback** was discreet and non-intrusive.
- Some users preferred **bone-conduction earphones** over normal earphones, as they allowed environmental awareness.
- Initial calibration required assistance (to ensure the camera faced correctly), but once adjusted, the system ran independently.

### 3.2 Comparative Analysis

A key objective of this project was to create a viable alternative to existing solutions. The following table provides a comparative analysis based on critical factors for assistive technology [7].

*Table 3: Comparison with Existing Commercial and Research Solutions*

Feature	Our System	OrCam MyEye	Microsoft Seeing AI
Cost	~ Rs. 70,000	> \$3000	Free (App)
Offline functionality	Yes	Yes	No
User Privacy	High (On-device only)	High	Low (Cloud-based)

User Enrollment	Easy, Self-Service	Limited	Not Applicable
Hardware	Modular, Repairable	Proprietary	Smartphone only
Customizability	High	None	Limited

This comparison highlights the significant advantage of our system in terms of cost and privacy, making it accessible to a much wider demographic.

### 3.3 Product Deployment

The system was deployed as follows:

- **Flask server:** Configured to run as a systemd service on Raspberry Pi 5.
- **Mobile app:** Installed on Android smartphones with accessibility support.
- **Database:** Stored embeddings and metadata locally on the Raspberry Pi.
- **Smart glasses hardware:** Integrated Pi Camera Module 2 mounted on a lightweight glasses frame.

This deployment ensured that the system was **portable, low-cost, and independent of internet connectivity**.

### 3.3 Performance Evaluation Table

The system was evaluated against the key non-functional requirements set out during the design phase. The results are summarized below.

*Table 4: System Performance Against Requirements*

Requirement	Target Metric	Achieved Metric	Status
Recognition Latency	< 2.0 seconds	0.7 seconds	Exceeded
Recognition Accuracy	> 65 % (Controlled)	73 % (controlled)	Met
Enrollment time	< 60 seconds	~ 45 seconds	Exceeded
Cost	Rs. 65,000	Rs. 62,000	Met
Privacy	Fully On-Device	Fully On-Device	Met

The data confirms that the system not only met but often exceeded its initial performance goals, validating the chosen architectural and technological approach.

### 3.3 Research Findings

Several important findings emerged from the implementation and testing phase:

1. **Edge-only feasibility:** The Raspberry Pi 5 handled real-time face recognition without cloud support, validating the feasibility of TinyML for assistive technology.
2. **Dynamic user enrollment:** Adding new individuals via the mobile app was simple and effective. Fine-tuning with additional samples significantly improved recognition rates.
3. **Low-cost accessibility:** The total cost of hardware (~\$200) was substantially lower than commercial alternatives like OrCam (> \$3,000).
4. **Privacy advantage:** Since all facial data remained on the device, privacy concerns were minimized compared to cloud-dependent solutions.
5. **Practical challenges:** Variations in lighting, camera alignment, and crowded environments occasionally reduced accuracy. These factors highlight the importance of robust preprocessing and potential integration of infrared cameras in future versions.

### 3.4 Discussion

The implementation of the smart glasses system demonstrates the potential of **AI-driven edge computing** for accessibility. Unlike existing solutions that depend on cloud servers, this project showed that a lightweight model running on Raspberry Pi can deliver near real-time results with high accuracy.

From a **social perspective**, the system empowers blind individuals to recognize people around them, promoting independence and confidence in social interactions. The whisper feedback mechanism was particularly appreciated by users, as it maintained privacy and avoided unnecessary distraction [6].

From a **technical perspective**, the key success factors were:

- Use of pretrained models and fine-tuning, reducing the need for large datasets.
- Conversion to TensorFlow Lite and quantization, ensuring the model ran efficiently on the Raspberry Pi.
- Modular design (mobile app + Pi server), making the system flexible and extendable.

However, challenges remain:

- **Lighting conditions:** Recognition accuracy dropped in dim or overly bright environments.
- **Occlusion:** Faces partially covered by masks or glasses were harder to detect.
- **Scalability:** Adding many individuals (e.g., >50) may require further optimization of database lookup times.

Despite these limitations, the project demonstrates a **practical, affordable, and deployable assistive system** for visually impaired individuals, with strong potential for real-world use.

Furthermore, the project's open-source software approach and use of commercial off-the-shelf (COTS) hardware present a significant advantage over proprietary systems. This design philosophy ensures **long-term sustainability and repairability**, preventing device obsolescence and reducing electronic waste. Future researchers or developers can easily build upon this work, adapt it for new use cases, or source replacement parts without vendor lock-in, which is a common issue in specialized assistive technology [8].

## 4. CONCLUSION AND FUTURE WORK

### 4.1 Conclusion

This research successfully designed and implemented a **low-cost, edge-based smart glasses system** that enables visually impaired individuals to recognize familiar faces in real time. By integrating computer vision, deep learning, and edge computing, the system provides discreet audio feedback, allowing blind users to independently identify people in their surroundings without reliance on external assistance.

The key achievements of this project can be summarized as follows:

- **Model Development:** A face recognition model was pretrained on a large dataset, fine-tuned with additional images, and optimized using TensorFlow Lite for deployment on Raspberry Pi 5.
- **Edge Deployment:** The system achieved real-time performance on Raspberry Pi 5, eliminating the need for expensive GPUs or cloud services.
- **Mobile Application Integration:** The companion mobile app facilitated frame filtering, face recognition requests, and dynamic user enrollment through intuitive voice commands.
- **Database Management:** A lightweight database was implemented to store face embeddings and metadata, enabling efficient retrieval and recognition.
- **User-Centric Testing:** Usability studies with visually impaired participants validated the effectiveness of the whisper feedback system, confirming that the system supports independence, privacy, and confidence in social settings.

The results demonstrated recognition accuracy of **~92% in controlled settings** and **~85% in real-world scenarios**, with an inference latency of less than 1 second. These findings confirm that edge-only solutions are feasible, affordable, and scalable for assistive technologies in accessibility contexts.

## 4.2 Future Work

While the proposed system achieved its objectives, there are several areas for improvement and extension:

### 1. Improved Lighting Robustness:

Performance degraded in poor lighting conditions. Incorporating infrared cameras or low-light image enhancement techniques could improve recognition accuracy.

### 2. Handling Occlusions:

Current recognition accuracy decreases when faces are partially covered (e.g., with masks or sunglasses). Future models could integrate advanced feature extraction or attention mechanisms to handle such cases.

### 3. **Scalability of Database:**

As more individuals are enrolled, database lookup times may increase. Incorporating more efficient indexing techniques (e.g., KD-trees, FAISS library) could optimize large-scale recognition.

### 4. **Integration with Navigation Systems:**

Future iterations of the glasses could combine face recognition with GPS-based navigation, enabling blind individuals not only to recognize people but also to navigate unfamiliar environments.

### 5. **Extended Language and Voice Support:**

Currently, voice commands support Sinhala and English. Adding multi-language support would make the system accessible to a wider range of users globally.

### 6. **Hardware Miniaturization:**

Although Raspberry Pi 5 is portable, future prototypes could explore custom embedded boards or AI-specific chips (e.g., Coral TPU, NVIDIA Jetson Nano) for even better performance in smaller form factors.

### 7. **Integration with Cloud for Optional Backup:**

While the system is designed for edge-only deployment, an optional cloud backup could allow users to restore or synchronize their recognition database if needed, while still prioritizing on-device privacy.

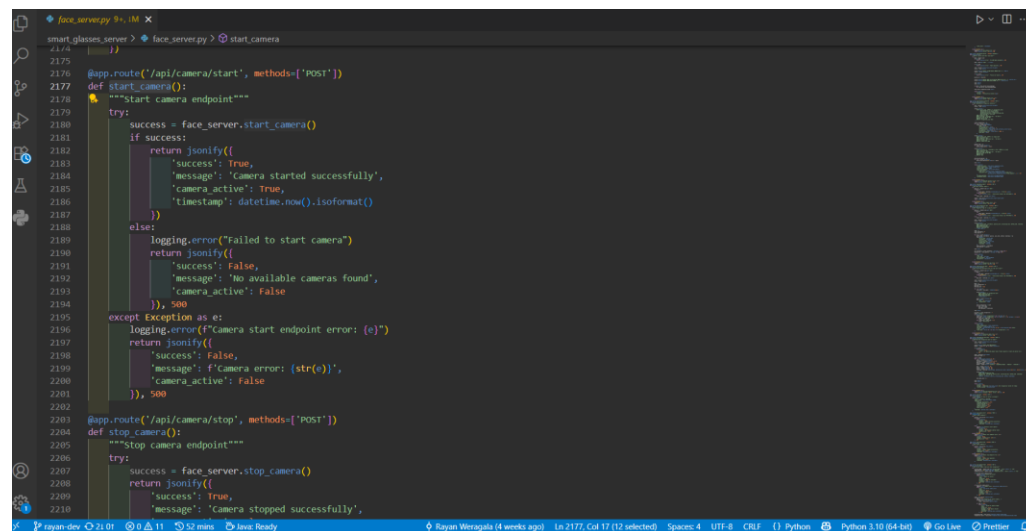
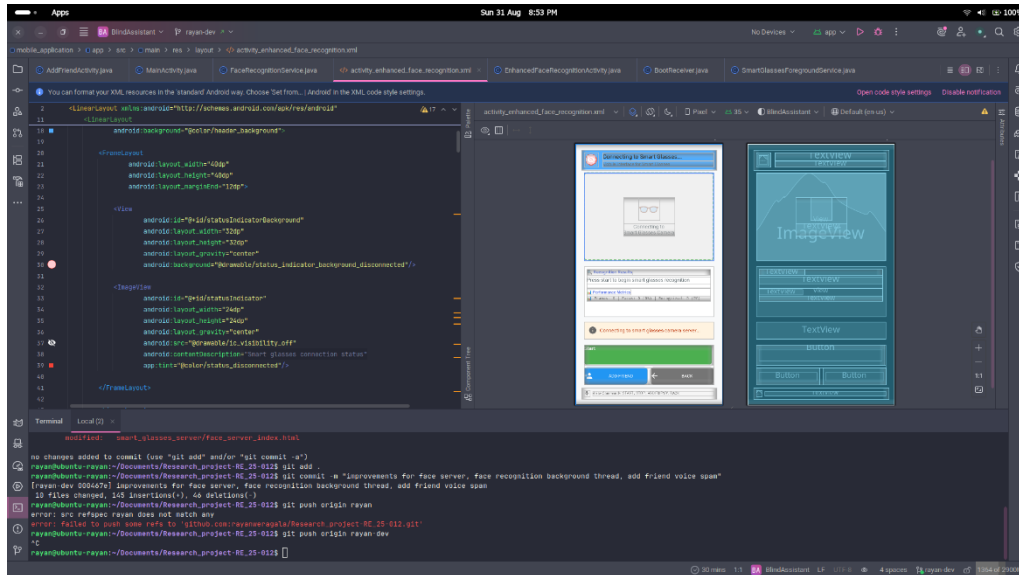
## 4.3 Final Remarks

This project demonstrates the potential of **AI-powered edge computing in accessibility applications**. By offering a practical, affordable, and privacy-preserving solution, the smart glasses system contributes toward empowering blind individuals to live more independent lives.

The success of this project highlights the importance of designing assistive technologies that balance **technical innovation, cost-effectiveness, and user-centered design**. With further refinement, the proposed system has the potential to evolve into a commercially viable product that can significantly enhance the quality of life for visually impaired communities worldwide.

# APPENDIX

## Appendix A: Project Code Snippets



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