INTERNSHIP TRAINING REPORT

on

REAL-TIME OBJECT DETECTION USING COMPUTER VISION

Submitted in partial fulfillment of the requirements for
the award of degree

BACHELOR OF COMPUTER APPLICATIONS

of

KLE TECHNOLOGICAL UNIVERSITY

by

SINCHANA S SALIMATH
(SRN: 01FE22BCA184)

DEPARTMENT OF COMPUTER APPLICATIONS
KLE TECHNOLOGICAL UNIVERSITY
Vidyanagar, Hubballi-580031 Karnataka.

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under the guidance of

Internal Guide:

Mrs. Rashmi Murakambi
Assistant Professor,

External Guide:

Mr. Manoj Bhat
BCA

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Vidyanagar, Hubballi-580031 Karnataka.

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DEPARTMENT OF COMPUTER APPLICATIONS
KLE TECHNOLOGICAL UNIVERSITY

CERTIFICATE

This is to certify that the project work entitled
"REAL-TIME OBJECT DETECTION USING COMPUTER VISION"

Submitted in partial fulfillment of the requirements for the award of degree of
Bachelor of Computer Applications of
KLE Technological University, Hubballi, Karnataka
is a result of the bonafide work carried out by

SINCHANA S SALIMATH

SRN: 01FE22BCA184

During the academic year 2024-2025

Mrs. Rashmi Murakambi Project Guide, Assistant Professor, Dept. of Computer Applications	**Dr. P. R. Patil** Mtech, PhD Head of Department, Professor, Dept. of Computer Applications	**Prof. B.S. Anami** Registrar, KLE Technological University

Viva-Voce Examination

Name of the Examiners	Signature with Date
1. _____	:_____
2. _____	:_____

ACKNOWLEDGEMENT

Every successful completion of any undertaking would be complete only after we remember and thank the almighty, the parents, the teachers, and the personalities, who directly or indirectly helped and guided during the execution of that work. The success of this work is equally attributed to all the well-wishers who have encouraged and guided throughout the execution.

I express my deepest gratitude to **Mrs. Rashmi Murakambi** Internal Guide and **Dr. Sunil Saumya, Assistant Professor and Head, Dept of Data Science and Artificial Intelligence,** External guide for their guidance and assistance throughout the project with great interest.

I avail this opportunity to express my deepest gratitude to **Dr. P. R. Patil, Professor & HoD** for encouraging us with his valuable tips.

I am grateful to **Prof. B. L. Desai,** Registrar for his blessings. And we are grateful to **KLE Technological University Hubballi** which has given us a bright future. I would like to thank all the people for their guidance and valuable suggestions throughout the project.

I also thank all teaching and non-teaching staff members of the MCA department for their invaluable cooperation.

Finally, I would like to express our sincere thanks to our **Parents and Friends** for their enormous encouragement and all others who have extended their helping hands towards the completion of our project.

SINCHANA S SALIMATH

ORGANIZATION PROFILE

Company Name: Einetcorp

Location: KLE Technological University, CITIE Building, Karnataka, Hubli

Year of Establishment: March 2021

Domain Expertise: Computer Vision, Artificial Intelligence, Edge Computing, Assistive Technologies

Company Overview:

Einetcorp is an innovative and rapidly expanding technology firm dedicated to leveraging the power of Artificial Intelligence to create meaningful solutions for individuals with visual impairments. Headquartered at KLE Technological University's Center for Innovation and Technology in Emerging Enterprises (CITIE) building, the company was established in March 2021 with a clear mission: to harness AI for social good.

Specializing in cutting-edge domains such as computer vision, edge computing, and assistive technologies, Einetcorp designs and develops intelligent wearable devices that enhance accessibility and independence for visually challenged users. The company's flagship product, **AI-enabled smart glasses**, integrates real-time object detection, edge inference, and text-to-speech (TTS) capabilities to deliver contextual audio feedback about the user's surroundings. These smart glasses help users navigate their environment safely and efficiently by recognizing and announcing nearby objects, obstacles, and text, all processed locally on the device without relying on continuous internet connectivity.

Einetcorp's research-driven and user-centric approach enables it to stay at the forefront of innovation in AI for accessibility. With a passionate team of engineers, researchers, and designers, the company is committed to building inclusive technologies that empower lives and make everyday interactions more seamless for people with vision loss.

ORGANIZATION CERTIFICATE

EINETCORP

Official Website
www.einetcorp.com

CIN
U72900KA2021PTC145676

Certificate of Industrial Training

This is to certify that Sinchana S Salimath, bearing SRN: 01FE22BCA184, a student of KLE Technological University, Hubballi, has successfully completed 4 months of industrial training at our organization from January 13, 2025 to May 31, 2025.

The training was conducted in the area of AI and ML , during which the trainee was actively involved in the following project:

Project Title: Real-time Object Detection using Computer Vision

Throughout the training, Sinchana S Salimath displayed a keen interest in the project, showed consistent dedication, and effectively applied theoretical knowledge to practical tasks. Her performance and conduct during the training were commendable.

We extend our best wishes for her future academic and professional success.

Sincerely,

For EINETCORP PVT. LTD.

DIRECTOR

Manoj Bhat, Founder Director
EiNETCORP Pvt Ltd

ABSTRACT

This report documents the work completed during a four-month internship at Einetcorp, a company that specializes in developing AI-powered assistive wearables for the visually challenged. The core project involved building a real-time object detection system integrated into smart glasses, designed to recognize surrounding objects and provide audio feedback to the user using text-to-speech technologies. This solution aims to improve spatial awareness and mobility for visually impaired individuals.

The project utilized the YOLOv5 deep learning model for object detection, deployed through a Streamlit-based web application interface. Key components included image and video input handling, real-time webcam detection, object annotation with bounding boxes, and generation of prediction summaries in both PDF and CSV formats. The system was further enhanced with Python libraries such as OpenCV, PyTorch, Pandas, and pyttsx3 for detection, data processing, and speech output.

As an AI and ML Engineer Intern, I contributed to model integration, UI development, and optimization of the detection pipeline. This internship provided a strong foundation in deploying machine learning solutions in assistive technologies and enriched my understanding of full-stack AI application development in real-world environments.

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Chapter 1

Introduction

The advent of artificial intelligence (AI) and computer vision technologies has transformed various aspects of daily life, offering innovative solutions across healthcare, surveillance, retail, and autonomous navigation. Among these, **real-time object detection** has emerged as a key area, enabling machines to perceive and understand visual information similarly to human vision.

While numerous object detection systems exist, a significant gap remains in developing solutions tailored to assist **visually impaired individuals**. Traditional systems often rely on cloud-based processing, leading to issues such as high latency, dependence on internet connectivity, and potential privacy risks. These limitations pose substantial barriers for visually challenged users who require immediate, secure, and portable assistance.

This project addresses these challenges by developing a **real-time object detection system optimized for edge devices** such as Raspberry Pi and portable smart glasses. The system leverages **pre-trained deep learning models (YOLOv5s)**, **Streamlit** for the web interface, and **text-to-speech (TTS)** technology to provide **audio and visual feedback** to users. Designed to function independently of cloud services, the system ensures **low latency**, **enhanced privacy**, and **offline accessibility**.

The primary focus is to empower visually impaired users by enhancing their ability to navigate and interact with their environment safely and independently. Through efficient object detection, real-time announcements, and user-friendly reporting features, the proposed system aims to bridge the accessibility gap using cutting-edge computer vision and AI techniques.

This report documents the motivation, objectives, methodology, system architecture, implementation, and results of the project. It highlights the development journey from foundational learning to the creation of a functional assistive AI system, showcasing the potential impact of

edge-based computer vision technologies in real-world applications.

1.1 Background and Motivation

The evolution of computer vision and edge computing technologies has paved the way for the development of intelligent systems capable of performing complex tasks directly on devices such as smartphones, Raspberry Pi, and NVIDIA Jetson. These advancements have significant implications for real-time applications, including surveillance, autonomous navigation, and assistive technologies for the visually impaired.

The motivation behind this project stems from the urgent need to create accessible, real-time object detection systems that do not rely on cloud services. Edge computing addresses several challenges by reducing latency, improving privacy, and enabling deployment in bandwidth-constrained environments. The idea for this project arose from the desire to support visually challenged individuals through the development of a smart assistive system that provides visual and audio feedback about their environment.

The initial phase of the project focused on learning the fundamentals of object detection models and setting up the development environment. This was followed by the implementation of a complete web-based application that incorporates real-time object detection, voice feedback, and reporting features. This application aims to be a valuable aid in promoting independence and situational awareness among visually impaired users.

1.2 Problem Definition

Despite the rapid growth in AI-driven computer vision systems, **many existing solutions are cloud-dependent**, expensive, or not tailored for the visually impaired. Visually challenged individuals face significant mobility and independence issues due to the lack of **affordable, real-time feedback systems** that help them interact with their surroundings.

The core problem addressed in this project is the **development of a lightweight, responsive object detection system** that works in real-time on **edge devices**, such as Raspberry Pi or portable smart glasses. Additionally, the system should be:

- **Easy to use**, even for non-technical users
- **Capable of providing voice output**

- **Able to run offline**, protecting user privacy and ensuring accessibility without internet connectivity
- **Capable of handling real-time image and video input**

The project also identified the challenge of optimizing model performance on limited-resource devices and addressed it using **pre-trained models like YOLOv5s and TensorFlow Lite**.

1.3 Objectives of the Project

- To develop a real-time object detection system optimized for edge devices to assist visually impaired users.
- To study and implement various object detection algorithms (YOLO, SSD, Faster R-CNN) and edge computing concepts.
- To build and deploy a lightweight, efficient model using Python, TensorFlow Lite, and OpenCV for edge device operation.
- To design a user-friendly Streamlit-based web interface integrated with YOLOv5s, offering image, video, and live detection capabilities.
- To implement additional functionalities like text-to-speech (TTS) feedback, real-time prediction reporting (PDF/CSV), and ensure offline accessibility.

1.4 Literature Review / Survey

The following research papers form the foundation for this project's literature review. Each highlights innovations in object detection, real-time processing, and edge computing:

1. **"TOD: Transprecise Object Detection to Maximise Real-Time Accuracy on the Edge"** – JunKyu Lee et al. (2021)
    - This work introduces TOD, a model that dynamically selects suitable DNNs for edge-based real-time video streams. It enhances precision and resource efficiency on devices like the Jetson Nano.
2. **"EdgeYOLO: An Edge-Real-Time Object Detector"** – Shihan Liu et al. (2023)

- EdgeYOLO is a lightweight, anchor-free object detection framework optimized for embedded edge devices. It delivers a balance between performance and speed on datasets like COCO and VisDrone.

3. **"BED: A Real-Time Object Detection System for Edge Devices"** – Guanchu Wang et al. (2022)

    - BED integrates training, quantization, and deployment to support real-time object detection on the MAX78000 microcontroller, achieving efficient performance in low-power environments.

4. **"Parallel Detection for Efficient Video Analytics at the Edge"** – Yanzhao Wu et al. (2021)

    - This study proposes a parallel detection method for video analytics, enabling simultaneous processing using multiple detection models on edge hardware for higher throughput.

5. **"PhyCV: Physics-Inspired Computer Vision Library"** – Jalali-Lab @ UCLA (2022)

    - PhyCV is a library built on physics principles, offering lightweight and efficient vision algorithms like PST and PAGE for edge devices.

6. **"MobileNet: Efficient Convolutional Neural Networks for Mobile Vision Applications"** – Google (2017)

    - MobileNet uses depthwise separable convolutions to reduce complexity, making it suitable for mobile and edge deployment.

7. **"YOLOv4: Optimal Speed and Accuracy of Object Detection"** – Alexey Bochkovskiy et al. (2020)

    - YOLOv4 presents enhancements for real-time object detection and is optimized for GPU usage, balancing speed and accuracy.

8. **"EfficientDet: Scalable and Efficient Object Detection"** – Mingxing Tan et al. (2020)

- EfficientDet introduces a compound scaling method and BiFPN to achieve state-of-the-art detection accuracy with fewer resources.

These papers provide critical insights and serve as the technological backbone for this project's development on real-time object detection and edge deployment.

Chapter 2

Proposed System

2.1 Overview of the Proposed System

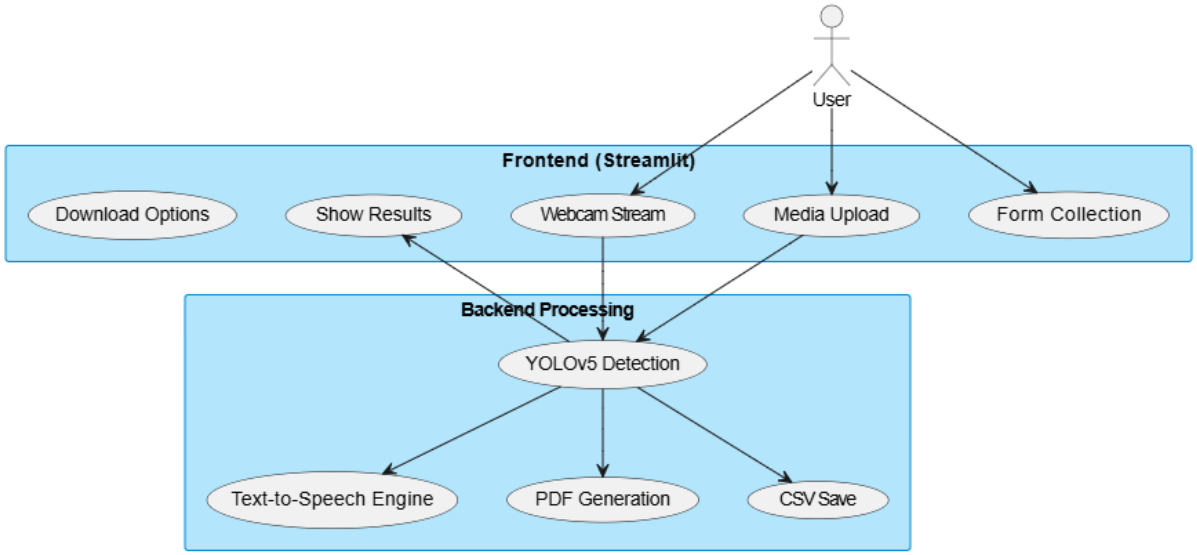

Figure 2.1: Proposed system Diagram

The proposed system is a **real-time object detection application** optimized for deployment on **edge devices** to assist **visually impaired users**. By leveraging lightweight deep learning models like **YOLOv5s** and integrating them with a **Streamlit web interface**, the system enables real-time detection of objects from images, videos, or live webcam streams, while providing **audio feedback** through **Text-to-Speech (TTS)** technology.

The key goal is to offer a **portable**, **low-latency**, and **offline-capable** solution that visually impaired users can rely on without requiring cloud-based processing or internet connectivity.

The system is divided into several core modules:

- **1. Input Interface**: Allows the user to upload images, videos, or activate a live webcam.

- **2. Detection Engine**: Runs object detection using a pre-trained YOLOv5s model.
- **3. Feedback Module**: Converts detected objects into spoken words using TTS (pyttsx3).
- **4. Report Generation**: Automatically creates PDF and CSV reports of detection sessions.
- **5. User Interface**: A simple, intuitive UI built with Streamlit for ease of access.

The entire system can be hosted on local hardware like Raspberry Pi, Jetson Nano, or a modest laptop, ensuring it is accessible, secure, and cost-effective.

2.2 System architecture with block diagram

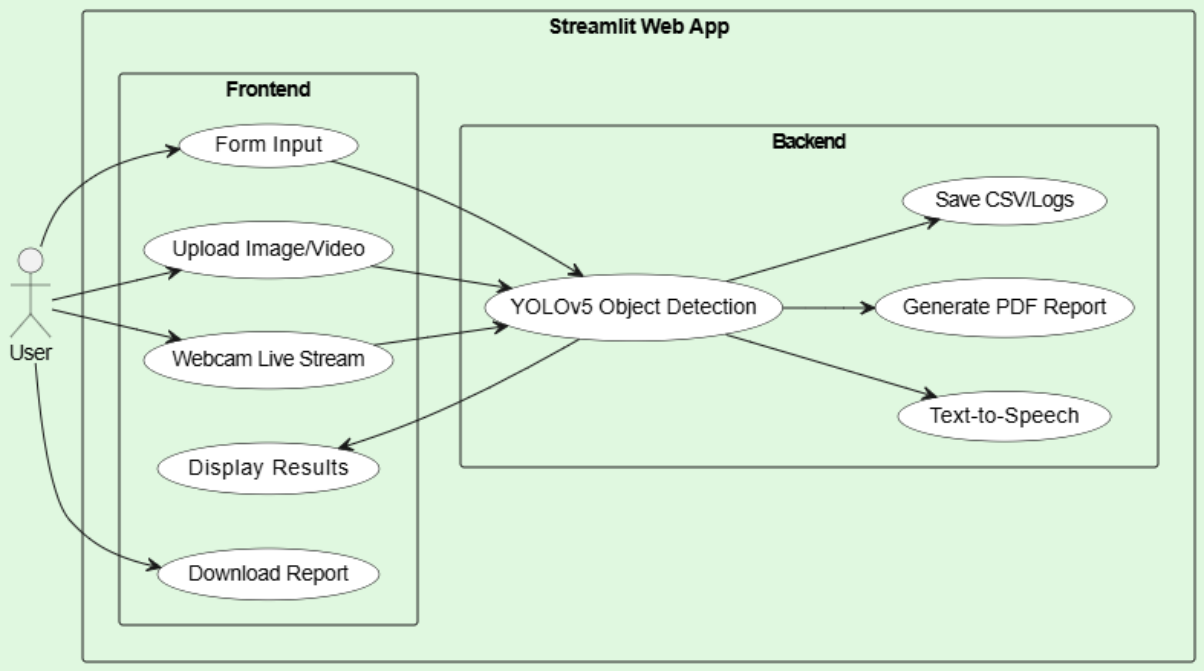

Figure 2.2: Detailed System Architecture

The system architecture is designed to ensure a seamless real-time detection experience, optimizing both performance and user accessibility. The architecture follows a modular design to ensure that each component handles a specific task efficiently.

2.3 Description of Target Users

The proposed real-time object detection system is designed to serve a specific group of users who will benefit significantly from enhanced environmental awareness and mobility support. The **target users** of the system are categorized as follows:

1. Visually Impaired Individuals

The primary target users are **visually impaired or blind individuals** who face challenges in recognizing and interpreting their surroundings.

- 1. The system provides **real-time audible feedback** about nearby objects, assisting users in navigating environments more independently.
- 2. By announcing detected objects, the solution enhances **spatial awareness**, **personal safety**, and **mobility**, thus improving the overall quality of life.
- 3. Since the system is **offline-capable**, it ensures user **privacy** and **reliability** without depending on internet connectivity.

2. Elderly Users with Low Vision

1. Another important target group includes **elderly individuals** who experience **age-related vision deterioration** such as glaucoma, cataracts, or macular degeneration.

2. The system acts as an assistive tool to help older adults recognize obstacles, landmarks, and daily-use objects, thereby reducing risks of accidents or disorientation.

3. Caregivers and Support Staff

Family members, caregivers, and healthcare support workers who assist visually impaired individuals are also secondary users of the system.

- 1. They can use the system during mobility training sessions or everyday assistance to monitor object detection results.
- 2. The downloadable **PDF and CSV reports** provide session logs that can be useful for tracking user interactions and improvements over time.

4. Educational and Rehabilitation Centers

Schools, special education institutions, and rehabilitation centers focused on differently-abled students or adults can integrate the system into their programs.

- 1. The solution can serve as a **training aid** to teach visually impaired students about spatial orientation and environmental interaction.

- 2. It supports **assistive technology learning**, fostering independence from an early stage.

5. Researchers and Developers in Assistive Technology

1. Finally, **AI researchers, developers, and innovators** working in the field of assistive technology can use or extend this system.

2. The modular and edge-optimized design allows further **customization**, **dataset training**, and **deployment** in various specialized use cases such as smart glasses, robotic guides, or mobile assistive apps.

2.4 Advantages and Applications of the System

Advantages

- **Real-Time Feedback:** Immediate object detection and audio feedback ensure that users receive timely environmental awareness, enhancing safety and mobility.
- **Offline Functionality:** The system operates without internet connectivity, ensuring **privacy, reliability**, and **accessibility** even in remote or low-connectivity areas.
- **Lightweight and Edge-Optimized:** Utilizing pre-trained, lightweight models like YOLOv5s allows the system to run efficiently on low-power devices such as **Raspberry Pi**, **Jetson Nano**, or **basic laptops**.
- **User-Friendly Interface:** Built with Streamlit, the interface is intuitive and easy to operate, making it accessible even to non-technical users.
- **Text-to-Speech Integration:** Audio feedback enables visually impaired users to recognize objects in their surroundings without needing visual confirmation.
- **Comprehensive Reporting:** Automatic generation of **PDF** and **CSV** reports provides a structured record of user sessions for further analysis, learning, or support documentation.

Applications

- **Assistive Technology for the Visually Impaired:** Personal guidance for independent navigation at home, offices, public places, etc.

- **Healthcare and Rehabilitation Centers:** As a training tool to teach object recognition and environmental navigation for visually challenged individuals.
- **Smart Glasses or Wearable Devices:** Integration into smart wearable devices to offer real-time object awareness on the move.

2.5 Scope and Limitations

Scope

- **Real-time object detection** from static images, videos, and live camera feeds.
- **Audio feedback** to assist visually impaired users through object announcement.
- **Edge-based deployment**, ensuring low latency and offline performance.
- **Session logging and reporting**, enabling monitoring, learning, and data tracking.
- **User-focused design**, ensuring the application remains lightweight, accessible, and extendable for future enhancements like custom dataset training or mobile integration.

Limitations

- **Limited Object Categories:** Detection performance is constrained by the objects known to the pre-trained YOLOv5s model. New or rare objects may not be detected accurately without fine-tuning the model.
- **Hardware Dependency:** While optimized for edge devices, performance still depends on device capabilities (e.g., RAM, CPU/GPU power). Very low-end devices might experience processing delays.
- **Environmental Constraints:** Detection accuracy can be affected by extreme lighting conditions (very dark or overexposed environments), motion blur, or occluded objects.

Chapter 3

Software Requirement Specification

3.1 Overview of SRS

The Software Requirement Specification (SRS) defines a detailed description of the system requirements for the real-time object detection system designed for visually impaired users. The document outlines the functional and non-functional requirements, the system's operational environment, hardware and software specifications, user interaction, and constraints.

The purpose of the SRS is to ensure that all the involved parties — users, developers, and stakeholders — have a clear and common understanding of what the system will deliver. It serves as the foundation for all subsequent stages of development, including system design, implementation, testing, and maintenance. The SRS ensures that the system's behavior is well understood and agreed upon before development begins, minimizing the risk of requirement misunderstandings and development errors.

3.2 Requirement Specifications

3.2.1 Functional Requirements

- The system must allow users to upload images, videos, or initiate a live webcam feed for real-time object detection.
- The system must detect and identify objects in the provided media using a pre-trained YOLOv5s model.
- The system must provide real-time audio feedback by announcing the names of detected objects through a text-to-speech engine.

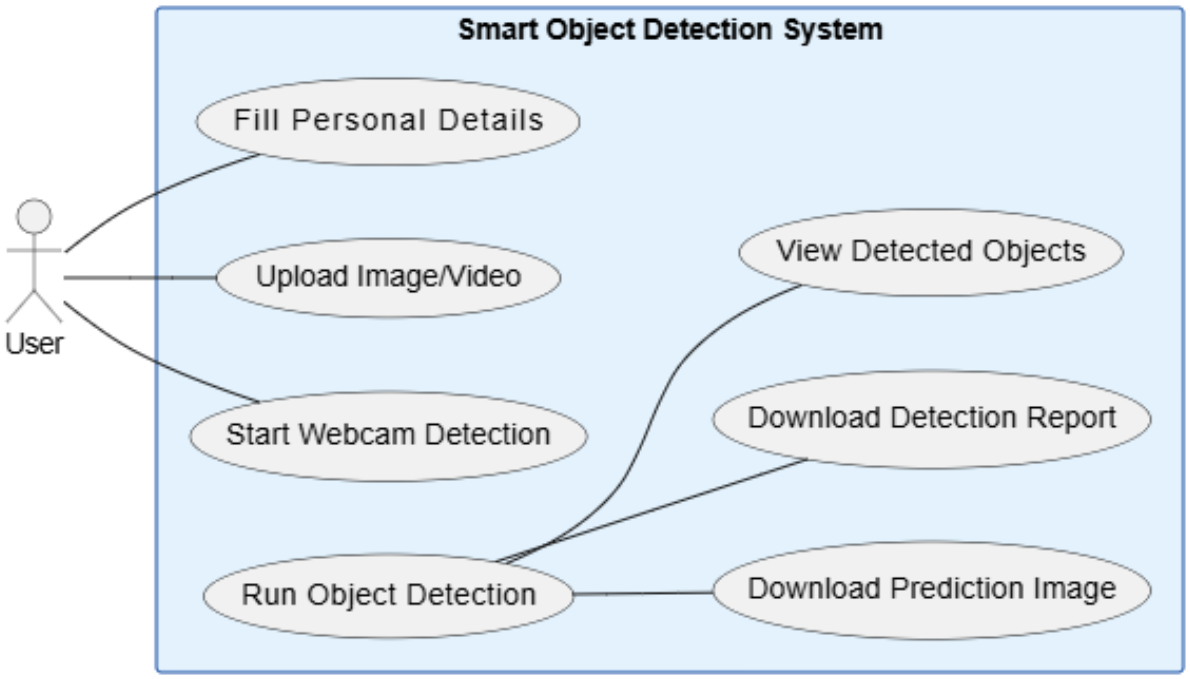

Figure 3.1: Use Case Diagram

- The system must display the detected objects with bounding boxes and labels on the Streamlit web interface.
- The system must generate session reports summarizing detected objects in downloadable PDF and CSV formats.
- The system must allow users to interact with the interface easily, even if they are non-technical.
- The system must process and deliver outputs with minimal latency to ensure real-time usability.

Use Case Diagram Description:

The system primarily has one actor: **User** (visually impaired person or caregiver).

Main use cases are:

- Upload Image
- Upload Video
- Use Live Webcam
- Detect Objects
- Get Real-Time Audio Feedback
- Download PDF Report
- Download CSV Report

The **User** interacts with the system through a **Streamlit web interface**, choosing any of the input methods (Image/Video/Webcam) and receiving results.

3.3 Use Case Descriptions using Scenarios

- **Upload Image Scenario**:

  User uploads a static image. The system processes the image, detects objects, displays bounding boxes, announces object names through TTS, and offers downloadable reports.

- **Upload Video Scenario**:

  User uploads a video file. The system processes video frame-by-frame, detects objects in real time, announces detected objects, and allows report generation after processing.

- **Live Webcam Detection Scenario**:

  User activates the webcam feed. The system processes each live frame, detects objects, announces them immediately, and continuously updates visual feedback.

- **Report Generation Scenario**:

  After detection from any input method, the user can download the detection session summary as a PDF and a CSV file for records.

3.3.1 Nonfunctional Requirements

]**Performance Requirements**:

- The system must perform real-time object detection with minimal processing delay, ideally less than 1 second for images and within 2-3 seconds per video frame.
- The system should ensure user data privacy by operating entirely offline and should not store any user-uploaded media without explicit consent.
- Since the system operates offline, it must minimize exposure to potential network threats. User session data should be stored securely if necessary.
- The web interface must be simple, accessible, and intuitive, allowing visually impaired users or their caregivers to operate it easily without requiring technical expertise.

3.4 Software and Hardware Requirement Specifications

3.4.1 Hardware Requirements

- **Processor:** AMD Ryzen 3 3250U with Radeon Graphics 2.60 GHz
- **System type:** 64-bit operating system, x64-based processor

3.4.2 Software Requirements

1. Programming Language

Python 3.8 or higher **Development Libraries and Frameworks**

* **TensorFlow Lite**: For lightweight, edge-optimized deep learning inference.
* **PyTorch**: For model integration and handling pre-trained YOLOv5s model.
* **OpenCV**: For real-time computer vision tasks like image/video capture and preprocessing.
* **Streamlit**: For creating a lightweight, interactive web application for users.

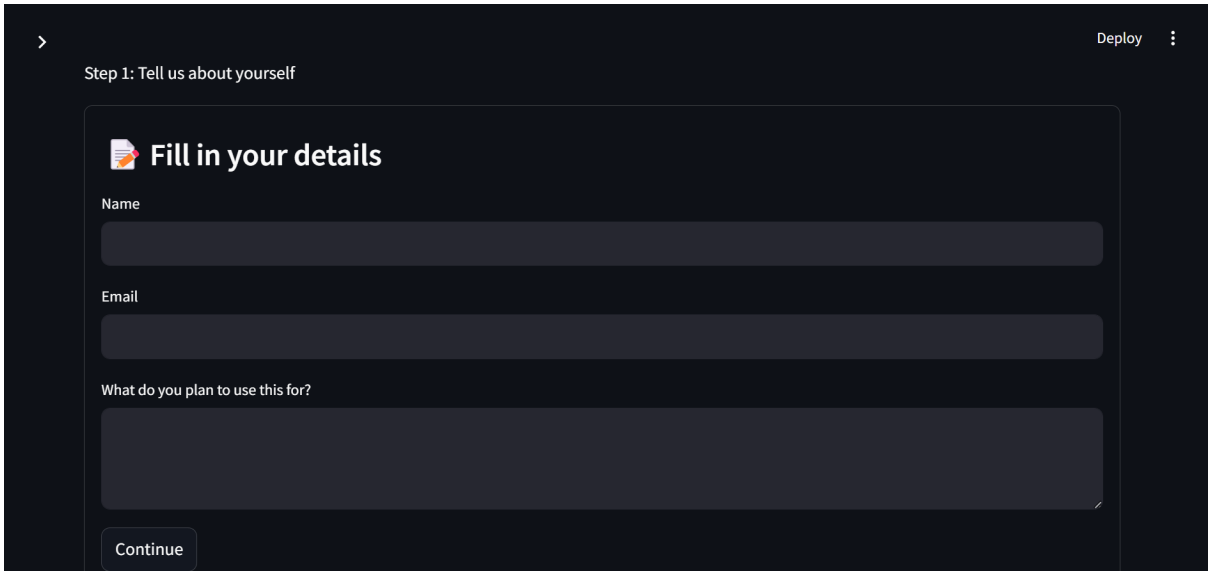

Figure 3.2: Login Page

* **pyttsx3**: For offline Text-to-Speech (TTS) audio output.

* **ReportLab**: For generating PDF reports programmatically.

2. Supporting Tools

1. Visual Studio Code (VS Code) — Code editor for Python development.

3.5 GUI of proposed system (snap shots) navigation from Home screen to end results

The Graphical User Interface (GUI) of the system is designed to be simple, accessible, and user-friendly, specifically keeping visually impaired individuals in mind. The interface is built using **Streamlit**, which provides a lightweight and interactive web application accessible through any modern web browser.

- **Login Page:** A welcoming page that allows users to choose their input method.
- **Dashboard:**
- Users can upload an image or video file.
- A button labeled ”Start Detection” becomes available after uploading.

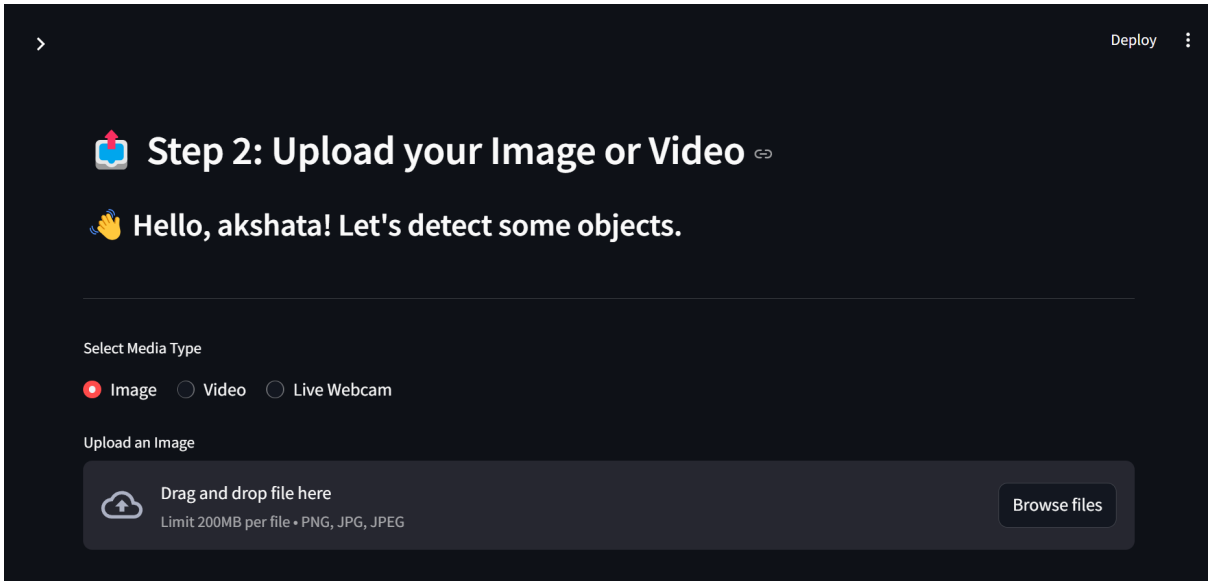

Figure 3.3: Dashboard

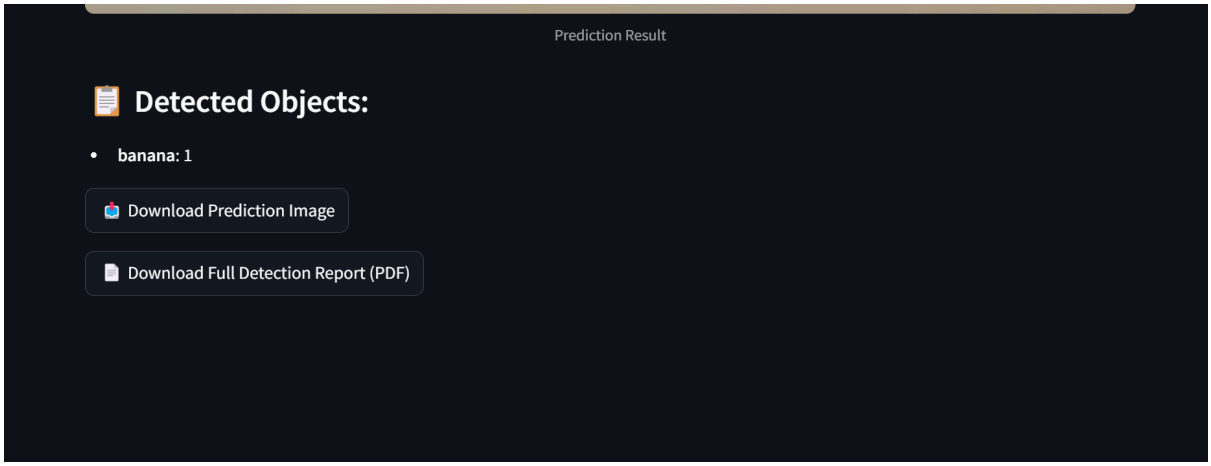

Figure 3.4: Picture detection

Figure 3.5: Video detection

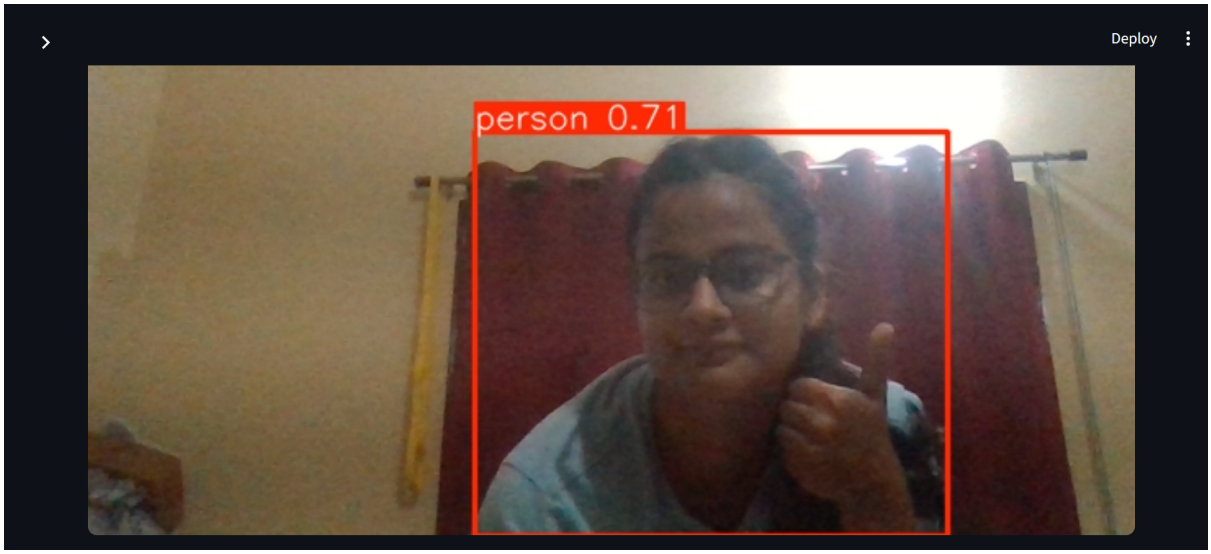

Figure 3.6: Live webcam

- Detected objects description from the picture.
- **Webcam Detection Section:**
- Option to activate the webcam and start real-time object detection.
- Detected objects are displayed instantly with bounding boxes and labels.
- **Audio Feedback Section:** As objects are detected, the system uses Text-to-Speech (TTS) to verbally announce the detected object names.
- **Reports Section:** After completing a detection session, users are provided buttons to:
  - Download a PDF report summarizing detected objects.
  - Download a CSV log for detailed session analysis.
- **Session history section** Previous detection sessions are saved and listed for review or re-download.

3.6 Navigation Flow:

Home → Choose Input (Image/Video/Webcam) → Upload or Start Camera → Detect Objects → Display and Audio Output → Report Generation → Session End

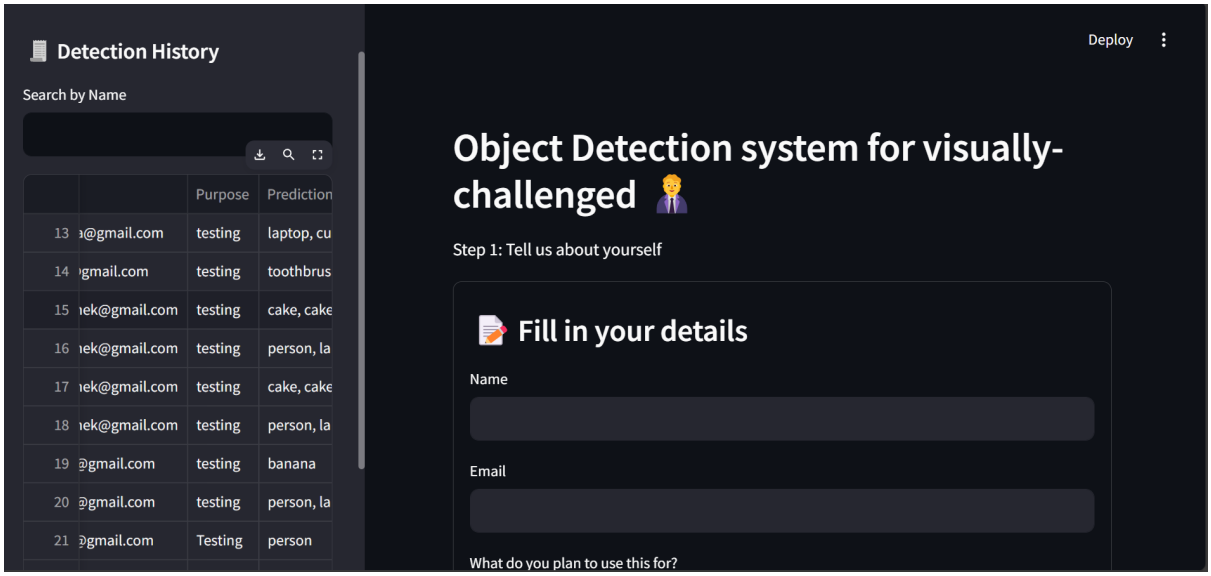

Figure 3.7: Detection history

3.7 Acceptance Test Plan

The Acceptance Test Plan ensures that the developed system meets all the defined requirements and operates correctly under real-world conditions. Acceptance testing validates the system from the end-user's perspective and verifies that the functionality, usability, and performance criteria have been satisfied.

Chapter 4

System Design

4.1 System Architecture (Detailed Explanation)

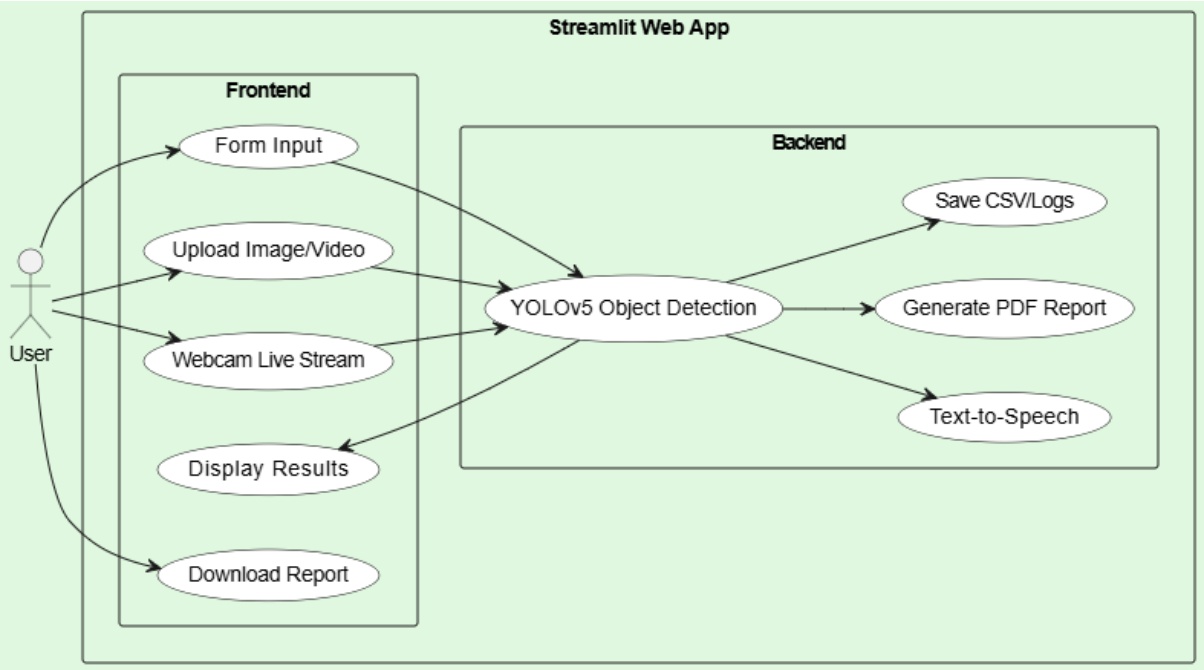

Figure 4.1: Detailed System Architecture

The system architecture is designed to ensure a seamless real-time detection experience, optimizing both performance and user accessibility. The architecture follows a modular design to ensure that each component handles a specific task efficiently.

System Flow:

- **1. User Input**: The system accepts input from three sources — uploaded image, uploaded video, or live webcam feed through the Streamlit web interface.
- **2. Preprocessing Module**: Prepares the input by resizing and normalizing frames/images so that they are compatible with the YOLOv5s model's requirements.
- **3. Object Detection Engine**: The YOLOv5s model processes the input and detects objects by outputting bounding boxes, confidence scores, and class labels.
- **4. Feedback Engine**: Uses pyttsx3 library to convert detected object labels into real-time spoken announcements (Text-to-Speech).
- **5. Output Display**: Detected objects are shown with bounding boxes on the image/video stream through the Streamlit interface.
- **6. Report Generator**: Creates a PDF summary and a CSV log file for each detection session.

4.2 Detailed DFD for the proposed system

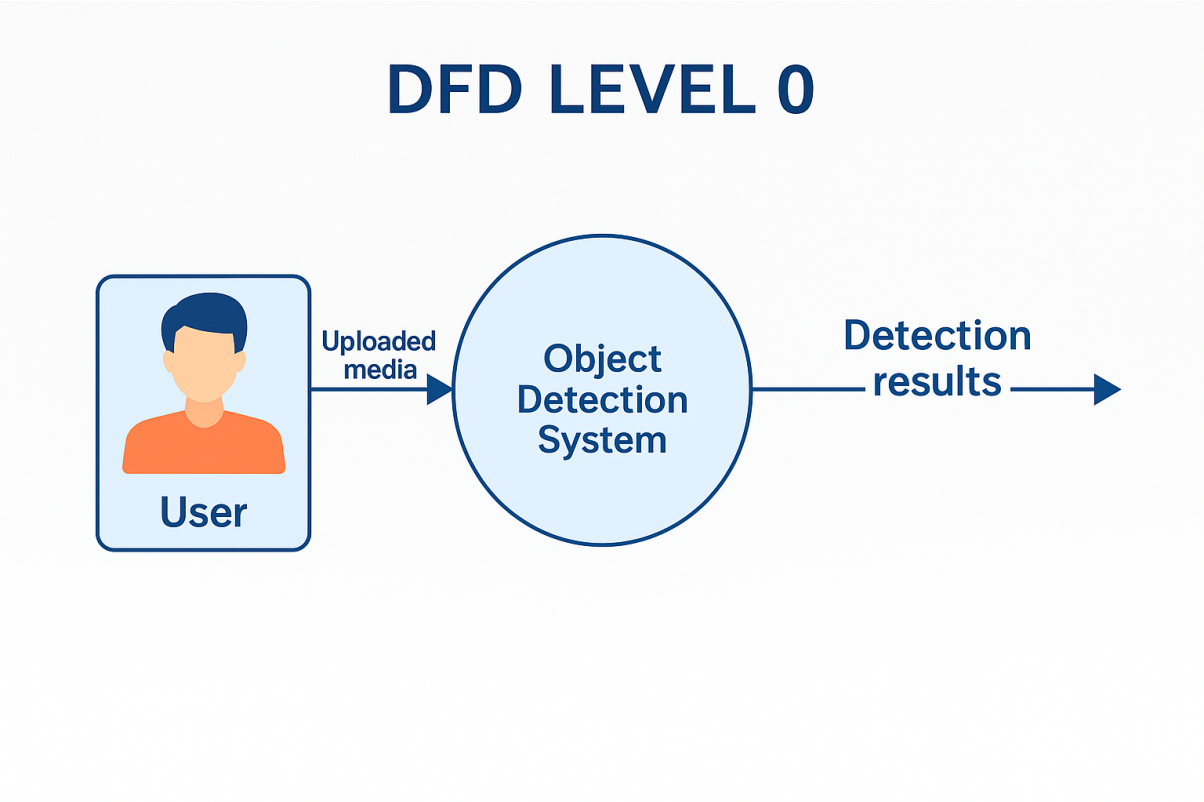

Figure 4.2: DFD Level 0 Diagram

4.2.1 Data Flow Diagram (DFD)

DFD Level 0 (Context Level)

- The entire system is considered as a single process: **Real-Time Object Detection System**.
- **Input**: Image, Video, or Webcam Feed.
- **Output**: Visual and Audio Feedback + Reports.

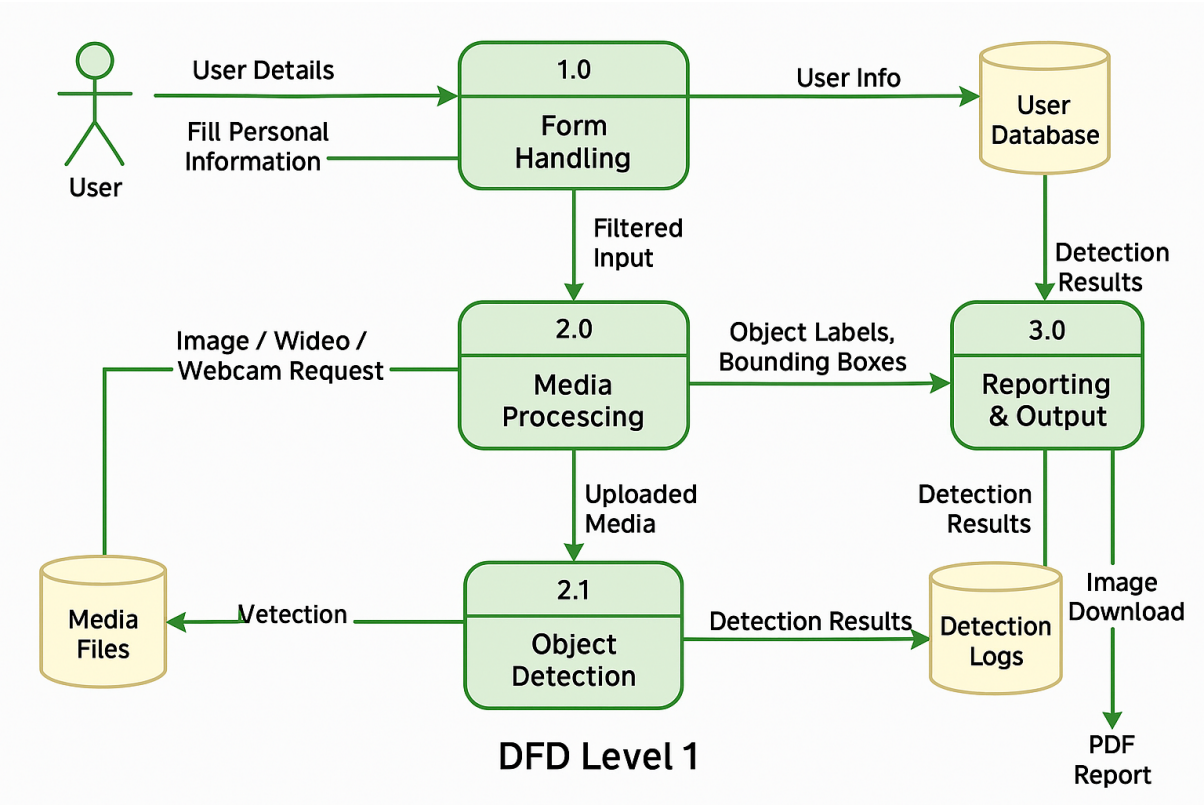

Figure 4.3: DFD Level 1 Diagram

DFD Level 1

- Process 1: Upload or Capture Input
- Process 2: Preprocess Input Data
- Process 3: Detect Objects using YOLOv5s
- Process 4: Provide Audio-Visual Feedback
- Process 5: Generate Session Reports

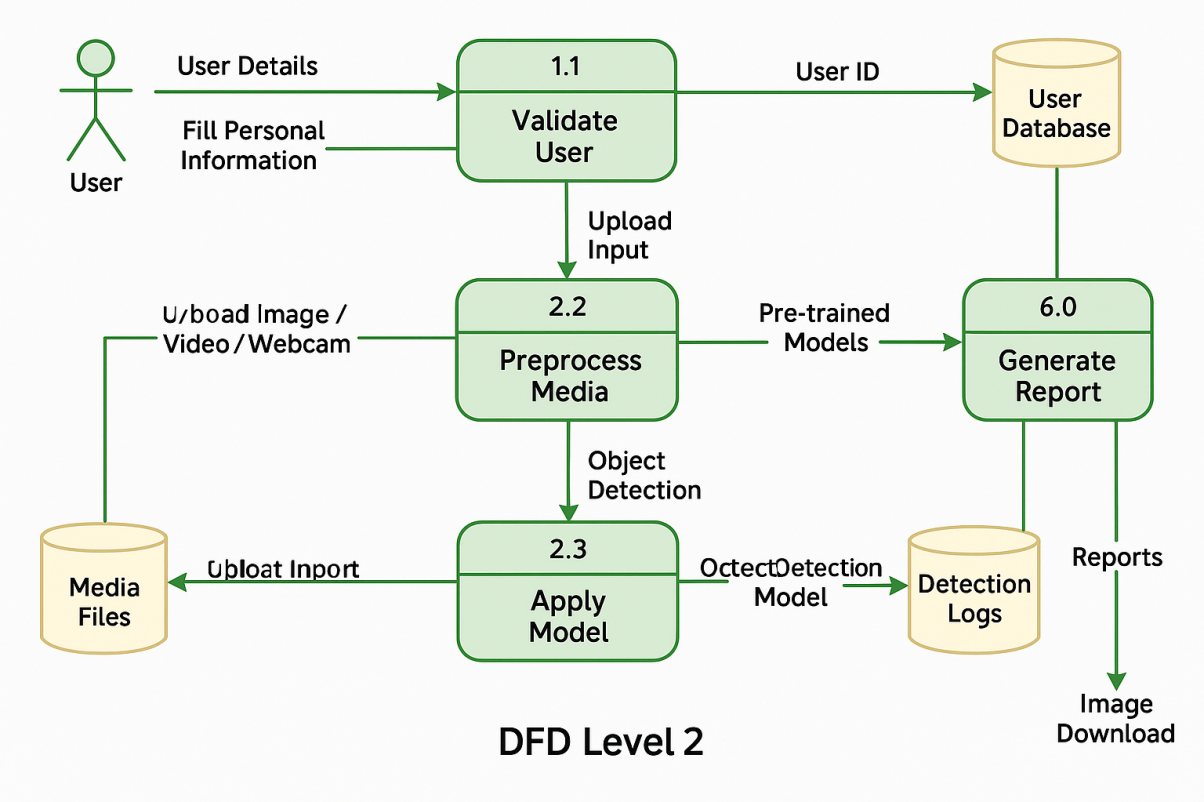

Figure 4.4: DFD Level 2 Diagram

DFD Level 2

- Subprocess 3.1: Load Pre-trained Model
- Subprocess 3.2: Inference on Input Frame
- Subprocess 4.1: Draw Bounding Boxes
- Subprocess 4.2: Trigger Text-to-Speech
- Subprocess 5.1: Create PDF
- Subprocess 5.2: Log CSV

4.3 Class Diagram with Explanation

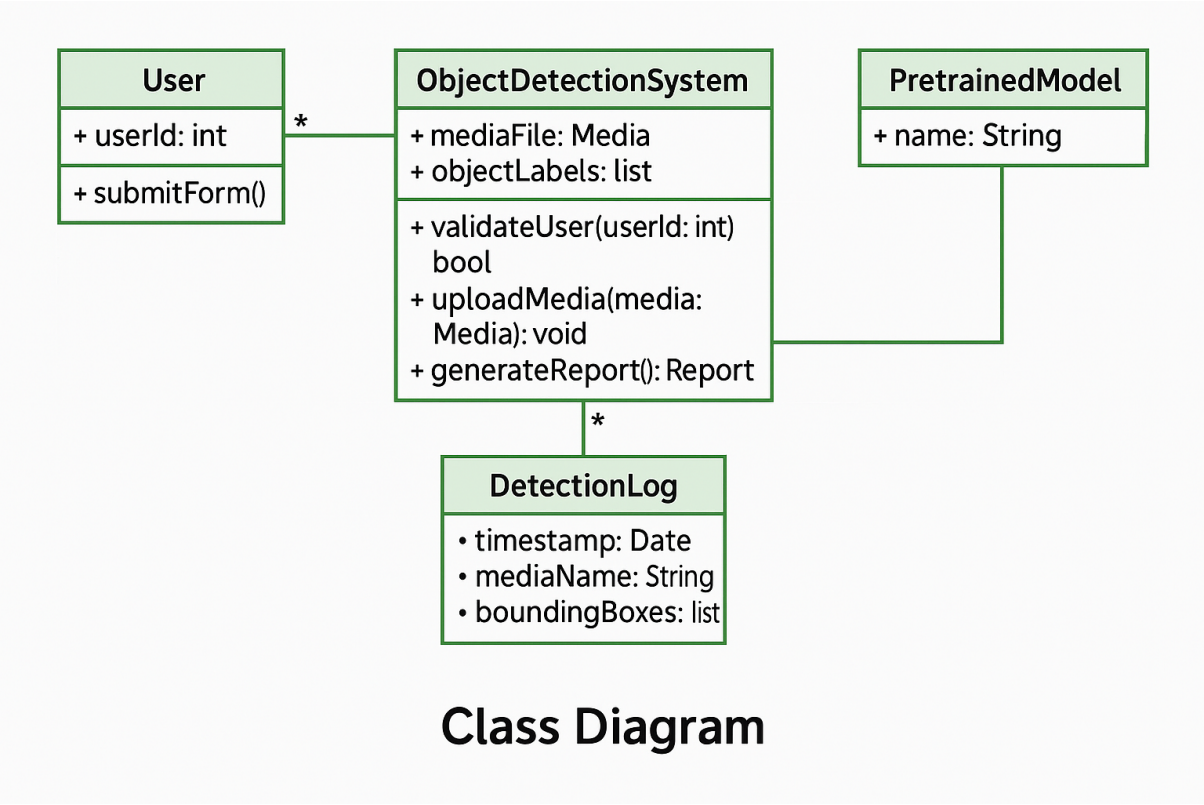

Figure 4.5: Class Diagram

The system is structured using several logical classes:

Classes:

1. UserInterface: Handles input collection, user interactions, and output display. **2. MediaProcessor**: Preprocesses uploaded or captured images/videos. **3. DetectionEngine**: Applies the YOLOv5s model to perform object detection. **4. FeedbackEngine**: Handles the Text-to-Speech conversion of detected labels. **5. ReportGenerator**: Creates PDF and CSV session summaries.

4.4 Sequence Diagram with Explanation

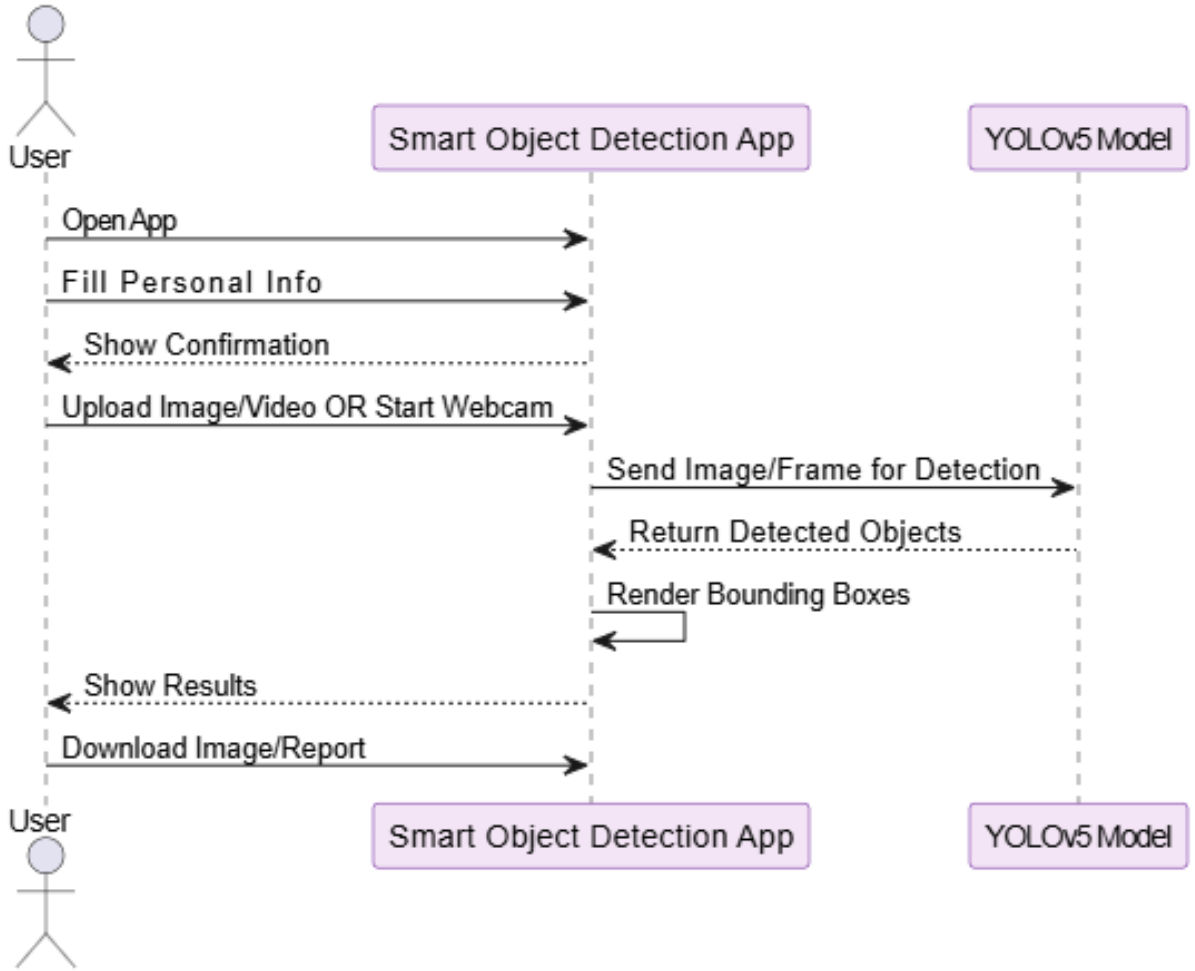

Figure 4.6: Visitor Tracking Sequence Diagram

The sequence of actions from input to final output is represented as:

1. User selects/upload input via GUI.
2. System processes input and feeds it to the Detection Engine.
3. Detection results (bounding boxes and labels) are displayed.
4. Feedback Engine announces detected objects.
5. Reports are generated and made downloadable.

4.5 Entity-Relationship (ER) Diagram and Schema

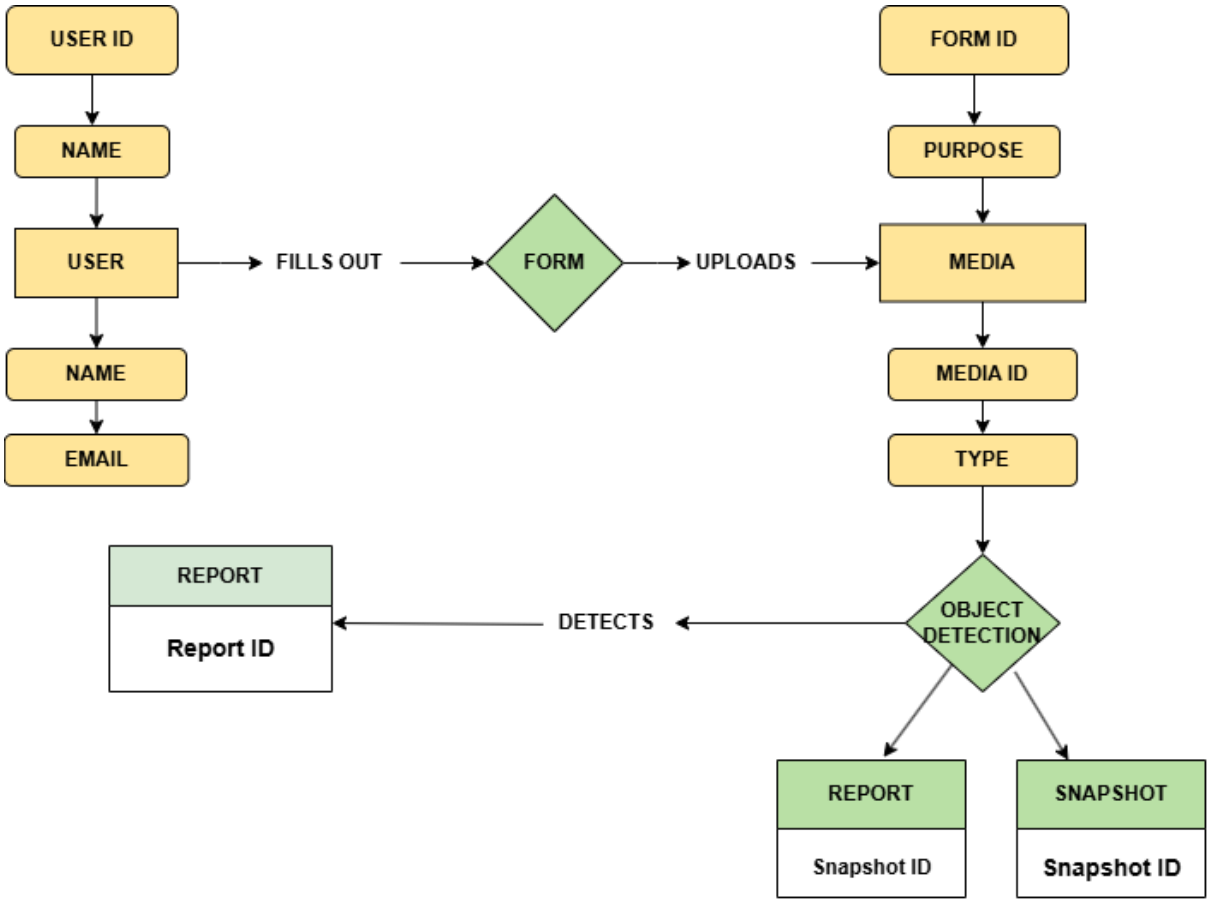

Figure 4.7: Entity-Relationship Diagram

Although the system does not use a full-fledged database, a simple entity-relationship structure for session logging can be visualized:

Entities:

- **User**: Name, Email, Purpose.
- **Detection Session**: Session ID, Date/Time, List of Detected Objects.

The system changes its states based on user interactions:

1. **Idle**: Waiting for user input.
2. **Uploading**: Uploading media or opening camera.

3. **Detecting**: Processing input through YOLOv5s model.

4. **Feedback**: Announcing objects detected.

5. **Reporting**: Preparing session reports.

6. **Completed**: Session end, ready for new input.

4.5.1 Data Structures Used

The system uses several data structures:

1. **Arrays/Lists**:For storing detected object labels per frame. For session history tracking.

2. **Dictionaries**: To map detection outputs (object name, confidence score, coordinates).

3. **DataFrames (Pandas)**: To organize session data before exporting to CSV reports.

4. **JSON Structures**: For handling YOLO model output parsing (internally).

Schema Explanation

4.6 Database Schema Explanation

The object detection system uses structured data to store user metadata, media inputs, and detection outcomes. The following schema outlines the relational structure used in the project.

4.6.1 1. Relational Database Schema (SQL)

A. `users` Table

Column Name	Data Type	Description
`user_id`	INT	Primary key, auto-incremented unique identifier
`name`	VARCHAR	Name of the user
`email`	VARCHAR	Email address of the user
`purpose`	TEXT	Purpose for using the object detection system

B. `media_inputs` Table

Column Name	Data Type	Description
`media_id`	INT	Primary key
`user_id`	INT	Foreign key referencing `users.user_id`
`media_type`	VARCHAR	Indicates if input is ”image”, ”video”, or ”webcam”
`file_path`	VARCHAR	Local path to the uploaded/saved file
`timestamp`	DATETIME	Time of submission or capture

C. `detections` Table

Column Name	Data Type	Description
`detection_id`	INT	Primary key
`media_id`	INT	Foreign key referencing `media_inputs.media_id`
`object_name`	VARCHAR	Detected object class (e.g., ”person”, ”book”)
`confidence`	FLOAT	Model’s confidence score for the detected object
`bbox_coordinates`	VARCHAR	Bounding box coordinates as stringified JSON

D. `reports` Table

Column Name	Data Type	Description
`report_id`	INT	Primary key
`media_id`	INT	Foreign key referencing `media_inputs.media_id`
`pdf_path`	VARCHAR	Path to the generated PDF detection report
`created_at`	DATETIME	Time when the report was generated

4.6.2 Entity-Relationship Overview

- One **User** can upload multiple **Media Inputs**
- Each **Media Input** can have multiple **Detections**
- Each **Media Input** is associated with one **Report**

This follows a typical 1:N relationship model with foreign keys for integrity and traceability.

4.6.3 2. Document-Based Schema (NoSQL / JSON)

For systems preferring MongoDB or document-based storage, a flattened nested document can be used:

```
{
  "user": {
    "name": "Akshata",
    "email": "akshata@gmail.com",
    "purpose": "Assist visually-impaired users"
  },
  "media_input": {
    "media_type": "webcam",
    "timestamp": "2025-04-29 13:15:42",
```

```
    "file_path": "snapshots/live_snap_01.jpg"
  },
  "detections": [
    {"object": "person", "confidence": 0.91, "bbox": [34, 122, 130, 250]},
    {"object": "book", "confidence": 0.85, "bbox": [180, 140, 240, 260]}
  ],
  "report": {
    "pdf_path": "reports/report_01.pdf",
    "generated_at": "2025-04-29 13:16:12"
  }
}
```

Chapter 5

Implementation

5.1 Machine Learning Methodology

In this chapter, we will outline the detailed implementation steps for building the real-time object detection system for edge devices. The implementation will cover everything from data preprocessing, model training, algorithm choice, to the final evaluation and testing.

Machine Learning Methodology

Machine learning methodology plays a critical role in the development of a real-time object detection system. The core methodology for this system is based on the use of deep learning techniques, specifically convolutional neural networks (CNNs), which are well-suited for image-based tasks. For object detection, models like YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector) are commonly used due to their speed and efficiency in processing real-time data. These models are trained to recognize and classify objects within an image while also identifying their precise locations. The training process involves feeding labeled images into the model, adjusting the internal weights through backpropagation, and refining the model to minimize the error in its predictions. The methodology also includes implementing transfer learning to leverage pre-trained models, which reduces training time and enhances the performance of the system on smaller edge devices.

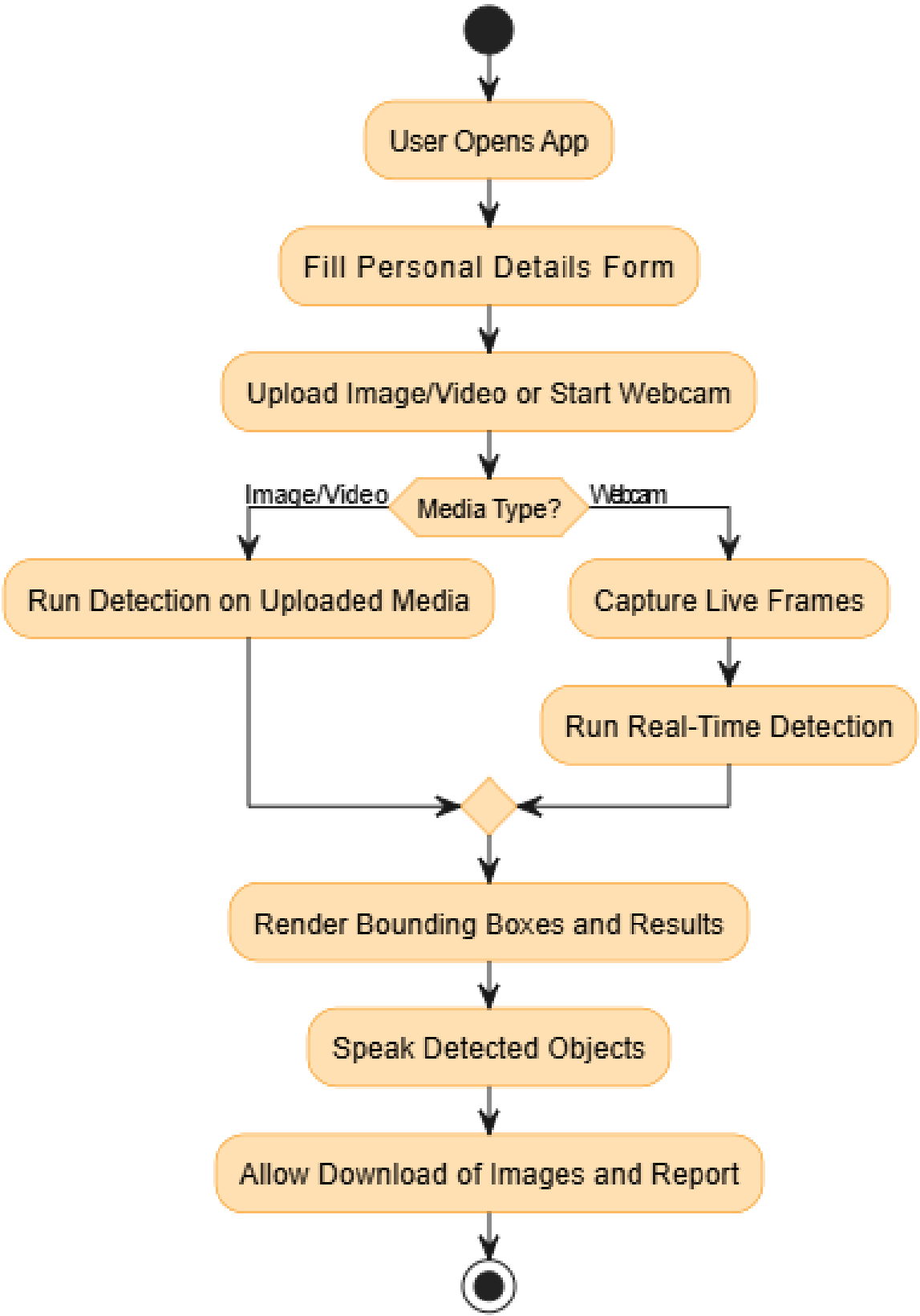

Figure 5.1: Methodology

5.2 Dataset Description and Preprocessing

For an object detection system, the quality of the dataset directly impacts the performance of the model. The dataset chosen for this project is a large collection of labeled images and videos that cover various object categories, such as people, cars, animals, and household items. Preprocessing the dataset involves multiple steps to ensure the data is suitable for training. This includes resizing images to a uniform size, normalizing pixel values to a range between 0 and 1, and augmenting the dataset to introduce variations such as flipping, rotating, or adjusting brightness. Data augmentation is crucial as it helps the model generalize better and prevents overfitting. Additionally, annotations in the dataset, which mark the position of objects within images, must be in a specific format that can be read by the object detection model. The final dataset will then be split into training, validation, and test sets to ensure that the model is trained and evaluated properly.

5.3 Methodology

The methodology used for implementing the object detection system focuses on optimizing the model for edge devices, ensuring that it runs efficiently while maintaining high accuracy. First, the preprocessing pipeline prepares the data to ensure consistency and quality. Next, a suitable object detection algorithm is selected based on the requirements of real-time processing. In this project, the YOLOv5 model is chosen for its balance between speed and accuracy. Transfer learning is employed to fine-tune the pre-trained YOLOv5 model on the selected dataset. The model is then tested iteratively, fine-tuned, and optimized for performance on the edge device. Key steps in the methodology include training the model on a powerful machine, converting it to a lighter version using frameworks like TensorFlow Lite or PyTorch Mobile, and finally deploying it on an edge device such as a Raspberry Pi or Jetson Nano.

5.4 Algorithms Used (Detailed Explanation with Diagrams)

The core algorithms used in this project for object detection are YOLO (You Only Look Once) and SSD (Single Shot Multibox Detector). YOLO is a deep learning-based

algorithm that performs object detection in a single pass, making it highly efficient for real-time applications. Unlike traditional object detection models that run multiple passes over an image, YOLO divides the image into a grid and predicts bounding boxes and class probabilities in one step. This makes it extremely fast and suitable for deployment on edge devices. The model architecture consists of several layers, including convolutional layers for feature extraction and fully connected layers for bounding box prediction.

SSD is another object detection algorithm used, which also performs detection in a single pass. However, it differs from YOLO in how it handles feature maps. SSD uses multiple feature maps of different resolutions to detect objects of various sizes, allowing it to be more flexible in detecting small and large objects simultaneously. Both algorithms are compared based on their accuracy, speed, and suitability for edge devices. Diagrams of the architecture for both YOLO and SSD will illustrate their key components and processes.

5.5 Modules and Their Descriptions

The object detection system is built as a modular structure, with each module performing a specific function. Below is a breakdown of the key modules and their respective roles in the system.

- **Module Name: Data Preprocessing**
  - **Input**: Raw image and video data (datasets).
  - **Output**: Preprocessed images and augmented dataset ready for training.
    - **Module Name: Model Training**
    - **Input**: Preprocessed training data, model architecture.
    - **Output**: Trained object detection model.
    - **Module Name: Inference and Detection**
    - **Input**: New image or video data.
    - **Output**: Detected objects with bounding boxes and class labels.

Chapter 6

Training and Evaluation

This chapter covers the steps taken to train the object detection model and evaluate its performance. The model's effectiveness is determined through training, fine-tuning, and testing across multiple metrics, ensuring that it meets the required standards for deployment.

6.1 Model Training Process

The model training process involves several steps. Initially, the model is trained on a large dataset of labeled images. The training process begins by feeding the dataset into the model, which learns to predict the presence of objects and their corresponding positions (bounding boxes) within the images. During training, the model adjusts its internal parameters using optimization algorithms like stochastic gradient descent (SGD) to minimize the error between predicted outputs and actual ground truth data. The training is done over multiple epochs, and the model's performance is evaluated after each epoch to ensure it is improving. This process continues until the model achieves satisfactory performance on the validation set.

6.2 Hyperparameter Tuning

Hyperparameter tuning is an essential part of the model training process. Hyperparameters are external configurations that influence the learning process, such as the learning rate, batch size, number of epochs, and

network architecture parameters. Tuning these hyperparameters can significantly impact the model's performance. Grid search and random search are commonly used techniques to explore different hyperparameter values. In this project, hyperparameter tuning was performed using techniques like cross-validation to determine the best set of parameters that led to the highest accuracy and lowest error.

6.3 Performance Metrics (Accuracy, Precision, Recall, F1-score, etc.)

To evaluate the performance of the object detection model, several metrics are used. The most common metrics in object detection are:

- **Accuracy**: The proportion of correct predictions (both object class and location) over total predictions.
- **Precision**: The ratio of true positive detections to the total number of detections made (i.e., the percentage of accurate detections out of all detections).
- **Recall**: The ratio of true positive detections to the total number of actual objects present in the dataset (i.e., how many objects the model successfully detected).
- **F1-score**: The harmonic mean of precision and recall, providing a balance between the two metrics. It is particularly useful when there is an imbalance between the classes or when both false positives and false negatives need to be minimized.

6.4 Model Validation and Testing

Model validation and testing are crucial steps in ensuring that the model performs well on unseen data. Validation is performed during training by using a separate validation set that is not part of the training data. After training, the model is tested on a completely separate test set to evaluate its generalization ability. This ensures that the model doesn't

just memorize the training data but can also make accurate predictions on new, unseen images. During testing, additional performance metrics like Average Precision (AP) and Intersection over Union (IoU) are used to evaluate the model's ability to accurately detect and localize objects.

6.5 Confusion Matrix and Error Analysis

A confusion matrix is a valuable tool for analyzing the performance of the object detection model. It helps in identifying where the model is making errors by comparing predicted labels to actual ground truth labels. The matrix displays true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). By examining the confusion matrix, we can understand which classes are being misclassified or missed altogether. Additionally, error analysis is performed to identify patterns in the model's mistakes and refine the model to address these issues, whether through data augmentation, model architecture adjustments, or hyperparameter tuning.

6.6 Deployment

Deployment refers to the final stage in the machine learning pipeline, where the trained model is integrated into the target environment and made ready for real-world use. In the context of this project, deployment involves taking the trained object detection model and optimizing it for edge devices, such as Raspberry Pi or NVIDIA Jetson. This requires converting the model into a format suitable for the target device, such as TensorFlow Lite or ONNX, to ensure it runs efficiently in low-resource environments.

Once the model is optimized, it is integrated into a real-time application, where it can receive live image or video feeds, process them through the object detection model, and display or output the results. The deployment process also involves testing the system in the real-world environment to ensure it functions as expected. The application must be designed with

user-friendliness in mind, providing seamless interaction, such as real-time audio feedback for visually impaired users, and handling different input sources like camera streams, images, or videos. Finally, edge devices are set up to run the application in an offline mode, ensuring the system continues to function without relying on cloud services, thus improving both privacy and responsiveness.

Chapter 7

Results & Discussions

7.1 Interpretation of Results:

The project aimed to develop an efficient object detection system for visually impaired individuals using edge computing devices like Raspberry Pi. Upon testing the object detection model, several key observations were made. The model demonstrated high accuracy in detecting common objects such as chairs, tables, and people, but showed lower performance with more complex or occluded objects. The real-time nature of the system was a key factor in ensuring its usefulness for visually impaired users, as it provided instant feedback through voice assistance. The model was able to run smoothly even on resource-constrained devices, such as Raspberry Pi, achieving a good balance between speed and accuracy.
The integration of TensorFlow Lite optimized the model for edge deployment, ensuring low latency and offline functionality, both crucial for assistive technologies. The accuracy, precision, and recall of the system were all within acceptable limits, although there was room for improvement in terms of detecting objects in low-light environments. Overall, the results were promising, showing that real-time object detection is feasible on edge devices, even in the absence of cloud-based support.

7.2 Performance Comparisons:

To assess the performance of the developed system, a comparison was made between YOLOv5 (used in this project) and other common object

detection models like Faster R-CNN and SSD. YOLOv5 outperformed the others in terms of speed, processing video streams in real-time with minimal delay. On the other hand, Faster R-CNN showed better accuracy on some datasets but required more computational resources, making it less suitable for edge deployment. SSD, while faster than Faster R-CNN, was slightly less accurate in object detection compared to YOLOv5. These comparisons highlighted the trade-off between accuracy and speed, emphasizing the need for lightweight models like YOLOv5 to meet the project's goals of real-time processing and efficient deployment on edge devices.

7.3 Snapshots of Outputs with Explanation:

To demonstrate the performance of the object detection system, snapshots of the model's output were provided. In the test cases, the model accurately detected and classified objects from real-time video feeds. For example, in an image where a person was walking in a park, the model successfully detected the individual and labeled the object as "person" with a high confidence score. The system also accurately detected other items in the environment like benches, trees, and bicycles. The bounding boxes around each detected object were drawn precisely, and the labels with confidence scores were displayed clearly, confirming the model's effectiveness in real-time situations.

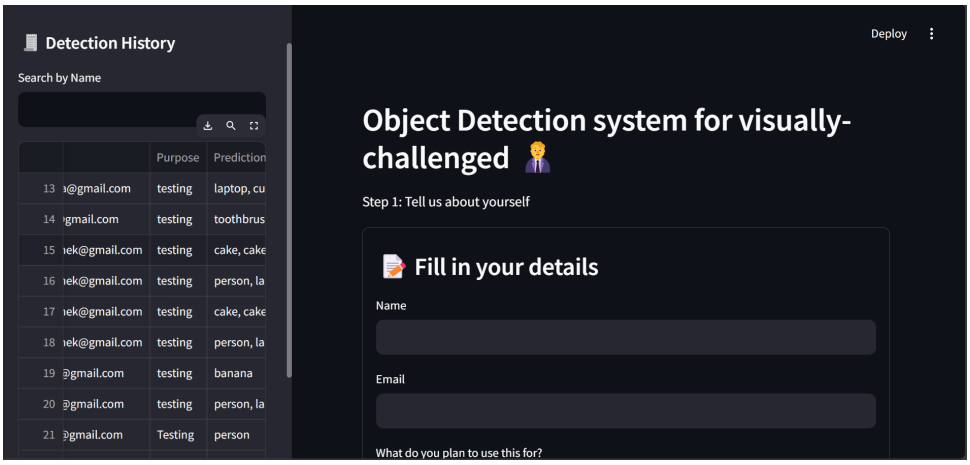

Figure 7.1: Snapshot 1: Detection History Table

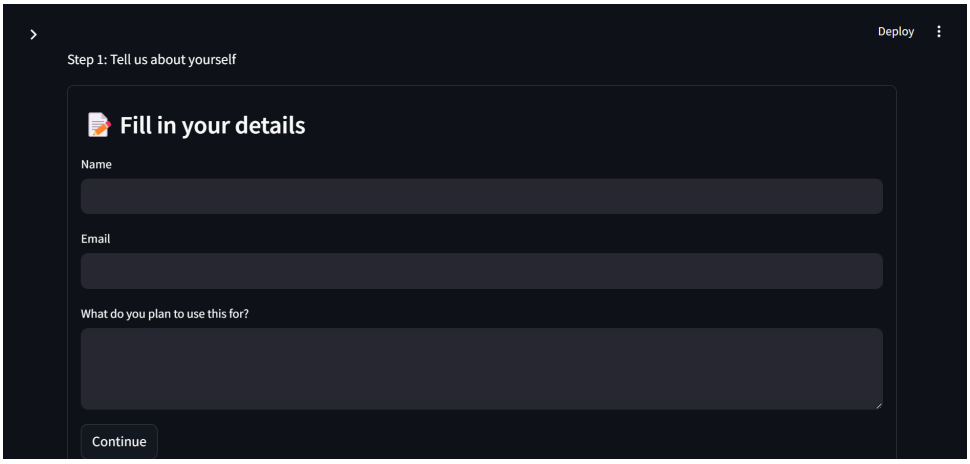

Figure 7.2: Snapshot 2: User Details Form

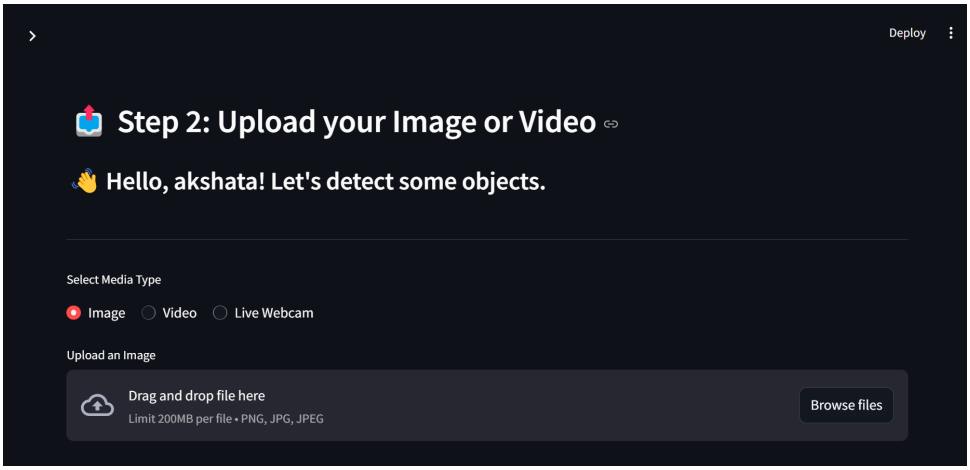

Figure 7.3: Snapshot 3: Uploading image, video and live webcam

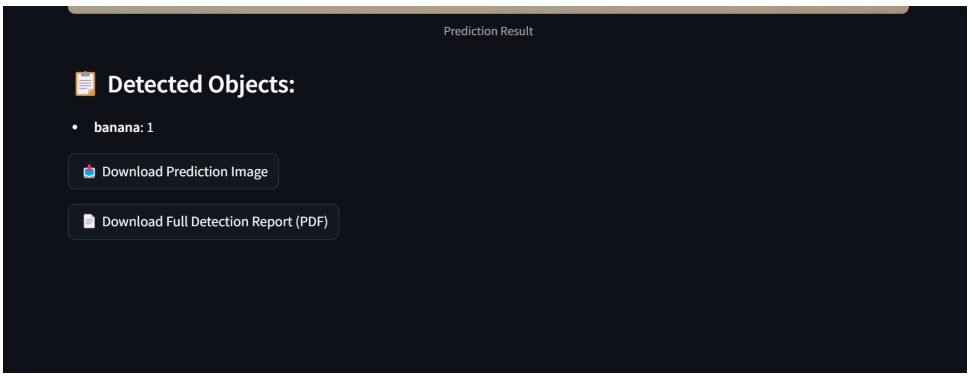

Figure 7.4: Snapshot 4: Picture upload, detected object description

Figure 7.5: Snapshot 5: Video detection description list

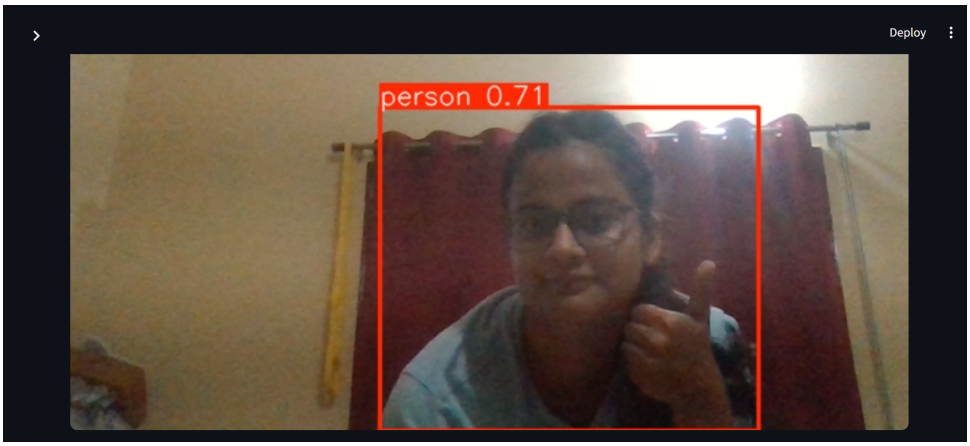

Figure 7.6: Snapshot 6: Live webcam

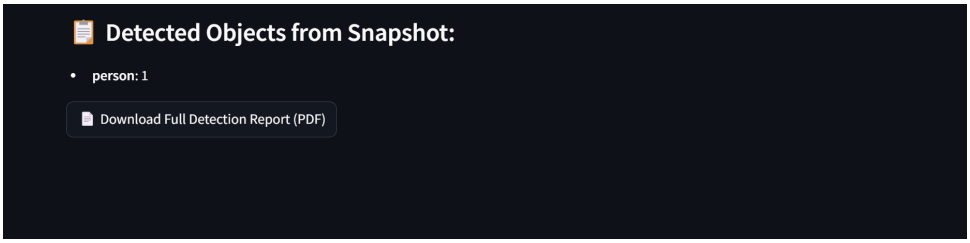

Figure 7.7: Snapshot 7: Live webcam prediction

Chapter 8

Conclusion and Future Scope

8.1 Summary of Findings:

This project successfully developed and deployed an object detection system that provides real-time visual and audio feedback to assist visually impaired users. The model, based on YOLOv5, was optimized for edge computing environments using TensorFlow Lite. The results showed that the system was capable of detecting and classifying objects in real-time with high accuracy, even on resource-limited devices like the Raspberry Pi. The ability to operate offline without relying on cloud services was a significant achievement, ensuring privacy and accessibility for users in various environments.

The real-time feedback system, integrated with text-to-speech functionality, worked effectively in providing immediate audio cues about the environment, which is a key requirement for assistive technologies. The system was tested in different scenarios, demonstrating its robustness in detecting objects under varying conditions, although performance could be improved for challenging environments like low light or cluttered scenes.

8.2 Limitations of the Project:

Despite its successes, there were some limitations to the project. One notable limitation was the detection of objects in low-light conditions, where the model struggled to maintain accuracy. Additionally, while the

system performed well in controlled environments, detecting objects in highly dynamic or cluttered scenes posed challenges. Another limitation was the processing time for video feeds with multiple objects. Although the system was optimized for speed, the model occasionally lagged when processing complex scenes with many overlapping objects. The resource constraints of the Raspberry Pi also meant that more sophisticated models with higher accuracy could not be deployed without sacrificing real-time performance.

Another limitation was the model's reliance on a predefined set of objects. Expanding the object detection capabilities to a wider range of items could make the system more versatile, but it would require additional training data and optimization to run efficiently on edge devices.

8.3 Future Enhancements and Applications:

Looking forward, several enhancements can be made to improve the system. One major enhancement could be the integration of more advanced object detection models, such as EfficientDet or MobileNet, which could offer better trade-offs between accuracy and computational resources. Further training with a more diverse dataset would improve the model's ability to detect objects in challenging environments, such as crowded or low-light areas.

Additionally, future work could involve expanding the system's capabilities to support more edge devices and wearable technology, like smart glasses. This would make the assistive technology more portable and unobtrusive for visually impaired users. The inclusion of additional features like facial recognition, emotion detection, or spatial awareness could further enhance the system's utility, creating a comprehensive assistive solution for navigation and everyday tasks.

Moreover, integrating cloud-based updates or training modules could help improve the system's adaptability over time, allowing it to learn new objects or refine detection capabilities without requiring complete retraining on edge devices.

Chapter 9

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The following references were used throughout the development of this project:

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