SMART MOBILITY AID
USING ML and IOT

A SUMMER INTERNSHIP PROJECT REPORT

Submitted by
KAVIYA G (2022115106)
RITHIK KUMAR (2022115056)

COLLEGE OF ENGINEERING GUINDY, ANNA UNIVERSITY
ANNA UNIVERSITY: CHENNAI 600 025
NOVEMBER 2024

BONAFIDE CERTIFICATE

Certified that this project report "**SMART MOBILITY AID USING MACHINE LEARNING AND INTERNET OF THINGS**" is the bonafide work of "KAVIYA G (2022115106),RITHIK KUMAR(2022115056)" who carried out the project work under my supervision.

PLACE: CHENNAI
DATE: 18.12.2024

Dr. MOHANA BINDHU
ASSOCIATE PROFESSOR
PROJECT GUIDE
DEPARTMENT OF IST, CEG
ANNA UNIVERSITY
CHENNAI 600025

COUNTERSIGNED

Dr. S. SWAMYNATHAN
HEAD OF THE DEPARTMENT
DEPARTMENT OF INFORMATION SCIENCE AND TECHNOLOGY
COLLEGE OF ENGINEERING, GUINDY
ANNA UNIVERSITY
CHENNAI 600025

ACKNOWLEDGMENT

We would firstly like to express our deep gratitude to our Professor, guide, and mentor, **Dr.Mohana Bindhu**, Associate Professor, Department of Information Science and Technology, who guided us throughout the project and gave useful tips until the end. We express our sincere thanks to **Dr.Swamynathan**, Professor and Head of the Department, Department of Information Science and Technology, for his guidance and support right from the initial stages of the project.

Kaviya G (2022115106)	Rithik Kumar (2022115056)

ABSTRACT

The Smart Mobility Aid project aims to empower visually impaired individuals by offering a solution that enhances their independence and safety while navigating the world. Traditional tools, like white canes and guide dogs, have limitations—white canes detect ground-level obstacles, and guide dogs are costly and require intensive training.

This mobility aid integrates IoT, machine learning (YOLOv8), and real-time feedback systems. It combines sensors, cameras, and voice assistance to provide situational awareness, detect obstacles, and navigate complex environments. It also features fall detection and caregiver notifications, enhancing safety and reducing risks.

The device enables users to move independently through diverse environments such as streets and malls, without relying on human assistance. Designed to be compact and wearable, it offers vital auditory feedback, alerting users to obstacles, steps, or any potential hazards, thus improving their autonomy.

This solution addresses the specific challenges faced by the visually impaired, contributing to a future where accessibility and independence are a reality for all. It represents a significant step in improving the quality of life for those affected by vision impairment.

Contents

Table of Contents5List of Figures5**1 Project Overview** **1**
1.1 Objectives . . . 1
1.1.1 Independence and Safety for Visually Impaired Individuals . . . 1
1.1.2 Fall Detection and Caregiver Notification System . . . 2
1.2 Problem Statement . . . 2
1.2.1 Dependence on Assistance . . . 2
1.2.2 Limited Safety Solutions . . . 3

2 Literature Review **4**
2.1 Existing Solutions for Obstacle Detection . . . 4
2.2 Fall Detection Technologies . . . 4
2.3 Real-time Obstacle Detection with YOLO Models . . . 4
2.4 IoT Applications in Assistive Technology . . . 5
2.5 Gaps in Current Solutions . . . 5

3 SYSTEM DESIGN **6**
3.1 System Architecture Overview . . . 6
3.1.1 Obstacle Detection Module . . . 6
3.1.2 Fall Detection Module . . . 7
3.1.3 Integration of Dual-Module System . . . 7
3.2 Use Case Diagram . . . 8

4 Technology Stack **9**
4.1 Hardware Components . . . 9
4.1.1 Laptop and Webcam . . . 9
4.1.2 MPU6050 Sensor and NodeMCU . . . 9
4.2 Software Components . . . 9
4.2.1 YOLOv8 for Obstacle Detection . . . 9
4.2.2 Arduino IDE and ESP8266 for Fall Detection . . . 9
4.3 Libraries and Frameworks . . . 10
4.3.1 OpenCV . . . 10
4.3.2 TensorFlow/PyTorch . . . 10

5 System Implementation **10**
5.1 Obstacle Detection . . . 10
5.1.1 Input: Video Stream from Webcam . . . 10
5.1.2 Processing: YOLOv8 Obstacle Detection Model . . . 10
5.1.3 Output: Auditory Alerts for Safe Navigation . . . 10
5.2 Fall Detection . . . 11
5.2.1 Input: Data from MPU6050 Sensor . . . 11
5.2.2 Processing: Fall Detection using NodeMCU . . . 11
5.2.3 Output: Notification to Caregiver via Wi-Fi . . . 11
5.3 Integration and System Workflow . . . 11
5.4 Testing and Calibration . . . 13
5.4.1 Obstacle Detection Testing . . . 13
5.4.2 Fall Detection Testing . . . 13
5.4.3 System Calibration . . . 13

5.4.4 User Testing . . . 13

6 Result and Analysis **14**

7 Conclusion **26**

8 Future Works **26**

List of Figures

1 System Architecture: Roadmap showing the integration of obstacle detection and fall detection modules. . . . 7
2 Use Case Diagram . . . 8
3 Notification sent to caregiver via Wi-Fi . . . 12
4 Detected staircases with bounding boxes using the YOLOv8 model . . . 14
5 confusion matrix stairs . . . 15
6 Confidence curve illustrating the relationship between confidence score and F1 performance for stair detection . . . 16
7 YOLOV8 Training Result . . . 17
8 Confusion Matrix Normalized stairs . . . 18
9 YOLOV8 Testing results . . . 19
10 YOLOV8 Testing results . . . 19
11 YOLOV8 Testing results . . . 20
12 YOLOV8 Testing potholes results-I . . . 21
13 YOLOV8 Testing potholes results-II . . . 21
14 YOLOV8 Testing potholes results-III . . . 22
15 Confusion matrix Normalized potholes . . . 22
16 YOLOV8 Testing potholes results-IV . . . 23
17 YOLOV8 Testing potholes results-IV . . . 24
18 Confusion Matrix Potholes . . . 25

1 Project Overview

The **Smart Mobility Aid** project aims to empower visually impaired individuals by enhancing their **independence** and **safety** through modern technologies. Traditional tools like white canes and guide dogs, while helpful, have certain limitations:

- *White canes*: Detect obstacles only at ground level.
- *Guide dogs*: Effective but costly and require extensive training.

To address these challenges, the Smart Mobility Aid integrates:

- **IoT, machine learning, and real-time feedback systems**.
- Sensors, cameras, and voice assistance for comprehensive situational awareness.

Key Features:

- **Obstacle Detection**: Identifies obstacles in real-time, including higher-level obstacles.
- **Voice Assistance**: Provides auditory feedback to help users navigate effectively.
- **Fall Detection and Caregiver Notification**: Alerts caregivers promptly in case of falls.

Designed as a **compact and wearable device**, this aid enables users to navigate *streets, malls, and unfamiliar places* without constant reliance on human guides. By improving accessibility and independence, it significantly enhances the quality of life for individuals with visual impairments.

1.1 Objectives

The primary goal of the Smart Mobility Aid is to provide a **reliable, accessible, and efficient** mobility solution for visually impaired individuals.

1.1.1 Independence and Safety for Visually Impaired Individuals

- **Challenge:** Lack of independence in tasks such as walking and navigating unfamiliar environments.
- **Solution:** Integration of technologies like:
  - *Ultrasonic sensors* and *cameras*: Map the user's surroundings.
  - *Artificial Intelligence (AI)*: Processes real-time data for accurate hazard detection.
- **Real-Time Guidance:** Provides auditory cues for:
  - Obstacle detection.
  - Spatial awareness and route planning.

The device promotes **confidence and control** for users while prioritizing **safety**. By ensuring real-time obstacle detection and hazard notification, it enhances the user's ability to move independently and improves overall **mental and emotional well-being**.

1.1.2 Fall Detection and Caregiver Notification System

Falls are a **critical concern** for visually impaired individuals, particularly when navigating:

- *Busy streets*,
- *Uneven surfaces*, or
- *Unexpected obstacles*.

A fall can result in severe injuries, complicating the already challenging task of moving without vision.

The **Smart Mobility Aid** addresses this issue with an advanced **Fall Detection System**, which:

- Utilizes sensors such as **accelerometers** and **gyroscopes** to monitor the user's movement.
- Detects *falls* or significant loss of balance in real time.
- **Sends immediate alerts** to a designated caregiver or family member when a fall occurs.

Key Benefits:

- Real-time notifications via *smartphone apps* or connected devices.
- Ensures help is available promptly, especially for individuals living alone.
- Adds an **extra layer of security** by combining independence with safety.

This system enhances user safety while reassuring caregivers of their loved one's well-being.

1.2 Problem Statement

While traditional mobility aids provide *basic assistance*, they fall short in delivering:

- **Comprehensive, real-time mobility support**,
- Advanced safety features such as fall detection, and
- Independence for users to navigate freely.

1.2.1 Dependence on Assistance

Visually impaired individuals often rely on:

- *Family members*,
- *Friends*, or
- *Professional guides*.

While this support is invaluable, it limits personal **freedom and autonomy**. Key challenges include:

- Difficulty traveling to new or unfamiliar places,
- Significant planning for even basic daily tasks, and
- Feelings of **isolation** and **frustration**.

The **Smart Mobility Aid** seeks to empower users by:

- Offering **real-time navigation** feedback,
- Integrating **obstacle detection** and **fall prevention**, and
- Reducing dependence on external assistance.

Outcome: Improved independence, confidence, and overall quality of life.

1.2.2 Limited Safety Solutions

Traditional mobility aids, such as:

- *White canes*: Detect ground-level objects but miss overhead obstacles or stairs.
- *Guide dogs*: Effective but costly and require ongoing maintenance.

Key Limitations:

- Inability to detect falls or notify caregivers,
- Lack of comprehensive situational awareness, and
- Inadequate support for navigating unfamiliar environments.

The **Smart Mobility Aid** addresses these limitations by offering:

- **Real-time obstacle detection** and navigation assistance,
- **Fall detection** with automatic caregiver alerts, and
- Continuous monitoring for enhanced safety and confidence.

This holistic solution prioritizes both **independence** and **safety**, ensuring that visually impaired individuals can navigate freely, knowing that help is just a notification away.

2 Literature Review

2.1 Existing Solutions for Obstacle Detection

Obstacle detection has long been a critical challenge in assistive technology for the visually impaired. Traditional methods, such as ultrasonic sensors and infrared sensors, are commonly used in systems for detecting obstacles in the environment. These sensors provide distance measurements but are limited in their ability to handle dynamic objects or provide real-time feedback on complex environments.

Recent advancements have moved towards computer vision-based approaches. The use of cameras paired with image processing algorithms has enabled more sophisticated obstacle detection. Techniques like stereo vision, depth sensing, and laser scanning have been applied, offering better detection of 3D obstacles and a more comprehensive understanding of the surrounding environment. However, these methods require significant processing power, and issues like low resolution, occlusion, and lighting conditions remain challenges.

LiDAR-based systems and RGB-D cameras are also increasingly being utilized for their ability to capture 3D data in real time. These systems offer higher accuracy but are often expensive and require bulky setups, limiting their practical applications in portable assistive devices.

2.2 Fall Detection Technologies

Fall detection systems are critical for providing real-time emergency alerts in assistive devices. Traditional fall detection systems rely on accelerometers and gyroscopes embedded in wearable devices, such as wristbands or pendants. These sensors monitor changes in acceleration and orientation, allowing the system to identify a sudden fall event. Upon detecting a fall, these devices typically alert caregivers or emergency services through a pre-programmed communication method (e.g., SMS, email).

Machine learning algorithms, including random forests and support vector machines (SVMs), have been employed to improve the accuracy of fall detection. These algorithms use data from sensors to learn patterns that distinguish between falls and other everyday activities. Recent innovations also incorporate deep learning approaches, utilizing recurrent neural networks (RNNs) and convolutional neural networks (CNNs) to enhance real-time fall detection accuracy and minimize false positives.

Despite these advancements, many fall detection systems still face challenges, including the inability to distinguish between different types of falls, slow response times in emergencies, and the need for user training to wear and use the system properly.

2.3 Real-time Obstacle Detection with YOLO Models

YOLO (You Only Look Once) is a state-of-the-art real-time object detection algorithm widely used for detecting static and dynamic obstacles. YOLO models use convolutional neural networks (CNNs) to classify and locate objects in images or video frames. The key advantage of YOLO is its ability to process images extremely quickly, making it ideal for real-time applications like navigation assistance for the visually impaired.

Recent versions, such as YOLOv4 and YOLOv5, have shown impressive results in object detection tasks with high accuracy and speed. These models are particularly effective at detecting common obstacles like manholes, fallen objects, pedestrians, and street signs. In the context of assistive technologies, YOLO models can be trained on large datasets of obstacle images, enabling the device to detect potential hazards in real time through video feeds captured by on-board cameras.

Integrating YOLO with other sensor data (such as depth information from stereo cameras or LiDAR) has the potential to provide more accurate 3D positioning of obstacles, thereby improving the user's ability to navigate complex environments safely. However, challenges related to training models on diverse environments, low lighting conditions, and real-time processing still remain.

2.4 IoT Applications in Assistive Technology

The Internet of Things (IoT) plays a significant role in enhancing assistive technologies. By connecting various devices, sensors, and systems, IoT allows for the collection and sharing of data in real time, enabling more intelligent and context-aware assistive devices.

In the case of mobility aids for the visually impaired, IoT can integrate various environmental sensors, wearables, and smart infrastructure (e.g., smart traffic lights, smart street signage) to provide real-time information to the user. For instance, smart traffic lights can send signals to mobility aids to indicate whether it is safe to cross the street, while environmental sensors can detect changes in the weather or ground conditions (such as ice or rain) and alert the user.

Additionally, IoT enables remote monitoring, where caregivers or family members can track the location and status of the visually impaired person through connected devices. This allows for immediate response in case of emergencies, such as falls or obstacles encountered. Despite its potential, IoT-based assistive technologies often face challenges with connectivity issues, power consumption, and ensuring user privacy and data security.

2.5 Gaps in Current Solutions

While there have been significant advances in assistive technologies for the visually impaired, several gaps still remain in current solutions:

1. **Limited Real-Time Obstacle Detection:** While existing systems provide obstacle detection, many rely on basic sensors that struggle with dynamic, real-time detection of complex obstacles (e.g., moving pedestrians or cars).

2. **Accuracy in Fall Detection:** Current fall detection systems often suffer from high rates of false positives or false negatives, failing to accurately distinguish between falls and other actions, or to detect falls in certain environments.

3. **Integration of Multi-Sensory Data:** Most current systems rely on individual sensor types, such as ultrasonic sensors or cameras, without fully integrating multi-sensory data from multiple sources (e.g., combining vision with LiDAR or depth sensors for better navigation).

4. **Personalization of User Experience:** Many assistive devices are not personalized enough to account for individual preferences or disabilities, leading to a less effective user experience. Customizable interfaces and adaptive responses based on user behaviors and environments are still underdeveloped.

5. **Real-World Scalability:** Many solutions work well in controlled environments or simulations but face difficulties in scaling to real-world conditions with diverse obstacles, unpredictable behaviors, and environmental changes.

Addressing these gaps requires a holistic approach combining advanced computer vision, machine learning, IoT integration, and personalized feedback systems to create a more reliable, adaptable, and real-time assistive technology for visually impaired individuals.

3 SYSTEM DESIGN

This section outlines the design of the system, focusing on the architecture and components required for obstacle detection and fall detection for the visually impaired. The design is structured to ensure real-time detection, accuracy, and user safety.

3.1 System Architecture Overview

The system architecture is a combination of hardware and software components working together to provide a seamless experience for the user. It includes modules for obstacle detection, fall detection, and the integration of both modules to ensure continuous monitoring.

3.1.1 Obstacle Detection Module

The Obstacle Detection Module is responsible for identifying obstacles in the user's path and providing feedback through audio or haptic alerts. This module uses real-time object detection algorithms, such as YOLO (You Only Look Once), to detect objects in the environment.

- **Camera:** The system utilizes a real-time camera (e.g., mounted on a headpiece or a handheld device) to capture the environment.

- **YOLO Algorithm:** The YOLOv8 (or another suitable version) model is used to detect objects like walls, furniture, steps, and other obstacles in the path of the user. The model is trained on a dataset that includes these obstacles.

- **Feedback Mechanism:** The system provides feedback using a speaker or vibrating motors. For example, the system may alert the user by stating the object detected (e.g., "Wall ahead" or "Step down").

3.1.2 Fall Detection Module

The Fall Detection Module aims to detect if the user has fallen and alert caregivers or emergency services if needed.

- **Sensors:** The module uses accelerometer and gyroscope sensors (such as the MPU6050 or similar modules) embedded in the wearable device. These sensors detect sudden changes in orientation and acceleration, signaling a fall.
- **Algorithm:** The system processes sensor data to differentiate between a fall and normal movement. If a fall is detected, the system triggers an alert.
- **Alert Mechanism:** Once a fall is detected, the system sends an alert via SMS or email to a designated caregiver. Additionally, an audible alarm may be triggered to notify nearby people.

3.1.3 Integration of Dual-Module System

The system integrates both the obstacle detection and fall detection modules to provide a comprehensive safety solution. This integration ensures continuous monitoring of the user's environment and physical status.

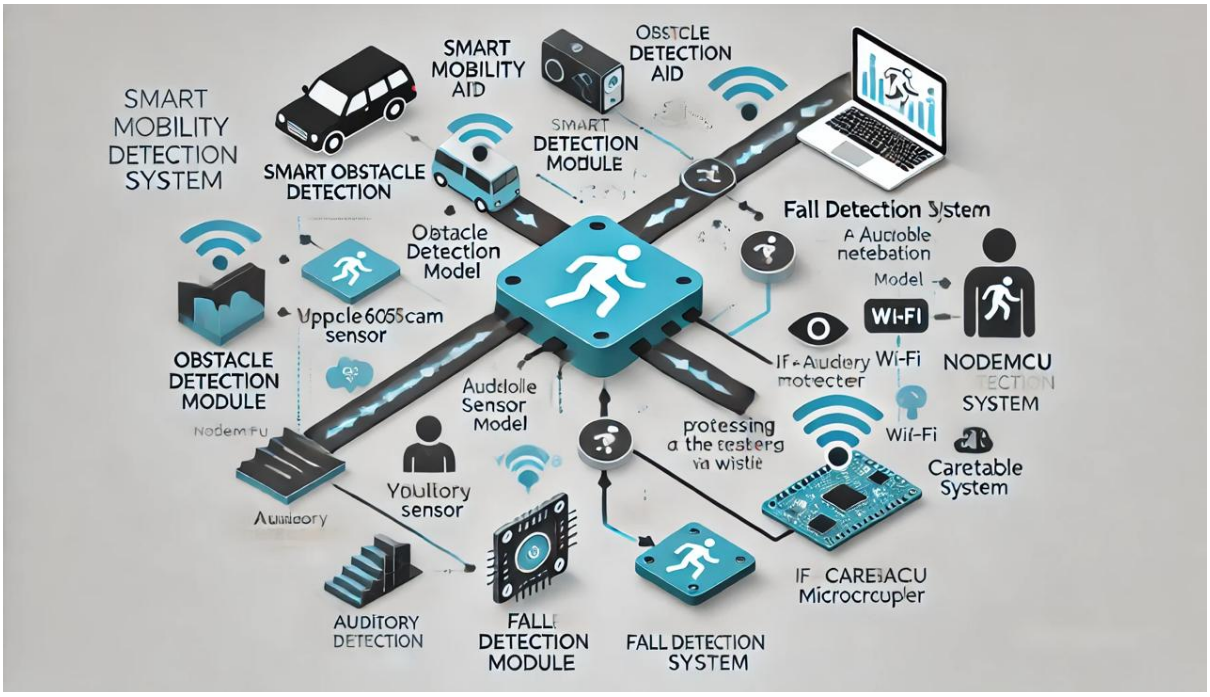

Figure 1: System Architecture: Roadmap showing the integration of obstacle detection and fall detection modules.

- **Central Processor:** Both modules communicate with a central processing unit (e.g., a microcontroller or Raspberry Pi) that processes data from the sensors and camera in real time.
- **Data Fusion:** The system uses data fusion techniques to combine input from both the obstacle detection and fall detection modules to make decisions. For example,

if a fall occurs while the user is approaching an obstacle, the system can prioritize fall detection and immediately alert caregivers.

- **Power Supply:** The integrated system is designed for low power consumption to ensure long-lasting performance, possibly with battery-saving modes when the system is idle or in standby mode.

3.2 Use Case Diagram

The Use Case Diagram will visually represent the interactions between the users (e.g., visually impaired individuals, caregivers) and the system. It will help explain how users engage with the system in different scenarios.

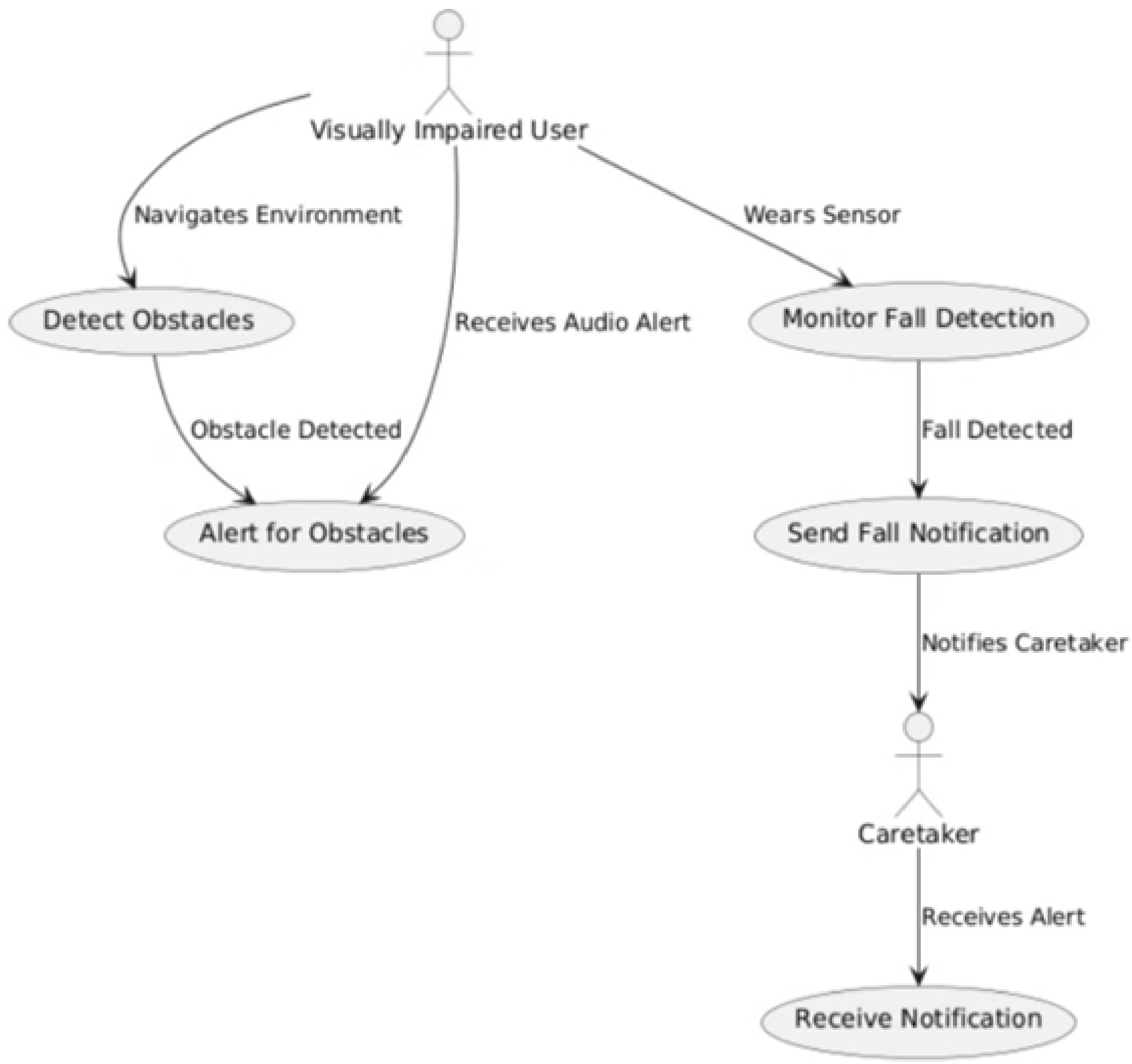

Figure 2: Use Case Diagram

Key Use Cases:

- **Obstacle Detection:** The user encounters an obstacle and receives a feedback alert (audio or haptic).

- **Fall Detection:** The user falls, and the system sends an alert to a caregiver or emergency service.
- **Caregiver Notification:** A caregiver receives an alert about the fall and can take appropriate action.

4 Technology Stack

This section delineates the hardware, software, and libraries/frameworks utilized in the development of the system. Each component plays a pivotal role in ensuring the seamless operation of the obstacle and fall detection functionalities.

4.1 Hardware Components

4.1.1 Laptop and Webcam

The laptop serves as the primary computational device for running the machine learning models and processing video inputs. The webcam captures real-time video streams, which are analyzed for detecting obstacles such as steps and potholes. The high-definition webcam ensures accurate video quality for better detection results.

4.1.2 MPU6050 Sensor and NodeMCU

The MPU6050 is a six-axis motion tracking device combining a 3-axis gyroscope and a 3-axis accelerometer. It detects sudden changes in motion, which helps in identifying falls. The NodeMCU ESP8266, a microcontroller with built-in Wi-Fi capabilities, processes data from the MPU6050 and transmits alerts to connected devices. These components enable real-time fall detection and notification.

4.2 Software Components

4.2.1 YOLOv8 for Obstacle Detection

YOLOv8 (You Only Look Once, version 8) is an advanced deep learning model for real-time object detection. It is used to identify obstacles such as steps and potholes in the video feed provided by the webcam. Its lightweight design ensures high-speed processing while maintaining detection accuracy.

4.2.2 Arduino IDE and ESP8266 for Fall Detection

The Arduino IDE is utilized for programming the NodeMCU ESP8266 microcontroller. The code developed in the IDE enables communication between the MPU6050 sensor and the NodeMCU. Using ESP8266's Wi-Fi module, the fall detection alerts can be transmitted to a server or other devices.

4.3 Libraries and Frameworks

4.3.1 OpenCV

OpenCV (Open Source Computer Vision Library) is employed for image processing tasks, such as capturing frames from the webcam and preprocessing them for input to the YOLOv8 model. It is also instrumental in visualizing the detection results.

4.3.2 TensorFlow/PyTorch

TensorFlow and PyTorch are the deep learning frameworks used to train and deploy the YOLOv8 model. These frameworks provide the necessary tools and libraries for developing robust machine learning models for obstacle detection.

5 System Implementation

The **System Implementation** section describes the technical details of how the **Smart Mobility Aid** system works, focusing on the two main functionalities: **Obstacle Detection** and **Fall Detection**. This section also covers the integration of both modules, the system's workflow, and the testing and calibration process to ensure optimal performance.

5.1 Obstacle Detection

Obstacle detection is crucial for visually impaired individuals to navigate safely. The system uses the **YOLOv8 object detection model** with a webcam as the input to identify hazards like steps and potholes in real-time.

5.1.1 Input: Video Stream from Webcam

The system captures real-time video using a laptop's webcam. The webcam continuously streams video footage, which serves as the primary input for the Obstacle Detection Module. The quality and accuracy of the detection depend significantly on the camera's resolution and positioning, as a clear view of the surroundings is required for obstacle recognition.

5.1.2 Processing: YOLOv8 Obstacle Detection Model

The core of the obstacle detection system is the **YOLOv8 (You Only Look Once)** object detection model. YOLOv8 is known for its speed and accuracy in detecting objects in real-time. In this system, YOLOv8 is trained to identify steps and potholes from the video frames captured by the webcam.

The model processes each frame of the video stream and applies bounding boxes around detected objects (e.g., steps, potholes), providing visual markers for obstacles. YOLOv8 is preferred because of its real-time performance, allowing it to work seamlessly while the user is moving.

5.1.3 Output: Auditory Alerts for Safe Navigation

Once an obstacle is detected, the system provides auditory alerts to the user. These alerts help the user navigate by indicating the presence of hazards. The audio output can be either a pre-recorded voice message or beeps indicating the type of obstacle detected. For instance, the system might say, *"Step ahead"* or beep twice to indicate a pothole.

These auditory alerts are essential for users to take precautionary actions, such as stopping or avoiding the obstacle ahead. The system's quick response ensures that the user can avoid the hazard before it becomes a threat.

5.2 Fall Detection

Fall detection is another critical function of the system. The **MPU6050 sensor** detects the user's movement, and **NodeMCU** processes the data to determine if a fall has occurred.

5.2.1 Input: Data from MPU6050 Sensor

The system uses an **MPU6050 sensor**, which integrates both an accelerometer and a gyroscope to measure linear acceleration and rotational movement. This sensor is worn by the user (typically as part of their clothing or attached to a belt) and constantly monitors their movements. When a fall occurs, it generates a distinctive pattern in the sensor data that indicates a sudden drop in acceleration or a sharp change in orientation.

5.2.2 Processing: Fall Detection using NodeMCU

The **NodeMCU microcontroller** is responsible for processing the data collected by the MPU6050 sensor. It analyzes the sensor data using a fall detection algorithm designed to recognize patterns such as rapid deceleration or a drastic change in body orientation (e.g., the person falling).

If the algorithm detects a fall, the NodeMCU triggers an action to notify caregivers immediately. This real-time processing is crucial for ensuring that any fall is identified and communicated without delay.

5.2.3 Output: Notification to Caregiver via Wi-Fi

Once a fall is detected, the system uses **Wi-Fi** to send an immediate notification to a caregiver. The notification includes important details, such as the time and location of the fall (if location data is available). This allows the caregiver to take prompt action and provide assistance to the individual in need.

5.3 Integration and System Workflow

The Obstacle Detection and Fall Detection modules are integrated into a single system to provide real-time assistance for the user. Both systems operate in parallel and ensure that the user receives timely alerts for obstacles and falls.

- **Obstacle Detection Module** continuously scans the surroundings for hazards, providing auditory alerts when obstacles are detected.

- **Fall Detection Module** constantly monitors the user's movement through the MPU6050 sensor and NodeMCU, sending fall notifications when necessary.

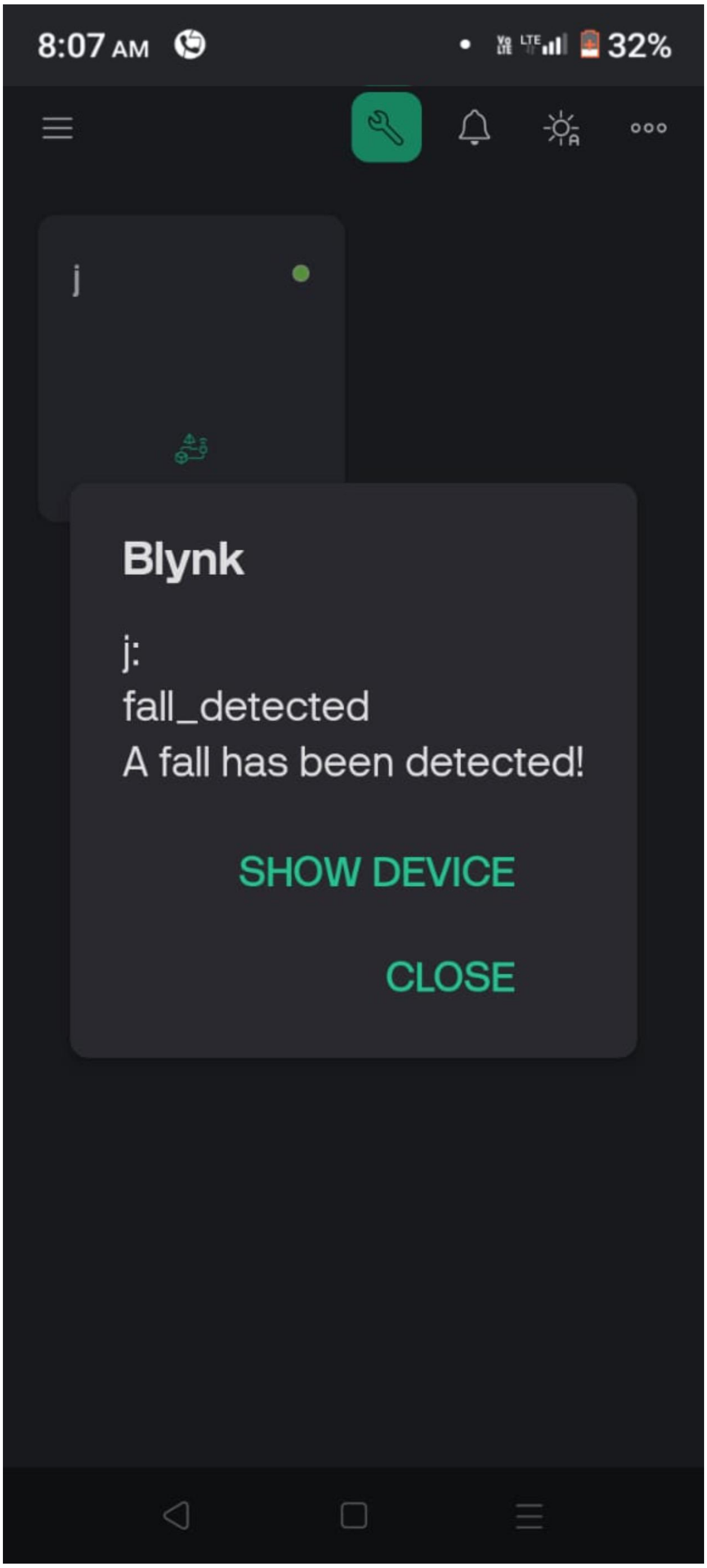

Figure 3: Notification sent to caregiver via Wi-Fi

5.4 Testing and Calibration

Testing and calibration ensure that the system functions as expected and meets the safety requirements. Several rounds of testing are conducted to ensure the system's reliability and accuracy.

5.4.1 Obstacle Detection Testing

The system is tested in different environments with various types of obstacles, such as steps, potholes, and uneven surfaces. The accuracy of the YOLOv8 model is evaluated by comparing its detected obstacles with manually labeled ground truth data. The system's response time is also tested to ensure that the alerts are provided promptly.

5.4.2 Fall Detection Testing

Simulated falls are conducted to evaluate the fall detection algorithm. The MPU6050 sensor data is analyzed for various fall scenarios, ensuring that the NodeMCU can accurately identify falls. Additionally, testing is performed to ensure that the caregiver is notified immediately.

5.4.3 System Calibration

The system's parameters, such as the sensitivity of obstacle detection and the threshold for fall detection, are calibrated based on the results of the testing phase. The system is fine-tuned to optimize performance for real-world use.

5.4.4 User Testing

Real users (visually impaired individuals) participate in testing the system's usability and effectiveness. Feedback is collected regarding the auditory alerts' clarity, the responsiveness of the system, and any difficulties the user might face during operation.

6 Result and Analysis

Figure 4: Detected staircases with bounding boxes using the YOLOv8 model

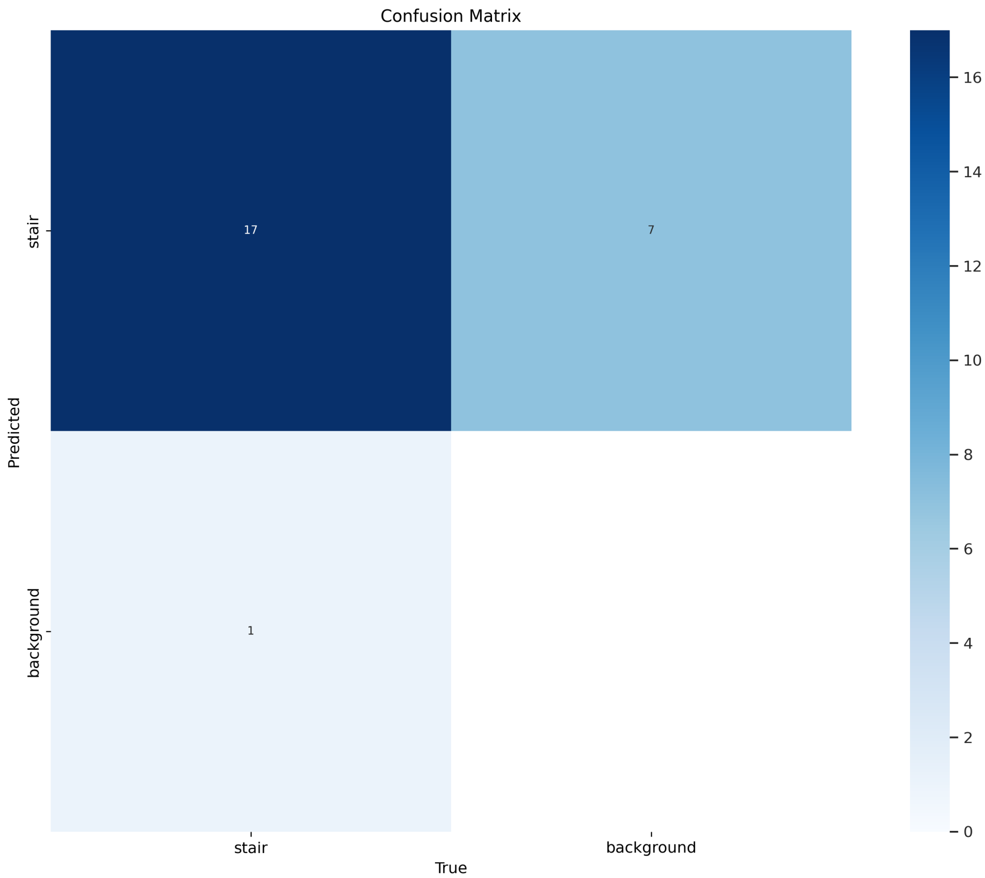

Figure 5: confusion matrix stairs

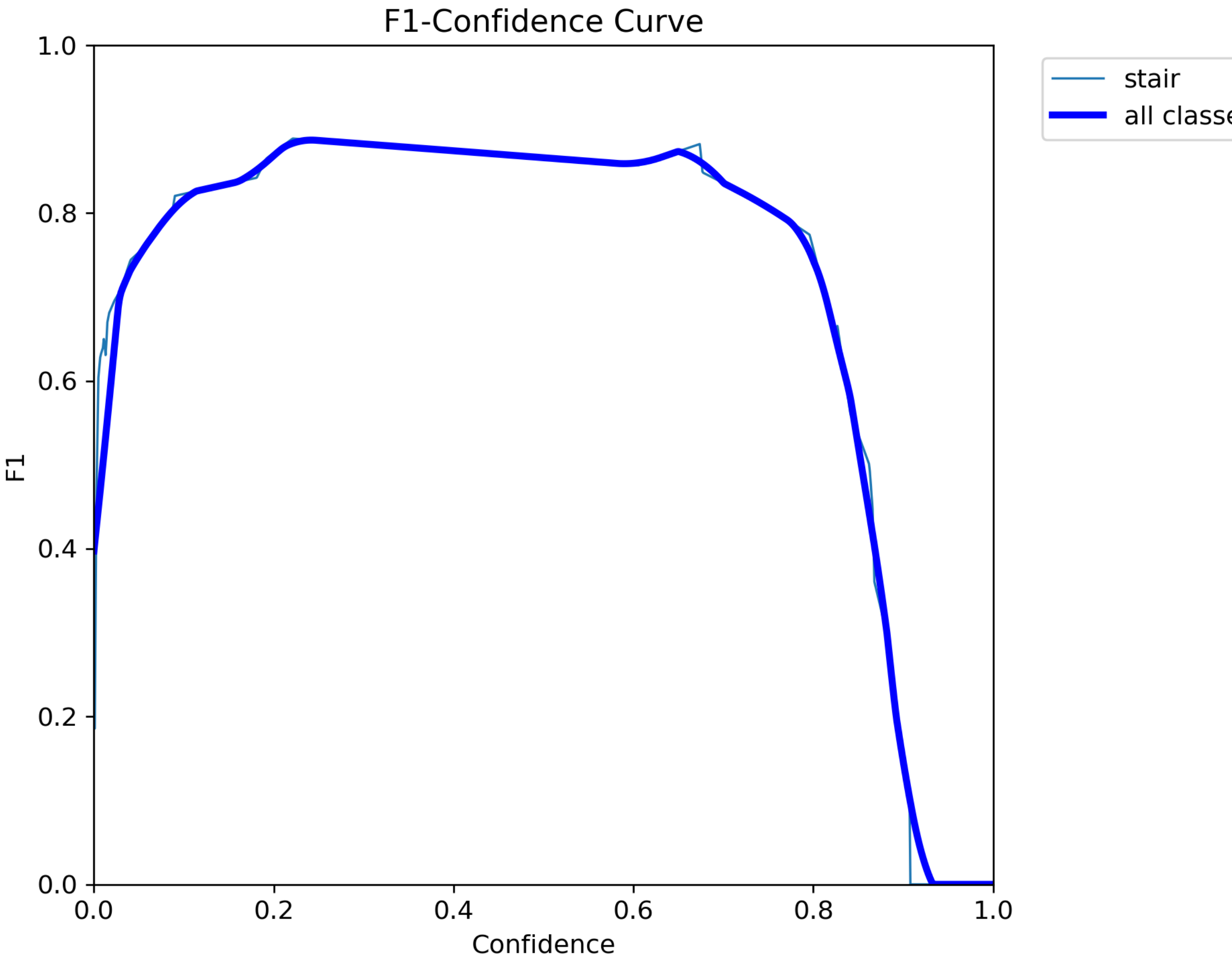

Figure 6: Confidence curve illustrating the relationship between confidence score and F1 performance for stair detection

Figure 7: YOLOV8 Training Result

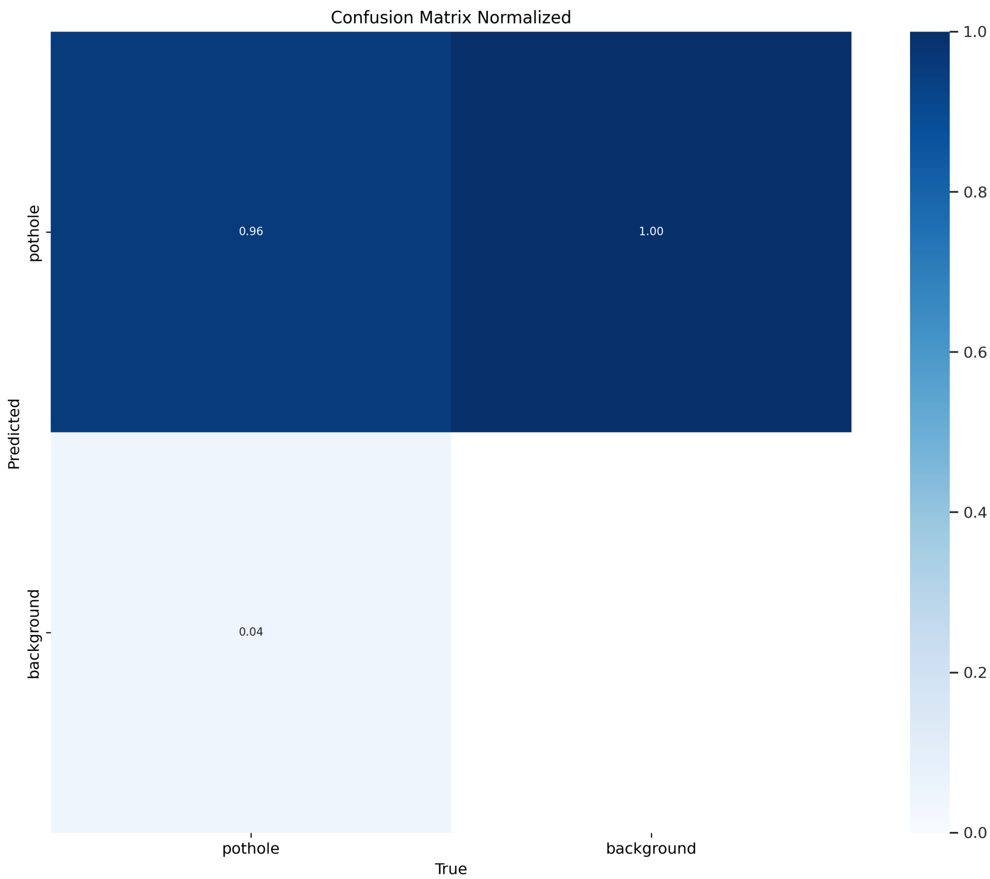

Figure 8: Confusion Matrix Normalized stairs

Figure 9: YOLOV8 Testing results

epoch	train/box_loss	train/cls_loss	train/dfl_loss	metrics/precision(B)	metrics/recall(B)	metrics/mAP50(B)	metrics/mAP50-95(B)	val/box_loss
97	0.80457	0.49877	1.642	0.88792	0.88064	0.86274	0.53411	1.2591
98	0.63153	0.44768	1.4384	0.83563	0.88889	0.85981	0.54709	1.2237
99	0.78015	0.53295	1.586	0.83466	0.88889	0.85993	0.53929	1.2138
100	0.62332	0.42209	1.4431	0.83314	0.88889	0.86035	0.55359	1.2061

Figure 10: YOLOV8 Testing results

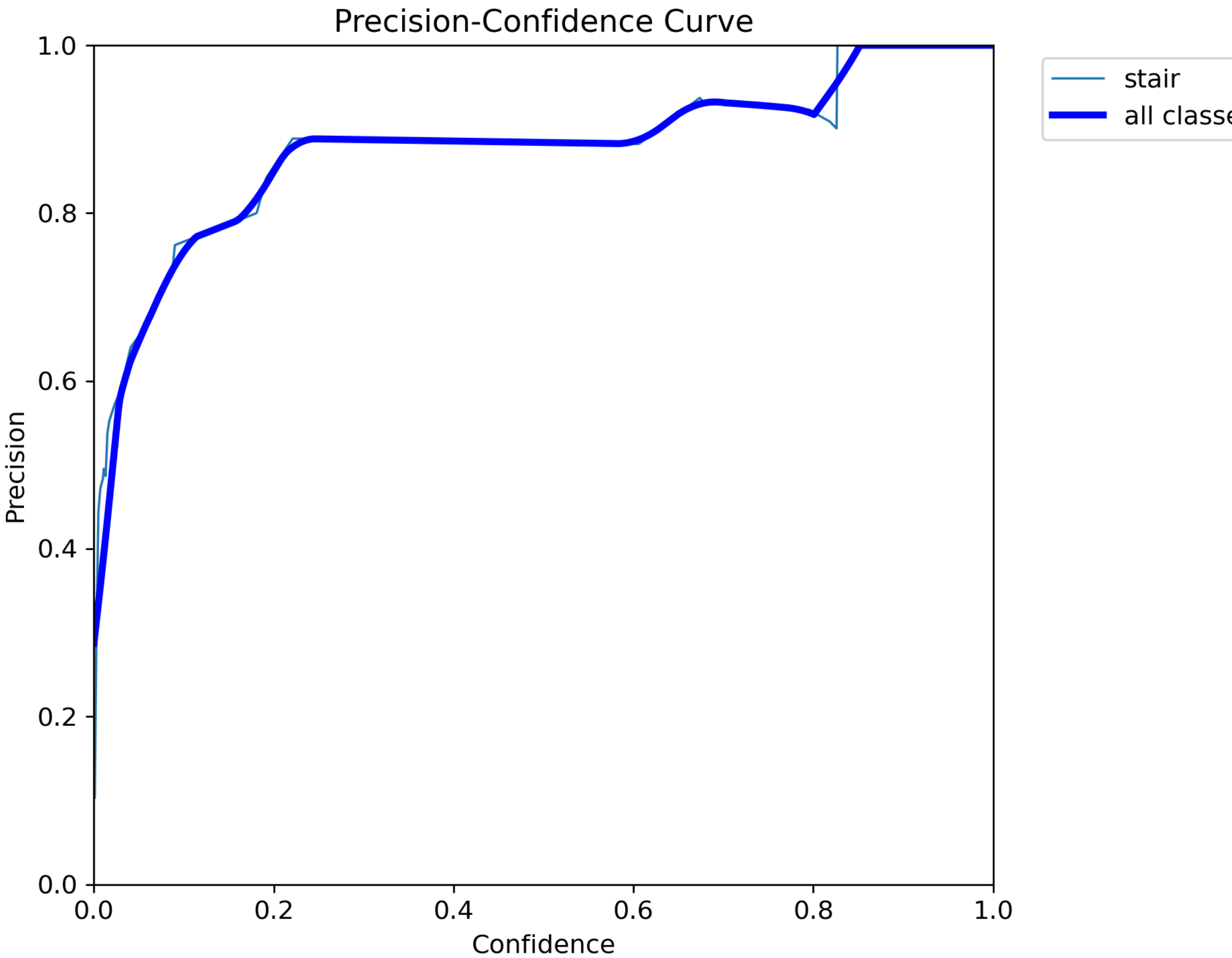

Figure 11: YOLOV8 Testing results

Figure 12: YOLOV8 Testing potholes results-I

epoch	train/box_loss	train/cls_loss	train/dfl_loss	metrics/precision(B)	metrics/recall(B)	metrics/mAP50(B)	metrics/mAP50-95(B)	val/box_loss
97	0.34432	0.28189	0.85242	0.95458	0.99286	0.99312	0.95769	0.33701
98	0.36454	0.30074	0.87346	0.95394	0.99286	0.99334	0.95745	0.32564
99	0.34271	0.28119	0.84304	0.95523	0.99067	0.99323	0.95617	0.32127
100	0.36476	0.2917	0.87154	0.95529	0.99212	0.99333	0.95662	0.32079

Figure 13: YOLOV8 Testing potholes results-II

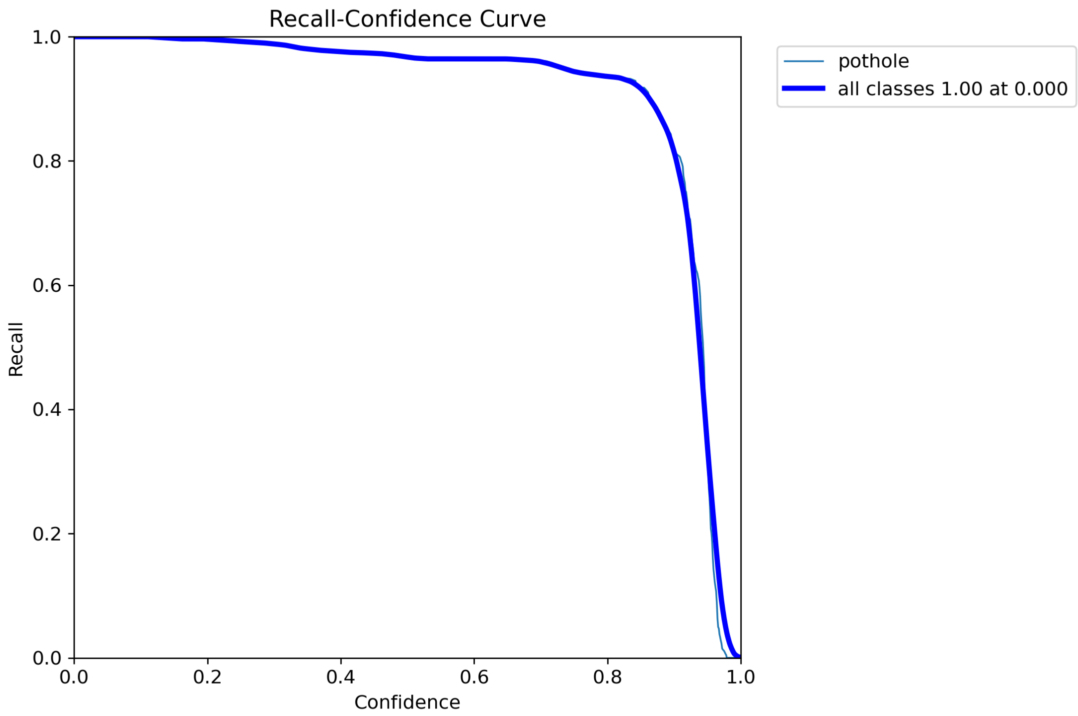

Figure 14: YOLOV8 Testing potholes results-III

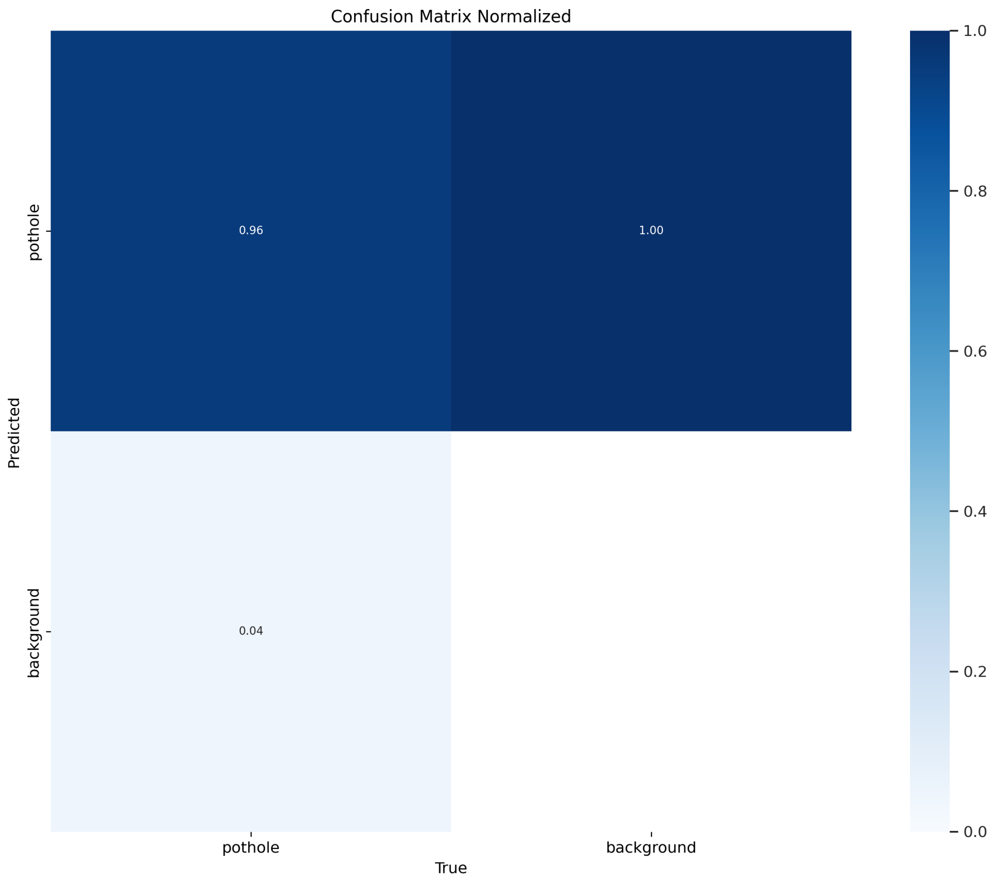

Figure 15: Confusion matrix Normalized potholes

Figure 16: YOLOV8 Testing potholes results-IV

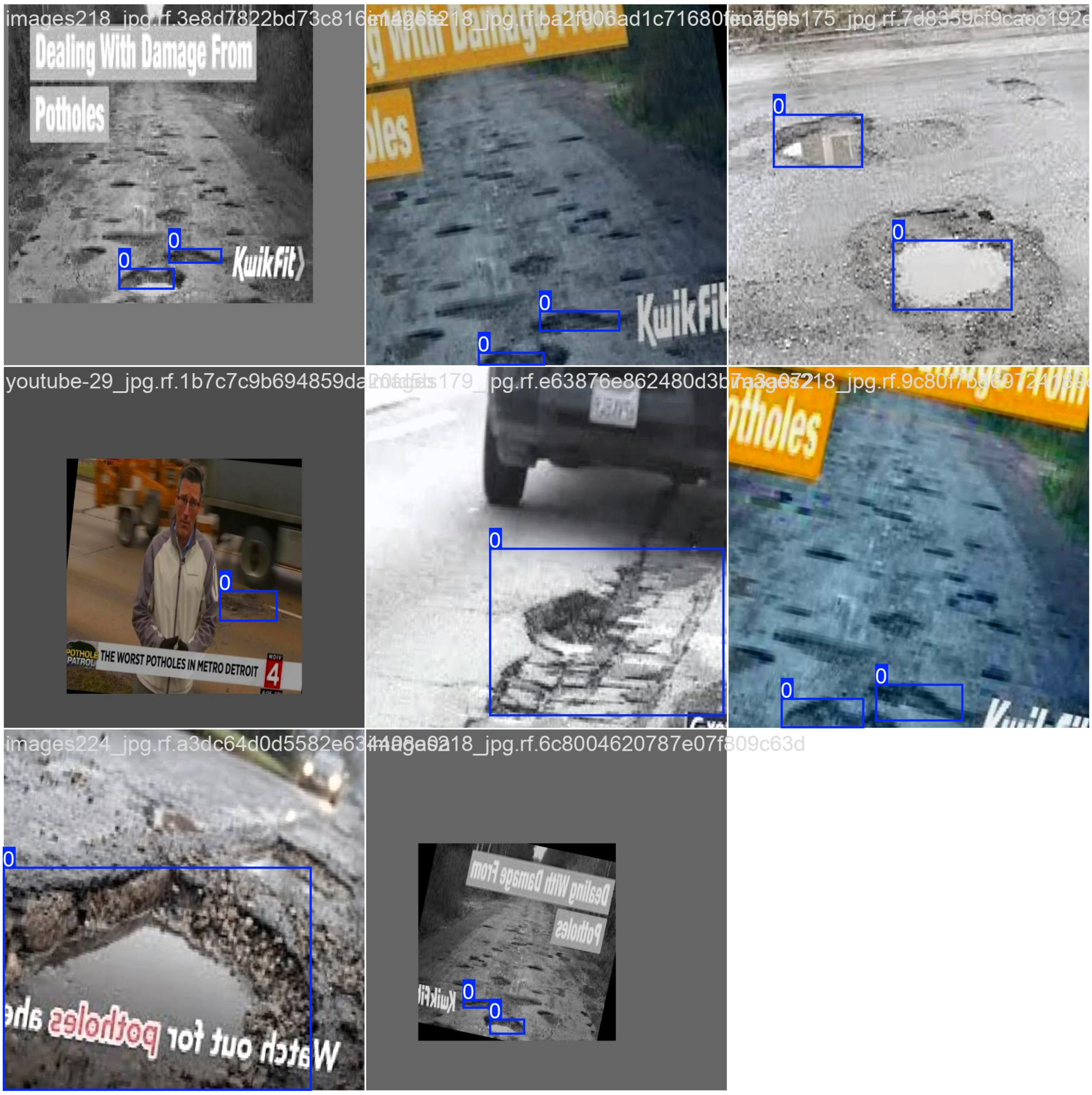

Figure 17: YOLOV8 Testing potholes results-IV

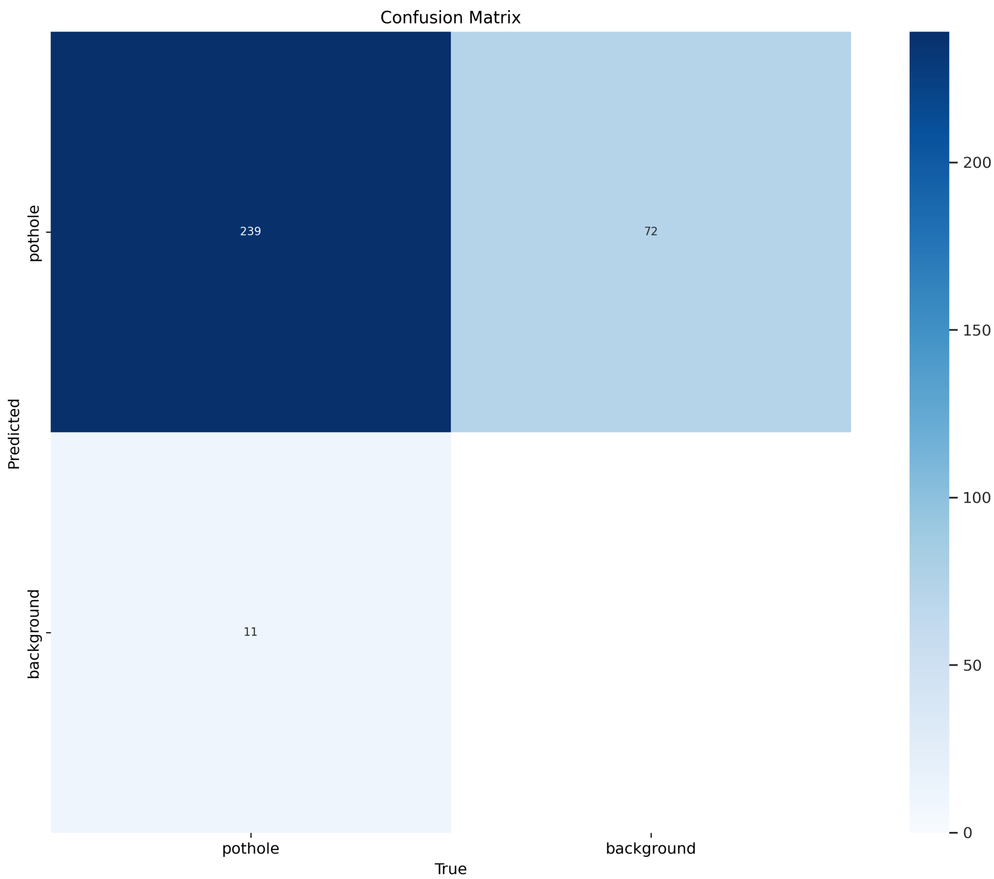

Figure 18: Confusion Matrix Potholes

7 Conclusion

This project addresses the critical challenges faced by visually impaired individuals in their daily navigation, particularly focusing on obstacle detection and fall prevention. By integrating advanced technologies such as YOLO for real-time obstacle detection and accelerometer-based fall detection systems, the proposed solution provides a holistic approach to mobility and safety. Additionally, IoT integration facilitates real-time caregiver notifications, offering an added layer of security and independence for the user.

The Smart Mobility Aid thus bridges the gap between existing assistive technologies and the need for comprehensive, real-time solutions that prioritize both autonomy and safety. While the project demonstrates significant advancements, it also highlights the potential for further improvements and customization.

Through this initiative, we aim to empower visually impaired individuals to navigate the world with confidence, freedom, and minimal dependence on external assistance.

8 Future Works

To deploy the system in a real-world environment and enhance its portability, the following future enhancements are proposed:

1. **Integration with Compact Cameras:** Transition from a laptop-based camera setup to a small, lightweight camera compatible with Raspberry Pi. This compact setup will allow the system to be worn as a necklace or mounted on a dollar chain for easy use.

2. **Deployment on Raspberry Pi:** Implement the entire system on a Raspberry Pi, enabling standalone operation without reliance on external computers. This deployment will optimize the device for real-world use, particularly in outdoor and mobile environments.

3. **Improved Hardware Efficiency:** Optimize the system to ensure low power consumption and efficient processing, crucial for long-term usability in portable devices.

These modifications aim to transition the Smart Mobility Aid from a prototype to a fully deployable assistive device. By integrating a compact camera and Raspberry Pi, the system will become more accessible, user-friendly, and ready for real-world application.

References

1. Redmon, J., Divvala, S., Girshick, R. B., Farhadi, A. (2016). *You Only Look Once: Unified, Real-Time Object Detection.* Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 779-788. https://doi.org/10.1109/CVPR.2016.91.

2. YOLOv8. (2024). *YOLOv8: The Latest in Object Detection Technology.* Ultralytics Documentation. Retrieved from `https://github.com/ultralytics/yolov8`.

3. Rajendra, R., Rajan, S., Bhuvaneshwari, R. D. (2021). *Smart Mobility Aid for Visually Impaired Using IoT and Machine Learning.* Journal of Ambient Intelligence and Humanized Computing, 12(3), 2043-2054. `https://doi.org/10.1007/s12652-020-02779-0`.

4. Chakraborty, P., Mukherjee, A. (2019). *Design and Development of Smart Mobility Aid for Visually Impaired Using IoT and Machine Learning.* Proceedings of the 2019 International Conference on Intelligent Sustainable Systems (ICISS), 100-104. `https://doi.org/10.1109/ICISS.2019.8883745`.

5. NodeMCU Community. (2016). *NodeMCU: An Open Source IoT Platform.* NodeMCU Documentation. Retrieved from `https://www.nodemcu.com/`.

6. Espressif Systems. (2020). *ESP8266 WiFi Module: Low Power, Low Cost Microcontroller.* Espressif Systems Documentation. Retrieved from `https://www.espressif.com/en/products/hardware/esp8266ex/overview`.

7. Salvi, V., Gupta, S. (2018). *IoT Based Blind Assistance System for Visually Impaired People.* International Journal of Advanced Research in Computer Science, 9(1), 1227-1230. `https://doi.org/10.26483/ijarcs.v9i1.6173`.

8. Krishna, P., Siva, K. (2018). *Smart Mobility Aids for Visually Impaired: Using IoT and Image Processing Techniques.* International Journal of Advanced Research in Computer Science, 9(12), 1056-1060. `https://doi.org/10.26483/ijarcs.v9i12.11848`.