INTELLIGENT NAVIGATION SYSTEM FOR THE VISUALLY IMPAIRED USING INTERNET OF THINGS

[1]Chen Xinjia, [1]Mohammad Kamrul Hasan

[1]Faculty of Information Science & Technology
Universiti Kebangsaan Malaysia
43600 Bangi, Selangor

Abstract

Projek ini memberi tumpuan kepada membangunkan sistem navigasi pintar untuk individu cacat penglihatan menggunakan teknologi Internet of Things (IoT). Ia menangani masalah yang sering dihadapi oleh pengguna cacat penglihatan perjalanan yang tidak selamat disebabkan pengesanan halangan yang lemah, kekurangan sokongan navigasi masa nyata dan pilihan komunikasi kecemasan yang terhad. Penyelesaian yang dicadangkan menyepadukan tongkat panduan pintar yang dilengkapi dengan sensor ultrasonik, inframerah, api, air dan kecondongan. Ia menggunakan Rangkaian Neural Cetek Rawak (RSNN) untuk pengesanan bahaya masa nyata dan model YOLOv11n dengan PiCamera untuk pengecaman objek. Sistem ini dibangunkan menggunakan seni bina IoT pelayan pelanggan tambahan dengan Python, Flask, Raspberry Pi 5, GPS, modul GSM dan teknologi web. Ia juga termasuk butang kecemasan untuk permintaan bantuan segera dan aplikasi web yang menyediakan navigasi langsung, perkongsian lokasi dan pemantauan persekitaran. Hasilnya ialah sistem navigasi pintar yang berfungsi sepenuhnya. Ketepatan pengesanan objeknya melebihi 90%, lebih tinggi daripada sistem ultrasonik tradisional yang tidak mempunyai keupayaan pengecaman visual. Sistem ini menyediakan klasifikasi kecemasan berasaskan AI, operasi dalaman dan luaran yang stabil dengan masa tindak balas di bawah dua saat. Ia juga menyediakan maklum balas fizikal yang berkesan melalui getaran, buzzer dan gesaan suara. Berbanding dengan sistem navigasi sedia ada, sistem ini mempunyai ketepatan pengesanan yang lebih tinggi, masa tindak balas yang lebih pantas dan lebih banyak ciri maklum balas. Ini membantu pengguna cacat penglihatan untuk melakukan perjalanan dengan lebih selamat, cekap dan berdikari sambil membenarkan keluarga mereka memantau lokasi dan persekitaran mereka dalam masa nyata, akhirnya meningkatkan mobiliti dan kualiti hidup pengguna.

Kata kunci: Internet of Things, Navigasi Pintar, Cacat Penglihatan, YOLOv11n, RSNN

Abstract

This project focuses on developing an intelligent navigation system for visually impaired individuals using Internet of Things (IoT) technology. It addresses the problem that visually impaired users often face unsafe travel due to poor obstacle detection, lack of real-time navigation support, and limited emergency communication options. The proposed solution integrates a smart guide cane equipped with ultrasonic, infrared, fire, water, and tilt sensors. It uses a Randomized Shallow Neural Network (RSNN) for real-time danger detection and a YOLOv11n model with PiCamera for object recognition. The system was developed using an incremental client-server IoT architecture with Python, Flask, Raspberry Pi 5, GPS, GSM modules, and web technologies. It also includes an emergency button for immediate help requests and a web application that provides live navigation, location sharing, and environment monitoring. The outcome is a fully functional intelligent navigation system. Its object detection accuracy is over 90%, higher than traditional ultrasonic systems that lack visual recognition capabilities. The system provides AI-based emergency classification, stable indoor and outdoor operation with response times below two seconds. It also provides effective physical feedback through vibration, buzzer, and voice prompts. Compared with existing navigation systems, the system has higher detection accuracy, faster response time and more feedback features. This helps visually impaired users to travel more safely, efficiently, and independently while allowing their families to monitor their location and environment in real time, ultimately enhancing user mobility and quality of life.

Keywords: Internet of Things, Intelligent Navigation, Visual Impairment, YOLOv11n, RSNN

1.0 INTRODUCTION

The advancement of Internet of Things (IoT) technology has significantly transformed various aspects of daily life, including smart homes, healthcare, and transportation. However, visually impaired individuals continue to face substantial difficulties in safe and independent navigation. Existing navigation systems often lack real-time obstacle detection, efficient sensor integration, and effective emergency communication features. These limitations make them inadequate in dynamic and complex environments.

According to the World Health Organization (2023), more than 2.2 billion people around the world are affected by some form of visual impairment. Despite this large population, many current navigation tools offer limited functionality, such as static GPS tracking or single-sensor obstacle detection. These solutions cannot provide visually impaired users with accurate and timely feedback that is essential for safe travel in unfamiliar or crowded environments.

Previous studies have introduced various assistive navigation systems using IoT and sensor-based technologies. For example, Rahman et al. (2018) developed a smart guide cane that combines ultrasonic sensors and a GSM module to deliver audio feedback. Ahmed et al. (2022) proposed a system with GPS and GSM for location tracking and emergency contact. Mahida (2021) implemented RFID and Bluetooth for indoor navigation. Roy and Shah (2022) created a cloud-connected cane that transmits environmental data to enhance obstacle awareness. Although these systems offer improvements in mobility support, many of them still lack real-time prediction, integrated multi-sensor logic, and user-friendly interaction models.

This project presents an intelligent navigation system for visually impaired individuals that integrates a smart guide cane with a supporting mobile application. The cane is equipped with multiple sensors, including ultrasonic, infrared, fire, water, and tilt sensors, for comprehensive obstacle detection. The system uses a YOLOv11n model for object recognition through a PiCamera, and a Randomized Shallow Neural Network (RSNN) to classify environmental danger in real time based on sensor data. A dedicated emergency button allows the user to send an instant SMS alert to family members. The mobile application provides real-time navigation, location sharing, and environment monitoring.

The system uses a modular client-server IoT architecture built with Python, Flask, and Raspberry Pi 5, along with GPS, GSM, and Firebase cloud services. Users receive alerts through vibration motors, buzzers, and voice prompts, allowing them to travel more safely and independently. Compared with traditional ultrasonic-based systems, the proposed solution offers higher detection accuracy, faster response time, and more reliable feedback mechanisms. This project ultimately aims to improve mobility, safety, and the overall quality of life for visually impaired individuals through accessible and intelligent technology.

2.0 LITERATURE REVIEW

Recent advancements in Internet of Things and Artificial Intelligence have enabled the creation of intelligent navigation systems that provide visually impaired individuals with improved independence, safety, and mobility. These systems typically combine real-time sensor data collection, local processing capabilities, and multimodal feedback to help users navigate complex environments more confidently.

Various researchers have proposed IoT-based solutions for assistive navigation. Guerrero et al. (2012) developed an indoor system using infrared sensors and a white cane attachment to detect obstacles and provide voice feedback. Rahman et al. (2018) introduced a smart cane that integrates ultrasonic sensors and a GSM module to detect obstacles and send emergency messages. Ahmed et al. (2022) enhanced this approach by incorporating Global Positioning System and Global System for Mobile Communications features, allowing the user to share their location and request assistance through a mobile application. Mahida (2021) applied Bluetooth and Radio Frequency Identification technology to improve indoor navigation accuracy, and Roy and Shah (2022) presented a cloud-based smart cane that sends real-time sensor data to enhance environmental awareness.

While these studies demonstrated the effectiveness of basic IoT navigation aids, they faced limitations in sensor synergy, response time, and context-sensitive feedback. Most systems rely on threshold-based logic without integrating advanced environmental modeling, and their user interaction features are often limited to basic audio or vibration signals.

To address these limitations, recent studies have explored the integration of Artificial Intelligence. Vorapatratorn (2021) used Convolutional Neural Networks and stereo cameras to detect obstacles and guide users through audio prompts. Parvadhavardhni et al. (2023) combined YOLO models with ultrasonic sensors, cameras, and Raspberry Pi to enable real-time object classification and feedback in both indoor and outdoor scenarios. Rathnayake et al. (2023) applied machine learning models such as k nearest neighbor, support vector machine, and decision trees to Received Signal Strength Indicator data for indoor positioning when Global Positioning System is not available. Ying et al. (2018) introduced a deep learning sensory navigation framework that runs on an embedded processor to recognize obstacles in real time. Kumar and Jain (2022) built a portable navigation system using YOLOv5, Raspberry Pi, ultrasonic sensors, and cameras to improve object recognition and navigation accuracy.

These intelligent systems demonstrate the power of Artificial Intelligence in improving object detection accuracy and decision making. However, most systems require substantial computational power or depend on cloud computing, which affects latency and power efficiency. Therefore, several studies have started exploring embedded models such as TinyML or randomized shallow neural networks. These lightweight solutions allow fast local processing, reduce power usage, and preserve user privacy by avoiding remote data transmission.

Moreover, many existing systems do not support flexible feedback mechanisms. Basic audio or vibration alerts may not be sufficient for every situation. Adaptive systems capable of adjusting their output based on the environment and user context can further improve safety and accessibility.

Another limitation in earlier studies is the lack of support for caregiver involvement. Most systems are designed only for user self-navigation. Ahmed et al. (2022) demonstrated the potential of location sharing through mobile applications, but few systems offer full web-based monitoring or remote emergency alerts. Newer architectures integrating cloud databases and web platforms allow caregivers to monitor system status, track location, and receive automatic notifications in emergencies.

In summary, current literature shows a clear transition from single-sensor smart canes to intelligent systems that use multisensor data and local Artificial Intelligence models. While great progress has been made, more work is needed to improve real-time responsiveness, sensor fusion accuracy, embedded processing efficiency, and user-centered interaction design. Future research should focus on developing comprehensive and accessible navigation systems that adapt to the real-world needs of visually impaired individuals, ultimately improving safety, mobility, and quality of life.

3.0 METHODOLOGY

This section outlines the methodology adopted for designing and developing the intelligent navigation system for visually impaired individuals. It includes needs analysis and conceptual model design to address the identified challenges in mobility and environmental awareness.

3.1 Needs Analysis

To ensure that the proposed intelligent navigation system meets the actual needs of visually impaired individuals, a comprehensive needs analysis was conducted using a multi-pronged approach that included literature review, prototype-based observation, and contextual design analysis. The objective was to understand the challenges encountered in real-world navigation and translate them into functional system requirements. The analysis focused on identifying gaps in existing solutions, determining usability constraints, and ensuring that the system remains effective in dynamic and unpredictable environments.

An early prototype of the smart guide cane was developed incorporating core sensing components such as ultrasonic sensors, infrared sensors, flame and water sensors, and a tilt sensor. This prototype was tested in real-world-like scenarios including indoor corridors, campus walkways, and open pedestrian areas. The field observations revealed several persistent issues: ultrasonic-only systems often failed to detect surface-level hazards like puddles, infrared sensors lacked reliability in extreme sunlight, and users experienced difficulty recognizing alerts in noisy environments. These findings demonstrated the need for diverse sensor types and emphasized the importance of multimodal feedback mechanisms.

In addition to field trials, prior studies and applications were reviewed to identify shortcomings in current navigation aids. Many commercial smart canes were found to be limited in scope, using only a single type of sensor and offering basic buzzer alerts. Systems based solely on GPS lacked responsiveness in obstacle detection, and none of the evaluated solutions provided emergency communication features such as real-time SMS alerts or location broadcasting. This review informed the decision to adopt an integrated architecture combining multiple sensors and wireless modules, aiming to increase both safety and situational awareness for users.

Figure 1 illustrates the overall system architecture of the proposed intelligent navigation system. The framework follows an Internet of Things (IoT) structure, linking physical sensing modules with local processing and wireless communication to deliver responsive feedback and remote monitoring functionality.

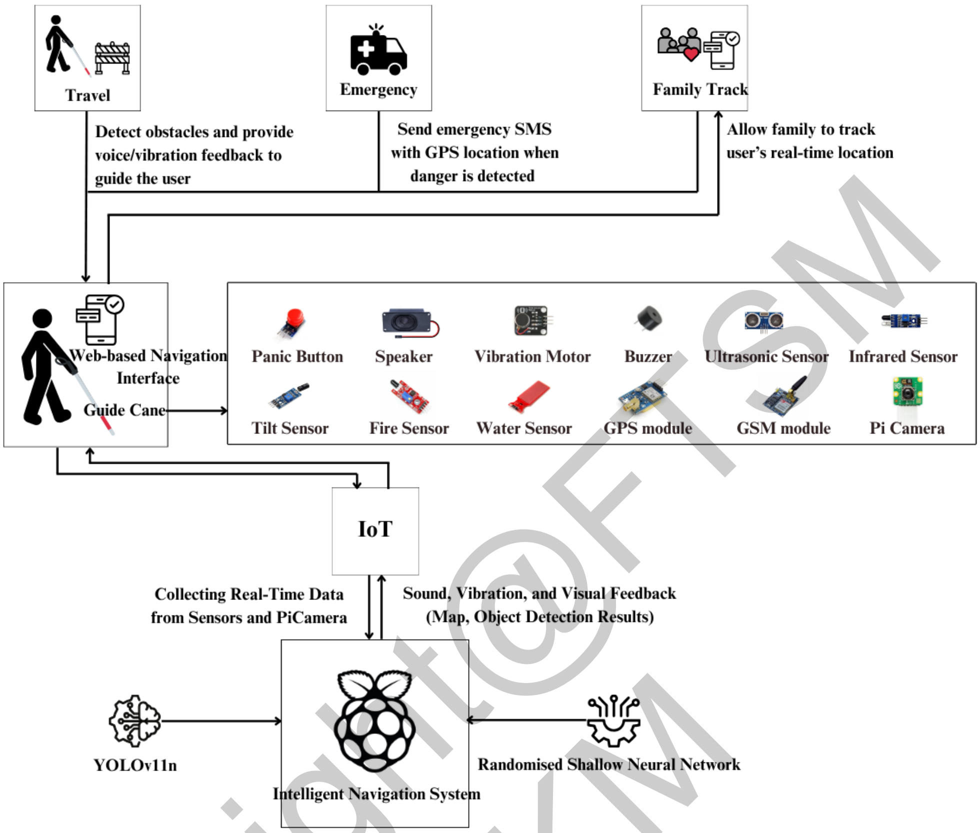

Figure 1: Proposed intelligent navigation system for the visually impaired using IoT

To ensure portability and efficient internal design, the hardware layout of the guide cane was organized to reduce weight and maximize modularity. As shown in Figure 2, each sensor module was strategically positioned to support specific spatial detection needs. Forward, downward, and lateral. This arrangement also facilitated convenient maintenance and replacement of components, making the device more durable and user-friendly in daily use.

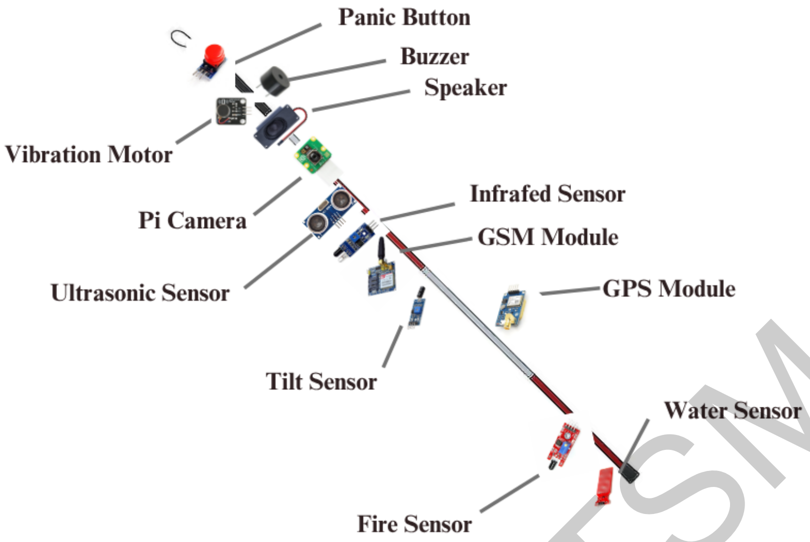

Figure 2: Arrangement of the components of the proposed guide cane

Furthermore, to interpret the raw sensor data intelligently and ensure low-latency reaction, embedded lightweight AI models were introduced. As illustrated in Figure 3, the data collected from the environment is processed using real-time classification logic that maps sensor inputs to specific feedback outputs such as vibration, audio alerts, and SMS messages. The embedded logic also determines emergency states, such as falls or flame detection, and immediately triggers predefined responses without requiring user intervention.

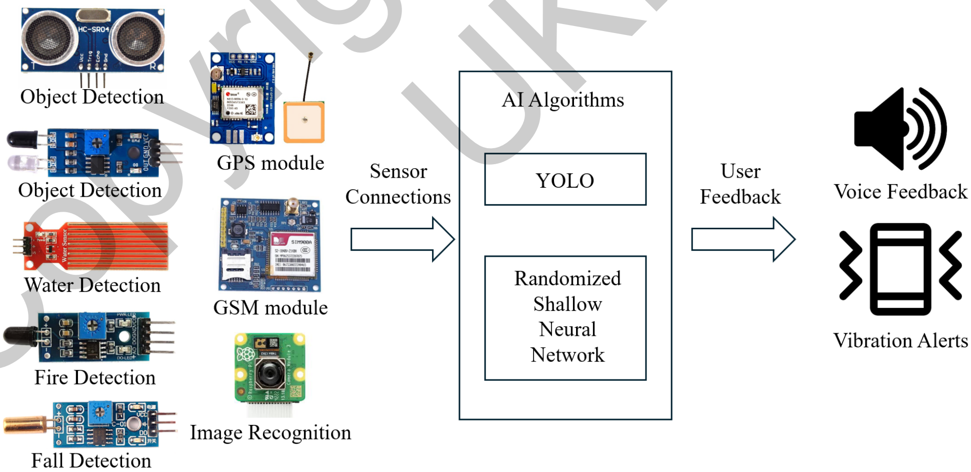

Figure 3: Sensor integration and AI-driven feedback mechanism in the proposed system

The user-side monitoring component was designed to support family members or caregivers in tracking system status remotely. The interface, displayed in Figure 4, presents real-time data from each sensor channel and displays environmental hazard alerts when triggered. Figure 5 shows the object detection interface that integrates live GPS coordinates, offering a map-based visualization of the user's position and surrounding threats, thereby enabling prompt action in emergencies.

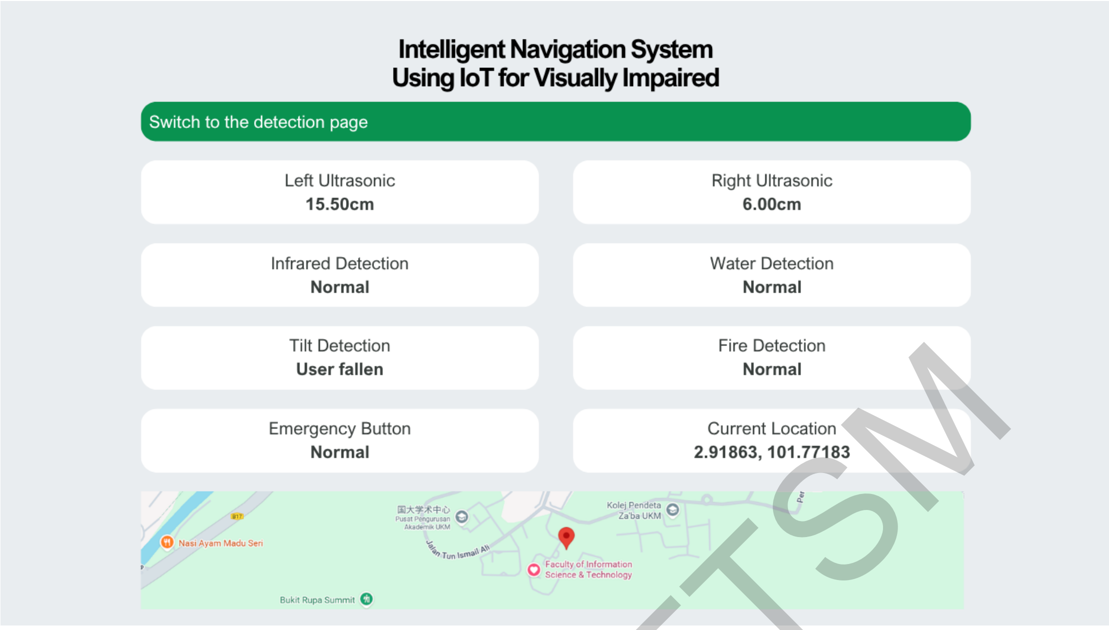

Figure 4: Sensor monitoring interface

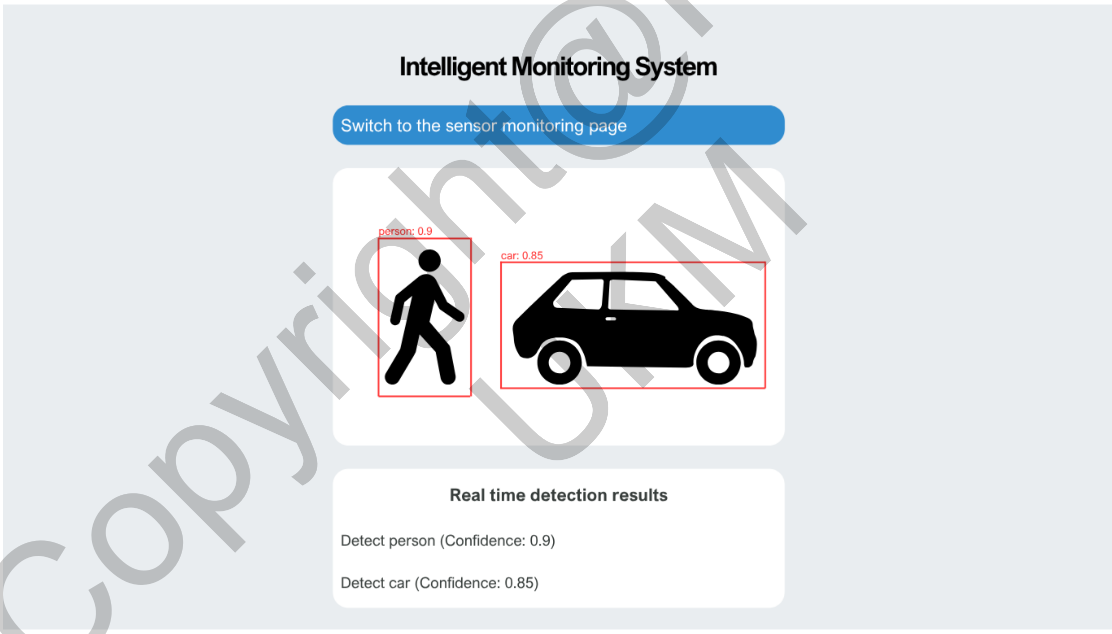

Figure 5: Object detection monitoring interface

This multi-layered needs analysis ensured that the resulting design addressed both technical feasibility and user comfort, accounting for the unpredictable nature of real-world travel. The combination of observational testing, critical literature review, and iterative prototype refinement contributed to a system that is responsive, resilient, and truly tailored to the needs of visually impaired individuals.

3.2 Conceptual Model Design

The conceptual model of the intelligent navigation system defines the logical structure and interaction flow between various modules, ensuring that both software and hardware components operate in a cohesive and user-oriented manner. The system is designed using a modular client server architecture, with the Raspberry Pi 5 serving as the core processing unit. This architecture was chosen to support scalable sensor integration, responsive feedback, and secure communication across modules.

At the highest level, the system behavior and user interactions are summarized through a case diagram, as shown in Figure 6. This diagram outlines essential functions such as initiating navigation, detecting obstacles, handling emergencies, and enabling remote monitoring. Each use case links system modules with user goals, ensuring that design priorities align with real-world usage scenarios. For example, when the user starts navigation, the system automatically initiates sensor checks, communication setup, and readiness confirmation through voice feedback.

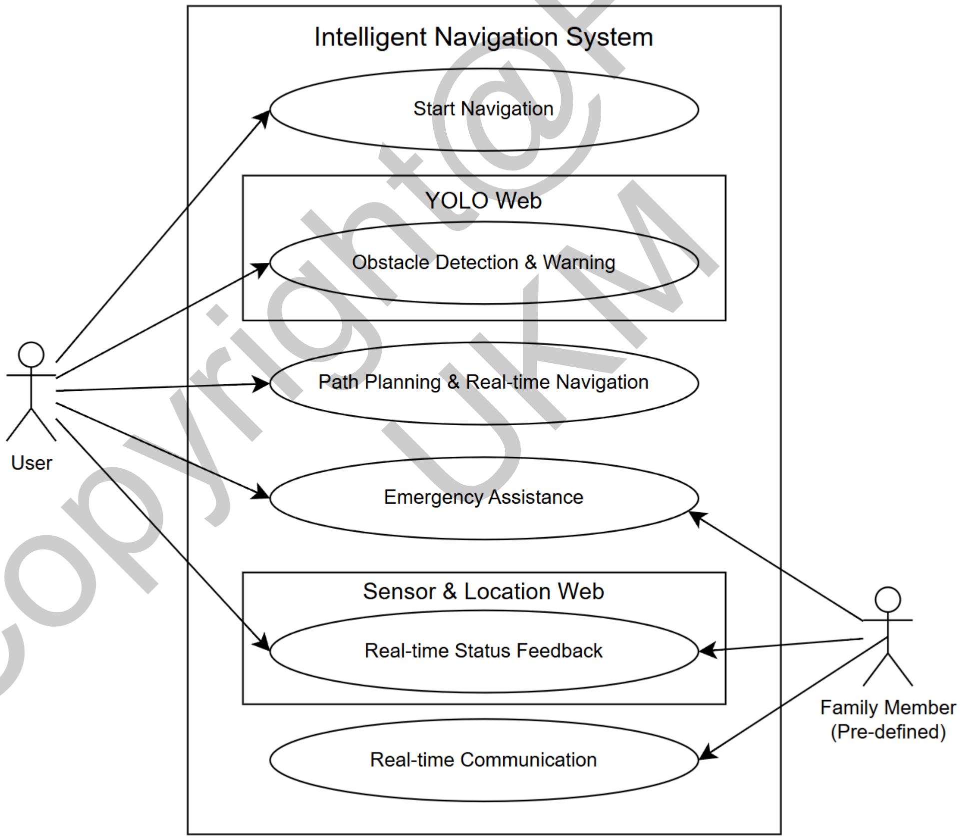

Figure 6: Case diagram of an intelligent navigation system

The architecture is further decomposed into five core functional modules: sensor, data processing, communication, feedback, and client. The sensor module, illustrated in Figure 7, includes the ultrasonic, infrared, flame, water, and tilt sensors, along with an emergency button. These components form the sensory layer of the system, continuously collecting data from the environment and detecting anomalies such as nearby obstacles, dangerous surfaces, or abnormal cane orientation.

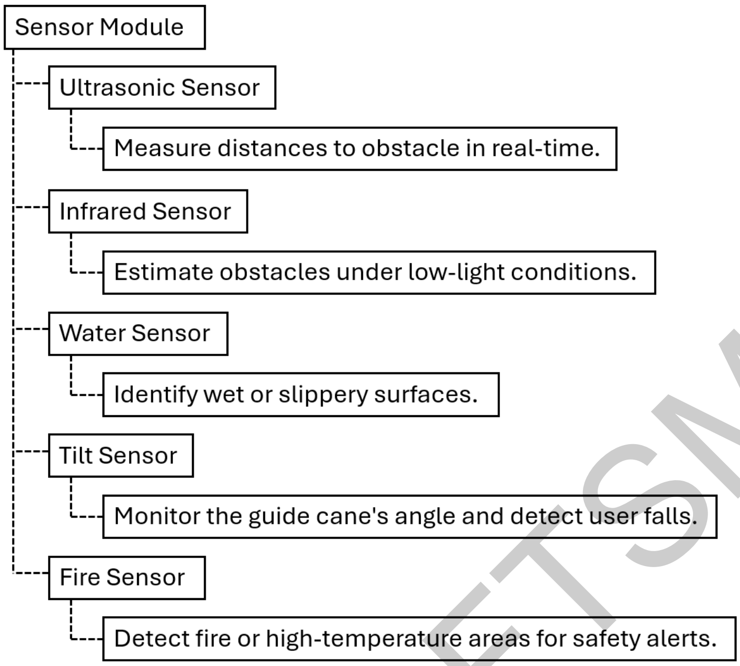

Figure 7: Sensor module hierarchy chart

The collected data is passed to the data processing module, shown in Figure 8. This module incorporates signal filtering and feature extraction routines, which normalize and interpret the incoming sensor data. It also includes lightweight embedded intelligence in the form of a Randonmized Shallow Neural Network (RSNN), enabling real-time emergency classification based on a seven dimensional input vector. The RSNN model executes directly on the Raspberry Pi and determines whether the current state is safe or requires alert triggers.

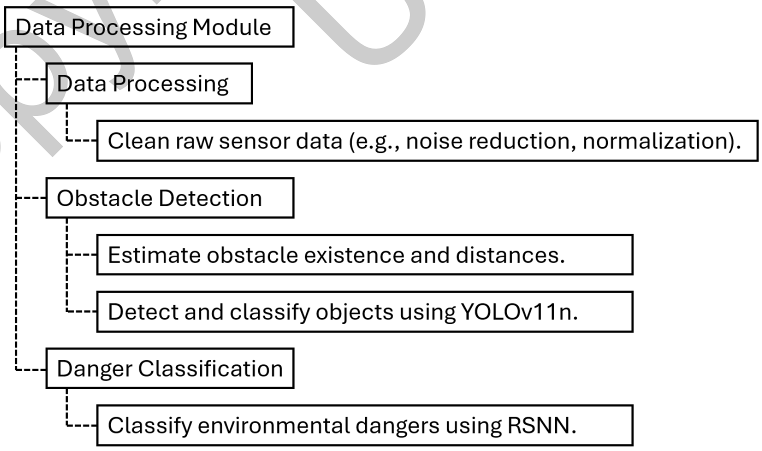

Figure 8: Data processing module hierarchy chart

Once the system classifies the context, the communication module, depicted in Figure 9, facilitates outbound interaction through GSM and GPS technologies. It sends emergency SMS alerts to predefined contacts along with real-time location coordinates and also transmits data to the web server for live monitoring. Communication is bidirectional because the server may also send configuration updates or polling requests to the client.

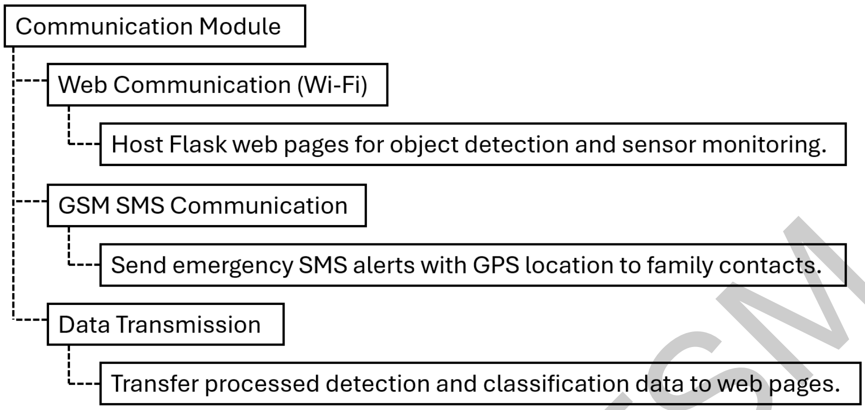

Figure 9: Communication module hierarchy chart

The feedback module, illustrated in Figure 10, is responsible for delivering immediate user alerts based on detection and classification results. It controls vibration motors, buzzers, and a speaker module that issues voice prompts. Depending on the detected threat, different feedback combinations are activated to ensure the user perceives the alert regardless of environmental conditions.

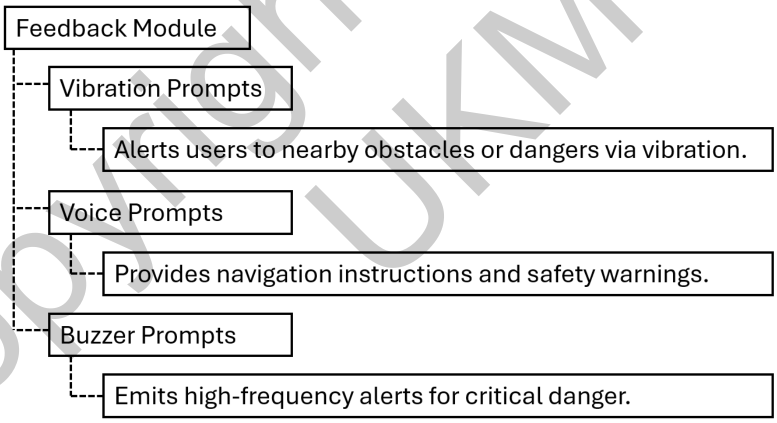

Figure 10: Feedback module hierarchy chart

The final module is the client interface module, visualized in Figure 11. This module handles front end display on web pages and mobile compatible browsers, allowing users and family members to view live sensor readings, object detection results, and location tracking. It integrates seamlessly with the Flask based backend and retrieves data asynchronously through JavaScript polling mechanisms.

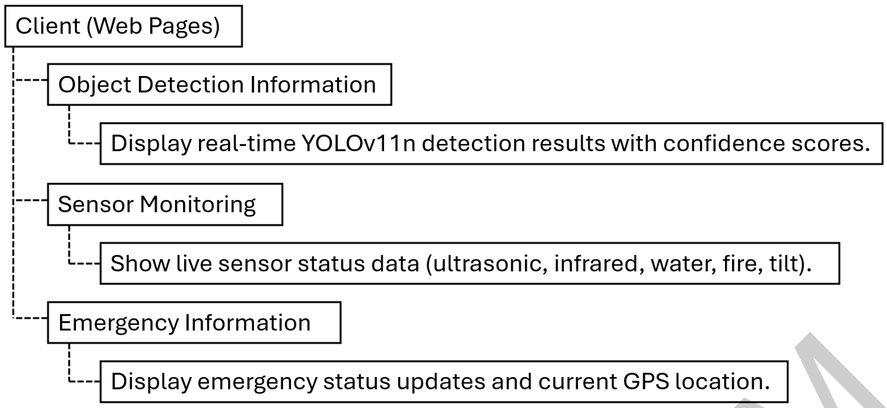

Figure 11: Client (mobile application) module hierarchy chart

An overall representation of module hierarchy and interactions is consolidated in Figure 12. This figure captures how data flows between the hardware sensors, the embedded AI processing units, the communication interfaces, and the user feedback or output layers. The design ensures that all modules are loosely coupled but tightly integrated in functionality, which simplifies debugging, supports feature updates, and improves system robustness.

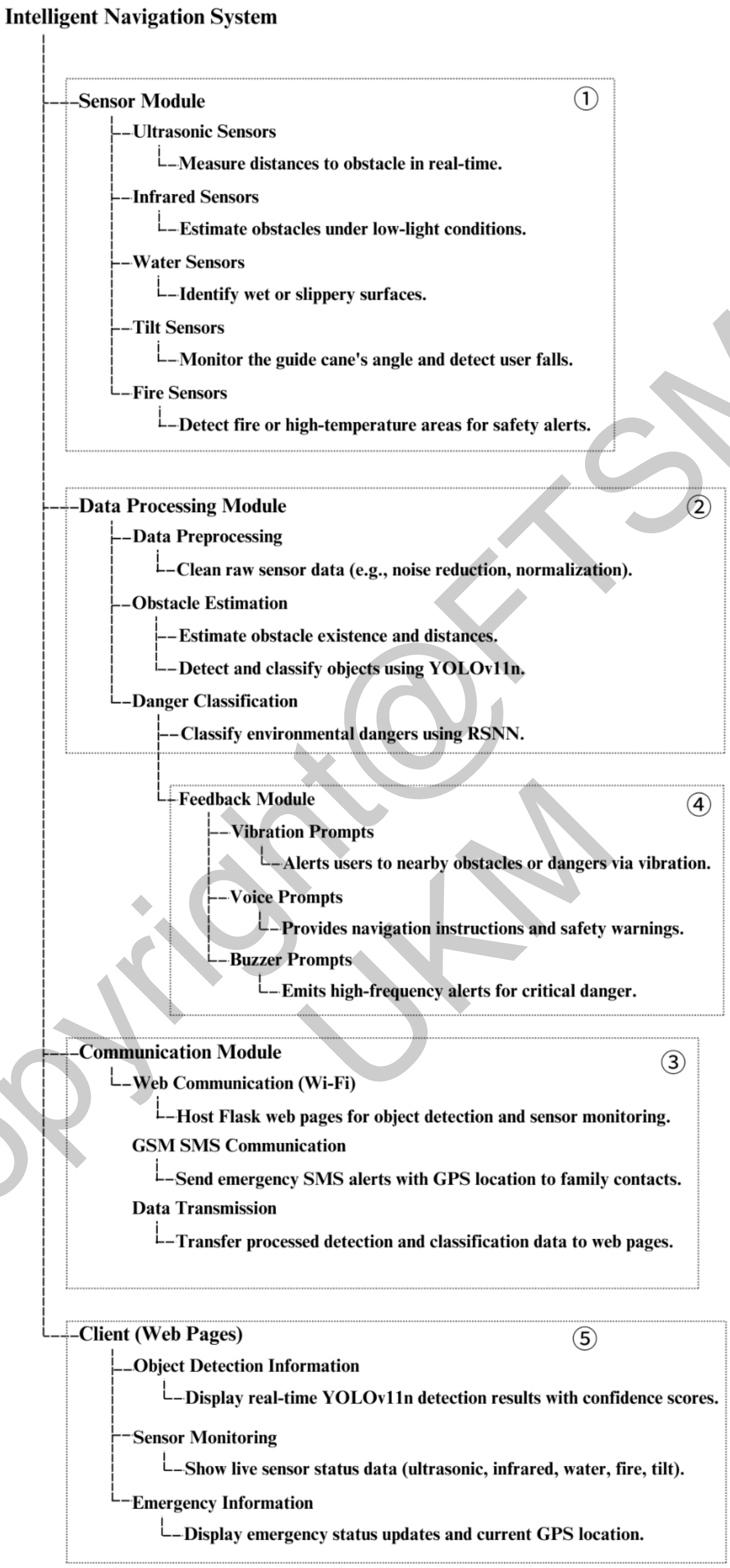

Figure 12: Intelligent navigation system module hierarchy chart

This conceptual model serves as the backbone of the system design, translating high level user expectations into specific module behavior. It guarantees real time responsiveness, modular adaptability, and practical usability, laying a strong foundation for the subsequent stages of development, testing, and deployment.

4.0 RESULTS

4.1 Application Development

The intelligent navigation system was developed using a combination of embedded hardware, machine learning models, web technologies, and real-time sensor integration, targeting practical deployment on a Raspberry Pi 5 platform. The system architecture follows a modular approach, with each component implemented using technologies suitable for resource-constrained environments while ensuring responsiveness, reliability, and ease of use.

The server-side application was implemented using the Flask web framework, written in Python. Flask provides lightweight routing and integration support for hardware modules, computer vision inference, and web communication. Core functionalities were mapped into specific Flask routes, such as /, /sensor, and /yolo, each serving different aspects of the system like real-time sensor status polling, object detection visualization, and emergency communication triggering.

The front-end interface was developed using HTML, CSS, and JavaScript, optimized for mobile and desktop browsers. JavaScript was used to implement asynchronous polling and auto-refresh functions, allowing real-time updates of sensor readings, YOLO detection frames, and GPS coordinates on the monitoring interface. All visual outputs were styled with minimal distraction and high accessibility, tailored to low-vision users and caregivers.

The obstacle detection module employs the YOLOv11n object detection model, trained on a custom dataset containing 13 relevant classes. The model was converted to an NCNN-compatible format and deployed on the Raspberry Pi to enable edge inference. Live video was captured using a PiCamera v3 and streamed through the /yolo route, where frames are passed to the YOLO engine, and the results are rendered and returned via the web interface.

Environmental danger detection and emergency classification were handled by the sensor.py module. This script initializes and reads GPIO inputs from six types of sensors: ultrasonic, infrared, water, flame, tilt, and an emergency button. Each input signal was processed in real-time, and a seven-dimensional vector was constructed representing the current environmental state. This vector was passed to a lightweight Ridge-based Shallow Neural Network (RSNN) model, trained and deployed using scikit-learn, which classified the situation as safe or dangerous. The inference was completed within milliseconds, making it suitable for immediate feedback response.

When dangerous conditions were detected, the system triggered alerts through vibration motors, buzzers, and voice output via a connected speaker. Simultaneously, the GPS module extracted the current coordinates, and the GSM module sent an SMS alert to predefined emergency contacts. The location and alert state were also updated on the web-based monitoring dashboard, which can be accessed remotely by family members.

The entire system was deployed on Raspberry Pi 5 running Raspberry Pi OS, using Thonny as the development IDE and systemd for autostart configuration. All dependencies were managed using pip, including Flask, OpenCV, scikit-learn, RPi.GPIO, pyserial, and ncnn-python bindings.

The full implementation was version-controlled using Git and uploaded to a public GitHub repository for reproducibility and code maintenance. The system underwent iterative testing across software and hardware layers to ensure all modules performed reliably under various environmental conditions.

4.2 Functional Implementation

The functional implementation of the intelligent navigation system combines real-time sensing, embedded AI inference, responsive user feedback, and intuitive front-end interaction through a unified architecture deployed on Raspberry Pi 5. At the core of the system is a Flask-based server application that manages all logic and communication. This backend exposes multiple routes to handle sensor readings, object detection processing, GPS location updates, and system status reporting. Sensor data collected via GPIO inputs—including ultrasonic, infrared, water, flame, tilt, and emergency button signals—is continuously polled and sent to the RSNN classifier, which produces a binary output indicating whether the current situation is safe or potentially dangerous. Based on the RSNN prediction, corresponding feedback mechanisms are activated, such as vibration motors, audio buzzers, and pre-recorded voice alerts.

Simultaneously, visual object detection is executed on image frames captured by PiCamera v3. These frames are passed through the YOLOv11n model optimized using NCNN, and the output includes bounding boxes and class predictions for 13 object categories. The detection result is rendered on the frame using OpenCV and streamed live via a Flask route. Users or remote caregivers can access this visual feedback through the dedicated /yolo page, which refreshes in near real-time using JavaScript-based polling. The front end is developed using HTML5, CSS3, and vanilla JavaScript to ensure lightweight compatibility across devices, including smartphones, tablets, and desktop browsers. The main dashboard displays a live sensor panel with color-coded indicators, a map panel showing GPS coordinates, and a system log that summarizes recent alerts and operational messages.

The web interface integrates seamlessly with the hardware-level triggers. For example, if water is detected on the walking surface, the sensor module updates its binary status, the RSNN classifier reevaluates the situation, and, if needed, an alert is triggered and shown instantly on the browser interface. In the case of an emergency classified by either the RSNN model or the panic button press, the GSM module sends out an SMS with current GPS coordinates to a pre-configured caregiver, while simultaneously displaying the alert on the dashboard. Figures 13 and 14 illustrate the vision-based detection interface and the live sensor monitoring interface, respectively.

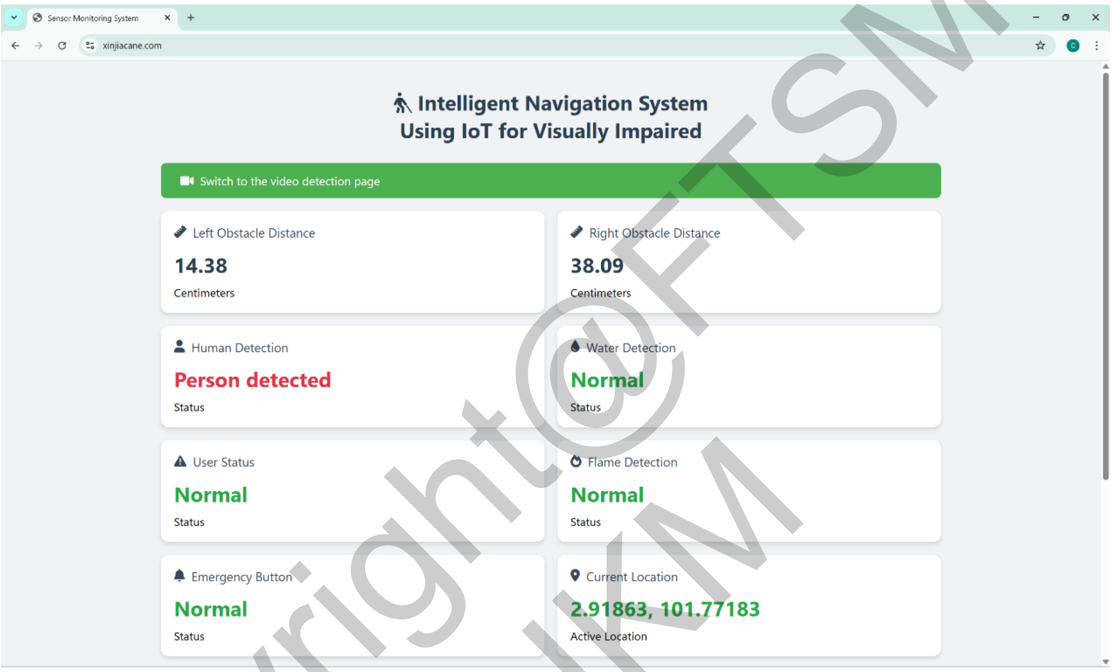

Figure 13: Sensor monitoring webpage (overview of sensor statues)

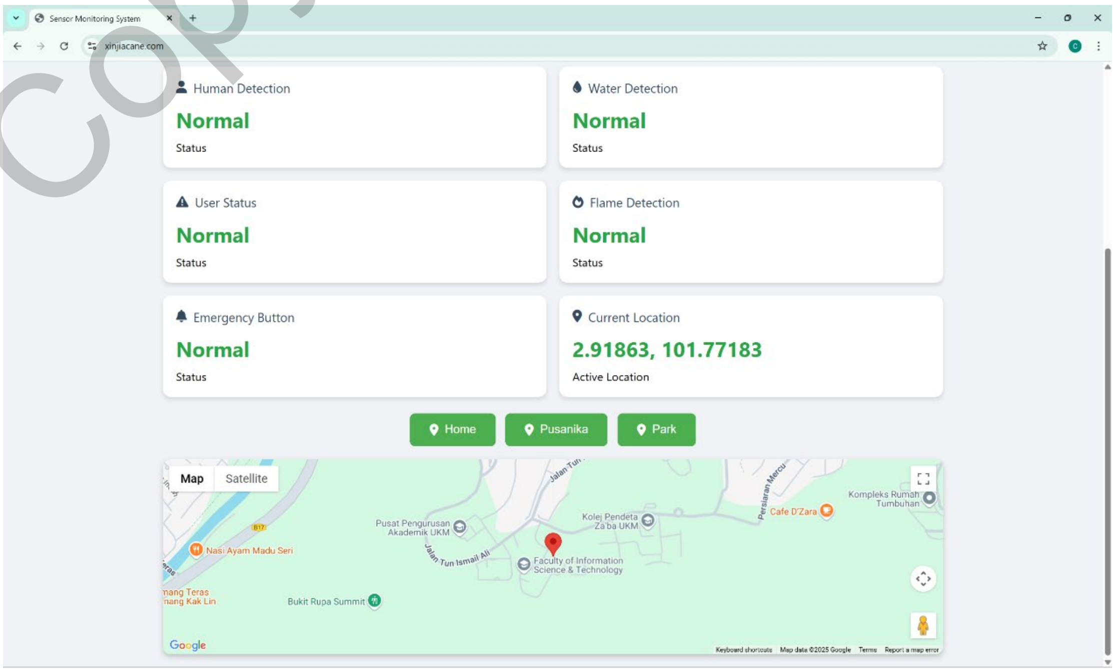

Figure 14: Sensor monitoring webpage (overview with current location map)

The entire system operates with an average end-to-end latency of less than 1.5 seconds under standard network conditions, ensuring that users receive timely notifications and feedback. Moreover, accessibility considerations such as large icons, clear color contrast, and voice feedback make the interface practical for visually impaired users and their families. The integration of Python, Flask, NCNN, GPIO control, and frontend web technologies into a single coherent platform ensures modularity, robustness, and real-world usability.

4.3 Testing and Results

System testing was conducted to evaluate the functionality, responsiveness, and integration of the intelligent navigation system. The testing phase covered both individual modules and overall system behavior under real-world conditions.

i. Functional Testing

Functional testing was carried out to evaluate whether each module of the intelligent navigation system operated in accordance with its specified requirements. The results are summarized in Table 1.

Table 1: Functional testing results

Module	Scenario	Expected Outcome	Actual Result	Status
Ultrasonic sensors (left/right)	Object placed at 5cm, 10cm, 20cm, 30cm	Measure distance within ±5cm; trigger vibration and voice prompt when within threshold	Distance measured within ±5cm; vibration and voice prompt triggered when object detected	Successful
Infrared sensor	Hand or object placed directly in front	Detect obstacle; trigger vibration and voice prompt	Obstacle detected; vibration and voice prompt triggered	Successful
Water sensor	Contact with wet cloth	Detect water; trigger voice prompt and vibration	Water detected; voice prompt and vibration triggered	Successful
Tilt sensor	Cane tilted sharply	Detect tilt; trigger buzzer alarm and send emergency SMS	Tilt detected; buzzer alarm and emergency SMS triggered	Successful
Fire sensor	Exposed briefly to open flame	Detect fire; trigger voice prompt, buzzer alarm, and emergency SMS	Fire detected; voice prompt, buzzer alarm, and emergency SMS triggered	Successful
Emergency	Button pressed	Trigger buzzer alarm	Button press	Successful

button	manually	and send emergency SMS	detected; buzzer alarm and emergency SMS triggered	
YOLOv11n Object detection	Present trained object classes	Detect object (>90% accuracy); trigger voice announcement	Objects detected accurately; voice announcement triggered	Successful
RSNN emergency classification	Simulated emergency input combinations	Classify input correctly as emergency or non-emergency; trigger SMS and buzzer if emergency detected	Inputs classified correctly; SMS and buzzer triggered for emergency cases	Successful

The functional testing results confirm that all modules of the system operated as expected. The ultrasonic sensors provided accurate distance measurements within an acceptable margin, triggering correct directional feedback when obstacles were detected. Other sensors, including infrared, water, fire, and tilt sensors, performed reliably, activating the appropriate alerts. The emergency button also functioned correctly, allowing manual initiation of emergency protocols.

In addition to sensor validation, the performance of the YOLOv11n object detection model was evaluated through training and validation metrics. As shown in Figure 15, the training loss decreased steadily across 100 epochs, while the validation loss remained low and stable, indicating effective learning and good generalization.

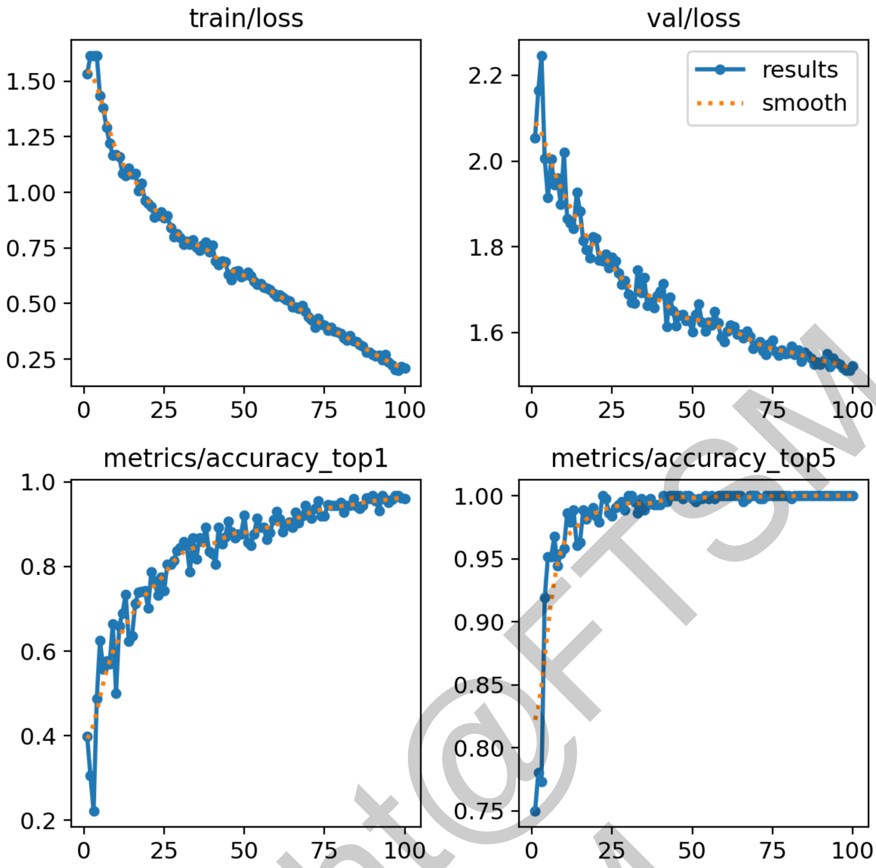

Figure 15: YOLOv11n model training performance

The top-1 accuracy gradually increased and exceeded 90 percent by the final epoch, demonstrating strong classification performance. The top-5 accuracy approached 100 percent early in training, suggesting the model consistently included the correct class among its top predictions.

Figure 16 presents real-world detection results. The left column displays raw input images, while the right column shows corresponding predictions with bounding boxes and confidence scores. The model successfully identified pedestrians, vehicles, and traffic signs in various outdoor scenes, validating its practical deployment in navigation assistance.

Original Image Classified Image (Augmented with BBoxes)

Figure 16: YOLOv11n model object detection results in real-world scenes

Web-based monitoring interfaces were also tested to confirm front-end responsiveness and back-end data handling. Figure 17 shows the YOLO detection page with no detected objects, where the interface correctly streamed live video and displayed a "No results" message. In contrast, Figure 18 shows multiple pedestrians detected in outdoor trials, where the system accurately rendered bounding boxes and provided real-time voice feedback with minimal latency.

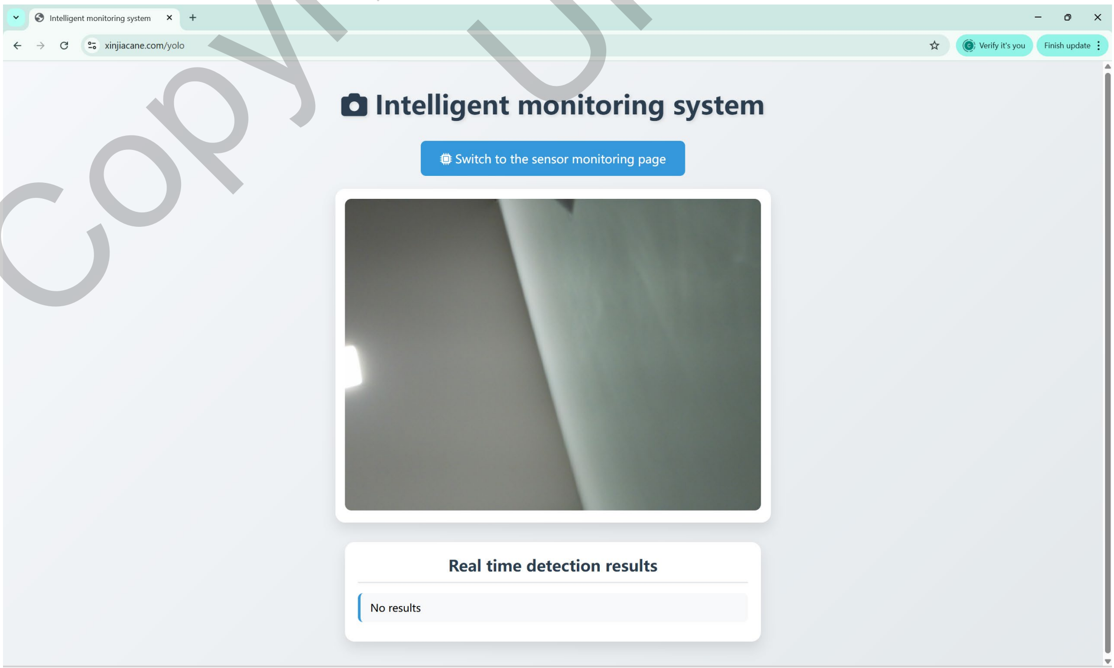

Figure 17: YOLO object detection webpage (no objects detected)

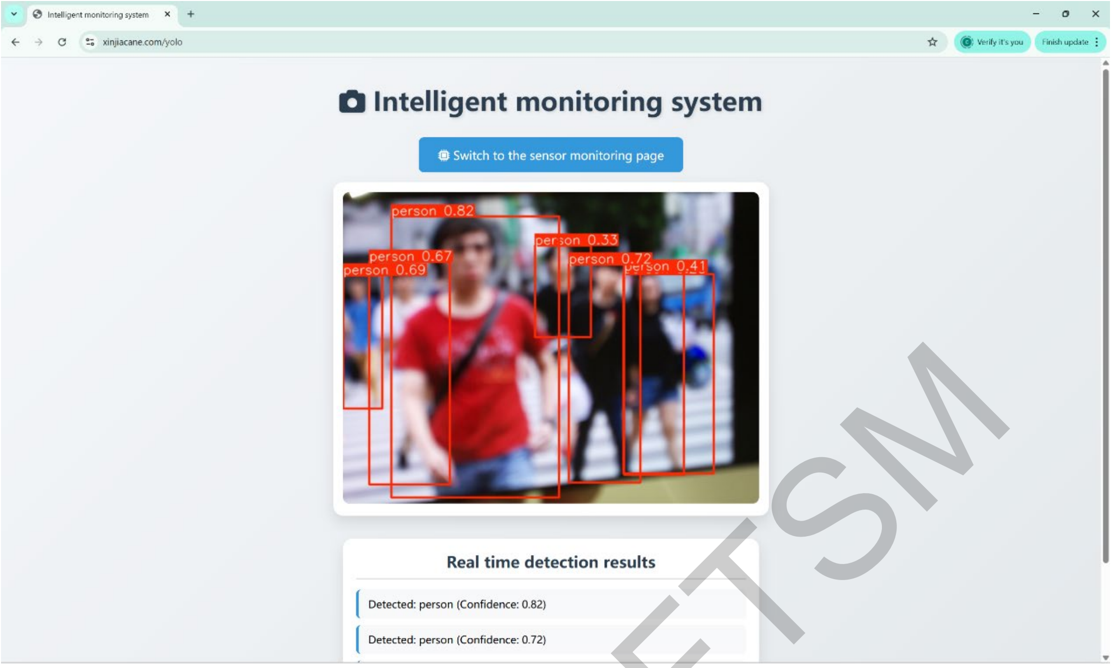

Figure 18: YOLO object detection webpage (multiple persons detected)

Further testing included the sensor monitoring webpage. Figure 19 shows the live sensor dashboard when human presence is detected. The page displayed current ultrasonic distances, sensor states, and GPS coordinates, all updating in real time. Figure 20 shows the integrated map view with the user's live location and preset destination buttons for commonly visited places. These features enhance daily navigation and increase route familiarity.

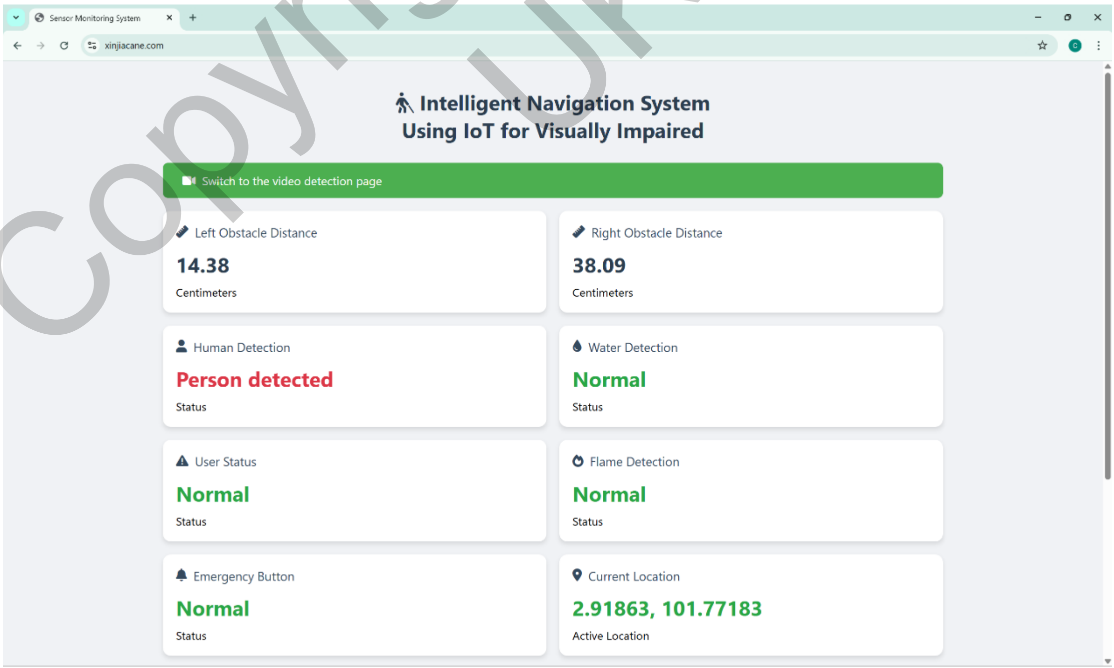

Figure 19: Sensor monitoring webpage (overview of sensor statues)

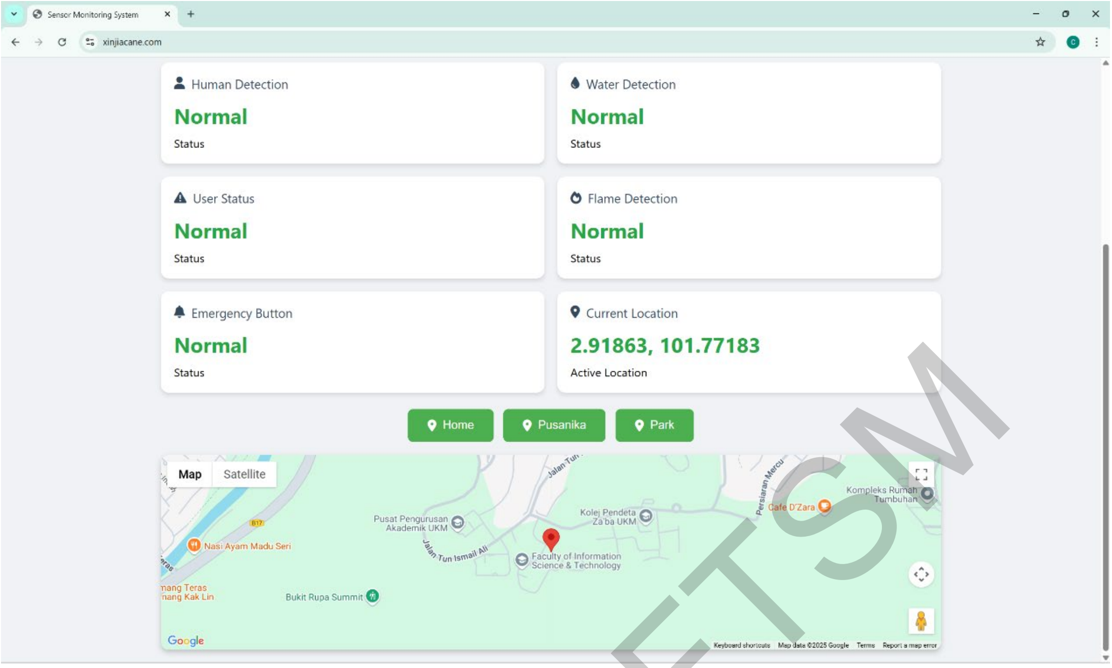

Figure 20: Sensor monitoring webpage (overview with current location map)

The emergency communication functions were verified using both SMS and mobile app push notifications. As shown in Figure 21 and Figure 22, alerts were successfully triggered by the emergency button, tilt or fire sensors, and RSNN-based AI classification. Each message included a clear event description and GPS location, supporting timely and informed responses by family members.

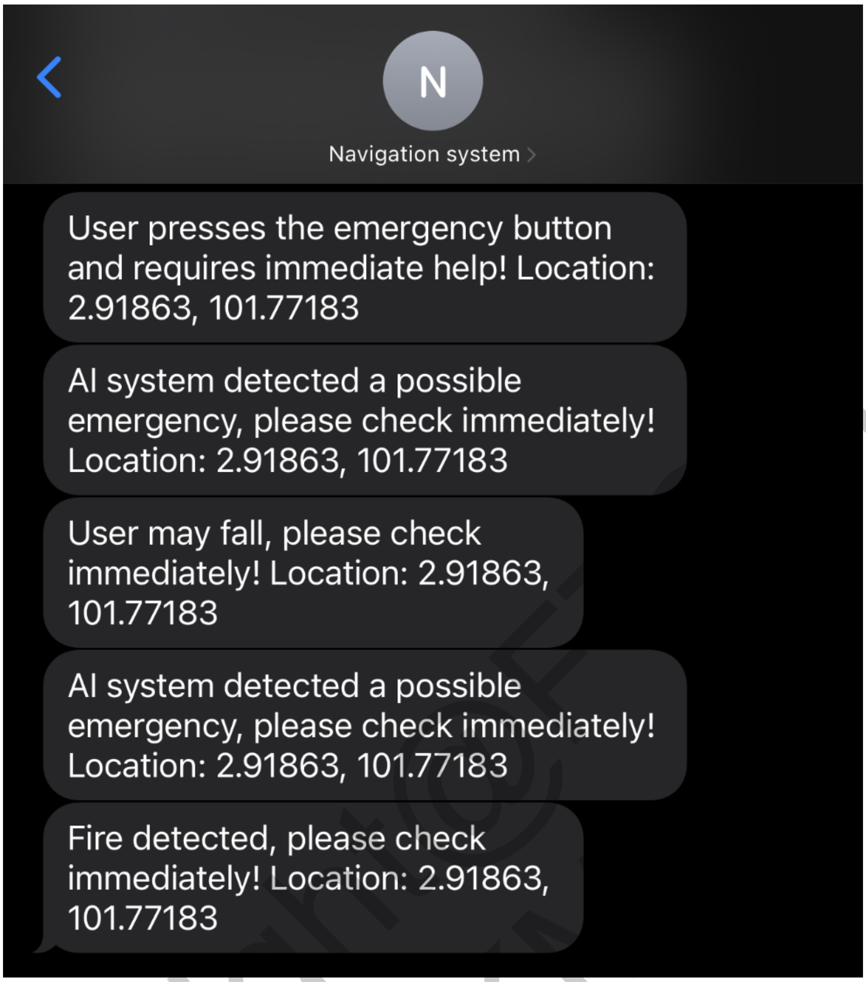

Figure 21: Emergency SMS messages with GPS location

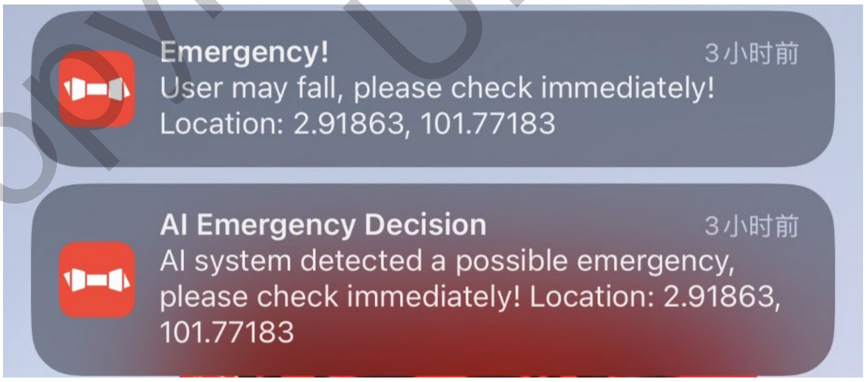

Figure 22: Emergency app push notifications with GPS location

In summary, the functional testing confirmed that the intelligent navigation system meets all core requirements. The system demonstrates reliable object detection, accurate sensor input handling, responsive user interfaces, and effective emergency communication, supporting its readiness for further non-functional and user-based evaluation.

ii. Non-Functional Testing

Non-functional testing was conducted to evaluate the system's performance, usability, and stability under realistic operating conditions.

In terms of performance, the system demonstrated fast response across all modules. Ultrasonic sensors triggered vibration, and voice prompts almost instantly when obstacles entered the detection range. The YOLOv11n vision module consistently detected objects in real time, with voice alerts delivered within one to two seconds after camera capture, providing timely guidance for navigation. RSNN emergency classification responded promptly, activating the buzzer and sending emergency SMS alerts without noticeable delay when emergency conditions were detected.

Usability aspects were assessed based on feedback clarity, comfort, and interface responsiveness. Voice prompts remained clear and understandable in both indoor and noisy outdoor environments. Vibration feedback was strong, easily perceptible through the cane handle, and comfortable during extended use. The buzzer volume was sufficient to attract attention in a variety of ambient noise conditions. The web-based monitoring interface, accessible via smartphones and laptops, displayed a clear layout, smooth navigation, and real-time updates of sensor status and GPS location. The overall interface behavior indicated it is suitable for remote monitoring of user safety and environmental status.

Stability testing involved continuous system operation for more than five minutes in both indoor and outdoor environments. During this time, the system maintained stable performance without crashes, freezing, or disconnections. Sensor readings updated consistently, object detection operated without interruption, and RSNN classification maintained reliable outputs. The web interface also remained fully accessible, with continuous real-time data refresh. These results confirm that the intelligent navigation system operates reliably, delivers user-friendly interaction, and maintains stable performance in realistic deployment scenarios.

iii. User Testing

User testing was conducted to evaluate the system's usability, comfort, and practicality from the perspective of real users. Six testers participated in various trials simulating daily indoor and outdoor navigation scenarios.

Testing began with User 1 walking through an empty home corridor to verify system silence in safe environments. No unnecessary alerts were triggered, and the user felt confident without distraction. User 2 encountered an obstacle on the left side, where ultrasonic sensors promptly activated vibration and voice prompts, effectively guiding safe path correction. User 3 walked toward a person placed ahead in the corridor, and the infrared sensor with YOLOv11n vision module announced "Detected may be people," which the user found clear and helpful.

Emergency detection was tested indoors with User 4 tilting the cane to simulate a fall. The system triggered a buzzer and sent an emergency SMS, reassuring the user of its reliability. Outdoor testing with User 5 involved navigating a campus path where cars and pedestrians passed by. The YOLOv11n model identified these objects and issued voice prompts. The user noted strong vibration feedback and adequate voice clarity but suggested increasing the speaker volume for roadside scenarios. User 6 activated the emergency button while walking, triggering the buzzer and SMS correctly. The button was reported to be easily accessible during movement. The outcomes of each scenario are summarized in Table 2, highlighting system performance, user observations, and suggested improvements.

Table 2: User testing results

User	Scenario	Observations	User Feedback	Suggested Improvements
User 1	Walked along indoor corridor without obstacles	No unnecessary alerts were triggered while walking	Felt confident as there were no false alarms	None
User 2	Walked along the same indoor corridor towards an obstacle on the left side	Obstacle was detected; vibration and voice prompt activated promptly	Feedback was clear and easy to understand	None
User 3	Approached a person placed directly ahead in indoor corridor	Infrared sensor and YOLOv11n announced "Detected may be people" clearly	Voice prompt was clear indoors	None
User 4	Tilted cane sharply while walking indoors to simulate a fall	Buzzer alarm sounded and emergency SMS was sent immediately	Felt relaxed emergency alerts would function properly	None
User 5	Walked along outdoor campus pathway with people and cars in view	YOLOv11n detected objects; voice prompts were audible	Voice volume generally sufficient; vibration feedback strong	Increase voice volume for very noisy roads
User 6	Pressed emergency button while walking outdoors	Buzzer alarm sounded and emergency SMS was sent as expected	Button was easy to press while holding cane	None

These tests confirmed the system's effectiveness, with all users expressing confidence in its navigation and emergency alert features.

5.0 CONCLUSION

This project successfully achieved its goal of developing an intelligent navigation system to support visually impaired individuals by integrating real-time obstacle detection, emergency alerting, multimodal user feedback, and remote monitoring features. Through the combination of Internet of Things technologies and embedded artificial intelligence, the system provides practical support for users in both indoor and outdoor scenarios. Key functionalities, such as accurate obstacle recognition, emergency classification, live location tracking, and GSM-based alert transmission, were all implemented and validated during testing, fulfilling the original design objectives of enhancing safety and independence for the visually impaired.

The system's architecture represents a technically integrated solution that combines multiple innovations. The YOLOv11n model, trained on 13 object categories, delivers lightweight yet effective real-time object detection, while the Randomized Shallow Neural Network (RSNN) enables fast and low-power emergency classification using multi-sensor input. The entire system is deployed on a Raspberry Pi 5 platform, ensuring self-contained and on-device operation without reliance on cloud computing. The Flask-based web interface further enables asynchronous communication with family members by displaying live sensor statuses and GPS location updates, enhancing user safety through environmental awareness and external supervision.

User testing demonstrated the system's practical usability. Participants found the voice prompts and vibration feedback intuitive and timely. The system operated reliably in both quiet and noisy environments, and emergency mechanisms such as the tilt sensor and physical panic button functioned accurately under real-world scenarios. Users also appreciated the ease of accessing system feedback while navigating, contributing to their overall confidence and sense of security.

Looking forward, future improvements may include more comprehensive testing under varied environmental conditions such as rain, fog, or high-traffic areas. System personalization features such as adjustable voice volume, feedback intensity, and language support could further improve accessibility and comfort for users with different needs. Power management should also be optimized for long-duration usage without reliance on fixed power sources, enhancing mobility in outdoor use. Furthermore, integrating external navigation data and expanding the vision model's object recognition capacity would make the system more adaptive to complex urban environments.

Finally, this intelligent navigation system demonstrates significant social value by empowering visually impaired individuals with a greater sense of autonomy, security, and confidence in daily movement. Its modular, scalable design lays the groundwork for future assistive technologies that combine embedded AI and IoT for inclusive, user-centric solutions in real-world applications.

6.0 APPRECIATION

I am deeply fortunate to have Professor Dr. Mohammad Kamrul Hasan as my research supervisor. His professional guidance and support during the process of my project was invaluable. I sincerely thank him.

I would also like to express my sincere gratitude to my parents for their strong support in my academic and personal life. Their love and encouragement provided me with the strength and motivation to achieve my goals.

Finally, I would like to thank everyone who has supported me in this process. Thank you.

7.0 REFERENCES

Abbas, M., Elhamshary, M., Rizk, H., Torki, M., & Youssef, M. (2019, March). WiDeep: WiFi-based accurate and robust indoor localization system using deep learning. In 2019 IEEE International Conference on Pervasive Computing and Communications (PerCom (pp. 1-10). IEEE, DOI: 10.1109/PERCOM.2019.8767421

Ahmed, F., Tasnim, Z., Rana, M., & Khan, M. M. (2022, June). Development of low cost smart cane with GPS. In 2022 IEEE World AI IoT Congress (AIIoT) (pp. 715-724). IEEE, DOI: 10.1109/AIIoT54504.2022.9817322

Alisetti, S. N., Purushotham, S., & Mahtani, L. (2019). Guiding and Navigation for the Blind using Deep Convolutional Neural Network Based Predictive Object Tracking. International Journal of Engineering and Advanced Technology (IJEAT), Vol. 9, pp. 306-313, DOI: 10.35940/ijeat.A1058.1291S319

Anandan, M., Manikandan, M., & Karthick, T. (2020). Advanced indoor and outdoor navigation system for blind people using raspberry-pi. Journal of Internet Technology, Vol. 21(1), pp. 183-195, DOI: 10.3966/160792642020012101017

Basheshankar, A., Lande, A., Nandeshwar, A., Sarkar, A., Udapure, A., & Chandankhede, P. H. (2022, April). Assistive Cane for Visually Impaired People. In 2022 10th International Conference on Emerging Trends in Engineering and Technology-Signal and Information Processing (ICETET-SIP-22) (pp. 1-5). IEEE, DOI: https://doi.org/10.1109/ICETET-SIP-2254415.2022.9791762

Boussihmed, A., El Makkaoui, K., Ouahbi, I., Maleh, Y., & Chetouani, A. (2024). A TinyML model for sidewalk obstacle detection: aiding the blind and visually impaired people. Multimedia Tools and Applications, pp. 1-28, DOI: https://doi.org/10.1007/s11042-024-20070-9

Chaudary, B., Pohjolainen, S., Aziz, S., Arhippainen, L., & Pulli, P. (2023). Teleguidance-based remote navigation assistance for visually impaired and blind people—usability and user experience. Virtual Reality, Vol. 27(1), pp. 141-158, DOI: 10.1007/s10055-021-00536-z

Dharani, A., Kumar, S. A., & Patil, P. N. (2023). Object Detection at Edge Using TinyML Models. SN Computer Science, Vol.5(1), pp.11, DOI: https://doi.org/10.1007/s42979-023-02304-z

Gallagher, T., Wise, E., Li, B., Dempster, A. G., Rizos, C., & Ramsey-Stewart, E. (2012, November). Indoor positioning system based on sensor fusion for the blind and visually impaired. In 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1-9). IEEE, DOI: 10.1109/IPIN.2012.6418882

Gharghan, S. K., Kamel, H. S., Marir, A. A., & Saleh, L. A. (2024). Smart Stick Navigation System for Visually Impaired Based on Machine Learning Algorithms Using Sensors Data. Journal of Sensor and Actuator Networks, Vol: 13(4), pp. 43, DOI: https://doi.org/10.3390/jsan13040043

Kumar, N., & Jain, A. (2022). A Deep Learning Based Model to Assist Blind People in Their Navigation. J. Inf. Technol. Educ. Innov. Pract., Vol. 21, pp. 95-114, DOI: https://doi.org/10.28945/5006

Mahida, P. T. (2021). Indoor navigation for the visually impaired: enhancements through utilisation of the Internet of Things and deep learning, Western Sydney University Thesis Collection, November 2021

Martínez-Cruz, S., Morales-Hernández, L. A., Pérez-Soto, G. I., Benitez-Rangel, J. P., & Camarillo-Gómez, K. A. (2021). An outdoor navigation assistance system for visually impaired people in public transportation. IEEE Access, Vol. 9, pp. 130767-130777, DOI: 10.1109/ACCESS.2021.3111544

Messaoudi, M. D., Menelas, B. A. J., & Mcheick, H. (2020). Autonomous smart white cane navigation system for indoor usage. Technologies, Vol. 8(3), pp. 37, DOI: https://doi.org/10.3390/technologies8030037

Narayani, T. L., Sivapalanirajan, M., Keerthika, B., Ananthi, M., & Arunarani, M. (2021, March). Design of Smart Cane with integrated camera module for visually impaired people. In 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) (pp. 999-1004). IEEE, DOI: https://doi.org/10.1109/ICAIS50930.2021.9395840

Parvadhavardhni, R., Santoshi, P., & Posonia, A. M. (2023, May). Blind navigation support system using Raspberry Pi & YOLO. In 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC) (pp. 1323-1329). IEEE, DOI: https://doi.org/10.1109/ICAAIC56838.2023.10140484

Rahman, M. W., Islam, R., & Harun-Ar-Rashid, M. (2018). IoT based blind person's stick. International Journal of Computer Applications, Vol 182(16), pp. 19-21, DOI: 10.5120/ijca2018917824

Rathnayake, R. M. M. R., Maduranga, M. W. P., Tilwari, V., & Dissanayake, M. B. (2023). RSSI and machine learning-based indoor localization systems for smart cities. Eng, Vol: 4(2), pp. 1468-1494, DOI: https://doi.org/10.3390/eng4020085

Roy, M., & Shah, P. (2022). Internet of Things (IoT) Enabled Smart Navigation Aid for Visually Impaired. In International Conference on Advanced Information Networking and Applications, Vol.451, pp. 232-244,. Cham: Springer International Publishing. DOI: https://doi.org/10.1007/978-3-030-99619-2_23

Setiadi, B., Supriyadi, T., Nugroho, H., & Solihin, R. (2020). Navigation and object detection for blind persons based on neural network. International Journal Applied Technology Research, Vol. 1(1), pp. 56-65, DOI: https://doi.org/10.35313/ijatr.v1i1.24

Shabaz (2017). Raspberry Pi 3 Block Diagram: https://community.element14.com/products/raspberry-pi/b/blog/posts/raspberry-pi-3-block-diagram

Vineeth, I., Sharan, Y. S., Karthik, Y., & Priya, B. K. (2021, June). Smart cane for visually impaired person. In 2021 International Conference on Intelligent Technologies (CONIT) (pp. 1-6). IEEE, DOI: https://doi.org/10.1109/CONIT51480.2021.9498563

Vorapatratorn, S. (2021, November). AI-based obstacle detection and navigation for the blind using convolutional neural network. In 2021 25th International Computer Science and Engineering Conference (ICSEC) (pp. 17-22). IEEE, DOI: https://doi.org/10.1109/ICSEC53205.2021.9684607

World Health Organization (2023). Blindness and vision impairment: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

Ying, J. C., Li, C. Y., Wu, G. W., Li, J. X., Chen, W. J., & Yang, D. L. (2018, June). A deep learning approach to sensory navigation device for blind guidance. In 2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems (HPCC/SmartCity/DSS) (pp. 1195-1200). IEEE, DOI: https://doi.org/10.1109/HPCC/SmartCity/DSS.2018.00201

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