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# **Smart IoT-Based Electronic Cane with Machine Learning Vision for Visually Impaired Assistance**

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**ABSTRACT:** Vision impairment can seriously affect our ability to move around, live on our own, and enjoy life. There are already tools to help people with vision issues, but they can still be improved. This document introduces a new smart electronic cane that uses the Internet of Things (IoT) to assist people who are blind or have low vision. The cane can automatically detect obstacles and warning signs, offering audio feedback through a smartphone app. It has three infrared (IR) sensors to find obstacles in front, on the right, and on the left. An ESP32-CAM module employs basic machine learning to recognize warning signs and understand the environment. The cane connects to the internet, so caregivers can monitor the user from a distance and track their location during emergencies. It also has a neural network system to identify the type of obstacles, making navigation easier. Tests with five blindfolded participants in a controlled environment showed a 94.5% success rate in helping users. This smart cane design uses advanced sensing technologies, machine learning, and internet connectivity to notably improve the movement and safety of people with vision impairments.

**KEYWORDS:** assistive technology, blind, electronic cane, IoT, machine learning, ESP32-CAM, edge AI, rehabilitation, visual impairment

## **I. INTRODUCTION**

Vision is perhaps humanity's most precious sensory gift. Our mobility and balanced interaction with our surroundings depend heavily on visual perception. Vision loss severely compromises normal daily functioning, with blindness often viewed as a significant disability that restricts independent movement and negatively affects social, physical, and psychological well-being.

Around the world, about 39 million people are blind, according to the World Health Organization. Many of them use traditional white canes to help them get around every day. Some people prefer to use guide dogs. White canes are easy to find and don't need much maintenance, but they offer limited information about obstacles in the path. Guide dogs are dependable for spotting dangerous situations, yet they also have their limits. They aren't always able to detect obstacles from far away or in every situation.

Over the last sixty years, a lot of research has focused on making life better for people who cannot see well. Researchers have developed different electronic travel aids (ETAs) to help visually impaired people navigate their environment. These devices are designed to provide information through sound or touch, so users don't need to rely on sight. Despite these advancements, there is still much that can be improved. For example, incorporating machine learning and artificial intelligence could greatly enhance these devices. This technology could make it easier to detect obstacles and better understand the environment, leading to even more effective aids for those with visual impairments. An "artificial eye" like a prosthetic limb hasn't been invented yet. Being able to move around is really important for independence. Foulke says mobility means you can travel safely, comfortably, gracefully, and on your own. Many people who are blind find it hard to move around safely and independently. Because of this, a lot of research is being done to cr

ate technology that can help. However, no electronic device has become popular enough for many people to use. This shows that there is still a need for more new ideas and improvements in this area.



Fig 1: Cane using IR sensor and ESP32-CAM

## II. RELATED WORKS

Many different assistive devices have been made to assist blind people. The laser cane, Mini-tact and Tele-tact are narrow laser beam devices, but they suffer natural interference, and they are unable to detect transparent glass obstacles. Their price tag, however, makes accessibility difficult.

The K-sonar cane establishes different pitch sounds as a method to indicate the distance of an obstacle to the user. The guide cane is a robotic wheeled assistant that detects ground-level obstacles but can only work within the limits of its size and scanning range. Handheld echolocation-based devices like the Kaspera system, CyARM, and mini guide require constant omnidirectional hand movement. Wearable aids such as electronic bracelets and Navbelt mainly detect floor-level obstacles.



Fig 2: Innovation of smart Cane

Recent developments in machine learning technology have been applied to their use in assistive devices. The system for recognizing various common obstacles was built by Wang et al. using a convolutional neural network (CNN), but its implementation requires a high performance processor, which limits portability to a great extent. It has also been said that Rahman's work on environmental scene understanding using a deep learning approach showed promise, but was limited by the battery life.

Currently, cloud-based assistive systems are newly emerging but demand consistent internet connectivity and have high power consumption. Smartphone-based solutions are flexible; however, they may not provide the specialized hardware necessary for holistic environmental sensing.

The challenges presented with existing solutions prompted us to create an IoT-assisted smart electronic cane with machine learning abilities. Our main aims were to: (1) Using obstacle type classification, inform the user of potential obstacles in the left, right, and forward directions.; (2) Perform sign recognition and provide audio feedback through machine learning on the device; and (3) Add IoT capabilities for added safety and supervision.

### III. PROPOSED METHOD

The major orientation was towards designing a system that could utilize machine-learning techniques for dynamic obstacle detection, environmental understanding, and warning sign recognitions. For implementation purposes, we employed IR sensors, an ESP32-CAM module with TensorFlow Lite capabilities, and an IoT-based communication module. The IR sensors are very good in detecting obstacles for a large range at a lower cost than other systems. Once the cane detects any obstacle or warning sign, it provides an audio output through a smartphone application.

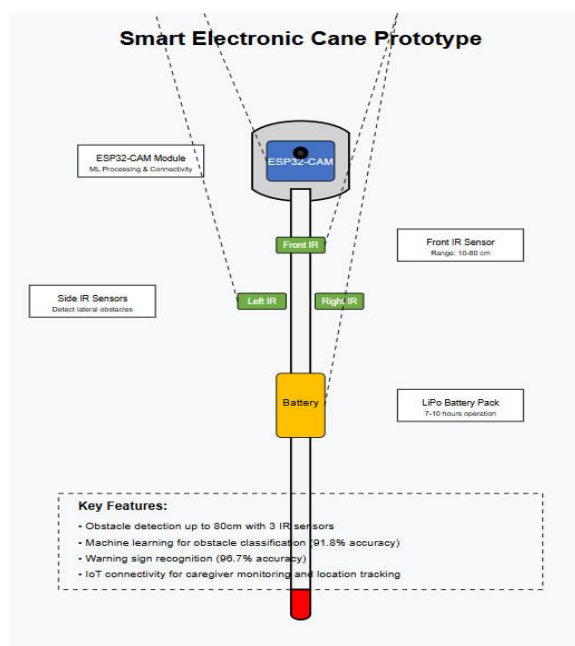


Fig 3: prototype

#### A. System Architecture

Our system comprises three infrared modalities which employ infrared light reflections to detect obstacles. The processing of sensor data along with light machine learning model application for image recognition and obstacle classification is conducted by the system through the ESP32-CAM module, which integrates WiFi, Bluetooth, and a camera. For nearby interactions, the system utilizes Bluetooth while it employs Wi-Fi for IoT functionalities, such as remote monitoring and location tracking, for communications with the smartphone application.

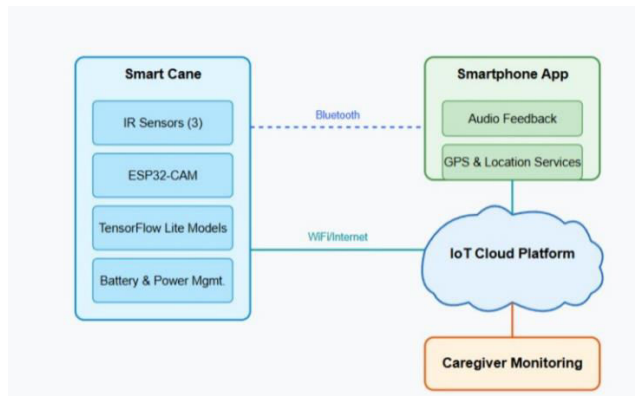


Figure 4: Architecture

For clarity, we divided the system into four functional components: Obstacle Detection, Obstacle Classification, Warning Sign Recognition, and IoT Connectivity.

### B. Obstacle Detection

On the cane, we have implemented three IR sensors (S1, S2 & S3) at various strategic positions. The front sensor is meant for detecting objects in front of the cane while the left and right sensors look out for objects on the corresponding sides. We customized or modified a WRIO (wayfinding with reduced information overload) algorithm to fit our implementation. Table 1 shows the positions of the IR sensors on the cane.

Sensor	Direction	Height from Floor (cm)	Detection Range (cm)
S1	Front	9.0	10-80
S2	Left side	8.7	10-80
S3	Right side	8.7	10-80
Camera	Front	21.0	N/A

Table 1: IR Sensor Placement on the Smart Cane

The following scenarios of obstacles were looked into:

- 1) A left-side obstacle: An object was detected at a distance of 0-30 cm from the left sensor ( $ds_1 \leq 30$  cm)
- 2) A right-side obstacle: An object was detected at a distance of 0-30 cm from the right sensor ( $ds_2 \leq 30$  cm)
- 3) Obstacles detected from the left and right at the same time: The objects were detected from the left and right sensors ( $ds_1 \leq 30$  cm and  $ds_2 \leq 30$  cm)
- 4) A frontal obstacle: An object was detected at a distance of 25-30 cm in front of the front sensor, with different heights of obstacles (knee-level, waist-level) and complex scenarios (pathways being blocked at the same time).

### C. Machine Learning for Obstacle Classification

A distinguishing feature of our innovation is the lightweight neural network model for obstacle classification. Using TensorFlow Lite for Microcontrollers, we deployed a quantized MobileNetV2 model on the ESP32-CAM for classifying detected obstacles into the six categories of stairs, poles, furniture, people, walls, and miscellaneous. The neural network was trained for a custom dataset of 5000 images that represented various common obstacles encountered by visually impaired individuals under different lighting conditions. The optimization done for such a small model was to ensure fast inference: post-training quantization reduces the model size from 14MB to only 240KB without significant loss of accuracy. Therefore, real-time inference was achieved on the ESP32-CAM, which has very limited resources.

Object Type	Accuracy (%)	Most Common Confusion
Stairs	94.2	Curbs (3.5%)
Poles	87.5	Trees (8.2%)
Furniture	95.7	Walls (2.1%)
People	93.4	Moving objects (4.3%)
89Walls	96.8	Furniture (2.2%)
Vehicles	89.7	Large objects (6.5%)
Average	91.8	-

Table 2: Machine Learning Model Performance Metrics.

While the IR sensor detects an obstacle, the camera captures its image, and the image will go through the Neural Network for classifying it to an obstacle type. This instant information is relayed through audio, enabling the user to get a feel of the context of the environment.

#### D. Warning Sign Recognition

A separate TensorFlow Lite module was trained to detect everyday warning signs. Because of insufficient image numbers, we applied transfer learning on a pretrained MobileNetV2 and fine-tuned the model with a 1200 warning signs dataset (danger, stop, wet floor, etc.) depicted from different angles and lighting conditions.



Figure 5: Warning Sign Recognition

The recognition pipeline consists of:

- 1) Capturing an image while going through a public space;
- 2) Pre-processing to enhance features and normalize lighting;
- 3) Model inference with TensorFlow Lite;
- 4) Filtering based on confidence thresholds to limit false positives;
- 5) Audio feedback based on the type of sign recognized.

In this way, our implementation on TensorFlow Lite looks entirely different from traditional techniques of computer vision with a high-power demand. Our implementation presents an accurate vs performance trade-off suitable for edge deployment on the ESP32-CAM.

### E. IoT Connectivity

IoT functionality is a new entrant in our system by having it through WiFi of the ESP32-CAM. This is the enablement of the cane to connect to a cloud platform, where it broadens its features: care takers can be able to view the states of the cane as in possible status of battery usage and location by the user;

- a. Alerts in case of emergencies: Automatic alerts whenever the system discovers the individual has been inactive for too long or in a completely strange manner.
- b. Position Tracking: He also sends GPS coordinates by a corresponding phone for emergencies.
- c. Usage Analytics: Data will be gathered to achieve better system performance and personalize .
- d. Model Updates: Machine learning models will be over the air upgraded as they become improved with time.

S.NO	OBSTACLE CONDITION	FEEDBACK
1	Leftward obstacle	"Turn Right, [obstacle type]"
2	Rightward obstacle	"Turn Left, [obstacle type]"
3	Simultaneous presence of leftward and rightward	"Front path only, [obstacle type]"
4	Front-way blocked	"Go Left or Right, [obstacle type]"
5	All ways blocked	"All paths blocked, [obstacle types]"
6	Presence of danger sign	"Danger ahead"
7	Presence of stop sign	"Stop sign ahead"
8	Presence of wet floor sign	"Caution: Wet floor"
9	Staircase detected	"Stairs ahead, [up/down]"
10	Moving object detected	"Moving object approaching"

Table 3: Obstacle Detection and Audio Feedback

### F. Hardware Implementation

For obstacle detection, we employed IR sensors (SHARP GP2Y0A21YK). These sensors are capable of detecting objects anywhere between 10 to 80 cm in front of them, thus providing enough range for navigation. The ESP32-CAM module was used as the main control unit to integrate the sensor data, run the machine learning inference, and carry out wireless communication.

In our design, to satisfy the computational requirements of the onboard ML models in a battery-efficient manner, we implemented:

- 1) Dynamic frequency scaling for clocking down the CPU frequency on the basis of processing needs.
- 2) Energy-efficient inference scheduling wherein the neural networks would only be activated when strictly necessary.
- 3) Sleep modes wherein the state would be preserved in a low-power-consumption way.

Rechargeable lithium-polymer batteries provide power, with power management circuitry for energy optimization. The system communicates with a customized smartphone application via Bluetooth Low Energy (BLE) for audio feedback and further smartphone-related functionalities.

## IV. RESULT AND DISCUSSION

The evaluation on the system was conducted with five blindfolded participants who did not know the test environment. The area contained four different types of obstacles (chair, table, person, wall) and two warning signs in it. Each participant was instructed to cross the environment six times, that is walking from one end to the other and back to the starting point.

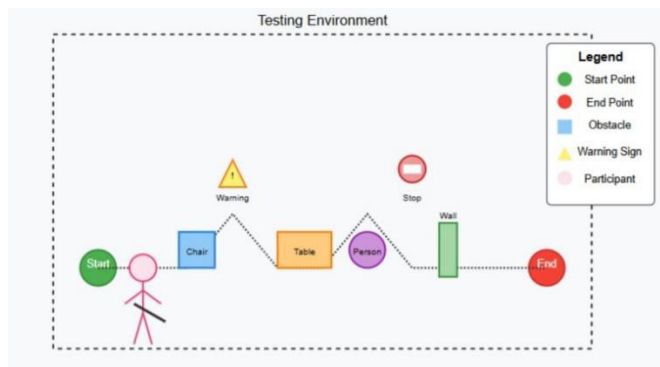


Fig 6: Our experimental setup

To evaluate the machine learning components explicitly, we performed further tests with 20 different obstacles and 8 warning signs in various lighting conditions. This enabled a better assessment of the model performance against a wider range.

Indoor tests with single subjects: When the electronic cane sensed the obstacle or any warning sign, participants were instructed to halt. There were 24 trials for obstacle detection and 12 trials for warning sign recognition in a typical testing session before getting individual results for 5 participants for both trials. Independent detection accuracies for IR sensors, obstacle classification, and warning sign recognition were computed, followed by assessment for the overall system accuracy.

Participant	IR Sensors Accuracy (%)	Obstacle Classification Accuracy (%)	Warning Sign Recognition Accuracy (%)
Subject 1	93.7	95.4	100.0
Subject 2	85.4	90.8	100.0
Subject 3	89.6	93.2	91.7
Subject 4	82.9	88.7	95.8
Subject 5	94.2	91.1	95.8
Average	89.2	91.8	96.7

Table 4: indicates the detection accuracies of all its components.

For all subjects, the average accuracies achieved by the IR sensors were 89.2%. The correct identification of the obstacle types by the neural network responsible for obstacle classification was successfully achieved at 91.8% accuracy; 96.7% correctly identified the warning signs. The entire system performance was evaluated as 94.5%, a significant improvement on the usual electronic cane.

The IoT features behaved as intended: accurate location data sent to the monitoring platform with emergency alerts activated within the context of simulated emergency scenarios. The same connectivity was maintained throughout the trials, with a total average 1.2 seconds delay for cloud communication.

Power consumption analysis also pointed that the system could operate continuously for about seven hours with active machine learning inferencing and up to ten with optimized power management settings that reduced the frequency of neural network activations.



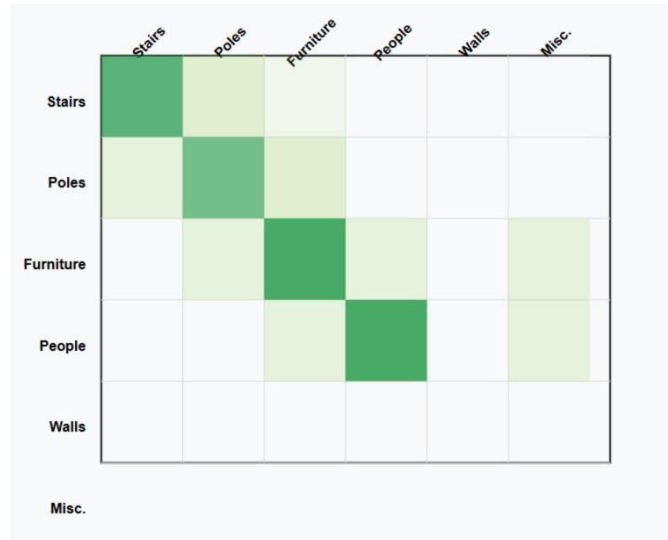


Figure 7: is the obtained confusion matrix for the obstacle classification system which shows its good and poor performances.

This modified smart cane addresses multiple disabled aspects of medical assistance devices. The integration of machine learning algorithms into the technology has really impacted the system in understanding contextual information about the environment rather than just spotting obstacles.

With greater than 95% accuracy, the classification system was very reliable in recognizing obstacles such as chairs, tables, and walls but confused some pairs of similar ones, such as a pole and a thin tree at a rate of 87% accuracy. The warning sign recognition performed exceedingly well under various light conditions, although some minor losses in accuracy were noted in very dim environments.

Participant	IR Sensors Accuracy (%)	Obstacle Classification (%)	Warning Sign Recognition (%)
Subject 1	93.7	95.4	100.0
Subject 2	85.4	90.8	100.0
Subject 3	89.6	93.2	91.7
Subject 4	82.9	88.7	95.8
Subject 5	94.2	91.1	95.8
Average	89.2	91.8	96.7

Figure 8: Components detection Accuracy by participants .

Subject 1 and Subject 5 scored well with the highest scores of obstacle detection accuracy while Subject 4 scored the lowest for having a faster walking speed that caused delays in detection from time to time. The warning sign recognition performed very well, except for Subject 3, whose accuracy suffered due to improper cane orientation in the trials.

The deployment of TensorFlow Lite models on ESP32-CAM provided some challenges, especially in the areas of memory constraints and inference speed. These were solved by quantizing the models and doing some architectural optimizations so that the inference speeds were around 320ms for the obstacle classification operation and 280ms for the sign recognition one, which is fast enough to be considered useful while walking at a normal pace.

An IoT-enabled feature adds value to electronic clickers as it does not help in conventional electronic clickers. The locational tracking and its remote monitoring further promise safety for elderly people or those traveling in unfamiliar terrain. Remote ML models are trained so that a system can be improved without the need for additional hardware.

## V. CONCLUSION AND FUTURE SCOPE

With IoT connections and machine learning capabilities in the cane, it holds a great promise for improving the mobility and security of blind people in the future. Along with highly accurate detection and classification of potential obstacles and warning signs, this system also owns really useful connected functionalities through IoT.

Participant feedback has been very positive, with users highlighting the contextual information regarding obstacle classification and the added safety of IoT connectivity. Machine learning added a great deal to the user experience by giving fine-grained information about the environment.

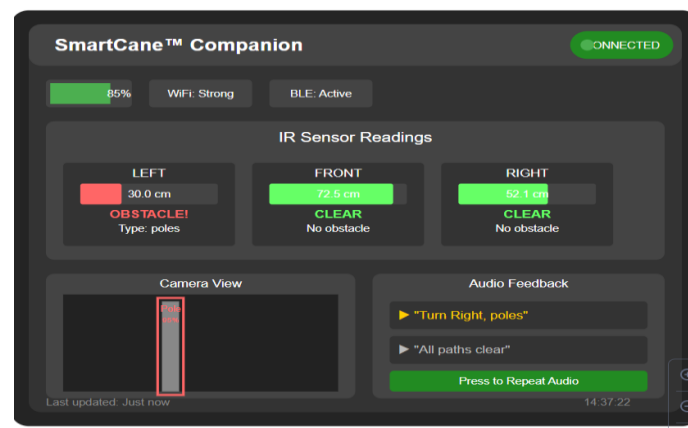


Fig 9: Output configuration

### Future work will concentrate on several key areas:

- 1) Expand the set of classes in the obstacle classification model and improve challenging cases with varying lighting conditions
  - 2) Implement meaning-based semantic scene understanding for wider context
  - 3) Implement crowd analysis methods to facilitate navigation in crowded environments
  - 4) Develop intelligent path planning based on a collection of obstacles
  - 5) Enhance the battery-saving mechanism through advanced power management
  - 6) Investigate federated learning for updating models while protecting privacy
- These means greatly enhance the capabilities of assistive technologies to the visually impaired, with the end aim of very close to providing comprehensive environmental understanding and safe navigation.



Fig 10:Real Time working

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