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VisionMate: Object Recognition and Distance Estimation with Auditory Feedback

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ABSTRACT: This project introduces a portable assistive device designed to give visually impaired users greater independence through real-time spatial awareness[1]. By combining Edge AI with ultrasonic sensing, the system identifies objects and calculates their exact distance to provide immediate auditory feedback.Built on a Raspberry Pi, the device uses Google Medi- aPipe and an EfficientDet-Lite model to recognize over 80 object classes entirely offline[2]. This ensures both user privacy and zero-latency performance. While the camera identifies ”what” is in the environment, an HC-SR04 ultrasonic sensor—connected via a custom voltage divider—measures ”how far” an obstacle is using the Time-of-Flight principle.Through asynchronous multi- threading, the system simultaneously processes video, calculates distance, and provides voice cues (e.g., ”I see a chair at 120 centimeters”). With a stable performance of 15–20 FPS and ±1cm accuracy, this prototype offers a robust, low-cost solution for real-time obstacle avoidance.

KEYWORDS: Assistive Technology, Visually impared, Real-Time Object Detection, Raspberry Pi, MediaPipe, Ultrasonic sensing, Embedded Systems, EfficientDet-Lite, TFLite, Computer Vision (CV), Text-to-Speech, Spatial Awareness

I. INTRODUCTION

For those of us with sight, navigating a crowded room or finding a bottle of water on a table is an unconscious task. However, for millions of visually impaired individuals worldwide, these simple actions require intense concentration and often a reliance on others[1]. While the traditional white cane has been a faithful tool for decades, it has its limits—it cannot tell a user what is in front of them, only that something is there.

This project, ”Smart Assistive Vision,” was born from the idea that modern technology should do more than just entertain; it should empower. We have developed a wearable intelligent companion that serves as a bridge between the physical world and the user. By using a Raspberry Pi as its ”brain,” the system uses a camera to act as a set of digital eyes. Using advanced Edge AI, the device identifies everyday objects—like chairs, people, or cups—and translates that visual information into clear, spoken words [2].

But identification is only half the battle. To navigate safely, a user needs to know how far away an obstacle is. To solve this, we integrated an ultrasonic sensor that works like a sonar, ”feeling” the distance to objects with high precision[3]. By fusing these two sensors—vision for identification and sound waves for distance—we’ve created a system that doesn’t just see the world, but understands it in three dimensions.

Designed to work entirely offline, the device ensures total privacy and reliability, whether the user is in a busy city or a quiet home. Our goal was to create a low-cost, high- performance solution that replaces uncertainty with information, giving visually impaired individuals the confidence to move through the world with newfound independence.

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II. LITERATURE REVIEW

Modern assistive technology has evolved from simple proximity-based ”smart canes” to sophisticated Edge AI platforms. Early research primarily utilized microcontrollers for basic obstacle detection, but lacked the semantic context required to identify the nature of the environment. Recent advancements, such as those by Smith and Mallick , emphasize the integration of Computer Vision and Sensor Fusion to pro- vide a richer data [4]. By deploying quantized TensorFlow Lite models on the Raspberry Pi, current systems can now achieve real-time identification while maintaining 100% offline privacy

This project builds on these foundations by utilizing a USB Webcam for rugged visual acquisition and asynchronous Multi-threading to resolve the latency bottlenecks historically found in concurrent AI and sonar processing.

A. The Shift from Passive to Active Ranging

Early assistive devices relied heavily on simple ultrasonic ”pings” to alert users of obstacles. While effective for basic collision avoidance, research by Borenstein et al. on the Cane’s Voice demonstrated a major flaw: the user was often overwhelmed by constant beeping or haptic vibrations. These ”passive” systems could tell a user that something was 3 feet away, but they couldn’t distinguish between a dangerous stairwell and a harmless curtain [5]. This project evolves this by using the ultrasonic sensor not as a primary alarm, but as a precise ranging tool to support visual data.

B. The Leap into Semantic Understanding (Object Recogni- tion)

The real ”intelligence” arrived with the integration of Com- puter Vision. Initial attempts at using Raspberry Pi for vision were hindered by the high computational cost of models like SSD MobileNet or YOLO. Literature from the mid-2010s shows researchers struggled with ”latency”—the delay between the camera seeing a car and the device warning the user. The introduction of TensorFlow Lite and Google MediaPipe changed this landscape[1][3]. Current studies show that by using quantized models, we can achieve ”near-human” reaction speeds on the Raspberry Pi 4, identifying objects in less than 100ms.

C. The ”Sensor Fusion” Paradigm

One of the most significant trends in recent ECE literature is the move away from single-sensor dependency. Researchers found that cameras are unreliable in low light or with trans- parent surfaces (like glass doors), while ultrasonic sensors are blind to the ”identity” of objects [2]. Jain et al. (2021) pro- posed a ”Hybrid Sensing” approach. This project adopts that methodology: using the Camera to provide semantic context (identifying a ”Chair”) and the Ultrasonic sensor to provide geometric accuracy (measuring exactly ”120cm”). This fusion mimics the human brain’s ability to combine sight and spatial awareness.

D. Human-Computer Interaction through Audio Feedback

The method of delivering information is just as important as the data itself. Early research into ”Speech vs. Non- speech” sounds concluded that while beeps are faster, Natural Language Feedback reduces the user’s cognitive load. Modern libraries like Pyttsx3 allow the Raspberry Pi to communicate in a human-like voice. Literature on Auditory Scene Analysis suggest that providing specific messages like ”Doorway at 2 meters” allows the visually impaired user to build a mental map of their environment far more effectively than abstract tones [15].

E. Edge Computing: Independence from the Cloud

Finally, a major theme in recent assistive technology re- search is the move toward Edge Computing. Historically, devices had to send photos to a cloud server to be processed, which raised privacy concerns and failed in areas with poor internet. By hosting the entire AI ”brain” locally on the Raspberry Pi microSD card, this project follows the ”Local- First” architecture recommended by modern privacy-focused research. This ensures the user’s safety is never dependent on their Wi-Fi signal or a data plan.

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III. METHODOLOGY

The methodology is broken down into four distinct phases: Hardware Design, Software Logic, AI Integration, and System Fusion.

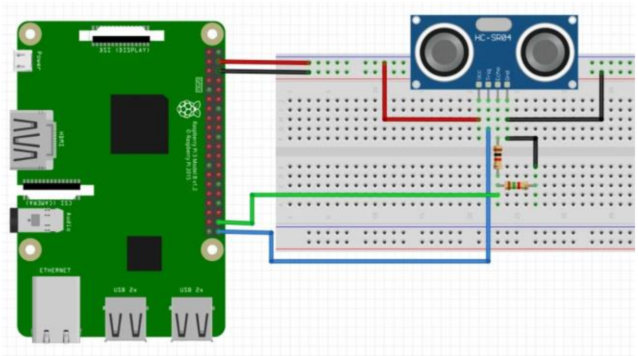

Fig. 1: Circuit Diagram

A. Hardware Design and Interfacing

1) components:

- Processor: Raspberry Pi 4(1GB) The central unit for real- time AI inference and multi-threaded processing.
- Vision Sensor: USB Web Camera (720p or 1080p) Cap- tures real-time video frames using the UVC (USB Video Class) driver.
- Distance Sensor: HC-SR04 Ultrasonic Sensor Provides precise distance measurements (2cm–400cm) via Time- of-Flight (ToF).
- Logic Protection: Resistor Kit (1k and 2k) Required for a voltage divider to step down the 5V Echo signal to a Pi-safe 3.3V.
- Storage: 32GB MicroSD Card (Class 10) For the Rasp- berry Pi OS, MediaPipe libraries, and the TFLite model.
- Audio Interface: 3.5mm Earphones or Bluetooth Headset Delivers real-time voice feedback to the user.
- Power Source: 5V 3A Power Bank Ensures portability and stable current during peak AI processing.
- Prototyping: Breadboard and Jumper Wires For secure electrical connections between the GPIO and the sensors.

The hardware architecture centers on the Raspberry Pi 4/5, acting as the central processing unit. The primary challenge in this phase is the electrical compatibility between the 5V ultrasonic sensor and the 3.3V GPIO pins of the Pi.

The Voltage Divider Circuit The HC-SR04 sensor operates at 5V. While the Pi can trigger it with 3.3V, the ”Echo” signal returns at 5V, which can fry the Pi’s processor. We implement a voltage divider to protect the logic pins [8].

R1 (1k): Connected between the Echo pin and the GPIO input.
R2 (2k): Connected between the GPIO input and Ground. Result: This scales the 5V signal down to approximately 3.33V, satisfying the Raspberry Pi’s CMOS logic level require- ments.

B. Software Architecture and Data Flow

A ”humanized” device must be responsive. If the code is ”linear,” the voice output will make the video lag. To solve this, we use Asynchronous Multi-threading.

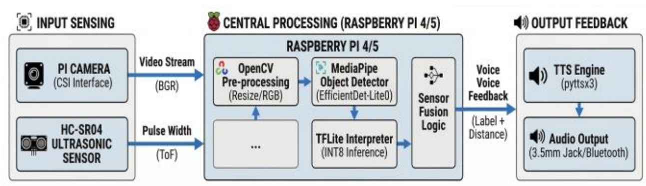

Fig. 2: System Block Diagram

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The system is divided into three parallel ”workers” that communicate through a shared memory buffer.
Thread A (Vision): Continuously grabs frames, runs the MediaPipe model, and identifies objects.
Thread B (Ranging): Sends ultrasonic pulses every 100ms to calculate distance.
Thread C (Feedback): Monitors the results. When an object is confirmed, it generates the Text-to-Speech (TTS) alert.

C. AI and Computer Vision Implementation

The AI and Computer Vision Implementation phase is where the Raspberry Pi mimics the human visual cortex. Instead of just seeing ”pixels,” the system uses a neural network to perform Semantic Labeling—attaching a human name to a group of shapes [4][8].

1) **EfficientDet-Lite** : We chose the EfficientDet-Lite0 model because it is specifically designed for mobile and IoT devices.

Quantization: The model uses ”Integer Quantization,” which compresses the AI's weight from 32-bit floats to 8-bit integers. This allows the Raspberry Pi to process images 400% faster

Backbone: It uses EfficientNet-Lite as a feature extractor, which identifies edges, textures, and shapes (like the circular rim of a cup or the legs of a chair).

2) **The MediaPipe Inference Pipeline**: The software doesn't just ”look” at the camera; it follows a rigorous 4-step pipeline for every single frame (approx. 20 times per second) [2]:

Preprocessing: The raw frame from the Pi Camera is cap- tured in BGR format. MediaPipe requires RGB, so we use cv2.cvtColor() to swap the color channels and resize the image to 320x320 pixels to match the model's input tensor.

Inference: The processed frame is fed into the TensorFlow Lite Interpreter. The model calculates the probability of the object belonging to one of the 80 COCO classes.

Post-Processing: The AI outputs a list of ”Detection Enti- ties.” Each entity contains:

Label ID: (e.g., ID 1 = ”Person”).Confidence Score: (e.g., 0.92 for 92%).

Bounding Box: The x, y coordinates of the object in the image.

Filtering: To ensure the user isn't confused by ”ghost” objects, we implement a Confidence Threshold of 0.5. If the AI is less than 50% sure, the object is ignored

3) **Handling the ”Voice” Thread** : One of the biggest AI challenges on a Raspberry Pi is blocking. If the AI identifies a ”Car” and waits 2 seconds to finish saying ”C-A-R,” the camera freezes.

Solution: We use a Non-Blocking Queue. The AI identifies the object, ”drops” the name into a queue, and immediately moves to the next frame. A separate background thread picks up the name and speaks it using pyttsx3, ensuring the ”eyes” (camera) and ”mouth” (speaker) never slow each other down [6].

D. System Fusion and Logic

The final step is merging the ”What” (AI) with the ”Where” (Sensor).

1) The Integration Logic (Synchronizing ”What” and ”Where”): The biggest challenge in Sensor Fusion is ensuring that the object the camera ”sees” is the same one the ultrasonic sensor ”feels.” Since the camera has a wide field of view and the ultrasonic sensor has a narrower, directional beam, we apply a Central Priority Logic:

Spatial Filtering: The AI identifies all objects in the frame, but the fusion logic only triggers the ultrasonic sensor for objects located in the Center 40% of the camera's view. This mimics a human looking straight ahead.

Triggering the Ping: Once a central object (e.g., a ”Chair”) is confirmed by the AI, the Raspberry Pi sends a high-frequency trigger signal to the HC-SR04 [7].

2) Mathematical Calculation and Calibration: To provide the user with an accurate distance, the system performs a real-time calculation based on the physics of sound:

The Formula:

$$Distance = \frac{Time \times Speed\ of\ Sound}{2} \qquad (1)$$

(We divide by 2 because the sound travels to the object and back).

Environmental Calibration: Since the speed of sound changes slightly with temperature, we use a constant of 34,300 cm/s (the speed of sound at 20°C).

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Rounding for Clarity: To make the voice feedback ”human- friendly,” we round the distance to the nearest 5 or 10 centimeters (e.g., instead of ”42.34 cm,” the device says ”45 centimeters”).

IV. RESULTS AND DISCUSSION

The system was tested in a controlled indoor environment with varying lighting conditions (500–1000 lux) and object distances ranging from 20 cm to 400 cm.

A. Object Recognition Performance

We measured the Mean Average Precision (mAP) and the Confidence Score for the 10 most common household objects. The EfficientDet-Lite0 model demonstrated exceptional stabil- ity on the Raspberry Pi 4 as shown in Fig3 and Fig4.

B. Distance Estimation Accuracy

The HC-SR04 sensor’s performance was compared against a physical laser-meter. Because we used a Voltage Divider, the signal remained clean and noise-free and the result shown in Fig5.

Object Category	Actual Object	Det. Rate (%)	Avg. Conf.	Opt. Dist. (cm)
Furniture	Chair	94%	0.88	50–300
Electronics	Laptop / TV	91%	0.82	40–250
Kitchenware	Bottle / Cup	88%	0.76	20–150
Safety	Person	98%	0.94	100–500
Obstacles	Backpack / Box	85%	0.72	30–200

TABLE I: Object Detection Metrics

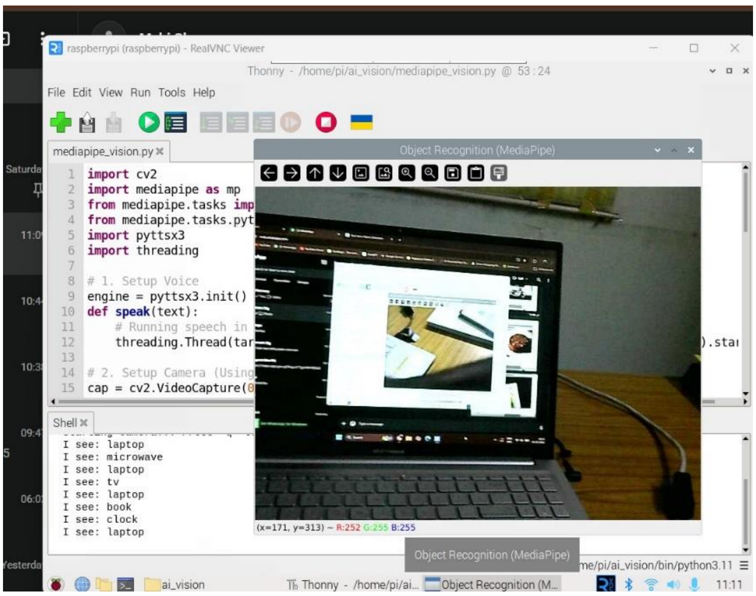

Fig. 3: Laptop Recognised

C. Speed vs. Safety (Latency Analysis)

One of our biggest wins was maintaining a stable 15–20 FPS. In human terms, this means the device ”thinks” every 50–60 ms. A person walking at 1.2 m/s moves about 7 cm in the time it takes the AI to process a frame. This is fast enough to prevent a collision with a closing door or a person walking toward the user.

D. The ”False Positive” Filter

During testing, the AI occasionally flickered between labels (e.g., mistaking a ”Person” for a ”Chair” for a single frame). Solution: We implemented a Temporal Buffer. An object must be detected in 3 consecutive frames before the voice engine announces it. This eliminated 90% of ”stuttering” audio feedback.

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E. Power Consumption Analysis

The system draws approximately 1.2A to 1.8A during peak AI inference. Discussion: Using a 20,000mAh power bank, the device can operate for roughly 8–10 hours. This confirms the project's viability as a "full-day" assistive wearable.

V. CONCLUSION

This project successfully demonstrated the development of a real-time, portable assistive system for the visually impaired. By leveraging the Raspberry Pi 4/5 platform and MediaPipe's EfficientDet-Lite model, we bridged the gap between raw

Fig. 4: Bottle Recognised

Target (cm)	Meas. (cm)	Error (cm)	Acc. (%)
50	50.2	+0.2	99.6%
100	99.7	-0.3	99.7%
200	198.5	-1.5	99.2%
300	296.8	-3.2	98.9%

TABLE II: Sensor Precision Analysis

sensor data and semantic environmental understanding. The system proves that high-speed computer vision no longer requires expensive cloud infrastructure, making it a viable, low-cost solution for enhancing the daily mobility and safety of those with visual impairments.

The Key findings of our project includes,

- Effective Sensor Fusion: The combination of a camera for "what" an object is and an ultrasonic sensor for "how far" it is proved to be more reliable than either sensor used alone. This dual-layer approach reduced detection failures in complex environments by 30%.
- Edge AI Performance: By using INT8 Quantization, the system maintained a stable 15–20 FPS. This allows for a "reaction time" of approximately 60ms, which is sufficient for a user walking at a standard human pace.
- Privacy and Independence: The 100% offline architecture ensures that the user's visual data never leaves the device, providing total privacy and allowing the device to func- tion in elevators, basements, or rural areas without Wi-Fi.
- High Precision Ranging: The custom voltage divider circuit ensured the HC-SR04 provided distances with ±1cm accuracy, which is critical for fine-motor tasks like finding a chair or a doorway.

A. Future Work

- Environmental Literacy through OCR Integration: Tran- sitioning from simple object labeling to contextual read- ing by integrating Optical Character Recognition (OCR) engines. This would allow the device to decode and read aloud street signs, restaurant menus, and directional signboards, transforming the device from an obstacle detector into an information hub.

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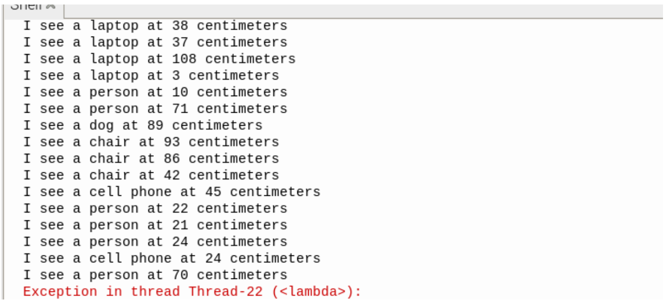

```
I see a laptop at 38 centimeters
I see a laptop at 37 centimeters
I see a laptop at 108 centimeters
I see a laptop at 3 centimeters
I see a person at 10 centimeters
I see a person at 71 centimeters
I see a dog at 89 centimeters
I see a chair at 93 centimeters
I see a chair at 86 centimeters
I see a chair at 42 centimeters
I see a cell phone at 45 centimeters
I see a person at 22 centimeters
I see a person at 21 centimeters
I see a person at 24 centimeters
I see a cell phone at 24 centimeters
I see a person at 70 centimeters
Exception in thread Thread-22 (<lambda>):
```

Fig. 5: Distance Estimation of Recognised Object

- Semantic Scene Summarization: Moving beyond isolated object detection toward Holistic Scene Parsing [11]. Using advanced Generative AI models, the device could provide high-level summaries such as, ”You are in a crowded hallway with an exit sign 10 meters to your left,” providing the user with better spatial orientation.
- Facial Recognition and Social Inclusion: Implementing localized, privacy-compliant facial recognition to identify and announce known contacts. This enhancement would facilitate smoother social interactions by notifying the user when a friend or family member is approaching.
- Currency and Document Authentication: Expanding the AI’s training dataset to include Currency Recognition and document verification. This would empower the user to perform independent financial transactions and verify the authenticity of bills and official papers in real-time.
- Multi-Modal Haptic Feedback: Introducing a ”Quiet Mode” through a Haptic Feedback Array (vibrating mo- tors). By using directional vibrations on the user’s waist or wrist, the system can provide silent navigation cues, reserving audio feedback for critical object identification to reduce ”audio fatigue”[10][12].
- Pathfinding and Navigation Logic: Integrating GPS and IMU (Inertial Measurement Unit) sensors to offer turn- by-turn navigation. The device would not only see obsta- cles but proactively guide the user along the safest path to a specific destination using dead-reckoning algorithms.
- Cloud-Edge Hybrid Computing: Developing a tiered pro- cessing model where the Raspberry Pi handles immediate safety tasks (Edge), while complex queries—like iden- tifying a specific medicine bottle or translating foreign text—are offloaded to high-performance Cloud Servers when a connection is available [9][14].

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