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VisionBot smart assistive robotic glasses for visually impaired people

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ABSTRACT

Sensory impairment, such as vision loss, affects balance, spatial awareness, and independent mobility. Traditional aids like white canes and guide dogs do not fully address hazards at mid-torso or overhead levels, nor do they solve issues related to availability or route instructions. Electronic Travel Aids (ETAs) have expanded capabilities but often compromise on sensing range, high computing and power costs, or ergonomic usability for non-experts. This paper describes an affordable wearable assistive device called VisionBot, which combines ultrasonic obstacle sensors, an ESP32 microcontroller, a DFPlayer Mini voice speaker, and GPS for outdoor use. The firmware is event-driven and non-blocking in nature, and initially verifies the presence of obstacles. It issues audible warnings where danger is imminent and displays turn-by-turn directions (using GPS) where the road is clear. In order to ensure stability of the system, we introduce moving-average filtering and a watchdog. The paper outlines the leading algorithms in audio and GPS prompts, which were all tested on smart glasses, and proves that they are effective in most environments. The future work will improve the robustness of indoor positioning, include a haptic response, and create more energy-efficient perception. VisionBot demonstrates the way in which multimodal tools may be transformed into cheap mobility tools to assist visually impaired people.

Keywords: smart glasses, visually impaired people, obstacle detection, GPS navigation, audio feedback system, system architecture, assistive system.

INTRODUCTION

Loss of sight not only affects sight, but it can also lead to difficulty in maintaining balance, spatial sense, and confidence in walking. According to the WHO, approximately 285 million individuals in the world suffer from visual impairments, and 39 million among them are completely blind [1]. Having a growing ageing population and increased infectious eye disease [1], the numbers are increasing, and there is more concern about the increasing burden of visual impairment in the world, as well as the necessity of lifetime health-care plans and sustainable technology solutions. Having little or no vision, people have to make numerous small choices in their motion, and it is complicated [2]. The basic activities, such as walking straight, crossing a road, climbing the stairs, and walking on bumpy ground can be challenging [2]. Unsafe overheads, low branches, signs, and scaffoldings can be hazards, and normal mobility equipment is not aware of them [3].

Traditional assistive tools have been instrumental but are still incomplete. The white cane remains the most widely used mobility aid due to its low cost and ease of use. However, it depends entirely on physical contact and offers limited protection against mid-torso and head-level obstacles [4]. The guide dog provides intelligent assistance and emotional support, yet the cost of breeding, training, and maintaining such dogs can reach tens of thousands of dollars. Due to limited availability, waiting lists are long, and accessibility is restricted to a small fraction of visually impaired individuals. The latest developments in the electronic travel aids (ETA) have been in making them more environmentally friendly and in helping the user identify systemic challenges without actual interaction [5]. There are shortcomings of each technology, though. As an example, infrared (IR) and ultrasonic systems have limited range and field of view [6], whereas camera-based systems have valuable context but are costly, not so mobile, and require high processing power, resulting in problems such as motion blur when head movements occur [7].

ETAs design needs to have accuracy, responsiveness, power efficiency, and ergonomics that will make them practical to use [5]. GPS technology is strong in the outdoors, but in the indoor environment, most of these systems have a weak signal, which causes them to be ineffective, and this has led to a hybrid system that can adapt depending on the surroundings [8]. GPS synchronisations with microcontrollers and smartphone interfaces have proven innovative in enhancing navigation for people with impaired eyesight, and prototypes provide practical outdoor navigation with voice direction interaction applications [9]. Also, the incorporation of geographic information systems (GIS) and mobile applications has helped provide customised navigation assistance to blind pedestrians.

Nevertheless, even now, the ETAs and wearable assistive devices have a number of challenges. Most of the systems are either costly or offer size or are restricted to a particular environmental situation [10]. In addition, most devices are concerned with the identification of obstacles at the ground level, and thus, they expose the user to injuries that are greater than the waist [3]. Moreover, a lack of a cheap and low-power device, which combines micro-navigation (avoiding obstacles) with macro-navigation (following through a route), is a research gap.

In response to these limitations, this study introduces VisionBot, which is a low-cost wearable gadget, a combination of voice feedback, ultrasonic obstacle detection, and GPS navigation. It is constructed on the basis of the ESP32 microcontroller and processes sensor inputs to identify obstructions and deliver audio feedback to direct the user and walk without having to constantly touch the ground [11]. Unlike technology-assisted smart-cane systems, which are primarily handheld and focused on ground-level obstacle detection [4], VisionBot is implemented as a glasses-mounted Electronic Travel Aid that integrates real-time micro-navigation through ultrasonic head-level obstacle detection with macro-navigation via GPS-based outdoor directional guidance on a single embedded platform. This hands-free configuration improves protection against mid-torso and overhead hazards while maintaining efficient embedded real-time processing through an event-driven, non-blocking firmware architecture. Experimental validation demonstrates a mean obstacle detection accuracy of 96.6% (483/500; 95% confidence interval: 95.0–98.2%) across 500 trials, with a median end-to-end latency of 84.5 ms, and a bill of materials of approximately USD 45, supporting its practical deployment. VisionBot is lightweight and portable, powered by a 3.7 V Li-ion battery with low-power components that enable extended operational use.

This paper (i) details the VisionBot hardware design, including the ESP32, ultrasonic sensors, DFPlayer Mini, and GPS module; (ii) presents the non-blocking, event-driven software architecture enabling low-latency sensing and feedback; and (iii) reports experimental results on accuracy, response time, and real-world usability. The study demonstrates a balance between performance, cost, and ergonomics in a wearable form. VisionBot also allows future extensions, such as environmental tagging or SOS alerts, while acknowledging limitations in GPS accuracy and energy efficiency.

BACKGROUND

Assistive technologies for visually impaired users have advanced significantly in the past decade, improving navigation safety and usability. Traditional tools such as the white cane remain essential but are limited to ground-level obstacle detection and cannot identify overhead hazards like signage or branches. These limitations have driven the development of ETAs, which integrate sensing and feedback systems. Research in this area has evolved from basic obstacle detection to more complex wearable systems combining multiple sensing and navigation methods.

Pham and Nguyen (2013) are pioneers in the field of technology electronic travel aids since they developed a GPS-enhanced ultrasonic tracking device that serves the needs of blind users by allowing them to navigate the world in real-time by locating objects and identifying obstacles around [12]. On these grounds, Fakhr, and Seddik (2015) came up with an ETA prototype that comprised the use of ultrasonic sensors as a valid alternative to infrared (IR) sensors [13]. Previous IR-based solutions had the disadvantage of sunlight interference as well as reflective noise interference that restricted outdoor usage. The introduction of ultrasonic sensors, in particular, the HC-SR04 module, allowed it to offer strong capabilities of distance measurements and stable sensing under different lighting conditions. Nevertheless, their study was mostly qualitative, as no specific numbers of performance metrics were mentioned. With the advancement in sensor and microcontroller technology, Real and Araujo (2019) emphasised the usefulness of an ultrasonic-based obstacle detection system in offering quality distance estimations and low implementation costs [14]. On the same note, Fernandes (2020) came up with a smartphone navigation application, which integrated GPS with audio guidance in terms of the turn-by-turn directions [15]. Both papers brought about the importance of spatial awareness and location guidance to provide efficient navigation assistance.

Multi-modal sensing and intelligent perception approaches have been proposed to enhance obstacle detection accuracy by combining complementary sensing and processing techniques, particularly in smartphone-based assistive systems [20]. Nevertheless, the majority of studies were devoted to the ground-level risks, and not much was done concerning head-level challenges. Further, ultrasonic sensors and microcontrollers have been integrated into conventional cane-based designs to enhance detection capability; however, such systems remain handheld and are primarily effective for ground-level obstacle detection, while offering limited protection against mid-torso and head-level hazards [4].

Although there is an improvement, a typical problem with such research is the absence of a quantitative assessment. Numerous papers define prototypes as being effective, not measured in exact specifications such as accuracy or latency. Several prior studies reported prototype implementations without comprehensive quantitative evaluation of detection accuracy or latency. This is particularly important in assistive systems, in which even small delays can endanger users. The electronic travel aid performance assessment has not been well investigated.

A similar development happened at roughly the same period, with Manikandan (2024) improving the design to include a microcontroller capable of processing ultrasonic information and providing audio feedback to the user, giving them real-time notifications about an approaching obstacle [17]. Their effort led to the perfection of integrated assistive systems that convey warnings and messages via simple and easily understandable auditory signals.

Recent studies have focused on wearable assistive devices that can be operated hands-free and have a better state of awareness. Mahadevan and Hairol Anuar (2024) developed a GPS-enhanced smart blind stick that includes crisis warnings based on user positioning and integrates local obstacle avoidance with route guidance [18]. Although it was superior in terms of real-time awareness, the device remained handheld and could not be used to provide head-level navigation. This limitation is consistent with the broader evaluation of technology-assisted cane systems reported by Khan et al. (2018) [4]. There are new trends to combine macro-navigation with micro-navigation. Nevertheless, not many designs have been able to incorporate real-time obstacle detection, precise GPS tracking, and wearability in a lightweight system.

In parallel, vision-based systems have been widely investigated in assistive navigation and robotic perception, particularly using deep learning-based object detection approaches [35]. Bochen and Ambrożkiewicz (2023) studied the influence of light intensity on the operation of vision systems in collaborative robots, demonstrating that illumination conditions can affect the stability and performance of vision-based detection [36]. Batsch et al. (2025) presented a vision-based control approach for a small educational robot arm, showing the integration of computer vision with real-time robotic actuation and control [37]. More recently, Al-Abbas et al. (2026) applied multiple YOLO object detection algorithms in UAV-based crop monitoring and reported strong detection performance in outdoor environments [38]. Although these works focus on industrial and agricultural domains rather than assistive mobility, they highlight the strengths and practical constraints of vision-based perception systems, supporting the motivation for lightweight embedded sensing approaches such as VisionBot.

The above studies reveal three main gaps in electronic travel aids: limited quantitative benchmarking, a focus on ground-level detection, and few compact systems that integrate real-time sensing with GPS navigation. VisionBot addresses these issues through a glasses-mounted design that combines ultrasonic obstacle detection with GPS-based path guidance, supporting both micro- and macro-navigation. Experimental results show 96.6% detection accuracy, a median latency of 84.5 ms, and a hardware cost below USD 45, indicating practical feasibility for assistive navigation.

METHODOLOGY

VisionBot integrates an ESP32 microcontroller with an ultrasonic sensor, a DFPlayer Mini, and a GPS module to enable real-time obstacle detection and navigation. This section details the system architecture, control flow, sensing logic, audio feedback mapping, and GPS-based navigation functions (NDS). The low-latency design supports its use as a wearable assistive solution for visually impaired users.

System architecture

The ESP32 microcontroller measures distances using an ultrasonic sensor and generates audio alerts through a DFPlayer Mini module [21], while the GPS module enables macro-navigation functionality. The overall hardware integration and signal flow are illustrated in Figure 1. The system features a lightweight, battery-powered structure, making it suitable for wearable smart glasses designed for visually impaired users [22].

ESP32 control system

ESP32 microcontroller-based VisionBot's control system incorporates an ultrasonic sensor input and a GPS receiver. To ensure smooth voice prompts, the whole thing runs real-time audio feedback through an even smaller digital chip called 'DFPlayer Mini' with Wi-Fi and Bluetooth onboard at your command. It can also easily connect to tomorrow's cloud services [21]. We denote the state of the sensors at time t by:

$$S(t) = [\ d(t), g(t)\ ] \tag{1}$$

The outputs of the ultrasonic sensors are distance data d(t) and coordinates g(t) from satellite navigation units. It is information based on these inputs that the ESP32 analyses to generate voice prompts for navigation.

Obstacle detection system

The VisionBot system employs an HC-SR04 ultrasonic sensor to estimate obstacle distance using the standard time-of-flight (ToF) principle [11], [23]. The sensor emits a high-frequency acoustic pulse and measures the echo return time to compute distance as:

$$d[k] = \frac{v.T[k]}{2} \tag{2}$$

In which d[k] is the distance at sampling instant k as measured, T[k] is the return time of the echo, and v is the speed of sound in air (normally 343 m/s at 25 °C) [24]. The obstacle sensing principle and trigger–echo timing relationship are illustrated in Figure 2(a) and Figure 2(b), respectively.

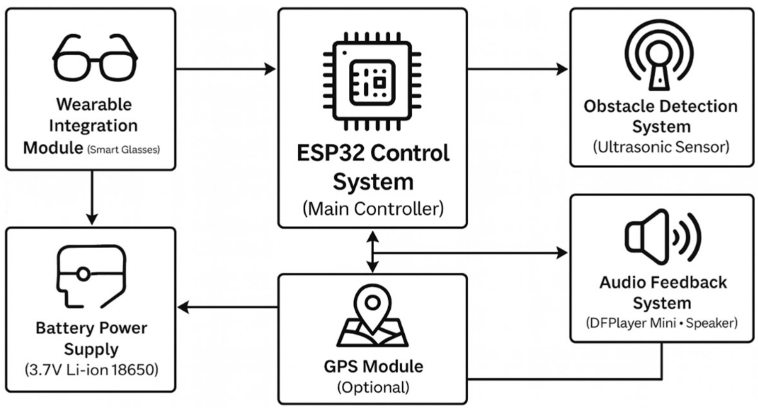

Figure 1. Architecture of the proposed system

To reduce spurious readings caused by environmental noise, surface absorption, and multipath reflections, the ESP32 controller implements moving-average filtering, hysteresis thresholds, and debouncing logic [27]. The filtered distance measurements are then processed by a finite-state classifier that categorises the environment into CLEAR, CAUTION, or NEAR states, triggering the corresponding audio feedback.

Audio feedback system

The audio feedback module translates sensor decisions into spoken alerts. VisionBot uses a DFPlayer Mini to store MP3 files on a microSD card and play them through a small speaker [26]. The ESP32 sends UART commands to trigger playback, enabling real-time audio output. As shown in Figure 3, processed distance data is mapped to specific audio files and delivered accordingly.

The system associates a particular audio track with the distance variable d that it receives from the obstacle-detecting system. The piecewise function track(d) is used to model this relationship:

$$track(d) = \begin{cases} 0001.mp3, & d \leq 5\ cm \\ 0002.mp3, & 5 < d \leq 15\ cm \\ 0003.mp3, & 15 < d \leq 55\ cm \\ \varnothing\ , & d > 55\ cm \end{cases} \tag{3}$$

Here Ø denotes a null output, meaning no audio is generated. The equation maps threshold-based distance measurements to corresponding audio files. Prior research on assistive auditory displays supports this discrete mapping approach, as it helps users distinguish proximity levels clearly [19]. The practical implementation of this model is summarized in Table 1.

To enhance audio decision reliability, use a 200–300 ms refresh rate, a moving-average filter to reduce noise, hysteresis to prevent quick state switching, and a cooldown mechanism to ensure only one critical alert sounds at a time.

GPS module for navigation

VisionBot uses a u-blox NEO-6M GPS receiver to obtain latitude (ϕ) and longitude (λ) data via UART (9600 bps) in NMEA format. The GPS subsystem integration and data flow are shown in Figure 4.

The great-circle distance between the user's present location (ϕ_1, λ_1) and the destination (ϕ_2, λ_2) is determined using the Haversine formula. In navigation systems, this is a commonly used technique for calculating geographic distance [29].

$$\begin{aligned} a &= sin^2\left(\frac{\Delta\phi}{2}\right) + cos(\phi_1)\,cos(\phi_2)\,sin^2\left(\frac{\Delta\lambda}{2}\right) \\ c &= 2 \cdot atan2(\sqrt{a}, \sqrt{1-a}) \\ d &= R \cdot c \end{aligned} \tag{4}$$

where: R is the Earth's radius (approximately 6371 km).

The system computes the great-circle bearing toward the predefined destination to generate directional guidance. Turn-by-turn navigation is

Table 1. Audio-to-distance prompt mapping of VisionBot (DFPlayer Mini Tracks)

Distance range	Action (MP3 file)	Spoken prompt
d≤5 cm	0001.mp3	"Stop immediately" (very close)
5<d≤15 cm	0002.mp3	"Obstacle ahead"
15<d≤55 cm	0003.mp3	"Proceed with caution."
d>55 cm	—	”Path is Clear" (no audio)

a) b)

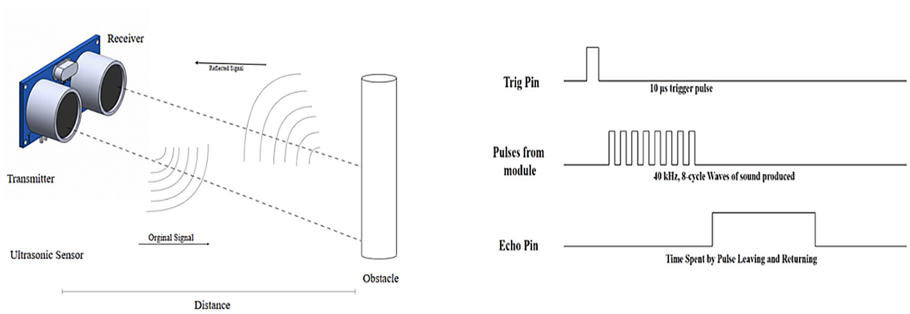

Figure 2. HC-SR04 ultrasonic sensor working principle: (a) obstacle detection concept; (b) timing relationship between trigger signal, ultrasonic burst, and echo response

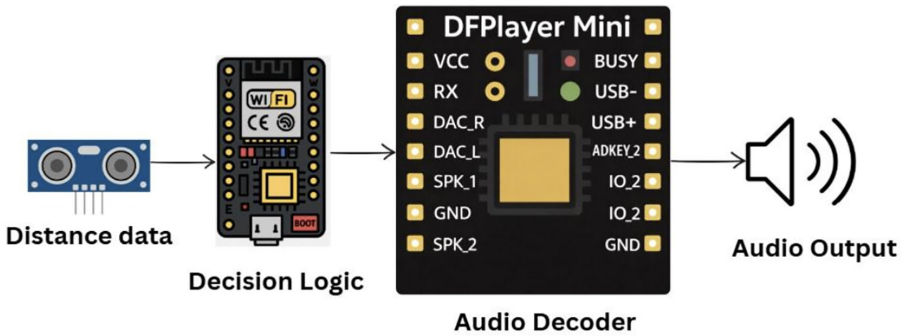

Figure 3. DFPlayer mini-based audio feedback system

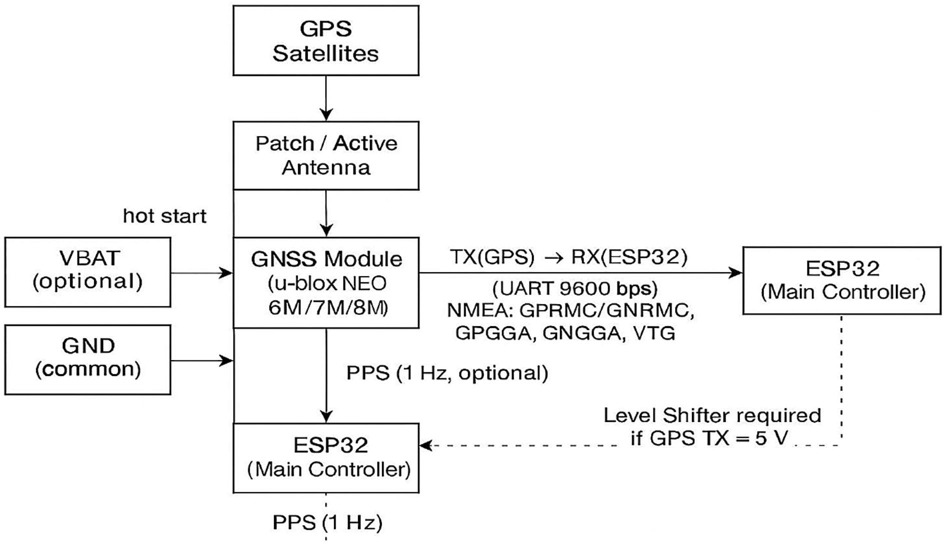

Figure 4. Block diagram of GPS navigation subsystem

implemented using a bearing-to-destination strategy rather than full street-network routing. Directional cues are produced based on the angular deviation between the current movement direction and the computed target bearing. Off-route detection and arrival confirmation are handled using predefined geofencing thresholds. Figure 5 illustrates the integration of GPS macro-navigation with real-time ultrasonic obstacle warnings. The combined macro- and micro-navigation framework supports safe outdoor mobility [25, 30].

Software architecture

The Visionbot software uses the ESP32 microcontroller for real-time sensor input, decision-making, and feedback, programmed in C/C++ with the Arduino IDE. Its modular algorithms enable responsive and safe navigation. Figure 6 shows the integration of data acquisition, decision logic, and audio feedback for obstacle avoidance and navigation.

IMPLEMENTATION

VisionBot consists of two main components: hardware and system software. The hardware integrates sensing, computation, and feedback to enable seamless real-time operation.

Hardware implementation

VisionBot consolidates hardware control and system management into a compact, energy-efficient design. It operates on low power and can be supplied by a battery or solar panel rather than relying on a fixed electrical source [31]. The system is built around a dual-core 240 MHz ESP32 processor, which coordinates obstacle detection, GPS navigation, audio output, and data acquisition, ensuring coherent subsystem integration and reliable decision-making [32].

The obstacle detection system employs an HC-SR04 ultrasonic sensor (2–400 cm range), interfaced with the ESP32 for distance

a) **b)**

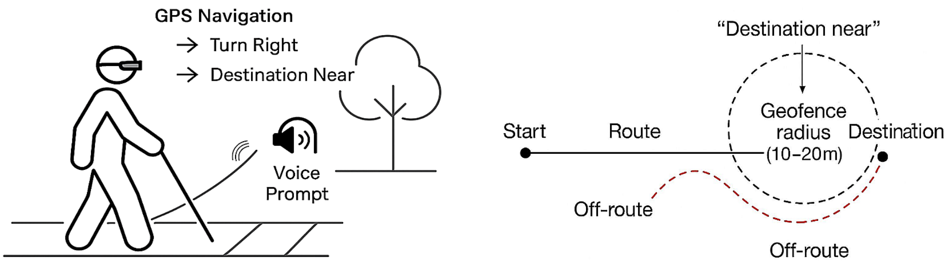

Figure 5. GPS-based navigation framework: (a) macro-navigation with real-time obstacle detection and audio feedback; (b) geofencing and off-route detection

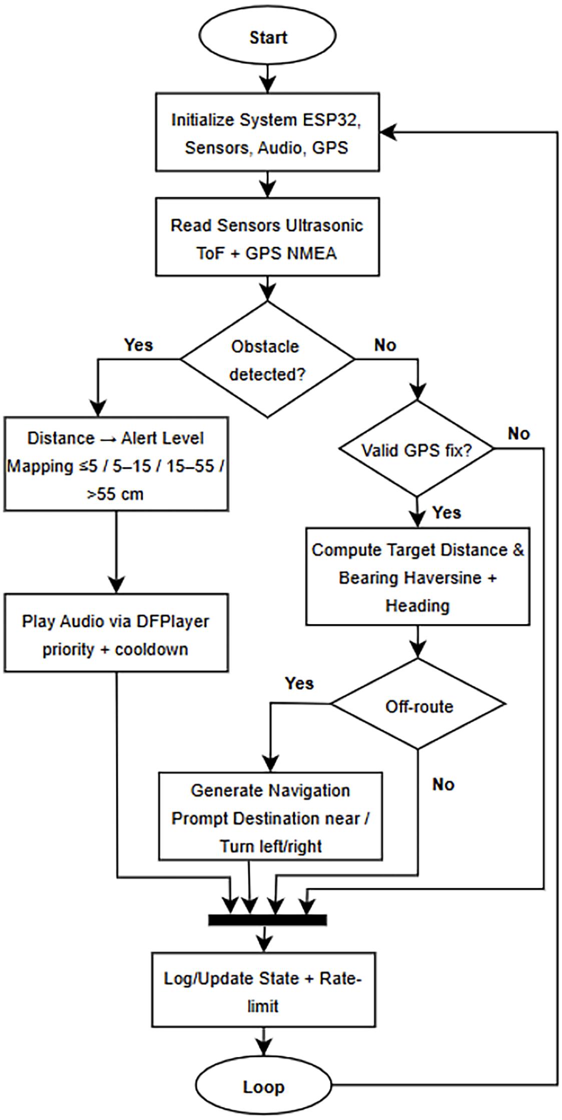

Figure 6. Software architecture flowchart of VisionBot

measurement and trigger processing. Operating at 660 Hz with ±3 mm precision and pulse interrogation up to 100 kHz, it provides reliable ranging performance [33]. Audio feedback is delivered through a DFPlayer Mini MP3 module via UART, playing pre-recorded warnings through an onboard speaker [34]. Outdoor turn-by-turn navigation is supported by a u-blox NEO-6M GPS module for positioning.

The system is powered by a 3.7 V lithium-ion rechargeable battery with TP4056 charging protection and a voltage booster supplying 5 V to all subsystems, supporting low-power operation. Figure 7 presents the interconnection diagram illustrating subsystem integration.

Hardware cost and power summary

The hardware components include an ESP32 development board (USD 8), an HC-SR04 ultrasonic sensor (USD 2.5), a u-blox NEO-6M GPS module (USD 10), a DFPlayer Mini audio module (USD 4), an 8 Ω mini speaker (USD 2), a 3.7 V 2000 mAh Li-ion battery (USD 6), a TP4056 charging module (USD 1.5), and auxiliary wiring and frame components (USD 11), resulting in a total hardware cost of approximately USD 45.

The average system current consumption during active operation is approximately 150–180 mA, including ESP32 processing, GPS tracking, ultrasonic sensing, and intermittent audio playback. With a 2000 mAh Li-ion battery, the estimated continuous runtime is approximately 8–11 hours per charge under typical usage. Solid-state components such as the ESP32 and GPS module have expected operational lifetimes exceeding 5 years under normal conditions, while the Li-ion battery is rated for approximately 300–500 charge cycles.

Software implementation

VisionBot is developed in C++ using the Arduino IDE and follows an event-driven, non-blocking

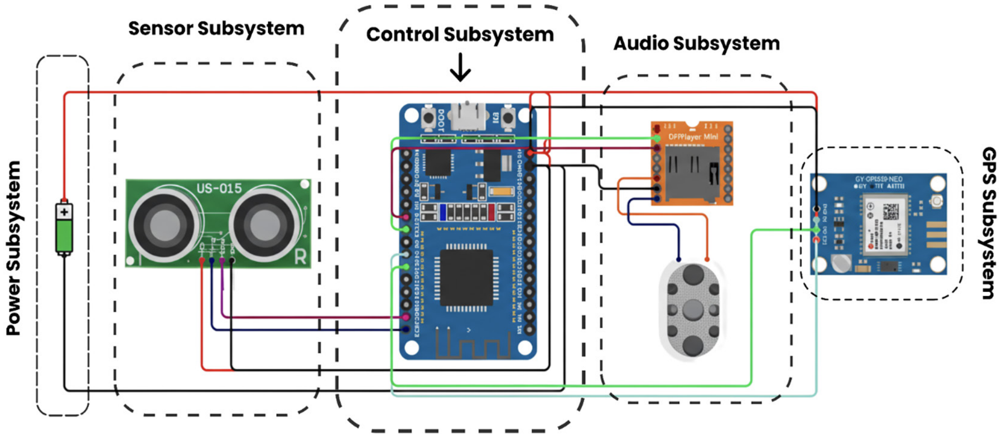

Figure 7. VisionBot smart glasses circuit diagram

architecture to leverage the ESP32's real-time capabilities. A hardware abstraction layer (HAL) manages communication between the GPS module, DFPlayer Mini, and ultrasonic sensor. A millis()-based scheduler governs firmware execution. Core algorithms handle data acquisition (Algorithm 2), safety prioritisation (Algorithm 3), and the main control loop (Algorithm 1), ensuring obstacle alerts override navigation prompts. Modular functions such as MeasureDistance and GPS parsing improve code maintainability and clarity. Algorithms 1–3 are listed:

Navigation uses bearing-to-destination logic instead of map-based routing. A predefined target coordinate is set, and the system computes the great-circle bearing from the current GPS position

```
Function InitializeSystem()
Input: None
Output: Subsystems ready (READY)
Initialize_Serial_Monitor
Configure_Pins(ULTRASONIC_TRIG, ULTRASONIC_ECHO)
Initialize_UART(DFPLAYER_SERIAL, 9600_BPS)
Initialize_UART(GPS_SERIAL, 9600_BPS)
if DFPlayer.begin() fails then
HaltSystem()
end if
Set_Volume(25)
Define_Thresholds(VERY_CLOSE, CLOSE, CAUTION)
return READY
end function
```

Algorithm 1. System initialization (VisionBot initialization)

```
Function GET_SENSOR_DATA()

Input: Ultrasonic echo signal; GPS NMEA serial stream
Output: distance (cm), gps_data (validated), prev_gps (previous fix)
Trigger_Ultrasonic_Pulse()
echo_time ← Measure_Echo_Pulse()
distance ← (echo_time × 0.0343) / 2
while GPS_Serial.available() do
Parse_GPS_Character(GPS_Serial.read())
end while
gps_data ← Get_Validated_GPS_Object()
prev_gps ← Update_Previous_Fix(gps_data)
return distance, gps_data, prev_gps
end function
```

Algorithm 2. Data acquisition and processing

```
Function GENERATE_FEEDBACK(distance, gps_data, prev_gps)
Input: distance (cm), gps_data (validated), prev_gps
Output: Obstacle alert or navigation cue
if 0 < distance ≤ CAUTION_THRESHOLD then
if distance ≤ VERY_CLOSE_THRESHOLD then Play_Audio(Track_1)
else if distance ≤ CLOSE_THRESHOLD then Play_Audio(Track_2)
else Play_Audio(Track_3)
else if Is_Valid(gps_data) then
if Arrived(gps_data, DESTINATION, ARRIVAL_RADIUS) then
Play_Audio(Track_ARRIVED)
else if OffRoute(gps_data, DESTINATION, OFFROUTE_RADIUS) then
Play_Audio(Track_NAV_ALERT)
else
θ ← Normalize_Angle(
Compute_Bearing(gps_data, DESTINATION)
− Compute_Heading(prev_gps, gps_data))
if |θ| ≤ STRAIGHT_THRESHOLD then Play_Audio(Track_GO_STRAIGHT)
else if θ > 0 then Play_Audio(Track_TURN_RIGHT)
else Play_Audio(Track_TURN_LEFT)
end if
```

Algorithm 3. Control of hierarchical feedback

to that destination. This bearing is compared with the user's heading estimated from consecutive GPS updates. Audio cues are generated according to the direction and magnitude of angular deviation. An arrival geofence radius stops prompts once the destination is reached.

RESULTS AND DISCUSSIONS

This chapter reviews how VisionBot performs by describing the experimental setup and measuring its accuracy, speed, and reliability. It also explains what these results mean for real-world use and compares them to earlier studies (Figure 8).

Performance metrics and evaluation criteria

To improve methodological clarity and reproducibility, formal evaluation criteria were defined prior to validation. Detection accuracy was computed as:

$$Accuracy(\%) = \frac{N_{correct}}{N_{total}} \times 100 \quad (5)$$

where: $N(correct)$ denotes trials with correct obstacle detection within the 10–55 cm range, and $N(total)$ is the total number of trials.

A detection was counted as successful when the appropriate audio alert matched the obstacle distance category. Detection delay was defined as the interval between ultrasonic pulse transmission and audio playback, measured using the ESP32 internal timer. Failures were classified as noise distortion, surface reflection loss, or out-of-range readings. Of 500 trials, 483 were successful, yielding 96.6% accuracy (95% confidence

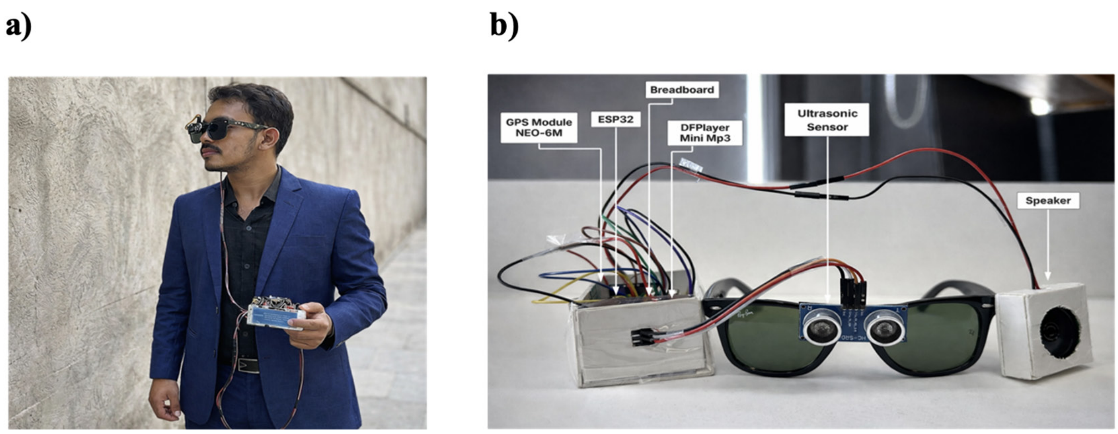

Figure 8. VisionBot wearable assistive system: (a) VisionBot wearable system in the real environment and (b) VisionBot smart-glasses hardware prototype with integrated modules

interval: 95.0–98.2%, binomial model). Mean detection latency was 83.8 ± 7.8 ms, with a 95% CI of 82.0–85.6 ms.

Experimental setup

Experimental validation was performed in a controlled 10-meter indoor corridor to assess obstacle detection under standardized conditions. Obstacles were placed at horizontal distances from 10 to 55 cm, with 50 trials per distance (500 total). Detection results and processing delay were measured using the ESP32 internal timer. Sensor orientation, tilt, firmware thresholds, obstacle material, lighting, and ambient noise were held constant, and no hardware or software parameters were changed. This repeated-trial design reduced random variability, allowing performance differences to be attributed primarily to obstacle distance (Table 2).

Extended validation in realistic conditions

Beyond the 10–55 cm corridor tests, additional evaluations examined more realistic conditions. For head-level validation, obstacles were placed at 120 cm, 150 cm, and 170 cm, with 30 trials per height using the same sensor configuration; accuracy remained above 94%. Outdoor testing was conducted under ambient noise levels of 55–75 dB, adding mild environmental variability. Across 100 additional trials within the validated distance range, detection accuracy ranged from 93% to 95%, with only slight changes in processing delay compared to indoor results. These results suggest stable performance under moderate acoustic and environmental disturbances.

System accuracy and reliability

The primary measure of VisionBot's viability is its detection accuracy, illustrated as a function of distance in Figure 9.

The system maintained high performance across the 10–55 cm range, achieving a mean accuracy of 96.6%. Perfect detection (100%) was recorded at 25 cm and 55 cm, while the lowest accuracy (92%) occurred at 30 cm due to environmental noise. Slight reductions at 20 cm and 50 cm (94%) were linked to reflection-related variability. Failures were limited and consistent with known ultrasonic constraints rather than system instability. The overall accuracy aligns with cane-based systems reported at 95–98% [14, 15], while extending detection capability to a glasses-mounted form factor suitable for head-level obstacles.

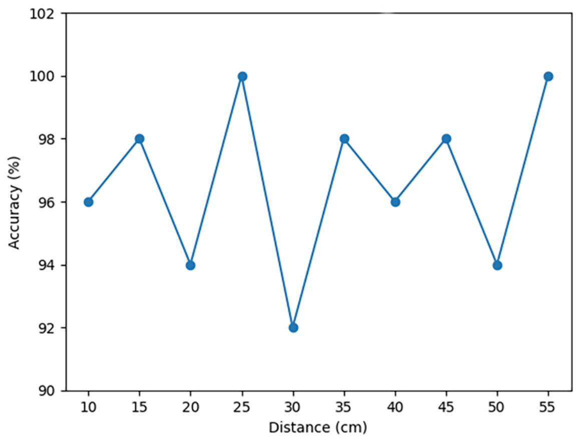

Figure 9. Detection accuracy (%) as a function of obstacle distance

Table 2. VisionBot performance test data summary

Test No.	Assumed distance (cm)	Total trials	Successes	Failures	Accuracy (%)	Detection delay (ms)	Failure cause
01	10	50	48	2	96%	80	Noise
02	15	50	49	1	98%	85	Out-of-range
03	20	50	47	3	94%	90	Reflection
04	25	50	50	0	100%	70	–
05	30	50	46	4	92%	95	Noise
06	35	50	49	1	98%	82	Out-of-range
07	40	50	48	2	96%	88	Reflection
08	45	50	49	1	98%	84	Noise
09	50	50	47	3	94%	91	Out-of-range
10	55	50	50	0	100%	73	–

Latency and real-time performance

For assistive systems, responsiveness is critical for safe navigation. The system's detection delay is analyzed in Figure 10.

The system recorded a median detection delay of 84.5 ms (IQR: 80–90 ms), with a mean latency of 83.8 ± 7.8 ms (95% confidence interval: 82.0–85.6 ms), indicating low variability across distances. This consistency is attributed to the deterministic, non-blocking ESP32 firmware. The latency is well below typical human reaction times (200–250 ms), supporting real-time obstacle avoidance. Compared with similar ultrasonic assistive prototypes [16, 17], VisionBot achieves competitive responsiveness in a lightweight wearable form.

Analysis of failure modes and holistic performance

The failure mode analysis (Figure 11) indicates that observed errors primarily arise from inherent limitations of ultrasonic sensing. Of the 17 failures recorded across 500 trials, noise-related distortion accounted for approximately 41%, while reflection effects and out-of-range measurements each contributed approximately 29%. These results are consistent with documented sensitivities of ultrasonic-based assistive systems to surface reflectivity and acoustic interference [13, 20]. The quantitative decomposition of failure sources provides a structured basis for future improvements, including sensor fusion and advanced signal filtering techniques.

GPS module integration and preliminary findings

The GPS module was tested to confirm hardware–software integration and macro-navigation function. The ESP32 interfaced with the u-blox NEO-6M via UART and correctly parsed NMEA 0183 data. Time to First Fix (TTFF) was measured in five outdoor cold-start trials under open-sky conditions (Figure 12), yielding 47–60 s with a mean of 52.8 ± 4.9 s. This aligns with typical consumer-grade GPS performance.

Beyond TTFF, additional navigation-related metrics were evaluated from the GPS data stream. In all trials, the receiver reliably transitioned from a "no fix" state to a valid position solution, demonstrating full navigation availability. After satellite lock, stable tracking of multiple satellites was maintained, and acceptable dilution-of-precision (DOP) indicators were observed, confirming reliable positioning stability for macro-level pedestrian navigation under open-sky conditions. Similar GPS-enabled assistive navigation frameworks have been reported in smart blind stick systems integrating GPS modules for outdoor guidance [18]. The observed TTFF values are consistent with typical performance reported for consumer-grade GPS modules in embedded navigation systems [12].

System limitations

While VisionBot demonstrates strong performance under controlled conditions, several limitations remain. The ultrasonic sensing approach is inherently sensitive to surface reflectivity, absorption characteristics, and environmental acoustic noise, which contributed

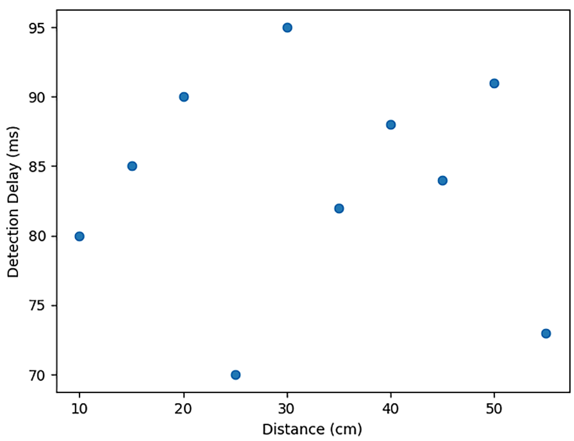

Figure 10. Detection delay (ms) as a function of obstacle distance

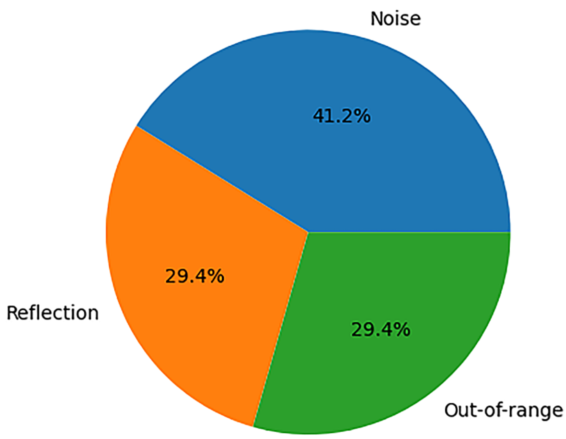

Figure 11. Distribution of failure causes in 500 validation trials (n = 17)

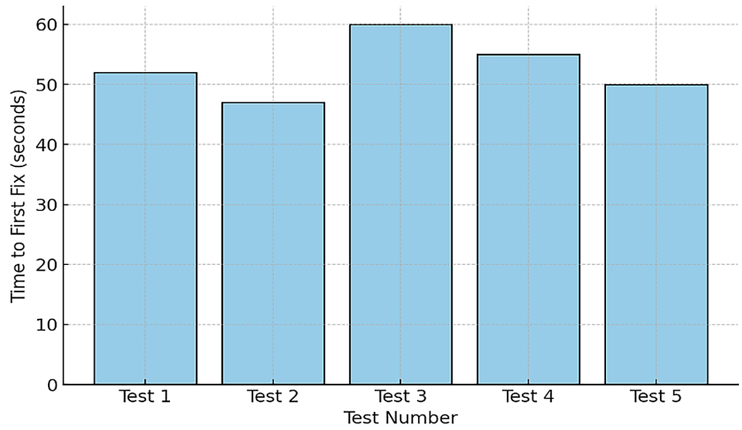

Figure 12. Time to first fix (TTFF) across five outdoor cold-start trials

to the minor failure cases observed. While primary evaluation was conducted in a structured corridor environment, supplementary head-level and outdoor tests were performed; however, broader validation in highly dynamic and crowded environments remains future work. GPS testing was limited to open-sky conditions, and accuracy may degrade in urban canyons or obstructed environments. Furthermore, navigation guidance is implemented using bearing-to-destination logic rather than full road-network routing, which may reduce turn precision in complex urban layouts. Finally, the absence of sensor fusion limits redundancy and robustness. Addressing these aspects represents key directions for future system enhancement.

CONCLUSIONS

This study introduces VisionBot, a cost-conscious wearable assistive system that integrates ultrasonic obstacle detection with GPS-based directional guidance on a compact embedded platform. Built around an ESP32 microcontroller with DFPlayer Mini audio output and a u-blox NEO-6M GPS module, the system employs a non-blocking, priority-based firmware to ensure obstacle alerts override navigation cues for safety.

Experimental validation across 500 trials demonstrated a detection accuracy of 96.6% (95% confidence interval: 95.0–98.2%) with a median latency of 84.5 ms, supporting real-time feasibility. GPS cold-start testing yielded a mean TTFF of 52.8 s under open-sky conditions. The final prototype remains lightweight and low-cost, with a total hardware expense of approximately USD 45.

Overall, the results indicate that integrated micro- and macro-navigation can be achieved on a low-cost wearable platform. Future enhancements will focus on extended real-world validation and improved robustness through multi-sensor integration.

There is additional video material showing the full setup and real-time validation of the proof of work of this system with the experiment, which can be viewed online: Project overview and Experimental live demo.

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