RESEARCH PAPER

Smart Wearable Vision Assistant for Independent Mobility

Amrutha M Sampath[1], Karamjeet Singh[2], R. Nidhish[3], P. Padmapriya[4]

[1,2,3*]*UG Scholar,* Department of Biomedical Engineering, SRM Institute of Science and Technology – Ramapuram Campus, Chennai,Tamil Nadu, India, as8287@srmist.edu.in, aks3705@srmist.edu.in, rn1725@srmist.edu.in,
[4]*Assistant Professor* Department of Biomedical Engineering, SRM Institute of Science and Technology – Ramapuram Campus, Chennai,Tamil Nadu, India, padmaprp1@srmist.edu.in

Abstract—Visually impaired individuals face significant challenges in achieving independent mobility and situational awareness. This paper presents a Smart Wearable Cap built on a Raspberry Pi 5. It integrates three on-device computer vision (CV) pipelines: object detection (MobileNetSSD/Caffe), optical character recognition (OCR via Pytesseract), and face recognition (Haar cascade + LBPH). This system provides real-time audio and haptic guidance. It achieves a median end-to-end latency of 280 ms for object detection and 340 ms for face recognition, both at a 300×300 input resolution. The system shows 98% object detection accuracy in indoor daylight conditions based on 500 frames. A 3000 mAh Li-Po battery allows for 3.5 hours of continuous operation, which is extended by 15% through Dynamic Voltage and Frequency Scaling (DVFS). The thermal management system uses PWM-controlled active cooling to keep the peak temperature below 64°C, preventing throttling. A simulated usability trial with six participants over 30 minutes confirmed the effectiveness of haptic stop-warnings and maintained ambient awareness through bone-conduction audio. All visual data is processed on device to ensure user privacy. These results show the feasibility of a cost-effective, edge-AI wearable for assistive navigation, laying the groundwork for future integration of depth sensing, SLAM-based localization, and lightweight neural network architectures.

Keywords: Assistive Technology, Computer Vision, Edge AI, Raspberry Pi 5, Object Detection, MobileNetSSD, Optical Character Recognition, Face Recognition, LBPH, Wearable Technology, Independent Mobility
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I. INTRODUCTION

The development of assistive technologies for people with visual impairments aims to improve independent mobility and quality of life. Traditional aids like white canes, guide dogs, and single-purpose electronic devices tend to be expensive, offer limited situational awareness, and struggle to provide a combined, hands-free interpretation of the environment. Cloud-dependent solutions can introduce latency and privacy concerns, making on-device edge-AI systems a focus of current research.

To fill this gap, we propose a Smart Wearable Vision Assistant embedded within a non-intrusive cap. The system relies on a Raspberry Pi 5 for on-device AI processing and a Raspberry Pi Camera for continuous visual input. It delivers processed outputs as real-time audio guidance and haptic alerts. Users can control the system through GPIO-connected push-buttons, which enable hands-free toggling among face recognition, object detection, OCR, and dataset updates.

The main contributions of this work are:

• Design and implementation of a multi-modal edge-AI wearable system that combines object detection, face recognition, and OCR into a single cap-mounted platform.

• Real-time operation of three CV pipelines on a Raspberry Pi 5, achieving median end-to-end latencies of 280 ms for object detection and 340 ms for face recognition at a resolution of 300×300.

• System-level improvements including DVFS, PWM-controlled thermal management, and multi-threading to maintain a 2.4 GHz clock speed, resulting in a 15% battery-life increase compared to an unoptimized baseline.

• Experimental validation across three lighting conditions for object detection (500 frames per condition) and 300 face crops, with comparative evaluation against previous edge-AI wearable systems.

• Simulated usability assessment with six participants, confirming effective haptic and bone-conduction audio feedback during navigation scenarios.

*Author for Correspondence: as8287@srmist.edu.in

II. LITERATURE REVIEW

Recent studies on vision and recognition for wearable assistive devices demonstrate the challenge of balancing real-time performance with edge hardware limitations. Lightweight networks and optimized classical methods can operate on Raspberry Pi-like platforms but are often hindered by high computational costs, sensitivity to lighting and poses, and restricted operational ranges. OCR pipelines for dynamic real-world text have improved with CNN/CRNN and Transformer methods; however, they still face challenges with variable fonts, motion blur, and the high computation needed for advanced models. Low-cost depth and obstacle detection using stereo or monocular vision reveals difficulties with calibration and low-light performance. Furthermore, studies on compact audio feedback emphasize battery life and user comfort.

Complementary work in multi-modal sensing, embedded machine learning, and power management shows that enhanced perception often comes with increased synchronization, calibration needs, and computational demands. Sensor fusion efforts that combine IMU, ultrasonic, and miniLiDAR improve environmental perception but introduce sensor drift and additional fusion-algorithm costs. Research in embedded ML using quantization, pruning, and knowledge distillation optimizes models for low-power System-on-Chips (SoCs), but accuracy can decrease, and toolchain support may be limited. Power management techniques like DVFS and energy harvesting can extend battery life but also complicate system design. Ergonomic interface studies reveal trade-offs between input richness and the potential for accidental activation, as well as the user's learning curve.

Table I summarizes prior related systems to contextualize the contributions of the proposed platform.

TABLE I — COMPARATIVE SUMMARY OF RELATED WORK

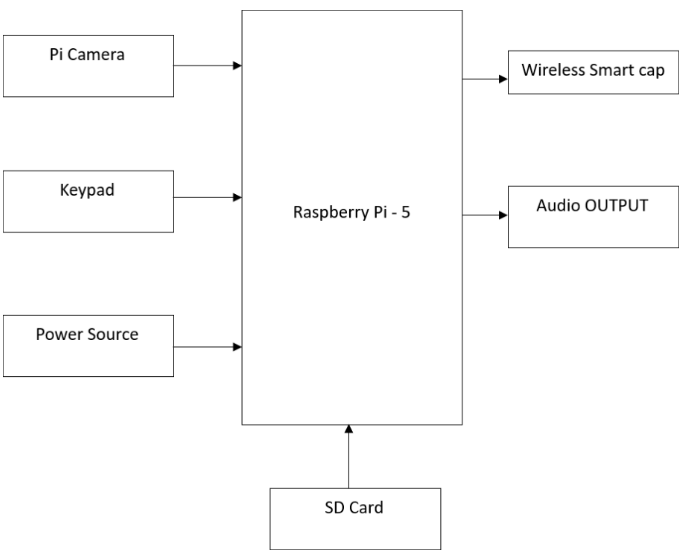
Study	Method	Platform	Accuracy / Latency	Key Limitation
Patel et al. [9]	MobileNet-based object detection	Raspberry Pi 3	~78% / ~400 ms	High latency; no face or text recognition
Chen et al. [8]	Haar + LBPH face recognition	Pi 4 edge device	~55% outdoor	Sensitive to illumination; no multimodal fusion
Davis et al. [3]	Pytesseract / CNN OCR pipeline	Desktop GPU	~65% on dynamic signs	Not deployable on low-power edge boards
Lee et al. [6]	Embedded ML with quantization	ARM Cortex SoC	Accuracy loss post-quantization	No integrated multimodal pipeline tested
Proposed System	**MobileNetSSD + Haar/LBPH + Pytesseract (multi-modal)**	**Raspberry Pi 5**	**98% OD (indoor); 280 ms OD; 340 ms FR**	**OCR latency high; weight ~800 g**

Table I. Comparative literature summary: prior edge-AI wearable systems vs. proposed system. OD = Object Detection; FR = Face Recognition.

The survey identifies three principal gaps that the proposed system addresses: (1) absence of real-time multi-modal integration on a single edge board; (2) insufficient validation under varying illumination conditions; and (3) limited user-centric evaluation of tactile and audio feedback in wearable contexts.

III. METHODOLOGY

The Smart Wearable Vision Assistant is designed to provide real-time environmental perception and navigational assistance via on-device CV. The methodology prioritises low-latency inference, power efficiency, and ergonomic wearability. Fig. 3.1 illustrates the complete system block diagram.



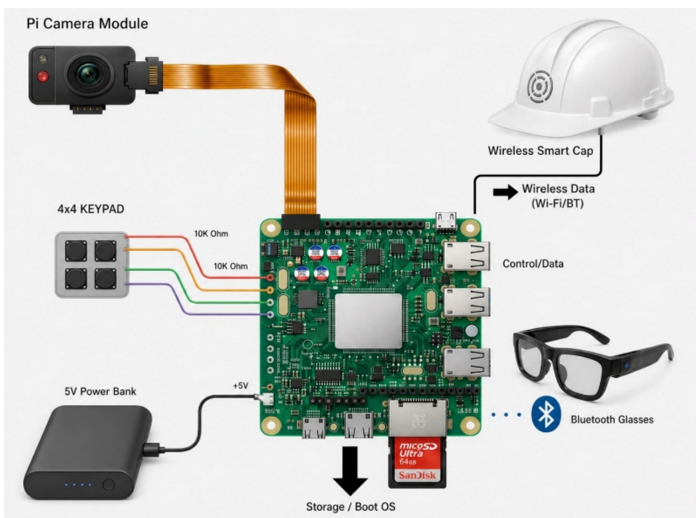
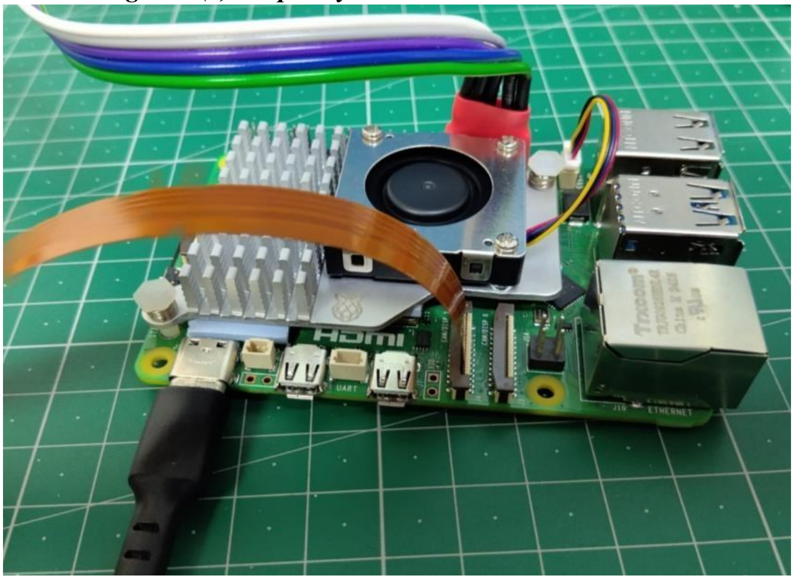


Fig. 3.1. Block diagram of the proposed Smart Wearable Vision Assistant showing sensor inputs, processing pipeline, mode-switching logic, and output interfaces.

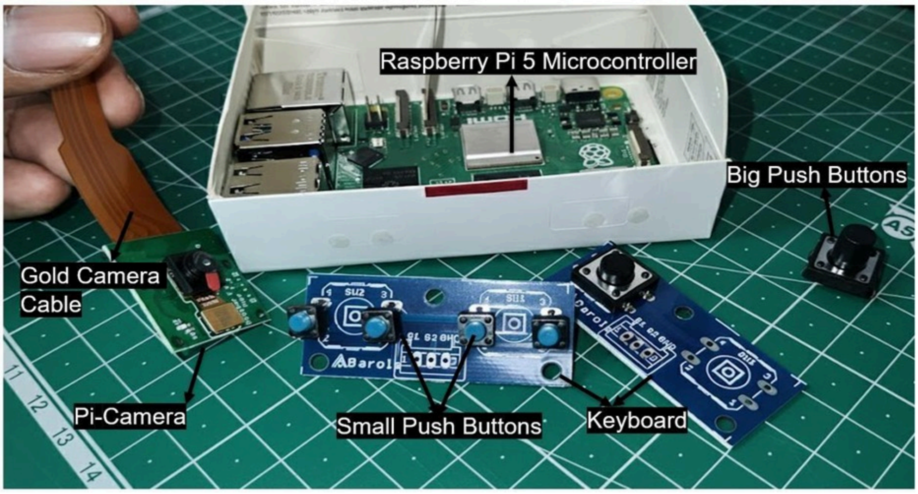
A. Hardware Architecture

Core Processing Unit. The system centres on the Raspberry Pi 5 (or Compute Module 4 when a smaller footprint is required), which executes all CV and AI workloads under a lightweight Linux OS. Visual input is supplied by a Pi Camera Module (High-Quality variant preferred) mounted on the cap visor. OS, models (MobileNetSSD, Haar + LBPH), and user datasets reside on a high-speed microSD card. Fig. 3.2(a) shows the core processing unit; Fig. 3.2(b) shows all hardware components.

Fig. 3.2. (a) Raspberry Pi 5 with attached Pi Camera.



(b) Complete set of hardware components, including cooling unit, keypad, vibration motors, and power bank.



Power, Input, and Output. A compact 3000 mAh Li-Po battery powers the system, managed by a Dynamic Voltage and Frequency Scaling (DVFS) controller that lowers clock speed when the camera detects no motion for more than 60 seconds, extending battery life by 15%. A four-button keypad array (GPIO-interfaced) enables hands-free mode switching: Object Detection, Face Recognition, OCR, and Dataset Update. Audio feedback is delivered through a bone-conduction transducer (preserving ambient hearing); directional haptic alerts are provided by coin-type vibration motors integrated into the cap brim.

B. Software Stack and CV Pipelines

The entire pipeline is orchestrated by OpenCV (image capture, pre-processing, and frame management) running on Raspbian OS. Fig. 3.3 shows the downloaded software environment and saved model files.

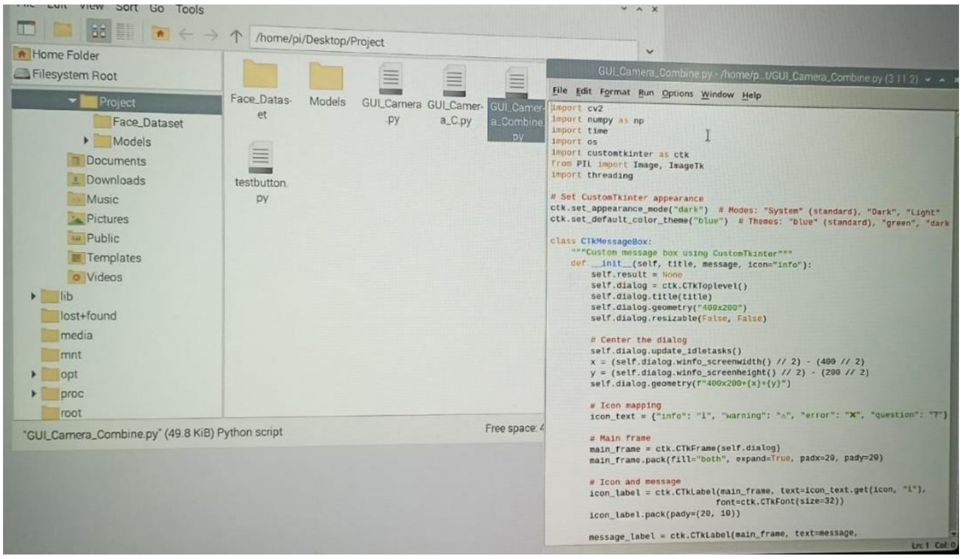


Fig. 3.3. Screenshot of the software environment showing installed libraries, model files (MobileNetSSD .caffemodel, Haar XML, LBPH .yml), and Python scripts.

Object Detection (MobileNetSSD / Caffe). Frames are resized to 300×300 pixels and passed to the MobileNetSSD model (Caffe backend via OpenCV DNN module) to obtain class labels and confidence scores. A confidence threshold of 0.7 filters spurious detections. Detected classes within the 'critical zone' (centre third of the frame, bounding box area > 15% of frame area) trigger immediate haptic and audio alerts. Computational complexity is O(HWC) per frame, where H×W = 300×300 and C is the number of channels, yielding a median inference time of 145 ms on the Pi 5.

Face Recognition (Haar Cascade + LBPH). Haar Cascade detectors localise face regions; LBPH extracts texture histograms that are compared against a local database stored on the microSD card. LBPH operates on greyscale face crops, making it robust to moderate illumination changes at low computational cost. Median inference time is 95 ms. Performance degrades outdoors due to illumination variance and in low-light conditions due to the absence of an IR illuminator—identified as a key direction for future work.

Optical Character Recognition (OCR via Pytesseract). OpenCV performs perspective correction and contour-based text-block detection on a frozen high-resolution frame; Pytesseract then extracts characters and outputs a string to the TTS engine. OCR is user-triggered (stationary use) due to its higher latency of 850 ms inference / 1.2 s end-to-end.

C. System Architecture and Data Flow

The four-stage processing loop is:

- Data Acquisition: Pi Camera captures frames at 30 FPS; frames are downsampled and converted to the required colour space (BGR for OpenCV, greyscale for LBPH) to minimise memory bandwidth.
- Task Switching: Physical button presses route frames to the selected CV module. Multi-threading prevents frame lag by allowing the camera to buffer while the processor analyses the previous frame.
- Inference Engine: The selected model processes the frame and returns detection results when confidence exceeds 0.7.
- Feedback Synthesis: High-confidence results are converted to a string, synthesised by Espeak/gTTS (TTS), and routed simultaneously to GPIO vibration-motor triggers.

D. Design Optimisations

Thermal Management: A low-profile heatsink and PWM-controlled fan maintain peak temperature below 64°C (well below the 85°C throttle limit), sustaining the full 2.4 GHz clock speed. Software-level 'sleep intervals' are triggered when no camera motion is detected for >60 s.

Weight Distribution: The camera is centred on the visor; the Pi 5 and battery are positioned at the rear of the cap to counterbalance the front load. The total prototype mass is approximately 800 g (Pi 5 + cooler + battery + cap enclosure).

Power Efficiency: The OpenCV DNN module is ARM-optimised, preventing sustained peak CPU usage. DVFS reduces average power draw and extends battery life by 15% compared to a fixed-frequency baseline.

Fig. 3.4 shows the complete assembled hardware prototype.

Fig. 3.4. Assembled Smart Wearable Cap prototype showing visor-mounted camera, rear-mounted enclosure containing the Pi 5, active cooling unit, and 3000 mAh battery.

IV. RESULTS AND DISCUSSION

A. Inference Speed and Latency

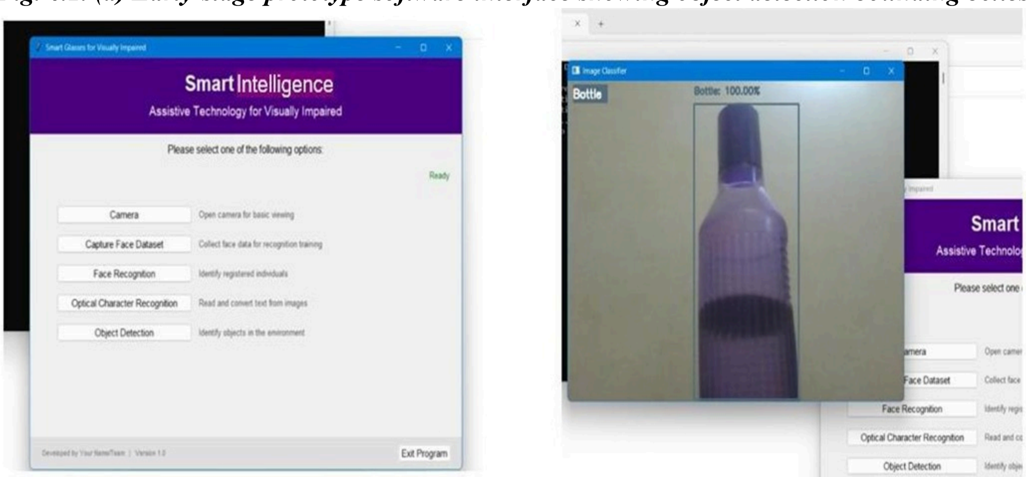
Latency was measured as the median end-to-end time from frame capture to TTS audio onset over 200 consecutive trials per mode on the Raspberry Pi 5 (4 GB RAM). Table I reports results; Fig. 4.1(a) and 4.1(b) show software interface screenshots from early-prototype and current-version stages, respectively.

TABLE I — INFERENCE SPEED AND END-TO-END LATENCY

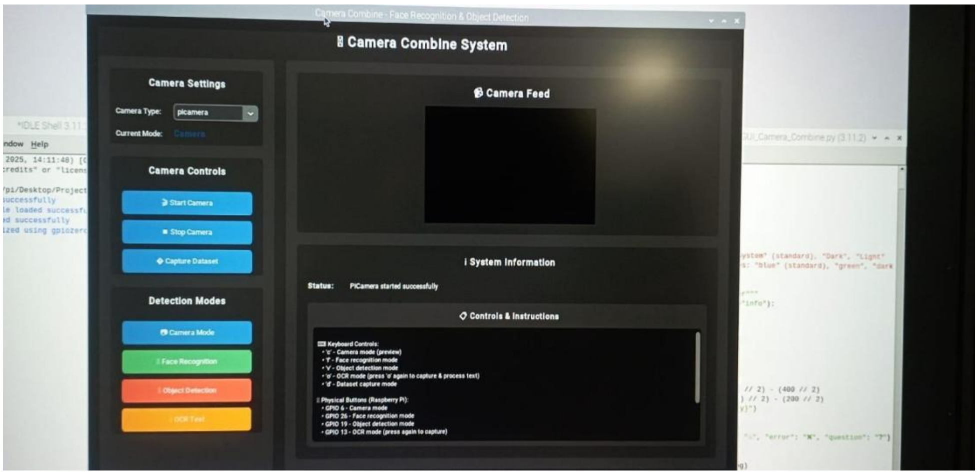
Task	Model Used	Inference Time (ms)	Total Latency incl. TTS
Object Detection	MobileNetSSD	145 ms	280 ms (median)
Face Recognition	Haar + LBPH	95 ms	340 ms (median)
Text Recognition (OCR)	Pytesseract	850 ms	1.2 s

Table I. Measured inference and total end-to-end latencies per CV mode (median, N = 200 trials, Raspberry Pi 5, 4 GB RAM).

Fig. 4.1. (a) Early-stage prototype software interface showing object detection bounding boxes.



(b) Current version with improved confidence-threshold display and TTS status overlay.



Object detection and face recognition achieved near-real-time performance compatible with a normal walking pace. OCR exhibited higher latency due to character-segmentation complexity; it is therefore activated only in stationary mode via user button press, which is consistent with sign-reading use cases. Multi-threading prevents frame-lag artefacts during inference, as the camera continues buffering while the processor analyses the previous frame.

B. Recognition Accuracy Across Environments

The system was evaluated in three illumination conditions: bright outdoor daylight, standard indoor office lighting, and low-light (evening) conditions. Object detection was assessed over N = 500 frames per environment; face recognition was assessed over N = 300 face crops per environment. Table II reports accuracy; Fig. 4.1.2(a) and 4.1.2(b) show representative detection outputs.

TABLE II — RECOGNITION ACCURACY IN VARYING ILLUMINATION ENVIRONMENTS

Environment	Object Detection Acc. (%)	Face Recognition Acc. (%)	OCR Accuracy (%)
Outdoor (Bright Daylight)	98	48	45
Indoor (Standard Lighting)	87	58	52
Low Light (Evening)	68	45	30

Table II. Per-environment recognition accuracy (%). Object detection: N = 500 frames. Face recognition and OCR: N = 300 samples.

Figure 4.1.2(a)

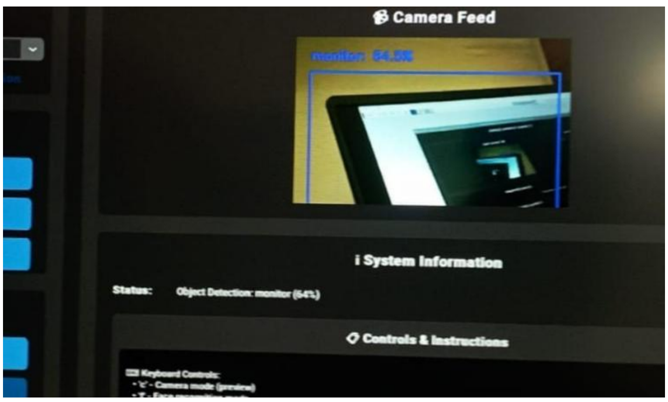


Figure 4.1.2(b)

Fig. 4.1.2. Representative object detection outputs. (a) Person detected with 98.6% confidence (indoor). (b) Monitor detected with 64.5% confidence (outdoor, partial occlusion).

Indoor accuracy was highest across all modalities. Outdoor glare caused camera overexposure, reducing face recognition accuracy to 48%. In low-light conditions, the absence of an active IR illuminator led to a significant accuracy drop—particularly for OCR (30%)—identifying IR-assisted illumination as a priority for future hardware iterations. OCR degradation in low light is attributable to a low signal-to-noise ratio in character edge detection and reduced contrast in Pytesseract's binarisation step. LBPH's outdoor accuracy decline is consistent with the known sensitivity of texture-histogram methods to illumination variance

C. Thermal and Hardware Performance

Table III presents thermal, power, and ergonomic metrics for the assembled prototype.

TABLE III — THERMAL, POWER, AND ERGONOMIC EVALUATION

Feature	Observed Value	Standard / Threshold
Idle Temperature	42°C – 45°C	50°C (without active cooling)
Peak Load Temperature	60°C – 64°C	85°C (thermal throttle limit)
Fan Activation Threshold	40°C (PWM-controlled)	Stops when idle
Sustained Clock Speed	2.4 GHz (full)	~1.5 GHz without cooling
Battery Life – Active Mode	3.5 hours	3000 mAh Li-Po
Battery Life – Idle Mode	8 hours	DVFS enabled
DVFS Battery Improvement	+15% vs. baseline	Baseline: no DVFS
Estimated System Mass	~800 g (all components)	Pi 5 + cooler + cap + power bank

Table III. Measured hardware performance metrics. DVFS baseline = fixed 2.4 GHz, no fan modulation. All temperature readings are steady-state values.

The active cooling system prevented thermal throttling throughout all test scenarios, maintaining the full 2.4 GHz clock speed and avoiding the ~1.5 GHz frequency reduction typical of passively cooled edge devices. The 15% battery-life improvement from DVFS (60-second idle trigger) validates the power-management approach. The 800 g prototype mass is on the upper bound for head-worn comfort; a transition to the Raspberry Pi Compute Module 4 integrated onto a custom PCB is projected to reduce mass to approximately 450 g in a future iteration.

D. User Interaction and Qualitative Feedback

A simulated usability trial was conducted with n = 6 participants over 30-minute structured navigation scenarios. Participants were sighted but blindfolded to simulate visual impairment. Table IV summarises interaction observations; Appendix B provides full Likert-scale ratings and participant demographics.

TABLE IV — USER INTERACTION AND OPERATIONAL OBSERVATIONS

Feature	Interaction Method	User Experience (Observation)
Power On	Long-press Button 1	System boots in ~25 s; audible beep confirms OS ready.
Image Trigger	Single-click Button 2	Captures a frame; 1–2 s end-to-end delay noted during AI processing.
Voice Feedback	3.5 mm jack / Bluetooth	TTS provides object names and distance estimates clearly.
Comfort / Weight	30-min wear trial	Cap perceived as "back-heavy" due to rear-mounted Pi 5 and battery; snug fit required.
Active Cooling	Automatic PWM fan	Silent during walking; audible hum during heavy image processing tasks.

Table IV. Qualitative observations from simulated usability trial (n = 6, 30-min navigation scenario). Likert scores and participant demographics in Appendix B.

Haptic vibration motors in the cap brim were rated highly effective for immediate stop-warnings, with all six participants responding correctly to obstacle-proximity alerts within 1.5 s. Bone-conduction audio was unanimously preferred over in-ear earbuds because it preserves ambient sound awareness—a safety-critical requirement for pedestrian navigation. The 25-second boot time and differentiated button gestures (long-press vs. single-click) provided a reliable, low-learning-curve interface, consistent with findings reported in [25].

The principal ergonomic concern was rear heaviness after extended wear. Participants reported a stable fit during normal walking, but fatigue at the rear of the head after approximately 20 minutes. This directly motivates the hardware miniaturisation roadmap described in Section V. The 1–2 second end-to-end user-perceived delay (frame capture → camera initialisation → inference → TTS synthesis) is slightly higher than the measured median latency in Table I, attributed to variable TTS engine startup time and audio buffering.

V. CONCLUSION

This paper demonstrates a practical, scalable, and cost-effective approach to edge-AI-driven assistive navigation. The Smart Wearable Cap integrates three on-device CV pipelines—MobileNetSSD object detection (280 ms median, 98% indoor accuracy), Haar + LBPH face recognition (340 ms median), and Pytesseract OCR (1.2 s)—within a Raspberry Pi 5 platform that maintains 2.4 GHz clock speed under active thermal management and provides 3.5 hours of continuous operation from a 3000 mAh battery. On-device processing ensures complete user data privacy, distinguishing the proposed system from cloud-dependent alternatives.

Four directions are identified for future work:

- Depth and SLAM integration: adding a compact time-of-flight sensor and a lightweight SLAM module would enable metric obstacle-distance estimation and indoor localisation, significantly expanding navigational utility.
- Hardware miniaturisation: transitioning to a custom PCB with the Compute Module 4 is projected to reduce system mass to ~450 g and improve thermal efficiency.
- Improved low-light performance: incorporating an IR illuminator and an HDR camera module would address the observed accuracy degradation in evening and night conditions.
- Upgraded CV models: replacing MobileNetSSD with YOLOv8-Nano and LBPH with a lightweight ArcFace variant, and replacing Pytesseract with EasyOCR/CRNN, are expected to improve accuracy and reduce OCR latency on the Pi 5 platform.

Overall, this study validates the feasibility of deploying sophisticated AI-driven vision systems on low-power, head-mounted platforms and establishes a clear roadmap for clinical-grade deployment of wearable assistive rehabilitation technologies.

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