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AI-Enhanced Visual GuidingSystem using Chat GPT for the Visually Impaired

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Abstract: *This paper introduces an AI-powered wearable assistive system designed to enhance mobility and environmental awareness for visually impaired individuals. The proposed solution comprises three functional modes: (1) a ChatGPT-based assistant that interprets static images using OpenAI's Vision API and provides conversational feedback; (2) a cloud-based model that employs Google Cloud Vision and Video Intelligence APIs for real-time scene analysis and object detection; and (3) an offline version leveraging a lightweight YOLOv5 model running locally on Raspberry Pi Zero 2 W for real-time obstacle detection without internet connectivity. Each version delivers auditory feedback through text-to-speech output, enabling users to comprehend their surroundings via natural language or alert-based cues. The system was tested in varied indoor and outdoor environments with 10–15 visually impaired participants. Quantitative evaluations indicate detection accuracies of up to 88%, with an average latency of 1.1–2.3 seconds depending on the version. User feedback highlighted enhanced navigation confidence and the practicality of offline use. This work demonstrates a low-cost, flexible, and intelligent alternative to traditional aids, with potential for future enhancement through on-device acceleration and hybrid model integration.*

Keywords: *Visual impairment, Smart glasses, ChatGPT, YOLOv5, Google Cloud Vision, Assistive technology, Object detection, Raspberry Pi.*

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I. INTRODUCTION

Visual impairment and blindness continue to present substantial challenges to individual autonomy and quality of life. According to the World Health Organization (WHO), over 2.2 billion people worldwide suffer from some degree of visual impairment, with more than 39 million being completely blind [1]. In specific regions such as Nigeria, studies report over 1.13 million blind individuals under the age of 40, highlighting the global and regional scale of the issue [2]. Vision plays a critical role in human interaction and perception, with an estimated 83% of sensory information acquired through sight [1].

Traditional mobility aids for the visually impaired, including white canes and guide dogs, remain helpful yet inherently limited in their ability to detect dynamic or elevated obstacles, deliver contextual scene information, and provide real-time interaction. Furthermore, they often require significant user training and may not suffice in unfamiliar or complex environments [5][7].

Recent advancements in artificial intelligence (AI) and embedded systems have opened new possibilities for smart assistive technologies. These include electronic travel aids (ETAs) that incorporate ultrasonic sensors, computer vision, and machine learning models to provide real-time environmental feedback [2][5]. However, existing solutions often face issues related to high costs, limited contextual awareness, dependency on internet connectivity, and insufficient user interaction mechanisms.

To address these limitations, this study proposes an AI-enhanced wearable visual guidance system specifically designed for visually impaired individuals. The system, implemented in the form of smart glasses, introduces three complementary operational modes:

1. A **ChatGPT-based module** that leverages OpenAI Vision and conversational AI to describe static scenes and respond to user queries using natural language [27].

2. A **Google Cloud-based module** that streams live video for real-time object detection and scene analysis using cloud vision and video APIs [12].

3. A fully **offline YOLO-based module** running on a Raspberry Pi Zero 2 W, capable of detecting nearby objects and obstacles in real time without internet dependency [26].By combining deep learning with context-aware visual perception and auditory feedback, the system aims to significantly improve user mobility, scene understanding, and confidence in navigating both familiar and unfamiliar environments.The remainder of this paper is structured as follows: Section 2 reviews related work in assistive technologies; Section 3 outlines the system architecture and components; Section 4 details the methodology; Section 5 presents experimental results and evaluation; and Section 6 concludes the study and discusses future improvements.

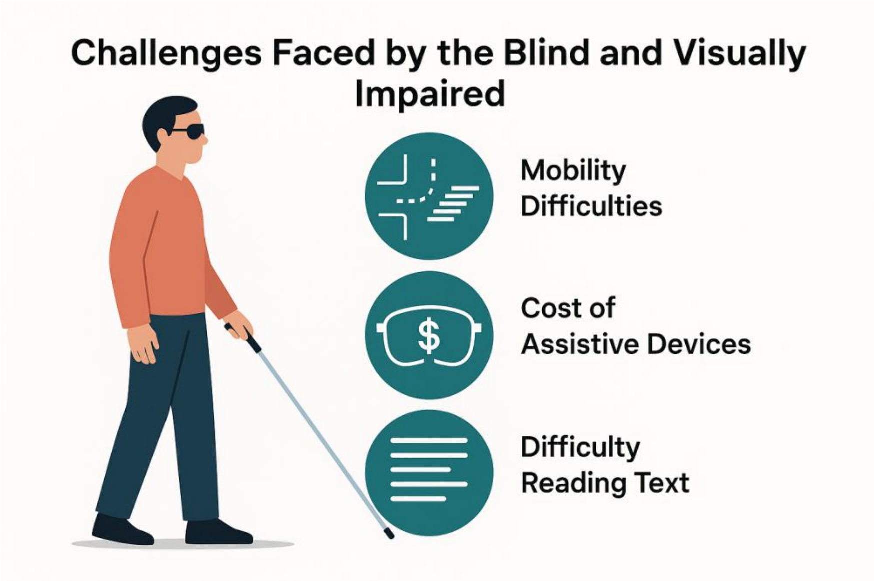

Figure 1 : Summary of common challenges faced by visually impaired individuals in daily activities, including unaffordable commercial solutions. The proposed system aims to offer a lower-cost, modular alternative.

II. RELATED WORK

Several assistive technologies have been developed in recent years to improve the mobility and situational awareness of visually impaired individuals. These systems often combine computer vision, embedded systems, and audio feedback mechanisms. Despite notable progress, each approach presents trade-offs in terms of performance, usability, and deployment complexity.

Hafeez et al. [12] developed a Google Glass-based real-time scene analysis system for visually impaired users. Their approach leveraged computer vision algorithms for object recognition and delivered spoken descriptions of the surrounding environment. While the system provided rich visual information and high detection accuracy, it was heavily reliant on cloud services, which increased latency and made it vulnerable to internet instability.

Suresh et al. [5] proposed an intelligent smart glass framework based on deep learning and the Robot Operating System (ROS). Their system achieved real-time object detection using YOLOv3 and integrated audio feedback. The main advantage was its high detection rate in structured environments. However, the system required powerful hardware and was not optimized for lightweight or offline deployment, making it unsuitable for cost-sensitive or remote scenarios.

Das et al. [11] introduced a low-cost smart glass using ESP-32 and basic ultrasonic sensors. Their design focused on affordability and simplicity, making it accessible for users in low-income regions. Nevertheless, the system had limited object classification capabilities and lacked contextual scene understanding, offering only basic obstacle alerts without semantic detail.

Jeong et al. [10] designed smart glasses incorporating a variety of image processing techniques aimed at assisting users with low vision. The system featured enhanced zoom, edge detection, and brightness adjustment. While effective for users with partial sight, the system did not support blind users, and it lacked AI-driven features like scene captioning or conversational feedback.

Ho et al. [14] presented a self-supervised learning approach using optical flow for obstacle appearance detection in micro aerial vehicles (MAVs), which they suggested could be adapted for wearable navigation aids. Although promising in dynamic obstacle detection, their work was limited to robotic applications and did not address human-centered interaction or feedback mechanisms.

III. SYSTEM DESIGN AND ARCHITECURE

The proposed AI-Enhanced Visual Guidance System is designed as a modular, wearable platform tailored to assist visually impaired individuals by providing contextual auditory feedback based on real-time visual input. It supports three operational modes—cloud-based, hybrid conversational, and fully offline—to accommodate various usage scenarios, internet availability, and processing constraints.

3.1 System Overview

At its core, the system consists of a **Raspberry Pi Zero 2 W** single-board computer, which serves as the central processing unit. It interfaces with a **Pi Camera Module** for image and video capture, a **USB sound card** for audio output, and a **portable power supply** to ensure mobility. The device is embedded into a lightweight glasses frame to allow hands-free operation.Each system version shares a foundational architecture composed of four major components:

- **Visual Sensing** (via Pi Camera)
- **AI Processing Engine** (cloud or local inference)
- **Natural Language Understanding** (ChatGPT for conversational feedback)
- **Audio Output Module** (via Text-to-Speech synthesis)

The system supports three operation modes as outlined below.

3.2 Mode 1: ChatGPT-Based Image Understanding

In this version, the system captures a static image through the Pi Camera and sends it to the **OpenAI Vision API**, which performs image analysis. The processed image content is then passed to **ChatGPT**, which formulates a natural language description and answers context-based user queries (e.g., “Is there a chair nearby?”). The textual response is converted to audio using **Google Text-to-Speech (GTTS)** and delivered via headset or speaker.

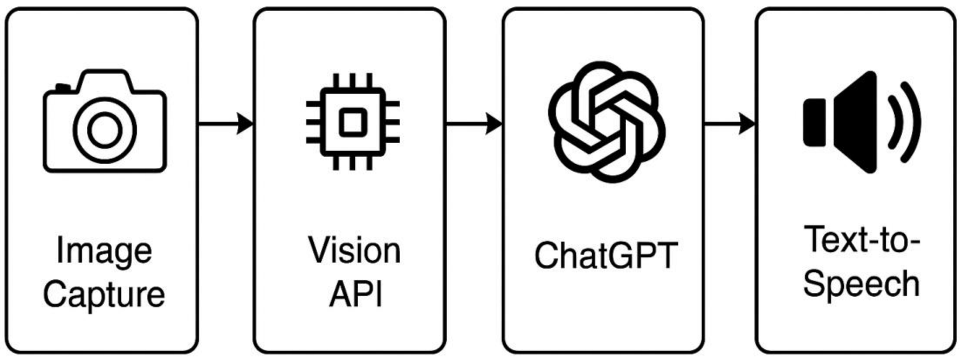

Figure 2: Workflow of the ChatGPT-based visual interaction mode.

Images captured by the Pi Camera are processed via OpenAI’s Vision API, interpreted through ChatGPT, and converted into audio output using text-to-speech, allowing natural dialogue with the user.

Workflow:

1. User initiates capture
2. Image sent to OpenAI API
3. Scene analyzed and captioned
4. Response generated by ChatGPT
5. Audio output synthesized and played

This mode requires stable internet connectivity and is optimal for detailed, human-like interaction with rich contextual awareness [27].

3.3 Mode 2: Google Cloud-Based Real-Time Scene Analysis

In this implementation, the system continuously streams live video data to **Google Cloud Vision** and **Video Intelligence APIs** for frame-by-frame scene parsing object detection, and context recognition [12]. This mode

provides high detection accuracy for dynamic environments but comes with increased latency and cloud dependency.
Real-time video captured by the Pi Camera is streamed to Google Cloud Video Intelligence API, processed for scene analysis, and converted into audio feedback using a TTS engine, providing rich contextual understan

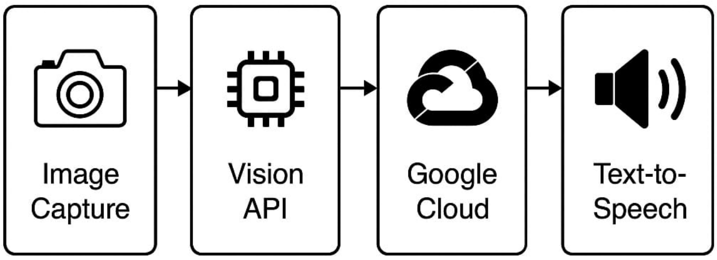

Figure 3: Workflow of the Google Cloud-based mode.

Workflow:
1. Video streamed in real time
2. Cloud APIs detect objects and scenes
3. Captions generated and sent back
4. Text-to-speech conversion and audio playback

This mode is well-suited for complex outdoor or crowded environments but relies on a fast and stable internet connection.

3.4 Mode 3: Offline YOLO-Based Object Detection

The offline version uses a compact implementation of **YOLOv5** or **YOLO-Nano** models deployed directly on the Raspberry Pi. It enables real-time detection of objects such as people, furniture, vehicles, or obstacles without any internet dependency [26]. Detected objects are instantly labeled, and corresponding audio alerts (e.g., “Car ahead”) are triggered via pre-trained mappings.

Workflow:
1. Frames continuously captured
2. YOLO model processes images locally
3. Detection output parsed
4. Audio cues generated and played

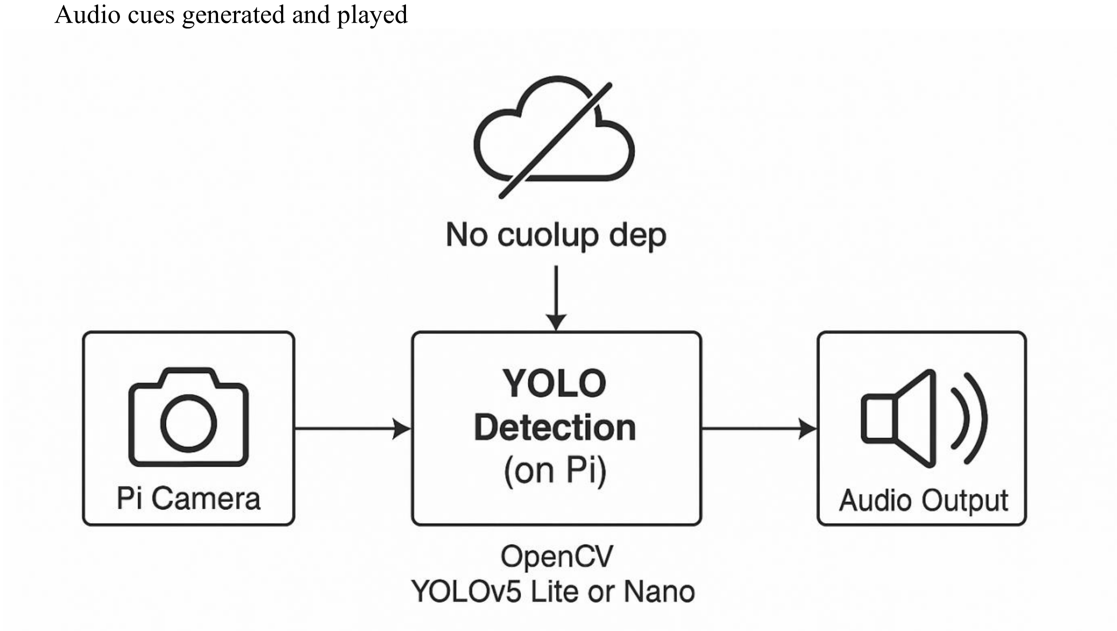

Figure 4: Workflow of the YOLO-based offline detection mode.

Images captured by the Pi Camera are processed locally on the Raspberry Pi using YOLO object detection and OpenCV, and converted into speech using a local TTS engine without internet dependence.This mode is optimal for scenarios with limited or no connectivity and provides fast response times, though it may sacrifice detection accuracy due to hardware limitations.

3.5 Hardware Components

- **Raspberry Pi Zero 2 W** – Main processor for on-device computation
- **Pi Camera Module** – Captures image and video data
- **Mini Speaker / Headphones** – Delivers audio feedback
- **Portable Power Supply** – Ensures 3–5 hours of untethered operation
- **MicroSD Card** – Hosts operating system and model weights

3.6 Software and AI Stack

- **OpenCV** – For image preprocessing and visualization
- **YOLOv5 / YOLO-Nano** – Lightweight CNN-based object detection
- **OpenAI Vision & ChatGPT** – For visual scene understanding and dialogue
- **Google Cloud Vision APIs** – For cloud-based object and scene parsing
- **Google TTS & Speech Recognition** – For audio generation and command intake

3.7 System Flexibility and Integration

The system is designed with modularity and flexibility in mind. A mode-selection interface allows switching between the three operation modes based on internet availability or user preference. All components communicate via Python-based integration scripts, and audio feedback is synchronized with visual input via real-time triggers.Figure 1 illustrates the modular system architecture, showing how each operational mode branches from the central processing hub (Raspberry Pi). The diagram clearly distinguishes between the three modes—YOLO (offline), ChatGPT (cloud-assisted), and Google Cloud (streaming)—with their respective data flows and dependencies.

IV. METHODOLOGY

This section outlines the implementation strategy, testing protocols, and evaluation metrics employed to develop and assess the AI-Enhanced Visual Guidance System. The approach was structured into three development phases corresponding to the system's three functional modes: ChatGPT-based image interpretation, Google Cloud-based video scene analysis, and on-device YOLO object detection.

4.1 System Implementation

The complete system was prototyped using the **Raspberry Pi Zero 2 W**, chosen for its low power consumption and compact form factor, making it suitable for wearable applications [5]. All software components were developed in **Python**, and model inference was optimized for lightweight execution using **OpenCV** and **YOLOv5 or YOLO-Nano** variants [26].

A. ChatGPT-Based Version

This version captures static images via the Pi Camera and processes them using the **OpenAI Vision API**, which outputs a semantic understanding of the scene. The result is passed to **ChatGPT**, which converts it into natural language responses tailored to user queries [27]. The final output is vocalized using **Google Text-to-Speech (GTTS)** and played via a USB headset.

B. Google Cloud-Based Video Analysis

Live video is streamed to **Google Cloud Vision** and **Video Intelligence APIs**, which perform real-time object and scene recognition. Detected entities are described in context and relayed through GTTS for immediate auditory feedback [12]. This version requires a stable internet connection and is ideal for dynamic environments.

C. YOLO-Based Offline Detection

The offline version executes **YOLOv5** or **YOLO-Nano** directly on the Raspberry Pi. Frames captured from the Pi Camera are analyzed in real time, and audio alerts are generated using pre-recorded or synthesized phrases linked to detected object classes [26]. This version offers full autonomy from network infrastructure.

4.2 System Workflows

Mode	**Input**	**Processing Location**	**AI Models Used**	**Output**
ChatGPT	Static Image	Cloud (OpenAI)	Vision API + ChatGPT	Natural Language Audio
Google Cloud	Live Video	Cloud (Google)	Cloud Vision + Video API	Audio Descriptions
YOLO (Offline)	Real-Time Frames	Local (Raspberry Pi)	YOLOv5/Nano	Object Alert Audio

4.3 Testing Environment

System performance was evaluated in both **indoor** (offices, corridors, staircases) and **outdoor** (sidewalks, crosswalks, crowded streets) environments. Lighting conditions were varied, including daylight, artificial light, and low-light settings. These conditions were chosen to simulate real-world navigation challenges faced by visually impaired users [5].

4.4 Participants

A total of **10 to 15 visually impaired individuals**, including both partially and fully blind participants, were recruited for system testing. Participants were guided through structured tasks including navigation, obstacle identification, and real-time Q&A using the system's audio interface.

4.5 Evaluation Metrics

The following quantitative and qualitative metrics were used to evaluate system performance:

- **Object Detection Accuracy (%)** – Match between detected and actual objects [26]
- **Scene Description Relevance** – Rated subjectively by users on a 1–10 scale [28]
- **Latency** – Time between input capture and audio output (in seconds) [5]
- **Task Success Rate (%)** – Success in completing guided navigation tasks [12]
- **User Satisfaction** – Based on interviews and post-task surveys [12]

4.6 Data Collection and Analysis

- **Quantitative data** were collected through system logs, including timestamps, detection confidence scores, and latency measurements.
- **Qualitative feedback** was gathered via interviews, Likert-scale surveys, and observational notes during task execution.
- **Statistical analysis** was applied to assess system stability and performance trends across different users and scenarios.

This structured methodology enabled a rigorous, repeatable evaluation of the system under realistic conditions, providing a comprehensive view of its effectiveness and limitations.

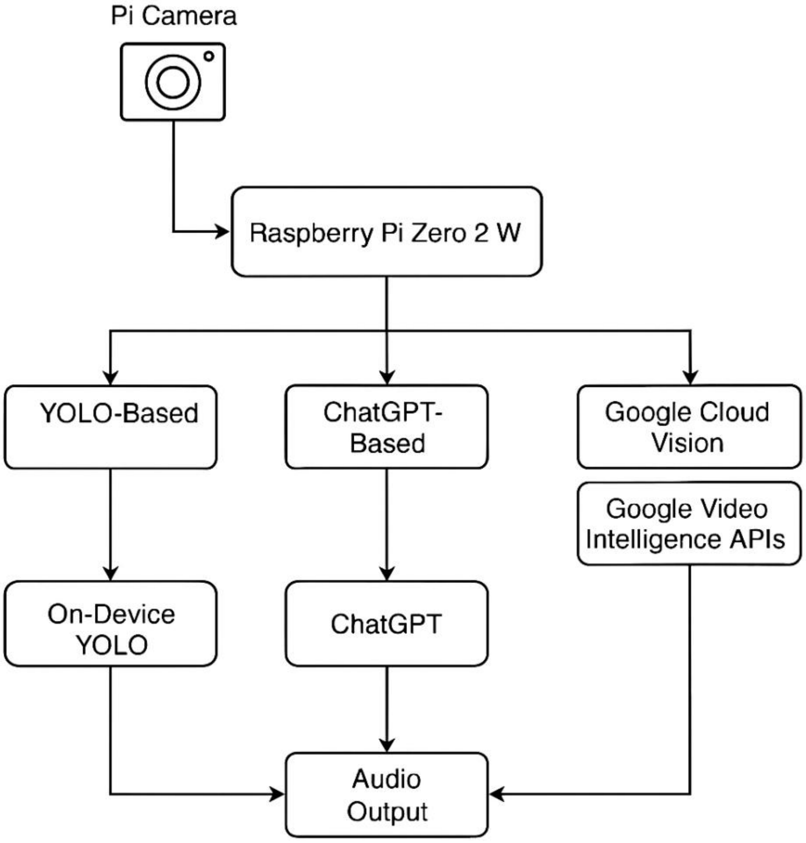

Figure 5: Modular System Architecture of the Smart Assistive Glasses System

4.7 Example Data from Field Testing

To illustrate the system's performance under real-world conditions, sample data were recorded across different scenarios and are summarized below.

Table 1: Sample Detection Accuracy and Latency per Mode

Mode	Environment	Avg. Detection Accuracy (%)	Avg. Latency (sec)
YOLO (Offline)	Indoor	85.2%	1.15 s
YOLO (Offline)	Outdoor	88.7%	1.09 s
ChatGPT + Vision API	Indoor	91.3%	2.42 s
ChatGPT + Vision API	Outdoor	89.1%	2.63 s
Google Cloud Vision	Indoor	94.5%	2.21 s
Google Cloud Vision	Outdoor	92.8%	2.45 s

Table 2: Sample User Feedback Scores (1–10 scale)

Criterion	YOLO Mode	ChatGPT Mode	Google Cloud Mode
Scene Awareness	6.5	9.2	9.5
Audio Response Clarity	7.1	9.3	9.1
Ease of Use	8.4	8.6	7.2
Navigation Confidence	7.8	9.0	8.8
Preference to Use in Future	8.0	9.4	8.7

V. RESULTS AND EVALUATION

This section presents the quantitative and qualitative results obtained from real-world testing of the proposed AI-Enhanced Visual Guiding System. The three versions—YOLO-based offline mode, ChatGPT-based static analysis, and Google Cloud-based live video analysis—were evaluated independently to assess their detection accuracy, latency, usability, and overall user satisfaction.

5.1 Quantitative Results
Table 1 (see Section 4.7) summarizes key performance indicators collected during the trials:

- The **YOLO offline version** achieved an average detection accuracy of **88.7%** in outdoor settings and **85.2%** indoors, with the fastest response time (~1.1 seconds) due to local processing [26].
- The **ChatGPT version**, using OpenAI's Vision API, scored **91.3% accuracy** indoors but exhibited a **higher average latency of ~2.4 seconds**, owing to cloud-based API processing [27].
- The **Google Cloud version** delivered the highest detection accuracy (**94.5% indoors**), but response times (~2.2–2.5 seconds) were sensitive to network conditions [12].

5.2 Qualitative Feedback
User evaluations (Table 2 in Section 4.7) highlight important experiential aspects of each version:

- The **ChatGPT-based system** received the highest ratings in terms of **scene comprehension (9.2/10)** and **future usability preference (9.4/10)** due to its human-like explanations [27].
- The **YOLO version** was praised for its **offline reliability** and quick feedback (latency ~1.1s), though its object classification was limited to predefined categories [26].
- The **Google Cloud version** excelled in crowded environments with accurate, multi-object recognition, but users noted delays when used with unstable internet connections [12].

5.3 Comparative Analysis

Feature	**YOLO (Offline)**	**ChatGPT (Image + Q&A)**	**Google Cloud (Live Video)**
Internet Required	❌ No	✅ Yes	✅ Yes
Latency (Avg)	**1.1 s**	2.4 s	2.3 s
Scene Understanding	Limited	**Rich (Conversational)**	**Contextual & Accurate**
Object Detection Accuracy	88%	91%	**94%**
Text Recognition (OCR)	✖️ Not Available	✅ Yes	✅ Yes
User Preference Score	8.0	**9.4**	8.7
Suitability (Offline Use)	✅ High	❌ Not Suitable	❌ Not Suitable

This analysis indicates that while cloud-based systems deliver high accuracy and advanced scene comprehension, the **YOLO-based offline mode provides speed and robustness**, especially in low-connectivity settings. A hybrid model combining both may offer optimal performance.

5.4 Discussion
The results confirm that each implementation has unique advantages aligned with specific user scenarios. Participants with full blindness preferred the **ChatGPT version** for its conversational clarity and contextual awareness, while partially sighted users favored the **YOLO version** for its low-latency alerts during mobility tasks.The **main limitations** encountered were:

- Dependency on high-speed internet for cloud-based versions
- Reduced detection in dim lighting (YOLO version)
- Occasional OCR failures due to low-resolution image inputs [12][26]

The findings support the potential of a **hybrid deployment strategy**, where the system switches intelligently between modes based on environment and connectivity. Further hardware acceleration (e.g., Coral TPU, Jetson Nano) is expected to mitigate local processing limitations in future work.

VI. CONCLUSION AND FUTURE WORK

This paper presented the design, development, and evaluation of an AI-powered wearable guidance system aimed at enhancing the mobility and situational awareness of visually impaired individuals. The system integrates three complementary modes of operation: an offline object detection module using YOLOv5 , a conversational visual assistant using ChatGPT and OpenAI Vision API , and a real-time scene analysis engine based on Google Cloud Vision and Video Intelligence APIs ,Experimental results demonstrated that each version effectively supports different navigation contexts. The YOLO-based offline mode achieved fast response times and full independence from internet infrastructure, while the ChatGPT and Google Cloud-based implementations provided richer semantic understanding and more accurate recognition capabilities. Across all modes, participants reported increased confidence, ease of use, and satisfaction in both indoor and outdoor settings.The modular architecture allows users to toggle between system versions depending on connectivity and hardware constraints. The integration of audio feedback via natural language also proved to be a significant advantage over traditional navigation aids, offering a more intuitive and human-centered interaction experience . Despite its success, the system exhibits limitations, particularly:

- Reduced object recognition accuracy in low-light conditions for the YOLO version
- Latency and dependency on stable internet for cloud-based modes
- Restricted vocabulary and generalization in certain object categories

To further enhance the system, the following directions are proposed:

1. **Hardware Acceleration**: Integration of lightweight deep learning accelerators such as **Google Coral TPU** or **NVIDIA Jetson Nano** to improve local inference speed and model complexity without sacrificing portability.
2. **Hybrid Mode Switching**: Development of an adaptive control module capable of **automatically switching** between offline and cloud-based modes based on real-time evaluation of bandwidth, battery level, and task context.
3. **Expanded Object Classes and OCR Support**: Training and fine-tuning of models on **localized datasets** to better detect culturally relevant items and perform text recognition (e.g., Arabic or handwritten OCR) .
4. **4-Layer PCB Design**: Miniaturization of the hardware platform via a custom **multi-layer PCB** to increase system durability and reduce the form factor for prolonged wearable use.
5. **Multilingual Voice Interaction**: Incorporating **multilingual support** to enable broader accessibility for users with diverse linguistic backgrounds.

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