

# Assistive Technologies for the Visually Impaired: A Comprehensive Survey

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**Abstract**—Visual impairment and blindness affects more than 285 million people in the world with significant barriers to education, employment and freedom of movement. Assistive technologies (ATs) play an extremely important role under such issues, transforming both the visual and spatial into a form that can be interpreted and accessed in the form of speech, braille and tactile feedback. A close explanation of five significant areas of technology will be made in this survey, which are Optical Character Recognition (OCR), Text-to-Speech (TTS), Screen Readers, Object Detection, and GPS-based Navigation. We make comparisons between the previous processes and the new innovations based on the deep learning, cloud computing, wearable devices and multimodal interaction. The assistive technologies are categorized as information access systems and mobility and navigation aids, the techniques underlying it, its performance and its trade-offs between its real performance and its budget as well as how the assistive technologies were adopted by its users is discussed. The tendencies in the area precondition the direction of the growth of the utilization of AI-based mobile and wearable solutions, offloading cognition multimodal interfaces, and user-centred design solutions. These have been developed; however, there are such obstacles as inadequate support of the low-resource languages, effective indoor navigation and scalability over time. In future research, there is a need to develop unifying cross platform ecosystems, which can be useful in the day to day life of the blind and the visually impaired people (BVIP).

**Index Terms**—Assistive Technology, Visual impairment, Optical Character Recognition, Text to speech, screen reader, object detection, GPS navigation, accessibility, Multimodal interaction, wearable devices.

## I. INTRODUCTION

### A. Background and Motivation

Visual impairment significantly affects the daily lives of millions of individuals worldwide, limiting independent access to information, digital content, and physical navigation [42].

Although traditional assistive tools such as braille and white canes continue to play an important role, they are often insufficient for addressing the demands of today's complex and fast-changing environments. Recent advances in artificial intelligence, computer vision, and mobile computing have created new opportunities for developing intelligent, adaptive, and context-aware assistive technologies that better support the needs of blind and visually impaired persons (BVIP) [31].

### B. Related Work

A number of technological sectors are identified to have been basis of the present day assistive systems in the visually impaired users. Optical Character Recognition (OCR) can be used to turn printed and handwritten text into machine readable formats, whereas Text-to-Speech (TTS) technologies can be used to convert text into sounding, like natural audio [6]. Screen readers can help people use the graphical user interface and digital platforms with ease [27]. Moreover, the methods of object recognition would enhance the awareness of the environment with a recognition of obstacles and objects around, which would facilitate the independent movement outside with the help of GPS-based navigation systems [38], [50]. Nonetheless, even with these significant advancements, these technologies are limited by such factors as real-world performance, cognitive load, and hardware.

### C. Research Problem

Many existing assistive technologies are designed to address specific tasks in isolation, resulting in fragmented solutions that lack seamless integration [46]. Users are frequently required to rely on multiple independent tools, each with its own interface and operational constraints. Furthermore, system

performance may degrade significantly when deployed outside controlled laboratory environments. These challenges highlight the need for unified, interoperable, and context-aware assistive systems that can deliver consistent and reliable support across diverse real-world scenarios.

#### D. Scope and Contribution

This paper presents a comparative survey of five core assistive technology domains: OCR, TTS, screen readers, object detection, and GPS-based navigation. In contrast to prior surveys that primarily examine these technologies independently, this work analyzes them collectively with a focus on their potential for integration into cohesive assistive ecosystems [24]. Key evaluation dimensions include accuracy, latency, usability, privacy, and scalability, enabling the identification of design principles and best practices for next-generation assistive solutions.

#### E. Paper Organization

The remainder of this paper is organized as follows: Section II presents a comprehensive review of the literature related to the five core technologies. Section III provides a detailed comparative analysis of existing approaches. Section IV discusses emerging trends and future research directions, and Section V concludes the paper.

## II. LITERATURE REVIEW

### A. Optical Character Recognition (OCR)

Optical Character Recognition (OCR) enables the conversion of printed, handwritten, and scene text into machine-readable formats that can be rendered as speech, braille, or

other accessible outputs. This capability supports essential tasks for visually impaired users, including document reading, product identification, and environmental navigation. OCR technology has evolved significantly from early mechanical and rule-based systems [9] to modern deep learning-based approaches. Contemporary OCR pipelines typically involve image preprocessing, text detection, character recognition, and post-processing, allowing them to handle irregular layouts, curved text, and multilingual scripts with improved accuracy [4].

Recent research has expanded OCR capabilities to include mathematical expression recognition [10], advanced document layout analysis, and robust support for complex scripts and mixed-language documents [1]. As summarized in Table I, deep learning-based models consistently outperform traditional techniques, while lightweight and optimized architectures enable real-time deployment on mobile and embedded devices [6]. Evaluation metrics have also evolved beyond conventional Character Error Rate (CER) and Word Error Rate (WER) to incorporate user-centered measures such as reading speed, comprehension, and usability.

Despite notable progress, several challenges remain. OCR systems still struggle with unconstrained handwriting, accurate layout preservation, and robustness under varying lighting and environmental conditions [3]. Nevertheless, continued advances in deep learning architectures, training strategies, and computational optimization ensure that OCR remains a critical component of assistive technology ecosystems for blind and visually impaired users [2].

TABLE I: Comparative Analysis of OCR Approaches for Assistive Technologies

Objective / Focus	Dataset Used	Methodology / Model	Key Results / Findings	Limitations	Future Scope
Historical review of OCR research and development [9]	Historical literature; industrial data	Template matching; structural analysis; neural networks	Three OCR generations identified; transition from logic to AI	Historical scope; lacks modern evaluation	Deep learning and multilingual advances
OCR with neural networks and post-correction for multilingual historical archives [8]	Finnish & Swedish corpora (1771–1939)	Calamari OCR; finite-state post-correction; ensemble voting	CER: 1.7% (Finnish), 2.7% (Swedish)	Limited font robustness	Coloured/grayscale images; rare font generalization
Review of English language OCR using pattern recognition [4]	English benchmark datasets	CNN segmentation; TableNet; pattern recognition	Up to 99% accuracy on printed English	Weak for blurred/handwritten scripts	Orientation detection; noisy handwriting handling
Ultra-lightweight OCR for device deployment (PP-OCR) [6]	Industry data ( $\approx 6622$ characters)	CNN + Transformer; pruning; quantization	3.5 MB model; 10 $\times$ faster performance	Struggles with complex layouts	Multilingual and scene-text OCR expansion
English OCR pipeline analysis with neural networks [5]	Standard English benchmark datasets	Feature extraction; hybrid CNN models	Accurate for clean documents	Fails on skewed/rotated pages	Layout variability handling
Real-time reading assistant for visually impaired users [3]	Captured label and product images	Connected component analysis; Tesseract OCR; TTS integration	Accurate real-time text extraction	Poor performance in cluttered backgrounds	Curved-text and multilingual support
AI-based document reader for blind users (Vietnamese) [2]	1,300 Vietnamese textbook images	YOLOv8 segmentation; Tesseract; Pix2Tex; ViT; MathML integration	98.3% mAP (tables); 88.2% formulas	Image quality dependent	Embedded real-time systems
Embedded Bangla OCR and TTS for visually impaired using Raspberry Pi [1]	Custom Bangla document images	Tesseract OCR; Raspberry Pi; TTS conversion	Effective text extraction and speech output for Bangla script	Limited to printed Bangla; hardware constraints	Optimization for low-resource languages; portable device integration
Assistive OCR for product label narration [7]	Product and package photo dataset	Binarisation; connected component analysis; OCR + TTS integration	Low-latency label reading	Lighting variation issues	AR glasses; IoT integration
Comparative study of OCR models for multilingual and mathematical text recognition [10]	52 document images (mixed languages and formats)	CNN; RNN; PaddleOCR; MMOCR; KerasOCR; Decision Tree fusion	PaddleOCR best (F1 = 0.71); Tesseract fastest	Limited dataset size	Hybrid ensemble OCR systems

### B. Text-to-Speech (TTS)

Text-to-Speech (TTS) technology converts digital text into spoken language and serves as the primary auditory interface for assistive applications such as OCR readers, screen readers, and navigation systems. Early TTS systems relied on concatenative and formant-based synthesis techniques [17], which offered limited naturalness and flexibility. Recent advancements in neural network-based models, including Tacotron [20] and Deep Voice [18], have significantly improved speech quality, achieving near-human levels of naturalness through neural vocoders.

Modern TTS pipelines typically consist of text normalization, acoustic modeling, and neural waveform generation. As illustrated in Table II, system performance is commonly evaluated using Mean Opinion Score (MOS) and intelligibility metrics. Recent innovations in transfer learning, multilingual embeddings, and semi-supervised learning have enabled TTS systems to better support low-resource languages [19].

Further optimization techniques allow neural TTS models to operate in real time on mobile and embedded platforms, while personalization approaches such as voice cloning enhance user experience and privacy [12]. Despite these strengths, challenges persist, including high computational requirements, limited coverage of low-resource languages, and difficulties in modeling expressive prosody and emotion [14]. Overall, neural TTS represents the state of the art, with hybrid approaches increasingly explored to balance speech naturalness, efficiency,

and scalability in assistive technology applications [13].

### C. Screen Readers

Screen readers translate on-screen content into speech or braille, enabling visually impaired users to access digital documents, web pages, and software applications. These systems have evolved from early terminal-based solutions to advanced desktop and mobile platforms such as VoiceOver and TalkBack [26]. Modern screen readers rely on accessibility APIs to extract semantic information from user interfaces and present it through Text-to-Speech (TTS) engines or refreshable braille displays [27].

As summarized in Table III, the evaluation of screen readers extends beyond compliance with accessibility standards such as WCAG to include user-centered metrics such as task completion time, error rates, and comprehension [29]. Studies indicate that novice users tend to rely on linear navigation, whereas experienced users adopt more efficient structural strategies, including heading navigation and landmark shortcuts [25]. Ongoing research focuses on reducing interaction latency and improving web-based screen reader solutions to enhance accessibility across platforms [28]. However, the steep learning curve associated with mastering gestures and navigation techniques remains a significant barrier, particularly for new users [26].

Screen readers are widely used across domains including web browsing, mobile applications, and STEM education. While modern systems offer multimodal navigation, plugin ex-

TABLE II: Comparative Analysis of TTS Approaches for Assistive Technologies

Objective / Focus	Dataset	Methodology / Model	Key Results / Findings	Limitations	Future Scope
Survey of DSP and NLP components of TTS [17]	Various datasets	DSP + NLP hybrid; rule-based & concatenative systems	Modular architectures; differentiates synthesis philosophies	Manual rule design; limited emotional expression	Integration of deep learning; expressive speech
End-to-end real-time neural TTS [18]	~20h English speech	DNN pipeline; phoneme segmentation; WaveNet vocoder	Real-time synthesis; 400× faster than prior WaveNet	Limited to English; noisy duration/F0	Multilingual, expressive TTS
Low-resource TTS and ASR with few paired data [19]	LJSpeech (200 paired + unpaired)	Denoising autoencoder; Transformer modeling	99.84% intelligibility; 2.68 MOS; 11.7 PER	Needs paired data; Griffin-Lim limits quality	Neural vocoder; unsupervised learning
End-to-end character-to-speech TTS [20]	24.6h female English speaker	Seq2Seq with attention; CBHG encoder; Griffin-Lim	3.82 MOS; natural prosody	Griffin-Lim artifacts; attention instability	Neural vocoders; prosody control
Voice cloning with few samples [12]	LibriSpeech + samples	Speaker encoder; Tacotron2; WaveRNN vocoder	MOS 4.12 (naturalness); 3.73 similarity	Small datasets; ethical concerns	Multilingual cloning; privacy safeguards
TTS system design for visually impaired users [11]	Recorded speech prompts	Concatenative synthesis; text normalization; speech database	Functional TTS prototype with intelligible output	Limited naturalness; small vocabulary	Integration with OCR; more natural voices
Machine learning based TTS converter for visually impaired [13]	English speech corpus	Neural network based acoustic model; vocoder	Improved naturalness over concatenative systems	High computational requirement; limited training data	Lightweight models; real-time deployment
Emotional Arabic TTS and depression detection [14]	Arabic tweets (1229 samples)	AraBERT + LSTM-BiGRU + WaveNet	95.8% accuracy; expressive speech	High data/computation needs	Real-time multimodal affect detection
Creation of Balinese speech corpus for TTS [15]	1187 audio recordings	Recording; denoising; dialect classification	First open Balinese speech dataset	Single dialect; limited speakers	Multi-dialect; multi-speaker expansion
Polyglot TTS implementation in assistive technologies [16]	Mixed multilingual data	Deep neural synthesis + contextual NLP	Improved multilingual interaction	Limited evaluation datasets	Transformer TTS + dialogue systems

tensibility, and increasing platform support [30], several challenges persist. These include difficulties in handling dynamic and interactive content, limited accessibility of complex visual elements such as charts, and economic barriers associated with commercial tools, despite the availability of free and open-source alternatives such as NVDA [24].

#### D. Object Detection

Object detection enables the identification and localization of objects within images or video streams, providing visually impaired users with auditory, haptic, or tactile feedback to support navigation and obstacle avoidance. The field has evolved from traditional handcrafted feature-based methods to modern deep learning approaches, particularly single-stage detectors such as YOLO and SSD, which are well suited for real-time operation on wearable and mobile platforms [34].

Typical object detection pipelines consist of a detection backbone, post-processing modules, and feedback mapping mechanisms that translate visual information into accessible outputs [39]. As summarized in Table IV, system performance is commonly evaluated using standard benchmark datasets and metrics such as mean Average Precision (mAP) and Frames Per Second (FPS) [38]. To support real-world deployment, many studies leverage transfer learning, model pruning, and edge optimization techniques to balance accuracy and computational efficiency [36].

Edge deployment on embedded platforms such as Raspberry Pi introduces inherent trade-offs between model complexity, inference speed, and power consumption [32], [40]. In addition, the design of feedback mechanisms plays a critical role in usability, as poorly structured audio or haptic cues can lead to cognitive overload for users [33].

Object detection has been integrated into a wide range of assistive applications, including smart glasses, wearable navigation aids, and mobile vision systems [37]. While these solutions offer real-time environmental awareness and high versatility, persistent challenges include sensitivity to lighting conditions, reliable distance estimation, and achieving an optimal balance between detection accuracy and system latency in dynamic real-world environments [35].

#### E. GPS Navigation

GPS navigation is a foundational assistive technology for visually impaired individuals, supporting independent mobility through positioning, route planning, and turn-by-turn guidance. Early systems based on standalone GPS receivers or smartphones typically offered coarse localization accuracy in the range of 10–15 meters and relied on basic speech-based interfaces [41]. These approaches performed reasonably well in open outdoor environments but faced significant limitations in urban canyons and were largely ineffective indoors. To address these challenges, contemporary systems increasingly combine Global Navigation Satellite System (GNSS) data with

TABLE III: Comparative Analysis of Screen Reader Research Studies

Objective & Focus	Screen Reader Types / Features	Key Findings & Observations	Validation / Evidence	Limitations	Future Scope
Review of screen reader solutions for internet navigation [24]	Browser extensions, apps, some hardware with haptics	Improves navigation efficiency and reduces cognitive load; multimodal input helps	User studies and implementation reviews	Limited haptic adoption; small sample sizes; cost constraints	Modular design; multimodal AT; open-source development
Survey of user browsing strategies with screen readers [25]	VoiceOver, JAWS, FireVox, non-visual browsers	Diverse strategies used: headings, mouse simulation, landmarks	Empirical user behavior analysis	Complex interfaces; inaccessible design; insufficient standards	Improve adaptive browsing; usability; developer training
Teaching and practice strategies for mobile gestures [26]	VoiceOver, TalkBack mobile screen readers	Gesture mastery difficult; lack of standardized training resources	User training evaluations	Complex gestures; training deficiencies	Develop accessible apps; personalized training; gamification
Survey on chart accessibility for blind users [23]	Desktop/mobile SRs, braille, audio-haptic aids	Screen readers fail on charts; CharVis technology emerging	Accessibility experiments on charts	Semi-automatic tools; hardware limits	AI-based CharVis; multimodal output
Study of web usability frustrations for blind SR users [29]	JAWS, NVDA	Common frustrations: poor layout, unlabeled forms, crashes	User feedback and usability studies	Web design flaws; unstable SR software	Focus on web design; stable tools; education
Examining SR user challenges with online data visualizations [22]	JAWS, NVDA, VoiceOver with JS charting libraries	Visual data 61% less accessible; double time needed	Comparative accessibility testing	Lack of alt text; cognitive load	Alternative text; tabular summaries; multi-modal access
Personas capturing SR user diversity and approaches [21]	Desktop & mobile SRs, Braille	Wide skill and preference variation; varied mental models	Persona-based qualitative research	Complex SR tools and navigation	Persona-driven design; adaptive and inclusive interaction
Examines mobile SR usage & challenges [27]	Mobile screen readers (VoiceOver, TalkBack)	Mobile SR use growing; display size limits navigation	Mobile usability studies	Gesture complexity; lack of practice resources	Develop training tools; standardized interaction guidelines
Design of web-based self-voicing browser for blind users [28]	WebAnywhere – web-based SR via sound-capable computer	Low cost; no installation; convenient for temporary use	Prototype deployment testing	Network dependency; limited offline capability	Enhance offline features; mobile compatibility
Research on accessibility challenges of AJAX-heavy sites [30]	Screen readers and ARIA roles	Dynamic content challenges; updates not announced	Web accessibility evaluation studies	ARIA role inconsistencies; event handling issues	Better ARIA compliance; real-time update notification

inertial measurement units (IMUs), Wi-Fi or Bluetooth Low Energy (BLE) beacons, RFID, ultrasonic sensors, LiDAR, and computer vision techniques. Such multimodal sensor fusion enables sub-meter localization accuracy while simultaneously supporting obstacle detection and situational awareness [42].

Typical system architectures integrate multiple functional components, including localization modules (GNSS, IMU, and indoor beacon networks), perception units for obstacle and hazard classification, mapping and path-planning algorithms such as shortest-path computation and SLAM, and user interaction interfaces based on Text-to-Speech (TTS), spatial audio, vibrotactile feedback, or smart canes and wearable devices [49]. As summarized in Table V, system evaluation commonly employs GNSS error metrics, radio fingerprinting accuracy, and user-centered measures such as route completion rates, navigation time, and cognitive load [50]. Kalman and particle filters are widely adopted for GPS-IMU sensor fusion, while smartphone-centric implementations remain popular due to their affordability and accessibility. In contrast, wearable platforms provide richer sensing capabilities but are often constrained by power consumption, cost, and ergonomic considerations [48].

GPS-based assistive systems are applied across a broad

range of scenarios, including outdoor wayfinding, indoor navigation within complex spaces such as shopping malls and airports, and integrated multimodal solutions that combine GPS with OCR, TTS, and object detection. Many systems additionally incorporate safety-oriented features such as emergency alerts and guardian tracking [47]. Key advantages of GPS navigation include global coverage, familiarity of guidance paradigms, and seamless integration with smartphones. However, limitations persist, including positioning errors of 3–10 meters near critical hazards, reliance on additional infrastructure for indoor environments, increased energy consumption due to sensor fusion, and the need to carefully regulate feedback frequency to avoid user distraction [46]. Overall, current research trends point toward hybrid, multimodal navigation systems that seek to balance accuracy, cost, and usability, enabling safer and more independent mobility for visually impaired users [43].

### III. COMPARATIVE ANALYSIS

The five technologies examined—Optical Character Recognition (OCR), Text-to-Speech (TTS), Screen Readers, Object Detection, and GPS Navigation—address different yet interconnected accessibility needs for blind and visually impaired persons. OCR and TTS work together to transform printed or

TABLE IV: Comparative Analysis of Object Detection Approaches for Assistive Technologies

Objective / Focus	Datasets Used	Methodology & Technology	Validation / Results	Limitations	Future Scope
YOLOv8-based object detection on Android apps for VI [38]	Custom dataset with 12 classes	YOLOv8 training with augmentation; TensorFlow Lite conversion; audio feedback	mAP50 $\approx$ 80.5%; real-time detection on Android	Accuracy-speed tradeoff	Optimize model size and robustness
Smart glasses for VI with object detection & vision-language models [40]	Custom + open OCR/face datasets	Raspberry Pi Zero 2W; vision-language model; OCR; object/face recognition; multilingual audio feedback	Real-time text/object narration on prototype	Hardware limits; high model complexity	Upgrade boards; enhance connectivity
Review of real-time object detection methods for VI [34]	COCO, VOC, custom datasets (survey)	Survey of YOLOv3, SSD, pruning, parallel GPU-CPU acceleration	Summarizes pruning/acceleration efficiency for mobile deployment	Trade-offs in mobile deployment	Compiler-assisted acceleration; dynamic pruning
Review on Raspberry Pi in prototyping vision assistive tech [31]	N/A (review paper)	Comparative analysis of Raspberry Pi models for embedded vision tasks	Analyzes prototype performance across Pi generations	Hardware limits for real-time tasks	Adopt higher compute boards
Deep learning-based detection and environment description [32]	Custom dataset with ambiance mode	MobileNet SSD; PSO hyperparameter tuning; Raspberry Pi deployment	88.9% accuracy; 2.15 FPS; scene description mode	Small dataset; low FPS	Extend dataset; improve NLP; add cloud/edge support
Vision AI: YOLOv7 object recognition for VI [36]	COCO (transfer learning)	YOLOv7; TensorFlow Lite; Raspberry Pi integration	High accuracy/speed; outperforms YOLOv5	Small/occluded object detection limitations	Expand models; improve bandwidth
MagicEye wearable for VI (object/currency recognition) [37]	Custom 35-class dataset	Custom CNN; GPS and proximity sensors; audio feedback	Real-time detection on wearable prototype	Prototype stage; limited real-world trials	Miniaturization; UX improvements
Indoor object detection and distance estimation for VI [39]	Custom indoor dataset	ESP32 camera + YOLOv8; audio navigation cues	85% detection accuracy; distance $R^2 = 0.975$	Wired headset; limited peripherals	Integrate ultrasound; wireless solutions
Deep learning-assisted object detection & scene description for VI [33]	Custom object and ambiance datasets	MobileNet SSD; transfer learning; audio feedback via Raspberry Pi	88.9% accuracy; real-time scene narration	Small dataset; limited scene complexity	Expand datasets; hardware optimization
Lightweight YOLOv8 object detection system [35]	Custom mobile dataset	YOLOv8 with pruning; TensorFlow Lite mobile deployment	Real-time detection; balanced speed/accuracy tradeoff	Limited robustness under varied lighting	Optimize model; adaptive inference

digital text into spoken output, while screen readers enable access to interactive digital interfaces. Object detection supports real-time environmental awareness, and GPS navigation facilitates large-scale orientation and wayfinding. When combined, these technologies form the backbone of multimodal assistive ecosystems, where effective integration and human-centered interaction design are as important as the performance of individual components [46].

#### A. Accuracy and Robustness

OCR systems demonstrate strong performance on clean, high-resolution printed text, typically achieving low character error rates (CER) in the range of approximately 1.7–3% under controlled conditions. Such accuracy reflects the maturity of modern convolutional and transformer-based text recognition models when applied to well-aligned, high-contrast documents. However, performance declines significantly in more challenging scenarios, including noisy or low-resolution images, handwritten scripts, mathematical notation, curved text, and documents with complex multi-column or mixed-layout structures, where error rates can exceed 10–15% depending on preprocessing quality and model robustness [3], [6]. Similarly, contemporary neural text-to-speech (TTS) systems achieve high intelligibility and naturalness, with mean opinion scores

(MOS) typically ranging between 3.8 and 4.3, reflecting substantial progress in end-to-end deep learning architectures and neural vocoders. Nevertheless, generating expressive prosody, emotional nuance, and speaker variability remains challenging, particularly when training data are limited in linguistic diversity, accent variation, or affective richness [14], [18]. Screen readers function reliably when interacting with semantically structured and properly annotated digital content, leveraging accessibility standards such as ARIA roles and labeled form elements; however, their effectiveness decreases in dynamic web applications, interactive dashboards, and data visualizations where accessibility metadata may be incomplete or improperly implemented, thereby increasing cognitive load and navigation difficulty for users [29]. Object detection systems frequently report precision and recall rates exceeding 90% in controlled datasets or domain-specific environments, yet real-world deployment introduces challenges such as variable illumination, motion blur, occlusion, small-object detection, and shifting camera viewpoints, all of which can significantly degrade detection reliability [38]. Finally, GPS-based navigation systems provide outdoor positioning with meter-level accuracy in consumer-grade devices, typically within 2–5 meters under open-sky conditions [41]. Although sensor fusion approaches—integrating GPS with inertial measurement units,

TABLE V: Comparative Analysis of GPS Navigation Approaches for Assistive Technologies

Objective / Focus	Methodology / Technologies Used	Validation / Results	Performance / Impact	Limitations	Future Scope
Review challenges and opportunities in VI navigation [46]	Systematic review of sensors (GPS, ultrasonic, RFID), AI, wearables	Identified trends and gaps in assistive tech	Growth of wearable solutions	Lack of longitudinal studies; cost concerns	User-centered design; multimodal sensing and feedback
Survey of recent tech advancements [48]	Systematic review; sensor fusion with GPS, Bluetooth, Ultrasonic, AI	Highlighted state-of-art; efficacy of sensor fusion	Improved localization performance	Energy consumption; adaptability issues	Seamless indoor/outdoor navigation; edge processing
Develop smart cane system integrating sensors [49]	GPS, ultrasonic, compass, RFID, app integration, voice commands	Prototype tested indoor/outdoor	Good obstacle detection accuracy	Cost; GPS accuracy limitations	AI-enhanced recognition; more user-friendly interfaces
IoT & ML-based system for obstacle detection [47]	Ultrasonic sensors, accelerometer, GPS, cameras, ML classification	Effective obstacle and fall detection	Reliable hazard alerting	Power consumption; real-time processing limits	Expand datasets; improve energy efficiency
GPS voice-guided navigation for VI [43]	GPS module; voice guidance	User studies show improved independence	Enhanced mobility confidence	No indoor support; limited obstacle detection	Multimodal integration; indoor positioning improvements
Low-cost outdoor GPS-based guidance [45]	Microcontroller, GPS module, voice output	Field test shows 92% success	Affordable navigation support	Route preloading; no indoor navigation	Dynamic routing; customizable paths
Voice-based navigation and obstacle detection [44]	Ultrasonic sensors, GPS, AI modules, voice commands	Prototype effective in obstacle alerts	Improved obstacle awareness	Lacks extensive user testing	AI-driven obstacle recognition and route planning
Prototype smart assistant for VI [50]	GPS, ultrasonic, accelerometer, gyroscope, machine learning	Preliminary tests promising	Integrated sensor performance	Early prototype; limited sample size	Refinement and broader deployment
Audible & haptic GPS+GSM navigation tool [41]	GPS and GSM modules for feedback and communication	Effective audio and haptic feedback	Multi-modal feedback support	GSM dependency; simple obstacle detection	Enhanced sensor fusion and AI integration
Systematic review of navigation aids and challenges [42]	Literature review: GPS, LiDAR, ultrasonic, computer vision, AI	191 studies analyzed; identified gaps	Comprehensive gap analysis	Cost, robustness, energy usage challenges	Personalized multi-sensor fusion and robust systems

Bluetooth beacons, LiDAR, or radio-frequency signals—can enhance localization to near sub-meter accuracy, these improvements come at the cost of increased computational complexity, energy consumption, hardware expense, and system integration challenges [44].

TABLE VI: Technical Performance Comparison

Technology	Evaluation Metrics	Representative Performance	Primary Limitations
OCR	CER, WER	CER $\approx$ 1.7–3% on clean printed text	Reduced accuracy with handwriting, mathematical notation, low-resolution images, and cluttered layouts
TTS	MOS, intelligibility	MOS $\approx$ 3.8–4.3 for neural TTS systems	Limited emotional expressiveness and prosody; high computational demand
Screen Readers	Task completion rate, SUS	High usability for semantically structured content	Limited support for dynamic content and inadequately labeled interfaces
Object Detection	mAP, Precision/Recall	>90% accuracy in controlled datasets []	Performance degradation under poor lighting, occlusion, and small-object scenarios
GPS Navigation	Positional error (m)	2–5 m accuracy for consumer devices; sub-meter with RTK or sensor fusion	Limited indoor functionality, multipath interference, and urban canyon effects

### B. Latency and Real-Time Responsiveness

Latency requirements vary considerably across assistive technologies, depending on how directly they support real-time user interaction. Object Detection places the most demanding constraints, typically requiring an end-to-end delay of less than 200 ms from scene capture to audio feedback to support safe walk-and-react navigation [39]. On embedded and wearable platforms, achieving such responsiveness generally requires lightweight or quantized models, efficient inference pipelines, or dedicated hardware accelerators [34]. GPS-based navigation systems operate at relatively low update rates, commonly around 1 Hz for consumer-grade GNSS receivers. While sufficient for high-level route guidance, this update frequency is inadequate for fine-grained, rapid navigation. Sensor fusion with inertial measurement units (IMUs) can substantially increase effective update rates and improve short-term responsiveness [50]. OCR systems are more tolerant to latency, as reading tasks are less time-critical. End-to-end processing delays of 1–3 s, encompassing image capture, text recognition, and speech output, are generally acceptable for document reading. However, applications such as signage interpretation or continuous reading benefit from optimized and accelerated processing pipelines [7]. Modern TTS systems

can operate in near real time when using optimized neural vocoders, often achieving sub-second synthesis latency. In contrast, high-fidelity vocoders may introduce noticeable delays unless supported by hardware acceleration or edge optimization techniques [18]. Screen Readers typically provide near-instantaneous feedback when applications expose proper semantic accessibility information. Responsiveness degrades primarily in cases involving dynamically rendered content, custom widgets, or when surrogate techniques such as OCR must be employed to interpret inaccessible visual elements [28].

TABLE VII: Latency and Responsiveness

Technology	Desirable Latency	Typical On-Device Reality
Object Detection	<200 ms	200–500 ms (tiny models) on mobile/Pi
GPS	<1 s for micro-navigation	$\sim$ 1 s (consumer GNSS)
OCR	1–3 s acceptable	1–5 s depending on device and preprocessing
TTS	<200–500 ms for interactivity	Sub-second with efficient vocoders
Screen Readers	Near-instant (event-driven)	Instant if accessibility hooks present

### C. Cognitive Load and Usability

Screen readers often impose a high cognitive load because they linearize complex visual layouts into sequential audio streams. While expert users develop efficient navigation strategies using shortcuts and structural cues, novice users typically face a steep learning curve that demands substantial training and practice [21].

Text-to-Speech (TTS) systems deliver information in an easily accessible auditory format; however, prolonged listening or monotonous speech patterns can lead to listening fatigue. Research shows that techniques such as content chunking, adjustable speech rates, and expressive prosody significantly enhance comprehension, engagement, and information retention [14].

OCR-based systems require precise camera positioning and stable capture conditions, which can be challenging for users with visual impairments. Recognition errors and repeated capture attempts often increase frustration and cognitive effort. Guided capture interfaces that provide real-time feedback and automatic quality assessment have been shown to substantially reduce this burden [3].

Object detection technologies can overwhelm users when every detected object triggers an audio announcement. To prevent cognitive overload, intelligent prioritization mechanisms, contextual grouping, and sparse or hierarchical notification strategies are essential [33].

GPS navigation systems, while effective for route guidance, may cause instruction fatigue due to excessive verbal prompts. Integrating haptic feedback and concise, well-timed audio cues helps maintain situational awareness while minimizing distraction and cognitive strain [50].

D. Cost, Scalability, and Adoption

OCR and Text-to-Speech (TTS) technologies are among the most scalable and cost-effective assistive solutions. The availability of open-source engines and widespread smartphone support allows these systems to be deployed at scale with minimal infrastructure requirements. However, reliance on cloud-based APIs can introduce recurring costs and raises important concerns related to data privacy and security [6], [12].

Screen readers also benefit from several mature, free implementations, either integrated directly into operating systems or developed as open-source projects. Despite this accessibility, effective adoption often depends on extensive user training, which remains a significant barrier, particularly for first-time users [26].

In contrast, object detection and GPS-based navigation systems frequently involve additional hardware considerations. While smartphone-based solutions help reduce cost and improve accessibility, specialized wearable devices incorporating depth sensors or LiDAR technology can substantially increase both hardware costs and physical bulk, potentially limiting widespread adoption [37], [47].

TABLE VIII: Practical Considerations for Assistive Technology Deployment

Technology	Cost & Accessibility	Adoption Barriers	Privacy Concerns
OCR	Low – works on most smartphones	Camera quality, user interface design	Document uploads to cloud services
TTS	Low to medium	Expressive voice quality on edge devices	Voice data processing, cloud-based synthesis
Screen Readers	Low (free options available)	Requires training, inconsistent app support	Mostly local processing; plugins may pose security issues
Object Detection	Medium	Power consumption and weight for wearables	Continuous video streaming to cloud
GPS Navigation	Low (phones) to high (RTK/LiDAR)	Limited indoor coverage; specialized hardware cost	Continuous location tracking risks

E. Privacy, Ethics, and Bias

Assistive technologies that rely on cloud-based workflows—particularly OCR, TTS, and object detection—carry potential privacy risks, as sensitive text, images, and location data may be exposed. For privacy-sensitive applications, on-device processing is strongly recommended [6], [37].

Bias and inclusivity remain critical concerns. Dataset imbalances can affect object detection (e.g., under-representation of certain environments or demographic groups), TTS systems (limited voice and dialect diversity), and OCR engines (unequal support for scripts and languages). Responsible design should integrate privacy-by-design principles and prioritize

comprehensive, representative datasets to reduce algorithmic bias [14], [38].

F. Practical Recommendations

- Favor on-device inference for privacy-sensitive or latency-critical tasks, particularly in OCR and object detection, whenever hardware resources allow [6], [34].
- Utilize multi-sensor fusion for navigation reliability (e.g., GNSS, IMU, and short-range proximity sensors) to overcome the limitations of individual technologies [49].
- Implement intelligent output prioritization: safety-critical alerts (hazards) should take precedence over navigation guidance, which in turn should take precedence over descriptive content, helping to prevent cognitive overload [33].
- Provide extensive personalization options: users should be able to configure output verbosity, voice characteristics, and modality preferences to suit individual needs [21].
- Invest in comprehensive training and longitudinal evaluation programs. Real-world, extended-duration trials are essential to validate practical utility and adoption barriers beyond laboratory settings [46].
- Address ethical and privacy concerns proactively: minimize cloud dependencies for sensitive data and actively diversify training datasets to mitigate algorithmic bias [14].

IV. FUTURE DIRECTIONS

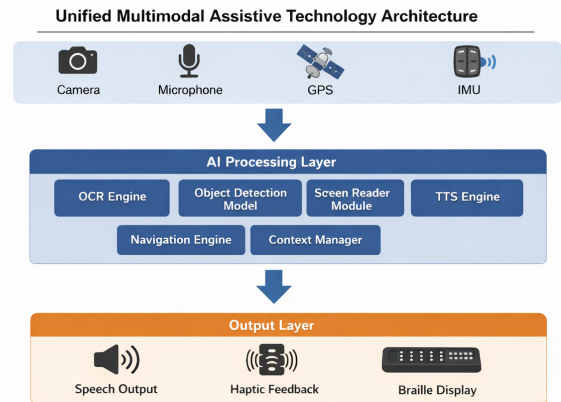


Fig. 1: Unified Multimodal Assistive Technology Architecture integrating OCR, TTS, Screen Reader, Object Detection, and GPS Navigation.

The next generation of assistive technologies for visually impaired individuals is likely to focus on seamless integration across multiple sensory modalities and technological domains [46]. While OCR, TTS, screen readers, object detection, and GPS navigation have each reached significant maturity, their combined potential can be fully realized through unified smart

glasses platforms that deliver these capabilities in real time [40].

As illustrated in Fig. 1, such a unified multimodal architecture integrates perception modules, intelligent processing engines, and adaptive output mechanisms within a single cohesive framework.

A comprehensive smart glasses system could simultaneously capture printed or scene text using OCR [6], vocalize content through high-quality TTS synthesis [18], and provide screen reader functionality for digital interfaces [21]. At the same time, object detection could deliver continuous obstacle alerts and environmental descriptions [39], while GPS modules support outdoor navigation and fine-grained micro-navigation assistance [49]. The key technical challenge is ensuring low-latency, on-device processing, which requires optimized models—such as quantized OCR, lightweight YOLO implementations, and efficient neural vocoders—running on embedded hardware without over-reliance on cloud services [34].

## V. CONCLUSION

This survey has examined the roles and capabilities of five key assistive technologies—OCR, TTS, screen readers, object detection, and GPS navigation—in improving accessibility for visually impaired individuals. Each technology contributes distinct functionality: OCR converts printed and handwritten text into accessible digital formats [6]; TTS delivers natural auditory communication [18]; screen readers enable structured interaction with digital environments [21]; object detection provides real-time awareness of the surroundings [38]; and GPS supports independent mobility, both outdoors and increasingly indoors [50]. Together, these technologies address critical aspects of daily life, including access to information, safe navigation, and educational opportunities.

Despite significant progress, challenges remain. OCR systems continue to face difficulties with handwriting, complex scripts, and accurate layout preservation [3]. TTS implementations struggle with expressive prosody, computational efficiency, and support for low-resource languages [14]. Screen readers rely heavily on well-structured content and present steep learning curves [29]. Object detection must balance accuracy and latency while maintaining robustness in real-world environments [34], and GPS navigation suffers from limited indoor coverage, as well as cost and power trade-offs when augmented with additional sensors [47].

A central insight is that no single technology is sufficient on its own; meaningful accessibility emerges from thoughtful integration [46]. Future assistive ecosystems are likely to combine OCR, TTS, screen readers, object detection, and GPS capabilities into cohesive platforms—such as smart glasses—offering seamless reading, navigation, and environmental awareness through unified interfaces [40]. Advances in lightweight deep learning, multi-sensor fusion, and intelligent multimodal feedback will make these integrated solutions increasingly practical, affordable, and user-friendly [37]. Achieving real impact also requires inclusive datasets, privacy-preserving system designs, and continuous user-centered eval-

uation to ensure that emerging technologies genuinely meet the needs and preferences of visually impaired users [21].

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