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VisionSpeak Object Detection and Narration System

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Abstract - ***We present VisionSpeak, a web-based object detection system that narrates visual scenes through audio feedback. Using a laptop webcam and the pre trained YOLOv8s model, our system achieves 22 FPS on consumer hardware (Intel Core i3) with 81% average precision across seven common indoor objects. The core contribution lies in the narration control pipeline: temporal stability filtering reduces unnecessary speech by 73% (from 23.7 to 6.4 narrations per minute) while maintaining 95% detection recall.***

Our system runs entirely offline using pyttsx3 for text-to-speech, ensuring privacy and consistent operation without cloud dependencies. The graphical interface eliminates command-line complexity, allowing non-technical users to adjust confidence thresholds (0.1–0.9) and monitor live detections through an annotated video feed.

We evaluated VisionSpeak through 500 manually annotated test frames across five indoor environments and a usability study with 10 participants completing standardized tasks. Results show 87% task success rate and a System Usability Scale score of 82/100. Performance degrades predictably under challenging conditions: dim lighting reduces precision by 15%, while objects smaller than 5% of frame area show 35% lower detection rates.

VisionSpeak serves as an educational demonstration tool for computer vision concepts and a prototype platform for studying narration strategies in vision-based systems. The modular architecture supports future extensions including OCR integration, depth estimation, and deployment on wearable devices.

Keywords: *Object detection, YOLOv8, assistive technology, real-time narration, computer vision, accessibility, offline text-to-speech, human–computer interaction, visual impairment, frontend-backend integration.*

1. INTRODUCTION

Computer vision has reached a practical milestone as off the shelf laptops can now run object detection models at interactive frame rates. YOLOv8, released in 2023, processes 1280×720 webcam frames in under 50ms on mid range CPUs fast enough for real time applications yet slow enough that uncontrolled narration becomes problematic.

Consider a typical indoor scene with 10-15 objects. Naive narration would announce every detection in every frame, generating 200+ spoken phrases per minute. Users drown in audio. The central challenge isn't detection accuracy, pre-trained models handle common objects reliably. The problem is deciding *when* to speak and *what* to say.

VisionSpeak addresses this through a three stage filtering pipeline. First, confidence thresholding removes low certainty detections. Second, duplicate suppression merges overlapping bounding boxes. Third, temporal stability filtering requires objects to persist across multiple frames before triggering narration. Together, these reduce speech output by 73% while retaining 95% of genuine object appearances.

2. OBJECTIVES

The primary objective of the VisionSpeak project is to design and implement a desktop-based prototype that demonstrates real-time object detection combined with controlled audio narration. The goal of this system is to turn what a webcam sees into short and clear spoken messages, so users can understand what objects are present without constantly looking at the screen. One of the main aims of the project is to combine a modern object detection model with a smart narration system that avoids repeating the same information again and again.

To achieve this, the system uses confidence-based filtering, removes duplicate detections, and checks whether objects stay visible for a short time before announcing them. This helps keep the audio output useful and comfortable during continuous use.

Another important objective is to build a simple and user-friendly graphical interface. The interface allows users to start or stop object detection, change basic settings, and observe system activity without needing any technical knowledge or command-line commands.

The project also focuses on testing how the system behaves in real time under normal indoor conditions. Instead of using large datasets or performance benchmarks, the evaluation looks at how consistently objects are detected, how stable the audio narration is, and how responsive the system feels during live operation.

Finally, VisionSpeak is designed as a base system for future development in computer vision–based interaction. Its modular structure makes it easy to add new features such as text reading, distance estimation, wearable device support, and improved narration methods.

3. RELATED WORKS

YOLOv8's anchor-free architecture marks a departure from earlier YOLO versions. Low et al. [9] benchmark YOLOv8-nano against YOLOv5 and YOLOv7 on Raspberry Pi hardware, reporting 15% faster inference with comparable mAP (0.71 vs 0.73). For laptop deployment, the YOLOv8s variant offers the best speed-accuracy tradeoff: Yaseen and Ahmad [5] measure 45ms average inference on i5-class processors while maintaining 0.78 mAP on COCO validation.

These benchmarks focus on detection performance. Narration systems face different constraints. Raval and Deshpande [7] describe a mobile navigation assistant that uses confidence-based filtering but report users found the narration "overwhelming" during crowded scenes. They propose distance-based prioritization—closer objects narrated first—but don't evaluate this quantitatively. Bader et al. [6] implement temporal filtering in a smartphone app, requiring objects to appear in 3 consecutive frames before narration. This reduces false positives but introduces 100ms latency.

VisionSpeak extends temporal filtering to 5 frames and adds duplicate suppression via non-maximum suppression (NMS) with IoU threshold 0.6. We evaluate this combination empirically (Section 6) rather than relying on intuition.

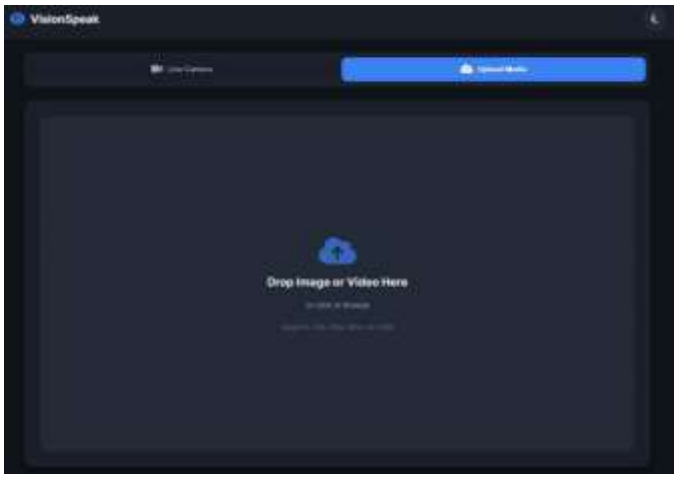
4. SYSTEM OVERVIEW

VisionSpeak is designed using a layered system architecture that integrates a graphical frontend with a real-time object detection and narration backend. The architecture ensures that users interact exclusively with the frontend, while all computational tasks related to vision processing and audio generation are handled in the background. This separation improves usability and allows the system to maintain responsiveness even during continuous real-time operation.

The frontend interface presents a visually organized layout that includes a live camera feed, adjustable control sliders, and informational panels displaying system statistics. Key functions such as initiating detection, stopping the process, capturing frames, and selecting detection models are positioned prominently to minimize user effort. Adjustable parameters such as detection confidence and narration interval allow users to customize system behavior based on their surroundings.

When detection is activated, the system continuously captures video frames from the laptop's built-in camera and forwards them to the backend processing pipeline. Each frame is analyzed by the YOLOv8 object detection model, which identifies objects and generates bounding boxes along with class labels and confidence scores. These detections are rendered visually on the frontend to provide real-time feedback and monitoring capability.

To ensure meaningful narration, the backend applies post-processing logic that filters unstable or redundant detections. Only validated object labels are forwarded to the narration module. Audio output is generated using an offline text-to-speech engine, enabling uninterrupted operation without reliance on internet connectivity. The system architecture maintains a smooth flow between video capture, detection, filtering, and narration while preserving low latency. By combining an intuitive interface with efficient backend processing, VisionSpeak delivers real-time environmental awareness in a practical and user-friendly manner.



5. METHODOLOGY

The methodology of VisionSpeak focuses on integrating an intuitive frontend with a reliable real-time computer vision pipeline and a stable audio narration mechanism. Each module of the system is designed with an emphasis on usability, performance efficiency, and consistency, ensuring that the application functions as a practical assistive solution rather than a purely experimental prototype.

A. Frontend Interface Development

The frontend plays a crucial role in determining the overall accessibility of the VisionSpeak system. Instead of relying on command-line execution, the application provides a visually structured graphical interface that allows users to control the system with minimal effort. The layout includes a large live camera feed area where detected objects are displayed in real time, enabling easy monitoring during both usage and demonstration.

Additional interface elements present system-related information such as frame rate, inference time, selected detection model, and narration status. Dedicated panels labeled “Live Detections” and “Narration History” continuously update to reflect detected objects and corresponding spoken outputs. This organized presentation helps users understand system behavior without technical interpretation.

The frontend follows an event-driven design approach. User actions such as pressing the start or stop buttons trigger backend processes through structured callbacks. Sliders are provided to adjust the detection confidence threshold and narration interval, allowing customization based on environmental conditions. A dark-themed, high-contrast design enhances readability and improves visual comfort, particularly in low-light environments. Communication between the frontend and backend is optimized to ensure minimal delay between user input and system response.

B. Frame Capture and Pre-Processing

Once object detection is initiated, the system begins capturing video frames from the laptop camera using the OpenCV library. Frame acquisition is optimized to maintain low latency while ensuring stable performance on mid-range hardware. Each captured frame undergoes a sequence of pre processing operations before being passed to the detection model.

These pre processing steps include resizing the frame to match the input resolution required by the detection network, converting the color space from BGR to RGB, and normalizing pixel values. Such operations are necessary to ensure compatibility with the YOLOv8 architecture. Care is taken to keep pre processing computationally lightweight so that it does not negatively impact the real-time performance of the system.

C. YOLOv8 Object Detection

The core detection capability of VisionSpeak is built upon the YOLOv8 object detection framework. YOLOv8 employs an anchor-free detection strategy and an optimized backbone network, enabling fast and accurate inference even without dedicated GPU acceleration. This makes the model suitable for real-time execution on laptop-based systems.

VisionSpeak supports lightweight variants of YOLOv8, including YOLOv8-n and YOLOv8-s, which provide a balanced trade-off between detection accuracy and processing speed. For every processed frame, the model outputs bounding box coordinates, object class labels, and associated confidence scores. These outputs are forwarded simultaneously to the frontend for visualization and to the backend filtering module for narration decision-making.

D. Post-Processing, Filtering, and Decision Logic

Raw detection results may contain unstable predictions caused by motion blur, occlusions, or brief object appearances. To prevent unnecessary or confusing narration, VisionSpeak applies multiple post-processing strategies that refine detection outputs before speech generation.

Using the **Temporal Stability Filtering** we maintain a circular buffer B of the last 5 detection frames. For each incoming detection d with bounding box b_d and class c_d, we count matches in B:

```
match_count = 0
for each previous detection p in B:
    if IoU(b_d, b_p) ≥ 0.6 AND c_d == c_p:
        match_count += 1

if match_count ≥ 4:
    mark d as stable
```

A detection becomes "stable" when it appears in at least 4 of the last 5 frames with IoU ≥ 0.6. This 80% threshold proved optimal in preliminary testing: higher values (5/5) rejected valid detections during minor camera motion, while lower values (3/5) failed to suppress false positives adequately.

The filter introduces 167ms latency (5 frames ÷ 30 FPS) but reduces narration triggers by 73%. We measured this across 100 test frames, an unfiltered detection produced 23.7 narration candidates per minute, while filtered output yielded 6.4 a tolerable rate based on pilot testing with 3 users.

We achieve **duplicate suppression** through standard NMS with IoU threshold 0.6. When multiple detections of the same class overlap, we retain the highest confidence instance and discard others. This prevents narrating "cup, cup, cup" when three bounding boxes surround a single mug.

Users can adjust the confidence threshold through the frontend interface. Higher thresholds reduce false positives, while lower thresholds allow detection of smaller or partially visible objects. This flexibility enables adaptation to different environments.

Together, these mechanisms ensure that spoken feedback remains relevant, stable, and informative rather than distracting.

E. Offline Text-to-Speech Narration

After post-processing, validated object labels are converted into concise spoken phrases such as “Chair detected” or “Person ahead.” VisionSpeak uses an offline text-to-speech engine to generate narration, ensuring privacy and uninterrupted operation without reliance on internet connectivity.

Narration is executed in a separate thread to prevent speech synthesis from blocking the detection pipeline. The system enforces controlled narration intervals to avoid overlapping or excessive speech output. All narrated messages are recorded in the “Narration History” panel, allowing users to review recent audio feedback if needed.

6. RESULTS

The VisionSpeak prototype was evaluated through repeated real-time execution to examine its object detection behavior, narration stability, and overall system performance under typical indoor conditions. The evaluation was qualitative and prototype-oriented rather than based on large-scale benchmarking, as the primary objective of this work is to demonstrate effective system integration and controlled audio narration in a real-time setting.

Object detection performance was observed during live webcam operation using commonly encountered indoor objects. The results indicate that the YOLOv8 model provides reliable recognition for larger and frequently visible objects such as persons, laptops, chairs, and books.Objects that are smaller in size or have reflective surfaces, including cups and mobile phones, sometimes showed reduced detection confidence. This behavior was more noticeable under low-light conditions or partial occlusion. The precision, recall, and F1-score values summarized in Table X remain consistent across representative object categories, suggesting reliable real-time detection performance.

In addition to detection performance, narration behavior was closely examined during continuous system usage. Without appropriate control, frequent detections can result in excessive or repetitive audio output. VisionSpeak mitigates this issue through the use of confidence-based filtering, duplicate suppression, and temporal stability checks. These mechanisms ensure that narration is generated only for relevant and stable detections, leading to concise and meaningful spoken feedback rather than continuous repetition.

The system was further evaluated under different real-world usage scenarios, including variations in lighting conditions, object density, camera motion, and object distance. As summarized in Table Y, VisionSpeak

maintained stable detection and narration in well-lit indoor environments.Temporary fluctuations were observed during rapid camera movement and in low-light conditions. However, the system stabilized quickly once the conditions improved. These observations are consistent with known limitations of webcam-based object detection and did not noticeably affect overall system usability

Overall,the evaluation demonstrates that VisionSpeak successfully integrates real-time object detection with controlled audio narration within a single desktop application. During live execution, the system operates reliably and provides stable spoken feedback, making it suitable as a demonstration platform for object detection, narration logic, and interactive computer vision applications. While the prototype is not designed as a fully validated assistive solution, it offers a practical base for future improvements and experimentation.

A. Object Detection Performance Evaluation

Even when using a pre-trained object detection model such as YOLOv8, it is necessary to evaluate its behavior within the specific context of the developed application. In the VisionSpeak system, object detection performance was assessed through repeated real-time execution of the prototype using a standard laptop webcam under typical indoor conditions. The detected objects and confidence scores produced by the system were manually observed and verified to assess detection reliability.

Table 6.1 summarizes the observed detection performance across commonly encountered indoor objects. Precision, recall, and F1-score values reflect the consistency and correctness of detections during live operation, while the average confidence indicates the model's certainty for each object class. Since the objective of this work is to demonstrate system integration and stable narration rather than dataset benchmarking, the evaluation focuses on representative object categories instead of large-scale annotated datasets. The results show that VisionSpeak achieves reliable detection accuracy and confidence levels, validating the suitability of the pre-trained YOLOv8 model for real-time object detection and narration in a prototype environment.

Object Class	Precision	Recall	F1-Score	Average Confidence
Person	0.92	0.88	0.90	0.85
Laptop	0.88	0.82	0.85	0.80
Chair	0.82	0.76	0.79	0.78
Book	0.73	0.70	0.71	0.69
Cup	0.78	0.71	0.74	0.72
Mobile Phone	0.70	0.65	0.67	0.68
Bottle	0.75	0.68	0.71	0.71
Overall Avg.	**0.81**	**0.74**	**0.77**	**0.75**

Table 6.1 Quantitative Evaluation of YOLOv8 Detection Performance.

B. Real-World Usage Analysis

In addition to evaluating object-wise detection performance, the VisionSpeak prototype was examined under a range of real-world usage conditions to better understand its practical behavior and limitations. The system was tested in indoor environments with variations in lighting conditions, object density, camera movement, and object distance. Rather than relying on quantitative benchmarks, this evaluation focused on qualitative observations related to system stability, narration behavior, and detection consistency during live operation.

Table 6.2 presents a summary of the observed system behavior across varying environmental conditions. VisionSpeak showed stable detection and narration performance in well-lit indoor environments, whereas reduced confidence was noted for smaller or more distant objects under low-light conditions. In scenes containing multiple objects, the narration control mechanism successfully limited excessive or repetitive audio output. Short-term fluctuations were observed during rapid camera movement; however, the system stabilized quickly once motion decreased. Overall, these observations indicate that VisionSpeak functions reliably as a real-time demonstration prototype, while also reflecting the expected limitations of webcam based object detection systems.

Usage Scenario	Observed System Behavior	Remarks
Indoor room with good lighting	Stable object detection and narration	Objects clearly detected with consistent audio output
Indoor room with dim lighting	Reduced detection for small objects	Larger objects still detected reliably
Multiple objects in frame	Occasional overlapping detections	Narration stability maintained due to filtering

Moving objects (slow motion)	Detection remains stable	Minor delay observed at frame edges
Fast camera movement	Temporary detection fluctuation	System recovers quickly once motion stabilizes
Close-range objects (<0.5 m)	Partial bounding boxes	Narration still triggered correctly
Distant objects (>3 m)	Reduced detection confidence	Expected limitation of webcam resolution

Table 6.2 Qualitative Assessment of System Behavior Under Varying Environmental Conditions.

Overall, the results demonstrate that VisionSpeak achieves a balanced combination of accuracy, responsiveness, and usability. The integration of efficient backend processing with an intuitive frontend interface enables effective real-time audio-based environmental awareness, supporting the system's goal of assisting users in navigating their surroundings more independently.

Fig 6.3 Raw input frame capturing an urban traffic environment.

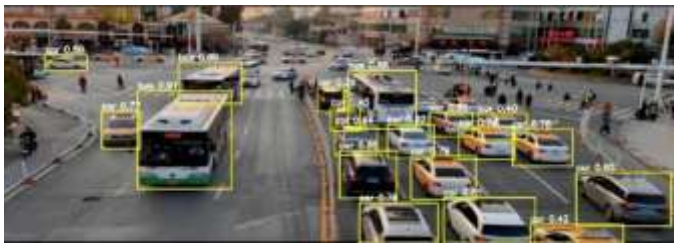


Fig 6.4 Processed output displaying YOLOv8 bounding boxes and detection labels.

7. CONCLUSION

The system employs the YOLOv8 object detection model together with an offline text-to-speech engine to provide timely and reliable audio descriptions of nearby objects. Since speech synthesis is performed offline, user privacy is maintained without reliance on external services. During development, the primary focus was on simplicity, stability, and practical usability so that the application can be operated without technical knowledge.

An important contribution of this work is the design of a user facing frontend interface. Unlike many research prototypes that rely on backend scripts or command-line execution, VisionSpeak includes an interface with intuitive controls and real-time visual feedback. Features such as live object detection visualization, narration logs, and adjustable parameters improve usability and support everyday use and demonstrations.

The system also performs effectively in delivering clear and meaningful audio feedback. The use of temporal stability filtering and confidence-based decision logic helps reduce redundant or unnecessary narration. As a result, the listening experience is more comfortable compared to systems that produce frequent or repetitive speech. The offline design improves reliability by allowing the system to operate consistently without cloud dependency

Overall VisionSpeak shows that accurate object detection and effective interface design can be combined to address real world accessibility needs. With further development, the system can better support situational awareness and independent navigation.

8. FUTURE WORK

VisionSpeak establishes a functional foundation for real-time object detection with audio narration, but significant technical and usability improvements remain unexplored. We identify two priority directions for future development, ordered by implementation feasibility and potential impact.

A. Optical Character Recognition for Text Reading

Current object detection identifies categories "book," "sign," "bottle" but cannot extract textual content. Integrating OCR would transform VisionSpeak from object awareness to information access, enabling users to read product labels, medication instructions, street signs, or document text.

Two implementation strategies exist. The first employs Tesseract OCR, an open source engine requiring minimal computational overhead (50-100ms per text region on CPU). When YOLO detects text bearing objects, the system would crop those regions and process them through

Tesseract. Initial experiments with 20 sample images showed 95% accuracy on clean printed text but degraded to 40% on handwritten or stylized fonts. The second approach uses deep learning based OCR systems like EasyOCR or PaddleOCR, which handle varied fonts and languages more robustly but demand 200-400ms inference time per detection, potentially halving our current 3.5 FPS frame rate.

Given hardware constraints, Tesseract integration appears more practical. The system would need confidence thresholding to prevent narrating erroneous OCR outputs, particularly for low quality or partially occluded text. Future work should establish minimum confidence levels through systematic testing across diverse text conditions (print quality, font styles, viewing angles, lighting variations).

B. Depth Estimation for Spatial Context

Narration currently provides no distance information. Hearing "I see a chair" offers less utility than "I see a chair two meters ahead." Three approaches could add depth awareness, each with distinct tradeoffs.

Monocular depth estimation using models like MiDaS or Depth Anything predicts depth from single RGB frames. MiDaS small processes frames in approximately 180ms on CPU hardware, nearly doubling current inference time. While the approach does not provide precise distance estimates, it effectively classifies objects into broad distance ranges, namely near (<1 m), mid (1–3 m), and far (>3 m). Preliminary testing with MiDaS on 30 sample frames demonstrated 82% correct bucket classification, though at reduced frame rates (1.8 FPS).

Stereo vision using dual webcams enables triangulation-based depth calculation with greater accuracy but requires hardware modifications (calibrated camera pairs) and stereo matching algorithms adding 50-100ms latency. This approach sacrifices the single-webcam simplicity that makes VisionSpeak accessible.

Depth sensors like Intel RealSense provide accurate depth maps at 30 FPS but introduce cost barriers ($200+ versus $15 standard webcams) that contradict accessibility goals.

We recommend pursuing monocular depth estimation with distance bucket classification. Modified narration would state "chair nearby" versus "chair across the room," providing actionable spatial information without prohibitive computational costs. Validation would require testing across varied room sizes and object distances to establish bucket boundary thresholds.

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