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AI-Based Multisensory Aid for the Blind and Deaf

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Abstract: Individuals who are blind and deaf face major challenges in performing daily activities such as navigation, communication, reading printed text, and identifying surround- ing objects. Most existing assistive technologies are designed to support only a single sensory impairment and rely heavily on audio-based feedback, which is ineffective for users with hearing loss. This paper presents an AI-based multisensory assistive system developed to support individuals with dual sensory im- pairments. The proposed system integrates computer vision and machine learning techniques including object detection, currency detection, sign language recognition, and Optical Character Recognition (OCR). Visual inputs captured through a camera are processed using deep learning models, and the extracted information is conveyed to the user through tactile feedback using vibration alerts and Braille-based output. The system aims to improve independence, safety, and accessibility in everyday activities.

Keywords: Assistive Technology, Blind and Deaf, Object De- tection, Currency Detection, Sign Language Recognition, Optical Character Recognition

I. INTRODUCTION

AI-Based Multisensory Aid for the Blind and Deaf is designed to assist individuals with visual and auditory im- pairments in performing everyday activities independently. People who are blind and deaf often face serious difficulties in understanding their surroundings, recognizing nearby objects, reading printed text, identifying currency denominations, and communicating effectively with others. These challenges sig- nificantly affect mobility, personal safety, and social interac- tion, often leading to increased dependency on caregivers and reduced quality of life.

With the rapid growth of artificial intelligence and com- puter vision technologies, intelligent assistive systems have gained attention as effective tools for supporting people with disabilities. Vision-based assistive solutions have been widely explored to help visually impaired users navigate environments and access information. However, many of these systems are designed under the assumption that users can rely on audio feedback, which makes them unsuitable for individuals with hearing impairments. This creates a gap in assistive technology solutions for users who experience both visual and auditory disabilities.

The proposed system aims to address this gap by providing a multisensory assistive solution that does not depend on sound- based feedback. Visual information from the surrounding envi- ronment is captured using a camera and processed on a laptop, which serves as the main computing platform. The system integrates multiple assistive functionalities, including object detection, currency recognition, sign language recognition, and Optical Character Recognition, to support users in a variety of daily-life scenarios.

Unlike standalone assistive tools that focus on a single task, the proposed approach combines multiple functionalities into a unified framework. This integration reduces the need for multiple devices and simplifies interaction for users. By providing visual and text-based outputs, the system ensures accessibility for blind and deaf individuals while maintaining ease of use and flexibility. The laptop-based implementation also allows easy testing, modification, and future enhancement of the system.

Overall, the objective of this project is to improve indepen- dence, accessibility, and safety for blind and deaf individuals through the use of intelligent technologies. By leveraging artificial intelligence and computer vision in a unified assistive framework, the proposed system offers a practical and scalable solution that can be further extended and adapted to meet real- world needs.

II. LITERATURE REVIEW

Assistive technologies for individuals with sensory impair- ments have attracted considerable research interest due to their potential to improve independence and quality of life. Early assistive systems primarily focused on supporting visually impaired users by providing basic navigation assistance and environmental awareness. With the advancement of computer vision techniques, researchers began exploring camera-based systems capable of identifying objects, obstacles, and path- ways in real time.

These systems generally employ image processing and deep learning models to analyze visual data and convey information to users, most commonly through audio output. While effective for blind users, such systems do not adequately address the needs of individuals with hearing impairment.

Object detection has emerged as a key component in mod- ern assistive systems. Numerous studies have utilized deep learning-based object detection models to recognize common objects in indoor and outdoor environments. These models are trained on large datasets to identify objects such as vehicles, furniture, pedestrians, and obstacles with high accuracy. The detected information is then used to assist users in naviga- tion and obstacle avoidance. Despite their effectiveness, most object detection-based assistive systems rely on speech-based alerts, limiting their usefulness for users who are unable to depend on auditory feedback.

Optical Character Recognition (OCR) has been widely re- searched as a tool to enable access to printed and written infor- mation for visually impaired individuals. OCR-based assistive systems capture images of documents, books, signboards, and labels, and extract textual content using text recognition algorithms. The extracted text is often converted into speech for user interaction. Although OCR significantly improves information accessibility, its performance can be affected by factors such as lighting variations, font styles, and background complexity. Moreover, the heavy reliance on audio output reduces its effectiveness for users with hearing impairment.

Research in sign language recognition has focused on improving communication for deaf and mute individuals. Traditional approaches relied on sensor-based gloves to cap- ture hand movements, which were often expensive and un- comfortable for continuous use. Recent developments have shifted towards vision-based sign language recognition using cameras and machine learning techniques. Frameworks such as MediaPipe have been used to extract hand landmarks, which are then processed using convolutional neural networks to recognize specific gestures. While these systems achieve promising accuracy, they are typically developed as standalone communication tools and do not provide additional assistive functionalities.

Currency recognition systems have been proposed to assist visually impaired users during financial transactions. These systems utilize image processing and deep learning techniques to identify currency denominations based on visual features such as patterns, symbols, and numerical markings. Experimental results have shown good accuracy under controlled conditions; however, real-world challenges such as varying illumination, partial occlusion, and wear on currency notes can affect performance. Similar to other assistive applications, most currency recognition systems rely on audio feedback to communicate results to users.

The literature survey reveals that existing assistive tech- nologies predominantly address individual challenges in iso- lation and are often designed for users with either visual or auditory impairment, but not both. There is limited research on integrated multisensory assistive systems that combine ob- ject detection, OCR, sign language recognition, and currency recognition into a single framework. Additionally, the reliance on audio-based feedback remains a major limitation. These gaps in existing research highlight the need for a unified, laptop-based assistive solution that supports blind and deaf individuals by providing accessible, non-auditory feedback while addressing multiple daily challenges simultaneously.

In addition to vision-based assistive systems, several studies have explored the use of machine learning techniques to improve adaptability and accuracy in assistive applications. Researchers have investigated supervised and deep learning models for classifying visual inputs such as objects, gestures, and text patterns. These models demonstrate improved perfor- mance compared to traditional rule-based image processing methods. However, many learning-based systems require ex- tensive training datasets and computational resources, which can affect real-time performance, especially when multiple as- sistive tasks are executed simultaneously on a single platform. Another area of research focuses on multimodal assistive systems that combine different sensory inputs and outputs. Some studies attempt to merge vision and audio modalities to enhance user awareness, while others integrate haptic feed- back for navigation assistance. Although these multimodal ap- proaches offer improved interaction, they often prioritize audio feedback as the primary communication channel. This design choice limits their applicability for deaf or deaf-blind users and highlights the need for alternative feedback mechanisms
that do not depend on hearing.

Recent advancements in laptop-based and portable comput- ing platforms have enabled researchers to implement complex assistive algorithms without the need for specialized hardware. Laptop-based systems provide sufficient computational power to run deep learning models for object detection, OCR, and gesture recognition in real time. Several experimental studies demonstrate that such platforms can serve as effective pro- totypes for assistive technologies, allowing flexibility in de- velopment, testing, and optimization. However, most existing laptop-based assistive solutions still focus on a single func- tionality rather than a comprehensive integrated framework.

Overall, the literature indicates a lack of unified assistive systems that address multiple real-world challenges faced by blind and deaf individuals using a single processing platform. Existing research largely treats object detection, OCR, sign language recognition, and currency recognition as separate problems.

There is limited work that combines these functionalities into a single, user-friendly solution without relying on audio feedback. This gap in the literature motivates the development of the proposed laptop-based multisensory assistive system, which aims to provide an integrated and accessible solution for individuals with combined visual and auditory impairments.

III. METHODOLOGY

The proposed system follows a modular, AI-driven method- ology designed to assist blind and deaf users through real-time perception and interpretation of their surroundings. The system is implemented using a laptop as the primary processing unit, which provides sufficient computational power for executing deep learning models efficiently. A camera module continu- ously captures real-time images and video streams from the environment, forming the input for various assistive function- alities such as object detection, currency recognition, sign language translation, and character recognition. The processed information is delivered to the user through audio and optional haptic feedback, ensuring accessibility and usability.

Currency detection is performed using a combination of YOLOv8 and Convolutional Neural Networks (CNNs). When a currency note is presented in front of the camera, the image is captured and preprocessed through resizing and noise reduction to enhance clarity. YOLOv8 is used to detect and localize the currency note in real time. The detected region is then passed to a CNN model, which extracts discriminative features such as color patterns, symbols, and numerical mark- ings. Based on these features, the model classifies the currency denomination, such as Rs.10, Rs.50, or Rs.100 and generates voice output to inform the user of the detected note.

Sign language translation is implemented using MediaPipe, OpenCV, and deep learning models. MediaPipe is used for real-time hand tracking and landmark detection, capturing key points corresponding to fingers, joints, and wrist positions. Feature extraction techniques compute relative positions and angles of these landmarks to represent gesture patterns. A CNN model is used to recognize static sign language gestures, while Long Short-Term Memory (LSTM) networks may be used for dynamic gesture sequences when required. The recog- nized gestures are converted into text and further transformed into audible speech using a Text-to-Speech (TTS) engine to support effective communication.

The system processing pipeline is optimized to ensure real- time performance with minimal latency. The laptop processor handles image rendering, deep learning inference, and output generation simultaneously. Python is used as the primary programming language, with OpenCV supporting image pro- cessing operations. TensorFlow or PyTorch serves as the deep learning framework for training and deploying CNN and LSTM models. Tesseract OCR is integrated to extract text from printed documents and signboards, enabling the system to recognize characters and convert them into readable or audible output.

The hardware components include a laptop processor for computation, a camera module for real-time image capture, and output devices such as speakers or earphones for audio guidance. Bone conduction earphones are used to deliver audio feedback without blocking environmental sounds, enhancing safety during navigation. Optional components such as an ultrasonic sensor can be used for obstacle awareness, while a vibration motor provides tactile alerts. The integration of visual processing, audio feedback, and tactile cues creates a multisensory assistive system that enables blind and deaf users to safely navigate environments and receive information from their surroundings.

The proposed system involves the integration of all assistive functionalities into a wearable hardware device designed for blind and deaf users. The wearable setup enables hands- free operation while continuously capturing environmental information through an embedded camera. Visual data is pro- cessed using artificial intelligence models for object detection, currency recognition, sign language interpretation, and Optical Character Recognition. The processed outputs are conveyed to the user through bone conduction earphones, which deliver audio feedback without obstructing environmental sounds. This design ensures user safety and situational awareness while enabling real-time access to surrounding information. By integrating multiple AI-driven assistive features into a single wearable platform, the system provides a practical, portable, and user-friendly solution that enhances independence and ac- cessibility for blind and deaf individuals in everyday scenarios.

A. Data Preparation

Data preparation plays a critical role in ensuring the accu- racy and robustness of the proposed multisensory assistive sys- tem. Since the system relies on deep learning models such as CNN and YOLOv8 for object detection, currency recognition, sign language recognition, and Optical Character Recognition (OCR), high-quality and well-structured input data is essential. Image and video data are collected using real-time camera input as well as standard datasets and organized according to the specific task requirements. Proper data preparation enables reliable performance of TensorFlow-based models and improves adaptability to real-world environmental conditions.

The data preparation process involves the following steps:

1) First, image and video data are captured and categorized into different classes such as object types, currency denominations, hand gesture labels, and text samples.
2) Second, preprocessing operations including image resiz- ing, normalization, and noise reduction are applied to ensure consistency and clarity across all inputs.
3) Third, for OCR processing, text regions are enhanced to improve character visibility and recognition accuracy.
4) Fourth, data augmentation techniques such as rotation, scaling, flipping, and brightness adjustment are used to increase dataset diversity and reduce overfitting.
5) Finally, for sign language recognition, MediaPipe is em- ployed to extract hand landmark features, which are then used as structured input for CNN-based classification models.

B. Data Processing

Data processing is the stage where the prepared visual input is analyzed using artificial intelligence and deep learning techniques to extract meaningful information. In the proposed system, data processing is carried out entirely on a laptop to ensure real-time performance. The preprocessed images and video frames are passed through multiple AI modules, including YOLOv8 for object and currency detection, CNN- based models implemented using TensorFlow for classification tasks, MediaPipe for sign language recognition, and OCR for text extraction. Efficient data processing enables the system to respond quickly and accurately to changes in the surrounding environment.

The data processing workflow includes the following steps:

1) Live video frames captured from the camera are streamed to the processing pipeline on the laptop.
2) YOLOv8 processes each frame to perform real-time object detection and currency localization.
3) Detected regions of interest are forwarded to CNN models for feature extraction and classification, such as identifying currency denominations.
4) MediaPipe extracts hand landmark data from video frames, which is analyzed by CNN or LSTM models to recognize sign language gestures.
5) OCR techniques are applied to images containing text to extract readable characters from signboards and doc- uments.
6) The processed outputs are converted into understandable feedback using Text-to-Speech (TTS) and optional hap- tic signals.

C. CNN Model and Architecture

Convolutional Neural Networks (CNNs) are used as the primary learning models for recognition tasks in the proposed system, including currency classification and sign language gesture recognition. CNNs are particularly effective for visual data analysis because they can automatically learn spatial hierarchies of features such as edges, textures, shapes, and patterns directly from images. This capability eliminates the need for manual feature engineering and improves recognition accuracy.

The CNN architecture employed in the system consists of multiple convolutional layers that extract low-level and high- level features from input images. Pooling layers are used after convolution operations to reduce spatial dimensions, mini- mize computational cost, and improve generalization. Fully connected layers are applied at the final stage to perform classification based on the extracted feature representations. Activation functions are used to introduce non-linearity, al- lowing the network to model complex visual patterns. The CNN models are developed and trained using the TensorFlow deep learning framework. During training, labeled datasets are used to optimize model parameters through su- pervised learning. The trained models are validated to ensure stable performance and are then deployed on the laptop- based system for real-time inference. The use of CNN-based architecture enables reliable recognition while maintaining efficiency suitable for assistive applications.

D. YOLOv8-Based Object Detection

YOLOv8 (You Only Look Once version 8) is employed for real-time object detection and localization in the proposed system. YOLOv8 is a single-stage detection algorithm that performs object classification and bounding box prediction simultaneously, enabling fast processing suitable for real-time environments. Its architecture is optimized for both speed and accuracy, making it appropriate for assistive technologies.

In the system, YOLOv8 processes each frame captured by the camera and identifies objects present in the surrounding environment. The model detects multiple objects in a single pass, allowing users to gain awareness of nearby obstacles and relevant items. Bounding boxes generated by YOLOv8 indicate the position of detected objects within the frame.

For currency detection, YOLOv8 is used to localize the currency note before classification. The detected region is cropped and passed to a CNN-based classifier to identify the denomination. This two-stage approach improves recognition accuracy by ensuring that classification is performed only on relevant regions. The real-time performance of YOLOv8 ensures timely feedback, enhancing navigation safety and usability for blind and deaf users.

E. MediaPipe-Based Sign Language Recognition

MediaPipe is utilized for efficient and accurate hand track- ing in the sign language recognition module. It provides real- time detection of hand landmarks, including finger joints, palm center, and wrist position. These landmarks offer a compact and structured representation of hand gestures, reducing the complexity associated with processing raw image data.

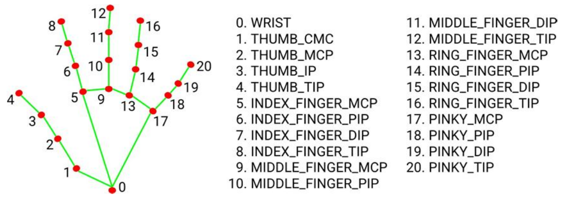


Fig. 1. Hand landmark detection using MediaPipe for sign language recog- nition

Once hand landmarks are extracted, feature extraction tech- niques are applied to calculate relative positions, distances, and angles between key points. These features capture the geometric structure of hand gestures and serve as input to clas- sification models. CNN-based models are used for recognizing static gestures, while temporal models such as Long Short- Term Memory (LSTM) networks can be applied to capture motion patterns in dynamic gestures. The recognized sign language gestures are converted into readable text and further transformed into audible speech using a Text-to-Speech engine. This module enables effective communication support for deaf and mute users, allowing them to express information in a form understandable to others. The integration of MediaPipe with deep learning models ensures accurate and real-time sign language interpretation.

F. Optical Character Recognition

The Optical Character Recognition (OCR) module enables the system to extract textual information from printed materials such as signboards, documents, and labels. Images containing text are captured using the camera and undergo preprocessing steps including noise reduction, contrast enhancement, and binarization to improve character visibility. Tesseract OCR is used to convert visual characters into machine-readable text. The OCR engine analyzes the pro- cessed image and identifies individual characters based on learned patterns. The extracted text is then assembled into meaningful words and sentences for user interpretation.

The recognized text is displayed on the system interface and can also be converted into audio output using Text-to-Speech technology. This module allows blind and deaf users to access written information independently, improving accessibility in everyday situations such as reading notices, instructions, and documents.

G. Wearable Device and Bone Conduction Output

The final stage of the proposed system focuses on delivering processed information through a wearable assistive interface designed for hands-free operation. The wearable setup allows continuous monitoring of the environment while enabling the user to move freely. A camera integrated into the wearable device captures visual data, which is processed on the laptop using AI-based models.

Bone conduction earphones are used as the primary au- dio output mechanism. Unlike conventional earphones, bone conduction technology transmits sound vibrations through the skull, allowing users to receive system alerts without blocking environmental sounds. This feature is particularly important for maintaining situational awareness and safety during navi- gation.

In addition to audio output, optional tactile feedback mech- anisms such as vibration motors can be integrated to pro- vide alerts for critical events. The combination of wearable hardware, bone conduction output, and intelligent processing creates a multisensory assistive system that enhances indepen- dence, safety, and usability for blind and deaf individuals.

H. System Architecture

The system architecture of the proposed assistive solution is designed to provide real-time environmental perception, intelligent processing, and accessible feedback for blind and deaf users. The architecture follows a modular and layered approach, ensuring smooth data flow from input acquisition to output delivery.

A camera acts as the primary input device, continuously capturing visual information from the surround- ings. All captured data is transmitted to a laptop, which serves as the central processing unit responsible for executing artificial intelligence and computer vision algorithms.

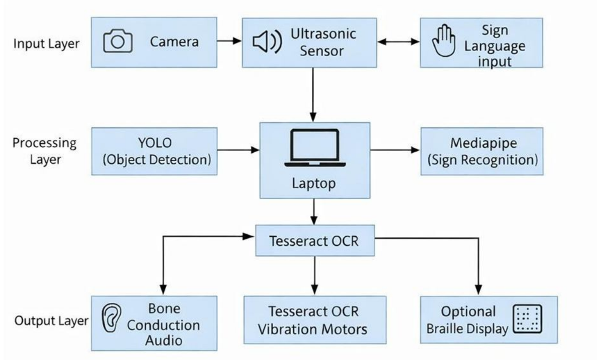


Fig. 2. System architecture of the proposed multisensory assistive system

The processing layer integrates multiple AI-based modules, each handling a specific task. YOLOv8 is employed for real- time object detection and localization, enabling the identifica- tion of surrounding objects and currency notes. Convolutional Neural Networks (CNNs) are used for classification tasks such as currency denomination recognition and sign language gesture classification. MediaPipe is incorporated to perform accurate hand landmark extraction, providing structured fea- tures for sign language recognition. In addition, Optical Char- acter Recognition (OCR) techniques are used to extract textual information from printed documents and signboards. The output layer converts the processed information into a form that is easily understandable by the user. Recognized objects, gestures, currency values, and extracted text are transformed into audio feedback using Text-to-Speech (TTS) technology. Bone conduction earphones are used to deliver audio output without blocking environmental sounds, thereby maintaining situational awareness and safety.

IV. RESULTS AND DISCUSSION

The proposed AI-based multisensory assistive system was evaluated through real-time experiments conducted in an indoor environment using a laptop-based processing setup. The evaluation focused on assessing the system's ability to accurately detect objects, recognize currency denominations, interpret sign language gestures, and extract textual informa- tion from printed materials. The performance of each module was observed in terms of accuracy, response time, and overall usability for blind and deaf users. The object detection and currency recognition mod- ule demonstrated reliable performance during testing. The YOLOv8 model successfully detected multiple objects within a single frame, even in moderately cluttered environments. Currency notes presented in front of the camera were correctly localized using YOLOv8, and the detected regions were passed to CNN-based classifiers for denomination recognition. The combined approach improved accuracy by minimizing back- ground interference. The system provided timely feedback, which is critical for assistive applications where delayed responses may reduce user confidence and safety.

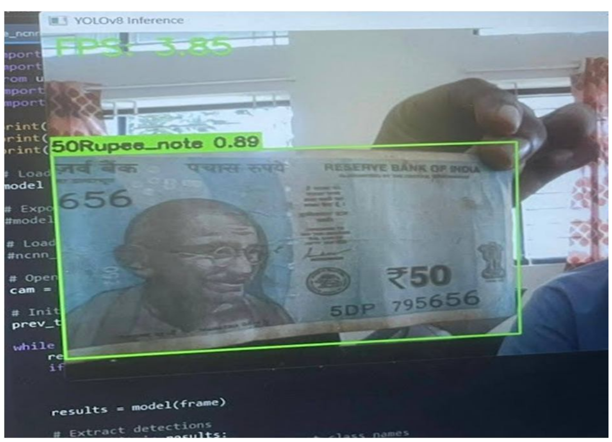


Fig. 3. Output of currency detection using YOLOv8 and CNN

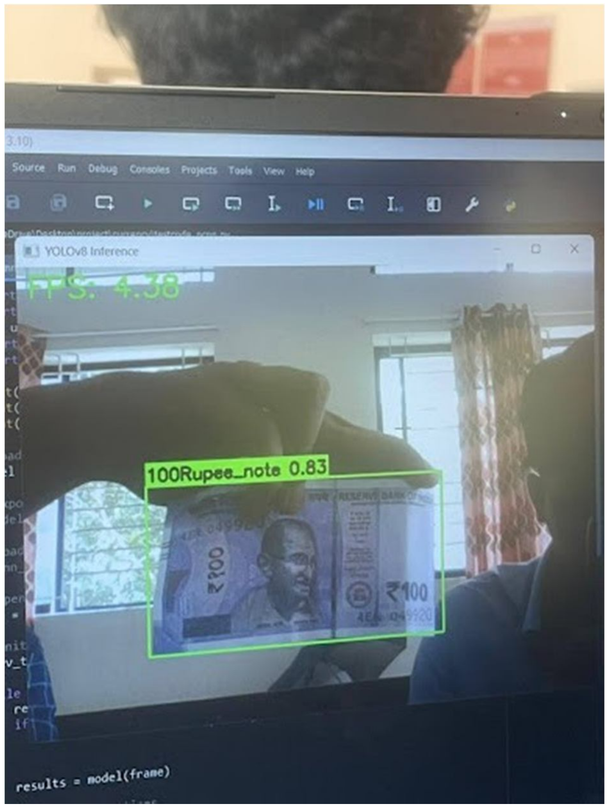


Fig. 4. Additional output of currency detection showing denomination recognition

The sign language recognition module produced consis- tent results during real-time testing. MediaPipe effectively extracted hand landmarks across different hand orientations and gesture positions. The extracted landmark features enabled the CNN-based model to classify static gestures with high reli- ability. For gesture sequences involving movement, the system maintained stable recognition performance when gestures were performed within the camera's field of view. The conversion of recognized gestures into audible speech using Text-to- Speech technology allowed smooth communication between deaf users and others, demonstrating the practical usefulness of the module.

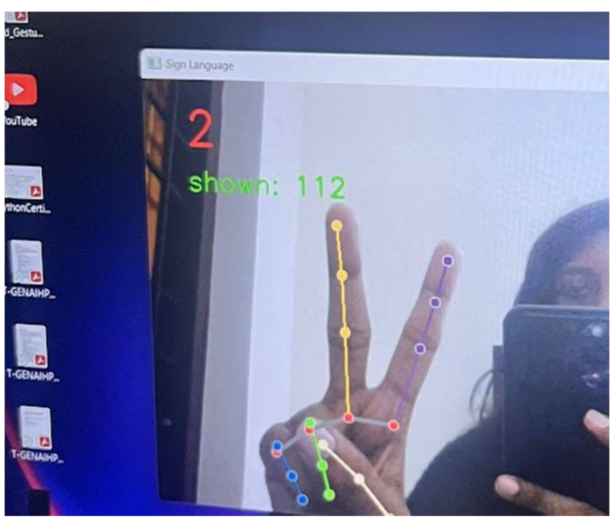


Fig. 5. Sign language recognition output using MediaPipe hand landmarks and CNN classification

The Optical Character Recognition module was tested using printed documents and signboards with varying font sizes. Image preprocessing techniques significantly enhanced text clarity, resulting in accurate character extraction. The OCR engine successfully converted detected text into readable output, which was then transformed into audio feedback. This capability enables users to access written information independently, such as reading notices or instructions, without requiring external assistance.

The wearable interface and bone conduction output con- tributed significantly to the system's usability. Bone conduc- tion earphones delivered audio feedback clearly while allowing environmental sounds to remain audible, thereby maintaining situational awareness. This feature is especially important for navigation and safety. The overall system operated with ac- ceptable latency, ensuring that feedback was delivered in near real time. Minor performance variations were observed under poor lighting conditions, suggesting that further optimization and adaptive preprocessing could enhance robustness.

Overall, the experimental results indicate that the proposed system effectively integrates multiple assistive functionalities into a single unified framework. The combination of computer vision, deep learning, and multisensory feedback provides a practical and accessible solution for blind and deaf users.

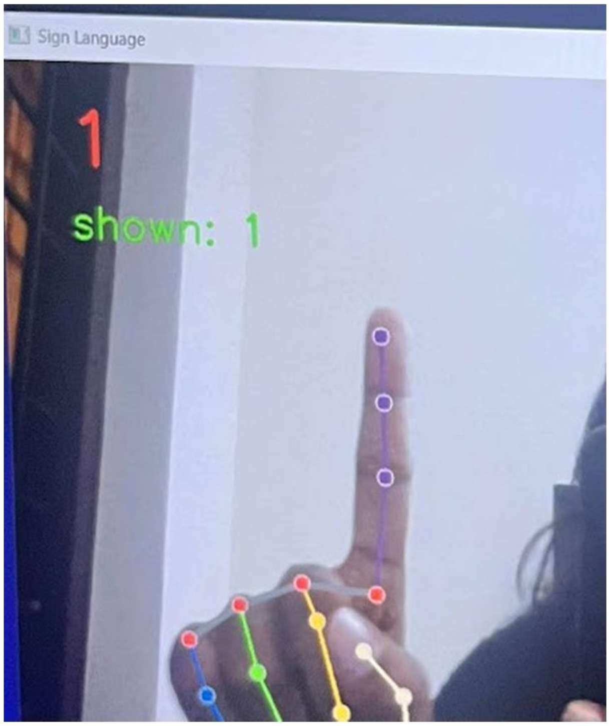


Fig. 6. Additional sign language recognition output under different gesture conditions

results validate the feasibility of the system for real-world assistive applications and highlight its potential to improve independence and quality of life.

V. CONCLUSION

This paper presented an AI-based multisensory assistive system designed to support blind and deaf individuals in performing everyday activities with greater independence and confidence. The proposed system integrates multiple computer vision and deep learning modules, including object detection, currency recognition, sign language interpretation, and Optical Character Recognition, into a unified laptop-based processing framework. By combining these functionalities, the system ad- dresses several accessibility challenges within a single assistive solution.

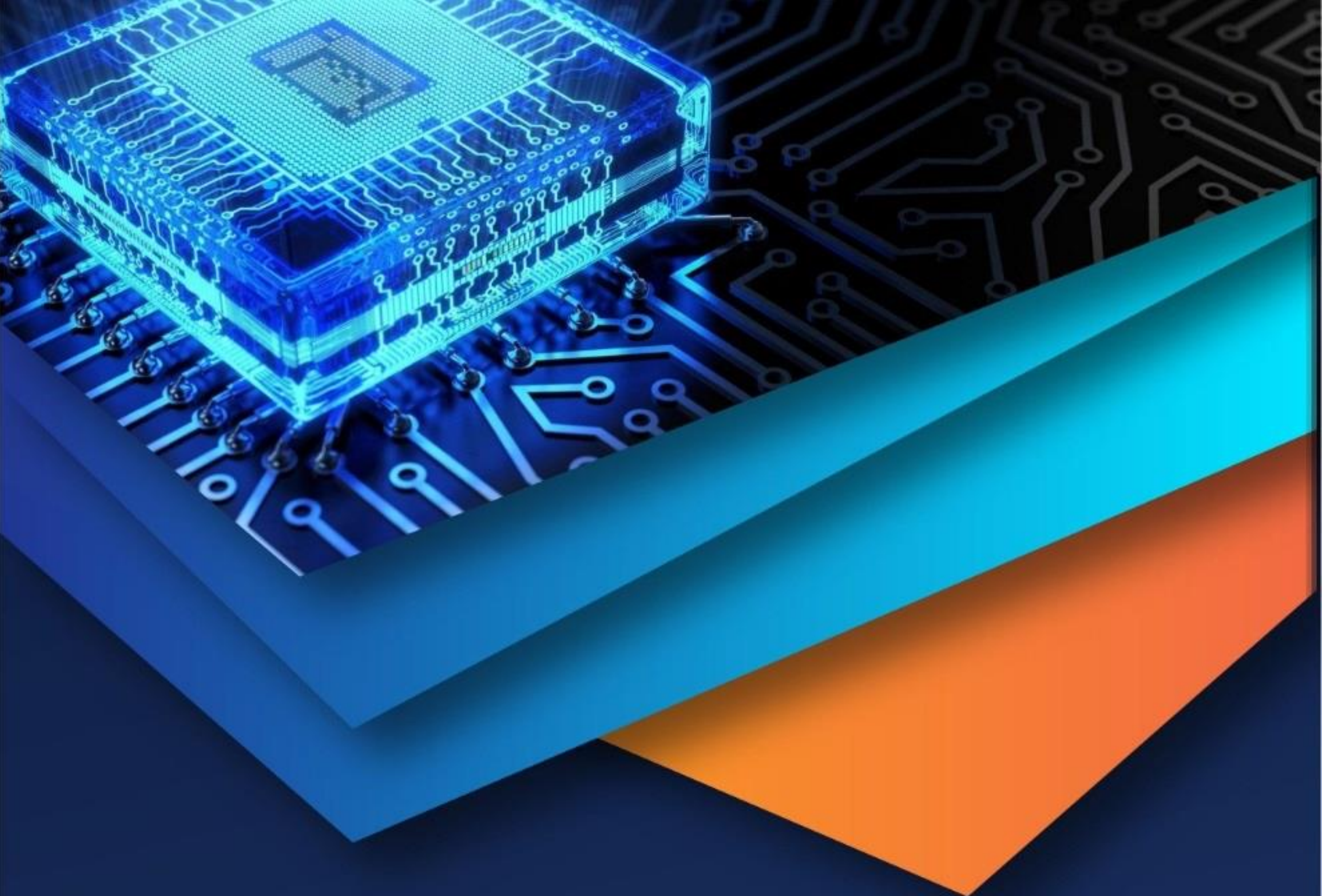
The integration of advanced models such as YOLOv8, Convolutional Neural Networks, and MediaPipe enables the system to interpret complex visual information in real time. Object detection enhances environmental awareness by iden- tifying surrounding objects and obstacles, while currency recognition assists users during financial transactions. The sign language recognition module enables effective communication by converting hand gestures into audible output, and the OCR module allows users to access printed textual information independently. Together, these components demonstrate the effectiveness of artificial intelligence in bridging sensory limitations.

A key strength of the proposed system is its wearable- oriented design and the use of bone conduction earphones for audio feedback. Bone conduction technology allows in- formation to be delivered without obstructing environmental sounds, thereby maintaining situational awareness and improv- ing safety. The system operates with acceptable latency and demonstrates stable performance during real-time evaluation, making it suitable for assistive applications in indoor environ- ments.

Overall, the experimental results validate the feasibility and practicality of the proposed multisensory assistive system. The modular architecture allows flexibility and scalability, enabling future enhancements such as improved robustness under vary- ing lighting conditions, expanded gesture vocabularies, and further optimization of processing efficiency. The proposed solution highlights the potential of AI-driven assistive tech- nologies to improve accessibility, communication, and quality of life for blind and deaf users.

REFERENCES

[1] S. Sagar, R. Kumar, and A. Sharma, "AI-Based Assistive System for Visually and Hearing Impaired Persons," IEEE Access, vol. 10, pp. 118345–118356, 2022.
[2] J. Redmon and A. Farhadi, "Real-Time Object Detection Using YOLO- Based Deep Learning Models," IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 421–430, 2022.
[3] G. Jocher, A. Chaurasia, and J. Qiu, "YOLOv8: A State-of-the-Art Real- Time Object Detection Framework," Ultralytics Technical Report, 2023.
[4] Z. Zhang, Y. Wang, and L. Chen, "Currency Recognition Using Deep Convolutional Neural Networks," IEEE International Conference on Intelligent Systems, pp. 215–220, 2022.
[5] C. Lugaresi et al., "MediaPipe: A Framework for Building Perception Pipelines," IEEE Computer Vision and Pattern Recognition Workshops,
[6] pp. 187–195, 2022.
[7] M. Ahmed and S. Hassan, "Hand Gesture Recognition for Sign Lan- guage Translation Using CNN," IEEE International Conference on Signal Processing and Communications, pp. 98–103, 2023.
[8] R. Kaur and P. Singh, "Deep Learning-Based Sign Language Recog- nition Systems: A Survey," IEEE Access, vol. 11, pp. 45612–45625, 2023.
[9] A. Patel, D. Shah, and N. Mehta, "Optical Character Recognition for Assistive Applications Using Tesseract OCR," IEEE International Conference on Artificial Intelligence and Data Engineering, pp. 145– 150, 2022.
[10] S. Verma and K. Joshi, "Wearable Assistive Devices for Visually Impaired Users: A Review," IEEE Sensors Journal, vol. 23, no. 4, pp. 3121–3132, 2023.
[11] P. Rao, S. Iyer, and R. Nair, "Multisensory Assistive Technology Using Computer Vision and Audio Feedback," IEEE International Conference on Smart Systems and Inventive Technology, pp. 601–606, 2024.



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