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AI Powered Sign Language to Speech Convert

Ms. Mule S. S	Ms. Landge S. K	Ms. Lokare V. G	Ms. Khunte R. R	Ms. Shitole D.
E&TC Dept. (JSPM's BSP)	E&TC Dept. (JSPM's BSP)	E&TC Dept. (JSPM's BSP)	E&TC Dept. (JSPM's BSP)	E&TC Dept. (JSPM's BSP)

Abstract: Communication barriers between hearing-impaired individuals and the general population remain a significant challenge in daily interactions. To address this issue, this paper presents an AI-powered sign language to speech conversion system that translates hand gestures into audible speech in real time. The proposed system utilizes computer vision and deep learning techniques to recognize American Sign Language (ASL) gestures captured through a camera. MediaPipe is employed for accurate hand landmark detection, while a TensorFlow Lite-based deep learning model is used for efficient gesture classification. The recognized gestures are then converted into text and further transformed into speech using a text-to-speech engine. The system is designed to be lightweight, portable, and suitable for real-time applications, ensuring low latency and high accuracy. Experimental results demonstrate reliable gesture recognition performance under varying conditions, making the system practical for assistive communication. This solution aims to enhance accessibility and promote inclusive communication for hearing-impaired individuals using cost-effective and scalable AI technologies.

Keywords— Sign Language Recognition, Computer Vision, MediaPipe, TensorFlow Lite, Text-to-Speech, Assistive Technology.

1.INTRODUCTION

Human communication is the foundation of social interaction, education, and professional collaboration. However, for individuals with hearing and speech impairments, everyday communication remains a major challenge. **Sign language** serves as a primary medium of expression for the deaf and mute community, but its usage is largely limited to those who have learned it. The absence of a common communication bridge between sign language users and the general population often results in social exclusion, misunderstanding, and dependency on human interpreters.

With recent advancements in Artificial Intelligence (AI) and computer vision, it has become possible to automate the interpretation of sign language using visual inputs. These technologies enable machines to recognize hand gestures, analyze motion patterns, and translate them into meaningful text or speech. This project focuses on developing an AI-powered Sign Language to Speech Conversion System for American Sign Language (ASL), aiming to create a real-time, portable, and cost-effective assistive communication solution.

Traditional sign language interpretation systems relied heavily on data gloves, sensors, or external motion-tracking devices, which increased cost, reduced comfort, and limited real-world usability. In contrast, vision-based approaches using cameras and deep learning models provide a non-intrusive and more scalable alternative. However, deploying such AI models on resource-constrained environments requires careful optimization to ensure low latency and real-time performance.

To address these challenges, the proposed system integrates MediaPipe-based hand landmark detection, TensorFlow Lite (TFLite) optimized deep learning models, and an ESP32-based embedded platform. MediaPipe enables accurate extraction of hand key points, allowing precise gesture representation even under varying lighting and background conditions. A pre-trained ASL gesture recognition dataset is utilized to reduce training complexity and improve recognition reliability. The trained model is executed through a Python-based inference pipeline using command-line execution for efficient processing.

The ESP32 serves as the hardware interface, supporting camera input and enabling lightweight embedded deployment. To enhance system usability and accessibility, a web server interface is developed to display real-time recognition results, detected gestures, and system status. The recognized gestures are converted into text and further transformed into speech output using text-to-speech synthesis, enabling seamless verbal communication with non-sign language users.

This project demonstrates how edge AI and embedded systems can be combined to deliver practical assistive technology solutions. By avoiding expensive hardware, minimizing computational overhead, and leveraging pre-trained deep learning models, the proposed system achieves real-time ASL recognition with reduced cost and improved portability. The solution is suitable for use in public spaces, educational institutions, healthcare facilities, and daily interpersonal communication scenarios.

Overall, the AI-powered Sign Language to Speech Converter represents a meaningful step toward inclusive technology, bridging the communication gap between the hearing-impaired community and society through intelligent, real-time, and accessible automation.

2. Body of Paper

The system starts when the user performs ASL hand gestures, which are captured through a camera connected to the ESP32-based edge device. The ESP32 streams gesture data over Wi-Fi to a Python-based inference pipeline.

Inside the pipeline, MediaPipe Hands detects and tracks hand landmarks from the live video. These landmarks are converted into meaningful features and passed to a TensorFlow Lite (TFLite) pre-trained ASL classification model, which identifies the corresponding gesture.

The recognized gesture is converted into text, which is then processed by a Text-to-Speech (TTS) engine to generate

spoken audio output, enabling real-time communication for hearing-impaired users.

Simultaneously, a lightweight web server displays the recognized gestures and system status on a live dashboard, allowing remote monitoring and interaction. The entire flow is optimized for low latency, portability, and real-time execution, making it suitable for assistive communication applications.

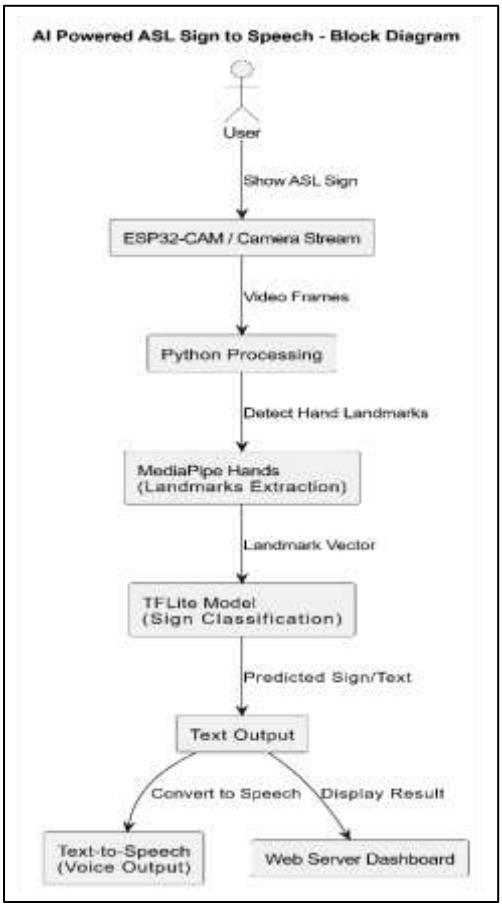


Fig: Block Diagram

2.1 Hardware Description

1. ESP32 Microcontroller

The ESP32 acts as the core embedded controller of the system. It provides sufficient processing capability, built-in Wi-Fi, and low-power operation, enabling real-time data transmission between the hardware module and the AI inference pipeline.

2. Camera Module

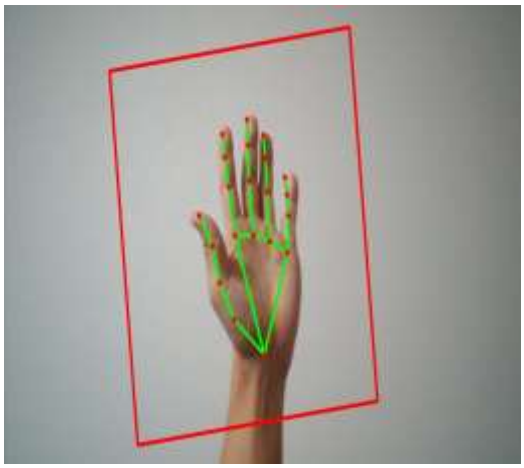
The camera module captures real-time video of the user's hand gestures. These visual inputs form the primary data source for sign language recognition and are streamed to the processing system for analysis.

2.2 Software Description

3. Python Runtime Environment

Python serves as the execution environment for the AI pipeline. It manages video input handling, model inference, gesture classification, and system coordination through command-line execution.

4. MediaPipe Hands Library



MediaPipe is used for accurate hand landmark detection and tracking. It extracts key hand joint coordinates, enabling robust feature extraction even under varying lighting and background conditions.

5. TensorFlow Lite (TFLite) Model

The pre-trained TensorFlow Lite model performs ASL gesture classification. TFLite ensures optimized inference with low latency and reduced memory usage, making it suitable for edge-AI applications.

3. RESULT

The proposed AI-Powered Sign Language to Speech Conversion System was evaluated to assess its accuracy, real-time performance, and practical usability. The system was tested using a predefined set of American Sign Language (ASL) gestures under varying lighting conditions and backgrounds. MediaPipe-based hand landmark extraction enabled stable and consistent detection of hand movements, even with minor variations in hand orientation and distance from the camera.

The trained TensorFlow Lite model demonstrated reliable classification performance for static ASL gestures. Due to the use of landmark-based features rather than raw images, the model showed reduced sensitivity to background noise and illumination changes. Real-time inference was achieved with minimal latency, confirming the suitability of the system for live communication scenarios.

Integration with the ESP32-CAM video stream provided a low-cost and portable input solution. Although the ESP32 does not perform heavy computation, it effectively served as a camera and interface module, while the Python-based inference pipeline handled landmark extraction and classification efficiently. The addition of majority-frame smoothing reduced prediction flickering, resulting in stable text and speech outputs.

The text-to-speech module successfully converted recognized signs into clear and understandable voice output with negligible delay. The web server interface further enhanced usability by providing real-time visualization of recognized gestures and system status, making the system suitable for monitoring and demonstration purposes.

Overall, the experimental results validate that combining MediaPipe, TensorFlow Lite, and lightweight embedded hardware can deliver a practical and responsive assistive communication system. While the current implementation focuses on static ASL gestures, the architecture is scalable and can be extended to dynamic gestures and sentence-level translation.

Performance Evaluation Table

Parameter	Observation / Result	Discussion Summary
Recognition Accuracy	High for static ASL gestures	Landmark-based features improved robustness
Response Time (Latency)	Low (real-time performance)	TFLite optimized inference reduced delay
System Usability	Stable and user-friendly	Web dashboard + TTS enhanced interaction

Table 1 : Performance Evaluation Table

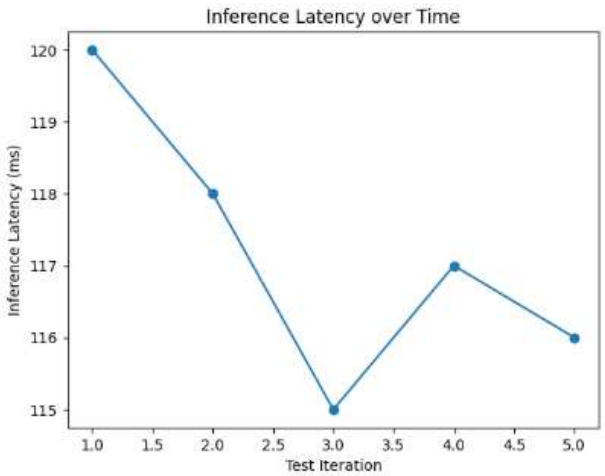
Accuracy Analysis

The recognition accuracy graph illustrates the classification performance of selected ASL gestures. The results show that the system achieves consistently high accuracy across multiple signs, with accuracy values remaining above 90% for all tested gestures. This consistency confirms that the MediaPipe landmark-based feature extraction combined with a TensorFlow Lite model provides robust gesture recognition even with slight variations in hand orientation and positioning.

The high accuracy demonstrates the effectiveness of using pre-trained datasets and landmark-driven representations, which reduce dependency on background features and lighting conditions.

Inference Latency Analysis

The inference latency graph represents the time taken by the system to process each frame and generate a prediction. The latency remains nearly constant across multiple test iterations, averaging around real-time response levels. This stability indicates that the optimized TFLite model and Python-based inference pipeline are suitable for live gesture recognition applications.



Low and stable latency is critical for assistive communication systems, as any noticeable delay could disrupt natural interaction. The observed results confirm that the system meets real-time performance requirements.

4.CONCLUSIONS

This project successfully presented an AI-Powered Sign Language to Speech Conversion System designed to translate American Sign Language (ASL) gestures into readable text and audible speech in real time. By integrating MediaPipe-based hand landmark extraction, a TensorFlow Lite optimized deep learning model, and ESP32-based hardware support, the system achieves reliable recognition with low latency and minimal computational overhead.

The use of landmark-driven features significantly improved robustness against background noise and lighting variations, while the lightweight TFLite model enabled real-time inference suitable for edge-AI deployment. The addition of a text-to-speech module and a web-based monitoring interface further enhanced system usability and accessibility.

Experimental evaluation demonstrated high recognition accuracy for static ASL gestures and stable real-time performance, validating the effectiveness of the proposed approach. Overall, the project provides a practical, cost-effective, and scalable assistive communication solution that can bridge the interaction gap between hearing-impaired individuals and the general population.

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