

Hand Talk: A Sign Language Translator

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Abstract: Sign language acts as a key communication method for individuals with hearing difficulties, but obstacles often arise in conversations between sign language users and the general population. People engage with one another to express their ideas, feelings, and experiences, but this is not true for those who are disabled or mute. Sign language enables individuals who are mute to communicate without relying on vocal sounds. The goal of this project is to create a system that can recognize sign language, facilitating communication between individuals with speech impairments and those without, thus bridging the communication divide between them. In comparison to other forms of gestures like those made with the arms, face, head, and body; hand gestures hold significant importance as they convey a person's thoughts more swiftly. The system employs machine learning and computer vision methodologies to identify and understand hand gestures linked to sign language. The Sign Language Translator system is designed to close this communication gap by converting sign language gestures into text or speech instantly.

Keywords: hand gestures, machine learning, hearing impairments, deaf.

I. INTRODUCTION

Deaf (hard of hearing) and mute individuals utilize Sign Language (SL) as their main method to communicate their ideas and thoughts with their community and other people through hand and body gestures. It possesses its own lexicon, significance, and syntax, which distinguishes it from spoken or written language. Spoken language refers to a language generated by articulated sounds mapped to specific words and grammatical structures to communicate meaningful messages. Sign language employs visual hand and body gestures to convey significant messages. There are approximately between 138 and 300 distinct types of Sign Language used worldwide today. In India, there are merely around 250 certified sign language interpreters available for a deaf population of roughly 7 million.

This presents a challenge in teaching sign language to deaf and mute individuals due to the limited number of sign language interpreters existing today. Sign Language Recognition represents an effort to identify these hand gestures and translate them into the corresponding text or speech. Currently, Computer Vision and Deep Learning have become quite popular. Utilizing Deep Learning algorithms and Image Processing, we can classify these hand gestures and generate corresponding text.

II. LITERATURE SURVEY

We are making this translator where one can convert signs to the text and also hear the signs they have performed. Not only this but we have provided some suggestions at the bottom on the detection screen for the words user want to perform. We have intergrated both learning and detection part in one module. Keeping the interaction buttons like help, speak, and clear, user can interact well the system we made.

TensorFlow has emerged as a widely used framework for constructing machine learning models for sign language recognition. It enables the training of deep learning models (CNN, RNN, etc.) to identify sign language gestures and translate them into text. TensorFlow's MediaPipe libraries facilitate pose estimation and hand tracking in real-time. They are particularly proficient at capturing intricate patterns and converting both static and dynamic gestures into significant outputs.



Impact Factor 8.102 $\,\,st\,$ Peer-reviewed & Refereed journal $\,\,st\,$ Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14226

OpenCV is crucial for processing and analyzing images or video feeds related to sign language recognition. It offers tools for image pre-processing, segmentation, and feature extraction, which are vital stages in real-time gesture recognition. OpenCV's functionalities enable rapid processing of video streams, which is crucial for systems that necessitate real-time feedback. Additionally, OpenCV can integrate with TensorFlow to effectively track and classify signs with greater accuracy.

III. METHODOLOGY

3.1 **Data Collection:** First, datasets containing a variety of ASL signs are collected. These datasets typically include images or 3D point clouds representing different signs performed by various individuals.

3.2 **Preprocessing:** Images or videos are pre-processed to standardize their size and remove noise. This may involve: Normalization (adjusting lighting, background), Cropping (to focus on the hands and face.), RGB-to-grayscale conversion or using colour space transformations., Frame extraction in the case of videos (to capture sequential hand movements).

3.3 **Hand Detection:** This step identifies the position of the hands within the image or video. Convolutional Neural Networks (CNNs) or other computer vision techniques like OpenCV might be used to isolate the hand regions.

3.4 **Key point Detection:** Models like the Media Pipe Hands API (by Google) is used to track key points in the hands and fingers. These points help identify the exact shape and movement of the hand.



Fig. 1 coordinates tracking

3.5 **Hand Shape:** The model identifies the shape of the hand by analysing the finger configurations, palm orientation, and other physical characteristics of the hand.

3.6 **Image-Based Recognition**: For static signs, where the hand is held in one position, CNNs are often used for classifying the gesture into a corresponding ASL sign (e.g., the "A" sign).

3.7 **Contextual Understanding:** After recognizing individual signs, the system may perform post-processing to understand the context of the sentence. This includes analysing the grammatical structure, word order, and any modifiers (e.g., time markers, negations).

3.8 **Text or Speech Translation:** Once the sign language is recognized, it can be converted into text or spoken language. This can be done in real-time for communication purposes or stored for further processing.

3.9 **Suggestions to User**: We also provide suggestions to user we the word the are trying to translate.

3.10 **Help Button**: The Help button offers guidance to users who may be unsure of the correct signs. By activating the button, the system could show a tutorial or visual cues about the gesture being made, helping the user improve their performance.

3.11 **Clear Button**: The Clear button allows the user to reset the interface, clearing any incorrect signs or inputs and enabling the user to start again. This ensures a smooth interaction without distractions from previous errors.

3.12 **Speak Button**: The Speak button converts the recognized signs into spoken language using text-to-speech (TTS) technology, which is vital for communication between the deaf and hearing individuals.



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Sr.no	Library name
1.	TensorFlow
2.	Keras
3.	scikit-learn
4.	OpenCV
5.	MediaPipe
6.	NumPy
7.	Matplotlib

TABLE I LIBRARIES AND FRAMEWORKS USED

1. TensorFlow

TensorFlow is an open-source machine learning framework developed by Google. It is widely used for building and deploying machine learning models, particularly deep learning models. TensorFlow provides a flexible ecosystem for researchers and developers to create models for various applications like image recognition, natural language processing, and time series forecasting.

Key Features:

• **Deep Learning**: It is well-known for its deep learning capabilities and supports neural networks such as CNN (Convolutional Neural Networks) and RNN (Recurrent Neural Networks).

• Scalability: TensorFlow can scale across different hardware, including CPUs, GPUs, and TPUs (Tensor Processing Units).

• **Ecosystem**: TensorFlow includes tools for model building (e.g., TensorFlow Keras, TensorFlow Lite for mobile, and TensorFlow.js for browser-based applications).

2. Keras

Keras is an open-source deep learning API written in Python. It was originally developed as an independent library, but it is now integrated as the official high-level API in **TensorFlow** (as tf.keras). Keras makes it easy to build neural networks and design deep learning models, providing a simpler interface for defining and training models compared to raw TensorFlow.

Key Features:

- User-friendly: Keras offers an easy-to-use interface for building models with fewer lines of code.
- **Modular and extensible**: You can quickly add layers, loss functions, optimizers, and metrics to your models.

• **Runs on top of TensorFlow**: Keras is designed to work seamlessly with TensorFlow, allowing you to leverage TensorFlow's advanced features while keeping code simple.

3. Scikit-Learn

Scikit-learn is one of the most popular libraries for traditional machine learning in Python. It provides simple and efficient tools for data mining and data analysis, including support for supervised and unsupervised learning algorithms. **Key Features**:

• **Machine Learning Algorithms**: It includes algorithms for classification (e.g., SVM, decision trees), regression, clustering (e.g., k-means), and dimensionality reduction (e.g., PCA).

• **Preprocessing**: It offers utilities for data preprocessing, feature selection, and feature extraction.

• **Model Evaluation**: Scikit-learn also provides tools for model evaluation, cross-validation, and hyperparameter tuning.



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DOI: 10.17148/IJARCCE.2025.14226

4. OpenCV

OpenCV (Open Source Computer Vision Library) is an open-source computer vision and machine learning library. It provides a vast set of tools to work with images and videos, perform image processing, and recognize objects and faces in real-time.

Key Features:

Image and Video Processing: OpenCV offers various functions for image manipulation, such as resizing, cropping, filtering, edge detection, and more.

Object Detection and Recognition: It includes pre-trained classifiers for detecting faces, objects, and human poses, as well as tools for building custom object detection systems.

Real-time Performance: OpenCV is optimized for real-time computer vision applications, making it useful for both desktop and embedded systems ..

5. MediaPipe

MediaPipe is an open-source cross-platform framework developed by Google for building multimodal machine learning pipelines. It is designed for real-time applications, such as gesture recognition, object detection, and face tracking. MediaPipe provides easy-to-use tools for developing vision-based models that work in real-time on mobile devices and desktops.

Key Features:

Real-Time Processing: MediaPipe excels in real-time performance for applications like gesture tracking, pose estimation, and hand tracking.

Pre-trained Models: It offers ready-to-use pre-trained models for tasks like face and hand tracking, pose • detection, and object detection.

Cross-platform: MediaPipe supports Android, iOS, Web, and desktop applications. •

6. NumPv

NumPy (Numerical Python) is a fundamental library for numerical computing in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays. **Key Features:**

Array Objects: The ndarray is the core data structure of NumPy, which allows for efficient storage and manipulation • of large data sets.

Mathematical Operations: NumPy provides a variety of functions for linear algebra, statistics, Fourier transforms, • and other mathematical operations.

• Integration with Other Libraries: It is the backbone of many scientific computing libraries, including SciPy, Pandas, and TensorFlow.

7. Matplotlib

Matplotlib is a comprehensive plotting library in Python used for creating static, animated, and interactive visualizations in 2D and 3D. It is widely used for plotting data and creating visual representations of numerical datasets.

Key Features:

Data Visualization: Matplotlib allows you to create a wide variety of plots such as line charts, bar charts, scatter plots, histograms, heatmaps, and more.

Customization: You can customize almost every aspect of the plot, from axis labels and legends to colors, markers, and gridlines.

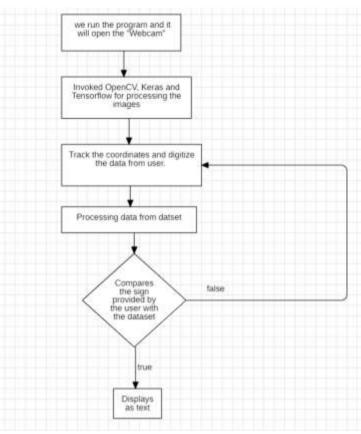
Integration with Other Libraries: It integrates seamlessly with NumPy for data manipulation and Pandas for DataFrame visualizations.

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International Journal of Advanced Research in Computer and Communication Engineering Impact Factor 8.102 🗧 Peer-reviewed & Refereed journal 😤 Vol. 14, Issue 2, February 2025

DOI: 10.17148/IJARCCE.2025.14226



IV. RESULTS







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V. CONCLUSION

The future of Sign Language Recognition technology, particularly for American Sign Language, is bright, with immense potential for improving communication, accessibility, and inclusion for the deaf community. As advancements in artificial intelligence, machine learning, and sensor technologies continue to evolve, SLR systems will become more accurate, real-time, and adaptable, enabling seamless communication between deaf and hearing individuals. The integration of ASL recognition with smart devices, healthcare, education, and social platforms will make these technologies indispensable tools for breaking down barriers in everyday life. However, challenges such as privacy concerns, bias in training data, the need for accurate real-time systems, and accessibility issues must be addressed for the technology to reach its full potential. Future research must continue to refine these systems, focusing on inclusivity, cultural sensitivity, and ethical considerations to ensure that ASL recognition benefits the entire deaf community without compromising privacy or equality. In conclusion, the development of Sign Language Recognition technologies represents a significant step toward creating a more inclusive and connected world, where language is no longer a barrier, and the diverse cultures of the deaf community can be fully represented, understood, and celebrated. With continued research, collaboration, and innovation, the potential for these technologies to transform the way we communicate and interact is boundless.

ACKNOWLEDGEMENT

We would like to extend our heartfelt gratitude to everyone who supported and guided us throughout the completion of this project. First and foremost, we would like to express our sincere thanks to our guide, **Mrs. Suwarna** Mam, for her constant support, guidance, and encouragement. Her expertise, valuable insights, and constructive feedback were instrumental in shaping the direction of this project. Her patience and willingness to help at every stage of the project were truly motivating and made a significant impact on the success of this endeavor. We would also like to express our deep appreciation to our mentor, **Mr. Mithun** Sir, for his continuous support and mentorship. His technical guidance and practical suggestions played a vital role in overcoming challenges during the development of the project. His dedication, knowledge, and problem-solving skills were essential in completing this project successfully. We are truly grateful for their invaluable contributions, which made this project not only possible but also a rewarding experience. Their encouragement and expert guidance have been crucial in the successful completion of this project

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