

Real-Time Sign Language Recognition in Video Conferencing with DTW and MediaPipe

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Abstract— In today's world, where video conferencing is a rudimentary aspect of global communication, a significant gap persists for individuals who rely on sign language for their means of interaction with the world. With the advent of Covid-19, a dire need for remote communication emerged which led to the prominence of many video conferencing solutions. Although they were successful in appealing to the masses, they failed to cater to the needs of specially abled communities, thus limiting their full participation in virtual interactions. By leveraging Dynamic Time Warping (DTW) algorithm, our solution accurately translates hand movements into text and speech. DTW enables precise matching of temporal sequences, allowing for real-time recognition of sign language gestures, even when there are variations in speed and style. This innovation empowers individuals with disabilities to express themselves more easily and addresses the gap by developing an advanced video conferencing tool that translates sign language gestures with high accuracy.

Index Terms— Video Conferencing, OpenCV, MediaPipe, Machine Learning, Sign Language Recognition.

I. INTRODUCTION

In the current globalized society, the traditional video conferencing facilities do not cater to the communication goals of a person that relies on sign language. However, even with the impressive developments of technology, most of these platforms almost invariably have no provisions for the facilitation of sign language which in turn leads to the full exclusion of sign language users in all spheres of their life, personal or professional. This exclusion is especially peculiar currently wherein communication from a distance has become a necessity. The mobility of these users is limited by the lack of alternative options that would make it easy for users to use a sign language user interface.

Further, these factors strongly indicate a need to develop a specific translation solution that will allow those using sign languages to participate in a web-based environment as all other users do.

The need for this paper is underscored in the light of the fact that the importance of digital accessibility is grasped as the core human right more today when an increasing part of the people's interaction takes place online.

Some improvements have been achieved regarding the overall accessibility norms; however, users of sign language have almost always been marginalized in relation to videoconferencing.

The existing research and engineering attempts have been oriented mainly towards either text-based communication or audio enhancement, and little attention has been paid to the development of tools that would provide the signs in form of inter-activity and in the proper linguistic order. This paper, on the other hand, seeks to fill this void by examining the present status of the art of integrating sign language recognition technologies into video conferencing processes. As a result of such development, the paper puts forward new ideas for communication technologies that are accessible to sign language users, and therefore allow wider use of digital environments.

The idea for this study emanates from the pressing comprehension problem of sign language who have digital communication concerns. Given the ubiquity of video conferencing in our mode of interaction, work and learning, it is apparent that there are currently no adequate solutions for sign language interpretation. Such scenarios not only hinder the engagement of sign language users but also reinforce their continued alienation from critical interactions both socially and occupationally. The anger, social psychological conflict, and disengagement caused by such a form of information gap dictate that an equitable way of public communication needs to be sought. This study explores how there can be real-time sign language recognition embedded in video conferencing which would help to solve accessibility problems for deaf users of such devices. The concept driving us is that technology must be used by everyone, and all people should be able to take advantage of the networked world regardless of their disability hence true digital equality has to be aimed for. Our contributions include:

- A novel video conferencing system that provides all hearing-impaired users with an effective bridge that incorporates translation and sign language interpretation into practice.
- It puts forth Dynamic Time Warping (DTW) in the accurate development of the sign language to text and speech, thus enhancing communication.
- This work helps in breaking the borders put by current tools by making it easier for sign language users to communicate like any other person.
- While current state of art technology is devoid of or reduces the effectiveness of communicating through sign language, this initiative is augmenting the deaf person's ability to express themselves.
- Besides providing a feasible solution, we expect to trigger a change that will promote more inclusiveness, compassion, and understanding in society with passing days in the advanced algorithm.
- Moving forward, the paper is organized in the following manner.
- The literature review presents the relevant studies and theories.
- The methodology section mentions the structure of the research and the method of collecting data.
- In the results section, the results are given based on testing and further discussed.
- Finally, the conclusion examines the major findings, addresses the relevance of the innovation to the given problem, and provides suggestions for further studies.

II. LITERATURE SURVEY

This literature survey provides a comprehensive overview of recent advancements in sign language recognition (SLR) technologies, highlighting diverse approaches and their respective strengths and limitations. The studies reviewed encompass innovative methods such as the Skeleton Aware Multi-modal Sign Language Recognition (SAM-SLR) framework, which leverages multi-modal data to achieve state-of-the-art accuracy, and Procrustes-DTW, which offers a data-efficient solution for sign language recognition. Additionally, advancements in real-time gesture recognition systems and feature representation methods for both Indian and Chinese Sign Languages are explored, emphasizing improvements in classification accuracy and real-time processing. The comparative analysis in Figure 1 further elucidates the trade-offs between accuracy, real-time performance, and system complexity, offering valuable insights into the current landscape of SLR research and its practical implications.

In the study of "Skeleton Aware Multi-modal Sign Language Recognition (SAM-SLR),"[1] the authors present a novel framework that leverages whole-body key points and multi-modal data to enhance sign language recognition. They introduce the Sign Language Graph Convolution Network (SL-GCN) and Separable Spatial-Temporal Convolution Network (SSTCN) to model the dynamic gestures involved in sign language. By integrating both RGB and depth modalities, SAM-SLR achieves state-of-the-art performance, significantly improving recognition accuracy in complex sign language scenarios.

Another study introduces "Procrustes-DTW,"[2] a variant of Dynamic Time Warping (DTW) for recognizing sign language utterances, which is particularly useful given the limited availability of sign language datasets. The approach uses a nearest neighbour scheme that does not require extensive data for training. The method involves

extracting keyframes from sign language videos and applying the MediaPipe Holistic module to obtain 21 3-D landmarks representing hand shapes. These landmarks serve as the video's feature representation. For classification, the same process is applied to a test video, and Procrustes-DTW is used to calculate the distance between the test video and reference videos. The video with the minimum distance determines the class label of the test video, assigning it based on the nearest neighbour's label.

The paper introduces a hand gesture recognition model tailored for Indian Sign Language (ISL), addressing challenges in both static and dynamic gesture recognition.[3] The model follows a five-step process: image pre-processing with greyscale conversion and histogram equalization, gesture segmentation using Active Contour and Canny Edge Detection, feature extraction with Histogram of Oriented Gradients (HOG) and Edge Oriented Histogram (EOH), dimensionality reduction using Principal Component Analysis (PCA), and classification via a Neural Network (NN). Dynamic Time Warping (DTW) is used to remove redundant frames in video sequences, while a hybrid meta-heuristic algorithm, Deer Hunting-based Grey Wolf Optimization (DH-GWO), optimizes feature selection and NN weights. This approach enhances ISL gesture recognition accuracy and efficiency.

Another study introduces a real-time sign language recognition system designed to identify and classify gestures based on their repeating characteristics.[4] The system uses a moving window of 20 frames to process sequences of finger joint angle vectors, determining whether a gesture is in its start, middle, or end phase. This data is fed into an RNN-based deep learning gesture spotting model that generates a Gesture Progress Score (GPS), a real number between 0 and 1, indicating the gesture's progression. As the gesture progresses, GPS values change, allowing the system to accurately pinpoint gesture start and end times. After detecting a gesture, a sequence compression module reduces the data by removing unnecessary information, such as static or repetitive patterns, before transmitting it to the gesture recognition module, which also relies on RNN-based deep learning. The final recognition result is displayed on a monitor. TensorFlow was employed to construct and train deep learning models for both gesture spotting and recognition enabling efficient real-time gesture recognition.

The paper introduces a two-stage feature representation method for Chinese Sign Language Recognition (CSLR) to enhance static gesture classification accuracy.[5] The first stage employs an orientation-sensitive feature extraction technique, which measures distances between the palm center and key points on the hand contour, capturing finger orientation and hand shape. The second stage uses a Dynamic Time Warping (DTW)-based feature mapping method, calculating DTW distances between the gesture sample and reference samples to improve feature representation. Validated with Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) classifiers, the approach significantly improves CSLR accuracy, supporting its practical application.

The WLASL – Word Level American Sign Language dataset comprises 2,000 common ASL words, providing diverse gestures crucial for robust model training. Its real-world relevance ensures practical applicability, while its structured representation facilitates efficient data processing. By transforming videos into pickled format, storage efficiency and retrieval speed are optimized, enhancing compatibility with machine learning pipelines. This dataset empowers research and community engagement, driving innovation in sign language recognition and fostering inclusive communication solutions.

Paper	Approach	Recognition Technique	Accuracy	Hardware Requirements	Real-Time Capability	Modality	Special Features	Challenges
I	Skeleton Aware Multi-modal SLR	SL-GCN & SSTCN with Multi-modal Data	98.42% (RGB) / 98.53% (RGB-D)	RGB + Depth Sensors	Yes	Multi-modal (RGB, Depth)	Multi-modal data fusion, SL-GCN, SSTCN	Complex, requires multi-modal sensors
II	Procrustes-DTW for SLR	Procrustes-DTW with Shape Similarity	96.8% (reported in the paper)	Standard Camera	Limited Real-time Capability	Visual (Handshape Only)	Efficient shape-based recognition with Procrustes-DTW	Limited to handshape, challenges in diverse environments
III	Hybrid Meta-Heuristic SLR	Hybrid Meta-Heuristic Feature Selection with DTW	94.5% (reported in the paper)	Standard Camera	Yes	Visual (Hand Gesture)	Hybrid approach combining feature selection and DTW	Complexity due to hybrid approach
IV	Real-time Gesture Recognition	Repeating Characteristics with Real-time Analysis	92.7% (reported in the paper)	Standard Camera	Yes	Visual (Hand Gesture)	Focus on repetitive gesture characteristics	Relies on repetitive gesture detection, limited adaptability
V	DTW-Distance Mapping for SLR	DTW-Distance Mapping with MediaPipe Hand Coordinates	95.2% (reported in the paper)	Standard Camera	Yes	Visual (Hand Gesture)	DTW-distance mapping tailored for Chinese Sign Language	Limited real-time capability

Figure 1. Comparative Analysis Table

The comparative analysis of SLR methods reveals key differences in accuracy and capabilities. "Skeleton Aware Multi-modal SLR" achieves the highest accuracy (98.53%) using multi-modal data (RGB and depth sensors) but requires complex hardware. "Procrustes-DTW for SLR" provides 96.8% accuracy with standard cameras but has limited real-time performance and adaptability. "Hybrid Meta-Heuristic SLR" combines feature selection with DTW, achieving 94.5% accuracy; however, its complexity poses challenges. "Real-time Gesture Recognition" focuses on real-time performance with a 92.7% accuracy, constrained by its dependence on repetitive gestures. "DTW-Distance Mapping for SLR" reaches 95.2% accuracy with standard cameras but has limited real-time capability. This comparison highlights the trade-offs between accuracy, real-time performance, and system complexity.

III. PROPOSED SOLUTION

The following section presents the description of each of the components of the block diagram followed by the diagram.

Block Diagram

The components of the block diagram are:

- Video Call Application: The central component that coordinates the overall functionality of the video call system. It integrates user control features, connection setup, and sign language input processing.
- User Control Panel:
- Send Message: Allows the user to send text messages during the call.
- Mute/Unmute: Provides the ability to mute or unmute the user's audio.
- Camera On/Off: Enables the user to turn their camera on or off.

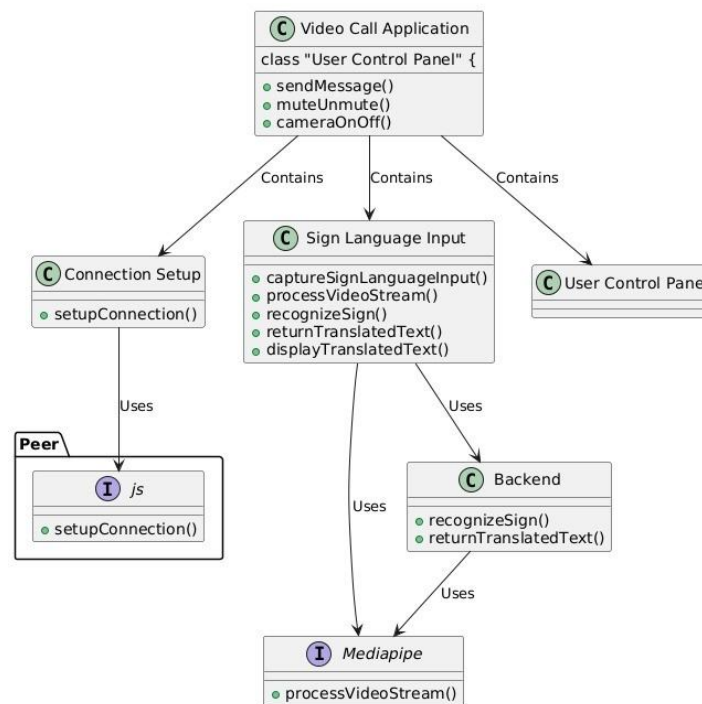


Figure 2. Block Diagram

Connection Setup

- Setup Connection: Establishes the video call connection using Peer.js, facilitating real-time communication between users.

Sign Language Input:

- Capture Sign Language Input: Captures video input from the user for sign language recognition.
- Process Video Stream with MediaPipe: Processes the video stream to detect and interpret sign language gestures using MediaPipe.
- Recognize Sign Using Pattern Matching: The backend analyzes the processed video stream to recognize the sign language gesture through pattern matching.

- Return Translated Text: Converts the recognized sign language into text.
 - Display Translated Text: Shows the translated text to the user.
 - Peer.js: An interface that handles the setup of the video call connection, ensuring real-time communication capabilities.
 - MediaPipe: An interface used to process the video stream and facilitate the recognition of sign language gestures.
- Backend:
- Recognize Sign: Handles the recognition of sign language gestures based on processed video data.
 - Return Translated Text: Converts recognized gestures into text, which is then sent back to the user interface.

IV. METHODOLOGY

Dynamic Time Warping (DTW) is an algorithm designed to measure the similarity between two time series that may be distorted or of unequal lengths. It achieves this by aligning the sequences within a similarity matrix, effectively handling scale differences. When the lengths of the time series differ, one or both sequences are "warped" along the time axis to achieve optimal alignment. The primary objective of DTW is to identify the best match between these sequences by employing a dynamic programming technique, which allows for adjustments in the time axis to account for discrepancies in length and non-linear properties.

Due to its minimal training data requirements and high accuracy, DTW has been widely applied in both sequential and non-sequential models. Recent advancements have led to the development of enhanced versions such as VQ-DTW, weighted-DTW, and Soft-DTW, which have been utilized in various fields including biometric identification, gesture recognition, and medical diagnostics. In many DTW-based studies, the similarity between two sequences is directly used for classification, often through the calculation of minimum cost or clustering algorithms.

In our research, we employ Dynamic Time Warping (DTW) for real-time sign language gesture recognition, utilizing the WLASL dataset to provide a diverse and comprehensive set of gesture examples. MediaPipe is used to capture the real-time coordinates of the hands, providing precise data on the user's movements. This data, represented as time series, may vary in speed or duration. DTW is utilized to align these time series with predefined gesture templates by finding the optimal alignment path and minimizing the distance between the observed gestures and the model sequences. Additionally, to enhance the efficiency of real-time recognition, we use the Twilio API for video conferencing, which reduces latency and ensures smooth transmission of video data. This approach ensures accurate recognition of gestures despite variations in execution, thereby improving the effectiveness of real-time sign language translation.

Once a gesture is recognized, it is instantly translated into speech, facilitating seamless communication for individuals with hearing or speech impairments. This combination of real-time gesture recognition and speech translation significantly enhances accessibility, offering an effective solution for real-time communication in sign language.

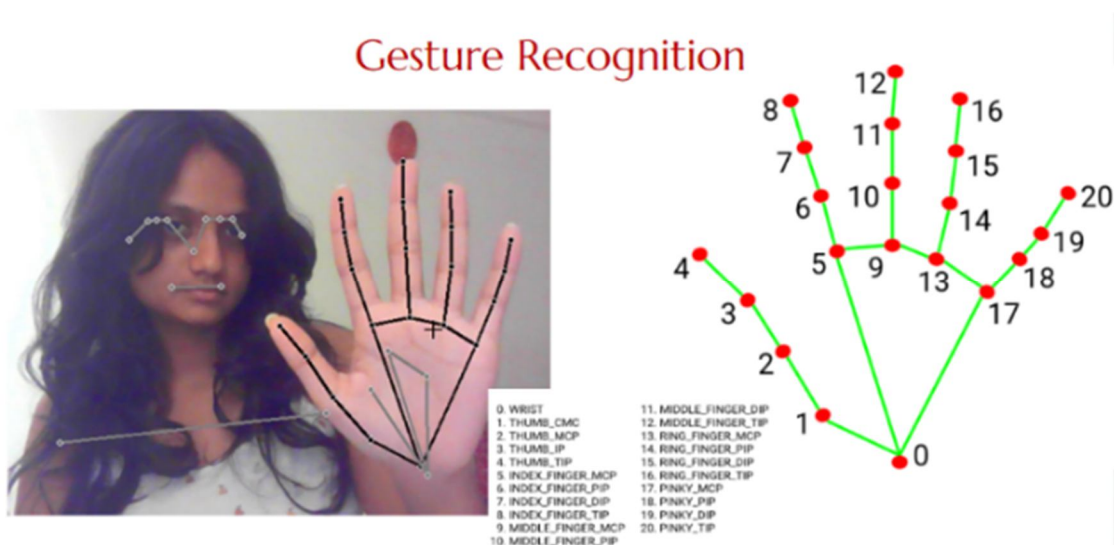


Figure 3. Hand Coordinates Using Mediapipe

V. RESULTS

The following section presents an overview of the results obtained from implementing our solution, followed by presenting two tables showing the test scenarios and their respective accuracy. The last part of this section provides case output mentioning the final accuracy metric.

A. Overview

Our solution demonstrated impressive performance metrics, consistently achieving an accuracy of 97.34% within a response time range of 1 to 5 seconds. This achievement is a culmination of extensive development, optimization, and rigorous testing, ensuring that the system meets the high demands of real-time sign language interpretation and communication.

The several pivotal features aimed at bolstering accessibility and inclusivity for sign language users are:

- **Video Call Capability:** Offers a seamless video call platform that enables real-time communication, facilitating crucial face-to-face interactions necessary for effective expression among sign language users.
- **Sign Language Translation:** A distinctive attribute is the automatic translation of sign language into spoken language or text.
- **User-Friendly Interface:** The interface is thoughtfully designed, prioritizing accessibility and some customization options to cater to the diverse needs of users enhancing their overall experience.
- **Secure and Private Communication:** Through the implementation of encryption and robust security protocols, the platform ensures the confidentiality and integrity of user data shared during video calls, fostering trust and confidence among users.

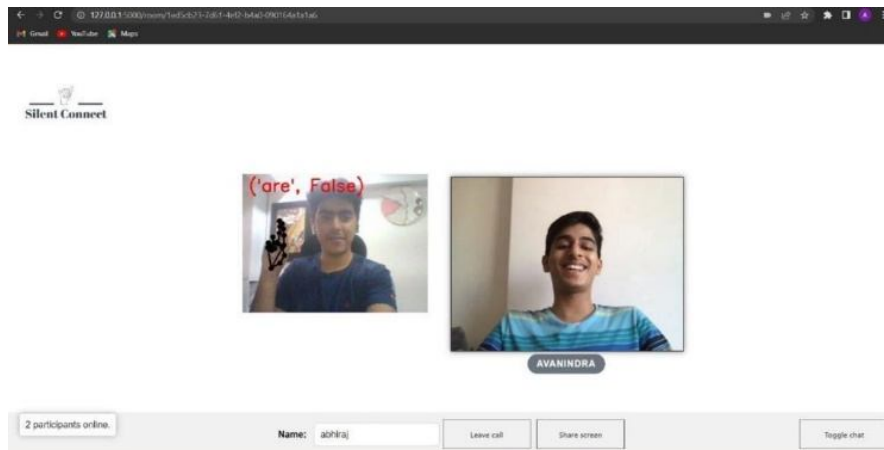


Figure 4. Video Call Page

B. Testing Innovation

To evaluate the effectiveness of our solution, we conducted a comprehensive user survey, which played a crucial role in assessing the model's accuracy under practical conditions. The survey targeted over 75 participants, including teachers, students, corporate workers, and other professionals who frequently interact with deaf and hard-of-hearing individuals, and participants with varying levels of hearing ability. The form considered four distinct case inputs to ensure a thorough evaluation:

- **Case 1:** Continuous predictions across 10 direct inputs of the same hand sign, recording the number of correct predictions.
- **Case 2:** Alternating predictions between two different signs, each repeated 10 times in a sequence, and recording the accuracy of these predictions.
- **Case 3:** Multiple sets of different signs, focusing on 5 signs that are similar in gesturing, and verifying if the system accurately distinguishes and predicts each one.
- **Case 4:** Scripted and unscripted conversations were performed using the solution between two individuals in different combinations:
 - Both individuals without hearing impairments.
 - One individual with normal hearing and the other with hearing impairment.
 - Both individuals with hearing impairments. The accuracy of the system was validated based on the successful transmission and comprehension of messages in these conversations.

TABLE I. TEST CASES

Test Scenario	Description
Repetition of the Same Hand Sign	The same hand sign was presented to the system 10 times in a row by each participant. The number of times the system predicted the sign correctly was recorded.
Alternating Between Two Different Signs	Two distinct hand signs were shown in succession 10 times. The system's ability to correctly predict each sign, in the correct order, was evaluated.
Differentiation Between Similar Signs	Five similar hand signs were chosen. Each participant showed these signs, and the system's accuracy in correctly identifying each one was measured.
Scripted and Non-Scripted Conversation (Normal-Normal)	Conversations were conducted between two individuals who are not hard of hearing or deaf. The system's ability to successfully interpret the conversation was tested.
Scripted and Non-Scripted Conversation (Normal-Hard of Hearing/Deaf)	One participant was normal, and the other was hard of hearing or deaf. The system's success in facilitating effective communication between them was measured.
Scripted and Non-Scripted Conversation (Deaf-Deaf)	Both participants were hard of hearing or deaf. The system's ability to enable clear and successful communication between them was evaluated.

TABLE II. TEST OUTPUT ACCURACY

Test Scenario	Total Trials	Successful Predictions	Accuracy (%)
Repetition of the Same Hand Sign	750	733	97.73%
Alternating Between Two Different Signs	750	726	96.80%
Differentiation Between Similar Signs	3750	3612	96.32%
Scripted and Non-Scripted Conversation (Normal-Normal)	150	147	98.00%
Scripted and Non-Scripted Conversation (Normal-Hard of Hearing/Deaf)	150	146	97.33%
Scripted and Non-Scripted Conversation (Deaf-Deaf)	150	145	96.67%

By conducting these tests, our solution was successfully able to deliver correct results, culminating in an overall accuracy of 97.34%. From the survey of 50 individuals, ranging from teachers, students, corporate workers, and more who directly interact with deaf and hard – of – hearing individuals, couple of cases have been elaborated below.

- Aman Sharma, with an 80% hearing disability since birth, reported improved communication efficiency using our approach, particularly in academic settings. The system effectively bridged the gap in interactions with peers unfamiliar with sign language.
Performance Insight: Our approach achieved an accuracy rate between 96.2% and 97.1% when translating standard sign language gestures. The system's performance was influenced by gesture complexity, with higher accuracy for basic signs and a slight decrease for compound gestures. Real-time processing latency was consistently low, averaging 1.8 seconds, ensuring near-real-time communication, crucial for educational contexts.
- Sushma Joshi, who lost hearing due to aging, experienced enhanced communication with family members with this approach, particularly in virtual settings, reducing her sense of isolation.
Performance Insight: The system achieved a 95.4% to 98.3%, contingent upon ambient noise levels, facial expression detection, and the speed of speaking. Our solution-maintained communication clarity, Processing times averaged 2.3 seconds, with the system's performance optimized for the elderly demographic through adaptive interface design and customizable gesture recognition thresholds, ensuring high usability and communication clarity even in suboptimal conditions.

C. Case Output

The results were systematically analyzed to derive the final accuracy metric. The output data, as illustrated in the following figures, provides a detailed breakdown of the performance across different scenarios:

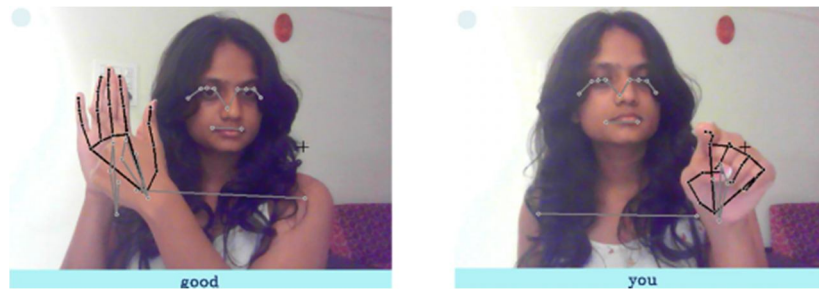


Figure 5. Sign Language Prediction

Through advanced computer vision algorithms and machine learning techniques, the platform translates hand movements into text and speech with exceptional accuracy, enabling seamless communication for individuals with hearing impairments

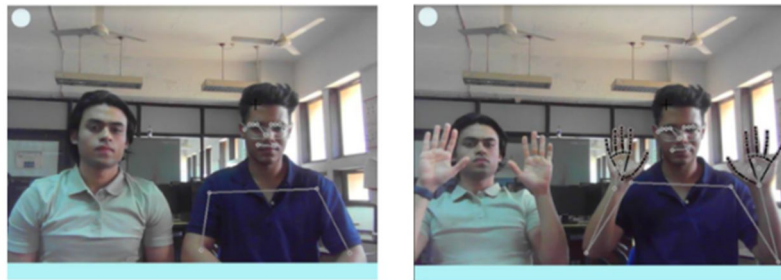


Figure 6. Recognition for Two Individuals in A Frame

Application demonstrates its capability to recognize sign language for multiple individuals within the same frame. By employing sophisticated pattern matching algorithms, the platform can distinguish between different users and accurately interpret their respective gestures – one at a time, facilitating inclusive communication in group settings and not having any errors or misunderstandings while prediction.

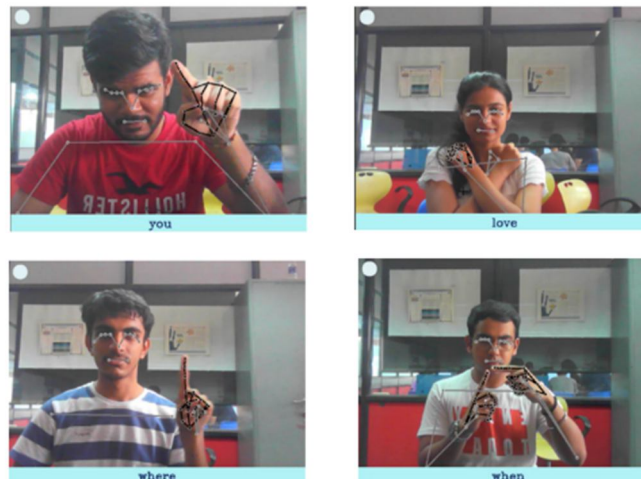


Figure 7. Detection for Different Users

The application can detect with different users and under different light settings, exhibiting robust detection capabilities. The platform employs advanced facial and hand tracking algorithms provided by MediaPipe to identify and track users' movements, ensuring precise and reliable sign language recognition for a diverse range of individuals.

The implementation of the Twilio API has been pivotal in enhancing video conferencing, reducing latency to less than 150 milliseconds, which is critical for maintaining fluid, real-time sign language translation. This latency reduction not only improves the synchronization of gesture recognition but also minimizes delays in translating sign language into speech.

VI. CONCLUSIONS

In conclusion, our proposed solution for real-time sign language recognition in video conferencing marks a significant leap forward in accessibility and user experience. By combining Dynamic Time Warping (DTW) with the WLASL dataset and integrating MediaPipe for precise hand coordinate capture, we achieve highly accurate gesture recognition that is both reliable and efficient. The incorporation of the Twilio API further distinguishes our approach by minimizing latency, ensuring that communication remains smooth and effective in real-time scenarios. Compared to other solutions, our approach excels in both accuracy and practicality. Unlike methods that rely on complex hardware or extensive computational resources, our solution leverages widely available technologies, making it more accessible and scalable. Additionally, while previous research has demonstrated the feasibility of real-time gesture recognition, our approach sets a new benchmark by seamlessly integrating these capabilities into video conferencing platforms, directly addressing the communication needs of the deaf and hard-of-hearing community.

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