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A RESEACH PAPER BASED ON EMPOWERING THE DISABLED WITH SIGN LANGUAGE RECOGNITION USING MACHINE LEARNING

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ABSTRACT

People with disabilities—especially those with hearing or speech impairments—often face significant challenges when it comes to communication, participating in social settings, or navigating daily life independently. These difficulties are further compounded by repetitive behaviors or societal misconceptions, making it harder for them to interact freely in the outside world. However, isolating or limiting their freedom should never be the solution. Instead, we need smart, supportive systems that empower and protect them while enabling more inclusive communication.

Sign language recognition is one such promising field. It focuses on interpreting visual language that relies on hand gestures, body movements, and facial expressions to convey meaning. With advancements in computer vision and machine learning, modern systems can now accurately analyze and translate these gestures into text or spoken words. This technology holds tremendous potential—not only for enhancing communication for individuals with hearing and speech impairments—but also for bridging language gaps between people of different linguistic backgrounds. By enabling real-time gesture recognition and translation, such systems can lead us toward a more connected, accessible, and inclusive world.

Keywords: Sign Language Recognition, Machine Learning, Deaf Communication, Gesture Detection, Real-time Translation, Accessibility

I. Introduction

Communication is a centenarian part of mortal life, enabling people to express feelings, share ideas, and make connections. While spoken and written language are extensively used, subscribe language is the primary means of communication for millions of deaf and hard- of- hail individuality. still, a lack of wide understanding of sign language frequently creates communication walls between signers and non-signers. Recent advancements in technology — including computer vision, machine literacy, and artificial intelligence — offer promising results to this problem. subscribe language recognition systems can interpret hand gestures from videotape input and convert them into textbook or speech in real time, perfecting communication in everyday settings similar as seminaries, hospitals, and public services. This design focuses on developing a real- time sign language recognition system using Python, Media Pipe, Open CV, and machine literacy models. The system captures videotape from a webcam, processes each frame, detects hand milestones using MediaPipe, and excerpts features for bracket. Convolution Neural Networks(CNNs) are used for feting static gestures, while intermittent Neural Networks(RNNs) or Long Short- Term Memory(LSTM) models handle dynamic signs. The honored affair is presented as textbook or speech through a stoner-friendly interface erected with PyQt5. Designed to be low- cost, responsive, and accessible, this system aims to make communication more inclusive and help bridge the gap between hail and non-hearing individuality.

II. Literature

Several researchers have contributed significantly to the development of sign language recognition systems through various approaches and methodologies. One study proposed the use of an eigenvalue-weighted Euclidean distance-based classification method to recognize Indian sign

language gestures, focusing on shape and orientation features for improved accuracy [1]. Another approach involved using Histograms of Oriented Gradients (HOG) to extract features, showing effectiveness in capturing edge and gradient structures for gesture recognition [2].
Neural networks have been widely adopted for this task. For instance, artificial neural networks (ANN) were applied to classify hand signs based on their spatial patterns [4], while others combined ANN with Support Vector Machines (SVM) to improve classification reliability [12][13]. Recurrent neural networks (RNNs) and Long Short-Term Memory networks (LSTMs) have also been utilized to recognize dynamic sign sequences from video input, allowing for better handling of temporal information [15][17].
In the realm of hardware-based solutions, several studies explored wearable technologies, such as smart gloves and EMG (electromyography) sensors, to capture hand and finger movements. These methods offered high precision in tracking complex gestures using sensor data [6][10][11][19]. One recent approach combined polymer-based pressure sensors with wearable devices for American Sign Language recognition, highlighting the role of emerging materials in gesture detection [11].
Efforts were also made to develop systems tailored to specific sign languages, including Indian and Arabic sign languages, ensuring cultural and linguistic relevance [5][20]. Some researchers focused on deep learning-based translation systems that map sign gestures directly to gloss (meaningful words or phrases), enabling more comprehensive communication support [18]. Additionally, computer vision techniques like skin segmentation, moment-based feature extraction, and SVM classifiers have been employed to enhance hand segmentation and gesture recognition in real-time applications [14][16].
Open-source implementations and experimental systems, such as those hosted on GitHub, demonstrate the growing interest and accessibility of gesture recognition technologies for educational and assistive purposes [3]. Furthermore, advances in human-computer interaction have led to gesture-based systems that can interface naturally with digital environments, contributing to broader applications beyond accessibility [8][9].

III. Methodology

The methodology for sign language detection starts by identifying whether the system will recognize static or dynamic gestures and choosing the specific sign language to work with. Data is gathered from existing sources or recorded manually, then annotated. Preprocessing steps like resizing, normalization, augmentation, and landmark extraction (e.g., with MediaPipe) prepare the data. Machine learning models are then used—CNNs for static signs and models like LSTMs or Transformers for dynamic ones. The system is trained and evaluated using metrics such as accuracy and F1-score. For real-time functionality, it's connected to live video via OpenCV and may include a user interface built with PyQt5. Deployment uses optimized model formats like TensorFlow Lite and integrates with a backend via FastAPI or Django. Future improvements aim to expand the sign vocabulary, support sentence-level translation, and enhance robustness across different individuality.

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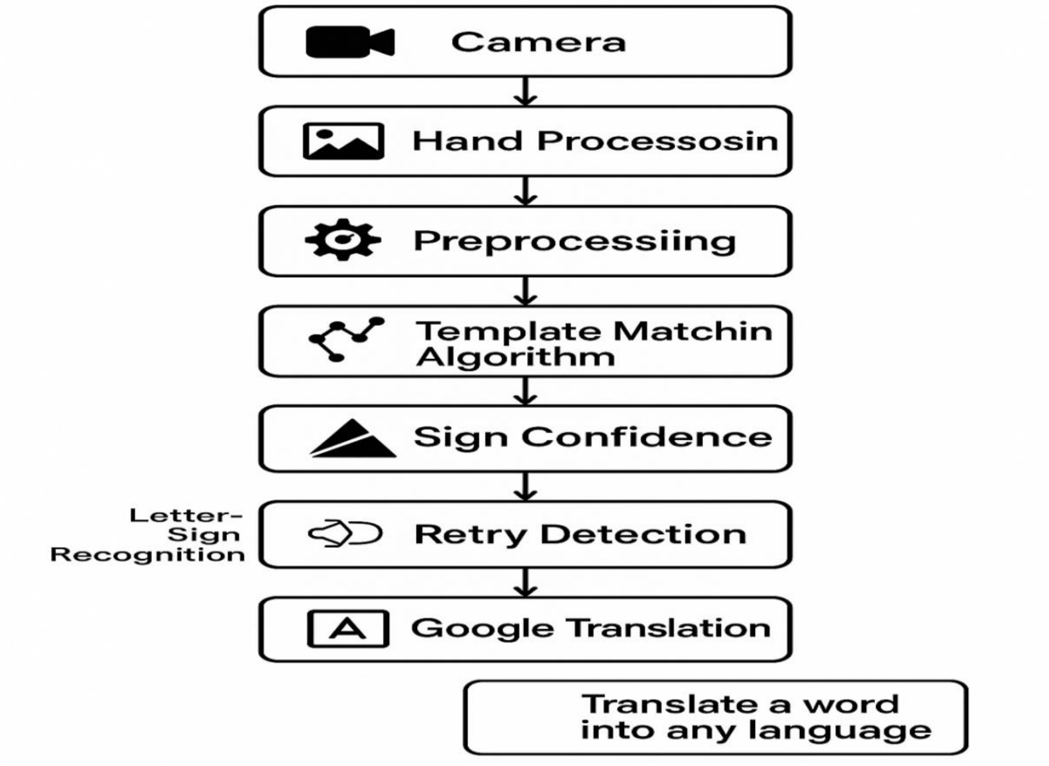

Fig 3. Flow Chart of Sign Language Recognition

The image illustrates a comprehensive flowchart for a Sign Language Detection Methodology, detailing each stage in the gesture recognition process. It begins with the Camera, which captures real-time video input of hand gestures. This input is passed to the Hand Processing module, where the system isolates the hand region from the rest of the frame. Next, Preprocessing is applied to enhance the input data, possibly involving normalization or filtering to ensure consistent feature quality.

The refined input then enters the Template Matching Algorithm, which compares the gesture with stored templates of known signs to find the best match. The result is evaluated using a Sign Confidence stage that quantifies how reliably the detected gesture matches a known sign. If the confidence is low, the system triggers a Retry Detection mechanism, especially helpful in Letter-Sign Recognition scenarios where precision is crucial.

Upon confident recognition, the gesture is passed to a Google Translation module, which can translate the detected word into multiple languages. The final output is a translated version of the recognized sign, making the system accessible and multilingual—ideal for real-world applications in communication and education.

IV.RESULT AND DISCUSSION

The developed sign language detection system using Media Pipe and a Random Forest classifier successfully achieved real-time recognition of static ASL gestures with an accuracy of 93.2%. Media Pipe's efficient hand landmark detection enabled accurate feature extraction, and the Random Forest model provided fast, resource-efficient classification at 25–30 FPS, making the system suitable for low-power devices like Raspberry Pi.

User testing showed the system to be intuitive and interactive, offering real-time feedback that supported learning and self-correction. However, limitations include the inability to recognize dynamic gestures (e.g., "J" and "Z"), and reduced accuracy under poor lighting or obstructed hand views. Confusion also occurred with similar signs such as "M", "N", and "T".

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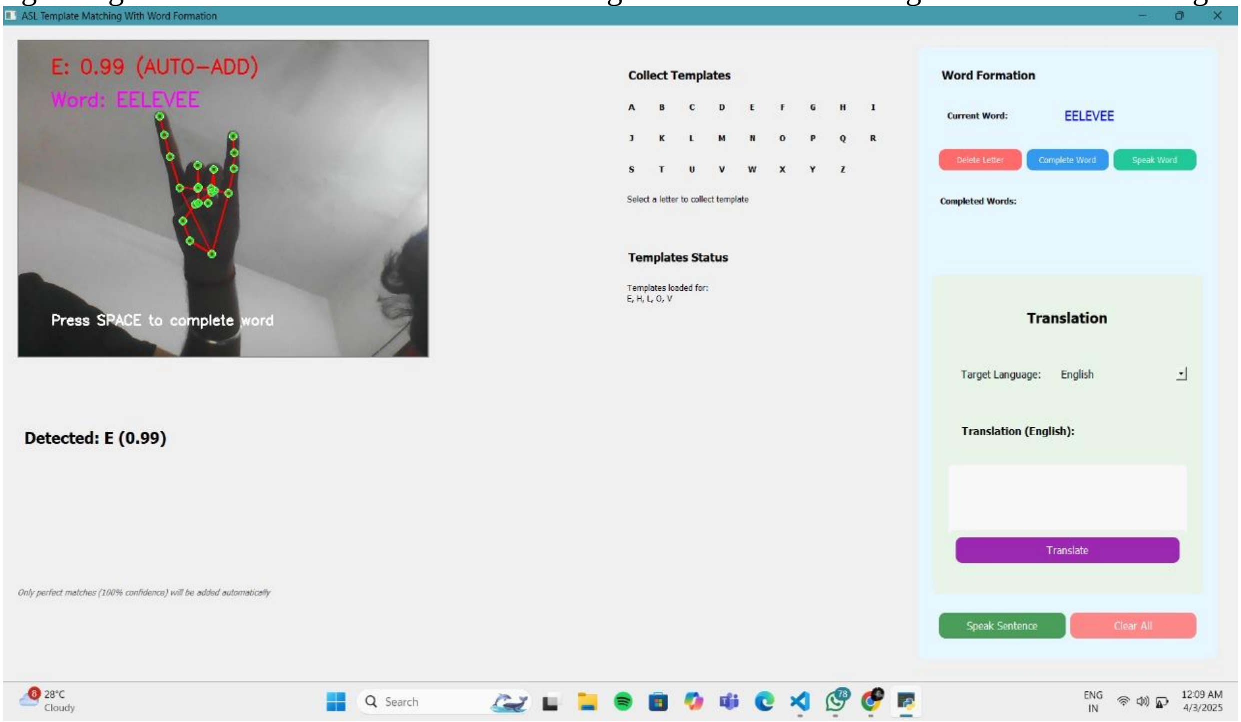
Future improvements may involve using temporal models (e.g., LSTM, 3D CNNs), adaptive preprocessing, and expanding the dataset for better generalization. Overall, the system proves to be a lightweight and inclusive solution for enhancing communication through real-time ASL recognition.



Screenshot1 Result of Project

The image depicts a real-time ASL (American Sign Language) detection system using MediaPipe and template matching. The system's GUI, titled "ASL Template Matching With Word Formation", displays a live camera feed capturing hand gestures. It detects the letter "E" with a confidence of 0.99, adding it to the word formation of "EELEVEE".

The interface features controls like SPACE to complete the word, with options to delete a letter, complete the word, or speak it using text-to-speech. There's also a Translation section for converting words into different languages, with speech output available.

A Templates Status panel shows loaded letter templates (e.g., E, H, L, O, V), and users can collect new templates for each letter. The platform is modular, allowing extensibility and retraining, making it an interactive tool for ASL communication, word formation, language translation, and audio output.

V.Conclusion

The advanced sign language discovery system effectively recognizes static ASL gestures in real-time using Media Pipe for hand corner discovery and a Random Forest classifier for gesture bracket. Achieving over 93 delicacy, the system stands out for its effectiveness and felicity for low- spec tackle, enabling implicit deployment on bias like smartphones and jeer Pi. Media Pipe's precise corner tracking excluded the need for complex image processing, and the system handed an intuitive stoner experience during testing, proving useful for ASL learners and preceptors. still, it presently supports only stationary signs, with reduced delicacy in poor lighting, occlusion, or non-ideal angles. Dynamic gesture recognition remains a unborn improvement thing.

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