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SIGN LANGUAGE TO TEXT CONVERSION USING MACHINE LEARNING

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Abstract: The deaf population uses sign language, a visual form of communication that uses hand gestures and movements instead of spoken words, to communicate. For efficient communication, deaf people frequently need sign language interpreters, which can be difficult and expensive. As such, there is a pressing need to create a system that enables communication using sign language. This kind of communication uses gestures, hand forms, and facial expressions to transmit information. Sign languages exhibit both national and regional diversity; examples include Arabic, American, Chinese, and Indian sign languages. Everyone needs effective communication, but those who are hard of hearing or deaf really need it. Closing the communication gap between hearing and non-hearing people is critical given the increasing incidence of hearing impairments. Therefore, we are presenting a novel system that uses machine learning and computer vision techniques to translate Sign Language into text.

Index Terms **- Machine Learning, Computer vision, CNN, Hand Gesture.**

I. Introduction

Communication obstacles between the deaf and hard of hearing and others who are not familiar with sign language can be greatly reduced with the help of a sign language to text converter. With its combination of body language, facial expressions, and hand gestures, sign language offers a special kind of communication. Although it is useful in the deaf community and among proficient signers, it can cause isolation for non-fluent speakers, possibly excluding those who are hard of hearing or deaf.

The development of a machine learning (ML) and artificial intelligence (AI) powered sign language to text converter offers a previously unheard-of chance to improve communication accessibility. With the use of sophisticated algorithms and deep learning models, AI and ML are now able to accurately recognize and interpret sign language motions in real time. With the help of this cutting-edge technology, sign language can be easily translated into written or spoken words. It also has the potential to be improved over time by being continuously trained on large datasets and adjusted to various dialects and signing styles. Therefore, it makes communication easier for those who are not proficient in sign language.

For many deaf and hard of hearing people in North America, American Sign Language (ASL) is their primary language. It is acknowledged as a full, natural language with unique linguistic qualities that set it apart from English. ASL employs hand movements, facial expressions, and body language to convey meaning, boasting its own grammar, lexicon, and syntax. ASL plays a pivotal role in communication within the deaf community, providing a means for interaction and self-expression. It is recognized as an official language in the United States and is taught in academic institutions as a foreign language, underscoring its significance in fostering inclusivity and communication accessibility for individuals who are deaf or hard of hearing.

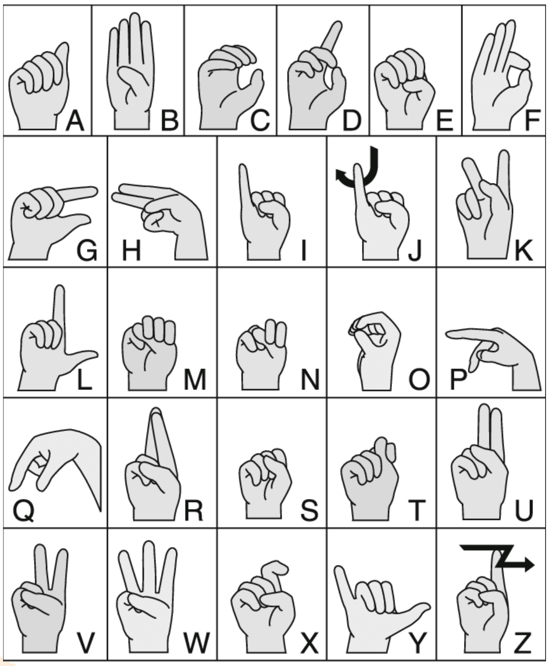


Fig-1: American Sign language. [14]

II. LITERATURE REVIEW

Various techniques for text sentiment analysis have been studied in many works, and machine learning techniques have proven to be particularly successful. This section looks at important research projects that academics have worked on and the conclusions they have drawn.

1) The article suggests the significance of sign language as a natural and expressive means of communication for individuals with hearing impairments. However, there is a lack of effort from those who can hear to learn sign language, resulting in the isolation of the deaf community. To address this, the paper proposes the development of a system capable of translating sign language into text, which could bridge the gap between the deaf community and those who can hear. This system accurately recognizes various alphabets of International Sign Language (ISL) while minimizing noise. It offers deaf individuals who are unable to speak a means to communicate with non-signing individuals without requiring an interpreter. Additionally, the paper contrasts the finger-spelling systems used in American Sign Language (ASL) and British Sign Language (BSL). ASL utilizes a one-handed finger-spelling system, whereas BSL employs a two-handed approach. Furthermore, the paper highlights that many BSL signs originate from English-based initialized signs, whereas ASL signs often develop without such initialization, reflecting distinct cultural values

2) This study investigates different methods employed for translating sign language into text or speech and evaluates their efficiency. Following the assessment, the researchers identify the most effective approach and create an Android application capable of translating live American Sign Language (ASL) gestures into text or speech. This application holds promise for enhancing immediate interaction between ASL users and non-users by facilitating smoother communication between them.

3) Enhancing meaningful communication between individuals with speech, hearing, or vision impairments is the goal of the proposed technology. It uses convolutional neural networks (CNNs) to translate American Sign Language (ASL) hand gestures into spoken or written words. With an 88% accuracy rate in hand gesture recognition and an intuitive interface, this system makes it possible for people with special needs to interact more successfully with people who do not know ASL. This project promotes inclusion and accessibility by offering a workable solution to the communication challenges faced by individuals with speech, hearing, or vision impairments.

4) The system presents an innovative approach to recognizing the American Sign Language alphabet and numbers by incorporating saliency detection, PCA, LDA, and neural networks. This method serves both communication with deaf individuals and interaction with computers. By utilizing standard letters in sign language for recognition, the system underwent extensive testing on a newly established dataset in the field, achieving an impressive recognition rate of 99.88% through 4-fold cross-validation across 4 training sessions on average. These findings showcase superior accuracy and performance compared to existing methodologies, providing an efficient means of sign language recognition that enhances communication between the deaf community and the broader hearing population.

5) This paper introduces a fresh approach to identifying sign language, employing Principal Component Analysis (PCA) to differentiate static hand positions. Operating at a pace of three frames per second, the technology identifies these static positions from live video feeds. It does so by analyzing three consecutive frames and cross-referencing the outcomes with a pre-existing database of gestures. Through real-time trials, the method demonstrated an approximate 90% matching rate, emphasizing its effectiveness in aiding communication with those who have hearing impairments.

6) This paper introduces a comprehensive system for recognizing Sign Language (SL) utilizing Hidden Markov Models (HMMs). By analyzing trajectories and hand-shape characteristics extracted from sign language videos, the system converts SL into either text or speech. Introducing a novel trajectory feature termed "enhanced shape context," the authors capture both spatial and temporal dynamics. Hand regions are delineated using Kinect mapping functions and characterized by HOG (processed via PCA).

7) The paper outlines a flexible framework based on GMM as Gaussian Mixture Model or also known as HMMs full-formed as Hidden Markov Models (HMMs) tailored for vision-based sign language recognition (SLR) with the aim of improving recognition accuracy. Adaptive Hidden Markov Models (HMMs) are introduced by the authors considering the difficulties of sign language and the dearth of available data. They use affinity propagation clustering to calculate the number of hidden states for each sign. Additionally, by adding Gaussian random disturbances to the training dataset, they propose a data augmentation strategy to enhance it. Comparing the suggested approach to alternative algorithms, experimental evaluations using a lexicon with 370 indications attest to its effectiveness.

8) An approach for video-based sign language recognition that can distinguish between distinct signs is described in the document. Recognizing 262 distinct signs that are specific to each signer highlights the manual features of sign language. Using doubly stochastic processes with hidden state sequences, the system represents sign language using hidden Markov modeling. Feature vectors taken from video frames are used to support observations. The remarkable recognition rates, which reached a maximum of 94%, highlight how effective this technique is at identifying individual signs in video-based sign language diagnosis.

9) The device recognizes 26 American Sign Language (ASL) movements instantly by using surface Electromyography (EMG) data collected from the subject's right forearm. The method performs feature extraction to retrieve pertinent hand movement characteristics associated with each ASL gesture after filtering the raw surface EMG data.

10) Using Hidden Markov Models (HMMs), the research presents a novel approach to picture preprocessing and feature extraction in Sign Language Recognition (SLR). With the help of a multi-layer neural network, the method uses the Cb and Cr color components of sample pixels to create a predicted skin model. In order to precisely identify and extract the hand region from each image, gesture films are segmented into image sequences and converted into the YCbCr color space.

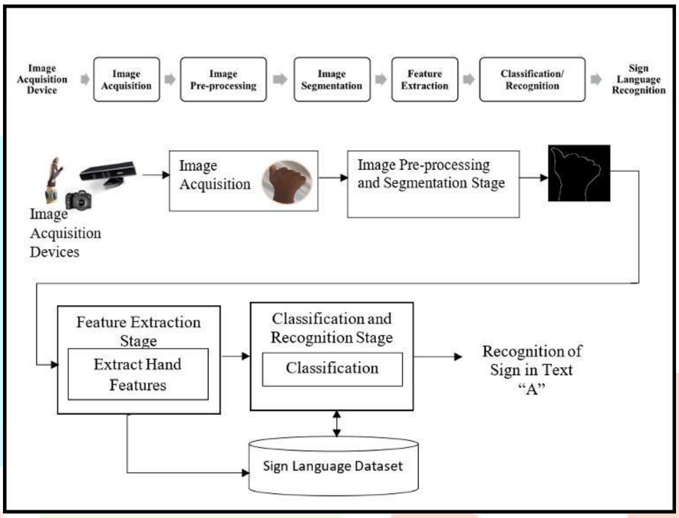
III. Proposed Framework

3.1Technology Used

Our proposed system utilizes Convolutional Neural Networks (CNNs) for sign language recognition, which involves capturing various hand gestures through video and converting them into frames. Subsequently, hand pixels are segmented, and the resulting images are compared to a trained model for recognition. This ensures the accuracy of text labels for letters.

The sign language recognition process comprises four key steps: data acquisition, pre-processing, feature extraction, and sign recognition. To implement our project, we begin by assembling a dataset containing numerous images depicting different signs. Once the dataset is compiled, it is divided into training and test data sets. The training data is used to train the algorithms, while the test data is employed to evaluate the efficiency of the algorithm.

3.2 Flowchart for the proposed study



IV. Methodology

4.1 Dataset Used

An array of varied Indian Sign Language hand gestures is required to develop the Sign Language to Text Conversion System. Using the Media Pipe library, which allows for real-time hand motion tracking, and a webcam, this dataset was gathered. Important spots on the user's hand can now be easily identified thanks to this. Afterward, the webcam records these motions and saves them as data samples, which are then assembled into datasets. With the help of this assembled dataset, the machine learning model that is in charge of identifying hand gestures and translating them into text is trained.

A broad and representative dataset spanning a wide range of hand gestures and movement variations is needed to ensure the system's efficacy and precision. To keep the dataset up to date and faithful to Indian Sign Language, continuous data collecting is essential. Using the webcam and Media Pipe library to their full potential allows the collection of high-quality data samples that are essential for developing a reliable and accurate Sign Language to Text Conversion System.

4.2 Data pre-processing

The pre-processing stage plays a crucial role in developing the Sign Language to Text Conversion System. Its main goal is to prepare hand gesture images for optimal use by the machine learning model, facilitating accurate recognition and translation of these gestures into text. Various adjustments are applied to the images during preprocessing to enhance their suitability for input into the machine learning model.

Initially, the hand gesture photos undergo transformations, resizing, and normalization. Resizing ensures consistent proportions across images, making processing easier for the model. Normalization addresses inconsistencies in background, lighting, or coloration, which could otherwise impede the model's performance. Additionally, techniques like cropping or rotation may be employed to minimize data variance and standardize the model's perspective of hand movements, thereby improving recognition.

Following pre-processing, the photos are ready for use in training and testing the machine learning model. By using pre-processed photos as input, the model learns the relationship between hand movements and the corresponding text, enabling precise translation. Ultimately, preprocessing enhances the Sign Language to Text Conversion System, facilitating meaningful interaction for individuals with speech and hearing impairments.

4.3 Labelling Text Data

Hand movement annotation is a crucial step in building the Sign Language to Text Conversion System. Throughout this procedure, a label designating the associated word or phrase is applied to every gesture contained in the dataset. For the machine learning model to recognize and convert gestures into text, it needs this categorization in order to supply the essential knowledge. In Indian Sign Language, labels follow the accepted vocabulary and grammatical conventions. Ensuring accuracy and consistency, they are allocated by a skilled person who is conversant in Indian Sign Language. Labelling is still primarily done by hand; however, computer vision techniques can help and even automate some steps of the process.

The hand gestures can now be used to train and assess the machine learning model after they have been labelled. The tagged dataset gives the model the knowledge it needs to comprehend how motions relate to the text they correspond with, facilitating precise translation. When properly labelled, the Sign Language to Text Conversion System can be a very useful tool for helping people who have speech and hearing problems communicate with each other.

4.4 Training and Testing

Throughout the training phase, the model is fed pre-processed images of hand gestures together with the text labels that go with them. With each new batch of data it processes, the model iteratively refines its parameters in order to better understand the relationship between the hand movements and the text. The primary goal of the training phase is to enable the model to accurately recognize and interpret hand gestures into text.

V. Application

Sign language has many important and varied uses in the fields of communication, education, accessibility, and technology, among others, when it comes to text conversion projects. Here are a few noteworthy uses:

1. **Accessibility in Communication**: Sign language to text conversion technology empowers individuals who are deaf or hard of hearing to communicate effectively with those unfamiliar with sign language. This applies to interactions in public settings, workplaces, healthcare facilities, and social gatherings.
2. **Education**: In educational environments, sign language to text conversion systems promotes the inclusion of deaf or hard of hearing students by providing real-time transcription of lectures, classroom discussions, and educational videos. This ensures equal access to educational materials and opportunities.
3. **Remote Communication**: With the increasing prevalence of remote work and virtual meetings, sign language to text conversion technology allows sign language users to participate in video conferences, webinars, and online discussions. Real-time transcription of sign language facilitates communication with remote colleagues, clients, or students.
4. **Training and Skill Development**: Projects that translate sign language into text offer useful training tools for people as sign language learners. These tools help students become more proficient in sign language by providing instant feedback and instantly transcribing hand gestures.
5. **Assistive Devices**: Accessibility for those who can't listen properly, hear hard is improved when assistive technology, such as smartphones, tablets, and wearables, include sign language to text conversion features. On their devices, users can obtain real-time transcription of sign language, facilitating more fluid communication in a variety of settings.
6. **Customer Service and Support**: Businesses and service providers leverage sign language to text conversion technology to enhance accessibility for deaf or hard of hearing customers. For instance, customer service centers may offer video chat support with real-time transcription of sign language, ensuring effective communication and support for all customers.

7. **Emergency Services**: Sign language to text conversion systems can be integrated into emergency response systems to facilitate accessible communication during emergencies. Deaf or hard of hearing individuals can communicate their needs and receive assistance from emergency responders through sign language interpretation and text transcription.

VI. Conclusions

The project's goal is to address the barriers to communication that people with speech and hearing impairments face. The technology reduces user stress and increases efficiency and accuracy by automating the recognition of sign language, which can be complex for non-signers. We work to construct this system by utilizing basic picture attributes and image processing principles and libraries. In this study, a vision-based method for translating hand motions from sign language into text is described. The suggested method demonstrates the ability of RNN models to identify hand motions through real-time testing. Subsequent work will focus on improving the system even more and running tests using large-scale language datasets.

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