IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.53
Volume 4, Issue 3, October 2024

Sign Language Detection with Voice Command

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Abstract*: The process of recognizing and deciphering the movements, gestures, and symbols used in sign language is known as sign language detection. This device facilitates communication between those who are deaf or hard of hearing and those who are not familiar with sign language. It functions by examining video footage and identifying important elements such as body language, face expressions, and hand and arm movements. Using machine learning, particularly convolutional neural networks, signs and gestures may be classified with 95–98% accuracy. Its utility can be increased by including record and history tabs, and the dataset can be modified to accommodate various sign languages. This technology has the potential to significantly enhance communication and education for those who are hard of hearing.*

Keywords: Detection, Recognition, Movements, Symbols, Gestures, Communication in Sign Language;

I. INTRODUCTION

For those who are deaf or hard of hearing, as well as others who do not understand sign language, sign language recognition technology is essential to enhancing accessibility and communication. In order to promote easy communication, this technology is being utilized in public areas more and more. Using a common camera to record gestures, a recent study presented an automatic approach for identifying one-handed and two-handed static glyphs in Indian Sign Language (ISL). With a unique ISL character present in every input image, the system concentrates on identifying isolated indications. Two datasets—one containing 2340 motions for two-handed characters (A-Z) and another containing 3000 photos of one-handed characters—were generated in order to handle real-world situations. Structural features, local histogram features, and grayscale pixel values were extracted from the gestures and used as input for the recognition system. The system employed a CNN classifier and a neural network classifier, achieving a recognition rate of 95.30% and 96% accuracy on the one-handed dataset, but only 37% recognition on the two-handed dataset.The motions were processed to extract structural information, local histogram features, and grayscale pixel values, which were then sent into the recognition algorithm. The system used a CNN classifier and a neural network classifier, and on the one-handed dataset, it achieved a recognition rate of 95.30% and 96% accuracy, whereas on the two-handed dataset, it only achieved 37% recognition.

Both accessibility for those with hearing impairments and human-computer interaction could be greatly improved by this technology. Communication in public places like government offices, schools, and hospitals can be made easier by using cameras and computer systems that can recognize sign language. The recognition system for Indian Sign Language serves as an example of how technology can facilitate efficient communication between people with different skill levels. Through precise gesture recognition and interpretation using structural, histogram, and pixel data, this system can significantly contribute to accessibility improvements and facilitate public communication for those with hearing impairments. A more inclusive and equitable society where everyone has access to communication and information is fostered by such technology, which helps bridge the communication gap between people with varied capacities.

Systems that recognize sign language can improve social and professional interactions for those who are hard of hearing, promoting greater inclusivity. In addition to fostering equality and diversity, these systems offer better access to healthcare, education, and employment possibilities. Barriers that restrict the potential of individuals with hearing impairments can be eliminated via the use of this technology. Such technologies can also help persons who speak different languages and cultures communicate with each other across linguistic divides. All things considered, there are

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many benefits to sign language recognition, which can significantly improve the lives of those who are hard of hearing while also encouraging diversity and inclusivity in society.

The study emphasizes how important sign language recognition technology is for enhancing accessibility and communication for those who are hard of hearing. It emphasizes how significant the recent advancement of an automatic ISL recognition system that interprets gestures utilizing cameras and computer systems is. By using feature extraction techniques, this technology greatly improves communication in public settings including government offices, schools, and hospitals. This technology helps create a more equal society where everyone has access to communication and knowledge by making communication easier.

By removing obstacles that prevent people with hearing impairments from accessing healthcare, education, and work, sign language recognition technology can help. Additionally, it can break down linguistic barriers across cultures. Technology that recognizes sign language has enormous potential to increase accessibility and communication for people who are hard of hearing. The accuracy and efficiency of these systems are always being improved by ongoing developments in this field, such as feature extraction and classification techniques. Research papers and related studies are readily available and offer insightful information for future innovation in this area. As these technologies advance, they will encourage more inclusivity by providing those with hearing impairments with more opportunities and access to necessary services.Therefore, by promoting diversity, inclusivity, and accessibility, sign language recognition technology has the potential to have a big influence on the lives of people with hearing impairments. We may expect these systems to be used increasingly more extensively and effectively in the public and private sectors as long as technology continues to improve.

II. LITERATURE SURVEY

Sr No	Title	Authors	Journal/ Conference	Year	Summary	Key Technologies/ Algorithms	Accuracy/ Performance
1	IMU-Based Hand Gesture Interface Implementing a Sequence-Matching Algorithm for the Control of Assistive Technologies	Frédéric Schweitzer, Alexandre Campeau-Lecours	Signals	2021	Development of an open-source interface for ATs control using a sequence-matching algorithm, with hand gestures captured by an inertial measurement unit (IMU).	Sequence-matching, SVM, Inertial Measurement Unit (IMU)	85% Accuracy
2	A Sign Language Recognition System for Helping Disabled People	HridoyAdhikari, Md. Sakib Bin Jahangir, et al.	IJARSCTE	2022	Focuses on the development of a sign language recognition system to assist disabled individuals, using image classification and machine learning techniques.	Machine Learning, Image Classification	91.67% Accuracy
3	Deep Learning Approach for Sign Language Recognition	BambangKrismonoTriwijoyo, LaluYudaRahmaniKarna	JurnalIlmiahTeknikElektroKomputerdanInformatika	2023	Development of a real-time hand sign language recognition system for the alphabet using a	Deep Learning, CNN, Image Processing	99% Accuracy

		en, AhmatAdil	(JITEKI)		CNN model, trained on 87,000 images.		
4	Sign Language Recognition for Mutism People	A.A. Nibe, G.K. Kotwal, et al.	IJARIIE	2024	A portable device for mutism people that uses flex sensors and an accelerometer to detect gestures and communicate via Bluetooth to an Android app, which speaks the detected message.	Flex Sensors, Accelerometer, Bluetooth	85% Accuracy
5	Sign Language Detection in Voice Output	NitinBarsagde, Ajay Deshmukh, et al.	IJARSCT	2023	Focuses on the detection of sign language gestures and movements using machine learning techniques, with an accuracy rate between 80-90%.	Machine Learning, CNN, Video Data Analysis	80-90% Accuracy
6	Sign Language Recognition using Machine Intelligence for Hearing Impairment Person	V. Gowtham, S. Karthick, T. Karthikeyan, P. Elayaraja	IJRASET	2023	Real-time vision-based system for recognizing hand signs using CNN and providing voice output for hearing-impaired individuals.	Convolutional Neural Networks, AI, Finger Detection	85% Accuracy
7	Real-Time Gesture Recognition for Sign Language Using CNN	P. Suresh Kumar, A. Nagalakshmi, et al.	IJERT	2023	Focuses on recognizing hand gestures in real-time for Indian sign language using CNN, addressing varying light conditions and occlusions.	CNN, Image Processing, Real-Time Detection	92% Accuracy
8	Hand Gesture Recognition System for Deaf and Mute People Using Machine Learning	VaibhavShelar, Sneha Thakur, et al.	International Journal of Engineering Research & Technology (IJERT)	2022	Designed to recognize and classify hand gestures for deaf and mute people using machine learning models, providing text and speech output.	Machine Learning, Gesture Recognition, SVM	85% Accuracy

III. METHODOLOGY

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are an effective tool for image processing, which includes technologies for recognizing sign language. Each layer of the network is made up of many separate neurons, and they are made to handle either 2D or 3D data. The number of factors involved is decreased because these neurons are connected to

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neighboring layers but not to the same layer. The design can be made more appropriate for image recognition applications, such as sign identification, by storing and reusing weights. CNNs are capable of learning features and filters to identify objects and prioritize various parts of an image with sufficient training. They are therefore a vital tool in sign language identification technology since they are very good at recognizing significant aspects of sign language motions. Communication between those with hearing impairments and those who do not understand sign language can be facilitated by the use of CNNs in sign language recognition technology, which can greatly increase recognition accuracy and efficiency. All things considered, the use of CNNs in sign language recognition technology has several advantages because of their capacity to process massive volumes of data and their precise recognition and interpretation of sign language motions, which eventually promotes more open and accessible communication.

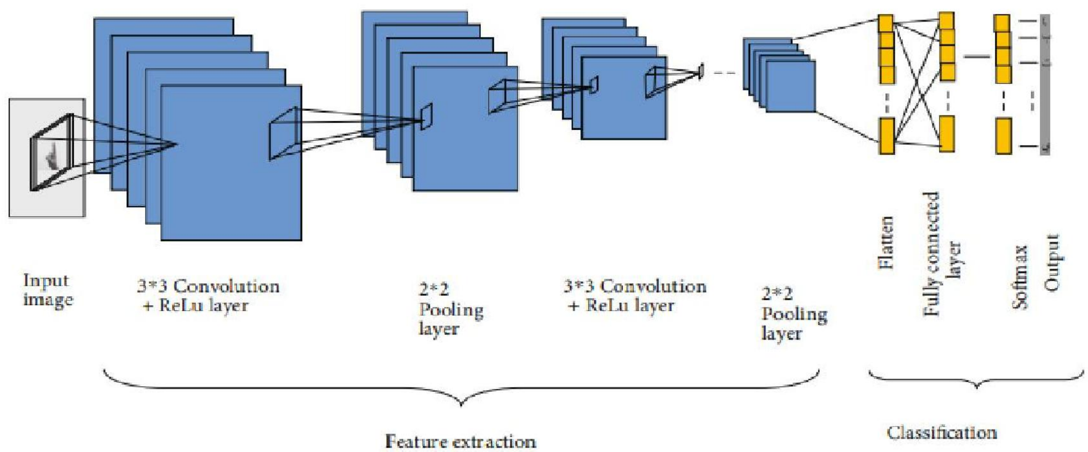

Figure1. Convolutional Neural Networks (CNNs)

Data Preprocessing

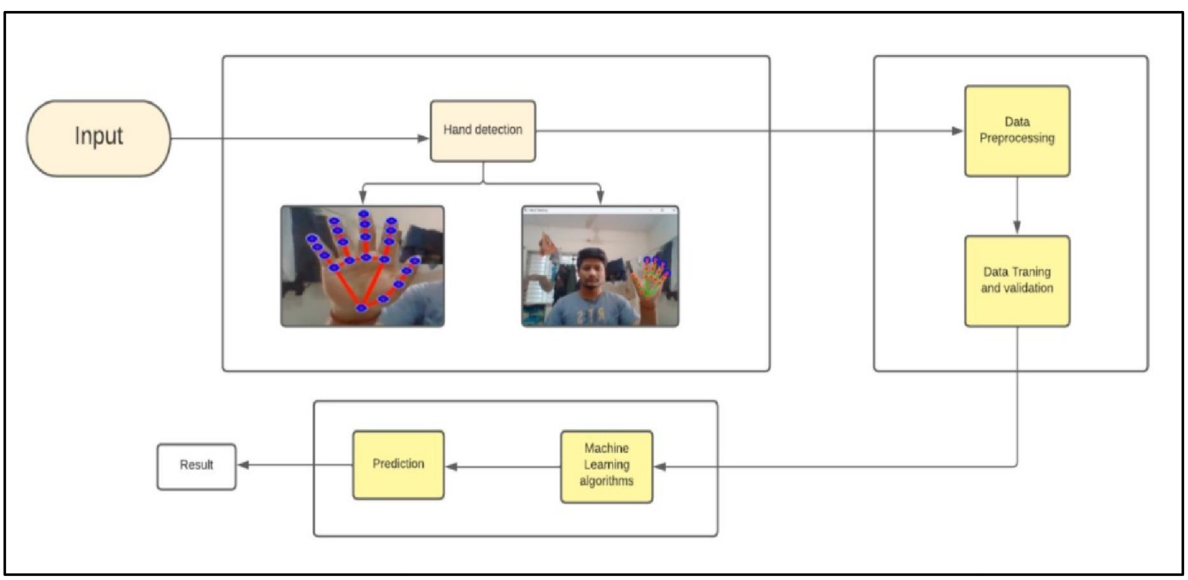

Figure 2. System Architecture

Building a successful deep learning model starts with data preprocessing. Converting raw data into an effective and useful format is its main goal. The procedure consists of multiple steps, as shown in Figure 1, and starts with gathering unprocessed pictures of hand signs with a camera in various settings, such as changing lighting, angles, object sizes,

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and distances. After that, these unprocessed photos are categorized into 31 groups (Figure 3), each of which stands for a letter of the alphabet, and kept in a subfolder inside the largest folder named "dataset." To concentrate only on the hand portion of the image, it is vital to eliminate extraneous features because the hand sign images have different backgrounds and sizes. The photos are then prepared for usage in the training and testing phases of the suggested system after being shrunk to 128 x 128 pixels and converted to RGB format. Thirty-one sample photos from the dataset created for this purpose are shown in Figure 3.

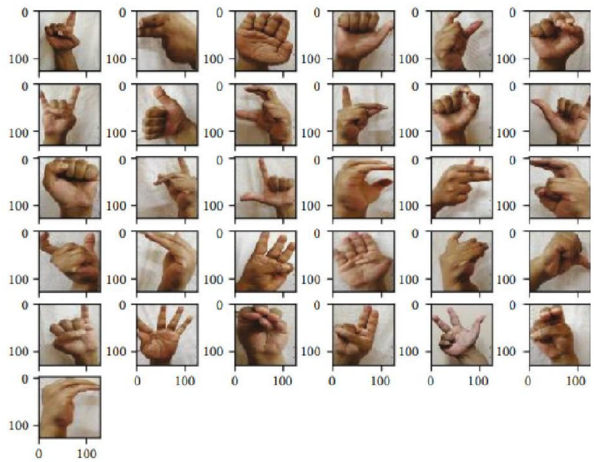

Figure 3. Sample Images for Preprocessing

All things considered, the preprocessing phase is essential to producing a dataset fit for deep learning model training. It removes any unnecessary elements that can impair the model's performance and guarantees that the data is in a format that the system can evaluate efficiently.

Shifts, flips, shears, and rotations are some of the processing techniques used in image augmentation to produce false images in order to enhance deep network performance. Image augmentation is required because real-time data is frequently erratic and unexpected due to different transformations. The suggested approach randomly shears photos with a range of 0.2 degrees and rotates them from 0 to 360 degrees. Some pictures are also horizontally flipped. A snapshot of the augmented photos is shown in Figure 3.

Data Transformation

In order to accurately classify various sign languages, hand movements and positions are examined through data transformation, a crucial step in sign language identification. The hand's center of gravity (COG) serves as an extra reference point, and a fixed point of reference is selected for the hand's contour. Finding local maxima in the distance vector allows for the extraction of location, and the distances between various locations on the contour are computed with respect to the COG. To cut down on noise from picture quantization and contour extraction techniques, a moving average filter is employed. The RGB color space is first transformed into a grayscale image and then into a binary image to distinguish between foreground and background pixels in order to improve image analysis even more.

This conversion creates a sharply detailed image, and skin color recognition and region clustering techniques are used to reject small objects. The nearest neighbor method is used to fine-tune the hand movement trajectory that results. Hearing-impaired people can communicate more easily by using the model described in the text for sign detection and recognition.By predicting which sign is shown frame by frame, this model can be used as a captioning tool for video communications. Additionally, it can precisely identify changes in motions, which improves the way American Sign Language (ASL) interprets the words that are shown. By recognizing not only individual signs but also phrases, this model might be used to create a fully effective sign language translator, which would greatly enhance virtual communication for those who are hard of hearing. This model's implementation entails detecting and identifying sign language gestures using computer vision techniques. The system uses a camera to record visual data, which is subsequently analyzed by deep learning methods like Long Short-Term Memory (LSTM) models and Convolutional

Neural Networks (CNNs). By breaking up the video input into separate frames, the model is able to anticipate the sign that will appear in each frame and, consequently, the full phrase that will be signed.

There are many advantages to this technique. First of all, by facilitating efficient communication in virtual settings, it enhances accessibility for people with hearing impairments. Second, by removing language barriers between those who understand sign language and those who do not, it encourages inclusive communication. Thirdly, it gives the hearing-impaired people a dependable way to communicate, which improves their quality of life. Additionally, it gives hearing-impaired people additional options in a variety of industries, such as healthcare, work, and education.

In conclusion, the implementation of this paradigm has enormous potential to improve communication and accessibility for those who are hard of hearing. Its accurate identification of sign language words and gestures could lead to the development of a fully functional sign language translator, greatly improving virtual communication for the hard of hearing. In addition to enhancing communication, this technology improves the general quality of life for those who are hard of hearing.

IV. CONCLUSION

In conclusion, deaf people can effectively communicate by gestures with the help of the suggested sign language detection system. With a 95–98% accuracy rate on the ASL alphabet dataset, the system presents a viable way to decrease the communication gap between the hearing and the deaf. Users can communicate with the system more easily because to the "talk back" feature and the application's user-friendly user interface. Even if the model has drawbacks including dim lighting and unmanaged backgrounds, more study and advancement can increase the system's accuracy. All things considered, the suggested system might improve the lives of those who are deaf.

V. ACKNOWLEDGEMENT

We would like to express our heartfelt gratitude to **Prof. H. S. Borse** for their invaluable guidance and support throughout this research. We also extend our sincere thanks to **Pune VidyarthiGriha's College of Engineering, Nashik** for providing the necessary resources and environment to carry out this study. Lastly, we are grateful to our peers and families for their constant encouragement.

VI. FUTURE SCOPE

Future advancements and enhancements to the suggested sign language detecting system are possible. Increasing the system's accuracy is one of the main topics of this project's future scope. Adding more images and unique motions to the dataset will increase the system's accuracy even more. This can improve the model's ability to identify signs in various backdrops and lighting situations.

Creating a mobile application: By incorporating the suggested method into a mobile application, deaf people can access and utilize it more easily. Additional functions like text-to-speech and speech-to-text capabilities can also be added to the mobile app.

Including natural language processing: By incorporating natural language processing methods, the system's accuracy and functionality can be enhanced by better comprehending the context and meaning of signs and gestures.

Using deep learning methods: More sophisticated models for sign language recognition can be created by utilizing deep learning methods like recurrent neural networks (RNNs) and convolutional neural networks (CNNs).

Adding support for additional sign languages: The suggested system can be expanded to identify and interpret additional sign languages from across the globe, providing a genuinely worldwide deaf communication solution.All things considered, the suggested sign language detection system has enormous potential for advancement and can greatly enhance the quality of life for deaf people by giving them an efficient means of communication with other

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