

# Sign Language Detection using ML Technologies

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**Abstract:** Sign language recognition is a leap forward for helping deaf-mute people. In sign language, every sign has a meaning assigned to it, so that it becomes easy to understand and interpret by the people. The main primary objective of our project is to bridge the gap between the deaf and dumb people and ordinary people without the need of an intermediary translator. Gesture recognition is a computer based visual technique used to detect and identify the object in an image or video. An application of this gesture recognition technique involves translating the sign language into the American language which can be further understood and interpreted by normal people. Many researchers have proposed their systems for the implementation of the ASL system. This report is a review of some studies related to the same topic. We addressed different approaches that used Convolutional Neural Networks (CNNs), K-Nearest Neighbours algorithm (KNN), Edge detection algorithm, Deep Neural Network (DNN), fuzzy clustering machine learning algorithm, Kernelized correlation filters (KCF) algorithm along with their results and drawbacks. Furthermore, we report on research gaps while summarizing these studies. From the above research papers, we got an average accuracy of 90.24%. To overcome the drawbacks, we propose a system which collects images for deep learning using webcam and OpenCV, with the help of TensorFlow Object Detection and Python that allows you to translate sign language in real time

**Keywords:** ASL, TensorFlow, Python, OpenCV

## I. INTRODUCTION

Sign language (SL) is the basic means by which deaf and mute people communicate with the normal people. As normal people cannot understand the sign language used by dumb people, it is difficult to understand the message conveyed by the dumb/deaf people. Gesture recognition is a technology that uses sensors to read and interpret hand movements and translate them in the form of text which can be interpreted by the normal people. Gestures are different movements employed in the communication process. Either the hand or the body makes gestures. Sign language uses gestures that typically use visually transmitted models. Gesture recognition is a computer-assisted visual technique that makes it possible to detect and identify an object in an image or video. An application of this gesture recognition technique implies translating the sign language into the American language which can be better understood and interpreted by normal people. Recognizing sign language is a step forward in helping people who are deaf-mute. In sign language, each sign has a meaning that is attributed to it, so that it becomes easy for the people to understand and interpret. As there is need of a system which translate the sign language into text which is helpful for the normal people to understand. There is much need of such system to convey the message of deaf and dumb people. The current system which we generated is only based on hand gestures which will detect hand gesture and with the help of different algorithm interpret the text from the given sign.

## II. LITERATURE REVIEW

[1] Amrutha K et al. performed ML Based Sign Language Recognition System in which they use the technique of convex hull method for feature extraction and finally KNN with Euclidean Distance for classification. They made candidates sign in front of the camera in a controlled environment and with the help of the same created dataset for each gesture. This model that they created showed an accuracy of 65%. The model showed less performance when the distance between the camera and the object is not considerable. The detection and recognition were less when the hand was moved at a fast pace.

[2] Soma Shrenika et al. performed two techniques (1) Performing pre-processing steps on the image, that is, convert the acquired image, which is in RGB model to grayscale image. (2) Track the edges by using canny edge detection algorithm. (3) Edge detection algorithm was used to detect the sign in the image. American Sign Language dataset has numbers labelled from zero to nine and alphabets from a to z. This data set has 70 samples for each of the 36 symbols. There are 70 samples for each symbol. The process includes removal of noise and other less important data and applying smoothing algorithm to image and displaying the sign alphabet for the given gesture. The features of ASL are all of right hand only. There is no provision for left hand.

[3] Diksha Hatibaruah et al. used Convolutional Neural Networks (CNNs) to train the system and Histogram Back Projection technique for segmentation of images. To train the system, they have used Indian SL database, consisting of 26 alphabets along with 10 digits. After training they achieved testing accuracy of 99.89% and validation accuracy of 99.85%

[4] Qinglian Yang et al. carried out a gesture recognition system based on the Deep Neural Network (DNN) and the Leap Motion controller. In this paper, a total of 2000 frames of each gesture were collected from each of the 5 volunteers. Dataset is divided in two sets Training and Testing where training set is 20000, and the testing set is 10000. The average precision rate can reach more than 98% at the end of the training. And after 10000 paces, the precision of the model is excellent with the loss function remained below 0.1. The limitation is that here we used the Leap motion controller while the work might also have been done simply using a webcam or any other technique. The use of the controller adds to the total cost of the project.

[5] Muthu Mariappan H et al. performed Training and prediction of hand gestures by applying fuzzy clustering machine learning algorithm. The Regions of Interest (ROI) are identified and tracked using the skin segmentation feature of OpenCV. The data samples were collected for 80 words and 50 sentences of everyday usage terms of ISL. The videos were recorded from ten volunteers of our collaborator school, using a digital camera. This sign language recognition system, for recognizing the words of Indian Sign Language has produced 75 % accuracy in gesture labelling.

[6] Saransh Sharma et al. implemented a system in which Skin color detection has been done in YCbCr color space. They have used Haar Cascade Classifiers and LBPH recognizer for face detection and recognition. A Database named SS100 has been created in which 6-10 images for each person has been stored, in total 100 images are stored. Each image has a different expression and postures. After the testing the model has accuracy of 95.2% and 92% in facial recognition. There are some limitations, which are needed to be addressed. Recognizing a greater number of gestures would be helpful for performing more tasks.

[7] Hung-Yuan Chung performed Kernelized correlation filters (KCF) algorithm to track the detected Region of Interest and they have done Skin segmentation is with YCbCr to remove the unwanted background. For the dataset 800 images were collected for each hand gesture so a total of 4800 training images were used for the training model. The training data set can reach a recognition rate of 99.90%, and the test data set has a recognition rate of 95.61%. The system is limited to only 6 hand gestures.

[8] Felix Zhan implemented a system in which he has used CNN classifier for dynamic hand gesture recognition and Spatio-temporal data augmentation techniques to get an additional 4000 images. The dataset used consisted of 500 images of 9 hand gestures using webcam to evaluate the model. This CNN classifier system showed an accuracy of 98.74% on the data set. The drawback of this system is that the dataset is limited to only 9 hand gestures.

### III. SUGGESTED MODEL

In this research, we present a machine learning-based system for real-time sign language detection. The workflow commences with data acquisition, where we assemble a comprehensive sign language image dataset encompassing a wide variety of signs. This dataset ensures diversity by including variations in lighting conditions, backgrounds, and signer characteristics. To prepare the data for model training, preprocessing steps are implemented. These steps, such as resizing, normalization, and noise reduction, guarantee consistency within the data and optimize the model's training efficiency. Following preprocessing, a critical step involves meticulously assigning labels to each image. This meticulous process establishes a well-defined mapping between the visual data and the corresponding signs they represent. The core of the system lies in the machine learning model itself. Given the image classification nature of sign language detection, we leverage a convolutional neural network (CNN) architecture. The specific details of this CNN

architecture, including the number and type of convolutional and pooling layers, will be outlined in a subsequent section. Finally, the model undergoes a rigorous training process using a pre-selected optimizer, loss function, and a predetermined number of training epochs. Hyperparameter tuning strategies may also be implemented to further enhance the model's performance. This comprehensive workflow, from data acquisition to model training, lays the foundation for our sign language detection system.

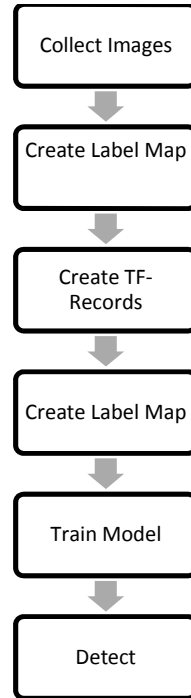


Figure 1: Basic flowgraph depicting the workflow of the system

#### IV. RESEARCH METHODOLOGY

This research is descriptive in nature and data is gathered using an information retrieval approach.

##### **Problem:**

The problem addressed in this research is the need for effective sign language recognition systems to bridge the communication gap between deaf and hearing individuals. Sign language serves as the primary means of communication for the deaf community, but understanding and interpreting it can be challenging for those who do not know the language. Therefore, there is a demand for machine learning-based systems that can accurately recognize and interpret sign language gestures in real-time, facilitating communication between deaf and hearing individuals without the need for an intermediary translator.

##### **Study:**

The study focuses on reviewing existing literature and research methodologies related to sign language recognition systems. It examines various approaches and techniques employed in previous studies, including Convolutional Neural Networks (CNNs), K-Nearest Neighbours algorithm (KNN), edge detection algorithms, Deep Neural Networks (DNNs), and fuzzy clustering machine learning algorithms. The study analyzes the performance, accuracy, and limitations of these approaches to identify gaps and opportunities for improvement in sign language recognition technology.

##### **Research Design:**

The research design involves developing a machine learning-based system for real-time sign language detection. It encompasses several key components, including data acquisition, preprocessing, model selection, training, evaluation,

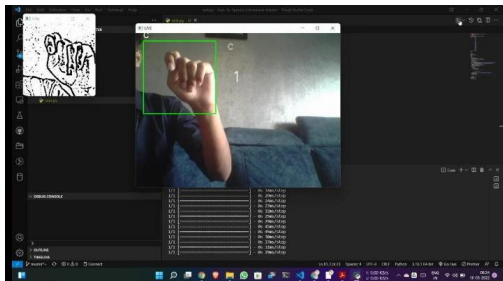
system integration, performance optimization, validation, and documentation. The design aims to address the specific challenges and requirements associated with sign language recognition, such as variations in hand gestures, lighting conditions, and background noise.

**Preprocessing:**

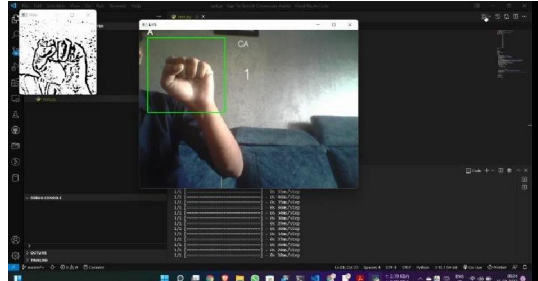
In the preprocessing stage, several steps are implemented to prepare the sign language dataset for model training. These steps include resizing the images to a standardized resolution, normalizing pixel values to enhance consistency, and reducing noise to improve the quality of the input data. Additionally, techniques such as edge detection and image enhancement may be employed to enhance the visibility of hand gestures and improve the accuracy of the recognition system. The preprocessing stage plays a crucial role in ensuring that the input data is clean, consistent, and suitable for training machine learning models.

**V. RESULTS**

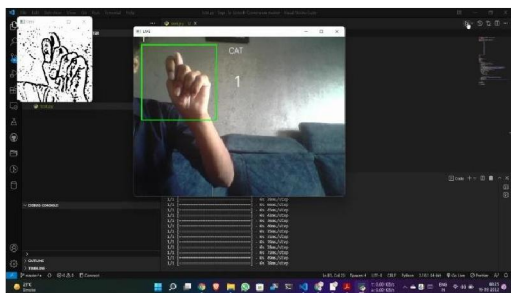
The sign language detection system's functionality is illustrated through a series of figures. Figures 2, 3, and 4 depict the individual hand gestures captured by the system during the signing of the word "CAT." Each figure likely corresponds to a single frame extracted from the video input, showcasing the hand postures associated with each letter of the word. Finally, Figure 5 presents the final recognized word, which is expected to be "CAT" based on the sequence of identified signs. This visual representation demonstrates the system's capability to accurately segment and classify individual signs within a continuous signing sequence, ultimately leading to successful word recognition.



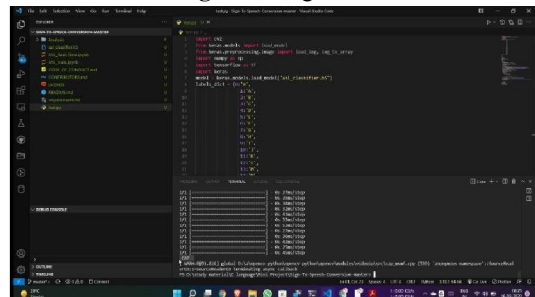
**Figure 2: Sign for "C"**



**Figure 3: Sign for "A"**



**Figure 4: Sign for "T"**



**Figure 5: Recognized Word "CAT"**

**VI. CONCLUSION**

This paper presented a novel machine learning approach for sign language detection, aiming to bridge the communication gap between deaf and hearing individuals. The proposed system leverages a pre-trained sign language classifier model (asl\_classifier.h5) to identify signs from video inputs captured by webcams or mobile phone cameras. This research contributes to the development of inclusive communication technologies by offering real-time sign-to-text conversion within practical application domains. The system's design incorporates well-established image processing techniques like grayscale conversion, Gaussian blurring, adaptive thresholding, and image resizing to optimize sign recognition accuracy. The predicted sign is then mapped to a human-readable interpretation using a dedicated label dictionary. This framework paves the way for integration into various platforms commonly used for

virtual meetings (e.g., Google Meetings, Zoom) and mobile applications, fostering more inclusive communication opportunities for the deaf community.

### VII. FUTURE ENHANCEMENTS

Future research directions can focus on improving the system's accuracy and robustness. Exploring techniques for handling background noise, variations in lighting conditions, and signer individuality can improve the system's generalizability. Furthermore, incorporating finger tracking and hand posture analysis can enable the system to capture the nuances of sign language, leading to a more comprehensive understanding of the conveyed message. Finally, development of a text-to-sign language translation module would complete the two-way communication aspect, fostering seamless interaction between deaf and hearing individuals.

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