SIGN LANGUAGE RECOGNITION MODEL USING MEDIAPIPE AND OPENCV

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Abstract - This research paper addresses the significant communication challenges faced by the global deaf and hard-of-hearing community, comprising approximately 5% of the world's population, totaling 39.5 million individuals affected by hearing and speech disorders. Traditional communication methods fall short for this demographic, prompting the adoption of alternative means such as "Sign Language" or "Finger Spelling," utilizing gestures and movements for expression. To overcome these challenges, the study employs Convolutional Neural Networks (CNNs) to develop a robust model capable of recognizing hand signs. CNNs, tailored for image processing, exhibit unparalleled proficiency in image recognition and processing. Notably, this research employs two distinct methods for dataset collection, utilizing both Google's Mediapipe for using handtracking and hand landmark points and second method uses Imgae process using OpenCV. Google's Teachable Machine is used for model development, training the models with the prepared dataset, experimenting with different network architectures and hyperparameters to improve the model's accuracy. Additionally, a user-friendly webpage hace created to disseminate information about American Sign Language (ASL), contributing to increased awareness and accessibility for users worldwide.

Index Terms - Convolutional Neural Networks (CNN), American Sign Language (ASL), Ajax, Flask, Open Source Computer Vision Library (OpenCV), Mediapipe

I. INTRODUCTION

In 2022, the world population reached 7.9 billion. Although the vast majority of people can communicate, 5% of the world's population (including approximately 39.5 million people) has hearing and speech impairments, making communication difficult. But as the saying goes, there is a need to innovate, and a solution has emerged for this population: Sign Language, also recognized as Finger Spelling.

This research promises a better way to recognize sign language, including collecting dataset, pre-processing those data, training the models, comparing their performance well, and the deployment on webpage. Two different methods were used to collect data. The first method uses Mediapipe for hand tracking and hand landmark to capture real-time hand signs corresponding to all 26 ASL alphabets. The second method, uses OpenCV to process images, generating a dataset using grayscale, Gaussian-blurr, and adaptive threshold of sign language gestures. These datasets function as the foundational training material for Convolutional Neural Networks (CNNs).

After training the data using CNN on Google's Teachable Machine, an evaluation of the accuracy of the model on this data is analyzed, then the best model for deployment is selected. The selected models have been compiled into a user-friendly website using Flask, a great Python library. This web platform facilitates real-time sign language recognition, enhancing accessibility for individuals reliant on sign language. Users are provided the flexibility to opt for either images or videos, catering to their individual preferences.

This research is a step towards improving the understanding and accessibility of sign language in our global community. This is the use of technology to bridge the communication gap and ensure that everyone has the opportunity to be heard and understood, regardless of how they communicate.

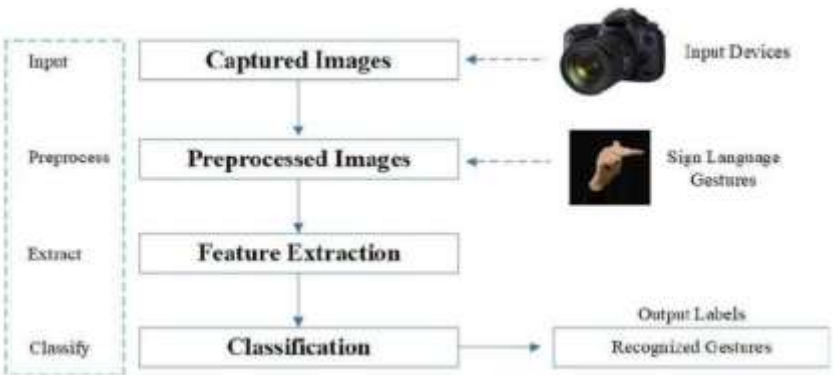

Fig. 1. Steps involved in the Sign Language Recognition

II. DETAILED METHODOLOGY

(1) Data Collection and Preparation

In the initial phase of this research, the primary focus was on gathering the necessary data for training the sign language recognition model. A custom code was developed using the OpenCV framework to capture live video from a webcam, identify and process hand images in real-time, and allow users to save the processed hand images for building a dataset essential for training the model. This code demonstrated the practical aspects of collecting and preprocessing hand images, a critical step in preparing data for subsequent machine learning model training.

2 methods were used for collecting dataset.The first method uses Mediapipe for hand tracking and hand landmark to capture real-time hand signs corresponding to all 26 ASL alphabets. The second method, uses OpenCV to process images, generating a dataset using grayscale, Gaussian-blurr, and adaptive threshold of sign language gestures.

(1.1) Using Google's Mediapipe

- Mediapipe, an open-source framework developed by Google, serves as a valuable tool for processing perceptual data, such as video and audio. In this research, we utilize the MediaPipe Hands module to track hand movements.

- Within the MediaPipe framework, the BlazePalm model serves as a dedicated palm detector, addressing the initial complexities associated with hand detection. The methodology involves training the palm rather than the hand detector. Subsequently, the non-maximum suppression algorithm is applied to the detected palms, which are modeled using square bounding boxes to eliminate other aspect ratios, thereby reducing the number of anchors by a factor of 3-5. To enhance scene context-awareness, an encoder-decoder feature extraction mechanism is employed, benefiting even smaller objects.

- The Hand Landmark model in MediaPipe achieves precise keypoint localization by identifying 21 key points with 3D hand-knuckle coordinates within the detected hand regions through regression. Each hand-knuckle landmark has coordinates composed of x, y, and z, where x and y are normalized to [0.0, 1.0] by image width and height, and z represents the depth of the landmark. The depth of the landmark found at the wrist serves as the ancestor point. Notably, the closer the landmark is to the camera, the smaller the corresponding value becomes.

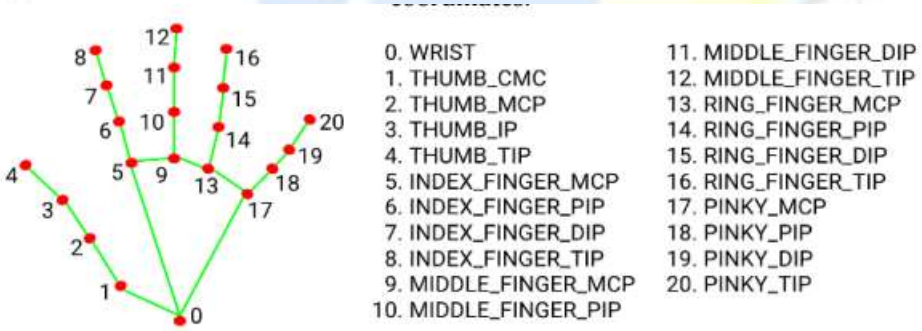

Fig 2. Hand Landmark Points

(1.2) Using Image Processing by OpenCV

- OpenCV, or Open Source Computer Vision Library, is an open-source computer vision and machine learning software library. Developed by Intel, it provides a comprehensive set of tools, functions, and algorithms for real-time computer vision applications. OpenCV is widely used in various domains, including robotics, image and video analysis, facial recognition, gesture recognition, and machine learning.

- Initially, the collected images undergo grayscaling, converting the colored images into grayscale. Following this, Gaussian blur is applied to eliminate noise and refine the overall image quality. This operation is particularly useful in smoothing irregularities and ensuring a more consistent dataset.

- After Gaussian blur, adaptive thresholding is employed to segment the images into areas of interest. This step is crucial for improving the clarity of hand contours and isolating relevant features for recognition purposes. Adaptive thresholding dynamically adjusts the threshold value, considering the local characteristics of the image, making it effective for handling varying lighting conditions.

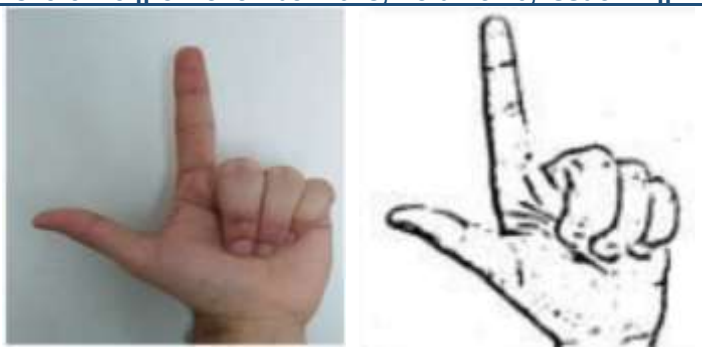

Fig 3. Before and After using OpenCV

(1.3) Dataset using both methods

Fig 4. Using Mediapipe

Fig 5. Using OpenCV

(2) Model Training using CNN

In this phase of research, the task was of training the sign language recognition model. The model training phase involved building CNNs for sign language recognition, utilizing Google's Teachable Machine for model development, training the models with the prepared dataset, experimenting with different network architectures and hyperparameters to improve the model's accuracy. These efforts are aimed at creating a robust and accurate sign language recognition system.

(2.1) Convolution Neural Network (CNN)

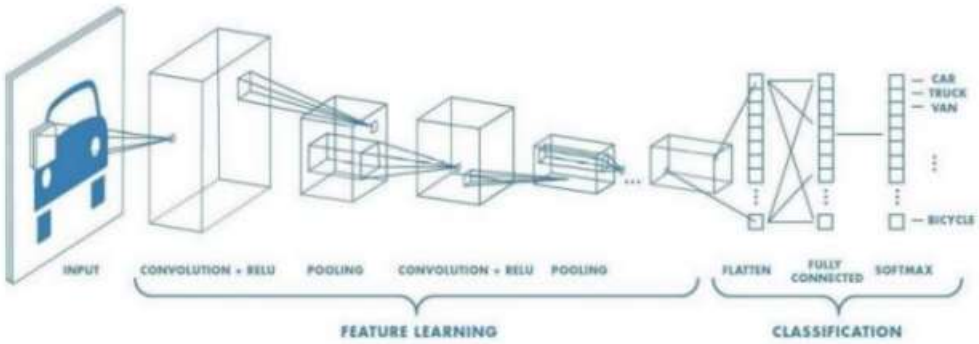

Fig 6. CNN Architecture

A CNN is a deep learning architecture commonly used for image-related tasks. It comprises three main parts:

- **Convolutional Layer:** This is the initial layer in a CNN, responsible for feature extraction. It performs a mathematical operation called convolution between the input image and a filter of a specific size (MxM). The filter, often referred to as a kernel, is slid over the input image to compute the dot product between the filter and image sections. The output of this operation is known as a "Feature Map," which provides information about features in the image, such as edges and corners. These feature maps are then passed to subsequent layers, enabling the network to learn more complex features from the input.

- **Pooling Layer:** Typically, a Pooling Layer follows a Convolutional Layer, and its primary purpose is to reduce the size of the feature maps. This reduction helps in lowering computational costs. Pooling layers operate independently on each feature map and involve various pooling methods, such as Max Pooling (selecting the largest element), Average Pooling (calculating the average of elements), or Sum Pooling (computing the sum of elements within a predefined section). Pooling layers serve as a bridge between the Convolutional Layer and the Fully Connected Layer, simplifying the data while preserving essential features.

- **Fully Connected Layer:** The Fully Connected (FC) layer includes weights, biases, and neurons, connecting neurons from different layers. It's often found just before the output layer and forms the final layers of a CNN. In this layer, the input data from previous layers is flattened into a vector and passed to the FC layer. Within the FC layer, mathematical operations and transformations are applied to the flattened vector. The classification process, which involves assigning labels to the input data (in the context of image classification), begins at this stage.

In addition to these core layers, there are two other crucial aspects:

- Dropout Layer: Dropout is a regularization technique used to prevent overfitting in deep learning models. It randomly deactivates a fraction of neurons during each training iteration, which encourages the network to learn more robust and generalized representations.

- Activation Function: Activation functions introduce non-linearity into the model and help the network learn complex patterns in data. Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh.

(2.2) Google's Teachable Machine

Google's Teachable Machine stands as an accessible and user-friendly platform meticulously crafted to streamline the machine learning model training process. Designed with the aim of catering to individuals with limited or no prior experience in machine learning or individuals who lack the resource to train the machine learning models, this platform represents a commendable effort by Google's Creative Lab.

Training Steps in Google's Teachable Machine:

- Data Input: Users can easily input their data, whether it be images, sounds, or poses, directly into the Teachable Machine interface. This simplicity eliminates barriers for users who may not possess advanced technical skills.

- Labeling: The platform allows users to label the data, providing crucial context for the model to learn and generalize patterns. Clear and concise labeling is pivotal for effective model training.

- Model Training: Teachable Machine simplifies the complex process of model training. Users can effortlessly initiate the training process, with the platform leveraging underlying machine learning algorithms to iteratively refine the model based on the provided data.

- Evaluation and Iteration: The platform facilitates the evaluation of the trained model, allowing users to assess its performance. If adjustments are required, the iterative nature of the training process enables users to refine and enhance the model for better accuracy.

(3) Web Interface Development

In this phase, the focus was on creating a web interface for real-time sign language recognition and deploying the better trained model. This interface is user-friendly and responsive, allowing it to work effectively on various devices. The technology stack used for the frontend and backend development includes HTML and CSS for the frontend, and JavaScript/JQuery for the backend.

- In our research, a seamless connection between the webpage and Python script was achieved through the strategic integration of Flask and jQuery AJAX. This collaborative framework played a crucial role in establishing efficient two-way communication, ensuring a responsive and user-friendly interface

- Flask Implementation: Flask, a lightweight web framework for Python, formed the foundation of our server-side application. Its straightforward design allowed for the creation of RESTful APIs, enabling endpoints that the frontend could use to communicate with the backend. Flask routes were carefully structured to handle incoming requests, process data, and generate appropriate responses.

- jQuery AJAX Integration: On the client side, jQuery's AJAX functionality was harnessed to establish asynchronous communication with the Flask backend. This combination facilitated the smooth transmission of data from the webpage to the Python script and back, enhancing user experience by providing real-time updates without requiring a full page reload.

- Data Flow: The flow of data was orchestrated with precision. User actions on the webpage triggered AJAX requests, which seamlessly traveled to the Flask backend. The Python script processed the incoming data, performed necessary computations, and generated responses. These responses were then efficiently relayed back to the webpage, dynamically updating the user interface without unnecessary delays.

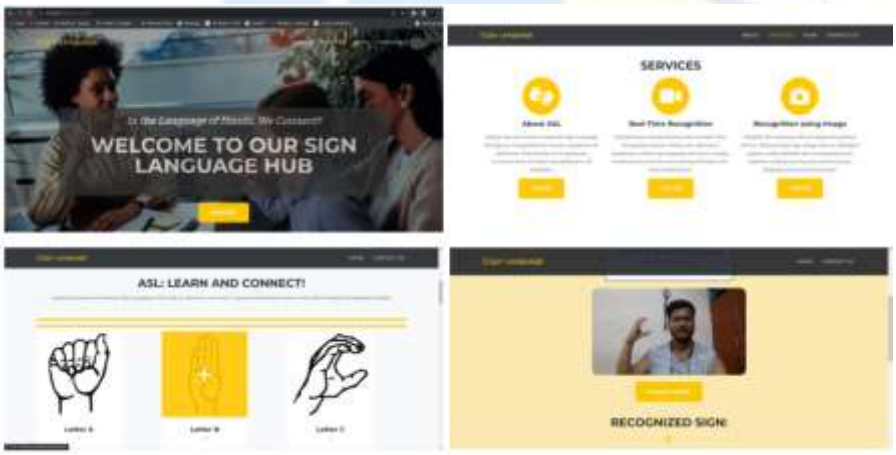

Fig 7. Sample Screenshot of the webpage

(4) Result

The research involved the training of a sign language recognition model using two distinct dataset collection methods: the first utilizing Google's Mediapipe for hand tracking and hand landmark points, and the second employing image processing with OpenCV, incorporating filters such as grayscaling, Gaussian blur, and adaptive threshold. The comparative analysis of these methods revealed varying degrees of accuracy and F-Score.

(4.1) Google's Mediapipe Method:

The model trained on the dataset generated through Google's Mediapipe demonstrated exceptional accuracy, achieving an impressive 99.18% overall accuracy rate. Leveraging the "Handtracking" module and hand landmark points provided by Mediapipe, this method excelled in capturing dynamic hand movements and intricate gestures in real-time video streams. The precision offered by this method makes it particularly advantageous for scenarios requiring real-time recognition of sign language expressions.

(4.2) OpenCV Image Processing Method:

In contrast, the model trained on the dataset created through image processing with OpenCV, applying filters such as grayscaling, Gaussian blur, and adaptive threshold, achieved a respectable accuracy of 88.2%. While this method proved effective, especially in environments with minimal background noise, its overall accuracy fell below that of the Mediapipe-based approach. The success of this method is contingent on favorable conditions, making it imperative to address background noise for optimal performance.

(4.3) Comparative Performance:

The comparative analysis underscores the superior accuracy of the Google's Mediapipe method, particularly in capturing the dynamic aspects of sign language. The OpenCV image processing method, while proficient, exhibits some limitations in scenarios with higher background noise. The research affirms the importance of selecting the appropriate dataset collection method based on specific application requirements and environmental conditions.

(4.4) Accuracy Table:

Accuracy Table	No. of Epochs the model is Trained				
Methods Used for Training		10	25	50	100
	Using Meadipipe	82.5 %	92.1 %	99.18 %	99.26 %
	Using OpenCV	68.3 %	79.6 %	88.2 %	89.8 %

III. CONCLUSIONS

In conclusion, our research delved into the development of a sign language recognition model using two distinct approaches: Google's Mediapipe and OpenCV image processing. The results spotlighted the strengths and considerations of each method.

Google's Mediapipe method emerged as a standout, showcasing exceptional accuracy at 99.18%. This approach, leveraging hand tracking and landmark points, excelled in capturing dynamic hand movements, proving ideal for real-time recognition of sign language expressions. Its precision and versatility make it a valuable choice, particularly for applications requiring instantaneous responsiveness.

On the other hand, the OpenCV image processing method, with an accuracy of 88.2%, demonstrated commendable effectiveness. By employing filters like grayscaling and Gaussian blur, it showcased proficiency, especially in quieter environments. However, its overall accuracy lagged slightly behind the Mediapipe approach, highlighting its sensitivity to background noise.

The comparative analysis accentuates the importance of method selection based on specific needs and environmental conditions. While Google's Mediapipe offers robust performance in dynamic scenarios, OpenCV's image processing method proves reliable in quieter settings. The research sheds light on the nuanced trade-offs between accuracy and environmental adaptability.

As technology continues to advance, our findings contribute valuable insights to the development of accessible and efficient sign language recognition systems. The journey from dataset collection to model training underscores the significance of tailoring methods to the intricacies of sign language expressions. This research serves as a stepping stone, fostering an understanding of the diverse tools available for bridging communication gaps and ensuring inclusivity. In future endeavors, the refinement and integration of these methods will further contribute to creating accessible communication solutions, promoting the universal right to be heard and understood.

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