Educational Learning-Based Sign Language System Using Machine Learning

Vijay. V. Chakole[1], Akansha Kadu[2], Kshitij Meshram[3], Trishala Mendhe[4]

[1,2,3,4] students, Department of Electronics & Telecommunication Engineering KDK college of Engineering, Nandanvan Nagpur, Maharashtra, 440009

---****---

***ABSTRACT*- This study proposes an innovative approach to multicultural education by integrating Indian Sign Language (ISL) and American Sign Language (ASL) through Machine Learning (ML) techniques. By collecting and preprocessing high-quality video data of ISL and ASL, we aim to develop ML models capable of recognizing and generating signs in both languages. Through bidirectional transfer learning and cross-language representation learning, we seek to enhance the learning experience and address common challenges in sign language acquisition. Additionally, personalized learning environments and culturally sensitive design, informed by collaboration with Deaf communities in India and America, ensure inclusivity and accuracy. Evaluation metrics and ethical considerations are integrated into the development process to promote responsible implementation and continuous improvement. Ultimately, this project aims to lay the groundwork for advancing multilingual sign language education globally.**

By employing advanced ML techniques, this study aims to bridge the gap between Indian Sign Language (ISL) and American Sign Language (ASL) education, fostering inclusivity and accessibility in learning environments. Through meticulous data collection, preprocessing, and collaborative development processes, our approach emphasizes accuracy, cultural sensitivity, and personalized learning experiences. By engaging with Deaf communities in both India and America, we ensure the authenticity and relevance of our platform. Evaluation metrics and ethical considerations are prioritized to uphold privacy, consent, and fairness principles. By establishing a robust foundation for multilingual sign language education, this project contributes to broader discussions on leveraging ML for enhancing accessibility and inclusivity in education systems worldwide.

Keywords- Hand Gesture, Sign language Recognition, OpenCV, Media-pipe, tensorflow.

I. INTRODUCTION

In the realm of inclusive education and communication accessibility, a groundbreaking fusion between sign language and advanced technological innovation has emerged—educational learning based sign language utilizing Machine Learning (ML). This innovative approach harnesses the power of artificial intelligence to revolutionize how we teach, learn, and interact with this unique visual-spatial language.

Sign languages are complex systems that convey meaning through hand shapes, body movements, facial expressions, and non-manual signals. They have evolved as natural human languages among deaf communities worldwide, serving as primary modes of communication for millions of individuals. However, traditional methods of teaching sign language often face challenges in terms of scalability, consistency, and individualized instruction.

Enter Machine Learning, which offers promising solutions by enabling personalized, adaptive, and interactive learning experiences tailored to each learner's needs and abilities. By leveraging ML algorithms, educators can develop intelligent tools and resources that enhance the learning process, making it more engaging, effective, and accessible to students from diverse backgrounds.

This emerging field combines the richness of sign language culture with cutting-edge technology, paving the way for new possibilities in education, research, and social inclusion. As we delve deeper into the world of educational learning based sign language using Machine Learning, we will explore its potential benefits, current applications, and future prospects, ultimately shedding light on the transformative impact this convergence is poised to bring about.

Many research works has been developed on sign language recognition but most of the research or work is done on American sign language. Other languages are not explored as much as ASL. ASL is done with single handed sign lamguage, which makes easier to work with , whereas in Indian sign language some signs are performed with one hand and some signs needs both the hands which makes it complex to work with it and we have been going to developed combined ASL and ISL recognition system which is originally helpful for the educational institutes to learning both the languages by one system and Numbers Table as well.

II. METHODOLOGY

This section explain the purposed methodology in detail. The input data can be capture by the web cam (web camera) has been used to record or capture hand gestures an obtained videos have been converted into the images frame by using python library open cv which is used to enables the web cam. And the image frame have been passed through a pre-processing phase using open computer vision (open CV) library. The pre-procesed frame is then passed through the media pipe. The media pipe is used to locates the landmarks in each frame. The frame is then going for the feature extraction processing, this library is responsible to used these landmarks to extract image features. Then the extracted feature sets has been passed to train classifiers. The overall system overview is as shown in below fig 1. general overview of the proposed system design

- **Sign Language Recognition System**

In this paper we are going to design a new and advanced sign language recognition system which combines both the sign languages like Indian sign language and American sign language. This system is new idea about the educational purposed to change the disable childrens to learn both traditional culture languages. This will expands the learning in such fields.

In this system we used the machine learning concept to learn the machine predict the real-time input by using computer vision library that is Open cv and media pipe libraries. During the input data training we find the one important is that the tensorflow library version is very crucial for learning system. So recommended the tensorflow 2.9.1 version and above versions. The latest version of the tensorflow is 2.16.0rc0 till this project.

- **Preprocessing**

Effective preprocessing plays a crucial role in sign language recognition systems, particularly when utilizing machine learning techniques. Preprocessing involves various operations aimed at optimizing computational efficiency, reducing noise, and improving overall system accuracy. Two popular libraries employed in sign language preprocessing are Open CV and Media Pipe.

OpenCV, a powerful computer vision library, supports numerous functions essential for sign language preprocessing, such as image conversion, filtering, and morphological operations. It simplifies the removal of noise, enhancement of edges, and binarization of images, thereby preparing them for subsequent processing stages.

MediaPipe, developed by Google, offers specialized modules for human pose estimation, which can serve as a strong basis for sign language preprocessing. Its holistic model tracks full-body movement, allowing for the precise identification of sign language gestures.

A typical sign language preprocessing pipeline may involve:
1. Frame selection: Stripping irrelevant frames from long videos to reduce computation load and increase accuracy.
2. Noise reduction: Applying filters to eliminate background distractions and enhance the visibility of hands and faces.
3. Edge detection: Identifying boundaries between foreground and background elements to isolate signers and their actions.
4. Morphological operations: Filling gaps and removing excess regions to produce clean silhouettes of signers' bodies.
5. Feature extraction: Deriving meaningful descriptors from processed images to support downstream machine learning tasks.

These preprocessing techniques lay the foundations for accurate sign language recognition and interpretation, contributing significantly to the success of machine learning applications in this domain.

- **Keras Module:**

The tf.keras module in TensorFlow is a high-level neural networks API that simplifies the process of building and training deep learning models. It provides a user-friendly interface for constructing neural networks, defining layers, compiling models, and training them efficiently.

1. Simplicity: tf.keras offers a straightforward and intuitive way to create complex neural network architectures by stacking layers using the Sequential model or the functional API.

2. Compatibility: It seamlessly integrates with TensorFlow, JAX, and PyTorch, allowing users to leverage the strengths of different frameworks while developing machine learning models.

3. Flexibility: Users can easily customize and extend models by subclassing built-in layers or models, enabling the creation of tailored architectures for specific tasks.

4. Interoperability: Models built with tf.keras can be exported as TensorFlow SavedModels, making them compatible

with various deployment and production tools across different frameworks.

Overall, the tf.keras module serves as a versatile tool for developing deep learning models efficiently and effectively within the TensorFlow ecosystem. It simplifies the process of building neural networks, making it accessible to both beginners and experienced practitioners in the field of machine learning.

III. BLOCK DIAGRAM

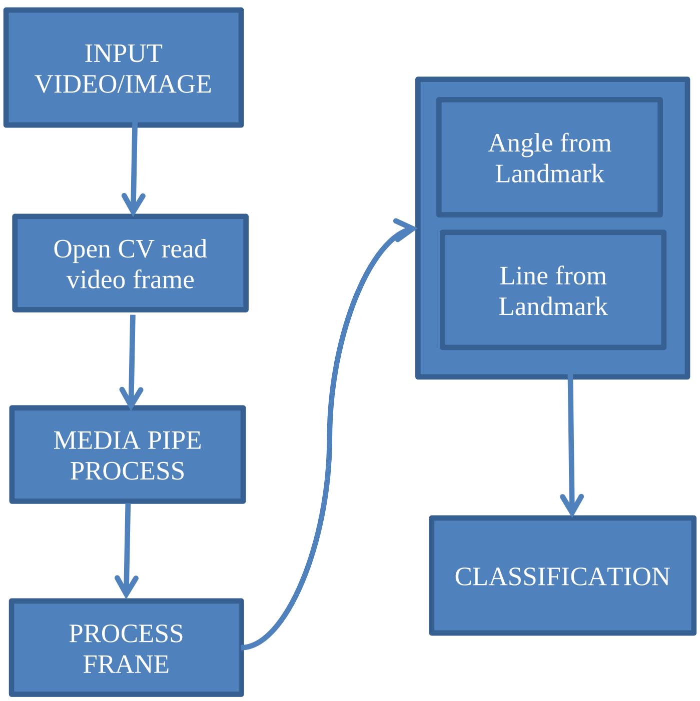

Fig 1: Block Diagram of Sign Language system

- **Features extraction**

As per the above fig 1 of sign language system, the Feature extraction process having two phases angle from Landmark and Line from Landmark are includes.

3.3.1 Angle Feature

The angle feature is based on the various angles of the image which means that the real time images having various angles and that angle must be matching to the all over that will help to predict

the real-time input, the big number of data we have to capture duing the training periods that period we collecting almost 500 to 600 real time images that images include various angles, direction and distance as well.

For extracting the angle feature, the slope between each pair of landmarks are calculated using Equation 1 as follows

$$Si,j = \frac{Yj-Yi}{Xj-Xi}$$

Where,

(Xi,Yi) and (Xj,Yj) = pair of landmark

$S_{i,j}$ = slope between pair of landmark

- **Line features**

The five finger are considered as line in this type of feature extraction. The labels are starts from 0 to 4 lines as shown in below fig (2) line representation of 5 fingers

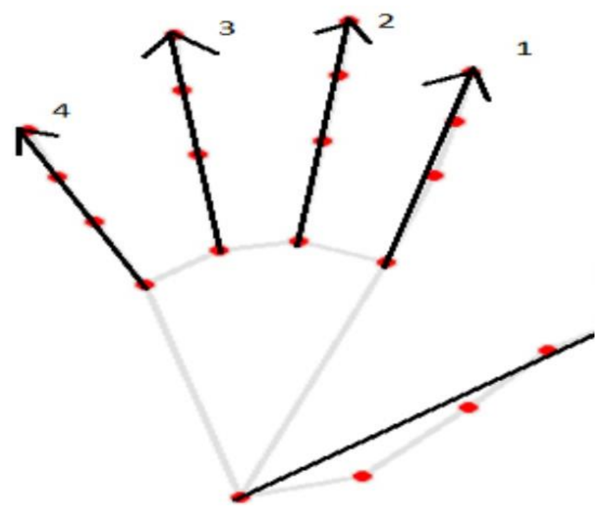

Fig 2: Line representation of 5 finger

Angle between all the fingers are calculated based on slope of fingers using Equation 3. these angles between fingers used as a new extracted features. The Equation3 is to calculate the angle between line i and j.

$$\Theta i,j = \frac{Si - Sj}{1 + SiSj}$$

Where

- **Algorith :**

Extraction of angle and line features between every pair of landmarks

Input: dataset ASL-alphabet/ISL-HS

Output: Extracted feature from hand pose

for n = 0 : m (for every frame)

1 Take each Frame and generate landmarks via media pipe.

for i = 0: p (for every possible pair)
2 Compute slopes between a pairi of land mark. Using Eq. (1)
3 Take slopes and compute angle via Eq. (2) and store it.
4 Take slopes and calculate lines via Eq. (3) and store it.
end
end
return( ) Extracted Features of angles and lines

- Model training

To train a model for sign language recognition using OpenCV, MediaPipe, and TensorFlow, the following steps can be followed based on the provided information:
Data Collection and Preprocessing:
Collect a dataset of sign language gestures, ensuring diverse samples for robust training.
Preprocess the images using OpenCV to enhance quality, remove noise, and standardize features .
Dataset Labeling and Splitting:
Label the images with corresponding sign language symbols.
Divide the dataset into training and validation sets (e.g., 80:20 ratio) for model evaluation 1.
Model Training:
Utilize TensorFlow for training a deep learning model, potentially leveraging transfer learning for efficiency

Implement a Convolutional Neural Network (CNN) architecture to learn features from sign language images

By following these steps and leveraging the capabilities of OpenCV, MediaPipe, and TensorFlow, a robust sign language recognition system can be developed, offering enhanced communication support for individuals using sign language.

Alphabet	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Success Rate
A	A	A	A	A	A	A	100
B	B	B	B	B	B	B	100
C	C	C	C	C	C	C	100
D	D	D	D	D	D	D	100
E	E	E	E	E	E	E	100
F	F	F	F	F	F	F	100
G	G	G	G	G	G	NI	83.33
H	H	H	H	H	H	H	100
I	I	I	I	I	I	I	100
K	K	K	K	K	K	K	100
L	L	L	L	L	L	L	100
M	M	M	M	M	H	M	83.33
N	N	N	N	N	NI	N	83.33
O	O	O	O	O	O	O	100
P	P	P	P	P	P	E	83.33
Q	Q	Q	Q	Q	NI	NI	66.66
R	R	R	R	R	R	R	100
S	S	S	S	S	S	S	100
T	T	T	T	T	T	T	100
U	U	U	U	U	U	U	100
V	V	V	V	V	T	V	83.33
W	W	W	W	W	R	W	83.33
X	X	X	X	X	M	X	83.33
Y	Y	Y	Y	Y	B	Y	83.33
Success Rate	100	100	100	100	70.83	87.5	93.05

Table 4.1 Sign language output in percentages

- **Classifications**

This methodology is evaluated using different machine learning classifiers such as naive Bayes, decision tree, and random forest.

IV. ADVANTAGES & DISADVANTAGES

Advantages

Sign language recognition systems leveraging machine learning offer numerous advantages that enhance communication accessibility and inclusivity for the deaf and hard of hearing community. Some key advantages include:

1. Real-Time Communication

Machine learning-based sign language recognition systems enable real-time interpretation of sign language gestures, facilitating immediate communication between signers and non-signers.

2. Cost-Efficiency

By utilizing standard web cameras and machine learning algorithms, these systems provide a cost-effective solution for recognizing sign language gestures without the need for specialized hardware or sensors.

3. Accessibility

Machine learning technologies make sign language more accessible to a wider audience by converting gestures into voice output and on-screen text, ensuring inclusivity for individuals unfamiliar with sign language.

4. High Accuracy

Recent advancements in machine learning techniques have significantly improved the accuracy of sign language recognition systems, leading to more reliable and precise interpretation of gestures.

5. Consistency and Availability

Machine learning models ensure consistent performance in recognizing a wide range of sign language gestures, promoting reliable communication accessibility across various contexts.

6. Education and Healthcare Applications

These systems find applications in education and healthcare settings, where they can assist in teaching sign language, providing communication support for individuals with hearing impairments, and enhancing accessibility to healthcare services.

7. Personalized Learning Experience

Adaptive machine learning algorithms can tailor educational content to individual learners' needs, offering personalized instruction and support to enhance skill development.

8. Increased Accessibility to Education

Educational learning-based sign language recognition systems empower individuals to learn sign language at their own pace, promoting accessibility to education and skill acquisition for both signers and non-signers.

Disadvantages

Limited Availability of Approved Datasets and Tools: Due to the vast variety of sign languages worldwide, acquiring sufficient and standardized datasets remains a challenge. Additionally, the lack of approved sign language interpreters contributes to the scarcity of resources for building and validating sign language recognition systems.

Complexity and Learning Curves: The complexity of sign language recognition systems, along with the intricate nature of sign language itself, leads to steep learning curves for users. This can result in slower adoption and lower engagement levels among students and educators.

V. CONCLUSION

The development of educational learning-based sign language systems using machine learning involves a comprehensive methodology that integrates various methods to recognize and interpret sign language gestures. Through a critical review and analysis of research in this field, several key approaches and conclusions have emerged from recent studies like Data Capture and Processing, Machine Learning Algorithms,

VI. REFERENCES

[1] Ulrich von Agris Æ Jo¨rg Zieren Æ Ulrich Canzler, Recent developments in visual sign language recognition, Univ Access Inf Soc DOI 10.1007/s10209-007-0104-x, Springer-Verlag 2007

[2]. Amrutha K, Prabu P from Dept. of Computer Science CHRIST(Deemed to be University) Bangalore, India, International Journal of Computer Applications (0975 – 8887)Volume 73– No.22, July 2013.

[3].Philippe Dreuw, David Rybach, Thomas Deselaers,Morteza Zahedi, and Hermann Ney, Speech Recognition Techniques for a Sign Language Recognition Syste.

[4]. Er. Aditi Kalsh1, Dr. N.S. Garewal2, Sign Language Recognition System, International Journal of Computational Engineering Research Volume 03, Issue, 6.

[5]. P. Subha Rajam, Dr. G. Balakrishnan, Real Time Indian Sign Language Recognition System to aid Deaf-dumb People, 978-1-61284-307-0/11/$26.00©2011IEEE,

[6]. Anuja V. Nair and Bindu V, A Review on Indian Sign Language Recognition, International Journal of Computer Applications (0975 – 8887) Volume 73– No.22, July 2013,.

[7] Intwala N, Banerjee A, Meenakshi, Gala N. Indian SignLanguage converter using Convolutional Neural Networks. In: 2019 IEEE 5th InternationalConference for Convergence in Technology (I2CT). IEEE. 2020.

[8] Miao Y, Li J, Liu J, Chen J, Sun S. Hand Gesture Recognition Based on Joint Rotation Feature and Fingertip Distance Feature. Chinese Journal of Computers.2020,Issue 1.

[9] Dhiman C, Vishwakarma DK. A Robust Framework for Abnormal Human Action Recognition Using R -Transform

and Zernike Moments in DepthVideos. IEEE Sensors Journal. 2019.

[10] Subudhi P, Mukhopadhyay S. A statistical active contour model for interactive clutter image segmentation using graph cut optimization. Signal Processing. July 2021.

[11] Liu J, Yuan J, Cui J, Liu Y, Liu X. Contour Resampling-Based Garlic Clove Bud Orientation Recognition for High-Speed Precision Seeding. Agriculture.2022, Issue 12.

[12] Khan US, Zhang X, Su Y. Active Contour Model Using Fast Fourier Transformation for Salient Object Detection. Electronics. 2021, Issue10.

[13] Kim T, Jung YH. Correlation of Roundness and Sphericity with Complex Fourier Descriptors of 2-Dimensional Projected Images of Soil Particles. KSCE Journal of Civil Engineering. 2022;26(3):1089–1094.