Gesturely: a Conversation AI based Indian Sign Language Model

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***Abstract*—Our project, "Gesturely: Indian Sign Language to words" aims to improve communication within educational settings for individuals with hearing impairments. Sign language, notably Indian Sign Language (ISL) in India, serves as a primary mode of expression for the deaf community. The form of expression among the deaf, relies on a rich vocabulary of gestures involving fingers, hands, arms, eyes, head, and face. Our research endeavors to develop an algorithm capable of translating ISL into English, focusing initially on words within the education domain. Through the integration of advanced computer vision and deep learning methodologies, our objective is to create a system capable of interpreting ISL gestures and converting them into written text. The project involves the creation of a comprehensive dataset, with 50 number of words and over 2500 videos. Our vision is to empower the deaf community with real-time translation capabilities, promoting inclusivity and accessibility in communication.**

***Index Terms*—Indian Sign Language, computer vision, gesture recognition, sign language dataset**

I. Introduction

Communication is vital for human interaction, yet individuals who are mute or deaf face challenges connecting with the hearing community. In India, Indian Sign Language (ISL) is widely used and recognized as the primary mode of communication. It is used by over 5 million deaf people in India. [1] The development of Natural Language Processing (NLP) systems for sign languages such as American Sign Language (ASL) [2], British Sign Language (BSL) [3], and Deutsche Gebärdensprache (DGS) [4] have benefited from the availability of translation datasets. However, there has been relatively limited focus on ISL due to the scarcity of large annotated datasets. This paper aims to address a new translation dataset focused on ISL, with a particular emphasis on the education domain. Additionally, it introduces a deep learning model for classifying gestures.

ISL presents unique challenges due to its limited resources and reliance on bodily gestures for communication, which adds complexity to training machine learning models. Annotating sign language at the gesture level, rather than the sentence level, poses scalability issues. Prior research has explored translating signs into gloss representations and then converting them into written language (Sign2Gloss2Text) [4]. *Glosses* are textual labels assigned to signed gestures, helping translation systems in working at a more detailed level of sign translation. However, generating gloss representations for entire signed sentences presents additional challenges in data annotation. Overall, in this research paper, we make the following contributions:

- We create a comprehensive ISL to English translation dataset containing more than 50 glosses spread across 2500 and more videos. We believe making this dataset available for the NLP community will facilitate future research in sign languages with a significant societal impact.
- We propose a deep learning model for ISL to English translation, inspired by SignAll SDK.[1]

II. Literature review

Unlike spoken languages, sign languages rely on body movements like hand shapes, head nods, eye gazes, and facial expressions to communicate. Translating these continuous movements into written text is quite challenging, opening up new opportunities for research in sign language translation. Many studies have looked into recognizing sign language, using different techniques like gloves, Microsoft Kinect sensors to track hand movements, classify frames based on segmentation masks or utilizing Mediapipe pose estimation pipeline[2].

A. Agarwal and M. K. Thakur [5] use Microsoft Kinect sensors to recognise sign language. They make use of depth

[1] https://developers.googleblog.com/2021/04/signall-sdk-sign-language-interface-using-mediapipe-now-available.html

[2] https://blog.research.google/2020/12/mediapipe-holistic-simultaneous-face.html

images that were captured using the sensor and a gesture is viewed as a sequence of frames. T. Pryor et al. [6] developed SignAloud, which incorporates a pair of gloves equipped with embedded sensors. These gloves track hand position and movement, enabling the conversion of gestures into speech. These hardware solutions are reliable and provide good accuracy but are usually expensive and not portable. Our system eliminates the need of external hardware by using any embedded camera.

In [7], Joshi et al. address the lack of resources for ISL in sign language processing. They present a dataset designed for word-level recognition in ISL from video recordings, with over 4700 words covering diverse topics. To overcome ISL's resource limitations, they use a prototype-based one-shot learner, leveraging ASL resources to improve ISL predictions. Ketan Gomase et al. [8] discuss the development of a sign language recognition system using the Mediapipe framework, which leverages machine learning to detect and interpret hand gestures. The framework identifies 21 3D landmarks on the hand from a single frame, making real-time hand and finger tracking possible. Joshi et al. in [9] introduce the ISLTranslate dataset and proposes a baseline model named Pose-SLT for ISL to English translation, leveraging pose estimation models and transformer architecture.

The dataset we are proposing draws inspiration from CISLR. [7] While CISLR focuses on supporting a one-shot learner model, our dataset diverges from this methodology. We aim to enhance the dataset's utility by including a higher number of videos per gloss, enabling a broader spectrum of research and applications.

III. Proposed Methodology

The primary aim of this study is to develop a framework for translating ISL glosses into English text, thereby improving accessibility and inclusivity for individuals with hearing impairments. To achieve this objective, we propose a multi-step approach that involved data collection, preprocessing, feature extraction, model development, and evaluation. By building upon recent advancements in machine learning and computer vision, our methodology aims at overcoming the challenges associated with ISL translation, including the lack of annotated datasets and the complexity of sign language recognition. In our approach, we follow the methodology laid out in [5], which involves carefully examining videos frame by frame.

A. Data Collection

Our dataset is created from the videos provided by CISLR [7], which has 57 distinct categories. Within our dataset, we emphasize the education domain, comprising more than 50 glosses distributed across 2500 videos. All videos maintain a consistent format, adhering to a 1:1 aspect ratio and recorded with a 720p resolution at 30 frames per second. This standardized recording setup ensures uniformity and quality across the dataset. Each gloss is represented by multiple videos, with diverse angles and lighting conditions to improve the training data and enhance model robustness.

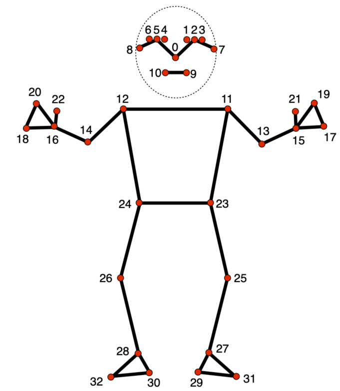

Fig. 1. Mediapipe Pose Landmarks [11]

B. Pre-processing and Feature extraction

Each video undergoes frame-by-frame processing, where pose coordinates are extracted from each frame as shown in Fig. 2. Mediapipe provides us with 33 coordinates detailing the human body from head to toe. However, as depicted in Fig. 2, body parts below the waist remain unseen, making coordinates below the waistline unusable. This discrepancy in data could introduce inconsistencies. To rectify this issue, all unused coordinates per frame, specifically coordinates 25 to 32 (8 coordinates), are filtered out before feeding the data to the model.

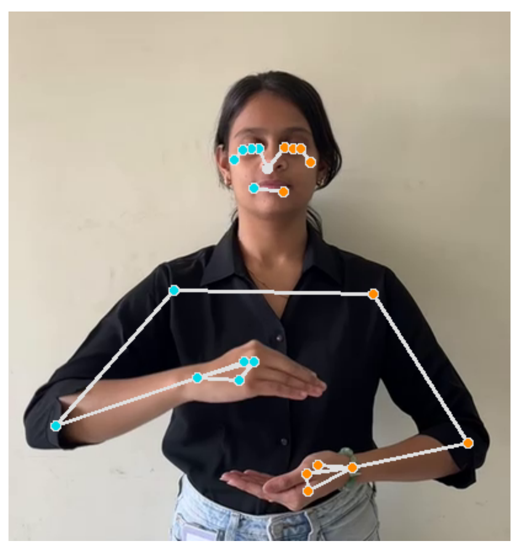

Fig. 2. Extracting coordinates from a frame of video for gloss *'grow'*

C. Model Development

After the coordinates are pre-processed and filtered, classification models will be trained. Following the approach outlined in [5], our focus is on training models capable of accurately distinguishing ISL glosses from the extracted pose data. We incorporate Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks to capture the complex patterns present in sign language gestures. These models are trained using optimization algorithms like Adam or SGD, with carefully selected hyperparameters to ensure effective learning. Throughout the model development process, we conduct thorough experimentation and validation to ensure the reliability and applicability of our approach.

D. *Evaluation*

In evaluation, we assess the performance of the developed model based on various parameters, including accuracy, precision, recall and test loss. We evaluate how well the model works when the data isn't seen or is retrieved real-time. We also test if the model is unbiased and doesn't favor a particular class.

IV. Proposed System

The system aims to address the challenge of translating ISL. It works by collecting the user input, processing the frames and classifying them into respective glosses. Once the video is processed and glosses are identified, the sentence is constructed. The proposed system can be seen in Fig. 3.

A. *Model selection and evaluation*

After evaluating various model architectures and their applications, we opted to adopt the model type outlined in [10], which leverages CNN and LSTM. Table I outlines the various classification techniques used, along with their specifications and corresponding test metrics. The Conv1D model was selected as the final model, leveraging classification based on Mediapipe Pose coordinates. Notably, this model achieved the highest accuracy and the lowest test loss score among all the models considered. For the model, labelled as Sign Language Classifier in Fig. 3, we're employing a sequential architecture comprising Conv1D, LSTM, Flatten, and Dense layers. This architecture processes each frame's 25 coordinates provided by Mediapipe, enabling the model to classify each video into specified glosses. The model learns patterns from the sequential data to accurately assign gloss labels to the videos during training.

B. *Gesture Classification*

User input is obtained either through computer vision or recorded video, wherein the user performs a series of ISL gestures to communicate. The collected input undergoes preprocessing, wherein each frame is analyzed, and the extracted landmarks are forwarded to the classifier model, depicted in Fig. 3. Landmarks generated per frame, acquired using Mediapipe, are refined to include only upper body landmarks (landmarks 0 to 24, as illustrated in Fig. 1). These refined landmarks are then sequentially sent to the model, which classifies the data into glosses.

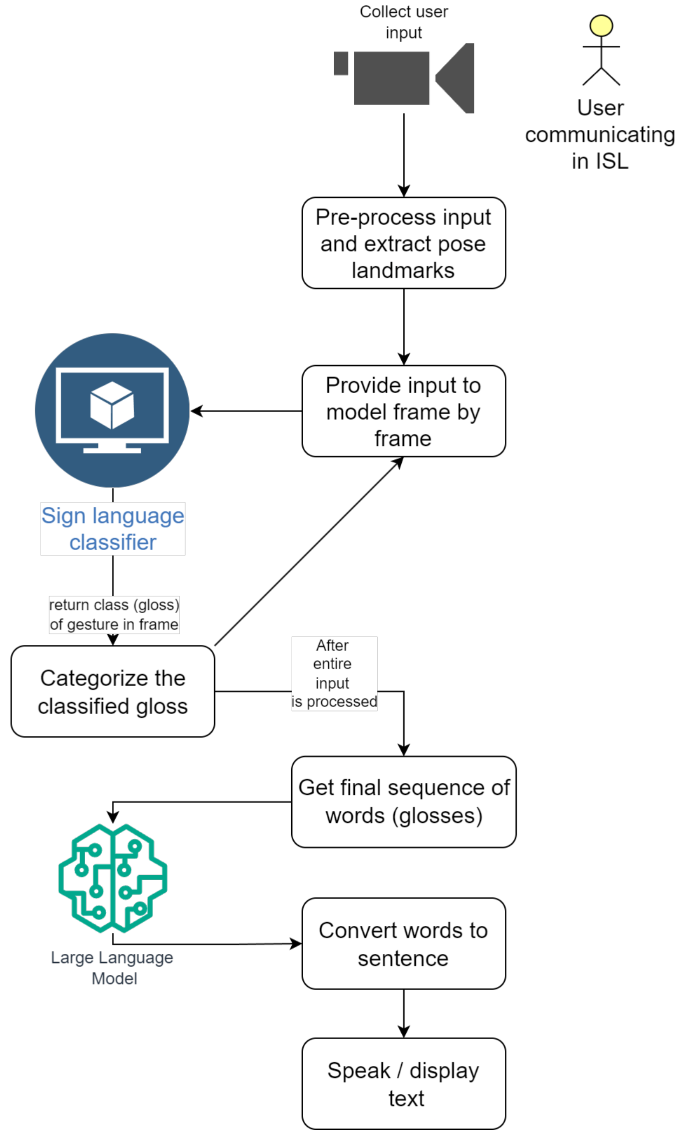

Fig. 3. Block diagram of proposed system

C. *Sentence Construction*

Following the identification of a sequence of glosses, the list of words is transmitted to a Large Language Model (LLM). The LLM generates a grammatically correct and contextually appropriate sentence that conveys the user's message.

V. Conclusion

We present a novel approach to Indian Sign Language (ISL) translation using advanced machine learning techniques. By using Mediapipe for pose estimation and a sequential model architecture comprising Conv1D and LSTM layers, we have developed a system capable of classifying ISL gestures into specified glosses with a 88% accuracy. Our approach, inspired by previous studies, shows promise in connecting the deaf and hearing communities better. Looking ahead, our work paves the way for more improvements in ISL translation tech, which

TABLE I
CLASSIFICATION MODELS SPECIFICATIONS
A - ACCURACY, P - PRECISION, R - RECALL, L - TEST LOSS

Model name	***Comparison metrics***												
	Specifications	***train = 0.8, test = 0.2***				***train = 0.75, test = 0.25***				***train = 0.7, test = 0.3***			
		A	**P**	**R**	**L**	**A**	**P**	**R**	**L**	**A**	**P**	**R**	**L**
Fine Tuned VideoMAE	learning rate = 0.001, sample rate=4, image resolution=224x224	0.79	0.75	0.74	0.49	0.78	0.74	0.74	0.52	0.75	0.74	0.72	0.52
Support Vector Machine (SVM)	Regularization parameter (C) = 1.0, kernel = 'linear'	0.84	0.84	0.83	-	0.82	0.81	0.81	-	0.80	0.80	0.79	-
Neural network model using 3D CNN	4 hidden NN layers, optimizer='adam', activation='softmax', loss='categorical _crossentropy', epochs=10, validation_split=0.2, batch_size=32	0.88	0.75	0.74	1.08	0.85	0.73	0.72	1.85	0.80	0.72	0.72	2.01
Neural network model using CNN & LSTM	4 hidden NN layers, optimizer='adam', activation='ReLU', loss='sparse _categorical _crossentropy', epochs=10, validation_split=0.2, batch_size=32	0.88	0.88	0.87	0.34	0.89	0.89	0.88	0.31	0.86	0.87	0.85	0.39

could make life easier and more inclusive for people with hearing challenges.

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