CONTINUOUS AMERICAN SIGN LANGUAGE TRANSLATION USING CONFORMER

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Abstract—In a world where communication is integral to opportunities and relationships, the hearing-impaired face significant challenges due to communication barriers. This project tackles the lack of popularity of sign language, creating a solution that automatically translates Sign Language gestures into spoken language. Leveraging Artificial Intelligence (AI) fields like Machine Learning, Deep Learning, Computer Vision, Object Detection, Object Recognition, and Natural Language Processing, the system aims to empower mute and deaf individuals. The initiative aligns with a wealth of related studies emphasizing the importance of sign language recognition and translation. Addressing the global prevalence of hearing loss, the project employs innovative approaches, including the Transformer and Conformer architectures. The models aim to enhance robustness and versatility through extensive preprocessing and data augmentation. The article structure covers background, methodology, challenges, acquired results, and unexplored techniques. This endeavour strives to break down communication barriers, fostering inclusivity for the hearing-impaired in our communication-dependent world.

Keywords—Continuous Sign Language Translation, Hand gestures, Machine Learning(ML), Deep Learning(DL)

I. INTRODUCTION

We are living in a world where communication is the key to achieving anything whether it is gaining information, getting a job or building relationships with others. So, being able to communicate freely without any barriers or restrictions is a blessing that we should be thankful for; because, in this communication-dependent world there is a group of people who encounter a lot of challenges in their daily lives that are caused mainly by the communication barriers.

The problem is that sign language is not popular, so there are not a lot of people who did learn it, therefore, this will create a communication gap between mute and deaf people and others, also, dealing with such a gap will make them suffer from loss of opportunities.

Our project is going to address this problem by providing mute and deaf people with an automatic translation for *Sign Language* (a) and that means the ability to convert the hand gestures into a spoken language. This is going to be done by applying many different fields and techniques that are related to the artificial intelligence, such *Machine Learning* [1] (b), *Deep Learning* [2] (c), *Computer Vision* [3] (d), *Object Detection* [4] (e), *Object Recognition* [5] (f) and *Natural Language Processing* [6] (g)).

Sign language processing is a hot topic in the communication field where many studies tried to develop methods and ways to improve the connection and the communication processes and the impact of other sign language applications, *Sign Language and Web 2.0 Applications* [7], this paper describes Dicta-Sign, a project aimed at developing the technologies required for making sign language-based Web contributions possible, by providing an integrated framework for sign language recognition(SLR), see Example in Figure 1, a Survey of *Advancements in Real-Time Sign Language Translators: Integration with IoT Technology*[8], the research aimed to analyze the advancements in real-time sign language translators developed over the past five years and their integration with IoT technology. By closely examining these technologies, it aimed to attain a deeper comprehension of their practical applications and evolution in the domain of SLT, *Sign Language Literature* [9], the goal of this paper is to emphasize the importance of sign language recognition and translation and provide a comprehensive review of relevant research conducted in this field. Of course, there are many more, so having all of these research and papers that address sign language emphasises how important this field is.

a. Problem Definition

Over 5% of the world's population or 430 million people, require rehabilitation to address their disabling hearing loss (432 million adults and 34 million children). It is estimated that by 2050, 700 million people—or 1 in every 10 people—will have disabling hearing loss. while 1.1 billion young people are at risk of hearing loss due to exposure to noise and other related problems. Unaddressed hearing loss results in a global cost of 750 billion US dollars [10]. Today, there are more than 300 different sign languages in the world,

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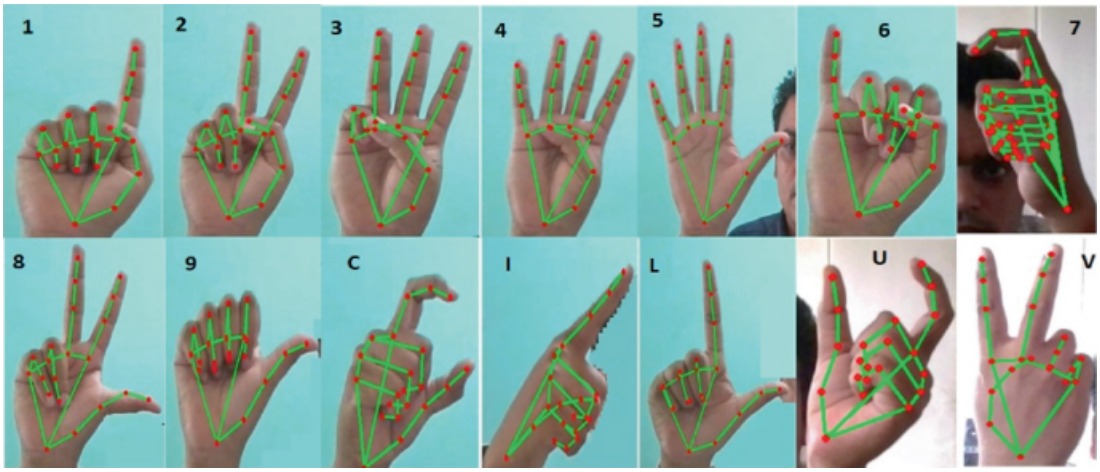

Fig. 1: Detect the Hand and then **Recognize** the Hand Gesture Meaning.

spoken by more than 72 million deaf or hard-of-hearing people worldwide [11], and some of them with their acronyms are presented in Table 1.

TABLE 1: SOME OF SIGN LANGUAGES AND THEIR ACRONYMS).

Sign language	Acronym
American Sign Language	ASL
Arabic Sign Language	ArSL
Argentinian Sign Language	ArgSL
Australian Sign Language	AusLan
British Sign Language	BSL
Brazilian Sign Language	LSB
Chinese Sign Language	CSL
Greek Sign Language	GSL
German Sign Language	DGS
Indian Sign Language	ISL
Irish Sign Language	IrSL
Japanese Sign Language	JSL
Malaysian Sign Language	MSL
Mexican Sign Language	MxSL
New Zealand Sign Language	NzSL
Pakistan Sign Language	PSL
Portuguese Sign Language	PorSL
Russian Sign Language	RSL
Spanish Sign Language	LSE
Turkish Sign Language	TSL

Sign language is a special type of language that is used by deaf individuals as their mode of communication. Unlike other natural languages, it makes use of meaningful body movements to convey messages, and these body movements are called gestures or signs. Hands and finger movements, head nodding, shoulder movements, and facial expressions are used to convey meaning. It is used by deaf people for communication between deaf–deaf or deaf–normal individuals.

Every particular sign means a distinct letter, word, or expression. A combination of signs makes a sentence just like words in spoken languages make sentences. Therefore, sign language is a complete natural language with its syntax and grammar[12]. Spoken languages vary from one region to another region, and about 6909 spoken languages exist in the world[13].

A Sign Language Gesture involves two types of features, namely `manual features` and `non-manual features`.

The Manual Features (MF) depend upon the *shape*, *movement*, *location*, and *orientation of the hand*. There are gestures which are performed by one hand, while the others are performed by involving both hands. Here are some examples showing manual features Figure 2.

Non-Manual Features (NMF): Non-manual features include different *facial expressions*, *head tilting/nodding*, *shoulder raising*, *mouthing*, and related actions which add meaning to our performed gesture/sign, see Figure 3. Mostly, non-manual markers are used along with manual markers. While Figure 4 gives examples showing non-manual features.

The gestures that involve hand movements are referred to as dynamic signs, while the gestures that do not involve any hand movement is termed a static sign gesture. Similarly, the gestures that involve both hands are called **doubled-handed gestures**, and the ones that are performed by a **single hand** are called *single-handed gestures*. As shown in Figure 5.

b. Challenges

As mentioned before, many research and papers have been published to deal with sign language and the gap that has been acquired in the communication field between mute/deaf people and the world. Each one of those papers has mentioned a unique approach, techniques and methods to address this gap. None of them was perfect since they all had some limitations and challenges.

Dicta-Sign [8], this project aimed for developing the technologies required for making *sign language-based Web* contributions possible. The following are some of the challenges encountered with this project.

Incompatibility of Sign Language with Web 2.0 Applications, This was acquired due to the lack of anonymization and easy editing of online sign language contributions. Challenges in Sign Language Recognition, the project faced issues with robustness, especially when low-resolution web-

`https : / / github . com / yazeedmshayekh2 / American-Sign-language-Recognition-Project/tree/main`

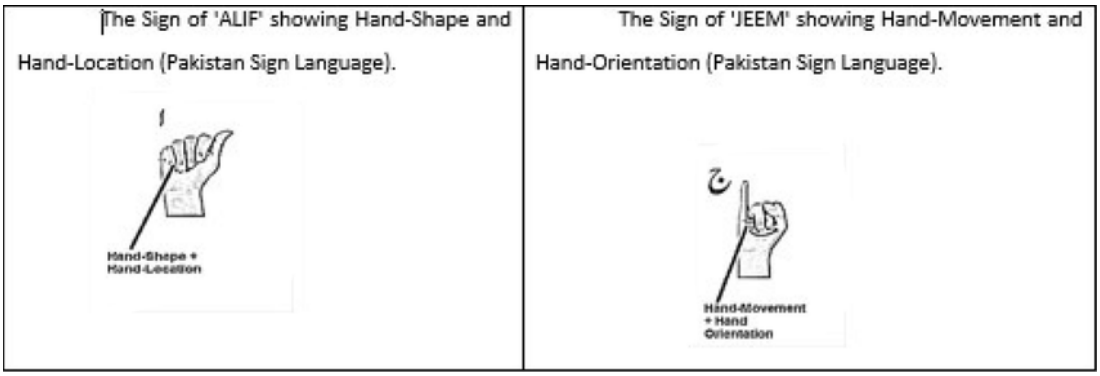

Fig. 2: Highlights the *Manual Features* with the help of some gestures.

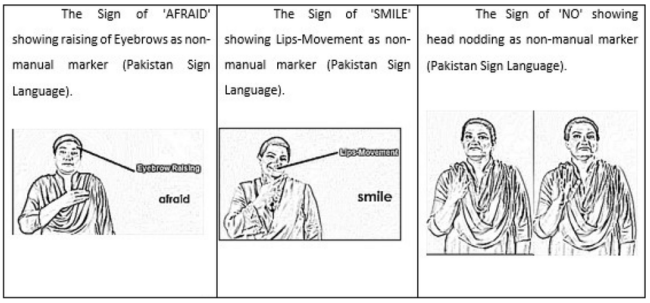

Fig. 3: Highlights some *Non-Manual Features* with the help of suitable gestures.

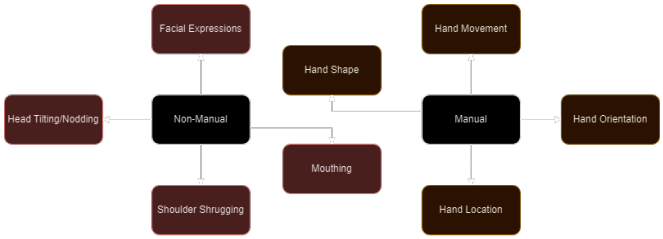

Fig. 4: Showing structural differences between *Manual* and *Non-Manual* gestures.

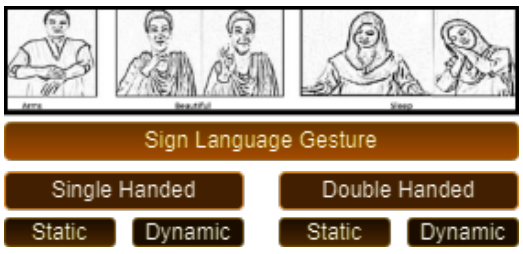

Fig. 5: Some suitable gestures that help understanding the concepts of *single-handed* and *double-handed static*(like one on the left) and *dynamic gestures*, where the dynamic gestures have been shown by presenting multiple frames (like two on the right).

cams are used, and difficulties in incorporating linguistic research results into recognition systems.

Camgoz_Neural_Sign_Language_CVPR [14], this paper used *the RWTH-PHOENIX-Weather 2014T* [15] dataset, which provides spoken language translations and gloss-level annotations for German Sign Language videos of weather broadcasts. Using such data will limit the usability of this project since the data is weather-related and it's in German, so it will be hard to have a generalized solution that can be used in other fields and languages.

Transfer Learning for British Sign Language Modelling [16], the salient idea of this paper is whether transfer learning is a legitimate method for modelling one language with the knowledge of another, assuming the languages are different, but share some common properties, such as vocabulary. The transfer learning approach is tested by applying models trained in one language (English) to another language (British Sign Language, - BSL) and vice versa. The perplexity scores are high in both cases, indicating that the probability distribution over the next word in one language is far from the true distribution of words in the other language. This highlights the challenge of transferring language models across different languages.

c. Proposed Solution

To advance sign language recognition and make AI more accessible for the Deaf and Hard of Hearing communities, it is crucial to address challenges faced by existing projects. Our objective is to create a reliable, efficient, and resilient model utilizing AI solutions such as automated speech recognition (ASR) and machine translation. Despite the global significance of sign language, over 70 million Deaf individuals and 1.5+ billion people with hearing loss lack access to these technologies [**?**].

Recognizing the need for improvement, we aim to leverage ASR and machine translation to enhance text entry through sign language. While many Deaf smartphone users can fingerspell words faster than they can type, existing sign language recognition AI for text entry falls behind voice-to-text and gesture-based typing due to the lack of robust datasets.

To achieve our goal, we prioritize obtaining a diverse and extensive dataset comprising a vast number of videos with varied backgrounds and lighting conditions. Training our model on such a dataset is essential to enhance its robustness and enable the development of a versatile model capable of handling diverse situations. We have chosen a dataset collected by Google [17], encompassing over three million fingerspelled characters from more than 100 Deaf signers. This dataset was captured via the selfie camera of smartphones, offering a wide range of backgrounds and lighting conditions for a more comprehensive and effective training process.

We will discuss in detail the methodology of our project in the methodology section, we will showcase the whole process, models and dataset.

d. Structure of the paper

The topics of the project will be as follows, Section 2 will showcase a background about the problem and some related works, Section 3 will discuss the followed methodology, work flow, dataset and model. Section 4 will include the challenges and limitations that encountered us throw the process. Section 5 will showcase the acquired results. Section 6 will talk about some methods and techniques that we wanted to try but didn't because of the time factor.

e. Glossary

`Sign Language` refers to a visual-gestural language used by individuals who are deaf or hard of hearing to communicate. Unlike spoken languages, sign languages rely on manual and facial expressions to convey meaning.

`Machine Learning` refers to a subset of artificial intelligence (AI) that empowers computer systems to learn patterns and make decisions without explicit programming.

`Deep Learning` stands as a pivotal branch of ML, specializing in the training and utilization of neural networks with multiple layers—commonly referred to as deep neural networks.

`computer vision` refers to a field within artificial intelligence that focuses on enabling machines to interpret and understand visual information from the world.

`Object Detection` refers to a computer vision technique employed to identify and locate specific objects or patterns within an image or video frame.

`Object Recognition` refers to the computer vision process of identifying and classifying specific objects or patterns within images or video frames.

`Natural Language Processing` refers to a branch of artificial intelligence that focuses on enabling machines to understand, interpret, and generate human language.

II. BACKGROUND

Many approaches and techniques has been developed to bridge the communication gap for the mute and deaf community. This section will cover those solutions starting from the very beginning.

a. Background of the problem

For the traditional methods, one of the approaches for addressing this gap was the presence of sign language interpreters to facilitate communication between deaf/mute individuals and those who do not understand sign language[18]. This method might be effective but it costs a lot of money[19], also, it's not a dependent solution since the whole communication process depends on the existence of the sign language interpreters. Another way was written communication, in this approach the mute/deaf individuals will write down but this method will consume a lot of time.

After many advancements in technologies and studies and getting access to more resources, all of this has paved the way for solutions to address these challenges and enhance communication for the deaf and mute community.

Gesture Recognition Technology(GRT)(A), with the rise of computer vision (B) and machine learning (C), GRT has been employed to interpret sign language gestures(SLG). This involves using cameras to capture and analyze hand movements, enabling the translation of sign language into text or speech [20]. Another way was the use of wearable devices equipped with motion sensors and ML algorithms have been developed to recognize and translate SLG. These devices aim to provide a portable and personalized solution for individuals with hearing and speech impairments [21]. Moreover, there are some mobile applications that leverage image and video processing algorithms to interpret sign language through smartphone cameras. These applications provide on-the-go translation (D), fostering independence and improving accessibility [22].

For the current state of the art, Machine translation from signed to spoken languages: state of the art and challenges [23]. This paper has adopted the video-based approach to translate sign languages, it will focus on translating videos containing sign language utterances to text, i.e., the written form of spoken language. This paper will discuss SLT (E) models that support video data as input, it also shows that this approach has benefits compared to wearable-based approaches, which require wearable bracelets or gloves or 3D cameras [21], they can be trained with existing data, and they could for example be integrated into conference calling software or used for automatic captioning in videos of signing vloggers.

b. Related Works

1. Sign Language Recognitionign Language Recognition

Early approaches for SLR rely on hand-crafted features `Tharwat et al., 2014`[24]; `Yang, 2010`[25] and use Hidden Markov Models `Forster et al., 2013`[26] or Dynamic Time Warping `Lichtenauer et al., 2008`[27] to model sequential dependencies. More recently, 2D convolutional neural networks (2D-CNN) and 3D convolutional neural networks (3D-CNN) effectively model spatio-temporal representations from sign language videos `Cui et al., 2017`[28]; `Molchanov et al., 2016`[29].

Most existing work on CSLR divides the task into three sub-tasks: alignment learning, single-gloss SLR, and sequence construction (`Koller et al., 2017`[30]; `Zhang et al., 2014`[31]) while others perform the task in an end-to-end fashion using deep learning (`Huang et al., 2015`[32]; `Camgoz et al., 2017`[30]).

2. Sign Language Translation

SLT was formalized in `Camgoz et al. 2018`[33] where they introduce the PHOENIX-Weather 2014T dataset[15] and jointly use a 2D-CNN model to extract gloss-level features from video frames, and a seq2seq model(Seq2Seq pipeline as shown in Figure 6) to perform German SLT. Subsequent works on this dataset `Orbay and Akarun, 2020`[34]; `Zhou et al., 2020`[35] all focus on improving the CSLR component in SLT. A contemporaneous paper `Camgoz et al., 2020`[36] also obtains encouraging results with multi-task Transformers for both tokenization and translation, however their CSLR performance is sub-optimal, with a higher Word Error Rate

than baseline models. Similar work has been done on Korean sign language by Ko et al. 2019[37] where they estimate human key points to extract glosses, then use seq2seq models for translation. Arvanitis et al. 2019[38] use seq2seq models to translate ASL glosses of the ASLG-PC12 dataset Othman and Jemni, 2012[39].

3. Neural Machine Translation

Neural Machine Translation (NMT) employs neural networks to carry out automated text translation. Recent methods typically use an encoder-decoder architecture, also known as seq2seq models. Earlier approaches use recurrent Kalchbrenner and Blunsom, 2013[40]; Sutskever et al., 2014[41] and convolutional networks Kalchbrenner et al., 2016[42]; Gehring et al., 2017[43] for the encoder and the decoder. However, standard seq2seq networks are unable to model long-term dependencies in large input sentences without causing an information bottleneck. To address this issue, recent works use attention mechanisms Bahdanau et al., 2015[44]; Luong et al., 2015[45] that calculates context-dependent alignment scores between encoder and decoder hidden states. Vaswani et al. (2017)[46] introduces the Transformer, a seq2seq model relying on self-attention that obtains state-of-the-art results in NMT.

c. Glossary

Gesture Recognition Technology (A): it involves using cameras to capture and analyze hand movements, enabling the translation of sign language into text or speech computer vision (B): refers to a field within artificial intelligence that focuses on enabling machines to interpret and understand visual information from the world. machine learning (C): refers to a subset of artificial intelligence (AI) that empowers computer systems to learn patterns and make decisions without explicit programming. on-the-go translation (D): On-the-go translation for sign language represents a revolutionary advancement in assistive technology, specifically designed to empower deaf and mute individuals by providing instant and portable translation of sign language gestures into written or spoken language.
SLT (E): sign language translation.
Data Augmentation (F): is a technique used in machine learning and deep learning to artificially increase the diversity of the training dataset by applying various transformations to the existing data.
Preprocessing (G): refers to the steps taken to prepare data for analysis or machine learning. It involves cleaning, transforming, and organizing raw data into a format that is suitable for further processing.

III. Methodology

The way that we are going to address this problem is by utilizing facial/hand/pose gestures. There are two approaches, the first one is using a transformer [46] while the second one is using a conformer [47] with data augmentation (F) [48].

For the first approach, we did a preprocessing (G) for the data, we emitted the missing hand gestures, and then we resized the videos to 256 frames. After that, we added for the data the phrase type (phone number/url/address). We set the maximum phrase length to (31 char+ 1 EOS token), the mean for the character length was 17.8 characters, the median was 17 characters and the mod was 12 characters. Since we only want to use the (x, y) coordinates we transformed the parquet files into numpy arrays (X_train, y_train, X_val, y_val).

The reason behind using the transformer is that we wanted to develop a sequence-to-sequence model (seq2seq problems as shown in 6) to deal with the input, which is videos consisting of a sequence of frames, so the flow of the process will be as follow, transforming the input video frames into embeddings using an activation function to capture the feature for each frame that we have. Then, those embeddings will go through positional encoding to know the position of each frame in the video for the rest of all other frames, after that, the output of this process will go to the encoder that belongs to the transformer.

The layers for the encoder: are the normalization layer, multihead attention layer (dimension 384), and another normalization layer. Feet forward network (DENSE layer without using bias and The Gaussian error linear unit activation function, dropout layer 0.3 dropout ratio, another DENSE layer, softmax activation function).

a. Preprocessing and Data Augmentation

1. PreProcessing without Data Augmentation in the First Solution

The Dataset preprocessing steps are as follows, first select the dominant hand based on the most number of non-empty hand frames, then filter out all frames with missing dominant hand coordinates, resize the video to 256 frames, and exclude samples with low frames per character ratio. one of the preprocessing steps was to add phrase type(Phone Number, URL, Address).

2. PreProcessing And Data Augmentation in the Second Solution

In this solution, we used multiple different data augmentation techniques, to reduce the overfitting problem. The preprocessing steps and data augmentation techniques that we used, were applied as follows:

Padding(short sequences), resizing(longer sequences), mean calculation with Ignoring Handling, standard deviation calculation with Ignoring NaN, normalization(Standardization), and global normalization(Standardization of the pose key points).

Splitting, Rearranging, Resizing (lips, hands, nose, eyes, and pose), interpolation(resizes the sequence to a target length, random interpolation).

Applies random rotations and scaling to finger data using Random Spatial Rotation (finger key points, degree(-10,10)) and Random Scaling(scales finger key points, scale(0.9, 1.1)).

Doing a combination of rotation, shear, and scaling to the data using Rotation, Shear, Scaling(degree=(-15,15),

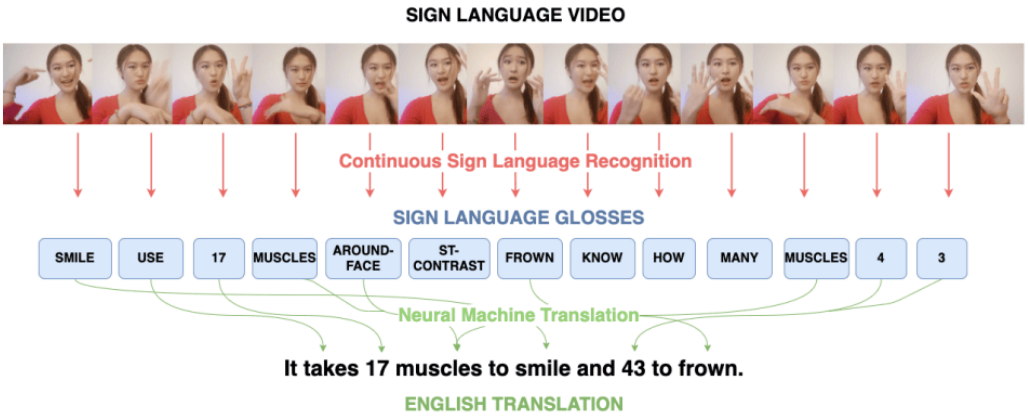

Fig. 6: Sign language translation sequence to sequence pipeline.

shear=(-0.10,0.10), scale=(0.75,1.5), Flips the data horizontally, either entirely or partially using inner flipping(around mean of coordinates) and left-right flipping(right, Left body like Left, Right hand and so on for each left, right data aspect).

Changes the temporal length of the data sequence by resampling it at a new rate using temporal resampling and subsequence resampling (resampling a subsection of the data sequence).

Masks parts of the data along a given axis, simulating missing information using masking, spatial masking (spatial mask to a random part of the data), and temporal masking (random temporal masking to a segment of the data). Applying random rotation and scaling (for each finger individually).

Randomly shifts the data within a specified range, simulating translation using Random Shifting (shift_range=0.1), rotations to parts of the data or individual fingers, with an option to apply these transformations only to a subsection by using partial rotation. Partial shifting, which shifts to either the whole sequence or a subsection. combined masking, which combines temporal and feature masking in one step, and composite augmentation, which applies a random combination of augmentation techniques.

b. Models

In this section we are to dive deeply in the models that we used and the architectures of these models.

1. Transformer

After the data is preprocessed and ready, it goes to the input embedding to extract the features from the input data(shape, hands, body posture, and facial expression), then positional encodings are added to add information to know the position of each frame in the video (to keep the sequence), and then the output from this layer goes to the attention heads, to capture the relationships between each frame with all other frames to add information about the relationships between frames by adding a value called Attention.

The decoder part from the transformer architecture takes the output from the encoder, which is the same as the encoder structure but there is one difference which is the masked attention to prevent the model when predicting the current token from seeing the future tokens. Then decoder-encoder attention, which is very important to see the whole input when predicting the next token. In the final step, the output from the decoder goes into a linear layer and then the softmax function adds probabilities for each possible output gloss to predict the one with the highest probability.

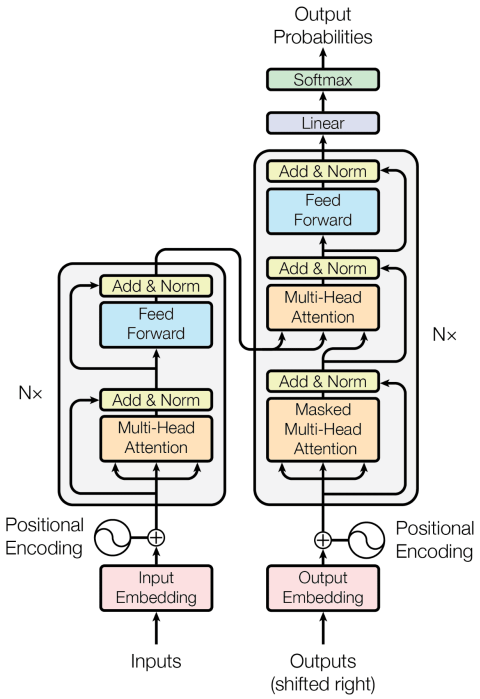

Fig. 7: Transformer Architecture

2. Conformer

In this approach, First we extract the features, then Convolutional Layers are added to capture features in each frame such as hand movement, the pose, body movements, and any other type of information in the frame, then the output goes into attention layers to understand the input as a sequence not as individual frames, then goes into Feet-Forward network, and the most important part, which is used to capture the features within the same frame and capture the features about the sequence as a one block(relationships between frames at the same video), is Conformer-attention block, and then the

decoder part comes to predict the word with the information provided by self-attention layers inside the decoder and the information comes from the Conformer Encoder block. Here we can take advantage of using CTC which is a mechanism to align the signs with the predicted glosses, which is very useful when dealing with Seq2Seq problems like SLT(our problem), **Note** I didn't use CTC mechanism.

IV. Experiments

In this section, we are going to highlight the values that we set for hyperparameters, the global configuration for the model, preprocessing and learning rate(maximum learning rate and learning scheduler), for both first and second solution, what are the hardware resources that we used, and what are the dataset that we found, what is the one that we chose, and why.

a. Dataset

In this section, we are going to talk about the dataset that we chose to solve our problem.

Google Dataset

While we don't have that much-powered resources to deal with the last datasets, we found a solution, which is to find a dataset that we can load it on a virtual machine environment without even downloading it locally, since the previous datasets are too large to store and deal with them locally. The dataset that we chose, was a dataset of competition for Google on Kaggle[49], the data includes more than three million fingerspelled characters produced by over 100 Deaf signers captured via the selfie camera of a smartphone with a variety of backgrounds and lighting conditions. The size of the dataset is 190GB.

Landmarks extracted from videos using the mediapipe holistic detection model, to know more about it Follow this link. Not all of the frames necessarily had visible hands or hands that could be detected by the model. The landmarks files were *.parquet* files. Google has given us the parquet files instead of us extracting the landmarks from videos, then saving them in parquet files. This allows you to take advantage of the Parquet format to entirely skip loading landmarks that you aren't using. The parquet file consisted of *sequence_id*, *frame*, *[x/y/z][type][landmark_index]*.

Lankmarks.parquet files

Sequence_id is a unique identifier for the landmark sequence. landmark files contain approximately 1,000 sequences. The sequence ID is used as the data frame index.

Frame is the frame number within a landmark sequence.

[x/y/z][type][landmark_index] There are now 1,629 spatial coordinate columns for the x, y, and z coordinates for each of the 543 landmarks. The type of landmark is one of ['face', 'left_hand', 'pose', 'right_hand'].

The spatial coordinates have already been normalized by MediaPipe. Note that the MediaPipe model is not fully trained to predict depth, so you may wish to ignore the z values. The landmarks have been converted to float 32.

character_to_prediction_index.json

It is a JSON file that contains the classes to predict; there are 59 classes.

[train/supplemental_metadata].csv file

path - The path to the landmark file, *file_id* - A unique identifier for the data file, *participant_id* - A unique identifier for the data contributor, *sequence_id* - A unique identifier for the landmark sequence. Each data file may contain many sequences, *phrase* - The labels for the landmark sequence.

The train and test datasets contain randomly generated addresses, phone numbers, and URLs derived from components of real addresses, phone numbers, and URLs. Any overlap with real addresses, phone numbers, or URLs is purely accidental. The supplemental dataset consists of finger-spelled sentences. Note that some of the URLs include adult content. This competition intends to support the Deaf and hard-of-hearing communities in engaging with technology on an equal footing with other adults.

b. Hardware Resources

In order to train the model on Google's dataset[49], we use Kaggle's 1 Tesla P100 GPU. Its 3584 CUDA cores and 16GB of HBM2 vRAM linked via a 4096-bit interface provide performance to the order of 9.3 TFLOPS at single precision, 18.7 TFLOPS at half precision, and 4.7 TFLOPS at double precision. 29 GB RAM, 73 Disk Space + 189 GB Disk Space for storing the data.

c. Models

1. Transformer

Transformer Model [46](Transformer Architecture as shown in Figure 7) with 4.887.936 million parameters (Embedding+ Landmark Embedding+ Encoder(2 Encoder Blocks)+ Decoder(2 Decoder Blocks)+ 4 Attention Heads in Encoder and Decoder+ Causal Attention Masking) without Data Augmentation.

Lips/Right_HAND/Left_HAND landmarks that we used, X/Y dimensions were used only without the z dimension. In the preprocessing steps, first, we fill Nan with zeros, then filter out empty hand frames, set the PAD token to zeros, and resize the images to 128.

The number of epochs was 100 epochs, POD/SOS/EOS Tokens Used, Batch Size set to 64, learning rate set to 0.001, Weight Decay Ratio set to 0.05, Maximum Phrase length set 31+1 for EOS Token, splitting 10% of the data(7878 samples) into validation set(val_dataset) and the other is for training, It took like 3 hours to train were the epochs was 100. You can find the code Here in This link, and you can find the MLops that we make in Neptune.ai Here in This link, we took reads for every run that we make and we save just the best, Note: ASL-32 was the best read and we used Transformer Model Architecture in this run.

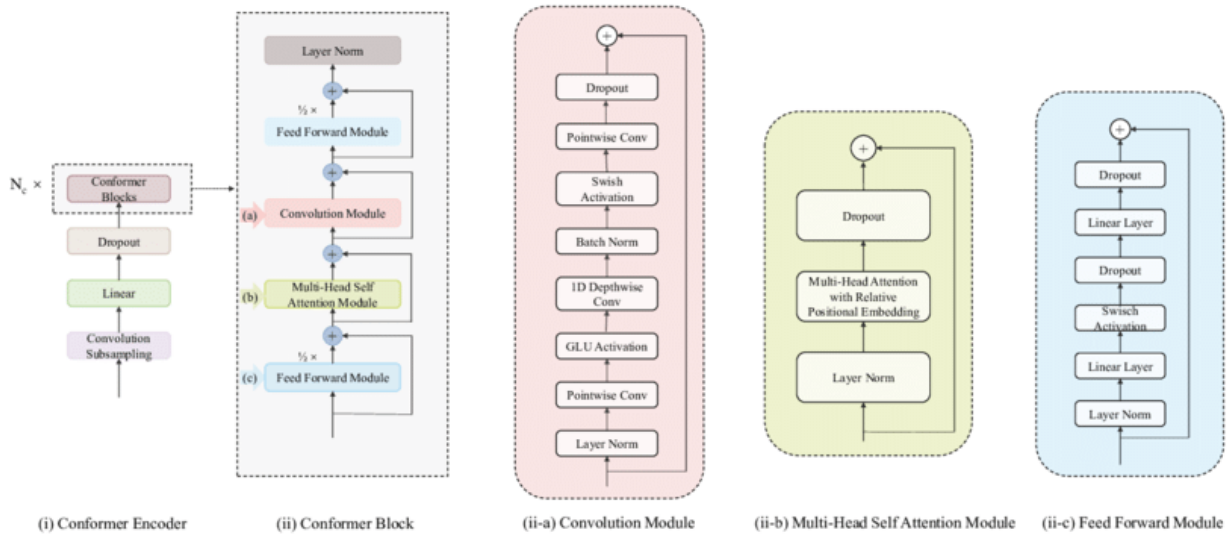

Fig. 8: Conformer Architecture.

2. Conformer

The model consists of 2 layer MLP landmark encoder + 6 layer 384-dim Conformer[47] + 1 layer GRU (You can see the conformer architecture in Figure 8). Total number of parameters was 15,892,142, there are 15,868,334 Trainable parameters and 23,808 Non-trainable parameters. It took like 7 hours to train where the epochs were 100, I stopped it because the loss didn't improve that much, I tried using Kaggle TPUs but it didn't so if you how to use them, **Note:** If the kaggle TPUs used the number of epochs will increase to 500 and the batch size will increase as well.

The number of Epochs was 100, and BATCH_SIZE was 64. The number of Unique Characters To Predict + Pad Token + SOS Token + EOS Token was 62. The maximum Learning Rate was 1e-3, weight decay ratio for the learning rate was 0.05. Maximum phrase length was 31 and 1 for Eos Token. The number of frames to resize the recording to is 384. The dropout ratio was 0.1. Causal Masking is applied. the number of landmarks that we choose to use (4 landmarks for Nose, 41 landmarks Lips, 17 landmarks for Pose, 32 landmarks Eyes 16(Right) and 16(left), 42 landmarks Hands) In Total 42+76+33 = 151 (42 landmarks HAND_NUMS, 76 landmarks FACE_NUMS, and 33 landmarks POSE_NUMS). X/Y/Z dimensions are used which means we add depth in this approach and finally we split the data into 66208 samples for training, and 1000 samples for evaluation on the validation dataset.

You can find the code Here in This link, and you can find the MLops that we make in Neptune.ai Here in This link, we took reads for every run that we make and we save just the best, Note: we used Conformer Model Architecture in this run ASL-27. It was not that good, because I didn't give that much time to modify the code to work in the best way and to modify the model architecture (change the number of heads, conformer blocks, decoder blocks, change the landmark indices, remove z, add or remove augmentation techniques), actually, there are a lot of reasons behind this or maybe the whole idea of conformer is wrong.

V. RESULTS

In this Section, we are going to talk about the model results, using loss and evaluation metrics.

a. Model Results

Using transformer we got **1.854708** SCRELM training loss, **0.861631** accuracy using Top1Accuracy, **0.959309** accuracy using Top5Accuracy, SCRELM loss **2.05572** was validation loss. Training Levenstein distance was **0.814**, Validation Levenstein distance was **0.686**. Validation Top1Accuracy **0.77** and for Top5Accuracy **0.92** Accuracy. For training set, BLEU-1: **23.19**, BLEU-2: **25.76**, BLEU-3: **27.04**, BLEU-4: **27.66** METEOR: **12.15** For validation set, BLEU-1: **12.41**, BLEU-2: **13.79**, BLEU-3: **14.47**, BLEU-4: **14.80** METEOR: **6.840**. Note: In Table 2, you can find more details about other related solutions compared with our solution.

Using Conformer we got **2.284645** SCRELM training loss, **0.657783** accuracy using Top1Accuracy, **0.895256** accuracy using Top5Accuracy, SCRELM loss **2.798254** was validation loss. Sorry because I didn't know how to implement Levenstein distance, BLEU, and METEOR in this solution approach.

b. Evaluation Metrics and Loss

In this section, we're going to talk about loss function that we choose and the evaluation metrics. Dive deeply into the equations for Loss, and Evaluation metrics.

1. Sparse categorical cross-entropy with label smoothing(SCRELM):

SCRELM is a variation of the standard cross-entropy loss function that is used for training neural networks for multi-class classification problems. It is similar to the standard cross-entropy loss function but with two main differences. First Instead of using a single target probability distribution, we use a set of target probability distributions, Second we add a label smoothing term to the loss function, which en-

TABLE 2: COMPARISON BETWEEN OUR SOLUTION AND OTHER SOLUTIONS, **NOTE** YOU CAN TAKE A LOOK AT THE SOLUTION BY CLICKING ON THE WORD [HERE] AT THE END OF EACH SOLUTION

Solution Architecture	Levenshtein Distance	
	Private LB	Public LB
1DConv + Transformer + Augmentation using train + supplemental data Here	0.665	0.713
16 CNN-Transformer Blocks + 8 Transformer Blocks + CTC loss Here	0.671	0.714
Transformer and 1D-CNN Here	0.699	0.706
Improved Squeezeformer + TransformerDecoder + Clever augmentations Here	**0.803**	**0.836**
joint CTC + AttentionHere	0.82	0.81
17 layers Squeezeformer with time reduce and ROPE Here	-	0.809
Conformer Encoder-Decoder Ensemble with beam search and edit_dist optimization Here	-	0.807
Vanilla Transformer + Data2vec Pretraining + CutMix + and KD Here	-	0.792
Our Solution	0.686	-

courages the model to produce probabilities that are close to the true labels[50]. The equation of SCRELM:

$$L(y,\hat{y}) = -\sum(y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})) + \alpha H(\hat{y}) \tag{1}$$

`L` is the loss function. `y` is the true label vector (a binary vector where each element is either 0 or 1). y_hat is the predicted probability distribution (a vector of probabilities, where each element is between 0 and 1). `a` is the hyperparameter controlling the strength of the label smoothing term (usually set to a small value such as 0.1 or 0.01). H(y_hat) is the entropic regularizer term, which encourages the model to produce probabilities that are well-calibrated and not too concentrated on a single class.

2. Levenshtein Distance:

$$d(x,y) = min(x,y) \tag{2}$$

Where x (let's consider it as an actual label) and y (let's consider it as a prediction) are the two strings being compared, d(x, y) is the Levenshtein distance[51] between them, and delta(x, y) represents the edit distance between the two strings. Like levenshtein distance between (3creekhouse, 3creek house) is 1.

3. TopKAccuracy Score:

Mathematically, the Top-k accuracy[52] score can be calculated using the following equation:

$$\text{Top-k Accuracy} = \frac{\text{No\_samples where T label is in top k predictions}}{\text{Total No\_samples}} \tag{3}$$

Where:

TP (True Positives) is the number of times that the true class label appears within the top-k predictions made by the model. **FN** (False Negatives) is the number of times that the true class label does not appear within the top-k predictions made by the model.

c. Bilingual Evaluation Understudy

BLEU[53] is computed using a couple of n-gram modified precisions. Specifically,

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \tag{4}$$

where p_n is the modified precision for n-gram, the base of log is the natural base e, w_n is the weight between 0 and 1 for log p_n and $\sum_{n=1}^{N} w_n = 1$, and BP is the brevity penalty to penalize short machine translations.

$$\text{BP} = \begin{cases} 1 & \text{if } c > r \\ \exp\left(1 - \frac{r}{c}\right) & \text{if } c \leq r \end{cases} \tag{5}$$

where c is the number of unigrams (length) in all the candidate sentences, and r is the best match lengths for each candidate sentence in the corpus. Here the best match length is the closest reference sentence length to the candidate sentences. For example, if there are three references with lengths 12, 14, and 17 words and the candidate translation is a terse 13 words, ideally the best match length could be either 12 or 14, but we arbitrarily choose the shorter one which is 12.

Usually, the BLEU is evaluated on a corpus where there are many candidate sentences translated from different source texts and each of them has several reference sentences. Then c is the total number of unigrams (length) in all the candidate sentences, and r is the sum of the best match lengths for each candidate sentence in the corpus.

It is not hard to find that BLEU is always a value between 0 and 1. It is because BP, w_n, and p_n are always between 0 and 1, and

$$\exp\left(\sum_{n=1}^{N} w_n \log p_n\right) = prod_{n=1}^{N} p_n^{w\_n} \in [0,1] \tag{6}$$

Usually, BLEU uses $N = 4$ and $w_n = \frac{1}{N}$.

VI. LIMITATIONS

The use of low-resolution cameras presents a significant challenge to the project. Because of this limitation, understanding gestures may be inaccurate, making it difficult to capture small differences in hand movements and facial expressions. The performance of the system is permanently linked to the quality of visual input, and the use of low-resolution cameras may compromise the overall effectiveness of gesture translation.

Furthermore, the project's only focus on translation into English introduces a significant constraint. This decision limits the system's generalization to other languages, limiting its reach to a broader segment of potential users.

When dealing with scenarios involving multiple people, a unique challenge arises If more than one person makes gestures in front of the camera at the same time. To address this challenge, robust algorithms capable of distinguishing and interpreting overlapping gestures in crowded visual environments are required.

An additional consideration is the possibility of unintentional signing movements. The system must effectively differentiate between deliberate signing and non-signing gestures to avoid misinterpretations.

On the technical front, the lack of devices with high specifications devices limits the possibilities. This limitation limits the project's ability to handle large datasets and necessitates the use of cloud computing for efficient data processing. Cloud-based solutions, on the other hand, have financial implications too.

Furthermore, due to the specialized nature of sign language, specific training and experience are required. While the system is intended to meet the needs of young users, the language acquisition patterns of children present a significant challenge. Children, unlike adults, may not acquire language skills quickly, making it a challenge to ensure their proficiency in using the system effectively.

VII. CONCLUSION

The results are not that good actually, because I didn't give that much time to modify the code to work in the best way and to modify the model architecture (change the number of heads, conformer blocks, decoder blocks, change the landmark indices, remove z, add or remove augmentation techniques), actually there are a lot of reasons behind this or maybe the whole idea of conformer is wrong.

Since there is no time to try these concepts to solve this problem, I think using clever augmentation from the first place solution with Flash-Attention, Squeezeformer, CTC with Conformer, or STMC transformer will give a better Performance. Try to solve this problem by using simple solutions and then go deeper with more complex solutions. Thanks a lot if you reach this part. Try to use the Supplementary dataset, since the top solutions in this competition used Supplementary dataset and they said it was useful.

By doing a lot of experiments, changing the hyperparameters, implementing different preprocessing techniques, and different augmentation techniques, I think it will give you a very good accuracy.

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