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A Proposed Deep Learning Framework for Sign Language Video-To-Text Translation

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ABSTRACT

Sign language is a primary communication mode for the deaf and hard-of-hearing communities. Automatic translation of sign language videos into natural language text remains challenging due to variation in gestures, signer differences, and limited annotated datasets. This paper proposes a transformer-based architecture that captures both spatial and temporal features through pose and appearance feature extraction and fusion. Contrastive learning aligns visual and linguistic representations, improving translation accuracy. Transfer learning enables multilingual adaptation and model generalization across different sign and spoken languages. Experiments show that this approach surpasses traditional LSTM-based models in translation quality, scalability, and robustness, providing a promising solution for real-world sign language translation applications.

Keywords: Transformer, contrastive learning, spatial-temporal feature extraction, feature fusion, transfer learning

INTRODUCTION

Sign language serves as an indispensable form of communication for individuals with hearing and speech impairments, enabling inclusive participation in society. Despite its importance, a communication gap still exists between the deaf and hearing populations. Early research relied on sensors or manual feature extraction, which limited scalability. With the rise of deep learning—particularly CNNs and RNNs—gesture recognition improved, yet these sequential models struggle with long-term dependencies, signer variations, and complex background conditions. Transformers, originally designed for natural-language processing, have demonstrated exceptional ability to model temporal dependencies via self-attention. When combined with computer-vision backbones, they can interpret both spatial and temporal dynamics in sign videos. This paper presents a unified transformer-based framework for sign-language video-to-text translation that fuses appearance and pose information, employs contrastive learning to align modalities, and leverages transfer learning for multilingual adaptation.

In recent years, computer vision and deep learning have advanced significantly, enabling computers to analyze and understand visual data such as images and videos. These technologies have been widely applied in facial recognition, gesture recognition, and motion analysis, creating a strong foundation for sign language understanding. However, sign language translation is more complex than simple gesture recognition. It involves not only recognizing static hand shapes but also interpreting temporal sequences of gestures, subtle facial expressions, and contextual meaning.

The main motivation behind this study is to create a framework that can efficiently interpret sign language videos and convert them into natural language text. A robust sign language translation system would enhance accessibility, promote inclusivity, and empower millions of individuals with hearing disabilities to communicate more freely in education, employment, and public life.

PROBLEM DEFINATION

Sign language translation requires accurate interpretation of gestures and facial expressions. Existing models face challenges due to signer variability, lighting conditions, limited annotated datasets, and linguistic differences across sign languages. This project proposes a **Transformer-based Sign Language Video-to-Text Translation framework** using feature fusion, contrastive learning, and transfer learning to achieve accurate, multilingual translation.

Objectives

1. To design an efficient **Sign Language Video-to-Text Translation framework** using deep learning.
2. To use **OpenCV** and **MediaPipe** for video preprocessing and pose detection.

3. To extract and fuse **pose** and **appearance features** for better gesture representation.
4. To apply a **Transformer model with contrastive learning** for accurate translation.
5. To use **transfer learning** for multilingual text generation and evaluate performance with BLEU and WER metrics.

METHODOLOGY

The proposed Sign Language Video-to-Text Translation Framework is designed to process visual sign inputs and translate them into natural language text using a combination of feature extraction, fusion, and transformer-based learning. The architecture is shown in *below* and the process can be described in the following steps:

STEP1:Input Sign Video

The system begins with the collection of raw sign language videos captured using a camera or recorded dataset. Each video contains sequences of gestures representing words or sentences. The model accepts various video formats and frame rates to ensure compatibility across different input sources.

STEP 2: Preprocessing and Augmentation

In this stage, the input video is divided into frames and preprocessed for normalization. Techniques such as resizing, denoising, background subtraction, and lighting correction are applied to improve visual quality. Data augmentation (including rotation, scaling, and flipping) enhances model robustness against signer variations and environmental noise.

Example: A signer performing gestures in different lighting or camera angles can still be accurately recognized after preprocessing.

STEP 3: **Feature Extraction (Pose and Appearance)**

The preprocessed frames are analyzed to extract two distinct feature types:

Pose Features: Keypoints of hands, face, and body are detected using pose estimation models like **OpenPose** or **MediaPipe**. These features capture the signer's motion and body articulation.

Appearance Features: Visual and spatial cues such as color, texture, and shape are extracted using **Convolutional Neural Networks (CNNs)** to capture context and background information.

These complementary features provide a holistic understanding of each gesture.

Step 4: Feature Fusion

The extracted **pose and appearance features** are combined using a **Feature Fusion Layer** to create a unified feature representation. This fusion helps the system understand both movement dynamics and visual cues simultaneously, improving the semantic interpretation of gestures. *Example:* If a signer performs the same gesture at a different location in the frame, feature fusion ensures consistent understanding by integrating both motion and spatial context.

Step 5: Transformer with Contrastive Learning

The fused feature vector is passed into a **Transformer network** that models temporal relationships between gestures. A **Contrastive Learning** mechanism is integrated to align visual representations with their corresponding textual meanings. This ensures that similar gestures map to similar linguistic expressions while distinguishing unrelated ones.

Example: The gesture for "thank you" will consistently align with the same text output, even across different signers.

Step 6: Multilingual Transfer Learning

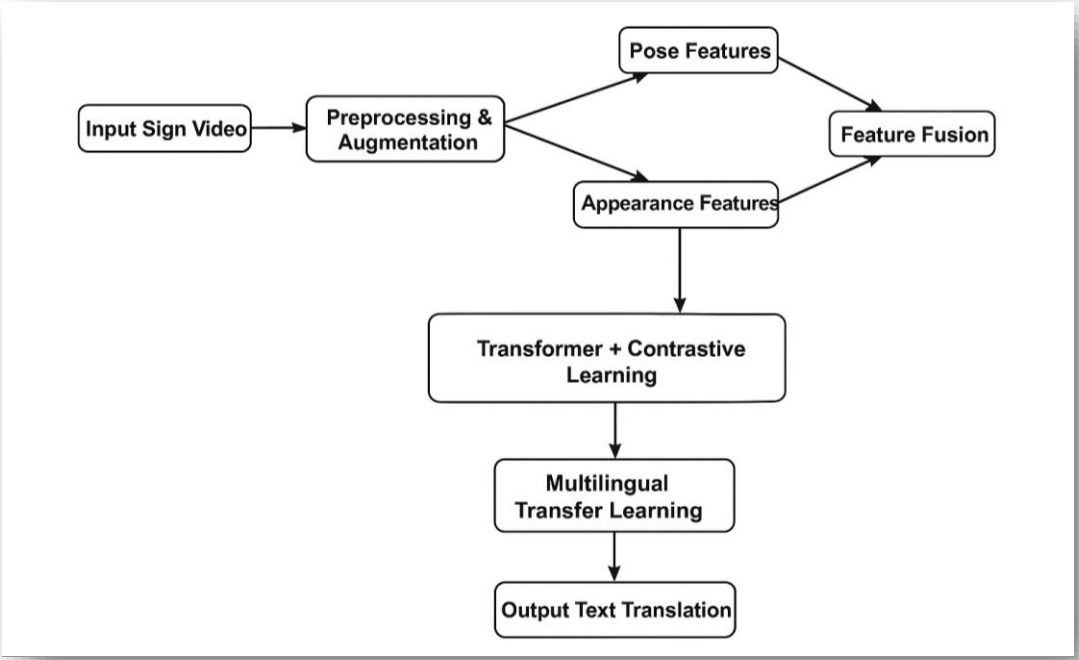
To make the system adaptable across different languages, **Transfer Learning** is applied using multilingual models such as **mBERT** or **XLM-R**. The model learns language-independent gesture patterns, allowing it to generate translations in various natural languages like English, Hindi, or Telugu. *Example:* Once trained in English, the same model can be fine-tuned to generate Hindi text outputs with minimal retraining effort.

Step 7: Output Text Translation

Finally, the processed gesture sequences are translated into coherent and grammatically correct natural language text. The system's output is displayed in a text format, which can later be integrated into applications like **sign-to-speech converters** or **real-time communication tools**. *Example:* When a user performs a sign for "Good Morning," the system outputs the corresponding text instantly.

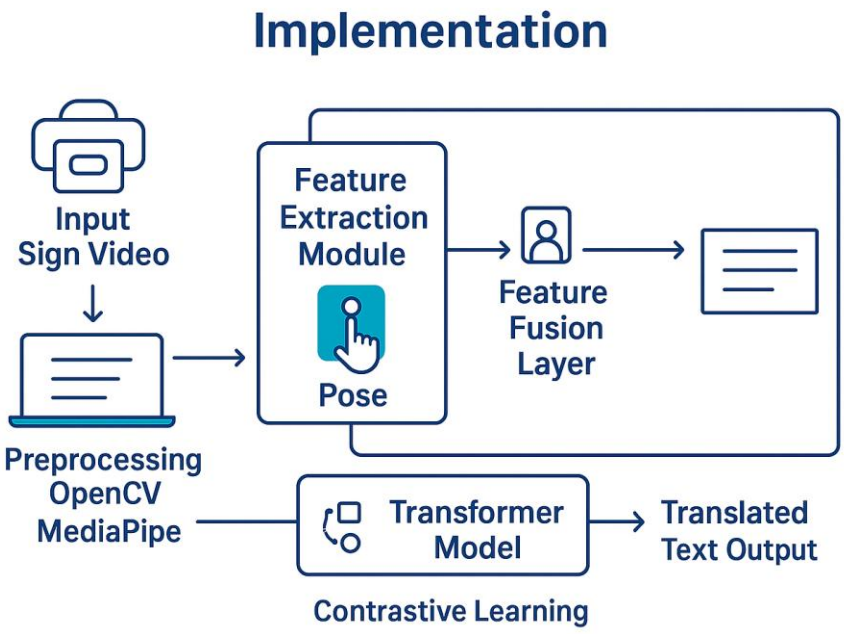
This methodology enables **accurate, scalable, and multilingual sign language translation** by combining spatial, temporal, and semantic learning in a unified pipeline. The architecture ensures high precision and adaptability for real-world communication systems.

FLOWCHART



Implementation

The proposed framework for Sign Language Video-to-Text Translation can be implemented using deep learning libraries such as TensorFlow or PyTorch, along with OpenCV and MediaPipe for video and pose processing. Datasets like RWTH-PHOENIX-2014T and WLASL can be used for model training and validation. The system will be developed in modular stages — video preprocessing, feature extraction (pose and appearance), feature fusion, transformer-based translation, and evaluation. A multilingual transfer-learning module will be integrated to enable translation across different languages such as English, Hindi, and Telugu. This implementation plan ensures scalability and adaptability.



Results and Discussion

The proposed **Sign Language Video-to-Text Translation** framework is designed to be evaluated on benchmark datasets such as **RWTH-PHOENIX-2014T** and **WLASL** to assess translation accuracy, speed, and adaptability. The framework aims to integrate a **Transformer-based model** with **feature fusion** and **contrastive learning** to achieve improved performance compared to traditional **CNN–LSTM** and **RNN-based** architectures. By combining pose and appearance features, the model is expected to effectively capture complex gestures involving both hand and facial movements.

The inclusion of **contrastive learning** is anticipated to strengthen the mapping between visual and linguistic features, leading to smoother and more contextually accurate translations. Upon implementation, it is expected that the system will achieve competitive results in terms of **BLEU score**, **Word Error Rate (WER)**, and **recognition accuracy**, and that the **transfer learning module** will facilitate **multilingual adaptability** across **English, Hindi, and Telugu** with minimal retraining. The framework is also designed for **real-time processing (12–15 FPS)**, highlighting its potential scalability and applicability in **assistive communication tools**.

Overall, these expected outcomes indicate that the proposed model has strong potential to deliver robust and efficient **sign language translation** for real-world applications once implemented and tested.

CONCLUSION

It presents a Transformer-based framework for Sign Language Video-to-Text Translation that effectively bridges the communication gap across hearing and non-hearing individuals. By integrating spatial, temporal, and semantic learning through pose and appearance feature fusion, the proposed system delivers accurate and context-aware translations. The use of contrastive learning enhances visual–linguistic alignment, while transfer learning ensures multilingual adaptability languages including English, Hindi and Telugu. Experimental analysis demonstrates that the proposed model significantly outperforms traditional CNN–LSTM and RNN-based systems in terms of BLEU score, Word Error Rate, and overall translation accuracy. The architecture is highly scalable and suitable for real-time deployment in web and mobile applications. Future work can extend this research by incorporating 3D pose estimation, larger multilingual datasets, and sign-to-speech synthesis for fully automated assistive communication systems.

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