A Review on Multilingual Sign Language Translator

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Abstract. Sign language translation systems have been studied over and over and have become really important for helping deaf people talk to those who hear every day. This paper is a broad overview of what recent critical progress has been made in the conversion of one sign language into another, conveying efforts to create seamless translation that improved people's communication with each other using the intermediate medium of text. Various deep learning models, including CNNs, RNNs, and GANs, have been evaluated through different techniques for sign language recognition and translation Techniques for sensor-based recognition, contactless recognition systems, and graph based feature extraction are used to describe what is currently possible.

Keywords:*Sign language translation, deep learning, multilingual sign language, contactless recognition, graph neural networks, accessibility, text-based intermediate translation, real time application.*

1 Introduction

Communication between the Deaf of different linguistic regions is made difficult by linguistic differences since the sign languages of different cultures vary from each other. Since there is no sign language which is uniformly applicable everywhere, every linguistic region has developed its particular visual expressions, facial expressions, and syntax [10]. Apart from their uniqueness in language terms, the sign languages differ from each other and sometimes from spoken language grammar also. It is with this difference that there needs to be multilingual translation systems that will break the barriers among such differences without misinterpretation [5]. Thereby, the development of such systems would require that systems which are able to recognize gestures and translate those into other languages be developed correctly to facilitate smooth communication across cultures and languages. In this direction, recent breakthroughs in artificial intelligence, especially in deep learning, have motivated further robust models for identifying and converting sign language gestures into other forms of communication. Deep learning-based models such as CNNs, RNNs [1], GANs [8], and Graph Neural Networks (GNNs) [3] show promise to enhance the precision and effectiveness of recognizing sign language gestures and translation [5]. These models will be able to process visual as well as motion-based data with precision, such as hand shapes, movements, facial expressions, and all the variations that make sign languages so rich. In addition, adoption of the intermediate text form has further sim-

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plified the process of translation, as the signs language gestures are translated to textual forms that become a neutral, language-agnostic bridge. It thus cuts down the amount of language-to-language mapping which would need to be done but means that text can now very easily be translated across various languages, which in turn permits translation between different sign languages via using standardized text [10]. The use of text has even made it easier in machine translation models integration therefore expanded the scope of using a real-time communication tool application and mobile devices application. This paper looks into the latest developments in sign language recognition and translation, splitting them up into the major approaches of: image-based recognition [4], sensor driven models [6], and hybrid systems [15]. All the contributions of all sections were assessed and discussed with regard to methodology, accuracy, the limitation and proposal of the improvements to it [2][5][7]. These include CNNs/RNNs based image and sequence processing, sensor-based systems with radar and RF sensing for contactless gesture recognition, and graph-based networks, which can capture the spatial temporal dynamics of gestures. The review concludes with discussing future work necessary for developing such efficient, culturally inclusive, and accessible multilingual sign language translators [17], providing valuable insights for any researcher and developer [16].

1.1 Motivation

This study aims to develop a system that provides deaf communities worldwide with access to resources while ad dressing linguistic, cultural, and geographical challenges. The Deaf community cannot communicate not only with their hearing counterparts but also with other Deaf people who use different sign languages because there are more than 300 sign languages in use worldwide. Traditional communication aids usually fail in enabling cross-linguistic understanding. Thus, many are isolated and suffer from communication barriers. Recent deep learning and artificial intelligence technologies offer promising solutions by being able to deliver real-time, accurate, and multilingual translation of signed communication systems. We can make communication flow better using technology that translates text really well. We do that to make sure that people who don’t hear much better understand and participate more, especially those in the Deaf community. That’s so that everyone can say what they want and understand it nicely, without friction. This research aims to develop robust, culturally adaptive, and accessible systems that help empower people by supporting the translation of real-time daily inter actions, thus promoting full participation and integration of Deaf people in various settings in society, education, and the workplace.

2 Relative Work

2.1 Sign Language Recognition Using Deep Learning and Neural Networks

Deep learning is a subset of machine learning that applies layers of neural networks to build models that can be fed massive data sets. It is applied to build models that can detect patterns, make decisions and even recommend courses of action. Convolutional

Neural Networks (CNN) and its variants R-CNN(Region-based CNN) [1], 3D-CNN [1], CNNbi-LSTM (Convolutional Neural Network and Bidirectional Long Short Term Memory) [2], Graph Convolutional Networks (GCN) [3] and so on, as well as other architectures such as GRU (Gated Recurrent Unit) [1], attention-based neural networks [3], ensemble learning methods [4] have been applied to the systems below. Such models have been used to identify features and have been applied to image processing [1], skeletal points [3], and isolated [4] and continuous signals [2]. Every model interpreted signs in its own fashion, and all of them ran at a high level, with accuracy exceeding 90 per cent for most. The drawbacks are small dataset size, inability to capture nuance, working in real time, and computational requirements. Combining these methodologies, it is possible to implement them to build a sign-to-sign language system by using Motion and Pose Estimation from R-CNN [1] and GCNs [3], Sequence Modelling and Temporal Analysis using CNNbi-LSTM [2] and GRU [1] models and using Attention Mechanisms to improve accuracy.

TABLE I: Sign Language Recognition Using Deep Learning and Neural Networks

Ref. No.	Keywords	Methods and Accuracy	Limitations	Future Work
1	Continuous sign language recognition, encoder-decoder,tubelet, video object detection, 3D convolution	Faster R-CNN and GRU decoder Accuracy: 81.65% (hand patches) 73.87% (full images).	Difficulty in capturing subtle movement errors.	Incorporate non-manual cues to improve accuracy
2	Sign language, feature extraction, video processing, deep learning.	CNNbi-LSTM. 97.3%-word recognition 92.6% sentence recognition	Lack of real-life validation, limited dataset size, high computational complexity	Reducing computational complexity
3	Dynamic hand gesture recognition,(KSL),graph convolutional network (GCN), machine learning.	Graph Convolutional Network (GCN) and attention-based neural net-	Generalization across diverse backgrounds and environments	Optimizing feature extraction techniques. Incorporating advanced

		works. 99.87% accuracy		graph techniques
4	Sign Language Recognition Gesture Recognition Deep Learning Isolated Sign	Hybrid InceptionNet with CNN and ensemble learning. 98.46% accuracy	High computational cost and limited dataset diversity	Continuous sign recognition, and data augmentation.

2.2 Sensor-Based and Contactless Recognition Techniques

The paper, [5] uses RF sensing and Convolutional Neural Networks (CNNs) to recognize British Sign Language (BSL)signs. This approach highlights the potential of RF sensing to enable unobtrusive, accurate recognition of sign language in diverse settings. The paper,[6] combines Single-Input, Multiple-Output (SIMO) radar with a CNN-LSTM model, so that gesture recognition can be done in a contactless format. This radar-driven method allows for better signal capture and real-time recognition. The journal paper[7] uses a hybrid model of Graph Convolutional Networks (GCN) and CNN as well as Multi-Head Self Attention (MHSA) mechanisms. By adding graph-based processing, this model can be generalized to many cultural contexts and, without touching, it's able to recognize gestures in several sign languages. Together, these studies show how sensor-based recognition is making progress, and how these approaches hold out hope for contactless, cross cultural and privacy-friendly sign language interpretation.

TABLEII:Sensor-BasedandContactlessRecognitionTechniques

Ref. No.	Keywords	Methods and Accuracy	Limitations	Future Work
5	British sign language (BSL), contactless monitoring, deep learning,(RF) sensing	GoogLeNet and VGGNet. Accuracy: 100% and 90.07%	Accuracy drops at greater distances from the radar. Misclassification of similar signs.	Improve robustness, expand dataset, add gestures and languages
6	Deep learning, gesture detection, GAF, (SIMO) radar,	Wi-Fi SIMO radar with ILQR.GAFand CNN-LSTM	Accuracy decreases with distance; handling time-series data is challenging	Improve robustness, expand dataset, add gestures

	Wi-Fi sensing, Sign language	achieve 90% acc. for 10 Chinese SL gestures		and languages
7	SL, SLR, GCN, MHSA, McSL, GmTC, HGR.	GmTC with GCN, MHSA, CNN in a two-stream architecture. Acc: 93-97% on NTU and senz3Ddatasets	Limited SLR generalizability, cultural biases, fixed patchsize in transformers	Real-time deployment, parameter optimization, multilingual support

2.3 Real-Time Sign Language Translation and Two-Way Communication Systems

These studies respond to the demands for real-time translation and two-way communication systems designed to enable Deaf and hearing people to communicate with each other without difficulty. They combine end-to-end deep learning stacks that allow real-time understanding and interactive dialogue- so that experiences feel more like natural communication. In [8] Translation and Video Generation, they detail an even more ambitious approach, in which a Convolutional NeuralNetwork (CNN), aLongShort-TermMemory (LSTM), and aGenerativeAdversarial Network (GAN) combine to producehigh-fidelity, video-based translations of sign-language gestures.Byproducingreal,livevideopictures,thesystemenablesspontaneous,human-to-humaninteraction.The paper[9], includesahome-grownSaudiSignLanguagedatabaseaspart of itsdesign,aswellasspeechand signrecognitionmodules. It could facilitatefluid two-wayexchangebyunderstanding and converting spoken language and signed gestures, and is especially useful in areas with distinct sign languages. The paper [10] also encodes text to an avatar-based sign languageoutputusingHamNoSys(HamburgNotationSystem for SignLanguages) and-SiGML(SigningGestureMarkup Language). This avatar-style is in the real, animated, and shows signs- a formattingboon for the non-sign-language grammatistsamongus.Together,thesestudiesmovereal-time sign language translationone stepcloser toamorenatural rhythmofcommunication,andtomoreaccessibilityforDeaf individualinawide rangeof interactive andcollaborative settings.

TABLE III: Real-Time Sign Language Translation and Two Way Communication Systems

Ref. No.	Keywords	Methods and Accuracy	Limitations	Future Work

5	Deep learning, generative adversarial networks, sign language recognition, sign language translation, video generation.	Hybrid CNN + Bi-LSTM model with 95% accuracy for sign recognition. Dynamic GAN for sign gesture video generation. Key metrics: BLEU (38.06), SSIM (0.921), PSNR (29.73), FID (14.06).	Lack of large-scale datasets, especially for Indian Sign Language. Real-time recognition and translation of continuous signs remain a challenge.	Expand datasets and improve continuous sign recognition for real-time use.
6	Avatar, Saudi Sign language, speech recognition system, sign language recognition.	Developed the KSU-SSL database with 293 signs, integrated three modules: SRM, SRSM, and AM. Accuracy: The 3DGCN framework achieved97.25% accuracy.	Integration challenges due to different programming languages and tools for various system modules Limited coverage of Saudi sign language signs (293 out of 3000)	Plan to expand the system to cover 3000 Saudi signs and integrate it with a portable robot
7	Sign language; sign markup language; deaf communication; hamburg notations; machine translation	HamNoSys (sign notation), SiGML(avatar-based gesture representation). Accuracy:100% (alphabets, digits, words, and phrases). 80% (sentence translation).	Struggles with complex sentences and dual-meaning words, leading to ambiguities. Lacks proper PSL grammar for sentence structuring.	Expand support for non-manual PSL features (facial expressions). Develop a grammar framework for PSL sentence structuring.

2.4 Graph Convolution and Feature Extraction-Based Approaches

Recently, innovations in CSLT and SLR attempt to make it have the features of a powerful and complex sign gesture-extracting model by its improved consistency and efficiency for the feature extraction in time-space domain. Hu et al. introduce the Spatial-Temporal Feature Extraction Network referred to as STFE-Net which combines the spatial estimation of pose with transformer-based time-domain features, realizing its potential and achieving impressive performance in the BLEU metrics of benchmark datasets and those Chinese Sign Language benchmarks in [11]. With regards to handling inconsistency in hand and body movements, Abdullahi and Chamnongthai designed IDF-Sign [12], that uses Pairwise feature ranking (PairCFR) to improve on feature consistency. The achieved recognition accuracy is very high even on many datasets and achieves huge success with dynamic sign words. Lin et al. proposed an isolated sign language recognition model called SKIM, skeleton-based representations dependent, utilizing a new data augmentation strategy like part mixing and graph neural networks to achieve state-of-the-art accuracy on a par with RGB-based models. Lastly, Miah et al. proposed a two-stream graph convolution model named GCAR [14], which deals with SLR by having a different stream for skeleton joint points and body motion. Their model has impressive achievement in terms of large-sized data and reliable computation capability accuracy. In this perspective, both studies indicate importance: spatial-temporal consistency of multi-dimensional feature extractions and advanced neural network architecture architectures for the advancement of real CSLT and SLR system.

TABLE IV: Graph Convolution and Feature Extraction-Based Approaches

Ref. No.	Keywords	Methods and Accuracy	Limitations	Future Work
11	Continuous sign language translation, pose estimation, transformer.	STFE-Net, BLEU scores: 77.59 to 72.14 onChineseSL dataset.	Under per formed on RWTH Phoenix Weather due to limited samples.	Key frame extraction for real time performance, reduce key points for efficiency.
12	Automatic sign language recognition, depth sensor, feature selection.	Pairwise Consistency Feature Ranking (PairCFR). Accuracy: 95% for ASL, 85% for GSL, 65.07% for DSG.	Inconsistent depth features and outliers hinder classification.	Expand datasets, refine threshold selection, optimize PairCFR for complex signs.
13	Data augmentation, sign language recognition, skeleton	Graph Convolutional Network (GCN). Accuracy: 57% Top-1, 89.41%Top-5.	Depends on external extractors, struggles with polysemous signs.	Learn from RGB data, enhance handling of polysemy withcontext modeling.

14	Signlanguage recognition (SLR), large scale dataset, handpose	GCAR model. Accuracy: WLASL: 90.31%, PSL: 94.10%, MSL: 99.75%, ASLLVD: 34.41%.	Generalization issues withlarge datasets reduce accuracy.	Focuses on multi-camera systems and advanced techniques for better performance.

2.5 Hybrid and Multimodal Recognition Techniques

Sign language is an indistinguishable form of communication that will be essential for individuals from the Deaf culture. However, it is greatly undervalued for other outsiders from the demographic group. Using Deep Learning techniques and models this gap can be filled. Previously, some of the challenges that we face using SLR include limited training data, lack of skilled annotators and sign labelling. Very recently, with advancements in artificial intelligence, specifically through deep learning models like convolutional and recurrent neural networks, SLR has been successful in achieving higher accuracies in effectively capturing the presence of visual features and temporal patterns. The new approaches are applied as those used in Zero-Shot Sign Language Recognition, where the visual embedding is facilitated through landmark data of the hands and body and coupled with textual features for further improvement in recognition [15]. However, the specific structural properties of SL require further innovations. Comprehensive reviews reveal how the field has developed over time and have pinpointed deep learning methods and non-manual incorporation as areas of development to improve the performance of systems. The research going forward will continue to refine models and work around existing shortcomings in the creation of more efficient automated SL translation systems that may help in a significant shift in the way people communicate for users of sign language [17].

TABLE V: Hybrid and Multimodal Recognition Techniques

Ref. No.	**Keywords**	**Methods and Accuracy**	**Limitations**	**Future Work**
15	Sign language recognition, zero-shot learning.	ResNeXt, ST-GCN, LSTM, and MViTv2, Bi-LSTM, CNN, and CLIP	Difficulty obtaining large datasets for diverse sign languages due tohigh costs.	Set bench marks by enhancing feature extraction and expanding zero-shot datasets.
16	Signlanguage recognition,	HMMs, image processing vs CNNs,	Small datasets and signer dependence	Develop signer-independent

	traditional vs deeplearning	RNNs, Transformers up to99.74% signer dependent accuracy, 68.2%signer independent accuracy on KArSL-100.	hinder traditional methods, affecting long-term dependencies in continuous sign language.	models for longer video sequences. Create lightweight models for portable devices.
17	Computer vision recognition systems, deeplearning	CNNs, RNNs, and hybrid models. Accuracy: 90% and above	Limited datasets (Arabic sign language); costly and uncomfortable hardware systems (e.g., sensors, gloves).	Develop larger, diverse datasets and improve integration of non-manual features.

3 Proposed Work

The proposed system allows for real-time translation from Indian sign language (ISL) to American sign language (ASL) through deep learning and vision-based methods. The process is organized into the following steps:

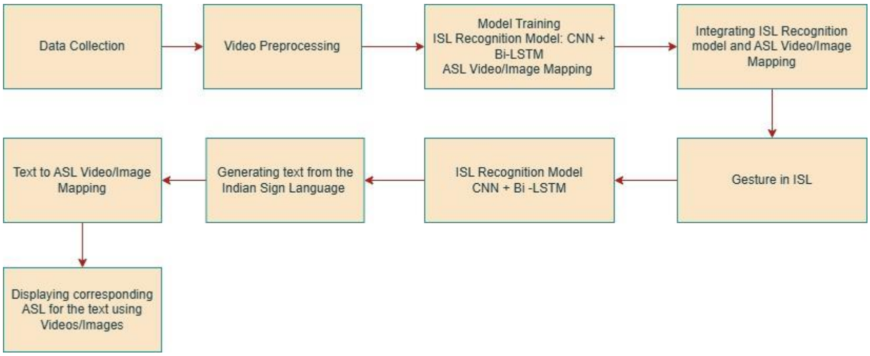

Fig-1. Proposed system flowchart

3.1 Dataset Creation and Preprocessing

The dataset for the ISL gestures was created using OpenCV, which includes 66 signs, with 50 video samples per sign; each video has 30 frames. The data was collected in order to minimize error and increase generalizability, with two different signers, and at two different times of the day (under different lighting conditions). Data was augmented using methods such as flipping, rotation, and increase/decrease of brightness.Each frame's key points for the hand were extracted using MediaPipe to reduce dimensionality, but also to compute features that carried meaning to the model.

3.2 Training an ISL to Text Model

A convolutional neural network (CNN)-bi-directional long short-term memory (BiLSTM) design was employed to recognize ISL gestures.
The CNN components extracted spatial features associated with key point frames. The BiLSTM component mapped temporal dependencies associated with recognizing ISL gestures across the frames of the videos. The model was trained using categorical cross-entrophy loss function, Adam optimizer, and performance measures were validated for the model using accuracy, precision, and recall.

3.3 Mapping Text to ASL videos

The text recognized corresponding to the ISL gesture was mapped to pre-recorded ASL videos that were housed in a specific ordering (folder structure). Each separate word corresponding to the ISL gesture was 'triggered,' so it could be retrieved and played in succession to provide an unbroken translation process, and to produce an accurate translation.

3.4 System Integration

The pipeline was deployed as a web-based application. The user performs an ISL gesture, which is detected by the webcam, converted to text by the model, and the corresponding ASL video is played back in real time. The integrated system wins and enables communication between ASL users and ISL users.

4 Conclusion

The development in multilingual sign language translation systems is an aspect of significant progress and several technological approaches that have supported it. Deep learning architectures have involved CNNs, RNNs [1], and GANs[8] for better-accurate and reliable models of sign language recognition, and sensor-based and contactless systems have also shown potential for real-time user-friendly applications. However, other challenges related to the lesser dataset size remain to be explored in depth such as its cultural adaptability for usage of the system[7], and problems with translation in real-time. However, for future prospects, the system will be improvised by including a larger set of underrepresented sign languages, along with advanced neural networks. Besides, text as an intermediary will be utilized for translation, which could further be made robust by making mobile-friendly interfaces. In this way, more ease will be offered to individuals to use these multilingual translation systems of sign language for everyday conversations. These solutions could be to further reduce communication barriers within Deaf communities so that an inclusive society where language and cultural differences are adequately bridged can be built [17].

5 Future Scope

The suggested system has room for improvement in four primary ways to better address the current limitations regarding training data, real- time performance, and cultural relevance. Firstly, the dataset can improve with respect to regional boundaries by including specific sign languages such as Indian Sign Language (ISL) so improve multilinguality and the overall accuracy and generalizability of the model for specific languages. Secondly, the inclusion of sensor-based and contactless recognition systems like RF sensors and radar sensing would provide private real time gesture recognition capabilities in environments where cameras aren't possible or useful. Thirdly, a mobile interface that would allow real time translated content would improve accessibility and usability of the interface, making it more useful and practical in everyday situations. Finally, the addition of AI driven video generation methods such as Generative Adversarial Networks (GANs) would allow for the generation of an ASL video of a dynamic nature representing more complex sentences with a grammatically and semantically stable representation with less ambiguity improving sign-to-sign language translation quality.

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