Sign Language Translation Techniques Using Artificial Intelligence for the Hearing Impaired Community in Sri Lanka: A Review

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Abstract— Hearing Impaired individuals routinely encounter limitations in their involvement in social interactions, access to intriguing information, and participation in everyday activities, among various other aspects. However, the hardest part of their interactions with regular people is communication, because sign language is the primary language of those who are hearing impaired. However, the general public is unaware of sign language. Each country has its own sign language. However, there are some striking similarities between them. In Sri Lanka, hearing impaired people use Sri Lankan Sign Language (SLSL) as their communication language. There is several research done on Sign Language recognition and translation. But no fully functioning system is utilized for Sri Lankan Sign Language translation. To find the gap in this area, we conducted a systematic literature review using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method that analyses 12 studies on Sign Language Translation (SLT). As per the literature review, Image Processing (IP) and Convolutional Neural Networks (CNN) are the most used techniques for Sign Language translation. But these methods have limitations: not enough data, differences in how people use sign language, difficulty in translating in real-time, not capturing cultural aspects, needing specific equipment, and understanding the context of conversations. Recognizing and solving these problems is important, especially for languages like SLSL. Future research should focus on getting more data, making translation work for different cultures, and improving real-time translation. This will help hearing impaired people communicate better with others.

Keywords—Sign Language Translation, Sri Lankan Sign Language, Hidden Markov Model , Image Processing, Machine Learning, Convolutional Neural Network, Support Vector Machine

I. Introduction

For many hearing impaired people, sign language is their major communication form. This sign language uses facial expressions, body movements, and hand gestures [5] [6]. There is no international sign language for the hearing impaired. There are numerous distinct sign languages used around the world [7] [8]. However, there are some striking similarities between them [1] [3]. Around the world, there are 135 distinct sign language variants [2]. Chinese Sign Language (CSL), French Sign Language (FSL), American Sign Language (ASL), Japanese Sign Language (JSL), Indian Sign Language (ISL), Arabic Sign Language, Mexican Sign Language (MSL), British Sign Language (BSL), Spanish Sign Language are only a few of them [2]. Sri Lankan Sign Language is the primary form of communication for Sri Lankan hearing impaired people [4]. British Sign Language

(BSL) served as the basis for Sri Lankan Sign Language's construction [4]. In Sri Lankan Sign Language, a spoken sign represents a Sinhala word or words, and a finger spelled sign represents an alphabet letter. Depending on the grammar and tenses of the Sinhala language, words have different forms. A fundamental Sinhala word is represented by one symbol in Sri Lankan Sign Language. The standard Sinhala curriculum is taught in some hearing impaired schools in Sri Lanka using Sri Lankan sign language. A sign language interpreter is necessary to speak with a hearing impaired Sri Lankan because the Sinhala populace is not familiar with Sri Lankan Sign language. A significant issue in Sri Lanka is the lack of trained sign language interpreters [4].

In their interactions with the Sinhala-speaking community daily, hearing impaired people face several difficulties. The hearing impaired community can now engage in activities that hearing people take part in, like social engagement and information access. The primary technical approaches used in this study area are machine learning (ML) and image processing (IP). Machine learning (ML) is the study of how to make computers work without being explicitly programmed.

II. Literature Review

Jin et al. [11] conducted research to implement a mobile application for Sign Language Translation. They have used a new framework with seeded region growing and canny edge detection techniques to detect images of sign language. The algorithms they have used to extract the features are Speed Up Robust Features (SURF) and Bag of Features (BoF) algorithms. The support Vector Machine (SVM) technique is used to classify the image dataset. All captured images are sampled to 320x240 resolution RGB format. They used a total of 1600 sample images to train the model. They trained the model for 16 different sign languages and used 100 sample images for each. There are 4 primary stages in sign recognition in this system. They are; calibration, segmentation, feature extraction, and classification. They got 97.13% accuracy in the testing stage. Researchers are planning to enhance the vocabulary to a wider range to improve the accuracy of the system.

Joshi et al. [10] have done a study on Sign Language translation with edge detection and Cross-correlation techniques. Their objective was to implement a Sign

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Language translation system that can translate American Sign Language to English text. They have provided 2 translation scenarios; English character translation and Complete English phrase translation. The image process is done by using segmentation and Edge detection techniques to extract the features. In segmentation, they have converted the RGB or Grayscale images to binary. In this conversation, they defined a threshold value and then applied the Otsu algorithm [25]. To recognize the gestures, they applied a cross-correlation algorithm. One limitation they have found is that their approach is sensitive to the background. So, they have to use a uniform background. However, they got a 94% accuracy rate in identifying sign gestures.

Jalal et al. [15] have done a study to implement a sign posture translator with a capsule-based deep neural network for American Sign Language. Unlike the other research in this research area, the presented system does not require a pre-trained network model. Researchers have used adaptive layer pooling which allows the model to be trained with various-size images and it could enhance the scale invariance. An American Sign Language Letter dataset called 'Kaggle' has been used to evaluate the system. The training data set had 27455 items and the testing dataset had 7172 items. The specialty in the proposed framework is that it is not limited to understanding sign language but also can non-verbal communication in Human-Robot interaction. This system has archived 99% accuracy in identifying sign language. The researchers expect to extend this framework to support non-static gestures also.

Thongtawee, Pinsanoh, and Kitjaidure [18], 3 researchers from Thailand introduced a feature extraction algorithm for Sign Language Signs recognition. This algorithm uses four main techniques for feature extraction. It employs an Artificial Neural Network for sign identification, focusing on extracting features from sign language alphabet gesture boundaries. The process consists of four phases: pre-processing, palm position identification, feature extraction using a contour-based technique, and classification. The system achieved a 95% accuracy rate in sign recognition. Their future plans involve extending the research to dynamic sign language gestures using the same techniques.

In their research [19], the goal was to create a real-time Sign Language Translation system. They trained a convolutional neural model using a dataset from Massy University in 2011. After training, they tested the network model and weights for real-time use, employing the convex hull technique for hand movement detection. The model was implemented using TensorFlow [26] and the Python library Keras, designed for efficient GPU processing. Training involved 900 images, with 25 images for each sign gesture, cropped, resized to 28x28 pixels, and converted to grayscale. The system achieved an accuracy of 98.05%.

Vanjikumaran and Balachandran [20], 2 researchers from Sri Lanka have done research on the fingerspelling recognition systems for Sri Lankan Tamil Sign Language. The researchers used a vision-based approach to address this problem. Their system is comprised of five main modules. They are; video capturing, Hand segmentation, Hand shape descriptor, classification, and Unicode mapping modules. In video capture, they used a video camera and then applied the Gaussian filter to the video data. Then the researchers used the canny edge algorithm to detect the edges of the hand. In the classification module, they used the Hidden Markov Model (HMM) algorithm. In the testing phase, this study achieved 73.76% accuracy.

Perera and Jayalal [21] did a study related to Sri Lankan Sign Language. They have focused on an approach which is combined CNN and SIFT and also used a vision-based approach. The main objective of using this combined approach was to get a higher accuracy rate in Sign Language gesture recognition with less training. Authors have used a web camera to image acquisition and used a skin segmentation method in the segmentation process. For the classification, the CNN-SIFT combination algorithm was used. Finally, the system maps the sign with the database and displays the relevant Sinhala text. This study was able to achieve 86.5% accuracy. But without the SIFT feature, the system was only able to get 68% of accuracy. The researchers expect to extend the approach to dynamic sign recognition and combine facial expressions with this system.

The 'Utalk' Sign Language translation mobile app was developed by [22] They have addressed the research gap in Sri Lankan Sign Language recognition in both dynamic and static gestures. Since this system comes as a mobile application they were able to make this more cost-effective than the other systems. As the input, this system takes the video and removes the background with image processing. Then the pre-processed frames are fed into the sign classifier module which is consisting of machine learning algorithms to classify the sign gesture and finally, the relevant Sinhala text is displayed. They used gray scaling and thresholding techniques in pre-processing and segmentation process. For the classification process, the authors have used a CNN. This system achieved 97% of accuracy in testing.

Guo et al. [12] proposed a framework using an adaptive Gaussian Mixture model (GMM) based Hidden Markov model (HMM) for sign language recognition. Also, they have proposed a data augmentation method by adding a Gaussian disturbance. In the data pre-processing, the data augmentation technique is used. They have used this data augmentation to introduce appropriate noises. In feature extraction, the Sketelon Pair (SP) algorithm is used. After doing some experiments with HMM-state adaption and data augmentation they found that the HMM-based method has more learning ability. The authors found that the proposed adaptive HMM-based framework improves the accuracy by 6.69%.

Aly et al. [13] conducted research on a sign language recognition system for the ASL alphabet using the Microsoft Kinect motion sensor. This system consists of 3 different stages. Pre-processing, feature extraction, and classification are what they are called. They applied a median filter during the pre-processing step and the Support Vector Machine (SVM) method during the feature extraction stage. To classify data, a convolutional neural network (CNN) was applied. To examine the performance of the system the authors have experimented. In this evaluation, they have used a publicly available dataset that contains more than 60,000 images. The proposed system achieved 88.7% accuracy.

Rishan et al. [38] present an innovative approach using Leap Motion technology for translating Sri Lankan Sign Language into Sinhala text. This paper marks a recent advancement in sign language translation, aiming to bridge communication gaps for the Sri Lankan hearing impaired community. The adoption of Leap Motion technology, known for its precision in hand motion tracking, adds a promising dimension to sign language translation systems. Researchers have presented a sensor-based approach using Leap Motion technology with geometric template matching and Natural Language Processing (NLP) [38] to identify unique signs and combine signs in SSL into text. The proposed approach includes three major stages which are “Sign training model”, “Sign identifying model” and “NLP unit”. The system shows an accuracy of 80% for static signs and 77% for dynamic signs.

Dahanayaka et al. [39] introduced a multi-modular approach that combines sign language and speech recognition for the hearing impaired and mute community. The inclusion of speech recognition alongside sign language translation is a notable advancement, offering a comprehensive communication solution. The study's achievement of a 94% accuracy rate in identifying sign gestures showcases its potential. Further enhancements could focus on reducing background sensitivity and expanding the supported sign languages and vocabularies.

Fernando and Wijayanayake [40] presented an innovative approach to real-time sign language communication by leveraging HU moments and image processing techniques. Real-time communication is a critical aspect for the hearing impaired and hard-of-hearing community, and this approach addresses it effectively. The HU moments-based approach scored 84% of accuracy. The integration of HU moments for feature extraction distinguishes this work. To maximize its impact, future research can explore scalability, adaptability to various sign languages, and environmental robustness.

III. METHODOLOGY

This literature review seeks to improve relationships between common people and hearing- and verbal-impaired individuals in Sri Lanka. To analyze the articles and extract the information, we made some research questions. The questions are:

Q1. What are the methods used for Image acquisition in Sign Language Translation?

Q2. What are the processes involved in the Sign Language Recognition process?

Q3. What are the algorithms used in the Sign classification process?

The selection of articles was done by using the PRISMA method, which is a guideline for undertaking a systematic literature review [9][23][24]. The researchers used IEEE, SPRINGER, and Google Scholar as databases as they contain large digital libraries for academics. The study was done in three stages as illustrated in Fig. 1. In the first stage, researchers searched for related articles in these databases using some related keywords to this research area and found 70 articles. The keywords are ‘Sri Lankan Sign Language’, ‘Sign Language Translation’, ‘Machine Learning’, ‘Image Processing’, ‘Sign language Recognition’, and ‘Neural Networks’. We excluded 8 duplicated articles and then selected 27 articles based on the title. In the final stage, we filtered out 12 articles out of 27 articles describing practically implemented Sign Language Translation systems with higher accuracy and efficiency for deep analysis.

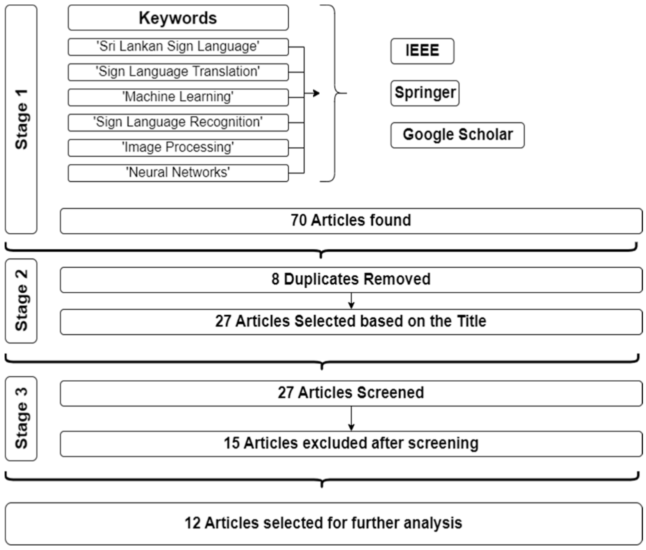

Figure 1 Selection Methods

We focused on studies conducted using the computer vision-based approach. In addition to that this review covers the studies in the 2015 to 2021 timeframe.

IV. DISCUSSION

Based on the result of our analysis, we found that there are five common methodologies followed by previous researchers in Sign Language Translation. These methodologies include Data acquisition, pre-processing, Segmentation, Feature extraction, and Image classification.

Then we conducted the review based on the research questions and compared the methods used with their advantages and disadvantages.

A. What are the methods used for Image acquisition in Sign Language Translation?

Various methods for acquiring image data have been compared in Table I. Researchers often use the Kinect motion-sensing camera [12] [13], originally designed for gaming. It can detect body movements through special sensors and has a depth sensor to separate foreground and background objects.

Another common method is using a standard 2D camera [10] [11] [17]. This approach is accessible to anyone, but image quality depends on the camera. Preprocessing can enhance the image before feature extraction.

Large, high-quality datasets are available online, saving time and resources [15] [22]. For example, Jalal et al. used the "Kaggle" dataset with 27,455 items [15]. This approach minimizes data acquisition and hardware costs

TABLE I IMAGE ACQUISITION METHODS

Ref.	Method	Advantages	Disadvantages
12,13	Kinect Sensor Camera	More detailed image data, Provide depth-aware details.	Sensitive to environmental changes.
10,11,17	Standard Camera	Easy usage, Easy to access	Image data should be preprocessed before analysis.
15,22	Datasets	Saves time/Resources	Sometimes it’s difficult to find a suitable dataset

B. What are the processes involved in the Sign Language Recognition process?

From the reviewed articles, we have identified Pre-processing, Feature Extraction, and Segmentation as processes that are involved in Sign Language Recognition. We have analyzed each process to identify what are the methods used in these processes and what are the advantages and disadvantages of each of them.

1) Pre-Processing

In Pre-processing phase, the obtained data is changed to give an accurate classification of image data by eliminating some unnecessary data which may cause the accuracy. In this paper, we have analyzed three common pre-processing techniques which are used for previous works and analyzed their advantages and disadvantages in Table II. The pre-processing techniques that we have analyzed are the Gaussian filter, Median filter, and Image cropping.

A low-pass filter called a Gaussian filter is used to blur particular parts of an image and decrease noise (high-frequency components). The filter is built as an odd-sized symmetric kernel (the DIP version of a matrix) and passed through each pixel in the region of interest to achieve the desired outcome. [17] [20]. These techniques reduce the noise in 2D images to enhance edge detection in the next stage. [20] Used a Gaussian filter in their study to remove noise from images because it's more efficient than the Median filter.

Image cropping is used to crop or resize the captured image so that it will reduce the unnecessary computations that could be done in the feature extraction stage [21].

2) Segmentation

The initial step in image compression is image segmentation, which effectively and rapidly separates a digital image into its structural components. Segmentation is influenced by various image features such as texture or hue, limiting the region of interest for the classifier [16]. Different segmentation techniques are compared in Table III.

Thresholding is the most common method used [18] [22] [15]. For instance, [22] applied thresholding after grayscale filtering, making it a straightforward technique based on intensity levels. Thresholding can be global or local, with local thresholding adapting to regional properties.

Gray-scaling is another widely used technique [10] [11] [18]. It transforms continuous-tone images into editable computer images, but it requires more memory due to increased bit representation.

Skin segmentation is a simple and popular method [19] [17], involving a predefined range of human skin colors for algorithm selection.

TABLE II PRE-PROCESSING METHODS

Ref.	Method	Advantages	Disadvantages
20,17	Gaussian Filter	Reduces noise in the image, Easy to implement	Lose fine image details and contrast
14	Median Filter	Preserve sharp features, Efficient for smoothing spiky noise	Difficult to treat analytically
21	Image Cropping	Remove unwanted objects and noise	-

TABLE III SEGMENTATION METHODS

Ref.	Method	Advantages	Disadvantages
10,11,18	Gray Scaling	Simplifies the algorithm, Reduces computational requirements	-
18,22	Thresholding	Fast performance, Reduces computational requirements	-
19, 17	Skin segmentation	Extract the objects of interest	Sensitive to environmental facts like light condition

3) Feature Extraction

Feature extraction is a crucial step in image classification, where important elements in an image are labeled. The accuracy of classification models relies on the numerical features extracted from images. Several feature extraction techniques have been developed and compared for Sign Language Translation systems (Table IV).

Principal Component Analysis (PCA) is widely used [17] [13]. PCA reduces correlated variables to uncorrelated principal components, preserving data variability. It's also applied for image compression.

Speeded Up Robust Features (SURF) is another common technique used in Sign Language translation [11]. SURF is known for its fast and reliable image encoding and comparison, making it suitable for real-time applications like tracking and object detection.

C. What are the algorithms used in the Sign classification process?

In Sign Language Translation systems, various learning algorithms are employed for sign classification. Table V compares the advantages and disadvantages of these techniques.

The most popular method is the Convolutional Neural Network (CNN), known for its high accuracy. CNN's effectiveness is due to its additional layers compared to Artificial Neural Networks (ANN). However, it can be more resource-intensive. For instance, Jalal et al. achieved a 99% accuracy rate using CNN [15].

Support Vector Machine (SVM) is another common method that can handle multiple continuous variables and create hyperplanes in multidimensional space for classification [11] [13].

Hidden Markov Model (HMM) is used in some Sign Language translation systems for modeling events with unobservable causes [12] [20].

TABLE IV FEATURE EXTRACTION METHODS

Ref.	Method	Advantages	Disadvantages
17,13	PCA	Easy to compute, Speeds up the machine learning algorithms	-
11	SURF	Faster than SIFT, Uses only 64-dimensional vector	A large number of computations

TABLE V CLASSIFICATION ALGORITHMS

Ref.	Method	Advantages	Disadvantages
15,14,19,22	CNN	Able to work without segmentation and pre-processing, with Higher accuracy	Lots of training data are required
11,13	SVM	Effective in high-dimensional spaces,	Low efficiency when the noise in the image
12,20	HMM	Efficient learning algorithm	Lots of training data required Higher computational requirement

After analyzing these previous works related to Sign Language recognition and translation, we have presented the techniques used in each stage and their accuracy in Table VI.

V. CONCLUSION

In this literature survey, we examined 12 previous research studies on Sign Language Translation, with a focus on the Sri Lankan context. The analysis revealed that several common phrases and techniques are prevalent in the majority of the research conducted in this field, including Image acquisition, Pre-processing, Segmentation, Feature extraction, and Image Classification. Our study found that the standard camera is commonly used for image acquisition, and some researchers have explored alternative methods using Kinect motion sensors and internet-obtained datasets.

For image segmentation, it was observed that Grey scaling and Thresholding are the most frequently employed techniques, while others have experimented with the Otsu algorithm, skin segmentation, and Morphological filters. Among the various studies analyzed, the most widely used image classification algorithm is the Convolutional Neural Network (CNN), known for its high accuracy rates in this domain.

However, while most of the reviewed studies demonstrated good performance, certain limitations were identified. For example, some systems achieved high accuracy but were limited to static images, while others, with lower accuracy rates, managed both static and dynamic images. Another significant limitation was the inability of these systems to capture facial expressions, a crucial aspect of Sign Language communication.

In conclusion, there is indeed a gap in the literature related to Sri Lankan Sign Language, which needs further exploration. It is important to highlight that most of the reviewed studies in our survey were conducted in different contexts, and specifying their country of origin can add clarity to the analysis. As a recommendation for future work, researchers should consider developing a system that specializes in recognizing and translating Sri Lankan Sign Language. Moreover, efforts can be directed toward enhancing the system's capabilities to recognize Sinhala voice inputs and translate them into corresponding Sign Language gestures, contributing to a more comprehensive and context-specific understanding of Sign Language Translation.

TABLE VI RESEARCH OVERVIEW

Ref.	Ref. Origin	Data Acquisition	Pre-processing	Segmentation	Feature extraction	Classification	Accuracy
10	Foreign	Standard Camera	Gray scaling, Morphological Filter	Otsu Algorithm	Cross-Correlation Coefficient	Cross-Correlation Coefficient	94%
11	Foreign	Standard Camera	Gray scaling	Canny Edge	SURF	SVM, Bag of Features (BoF)	97.13%
15	Foreign	Dataset (Kaggle)	-	-	CNN	CNN	99.74%
12	Foreign	Kinect	-	-	Skeleton Pair (SP)	HMM	-
18	Foreign	Standard Camera	Gray scaling	Thresh-holding		ANN	95%
13	Foreign	Kinect	Median Filter	-	PCANet	SVM	88.7%
19	Foreign	Dataset	-	Skin Segmentation	CNN	CNN	98.05%
14	Foreign	Kinect	Median Filter, Image cropping	Thresh-holding	CNN	CNN	91.7%
16	Foreign	Dataset (ASL Finger Spelling dataset)	Image Cropping	-	CNN	CNN	98%
20	Sri Lankan	Standard Camera	Gaussian Filter	Canny Edge Detector	HMM	ANN	73.76%
21	Sri Lankan	Web Camera	Image Cropping	Skin Segmentation	SIFT	CNN	86.5%
22	Sri Lankan	Standard Camera	Gray scaling	Thresh-holding	-	CNN	97%

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