# A Comprehensive Review of Sign Language Recognition: Different Types, Modalities, and Datasets

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Abstract—A machine can understand human activities, and the meaning of signs can help overcome the communication barriers between the inaudible and ordinary people. Sign Language Recognition (SLR) is a fascinating research area and a crucial task concerning computer vision and pattern recognition. Recently, SLR usage has increased in many applications, but the environment, background image resolution, modalities, and datasets affect the performance a lot. Many researchers have been striving to carry out generic real-time SLR models. This review paper facilitates a comprehensive overview of SLR and discusses the needs, challenges, and problems associated with SLR. We study related works about manual and non-manual, various modalities, and datasets. Research progress and existing stateof-the-art SLR models over the past decade have been reviewed. Finally, we find the research gap and limitations in this domain and suggest future directions. This review paper will be helpful for readers and researchers to get complete guidance about SLR and the progressive design of the state-of-the-art SLR model.

Index Terms—Artificial Intelligence, Sign Language Recognition, Datasets, and Human-Computer Interaction.

### I. Introduction

Ccording to the WHO (World Health Organization) report, over 466 million people are speech or hearing impaired, and 80% of them are semi-illiterate or illiterate [1]. Non-verbal manner conveys and communicates our views, emotions, and thoughts visually through sign language. Compared to spoken language, sign language grammar is quite different. A sign comprises specific hands, shapes, or signals produced in a particular location on or around the signer's body combined with a specific movement.

Hand gestures, signals, body movements, facial expressions, and lip movements are the visual means of communication used by the hand-talk community and ordinary people to convey the meaning; We recognize this language as a sign language. Sign language recognition (SLR) is challenging and complex, and many research opportunities are available with

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the present technology of artificial intelligence. A taxonomy of SLR is shown in Figure 1. It comprises datasets, input modality, features, classification, computational resources, and applications. The dataset is further classified into isolated sign dataset and continuous sign dataset. Vision-based modality and sensor-based modality are the general types of input modality. Hand movement, facial expression, and body movement are the major features that concern SLR. Classification is typified into traditional methods (HMM, RNN, etc.), deep learning (CNN), and hybrid method (combination of traditional and deep learning or combination of deep learning and optimization algorithm).

SLR aims to understand the gestures by suitable techniques, which requires identifying the features and classifying the sign as gesture recognition. In the literature, there is no comprehensive review paper addressing the aspect of the modality (vision and sensor), different types (isolated (manual and no manual) and continuous (manual and no manual)), various sign language datasets, and state-of-the-art methods based studies. This review study focuses on SLR-based research work, recent trends, and barrier concerns to sign language. Different sign languages, modalities, and datasets in sign language have been discussed and presented in tabular form to understand better. From databases like IEEE explore digital library, science direct, springer, web of science, and google scholar, we used the keywords sign language recognition to identify significant related works that exist in the past two decades have included for this review work. We excluded papers other than out-ofscope sign language recognition and not written in English. The contributions to this comprehensive SLR review paper are as follows:

- Carried out a review of the past two decades of published related work on isolated manual SLR, isolated nonmanual SLR, continuous manual SLR, and continuous non-manual SLR.
- Discussed different sensing approaches for sign language recognition and modality
- This paper presents SLR datasets concerned with isolated and continuous, various sign languages, and the complexity of the datasets discussed.
- Discussed the framework of SLR and provided insightful guidance on SLR

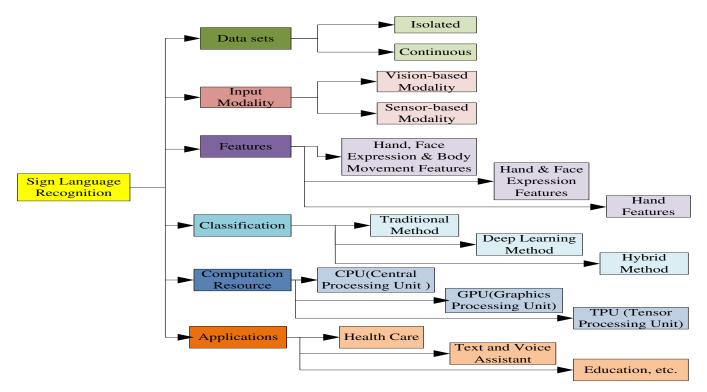


Fig. 1: SLR Taxonomy: the fundamental attributes of SLR like datasets, modality, features, classification, computation resources, and application, along with each attribute's categorization are shown here. Large-scale datasets and modalities affect the recognition performance. The efficient features extraction method and classification model with efficient power computation resources lead to high performance.

- Point out the limitations related to the dataset and current trends available in the SLR and potential application of SLR with human-computer interaction.
- This paper studied the results of the current state-of-theart SLR model regarding the various benchmark SLR datasets for isolated and continuous SLR.
- This paper analyzes current SLR issues and advises future SLR research direction.

## A. Need of SLR

As per WHO statistics, around 5% of the population in the world suffers from a lack of hearing power. According to the prediction of the United Nations, the number of deaf people in 2050 will be 900 million [1]. Hence, SLR receives a lot of attention at present. SLR can eliminate the communication gap between the hand-talk community (deaf and dumb). Also, SLR helps to improve communication in the following ways.

- It reduces the frustration of the hand-talk community.
- The communication barrier overcome by SLR leads to effective communication.

Much research endeavored to develop high-performance SLR. Despite that, it is challenging, and it is one of the recent research fields with enormous research scope.

# B. Challenges

SLR comprises numerous gestures and facial expressions, making it complex and challenging. In addition, to the manual

components, lip shapes and eyebrow positions distinguish similar signs; e.g., many manual signs seem to be of a similar pose. However, these can be differentiated with the help of facial expression and lip movement. Sign language comprises hand movement, shape, position, orientation, palm posture, finger movement, facial expression, and body movements. These components highly influence the performance of SLR. Some of the barriers and problems of SLR are tabulated in Table I. With the advance of hardware, efficient algorithms can improve the processing speed. The scaling and image orientation problems can be resolved with recent deep learning techniques. The illumination problem can be overcome if the RGB is converted to HSV (Hue Saturation Value) or Yeber (Luminance Chrominance). Dynamic and non-uniform background environment problems could be resolved using the skin region and background subtraction method.

## C. Procedure involved in SLR

The SLR involves data collection, preprocessing, feature extraction, and classification phase. The block diagram of SLR and its general process is demonstrated in Figure 2. These stages are discussed in the following. Note that, for the sensor-based approach, preprocessing and segmentation are optional.

**Data Collection:** In SLR, the data acquisition is performed using one of two modes; Vision and Sensor. In a vision-based approach, the input is an image or video [2], [3]. A single

TABLE I: SLR Barrier, and Problem: We discussed how the barriers (dynamics, illumination of lights and environment, scaling, and computation time) of SLR cause a problem.

| Barrier  | Problem   |
|--|---|
| Computation speed and time                     | Create complexity to the system and take a lot of computation time.                             |
| Scaling and image orientation problem          | The distance of input data capturing various signers.   |
| Illumination of light                          | Performance varies with different illumination scenarios because most models use the RGB model. |
|  | It is highly illumination sensitive.  |
| Dynamic and non-uniform background environment | The noise, improper detection of hand, and face lead to affect the performance and mislead the  |
|  | sign recognition system.  |

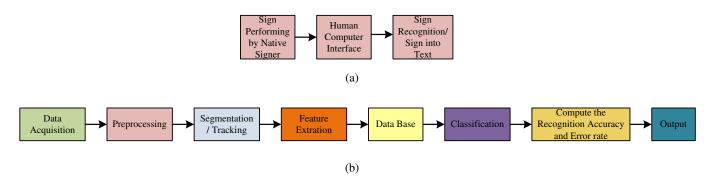


Fig. 2: (a) SLR (b) General process flow of SLR. Figure (a) illustrates the native signer performing sign conversion into text with the help of a human-computer interface, and figure (b) illustrates the procedural stages of SLR. The recognition rate highly depends on the data set, preprocessing, feature extraction, and classifier.

camera is used to collect standard signs while multiple cameras, active and invasive devices, help collect the depth information. Video camera, webcam, or smartphone device [4], [5], [6], [7] captured the continuous motion. The sensor-based approach collects the signal with the use of the sensor [8], [9], [10], [11].

**Image Preprocessing:** The performance of the SLR system can be improved by preprocessing methods such as dimension reduction, normalization, and noise removal. [12].

**Segmentation:** The segmentation stage splits the image into various parts or ROI (Region of Interest) [13], Skin Colour Segmentation [14], HTS (Hands Tracking and Segmentation) [15], Entropy Analysis and PIM (Picture Information Measure) [16]. The background requires the hand gesture extraction to be done effectively by segmentation and tracking process.

**Tracking:** Tracking of hand position and facial expression from the acquired image/video can be performed using camshaft (continuously adaptive mean shift used to track the head position) [17], Adaboost with HOG (Histogram of the gradient) [18], Particle filtering (KPF-Kalman Particle Filter) [19].

**Feature Extraction:** Transforming preprocessed input data into the feature space is known as feature extraction. Further, it is discussed in detail in section 2.

**Data Base:** The acquired data (image/video) is stored in the database and classified into two sets, namely training and testing datasets [20]. The classifier learns by training dataset

and the performance is evaluated by testing data.

Classification: The classifiers perform the classification by extracting features and classify the sign gesture. The Hidden Markov Model (HMM) [9], [21], Long-Short Term Memory (LSTM) [22] Deep Learning network [23], and hybrid classifier [2], [24] are used as classifiers to recognize sign language.

**Evaluation Stage:** The performance of a trained classifier is validated with a testing dataset (unseen data during training) [25]. The error incurred during classification gauges sign recognition performance.

Although there are few review papers in the literature [26], [12], however, they lack focus and understanding of SLR. This paper provides a comprehensive SLR preamble, recent research progress, barriers or limitations, research gap, and future research direction and scope. We organized the rest of the review paper as follows. Section 2 presents sign language modality, preprocessing, and the various feature extraction methods in SLR. Carried out a literature review concerning the manual and non-manual aspects of SLR in Section 3; Section 4 discusses and illustrates the classification architecture of SLR. Section 5 presents various types of SLR, datasets concerning SLR, and reviews work related to the modalities, current stateof-the-art models based on SLR. The recent trends, challenges, and limitations are highlighted in Section 6. Sections 7 and 8 pointed out future research discussion and conclusion, respectively.

TABLE II: The importance of vision-based and sensor-based methods are shown here according to the obstacle, cost, merits, and demerits. Much research work focuses on vision-based SLR because of its feasibility in real-time applications.

| Method  | Capturing<br>Device | Obstacle                                   | Efficiency   | Cost | Limitation   | Advantage   |
|---|---------------------|--|--|------|--|---|
| Vision-based<br>Method                        | Video Camera        | Environment,<br>disturbance, and<br>noise. | Low (depends on the resolution).   | Low  | Possess challenging concerns for<br>time, speed, and overlapping. More<br>Feature extraction techniques are<br>required. | Fast Speed.   |
| Sensor-<br>based or<br>gloves-based<br>Method | Sensors and gloves  | Environment,<br>disturbance, and<br>noise. | Better than vision-<br>based method<br>(depends on sensor<br>performance). | High | Not suitable for real-time application.  | Better performance. Require minimal feature extraction. |

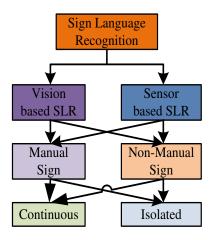


Fig. 3: SLR Types: Vision-based SLR and sensor-based SLR are the SLR types. It is further, classified into manual and non-manual, then isolated and continuous.

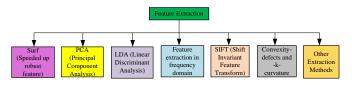


Fig. 4: Various methods are used to extract the significant features.

## II. MODALITIES OF SLR

SLR is one of the most prominent research areas in computer vision and natural language processing. In concern to the acquisition process, the SLR system is classified as a sensor-based and vision-based approach. Both approaches are next classified as manual and non-manual, and further classified as isolated and continuous. Figure 3 illustrates the SLR types. Much research work focused on isolated manual-based SLR. Only a little research work addressed continuous non-manual SLR.

**Sensor-based approach:** Physically attached sensors acquire trajectories of the head, finger, and motion of the signer. Sensor-associated gloves track the signer's hand articulations and recognize the sign. The comparison of SLR methods shown in Table II clarifies vision and sensor-based approaches. In contrast with vision-based SLR, sensor-based

TABLE III: Various features extraction methods associated with SLR work exist in the literature.

| Method                               | Year | Author                 |
|--------------------------------------|------|------------------------|
| FPM (Feature Pooling Module)         | 2020 | Sincan and Keles [27]  |
| Histograms of oriented gradients     | 2016 | Chansri and Srinonchat |
|                                      |      | [28]                   |
| Euclidean distance                   | 2016 | Pansare and Ingle [29] |
| Euclidean distance                   | 2013 | Singha and Das [30]    |
| DWT (Discrete Wavelet Transform)     | 2017 | Ahmed et al. [31]      |
| BWT (Bisciete Wavelet Hanstollin)    | 2016 | Prasad et al. [32]     |
| SIFT (Scale Invariant Feature Trans- | 2012 | Gurjal P [33]          |
| form)                                |      |                        |
| SURF (Speeded Up Robust Feature)     | 2012 | Yao and Li [34]        |
| Fourier Descriptors                  | 2017 | Kumar [35]             |
| Tourier Descriptors                  | 2015 | Shukla et al. [36]     |
| PCA (Principal Component Analysis)   | 2021 | Gurbuz et al. [37]     |
| . 1 1                                | 2015 | Tripathi and Nandi [4] |
| Fuzzy neural network                 | 2016 | Dour and Sharma [38]   |

SLR provides efficient performance.

Vision-based approach: The gestures captured by multiple cameras (or webcam) are recognized using the vision/image-based approach. From the captured image/video, it extracts palm, finger, and hand movement features. With the help of these extracted features, classification was performed. Poor illumination or lighting environment, noisy background, and blurring present in the image result in misclassification. Although vision-based SLR is suitable for real-time conditions, it must adequately care for preprocessing, feature extraction, and classification.

## A. Preprocessing

The computational burden of data processing could be reduced by preprocessing methods. Image reduction and image conversion methods do the size reduction and conversion from color to gray scale. Image reduction methods reduce the burden of data processing. The unwanted object can be removed by the histogram equalization [39]. The noise present in the image are removed using the filter, like median, moving average method, and so on [40]. Gaussian average methods are used to remove the image background component [41]. Filters perform removal of the unwanted components and minimize the size of the data with the help of image edge detection algorithm [42]. The filter process speeds up with the help of fast Fourier transformation because instead of an image, the frequency domain is used [43]. The image is split into possible segments [44]; masking is used in segmentation

to improve processing. Elimination of background effect using binarization histogram equalization aid for better image contrast. Normalization methods can effectively handle the variance in the data [45].

### B. Feature Extraction

In SLR, relevant feature extraction plays a vital role. It is crucial for sign language, as irrelevant features lead to misclassification [46]. The feature extraction aid in accuracy improvement, and speed [47]. Some of these feature extraction method include SURF (Speeded Up Robust Feature) [34], speed up robust feature (Laplace of Gaussian with box filter) [34], SIFT (shift-invariant feature transform) [33], PCA (Principal Component Analysis) [37], [4], LDA (Linear Discriminant Analysis) [48], Convexity defects and k-curvature [49], time domain to frequency domain [31], [35], Local binary pattern, etc. The feature extraction methods used for SLR-based study is tabulated in Table III. Various feature extraction methods are showed in Figure 4. Feature vector dimension reduction performed by PCA, LDA, etc. aid in reducing the computational burden on the classifiers. The dimensionality pruning, features reduction, and lowering of the dimension keep the significant features of high variance and minimizing remaining features, thus, reduces the training complexity. Fourier descriptors are noise resistance and invariant to scale, orientation, and normalization is easy. The process of transforming the correlated into an uncorrected value is known as principal component analysis. Original data are linearly transformed effectively, and the feature vectors get reduced.

The preprocessing and feature extraction methods aid the classifier. Also, they reduce the computation burden, avoid overfitting issues, and wrong recognition possibilities. SIFT's merits are invariant to lighting, orientation, and scale. However, the performance is not satisfactory [33]. Using Histogram of Oriented Gradients (HOG) [28], the unwanted information is removed, keeping the significant features to ease the image processing. The feature vectors are obtained using the computation of gradient margin and angle. As HOG cell size and the number of bins increase, the extracted feature also increases. Larger subdivisions furnish global information, and small subdivisions given local information that is worthwhile. The demerits of both the methods are that they require more memory. SURF is invariant to image transformation and a faster feature extractor than SIFT. Still, it has the requirement of camera setup in horizontal position for better performance, and the disadvantage is illumination-dependent, not rational. Location and frequency captured using a Discrete Wavelet Transform. Temporal resolution is the critical merit of DWT [31], [32].

## III. LITERATURE STUDIES ABOUT SLR

Sign language is not generic; it varies according to the region and country [1]. The sign language classification is available in over 300 sign languages worldwide, namely ASL, BSL, ISL, etc. According to Ethnologue 2014 [50]

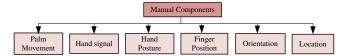


Fig. 5: Manual Components. The important manual features related to sign language are shown here.

in the United States, ASL is a native language for around 2,50,000-5,00,000 people. Chinese Sign Language is being used in China by approximately 1M to 20M deaf people. Approximately 1,50,000 people in the United Kingdom use British Sign Language (BSL). In Brazil, approximately 3 million signers use Brazilian Sign Language to communicate, like Portuguese Sign Language or French Sign Language. According to Ethnologue 2008 in India, approximately 1.5 million signers use Indo-Pakistani Sign Language.

SLR is not only meant for deaf and mute people. Ordinary people also communicate information in the noisy area of public places and the library without disturbing others. Manuel (communication by hands) and non-manual (communication by body posture or facial expression) medium are usually used in sign language. People use sometimes finger spelling which is communicated by splitting words into letters, then spelling the letter using fingers). Manual and non-manual SLR are discussed in detail in following subsections.

#### A. Manual SLR

Hand motion, hand posture, hand shape, and hand location are the manual sign components. Figure 5 shows the manual sign components. With one hand or two hands, the signer usually communicates with others. The manual SLR is classified into isolated and continuous.

1) Isolated Manual SLR: The literature work on isolated manual SLR are as follows:

Classical methods: Ong et al. [51] suggested sequential Pattern Tree-based multi-class classifier for DGS (German Sign Language (Deutsche Gebärdensprache) and Greek Sign Language (GSL) recognition. Their proposed SP-Tree Boosting algorithm-based recognition model performs better than the Hidden Markov Model. Chansri and Srinonchat [28] proposed data fusion incurred ANN-based Thai SLR model. They extracted the hand feature using histograms of oriented gradients, and they did classification using a back-propagation algorithm associated with an ANN. Yin et al. [52] performed hand gesture recognition using a joint algorithm based on BP and template matching method combination. The joint algorithm takes computation time as 0.0134 and an accuracy of 99.8% was achieved for isolated hand gesture recognition. Jane and Sasidhar [53] carried out an ANN classifier with an association of data fusion. They performed three hidden layers of artificial neural network with wavelet denoising and TKEO (TeagerKaiser energy operator) methods for a SEE (Signing Exact English). Based on this approach, the recognition rate is 93.27%. Korean finger language recognition model was developed based on ensemble ANN [11]. The performance was analyzed by varying dataset size (50 to 1500) and classifier (1 to 10). The comparative analysis of eight ANN classifier-associated ensemble models identifies 300 training datasets as an optimal structure to lead to 97.4 % recognition accuracy for Korean finger language recognition.

Almeida et al. [54] extracted seven vision-based features using RGB-D sensor. They recognized Brazilian Sign Language with an average of 80% using the SVM. They did phonological structure-based decomposition and extraction of signs. Hence, they suggested a model suitable for other SLR purposes. Fatmi et al. [9] performed SLR based on ANN and SVM. They have compared their performance with HMM. Comparison with other machine learning techniques to ASL words, higher accuracy achieved by proposing ANN. Lee and Lee [55] developed SVM based on a sign language interpretation device with 98.2 % recognition accuracy. SVM classifier-based sign interpretation device developed system. Wei et al. [10] presented the CSL sign recognition model using a code matching method by including a fuzzy Kmean algorithm. They determined subclass by a fuzzy Kmean algorithm and classification was done with the Code matching method. Li et al. [56] suggested ASL recognition prototype model based on KNN, LDA, and SVM classifiers. They carried out a prototype model based on LDA, KNN, and SVM classifiers using a firmly stretchable strain sensor for ASL 0-9 number sign recognition. The authors reported that the model achieved an average accuracy of 98%.

Yang et al. [57] performed a Chinese Sign Language (CSL) recognition model based on sensor fusion decision tree and Multi-Stream Hidden Markov Models classifier. They developed a wearable sensor associated with the Chinese SLR model with user-dependent and user-independent using Multi-Stream Hidden Markov Models. The searching range improved by optimized tree-structure classification. Dawod and Chakpitak [58] carried out work on real-time recognition model for ASL alphabets and numbers sign recognition. They used RDF (Random Decision Forest) and HCRF (Hidden Conditional Random Field) based classifiers and Microsoft Kinect sensor v2 for the data collection. The HCRF classifierbased recognition model gets the mean accuracy for numbersbased sign recognition as 99.99% and alphabets sign recognition as 99.9%. The RDF-based recognition model achieved mean accuracy for number sign recognition as 96.3% and alphabets sign recognition as 97.7%. Hence, the HCRF based sign recognition model leads to better performance than RDF for both ASL numbers and alphabets recognition. Hrúz et al. [59] presented a Hidden Markov Model-based Czech SLR model with an association of kiosk. Also, they performed SLR, automatic speech recognition, and sign language synthesis.

Mummadi et al. [60] proposed an LSF model based on IMU sensors associated with wearable hand gloves with various classifiers like naïve Bayes, MLP, and RF. Real-time wearable IMU sensor-based glove-associated sign recognition model developed for LSF recognition instead of complimentary filter advanced fusion strategy and the advanced classifier can improve the accuracy rate. Botros et al. [8] presented a comparative analysis of wrist-based gesture recognition using EMG signal. Forearm and wrist level-based gesture

are recognized using EMG signal. Gupta and Kumar [61] performed a wearable sensor-based multi-class label incurred SLR model. The LP-based SLR model has a minimal error and computation time than the tree-based, BR (binary relevance), and CC (Classifier Chain) based sign recognition models. Compared to the classic tree classification model, the suggested model performs well with minimal classification errors. Hoang [62] presented a new vision-based captured ASL alphabets sign dataset (HGM-4). With this dataset, using a classifier, developed a contactless SLR system.

Deep learning approaches: Al-Hammadi et al. [46] performed sign dependent and sign independent SLR using three datasets using single and fusion parallel 3DCNN. The proposed model gets a better recognition rate than other considered six existing literature methods. Sincan and Keles [27] performed CNN and LSTM based SLR model for Turkish SLR. The feature extraction improved by FPM (Feature Pooling Module), convergence speeds up using the attention model. Yuan et al. [24] pointed out DCNN (deep convolution neural network and LSTM (long short-term memory) based model for hand gesture recognition. The residual module has overcome the gradient vanishing and overfitting problem. Complex hand gesture long-distance dependency problem addressed by improved deep feature fusion network. Compared to Bayes, KNN, SVM, CNN, LSTM, and CNN-LSTM, the DFFN based model performs well on ASL and CSL datasets.

Aly and Aly [2] designed an Arabic SLR model using BiLSTM (deep Bi-directional Long Short Term Memory recurrent neural network). Convolutional Self-Organizing Map for hand shape feature extraction, and DeepLabv3+ extracts hand regions. The suggested model proved validity on signerindependent real Arabic SLR. The proposed model is suitable for an isolated sign, and continuous sign-based analysis can be a future direction. Rastgoo et al. [3] carried out work on a multi-modal and multi-view hand skeleton-based SLR model. Features fusion and single-view vs. a multiview projection of hand skeleton-based performance analysis performed. SSD (Single Shot Detector), 2DCNN (2D Convolutional Neural Network), 3DCNN (3D Convolutional Neural Network), and LSTM (long short-term memory) based deep pipe-line architectures were proposed to recognize the hand sign language automatically. Lee et al. [22] designed the k-Nearest-Neighbour method associated with Long-Short Term Memory (LSTM) recurrent neural network-based American SLR model. The leap motion controller is used to gain the sign data. Compared to SVM, RNN, and LSTM models, the proposed model (LSTM with KNN) outperforms 99.44%.

For a clear understanding, the research work related to isolated manual SLR are tabulated in Table IV and graphical representation is shown in Figure 6. The recognition model results in good accuracy for isolated sign recognition, not assured to be generalized for continuous sign recognition with better precision.

2) Continuous Manual SLR: Processing one-dimensional data is simpler compared to handling a high-dimension dataset like video [63]. Continuous SLR with uncontrolled environment-based SLR is quite complex as there is no clear pause after each gesture.

TABLE IV: Isolated Manual SLR Literature Work. Related work with regard to vision and sensor based SLR model concerns the isolated manual sign comprehensively summarized in a tabular form for better understanding.

| Dataset            | A total of 5178 hand motions of ASL alphabets and 100 daily life activities sign of CSL with a total of 34452 hand motions. | 72 repetitions per participant of 5 single-finger, 6 multi-finger gestures, and 6 wrist gestures are collected.             | 2600 samples (26 *100 samples).   | 20,000 samples.   | 4,160 samples.   | Danset 1: signer dependent total 8000 samples, signer independent total 6400 video samples. Danset 2: signer dependent ontol 3444 samples, signer independent total 3444 samples. Dataset 2: signer dependent total 280 samples, signer independent total 280 samples.  | 3450 samples.   | First-Person (45 hand action, 100 K frames), NPU (36 joints, 81,009 image sequence), and RKS-PERSIANSIGN (100 signs, 10,000 samples) datasets.      | AUTSL: 38,336 samples, Montalbano: 14,000 samples.   | 345000 samples.  | 26,000 instances captured, among 66 % used for training and remaining used for testing. | 3 trials of datasets.  | 1.25 million samples.  | 1500 training data.   | 4927 samples, 204 features.   | 10 trials of each gesture by 6 subjects, 540 data samples.  |
|--------------------|---|---|---|---|--|---|---|---|--|--|---|--|--|---|---|---|
| Model Type         | America sign language,<br>Chinese sign language.  | human-computer inter-<br>action: Hand gesture<br>sign.  | American SLR  | Indian SLR  | America sign language.   | SAUDI<br>LANGUAGE,<br>LANGUAGE,<br>SIGN<br>LANGUAGE,<br>AMERICAN<br>LANGUAGE.   | Arabic sign language.   | Persian signs language.   | Turkish Sign Language (TSL).   | American Sign<br>Language.   | American Sign<br>Language.  | Human-computer interaction: Hand gesture Sign (Signing Exact English).   | French Sign Language (LSF).  | Korean finger language.   | Signing Exact English<br>(SEE-II).  | American sign<br>language.  |
| Sample and Lexi-   | con Size 26 ASL aphabets, daily activities for CSL, 6 subjects  | 17 various single fingers, multi-finger, and wrist gestures, 21 subjects  | 26 ASL alphabets,<br>100 subjects.  | 100 signs, 10 sub-<br>jects.  | 26 letter sign, 5 sub-<br>jects.                               | Dataset 1 (40) gustine classes/200 gesture), dataset 2 (3 subjects, 3 gestures, 150 sumples), dataset sumples), dataset sumples), dataset sumples)  | 23 words, 150 sequences, and 3 subjects.                                    | 100 sign words, 10<br>subjects, 10 various<br>environment.  | AUTSL and Montal-<br>bano datasets, 226<br>signs, 43 subjects.   | A-Z alphabets and 1-<br>20 numbers, 30 sub-<br>jects (signer).   | 13 ASL gestures signs, 3 subject.   | 8 air gestures and 4 surface gestures with 2 distinct force levels, 10 subjects.   | 22 hand gestures, 57 subjects.   | 7 numbers, 17 vow-<br>els and 14 conso-<br>nants, 17 subjects.  | 48 lexicon word.  | Six subjects. 0-9<br>ASL sign.  |
| Sensor             | 3-dimensional flex<br>sensor-based data<br>gloves, gyroscope,<br>accelerometer, and<br>bending sensor.                      | EMG sensor  | Leap motion con-<br>troller   | Surface<br>electromyogram and<br>inertial measurement<br>units.     | 4 cameras (front,<br>back, right, and left),<br>laptop camera. | RGB cameras, Mi-<br>crosoft Kinect, ana-<br>log cameorder.  | Video camera: 25 fps<br>(frames per second).                                | Video camera (RGB).   | Microsoft Kinect v2.   | Kinect sensor v2.  | Myo Armband (x2) (sense motion and depth).  | Sensing fusion using<br>4-Channels sEMG<br>Electromyography,<br>one IMU inertial<br>measurement unit.                      | 3D magnetometer, 3D gyroscope (GYRO), and 3D accelerometer (ACC).  | Armband module (8-<br>channel electromyo-<br>graphy) sensors.   | Myo Armband (gyroscope, accelerometer, magnetometer, and sEMG (surface electromography)) sensors.       | Firmly stretchable<br>strain sensor<br>(Custom Glove).  |
| Accuracy or Result | Recognition accuracy: 99,93% for ASL and 96.1% for CSL.   | For multi-finger gestures, accuracy: 91.2%, single finger accuracy: 92.1%, and conventional wrist gestures accuracy: 94.7%. | Recognition accuracy: 99.44% and validation (5-fold cross-validation) accuracy: 91.8%.            | LP (label power set) model average classification error: 2.73%.     | NA   | Recognition rate for dataset 1 (SSL-SAUD) SIGN LANGUAGE) single 3DCNN signer- dependent mode: 96.69%, signer independent recognition rate 22.28%, partialed 3DCNN signer- dependent mode: 98.12%, and signer independent recognition rate: 84.38%, for dataset 2 (AsSL- ASABEN GISIO LANGUAGE) signer-dependent mode: 10f8, signer independent recognition rate: 34.9%, for dataset 3 (ASL-AMERICAN SIGN LANGUAGE) signer-dependent mode: 76.7% and signer independent recognition rate: also signer independent recognition rate: also signer independent recognition rate: and signer independent recognition rate: The signer independent recognition rate in the signer independent recognition rate. | Accuracy without segmentation: 69.0% and with segmentation accuracy: 89.5%. | Accuracy: 96.2% for the RKS-PERSIANSIGN adazet, 82.10% for First-Person datasets, and an average estimation error: 12.82 for the NVU dataset.       | AUTSL dataset based recognition model ac-<br>eracy; 95.46%. Monathano dataset based<br>recognition model accuracy; 96.11% and for<br>user-independent benchmark dataset accuracy;<br>62.02%. | HCRF classifier mean accuracy (numbers): 99,99% and alphabets: 99,9%, and the RDF mean accuracy (number):96,3% and (alphabets): 97,7%. | 1. ANN: 93.79%, 2. HMM: 85.90%, and 3. SVM: 85.56%.                                     | Accuracy for air gesture: 92.6% and for surface gestures: 88.8%.   | Naïve Bayes method accuracy. 89,1%, and Fl score; 87%, MLP method accuracy; 92,5%, and Fl score; 91,1%, RF method accuracy; 92,5%, and Fl score; 91,8%. Mean accuracy; 92% and mean Fl score; 91%. | E- ANN with 8 Classifiers accuracy: 97.4%.  | Avenge accuney; 97,12%.   | LDA accuracy: 97.81%, KNN accuracy: 97.86%, SVM accuracy: 97.89%, and ASL recognition for 0-9 average accuracy: 98%.                |
| Cons               | Real-time live data-based analysis<br>with the uncontrolled environment<br>not performed to prove the validity.             | Continuous sign based experimentation was lacking limited regard to the dataset.  | One hand sign (right hand) only considered for recognition.                                       | Expensive and continuous sign based on experimentation was lacking. | Gesture recognition not performed.                             | Optimal selections of hyperparam-<br>eter problem, real-time practical<br>implementation with a live sign,<br>was lacking.  | Experimentation performed with a limited number of signers.                 | Complex model.  | Accuracy is lagging state-of-the-<br>art methods. It is affected by the<br>dynamic background.   | The authors fail to perform quantitative-based analysis.   | The limitation is not considered non-manual, and dictionary size is limited.            | The limitation is that calibration is required, and classification accuracy depends on calibration, and time also clapsed. | The performance of the model is depending on season noise and drift. Distance between sensor and hand increase, accuracy decreased.  | Selection of hyperparameter was<br>not addressed, suffered by conver-<br>gence and computation problem. | Two-handed and user-<br>independence signs recognition<br>was not addressed.                            | The model was not robust in na-<br>ture. Hysteresis characteristics and<br>noise present in the sensor lead to<br>misclassification |
| Pros               | Wearable gloves based hand ges-<br>ture recognition model.  | The reliable wearable device, less<br>affected by noise   | Suitable for real-time environment/applications.  | Computation time is less.   | Different position of hand gesture captured                    | Better recognition rate, generalize well with three datasets.   | Signers independent combinational sign recognition model.                   | Large-scale hand sign language<br>dataset presented   | New AUTSL dataset presented  | Higher recognition rates   | Functioning ability on a PC with Bluetooth Low-Energy (BLE) connections.                | Simpler than forearm device.   | 63 milliseconds uken to recognize<br>the sign (settling times and delays<br>are faster and minimal respectively<br>than local fusion algorithm with<br>IMU motion sensor-based method).            | Easy to wear, adaptable to portable devices.  | Easy to implement.  | Less interference, stretchable and<br>wearable comfort.   |
| Method             | CNN (Convolutional Neural Network) and LSTM (Long Short-Term Memory)  | Linear Discriminant Analysis (LDA) used as a classifier, PCA used to reduce the dimension.                                  | K-Nearest-Neighbour method,<br>Long-Short Tern Memory<br>(LSTM), and Recurrent Neural<br>Network. | Multi class classification.   | Multi camera-based sign (ASL)<br>data collection.              | Single 3DCNN, and PARALLEL. 3DCNN.  | Convolutional SOM, deep Bidirectional LSTM network, and DeepLabv3+.         | Midpoint algorithm, SSD (Single Shorton Cabon Comolutional Neural Network), 3DCNN (3D Comolutional Neural Network), and LSTM (Long Shortem Memory). | CNNs (Convolutional Neural Networks), Feature Pooling Module, unidirectional and bidirectional LSTM (Long Short-Term Memory).  | HCRF (Hidden Conditional Random Field), and RDF (Random Decision Forest).  | ANN, SVM, and HMM.  | Linear Discriminant Analysis (LDA).  | Naïve Bayes, Feed-forward Neural Network/MLP), Random Forest are used as a classifier. A complementary Fliter with a coefficient factor of 0.93 was used to obtain low drift and less noise data.  | Ensemble Feed-forward Neural<br>Networks.   | Artificial neural network, wavelet<br>densising techniques, and TKEO<br>(TeagerKaiser energy operator). | K-Nearest Neighbour, Linear Dis-<br>criminant Analysis, and Support<br>Vector Machines.   |
| Author             | Yuan et al. [24]  | Botros et al. [8]   | Lee et al. [22]   | Gupta and<br>Kumar [61]   | Hoang [62]   | Al-Hammadi<br>et al. [46]   | Aly and Aly<br>[2]  | Rastgoo et al. [3]  | Sincan and<br>Keles [27]   | Dawod and<br>Chakpitak<br>[58]   | Fatmi et al. [9]  | Jiang et al.<br>[48]   |  | Kim et al. [11]   | Jane and Sasidhar [53]  | Li et al. [56]  |
| Year               | 2021  | 2021  | 2021  | 2020  | 2020   | 2020  | 2020  | 2020  | 2020   | 2019   | 2019  | 2018   | 2018   | 2018  | 2018  | 2018  |

| Year | Author                            | Method   | Pros   | Cons  | Accuracy or Result  | Sensor   | Sample and Lexi-<br>con Size  | Model Type   | Dataset  |
|------|-----------------------------------|--|--|---|---|--|---|--|--|
| 2018 | Yin et al. [52]                   | Template Matching, BP neural network, and Combined Model.              | High recognition rate data glove.  | Dynamic gesture recognition based research was not performed, and data glove burrer is there, and only a single background effect considered for the experiment fail to generalize in other background.   | Template Matching accuracy: 96.7%, 2. Feed-forward Neural Network accuracy: 98.4%, combined model accuracy: 98.8%.  | Custom Glove (Bend Sensors (x5), FLEX2.2).   | 6 numbers, 3 letters, 5 subjects.   | Hand gesture sign.   | 1000 different data for each gesture<br>from 5 different signers, a total of<br>9000 data. |
| 2018 | Lee and Lee [55]                  | Support Vector Machines.   | Custom-made devices not required because 3D-printed based device used it can fit different sign irrespective of hand and finger sizes holders. | The crucial factor like background light and other effects fall to be addressed. Sign respect to words and sentences not considered for experiments, and implementation can be on a smaller-sized printed circuit board if the research gap is not addressed. | Without pressure sensor accuracy: 65.7%, with a fusion of pressure sensors accuracy: 98.2%.   | Custom Glove (9-<br>Axis IMU, Flex<br>Sens.(x5), Pressure<br>Sens. (x2), twe flex<br>sensors, two pressure<br>sensors, and a three-<br>axis inertial motion<br>sensor. | 28 gesture patterns<br>(26 ASL letters, 2<br>signs), 12 subject.  | American sign<br>language.   | 6.480,000 datasets (13 subjects 20 times $\times$ 10 s $\times$ 100 Hz $\times$ 27 signs). |
| 2017 | Yang et al. [57]                  | Multi-Stream Hidden Markov<br>Models, and Decision Tree<br>classifier. | Time consumption is reduced, and recognition accuracy is improved by the decision tree based classifier.                                       | The proposed model result still lagging behind the literature state of the methods.   | User dependent model accuracy: 94.31%, user-<br>independent model accuracy: 87.02%.   | 4-Channel sEMG, 3-<br>Axis (gyroscope, ac-<br>celerometer) sensor.   | 150 signs (one-handed sub-words sign: 81, two-handed sub-words sign: 69, hand orientations: 3, hand amplitude levels: 3), 8 subjects. | Chinese Sign Language (CSL).   | 30000 sub word data sample (total 3750 sub-word samples per sub-ject).                     |
| 2016 | Wei et al. [10]                   | Code matching method, and fuzzy K-mean algorithm.                      | User's training burden minimized.  | Target set size is limited; instead of code matching method, advanced fusion method can improve the recognition accuracy.   | The recognition accuracy of two reference subject for one-third gestures of the target set: $(82.6 \pm 13.2)\%$ , and $(79.7 \pm 13.4)\%$ and half of the target set: $(88 \pm 13.7)\%$ and $(86.3 \pm 13.7)\%$ . | sEMG (surface electromyographic), GYRO (gyroscopes), and ACC (accelerometers).   | 110 sign words, 5 subjects.   | Chinese Sign Language (CSL).   | 13750 (2750 sign word samples for each subject).   |
| 2016 | Chansri and<br>Srinonchat<br>[28] | Histograms of oriented gradients, and artificial neural network (BP).  | Simple model.  | The author can not perform statis-<br>tical analysis.   | Accuracy: 84.05%.   | Microsoft Kinect (color and depth).  | 42 letters, 24 hand gestures.   | Thai Sign Language.  | 420 hand gesture samples.  |
| 2014 | Almeida et al.<br>[54]            | Support Vector Machines (SVM).   | Simplified model with generic nature.  | Fail to address the aspect of fea-<br>ture selection and recognition rate<br>based on uncertainty presented in<br>the suggested model.  | Average accuracy; 80%.  | Kinect sensor,<br>nuiCapture Analyze<br>software (RGB-D<br>sensor).  | 34 specific sign, 1 subject.  | Brazilian Sign<br>Language.  | 170 video samples.   |
| 2012 | Ong et al. [51]                   | Sequential Pattern Trees Boosting algorithm.                           | Run-time complexity is less.   | Stability issue.  | Accuracy: 55% for the first ranked sign and 87% for within the top 10 signs.  | Kinect TM camera.  | 1. 40 signs, 14 sub-<br>jects, 2. 982 signs, 1<br>subject.  | DGS (German Sign<br>Language (Deutsche<br>Gebärdensprache),<br>Greek Sign Language<br>(GSL). | 2800 samples for DGS Kinect 40 dataset and 4910 samples for GSL 982 Signs dataset.         |
| 2009 | Hrúz et al.<br>[59]               | Hidden Markov Model, and kiosk.  | Less difficult concern to usability.   | Dataset is tiny, and performance improvement needs more data.   | 8 states HMM Model recognition rate: 81.63%.  | Camera.  | 50 sign, 2 subject.   | CzSL (Czech sign lan-<br>guage).   | 338 samples.   |

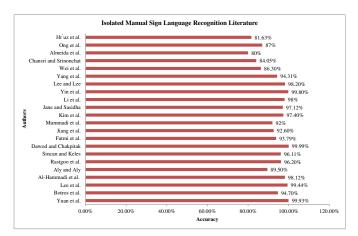


Fig. 6: Isolated Manual SLR Literature. This bar chart representation depicts the mean accuracy and recognition rate achieved in the literature related to the isolated manual SLR concerning different sign languages, models, and modalities.

It makes SLR performance way behind performance of speech recognition. The existing research work on continuous manual SLR are as follows:

Traditional methods: Nayak et al. [64] pointed out the feature extraction approach for continuous sign. Relational distribution are captured from the face and hand present in the images. The parameters are optimized by ICM, so convergence speeds up; they used dynamic time warping for distance computation between two sub-strings. The continuous sign sentence extracts the recurrent features using RD, DWT, and ICM based approaches. Kong and Ranganath [65] performed continuous SLR by merging of CRF (conditional random field) and SVM in a framework of Bayesian network. They performed a semi-Markov CRF decoding scheme-based merge approach for independent continuous SLR. Tripathi and Nandi [4] carried out a gesture recognition model for continuous Indian Sign Language. They extracted meaningful gesture frames using the Key-frame extraction method. The orientation histogram technique extracted each gesture-relevant feature and used the Principal Component Analysis to reduce the feature dimension. They used the distance classifier for classification. According to performance analysis with other considered classifiers, the Correlation and Euclidean distancebased classifier perform with a better recognition rate. Gurbuz et al. [37] developed an ASL model for the RF sensing-based feature fusion approach. They use LDA, SVM, KNN, and RF as classifiers. The random forest classifier-based model for five signs results in 95% recognition accuracy, while 20 signs result in 72 %. They can use the deep learning classifier in the future to improve recognition accuracy. Hassan et al. [5] proposed Modified k-Nearest Neighbor and Hidden Markov Models based on Continuous Arabic SLR. Window-based statistical features and 2D DCT transformation extract the features. The proposed model performance analyzed with sensors, visionbased datasets, and motion tracker dataset leads to a better recognition rate. For sentence recognition (MKNN) Modified k-Nearest Neighbor yields the best recognition rate than the HMM-based Toolkit. For word recognition, RASR performs

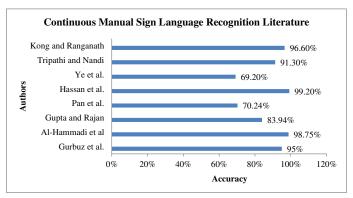


Fig. 7: Continuous Manual SLR Literature. This bar chart presents the mean accuracy and recognition rate achieved in the literature on continuous manual SLR concerning different sign languages, models, and modalities.

better with a higher recognition rate than MKNN GT2K.

CNN, LSTM and Cross model based related work on continuous manual SLR: Ye et al. [66] pointed out a 3D convolutional neural network (3DCNN) with a fully connected recurrent neural network (FC-RNN) to localize the continuous video temporal boundaries and recognize sign actions using an SVM classifier. Designed Convolutional 3D and recurrent neural network-based integrated SLR model for continuous ASL sign recognition. Al-Hammadi et al. [23] presented a single modality-based feature fusion adopted 3DCNN model for dynamic hand gestures recognition. They captured the hand feature using an open pose framework. MLP and auto encoder-based feature extracted 3DCNN model with open pose framework based on hand sign capturing model result in good recognition accuracy for KSU-SSL (King Saud University Saudi Sign Language) dataset using a batch size of 16. Gupta and Rajan [67] examined the performance of three models, namely modified time-LeNet, t-LeNet (time-LeNet), and MC-DCNN based on Indian SLR. continuous Indian SLR models based on MCDCNN, t-Lenet, and modified t- Lenet classifier using sensor-based dataset presents and performance-based investigation carried out. Pan et al. [68] spatial and temporal fused Attention incurred Bi directional long term memory network-based SLR model developed. They detected captured video key action by optimKCC. Multi-Plane Vector Relation (MPVR) is used to get skeletal features. They performed two dataset-based analyses to prove the validity of continuous Chinese SLR concerns sign independent and dependent cases. Papastratis et al. [69] suggested a cross-modal learning-based continuous SLR model, and they have proved validity with three public datasets, namely RWTH-Phoenix-Weather-2014, RWTH- Phoenix-Weather-2014T, and CSL. They achieved the performance improvement of the suggested model by considering additional modalities.

Table V and Figure 7 provide a better understanding of literature work regarding continuous manual SLR.

### B. Non-Manual SLR

Facial expressions, head movement, mouth movement, eye movement, eyebrow movement, and body posture are the non-

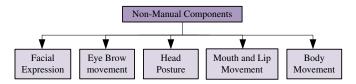


Fig. 8: Non-Manual Components. We showed the important non-manual features related to sign language. These non-manual components are helpful to make sensible recognition of similar types of signs.

manual sign parameters. Non-manual sign components showed in Figure 8. A facial expression considering the lowering and raising of eyebrows expresses grammatical information and emotions. Signers are good listeners and follow eye contact. Similar hand pose signs can be recognized by considering non-manual features. The isolated and continuous are the two types of non-manual SLR models.

1) Isolated Non-Manual SLR: The study of related research works in isolated non-manual-based SLR as follows:

**HMM based work:** Von Agris et al. [70] designed Hidden Markov Model-based British SLR with manual and nonmanual features. Aran et al. [7] performed a Turkish SLR model using a cluster-based Hidden Markov Model. They proved the validity by cross-validation with eight folds (sign independent) and five folds (sign dependent). Sarkar et al. [71] presented an isolated American SLR model using Hidden Markov Model. They improved the segmentation process by a dynamic programming-based approach. Fagiani et al. [72] carried out the Hidden Markov Model-based isolated Italian sign recognition in concern to signer independence. The suggested model gets better accuracy than the support vector machine-based recognition model. Zhang et al. [73] suggested adaptive hidden states incurred Hidden Markov Model for Chinese SLR. The carried-out fusion of trajectories and hand shapes leads to better recognition. Kumar et al. [74] performed an Indian SLR model based on a decision fusion approach with two modalities (facial expression and hand gesture). They used an HMM-based classifier for recognition and used IBCC for decision fusion purposes. They have carried out two modalities (facial expression and hand gesture) associated with IBCC based on HMM classifier decision fusion approach for Indian SLR. Using advanced classifiers and feature extraction algorithms can improve recognition accuracy.

Logistic regression and CNN based work: Sabyrov et al. [75] developed K-RSL(Kazakh-Russian Sign Language) interpreted as a human-robot model using Logistic Regression with incurred non-manual components. Mukushev et al. [76] performed Logistic Regression-based SLR using manual and non-manual features. In the captured video, they got key points using OpenPose. Kishore et al. [77] performed Adaptive Kernels Matching algorithm that incurred 3-D Indian SLR model claims improved classification accuracy compared with state-of-the-art methods. Better classification accuracy achieved by 3D motion capture models than Microsoft Kinect and leap motion sensor-based model.Liu et al. [78] pointed out ST-Net (Spatial-Temporal Net) associated with self-boosted intelligent

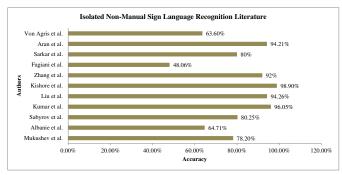


Fig. 9: Isolated Non-Manual SLR Literature. This bar chart represents the mean accuracy and recognition rate achieved in the literature concerning the isolated non-manual SLR regarding the different sign languages, models, and modalities.

systems for Hong Kong SLR. Compared to a Kinect-based system, the suggested approach performs well with a better recognition rate. Albanie et al. [6] proposed a Spatio-temporal convolutional neural network-based British SLR model. The pretraining has improved by presenting new larger-scale data, namely BSL-1K.

We perform a comprehensive study of the recent developments concerning non-manual SLR. Table VI and Figure 9 show isolated non-manual SLR-related literature work to make a clear understanding.

2) Continuous Non-Manual SLR: Continuous non-manual SLR is highly complex because the issue related to the context sequence has to be handled appropriately for effective performance or enriched accuracy [79]. The temporal boundaries-related problem makes continuous SLR a complex and arduous task. We discuss the related research work as follows:

Classical methods: Farhadi and Forsyth [80] carried out the HMM-based continuous ASL to English subtitles alignment model. With simple HMMs based on a discriminative word model, they perform word spotting. Infantino et al. [81] developed a common-sense engine integrated self-organizing map (SOM) neural network-based SLR model for LIS (Italian sign language). Sarkar et al. [71] performed a HMM-based continuous ASL. They used a dynamic programming-based approach to improve the segmentation. Forster et al. [21] pointed out the German SLR model using Multi-stream HMMs based on combination methods. Compared to system combination and feature combination approaches, synchronous and asynchronous combination-based models achieved better performance. Yang and Lee [82] presented CRF and SVM associated with a continuous ASL using both manual and non-manual features. BoostMap embeddings verified the hand shape, segmenting done by hierarchical CRF, and recognition was performed using SVM. Zhang et al. [83] suggested a Linear SVM based on an automatic ASL by fusing five modalities. The large-scale dataset-based investigation could be future work to improve recognition accuracy.

TABLE V: Continuous Manual SLR Literature Work. Related work concerning the vision and sensor-based SLR model concerns the continuous manual sign, comprehensively summarized here.

| Vear | Author                        | Method   | Pros  | Cons  | Accuracy or Result  | Sensor   | Sample and Levicon Size   | Model Type                                     | Dataset  |
|------|-------------------------------|--|---|---|---|--|---|--|--|
|      | Aumor                         | -1   | 1108  | Coms  | Accuracy of result  | -1   | Sample and Lexicon Size   | Model 19 pe                                    | Dataset  |
|      | Gurbuz et al.<br>[37]         | Principal Component Analysis (PCA), short term Fourier transform, and RBF (Radial Basis Function) associated SVM (Support Vector Machine). | Contactless sensing, environment independent                    | The author can not perform a com-<br>parative analysis with the existing<br>method.   | Recognition accuracy for 20 sign, 150 features: 72.5% and for 5 sign, 95%.  | RF sensors and<br>Kinect sensor.                                       | 20 signs, 7 subjects.   | American SLR.                                  | 240 samples.   |
|      | Al-Hammadi<br>et al. [23]     | 3D convolutional neural network (3DCNN), auto-encoders, Multi-layer perceptron, and open pose framework.                                   | The expense concerning the training is minimal.                 | Model results in good accuracy for a small batch.   | The based feature extraction model achieved recognition accuracy as 98.62% for sign dependent and 87.69% for sign independent and auto encoder based feature extraction model achieved recognition accuracy as 98.75% for sign independent and 48.89% for sign independent. | RGB video camera.  | 40 dynamic hand gestures, 40 subjects.  | Saudi Sign Language.                           | 8000 data samples.   |
|      | Gupta and<br>Rajan [67]       | Modified time-LeNet, MC-DCN (Multi channel deep convolution neural network), t-LeNet (time-LeNet), and SGD (stochastic gradient descent).  | Sensor-based on continuous sign<br>recognition model.           | Trainable parameters are a large, over-fitting problem.   | MCDCNN accuracy: 83,94%, modified t-LeNet accuracy: 79,70%.   | Wireless IMUs (inertial measurement units).                            | 11 sentences with 15 words, 10 subjects.  | Indian Sign Language.                          | 1100 samples.  |
|      | Papastratis<br>et al. [69]    | Cross-modal learning approach.   | Recognition of accuracy improved by latent representations.     | Sensitive to Multi modalities.  | <ol> <li>WER: 24.0% (RWTH-Phoe-nix-Weather-<br/>2014), 2. WER: 24.3% (RWTH- Phoe-nix-<br/>Weather-2014T), 3. WER: 2.4% (CSL).</li> </ol>  | Stationary color<br>camera, Kinect 2.0.                                | For Dataset 1: 9 subjects, vocabulary: 1088.dataset 2: 9 subjects, sign:1295, dataset 3: 50 subject, 100 sentences. | German sign language,<br>Chinese Sign Language | RWTH-Phoenix-Weather-<br>2014, RWTH- Phoenix-<br>Weather-2014T, CSL. |
|      | Pan et al. [68]               | Attention-Based BLSTM, KCC (key-frame-centered clips), and MFVR (Multi-Plane Vector Relation).   | Speed up convergence.   | Real-time practical implementation<br>was lacking.  | Fueed Attention incurred BLSTM with optimum KCC and MVPR based sign recognition model accuracy. 70.24% (CSL dataset) and 60.31% (DEVISIGN dataset) for sign dependent and 68.25% (CSL dataset) and 58% (DEVISIGN dataset) and 58% (DEVISIGN dataset) for sign independent.  | Kinect-1.0, Kinect-2.0.  | DEVISIGN dataset: 500<br>sign words, 8 subjects, CSL<br>dataset: 10 subjects, 200<br>sign words.                    | Chinese Sign<br>Language.                      | CSL dataset: 20000 samples.  |
|      | Hassan et al.<br>[5]          | Modified k-Nearest Neighbor, and Hidden Markov Models (GT <sup>2</sup> K and RASR).  | Require less computation time.                                  | Robustness needs to be improved.  | For senience recognition, MKNN based model: 97.78% (DGS-VHand dataset), and for words recognition RASR based model: 99.20% (DGS-VHand dataset).   | Camera, DG5-<br>VHand data glove<br>and Polhemus G4<br>motion tracker. | 80 sign, 40 sentences, 1 sub-<br>ject.  | ArSL (Arabic sign language).                   | 800 words samples, 400 sentence samples.                             |
| l    | Ye et al. [66]                | 3DRCNN (3D recurrent convolu-<br>tional neural networks) with SVM<br>classifier.   | RGB, motion, and depth channels fusing lead to better accuracy. | Facial information was not con-<br>sidered. Hence, the performance is<br>poor.  | Accuracy: 69.2% for Person-dependent and an accuracy: 65.8% for Person-independent.   | Kinect 2.0 sensor.   | 99 sign, 5 sentences, 15 subjects.  | American Sign<br>Language.                     | Sentence videos (100) and<br>Sequence videos (27) are<br>collected.  |
| l    | Tripathi and<br>Nandi [4]     | OH (Orientation Histogram), PCA (Principal Component Analysis), and distance-based classifier.   | New ISL continuous dataset pre-<br>sented.                      | Misclassification for a similar type of gesture.  | Average recognition rate for Euclidean distance: 90% (18 bins OH), 13% (36 bins OH), and Average recognition rate for correlation: 89% (18 bins OH), 89.8% (36 bins OH).  | Canon BOS camera.  | 10 sentences, 5 subjects  | Indian Sign Language.                          | 500 video samples.   |
|      | Kong and<br>Ranganath<br>[65] | Semi-Markov CRF decoding<br>scheme based probabilistic<br>approach.  | Complexity related to decoding reduced.                         | Larger vocabularies' scalability issue.   | For an unseen sign from considered signer, accuracy: 96.6% and recall rate: 95.7%, for unseen signers' accuracy: 89.9% and recall rate: 86.6%.  | CyberGlove(x2) and 3D Trackers.  | 74 sentences (107 ASL signs), 8 subjects.   | American sign<br>language.                     | 2393 sentences and 10852 sign instances.                             |
|      | Nayak et al.<br>[64]          | Relational Distributions, ICM (iterative conditional modes) algorithm, and DTW (Dynamic Time Warring).                                     | Aid for faster training set genera-<br>tion.                    | They did not address the amplitude variation of the various signer.  Comparative qualitative and quantitative analysis are lacking. | NA  | Video camera.  | 155 American Sign Language (ASL), 12 groups.  | American Sign<br>Language.                     | 155 video sequences.   |

TABLE VI: Isolated Non-Manual SLR Literature Work. Related work with regard to vision and sensor based SLR model concern the isolated non-manual sign comprehensively summarized in the tabular form for better understanding.

| Voor | Author                   | Mothod  | Perce   | Come   | A common on Dornle  | Concon                               | County and I order Sire   | Model Tree   | Detect  |
|------|--------------------------|---|---|--|---|--------------------------------------|---|--|---|
| 0000 | +                        | nonatri L   | 11.03   | South N  | 1 20 200 1  | TOO THE OUT                          | Sumple and reason such  |  | 12000   |
| 2070 | Mukushev<br>et al. [76]  | Logistic Kegression.  | Non-manual components considered as input lead to better accuracy.  | Need improvement concern to accuracy.  | Acuracy: /8.2%.   | LOGITECH-<br>C920 HD PRO<br>WEBCAM.  | 20 signs, 5 subjects.   | K-RSL (Kazakh-<br>Russian sign language).                        | 5200 samples.   |
| 2020 | Albanie et al.<br>[6]    | Spatio-temporal convolutional neural network.   | Large-scale dataset (BSL-1K) pre-<br>sented.  | Fails to address visual similarity issue.  | Accuracy: 46.82% (WLASL) and 64.71% (MSASL) top-1 case.   | Camera.                              | MS-ASL: 1000 words, 222,<br>WS-ASL: 2000 words, 119<br>subjects BSL-1K: 1064.   | BSL (British Sign Language), ASL (American Sign Language).       | WSASL: 21K MS-ASL:<br>25K BSL-1K: 273K.   |
|      | _                        |   |   |  |   |                                      | 40subjects.   | organ company.   |   |
| 2019 | Sabyrov et al. [75]      | Logistic Regression.  | Huge dataset not required a hu-<br>manoid robot sign interpreter.   | Experimentation in real-world is lacking.  | For 20 sign dataset accuracy: 73% and for 2 class accuracy: 80.25%.   | LOGITECH<br>C920HD PRO<br>WEBCAM.    | 20 words, 3 subjects.   | K-RSL n (Kazakh-<br>Russian Sign<br>Language).                   | 2000 videos.  |
| 2018 | Kumar et al. [74]        | HMM (Hidden Markov Model) and IBCC (Independent Bayesian Classification Combination). | The suggested model performed better than BLSTM-NN.   | Possibility to classify wrongly fails to present a comparative analysis based on recent methods for the considered applications. | Double hand gestures based recognition rate: 94.27%, and the single-hand sign based recognition rate: 96.05%.   | Leap Motion and<br>Kinect sensor.    | 51 dynamic sign words (31 sign with two hands, 20 sign with a single hand), 10 subjects.  | Indian Sign Language (ISL).                                      | 4080 data samples include both single and two hands sign.                                   |
| 2018 | Liu et al. [78]          | ST-Net (SpatialTemporal Net).   | Light-weight and robust.  | Require more computation time.   | Accuracy: 94.26% for Person dependent and 91.19% for Person independent sign.   | Microsoft Kinect.                    | 227 words, (86 words – single hand, 33 words), 2 hands separated, and 108 words. 2 hands intersected, 3 subjects based 1802 mouth images. | HKSL (Hong Kong<br>Sign Language).                               | 5221 samples videos.  |
| 2018 | Kishore et al. [77]      | Adaptive Kemels Matching algorithm.   | Overcome the issue of spatio-<br>temporal misalignment, Small ac-<br>tion changes discovered effectively. | The author fails to perform real-<br>time, live data-based analysis.   | Accuracy: 98.9%   | Kinect and leap mo-<br>tion sensors. | Five sets of data with 500 signs, 5 subjects each set.  | IndianSL (Indian Sign<br>Language).                              | 18000 signs with 36 variations per sign comprises a testing set.                            |
| 2016 | Zhang et al. [73]        | Adaptive Hidden Markov Models,<br>enhanced shape context.                             | Computational cost reduced.   | Fail to assure accuracy for the larger dataset.  | Accuracy rate for dataset 1: 92% in the top 1, 99% in the top 5, and 100% in the top 10. For dataset 2 accuracy: 86% in the top 1, 96.8% in the top 5, and 98.8% in the top 10. | Microsoft Kinect.                    | 1. 100 signs 1 subject, 2. 500 signs 1 subjects, 99 signs, 5 subjects.  | CSL (Chinese sign language).                                     | 1. 500 videos, 2. 2500 videos.  |
| 2015 | Fagiani et al.<br>[72]   | Hidden Markov Models.   | Easy to implement in real-time case.  | Overlapping issue.   | Average accuracy rate: 48.06%.  | Digital Video Cam-<br>era.           | 147 signs, 10 subjects.   | LIS (Italian sign lan-<br>guage / Lingua Italiana<br>dei segni). | 1,470 videos samples (A3LJS-147).   |
| 2011 | Sarkar et al.<br>[71]    | Dynamic programming methods,<br>and Hidden Markov Models.                             | Adaptable to uncontrolled domain.   | Sensitive to dataset.  | Recognition rate: 80%.  | Video Camera.                        | 147 signs, 10 subjects.   | ASL (American sign language).                                    | 294 samples.  |
| 2009 | Aran et al. [7]          | Hidden Markov Models with cluster algorithm.  | Classify the similar sign accurately.   | The small dataset used for validation.   | Average accuracy rate: 79.1% (Signer-independent) and 94.21% (Signer-dependent).  | Camera.                              | 19 signs, 8 subjects.   | TSL (Turkish sign language).                                     | 760 samples for each fold (8 folds for Signer-independent and 5folds for Signer-dependent). |
| 2008 | Von Agris<br>et al. [70] | Hidden Markov Models.   | User-friendliness.  | Recognition accuracy decay with low resolutions.   | Average recognition rates: 63.6%.   | Video camera                         | 263 signs, 4 subjects.  | BSL (British sign lan-<br>guage).                                | 8100 video samples.   |

TABLE VII: Continuous Non-Manual SLR Literature Work. Related work concerning the vision and sensor-based SLR model concern the continuous non-manual sign, comprehensively summarized here.

| Dataset                      | DJSLC corpus a total of 1432 sequential sign.                          | CSL:5000 videos, PHOENIX-<br>2014:6841 samples, PHOENIX-<br>2014-T:8257 samples.  | One million hand shape images from 23 subjects, Phoenix14T, Phoenix14. | One million hand shape images<br>Phoenix14, Signum.         | 61 video sequences (segmented in to set of 673 video clips). | 98 ASL signed sentences.   | Signum dataset consists 530850 to-<br>tal number of frame and PHOENIX<br>dataset consists 53033 total number<br>of frame. | 30 sentences.                      | 160 video samples.   | 80000 frames of film.  |
|------------------------------|--|---|--|---|--|--|---|------------------------------------|--|--|
| Model Type                   | JSL (Japanese Sign Language).  | CSL (Chinese sign language), DGS (German Sign Language).  | DGS (German Sign<br>Language (Deutsche<br>Gebärdensprache).            | DGS (German Sign<br>Language (Deutsche<br>Gebärdensprache). | ASL (American sign lan-<br>guage).                           | ASL (American sign language)   | DGS (German Sign<br>Language (Deutsche<br>Gebärdensprache).   | ASL (American sign lan-<br>guage). | LIS (Italian sign lan-<br>guage / Lingua Italiana<br>dei segni).   | ASL (American sign language).  |
| Sample and Lexi-<br>con Size | 1432 signs, 1 sub-<br>ject.  | PHOENIX-2014: 9 subjects 1295 sign, PHOENIX-2014-T 1115 for sign gloss CSL: 10 subjects, 500 words.   | 1. 1066 signs 9 sub-<br>jects, 2. 1080 sign 9<br>subjects.             | 1.1080 sign 9 sub-<br>jects, 2. 455 sign 1<br>subjects.     | 99 signs, 5 subjects.  | 24 signs, alphabets-<br>17, and facial<br>expressions-5.                               | 1. 266 signs 1 sub-<br>jects, 2. 455 signs<br>1 subjects, 3. 455<br>signs, 25 subjects.                                   | 65 signs subjects.                 | 40 signs.  | 31 words signs.  |
| Sensor                       | Single-camera video.   | Video camera.   | Video camera.  | Video camera.   | Kinect sensor.   | Cameras.   | Video Camera.   | Video Camera.                      | Video camera.  | Video camera.  |
| Accuracy or Result           | Average Word Error Rate (WER): 15.71% for Non-Manual Expression label. | STMC WER: 28.6% (CSLinscen), 20.7% (PHOENIX-2014), 21.0% (PHOENIX-2014-T).  | For RWTHPHOENIX-Weather 2014 dataset, WER: 26.0%.                      | Recognition accuracy: 62.8%.                                | Recognition rate: 36.07% for all lexical items.              | Recognition rate: 84.1%.   | For SIGNUM danset WER: 10.7%, and for PHOENIX danset WER: 41.9%.  | Correct detection: 92%.            | Correctly recognized sentence accuracy. 82.3% for Exp 1(30 videos of sentences with 20 signs) and 82.5% for Exp 2(80 videos of sentences with 40 signs). | NA   |
| Cons                         | Expensive.   | Training time and complexity is high.   | Sensitive to overlapping and computation is difficult.                 | Convergence took much time.                                 | Unbalancing of data leads to mis-<br>classification.         | The author can not perform experimentation with real-time live data.                   | An asynchronous combination, not<br>flexible to handle the large-scale<br>dataset.  | Sensitive to dataset.              | Selection of input weights is diffi-<br>cult.  | The author cannot perform quanti-<br>tative and qualitative results analy- |
| Pros                         | Complex linguistic content han-<br>dling ability.                      | Able to handle different cues at the same time.   | Speedup convergence.   | Training is easy.   | Simple concatenation approach.                               | Issues of label bias not occurred.   | Robust model.   | Adaptable to uncontrolled domain.  | Simple and robust.   | The simple discriminative word model.                                      |
| Method                       | Convolutional Neural Network.  | Spatial-temporal multi-cue (STMC) network, spatial multi-cue (SMC) module and a temporal multi-cue (TMC) module, joint optimization strategy. | Hybrid CNN-LSTM-HMMs.  | Iterative Expectation Maximization incurred CNN.            | Linear Support Vector Machine.                               | Conditional random field support<br>vector machine and BoostMap em-<br>bedding method. | Multi-stream HMMs based on combination methods  | Hidden Markov Model.               | Self-organizing map (SOM) neural network.  | Hidden Markov Model.   |
| Author                       | Brock et al.<br>[84]   | Zhou et al. [85]  | Koller et al.<br>[86]  | Koller et al.<br>[87]                                       | Zhang et al.<br>[83]   | Yang and Lee<br>[82]   | Forster et al.<br>[21]  | Sarkar et al.<br>[71]              | Infantino<br>et al. [81]   | Farhadi and<br>Forsyth [80]  |
| Year                         | 2020   | 2020  | 2020   | 2016  | 2016   | 2013   | 2013  | 2011                               | 2007   | 2006   |

TABLE VIII: Sensing approach based SLR. Although the sensor-based approach provides better accuracy than the vision-based approach, the sensor-based approach is not an optimal choice in real-time applications.

| Sensing  | Devices  | Year | Authors                 |
|----------|--|------|-------------------------|
| Approach |  |      |                         |
|          | 3-dimensional flex sensor-based data gloves, gyroscope, accelerometer, | 2021 | Yuan et al. [24]        |
|          | and bending sensor   |      |                         |
|          | EMG sensor   | 2021 | Botros et al. [8]       |
|          | Surface electro-myogram and inertial measurement units                 | 2020 | Gupta and Kumar [61]    |
| Sensor   | 4-Channels sEMG-Electromyography, one IMU inertial measurement         | 2018 | Jiang et al. [48]       |
| Selisoi  | unit   |      |                         |
|          | 3D magnetometer, 3D gyroscope (GYRO), and 3D accelerometer (ACC)       | 2018 | Mummadi et al. [60]     |
|          | Armband module (8-channel electromyography) sensors.                   | 2018 | Kim et al. [11]         |
|          | Myo Armband (gyroscope, accelerometer, magnetometer, and sEMG          | 2018 | Jane and Sasidhar [53]  |
|          | (surface electromyography)) sensors                                    |      |                         |
|          | Firmly stretchable strain sensor (Custom Glove)                        | 2018 | Li et al. [56]          |
|          | Wireless IMUs (inertial measurement units)                             | 2020 | Gupta and Rajan [67]    |
|          | CyberGlove (x2) and 3D Trackers  | 2014 | Kong and Ranganath [65] |
|          | Microsoft Kinect v2  | 2020 | Sincan and Keles [27]   |
|          | Video camera   | 2020 | Aly and Aly [2]         |
|          | Video camera   | 2020 | Rastgoo et al. [3]      |
|          | RGB video camera   | 2020 | Al-Hammadi et al. [23]  |
|          | Laptop camera  | 2020 | Hoang [62]              |
| Vision   | Single camera video  | 2020 | Brock et al. [84]       |
|          | LOGITECH C920 HD PRO WEBCAM  | 2019 | Sabyrov et al. [75]     |
|          | Kinect and leap motion sensors   | 2018 | Kishore et al. [77]     |
|          | Leap Motion and Kinect sensor  | 2018 | Kumar et al. [74]       |
|          | KinectTMcamera   | 2012 | Ong et al. [51]         |
|          | Video camera   | 2007 | Infantino et al. [81]   |

TABLE IX: Various Datasets in SLR. (P-Publicly available, PP-Publicly available with a password, CA-Contact Author, OR-On Request, SA-Send request along with release agreement)

| Language<br>Level | Language         | Dataset                | Data<br>Type                            | Subjects | Classes | Samples | Country          | Data<br>Size            | Link  | Data<br>Avail-<br>ability |
|-------------------|------------------|------------------------|---|----------|---------|---------|------------------|-------------------------|---|---------------------------|
|                   | Indian           | IIITA<br>-ROBITA       | Videos                                  | -        | 23      | 605     | India            | 284<br>MB               | https://robita.iiita.ac.in/<br>dataset.php  | SA                        |
|                   |                  | INCLUDE<br>[88]        | Videos                                  | 7        | 266     | 4287    | India            | 56.8<br>GB              | https://zenodo.org/record/<br>4010759#.YdqY9lRfg5k  | Р                         |
|                   |                  | Boston<br>ASL LVD      | Videos,<br>multiple<br>angles           | 6        | 3300+   | 9800    | United<br>States | 1-2<br>GB               | http://www.bu.edu/asllrp/<br>av/dai-asllvd.html   | P                         |
| Isolated          | American         | ASLLVD                 | Videos<br>(multiple<br>angles)          | 6        | 3,300   | 9,800   | United<br>States | 1-2<br>GB<br>of<br>each | http://www.bu.edu/asllrp/<br>av/dai-asllvd.html   | P                         |
|                   |                  | Purdue<br>RVL-<br>SLLL | Videos                                  | 14       | 39      | 546     | United<br>States | -                       | https://engineering.<br>purdue.edu/RVL/<br>Database/ASL/<br>asl-database-front.htm        | OR                        |
|                   |                  | ASLLVD-<br>Skeleton    | Skeleton                                | -        | 3,300   | 9,800   | United<br>States | 1-2<br>GB<br>of<br>each | https://www.cin.ufpe.br/<br>~cca5/asllvd-skeleton/<br>index.html                          | P                         |
|                   |                  | RWTH-<br>BOSTON-<br>50 | Videos<br>(multiple<br>angles)          | 3        | 50      | 483     | United<br>States | 295<br>MB               | https://www-i6.<br>informatik.<br>rwth-aachen.de/aslr/<br>database-rwth-boston-50.<br>php | P                         |
|                   |                  | WLASL                  | Videos                                  | 100      | 2,000   | 21,083  | United<br>States | 64<br>GB                | https://dxli94.github.io/<br>WLASL/   | Р                         |
|                   |                  | MS-ASL<br>[89]         | Videos                                  | 222      | 1,000   | 25,513  | United<br>States | 1.9<br>MB               | https://www.microsoft.<br>com/en-us/download/<br>details.aspx?id=100121                   | P                         |
|                   | Argen<br>-tinian | LSA64                  | Videos                                  | 10       | 64      | 3,200   | Argen<br>-tina   | 1.9<br>GB               | http://facundoq.github.io/datasets/lsa64/   | P                         |
|                   | Chinese          | Isolated<br>SLR500     | Videos<br>& Depth<br>from<br>Kinect     | 50       | 500     | 125,000 | China            | -                       | http://home.ustc.edu.<br>cn/~pjh/openresources/<br>cslr-dataset-2015/index.<br>html       | PP                        |
|                   |                  | NMFs-<br>CSL           | RGB<br>videos                           | 10       | 1,067   | 32,010  | China            | -                       | http://home.ustc.edu.cn/<br>~alexhu/Sources/index.<br>html                                | SA                        |
|                   | German           | DGS<br>Kinect 40       | Videos<br>(multiple<br>angles)          | 15       | 40      | 3,000   | Germany          | 39.7<br>MB              | https://www.cvssp.<br>org/data/KinectSign/<br>webpages/downloads.<br>html                 | CA                        |
|                   | Greek            | GSL isol.              | Videos<br>& Depth<br>from Real<br>Sense | 7        | 310     | 40,785  | Greece           | 155<br>KB               | https://vcl.iti.gr/dataset/<br>gsl/   | P                         |
|                   | Polish           | PSL<br>Kinect          | Videos<br>& Depth<br>from<br>Kinect     | 1        | 30      | 300     | Poland           | 1.2<br>GB               | http://vision.kia.prz.edu.<br>pl/dynamickinect.php  | P                         |
|                   |                  | PSL ToF                | Videos<br>& Depth<br>from ToF<br>camera | 1        | 84      | 1,680   | Poland           | 33<br>GB                | http://vision.kia.prz.edu.<br>pl/dynamictof.php   | P                         |
|                   | Spanish          | LSE-Sign               | Videos                                  | -        | 2,400   | 2,400   | Spain            | -                       | http://lse-sign.bcbl.eu/<br>web-busqueda/   | CA                        |
|                   | Turkish          | BUHMAP-<br>DB          | Videos                                  | 11       | 8       | 440     | Turkey           | 505<br>MB               | https://www.cmpe.boun.<br>edu.tr/pilab/pilabfiles/<br>databases/buhmap/                   | P                         |

| Language<br>Level | Language |  | Data<br>Type                              | Subjects | Classes   | Samples | Country          | Data<br>Size | Link  | Data<br>Avail-<br>ability |
|-------------------|----------|--|---|----------|---|---------|------------------|--------------|---|---------------------------|
|                   |          | Bosphoru<br>Sign22k<br>[90]                    | Videos                                    | 6        | 744   | 22,542  | Turkey           | -            | https://www.cmpe.<br>boun.edu.tr/pilab/<br>BosphorusSign/home_en.<br>html                           | Р                         |
|                   |          | AUTSL  | Videos                                    | 43       | 226   | 38,336  | Turkey           | -            | https://chalearnlap.<br>cvc.uab.cat/dataset/40/<br>description/                                     | PP                        |
|                   | Indian   | ISL-<br>CSLTR                                  | Videos                                    | 7        | 100   | 700     | India            | 8.29<br>GB   | https://data.mendeley.<br>com/datasets/<br>kcmpdxky7p/1   | P                         |
| Contin-<br>uous   |          | BVCSL3D  | Videos<br>(RGB,<br>depth and<br>skeletal) | 10       | 200   | 20,000  | India            | 256 B        | https://ars.els-cdn.com/<br>content/image/1-s2.<br>0-S1045926X18301927-mn<br>xml                    | OR<br>nc1.                |
|                   | American | RWTH-<br>BOSTON-<br>104                        | Videos<br>(multiple<br>angles)            | 3        | 104   | 201     | United<br>States | 685<br>MB    | https://www-i6.<br>informatik.<br>rwth-aachen.de/aslr/<br>database-rwth-boston-104.<br>php          | P                         |
|                   |          | RWTH-<br>BOSTON-<br>400                        | Videos                                    | 5        | 400   | 843     | United<br>States | -            | http://www-i6.informatik.<br>rwth-aachen.de/~dreuw/<br>database.php                                 | OR                        |
|                   | Chinese  | Continuous<br>SLR100                           | Videos<br>& Depth<br>from<br>Kinect       | 50       | 100   | 25,000  | China            | -            | http://home.ustc.edu.<br>cn/~pjh/openresources/<br>cslr-dataset-2015/index.<br>html                 | PP                        |
|                   |          | DEVISI-<br>GN-D                                | Videos                                    | 8        | 500   | 6,000   | China            | -            | http://vipl.ict.ac.cn/<br>homepage/ksl/data.html#<br>page2  | SA                        |
|                   |          | DEVIS-<br>IGN-G                                | Videos                                    | 8        | 36  | 432     | China            | -            | http://vipl.ict.ac.cn/<br>homepage/ksl/data.html#<br>page2  | SA                        |
|                   |          | DEVIS-<br>IGN-L                                | Videos                                    | 8        | 2000  | 24,000  | China            | -            | http://vipl.ict.ac.cn/<br>homepage/ksl/data.html#<br>page2  | SA                        |
|                   | German   | RWTH-<br>PHOENIX-<br>Weather<br>2014<br>SIGNUM | Videos                                    | 9 25     | 1,081   | 33,210  | Germany          | 52<br>GB     | https://www-i6.<br>informatik.<br>rwth-aachen.de/~koller/<br>RWTH-PHOENIX/<br>https://www.phonetik. | P                         |
|                   |          | RWTH-  | Videos                                    | _        | 1,066   | 8,257   | Germany          | GB<br>39     | uni-muenchen.de/<br>forschung/Bas/SIGNUM/<br>https://www-i6.  | P                         |
|                   |          | PHOENIX-<br>Weather<br>2014 T                  |   |          | ,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,               | ., .    | , , , ,          | GB           | informatik.<br>rwth-aachen.de/~koller/<br>RWTH-PHOENIX-2014-T/                                      |                           |
|                   | Greek    | GSL SD   | Videos<br>& Depth<br>from Real<br>Sense   | 7        | 310   | 10,290  | Greece           | -            | https://vcl.iti.gr/dataset/<br>gsl/   | CA                        |
|                   |          | GSL SI   | Videos<br>& Depth<br>from Real<br>Sense   | 7        | 310   | 10,290  | Greece           | -            | https://vcl.iti.gr/dataset/<br>gsl/   | CA                        |
|                   | Korea    | KETI<br>[91]                                   | Videos                                    | 14       | 524<br>(419<br>words<br>and<br>105<br>sen-<br>tences) | 14,672  | South<br>Korea   | -            | https://arxiv.org/pdf/1811.<br>11436.pdf  | CA                        |

TABLE X: SLR Datasets Vs. Modality. Highlight the related work in the literature regarding the various datasets and modalities. Dynamics and multi-modality like RGB, depth, and skeleton lead to better recognition rate in SLR.

| Year | Authors                    | Datasets                                     | Modality            |
|------|----------------------------|--|---------------------|
| 2020 | Elboushaki et al. [92]     | isoGD, SBU, NATOPS, SKIG                     | RGB, Depth, Dynamic |
| 2020 | Rastgoo et al. [3]         | RKS-PERSIANSIGN, NYU                         |                     |
| 2019 | Köpüklü et al. [93]        | EgoGesture, NVIDIA benchmarks                | DCD Damania         |
| 2019 | Lim et al. [94]            | RWTH-BOSTON-50, ASLLVD                       | RGB, Dynamic        |
| 2019 | Chen et al. [95]           | DHG-14/28 Dataset, SHREC'17 Track Dataset    |                     |
| 2019 | Ferreira et al. [96]       | Real video samples                           |                     |
| 2019 | Gomez-Donoso et al. [97]   | STB  | RGB, Depth, Static  |
| 2018 | Spurr et al. [98]          | NYU, STB, MSRA, ICVL                         |                     |
| 2018 | Kazakos et al. [99]        | NYU  |                     |
| 2019 | Li et al. [100]            | B2RGB-SH, STB                                |                     |
| 2018 | Mueller et al. [101]       | EgoDexter, Dexter, STB                       | RGB, Static         |
| 2017 | Victor [102]               | Egohands                                     |                     |
| 2018 | Baek et al. [103]          | BigHand2.2M, MSRA, ICVL, NYU                 |                     |
| 2018 | Moon et al. [104]          | MSRA, ICVL, NYU                              |                     |
| 2018 | Ge et al. [105]            | MSRA, ICVL, NYU                              | Dandh Statis        |
| 2017 | Ge and et. al [106]        | MSRA, NYU                                    | Depth, Static       |
| 2017 | Dibra et al. [107]         | ICVL, NYU                                    |                     |
| 2016 | Sinha et al. [108]         | NYU  |                     |
| 2017 | Zimmermann and Brox        | Dexter, STB                                  | 3D, RGB             |
|      | [109]                      |  |                     |
| 2018 | Marin-Jimenez et al. [110] | UBC3V, ITOP                                  |                     |
| 2017 | Deng et al. [111]          | NYU  | 3D, Depth           |
| 2016 | Oberweger et al. [112]     | MSRA   | - 3D, Deptii        |
| 2015 | Oberweger et al. [113]     | NYU  |                     |
| 2018 | Rastgoo et al. [114]       | Massey 2012, ASL Fingerspelling A, SL Surrey | 2D, Depth, RGB      |
| 2016 | Duan et al. [115]          | RGBD-HuDaAct, isoGD                          | ZD, Deptil, KGB     |
| 2020 | Chen et al. [116]          | NYU, ICVL, MSRA                              |                     |
| 2019 | Dadashzadeh et al. [117]   | OUHANDS                                      |                     |
| 2018 | Wang et al. [118]          | Human3.6M                                    |                     |
| 2017 | Yuan et al. [119]          | BigHand2.2M, MSRA, ICVL, NYU                 |                     |
| 2017 | Guo et al. [120]           | ITOP, MSRA, ICVL, NYU                        | 2D, Depth           |
| 2017 | Fang and Lei [121]         | ICVL, NYU                                    | 2D, Beptii          |
| 2017 | Madadi et al. [122]        | MSRA, NYU                                    |                     |
| 2016 | Wang et al. [123]          | isoGD  |                     |
| 2016 | Haque et al. [124]         | EVAL, ITOP                                   |                     |
| 2015 | Tagliasacchi et al. [125]  | Real video samples                           |                     |
| 2020 | Rastgoo et al. [126]       | isoGD  |                     |
| 2016 | Wei et al. [127]           | MPII, FLIC, LSP                              |                     |
| 2016 | Newell et al. [128]        | MPII, FLIC                                   | 2D, RGB             |
| 2015 | Koller et al. [129]        | RWTH-PHOENIX-Weather                         |                     |
| 2014 | Toshev and Szegedy [130]   | LSP, FLIC                                    |                     |

TABLE XI: Study of current state-of-the-art SLR model results with various datasets.

| State-of-the-art<br>SLR Model         | Author                          | Year | Results   | Datasets   |
|---------------------------------------|---------------------------------|------|---|--|
| CoT4 CNN                              | Ravi et al. [131]               | 2019 | Recognition rate -89.69%  | BVCSL3D dataset  |
| 3 D CNN with score level fusion       | Gökçe et al. [132]              | 2020 | Accuracy -94.94 %   | Bosphorus Sign22K  |
| STMC                                  | Zhou et al. [85]                | 2020 | WER- 2.1 for Continuous SLR 100 dataset<br>Split I case and WER - 28.6 for Split II case<br>WER-20.7 for RWTH-PHOENIX-Weather 2014<br>WER - 21.0 for RWTH-PHOENIX-Weather | Continuous SLR 100     RWTH-PHOENIX-Weather 2014             |
|                                       |                                 |      | 2014 T  | 3. RWTH-PHOENIX- Weather 2014-T                              |
| TK-3d convNet                         | Li et al. [133]                 | 2020 | Recognition accuracy - 77.55 % for WLASL 100 and 68.75 % for WLASL 200 Recognition accuracy - 83.91 % for MSASL 100 and 81.14 % for MSASL 200                             | 1. WLASL 100<br>2. WLASL 300<br>3. MSASL 100<br>4. MSASL 200 |
| SLRT                                  | Camgoz et al. [134]             | 2020 | BLEU 4 scores -21.80  | RWTH-PHOENIX- Weather 2014-T                                 |
| TSPNet –Joint                         | Li et al. [135]                 | 2020 | BLEU 4 -13.41   | RWTH-PHOENIX- Weather 2014-T                                 |
| Multi-<br>stream Conv<br>Architecture | Zheng et al. [136]              | 2021 | BLEU 4 score – 10.89 (RoI) and 10.73 (stream)   | RWTH-PHOENIX- Weather 2014-T                                 |
| DF- WiSLR (SVM augmented)             | Ahmed et al. [137]              | 2021 | Dynamic sign accuracy - 98.5 % and Static sign accuracy - 99.9 %  | Wi-Fi CSI dataset (49 gesture (static and dynamic)           |
| SAN                                   | Slimane and<br>Bouguessa [138]  | 2021 | WER – 29.78 %   | RWTH-PHOENIX-Weather 2014                                    |
| Inflated deep<br>CNN                  | Töngi [139]                     | 2021 | Accuracy -0.75  | SIGNUM   |
| GLEN                                  | Hu et al. [140]                 | 2021 | Accuracy -69.9 % for NMFs-CSL and accuracy -96.8 % for Isolated SLR 500 dataset   | NMFs-CSL     Isolated SLR 500                                |
| VTN-PF                                | De Coster et al. [141]          | 2021 | Accuracy 92.92%   | AUTSL  |
| SAM SLR                               | Jiang et al. [142]              | 2021 | Accuracy -98.42 % for RGB and 98.53% for RGB-D  | AUTSL  |
|                                       |                                 |      | Deaf-to-Deaf SLRGAN WER - 36.05 for<br>GSL SD and WER -2.26 for GSL SI<br>SLRGAN WER - 2.98 for GSL SI  | 1. GSL SD<br>2. GSL SI                                       |
| SLRGAN                                | Papastratis et al. [143]        | 2021 | SLRGAN WER - 37.11 for GSL SD   | 3. RWTH-PHOENIX- Weather 2014-T                              |
|                                       |                                 |      | WER - 23.4 % for RWTH-PHOENIX-<br>Weather 2014-T  | 4. Continuous SLR 100  |
|                                       |                                 |      | WER - 2.1 % Continuous SLR 100  |  |
| VMC                                   | Min et al. [144]                | 2021 | WER - 1.6 % for Continuous SLR 100  | 1. Continuous SLR 100  |
|                                       |                                 |      | WER -22.3 % for RWTH-PHOENIX-<br>Weather 2014   | 2. RWTH-PHOENIX-Weather 2014                                 |
| SMA-SLR- v2                           | Jiang et al. [145]              | 2021 | Accuracy -98.53 % for AUSTL<br>Accuracy - 59.39 % WLASL2000 dataset<br>per instance case and 56.63% per class<br>Accuracy - 99 % for Isolated SLR 500                     | 1. AUSTL 2. WLASL 200 3. Isolated SLR 500                    |
| SLR-Net- J+B                          | Meng and Li [146]               | 2021 | Accuracy -98.08 % for Isolated SLR -500 and 64.57 % for DEVISIGN-L  | <ol> <li>Isolated SLR -500</li> <li>DEVISIGN-L</li> </ol>    |
| SVM with RBFK (sEMG and acc)          | Pereira-Montiel<br>et al. [147] | 2022 | Accuracy -96.66%  | Colombian sign language (3 subjects, 360 signs, 12 words)    |
| SPOTER                                | Boháček and<br>Hrúz [148]       | 2022 | Accuracy - 100% for LSA64<br>Accuracy -63.18% for WLASL 100 and<br>43.78 % for WLASL 300  | 1. LSA64<br>2. WLASL   |

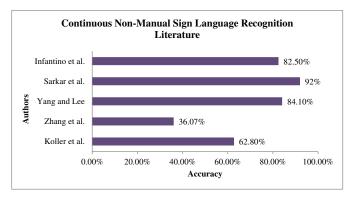


Fig. 10: Continuous Non-Manual SLR Literature. This bar chart representation shows that the literature's mean accuracy and recognition rate concerning the continuous non-manual SLR concerning different sign languages, models, and modalities.

CNN and Hybrid methods: Koller et al. [87] designed a continuous German SLR model using Iterative Expectation Maximization, incurred CNN. They trained the classifier with over a million hand shape sign data. Brock et al. [84] performed Continuous Japanese SLR using CNN. They used frame-wise binary Random Forest for segmentation. The improvement of reliability, accuracy, and robustness for large-scale datasets could be a future research direction. Zhou et al. [85] carried out a continuous SLR model using STMC (Spatial-Temporal Multi-Cue Network) to overcome the vision-based sequence learning problem. Koller et al. [86] proposed a Hybrid CNN-LSTM-HMMs Continuous German SLR model. They performed sign language learning by sequential parallelism and validated it with three public sign language datasets.

The continuous non-manual SLR-related research works are presented in tabular form in Table VII and in graphical chart in Figure 10 for better understating. The research on a continuous sign with a signer independent generic model is important because it has carried very little research on continuous SLR in the past decade.

### IV. CLASSIFICATION ARCHITECTURES

The classification is the brain of the SLR model. It aims to classify the sign accurately with minimum error. Researchers used various classifiers, e.g., traditional machine learning-based approach, deep learning-based approach, and hybrid approach.

ANN like back propagation, multi-layer, and recurrent neural networks are employed as classifiers, but handling large data is difficult. It requires enormous data for training to learn to challenge problems using a machine learning-based approach. The complication associated with HMM: 1. Likelihood of observation, 2. Best hidden state sequence decoding, 3. HMM, parameter framing. The parameter need for the 2 DCNN is excessively more, which makes the design process complex; this is the major drawback of 2 DCNN. In 3DCNN, the Spatio-temporal data has directly represented

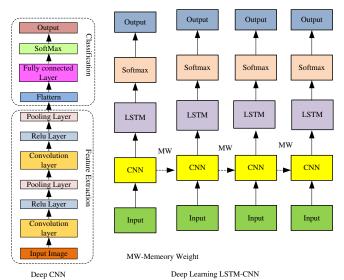


Fig. 11: Deep Learning Architectures (a) Deep CNN, (b) Deep Learning LSTM-CNN Architecture. The Deep CNN (3D) model and hybrid (LSTM+CNN) are recent classifier models. Hybrid deep learning-based classifier enhances recognition rate in SLR.

hierarchically, which is one of the unique features of 3 DCNN. Concerns to the long-term temporal dependence sign capturing 3 DCNN cannot assure robustness. LSTM eliminates the long-term dependence problem. The hybrid-based approach is adopted as a classifier to improve the accuracy.

## A. Traditional Architectures

The Artificial Neural Network (ANN), Hidden Markov Model (HMM), and Recurrent Neural Network (RNN) are the most widely used classifiers in SLR due to their sequential data processing ability. Fatmi et al. [9], Lee et al. [22], Von Agris et al. [70] carried the general ANN, RNN, and HMM-based SLR work.

## B. Deep Learning Architectures

Deep learning makes massive growth in SLR recently. The spatial and temporal features are easy to handle by the deep learning models. LSTM can handle long-term dependence. Figure 11 highlights the deep learning-based SLR architectures, namely Deep CNN and LSTM-CNN Architecture.

#### C. Evaluation Metrics

Computation of word error rate, accuracy, and recognition rate evaluates SLR models' performance. The formulations used for evaluation are as follows:

$$Accuracy = (TruePositive + TrueNegative)/(Total)$$

$$WER(WordErrorRate) = (Number of substitutions + Number of deletions + Number of insertions)/$$

$$(Total number of words in reference)$$

$$(2)$$

# Recognition Rate = (Number of correctly identified images/Total Number of images) \* 100(3)

The cross-validation scheme, namely leave-one-subject-out (LOSO) and k-fold cross-validation, is used to validate the SLR model's effectiveness. The Area Under the Curve (AUC) and ROC (Receiver Operating Characteristic) curve show the trade-off between true positive rate and false positive rate: it is used to measure the classifier performance. The Bilingual Evaluation Understudy (BLEU) score is used to measure the effectiveness of the translation.

## V. DIFFERENT TYPES OF SENSING APPROACH

According to the acquisition, it classifies SLR into two types, vision and sensor-based approaches. Many research works conducted both vision-based and sensor-based SLR to help the hand-talk community. Table VIII depicts sensing approach-based SLR existing work in literature.

**Vision-based sensing devices:** Types of cameras used for the vision-based approach are as follows:

Invasive device (body marker method): Examples: LED light, writ band, colored gloves.

Active devices: Kinect sensor, Leap motion sensor.

Stereo camera (depth camera): Capture depth information.

Single-camera: Smartphone, video camera, webcam, thermal camera, etc.

LMC (Leap Motion Controller): The LMC comprises three infrared LEDs and two cameras. It possesses the ability to track 850 nanometers' wavelength of light. The range is 60 cm (2 feet). Hand movement detection converts them into a suitable form of computer (commands) with the leap motion controller. Images are in a gray scalar format, and it acquired raw images using leap motion service software. Demerit: Accuracy is minimal.

Kinect Sensor: The skeleton (depth) image and movement creation done from three-dimensional image data. Multi-array microphone depth sensor and RGB camera are the comprised components in the Kinect sensor. Demerits: it requires more space (6 to 10 feet) distance between the sensor and signer.

**Sensor-based sensing devices:** The inexpensive and wearable sensor devices such as ACC (Accelerometer), Gyro (gyroscope), and sEMG (surface electromyogram) make sensorbased SLR a prominent tool for SLR.

Data Gloves (sensor-based): Analog form of signal converted into digital format by an ADC converter. It detects hand gestures and signs with the help of various sensors. It comprises an accelerometer and flex sensor (bend signal detection). A gyroscope gets orientation and angular and gains acceleration information with the help of an accelerometer. Finger bending information got by flex sensor. IMU (Inertial measurement units) used for hand movement estimation.

EMG (Electromyography): attach or insert the electrodes into the human muscle. With the help of the inserted electrodes, it recorded muscle movement as an electrical form. sEMG (surface electromyogram) is used for finger movement capturing and distinguishing.

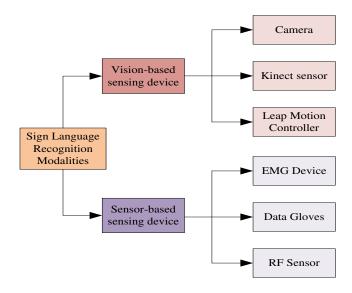


Fig. 12: SLR Modalities. It widely used Kinect and Leap Motion Controller sensor for vision-based SLR. EMG devices produce better results for sensor-based SLR, and it is an ongoing research area.

The RF sensor possesses salient features that make it likable to acquire the sign in the dark environment, contact-less. Radar and Wi-Fi: The motion of hand movements is col-

lected from the multiple antennas. It extracts features based on Doppler shift and the difference between the magnitude. Advantage orientation and position are flexible.

It has captured the interaction between the environment background and the signer performing the sign using an ambient sensor. Example: 1. Temperature Sensor, 2. Radar Sensor, 3. Pressure Sensor, 4. Sound Sensor. In Figure 12, some SLR modalities are shown.

## A. Various Datasets in SLR

There is a limitation on the datasets because most of the public datasets lack quality and quantity. The datasets are collected from native signers and ordinary people. Imitation of data was acquired to augment the dataset. We summarize the datasets available to SLR in Table IX. The benchmark dataset details, including the URL link, are detailed here.

- 1) Datasets Vs. Modality: Datasets and modalities affect largely the performance of SLR models. Many researchers have implemented various SLR models using various methods and datasets. Table X shows Datasets Vs. Modality-based study concerns SLR. The RGB, depth, dynamic-based modality facilitates better performance. Hence, modality-based fusion leads to enhanced performance.
- 2) The Complexities of SLR Datasets: The acquisition of sign language is performed using the camera and sensor-based sensing devices like Kinect and leap motion controllers, armbands, gloves, electrodes (EMGs), etc. All datasets comprise its specific capturing format, modalities, mapping, environment, and illumination specific to the region or country sign language among 300 sign languages. Some of

the complexities in these datasets are as follows:

- Acquire the SLR with various linguistic components based on multiple sensing devices is an arduous task, and the tedious process requires much time and effort.
- Redundant and blur frames in data collection are a significant complexity that affects the SLR model recognition rate.
- Complex background and various lighting are not considered in most datasets and have constraints; therefore, they cannot accurately recognize in a real-time application.
- Most of the datasets were collected with a few native signers, only with a few repetitions. Therefore, it may not guarantee the signer independent recognition performance.
- The signer wearing a long sleeve, occlusion, and object interaction during data collection makes it challenging to preprocessing and recognition.
- The problem of handling real-time applications because most datasets are acquired using the constant background and illumination in a controlled environment.
- Recognition of unseen sign words or sentences is difficult because the limited number of vocabularies and sentences present in the data make them incompatible in the real-time use case.
- 3) The Solutions to Overcome the SLR Datasets Complexities: The solutions to overcome the SLR datasets complexities are as follows:
  - During sign data acquisition, the sample collection must consider various environments, lighting based on multiple times, performing the same words with different signers leads to sign independent SLR model and improves the generic ability.
  - The distance between the signers and the recording device should be feasible to overcome the blurring data issue.
  - Hand shape-based modality alone is not good enough to recognize the sign; thus, a non-manual feature-based dataset is required to perceive the grammar of the sign language. The isolated and continuous words/sentences include many signers and more repetitions based on a dataset with a more significant number of cues and corpus to improve accuracy, robustness, and generalization.
  - Versatile and massive corpus SLR dataset to address all sign components using multi-modal sensing with a

complex and more extensive isolated, continuous sign without constraints based on capturing. Thus, it serves as a benchmark for SLR research to validate SLR model validity.

B. Study of current state-of-the-art models for sign language recognition

This paper further explores the state of the models presented in the sign language recognition as follows Ravi et al. [131] performed Indian sign language recognition using RGB-D data using CNN models. They used four-stream inputs for training and tested performance on two streams (RGB spatial and temporal). They got a recognition accuracy rate of 89.69 % for the BVCSL3D dataset. Gökce et al. [132] carried out an isolated Turkish sign language recognition using 3 D residual CNN with score level fusion and got top 1 accuracy of 94.94 % for the Bosphorus Sign22K dataset. Li et al. [133] presented isolated sign language recognition using TK-3d convNet (transferring cross-domain knowledge-based 3D convolution network). Recognition accuracy of 77.55% for WLASL 100 and 68.75% for WLASL 200, 83.91% for MSASL 100 and 81.14% for MSASL 200 achieved based on the TK-3d convNet SLR model. Camgoz et al. [134] SLRT (Sign language recognition and translation using transformer) applicability verified with RWTH-PHOENIX- Weather 2014-T dataset achieved 21.80 as BLEU 4 score. Li et al. [135] suggested TSPNet - Temporal sematic pyramid network association of hierarchical feature learning based on continuous sign language recognition and result in BLEU 4 of 13.41 for RWTH-PHOENIX- Weather 2014-T dataset.

Zheng et al. [136] suggested a non-independent multistream convolutional and RoIs based multi-region convolutional architecture for sign language translation and obtained BLEU 4 scores - 10.89 (RoI) and 10.73 (stream) for RWTH-PHOENIX- Weather 2014-T. Ahmed et al. [137] presented Wi-Fi CSI (channel state information) dataset and developed sign language recognition using device-free Wi-Fi. SVM augmented-based model results with an accuracy of 98.5 % for Dynamic sign and 99.9 % for Static sign. Zhou et al. [85] designed a continuous sign language recognition based on STMC (spatial-temporal multi-cue network). They got the WER (word error rate) of 2.1, 28.6, 20.7, and 21.0 for Continuous SLR 100 dataset Split I case, Split II case, RWTH-PHOENIX-Weather 2014, and RWTH-PHOENIX-Weather 2014 T datasets, respectively. Slimane and Bouguessa [138] performed self-attention network (SAN-sign attention network)-based continuous sign language recognition. They used 2 D CNN with self-attention considered both hand and full-frame as inputs and combined to get final word glosses on evaluation on RWTH-PHOENIX-Weather 2014 dataset achieved WER of 29.78 %. Töngi [139] suggested the inflated deep CNN based on isolated SLR. They used the MSASL dataset to transfer the ASL knowledge to recognize GSL (German Sign Language) on the SIGNUM dataset and achieved an accuracy of 0.75 for high target data. Hu et al. [140] pointed out non-manual feature-aware GLEN (Global

local enhancement network) based on the SLR model. They achieved a top 1 accuracy of 69.9% for NMFs-CSL datasets and 96.8% for isolated SLR 500 datasets. De Coster et al. [141] proposed Pose flow and hand cropping associated to video transformer network-based isolated sign language recognition. The VTN-PF (Video Transformer Network with hand cropping and pose) model evaluation on the AUTSL dataset got an accuracy of 92.92 %.

Jiang et al. [142] devised a SAM SLR (Skeleton Aware multimodal framework Sign language recognition) concerning isolated sign language recognition. The skeleton-aware multi-modal (SSTCN-Separable spatial-temporal convolution network) results in better accuracy on the AUTSL dataset, with a top 1 accuracy of 98.42% for RGB and 98.53% for RGB RGB-D. Papastratis et al. [143] performed a generative adversarial network with transformer-based continuous sign language recognition. They used four datasets to validate the performance of SLRGAN (sign language recognition generative adversarial network). SLRGAN Deaf-to-Deaf SLRGAN achieves WER of 36.05 for GSL SD, WER of 2.26 for GSL SI, and SLRGAN WER of 2.98 for GSL SI, WER of 37.11 for GSL SD, WER of 23.4% for RWTH-PHOENIX-Weather 2014-T, and WER of 2.1% Continuous SLR 100. Min et al. [144] conducted VMC (visual alignment constraint) associated Resnet 18 backbone based on continuous sign language recognition model validated on Continuous SLR 100, and RWTH-PHOENIX-Weather 2014 datasets obtained a WER of 1.6% and 22.3%, respectively.

Jiang et al. [145] designed SMA-SLR- v2 (Skeleton aware multimodal framework with global ensemble model) based on isolated sign language recognition. They achieved the top 1 accuracy of 98.53% for AUSTL (RGBD all), the top 1 accuracy of 59.39% for the WLASL2000 dataset per instance case, and 56.63% per class, and the top 1 accuracy of 99% accuracy for isolated SLR 500 dataset. Meng and Li [146] presented a GCN (graph convolution network)-based SLR network (dual sign language recognition model). The fusion of the two-stream models is SLR-Net-J+B, which results in the top 1 accuracy of 98.08% for the isolated SLR -500 dataset and 64.57% for the DEVISIGN-L dataset. Pereira-Montiel et al. [147] devised Colombian sign language automatic recognition using SVM (support vector machine) with RBFK (radial basis function kernel) with four channels of sEMG (surface electromyography) and three-axis acc (accelerometer). Achieve accuracy 96.66% for 12-word recognition. Boháček and Hrúz [148] performed isolated sign language recognition using SPOTER (Sign pose base transformer) validated with LSA64 and WLASL datasets, resulting in a 100% accuracy for LSA64 and 63.18% and 43.78% accuracy for WLASL 100 and WLASL 300, respectively. The current state-of-the-art SLR model is summarized in a Table XI for better understanding. We hope this review paper sets a baseline for futuristic and advanced research in the SLR domain.

### VI. DISCUSSION

Sign language possesses dynamic gestures, trajectory property, and multi-dimensional feature vectors. These factors

make it challenging to recognize sign language. Still, many researchers are attempting to develop a generalized, reliable, and robust SLR model. Multi-dimensional features are a novel approach that leads to a better recognition rate. This review paper aims to provide an easy understanding and helpful guidance to the research community. To perform research to develop an effective SLR model to assist the hand-talking community is one of the prominent domains in computer vision, pattern recognition, and natural language processing.

### A. Limitation of Current Datasets and their sizes

The ambiguities and lack of training dataset make the SLR vulnerable. Therefore, the standardized and large-scale datasets with manual and non-manual features are important. The limitation of the current datasets and their sizes are as follows:

Barrier concerning the recording/ collection/ measuring equipment:

- Poor camera quality affect the clarity of the sign in the vision-based system when the resolution is reduced leads to decreased accuracy.
- Improper camera setup is another barrier because it leads to loss of important sign information when a sign is dynamic or static, performing the signer.
- If a multi-camera set-up is used to acquire the signer data, the lack of synchronization lead to information loss, leading to poor performance.
- Device dependability should be reliable, cost-effective, and easy to maintenance.

The environment, background, and illumination profoundly affect the dataset preparation.

- When the background setup comprises noise, it creates misclassification and reduces the recognition rate, so it should be properly dealt with to overcome this barrier.
- Improper light and illumination reduce the clarity and also affect accuracy.
- The distance between the camera and the signer should be maintained at a nominal and workable range. Very much closer and farther, much long distance between the signer and the camera affect the performance.

# B. Limitation of Current Trends

The limitations of the current trends in SLR are as follows:

The barrier regarding the different signers affects the accuracy:

- Break off between the letter/ sign and speed up sign performing: The speedy, continuous, and frequent sign performed by the signer creates challenges for segmentation and feature extraction.
- Blockage of overlapping, occlusion of hand-face, handhand
- Wearing a dress with long sleeves and wearing colored gloves also affects the sign recognition process.
- High variation concerns the interpersonal: Sign varies between signers and instants.

The barrier concerning the video domain:

 The problem of handling the video data in the limited GPU memory is not tractable. Most CNN techniques are only image-based, videos that have an additional temporal dimension. A simple resizing process may cause a loss of crucial temporal information to perform the fine-tuning and classification process on each frame independently.

The barrier concerning network design in machine learning:

- The recognition and classification ability prevailed by the location, illumination, and so on.
- Higher batch size causes a fall in local convergence instead of global convergence. Smaller batch sizes lead to larger iterations and a rise in training expenses.
- Selection of the loss functions during training cause expenses.
- Selection of optimal hyperparameters.

The active research domain is AI-based realistic modeling SLR translation and production of Avatar modeling (manual and non-manual). Developing AI Sign language learning and translation applications (web-based or smartphone) is one of the current trends. Although the advent of deep learning networks improves SLR accuracy, the limitations mentioned above still need to be addressed in the SLR domain.

C. Other Potential Applications of SLR with Human-Computer Interaction

Some potential applications of SLR with human-computer interaction are as follows:

- Virtual reality: With the help of the electronics equipment, the user experiences artificial simulation of real world.
- Smart home: Home attributes to monitor, access, and control using artificial intelligence and electronics

devices. It includes a security and alarm alert system.

- Health care: Intended to assist the patients in a better quality of life and good health care service.
- Social safety: To ensure safe and social engagement and to minimize social threats.
- Telehealth: Remotely accessing clinical contacts and care services to enhance patients' health care.
- Virtual shopping: To provide hassle-free, more comfortable shopping with virtual stores.
- Digital signature: To transfer the information as an electronics sign.
- Gaming and playing: To facilitate more entertaining, and gaming experience to users.
- Text and voice assistance: To provide better communication using technology and ease of user comfort.
- Education: To facilitate enhanced learning skills using advanced techniques.

### VII. FUTURE DIRECTION AND RESEARCH SCOPE

Compared to the recent developmental achievement in automatic speech recognition, SLR is still lagging with a vast gap and remains at an early development stage. According to the literature study, a good number of research exists in SLR. Much research is struggling to achieve a high performance SLR model by exploring advanced techniques like deep learning, machine learning, optimization, and advanced hardware and sensor experimentation. Finally. We need a thorough exploration to solve the following issues in SLR.

- Distinctiveness/contract of sign handling problem.
- Multiple sensors/camera fusion problems.
- Multi-modalities data handling issues.
- Computation problem.
- · Consistency issues.
- Difficult to handle a large vocabulary.
- Requirement of standard datasets.

## **Future Directions**

Future directions for SLR are as follows:

- SLR model design needs a better understanding of optimal hyperparameter estimation strategy.
- Building uncontrolled surrounding/environment-based SLR models is a thrust area because researchers develop most of the existing models in the literature with respect to the lab environment-based datasets. Hence, it is demanding.
- Designing a user-friendly, realistic, and robust sign language model is one of the high-scope domains of SLR.
- Design a high-precision sign language capturing device (sensor and camera).
- Devise a novel training strategy to reduce computational training difficulty.
- The lightweight CNN model for SLR is another research scope.
- Develop an SLR with the association multi-modal based leverage to improve recognition accuracy.
- Devising a generic automatic SLR model.

This review paper is presented to provide a complete guide to the research and allow the reader to know about the existing SLR works. It demonstrates challenging problems, research gaps, future research direction, and dataset resources. Therefore, the readers and researchers can move forward towards developing novel models and products to assist the hands-talk community and contribute to social benefits.

## VIII. CONCLUSION

There are several review papers on hand gestures and SLR. Still, existing review papers do not comprehensively discuss facial expression, modality, and dataset-based sign language, lacking in-depth discussion. With this motivation, this review paper studied different types of SLR, various sensing approaches, modalities, and various SLR datasets and listed out the issues of SLR and the future direction of SLR. However, further complete guidance will provide a more precise understanding and acquire knowledge and awareness of the problem's complexity, state-of-the-art models, and challenges in SLR.

This comprehensive review paper will help to guide upcoming researchers about the SLR introduction, needs, applications, and processes involved in SLR. It discussed various manual and non-manual SLR models. Also, it reviewed isolated and continuous of each type (manual and non-manual) and provided easy understanding to the reader with the help table and diagram. The manual and non-manual type-based SLR present effectively and then examine the works related to the various modalities and datasets. Finally, we reviewed recent research progress,

challenges, and barriers of existing SLR models, organized in an informative and valuable manner concerning the various types, modalities, and dataset. The improvisation of accuracy concerns vision-based SLR, one of the ongoing and hot research topics. The sensor-based approach is highly suitable for laboratory-based experimentation. But not an appropriate choice for practical real-time applications. The vision-based SLR model's accuracy is less than the sensor-based approach and very much less than the speech recognition model. A robust and sophisticated method is essential for extracting manual and non-manual features and overcoming the barriers. Therefore, a lot of scopes are available to the SLR domain. We hope this review paves insight for readers and researchers to propose a state-of-the-art method that facilitates better communication and improves the hand-talk community's human life.

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**Competing interests-** The authors declare no conflict of interest.

**Availability of data and materials-** Not Applicable. **Code availability-** Not Applicable.

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