Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 10 Issue 02
2026

Review Article
https://doi.org/10.56979/1002/2026/1140

Systematic Literature Review on Computational Models Used For Sign Language Recognition

Mohsin Sami[1], Rabia Tehseen[1&2], Uzma Omer[3], Muhammad Farrukh Khan[4], Shahan Yamin Siddiqui[5], Nabeel Sabir Khan[6], and Danish Ali Khan[6]

[1]Department of Computer Science, University of Central Punjab, Lahore, Pakistan.
[2]Department of Computer Science, University of Management and Technology, Lahore, Pakistan.
[3]Department of Information Sciences, University of Education, Lahore, Pakistan.
[4]Department of Artificial Intelligence, NASTP Institute of Information Technology Lahore, Pakistan.
[5]Department of Computer Science, NASTP Institute of Information Technology Lahore, Pakistan.
[6]Department of Software Engineering, University of Central Punjab, Lahore, Pakistan.
[*]Corresponding Author : Rabia Tehseen. Email: rabia.tehseen@ucp.edu.pk

Received: October 03, 2025 **Accepted:** January 13, 2026

Abstract: Sign Language Recognition (SLR) is a popular research area, but it's not much focused due to its complex nature and resource limitation. In this review, a unique method for developing a SLR have been studied in which an automatic sign-language recognition system has been proposed. A comprehensive review of different studies and working models from 2015 to 2025. Total 60 different studies with different methodology are reviewed in this systematic literature review. It has been found that American Sign Language (ASL) is one of the most commonly used data set for various studies. MediaPipe Holistic model, Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN), Artificial Neural Network (ANN) and Support Vector Machine (SVM) are some of the techniques which are most focused in various studies. Our work is unique, we have presented a comprehensive taxonomy of approaches and we established timeline of approaches that have been focused in literature guiding us to suggest which approach can be followed in future. We have also identified the most focused dataset, mostly processed in literature and region focused. As valuable contribution in SLR, our systematic literature review presents state of the art review exploring multiple dimensions of SLR field and would serve research.

Keywords: Sign Language; Systematic Literature Review; American Sign Language; Sign Language Recognition; CNN; LSTM; Mediapipe

1. Introduction

Speech is the primary mode of communication for most people, but not everyone has the ability to speak or hear. Hearing loss can result from various causes such as genetic factors, complications during birth, illnesses, repeated ear infections, prolonged exposure to loud noise, certain medications, or simply aging. Similarly, the inability to speak may stem from medical procedures or damage to the vocal cords due to diseases or injuries. Interestingly, speech disabilities are often closely linked to hearing impairments [1].

According to the World Health Organization (WHO), more than 5% of the global population; approximately 430 million people, including 432 million adults and 34 million children; require assistance due to hearing problems. It is projected that by 2050, over 700 million people, or about one in every ten individuals, will experience hearing loss, which correlates closely with speech impairments. Despite the advancements in preventive measures and treatments, many individuals rely on sign language for effective communication [2].

Sign languages have been in use since the 5th century B.C., with several variants such as ASL, Indian Sign Language (ISL), and Chinese Sign Language (CSL) [3]. However, this selected studies for this review highlighted a clear trend towards using ASL. Sign language serves as a vital bridge for deaf and mute individuals to interact with each other, yet communication barriers remain with the larger society due to a general lack of sign language knowledge among the public. [4] To overcome these communication barriers, technological solutions are necessary to facilitate real-time translation of sign language into spoken or written languages [5-8]. Proposed research aims to explore methods and models that can automatically recognize ASL in a way easily understood by non-signers, ultimately enabling seamless and inclusive communication for all individuals.

Proposed research explored the advancements in SLR techniques. It includes a review of related works, datasets used in literature, different machine learning and deep learning approaches applied to ASL recognition, challenges in the field, and future directions for research to enhance the accessibility and effectiveness of sign language translation systems.

This paper has been organized into multiple sections. Introduction to the domain is presented in section 1. Comprehensive literature review has been presented in section2. Section 3 explores the methodology used to extract multiple fields from selected studies. Results have been discussed in section 4. Section 5 concludes our research.

2. Related Work

[9] proposed a Dynamic Time Warping (DTW) and Fourier descriptor-based approach for Indian SLR, demonstrating how classical pattern recognition methods could capture temporal variations in hand movements. [10] Developed a real-time hand gesture recognition system optimized for Android devices, highlighting the growing need for mobile-friendly recognition models. [11] Addressed signer independence in isolated Italian Sign Language (LIS) recognition using Hidden Markov Models (HMMs) and a dataset collected from multiple signers. [12] Advanced continuous sign language recognition by proposing scalable recognition systems capable of handling large vocabularies and multiple signers, focusing on real-world applicability. [13] Designed a component-based extensible framework that allowed modular extension for different sign language gestures, enabling adaptability across various languages. [14] Enhanced recognition robustness in cluttered backgrounds by fusing RGB and depth video streams, a significant step towards more generalized environments.

[15] Proposed a vision-based ASL recognition method using Edge Orientation Histograms (EOH), offering a computationally efficient feature extraction process. [16] Discussed the critical role of data preprocessing; such as filtering, normalization, and augmentation; for improving neural network performance in sign language applications. [17] Introduced adaptive HMMs to recognize CSL, adjusting model parameters dynamically based on signer variability. [18] Utilized CNNs for large-scale isolated gesture recognition tasks, leveraging the deep feature extraction capabilities of CNNs to improve accuracy. [19] Developed a classifier for hand gestures used by hearing-impaired individuals, employing image processing and classification techniques to aid communication. [20] Employed CNNs on depth and color images for fingerspelling recognition, successfully improving the system's robustness to lighting conditions.

[21] Focused on enhancing static hand gesture recognition by applying edge detection and cross-correlation, which helped in recognizing subtle shape differences. [22] Demonstrated CNNs' ability to handle different feature invariants such as rotation and scaling, crucial for real-world usability. [23] Proposed an ensemble of ANNs combined with EMG sensors for finger spelling, integrating bio signals for improved recognition. [24] Enhanced region-of-interest (ROI) segmentation by employing object detection techniques, making the systems more efficient for learning ASL. [25] Used sEMG and IMU sensors in wrist-worn devices for real-time gesture recognition, promoting wearable technology as a practical solution. [26] Recognized signs with facial expressions by fusing facial and hand features through Bayesian classifier combinations.

[27] Proposed a multiple proposals framework for continuous Arabic SLR, which efficiently managed large sign vocabularies. [28] Compared ANNs, SVM, and HMMs in a wearable sensor-based recognition context, providing insights into the best performing classifiers. [29] Provided an exhaustive review of hand gesture recognition techniques, emphasizing the shift towards deep learning models. [30] Applied deep CNNs to static hand gesture datasets and achieved remarkable improvement over traditional methods.

[31] Proposed a deep feature fusion network combining data from multiple wearable sensors to recognize dynamic gestures, enhancing temporal modeling. [32] Developed a real-time ASL system based on CNNs trained on real-world datasets, emphasizing deployment feasibility. [33] Presented a lightweight deep learning model that efficiently recognized hand gestures in complex scenarios. [34] Provided a comprehensive survey on wearable systems, outlining challenges in hardware, algorithms, and datasets. [35] Released the AUTSL dataset, a large-scale Turkish Sign Language (TSL) corpus that has since become a benchmark for developing and testing models. [36] Introduced an attention mechanism for key frame sampling in continuous CSL recognition, reducing computational load while improving recognition rates.

[37] Proposed a cross-modal learning framework aligning video features with text embedding's, enabling continuous recognition without needing strict frame-level annotations. [38] utilized CNNs for feature extraction and classification in sign language translation tasks, targeting word-level recognition. [39] Incorporated recurrent neural networks (RNNs) for capturing temporal dependencies in ASL signs, showing improved performance over static methods. [40] Further investigated CNNs for hand gesture classification, validating their generalization capabilities across small and medium-sized datasets.

[41] Introduced a novel network combining multi-scale information and dual recognition strategies using Graph Convolutional Networks (GCNs), a new trend in modeling hand pose and skeleton dynamics. [42] Used pose flow and self-attention layers to enhance isolated sign recognition, particularly focusing on continuous motion capture. [43] Proposed a context-aware Generative Adversarial Network (GAN) to simulate unseen gestures and improve model generalization.

[44] Explored transformer architectures for word-level recognition from sign poses, marking the shift towards attention-based models in the field. [45] Implemented Media Pipe for hand tracking combined with LSTM networks for ASL alphabet recognition, optimizing performance in mobile devices. [46] Applied multi-mode data fusion techniques for dynamic gesture recognition in CSL, combining RGB, depth, and skeletal data. [47] Introduced a complete pipeline covering recognition, translation, and video generation of sign language using deep learning.

[48] designed an efficient two-stream CNN to capture accumulative video motion, effectively modeling both spatial and temporal information. [49] Proposed using prosodic and angular features in a sequential learning setup, boosting performance for dynamic word recognition. [50] Continued by addressing inconsistent depth features, proposing corrective measures to improve dynamic word recognition.

[51] Introduced Sign Graph, a graph convolutional approach that modeled joint dependencies in pose estimation data. [52] Developed lightweight models optimized for edge device deployment, ensuring real-time recognition capabilities. [53] Aimed at building an accessible SLR system for disabled users, promoting inclusivity. [54] presented a text-to-sign language translator for Arabic, bridging the gap between text and signs.

[55] Proposed consistency constraints and signer removal techniques for enhancing continuous SLR models. [56] Developed deep learning-based ASL classification models using CNNs and transfer learning to improve training efficiency. [57] Presented a multilingual SLR system using machine learning techniques, addressing linguistic diversity. [58] Introduced a hybrid CNN model combining traditional and modern architectures for isolated dynamic sign recognition tasks.

[59] Implemented a neural-network-based web application for real-time Pakistani SLR, demonstrating practical deployment. [60] Reviewed the major deep learning advancements, discussing challenges such as signer independence and small datasets. [61] Reviewed AI-based recognition techniques, advocating for multimodal approaches combining hand shape, movement, and facial expressions.

[62] Comprehensively discussed current trends, available datasets, and future research opportunities in SLR. [63] Introduced Step Net, a novel spatial-temporal network architecture designed to recognize isolated signs efficiently. [64] Investigated the use of ANN and CNN classifiers for ASL alphabet recognition, showing comparative performance metrics.

[65] Proposed deep learning methods for Indian SLR, focusing on dataset creation and model optimization. [66] Analyzed the role of AI in enhancing sign language interpretation systems, particularly in low-resource settings. [67] Critically assessed deep learning approaches for continuous sign recognition, suggesting future research pathways. Finally, [68] explored various deep learning strategies for automating sign language processing, identifying key challenges and promising solutions for the future work.

3. Research Methodology

The method for conducting this review is to perform careful and organized process to find, assess, and combine existing research on SLR. The main steps of the research methodology of this systematic literature review are shown in Figure 1.

After identifying research problem, the initial step involved defining the research objective. Subsequently, research questions are formulated in alignment with the established research objective. Following this, a search strategy is developed to identify related literature. The next steps include the creation of inclusion/exclusion criteria and the implementation of quality scoring.

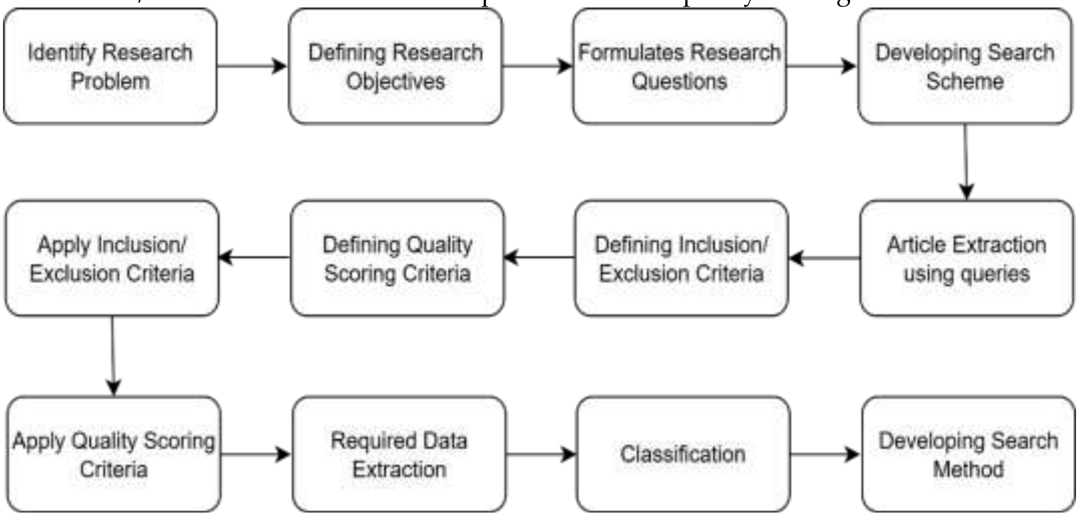

Figure 1. Research Methodology

The studies are then shortlisted through the application of the inclusion/exclusion criteria, and are subsequently ranked based on the established quality scoring criteria. Next, the selected studies are classified and synthesized according to the specific investigation areas of this study. Finally, a discussion and analysis of the results are conducted.

3.1. Research Objectives (ROs)

The main goal of this study is to review SLR systems proposed in literature to highlight the available techniques applied on specific dataset. In this context, the more detailed objectives of this Systematic Literature Review include:

RO1: To investigate venue of articles publish in the specified timespan.

RO2: To explore state of the art techniques for SLR.

RO3: To evaluate the availability, diversity, and limitations of datasets used for training sign language models.

RO4: To investigate the diversity of spoken and signed languages highlighting SLR system performance.

RO5: To identify geographic trends and regional biases in sign language.

RO6: To evaluate the quality and impact of published research using standardized ranking systems.

3.2. Research Questions (RQs)

RQ1: What is the timeline and venues mostly focused for SLR system research?

RQ2: Which techniques have been most commonly applied in SLR?

RQ3: What are the most frequently used datasets in SLR research?

RQ4: Is the model targeting diverse sign languages?

RQ5: Which regions contributed most to research in sign language?

RQ6: What will be the quality of the research according to indexing (Q-rank, CORE)?

3.3. Search Scheme

The crucial step in conducting a Systematic Literature Review is to create a plan for searching and gathering relevant and significant research in a specific area. This involves identifying where to look for relevant literature, creating a search string, and establishing criteria for what to include or exclude. The articles chosen for this review are sourced from reputable digital repositories such as IEEE, Springer Link, Science Direct, and ACM Digital Library. Additionally, Snow balling is used to find articles that may have been missed in previous searches. Document repositories are explored using various keywords categorized as primary, secondary, and tertiary. The keywords used to create the search string are outlined in Table 1.

Table 1. Keywords Used for Searching

Primary Keywords	Secondary Keywords	Tertiary keywords
• Sign Language • American Sign Language	• Recognition • Prediction • Classification	• Deep learning • Machine learning • Artificial intelligence

The search string which is used to find relevant records, created by combining different types of keywords along with Boolean operators. This search string is then mapped with specific primary, secondary, and tertiary keywords. Table 2 provides the search string applied to specific digital repositories.

The Figure 2 illustrates stage-wise shortlisting of studies. The process begins with Identification, where 4,354 records are gathered from databases includes ACM, IEEE, ScienceDirect, and Springer. After removing 1,985 duplicates, 2,369 records proceed to Screening, where titles and abstracts are evaluated, reducing the count to 312. In the Eligibility phase, introductions and conclusions are assessed, leaving 154 records. Finally, full-text assessment in the included stage results in 60 studies selected for synthesis. Each step shows exclusions: 2,057 records removed during screening, 158 during eligibility checks, and 94 after full-text review. The structured approach ensures a rigorous and transparent selection process.

In addition to conducting systematic searches using a defined search string across major digital libraries (such as IEEE Xplore, SpringerLink, ScienceDirect, and ACM DL), an additional search cycle was carried out using backward snowballing as proposed by Wohlin (2014). This method involved examining the reference lists of previously shortlisted studies related to SLR and translation.

Repository	Search Key	No of papers
ACM Digital Library	"Sign Language" OR "American Sign Language" **AND** "Classification" OR "Prediction" OR "Recognition" **AND** "Machine Learning" OR "Deep Learning" OR "Artificial Intelligence"	1296
Springer link	"Sign Language"OR"American Sign Language" "Classification"OR"Prediction"OR"Recognition" "Machine Learning"OR"Deep Learning"OR"Artificial Intelligence"	395
IEEE Xplore	"Sign Language" OR "American Sign Language" **AND** "Classification" OR "Prediction" OR "Recognition" **AND** "Machine Learning" OR "Deep Learning" OR "Artificial Intelligence"	1298 -
Science Direct	{Sign Language}OR{American Sign Language} {Classification}OR{Prediction}OR{Recognition} {Machine Learning}OR{Deep Learning}OR{Artificial Intelligence}	1365

Table 2. Specific search strings with respect to digital repositories.

The purpose of backward snowballing was to ensure the inclusion of any potentially relevant studies that may have been missed during the initial search process. This manual investigation enabled a broader and more inclusive collection of studies within the domain.

As a result of this secondary snowballing process, 9 additional articles were identified and included in the final review pool. These studies provided additional insights and helped fill gaps in areas such as multimodal approaches and regional sign language datasets.

In total, 60 papers were finalized for in-depth analysis. The shortlisting was independently performed by the authors based on defined inclusion and exclusion criteria. To ensure the reliability of the selection process, the results were evaluated by two independent reviewers. The Cohen's Kappa coefficient was calculated to assess inter-rater agreement, which yielded a value of 0.91, indicating strong consistency between reviewers.

For this study inclusion criteria (IC) and exclusion criteria (EC) is setup. Defined criteria help us to choose the right studies from literature we found using our search strategy. The criteria we apply to include studies is listed below:

IC-1: Papers should be published in duration of 2015 to 2025.

IC-2: Papers that have open dataset access or addressing words/sentences for SLR systems only.

IC-3: Papers present in English language.

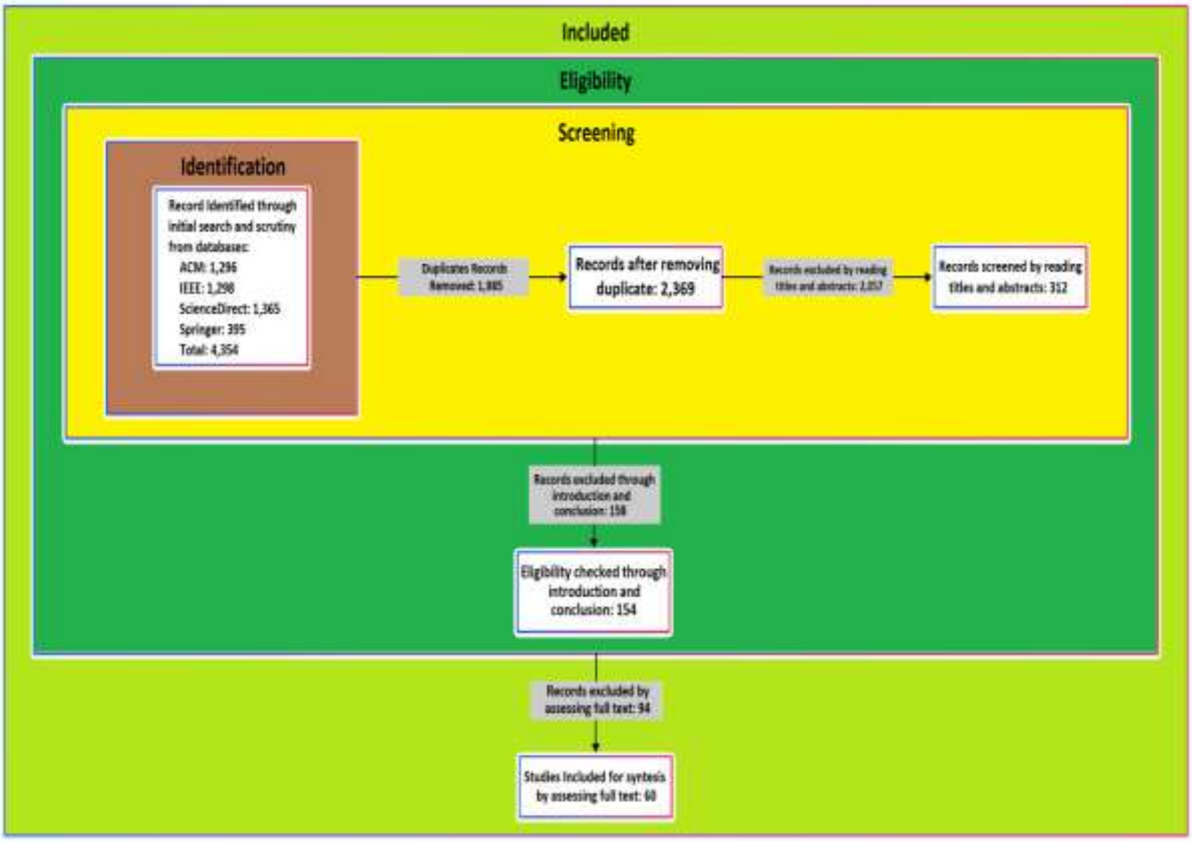

Figure 2. Stage-wise shortlisting of studies

Here are the criteria we used to exclude studies:

EC-1: Papers are not considerable that is published before 2015.

EC-2: Papers with incomplete or inaccessible data.

EC-3: Papers not written in English language or not related to SLR systems.

EC-4: Web document.

3.4. Quality Scoring:

Checking the quality of the selected article is an important part of systematic literature review to evaluate how good they are. We gave scores to the chosen studies based on scoring criteria mention in Table 3.

Table 3. Quality scoring criteria.

Criteria	Description	Rank	Score
	Internal scoring		
a)	Did the abstract clearly define the method of proposed solution?	Yes Partially No	1 0.5 0
b)	Did the study show comparison of proposed method with previously defined methods?	Yes Partially No	1 0.5 0

c)	Was methodology clearly defined?	Yes Partially No	1 0.5 0
d)	Was the experiment conducted?	Yes Partially No	1 0.5 0
	External scoring		
e)	What is the ranking of the publication source?	Q1 Q2 Q3& Q4 Core A Core B Core C	2 1.5 1 1.5 1 0.5

3.5. Results and Findings

This section discusses the results obtained after sorting and combining sixty articles selected for review. The classification of studies into different investigation areas and their quality scores are displayed in Table 4. If a study didn't clearly provide necessary information for a specific area, it's marked as "None."

Table 4a. Classification of shortlisted studies

Ref.	Year	Technique	Dataset	Language
[9]	2015	Fourier descriptors KNN	ISL	INDIAN LANGUAGE
[10]		Open CV library for Android	hand gesture recognition	ENGLISH
[11]		HMMs OpenCV SVM	LIS	ITALIAN
[12]		ASLR	SIGNUM database RWTH-PHOENIX-Weather	MULTIPLE
[13]	2016	sEMG sensors Accelerometers (ACC) Gyroscopes (GYRO)	CSL	CHINESE
[14]		ANN Kinect sensor	None	THAI
[15]		ANN	ASL	ENGLISH
[16]		ANN	Latvian sign language	LATVIA
[17]		HMM Kinect mapping	Self-building Kinect-based dataset Kinect-based CSL datasets	CHINESE
[18]		HOG ConvNets CNN	ChaLearn LAP IsoGD Dataset	CHINESE

[19]	2017	NN Discrete Wavelet Transform(DWT) SVM LDA	ASL	AMERICAN
[20]		ConvNets CNN	ASL	AMERICAN
[21]	2018	NN	ASL	ENGLISH
[22]		CNN	sign language of Peru	PERU
[23]		E-ANN EMG sensors	Korean finger language	KOREAN
[24]		YOLO CNN	Images of 12 gesture in 60 situation	ENGLISH
[25]		sEMG IMU sensing fusion	None	None
[26]		HMMs Bayesian Classification Combination (IBCC)	ISL	INDIAN
[27]	2019	Modifed k-Nearest Neighbor (KNN) HMM	ArSL datasets (40 Arabic sentences) An existing glove-based dataset	ARABIC TRANSLATOR
[28]		ANN, SVM	ASL	ENGLISH
[29]		Data acquisition Pre-processing Segmentation Feature Extraction Classification	Purdue RVL-SLLL [124] RWTH-PHOENIX-Weather [125] ATIS Sign Language Corpus [127] SIGNUM Corpus [78] RWTH-BOSTON-50 RWTHBOSTON-104 RWTH-BOSTON-400	MULTIPLE
[30]		CNN	NUS hand posture dataset American fingerspelling	MULTIPLE
[31]	2020	DFFN	ASL 26 English letters CSL daily activities	MULTIPLE

[32]		CNN	ASL	ENGLISH
[33]		novel system is proposed, 3DCNN	KSU-SSL dataset	ARABIC
[34]		it is a comparative study of existing researches	None	None
[35]		CNN, LSTM	TSL	TURKEY
[36]		Attention-Based network MPVR skeletal feature Attention-Based Bidirectional long short-term memory (BLSTM)	CSL dataset Public DEVISIGN dataset	CHINESE
[37]		Spatial AttentionBased BLSTM CNN Temporal convolution layers (TCL) Short-term temporal modelling (BLSTM)	RWTH-Phoenix-Weather2014 RWTH-Phoenix-Weather-2014T CSL	MULTIPLE
[38]		Single Shot Multi Box Detection (SSD) SVM	Sign language fingerspelling ASL	ENGLISH
[39]		RNN	ASL	ENGLISH
[40]		Modified AlexNet Modified VGG16 models	ASL	ENGLISH
	2021			
[41]		SLR-Net GCN	CSL-500 DEVISIGN-L	MULTIPLE
[42]		Video Transformer Network (VTN)	AUTSL dataset	TURKEY

[43]		SLRGAN	e RWTH-Phoenix-Weather-2014 CSL Greek Sign Language (GSL) Signer Independent (SI)	MULTIPLE
[44]		SPOTER	WLASL LSA64	MULTIPLE
[45]		MediaPipe Holistic model LSTM	ASL	AMERICAN
[46]		BLSTM Connectionist Temporal Classification (CTC)	CSLD	CHINESE
[47]	2022	MediaPipe library Hybrid CNN + BLSTM Hybrid NMT + MediaPipe + DGAN model	RWTH-PHOENIXWeather 2014T How2Sign dataset ISL-CSLTR datasets multilingual benchmark sign corpus	MULTIPLE
[48]		Dynamic motion network (DMN) Accumulative motion network (AMN) Sign recognition network (SRN) Accumulative video motion (AVM)	KArSL-190 KArSL-502 ArSL LSA64	MULTIPLE
[49]		FFV-BLSTM	ASL LMDHG SHREC	MULTIPLE
[50]		PairCFR approach	ASL GSL DSG	MULTIPLE
[51]	2023	GCN	WLASL LSA-64	MULTIPLE
[52]		RTG-Net	Phoenix 2014 dataset Phoenix 2014T CSL dataset	MULTIPLE

[53]		CNN	ASL	AMERICAN ENGLISH
[54]		MediaPipe Holistic model LSTM	ASL	ARABIC TRANSLATOR
[55]		NN Transformer + signer removal	PHOENIX-2014, CSL	German, Chinese
[56]		CNNs, SVM, k-NN	ASL Alphabet dataset	ASL
[57]		ML classifiers	None	Multiple
[58]		Hybrid CNNs	BdSL_OPA_23_GESTURES	Bangal Sign Lang
[59]		Neural networks	Pakistani Sign Language	Pakistani
[60]		Review (DL-based models)	MS-ASL, WLASL, BSL-1K, SIGNUM, AUTSL, ArSL2018, NMFs-CSL, SLR500	Multiple
[61]	2024	Review of different techniques (ML Algos, DL Models, Hybrid Approches)	ISL, ASL	Multiple
[62]		Review of different techniques (CNN, RNN, Hybrid Models, Transformer, Sensor based Approaches)	RWTH-PHOENIX-Weather 2014, ASL Fingerspelling Dataset, BSL-1K	Multiple
[63]		StepNet (ST-GCN)	WLASL, BOBSL, NMFs-CSL	ASL, CSL
[64]		ANN, CNN, ML classifiers	Sign Language MNIST	ASL
[65]		CNN, RNN, Hybrid	ISL Alphabet Dataset	ISL
[66]	2025	Bidrectional Interpretation, Multimodal Recognition, Animation Tools	RWTH-PHOENIX-Weather 2014, ASL Fingerspelling Dataset, BSL-1K	Multiple
[67]		Review of different techniques (CNN-HMM, CNN-BLS)	RWTH-PHOENIX-Weather 2014, ASL Fingerspelling Dataset, BSL-1K	Multiple

[68]	DL architectures includes(SLR, SLT, SLP, SLD)	RWTH-PHOENIX-Weather 2014, ISL Alphabet Dataset, BSL-1K	Multiple

Table 4b. Classification of shortlisted studies

Region of study	Published	Internal Score				External Score	Total Score
INDIA	C	1	0.5	1	1	0	3.5
TUNISIA	C	1	0	1	1	0.5	3.5
ITALY	J	1	1	1	1	1.5	5.5
GERMANY	J	1	1	1	1	2	6
CHINA	J	1	0.5	1	1	2	5.5
THAILAND	J	1	0	1	1	0	3
INDIA	C	1	0.5	1	1	0	3.5
LATVIA	J	1	1	1	1	1	5
CHINA	C	1	1	1	1	1.5	5.5
CHINA	C	1	1	1	1	1	5
INDIA	C	1	0.5	1	1	0	3.5
ENGLAND	J	1	1	1	1	1.5	5.5
CHINA	C	1	0.5	1	1	0	3.5
AMERICA	C	1	0.5	1	1	0	3.5
SOUTH KOREA	J	1	1	1	1	1	5
SOUTH KOREA	C	1	0.5	1	1	0	3.5
CHINA	J	1	1	1	1	2	6
INDIA	J	1	1	1	1	2	6

UAE	J	1	0.5	1	1	1	4.5
USA	C	1	1	1	1	0	4
MALAYSIA	J	1	0.5	1	1	2	5.5
INDIA	J	1	1	1	1	0	4
CHINA	J	1	0.5	1	1	2	5.5
IRAQ	J	1	0	1	1	1	4
SAUDI ARABIA	J	1	1	1	1	2	6
CANADA	J	1	0.5	1	1	2	5.5
TURKEY	J	1	1	1	1	2	6
CHINA	J	1	0.5	1	1	2	5.5
GREECE	J	1	1	1	1	2	6
TURKEY	J	1	0.5	1	1	1	4.5
CHINA	J	1	0.5	1	1	2	5.5
INDIA	J	1	1	1	1	2	6
CHINA	J	1	1	1	1	2	6
BELGIUM	C	1	0.5	1	1	2	5.5

GREECE	J	1	0	1	1	2	5
CZECH REPUBLIC	C	1	1	1	1	1.5	5.5
INDIA	J	1	1	1	1	0	4
CHINA	J	1	0.5	1	1	2	5.5
INDIA	J	1	1	1	1	2	6
SAUDI ARABIA	J	1	1	1	1	2	6
THAILAND	J	1	0.5	1	1	2	5.5
THAILAND	J	1	1	1	1	2	6
PAKISTAN	J	1	1	1	1	2	6
CHINA	C	1	0.5	1	1	2	5.5
INDONESIA	J	1	0.5	1	1	0	3.5
UAE	J	1	1	1	1	0	4
CHINA	J	1	1	1	1	2	6
INDIA	J	1	0.5	1	1	1	4.5
MALAYSIA	J	1	0.5	1	1	1.5	5
BANGLADESH	J	1	1	1	1	2	6
PAKISTAN	J	1	1	1	1	2	6
CHINA	J	1	0.5	1	1	1.5	5
INDIA	C	1	1	1	1	0.5	4.5

SAUDI ARABIA	J	1	1	1	1	2	6
CHINA	J	1	0.5	1	1	2	5.5
INDIA	C	1	0.5	1	1	0.5	4
INDIA	C	1	1	1	1	0.5	4.5
EGYPT	J	1	0.5	1	1	2	5.5
IRAQ	J	1	0.5	1	1	1	4.5
SOUTH KOREA	J	1	1	1	1	2	6

Figure 3 illustrates the work done on SLR across 2015-2025. Figure 3 clearly depicts that there is a growing trend in publications, with a notable increase from 2024. Out of the 60 papers in the review, 16 were presented in conferences (which is 27%), and 44 were published in journals (which is 73%). Journal publications were more prominent in year 2020 onwards, whereas conference papers were more common in 2015, 2016, and 2017. Interestingly, there were no conference paper in 2020 among the selected studies for this review.

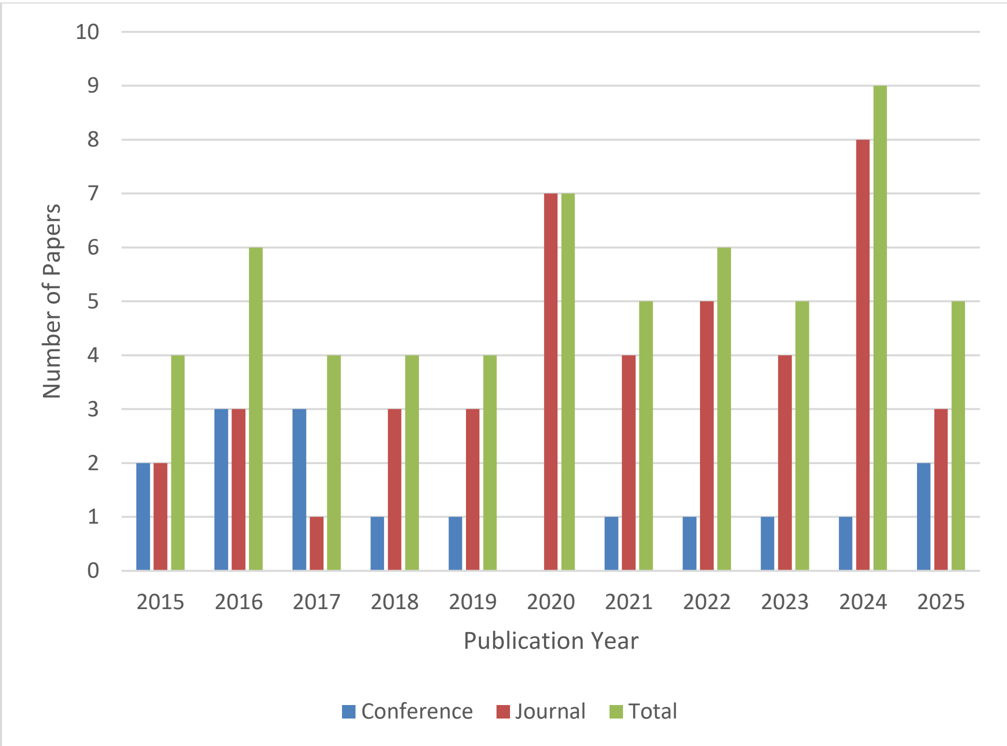

Figure 3. Year-wise Analysis

The SLR system uses various techniques to recognize sign language. Some of the most commonly used techniques are CNN, LSTM, ANN, and sensor-based solutions. Figure 4 contains the details of the techniques used in various studies in this review.

Several datasets are available for SLR system eg: ASL, ISL, CSL, TSL, ArSL. ASL is the most commonly used dataset as in our SLR 17 out of 60 shortlisted studies use ASL. In some studies dataset is generated by Kinect sensors or other methods. Figure 5 illustrates the use of different datasets in the shortlisted studies.

In the shortlisted papers, there are two types of studies. First type include those conducted in specific single languages such as ASL, ISL, CSL, and TSL. Other studies that are conducted on multiple languages simultaneously. Figure 6 represents the details of the languages studied.

The region of study in SLR research varies widely, reflecting global interest in developing systems that can assist individuals across diverse linguistic and cultural contexts. Among the shortlisted papers, China accounts for 14 out of 60 studies, India for 12, while Thailand, Saudi Arabia, and South Korea each contribute 3 studies. This regional diversity highlights the importance of tailoring SLR systems to the specific needs of local populations, ensuring that the technology remains effective and accessible for users worldwide. Figure 7 presents the region-wise distribution of the studies.

Figure 8 presents the outcomes of the quality assessment conducted on the shortlisted studies. The results are categorized into distinct scoring classes: above average, average, and below average. Average score is considered as 3.0. Studies having score above 3.0 are considered as above average and studies having score below 3.0 are considered as below average. This classification helps to evaluate the methodological rigor and overall quality of the research. By identifying studies with higher quality scores, researchers and practitioners can focus on the most reliable findings, ensuring that future work builds upon a strong foundation.

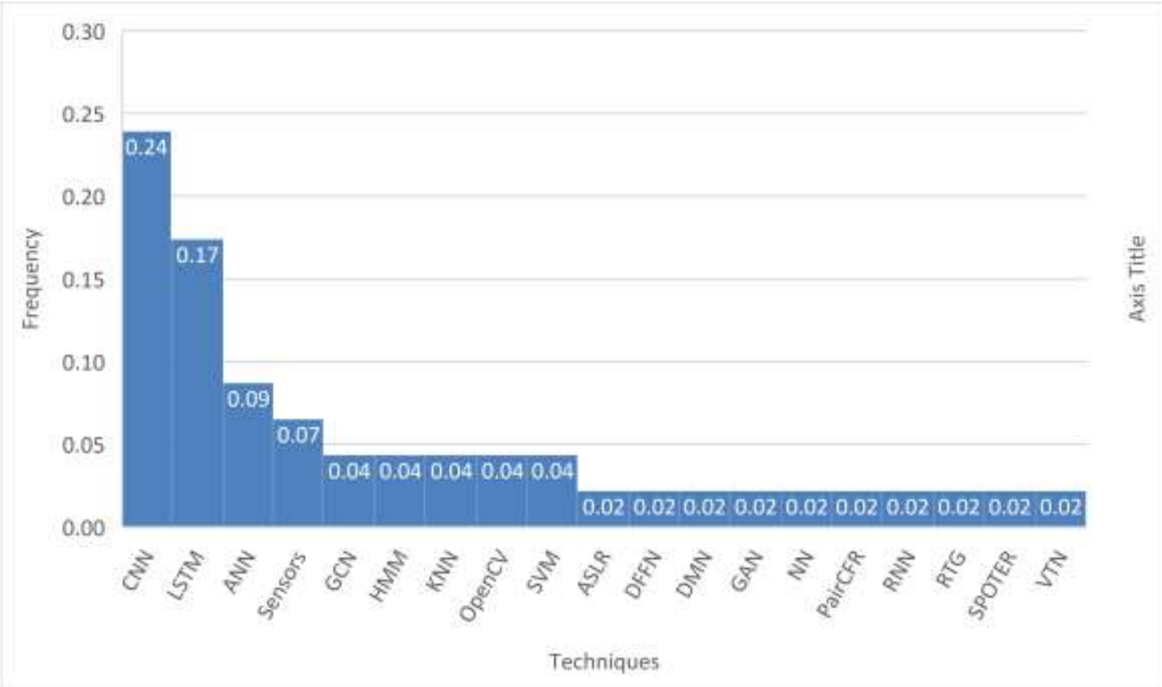

Figure 4. Techniques used in SLR

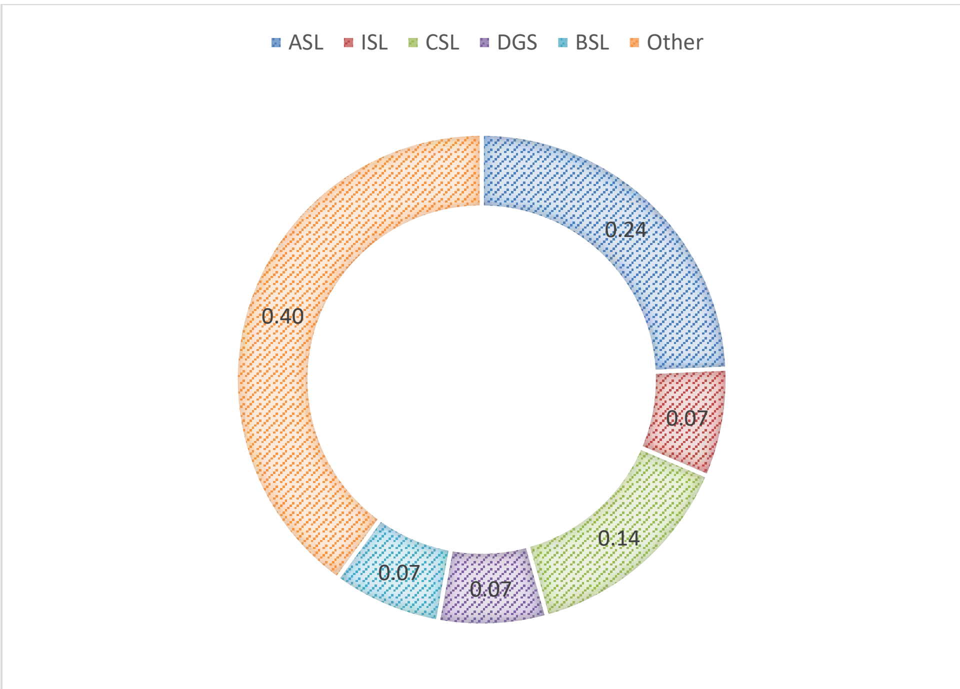

Figure 5. Dataset Detail

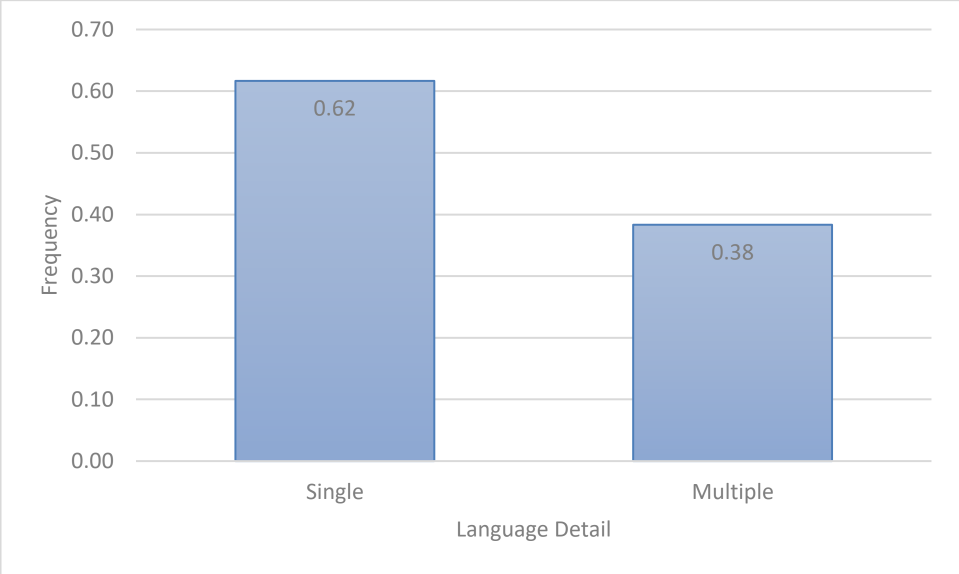

Figure 6. Language Detail

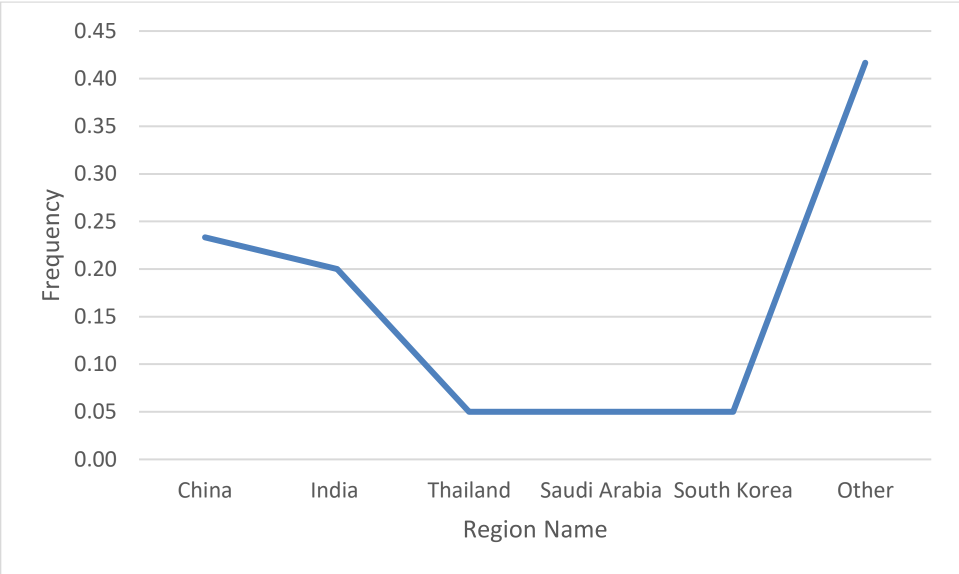

Figure 7. Region Detail

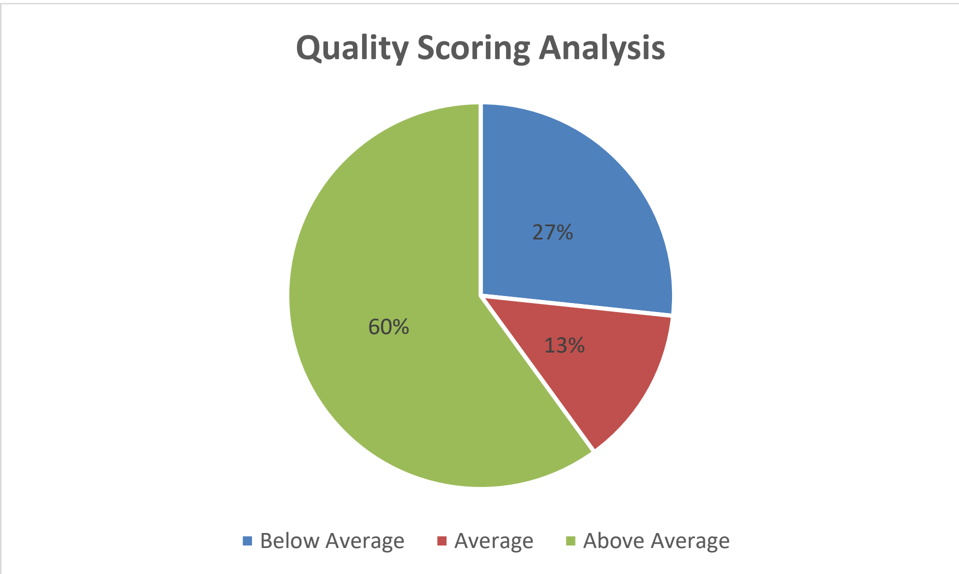

Figure 8. Quality Scoring Analysis

4. Discussion

In this study, we reviewed 60 research articles focusing on SLR. The taxonomy of the existing work can be organized into several aspects including Data Type, Input Modalities, Feature Extraction Techniques, Recognition Models, Linguistic Units, Output Modality, and Application Domains. In terms of language focus, the majority of studies target English-based sign languages, particularly ASL. Regarding dataset sources, 24% studies utilized ASL datasets, with variations depending on the technology used for data collection. Some researchers employed Kinect sensors to capture 3D motion data, while others used sensor-based gloves to record fine hand and finger movements. Typically, each study relied on a single dataset; however, a few incorporated multiple datasets to enhance model generalization. In classification techniques, CNNs were found to be the most common approach, appearing in 37% reviewed studies. CNNs are preferred for their ability to achieve high recognition accuracy, often exceeding 90%. Most models focused primarily on static image input, and only a limited number of articles addressed dynamic gestures, which are essential for recognizing movement-based signs in ASL.

4.1. Trend Identification

Based on the analysis of the reviewed articles, the following trends in techniques and datasets can have been identified:

4.1.1. Technique Trends (2015–2025):

2015–2017: Classical machine learning models, such as KNN, HMM, and ANN, were prevalent in early SLR systems. These models were often used for static image recognition.

2018–2021: There was a significant shift towards deep learning techniques, particularly CNNs, which became the dominant approach for SLR. Hybrid models combining CNNs with LSTMs or attention-based architectures also gained traction, especially for dynamic gesture recognition.

2022–2025: Advanced deep learning models, such as Transformers, GANs, and GCNs, started to dominate the research landscape. These techniques offer greater flexibility and performance, particularly for handling complex datasets and improving signer independence.

Figure 9 presents Trends in techniques used in SLR systems from 2015 to 2025, showing a shift from classical machine learning models (e.g., KNN, HMM) to advanced deep learning and hybrid architectures (e.g., CNNs, Transformers, GCNs).

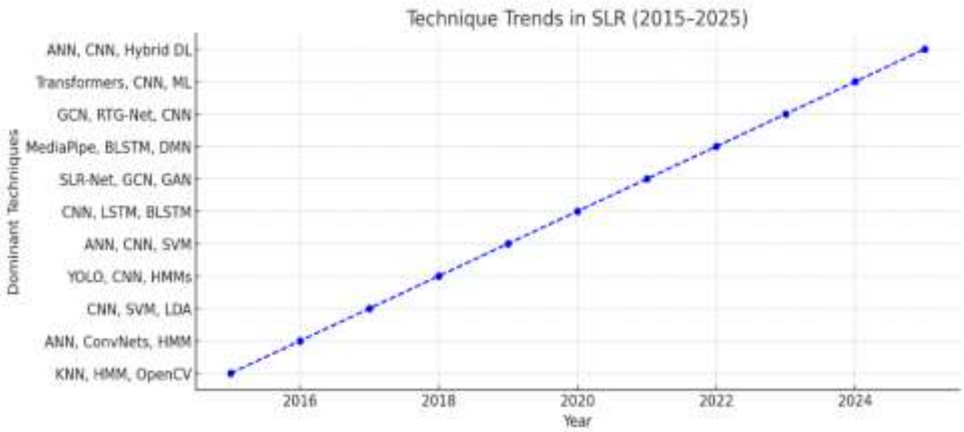

Figure 9. Technique Trends in SLR (2015-2025)

4.1.2. Dataset Trends (2015–2025)

2015–2017: Early datasets were mostly region-specific, with significant focus on datasets like ISL, SIGNUM, and RWTH-PHOENIX-Weather, representing smaller, often localized sign language systems.

2018–2021: Datasets such as ASL, RWTH-PHOENIX, and CSL became more widely adopted, reflecting the growing global interest in SLR. These datasets were primarily used for static gesture recognition.

2022–2025: There has been a noticeable shift towards large-scale, multilingual, and hybrid datasets. Datasets like WLASL, BSL-1K, and How2Sign have enabled the development of more robust and inclusive SLR systems. The focus is now on creating signer-independent datasets and those based on motion, improving generalization and system scalability. Additionally, review papers have highlighted the use of broader dataset collections, such as MS-ASL and SIGNUM, to evaluate and compare models across multiple languages and contexts.

Figure 10 presents Trends in datasets used in SLR systems from 2015 to 2025, highlighting the evolution from region-specific datasets to large-scale, multilingual, and signer-independent corpora in recent years.

Figure 11 highlight the taxonomy detail of SLR systems. SLR is a multidisciplinary field combining computer vision, machine learning, and linguistics to translate sign language gestures into text, speech, or animated avatars, enhancing communication accessibility for deaf and hard-of-hearing individuals. SLR systems process two primary data types: static gestures (isolated poses like finger-spelled letters) and dynamic gestures (movement-based phrases requiring temporal analysis). Input modalities vary between vision-based methods (RGB cameras, depth sensors like Kinect, or infrared cameras for low-light conditions) and sensor-based approaches (data gloves, IMU sensors for motion tracking, or EMG sensors detecting muscle activity). Feature extraction techniques include traditional handcrafted features (HOG for edge patterns, SIFT for scale-invariant keypoints, optical flow for motion tracking) and modern deep features (CNNs for spatial analysis, LSTMs for sequential modeling, or transformers for context-aware processing). Recognition models range from classical machine learning (SVMs, KNN, HMMs) to advanced deep learning (CNN-LSTM hybrids, transformer-based architectures, or emerging LLMs for contextual translation) and hybrid systems (like agentic AI combining symbolic reasoning with neural networks). SLR can operate at different linguistic levels, recognizing isolated signs, continuous signing, or finger-spelled letters, and produces outputs in text, synthetic speech (TTS), or avatar animations for bidirectional communication. Applications span education (interactive learning tools), healthcare (patient-provider communication), sports accessibility (real-time sign language commentary), human-computer interaction (gesture-controlled interfaces), and accessibility services (public kiosks or customer support). Despite progress, challenges remain, including cross-regional sign language variability, real-time processing demands, and robustness to occlusions or lighting conditions, driving ongoing research in this socially impactful domain.

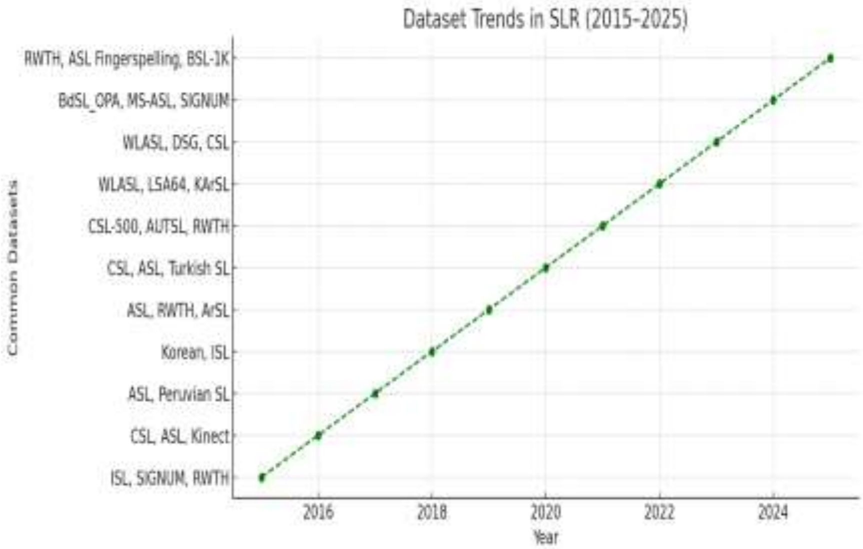

Figure 10. Dataset Trends in SLR (2015-2025)

4.2. Limitations

Despite these advancements, several limitations were observed across the studies. One major limitation is the restriction to static image input, which significantly hinders real-world applicability, especially for signs that require hand movement. Additionally, there is a noticeable bias towards English-based sign languages like ASL, while many regional sign languages remain underrepresented. The dependence on specialized hardware, such as Kinect sensors or sensor gloves, also restricts the accessibility of these systems for broader populations. Furthermore, models trained on a single dataset often suffer from poor generalization when exposed to new environments, different signers, or varied lighting conditions.

4.3. Recommendations to practitioners

Based on these findings, several recommendations can be made for practitioners. Future SLR systems should prioritize dynamic gesture and continuous sign recognition to ensure practical, real-time applications. It is also important for researchers to broaden their scope for including various underrepresented sign languages, such as Pakistani Sign Language (PSL), to enhance inclusivity and global applicability of SLR systems. Efforts should be directed toward creating models that are not heavily dependent on specialized hardware and can function effectively with standard cameras such as those found in smartphones. Finally, using multiple datasets during model development and adopting cross-dataset evaluation strategies can significantly improve the generalizability and robustness of SLR systems.

Recent advancements in Large Language Models (LLMs), such as GPT and BERT-based architectures, offer promising opportunities to enhance SLR systems. LLMs can improve the semantic understanding of sign language by providing contextual interpretation, which is crucial for continuous and sentence-level sign recognition. When integrated with vision models, LLMs can enable multimodal frameworks that align visual gestures with textual meaning, thus improving the accuracy of translation and natural language generation. Additionally, LLMs can support signer-independent and multilingual SLR by learning generalized patterns across diverse linguistic and cultural contexts. Future research should explore the integration of LLMs into end-to-end SLR pipelines, particularly for tasks like Sign Language Translation (SLT) and Sign Language Production (SLP), where language generation and understanding are essential.

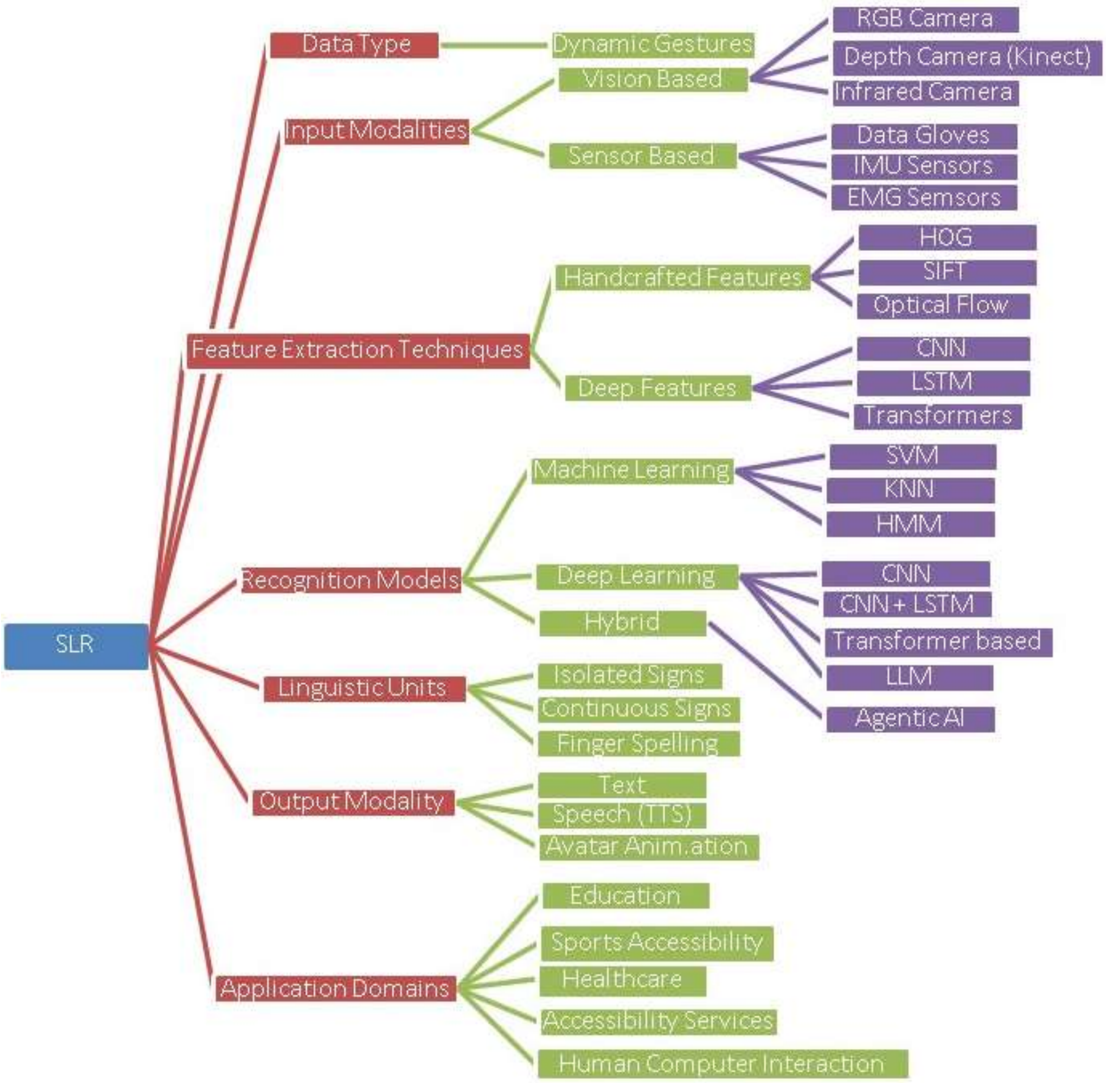

Figure 11. Taxonomy of SLR systems

5. Conclusion

This review analyzed 60 research studies in the domain of SLR. The results demonstrate that existing research predominantly focuses on ASL and static datasets, with CNNs emerging as the most widely used classification method. While many models achieve high recognition accuracy, their dependence on static inputs and specialized hardware limits their applicability to dynamic, real-world settings. Nevertheless, the diversity of approaches and the continual advancements in model accuracy reflect substantial progress in the field and offer a strong foundation for future development.

Future research in SLR should focus on dynamic and continuous recognition models capable of handling real-time sign language translation. There is also a need to expand beyond English-based sign languages by including a broader range of regional and national sign systems. Researchers should aim to design lightweight models that can be deployed on standard, widely accessible devices without the need for specialized hardware. Additionally, incorporating cross-dataset training and domain adaptation methods can enhance model robustness, ensuring better generalization across varied users and environmental conditions. These directions will help bridge the existing gaps and bring SLR technologies closer to practical, real-world use.

Another critical area that requires attention is the generation and availability of high-quality, diverse sign language corpora. Most current datasets are limited in size, language scope, signer diversity, and contextual variability. Creating large-scale, multimodal corpora that capture natural, continuous signing across different demographics, environments, and linguistic contexts is essential for training robust and inclusive models. Collaboration with Deaf communities and native signers can ensure linguistic accuracy and cultural relevance. Moreover, leveraging automated annotation tools and synthetic data generation techniques, such as motion capture and avatar-based simulation, can significantly accelerate corpus development and address data scarcity in low-resource sign languages.

Declarations

Ethics approval and consent to participate: Not Applicable

Availability of data and material : Not Applicable

Competing interests: Authors declare that they have no competing interests.

Funding: Not Applicable

Authors' contributions: M.S. and R.T. performed the measurements and analysis of the article. R.T., M.S., A.R.H were involved in planning and supervised the research work. N.S.K., R.T. and M.S. processed the experimental data, performed the analysis, drafted the manuscript and designed the figures. M.S., A.R.H and I.A.C obtained the dataset and characterized it. R.T., N.S. and M.S. performed the experimental work and worked on different analysis tools and article repositories. M.S., I.A.C, A.R.H. and R.T. aided in interpreting the results and worked on drafting the manuscript. All authors discussed the results and commented on the manuscript.

Acknowledgements: We are thankful to University of Central Punjab for their support throughout this research.

References

1. World Health Organization, World report on hearing, Geneva: World Health Organization, 2021. [Online]. Available: https://www.who.int/publications/i/item/world-report-on-hearing
2. World Health Organization, "Deafness and hearing loss," 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/deafness-and-hearing-loss
3. M. Marschark and P. E. Spencer, The Oxford Handbook of Deaf Studies in Language, Oxford University Press, 2016.
4. Q. Fang, H. Wang, and C. Wang, "Sign language recognition using deep learning: Current challenges and future directions," Pattern Recognition Letters, vol. 129, pp. 6–13, 2020.
5. A. Kaur, A. Arora, and R. Vig, "A review on sign language recognition systems," Multimedia Tools and Applications, vol. 81, no. 17, pp. 24601–24641, 2022.
6. V. Adithya and N. Rajeswari, "Survey on Sign Language Recognition using Deep Learning Techniques," International Journal of Engineering and Advanced Technology (IJEAT), vol. 9, no. 3, pp. 553–557, Feb. 2020.
7. J. Wu and S. Jin, "Research progress of sign language recognition based on deep learning," Journal of Physics: Conference Series, vol. 1237, no. 2, p. 022063, 2019.
8. R. Cui, H. Liu, and C. Zhang, "A deep neural framework for continuous sign language recognition by iterative training," IEEE Transactions on Multimedia, vol. 21, no. 7, pp. 1880–1891, Jul. 2019.
9. P. Shukla, A. Garg, K. Sharma, and A. Mittal, “A dtw and fourier descriptor based approach for indian sign language recognition,” in 2015 Third International Conference on Image Information Processing (ICIIP). IEEE, 2015, pp. 113–118
10. H. Lahiani, M. Elleuch, and M. Kherallah, “Real time hand gesture recognition system for android devices,” in 2015 15th International Conference on Intelligent Systems Design and Applications (ISDA). IEEE, 2015, pp. 591–596.
11. M. Fagiani, E. Principi, S. Squartini, and F. Piazza, “Signer independent isolated italian sign recognition based on hidden markov models,” Pattern Analysis and Applications, vol. 18, no. 2, pp. 385–402, 2015
12. O. Koller, J. Forster, and H. Ney, “Continuous sign language recognition: Towards large vocabulary statistical recognition systems handling multiple signers,” Computer Vision and Image Understanding, vol. 141, pp. 108–125, 2015.
13. S. Wei, X. Chen, X. Yang, S. Cao, and X. Zhang, “A component-based vocabulary-extensible sign language gesture recognition framework,” Sensors, vol. 16, no. 4, p. 556, 2016
14. [14]C. Chansri and J. Srinonchat, “Hand gesture recognition for thai sign language in complex background using fusion of depth and color video,” Procedia Computer Science, vol. 86, pp. 257–260, 2016
15. J. R. Pansare and M. Ingle, “Vision-based approach for american sign language recognition using edge orientation histogram,” in 2016 International Conference on Image, Vision and Computing (ICIVC). IEEE, 2016, pp. 86–90.
16. A. Zorins and P. Grabusts, “Review of data preprocessing methods for sign language recognition systems based on artificial neural networks.” Information Technology & Management Science (Sciendo), vol. 19, no. 1, 2016.
17. J. Zhang, W. Zhou, C. Xie, J. Pu, and H. Li, “Chinese sign language recognition with adaptive hmm,” in 2016 IEEE International Conference on Multimedia and Expo (ICME). IEEE, 2016, pp. 1–6
18. P. Wang, W. Li, S. Liu, Z. Gao, C. Tang, and P. Ogunbona, “Large-scale isolated gesture recognition using convolutional neural networks,” in 2016 23rd International Conference on Pattern Recognition (ICPR). IEEE, 2016, pp. 7–12.
19. N. Kumar, “Sign language recognition for hearing impaired people based on hands symbols classification,” in 2017 International Conference on Computing, Communication and Automation (ICCCA). IEEE, 2017, pp. 244–249.
20. Ameen, S., & Vadera, S. (2017). A convolutional neural network to classify American Sign Language fingerspelling from depth and colour images. Expert Systems, 34(3), e12197.
21. A. Joshi, H. Sierra and E. Arzuaga, "American sign language translation using edge detection and cross correlation," 2017 IEEE Colombian Conference on Communications and Computing (COLCOM), Cartagena, Colombia, 2017, pp. 1-6
22. C. J. L. Flores, A. E. G. Cutipa and R. L. Enciso, "Application of convolutional neural networks for static hand gestures recognition under different invariant features," 2017 IEEE XXIV International Conference on Electronics, Electrical Engineering and Computing (INTERCON), Cusco, Peru, 2017, pp. 1-4,
23. S. Kim, J. Kim, S. Ahn, and Y. Kim, “Finger language recognition based on ensemble artificial neural network learning using armband emg sensors,” Technology and Health Care, vol. 26, no. S1, pp. 249–258, 2018
24. S. Kim, Y. Ji, and K.-B. Lee, “An effective sign language learning with object detection based roi segmentation,” in 2018 Second IEEE International Conference on Robotic Computing (IRC). IEEE, 2018, pp. 330– 333

25. S. Jiang, B. Lv, W. Guo, C. Zhang, H. Wang, X. Sheng, and P. B. Shull, “Feasibility of wrist-worn, real-time hand, and surface gesture recognition via semg and imu sensing,” IEEE Transactions on Industrial Informatics, vol. 14, no. 8, pp. 3376–3385, 2018.
26. P. Kumar, P. P. Roy, and D. P. Dogra, “Independent bayesian classifier combination based sign language recognition using facial expression,” Information Sciences, vol. 428, pp. 30–48, 2018
27. M. Hassan, K. Assaleh, and T. Shanableh, “Multiple proposals for continuous arabic sign language recognition,” Sensing and Imaging, vol. 20, no. 1, p. 4, 2019
28. R. Fatmi, S. Rashad, and R. Integlia, “Comparing ann, svm, and hmm based machine learning methods for american sign language recognition using wearable motion sensors,” in 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC). IEEE, 2019, pp. 0290–0297
29. M. J. Cheok, Z. Omar, and M. H. Jaward, “A review of hand gesture and sign language recognition techniques,” International Journal of Machine Learning and Cybernetics, vol. 10, no. 1, pp. 131–153, 2019
30. Adithya V., Rajesh R., A Deep Convolutional Neural Network Approach for Static Hand Gesture Recognition, Procedia Computer Science, Volume 171, 2020, Pages 2353-2361,
31. [G. Yuan, X. Liu, Q. Yan, S. Qiao, Z. Wang, and L. Yuan, “Hand gesture recognition using deep feature fusion network based on wearable sensors,” IEEE Sensors Journal, vol. 21, no. 1, pp. 539–547, 2020
32. R. A. Kadhim and M. Khamees, “A real-time american sign language recognition system using convolutional neural network for real datasets,” TEM Journal, vol. 9, no. 3, p. 937, 2020.
33. M. Al-Hammadi, G. Muhammad, W. Abdul, M. Alsulaiman, M. A. Bencherif, T. S. Alrayes, H. Mathkour, and M. A. Mekhtiche, “Deep learning-based approach for sign language gesture recognition with efficient hand gesture representation,” IEEE Access, vol. 8, pp. 192 527–192 542, 2020.
34. K. Kudrinko, E. Flavin, X. Zhu, and Q. Li, “Wearable sensor-based sign language recognition: A comprehensive review,” IEEE Reviews in Biomedical Engineering, vol. 14, pp. 82–97, 2020
35. O. M. Sincan and H. Y. Keles, “Autsl: A large scale multi-modal turkish sign language dataset and baseline methods,” IEEE Access, vol. 8, pp. 181 340–181 355, 2020
36. W. Pan, X. Zhang, and Z. Ye, “Attention-based sign language recognition network utilizing keyframe sampling and skeletal features,” IEEE Access, vol. 8, pp. 215 592–215 602, 2020.
37. I. Papastratis, K. Dimitropoulos, D. Konstantinidis, and P. Daras, “Continuous sign language recognition through cross-modal alignment of video and text embeddings in a joint-latent space,” IEEE Access, vol. 8, pp. 91 170–91 180, 2020
38. Abiyev, R. H., Arslan, M., & Idoko, J. B. (2020). Sign language translation using deep convolutional neural networks. KSII Transactions on Internet and Information Systems, 14(2), 631–653
39. C. K. Lee, K. K. Ng, C.-H. Chen, H. C. Lau, S. Chung, and T. Tsoi, “American sign language recognition and training method with recurrent neural network,” Expert Systems with Applications, vol. 167, p. 114403, 2021.
40. Barbhuiya, A. A., Karsh, R. K., & Jain, R. (2021). CNN based feature extraction and classification for sign language. Multimedia Tools and Applications, 80(2), 3051–3069.
41. L. Meng and R. Li, “An attention-enhanced multi-scale and dual sign language recognition network based on a graph convolution network,” Sensors, vol. 21, no. 4, p.1120, 2021.
42. M. De Coster, M. Van Herreweghe, and J. Dambre, “Isolated sign recognition from rgb video using pose flow and self-attention,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 3441–3450.
43. I. Papastratis, K. Dimitropoulos, and P. Daras, “Continuous sign language recognition through a context-aware generative adversarial network,” Sensors, vol. 21, no. 7, p. 2437, 2021.
44. M. Boha´cek and M. Hr ˇ uz, “Sign pose-based trans- former for word-level sign language recognition,” in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2022, pp. 182–191.
45. B Sundar, T Bagyammal, American Sign Language Recognition for Alphabets Using MediaPipe and LSTM, Procedia Computer Science, Volume 215, 2022, Pages 642-651.
46. J. Li, J. Meng, H. Gong and Z. Fan, "Research on Continuous Dynamic Gesture Recognition of Chinese Sign Language Based on Multi-Mode Fusion," in IEEE Access, vol. 10, pp. 106946-106957, 2022.
47. B. Natarajan et al., "Development of an End-to-End Deep Learning Framework for Sign Language Recognition, Translation, and Video Generation," in IEEE Access, vol. 10, pp. 104358-104374, 2022.
48. H. Luqman, "An Efficient Two-Stream Network for Isolated Sign Language Recognition Using Accumulative Video Motion," in IEEE Access, vol. 10, pp. 93785-93798, 2022,

49. S. B. Abdullahi and K. Chamnongthai, "American Sign Language Words Recognition Using Spatio-Temporal Prosodic and Angle Features: A Sequential Learning Approach," in IEEE Access, vol. 10, pp. 15911-15923, 2022,
50. S. B. Abdullahi and K. Chamnongthai, "IDF-Sign: Addressing Inconsistent Depth Features for Dynamic Sign Word Recognition," in IEEE Access, vol. 11, pp. 88511-88526, 2023,
51. N. Naz, H. Sajid, S. Ali, O. Hasan and M. K. Ehsan, "Signgraph: An Efficient and Accurate Pose-Based Graph Convolution Approach Toward Sign Language Recognition," in IEEE Access, vol. 11, pp. 19135-19147, 2023,
52. Shiwei Gan, Yafeng Yin, Zhiwei Jiang, Lei Xie, and Sanglu Lu. 2023. Towards Real-Time Sign Language Recognition and Translation on Edge Devices. In Proceedings of the 31st ACM International Conference on Multimedia (MM '23). Association for Computing Machinery, New York, NY, USA, 4502–4512.
53. Yulius Obi, Kent Samuel Claudio, Vetri Marvel Budiman, Said Achmad, Aditya Kurniawan, Sign language recognition system for communicating to people with disabilities, Procedia Computer Science, Volume 216, 2023, Pages 13-20,
54. Amani Abdalla, Aayah Alsereidi, Nouf Alyammahi, Fatima Ba Qehaizel, Henry Alexander Ignatious, Hesham El-Sayed, An Innovative Arabic Text Sign Language Translator, Procedia Computer Science, Volume 224, 2023, Pages 425-430,
55. R. Zuo, F. Wei, Z. Chen, and B. Mak, “Improving continuous sign language recognition with consistency constraints and signer removal,” ACM Trans. Multimedia Comput. Commun. Appl., vol. 20, no. 1, pp. 1–22, 2024, doi: 10.1145/3640815.
56. H. Parikh, N. Panchal, V. Patel, and A. K. Sharma, “American Sign Language classification using deep learning,” International Journal of Biometrics, vol. 16, no. 4, pp. 640–659, 2024, doi: 10.1504/IJBM.2024.141950.
57. F. M. Najib, “A multi-lingual sign language recognition system using machine learning,” Multimedia Tools Appl., vol. 83, pp. 18245–18266, 2024, doi: 10.1007/s11042-024-20165-3.
58. S. G. M. Ameer, M. M. A. M. Ali, and M. G. Mohamed, “Computer vision-based hybrid efficient convolution for isolated dynamic sign language recognition,” Neural Computing and Applications, vol. 36, pp. 7077–7091, 2024, doi: 10.1007/s00521-024-10258-3.
59. A. Naveed, H. Arif, A. W. Malik, and M. A. Khan, “A neural-network based web application on real-time recognition of Pakistani sign language,” Engineering Applications of Artificial Intelligence, vol. 126, 2024, Art. no. 108761, doi: 10.1016/j.engappai.2024.108761.
60. Y. Zhang and X. Jiang, “Recent advances on deep learning for sign language recognition,” Comput. Model. Eng. Sci., vol. 138, no. 1, pp. 101–121, 2024, doi: 10.32604/cmes.2023.045731.
61. S. Kumar and A. Sharma, “A review on artificial intelligence based sign language recognition techniques,” in Proc. Int. Conf. Adv. Comput. Commun. Technol. (ICACCT), 2024, doi: 10.1109/ICACCT.2024.10073000.
62. B. A. Al Abdullah, G. A. Amoudi, and H. S. Alghamdi, “Advancements in sign language recognition: A comprehensive review and future prospects,” IEEE Access, vol. 12, pp. 1–20, 2024, doi: 10.1109/ACCESS.2024.3457692.
63. X. Shen, Z. Zheng, and Y. Yang, “StepNet: Spatial-temporal part-aware network for isolated sign language recognition,” ACM Trans. Multimedia Comput. Commun. Appl., vol. 20, no. 2, 2024, doi: 10.1145/3656046.
64. S. Kaur and M. Sharma, “Effective recognition system of American Sign Language alphabets using machine learning classifiers, ANN and CNN,” in Proc. Int. Conf. Adv. Comput. Commun. Technol. (ICACCT), 2025, doi: 10.1109/ICACCT.2025.10119336.
65. K. Patel and R. Mehta, “Deep learning based Indian Sign Language recognition for people with speech and hearing impairment,” in Proc. Int. Conf. Adv. Comput. Commun. Technol. (ICACCT), 2025, doi: 10.1109/ICACCT.2025.10649094.
66. F. M. Najib, “Sign language interpretation using machine learning and artificial intelligence,” Neural Comput. Appl., Jan. 2025, doi: 10.1007/s00521-024-10395-9.
67. T. H. Taher and S. Zeebaree, “A critical study of recent deep learning-based continuous sign language recognition,” Rev. Socionetwork Strateg., vol. 19, 2025, doi: 10.1007/s12626-025-00180-y.
68. M. Toshpulatov, W. Lee, J. Jun, and S. Lee, “Deep learning pathways for automatic sign language processing,” Pattern Recognition, vol. 126, 2025, Art. no. 108761, doi: 10.1016/j.patcog.2025.108761.