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Review Article

Exploring Sign Language Detection on Smartphones: A Systematic Review of Machine and Deep Learning Approaches

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In this modern era of technology, most of the accessibility issues are handled with the help of smart devices and cutting-edge gadgets. Smartphones play a crucial role in addressing various accessibility challenges, including voice recognition, sign language detection and interpretation, navigation systems, speech-to-text conversion, and vice versa, among others. They are computationally powerful enough to handle and run numerous machine and deep learning applications. Among various accessibility challenges, speech disorders represent a disability where individuals struggle to communicate verbally. Similarly, hearing loss is a disability that impairs an individual's ability to hear, necessitating reliance on gestures for communication. A significant challenge encountered by people with speech disorders, hearing loss, or both is their inability to effectively convey or receive messages from others. Hence, these individuals heavily depend on the sign language (a gesture-based communication) method, typically involving hand movements and expressions. To the best of our knowledge, there are currently no comprehensive review and/or survey articles available that cover the literature on speech disabilities and sign language detection and interpretation via smartphones utilizing machine learning and/or deep learning approaches. This study fills the gap in the literature by analyzing research publications on speech disabilities, published from 2012 to July 2023. A rigorous search and standard strategy for formulating the literature along with a well-defined theoretical framework for results and findings have been used. The paper has implications for practitioners and researchers working in accessibilities in general and smart/intelligent gadgets and applications for speech-disabled people in specific.

1. Introduction

A speech disorder, also known as a speech disability, is a condition where an individual faces difficulty in effectively communicating verbally with others. One of the primary challenges for individuals with speech disorders is their inability to convey messages directly through spoken language. Furthermore, some individuals with speech disorders may also experience hearing loss, a prevalent issue worldwide. The prevalence of speech disorders and hearing loss is steadily on the rise, with an increasing number of individuals affected by these conditions each day. According to the World Health Organization (WHO), an estimated 430 million people, which is 5% of the total world population, have a speech disability and this number is expected to rise to 1 in 4 by 2050. The impacts of hearing loss are very serious. For example, people with speech disabilities are unable to communicate with others which may lead to social isolation, loneliness, and frustration. These conditions significantly impact individuals' lifestyles and academic performance, often resulting in employment challenges. In many developing countries, there are a very limited number of specialized schools to cater to the needs of students with speech disabilities and hearing impairments [1].

Sign language is a way of communication among people suffering from speech disorders and/or hearing loss problems. It is a language for speech-disordered people through which they can communicate with other people and convey their messages. Sign alphabets rely on static hand poses to symbolize individual letters of the alphabet, employing gestures as a form of nonverbal communication. The progression in computer vision has opened doors to the development of sophisticated models capable of recognizing these signs, interpreting hand configurations, and seamlessly translating them into both text and voice [2]. For instance, in a study by Raziq and Latif [3], the authors proposed a gesture-based approach for Pakistan Sign Language (PSL) recognition, focusing on training and communication modules to detect sign language and convert it to text.

There is no universal sign language in the world, and most people rely on region-specific sign languages. Today, there are 138–300 varieties of sign language across the world [4]. Moreover, there is a persistent communication gap between hearing-disabled people, because they rely on sign language, which is a problem for normal people due to their less understanding of sign language. Typically, sign language recognition through gadgets entails a two-step process: first, the detection of hand gestures within the image, followed by their classification into the corresponding alphabet. Numerous methodologies incorporate the use of hand-tracking devices such as Leap Motion and Intel RealSense, accompanied by the application of machine learning algorithms like support vector machines (SVMs) to classify these gestures [5]. Hardware devices, such as Microsoft's kinetic sensors, are capable of constructing a three-dimensional (3D) model of the hand while tracking hand movements and their orientations [6]. Although hardware-based techniques can offer a relatively high level of accuracy, their widespread adoption is impeded by the significant initial setup costs.

Numerous information and communication technologies (ICTs) are used for the detection and translation of different sign languages used by speech-disordered people. However, some of these technologies are either expensive or socially unacceptable to many people suffering from speech disabilities. The computer-based techniques were widely used; however, the computer is not portable and hence cannot be used by most people on the go. For such, a specialized environment is necessary. Furthermore, it is crucial to employ socially accepted devices to address these challenges.

The ubiquitous presence of smartphones is undeniable. These devices can efficiently execute a wide range of machine and deep learning applications. Notable examples include convolutional neural networks (CNNs), K-nearest neighbors (KNN), deep convolutional generative adversarial networks (DCGANs), deep neural networks (DNNs), support vector machines (SVMs), recurrent neural networks (RNNs), and 3-D convolutional neural networks. The smartphone can translate a sign language gesture to speech and vice versa in real time to convey a proper message to other people. Some prototypical-level applications also exist; however, they are either region-specific or not accurate and hence rarely used. This problem highlights the need for a universal sign language with no geographical boundaries and specifications.

The smartphone processor and camera can be used for the detection of sign language. As mobile hardware technology is getting more sophisticated over time and moving towards cloud infrastructure, maintaining a user-friendly interface and keeping low latency on the cloud processing remains a major issue [7]. Smartphones equipped with an increasing number of cameras have prompted researchers to explore their potential in vision-based sign language recognition applications. In the vision-based approach, a smartphone's camera is employed to capture images or videos of hand gestures. Subsequently, these frames undergo processing to recognize the signs and generate text or speech output. It is important to note that vision-based approaches may entail a trade-off in accuracy compared to sensor-based methods. This is among various challenges in image processing, including variations in lighting conditions, sensitivity to the user's skin color, and the presence of complex backgrounds within the image [8].

Numerous review articles have been written on accessibility for speech disorder problems, regional and global sign languages, sensors-based approaches, and gesture-based recognition systems. The following few paragraphs summarize and discuss the contributions in terms of *survey papers or reviews* and their contributions along with a discussion on the research gap.

In a study by Ardiansyah, et al. [9], a review of studies has been performed between 2015 and 2020. They selected the 22 most relevant studies regarding their research questions. In this study, the most popular method to obtain data is through a camera. Different techniques were compared and CNN was the most popular as it was more accurate and used by 11 researchers out of 22. Similarly, a brief review of recent trends in sign language recognition by Nimisha and Jacob [10] discussed the two main approaches, which are the vision-based approach (VBA) and the gesture-based approach (GBA). The image or vision-based systematic literature review (SLR) and their approach comprising feature extraction and classification are mainly discussed. Moreover, a comparative analysis of the techniques and achievements (in terms of accuracy) of nine different studies on VBA and three studies on GBA is also available in this study.

A review of smart gloves for the conversion of signs to speech for the mute community was proposed [11]. In this study, there was an absence of comparisons across various research papers. The study primarily concentrated on a single approach, specifically the glove-based approach for gesture recognition. Similarly, the *perspective and evolution of gesture recognition for sign language* are presented [12]. They analyzed different gesture recognition devices through a timeline with important features and achieved recognition rates. They concluded that Leap Motion is a good option for sign language as it is cheap, easy to use, and accurately recognizes the hands. Some work on vision-based sign language recognition systems is also proposed by Sharma and Singh [8]. In this study, different vision-based methods are analyzed along with the datasets used.

A comprehensive *review of wearable sensor-based sign language recognition* is discussed by Kudrinko et al. [13]. They conducted a review of studies between 1991 and 2019, focusing on a total of 72 different research efforts. This review paper aimed to discern prevailing trends, best practices, and existing challenges within the field. Various attributes, such as sign language variation, sensor configuration, classification methods, study designs, and performance metrics, were systematically analyzed and compared. It is important to note that this particular study exclusively examined the sensor-based approach. Additionally, the paper proposed a review specifically centered around hand gestures and sign language recognition techniques [14]. They focused on a comprehensive exploration of the challenges, diverse approaches, and the application domain of gesture recognition. Furthermore, they studied the various techniques and technologies utilized in sensor-based gesture recognition, providing valuable insights into this area of research.

A technical approach to Chinese Sign Language processing is discussed in the study by Kamal et al. [15]. They provided an overview of Chinese Sign Language Recognition (CSLR). The paper discusses numerous issues related to Chinese Sign Language. Similarly, another review on system-based sensory gloves for sign language recognition and state of the art between 2007 and 2017 was presented by Ahmed et al. [16]. They reviewed the studies published between 2007 and 2017. The authors explored and investigated the SLR using the glove sensor approach. The articles are divided into four categories that are framework, review and study, development, and hand gesture types. Numerous recommendations put forth by researchers aim to address both current and anticipated challenges, offering a wealth of opportunities for further research in this field.

The study on a review of automatic translation from Arabic to Arabic Sign Language is presented in the study by Ayadi et al. [17]. The authors presented work related to Arabic Sign Language (ArSL). They discussed the classical machine translation approach (direct, transfer-based, and interlingua) and the corpus-based approach (memory, example, and statistical). The authors also described the language challenges, such as morphology, syntax, and structure. The study provides an extensive list of important works related to ArSL machine translation. Additionally, it offers a comprehensive review of feature extraction methods in sign language recognition systems by Suharjito et al. [18]. The review of studies published between 2009 and 2018 was analyzed. The authors reviewed and presented the progress of feature extraction in sign language recognition. The authors conclude that there is a considerable improvement in tracking hand regions by active sensors but still, there is room for improvements in vision-based approaches.

A review of gesture recognition focusing on sign language in a mobile context is presented in the study by Neiva and Zanchettin [19]. A review of studies published between 2009 and 2017 is presented. The total number of papers that were analyzed and compared was 43. The authors covered static and dynamic gestures, simple and complex backgrounds, facial and gaze expressions, and the use of special mobile hardware. Similarly, a review of vision-based American Sign Language (ASL) recognition, its techniques, and outcomes are discussed in the study by Shivashankara and Srinath [20]. The authors presented a review of ASL. The authors highlighted the work and comparison of several researchers for vision-based sign language recognition.

A comprehensive survey on sign language recognition using smartphones is presented in the study by Ghanem et al. [7]. In this paper, the authors explored the latest advancements in mobile-based sign language recognition. They categorized existing solutions into sensor-based and vision-based approaches, highlighting their respective advantages and disadvantages. The authors' primary focus was on feature detection and sign classification algorithms. Similarly, an automatic sign language recognition survey was done in the study [21]. They reviewed the studies published between 2008 and 2017. The authors discussed the advancement of sign language recognition. The authors also provided an overview of state-of-the-art building blocks of automatic sign language recognition like feature extraction, classification, and sign language databases.

A study by Suharjito et al. [22] conducted a review of sign language recognition application systems for hearing loss or speech-disordered individuals, employing an input-process-output framework. They evaluated various sign language recognition approaches and identified the most effective approach. Additionally, the study focused on different acquisition methods and classification techniques, presenting their respective advantages and disadvantages. This comprehensive analysis offers valuable insights for researchers seeking to develop improved sign language recognition systems.

In summary, this discussion above has encompassed selected systematic literature reviews (SLRs) and survey papers covering diverse topics of interest, while also highlighting notable contributions in these areas. Certain reviews are specifically tailored to region-based sign languages, such as Chinese and American Sign Languages. Meanwhile, others have become obsolete, offering minimal relevance to contemporary modern approaches. To address this research gap, this paper conducts a comprehensive analysis and review of publications focused on sign language detection and interpretation techniques, particularly those employing machine and deep learning approaches. The review encompasses publications from esteemed journals and prestigious conferences spanning the past decade, ranging from 2012 to July 2023. The insights derived from this review hold significant implications for a wide spectrum of stakeholders, including practitioners, researchers, developers, and industries engaged in accessibility solutions, software, and hardware development, and the creation of smart devices tailored to individuals with speech disorders. The major contributions of this paper include

(i) A complete up-to-date analysis of the publications published from 2012 to July 2023 through a rigorous search and standard selection criteria.

(ii) A detailed yet comprehensive discussion on current trends in the field of disabilities specifically for speech disorder people.

(iii) A discussion on different machine learning approaches for smart gadgets (smartphones in particular) along with sensor-based approaches used in smart gloves.

This paper organized and categorized (in a comprehensive manner) the available literature from different perspectives and points of view discussed in the Materials and Methods section. A compact and concise literature is presented in respect of sign language recognition. This study may help the practitioners to better understand the area, specifically in mobile-based sign language detection and recognition systems. It may also help the researchers to be fully aware of different approaches and research progress in this field. This work comes under the category of accessibility for people suffering from hearing loss or speech disorders.

The remainder of the paper is structured as follows. Section 2 encompasses the "Materials and Methods," outlining the approach used for examining the existing literature. Section 3, titled "Findings and Discussion," investigates the explanation of seven research questions. Section 4, labelled "Meta-Analysis," provides a comprehensive overview of the paper's analysis, and it also touches upon potential avenues for future research in Section 5 "Open Research Questions." Finally, Section 6 serves as the conclusion, and the references are listed at the end of the paper.

2. Materials and Methods

This study presents a systematic literature review (SLR) on sign language detection and interpretation via smartphone-based machine or deep learning approaches. This study is mapped and conducted based on the guidelines presented by Kitchenham et al. [23] and Moher et al. [24]. The research questions are designed to identify the research gap and are framed in Table 1.

2.1. Search Strategy. This section discusses the search strategy for searching and mapping the relevant literature. We used the PRISMA framework for selecting the most relevant studies. We have adhered to the PRISMA framework [24] for structuring our search and selection methodology, illustrated in Figure 1. The PRISMA framework is a widely recognized and established methodology for conducting systematic literature reviews. It offers a set of guiding principles and a flowchart (refer to Figure 1) that aids researchers in adopting a systematic approach to ensure the reporting quality is accurate, comprehensive, and transparent. This, in turn, forms the foundation for making well-founded and evidence-based decisions when selecting relevant literature. Figure 1 illustrates the initial search results, which amounted to 233,860 records. After screening and removing duplicates, 281 studies were left of which 163 studies were the most relevant and are included for analysis.

The criteria for inclusion/exclusion of publication are defined in Table 2. The literature has been tabulated, analyzed, and mapped based on criteria defined in Table 2.

2.2. Time Frame and Digital Repositories. The time for searching the relevant literature is from 2012 to July 2023 (both years included) shown in Table 2. The use of smartphones for sign language detection and identification has evolved over the years due to the widespread adoption of smartphones and their growing role in assisting individuals with disabilities, including speech disorders, visual impairments, and related challenges. Since then, a reasonable amount of literature is available and mapped in this paper. We selected IEEE Xplore, ScienceDirect, ACM Digital Library, and Google Scholar for searching the literature. These repositories were selected due to the reasons that they provide relevant publications, results, and analytics. Academic search engines, such as Google Scholar, are also used for meaningful searches and insights.

2.3. Theoretical Framework and Initial Results. Table 3 shows a list of strings that we have used for searching and mapping the literature. The search strings were searched using different web search engines (discussed above). The search strings tabulated in Table 3 were applied in the selected digital repositories. The results are recorded in Table 3.

The publications are categorized as journal papers and conferences. Only prestigious conferences, i.e., supported by ACM, IEEE, or Springer, are considered. The ratio is shown in Figure 2.

Similarly, the year-wise frequency of the selected publication is shown in Figure 3. We selected papers from 2012 to July 2023. We have seen a healthy growth of publications on these accessibilities, sign language, and smartphones as tools for speech-disordered people.

Table 4 presents the summary *(most relevant papers)* of the publications along with years, types, and publishers. We selected only well-reputed journals and conferences.

3. Findings and Discussion

This section is dedicated to addressing the research questions raised and discussed in Table 1. Additionally, it provides an exhaustive review of the selected publications from a pool of 163 research papers. It covers a wide range of aspects within the research on smartphones as assistive devices, the application of machine and deep learning approaches for individuals with speech disorders, the compilation of comprehensive datasets utilized in research, region-specific sign languages, and a detailed examination of the evaluation metrics employed in experiments, each discussed in dedicated subsections. Moreover, this section discusses the findings, research gap, and possible directions for future research.

3.1. RQ1: What Is the Current Status of Smartphone-Based Sign Language? In a study by Ghanem et al. [7], the authors discussed in detail a survey of existing techniques used for smartphone-based sign languages. Moreover, the authors

Table 1: Research questions.

RQ#	Research question	Motivation
RQ1	What is the current status of smartphone-based sign language?	To study and map the current status of overall sign languages using smartphones as a device for detection and interpretation, especially in 2023
RQ2	How machine learning, deep learning, and lightweight deep learning techniques are used for the detection and interpretation of sign languages?	To study deep learning and lightweight deep learning techniques used for the detection and interpretation of sign languages
RQ3	What are the types of datasets used for sign language recognition?	To specify the different datasets, used for detection and interpretation of sign languages
RQ4	What are the most popular approaches for recognizing sign language?	To study and map the most popular approaches to sign language detection and interpretation
RQ5	Which sign languages are targeted?	To study the sign languages which are detected and interpreted
RQ6	What evaluation metrics are used in the experiments?	To study what metrics are used in the experiments of the sign languages
RQ7	Which models have demonstrated better performance for specific sign languages?	To summarize the performance of models in sign language recognition, specifically highlighting which models have demonstrated better performance for specific sign languages

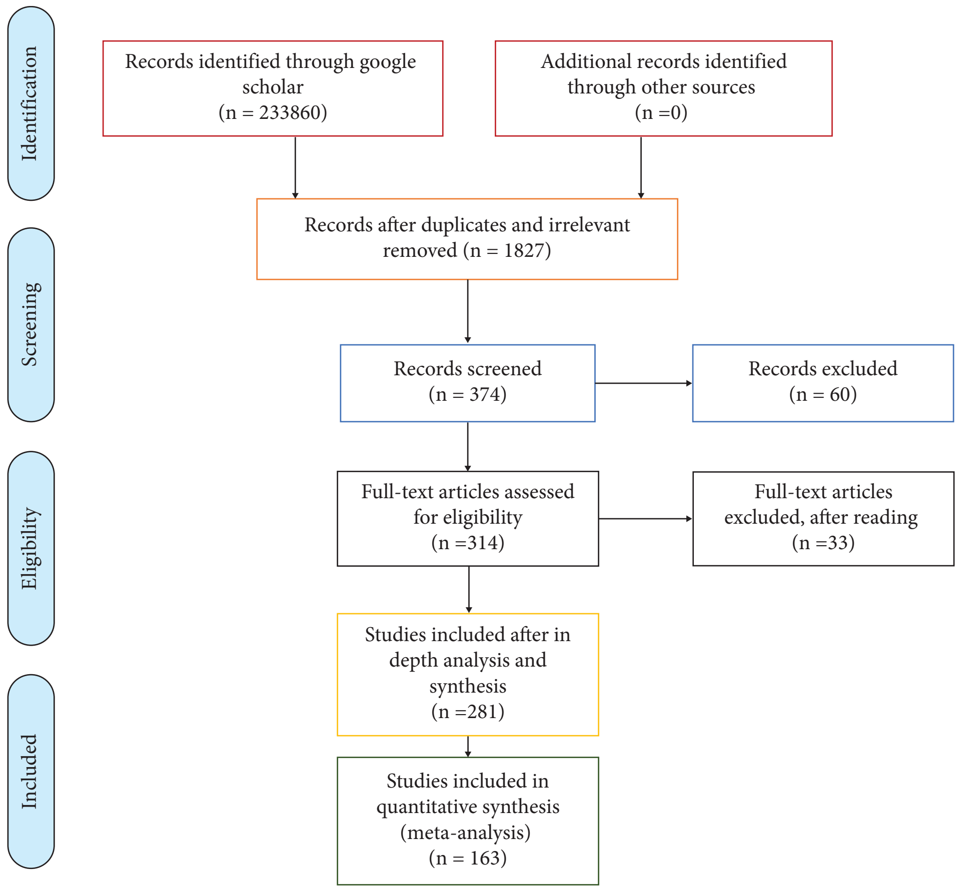

Figure 1: The identification process of primary studies [24].

Table 2: Inclusion and exclusion criteria.

Inclusion criteria	The searched string appeared in the title, abstract, or keywords of the study The publication is written only in the English language Studies in journals, conferences, and book chapters from 2012 to July 2023
Exclusion criteria	Blogs, keynotes, and weak reference studies, such as Wikipedia, dictionaries, and thesaurus Duplicate studies, i.e., studies published in more than one publisher's database

developed an interactive Android mobile application centered around machine learning, aimed at bridging the communication gap between individuals with hearing loss and the general population. In this connection, they introduced the PSL dataset [141]. The approach used in this study involved training the data through the SVM model, enabling automatic recognition of captured signs using the static symbols stored in the database. Numerous approaches to machine and deep learning are used in various applications. Table 5 provides a list of several of these approaches.

Table 5 shows a range of techniques organized according to the year of study and evaluation metric. Notably, the CNN deep learning model has gained widespread acceptance among recent researchers for sign language detection and or recognition. Furthermore, the major evaluation metric employed across the studies is *"accuracy,"* as indicated in Table 5.

3.2. RQ2: How Machine Learning, Deep Learning, and Lightweight Deep Learning Techniques Are Used for the Detection and Interpretation of Sign Languages? Over time, numerous techniques have been investigated for efficient recognition of sign and gesture languages. The majority of sign language recognition systems rely on machine learning, deep learning, and lightweight deep learning approaches. Table 6 presents a compilation of selected studies and their respective approaches for detecting sign languages through deep learning methods. Analyzing the table, we can see that *CNN* is the most dominant technique. These techniques are general and not associated with specific hardware, such as smartphones. Moreover, most of the studies use hand gestures as input and recognize it via some devices, such as custom-built gloves. It is also observed that *CNN* is still widely used even in recent years. It is important to recognize that any sign recognition system

Table 3: Studies found in the selected repositories.

String	Digital repository	Studies found	Selected
Sign language detection smartphone	IEEE Xplore	8	5
	ScienceDirect	711	7
	ACM Digital Library	26053	16
	Google Scholar	17900	37
	Total	44672	65
Sign language recognition using a smartphone	IEEE Xplore	21	13
	ScienceDirect	593	7
	ACM Digital Library	62275	22
	Google Scholar	17600	35
	Total	80489	77
Sign language smartphone deep learning	IEEE Xplore	7	4
	ScienceDirect	1231	5
	ACM	39102	23
	Google Scholar	17100	29
	Total	57437	61
Real-time smartphone sign language	IEEE Xplore	19	7
	ScienceDirect	1233	6
	ACM	32921	21
	Google Scholar	17100	44
	Total	51262	78
	Grand total	233860	281
After removing duplicates			163

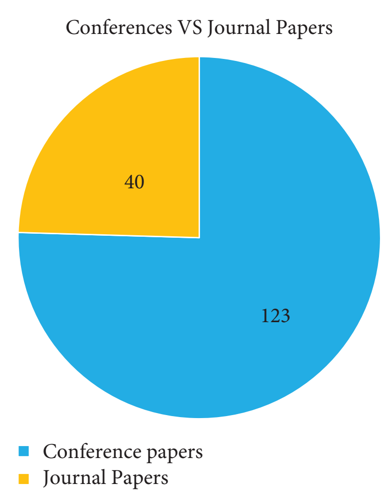

Figure 2: Studies published in conferences and journals.

typically involves several key steps. First, input data are acquired, often through sources such as smartphone cameras or sensors. The subsequent step requires feature extraction from the acquired input data. Finally, the signs are classified using algorithms that are well-suited to the extracted features. The accuracy of the detection and extraction system significantly influences the quality of recognition results. Various approaches have been employed in sign recognition systems, including CNN, KNN, ANN, and SVM, among others. Among these techniques, CNN stands out as a leading approach compared to the other methods listed in Table 6. Table 6 also depicts the studies and their associated information with each study.

3.3. RQ3: What Are the Types of Datasets Used for Sign Language Recognition? Table 7(a) provides a comprehensive discussion of the various types of datasets and their utilization in numerous studies. Furthermore, in Table 7(b), links to publicly available datasets are provided. Upon analyzing these tables, it is observed that most of the studies have developed their custom datasets. Additionally, it is notable that many of these datasets are language-dependent, such as the PSL, American Sign Language (ASL), Malaysian Sign Language, Taiwan Sign Language (TSL), and China Sign Language (CSL), among others. Table 7 showcases the studies along with their respective years, datasets used, and remarks for each study.

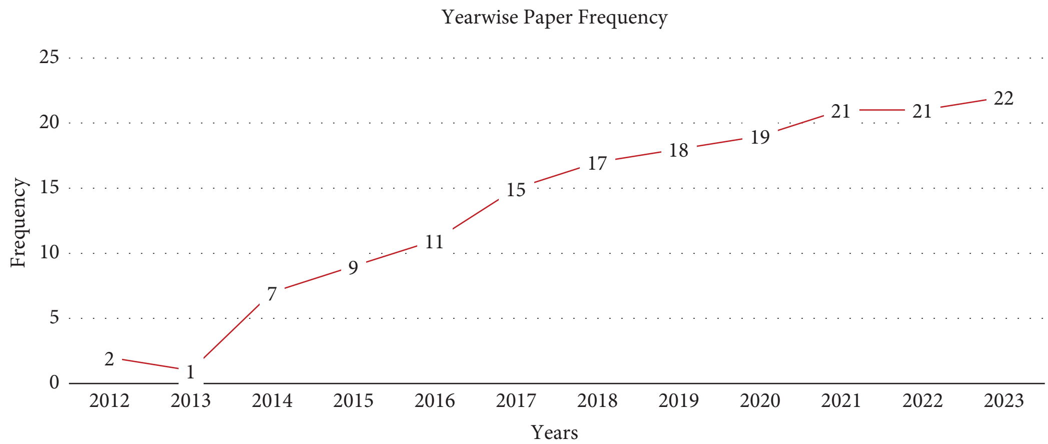

FIGURE 3: Number of studies published from 2012 to 2023.

TABLE 4: Summary of the included literature.

Study	Year	Type	Publisher
[25, 26]	2012	Conference	ACM
[27]	2013	Conference	ACM
[28–33]	2014	Conference	IEEE
[34]	2014	Journal	Pensee Journal
[35–41]	2015	Conference	IEEE
[42]	2015	Conference	Elsevier
[43]	2015	Conference	ACM
[44–46]	2016	Conference	ACM
[47]	2016	Conference	British Machine Vision Conference
[48–50]	2016	Conference	IEEE
[51]	2016	Journal	Elsevier
[52]	2016	Journal	International Journal of Electrical and Computer Engineering (IJECE)
[53]	2016	Journal	Journal of Information Assurance & Security
[54]	2016	Journal	Technology and Health Care
[55]	2017	Conference	Heriot-Watt University
[56–59]	2017	Conference	ACM
[2, 60–63]	2017	Conference	IEEE
[64]	2017	Journal	ACM
[65]	2017	Journal	Computer Vision and Pattern Recognition
[66]	2017	Journal	Far East Journal of Electronics and Communications
[67]	2017	Journal	International Journal of Information Technology
[68]	2017	Journal	Sensors
[69–71]	2018	Conference	ACM
[72–78]	2018	Conference	IEEE
[79, 80]	2018	Conference	Springer
[81]	2018	Journal	Entropy
[82]	2018	Journal	Informatics
[83]	2018	Journal	Elsevier
[84]	2018	Journal	International Journal on Recent and Innovation Trends in Computing and Communication
[85]	2018	Journal	Springer
[86–99]	2019	Conference	ACM
[100]	2019	Conference	Association for Computational Linguistics
[101]	2019	Conference	Elsevier
[102–114]	2019	Conference	IEEE
[115]	2019	Conference	Springer
[116]	2019	Journal	Journal of Education and Practice
[117]	2019	Journal	International Journal of Ambient Computing and Intelligence (IJACI)
[118]	2019	Journal	International Journal of Interactive Multimedia and Artificial Intelligence

Table 4: Continued.

Study	Year	Type	Publisher
[119]	2019	Journal	ACM
[120–125]	2020	Conference	ACM
[126]	2020	Conference	European Language Resources Association (ELRA)
[127, 128]	2020	Conference	IEEE
[129, 130]	2020	Conference	Springer
[131]	2020	Journal	Applied Sciences
[132]	2020	Journal	Computer Vision and Pattern Recognition
[133]	2020	Journal	Telkomnika
[134]	2020	Journal	Springer
[135]	2020	Journal	International Journal of Advanced Trends in Computer Science and Engineering
[136]	2020	Journal	Elsevier
[137]	2020	Journal	ACM
[138]	2020	Journal	IEEE
[139]	2021	Conference	Atlantis Press
[140]	2021	Conference	IEEE
[141]	2021	Journal	Elsevier
[142]	2021	Journal	Springer
[143]	2022	Journal	IEEE
[144–146]	2022	Conference	Springer
[147]	2023	Journal	Elsevier
[148–150]	2023	Journal	Springer
[151]	2023	Journal	ACM
[152]	2023	Conference	Springer

Numerous publicly available datasets are used by different articles. Some of them can be accessed via links shown in Table 7(b). Some datasets are custom-made and not publicly available.

3.4. RQ4: What Are the Most Popular Approaches for Recognizing Sign Language? Sign language recognition commonly utilizes sensor-based and vision-based techniques to observe hand motion and posture [7]. The sensor-based approach involves the use of sensors, such as those embedded in gloves or smartphones, to track hand movements. These sensors, whether external or internal to the mobile device, capture data related to hand gestures. For example, glove-based approaches utilize multiple sensors within the gloves to monitor the position and movement of fingers and the palm, providing coordinates for subsequent processing. These devices may be connected wirelessly via Bluetooth. The glove contains ten flexors for tracking finger posture [39]. In the sensor-based approach, a combination of sensors, including a G-sensor and a Gyroscope sensor, is employed to monitor hand orientation and motion. These sensors continuously capture signals related to hand data, which are then wirelessly transmitted to a mobile device for hand state estimation. The choice of recognition method depends on the input data and the dataset utilized. In this particular case, the authors utilized template matching as a classification method, which encompasses five dynamic sign classes. In the vision-based approach, hand gestures are observed through the mobile camera, and a series of processing steps are applied to identify the signs within the video stream.

3.5. RQ5: Which Sign Languages Are Targeted? Different countries used their regional sign languages for research and contributed to the accessibility domain for speech disorder people. The American Sign Language is the dominant sign language in the research as shown in Table 8.

3.6. RQ6: What Evaluation Metrics Are Used in the Experiments? The systems that use sign language dataset(s) are usually evaluated using standard metrics such as accuracy, precision, recall, and F1 score. From the literature, most of the systems were evaluated by detecting and interpreting the sign languages, and hence accuracy is the frequently used metric as shown in Figure 4. Similarly, precision and recall were also used.

3.7. RQ7: Which Models Have Demonstrated Better Performance for Specific Sign Languages? Numerous machine and deep learning models have been employed for detecting and recognizing diverse sets of sign languages. This process encompasses the training and testing of data using specific sign language datasets, which can include data ranging from hand gestures to video frames, as well as data collected from wearable sensors. As previously discussed, gestures are captured using mobile cameras, while data from wearable sensors are collected through gloves. Table 9 provides an overview of studies centered on various sign languages, offering insights into their respective accomplishments, primarily evaluated in terms of accuracy.

Table 5: Techniques of sign language recognition using smartphones.

Study	Year	Techniques	Evaluation metric
[153]	2023	DeepVision transformers	Accuracy, precision
[154]	2023	8-Layer CNN	Accuracy
[155]	2023	K-nearest neighbors (KNN)	Accuracy
[150]	2023	Deep learning (DL) combined with CNN and RNN	Accuracy
[147]	2023	DNN	Accuracy with mAP@.5
[146]	2022	CNN	Accuracy
[144]	2022	SVM	Accuracy
[143]	2022	Inaudible acoustic signal to estimate channel information and capture the sign language in real time	Accuracy
[156]	2022	CNN	Accuracy
[157]	2022	CNN, DCGAN	Accuracy
[141]	2021	SVM	Accuracy, precision, recall, F1 score
[158]	2021	CNN	Accuracy
[159]	2021	3DCNN	Accuracy
[160]	2021	CNN, RNN	Accuracy
[137]	2020	ISL parser, Hamburg notation system, signing gesture markup language, 3D avatar	BLEU score, accuracy
[138]	2020	CNN	Word recognition rate
[127]	2020	Long short-term memory (LSTM)	Accuracy
[128]	2020	AutoML, transfer learning	Precision, recall, F1 score, accuracy
[129]	2020	MobileNet and ResNet	Accuracy
[133]	2020	MobileNet	Accuracy
[132]	2020	MobileNet-V3	Accuracy
[120]	2020	Artificial neural networks (ANNs)	Accuracy
[102]	2019	State-of-the-art pose estimation method	Accuracy
[110]	2019	CNN	Accuracy
[105]	2019	Simple classification algorithms from machine learning	Accuracy
[103]	2019	SVM	Accuracy, precision, recall, *F* measure
[104]	2019	SVM	Accuracy, precision, recall, specificity, F1 measure
[109]	2019	Elliptical Fourier descriptor and LSTM	Training time, testing time, accuracy
[119]	2019	AdaBoost, multilayer perceptron, Naïve Bayes, random forest, SVM, dynamic feature selection and voting	Accuracy
[91]	2019	CNN, LSTM, and connectionist temporal classification (CTC)	Accuracy, WER
[101]	2019	MIT invertor	Accuracy
[90]	2019	LSTM and CTC	Accuracy, WER
[87]	2019	OpenPose, hidden Markov model	Accuracy
[115]	2019	Gesture recognition algorithm of talking hands	Accuracy
[74]	2018	Flex sensor with Arduino	Accuracy
[70]	2018	CNN	Accuracy
[84]	2018	CNN	Accuracy, recognition time
[82]	2018	Naïve Bayes, multilayer perceptron (MLP)	Accuracy, F1 score
[75]	2018	KNN	Accuracy, recognition time
[79]	2018	ANN	Word matching score (WMS)
[83]	2018	ANN, minimum distance classifier	WMS
[60]	2017	Neural network	N.A

Table 5: Continued.

Study	Year	Techniques	Evaluation metric
[62]	2017	Principle component analysis	Accuracy
[66]	2017	Word matching score (WMS) and ANN	WMS
[56]	2017	SVM, Naïve Bayes, random forest	Accuracy, F1 score
[57]	2017	Binarized neural network, LSTM	Detection ration (DR), reliability ration (RR), WER
[2]	2017	KNN, SVM linear, radial basis function SVM, random forest	*F* measure, ROC, accuracy
[67]	2017	Discrete-time warping	Accuracy
[61]	2017	Arduino	N.A
[50]	2016	SVM	Accuracy
[49]	2016	Backpropagation neural network	Accuracy
[45]	2016	Dynamic time warping	Recognition time, extensibility, recognition time (accuracy)
[52]	2016	Euclidean, normalized Euclidian, and Mahalanobis distance	WMS
[51]	2016	Optical character recognition, Microsoft Arabic Toolkit Service (ATKS), named entity recognizer (NER)	Recognition time, usability
[41]	2015	Neural networks (NNs) with log-sigmoid, NN with symmetric Elliott, and SVM	Accuracy, classification time, memory usage, battery consumption
[42]	2015	Microcontroller	Accuracy
[39]	2015	Flex sensors, inertial sensors	Sensitivity, accuracy
[37]	2015	KNN classification. The time needed by the system to recognize a single sign is between 6 frames per second (FPS) and 20 FPS.	Accuracy
[40]	2015	Arduino	Accuracy, error rate
[28]	2014	Recognition algorithm using histogram of oriented gradients (HOG)	Recognition rate, processing time
[33]	2014	Principle component analysis (PCA) for feature extraction and Euclidean distance for classification	Accuracy
[26]	2012	Sign modeling language (SML), animation engine	N.A

Table 6: Techniques of sign language recognition using deep learning.

Study	Year	Techniques	Evaluation metric
[153]	2023	DeepVision transformers	Accuracy, precision
[154]	2023	8-Layer CNN	Accuracy
[155]	2023	KNN	Accuracy
[161]	2023	Attention-based Bi-LSTM	Accuracy
[150]	2023	Deep learning (DL) combined with CNN and RNN	Accuracy
[147]	2023	DNN	Accuracy with mAP@.5
[146]	2022	CNN	Accuracy
[144]	2022	SVM	Accuracy
[143]	2022	Inaudible acoustic signal to estimate channel information and capture the sign language in real time	Accuracy
[162]	2022	Hybrid convolutional neural network + bidirectional long short-term memory (CNN + Bi-LSTM)	Peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), Fréchet inception distance (FID), temporal consistency metric (TCM)
[163]	2022	3D convolution net	Accuracy
[156]	2022	CNN	Accuracy
[157]	2022	CNN, DCGAN	Accuracy
[164]	2022	VGG-19	PSNR, SSIM, FID, TCM
[141]	2021	SVM	Accuracy, precision, recall, F1 score
[158]	2021	CNN	Accuracy
[159]	2021	3DCNN	Accuracy
[160]	2021	CNN, RNN	Accuracy
[139]	2021	Spyder, TensorFlow, OpenCV, Keras	Accuracy
[140]	2021	KNN	Accuracy
[142]	2021	2D CNN, SVD, and LSTM	Time recognition, accuracy
[125]	2020	3D CNN Siamese network	Accuracy
[131]	2020	Conv3D	Sentence error rate (SER), accuracy
[122]	2020	ResNet-D model	Accuracy, time
[134]	2020	CNN	Accuracy, precision, recall, F1 score
[135]	2020	Hidden Markov model (HMM)	Accuracy
[123]	2020	CNN-LSTM-HMM	Accuracy
[136]	2020	CNN	Accuracy
[126]	2020	CNN	Accuracy
[130]	2020	Stochastic multistate (SMS)	WER
[124]	2020	CNN LSTM	Accuracy, precision, recall, F1 measure
[116]	2019	CNN	NA
[99]	2019	3D-ResNet, CTC	WER
[97]	2019	Visual Geometry Group (VGG)-16, VGG-19	Accuracy
[94]	2019	CNN	Accuracy
[93]	2019	Convolutional-based attention module (CBAM)-ResNet	Accuracy
[86]	2019	Neural network and QuadroConvPoolNet	Accuracy
[95]	2019	MLP, SVM, and CNN	Accuracy
[106]	2019	ANN, SVM, HMM	Accuracy
[117]	2019	CNN	Accuracy
[114]	2019	CNN, LSTM	Accuracy
[118]	2019	VGG-19	Recognition rate

Table 6: Continued.

Study	Year	Techniques	Evaluation metric
[100]	2019	K-means clustering	Accuracy
[96]	2019	Inception v3, MobileNet	Precision, recall, F1 score, accuracy
[107]	2019	LSTM	Accuracy
[108]	2019	ResNet50-BiLSTM, MobileNetV2-BiLSTM	Precision, recall, F1 score, accuracy
[98]	2019	Deep feedforward neural network	Accuracy
[113]	2019	CNN	Precision, recall, F1 score, accuracy
[88]	2019	WebGL, SiGML, CoreNLP	Recognition rate
[112]	2019	CNN	Accuracy
[92]	2019	3DCNN	Accuracy
[89]	2019	CNN	Precision, recall, F1 score, accuracy
[71]	2018	SVM, KNN, CNN, ANN	Success rate
[72]	2018	LSTM and VGG-16	Accuracy
[73]	2018	CNN	Accuracy
[77]	2018	CNN	Accuracy
[80]	2018	CNN	Accuracy
[85]	2018	Adaptive graph matching	Accuracy, TWRF, FWRF
[81]	2018	Restricted Boltzmann machine	Top-1 accuracy, Top-5 accuracy
[78]	2018	Inception v3	Accuracy
[69]	2018	RNN	Accuracy
[76]	2018	LSTM	Accuracy
[68]	2017	Dynamic vision sensor, CNN, RNN	Accuracy
[64]	2017	3D signing avatar, Blender animation software	Accuracy
[58]	2017	Nearest neighbor	Accuracy
[63]	2017	CNN	Accuracy
[59]	2017	Finite Legendre transform, linear discriminant analysis, KNN	Accuracy
[55]	2017	LSTM	Accuracy
[65]	2017	CNN	Accuracy
[48]	2016	CNN	Top-1 accuracy, Top-5 accuracy
[47]	2016	Hybrid-CNN HMM	Accuracy
[3]	2016	Correlation classification algorithm	Accuracy, precision, recall
[44]	2016	CNN	Accuracy
[46]	2016	SVM	Accuracy
[54]	2016	Maximum a posteriori (MAP)	Accuracy
[43]	2015	Leap Motion Technology	Accuracy
[36]	2015	CNN	Accuracy
[34]	2014	ANN, vision-based	Accuracy, MSE
[31]	2014	A skin and motion detector, hand detection using multiple proposals, chains model	Accuracy
[29]	2014	KNN, cross-correlation	Accuracy
[30]	2014	Deep belief network	Precision, recall
[32]	2014	Microcontroller	Precision, recall
[27]	2013	K-nearest neighbor	Accuracy
[25]	2012	Multilayer perceptron	Mean, standard deviation, aspect ratio hand cropping algorithm (ARHCA), no ARHCA

Table 7: (a) Datasets used in sign language recognition. (b) Links to publicly available dataset.

Study	Year	Dataset	Remarks
(a)			
[141]	2021	PSL dataset	37 alphabets
[165]	2021	ISLAN (Indian Sign Language)	Collection of 700 sign images, and 24 sign videos
[139]	2021	SIBI dataset	8 static word signs. 19200 total images are included
[140]	2021		Custom made numbers from 1 to 5
[142]	2021	RKS persiansign, first-person, ASVID, isoGD	(i) RKS-PERSIANSIGN: this dataset comprises 10,000 RGB videos showcasing 100 Persian sign words. These videos are contributed by 10 individuals, including 5 women and 5 men, with 100 video samples available for each Persian sign word (ii) First-person: this dataset consists of 100,000 RGB-D frames depicting 45 different hand action categories performed with 26 distinct objects, capturing various hand configurations. Only the RGB sequences from the ASVID dataset are used in this context (iii) isoGD: this dataset contains a total of 47,933 RGB and depth video samples across 249 class labels. For your reference, only the RGB samples are utilized in this dataset. It is further divided into three subdatasets, with 35,878 samples designated for training, 5,784 samples for validation, and 6,271 samples for testing
[137]	2020	HamNoSys database	3000 words
[138]	2020	Chinese Sign Language	The dataset generated consists of 51 common word signs from which 60 sentences were created. Instances of sentences are 20400 from 34 volunteers
[127]	2020	Korean Sign Language	17 words used for training
[128]	2020	China Sign Language	Data augmentation is used to obtain a benchmark dataset based on Chinese Sign Language (CSL). One dataset is obtained from Kaggle and the other is built from 30-second video frames
[120]	2020	American Sign Language (ASL) and Bengali Sign Language (BdSL)	A dataset is generated which contains 1000 data points for each of the letters of ASL and BdSL
[132]	2020	MS-ASL dataset	This dataset has 25000 clips over 222 signers and covers 1000 most frequently used ASL gestures
[133]	2020	Bangla Sign Language	This dataset has 30 consonants and 6 vowels of BSL characters. The dataset holds $36 \times 50 = 1800$ images in total as it has 50 samples for each sign
[129]	2020	German Sign Language	The dataset has 301 videos with an average duration of 9 minutes

Table 7: Continued.

Study	Year	Dataset	Remarks
[125]	2020	American Sign Language	A dataset consisting of 80 video clips that focus on finger movement. These video clips were sourced from two different origins: 32 were extracted from publicly available videos, while the remaining 48 clips were recorded manually. Within this dataset, there are 20 instances for each of the four alphabets: D, I, J, and Z
[131]	2020	Croatian Sign Language	The dataset was generated which consists of 25 languages and their signs. 40 volunteers performed each gesture twice which resulted in 2000 sign videos
[122]	2020	Hong Kong Sign Language (HKSL)	The dataset was created by the authors. It consists of 45 most common words. For each word, 30 videos from different signers were recorded. Total videos are 1500
[134]	2020	Indian Sign Language	Custom created. The dataset includes 100 static signs, that is, 23 English alphabets, 0–10 digits, and 67 commonly used words. There are 300 images of each instance totaling 35000 images
[135]	2020	Custom made	The dataset has four unique word signs. Each sign has 50 images with different positions and light levels. The total number of images is 1000
[123]	2020	German Sign Language	Public dataset. RWTH-PHOENIX-weather 2014
[136]	2020	RKS-PERSIANSIGN first-person dataset NYU hand pose dataset	(i) RKS-PERSIANSIGN: (1) Contains: 10,000 RGB videos (2) Content: 100 Persian words (3) Contributors: 10 individuals (4) Purpose: likely used for Persian sign language recognition. This dataset provides video samples for training and evaluating models for recognizing (ii) Persian sign language gestures First-person dataset: (1) Contains: 100,000 RGB-D frames (2) Content: 45 hand action categories for 26 different objects (3) Purpose: this dataset seems focused on recognizing hand actions related to interactions with various objects. The RGB-D frames can be used for training and evaluating models capable of understanding hand-object interactions (iii) NYU hand pose dataset: (1) Contains: 81,009 image sequences (2) Content: 36 joints (3) Purpose: likely used for hand pose estimation. This dataset provides a large number of image sequences capturing various hand poses, which can be used to train and test models for hand pose estimation tasks

Table 7: Continued.

Study	Year	Dataset	Remarks
[126]	2020	Flemish Sign Language	Public dataset The total samples are 18730 from 67 native signers with 100 classes
[102]	2019	The dataset contains three gestures	The three gestures are feeling uncomfortable, seeing a doctor, and taking medicine
[110]	2019	ASL alphabet dataset. Sign language and static gesture recognition dataset	(i) The ASL alphabet dataset contains 87,000 images. The sign language and static gesture recognition dataset contains 1,687 images (ii) The authors created their dataset from these two datasets which contain 73,488 images
[105]	2019	American Sign Language	A total of 10 samples of each alphabet were taken for accuracy
[103]	2019	Arabic Sign Language	10 alphabets Alif, Ba, Ta, Kha, Dal, Dhad, Thah, Ghayn, Lam, and La. 2000 images used for training
[104]	2019	British Sign Language	26 letters A to Z Training performed on 520 samples (26 classes with 20 samples per class)
[109]	2019	Indonesian language inflectional words	Custom made (i) Word count: the dataset consists of a total of 1,440 inflectional words (1) Training data: 954 inflectional words (2) Testing data: 486 inflectional words (ii) Data sources: the data were recorded by three teachers from Santi Rama school for the hearing impaired in Jakarta
[91]	2019	ASL dataset	Two datasets: one is word-level (70 ASL words) and the other is sentence-level (100 sentences)
[101]	2019	Arabic Sign Language	Only 5 letters were taken for the experiment
[90]	2019	Custom-made	5 volunteers to perform 26 alphabet signs with 30 repetitions. That is, $26 \times 30 \times 5$ alphabet signs (3,900) in the dataset
[87]	2019	Swedish Sign Language signs dataset	Swedish keyword signing targeted children with communicative disorders
[115]	2019	Custom-made	40 signs five times each totaling 200 for testing

Table 7: Continued.

Study	Year	Dataset	Remarks
[116]	2019	Custom-made PSL	(i) Dataset generation: the dataset was generated by capturing videos of sign language gestures. Afterward, frames were extracted from these videos using the Matlab image processing toolbox (ii) Signs: the dataset includes various sign language gestures, with each sign represented by a substantial number of pictures (iii) Number of signs: not specified, but there are multiple signs (iv) Pictures per sign: each sign is represented by approximately 1,500 to 2,000 pictures (v) Total pictures: the dataset contains a total of around 21,000 pictures
[99]	2019	German Sign Language weather forecast program	RWTH-PHOENIX-weather-2014 (i) Training set: (1) Number of videos: 5,672 (2) Use: typically used to train machine learning or deep learning models (ii) Validation set: (1) Number of videos: 540 (2) Use: used during the model development process to fine-tune hyperparameters and assess model performance (iii) Test set: (1) Number of videos: 629 (2) Use: reserved for evaluating the final model's performance and assessing its generalization to unseen data
[97]	2019	Ghanaian Sign Language	Custom-made The dataset consists of 66000 images in RGB color with 33 classes of static gestures having 24 alphabets and 9 digits
[94]	2019	Korean Sign Language	Custom-made Ten words were selected. A different number of videos were selected from the Internet for each word. The total no. of videos is 421
[93]	2019	CSL	The authors selected 100 kinds of sign language words. The training set consists of 2964, the validation set has 1044, and the testing set has 1005 videos
[119]	2019	ASL	Custom-made 26 alphabets

Table 7: Continued.

Study	Year	Dataset	Remarks
[86]	2019	ASL Russian Sign Language (RSL)	ASL dataset: Massey University of researchers This dataset consists of 2425 images from 5 individuals RSL: Custom-made The data for RSL are collected from five YouTube videos. The total number of gestures in RSL is 33. Only the 26 static gestures are taken and the rest of the dynamic gestures are not included in this work
[95]	2019	Custom made	The static sign language has 24 alphabets. J and Z are excluded because they are dynamic. Also, it included and captured from seven native and nonnative signers with alike lighting
[106]	2019	ASL	There are 6000 words in the ASL dictionary
[117]	2019	ASL	Public dataset The dataset collected from Kaggle contains pictures of static hand motions of ASL with 24 classes. The database consists of 47475 pictures from which 33000 (70%) pictures were used in the training set and 1445 (30%) pictures for testing
[114]	2019	LSA64 dataset Argentinian Sign Language	Public dataset: The authors selected 30 gestures and 50 video streams for each gesture. After video processing, 90,000 images were created representing the sequence of dynamic gestures. The number of images for each category is 3000
[6, 118]	2019	ASL	A comprehensive collection of American Sign Language (ASL) gestures representing 24 English letters (excluding "Y" and "Z"). These gestures are captured in the form of expressive hand movements, providing a rich resource for ASL recognition These ASL gestures used Kinect technology with contributions from 5 different individuals
[100]	2019	ASL	Public dataset ASLLVD, the American Sign Language lexicon video dataset, features nearly 10,000 ASL signs by 6 native signers. The dataset focuses on 50 hand-picked ASL signs, each signed by 6 different individuals, totaling 300 videos. These videos include various angles, but our analysis concentrated on front-view recordings
[96]	2019	ASL	Custom-made The authors collected video data for 25 ASL signs from 100 users where each sign was executed three times each. The total number of instances was 7500

Table 7: Continued.

Study	Year	Dataset	Remarks
[107]	2019	ISL	Custom-made The authors selected 26 common signs. Each sign sample comprises 50 consecutive readings, representing 50-time points of gesture motion. A single sample is structured as a 50×11 matrix, forming 2D data stored in a CSV file
[108]	2019	SIBI	Custom-made The number of videos is 2275 which consists of 28 common sentences
[98]	2019	ASL	Custom-made 26 letters of the ASL alphabet are included. The signers are 3 and each signer took 10 signs for each alphabet which totals 30 for one alphabet. Thus, the total number of instances is 780
[113]	2019	ISL	The dataset consists of 2500 images for alphabets and dynamic words. The authors augmented this dataset and produced 5157 images
[88]	2019	CSL ASL	The authors have created a database of four tables to store symbols with important descriptions. They have used HamNoSys which consists of 200 symbols consisting of hand shapes, hand orientation, location, and movements
[112]	2019	ASL	Custom-made The study concentrates on static ASL gestures from A to Y, omitting J and Z due to their dynamic nature. The dataset comprises 24 gesture images captured with a smartphone camera. Each gesture is represented by 200 images taken by two users, accounting for a total of 4800 images
[92]	2019	Thai Sign Language (TSL)	Custom-made The authors used Microsoft Kinect to record the video stream dataset. It consists of 64 isolated vocabularies. Each word was performed by 8 nonnative TSL signers and each signer acted 5 times for each word. Thus, there are $64 \times 8 \times 5 = 2560$ video samples in total
[89]	2019	Brazilian Sign Language	Custom-made Authors recorded videos for 26 letters of the alphabet in Libras with 13 users. The total number of videos was 338
[74]	2018	Indonesian Sign Language	Alphabets A to Z and numbers 1 to 10 used in this experiment
[70]	2018	Indonesian Sign Language	Alphabets A to Z taken
[84]	2018	The open dataset given at Kaggle called sign language MNIST	A set of 28×28 images representing the standard American Sign Language (ASL) alphabet, excluding J and Z

Table 7: Continued.

Study	Year	Dataset	Remarks
[82]	2018	French Sign Language	22 gestures were taken out of 26 from French Sign Language. 4 gestures, that is, J, P, Y, and Z, were left out because of their nonstatic nature. Each gesture was performed by 57 participants. The total dataset contains 1.25 million samples
[75]	2018	Indian Sign Language (ISL)	Digits 0 to 9 and alphabets a to z were taken for the experiment
[79]	2018	Indian Sign Language (ISL)	Digits 0 to 9 and alphabets a to z were taken for the experiment
[83]	2018	Custom built. Indian Sign Language	18 signs with each sign by 10 different signers recorded
[71]	2018	Indian Sign Language American Sign Language British Sign Language Turkish Sign Language	(i) ISL dataset: used SVM for this dataset Contains 4 signs, that is, A, B, C, and the word "Hello" (ii) ASL dataset: used KNN for this dataset Contains 10 ASL fingerspelling alphabets from a to i and k. The letter j is not included. The total number of samples was 5254 (iii) ISL: used CNN for this dataset The total dataset is 5000 samples for 200 signs done by five Indian Sign Language users (iv) Authors used ANN for the following 3 datasets (v) ASL: consists of letters from A to Z (vi) British Sign Language: contains alphabets from A to Z (vii) Turkish Sign Language: Consists of alphabets from A to Z. The letters Q, W, and X are excluded
[72]	2018	Argentinian Sign Language	LSA64 dataset: 10 subjects, 5 repetitions, 64 sign types, 3200 videos RWTH-PHOENIX-weather database: 50 classes, 1297 training videos, 238 testing videos
[73]	2018		Public dataset There are 900 pictures including 25 samples for each of 36 characters consisting of 26 letters and 10 digits
[77]	2018	ISL	Custom-made 200 sign language words. Each sign is performed by 5 different signers
[80]	2018	ISL	Custom-made A dataset of 5000 images and 100 images each for 50 most commonly used words was created
[85]	2018	ISL	Custom-made The dataset consists of 200 words to form sentences

Table 7: Continued.

Study	Year	Dataset	Remarks
[81]	2018	ASL	Massey University gesture dataset 2012: Consists of 36 classes with 2524 images ASL fingerspelling A dataset: Consists of 24 classes with 131,000 images NYU: Consists of 36 classes with 81,009 images ASL fingerspelling dataset of the Surrey University: Consists of 24 classes with 130,000 images
[78]	2018	ASL	ASL alphabet dataset: public dataset There are 24 static gestures from letters A–Y. J is excluded as it is dynamic. There are 100 images for each class
[69]	2018	Korean Sign Language	Custom-made The dataset consists of 10,480 videos collected from ten Korean professional signers
[76]	2018	SIBI (Sistem Isyarat Bahasa Indonesia)	Custom-made The dataset consists of SIBI words performed by 2 teachers fluent in this language. It consists of 21 root words and 155 inflectional words. Each word is recorded 5 times by each teacher, thus resulting in a total of 1760 signs
[60]	2017	Custom-made	Static gestures for the English alphabets from A to Z and digits from 0 to 9
[62]	2017	Custom-made	Static gestures for the English alphabets from A to Z and digits from 0 to 9
[2]	2017	Custom-made	Static gestures for the English alphabets from A to Z and digits from 0 to 9
[67]	2017	Indonesian Sign Language	Dataset: 1000 samples, 50 Indonesian sign words, 20 samples per sign, 500 for training, 500 for testing
[61]	2017	ISL	Custom-made 26 alphabets from A to Z and 12 basic words
[66]	2017	ISL	Custom-made 18 different words were included in the dataset
[56]	2017	Ubicomp.eti.uni	18 different words were included in the dataset
[57]	2017	ASL	103 signs
[68]	2017	ASL	The dataset has a total of 720 images (30 for every ASL sign image). The dataset consists of alphabets from A to Y. The letters J and Z are excluded
[64]	2017	Sinhala Sign Language (SSL)	Custom-made The dataset consists of 61 SSL fingerspelling signs (words) and 40 SSL number signs

Table 7: Continued.

Study	Year	Dataset	Remarks
[58]	2017	Greek Sign Language	Custom-made 5 participants (2 male, 3 female) learned and performed 15 signs, four times each, totaling 300 evaluation samples
[63]	2017	Korean Sign Language	Custom-made 30 different gestures are included in this dataset. The training data are 72% and the testing data are 28%
[59]	2017	Thai Sign Language (TSL)	The dataset consists of 10 words. Each word has 10 samples
[55]	2017	NGT (Nederlandse Gebarentaal) sign language of the Netherlands	Public dataset The dataset consists of 40 glosses (words) taken from the NGT dataset
[65]	2017	ASL	Custom-made The dataset consists of 25 images from 5 people for each alphabet and digits 0–9
[50]	2016	ASL	16 alphabets taken for training and testing
[49]	2016	Indonesian Sign Language	24 gestures from A to Y excluding J and Z
[45]	2016	ASL	Custom-made The dataset consists of 20 ASL signs
[51]	2016	Arabic Sign Language (ArSL)	Public dataset: This dataset consists of 588 signs which include 10 numbers from 0 to 9, 28 alphabets, and different categories like family, job, colors, and sports
[3]	2016	Pakistan Sign Language	6 alphabets from A to F with 20 samples for each letter collected
[52]	2016	Continuous sign language	18 signs with each sign by 10 different signers recorded
[48]	2016	Danish Sign Language New Zealand Sign Language RWTH-PHOENIX-weather 2014	(i) Danish Sign Language: this dataset consists of 2,149 signs (ii) New Zealand Sign Language: this dataset consists of 4,155 signs (iii) RWTH-PHOENIX-weather 2014: this dataset consists of 65,227 signs
[47]	2016	German Sign Language	RWTH-PHOENIX-weather 2012 RWTH-PHOENIX-weather multisigner 2014 This dataset consists of 65,227 signs SIGNUM single signer: This dataset consists of 450 basic signs. Isolated signs are 450 and continuous sentences are 780. The total number of images is 5,970,450
[44]	2016	American Sign Language image dataset (ASLID) American Sign Language lexicon video dataset (ASLLVD)	Public datasets Training set: 808 ASLID images from six signers. Test set: 479 ASLID images from two signers

Table 7: Continued.

Study	Year	Dataset	Remarks
[46]	2016	Greek Sign Language	Custom-made 24 Greek Sign Language letters, 10 samples each, 6 subjects, totaling 1440 samples
[54]	2016	Korean Sign Language	Custom-made Experiment: 5 subjects, 1–9 numbers repeated 5 times. 3 males and 2 females were the participants
[41]	2015	South African Sign Language (SASL)	Taken only three alphabets A, B, and C and three digits 1, 2, and 3
[42]	2015	Malaysian Sign Language	Taken only three alphabets A, B, and C and three digits 1, 2, and 3
[39]	2015	Taiwan Sign Language	51 fundamental postures in Taiwan Sign Language
[35]	2015	ASL	Custom built (real-time hand gesture recognition system)
[37]	2015	Indonesian Sign Language	Alphabets A to Z
[40]	2015	ASL	Only the letters A to Z are included for testing
[43]	2015	Greek Sign Language	Greek Sign Language alphabets
[36]	2015	German Sign Language (DGS)	Public dataset RWTH-PHOENIX-weather corpus: Dataset: 2137 sentence segments, 14717 gloss annotations, 189,363 frames
[28]	2014	Custom built	Hand gesture image database The test dataset was prepared by four persons each of whom showed 19 signs with three rotation variations
[33]	2014	PSL	300 samples taken from 30 individuals with 10 signs each
[34]	2014	PSL	Custom-made This dataset consists of 500 images of 37 alphabets. 426 images were utilized for training and 74 for testing
[31]	2014	Dataset DS1	The number of one-handed videos and frames is 42 and 902 The number of two-handed videos and frames is 48 and 1337 Dataset DS2: The number of one-handed videos and frames is 42 and 1276 The number of two-handed videos and frames is 48 and 1945 Dataset DS3: The number of one-handed videos and frames is 42 and 1197 The number of two-handed videos and frames is 48 and 1735

Table 7: Continued.

Study	Year	Dataset	Remarks
[29]	2014	PSL	Custom-made The dataset consists of 37 alphabets. 6 samples are recorded for each alphabet
[30]	2014	ASL	Custom-made dataset Dataset: 24 static letters signed by 5 individuals, 60,000 images
[32]	2014	ArSL	The sign-to-letter translation by using a hand glove, microcontroller, and display unit
[27]	2013	Thai Sign Language (TSL)	Custom-made The dataset consists of 42 TSL alphabets. Several videos are taken for each alphabet
[26]	2012		Custom-built A word is an input to the smartphone which is converted to video animation
[25]	2012	Brazilian Sign Language (Libras)	Custom-made The dataset consists of two sets. One is the vowel set which is A, E, I, O, and U. The other set has the set which has B, C, F, L, and V

Name	Link (access date 25-August-2023)
(b)	
PSL	https://data.mendeley.com/datasets/y9svrbh27n/1
First-person	https://guiggh.github.io/publications/first-person-hands/
Purdue RVL-SLLL	https://engineering.purdue.edu/RVL/Database/ASL/asl-database-front.htm
Corpus NGT	https://www.ru.nl/en/cls/research
isoGD	http://www.cbsr.ia.ac.cn/users/jwan/database/isogd.html
SIGNUM	https://www.phonetik.uni-muenchen.de/forschung/Bas/SIGNUM/
WLASL	https://dxli94.github.io/WLASL/
ASLID	http://vlm1.uta.edu/~srujana/ASLID/ASL_Image_Dataset.html
German Sign Language	https://www-i6.informatik.rwth-aachen.de/~koller/RWTH-PHOENIX/
Danish Sign Language	https://www.tegnsprog.dk/
ArSL	https://menasy.com/

Table 7: Continued.

Study	Year	Dataset	Remarks
How2Sign	https://how2sign.github.io/		
GSL dataset	https://vcl.iti.gr/dataset/gsl/		
AUTSL	https://chalearnlap.cvc.uab.cat/dataset/40/ description/		
LSA64	https://facundoq.github.io/datasets/lsa64/		
Ubicomp	https://ubicomp.eti.uni-siegen.de/home/datasets/		
ASL finger spelling	https://www.kaggle.com/datasets/mrgeislinger/ asl-rgb-depth-fingerspelling-spelling-it-out		
Sign language MNIST	https://www.kaggle.com/datasets/datamunge/ sign-language-mnist		
Indian Sign Language	https://data.mendeley.com/datasets/rc349j45m5/1 doi: 10.17632/rc349j45m5.1		

Table 8: Sign languages targeted.

Sign language	Study
American Sign Language	[30, 40, 44, 45, 50, 57, 65, 68, 71, 78, 81, 84, 86, 88, 91, 96, 98, 100, 105, 106, 110, 112, 117–120, 132]
Arabic Sign Language	[51, 101, 103]
Argentinian Sign Language	[114]
Bangla Sign Language	[120, 133]
Brazilian Sign Language	[25, 89]
British Sign Language	[71, 104]
China Sign Language	[88, 93, 128, 138]
Croatian Sign Language	[131]
Danish Sign Language	[48]
Flemish Sign Language	[126]
French Sign Language	[82]
German Sign Language	[36, 47, 99, 123, 129]
Ghanaian Sign Language	[97]
Greek Sign Language	[43, 46, 58]
Hong Kong Sign Language	[122]
Indian Sign Language	[61, 66, 71, 75, 77, 80, 83, 85, 107, 113, 134]
Indonesian Sign Language	[37, 49, 67, 70, 74, 76, 108, 139]
Korean Sign Language	[54, 63, 69, 94, 127]
Malaysian Sign Language	[42]
New Zealand Sign Language	[48]
Pakistan Sign Language	[3, 29, 33, 34, 116, 141]
Persian Sign Language	
Russian Sign Language	[86]
Sign language of Netherlands	[55]
Sinhala Sign Language (SSL)	[64]
South African Sign Language	[41]
Thai Sign Language	[27, 59, 92]
Turkish Sign Language	[71]

Figure 4: Evaluation metrics by frequency used in different research.

4. Meta-Analysis

This section offers a multilayered examination of the collected literature, exploring various dimensions, including publisher contributions, contributions by country, and citation analysis. Numerous approaches have been thoroughly tested and validated on specific sign languages, as extensively discussed earlier. For instance, Figure 5 provides a comparative analysis of various studies on American Sign Language (ASL) along with the achieved accuracy levels. It is important to note that the accuracy of these approaches and models is contingent upon the complexity and variability of signs within a specific sign language.

The contribution of publishers has been analyzed based on the selected publications. While it is evident that each publisher has made substantial contributions to research in the field of accessibility for individuals with speech disorders, it is noteworthy that a majority of the selected papers in this paper were published in IEEE journals and conferences, as illustrated in Figure 6.

Moreover, the most highly cited paper among the selected publications has been identified. The paper with the highest number of citations was authored by Cheok et al. in 2019, titled "*A review of hand gesture and sign language recognition techniques* [14]." As of the latest available data, it has accumulated 456 citations, as illustrated in Figure 7.

Similarly, the analysis of the selected literature for this paper has been conducted with a focus on country-wise contributions. In terms of country-wise contributions, India stands out as a significant contributor to publications related to speech disorders, as depicted in Figure 8. The United States follows as the second most prominent contributing country.

5. Open Research Questions

This section explores the potential open research questions and challenges that currently exist. While the advancing hardware and software capabilities of smartphones are no longer a computational constraint, the multifaceted nature of sign languages, each with its diverse set of gestures,

Table 9: Models and their evaluation performance on specific sign languages.

Study	Year	Model	Sign language	Results/performance
[154]	2023	8-layer CNN	ISL	99.34% accuracy
[156]	2022	CNN	ISL	70.0% accuracy
[160]	2021	CNN and RNN	ISL	Top-1 (95.99%) accuracy Top-3 (99.46%) accuracy
[158]	2021	CNN	ASL	87.5% accuracy
[143]	2022	Built-in speakers and microphones, inaudible acoustic signal	ASL	97.2% accuracy at word-level
[166]	2021	AutoML	ASL	100% accuracy
[159]	2021	3DCNN	KSL	91.0% accuracy
[51]	2016	Cloud computing-based approach	ArSL	77%–84% for short sentences
[103]	2019	SVM	ArSL	92.5% accuracy
[49]	2016	Backpropagation neural network	Indonesian SL	91.66% accuracy
[76]	2018	2-Layer LSTM	Indonesian SL	95.15% accuracy
[70]	2018	CNN	Indonesian SL	100% accuracy

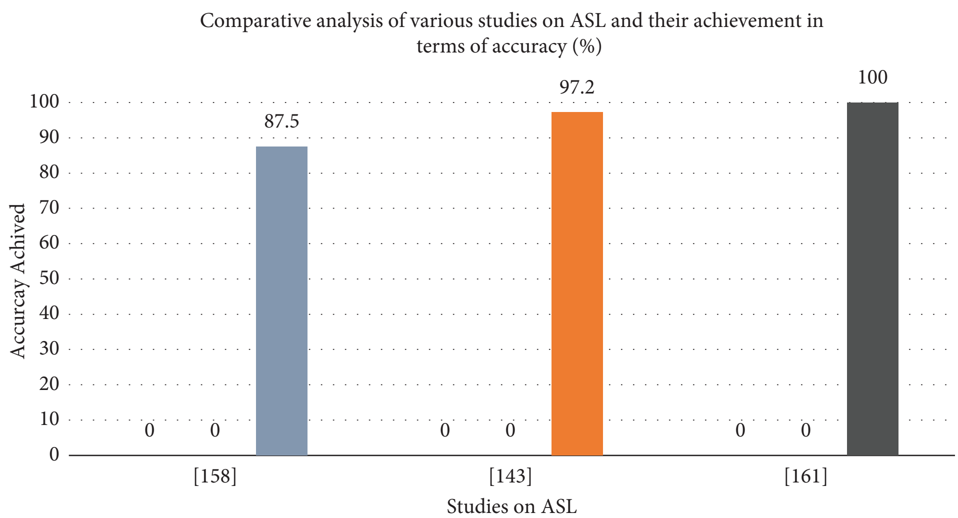

Figure 5: Comparative analysis of various studies in terms of accuracy.

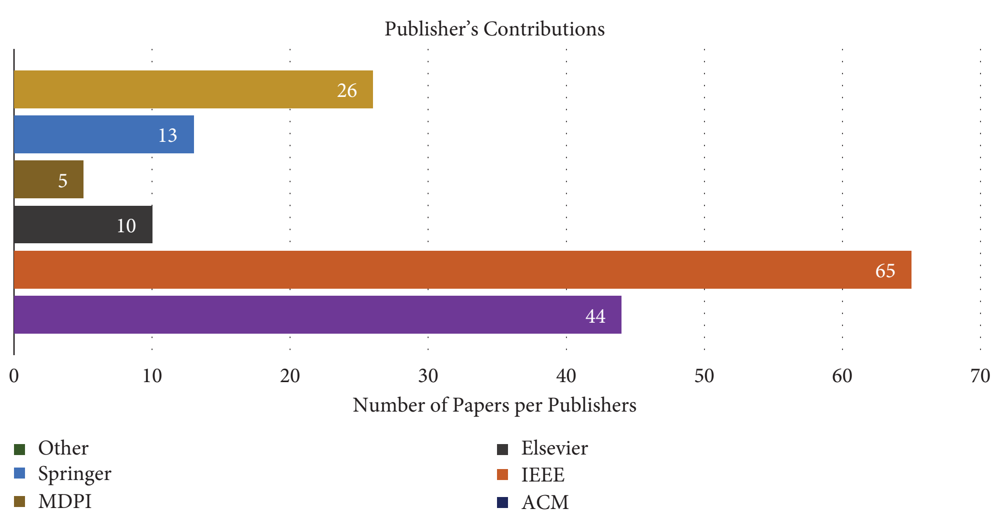

Figure 6: Number of studies based on publisher's contributions.

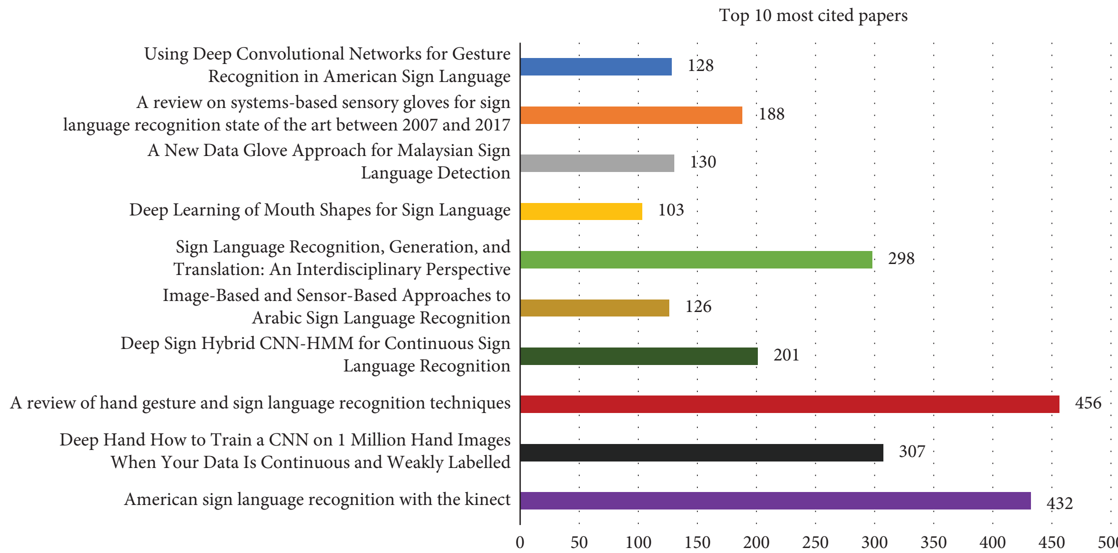

Figure 7: Top ten most cited papers.

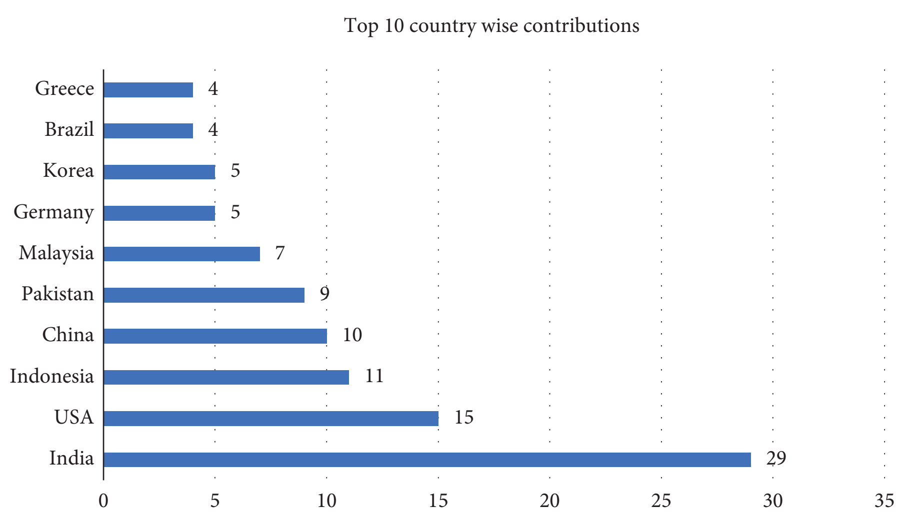

Figure 8: Number of papers country-wise.

continues to present significant challenges. Moreover, the challenges also include social acceptability and pervasiveness at low cost. Besides, the reliance on sign language(s) and its translation for individuals suffering from speech disorders has unique challenges that need proper investigation, for example, compatibility issues, multilingual translation, education level, real-time gesture generation, and translation. The following subsection provides an in-depth elaboration of the most salient issues and challenges identified in the existing literature.

5.1. Accuracy, Robustness, and Real-Time Detection. The accuracy of real-time translation of sign language is challenging due to various factors, such as light conditions, power consumption, social acceptability, and privacy constraints. The question is "*How can we improve the accuracy and robustness of sign language detection and interpretation on smartphones to ensure reliable and real-time communication for users?*" This is because it involves real-time image processing and source constraints, such as processing and storage [148]. Delays in processing with false positive responses may further increase frustration for speech-disabled people. While smartphones are portable, the input of gestures on smartphones may require specific tools or the presence of an individual to operate the smartphone's camera for individuals with disabilities. Without these provisions, there is a risk of improper gesture input and consequently an increased chance of errors.

5.2. Multilingual Support. Every region of the world has its own sign language for its speech-disabled people. This makes it difficult to translate one sign language to another and hence the scope becomes narrow [148]. The question of "*What techniques can be developed to support multiple sign languages on smartphones, accommodating diverse user needs?*" still exists. Furthermore, there is a pressing need to establish a universal standard for sign language. Such a standardized language could facilitate the development of universal smart devices, ultimately leading to a reduction in the overall cost of equipment designed for these purposes.

5.3. Gesture Recognition. As mentioned, the sign languages are detected via sensor (hardware approach) or by vision approach. The sensor approaches, i.e., gloves or other wearable devices, are not socially acceptable and hence rarely used by speech-disordered people. In the vision-based approach, we have image processing, which itself requires lots of energy, power, and storage [167]. The question *"How can machine learning algorithms be optimized to recognize a wide range of sign language gestures and expressions accurately?"* is yet to be answered. One reason may be that machine and deep learning algorithms are resource-intensive, and hence little attention is given to smartphones. Therefore, existing machine and deep learning algorithms require proper optimization for smartphones.

5.4. Data Privacy and Security. Privacy is everyone's right and also for people with special needs including the visually impaired [168, 169] and people suffering from speech disorders. The sign language talking patterns are vulnerable due to processing by a machine [170]. Moreover, the sign language talking in public may lead to privacy breaches. Therefore, the following question arises: "What measures can be implemented to ensure the privacy and security of sign language data transmitted and processed on smartphones?" This question needs proper attention. The messages in digital form have numerous security issues, such as chat leakages and hacking, among others. As a case study, some attempts have been made by Michigan State University (https://msutoday.msu.edu/news/2019/new-technology-breaks-through-sign-language-barriers) to address numerous pressing issues. However, more work is needed in this domain to ensure that sign language interpretation is risk-free. Proper encryption/decryption by the machine (used for translation) could also improve privacy issues.

5.5. Low-Light and Noisy Environments. Image processing in low light generates false positives, which directly affect the performance and results [171, 172]. The question *"How can sign language detection systems on smartphones perform effectively in low-light conditions and noisy environments?"* still exists. Moreover, due to battery constraints, smartphones have limited battery life, which tends to deplete rapidly during image processing activities under low-light conditions. The machine and deep learning application(s) may further contribute to battery depletion.

These research questions include various aspects of sign language(s) detection on smartphones and offer opportunities to advance this field to better serve the needs of individuals with hearing and speech disability problems. Researchers/academia and practitioners can focus on one or more of these questions to contribute to the development of innovative, low-cost, socially acceptable, and effective solutions.

6. Conclusion

The detection and interpretation of sign language for people with speech disorders, utilizing cost-effective off-the-shelf devices, particularly smartphones, has gained substantial attention within the research and academic communities. Using a smartphone for accessibility solutions is not an exception due to its growing capabilities in terms of processing, mobility, storage capacity, and social acceptability. This paper presented a systematic literature review (SLR) on sign language detection and interpretation using pervasive and ubiquitous computing devices, such as smartphones. The objective is to comprehensively analyze the progress achieved thus far in the machine and deep learning approaches using smartphones. Moreover, to analyze the approaches employed in enhancing accessibility for individuals with speech disorders, it is important to gather insights regarding the recent machine and deep learning approaches, available datasets, evaluation metrics, and current research and emerging trends. In this connection, this paper is intended to provide valuable insights for researchers and practitioners engaged in accessibility initiatives, particularly in the domain of speech disorders. This study highlighted the most valuable literature published from 2012 to July 2023. Moreover, it highlighted a detailed yet comprehensive literature, datasets, and numerous machine and deep learning approaches used on smartphones. The paper specifically focuses on the detection and interpretation of sign languages via smartphones. This study suggests that the development of a *universal sign language* could greatly benefit both practitioners and developers in this field since it may mitigate the overhead costs associated with learning, detecting, and translating multiple sign languages. Moreover, the focus should be on socially acceptable devices instead of expensive or complex wearable devices. This review paper may serve as a valuable contribution to the existing body of knowledge and is expected to offer a roadmap for future research in the domain of accessibility, specifically for speech-disabled individuals. Future work can be carried out in different areas, such as real-time accurate translation by smartphones, preserving privacy during translation, and accurate gesture recognition in low-light conditions.

Data Availability

The collected data (in an Excel sheet) will be provided upon request. Most of the basic statistics regarding the systematic literature review are discussed within the paper.

Disclosure

This study was conducted at the Department of Computer Science, City University of Science and Information Technology, Peshawar, Pakistan.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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