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ORIGINAL PAPER

Sign Language Recognition Systems: A Decade Systematic Literature Review

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Abstract

Despite the importance of sign language recognition systems, there is a lack of a Systematic Literature Review and a classification scheme for it. This is the first identifiable academic literature review of sign language recognition systems. It provides an academic database of literature between the duration of 2007–2017 and proposes a classification scheme to classify the research articles. Three hundred and ninety six research articles were identified and reviewed for their direct relevance to sign language recognition systems. One hundred and seventeen research articles were subsequently selected, reviewed and classified. Each of 117 selected papers was categorized on the basis of twenty five sign languages and were further compared on the basis of six dimensions (data acquisition techniques, static/dynamic signs, signing mode, single/double handed signs, classification technique and recognition rate). The Systematic Literature Review and classification process was verified independently. Literature findings of this paper indicate that the major research on sign language recognition has been performed on static, isolated and single handed signs using camera. Overall, it will be hoped that the study may provide readers and researchers a roadmap to guide future research and facilitate knowledge accumulation and creation into the field of sign language recognition.

1 Introduction to Sign Language

In the communicative hand/arm gesture taxonomies, sign language (SL) is considered as the most organized and structured form out of various gesture categories. Sign language is an important means of communication among hearing impaired and deaf community. Instead of using oral communication and sound patterns, signs in visual space are used by hearing impaired people for communication. SL not only involves hand/arm gestures but also deals with the non-manual signs that use facial expressions and various body postures for conveying semantic meaning.

Sign language recognition is a collaborative research area which involves pattern matching, computer vision, natural language processing, and linguistics. Its objective is to build various methods and algorithms in order to identify already produced signs and to perceive their meaning. Sign language recognition systems are Human Computer Interaction (HCI) based systems that are designed to enable effective and engaging interaction. These system follows a multidisciplinary approach of data acquisition, SL technology, SL testing and SL linguistics. Such a system can be deployed in public services like hotels, railways, resorts, banks, offices etc. to enable hearing impaired people learn new concepts and facts and to control emotional behavior [1].

1.1 Sign Language Symbols

The linguistic studies of sign language have started in 1970s [2]. It contains lingual information which includes different symbols and letters. Sign language symbols are able to indicate all the sign parameters that include hand shapes, movement, location and palm orientation. The classification of SL symbols is shown in Fig. 1. SL symbols are classified into single handed and double handed signs. Further, these signs are classified into static and dynamic signs.

One Handed Signs For representing one handed signs single dominant hand is used. It can be represented by any static gesture or a gesture with motion.

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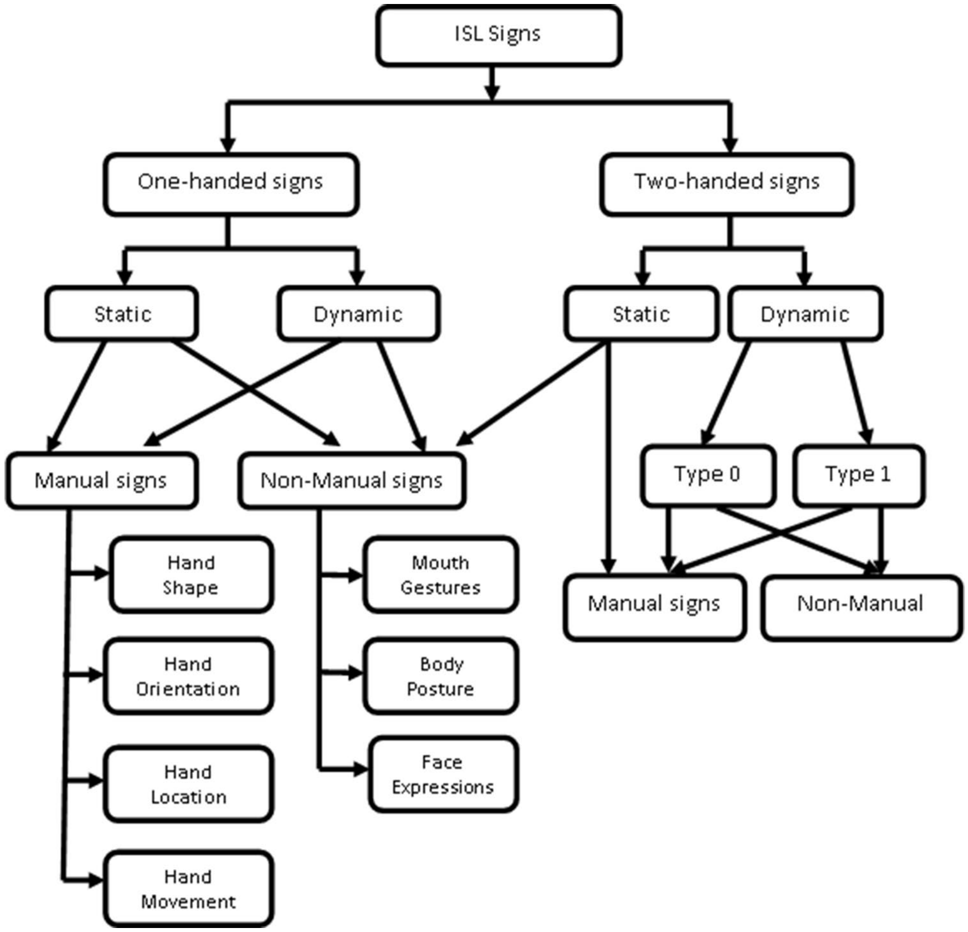

Fig. 1 Hierarchy of signs [3]

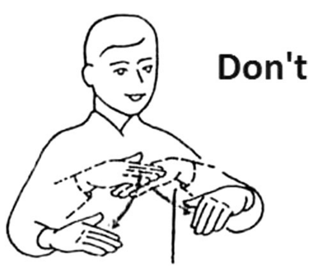

Fig. 2 Two handed type 0 sign (both the hands are active)

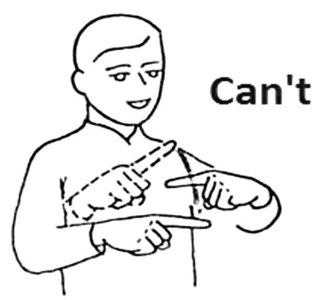

Fig. 3 Two handed type 1 sign (only dominant hand is active)

Two Handed Signs To represent two handed signs both the dominant and non-dominant signs are used while signing. These are further classified as type 0 and type 1 sign. In type 0 sign both the hands are active, as shown in Fig. 2 whereas, in Type 1 dominant hand is more active as compared to non-dominant hand, as shown in Fig. 3.

Sign language consists of manual and non-manual elements as well [4]. In manual signs only hands are used to express any sign and in non-manual signs body postures, mouth gestures and face expressions are used. Single handed static manual and non-manual signs are shown in Fig. 4a, b respectively.

The rest of this paper is organized as follows. Section 2 describes the research methodology used to find and analyze the available existing research, research questions and search criteria. The extraction outcomes of literature survey and discussions are presented in Sect. 3. In Sect. 4 the issues and challenges are presented. Finally, the last section presents the conclusion and future work.

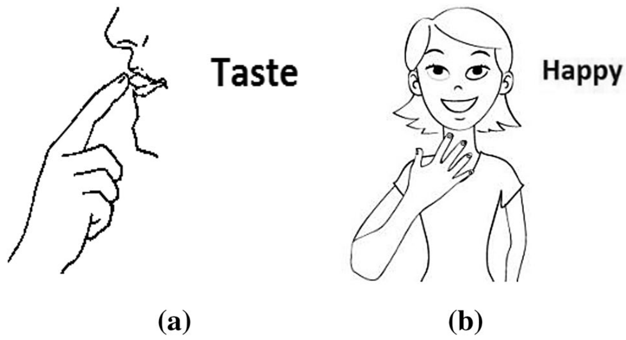

Fig. 4 **a** Single handed static manual sign. **b** non-manual sign [5]

2 Research Methodology

Research methodology is a process of conducting research in a systematic way. It consists of theoretical analysis of all principles associated with the particular field of study. Generally, it includes the concepts of phases, model, qualitative and quantitative techniques. This paper follow the review process suggested by Kitchenham and Charters [6], which includes planning, conducting and reporting the review as shown in Fig. 5.

2.1 Planning Review

Planning starts with the identification of needs for a Systematic Literature Review (SLR) and ends with developing and validating the review protocol.

The need of systematic review is to identify, classify and compare the already existing work in sign language recognition. A huge number of surveys on sign language recognition are noticed in last decade but none of them target the Systematic Literature Review (SLR) process. So, this paper presents a comprehensive survey to systematically classify and compare all the existing methods and techniques on sign language recognition. The research questions given in Table 1 are framed to perform SLR.

2.2 Conducting Review

This phase consists of selecting the studies, extracting required data and synthesis of information.

Selecting studies aims to select the time frame for review process. The SLR includes research papers published in last 10 years from 2007 to 2017. It discusses the research papers from journals, magazines, conferences, workshops and symposiums. The studies were explored and inclusion/exclusion criterions have been framed as shown in Fig. 6 to select different papers. The "Sign Language Recognition" keyword has been used to search the research papers on the given databases. Our search fetched 381 research papers on sign language recognition from the sources of IEEE, ACM, Elsevier and Springer. The fetched data were then reduced to 323 based on their titles, after that papers were excluded based on abstracts and conclusions, and in the end 117 research papers were obtained after going through the full text as shown in Fig. 6.

The source of final selected paper for this survey has been given in Table 2.

The number of research papers extracted on the basis of their year of publication is shown in Fig. 7. It has been observed that there is gradual increase in the number of research papers from year 2012 onwards. This analysis helps us to achieve the answer for RQ1.

From previous published papers, it has been observed that very limited amount of work has been done on the survey of the sign language recognition as shown in Table 3. Khan et al. [124] reviewed sign language components and the challenges and research issues have been discussed. Kausar and Javed [125] presented a survey of current research trends and the challenges faced by the researchers. Bilal et al.

Fig. 5 Overview of research methodology [6]

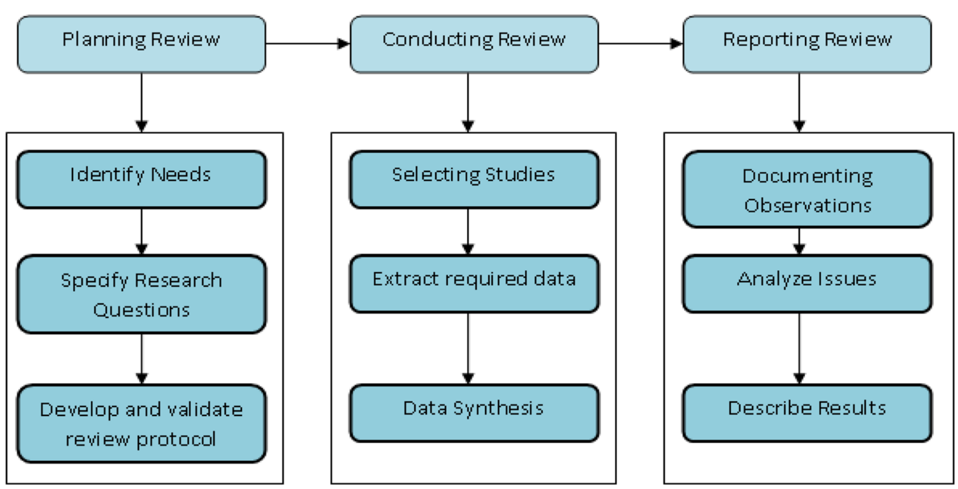

Table 1 Research questions and their motivation

Research questions	Motivation
RQ1: What is the number of research papers published per year on sign language recognition?	To identify the time frame and sources of publications in which the most relevant articles has been published
RQ2: What is the usage of different data acquisition techniques in sign language recognition systems?	To identify and analyze various data acquisition devices that are required to capture data for sign language recognition
RQ3: What is the percentage of research carried out on static/dynamic signs in sign language recognition systems?	To classify static/dynamic signs based on the research work carried out on SL recognition
RQ4: What is the percentage of research work carried out on the basis of signing mode of SL?	To identify different signing modes like isolated and continuous signs
RQ5: What is the percentage of research work carried out on the basis of single and double handed signs?	To identify the work done on single and double handed signs
RQ6: What are the existing methodologies and techniques to recognize sign language recognition?	To identify and compare the existing methodologies and techniques used for sign language recognition
RQ7: What is the accuracy and coverage of existing sign language recognition systems?	To identify the recognition rate of existing sign language recognition systems on the trained dataset

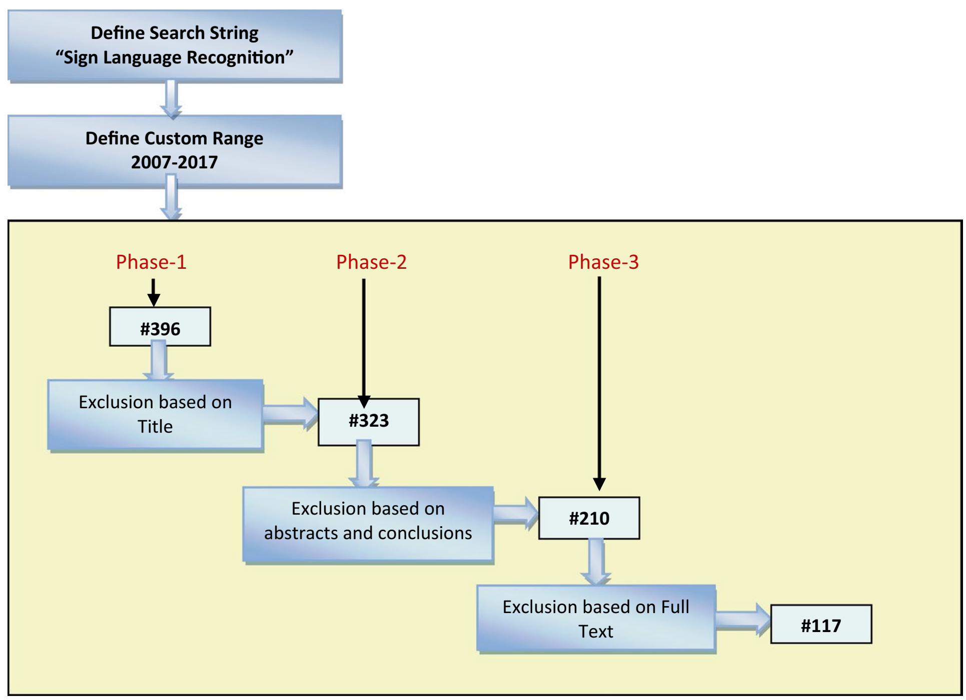

Fig. 6 Inclusion/exclusion technique used in this systematic review

Table 2 Number of outcomes retrieved

Serial number	Search databases	Number of outcomes	Time frame	Content type
1.	IEEE	80	2007–2017	Journals, Magazines, Conferences, Workshops and Symposiums
2.	ACM	10		
3.	Elsevier	14		
4.	Springer	13		
	Total	117		

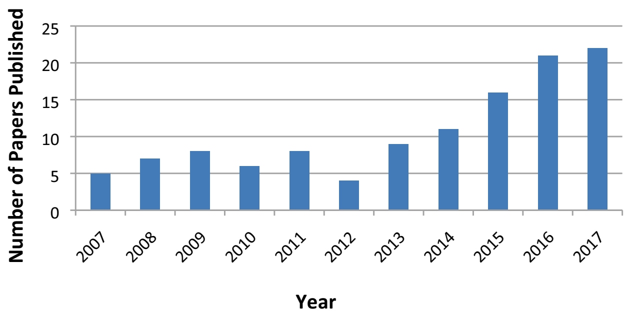

Fig. 7 Year wise number of papers from 2007 to 2017

[126] reviewed the approaches for hand posture detection and showed that the feature extraction is essential while recognizing signs. Mohandes et al. [59, 127] reviewed sensor based and image based approaches used for Arabic sign language recognition. They also highlighted the main challenges for sign language recognition. Ghanem et al. [128] aimed to cover the classification techniques and components used for sign language recognition. The performed surveys are limited in terms of sign language components, hand posture, classification techniques, challenges and research issues. None of the survey has been reported that falls under the category of Systematic Literature Review. So, this motivate us to perform Systematic Literature Review of literature for sign language recognition.

3 Literature Review

The classification of different comparison parameters used in this review is shown in Fig. 8. The strategy that we have followed for Systematic Literature Review includes acquisition mode, static/dynamic signs, signing mode, single/double handed signs, techniques used and average accuracy as their parameters. On the basis of these parameters, the review for different sign languages like American Sign Language (ASL), Indian Sign Language (ISL), Arabic Sign Language (ArSL), Chinese Sign Language (CSL), Persian, Brazilian, Greek, Irish, Malaysian, Mexican, Taiwanese, Thai, German, Japanese, South African, Sri Lankan, Auslan, Bangladeshi, Ecuadorian, Ethiopian, Farsi, Italian, Polish, Spanish and Ukrainian Sign Languages have been analyzed and documented respectively.

3.1 American Sign Language

American Sign Language (ASL), originated from French Sign Language is a predominant sign language used in the

Table 3 Comparative analysis of existing surveys

Author	Prospects				
	Sign language components	Hand posture	Classification techniques	Challenges and research issues	SLR
Khan et al. [124]	✓	×	×	✓	×
Kausar and Javed [125]	×	×	×	✓	×
Bilal et al. [126]	×	✓	×	×	×
Mohandes et al. [59, 127]	✓	×	×	✓	×
Ghanem et al. [128]	✓	×	✓	×	×
Proposed survey	✓	✓	✓	✓	✓

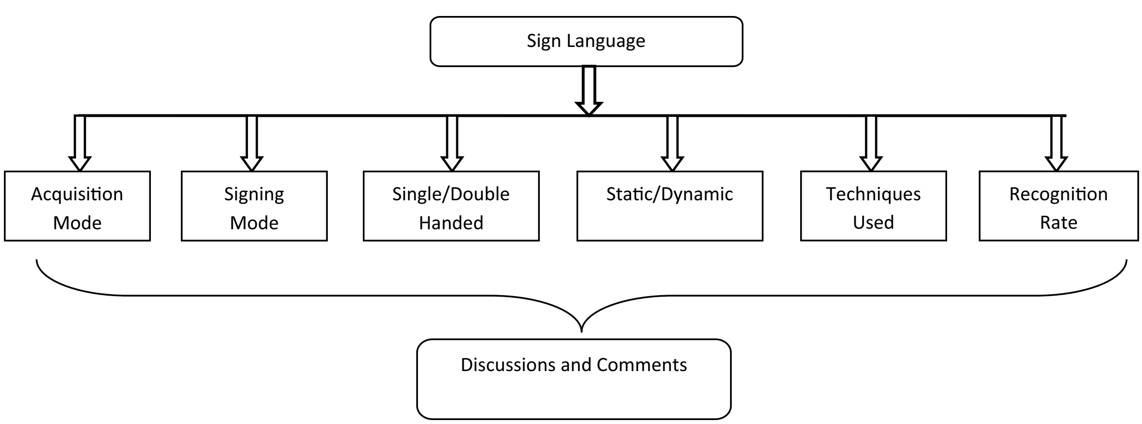

Fig. 8 Comparison parameters

areas of United States and most of Anglophone Canada. The estimate for ASL users range from 2,50,000 to 5,00,000 [129]. The dialects of ASL are also used in west and central Africa. Signs in ASL consists of number of phonemic components which includes face and hand movements. The work done on American Sign Language recognition in the last decade is presented in the next subsection.

3.1.1 American Sign Language Recognition Techniques

Munib et al. [7] presented American Sign Language recognition of static words based on Hough transform. They collected 300 samples of 20 sign images and extracted features of reference origin, shape orientation and orthogonal scale factors. The experimental results showed that the proposed method is robust against changes in size, position and direction of signs. Oz and leu [8] used a Cyberglove and a 'Flock of Birds', i.e., a 3D motion tracker for extracting features of hand. To get the joint angle values of fingers Cyberglove was used. Features like shape of hand, location of hand, orientation of hand, its movement, bounding box, and its distance were extracted. The system was trained and tested by using artificial neural network for identification of American Sign Language and the accuracy of 95% was achieved with word recognition network.

Oz and Leu [9] developed a recognition system using sensory gloves to convert ASL words into English. They collected static single handed samples from 50 words and obtained an accuracy of 90% by using neural network classification technique.

Ragab et al. [10] presented a method for the recognition of single handed static American sign images acquired using camera. They adopted Hilbert space-filling curve technique to extract features because it helps in preserving the localization property of the pixels and it results in the improved efficiency in representing shapes with uniform background. Sun et al. [11] developed a Latent Support Vector Machine model for classifying American sentences. They extracted Kinect features, Histogram of Oriented Gradient (HOG) features and optic flow features and the accuracy of 86% was achieved for continuous signs. Sun et al. [12] proposed a discriminative exemplar coding method for recognition of American Sign Language. The dataset consisted of 1971 samples collected from 73 signs and features of body pose, hand shape and hand motion were extracted. The system was trained with mi-SVM and the collected data was classified using Adaboost.

Chuan et al. [13] developed an American Sign Language recognition system using leap motion sensor. The system was classified using K-Nearest Neighbor and Support Vector machine and the accuracy of 72.78% and 79.83% was achieved respectively. Tangsuksant et al. [14] proposed a method for identifying American Sign Language alphabets. They captured 2880 images and features of area and angle were extracted. The collected data was classified using feed forward back propagation of neural network. Zamani and Kanan [15] developed a camera based method for recognizing American alphabets and numerals. They collected 2520 images of single handed static signs and the accuracy of 99.88% was achieved. Jangyodsuk et al. [16] developed an American Sign Language recognition system in which they have used both camera and Kinect for capturing double handed dynamic signs. The features of hand shape, velocity vector, motion vector were extracted using HOG. The experimental results showed that the accuracy of the system get improved by using HOG features.

Wu et al. [17] proposed a sign language recognition system using electromyography and arm sensors. They have collected 40 American signs and classify them using four classifiers named as Naïve Bayes, Nearest Neighbor, Decision tree and LibSVM. The experimental results showed that the SVM outperforms all other classification methods. Usachokcharoen et al. [18] presented a sign language recognition method using Kinect and colored gloves. They extracted depth, motion and color features from eight American signs. It has been found that the color feature enhance the accuracy of the system. Savur and Sahin [19] proposed an American Sign Language recognition system using arm band. In this system, a total of 2080 samples of American sign alphabets were collected and classified using SVM. The results show that the accuracy of 82.3% was obtained in real-time. Sun et al. [20] proposed a Latent Support Vector Machine modeling based recognition system. To evaluate the developed method, 73 signs and 63 sentences in American Sign Language were collected using Kinect sensor and the accuracy of 86% and 82.9% was achieved respectively. The experiments showed that the accuracy of 96.67% was obtained by fusing camera and data glove together. Aryanie and Heryadi [21] developed a camera based finger-spelling recognition system. They have captured 5000 samples of American alphabets in total. In this system, the features were extracted using color histogram and PCA was employed for reducing the dimensions of the extracted feature set. The collected signs were classified by using KNN and the best accuracy of 99.8% was achieved.

Kumar et al. [22, 41] developed sign language recognition system for recognizing both static and dynamic signs in American Sign Language. They used Zernike moments for identifying hand orientation in static signs and for dynamic signs center of gravity of a fingertip was tracked. Savur and Sahin [23] developed American Sign Language system using arm band for dynamic signs. They extracted time and frequency domain features and it has been observed that the accuracy of the system get enhanced by adopting average power feature. Saha et al. [24] proposed a framework for recognizing single handed American alphabets. They employed

MAdline network for classification and observed that it has outperformed all other traditional networks.

AlQattan and Sepulveda [25] proposed a neural network based ASL recognition system. They collected six single handed dynamic signs and discrete wavelet transform was used for extracting features. The system was classified using LDA and SVM and the best accuracy of 75% and 76% was achieved respectively. Kim et al. [26] developed a hand recognition system using impulse radio sensor for ASL. The collected signs were classified using Convolutional Neural Network (CNN) and the average accuracy of greater than 90% was obtained. Islam et al. [27] presented a real-time hand gesture recognition system using NN. They collected 1850 single handed static signs using mobile camera and the accuracy of 94.32% was achieved. Karayilan and Kiliç [28] proposed a NN based sign language recognition system. They collected signs using camera from which raw and histogram features were extracted. The average accuracy of 70% and 85% was achieved for raw and histogram features respectively. Ferreira et al. [29] developed a multimodal fusion sign language recognition system. They collected 1400 single handed static signs in total using Kinect and leap motion. The system was classified using CNN and the best accuracy of 97% was obtained using color, depth and leap motion data. Oyedotun and Khashman [30] presented a vision-based static hand recognition system in which they collected 2040 alphabet signs in total. The collected signs were segmented using median filtering and the accuracy of 91.33% was achieved using CNN.

The summarized literature review of American Sign Language recognition systems are shown in Table 4.

3.1.2 Discussion and Comments

The goal of this study is to explore the available literature as per the research questions mentioned in Sect. 2.1. The report on the results of our review regarding research questions is addressed below.

In order to address RQ2, i.e., "What is the usage of different data acquisition techniques in sign language recognition systems?" data has been analyzed to plot graph as shown in Fig. 9a.

It has been observed that 44% of the research work on American Sign Language has been performed using cameras, followed by 23% using Kinect, 13% using arm band, 8% using gloves, and 12% using leap motion, electroencephalogram and impulse radio sensor as shown in Fig. 9a.

In order to address RQ3, i.e., "What is the percentage of research carried out on static/dynamic signs in sign language recognition systems?" data has been analyzed to plot graph as shown in Fig. 9b.

It has been observed that the majority of research in ASL has been done for static signs (54%), followed by dynamic signs (21%), while 17% of the work has been done on both static and dynamic signs as shown in Fig. 9b.

In order to address RQ4, i.e., "What is the percentage of research work carried out on the basis of signing mode of SL?" data has been analyzed to plot graph as shown in Fig. 9c.

It has been observed that the majority of work has been performed on isolated signs (88%), followed by continuous signs (4%) while 8% on both isolated and continuous signs as shown in Fig. 9c.

In order to address RQ5, i.e., "What is the percentage of research work carried out on the basis of single and double handed signs?" data has been analyzed to plot graph as shown in Fig. 9d.

It has been observed that that 75% of work in ASL has been performed on single handed signs, followed by 4% on double handed signs and 21% on single and double handed both types of signs as shown in Fig. 9d.

In order to address RQ6, i.e., "What are the existing methodologies and techniques to recognize sign language recognition?" data has been analyzed to plot graph as shown in Fig. 9e.

Fig 9e depicts that the majority of the work on ASL has been performed using neural networks (33%), followed by SVM (21%), hybrid techniques (21%), CNN (13%) while the least amount of work has been performed using AdaBoost, KNN and DTW techniques.

In order to address RQ7, i.e., "What is the accuracy and coverage of existing sign language recognition systems?" data has been analyzed to plot graph as shown in Fig. 9f.

It has been observed that there are 65% of sign language recognition systems who achieved average accuracy of greater than 90%, while 23% of the systems have accuracy between 80 and 89%. There are only 12% systems whose accuracy is less than 80% as shown in Fig. 9f.

3.2 Indian Sign Language

Indian Sign Language (ISL) is a predominant sign language used in the areas of South Asia. The estimate of ISL users is 2,700,000 [130]. The dialects of ISL are Bangalore–Chennai–Hyderabad Sign Language, Mumbai–Delhi Sign Language and Punjab–Sindh Sign Language.

Sign language recognition techniques for ISL which have been reported in last decade are given in the next subsection.

3.2.1 Indian Sign Language Recognition Techniques

Rekha et al. [31] presented an ISL recognition system for double handed signs. In this system, authors collected dataset from 26 signs out of which 23 are static and 3 are dynamic. All the static signs were classified by using SVM and the dynamic signs were classified using Dynamic Time

Table 4 Summarized review of American Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Munib et al. [7]	Camera	Both	Static	Isolated	Neural networks	92.33%
Oz and leu [8]	Gloves	Single handed	Dynamic	Isolated	Neural networks	95%
Oz and Leu [9]	Gloves	Single	Static	Isolate	Neural networks	90%
Ragab et al. [10]	Camera	Single	Static	Isolated	SVM and random forest	94%
Sun et al. [11]	Kinect	Both	Dynamic	Continuous	Latent support vector machine	86%
Sun et al. [12]	Kinect	Both	Dynamic	Isolated	Adaboost	86.8%
Chuan et al. [13]	Leap motion sensor	Single	Static	Isolated	KNN and SVM	72.78% (KNN) 79.83% (SVM)
Tangsuksant et al. [14]	Camera	Single	Static	Isolated	Neural network	95%
Zamani and Kanan [15]	Camera	Single	Static	Isolated	Neural network	99.88%
Jangyodsuk et al. [16]	DB1:Camera; DB2: Kinect	Double	Both	Isolated	DTW	DB1: 93.38%, DB2: 92.54%
Wu et al. [17]	Arm sensors	Single	Dynamic	Isolated	Decision tree, SVM, NN, Naïve Bayes	81.88, 99.09, 98.56, 84.11%
Usachokcharoen et al. [18]	Kinect	Single	Dynamic	Isolated	SVM	95%
Savur and Sahin [19]	Arm band	Single	Both	Isolated	SVM	82.3% (real-time system)
Sun et al. [20]	Kinect	Both	Both	Both	Latent SVM	86% (words), 82.9% (sentences)
Aryanie and Heryadi [21]	Camera	Single	Static	Isolated	KNN	99.8% for k = 3 best
Kumar et al. [22, 41]	Camera	Single	Both	Isolated	SVM	93% (static), 100% (dynamic)
Savur and Sahin [23]	Armband	Single	Dynamic	Both	SVM and ensemble learner	Average power: 60.85%
Saha et al. [24]	Camera	Single	Static	Isolated	Madaline neural network	> 90%
AlQattan and Sepulveda [25]	Electroencephalogram	Single	Dynamic	Isolated	LDA and SVM	LDA: 75%; SVM: 76%
Kim et al. [26]	Impulse radio sensor	Single	Static	Isolated	CNN	> 90%
Islam et al. [27]	Camera	Single	Static	Isolated	ANN	94.32%
Karayilan and Kiliç [28]	Camera	Single	Static	Isolated	NN	85% (histogram features)
Ferreira et al. [29]	Kinect	Single	Static	Isolated	CNN	97%
Oyedotun and Khashman [30]	Camera	Single	Static	Isolated	CNN	91.33%

Warping. Agrawal et al. [32] proposed a double handed sign language recognition system. They captured 235 images of 36 signs in total using camera. The results showed that the fusion of shape descriptors, HOG and SIFT feature extraction method enhances the performance of the system.

Adithya et al. [33] proposed a method for recognizing single and double handed signs. They collected 720 Indian signs in total consisting of alphabets and numbers using camera. The collected signs were segmented using skin color in YCbCr color space. Rahaman et al. [34] proposed a real-time camera based sign language recognition system. The dataset contains 7200 double handed Bengali signs which include signs of 6 vowels and 30 consonants. Features of finger position and fingertip were extracted and signs were classified using KNN. The disadvantage of the system is that it is not able to segment hand area accurately if objects with skin color appears.

Mehrotra et al. [35] presented a system for recognizing double handed Indian signs. In this system, Microsoft Kinect was used for capturing 37 signs and the features

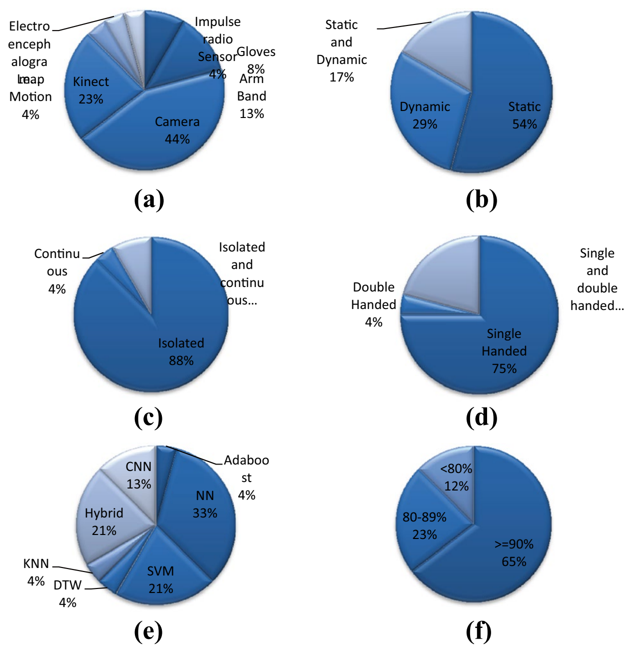

Fig. 9 **a** Usage of different data acquisition techniques used in ASL systems. **b** Research work carried out on static/dynamic signs in ASL. **c** Percentage of research work carried out on the basis of signing mode in ASL. **d** Percentage of research work carried out on the basis of single/double handed signs in ASL. **e** Percentage of research work carried out on technique used for recognition of signs. **f** Accuracy of research for different ASL systems

from skeleton joints were extracted. The system was classified with multi-class SVM and the accuracy of 86.16% was obtained. Tripathi et al. [36] proposed a system for recognizing sentences in ISL. In this system, they captured total 500 samples from 10 sentences which include both the single handed and double handed dynamic samples. In the feature extraction phase key frame extraction was used which helps in reducing the training and testing time. The signs were classified using HMM and overall accuracy of 91% was achieved. Yasir et al. [37] presented a SIFT based approach for recognizing static double handed Bangla signs. The system was trained with 150 samples of alphabets and words and the features of gradient magnitude and orientation were extracted for classification using SVM.

Kishore et al. [38] proposed a system for recognizing ISL sentences. The dataset consisted of 580 sentences in total and optic flow hand tracking and hand shape features were extracted. The experimental results show that the recognition rate of 90.17% was achieved. Naglot and Kulkarni [39] presented an ANN based ISL recognition of numbers using Leap Motion Controller (LMC). They used Multilayer Perceptron (MLP) for classifying single handed dynamic signs and achieved 100% accuracy. Hasan et al. [40] proposed a machine learning based approach for detecting Bangla Sign Language. They captured 16 static signs using web camera and collected 320 samples in total. The magnitude and direction of gradient at each pixel were extracted and the accuracy of 86.53% was achieved. Kumar et al. [22, 41] proposed a continuous sign language recognition system in which they have used front camera of the mobile for collecting signs. They extracted head and hand contour energies from the collected signs and achieved an accuracy of 90%. Ahmed et al. [42] presented a vision based hand gesture recognition approach which recognizes double handed dynamic signs. They captured 24 isolated signs using web camera and features from hands and face were extracted using trajectory tracking of the moving hand. The experimental results showed that the accuracy of 90% was achieved. Uddin and Chowdhury [43] developed a camera based Bangla Sign Language recognition system for recognizing double handed static signs. The dataset consisted of 4800 samples and Gabor filter was used for extracting features.

Kumar et al. [44] developed a framework for sensor based sign language recognition. They used Kinect and leap motion device for collecting 7500 total samples from 50 sign words. The features of fingertip position and direction were extracted using leap motion API. The system was classified using HMM and Bidirectional Long Short-Term Memory Neural Network (BLSTM-NN). The results showed that the overall accuracy of 95.60% and 84.57% was obtained respectively. Rao et al. [45] proposed a continuous sign language recognition system in which they have used mobile front camera for capturing signs. Kumar et al. [46] proposed a coupled HMM based sign language recognition system. They collected single handed dynamic signs from 25 words using Kinect and leap motion. Rao and Kishore [47] presented a selfie video based continuous Indian Sign Language recognition system. They used DCT for extracting features from the collected signs and the average accuracy of 90% was obtained using ANN. Kumar et al. [48] proposed a real-time sign language recognition system. They collected 2240 single handed static signs using leap motion sensor. The experiments were performed using SVM and BLSTM-NN and the accuracy of 63.57% was achieved. Kumar et al. [49] presented a position and rotation invariant based framework for sign language recognition using Kinect. They collected 2700 static signs in total and the accuracy of 83.77% was achieved using HMM.

The summarized literature review of ISL recognition systems are shown in Table 5.

3.2.2 Discussion and Comments

The report on the results in ISL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that 68% of the research work on ISL has been performed using cameras, followed by 11% using leap motion, 10% using Kinect

Table 5 Summarized review of ISL recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Rekha et al. [31]	Camera	Double	Both	Isolated	SVM (static) and DTW (dynamic)	86.3% (SVM), 77.2% (DTW)
Agrawal et al. [32]	Camera	Double	Static	Isolated	Multi-class SVM	93%
Adithya et al. [33]	Camera	Both	Static	Isolated	ANN	91.11%
Rahaman et al. [34]	Camera	Double	Static	Isolated	KNN	98.17% (vowels) and 94.75% (consonants)
Mehrotra et al. [35]	Kinect	Double	Both	Isolated	Multi-class SVM	86.16%
Tripathi et al. [36]	Camera	Both	Dynamic	Continuous	HMM	91%
Yasir et al. [37]	Camera	Double	Static	Isolated	SVM	86%
Kishore et al. [38]	Camera	Both	Dynamic	Continuous	ANN	90.17%
Naglot and Kulkarni [39]	Leap motion	Single	Dynamic	Isolated	ANN	100.00%
Hasan et al. [40]	Web camera	Both	Static	Isolated	SVM	86.53%
Kumar et al. [22, 41]	Camera	Single	Dynamic	Continuous	ANN	90.00%
Ahmed et al. [42]	Web camera	Double	Dynamic	Isolated	DTW	90.00%
Uddin and Chowdhury [43]	Camera	Double	Static	Isolated	SVM	97.70%
Kumar et al. [44]	Kinect and leap motion	Both	Dynamic	Isolated	HMM and BLSTM-NN	95.60% (all signs)
Rao et al. [45]	Camera	Single	Dynamic	Continuous	ANN	91%
Kumar et al. [46]	Kinect and leap motion	Single	Dynamic	Isolated	Coupled HMM	90.80%
Rao and Kishore [47]	Camera	Single	Static	Continuous	ANN	90.00%
Kumar et al. [48]	Leap motion	Single	Static	Isolated	SVM and BLSTM-NN	63.57%
Kumar et al. [49]	Kinect	Both	Static	Isolated	HMM	83.77%

and 11% using both Kinect and leap motion as shown in Fig. 10a.

In order to address RQ3, Fig. 10b depicts that the majority of research in ISL has been done for static signs (47%), followed by dynamic signs (42%) and both static and dynamic signs (11%).

In order to address RQ4, it has been observed that the majority of research work has been performed on isolated signs (74%), followed by continuous signs (26%) as shown in Fig. 10c.

In order to address RQ5, Fig. 10d depicts that 37% of work in ISL has been performed on double handed signs, followed by 31% on single handed signs and 32% on both single and double handed signs.

In order to address RQ6, Fig. 10e depicts that the majority of the work on ISL has been performed using neural networks (32%), followed by SVM (26%), HMM (16%), hybrid techniques (16%), while the least amount of work has been performed using KNN and DTW.

In order to address RQ7, it has been observed that for ISL there are 68% of sign language recognition systems who achieved average accuracy of greater than 90%, while 24% of the systems have accuracy between 80 and 89%. There are only 8% systems whose accuracy is less than 80% as shown in Fig. 10f.

3.3 Arabic Sign Language

Arabic Sign Language (ArSL) is the language which is distributed across Mideast and North Africa regions. Sign language recognition techniques for ArSL which have been reported in last decade are given below.

3.3.1 Arabic Sign Language Recognition Techniques

Mohandes et al. [50] developed an ArSL recognition system in which they collected 4500 dynamic samples in total. They have used region growing technique for tracking hands and the features of centroids, eccentricity of the bounded ellipse, angle of the first principal component and area of both the hands were extracted. The system is classified using 5-state HMM and the highest accuracy of 97.3% was achieved with equal number of training and testing samples.

Maraqa and Abu-Zaiter [51] proposed a camera based ArSL recognition system for recognizing single handed static words. The collected dataset consisted of 1200 images

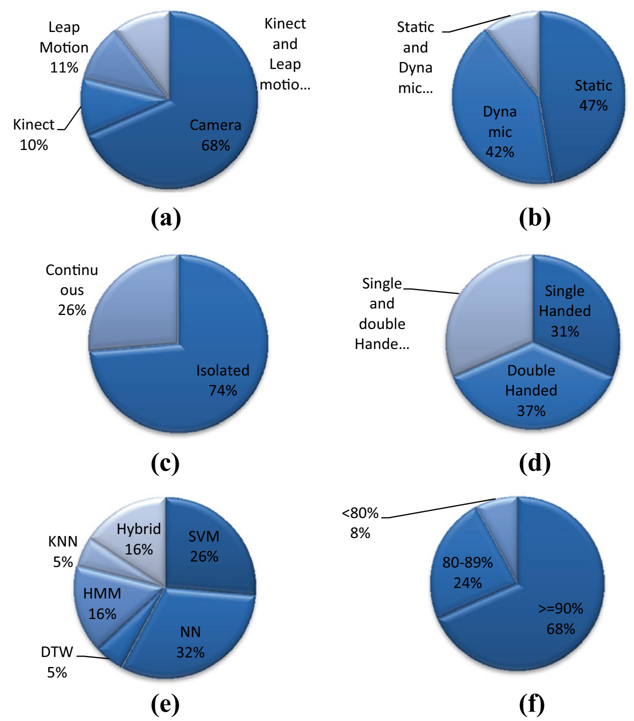

Fig. 10 **a** Usage of different data acquisition techniques used in ISL systems. **b** Research work carried out on static/dynamic signs in ISL. **c** Percentage of research work carried out on the basis of signing mode in ISL. **d** Percentage of research work carried out on the basis of single/double handed signs in ISL. **e** Percentage of research work carried out on technique used for recognition of signs. **f** Accuracy of research for different ISL systems

in total which were classified using recurrent neural network and the accuracy of 95.11% was achieved. Assaleh et al. [52] proposed a camera based user dependent continuous sign language recognition system. In this system, they gathered dynamic words as well as sentences and DCT and zonal coding feature extraction was employed. The system was classified using 9-state HMM and the accuracy of 75% for sentence recognition and 94% for word recognition was obtained.

Al-Rousan et al. [53] proposed a camera based isolated sign language recognition system. They collected dynamic double handed signs from 30 words. The features of location, movement and orientation were extracted using DCT and zonal coding. The system was classified using HMM and the accuracy of 93.8% in signer dependent mode and 90.6% in signer independent mode was achieved. Shanableh and Assaleh [54] presented a user-independent ArSL recognition system. They captured 3450 video segments of isolated signs using camera and colored gloves. The collected signs were preprocessed using median filtering and the features of bounding boxes were extracted. For further classification, KNN was applied and the accuracy of 87% was achieved.

Mohandes et al. [55] presented a signer-independent ArSL recognition system. They used camera and colored gloves for collecting double handed static signs. They have also used region growing technique for tracking hands and the features of centroids, eccentricity of the bounded ellipse, angle of the first principal component and area of both the hands were extracted. It has been observed that the performance of the system get increased as the number of training sequences per sign is increased.

Dahmani and Larabi [56] proposed a framework for recognizing sign language alphabet. They used camera and colored gloves for acquiring static single handed Arabic signs. The recognition is based on shape descriptors named as Discrete orthogonal Tchebichef moments, Hu moments and a set of geometric features derived from the convex hull. The classification is performed using KNN and SVM. Elons et al. [57] presented a leap motion sensor based ArSL recognition system, in which they collected dynamic double handed samples of isolated words. The features of finger position and distance between the fingers were extracted and the signs were classified using multilayer perceptron neural networks. Ahmed and Aly [58] developed an appearance based ArSL recognition system. The dataset contains 3450 sample in total from 23 words. The features of texture and shape were extracted using Local Binary Patterns (LBP) and PCA and classified using HMM. Mohandes et al. [59, 127] developed an ArSL recognition system, in which they used Leap Motion Controller (LMC) for capturing input data. They captured 6400 single handed static signs. All the collected signs were classified using MLP neural network and Naïve Bayes classifiers. The results showed that Naïve Bayes outperforms neural network.

Tubaiz et al. [60] proposed a user-dependent ArSL recognition system. They used gloves and camera for collecting dynamic continuous signs. The collected data was preprocessed using re-sampling and z-score normalization and modified KNN was used for classification. Sarhan et al. [61] developed a sign language recognition system using Kinect. They collected 215 dynamic samples from 16 Arabic words. The features of articulation point, hand orientation, hand shape and hand movement were extracted using skeletal and depth information obtained from Kinect.

Hassan et al. [62] proposed a recognition system in which they have used gloves and Polhemus tracker for collecting sentences. The features were extracted using sliding window based approach and the system was classified using Modified KNN (MKNN) approach and HMM. The experimental results showed that MKNN outperforms HMM in sentence classification and HMM outperforms MKNN in word classification. Hamed et al. [63] presented a recognition system based on HOG-PCA using Kinect in complex backgrounds for recognizing Arabic signs. Darwish [64] developed a man–machine interaction system for ArSL recognition. They collected greater than 6000 single handed static signs in total using camera. The developed system was classified using fuzzy HMM and the accuracy of 92.4% was achieved.

The summarized literature review of ArSL recognition systems are shown in Table 6.

3.3.2 Discussion and Comments

The report on the results in ArSL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that 54% of the research work on ArSL has been done using cameras, followed by 13% using Kinect, gloves and leap motion individually and 7% using polhemus tracker as shown in Fig. 11a.

In order to address RQ3, Fig. 11b depicts that the majority of research in ArSL has been done for dynamic signs (57%), followed by static signs (43%).

In order to address RQ4, it has been observed from Fig. 11c that majority of work has been performed on isolated signs (79%), followed by continuous signs (14%) and isolated and continuous both the signs (7%) in ArSL.

In order to address RQ5, Fig. 11d demonstrates that 29% of work in ArSL has been performed on single handed signs, followed by 21% on double handed signs and 50% on both single and double handed signs.

In order to address RQ6, Fig. 11e depicts that the majority of the work on ArSL has been performed using HMM (47%), followed by hybrid techniques (20%), while the minimum amount of work has been performed using NN and SVM.

In order to address RQ7, it has been observed that for ArSL there are 70% of sign language recognition systems who achieved average accuracy of greater than 90%, while 23% of the systems have accuracy between 80 and 89%. There are only 7% systems whose accuracy is less than 80% as shown in Fig. 11f.

Table 6 Summarized review of ArSL recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Mohandes et al. [50]	Camera	Both	Dynamic	Isolated	HMM	97.3%
Maraqa and Abu-Zaiter [51]	Camera	Single	Static	Isolated	Recurrent neural network	95.11%
Assaleh et al. [52]	Camera	Both	Dynamic	Both	HMM	75% (sentence), 94% (Word)
Al-Rousan et al. [53]	Camera	Double	Dynamic	Isolated	HMM	93.8% (signer dependent), 90.6% (Signer-independent)
Shanableh and Assaleh [54]	Camera	Both	Dynamic	Isolated	KNN	87%
Mohandes et al. [55]	Camera	Double	Static	Isolated	HMM	95.2% (signer dependent mode), 94.4% (signer independent mode)
Dahmani and Larabi [56]	Camera	Single	Static	Isolated	KNN and SVM	DB1: 88.87%, DB2: 96.88%
Elons et al. [57]	Leap motion sensor	Double	Dynamic	Isolated	Multilayer perceptron neural networks	88%
Ahmed and Aly [58]	Camera	Both	Static	Isolated	HMM	99.97%
Mohandes et al. [59, 127]	Leap motion	Single	Static	Isolated	MLP neural networks and Naïve Bayes	MLP: 98%, Naïve Bayes: > 99%
Tubaiz et al. [60]	Gloves	Both	Dynamic	Continuous	Modified KNN	98.90%
Sarhan et al. [61]	Kinect	Both	Dynamic	Isolated	HMM	80.47%, 64.61% (signer independent)
Hassan et al. [62]	DB1: gloves, DB2: Polhemus G4 tracker	Both	Dynamic	Continuous	HMM and modified KNN	DB1: 97% (word), 86% (sentence); DB2: 97% (word), 85% (sentence)
Hamed et al. [63]	Kinect	Single	Static	Isolated	SVM	99.2%
Darwish [64]	Camera	Single	Static	Isolated	Fuzzy HMM	92.40%

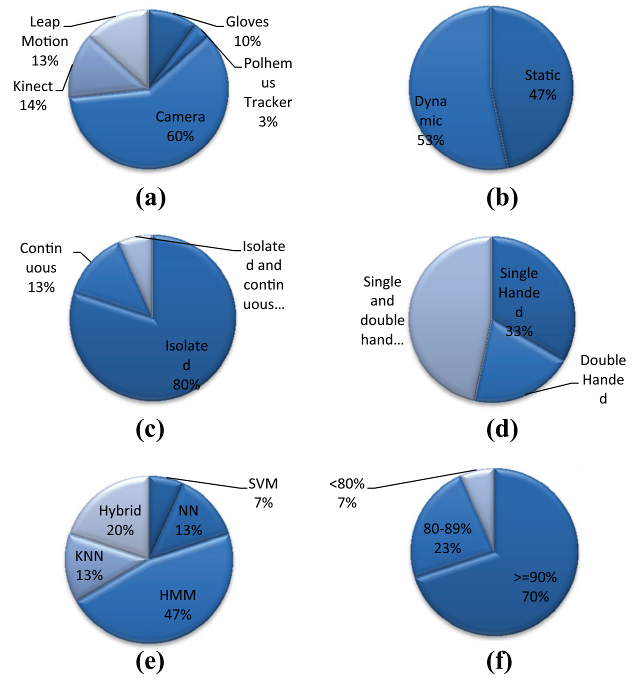

Fig. 11 **a** Usage of different data acquisition techniques used in ArSL systems. **b** Research work carried out on static/dynamic signs in ArSL. **c** Percentage of research work carried out on the basis of signing mode in ArSL. **d** Percentage of research work carried out on the basis of single/double handed signs in ArSL. **e** Percentage of research work carried out on technique used for recognition of signs. **f** Accuracy of research for different ArSL systems

3.4 Chinese Sign Language

Chinese Sign Language (CSL) is an isolated language used in the areas of china. It is also spoken in Malaysian and Taiwan. The estimate for CSL users range from 1,000,000 to 20,000,000 [131]. Sign language recognition techniques for CSL which have been reported in last decade are given below.

3.4.1 Chinese Sign Language Recognition Techniques

Wang et al. [65] proposed a multilayer architecture for CSL recognition. They collected dynamic double handed signs using cyber gloves and Polhemus 3 space position tracker. The features of hand shapes were extracted using cyber gloves and features of orientation, position and movement trajectory were extracted using position tracker. The data classification has been performed by first employing DTW and then HMM and the accuracy of 87.39% was achieved. Quan and Jinye [66] and Quan et al. [67] presented a vision based CSL recognition system. They collected 30 single handed static manual alphabets. They aimed at extracting both global and local features rather than focusing only on the local features. The experimental results showed that the system was classified using SVM.

Yang [68] proposed a CSL recognition system for recognizing single handed static alphabets. They used spatio-temporal appearance modeling for extracting features and the accuracy of 95.55% was obtained. Li et al. [69] developed an automatic CSL recognition system based on arm sensors. They collected 2420 subwords in total and features of change of velocity along x, y and z axis, 3-axis mean value of each accelerometer, 3-order autoregressive coefficients and mean absolute value were extracted from arm sensors.

Agarwal and Thakur [70] presented a Chinese number sign language recognition system. They have collected depth and motion profiles of digits from 0 to 9 using Microsoft Kinect for recognition using SVM classifier based on linear and RBF kernel.

Geng et al. [71] proposed a novel feature descriptor for recognizing Chinese signs. They have combined the features from depth images and spherical coordinates for representing feature vector. It has been observed that the accuracy of the system get increased by adding hand shape features. Zhang et al. [72] presented a CSL system for recognizing double handed continuous signs. They have used Kinect for collecting signs and features were extracted using threshold matrix. The system gets trained with discrete HMM and the collected signs were classified by using DTW.

Zhang et al. [73] proposed a Microsoft Kinect system for recognizing 30 isolated signs. The features were extracted using Histogram of Oriented Displacements and the accuracy of 88% was achieved. Yang et al. [74] presented a Kinect based sign language recognition system, in which they collected data from 156 single and double handed words. The features of hand shape, position, orientation and movement were extracted and weighted HMM was employed for classification which leads to the accuracy of 97.74%.

Yang et al. [75] proposed a continuous sign language recognition system based on Kinect. They collected 20 dynamic sentences and features of motion trajectory were extracted. The proposed system was classified using LB-HMM (Level Building HMM) and LB-Fast-HMM. The experimental results showed that the computational cost get decreased by employing LB-fast HMM algorithm for classification. Pu et al. [76] presented a trajectory modeling based CSL recognition system. They have employed Kinect for collecting 25,000 sign samples from 100 words. The results showed that the accuracy of the system get decreased by increasing the number of testing samples. Zhang et al. [77] developed a CSL recognition system based on Adaptive HMM. They have maintained two datasets of dynamic words. The first dataset consists of 100 sign words and second consists of 500 sign words. The features of trajectory and shape were extracted using shape context and HOG. It has been observed that the adaptive HMM method performs better as compared to the baseline methods.

Guo et al. [78] proposed an adaptive HMM based sign language recognition system. The features from the captured signs were extracted using HOG and PCA and the accuracy of 67.34% was obtained.

The summarized literature review of Chinese Sign Language recognition systems are shown in Table 7.

3.4.2 Discussion and Comments

The report on the results in CSL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that 64% of the research work on CSL has been performed using Kinect, followed by 22% using camera, 7% using gloves and rest 7% using arm band as shown in Fig. 12a.

In order to address RQ3, Fig. 12b depicts that the majority of research in CSL has been done for dynamic signs (50%), followed by static signs (36%) and both static and dynamic signs (14%).

In order to address RQ4, it has been observed that the majority of work has been performed on isolated signs (79%), followed by continuous signs (14%) and both isolated and continuous signs (7%) in CSL as shown in Fig. 12c.

In order to address RQ5, it has been observed that 36% of work in CSL has been performed on single handed signs, followed by 21% on double handed signs and 43% on both single and double handed signs as shown in Fig. 12d.

In order to address RQ6, Fig. 12e depicts that 36% of the work on CSL has been performed using HMM, followed by hybrid techniques (36%), while the minimum amount of work has been performed using SVM (28%).

In order to address RQ7, it has been observed that for CSL there are 43% of sign language recognition systems who achieved average accuracy of greater than 90%, while 50% of the systems have accuracy between 80 and 89%. There are only 7% systems whose accuracy is less than 80% as shown in Fig. 12f.

3.5 Persian Sign Language

Persian Sign Language is the sign language used by deaf people in Iran. Sign language recognition techniques for Persian SL which have been reported in last decade are given below.

3.5.1 Persian Sign Language Recognition Techniques

Sarkaleh et al. [79] developed a neural network based system for recognition of Persian Sign Language. The total dataset consisted of 240 single handed static words captured by using camera. The accuracy of 98.75% was achieved by using 10 neurons in the hidden layer of multilayer perceptron neural network.

Table 7 Summarized review of Chinese Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Wang et al. [65]	Cyber gloves	Double	Dynamic	Isolated	HMM and DTW	87.39%
Quan and Jinye [66]	Camera	Single	Static	Isolated	SVM	95.03%
Quan et al. [67]	Camera	Single	Static	Isolated	SVM	93.09%
Yang [68]	Camera	Single	Static	Isolated	SVM	95.55%
Li et al. [69]	Arm sensors	Both	Both	Isolated	Decision tree and HMM	95.78%
Agarwal and Thakur [70]	Kinect	Single	Static	Isolated	Multiclass SVM	81.48% (linear), 87.67% (RBF)
Geng et al. [71]	Kinect	Single	Static	Isolated	ELM and SVM	80.36%
Zhang et al. [72]	Kinect	Double	Dynamic	Continuous	HMM and DTW	82.2%
Zhang et al. [73]	Kinect	Both	Dynamic	Both	Multi-SVM and DTW	88% (isolated), 85.2% (continuous)
Yang et al. [74]	Kinect	Both	Dynamic	Isolated	Weighted HMM	97.74%
Yang et al. [75]	Kinect	Both	Dynamic	Continuous	HMM	88%
Pu et al. [76]	Kinect	Both	Dynamic	Isolated	HMM	89.8% (1000 testing samples), 82.7% (18,000 testing samples)
Zhang et al. [77]	Kinect	Both	Dynamic	Isolated	Adaptive HMM	100% (100 words), 98.8% (500 words)
Guo et al. [78]	Kinect	Both	Both	Isolated	Adaptive HMM	67.34%

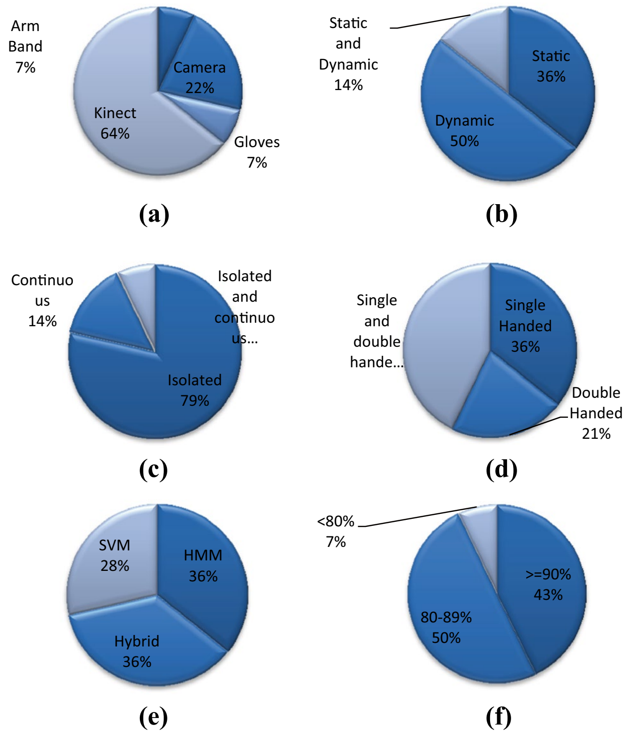

Fig. 12 **a** Usage of different data acquisition techniques used in CSL systems. **b** Research work carried out on static/dynamic signs in CSL. **c** Percentage of research work carried out on the basis of signing mode in CSL. **d** Percentage of research work carried out on the basis of single/double handed signs in CSL. **e** Percentage of research work carried out on technique used for recognition of signs. **f** Accuracy of research for different CSL systems

Karami et al. [80] developed a sign language recognition system based on wavelet transform. They have captured static single handed Persian alphabets and discrete wavelet transform has been employed to extract features from different signs. Moghaddam et al. [81] proposed a kernel based feature extraction method for recognizing static signs in Persian SL. They adopted Kernel Principle Component Analysis (KPCA) and Kernel Discriminant Analysis (kDa) methods for extracting features. The system was tested with 35 alphabets using SVM and NN classifiers and the accuracy of 95.51% and 95.91% was achieved respectively.

Madani and Nahvi [82] presented a sign language recognition system for 20 dynamic signs. All the collected signs were segmented using CAMSHIFT algorithm. They have used radon transform for extracting features and found that it has a good effect on obtaining maximum recognition rate.

Azar and Seyedarabi [83] developed a dynamic Persian SL recognition system. The dataset contains 750 videos from 15 signs and extract hand trajectory using Spline interpolation method. The developed system was classified using HMM and the accuracy of 95.3% in signer dependent mode and 78% in signer independent mode was achieved.

The summarized literature review of Persian Sign Language recognition systems are shown in Table 8.

3.5.2 Discussion and Comments

The report on the results in Persian SL for our review regarding research questions is addressed below.

In order to address RQ2, the review on Persian SL specifies that 100% of the research on Persian SL has been done using camera as an acquisition device.

In order to address RQ3, Fig. 13a depicts that the majority of research in Persian SL has been done for static signs (60%), followed by dynamic signs (40%).

In order to address RQ4, the review on Persian SL specifies that 100% of the research on Persian SL has been done for isolated signs.

In order to address RQ5, it has been observed that the majority of research work in Persian SL has been performed on single handed signs (80%), followed by both single and double handed signs (20%) as shown in Fig. 13b.

In order to address RQ6, Fig. 13c depicts that 80% of the work on Persian SL has been performed using NN and

Table 8 Summarized review of Persian Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Sarkaleh et al. [79]	Camera	Single	Static	Isolated	NN	98.75%
Karami et al. [80]	Camera	Single	Static	Isolated	NN	94.06%
Moghaddam et al. [81]	Camera	Single	Static	Isolated	NN and SVM	95.91% (neural network) 95.51% (SVM)
Madani and Nahvi [82]	Camera	Both	Dynamic	Isolated	KNN, NN and SVM	92.22% (Gaussian Kernel + SVM)
Azar and Seyedarabi [83]	Camera	Single	Dynamic	Isolated	HMM	95.3% (Signer dependent), 78% (Signer Independent)

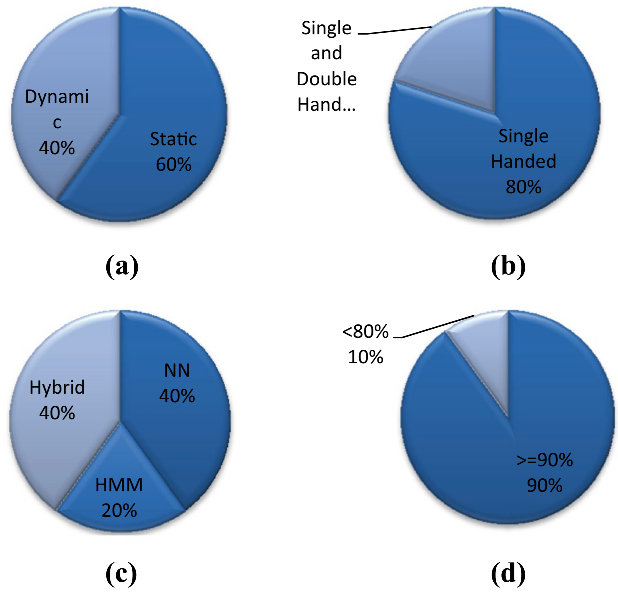

Fig. 13 **a** Research work carried out on static/dynamic signs in Persian SL. **b** Percentage of research work carried out on the basis of single/double handed signs in Persian SL. **c** Percentage of research work carried out on technique used for recognition of signs. **d** Accuracy of research for different Persian SL systems

hybrid techniques, while the least amount of work has been performed using HMM (20%).

In order to address RQ7, it has been observed that for Persian SL there are 90% of sign language recognition systems who achieved average accuracy of greater than 90%, while there are only 10% systems whose accuracy is less than 80% as shown in Fig. 13d.

3.6 Brazilian Sign Language

Brazilian SL is used by deaf people in the region of Brazil. The estimate for Brazilian SL speakers is 3,000,000 [130]. Sign language recognition techniques for Brazilian SL which have been reported in last decade are given in the next subsection.

3.6.1 Brazilian Sign Language Recognition Techniques

Dias et al. [84] developed a hand movement recognition system for Brazilian SL. The collected single handed signs were classified using distance-based neural networks. The experimental results show that the unsupervised fuzzy learning vector quantization model outperformed and the accuracy of 98.89% was obtained.

De Paula Neto et al. [85] proposed an Extreme Learning Machine (ELM) based system for recognition Brazilian signs in real-time. They captured 990 single handed static signs from 18 alphabets. In feature extraction phase, features of magnitude and direction of the edges were extracted and the accuracy of 95.92% was obtained. Abreu et al. [86] evaluated the performance of the electromyogram data collected by arm band. They captured 20 static single handed Brazilian signs and the cross-validation accuracy of 98.56% was achieved.

The summarized literature review of Brazilian Sign Language recognition systems are shown in Table 9.

3.6.2 Discussion and Comments

The report on the results in Brazilian SL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that the majority of the research work on Brazilian Sign Language has been done using cameras (67%) followed by arm band (33%) as shown in Fig. 14a.

In order to address RQ3, it has been observed that the majority of research work in Brazilian SL has been performed on static signs (67%) followed by dynamic signs (33%) as shown in Fig. 14b.

In order to address RQ4 and RQ5, the review on Brazilian Sign Language depicts that 100% of the research has been done only on isolated and single handed signs respectively.

In order to address RQ6, Fig. 14c depicts that 67% of the work on Brazilian SL has been performed using NN, followed by 33% using SVM.

Table 9 Summarized review of Brazilian Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Dias et al. [84]	Camera	Single	Dynamic	Isolated	NN	93% (supervised), 98.89% (unsupervised)
De Paula Neto et al. [85]	Camera	Single	Static	Isolated	ELM	95.92%
Abreu et al. [86]	Myo Armband	Single	Static	Isolated	SVM	41.15% (in real-time), 98.56% (cross-validation)

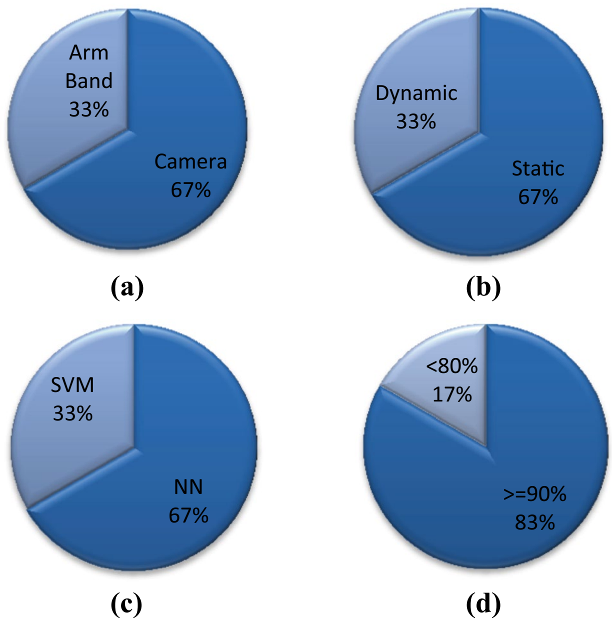

Fig. 14 **a** Usage of different data acquisition techniques used in Brazilian SL systems. **b** Research work carried out on static/dynamic signs in Brazilian SL. **c** Percentage of research work carried out on technique used for recognition of signs. **d** Accuracy of research for different Brazilian SL systems

In order to address RQ7, it has been observed that for Brazilian SL there are 83% of sign language recognition systems who achieved average accuracy of greater than 90%, while there are only 17% systems whose accuracy is less than 80% as shown in Fig. 14d.

3.7 Greek Sign Language

Greek SL is legally recognized as official language of Greece. The estimates for the number of speakers run from 6000 to 60,000 [132]. Sign language recognition techniques for Greek SL which have been reported in last decade are given in the next subsection.

3.7.1 Greek Sign Language Recognition Techniques

Kosmidou and Hadjileontiadis [87] proposed an intrinsic mode entropy based Greek SL gesture recognition system, in which they have collected both single and double handed words using arm band. The results showed that the accuracy of 100% was achieved.

Theodorakis et al. [88] developed a sign language recognition system for recognizing Greek words. They collected dynamic double handed signs from 93 words and extracted movement and hand shape features. The experimental results showed that the performance get increased by fusing movement and hand shape information with Product HMM. Simos and Nikolaidis [89] presented a method for recognizing Greek SL alphabets collected using Leap Motion. The system extracts features using Leap motion APIs and Radial Basis Function kernel of SVM was applied.

The summarized literature review of Greek Sign Language recognition systems are shown in Table 10.

3.7.2 Discussion and Comments

The report on the results in Greek SL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that maximum of the research work on Greek SL has been performed using camera (34%), followed by arm band (33%) and leap motion (33%) as shown in Fig. 15a.

In order to address RQ3, Fig. 15b depicts that the majority of research work on Greek SL has been performed on static signs (34%), followed by dynamic signs (33%) and both static and dynamic signs (33%).

In order to address RQ4, the review on Greek SL depicts that 100% of the research has been done for isolated signs only.

In order to address RQ5, it has been observed that the maximum amount of work on Greek SL has been performed for single handed signs (34%), followed by double handed signs (33%) and both single and double handed signs (33%) as shown in Fig. 15c.

Table 10 Summarized review of Greek Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Kosmidou and Hadjileontiadis [87]	Arm band	Both	Both	Isolated	Intrinsic mode entropy and Mahalanobis distance	100%
Theodorakis et al. [88]	Camera	Double	Dynamic	Isolated	Product HMM	87.10%
Simos and Nikolaidis [89]	Leap motion controller	Single	Static	Isolated	SVM	98.96% (palm translation), 99.28% (bone translation)

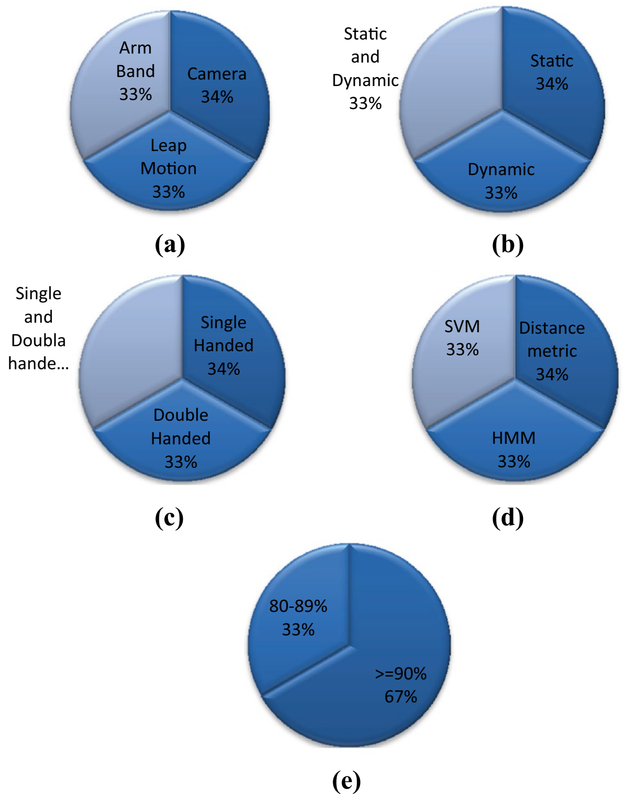

Fig. 15 **a** Usage of different data acquisition techniques used in Greek SL systems. **b** Research work carried out on static/dynamic signs in Greek SL. **c** Percentage of research work carried out on the basis of single/double handed signs in Greek SL. **d** Percentage of research work carried out on technique used for recognition of signs. **e** Accuracy research of different Greek SL systems

In order to address RQ6, Fig. 15d depicts that 34% of the work on Greek SL has been performed using distance metric, followed by 33% using SVM and 33% using HMM.

In order to address RQ7, it has been observed that for Greek SL there are 67% of sign language recognition systems who achieved average accuracy of greater than 90%, while there are only 33% systems whose accuracy of 80–89% as shown in Fig. 15e.

3.8 Irish Sign Language

Irish SL, originated from French and is used in the areas of Republic of Ireland and Northern Ireland. The number of deaf people in Irish is 5000 [132]. Sign language recognition techniques for Irish SL which have been reported in last decade are given in the next subsection.

3.8.1 Irish Sign Language Recognition Techniques

Kelly et al. [90, 91] presented a framework for continuous sign language recognition. They have captured double handed dynamic signs in Irish language using camera. The features of right and left hand were extracted using mean shift algorithm and features of face position, width and eye position were extracted using haar cascade algorithm. The system was classified using Multi-channel HMM, which leads to the accuracy of 95.7%. Kelly et al. [90, 91] proposed a framework for recognizing Irish SL sequences. They have incorporated facial features along with multi-channel gesture recognition system. The system was classified using HMM and the accuracy of 95.10% was achieved.

Kelly et al. [92] presented a person independent hand posture recognition system. In this system, they have used camera and colored gloves to collect two different Irish Sign Language datasets. Features with Hu moments and Eigen space size function were extracted from the data collected using camera and contour of hand blob from signs were collected using colored gloves.

The summarized literature review of Irish Sign Language recognition systems are shown in Table 11.

3.8.2 Discussion and Comments

The report on the results in Irish SL for our review regarding research questions is addressed below.

In order to address RQ2, the review on Irish SL depicts that 100% of the research on Irish SL has been performed using camera as an acquisition device.

In order to address RQ3, Fig. 16a depicts that the majority of research work on Irish SL has been performed on dynamic signs (67%) followed by static signs (33%).

Table 11 Summarized review of Irish Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Kelly et al. [90]	Camera	Double	Dynamic	Continuous	Multi-channel HMM threshold	95.7%
Kelly et al. [91]	Camera	Double	Dynamic	Continuous	HMM	95.10%
Kelly et al. [92]	Camera	Single	Static	Isolated	SVM	93.5% (camera); 97.3% (colored gloves)

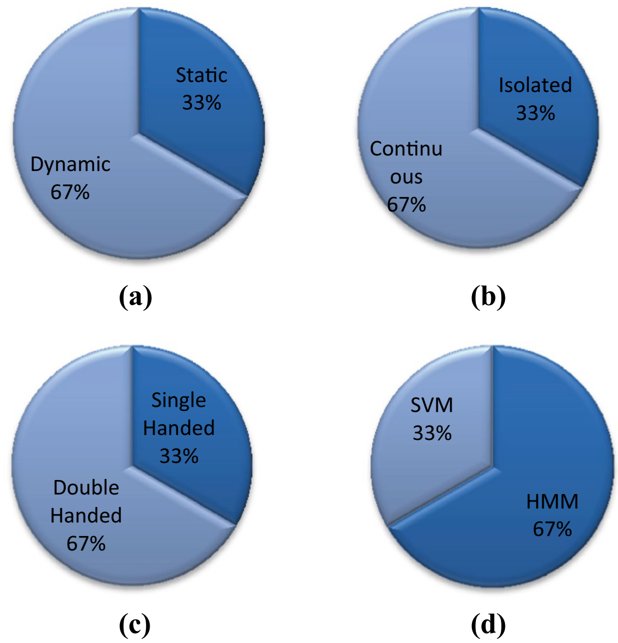

Fig. 16 **a** Research work carried out on static/dynamic signs in Irish SL. **b** Percentage of research work carried out on the basis of signing mode in Irish SL. **c** Percentage of research work carried out on the basis of single/double handed signs in Irish SL. **d** Percentage of research work carried out on technique used for recognition of signs

In order to address RQ4, it has been observed that maximum work on Irish SL has been done on continuous signs (67%) followed by isolated signs (33%) as shown in Fig. 16b.

In order to address RQ5, Fig. 16c demonstrates that the majority of work on Irish SL has been done for double handed signs (67%) followed by single handed signs (33%).

In order to address RQ6, Fig. 16d depicts that 67% of the work on Irish SL has been performed using HMM, followed by 33% using SVM.

In order to address RQ7, the review depicts that for Irish SL 100% of sign language recognition systems achieved an average accuracy of greater than 90%.

3.9 Malaysian Sign Language

Malaysian SL is the principal sign language for deaf people of Malaysia. It is based on ASL and Indonesian Sign Language. The estimate number of speakers for Malaysian Sign Language is 24,000 [133]. Sign language recognition techniques for Malaysian SL which have been reported in last decade are discussed below.

3.9.1 Malaysian Sign Language Recognition Techniques

Akmeliawati et al. [93] proposed a real-time Malaysian SL recognition system. They collected 36 static and 10 dynamic signs using camera. The collected numbers, alphabets and words were classified using neural network. Paulraj et al. [94] presented an approach for extraction of head and hand gestures which helps in recognizing Malaysian SL. They captured 624 signs in total from 32 double handed dynamic signs. The collected signs were classified using back propagation neural networks and the accuracy of 92.07% was obtained.

Majid et al. [95] proposed a Malaysian SL recognition system using skeleton data received from Kinect. They captured 375 signs in total from 15 double handed dynamic signs. The features of 3D coordinates from 8 joints were extracted and it has been observed that the spherical coordinate features performed better as compared to the Cartesian coordinate system.

The summarized literature review of Malaysian SL recognition systems are shown in Table 12.

3.9.2 Discussion and Comments

The report on the results in Malaysian SL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that the majority of research work in Malaysian SL has been performed using camera (67%), followed by Kinect (33%) as shown in Fig. 17a.

In order to address RQ3, Fig. 17b depicts that the majority of research work in Malaysian SL has been done on dynamic signs (67%) followed by both static and dynamic signs (33%).

In order to address RQ4, the research on Malaysian SL depicts that 100% of the research on Malaysian SL has been performed on isolated signs.

Table 12 Summarized review of Malaysian SL recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Akmeliawati et al. [93]	Camera	Both	Both	Isolated	NN	Numbers: 99.33%, alphabets: 95.67%, words: 95%
Paulraj et al. [94]	Camera	Double	Dynamic	Isolated	NN	92.07%
Majid et al. [95]	Kinect	Double	Dynamic	Isolated	NN	80.54% (spherical coordinate)

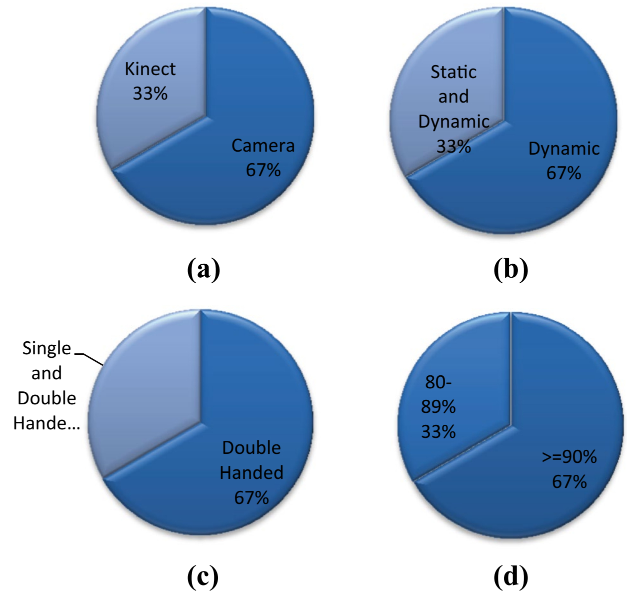

Fig. 17 **a** Usage of different data acquisition techniques used in Malaysian SL systems. **b** Research work carried out on static/dynamic signs in Malaysian SL. **c** Percentage of research work carried out on the basis of single/double handed signs in Malaysian SL. **d** Accuracy research of different Malaysian SL systems

In order to address RQ5, Fig. 17c shows that the maximum work on Malaysian SL has been performed for double handed signs (67%) followed by both single and double handed signs (33%).

In order to address RQ6, the review depicts that 100% of the work on Malaysian SL has been performed using NN.

In order to address RQ7, it has been observed that for Malaysian SL there are 67% of sign language recognition systems who achieved an average accuracy of greater than 90%, while there are only 33% systems whose accuracy of 80–89% as shown in Fig. 17d.

3.10 Mexican Sign Language

Mexican Sign Language is the language for deaf people in the urban regions of Mexico. It is originated from French Sign Language family and the estimate number of speakers is 130,000 [132]. Sign language recognition techniques for Mexican SL which have been reported in last decade are discussed below.

3.10.1 Mexican Sign Language Recognition Techniques

Luis-Pérez et al. [96] developed a neural network based system which controls a service robot using Mexican SL. They collected 23 static single handed alphabets. The collected signs were segmented using active contours and the accuracy of 95.80% was achieved. Galicia et al. [97] proposed a system which converts Mexican SL into Spanish language. They used Kinect sensor for capturing 867 images which were trained by using decision tree algorithm. The trained images were recognized by using neural network and the accuracy of 76.19% was achieved.

García-Bautista et al. [98] proposed a Mexican SL recognition system using Kinect. They collected 700 samples of 20 Mexican words, from which skeleton data was extracted and forwarded to the training phase. The signs were then classified by using DTW and the accuracy of 98.57% was achieved on real-time data.

The summarized literature review of Mexican Sign Language recognition systems are shown in Table 13.

3.10.2 Discussion and Comments

The report on the results in Mexican SL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that the majority of work in Mexican SL has been performed using Kinect (67%) followed by camera (33%) as shown in Fig. 18a.

In order to address RQ3, Fig. 18b depicts that the maximum work on Mexican SL has been done for static signs (67%) followed by dynamic signs (33%).

In order to address RQ4, the review on Mexican SL depicts that 100% of the research has been performed on isolated signs only.

In order to address RQ5, it has been observed that 67% of work in Mexican SL has been performed on single handed signs and followed by 33% using both single and double handed signs as shown in Fig. 18c.

Table 13 Summarized review of Mexican Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Luis-Pérez et al. [96]	Camera	Single	Static	Isolated	NN	95.80%
Galicia et al. [97]	Kinect	Single	Static	Isolated	NN	76.19%
García-Bautista et al. [98]	Kinect	Both	Dynamic	Isolated	DTW	98.57% (real-time data)

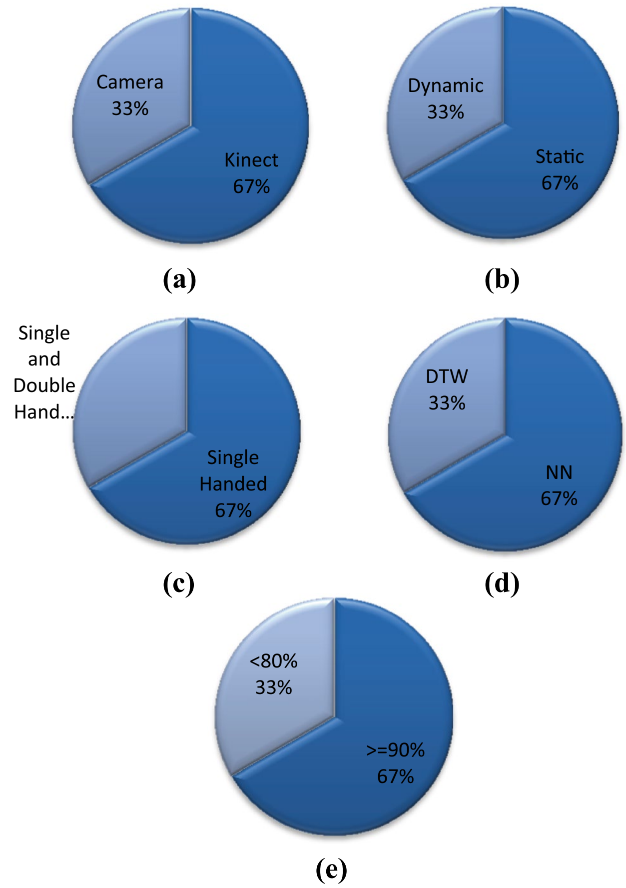

Fig. 18 **a** Usage of different data acquisition techniques used in Mexican SL systems. **b** Research work carried out on static/dynamic signs in Mexican SL. **c** Percentage of research work carried out on the basis of single/double handed signs in Mexican SL. **d** Percentage of research work carried out on technique used for recognition of signs. **e** Accuracy of research for different Mexican SL systems

In order to address RQ6, it has been observed that 67% of the work on Mexican SL has been performed using NN, followed by 33% using DTW as shown in Fig. 18d.

In order to address RQ7, it has been observed that for Mexican SL there are 67% of sign language recognition systems who achieved an average accuracy of greater than 90%, while there are only 33% systems whose accuracy is below 80% as shown in Fig. 18e.

3.11 Taiwanese Sign Language

Taiwanese Sign Language (TSL) is the language of deaf community used in the areas of Taiwan. The origins of TSL developed from Japanese Sign Language and the estimated number of users is 20,000 [134]. Sign language recognition techniques for TSL which have been reported in last decade are discussed below.

3.11.1 Taiwanese Sign Language Recognition techniques

Lee and Tsai [99] presented a TSL recognition based on 3D data collected using camera. They collected static single handed 2788 signs and extracted 15 geometric distance values. Experiments were performed on 1438 signs of testing data and the accuracy of 94.65% was achieved.

Huang and Tsai [100] developed a vision based TSL recognition system in which they combined both camera and colored gloves for acquiring data. In this hand shape features were extracted using Fourier descriptors and Hu moments and the accuracy of 89% for dynamic signs was obtained. Yu et al. [101] proposed a vision based continuous TSL recognition system. The features from the collected signs were extracted using CAMSHIFT algorithm. The Product HMM was employed for classifying the collected signs and the average accuracy of 67% was achieved.

The summarized literature review of TSL recognition systems are shown in Table 14.

3.11.2 Discussion and Comments

The report on the results in TSL for our review regarding research questions is addressed below.

In order to address RQ2, the review on TSL depicts that 100% of the research in this SL has been performed using camera as an acquisition device.

In order to address RQ3, Fig. 19a depicts that the majority of research work on this SL has been done on static signs (34%), followed by dynamic signs (33%) and both static and dynamic signs (33%).

In order to address RQ4, Fig. 19b depicts that the majority of the research work on TSL has been done for both isolated and continuous signs (67%) followed by isolated signs (33%).

In order to address RQ5, it has been observed that the maximum of the work on TSL has been done for both single handed and double handed signs (67%) followed by single handed signs (33%) as shown in Fig. 19c.

In order to address RQ6, it has been observed that 34% of the work on TSL has been performed using NN, followed by 33% using SVM and hybrid techniques respectively as shown in Fig. 19d.

In order to address RQ7, it has been observed that for TSL there are 34% of sign language recognition systems who achieved an average accuracy of greater than 90%, while there are only 66% systems whose accuracy lies between 80 and 89% and below 80% as shown in Fig. 19e.

3.12 Thai Sign Language

Thai sign language is the national sign language of deaf community of Thailand. It belongs to French language

Table 14 Summarized review of TSL recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Lee and Tsai [99]	Camera	Single	Static	Isolated	NN	96.58%
Huang and Tsai [100]	Camera	Both	Both	Both	Static: SVM; dynamic: HMM	89% (dynamic signs)
Yu et al. [101]	Camera	Both	Dynamic	Both	HMM	67% (sentence)

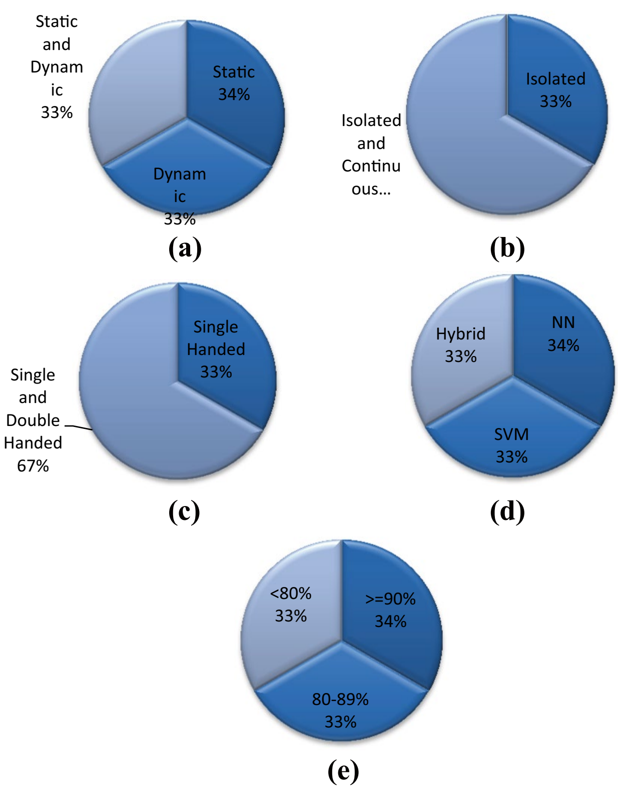

Fig. 19 **a** Research work carried out on static/dynamic signs in TSL. **b** Percentage of research work carried out on the basis of signing mode in TSL. **c** Percentage of research work carried out on the basis of single/double handed signs in TSL. **d** Percentage of research work carried out on technique used for recognition of signs. **e** Accuracy of research for different TSL systems

family as ASL. It is used in most parts of the country by the 20 percent of the estimated 56,000 pre-linguistically deaf people [134]. Sign language recognition techniques for Thai SL which have been reported in last decade are discussed below.

3.12.1 Thai Sign Language Recognition Techniques

Saengsri et al. [102] proposed a Thai finger-spelling sign language recognition system. They employed data gloves and motion tracker for capturing single handed static signs. The collected signs were classified using Elman BPNN by extracting finger flexures, abductions between fingers, positions and orientation features of hand. Adhan and Pintavirooj [103] developed a sign language recognition system based on geometric invariant and ANN. The dataset consisted of 1470 Thai alphabets out of which 1050 were used for training and 420 for testing. The collected signs were classified by using feed forward NN and the accuracy of 96.19% was obtained.

Pariwat and Seresangtakul [104] presented a finger-spelling recognition system for recognizing 15 Thai alphabets acquired using camera. The experimental results show that the combination of local and global features enhanced the accuracy of the system and RBF kernel outperformed polynomial, linear and sigmoid based classification.

The summarized literature review of Thai Sign Language recognition systems are shown in Table 15.

3.12.2 Discussion and Comments

The report on the results in Taiwanese SL for our review regarding research questions is addressed below.

In order to address RQ2, it has been observed that the majority of research in Thai SL has been performed using camera followed by 33% using gloves as shown in Fig. 20a.

In order to address RQ3, Fig. 20b depicts that the majority of the research work on Thai SL has been performed on static signs (67%) followed by both static and dynamic signs (33%).

In order to address RQ4, the review on Thai SL specifies that 100% of the research in this SL has been done on isolated signs.

In order to address RQ5, it has been observed that the majority of the research work in Thai SL has been done on single handed signs (67%) followed by both single and double handed signs (33%) as shown in Fig. 20c.

In order to address RQ6, it has been observed that 67% of the work on Thai SL has been performed using NN, followed by 33% using SVM as shown in Fig. 20d.

In order to address RQ7, it has been observed that for Thai SL there are 100% of sign language recognition systems who achieved an average accuracy of greater than 90%.

The majority of the research on sign language recognition has been done for American Sign Language, Indian Sign

Table 15 Summarized review of Thai Sign Language recognition systems

Author	Acquisition mode	Single/double handed	Static/dynamic	Signing mode	Technique used	Recognition rate
Saengsri et al. [102]	Data gloves	Single	Static	Isolated	NN	94.44%
Adhan and Pintavirooj [103]	Camera	Both	Both	Isolated	NN	96.19%
Pariwat and Seresangtakul [104]	Camera	Single	Static	Isolated	SVM	91.20% (RBF kernel)

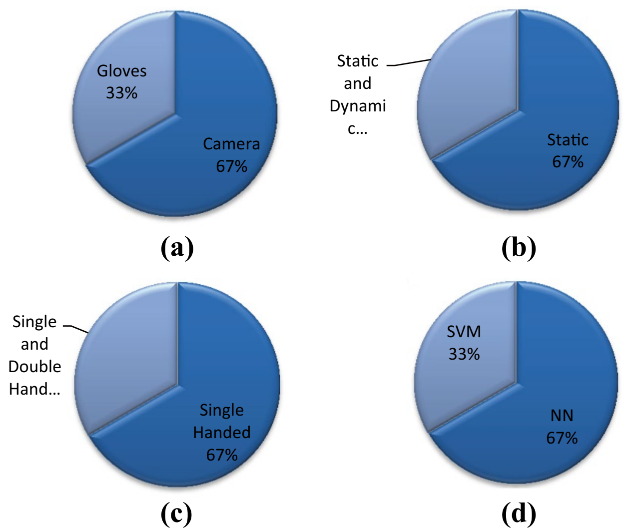

Fig. 20 **a** Usage of different data acquisition techniques used in Thai SL systems. **b** Research work carried out on static/dynamic signs in Thai SL. **c** Percentage of research work carried out on the basis of single/double handed signs in Thai SL. **d** Percentage of research work carried out on technique used for recognition of signs

Language, Arabic Sign Language, Chinese Sign Language, Persian, Brazilian, Greek, Irish, Malaysian, Mexican, Taiwanese and Thai Sign Languages. The minimum amount of work done for sign languages like German, Japanese, South African, Sri Lankan, Auslan, Bangladeshi, Ecuadorian, Ethiopia, Farsi, Italian, Polish, Spanish and Ukrainian sign language has been discussed in the next section.

3.13 Other Languages

Kim et al. [105] proposed Bi-channel sensor fusion based automatic German sign language recognition system. Lang et al. [106] presented a German Sign Language recognition system using Kinect. Sako and Kitamura [107] presented a Japanese Sign Language recognition system, which was classified using Product HMM. Mukai et al. [108] developed a Japanese fingerspelling and SVM based recognition system. Hosoe et al. [109] proposed a Japanese fingerspelling system in which the CNN was employed for classification and the accuracy of 93% was achieved.

Nel et al. [110] presented an integrated South African Sign Language recognition method in which signs were captured using camera. Seymour and Tšoeu [111] developed a mobile based application for recognizing South African Sign Language.

Vanjikumaran and Balachandran [112] presented an automated vision based system for recognizing SriLankan Tamil finger spelling. Madushanka et al. [113] developed a framework for Sinhala Sign Language recognition. Thang et al. [114] studied the effectiveness of vector based machine learning methods named as SVM, Simplification of SVM and Relevance Vector Machine (RVM) for Auslan signs. Thang et al. [115] compared the effectiveness of SimpSVM and RVM for Auslan Sign Language recognition.

Admasu and Raimond [118] presented an Ethiopian Sign Language recognition system based on camera and artificial neural network. Zare and Zahiri [119] proposed a real-time signer independent static Farsi Sign Language recognition system based on camera. Ahmed and Akhand [116] presented a camera based Bangladeshi Sign Language recognition system. Jiménez et al. [117] developed a gesture recognition system for single and double handed Bangladeshi words.

Infantino et al. [120] presented a framework for recognition of sentences of Italian Sign Language. Oszust and Wysocki [121] proposed a recognition system for recognizing Polish signs using Kinect. Parcheta and Martínez-Hinarejos [122] developed a Spanish Sign Language gesture recognition system using HMM. Davydov et al. [123] proposed a real-time camera based Ukrainian Sign Language recognition system.

4 Overall Observation by Considering the Research Work on All Sign Language Recognition Systems

The overall report for the results on sign language recognition systems regarding research questions is addressed below.

In order to address RQ2, we observed that 55% of the research work on sign language recognition systems has been done using cameras, followed by 20% using Kinect, 8% using gloves, 7% using arm band, 6% using leap motion and rest 4% using other acquisition devices as shown in Fig. 21a. In order to address RQ3, Fig. 21b depicts that the majority of research on sign language recognition systems has been done for static signs (45%), followed by dynamic signs (40%) and for both static and dynamic signs (15%). In order to address RQ4, it has been observed from Fig. 21c that majority of work has been performed on isolated signs (83%), followed by continuous signs (12%) and isolated and continuous both the signs (5%) sign language recognition systems. In order to address RQ5, we found that 48% of work on sign language recognition systems has been performed on single handed signs, followed by 20% on double handed signs and 32% on both single and double handed signs as shown in Fig. 21d. In order to address RQ6, Fig. 21e depicts that the majority of the work on sign language recognition systems has been performed using NN (28%), followed by hybrid techniques (21%), SVM (20%), HMM (20%), while the minimum amount of work has been performed using DTW, KNN, CNN and other techniques. In order to address RQ7, we observed that for all the sign language systems there are 66% of sign language recognition systems who achieved average accuracy of greater than 90%, while 23% of the systems have accuracy between 80 and 89%. There are only 11% systems whose accuracy is less than 80% as shown in Fig. 21f.

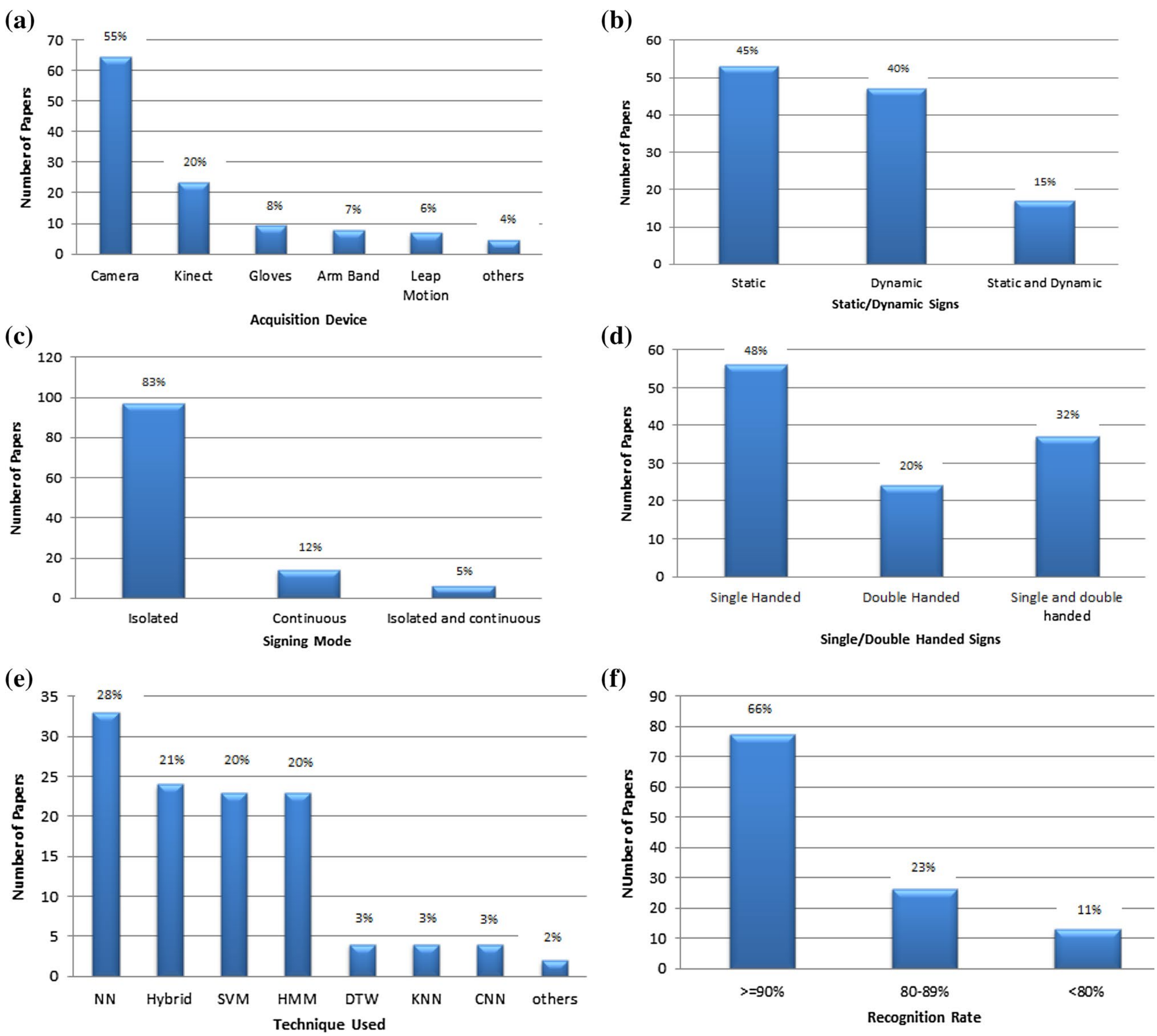

Fig. 21 **a** Usage of different data acquisition techniques used in sign language systems. **b** Research work carried out on static/dynamic signs in different sign languages. **c** Research work carried out on the basis of signing mode in different sign languages. **d** Research work carried out on the basis of single/double handed signs in different sign languages. **e** Research work carried out on technique used for recognition of signs. **f** Accuracy of research for different sign language systems

5 Conclusion and Future Scope

Application of sign language recognition systems is an emerging trend in the society. It has attracted the attention of academics and practitioners. This paper has identified one hundred and seventeen research articles related to sign language recognition, and published between 2007 and 2017. It aims to present the research summary on the basis of sign language which is further categorized in different dimensions like data acquisition technique, static/dynamic signs, signing mode, single/double handed signs, classification technique and recognition rate. Although this review cannot claim to be comprehensive, it does provide reasonable insights and shows the incidence of research on this subject. The results presented in this paper have several important consequences:

- Research on sign language recognition systems will increase significantly in the future based on past publication rates and the increasing interest in the area.
- During Systematic Literature Review we observed that the maximum research has been performed for American Sign Language (21%). 16% of studies focused on Indian Sign Language, followed by Arabic Sign Language (13%), Chinese Sign Language (12%), Persian Sign Language (4%) and rest 34% for other sign languages which include Brazilian, Greek, Irish, Malaysian, Mexican, Taiwanese, Thai, German, Japanese, Italian, Ethiopian, Ecuadorian, Farsi, South African, Sri Lankan, Auslan, Bangladeshi, Spanish, Polish and Ukrainian Sign Languages.
- With respect to RQ2, we observed that the most widely used data acquisition component were camera (55%) and Kinect (20%). With respect to RQ3 and RQ4, we find that the most of the work on sign language recognition systems has been performed for static signs (45%) and isolated sign (83%) respectively. With respect to RQ5, it has been observed that the majority of work has been performed using single handed signs (48%) for different sign language systems. In order to address RQ 6 and RQ7, it has been found that the maximum of the work has been performed using neural networks (28%) and there are 66% of the systems whose accuracy is greater than 90% respectively.
- Since it takes a lot of time and effort to conduct a Systematic Literature Review, this literature review aims to save the time and effort of other researchers by providing a complete and thorough review of sign language recognition systems for different sign languages.

This study might have some limitations. Firstly, this study only surveyed research articles published between 2007 and 2017, which were extracted based on a keyword "sign language recognition". Research articles which mention the face expression recognition could not be extracted. Secondly, this study limited the search for research articles to online databases. There might be other academic journals which may be able to provide a more comprehensive picture of the articles related to the sign language recognition.

Although research in sign language recognition began several years ago, it is still in inception, as no such systems have been deployed on a large scale that can interpret a large vocabulary of signs in real-time. The barriers to achieve a robust system still exists which include hand occlusion, database scalability, different background illumination environments and high computational cost. Futuristic research on sign language recognition can be extended in several directions. Most of the works in sign language recognition have been performed on isolated signs. There is need to apply more effort for recognizing continuous signs. Very little amount of work has been done on deep learning techniques. So, it is highly required to classify signs using deep learning neural networks.

I hereby confirm that this work is original and has not been published elsewhere nor is it currently under consideration for publication elsewhere. No potential conflict of interest was reported.

References

1. Garg P, Aggarwal N, Sofat S (2009) Vision based hand gesture recognition. World Acad Sci Eng Technol 49(1):972–977
2. Badhe PC, Kulkarni V (2015) Indian Sign Language translator using gesture recognition algorithm. In: Proceedings of IEEE international conference on computer graphics on vision and information security (CGVIS), Bhubaneshwar, India, pp 195–200
3. Dour S, Kundargi M (2013) Design of ANFIS system for recognition of single hand and two hand signs for Indian Sign Language. Int J Appl Inf Syst, pp 18–25
4. Amrutha CU, Davis N, Samrutha KS, Shilpa NS, Chunkath J (2016) Improving language acquisition in sensory deficit individuals with mobile application. Procedia Technol 24:1068–1073
5. Dasgupta T, Shukla S, Kumar S, Diwakar S, Basu A (2008) A multilingual multimedia Indian Sign Language dictionary tool. In: Proceedings of international joint conference on natural language processing, Hyderabad, India, pp 57–64
6. Kitchenham B, Charters S (2007) Guidelines for performing systematic literature reviews in software engineering. Technical report, EBSE Technical Report EBSE-2007-01, 2.3
7. Munib Q, Habeeb M, Takruri B, Al-Malik HA (2007) American sign language (ASL) recognition based on Hough transform and neural networks. Expert Syst Appl 32(1):24–37
8. Oz C, Leu MC (2007) Linguistic properties based on American Sign Language isolated word recognition with artificial neural networks using a sensory glove and motion tracker. Neurocomputing 70(16):2891–2901

9. Oz C, Leu MC (2011) American Sign Language word recognition with a sensory glove using artificial neural networks. Eng Appl Artif Intell 24(7):1204–1213
10. Ragab A, Ahmed M, Chau SC (2013) Sign language recognition using Hilbert curve features. In: International conference image analysis and recognition. Springer, Berlin, Heidelberg, pp 143–151
11. Sun C, Zhang T, Bao BK, Xu C (2013a) Latent support vector machine for sign language recognition with Kinect. In: 20th IEEE international conference on image processing (ICIP), pp 4190–4194
12. Sun C, Zhang T, Bao BK, Xu C, Mei T (2013) Discriminative exemplar coding for sign language recognition with kinect. IEEE Trans Cybern 43(5):1418–1428
13. Chuan CH, Regina E, Guardino C (2014) American Sign Language recognition using leap motion sensor. In: 13th IEEE international conference on machine learning and applications (ICMLA), pp 541–544
14. Tangsuksant W, Adhan S, Pintavirooj C (2014) American Sign Language recognition by using 3D geometric invariant feature and ANN classification. In: 7th international conference on biomedical engineering (BMEiCON), pp 1–5
15. Zamani M, Kanan HR (2014) Saliency based alphabet and numbers of American Sign Language recognition using linear feature extraction. In: 4th IEEE International eConference on computer and knowledge engineering (ICCKE), pp 398–403
16. Jangyodsuk P, Conly C, Athitsos V (2014) Sign language recognition using dynamic time warping and hand shape distance based on histogram of oriented gradient features. In: Proceedings of the 7th international conference on pervasive technologies related to assistive environments. ACM, p 50
17. Wu J, Tian Z, Sun L, Estevez L, Jafari R (2015) Real-time American Sign Language recognition using wrist-worn motion and surface EMG sensors. In: IEEE 12th international conference on wearable and implantable body sensor networks (BSN), pp 1–6
18. Usachokcharoen P, Washizawa Y, Pasupa K (2015) Sign language recognition with microsoft Kinect's depth and colour sensors. In: IEEE international conference on signal and image processing applications (ICSIPA), pp 186–190
19. Savur C, Sahin F (2015) Real-time american sign language recognition system using surface EMG signal. In: IEEE 14th international conference on machine learning and applications (ICMLA), pp 497–502
20. Sun C, Zhang T, Xu C (2015) Latent support vector machine modeling for sign language recognition with Kinect. ACM Trans Intell Syst Technol: TIST 6(2):20
21. Aryanie D, Heryadi Y (2015) American Sign Language-based finger-spelling recognition using k-nearest neighbors classifier. In: 3rd IEEE international conference on information and communication technology (ICoICT), pp 533–536
22. Kumar A, Thankachan K, Dominic MM (2016) Sign language recognition. In: 3rd IEEE international conference on recent advances in information technology (RAIT), pp 422–428
23. Savur C, Sahin F (2016) American Sign Language recognition system by using surface EMG signal. In: IEEE international conference on systems, man, and cybernetics (SMC), pp 002872–002877
24. Saha S, Lahiri R, Konar A, Nagar AK (2016) A novel approach to American Sign Language recognition using MAdaline neural network. In: IEEE symposium series on computational intelligence (SSCI), pp 1–6
25. AlQattan D, Sepulveda F (2017) Towards sign language recognition using EEG-based motor imagery brain computer interface. In: 5th IEEE international winter conference on brain–computer interface (BCI), pp 5–8
26. Kim SY, Han HG, Kim JW, Lee S, Kim TW (2017) A hand gesture recognition sensor using reflected impulses. IEEE Sens J 17(10):2975–2976
27. Islam MM, Siddiqua S, Afnan J (2017) Real time hand gesture recognition using different algorithms based on American Sign Language. In: IEEE international conference on imaging, vision & pattern recognition (icIVPR), pp 1–6
28. Karayılan T, Kılıç Ö (2017) Sign language recognition. In: IEEE international conference on computer science and engineering (UBMK), pp 1122–1126
29. Ferreira PM, Cardoso JS, Rebelo A (2017) Multimodal learning for sign language recognition. In: Iberian conference on pattern recognition and image analysis. Springer, Cham, pp 313–321
30. Oyedotun OK, Khashman A (2017) Deep learning in vision-based static hand gesture recognition. Neural Comput Appl 28(12):3941–3951
31. Rekha J, Bhattacharya J, Majumder S (2011) Shape, texture and local movement hand gesture features for Indian Sign Language recognition. In: 3rd IEEE international conference on trendz in information sciences and computing (TISC), pp 30–35
32. Agrawal SC, Jalal AS, Bhatnagar C (2012) Recognition of Indian Sign Language using feature fusion. In: 4th IEEE international conference on intelligent human computer interaction (IHCI), pp 1–5
33. Adithya V, Vinod PR, Gopalakrishnan U (2013) Artificial neural network based method for Indian Sign Language recognition. In: IEEE conference on information & communication technologies (ICT), pp 1080–1085
34. Rahaman MA, Jasim M, Ali MH, Hasanuzzaman M (2014) Real-time computer vision-based Bengali Sign Language recognition. In: 17th IEEE international conference on computer and information technology (ICCIT), pp 192–197
35. Mehrotra K, Godbole A, Belhe S (2015) Indian Sign Language recognition using Kinect sensor. In: International conference on image analysis and recognition. Springer, Cham, pp 528–535
36. Tripathi K, Baranwal N, Nand GC (2015) Continuous dynamic Indian Sign Language gesture recognition with invariant backgrounds. In: IEEE international conference on advances in computing, communications and informatics (ICACCI), pp 2211–2216
37. Yasir F, Prasad PC, Alsadoon A, Elchouemi A (2015) Sift based approach on Bangla Sign Language recognition. In: IEEE 8th international workshop on computational intelligence and applications (IWCIA), pp 35–39
38. Kishore PVV, Prasad MVD, Kumar DA, Sastry ASCS (2016) Optical flow hand tracking and active contour hand shape features for continuous sign language recognition with artificial neural networks. In: IEEE 6th international conference on advanced computing (IACC), pp 346–351
39. Naglot D, Kulkarni M (2016) ANN based Indian Sign Language numerals recognition using the leap motion controller. In: IEEE international conference on inventive computation technologies (ICICT), vol 2, pp 1–6
40. Hasan M, Sajib TH, Dey M (2016) A machine learning based approach for the detection and recognition of Bangla Sign Language. In: IEEE international conference on medical engineering, health informatics and technology (MediTec), pp 1–5
41. Kumar DA, Kishore PVV, Sastry ASCS, Swamy PRG (2016) Selfie continuous sign language recognition using neural network. In: IEEE annual India conference (INDICON), pp 1–6
42. Ahmed W, Chanda K, Mitra S (2016) Vision based hand gesture recognition using dynamic time warping for Indian Sign Language. In: IEEE international conference on information science (ICIS), pp 120–125
43. Uddin MA, Chowdhury SA (2016) Hand sign language recognition for Bangla alphabet using support vector machine. In: IEEE

international conference on innovations in science, engineering and technology (ICISET), pp 1–4
44. Kumar P, Gauba H, Roy PP, Dogra DP (2017) A multimodal framework for sensor based sign language recognition. Neurocomputing 259:21–38. https://doi.org/10.1016/j.neucom.2016.08.132
45. Rao GA, Kishore PVV, Sastry ASCS, Kumar DA, Kumar EK (2018) Selfie continuous sign language recognition with neural network classifier. In: Proceedings of 2nd international conference on micro-electronics, electromagnetics and telecommunications. Springer, Singapore, pp 31–40
46. Kumar P, Gauba H, Roy PP, Dogra DP (2017) Coupled HMM-based multi-sensor data fusion for sign language recognition. Pattern Recogn Lett 86:1–8
47. Rao GA, Kishore PVV (2017) Selfie video based continuous Indian Sign Language recognition system. Ain Shams Eng J 9(4):1929–1939. https://doi.org/10.1016/j.asej.2016.10.013
48. Kumar P, Saini R, Behera SK, Dogra DP, Roy PP (2017c) Real-time recognition of sign language gestures and air-writing using leap motion. In: Fifteenth IEEE international conference on machine vision applications (MVA), pp 157–160
49. Kumar P, Saini R, Roy PP, Dogra DP (2017) A position and rotation invariant framework for sign language recognition (SLR) using Kinect. Multimed Tools Appl 77(7):8823–8846. https://doi.org/10.1007/s11042-017-4776-9
50. Mohandes M, Quadri SI, Deriche M (2007) Arabic Sign Language recognition an image-based approach. In: 21st IEEE international conference on advanced information networking and applications workshops, AINAW'07, vol 1, pp 272–276
51. Maraqa M, Abu-Zaiter R (2008) Recognition of Arabic Sign Language (ArSL) using recurrent neural networks. In: First IEEE international conference on the applications of digital information and web technologies, 2008. ICADIWT, pp 478–481
52. Assaleh K, Shanableh T, Fanaswala M, Bajaj H, Amin F (2008) Vision-based system for continuous Arabic Sign Language recognition in user dependent mode. In: 5th IEEE international symposium on mechatronics and its applications, ISMA, pp 1–5
53. Al-Rousan M, Assaleh K, Tala'a A A (2009) Video-based signer-independent Arabic Sign Language recognition using hidden Markov models. Appl Soft Comput 9(3):990–999
54. Shanableh T, Assaleh K (2011) User-independent recognition of Arabic Sign Language for facilitating communication with the deaf community. Digit Signal Process 21(4):535–542
55. Mohandes M, Deriche M, Johar U, Ilyas S (2012) A signer-independent Arabic Sign Language recognition system using face detection, geometric features, and a Hidden Markov Model. Comput Electr Eng 38(2):422–433
56. Dahmani D, Larabi S (2014) User-independent system for sign language finger spelling recognition. J Vis Commun Image Represent 25(5):1240–1250
57. Elons AS, Ahmed M, Shedid H, Tolba MF (2014) Arabic Sign Language recognition using leap motion sensor. In: 9th IEEE international conference on computer engineering & systems (ICCES), pp 368–373
58. Ahmed AA, Aly S (2014) Appearance-based Arabic Sign Language recognition using hidden markov models. In: IEEE international conference on engineering and technology (ICET), pp 1–6
59. Mohandes M, Aliyu S, Deriche M (2014) Arabic Sign Language recognition using the leap motion controller. In: 23rd IEEE international symposium on industrial electronics (ISIE), pp 960–965
60. Tubaiz N, Shanableh T, Assaleh K (2015) Glove-based continuous Arabic Sign Language recognition in user-dependent mode. IEEE Trans Hum Mach Syst 45(4):526–533
61. Sarhan NA, El-Sonbaty Y, Youssef SM (2015) HMM-based Arabic Sign Language recognition using Kinect. In: Tenth IEEE international conference on digital information management (ICDIM), pp 169–174
62. Hassan M, Assaleh K, Shanableh T (2016) User-dependent sign language recognition using motion detection. In: IEEE international conference on computational science and computational intelligence (CSCI), pp 852–856
63. Hamed A, Belal NA, Mahar KM (2016) Arabic Sign Language alphabet recognition based on HOG-PCA using microsoft Kinect in complex backgrounds. In: IEEE 6th international conference on advanced computing (IACC), pp 451–458
64. Darwish SM (2017) Man–machine interaction system for subject independent sign language recognition. In: Proceedings of the 9th international conference on computer and automation engineering. ACM, pp 121–125
65. Wang X, Jiang F, Yao H (2008) DTW/ISODATA algorithm and multilayer architecture in sign language recognition with large vocabulary. In: IEEE international conference on intelligent information hiding and multimedia signal processing, IIHMSP, pp 1399–1402
66. Quan Y, Jinye P (2008) Chinese Sign Language recognition for a vision-based multi-features classifier. In: IEEE international symposium on computer science and computational technology, ISCSCT'08, vol 2, pp 194–197
67. Quan Y, Peng J, Yulong L (2009) Chinese sign language recognition based on gray-level co-occurrence matrix and other multi-features fusion. In: 4th IEEE conference on industrial electronics and applications, ICIEA, pp 1569–1572
68. Yang Q (2010) Chinese sign language recognition based on video sequence appearance modeling. In: 5th IEEE conference on industrial electronics and applications (ICIEA), pp 1537–1542
69. Li Y, Chen X, Tian J, Zhang X, Wang K, Yang J (2010) Automatic recognition of sign language subwords based on portable accelerometer and EMG sensors. In: International conference on multimodal interfaces and the workshop on machine learning for multimodal interaction. ACM, p 17
70. Agarwal A, Thakur MK (2013) Sign language recognition using Microsoft Kinect. In: Sixth IEEE international conference on contemporary computing (IC3), pp 181–185
71. Geng L, Ma X, Wang H, Gu J, Li Y (2014) Chinese Sign Language recognition with 3D hand motion trajectories and depth images. In: 11th IEEE World Congress on intelligent control and automation (WCICA), pp 1457–1461
72. Zhang J, Zhou W, Li H (2014) A threshold-based HMM-DTW approach for continuous sign language recognition. In: Proceedings of international conference on internet multimedia computing and service. ACM, p 237
73. Zhang J, Zhou W and Li H (2015) A new system for chinese sign language recognition. In: 2015 IEEE China summit and international conference on signal and information processing (ChinaSIP), pp 534–538
74. Yang W, Tao J, Xi C, Ye Z (2015) Sign language recognition system based on weighted hidden Markov model. In: 8th IEEE international symposium on computational intelligence and design (ISCID), vol 2, pp 449–452
75. Yang W, Tao J, Ye Z (2016) Continuous sign language recognition using level building based on fast hidden Markov model. Pattern Recogn Lett 78:28–35
76. Pu J, Zhou W, Zhang J, Li H (2016) Sign language recognition based on trajectory modeling with HMMS. In: International conference on multimedia modeling. Springer, Cham, pp 686–697
77. Zhang J, Zhou W, Xie C, Pu J, Li H (2016) Chinese sign language recognition with adaptive hmm. In: IEEE international conference on multimedia and expo (ICME), pp 1–6
78. Guo D, Zhou W, Li H, Wang M (2017) Online early-late fusion based on adaptive HMM for sign language recognition. ACM Trans Multimed Comput Commun Appl: TOMM 14(1):8

79. Sarkaleh AK, Poorahangaryan F, Zanj B, Karami A (2009) A neural network based system for persian sign language recognition. In: IEEE international conference on signal and image processing applications (ICSIPA), pp 145–149
80. Karami A, Zanj B, Sarkaleh AK (2011) Persian sign language (PSL) recognition using wavelet transform and neural networks. Expert Syst Appl 38(3):2661–2667
81. Moghaddam M, Nahvi M, Pak RH (2011) Static Persian Sign Language recognition using kernel-based feature extraction. In: 7th IEEE Iranian on machine vision and image processing (MVIP), pp 1–5
82. Madani H, Nahvi M (2013) Isolated dynamic Persian Sign Language recognition based on Camshift algorithm and radon transform. In: First IEEE Iranian conference on pattern recognition and image analysis (PRIA), pp 1–5
83. Azar SG, Seyedarabi H (2016) Continuous hidden markov model based dynamic Persian Sign Language recognition. In: 24th IEEE Iranian conference on electrical engineering (ICEE), pp 1107–1112
84. Dias DB, Madeo RC, Rocha T, Bíscaro HH, Peres SM (2009) Hand movement recognition for Brazilian sign language: a study using distance-based neural networks. In: IEEE international joint conference on neural networks, IJCNN, pp 697–704
85. De Paula Neto FM, Cambuim LF, Macieira RM, Ludermir TB, Zanchettin C, Barros EN (2015) Extreme learning machine for real time recognition of Brazilian Sign Language. In: IEEE international conference on systems, man, and cybernetics (SMC), pp 1464–1469
86. Abreu JG, Teixeira JM, Figueiredo LS, Teichrieb V (2016) Evaluating sign language recognition using the myo armband. In: XVIII IEEE symposium on virtual and augmented reality (SVR), pp 64–70
87. Kosmidou VE, Hadjileontiadis LJ (2008) Intrinsic mode entropy: an enhanced classification means for automated Greek sign language gesture recognition. In: 30th IEEE annual international conference engineering in medicine and biology society, EMBS, pp 5057–5060
88. Theodorakis S, Katsamanis A, Maragos P (2009) Product-HMMs for automatic sign language recognition. In: IEEE international conference on acoustics, speech and signal processing, ICASSP, pp 1601–1604
89. Simos M, Nikolaidis N (2016) Greek sign language alphabet recognition using the leap motion device. In: Proceedings of the 9th Hellenic conference on artificial intelligence. ACM, p 34
90. Kelly D, Delannoy JR, McDonald J, Markham C (2009a) Incorporating facial features into a multi-channel gesture recognition system for the interpretation of Irish Sign Language sequences. In: IEEE 12th international conference on computer vision workshops (ICCV), pp 1977–1984
91. Kelly D, Reilly Delannoy J, McDonald J, Markham C (2009b) A framework for continuous multimodal sign language recognition. In: Proceedings of the 2009 international conference on multimodal interfaces. ACM, pp 351–358
92. Kelly D, McDonald J, Markham C (2010) A person independent system for recognition of hand postures used in sign language. Pattern Recogn Lett 31(11):1359–1368
93. Akmeliawati R, Ooi MPL, Kuang YC (2007) Real-time Malaysian Sign Language translation using colour segmentation and neural network. In: IEEE conference proceedings on instrumentation and measurement technology, IMTC, pp 1–6
94. Paulraj MP, Yaacob S, Desa H, Hema CR, Ridzuan WM, Ab Majid W (2008) Extraction of head and hand gesture features for recognition of sign language. In: IEEE international conference on electronic design, ICED, pp 1–6
95. Majid MBA, Zain JBM, Hermawan A (2015) Recognition of Malaysian Sign Language using skeleton data with neural network. In: IEEE international conference on science in information technology (ICSITech), pp 231–236
96. Luis-Pérez FE, Trujillo-Romero F, Martínez-Velazco W (2011) Control of a service robot using the mexican sign language. In: Mexican international conference on artificial intelligence, Springer, Berlin, Heidelberg, pp 419–430
97. Galicia R, Carranza O, Jiménez ED, Rivera GE (2015) Mexican Sign Language recognition using movement sensor. In: 24th IEEE international symposium on industrial electronics (ISIE), pp 573–578
98. García-Bautista G, Trujillo-Romero F, Caballero-Morales SO (2017) Mexican Sign Language recognition using Kinect and data time warping algorithm. In: International conference on electronics, communications and computers (CONIELECOMP), pp 1–5
99. Lee YH, Tsai CY (2009) Taiwan Sign Language (TSL) recognition based on 3D data and neural networks. Expert Syst Appl 36(2):1123–1128
100. Huang CL, Tsai BL (2010) A vision-based Taiwanese Sign Language recognition. In: 20th IEEE international conference on pattern recognition (ICPR), pp 3683–3686
101. Yu SH, Huang CL, Hsu SC, Lin HW, Wang HW (2011) Vision-based continuous sign language recognition using product HMM. In: IEEE first Asian conference on pattern recognition (ACPR), pp 510–514
102. Saengsri S, Niennattrakul V, Ratanamahatana CA (2012) TFRS: Thai finger-spelling sign language recognition system. In: Second international conference on digital information and communication technology and it's applications (DICTAP), pp 457–462
103. Adhan S, Pintavirooj C (2016) Thai sign language recognition by using geometric invariant feature and ANN classification. In: 9th IEEE international conference on biomedical engineering (BMEiCON), pp 1–4
104. Pariwat T, Seresangtakul P (2017) Thai finger-spelling sign language recognition using global and local features with SVM. In: 9th IEEE international conference on knowledge and smart technology (KST), pp 116–120
105. Kim J, Wagner J, Rehm M, André E (2008) Bi-channel sensor fusion for automatic sign language recognition. In: 8th IEEE international conference on automatic face & gesture recognition, pp 1–6
106. Lang S, Block M, Rojas R (2012) Sign language recognition using Kinect. In: Artificial intelligence and soft computing. Springer, Berlin, pp 394–402
107. Sako S, Kitamura T (2013) Subunit modeling for Japanese Sign Language recognition based on phonetically depend multi-stream hidden markov models. In: International conference on universal access in human–computer interaction. Springer, Berlin, Heidelberg, pp 548–555
108. Mukai N, Harada N, Chang Y (2017) Japanese fingerspelling recognition based on classification tree and machine learning. In: Nicograph international (NicoInt), pp 19–24
109. Hosoe H, Sako S, Kwolek B (2017) Recognition of JSL finger spelling using convolutional neural networks. In: IEEE fifteenth IAPR international conference on machine vision applications (MVA), pp 85–88
110. Nel W, Ghaziasgar M, Connan J (2013) An integrated sign language recognition system. In: Proceedings of the South African Institute for computer scientists and information technologists conference. ACM, pp 179–185
111. Seymour M, Tšoeu M (2015) A mobile application for South African Sign Language (SASL) recognition. In: AFRICON, IEEE, pp 1–5
112. Vanjikumaran S, Balachandran G (2011) An automated vision based recognition system for Sri Lankan Tamil Sign Language

finger spelling. In: IEEE international conference on advances in ICT for emerging regions (ICTer), pp 39–44
113. Madushanka ALP, Senevirathne RGDC, Wijesekara LMH, Arunatilake SMKD, Sandaruwan KD (2016) Framework for Sinhala Sign Language recognition and translation using a wearable armband. In: Sixteenth IEEE international conference on advances in ICT for emerging regions (ICTer). IEEE, pp 49–57
114. Thang PQ, Thuy NT, Lam HT (2017a) The SVM, SimpSVM and RVM on sign language recognition problem. In: Seventh IEEE international conference on information science and technology (ICIST), pp 398–403
115. Thang PQ, Dung ND, Thuy NT (2017b) A comparison of SimpSVM and RVM for sign language recognition. In: Proceedings of the 2017 international conference on machine learning and soft computing. ACM, pp 98–104
116. Ahmed ST, Akhand MAH (2016) Bangladeshi Sign Language recognition using fingertip position. In: IEEE international conference on medical engineering, health informatics and technology (MediTec). IEEE, pp 1–5
117. Jiménez LAE, Benalcázar ME, Sotomayor N (2017) Gesture recognition and machine learning applied to sign language translation. In: VII Latin American Congress on biomedical engineering CLAIB. Springer, Singapore, Bucaramanga, Santander, Colombia, October 26th–28th, 2016, pp 233–236
118. Admasu YF, Raimond K (2010) Ethiopian sign language recognition using artificial neural network. In: 10th international conference on intelligent systems design and applications (ISDA), pp 995–1000
119. Zare AA, Zahiri SH (2016) Recognition of a real-time signer-independent static Farsi Sign Language based on fourier coefficients amplitude. Int J Mach Learn Cybern 9(5):727–741. https://doi.org/10.1007/s13042-016-0602-3
120. Infantino I, Rizzo R, Gaglio S (2007) A framework for sign language sentence recognition by commonsense context. IEEE Trans Syst Man Cybern Part C (Appl Rev) 37(5):1034–1039
121. Oszust M, Wysocki M (2013) Polish Sign Language words recognition with Kinect. In: 6th IEEE international conference on human system interaction (HSI), pp 219–226
122. Parcheta Z, Martínez-Hinarejos CD (2017) Sign language gesture recognition using hmm. In: Iberian conference on pattern recognition and image analysis. Springer, Cham, pp 419–426
123. Davydov MV, Nikolski IV, Pasichnyk VV (2010) Real-time Ukrainian sign language recognition system. In: IEEE international conference on intelligent computing and intelligent systems (ICIS), vol 1, pp 875–879
124. Khan S, Gupta GS, Bailey D, Demidenko S, Messom C (2009) Sign language analysis and recognition: a preliminary investigation. In: 24th IEEE international conference on image and vision computing New Zealand, pp 119–123
125. Kausar S, Javed MY (2011) A survey on sign language recognition. In: Frontiers of information technology (FIT). IEEE, pp 95–98
126. Bilal S, Akmeliawati R, El Salami MJ, Shafie AA (2011) Vision-based hand posture detection and recognition for sign language—a study. In: 4th IEEE international conference on mechatronics (ICOM), pp 1–6
127. Mohandes M, Deriche M, Liu J (2014) Image-based and sensor-based approaches to Arabic Sign Language recognition. IEEE Trans Hum Mach Syst 44(4):551–557
128. Ghanem S, Conly C, Athitsos V (2017) A survey on sign language recognition using smartphones. In: Proceedings of the 10th international conference on pervasive technologies related to assistive environments. ACM, pp 171–176
129. Mitchell R, Young T, Bachleda B, Karchmer M (2006) How many people use ASL in the United States? Why estimates need updating (PDF). Sign language studies, vol 6, no 3. Gallaudet University Press. ISSN: 0302-1475. Retrieved 27 Nov 2012
130. Lewis MP, Simons GF, Fennig CD (eds) (2014) Ethnologue: languages of the world, 7th edn. SIL International, Dallas. http://www.ethnologue.com/17/
131. Chinese Sign Language. https://en.wikipedia.org/wiki/Chinese_Sign_Language. Accessed 16 Mar 2018
132. Lewis MP, Simons GF, Fennig CD (eds) (2015) Ethnologue: languages of the world, 18th edn. SIL International, Dallas. http://www.ethnologue.com
133. Lewis MP (ed) (2009) Ethnologue: languages of the world, 16th edn. SIL International, Dallas. http://www.ethnologue.com/16
134. Reilly C, Suvannus S (1999) Education of deaf people in the kingdom of Thailand. In: Brelje HW (ed) Global perspectives on education of the deaf in selected countries. Butte, Hillsboro, pp. 367–382