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A Systematic Literature Review on Vision-Based Hand Gesture for Sign Language Translation

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ABSTRACT

Deaf and hard of hearing people use sign language to communicate. People around mute and deaf people have difficulty communicating with each other if they do not understand sign language. This problem has prompted many researchers to conduct studies on sign language translation. However, there is a lack of compilation of SLR on this topic. Therefore, this paper aims to provide a thorough literature review of previous studies on sign language to text translation based on the vision method. PRISMA (Preferred Reporting Items to writing a standard Systematic Review and Meta-Analyses) is used in this systematic review. Two primary databases, Web of Science and Scopus, have been used to search for relevant articles and resources included in this systematic literature review. Based on the outcome of the systematic review of the topic, the primary studies on sign language translation systems were conducted using self-generated datasets more than public datasets. More static action sign language was studied compared to dynamic action sign language. For the type of recognition, more alphabet sign language was studied compared to digit, word, or sentence sign language. Other than that, most studies used digital cameras rather than Microsoft Kinect or a webcam. The most used classification method was Convolution Neural Network (CNN). The study is intended to guide readers and researchers for future research and knowledge enhancement in the field of sign language recognition.

Keywords: Systematic review; hand gesture; vision-based; machine learning; computer vision

INTRODUCTION

The World Federation of the Deaf (WFD) claims that there are 70 million persons worldwide who communicate using sign language, and there are more than 200 types of sign languages in the world. Sign language is a medium through which deaf people communicate (World Federation of the Deaf, 2000). Hard of hearing people can communicate their thoughts, feelings, and ideas by using sign language (Mohd Rashid, S. M. 2021). The deaf and mute community's primary language is sign language. Hearing loss is increasingly impacting people. The recognition, generation, and translation of sign language is a field of research that has high potential impact (Bragg et al. 2019). Within the deaf and mute community, sign languages have evolved as a useful tool. Although signing is primarily used by the deaf community, it can also be used by hearing people who are unable to speak, people who have problems speaking verbally due to a disability or condition, and people who have deaf family members, or when one or more of the potential communicators are deaf, sign language can help fill the gap. This has an impact on communicating with the deaf and creates communication problems between both the hearing-impaired and the deaf (Bai et al. 2020).

The field of sign language translation or recognition has seen a lot of progress. There are two ways to interpret sign language. The sensor-based method is the first approach to recognize hand gestures in sign language. Sensor-based techniques include the signatory wearing a glove or a specific sensor that displays information on hand orientation, position, rotation, and movement (Aly et al. 2019). Although users often find this method heavy and difficult, the result is more uniform and reliable. This application needs the use of specialized hardware such as using a specific camera or based on sensors. The second approach is the vision-based methodology. On the other hand, vision-based systems recognize images or videos based on functionality gained from various image or video processing techniques. This approach provides a natural environment for the users.

RESEARCH GAP – THE EXISTING STUDY RELATED TO VISION-BASED SIGN LANGUAGE RECOGNITION

The importance of recognition of sign language based on vision has piqued the curiosity of researchers who want to learn more about how to create an effective sign language recognition or translation system based on vision as well as other studies that have summarised the various contributing factors (Al-Jarrah et al. 2001; Camgoz et al. 2018). The existence of this large study volume requires a systematic literature review effort so that the findings of previous studies can be collected and better understood. While many studies focused on recognizing sign language based on vision, there were still not enough researchers systematically reviewing existing studies. Traditional literature reviews face several issues, not concentrating on specific or practice-relevant topics, employing a wide range of methodologies and structures, not using specific methods or explicitly declaring methods used to conduct a review, and most significantly, are more prone to bias (Briner et al. 2014). By conducting a thorough literature evaluation of the methodologies of the vision-based sign language recognition system, this publication aims to add to the current body of knowledge. One way to do a more thorough overview of current literature is to conduct a systematic literature review. A systematic review is necessary because the systematic review is as transparent, robust, and free of bias as possible (Stewart et al. 2012). Researchers will be able to identify gaps in the field of study and the need for additional research through systematic literature reviews. (Wan Jaafar, W. N. 2020). Although various research sought to address the topic of sign language recognition in a systematic manner, nevertheless, their focus is not on the sign language recognition system based on vision. It is undeniable that there are few studies from Ardiansyah et al. (2021); Naranjo et al. (2019) that have done SLR on an issue related to sign language translation, but we have to consider that Ardiansyah et al. (2021) study only touches on American Sign Language although there are many more sign languages in the world. Meanwhile, Naranjo et al. (2019) do not focus on the vision-based method. The lack of studies focusing on vision-based sign language recognition systems has resulted in a lack of comprehension and a systematic failure to comprehend the related existing literature systematically.

The central search question directs the review - what are the main vision-based recognition techniques and algorithms used for recognition in particular? The goal of this study was to close the gap by thoroughly examining past similar studies in an organized and comprehensive manner in order to obtain a better knowledge of identifying and describing the methodologies and techniques that have been studied in the area of vision-based sign language translation or recognition. The work makes numerous key contributions to the field of practice and understanding. The study adds to the sphere of practice and understanding in a number of ways. Interested parties, such as scholars and organizations, can now grasp the importance of having a huge public dataset in any sign language for researchers' ease, and also for the deaf, mute, and any users to refer to. Furthermore, the study allows the parties to adjust strategies and plan the research related to the vision-based sign language translation system.

METHODOLOGY

This section explains how to find publications that cover vision-based hand gesture detection for sign language translation. The reviewers used the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analyses) approach, which includes systematic review resources (Scopus and Web of Science), eligibility and exclusion criteria, review process steps (identification, screening, and eligibility), and data abstraction and analysis.

THE REVIEW PROTOCOL -PRISMA

A research technique is a way to conduct research that is organized and methodical. It is made up of a theoretical analysis of all the concepts that are relevant to the topic of study. It includes concepts such as stages, models, and qualitative and quantitative techniques in general. This document follows the review process suggested by Xiao & Watson (2019), which involves the planning, execution, and presentation of the review. To form this SLR, the authors referred to PRISMA. PRISMA is a standardized publication widely used in medical and public health. PRISMA's guidelines include a four-stage organization chart and a 27-point checklist. The flowchart describes the criteria for the identification, screening, eligibility, and inclusion of reports that are within the scope of a review. The checklist includes a list of 27 recommendations that address topics such as title, summary, introduction, methods, results, and discussion. PRISMA components provide a guide to authors, editors, and writers via this diagram and checklist (Selcuk 2019). Although this SLR is in the field of engineering, nevertheless, PRISMA is still suitable to be referred to, as it helps to form clear research questions and allows systematic searches to be done. Furthermore, PRISMA minimizes bias and assists authors in synthesizing the study (Swartz 2021). Having developed the PRISMA standard publication, this SLR was initiated by the formation of research questions, followed by a systematic search strategy, conducting article quality assessments as well as extracting and analyzing data from selected articles.

SOURCE OF REFERENCE

To find articles and resources relevant to be included in this SLR, two main databases which are Web of Science and Scopus have been used. The Institute for Scientific Information (ISI) invented WOS (Web of Science). Now, WOS is maintained by Clarivate Analytics, formerly known as Thomson Reuters' Intellectual Property and Scientific Affairs. The Science Citation Index Expanded TM, which began as SCI in 1964, now indexes over 9,200 of the world's leading journals across 178 science disciplines. There have been over 53 million documents and 1.18 billion references referred to since 1900 (website: Web of Science Collection, 2021). The Web of Science Core Collection indexes each piece of information from beginning to end, providing a complete and secure view of more than 115 years of high-quality research. Scopus is the second database used in the review. Scopus is the most comprehensive database of abstracts and citations from peer-reviewed journals, books, and conference proceedings in the world. Scopus may provide a comprehensive overview of worldwide research findings in science, technology, health, social sciences, and the arts and humanities. Scopus provides intelligent tools for monitoring, analyzing, and visualizing research (website: Scopus – document search, 2021).

FORMATTING OF RESEARCH QUESTIONS

The initial step in the formation of this SLR is to formulate appropriate research questions. Identifying and illustrating ways of recognizing sign language is not a new subject. Over the years, various processes, methodologies, and techniques were developed to illustrate the factors involved in recognizing sign language. Based on the focus of this SLR related to the vision-based sign language recognition systems, some research questions were raised.

RQ1: What database has been used in this study?
RQ2: What are the devices used in sign language translation systems?
RQ3: What types of recognition have been used in the studies? (word, alphabet, sentences, number, etc)
RQ4: Which action sign (static / dynamic) has the most study in sign language translation systems?
RQ5: What are the algorithms used in the classification technique?
RQ6: What is the recognition rate of the existing sign language translation system?

SYSTEMATIC SEARCH STRATEGY

Performing a systematic review involves several discrete activities, which can be grouped into five main phases: identification; screening; eligibility, quality appraisal, and data abstraction and analysis. Figure 1 illustrates the overall 5-stage of the systematic searching methods process.

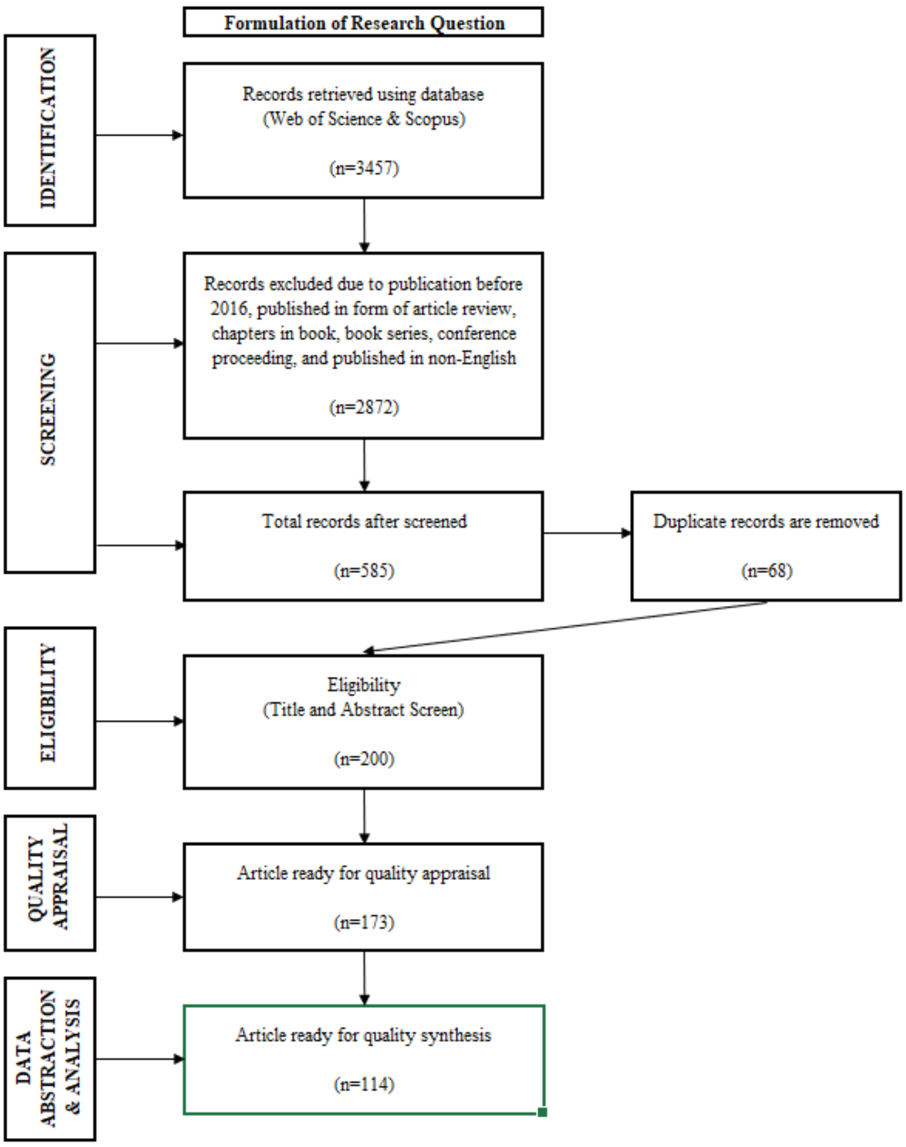


FIGURE 1. PRISMA flow diagram of the systematic research strategy

IDENTIFICATION

The process of selecting and diversifying acceptable keywords used in the article or reference search process for SLRs is known as identification.

Keywords are needed in the search process, as they can improve the accuracy of articles/references obtained for references in SLR. Based on the previously stated research questions, three main keywords were selected, namely sign language, recognition, translation, and vision based. To diversify the keywords that can be used, synonyms, related words, and variations to the main keywords were searched. This search effort was conducted through an online thesaurus, referring to past research keywords and the Scopus database as well as by obtaining expert views. The outcomes of this method of identification can be referred to in Table 1.

TABLE 1. Search string formed for articles / references research

Source	Search String	Total
Scopus	Title-abs-key= ((“sign language”) AND (translat* OR recog*) AND (image* OR “vision based” OR vision OR “video -based” OR video* OR depth OR colour OR color OR 3d OR 3d OR “three-dimensional”) AND NOT (glove* OR signal* OR wearable OR armband OR sensor))	2096
Web of Science	TS= ((“sign language”) AND (translat* OR recog*) AND (image* OR “vision-based” OR vision OR “video-based” OR video* OR depth OR colour OR color OR 3d OR 3-d OR “three-dimensional”) NOT (glove* OR signal* OR wearable OR armband OR sensor))	1361

Based on the keywords that have been selected, the article/reference search process has been done in two major databases, namely Web of Science and Scopus. All of these databases were chosen because of some of their benefits. First, databases like Web of Science and Scopus, according to Gusenbauer &

Haddaway (2020), has a more complete search, more consistent search results, and capabilities from more complex searches than any other database. In their analysis, Martin et al. (2018) databases are found using search algorithms. Table 1 demonstrates the fundamental operations needed to highlight the benefits of Web of Science and Scopus in terms of quality control and a systematic indexing method. Articles in the search of this data, such as Boolean Operators (AND, OR), phrase searching, truncation, wild card, and field codes (Web of Science and Scopus). Based on the keywords, databases, and search techniques used, a total of 3457 articles were successfully obtained. These articles/references will go through the second stage in the systematic search strategy, which is screening.

SCREENING

A total of 3457 articles were successfully obtained in the identification process earlier and will go through a screening process. Screening is a process in which criteria for inclusion or exclusion will be set and it will be used to select articles/references appropriate to the SLR to be formed (Shaffril et al., 2020). This means that articles in the form of reviews are not included because the main objective of this SLR is to know and identify the findings of past studies, rather than the reviews of past studies. Once again, the inclusion criterion used is the focus of the findings. The article selected should have findings that focus on vision-based sign language recognition or translation. If any article states that their study examines hand gesture recognition for other applications, such as games, then the article will not be issued. This is important to allow all selected articles to offer findings related to the SLR to be formed (Refer to Table 2). After conducting the screening process, a total of 2872 articles were released because they did not meet the set criteria, and this makes the balance of the articles available for the next process to be 585.

ELIGIBILITY

All selected articles will go through a second screening process, this process is known as eligibility. Eligibility is done to ensure all selected articles are relevant and can be used in this SLR. This process is done according to the title of selected articles and abstracts. If the results of the article selected, relevant or not, are unable to be obtained after reading the title and the study abstract, then the methodology, results, and discussion section of the article will serve as a reference. In the process, a total of 268 articles were excluded because their focus was not on the vision-based, provided focus to hand gesture recognition for sign language, same article (duplicated records) as well as articles in the form of scoping reviews. Based on this process, 200 articles were selected to go through the next process, namely quality assessment.

QUALITY ASSESSMENT

The remaining articles are evaluated through a quality assessment process in order to ensure that the substance of the articles is of high quality. A total of three evaluators were selected among authors for the purpose of this evaluation. Each article/reference will be evaluated based on two criteria which are - Is the stated research question clear? And is the data obtained able to answer the stated research questions? The evaluated article must have both aspects before it can go to the next stage. For each criterion, the evaluators will be given two answer options, which are Yes or No. In order to evaluate each of these articles, the three evaluators must have a mutual agreement for each evaluation done. Only articles/references that meet the criteria can be considered as quality articles. This procedure returned 173 high-quality articles.

TABLE 2. Search string formed for articles / references research

Item	Inclusion Criteria
Year Published	5 years (2017 to 2021)
Document Type	Journal article
Language	English
Type of Finding	Empirical
Focus of finding	Related to vision-based sign language translation

DATA EXTRACTION AND ANALYSIS

The papers that remained were analyzed and evaluated. A specific study was focused on in order to provide answers to the issues that had been raised. Reading the abstracts first, then the whole papers (in-depth) to uncover pertinent research questions was how the information was acquired. the data extraction process was focused on three main part of the article which are the abstract, research results and discussion research. If necessary, reading in other parts of the article offering relevant data also be done.

RESULT

This section presents the analysis done based on the research question's trend pattern and discussion on the research done in the field of vision-based hand gesture recognition techniques for sign language.

BACKGROUND OF THE SELECTED ARTICLES

Before commenting on the main findings, this section will provide focus on the background of the selected articles/references in the SLR. Out of 114 selected articles/ references, 12 were published in 2017, 16 were published in 2018, 20 were published in 2019, 32 were published in 2020, and 34 were published in 2022. Figure 2 shows the number of research publications retrieved depending on their publication year. Between 2017 and 2021, the number of research publications published gradually increased.

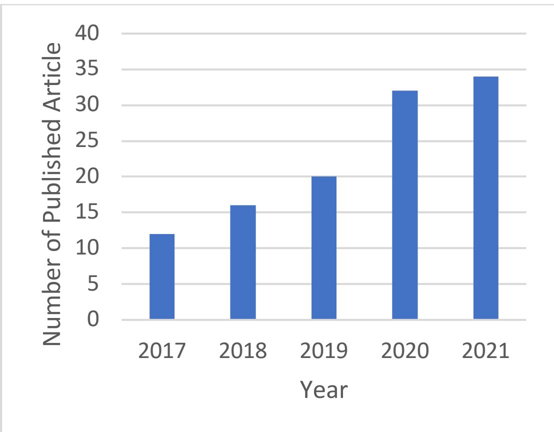


FIGURE 2. Number of articles published each year from 2017 to 2021

There is no such thing as a universal sign language exists. Various sign languages are used in different nations or areas. British Sign Language (BSL) differs from American Sign Language (ASL), and Americans who are familiar with ASL may struggle to grasp BSL. ASL has been adopted into the sign languages of other nations. From previously published papers, it has been observed that the sign language that has been studied the most is American Sign Language, with 32 studies. 23 studies concentrated on Arabic Sign Language, 18 studies concentrated on Indian Sign Language, followed by nine studies focused on Chinese Sign Language. Furthermore, five studies focused on Pakistani and Thai Sign Language, and three studies concentrated on Malaysian and Bengali Sign Language. Two studies focused on Germany, Japanese, Persian and Turkish Sign Language. Furthermore, one study concentrated on Amharic, Colombian, Croatian, Greek, Indonesia, Kazakh, Korean and Tanzania Sign Language, respectively. Figure 3 shows the number of research publications retrieved depending on their language of sign language.

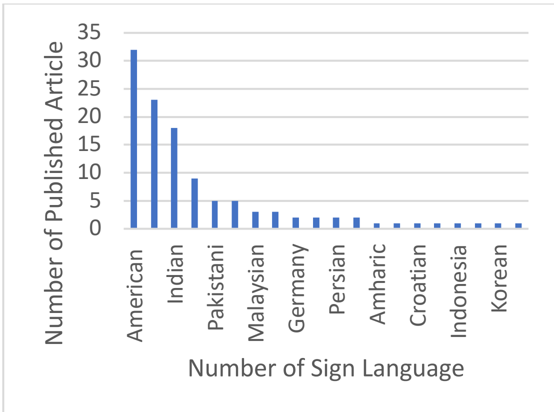


FIGURE 3. Number of articles published based on the sign language

ANSWERING RESEARCH QUESTION

In this section, the authors will answer the research questions stated above. All the research questions have been answered.

RQ1- What database has been used in this study?

The American Sign Language Dataset by Pugeault & Bowden (2011) has been used by many authors such as Xie et al. (2018); Khari et al. (2019); Hu (2018); Hu et al., (2018); Tan et al. (2020) to recognize the static alphabet of American

Sign Language. A total of 60,000 hand movements from five people are included in the dataset. It has 24 English letters from a to z, with the exception of j and z, which are dynamic in American Sign Language. The NTU Hand Digits dataset which has been used in Nasreddine & Benzinou (2018); Suneetha et (2021) study is the hand gesture dataset with a Kinect sensor. There are ten gestures gathered from ten people in the dataset. For the same motion, each person does ten distinct gestures. Thus, in total, the dataset captures 1000 hand gestures. Some research universities have built their own sign language for public users. The Massey University dataset used by Sahoo et al. (2018), public American Sign Language by the University of Surrey's Center for Vision, Speech and Signal is used by Saha et al. (2018), and the National University of Singapore (NUS) hand posture public dataset is used by Mohammed & Rada (2020); Tan et al. (2021). Thomas Moeslund's hand gesture database used by Oyedotun & Kahsman (2017) consists of 24 different static hand gestures. Other public American Sign Language datasets can be downloaded on the website Kaggle.com, which has been used by Ashiquzzaman et al. (2020); Abiyev et al. (2020); Butt et al. (2019). The majority of these datasets are the static alphabet and digits in American Sign Language.

Jochen Triesch Static Hand Posture database is used by (Kaur and Joshi, 2016; and Kaur et al., 2017). The collection contains 10 distinct hand signals performed by 24 different people against various backdrops. There are three sorts of greyscale graphics and backgrounds: uniform bright, uniform dark, and complicated. Kaur and Joshi have compared the Jochen Triesch Static Hand Posture database with the public Indian Sign Language database. Maximum accuracy of 90% is achieved for the ISL dataset meanwhile for the Jochen-Triesch dataset, 84.9% accuracy has been achieved. HDM05 dataset, CMU action datasets and own datasets have been compared by Kumar et al. (2018) in their study. The author's dataset consists of a total of 20,000 3-D sign videos, with 100 signs per class. The result shows that HDM05 has achieved the highest accuracy, followed by the CMU dataset and their own built dataset. Others Indian Sign Language studies are using their own built dataset.

Luqman et al. (2020) using three datasets; MNIST-ASL, Arabic Alphabet Sign Language Dataset by Latif et al. (2018), and MU HandImages ASL by Barczak (2011) in their study. Elatawy et al, (2020), used a Sign Language dataset from the Al-Amal Institute in Damietta for deaf pupils and King Saud University Saudi Sign Language (KSU-SSL) dataset used by Hammadi et al. (2020). Another Arabic Sign Language is called Arabic Sign Language 2018 is used by Saleh & Issa (2020).

Koulierakis et al. (2021) used Danish Sign Language dataset and POLYTROPON dataset for Greek Sign Language. In Chinese Sign Language, Pan et al. (2020); Meng & Li (2021) used the DEVESIGN dataset, and Zhang et al. (2019) used a dataset from the University of Science and Technology of China as well as the IsoGD dataset. Ko et al. (2019) presented the KETI (Korea Electronics Technology Institute) sign language dataset in the Korea Sign Language study, which consists of 14,672 videos of high resolution and quality. It is found that other sign language recognition studies use their own built dataset. The list of the datasets is summarised in Table 3.

RQ2- What are the devices used in sign language translation systems?

Vision-based approaches have grown more common in recent years, including input from digital cameras such as DSLR cameras, video cameras, smartphone cameras, web cameras, and compact cameras. The most popular way is to use a two-dimensional picture from a regular video camera. Ashiquzzaman et al. (2020); Abiyev et al. (2020) used the modern video camera, which has the standard of 20.1-megapixel camera and has a frame rate of 30 fps respectively. Csoka et al. (2019) used a DSLR camera for capturing the videos, which are signed by native signers to create their dataset. Imran & Raman (2020) used a thermal camera to acquire a new sign language dataset to demonstrate the efficiency of their technique on a thermal video camera as well. Muthukumar et al. (2019) dataset is captured using a compact camera.

TABLE 3. Investigation on car-driver interaction

Reference	Sign Language	Reference
ASL by Pugeault and Bowden	ASL	Xie et al. (2018); Khairi et al. (2019); Hu et al. (2018); Hu (2018).
Public ASL from Kaggle.com	ASL, MySL, InSL	Ashiquzzaman et al. (2020); Abiyev et al. (2020); Tan et al. (2020).
NTU hand digits dataset	ASL	Nasreddine & Benzinou. 2018
NUS hand posture public	ASL	Mohammed & Rada (2020); Tan et al. (2021)
Public ASL (not mention source)	ASL	Beena et al. (2020); Nasreddine & Benzinou (2018)
Massey University dataset	ASL	Sahoo et al. (2018)
University of Surrey's Center for Vision, Speech and Signal	ASL	Saha et al. (2018)
Triesch (2002)	ASL	Sahoo et al. (2018), Sharma & Singh (2021)
GESTURES database by Milios and Petrakis(2000)	ASL	Nasreddine & Benzinou (2018)
ASL Gestures by Barczak et al. (2011)	ASL	Tan et al. (2020)
Thomas Moeslund's hand gesture database	ISL	Oyedotun & Khashman (2017)
Github	ISL	Abhilash et al. (2020)
Jochen-Triesch's Database, ISL	ISL	Kaur et al. (2017)
HMD05 and CMU	ISL	Kumar et al. (2018)
MNIST-ASL, ArSL by Ghazanfar et al. (2018) and MUASL	ArSL	Luqman et al. (2018)
From Al-Amal Institute Damietta for deaf students	ArSL	Elatawy et al. (2020)
King Saud University Saudi Sign Language (KSU-SSL)	ArSL	Al-Hammadi et al. (2020)
ArASL: Arabic Alphabets Sign Language Dataset by Latif et al. (2019)	ArSL	Saleh & Issa (2020)
Unified Arabic Sign Dictionary 2006	ArSL	Ibrahim et al. (2018)
Database-01 by Shanableh and Assaleh (2007)	ArSL	Sidig et al. (2019)
DEVESIGN	Chinese SL	Pan et al. (2020)
CSL by University of Science and Technology of China, IsoGD	Chinese SL	Zhang et al. (2019)
KETI	Korea SL	Ko et al. (2019)
Danish Sign Language dataset, POLYTROPON	Greek SL	Koulierakis et al. (2021)
OWN	Others	Others

It is also found that many authors used Kinect in their studies, Beena et al. (2019); Prathap & Kumar (2019); Raghuveera et al. (2019); Ravi et al. (2019); Hisham & Hamouda (2019); Sidig et al. (2019); Elpeltagy et al. (2018); Sidiq et al. (2021). Kinect uses sensors and a camera to collect coloured pictures of objects, including their depths. These give more specific information that can help with classification. By detecting background and foreground images, the depth feature can enhance segmentation. The other device in sign language systems is webcam or computer camera. Tolentino et al. (2019) used a 1080P Full-HD web camera. Rahim et al. (2020); Baligod et al. (2017) created a dataset using a low-cost webcam. The webcam is also used in Kadhim & Khamees (2020); Rahim (2019); Sharma et al. (2020); Wadhawan & Kumar (2020); Sharma et al. (2021); Rivera-Acosta et al. (2021); Khan et al. (2021).

Most individuals nowadays have a smartphone with a built-in camera. So many researchers also use smartphone cameras as their acquisition method. In Kagalkar (2018) study, for image acquisition, the frontal camera of a smartphone is used. Rao & Kishore (2017) proposed a new way to bring sign language closer to real-time mobile applications. In Ravi et al. (2017) study, a mobile camera with 2M pixel resolution is used to capture video signs. The list of device types is summarised in Table 4.

RQ3: What types of recognition have been used in the studies? (words, alphabets, sentences, numbers, etc.)

There are many types of sign language recognition: Numbers, alphabet, words, and sentences. It is found that most of the studies recognized the alphabet. Sharma & Kumar (2021); Juneja et al. (2021); Awwad et al. (2021) studies show that they recognize the American Sign Language alphabet. Sharma & Singh (2021) recognize the Indian Sign Language alphabet and words. Alawwad et al. (2021); Alzohairi et al. (2018) recognize the Arabic Sign Language alphabet. Abdul et al. (2021); Sidiq et al. (2021); Bencherif et al. (2021);Rahaman et al. (2020) recognized alphabets, numbers, and words. Shaik et al. (2021), Gunduz & Polat (2021); Rastgoo et al. (2021); Myagila & Klavo (2021) recognized words in American Sign Language, Turkish Sign Language, Persian Sign Language, and Tanzania Sign Language respectively. The studies focused least on the sentence of a sign language. Mistree et al. (2021) focus on the sentence of Indian Sign Language recognition. Xiao et al. (2019); Xu et al. (2021) focus on the sentence of Chinese Sign Language. The list of types of recognition that have been used in the studies is summarized in Table 5.

TABLE 4. List of device type

Device	Reference
Digital camera	Ashiquzzaman et al. (2020); Kim et al. (2017); Beena et al. (2020); Csóka et al. (2019); Koh & Ali (2017); Sahoo et al. (2018); Nasreddine & Benzinou (2018)
Microsoft Kinect	Prathap & Kumar (2019); Xie et al. (2018); Hu et al. (2018); Hu (2018); Raghuveera et al. (2018); Ravi et al. (2019); Shaik (2021)
Webcam	Wadhawan & Kumar (2019); Choudhury et al. (2017); Latif et al. (2020); Sidig et al. (2019); Alzohairi et al. (2018); Arshad et al. (2018)
Mobile Phone	Rao & Kishore (2018); Dangarwala & Hiran (2019)

TABLE 5. List of recognition type

Recognition Type	Reference
Alphabet	Khari et al. (2019); Rahim et al. (2020); Al-Amin (2017); Cui et al. (2018); Abiyev et al. (2020); Rahim et al. (2019);
Digit	Mohammed & Rada (2020); Butt et al. (2019); Tan et al. (2020); Muthukumar et al. (2019); Ahmed et al. (2020)
Word	Imran & Raman (2020); Ravi et al. (2017); Kaur et al. (2017); Kumar et al. (2018; Ravi et al. (2018)
Sentence	Kagalkar & Gumaste (2018); Nagendraswamy & Kumara (2017); Ko et al. (2019)

RQ4: Which action sign (static / dynamic) has the most studies in sign language translation systems?

There are two types of actions in sign language recognition: Static and dynamic. In the majority of the articles (115 articles), gestures were static. Most alphabet and number recognition are in static action. Like Al-Amin (2017); Bendarkar et al. (2021) studies in the American Sign Language recognition system, all the alphabets are in static action, except j and z alphabet, which are in dynamic action.

Other sign languages show that the alphabets are in static action such as Kwolek at al. (2021); Nihal et al. (2021); Kenshimov et al. (2021) in Japanese Sign Language, Bangla Sign Language and Kazakh Sign Language recognition study respectively. Saqib & Kazmi (2018); Ali et al. (2020); Ismail et al. (2021) in Arabic Sign Language recognition study and Pariwat & Seresangtakul (2019) in Thai Sign Language recognition study. Most of the word and sentence recognition is in the dynamic study. This can be seen in Xiao et al. (2020); Kraljevic et al. (2020); Sutarman et al. (2017); Elakkiya et al. (2021) in Chinese Sign Language recognition, Persian Sign Language recognition, Malaysian Sign Language recognition and American Sign Language recognition respectively. The list of action types is summarised in Table 6.

TABLE 6. List of action type

Action Type	Reference
Static	Kadhim, & Khamees, M. (2020); Sharma et al. (2020); Saha et al. (2018); Oyedotun & Khashman (2017); Abhilash et al. (2020); Sharma et al. (2020); Silanon (2017)
Dynamic	Mohammed & Rada (2020); Dangarwala & Hiran, (2019); Choudhury et al. (2017); Xiao et al. (2020)
Static and Dynamic	Al-Hammadi et al. (2020); Ahmed et al. (2019); Elpeltagy et al. (2018); Ibrahim, et al. (2018); Sidiq et al (2018); Pan et al. (2020);

RQ5: What are the algorithms used in the classification technique in Sign Language recognition?

Table 7 lists the different approaches utilized in the classifying process. The Convolutional Neural Network (CNN) is discovered to be the most popular approach. CNN has also been chosen the most for two to three years. An example of CNN can be found in Noreen et al. (2021); Dayal et al. (2021). All these works achieved almost 100% accuracy. The second most popular method used is the Support Vector Machine (SVM). SVM is a supervised machine learning technique that may be used for both classification and regression analysis. Even with high-dimensional data, the support vector machine is very effective. This can be found in Ito et al. (2019); Dangarwala & Hiran (2019); Moghaddam et al. (2020). Another method is the K-Nearest Neighbour (KNN), which can be found in Alksasbeh et al. (2020); Arshad et al. (2018); Tabassum et al. (2020); Klomsae et al. (2017). K-Nearest Neighbour (KNN) is a simple algorithm that maintains all available cases and classifies new ones using a similarity score. Kim et al. (2017); Tamiru et al. (2021) used the Artificial Neural Network method. Ahmed et al. (2019); Ibrahim et al. (2018); Indra et al. (2017) used the Euclidean distance in their classification method. By using the Euclidean distance in their proposed system of automatic recognition and translation, it has proven to be effective and highly accurate. There are many other methods such as Hidden Markov Model, Deep Believe Network, Bidirectional Long Short-Term Memory, and many more. However, each of the above-mentioned algorithms has its advantages and disadvantages regarding the degree of accuracy and performance. The list of the main algorithms used in the classification technique is summarised in Table 7.

RQ6: What is the recognition rate of the existing sign language translation system?

High accuracy is important in every sign language system so that the results show the correct sign language translation to avoid any miscommunication or misunderstanding. In the last five years, the system has achieved from 60% to 100% accuracy. The summary of the accuracy has been concluded in Table 8. It is found that most vision-based sign language systems have achieved accuracy in the range of 96% to 100%. To attain high accuracy, multiple classification methods are applied. Sidiq & Mahmoud (2018); Sidiq et al. (2019) have achieved 99.9% accuracy by using the k-Nearest Neighbour and Hidden Markov Model respectively in the Arabic Sign Language system. Paraiwat & Saresangtakul (2021); Martinez et al. (2020); Jiang et al. (2020) used the Convolution Neural Network and have achieved 88% to 89% accuracy. Low accuracy, which is below 75%, has also been found. Elpeltagy et al. (2018) used Canonical Correlation Analysis and Random Forest Classifiers for classification, and Microsoft Kinect as the device. The achieved accuracy is 55.57% over 150 Arabic Sign Language signs. Another low accuracy can be found in the works of Asri et al. (2019). They used Bi-directional Long Short-Term Memory and You Only Look Once (YOLO) V3 for their classification method. The list of achieved accuracy of the existing sign language recognition system is summarised in Table 8.

TABLE 7. List of algorithms used in the classification technique

Classification Method	Reference
CNN	Luqman et al. (2020); Kamruzzaman (2020); Jiang et al. (2020); Saqib et al. (2020); Martinez et al. (2020); Kraljević et al. (2020); Pratama et al. (2020)
SVM	Muthukumar et al. (2019); Raghuveera et al. (2020); Kaur et al. (2017); Hisham & Hamouda (2019); Ito et al. (2020); Moghaddam, et al. (2020)
KNN	Hisham & Hamouda (2019); Sidig et al. (2018); Pariwat & Seresangtakul 2019; Klomsae et al. (2017); Mangla et al. (2020); Arshad et al. (2018)
NN	Kim et al. (2017); Al-Amin (2017); Saha et al. (2018); Rao & Kishore (2018); Ravi et al. (2018); Sutarman et al. (2017)
Euclidean Distance	Rao & Kishore (2018); Ahmed et al. (2019); Ibrahim et al. (2018); Ahmed et al. (2020); Indra et al. (2017)

4. Overall Observation of all research work on vision-based sign language recognition

The following is a summary of the findings on sign language recognition systems in relation to the research questions.

To answer Research Question 3, we discovered that 41% of studies on vision-based sign language recognition systems relied on public datasets or other earlier study datasets, whereas 59% created their own, as shown in Figure 4a.

To answer Research Question 4, we discovered that most of the studies on vision-based sign language recognition systems with 71% used a digital camera as the device, 18% of the work used Microsoft Kinect, 9% of the work used a webcam, and 2% used a mobile phone as shown in Figure 4b.

To answer Research Question 5, 'What types of recognition have been used in the studies? Is it alphabet, number, word, or sentence?' The data has been evaluated in order to create the graph as shown in Figure 4c. It is found that 50% work on the alphabet, 30% work on words, 16% work on digits, and 4% work on sentences.

TABLE 8. List of achieved accuracy of the existing sign language recognition system

Accuracy (%)	Reference
96 >	Zhang et al. (2019); Pariwat, & Seresangtakul (2019); Mangla et al. (2020); Pratama et al. (2020); Moghaddam et al. (2020); Aksoy et al. (2021)
91 - 95	Ahmed et al. (2020); Tabassum et al. (2020); Rahaman et al. (2020); Sutarman et al. (2017); Indra et al. (2017); Ko et al. (2019)
86 - 90	Kamruzzaman (2020); Hisham & Hamouda (2019); Jiang et al. (2020); Klomsae et al. (2017); Saqib et al. (2020); Saqib & Kazmi (2018); Martinez et al. (2020)
81 - 85	Dangarwala & Hiran (2019); Nagendraswamy & Kumara (2017); Xiao et al. (2020); Xioa et al. (2019); Arshad et al. (2018)
76 - 80	Hisham, B. & Hamouda, A. (2019)
< 75	Elpaltagy et al. (2018); Asri et al. (2019)

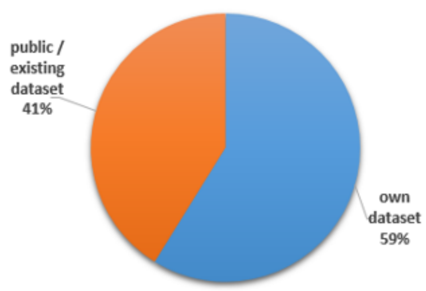
To answer Research Question 6, we observed that most of the studies on vision-based sign language recognition systems work on the static sign with 75%, 23% work on dynamic sign, and only 2% work on both static and dynamic sign. The chart is shown in Figure 4d.

To answer Research Question 7, we observed that 28% of the studies on vision-based sign language recognition systems used Convolutional Neural Network (CNN), 21% used Support Vector Machine (SVM), 11% used the K-Nearest Neighbour Method, 8% used Neural Network, whereas Euclidian Distance was at 5%. Twenty-seven percent work on the other methods. The data has been evaluated in order to create the graph as shown in Figure 4e.

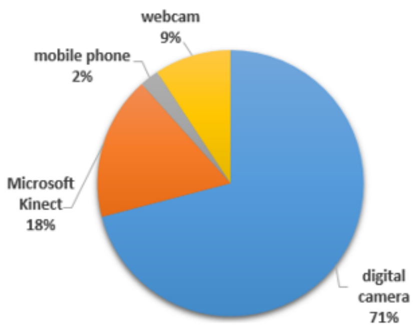
To answer Research Question 8, we discovered that 36% of the studies on vision-based sign language recognition systems have achieved 96% to 100% accuracy, followed by 29% of the research with 91% to 95% accuracy. Twenty percent of the work has obtained 86% to 90% accuracy, 7% of the work has achieved 81% to 85% accuracy and less than 75% accuracy, respectively. The least achieved is 76% to 80% with only 1% of the work. The data has been evaluated in order to create the graph shown in Figure 4f.

RESEARCH SUGGESTION

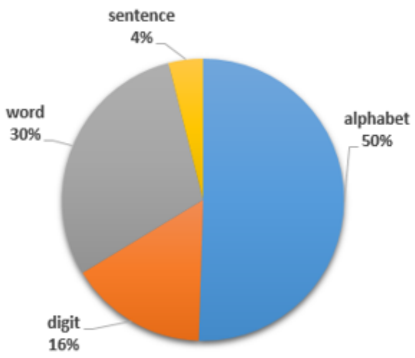
Based on the Systematic Literature Review performed on previous studies, it was found that there was a lack of public datasets available. We can see that there are many public American Datasets that can be found on the websites, but for other sign languages, there are limited public datasets. This public dataset is necessary so that researchers do not have to create their own dataset every time they wish to do research on the sign language system. Among the suggestions that can be made to address this issue is every sign language should have its organization. The dataset that has been built during the researcher's studies can be gathered on the organization's website so that the researcher can save time during their sign language recognition studies. Additionally, more datasets allow researchers to achieve more accurate sign language recognition results. This dataset is not only for the previous studies, it was found that most of the research was on alphabet signs. It is important to have more research on words and sentences, so that we can implement the research for daily life for the user to promote easier communication. Although the alphabet can be continued as fingerspelling understand words, fingerspelling may take some time when compared to having direct words or sentence translation. A good sign language translation system will help the user communicate better.



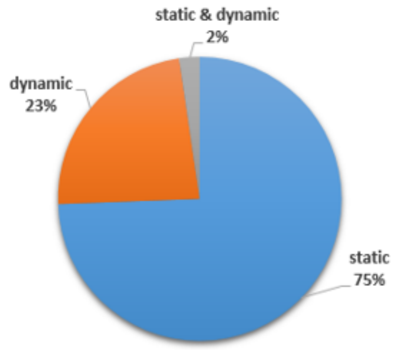
(a) Dataset type



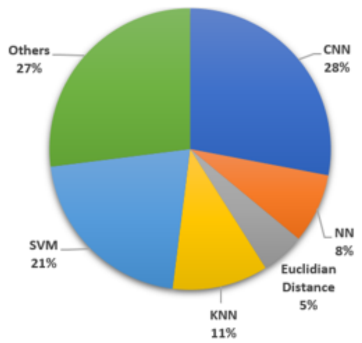
(b) Device type



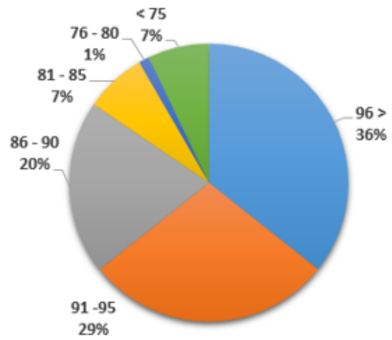
(c) Recognition type



(d) Action type



(e) Classification method



(f) Recognition rate

FIGURE 4. Percentage of all types of data studied

It is found also most of the researchers was on static sign language compared to dynamic sign language. Most of sign language is in dynamic sign language especially words and sentence sign language. Static sign language can be found in alphabet, numbers, and very less in word sign languages. It is important to have more research on words and sentences sign language because it is using every day more than alphabet and numbers sign language.

Other than that, it was found that very less of the researchers used mobile phone to recognize and translate sign language. It is suggested that researchers should use mobile phone to recognize and translate sign language and researchers should develop mobile application for their translation system. Nowadays, most people have their own mobile phone. By using mobile phone to recognize and translate sign language will be much helpful for the needs.

CONCLUSION

The recent literature on vision-based sign language recognition systems has illustrated a basic understanding of the methodology conducted by the researcher. This SLR has been formed to create a recognition systems. There is no perfect comprehensive, structured, and transparent manner research, and this SLR has a limitation whereby a highlight of the literature in a systematic, over past studies that are related to vision-based sign language total of two articles were not successfully accessed despite searches in some databases and an email to the main author of the article. The performed analysis has produced seven main themes: Dataset, device type, recognition type, static or dynamic sign, classification method, and accuracy achieved. This paper has identified 114 research articles on topics relating to sign language recognition that were published between 2017 and 2020. As a Systematic Literature Review requires a lot of time and effort, this literature assessment seeks to save other researchers' time and effort by offering a full and detailed review of sign language recognition systems for various sign languages. Other than that, referring to the results of this study is expected to help the parties concerning each sign language to develop a website with the purpose of gathering all sign language datasets, so that other researchers can refer and use the dataset for their research. This can avoid redundant work, which is the need to build a dataset, as previous researchers have done the work. Therefore, it can be concluded that from the SLR analysis, most of the studies of sign language translation systems have been conducted on static action sign language versus dynamic action sign language, alphabet sign language versus digit, word or sentence sign language. Most of the studies also utilize digital camera than using Microsoft Kinect or webcam. Most classification method has been used was Convolution Neural Network (CNN). The study served as a road map for future research and knowledge advancement in the field of sign language recognition for both readers and researchers.

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DECLARATION OF COMPETING INTEREST

None

REFERENCES

Abdul, W., Alsulaiman, M., Amin, S. U., Faisal, M., Muhammad, G., Albogamy, F. R., Bencherif, M. A., & Ghaleb, H. (2021). Intelligent real-time Arabic sign language classification using attention-based inception and BiLSTM. *Computers and Electrical Engineering*, *95*(September 2020), 107395.

Abhilash Abhilash, N. S., Sebastian, R., Sreejith Menon, M., and Pai, M. L. 2020. Classification of static Indian sign language alphabets. *International Journal of Advanced Science and Technology*, *29*(3), 5626–5632.

Abiyev, R. H., Arslan, M., and Idoko, J. B. 2020. Sign language translation using deep convolutional neural networks. *KSII Transactions on Internet and Information Systems* 14(2): 631–653.

Ahmed, A. M., Abo Alez, R., Tharwat, G., Taha, M., Belgacem, B., and Al Moustafa, A. M. J. 2020. Arabic sign language intelligent translator. *Imaging Science Journal*, *68*(1), 11–23.

Ahmed, A. M., Alez, R. A., Tharwat, G., Taha, M., Belgacem, B., Al Moustafa, A. M. J., and Ghribi, W. 2019. Arabic sign language translator. *Journal of Computer Science*, *15*(10), 1522–1537.

Aksoy, B., Salman, O. K. M., & Ekrem, Ö. (2021). Detection of Turkish Sign Language Using Deep Learning and Image Processing Methods. *Applied Artificial Intelligence*, *35*(12), 952–981.

Al-Amin Bhuiyan, M. 2017. Recognition of ASL for Human-robot Interaction. *IJCSNS International Journal of Computer Science and Network Security*, *17*(7), 66–71.

Alawwad, R. A., Bchir, O., & Ismail, M. M. Ben. (2021). Arabic Sign Language Recognition using Faster R-CNN. *International Journal of Advanced Computer Science and Applications*, *12*(3), 692–700.

Al-Hammadi, M., Muhammad, G., Abdul, W., Alsulaiman, M., Bencherif, M. A., Alrayes, T. S., Mathkour, H., et al. (2020. Deep learning-based approach for sign language gesture recognition with efficient hand gesture representation. *IEEE Access* 8: 192527–192542.

Ali, S. K., Al-Sherbaz, A., and Aydam, Z. M. 2020. Convert Gestures of Arabic Words into Voice. *Journal of Physics: Conference Series*, *1591*(1), 012023.

Al-Jarrah, O., & Halawani, A. (2001). Recognition of gestures in Arabic sign language using neuro-fuzzy systems. *Artificial Intelligence*, *133*(1–2), 117–138.

Alksasbeh, M. Z., AL-Omari, A. H., Alqaralleh, B. A. Y., Abukhalil, T., Abukarki, A., Alshalabi, I. A., and Alkaseasbeh, A. 2021. Smart hand gestures recognition using K-NN based algorithm for video annotation purposes. *Indonesian Journal of Electrical Engineering and Computer Science*, *21*(1), 242.

Aly, W., Aly, S., and Almotairi, S. 2019. User-independent american sign language alphabet recognition based on depth image and PCANet features. *IEEE Access* 7(2019). 123138–123150.

Alzohairi, R., Alghonaim, R., Alshehri, W., Aloqeely, S., Alzaidan, M., and Bchir, O. 2018. Image based Arabic Sign Language recognition system. *International Journal of Advanced Computer Science and Applications* 9(3): 185–194.

Ardiansyah, A., Hitoyoshi, B., Halim, M., Hanafiah, N., and Wibisurya, A. 2021. Systematic Literature Review: American Sign Language Translator. *Procedia Computer Science*, *179*(2020), 541–549.

Arshad Malik, M. S., Kousar, N., Abdullah, T., Ahmed, M., Rasheed, F., and Awais, M. 2018. Pakistan sign language detection using PCA and KNN. *International Journal of Advanced Computer Science and Applications*, *9*(4), 78–81.

Ashiquzzaman, A., Lee, H., Kim, K., Kim, H. Y., Park, J., and Kim, J. 2020. Compact spatial pyramid pooling deep convolutional neural network based hand gestures decoder. *Applied Sciences (Switzerland)* 10(21): 1–22.

Asri, M. A. M. M., Ahmad, Z., Mohtar, I. A., and Ibrahim, S. 2019. A Real Time Malaysian Sign Language Detection Algorithm Based on YOLOv3. *International Journal of Recent Technology and Engineering*, *8*(2 Special Issue 11), 651–656.

Awwad, S., Idwan, S., & Gharaibeh, H. (2021). Real-time sign languages character recognition. *International Journal of Computer Applications in Technology*, *65*(1), 36.

Bai, Y., Dt, D., and Bruno. 2020. Addressing Communication Barriers Among Deaf Populations who Use American Sign Language in Hearing-Centric Social Work Settings. *37 | Columbia Social Work Review* 18(1): 37–50.

Baligod, R., Alemania, L., Dabatos, A. P., and Ilao, A. L. 2017. Skin-tone segmentation in real-time vision of basic hand sign through pattern recognition using hidden Markov. *Journal of Telecommunication, Electronic and Computer Engineering* 9(2–3): 145–148.

Barczak, A. L. C., Reyes, N. H., Abastillas, M., Piccio, A., and Susnjak, T. 2011. A New 2D Static Hand Gesture Colour Image Dataset for ASL Gestures. *Res. Lett. Inf. Math. Sci*, *15*, 12–20.

Beena, M. V., Namboodiri, A., and Thottungal, R. 2020. Hybrid approaches of convolutional network and support vector machine for American sign language prediction. *Multimedia Tools and Applications* 79(5–6): 4027–4040.

Bencherif, M. A., Algabri, M., Mekhtiche, M. A., Faisal, M., Alsulaiman, M., Mathkour, H., Al-Hammadi, M., & Ghaleb, H. (2021). Arabic Sign Language Recognition System Using 2D Hands and Body Skeleton Data. *IEEE Access*, *9*, 59612–59627.

Bendarkar, D. S., Somase, P. A., Rebari, P. K., Paturkar, R. R., & Khan, A. M. (2021). Web Based Recognition and Translation of American Sign Language with CNN and RNN. *International Journal of Online and Biomedical Engineering (IJOE)*, *17*(01), 34.

Bragg, D., Koller, O., Bellard, M., Berke, L., Boudreault, P., Braffort, A., Caselli, N., Huenerfauth, M., Kacorri, H., Verhoef, T., Vogler, C., and Morris, M. R. 2019. Sign language recognition, generation, and translation: An interdisciplinary perspective. In *ASSETS 2019 - 21st International ACM SIGACCESS Conference on Computers and Accessibility* (pp. 16–31). New York, NY, USA: ACM.

Briner, R. B., and Walshe, N. D. 2014. From passively received wisdom to actively constructed knowledge: Teaching systematic review skills as a foundation of evidence-based management. *Academy of Management Learning and Education*, *13*(3), 415–432.

Butt, U.M., Husnain, B., Ahmed, U., Tariq, A., Tariq, I., Butt, M.A., Zia, M.S., 2019. Feature based algorithmic analysis on American sign language dataset. Int. J. Adv. Comput. Sci. Appl. 10, 583–589.

Camgoz, N. C., Hadfield, S., Koller, O., Ney, H., and Bowden, R. 2018. Neural Sign Language Translation. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (pp. 7784–7793). IEEE.

Csoka, F., Polec, J., Csóka, T., and Kačur, J. 2019. Recognition of sign language from high resolution images using adaptive feature extraction and classification. *International Journal of Electronics and Telecommunications* 65(2): 303–308.

Cui, Q., Zhou, Z., Yuan, C., Sun, X., and Jonathan Wu, Q. M. 2018. Fast American Sign Language Image Recognition Using CNNs with Fine-tuning. *Journal of Internet Technology* 19(7): 2207–2214.

Dangarwala, K. J., and Hiran, D. 2019. Deep learning feature extraction using pre-trained alex net model for Indian sign language recognition. *International Journal of Recent Technology and Engineering*, *8*(2), 6326–6333.

Dayal, A., Paluru, N., Cenkeramaddi, L. R., Soumya, J., & Yalavarthy, P. K. (2021). Design and implementation of deep learning based contactless authentication system using hand gestures. *Electronics (Switzerland)*, *10*(2), 1–15.

Elakkiya, R., Vijayakumar, P., & Kumar, N. (2021). An optimized Generative Adversarial Network based continuous sign language classification. *Expert Systems with Applications*, *182*(May), 115276. https://doi.org/10.1016/j.eswa.2021.115276

Elatawy, S. M., Hawa, D. M., Ewees, A. A., and Saad, A. M. 2020. Recognition system for alphabet Arabic sign language using neutrosophic and fuzzy c-means. *Education and Information Technologies* 25(6): 5601–5616.

Elpeltagy, M., Abdelwahab, M., Hussein, M. E., Shoukry, A., Shoala, A., and Galal, M. 2018. Multi-modality-based Arabic sign language recognition. *IET Computer Vision*, *12*(7), 1031–1039.

Gusenbauer, M., and Haddaway, N. R. 2020. Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources. *Research Synthesis Methods* 11(2): 181–217.

Hisham, B., and Hamouda, A. 2019. Arabic dynamic gesture recognition using classifier fusion. *Journal of Advances in Information Fusion* 14(1): 66–85

Hu, Y. 2018. Finger spelling recognition using depth information and support vector machine. *Multimedia Tools and Applications* 77(21): 29043–29057.

Hu, Y., Zhao, H. F., and Wang, Z. G. 2018. Sign Language Fingerspelling Recognition Using Depth Information and Deep Belief Networks. *International Journal of Pattern Recognition and Artificial Intelligence* 32(6).

Ibrahim, N. B., Selim, M. M., and Zayed, H. H. 2018. An Automatic Arabic Sign Language Recognition System (ArSLRS). *Journal of King Saud University - Computer and Information Sciences*, *30*(4), 470–477.

Imran, J., and Raman, B. 2020. Deep motion templates and extreme learning machine for sign language recognition. *Visual Computer* 36(6): 1233–1246.

Indra, D., Madenda, S., and Wibowo, E. P. 2017. Recognition of Bisindo alphabets based on chain code contour and similarity of Euclidean distance. *International Journal on Advanced Science, Engineering and Information Technology*, *7*(5), 1644–1652.

Ismail, M. H., Dawwd, S. A., & Ali, F. H. (2021). Static hand gesture recognition of Arabic sign language by using deep CNNs. *Indonesian Journal of Electrical Engineering and Computer Science*, *24*(1), 178–188.

Ito, S., Ito, M., and Fukumi, M. 2020. Japanese Sign Language Classification Using Gathered Images and Convolutional Neural Networks. In *2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech)* (Vol. 5, pp. 349–350). IEEE.

Jiang, X., Lu, M., & Wang, S.-H. (2020). An eight-layer convolutional neural network with stochastic pooling, batch normalization and dropout for fingerspelling recognition of Chinese sign language. *Multimedia Tools and Applications*, *79*(21–22), 15697–15715.

Juneja, S., Juneja, A., Dhiman, G., Jain, S., Dhankhar, A., & Kautish, S. (2021). Computer Vision-Enabled Character Recognition of Hand Gestures for Patients with Hearing and Speaking Disability. *Mobile Information Systems*, *2021*, 1–10.

Kadhim, R. A., and Khamees, M. 2020. A real-time american sign language recognition system using convolutional neural network for real datasets. *TEM Journal* 9(3): 937–943.

Kagalkar, R. M., and Gumaste, S. V. 2018. Mobile Application Based Translation of Sign Language to Text Description in Kannada Language. *International Journal of Interactive Mobile Technologies (IJIM)*, *12*(2), 92.

Kamruzzaman, M. M. 2020. Arabic Sign Language Recognition and Generating Arabic Speech Using Convolutional Neural Network. *Wireless Communications and Mobile Computing*, *2020*, 1–9.

Kaur, B., Joshi, G., and Vig, R. 2017. Identification of ISL Alphabets Using Discrete Orthogonal Moments. *Wireless Personal Communications* 95(4): 4823–4845.

Kenshimov, C., Mukhanov, S., Merembayev, T., & Yedilkhan, D. (2021). A Comparison Of Convolutional Neural Networks For Kazakh Sign Language Recognition. *Eastern-European Journal of Enterprise Technologies*, *5*(2–113), 44–54.

Khan, R. U., Khattak, H., Wong, W. S., Alsalman, H., Mosleh, M. A. A., & Rahman, S. M. (2021). *Convolutional-Based Attention Module with Residual Network*. *2021*.

Khari, M., Garg, A. K., Gonzalez-Crespo, R., and Verdú, E. 2019. Gesture Recognition of RGB and RGB-D Static Images Using Convolutional Neural Networks. *International Journal of Interactive Multimedia and Artificial Intelligence* 5(7): 22.

Kim, T., Keane, J., Wang, W., Tang, H., Riggle, J., Shakhnarovich, G., Brentari, D. 2017. Lexicon-free fingerspelling recognition from video: Data, models, and signer adaptation. *Computer Speech and Language* 46: 209–232.

Klomsae, A., Auephanwiriyakul, S., and Theera-Umpon, N. 2017. A novel string grammar unsupervised possibilistic C-medians algorithm for sign language translation systems. *Symmetry*, *9*(12), 321.

Ko, S. K., Kim, C. J., Jung, H., and Cho, C. 2019. Neural sign language translation based on human keypoint estimation. *Applied Sciences (Switzerland)*, *9*(13).

Koh, J. H., and Ali, S. H. A. 2017. ASL finger spelling recognition system for interactive learning and education purpose. *Journal of Telecommunication, Electronic and Computer Engineering* 9(3–7): 43–47.

Koulierakis, I., Siolas, G., Efthimiou, E., Fotinea, S.-E., & Stafylopatis, A.-G. (2021). Sign boundary and hand articulation feature recognition in Sign Language videos. *Machine Translation*, *35*(3), 323–343.

Kraljević, L., Russo, M., Pauković, M., and Šarić, M. 2020. A dynamic gesture recognition interface for smart home control based on croatian sign language. *Applied Sciences (Switzerland)* 10(7): 1–16.

Kumar, E. K., Sastry, A. S. C. S., Kishore, P. V. V., Kumar, M. T. K., and Kumar, D. A. 2018. Training CNNs for 3-D Sign Language Recognition with Color Texture Coded Joint Angular Displacement Maps. *IEEE Signal Processing Letters* 25(5): 645–649.

Kwolek, B., Baczynski, W., & Sako, S. (2021). Recognition of JSL fingerspelling using Deep Convolutional Neural Networks. *Neurocomputing*, *456*, 586–598.

Latif, G., Mohammad, N., Alghazo, J., AlKhalaf, R., and AlKhalaf, R. 2019. ArASL: Arabic Alphabets Sign Language Dataset. *Data in Brief*, *23*, 103777.

Latif, G., Mohammad, N., AlKhalaf, R., AlKhalaf, R., Alghazo, J., and Khan, M. A. 2020. An automatic arabic sign language recognition system based on deep CNN: An assistive system for the deaf and hard of hearing. *International Journal of Computing and Digital Systems* 90(4): 715–724.

Luqman, H., El-Alfy, E. S. M., and BinMakhashen, G. M. 2020. Joint space representation and recognition of sign language fingerspelling using Gabor filter and convolutional neural network. *Multimedia Tools and Applications*.

Mangla, F. U., Bashir, A., Lali, I., Bukhari, A. C., and Shahzad, B. 2020. A novel key-frame selection-based sign language recognition framework for the video data. *Imaging Science Journal* 0(0): 156–169.

Martínez S., F. H., Betancourt, F. R., & Arbulú, M. (2020). A gesture recognition system for the Colombian sign language based on convolutional neural networks. *Bulletin of Electrical Engineering and Informatics*, *9*(5), 2082–2089.

Martín-Martín, A., Orduna-Malea, E., Thelwall, M., and Delgado López-Cózar, E. 2018. Google Scholar, Web of Science, and Scopus: A systematic comparison of citations in 252 subject categories. *Journal of Informetrics* 12(4): 1160–1177.

Meng, L., & Li, R. (2021). An Attention-Enhanced Multi-Scale and Dual Sign Language Recognition Network Based on a Graph Convolution Network. *Sensors*, *21*(4), 1120.

Mistree, K., Thakor, D., & Bhatt, B. (2021). Towards Indian Sign Language Sentence Recognition using INSIGNVID: Indian Sign Language Video Dataset. *International Journal of Advanced Computer Science and Applications*, *12*(8).

Moghaddam, M., Nahvi, M., and Pourmomtaz, N. 2020. Fast recognition and classification of static and dynamic signs for Persian sign language. *International Journal of Computer Applications in Technology*, *63*(3), 228–240.

Mohamed Shaffril, H. A., Samsuddin, S. F., & Abu Samah, A. (2021). The ABC of systematic literature review: the basic methodological guidance for beginners. *Quality and Quantity*, *55*(4), 1319–1346.

Mohammed, S. N., and Rada, H. M. 2020. English numbers recognition based on sign language using line-slope features and PSO-DBN optimization method. *Journal of Engineering Science and Technology* 15(3): 1855–1867.

Mohd Rashid, S. M. Bin, Mohd Yasin, M. H. Bin, Ashaari, N. B. S. @, Hashim, H., & Jamaludin, K. A. (2021). Undergraduate Students of Special Education's Readiness Towards the Use of Application Mobile in Teaching and Learning the Sign Language. *International Journal of Academic Research in Business and Social Sciences*, *11*(12).

Muthukumar, K., Amudha, A., and Gomathy, V. 2019. Hybrid topology for feature extraction and classification of vision based hand gesture recognition. *Journal of Advanced Research in Dynamical and Control Systems* 11(4 Special Issue): 761–769.

Myagila, K., & Kilavo, H. 2022. A Comparative Study on Performance of SVM and CNN in Tanzania Sign Language Translation Using Image Recognition. *Applied Artificial Intelligence*, *36*(1).

Nagendraswamy, H. S., and Kumara, B. M. C. 2017. LBPV for Recognition of Sign Language at Sentence Level: An Approach Based on Symbolic Representation. *Journal of Intelligent Systems*, *26*(2), 371–385.

Naranjo-Zeledón, L., Peral, J., Ferrández, A., and Chacón-Rivas, M. 2019. A systematic mapping of translation-enabling technologies for sign languages. *Electronics (Switzerland)* 8(9).

Nasreddine, K., & Benzinou, A. 2019. Shape geodesics for robust sign language recognition. *IET Image Processing*, *13*(5), 825–832.

Nihal, R. A., Rahman, S., Broti, N. M., & Ahmed Deowan, S. 2021. Bangla Sign alphabet recognition with zero-shot and transfer learning. *Pattern Recognition Letters*, *150*, 84–93.

Noreen, I., Hamid, M., Akram, U., Malik, S., & Saleem, M. 2021. Hand Pose Recognition Using Parallel Multi Stream CNN. *Sensors*, *21*(24), 8469.

Our Work | WFD. (n.d.). Retrieved June 13, 2021, from https://wfdeaf.org/our-work/

Oyedotun, O.K., and Khashman, A. 2017. Deep learning in vision-based static hand gesture recognition. Neural Comput. Appl. 28, 3941–3951.

Pan, W., Zhang, X., and Ye, Z. 2020. Attention-Based Sign Language Recognition Network Utilizing Keyframe Sampling and Skeletal Features. *IEEE Access* 8: 215592–215602.

Parcheta, Z., & Martínez-Hinarejos, C.-D. (2017). Sign Language Gesture Recognition Using HMM. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 10255 LNCS* (pp. 419–426).

Pariwat, T., & Seresangtakul, P. (2019). Thai finger-spelling sign language recognition employing PHOG and local features with KNN. *International Journal of Advances in Soft Computing and Its Applications*, *11*(3), 94–107.

Pariwat, T., & Seresangtakul, P. (2021). Multi-Stroke Thai Finger-Spelling Sign Language Recognition System with Deep Learning. *Symmetry*, *13*(2), 262.

Pratama, Y., Marbun, E., Parapat, Y., and Manullang, A. 2020. Deep convolutional neural network for hand sign language recognition using model E. *Bulletin of Electrical Engineering and Informatics*, *9*(5), 1873–1881.

Prathap, C., and Pradeep Kumar, B. P. 2019. Framework of ASL silhouette gesture recognition system. *International Journal of Innovative Technology and Exploring Engineering* 8(6): 66–72.

Pugeault, N., and Bowden, R. 2011. Spelling it out: Real-time ASL fingerspelling recognition. *Proceedings of the IEEE International Conference on Computer Vision*, 1114–1119.

Raghuveera, T., Deepthi, R., Mangalashri, R., and Akshaya, R. 2020. A depth-based Indian Sign Language recognition using Microsoft Kinect. *Sadhana - Academy Proceedings in Engineering Sciences* 45(1).

Rahaman, M. A., Jasim, M., Ali, M. H., and Hasanuzzaman, M. 2020. Bangla language modeling algorithm for automatic recognition of hand-sign-spelled Bangla sign language. *Frontiers of Computer Science*, *14*(3), 143302.

Rahim, M. A., Islam, M. R., and Shin, J. 2019. Non-touch sign word recognition based on dynamic hand gesture using hybrid segmentation and CNN feature fusion. *Applied Sciences (Switzerland)* 9(18).

Rahim, M.A., Shin, J., Yun, K.S., 2020. Hand gesture-based sign alphabet recognition and sentence interpretation using a convolutional neural network. Ann. Emerg. Technol. Comput. 4, 20–27.

Rao, G. A., and Kishore, P. V. V. 2018. Selfie video based continuous Indian sign language recognition system. *Ain Shams Engineering Journal*, *9*(4), 1929–1939.

Ravi, S., Maloji, S., Polurie, V. V. K., and Eepuri, K. K. 2018. Sign language recognition with multi feature fusion and ANN classifier. *Turkish Journal of Electrical Engineering and Computer Sciences* 26(6): 2871–2885.

Ravi, S., Suman, M., and Kishore, P. V. V. 2017. Video based Indian sign language recognition using block zig-zag DCT features and Mahalanobis distance classifier. *ARPN Journal of Engineering and Applied Sciences* 12(16): 4717–4728.

Ravi, S., Suman, M., Kishore, P. V. V., Kumar E, K., Kumar M, T. K., and Kumar D, A. 2019. Multi modal spatio temporal co-trained CNNs with single modal testing on RGB–D based sign language gesture recognition. *Journal of Computer Languages*, *52*, 88–102.

Rivera-Acosta, M., Ruiz-Varela, J. M., Ortega-Cisneros, S., Rivera, J., Parra-Michel, R., & Mejia-Alvarez, P. 2021. Spelling correction real-time american sign language alphabet translation system based on yolo network and LSTM. *Electronics (Switzerland)*, *10*(9).

Saha, S., Saha, A., Khalid, Z., Paul, P., and Biswas, S. 2018. A machine learning framework using distinctive feature extraction for hand gesture recognition. *Advances in Science, Technology and Engineering Systems* 3(5): 72–81.

Sahoo, J.P., Ari, S., Ghosh, D.K., 2018. Hand gesture recognition using DWT and Fratio based feature descriptor. IET Image Process. 12, 1780–1787.

Saleh, Y., and Issa, G. F. 2020. Arabic sign language recognition through deep neural networks fine-tuning. *International journal of online and biomedical engineering* 16(5): 71–83.

Saqib, S., and Kazmi, S. A. R. 2018. Recognition of static gestures using correlation and cross-correlation. *International Journal of ADVANCED AND APPLIED SCIENCES*, *5*(6), 11–18.

Saqib, S., Ditta, A., Khan, M. A., Kazmi, S. A. R., and Alquhayz, H. 2020. Intelligent dynamic gesture recognition using CNN empowered by edit distance. *Computers, Materials and Continua*, *66*(2), 2061–2076.

Scopus - Document search. (n.d.). Retrieved June 1, 2021, from https://www-scopus-com.ezplib.ukm.my/search/form.uri?display=basic#basic

Selcuk, A. A. 2019. A Guide for Systematic Reviews: PRISMA. *Turkish Archives of Otorhinolaryngology* 57(1): 57–58.

Shaik, A. A., Mareedu, V. D. P., & Polurie, V. V. K. 2021. Learning multiview deep features from skeletal sign language videos for recognition. *Turkish Journal of Electrical Engineering and Computer Sciences*, *29*(2), 1061–1076.

Sharma, A., Sharma, N., Saxena, Y., Singh, A., & Sadhya, D. 2021. Benchmarking deep neural network approaches for Indian Sign Language recognition. *Neural Computing and Applications*, *33*(12), 6685–6696.

Sharma, A., Sharma, N., Saxena, Y., Singh, A., and Sadhya, D. 2020. Benchmarking deep neural network approaches for Indian Sign Language recognition. *Neural Computing and Applications*, *33*(12), 6685–6696.

Sharma, S., & Kumar, K. 2021. ASL-3DCNN: American sign language recognition technique using 3-D convolutional neural networks. *Multimedia Tools and Applications*, *80*(17), 26319–26331.

Sharma, S., & Singh, S. 2021. Vision-based hand gesture recognition using deep learning for the interpretation of sign language. *Expert Systems with Applications*, *182*(June), 115657.

Sharma, S., Kumar, K., and Singh, N. 2020. Deep Eigen Space Based ASL Recognition System. *IETE Journal of Research* 0(0): 1–11.

Sidig, A. A. I., Luqman, H., & Mahmoud, S. A. 2019. Arabic sign language recognition using vision and hand tracking features with HMM. *International Journal of Intelligent Systems Technologies and Applications*, *18*(5), 430–447.

Sidig, A. A. I., Luqman, H., Mahmoud, S., & Mohandes, M. 2021. KArSL. *ACM Transactions on Asian and Low-Resource Language Information Processing*, *20*(1), 1–19.

Sidig, A. addin I., & Mahmoud, S. A. 2018. Trajectory based Arabic sign language recognition. *International Journal of Advanced Computer Science and Applications*, *9*(4), 283–291.

Silanon, K. 2017. Thai Finger-Spelling Recognition Using a Cascaded Classifier Based on Histogram of Orientation Gradient Features. *Computational Intelligence and Neuroscience* 2017: 1–11.

Stewart, L., Moher, D., & Shekelle, P. 2012. Why prospective registration of systematic reviews makes sense. *Systematic Reviews*, *1*(1), 7.

Suneetha, M., M.V.D., P., & P.V.V., K. 2021. Multi-view motion modelled deep attention networks (M2DA-Net) for video based sign language recognition. *Journal of Visual Communication and Image Representation*, *78*(May), 103161.

Sutarman, Majid, M. A., and Sela, E. I. 2017. Performance evaluation of combined consistency-based subset evaluation and artificial neural network for recognition of dynamic Malaysian sign language. *Journal of Theoretical and Applied Information Technology* 95(11): 2489–2496.

Swartz, M. K. 2021. PRISMA 2020: An Update. *Journal of Pediatric Health Care*, *35*(4), 351.

Tabassum, T., Mahmud, I., Uddin, M. D. P., Emran, A. L. I., Afjal, M. I. B. N., and Nitu, A. M. 2020. Enhancement of single-handed Bengali sign language recognition based on HOG features. *Journal of Theoretical and Applied Information Technology*, *98*(5), 743–756.

Tamiru, N. K., Tekeba, M., & Salau, A. O. 2021. Recognition of Amharic sign language with Amharic alphabet signs using ANN and SVM. *Visual Computer*, *38*(5), 1703–1718.

Tan, Y. S., Lim, K. M., & Lee, C. P. 2021. Hand gesture recognition via enhanced densely connected convolutional neural network. *Expert Systems with Applications*, *175*(November 2020), 114797.

Tan, Y. S., Lim, K. M., Tee, C., Lee, C. P., and Low, C. Y. 2020. Convolutional neural network with spatial pyramid pooling for hand gesture recognition. *Neural Computing and Applications* 33(10): 5339–5351.

Tolentino, L. K. S., Serfa Juan, R. O., Thio-ac, A. C., Pamahoy, M. A. B., Forteza, J. R. R., and Garcia, X. J. O. 2019. Static sign language recognition using deep learning. *International Journal of Machine Learning and Computing* 9(6): 821–827.

Wadhawan, A., and Kumar, P. 2019. Sign Language Recognition Systems: A Decade Systematic Literature Review. *Archives of Computational Methods in Engineering* 28(3): 785–813.

Wan Jaafar, W. N., & Maat, S. M. 2020. The Relationship Between Self Efficacy and Motivation with Stem Education: A Systematic Literature Review. *International Journal of Modern Education*, *2*(4), 19–29.

Web of Science Core Collection. (n.d.). Retrieved June 1, 2021, from https://www-webofscience-com.ezplib.ukm.my/wos/woscc/basic-search

Xiao, Q., Chang, X., Zhang, X., and Liu, X. 2020. Multi-Information Spatial–Temporal LSTM Fusion Continuous Sign Language Neural Machine Translation. *IEEE Access*, *8*, 216718–216728.

Xiao, Q., Qin, M., Guo, P., and Zhao, Y. 2019. Multimodal Fusion Based on LSTM and a Couple Conditional Hidden Markov Model for Chinese Sign Language Recognition. *IEEE Access*, *7*, 112258–112268.

Xiao, Y., and Watson, M. 2019. Guidance on Conducting a Systematic Literature Review. *Journal of Planning Education and Research*.

Xie, B., He, X., Li, Y., 2018. RGB-D static gesture recognition based on convolutional neural network. J. Eng. 2018, 1515–1520.

Xu, B., Huang, S., & Ye, Z. 2021. Application of Tensor Train Decomposition in S2VT Model for Sign Language Recognition. *IEEE Access*, *9*, 35646–35653.

Zhang, S., Meng, W., Li, H., and Cui, X. 2019. Multimodal spatiotemporal networks for sign language recognition. *IEEE Access* 7: 180270–180280.