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TOPICAL REVIEW

A Systematic Review on Systems-Based Sensory Gloves for Sign Language Pattern Recognition: An Update From 2017 to 2022

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ABSTRACT Sign language is the predominant mode of communication for the Hearing impaired community. For the millions of people who suffer from hearing loss around the world, interaction with people who have the ability to hear and do not suffer from hearing impairment or loss is considered as complicated. In line with this issue, technology is perceived as a crucial factor in being an enabler of providing solutions to enhance the quality of life of the hearing impairment by increasing accessibility. This research aims to review and analyze articles related to sign language recognition based on the sensor-based glove system, in order to identify academic motivations, challenges, and recommendations related to this field. The search for the relevant review materials and articles was performed on four major databases ranging from 2017 to 2022: Science Direct, Web of Science, IEEE Xplore, and Scopus. The articles were chosen based on our inclusion and exclusion criteria. The literature findings of this paper indicate the dataset size to be open issues and challenges for hand gesture recognition. Furthermore, the majority of research on sign language recognition based on data glove was performed on static, single hand, and isolated gestures. Moreover, recognition accuracy typically achieved results higher than 90%. However, most experiments were carried out with a limited number of gestures. Overall, it is hoped that this study will serve as a roadmap for future research and raise awareness among researchers in the field of sign language recognition.

INDEX TERMS Gesture recognition, glove, sign language, sensor, man-machine interface, pattern recognition.

I. INTRODUCTION

Communication is such an essential and intrinsic aspect entrenched in the lives of people, which is used in a variety of ways, so much so that they were not consciously aware of its importance. Significantly, it has a social and emotional impact, and a lack of communication can lead to feelings of alienation, anger, and loneliness. For example, people with hearing impairment are not able to hear all the sounds around them, including their voices. This communication among themselves. However, they find it hard to communicate with ordinary people who do not suffer from hearing impairment. Sign language is a structured form of hand gestures involving

visual motions and signs, which are used as a communication system. Sign language involves the usage of different parts of the body, such as fingers, hand, arm, shoulder, head and facial expression [1]. Nonetheless, sign language is not widely used by the hearing community and only a small percentage of them can understand it. This in turn creates a real contact barrier issue between the Hearing impaired and the rest of society, which has yet to be completely resolved. To address this issue, a sign language recognition system [2] is expected to be the solution that helps alleviate the problems faced by the Hearing impaired as well as the rest of the community [1]. Thus, a system was developed to assist in recognizing sign language and is known as sign language recognition (SLR) system. It is a technology that enables the automatic conversion of Sign language gestures into a text or a voice format.

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Hence, this ability makes it one of the most useful forms of human-computer interaction, through the development of assistive systems such as sign language interpreters. This is to address and eliminate the communication barriers between (hearing impaired) and general public. Currently, there are few individuals with normal hearing capabilities who possess the ability to use sign language for the hearing impaired to communicate. Thus, to improve social engagement among the hearing impaired, there is a need to increase the number of people who can communicate with sign language [3]. Pertaining to signs, there are two components for any particular sign language, comprising the manual and non-manual components. Hand movement, orientation, location, and shape are manual components of manual signs. Whereas, body posture, mouth gestures, and facial expressions are the non-manual components of signs. Most of the signs are conveyed through manual components [4]. The components of sign language can be seen in FIGURE 1.

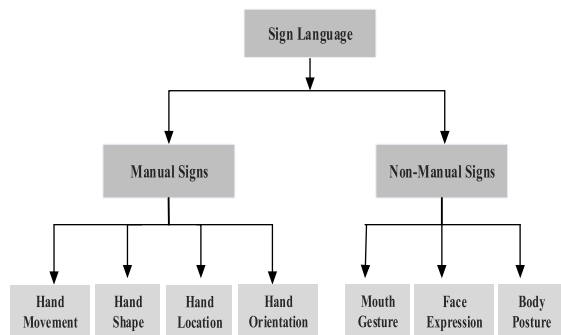


FIGURE 1. Sign language components.

For one of the components of manual signs, hand gestures or hand movements vary from static gestures to dynamic gestures, depending on the application that is used. For example, static gestures are instances where the hands are positioned at specific positions, whereas dynamic gestures are instances where the hands perform particular actions and move through a series of positions quickly [5]. Hand gesture recognition has been carried out using three techniques, which are vision-based technique, glove-based technique, and hybrid-based technique [6], as shown in FIGURE 2.

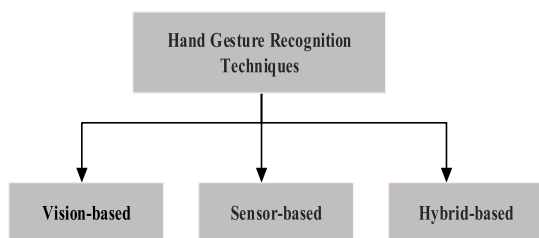


FIGURE 2. Hand gesture recognition techniques.

The vision-based technique is to obtain gesture image data through the camera and then use image processing technology to recognize gestures [7]. The vision-based system is user-friendly as no gadgets are needed to be worn by the user. However, it is difficult to be developed because complex and extensive computations are required in developing algorithms for feature and movement recognition [8]. Furthermore, it is sensitive to changes in the case of changing conditions of lighting [4], [9], [10]. The sensor-based technique, on the other hand, necessitated the wearing of a sensory glove device to capture the bending of fingers, and the position, and movement of the hand. The data glove-based approach achieves higher accuracy, fast reaction, and good mobility [11]. This method requires an absolute restriction on the hand anatomy, and hence such systems have resulted in a certain level of discomfort [12], [13]. Furthermore, this method eliminates the need for pre-processing and segmentation, which are critical steps in vision-based gesture recognition [1].

Meanwhile, the hybrid-based technique which entails a combination of the vision-based technique and glove-based technique was offered as a way to improve the value of the vision data collected by using sensor readings. However, due to the expenses and calculational overheads of the whole setup, not many papers have been carried out in this direction [14], [15].

This research aims to study glove systems used for sign language recognition. This is to gain pertinent knowledge of the current systems and of assisting researchers in this area through understanding the options and limitations available by providing essential ideas on technology use. Furthermore, in this paper, a road map for the future of technology is presented; it demonstrates features of sign language recognition systems and addresses the shortcomings of current technology. In this paper, we extend the analysis in a previous systematic review based on the sensory glove recognition system, which had included only 72 articles published between 2007 and 2017, [14]. However, in the past few years, we observed that there has been an increase in publications in this field between 2017 to 2022. Thus, this current paper has included relevant updates from 2017 to 2022. By answering, the following research questions, the objectives of this paper as aforementioned can be achieved: (1) How many studies have been published on glove-based Sign Language recognition between the years 2017 to 2022? (2) What is the number and type of gestures recognized in previous studies? (3) What types of sensors have been used in previous studies? (4) What are the existing gesture recognition techniques which have been used in previous studies?

II. OVERALL SYSTEMATIC REVIEW PROTOCOL

This research is based on a systematic literature review. This form of analysis allows for a deep understanding of a specific topic of interest. The systematic review process involves several steps, such as identifying the research field, the search method, study selection criteria, the process of data extraction, and the synthesis of data. This method is widely

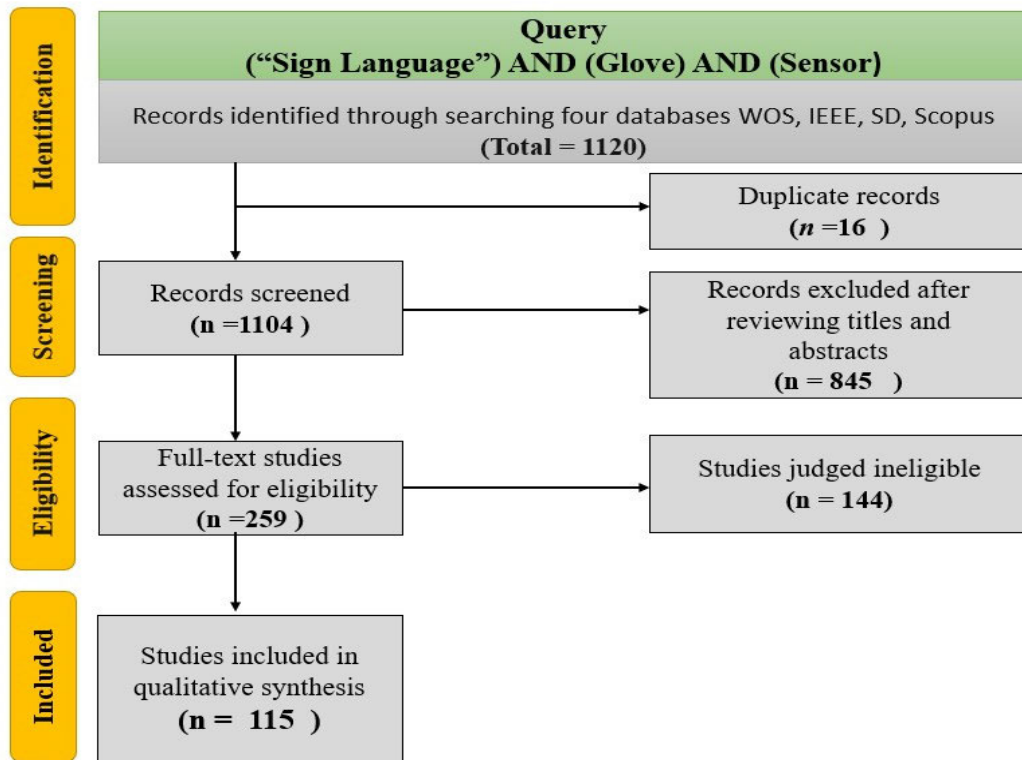


FIGURE 3. Flowchart of the search query and inclusion criteria for study select.

recognized for its essential significance and its capacity to accommodate different types of study methods. The aim of using systematic literature is to summarize the subject being studied and in finding that gaps in the existing research to position new research activities [16].

A. INFORMATION SOURCES

We proceed with the research on the targeted articles and selected the following digital databases:

1. The Science Direct database provides detailed access to research papers across various fields. This database is selected to provide a comprehensive assessment of scientists' endeavors with an extensive view and cover relevant technical literature.
2. The Database Scopus. It also provides numerous publication materials relating to different fields of research.
3. The Xplore database of the Institute of Electrical and Electronics Engineers (IEEE) consistency and publications on technology and engineering experiences on various subjects domains in technology.
4. The Web of Science (WoS). There is a wide variety of publications in various disciplines, such as social sciences, arts, and humanities.

B. RESEARCH STRATEGY

This research was initiated in the middle of May 2020. It utilized the advanced search boxes in the WoS, Science

Direct, IEEE Xplore, and Scopus and considered the distribution of scientific papers from 2017 to 2022 as a source of database. In this paper, a combination of keywords was used to perform our analysis, which is 'Sign Language', 'sensors', and 'gloves'. Such keywords have been paired with 'AND' Operator. The exact query text is ("Sign Language") AND (Glove) AND(Sensors) has been used in this study, are shown in FIGURE 3.

C. STUDY SELECTION

This paper concentrated on two kinds of articles: Journal and conference papers in particular and used to exclude other styles in each search engine, studies preferences, and book chapters. The number of records identified through searching the five selected databases was 1,120 articles as primary research results, including 99 from ScienceDirect, 400 from IEEE Xplore, 64 from Web of Science, and 557 from Scopus. Sixteen duplicate records were removed during manual elimination, resulting in the remaining 1,104 unique papers. The subsequent screening of abstracts and titles had further excluded 845 papers due to their inability to match any of our inclusion criteria. After the exclusions, there were 259 studies left for full-text review. Ensuing that, a further 144 data were removed from the analysis because they did not match the inclusion criteria. This resulted in a total of 115 studies that were included in the qualitative synthesis. To develop glove sensor-based Sign Language

Recognition (SLR), studies should be appropriate and should have full-text versions that are accessible online. Besides, only articles written completely in English were considered. This study’s articles selection procedure is described in FIGURE 3. A total of 115 articles remained in the final set.

III. MOTIVATION, CHALLENGES, AND RECOMMENDATIONS

The data through an academic literature review of sign language recognition were compiled. The following subsections present three aspects. These elements are given as follows: the motives of using the recognition of sign language to help the Hearing impaired in subsection A; the understanding of the possible challenges and limitations in the recognition of sign language recognition to overcome them in subsection B; and the recommendations for alleviating the challenges related to the sensory glove in subsection C.

A. MOTIVATIONS

The motivations for using a sensory data glove for the recognition of sign language are clear and persuasive. This section introduces several advantages as mentioned in the literature. Based on similar motives, the outcome can be categorized into four stages in general, which are: communication tools, benefits of using the glove-based system, design enhancement, and environmental obstacles of SLR, as shown in FIGURE 4.

rights and opportunities [17], [18]. Communication tools can be grouped into four fields, which are based on the needs of the speech/hearing impaired for them to improve their communication with the world. These fields include a human-computer interface (HCI), aid devices, industry 4.0, and education.

The field of human-computer interface concepts (HCI) provides a better user experience, through the employment of wearable sensor-based devices, with the assurance of providing a more natural hand movement technique for the operators, thus putting lesser movement restrictions on users [19]. The capability of machines in understanding human activities can be applied in a wide range of applications, which subsequently provide a more comfortable way of life for the Hearing impaired [3]. It is important to develop aid devices that enable people with various types of disabilities the use electronic systems to ease their daily activities, such as enabling speech/hearing impaired people to describe their illnesses to medical staff without the assistance of interpreters [20]. Furthermore, it improves the lives of elderly people by providing them with a more detailed and flexible method for interacting such as replacing the remote-control function with the electronic glove features. [21], [22]. Another field is the adoption of sensory gloves in the industry, as a sign recognition technology which can be used in factories to monitor of all manufacturing operations. Furthermore, the sensory glove could be utilized as a teaching tool to increase Hearing impaired students’ educational interest and support them in situations where they are unable to be accompanied by translators [23], [24]. Likewise, the use of sensory gloves in teaching can reduce teacher stress and enhances students a sense of immersion in the classroom [25].

2) BENEFITS OF USING A GLOVE-BASED SYSTEM

Sign language is the only means of communication between Hearing impaired and the general public in our daily lives as a result, numerous studies have examined at the development of techniques for interpreting hand gestures which are used in sign language. Glove-based techniques provide efficient and more feasible recognition rates comparative to vision-based techniques, especially in dark environments [26]. The low-and middle-income countries are the most affected by hearing impairment problems due to ear infections according to World Health Organization (WHO) reports [27]. This had been the impetus towards the motivation to find a low-cost, affordable device, that can translate the sign language into an oral language, to enable independent communication and movement for the speech/hearing impaired people in society [20], [28], [29]. The glove-based system requires low-cost hardware, making it affordable for the users [30], [31], [32]. Another benefit of the glove-based technique is in its wearability, in which case the glove can be worn by anyone whose hand can fit the glove [33], [34]. In addition to that is in its portability [35], [36], the sensory glove can wirelessly transfer data through the use of bluetooth and needs no wired

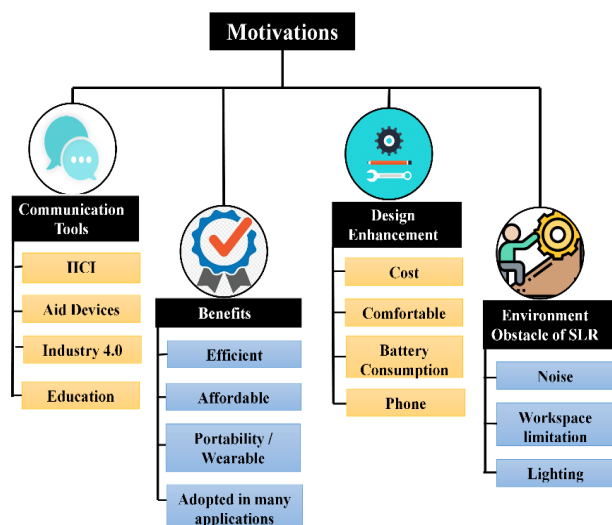


FIGURE 4. Categories of motivations for the use of glove-based SL recognition.

1) NEED FOR COMMUNICATION TOOLS

Sign language is significant for facilitating communication between hearing-impaired sufferers and the rest of society. However, not all of the rest of society know this language, which consequentially affects the social and economic lives of the speech/hearing impaired. Thus, these people encounter problems in societal participation and the enjoyment of equal

link to the device so that the user can port the glove and use it anytime and wherever the user likes [35], [37]. furthermore, it is reiterated that the benefit of the glove-based technique in its wearability and portability is obvious. It provided comfort in terms of ease of 'wear' in the daily lives of disabled people with enhanced ease of the user's mobility [14], [30], [34]. Glove-based systems are also adopted in various applications such as medical emergencies [38], google api, remote control robots [1], and others. This is indeed an added advantage due to its versatility in applications.

3) DESIGN ENHANCEMENT

Another literature that had formed the motivation towards the research into and use of glove-based technique indicated that there is a need to take into account the design enhancement aspects, which can be categorized as cost, comfortable, battery consumption, and phone as can be seen in FIGURE 4.

The understanding of sign language has become an academic task as it consists of various hand movements and gestures [39]. Thus, the factor of cost-effectiveness; in having a system based on low-cost gloves which people with a speech impairment can wear and use to translate signs into speech is be considered as a paramount motivation [40], [41], [42]. Another aspect related to the hardware is its comfortability. There is a need for a comfortable and simplified life that paves the way for opportunities to enhance the existing technology. This is because certain kinds of data gloves still offer an inferior wearing experience that causes discomfort due to the rigid and thick characteristics of the sensors [43], [44].

Designing the device with minimal energy consumption using an electromagnetic harvesting system and using it only when needed is another motivation for hardware optimization [45]. The prototyping of the new glove-based system can be enhanced by connecting the mobile device to the glove, since mobile technology has become the personal carry-on machine of people, raising the likelihood of interaction by sign language users [46], [47] Thus, this will subsequently offer the window of opportunity to open more user-friendly mobile applications for sign language users [48]. Another motivation related to design enhancement is the need to find a translation technique for two-sided translation, which translates from text or speech to the sign language gestures and vice versa [49].

4) ENVIRONMENTAL OBSTACLE ON SIGN LANGUAGE RECOGNITION

Hand gesture recognition had undergone certain development. However, prevalent commonly used techniques of recognition based on visual sensors and inertia have significant environmental constraints, such as sensor recognition that employs wireless communications that are readily influenced by ambient noise [50], [51]. Conversely, since vision-based systems are influenced by the backdrop and low light, this technique of recognition is inaccurate [52].

B. CHALLENGES AND LIMITATIONS

There have been several studies conducted to develop hand gesture recognition systems using sensory gloves to assist the Hearing impaired to communicate. However, the academic literature has identified various challenges and research limitations that must be addressed in the future.

For a systematic review of hand gesture recognition, challenges are scattered over different categories, and they are grouped based on common characteristics to ease their understanding for future researchers and studies. There are four main challenges which are related to the users, hardware, processing, limitations of signs as can be seen in FIGURE 5.

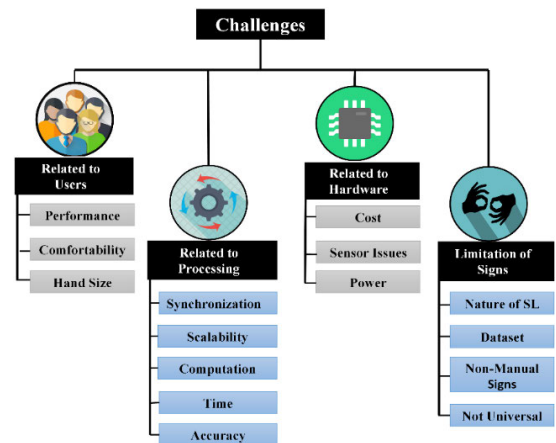


FIGURE 5. Categories of challenges for glove-based SL recognition.

1) THE CHALLENGES RELATED TO USERS

The challenges that are related to users are related to the performance of the users, the comfortability felt by the user in using the data gloves equipped with sensors, and the size of the user's hand. The first set of challenges is related to users' performance because certain gestures create confusion, and are often wrongly matched with other signs that cause the deterioration of the recognition performance [53]. Furthermore, the accuracy of the recognition depends on the performance of the user, i.e. when the recognition is used by a trained user who is familiar with Sign Language, the achieved accuracy is high [54], but decreases in other situations when the users are untrained [55]. The second set of challenges involved user comfort, as a using of sensory glove required the user to wear a bulky glove contain of sensors, cables and circuit board which limited the user's hand mobility [8], [14], [39]. Wearable technology is often used with Arduino boards, sensors, and circuits, making the system a little bulky and huge [56]. The third set of challenges is related to the user is the difference in the size of the user's hand, which affects the system of hand gesture recognition such as in the case of a user with a smaller sized hand has less discrepancy when compared with a user with larger hands [57]. With the short finger, the flex sensor's mid-point may no longer be exactly

on the PIP joint, which impacts the accuracy of the bending angle [58].

2) THE CHALLENGES RELATED TO HARDWARE

Challenges that are related to the hardware are pertaining to the cost, sensor issues, and power issues. There are a number of glove-based systems that are available on the market, which are generally expensive. In addition, they require specific drivers as well as configuration and tuning procedures [12], [39]. Firstly, it is noted that such devices incurred high expenditure with high-cost prices, of approximately \$220 to design a glove-based sign interpreter [59]. Secondly, other challenges that are related to sensors involved sensor issues, such as sensors that are highly sensitive, with the flex sensor technique showing a considerable number of errors. The flex sensor-based technique depends on the flex sensor's resistance change, which can be affected by the sheer misfit of the glove or the high sensitivity issues of the flex sensor [60]. Furthermore, the way a sensor is mounted, the types and numbers of sensors, and the placement of the sensors in the gloves are important. Notably, in cases where the flex sensors were positioned in such a way that posits the end of the flex sensor not being in the fold of the hand, would result in the sensor breaking, and thus affecting the recognition responses [61]. This matter specifies the biggest problem that is related to the sensors found on the market [44], [62], [63]. In addition to that, researchers pointed that the third aspect that is related to hardware issues is the need for computational power which posed a challenge if applied to a portable device. Therefore, the computation was done on board the wearable device to limit the amount of information that needed to be sent wirelessly and to keep the power consumption of the system low [64], [65], [66].

3) CHALLENGES RELATED TO PROCESSING

Literature has shown that there are five key factors, synchronization, scalability, computation issues, time, and accuracy that are related to processing challenges for glove-based recognition systems. Firstly, among the challenges related to processing is issues on synchronization. This type of processing challenges can be experienced as a result of the occurrence of restriction due to the transmission of data from using a pair of gloves, which can lead to unsynchronized processing of data [67], and this can result in mismatched data in time, resulting in incorrect predictions [68], [69]. The second challenge related to processing is scalability issues. When creating a hand gesture recognition system, one of the most difficult issues is introducing new additional detectable gestures without incurring a large cost [1], [70]. The third challenge related to processing involves computational issues. The computational cost of recognizing thousands of gestures is quite challenging [46]. The processing of data is often computationally expensive [71], and, in the case of multiple data flows, must be optimized to achieve the desirable performance [69]. The fourth challenge related to processing is time issues that arise due to the lack of process

data of hand gestures in the time dimension [72]. Various problems faced during segmentation, such as neural networks technique needs high processing time, and tuning of hyper-active parameters is non-trivial [12], but it does not affect the accuracy of gestures [7]. Finally, the fifth challenge related to processing involves the accuracy factor which depends on numerous variables such as the hand's positioning during the testing phase, the force involved during the opening or closing of the hand. They also affect the value of the sensors used to measure the changes in finger flexions and movements of the hand [73]. All of these challenges to processing are indicated in FIGURE 5.

4) RELATED TO LIMITATIONS OF SIGN

Previous studies have shown that there are four challenges related to the limitations of sign: nature of the sign language, dataset, lack of non-manual signs, and signs that are not universal. On the first limitation, there are two factors used for assigning the nature of Sign Language, which are the type of posture and similarity. Postures in Sign Language can be either static or dynamic. Certain papers could not find the representation for dynamic gestures as it involves a kind of rotation on the wrist [47] and palm-turning motions [74]. These could not be identified by bending motions or acceleration sensors [74]. It was observed that certain gestures are not correctly identified because certain signs have similarities with other signs as shown in FIGURE 6 [27]. This occurrence is due to the gesture from each sign bear similarities in terms of several finger movements, position, and orientation of the hands [75]. For example, confusion is involved in the interpretation of a sign related to the motion of the hand in a vertical plane concerning the body. This will be interpreted in the same way as the sign involving the motion in a horizontal plane concerning the body if the finger orientations and hand motion are similar [33].

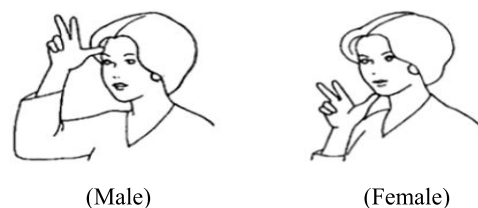


FIGURE 6. Two MSL gestures sharing the same hand shape with different positions [77].

The second challenge for glove-based sign language recognition is related to the limitations in signs that are associated with the challenge in a dataset. The majority of work in this field of study uses a smaller size of the data set in comparison to the other sign language recognition systems [1], [46], [67]. In addition to this, the majority of gesture recognition research is focused on simple recognition datasets such as letters and numbers [76]. Furthermore, the current research and study for both hands are also restricted, as most previous works concentrate only on gestures involving a single hand.

Consequently, this situation restricts access to a wide variety of Sign Language vocabulary [67]. Sign language recognition systems concentrate only on hand motion detection, ignoring non-manual signs, which is the third challenge related to the use of signs. Thus, this is one of the major challenges related to the limitations in signs involving captured non-manual-signs such as facial expressions [64], eye movements [14], mouth movements [75], and head movements [77]. The fourth challenge, related to the use of sign languages is related to its non-universality. This current study noted that various sign languages exist globally, and each has its own vocabulary and movements. Thus far, there is no universal framework that includes a clearly defined, internationally acknowledged set of rules for sign language [77].

C. RECOMMENDATIONS

There are three main categories for the recommendations linked with the gesture recognition of sign language using gloves. Researchers have taken various approaches in sharing their most valuable reservations in the form of recommendations, which can be a message for their future peers when working on such a domain. In this domain, three main recommendations are related to developers, researchers, and to applications as indicated in FIGURE 7.

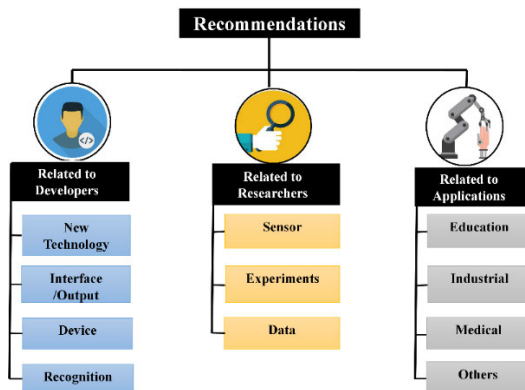


FIGURE 7. Categories of recommendations for SL recognition using gloves.

1) RECOMMENDATIONS RELATED TO RESEARCHERS

Literature has shown that three major aspects need to be considered with regards to recommendations related to researchers: Sensors, Experiments, and Data. Firstly, for the sensors-related recommendations, there is an obvious need for more sensors to be added so that all the fingers are covered to increase the accuracy of the system [19], [78], and [79]. Undeniably, another vital factor with regards to sensors is the question of the type of sensors that is to be used, such as using gyroscope sensor [80], accelerometer sensor [81], and force sensors which will allow the detection of even more complex gestures and hand positions as the user interacts with the device [59]. Secondly, aside from sensors, another category of recommendations by the researchers was more associated

with experiments, and its factors such as using operations like addition and more advanced analysis like machine learning which has been stated in the work of [62], [72], [82]. Teaching gloves to understand hand gestures through the use of the concept of machine learning was another recommendation made [83].

With better algorithms, the capability of detecting hand gestures is further enhanced, and more sign gestures can be reliably translated [82], [84]. As part of experiments are several suggested methods for hand gesture recognition, and hybrid methods are being more commonly used to resolve the limitations of the single method [1]. Thirdly, aside from the aforementioned, it is recommended that two technical aspects be employed such as using a pair of gloves for data collection, as stated in [85], [86], and [87]. Using a combination of two gloves instead of a wide range of hand gestures can be added [26], [88]. Another recommended technique associated with data was the inclusion of words and sentences; the technique will be extended towards complete sign words and sentences recognition with the help of the lexicon of sign words [34], [75], [89], [90]. At the researchers' recommendation, it was clear that data in itself is another important factor, and researchers in the literature have agreed on its importance to involve fluent users of American sign language (ASL) in a more natural setting [91]. Based on the recommendations of a large number of researchers, additional progress may be achieved by expanding the database set [16], so that the Hearing impaired population can easily interact with others using an extensive vocabulary of Sign Language [31], [92].

2) RECOMMENDATION TO APPLICATIONS

Using a sensory glove to identify gestures is a new research technique that can be used to a variety of fields. Thus, since it is a new research technique, the researchers of this current research recognized the importance of forwarding a few recommendations to further enhance the field. Recommendations that are related to applications can be categorized into four sectors, which are education, industrial, medical, and computing technology (others). It is noted that glove-based sensors can be used in industry to control mobile robots [93]. Firstly, in the education sector, there are a plethora of applications that can be used as a learning method for the speech/hearing impaired students at their school. This in turn will increase the students' interest to learn through the use of technology in education [94]. In order to learn and practice sign language, users can connect this device to laptops or mobile phones and use an interactive visual user interface [29], [95]. Secondly, the recommendation for the use of data gloves equipped with sensors is for the industrial sector use such as the gaming industry [96], robotic arm controls [97], visual reality [83], and entertainment [20].

Thirdly, it is also recommended for employment in the medical sector by helping patients to use it to measure their dexterity test performance [98], and securing necessary readings to gather biometric and diagnostic data [66], enable critically injured patients (vocal injury) to communicate with

medical staff in cases where verbal contact is restricted or impaired [87]. Furthermore, the sensor data glove technique allows the expertise of specialized surgeons to be made available to patients worldwide, without the need for patients to travel beyond their local hospital by using the gloves through remote medical surgery [96], [99].

The fourth sector recommended to employ the sensor data gloves technology is in the computing technology industry. In the computing technology sector, two technical aspects must be considered, the Internet of Things (IoTs) which is used to interact remotely with objects, for example, to communicate with objects across the house [83], [37], [100]. It is used in the human-machine interface due to numerous wide applications, such as controlling mouse movements in PCs, controlling the traffic signals [6], and others.

3) RECOMMENDATIONS RELATED TO DEVELOPERS

The development of sensory gloves holds great importance, and it plays a key role in the successful translation device for speech/hearing impaired. By taking into consideration some of the most important key factors in this regard from the literature, the researchers of this research forward several recommendations related to developers. Recommendations that are related to developers can be categorized into four sectors, which are: new technology, interface & output, device, and recognition as indicated in FIGURE 7.

Firstly, in terms of new technology, it is clear that many recommendations are dedicated to using a wireless connection technology through the employment of Wi-Fi technology [27], Bluetooth technology [56] between devices, and the use of a microcontroller to solve the problem of cables that can disturb the hand movements [8], [101]. On the other hand, incorporating a processing unit together with Wi-Fi connectivity will give the system the ability to use online free translation engines and increase the speed and accuracy of the resulting words, sentences, and phrases [80]. Secondly, another aspect that is recommended to be employed is the interface and output phase since most sensory gloves rely on a computer for their working. Consequently, it is difficult to use for practical purposes [60]. Thus, for future use, it is recommended that the system is made are compatible with a smartphone by a mobile application that can automatically translate hand gestures, to make it more interactive [57].

Likewise, it is recommended that cloud computing be used to push the boundaries further by alleviating the hardware requirement issues on mobile devices [48]. For future work, it is also recommended that the application software be upgraded, which not only displays subtitles but also includes an audible sound of all the gestures generated using the sensory glove [34], [52], [57]. Furthermore, it is recommended that the 3D avatar be developed to improve the presentation and making it easier for Sign Language speakers to understand [89]. On the other hand, the processing GUI delivered most of the functions that were needed in the two-way translation process [49], in addition to defining grammar and syntax rules that can be applied to improve translation [89].

Thirdly, another recommendation is related to devices. Numerous factors need to be considered such as cost, material, and size of hardware. It is recommended that further research should be done to reduce the cost of gloves so that it is more affordable for the Hearing impaired without losing accuracy and convenience [38]. It is also recommended that the material of the data glove should be improved [58], [102], by expanding the flexibility of the material for utilization of the glove, so it can be used by other people suffering from impairment with automatic adjustments to different hand sizes [84]. The recommendation incorporated the minimization of the size of the hardware, such as the development of smaller sized printed circuit board and wiring. This is particularly significant to best fit the back of hands to enhance the reliability and comfort of the device when worn [34], [103].

Lastly, the fourth aspect to be considered in the recommendations is related to recognition elements. The researchers of this current research put forth numerous recommendations related to recognition such as aspects on accuracy, performance, real-time, and analysis. The accuracy of the system can be improved by observing the physical characteristics of the user through training the user to perform the signs [28], [82]. In addition to this, the second aspect of recognition to be improved is with regards to performance. Performance can be further improved by placing the hand in the correct orientation to avoid any misinterpretation of the gestures for the accurate recognition of the signs [104]. Likewise, it is recommended that more sensors are added to improve hand mimic accuracy [88]. Another recommendation that is related to recognition is the third aspect as aforementioned, which is the real-time aspect as there is a need for the recognition of sign gestures in real-time [105]. A further recommendation on the aspect of real-time is to improve and optimize the prototype data sensory glove, for its employment in extensive real-life gesture recognition scenarios. [43] Another recommendation related to recognition is on the aspect of analysis. The many recommendations targeted for developers, including the ones recommended by the researchers of this current research suggested the introduction of advanced concepts of machine learning algorithms [62]. From the existing literature available, it has been ascertained that there are a number of works that have performed the Deep Learning technique. Therefore, it is an important recommendation that deep learning neural networks are employed for the recognition of signs [70].

Machine learning algorithms have the ability to teach the gloves to understand the gestures [83]. Furthermore, recent advancements in machine learning have offered SL recognition methods with the need for considerable training data [77]. In addition, the researchers of this research also recommend those important components in Sign Languages that remain to be addressed be covered such as non-manual signs [76]. These include mouth morphemes [76], facial expressions [75], body shifting, and head tilting [53]. In addition, it is recommended that future work should include words that detect wrist movement and elbow movement [30], [106].

IV. DATASET

In the past years, sign language recognition based on sensory gloves has gained increasing attention, especially due to the many affordable sensors that have been released commercially. Researchers have created datasets or have taken data from publicly available databases such as (American, Chinese) databases. However, the number of studies that use an available database is significantly lower than the number of studies that use their own database. The majority of the papers reviewed were focused on each selected author’s data set. The vast majority of studies have focused on a small number of gestures such as some alphabets [27], [31], [34], [66], [107] [108] and some numbers [65], [51], few words gestures [8], [47], [89], [101] or a combination of the alphabets, numbers, and words [82], [109]. Figure 8 indicated the American Sign Language (ASL) alphabets and numbers [57]. Others contributed to their effort by including sentences and certain positions that were selected to cover a broad range of real-life situations and basic daily activities [59], related to medical [69], and sports matters [50]. FIGURE 8, illustrates the number of articles and types of gestures covered by previous works and papers.

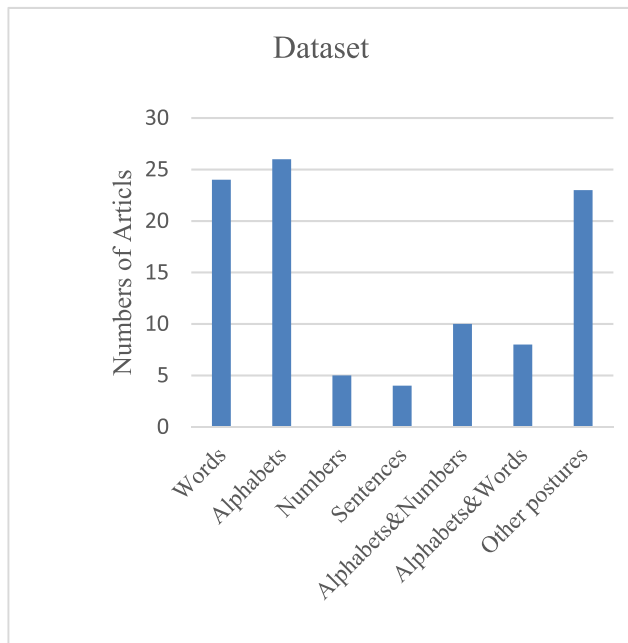


FIGURE 8. The number of articles on each type of gesture.

V. SENSOR

The sensor is the most important component in measuring hand gestures such as bending (curve), motion, rotation, and orientation. There are various sensors used to detect hand bending, such as flex sensor, as shown in FIGURE 9. A flex sensor is a device that adjusts its resistance in response to the degree of bend it experiences. The bent made on flex is decided by checking the resistance. The value of 10 to 30K ohm resistance is the natural resistance value, and when its

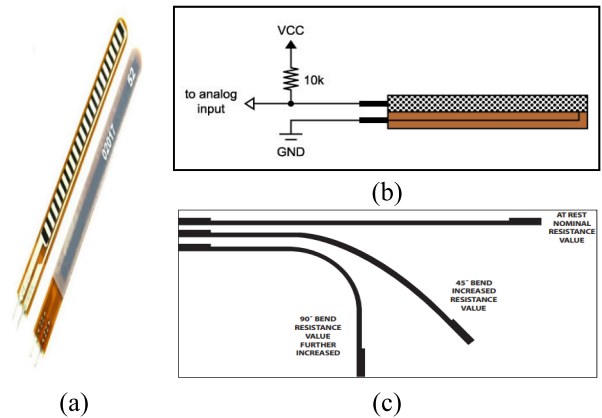


FIGURE 9. (a) flex sensor, (b) basic flex sensor circuit, (c) available resistor reading of flex sensor.

position is changed, the resistance value increases to a 100K ohm value [110]. This sensor is the conductive polymer-based sensor. It is made using resistive polymer on the side. The length of these polymers increases when the sensor is bent thus increasing the resistance of the sensor. This change in resistance gives us the bend angle of the finger [62]. Aside from the flex sensor, the 5DT data glove embedded with fiber optic sensors consists of a plastic fiber optic, a light source, and a photosensitive receiver. Light is sent from one end of the fiber optic cable and received at the other. When the optical fiber is bent, the light intensity at the receiving end changes, and thus the bending angle can be detected [21], [98]. Another sensor was exploited to detect the shape of the finger by an applied magnetic field sensor.

The sensor uses a magnetic induction technology which provides high accuracy in measurement and the ability to measure a high degree of freedom of hand movements (DOF) [65], is lightweight, and has a low manufacturing cost [14]. In addition to this, a different sensor that was used for measuring the bending of the fingers is the strain sensor. Numerous approaches have been used to develop wearable strain sensors and integrate them with computation and communication capabilities [103]. The sensors measure the change in resistance when bent on the knuckles and output a consistent electrical signal over many strain cycles without interfering with the glove’s movement [66]. Stretchable piezoresistive strain sensors are made from patterned silicon nanomembranes composite nanomaterials, conjugated polymers, graphene, and other materials. It possesses several desirable qualities such as ultra-thinness, flexibility, or stretchability [66]. The strain sensor base formed an integrated fabric structure, ensuring the comfort of the data gloves when worn, enabling the user to make a gesture without any obstacles or rigidity [43]. The strain sensor is illustrated in FIGURE 10.

Since sign language gestures consist of hand and wrist movements, the accelerometer sensor’s features include the capacity to recognize hand direction and rotation, as well as

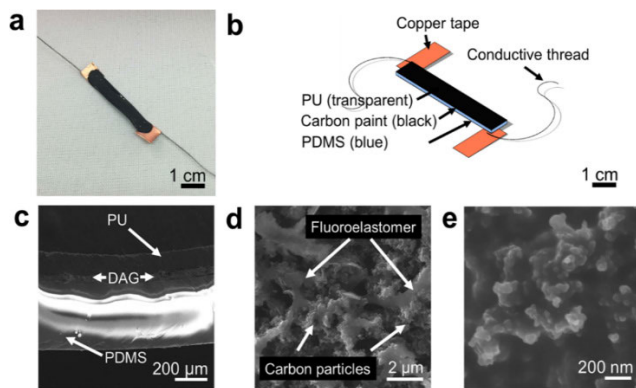


FIGURE 10. Strain sensor embedded in glove Overview of the wearable piezoresistive sensors. (a) Photograph of the sensor, (b) Schematic diagram of the sensor, (c) Cross-sectional optical micrograph of the sensor, (d) SEM image of the surface of the conductive fluor elastomer, (e) SEM image of the nanoscopic carbon particles [67].

the ability to determine the curvature of the finger [40]. The accelerometer is an electromechanical device that measures the acceleration forces. It detects the rotation and motion gestures such as the swinging of the hand [31]. It is used collectively with gyroscopes and magnetometers to form an inertial measurement unit (IMU), which provides relatively accurate readings of acceleration, rate-of-turn, and magnetic field, respectively [98] as indicated in FIGURE 11.

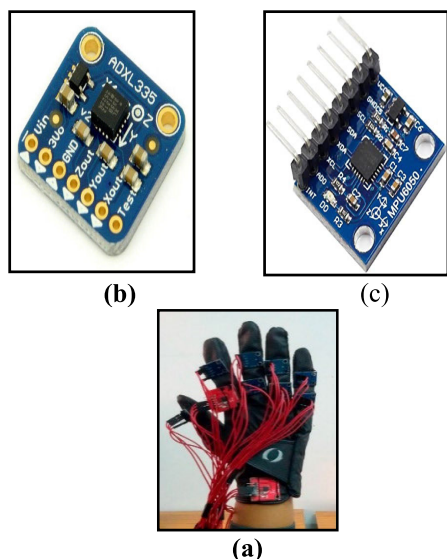


FIGURE 11. (a) the glove was customized with ten Accelerometer sensors [41]. (b) Accelerometer ADXL335(c) IMU - MPU6050.

Furthermore, another type of sensor is the force-sensitive sensor or the contact sensor also known as the pressure sensor, which possesses a sensing area sensitive to touch or contacts [58]. In addition to this, used to detect the force exerted by the changes in its resistance is an impact sensor. It can measure force from 1 kilo Newton to 100 kilos Newton [110]. The force-sensitive sensors in the system detect the opening

or closing gap between the fingers and detect the abduction-adduction as indicated in FIGURE 12.

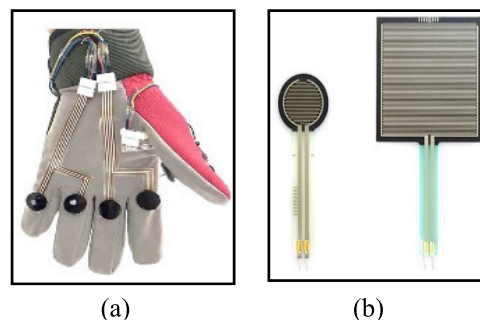


FIGURE 12. (a) Glove with pressure sensors [112] (b) Types force-sensitive sensors.

VI. GESTURE RECOGNITION TECHNIQUES

The fundamental objective of hand gesture recognition is an analysis of postures or locations of hand movement. Sensor-based hand gesture recognition techniques can be divided into two categories: dynamic and static gesture recognition. To find static signs template matching technique which is a common technique to carry out static gestures recognition or a general classifier can be used as shown in TABLE 1, which indicates a summarization of the literature review of sign language recognition based on conventional techniques. To find dynamic signs, integration of techniques is required, one such technique is the Dynamic Time Warping (DTW) is widely applied to classify direction, velocity information, and resultant shape of the hand gesture. Hand gesture segmentation is critical because it has a direct impact on feature extraction, and sign language classification, which affects the overall performance. In reference [10], suggested a system for processing pressure inputs in real-time to recognized dynamic gestures. A threshold-based algorithm was utilized to segment effective sign language signs, and the approach for recognizing endpoints was based on (DTW) in references.

The Machine Learning (ML) algorithms have also been applied to recognize hand gestures because of the ability of ML to make decisions based on previous experience (data) [51]. The most widely used ML classification algorithms involved the Hidden Markov Model (HMM), which is a commonly algorithm that has been used to detect dynamic gestures [55], [104]. The K-Nearest Neighbors (KNN) [62], [51] and Support Vector Machine (SVM) are both non-parametric methods employed [34], [40], [57], [78]. Those algorithms remain simple to implement and to use, powerful and efficient.

Fuzzy logic has been utilized in various of sectors that require human decision-making, including the recognition of Sign Language [88]. Furthermore, the Neural Network algorithm has been used to detect static gestures [65], [72]. For hand gesture recognition, a combination of fuzzy logic and neural networks has been used to improve an individual's hand gesture recognition rate [111]. Moreover, numerous

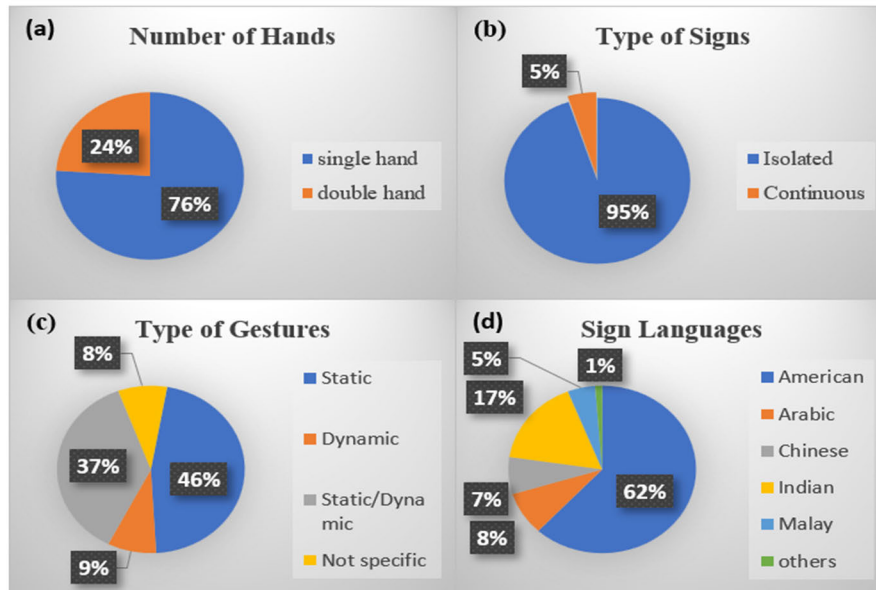


FIGURE 13. (a) percentage of studies conducted using single/double-handed signs. (b) Percentage of research work carried out based on the types of signs mode. (c) Research work carried out on static/dynamic signs (d) Percentage of research work carried out based on sign languages.

studies have been conducted to compare recognition algorithms in order to choose the best method [41], [68], [100], as shown in TABLE 2 indicating the summarized literature review Sign Language recognition systems based on machine learning (ML).

In addition, Deep learning was collection of learning techniques used for determining and representing data with complex structures as well as integrate various non-linear changes [9]. TABLE 1 shows some basic work that covered simple gesture recognition such as alphabets, and numbers for a variety of Sign Languages. Furthermore, the Convolutional Neural Networks (CNN) was used for the recognition of isolated words in the American Sign Language (ASL) [112], as well deep learning has been used for continuous sign language recognition. Meanwhile, [113] uses the CNN models for gesture recognition of the Indian Sign Languages. In [61] used the ANN to recognize alphabets and numbers in ASL, where each sign was performed 100-times, with the recognition accuracy of an Artificial Neural Network (ANN), which was at 95.8% accuracy. In [33] and [87] proposed a framework based on the Recurrent Neural Network (RNN) which has been applied for the classification of static and dynamic words of isolated sign recognition as shown in TABLE 3.

VII. FEATURE EXTRACTION

Feature Extraction involves the process of converting training data and adding more features to it to make machine learning algorithms more accurate. Typically, the features are extracted via a heuristic and hand-crafted method, which is highly dependent upon human experience or domain knowledge. Therefore, three feature extraction techniques have

been applied. Statistical methods are used to compute the data obtained from the raw sensor data as features because the information in raw sensor data is not suitable as input features. Moreover, in [88] the statistical method has been used with deep learning technique as a recognition model which achieved an average recognition rate of 99.81% for dynamic ASL gestures. Additionally, in [60], the authors have chosen the mean and the standard deviation to extract features from the common 7 gestures from the ASL and achieved an accuracy proximal to 100%. In addition, Principal Component Analysis (PCA) is a dimensionality reduction approach that has been widely utilized. Furthermore, PCA is used in [52] to extract features of 10 ASL. Likewise, the PCA features are also used in [56] as measures of hand configuration and orientation of 30 words. To improve accuracy rate, the authors combined PCA with HMM. Besides PCA, the Linear Discriminant Analysis [58] approach finds the linear combination of features that most accurately describes the data. Moreover, in [107] the LDA is compared with Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbors (KNN) to extract features from 26 ASL alphabets and 10 ASL numbers. Among these approaches, the LDA offered the highest average classification accuracy of above 80%. Furthermore, the LDA was applied in [115] to extract numeric features from 9 numbers in the ASL so as to make the dataset suitable for the development of an accurate ML classification model.

VIII. SUBSTANTIAL ANALYSIS

This section presented a substantial analysis conducted on the related work. Statistics were acquired in the form of the percentage derived from the total number of studies

TABLE 1. Summarized literature review of sign language recognition systems based on conventional techniques.

Ref.	Technique	Feature Extraction	Language/Sample Size	Number of Repeats	Type of Sensor	Number of Participants	Accuracy Rate (%)	Type of Sign	Number of Hands	Gesture	Total sample size
[47]	Heuristic algorithm		Japan/ 20 words		5Flex sensor, Accelerometer	8	50.00%	Isolated	One hand	Dynamic	
[27]	Template Matching		Malay/18 Alphabets	5	5Flex sensor, Accelerometer	1	60-100%	Isolated	One hand	Static	
[30]	Mapping algorithm		Indian/90 Words		8 Flex sensors, Accelerometer	1		Isolated	Two hands	Static	
[39]	Template Matching		Indian		5Flex sensors, sensors			Isolated	Two hands	Static	
[31]	Template Matching		Arabi/5 Alphabets	4	5 Flex sensors, Accelerometer	4		Isolated	One hand	Static	
[64]	Distance Function algorithm		American/40 Signs	5	10 Flex sensors 2 IMU	1	90%	Isolated	One hand	Static	200 Samples
[85]	If-else conditioning		American/ 26 Alphabets		5 Flex sensors			Isolated	One hand	Static	
[74]	Template Matching		American/ 25 Alphabets		5 Flex Sensors			Isolated	One hand	Static	
[101]	Template Matching		American/2 words		5Flex sensors, Accelerometer			Isolated	One hand	Static/Dynamic	
[52]	Mapping algorithm		Malaysian/9 words	3	5Flex sensors, Accelerometer	1		Isolated	One hand	Static	
[20]	Template matching	PCA	Indian/14 gestures		5 Flex sensors		93.75%	Isolated	One hand	Static	
[42]	Bit Stream Error Elimination		Eight globally used sign languages/45 gestures	100	9 Flex sensors, 8 Contact sensors	1	93.16%	Isolated	One hand	Static	4500 Samples
[7]	Template matching, BP neural network algorithm	PCA	American/ 6 Numbers 3Alphabets	200	5 Flex sensors	5	99.80%	Isolated	One hand	static	1000 Samples
[11]	Time-domine analysis		Chinese/4 Words		5Flex sensors, MPU6050 sensor			Isolated	Two hands	static	
[83]	Template Matching		Indian/ English letters & words		5 Flex sensors, Gyroscope			Isolated	One hand	Static/Dynamic	
[108]	DTW and Nearest Mapping algorithms		American/26 Alphabets	10	5Flex sensors, MPU6050 sensor	8	96.5%.	Isolated	One hand	Static/Dynamic	
[38]	If-else conditioning algorithm		American/ Words		5Flex sensors, MPU6050 sensor			Isolated	One hand	Static	
[103]	Mapping algorithm		American/26 alphabet		5Strain sensors 5 Pressure sensor			Isolated	One hand	Static/Dynamic	
[82]	If-else conditioning algorithm		Malaysian/20 Sign gesture (alphabet), numbers ,words)	10	5 Flex sensors, Accelerometer, Gyroscope	3	66.67% -100%	Isolated	One hand	Static	
[60]	If-else conditioning		American/5 Words		5 Flex sensors	5	86%	Isolated	One hand	Static	

TABLE 1. (Continued.) Summarized literature review of sign language recognition systems based on conventional techniques.

[28]	Template matching		Arabic/45 (words / expressions)	10	5Flexensors, Contact sensors, MPU6050 sensor	2	90%	Isolated	One hand	Static	
[58]	Template Matching		American/35 (Alphabet /Numbers)		5Flex sensors, 3Force sensitive sensors, Accelerometer	3		Isolated	One hand	Static/Dy namic	
[26]	Mapping algorithm		Bengal/10 Gestures		4 Flex sensors, Gyroscope			Isolated	One hand	Static/Dy namic	
[32]	Manhattan Distance		American/26 Alphabets	5	5 Contact Sensors 4 Flex sensors, MPU6050 sensor	3	92% and 81%	Isolated	One hand	Static/Dy namic	
[79]	Template Matching		American/Alp habets		5 Flex sensors, Accelerometer			Isolated	One hand	Static	
[84]	Mapping algorithm		Indonesian/36 (Alphabet/ Numbers)	10	5 Flex sensors Accelerometer gyroscope		91%	Isolated	One hand	Static/Dy namic	
[35]	Manhattan Distance		American/24 Alphabets	100	5Accelerometer sensors	3	95.3% - 87.0%,	Isolated	One hand	Static	
[114]	If-else conditioni ng		American/35 (Alphabets/ Numbers)		5 Flex sensors, MPU6050 sensor			Isolated	One hand		
[102]	DTW algorithm		American/ 9 words	20	MPU9250 sensor, Conductive glove		93.88%	Isolated	One hand	Static/Dy namic	
[81]	Template matching		American/26 alphabet		5Flex sensor, Accelerometer			Isolated	One hand	Static/Dy namic	
[92]	Template matching		Pakistani/26 Alphabet & 10 Numbers	20	10 Flex sensors, 2 MPU6050 sensor, Contact sensor		93.4%	Isolated	Two hands	Static/Dy namic	
[110]	Template matching		American/26 Alphabets		5Flex sensors, Force sensor, Accelerometer			Isolated	One hand	Static	
[21]	Standard deviation		American/ 4 words	6	5DT data glove (fourteen flexure fiber optics sensors)	10		Isolated	One hand	Static	
[115]	Template Matching		Bengal/72 Words	10	10 Flex sensors, 4 MPU6050 sensor	8	99.5%	Isolated	Two hands	Static	
[107]	Template Matching		American/10 Alphabets	10	5 DT hand glove (14 Flex sensors)	6		Isolated	One hand	Static	600 Simple s
[80]	Mapping algorithm		American/ Alphabet		5 Flex sensors, Accelerometer		90%	Isolated	One hand	Static	
[97]	Template matching		Indian/ Alphabets		5 Flex sensors, Accelerometer			Isolated	One hand	Static	
[73]			Thai/24 (Alphabets/W ords)	10	5Flex sensor, MPU6050 sensor		70- 100%	Isolated	One hand	Static/Dy namic	
[25]	Harsdorf Distance		Chinese/ 10 Gestures	5	5DT-Glove (7 Optic fibers)	10	98%	Isolated	One hand	Dynamic	
[109]	Template Matching		Malay/75 Gestures	20	7 Flex sensors, 4 force sensitive, 6 MPU9250, TOF sensor	5	93.40%	Isolated	One hand	Static	

related to Sign Language Recognition systems based on data glove.

The pie charts in FIGURE 13, explain how to summarize the data by selecting the most important elements in sign language recognition. In Chart (a) The majority of research

on sign language identification using sensory gloves has been done on single-handed gestures, according to the findings (76%) followed by double-handed gestures (24%). Chart (b) shows that most studies on sensor glove-based sign language were conducted on isolated gestures (95%), followed

TABLE 2. Summarized literature review of sign language recognition systems based on machine learning.

Ref.	Technique	Feature Extraction	Language/Sample Size	Number of Repeats	Type of Sensor	Number of Participants	Accuracy Rate (%)	Type of Sign	Number of Hands	Gesture	Total sample size
[37]	Machine learning	/	American/41 Gestures (Alphabets / Words)	10	8 Flex sensors , MPU6050 sensor	1	94.23%	Isolated	One hand	Static/Dynamic	
[51]	KNN	PCA	American/10 Numbers	5	5 Flex sensors	10	85.00%	Isolated	one hand	Static	5000 Samples
[40]	SVM	Statistic method	American Indian/42 Alphabets	5	10 Accelerometers	4	%96.70	Isolated	One hand	Static/Dynamic	
[100]	Naive Bayes, Multi-Layer Perceptron (MLP), Random Forest (comparison)		French/22 Alphabets	1000	5 MPU9250 sensors	57	92.00%	Isolated	One hand	Static	57,000 Samples
[41]	Decision Tree, Sequential minimal optimization, Multi-layered perceptron (comparison)	statistic method	Spanish/Alphabets	50	5 Accelerometer sensors	25	96.00%	Isolated	One hand	Static	
[34]	SVM		American/26 Alphabets	20	5 Flex sensors, 2 Pressure sensors, IMU sensor	12	98.2%	Isolated	one hand	static/dynamic	
[106]	Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbour (KNN) (comparison)	LDA	American/36 (Alphabets/Numbers)	20	5 MEMS sensors	3	80%	Isolated	One hand	Static/Dynamic	
[111]	Fuzzy logic-Neural network		American/26 Alphabets	50	5 Flex sensors , Accelerometer		92.58%	Isolated	One hand	Static/Dynamic	
[3]	Neural Network		Arabic/Alphabets	5	5 Flex sensors, Accelerometer			Isolated	Two hands	Static/Dynamic	
[55]	HMM	PCA	American/30 words	5	2 MPU6050 sensor	10	%98-97%	Isolated	Two hands	Dynamic	1500 Samples
[78]	SVM		Indian/22 Gestures		5flex sensors, IMU sensor		98.91% - 100%	Isolated	One hand	Not specific	
[62]	KNN		American/26 Alphabetical	1	5 Flex sensors, 3 Contact sensors , Accelerometer	1	89.00%	Isolated	One hand	Static/Dynamic	
[71]	Nearest Neighbour (NN)		American/5 Numbers	5	5 Flexmeters	5	81%	Isolated	One hand	Static	
[57]	Support Vector Machine (SVM)		Indian/26 Alphabet		5 Flex sensors , 2 Pressure sensors	20	95.91%	Isolated	Two hands	Static	

TABLE 2. (Continued.) Summarized literature review of sign language recognition systems based on machine learning.

[116]	Back propagation		American/ (Alphabets, Numbers)		Flex sensors Accelerometer,			Isolated	One hand	Static/Dynamic	
[59]	KNN, Random Forest	Statistical method	American/7 Gestures	5	10 Flex sensors, 5 Force sensors	5	Closed to 100%.	Isolated	One hand	Static	
[93]	Fuzzy logic		American/5 words		5 Flex sensors		100%	Isolated	One hand	Static	
[104]	HMM		Tamil language/16 gestures	10	6-Axis IMU	3	87.5% and 100%	isolated	one hand	dynamic	100 samples
[88]	Fuzzy logic		Arabic/14 Gestures	10	5 Flex sensors		94%-95%	Isolated	One hand	Static	
[68]	KNN, Decision Tree, Random Forest, SVM Kernel SVM, Naive Bayes and Logistic Regression.		American/26 alphabets	5	10 Flex sensors, 2 MPU6050 sensor	40	91%	Isolated	Two hands	Static	
[72]	Neural Networks		American/ 16 Gestures		6 Flex sensors		98.29%	Isolated	Two hands	Static	
[54]	KNN, SVM, NB		Portuguese /42 Gestures	10	5DT data gloves (14 Flex sensors)	3		Isolated	One hand	Static	1260 Samples
[43]	Neural Network, DWT		Chinese/ 19 (Numbers, Words)	20	Strain sensor	4	98.3%-98.5%	Isolated	One hand	Static/Dynamic	180-2000 Samples
[63]	SVM, DTW	Statistical method	8 Gestures	2	4 Pressure sensors	10	86.20 - 95.28% -	Isolated	One hand	Static/Dynamic	3600 samples
[4]	Modified KNN, HMM (comparison)	Statistical features	Arabic/40 Sentences (create from 80 words)	10	DG5-V Hand data glove (five bend sensors & accelerometer)		96.7%	Continuous	Two hands	Not specific	
[65]	Neural Network		American/5 Numbers (0 to 4)		Magnetic field sensors, IMU (simulation)			Isolated	One hand	Static	5000 Samples
[19]	Neural Network algorithm /Random Forest comparison	Statistical features	5 postures		2 6-Axis IMU	5	69% and 97%	Isolated	One hand	Static	300 Samples
[117]	, Naïve Bayes (NB), Logistic Regression, Quadratic Discriminant Analysis (QDA), SVM, KNN, Random Forest (comparison)	LDA	American/0-9 numbers	3	16 Pressure sensors	3	99.7%	Isolated	One hand	Static	10,000 Samples
121	KNN, DTW, CNN (comparison)	Statistical features	Italian/10 Words	100	10 Flex sensors, IMU sensors	7	96.6%-98%	Isolated	One hand	Not specific	7000 Samples
[118]	ELM		American/26 gestures		18 MPU9250 sensors	2	82.5%	Isolated	One hand	Static/Dynamic	

TABLE 3. Summarized literature review of sign language recognition systems based on deep learning.

Ref.	Technique	Feature Extraction	Language/Sample Size	Number of Repeats	Type of Sensor	Number of Participants	Accuracy Rate (%)	Type of Sign	Number of Hands	Gesture	Total sample size
[113]	CNN		Indian /11 Sentences	10	2 IMU Sensor	10	%81.62	Continuous	Two hands	not specific	1100 Samples
[61]	ANN		Not mention / (Alphabets, Numbers)	100	8 Flex sensors, IMU Sensors		95.8% - 89.6% - 60%	Isolated	One hand	not specific	
[112]	CNN		American/23 Gestures	20	7 IMU sensors	15	98%	Isolated	Two hands	Static/ Dynamic	6700 Samples
[33]	RNN		Indian/26 words	40	5Flex sensors, IMU sensors		98%	Isolated	One hands	Static/ Dynamic	
[87]	RNN		American/27 Words		6 IMU sensors	12	99.81%	Isolated	One hand	Dynamic	38,451 samples

by continuous gestures (5%) percentage. As illustrated in Chart (c), a huge proportion of work has been conducted on static gestures (46%), followed by a combination of both static and dynamic gestures (37%), followed by dynamic gestures (9%), and (8%), not specific gestures. Research in the related work was conducted in different sign language types worldwide, as shown in Chart (d) the American sign language is the first country that developed research in this area with (62%) of articles in the related work. The Indian sign language ranked second with (17%) of articles. The Arabic sign language ranked third with (8%) of articles. The Chinese sign language ranked fourth with (7%) of articles. The Malaysian sign language ranked fifth with (5%) of articles. Other Sign Languages such as Portuguese and Bengal sign languages ranked sixth with (2%) of articles. Lastly, sign languages with (1%) article each were Indonesian, French, Pakistan, Filipino, Japanese, Spanish, Italian, and Thai sign languages.

The summarized literature review on sign language recognition systems is shown in TABLE 1, TABLE 2, and TABLE 3. The tables present the reference paper, techniques, language, types of sensors, types and number of gestures used with the frequency of the gestures, alongside with the total number of samples and the number of performers.

IX. DISCUSSIONS

A careful analysis and inspection of the literature on sign language recognition, however, reveals several gaps and shortcomings.

- A. From the previous studies, we reveal a database that belongs to many researchers in this area which we discovered to be very limited and may only contain numbers, alphabets, or an extremely limited number of words. That small database is usually the most problematic to researchers because of the fact that data collection is extremely difficult and expensive.
- B. The majority of sign language recognition research was conducted on isolated signs, where the user of the signs of the isolated systems used only one gesture at a time. In the

case of continuous gesture recognition, the researchers have used approximately (11) sentences. However, it is necessary to put in more effort in order to use continuous systems where the performer signs complete sentences, by developing reliable segmentation methods and increasing the dataset.

- C. Most early studies, as well as current works, focus on static gestures. Thus, there is a need for a developed dynamic gesture recognition technology to improve translation system performance.
- D. The vast majority of existing sign language recognition systems concentrate solely on hand movement processing, ignoring non-manual signs. It is difficult to capture both manual and non-manual signs at the same time. However, more research is needed in combining recognition of manual and non-manual signs to convey meaning (exclamation, question, emotion, etc.), and is a new direction for this area of study.
- E. The price of the glove is also a significant consideration. It is necessary to reduce the cost of hardware so that it is affordable for Hearing impaired to use. In addition, the design of gloves must not only serve the real purpose but also be easy to use (user-friendly), comfortable and flexible.
- F. Mobile phones have become personal carry-on computers for the majority of people. However, it is important to continue improving and enhance the robustness of mobile gesture recognition to translate speech and text into gestures on smartphones. This opens up possibilities to overcoming barriers to communications between the Hearing impaired and ordinary people.
- G. Feature extraction methods have been applied to dimensionality reduction of input variables or columns in raw data. Therefore, the hybrid feature extraction method is required for the provision of a more robust feature for recognition.
- H. Deep learning methods are important for gesture recognition, especially when dealing with big datasets. However,

deep learning methods have attracted very little attention in previous studies. Thus, it is highly required to classify signs using deep learning methods which demonstrate great possibilities for improving gesture recognition. It also made it easier for features extraction by learning automatically [120]. In addition to that, it also incorporates an automated network hyperparameter fine-tuning algorithm for network optimization.

- I. During the systematic literature review, we observed that the majority of research papers on sign language recognition systems achieved an average accuracy of greater than 90% with a small number of gestures, thus making it easier to achieve a good classification accuracy. However, we consider it credible and justifiable that an investigation on the ability of systems to recognize huge and extensive amounts of data such as those exceeding 200 dynamic gestures be launched. To the best of our understanding and knowledge, no previous research has yet investigated the accuracy rate from a large dataset.

X. CONCLUSION

Current and prevalent scenario indicates that there is a dearth of people can use sign language for the hearing impaired to communicate. The number of people who can communicate using sign language needs to be increased to promote social interaction with the hearing impaired. There exist several perspectives with regards to the sign language recognition (SLR) system, particularly SLR that uses a glove sensor approach. In this respect, we have searched and investigated the subject matter through a systematic literature review in addressing, describing the challenges, motivations, and recommendations related to sign language recognition. We, as the researchers of this research, have advocated numerous constructive recommendations to solve existing and expected challenges, that provide highly justifiable and viable research in this area with prospective results.

This research paper forwards several proposals by the researchers to address current and expected problems in the related field. The major advantage of a sensory-based approach is that the gloves enable the acquisition of data directly from the sensors (bend, hand orientation, hand rotation, etc.) with its capabilities. Furthermore, this approach is not affected by environmental conditions, such as the location of the performer and background conditions, which consequently enables the generation of more accurate data. The sensor-based approach might be cumbersome and bulky because it requires several boards and sensors to be worn so as to accurately capture the signs.

The authors believe that future research on sign language might extend to the translation of non-manual signs, which have been neglected and are still being currently left out from most works. Additionally, it is imperative that the dataset be increased to include a more extensive group of words, especially dynamic words. While most of the presented models are in the scope of isolated sign language recognition due to, the difficulty of identifying continuous gestures, as well

as the lack of current systems to detect these gestures with sufficient precision. Authors expect the community to move in a near future into the direction of addressing the challenges of continuous sign language recognition. According to the authors' observations and findings, it is critical to classify signs using deep learning algorithms that have the potential to improve gesture recognition. Furthermore, it is recommended that the size of the hardware used in the glove system be reduced to increase the system's conformability and mobility further. Finally, it is recommended that the trade-off between device robustness and sensitivity be investigated in the future.

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