 https://doi.org/10.24191/jeesr.v27i1.001

A Systematic Review of Sign Language Classification System for Real-Time Application

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***Abstract*— Sign language (SL) has been a crucial form of communication for the deaf and hard of hearing (DHH) community for the longest time. SL allows DHH individuals to express their thoughts and ideas without verbalizing. However, there are significant challenges to ensure its accessibility to a broader society due to the lack of understanding SL. This creates a communication barrier among the community widely. With the current advancement of recognition systems that use deep learning (DL), an automatic SL recognition system can be developed to bridge the communication gap. This study performs a systematic literature review (SLR) that explores the different approaches for SL classification system, common challenges in SL classification and the hardware implementation for SL classification. Through this study, 737 papers were selected and have been narrowed down to 85 papers that have been thoroughly viewed based on regions of interest of DL vision-based SL classifications system. Additionally, SL classification system papers published between 2020 to 2024 have been studied and analyzed. The presented findings prove that DL vision-based system is the suitable approach for SL classification while overcoming the main challenge addressed which is environmental factors. Finally, the SLR also proves Field-Programmable Gate Array (FPGA) as the viable hardware for DL vision-based SL classification system.**

***Index Terms*— Classification System, Deep Learning, Sign Language, Field-Programmable Gate Array (FPGA), Systematic Literature Review.**

I. INTRODUCTION

Sign language (SL) has been the primary mode of communication for the deaf and hard of hearing (DHH) individuals for a long period of time [1]. SL is a way for DHH individuals to express their thoughts and ideas by using hand gestures without the need for a verbal explanation. DHH community have been relying on SL to cope in society for social integration, education and medical needs. However, there is a communication gap among the DHH community with the rest of society due to the lack of understanding on SL.

Previously, an interpreter was needed for DHH individuals to help them interpret SL to communicate [1]. However, with the shortage of SL interpreters, the DHH community struggles to carry out their daily living independently. Therefore, a SL classification system is developed to bridge the gap of communication and gives an equal opportunity for DHH individuals [2].

The existing SL classification systems have been a help in addressing the problem of communication for the DHH community. With the advancement of deep learning (DL), such as convolutional neural network (CNN), deployed in the system, SL can be recognized and interpreted accurately. DL models can adapt with the complexity of SL that differ significantly based on the spoken language of the society [3]. Deploying DL classification models like CNN gives an upper hand to the ability of the system to classify various SL as it demonstrates a high classification accuracy and robustness [4], [5], [6], [7], [8].

Although the developed system successfully classifies SL, the system performs inconsistently accurately due to variations of challenges in SL classification especially under real-life environment. This is due to the uncontrolled environment such as variations of background noise within the input image data. Hence, previous research has proposed various methods of handling background noise [9], [10]. This approach refines the performance of the system in real-time applications.

Real-time application of the systems requires viable hardware that can fulfill the system's computational demands and convenient to users especially DHH individuals. The hardware required for the system must have high memory resources, high computational cost and low power consumption to optimize the DL model [10]. There are 5 categories of hardware implementation in DL deployment which are FPGA and SoC (System on Chip), Graphics Processing Unit (GPU), edge Artificial Intelligence (AI) platforms, camera and imaging sensors and embedded computing platforms.

As the design of DL models advances and becomes more complex, classification tasks can be enhanced, and the performance of DL model is refined. As a result, various papers were published to investigate the adaptability of refined DL models in SL classification and the functionality of hardware platforms in deploying the models [6], [7], [11], [12], [13], [14].

Systematic Literature Review (SLR) was conducted in this study with a systematic way of providing a scope for research papers on SL classification system. A comparison review of different approaches on SL classifications will be carried out.

This manuscript is submitted on 21st February 2025, revised on 26th March 2025, accepted on 15th April 2025 and published on 31st October 2025. Joel Laing Luyoh, Samsul Setumin, Emilia Noorsal and Siti Juliana Abu Bakar are from the Faculty of Electrical Engineering, Universiti Teknologi MARA, 13500 Permatang Pauh, Pulau Pinang, Malaysia.

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Moreover, the studies of common challenges addressed in SL classification will be evaluated. Finally, a comparison of hardware implementation in SL classification system is reviewed for a suitable solution of hardware. The analysis of research paper extraction will be evaluated and reported along with the selection of criteria for the suitable paper. Fig. 1 illustrates the rising level of published papers activity on SL classification system through a scientific indexing service Web of Science (WoS) from 2014 to 2024. An expected line is added to Fig. 1 to compare to the actual trends of the SL classification system. The expectation of SL classification system's development is based on the rapid growth of advancement in DL models through the years that contributes to a high accuracy and efficient system in executing classification tasks. This indicates a trend towards a robust and real-time classification system capable of handling complex and large datasets effectively.

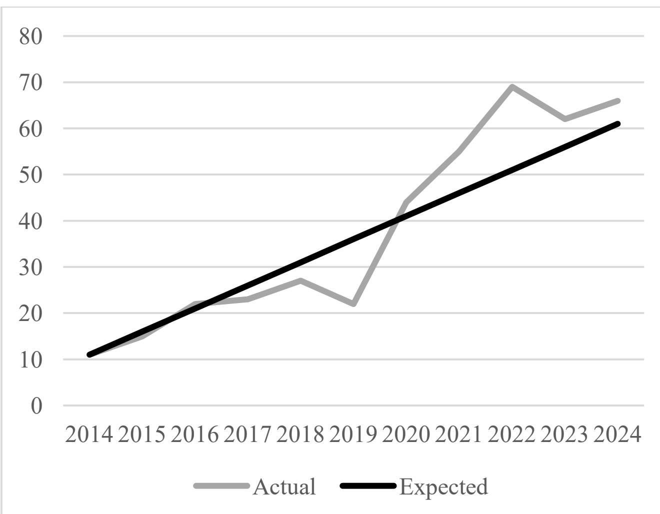

Fig. 1. Published papers of sign language classification system indexed by Web of Science from 2014 to 2024. Search string "Sign Language Classification System"

II. Process Of Systematic Review

An SLR aims to identify, classify and analyze existing research to provide research directions and facilitates the compilation of information provided [1]. The SLR consists of comprehensive surveys and comparative analysis of all the previous works systematically. The review requires developing a search strategy with focused key points and fixed criteria for the study. This helps to negate biases and results in conclusions to the required scope of research. The actions are carried out in three stages which are planning, conducting and reporting. Fig. 2 displays the work process conducted in each stage of the SLR in this study.

A. Research Objective and Questions

The objective of the SLR reported in this paper is to investigate the developed SL classification system prototype from 2020 to 2024. The investigation will focus on three aspects which are the different approaches of SL classification, common challenges in SL classification and hardware implementation for real-time application of SL classification. These aspects are linked to research questions provided as a guide to discuss in the following section. The research questions in this review are as follows :

- Research Question 1: What is the approach used for sign language classification?
- Research Question 2: What is the common challenge addressed in sign language classification?
- Research Question 3: What is the most suitable hardware platform for sign language classification system?

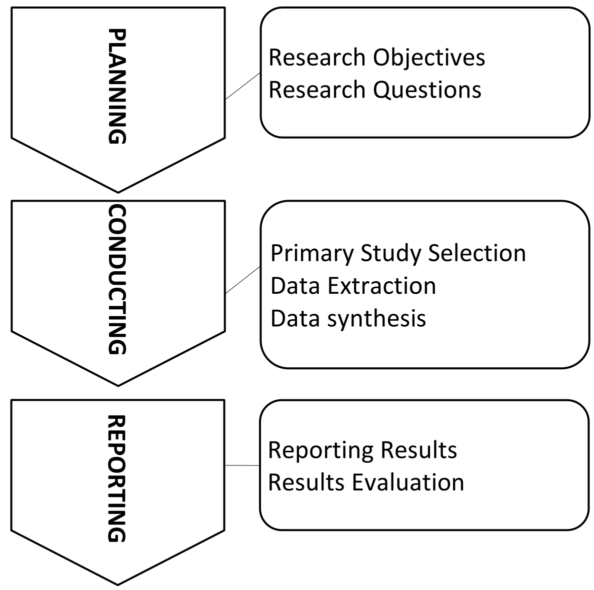

Fig. 2. Systematic literature review stages and processes

B. Automated and Manual Search

In this study, the automated search was conducted on three platform databases which were Scopus, Web of Science (WoS) and IEEE Xplore. All the databases were selected due to the availability of online databases access by the university. At the same time, all databases are common and well-known for research papers and journal query in the fields of science and technology. The search was conducted in January 2025 and the studies searched are limited to papers published between 2020 to 2024. The papers searched also were limited to only to journal articles and only in English. Across different data bases, same search string is used which is "*sign language classification system*". For WOS, the search string is search in "*all fields*" search category. Meanwhile, in Scopus and IEEE databases, the search string is filled in the search in "*article title, abstract, keywords*" and "*all metadata*" respectively.

On the other hand, the manual search was conducted by consulting the reference lists of the secondary studies listed in the primary studies. This was intended to be a complementary alternative for potentially relevant studies which were not found through the search string. To accomplish this, manual surveys were conducted on the secondary studies which were published in the last 5 years and research revolves around SL classification.

C. Selection Criteria

Complements to the automated and manual search, a manual selection of targeted documents is carried out in 2 main stages which are preliminary selection and final selection. The preliminary selection stage will be a crucial step to reduce the number of documents by reading specific parts of the documents for evaluation such as the abstract and discussion parts. The accepted documents went through second evaluation by reading the full text of the documents. In the evaluations, two sets of selection criteria were defined to ensure the reliability of the selected documents. The inclusion and exclusion criteria are described in Table I.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria	
IC01	Study the sign language classification system.
IC02	Study the methods of sign language classification.
IC03	Study that implements hardware for the sign language classification system.
Exclusion criteria	
EC01	Study is not available in full text.
EC02	Study is not available in English.
EC03	Study is only focus on hand gestures.
EC04	Study is only focus on human-robots interaction.
EC05	Study is not conducted for real-time application
EC06	Study does not mention the use of machine learning, deep learning, convolutional neural network

There are three inclusion criteria that are linked with the research questions and objective stated in the earlier section. Documents that meet the three inclusion criteria will be considered for final selection. The exclusion criteria consist of characteristics of a paper that provides information out of the research scope. The common exclusion criteria stated in EC01 and EC02 become the based criteria before diving into the objectives of the studies. EC03 and EC04 are related to their application revolving around the advancement of human interaction with computers and robots. Moreover, it does not include the application of SL classification. EC05 is a criterion of a study that only has the developed SL classification system for training and testing not for real-time application. Finally, EC06 negates studies that doesn't mention the use of machine learning (ML) or DL for SL classification which is crucial in this study.

A document is finally approved when there are not single exclusion criteria are met. The exclusion criteria are prepared for verification and require a thorough review for the next selection phase.

D. Search and Selection Result

In this section, there are three main stages for the search and selection result as illustrated in Fig. 3 which are duplicates removal, preliminary selection and final selection. In the duplicates removal stage, duplicated documents are expected to be obtained across the three databases. It's common to have one paper in two different databases. After removing the duplicates, there were 253 documents.

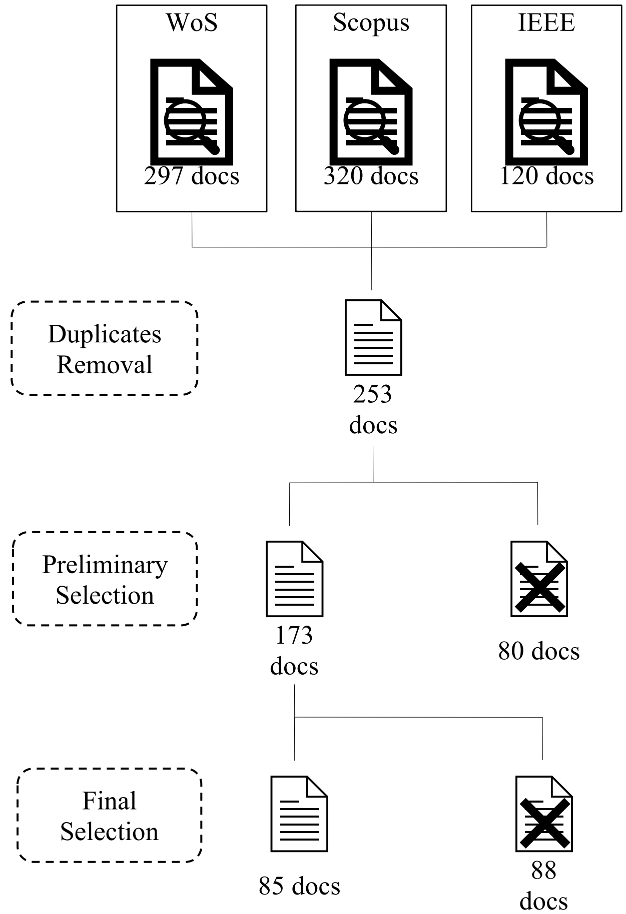

Fig. 3. Documents search and selection process.

Then, 253 documents were reviewed during the preliminary stage. The title and abstract were being reviewed based on the inclusion and exclusion criteria made as summarized in Table I. As a result, 173 documents were evaluated for further investigation from the 253 documents.

Lastly, the remaining documents undergo full-text reading for context evaluation. This is to ensure that the documents are relevant to the research objectives. The final selection stage shows that 85 documents have been retrieved, which compromise 33.6% of the initial set documents.

III. SIGN LANGUAGE CLASSIFICATION APPROACHES

In this section, different approaches of SL classification system are being reviewed and discussed. In 2022 Subburaj et al. [3] had conducted a survey and analysis of various approaches on sign language recognition. In this study the author provides information and have only focus on the comparison of two approaches on SL which are appearance-based and the deep-learning based approach for SL classification. The survey conducted was based on past literature published between 2010 until 2021. Meanwhile in this SLR, the systems' design-based category comprises a similar approach to the previous study with the additional of hybrid-based that utilized both approaches as well as the data acquisition method utilized in the studies for SL classification. The data acquisition approach is vision-based, sensor-based and a combination of vision and sensor based. The hierarchy of the approach is illustrated in Fig. 4.

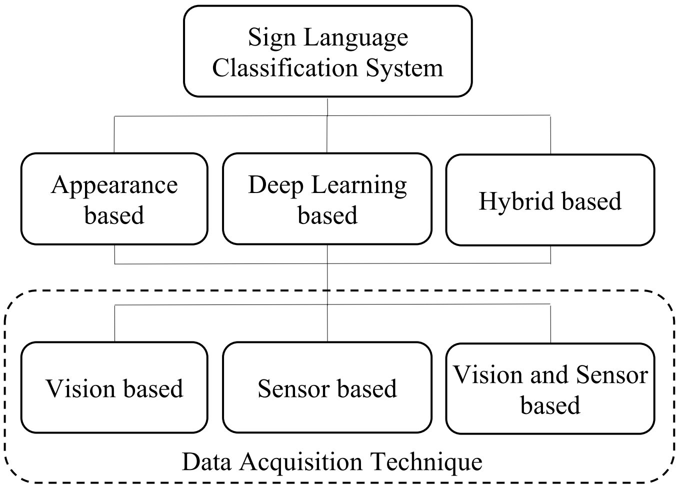

Fig. 4. Sign language classification system approach and data acquisition technique utilized.

With the guide of the hierarchy of the approach for SL classification system with its data acquisition method used, the SLR will elaborate and discuss more on the current study from 2020 to 2024. The comparative analysis and trend of the SL classification system is tabulated in Table II. The SL classification system functions by acquiring data from either a vision-based or sensor-based system or even both. The input data can be in the form of images or sensory data that is acquired into the system. The input data then undergoes pre-processing. After pre-processing, the data will either be segmented or go through a neural network (NN) models before feature extraction for final classification of the image. This determination of the process after pre-processing lies in the selected based approach for SL classification. There are three types of approaches which are appearance-based approach, DL-based approach and hybrid-based approach. In addition, the accuracy performance of the literature has been derived to display the outcome of the SL classification system based on its approach and method of data acquisition. The variation of the accuracy results for each study is due to the different data acquisition and challenges faced by the respective authors such as environmental factors and hardware configurations.

TABLE II. SIGN LANGUAGE CLASSIFICATION SYSTEM APPROACH WITH DATA ACQUISITION METHOD

Type of Approach	Data Acquisition	Accuracy (%)	Studies
Appearance-based	Vision-based	97.30	[15]
		88.00	[16]
		99.50	[17]
		96.27	[18]
		98.86	[19]
	Sensor-based	91.00	[20]
		93.57	[21]
		90.00	[22]
	Vision and Sensor-based	99.70	[23]
Deep Learning-based	Vision-based	98.43	[24]
		98.75	[25]
		99.59	[26]
		98.84	[27]
		99.81	[28]
		99.88	[29]
		96.45	[30]
		98.90	[31]
		98.00	[32]
		99.87	[33]
		90.00	[34]
		96.99	[35]
		98.77	[6]
		70.00	[36]
		88.09	[37]
		97.20	[38]
		67.77	[39]
		99.14	[40]
		89.99	[41]
		77.00	[42]
		90.26	[43]
		92.00	[44]
		99.00	[45]
		99.10	[46]
		99.99	[47]
		93.68	[48]
		92.88	[49]
		90.00	[50]
		98.70	[51]
		98.87	[52]
		99.52	[53]
	Sensor-based	95.94	[54]
		91.00	[55]
		99.50	[56]
		99.93	[57]
		90.07	[58]
		92.31	[59]
		92.00	[60]
		93.17	[61]
		95.00	[62]
		97.34	[63]
		93.40	[64]
		89.90	[65]
		99.70	[23]
	Vision and Sensor based	99.96	[66]
		99.59	[7]
Hybrid-based	Vision-based	61.00	[67]
		95.83	[68]
		98.40	[69]
		95.84	[70]
		99.64	[71]
		95.00	[72]
		97.40	[73]
		89.00	[74]
		96.00	[75]
		94.00	[76]

	94.42	[77]
	98.51	[12]
	95.00	[13]
	99.90	[4]
	98.50	[78]
Sensor-based	97.01	[79]
	98.66	[80]
	92.67	[8]
	97.70	[81]
	91.10	[82]
	99.00	[83]
	99.75	[84]
	98.00	[85]
	98.00	[2]
	99.90	[11]
	100.00	[86]
Vision and Sensor based	88.55	[14]
	74.00	[87]
	72.50	[88]
	91.09	[89]

For an appearance-based approach, the SL classification system will rely on handcrafted features extracted from the input image or videos of SL. This can be done by extracting the hand region from the rest of the input image using either segmentation or edge detection. Features like hand shape, hand orientations, skin colour or hand motions commonly extracted by utilizing histogram of oriented gradients (HOG) [15], speeded-up robust features (SURF) [71] or scale-invariant feature transform (SIFT). This is applicable for 2D images without spatial vision of the input image. After the features being extracted, the system uses traditional ML techniques for classification. This is common for appearance-based approach that utilize support vector machines (SVM) [71], or K-Nearest neighbors (KNN).

On the other hand, DL approach SL classification system uses CNN models to learn the features automatically from the input image or videos. This approach is suitable for motion image that comprises the different angle of the hand gestures. The system will convert the input into frames in pre-processing. Then the frames are used by the CNN for automatic spatial features extraction. With the architecture of CNN models, the systems can classify the image by the final layer of the CNN. There are few common CNN classification models used for SL classification such as 3D CNN[34], VGG16 [67] or ResNet50 [24].

Lastly, there are hybrid-based approaches whereas both appearance and DL-based approach are combined for a refined SL classification system performance. In 2024 Zhang J et al. [9] developed a system that leverages edge detection during pre-processing to negate the hand features and feed in the data into CNN for further automatic feature extraction.

A. Discussions on sign language classification approaches

Based on the comparative analysis on 85 studies illustrated in Fig. 5, studies with 54% of majority approach are DL approach. This approach can achieve consistent high accuracy performance with large and complex datasets due to the ability of CNN models in adapting to different scenarios [38]. With CNN's capability of learning spatio-temporal features automatically, this proves the system's flexibility of processing information from different formats or sources [7]. Furthermore, the system's accountability on CNN model's flexibility can avoid overfitting without the need for another feature extraction process. However, the limitation of DL-based system is the data dependency on large data. DL model requires a large amount of data to perform well as this is to prevent overfitting and ensure the generalization of the system. Therefore, it's crucial for every study to begin with preparing a large dataset for the system in order to ensure its high-performance execution.

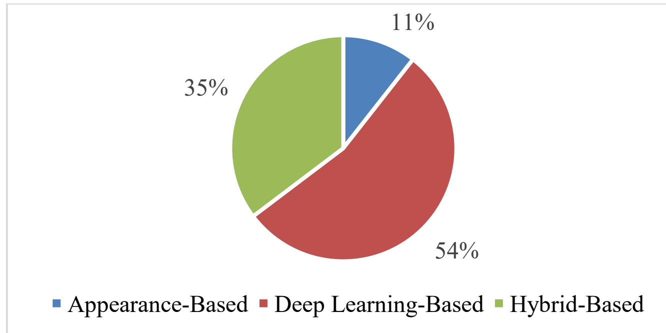

Fig. 5. Different approaches for sign language classification.

The second preferred approach with 35% of overall studies conducted is the hybrid-based approach. Hybrid-based system consists of both appearance and DL approach for SL classification. The advantage of this approach is that the system embodies a combination of traditional feature extraction which uses ML and DL methods. Traditional ML can work well with small datasets whereas feature extraction is critical, while DL can handle a large dataset with complex patterns. Thus, a wide range of different data sources and types can be handled in a system without the need of an additional system. This improves the system's robustness to various types of data and provides better generalization across different gesture recognition scenarios [7]. Additionally, traditional ML relies on handcrafted features where data is pre-processed with domain-specific knowledge to extract key features useful for classification, while DL excels in automatic learning features from raw data. With the combination of both traditional ML and DL, the system has benefits of expert-designed features from the ML and automated feature learning by the DL that gives an enhanced feature extraction for the system [78]. The hybrid approach proves of a potentially improved system for SL classification system. However, the system may require a longer period for pre-processing due to much data being fed into the system in real-time implementation [9]. The system also requires a resource-intensive to fulfill the needs of the computational demands to maintain a high performance. This sets a limitation for the hybrid-based system for real-time performance.

Finally, the least approach with 11% of overall studies is the appearance-based approach. This approach is suitable for classical feature extraction methods and only effective under controlled conditions for real-time applications [50]. The classic feature extraction method often struggles in handling background noises and background lighting which impacts the data feed into the ML for classification. Moreover, with datasets sizes growing and more complex, the approach may not scale effectively. Therefore, the approach has become an obsolete alternative for a real-time SL classification system.

Looking at the trends of the different approaches for SL classification throughout the year 2020 until 2024 as illustrated in Fig. 6, the implementation of DL-based approach shows a drastic increase after the year 2020 and has a consistent average usage. While appearance-based approaches display less interest among researchers, the approach becomes an obsolete choice as a standalone system. Meanwhile, there are studies that include the appearance-based approach by combining them with DL based as hybrid-based to obtain a refined SL classification system.

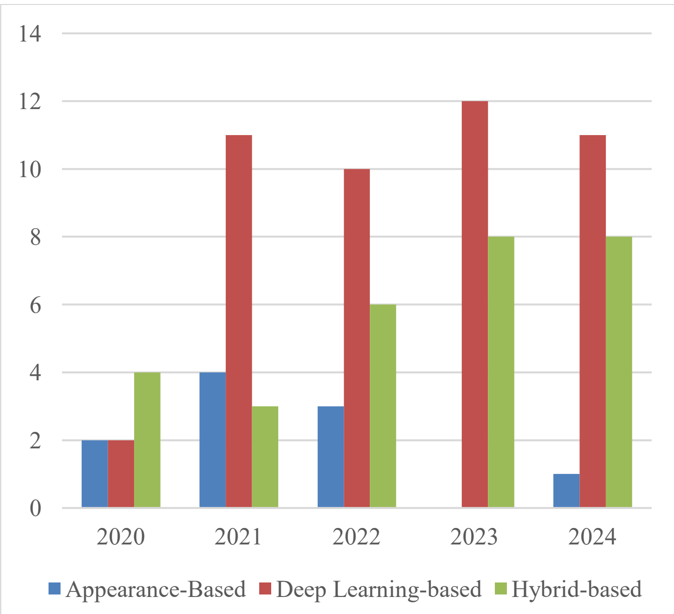

Fig. 6. Trends of Different approach for sign language classification.

In summary, the SLR proves that DL-based approach is the most preferred solution for SL classification for the last 5 years for its capabilities and flexibility to modify complex developed systems while performing with consistent high accuracy results.

B. Discussions on data acquisition approaches

Based on the SLR, there are 3 types of data acquisition for a DL-based SL classification system which are vision-based, sensor-based and hybrid-based. A vision-based approach commonly uses image-based systems using mobile cameras, web cameras, and depth cameras. While the sensor-based approach involves the use of gloves, sensors, and wearable bands with pressure sensors, accelerometers, gyroscopes, and electromyograms [31]. Meanwhile, hybrid-based approach incorporates both vision and sensor for data acquisition process.

Based on comparative analysis on 86 studies illustrated in Fig. 7, studies with 59% of overall employ a vision-based system. This approach offers mobility and comfort to DHH individuals as they only need to display SL gestures without the need of a wearable devices [31]. At the same time, this approach provides flexibility and accessibility to DHH community as they are not required to be in close proximity to hardware prototype of SL classification system [75]. However, this approach still faces challenges related to background noises, occlusions and lighting conditions that affect the SL classification in real-time. This caused the inconsistency of obtaining a high-performance SL classification system prototype.

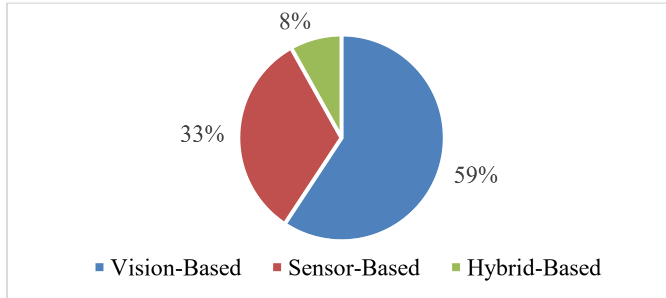

Fig. 7. Data acquisition approach for deep learning-based system.

The second data acquisition, 33% of overall studies conducted, is the sensor-based approach. This approach has shown a consistent high accuracy performance of SL classifications as shown in Table I previously. This is due to the system acquired direct human movement as an input data which is not affected by background noise for vision-based approach [63]. However, the system faces a different challenge in portability, cost and user's accessibility [90].

Finally, the least with 8% of overall studies conducted is the hybrid-based approach. This approach aims to provide multi-mode information with comprises a more comprehensive and accurate data acquisition [70]. Unfortunately, this requires an effective feature extraction and a high-performance CNN model to operate successfully. This also leads to the same challenge of having a sensor-based approach. Therefore, a hybrid-based approach is not suitable for a real-time SL classification system prototype.

In a nutshell, the SLR shows that vision-based approach for data acquisition is the preferred alternative by studies from the year 2020 until 2024 due to its mobility and flexibility to obtain data for users of SL.

IV. CHALLENGES OF SIGN LANGUAGE CLASSIFICATION

In this section, the SLR categorizes the common challenges faced in SL classifications as shown in Table III. These challenges were addressed due to their impacts to the accurate performance of SL classification especially for real-time application.

One of the major challenges is classifying a hand motion or trajectory that gives a blur captured input image for the system. In 2024 Ihsan M. et al [68] face a limited functionality of the developed SL classification system due to an inadequate incorporation of hand motion classification blocks. This caused the lack of precision of classification of SL with movements.

Besides the motion of hands, the variations and similarity of SL hand gestures too affects the accuracy results of classifications. The variations of hand gestures refer to the different angles of the captured SL image. The system inconsistently classifies the right SL gestures due to the changes in the features of the input image. The variations also give a similar answer for two distinct SL gestures [87]. This confused the system to accurately classify SL.

TABLE III. CHALLENGES OF SIGN LANGUAGE CLASSIFICATION

Challenges	Studies
Blur hands motion and trajectory	[29], [30], [35], [36], [37], [45], [48], [63], [67], [68], [72], [75], [78], [79], [81], [83]
Variations and similarity of hand gesture	[11], [14], [19], [24], [26], [28], [38], [53], [55], [60], [61], [62], [66], [69], [78], [84], [85], [86], [87], [89]
Lack of dataset for training	[2], [8], [14], [31], [44], [63], [65], [80], [84]
Distances from subject	[45], [58], [59]
Environmental factors	[4], [12], [13], [17], [18], [26], [28], [29], [34], [36], [38], [43], [44], [45], [47], [48], [56], [65], [70], [71], [77], [78], [80], [82], [86]
High computational demands	[6], [7], [12], [15], [16], [20], [23], [25], [27], [32], [33], [40], [41], [42], [44], [46], [51], [55], [57], [69], [73], [74]

Moreover, challenges involving the subject of SL hand gesture is the distance between the SL classification system prototype and the subject. This is often involved with the hardware for data acquisition of the prototype. The hardware plays a vital role in acquiring a quality image for pre-processing. With low quality of input image, SL cannot be recognized for classification within a distance [45]. This requires the user to move closer to the device for better recognition. However, this produces an inconvenient device for a real-time application of SL classification.

Challenges that involve the recognition of SL for classification require modification of the design system to obtain a better classification performance. The modification takes account of the training of CNN models deployed in the system. Most of the time, it's the lack of dataset for CNN training that caused the poor performance of classification. In 2022 Zahid H. et al [2] developed SL classification system prototype underperforms for real-time applications due to the lack of publicly available Urdu SL datasets for training. Thus, the need for ample datasets to improve the performance of the system proves the need for ample datasets.

Besides, the environmental factors also influence the performance of prototypes. These environmental factors are due to lighting, background conditions, or shadows captured within the input image [63]. These factors present noisy data with uncontrolled environments to the system. The system faces a lot of data loss due to the impact of noises on the image. This data loss gives a low accuracy outcome for the SL classification system.

Lastly, the systems computation demands affect the performance of the hardware implemented. In most studies, the designated system requires a high computational cost. This leads to the trade-off between accuracy and latency of the whole system [57]. Most systems favor one another for high accuracy and low latency. With both possibilities of favor selected, this gives an intricate decision to maintain a high-performance SL classification system and maintenance of intensive hardware.

A. Discussions on challenges of sign language classification

In this section, the common challenges are addressed and the frequency of challenges reviewed in studies from 2020 until 2024 are plotted in Fig 8. The SLR displays that the most common challenges addressed by SL classification studies are the environmental factors with 25 reported problems in 85 overall studies which are the environmental factors.

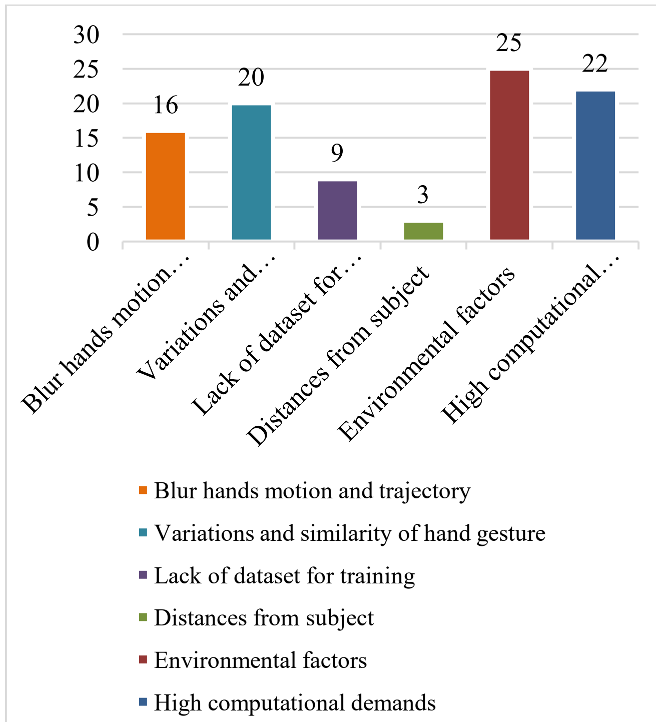

Fig. 8. Challenges of sign language classification.

This challenge is common for every SL classification system, especially when implementing real-time applications. The system's model may undergo training and have a high accuracy outcome due to the training is done by using datasets with controlled environments whereby there are no noises or occlusions that can affect the system for SL classification. However, the changes in the environment are unpredictable, so many methods are studied and tested to gain a solution that requires no training of the system. One of the methods is by implementing the hybrid-based approach for SL classifications. The traditional ML method used in appearance-based for data acquisition is utilized to diminish and negate the noise as much as possible to provide quality input data for the DL model [4]. With a filtered input image, this eases the DL model to automatically gain more feature of the input image with less losses gained.

The second highest challenge addressed is the high computational demands by the systems. Different systems contain complex design DL models that require high-performance hardware to conduct SL classifications with high accuracy. Hardware that does not meet these demands shows incompatibility for SL classification's real-time application. Therefore, a series of hardware variations is reviewed for most studies to find the hardware that suits the system's specifications [52].

The third highest challenge addressed is the variations and similarities of hand gestures. These variations challenge is due to the lack of training of the system with ample number of datasets that consist of different angles and hand gestures of SL. When the system is newly developed, it requires time to learn and train to recognize then classify the correct SL. This challenge can be overcome compared to the main 2 challenges addressed earlier.

In summary, the SLR shows that the environmental factors are a main concern to overcome to ensure that the SL classification system is ready and fully utilized for real-time applications.

V. HARDWARE IMPLEMENTATIONS

In this section, the SL classification system is reviewed only on the hardware implementation of DL vision-based SL classification system used. The hardware are categorized and tabulated with details in Table IV. All of the hardware belongs to different levels of hardware ecosystem. The hardware ranged from specialized hardware like FPGA and SoC (System on Chip) that used for custom applications, to general purpose computing platforms like Graphics Processing Unit (GPU) which are often used for a high-performance task. Moreover, hardware for edge Artificial Intelligence (AI) platforms and embedded computing enable real-time and localized processing. Meanwhile, camera and imaging sensors act as the acquisition tools and help in assessing the data gain for SL classifications.

One of the known hardware in DL-based model deployment is FPGA. FGPA is well known for its ability of parallel processing and low power consumption. For example, in 2021 Wang C. et al. [29] developed a FPGA-based SL classification system that obtained high power efficiency while consume low power in real-time performance. The author also was able to interpret gestures of American SL data into text smoothly with 99.96% accuracy.

Besides FPGA, Graphics Processing Unit (GPU) have been the major contribution of giant technology today that involves the development of deep-learning models. GPU commonly comes with a Central processing unit (CPU) that complements the system for a high-performance hardware in SL classification. In 2024 Singh R. et al. [26] has developed a CPU for SL recognition with transformer-based decoding. The author has achieved computational efficiency and real-time processing of SL with 99.59% accuracy. The hardware capabilities can scale for a complex system to capture complex features and achieve high accuracy results for SL classification. In addition, there is a category named camera and imaging sensors which plays a vital role in capturing variants of data according to respective hardware to be processed by the computer vision algorithm.

Moreover, there are also edge AI platforms that implemented for SL classification. For example, in 2022 Gedkhaw E. [40] developed a system with the NVIDIA Jetson Nano Developer Kit that runs with only 5 watts of power and able to run the CNN at the same time. The author has developed a system that uses low power consumption and as well run it in real time with 99.14% accuracy. This hardware complements the automatic feature extraction process conducted by the DL model within the system for SL classification.

Finally, the embedded computing platform shows an outstanding performance in SL classifications despite the small size of hardware. Most microcontroller functions similarly to FPGA but their capabilities are not on par. This hardware has contributed to AI task execution and edge computing application for SL real-time classification. Raspberry Pi 4 as controller of the system offers a low solutions device with real-time processing capabilities and low latency [46]. This is suitable for a simpler SL classification with low system specifications and requirements.

A. Discussions on hardware implementations for sign language classification system

In this section, the review will be conducted on purpose of the hardware and its contribution to SL applications, especially for real-time applications. Fig. 9 shows the purpose of hardware implementations for SL classification system based on studies published between 2020 and 2024. Based on the SLR, most systems only focus on the execution of real-time applications with comprises of 61% of the studies. Most of these studies don't concern the implementation of hardware but rather focus on the execution of the developed DL model. For example, in 2023 Nareshkumar M. et al [6] developed a DL model architecture that achieved 98.77% by implementing GeForce RTX 4090 GPU machine and outperforming existing state-of-the-art systems.

This hardware, in other terms, generally is a computer, majorly is heavy and bulky hardware. This makes it inconvenient for users as the system is placed static in one position only and require the user to at least within the range of the prototype. This gives an advantage to hardware that focuses on the execution of systems only. This too include the hardware that is utilized only for training which comprises 19% of the overall studies. Therefore, a total of 80% of the overall studies are unfavorable of the contribution of hardware for SL classification and centered around the functionality of the system on the hardware. Looking into the needs of consumer, especially the DHH community, an ideal hardware would provide comfort and require minimal effort of usage [90]. At the same time, it's essential for the system to be practical, user-friendly and accessible.

TABLE IV. HARDWARE IMPLEMENTATION FOR SIGN LANGUAGE CLASSIFICATION SYSTEM

Category	Hardware	Purposes	Accuracy (%)	Studies
FPGA and SoC (System on Chip)	PYNQZ2 development board, ZC7Z020 FPGA chip	Application specific integrated circuit (ASIC)	98.87	[52]
	ZCU 102 SoC Evaluation Board	Application specific integrated circuit (ASIC)	99.96	[29]
	PYNQ Zynq Ultrascale (ZU) FPGA	Application specific integrated circuit (ASIC)	92.00	[44]
Graphics Processing Unit (GPU)	Computer Webcam	For real-time application	99.29	[24]
	Training in computer only	For training	99.80	[25]
	CPU with i7 processor, 32 GB of RAM, 8GB NVIDIA GTX 4060 GPU	For real-time application	99.59	[26]
	Computer Webcam	For real-time application	97.00	[27]
	Computer Webcam	For real-time application	98.07	[28]
	GeForce RTX 4090 GPU machine	For real-time application	99.81	[33]
	Depth camera (OAK-D) + GPU	For real-time application	90.00	[34]
	Mention only computer vision	For real-time application	99.26	[38]
	Computer Webcam	For training	83.58	[39]
	Camera + GPU	For training	89.99	[41]
	Core i9 3.3 GHz CPU with 20 cores	For real-time application	98.80	[45]
	Mention only computer vision	For real-time application	99.99	[47]
	Computer Webcam	For training	92.88	[49]
	Computer Webcam	For real-time application	98.70	[51]
Edge Artificial Intelligence (AI) Platforms	NVIDIA Jetson Nano Developer Kit	AI edge computing	98.77	[6]
	Nvidia Jetson TX2	AI edge computing	90.00	[36]
	NVIDIA Jetson Nano Developer Kit	AI edge computing	99.14	[40]
Specialized Camera and Imaging Sensors with GPUs	Microsoft Kinect V2 + Tesla 100 Machine (GPU)	For real-time application	89.45	[30]
	Digital Camera + Dell OptiPlex 7450 AIO with i7-7500	For real-time application	99.32	[31]
	Leap Motion Controller + i7-3632QM processor	For real-time application	98.00	[32]
	Leap Motion Controller + GPU	For real-time application	97.98	[35]
	Kinect V1 + Kinect V2 + Sony handheld camera + GPU	For real-time application	88.09	[37]
	Event camera DAVIS346 + GPU	For real-time application	77.00	[42]
	Kinect V2 + Intel Xeon CPU and NVIDIA GPU	For real-time application	90.26	[43]
	Mobile camera + i5-5200U @2.20GHz processor	For training	93.68	[48]
	Microsoft Kinect V2 + Leap Motion Controller + Data Glove + i7-4 Gen with a 2.10 GHz processor	For training	99.00	[50]
Embedded Computing Platform	Raspberry Pi 4 Model B microprocessor	For real-time application	99.52	[53]
	Raspberry Pi 4 Model B microprocessor	For real-time application	99.10	[46]

On the other hand, there are 10% of the studies that are utilized for AI edge computing purposes. These hardware such as Nvidia Jetson TX2 involves AI inference for real-time performance to give a refined experience for users [39]. At the same time, it is accessible for users due to its portability. Still, Ai edge platforms pose a risk for SL classification performance due to their lack of computational resources. This may result in slower performance with reduced accuracy.

Lastly, the remaining 10% of the studies are the Application specific integrated circuit (ASIC) purposed hardware. The hardware commonly is FPGA developed by Intel that purposely for the development of ASIC. ASIC is made as an embedded system that can be implanted in small devices and FPGA sets a benchmark for its application. FPGA is capable to fulfil the classification system due to its parallel computing capabilities for high accuracy performance [28]. Moreover, FPGA's scalability allows custom design circuits that can speed up the processing time while on low power consumption[29]. Furthermore, FPGA offers portability and reduced system's complexity with low cost.

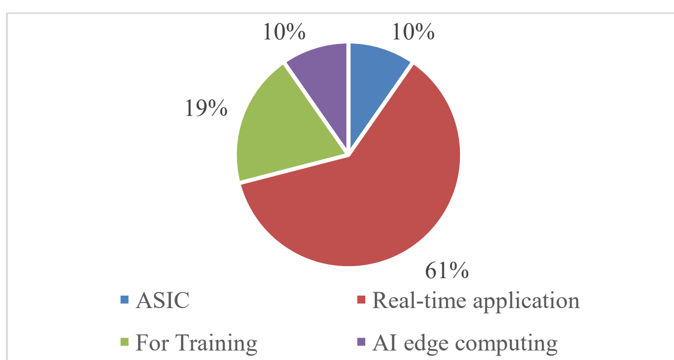

Fig. 9. Hardware implementations for SL classification system.

B. Selection of compatible hardware for sign language classification system.

In this section, the selection of the compatible hardware for SL classification system lies in the performance and efficiency as well as the functionality of the hardware for real-time SL classification application. As most of the hardware listed in Table IV shows similar high accuracy results, another metrics evaluation is conducted. The literature reviews have set demands of hardware with high computational power and high processing speed to achieve the ideal prototype for SL classification system [29], [43]. While most hardware offers flexibility and good optimization, they struggle to fulfil the requirements of large and complex DL models. Additionally, an ideal prototype for real-time application would offer power-efficient solutions to run the SL classification system [31]. The trade off between achieving high performance and maintaining low power consumption sets a benchmark for the ideal prototype for SL classification system in real-time performance.

With the demands of the compatible prototype for SL classification system in real-time performance, FPGA shows the suitable hardware that fits the needs. FPGA offers flexibility in design which is crucial for custom programming and implementation of complex DL models [91]. Moreover, FPGA also has a massive parallel processing design which allows multiple operations to be executed simultaneously and speed up the computation process. Therefore, FPGA is able to run SL classification system efficiently and effectively to achieve high accuracy results. Finally, FPGA is known for its low consumption capabilities compared to other hardware [29]. This proves FPGA able to execute in high performance while maintaining low power consumption.

Thus, FPGA shows a compatible choice of deploying a SL classification system with high performance with low power consumption for a real-time application.

VI. Conclusion

The results of the SLR in this paper give a clearer picture of the three key research for developing a SL classification system prototype based on the different approach of SL classification task, realizing the common challenges of SL classification system and selecting the suitable hardware for real-time implementation. These key points are achieved based on research questions for reviewing past studies published between 2020 and 2024. The selected documents are further analyzed for the SL classification system implemented. The performance of SL classification system is affected by various factors such as the design of the system and its execution in tackling challenges of classification. Based on the SLR, DL vision-based approach has shown a promising choice for SL classification system. However, there are still modifications required to be carried out to overcome the main challenge while achieving high accuracy results which are environmental factors that affect the accuracy result of the system. To deploy the system for real-time application, FPGA appears to be the viable hardware implementation due to its capabilities that meet the high computational demands of the system. With these three factors being emphasized in the future works of the development of SL classification system, more prototypes with high accuracy performance will be developed.

Acknowledgment

The authors would like to give thanks to Universiti Teknologi MARA, Cawangan Pulau Pinang, Permatang Pauh for supporting throughout the research work and studies, especially the members of the Machine Learning Research Group (MLRG), Electrical Engineering Studies, College of Engineering.

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