Deep Learning Method for Sign Language Recognition: A Systematic Literature Review

Sekar Ayu Nadita
Computer Science Department,
School of Computer Science
Bina Nusantara University
Jakarta, Indonesia 11480
sekar.nadita@binus.ac.id

Lavender Nathania Adelya
Computer Science Department,
School of Computer Science
Bina Nusantara University
Jakarta, Indonesia 11480
lavender.adelya@binus.ac.id

Daniel Hendra Susanto
Computer Science Department,
School of Computer Science
Bina Nusantara University
Jakarta, Indonesia 11480
daniel.susanto001@binus.ac.id

Gusti Pangestu
Computer Science Department,
School of Computer Science
Bina Nusantara University
Jakarta, Indonesia 11480
gusti.pangestu@binus.edu

***Abstract*— This systematic literature review will discuss and explore the implementation of different types of artificial intelligence models including deep learning in recognizing and interpreting sign language. Nowadays, communication is an important aspect of human life. However, the communication ability of each human being is not the same, some have limitations in communicating such as deaf and speech impaired people so they need tools such as sign language. Unfortunately, not everyone can understand sign language and it has become a limitation in communication. This encourages researchers to continue developing various systems to solve this problem. In this review, we conducted an in-depth evaluation of 14 published articles that have been published with a focus on developing artificial intelligence systems for sign language recognition. The review was conducted by looking at the models, techniques, accuracy, and datasets used in each article. The expected results will be used as considerations for the creation of more advanced systems in the future. The results show the challenges of AI in understanding complex sign language gestures and expressions, but also show positive progress with various AI models, where ResNet-50 shows the highest accuracy rate reaching 99.98%.**

Keywords—artificial intelligence, deep learning, sign language recognition, AI models

I. Introduction

Communication is a process of transmitting messages used by humans in order to exchange information. Communication empowers people to exchange thoughts, opinions, and their ideas. However, not all individuals exhibit uniform in auditory reception and verbal articulation ability. A World Health Organization (WHO) estimated that in 2019, approximately 466 million people (5% of the world's population) suffered from hearing loss. This includes 432 million (83%) are adults and 34% million (17%) are children. Over time, the WHO anticipates a twofold increase of this disorder that prevents people from communicating like typical humans. Sign language serves as an intermediary tool of communication that is widely used between individuals with speech and hearing impairments [1]. It also bridges the interaction between society and people with such disabilities. Unfortunately, not everyone in their daily lives implemented sign language as their common tool for communication. This situation leads to difficulties for people with hearing impairment to communicate with society [2].

Consequently, many researchers have conducted various studies to develop the solution to address this issue by using the application of artificial intelligence(AI) [3-4]. It requires an AI model that can help improve the use of sign language to high accuracy and speed up communication between disabled and non-disabled. There are several artificial intelligence methods which have been developed by researchers to overcome these obstacles, such as deep learning methods with various AI models. Processing complex spatial and temporal data and interpreting the environment and meaning of sequences of gestures and expressions is a challenge for researchers in building a model to recognize sign language [5].

The objective of this paper is to do a systematic review of the literature to investigate and compare artificial intelligence models used for sign language interpretation. Sign language, a sophisticated system of visual and gestural communication used by the deaf people all over the world, has witnessed tremendous breakthroughs in interpretation in recent decades thanks to the development of various AI models and approaches [6]. Therefore, the research in this field frequently involves the AI models such as CNN, ANN, LSTM, etc in image processing, stir analysis, model evaluating and verbal modeling of sign language interpretation [7][15].

Moreover, the literature review will depict the current advancements and developments in the AI applications used for sign language recognition, in addition to recommendations for upcoming explorations that identified areas which require more focused work to improve the effectiveness and mileage of the system [8].

II. Sign Language Recognition Methods

Researchers classified the system into four different stages of processing images based on the input photos. These stages include hand acquisition and segmentation, feature extraction, classification, and recognition method [9-10][14] as depicted in Fig. 1.

In this part, there are different types of AI models used for recognition and extraction from various datasets such as Continuous sign language recognition (CLSR), Isolated Sign Language Recognition (ISLR), etc [11]. These models include implementations of CNN, ANN, RNN, LSTM, and others.

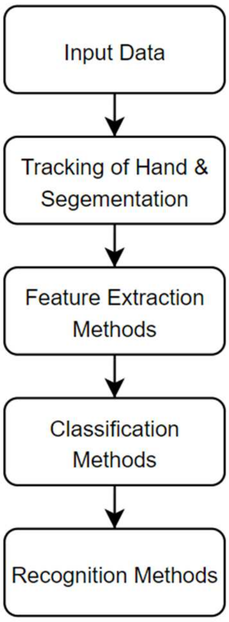

Fig. 1. General Process of Sign Language Recognition.

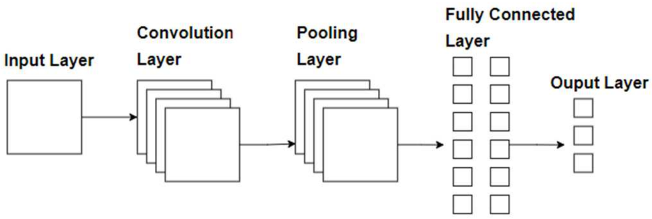

Fig. 2. Convolutional Neural Network Process.

A. *Convolutional Neural Network (CNN)*

The CNN models are widely used for image recognition [13]. This model is also recognized as a shift invariant artificial neural network because it consists of multiple layers such as input, output, and hidden layers. CNNs are formed of many neurons which each receive the input, process, and optionally integrate it with non-linearity [12] as shown in Fig. 2. The most common deep learning models applied to the sign language recognition ConvNet architecture. In general, this architecture leverages the convolution processing by applying a convolution kernel (filter) of a particular length to an image, the computer will obtain new information from the result of the multiplication between sections of the image along with the filters applied [14].

CNN is a very suitable model for image classification. This is reinforced by the fast process of creating artificial neural networks, which allows researchers to create powerful multilayer networks in sign language recognition systems. There are several architectures that implement CNN models such as ResNet, LeNet-5, AlexNet, and others [29].

B. *Artificial Neural Network (ANN)*

The majority of previous researchers have focused on gesture recognition in sign language (SL) using Artificial Neural Networks (ANN), which can also be applied to classifying gestures and extracting hand shapes [29]. ANN is a high-performance information processing system that resembles the characteristics of biological neural networks. Commonly, an ANN algorithm has three main variables such as activation function, binding weights, and the interconnection model between different layers of neurons. A study has presented a system that uses ANN to translate Sign Language, specifically from American Sign Language (ASL) words into English.

C. *Recurrent Neural Network (RNN)*

Regarding sign language recognition systems, a Recurrent Neural Network (RNN) has the capacity of receiving and processing a series of visual representations of sign language gestures by properly considering the temporal context between the sequences of gestures represented in feature vectors.. Furthermore, the RNN also learns the temporal patterns that occur when hand positions form a series of gestures and maintains an internal "memory" that stores information about the previous temporal context.

D. *Long Short-Term Memory (LSTM)*

The LSTM model was proposed by Schmidhuber and Hochreiter to address the issue of networks often vanishing and exploding. In general, the LSTM model is composed of 3 phases with the aim of protecting and controlling the cell state. LSTM also has its key role in sign language recognition for its ability to capture the sequence of hand movements. LSTM is a specifically designed type of RNN to deal with the problem of information loss in traditional RNN systems. Different from previous systems, the long-term memory possessed by the LSTM allows it to perform sign language recognition in a particular order [23]. Hence, this model is also widely used in building systems that can recognize complex patterns in sign language gesture sequences.

III. METHODOLOGY

To accomplish the aim of this paper, the systematic literature review (SLR) involves three principal phases such as Planning the Review, Conducting the Review, and Reporting the Review. The diagram in Fig. 1. shows the main and sub phases of the systematic literature review (SLR) principle. SLR is a methodological process for collecting and summarizing empirical evidence based on the available literature [16]. These phases can be iteratively implemented for the need of additional review.

Summary of the available literatures associated both are relevant and precise AI models developed for recommender models in the context of utilizing artificial intelligence models for sign language recognition based on its accuracy that is emphasized.

Based on the diagram in Fig. 4, there are ten sequence stages of the review protocol. To obtain optimal outcome, it is necessary to implement the sequence prior before conducting the paper review process [17].

First, defining the research question as the essential sequence of the process. During the process of review protocol, research questions played a significant role as the pillar of critical thinking and problem-based that guide the researcher exploring and understanding the related topics [18].

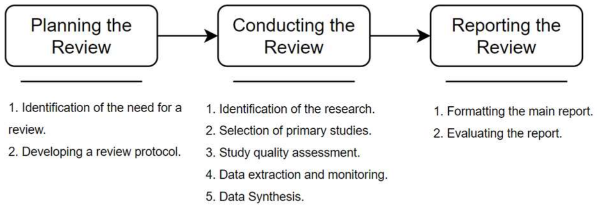

Fig. 3. Systematic Literature Review (SLR) Phases.

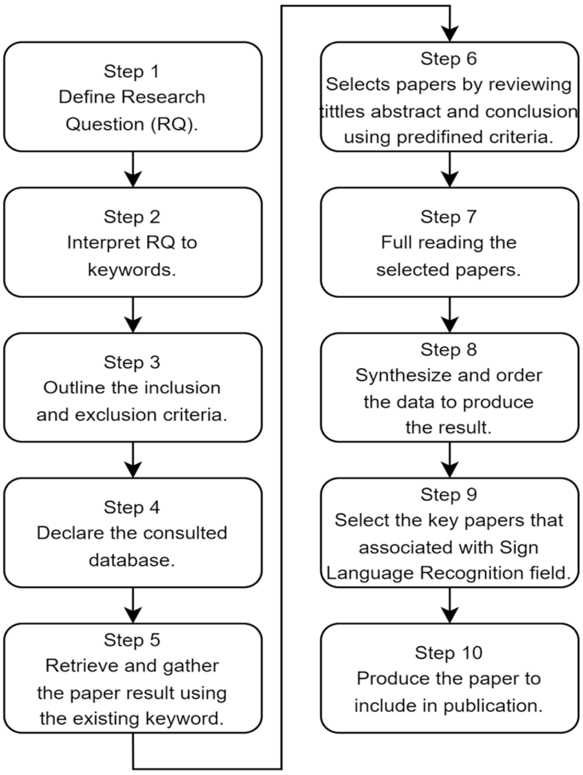

Fig. 4. Review Protocol Stages.

RQ1	What is the main problem?
RQ2	What kind of models are employed?
RQ3	How do the results compare to each model?

Fig. 5. Defined Research Question.

String1	Sign Language Recognition (SLR).
String2	Sign Language Interpretation (SLI).
String3	Sign Language Detection Deep Learning (SLDDL).

Fig. 6. Search Strings.

TABLE I. INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	**Justification**
Published papers in 2019-2024.	Avoiding untested research.
Papers explain sign language recognition utilized AI Models.	Use the most recent paper only.
Paper within credible journal and conference only.	Avoiding unexamined research.
Exclusion Criteria	**Justification**
Paper is not written in English.	Paper must be accomplished using the English language.
Paper is not published.	Focus on primary research.

Fig. 3. showed an example of the associated research question. After the research question has been developed, the next activity is to interpret RQ to the keywords as shown as in Fig. 6.

The next step is making an outline of the inclusion and exclusion shown in Table 1. it should be done to select and specify the data according to the provided criteria. Consequently. The next step is defining credible databases such as Springer, Elsevier, IEEE, Science Direct, etc. The following databases help to uphold a comprehensive exploration and understanding, while optimizing the efficiency of the search process [9]. The fifth step is retrieving and gathering the paper result using the existing keyword. This results in the paper to be removed and choosing the paper that meets the criteria. The sixth step involves selecting the paper for a comprehensive review by its title, abstract, dataset, models, methods, etc.

The seventh step is conducting a comprehending reading of papers already selected before. The step is undertaken to understand the process, methods, and outcomes that can be found within the paper. Moreover, synthesize and compare the data to produce the result related to the most accurate AI models applying for sign language recognition. Finally, the following steps are selecting the key papers that are associated with sign language recognition utilizing AI Models and producing the paper to be submitted in the international publication.

IV. RESULT AND DISCUSSION

In this chapter, the focus is on obtaining the results of a systematic literature review of several papers that illustrate the use of deep learning methods in understanding and translating sign language. This process involves searching and filtering papers from various data sources by focusing on the application of deep learning technology in sign language recognition. The search and filtering step is performed from the database according to the string specified in Fig. 2 into the search results in Table II.

TABLE II. SEARCH RESULT

Topic	Review	Deep Review	Relevant	Selected
SLR	12	8	5	5
SLI	12	5	3	1
SLDDL	26	15	11	9
TOTAL	**50**	**28**	**19**	**15**

TABLE III. SELECTION OF PAPERS BASED ON DATABASE AND YEAR OF PUBLICATION

Database	Years						Total
	2019	2020	2021	2022	2023	2024	
MDPI	0	1	0	0	2	1	**4**
IEEE	3	3	0	0	0	1	**7**
Springer	0	0	1	0	0	0	**1**
Science Direct	0	1	1	0	1	0	**3**
TOTAL	**3**	**5**	**2**	**0**	**3**	**2**	**15**

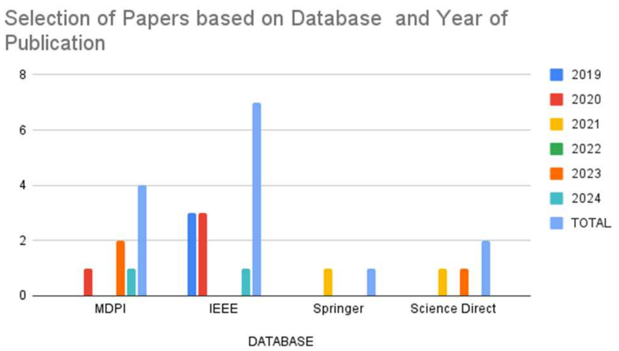

Fig. 7. Selection of Papers based on Database and Year of Publication

TABLE IV. SELECTION OF PAPERS BASED ON REGIONS

Regions	Topics			Total
	SLR	SLI	SLDDL	
Asia	1	0	2	**3**
Europe	0	1	0	**1**
Global	4	0	7	**11**
TOTAL	**5**	**1**	**9**	**15**

A summary of the search and filtering results is presented in Table III, which illustrates the publication period of the papers, the databases used, and the distribution of the research by geographic region. For graphical details in Table III, please refer to Fig. 7, where the papers we filtered are mostly found in the IEEE database with a total of 7 papers. Based on the location of the research results, most of them are located in Asia, Europe, and several global regions. More detailed information can be seen in Table IV.

Furthermore, this chapter will discuss the Research Question (RQ) that has been made in Fig. 5. From the papers we have selected, we can answer basic questions that include what, why, how, when, where, and who in accordance with the topic to be discussed. The thing to do is to analyze starting from the method used, the accuracy results based on the method used, and sort out the data from each paper that seems important. With this, we can answer the Research Question (RQ).

A. *RQ 1, What is the main problem?*

In everyday life, communication is important and is always practiced by the general public. However, there are challenges for hearing and speech impaired individuals that make communication difficult due to the limited sign language available in the community. Although sign language is important to them, people still rarely use it. With the development of AI, it can help people with disabilities to communicate. Because in the development of AI, it can help to recognize and understand sign language. But it is not easy to get the highest complexity of sign language in hand gestures and facial expressions. So, that is the challenge for AI developers to get the highest and best complexity.

B. *RQ 2, What kind of models are employed?*

From the 14 selected papers, there are various methods and models in AI used to recognize, understand, and translate sign language. There are many good and highly accurate methods such as Convolutional Neural Network (CNN), there are also models of RNN such as Long Short-Term Memory Recurrent Neural Network (LSTM-RNN), and Deep Convolutional Neural Network (DeepConvLSTM), and there are also combinations of various methods such as Sensor-fusion, DCT & KNN, and Xception & CNN. Each technique has its own way of processing and analyzing sign language data. The accuracy of the various techniques varies; ResNet-50 has the highest accuracy with 99.98% accuracy [33], while ResNet-34 CNN recorded the lowest accuracy of 78.5% [34]. However, methods such as LSTM-RNN, DeepLabv3+, and Xception & CNN also stand out with accuracies above 90%.

C. *RQ 3, How do the results compare to each model?*

Based on Table V, the highest accuracy result of 99.98% is the ResNet-50 method [33]. Then, the lowest accuracy result of 78.5% is the ResNet-34 CNN method[34]. Although ResNet-50 is the method with the most accurate accuracy, there are other methods whose accuracy reaches 99%, namely LSTM-RNN with Sensor-fusion [23], there is DeepLabv3 with CSOM & BiLSTMNet around 89.5%, and Xception & CNN around 98.93%. Other methods such as DCT & KNN around 87% and DeepConvLSTM & CNN around 91.1%, and others.

TABLE V. TABLE OF THE ACCURACY

Ref	Method Recognition	Accuracy Outcome
[19]	CNN	98.9%
[25]	LSTM-RNN	91.8%
[23]	LSTM-RNN, Sensor-fusion	99%
[31]	DeepLab v3+, CSOM, & BiLSTMNet	89.5%
[26]	DCT & KNN	87%

Ref	Method Recognition	Accuracy Outcome
[19]	CNN	98.9%
[21]	DeepConvLSTM and CNN	91.1%
[29]	ANN	86.9%
[30]	Xception & CNN	98.93%
[27]	TCN, GCN, & GCAR	90.31%
[22]	CNN & DNN	98.65%
[28]	3DCNN & MLP	84.38%
[34]	ResNet-34 CNN	78.5%
[24]	CNN & SVM	98.30%
[32]	ConvLSTM	95,6%
[33]	ResNet-50	99,98%

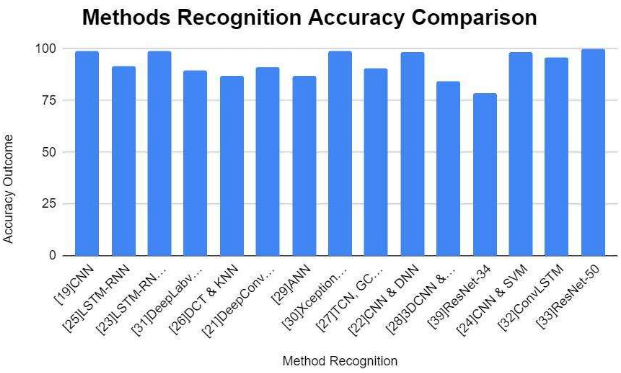

Fig. 8. Sign Language Recognition Methods List and Its Accuracy

There are 3 methods with the highest accuracy including ResNet-50, LSTM-RNN & Sensor-fusion, and Xception & CNN. They are methods used in artificial intelligence applications and have their own advantages. For ResNet-50, it has an advanced deep learning architecture and is popular for its ability to handle deep network degradation problems. For LSTM-RNN & Sensor-fusion has superior temporal and multi-sensor data processing, so it is very effective in information processing. And Xception & CNN have advantages in computational efficiency and excellent performance.

With this discussion, it can be concluded that the existence of various AI methods for interpreting sign language and the growing technology can increase the chance of performance to achieve high accuracy.

V. CONCLUSION

Based on the literature review that has been discussed, AI technology methods have been found to be developed in translating and recognizing sign language. Starting from the most frequently used methods and their accurate results reach 90% such as CNN and there are combination methods from other techniques such as LSTM-RNN & Sensor-fusion, Xception & CNN, CNN & DNN, CNN & SVM. The method with the highest accuracy of 99.98% is the ResNet-50 method, while the method with the lowest accuracy of 78.5% is the ResNet-34 CNN method. Although a method with 100% accuracy has been found, there is still a big challenge due to the complexity of movements such as hand movements and facial expressions.

The implications of this research are valuable for technology developers by providing reference material and inspiration for other innovations in the application of deep learning technology in sign language interpretation. By the results obtained, it helps researchers to discover which deep learning model offers the best accuracy for further innovation. It also brings significant implications for the deaf community in order to improve their quality of life in various aspects by facilitating communication with the wider community.

Through the development of artificial intelligence, the opportunity to improve accuracy is still open. Further research is encouraged by emphasizing the development of more advanced deep learning algorithms to interpret sign language continuously in real-time following the rapid communication. In particular, continuous evaluation is required to improve the functionality of the implementation of this technology by integrating several fields of knowledge such as language, computer science, and psychology for long-term development. Furthermore, extensive research should be conducted to support and minimize the limitations for individuals with hearing and speech impairments as well as the community.

REFERENCES

[1] I. Papastratis, C. Chatzikonstantinou, D. Konstantinidis, K. Dimitropoulos, and P. Daras, “Artificial Intelligence Technologies for sign language,” *Sensors*, vol. 21, no. 17, p. 5843, Aug. 2021. doi:10.3390/s21175843.

[2] S. Siddique et al., “Deep learning-based Bangla sign language detection with an edge device,” *Intelligent Systems with Applications*, vol. 18, p. 200224, May 2023. doi:10.1016/j.iswa.2023.200224.

[3] [1] Suharjito, R. Anderson, F. Wiryana, M. C. Ariesta, and G. P. Kusuma, “Sign language recognition application systems for deaf-mute people: A review based on input-process-output,” *Procedia Computer Science*, vol. 116, pp. 441–448, 2017. doi:10.1016/j.procs.2017.10.028.

[4] M. Alaghband, H. R. Maghroor, and I. Garibay, “A survey on Sign Language Literature,” *Machine Learning with Applications*, vol. 14, p. 100504, Dec. 2023. doi:10.1016/j.mlwa.2023.100504.

[5] Pfister, T., Charles, J. and Zisserman, A. (2015). Flowing ConvNets for human pose estimation in videos, *2015 IEEE International Conference on Computer Vision (ICCV)*, Santiago, Chile, pp. 1913–1921.

[6] Md. M. Hasan, A. Y. Srizon, A. Sayeed, and Md. A. Hasan, “Classification of sign language characters by applying a deep convolutional neural network,” *2020 2nd International Conference on Advanced Information and Communication Technology (ICAICT)*, Nov. 2020. doi:10.1109/icaict51780.2020.9333456.

[7] L. Gao, W. Feng, F. Lyu, and L. Wan, “Combinational sign language recognition,” *Computer Vision and Image Understanding*, vol. 241, p. 103972, Apr. 2024. doi:10.1016/j.cviu.2024.103972.

[8] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, "Connectionist Temporal Classification: Labelling Unsegmented Sequence Data with Recurrent Neural Networks," *in Proceedings of the 23rd International Conference on Machine Learning*, 2006, pp. 369-376.

[9] I. A. Adeyanju, O. O. Bello, and M. A. Adegboye, “Machine learning methods for sign language recognition: A critical review and analysis,” *Intelligent Systems with Applications*, vol. 12, p. 200056, Nov. 2021. doi:10.1016/j.iswa.2021.200056.

[10] M. Papatsimouli, P. Sarigiannidis, and G. F. Fragulis, “A survey of advancements in real-time sign language translators: Integration with IOT Technology,” *Technologies*, vol. 11, no. 4, p. 83, Jun. 2023. doi:10.3390/technologies11040083.

[11] I. Papastratis, C. Chatzikonstantinou, D. Konstantinidis, K. Dimitropoulos, and P. Daras, “Artificial Intelligence Technologies for sign language,” *Sensors*, vol. 21, no. 17, p. 5843, Aug. 2021. doi:10.3390/s21175843.

[12] Z. Zhang, L. Yang, Yefeng Zheng, Chapter 8 - Multimodal medical volumes translation and segmentation with a generative adversarial network, Editor(s): S. Kevin Zhou, Daniel Rueckert, Gabor Fichtinger, Handbook of Medical Image Computing and Computer-Assisted Intervention, Academic Press,2020, Pages 183-204

[13] D. Bala et al., "Effective recognition system of american sign language alphabets using machine learning classifiers, Ann and CNN," *2022 IEEE Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, Dec. 2022. doi:10.1109/iatmsi56455.2022.10119336.

[14] H. Orovwode, I. D. Oduntan, and J. Abubakar, "Development of a sign language recognition system using machine learning," *2023 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*, Aug. 2023. doi:10.1109/icabcd59051.2023.10220456.

[15] H. Alsolai et al., "Automated sign language detection and classification using reptile search algorithm with hybrid deep learning," *Heliyon*, vol. 10, no. 1, Jan. 2024. doi:10.1016/j.heliyon.2023.e23252.

[16] A. Bajaj and O. P. Sangwan, "A systematic literature review of test case prioritization using genetic algorithms," *IEEE Access*, vol. 7, pp. 126355–126375, 2019. doi:10.1109/access.2019.2938260.

[17] C. Huda, A. Ramadhan, A. Trisetyarso, E. Abdurachman, and Y. Heryadi, "Smart tourism recommendation model: A systematic literature review," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 12, 2021. doi:10.14569/ijacsa.2021.0121222.

[18] M.-S. Hosseini, F. Jahanshahlou, M. A. Akbarzadeh, M. Zarei, and Y. Vaez-Gharamaleki, "Formulating research questions for evidence-based studies," *Journal of Medicine, Surgery, and Public Health*, vol. 2, p. 100046, Apr. 2024. doi:10.1016/j.glmedi.2023.100046.

[19] N. F. Attia, M. T. Ahmed, and M. A. M. Alshewimy, "Efficient deep learning models based on tension techniques for sign language recognition," *Intelligent Systems with Applications*, vol. 20, p. 200284, Nov. 2023. doi:10.1016/j.iswa.2023.200284.

[20] S. Sharma, R. Gupta, and A. Kumar, "Continuous sign language recognition using isolated signs data and deep transfer learning," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 3, pp. 1531–1542, Aug. 2021. doi:10.1007/s12652-021-03418-z.

[21] Hernandez V, Suzuki T, Venture G (2020) Convolutional and recurrent neural network for human activity recognition: Application on American sign language. PLoS ONE 15(2): e0228869. https://doi.org/10.1371/journal.pone.0228869.

[22] M. Mosleh, A. Assiri, A. H. Gumaei, B. F. Alkhamees, and M. Al-Qahtani, "A bidirectional Arabic sign language framework using Deep Learning and fuzzy matching score," *Mathematics*, vol. 12, no. 8, p. 1155, Apr. 2024. doi:10.3390/math12081155.

[23] B. G. Lee, T.-W. Chong, and W.-Y. Chung, "Sensor fusion of motion-based Sign language interpretation with deep learning," *Sensors*, vol. 20, no. 21, p. 6256, Nov. 2020. doi:10.3390/s20216256.

[24] H. B. D. Nguyen and H. N. Do, "Deep Learning for American Sign Language Fingerspelling Recognition System," *2019 26th International Conference on Telecommunications (ICT)*, Hanoi, Vietnam, 2019, pp. 314-318, doi: 10.1109/ICT.2019.8798856.

[25] C. K. M. Lee et al., "American Sign Language Recognition and training method with recurrent neural network," *Expert Systems with Applications*, vol. 167, p. 114403, Apr. 2021. doi:10.1016/j.eswa.2020.114403.

[26] T. Shanableh and K. Assaleh, "User-independent recognition of Arabic sign language for facilitating communication with the deaf community," *Digital Signal Processing*, vol. 21, no. 4, pp. 535–542, 2020.

[27] A. S. M. Miah, M. A. M. Hasan, S. Nishimura and J. Shin, "Sign Language Recognition Using Graph and General Deep Neural Network Based on Large Scale Dataset," *in IEEE Access*, vol. 12, pp. 34553-34569, 2024, doi: 10.1109/ACCESS.2024.3372425.

[28] M. Al-Hammadi, G. Muhammad, W. Abdul, M. Alsulaiman, M. A. Bencherif and M. A. Mekhtiche, "Hand Gesture Recognition for Sign Language Using 3DCNN," *in IEEE Access*, vol. 8, pp. 79491-79509, 2020, doi: 10.1109/ACCESS.2020.2990434.

[29] S. Hayani, M. Benaddy, O. El Meslouhi and M. Kardouchi, "Arab Sign language Recognition with Convolutional Neural Networks," *2019 International Conference of Computer Science and Renewable Energies (ICCSRE)*, Agadir, Morocco, 2019, pp. 1-4, doi: 10.1109/ICCSRE.2019.8807586.

[30] P. P. Urmee, Md. A. Mashud, J. Akter, A. S. Jameel, and S. Islam, "Real-time bangla sign language detection using XCEPTION model with augmented dataset," *2019 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE)*, Nov. 2019. doi:10.1109/wiecon-ece48653.2019.9019934.

[31] S. Aly and W. Aly, "DeepArSLR: A Novel Signer-Independent Deep Learning Framework for Isolated Arabic Sign Language Gestures Recognition," *in IEEE Access*, vol. 8, pp. 83199-83212, 2020, doi: 10.1109/ACCESS.2020.2990699.

[32] T. Adão et al., "Empowering deaf-hearing communication: Exploring Synergies between predictive and generative AI-based strategies towards (Portuguese) sign language interpretation," *Journal of Imaging*, vol. 9, no. 11, p. 235, Oct. 2023. doi:10.3390/jimaging9110235.

[33] B. Alsharif, A. S. Altaher, A. Altaher, M. Ilyas, and E. Alalwany, "Deep Learning Technology to recognize American sign language alphabet," *Sensors*, vol. 23, no. 18, p. 7970, Sep. 2023. doi:10.3390/s23187970

[34] P. Kurhekar, J. Phadtare, S. Sinha and K. P. Shirsat, "Real Time Sign Language Estimation System," *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, Tirunelveli, India, 2019, pp. 654-658, doi: 10.1109/ICOEI.2019.8862701.