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Review on Emergency Alerts using Sign Language Recognition

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Abstract: *Sign language is a vital form of communication for individuals with hearing and speech impairments, yet it remains incomprehensible to the general population, creating a significant communication barrier. This project aims to develop a highly accurate and efficient sign language recognition system using deep learning techniques, specifically Convolutional Neural Networks (CNNs) and transfer learning with VGG16, to interpret Indian Sign Language (ISL). The system translates these gestures into readable text by recognizing static hand gestures representing alphabets and numerals in ISL, enabling seamless communication between sign language users and the general population. The proposed system addresses the limitations of traditional glove-based recognition systems, offering a vision-based method that enhances accuracy and usability. The project focuses on preprocessing noisy datasets, applying thresholding techniques for segmentation, and using CNN and VGG16 to train and classify hand gestures. The expected outcomes include high accuracy rates for gesture recognition, real-time performance, and a user-friendly interface, significantly improving communication for individuals with hearing impairments.*

Keywords: Sign Language Recognition, Indian Sign Language (ISL), Convolutional Neural Networks (CNN), Deep Learning, Transfer Learning, VGG16, Gesture Recognition, Image Classification, Communication Barrier, Hearing Impairment.

I. INTRODUCTION

The ability to communicate is fundamental to human interaction, enabling individuals to convey thoughts, share ideas, and connect socially. However, individuals with hearing and speech impairments often face significant communication barriers when interacting with those unfamiliar with sign language, their primary communication means. This gap restricts their participation in social, educational, and professional settings, underscoring the need for effective automated sign language recognition systems to bridge this divide.

Traditional approaches to sign language recognition, such as glove-based systems, have been explored. Although effective, these systems often have limitations, including bulky designs, high costs, and limited applicability in real-world environments [1]. Vision-based approaches that use image processing and machine learning algorithms provide a more scalable and practical alternative. However, many of these systems lack the robustness for accurate real-time recognition of complex hand shapes and finger orientations, particularly in dynamic and varied environments [2].

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and transfer learning, offer new potential for overcoming the limitations of traditional sign language recognition systems. CNNs have demonstrated significant success in image classification by learning hierarchical features from input images, making them suitable for recognizing static hand gestures in sign language [3]. Using models like VGG16, transfer learning allows systems to utilize pre-trained models on extensive datasets, enhancing accuracy and reducing the need for large, task-specific datasets [4].

This study proposes a deep learning-based system designed specifically for Indian Sign Language (ISL). It presents unique challenges due to its extensive set of gestures and lack of standardized datasets. By employing CNNs and transfer learning, the proposed system aims to recognize static hand gestures in ISL and convert them into readable text, facilitating communication for individuals with hearing impairments. This approach addresses several limitations of previous systems, offering improvements in accuracy, real-time performance, and accessibility. The research contributes to an inclusive, technology-driven solution for human-computer interaction, aiming to enhance social integration and independence for the deaf and speech-impaired communities.

A. Scope and Objectives

This paper aims to develop and evaluate a deep learning-based system for static gesture recognition in Indian Sign Language (ISL) to reduce the communication gap between the hearing-impaired community and the general public. Utilizing Convolutional Neural Networks (CNNs) and transfer learning, specifically with the VGG16 model, the proposed system offers a practical, vision-based solution that overcomes the limitations of traditional glove-based and existing vision-based methods. This study explores various aspects of CNN and transfer learning applications for ISL, developing a robust image preprocessing and segmentation approach to enhance the system's accuracy. Additionally, the scope extends to evaluating the system's performance in varied environmental conditions to assess its real-world applicability.

The primary objectives of this paper are as follows. First, to design and implement a deep learning-based recognition system that accurately interprets static hand gestures in ISL and translates them into readable text. This objective addresses the need for an effective communication aid for individuals with hearing impairments. Second, the paper aims to leverage CNNs to recognize complex hand shapes, orientations, and features in static images, thereby ensuring precise gesture identification. Another objective is incorporating transfer learning with VGG16, which enhances model performance and reduces training time by utilizing pre-trained knowledge from large datasets. Furthermore, the study emphasizes developing preprocessing techniques, such as noise reduction and segmentation, that isolate and highlight essential gesture features, improving recognition reliability. Finally, the paper aims to evaluate and compare the performance of CNNs and transfer learning models through metrics like accuracy, precision, recall, F1 score, and real-time processing capabilities, ensuring that the proposed system can meet the demands of practical, everyday use.

II. LITERATURE SURVEY

J. Koller et al. (2020) [5] presented a detailed review of deep learning methods in SLR, focusing on the shift from traditional machine learning techniques to advanced neural networks like CNNs and RNNs. By examining various architectures, the authors demonstrate how CNNs excel at feature extraction, which is crucial for interpreting static and dynamic gestures. RNNs, particularly LSTM models, handle sequential data, enabling the recognition of gesture transitions. This work underscores the importance of selecting appropriate models for SLR tasks and highlights challenges such as the scarcity of large datasets and high computational requirements for real-time applications. The review sets a foundation for future work, pointing towards integrating transfer learning and multimodal approaches for increased robustness and accuracy in diverse settings.

M. Ghadami et al. (2024) [6] proposed a transformer-based multi-stream approach for isolated Iranian Sign Language recognition, utilizing transformers to manage complex, sequential data efficiently. The multi-stream architecture allowed for the simultaneous processing of multiple input modalities, which proved advantageous in distinguishing subtle variations in hand gestures. The study reported a marked improvement in recognition accuracy, attributed to the transformer's attention mechanism, which focuses on relevant features while ignoring background noise. Although designed for a specific sign language, this approach offers valuable insights into the adaptability of transformers in SLR. Ghadami’s work suggests that transformers, commonly used in natural language processing, can effectively enhance gesture recognition and be applied to other global sign languages.

A. Alyami and R. Luqman (2024) [7] examined continuous SLR by comparing temporal modeling techniques across various datasets and sign languages. This study addresses a critical challenge in SLR—recognizing dynamic gestures that involve fluid hand movements and transitions. The authors compared methods like 3D CNNs, LSTM, and GRU, identifying that 3D CNNs excel in capturing spatial features, while LSTMs are superior in temporal handling. They recommend a hybrid approach combining CNN and LSTM for continuous SLR tasks. The study highlights the need for comprehensive datasets to improve the generalizability of models across languages and emphasizes the significance of real-time processing capabilities for practical applications.

C. Töngi (2021) [8] explored the application of transfer learning in SLR using an inflated 3D CNN for German Sign Language, built upon pre-trained models trained on American Sign Language data. This approach helped overcome the challenges of limited annotated data by transferring learned knowledge from one sign language to another. The model demonstrated impressive accuracy improvements in static and dynamic gesture recognition, showing transfer learning's potential to bridge the data gap in underrepresented sign languages. This study underlines the value of transfer learning in SLR and suggests that pre-trained models could provide a foundation for recognizing less-studied languages.

W. Zhang et al. (2023) [9] introduced a multimodal sensor-based system integrating data from bending sensors with computer vision for Japanese Sign Language recognition. By fusing information from visual and sensor inputs, the system improved its ability to interpret complex gestures, especially in conditions with partial occlusions. This study showcases the potential of multimodal approaches in SLR, enhancing recognition accuracy through data fusion. Zhang's work suggests that sensor integration can help address limitations in traditional vision-based methods, especially in real-world environments with challenging lighting or movement restrictions.

S. Alam et al. (2023) [10] developed "ASL Champ!", a virtual reality game for American Sign Language learners, integrating deep learning-based sign recognition in a real-time, interactive platform. By combining sign recognition with VR, the system offered an engaging educational tool for users to learn ASL in an immersive environment. The authors demonstrated that real-time SLR applications could extend beyond simple translation, supporting education and enhancing learning experiences. This study provides evidence of SLR's potential to impact educational technology, particularly in gamified learning, making ASL accessible to a broader audience.

T. Nakamura and M. Ito (2021) [11] investigated hand pose estimation for SLR using 3D CNNs and depth sensors. Their approach leveraged depth data to enhance recognition accuracy by capturing the hand's spatial positioning and orientation. The authors found that depth information significantly improved the model's ability to recognize gestures in varied lighting conditions, reducing the impact of shadows and background noise. This study demonstrates the benefits of incorporating 3D data in SLR, which could be particularly useful for complex sign languages with subtle finger movements.

H. Chang et al. (2022) [12] applied a hybrid approach combining CNN and LSTM networks for continuous American Sign Language recognition. The model achieved high accuracy in recognizing gesture sequences using CNN for feature extraction and LSTM for sequential processing. This work emphasizes the effectiveness of hybrid models in handling dynamic, continuous gestures and highlights the importance of capturing both spatial and temporal information in SLR.

Y. Li and X. Wang (2022) [13] introduced an attention-based model for SLR, which dynamically focuses on critical gesture regions while ignoring irrelevant background features. The model, based on attention mechanisms commonly used in NLP, demonstrated significant improvements in accuracy for Chinese Sign Language recognition. This approach shows the potential of attention mechanisms to refine SLR models by emphasizing relevant visual details, making the system more robust against background noise.

R. Gupta et al. (2023) [14] explored real-time SLR for Indian Sign Language using transfer learning and mobile deployment. The model, built upon MobileNetV2, achieved high accuracy while maintaining computational efficiency, enabling deployment on mobile devices. This study demonstrates the feasibility of mobile-based SLR solutions, which could significantly enhance accessibility for users in low-resource settings.

J. Kim and P. Johnson (2021) [15] developed a CNN-based model employing data augmentation techniques to enhance recognition accuracy for American Sign Language (ASL). By introducing diverse hand shapes, orientations, and variations in lighting conditions into the training dataset, the model's robustness and generalization capability improved significantly, allowing it to perform well across various real-world scenarios. This augmentation helped address the common issue of overfitting in deep learning models, where limited diversity in training data can cause models to perform poorly in variable environments. This study underscores the necessity of data diversity in SLR models, especially for practical applications where gestures vary in hand shape, position, and lighting. The findings emphasize

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that thoughtful data augmentation is crucial in SLR model development, particularly for scalable, real-world deployments.

L. Tang et al. (2023) [16] examined the impact of transfer learning on SLR for low-resource languages, explicitly focusing on Korean Sign Language. They used pre-trained CNN models from larger datasets, such as ImageNet, and fine-tuned them for Korean sign gestures, achieving high recognition accuracy even with limited native data. The model could capitalize on generalized visual features learned from larger datasets by employing transfer learning, enhancing performance without needing extensive labeled data in Korean Sign Language. This study illustrates the value of transfer learning in making SLR more accessible globally, especially for languages with fewer resources. The approach is a model for adapting SLR to underrepresented languages and offers a cost-effective solution for expanding SLR technology across diverse linguistic contexts.

N. Patel and A. Shah (2023) [17] employed Generative Adversarial Networks (GANs) to create synthetic hand gesture data, addressing the common challenge of limited labeled datasets in SLR. By generating realistic synthetic gestures, the GAN-based approach significantly increased the size and diversity of the training dataset, enhancing the overall recognition accuracy of the SLR model. The augmented dataset included a broader range of gestures, hand positions, and orientations, which improved the model's robustness in recognizing various signs. This innovative use of GANs showcases its potential for data augmentation in SLR, especially for languages and sign variations where annotated data is scarce. Patel and Shah's work highlights GANs as a viable solution for overcoming data limitations in SLR, suggesting that synthetic data generation could be a crucial tool in SLR research and application development.

D. Lee et al. (2024) [18] developed a multi-task learning framework for SLR, integrating hand shape recognition and gesture classification to improve the model's overall accuracy and generalization ability. Multi-task learning allowed the model to learn complementary features across related tasks, thus enhancing its generalization capacity across different signs and gestures. This framework was particularly beneficial for complex gestures, where hand shape is essential for accurate recognition. The model achieved higher recognition accuracy and demonstrated greater adaptability to unseen gestures by learning from multiple related tasks. This study illustrates the potential of multi-task learning to create robust SLR systems capable of handling intricate gestures, offering a promising direction for future SLR research and real-world applications.

K. Singh et al. (2022) [19] introduced a transfer learning-based framework for Indian Sign Language (ISL) by combining CNNs with VGG19. This approach utilized VGG19's deep feature extraction capabilities to achieve high accuracy in static gesture recognition for ISL, which has a limited annotated dataset. Transfer learning enabled the model to leverage features learned from larger datasets, improving performance and reducing the computational resources needed for training. The study demonstrates the suitability of VGG-based models for SLR, especially in low-resource settings where data collection is challenging. Singh et al.'s work suggests that transfer learning can facilitate the development of effective SLR models for less commonly represented languages, thus enhancing the accessibility and scalability of SLR technology.

III. SYSTEMATIC REVIEW

The summary of the literature reviews is presented in Table I.

Table 1: Systematic Review

Sr. No	Authors	Title of the project	Year of Publication	Methodology	Research gap
1	J. Koller et al. [5]	Deep Learning Methods in SLR	2020	Review of deep learning methods in SLR, focusing on CNN and RNN models	Challenges include limited large datasets and high computational needs
2	M. Ghadami et al. [6]	Transformer-based Multi-Stream Approach	2024	Transformer-based multi-stream approach for isolated	Applicability of transformer-based

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		for Isolated Iranian Sign Language		sign language recognition	model for other sign languages
3	A. Alyami and R. Luqman [7]	Temporal Modeling Techniques for Continuous SLR	2024	Comparison of temporal modeling techniques like 3D CNN, LSTM, and GRU	Need for comprehensive datasets for generalizability
4	C. Tangi [8]	Transfer Learning in German Sign Language using Inflated 3D CNN	2021	Transfer learning using inflated 3D CNN on German Sign Language	Transfer learning potential for underrepresented languages
5	W. Zhang et al. [9]	Multimodal Sensor-based System for Japanese Sign Language	2023	Multimodal sensor-based system integrating bending sensors with computer vision	Multimodal approaches' effectiveness in real-world conditions
6	S. Alam et al. [10]	ASL Champ! Virtual Reality Game for ASL Learners	2023	Virtual reality game for ASL learners with deep learning-based sign recognition	Potential of SLR in educational technology and gamified learning
7	T. Nakamura and M. Ito [11]	Hand Pose Estimation using 3D CNN and Depth Sensors	2021	3D CNN and depth sensor for hand pose estimation	Benefits of depth data for complex sign languages
8	H. Chang et al. [12]	Hybrid CNN-LSTM Approach for Continuous American Sign Language	2022	Hybrid CNN-LSTM model for continuous sign language recognition	Effectiveness of hybrid models for spatial-temporal recognition
9	Y. Li and X. Wang [13]	Attention-based Model for Chinese Sign Language	2022	Attention-based model focusing on gesture regions for Chinese Sign Language	Enhancing SLR robustness using attention mechanisms
10	R. Gupta et al. [14]	Real-Time SLR for Indian Sign Language using Transfer Learning	2023	MobileNetV2 with transfer learning for Indian Sign Language Recognition	Feasibility of mobile-based SLR solutions for accessibility
11	J. Kim and P. Johnson [15]	CNN-based Model with Data Augmentation for ASL	2021	CNN model with data augmentation for improved ASL recognition	Necessity of data diversity to improve model generalization
12	L. Tang et al. [16]	Impact of Transfer Learning on Korean Sign Language	2023	Transfer learning with pre-trained CNN models for Korean Sign Language	Adapting SLR to low-resource languages using transfer learning
13	N. Patel and A. Shah [17]	Synthetic Gesture Data Generation using GANs	2023	GANs to create synthetic hand gesture data for SLR	Synthetic data generation as a tool to overcome data scarcity
14	D. Lee et al.	Multi-Task Learning	2024	Multi-task learning	The potential of

	[18]	Framework for SLR		framework integrating hand shape and gesture classification	multi-task learning for intricate gesture recognition
15	K. Singh et al. [19]	Transfer Learning Framework for Indian Sign Language using VGG19	2022	Transfer learning-based framework using VGG19 for Indian Sign Language	Transfer learning to facilitate low-resource SLR development

IV. DISCUSSION

The advancements in Sign Language Recognition (SLR) over recent years have significantly enhanced the field's accuracy, robustness, and real-time applicability. A comparative analysis of methodologies reveals that convolutional neural networks (CNNs) have become foundational in SLR for their ability to capture spatial features crucial for static gesture recognition. However, recent studies also show that hybrid models, such as CNN-LSTM and transformer-based architectures, offer substantial improvements, particularly for continuous SLR, where temporal information is critical. These hybrid models effectively address the limitations of CNNs alone by combining spatial and temporal data processing, thus enabling models to better recognize complex, sequential gestures.

An essential factor contributing to the success of SLR models is data diversity. Studies have shown that data augmentation and synthetic data generation through Generative Adversarial Networks (GANs) provide vital improvements, especially in low-resource settings. This approach addresses the scarcity of labeled data by generating realistic training samples, which helps models generalize better to real-world scenarios where variations in hand shape, lighting, and background are common. Additionally, transfer learning has proven valuable, as demonstrated by models that leverage pre-trained weights from larger datasets to adapt to less-represented sign languages, including Korean, Indian, and German sign languages. Transfer learning not only reduces the need for extensive native datasets but also accelerates the development of SLR systems for underrepresented languages.

Emerging techniques such as attention mechanisms and multimodal approaches enhance SLR's robustness. Attention mechanisms allow models to focus on gesture-relevant regions within an image, reducing the impact of irrelevant background noise, a common issue in real-world environments. Meanwhile, multimodal systems that integrate additional sensory data, such as depth sensors or bending sensors, provide better recognition accuracy under challenging conditions, such as occlusions or low lighting. This data fusion helps the models interpret complex gestures more reliably and offers practical solutions for scenarios where traditional vision-based methods fall short.

While these advancements demonstrate significant progress, several challenges remain. Real-time SLR, especially on mobile and low-power devices, poses a challenge due to the high computational demands of deep learning models. Lightweight architectures, such as MobileNetV2, and model optimization techniques are critical for enabling real-time applications on mobile devices. Additionally, there is a need for standardized and comprehensive datasets to improve model generalizability across different sign languages and regional dialects.

Integrating hybrid deep learning architectures, transfer learning, and multimodal approaches has propelled SLR toward practical, real-time applications. Future research should focus on refining these models for deployment on low-resource devices, expanding dataset diversity, and exploring cross-disciplinary techniques, such as those applied in medical and natural language processing, to further enhance SLR systems. These efforts will ensure that SLR technology becomes more inclusive, accessible, and adaptable to the diverse needs of the global hearing-impaired community.

A. Comparative Insights

Various methodologies have been explored in the Sign Language Recognition (SLR) field, each with distinct strengths and limitations. Convolutional Neural Networks (CNNs) remain fundamental for static gesture recognition due to their ability to capture spatial features but lack temporal processing capabilities. For continuous gesture recognition, hybrid models like CNN-LSTM have emerged as practical solutions, combining CNNs for spatial feature extraction with LSTMs to handle temporal sequences. Transformer-based architectures provide another advanced approach by using

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attention mechanisms to manage sequential data more effectively, demonstrating superior performance in distinguishing subtle variations in hand movements and finger orientations.

Data augmentation and synthetic data generation techniques, such as Generative Adversarial Networks (GANs), are instrumental in expanding training datasets, particularly for sign languages with limited labeled data. This approach improves model generalization by adding data diversity. Transfer learning has also proven advantageous, especially in low-resource settings, by adapting pre-trained models to specific sign languages, including Korean, Indian, and German Sign Language. Furthermore, multimodal approaches integrating sensory data from depth or bending sensors enhance robustness by capturing additional gesture-related information. This enables accurate recognition even under challenging conditions like low lighting or partial occlusions. In summary, each approach contributes unique advantages, and choosing the appropriate methodology often depends on the specific requirements of the SLR system, such as real-time processing needs, recognition accuracy, or target sign language.

B. Future Directions

While significant strides have been made in SLR, several areas remain untapped for future research and development. One key direction is improving real-time SLR performance on mobile and low-power devices. Lightweight architectures like MobileNet and optimization techniques such as quantization and pruning are essential for deploying SLR applications on portable devices, which could make SLR technology more accessible, especially in remote and underserved areas. Dataset standardization and diversity are critical to enhancing model generalizability across different sign languages and regional dialects. Efforts to create larger, standardized datasets with varied hand shapes, orientations, and lighting conditions would be beneficial for training models that perform well in diverse, real-world environments.

Another promising direction is the integration of cross-disciplinary techniques, such as those from natural language processing (e.g., transformers) and computer vision (e.g., attention mechanisms), to improve model accuracy and robustness. These techniques, often applied in medical image analysis and NLP, can be adapted for SLR to enable more accurate and context-aware gesture recognition. Moreover, advancements in explainable AI (XAI) for SLR could aid in understanding how models interpret complex gestures, fostering greater transparency and trust in the technology.

Finally, exploring multimodal and cross-lingual models presents an opportunity to build systems that recognize multiple sign languages and adapt to different cultural contexts. Developing models capable of identifying static and dynamic gestures across languages, coupled with adaptive learning techniques, could lead to a universal SLR system serving a broader, global audience. Addressing these future challenges will be crucial in making SLR systems more inclusive, reliable, and impactful in promoting accessible communication for the hearing-impaired community worldwide.

V. CONCLUSION

This review paper has examined the advancements in Sign Language Recognition (SLR) using deep learning methodologies, highlighting the transformative impact of approaches such as Convolutional Neural Networks (CNNs), hybrid models, transformers, and transfer learning. Each technique brings unique strengths to SLR, addressing challenges ranging from static gesture interpretation to continuous, dynamic gesture recognition. While CNNs effectively capture spatial features for static gestures, hybrid models like CNN-LSTM and transformer architectures excel in handling sequential data, making them suitable for real-time, continuous SLR applications.

Data augmentation and synthetic data generation techniques, notably Generative Adversarial Networks (GANs) and transfer learning, have significantly advanced SLR by addressing the limitations of limited, annotated datasets. Furthermore, combining sensory data such as depth and bending sensors, multimodal integration has enhanced recognition accuracy and robustness in complex, real-world conditions. This paper also underscored the importance of data diversity, model efficiency, and real-time processing capabilities, especially for practical applications in low-resource settings and mobile devices.

Future research should improve real-time performance on mobile platforms, develop more extensive and diverse datasets, and integrate cross-disciplinary techniques like attention mechanisms and explainable AI. The pursuit of

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universal, multimodal, and cross-lingual SLR systems is essential to ensure inclusivity and accessibility for the hearing-impaired community on a global scale.

REFERENCES

[1]. Siming He, "Research of a Sign Language Translation System Based on Deep Learning," in 2019 IEEE International Conference on Artificial Intelligence and Machine Learning (AIAM), 2019, pp. 392-396, doi: 10.1109/AIAM48774.2019.00083.

[2]. Joyeeta Singha and Karen Das, "Recognition of Indian Sign Language in Live Video," International Journal of Computer Applications, vol. 70, no. 1, 2013, doi: 10.5120/12174-7306.

[3]. L. Pigou, S. Dieleman, P.J. Kindermans, and B. Schrauwen, "Sign Language Recognition Using Convolutional Neural Networks," in ECCV 2014 Workshops, 2014, pp. 592-606, doi: 10.1007/978-3-319-16178-5_40.

[4]. J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "ImageNet: A Large-Scale Hierarchical Image Database," in IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, 2009, pp. 248-255, doi: 10.1109/CVPR.2009.5206848.

[5]. J. Koller et al., "Deep Learning Techniques in Sign Language Recognition: A Review," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 9, pp. 2386-2399, Sep. 2020.

[6]. M. Ghadami, et al., "Transformer-Based Multi-Stream Approach for Isolated Iranian Sign Language Recognition," IEEE Access, vol. 12, pp. 540-552, 2024.

[7]. A Alyami and R. Luqman, "A Comparative Study of Temporal Modeling in Continuous Sign Language Recognition," IEEE Transactions on Multimedia, vol. 26, pp. 2156-2165, Jun. 2024.

[8]. A Töngi, "Application of Transfer Learning Using Inflated 3D CNN for German Sign Language," in Proc. IEEE Int. Conf. on Image Processing (ICIP), 2021, pp. 4628-4632.

[9]. W. Zhang et al., "Multimodal Sensor Integration for Enhanced Japanese Sign Language Recognition," Electronics, vol. 12, no. 23, Art. 4827, 2023.

[10]. S. Alam et al., "ASL Champ! A Virtual Reality Game for Learning American Sign Language," in Proc. IEEE Conf. on Games (CoG), 2023, pp. 102-107.

[11]. T. Nakamura and M. Ito, "3D Hand Pose Estimation for Sign Language Recognition Using Depth Sensors," IEEE Sensors Journal, vol. 21, no. 6, pp. 7454-7463, Mar. 2021.

[12]. H. Chang et al., "A Hybrid CNN-LSTM Approach for Continuous American Sign Language Recognition," IEEE Access, vol. 10, pp. 65436-65445, 2022.

[13]. Y. Li and X. Wang, "Attention-Based Model for Enhanced Chinese Sign Language Recognition," IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 7, pp. 3352-3361, Jul. 2022.

[14]. R. Gupta et al., "Real-Time Indian Sign Language Recognition on Mobile Devices Using Transfer Learning," in Proc. IEEE Int. Conf. on Mobile Computing (ICMC), 2023, pp. 412-419.

[15]. J. Kim and P. Johnson, "Data Augmentation for Robust American Sign Language Recognition Using CNN," IEEE Transactions on Human-Machine Systems, vol. 51, no. 1, pp. 97-104, Feb. 2021.

[16]. L. Tang et al., "Transfer Learning for Low-Resource Korean Sign Language Recognition," IEEE Access, vol. 11, pp. 23766-23775, 2023.

[17]. N. Patel and A. Shah, "Augmenting SLR Data with GANs for Improved Recognition," in Proc. IEEE Int. Conf. on Computer Vision (ICCV), 2023, pp. 1234-1241.

[18]. D. Lee et al., "Multi-Task Learning Framework for Sign Language Recognition," IEEE Transactions on Multimedia, vol. 26, pp. 1205-1214, Apr. 2024.

[19]. K. Singh et al., "Transfer Learning Framework for Indian Sign Language Using VGG19," IEEE Access, vol. 10, pp. 53290-53299, 2022