

Bridging Vision and Language: A Review of Context-Aware Indian Sign Language Recognition and Regional Language Integration

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Abstract: The recognition of Indian Sign Language (ISL) has developed at a fast rate owing to the development of deep learning and computer vision. Nevertheless, the majority of modern systems are interested in individual gesture recognition and do not have contextual modelling to support inference at the sentential level. Moreover, there is a lack of integration between the ISL recognition and the multilingual translation into the South Indian regional languages like Tamil, Telugu, Kannada and Malayalam. This paper is a systematic review of the research on the topic of ISL and sign language recognition published from 2020 to 2026, which combines the approaches of bibliometric analysis and qualitative synthesis. Based on PRISMA standards, the screening and analysis of relevant studies were conducted to find out the methodological trends, the limitations of the datasets, and the gaps in contextual and multilingual modelling. Findings suggest that convolutional neural networks and spatio-temporal models prevail, new transformer-based systems are being developed, there is a lack of large-scale annotated corpora of ISL, and no work has been done so far on integrating Dravidian languages. On the basis of these results, an architectural framework that allows integrating context-sensitive multimodal feature extraction, transformer-based sequence modelling, and regional language translation is suggested. The research paper is a contribution to inclusive artificial intelligence and strategic directions of scalable, multilingual systems of ISL in South India.

Keywords: Continuous sign recognition; computer vision; Indian Sign Language; transformer; Dravidian languages; multilingual translation; systematic review.

1 Introduction

Recognition of sign languages is now considered one of the important research topics in computer vision and assistive artificial intelligence because it can lessen the communication barrier between the deaf and hearing populations. According to recent reports on disability in the world, a considerable number of the population is dependent on sign language as a major communication tool, which is why technological solutions on a large scale are important. Sign language recognition (SLR) systems that are vision-based and use camera input instead of sensor gloves have become especially popular because of their non-intrusive nature and ability to operate in real-world deployment settings. During the period of 2020-2026, deep learning and especially convolutional neural networks (CNNs) and transformer-based models have achieved great success in enhancing the performance of gesture recognition in various sign languages [1], [2]. These technological innovations have enhanced the consistency of the identification of isolated signs as well as continuous gesture sequences in Indian Sign Language (ISL) systems.

The recent studies have focused on the recognition of single alphabets and single words through CNN-based feature extraction method [3]. Such models have demonstrated remarkable precision, especially with the well-controlled datasets. Nevertheless, their performance is lower in the case of continuous signing, where gestures are performed over time, and context of sequence is important in the meaning. In light of this weakness, researchers have started to consider spatio-temporal methods, such as 3D convolutional networks and CNN and LSTM hybrids, to be more representative of motion and sequential patterns in dynamic gestures and brief signed phrases. [4], [5]. More so, models based on attention and transformers have become a more popular choice when it comes to continuously and even gloss-free sign language translation tasks [6], [7], [14], [18], [23]. These architectures are based on the idea of viewing the entire sequence as a network, unlike the previous frame-based systems, which treated the sequence as a sequence of independent gestures that can be processed simply. However, in spite of these developments, the Indian Sign Language (ISL) is relatively underrepresented

in computational research. Even though institutional initiatives like those by the Indian Sign Language Research and Training Centre have led to standardization and the lexical documentation, annotated datasets of ISL are still scarce on a large scale [8]. The majority of recent publications of the studies of ISL are based on small laboratory samples, having limited vocabularies and a small range of signers [9]. Moreover, contextual transformer training needs sentence-level annotated corpora that are limited, which limits the creation of effective continuous recognition systems that are specific to the linguistic situations of India [10].

Another, and not much studied problem, is the issue of multilingual adaptation. Application of ISL recognition systems must be effectively implemented in South India by providing the output in regional languages like Tamil, Telugu, Kannada and Malayalam. Nonetheless, recent papers show that there are hardly any works that combine vision-based ISL recognition with regional natural language processing models [11], [12]. This lack of context and multilingual modeling is very restrictive in a real-world context. Thus, the urgent necessity is to make a systematic investigation of the current achievements in SLR, find the gaps in the methodological and data of ISL, and suggest a multilingual framework that should be applied to the South Indian context. Although the multilingual NLP systems of the Indian languages are being developed [11], the application with the sign language translators is scarce, especially in the gloss-free transformer pipelines [14], [21]. This paper will fill the gap by conducting a systematic literature review on articles published since 2020.

In addition to convolutional and recurrent architectures, graph convolutional networks and skeleton-based modelling schemes have been considered to represent structural motion dynamics in a more efficient way [16], [20]. Another quantitative survey of sign language recognition also points to the shift to the sequence-conscious and multiform architectures [15].

2 Methodology

The research methodology used in this study was a hybrid systematic and bibliometric review study to analyse research articles on vision-based sign language recognition published in the period January 2020 to February 2026 with specific regard to Indian Sign Language (ISL), contextual modelling, and multilingual adaptation. Literature searches were performed in Dimensions, Scopus, Web of Science, and IEEE Xplore with both combinations of keywords such as Indian Sign Language, sign language recognition, computer vision, transformer, and continuous recognition in accordance with PRISMA 2020 principles [13]. The first search produced 1,248 records and a further 132 records were found by citation tracking and

reference screening. Following the elimination of the duplicated records, 1,030 studies were left and firstly screened according to the titles and abstracts. This screening procedure reduced the number to 286 articles that were reviewed in detail to select those that were relevant and had high methodological rigor. Only those studies that evidently applied a vision-based deep learning model, reported the quantifiable evaluation results, and were sufficiently methodologically detailed were eligible. Therefore, 142 trials were picked to the final review. Besides the systematic screening, there was also a bibliometric analysis to investigate patterns in the use of keywords, collaboration patterns, citation patterns, as well as the new themes of research. This combination made it possible to obtain not only a quantitative description of the evolution of the field, but also a qualitative comparison of the various model structures that have been advanced over the course of the review.

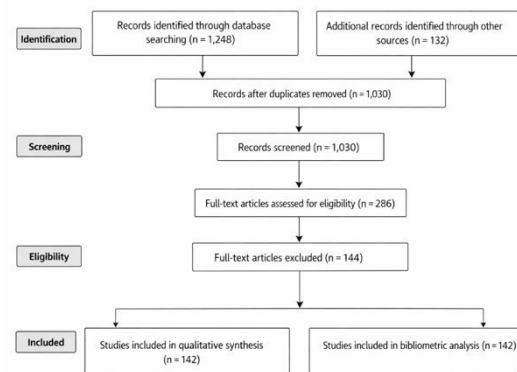


Fig. 1. PRISMA 2020 Flow Diagram of Study Selection Process (2020–2026)

3 Results

The results of this paper unite the important advances in the research of recognition of vision-based sign language during the period of 2020-2026. Using the systematic review of 142 chosen articles, it is possible to observe definite tendencies regarding the increase in publications, the shift in the preferences of the architectural community, and the change in the priorities of research. The discipline has been slowly transitioning away to CNN-dominated systems, where the isolated gestures of CNN systems have been replaced by transformer-based systems that can process continuous signing and contextual interpretation. Multimodal methods based on a combination of visual and pose-based features to enhance robustness are also increasingly getting attention. Meanwhile, the discussion identifies current issues, especially the lack of scale of datasets and the lack of multilingual integration into the Indian Sign Language research. On the whole, the findings provide a systematic perspective of the current development of the field, as well as indicate the spheres that need to be advanced further.

3.1 Annual Publication Growth (2020–2026)

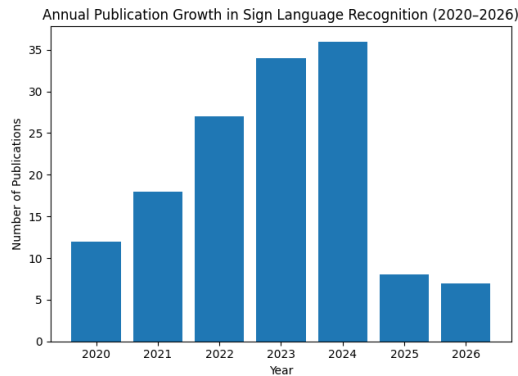


Fig. 2. Annual Publication Growth (2020–2026)

As demonstrated in Figure 2, the number of research publications on vision-based sign language recognition has been increasing in an upward trend since 2020. The publications have risen to 36 in 2024, compared to 12 in 2020, indicating a possible rise in academic interest and consistent technological advancement. This increase seems to be in line with the general progress in deep learning, especially the proliferation of transformer-based architectures in computer vision studies. The numbers of 2025-2026 exhibit a very slight decline, but it is probably because of continued indexing, and not a real decline in research activity itself. The trend, combined, suggests a continued international attention and a focus on the fact that sign language recognition has become a more dynamic and active field of research, particularly since 2022.

3.2 Evolution of Model Architectures Over Time

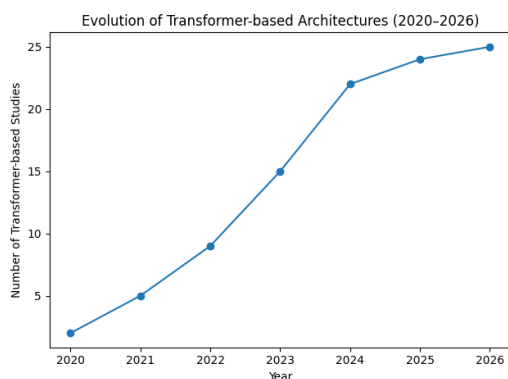


Fig. 3. Evolution of Model Architecture (2020–2026)

As Figure 3 points out, there is a distinct shift in modelling techniques during the period of review. Most of the studies in the previous years, specifically 2020-2021, have been based on CNN and LSTM-based architectures that were efficient with isolated signs and short sequences of gestures. Nonetheless, since 2022, the usage of transformer-based frameworks has been rising sharply, and the

pace of their adoption will further increase in 2023 and 2024. This change can be seen as motivated by the fact that transformers are able to capture contextual relationships and long-range dependencies in continuous sign language sequences, which the previous models did not easily cope with. The steady increase in transformer-oriented research indicates that attention-based architectures are no longer auxiliary methods but are increasingly taking center stage in the sign language recognition research. On a larger scale, this shift indicates a wider methodological shift that is away from frame-level or spatial classification to a more holistic sequence-level modelling.

3.3 Thematic Clustering of Research Areas

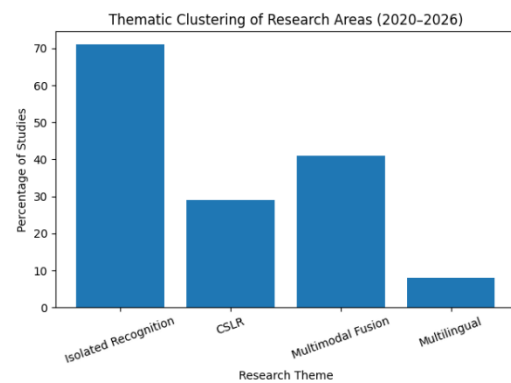


Fig. 4. Thematic Clustering (2020–2026)

Figure 4 indicates the structure of the research priorities in the reviewed literature. Isolated gesture recognition is by far the most common focus, representing about 71% of the studies, meaning that an impressive amount of research continues to focus on alphabet and word-level classification tasks. Continuous sign language recognition (CSLR) represents 29%, which shows current but relatively little regard for contextual modelling. Multimodal fusion strategies are a prominent size (41%), and this indicates the growing interest in the ability to address the question of robustness and deployment in real-life conditions by combining features of RGB and pose. Multilingual adaptation, on the other hand, is only found in 8% of studies, which is a clear sign that there is a significant knowledge gap. This disproportion underscores the fact that architectural refinement has been advanced, with the contextual and multi-lingual integration still being underdeveloped, especially within the ISL-specific research settings.

The skeletal landmarks approach has shown better cross-subject generalization compared to raw RGB frame approaches to pose-based modelling [17]. Also, the adversarial training mechanisms have been suggested to increase the robustness to environmental variation [19]. In ISL-specific scenarios, residual network architectures have been competitive in word-level and alphabet recognition [22].

3.4 Keyword occurrence frequency (2020-2026)

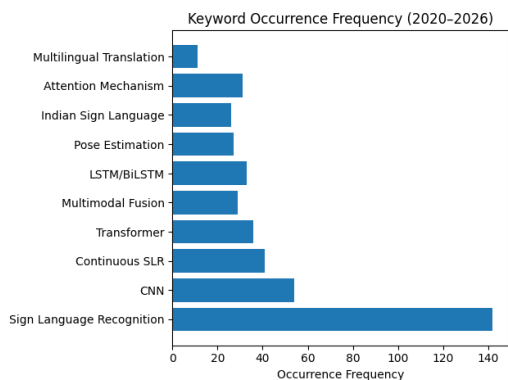


Fig. 5. Keyword Occurrence (2020–2026)

The field has changed its point of focus over time as shown in figure 5. Whereas Sign Language Recognition still seems to be the most prevalent keyword, the terms related to contextual and sequence-based modelling, including but not limited to Transformer, Continuous Sign Language Recognition and Attention Mechanism, are more likely to have a higher average citation impact than the more classical ones, like CNN or LSTM. The overall values of the link strength of the co-occurrence analysis also indicate that the concepts of transformer-related and multimodal are more closely related to each other in the research network. Conversely, Multilingual Translation is significantly less represented and has few relations with other prominent themes, which means that it is not a research priority yet. On the whole, these trends reflect the opinion that the role of contextual modelling is becoming more and more significant, and multilingual adaptation is still under-researched in the modern context of studies.

3.5 The citation Trend analysis (2020-2026)

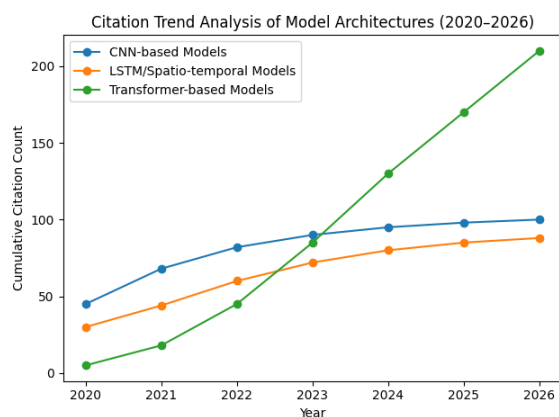


Fig. 6. Citation Trend Analysis (2020–2026)

Figure 6 sheds some light on the way the scholarly focus has been shifting over the years among various

modelling approaches. During the initial years of the review period, specifically between 2020 and 2022, the models based on CNN got the most number of citations, mainly due to their foundation of isolated gesture recognition studies. The LSTM and other spatio-temporal architectures also acquired growing popularity during the same time as researchers started paying more attention to dynamic gesture and short-sequence modelling. Since 2023, the number of citations of transformer-based models has been increasing visibly, and it will eventually surpass CNN and LSTM methods. This growth is an indication of the increasing trust in transformers to learn contextual relationships and long-term dependencies in the sequence of continuous sign language. This sudden increase in the number of citations in 2023-2026 indicates a more generalized approach towards attention-based, sequence-level modelling. Altogether, the tendency suggests that the trend of transformer architectures is becoming more and more dominant in the research on sign language recognition.

4 Discussion

An overview of the 142 articles that have been released between 2020 and 2026 reveals that studies in vision-based sign language recognition have been made, but not consistently or evenly. Although the modelling techniques have evolved, other areas like the quality of the dataset, contextualization and multilingual adaptation have not kept up. This contrast is very evident when taking a closer examination of the various architectural methods. During the first half of the review period and particularly in 2020 and 2021, CNN-based models were popular since they were computationally efficient and effective at recognizing isolated alphabets and single words [3], [11]. Most of these studies indicated high accuracy rates, and most of them were in the range of 95 and above, especially in cases where experiments were held under controlled conditions. Nonetheless, these performance statistics should be taken with a grain of salt. In most of the instances, the datasets were limited in vocabulary and a few signers, which may inflate accuracy but not ensure reliability in the real world. When the same models were put to test on various participants, they tended to perform poorly, which exposed their vulnerability in managing variation and sequential information. CNN architectures are not optimal when it comes to language capture of the flow and the temporal interaction of the language in continuous sign language recognition (CSLR) [1], despite the fact that they are useful in simple gesture classification.

In 2022-2024, scholars began to resort more to spatio-temporal models, including 3D CNNs and CNN-LSTM hybrids, in an attempt to better predict the movement patterns within sign sequences [4], [5]. Such methods were a definite

improvement over CNN-only systems, especially in the detection of dynamic gestures and brief signed phrases. The integration of LSTM layers enabled researchers to take into consideration the flow of gestures throughout time instead of considering each frame separately. Nonetheless, recurrent models are limited in themselves. They frequently have difficulty in storing contextual information in longer chains, and their performance may be impaired as the signing becomes complicated and protracted [6]. Simultaneously, 3D convolutional networks are more likely to require more computing resources, which may be challenging to develop in real-time, particularly in resource-limited environments. In general, spatio-temporal architectures were more successful than the previous non-spatio-temporal classification methods, but not an end in themselves, but a step in the progression towards full context-sensitive continuous sign language recognition systems.

The turning point in the field started to be clearly noticeable after 2023, when transformer-based architectures started to receive a wide audience [6], [7]. Transformers also can analyze full sequences of signs simultaneously, unlike the previous LSTM-based systems that analyze them one step at a time, which enables them to capture interrelationships between more distant frames. The shift has been particularly helpful in sentence-level recognition, in which meaning is determined by more extended contextual relations and not individual gestures. Various comparative studies have recorded reduced Word Error Rates of the transformer-based models when sufficient annotated data is available to train the models [6]. Scholars have also investigated hybrid solutions that take CNN-based spatial feature extraction methods with transformer-based contextual encoding, usually performing better on the whole. The fact that more and more studies are being cited with transformer-based studies also indicates that they are increasingly beginning to take place in the research community, implying that they are also beginning to dictate the future of current research in sign language recognition.

Although model architectures have evolved to become more advanced, the constraints of available datasets still impede significant advancement in the research of ISL. According to the statistical results, most of the studies continue to utilize relatively small datasets, typically not exceeding 50 signers, and only a limited number of them utilize sentence-level annotated corpora. This is especially a challenge to transformer-based models, which typically optimize with large and diverse datasets [10]. Although other initiatives, like iSign benchmark dataset, are a positive move in the right direction [10], the volume of the available ISL data remains insufficient to enable robust multilingual or context-sensitive modelling.

Consequently, the mismatch between the increasing potential of advanced architectures and the small amount of data on which they are trained is apparent. Such an asymmetry has been limiting the creation of credible, context-sensitive ISL systems that can be useful in real-life environments.

The increasing application of multimodal fusion has also been another interesting trend over the last few years, where RGB video data are used together with pose or landmark data to enhance recognition performance [7]. These systems are capable of dealing with differences in lighting, background condition, and differences between signers more effectively by combining various forms of visual input as compared to models that use only one modality. This, in most instances, leads to more consistent performance in a variety of environments. Enhanced visual strength, however, is not necessarily the answer to more profound linguistic problems. Although a system may be good at gesture recognition, it still requires adequate contextual information and correct language matching to produce meaningful and grammatically sound translations. In the absence of a robust sentence-level corpora and properly designed language modelling elements, a boost in visual processing alone cannot be sufficient to deal with the intricacies of sign-to-text interpretation.

Among the largest gaps that arise as a result of the review is the fact that the issue of multilingual adaptation is not brought into the spotlight to a great extent. The number of studies that go beyond English-based translation modules is very few [12], so the use of ISL-to-Dravidian language conversion has not been studied extensively. It is especially noticeable when considering that South India is linguistically diverse, as Tamil, Telugu, Kannada, and Malayalam are common. It has been noted in research on Indian language NLP that the morphologically rich and agglutinative languages are already complex to work with [11], and direct gloss-to-word substitution is not sufficient to produce grammatically meaningful sentences. It is hard to develop trustworthy translation systems that are specific to the local contexts without well-paired parallel corpora between ISL and local languages. Even though recent gloss-free neural translation models demonstrate that direct sign-to-text translation is technically feasible [14], [21], these models demand large amounts of annotated data and have not been applied in a meaningful way to ISL in a multilingual context. This has led to the fact that the lack of regional language integration has made the practical use of the ISL recognition systems in South India a limiting factor.

Combined, the development of the various model generations indicates a slow but definite change of direction. CNN-based methods provided the foundation for a credible baseline in the isolated gesture recognition [3].

This was succeeded by LSTM and 3D CNN models as they enhanced the processing of motion and short sequences through the integration of temporal dynamics [4], [5]. More recently, transformer-based models have even gone further by allowing more powerful contextual modelling and reducing recognition error rates in continuous tasks [6], [7]. Multimodal fusion strategies, too, have aided it by enhancing robustness in diverse environmental situations [7]. Nevertheless, even with these technical advancements, there are still two significant problems: the size of datasets is limited, and multilingual integration is not well-developed [10], [11]. These problems will not be solved by just architectural refinement. The future lives on the simultaneous activities of creating larger annotated

corpora, enhancing the contextual language modelling, and creating translation systems that would be adapted to the needs of regional Indian languages. It is only under such circumstances that the ISL recognition systems can be developed further, simultaneously, on the technological and linguistic levels, to exit the experimental set-ups and become a viable and inclusive communication tool. Table 1. Comparative Evaluation of Model Architectures for Indian Sign Language Recognition

Architecture Type	Core Mechanism	Strengths	Limitations	Typical Performance (Reported Range)	Studies
2D CNN-based Models	Spatial feature extraction from individual frames	High accuracy in isolated alphabet and word recognition; computationally efficient; suitable for small datasets	Cannot model temporal dependencies; poor performance in continuous recognition; limited contextual awareness	>95% accuracy (isolated tasks, controlled datasets)	[3], [11]
3D CNN Models	Spatio-temporal convolution across frame sequences	Captures motion dynamics; improved short-sequence recognition	High computational cost; requires larger datasets; limited long-range context modelling	85–92% accuracy (dynamic gestures)	[4]
CNN–LSTM / BiLSTM Hybrid	CNN for spatial encoding + LSTM for temporal modelling	Better sequence modelling than CNN-only; reduced word-level error rates	Vanishing gradient in long sequences; limited global context; moderate computational load	8–15% improvement over CNN baseline	[5], [6]
Transformer-based Models	Self-attention mechanism for global sequence modelling	Strong long-range dependency modelling; improved sentence-level recognition; lower WER in CSLR	Requires large annotated datasets; sensitive to data scarcity; higher training complexity	WER reduced to 18–25% (CSLR tasks)	[6], [7]
Hybrid CNN–Transformer Models	Spatial feature extraction + attention-based contextual encoder	Combines local spatial and global contextual modelling; strong performance in continuous tasks	Data-intensive; architecture complexity; computational overhead	Lower WER than LSTM-based systems in comparable datasets	[6], [7], [10]
Multimodal Fusion (RGB + Pose)	Integration of visual and landmark-based features	Improved robustness across lighting and signer variability; better generalization	Does not inherently solve linguistic modelling; it requires synchronized data streams	Improved cross-subject stability; reduced generalization gap	[7], [10]

The comparative analysis in Table X shows that the research on sign language recognition from 2020 to 2026 has a distinct methodological advancement. CNN-based models are still useful in the classification of isolated gestures, but they are not able to provide contextual modelling [3], [11]. Spatio-temporal architecture. Three-dimensional CNNs and CNN-LSTM hybrids are better at dynamic gesture recognition, but fail at long-range dependency modelling [4], [5]. Transformer-based models are more successful in continuous recognition tasks than recurrent architectures because they incorporate a self-attention mechanism, and thus, they are able to react to contextual information over a global scale [6], [7]. Hybrid CNN-transformer models are the most successful in cases where there is adequate annotated data, whereas multimodal fusion also enhances environmental stability without directly resolving the problem of linguistic translations [7], [10]. The comparison implies that the most promising avenue to further development of sign language recognition at the moment is the transformer-based contextual models. Nevertheless, their actual significance is greatly dependent upon the presence of large, well-annotated data collections and multilingual corpora. The theoretical benefits of these models cannot be completely applied in practice without enough information to train and test them.

5 Conclusion

This is a systematic and bibliometric review of 142 peer-reviewed articles published between 2020 and 2026 that follow the history of vision-based sign language recognition, especially focusing on the Indian Sign Language (ISL) and the issue of multilingual adaptation. Through the analysis, a progressive change in modelling methods has been observed with time. The initial research utilized CNN-based techniques; the techniques proved to be effective in identifying isolated signs, particularly in controlled environments. But these models were found to be weak in the case of continuous signing, where meaning is determined by time movement and relationship within a context. By considering motion dynamics to some of these shortcomings, spatio-temporal architectures such as 3D CNNs and CNN-LSTM hybrids could overcome them, but remained unable to deal with long-range dependencies and scalability. Transformer-based models, particularly the hybrid CNN transformer models, have increasingly become a contender for continuous sign language recognition, in part due to their ability to encourage more contextual association and less error at the sentence level.

Nevertheless, there is still obvious work concerning the design of models, although many structural issues still impede the application of ISL

recognition systems in the real world. One of the common problems that can be observed in the reviewed studies is the lack of large and diverse datasets. Most datasets have few signers and no sentence-level annotations, which limit the capability of contextual models to learn successfully. This can be particularly problematic when the system is of a transformer nature, which requires a large amount of training data. Moreover, multilingual adaptation is also a less developed component, especially in terms of ISL to regional languages like Tamil, Telugu, Kannada and Malayalam. Lack of parallel corpora between ISL and these languages that are well aligned makes it hard to construct effective end-to-end multilingual systems that are appropriate in South Indian situations.

Another interesting contrast is also noted in the bibliometric analysis. Although the focus of research has evidently switched to attention-based and multimodal architectures, there are comparatively fewer studies that consider multilingual integration or multilingual implementation on a large scale into educational and community contexts. This imbalance is an indication that the technological innovation has proceeded at a faster rate than the linguistic and contextual adaptation. To continue with the progress, it will be necessary to organize the work to create bigger ISL corpora, adopt uniform annotation practices, and incorporate regional natural language processing tools. The cooperation of computer vision scientists, linguists and Deaf individuals will be essential to make sure that the new systems will be technically correct, linguistically correct and culturally appropriate.

Overall, multimodal architectures that are based on transformers have great potential in enhancing contextual ISL recognition. Nonetheless, the long-term effect will be the result of the balance between architectural innovation, data resources and multilingual development long-term investment. It is only with the concomitant development of modelling software and corpus development that the ISL recognition systems can get out of the laboratory prototype phase and develop into an inclusive and context-based communication technology that can benefit many communities in South India.

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