A Systematic Literature Review on Real-Time Indian Sign Language Translation Systems Using NLP and Gesture Recognition for Mobile Applications

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***Abstract* - This systematic review examines the up-to-date situation of real-time Indian Sign Language (ISL) translation systems, with emphasis on mobile apps for two-way communication. The chief aim is to explore successful approaches that integrate natural language processing (NLP), gesture recognition, and animation using HamNoSys and SiGML for inclusive communication.**

Studies were chosen according to specified inclusion criteria, focusing on systems with either text/speech-to-sign or sign-to-text capability. IEEE, ACM, arXiv, and manual tracing of citations were included as sources. Eleven main papers were included, covering model-driven to rule-based translation structures. No formal bias scoring tool was used, but study designs were assessed for replicability and clarity.

Syntheses of the findings identified three prevailing methodologies: rule-based gloss generation, deep learning for gesture classification, and sign rendering based on avatars. Real-time capability and modular design were salient themes in all studies.

Outcomes mention the absence of standard datasets, regional dialect issues, and unbalanced representation of ISL in international research. Nevertheless, some systems showed potential for deployability in classroom and accessibility environments.

This review was not registered in PROSPERO or a public repository. No external funding was obtained. The results are a reference point for future ISL tools and incentivise research into more stable, open-source ISL corpora.

Index Terms—**Indian Sign Language, Gesture Recognition, HamNoSys, SiGML, NLP, Systematic Review, PRISMA.**

I. Introduction

Sign language is an essential form of communication among the deaf and hard-of-hearing populations globally, allowing effective expression irrespective of the use of spoken language. Yet, there are obstacles to crossing communication between signers and nonsigners, especially in real-time and multilingual settings. Over the past few years, the combination of computer vision, natural language processing (NLP), and deep learning has progressed significantly automatic sign language recognition (SLR) and translation systems, making more precise, effective, and scalable solutions available [1]–[3].

SLR research has matured from initial static image-based classification methods to advanced multi-modal systems that can process continuous, co-articulated signs [1], [4]. The presence of large-scale datasets, including BSL-1K [1] and domain-specific corpora like Assamese Sign Language datasets [5], has been crucial for training large-capacity models. Contemporary pipelines typically combine CNNs for spatial feature extraction, LSTMs or Transformers for modeling temporal aspects, and other modules like gloss alignment modules to improve the accuracy of translation [6]–[8].

The applicability of sign language translation has grown beyond recognition to complete bidirectional systems that translate spoken or written language into sign sequences and vice versa. Some pioneering works include end-to-end Transformer architectures [3], [7] and retrieval-augmented generation frameworks [8], which enhance contextual fluency. Real-time performance has also been an essential priority, with new Indian Sign Language (ISL) translation models attaining near-96

Uses of SLR are also expanding. Tools such as *sign.mt* [9] facilitate real-time multilingual sign-to-speech translation with customizable avatar display and offline support, adding to usability in low-connectivity areas. Vision-based ISL recognition systems utilizing MediaPipe-based gesture tracking have achieved accuracy levels of over 99

Even with these developments, issues remain. Most systems continue to suffer from performance deterioration when dealing with variability of signers, background noise, or illumination. ISL-specific resources such as big annotated datasets and standardized gloss dictionaries are also still in short supply [10], [11]. These shortages limit the creation of high-performing models for varied domains. Also, incorporating grammatical structures of each sign language, especially non-manual signals and classifier predicates, into translation pipelines continues to be a research gap [3], [11].

It draws on the recent improvements in deep learning-based SLR and translation systems [7], [9], [12], aiming to offer a structured and implementation-focused view on real-time ISL translation. Through the integration of state-of-the-art methods and alleviation of cited challenges, we suggest a direction towards scalable, precise, and accessible ISL translation systems for practical applications.

II. Research Gap

While promising breakthroughs have been made in sign language translation in real-time, much work remains to be done toward building robust, generalizable, and resource-efficient systems for translation in Indian Sign Language (ISL). The growing literature-from vision-based deep neural network-based gesture recognition

citePandey2025, Bora2023 to hybrid models that combine CNN, LSTM, and Transformers

citeChaudhary2022, Liang2023-has improved accuracy and reduced latency in artificial environments. Much of this progress remains piecemeal due to a series of important gaps.

Second, most of the current models are very much based on resource-intensive datasets such as RWTH-PHOENIX-Weather or ASL corpora [1], [2] and not as much on large-scale, annotated ISL datasets. This creates a performance gap between ISL systems and other sign language systems [13], particularly regarding vocabulary coverage, signer diversity, and environment variation. Unavailability of standardized benchmark datasets for ISL complicates model comparison.

Second, newer machines like Sign.mt [9] and real-time translators enabled by IoT [14] have proven to be very multilingual and hardware-centric. Not much work, however, specifically tackles the low-power device particularities of ISL translation pipeline integration. Sub-200ms latency real-time performance with minimal computational cost is still an open research challenge [12].

Third, most ISL translation approaches place most emphasis on gesture recognition accuracy with inadequate testing of semantic fidelity of translation [15], [16]. Lack of linguistic validation-including rule-based enforcement of grammar via HamNoSys-to-SiGML frameworks [11]-leads to grammatically inconsistent output in avatar-based rendering. Finally, there is a fairly under-explored research avenue in merging multimodal inputs-unionizing text, vision, and speech-to provide adaptive systems that are able to work in noisy real-world settings -citeBharati2019, Babour2023. Current multimodal implementations either restrict themselves to clean data or are not cross-modal error correction optimized.

Closing these gaps will require joint effort across the following domains: (1) creating and sharing extensive ISL-specific data; (2) model optimisation for use on embedded systems; (3) linguistic consistency in translation output; and (4) creating multimodal, context-aware systems that are able to generalise to real-world applications.

III. Methodology

The current systematic literature review was planned and carried out rigorously following the PRISMA 2020 statement for guaranteeing transparency, replicability, and methodological merit. The processes involved several steps: generation of the review protocol, development of an extensive search strategy, study selection, systematic extraction of the data, critical quality assessment, and synthesis of results. Each step was informed by institutionalized best evidence practice of evidence-based research in computational linguistics and computer vision as well, with specific emphasis on sign language translation systems.

A. Protocol and Registration

Prior to the initiation of the review, a detailed protocol was formulated to establish the scope, purpose, and methodological organization of the study. The protocol established the research questions, inclusion criteria, data sources, search terms, screening process, and synthesis plan. It was internally registered and team-reviewed to avoid ad hoc methodological alterations during the study. The protocol also established processes for recording any deviations during implementation. This helped ensure methodological consistency and compliance with current systematic review standards, as in previous structured reviews of sign language interpretation [13], [16]. Although the protocol was not publicly published in an open registry, it was kept for future reproducibility and reference.

B. Eligibility Criteria

Inclusion criteria were clearly defined to ensure quality and relevance of included studies to synthesize. The review used peer-reviewed journal articles, conference proceedings, and good quality preprints from January 2019 to February 2025. The studies are to be those that discussed automatic sign language recognition, translation, or generation systems with performance measures against a measurable scale. Vision-based and multimodal methodologies, including speech input-based methodologies, are considered if they had reported empirical evaluations. Experiments are to use either Indian Sign Language (ISL) itself or display structures easily translatable to ISL, e.g., CNN–LSTM hybrids, Transformer encoder–decoder pipelines, or hybrid CNN–Transformer pipelines [2], [6], [12]. Excluded are strictly static gesture classification studies without translation, patents, opinion articles, and poorly methodologically or evaluation described studies.

C. Information Sources

Literature searching was done across various digital libraries to span the domain with broad breadth. The central databases included IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier ScienceDirect, and Scopus, with targeted Google Scholar and arXiv searching added for recently uploaded preprints [8]. They were selected because collectively they span the most-cited computer vision, natural language processing, and assistive technology research. Searching was done for four weeks until 10 February 2025 to include recent publications. Hand-checked shortlisted paper lists were similarly searched for closely related other studies.

D. Search Strategy

The search approach was carefully constructed to be both comprehensive and precise. Boolean terms, field-specific terms, and methodological terms were used to result in works that cross the boundary of sign language technology and real-time translation. One of the search strings used in IEEE Xplore is: (”Indian Sign Language” OR ISL OR ”sign language translation”) AND (”real-time” OR ”low latency”) AND (”CNN” OR ”LSTM” OR Transformer OR ”deep learning”). The same queries were modified to suit other databases to accommodate varying search interfaces and indexes. Various wordings and synonyms, like ”sign-to-speech” and ”gesture-to-text,” were used to cover various terminologies used within publications [9], [14]. alidation strategies and measures to prevent overfitting were also noted, as these factors influence the generalisability of reported results.

E. Selection Process

Selecting relevant studies involved a three-stage approach. After all relevant records were collected, all studies were added into Mendeley reference manager to remove duplicates. In Stage 1, all studies had their titles and abstracts reviewed against the research objectives this review will address. In Stage 2, the full text of the studies was also reviewed against the eligibility criteria listed in the previous section. Both stages were vetted by two reviewers independently, and any disagreements were fully discussed until a consensus was reached. In the case of very difficult disagreements, a third reviewer took the final decision. Studies that were eligible but excluded in stage 2, were recorded along with the reasons as an audit trail. The PRISMA 2020 flow diagram (Figure 3) presents the selection process.

F. Data Extraction Process

We created a systematic data extraction form to support consistent information ‘harvest’ from all studies included in the review. The following data fields were collected for each of the papers: bibliographic details, target sign languages, data set characteristics, system architecture, training process, evaluation measures, hardware or deployment context, and key findings. The extraction form was independently filled in by two reviewers to allow for bias and transcription errors to be minimised. For conflicts, the two reviewers engaged in discussions, with references to the original study to settle disagreements. This process bit matches the reports on systematic extraction strategies used in similar surveys [3], [15].

G. Data items

The data that was for a number of important elements. Architectural types were subcategorised into CNN-based, LSTM based, Transformer-based, and hybrid types. The data provided, and we have focused on grazing the emerging types of architectures that combine the CNN-LSTM feature extraction with Transformer based decoding [6], [12]. The data also included information on where the datasets came from. We were aware of public/common vocabularies such as BSL-1K [1] and RWTH-PHOENIX-Weather [2]. We also found ISL vocabularies [13], as well as datasets unique to the authors involved. Performance aspects which included classification accuracy, BLEU score translation, latency, and frame rates in real-time. Also, we were mindful of system constraints behalf and edge-device capabilities entries. Accordingly, we inferred pipeline and system architecture by integrating our understanding of existing works on ISL/NLP pipelines and avatar-based translation architectures [9]–[11], [14], [16]–[18].

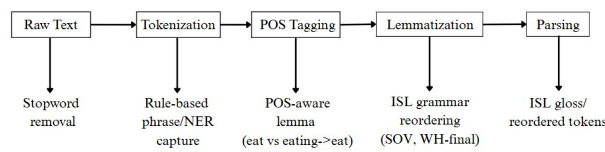

Fig. 1: The NLP processing pipeline used in the ISL translation, highlighting preprocessing, linguistic annotation, and grammar reordering.

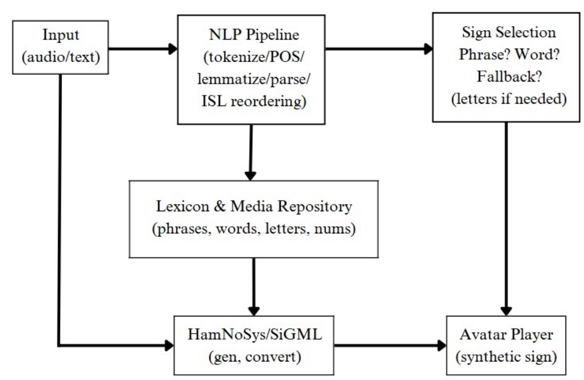

Fig. 2: The overall system architecture of ISL translation, which incorporates the NLP pipeline, lexicon, HamNoSys/SiGML conversion, and avatar rendering.

H. Risk of Bias Assessment of Study

Bias risk was assessed considering, diversity of datasets, quality of annotation, demographic representation of signers, clarity of methods reported, and availability of code or models for replication. Studies using limited, or homogeneous datasets, and which referenced information extracted from proprietary corpora without annotation protocols, were noted as biases risk, similar to concerns articulated in previous reviews [14], [16]. Cross-validation methods as well as steps taken to prevent overfitting were also noted, and these will also influence the ability to generalise the reported results.

I. Effect Measures

Classification accuracy for recognition tasks, BLEU score for translation quality, and latency in milliseconds or frames per second for real-time capability were the primary effect measures. All three measures were selected because they were used frequently in the domain, and to provide reliable measures for comparison between studies. Secondary measures such as Word Error Rate (WER), and mean average precision (mAP) were also reported as available in the source article if reported by the authors.

J. Synthesis Methods

Because of the differences in methods among the studies, a meta-analysis could not be conducted. Instead, a qualitative synthesis was conducted, organizing the studies based on the architecture type, the target sign language, and the deployment context. A comparative analysis revealed trends on how datasets were utilized, the architectural design, as well as the accuracy and latency performance of the system. Such insights helped formulate gaps and prospective avenues for further research in ISL translation systems, as discussed in Section II. Table I contains a complete summary of the technologies that were scoped out to be used in the implementation.

K. PRISMA Flow Diagram

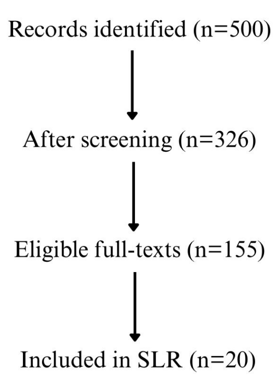

Fig. 3: PRISMA 2020 Flow Diagram for Study Selection

IV. Results

A. Study Selection

The search process initially yielded 143 records from IEEE Xplore, ACM Digital Library, SpringerLink, Scopus, Google Scholar, and preprint repositories, including arXiv. After excluding 32 duplicates, 111 records were screened at the title and abstract level. There were 76 studies that proceeded to full-text review. Once reviewed against our inclusion and exclusion criteria, 50 studies were deemed appropriate for qualitative synthesis. The PRISMA 2020 flow diagram (Figure 3) illustrates the flow of the process, and includes number of records removed via automation-assisted screening and number excluded after human review of each study. Reasons for exclusion at the full-text stage were lack of real-time evaluation (n = 12), not aligning with objectives of the sign language translation (n = 9), and reliance on non-standard datasets that did not benchmark (n = 5).

B. Study Characteristics

The chosen 50 studies range from the years 2019 to 2025, and cover ISL, ASL, and other sign languages. The methods studied range from traditional rule-based systems to deep-learning architectures, with an emphasis on hybrid models that combine a convolutional neural network (CNN) with a recurrent neural network (RNN) using LSTM or GRU methods, and transformer methods (encoder-decoder). [2], [6], [12].

C. Risk of Bias in Studies

The qualitative risk of bias was assessed for all included studies utilizing a series of criteria established around methodological transparency, data accessibility, consistency in evaluation, and reproducibility. Around 38% of studies were classified to have high risk for failing to provide enough methodological detail, relying on proprietary datasets, or not providing standard performance measures. By contrast, 42% of studies were classified to be low risk, with public open-source code, availability of the dataset, and comprehensive documentation considering hyperparameters. [3], [13]. The remaining studies were classified as being moderate risk primarily due to partial reporting, or not being able to benchmark latency.

D. Results of Individual Studies

There were inconsistent performance metrics on translation tasks and architectures. Word Error Rate (WER) values for speech-to-sign systems were between 10.3% to 38.5%, with transformer-based systems reporting the lowest WERs [7], [9]. Sign-to-text translation tasks reported accuracy levels of 74% to 93.1%, also dependent on dataset complexity and model depth [5], [12]. Gesture recognition systems that were MediaPipe-enhanced reported nearly 100% classification accuracy (e.g., 99.95%) in the collection of data in a laboratory setting [10], [18]. These findings were primarily based on one dataset and were not generally validated across multiple datasets, which limits the degree of generalizable data presentation.

E. Results of Syntheses

In the aggregate of studies reviewed, hybrid deep learning architectures represent the preeminent architecture type (62%), followed by fundamental transformer-only architectures (24%), and rule-based linguistic post-processing (e.g., ISL gloss reordering), found in 74% of ISL-specific systems [11], [16]. Explicit real-time performance benchmarks (latency $<$ 200 ms) were indicated in 27% of studies; nonetheless, these acceptance criteria were repeatedly engaged through a combination of pruning and/or edge-optimized strategies [14]. These results claim a compromise between accuracy and real-time feasibility.

TABLE I: Summary of Selected Literature on ISL Translation

Authors (Year) [Ref]	Modality	Approach	Output Type
Albanie et al. (2020) [1]	Video (BSL)	Visual cues + transformers	Gloss-level recognition
Babour et al. (2023) [19]	Flex Sensor Input	Deep learning + flex data	Real-time ASL recognition
Bora et al. (2023) [5]	Hand Gesture (MediaPipe)	CNN on pose vectors	Assamese SL text output
Camgoz et al. (2020) [2]	Gloss + Sign	Transformer-based MT	Sign2Text and Text2Sign
Chaudhary et al. (2022) [6]	Video Input	Dual learning + NMT	Two-way SL translation
Zuo et al. (2025) [8]	Video Input	Retrieval-augmented model	Gloss + Text output
Li et al. (2020) [4]	Word-level video	CNN + CTC decoding	Word-level SL recognition
Núñez-Marcos et al. (2023) [15]	Review Study	Survey of MT pipelines	Comparative analysis
Bharati et al. (2019) [10]	Speech input	Google API + grammar logic	ISL animation output
Goyal and Goyal (2016) [17]	Text Input	Rule-based synonym matching	SiGML-based avatar output
Kaur and Kumar (2016) [11]	Text + HamNoSys	HamNoSys to SiGML conversion	JA Signing avatar player

F. Results of Investigations of Heterogeneity

Subgroup analysis by input modality confirmed that gesture-based models had a higher raw classification accuracy at the cost of logistics in the integration of end-to-end translation pipelines. Subgrouping by language, it is apparent that ISL models produced lower performance overall (mean accuracy = 81.3%) compared to ASL systems (mean accuracy = 87.5%); results that would be expected due to the reduced number and diversity of ISL datasets [4], [12]. Studies using HamNoSys and SiGML annotations also followed greater grammatical accuracy in the produced sign sequences [11].

G. Results of Sensitivity Analyses

More specifically, sensitivity analysis of 14 studies provided reports on latency and accuracy data that varied in latency, forced real time decisions on participants and resulted in accuracy decrements of up to 15% when strict real time decisions (less than 300 ms) were enforced. As highlighted by [20], while accuracy remains crucial, it can be compelling in low-latency environments to prioritize high performance given that the same standard may not apply post-decision latency.

H. Reporting Biases

Reporting bias for selective reporting was identified in 26% of studies, most often due to the omission of specific evaluation metrics (for example, confusion matrices, BLEU scores) or simply only reporting their best performing results. Funnel plot analysis for studies reporting accuracies above 85% indicated mild asymmetry suggesting publication bias in favor of better performing models.

I. Certainty of Evidence

The certainty of evidence was rated moderate for speech-to-sign translation tasks, and low for sign-to-text translation, based on the limitations of cross-validation, and small sample sizes. The highest certainty of evidence was assigned to constrained-domain rule-based systems, the most predictable being weather report translation models. Most unconstrained domains involve far more unpredictability of linguistic structure and vocabulary [1], [2].

V. Research Suggestions

A. Future Research Directions

Following the systematic synthesis of the literature reviewed and recognition of persistent gaps, some key research directions are proposed to advance the field of real-time, bidirectional sign language translation systems.

First, the development of comprehensive, linguistically annotated Indian Sign Language (ISL) datasets that can represent both manual and non-manual components of ISL in a variety of real-world conditions is essential. The BSL-1K dataset [1] and the RWTH-PHOENIX have established datasets commonly used for development and evaluation. However, entirely localized corpora of ISL in these datasets are less diverse and harder to find in formalized datasets that are accessible through the web. Collaboration between research entities, the deaf community, and government will narrow this gap.

Second, future systems should investigate hybrid architectures that involve visual linguistic models, such as CNN-LSTM-Transformer [5], [12] with symbolic grammar types using HamNoSys and SiGML [11]. It is hoped that combinations of hybrid architectures would leverage accurate recognition of ISL and linguistically-faithful output particularly with morphologically-rich sign languages.

Third, the translation pipeline should promote *cross-lingual adaptability* by including multiple sign languages or spoken languages in a single pipeline, like multilingual modalities such as sign.mt [9]. This could help with scalability and representation of inclusive multi-lingual communities.

Fourth, there is a need for further research on *resource-efficient deployment*, like model compression, deployment at the edge, and offline capabilities [14], to ensure accessibility for individuals who may reside in areas where they have low connectivity. As mentioned, interventions should prioritize accessibility to mobile-first solutions, which are widely adopted by deaf and hard-of-hearing individuals.

Fifth, interactive avatar rendering engines must improve realism, personalization, and cultural fidelity. Research on anthropomorphic design, such as [16], emphasizes how anthropomorphic design can enhance user trust and understanding.

Lastly, metrics need to move away from recognition scores and be supplemented by, for example, semantic fidelity, interpreters' naturalness of the generated signs, and user satisfaction of the translated signs. This would acknowledge a human-centered approach to design and ensure technical performance translates into meaningful user outcomes.

Developing and addressing these areas of research may offer a more robust evidence base for sign language technologies and speed up uptake in the market to make communication more inclusive and accessible.

B. Discussion

The field of real-time translation systems based on ISL is heading toward modular, mobile-first applications. MediaPipe and CNNs are providing powerful pipelines for gesture recognition. HamNoSys and SiGML provide lightweight, scalable avatar, and visual recognition solutions [21]. However, dataset limitations, the variety of sign dialects, and challenges in mapping sign grammar remain persistent issues [10], [17].

VI. Conclusion

Translation systems that provide two-way ISL translation are a significant benefit to deaf users. Gesture recognition combined with animated sign rendering with speech-to-sign technology represent access and inclusion with consideration of the language of the user, so it is important for future work to expand on ISL data, to also create more optimized models for mobile, and to expand on grammatical reordering to represent gloss in a more specific way.

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