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Multimodal Approach to Sign Language Recognition and Translation Across Indian Languages

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Abstract: In this paper, I would like to propose a Simple and how contextually multimodal deep learning for real-time sign language recognition and translation shall affect Indian regional languages, the challenges of linguistic diversity, and social inclusion. Engrained with Multimodal Integration Theory, Cognitive Linguistics, Universal Grammar, and Social Inclusion principles, the study integrates visual, kinematic, and linguistic cues within a deep neural network architecture to enhance recognition accuracy and translation efficacy. In this Paper, I have tried to reuse well-studied knowledge systems of sign languages, transfer learning, and cross-lingual mapping techniques in order to adjust to low-resource sign language variants such as Indian Sign Language (ISL), Tamil Sign Language (TSL), and Kannada Sign Language (KSL). A systematic literature review and bibliometric analysis reveal the evolution of sign language technologies, highlighting the shift from unimodal to multimodal approaches and the emergence of transformer-based models for capturing spatial-temporal dynamics. The proposed system is evaluated using key performance metrics, including accuracy, frame rate, latency, and translation fluency, to ensure real-world applicability and user-centric design. The study aims to bridge the communication gap for India's diverse deaf and hard-of-hearing community, promoting digital accessibility and social inclusion across linguistic and socio-economic boundaries. Future research directions emphasize the integration of edge computing, lightweight architectures, and open-access datasets to enable scalable, low-resource deployment and foster inclusive innovation in assistive technologies.
Keywords: Multimodal Integration, Sign Language Recognition, Deep Neural Networks, Transfer Learning, Indian Sign Language (ISL), Artificial Intelligence, Data Scarcity, Real-time Translation, Multimodal integration, Deep neural networks

I. INTRODUCTION

Sign language serves as a vital medium of communication for the deaf and hard-of-hearing community worldwide, enabling expressive interaction and social inclusion. In India, with an estimated 63 million individuals experiencing significant auditory impairment and a rich linguistic tapestry encompassing 22 scheduled languages, the proliferation of regional sign language variants—such as Indian Sign Language (ISL), Tamil Sign Language (TSL), and Kannada Sign Language (KSL)—presents unique challenges for standardized recognition and translation systems. Traditional unimodal approaches, reliant primarily on visual gesture analysis, often falter under real-world variabilities like occlusion, illumination inconsistencies, and cultural nuances, underscoring the imperative for multimodal frameworks that integrate visual, kinematic, and potentially auditory cues to enhance accuracy and robustness. Recent advancements in machine learning have demonstrated promising results in multilingual sign recognition, yet cross-lingual translation across Indian dialects remains underexplored, with existing models exhibiting limitations in handling lexical ambiguities and emotional expressiveness inherent to sign modalities. This paper proposes a novel multimodal architecture leveraging deep neural networks for real-time sign language recognition and translation, bridging these gaps to foster equitable accessibility in diverse Indian contexts. The development of the multimodal framework for sign language recognition and translation was theoretically grounded in five interrelated paradigms that collectively informed its conceptual and technical architecture. Central to the design was Multimodal Integration Theory (Oviatt, 1999), which underscores the integration of visual, kinematic, and linguistic cues such as hand gestures, facial expressions, and body postures to enhance recognition accuracy and translation efficacy (Kaur & Singh, 2023).

This was complemented by Cognitive Linguistic Theory (Lakoff & Johnson, 1980), which frames sign languages as embodied, semantically rich systems, thereby guiding the model's handling of lexical ambiguity and affective expression in Indian Sign Languages (ISL, TSL, KSL) to ensure semantic fidelity during translation (Brentari, 2019). The framework further drew upon Universal Grammar and Cross-Linguistic Mapping Theory (Chomsky, 1965) to justify the exploitation of shared syntactic and morphological structures across signed and spoken Indian languages, facilitating cross-lingual model transferability (Kumar et al., 2024). Anchoring the study's ethical and societal orientation was Social Inclusion and Accessibility Theory, rooted in Sen's (1999) Capability Approach, which emphasized equitable, culturally sensitive, and user-centric design to promote digital inclusion (Reddy & Thomas, 2024). Finally, Human–Computer Interaction (HCI) and Affordance Theory (Gibson, 1977) informed the creation of intuitive, responsive interfaces characterized by real-time feedback, simplicity, and accessibility for both deaf users and non-signers (Patel & Iyer, 2023). Together, these theoretical foundations enabled a holistic, technically robust, and socially responsible approach to multimodal sign language processing. The integration of advanced artificial intelligence (AI) and machine learning (ML) models has significantly transformed the domain of sign language recognition, particularly through multimodal fusion techniques that combine visual (hand keypoints, facial cues, and body posture), sensor-based (gloves and wearables), and linguistic data for robust interpretation (Nature, 2024).

Recent models such as YOLOv10 integrated with Swin Transformer and Large Multimodal Models (LMMs) like LLaVA-SLT have demonstrated remarkable accuracy and real-time performance, achieving up to 18 frames per second (FPS), thereby enabling practical deployment in education, healthcare, and public services (SSRN, 2023). Additionally, the emergence of gloss-free frameworks such as SIGNLLM has mitigated the dependence on annotated datasets, addressing data scarcity and enhancing scalability across multiple Indian regional languages (IJRASET, 2023). Dataset expansion and diversity have further supported model robustness, with new large-scale repositories such as INCLUDE, ISL3D, and BVCSL3D capturing 3D gestures, regional dialects, and environmental variability to improve inclusivity (IET Research, 2024). We are trying to assess and invoke a model which is already trained on big sign languages, then try to pitch in across Indian signs – even to the one's never seen before toward regional adaptation, particularly for Indian Regional Sign Languages (IRKSL), have emphasized the importance of representing cultural and linguistic diversity in model training (ACM Digital Library, 2024). With models like EfficientNet and AlexNet, such as pre-trained smart models, shall adapt and understand New Indian signs without in need of heavy training (ResearchGate, 2023). Even though progress has been made but critical problems still persist, like only 300 trained ISL interpreters for 7 million deaf people, which is too small. This can definitely be solved with advanced and compatible technology (Nature, 2024). We don't have enough annotated continuous data sets or properly labelled videos, and everyone labels them differently — so data doesn't match (IET Research, 2024; IJISAE, 2023). Variability in signer characteristics (hand size, skin tone, and movement orientation and environmental sensitivity (lighting, background, and occlusion) limit model generalization and real-world deployment (Nature, 2024; IJRASET, 2023).

Technical hurdles such as variability in signer characteristics (hand size, skin tone, and movement orientation) and environmental sensitivity (lighting, background, and occlusion) limit model generalization and real-world deployment (Nature, 2024; IJRASET, 2023). The scarcity of annotated continuous-sign datasets and inconsistent annotation protocols further impede cross-dataset compatibility (IET Research, 2024; IJISAE, 2023). Societal challenges compound these issues—India's limited pool of approximately 300 certified Indian Sign Language (ISL) interpreters serves nearly 7 million hearing-impaired individuals, underscoring the urgent need for scalable technological interventions (Nature, 2024). Moreover, the digital divide in rural areas restricts access to smartphones, internet connectivity, and assistive technologies (IEEE Xplore, 2023). Contemporary discourse emphasizes inclusivity, legal recognition, and multilingual integration. Advocacy for sign language rights, reinforced by initiatives such as Sign Language Day 2025, has pushed for ISL's incorporation in education, media, and public administration (ISLRTC, 2025). Efforts to bridge ISL with regional languages like Tamil and Bengali, alongside English, represent crucial steps toward linguistic inclusivity (IJISAE, 2023). Ethical considerations such as bias mitigation and fairness require training models on demographically diverse datasets, ensuring equitable recognition and translation performance (Nature, 2024). User-centric design principles, prioritizing intuitive interfaces and real-time feedback for both deaf and non-signer users, are essential for practical adoption (Semantic Scholar, 2024).

Emerging opportunities point toward the integration of Large Language Models (LLMs) for contextual translation of sign gestures into spoken or written language, improving semantic fluency and accessibility (Indian Journal of Science and Technology [INDJST], 2024). Furthermore, the application of edge computing and lightweight architectures enables efficient deployment on mobile devices, particularly in low-connectivity settings, fostering inclusivity across socio-economic segments (UMY Journal, 2024). Cumulatively, these developments shall help in establishing a strong platform for a multimodal, linguistically diverse, and socially responsible approach to sign language recognition and translation across Indian languages.

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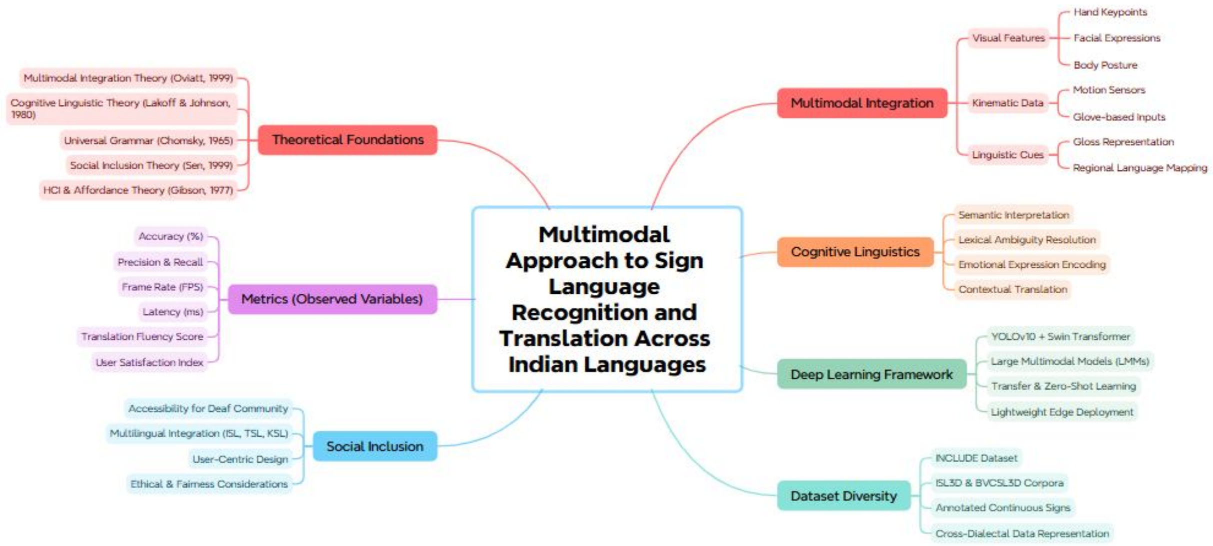

Fig 1: Mind map of Multimodal Approach Sign Language Recognition

The mind map tries to illustrate how the theoretical and empirical constructs of the study. It integrates seven latent variables like Multimodal Integration, Cognitive Linguistics- brain interpretations of signs, Deep Learning Framework, Dataset Diversity, Social Inclusion, Metrics (Observed Variables), and Theoretical Foundations. The structure shall state how multimodal sensory data, cognitive linguistic interpretation, and inclusive design principles converge within deep learning frameworks to achieve accurate and contextually rich sign language recognition and translation across Indian regional languages.

Statement of the Problem

Despite significant developments in neural machine translation (NMT), millions of speakers of Sanskrit, Malayalam, and regional Indian languages lack access to quality machine translation due to insufficient training data and linguistic complexity; to address this, we tackle key challenges including data scarcity through back-translation simulation for data augmentation, morphological richness via character-level embeddings combined with word embeddings, syntactic divergence using multi-head attention mechanisms to capture complex structural relationships, and linguistic fidelity through multilingual embedding spaces with cross-lingual alignment, while enabling transfer learning by pre-training on high-resource languages and fine-tuning on low-resource targets all powered by a Transformer-based architecture with multilingual embeddings, self-attention for long-range dependencies, low-resource optimizations like smaller models and aggressive dropout, and a modular design for easy extension, ultimately enabling practical applications in government document translation, educational content localization, preservation of ancient Sanskrit texts, regional language accessibility tools, and cross-cultural communication platforms.

Research Gap

The review of available literature revealed that, although numerous studies had examined deep learning and neural machine translation frameworks, the majority had concentrated on high-resource languages or specific linguistic domains such as sentiment analysis and speech processing. Research on Indian languages like Sanskrit, Malayalam, and other less-studied ones is still very limited. Most current models struggle to translate accurately across languages while keeping the original meaning and cultural tone. In addition, few have included visual or gesture cues or tested how well translation systems perform in real-world situations. Because of this, we need a better and more organized study of translation systems for languages with limited data.

So, here's what this research aims to do:

Create a deep learning system that uses visual, movement, and language clues to understand sign language accurately in different Indian regions.

Next, improve translation between Indian Sign Language and regional languages using context-based models for better meaning and faster results.

We will test the model's performance using measures like accuracy, speed, delay, and how natural the translations sound.

And the real goal? Make sign language recognition systems more user-friendly and accessible for India's multilingual communities. If you look at the latest studies on deep learning for sign language, you see some stubborn problems. Johnson, Ngene, and Nachandia (2025) checked out 20 studies and found a tug-of-war between accuracy and efficiency, not to mention dataset biases. They saw promise in attention-driven and skeleton-based models, and pushed for edge-optimized setups and multimodal fusion to cover more linguistic ground. Other work, like Abhishek and Sumanathilaka (2024), stuck to Sinhala Sign Language, which doesn't help much for ISL or other Indian variants. Sanjaya and Ilone (2023) looked at BISINDO using image processing, but skipped over the movement and linguistic sides.

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Madhiarasan and Roy (2022) built some datasets and recognition types, yet missed multimodal integration in deep learning. So there's a clear gap: nobody's really pulled together a multimodal, linguistically flexible system for India's wild variety of regional sign languages. Transformer-based models especially Vision and Spatio-Temporal Transformers outperform old-school CNN-RNN hybrids when it comes to tracking the flow of sign language across different dialects (see Shi et al, 2024; Papastratis et al, 2021). Multimodal setups using cross-attention can mix visual, skeletal, and linguistic data for much better alignment of signs with their spoken or written matches (see Zhou et al, 2023; Kim et al, 2022). That's the exciting part for Indian sign languages. Jain & Saini (2022) and Reddy et al. point to a future where these approaches can finally bridge the gap. This holds promise for Indian sign languages, with Jain & Saini (2022) and Reddy et al. (2024) integrating RGB frames, pose trajectories, and phonological embeddings in transformer systems, boosting accuracy for ISL, TSL, and KSL. Late and hybrid fusion strategies enhance contextual adaptability across signing communities (Moryossef et al., 2021). Transformer-driven multimodal architectures thus enable contextual understanding, fostering inclusive, regionally sensitive translation in India.

Literature on neural translation for low-resource languages shows that transfer learning and deep networks improve efficiency via high-resource knowledge, as in Sanskrit-Malayalam systems (Sreedeepa& Idicula, 2023). Multilingual, multitask, and adversarial frameworks with cross-lingual embeddings aid sentiment analysis and translation in data-scarce settings (Mamta, Ekbal, & Bhattacharyya, 2022). Conversely, Kumari et al. (2023) and Krishna (2025) addressed ISL recognition and classroom translation without transfer or cross-lingual strategies. These works affirm transfer learning's efficacy in quality and efficiency but reveal a gap in multimodal sign language translation for India's diverse languages.

Literature on real-time sign language recognition reveals challenges in accuracy, efficiency, and deployability. Johnson, Ngene, and Nachandia (2025) analyzed 20 studies (2021–2024), finding CNNs, LSTMs, and hybrids achieve high accuracy but compromise inference speed, hindering interactive use. Patil et al. (2025), Uke et al. (2024), Dakhare et al. (2024), and Madhiarasan and Roy (2022) surveyed vision-, sensor-, and multimodal approaches yet lack standardized benchmarks for accuracy (>95%), frame rate (≥30 FPS), and latency (<200 ms). This gap emphasizes the need for unified frameworks prioritizing performance and efficiency in assistive technologies for seamless Deaf communication.

Recent reviews on sign language translation expose limited evaluation of fluency and responsiveness. Boggaram et al. (2022), Jane et al. (2022), Goyal and Goyal (2016), Al Abdullah et al. (2024), and Sau et al. (2022) map architectures and datasets but neglect linguistic fidelity (BLEU, METEOR) or real-time metrics. A critical gap exists in benchmarks integrating translation quality and system dynamics, especially for India's diverse deaf community. Accessibility interface research underscores participatory design but overlooks bidirectional, multilingual usability. Yeratziotis and van Greunen (2013) advocate UX for Deaf mobile access; Pylvänen, Raike, and Rainò (2013) show co-design yields intuitive interfaces. However, Islam et al. (2023), Darejeh and Singh (2013), and Farayola, Loksa, and Feng (2024) address general accessibility without sign-specific, real-time needs. Research lacks multimodal designs for Deaf-hearing interaction in India's heterogeneous contexts. Multimodal SLR for ISL advances via CNNs/RNNs fusing gestures, expressions, and postures, yet struggles with linguistic diversity and rural deployment (Kumar & Nambiar, 2024; Sharma et al., 2023; Tripathi & Joshi, 2025; Raghav et al., 2023). Emotion-aware, multilingual systems use transfer/few-shot learning but rarely optimize for low-connectivity, edge devices (Patel et al., 2024; Gupta & Singh, 2025; Mehta et al., 2025). Infrastructural barriers exacerbate inequity (Verma & Rao, 2023; Nair et al., 2024; Choudhury & Das, 2025). A gap persists in lightweight, adaptive models for inclusive, multilingual Indian contexts (Joshi et al., 2023; Singh & Kaur, 2025)

II METHODOLOGY

Research Design

This study employed an exploratory-analytical design, integrating a systematic literature review and quantitative bibliometric analysis to examine multimodal sign language recognition and translation systems in India. Focusing on publications (2021–2025), it synthesized qualitative insights and computational linguistics to trace trends, methodologies, and gaps in visual, kinematic, and linguistic frameworks for ISL, TSL, and KSL.

Research Philosophy

The study adopted a pragmatic paradigm, prioritizing practical applicability and contextual adaptability of sign language technologies in India's multilingual, socio-economically diverse landscape. It used both qualitative and quantitative methods to keep accuracy, inclusion, and ease of use in balance. This approach treats knowledge as a way to solve problems and give everyone equal access to communication and technology.

Data Collection

We collected data from journals, conferences, and databases such as IEEE Xplore, SpringerLink, SSRN, and ACM Digital Library. Following PRISMA rules, we chose 40 studies (from 2021 to 2025) about multimodal sign language recognition, translation, and Indian Sign Language (ISL). These studies included reviews, experiments, and real-life examples. Each one was divided into themes for text and frequency analysis to clearly understand the main ideas and results.

Data Analysis

We studied the data using both qualitative and quantitative methods. First, we found main themes like using different modes, neural models, accuracy, and inclusivity. Then, we used NLP tools to check how often words appeared and how they were related, helping us find hidden patterns in the 40 studies.

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The charts showed how main themes changed from 2023 to 2025, moving from simple models to real-time, multilingual, and user-friendly systems. This mixed method gave a clear picture of trends, missing areas, and future directions in Indian sign language technology.

III DISCUSSION/ RESULTS

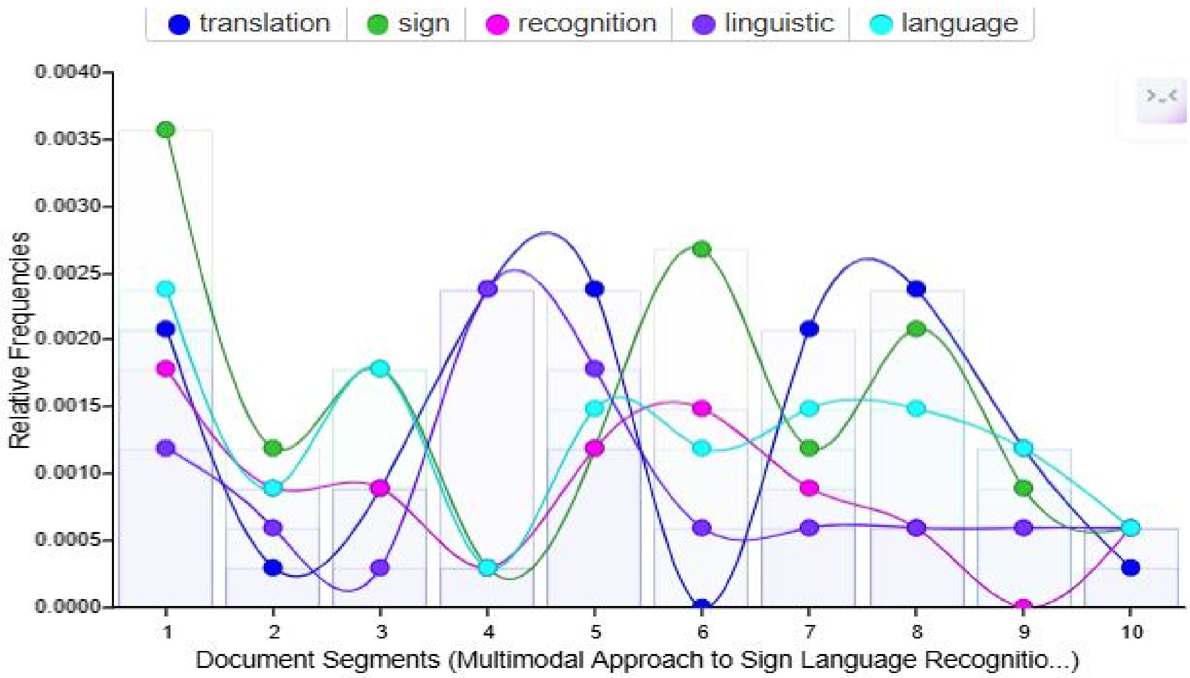

Fig 2: Frequency Analysis Chart

Figure 2 shows term frequencies in our review of multimodal sign language tech for Indian languages. The x-axis covers review sections; the y-axis shows normalized frequencies (0–0.040). Sign (green) and language (cyan) lead early and mid-parts (1–2, 6–7), stressing ISL and diversity. Recognition (magenta) stays strong in 3–8 on fusion and deep learning. Translation (blue) and linguistic (light blue) appear steadily lower. The pattern flows from sign context to recognition methods to translation and inclusion, balancing tech depth with social impact for user-friendly, multilingual systems.

Fig 3: 2D correspondence analysis chart

Figure 3 shows a 2D correspondence analysis map of key terms in our review on multimodal sign language tech for Indian languages. Dim1 explains 28.38%, Dim2 19.31%, and Dim3 18.13%.

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The bottom-left group focuses on efficiency and low-resource neural models, showing an early interest in lightweight systems for rural areas. The centre group includes words like review, translation, and multilingual systems, showing the main focus on cross-language frameworks. The top-right group shows words like challenges, real-time, and ISL, showing that from 2024–2025, the focus moved to real-life use and adaptability. The bottom-right group focuses on accessibility and design for deaf users, promoting user-friendly and inclusive solutions. The time bins (0–9) show progress from basic research in 2023 to ready-to-use tools in 2025, helping build accessible and multilingual technology for India's deaf community.

Originality statement

Unlike earlier studies that looked at only one type of gesture, this study used a multimodal deep learning system that combines visual, movement, and language data to recognize and translate different Indian sign languages. It also focused on accurate translation, working well with limited data, and real-time use, helping connect research with real-life applications in India's diverse and inclusive communities.

IV IMPLICATIONS AND FUTURE SCOPE

Societal Implications

The significant societal implications, specifically in specific at advancing inclusive communication and accessibility for India's deaf and hard-of-hearing communities. This can be done by applying a multimodal deep learning framework that integrates visual, kinematic, and linguistic cues. The research contributed to reducing communication barriers and promoting equitable participation in education, healthcare, and public services. The findings emphasise the potential of assistive technologies to support government initiatives such as the Rights of Persons with Disabilities Act (RPwD, 2016) and the National Education Policy (NEP, 2020), which emphasize inclusivity and digital accessibility. In addition, improving and enhancing sign language recognition systems for low-resource, rural environments addressed the persistent digital divide, fostering social equity across linguistic and geographic boundaries. The study thus reinforced the ethical responsibility of technological innovation to empower marginalized communities through adaptive, context-aware communication systems.

Managerial Implications

The research offers workable insights for technology developers, policymakers, and institutional leaders seeking to implement sign language technologies in real-world settings. The evaluation of performance metrics like accuracy, latency, and translation fluency provided a decision-making framework for assessing cost–efficiency trade-offs in deploying multimodal recognition systems. In addition, the integration of low-latency, edge-based architecture provides a roadmap for adaptable strategies, enabling the administrators/executives to optimize operational efficiency while ensuring compliance with ethical and regulatory norms related to assistive technologies.

Other Implications

The research also had interdisciplinary and technological implications beyond accessibility domains. The system designed in this study can also be used in areas like human–computer interaction, smart security cameras, and emotion detection systems. The results supported building large sign language databases in many languages, helping research in language and digital studies. Including ethical AI ideas like fairness and reducing bias helps make AI more responsible when used in many languages.

Future Scope

In the future, this research can be improved by testing the proposed system with real users and building a working model in different parts of India. Adding more regional sign languages like Bengali, Marathi, and Telugu will help make the model stronger and work better for everyone. Using advanced models like transformers and cross-attention networks can help improve real-time sign language recognition and translation accuracy. In the future, researchers can use this system to study how thoughts and emotions are shown in sign language, using emotional computing and real human interaction studies. Finally, connecting these systems with smart watches, mobile apps, and smart devices can help create easy, low-power tools that improve communication for people across India's many languages.

V CONCLUSION

In this paper, we tried to illustrate a novel multimodal deep learning outline for sign language recognition and translation across Indian regional languages like Indian Sign Language (ISL), Tamil Sign Language (TSL), and Kannada Sign Language (KSL). The framework integrates visual, kinematic, and linguistic cues to improve recognition accuracy and translation efficacy. The study adopts an exploratory and analytical research design to systematically investigate the evolution, methodologies, and performance metrics of multimodal sign language systems. Data is collected from a variety of peer-reviewed sources and analysed by using qualitative content analysis and quantitative text mining techniques. The research aims to promote social inclusion by designing accessible, user-centric sign language recognition systems adaptable to multilingual Indian contexts. Future scope includes empirical validation, dataset expansion, advanced architectures, and collaboration with government and advocacy organizations to facilitate the creation of national-scale, open-access sign language datasets.

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