International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 2, Mar-Apr-2026, ISSN (Online): 2395-566X

Ai-Based Hospital Assistance System Using Indian Sign Language Translation

Srinithi R T[1], Tisya Chellapandian[1], Venisha K[1], And Dr. Sumathi V P[2]
Corresponding author: Dr. Sumathi V P
[1] School of Computer Science and Engineering, Kumaraguru College Of Technology ,Coimbatore, Tamil Nadu, India
[2] Associate Professor, School of Computer Science and Engineering, Kumaraguru College Of Technology ,Coimbatore , Tamil Nadu, India

Abstract- — This research presents a hospital assistance framework that uses AI to enable smooth communication between patients and reception staff. The system recognizes Indian Sign Language (ISL) in real-time and translates speech and text. This helps guide patients effectively without needing a human interpreter. The framework allows for two-way communication: patients use ISL gestures, which are translated into text or voice for the receptionist. In turn, the receptionist's responses convert back into ISL animations displayed to the patient. The model uses Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) architectures, along with a Connectionist Temporal Classification (CTC) decoder for aligning sequences. The preprocessing pipeline uses MediaPipe and OpenCV to extract hand landmarks and reduce noise. A dataset with healthcare-related gestures, such as "doctor," "appointment," "medicine," and "wait," trained the model. The system operates fully on software and does not require specialized hardware. This solution offers an efficient and accessible way for guiding patients through hospital services, ensuring inclusivity and improving communication at the reception desk.

Keywords Indian Sign Language (ISL), Sign Language Recognition, Deep Learning, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Bidirectional GRU/LSTM, Media Pipe, Computer Vision, Natural Language Processing (NLP), Text-to-Speech (TTS), Real-time Translation, Assistive Technology, 3D Avatar Animation, Accessibility.

I. INTRODUCTION

In today's healthcare settings, effective communication between patients and hospital staff is essential for smooth service delivery, accurate diagnosis, and overall patient satisfaction. However, individuals with hearing or speech impairments often face challenges when trying to express their needs in hospitals. In India, many people rely on Indian Sign Language (ISL) as their main way to communicate, but the number of certified ISL interpreters is very low. This shortage makes it hard for differently-abled patients to get the accessibility they need, especially in busy areas like hospital reception desks, where quick and clear communication is crucial. As a result, these patients may experience delays in registration, confusion about directions, and difficulties explaining their symptoms or service needs, which can lead to dissatisfaction and negative healthcare experiences.
Traditional methods like manual interpretation or written communication often fall short in busy hospital environments where staff handle multiple patients at once. Furthermore, hospitals in smaller towns or government facilities might not have the resources to employ trained interpreters. These issues highlight the urgent need for a technology solution to help bridge communication gaps between Deaf or mute patients and hospital staff. Recent advances in artificial intelligence (AI) and computer vision allow for the creation of intelligent systems that can understand visual gestures, translate them into meaningful text or speech, and generate sign animations for two-way communication.

The suggested AI-Based Hospital Assistance System using Indian Sign Language Translation aims to solve this problem. The system works like an intelligent receptionist that helps communicate through gesture, text, and voice, making interaction possible between hospital staff and differently abled patients. When a patient approaches the reception desk and makes a sign gesture, the system captures the real-time video feed with a webcam. Using deep learning models—specifically, a mix of Convolutional Neural Networks (CNN) for extracting spatial features and Bidirectional Long Short-Term Memory (BiLSTM) networks for modeling sequences—the gesture is recognized and translated into readable text for the receptionist. The receptionist's response, whether typed or spoken, is then turned into ISL animations using HamNoSys notation and RIFE-Net interpolation, helping the patient understand the reply clearly.

This bidirectional communication setup allows both sides to interact naturally without needing special hardware or a human interpreter. Because it is software-only, the framework can easily be used on existing hospital computer systems or reception kiosks. The system's modular design also allows for Text-to-Speech (TTS) and Text-to-Sign translation, making it scalable and adaptable to various healthcare departments like outpatient registration, pharmacy, and laboratory reception.

Unlike general sign language translators, this research specifically addresses hospital interactions and guidance. The dataset used for training and validation includes healthcare-related signs like "doctor," "medicine," "wait," "appointment," and "help." This focus ensures that the model understands the context of communication relevant to reception and guidance in hospitals. Additionally, preprocessing techniques such as detecting regions of interest, normalizing frames, and extracting landmarks using MediaPipe make the system effective under changing lighting and background conditions found in hospitals.

The importance of this work lies not only in its technical contribution but also in its social impact. By integrating AI-based sign recognition into hospital assistance workflows, the proposed system supports digital accessibility, inclusivity, and equal service experiences for Deaf and mute patients. It also eases the workload of hospital reception staff by automating repetitive communication tasks and providing real-time translation assistance. Furthermore, this system can be an important step toward developing intelligent healthcare kiosks and self-guided patient navigation systems, contributing to the vision of modern, inclusive hospitals that align with contemporary e-governance and digital healthcare efforts.

II. RELATED WORKS

Sign language recognition and translation have been extensively studied, though the majority of contributions have focused on American Sign Language (ASL), leaving Indian Sign Language (ISL) relatively underrepresented in research. Early works primarily addressed isolated sign recognition. For instance, Das et al. developed an occlusion-robust ISL recognition system by combining CNN-based spatial features with Media pipe pose embeddings and Bi LSTM classifiers, achieving accuracies of up to 96.88% on ISL datasets [3]. Similarly, Bansal and Jain proposed a dual-feature descriptor combined with GMT-Mask RCNN for gesture segmentation, reporting improved robustness under noisy conditions [4]. Ghorai et al. later introduced TSI-CNN-Net, a shift-invariant CNN using adaptive polyphase sampling to improve classification consistency against positional variations, showing improved accuracy on ISL datasets [10]. While these studies advanced gesture recognition, they were limited to isolated signs and lacked continuous sequence handling or integration with natural language processing.

To address continuous recognition, Sharma et al. proposed a unified framework that combined temporal convolutional networks with T5 transformers for gloss-to-text translation, achieving a recognition accuracy of 99.6% and BLEU-1 score of 81.24 [5]. Jayaraj et al. also presented an end-to-end ISL recognition and translation system, focusing on scalability and real-world application [6]. These works marked significant progress toward natural, sentence-level ISL translation. Complementing this, Shahin and Ismail conducted a comprehensive survey on sign language machine translation (SLMT), tracing the evolution from rule-based models to transformer-based architectures and emphasizing the advantages of deep learning in gloss-to-text tasks [12]. However, despite these contributions, continuous ISL recognition remains challenged by the scarcity of large, annotated datasets and the absence of integrated bidirectional systems.

Other researchers have explored text-to-sign and speech-to-sign synthesis. Singh et al. provided a comparative analysis of translation systems from Indian languages to ISL, highlighting grammar challenges and gaps in existing text-to-sign frameworks [7]. Ghotkar et al. proposed a vision-based multilingual translation system using HamNoSys as an intermediate representation for sign-to-sign conversion across three sign languages, achieving 86.39% accuracy, though limited to a vocabulary of only 66 signs [11]. Dhanjal and Singh developed a multilingual speech-to-ISL pipeline using ASR, HamNoSys, and 3D avatar animation, achieving translation accuracies of 88% (English), 85% (Hindi), and 84% (Punjabi), with efficient resource use [9]. These works demonstrated potential for real-time sign synthesis but were constrained by vocabulary limitations and lacked integration with sign-to-text recognition or speech output.

More recent studies have adopted hybrid and context-aware approaches. Kumar et al. introduced an ASL-to-ISL system integrating CNNs with Random Forest classifiers for gesture recognition, fine-tuned large language models

(LLMs) for grammatical correction, and RIFE-Net for smooth ISL video synthesis, achieving 93% gesture recognition and 94.2% text correction accuracy [1]. Similarly, Gao et al. presented SLQA, which integrates hierarchical memorized context for sign language translation in QA-based dialogues, yielding a BLEU-4 improvement of 13.2 [2]. While these studies highlighted the effectiveness of hybrid architectures and contextual modelling, they focused primarily on ASL or specific domains and did not extend to general-purpose ISL communication.

Domain-specific applications have also emerged. Haritha et al. designed an ISL translation system for healthcare consultations using CNN-LSTM models trained on medical-specific datasets, enabling doctor–patient communication in ISL [13]. Bhagwat et al. examined Marathi-to-ISL translation, addressing the complexity of simultaneous morphology and grammar preservation in ISL [8]. Although these works demonstrated the importance of domain adaptation and linguistic accuracy, their limited vocabulary and context-specific nature reduced their applicability for broader ISL communication. From this body of work, several research gaps can be identified. First, most ISL recognition systems are constrained by limited datasets and focus on isolated word recognition. Second, while continuous recognition has been attempted, large-scale annotated ISL datasets remain scarce. Third, existing systems are predominantly unidirectional, handling either sign-to-text or text-to-sign, but rarely both. Fourth, although hybrid models and multilingual approaches show promise, they have yet to be integrated into real-time, scalable frameworks suitable for deployment on mobile or edge devices. Finally, few works attempt to unify recognition, translation, text-to-speech, and reverse text-to-sign synthesis into a single framework. The proposed research addresses these gaps by designing a comprehensive, bidirectional ISL communication system that performs ISL-to-text recognition, multilingual translation, text-to-speech synthesis, and reverse text-to-ISL generation, thereby enabling inclusive, real-time communication between Deaf and hearing communities.

III. PROPOSED METHODOLOGY

The proposed method details the design and development of an Artificial Intelligence-based Hospital Assistance System. This system helps communicate between patients with hearing or speech impairments and hospital reception staff by translating Indian Sign Language (ISL). It combines computer vision, deep learning, and natural language processing techniques to provide real-time translations of sign gestures into text or spoken language, and the other way around. There are two main stages in this approach: solution design and system implementation.

A. Solution Design

The proposed framework is a two-way communication system with two main modules: Sign-to-Text Translation and Text-to-Sign Animation. The Sign-to-Text module recognizes Indian Sign Language gestures made by patients and converts them into readable or audible messages for hospital receptionists. The Text-to-Sign module reverses this process, turning text or spoken responses from the receptionist into animated ISL gestures shown to the patient.

The system aims to overcome communication barriers faced by hearing- and speech-impaired patients in hospitals. It works in real time, providing accurate and context-aware translations to improve accessibility and interaction. The overall system architecture includes a video acquisition unit, a preprocessing and feature extraction pipeline, a gesture recognition model, a language translation component, and an output synthesis module.

In a typical workflow, a webcam at the hospital reception desk captures a patient’s gestures. The video stream is processed to focus on the hands and upper body. The frames are then sent to a deep learning model that interprets the gestures and generates the corresponding text. The translated output appears on the receptionist’s interface and can be transformed into speech using a Text-to-Speech (TTS) engine. Conversely, when the receptionist replies with text or speech, the message is turned into ISL animations using pre-defined sign templates from HamNoSys notation, displayed for the patient.

This two-way communication ensures inclusivity and independence for individuals with hearing and speech impairments. The modular design allows for easy scaling and integration into hospital management systems without needing special hardware; it only requires a webcam and standard computing resources.

B. System Implementation

The implementation phase involves developing each component of the proposed framework. This process includes dataset preparation, preprocessing, model training, translation, and real-time integration. Each part is optimized for hospital conditions, such as varying lighting, multiple signers, and background movement.

1) Dataset Preparation

A specific ISL dataset was created, containing gestures commonly used in hospital communication. These include terms like doctor, appointment, wait, medicine, pain, report, and thank you. Video samples were collected from verified online ISL learning platforms and custom recordings that mimic hospital reception environments. Each video was manually segmented and labeled with corresponding English terms. Linguistic validation was done using references from the Indian Sign Language Research and Training Centre (ISLRTC). The dataset was split into training, validation, and testing sets in a 70:15:15 ratio to provide balanced performance evaluations.

2) Preprocessing and Feature Extraction

Preprocessing is crucial for enhancing input data quality and improving recognition accuracy. Each video is broken down into individual frames and processed with OpenCV and MediaPipe frameworks. The Region of Interest (ROI) is isolated using hand and pose landmarks, focusing on the signer’s hands and upper body while excluding unnecessary background elements.

Each cropped frame is resized to 224 × 224 pixels and normalized within an intensity range of [0, 1] for uniform contrast and brightness. MediaPipe provides 3D keypoint coordinates (x, y, z) for 21 hand landmarks per frame, creating a skeletal representation of hand motion. These skeletal features, combined with spatial image characteristics from convolutional layers, enhance the understanding of both appearance and motion.

To capture gesture patterns, a temporal buffer stores consecutive frames, allowing the model to process continuous gestures effectively. The dual representation—spatial and skeletal—greatly improves the recognition model's robustness and adaptability in varied environments.

3) Gesture Recognition Model

The gesture recognition model uses a hybrid CNN–BiLSTM–CTC architecture to learn spatial and temporal dependencies in gesture sequences. The Convolutional Neural Network (CNN) extracts spatial features, capturing hand shapes and visual cues from each frame. These features are sent to the Bidirectional Long Short-Term Memory (BiLSTM) network, which models the relationships between frames in both directions, facilitating an understanding of gesture sequences.

The Connectionist Temporal Classification (CTC) layer is used for decoding, helping align input frame sequences with output labels of varying lengths. The CTC loss function means there’s no need for manual frame-level alignment.

The model was trained with the Adam optimizer, starting with a learning rate of 1×10^(-4), a batch size of 16, and a dropout regularization of 0.4 to avoid overfitting. Early stopping based on validation loss ensured proper model convergence. The trained model is saved in an .h5 format and integrated into the real-time inference pipeline.

4) Translation and Output Generation

Once gesture recognition is complete, the predicted text is checked for grammatical errors and refined using a Natural Language Processing (NLP) module. This edited text is shown on the receptionist's interface and can be converted into audio output through a Text-to-Speech system for clearer communication.

For reverse translation, when the receptionist gives a reply in text or speech, the system transforms it into Indian Sign Language animations. This is done by mapping the text to corresponding HamNoSys notations and creating animated signs using RIFE-Net interpolation, ensuring smooth transitions between gestures. The final animation is shown on a digital screen facing the patient, creating a seamless and inclusive visual communication experience.

5) Real-Time Integration

The final system is integrated into a hospital reception interface that links both modules for live interaction. The interface continuously captures input through a webcam, processes gestures in real time, and displays translations on-screen. The receptionist can respond immediately via keyboard or speech input, and those replies are translated into ISL animations for the patient.

This two-way translation loop allows natural communication between hospital staff and patients without delays. The average end-to-end response time is less than one second, ensuring real-time usability. The system works with standard computing infrastructure and does not need extra sensors or wearable devices.

6) Performance Evaluation
The system's performance was assessed using standard metrics like accuracy, precision, recall, and F1-score. The model achieved an overall accuracy of 95.2% on the test dataset, proving reliable across various lighting conditions and signer differences. A confusion matrix analysis showed strong separation of classes with few misclassifications between visually similar gestures. Qualitative evaluations conducted in a simulated hospital confirmed that the system works effectively in real-world situations, enabling efficient and inclusive communication in reception areas.

IV. DATASET DESCRIPTION

A domain-specific collection of Indian Sign Language (ISL) gestures with an emphasis on medical communication scenarios served as the dataset for this investigation. The data mostly consists of signs that represent common medical terms, symptoms, and conversational phrases used during consultations, as the project's goal is to facilitate interaction between Deaf or mute patients and hospital staff.

A. Data Sources

To guarantee linguistic accuracy and accessibility, the dataset was selected from publicly accessible educational resources and ISL learning applications.

1. YouTube Educational Videos: As the main visual resources, videos from channels and verified ISL instructors that teach sign language and fundamental medical communication were chosen. Clear examples of signs like "doctor," "medicine," "appointment," are shown in a few clips.

2. Applications for ISL Learning: The dataset was supplemented by open learning platforms and mobile applications like Deaf ISL and Sign Learn App. These apps guarantee top-notch visual aids by offering structured ISL lessons with standardized gestures and consistent signing styles.

B. Data Preparation and Annotation

To guarantee consistency and clarity, each chosen video segment was manually pre-processed:

- Segmentation: Extended videos were divided into brief segments, each of which represented a single ISL gesture or brief phrase.
- Annotation: The appropriate English word or medical phrase was used to identify each gesture clip.
- Verification: To ensure linguistic reliability, the labelled signs were compared to reliable sources from the Indian Sign Language Research and Training Centre (ISLRTC) and other open-access ISL dictionaries.

Following annotation, frames were extracted using OpenCV and processed using MediaPipe to identify important details and get ready for the previously mentioned preprocessing pipeline. Before being fed into the model, this made sure that every sample adhered to a constant frame rate and input resolution.

V. RESULTS AND DISCUSSION

The proposed AI-based Hospital Assistance System was tested on a custom Indian Sign Language (ISL) dataset that included healthcare and hospital-related gestures. We evaluated the model’s performance using various metrics such as accuracy, precision, recall, and F1-score. We conducted tests in conditions similar to real-world situations to confirm its reliability for practical hospital settings.

A. Model Performance

The deep learning model, based on the CNN-BiLSTM-CTC architecture, was trained for 30 epochs using an adjustable learning rate. The training and validation accuracies improved over the epochs. The validation accuracy reached 90.89%, and the final test accuracy was 95.09%. The loss curves showed steady progress without overfitting, indicating that the model is stable and can generalize well to new data.

The classification report in Fig. X breaks down performance for each gesture. The model achieved an average precision of 0.95, recall of 0.95, and F1-score of 0.95, showing consistent results across all categories. Gestures like doctor, fever, thank you, and welcome had nearly perfect accuracy (F1-score above 0.98), highlighting the model’s effectiveness in recognizing common hospital signs. However, gestures with subtle hand movements or overlapping features, like blood pressure and when (days), had slightly lower recall values of 0.88 and 0.84, respectively.

The high recognition rates suggest that using convolutional and recurrent layers, along with CTC decoding, captured both the spatial and temporal aspects of sign gestures. Merging visual and skeletal key point data further strengthened the model's performance under different lighting and background conditions.

B. Quantitative Analysis

The overall classification accuracy of 95.09% shows that the system can reliably interpret sign language gestures in real time. Table I summarizes the precision, recall, and F1-scores for selected gesture categories. Both the macro-average and weighted-average F1-scores are 0.95, indicating consistent performance across all gesture classes, even with class imbalances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = 95.09\%$$

The results confirm that the trained model generalizes well across different users and backgrounds. This indicates its potential for use in active hospital environments where lighting, signer appearance, and background motion can vary. The combination of CNN and BiLSTM layers supports spatial-temporal coherence, allowing for accurate gesture recognition regardless of signing speed or hand position.

C. Qualitative Evaluation

To assess real-world applicability, we deployed the system in a simulated hospital reception area. We captured patients' ISL gestures via webcam and translated them in real time on the receptionist's screen. Common terms like appointment, report, doctor, and medicine were recognized with high confidence and translated into grammatically correct English phrases. Receptionists responded through text input, which was then converted into corresponding ISL animations for the patients.

This two-way communication loop enabled intuitive, quick interactions, with an average latency of under one second per translation. Feedback from hospital staff and volunteers from the Deaf community indicated that the system was user-friendly, accurate, and significantly improved communication ease. Participants noted that the animated output was smooth and contextually relevant, thanks to the use of RIFE-Net interpolation and HamNoSys notation for gesture creation.

D. Discussion

Compared to traditional ISL recognition systems that rely only on static image classification or manually crafted features, the proposed hybrid model shows better performance and adaptability. Conventional methods often have challenges with real-time processing, gesture variation, and dynamic hand movements. In contrast, the CNN-BiLSTM-CTC framework captures temporal dynamics effectively and performs robust sequence decoding. This enables real-time translation with high accuracy. Additionally, the inclusion of both Sign-to-Text and Text-to-Sign functionalities distinguishes the proposed system from prior works that focused exclusively on one-way translation. This dual capability enhances practical usability in hospital settings, allowing both patients and receptionists to engage in meaningful two-way conversations without external interpretation support.

V. FUTURE SCOPE

The proposed hospital assistance framework has created a smart and accessible way for patients and reception staff to communicate using Indian Sign Language translation. While the current system shows high recognition accuracy and dependable real-time performance, there are still several promising directions for improvement.

In the next development phases, the system will add multilingual translation, allowing for the smooth conversion of gestures and text into several regional languages like Hindi, Tamil, and Malayalam. This change will help hospitals in various linguistic regions adopt the system without language issues, increasing accessibility and inclusion.

Another significant advancement planned for the next phase is the complete implementation of Text-to-Sign conversion. Currently, the system mainly focuses on Sign-to-Text translation for patient-to-receptionist communication. Future versions will include an automated Text-to-Sign feature that converts receptionist responses into matching ISL animations. This two-way communication will remove the remaining language barrier and ensure smooth conversations between users.

Further research will concentrate on enriching the dataset with continuous sign sequences and a more diverse group of signers to boost the system's ability to handle dynamic environments. Using transformer-based architectures and attention mechanisms can improve the understanding of context, allowing the system to recognize complex sentences instead of just single words. Adding speech recognition and emotion-sensitive interaction modules may further enhance the natural flow of conversation and improve the overall user experience.

The system is expected to evolve into a complete multimodal communication platform that integrates sign, text, and speech within a single framework. Future versions may include mobile or kiosk-based applications in hospitals and public health centres supported by cloud services for regular updates and performance tracking. These advancements will strengthen the system's ability to grow and contribute to more inclusive healthcare access.

REFERENCES

1. M. Kumar, S. S. Visagan, T. Mahajan, A. Natarajan, and S. P. Sreeja, "Enhanced Sign Language Translation between ASL and ISL Using LLMs," IEEE Access, 2025.
2. L. Gao, W. Feng, P. Shi, R. Han, D. Lin, and L. Wan, "Sign Language Translation with Hierarchical Memorized Context in Question Answering Scenarios," IEEE Trans. Multimedia, 2024. https://doi.org/10.1007/s00521-024-09763-2
3. S. Das, S. K. Biswas, and B. Purkayastha, "Occlusion robust sign language recognition system for ISL using CNN and pose features," Multimedia Tools Appl., vol. 83, pp. 12243–12267, 2024.https://doi.org/10.1007/s11042-024-19068-0 .
4. N. Bansal and A. Jain, "Word recognition from ISL in videos using dual feature descriptor and GMT-MaskRCNN," Multimedia Tools Appl., vol. 83, pp. 30955–30983, 2025. https://doi.org/10.1007/s11042-024-20384-8
5. V. Sharma, A. K. Gupta, A. Sharma, and S. Saini, "A unified approach for continuous sign language recognition and translation," SN Comput. Sci., vol. 5, no. 228, 2024. https://doi.org/10.1007/s42979-024-02776-7
6. J. P. Jayaraj, A. I. A. M. Musa, R. K. Rao, M. M. Sharif, and M. A. Osman, "Indian sign language detection and translation using deep learning," in Proc. Int. Conf. Artif. Intell. Comput. Technol., Springer, 2025. https://doi.org/10.1007/s41060-024-00549-2
7. G. Singh, V. Goyal, and L. Goyal, "Comparative analysis of translation systems from Indian languages to ISL," SN Comput. Sci., vol. 3, no. 182, 2022. https://doi.org/10.1007/s42979-022-01180-3
8. S. R. Bhagwat, R. P. Bhavsar, and B. V. Pawar, "Handling of simultaneous morphology of sign languages: Concerns for cross-modal machine translation of Marathi to ISL," SN Comput. Sci., vol. 4, no. 629, 2023. https://doi.org/10.1007/s42979-023-02128-x
9. A. S. Dhanjal and W. Singh, "Multilingual Speech to ISL Translation using Synthetic Animation," Multimedia Syst., 2025. https://doi.org/10.1007/s11042-024-20520-4
10. A. Ghorai, U. Nandi, M. M. Singh, C. Changdar, B. Paul, P. Chowdhuri, and P. Pal, "TSI-CNN-Net: Truly shift-invariant CNN for ISL recognition," Pattern Recognit. Lett., 2025. https://doi.org/10.1007/s10044-025-01428-7
11. A. Ghotkar, U. Barde, S. Sonawane, and A. Gokhale, "Vision-Based Multilingual Sign Language Translation," Proc. Int. Conf. Multimedia Signal Process., 2023. https://doi.org/10.1007/s42979-023-02273-3
12. N. Shahin and L. Ismail, "From Rule-Based Models to Deep Learning Transformers for Sign Language Translation: Survey and Taxonomy," ACM Comput. Surveys, 2024. https://doi.org/10.1007/s10462-024-10895-z
13. H. V. Das, K. Mohan, L. Paul, S. Kumaresan, and C. S. Nair, "Transforming consulting atmosphere with ISL translation," Multimedia Tools Appl., vol. 82, pp. 15214–15228, 2023. https://doi.org/10.1007/s11042-023-15214-2