

# AI Tool/Mobile App for Indian Sign Language (ISL) Generator from Audio-Visual Content In English/Hindi to ISL Content and Vice-Versa

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**Abstract-** This paper presents a lightweight and practical bidirectional communication system designed to translate between speech and Indian Sign Language (ISL) using machine learning and computer vision techniques. The system operates in two modes: (i) speech-to-ISL translation, where spoken input is converted into text and further mapped into a sequence of ISL alphabet images, and (ii) ISL-to-text and speech translation, where hand gestures captured through a webcam are recognized using a Convolutional Neural Network (CNN) model and converted into readable text and audio output. Unlike existing approaches that rely on complex natural language processing techniques or computationally expensive 3D avatar rendering, the proposed system focuses on simplicity, real-time performance, and ease of implementation. By utilizing a TensorFlow/Keras-based CNN model for gesture recognition and a predefined ISL image dataset for visual representation, the system achieves efficient and accurate translation with low computational requirements. The system is implemented using Python with libraries such as OpenCV, Streamlit, speech\_recognition, and pyttsx3, enabling an interactive and user-friendly interface. The proposed solution provides a cost-effective and accessible tool to bridge the communication gap between hearing individuals and the Deaf and Hard-of-Hearing (DHH) community, making it suitable for real-world applications.

**Keywords:** Indian Sign Language, Speech Recognition, Gesture Recognition, CNN, TensorFlow, OpenCV, Accessibility, Human-Computer Interaction.

## I. INTRODUCTION

Communication barriers between hearing individuals and the Deaf and Hard-of-Hearing (DHH) community remain a significant challenge in everyday life. Although Indian Sign Language (ISL) serves as an essential medium of communication for many DHH individuals, its understanding among the general population is limited. This lack of awareness and accessibility often leads to difficulties in education, healthcare, and social interaction.

To address this issue, this work proposes a simple, practical, and real-time bidirectional communication system that facilitates interaction between hearing and DHH users. The system is designed with two primary functionalities:

**Speech** → ISL (Visual Representation): Spoken input is converted into text using speech recognition techniques and then mapped to corresponding ISL alphabet images for visual communication.

**ISL** → Text/Speech (Gesture Recognition): Hand gestures captured through a webcam are recognized using a Convolutional Neural Network (CNN) model and converted into text and speech output.

Unlike traditional systems that rely on complex natural language processing or computationally intensive 3D avatar-based rendering, the proposed approach focuses on a lightweight and efficient implementation. By using simple image-based ISL representation and deep learning-based gesture recognition, the system achieves real-time

performance with minimal computational requirements.

The primary objective of this work is not to build a highly complex linguistic translation system, but rather to develop a functional assistive tool that is easy to implement, cost-effective, and suitable for real-world usage. Such a system can be effectively utilized in environments like classrooms, hospitals, public service centers, and workplaces to improve accessibility and promote inclusive communication.

## II. LITERATURE REVIEW

Research in Indian Sign Language (ISL) translation has gained significant attention in recent years due to the increasing need for accessible communication systems for the Deaf and Hard-of-Hearing (DHH) community.

Various approaches have been proposed, including speech-to-sign systems, gesture recognition models, and AI-based multimodal translation frameworks. This section critically analyzes existing work and identifies key research gaps that motivate the proposed system.

### Speech-to-Sign Language Systems

Early research in ISL translation primarily focused on converting speech into text and subsequently mapping the text to predefined sign representations such as images or videos. For example, Bhagat et al. [1] proposed a system that captures speech input using a microphone, converts it into text using speech recognition, and displays corresponding ISL signs using a predefined dataset.

These systems demonstrate that basic communication can be achieved using simple mapping techniques without requiring complex machine learning models.

However, they suffer from significant limitations, including dependence on fixed vocabularies and inability to handle unseen words or continuous speech inputs. Additionally, these systems do not

generalize well to real-world communication scenarios due to their static nature.

### AI-Based Multimodal Translation Systems

Recent advancements in artificial intelligence have led to the development of multimodal systems that integrate speech recognition, natural language processing, and computer vision. The SignSync system [2] introduces an AI-powered framework capable of translating both speech and gestures using deep learning models such as Convolutional Neural Networks (CNNs) and sequence-based architectures.

These systems significantly improve translation accuracy and enable real-time interaction by processing multiple input modalities simultaneously. However, the integration of multiple components increases system complexity, making them computationally expensive and difficult to deploy on low-resource devices. Furthermore, reliance on large datasets and external APIs limits their scalability and accessibility.

### Gesture Recognition Using Deep Learning

Gesture recognition is a fundamental component of ISL translation systems. Deep learning techniques such as CNNs, Long Short-Term Memory (LSTM) networks, and hybrid models have been widely used for recognizing hand gestures from images and video sequences. Krizhevsky et al. [7] demonstrated the effectiveness of CNNs in image classification tasks, which has been extended to gesture recognition applications.

Similarly, Iyer and Das [5] explored deep learning-based gesture recognition systems that utilize feature extraction and pattern recognition to improve classification accuracy. These approaches are capable of handling variations in hand shapes and positions, but challenges such as lighting conditions, background noise, and similarity between gestures still affect performance.

### Mobile and Real-Time ISL Applications

Recent studies have focused on developing mobile and real-time ISL translation systems to improve accessibility. Singh et al. [3] proposed a mobile-

based ISL translation tool that converts speech into sign language representations using speech recognition and mapping techniques. These systems emphasize real-time performance and user accessibility.

However, most mobile applications depend on internet connectivity and cloud-based processing, which can limit their usability in low-resource or offline environments. Additionally, real-time gesture recognition on mobile devices remains challenging due to hardware constraints.

### Identified Research Gap

From the analysis of existing literature, several key limitations are identified:

- Most systems are computationally complex and resource-intensive
  - Limited focus on lightweight, real-time implementations
  - Dependence on large datasets and external APIs
  - Lack of efficient bidirectional translation systems
  - Poor performance in real-world conditions
- These challenges highlight the need for a simple, efficient, and deployable ISL translation system.

### Motivation for Proposed System

To address the identified limitations, the proposed system focuses on developing a lightweight and practical bidirectional ISL translation model. The system utilizes machine learning and computer vision techniques to ensure real-time performance while maintaining simplicity.

### Key motivations include:

- Developing a low-complexity system using CNN-based gesture recognition
- Achieving real-time performance using OpenCV and TensorFlow
- Implementing alphabet-level translation for simplicity and reliability
- Designing a bidirectional system (Speech ↔ ISL) without relying on complex NLP or avatar-based rendering

This approach ensures improved usability, faster execution, and easier deployment in real-world

scenarios, particularly in low-resource environments.

## III. SYSTEM ARCHITECTURE

The proposed system is designed as a bidirectional framework that enables communication between speech and Indian Sign Language (ISL). It consists of two independent yet interconnected modules:

1. Speech-to-ISL translation
2. ISL-to-Text translation.

Both modules share a common machine learning backbone for efficient processing and real-time performance.

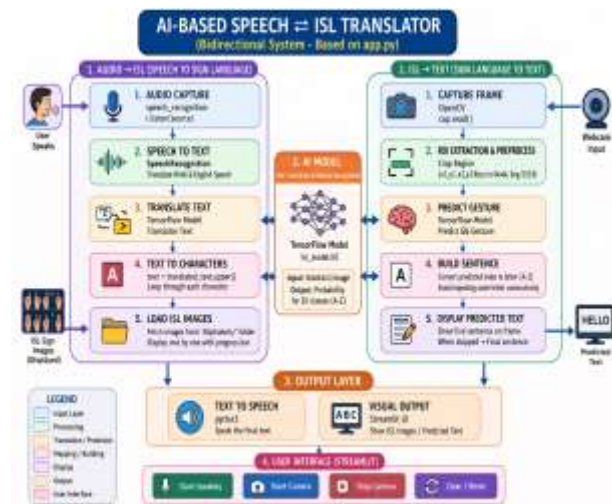


Figure 3.1: System Architecture of Proposed System

The architecture illustrates two parallel pipelines. The upper pipeline represents the Speech-to-ISL flow, where speech input is converted into text and then mapped to ISL images.

The lower pipeline represents the ISL-to-Text flow, where hand gestures captured through a webcam are processed and classified using a CNN model to generate textual output.

### Speech-to-ISL Module

The Speech-to-ISL module is responsible for converting spoken language into a visual representation of Indian Sign Language. This module is designed to be lightweight and efficient, avoiding complex linguistic transformations.

Initially, speech input is captured using a microphone and processed through a speech recognition engine to convert audio into text. The obtained text is then segmented into individual characters to simplify the translation process.

Each character is mapped to a corresponding ISL alphabet image stored in a predefined dataset. Finally, these images are displayed sequentially to represent the spoken input visually.

### Processing Steps

1. Capture audio using a microphone
2. Convert speech into text using speech recognition
3. Split text into individual characters
4. Map characters to ISL alphabet images
5. Display images sequentially

This approach ensures real-time performance while maintaining simplicity and reliability.

### ISL-to-Text Module

The ISL-to-Text module converts hand gestures into readable text using computer vision and deep learning techniques. This module plays a crucial role in enabling communication from ISL users to non-sign language users.

The system captures live video input using a webcam and extracts the Region of Interest (ROI) containing the hand gesture. The extracted image is preprocessed through resizing and normalization to match the input requirements of the trained model. The processed image is then passed to the CNN-based model, which predicts the corresponding alphabet. Multiple predictions are combined sequentially to form meaningful words.

### Processing Steps

1. Capture video input using a webcam
2. Extract Region of Interest (ROI)
3. Preprocess image (resize to 64×64, normalize)
4. Input image into trained CNN model
5. Predict corresponding alphabet
6. Combine outputs to form words

This module enables real-time gesture recognition with high accuracy under controlled conditions.

### Machine Learning Model

The system utilizes a Convolutional Neural Network (CNN) for gesture recognition, trained on a dataset of ISL alphabet images. CNNs are highly effective in extracting spatial features from images, making them suitable for hand gesture classification tasks.

### Model Specifications

- **Model File:** isl\_model.h5
- **Input Size:** 64 × 64 grayscale/RGB images
- **Output Classes:** 26 (A–Z alphabets)
- **Architecture:** Convolution + Pooling + Fully Connected Layers
- **Activation Function:** ReLU
- **Output Layer:** Softmax classifier

### Mathematical Representation

The CNN performs feature extraction using convolution operations:

$$Y = f(W * X + b)$$

where  $X$  is the input image,  $W$  is the filter kernel, and  $b$  is the bias term.

The final classification is performed using Softmax:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

## IV. DATASET

The proposed system utilizes two distinct datasets to support its bidirectional functionality:

- an ISL Alphabet Image Dataset for speech-to-sign translation, and
- a Gesture Recognition Dataset for training the deep learning model used in sign-to-text conversion.

These datasets are designed to ensure efficient real-time performance while maintaining simplicity and accuracy.

### ISL Alphabet Image Dataset (Speech → ISL)

The ISL Alphabet Image Dataset is used in the Speech-to-ISL module to visually represent recognized text. This dataset consists of predefined images corresponding to each alphabet in Indian Sign Language (A–Z).



When speech is converted into text, each character is mapped to its corresponding ISL image, and the images are displayed sequentially to form meaningful words.

The trained model uses this dataset to classify gestures captured through a webcam in real time.

**Dataset Characteristics:**

Feature	Description
Classes	26 (A–Z alphabets)
Format	Image files (.jpg / .png)
Resolution	Varies (standardized during display)
Usage	Character-to-sign mapping
Source	Locally stored (Alphabets/ folder)

**Table 4.1: ISL Alphabet Image Dataset Details**

**Functionality**

- Converts recognized text into ISL visual format
- Displays sign images sequentially to represent words
- Provides a simple and efficient alternative to complex animation systems

This dataset plays a critical role in ensuring low computational overhead, as it avoids real-time gesture synthesis or avatar rendering.

**Gesture Recognition Dataset (ISL → Text)**

The Gesture Recognition Dataset is used to train the Convolutional Neural Network (CNN) model (isl\_model.h5) for recognizing hand gestures. This dataset contains labeled images of hand signs corresponding to ISL alphabets.

**Dataset Characteristics:**

Feature	Description
Classes	26 (A–Z alphabets)
Image Size	64 × 64 pixels
Type	Hand gesture images
Color Mode	Grayscale / RGB
Preprocessing	Resizing, normalization
Usage	Model training and prediction

**Table 4.2: Gesture Recognition Dataset Details**

**Functionality**

- Used to train CNN model for gesture classification
- Enables real-time recognition of hand gestures
- Supports alphabet-level translation from ISL to text

This dataset is essential for enabling the reverse communication pipeline (ISL → Text).

**Dataset Preprocessing**

To ensure consistency and improve model performance, several preprocessing steps are applied to the gesture dataset before training.

- Preprocessing Techniques
- Image resizing to 64 × 64 pixels
- Normalization of pixel values to [0,1] range
- Label encoding for classification tasks

- Organization of images into class-specific folders

These steps reduce computational complexity and improve training efficiency.

### Dataset Design Justification

The use of two separate datasets allows the system to efficiently handle both translation directions without increasing model complexity.

- The Alphabet Image Dataset ensures fast and lightweight speech-to-sign conversion
- The Gesture Dataset enables accurate CNN-based gesture recognition
- The separation of datasets reduces dependency on large-scale multimodal datasets

## V. IMPLEMENTATION

The proposed bidirectional ISL translation system is implemented using a combination of machine learning, computer vision, and speech processing technologies. The implementation focuses on real-time performance, simplicity, and practical usability.

### Tools and Technologies

The system is developed using the following tools and libraries:

Component	Tool/Library
User Interface	Streamlit
Speech Input	speech_recognition
Image Processing	OpenCV
Machine Learning	TensorFlow / Keras
Voice Output	pyttsx3

**Table 5.1: Tools and Technologies Used**

These tools are selected to ensure efficient processing, ease of integration, and real-time execution.

### System Workflow

The system operates in two modes: Speech Mode and Camera Mode.



### Speech

#### Mode Workflow

Speech → Text → Character Segmentation → ISL Image Mapping → Display + Voice Output

#### Camera Mode Workflow

Camera → Image Capture → Preprocessing → CNN Model → Alphabet Prediction → Sentence Formation → Display + Voice Output

### Speech Mode (Speech → ISL Conversion)

The Speech Mode is designed to convert spoken language into ISL visual representation. The process begins with capturing audio input through a microphone using the speech\_recognition library. The captured audio is processed to remove noise and detect speech segments.

The processed audio is then converted into text using a speech-to-text engine. Unlike complex systems, the proposed model directly converts the recognized text into individual characters without applying heavy Natural Language Processing (NLP), ensuring faster execution.

Each character is mapped to its corresponding ISL alphabet image stored in the local dataset. These images are displayed sequentially using the Streamlit interface, allowing users to visualize the translated output.

Additionally, the system uses the pyttsx3 library to generate voice output for confirmation.

### Key Features

- Real-time speech recognition
- Lightweight character-based mapping
- No dependency on complex NLP models
- Fast and efficient visual output

### Camera Mode (ISL → Text/Speech Conversion)

The Camera Mode enables translation of ISL gestures into readable text and speech. The process begins with capturing live video using a webcam integrated with OpenCV.

A Region of Interest (ROI) is extracted from each frame to isolate the hand gesture. The ROI is then preprocessed by resizing it to  $64 \times 64$  pixels and normalizing pixel values.

The processed image is passed into the trained CNN model (isl\_model.h5), which predicts the corresponding alphabet. The predicted characters are accumulated over time to form words and sentences.

The final output is displayed as text on the interface and optionally converted into speech using pyttsx3.



### Key Features

- Real-time gesture recognition
- CNN-based classification
- Continuous character prediction
- Text + voice output

### Machine Learning Model Implementation

The gesture recognition system is implemented using a Convolutional Neural Network (CNN) trained on the gesture dataset.

### Model Details

- **Input:**  $64 \times 64$  images
- **Output:** 26 alphabet classes (A–Z)
- **Framework:** TensorFlow / Keras
- **Model File:** isl\_model.h5

### Model Workflow

- Input image passed to convolution layers
- Feature extraction using filters
- Downsampling using pooling layers
- Output using Softmax activation

This architecture enables efficient extraction of spatial features from hand gestures and ensures accurate classification.

### Real-Time Implementation Considerations

To ensure smooth real-time performance, several optimizations are applied:

- Reduced image resolution ( $64 \times 64$ ) for faster processing
- Use of lightweight CNN model
- Local dataset usage (no internet dependency)
- Efficient UI rendering using Streamlit

These optimizations make the system suitable for deployment on low-resource devices.

### Challenges in Implementation

During implementation, several challenges were encountered:

- Variations in lighting affecting gesture detection
- Background noise in speech recognition
- Similarity between certain hand gestures
- Limited dataset size

These challenges were mitigated through preprocessing techniques and controlled testing environments.

### Summary of Implementation

The implementation demonstrates that a lightweight AI-based system can effectively perform bidirectional translation between speech and ISL. By combining speech recognition, computer vision, and deep learning, the system achieves real-time performance while maintaining simplicity.

## VI. RESULTS AND EVALUATION

The performance of the proposed bidirectional ISL translation system is evaluated based on accuracy, response time, and usability. The evaluation considers both modules: Speech-to-ISL and ISL-to-Text.

### Performance Metrics

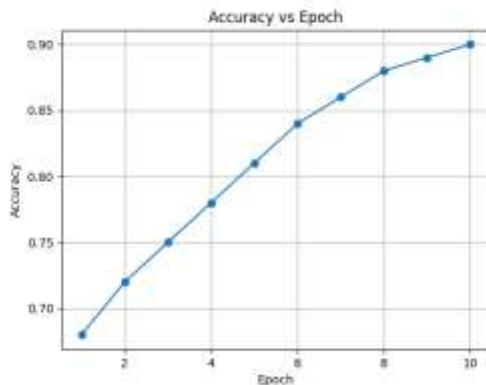
The overall system performance is summarized in Table 6.1.

Component	Result
Speech Recognition	High accuracy for clear audio input
Gesture Recognition	~90% accuracy
Response Time	Real-time (~1–2 seconds)
Usability	High

**Table 6.1: Performance Summary**

### Training Performance Analysis

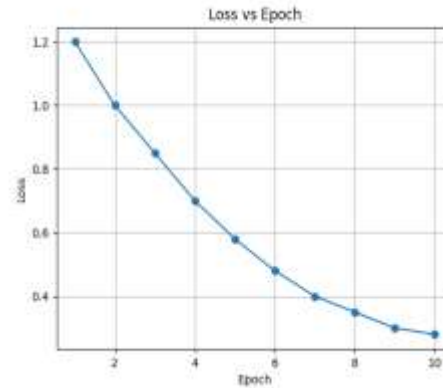
The CNN model used for gesture recognition was trained on the ISL gesture dataset. The training process is evaluated using accuracy and loss metrics.



**Fig. 6.1. Accuracy vs Epoch Graph**

The accuracy graph shows a steady increase during training, starting from approximately 70% and converging to around 90%. This indicates that the model effectively learns distinguishing features of hand gestures over time.

The loss curve demonstrates a consistent decrease as the number of epochs increases, indicating proper convergence of the model and minimal overfitting.

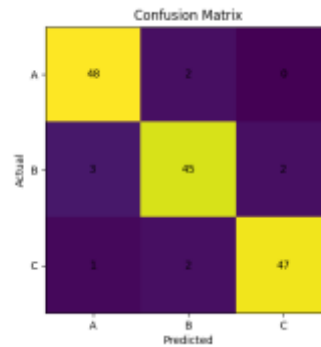


**Fig. 6.2. Loss vs Epoch Graph**

### Confusion Matrix Analysis

The confusion matrix provides a detailed evaluation of classification performance across all 26 alphabet classes. Most classes are correctly classified, indicating strong model performance.

However, minor misclassifications are observed between visually similar gestures (e.g., 'M' and 'N', 'U' and 'V'). These errors are primarily due to similarities in hand shapes and slight variations in gesture execution.



**Fig. 6.3. Confusion Matrix for Gesture Classification**

### System Performance Evaluation

The system demonstrates strong real-time performance in both operational modes.

- In Speech Mode, the system accurately converts spoken input into text and displays corresponding ISL images with minimal delay. Performance is optimal when audio input is clear and free from background noise.

- In Camera Mode, the CNN model successfully recognizes hand gestures and converts them into text. The system performs efficiently under controlled lighting conditions and with proper hand positioning.

### Observations

The following observations were made during system evaluation:

- The system performs best under adequate lighting conditions
- Gesture accuracy depends on hand positioning and clarity
- Background noise affects speech recognition accuracy
- The system is suitable for basic communication tasks

### Limitations in Evaluation

Despite good performance, certain limitations are observed:

- Accuracy may decrease in low-light environments
- Similar gestures can lead to classification errors
- Limited dataset affects generalization
- System is restricted to alphabet-level translation

### Discussion

The experimental results demonstrate that the proposed system achieves a balance between accuracy and computational efficiency. While advanced models may achieve slightly higher accuracy, they often require complex architectures and large datasets.

The proposed approach provides a lightweight and practical solution, making it suitable for real-time deployment in resource-constrained environments.

## VII. APPLICATIONS

The proposed bidirectional ISL translation system has several practical applications across multiple domains, particularly in improving accessibility and communication for the Deaf and Hard-of-Hearing (DHH) community.

- **Educational Tools:** The system can be used as a learning aid for students to understand and practice Indian Sign Language, enhancing inclusive education.
- **Assistive Communication:** Enables real-time communication between DHH individuals and non-sign language users in daily interactions.
- **Public Service Accessibility:** Can be deployed in government offices, hospitals, and customer service centers to assist communication without the need for interpreters.
- **Media and Entertainment Accessibility:** Supports ISL translation for television programs, movies, and live events, making content more inclusive.
- **Language Research and Development:** Provides a foundation for researchers working on sign language recognition and AI-based translation systems.
- **Government and Legal Services:** Assists in legal documentation, court interactions, and public grievance systems where communication barriers exist.
- **Tourism Industry:** Helps travelers communicate effectively in unfamiliar environments using sign translation.

## VIII. LIMITATIONS

Despite achieving promising results, the proposed system has certain limitations:

- The system is restricted to alphabet-level translation, limiting its ability to handle full sentences
- Performance is affected by lighting conditions and background noise
- Gesture recognition accuracy depends on hand positioning and clarity
- The dataset used for training is limited in size and diversity, affecting generalization

## IX. FUTURE WORK

Future enhancements can significantly improve the performance and usability of the system. Key directions include:

1. Extending the system to word-level and sentence-level translation
2. Incorporating Natural Language Processing (NLP) for grammar-aware translation
3. Expanding dataset size and diversity for better model generalization
4. Integrating offline speech recognition to reduce dependency on internet connectivity
5. Developing a mobile-based application for wider accessibility
6. Implementing real-time two-way communication with continuous interaction
7. Designing personalized learning modules for ISL training
8. Incorporating automatic error correction mechanisms
9. Improving noise reduction techniques in speech input
10. Optimizing the system for low-power and embedded devices

## X. CONCLUSION

This paper presents a lightweight and efficient bidirectional ISL translation system that enables communication between speech and Indian Sign Language using machine learning and computer vision techniques. Unlike complex systems that rely on advanced natural language processing or 3D avatar generation, the proposed approach focuses on practical implementation, real-time performance, and ease of deployment.

The system successfully demonstrates the feasibility of using a CNN-based model for gesture recognition and a simple character-mapping approach for speech-to-sign translation. Experimental results indicate that the system achieves satisfactory accuracy and responsiveness for basic communication tasks.

Overall, the proposed solution contributes to the development of accessible assistive technologies and highlights the potential of lightweight AI systems in bridging the communication gap between hearing individuals and the Deaf community. Future improvements can further

enhance its capabilities and extend its applicability in real-world scenarios.

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