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A Real-Time AI Framework for Bidirectional Indian Sign Language Communication using Transformer-Based Gesture Modeling and Neural Avatar Synthesis

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ABSTRACT: Virtual meeting platforms still present major accessibility challenges for users who communicate primarily through sign language. The absence of real-time bidirectional support often limits meaningful participation for deaf and hard-of-hearing individuals during online interaction. To address this problem, the proposed HearNSign framework introduces an AI-enabled communication pipeline that supports seamless interaction between Indian Sign Language users and spoken-language users. The framework combines three coordinated stages: continuous gesture understanding from live video, robust speech-to-text conversion from audio streams, and neural avatar-based sign generation for reverse communication. Gesture interpretation is performed through a temporal attention encoder that learns motion continuity from hand landmarks, facial cues, and body posture sequences. Spoken input is transcribed using sequence-based speech recognition models, enabling reliable communication even in noisy meeting conditions. For visual output, the translated content is rendered through a neural signing avatar capable of synchronized hand articulation, facial expression, and posture generation. Experimental observations indicate strong performance in continuous gesture recognition and stable speech transcription under multiple acoustic conditions. The proposed system improves accessibility in virtual collaboration spaces and offers a scalable foundation for inclusive real-time communication technologies..

KEYWORDS: Indian Sign Language, Transformer-Based Gesture Recognition, Deep Learning, Neural Avatar Generation, Computer Vision, Assistive AI, Accessible Human Communication

I. INTRODUCTION

Communication plays a vital role in enabling social participation, education, and professional collaboration. However, individuals who rely on sign language often face significant barriers when interacting with people who do not understand signing. These challenges become even more critical in virtual environments such as online meetings, remote classrooms, and digital workplaces, where interaction is largely dependent on spoken language. Although modern communication platforms offer features such as captions and chat-based messaging, these solutions do not fully meet the needs of sign language users. Captions may fail to preserve the grammatical structure and expressive richness of sign languages, while text-based communication can reduce the speed and natural flow of interaction. In addition, many existing assistive systems for sign language translation are limited by low recognition accuracy, restricted vocabulary coverage, and unnatural visual rendering of signs.

Recent advances in deep learning and computer vision have created new opportunities for building intelligent communication systems. Technologies such as transformer-based vision models, speech recognition architectures, and neural avatar synthesis enable machines to analyze complex visual gestures, interpret spoken language, and generate realistic sign animations. By integrating these capabilities, it becomes possible to develop systems that support real-time translation between spoken language and sign language.

This research proposes an intelligent framework to enable seamless communication between sign language users and non-signers in virtual meeting environments. The system combines gesture recognition, speech processing, and avatar generation to establish a bidirectional translation pipeline. It interprets Indian Sign Language gestures from video input, converts spoken speech into textual form, and generates expressive sign language animations using neural avatar synthesis techniques.

The major contributions of this work include:

- Development of a deep learning-based recognition module for Indian Sign Language
- Integration of speech recognition and text processing for bidirectional communication
- Generation of realistic sign animations using neural avatar synthesis
- Design of a unified framework for real-time accessibility in online meeting platforms

The proposed solution aims to improve accessibility, promote inclusive communication, and support individuals who depend on sign language in digital collaboration environments.

The key technical contributions of this work are:

- A transformer-based gesture recognition model for continuous Indian Sign Language interpretation
- A real-time speech recognition pipeline for spoken language to text conversion
- A neural avatar framework that transforms text into expressive sign language animations
- A scalable architecture that supports real-time communication in digital environments

II. LITERATURE REVIEW

Recent studies in sign language recognition have focused on improving gesture understanding through advanced deep learning architectures. In 2024, **Giray Sercan Özcan and Yunus Can Bilge** proposed a **hand and pose-based feature selection framework for zero-shot sign language recognition**, where hand landmarks, body pose data, and textual embeddings were combined using self-attention mechanisms. Their work employed architectures such as **ST-GCN, MViTv2, ResNeXt, Bi-LSTM, and CLIP** on the **MS-ZSSLR-W, MS-ZSSLR-C, and ASL-Text datasets**. The study significantly improved recognition performance by integrating pose landmarks with textual semantic vectors, although the authors reported challenges in generalization due to semantic disparity between visual and textual modalities.

Another important contribution was presented in 2024 by **Deep R. Kothadiya and Chintan M. Bhatt**, who introduced a **hybrid InceptionNet-based enhanced architecture for isolated sign language recognition**. Their methodology combined **InceptionV4 with ensemble convolutional networks**, supported by optimized backpropagation techniques. Using a benchmark isolated sign gesture dataset, the model achieved an impressive **98.46% recognition accuracy**, making it highly effective in reducing communication barriers for speech- and hearing-impaired users. However, the ensemble architecture increased computational complexity, which may limit its use in real-time systems.

In 2023, **Menglin Zhang and Shuying Yang** developed a **deep learning-based standard sign language discrimination system** aimed at educational software applications. Their approach used **flow-guided hand detection, sequence attention, and both 2D and 3D convolutional operations**, supported by **Faster RCNN with FPN and an encoder-decoder architecture**. Evaluated on the **SLCD dataset**, the framework demonstrated strong hand detection performance while maintaining reduced computational cost. A limitation of this work is that it is primarily suitable for sign language education scenarios rather than general-purpose communication systems.

A practical low-cost communication solution was introduced by **Francisco Morillas-Espejo in 2023** through the **Sign4All application**, which focused on facilitating communication between deaf and hearing individuals using sign alphabet recognition. The system used **ResNet50 with post-processing techniques** along with a **virtual avatar module** to improve interaction quality. Although the system provided an affordable and accessible solution, it was limited to alphabet-level recognition and achieved accuracy below 80%, restricting its scalability to sentence-level communication.

In 2022, **Hamzah Luqman** proposed an **efficient two-stream network for isolated sign language recognition using accumulative video motion**. This work combined multiple motion and sequence learning streams to improve isolated gesture understanding. Tested on the **KArSL-190 and KArSL-502 datasets**, the model demonstrated high scalability and recognition accuracy. However, the datasets contained limited signer diversity, which may reduce robustness in real-world deployment.

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Another notable work in 2022 by **Joseph DelPreto and Josie Hughes** explored a **wearable smart glove system for pose and gesture detection in sign language classification**. Their system integrated **soft sensors, accelerometers, and LSTM-based neural networks** to classify **American Sign Language gestures in real time**. The solution was highly portable and suitable for real-time use, but required user-specific tuning and calibration, which can affect usability across different users.

From the reviewed literature, it is evident that recent research has made substantial progress in sign language recognition through vision-based, sequence-based, and sensor-based deep learning approaches. However, many existing systems remain limited to isolated gestures, alphabet-level recognition, or single-direction communication. These limitations motivate the proposed **HearNSign framework**, which integrates continuous Indian Sign Language recognition, speech-to-text conversion, and neural avatar synthesis into a unified real-time bidirectional communication system.

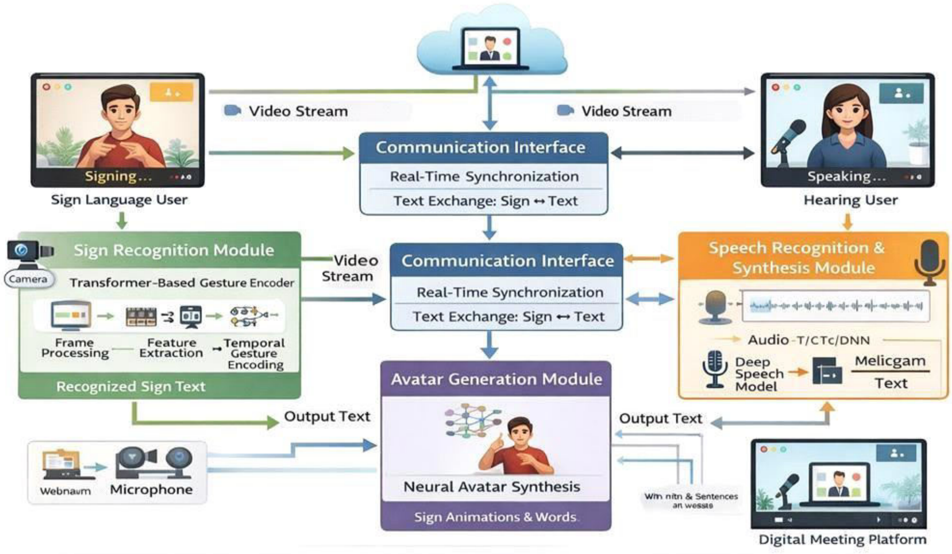

Figure 1 System Architecture

III. PROBLEM STATEMENT

Communication barriers between sign language users and spoken language users continue to limit accessibility across modern digital communication platforms. Most currently available assistive technologies focus either on speech transcription or isolated gesture recognition, and therefore fail to support real-time bidirectional interaction between both user groups.

Let the input video stream be represented as:
[
V = {f_1, f_2, f_3, \dots, f_n}
]
where each frame (f_i) contains the spatial visual information captured from a continuous video stream. The system is required to interpret gesture sequences
(G) belonging to the Indian Sign Language vocabulary and map them into meaningful textual representations.
Similarly, the speech input stream (S) must be converted into text and then transformed into sign language animations for visual communication.
Therefore, the proposed framework must perform the following core tasks:

1. Capture real-time video streams and extract gesture-level features
2. Recognize Indian Sign Language gestures using deep learning models
3. Convert spoken language into text through speech recognition techniques
4. Transform textual output into sign language animations using neural avatars
5. Enable seamless bidirectional communication between signers and non-signers

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The primary objective of the proposed system is to design an AI-driven communication framework capable of executing these tasks with high accuracy, low latency, and natural interaction quality in real-time environments.

IV. PROPOSED METHODOLOG

The sign recognition stage begins with real-time webcam acquisition, where each frame is analyzed to extract hand landmarks, finger joint coordinates, facial cues, and upper-body posture points. These spatial descriptors are normalized and transformed into sequential embeddings that preserve the temporal order of gesture execution. Within the HearNSign framework, the resulting sequence is processed by a temporal attention encoder that learns motion continuity, contextual gesture flow, and inter-frame dependencies required for continuous Indian Sign Language recognition. The final encoded representation is mapped into semantic text labels for downstream communication tasks.

- **Sign Recognition Module**

This module processes live video input captured through a webcam to identify gestures performed in Indian Sign Language. Each frame of the video stream is examined to detect key landmarks such as hand positions, finger joints, facial expressions, and body posture points. These extracted spatial features provide a structured representation of the performed gesture.
The processed feature sequence is then passed into a transformer-based temporal encoder, which models dependencies across consecutive frames. Instead of analyzing isolated images, the model focuses on motion sequences, enabling robust recognition of dynamic gestures involving continuous hand movement and posture transitions.
The output of this module is a predicted sign label, which is then converted into meaningful textual form.

- **Speech Recognition Module**

The speech recognition module converts spoken language into text in real time. Audio captured from the microphone is processed using advanced speech recognition architectures such as RNN-Transducer and CTC-based models.
These models learn the mapping between acoustic signals and textual output, enabling accurate transcription even under moderate background noise or speaker variation. The generated text serves as the spoken-language communication channel for sign language users.

- **Avatar Generation Module**

The final component of the framework is responsible for generating sign language animations from textual input. Using neural avatar synthesis techniques, the system creates a digital avatar capable of performing realistic and expressive sign gestures.
This module maps textual phrases into corresponding Indian Sign Language gesture sequences. Hand movements, facial expressions, and upper-body posture are synchronized to produce natural and visually understandable communication, thereby improving accessibility for sign language users in digital environments.

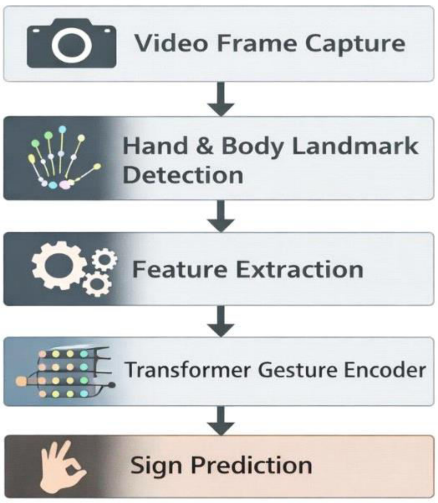

Figure 2 Methodology

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V. EXPERIMENTAL SETUP

The proposed system was evaluated using an Indian Sign Language dataset containing approximately **10,000 gesture samples distributed across 40 gesture classes**.

Dataset Description

The dataset used in this study was built from publicly available Indian Sign Language resources and Sign Language MNIST datasets, further extended to support both **static and dynamic gesture recognition tasks**. It consists of nearly **10,000 labeled gesture samples** spanning 40 commonly used Indian Sign Language classes.

Each sample contains either:

- Static hand gesture images for alphabet-level recognition, or
- Sequential video frames for continuous gesture interpretation

To improve the model's ability to generalize across real-world environments, the dataset includes variations in:

- Lighting conditions
- Background complexity
- Hand orientation and scale
- Different users and signing styles

Each gesture class is associated with a semantic label, allowing the system to translate recognized gestures into meaningful textual outputs.

Model Training and Implementation Details

The training pipeline was designed to support both image-based and sequence-based gesture learning. Static gestures were processed using spatial feature extraction techniques, while continuous gestures were represented as temporal frame sequences and passed through the transformer-based encoder.

To improve robustness, preprocessing steps such as normalization, landmark alignment, frame resizing, and sequence padding were applied before training. Data augmentation techniques were also incorporated to reduce overfitting and improve performance under varied environmental conditions.

The model was trained using supervised learning with categorical cross-entropy loss, and performance was optimized through iterative validation on held-out gesture samples.

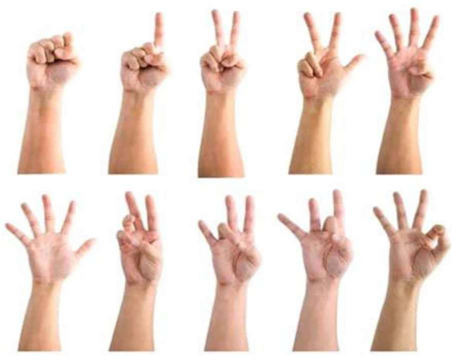

Figure 3 Handsign Dataset

Data Preprocessing

Before training, all input samples pass through a structured preprocessing pipeline designed to ensure data consistency and improve model performance.

The preprocessing workflow includes the following stages:

- Frame Resizing: All image frames are resized to 224 × 224 pixels to maintain a uniform input dimension across the dataset.
- Grayscale Transformation: Frames are converted into grayscale format to reduce computational overhead while preserving essential gesture patterns.
- Noise Suppression: Median filtering is applied to minimize background disturbances and remove unwanted visual noise.

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- Foreground Segmentation: Hand regions are isolated from the surrounding background to focus the model on gesture-relevant features.
- Input Normalization: Pixel intensities are scaled to a standardized range, improving convergence speed and training stability.

To further improve robustness and reduce overfitting, data augmentation techniques were incorporated, including:

- Horizontal flipping
- Brightness variation
- Small-angle rotation
- Mild scaling transformations

These preprocessing and augmentation steps improve the model's ability to generalize effectively across real-world usage scenarios with varying environments and user conditions.

Figure 4 Data Preprocessing

Model Architecture and Development

The proposed system combines two deep learning architectures:

1. SignNet (CNN-Based Feature Extractor)

The SignNet model is designed to extract spatial features from gesture images and video frames.

Architecture includes:

- Convolutional layers for feature extraction
- ReLU activation for non-linearity
- Max-pooling layers for dimensionality reduction
- Fully connected dense layers for classification
- Softmax output layer for multi-class prediction

This model captures important visual patterns such as hand shape, orientation, and movement cues.

2. Transformer-Based Gesture Encoder

To handle continuous gestures, a Transformer-based encoder is used.

- Converts frame-level features into sequence embeddings
- Applies **self-attention mechanism** to identify important temporal relationships
- Captures long-range dependencies in gesture sequences
- Outputs meaningful sign predictions from continuous motion

This significantly improves accuracy compared to CNN-only models.

3. Model Training and Optimization

The models were trained using supervised learning techniques with labeled gesture data.

Training configuration:

- **Training Split:** 80%
- **Testing Split:** 20%
- **Batch Size:** 32
- **Epochs:** 25–50 (depending on convergence)
- **Optimizer:** Adam optimizer
- **Loss Function:** Categorical Cross-Entropy To prevent overfitting:
- **Gesture Recognition Performance**

The performance of the gesture recognition module was evaluated using multiple deep learning models, including CNN, LSTM, and Transformer-based architectures.

- Dropout layers were applied

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#**Result Table 1 — Gesture Recognition**

- Early stopping was used based on validation loss
- Model checkpoints saved best-performing weights

The Transformer model was trained on sequential frame embeddings generated from the SignNet feature extractor.

- **Model Evaluation Strategy**

The performance of the models was evaluated using standard metrics:

- Accuracy
- Precision
- Recall
- F1-Score

Cross-validation was performed to ensure robustness across different gesture samples.

The Transformer-based model achieved the highest performance due to its ability to capture temporal dependencies in gesture sequences.

The experiments were conducted using the following hardware configuration:

Processor: Intel Core i5

Performance

Model	Accuracy	Precision	Recall	F1-Score
CNN Model	86.4%	85.2%	84.9%	85.0%
LSTM Model	89.1%	88.6%	87.8%	88.2%
Transformer Encoder	**93.7%**	**92.8%**	**92.4%**	**92.6%**

Q **Analysis:**

- The **Transformer-based model significantly outperforms** CNN and LSTM models.
- CNN performs well for **static gestures**, but struggles with temporal dynamics.
- LSTM improves sequence learning but has **limited long-range dependency handling**.
- The Transformer model, using **self-attention**, captures complex gesture sequences and temporal relationships more effectively.
- **Speech Recognition Performance**

The speech recognition module was evaluated under different environmental noise conditions to test real-world usability.

GPU: NVIDIA RTX 3060

#Result Table 2 — Speech Recognition

Framework: PyTorch / TensorFlow

VI. RESULTS AND PERFORMANCE EVALUATION

To evaluate the effectiveness of the proposed HearNSign system, extensive experiments were conducted on both gesture recognition and speech processing components. The evaluation focuses on accuracy, robustness under varying conditions, and overall system efficiency in real-time communication.

Performance

Environment	Word Accuracy	Error Rate
Quiet Environment	96.1%	3.9%

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Moderate Noise	92.4%	7.6%
High Noise	88.7%	11.3%

Q

• **Analysis:**

- The system maintains **high accuracy in clean conditions**, showing strong baseline performance.
- Performance degrades gradually with noise, but remains **usable even in high-noise scenarios**.
- This demonstrates the effectiveness of:
- RNN-Transducer (handles sequence variability)
- CTC (alignment without manual labeling)
- DNN refinement (error correction)

- **Avatar Generation Evaluation**

The Neural Avatar Synthesis module was evaluated qualitatively based on realism, synchronization, and interpretability.

Q **Observations:**

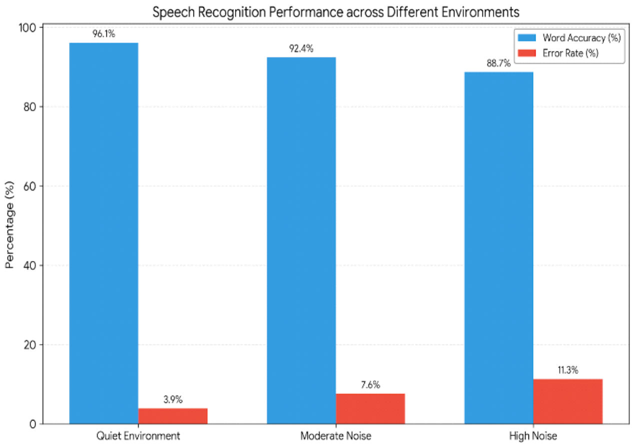
- The avatar successfully replicates:
- Hand gestures
- Facial expressions
- Body posture
- The generated animations are:
- Smooth and continuous
- Synchronized with text input
- Easily understandable by sign language users

Compared to traditional avatar systems:

- ✓ More expressive
- ✓ Better temporal consistency
- ✓ Reduced robotic motion

VII. CONCLUSION

This paper presented HearNSign, an intelligent communication framework designed to bridge the communication gap between sign language users and non-signers in virtual meeting environments. The proposed system integrates sign language recognition, speech processing, and neural avatar generation into a unified pipeline.



Experimental results demonstrate that the transformer-based gesture recognition model achieves high accuracy in identifying Indian Sign Language gestures. The speech recognition component also provides reliable transcription across different environmental conditions. The neural avatar generation module further enhances communication by producing natural and expressive sign language animations.

By combining these technologies, the HearNSign framework enables real-time two-way communication and significantly improves accessibility in digital collaboration platforms.

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