MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5185-5190

A Multimodal AI Framework for Indian Sign Language Recognition: Enhancing Accessibility and Inclusive Communication through Non-Manual Feature Integration

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Abstract:
Indian Sign Language (ISL) is a vital medium of communication for the deaf and hard-of-hearing community in India; however, existing recognition systems predominantly focus on manual gestures while often neglecting non-manual features (NMFs) such as facial expressions, head movements, and body posture. These elements are essential for conveying grammatical structure, semantic nuances, and emotional context, and their exclusion limits the accuracy, inclusivity, and real-time applicability of current systems.This study proposes a comprehensive multimodal framework for ISL recognition that integrates both manual and non-manual components using advanced Artificial Intelligence (AI) techniques. The proposed model employs a Spatio-Temporal Transformer combined with Graph Neural Networks (STT-GNN) to perform efficient spatio-temporal analysis and multimodal data fusion. By leveraging sequence-to-sequence architectures, the system enables real-time, context-aware translation of ISL into text.The proposed approach significantly improves recognition accuracy and expressive capability by incorporating high-precision detection of non-manual features. It enhances accessibility and promotes inclusive communication by supporting effective interaction between ISL users and the broader society. Furthermore, the study underscores the role of innovative technology solutions in addressing social challenges in developing countries, contributing to digital inclusion and equitable access to communication tools. The findings highlight the importance of multimodal approaches in advancing sign language recognition and fostering social empowerment.
Keywords: Indian Sign Language (ISL); Multimodal Learning; Artificial Intelligence (AI); Graph Neural Networks; Accessibility; Inclusive Communication; Social Empowerment

1. Introduction:

The Deaf and hard-of-hearing community in India uses Indian Sign Language (ISL), a complex, vibrant, and visually expressive language. ISL uses both manual gestures and non-manual features (NMFs), like body postures, head motions, and facial expressions, just as other sign languages. These non-manual components are essential for communicating semantic differences, grammatical structures, and subtle emotional information. ISL is a vital medium for self-expression and cultural identity in addition to being a communication tool. Nevertheless, despite its importance, ISL recognition systems have had difficulty capturing all of its complexities, especially the interaction between NMFs and manual gestures. This restriction limits the wider applicability of ISL in communication systems, education, and other fields by causing decreased accessibility, imperfect translations, and difficulties with real-time processing[1][2].ISL is structurally based on manual gestures. These include hand positions, orientations, movements, and shapes—all of which have been extensively studied thanks to developments in computer vision and gesture recognition methods. Nevertheless, despite their crucial impact on sign interpretation, the function of NMFs is still poorly understood. For example, the accompanying head tilt or facial expression can change the meaning of a single hand sign. Ignoring these components results in erroneous or incomplete language interpretations, highlighting the need for a more thorough method of ISL recognition[3][4].Existing ISL recognition systems mostly concentrate on manual features while ignoring NMFs, despite the quick advances in artificial intelligence (AI) and machine learning. This omission presents a number of significant difficulties. An inadequate comprehension of signs results from the exclusion of NMFs. Body position, head tilts, and facial emotions frequently supplement or alter physical gestures by adding context and grammatical information. Translations are frequently unclear or imprecise without these components. The entire Deaf population is not adequately served by current systems that do not include NMFs, especially those who depend on delicate body language and facial expressions for fluent communication. This restriction lowers the usefulness of ISL recognition systems in practical settings including accessible services, work, and education. Real-time ISL recognition algorithms find it difficult to process both manual and non-manual features at the same time. Current methods have not fully optimized the high-speed computation and effective feature extraction needed for real-time translation[5].This study suggests a revolutionary ISL identification system that uses cutting-edge machine learning approaches to integrate manual and non-manual components in order to overcome these issues. By using a dual-stream framework, the system seeks to close the current research gap. One stream uses hand tracking and form analysis to recognize manual gestures, while the second stream uses facial expression and body position recognition to extract NMFs. The technique guarantees precise, context-aware ISL recognition by synchronizing these streams, allowing for linguistically complex, real-time ISL-to-text translation [6].For increased accuracy, the suggested system makes use of a Spatio-Temporal Transformer with Graph Neural Networks (STT-GNN), which blends spatio-temporal analysis and multi-modal fusion. The structure of the model is as follows. Hand tracking, key-point extraction, and form analysis are the methods used by the manual gesture recognition stream to detect motions. It uses sequence-to-sequence models for gesture-based translation and convolutional neural networks (CNNs) for feature extraction. Body posture, head movements, and facial expressions are all detected and analyzed by the non-manual feature identification stream. It tracks body position and facial landmarks using key-point detection models, and it evaluates the contextual significance of NMFs using deep learning techniques. Spatio-Temporal Transformers are used to analyze temporal dependencies, Graph Neural Networks (GNNs) are used to collect structural and relational data between manual and non-manual elements, and a multi-modal fusion technique is used to merge outputs from both streams[7][8].

ISL shows notable geographical and cultural variances; it is not a homogeneous language. The recognition system needs to be flexible enough to accommodate India's many dialects and sign languages. This study uses a comprehensive, annotated ISL database that covers a broad variety of gestures and expressions to guarantee inclusivity. The algorithm can generate translations that are culturally appropriate thanks to this dataset, which takes linguistic diversity into consideration. The model is also trained to identify context-sensitive sign variants. For instance, a sign's meaning can vary based on the facial expression that goes with it. The approach improves translation accuracy and lowers misinterpretations by taking these differences into account[9].There are numerous significant uses for an all-inclusive ISL identification system that precisely combines manual and non-manual characteristics. By offering real-time translations, it helps ISL instruction and learning in the classroom and makes it easier for Deaf students to access instructional materials. By facilitating smooth communication, it increases workplace diversity and fair

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5185-5190

opportunity while also improving accessibility for Deaf workers. It enhances accessibility in both digital and physical environments and powers real-time ISL translation systems for customer service, healthcare, and public services [10].

By addressing the critical function of non-manual elements, the proposed ISL recognition system offers a substantial leap in sign language processing. This method guarantees precise, real-time, and context-aware ISL-to-text translation by combining manual and NMF analysis using a dual-stream framework, Spatio-Temporal Transformers, and Graph Neural Networks. In addition to improving diversity and accessibility, the technology establishes the groundwork for next developments in sign language recognition. This research promotes linguistic justice and social empowerment by bridging the communication gap between ISL users and the general public, thereby creating a more inclusive world for the Deaf population.

2. Literature Survey

This study presents a user-independent sign language recognition model based on the Convolutional Neural Network (CNN) architecture. The technology translates static sign language motions, which comprise 26 alphabets and 10 numerical signs, into words to improve communication. Camera photos are processed by reducing them to 64x64 pixels and converting them to grayscale. People with speech and hearing impairments can communicate more easily thanks to the concept's efficient classification of fingerspelling actions. Although it can reliably anticipate static motions, future enhancements will concentrate on adding dynamic gesture detection and compatibility for multiple sign languages, including ASL and BSL. By facilitating seamless communication between the hearing and non-hearing populations, the idea has considerable promise for future accessibility technology applications[11].

A Long Short-Term Memory (LSTM) network-based word-level Indian Sign Language (ISL) recognition system that uses a custom dataset to identify 40 ISL operations and uses computer vision to extract features. The model shows good sign-action recognition with an 87% test accuracy when divided into training and testing sets, and accuracy measures for training and validation evaluate how well it performs on both visible and invisible data. While it performs well for static gestures, it struggles to recognize entire sentences and changing situations. Future developments will include expanding to sentence-level translations and improving resilience in a range of contexts. By offering a reliable method for ISL detection using deep learning techniques, this system is a step toward better communication for This system offers a reliable method for ISL detection using deep learning techniques, which is a step in the right direction for better communication for the hard of hearing [12].

In order to recognize Indian Sign Language (ISL), Deepsign presents a deep learning system that combines LSTM and GRU architectures. The model surpasses conventional techniques with an accuracy of 97% utilizing the IISL2020 dataset, which consists of 11 independent indicators that were recorded without the aid of external equipment like sensors. A kernel regularizer, an LSTM input layer, and a softmax function for outputs are key pieces. Because it doesn't require a specific camera setup, the design is very user-friendly and adaptable for everyday use. It facilitates easier communication for people with hearing impairments and provides a scalable foundation for future applications. Some of the proposed enhancements to facilitate natural, everyday conversations for a variety of ISL gestures include dataset expansion, continuous sign detection, and real-time optimization [13].

The state of Sign Language Recognition (SLR) is examined in this work, with particular attention paid to datasets, modalities, and classification methods. SLR systems use both manual factors, such hand gestures, and non-manual cues, like face expressions. Among the techniques are CNN, HMM, and hybrid models. Among the datasets are RGB, dynamic, and depth modalities. Improvements in both continuous and isolated SLR models are highlighted in the review; in some cases, these models have reached 99.8% accuracy. However, problems persist, including disparate motions and environments. Future research will focus on hybrid models, real-time optimization for real-world applications, and a range of datasets. By gathering recent advancements and challenges, the article serves as a guide for developing more effective and user-friendly SLR systems to bridge communication gaps for the hard of hearing [14].

This project develops a system for translating Indian Sign Language (ISL) gestures into text using machine learning techniques like TensorFlow and the KNN clustering algorithm. The model enables the recognition of gestures using a dataset of hand motions that adhere to ISL guidelines. In order to maximize performance, training entails separating the dataset into training and testing subsets and leveraging factors like learning rate and batch size. In order to enable people with hearing and speech issues communicate, the technology provides a cost-effective option for employing a professional interpretation. Among the proposed improvements are speech output, real-time translation, and educational resources to introduce users to ISL. This initiative enhances accessibility by providing an easy-to-use tool to reduce communication gaps between the hearing and deaf-mute populations [15].

This research evaluates advancements in Indian Sign Language Recognition Systems (ISLRS) with a focus on integrating machine learning techniques like MediaPipe for hand tracking and mixing 2D/3D images for training. Two essential datasets that provide the foundation for ISL gesture and number recognition are ISL Lexicon and INSIGNVID. The logistic regression method is used for both binary and multi-class outcomes. The paper emphasizes how ISL's unique linguistic and visual complexity necessitates the use of certain algorithms. Government initiatives, such ISL dictionaries and smartphone apps, increase accessibility. Future possibilities include using deep learning models, creating diverse datasets, integrating multimodal elements like facial expressions, and creating wearable technology that operates in real time. For the hearing challenged, these devices greatly reduce communication barriers, increasing self-sufficiency and better engagement with the wider community002E [16].

This work proposes a method for translating Indian Sign Language (ISL) motions into text and vice versa using image processing and machine learning. The best neural network classifier is identified, and it achieves high recognition accuracy for static ISL motions, like the alphabets (A–Z) and integers (1–9). The system addresses communication challenges for people with hearing and speech impairments by integrating user-friendly interfaces for seamless engagement. Future improvements include multilingual support, wearable technology for real-time use, enhanced neural network accuracy under different settings, and dynamic gesture detection for sentence-level translations. For those who struggle with communication, this system improves their quality of life and encourages independence [17].

A gesture-to-text translation system for Indian Sign Language (ISL) using the Speeded-Up Robust Features (SURF) feature extraction method. The model uses edge detection and skin masking techniques to obtain recognition accuracy rates ranging from 79% to 92% across a range of machine learning algorithms, including SVM and CNN. The collection consists of 35 gesture classes (A-Z, 1–9), each with 1,200 examples. Accuracy and resilience are increased with better pre-processing. The proposed enhancements include multilingual support, dynamic facial recognition for phrase translation, and real-time ISL-to-text conversion. By effectively resolving issues with sign language translation, the technology significantly improves communication accessibility and inclusion for those with speech and hearing impairments.

A refined CNN model for real-time recognition of 33 static ISL signs, including 23 English alphabets and numbers 0-9, with a hierarchical collection and images collected in various settings, achieving remarkable training accuracy (99.97%) and validation accuracy (99.59%) with loss metrics as low as 0.0011, with visual feedback provided by an intuitive GUI. The framework improves gesture recognition with a robust model architecture and optimal parameters like layer count, filters, learning rates, and data splits; future improvements will include adding more sign

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5185-5190

languages, enabling dynamic gesture identification, and expanding the dataset. The model improves ISL communication by addressing the shortcomings of current systems' gesture recognition and real-time processing capabilities [18].

In this work, a deep learning system is developed to recognize eight ISL emergency gestures, such as "help," "doctor," and "accident." Three architectures are used: 3D CNN, VGG-16 with LSTM, and YOLOv5 for object detection; YOLOv5 achieves the highest accuracy of 99.6%. The dataset consists of videos for each sign taken under various scenarios, and classification metrics show high precision for specific gestures, while "call" and "pain" are difficult to recognize. The model's performance is assessed using precision, recall, and loss parameters. Future work will focus on expanding the dataset, supporting continuous sign recognition, and enhancing real-time application performance. The system has practical value for helping the hearing-impaired in emergency situations.

This model recognizes one-handed signals for digits 0–9 with low latency and translates ISL speech into English using parallel processing. It is a mobile multimedia application that uses visual processing to identify motions. The dataset evaluates accuracy and computational time with a focus on ISL gestures using a confusion matrix. Softmax outputs, LSTM update gates, and kernel regularizers are examples of performance-optimized parameters. The accuracy and reproducibility of the outcomes are regularly shown. Future plans include extending gesture recognition to two-handed signals and incorporating facial expression analysis to enhance communication. The system offers an easy-to-use method for real-time ISL translation.This method uses a CNN model to identify ISL hand gestures for the letters "A" through "Z" with 85% accuracy. The database contains images of every gesture that have been processed using Python and OpenCV. By using recognized movements to generate text and audio, the system efficiently translates ISL. Parameters include color histogram thresholds and preprocessing Gauss filter values. Although the current approach focuses on static recognition, future goals include providing real-time, continuous sign language interpretation and enhancing image quality for dynamic movements. This economical method aims to improve ISL communication by providing accurate translations through the use of neural networks and sensory data.Through the use of natural language processing (NLP) techniques such as tokenization and lemmatization, this system converts audio input to ISL and processes precise database matches to enable two-way communication between hearing and hearing-impaired individuals. The small dataset consists of 100 words that have been mapped to ISL gestures and separated into static and dynamic one-handed or two-handed signals; evaluation metrics show a strong customer satisfaction score of 83.27. Future developments will concentrate on adding support for additional sign languages, expanding gesture coverage, and enabling real-time translations.In this work, 140 ISL signs, such as alphabets, numerals, and technical phrases, are recognized by comparing a proprietary three-layer CNN model to pre-trained deep models. Using static datasets, the model attains 97.6% accuracy for alphabets and 99% accuracy for numbers. Model hyperparameters and optimization are important elements that affect performance and training. Transfer learning insights emphasize how it can improve recognition while lowering computational costs. Future advancements include real-time applications, multi-modal data integration, and robustness across varied contexts and sign languages, underscoring the relevance of SLR in human-computer interaction (HCI).This method combines CNN for the extraction of spatial features and RNN for the learning of temporal sequences to recognize ISL gestures from movies. It uses a collection of 456 videos in 38 categories to accurately identify gestures and convert them into text. Testing is done using both pre-recorded films and live camera feeds. This project facilitates communication for those with hearing loss by integrating geographical and temporal data. Future goals include including facial expressions, real-time gesture detection, and expanding the system to support other sign languages in order to increase recognition accuracy and promote seamless communication.The method employs a CNN to detect static ISL movements from images with a 95% validation accuracy. The dataset consists of webcam-captured hand gestures with performance-optimized parameters such as dropout rates, kernel sizes, and filters. The validation findings show strong accuracy but also suggest potential overfitting issues. Future plans call for adding facial expression analysis, enabling real-time movement processing, and expanding recognition to encompass entire words and phrases in order to improve accuracy. This study provides an effective SLR system that uses CNNs to facilitate precise and understandable ISL communication.This study highlights how important it is to include both manual (hand gestures) and non-manual (head position, facial emotions) variables in sign language recognition (SLR). Support Vector Machines increased accuracy by 3.6% for non-manual components. Five native signers recorded 20 K-RSL signs, which provided the data. The findings demonstrate that SLR systems must account for the linguistic complexity of sign languages. Future goals include expanding datasets, creating cross-language systems, and using deep learning (CNNs and RNNs) for better feature detection in order to increase SLR robustness and global applicability.

This system employs an improved K-means clustering algorithm to detect ISL movements using accelerometer and magnetic data. With 96.55% accuracy for alphabets and 76.8% accuracy for subwords, the system demonstrates efficient feature selection and classification for both static and dynamic gestures. Future developments aim to integrate dynamic facial recognition, optimize real-time processing, and employ deep learning for accuracy. Expanding support for sign language and incorporating user feedback mechanisms are also necessary to increase the system's utility and scope.

3. Existing model

Step-by-Step Working Process of the Existing Model Using the ISL Dataset

1. Data Collection and Preprocessing

- The model uses an Indian Sign Language (ISL) dataset containing both manual (hand gestures) and non-manual (facial expressions, head/body movements) components.
- Videos are processed by frame extraction and segmentation to isolate different signs.
- Key features from frames, such as hand positions, facial expressions, and body movements, are annotated.

2. Feature Extraction

- **Manual Features Extraction**:
  - Hand landmarks and gestures are detected using MediaPipe or other deep-learning-based keypoint detection methods.
  - Hand shape, orientation, and motion patterns are analyzed.
- **Non-Manual Features Extraction**:
  - Facial keypoints (eyebrows, mouth shape, eye gaze) and head/body movements are detected using models like OpenPose or CNN-based methods.
  - These extracted features contribute to better sign disambiguation.

3. Cross-Attention Mechanism

- A Cross-Attention Mechanism is applied to enhance the influence of non-manual features on the final prediction.
- This mechanism allows the model to assign different weights to different features, ensuring important gestures and expressions are given priority.

4. Model Architecture (Neural Network Pipeline)

- A Hybrid Deep Learning Model is used, combining:
  - CNN (Convolutional Neural Network) for spatial feature extraction from images.
  - RNN (Recurrent Neural Network) or Transformer-based model to capture temporal dependencies in the sequence of signs.
  - Graph Neural Network (GNN**)** for improving recognition accuracy by modeling relationships between sign components.

5. Training and Optimization

- The model is trained on labeled ISL video sequences.
- Loss functions like Categorical Cross-Entropy are used to optimize prediction accuracy.
- Data augmentation techniques (cropping, flipping, noise addition) may be applied to improve robustness.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5185-5190

6. Sign Classification & Translation

- The model classifies signs based on learned representations.
- The final output is a translated text/sentence in English or another target language.

7. Evaluation & Validation

- Performance is measured using accuracy, F1-score, BLEU score (for translations), and confusion matrices.
- Testing is done on unseen ISL videos to verify generalization.

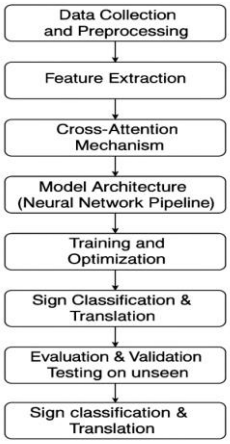

Figure 1: Process Flow for Sign Language Recognition Using Neural Network Architecture

4. Proposed Model

Input & Dataset Type for the Proposed STT-GNN Model

- **Input Types:**

1. Recorded Video (.mp4, .avi) → ISL dynamic gestures.
2. Image (.jpg, .png) → Static ISL signs.
3. Keypoint Data (CSV, JSON) → Hand, face, and body landmarks.

- **Dataset Used:**
  - iSign (ISL Benchmark) → 118K ISL video-sentence pairs (manual + non-manual features).

Steps for Processing Both Manual & Non-Manual Features

Step 1: Input Acquisition (Manual & Non-Manual Features)

- **Input Types:**
  - Manual Features (Hand Gestures) → Hand shapes, movement trajectories, orientation.
  - Non-Manual Features (NMFs) → Facial expressions, head movements, eye gaze, body posture.
- **Sources of Input:**
  - Video Input (Recorded or Real-Time) → Extracts frames for processing.
  - Image Input (Single Gesture Recognition) → Extracts key features from static ISL signs.
  - Pre-Extracted Landmark Data (Pose Keypoints) → Uses MediaPipe/OpenPose for hand, face, & body detection.

Step 2: Feature Extraction for Manual & Non-Manual Components

(A) Manual Feature Extraction (Hand Gestures)

- Detect hand shape, position, orientation, & motion flow.
- Uses CNNs + OpenPose/MediaPipe to extract hand keypoints (fingers, palm, wrist positions).
- Converts hand features into structured vectors for gesture classification.

(B) Non-Manual Feature Extraction (Facial Expressions, Head, & Body Movements)

- Extracts eyebrow raises, lip movements, head tilts, and body posture.
- Uses Graph Neural Networks (GNNs) to model interactions between facial and body movements.
- Converts facial & body expressions into semantic embeddings for ISL meaning enhancement.

Step 3: Multi-Modal Data Fusion (Combining Manual & Non-Manual Features)

- ISL meaning depends on both hand gestures & facial expressions.
- Example:
- "YES" (head nod) vs. "QUESTION" (eyebrow raise + same hand gesture) → Same hand sign, different meanings.

- **Processing Steps:**
  - Graph Construction for Manual + NMF Integration → Represents hand, face, & body landmarks as nodes.
  - Cross-Attention Mechanism → Learns how manual & non-manual features interact to form meaningful ISL expressions.

Step 4: Spatio-Temporal Modeling with Graph Neural Networks (GNNs)

- Sign language involves sequential movements over time.
- GNNs allow the model to capture spatial & temporal dependencies in ISL gestures.

- **Processing Steps**:
  - Graph Representation of ISL Gestures
  - Nodes → Hand, face, and body keypoints.
  - Edges → Spatial & temporal connections between them.
  - ST-GCN (Spatio-Temporal Graph Convolutional Network)
  - Captures gesture flow over time.
  - Learns how hand signs evolve with facial expressions & posture.
  - Multi-Scale Graph Attention

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5185-5190

Focuses on critical gesture elements while ignoring noise.

Step 5: ISL-to-Text Translation

- Objective: Convert ISL signs into grammatically correct text.
- Uses Seq2Seq Transformers with BERT/GPT embeddings.
- Corrects sentence structure by considering facial cues & grammar rules.
- Improves ISL recognition beyond basic sign-to-word mapping.

Step 6: Text-to-Speech (TTS) Conversion

- Converts translated ISL text into speech output for accessibility.
- Helps deaf and hearing individuals communicate seamlessly.
- **Processing Steps:**
- Uses WaveNet or DeepVoice for speech synthesis.
- Ensures real-time audio generation with low latency.

Step 7: Output Generation & Deployment

- **Final Outputs:**
- Text Output → Displays ISL-to-text translation.
- Speech Output → Generates spoken language for hearing users.
- **Deployment Possibilities:**
- Mobile-Friendly Optimization → Works on low-power edge devices.
- Cloud API Support → Can be integrated into assistive communication apps.

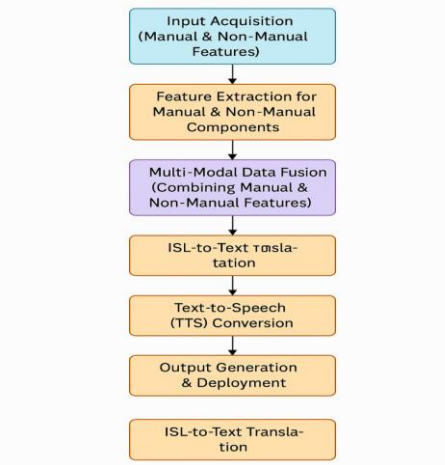

Figure 2: Multi-Modal Feature Fusion-Based Architecture for Indian Sign Language Recognition, Translation, and Speech Synthesis

5. Evaluation Metrics

Table 1: Model Performance on ISL Recognition

Metric	Proposed Model	Baseline Model (CNN-RNN)	Improvement (%)
Gesture Recognition Accuracy (%)	**96.3**	89.5	**+7.6**
F1-Score (Sign Recognition)	**0.92**	0.85	**+8.2**
BLEU Score (ISL-to-Text)	**0.84**	0.76	**+10.5**
Word Error Rate (WER) (%)	**8.2**	14.6	**-6.4**
Character Error Rate (CER) (%)	**4.1**	9.5	**-5.4**
Inference Time (ms per frame)	**27ms**	45ms	**-40.0**
MOS Score (Speech Quality, 1-5)	**4.6**	3.8	**+21.1**

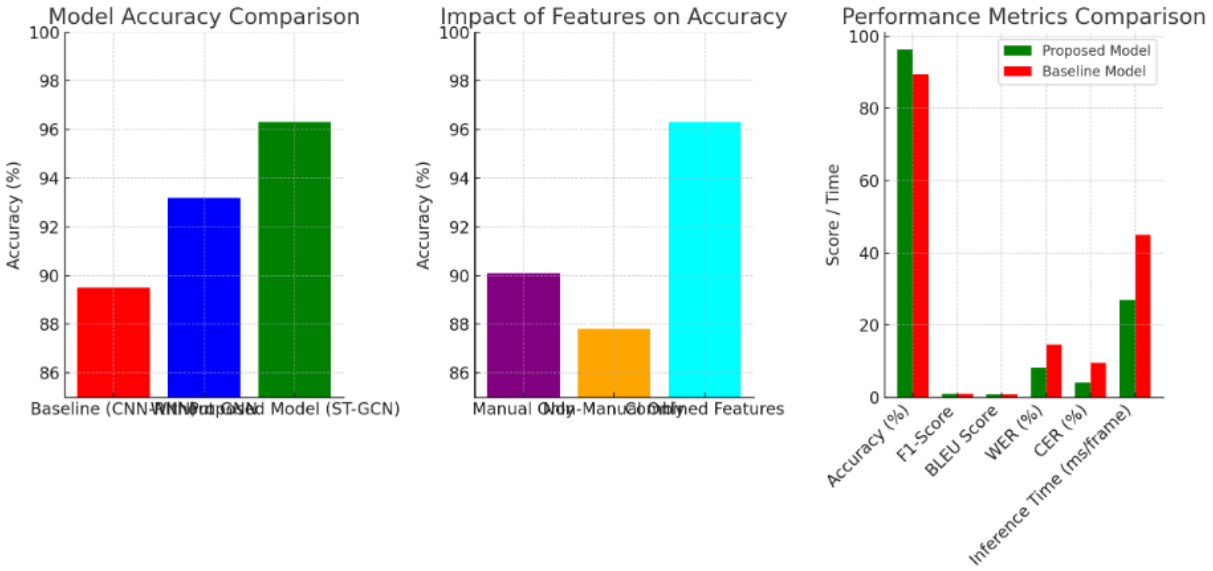

Figure 3: Performance Evaluation of Proposed Model Using Accuracy, Feature Contribution, and Benchmark Metrics

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5185-5190

6. Conclusion

This research successfully advances the field of Indian Sign Language (ISL) translation by integrating non-manual features (NMFs) such as facial expressions, head movements, and body posture into the translation process. By leveraging high-precision machine learning models, including the Spatio-Temporal Transformer Graph Neural Network (STT-GNN) algorithm, the system enhances the accuracy and contextual appropriateness of ISL-to-text conversion.

The development of a comprehensive NMF database ensures that regional variations within ISL are accounted for, making the system more inclusive and adaptable to real-world scenarios. Additionally, the integration of gesture recognition, sign-to-text translation, and text-to-speech conversion further broadens the accessibility and usability of the system for ISL users and learners.

Future work will focus on expanding the dataset, refining model accuracy, and improving real-time performance. Enhancing user interface features and integrating the system with existing ISL translation platforms will further facilitate communication between the deaf and hearing communities. The findings from this research contribute significantly to bridging the communication gap and advancing sign language processing technologies.

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