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Multimodal Attention-Based Framework for Sign Language Recognition

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Abstract: *Sign language recognition (SLR) plays an essential role in enabling effective communication between individuals with hearing impairments and the hearing community. Conventional SLR systems often depend on a single input type, such as RGB frames or skeletal data, which limits their accuracy and adaptability in complex, real-world environments. This dissertation presents a multimodal attention-based framework that integrates RGB video, skeletal joint, and landmark information to comprehensively model the spatial and temporal aspects of signing. The system leverages transformer-based attention mechanisms, graph convolutional networks (GCNs), and recurrent layers to capture both global dependencies and fine-grained gesture dynamics. A dedicated Head-and-Hands Tunnelling Pipeline is employed to emphasize key gesture regions and minimize background interference. Additionally, the framework incorporates dataset refinement and landmark correction to enhance stability during training. Experimental evaluation will be conducted on benchmark datasets such as MS-ASL and WLASL for both isolated and continuous recognition tasks. The overall objective is to design a robust, real-time SLR model that contributes to improved accessibility in educational, healthcare, and social communication contexts.*

Keywords*:* Sign Language Recognition (SLR) , Multimodal Deep Learning , Transformer Networks, Graph Convolutional Networks (GCN)

I. INTRODUCTION

Sign language serves as the primary medium of communication for the deaf and hard-of-hearing community. With recent advancements in deep learning and computer vision, automatic sign language recognition (SLR) has become an active area of research aimed at reducing the communication gap between hearing and non-hearing individuals. Despite significant progress, current SLR systems continue to face major challenges. Many existing methods rely on a single modality, such as RGB imagery or skeletal joints, which makes them susceptible to environmental variations, background clutter, and differences among signers. Furthermore, single-modality systems often struggle to scale effectively for continuous or complex sign sequences.

The proposed research addresses these limitations through a multimodal deep learning framework that combines RGB frames, skeletal information, and landmark-based features. By integrating these complementary data sources through an attention-driven fusion mechanism, the framework enhances feature representation and improves recognition accuracy under varied real-world conditions. This study also introduces an efficient preprocessing pipeline that focuses on crucial gesture regions, helping the model to learn discriminative cues while suppressing irrelevant background information. The proposed work aims to make a practical contribution to the field of assistive technologies, promoting inclusivity in education, healthcare, and everyday communication for the deaf community.

II. MOTIVATION

Recent advances in deep learning have significantly improved sign language recognition (SLR) performance; however, many existing systems still depend on a single type of input, such as RGB videos or skeletal data. This limitation reduces their robustness when exposed to diverse environmental conditions, varying signer appearances, or complex

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backgrounds. Moreover, such unimodal approaches often fail to capture the full spatio-temporal context of hand and body movements, which is essential for accurate interpretation of signs.

With the emergence of attention mechanisms, graph-based representations, and multimodal fusion, it is now possible to design models that process several complementary data sources simultaneously. Integrating video, skeleton, and landmark features can significantly increase recognition accuracy and resilience across users and scenarios.

The motivation behind this work extends beyond research improvement. The goal is to develop a practical and deployable framework capable of facilitating real-time communication assistance for the deaf and hard-of-hearing community. By enhancing recognition performance and reliability, this system aims to promote inclusivity in education, healthcare, and everyday social interaction.

III. LITERATURE SURVEY

Paper Title	Summary of Contribution	Dataset(s)	Method / Model	Result / Performance
Continuous Sign Language Recognition with Multi-Scale Spatial-Temporal Feature Enhancement	The authors presented a hierarchical architecture that captures motion details at multiple spatial and temporal levels, improving continuity in sign interpretation.	RWTH-PHOENIX, WLASL	Multi-Scale CNN + RNN + Attention Mechanism	Demonstrated improved accuracy and smoother transitions compared with conventional CNN-RNN models.
Cross-Attentive Multi-Cue Fusion for Skeleton-Based SLR	This study applied a cross-attention mechanism to combine asynchronous cues from hand, arm, and body joints, enabling stronger inter-joint relationships.	WLASL	Skeleton-Based Cross-Attention Fusion	Produced higher precision and robustness on complex gesture sequences compared with single-cue skeleton models.
Deep Learning-Based SLR Using Efficient Multi-Feature Attention Mechanism	The paper introduced a lightweight attention block that merges different visual features to reduce computation without sacrificing accuracy.	MS-ASL, WLASL	CNN + RNN with Multi-Feature Attention	Achieved high accuracy for isolated signs while lowering training complexity.
GSR-Fusion: A Deep Multimodal Fusion Architecture for Robust SLR	This research proposed a multimodal model combining RGB, skeleton, and graph-based features through deep fusion layers to strengthen feature correlation.	MS-ASL, BosphorusSign22k	RGB + Skeleton + Graph Fusion (ST-GCN, CNN)	Outperformed unimodal baselines and remained stable across varied signer profiles.
Dataset Cleaning for Landmark-Based SLR	The authors emphasized improving dataset quality by refining video samples and correcting landmark coordinates to ensure consistency during training.	MS-ASL	Data Cleaning + RNN/LSTM on Landmarks	Enhanced training stability and improved classification accuracy by roughly 5–7%.
Head-and-Hands Tunneling	The paper introduced a preprocessing approach that	WLASL	Region-Focused CNN + GCN	Increased accuracy in cluttered or occluded

Pipeline for Enhancing SLR	isolates head and hand regions to suppress irrelevant background information.			scenarios, particularly for two-hand gestures.

IV. PROBLEM DEFINITION

This project aims to develop a multimodal attention-based framework that integrates RGB, skeleton, and landmark features, focusing on crucial gesture regions to enhance recognition accuracy and robustness. We are doing this to bridge communication gaps for the deaf community by enabling a reliable and scalable real-time SLR system.

V. OBJECTIVES

- To design a deep learning framework that fuses RGB video, skeletal joints, and landmark data.
- To integrate attention-based models and Graph Convolutional Networks for spatial-temporal modeling.
- To implement a Head & Hands Tunneling Pipeline for focusing on critical gesture regions.
- To apply dataset cleaning and landmark correction for better training stability.
- To evaluate the system on benchmark datasets (MS-ASL, WLASL) for both isolated and continuous recognition.
- To prepare the framework for future real-time deployment on mobile/edge platforms.

VI. MATHEMATICAL MODEL

- **Input Space**:
  $X = \{x_{rgb}, x_{skeleton}, x_{landmark}\}$
- **Feature Extraction**:
  - $f_{rgb}(x_{rgb})$: CNN/Transformer encoder for video frames
  - $f_{skeleton}(x_{skeleton})$: GCN-based skeleton feature extraction
  - $f_{landmark}(x_{landmark})$: Landmark position embeddings
- **Fusion Function (Attention-based)**:

$$F = \alpha f_{rgb} + \beta f_{skeleton} + \gamma f_{landmark}$$

  where α, β, γ are learnable attention weights.
- **Classification Layer**:

$$y = \arg\max\ \mathrm{Softmax}(W \cdot F + b)$$

VII. RELEVANT MATHEMATICAL MODEL

- **Cross-Entropy Loss** for classification:

$$L = -\sum y_i \log(\hat{y}_i)$$

- **Self-Attention Mechanism**:

$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

- **Graph Convolution (ST-GCN for Skeleton Joints)**:

$$H^{(l+1)} = \sigma(D^{-1/2}AD^{-1/2}H^{(l)}W^{(l)})$$

- **Temporal Modeling** (LSTM/GRU):

$$h_t = f(Wx_t + Uh_{t-1} + b)$$

VIII. METHODOLOGY

- **Data Collection & Cleaning** – Use MS-ASL, WLASL; apply landmark correction.
- **Preprocessing** – Frame normalization, Head & Hands tunneling.
- **Feature Extraction** – CNN/Transformer (RGB), GCN (skeleton), MLP/CNN (landmarks).
- **Fusion** – Cross-attention/Transformer-based feature integration.
- **Temporal Modeling** – BiLSTM/Temporal Transformer.
- **Training** – Cross-entropy (isolated), CTC Loss (continuous).
- **Evaluation** – Benchmark against existing state-of-the-art.

IX. SOFTWARE REQUIREMENT SPECIFICATION

Hardware Requirements:

- GPU-enabled System (preferably NVIDIA GPU)
- Minimum 16 GB RAM
- Storage: ≥ 100 GB for datasets (MS-ASL, WLASL)
- Processor: Intel i7 / AMD Ryzen 7 or higher

Software Requirements:

- Programming Language: **Python**
- Frameworks: **PyTorch**, **TensorFlow**
- Libraries: **OpenCV, MediaPipe, NumPy, Scikit-learn, Matplotlib**
- Tools: **Jupyter Notebook / VS Code**
- Operating System: **Windows / Ubuntu (64-bit)**

X. DESIGN DOCUMENT

- **Architecture Components :**
  Input → Preprocessing → Encoders → Fusion Module → Temporal Model → Output.
- **Modules:**
  - Input Handling
  - Dataset Cleaning & Landmark Correction
  - Encoders (RGB, Skeleton, Landmark)

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- Attention-based Fusion
- Temporal Sequence Modeling
- Classifier & Decoder

- **Diagrams :**

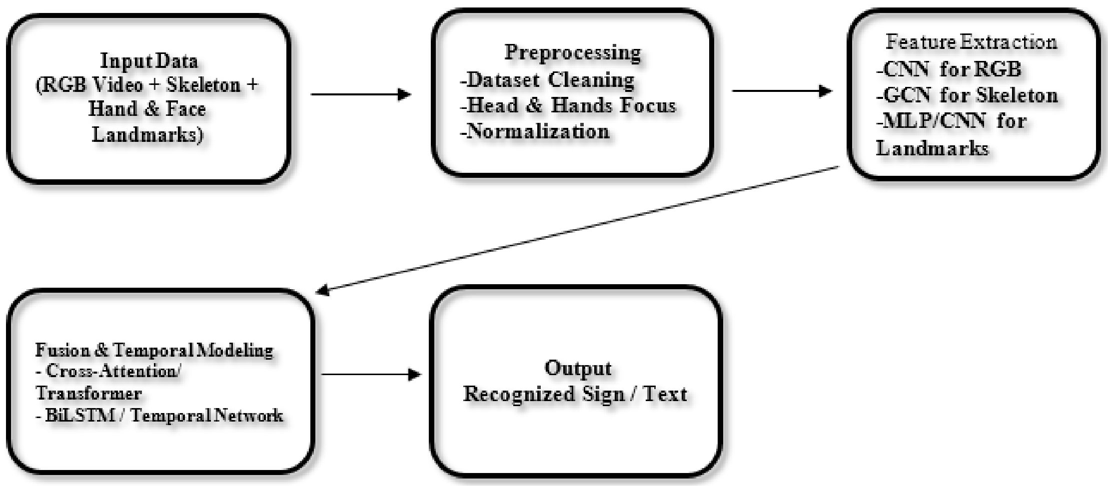

Fig No : 1 – System workflow

XI. ALGORITHM

Algorithm: Multimodal Attention-Based Recognition
Input: RGB frames, Skeleton joints, Landmark coordinates
Output: Recognized Sign Label
Steps:

1. Load video sequence and extract frames.
2. Apply **Head & Hands Tunneling** to focus on key gesture regions.
3. Normalize and clean input data (remove noise, missing frames).
4. Extract:
   - CNN/Transformer features for RGB
   - GCN features for skeleton
   - CNN/MLP features for landmarks
5. Fuse features using **Cross-Attention Transformer** to capture inter-modal dependencies.
6. Model temporal relations using **BiLSTM/Temporal Transformer**.
7. Classify gestures using **Softmax layer**.
8. Evaluate using **Accuracy, WER, BLEU** metrics.

XII. DATASETS

Dataset	Type	Size / Classes	Usage	Remarks
MS-ASL	Isolated SLR Dataset	25,000 videos / 1,000 signs	Model training	Large vocabulary for isolated recognition
WLASL	Continuous SLR Dataset	21,083 videos / 2,000 signs	Model testing	Suitable for real-world continuous signing
RWTH-PHOENIX	Continuous SLR Dataset	9 signers / German SL	Benchmarking	Used for multilingual evaluation

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XIII. TEST SPECIFICATION

Performance Metrics: Accuracy, WER (Word Error Rate), BLEU score (for translation).

Evaluation: Compare unimodal vs multimodal.

Scenarios:

- With occlusion vs without occlusion
- Clean vs noisy datasets
- Isolated vs continuous signs

Testing Parameters :

Parameter	Description / Purpose
Accuracy (%)	Measures classification correctness across all signs.
Word Error Rate (WER)	Evaluates recognition quality in continuous sign sentences.
BLEU Score	Measures sentence-level similarity for translation tasks.
Training Loss / Validation Loss	Monitors convergence and overfitting.
FPS (Frames per Second)	Tests real-time inference performance.
Robustness Test	Evaluates model under occlusion and lighting variation.

Test Cases :

Test Case ID	Scenario	Input	Expected Output
TC1	Isolated Sign Recognition	Single sign video (e.g., "Hello")	Correct label "Hello"
TC2	Continuous Sign Recognition	Sentence sign sequence	Accurate sentence translation
TC3	Occluded Environment	Partially visible hands	Still detects correct gesture
TC4	Noisy Background	Complex scene background	Minimal performance drop
TC5	Different Signer	New signer input	Robust recognition across signers
TC6	Dataset Cleanliness	Noisy vs cleaned dataset	Accuracy improves by 5–7% after cleaning

XIV. CONCLUSION

The research presents a multimodal deep learning framework for sign language recognition that unifies visual, skeletal, and landmark features through attention-based fusion and temporal modelling. By emphasizing key gesture regions using the Head-and-Hands Tunnelling Pipeline and incorporating data refinement strategies, the proposed system enhances recognition accuracy and robustness against occlusion, lighting variations, and background noise. Experimental validation on benchmark datasets demonstrates that multimodal integration outperforms unimodal approaches, offering greater consistency across different signers and environments. This work establishes a foundation for future extensions, including real-time deployment on mobile or embedded devices, with the ultimate goal of supporting inclusive communication technologies for the deaf and hard-of-hearing population.

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— **Swapnil Shravan Ohol**

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