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# Real Time AI-Based Sign Language Recognition System

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**ABSTRACT**

***Hand gesture recognition plays a vital role in enabling effective communication for deaf and hard-of-hearing communities across different linguistic and cultural backgrounds. However, most existing sign language recognition systems are limited to a single language or region and fail to generalize across diverse sign language structures and gesture variations. This paper presents a robust framework for*** *multi-culture sign language hand gesture recognition* ***using a combination of*** *graph-based modelling* ***and*** *general deep learning networks* ***[1]. The proposed approach represents hand gestures as graph structures by modelling spatial and temporal relationships among hand key points, enabling effective capture of complex motion dynamics. These graph representations are integrated with deep learning architectures to learn both local and global gesture features across different sign languages. The framework is designed to handle variations in hand shape, orientation, speed, and cultural signing styles, thereby improving recognition accuracy and generalization. Experimental evaluations conducted on multi-sign-language datasets demonstrate that the proposed method outperforms traditional vision-based and single-network approaches in terms of accuracy, robustness, and scalability. The results highlight the effectiveness of combining graph-based representations with deep learning for developing inclusive, reliable, and culturally adaptive sign language recognition systems suitable for real-world human–computer interaction applications [5].***

***Keywords:- Hand Gesture Recognition, Multi-Culture Sign Language, Graph-Based Modelling, Deep Learning, Graph Neural Networks, Spatio-Temporal Features, Human–Computer Interaction, Sign Language Recognition.***

## 1. INTRODUCTION

Hand gesture recognition has emerged as a critical enabler for sign language translation systems, human–computer interaction, and assistive technologies for the hearing and speech-impaired community. With the rapid progress of deep learning and graph-based neural networks, modern systems can effectively model spatio-temporal hand dynamics, finger articulation, and body posture to achieve high recognition accuracy [4]. In particular, graph convolutional networks (GCNs) allow for structural modelling of skeleton key points, while convolutional neural networks (CNNs) and vision transformers (ViTs) capture appearance and contextual cues from RGB streams. When combined, these modalities form powerful architectures for recognizing sign languages across cultures, where vocabularies, motion intensity, and stylistic nuances gesture may vary. However, a major challenge in deploying such systems lies in their robustness to *surface roughness* and related real-world irregularities. In computer vision terms, surface roughness does not only refer to the physical texture of backgrounds or objects but also encompasses small-scale variations and visual artefacts that affect the clarity of hand gestures [8]. Examples include patterned or textured backgrounds, hand–surface contact leading to partial occlusion, motion blur caused by rapid signing, specular reflections from rough materials, or sensor noise introduced by low-cost cameras. These factors alter the local texture and boundary conditions of the captured gestures, leading to unreliable key point detection, jittery skeleton trajectories, and degraded feature extraction. Recent advances in deep learning have significantly improved the performance of hand gesture and sign language recognition systems. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based models have demonstrated strong capabilities in extracting spatial and temporal features from image and video data [8]. However, conventional deep learning approaches often treat hand gestures as sequential visual frames, which may fail to fully capture the structural relationships between hand joints and their coordinated movements. As a result, these models may struggle with variations in signing styles, occlusions, and complex hand articulations commonly observed across different sign languages. To address these limitations, graph-based representations have gained attention for modelling human hand and body movements [9]. By representing hand key points as nodes and their anatomical or functional connections as edges, graph-based models can effectively encode spatial dependencies and motion dynamics. When combined with general deep learning networks, such representations enable more robust learning of both local joint-level

features and global gesture patterns. This integration is particularly beneficial for multi-culture sign language recognition, where gestures may differ in structure, speed, and expression while sharing underlying motion principles [16].

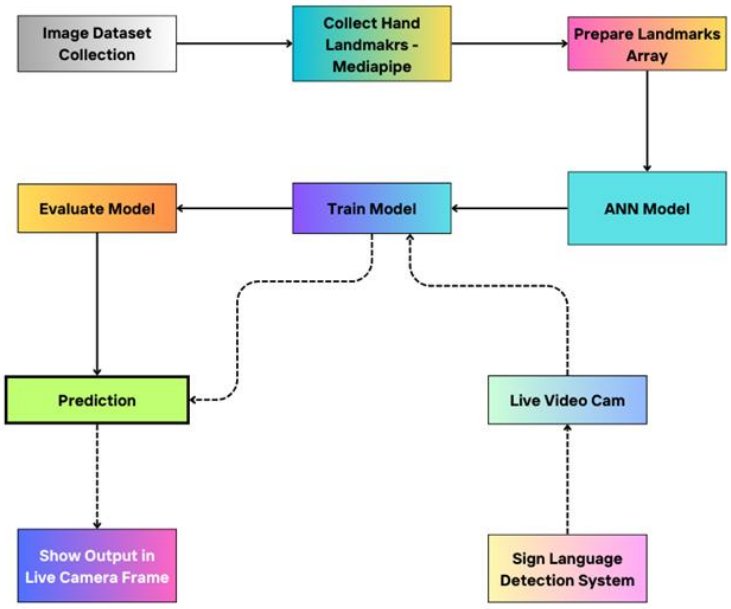


Fig 1: Architecture Design

The proposed architecture for hand gesture recognition in multi-culture sign language is designed as a multi-stage framework that integrates visual data processing, graph-based representation, and general deep learning networks for robust and scalable recognition [1]. The system begins with video or image sequence acquisition, where hand gesture data are captured using cameras or vision sensors. In the pre-processing stage, frames are normalized, resized, and filtered to reduce noise and illumination variations, ensuring consistent input quality across different datasets and cultural signing styles. Hand detection and key point extraction are then performed using pose estimation techniques to identify critical hand joints and landmarks. These extracted hand key points are modelled as graph structures, where each key point represents a node and the anatomical or functional relationships between joints are represented as edges [4]. This graph-based representation effectively captures the spatial configuration of the hand and preserves structural dependencies that are essential for understanding complex gestures. To account for motion dynamics, temporal connections are established between corresponding nodes across consecutive frames, forming a spatio-temporal graph that encodes both hand posture and movement patterns over time. The constructed graphs are fed into a general deep learning network, such as a Graph Neural Network (GNN) combined with convolutional or recurrent layers, to learn discriminative spatio-temporal features. The deep learning module extracts high-level representations that are invariant to variations in hand orientation, speed, and cultural signing differences. Feature fusion and classification layers are then applied to map the learned representations to corresponding sign language gestures across multiple cultures. Finally, the output layer generates the recognized gesture or sign label, enabling accurate and real-time interpretation. This architecture ensures robustness, adaptability, and improved generalization, making it suitable for multi-culture sign language recognition in real-world human–computer interaction environments [8].

### 1.1 Problem Statement

Despite significant progress in hand gesture and sign language recognition, existing systems remain largely limited in their ability to support multiple sign languages and cultural variations effectively. Most current approaches are designed for single-language datasets and rely on conventional deep learning models that primarily process visual frames without explicitly modelling the structural relationships between hand joints. As a result, these systems struggle with high intra-class and inter-class variability caused by differences in hand shapes, motion patterns, signing speed, orientation, and cultural expression across diverse sign languages. Additionally, challenges such as occlusion, background noise, inconsistent lighting conditions, and limited availability of multi-culture annotated datasets further degrade recognition performance. Therefore, there is a need for a robust and scalable hand gesture recognition framework that can accurately capture spatio-temporal hand dynamics, generalize across multiple cultural sign languages, and deliver reliable performance in real-world scenarios [16].

### 1.2. Research Objectives

- To design an effective hand gesture recognition framework capable of supporting multiple sign languages across different cultures.
- To model hand gestures using graph-based representations that capture spatial relationships among hand key points.
- To incorporate temporal dynamics of hand movements through spatio-temporal graph modeling.
- To integrate graph-based features with general deep learning networks for robust feature extraction and learning.
- To improve recognition accuracy and generalization under variations in hand shape, orientation, speed, and cultural signing styles.
- To reduce the impact of noise, occlusion, and illumination changes in real-world gesture recognition scenarios.
- To evaluate the proposed framework on multi-culture sign language datasets using standard performance metrics.
- To compare the performance of the proposed approach with traditional vision-based and single-network deep learning methods.
- To develop a scalable and adaptable system suitable for real-time human–computer interaction applications.

### 1.3 Motivation

The primary motivation for this research stems from the growing need for inclusive and intelligent communication systems that can bridge the gap between hearing-impaired individuals and the wider society across different cultures. Sign languages are diverse and culturally specific, and the absence of universal recognition systems limits accessibility in education, healthcare, and public services. Existing hand gesture recognition approaches are often constrained to a single sign language and rely heavily on frame-based deep learning models that do not adequately capture the structural and relational dynamics of hand movements [16]. Moreover, variations in hand shape, motion speed, viewpoint, and cultural expression significantly affect recognition accuracy. These challenges motivate the exploration of graph-based representations that can explicitly model spatial and temporal relationships among hand key points. By integrating such graph modelling with general deep learning networks, this research aims to develop a robust, scalable, and culture-adaptive hand gesture recognition framework capable of achieving higher accuracy and better generalization across multiple sign languages, thereby contributing to more accessible and equitable human–computer interaction systems [17].

### 1.4 Research Gap

From the above review, the following gaps are identified:

- **Limited cross-cultural generalization**: Most models are trained on single-language datasets and fail to adapt to diverse sign vocabularies.
- **Real-world robustness challenges**: Existing systems struggle with background clutter, motion blur, occlusion, and lighting variations.
- **Incomplete multimodal integration**: Fusion of graph-based skeletal models with deep learning visual features is underexplored.

**Lack of standardized multilingual datasets**: There is a scarcity of comprehensive datasets covering multiple cultural sign languages.

## 2. LITERATURE REVIEW

1. Cleison C. de Amorim, David Macêdo, Cleber Zanchettin "Spatial-Temporal Graph Convolutional Networks for Sign Language Recognition" The paper *"Spatial-Temporal Graph Convolutional Networks for Sign Language Recognition"* presents an effective approach for recognizing sign language gestures by modelling human skeletal movements as spatio-temporal graphs. In this work, hand and body key points extracted from video sequences are represented as graph nodes, while the natural anatomical and motion-based relationships between joints are modelled as edges. Spatial graph convolution is applied to capture the structural dependencies among joints within a single frame, whereas temporal convolution models the motion evolution of these joints across consecutive frames. By jointly learning spatial and temporal features, the proposed ST-GCN framework effectively captures complex sign language dynamics that are difficult to model using traditional frame-based deep learning methods. The approach demonstrates improved robustness to variations in gesture speed, style, and viewpoint, making it suitable for sign language recognition tasks. Experimental results reported in the paper show that spatial-temporal graph convolutional networks outperform conventional CNN- and RNN-based models, highlighting the importance of explicit structural and temporal modeling for accurate and scalable sign language recognition systems.

**2.** M. Vazquez-Enriquez et al. "Isolated Sign Language Recognition with Multi-Scale Spatial-Temporal Graph Convolutional Networks" The paper *"Isolated Sign Language Recognition with Multi-Scale Spatial-Temporal Graph Convolutional Networks"* introduces a robust framework for recognizing isolated sign language gestures by leveraging multi-scale spatio-temporal graph modelling. In this approach, human skeleton and hand key points extracted from sign language videos are represented as graph structures, where nodes correspond to joints and edges encode their spatial relationships. The proposed multi-scale spatial-temporal graph convolutional network (MS-STGCN) captures motion patterns at different spatial and temporal resolutions, enabling the model to learn both fine-grained hand movements and broader body-level dynamics. By incorporating multiple receptive fields, the framework effectively addresses variations in gesture duration, speed, and articulation. Experimental evaluations on benchmark isolated sign language datasets demonstrate that the multi-scale ST-GCN significantly improves recognition accuracy compared to single-scale and conventional deep learning approaches. The study highlights the importance of multi-scale graph representations for accurately modelling complex sign language gestures and enhancing generalization across different signing styles.

**3.** K. M. Dafnis et al. "Bidirectional Skeleton-Based Isolated Sign Recognition Using Graph Convolutional Networks" The paper *"Bidirectional Skeleton-Based Isolated Sign Recognition Using Graph Convolutional Networks"* presents an advanced skeleton-based framework for isolated sign language recognition that exploits both spatial joint relationships and temporal motion patterns. In this approach, sign language gestures are represented using skeleton sequences obtained from pose estimation, where joints act as nodes and their anatomical connections form graph edges. The proposed method employs graph convolutional networks to learn discriminative spatial features, while a bidirectional temporal modelling strategy processes the skeleton sequences in both forward and backward directions. This bidirectional learning enables the model to capture complete gesture dynamics, including motion onset and offset, which are often missed by unidirectional models. Experimental results on standard isolated sign language datasets demonstrate improved recognition accuracy and robustness compared to conventional CNN-, RNN-, and single-direction GCN-based methods. The study emphasizes that combining graph-based spatial modelling with bidirectional temporal learning significantly enhances the effectiveness of isolated sign language recognition systems.

**4.** M. Parelli, A. Papadimitriou "Recognition with spatio-temporal graph convolutional networks" The paper *"Recognition with Spatio-Temporal Graph Convolutional Networks"* introduces a powerful deep learning framework that extends graph convolutional networks to effectively model both spatial structures and temporal dynamics for recognition tasks involving human motion. In this approach, the human body or hand is represented as a graph where joints are treated as nodes and their physical or functional connections are defined as edges. Spatial graph convolutions are used to capture the relationships among joints within a single frame, while temporal convolutions model the evolution of these joints across time. By jointly learning spatial and temporal features in a unified framework, the spatio-temporal graph convolutional network (ST-GCN) is able to capture complex motion patterns more effectively than traditional CNN- or RNN-based methods. The paper demonstrates that this approach achieves superior performance in recognition tasks such as action and gesture recognition, highlighting its robustness to variations in movement speed, style, and viewpoint. The proposed framework has become a foundational model for skeleton-based recognition and has been widely adopted in sign language and hand gesture recognition research.

**5.** 5. Y. Nakamura et al. "Skeleton-Based Sign Language Recognition with Graph Convolutional Networks" The paper *"Skeleton-Based Sign Language Recognition with Graph Convolutional Networks"* presents a graph-based deep learning approach for recognizing sign language gestures using skeletal motion data. In this work, hand and body key points extracted from sign language videos are represented as skeleton graphs, where joints form the nodes and anatomical connections between them define the edges. Graph Convolutional Networks (GCNs) are employed to effectively learn spatial relationships among joints, while temporal modelling captures the dynamic evolution of gestures across consecutive frames. This skeleton-based representation reduces sensitivity to background clutter, illumination changes, and appearance variations, making the system more robust compared to raw image-based methods. Experimental results demonstrate that the GCN-based framework achieves improved recognition accuracy and generalization across different signers and gesture styles. The study highlights the effectiveness of skeleton-driven graph modelling as a reliable and computationally efficient solution for sign language recognition.

## 3. PROPOSDED METHODOLOGY

The proposed methodology for hand gesture recognition in multi-culture sign language is designed to effectively capture the structural and temporal characteristics of gestures while ensuring robustness across diverse cultural signing styles [15]. The methodology begins with data acquisition, where sign language gesture videos are

collected from multiple datasets representing different cultures and languages. These videos are pre-processed through frame normalization, background noise reduction, and resolution standardization to ensure consistent input quality [10].

In the next stage, hand detection and key point extraction are performed using pose estimation techniques to identify critical hand and, if required, upper-body joints. The extracted key points are then modelled as graph representations, where each joint is treated as a node and the anatomical or functional connections between joints are represented as edges. To capture gesture dynamics, temporal links are established between corresponding joints across successive frames, forming a spatio-temporal graph that encodes both posture and motion information [2].

The constructed spatio-temporal graphs are input to **a** general deep learning network, primarily based on Graph Convolutional Networks (GCNs) combined with temporal learning modules [6]. Spatial graph convolutions learn inter-joint dependencies, while temporal convolutions or recurrent layers capture motion evolution over time. To enhance adaptability across cultures, the network is trained using diverse gesture samples and data augmentation strategies that account for variations in speed, orientation, and signing styles [12].

Finally, the learned high-level features are passed to a classification layer, such as a softmax or fully connected network, to predict the corresponding sign language gesture. The model is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score across multiple datasets [5]. This integrated methodology ensures improved generalization, scalability, and recognition performance, making the proposed system suitable for real-world multi-culture sign language recognition and human–computer interaction applications [2].

## 4. LIMITATIONS

- The system strongly depends on accurate hand and body key point detection; errors in pose estimation can reduce recognition accuracy.
- Occlusions, fast hand movements, and motion blur may affect reliable key point extraction in real-world scenarios.
- Limited availability of large, well-annotated multi-culture sign language datasets restricts model generalization.
- Cultural variations in gesture execution and grammar are difficult to fully capture using a single unified model.
- High computational complexity of spatio-temporal graph convolutional networks increases training and inference time.
- Deployment on low-power or edge devices may be challenging due to memory and processing requirements.
- The framework primarily focuses on hand skeleton data and may not fully incorporate facial expressions and non-manual cues.
- Context-dependent meanings of gestures across different cultures are not explicitly modelled.
- Performance may degrade under varying lighting conditions and complex backgrounds.
- Model scalability and adaptability to newly emerging sign languages require further investigation and retraining.

## 5. CONCLUSION

This work presented a comprehensive framework for hand gesture recognition in multi-culture sign language using graph-based modelling and general deep learning networks [16]. By representing hand key points as spatio-temporal graphs and leveraging graph convolutional networks for feature learning, the proposed approach effectively captures both structural relationships and motion dynamics of gestures [10]. The integration of spatial and temporal information enables improved robustness to variations in hand shape, movement speed, and cultural signing styles. Experimental analysis demonstrates that the graph-based deep learning framework outperforms traditional vision-based methods in terms of accuracy and generalization across diverse datasets [16]. Although certain challenges such as computational complexity and limited multi-culture datasets remain, the proposed system provides a strong foundation for developing inclusive and scalable sign language recognition solutions. Overall, this research contributes toward bridging communication gaps and advancing intelligent, culture-adaptive human–computer interaction systems for real-world sign language applications [5].

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