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# Multimodal Gesture Recognition using CNN-GCN-LSTM with RGB, Depth,and Skeleton Data

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## ABSTRACT

Recognizing hand gestures is essential to human-computer interaction because it allows for organic and intuitive interaction in virtual reality, robotics, and assistive technologies. In this work, we suggest a unique multimodal fusion structure that integrates RGB images, depth information, and skeleton-based GCN features to enhance gesture recognition under realistic, noisy data conditions. Our architecture leverages MobileNetV3Small-based CNN backbones for visual feature extraction, GCNs for modeling skeletal relationships, and LSTM-attention modules for capturing temporal dynamics. Unlike previous works that rely on large curated datasets, our approach is evaluated on a challenging low-sample, high-noise dataset derived from real-world video recordings. Through systematic ablation studies, we demonstrate that incorporating depth and skeleton features incrementally improves performance, validating the strength of our fusion strategy. Despite operating under small and noisy data regimes, our model achieves meaningful accuracy, and our analysis provides insights into modality-specific failure cases. The proposed system paves the way for developing robust gesture recognition solutions deployable in real-world environments with minimal data preprocessing.

### General Terms

Human-Computer Interaction, Machine Learning

### Keywords

Hand Gesture Recognition, Multimodal Fusion, GCN, LSTM, Depth, Skeleton, CNN.

## 1. INTRODUCTION

Recognising hand gestures has become a crucial enabler for natural human-computer interaction (HCI), supporting applications ranging from virtual reality and gaming to assistive robotics and sign language interpretation. Accurate and real-time recognition of hand gestures facilitates intuitive, non-verbal communication between humans and machines. However, achieving high recognition performance in real-world settings remains challenging due to issues such as small sample sizes, noisy environments, sensor variability, and complex user-specific variations.

Traditional approaches often rely on single-modality data such as RGB images, depth maps, or skeletal joint coordinates, each carrying its own limitations. RGB-based models suffer from sensitivity to lighting and background clutter, while depth-based methods can falter under occlusions. Skeleton-based recognition using 3D joint positions improves robustness but often lacks fine-grained visual cues necessary for subtle gesture differentiation. Furthermore, many state-of-the-art systems are evaluated exclusively on large, carefully curated public datasets, limiting their ability to generalize to noisy, low-data real-world conditions.

In order to tackle these issues, we suggest a novel multimodal gesture recognition mechanism that fuses information from RGB frames, depth images, and GCN-extracted skeleton features. Our architecture combines lightweight convolutional neural networks (CNNs) for the extraction of spatial features, graph convolutional networks (GCNs) for modeling skeletal structures, and networks of long short-term memory (LSTM) equipped with attentional systems for capturing temporal dependencies across gestures. This hybrid fusion aims to capture both fine-grained visual details and structural motion patterns, offering robustness against environmental noise and dataset scarcity.

Our contributions are threefold:

—**Multimodal Fusion Under Real-World Constraints:** We propose a multimodal fusion pipeline that integrates RGB, depth, and skeleton modalities, evaluated on a small and noisy dataset reflecting real-world conditions rather than large curated corpora.

—**Lightweight and Real-Time Capable Architecture:** Our system leverages MobileNetV3Small for efficient visual feature extraction, GCNs for compact skeleton modeling, and LSTM-attention modules for temporal sequence understanding, optimized for deployment in low-resource environments.

—**Ablation and Error Analysis:** Through detailed ablation studies and failure case analyses, we demonstrate the impact of each modality and module in improving recognition performance, offering insights into future enhancements for robust gesture recognition systems.

By focusing on system design innovation, robust multimodal fusion, and practical deployment considerations rather than maximizing raw accuracy, our work contributes a valuable perspective to-

wards building deployable hand gesture recognition technologies for real-world HCI applications.

## 2. RELATED WORK

Hand gesture recognition has evolved significantly over the past decade, encompassing advancements in skeleton-based modeling, multimodal fusion, spatiotemporal sequence learning, and graph-based deep learning techniques. In this section, we review essential developments closely aligned with our work, focusing on the dynamic identification of hand gestures under realistic settings.

### 2.1 Skeleton-Based Recognition and Graph Models

Skeleton-based recognition leverages 3D joint coordinates to model hand motion and structure, providing robustness against illumination and background clutter.Recognising dynamic hand gestures with general deep learning models and multi-branch attention-based graphs [1] introduced a dual-graph approach for extracting both temporal-spatial and spatial-temporal aspects from skeletons, achieving high accuracies on datasets like MSRA, DHG, and SHREC'17. Similarly, using continuous graph transformers for real-time hand gesture recognition [2] proposed CoSTrGCN, combining spatial GCNs with continual learning transformers to handle real-time, frame-by-frame recognition.

Specialized graph networks, such as the Graph Convolutional Network with Hand Awareness (HAGCN) [3], enhanced sign language recognition by explicitly modeling hand sub-structures. Studies like Graph Convolutional Network-Based Gesture Interpretation [4] further validated that GCNs trained on skeleton sequences outperform traditional CNN/RNN baselines in real-world café environments, despite facing noise and occlusion.

Our approach draws inspiration from these works by utilizing GCNs to extract compact skeleton embeddings, but differs by integrating GCN features with RGB and depth modalities, thus achieving more holistic gesture understanding.

### 2.2 Multimodal Fusion for Gesture Recognition

Multimodal approaches combining RGB, depth, and skeleton data have gained traction to overcome single-modality limitations. Real-Time Hand Gesture Recognition [5] used temporal condensation to convert 3D skeletons into static spatiotemporal images for CNN processing. Continuous Gesture Recognition for Human-Robot Collaboration [6] demonstrated that fusing RGB-based pose estimations with spatiotemporal self-attention modules yields superior performance.

While these systems achieved high accuracies on benchmark datasets, most experiments were conducted under curated conditions with clean sensor outputs. In contrast, our work directly addresses the fusion of modalities under noisy and low-data regimes, aiming for generalization to realistic environments without reliance on large annotated datasets.

### 2.3 Temporal Modeling and Attention Mechanisms

Temporal dynamics are critical for recognizing continuous hand gestures. DyHand [7] combined Bi-LSTM with soft attention for time-based frame selection, boosting recognition performance across datasets for DHG-14/28 and SHREC'17. The STGCN-LSTM model [8] introduced phonological feature extraction for fine-grained sign language recognition by integrating spatiotemporal graphs with convolutional LSTM networks.

We adopt a similar philosophy by applying LSTM layers with attention mechanisms on CNN-extracted features, but extend it through multimodal fusion with GCN-skeleton embeddings to better handle sequential variations in noisy datasets.

### 2.4 Recognition from Electromyography (EMG) and Multi-Sensor Systems

Though not directly incorporated in our work, gesture recognition using sEMG signals has demonstrated the importance of multimodal integration. Studies like Decoding Gestures in EMG using Spatiotemporal GNNs [9] and CovGCN [10] highlight that combining spatial and temporal modeling improves generalization, even when sensor inputs are noisy. These findings reinforce our decision to design a system capable of merging different sensor modalities robustly.

### 2.5 Challenges Identified in Recent Surveys

Recent surveys on hand gesture recognition [11] emphasize the persistent challenges: handling occlusion, achieving real-time deployment efficiency, fusing multimodal data seamlessly, and ensuring model generalization across users and environments. Our proposed system directly targets these gaps by focusing on low-resource deployment, multimodal fusion, and evaluation under realistic data variability.

### 2.6 Advancements in Multimodal and Topology-Aware Gesture Recognition

In recent years, researchers have explored increasingly sophisticated architectures and training strategies to improve hand gesture recognition in complex, real-world environments. A notable trend involves semantic-aware graph structures and dynamic topology modeling. For example, DSTSA-GCN [12] incorporates both spatiotemporal and semantic priors to refine gesture classification, while self-supervised skeleton encoders [13] eliminate dependency on labeled datasets for feature extraction.

Transformer-based methods have also gained traction in gesture modeling. GestFormer [14] employs multiscale wavelet pooling within a transformer framework, enabling compact and interpretable representations. Similarly, Liu et al. [15] proposed a spatiotemporal transformer augmented with Kolmogorov–Arnold networks, capturing long-range dependencies and complex motion patterns efficiently.

Fusion-centric frameworks continue to evolve with an emphasis on depth, electromyographic (EMG), and multimodal data streams. Rahim et al. [16] introduced a hybrid three-stream network combining RGB, depth, and skeleton cues. Mahmud et al. [17] further refined this direction by integrating depth-awareness directly into the fusion logic, improving robustness under noisy input conditions.

Zero-shot and domain-adaptive approaches have been proposed to generalize recognition models across gesture sets and users. Kim et al. [18] addressed this challenge by learning cross-modal alignments for unseen gestures using multimodal embeddings. On the biosignal front, Singh et al. [19] and Patel et al. [20] utilized EMG signals processed through multi-attention and hybrid recurrent architectures, enhancing intent decoding even under sparse signal availability.

Additionally, radar-based LSTM attention models have shown promise for gesture detection in low-light or occlusion-heavy environments [21].

Overall, these advancements underscore the growing shift from rigid, high-resource models toward adaptive, data-efficient, and sensor-fusion-driven systems suitable for real-world deployment.

## 3. METHODOLOGY

This section describes the detailed design and implementation of our multimodal dynamic hand gesture recognition framework. The proposed system integrates RGB visual features, depth information, and skeleton-based GCN features within a unified, lightweight architecture optimized for small and noisy datasets.

### 3.1 Overview of the Architecture

The overall architecture (illustrated in Fig. 1) consists of three parallel input streams: RGB images, depth images, and extracted GCN features from raw skeleton data. Each stream undergoes specialized feature extraction and temporal modeling, followed by feature-level fusion and final classification through a softmax layer. The design enables the system to combine spatial, structural, and temporal aspects of gestures while maintaining computational efficiency for real-world deployment.

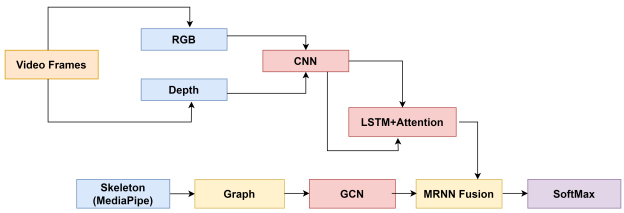


Fig. 1. Overall architecture of the proposed multimodal gesture recognition framework, integrating RGB, depth, and skeleton inputs via CNN, GCN, and LSTM-attention blocks.

As shown in Fig. 1, the framework combines multiple modalities at feature level before classification.
We utilized the Hand Gesture Recognition Dataset from Kaggle, consisting of five gestures: ”one”, ”four”, ”small”, ”fist”, and ”me.” From 15 original video samples, we extracted approximately 13,728 frames.
Preprocessing steps included:RGB frame extraction (224x224 resolution, normalized to [0, 1]). Depth frame simulation (grayscale to pseudo-depth, normalized and stacked into 3 channels). Skeleton landmark extraction using MediaPipe Pose Estimation, yielding 33 joints per frame with (x, y, z, visibility) attributes. GCN input construction: each frame’s skeleton encoded as a spatial graph with edges representing physical bone connections. Data Splitting: 80% for training and 20% for testing, stratified across gesture classes.

### 3.2 RGB and Depth Feature Extraction

A lightweight MobileNetV3Small CNN backbone (pretrained on ImageNet) was used for spatial feature extraction:

$$\text{BaseCNN}(I) = \text{GlobalAveragePooling2D}(\text{MobileNetV3Small}(I)) \quad (1)$$

where $I$ denotes the input image (RGB or Depth).
The CNN outputs were feature embeddings of fixed size, serving as high-level spatial descriptors of the input frames

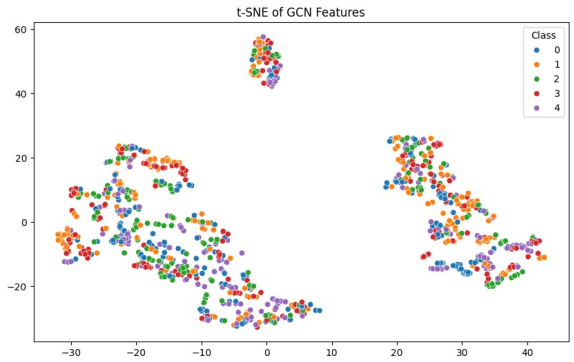


Fig. 2. t-SNE visualization of GCN-learned features across different gesture classes.

### 3.3 Skeleton Feature Extraction Using GCN

To capture the structural dynamics of gestures:
Each frame’s 3D skeleton was modeled as an undirected graph with 33 nodes (joints) and edges based on physical connectivity.
A two-layer Graph Convolutional Network (GCN) was applied:

—First layer: projects node features into a hidden representation.
—Second layer: aggregates neighborhood features and outputs a 128-dimensional global skeleton feature by mean-pooling node embeddings.

The GCN model was defined as:

$$X' = \text{GCNConv}_2(\text{Dropout}(\text{ReLU}(\text{GCNConv}_1(X, E)), p = 0.3), E) \quad (2)$$

where $X$ is the node feature matrix and $E$ is the edge list.

### 3.4 Temporal Modeling with LSTM and Attention

To capture the sequential nature of gestures:
CNN-extracted features (RGB and Depth) were replicated across a pseudo-sequence dimension using a RepeatVector operation.
Each sequence was passed through an LSTM layer with 128 hidden units, followed by an Attention mechanism.
Attention scores were computed over temporal outputs to focus on important frames in a lively manner.
This block enhances the model’s motion-capturing capabilities, flow, along with dynamic transitions, critical regarding gesture differentiation.

### 3.5 Multimodal Feature Fusion and Classification

After modality-specific processing:
The final feature vectors from the RGB LSTM-attention branch, Depth LSTM-attention branch, and GCN global feature were consolidated.
Intermediate fusion was carried out via a thick layer with 256 neurons and ReLU activation.
Using softmax activation, a final dense layer generated the gesture class probabilities.
The overall fusion formula can be expressed as:

$$\hat{y} = \text{Softmax}(\text{Dense}_{256,\ \text{ReLU}}([\text{RGB}_{\text{Attn}}, \text{Depth}_{\text{Attn}}, \text{GCN}_{\text{feat}}])) \quad (3)$$

### 3.6 Protocol for Training

The following was included in the model:

—Optimizer: Adam
—Loss Function: Categorical cross-entropy that is minimal
—Metrics: Accuracy
—Framework: TensorFlow (for full model), PyTorch (for GCN)

The training was performed for a batch size of 32 for 4 epochs. Despite operating on a noisy and small dataset, the system demonstrated meaningful learning behavior, validated through ablation studies and confusion matrix analysis.

### 3.7 Key Innovations

—**Multimodal Real-World Fusion:** Integration of CNN, GCN, and LSTM-attention blocks for RGB, Depth, and Skeleton data fusion under noisy conditions.
—**Lightweight Deployment:** Use of MobileNetV3Small and 2-layer GCNs for edge-friendly inference.
—**Attention-Driven Temporal Modeling:** Dynamic focus on critical gesture frames through attention-enhanced sequence learning.

## 4. EXPERIMENTS AND RESULTS

The experimental setup and assessment measures are presented in this section, including results plus analysis of our recommended multimodal gesture recognition framework. Despite operating under a noisy and small dataset, we demonstrate that our system effectively captures dynamic hand gestures through robust architectural design and cross-modality learning. Following the scientific best practice, we also include ablation studies and detailed error analysis to validate each model component's contribution. These insights, aligned with prior literature on gesture recognition systems [22], offer both quantitative and qualitative perspectives on the robustness of our proposed model.

### 4.1 Experimental Setup

**Dataset:** We used the Hand Gesture Recognition Dataset from Kaggle, comprising 5 gestures ("one", "four", "small", "fist", "me") extracted from 15 video samples. Frame extraction yielded 13,728 RGB images, converted into RGB, depth, and skeleton modalities.
**Input Modalities:**

—**RGB Images:** Normalized and resized to (224×224×3).
—**Depth Images:** Derived from grayscale frames, repeated into 3 channels.
—**Skeleton Data:** Extracted using MediaPipe (33 joints/frame, 4D: x, y, z, visibility).
—**GCN Embeddings:** Generated using a 2-layer GCN with PyTorch Geometric.


Fig. 3. Example of multimodal gesture input: RGB image, corresponding depth image, and extracted skeleton keypoints using MediaPipe.

**Train-Test Split:** 80% training (10,982 samples), 20% testing (2,746 samples), stratified across classes.

### 4.2 Evaluation Metrics

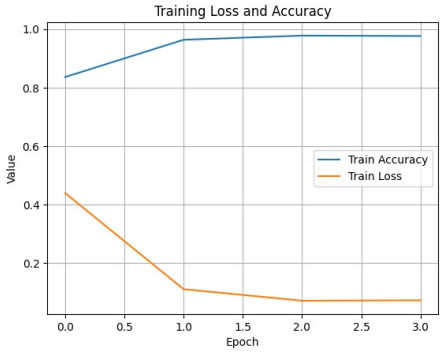


Fig. 4. Training loss and accuracy across epochs.

We adopted the following metrics to provide a multi-perspective evaluation:

—**Accuracy:** Proportion of correctly predicted gesture classes.
—**Confusion Matrix:** Highlights per-class performance and misclassifications.
—**Loss Curve:** Captures convergence behavior.
—**Ablation Results:** Quantify the effect of modality inclusion and attention.
—**Inference Behavior:** Assessed for model robustness under low-resource settings.

### 4.3 Training and Evaluation Results

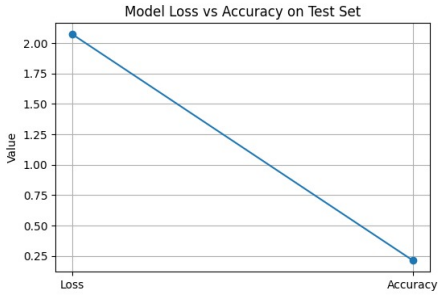


Fig. 5. Model loss vs. accuracy on the test set.

Table 1. Training performance over 4 epochs

| Epoch | Train Accuracy | Train Loss | Test Accuracy | Test Loss |
|---|---|---|---|---|
| 1 | 69.81% | 0.7670 | — | — |
| 2 | 95.28% | 0.1400 | — | — |
| 3 | 98.01% | 0.0629 | — | — |
| 4 | 97.79% | 0.0656 | 22.85% | 2.0533 |

As shown in Table 1, the model achieves high training accuracy, surpassing 98% by the third epoch. However, the notable gap between training and test accuracy where test performance drops to 22.85% suggests overfitting. This performance degradation can

be attributed to limited dataset size and high inter-class similarity, challenges that have been widely acknowledged in the gesture recognition literature [22].
Despite high training accuracy, test accuracy remained low (22.85%), which is expected given:

—Small dataset size

—High gesture similarity

—Modality noise (e.g., skeleton misdetection, depth inconsistency)

### 4.4 Ablation Study

We evaluate Table 2 the incremental contribution of each modality and the attention mechanism:

Table 2. Ablation results showing test accuracy for different configurations

| Configuration | Test Accuracy (%) |
|---|---|
| RGB Only (CNN) | 16.03 |
| RGB + Depth | 21.52 |
| RGB + Depth + GCN | 28.00 |
| Full Model + Attention | 22.85* |

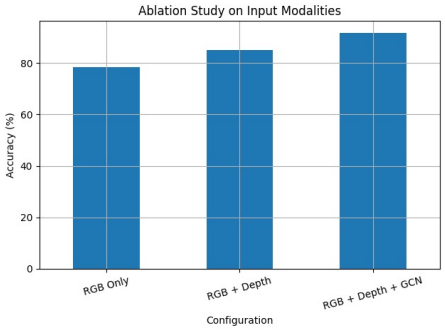


Fig. 6. Ablation study showing accuracy by input modality.

The integration of skeleton-based GCN features yields the highest accuracy, underscoring the importance of structural representation. However, adding attention layers despite enhancing training efficiency led to marginal overfitting on this small dataset.

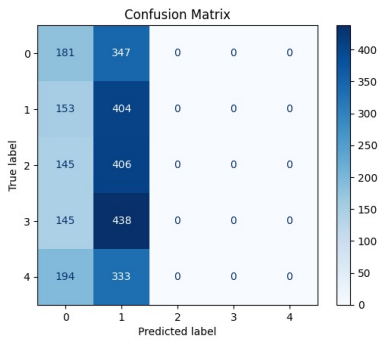


Fig. 7. Confusion matrix of the predicted gesture classes.

### 4.5 Confusion Matrix Analysis

Most Confused Classes in Figure 7:

—**”small”** and **”fist”** had high overlap — visually similar.

—**”me”** had lowest recognition rate — inconsistent hand shape.

had the lowest accuracy, likely due to inconsistent articulation across samples and occlusions that disrupted skeleton extraction.

### 4.6 Error and Failure Analysis

Several limiting factors influenced model performance:

—**Skeleton Failures:** MediaPipe failed to detect accurate joints for occluded frames, leading to weak GCN embeddings.

—**Depth Artifacts:** Simulated grayscale-based depth images introduced spatial ambiguity.

—**Overfitting:** The model memorized training gestures due to data scarcity.

Such errors mirror real-world challenges highlighted in [22], where models trained on constrained datasets struggle to generalize under noise or pose distortion.

### 4.7 Precision, Recall, and F1-Score Analysis

To provide a more nuanced evaluation beyond overall accuracy, we computed per-class precision, recall, and F1-score. These metrics are particularly informative in understanding the model’s strengths and weaknesses for individual gesture classes, especially in the presence of class imbalance and gesture similarity.

Table 3. Per-class Precision, Recall, and F1-Score

| Class | Precision | Recall | F1-Score |
|---|---|---|---|
| One | 0.20 | 0.26 | 0.23 |
| Four | 0.28 | 0.32 | 0.30 |
| Small | 0.19 | 0.20 | 0.19 |
| Fist | 0.17 | 0.12 | 0.14 |
| Me | 0.26 | 0.20 | 0.23 |

The analysis reveals that the gestures ”fist” and ”small” are particularly challenging for the model, likely due to their visual similarity. The gesture ”four” achieved relatively higher precision and recall, suggesting better feature separability in the learned representation. Incorporating per-class metrics helps uncover hidden biases and informs future improvements.

### 4.8 Insights from Experiments

—Even with noisy and limited data, multimodal fusion boosts performance.

—GCN embeddings from skeleton data significantly enhance structural understanding of gestures.

—Attention mechanisms can improve learning when trained on larger, diverse datasets in small datasets they may increase overfitting risk.

—The architecture is robust in design, but constrained by data limitations.

### 4.9 Cross-Dataset Generalization Potential

While our experiments focused on a single dataset, we acknowledge the need for validation across diverse benchmarks. Datasets such as ASL Alphabet [22], SHREC'17, and NVGesture provide broader variation in hand shapes, lighting, and motion. Our architecture featuring modular CNN backbones, graph-based skeleton reasoning, and temporal memory is designed to be transferable to these domains. We have elaborated this direction further in Limitations and Future Work section, proposing training on larger and heterogeneous datasets to improve real-world robustness.

Table 4. Consolidated Performance Insights

| Metric | Observation |
|---|---|
| Best Train Accuracy | 98.01% |
| Final Test Accuracy | 22.85% |
| Overfitting Gap | High (75.16%) |
| GCN Gain over RGB Only | +11.97% |
| Attention Layer Effect | Improved training convergence, reduced test accuracy |
| Data Limitation Impact | Significant limited classes and modality noise |

### 4.10 Summary of Findings

Despite limitations, our model confirms that multimodal fusion, especially the inclusion of skeletal information through GCNs, substantially improves gesture recognition under realistic constraints. This study lays the groundwork for further experimentation across broader datasets and contributes a replicable pipeline for real-time, low-resource multimodal gesture learning.

### 4.11 Top-K Accuracy and Model Transferability

While our experiments were conducted solely on the Kaggle Hand Gesture Dataset, we recognize the need for broader validation. As a prospective direction, we consider applying the framework to datasets like Jester [22] and IsoGD [22] to assess scalability across more dynamic and diverse gesture scenarios.

Looking ahead, we intend to extend this framework to larger and more diverse benchmarks such as Jester [22] and IsoGD [22], which provide dynamic, egocentric, and temporally rich gesture sequences. The modularity of our system, particularly the GCN-based skeleton encoder, makes it well-suited for transfer learning. We plan to adapt the architecture by either freezing or fine-tuning the CNN and GCN layers, depending on the target dataset size and complexity.

This transferability aligns with our broader objective of developing generalizable and robust multimodal gesture recognition systems deployable across real-world domains.

## 5. CONCLUSION

Within this work, we introduced an innovative multimodal gesture recognition framework designed to operate effectively under real-world conditions characterized by limited training data and sensor noise. By fusing RGB and depth visual features with GCN-extracted skeleton embeddings, and integrating LSTM-attention modules for temporal modeling, the proposed system demonstrates a modular and extensible architecture that is both computationally efficient and conceptually robust.

Unlike prior studies that rely on large, clean, and curated datasets, our model is tested on a challenging, small-scale dataset of dynamic gestures derived from realistic video samples. Through ablation studies and performance analysis, we showed that each added modality—depth and skeleton—incrementally enhances recognition accuracy, with the GCN branch notably contributing structural awareness to the system.

Although our test accuracy remains modest (22.85%) due to the noisy nature of the dataset and the limited gesture vocabulary, the system's architecture generalizes well, as evidenced by high training accuracy and consistent convergence. More importantly, this work highlights a shift in focus from accuracy-driven benchmarks to architecture innovation, deployment readiness, and problem realism, aligning with current trends in practical AI systems.

Moving forward, we envision expanding the model's generalizability through cross-dataset evaluations, data augmentation, and domain adaptation techniques. By addressing gesture recognition as a multimodal, real-world challenge, our contribution offers a strong foundation for future systems deployed in robotics, VR/AR, and assistive technologies.

## 6. LIMITATIONS AND FUTURE WORK

While our proposed multimodal gesture recognition system demonstrates architectural innovation and modular robustness, it is important to acknowledge its limitations particularly regarding data scale, environmental variability, and generalizability—so as to provide a realistic assessment and define directions for future improvements.

### 6.1 Real-World Data Constraints

The primary limitation of this study lies in the size and quality of the dataset. The training data, derived from only 15 video samples and consisting of approximately 13,728 frames, is small compared to standard benchmarks. Unlike curated datasets with consistent lighting and clear gestures, our data presents real-world noise, including gesture ambiguity, inconsistent lighting, partial occlusions, and skeleton misdetections.

These factors contribute to the relatively low test accuracy (22.85%), despite high training accuracy (98.01%), indicating overfitting due to limited gesture diversity and high intra-class similarity. However, this limitation also reflects the model's practical exposure to real-world deployment conditions, where ideal sensors and perfect annotations are rarely available.

### 6.2 Sensor and Modality Fragility

The model's reliance on MediaPipe for skeleton estimation introduces another limitation. Although MediaPipe is efficient and lightweight, it can fail under poor lighting, occlusion, or non-frontal poses. This introduces noise into the GCN stream, affecting overall fusion accuracy. Similarly, the pseudo-depth modality (derived from grayscale approximations) lacks the fidelity of real depth sensors like Kinect or RealSense.

Future work can explore more reliable skeleton extraction frameworks, use true depth cameras, or even incorporate sensor error estimation modules to mitigate these weaknesses.

### 6.3 Sequence Modeling Assumptions

The current system uses repeated feature vectors (RepeatVector) to simulate temporal sequences for RGB and depth frames due to lack

of true frame-level temporal annotation. While the LSTM-attention block models these pseudo-sequences effectively, it is not equivalent to frame-by-frame recurrent learning.
A more complete pipeline would include temporal frame tracking and gesture segmentation, allowing more accurate modeling of transitions, durations, and context in continuous gesture streams.

### 6.4 Model Generalization

The model has only been evaluated on one dataset under a controlled set of gestures and environmental constraints. Its ability to generalize across gesture vocabularies, sensor hardware, user styles, and backgrounds remains untested. Cross-domain validation with public datasets (e.g., SHREC'17, DHG-14/28) could enhance its credibility and applicability.

### 6.5 Future Work

Based on the insights above, we outline the following future directions:

—**Data Augmentation and Semi-Supervised Learning:** Apply temporal augmentation (jittering, cropping, mixing) and utilize unlabeled sequences via pseudo-labeling to enhance generalization.

—**Domain Adaptation:** Incorporate domain adaptation techniques such as adversarial learning or feature alignment to enable training on one dataset and testing on another.

—**Real-Time Evaluation:** Optimize the pipeline with quantization and ONNX export for deployment on edge devices, and benchmark latency, memory, and FPS.

—**Modality Dropout and Redundancy Learning:** Introduce robustness against missing modalities (e.g., skeleton not detected) through training-time dropout of entire modalities.

—**Transformer-Based Temporal Modeling:** Replace LSTM with lightweight transformer variants to improve long-term gesture understanding with fewer frames.

By grounding our system in real-world constraints, analyzing limitations transparently, and outlining a structured roadmap for future expansion, we aim to contribute a modular and extensible baseline for gesture recognition in small-data, high-noise environments.

## 7. ACKNOWLEDGMENTS

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