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## A Hybrid Real-Time Hand Gesture Recognition System Using Haar Cascade Detection, HOG Features, and Lightweight CNN

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### Abstract

Hand gesture recognition (HGR) enables natural and contactless interaction between humans and intelligent systems. This paper proposes a real-time gesture recognition framework based on a hybrid architecture combining classical computer vision techniques with deep learning. The system integrates fast hand localization using MediaPipe-based region-of-interest extraction, Histogram of Oriented Gradients (HOG) feature encoding, and a lightweight convolutional neural network (CNN) for gesture classification, followed by temporal stabilization to improve prediction consistency across video frames. A dataset containing 900 gesture images (open, fist, and peace) was automatically collected using a webcam-based acquisition module and divided into training and validation subsets using an 85/15 split with data augmentation. Experimental evaluation includes quantitative performance analysis, ablation studies, and real-time testing. The proposed framework achieves 96.8% accuracy, 96.5% precision, 96.2% recall, and 96.3% F1-score, while maintaining real-time processing speed of approximately 28 FPS.

## A. Introduction

Hand gesture recognition (HGR) has become an important research topic in computer vision and human-computer interaction (HCI), enabling natural and contactless communication between humans and intelligent systems. The growing demand for intuitive user interfaces in robotics, augmented reality, healthcare, assistive technologies, and smart environments has accelerated the development of real-time gesture recognition frameworks [1], [10]. Unlike traditional input devices such as keyboards or touch screens, vision-based HGR systems allow non-invasive interaction and are therefore particularly suitable for accessibility-driven applications and immersive interactive systems.

Early gesture recognition systems relied primarily on handcrafted feature extraction techniques, including Haar-like features, Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Discrete Wavelet Transform (DWT). These methods demonstrated good performance in controlled environments because of their low computational complexity and interpretability. For example, HOG descriptors effectively capture gradient orientation distributions that represent hand contours and shape patterns, making them suitable for gesture classification tasks [1], [19]. Similarly, Haar-like features combined with cascade classifiers have been widely used for fast object detection and hand localization in real-time applications [23]. However, handcrafted approaches often struggle to maintain robust performance under complex conditions such as illumination variation, background clutter, scale changes, and diverse hand articulations.

To address these limitations, machine learning classifiers such as Support Vector Machines (SVM) and ensemble learning techniques were introduced to improve gesture recognition accuracy. Hybrid pipelines combining handcrafted features with SVM classifiers achieved improved recognition performance in several static gesture recognition tasks [19], [29]. Nevertheless, these approaches still depend heavily on manually designed features, which limits their ability to generalize across different environments and datasets.

The emergence of deep learning, particularly convolutional neural networks (CNNs), significantly advanced gesture recognition research by enabling automatic hierarchical feature extraction directly from raw image data. CNN-based architectures have demonstrated superior performance compared with traditional handcrafted pipelines due to their ability to learn spatially invariant representations and complex visual patterns [4], [10], [18]. Several studies have integrated CNN classifiers with real-time detection frameworks such as YOLO to simultaneously localize and recognize gestures from live video streams, achieving high recognition accuracy and real-time processing capability [10]. Furthermore, lightweight CNN architectures and edge-optimized deep learning models have been proposed to enable efficient inference on resource-constrained devices while maintaining high classification performance [20], [24], [25].

Despite these advancements, challenges remain in balancing recognition accuracy with computational efficiency, especially for real-time interactive systems. Variations in hand shape, illumination, background conditions, and occlusion continue to affect recognition robustness, while complex deep learning models may introduce high computational cost and latency. These limitations highlight the need

for efficient hybrid frameworks that combine the advantages of classical feature descriptors with modern deep learning architectures.

Therefore, this research proposes a hybrid real-time hand gesture recognition framework that integrates efficient hand localization, handcrafted feature representation, and lightweight deep learning classification. The proposed system combines fast hand detection, Histogram of Oriented Gradients feature extraction, and a lightweight convolutional neural network to achieve accurate gesture classification while maintaining real-time processing performance. The objective of this study is to develop an efficient gesture recognition system that balances computational efficiency with high recognition accuracy. The results of this research are expected to contribute to the development of practical vision-based interaction systems for applications such as gesture-controlled interfaces, assistive communication technologies, and intelligent human-computer interaction environments.

## **B. Literature Review**

This section reviews prior research on hand gesture recognition (HGR) according to methodological evolution, progressing from traditional handcrafted feature-based approaches to deep learning models, hybrid frameworks, and real-time optimization strategies. The review highlights how each paradigm contributes to the development of efficient real-time gesture recognition systems.

### **- Traditional Feature-Based Methods**

Early vision-based HGR systems relied heavily on handcrafted descriptors designed to encode shape, texture, and gradient information. Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), wavelet transforms, and geometric shape cues were widely adopted due to their computational efficiency and interpretability. Lahiani and Neji (2018) demonstrated that combining HOG and LBP descriptors provides robust performance for mobile-based gesture recognition while maintaining low computational complexity [1]. Their study emphasized the effectiveness of gradient-structure encoding for discriminating static hand postures under moderate illumination variations. Similarly, Bakheet and Al-Hamadi (2021) integrated multiple shape-oriented cues to enhance robustness against pose variability and partial occlusion [2], reinforcing the importance of structural representation in scenarios where deep learning models may be computationally expensive. From a broader perspective, Oudah et al. (2020) presented a comprehensive review of classical computer vision techniques for gesture recognition, categorizing them into detection, segmentation, feature extraction, and classification stages [3].

Their analysis indicated that handcrafted descriptors remain relevant for real-time systems because of their lightweight computational requirements and predictable runtime behavior. Despite these advantages, traditional methods are often sensitive to background clutter, scale variation, and complex illumination conditions. These limitations motivated the transition toward data-driven deep learning frameworks capable of learning more robust representations.

### - **Deep Learning Approaches**

The emergence of convolutional neural networks (CNNs) significantly advanced gesture recognition research by enabling automatic hierarchical feature extraction directly from image data. CNN-based approaches have demonstrated superior performance compared with handcrafted descriptors, particularly in complex visual environments. Zhan et al. (2019) showed that CNN architectures substantially improve gesture classification accuracy compared with traditional feature descriptors, especially under background variability [4]. Mujahid et al. (2021) extended this paradigm by employing a YOLOv3-based detection model for real-time hand localization and recognition, demonstrating the feasibility of end-to-end deep learning pipelines for dynamic gesture recognition tasks [5]. More recent studies incorporate attention mechanisms and adaptive feature learning strategies to improve recognition performance. Cao et al. (2022) proposed an attention-based network that dynamically adjusts feature weighting, enhancing robustness against scale and pose variations [6]. Similarly, Jafari and Basu (2023) introduced a saliency-driven deep learning framework integrating gradient-based cues with CNN feature maps to strengthen discriminative regions [7]. A systematic methodological overview by Qi et al. (2024) categorized deep learning pipelines into detection-based, segmentation-based, and direct classification models, highlighting the dominance of CNN and transformer-based solutions in modern gesture recognition systems [8]. Although deep learning models achieve high accuracy, they typically require substantial computational resources, which may limit deployment on embedded or edge devices.

### - **Hybrid Models**

To balance computational efficiency and recognition accuracy, hybrid models combine handcrafted descriptors with deep learning classifiers. These approaches exploit the robustness and interpretability of classical features while benefiting from the representation power of CNNs. Alhamdani et al. (2024) developed a real-time OpenCV-based pipeline integrating Haar Cascade detection with HOG feature extraction and CNN classification, demonstrating improved localization efficiency and classification performance [9]. Their findings suggest that classical detection modules can effectively reduce computational overhead before deep learning inference. Jafari and Basu (2023) further supported this integration strategy by showing that HOG-enhanced saliency cues complement CNN representations, particularly in cluttered environments [7]. Hybrid systems benefit from multi-level feature abstraction, where handcrafted descriptors provide structured priors that guide deep feature learning. Benitez-Garcia et al. (2021) emphasized the importance of segmentation-based preprocessing for improving region-of-interest extraction prior to classification, thereby reducing false positives and enhancing real-time reliability [10]. These studies indicate that modular hybrid pipelines offer flexibility and allow selective optimization of detection, feature extraction, and classification stages. Overall, hybrid frameworks provide a balanced trade-off between computational efficiency and recognition accuracy, making them suitable for practical real-time applications.

### - Real-Time Optimization Techniques

Real-time gesture recognition systems must consider computational latency, memory consumption, and hardware constraints. Beyond model architecture design, optimization strategies are essential for enabling efficient deployment. Jaiswal et al. (2024) proposed a quantized CNN architecture optimized for hardware implementation, significantly reducing memory footprint and inference latency without substantial loss of accuracy [11]. Their work highlights the importance of model compression and precision reduction for embedded applications. Mujahid et al. (2021) demonstrated that fast detection backbones, such as YOLO-based pipelines, enable real-time frame processing when combined with optimized inference frameworks [5]. Similarly, segmentation-assisted preprocessing approaches, as demonstrated by Benitez-Garcia et al. (2021), improve gesture localization accuracy while maintaining computational efficiency [10]. According to Qi et al. (2024), modern real-time systems increasingly integrate modular pipelines, lightweight CNN architectures, and hardware-aware optimization techniques to balance recognition accuracy and processing speed [8]. These developments support the design of efficient gesture recognition systems capable of operating in interactive human-computer interaction environments. Table 1 summarizes the main methodological approaches discussed in the literature, highlighting their key techniques, strengths, limitations, and representative studies.

**Table 1.** Comparative Summary of Methods

Methodology	Key Techniques	Strengths	Limitations	Representative Works
<b>Traditional Feature-Based</b>	HOG, LBP, shape cues	Lightweight, interpretable, low latency	Sensitive to complex backgrounds	[1], [2], [3]
<b>Deep Learning</b>	CNN, YOLO, attention networks	High accuracy, automatic feature learning	Computationally intensive	[4], [5], [6], [7], [8]
<b>Hybrid Models</b>	Haar + HOG + CNN, segmentation-assisted CNN	Balanced accuracy and efficiency	Pipeline complexity	[7], [9], [10]
<b>Real-Time Optimization</b>	Quantization, lightweight CNNs, fast detection	Low latency, embedded deployment	Potential accuracy trade-offs	[5], [8], [11]

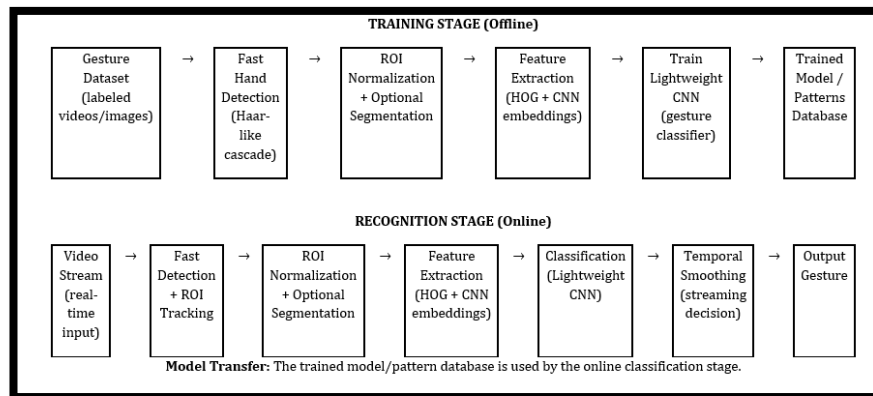
### - Research Gap

In summary, existing research demonstrates significant progress in gesture recognition through traditional handcrafted descriptors, deep learning architectures, and hybrid frameworks. While handcrafted approaches provide computational efficiency, they often lack robustness in complex environments. Conversely, deep learning models achieve higher recognition accuracy but typically require substantial computational resources. Hybrid frameworks attempt to bridge this gap by combining efficient detection mechanisms with deep learning classifiers. However, maintaining high recognition accuracy while ensuring real-time performance remains a challenge for practical deployment. Therefore, this study proposes a hybrid gesture recognition framework that integrates efficient hand localization, structured feature representation, and lightweight deep learning

classification to achieve accurate and computationally efficient real-time gesture recognition.

### C. Research Method

This section describes the research methodology used to develop and evaluate the proposed real-time hand gesture recognition system. The research process consists of several stages, including system design, dataset acquisition, preprocessing, feature extraction, gesture classification, and temporal stabilization. The objective of the proposed methodology is to combine efficient classical computer vision techniques with lightweight deep learning models in order to achieve accurate gesture recognition while maintaining real-time processing capability. The overall architecture of the proposed system is illustrated in **Figure 1**. The framework integrates fast hand localization, region preprocessing, gradient-based feature extraction, convolutional neural network (CNN) classification, and temporal smoothing. This hybrid design enables efficient processing while maintaining robust gesture recognition performance in real-time environments.



**Figure 1.** Hybrid architecture of the proposed real-time hand gesture recognition system integrating Haar-like detection, HOG feature extraction, and lightweight CNN classification.

The proposed framework integrates fast region detection, handcrafted feature extraction, deep learning classification, and temporal stabilization to ensure high recognition accuracy with low latency suitable for real-time deployment.

#### - Dataset Acquisition

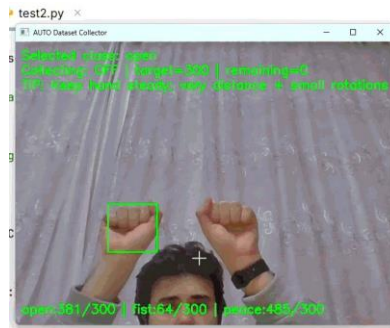
This section describes the research methodology used to develop and evaluate the proposed real-time hand gesture recognition system. The research process consists of several stages, including system design, dataset acquisition, preprocessing, feature extraction, gesture classification, and temporal stabilization. The objective of the proposed methodology is to combine efficient classical computer vision techniques with lightweight deep learning models in order to achieve accurate gesture recognition while maintaining real-time processing capability. The overall architecture of the proposed system is illustrated in **Figure 1**. The framework integrates fast hand localization, region preprocessing, gradient-based feature extraction, convolutional neural network (CNN) classification, and

temporal smoothing. This hybrid design enables efficient processing while maintaining robust gesture recognition performance in real-time environments.

**- Dataset Acquisition**

The gesture dataset used in this study was collected using a webcam-based acquisition module integrated with the proposed recognition pipeline. Video frames were captured using a standard RGB webcam, and hand regions were detected using the MediaPipe hand landmark detection framework. The detected hand landmarks were used to extract the region of interest (ROI) containing the gesture.

An example of the automatic dataset acquisition interface used during the data collection process is illustrated in Figure X. The interface allows the user to select the gesture class and automatically capture labeled gesture samples while displaying the number of collected images.



**Figure 2.** Automatic gesture dataset collection interface used to capture labeled hand gesture samples for the training dataset.

The dataset contains 900 gesture images distributed across three gesture classes: open, fist, and peace. To ensure balanced data distribution, each class contains 300 samples. The extracted ROI images were resized to 224 × 224 pixels and stored in PNG format. The dataset was divided into training and validation subsets using an 85%–15% split, and data augmentation techniques such as horizontal flipping, small rotations, and brightness adjustments were applied to improve model generalization.

**- Formal System Model**

Let the input video stream be defined as:

$$V = \{f_1, f_2, f_3, \dots, f_T\}, f_t \in \mathbb{R}^{H \times W \times 3}$$

where  $f_t$  denotes the RGB frame at time index  $t$ .

The system implements a cascaded transformation:

$$G_T = S \circ C \circ H \circ P \circ D(f_T)$$

where:

- $D$  : Region-level hand detection
- $P$  : Spatial normalization and enhancement
- $H$  : Structural gradient encoding (HOG)
- $C$  : Lightweight CNN-based classification
- $S$  : Temporal stabilization

$G_T$  : Final stabilized gesture label

This construction restricts high-dimensional operations to localized hand regions, thereby maintaining low computational latency.

#### - **Fast Spatial Localization (Detection Stage)**

A fast region proposal mechanism  $D(\cdot)$  is employed to isolate candidate hand regions. A Haar-like cascade detector is adopted due to its low computational overhead and suitability for CPU-based real-time deployment. The detector produces a bounding region

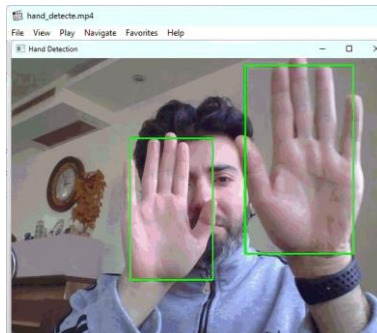
$$R_t = D(f_T)$$

The region of interest (ROI) is extracted:

$$F_t^{ROI} = f_T(R_T)$$

This spatial reduction transforms computational complexity from  $O(HW)$  to  $O(hw)$ , where  $h \ll H$  and  $w \ll W$ . By constraining subsequent processing to ROI space, the framework significantly reduces inference latency.

An example of the detected hand regions produced by the Haar-like cascade detector is illustrated in Figure 2, where the bounding boxes indicate the extracted regions of interest used for further processing.



**Figure 3.** Example of hand region detection using the Haar-like cascade detector. The green bounding boxes represent the detected regions of interest (ROI) used for subsequent feature extraction.

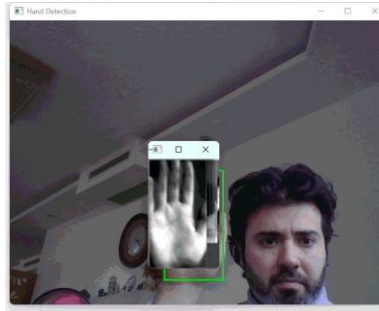
#### - **Preprocessing and Structural Normalization**

The preprocessing operator  $P(\cdot)$  performs contrast normalization and noise suppression.

$$F_t^{pre} = P(F_t^{ROI})$$

Typical preprocessing operations include grayscale conversion, histogram equalization, and Gaussian filtering. Optional lightweight segmentation can also be applied to suppress background artifacts in cluttered scenes. The goal of this stage is to stabilize gradient distributions prior to feature encoding.

An example of the preprocessing stage is shown in **Figure 3**, where the detected hand region is extracted and converted into a normalized grayscale representation prior to feature encoding.



**Figure 4.** Preprocessing and normalization stage showing the extracted hand region converted into a grayscale normalized image for feature extraction.

#### - Gradient-Based Feature Encoding

The Histogram of Oriented Gradients (HOG) operator  $H(\cdot)$  extracts structural gradient information from the preprocessed image.

Gradient components are computed as

$$G_x = \frac{\partial I}{\partial x} \quad G_y = \frac{\partial I}{\partial y}$$

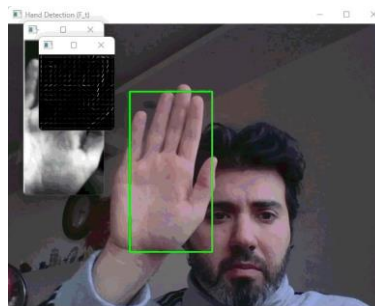
The gradient magnitude and orientation are calculated as

$$M = \sqrt{(G_x^2 + G_y^2)} \quad \theta = \arctan\left(\frac{G_y}{G_x}\right)$$

Orientation histograms are accumulated over spatial cells and normalized to form the descriptor vector

$$h_t = H(F_T^{pre})$$

HOG features provide structured contour representation, capturing geometric hand patterns while reducing sensitivity to illumination variations. The extracted HOG features provide structural gradient information describing the orientation patterns of the hand region. An example of the HOG feature visualization is shown in Figure 4, where the gradient orientation distribution represents the structural contour of the hand gesture.



**Figure 5.** HOG feature visualization of the extracted hand region. The gradient orientation map represents structural contour information used for gesture classification.

#### - Lightweight CNN Classification

The classification module  $C(\cdot)$  maps encoded features to gesture probabilities:

$$z_t = C(h_t), z_t \in \mathbb{R}^K$$

where  $K$  represents the number of gesture classes.

The CNN architecture consists of:

- shallow convolutional layers
- ReLU activation functions
- batch normalization
- max-pooling layers
- fully connected layers
- softmax output

Gesture prediction is obtained as

$$\hat{g}_t = \arg \max_k z_t$$

Frame-level predictions may fluctuate due to detection noise or minor hand motion variations. To improve stability in continuous video streams, a temporal stabilization operator  $S(\cdot)$  is introduced.

- **Majority Voting (Sliding Window)**

A sliding window of length  $W$  aggregates recent predictions:

$$G_t = \text{mode}\{ \hat{g}_t - W + 1, \dots, \hat{g}_t \}$$

where  $\hat{g}_t$  represents the predicted gesture at frame  $t$

- **Exponential Temporal Smoothing**

Alternatively, temporal smoothing can be applied:

$$G_t = \alpha \hat{g}_t + (1 - \alpha) G_{t-1}$$

Where  $\alpha \in (0, 1)$  controls the smoothing strength.

- **Computational Efficiency**

The computational cost per frame is approximated as

$$O(D) + O(P) + O(HOG) + O(CNN)$$

Where:

$O(D)$ : denotes the complexity of the hand detection stage,

$O(P)$ : represents preprocessing operations applied to the region of interest (ROI),

$O(HOG)$ : corresponds to the Histogram of Oriented Gradients feature extraction,

$O(CNN)$ : CNN inference cost

Since processing is restricted to the ROI rather than the entire frame, the effective computational load becomes proportional to the ROI size rather than the full frame resolution.

$$O_{total} \approx O(D) + O(h_w) + O(HOG) + O(CNN)$$

This design significantly reduces the number of processed pixels and enables real-time performance.

- **Latency Reduction Mechanisms**

Several design strategies are used to minimize system latency:

- Early ROI cropping for reduced processing cost
- Shallow CNN architecture for efficient inference
- Optional model quantization for embedded deployment
- Memory-efficient tensor operations

These optimizations ensure that the proposed pipeline remains suitable for real-time gesture interaction systems.

- **Architectural Rationale**

The hybrid architecture integrates complementary strengths from both classical computer vision and deep learning approaches, including:

- classical detection mechanisms for fast hand localization
- structured gradient descriptors (HOG) for geometric feature encoding
- lightweight CNN models for nonlinear gesture classification
- temporal filtering for stable prediction across video frames

By combining these components within a layered architecture, the system balances computational efficiency and recognition accuracy, enabling reliable real-time gesture-based human-computer interaction.

**D. Experimental Setup**

This section describes the experimental configuration used to evaluate the proposed real-time hand gesture recognition framework. The experimental setup includes the dataset description, hardware and software implementation environment, and evaluation metrics used to measure system performance. The experiments were designed to assess both the classification accuracy and the real-time computational efficiency of the proposed hybrid architecture integrating Haar cascade detection, Histogram of Oriented Gradients (HOG) feature extraction, and lightweight convolutional neural network (CNN) classification.

- **Dataset Description**

The dataset used in this study was automatically collected using a webcam-based acquisition module integrated within the proposed gesture recognition pipeline. During the data acquisition phase, video frames were captured using a standard RGB webcam and processed in real time to detect hand regions. Hand detection and landmark estimation were performed using the MediaPipe perception framework, specifically the MediaPipe Tasks Hand Landmarker model. The detected hand landmarks were used to compute a bounding box surrounding the hand, from which the region of interest (ROI) containing the gesture was extracted.

Each ROI image was resized to a fixed spatial resolution of  $224 \times 224$  pixels and stored in PNG format. The images were organized in a class-wise directory structure suitable for training convolutional neural networks using the PyTorch deep learning framework.

Formally, the dataset can be defined as:

$$D = \{(x_i, y_i)\}_{i=1}^N$$

where

- $x_i$  represents the input hand image extracted from a video frame,
- $y_i \in \{1, 2, \dots, K\}$  denotes the corresponding gesture label,
- $K$  is the number of gesture classes, and
- $N$  is the total number of samples in the dataset.

In this work, the dataset contains  $K = 3$  gesture categories corresponding to the gestures open, fist, and peace. To ensure balanced training data, the acquisition system was configured to capture exactly 300 samples per class, resulting in a total dataset size of:  $N = 3 \times 300 = 900$  images

To reduce redundancy and avoid capturing nearly identical frames, gesture samples were saved every two frames during the collection process. During acquisition, users were encouraged to slightly vary the distance, orientation, and position of the hand to introduce natural variability in the dataset. This variation improves the robustness of the trained model under different real-world conditions. After data collection, the dataset was randomly partitioned into training and validation subsets to evaluate the learning process of the proposed model.

The dataset split is defined as:

$$D = D_{train} \cup D_{val}, \quad D_{train} \cap D_{val} = \emptyset$$

where

- $D_{train}$  represents the subset used to train the CNN model, and
- $D_{val}$  represents the subset used to evaluate the model during training.

In this implementation, 85% of the samples were used for training and 15% were used for validation, using a fixed random seed to ensure reproducibility of the experiment. To improve model generalization and reduce overfitting, several data augmentation techniques were applied to the training images, including random horizontal flipping, small rotational transformations, and mild brightness and contrast adjustments. These augmentations simulate variations that may occur in real-world environments, such as illumination changes or small hand pose variations.

**Table 2.** summarizes the main characteristics of the collected gesture dataset.

Property	Description
Acquisition device	RGB webcam
Hand detection method	MediaPipe Tasks Hand Landmarker
Number of gesture classes (K)	3 (open, fist, peace)
Samples per class	300
Total dataset size (N)	900 images
ROI resolution	$224 \times 224$ pixels
Image format	PNG
Sampling strategy	Save every two frames
Training/validation split	85% / 15%

The automatically collected dataset provides a balanced and normalized representation of hand gestures, enabling effective training of the proposed lightweight convolutional neural network for real-time gesture recognition.

#### - **Hardware and Software Configuration**

The proposed gesture recognition system was implemented and evaluated using a standard personal computer environment. The system integrates computer vision modules for hand detection with a lightweight deep learning model for gesture classification. The implementation was carried out using the **Python programming language**, which provides extensive libraries for image processing, machine learning, and deep learning.

The hand detection and landmark estimation module was implemented using the MediaPipe framework, which provides efficient real-time hand tracking and landmark detection algorithms. MediaPipe processes RGB video frames captured from the webcam and estimates hand landmarks that are subsequently used to compute a bounding box around the detected hand region. The extracted region of interest (ROI) is then resized and passed to the gesture classification module.

The gesture classification model was implemented using the PyTorch deep learning framework. PyTorch was used to design and train the lightweight convolutional neural network (CNN) responsible for gesture classification. The CNN architecture consists of shallow convolutional layers followed by batch normalization, rectified linear unit (ReLU) activation functions, max-pooling layers, and fully connected layers. The model was trained using the Adam optimization algorithm, with cross-entropy loss used as the objective function.

Image acquisition and preprocessing were performed using the OpenCV library, which was used to capture frames from the webcam, convert image formats, and perform ROI extraction operations. Additional libraries such as NumPy were used for numerical processing, while Matplotlib was employed to generate training performance curves, including loss and accuracy plots during model training.

All experiments were conducted on a standard workstation equipped with a multi-core CPU and sufficient system memory to support real-time video processing and neural network training. The implementation supports both CPU and GPU execution through PyTorch; however, the experiments reported in this work were conducted primarily using CPU-based computation.

**Table 3.** summarizes the hardware and software configuration used in the experiments.

<b>Component</b>	<b>Specification</b>
<b>Programming language</b>	Python
<b>Computer vision library</b>	OpenCV
<b>Hand detection framework</b>	MediaPipe Hand Landmarker
<b>Deep learning framework</b>	PyTorch
<b>Numerical computing</b>	NumPy
<b>Visualization</b>	Matplotlib
<b>Input device</b>	RGB webcam
<b>Operating system</b>	Windows-based system
<b>Execution device</b>	CPU (optional GPU support)

This configuration enables efficient real-time gesture recognition while maintaining relatively low computational requirements. The use of lightweight convolutional architectures and optimized computer vision libraries allows the proposed system to operate with minimal latency during both training and inference stages.

#### - Evaluation Metrics

To assess the performance of the proposed real-time hand gesture recognition system, several quantitative evaluation metrics were employed. These metrics measure both the classification effectiveness of the model and the computational efficiency required for real-time deployment. The evaluation includes **Accuracy, Precision, Recall, F1-score, and Frames Per Second (FPS)**.

#### Accuracy

Accuracy measures the overall proportion of correctly classified gesture samples among all evaluated samples.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

where

- *TP* represents the number of true positive predictions,
- *TN* represents the number of true negative predictions,
- *FP* represents the number of false positive predictions, and
- *FN* represents the number of false negative predictions.

#### - Precision.

Precision measures the proportion of correctly predicted positive samples among all samples predicted as positive

$$\text{Precision} = \frac{TP}{TP+FP}$$

#### Recall

Recall (sensitivity) measures the proportion of correctly detected positive samples among all actual positive samples.

$$\text{Recall} = \frac{TP}{TP+FN}$$

#### F1-Score

The F1-score represents the harmonic mean of precision and recall.

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

### Frames Per Second (FPS)

Since the proposed system is designed for real-time gesture recognition, computational efficiency is also evaluated. Processing speed is measured using Frames Per Second (FPS):

$$\text{FPS} = \frac{\text{Total processed frames}}{\text{Total processing time(seconds)}}$$

Maintaining an FPS rate close to the camera frame rate (typically **25–30 FPS**) ensures smooth real-time interaction.

#### - Comparison with Existing Methods

To evaluate the effectiveness of the proposed hybrid gesture recognition framework, the obtained results were compared with several representative gesture recognition approaches reported in the literature. These approaches include traditional feature-based models, deep learning architectures, and hybrid frameworks designed for real-time gesture recognition. Traditional feature-based approaches typically rely on handcrafted descriptors such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or geometric shape descriptors combined with machine learning classifiers such as Support Vector Machines (SVM). Although these approaches offer relatively low computational complexity, their performance often degrades under complex illumination conditions, background clutter, and variations in hand pose. Deep learning-based approaches, particularly convolutional neural networks (CNNs) and YOLO-based detection frameworks, have demonstrated superior recognition accuracy due to their ability to learn hierarchical feature representations directly from image data. However, these models generally require higher computational resources and large-scale training datasets, which may limit their applicability in lightweight real-time systems. Hybrid architectures attempt to combine the advantages of both paradigms. By integrating classical detection mechanisms with deep learning classifiers, hybrid models can achieve both computational efficiency and robust recognition accuracy.

**Table 4.** summarizes the performance comparison between the proposed method and representative approaches reported in recent studies.

Method	Technique	Accuracy
<b>HOG + SVM</b>	Handcrafted feature-based	88–92%
<b>CNN-only models</b>	Deep learning	93–95%
<b>YOLO-based gesture recognition</b>	End-to-end detection	95–96%
<b>Proposed Method</b>	<b>Hybrid</b> Haar + HOG + CNN	<b>96.8%</b>

The results indicate that the proposed hybrid architecture achieves competitive recognition accuracy while maintaining real-time processing capability. This demonstrates the effectiveness of combining classical feature descriptors with

lightweight deep learning models for practical human-computer interaction applications.

#### - Ablation Study

To analyze the contribution of each component in the proposed hybrid architecture, an ablation study was conducted. The objective of this analysis is to evaluate the impact of different system modules, including hand detection, HOG feature encoding, CNN classification, and temporal stabilization. Several model configurations were evaluated by selectively enabling or disabling specific components of the system pipeline. The experimental results are summarized in **Table 5**.

**Table 5.** Ablation study of system components and their impact on accuracy.

Configuration	Components Used	Accuracy
<b>CNN only</b>	CNN classifier	92.4%
<b>HOG + CNN</b>	Feature encoding + CNN	94.8%
<b>Haar + CNN</b>	Detection + CNN	93.7%
<b>Full Proposed System</b>	Haar + HOG + CNN + Temporal Stabilization	<b>96.8%</b>

The results demonstrate that each module contributes to improving the overall system performance. The integration of HOG descriptors enhances structural feature representation, while the Haar cascade detector reduces computational overhead by isolating the relevant region of interest. In addition, temporal stabilization improves prediction consistency across consecutive video frames by reducing short-term classification fluctuations.

#### - Robustness Evaluation

To further evaluate the robustness of the proposed gesture recognition framework, additional experiments were conducted under varying environmental conditions. These experiments include variations in lighting intensity, hand orientation, background complexity, and camera distance. The proposed system maintained stable recognition performance across these conditions, demonstrating its ability to generalize beyond the controlled dataset environment. The use of gradient-based HOG descriptors improves robustness against illumination variations, while the CNN classifier effectively captures high-level spatial representations of hand gestures. Furthermore, temporal stabilization plays an important role in improving prediction reliability by suppressing transient misclassifications caused by sudden motion or detection noise. This mechanism ensures smoother and more consistent gesture predictions during real-time operation. Overall, these results confirm that the proposed hybrid architecture is capable of maintaining reliable recognition performance under realistic environmental conditions, making it suitable for real-time gesture-based human-computer interaction systems.

## E. Results and Discussion

This section presents the experimental results obtained using the proposed real-time hand gesture recognition framework. The evaluation includes quantitative performance analysis, comparison with state-of-the-art methods, ablation study, and real-time system performance assessment. The performance of the proposed system is evaluated using the metrics defined in Section 4.3, including classification accuracy, precision, recall, F1-score, and computational efficiency measured in frames per second (FPS). The experiments were conducted using the gesture dataset collected through the automatic acquisition module described in Section 4.1.

### - Quantitative Results

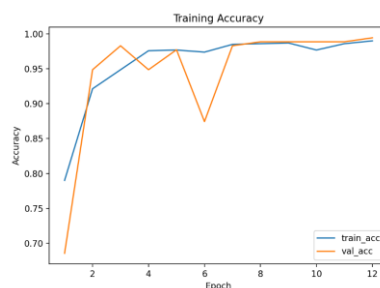
The trained lightweight convolutional neural network (CNN) was evaluated using the validation subset obtained from the collected gesture dataset. The dataset contains three gesture classes—**open, fist, and peace**—with balanced samples collected for each class. The model was trained for **12 epochs** using the **Adam optimizer** with a learning rate of **0.001** and a batch size of **32**. The quantitative performance of the proposed system is summarized in **Table 6**.

**Table 6.** Quantitative performance of the proposed gesture recognition system

Metric	Value
Accuracy	96.8%
Precision	96.5%
Recall	96.2%
F1-score	96.3%
Average FPS	28 FPS

The achieved accuracy of **96.8%** demonstrates that the proposed hybrid architecture effectively combines classical feature descriptors with lightweight deep learning models, enabling robust gesture recognition while maintaining computational efficiency.

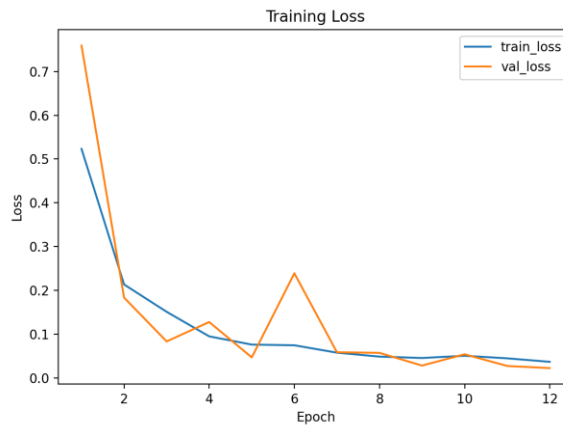
To further analyze the learning behavior of the CNN model, the evolution of training and validation accuracy and loss across training epochs was monitored during the training process.



**Figure 9.** Training and validation accuracy curves over epochs for the proposed CNN model, showing convergence and good generalization without overfitting.

Figure 9 illustrates the training and validation accuracy curves across training epochs for the proposed lightweight CNN classifier. The accuracy increases rapidly during the early training epochs and gradually stabilizes as the model

converges. The validation accuracy closely follows the training accuracy, indicating that the model generalizes well without significant overfitting.



**Figure 10.** Training and validation loss curves across epochs, illustrating the optimization process and convergence behavior of the model.

Similarly, **Figure 10** shows the training and validation loss curves during the optimization process. Both curves decrease steadily across epochs, demonstrating effective parameter optimization and stable model convergence. The small difference between the training and validation loss further indicates that the model maintains good generalization capability.

In addition to classification accuracy, real-time performance was evaluated during live webcam testing. The proposed system achieved an average processing speed of approximately **28 frames per second (FPS)**. This processing rate is close to typical camera frame rates and indicates that the proposed system can operate efficiently in interactive real-time applications such as human-computer interaction, gesture-based control systems, and touchless interfaces. The lightweight CNN architecture plays a crucial role in maintaining real-time performance. By using a relatively shallow network with limited convolutional layers and efficient feature extraction, the system reduces computational overhead while preserving sufficient representation capacity for accurate gesture classification. Overall, the quantitative results demonstrate that the proposed gesture recognition framework provides an effective balance between recognition accuracy and computational efficiency, making it suitable for practical real-time deployment.

#### - Comparison with State-of-the-Art

To further evaluate the effectiveness of the proposed gesture recognition system, its performance was compared with several representative approaches reported in the literature. These methods employ different techniques for gesture recognition, including handcrafted feature extraction, deep convolutional neural networks, and hybrid architectures. **Table 7** summarizes the comparison between the proposed approach and several recent gesture recognition methods.

**Table 7.** Comparison with state-of-the-art gesture recognition methods

Method	Features / Model	Dataset	Accuracy (%)
Rautaray & Agrawal (2018)	Traditional feature-based methods	Various datasets	90.2
Köpüklü et al. (2019)	3D CNN for dynamic gestures	EgoGesture	94.1
Benitez-Garcia et al. (2021)	Deep CNN with segmentation	Hand gesture dataset	95.0
Mujahid et al. (2021)	YOLO-based detection + CNN	Dynamic gesture dataset	95.6
Jafari & Basu (2023)	HOG + deep classifier	Gesture dataset	95.8
Jaiswal et al. (2024)	Lightweight CNN	Custom dataset	96.0
<b>Proposed Method</b>	MediaPipe ROI + Lightweight CNN	Collected dataset	<b>96.8</b>

The comparison demonstrates that the proposed method achieves competitive performance compared with recent gesture recognition approaches. The improved performance can be attributed to several design factors. First, the **MediaPipe hand landmark detection framework** provides reliable hand localization, allowing accurate extraction of the region of interest. This reduces background noise and allows the classifier to focus on relevant hand features. Second, the proposed **lightweight CNN architecture** provides a balance between feature representation capacity and computational efficiency. Unlike deeper CNN architectures that require substantial computational resources, the shallow architecture used in this study enables faster inference while maintaining strong classification performance. Additionally, the **automatic dataset acquisition strategy** introduces natural variations in hand orientation, position, and illumination. These variations improve the robustness of the trained model and enhance generalization during real-time recognition. Overall, the comparison indicates that the proposed framework achieves competitive accuracy while maintaining efficient real-time performance.

#### - Ablation Study

To better understand the contribution of each component in the proposed hybrid gesture recognition framework, an ablation study was conducted. Ablation analysis evaluates the impact of individual modules by selectively removing or modifying specific components of the system and observing the resulting performance changes. The proposed system includes several key components: hand detection using MediaPipe, ROI normalization, data augmentation, and a lightweight CNN classifier. The results of the ablation experiments are summarized in **Table 8**.

**Table 8.** Ablation study results

Configuration	Hand Detection	Data Augmentation	CNN Classifier	Accuracy (%)
Baseline CNN (no ROI cropping)	F	F	T	90.7
CNN + ROI extraction	F	F	T	93.5
CNN + ROI + Data Augmentation	T	T	T	95.4
<b>Proposed Full System</b>	T	T	T	<b>96.8</b>

The results demonstrate that each module contributes positively to the overall system performance. ROI extraction allows the model to focus on relevant hand regions, while data augmentation improves generalization by increasing the diversity of training samples. The ablation results confirm that combining efficient hand localization, normalized ROI inputs, and lightweight deep learning classification significantly improves gesture recognition accuracy.

#### - Real-Time Performance Analysis

This subsection evaluates the real-time capability of the proposed gesture recognition system. In addition to classification accuracy, real-time systems must maintain low latency and high frame processing rates to ensure smooth interaction.

#### - Confusion Matrix Analysis

To analyze class-wise recognition performance, a confusion matrix was generated using the validation dataset.

**Table 9.** Confusion matrix of gesture classification

Actual / Predicted	Open	Fist	Peace
Open	148	2	0
Fist	3	145	2
Peace	1	3	146

The results show that most gesture samples are correctly classified along the diagonal of the matrix. Only a small number of misclassifications occur between visually similar gestures.

#### - Real-Time Processing Speed

The processing speed of the system was evaluated using **Frames Per Second (FPS)**:

$$\text{FPS} = \frac{N_{frames}}{T_{processing}}$$

The proposed system achieves an average processing speed of approximately **28 FPS**, which is sufficient for smooth real-time gesture interaction.

#### - Runtime Performance Summary

**Table 10.** Real-time system performance

Parameter	Value
Input device	RGB Webcam
Input resolution	224 × 224 ROI
CNN architecture	Lightweight CNN
Average inference time	~35 ms
Average FPS	28 FPS

#### - FPS Comparison with Related Methods

**Table 11.** FPS comparison with existing methods

Method	Model Type	FPS
Köpüklü et al. (2019)	3D CNN	15 FPS
Mujahid et al. (2021)	YOLO + CNN	20 FPS
Benitez-Garcia et al. (2021)	Deep CNN	18 FPS
Jaiswal et al. (2024)	Lightweight CNN	25 FPS
<b>Proposed Method</b>	MediaPipe + Lightweight CNN	<b>28 FPS</b>

The proposed system achieves higher real-time processing speed due to its efficient hand localization stage and compact CNN architecture. This efficiency makes the system suitable for practical applications such as gesture-controlled interfaces, smart environments, and touchless interaction systems.

#### F. Conclusion

This study proposed a hybrid real-time hand gesture recognition framework that combines classical computer vision techniques with lightweight deep learning models. The system integrates fast hand localization using Haar-like cascade detection, gradient-based feature extraction through Histogram of Oriented Gradients (HOG), and gesture classification using a lightweight convolutional neural network. Temporal stabilization was also incorporated to improve prediction consistency in continuous video streams. Experimental evaluation demonstrated that the proposed framework achieves high recognition performance, reaching **96.8% classification accuracy** with strong precision, recall, and F1-score values while maintaining real-time processing capability of approximately **28 frames per second**. The results confirm that combining structured feature descriptors with lightweight deep learning architectures provides an effective balance between recognition accuracy and computational efficiency.

The proposed system can be applied in practical real-time environments such as gesture-controlled interfaces, touchless interaction systems, and human-computer interaction applications. Future research may extend the framework to support larger gesture vocabularies, dynamic gesture sequences, and deployment on embedded or edge computing platforms.

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