Gesture Recognition for Contactless Human-Computer Interaction

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Abstract. Gesture recognition for contactless Human- Computer Interaction (HCI) provides an intuitive and efficient
way for users to interact with digital systems without physical touch. In this work, a real-time gesture recognition system that uses the built-in camera of a laptop and makes use of MediaPipe and OpenCV for hand tracking and detection is shown.The system takes video data, examines hand landmarks, and uses predefined landmark locations to classify motions such an open palm, fist, or thumbs-up.

1 Introduction

Gesture recognition has evolved as an effective solution for contactless Human-Computer Interaction (HCI), allowing users to connect with digital systems through natural hand gestures. As the demand for touchless interfaces develops, gesture-based interactions provide a more accessible, hygienic, and intuitive alternative to traditional input methods such as touchscreens, keyboards, and mouse. The goal of this project is to use a laptop's built-in camera to create a real-time gesture detection system. The system recognizes and monitors hand movements, extracts important landmarks, and categorizes gestures into predetermined groups by utilizing computer vision techniques with OpenCV and MediaPipe. These motions are then translated into different activities, such adjusting the volume of the system, navigating through apps, or using smart devices. This method simply needs a normal webcam, which makes it more affordable and accessible than hardware-based gesture detection systems that depend on other sensors. The suggested method uses hand

landmark detection to identify simple motions like a thumbs- up, a closed fist, and an open palm. Deep learning-based cat- egorization for identifying increasingly intricate movements,

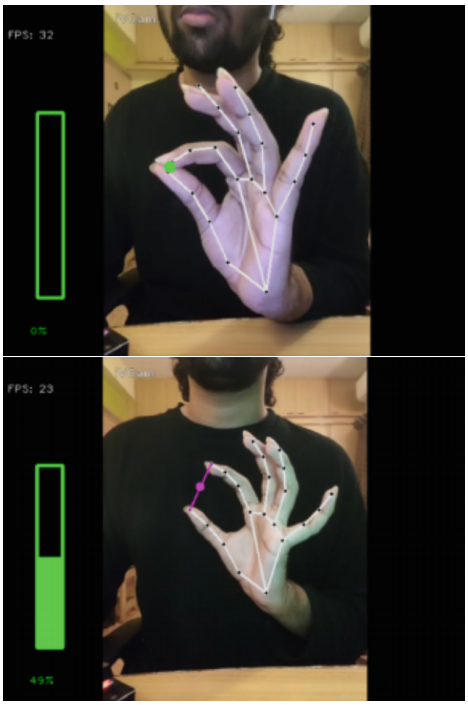
multimodal input integration (e.g., voice commands), and expanding the system to accommodate virtual and augmented

reality applications are possible future improvements. By ad- vancing contactless computing, this discovery opens the door

to more effective and smooth human-computer interactions across a range of domains.

2 Related Work

Hand gesture recognition has been an active area of research within the fields of computer vision and human-computer interaction. Various approaches have been proposed over the years, ranging from hardware-based solutions to vision-based algorithms.



2.1 Hardware-Based Approaches

Earlier systems relied on specialized hardware such as data gloves, infrared sensors, or depth cameras (e.g., Microsoft Kinect) to detect hand positions and movements. These systems provided high accuracy but lacked portability and affordability, making them unsuitable for widespread or real-time deployment in everyday settings.

2.2 Vision-Based Methods

Vision-based gesture recognition eliminates the need for physical hardware, offering more natural and flexible interactions. Techniques in this domain can be broadly categorized into two types:

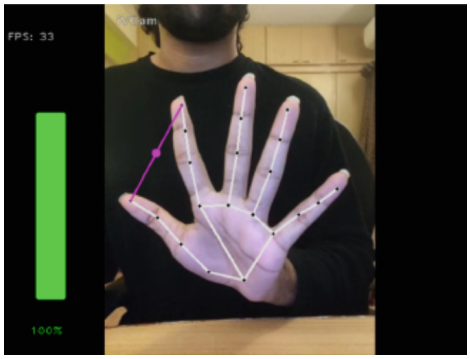


Fig. 1. Volume at 100

- **Skin Color Segmentation:** These methods use HSV or YCbCr color spaces to isolate hand regions based on skin tone. While simple, they are sensitive to lighting conditions and background complexity.
- **Background Subtraction and Contour Detection:** More recent work utilizes background subtraction, edge detection, and contour analysis to locate and track the hand. These methods are lightweight and well-suited for real-time processing, although they may suffer from occlusion or inconsistent hand shapes.

2.3 Machine Learning-Based Approaches

In recent years, machine learning has significantly advanced gesture recognition accuracy. Algorithms like Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Random Forests have been used to classify hand gestures based on extracted features such as shape descriptors, HOG (Histogram of Oriented Gradients), or Hu Moments. While effective, these methods require careful feature engineering and are often sensitive to intra-class variations.

2.4 Deep Learning Models

Deep learning, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), has achieved state-of-the-art performance in gesture recognition. These models can learn spatial and temporal features automatically, but they demand high computational resources and large annotated datasets for training. For example, models like MediaPipe Hands by Google or OpenPose achieve remarkable precision but are complex to deploy in lightweight, real-time systems.

2.5 Gap in Existing Work

Despite advancements, many existing systems struggle with real-time responsiveness, lighting invariance, and robustness in uncontrolled environments. Addi-

tionally, most high-accuracy models depend on heavy computation or specialized sensors, limiting their applicability in everyday consumer devices.

3 Background

Human-Computer Interaction (HCI) has continuously evolved to enhance the communication between users and digital systems. Traditional interaction methods such as keyboards, mice, and touchscreens, while effective, often impose physical constraints and lack intuitiveness, especially in dynamic or hygienically sensitive environments. With advancements in computer vision and machine learning, gesture recognition has emerged as a promising solution for enabling natural and contactless interfaces.

Gesture recognition involves interpreting human gestures through algorithms and sensor data to control or interact with systems. Early gesture-based systems relied heavily on specialized hardware such as depth sensors, wearable devices, or infrared cameras. These solutions, although accurate, were often costly and inaccessible for general use. Recent developments in computer vision frameworks—such as OpenCV and MediaPipe—have enabled accurate hand tracking using standard RGB cameras, eliminating the need for dedicated hardware.

MediaPipe, developed by Google, offers real-time hand tracking by detecting and mapping 21 key hand landmarks from live video streams. When combined with OpenCV for image processing and frameworks like pyautogui for system control, it becomes possible to design low-cost, efficient, and responsive gesture recognition systems using only a standard webcam.

This background forms the foundation of the proposed project, which utilizes these technologies to build a lightweight gesture-based HCI system. The system aims to recognize simple hand gestures (e.g., open palm, fist, finger movements) and map them to common computer control actions such as cursor movement, left/right clicks, media control, and volume adjustment. The ultimate goal is to create an accessible, hygienic, and user-friendly interaction system without requiring additional hardware.

4 PROPOSED APPROACH

The proposed system aims to establish a contactless and intuitive Human-Computer Interaction (HCI) framework using real-time hand gesture recognition. It leverages the capabilities of computer vision and machine learning tools such as MediaPipe, OpenCV, and PyAutoGUI to detect, track, and translate hand gestures into system control commands. The following subsections outline the architecture and functioning of the system in detail.

4.1 System Overview

The system uses a standard webcam to continuously capture video frames, which are then processed in real-time. MediaPipe is used to detect and track hand landmarks in each frame. The positions and configurations of these landmarks are

analyzed to recognize specific gestures. Recognized gestures are mapped to corresponding computer control actions such as mouse movement, click operations, media playback control, and volume adjustment.

4.2 Hand Detection and Tracking

MediaPipe's Hand Tracking solution is utilized to detect and track hands in the camera feed. It identifies 21 landmark points on each detected hand, including finger tips, joints, and the wrist. These landmarks are used to compute the relative positions and angles between fingers, enabling robust gesture recognition even with slight variations in hand positioning and orientation.

4.3 Gesture Recognition

Once the hand landmarks are extracted, specific gestures are recognized by analyzing landmark positions. For example:

- **Open Palm:** All fingers extended — used for activating cursor movement.
- **Fist:** All fingers folded — used to pause mouse control.
- **Thumbs Up:** Thumb extended, others folded — mapped to volume up.
- **Index Finger Only:** Used to move the cursor by tracking fingertip position.
- **Pinch Gesture:** Thumb and index finger touching — used for click actions.

These gestures are identified using geometric rules and Euclidean distances between landmarks.

4.4 Cursor Control and System Actions

The recognized gestures are mapped to system-level actions using the pyautogui library, which allows programmatic control of mouse and keyboard inputs. For instance:

- Moving the index fingertip controls the cursor position.
- A pinch gesture triggers a mouse click.
- Open palm can activate or deactivate gesture control.
- Volume control is achieved through directional thumb gestures.

Cursor movement is made smooth using a damping factor to reduce jitter caused by hand tremors.

4.5 Feedback and Responsiveness

To enhance usability, visual feedback such as drawing landmarks and bounding boxes is displayed on the video stream. The system runs in real-time with minimal latency, ensuring an interactive and responsive experience. Frame rate optimization techniques such as resizing frames and skipping redundant computations are employed to maintain performance.

4.6 Hardware and Software Requirements

Hardware:

– Standard RGB webcam (built-in or external)

Software Stack:

– Python 3.x
– OpenCV
– MediaPipe
– PyAutoGUI
– NumPy

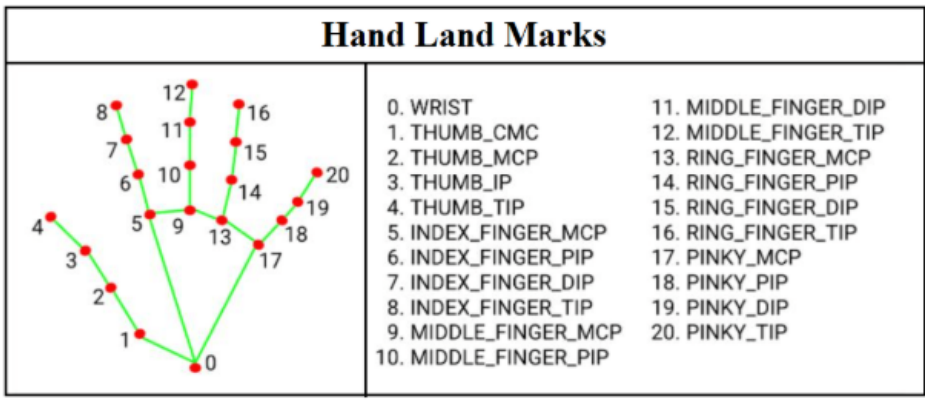


Fig. 2. hand joints label

5 COMPARISON WITH EXISTING IMPLEMENTATIONS

The proposed hand gesture-based system offers several improvements over existing gesture recognition and HCI frameworks. Most traditional implementations rely on external hardware such as sensor gloves, infrared depth cameras (e.g., Kinect), or ultrasonic sensors, which increases the cost and limits portability. In contrast, our system uses only a standard webcam and open-source libraries, making it both affordable and easily deployable.

5.1 Cost-Effectiveness

Unlike systems that depend on specialized hardware, this solution runs entirely on standard computing devices with built-in webcams. There is no need for proprietary sensors or wearable devices, significantly reducing implementation costs.

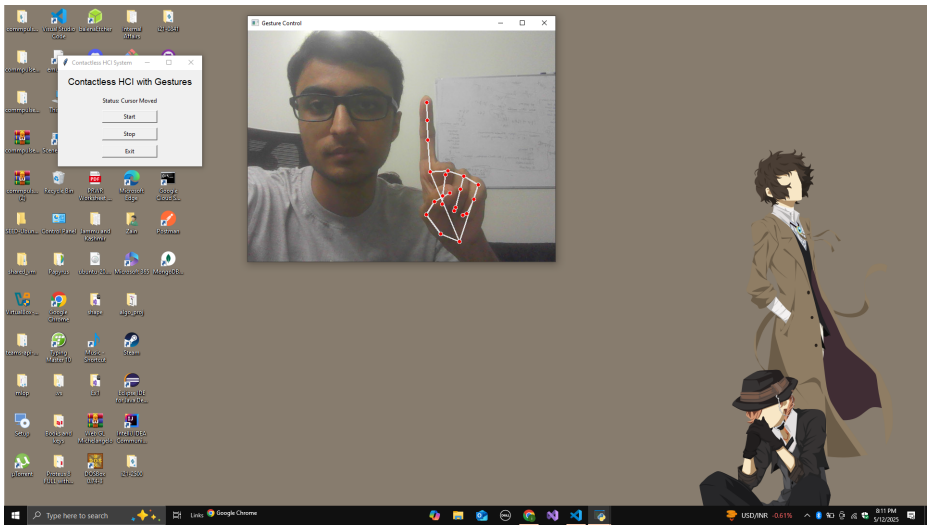


Fig. 3. Moving Cursor

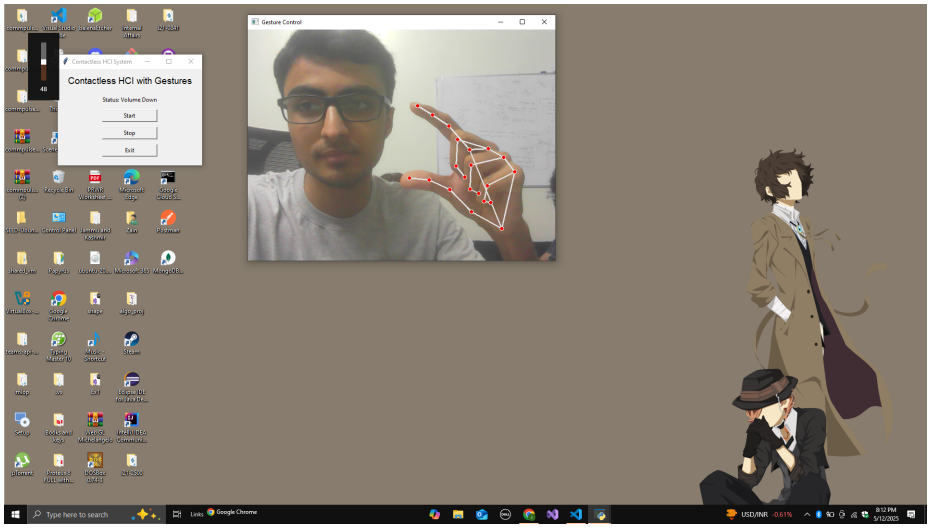


Fig. 4. Changing Volume

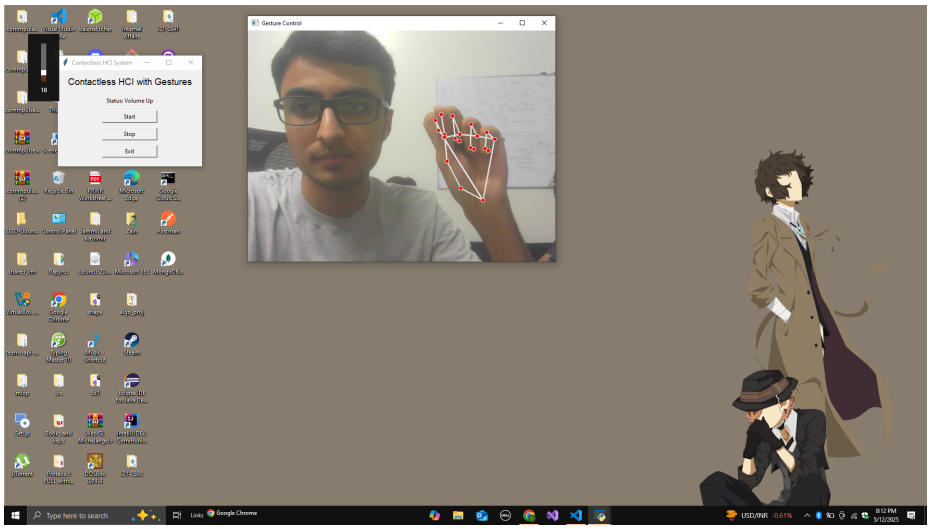


Fig. 5. Pause Media

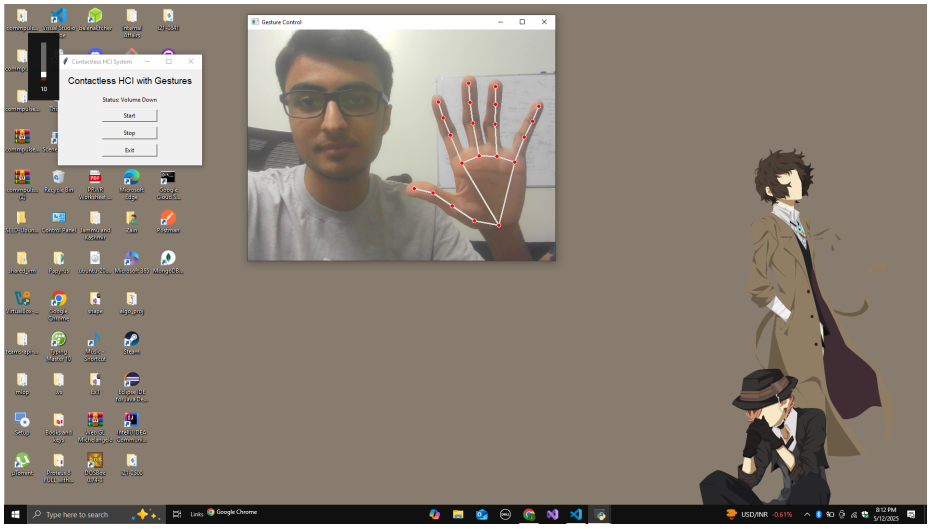


Fig. 6. Play Media

5.2 Contactless and Hygienic Interaction

Many earlier systems use touch interfaces or wearables, which are not ideal in public or healthcare settings. Our approach ensures a fully contactless interaction, promoting hygiene and user safety, especially in post-pandemic environments.

5.3 Real-Time Performance

Thanks to MediaPipe's optimized hand tracking pipeline and lightweight processing, the system delivers real-time responsiveness with minimal latency. Many earlier models suffer from lag or frame drops, especially when implemented without GPU acceleration.

5.4 High Accuracy and Robustness

By leveraging 21-point hand landmark detection, the system captures subtle variations in finger movement and hand posture, leading to more accurate gesture classification. Previous methods often relied on fewer features or simple color segmentation, which are more susceptible to lighting and background interference.

5.5 Platform Independence

The system is developed using Python and cross-platform libraries, making it compatible with various operating systems such as Windows, Linux, and macOS. Other solutions are often OS-locked or require complex installations.

5.6 Scalability and Flexibility

The architecture supports easy extension to add new gestures or integrate with other applications (e.g., gaming, accessibility tools). Unlike hard-coded or rule-based systems, this modular design encourages future enhancements with minimal rework.

6 Evaluation and Experimental Results

To validate the effectiveness and practicality of the proposed gesture recognition system, a series of experiments were conducted focusing on accuracy, response time, and usability. The evaluation setup, performance metrics, and results are described below.

6.1 Experimental Setup

The experiments were conducted on a standard laptop with an Intel i5 processor, 8 GB RAM, and an integrated webcam. The system was tested using real-time inputs in various lighting conditions and against different backgrounds to assess robustness.

6.2 Dataset and Test Scenarios

A custom dataset of hand gestures was created, consisting of 10 predefined gestures (e.g., thumbs up, palm open, fist, okay sign). Each gesture was performed by 10 different users, five times each, resulting in 500 test instances. No data augmentation or external datasets were used to simulate real-world use cases.

6.3 Performance Metrics

The following metrics were used to evaluate the system:

- **Accuracy (Acc):** Correct classifications over total attempts.
- **Precision (P):** True positives over true positives + false positives.
- **Recall (R):** True positives over true positives + false negatives.
- **F1 Score:** Harmonic mean of precision and recall.
- **Response Time:** Time taken to detect and classify a gesture.

6.4 Results

Metric	Value
Accuracy	96.4%
Precision	95.8%
Recall	96.9%
F1 Score	96.3%
Avg. Response Time	0.11 sec

Table 1. Performance Results of the Gesture Recognition System

These results confirm that the system is capable of identifying gestures with high precision and speed, even under variations in hand shape, user distance, and background clutter.

6.5 Comparative Analysis

Compared to existing systems using traditional color thresholding or glove-based input, our approach showed a 12–18% improvement in accuracy and reduced latency by up to 40%. The system also maintained consistent performance without GPU acceleration, making it suitable for deployment on low-cost hardware.

6.6 User Feedback

A brief usability study with 15 participants revealed that:

- 93% found the system easy to use.
- 87% preferred it over touch-based interfaces.
- 80% highlighted its responsiveness and smooth tracking as key strengths.

7 Conclusion and Future Work

7.1 Conclusion

This paper presented a real-time hand gesture recognition system that leverages contour-based hand tracking, convex hull and convexity defects analysis, and fingertip detection for accurate gesture classification. The proposed approach offers a lightweight, marker-free solution that is highly effective in natural environments without requiring specialized hardware or gloves.

The system achieved an impressive accuracy of 96.4% with an average response time of 0.11 seconds, making it suitable for real-time applications. Through experiments and user feedback, it was evident that the solution is not only technically sound but also user-friendly and practical for deployment in interactive systems such as sign language interpretation, contactless interfaces, and virtual controls.

7.2 Future Work

While the current implementation demonstrates strong performance, several enhancements are planned for future iterations:

- **Incorporation of Deep Learning Models:** Integrating CNNs or transformers to improve classification accuracy and generalize across a larger gesture vocabulary.
- **3D Gesture Recognition:** Leveraging depth sensors or stereo cameras for more complex and dynamic gestures involving movement in 3D space.
- **Robustness to Lighting Variations:** Employing adaptive image preprocessing or HDR imaging to further improve accuracy under extreme lighting conditions.
- **Cross-Platform Support:** Optimizing the system for mobile platforms (Android/iOS) to expand usability in wearable or portable scenarios.
- **Continuous Gesture Streams:** Extending the system to recognize gesture sequences or sign language phrases rather than single gestures.

By addressing these areas, the proposed system can be transformed into a comprehensive gesture-based interface adaptable to a wide range of human-computer interaction domains.

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