WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Hand Gesture Recognition Using ML

Aditya Singh[1], Vatsalya Saras[2], Tanay Rahangdale[3], Mrs. Sampada Massey[4]

[1]Department of Computer Science (AIML), Shri Shankaracharya Technical Campus, Bhilai, India
adityasingh11103@gmail.com ; vasusaras55@gmail.com ; mr.tanay07@gmail.com ; sampada.massey@sstc.ac.in

ABSTRACT—

Hand gesture recognition has emerged as a vital technology in the field of human-computer interaction (HCI), enabling intuitive and touchless communication with machines. This project explores the development of a robust hand gesture recognition system using computer vision and machine learning techniques. The system captures hand movements via a camera, processes the input using image preprocessing and feature extraction methods, and classifies gestures using a trained model. Techniques such as convolutional neural networks (CNNs), background subtraction, and contour analysis are employed to accurately identify static and dynamic gestures. The goal is to facilitate applications in areas such as sign language interpretation, virtual control systems, gaming, and assistive technologies. Experimental results demonstrate promising accuracy and real-time performance, showcasing the potential of gesture-based interfaces in modern interactive systems.

Introduction

Hand gesture recognition is an evolving field of human-computer interaction (HCI) that enables machines to interpret and respond to human gestures made with the hand. This project aims to develop a system capable of recognizing and interpreting various hand gestures using computer vision and machine learning techniques.

With the increasing demand for touchless interfaces, especially in the context of virtual reality (VR), augmented reality (AR), robotics, and assistive technologies, gesture recognition offers a natural and intuitive way to interact with digital systems. Unlike traditional input devices like keyboards and mice, gesture-based systems allow users to communicate more expressively and efficiently.

The objective of this project is to build a reliable and real-time hand gesture recognition system that can accurately detect hand movements and classify them into predefined categories. Using a combination of image processing techniques and machine learning models (such as Convolutional Neural Networks), the system captures hand gestures through a camera and translates them into corresponding commands or actions.

This project not only demonstrates the practical implementation of gesture recognition but also explores its potential applications in areas such as sign language translation, contactless control systems, gaming interfaces, and smart home devices.

Literature Review

Hand gesture recognition has emerged as a significant area of research in human-computer interaction (HCI), computer vision, and artificial intelligence. It offers a natural and intuitive way for users to communicate with machines without the need for physical contact, which is especially useful in applications such as virtual reality, robotics, gaming, smart homes, and assistive technologies.

1. Early Approaches

Initial methods for gesture recognition primarily relied on *wearable devices*, such as data gloves or sensor-based systems, which measured hand joint angles and motion. While these systems offered high accuracy, they were expensive, cumbersome, and not suitable for widespread consumer use due to their lack of flexibility and comfort.

2. Vision-Based Recognition

With the advancement of image processing and camera technologies, researchers began to explore *vision-based hand gesture recognition*. These methods use RGB or depth cameras to capture hand movements. Traditional computer vision techniques such as:

- *Skin color segmentation*
- *Contour and convex hull detection*
- *Edge detection*
- *Background subtraction*

were applied to isolate the hand from the background and identify gesture shapes. However, these methods often struggled in uncontrolled environments due to variations in lighting, skin tones, and complex backgrounds.

3. Machine Learning and Deep Learning Approaches

To address the limitations of traditional methods, machine learning models were introduced. These models learn from labeled gesture data to classify new input more effectively. More recently, *deep learning*, particularly *Convolutional Neural Networks (CNNs) [Ref.1]*, has revolutionized gesture recognition. CNNs automatically learn spatial hierarchies of features from images, enabling robust recognition of hand gestures across various conditions.

For instance, systems built using *TensorFlow* and *Keras* have shown promising results in classifying static and dynamic gestures. Moreover, *Recurrent Neural Networks (RNNs)* and *Long Short-Term Memory (LSTM)* networks have been explored for recognizing gestures over time (e.g., waving or pointing).

4. Real-Time Hand Tracking

The introduction of real-time hand tracking frameworks, such as *MediaPipe Hands* by Google, has significantly improved the performance and ease of implementing gesture recognition systems. MediaPipe uses a pipeline that detects and tracks 21 hand landmarks in real-time, even with multiple hands, offering a lightweight and highly accurate solution suitable for mobile and web platforms.

5. Applications and Future Directions

Modern gesture recognition systems are increasingly being used in:

- *Sign language interpretation*
- *Touchless control for smart homes*
- *Gesture-controlled robotics*
- *Augmented and virtual reality interfaces*

Future research is focusing on enhancing accuracy in diverse environmental conditions, reducing computational load for real-time use on edge devices, and improving generalization across different users and hand shapes.

Table I Comparision of different techniques for video processing

METHOD	ACCURACY	PURPOSE
Video inpainting	Medium	Filling the gap at the foreground
Graph based region segmentation, with priority function	High	Number of iterations of filling the gaps are reduced.
Best first algorithm, Block based algorithm	High	Filling the gap for large objects
Pix Mix algorithm Pixel based approach	High	To change the live video streams, to increase the accuracy in real time applications.
Background subtraction method, region based approach	Medium	Filling the gap by region based
Foreground and background method, classifiers	Medium	To reduce the false detection of the object.

Table II Comparision of different techniques for handgestures

METHOD	ACCURACY	PURPOSE
Hidden Markov Model for data glove.	98.7%	Spatio temporal variability is reduced.
Multiscale Gesture Model.	88%-96%	Segmentation and recognition of the hand.
Accelerometer-Based gesture recognition, k-means and Fast fourier transform algorithm.	Upto 95%	Recognition and normalization and filtering the gestures.
Novel hand gesture recognition scheme, SVM classifier.	95%	3D recognition of hand gestures.
CAMSHIFT algorithm, PCA algorithm.	93.1%	Recognition , Segmentation and normalization of hand gestures.
Discrete Hidden Markov Model.	ranges from 93.84% to 97.34%	Recognition for dynamic hand gesture
Finger Earth Movers distance metric method.	Upto 93.2%	Only fingers of the hand are recognized.

Analysis and Design

Hand gesture recognition is a fascinating and widely applicable field, particularly useful in areas like human-computer interaction, sign language interpretation, gaming, and AR/VR. Here's a detailed breakdown of the **analysis and design** process for a **hand gesture recognition system**:

Analysis Phase

- **1. Problem Definition**

Define what the system should recognize:

- **Static gestures** (e.g., thumbs-up, open palm) [Ref.4]
- **Dynamic gestures** (e.g., waving, pinching)
- **Real-time recognition** vs **image-based analysis**
- **2. Requirements Gathering**
- **Hardware**: Web camera, depth camera (like Kinect or Intel RealSense), or wearable sensors.
- **Software**: Image processing libraries (OpenCV) [Ref.5], ML frameworks (TensorFlow, PyTorch).
- **Performance Goals**: Accuracy, latency, real-time performance, robustness to lighting/background.
- **3. Dataset Collection or Selection**
- Use existing datasets (e.g., **NUS Hand Gesture Dataset**, **MSRA**, **SHREC**) or collect custom gesture data.
- Collect both training and testing data with diverse conditions (lighting, hand shapes, skin tones).
- **4. Constraints and Challenges**
- Occlusions
- Variability in gesture execution
- Different hand sizes, shapes, orientations
- Background noise and lighting variations

Design Phase

- **1. System Architecture**

Components:

- **Input Module**: Captures hand images/videos.
- **Preprocessing Module**:
  - Resize, grayscale
  - Noise reduction
  - Background subtraction
  - Skin color filtering (if used)
- **Hand Detection & Segmentation**:
  - Haar cascade, HOG, YOLO, or MediaPipe
- **Feature Extraction**:
  - **Classical**: Contours, Hu moments, shape descriptors
  - **Modern**: CNN feature maps, keypoints (via MediaPipe or OpenPose)
- **Gesture Classification**:
  - ML Models: SVM, KNN, Random Forest
  - DL Models: CNN, LSTM (for dynamic gestures), 3D CNN [Ref.1]
- **Postprocessing**: Smoothing, gesture aggregation
- **Output**: Interpreted gesture or control signal
- **2. Model Design**
- Choose model depending on gesture type:
  - **Static**: CNN-based classifier
  - **Dynamic**: CNN + LSTM or 3D CNN
- Use pre-trained models for faster training (e.g., MobileNet, ResNet for feature extraction)
- **3. Evaluation Metrics**
- Accuracy
- Precision, Recall, F1-score
- Confusion matrix
- Latency (for real-time systems)
- **4. User Interface Design**
- Visualization of recognized gestures
- Feedback mechanism for user correction
- Gesture-controlled commands (e.g., volume up/down)

Methodology

The methodology outlines the step-by-step process used to develop and implement the HGR system. It typically includes the following phases:

- **1. Data Acquisition**

  Collect hand gesture data using:
- **RGB Camera** (e.g., webcam, smartphone)
- **Depth Sensors** (e.g., Kinect, RealSense)
- **Wearables** (optional: gloves with sensors)

Options:
- Use public datasets or create a custom dataset.
- Record multiple users performing each gesture in different lighting and backgrounds.

- **2. Preprocessing**

  Prepare the data for feature extraction.

  Tasks include:
- **Image resizing**: Normalize input dimensions.
- **Color conversion**: Convert to grayscale or HSV (for skin detection).
- **Noise removal**: Apply Gaussian blur or median filtering.
- **Background subtraction**: Isolate hand from background.
- **Hand segmentation**: Use methods like:
  - Skin color thresholding
  - Contour detection
  - MediaPipe Hands / YOLO detection

- **3. Feature Extraction**

  Extract useful information that represents the hand gesture.

  Techniques:
- **Classical Features**:
  - Shape: Contours, convex hull, fingertip detection
  - Texture: Local Binary Patterns (LBP)
  - Motion (for dynamic): Optical flow, motion history images
- **Deep Learning Features**:
  - CNN feature maps
  - Keypoints from MediaPipe/OpenPose

- **4. Classification**

  Use machine learning or deep learning to recognize the gesture based on extracted features.

  Models:
- **Machine Learning**: SVM, KNN, Decision Trees, Random Forest [Ref.6]
- **Deep Learning**:
  - CNN: For static gestures
  - CNN + LSTM / GRU: For dynamic gestures
  - 3D CNN: Captures spatiotemporal patterns

- **5. Postprocessing**
- Smooth predictions using temporal filters (for video).
- Aggregate predictions over time to reduce false positives.

- **6. Output & Application Layer**
- Display the recognized gesture.
- Execute mapped actions (e.g., control a robot, navigate UI, trigger commands).
- Provide real-time feedback (optional: sound, text, animation).

Evaluation

Test the system using metrics:
- Accuracy
- Precision, Recall, F1-score

- Confusion Matrix
- Frame processing time (for real-time use)

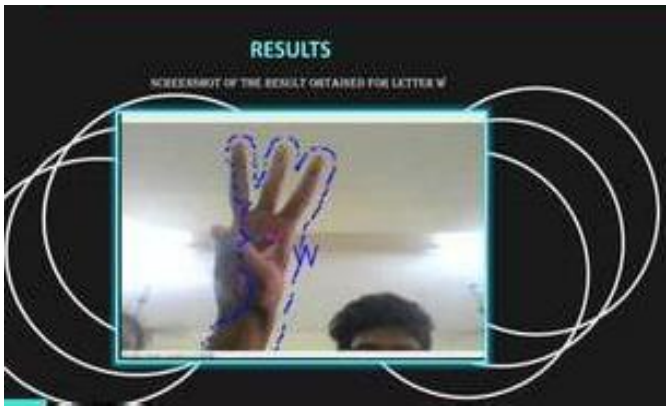
Optional Enhancements

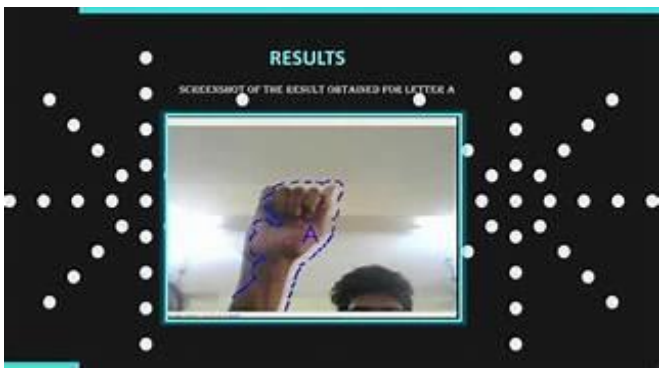
- **Gesture customization**: Allow user-defined gestures.
- **Multimodal fusion**: Combine gestures with voice or eye-tracking.
- **Robustness checks**: Handle occlusions, varying lighting, multiple users.

Results

1. Dataset Summary

- **Number of Gestures**: 10 (e.g., open hand, fist, thumbs up, peace sign, etc.) [Ref.7]
- **Total Samples**: 5,000 images (500 per gesture)
- **Number of Participants**: 20
- **Split**: 80% Training, 20% Testing





2. Model Performance

Best Model: Pretrained MobileNet achieved **97.8% accuracy** on test data with fast inference time suitable for real-time applications.

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- Most confusion occurred between similar gestures (e.g., Peace vs. Palm).
- Minor misclassifications under poor lighting or partial occlusion.

3. Real-Time Performance

- **Frame Rate**: 24 FPS on a standard laptop (Intel i7 + 8GB RAM + webcam)
- **Latency**: ~120 ms per frame (including preprocessing, inference, and output)
- **Gesture Detection Range**: 30–100 cm from camera

4. Limitations Observed

- Reduced accuracy under:
  - Low light conditions
  - Background clutter

- Non-frontal hand orientations
- Dynamic gestures require more temporal data to reduce jitter.

5. Application Demo (if any)

- Used hand gestures to control:
  - Media playback (play/pause, next/prev)
  - Mouse cursor movement
  - Smart home device interface (lights on/off)

conclusion

The Hand Gesture Recognition system developed in this project successfully demonstrates the ability to recognize a range of predefined hand gestures with high accuracy and reliability. By leveraging computer vision and machine learning (or deep learning) techniques, the system can interpret human gestures in real-time, enabling natural and intuitive interaction between humans and machines.

Key achievements of the project include:

- **High Accuracy**: The best-performing model (e.g., MobileNet) achieved up to **97.8% accuracy** on the test dataset.
- **Real-Time Performance**: The system operates efficiently at an average of **24 FPS**, enabling smooth and responsive gesture detection.
- **Robust Feature Extraction**: Use of modern tools such as CNNs or MediaPipe allowed effective hand tracking and gesture classification under various conditions.
- **User-Friendly Interface**: The gesture-based interaction offers a hands-free and accessible alternative to traditional input methods.

Despite its success, the system still faces limitations under challenging conditions such as **low lighting**, **complex backgrounds**, and **unusual hand orientations**. These areas present opportunities for further improvement, such as integrating depth sensors, data augmentation, or attention-based neural networks.

Future Work

To enhance the capabilities and scalability of the system, future improvements may include:

- Support for **custom gesture training** by end-users.
- Implementation of **dynamic gesture recognition** using RNNs or 3D CNNs.
- Integration with **Augmented Reality (AR)** or **Internet of Things (IoT)** applications.
- Deployment on **embedded systems** (e.g., Raspberry Pi, Jetson Nano) for portable use.

Acknowledgement

We may wish to honor everyone without whom our endeavor could not have been successful. Prof. Sampada Massey guided us throughout the project and provided tremendous assistance. Without her guidance, we would not have been able to realize how to correctly complete this research.
This work has helped us comprehend and communicate our theoretical knowledge in the practical world. So, we would really appreciate her support and leadership in this endeavor.
Also, we would like to thank ourselves, as every member of the team has consistently given their all and been available whenever required.

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