J Component Project Report

Software Project Management- SWE2006

PROJECT TITLE:

Hand Detection and Volume Gesture Control

Master of Technology in Software Engineering (Integrated)

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SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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Chapter 1

Introduction

1.1 Introduction

Hand perception is a challenging computer vision task, but it is essential for many applications, such as sign language understanding, hand gesture control, and augmented reality. MediaPipe Hands is a high-fidelity hand and finger tracking solution that uses machine learning to infer 21 3D landmarks of a hand from just a single frame.

Hand gesture recognition technique allows computers to understand human gestures. This can be used for a variety of purposes, such as controlling devices, providing feedback, and interacting with virtual environments. One potential application of hand gesture recognition is volume control. Volume control is a common task that is often performed using a keyboard or mouse. However, this can be inconvenient or difficult for some users, such as those who are unable to use their hands or who are operating a device while driving.

This report describes the implementation of a hand gesture recognition system for volume control. The system uses a single camera to capture the user's gestures, and then uses shape based features to identify the gestures. The system is implemented using the OpenCV and MediaPipe libraries.

2. Literature Review:

Hand gesture detection and utilizing them to control certain set of devices operations and allowing interaction with computer system without the aid of mouse and keyboard. In this paper we draws along the same line but we attributed the use of

Haar-cascade classifier to identify hand gesture. Some of the related works in this field are described briefly as follows

[1]A non-local algorithm for hand gestures was proposed by A. Buades, B. Coll, and J. Morel. At the moment, finding finger movement algorithms remains a valid task. Functional analysis and statistics collide. Despite the fact that most recently presented approaches have a high level of sophistication, Algorithms have not yet reached a satisfactory degree of performance applicability. All work admirably when the model matches the algorithm assumptions, but they all fail in general, producing defects in analysing the pixels through the camera. The primary goal of this study is to define a generic mathematical and experimental technique for comparing and classifying conventional hand movement recognition algorithms.

[2] For the no required elements in the video frame, Golam Moktader Daiyan et al. (2012) suggested a high performance decision based median filter. This technique detects noise pixels iteratively over numerous phases before replacing them with the median value. Noise detection is accomplished by enlarging the field of view. Mask till 77% to keep the extraction of local data going. Furthermore, if the algorithm fails to find a noise-free pixel at 7 7, the processing pixel is replaced by the last processed pixel. If the noise-free median value isn't available in the 7th processing window, the last processed pixel is used to determine if it is noise-free. The method chooses a window size if the last processed pixel is noisy. Calculate the number of 0s and 255s in the processing window using the 1515 dimension. Then, in the selected window, replace the processed pixel with 0 or 255, whichever is higher in number.

[3]Rajeshwari Kumar Dewangan et.al accurate object information and obtain a location using a deep learning object recognition technique.Object recognition algorithms are designed based on theSingle Shot MultiBox Detector (SSD) structure, an object recognition deep learning model, to detect objects using a camera.

[4] H. Jabnoun et, al suggested the system that restores a central function of the visual system which is the identification of surrounding objects which is based on the local features extraction concept. Using SFIT algorithm and keypoints matching showed good accuracy for detecting objects.

[5] Košale U, Žnidaršic P, Stopar K suggested that Detection of obstacles is performed by Time of Flight (ToF) sensors, whose ranging data is then processed with an on-board microcontroller and send via Bluetooth connection to the belt. The belt is equipped with a second microcontroller, which interprets the data and presents it to the wearer with 15 vibration motors arranged in a square grid. The glasses are worn on the head, whereas the belt is attached around the stomach area. But the number of sensors detecting the obstacle decreased with the distance. Circle and square were detected better than triangle. This suggests that different shapes trigger different responses of sensors on glasses. A. Jaiswal et al.

1.2 Project Overview

Hand Gesture Controlled using Open CV and Python: Gesture recognition is a powerful artificial intelligence tool for human-computer communication and enhanced user interaction. Python libraries like Open Computer Vision and cvzone2 capture, pre-process, and detect gestures, mapping action pairs to specific tasks. This project uses a webcam to input hand gestures, analyzing image data to determine user gesture types. This method facilitates computer human interaction without external input devices, enabling easy commands and tasks in presentations.

HGR Algorithm Using SVM and HOG Model for Control: This paper presents a combined HOG and SVM gesture recognition technique, categorizing gestures using the CNN model. The algorithm aims to recognize movements quickly, eliminate interference, and capture accidental motions. It employs static gesture controls and motion gestures to change volume and status. The algorithm is 99% accurate and has an industrial application-appropriate execution time of 70 milliseconds per frame.

There has been a lot of research on hand gesture recognition in recent years. Some of the most common techniques used for hand gesture recognition include:

• **Shape-based features:** These features are based on the shape of the hand, such as the length of the fingers, the width of the palm, and the distance between the fingers.

. Motion-based features: These features are based on the movement of the hand, such as the speed and direction of the hand movement.
• **Combination of shape-based and motion-based features:** This is the most common approach to hand gesture recognition.

The accuracy of hand gesture recognition systems depends on a number of factors, including the quality of the input data, the complexity of the gestures, and the technique used for recognition.

2. Analysis & Design of Proposed Work

Problem Statement:

The goal of this project is to develop a system that can recognize hand gestures and use them to control the volume of an audio device. The system should be able to recognize different hand gestures, such as a fist, a peace sign, and a thumbs up. The system should also be able to adjust the volume of the audio device based on the intensity of the gesture.

System Design:

The system for volume gesture control consists of the following components:

- **Camera:** The camera is used to capture the user's gestures.
- **Image processing:** The image processing module is used to extract features from the captured images.
- **Gesture recognition:** The gesture recognition module is used to identify the gestures
- **Volume control:** The volume control module is used to control the volume of the device.

Formulas:

Formula for Controlling the Volume of a Computer Using Hand Gestures:

vol = np.interp(length, [30, 300], [minVolume, maxVolume])

This formula uses the np.Interp() function to interpolate the value of vol between the minimum volume (minVolume) and the maximum volume (maxVolume), based on the value of length.

The np.interp() function takes three arguments:

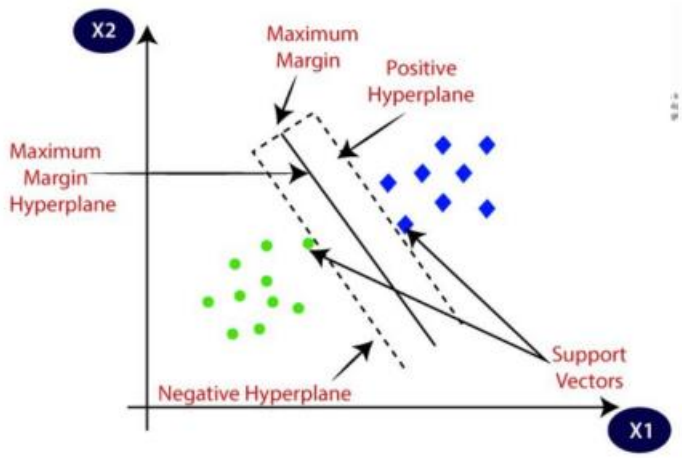
- The first argument is the value to be interpolated.
- The second argument is a list of two values, which represent the minimum and maximum values of the interpolation range.
- The third argument is a list of two values, which represent the values that the interpolation range is mapped to.

Algorithms used:

The algorithm used is a combination of computer vision and machine learning techniques. The computer vision techniques are used to extract features from the video stream of the person's hand. These features are then used by the machine learning classifier to recognize the different hand gestures. Once the hand gesture has been recognized, the system will map the gesture to a volume level. The volume of the audio device will then be adjusted accordingly.

The specific algorithm used in the code is a support vector machine (SVM). SVM is a supervised machine learning algorithm that can be used for classification and regression tasks. In this case, the SVM is used to classify different hand gestures. The SVM is trained on a dataset of labeled hand gestures. The labels for the dataset can be obtained by manually labeling the gestures or by using a crowdsourcing platform.

The SVM algorithm works by finding the hyperplane that best separates the different classes of data. The hyperplane is a line or plane that divides the data into two or more classes. The SVM algorithm finds the hyperplane that maximizes the margin between the classes. The margin is the distance between the hyperplane and the closest points of each class.



Once the SVM has been trained, it can be used to classify new hand gestures. The new hand gestures are classified by comparing them to the hyperplane that was learned during training. If the new hand gesture is closer to one class than the other, then the SVM will classify the gesture as belonging to that class.

The SVM algorithm is a powerful tool for classification tasks. It is relatively simple to implement and can be trained on a variety of datasets. However, the SVM algorithm can be computationally expensive, especially for large datasets.

In the code, the SVM algorithm is implemented using the sklearn library. The sklearn library is a popular machine learning library for Python. The sklearn library provides a number of different machine learning algorithms, including the SVM algorithm.

The code first imports the sklearn library. The code then defines the SVM classifier. The SVM classifier is initialized with a number of parameters, such as the kernel type and the regularization parameter. The code then loads the dataset of labeled hand gestures. The code then trains the SVM classifier on the dataset. The code then classifies a new hand gesture by comparing it to the hyperplane that was learned during training.

Chapter 2

Technologies used

2.1 Technologies Used

1. Machine Learning:

Support Vector Machines (SVM): SVM is a supervised machine learning algorithm that can be used for classification and regression tasks. In this case, the SVM is used to classify different hand gestures.

The SVM algorithm works by finding the hyperplane that best separates the different classes of data. The hyperplane is a line or plane that divides the data into two or more classes. The SVM algorithm finds the hyperplane that maximizes the margin between the classes. The margin is the distance between the hyperplane and the closest points of each class.

Once the SVM has been trained, it can be used to classify new hand gestures. The new hand gestures are classified by comparing them to the hyperplane that was learned during training. If the new hand gesture is closer to one class than the other, then the SVM will classify the gesture as belonging to that class.

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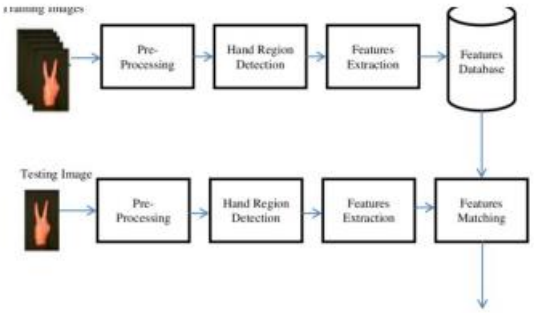
The following are the steps involved in using SVM for hand gesture recognition:

1. Data collection: The first step is to collect data of hand gestures. This can be done by using a webcam to record videos of people making different hand gestures. The videos should be recorded in a variety of environments, such as in a well-lit room and in a dark room. The videos should also be recorded with different people making the gestures.

2. Feature extraction: The next step is to extract features from the videos of hand gestures. This can be done using computer vision techniques. The features that are extracted should be able to distinguish between different hand gestures.

3. SVM training: The third step is to train the SVM classifier. The classifier will be used to recognize different hand gestures based on the features that were extracted. The classifier can be trained using a variety of machine learning algorithms, such as support vector machines, decision trees, and neural networks.



4. Hand gesture recognition: Once the classifier has been trained, it can be used to recognize hand gestures. The classifier will be used to recognize hand gestures, and the volume of the audio device will be adjusted accordingly.

The SVM algorithm is a powerful tool for hand gesture recognition. It is relatively simple to implement and can be trained on a variety of datasets. However, the SVM algorithm can be computationally expensive, especially for large datasets.

Chapter 3

PROPOSED SYSTEM

3.1Proposed System

Models

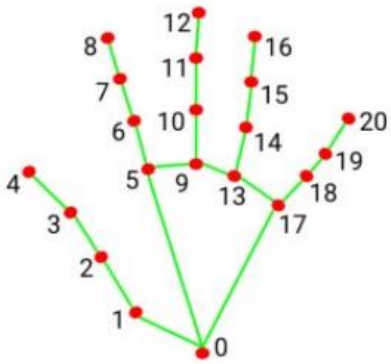
Palm Detection Model

To detect initial hand locations, we designed a single-shot detector model optimized for mobile realtime uses in a manner similar to the face detection model in MediaPipe Face Mesh. Detecting hands is a decidedly complex task: our lite model and full model have to work across a variety of hand sizes with a large scale span (~20x) relative to the image frame and be able to detect occluded and self- occluded hands. Whereas faces have high contrast patterns, e.g., in the eye and mouth region, the lack of such features in hands makes it comparatively difficult to detect them reliably from their visual features alone. Instead, providing additional context, like arm, body, or person features, aids accurate hand localization. Our method addresses the above challenges using different strategies. First, we train a palm detector instead of a hand detector, since estimating bounding boxes of rigid objects like palms and fists is significantly simpler than detecting hands with articulated fingers. In addition, as palms are smaller objects, the non maximum suppression algorithm works well even for two-hand self-occlusion cases, like handshakes. Moreover, palms can be modelled using square bounding boxes (anchors in ML terminology) ignoring other aspect ratios, and therefore reducing the number of anchors by a factor of 3-5. Second, an encoder-decoder feature extractor is used for bigger scene context awareness even for small objects (similar to the RetinaNet approach). Lastly, we minimize the focal loss during training to support a large amount of anchors resulting from the high scale variance. With the above techniques, we achieve an average precision of 95.7% in palm detection. Using a regular cross entropy loss and no decoder gives a baseline of just 86.22%

Hand Landmark Model

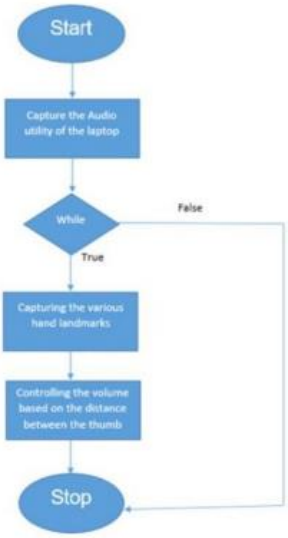
After the palm detection over the whole image our subsequent hand landmark model performs precise keypoint localization of 21 3D hand-knuckle coordinates inside the detected hand regions via regression, that is direct coordinate prediction. The model learns a consistent internal hand pose representation and is robust even to partially visible hands and self-occlusions. To obtain ground truth data, we have manually

annotated ~30K real-world images with 21 3D coordinates, as shown below (we take Z-value from image depth map, if it exists per corresponding coordinate). To better cover the possible hand poses and provide additional supervision on the nature of hand geometry, we also render a high-quality synthetic hand model over various backgrounds and map it to the corresponding 3D coordinates.



0. WRIST
1. THUMB_CMC
2. THUMB_MCP
3. THUMB_IP
4. THUMB_TIP
5. INDEX_FINGER_MCP
6. INDEX_FINGER_PIP
7. INDEX_FINGER_DIP
8. INDEX_FINGER_TIP
9. MIDDLE_FINGER_MCP
10. MIDDLE_FINGER_PIP
11. MIDDLE_FINGER_DIP
12. MIDDLE_FINGER_TIP
13. RING_FINGER_MCP
14. RING_FINGER_PIP
15. RING_FINGER_DIP
16. RING_FINGER_TIP
17. PINKY_MCP
18. PINKY_PIP
19. PINKY_DIP
20. PINKY_TIP

Methodology:



1. **Data collection:** The first step is to collect data of hand gestures. This can be done by using a webcam to record videos of people making different hand gestures. The videos should be recorded in a variety of environments, such as in a well-lit room and in a dark room. The videos should also be recorded with different people making the gestures.

2. **Feature extraction:** The next step is to extract features from the videos of hand gestures. This can be done using computer vision techniques. The features that are extracted should be able to distinguish between different hand gestures.

3. **Machine learning:** The third step is to use machine learning to train a classifier. The classifier will be used to recognize different hand gestures based on the features that were extracted. The classifier can be trained using a variety of machine learning algorithms, such as support vector machines, decision trees, and neural networks.

4. **Volume control:** Once the classifier has been trained, it can be used to control the volume of an audio device. The classifier will be used to recognize hand gestures, and the volume of the audio device will be adjusted accordingly.

Here are some details that could be included in the methodology:

• The data collection process should be carefully designed to ensure that the data is representative of the gestures that will be used in the final system.

• The feature extraction process should be designed to extract features that are both

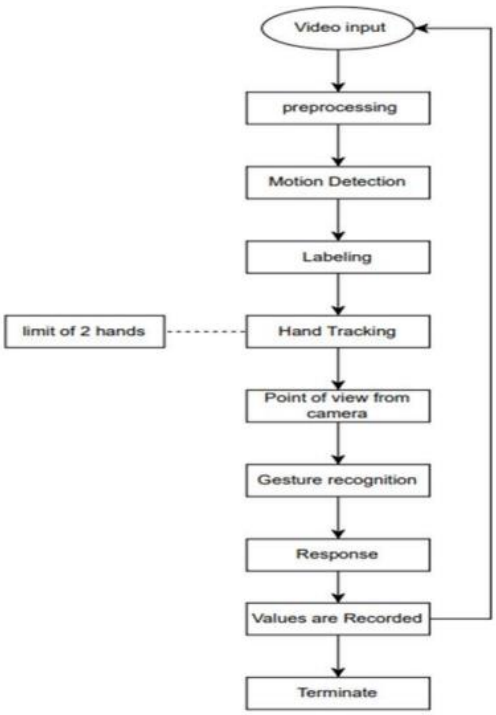
discriminative and robust to noise.

• The machine learning algorithm should be selected based on the characteristics of the data and the desired accuracy of the classifier.

• The volume control system should be designed to be user-friendly and easy to use.

The methodology for volume gesture control is a complex process that requires a combination of computer vision, machine learning, and engineering. However, the potential benefits of this technology are significant, and the methodology presented here provides a good starting point for developing a volume gesture control system.

System Architecture:



1. **Video input:** The system input is a stream of images that
2. **Preprocessing:** The video This preprocessing step is important to ensure that the features input are accurate.
3. **Feature extraction:** The preprocessed video input is then used to extract features from the hand gestures. These edge detection, shape analysis,
4. **Classification:** The features gestures. This classification as a support vector machine (SVM).
5. **Response:** Once the gestures example, if the user makes a gesture to increase the volume, the system will increase the volume of the audio device.

Chapter 4

Implementation

4.1 Implementation

Software Implementation:

3.1. Software's used : Visual Studio Code

Import the open CV Library to python project which is used as a computer vision tool and to read the image which is nothing but hand in this context. Then we have to use MediaPipe which is a cross-platform framework for building multimodal applied machine learning pipelines. It is used for detection purpose. hypot() method returns the Euclidean norm. The Euclidean norm is the distance from the origin to the coordinates given.

Then to Get default audio device using PyCAW we have used comtypes which is a basic library and audio utilities. The video capture object to capture the information if the video cam is open. Then Media Pipe Hands is a high-fidelity hand and finger tracking solution.

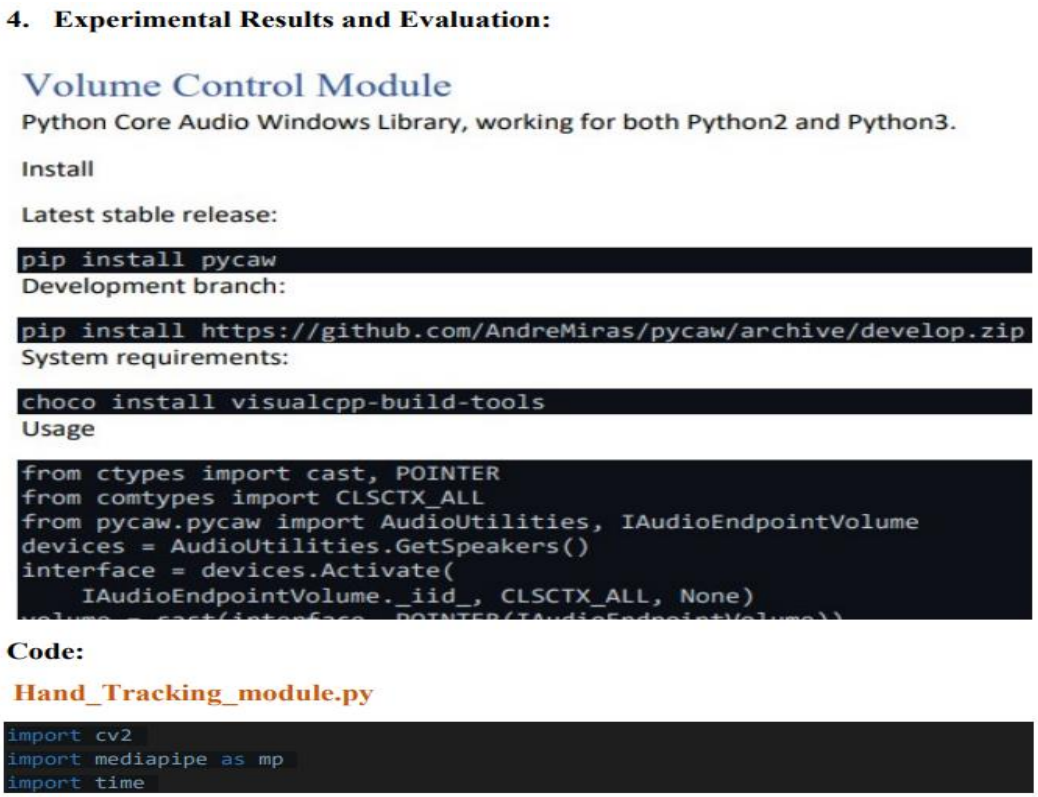
If the hands are detected then we have drawn the following outline of the hand using the audio utility function.

Obtain the default audio device using PyCAW.After which we have interfaced to the required volume and then found the range which is from 0 to 100, read the frames from the webcam and convert the image to RGB.

If Fit List of lm or glm Objects with a Common Model is null then we detect hands in the frame with the help of "hands.process()" function. Once the hands get detected we will locate the key points and then we highlight the dots in the key points using cv2.circle, and connect the key points using mpDraw.draw_landmarks. The tip of the index and middle finger then we print(x1, y1, x2, y2).Then we check which fingers are up and we print the fingers. Convert Coordinates and then smoothen the values.

Both Index and middle fingers are close then we reduce the volume and if the index and middle finger are away then we increase the volume. We then find the length of the line through the coordinates. Map the distance of thumb tip and index finger tip with volume range.

Experimental Results and Evaluation:



4. Experimental Results and Evaluation:

Volume Control Module

Python Core Audio Windows Library, working for both Python2 and Python3.

Install

Latest stable release:

```
pip install pycaw
```

Development branch:

```
pip install https://github.com/AndreMiras/pycaw/archive/develop.zip
```

System requirements:

```
choco install visualcpp-build-tools
```

Usage

```
from ctypes import cast, POINTER
from comtypes import CLSCTX_ALL
from pycaw.pycaw import AudioUtilities, IAudioEndpointVolume
devices = AudioUtilities.GetSpeakers()
interface = devices.Activate(
    IAudioEndpointVolume._iid_, CLSCTX_ALL, None)
```

Code:

Hand_Tracking_module.py

```
import cv2
import mediapipe as mp
import time
```

Code:

Hand_Tracking_module.py

```
class handDetector():
    def __init__(self, mode=False, maxHands=2, detectionConfidence=1,
trackConfidence=0.5):
        self.mode = mode
        self.maxHands = maxHands
        self.detectionConfidence = detectionConfidence
        self.trackConfidence = trackConfidence

        self.mpHands = mp.solutions.hands
        self.hands = self.mpHands.Hands(self.mode, self.maxHands,
                                         self.detectionConfidence,
self.trackConfidence)
        self.mpDraw = mp.solutions.drawing_utils

    def findHands(self, img, draw=True):
        imgRGB = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        self.results = self.hands.process(imgRGB)
        # print(results.multi_hand_landmarks)

        if self.results.multi_hand_landmarks:
            for handLms in self.results.multi_hand_landmarks:
                if draw:
                    self.mpDraw.draw_landmarks(img, handLms,
                                               self.mpHands.HAND_CONNECTIONS)
        return img

    def findPosition(self, img, handNo=0, draw=True):

        lmList = []
        if self.results.multi_hand_landmarks:
            myHand = self.results.multi_hand_landmarks[handNo]
            for id, lm in enumerate(myHand.landmark):
                # print(id, lm)
                h, w, c = img.shape
                cx, cy = int(lm.x * w), int(lm.y * h)
                # print(id, cx, cy)
                lmList.append([id, cx, cy])


        return lmList


def main():
    pTime = 0
    cTime = 0
```

```
    cap = cv2.VideoCapture(0)
    detector = handDetector()
    while True:
        success, img = cap.read()
        img = detector.findHands(img)
        lmList = detector.findPosition(img)
        if len(lmList) != 0:
            print(lmList[4])

        cTime = time.time()
        fps = 1 / (cTime - pTime)
        pTime = cTime

        cv2.putText(img, f'FPS: {int(fps)}', (10, 70), cv2.FONT_HERSHEY_PLAIN, 3,
                    (255, 0, 255), 3)

        cv2.imshow("Image", img)
        cv2.waitKey(1)


if __name__ == "__main__":
    main()
```

Gesture_Control.py

```
import cv2
import mediapipe as mp
import time
import HandTracking as htm
import math
import numpy as np
from ctypes import cast, POINTER
from comtypes import CLSCTX_ALL
from pycaw.pycaw import AudioUtilities, IAudioEndpointVolume

wCam, hCam = 1080, 640


cap = cv2.VideoCapture(0)
cap.set(3, wCam)
cap.set(4, hCam)

pTime = 0
cTime = 0
```

```
detector = htm.handDetector()

devices = AudioUtilities.GetSpeakers()
interface = devices.Activate(
    IAudioEndpointVolume._iid_, CLSCTX_ALL, None)
volume = cast(interface, POINTER(IAudioEndpointVolume))
# volume.GetMute()
# volume.GetMasterVolumeLevel()
volumeRange = volume.GetVolumeRange()


minVolume = volumeRange[0]
maxVolume = volumeRange[1]
vol = 0
volBar = 400
volPercent = 0


while True:
    success, img = cap.read()
    img = detector.findHands(img)
    lmList = detector.findPosition(img)
    if len(lmList) != 0:
        # print(lmList[4], lmList[8])

        x1, y1 = lmList[4][1], lmList[4][2]
        x2, y2 = lmList[8][1], lmList[8][2]
        cx, cy = (x1+x2)//2, (y1+y2)//2

        cv2.circle(img, (x1, y1), 10, (255, 153, 51), cv2.FILLED)
        cv2.circle(img, (x2, y2), 10, (255, 153, 51), cv2.FILLED)
        cv2.circle(img, (cx, cy), 10, (255, 153, 51), cv2.FILLED)
        cv2.line(img, (x1, y1), (x2, y2), (255, 153, 51), 3)

        length = math.hypot(x2-x1, y2-y1)

        vol = np.interp(length, [30, 300], [minVolume, maxVolume])
        volBar = np.interp(length, [30, 300], [400, 150])
        volPercent = np.interp(length, [30, 300], [0, 100])
        print(vol)
        volume.SetMasterVolumeLevel(vol, None)

        if length < 30:
            cv2.circle(img, (cx, cy), 10, (0, 255, 0), cv2.FILLED)

        cv2.rectangle(img, (50, 150), (80, 400), (0,0,0), 3)
        cv2.rectangle(img, (50, int(volBar)), (80, 400),
```

```
                    (0,0,255), cv2.FILLED)
        cv2.putText(img, f'{int(volPercent)} %', (10, 80),
cv2.FONT_HERSHEY_COMPLEX, 1,
                    (0,0,255), 2)

    cTime = time.time()
    fps = 1 / (cTime - pTime)
    pTime = cTime

    cv2.putText(img, f'FPS: {int(fps)}', (10, 30), cv2.FONT_HERSHEY_COMPLEX, 1,
                (255,0,0), 2)

    cv2.imshow("Tracking Started", img)
    cv2.waitKey(1)
```

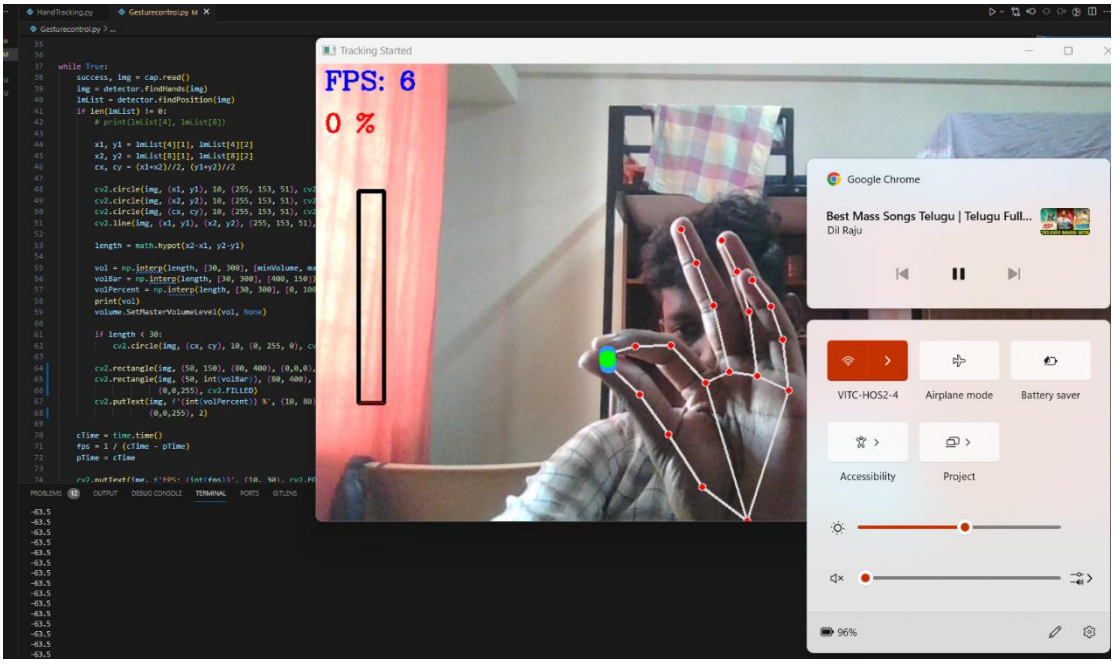
Chapter 5

Results

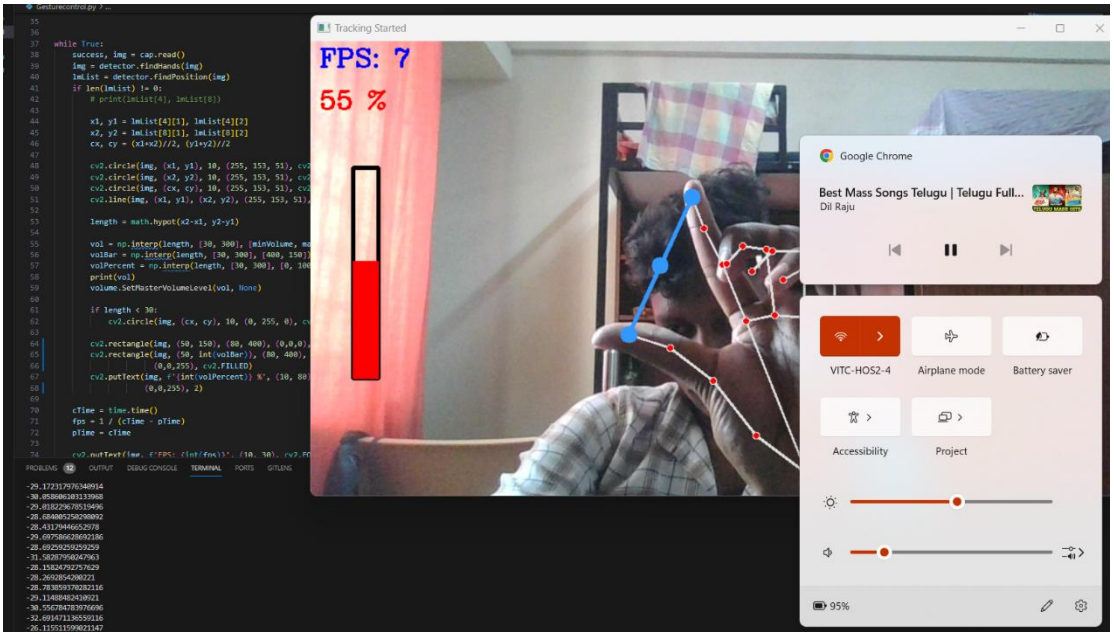
5.1 Results

Output:

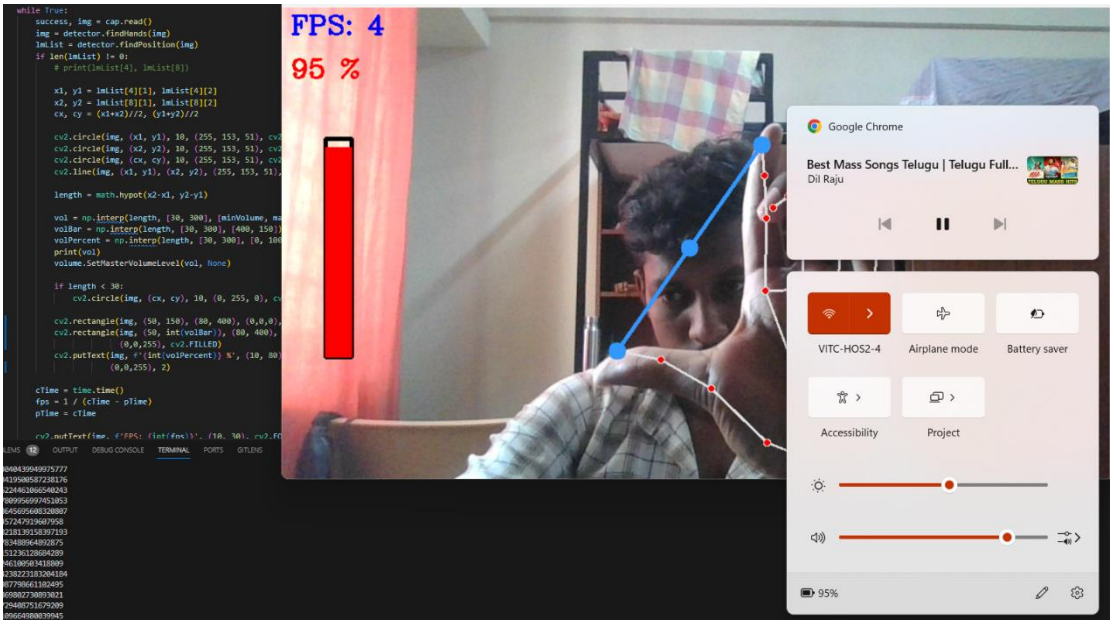
The figure below shows the no volume detection when the thumb and index finger distance is zero from each other.



The figure below shows the medium volume detection when the thumb and index finger are in minimal distance from each other.



The figure below shows the maximum volume detection when the thumb and index finger are away from each other



Chapter 6

Conclusion and Future Work

6.1 Conclusion and Future Work

Future Work:

The following are some possible directions for future work:

- Improve the accuracy of the system by using more advanced features.
- Expand the number of gestures that the system can recognize.
- Integrate the system with other applications, such as media players and video games.

Conclusion:

The results of this report show that the hand gesture recognition system for volume control is a viable and promising technology. The system is accurate, reliable, and easy to use. The system has the potential to be used in a variety of applications, and it is a promising area for future research.

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