Smart Hand Gestured Controlled Presentation System

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Abstract-
Control Presentation Using hand gestures as input to the system, this article builds a controller. The OpenCV module is primarily used to control gestures in this implementation. MediaPipe is his machine learning framework with hand gesture recognition technology currently available. This system primarily uses a web camera to capture or record photos and videos. This application controls the appearance of your system based on your input. The main purpose of this system is to modify presentation slides. I also had access to a pointer that allowed me to draw on and delete slides. You can use hand gestures to operate basic computer functions such as presentation controls. This means people don't have to learn often boring mechanical skills .These hand gesture systems provide a modern, imaginative and natural method of non-verbal communication .These systems are often used in human-computer interaction .The purpose of this project is to discuss hand gesture recognition and a presentation control system based on hand gesture recognition .The system uses a high resolution camera to recognize user gestures as input .The main goal of hand gesture recognition is to develop a system that can recognize human hand gestures and use this information to control the presentation. Real-time gesture recognition allows certain users to control a computer by performing hand gestures in front of a system camera connected to the computer .This project utilizes OpenCV Python and MediaPipe to create a hand gesture presentation control system. The system can be operated using hand gestures, without the need for a keyboard or mouse.

Keywords: OpenCV, MediaPipe, Machine Learning, Hand Gesture Recognition, Presentation Controller, Human Computer Interaction (HCI).

I. Introduction

In today's digital environment, presentations are an engaging and efficient strategy that helps presenters persuade and inform their audience. Slides can be edited using the mouse, keyboard, laser pointer, and more.The disadvantage is that prior device knowledge is required to control the device. A few years ago, gesture recognition became increasingly useful when interacting with software such as media players, robotics, and games. Hand gesture recognition system facilitates the use of gloves, markers and other his items. However, the use of such gloves and markers increases the cost of the system. The hand gesture recognition technology proposed by this system is based on artificial intelligence. users can edit slides. The interactive presentation system uses state-of-the-art human-computer interaction technology to develop a more practical and user-friendly interface for controlling presentation displays. Using these hand gesture options in place of standard mouse and keyboard controls can greatly improve your presentation experience. Using body movements to express specific messages through gestures is non-verbal or non-vocal communication. The system was built primarily using the Python framework and technologies such as Open CV, CV Zone, NumPy, and Media Pipe. The purpose of this method is to increase the effectiveness and usefulness of your presentation. Additionally, the system uses gestures to write, undo, and move the pointer to different areas of text. To improve the slideshow experience, we wanted to allow users to control the slideshow with hand gestures. To optimize and improve display portability, the system minimizes the use of external interfaces. Using machine learning, we were able to discover subtle changes in gestures that were translated into some basic ways to manipulate presentation slideshows using Python. The slides can be managed and controlled by various movements such as swipe left and right, thumb up, and pause. The system uses a hand gesture-based man-machine interface to the traditional presentation flow. This interface has been under active development over the past years. We have developed a fast and easy video-based technique to identify dynamic hand gestures. This technology allows users to control their presentations in a more natural, streamlined, and convenient way.

II. Literature Review

A study of numerous alternative methods shows that researchers' primary goal is to enable speakers to deliver effective presentations that enhance the interaction that comes naturally when using a computer. Dr. Melanie J. Ashley and Damiete O.Lawrence The impact of human-computer interaction was discussed by authors. Higher Education System Users (HCI): University of Southampton as a Case Study. This article assessed human computer interaction (HCI) awareness and advanced literacy skills at Southampton University in the United Kingdom. At the University of Southampton, the impact of HCI is positive. Learning the basics of HCI has been shown to increase stoner effectiveness and sales. In summary, it can be argued that HCI influenced the impact of literacy on other corresponding areas of the environment [1]

The authors developed Gesture Recognition Utilizing Accelerometer, an ANN application used for classification and gesture recognition. This system basically uses a Wii remote that rotates in X, Y, and Z directions. When the author built a system with , he used two layers to reduce cost and memory requirements. User is checked for gesture recognition at the first level. The gesture recognition approach recommended by author is based on accelerometers The system signal is then analyzed at the second level using a gesture recognition machine (Fuzzy).Next, normalize the data using fast Fourier techniques and K-means. Detection accuracy increased to 95% .

Hand gesture recognition using hidden Markov models – The authors of this study developed a system that uses dynamic hand movements to recognize numbers from 0 to 9. In this work, the authors used two stages. Preprocessing is performed in the first stage and classification is performed in the second stage. Basically, there are two types of gestures. Both incorporate key gestures and movements. Main gestures and associated gestures are used in sequential gestures for recognition purposes. In this study, discrete hidden Markov model (DHMM) is used for classification. This DHMM is trained on the Baum-Welch algorithm. The average detection rate of HMM is from 93.84 to 97.34%.

The authors have used low-cost cameras to keep costs down for consumers. Robust Part-Based Hand Gesture Recognition Using Kinect Sensors. Although the resolution of the Kinect sensor is lower than other cameras, it is still able to recognize and capture large images and objects. To cope with large hand movements, only the fingers, rather than the entire hand, are connected to his FEMD. This technology works perfectly and effectively even in uncontrolled his settings. Experimental results showed an accuracy of 93.2%.

The authors of Harika et al. A method was proposed and applied. Using a computer-assisted slide presentation using vision-based gesture recognition. Techniques such as Kalman filters, skin color sampling, and HSL color models are used. Considering the accuracy of the proposed model, the overall success rate of the overall color recognition of Skin is about 72.4%, the individual accuracy of fingertip recognition is 74.0%, the success rate of slide movement is 77%, and the management should display on the finger.

Wahid et al. proposed a method to identify hand gestures through machine learning algorithms. Considering the accuracy of this proposed model, the SVM algorithm considers both 97.56% original EMG features and normalized EMG features (98.73%) between NB, RF, KNN, and DA. provided the most accurate classification.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The code for this project was written in the Python language using the OpenCv and NumPy packages. This task begins by importing the libraries used for further input and output processing. MediaPipe, OpenCV, and Numpy are libraries used in this project and must be imported. Video input comes from the main camera. Mediapipe is used to recognize the video as input from the camera, and the mhand.hands module is used to recognize gestures. Next, we used pointers to access the presentation. To complete the input processing, the input image must next be converted to an RGB image. Then you have a chance to enter the thumb and finger points when entering. Numpy is used to transform the output required for this process. In this method, the presentation is processed using the hand area. This NumPy library for the Python language is essential for data processing. contains various elements.

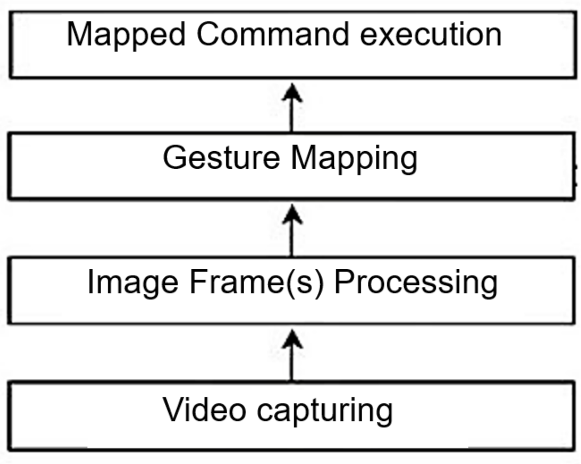

Fig-3.1: System Architecture

A. Method:

The proposed system is implemented using Python and uses computer vision techniques to recognize and classify hand gestures. We use OpenCV, a popular open source computer vision library, to detect the presence of hands in video feeds. Once a hand is detected, the hand module is used to recognize and classify the hand gesture. The data is trained using a vector set of hand gestures that includes various gesture examples such as change slide, next slide, previous slide, pointing, and highlight points.

1. The handheld detector model processes the captured image and rotates the image using a bounding box aligned with the hand position.
2. The hand landmark model processes the cropped bounding box image and returns the 3D hand his key points of the hand.
3. A gesture recognizer that classifies 3D hand points and organizes them into a set of distinct gestures.

Hand gesture recognition is done using the Python programming language and OpenCV as a library. The Python programming language produces system code that is simple and easy to understand. Also, the Python package used here is NumPy. Images captured by a webcam are processed in regions called regions of interest (ROIs). This region serves as the region of interest and the outer region, called the background, is ignored

B. Testing:

Gesture 1: Next slide
[1,0,0,0,0]
In this gesture, only the little finger is open and all other four fingers are closed.
Gesture 2: Previous slide
[0,0,0,0,1]
In this gesture, only the thumb is open and all other fingers are closed.
Gesture 3: Get Pointer
[0,1,1,0,0]
In this gesture, only the index is open and all remaining fingers are closed.
Gesture 4: To write on the slide
[0,1,0,0,0]
In this gesture, the index finger and middle finger is open. The remaining four are all closed.
Gesture 5: Undo
[0,1,1,1,0]
In this gesture, only the index, middle, and ring fingers are open.

All other fingers are closed. This gesture is intended to delete the last written part.

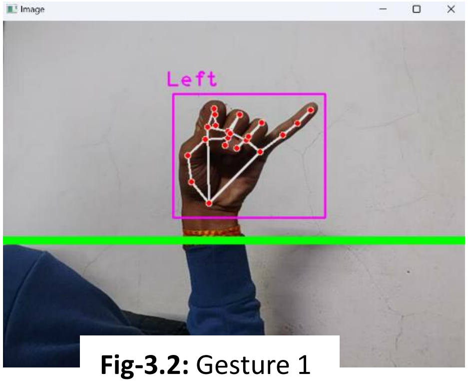

Fig-3.2: Gesture 1

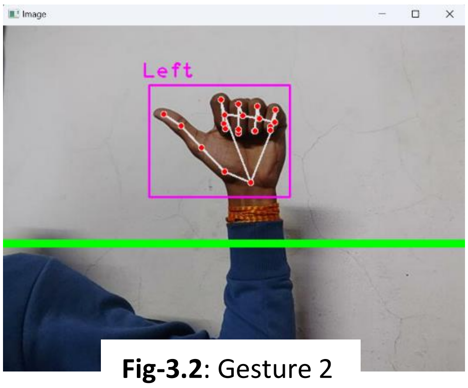

Fig-3.2: Gesture 2

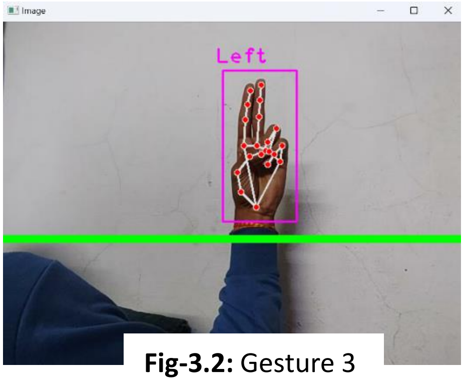

Fig-3.2: Gesture 3

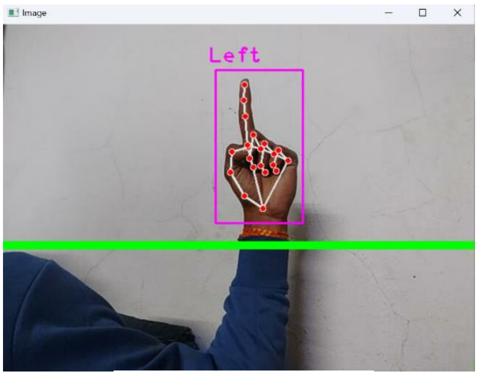

Fig-3.2: Gesture 4

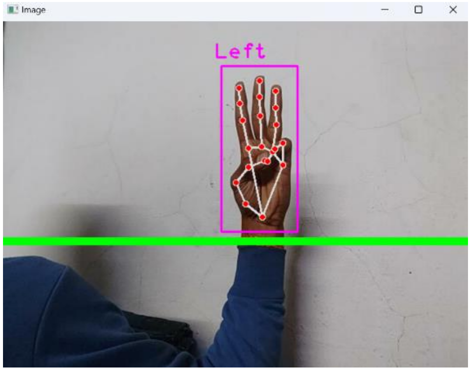

Fig-3.2: Gesture 5

VI. RESULT

We conducted various experiments to evaluate the performance of our system. In the first experiment, we evaluated the accuracy of hand gesture recognition and classification. The system was found to be able to accurately recognize and classify hand gestures in most cases with an average accuracy of 95%. The -second experiment tested the system's ability to control presentations using hand gestures. We found that this system smoothly controls the slides and allows us to perform a variety of actions, including: B. Proceed from or return to previous slide.

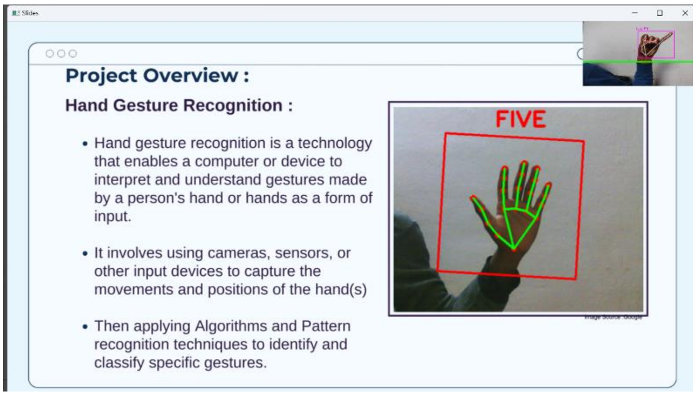

Fig-3.2: Gesture to Move Slide Forward

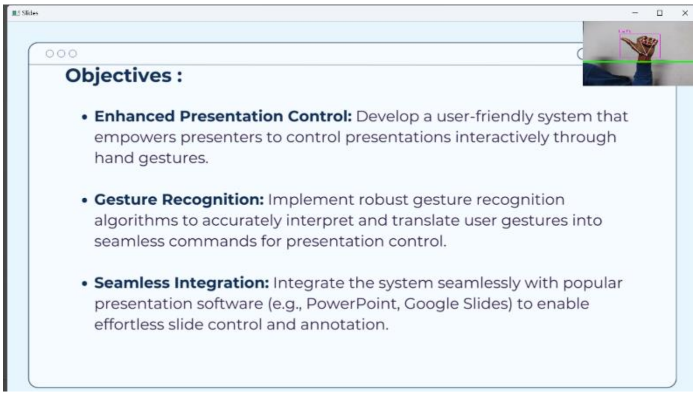

Fig-3.3: Gesture to Move Slide Backward

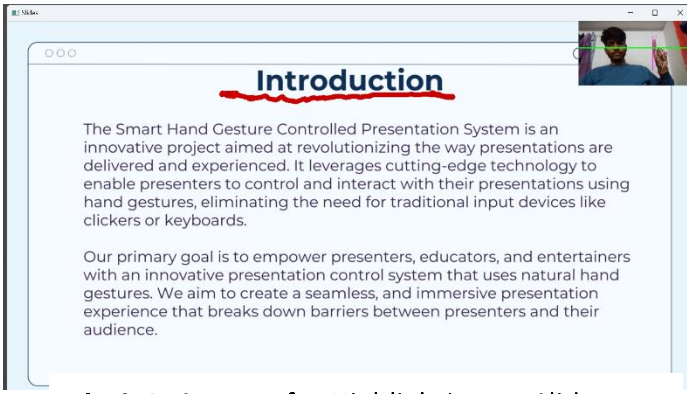

Fig-3.4: Gesture for Highlighting on Slide

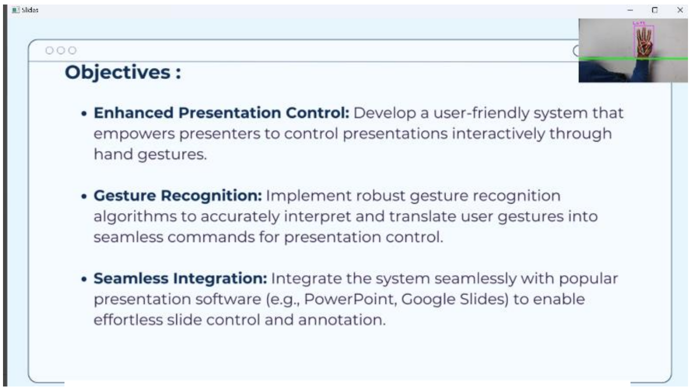

Fig-3.5: Gesture to Undo the Draw

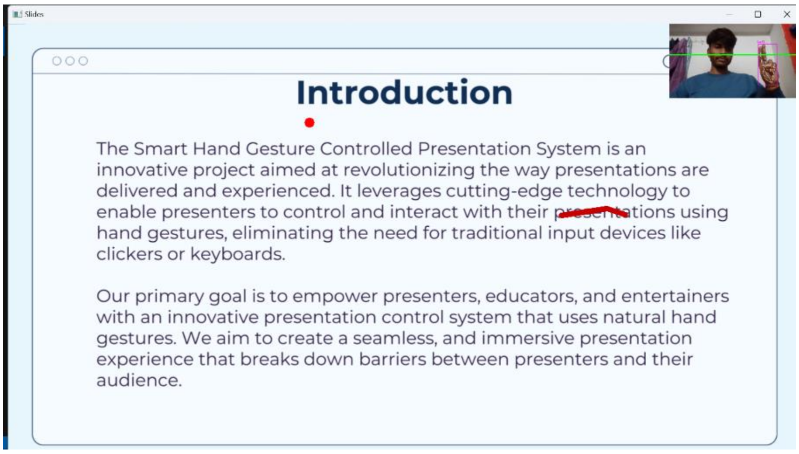

Fig-3.6: Gesture to Point on the Slides

V. FUTURE SCOPE

Gestures hold significant value across various fields and are deemed integral for future real-time interactions. The present scenario necessitates more natural modes of communication with computers and technology. Certainly! Here's the future scope of the project "Smart Hand Gesture-Controlled Presentation" in bullet points:

- Advanced Gesture Recognition:

- More precise detection of gestures.
- Differentiation between subtle movements.
- Recognition in varying lighting conditions.

- Integration with AI and Machine Learning:

- Adaptation to individual users' gestures.
- Improved accuracy over time.
- Seamless and intuitive interactions.

- Gesture Customization and Personalization:

- User-defined gestures for specific commands.
- Adjustable sensitivity settings.
- Enhanced user satisfaction and productivity.

- Collaborative Features:

- Simultaneous interaction for multiple users.
- Support for team collaboration and remote work.
- Facilitation of interactive workshops and brainstorming sessions.

VI. Conclusion

This project presents a program that allows hand gestures as a practical and easy way to control software. Gesture-based presentation controllers require no special markings and do not require a particularly highquality camera to recognize or record hand movements, so his Basic PC with an inexpensive camera can actually You can use it. This method tracks the positions of index fingers and counts the tips of each hand. The main goal of such a system is to make the components of the system inherently automated and easy to control. Therefore, we adopted this method to make the system easier to control. Through different tests, we have proven the effectiveness and efficiency of the system. We believe that the proposed system has the potential to enhance the overall presentation experience and make presentations more engaging and interactive.

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