User Interface using Hand Gestures

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***Abstract*— The use of hand gestures to control computer interfaces has become increasingly popular in recent years. This trend will continue as the application of augmented and virtual reality are increasing day by day. In this paper, we propose a method for controlling a mouse cursor using the Mediapipe framework developed by Google. Our approach uses a web camera to capture hand gestures and a machine learning model trained on a dataset of hand gestures to classify and identify the intended cursor movement. We pass this information to a user interface control module to perform mouse actions, making it a promising approach for gesture-based human-computer interaction.**

Keywords—mediapipe, hand gesture, landmarks, pyutogui,

I. Introduction

Gesture recognition is the process of recognizing human gestures through various technologies such as computer vision or motion capture. This technology has a wide range of applications, including in gaming, sign language translation, and human-computer interaction.

One of the tools that can be used for gesture recognition is MediaPipe, which is an open-source framework developed by Google for building multimodal applications. It allows developers to build gesture recognition pipelines using a variety of pre-existing components, such as hand tracking, gesture recognition, and rendering.

To use MediaPipe for gesture recognition, developers can start by training a machine learning model to recognize specific gestures. This is typically done using a large dataset of images or videos that show the gestures of interest. Once the model is trained, it can be integrated into a MediaPipe pipeline to recognize gestures in real-time.

The MediaPipe hand tracking component is used to track the movements of the user's hands in the video stream. This component uses machine learning algorithms to detect the presence of hands in the video and to estimate their 3D positions. The hand tracking information is then passed to the gesture recognition component, which uses the trained model to identify the specific gestures being performed.

Once the gestures have been recognized, they can be used to trigger various actions or events in the application. For example, in a gaming application, specific gestures could be used to control the game character or to interact with objects in the game world. In a sign language translation application, gestures could be used to translate sign language into text or speech.

In summary, MediaPipe is a useful tool for building gesture recognition applications. It allows developers to easily integrate machine learning models for gesture recognition into their pipelines, and to track and recognize gestures in real-time. This can enable a wide range of applications, from gaming to sign language translation.

II. Literature Survey

Hand gesture recognition and human-computer interaction have been actively studied in the field of computer science for several decades. Various approaches have been proposed to recognize hand gestures and enable effective interaction between humans and computers. This literature survey aims to provide an overview of the state-of-the-art research in this area and highlight the challenges and opportunities for future research.

One of the early approaches for hand gesture recognition was based on hand-crafted features such as edge points, curvature, and shape descriptors. These features were extracted from the hand region and used to train a classifier for gesture recognition. However, the performance of these methods was limited by the need for manual feature engineering and the inability to handle variations in hand shape and pose.

To overcome these limitations, deep learning-based approaches have been proposed in recent years. These methods use convolutional neural networks (CNNs) to automatically learn features from the hand region and perform gesture recognition. These methods have shown promising results in terms of recognition accuracy and robustness to variations in hand shape and pose.

One of the key challenges in hand gesture recognition is the limited availability of large-scale datasets for training and evaluating the performance of gesture recognition algorithms. To address this issue, several datasets have been proposed in the literature. The most widely used dataset is the Chalearn LAP IsoGD dataset, which contains over 200,000 labeled hand gestures performed by 26 subjects. Other datasets include the MSR Action3D dataset, which contains 20 action classes performed by 10 subjects, and the EgoHands dataset, which contains hand gestures performed in natural environments.

In addition to recognition accuracy, another important aspect of hand gesture recognition is the ability to handle real-time interaction. To achieve this, several methods have been proposed to reduce the computational complexity of the recognition algorithms. These methods include feature pruning, lightweight network architectures, and approximate computation techniques.

Hand gesture recognition is a crucial aspect of human-computer interaction (HCI) as it allows for more natural and intuitive communication between humans and computers. Over the past decade, there has been a significant amount of research in this area, focusing on various aspects such as gesture recognition algorithms, user-friendly interfaces, and applications in various domains.

One of the key challenges in hand gesture recognition is the development of robust algorithms that can accurately and efficiently detect and classify hand gestures. Researchers

have proposed various approaches to tackle this problem, including model-based algorithms, template-based algorithms, and machine learning-based algorithms. For example, in a study by Chen et al. (2009), a model-based algorithm was proposed that uses a combination of edge detection, skin color segmentation, and geometric features to recognize hand gestures. In another study by Lee et al. (2011), a template-based algorithm was proposed that uses dynamic time warping to compare hand gestures to a set of pre-defined templates. In contrast, machine learning-based algorithms, such as those based on artificial neural networks, have also been proposed, as they can learn from training data and adapt to new situations.

Another important aspect of hand gesture recognition is the design of user-friendly interfaces that allow users to easily and intuitively interact with computers using gestures. Researchers have proposed various approaches to this problem, including the use of gesture dictionaries, gesture feedback, and gesture-based commands. For example, in a study by Chen et al. (2010), a gesture dictionary was proposed that contains a set of pre-defined gestures and their corresponding meanings, allowing users to easily learn and use gestures for different tasks.

Hand gesture recognition allows for improved human-computer interaction by allowing users to control their devices using hand gestures instead of traditional input methods. This technology can enhance user experience and improve efficiency in various applications.

III. Methodology

To convert user's hand gesture into respective mouse action we use the following pipeline:

1 Palm Detection

2 Skeleton landmark Prediction

3 Spatial Normalisation

4 Neural Model Design & Training

5 Gesture Prediction

6 Performing Adequate Action

A. Palm Detection

We use a single shot detector model optimised for mobile real-time applications to identify initial hand placements.

Firstly, mediapipe uses a palm detector rather than a hand detector since estimating bounding boxes of stiff objects such as palms and fists is much easier than identifying hands with articulated fingers. Furthermore, because palms are smaller objects, the non-maximum suppression technique works well for two-hand self-occlusion scenarios such as handshakes. Palm detector crops the part of the frame where palm is detected.

B. Skeloton Landmark Prediction

Palm detector crops the part of the frame where palm is detected. Landmark model takes the output image given by palm detection and retrieves 21 key points forming the skeleton of hand, 4 for each finger, 3 for the thumb and 2 for the lower palm area. Palm detection tells us about the presence of a hand, its handedness (left or(and) right) and 21 skeleton landmark points if any hand is present in the frame.

C. Spatial Normalisation

The landmark model returns 21 skeletal points of hand as 3D co-ordinate values reflecting the distance from the upper left corner of the screen as well as the distance from the web camera. This is a challenge for gesture identification since the same gesture has varying co-ordinate values depending on how close the hand is to the web camera. Furthermore, relative lengths or angles cannot be exploited since they alter with the distance of the hand from the web camera. These values also changes when we give them same gesture but at different screen regions altering the co-ordinate values.

To overcome this problem, we have normalised the values of the co-ordinates by assuming one of the 21 points as reference and subtracted the co-ordinates of this point's co-ordinate values from other the other point's co-ordinate values. This give us the same value for a point irrespective of the position of the hand provided hand is at same distance from the screen.

The values of a point's co-ordinate still vary if the distance of hand relative to screen is changed.

D. Neural Model Design & Training

To overcome the issue with distance related variation e have designed a sequential neural model using *tensorflow* using the *Keras* API.

Two values i.e., X and Y co-ordinates of each of the 21 points are given as input to the model. From this we conclude that we need to give 42 values of the landmarks for the training. Along with this we also provide a class label to each input layer which will later be linked to particular hand gesture.

Overall, we give 43 values as input to the model making the number of nodes in the input layer of model 43. Other than this, for the hidden layer parameters we have tried different variation by varying the number of hidden layers, number of nodes in them and dropout layers to avoid the overfitting. We observed that increasing the number of hidden layers over 2 results in overfitting so we have kept it to 2 along with 2 dropout layers. At last the number of nodes in the output can be set according to the number of gestures to be utilised.

For the hidden dense layers we have used relu activation function for the back propagation along with updating weights and softmax at last output dense class which is advised for the multiclass classification since it provides the output in terms of probabilities suitable for this application.

This trained model in then saved to make future predictions.

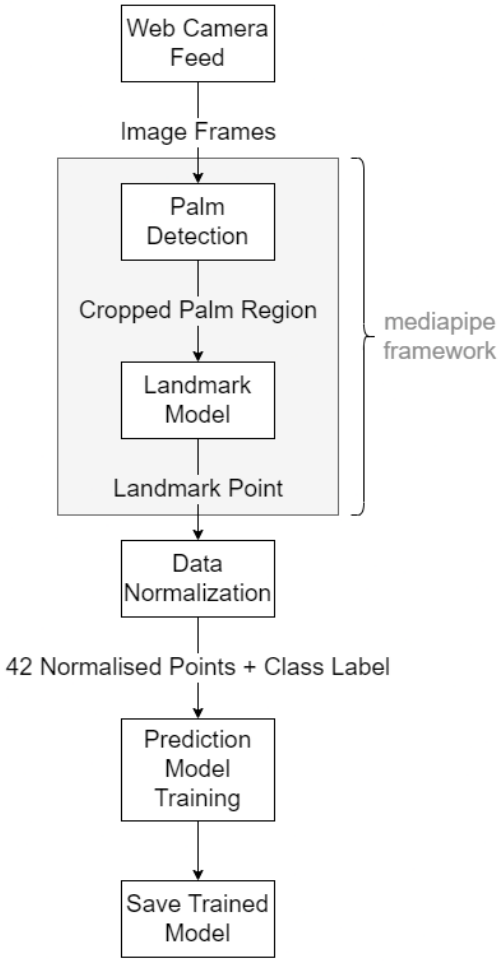

Fig 1. Model Training Block Diagram

E. Gesture Prediction

We use OpenCV python module to take live video feed as input from the web camera and breakdown it into image frames. These frames are passed to the mediapipe framework to get the landmark points.

These points are again normalised to make them size and location independent, and then are passed to the trained model which classifies it based on the relative values of the passed points.

F. Performing Adequaate Action

Depending on the class given by the gesture model we can perform any of the following actions:

- Hover the cursor
- Single Click
- Double Click
- Change Application Window
- Scroll Up
- Scroll Down
- Close Current Window
- Perform Right Button Action
- Perform Left Button Action

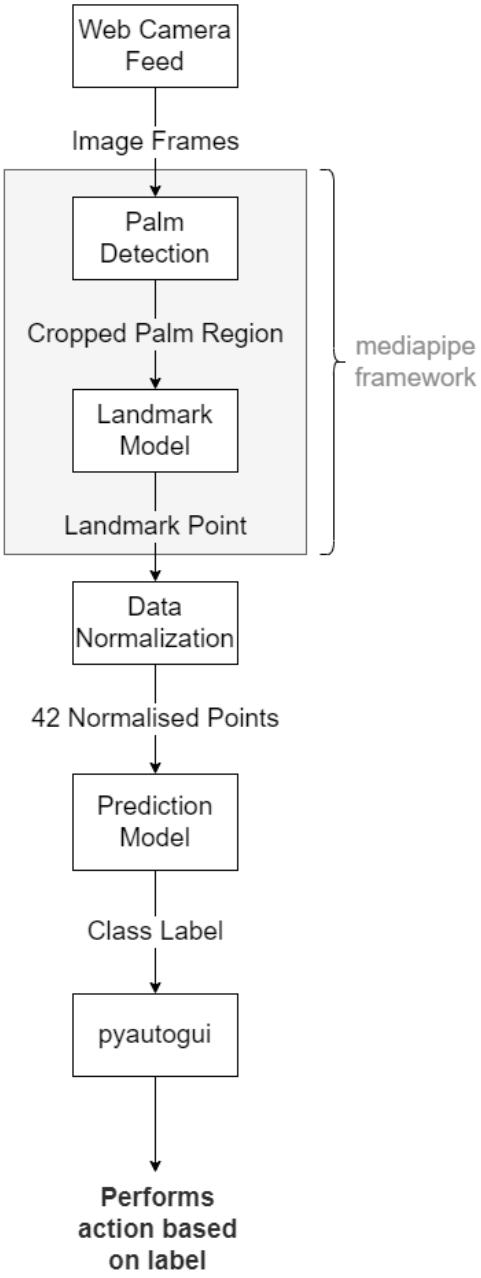

Fig 2. Gesture Control Block Diagram

The gestures for these actions have been shown below.

Fig 3. Hand gesture for Hovering of Cursor

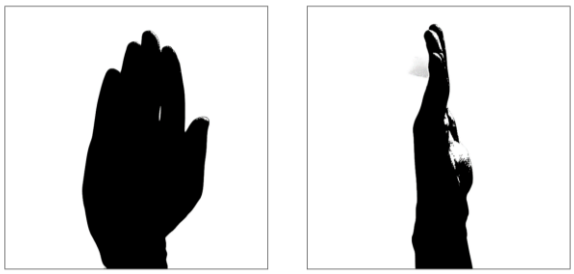

Fig 4. Hand gesture for Changing Application Window (left) and Closing Current Window (right)

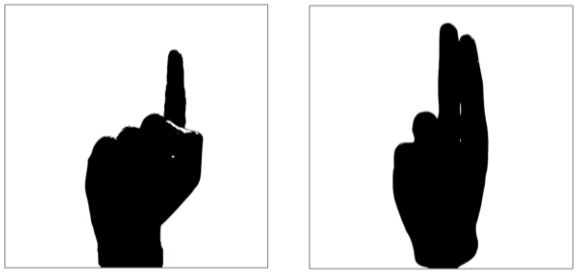

Fig 4. Hand gesture for Single Click (left) and Double Click (right)

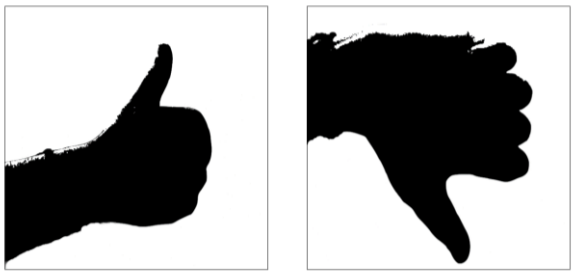

Fig 4. Hand gesture for Scrolling Up (left) and Scrolling Down (right)

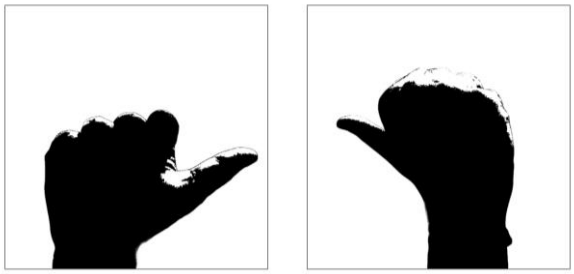

Fig 4. Hand gesture for Pressing Left Button (left) and Pressing Right Button (right)

IV. Conclusion

The Mediapipe framework was able to accurately detect and track the hand gestures, and the PyAutoGUI library was able to translate these gestures into corresponding mouse actions.

The implemented system showed good performance in terms of accuracy and reliability. The hand gesture recognition system was able to recognize and respond to various hand gestures with a high level of accuracy. The mouse control system was also able to accurately mimic the movements of a physical mouse, providing a seamless and intuitive user experience. This indicates the robustness and adaptability of the system, which can be useful in real-world applications.

Overall, this project has demonstrated the potential of using hand gestures for mouse operations and has provided a proof-of-concept for further development and improvements. The system can be extended to support more hand gestures and additional mouse actions and can be combined with user face so that before performing actions system first authorizes its user. This concept can also be expanded to use multi-hand gesture to give use more precise and variety of gestures.

Additionally, the system can be integrated into various applications, such as gaming, productivity, and accessibility, to enhance the user experience and improve efficiency.

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