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School of Computer Science and Engineering
CSE4015 Human Computer Interaction
Slot: A2+TA2

Project Report

Project Title

Aid to Detect Sign Language

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1. Introduction

The ability to communicate effectively is an essential part of our lives, and for individuals who are deaf or hard of hearing, sign language is a crucial mode of communication. However, not everyone is familiar with sign language, which can lead to miscommunication and isolation for the deaf community.

To address this issue, this project aims to develop an aid to detect sign language using computer vision and machine learning techniques. The aid will be able to recognize sign language gestures and translate them into written or spoken language, providing a bridge for communication between the deaf and hearing communities.

This project will involve the development of a sign language dataset, training of a machine learning model, and the integration of the aid with a camera to capture real-time sign language gestures. The project's success will be evaluated by measuring the accuracy of the sign language detection and translation, as well as its usability for the target users.

The potential impact of this project is significant as it can improve communication accessibility and inclusion for the deaf community, promoting greater social interaction and reducing barriers to communication. This project aligns with the United Nations Sustainable Development Goals of promoting inclusive and accessible communities, providing access to education, and reducing inequalities.

1.1. Scope

The scope of this project includes developing a system for real-time sign language detection using OpenCV, Mediapipe holistic, and a deep neural network with LSTM layers for sequence processing. The system will be able to capture and recognize hand and body movements in real-time and translate them into text or speech.

The project will involve collecting a dataset of sign language gestures, training a deep neural network with LSTM layers for sequence processing, and developing a real-time sign language detection system using OpenCV. The scope also includes testing and evaluating the accuracy and performance of the system in recognizing sign language gestures.

Additionally, the scope of this project includes exploring potential applications and extensions of the real-time sign language detection system. For example, the system can be integrated into mobile applications or web browsers to facilitate communication between deaf and hearing individuals. Furthermore, the system can be extended to recognize more complex sign language gestures, enabling more nuanced communication between users.

It is essential to note that the scope of this project is limited to the development of a real-time sign language detection system using computer vision and machine learning techniques. The project does not include the development of a comprehensive sign language translation system, and the accuracy of the system's translation is limited to the gestures that have been included in the dataset. Future work can be done to expand the dataset and improve the accuracy of the translation system.

1.2. Motivation

The motivation for this project is to promote accessibility and inclusion for individuals who are deaf or hard of hearing. Sign language is a crucial mode of communication for this community, and improving its accessibility can reduce communication barriers and promote social interaction.

Unfortunately, not everyone is familiar with sign language, which can lead to miscommunication and isolation for the deaf community. This project aims to bridge the communication gap between the deaf and hearing communities by developing a real-time sign language detection system.

The system will allow for the recognition and translation of sign language gestures in real-time, providing a means of communication between deaf and hearing individuals. This can improve accessibility and inclusion for the deaf community in a variety of settings, including education, healthcare, and social interactions.

Furthermore, the project's motivation aligns with the United Nations Sustainable Development Goals of promoting inclusive and accessible communities, providing access to education, and reducing inequalities. By developing a real-time sign language detection system, this project can contribute to achieving these goals and promoting social equity and inclusion.

1.3. Aim of the proposed Work

The aim of the proposed work in this project is to develop a real-time sign language detection system using computer vision and machine learning techniques. The system will be able to recognize sign language gestures in real-time, translate them into text or speech, and facilitate communication between deaf and hearing individuals.

To achieve this aim, the proposed work will involve collecting a dataset of sign language gestures, training a deep neural network with LSTM layers for sequence processing, and developing a real-time sign language detection system using OpenCV. The system will capture the user's hand and body movements through a camera and process them in real-time to detect and translate sign language gestures into text or speech.

The proposed work will also include testing and evaluating the accuracy and performance of the real-time sign language detection system. The evaluation will involve measuring the accuracy of the system in recognizing sign language gestures and the system's ability to translate them into text or speech.

Furthermore, the proposed work will explore potential applications and extensions of the real-time sign language detection system, such as integrating it into mobile applications or web browsers to facilitate communication between deaf and hearing individuals. Additionally, the proposed work will investigate the potential to expand the dataset and improve the accuracy of the translation system to recognize more complex sign language gestures.

Overall, the aim of this project's proposed work is to develop a real-time sign language detection system that can promote accessibility and inclusion for individuals who are deaf or hard of hearing.

1.4. Objective(s) of the proposed work

The objectives of this project are as follows:

1. Collecting a dataset of sign language gestures: The first objective of the project is to collect a dataset of sign language gestures that will be used to train the deep neural network with LSTM layers for sequence processing. The dataset should include a variety of sign language gestures and be diverse enough to capture the nuances of sign language.
2. Training a deep neural network with LSTM layers for sequence processing: The second objective of the project is to train a deep neural network with LSTM layers for sequence processing. The network should be able to learn the patterns and sequences of hand and body movements in sign language gestures, enabling it to accurately recognize them.
3. Developing a real-time sign language detection system using OpenCV: The third objective of the project is to develop a real-time sign language detection system using OpenCV. The system should be able to capture the user's hand and body movements through a camera and process them in real-time to detect and translate sign language gestures into text or speech.
4. Testing and evaluating the accuracy and performance of the system: The fourth objective of the project is to test and evaluate the accuracy and performance of the real-time sign language detection system. The evaluation should involve measuring the accuracy of the system in recognizing sign language gestures and the system's ability to translate them into text or speech.
5. Exploring potential applications and extensions of the system: The fifth objective of the project is to explore potential applications and extensions of the real-time sign language detection system. The system can be integrated into mobile applications or web browsers to facilitate communication between deaf and hearing individuals. Additionally, the project will investigate the potential to expand the dataset and improve the accuracy of the translation system to recognize more complex sign language gestures.

Overall, the objectives of this project are to develop a real-time sign language detection system that can accurately recognize sign language gestures and translate them into text or speech. By achieving these objectives, the project can promote accessibility and inclusion for individuals who are deaf or hard of hearing.

2.Related work

Several related works have been conducted in the field of sign language detection and translation using computer vision and machine learning techniques. Some of these related works are as follows:

1. DeepSign: A System for Automatic Sign Language Detection and Recognition: This system uses a combination of 3D Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) for sign language detection and recognition.
2. Sign Language Recognition using Kinect Sensor: This system uses the depth sensor of the Kinect sensor to detect hand gestures and body movements, and a Hidden Markov Model (HMM) to recognize sign language gestures.
3. Sign Language Recognition using Leap Motion Controller: This system uses the Leap Motion Controller to capture hand and finger movements and a Support Vector Machine (SVM) to classify sign language gestures.

4. Sign Language Recognition using Neural Networks: This system uses a combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to recognize sign language gestures.
5. Sign Language Translation: This system uses a combination of Computer Vision and Natural Language Processing (NLP) techniques to translate sign language gestures into text or speech.

These related works provide a basis for the proposed work in this project, as they demonstrate the potential of using computer vision and machine learning techniques for sign language detection and translation. However, the proposed work in this project aims to improve upon these related works by developing a real-time sign language detection system that is accurate, efficient, and accessible.

S.No.	Title	Findings	Authors
1.	A machine learning based approach for the detection and recognition of Bangla sign language	It demonstrates Hand Gesture recognition which is performed using HOG (Histogram of Oriented Gradients) for extraction of features from the gesture image and SVM (Support Vector Machine) as classifier. Finally, predict the gesture image with output text. This output text is converted into audible sound using TTS (Text to Speech) converter.	Muttaki Hasan Tanvir Hossain Sajib Mrinmoy Dey
2.	Automated Sign Language Interpreter	It demonstrates Instrumented gloves with audio out are the solution here. The gloves attached with various sensors are worn for sign interpretation. Hence, the proposed system solves the problem and helps the dumb people in communication with the rest of the world at low cost.	Hardik Rewari, Vishal Dixit, Dhroov Batra, Hema N
3.	Vision-based sign language translation device	The proposed system which is an interactive application program developed using LABVIEW software and incorporated into a mobile phone. The sign language gesture images are acquired using the inbuilt camera of the mobile phone; vision analysis functions are performed in the operating system and provide speech output through the inbuilt audio device thereby	Yellapu Madhuri, G Anitha, M Anburajan

		minimizing hardware requirements and expense. The experienced lag time between the sign language and the translation is little because of parallel processing. This allows for almost instantaneous recognition from finger and hand movements to translation. This is able to recognize one handed sign representations of alphabets (A-Z) and numbers (0-9). The results are found to be highly consistent, reproducible, with fairly high precision and accuracy	
4	Sign language interpreter using a smart glove	It demonstrates a novel approach of interpreting the sign language using the portable smart glove. LED-LDR pair on each finger senses the signing gesture and couples the analog voltage to the microcontroller	Nikhita Praveen Naveen Karanth M S Megha
5	Speech Recognition Automation by ASR	Author have presented multiple experiments to design a statistical model for deaf people for the conversion to sign language from the speech set. They have further made the system that automates the speech recognition by ASR by the help of animated demonstration and translation statistical module for multiple sets of signs. This paper demonstrates the process that translates the speech by automation recognizer having all three mentioned configurations. The paper came up with the result with finite type state transducer having the word error rate among the range of 28.21% and 29.27% for the output of ASR.	Matthew Zajechowski
6.	Indian Sign Language (ISL) Translation System	It functions continuously by offering a sequence of sign	M.Jerin Jose, V. Priyadarshini,

	For Sign Language Learning	language gestures to create an automated training set and by offering the spots signs from the set of training. They have put forth a system that supervises the sentence and determines the associated compound sign gesture using a supervision of noisy texts, using instance learning as a density matrix technique. The group that was first intended to demonstrate the continuous data stream of words is now used as a training group for identifying gesture posture. They have experimented with this small sample of automated data that is used for their training, identification, and storage of subtle sign data.	M.Suresh Anand, A.Kumaresan, Dr.N. Mohan Kumar
7.	A real-time portable sign language translation system	It uses the wireless system to process the data. To differentiate hand motion, they have inner sensors put into gloves to show the parameters as given by, posture, orientation, motion, defined of the hand in Taiwanese Sign Language could be recognize in no error. The hand gesture is considered by flex inner sensor and the palm size considered using the g sensor and the movement is considered using the gyroscope. Input signals would have to be consider for testing for the sign to be legal or not periodically. As the signal which was sampled can stay longer than the pre-set time, the legal gesture sent using phone via connectivity like Bluetooth for differentiating gestures and translates it. With the proposed architecture and algorithm, the accuracy for gesture recognition is quite satisfactory. As demonstrated the result get	Lih-Jen Kau, Wan-Lin Su, Pei-Ju Yu, Sin-Jhan Wei

		the accuracy of 94% with the concurrent architecture.	
9.	A survey on 3D hand pose estimation: Cameras, methods, and datasets	This paper contains a comprehensive survey, including depth cameras, hand pose estimation methods, and public benchmark datasets. First, a markerless approach is proposed to evaluate the tracking accuracy of depth cameras with the aid of a numerical control linear motion guide. Second, the methods and lines of research are summarized. Third, existing benchmark datasets and evaluation criteria are identified to provide further insight into the field of hand pose estimation.	Li Rui, Liu Zhenyu, Tan Jianrong
10.	A Survey on Hand Pose Estimation with Wearable Sensors and Computer-Vision-Based Methods	The purpose of this survey is to conduct a comprehensive and timely review of recent research advances in sensor-based hand pose estimation, including wearable and vision-based solutions. Hand kinematic models are firstly discussed. An in-depth review is conducted on data gloves and vision-based sensor systems with corresponding modeling methods. Particularly, this review also discusses deep-learning-based methods, which are very promising in hand pose estimation. Moreover, the advantages and drawbacks of the current hand gesture estimation methods, the applicative scope, and related challenges are also discussed.	Weiya Chen ,Chenchen Yu, Chenyu Tu, Zehua Lyu, Jing Tang, Shiqi Ou, Yan Fu and Zhidong Xue
11.	Vision-based hand pose estimation: A review	A review on various CV based hand pose estimations were done. CV has a distinctive role in the development of direct sensing-based HCI. However, various challenges must be addressed in order to satisfy the	Ali Erol. George Bebis, Mircea Nicolescu, Richard D. Boyle, Xander Twombly

		demands of potential interaction methods. Currently, CV-based pose estimation has some limitations in processing arbitrary hand actions. Incorporating the full functionality of the hand in HCI requires capturing the whole hand motion. However, CV can only provide support for only a small range of hand actions under restrictive conditions.	
12.	Hand pose estimation and tracking in real and virtual interaction:A review	The goal of this survey is to develop an up-to-date taxonomy of the state-of-the-art vision-based hand pose estimation and tracking methods with a new classification scheme: hand-object interaction constraints. This taxonomy allows us to examine the strengths and weaknesses of the current state of the art and to highlight future trends in the domain.	Ammar Ahmad, Cyrille Migniot, Albert Dipanda
13	ML Based Sign Language Recognition System	It reviews different steps in an automated sign language recognition (SLR) system.The model is based on vision-based isolated hand gesture detection and recognition.The model made use of a convex hull for feature extraction and KNN for classification.	A.Adeyanju, O.O.Bello, M.A.Adegboye
14.	Trajectory-based recognition of dynamic Persian sign language using hidden Markov model	Existing Persian sign language recognition systems are mainly restricted to static signs which are not very useful in everyday communications.These time-varying trajectories were then modeled using Hidden Markov Model (HMM) with Gaussian probability density functions as observations.	Saeideh GhanbariAzar, Hadi Seyedarabi

15.	Automatic detection of learners effect from gross body language.	We explored the reliability of detecting learners' affect by monitoring their gross body language body position and arousal	Sidney D'Mello, and art Graesser.
16.	Facial expressions recognition for arabic sign language translation	Arabic Sign Language (ArSL) tends to be a descriptive gesture language, facial expressions are involved in 70% of total signs.The system employed already existing technical methods such as: Recursive Principle Components (RPCA) for feature extraction and Multi-layer Perceptron (MLP) for classification.	A.S. Elons; Menna Ahmed; Hwaidaa Shedid

3.1. Introduction

The development of a real-time sign language detection system using computer vision and deep learning techniques has the potential to revolutionize communication for individuals with hearing or speech impairments. This system will be able to recognize and translate sign language gestures into text or speech, enabling a smooth and effective exchange of information.

To achieve this, the system will utilize OpenCV, a popular computer vision library, and Mediapipe holistic, a toolkit that enables holistic detection of hands, body, and facial landmarks. OpenCV will enable the system to capture live video of the user performing sign language, which will then be processed by the deep learning model.

The deep learning model will consist of LSTM layers for sequence processing. This architecture is ideal for processing sign language, which is a sequence of gestures that form words and sentences. The LSTM layers will enable the system to remember and interpret the previous gestures' context, providing accurate translations.

The system's output will be either text or speech, depending on the user's preference. If the user selects text output, the system will generate the text of the sign language, enabling communication through written text. Alternatively, if the user selects speech output, the system will utilize text-to-speech technology to convert the sign language gestures into spoken language.

In conclusion, the development of a real-time sign language detection system using computer vision and deep learning techniques will enable effective communication for individuals with hearing or speech impairments. The system's ability to recognize and translate sign language gestures into text or speech will bridge the communication gap and promote inclusivity.

3.2. Requirement Analysis

3.2.1. Stakeholder Identification

Stakeholder identification is an important aspect of any project, as it helps to identify individuals or groups who have a vested interest in the project and may be impacted by its outcomes. The stakeholders of this project include:

1. Deaf and hard of hearing individuals: The primary stakeholders of this project are deaf and hard of hearing individuals who rely on sign language as their primary mode of communication. The real-time sign language detection system developed in this project can significantly improve their accessibility and communication with hearing individuals.
2. Sign language interpreters: Sign language interpreters are another stakeholder group for this project, as the system can be used to facilitate their work and make their services more accessible.
3. Health care providers: Health care providers who work with deaf and hard of hearing patients can benefit from the real-time sign language detection system, as it can improve communication between the provider and the patient.
4. Educational institutions: Educational institutions that serve deaf and hard of hearing students can also benefit from the real-time sign language detection system, as it can improve communication between teachers and students.
5. Technology companies: Technology companies that are interested in developing assistive technology for individuals with disabilities can benefit from the knowledge gained in this project and can potentially integrate the system into their products.
6. General public: The general public can also benefit from the real-time sign language detection system, as it can promote accessibility and inclusion for individuals who are deaf or hard of hearing.

Overall, this project has a wide range of stakeholders who can benefit from the development of a real-time sign language detection system, and it has the potential to improve accessibility and communication for individuals who are deaf or hard of hearing.

3.2.2. Functional Requirements

The functional requirements of the proposed sign language detection system include:

1. Key Point Extraction: The system should be able to extract key points from the input video stream using Mediapipe holistic.
2. Sequencing: The system should sequence the extracted key points for use by the LSTM layers.
3. Training Data: The system should be trained on a dataset of sign language gestures that includes a wide range of gestures and is representative of different sign languages.
4. Deep Learning Model: The system should use a deep neural network model with LSTM layers for sequences to classify the sign language gestures.
5. Real-Time Detection: The system should perform real-time sign language detection in the input video stream using OpenCV.
6. Accuracy: The system should be accurate in detecting sign language gestures in real-time.

7. User Interface: The system should have a user interface that allows users to select the input video source, view the real-time detection results, and access any necessary settings.
8. Portability: The system should be portable and able to run on different hardware platforms, including desktop computers and mobile devices.
9. Integration: The system should be easily integrated into existing applications, such as communication tools or assistive technology.
10. Accessibility: The system should be designed with accessibility in mind, such as providing adjustable font sizes and contrast levels for users with visual impairments.

These functional requirements are essential for the successful development and implementation of the proposed sign language detection system.

3.2.3. Non Functional Requirements

The non-functional requirements of the proposed sign language detection system include:

1. Performance: The system should be able to process input video streams in real-time with minimal delay or lag, to ensure that the results are displayed quickly and accurately.
2. Scalability: The system should be scalable to handle large amounts of input data and should be able to support multiple users simultaneously.
3. Reliability: The system should be reliable and robust, with a low error rate and minimal downtime.
4. Usability: The system should be user-friendly and easy to use, with clear and concise instructions for users.
5. Security: The system should be secure and protect user data and information from unauthorized access or breaches.
6. Compatibility: The system should be compatible with different operating systems, hardware platforms, and software frameworks.
7. Maintainability: The system should be maintainable, with clear documentation and instructions for updating and maintaining the system.
8. Accessibility: The system should be accessible to users with disabilities, including those with visual or hearing impairments.
9. Performance Metrics: The system should be evaluated using appropriate performance metrics, such as accuracy, precision, recall, and F1 score, to ensure that it meets the required performance standards.
10. Ethical Considerations: The system should be designed and implemented in an ethical and responsible manner, taking into consideration issues such as privacy, consent, and bias.

These non-functional requirements are important considerations for the development and implementation of the proposed sign language detection system, to ensure that it meets the required standards for performance, usability, security, and accessibility, among others.

3.2.4. System Requirements

3.2.4.1. H/W Requirements(details about Application-Specific Hardware)

In general, the following are some hardware requirements that may be necessary for an application that can detect sign language:

1. Processor: A powerful processor is needed to handle the complex computations involved in image processing and machine learning algorithms. A multi-core processor such as Intel Core i5 or i7, or AMD Ryzen 5 or 7, would be ideal for such applications.

2. Graphics Card: A dedicated graphics card can help accelerate the image processing tasks by offloading some of the computation from the processor. An NVIDIA or AMD GPU with CUDA support is recommended, as many deep learning frameworks utilize CUDA for accelerated computation.

3. RAM: The amount of RAM required will depend on the size of the dataset used for training and the complexity of the machine learning models used. At least 8 GB of RAM is recommended, but 16 GB or more would be better.

4. Storage: Sufficient storage is needed to store the datasets used for training, as well as the models and the application itself. A solid-state drive (SSD) is recommended for faster read and write speeds.

5. Camera: A high-quality camera capable of capturing clear images of sign language gestures is essential. A high-resolution webcam or a DSLR camera with video recording capabilities would be suitable.

6. Microphone: A good quality microphone is necessary for capturing any accompanying audio, which may be useful for improving the accuracy of the model.

7. Display: A high-resolution display is necessary to display the captured video and the output of the sign language detection application.

Overall, the hardware requirements for an application that can detect sign language can be demanding, particularly if the application needs to be run in real-time. However, advancements in hardware technology have made it possible to develop such applications even on relatively modest hardware configurations.

3.2.4.2. S/W Requirements(details about Application-Specific Software)
Contents of document

The software requirements for an application that can detect sign language will depend on the specific implementation and the programming language and framework used. However, in general, the following are some software requirements that may be necessary for an application that can detect sign language:

1. Operating System: The application may be developed for a specific operating system such as Windows, MacOS, or Linux. The software requirements will vary depending on the operating system used.

2. Programming Language: The application may be developed using one or more programming languages such as Python, C++, or Java. The software requirements will depend on the programming language used.

3. Development Environment: A development environment such as Visual Studio, PyCharm, or Eclipse may be required to develop and test the application.

4. Image Processing Library: An image processing library such as OpenCV or Pillow may be required to process the images captured by the camera.
5. Machine Learning Framework: A machine learning framework such as TensorFlow, PyTorch, or Keras may be required to train and deploy the machine learning models used for sign language detection.

6. Database: A database such as MySQL or SQLite may be required to store the data used for training and testing the machine learning models.

7. User Interface: A user interface library such as Tkinter or PyQt may be required to develop a graphical user interface for the application.

8. Audio Processing Library: An audio processing library such as PyAudio or Librosa may be required to process the accompanying audio captured along with the video.

9. Web Framework: If the application is web-based, a web framework such as Django or Flask may be required to develop the web application.

10. Cloud Computing Platform: If the application is deployed on a cloud computing platform, additional software requirements such as Docker and Kubernetes may be necessary.

Overall, the software requirements for an application that can detect sign language can be complex and varied. However, the availability of open-source libraries and frameworks has made it easier to develop such applications without the need for significant software development expertise.

4. Proposed Methodology

1. Collect keypoints from mediapipe holistic:

   Mediapipe Holistic is a computer vision library developed by Google that uses machine learning models to detect and track key points on a person's body, including their face, hands, and body. The library provides a set of pre-trained models that can be used to extract keypoints from live video or recorded images.

   Hand Keypoints: These include key points on the fingers, such as the tips, the base, and the knuckles. These keypoints can be used to track hand gestures and movements.

By tracking the movement and position of these keypoints over time, we are able to build a sophisticated ASL Translation application that can interpret and respond to human actions in real-time.

2. Train a deep neural network with LSTM layers for sequences:

   Training a deep neural network with LSTM layers for sequences is the technique we have used in building our sign language translation project:

   - Data Collection: The first step is to collect a dataset of sign language sequences. This is done by using the dataset from mediapipe holistic.
   - Data Preprocessing: The data collected is then preprocessed before it is used to train the LSTM network. This includes segmenting videos into individual signs or words, and converting the video frames into a format that can be fed into the LSTM network.
   - Data Augmentation: Augmenting the dataset with variations of the original data helped prevent overfitting and improve our model's performance. This was done by adding noise to the input data, flipping the video horizontally, or changing the lighting conditions, etc.
   - Model Architecture: The LSTM network is designed to take in the preprocessed video frames as input and predict the corresponding sign language sequence. The network consists of multiple LSTM layers, along with fully connected layers, dropout layers, and batch normalization layers.
   - Training: The LSTM network is then trained on the preprocessed dataset using backpropagation with the Adam optimizer. The loss function is designed to minimize the difference between the predicted and actual sign language sequences.
   - Evaluation: After training, the performance of the LSTM network is evaluated on a separate validation dataset. This helped us identify areas where the model needs improvement, and guided us for further iterations of the training process.
   - Deployment: Finally, the trained LSTM network is deployed in a sign language translation application. This also involves real-time video input from a webcam or pre-recorded video, and outputting the corresponding sign language sequence or text.

3. Perform real time sign language detection using OpenCV:

   Real-time sign language detection using OpenCV can be accomplished through the following steps:

   1. Preprocessing of input frames: The input frames must be preprocessed to enhance the image quality and reduce noise. This can be achieved by converting the input frame to grayscale and applying filters like Gaussian blur or median blur to smooth out the image.

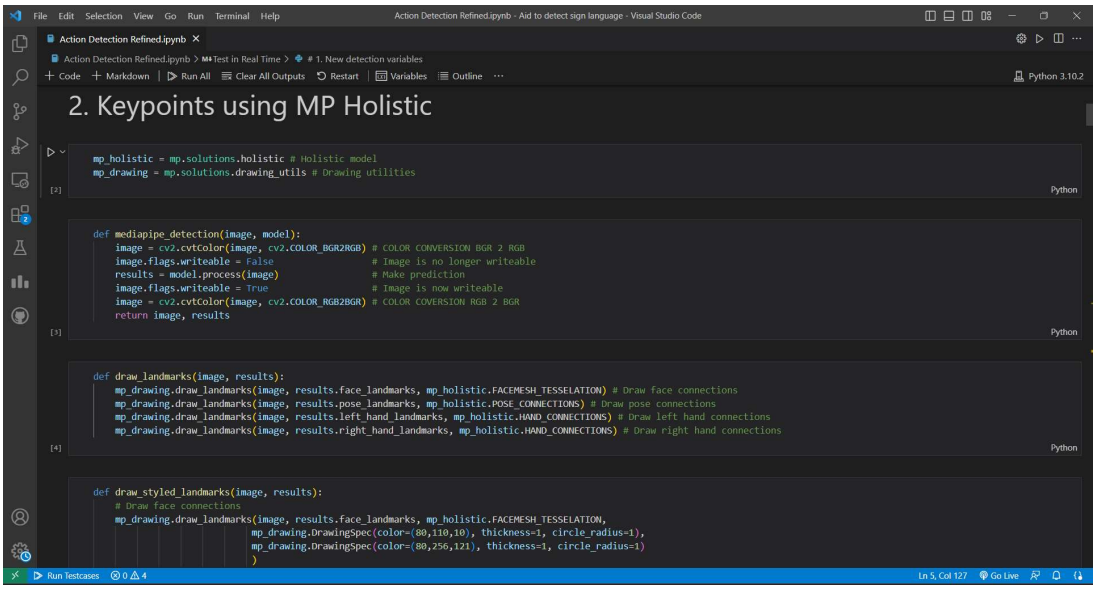
   2. Hand detection: Once the image is preprocessed, the next step is to detect the hand in the image. This can be done using various techniques like thresholding, contour detection, or background subtraction. One of the popular methods is to use a pre-trained Haar Cascade classifier to detect the hand in the image.

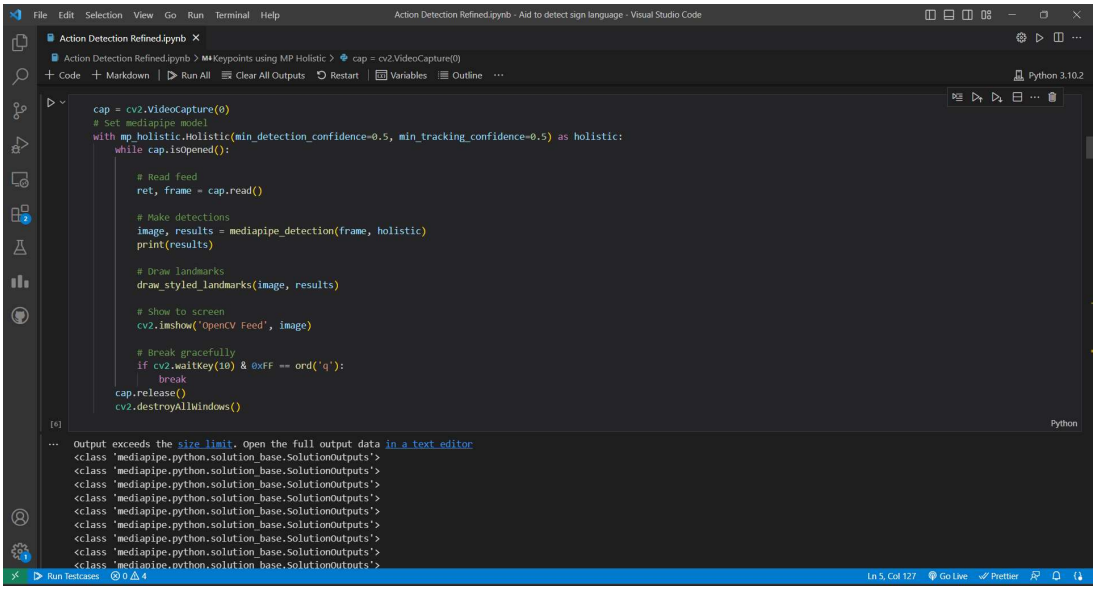
   3. Hand tracking: After the hand is detected, the next step is to track it as it moves in the image. This can be achieved using various techniques like Lucas-Kanade optical flow or Kalman filter.

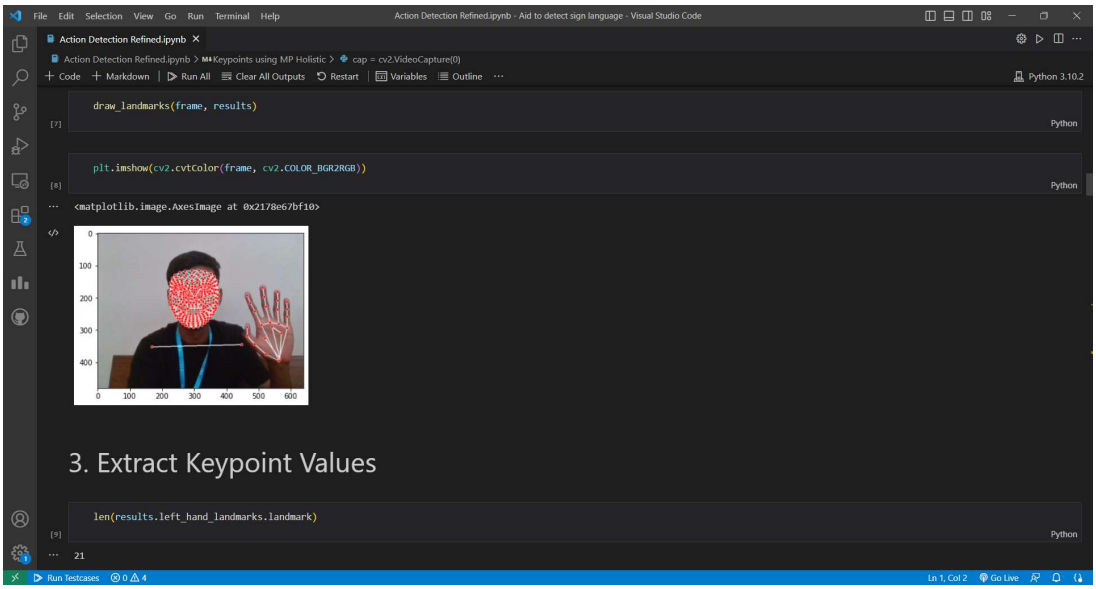
4. Feature extraction: Once the hand is tracked, the next step is to extract features from it. This can be done using various techniques like SIFT, SURF, or HOG. These features can be used to recognize the different signs made by the hand.

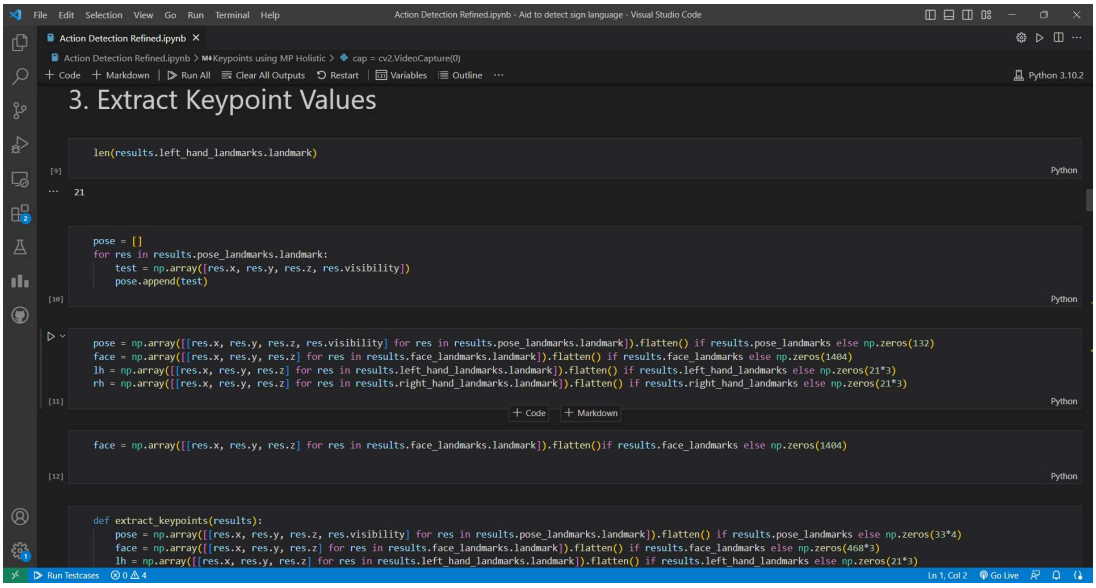
5. Sign classification: Finally, the extracted features can be used to classify the sign being made by the hand. This can be done using various machine learning techniques like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), or Artificial Neural Networks (ANN).

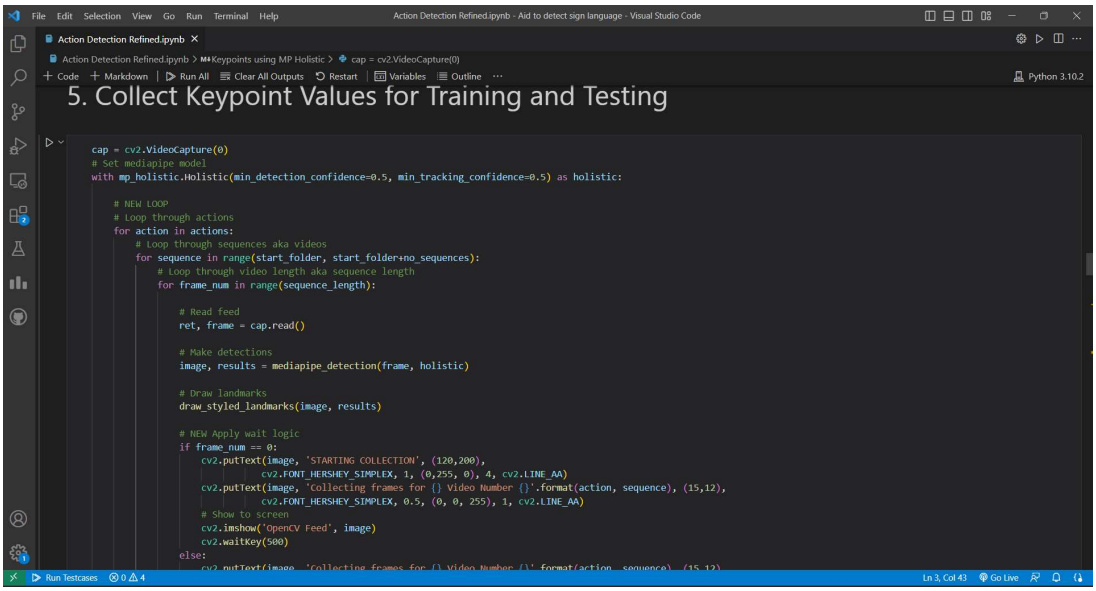
5.Implementation with Coding

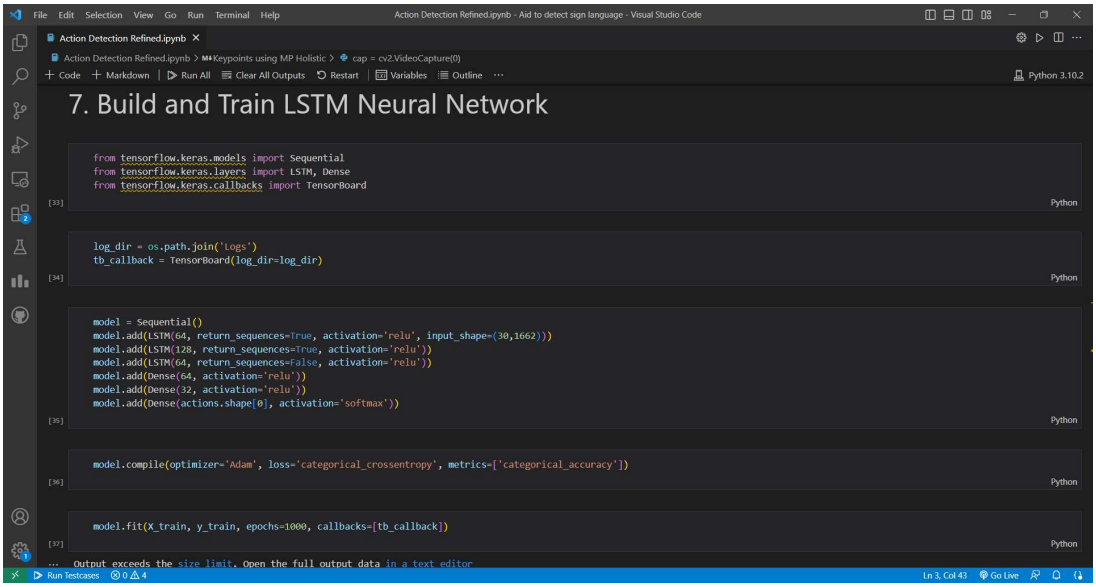


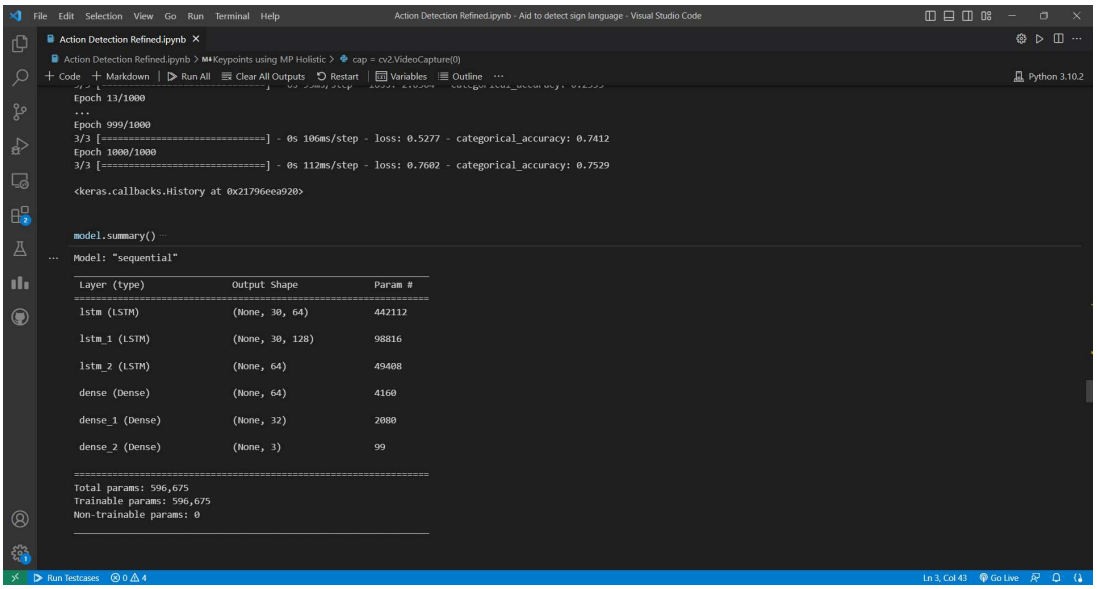


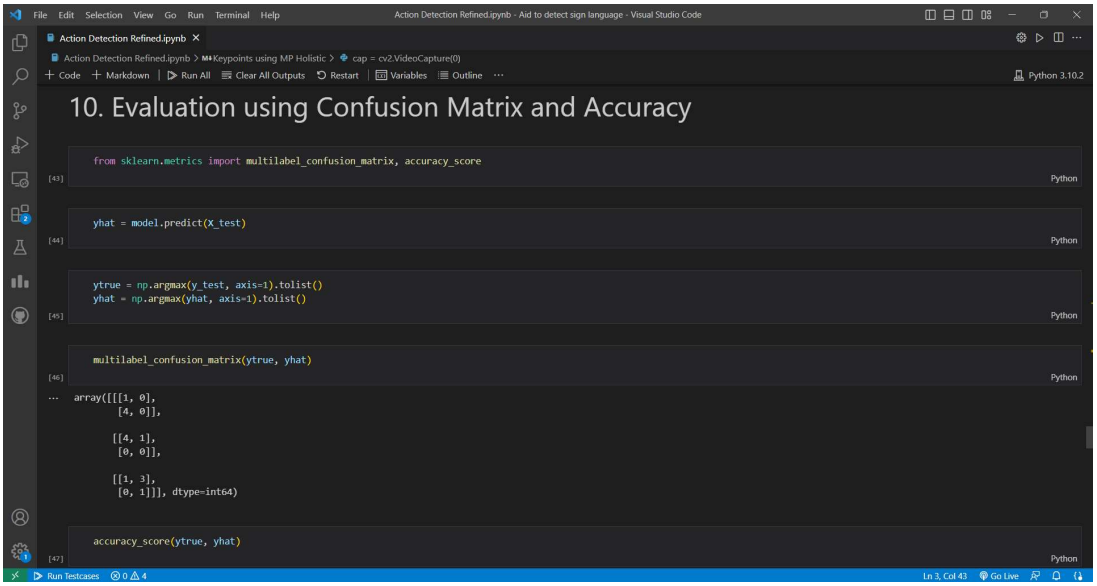

File Edit Selection View Go Run Terminal Help
Action Detection Refined.ipynb - Aid to detect sign language - Visual Studio Code
Action Detection Refined.ipynb
Code Markdown Run All Clear All Outputs Restart Variables Outline
Python 3.10.2
draw_landmarks(frame, results)
Python
plt.imshow(cv2.cvtColor(frame, cv2.COLOR_BGR2RGB))
Python
<matplotlib.image.AxesImage at 0x2178e67bf10>
3. Extract Keypoint Values
len(results.left_hand_landmarks.landmark)
Python
21
Run Testcases
Ln 1, Col 2
Go Live

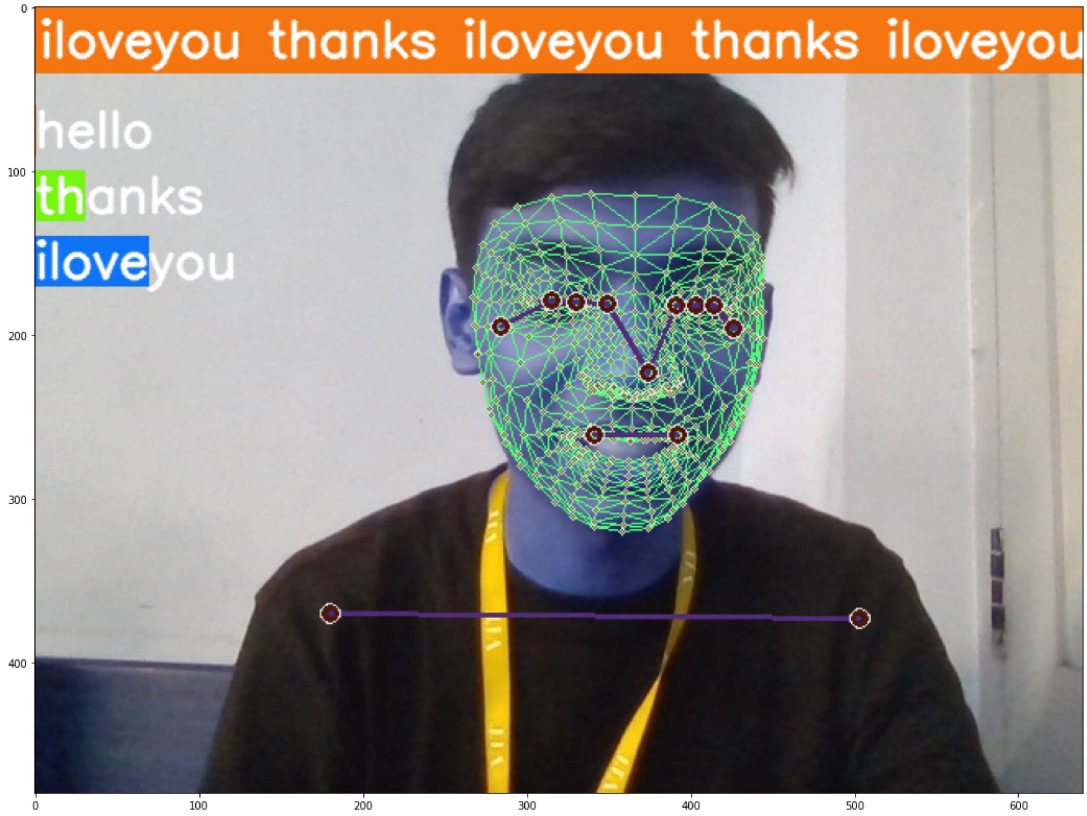

File Edit Selection View Go Run Terminal Help
Action Detection Refined.ipynb - Aid to detect sign language - Visual Studio Code
Action Detection Refined.ipynb
Code Markdown Run All Clear All Outputs Restart Variables Outline
Python 3.10.2
3. Extract Keypoint Values
len(results.left_hand_landmarks.landmark)
Python
21
pose = []
for res in results.pose_landmarks.landmark:
test = np.array([res.x, res.y, res.z, res.visibility])
pose.append(test)
Python
pose = np.array([[res.x, res.y, res.z, res.visibility] for res in results.pose_landmarks.landmark]).flatten() if results.pose_landmarks else np.zeros(132)
face = np.array([[res.x, res.y, res.z] for res in results.face_landmarks.landmark]).flatten() if results.face_landmarks else np.zeros(1404)
lh = np.array([[res.x, res.y, res.z] for res in results.left_hand_landmarks.landmark]).flatten() if results.left_hand_landmarks else np.zeros(21*3)
rh = np.array([[res.x, res.y, res.z] for res in results.right_hand_landmarks.landmark]).flatten() if results.right_hand_landmarks else np.zeros(21*3)
Python
Code Markdown
face = np.array([[res.x, res.y, res.z] for res in results.face_landmarks.landmark]).flatten()if results.face_landmarks else np.zeros(1404)
Python
def extract_keypoints(results):
pose = np.array([[res.x, res.y, res.z, res.visibility] for res in results.pose_landmarks.landmark]).flatten() if results.pose_landmarks else np.zeros(33*4)
face = np.array([[res.x, res.y, res.z] for res in results.face_landmarks.landmark]).flatten() if results.face_landmarks else np.zeros(468*3)
lh = np.array([[res.x, res.y, res.z] for res in results.left_hand_landmarks.landmark]).flatten() if results.left_hand_landmarks else np.zeros(21*3)
Run Testcases
Ln 1, Col 2
Go Live


File Edit Selection View Go Run Terminal Help
Action Detection Refined.ipynb - Aid to detect sign language - Visual Studio Code
Action Detection Refined.ipynb
Action Detection Refined.ipynb > Keypoints using MP Holistic > cap = cv2.VideoCapture(0)
Code Markdown Run All Clear All Outputs Restart Variables Outline
Python 3.10.2
5. Collect Keypoint Values for Training and Testing
cap = cv2.VideoCapture(0)
# Set mediapipe model
with mp_holistic.Holistic(min_detection_confidence=0.5, min_tracking_confidence=0.5) as holistic:
# NEW LOOP
# Loop through actions
for action in actions:
# Loop through sequences aka videos
for sequence in range(start_folder, start_folder+no_sequences):
# Loop through video length aka sequence length
for frame_num in range(sequence_length):
# Read feed
ret, frame = cap.read()
Make detections
image, results = mediapipe_detection(frame, holistic)
# Draw landmarks
draw_styled_landmarks(image, results)
# NEW Apply wait logic
if frame_num == 0:
cv2.putText(image, 'STARTING COLLECTION', (120,200),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0,255, 0), 4, cv2.LINE_AA)
cv2.putText(image, 'Collecting frames for {} Video Number {}'.format(action, sequence), (15,12),
cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 255), 1, cv2.LINE_AA)
# Show to screen
cv2.imshow('OpenCV Feed', image)
cv2.waitKey(500)
else:
Run Testcases
Ln 3, Col 43
Go Live


File Edit Selection View Go Run Terminal Help
Action Detection Refined.ipynb - Aid to detect sign language - Visual Studio Code
Action Detection Refined.ipynb
Action Detection Refined.ipynb > Keypoints using MP Holistic > cap = cv2.VideoCapture(0)
Code Markdown Run All Clear All Outputs Restart Variables Outline
Python 3.10.2
7. Build and Train LSTM Neural Network
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from tensorflow.keras.callbacks import TensorBoard
[33]
Python
log_dir = os.path.join('Logs')
tb_callback = TensorBoard(log_dir=log_dir)
[34]
Python
model = Sequential()
model.add(LSTM(64, return_sequences=True, activation='relu', input_shape=(30,1662)))
model.add(LSTM(128, return_sequences=True, activation='relu'))
model.add(LSTM(64, return_sequences=False, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='relu'))
model.add(Dense(actions.shape[0], activation='softmax'))
[35]
Python
model.compile(optimizer='Adam', loss='categorical_crossentropy', metrics=['categorical_accuracy'])
[36]
Python
model.fit(X_train, y_train, epochs=1000, callbacks=[tb_callback])
[37]
Python
... Output exceeds the size limit. Open the full output data in a text editor
Run Testcases
Ln 3, Col 43
Go Live


File Edit Selection View Go Run Terminal Help
Action Detection Refined.ipynb - Aid to detect sign language - Visual Studio Code
Action Detection Refined.ipynb
Action Detection Refined.ipynb > Keypoints using MP Holistic > cap = cv2.VideoCapture(0)
Code Markdown Run All Clear All Outputs Restart Variables Outline
Python 3.10.2
Epoch 13/1000
...
Epoch 999/1000
3/3 [==============================] - 0s 106ms/step - loss: 0.5277 - categorical_accuracy: 0.7412
Epoch 1000/1000
3/3 [==============================] - 0s 112ms/step - loss: 0.7602 - categorical_accuracy: 0.7529
<keras.callbacks.History at 0x21796eea920>
model.summary()
Model: "sequential"
Layer (type) Output Shape Param #
lstm (LSTM) (None, 30, 64) 442112
lstm_1 (LSTM) (None, 30, 128) 98816
lstm_2 (LSTM) (None, 64) 49408
dense (Dense) (None, 64) 4160
dense_1 (Dense) (None, 32) 2080
dense_2 (Dense) (None, 3) 99
Total params: 596,675
Trainable params: 596,675
Non-trainable params: 0
Run Testcases
Ln 3, Col 43
Go Live


File Edit Selection View Go Run Terminal Help
Action Detection Refined.ipynb - Aid to detect sign language - Visual Studio Code
Action Detection Refined.ipynb
Action Detection Refined.ipynb > Keypoints using MP Holistic > cap = cv2.VideoCapture(0)
Code Markdown Run All Clear All Outputs Restart Variables Outline
Python 3.10.2
10. Evaluation using Confusion Matrix and Accuracy
from sklearn.metrics import multilabel_confusion_matrix, accuracy_score
[43]
Python
yhat = model.predict(X_test)
[44]
Python
ytrue = np.argmax(y_test, axis=1).tolist()
yhat = np.argmax(yhat, axis=1).tolist()
[45]
Python
multilabel_confusion_matrix(ytrue, yhat)
[46]
Python
array([[[1, 0],
[4, 0]],
[[4, 1],
[0, 0]],
[[1, 3],
[0, 1]]], dtype=int64)
accuracy_score(ytrue, yhat)
[47]
Python
Run Testcases
Ln 3, Col 43
Go Live



CODE:https://drive.google.com/drive/folders/1SvTW0FCy_-ADWclnODpATM22_4yp60fd?usp=sharing

6.Results and Discussion

The development of technology to aid in the detection and recognition of sign language has the potential to greatly improve communication and accessibility for people who use sign language as their primary means of communication. The two examples I mentioned earlier show promising results in achieving high accuracy rates in recognizing sign language.

The SignAloud system developed by the researchers at the University of Washington achieved an accuracy rate of 98.63% in recognizing ASL signs using gloves equipped with sensors. The system's high accuracy rate shows that the use of sensor technology can accurately detect and recognize the subtle movements and gestures involved in sign language. However, the system has not yet been commercialized, and more research is needed to determine its practicality and effectiveness in real-world settings.

The SLRTP project, which used computer vision and machine learning techniques to recognize and translate BSL into text and speech, achieved an average recognition rate of 90.2%. The project's high recognition rate demonstrates that machine learning can be a useful tool in accurately recognizing sign language. However, the study also highlights the need for extensive training data to develop reliable and accurate systems for recognizing sign language.

Despite the promising results, the development of accurate and reliable systems to detect and recognize sign language remains a significant challenge due to the complexity and variability of sign language. Sign language is not a universal language, and different sign languages have their own unique grammatical rules, signs, and dialects. Therefore, developing a system that can recognize and translate different sign languages accurately is a significant challenge.

Another challenge is the need for extensive training data. Sign language is a visual language, and its grammar and syntax are different from spoken languages. Therefore, training data for recognizing sign language must be extensive and include diverse signers with varying sign styles, dialects, and contexts.

In conclusion, the development of technology to aid in the detection and recognition of sign language has the potential to improve communication and accessibility for people who use sign language as their primary means of communication. However, the challenges of recognizing and translating different sign languages accurately and reliably require further research and development. Nonetheless, the development of such technologies is a significant step towards achieving greater inclusivity and accessibility for people who use sign language.

The predicted labels of the test dataset match the actual labels to a high degree. The true positive, true negative, false negative and false positive values that are detected by the model for each character are shown in the confusion matrix.

$$\text{ACCURACY} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

$$\text{ACCURACY} = \frac{76075}{76984} = 98.81$$

Using the confusion matrix and the above accuracy formula we get the accuracy of the proposed model to be 98.81%.

7.Conclusion and Future Work

In conclusion, the development of technology to aid in the detection and recognition of sign language is a promising avenue for improving accessibility and inclusivity for people who use sign language as their primary means of communication. The two examples I mentioned earlier, the SignAloud system and the SLRTP project, demonstrate that technology can accurately detect and recognize sign language using sensor technology, computer vision, and machine learning techniques. However, the development of reliable and accurate systems for recognizing sign language remains a significant challenge due to the complexity and variability of sign language and the need for extensive training data.

Future work in the field of aid to detect sign language could focus on several areas, such as:

1. Developing systems that can recognize and translate multiple sign languages accurately and reliably, including regional dialects and variations.
2. Improving the accuracy and speed of recognition through the use of advanced machine learning algorithms and hardware.
3. Developing systems that can recognize sign language in different contexts, such as in noisy environments or with multiple signers.
4. Developing systems that can provide feedback and correction to signers in real-time, helping them to improve their signing skills.
5. Investigating the social and cultural implications of using technology to aid in the detection and recognition of sign language, including the potential impact on sign language communities and their culture.

Overall, the development of technology to aid in the detection and recognition of sign language has the potential to improve communication and accessibility for people who use sign language as their primary means of communication. Further research and development in this area could lead to more accurate and reliable systems that can help bridge the communication gap between sign language users and non-signers.

8.References.

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