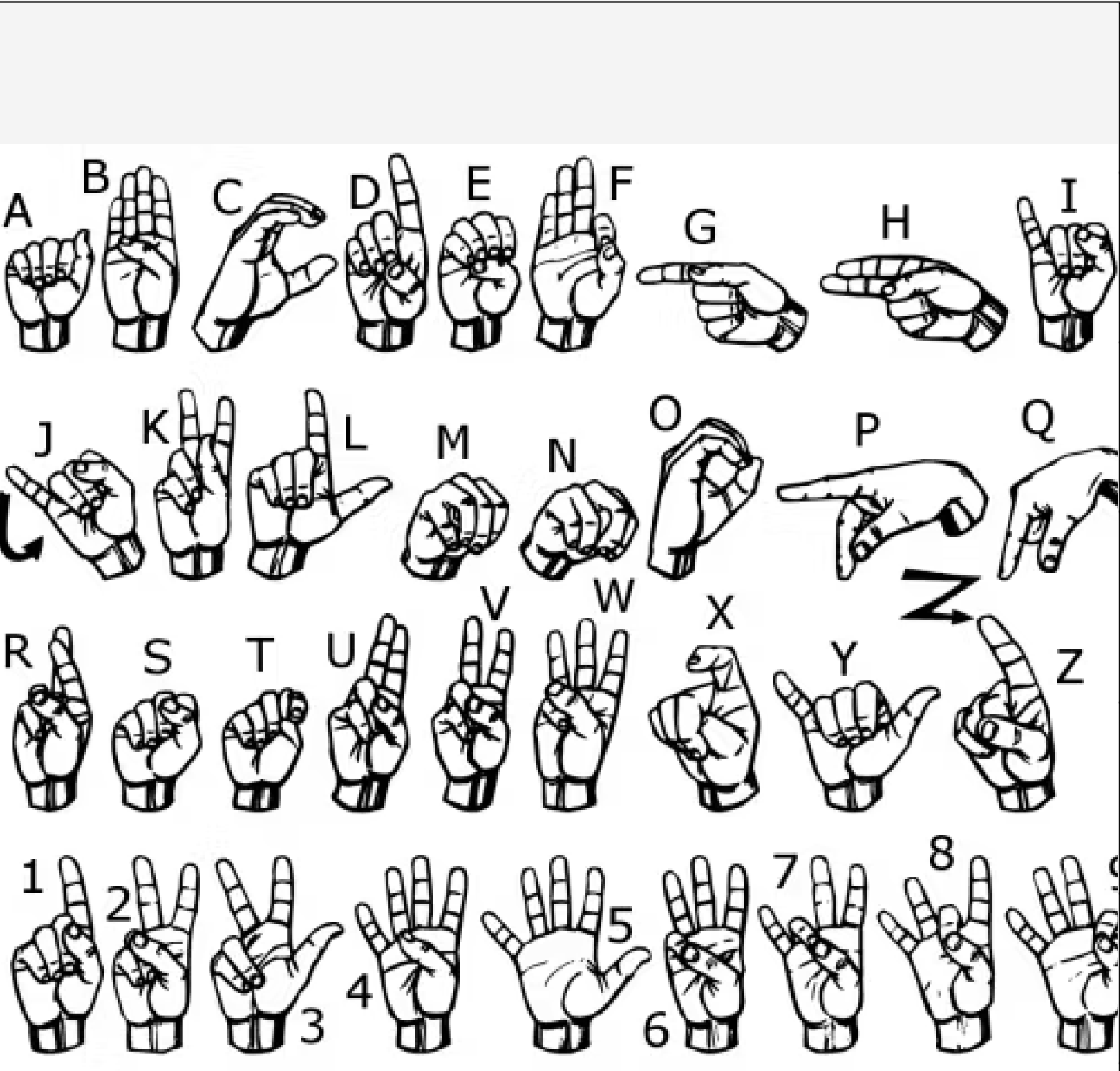


# **“BREAKING BARRIERS - FOR DEAF AND MUTE”**

## **MINOR PROJECT**

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# Introduction

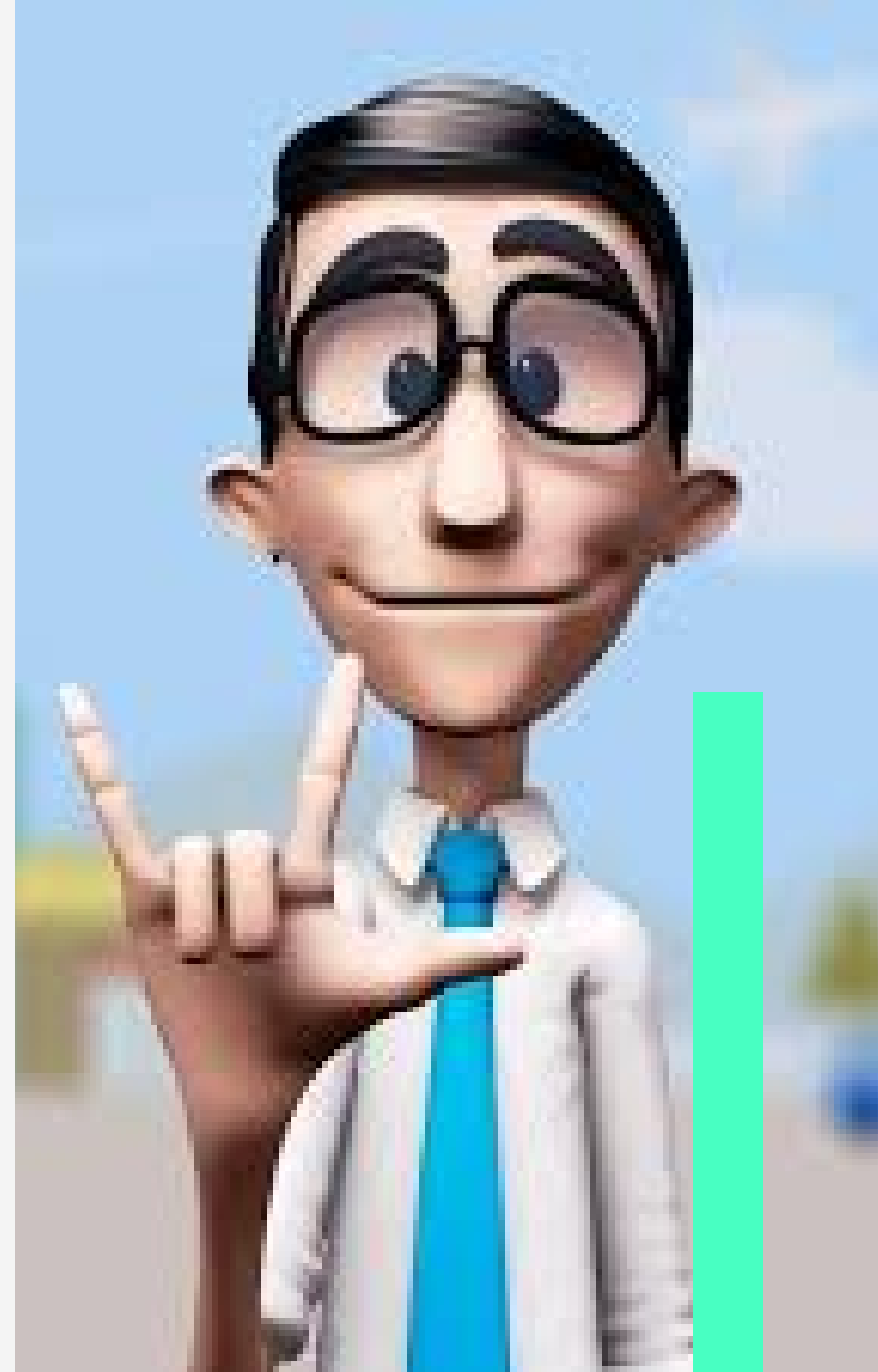
## Abstract

In our society, there are individuals with disabilities who face challenges in communicating with others.

Despite advancements in technology, not enough has been done to improve the lives of these individuals.

Roughly nine billion people worldwide are deaf and mute, and communicating with others can be a daunting task.

This is especially true when attempting to convey important information during emergencies.



# BASIC CONCEPTS

- **The proposed approach for Indian Sign Language (ISL) recognition is divided into three stages: image segmentation, feature extraction, and machine learning on feature vectors**
  1. Computer vision
  2. Hand tracking
  3. Image Segmentation
  4. Feature Extraction
  5. Machine Learning on Feature Vectors
  6. Classification Algorithms
  7. Human-Computer Interaction

# PROBLEM STATEMENT

"Individuals with disabilities, such as the deaf and mute, face significant communication challenges." Despite technological developments, there is a scarcity of accessible and effective communication tools that can help these people communicate. Sign language is a common means of communication, but it can be difficult for others to understand without prior knowledge of sign language. This project's purpose is to address this issue by creating a Text Conversion System with Hand Gesture Recognition and Translation. This system will use computer vision to recognize and interpret various hand movements, allowing sign language to be converted into audible speech in any desired language, as well as speech to comprehensible sign language.



# REQUIREMENT SPECIFICATION

Some specifications and needs for an AI model of hand sign recognition are as follows:

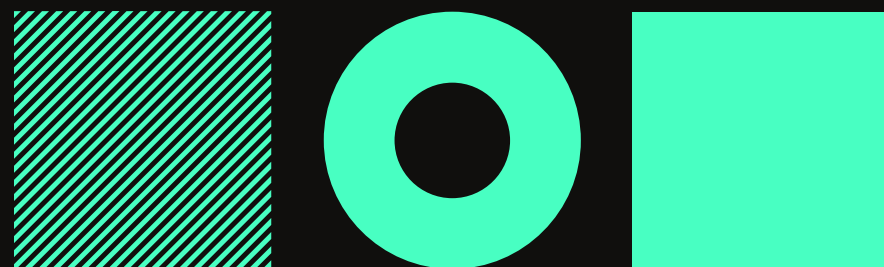
**Datasets:** To train and validate the model, a big and diverse collection of hand signs photos or videos is required. To ensure the model's resilience, the dataset should include differences in lighting conditions, camera angles, hand sizes, and skin tones.

**Pre-processing:** Pre-processing techniques should be included in the model to normalise the input images and eliminate any background noise or other irrelevant elements that could affect the model's performance.

**Model Architecture:** The model architecture should be selected based on the problem's complexity and the size of the dataset. To extract features, a deep learning model such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) might be utilised.



# CONTINUE



**Real-time Performance:** The model must perform in real-time, with low latency and high accuracy, to enable its use in various applications.

**Accuracy and Evaluation Metrics:** The model's accuracy must be evaluated using appropriate evaluation metrics, such as precision, recall, and F1 score, to ensure its reliability and performance.

**User Interface:** The model's user interface should be user-friendly, enabling users to interact with the system via natural hand gestures or voice commands.

**Accessibility:** The model should be accessible to individuals with various disabilities, including those with visual or hearing impairments.

# CONTINUE



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**Hardware and Software Requirements:** The model's hardware and software requirements should be specified to ensure that it can run efficiently on the intended platform. This includes the type of GPU, CPU, RAM, and operating system required to run the model.

**Privacy and Security:** The model should comply with privacy and security regulations and must be protected against unauthorized access, misuse, or theft of data.

**Scalability:** The model should be scalable, enabling it to handle large volumes of data, and should also be able to accommodate new hand signs that may be added in the future



# IMPLEMENTATION

## Methodology :

My team created a sign language recognition model using computer vision and sensors, speech-to-text using AI, and IoT devices like smartphones and smartwatches. We used tools like TensorFlow, NumPy, Hand Detector, and Keras. The code was written on PyCharm, and we captured images of each alphabet to train the model using Teachable Machine. The resulting TensorFlow Keras code was included in our directory. The trained model successfully recognized sign language. Computer vision, AI, and machine learning are technical terms used in computer science. Computer vision enables machines to understand visual data, AI creates intelligent machines that can make decisions and learn, and machine learning trains machines to learn and improve. These technologies are used in speech and image recognition, natural language processing, and autonomous vehicles.



PC .gitignore Version control Testing

Open Files DataCollection.py .gitignore Testing.py

C:\Users\KIIT\OneDrive\Desktop

venv

Image

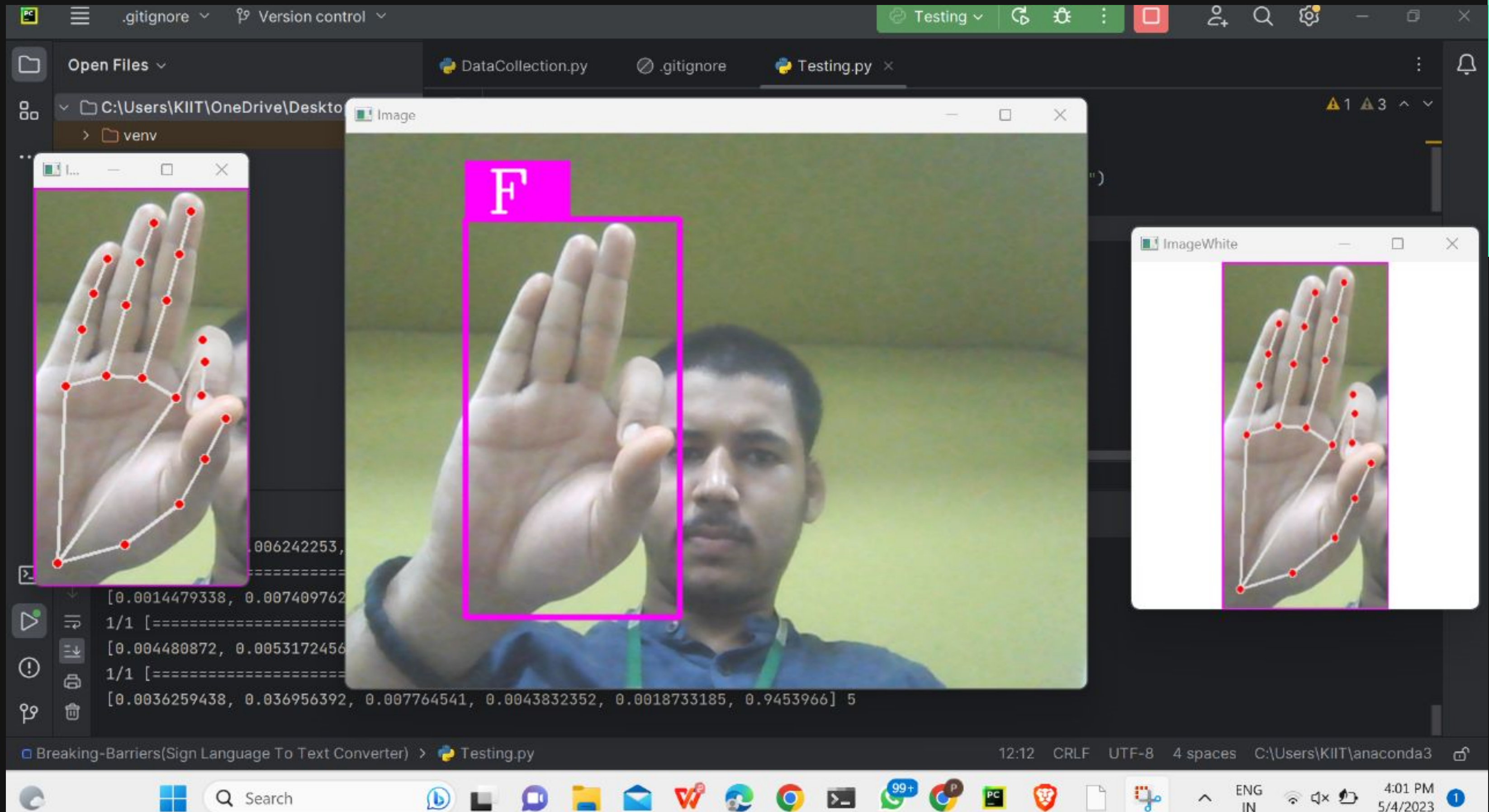
ImageWhite

006242253,  
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1/1 [=====  
[0.004480872, 0.0053172456  
1/1 [=====  
[0.0036259438, 0.036956392, 0.007764541, 0.0043832352, 0.0018733185, 0.9453966] 5

Breaking-Barriers(Sign Language To Text Converter) Testing.py 12:12 CRLF UTF-8 4 spaces C:\Users\KIIT\anaconda3

Search

ENG IN 4:01 PM 5/4/2023



The image is a screenshot of a Python IDE (likely VS Code) running a sign language recognition application. The main window, titled 'Image', shows a video frame of a person's hand. A pink bounding box is drawn around the hand, and a pink box with the letter 'F' is overlaid on the top left of the hand. To the left of the main window is a smaller window showing the same hand with a skeletal model overlay, consisting of red dots connected by white lines. To the right of the main window is another smaller window titled 'ImageWhite' showing the same hand with the skeletal model overlay. The terminal at the bottom of the IDE displays numerical data and a list of coordinates: [0.0014479338, 0.007409762, 0.004480872, 0.0053172456, 0.0036259438, 0.036956392, 0.007764541, 0.0043832352, 0.0018733185, 0.9453966]. The taskbar at the bottom shows various application icons and the system clock indicating 4:01 PM on 5/4/2023.

# STANDARD ADOPTED

## CODING STANDARDS:

To ensure high-quality code for our project, we followed a set of coding standards, which included:

1. Writing concise and readable code for the CNN model and OpenCV.
2. Using appropriate naming conventions to clearly indicate the purpose and function of each component.
3. Use indentation to marks the beginning and end of control structures. Clearly specify the code between them.
4. Following best practices for structuring code and using indentation to mark control structures and other code blocks.



# TESTING STANDARDS:

To ensure the accuracy and reliability of our sign language translator, we followed a set of testing standards, including:

1. Conducting extensive validation and verification testing of the CNN model using labeled image datasets.
2. Adhering to ISO and IEEE standards for quality assurance and testing throughout the development process.

# Conclusion

Our study explores the development of an automated system for recognizing sign language gestures in real-time, utilizing a range of tools. While our research aims to identify sign language and translate it into text, there remains significant potential for future work in this area.

# FUTURE SCOPE

The future scope of a hand sign translator AI model is immense and holds great potential for the deaf and hard-of-hearing communities. Here are some possible directions in which this technology may evolve:

**Improved accuracy:** One of the primary focuses for the future development of a hand sign translator AI model is to improve its accuracy in recognizing and translating sign language. This can be achieved by expanding the dataset used to train the model, including more sign language variations and dialects, and incorporating more advanced machine learning techniques.

**Real-time translation:** Another significant advancement that is expected in the future is real-time translation of sign language. With advancements in computer vision and machine learning, it is possible to develop models that can recognize and translate sign language in real-time, making communication much more seamless and natural.

**Incorporation of facial expressions:** Sign language is not just about hand signs; facial expressions also play a critical role in conveying meaning. In the future, hand sign translator AI models can incorporate facial recognition technology to better understand the nuances of sign language and provide more accurate translations.

**Mobile integration:** The integration of hand sign translator AI models into mobile devices like smartphones and tablets can make them accessible to a wider audience. This will enable people to communicate with deaf and hard-of-hearing individuals more effectively, regardless of their location.

Overall, the future of a hand sign translator AI model is bright, and its development can have a significant impact on improving accessibility and communication for the deaf and hard-of-hearing communities.



A photograph of a person's hands typing on a laptop keyboard. The scene is dimly lit, with a white coffee cup and a glass vase containing sticks of wood or herbs in the background. The text "THANK YOU" is overlaid in a bright cyan color.

**THANK YOU**