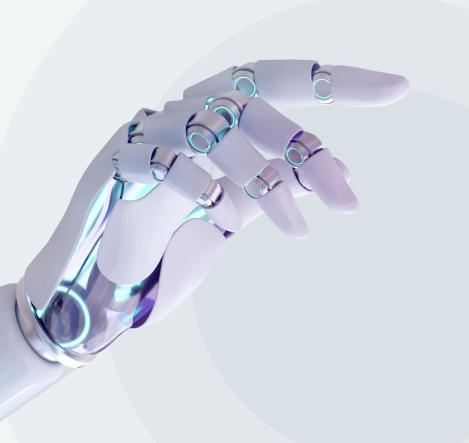


SIGN LANGUAGE DETECTION

Guided By, Prof. KALPANAPRIYA D. Presented by, HARINI M(23MDT0037)

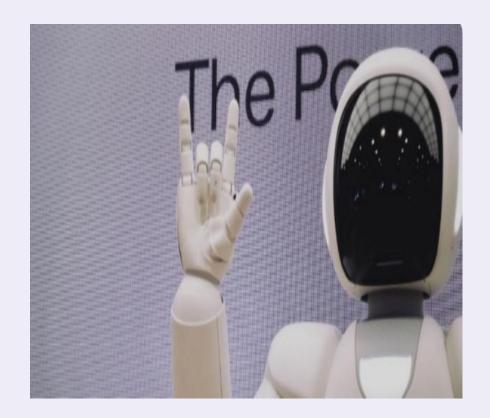




- INTRODUCTION
- PROBLEM STATEMENT
- OBJECTIVE
- LITERATURE SURVEY
- DATA PREPARATION
- MODEL SELECTION & TRAINING
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INTRODUCTION

- □ **Sign language is essential** in bridging interaction gaps for hearing-impaired individuals.
- ☐ Millions of people worldwide use sign language as their primary communication method.
- ☐ There is a **growing demand** to develop systems that can interpret sign language into text or speech, facilitating easier interaction between deaf and hearing individuals.
- □ **Sign language varies** from country to country and region to region, with different gestures and symbols representing different meanings.
- ☐ This **variation makes it challenging** to create a universal system for recognizing sign language.



PROBLEM STATEMENT

People with hearing or speech impairments face challenges in communicating effectively with nonsigners in real-time environments. Traditional sign language recognition systems rely heavily on visual data alone, which can lead to misinterpretation of similar gestures, especially in dynamic or noisy settings. There is a need for an accurate, real-time system that can recognize sign language gestures and provide audio **feedback** to bridge the communication gap.



OBJECTIVE

- □ Develop an AI Model: Create a deep learning model capable of recognizing and translating sign language.
- □ Enhance Accessibility: Enable real-time communication between sign language users and non-signers.
- ☐ Integrate Audio Output: Convert detected signs into corresponding speech for improved interaction.



LITERATURE SURVEY

□ Comparative Study on Sign Language Recognition

Paper Title: Deep Learning for the Recognition of Sign Language: A Comparative Study of Visual and Audio-Visual Approaches

Authors: L. Zhang, H. Zhao, W. Liu

Year: 2024

Key Contributions:

- Comparative analysis of **visual-only vs. audio-visual** recognition systems.
- Advanced audio feature extraction method using Playsound.
- > Insights into the challenges and prospects of building multi-modal sign language datasets.

□ Enhancing YOLO-Based Sign Language Recognition with Audio Feedback

Paper Title: Improving YOLO-Based Sign Language Recognition with Audio Feedback for Better Communication

Authors: M. Fernandes, T. Nakamura, A. Patel

Year: 2024

Key Contributions:

- > YOLOv8 + Audio Feedback integration for real-time sign interpretation.
- > Evaluation of accuracy vs. speed trade-offs when using text-to-speech.
- > Exploration of **latency reduction techniques** like **model quantization** and **TensorRT deployment**.

LITERATURE SURVEY(Cont.)

□ Real-Time Static Sign Recognition Using YOLOv8

Paper Title: YOLO-Based Instantaneous Sign Language Gesture Recognition

Authors: K. Johnson, P. Wang, L. Rodriguez

Year: 2023

Key Contributions:

- > Application of **YOLOv8** for static sign recognition with high detection accuracy.
- **Performance comparison**: YOLOv8 vs. YOLOv5 in terms of mAP and real-time capability.
- > Discussion on challenges like **overlapping gestures** and suggestions for **dataset improvement**.
- □ Audio-Visual Fusion for Real-Time Sign Language Recognition

Paper Title:

Audio-Visual Fusion-Based Recognition of Sign Language with Deep Learning

Authors: Sharma, P. Singh, S. Gupta

Year: 2023

Key Contributions:

- > Introduces a **multi-modal framework** combining gestures and speech for robust sign recognition.
- > Compares **multiple fusion strategies** to determine the most effective method.
- > Demonstrates **real-time performance** under **challenging conditions** like background noise or gesture overlap.

DATASET PREPARATION



Hand Gesture Categories

The dataset includes six hand gesture categories: "Hello", "Thanks", "Please", "Yes", "No", "Eat", "Home", "Help", "See_You_Later" Each represented by 25 images to ensure comprehensive coverage.



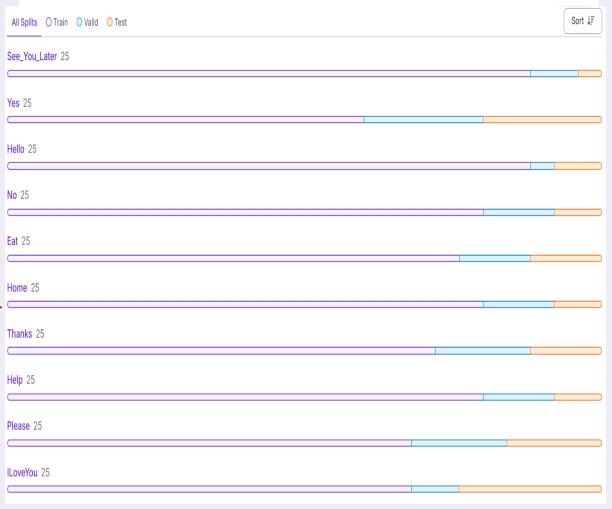
Image Collection Process

Images were captured using Jupyter Notebook, ensuring high-quality visuals and consistency across the dataset for effective model training.



Labeling with Roboflow

Roboflow was used to label the images, creating precise bounding boxes around the hand gestures to facilitate accurate model training and evaluation.



Audio Feature Integration in Sign Language Detection

- □ Audio Playback:Upon detecting a sign, the system triggers an audio file corresponding to the sign's meaning. This adds auditory feedback to the visual interpretation, making the system more accessible, especially for individuals who are not familiar with sign language.
- ☐ Integration Details: The audio files were stored in MP3 format and implemented using the playsound module in Python. These audio files are played directly from the same folder in the Jupyter Notebook environment where the project is executed.
- ☐ Impact: This audio feature ensures that the detected sign is clearly communicated, bridging gaps in interaction for users who may have hearing impairments or those unfamiliar with sign language.

Eat.mp3 Hello.mp3 Help.mp3 ☐ Home.mp3 ILoveYou.mp3 □ No.mp3 Please.mp3 See You Later.mp3 Thanks.mp3 Yes.mp3

MODEL SELECTION & TRAINING



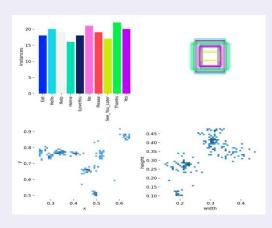
Choosing YOLO for Detection YOLO

(You Only Look Once) was selected for its real-time detection capabilities and efficiency.



Training on Google Colab

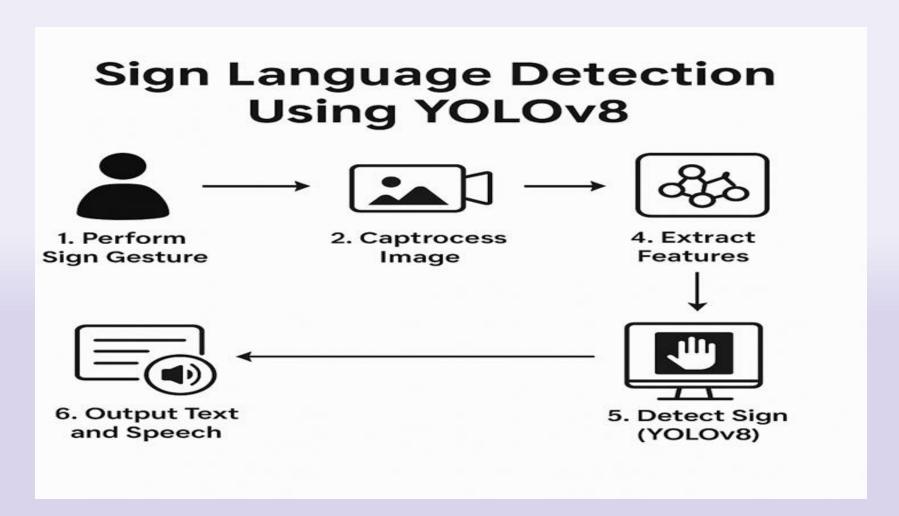
The model was trained using Google Colab, leveraging T4 GPU acceleration for faster computations.



Performance Metrics

Evaluation was done using accuracy, precision, recall, and F1- score to measure effectiveness.

ARCHITECTURE DIAGRAM



IMPLEMENTATION & EVALUATION

- **Recognition of 10 Signs**: The model was trained to detect 10 different hand signs with high accuracy.
- Audio Integration: Detected signs trigger corresponding audio output for speech synthesis.
- **Performance Metrics**: Model evaluated based on mAP, precision and recall.



CONCLUSION & FUTURE SCOPE

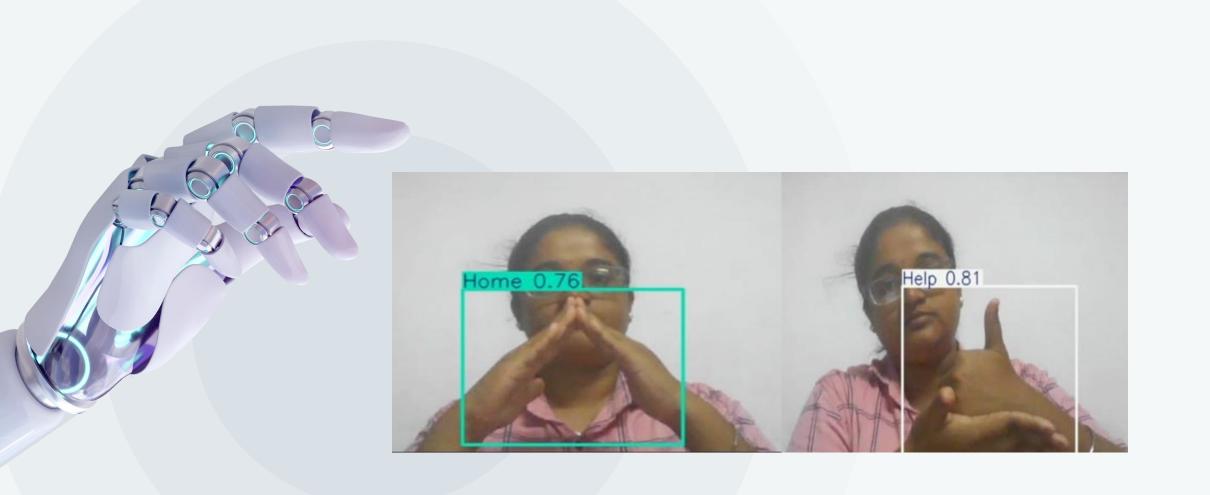
- ☐ Impact on Accessibility: This project improves communication for the Deaf community by bridging the gap between sign language users and non-signers.
- □ Enhancements for Future: Expanding the dataset and incorporating more signs to improve model robustness and accuracy.
- ☐ Integration with Smart Devices: Potential for deployment in mobile apps and smart assistants for real-time sign language translation.



SIGNS DETECTED:







SAMPLE OUTPUT

```
0: 480x640 1 Hello, 236.4ms
Speed: 2.2ms preprocess, 236.4ms inference, 2.0ms postprocess per image at shape (1, 3, 480, 640)
Speaking: Hello
0: 480x640 1 Home, 281.6ms
Speed: 4.0ms preprocess, 281.6ms inference, 2.0ms postprocess per image at shape (1, 3, 480, 640)
Speaking: Home
0: 480x640 1 Yes, 204.4ms
Speed: 3.0ms preprocess, 204.4ms inference, 1.0ms postprocess per image at shape (1, 3, 480, 640)
Speaking: Yes
0: 480x640 1 Help, 208.9ms
Speed: 2.0ms preprocess, 208.9ms inference, 1.0ms postprocess per image at shape (1, 3, 480, 640)
Speaking: Help
0: 480x640 1 Thanks, 229.6ms
Speed: 3.2ms preprocess, 229.6ms inference, 1.0ms postprocess per image at shape (1, 3, 480, 640)
Speaking: Thanks
```



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PLAYGARISM

ORIGIN	ALITY REPORT				
4 SIMIL	% ARITY INDEX	2% INTERNET SOURCES	3% PUBLICATIONS	2% STUDENT	PAPERS
PRIMA	RY SOURCES				
1	P. Sivakı Informa	nila, S. Kannadh umar, V. Vennila tion, Communio ogy", CRC Press	a. "Challenges cation and Cor	in	1%
2	Submitte Student Paper	ed to Nottingha	ım Trent Unive	ersity	1%
3	Student Paper Submitte	ed to National S ment NSBM, Sr	School of Busir		1%

