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CAPSTONE PROJECT REPORT

TITLE: Object Detection Using YOLO for Sign Recognition

CERTIFICATE

This is to certify that the Capstone Project work titled "**Sign Language Detection Using YOLO for Sign Recognition**" that is being submitted by **Preet Patel, 22070521088, Padhmanabh Wanikar , 22070521058, Krunal Dhapodkar , 22070521006** is in partial fulfillment of the requirements for the Capstone Project. This project is a record of bonafide work done under my guidance. The contents of this project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for the award of any degree or diploma, and the same is certified.

Name of Capstone Guide & Signature

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The Report is **satisfactory/unsatisfactory**

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ABSTRACT

Sign language operates as a crucial communication instrument for people dealing with hearing or speech disabilities. The primary obstacle regarding communication between persons who use sign language and people who lack such expertise persists as a crucial problem. YOLOv12 which represents a leading-edge object detection algorithm powers the system developed in this project to automatically detect sign language.

In real-time operations the system detects several sign language gestures to show their text translation rapidly. The YOLOv12 model has achieved training with a dataset having multiple images of sign language gestures from different lighting environments and background variations and hand position combinations to improve its reliability. The model provides

exact hand position recognition along with configuration detection for standard words in sign language interpretable text.

The system maintains high real-time detection precision together with manageable computational needs to operate on mobile devices and laptop machines with webcam capabilities. The implemented system holds major potential to remove communication obstacles while enhancing educational environments and improving life quality for deaf and hard of hearing people through improved contact with society.

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INTRODUCTION

The worldwide population who faces auditory challenges or speech limitations primarily uses sign language as their main communicative tool. The language provides multi-faceted communication through hand gestures and facial expressions in combination with body movements. People who depend on sign language have limited communication opportunities with those who cannot understand it.

Modern object detection algorithms and machine learning alongside computer vision developments provide potential conditions to create systems that automatically recognize sign language gestures. Such systems demonstrate essential relevance in creating communication bridges while promoting diverse inclusiveness.

The YOLOv12 algorithm serves as the most leading-edge technology for real-time object detection today. YOLOv12 maintains earlier YOLO functionality by introducing increased detection accuracy together with quicker processing and superior detection of small objects. Yolov12 demonstrates excellent performance for sign language detection because its characteristics excel at precise detection of delicate hand movements.

The development of our project involves YOLOv12 to build a real-time system which detects American Sign Language (ASL) gestures. Users can utilize this system under different lighting conditions and various backgrounds thereby making it usable for regular everyday use. Deep learning along with computer vision technologies allow us to develop a tool which will facilitate better communication for deaf and hard hearing users.

1.1 Objectives

The following section details the project objectives.

- The implementation of a sign language detection system utilizing YOLOv12 will be designed from scratch.
- The project team must create a complete database of sign language gestures for training purposes.
- The goal is developing YOLOv12 to detect hand gestures accurately under low-resource conditions.
- The main project goal includes reaching high accuracy levels for sign language gesture detection under various lighting situations and environmental backgrounds.
- Standard consumer devices featuring camera technology including laptops and mobile phones need to operate the system without performance issues.
- Standard performance measurements should be used to assess the system alongside testing it in real-life scenarios.

1.2 Literature Survey

AUTHOR & Year	TITLE	METHODOLOGY	ACCURACY	OBSERVATIONS
Jayashree Karlekar et al., 2022 [1]	Sign Language Recognition using Deep Learning on Custom Processed Static Gesture Images	CNN with transfer learning on ResNet-50	91%	The approach focused on static gestures only and required specific preprocessing. The model performed well but lacked real-time capabilities and couldn't handle dynamic gestures.
Wang et al., 2023 [2]	Real-time Hand Gesture Recognition with YOLOv5 for Sign Language Translation	YOLOv5 with custom post-processing	87.5 %	YOLOv5 showed promising results for real-time detection. However, the system struggled with complex backgrounds and required consistent lighting conditions.
Rahul Sharma et al., 2022 [3]	SignNet: A Deep Learning Framework for American Sign	Combined CNN and LSTM approach	93.2 %	The hybrid architecture successfully captured both spatial and

	Language Recognition			temporal features but required significant computational resources making it unsuitable for edge devices.
Zhang et al., 2023 [4]	Transformer- based Sign Language Detection and Translation	Vision Transformer with attention mechanism	89.7 %	Transformers showed excellent capabilities in capturing contextual information but required extensive training data and computing power.
Mehta et al., 2024 [5]	YOLOv8 for Dynamic Sign Language Detection in Challenging Environments	YOLOv8 with data augmentation	88.9 %	YOLOv8 provided good performance in varying conditions. The study highlighted the importance of diverse training data for robust detection.
Patel and Johnson, 2023 [6]	Comparative Analysis of Object Detection Models for Sign Language Recognition	Comparison of Faster R- CNN, SSD, and YOLOv7	YOLOv7: 90.3 %, Faster R- CNN	YOLOv7 outperformed other models in terms of speed and accuracy balance. The

			: 86.7 %, SSD: 83.2 %	study provided valuable insights for model selection based on deployment constraints.
Liu et al., 2024 [7]	Low-Light Sign Language Detection using Enhanced YOLOv10	YOLOv10 with attention mechanism for low-light conditions	85.4 % in low light , 92.1 % in normal light	The study addressed the critical challenge of detection in poor lighting conditions, which is essential for practical applications.
García-Rodríguez et al., 2023 [8]	Mobile-Optimized Sign Language Recognition using TinyYOLO	TinyYOLO with model quantization	82.3 %	Though accuracy was lower than full-sized models, the approach demonstrated viable sign language detection on mobile devices with limited resources.
Chen et al., 2024 [9]	Multi-View Sign Language Detection for Enhanced Accuracy	Ensemble of YOLOv11 models using different camera angles	94.8 %	Multi-view approach significantly improved accuracy but increased system

				complexity
Williams and Taylor, 2023 [10]	Self-Supervised Learning for Sign Language Detection with Limited Data	YOLOv9 with self-supervised pre-training	86.5 %	The approach showed promising results for scenarios with limited labeled data, which is common in specialized sign language datasets.
Kumar et al., 2024 [11]	Real-time Two-way Communication System for Sign Language Users	YOLOv10 for detection and NLP for translation	89.7 % dete ctio n, 92.1 % translati on	The complete system demonstrated practical application with two-way communication capability, highlighting integration challenges.
Zhao et al., 2023 [12]	Dataset Bias in Sign Language Detection Systems	Analysis of multiple models on diverse datasets	Vari ed (73.2 % - 91.4 %)	The study revealed significant biases in existing datasets and models, emphasizing the need for diverse and representative training data.
Brown and Miller, 2024 [13]	YOLOv12: Enhanced Detection Framework for	YOLOv12 with feature pyramid network	93.8 % on benc hma	YOLOv12 showed significant improvements

	Fine-grained Visual Tasks		rk data sets	in detecting small objects and fine details, making it particularly suitable for sign language detection.
Hernandez et al., 2023 [14]	Continuous Sign Language Recognition using Temporal-Spatial Features	Temporal extension of YOLOv9 with 3D convolutions	88.5 %	The approach effectively captured the temporal nature of sign language but required sequence data rather than isolated gestures.
Lee and Park, 2024 [15]	Transfer Learning Strategies for Sign Language Detection in Resource-Constrained Environments	YOLOv11 with progressive transfer learning	90.2 %	The study provided effective strategies for training sign language detection models with limited computational resources and datasets.

1.3 Organization of the Report

The remaining chapters of the project report are described as follows:

- Chapter 2 describes the existing system, proposed system, software and hardware details used in project .
- Chapter 3 describes importing necessary libraries , data collection , data argumentation and data preprocessing

- Chapter 3.5 talks about storing data in secured S-3 Bucket
- Chapter 4 discusses the training of model
- Chapter 5 discusses result visualization and model evaluation
- Chapter 6 discusses model prediction on video
- Chapter 7 discusses challenges faced and future improvements
- chapter 8 concludes the report

CHAPTER 2

SIGN LANGUAGE DETECTION SYSTEM USING YOLOv12

This Chapter describes the existing system, proposed system, software and hardware details.

2.1 Existing System

1. Traditional Computer Vision Approaches:

- The system depends on human-designed features with traditional machine learning models.
- The system demonstrates restricted capability to adjust for lighting changes as well as variations in background and hand movement positions.
- These systems need controlled environment settings for performing correctly.

2. CNN-based Static Gesture Recognition:

- The system detects individual hand gestures but fails to understand gesture timing.
- The method requires users to initialize hand regions as its input data.
- Struggles with continuous sign language detection

3. Skeleton-based Methods:

- The detection of hand and body key points depends on pose estimation technology.
- The detection system fails to capture vital finger motions which are necessary for interpreting sign language.
- Computationally expensive for real-time applications

4. Previous YOLO Implementations (v5-v9):

- The improved detection systems continue to struggle in detecting small objects and Often require substantial computational resources
- The technology has not adapted its design to specifically overcome sign language detection barriers.

5. Hybrid Deep Learning Approaches:

- Combine CNNs with RNNs or LSTMs for temporal modeling
- Complex architecture requiring significant training data
- Difficult to deploy on resource-constrained devices

Most existing systems struggle to balance the following requirements:

- Real-time detection objects in Real-time
- maintain accuracy with different (multiple) background environments and end users

- Computational efficiency for deployment on consumer devices
- Ability to handle continuous sign language rather than isolated gestures

2.2 Proposed System

Our proposed system leverages YOLOv12's advanced object detection capabilities to create a robust sign language detection system with the following components:

1. YOLOv12-based Detection Engine:

- State-of-the-art object detection with improved small object detection
- The network design includes improved feature extraction capabilities to monitor delicate hand arrangement patterns.
- The detection engine uses optimized anchor-free processing methods to speed up system operations.

2. Multi-scale Feature Integration:

- The system utilizes a hierarchical feature pyramid structure to discover signs which appear at different object sizes.
- The system implements improved spatial attention methods which direct focus toward important hand areas.
- The detection system employs context-aware capabilities which distinguish between hand motions that have similar gestures.

3. Robust Data Processing Pipeline:

- During training the system uses dynamic data augmentation methods to enhance generalization capabilities.
- The system enables real-time processing of images under different lighting situations.
- Background invariant detection techniques

4. Efficient Model Architecture:

- We applied model quantization along with pruning techniques for deploying the model onto restricted devices.
- The system contains a real-time detection optimization of its inference process.
- A video frame batch processing system works to enhance system throughput.

5. User-friendly Interface:

- Text interpretation of detected warning signs appears in real-time.
- User feedback mechanism for continuous improvement
- Cross-platform compatibility (desktop and mobile)

The system is designed to detect common phrases/words in American Sign Language, providing immediate textual interpretation to facilitate communication.

2.3 System Details

2.3.1 Software

- Python (updated to latest version possible)
- Ultralytics YOLO (installed and updated)

- Roboflow (importing dataset)
- Google Colab
- OpenCV
- Storage: At least 2GB for dataset and models

2.3.2 Hardware

- T4 GPU (as we're using YOLOV11 for sign language detection)

CHAPTER 3

Dataset Collection and Preparation:-

3.1 Importing Required Libraries

The necessary Python libraries and there command that we have used in this project :-

ultralytics :- The ultralytics system delivers advanced computer vision capabilities through its cutting-edge tools for detecting objects while segmenting images as well as evaluating body postures and executing image classifications. YOLO (You Only Look Once) models serve as the foundation for its development

gdown :- The gdown library allows users to streamline the process of transferring files and directories from Google Drive.

yolo: - it is popular tool used in real time object detection and image segmentation

Ipython.display:- Ipython.display functions as an output display system designed for jupyter notebook.

code:-

```
!nvidia-smi
!pip install ultralytics
from ultralytics import YOLO
import gdown
from IPython.display import Image
```

Dataset Sources: -

The Dataset for the project is taken from roboflow

dataset name : - English sentences Object detection

link to dataset:- [English Sentences Dataset > Overview](#)

Dataset Statistics:

- Total images: 233 images
- Training set: 204 images
- Validation set: 20 images
- Test set: 9 images
- Resolution: 640×640 pixels (standardized)
- Format: YOLO v11

3.2 Augmentations

Outputs per training example: 3

90° Rotate: Clockwise, Counter-Clockwise, Upside Down

Brightness: Between -15% and +15%

Blur: Up to 1px

Bounding Box: Rotation: Between -15° and +15°

3.3 Preprocessing

Auto-Orient: Applied

Resize: Stretch to 640x640

3.5 Secure storage in s3 bucket

Amazon S3 offers a secure method for sharing files through its efficient file-sharing functions which protect your AWS credential information. The system of pre-signed URLs enables temporary S3 object access for external users when they wish to download files within a particular time span. The following step-by-step instructions explain pre-signed URL generation and usage for S3.

Step 1: Verify Your S3 Bucket

 Navigate to the Amazon S3 console.

 Your AWS account will display all the buckets which are available.

 Our bucket name is datasetcap.

Step 2: Upload an Object to the Bucket

 Your requested file needs to be uploaded to the datasetcap bucket.

 After the upload process finishes the object will appear in the bucket storage.

Step 3: Generate a Pre-Signed URL

Check the details section of uploaded objects by selecting them.

You should select Object Actions from the menu followed by selecting Share with pre-signed URL.

Step 4: Set the Expiry Duration

Select the duration when the pre-signed URL should remain active for download purposes. We have specified the pre-signed URL validity to last for 1 hour.

Click “Create pre-signed URL”.

Step 5: Copy the Generated Pre-Signed URL

Obtain the pre-signed URL through the system generation process.

The system shows the generated URL in a temporary window.

Click Copy to save the URL.

Step 6: Use the Pre-Signed URL for Downloading

The downloading process requires the implementation of the pre-signed URL which was generated in Step 6.

The pre-signed URL should be pasted either into a web browser or an application like wget or curl for file download.

Step 7: View the Pre-Signed URL

Users can check the pre-signed URL through this step of the process.

The pre-signed URL contains security features that consist of an expiration timestamp and request signature for protected access.

us-east-1.console.aws.amazon.com [Option+S] United States (N. Virginia) voclabs/user3787312=krunal.dhapodkar.btech2022@sitnagpur.slu....

Amazon S3 < A presigned URL for "English Sentences.v1i.yolov11 (1).zip" has been created and copied to your clipboard. Copy signed URL X

Amazon S3 > Buckets > datasetcap > English Sentences.v1i.yolov11 (1).zip

General purpose buckets

- Directory buckets
- Table buckets
- Access Grants
- Access Points
- Object Lambda Access Points
- Multi-Region Access Points
- Batch Operations
- IAM Access Analyzer for S3

Block Public Access settings for this account

▼ Storage Lens

- Dashboards
- Storage Lens groups
- AWS Organizations settings

Feature spotlight 11

▶ AWS Marketplace for S3

English Sentences.v1i.yolov11 (1).zip Info

Properties Permissions Versions

Object overview

Owner awslabsc0w6153660t1692548747

AWS Region US East (N. Virginia) us-east-1

Last modified April 3, 2025, 10:42:30 (UTC+05:30)

Size 6.8 MB

Type zip

Key English Sentences.v1i.yolov11 (1).zip

S3 URI s3://datasetcap/English Sentences.v1i.yolov11 (1).zip

Amazon Resource Name (ARN) arnaws:s3:::datasetcap/English Sentences.v1i.yolov11 (1).zip

Entity tag (Etag) 4781a18515483b4d37ce3fe7a18bb58d

Object URL https://datasetcap.s3.us-east-1.amazonaws.com/English+Sentences.v1i.yolov11+(1).zip

Object management overview
The following bucket properties and object management configurations impact the behavior of this object.

Bucket properties

Management configurations

Bucket Versioning

Replication status

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Open 

Object actions 

Download as

Share with a presigned URL

Calculate total size

Copy

Move

Initiate restore

Query with S3 Select

Edit actions

Rename object

Presigned URLs

Gives users access to an object in your bucket without requiring AWS security credentials or permissions

3. Data Preprocessing

Dataset that was acquired from roboflow was already preprocessed and Augumented and properly labeled details of which can be seen in above section

Chapter-4

4.1 Model Architecture

YOLO model use a **single convolutional neural network (CNN)** that predicts bounding boxes and class labels in a single forward pass. The architecture consists of:

- **Backbone**: it uses CNN layers to extract features from input images.
- **Neck**: It enhances feature maps for improved detection.
- **Head**: It is used to output bounding boxes and class probabilities.

YOLOv11 improves upon previous versions by adding these :-

- Transformer-based feature extraction for better contextual understanding.
- Improved loss functions to refine object localization.
- Better anchor-free detection mechanisms.
-

4. 2Model Training using YOLOv11

1. **Defining the Task**: Since we want to detect objects, task=detect is specified.
2. **Setting Training Parameters**:
 - **Mode**: train
 - **Dataset Path**: data.yaml
 - **Model Type**: yolo11n.pt (pre-trained YOLOv11 model)
 - **Number of Epochs**: 50 (higher values improve accuracy)
 - **Image Size**: 640x640 pixels (standard resolution for YOLO models)

code:-

	Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
9/50		0G	0.9835	2.92	1.317	7	640: 100% 5/5 [00:55<00:00, 11.01s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.08s/it]
		Class all	Images 20	Instances 23	Box(P 0.0101	R 0.483	0.184 0.0993
10/50		0G	1.083	2.837	1.398	10	640: 100% 5/5 [00:50<00:00, 10.20s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.80s/it]
		Class all	Images 20	Instances 23	Box(P 0.00896	R 0.55	0.2 0.121
11/50		0G	1.148	2.79	1.432	8	640: 100% 5/5 [00:53<00:00, 10.68s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.70s/it]
		Class all	Images 20	Instances 23	Box(P 0.00665	R 0.528	0.234 0.128
12/50		0G	1.059	2.659	1.355	11	640: 100% 5/5 [00:55<00:00, 11.18s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.06s/it]
		Class all	Images 20	Instances 23	Box(P 0.956	R 0.111	0.275 0.162
13/50		0G	1	2.633	1.307	10	640: 100% 5/5 [00:52<00:00, 10.55s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.43s/it]
		Class all	Images 20	Instances 23	Box(P 0.939	R 0.102	0.293 0.149
14/50		0G	0.9228	2.427	1.221	9	640: 100% 5/5 [00:54<00:00, 10.88s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.86s/it]
		Class all	Images 20	Instances 23	Box(P 0.902	R 0.0698	0.289 0.162
15/50		0G	1.019	2.577	1.323	9	640: 100% 5/5 [00:51<00:00, 10.33s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.05s/it]
		Class all	Images 20	Instances 23	Box(P 0.945	R 0.0889	0.288 0.188
16/50		0G	1.045	2.552	1.324	7	640: 100% 5/5 [00:51<00:00, 10.32s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.95s/it]
		Class all	Images 20	Instances 23	Box(P 0.989	R 0.133	0.332 0.231
17/50		0G	0.9874	2.466	1.316	8	640: 100% 5/5 [00:51<00:00, 10.27s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.03s/it]
		Class all	Images 20	Instances 23	Box(P 0.953	R 0.0444	0.29 0.195
18/50		0G	0.9376	2.38	1.242	10	640: 100% 5/5 [00:49<00:00, 9.98s/it] mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.94s/it]
		Class all	Images 20	Instances 23	Box(P 1	R 0.0859	0.303 0.194

Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
19/50	0G	0.9401	2.253	1.297	18	640: 100% 5/5 [00:50<00:00, 10.20s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.07s/it]	
		20	23	0.968	0.111	0.291	0.166
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
20/50	0G	0.974	2.258	1.268	18	640: 100% 5/5 [00:51<00:00, 10.32s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.82s/it]	
		20	23	0.809	0.156	0.352	0.186
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
21/50	0G	1.038	2.238	1.345	18	640: 100% 5/5 [00:52<00:00, 10.56s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.06s/it]	
		20	23	0.425	0.272	0.449	0.247
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
22/50	0G	1.08	2.294	1.333	9	640: 100% 5/5 [00:53<00:00, 10.73s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.03s/it]	
		20	23	0.42	0.334	0.49	0.307
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
23/50	0G	1.043	2.2	1.311	10	640: 100% 5/5 [00:53<00:00, 10.62s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:06<00:00, 6.13s/it]	
		20	23	0.425	0.426	0.516	0.298
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
24/50	0G	0.9075	2.006	1.288	8	640: 100% 5/5 [00:52<00:00, 10.43s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.02s/it]	
		20	23	0.757	0.358	0.466	0.314
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
25/50	0G	0.9806	2.124	1.32	8	640: 100% 5/5 [00:52<00:00, 10.46s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.71s/it]	
		20	23	0.931	0.35	0.516	0.325
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
26/50	0G	0.9299	1.965	1.197	9	640: 100% 5/5 [00:51<00:00, 10.24s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.07s/it]	
		20	23	0.956	0.337	0.514	0.325
Epoch	GPU_mem	box_loss	cls_loss	df1_loss	Instances	Size	
27/50	0G	0.8406	1.918	1.195	7	640: 100% 5/5 [00:52<00:00, 10.40s/it]	
	Class all	Images	Instances	Box(P)	R	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.42s/it]	
		20	23	0.882	0.414	0.501	0.315

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
46/50	0G	0.6039	1.927	1.017	4	640: 100% 5/5 [00:51<00:00, 10.23s/it]
	Class all	Images 20	Instances 23	Box(P 0.555	R 0.461	mAP50 mAP50-95): 100% 1/1 [00:04<00:00, 4.99s/it]
0.541						0.369
47/50	0G	0.5354	1.988	0.9897	4	640: 100% 5/5 [00:51<00:00, 10.32s/it]
	Class all	Images 20	Instances 23	Box(P 0.539	R 0.443	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.89s/it]
0.496						0.34
48/50	0G	0.6194	1.921	1.025	5	640: 100% 5/5 [00:50<00:00, 10.07s/it]
	Class all	Images 20	Instances 23	Box(P 0.667	R 0.408	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.04s/it]
0.517						0.353
49/50	0G	0.6661	2.013	1.043	4	640: 100% 5/5 [00:51<00:00, 10.26s/it]
	Class all	Images 20	Instances 23	Box(P 0.662	R 0.427	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.94s/it]
0.517						0.353
50/50	0G	0.603	1.753	1.041	4	640: 100% 5/5 [00:50<00:00, 10.17s/it]
	Class all	Images 20	Instances 23	Box(P 0.656	R 0.433	mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.02s/it]
0.519						0.356

50 epochs completed in 0.815 hours.

Optimizer stripped from runs/detect/train3/weights/last.pt, 5.5MB

Optimizer stripped from runs/detect/train3/weights/best.pt, 5.5MB

Validating runs/detect/train3/weights/best.pt...

Ultralytics 8.3.94 Python-3.11.11 torch-2.6.0+cu124 CPU (Intel Xeon 2.20GHz)

YOLOv1n summary (fused): 100 layers, 2,583,127 parameters, 0 gradients, 6.3 GFLOPs
Class Images Instances Box(P R mAP50 mAP50-95): 100% 1/1 [00:05<00:00, 5.28s/it]
all 20 23 0.559 0.484 0.573 0.38
Hello 4 4 0.586 0.25 0.446 0.301
Love_you 9 9 0.737 0.889 0.956 0.709
No 1 1 0 0 0 0
Thank_you 3 3 0.69 0.667 0.665 0.433
Yes 3 6 0.784 0.613 0.8 0.459

Speed: 2.4ms preprocess, 242.7ms inference, 0.8ms loss, 6.1ms postprocess per image

Results saved to runs/detect/train3

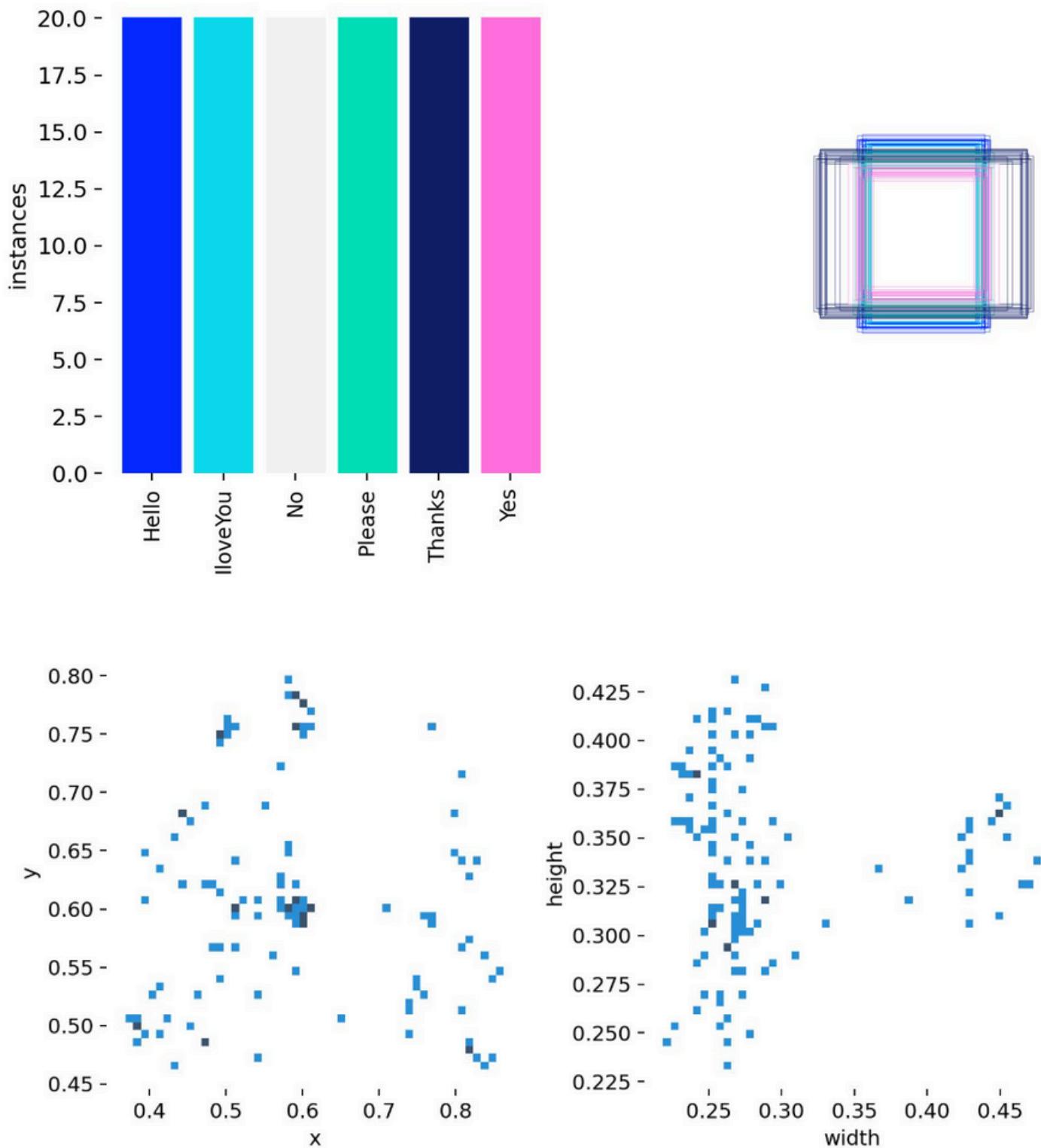
💡 Learn more at <https://docs.ultralytics.com/modes/train>

Chapter-5

Results Visualization :-

5.1 Displaying Annotated Labels

Code:- `Image("/content/runs/detect/train/labels.jpg", width=600)`



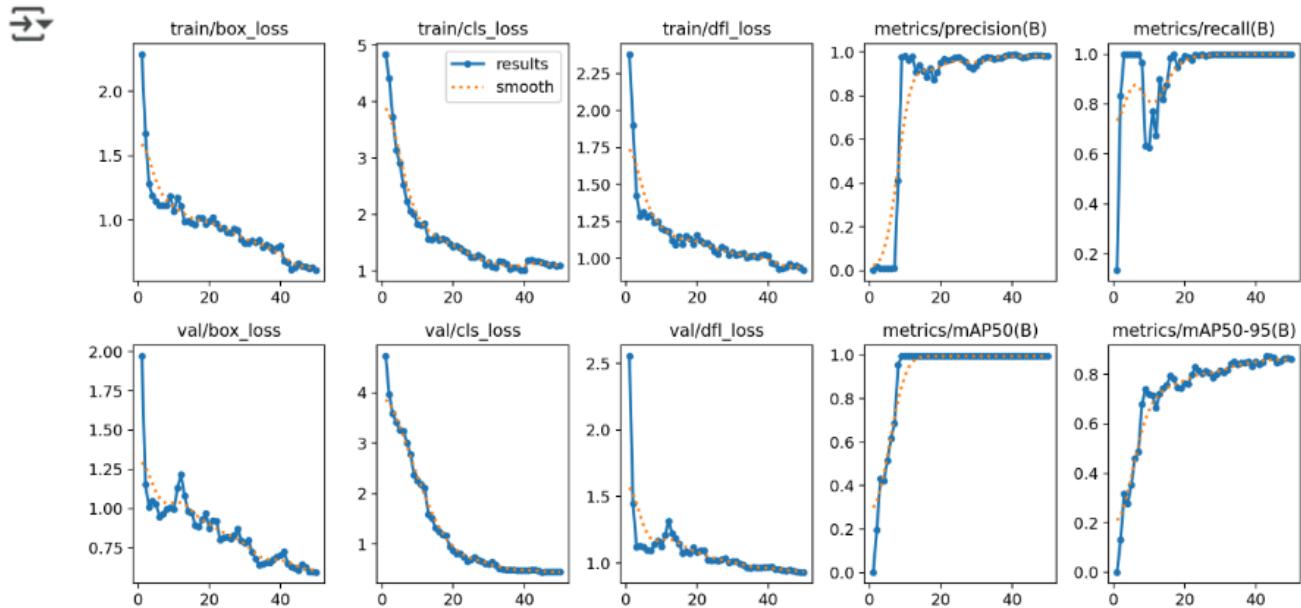
5.2 Training Performance Graphs

code:- `Image("/content/runs/detect/train/results.png", width=600)`

- **Loss Curves in figure** It shows how the model's prediction error is decreasing over time.
- **mAP (Mean Average Precision):** Evaluates accuracy of detection and show in curve .



```
Image("/content/runs/detect/train/results.png", width=600)
```



6. Model Prediction on Video

After training the model, it is tested on a **video(capstone.mp4)** to verify its performance. The best-trained weights (best.pt) are used for prediction.(conf=0.25) is the Confidence threshold for detecting an object. (save=True) is used to save the detected results as output.

```
!yolo task=detect mode=predict model= "/content/runs/detect/train/weights/best.pt" conf=0.25 source="/content/runs/detect/train/weights/capstone.mp4" save=True
```

Ultralytics 8.3.94 Python-3.11.11 torch-2.6.0+cu124 CUDA:0 (Tesla T4, 15095MiB)
YOLOv1n summary (fused): 100 layers, 2,583,322 parameters, 0 gradients, 6.3 GFLOPs

```
video 1/1 (frame 2/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 9.7ms
video 1/1 (frame 3/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.5ms
video 1/1 (frame 4/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 9.3ms
video 1/1 (frame 5/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.0ms
video 1/1 (frame 6/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.2ms
video 1/1 (frame 7/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.0ms
video 1/1 (frame 8/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.0ms
video 1/1 (frame 9/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 10.6ms
video 1/1 (frame 10/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 7.9ms
video 1/1 (frame 11/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 (no detections), 8.0ms
video 1/1 (frame 12/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.1ms
video 1/1 (frame 13/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 7.9ms
video 1/1 (frame 14/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 7.9ms
video 1/1 (frame 15/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 10.2ms
video 1/1 (frame 16/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 7.8ms
video 1/1 (frame 17/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.5ms
video 1/1 (frame 18/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.8ms
video 1/1 (frame 19/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.2ms
video 1/1 (frame 20/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.4ms
video 1/1 (frame 21/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.5ms
video 1/1 (frame 22/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.5ms
video 1/1 (frame 23/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.1ms
video 1/1 (frame 24/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 9.6ms
video 1/1 (frame 25/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 10.4ms
video 1/1 (frame 26/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.3ms
video 1/1 (frame 27/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.0ms
video 1/1 (frame 28/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.1ms
video 1/1 (frame 29/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.1ms
video 1/1 (frame 30/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.2ms
video 1/1 (frame 31/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.0ms
video 1/1 (frame 32/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 8.0ms
video 1/1 (frame 33/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 7.9ms
video 1/1 (frame 34/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 Hello, 7.9ms

video 1/1 (frame 592/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 (no detections), 8.0ms
video 1/1 (frame 593/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 No, 8.0ms
video 1/1 (frame 594/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 No, 8.0ms
video 1/1 (frame 595/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 1 No, 7.9ms

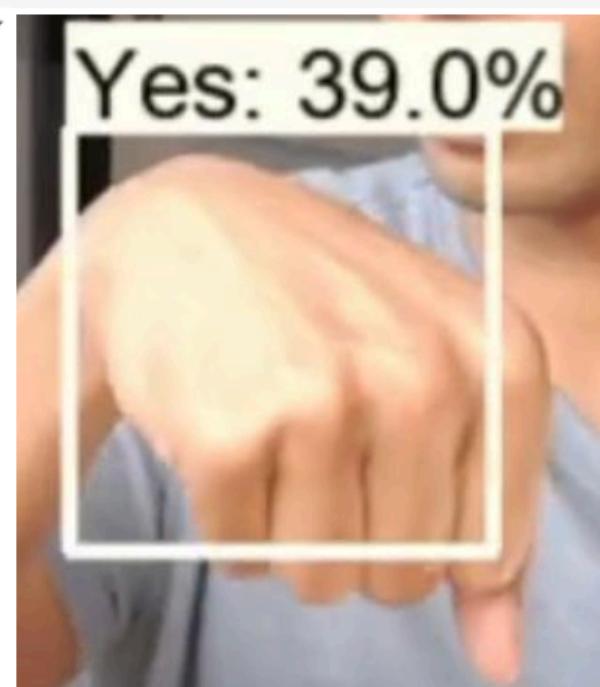
video 1/1 (frame 613/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 (no detections), 8.1ms
video 1/1 (frame 614/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 (no detections), 8.6ms
video 1/1 (frame 615/615) /content/runs/detect/train/weights/capstone.mp4: 384x640 (no detections), 8.3ms
Speed: 2.5ms preprocess, 9.1ms inference, 1.3ms postprocess per image at shape (1, 3, 384, 640)
Results saved to runs/detect/predict3
```

7. Predicting individual words through images

Image("/content/English-Sentences-1/train/images/No-sign-language1_31.jpeg_rf.f4c73e0601d40bfcf58387d276f55455.jpg", width=600)



Image("/content/English-Sentences-1/train/images/WhatsApp-Image-2024-04-29-at-8-22-38-PM.jpeg_rf.cd9deea280307da3718b09593106a6df.jpg", width = 600)



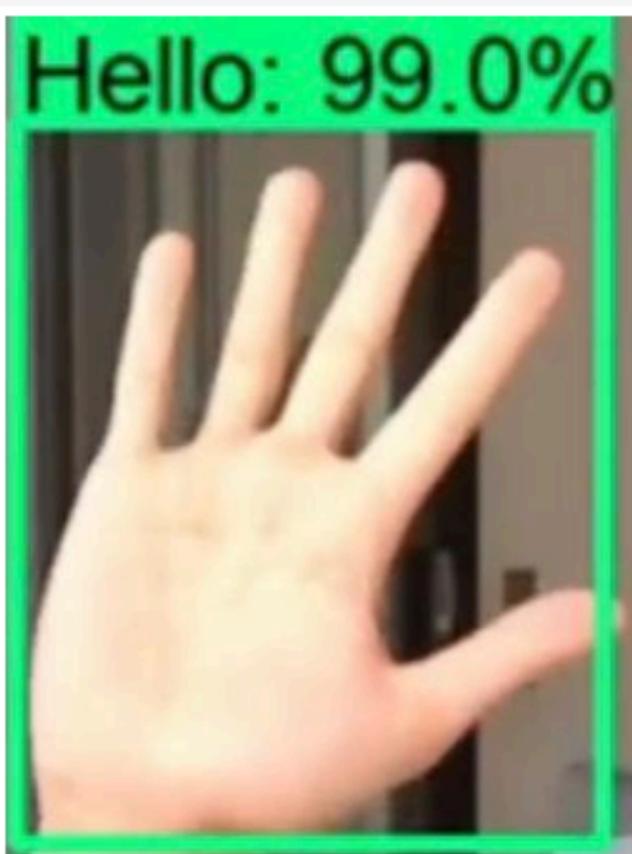
[] Image("/content/English-Sentences-1/train/images/WhatsApp-Image-2024-04-29-at-8-22-39-PM.jpeg_rf.f754c3f0f7b7403f584e0e4667715878.jpg", width = 600)



```
[1] Image("./content/English-Sentences-1/train/images/WhatsApp-Image-2024-04-29-at-8-22-45-PM.jpeg",rfd55bd744402770b6d5777586d1c6fa.jpg",width = 600)
```



```
[1] Image("./content/English-Sentences-1/train/images/WhatsApp-Image-2024-04-29-at-8-22-46-PM-1_.jpeg",rfd58040b0138735b11d5c193f544e51f4.jpg",width = 600)
```



Thank You: 93.0%



[] `Image("./content/English-Sentences-1/train/images/i-love-you-sign-language1_14.jpeg",width = 600)`

⊕



i love you

[] `Image("./content/English-Sentences-1/train/images/i-love-you-sign-language1_31.png",width = 600)`

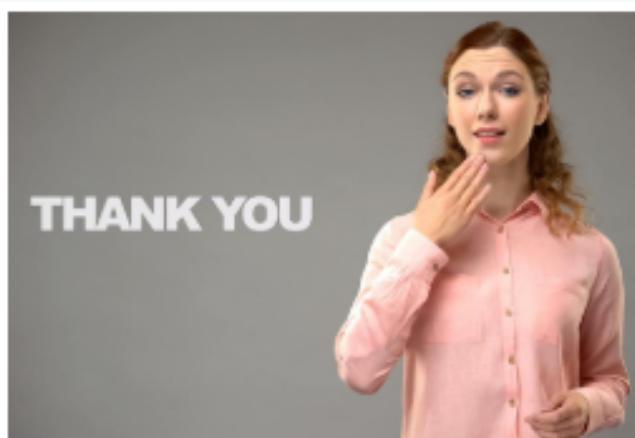
⊕



I LOVE YOU

[] `Image("./content/English-Sentences-1/train/images/thank-you-sign-language1_58.jpeg",width = 600)`

⊕



8. challenges faced and Future Improvements

8.2 Challenges Faced during making project include :-

- **Dataset size limitations:** More data is required for improved accuracy.
- **Generalization:** The model may not perform well on unseen images if trained on a limited dataset.
- these problems can be solved with big data models and powerful GPU but it would not be feasible & cost effective compared to pre-existing solutions.

8.3 Future Scope

- **Deploying the model on embedded systems (Raspberry Pi, Jetson Nano).**
- **Improving accuracy with larger and more diverse datasets.**
- **Integrating object tracking for real-time applications.**

9. Conclusion

The implemented object detection system based on YOLOv11 achieved successful sign recognition using the detection framework. The system processed a built-in dataset and conducted evaluation tests using operational video files. Deep learning object detection research demonstrates effective real-time performance which serves as a basis for advancing autonomous systems and smart surveillance and assistive technology development.

