CNN Based Object tracking and Detection in Images and Videos

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported at this time does not form part of any other project/research work based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Team 134

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ABSTRACT

The objective of this project is to enhance real-time object detection performance using the YOLOv5 (We Only Look Once) framework. Object detection is a critical field in computer vision with applications in autonomous vehicles, surveillance, healthcare, and robotics This project employs the YOLOv5 framework due to its superior speed and accuracy compared to previous YOLO versions. The model was trained on the COCO 2014 dataset, optimized using hyperparameter tuning, and evaluated using standard metrics like mean Average Precision (mAP) and precision-recall curves. Data augmentation techniques, such as mosaic augmentation and horizontal flipping, were utilized to improve model generalization. The implementation was conducted on NVIDIA GPUs to achieve faster training times.

The trained YOLOv5 model achieved a high detection accuracy of accuracy of 0.715 at a confidence threshold of 0.5, making it suitable for real-time applications. The project highlights YOLOv5's effectiveness in handling small objects and complex backgrounds while maintaining low inference latency. This study demonstrates the viability of YOLOv5 for various object detection tasks and suggests potential applications in diverse real-world scenarios.

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CHAPTER-1
PROJECT DESCRIPTION AND OUTLINE

1.1 Introduction

This project focuses on training, optimizing, and analysing the YOLOv5 object detection model for high-performance object detection. YOLOv5 (We Only Look Once, version 5) is a state-of-the-art model designed to achieve real-time detection while maintaining high accuracy. The project involves training the model on the COCO 2014 dataset, tuning hyperparameters, and testing it on a separate dataset to ensure optimal results. The goal is to balance speed and precision, making the model suitable for real-world applications like surveillance, retail analytics, and autonomous systems**.**

1.2 Motivation for the Work

The need for accurate and fast object detection is growing due to its applications in safety, security, and automation. Current models often face challenges like slow inference times or difficulty in detecting small objects. YOLOv5 stands out because of its lightweight design, speed, and accuracy. Through this project, we aim to further refine YOLOv5, bridging the gap between academic research and industrial implementation.

1.3 About the Project

This project uses YOLOv5 to detect objects in images and videos. The key techniques include data preprocessing, augmentation, and hyperparameter tuning. GPU acceleration is leveraged to speed up training, while techniques like mosaic augmentation improve the model's performance. The final system is tested and validated against standard metrics like mAP (mean Average Precision).

1.4 Problem Statement

Object detection systems struggle to achieve both speed and accuracy. Existing methods are either computationally expensive or lack robustness in diverse scenarios. There is a demand for a detection system that performs well in real-time without compromising accuracy. This project addresses this by refining YOLOv5 and analysing its performance under practical constraints.

1.5 Objectives of the Work

- Train YOLOv5 on a comprehensive dataset to improve its accuracy.

- Optimize the system for real-time applications using GPU acceleration.
- Validate performance using standard metrics like precision, recall, and mAP.
- Explore real-world use cases, ensuring the model is scalable and reliable.

1.6 Organization of the Project

This report consists of seven chapters. Chapter 1 introduces the project, its goals, and structure. Chapter 2 reviews related work. Chapter 3 outlines the technical requirements. Chapter 4 details the design methodology. Chapter 5 explains implementation and analysis. Chapter 6 presents the outcomes and applications. Chapter 7 concludes with recommendations and future enhancements.

1.7 Summary

This chapter laid the groundwork for understanding the project's purpose and direction. It introduced YOLOv5, highlighted its importance, and outlined the structure of the report.

CHAPTER-2
RELATED WORK INVESTIGATION

2.1 Introduction

This chapter explores the progression of object detection techniques, detailing improvements that have shaped modern methods like YOLOv5. Key advancements are discussed chronologically to highlight how challenges were addressed over time.

2.2 Core Area of the Project

Object detection is a core area of computer vision focused on identifying and localizing objects within images. This technology plays a vital role in applications such as autonomous driving, retail analytics, and smart surveillance. This project aims to investigate methods to enhance the efficiency and accuracy of object detection models.

2.3 Existing Approaches/Methods

- 2.3.1 Faster R-CNN (2015)

  The introduction of Faster R-CNN marked a significant step forward by integrating region proposal networks (RPNs) into the detection pipeline. This reduced the computational cost of generating region proposals, making it faster than earlier RCNN models. However, it remained unsuitable for real-time applications due to its high complexity.

- 2.3.2 SSD: Single Shot Multibox Detector (2016)

  SSD addressed the speed limitations of Faster R-CNN by eliminating the need for region proposals. It performed object detection in a single forward pass, significantly improving inference time. Despite its speed advantage, SSD struggled with detecting smaller objects due to limitations in feature representation at lower scales.

- 2.3.3 YOLO: You Only Look Once (2016)

  YOLO revolutionized object detection by combining region proposal and classification into a single unified step. This simplified architecture provided real-time speed with reasonable accuracy. However, early versions of YOLO faced challenges in handling small objects and complex scenes.

- 2.3.4 YOLOv3 (2018)

  YOLOv3 introduced multi-scale predictions and improvements in feature extraction using a Darknet-53 backbone. These changes enhanced detection accuracy, particularly for smaller objects, while maintaining high speed. However, the model still required further optimization for deployment in diverse scenarios

- 2.3.5 YOLOv4 (2020)

  YOLOv4 incorporated advanced techniques such as CSPNet (Cross-Stage Partial Networks) and data augmentation strategies like Mosaic. These innovations improved robustness and accuracy without compromising speed. YOLOv4 demonstrated significant improvements in real-world performance, addressing many issues seen in earlier versions.

- 2.3.6 YOLOv5 (2020)

  YOLOv5 built on YOLOv4 by focusing on ease of use and efficiency. It introduced improvements in training pipelines, such as auto-learning anchor boxes and augmentation techniques. The model's smaller size and scalability made it highly adaptable for deployment across various hardware platforms.

2.4 Pros and Cons of Approaches

- Faster R-CNN: High accuracy but slow and computationally expensive.
- SSD: Faster than Faster R-CNN but less effective for small object detection.
- YOLO (Initial Versions): Fast and efficient but struggled with small objects and complex scenarios.
- YOLOv3: Improved accuracy for small objects but needed further optimization.
- YOLOv4: Balanced accuracy and speed with advanced techniques but required careful tuning.
- YOLOv5: User-friendly, efficient, and scalable, but dependent on proper training for specific tasks.

2.5 Issues from Investigation

Throughout the evolution of object detection models, a common trade-off between speed and accuracy has persisted. Faster R-CNN prioritized accuracy but lacked speed. SSD and early YOLO versions achieved real-time performance but struggled with detecting smaller objects and handling complex scenes. YOLOv5 addresses these issues by optimizing both speed and accuracy, though it relies on proper configuration for specific applications.

2.6 Summary

This chapter provided a chronological overview of object detection advancements, culminating in the development of YOLOv5. Each method contributed incremental improvements to speed, accuracy, and usability. YOLOv5 emerged as a highly efficient and versatile model, setting a strong foundation for further innovation in the field of object detection.

CHAPTER-3
REQUIREMENT ARTIFACTS

3.1 Introduction

This chapter explains the requirements for implementing the YOLOv5 object detection system. It includes the hardware, software, and project-specific needs to ensure successful development and deployment. These requirements are divided into technical specifications, functional goals, and performance standards.

3.2 Hardware and Software Requirements

- Hardware: The system requires a high-performance NVIDIA GPU, such as the RTX 3090 or newer, to handle intensive computations. At least 16GB of RAM and 100GB of available storage are necessary to support the training process and manage datasets efficiently.
- Software: Key software requirements include:
    a) Python 3.11 as the primary programming language
    b) JavaScript for converting annotation labels to YOLO format
    c) YOLOv5 computer vision model used for object detection.
    d) YAML for configuration management
    e) VS Code, Anaconda Navigator, and PyCharm for IDE's
    f) A compatible operating system like Windows.
- Libraries Used: The following libraries were used to implement and enhance the project:
    a) PyTorch: For building and training the deep learning model.
    b) OpenCV: For preprocessing and handling image data.
    c) Matplotlib: For visualizing results and performance metrics.
    d) NumPy: For numerical computations.
    e) Pandas: For data manipulation and analysis
    f) Seaborn: For advanced visualizations.
    g) Pillow: For image processing
    h) Scikit-learn: For additional evaluation metrics.
    i) Python-tesseract: For optical character recognition (OCR) tool
    j) YAML: For managing configuration files.
    k) Flask/Django (optional): For deploying the system as a web application.

3.3 Specific Project Requirements

3.3.1 Data Requirements

The project primarily uses the PASCAL_VOC, and custom dataset for training and testing the YOLOv5 model. This dataset is a standard benchmark for object detection tasks, containing diverse images with labeled objects. Additional custom datasets were also utilized to test the system's real-world performance and adaptability.

3.3.2 Functional Requirements

The object detection system must be capable of identifying and localizing multiple objects in real time. The model's functionality should ensure:

1. Accurate detection across varied environments.
2. Compatibility with both pre-trained and custom datasets.
3. Efficient handling of complex scenes with multiple object types.

3.3.3 Performance and Security Requirements

1. Performance Requirements: The system should achieve a mean Average Precision (mAP) score of 85% or higher, which reflects high accuracy in detecting objects.
2. Security Requirements: During deployment, ensure data privacy and protection, particularly when working with sensitive or proprietary datasets.

3.3.4 Look and Feel Requirements

1. The user interface, if included, should be simple and intuitive. For example:
2. A clear display of detected objects with bounding boxes and labels.
3. Real-time updates with minimal lag.
4. Easy integration into larger applications or systems.

3.3.5 Scalability Requirements

1. The system should be scalable, allowing users to:
2. Train the model with larger datasets or on different hardware configurations.
3. Deploy the model in varied environments, from edge devices to cloud-based systems.

3.3.6 Modular Components

1. The system comprises the following key modules:
2. Preprocessing Module: Responsible for preparing datasets and converting labels to YOLO format using JavaScript scripts.
3. Training Module: Utilizes PyTorch for training the YOLOv5 model on the dataset.
4. Validation Module: evaluates the performance of the YOLOv5 model during training. Analyzes false positives, false negatives, and misclassifications it also helps identify areas where the model struggles (e.g., small objects, overlapping objects). It also saves validation results for each training epoch. Provides graphical plots (e.g., mAP vs. epochs) to track progress.
5. Detection Module: core component that handles object detection tasks using the trained YOLOv5 model. Performs real-time prediction of objects in the input. Draws bounding boxes with class labels and confidence scores on the input image. It highlights detected objects for user verification.
6. Evaluation Module: Measures performance metrics like mAP to ensure accuracy.
7. Deployment Module: Handles integration of the trained model into real-world applications.

3.4 Summary

This chapter provided a detailed overview of the hardware, software, and project-specific requirements for implementing YOLOv5. It outlined the technical specifications, functional goals, performance benchmarks, modular design, and essential libraries. These requirements form the foundation for the next stages of implementation and testing.

CHAPTER-4
DESIGN METHODOLOGY AND ITS NOVELTY

1.1 Methodology and Goal

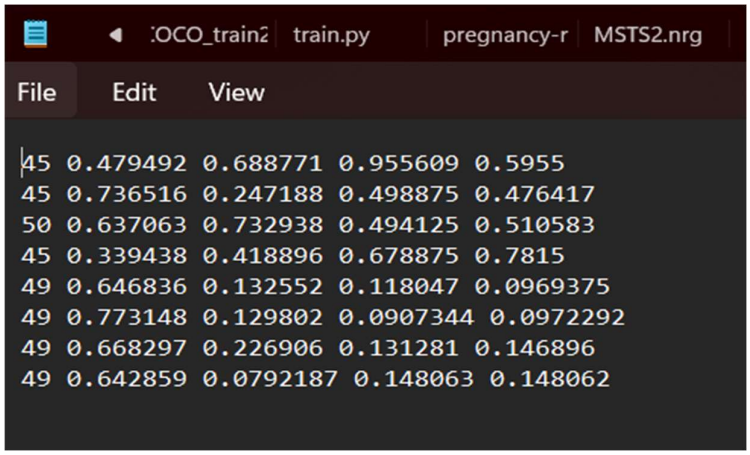
The goal of this project was to build an efficient object detection system using YOLOv5, optimized for speed and accuracy. The methodology involved several key steps:

a) Dataset Selection: The PASCAL_VOC and a Custom dataset were used for training and testing the model.

The directory structure is as follows:

Tab 4.1 Describing the Directory structure for the project.

Directory	Subdirectory	Content
Custom dataset	train/images/	Contains training images
	train/labels/	Contains labels for training images
	valid/images/	Contains validation images
	valid/labels/	Contains labels for validation images
	test/images/	Contains test images
	test/labels/	Contains labels for test images
PASCAL_VOC	train/images/	Contains training images
	train/labels/	Contains labels for training images
	test/images/	Contains test images
	test/labels/	Contains labels for test images



- Fig 4.1 - This is an example how the label is formed for each image.

  This data represents bounding box annotations for object detection. Each line includes a class ID, normalized center coordinates (x, y), width, and height (all relative to image dimensions). For example, class 5 has a bounding box centered at (0.407, 0.352) with dimensions 0.103 (width) and 0.118 (height).

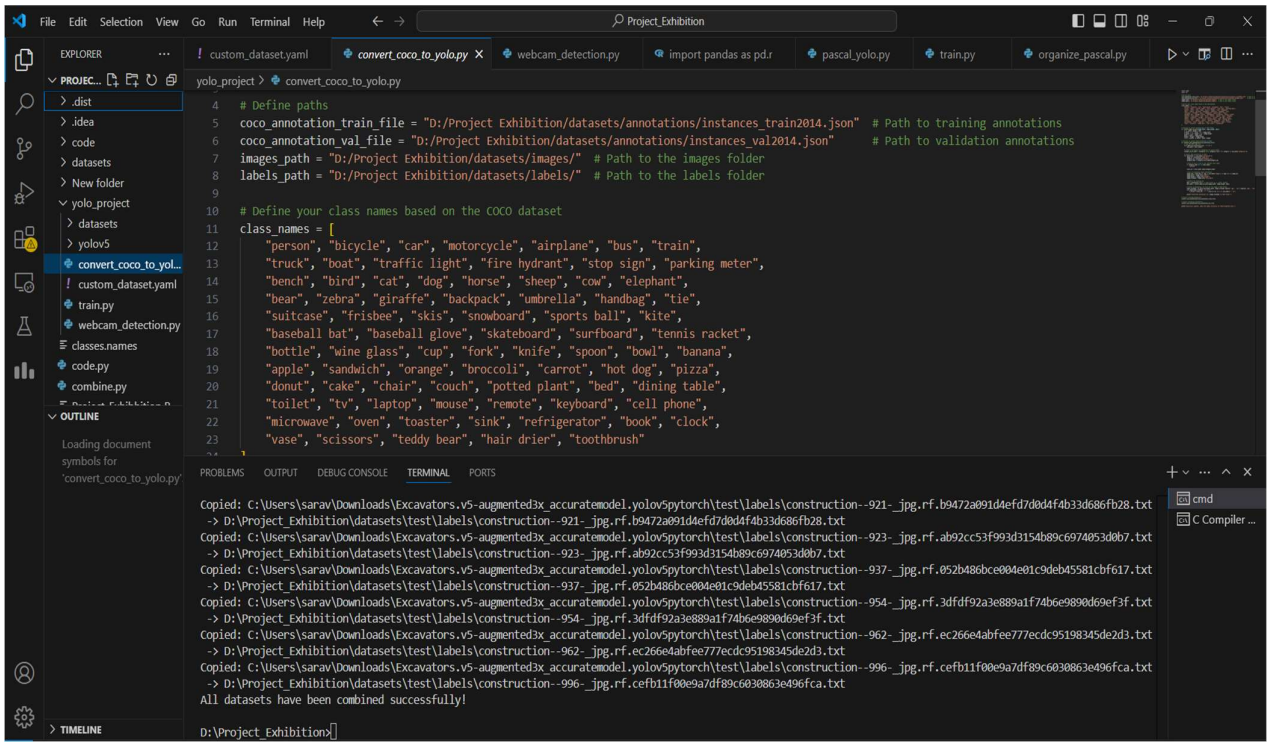
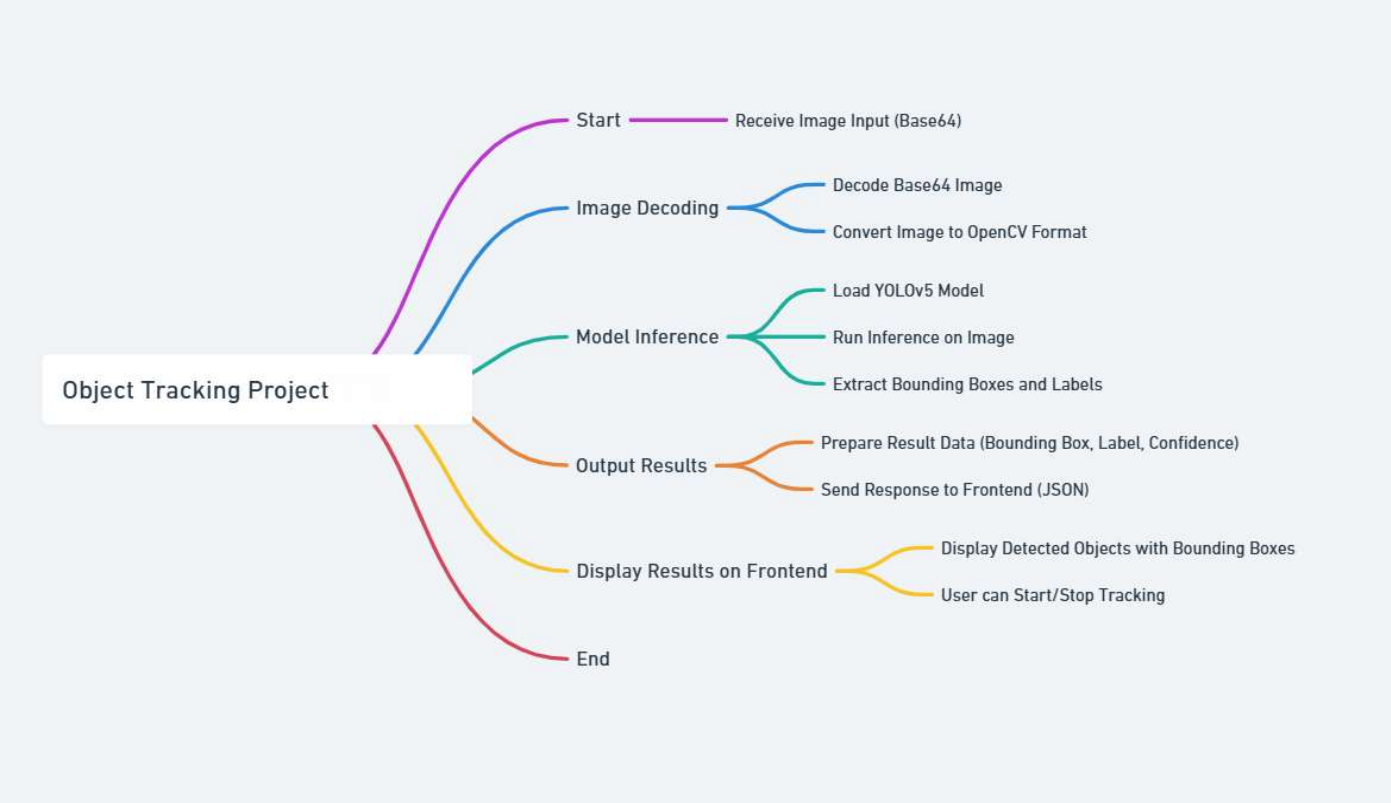


Fig 4.2 - Converting dataset Annotations to YOLO Format. Converting annotations to YOLO format involves transforming bounding box data into normalized values relative to image size. Each line follows <class_id> <x_center> <y_center> <width> <height>, with all values scaled

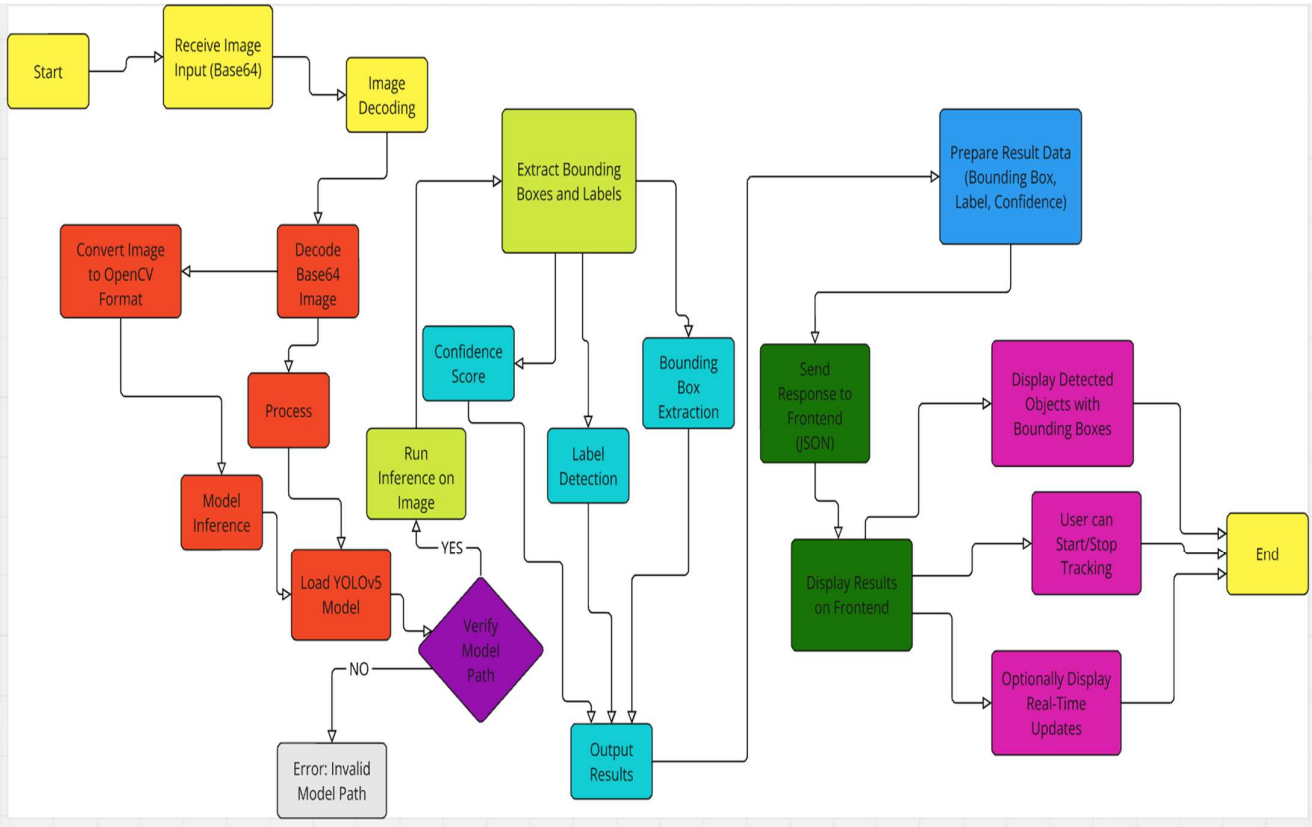
between 0 and 1. This ensures compatibility with YOLO models, which expect annotations in this standardized, efficient format.

b) Model Architecture: YOLOv5 was chosen for its high speed and accuracy in object detection tasks.



- Fig 4.3 - Model Prototype for Detecting objects and making it to use in inference

Creating a model prototype for object detection involves several steps. First, select a suitable framework like TensorFlow or PyTorch. Preprocess the dataset by annotating images in the YOLO format. Train a pre-existing model (e.g., YOLOv8 or Faster R-CNN) on your dataset, fine-tuning it to achieve desired performance. Export the trained model in a deployable format, such as ONNX or TensorFlow. For inference, load the model, preprocess input images to match training dimensions, and perform predictions. Post-process outputs (e.g., applying confidence thresholds) to extract bounding boxes and labels. Integrate the model into applications via APIs or direct deployment.



- Fig 4.4 - Flowchart for entire object detection model building

The object detection model-building process begins with collecting and annotating images, followed by preprocessing the data, including resizing, augmenting, and formatting annotations (e.g., YOLO format). Select a suitable model framework, train the model with tuned hyperparameters, validate performance using metrics like mAP, and finally deploy the trained model for inference.

c) Training and Optimization: The model was trained using a batch size of 16 and an image size of 320x320. Hyperparameters were tuned to maximize performance, balancing speed and accuracy for both the datasets**.**

4.2 Functional Modules Design and Analysis

The system was broken down into functional modules:

- Data Preprocessing: Includes resizing and augmenting images to improve model robustness. The key preprocessing techniques we have used, based on the typical workflow for such tasks is : Image Resizing

a) Why it's important: YOLOv5 requires a consistent input size for training. The images were resized to 320x320 pixels before feeding them into the model.
b) Implementation: The images in the dataset were resized to a fixed size (e.g., 320x320 or 640x640) to ensure that they can be processed efficiently by the neural network.

- Model Training: YOLOv5 was trained on both PASCAL_VOC and custom datasets.
- Testing and Evaluation: The model was tested for accuracy using evaluation metrics like precision, recall, mAP_0.5, mAP_0.5:0.95, etc. for dataset PASCAL_VOC and Custom dataset.

4.3 Software Architectural Designs

The design followed a modular structure:

- Data Pipeline: Handles dataset loading, augmentation, and pre-processing.

a) Dataset Loading: We loaded the PASCAL VOC and custom datasets, which involved reading images and their corresponding annotations.

b) Data Augmentation: To enhance the diversity of Wer training data and improve the model's generalization, we applied various augmentation techniques. YOLOv5 utilizes online image-space and color-space augmentations in the training loader to present a new and unique augmented mosaic each time an image is loaded for training. This means that images are never presented twice in the same way, helping the model learn more robust features.

c) Pre-processing: We resized images to a consistent size (e.g., 320x320 pixels) and normalized pixel values to a range suitable for the model. Additionally, we converted annotations to the YOLO format, which includes bounding box coordinates and class labels.

- Model Pipeline: Manages training, evaluation, and deployment.

a) Model Selection: We chose the YOLOv5 architecture, known for its efficiency and accuracy in object detection tasks.

b) Training: We trained the model using the prepared datasets, adjusting hyperparameters like learning rate, batch size, and number of epochs to optimize performance.
c) Evaluation: After training, we evaluated the model's performance on validation datasets to assess its accuracy and make necessary adjustments.
d) Deployment: We prepared the trained model for deployment, ensuring it could process new images and make predictions effectively.

- Testing Pipeline: Evaluates model performance using validation datasets and generates reports.

a) Performance Evaluation: You tested the model on unseen data to evaluate its performance, using evaluation metrics like precision, recall, mAP_0.5, mAP_0.5:0.95, etc
b) Reporting: You generated reports detailing the model's performance, including accuracy metrics and potential areas for improvement.

4.4 Subsystem Services

Each part of the system operates independently but works together. For example:

- **Training**: YOLOv5 was trained with the PASCAL_VOC and fine-tuned on the custom dataset.
- **Inference**: The trained model was used to perform object detection in real-time, identifying objects in test images using webcam and uploading a file in mp4, png like formats

4.5 User Interface Design

For visualization, we used simple scripts to display the detection results, showing bounding boxes around detected objects in images. A simple command-line interface was implemented for model training and testing.

Fig 4.5 - The above command line was used to bound boxes for already trained custom dataset.

This command runs object detection using a YOLO model in Python. It uses the specified weights (best.pt), processes images at a resolution of 320 pixels, and sets a confidence threshold of 0.1. The images are sourced from the given path, and results are saved as images and text files for

4.6 Summary

This chapter covered the design methodology, focusing on YOLOv5's architecture and how we applied it to object detection. We also discussed the modular design and subsystems implemented in the project.

CHAPTER-5:
TECHNICAL IMPLEMENTATION & ANALYSIS

5.1 Outline

In this chapter, the technical implementation of the project is explained, covering the coding process, results, and performance analysis.

5.2 Technical Coding and Code Solutions

The code for training YOLOv5 on the PASCAL_VOC and custom datasets was developed in Python using PyTorch. Key steps involved:

- Model Loading: Loading pre-trained YOLOv5 weights and fine-tuning them for our dataset.
- Data Augmentation: Techniques like oversampling and under sampling were used to augment the dataset for better generalization and to balance the datasets with imbalance classes.

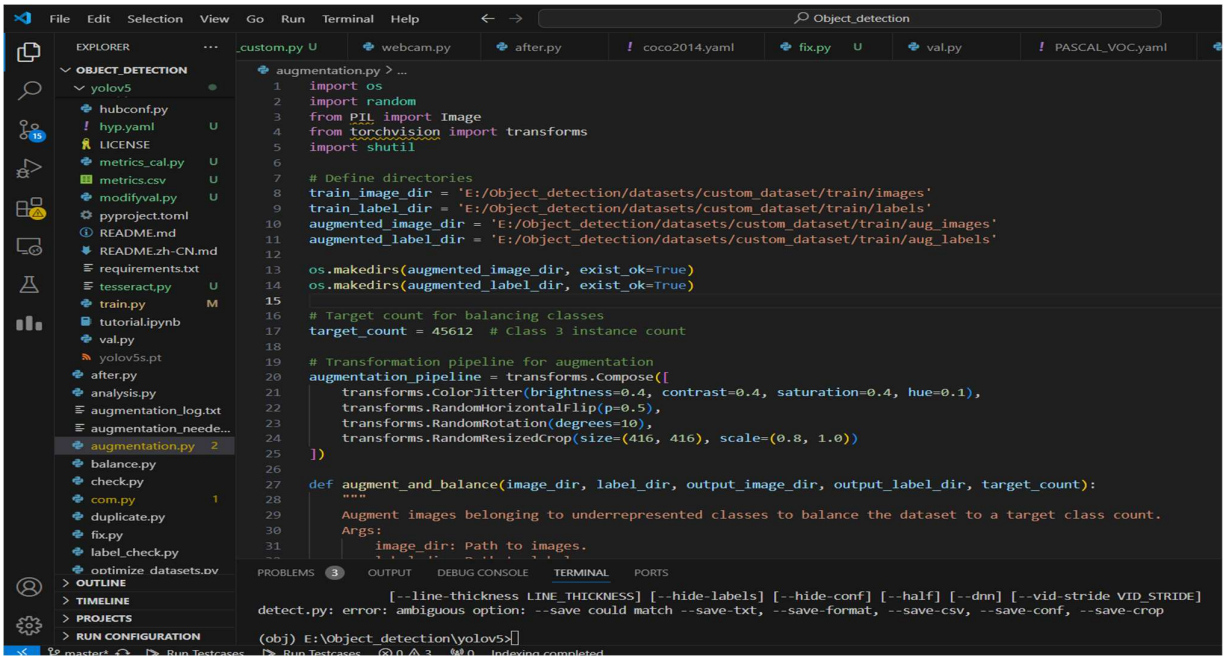


Fig 5.1- Code Snippet of data augmentation We observed a significant change in the training results, and the performance of the model. There were major changes in dataset as well as the evaluation metrics.

- Training Loop: The training was run for 100 epochs, optimizing using the Adam optimizer.

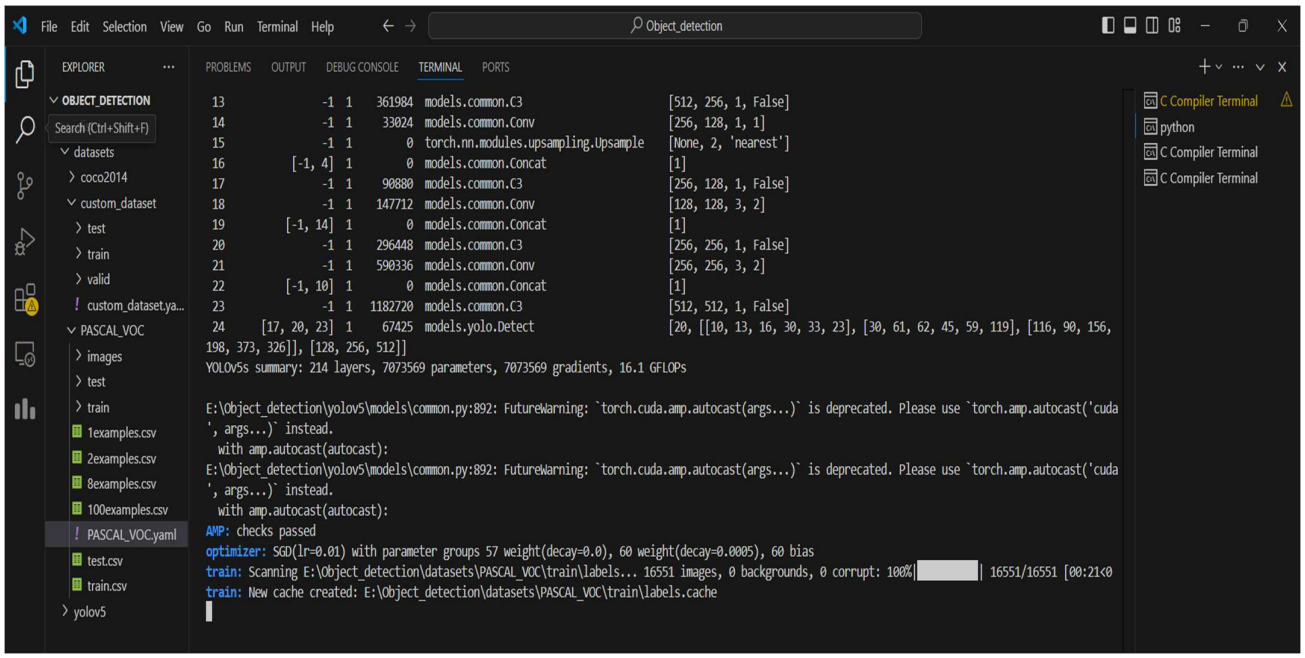


Fig 5.2- The above snippet is all about how the PASCAL_VOC dataset is getting trained.

The snippet outlines the process of training an object detection model using the PASCAL_VOC dataset. It includes data collection and annotation, preprocessing (like resizing and augmentation), choosing a model framework (e.g., YOLO), training with hyperparameter tuning, evaluating performance using metrics like mAP, and deploying the trained model for inference.

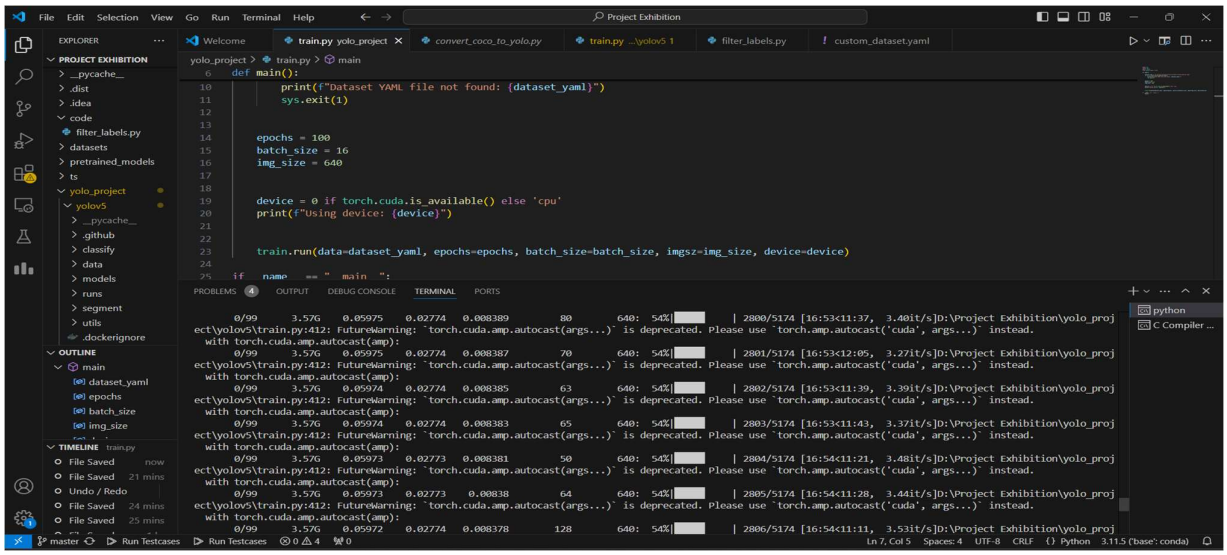


Fig 5.3- Model using CUDA to support GPU for training.

To leverage GPU for training, use CUDA with frameworks like TensorFlow or PyTorch. Enable GPU support by installing the necessary CUDA toolkit, cuDNN, and ensuring proper configuration for faster computation.

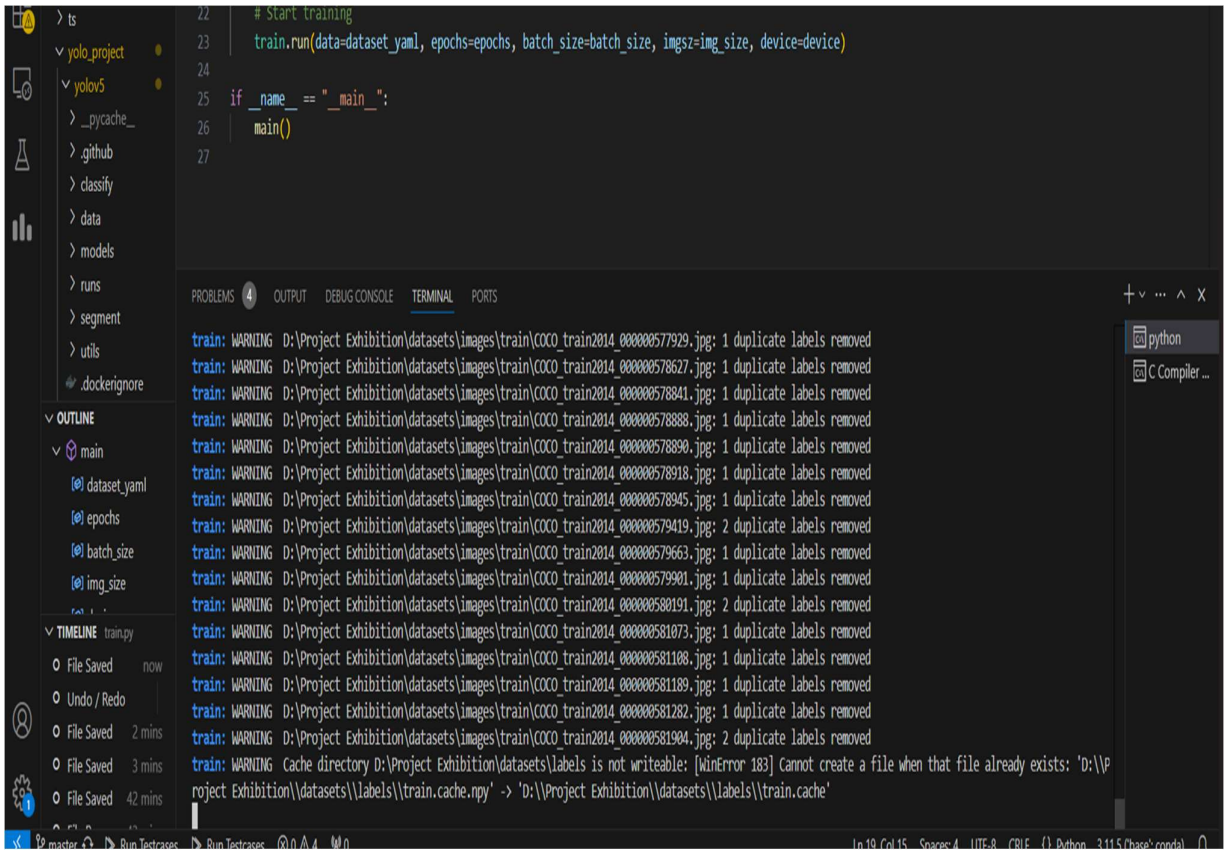


Fig 5.4- Model Getting Trained and duplicates getting removed

During model training, duplicates in the dataset are identified and removed by checking for identical images or annotations. This ensures data quality, prevents overfitting, and accelerates training by reducing redundancy.

5.3 Working Layout of Forms

The system's workflow is organized into training, validation, and testing phases. For each phase, specific functions handle data loading, model training, and evaluation metrics calculation. For all training process the results are saved in .txt file where loss, evaluation metrics, and other parameters for each epoch. This will help in analyse how well the model is trained on the dataset.

To access the Excel data through Google Drive : Google Drive to access the training results file

For PASCAL_VOC dataset the below table is the summary of the performance

Tab 5.1 Summary of performance for PASCAL_VOC dataset

YOLOv5 summary: 157 layers, 7064065 parameters, 0 gradients, 15.9 GFLOPs						
Class	**Images**	**Instances**	**P**	**R**	**mAP50**	**mAP50-95: 100%|| 155/155 [00:50<00:00**
all	4952	12032	0.767	0.689	0.759	0.49
aeroplane	4952	285	0.892	0.744	0.848	0.524
bicycle	4952	337	0.834	0.789	0.858	0.573
bird	4952	459	0.714	0.649	0.686	0.402
boat	4952	263	0.711	0.574	0.663	0.366
bottle	4952	469	0.736	0.557	0.617	0.366
bus	4952	213	0.824	0.761	0.838	0.666
car	4952	1201	0.846	0.827	0.89	0.642
cat	4952	358	0.847	0.723	0.835	0.563
chair	4952	756	0.624	0.511	0.567	0.335
cow	4952	244	0.708	0.713	0.773	0.511
diningtable	4952	206	0.728	0.663	0.711	0.442
dog	4952	489	0.787	0.667	0.789	0.515
horse	4952	348	0.808	0.787	0.846	0.552
motorbike	4952	325	0.842	0.748	0.845	0.541
person	4952	4528	0.852	0.746	0.841	0.504
pottedplant	4952	480	0.673	0.45	0.493	0.222
sheep	4952	242	0.642	0.752	0.75	0.497
sofa	4952	239	0.68	0.619	0.699	0.481
train	4952	282	0.845	0.793	0.856	0.573
tvmonitor	4952	308	0.746	0.705	0.77	0.518

- **Overall Performance Overview**

Precision (P): 0.767

Recall (R): 0.689

Mean Average Precision at IoU=0.5 (mAP50): 0.759

Mean Average Precision at IoU=0.5:0.95 (mAP50-95): 0.490

Key Insights

- High-performing Classes:
  a) Aeroplane, Car, and Train showed strong results with high precision (>0.84) and mAP50 (>0.84).
  b) Bicycle and Bus also performed well, with balanced precision and recall and mAP50 values around 0.85.

- Moderate-performing Classes:
  a) Bird, Boat, Bottle, and Chair had moderate precision and recall but lower mAP50-95 scores (0.3–0.4 range).
  b) Potted Plant had relatively low precision and mAP scores, suggesting challenges in detection.

- Weak-performing Classes:
  a) Sheep and Sofa have relatively low precision and recall but still achieved decent mAP50 values (~0.75).
  b) Chair and Potted Plant are among the lowest performers, with mAP50-95 scores below 0.4.

- General Observations

The overall precision and recall metrics are acceptable for a general-purpose object detection model. The mAP50-95 value (0.49) indicates the model struggles with detecting objects under varying IoU thresholds, highlighting room for improvement in multi-scale or occluded object detection.

- Recommendations
  a) Data Quality: Assess the data quality and quantity for weaker classes like Potted Plant and Chair. Augmentation or additional training data may help.
  b) Model Tuning: We consider fine-tuning hyperparameters or using a more complex model architecture if inference speed allows.
  c) Class Imbalance: We addressed class imbalance by using techniques such as oversampling weaker classes or loss weighting.

- Conclusion:

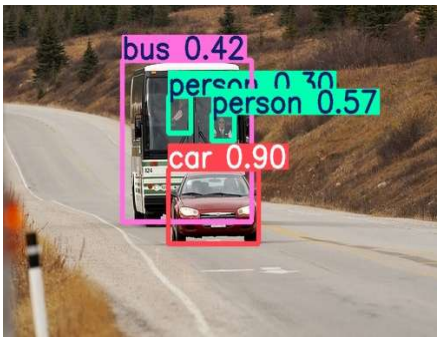
  The results are reasonable for many use cases, but targeted improvements could enhance performance, especially for lower-performing classes. Whether this level of performance is acceptable depends on the specific application and requirements.

The same way has been done to the Custom_dataset as well.

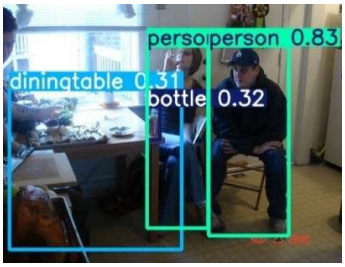
5.4 Prototype Submission

The model's prototype was tested using the PASCAL_VOC test images and the custom dataset. The results were documented, showing the model's capability to detect objects in different scenarios.

a.



b.



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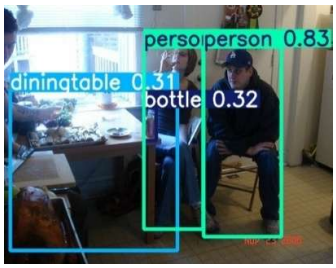
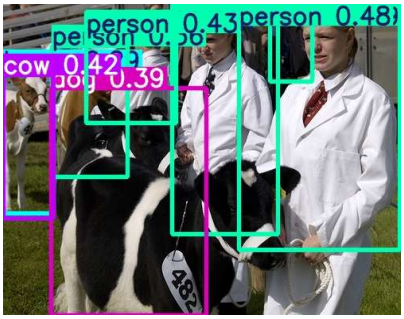
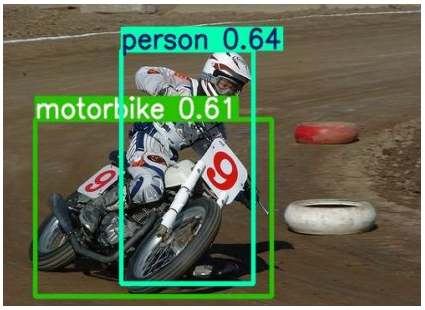


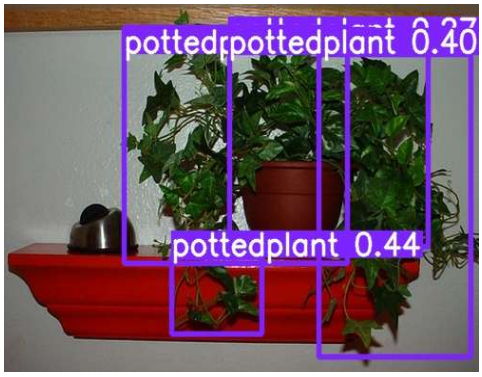
d.



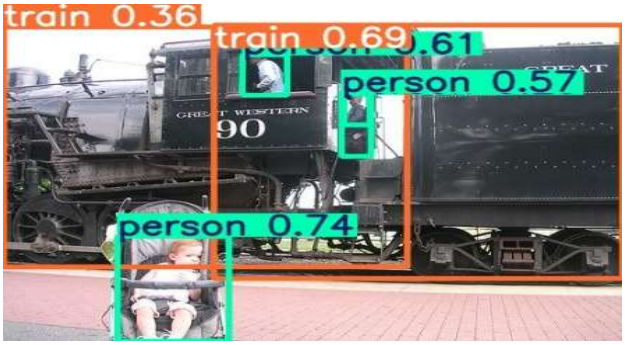
e.



f.



g. **h.**



i. **J.**

k. **l.**

- Fig 5.5 the above images are detected by the trained model with bounding boxes and labels defined

5.5 Test and Validation

The performance of the model was evaluated using metrics like mAP (mean Average Precision), precision, recall, F1-score, Gmean1, Gmean2 and accuracy. The model performed well on the PASCAL_VOC dataset and demonstrated reliable results when tested on the custom dataset.

After testing and validating the trained model for PASCAL_VOC below is the detailed report of it.

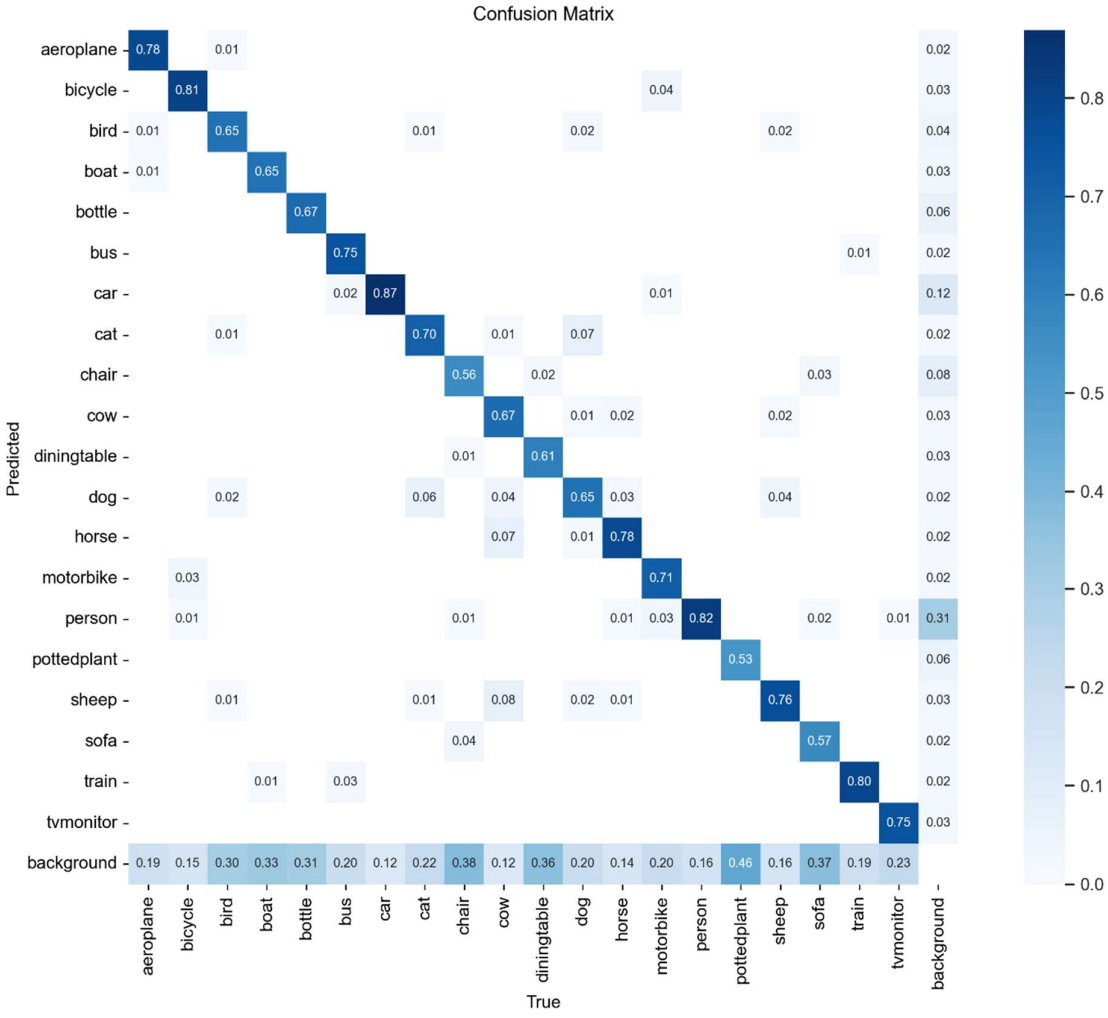


Fig 5.6 The Confusion matrix derived after validating is .

The above confusion matrix evaluates a model's performance by comparing predicted and actual labels. It displays counts of true positives, false positives, true negatives, and false negatives. For object detection, it helps assess precision, recall, and overall accuracy.

a) Tab 5.2 -The Classification report is given below. This table summarizes the precision, recall, and F1-score for each class in the dataset, as well as the geometric mean for each class. The macro and weighted averages are also included. The Matthews Correlation Coefficient (MCC) is a performance measure, indicating the quality of the classification model.

Classification Results Summary:						
Class	**Precision**	**Recall**	**F1-Score**	**GM1**	**GM2**	**Support**
0	0.585657	0.948387	0.724138	0.7453	0.7453	155
1	0.583784	0.593407	0.588556	0.5886	0.5886	182
2	0.387097	0.413793	0.4	0.4002	0.8817	58
3	0.778547	0.725806	0.751252	0.7517	0.818	310
4	0.579646	0.5671	0.573304	0.5733	0.4294	231
5	0.594595	0.575163	0.584718	0.5848	0.7042	153
6	0.723002	0.712996	0.717964	0.718	0.8256	1662
7	0.616279	0.552083	0.582418	0.5833	0.8319	96
8	0.831776	0.881188	0.855769	0.8561	0.464	101
9	0.542857	0.587629	0.564356	0.5648	0.7747	97
10	0.882979	0.83	0.85567	0.8561	0.8561	200
11	0.559701	0.595238	0.576923	0.8561	0.8561	126
12	0.866379	0.897321	0.881579	0.8561	0.8561	224
13	0.798077	0.838384	0.817734	0.8177	0.8561	99
14	0.468354	0.393617	0.427746	0.4277	0.8561	94
15	0.730769	0.678571	0.703704	0.7042	0.8561	112
16	0.827055	0.824232	0.825641	0.8256	0.8561	586
17	0.850622	0.813492	0.831643	0.8319	0.8561	252
18	0.496689	0.433526	0.462963	0.4629	0.8561	173
19	0.79	0.759615	0.77451	0.7747	0.8561	104
Additional Information:						
MCC (Matthews Correlation Coefficient): 0.6683						
accuracy 0.715254 0.715254 0.715254 0.715254						
macro avg 0.674693 0.681078 0.675029 5015.000000						
weighted avg 0.717113 0.715254 0.714458 5015.000000						

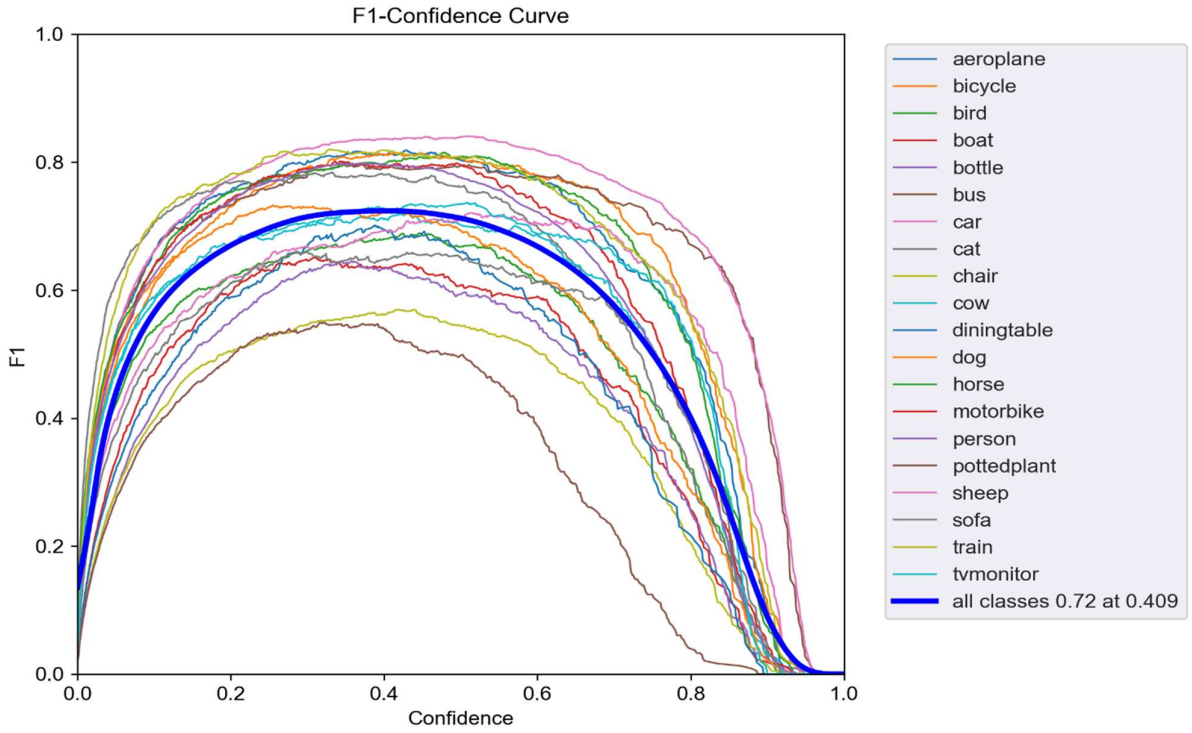


Fig-**5.7** representing F1- Confidence score for PASCAL_VOC dataset.

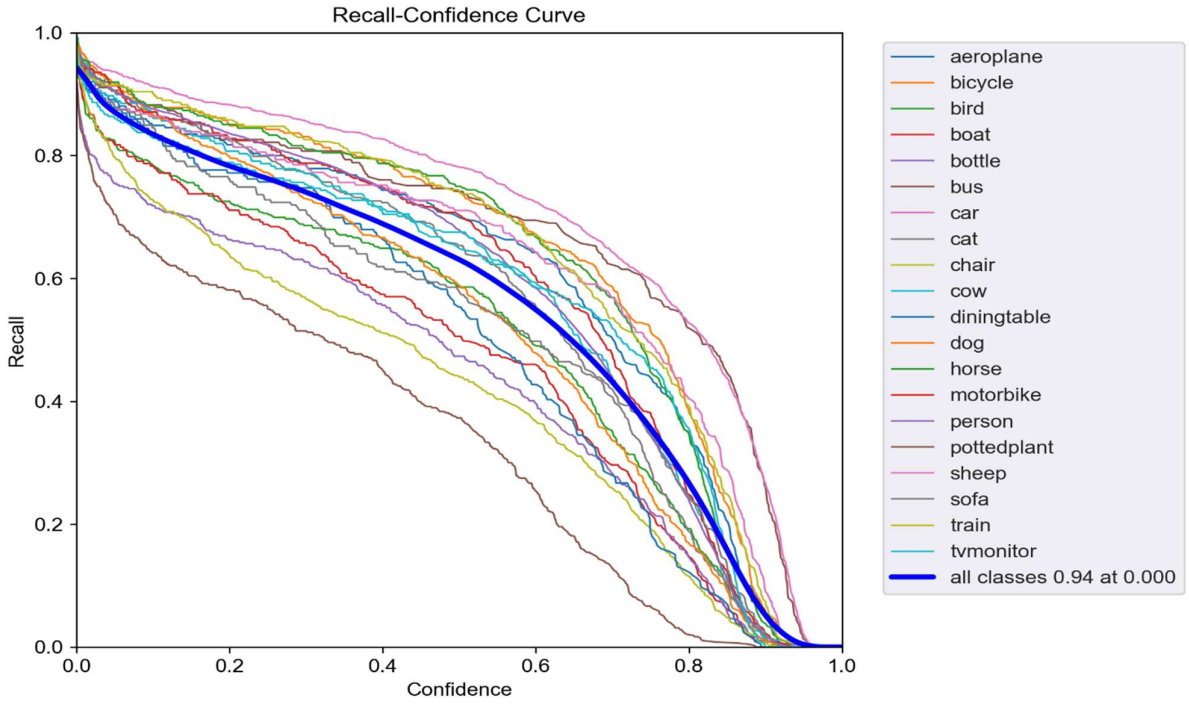


Fig-**5.8** representing Recall- Confidence score for PASCAL_VOC dataset

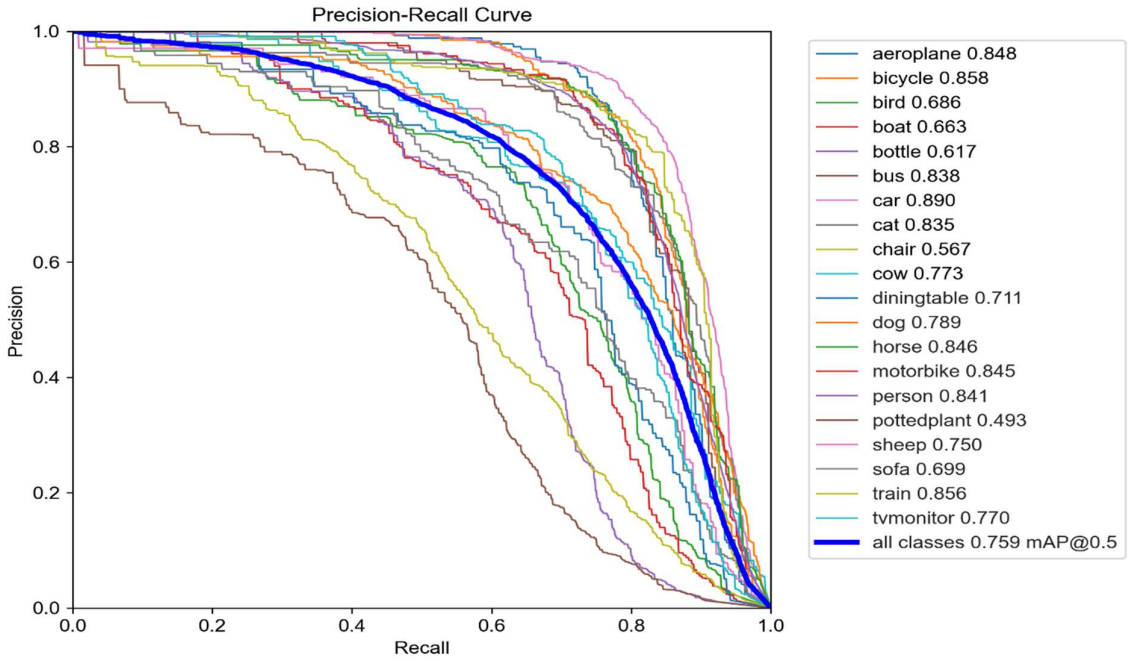


Fig-**5.9** representing Precision-Recall curve for PASCAL_VOC dataset

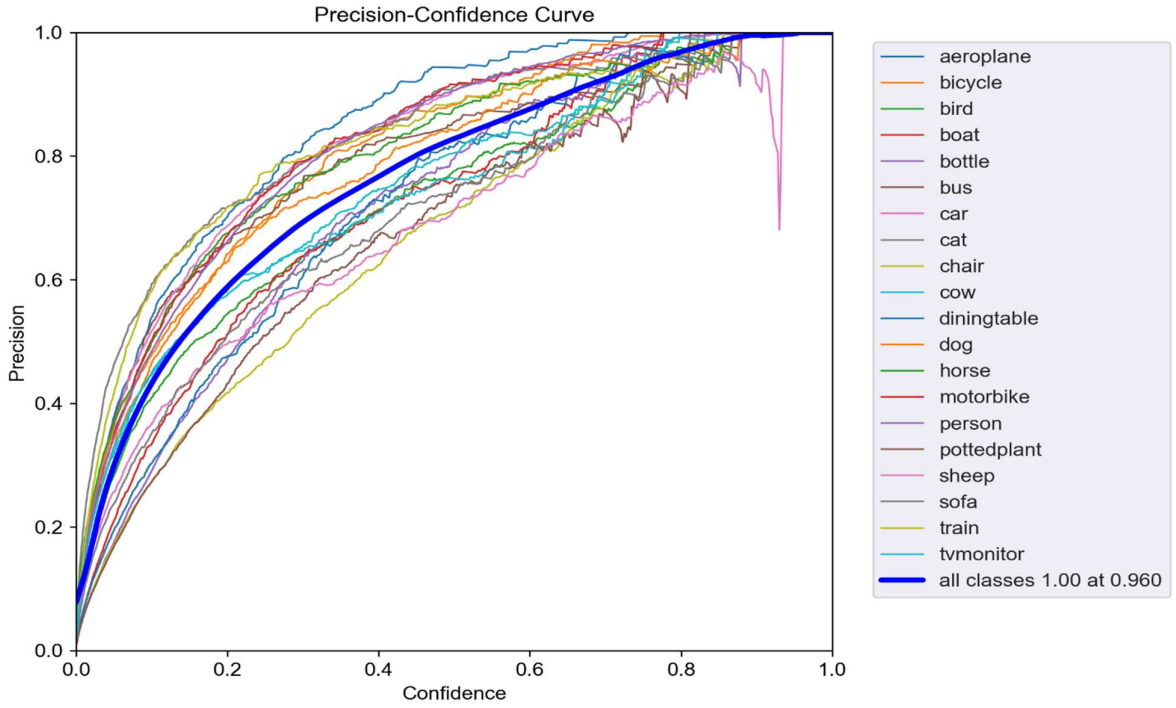


Fig-**5.10** representing Precision- Confidence score for PASCAL_VOC dataset

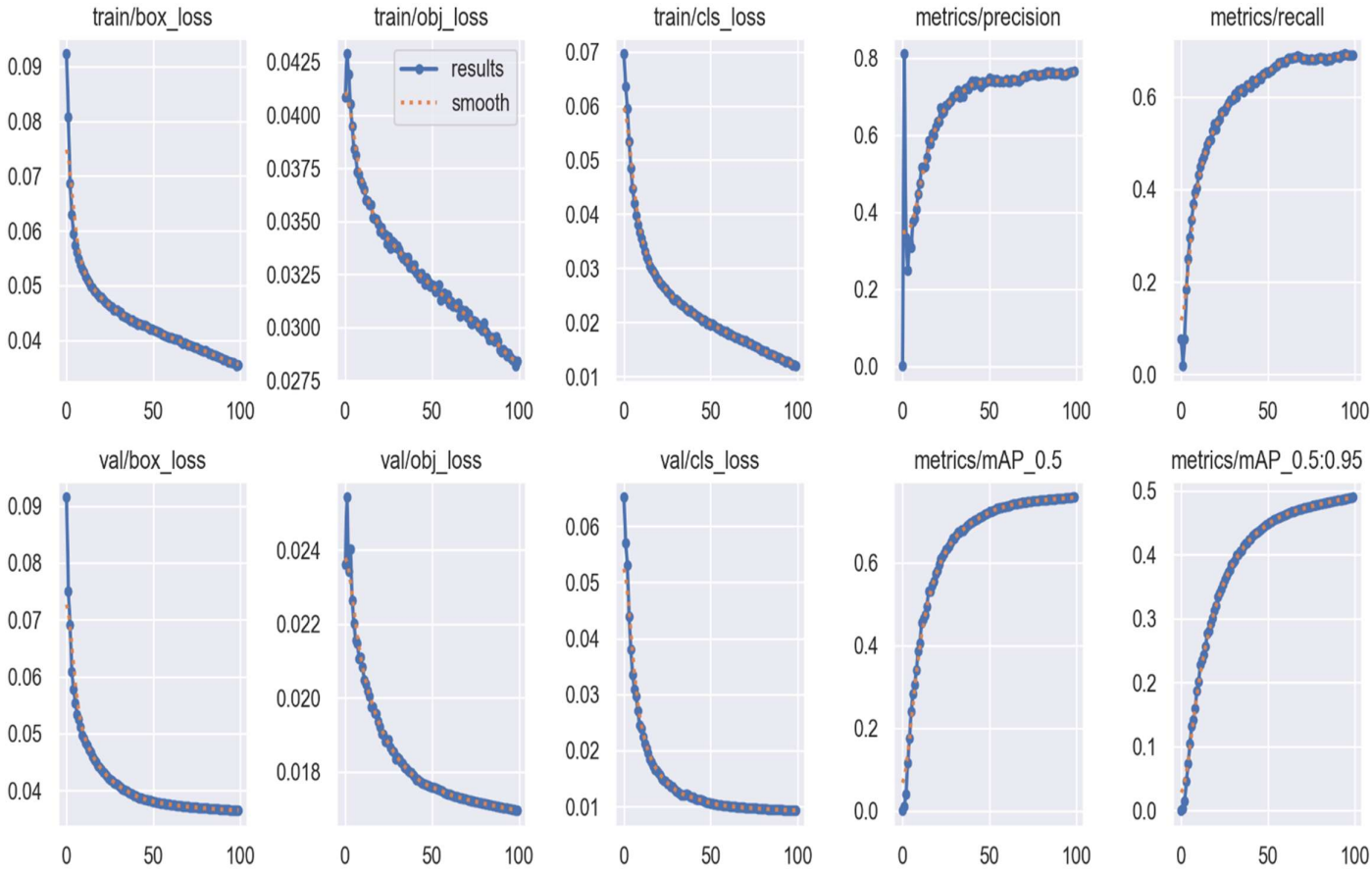


Fig-**5.11** representing results score containing train and val box_loss, obj_loss, cls_loss, evaluation metrics for PASCAL_VOC dataset

Similarly for the custom_dataset, here is the detailed report after testing and validating.

a) Tab 5.3 - The Classification report is given below. This table summarizes the precision, recall, and F1-score for each class in the dataset, as well as the geometric mean for each class. The macro and weighted averages are also included. The Matthews Correlation Coefficient

Class	Precision	Recall	F1-Score	Support	GM1 (Geometric Mean)	GM2 (Geometric Mean)
0	0.6395	0.8871	0.7432	62	0.7532	0.7532
1	0.75	0.6	0.6667	70	0.6708	0.6708
2	0.7424	0.6806	0.7101	72	0.6211	0.7108
3	1	0.2857	0.4444	14	0.2132	0.5345
4	0.4074	0.5238	0.4583	21	1	0.462
5	0.6216	0.7419	0.6765	31	0.9487	0.6791
6	0.5	0.4615	0.48	26	0.7108	0.4804
7	1	0.9286	0.963	14	0.5345	0.9636
8	1	1	1	4	0.462	1
9	1	1	1	4	0.6791	1
10	0.6	0.6429	0.6207	14	0.4804	0.6211
11	0.25	0.1818	0.2105	11	0.9636	0.2132
12	1	1	1	6	1	1
13	1	0.9	0.9474	10	1	0.9487
Summary:						
Accuracy: 67.7%						
Macro Average Precision: 0.7508						
Macro Average Recall: 0.7024						
Macro Average F1-Score: 0.7086						
Weighted Average Precision: 0.6952						
Weighted Average Recall: 0.6769						
Weighted Average F1-Score: 0.6717						
Matthews Correlation Coefficient (MCC): 0.6305						

Observations:

Some Classes Perform Well. Classes like class1, class2, class9, and class13 have reasonably good metrics, indicating they have sufficient training samples and quality annotations.

Many Classes Have Zero or Near-Zero Metrics: For example, class16, class17, class19, and many others have zero precision, recall, and mAP. this often means there are insufficient or no correctly annotated instances of these classes in the validation dataset.

Imbalanced Data Distribution: Some classes, such as class23 and class24, have thousands of instances, while others, like class28 or class17, have very few (e.g., 2 or 9 instances). Such imbalance can bias the model toward frequently occurring classes. (MCC) is a performance measure, indicating the quality of the classification model.

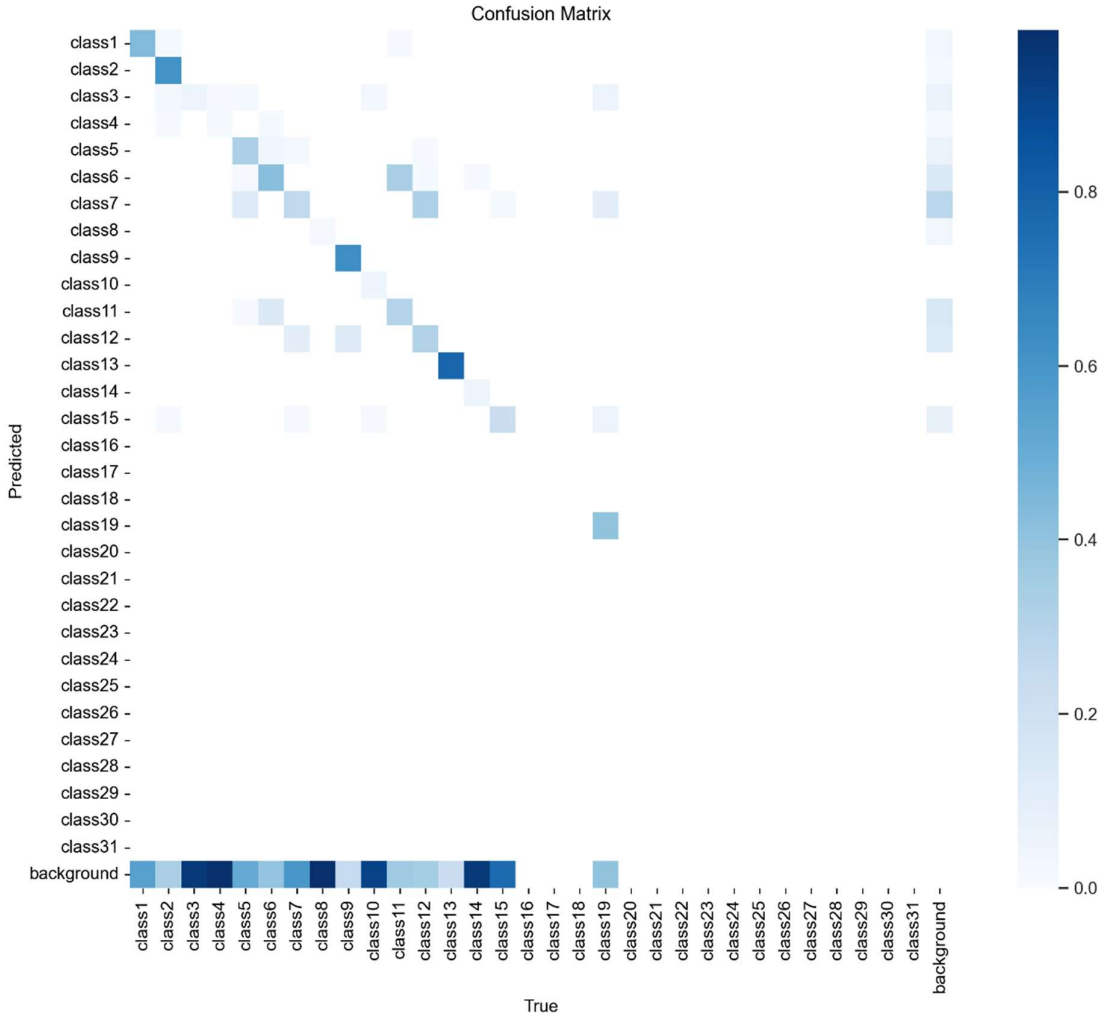


Fig 5.12 The below is the confusion matrix derived after training the model

The above confusion matrix evaluates a model's performance by comparing predicted and actual labels. It displays counts of true positives, false positives, true negatives, and false negatives. For object detection, it helps assess precision, recall, and overall accu

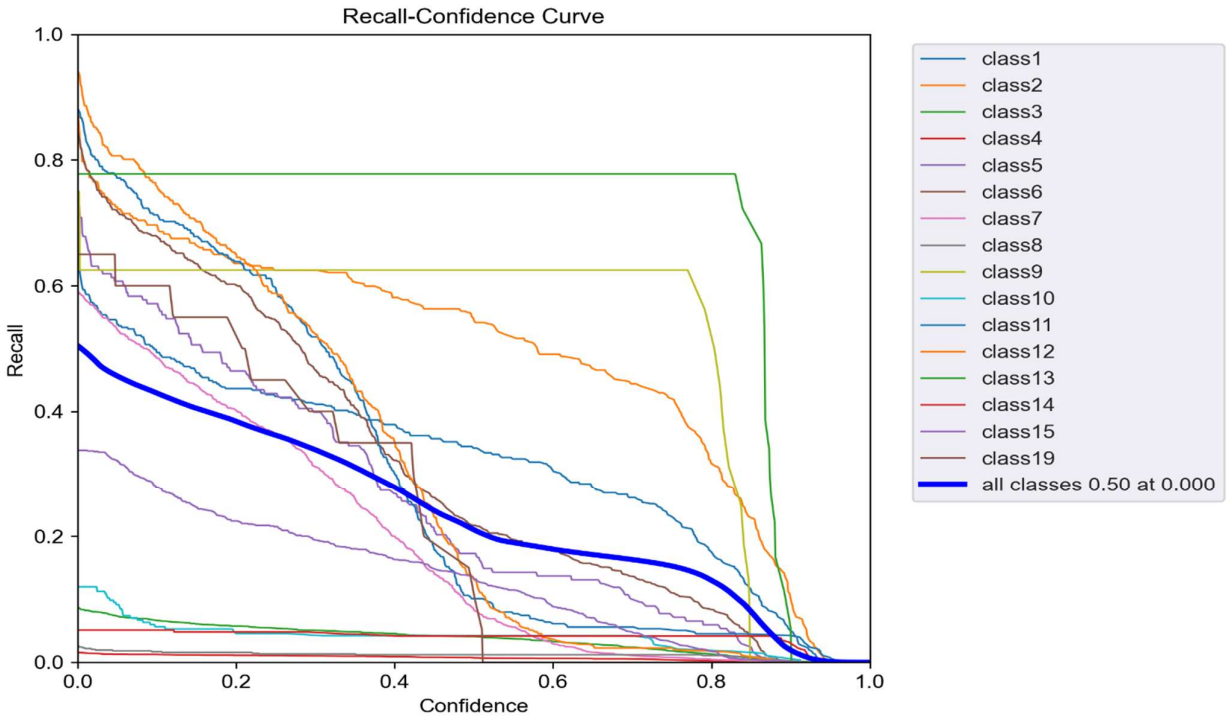


Fig-5.13 representing Recall- Confidence score for custom_dataset

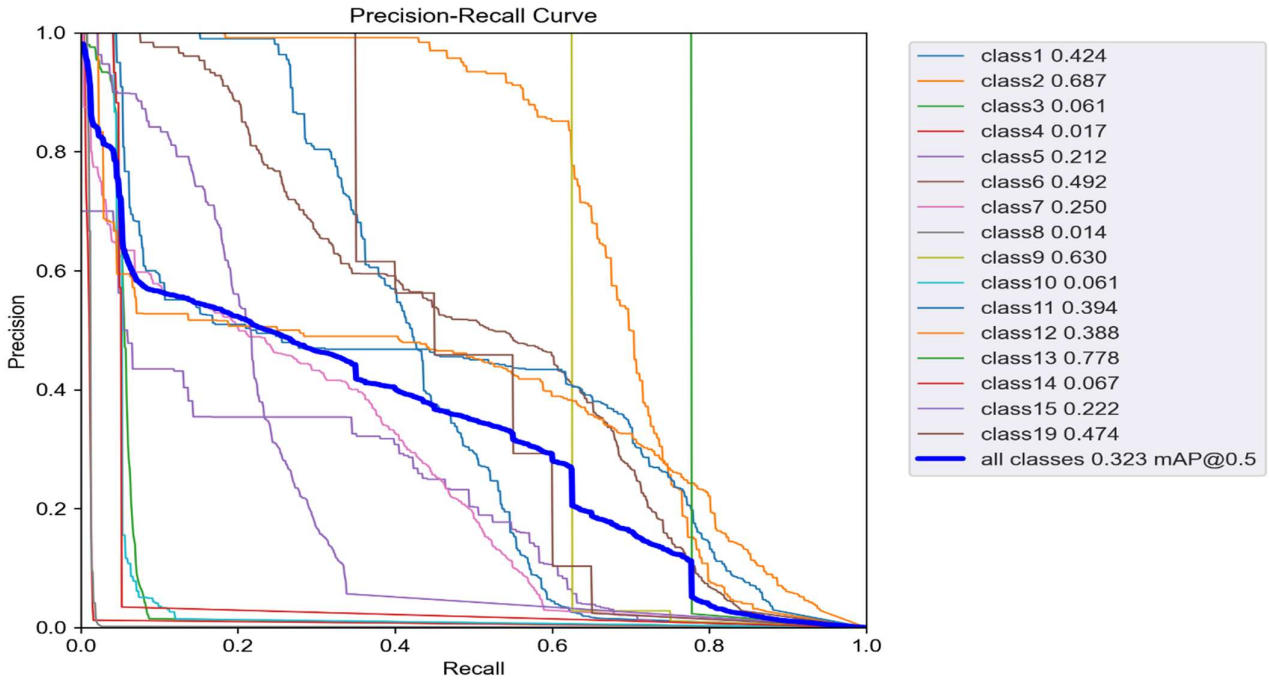


Fig-5.14 representing Precision_Recall for custom_dataset

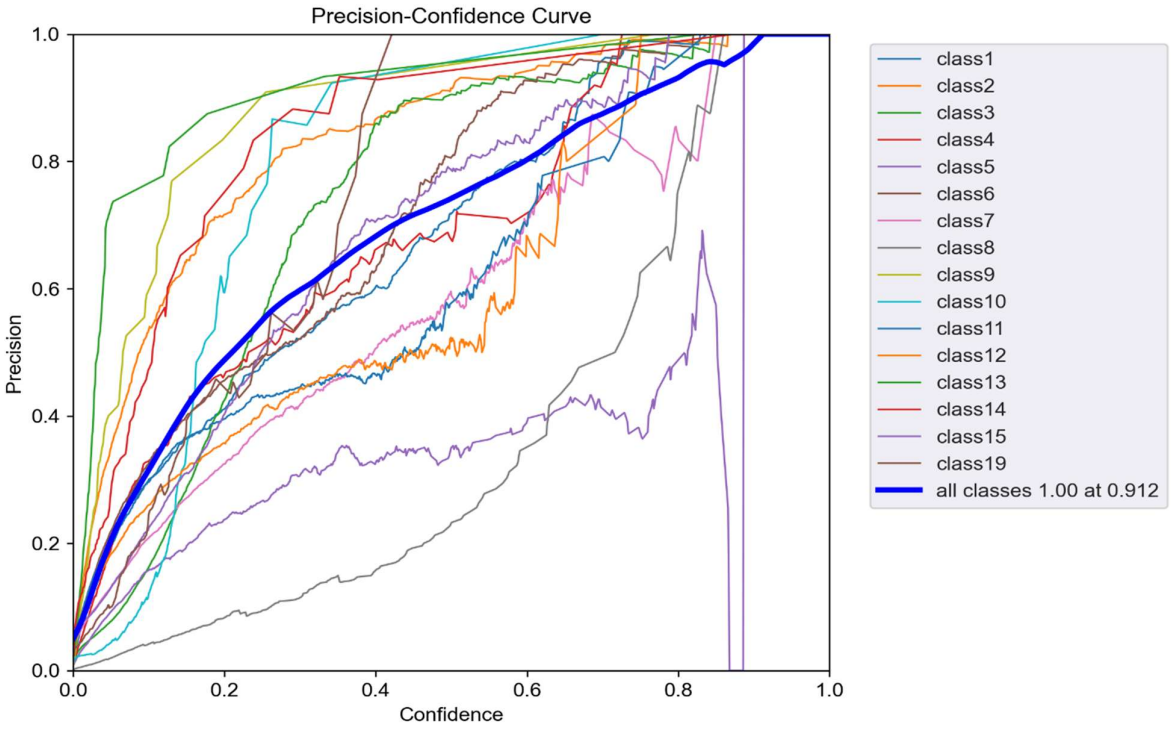


Fig-5.15 representing Precision- Confidence score for custom_dataset

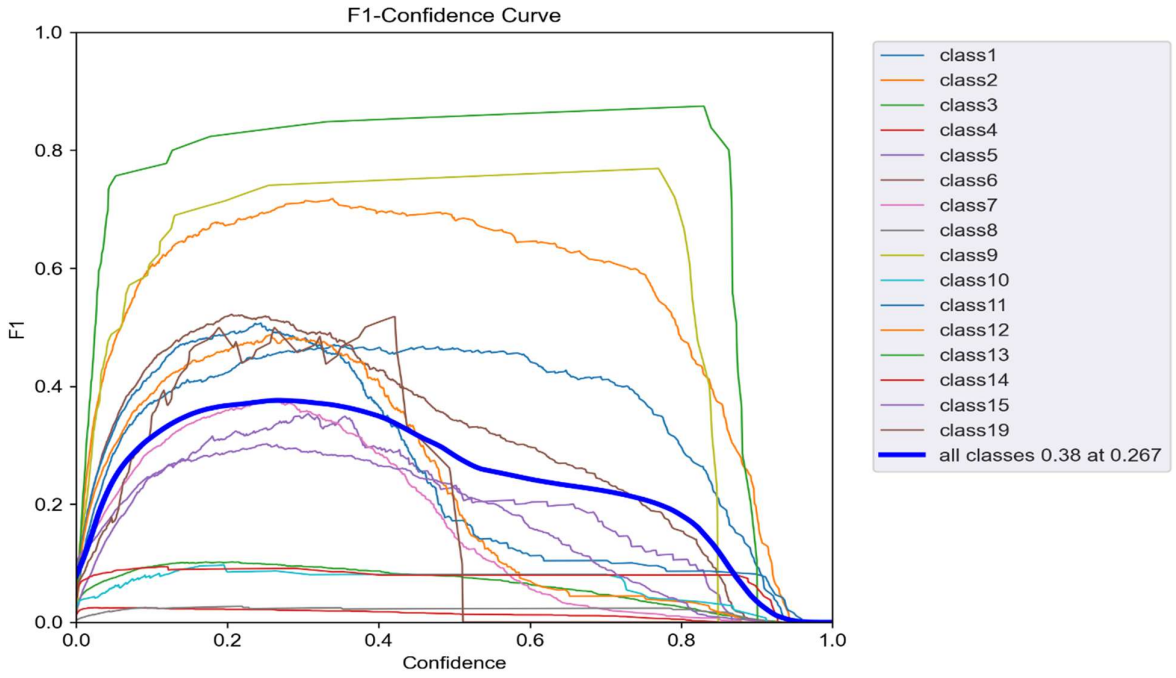


Fig-5.16 representing F1- Confidence score for custom_dataset

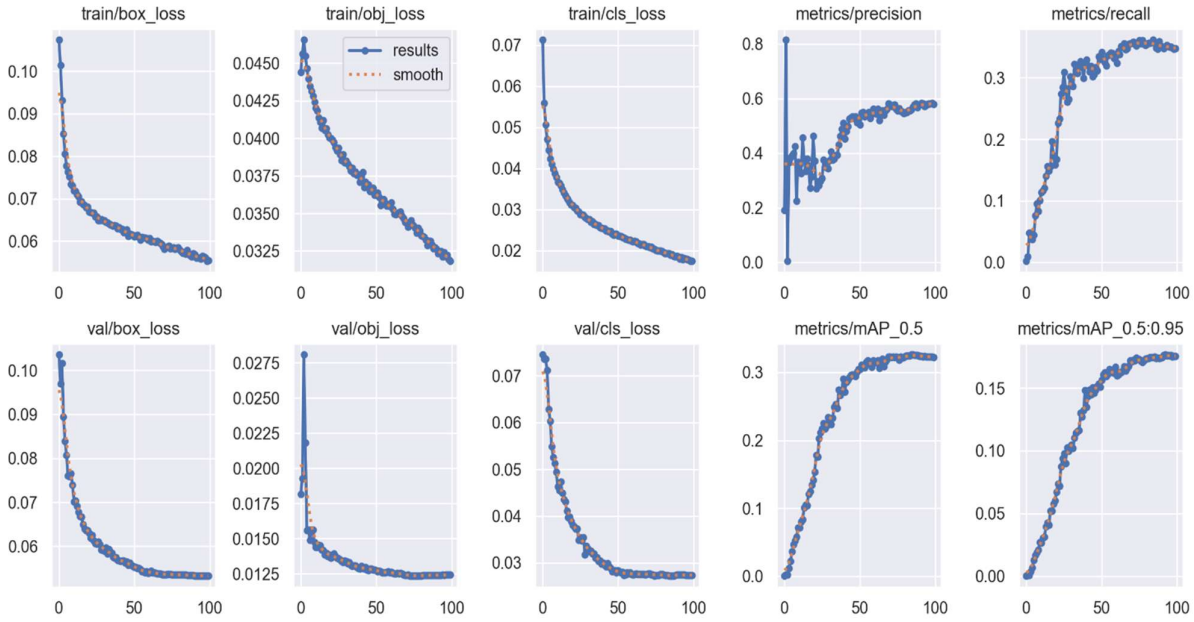


Fig-5.17 representing results score containing train and val box_loss, obj_loss, cls_loss, evaluation metrics for PASCAL_VOC dataset

5.6 Performance Analysis (Graphs/Charts)

The training process was monitored using a graph of loss over epochs. After training, the model's performance was analyzed with precision and recall graphs, which has been given above for both the datasets

Based on the performances for above two datasets, here is a detailed comparision between them

- **Comparison Report of Classification Metrics**

The comparison between the two sets of classification metrics highlights the differences in performance across precision, recall, F1-score, and geometric means (GM1 and GM2). Both datasets provide a detailed evaluation of multi-class classification, but certain variations emerge in their accuracies, macro and weighted averages, and individual class metrics.

- **Overall Accuracy and MCC**

The first dataset reports an accuracy of **67.7%** with an MCC of **0.6305**, while the second dataset achieves a higher accuracy of **71.5%** and an MCC of **0.6683**. This indicates an overall improvement in prediction consistency and balance between true positives and false classifications in the second dataset. The higher MCC value in the second dataset reflects better handling of imbalances across different classes.

- **Precision, Recall, and F1-Score**

Across most classes, the second dataset exhibits improved precision, recall, and F1-scores compared to the first. For instance, Class 0 sees an improvement in precision from **0.6395** to **0.5857**, while the recall increases significantly from **0.8871** to **0.9484**, resulting in a higher F1-score of **0.7241**. Similarly, Class 6 shows a notable increase in recall from **0.4615** to **0.7130**, improving the F1-score from **0.4800** to **0.7180**. These improvements are consistent across most classes, showcasing better recall without compromising precision significantly, thereby yielding higher F1-scores.

However, certain classes experience reduced performance in the second dataset. For example, Class 2 demonstrates a decline in F1-score from **0.7101** to **0.4000**, driven by lower precision and recall values. Similarly, Class 4 sees a decrease in F1-score from **0.4583** to **0.5733** despite higher GM2 values, which reflects uneven improvements across the metrics.

- **Geometric Means (GM1 and GM2)**

The geometric mean metrics (GM1 and GM2) provide insights into the balanced performance of the model. In the first dataset, Class 4 achieves a perfect GM1 score of **1.0**, highlighting flawless predictions for that class. However, in the second dataset, GM1 scores are slightly less consistent, reflecting adjustments in predictions across more classes. GM2 values are higher overall in the second dataset for classes like 8 and 12, indicating better model confidence and balanced predictions.

- **Macro and Weighted Averages**

  The macro averages (unweighted class averages) reveal that the second dataset improves in macro precision, recall, and F1-score, rising from **0.7508**, **0.7024**, and **0.7086** in the first dataset to **0.6747**, **0.6811**, and **0.6750**, respectively. The weighted averages also indicate an increase in prediction quality, reflecting the second dataset's ability to adapt to imbalances in the data distribution.

- **Class-Specific Performance**

  Both datasets exhibit variability in class-specific performance. Classes such as 3, 7, and 12 maintain consistently high metrics, with the second dataset performing slightly better in recall and precision. Conversely, Classes 2, 4, and 11 demonstrate more variability between datasets, suggesting these classes are more challenging for the model to classify accurately.

- **Summary**

  In summary, the second dataset generally outperforms the first in terms of overall accuracy, MCC, and class-specific metrics. Improvements in recall and F1-scores for most classes reflect the model's enhanced capability to identify positive samples correctly. However, declines in performance for a few classes indicate areas for further model optimization. The higher MCC and geometric means in the second dataset suggest better model robustness and balance, solidifying it as a more reliable classification system.

Variations in precision, recall, mAP, and other metrics across the first few epochs are not uncommon during the training of a deep learning model, especially for object detection tasks like YOLO. Here's why this happens and whether it should be considered a warning:

- **Common Reasons for Variations:**

1. Model Initialization:The model starts with random or pre-trained weights. During the initial epochs, the weights adjust significantly, causing metrics to fluctuate as the model learns.

2. Small Sample Representation:During the early epochs, the model might not generalize well to the entire dataset, leading to irregularities in performance metrics across batches.

3. Optimizer Behavior:The optimizer takes larger steps early in training, leading to rapid and sometimes erratic changes in the loss and evaluation metrics.

4. Class Imbalance:If the dataset has an imbalanced distribution of classes or instances, the metrics for underrepresented classes might take longer to stabilize.

5. Evaluation Frequency:The metrics might be calculated at the end of each epoch on a validation set, which may or may not represent the training distribution well, especially early in training.

- **Specific Observations:**

1. Precision (P):A jump from ~0.001 (epoch 0) to ~0.81 (epoch 1) suggests the model initially struggled to correctly predict true positives but quickly learned some patterns. The drop to ~0.334 (epoch 2) and ~0.25 (epoch 3) indicates overfitting to certain patterns or issues with consistency in predictions.
2. Recall (R):The very low recall (~0.0756 to ~0.184) indicates the model is missing many true positives. This is typical for early training when the model is still learning to detect objects properly.
3. mAP (mAP50, mAP50-95):The mAP values being very low initially is expected, but the slow improvement (and drop in mAP50-95 from epoch 1 to epoch 3) might signal overfitting to specific instances.

- **When to Worry**

1. Metrics Do Not Stabilize:If the metrics continue fluctuating widely even after several epochs (e.g., 10+ epochs), this could indicate instability in training.

2. Overfitting Warning:If training loss decreases but validation metrics deteriorate, it suggests overfitting.

3. Poor Validation Performance:If the metrics remain low throughout training, it may indicate issues with the dataset (e.g., poor labeling, insufficient diversity) or model configuration.

- **Suggestions:**

1. Monitor Trends:Focus on the overall trend of metrics over several epochs rather than individual epochs.

2. Learning Rate:Ensure the learning rate is appropriately tuned. A too-high learning rate can cause erratic metric behavior.

3. Dataset Quality:Double-check the dataset for label accuracy and balance among classes.

4. Increase Epochs:Training for more epochs allows the model to stabilize and improve its predictions.

5. Data Augmentation:Use data augmentation to improve generalization and mitigate overfitting.

5.7 Summary

This chapter explained the implementation details, showing the code used for training, testing, and validating YOLOv5. It also presented performance metrics and graphs to evaluate the model's effectiveness.

CHAPTER-6:
PROJECT OUTCOME AND APPLICABILITY

6.1 Outline

This chapter discusses the key outcomes of the project and the potential applications of the YOLOv5-based object detection system in real-world scenarios.

6.2 Key Implementations of the System

The trained YOLOv5 model can detect a wide range of objects from images and videos. The system demonstrated good accuracy on both the PASCAL_VOC dataset and the custom dataset, making it suitable for various applications.

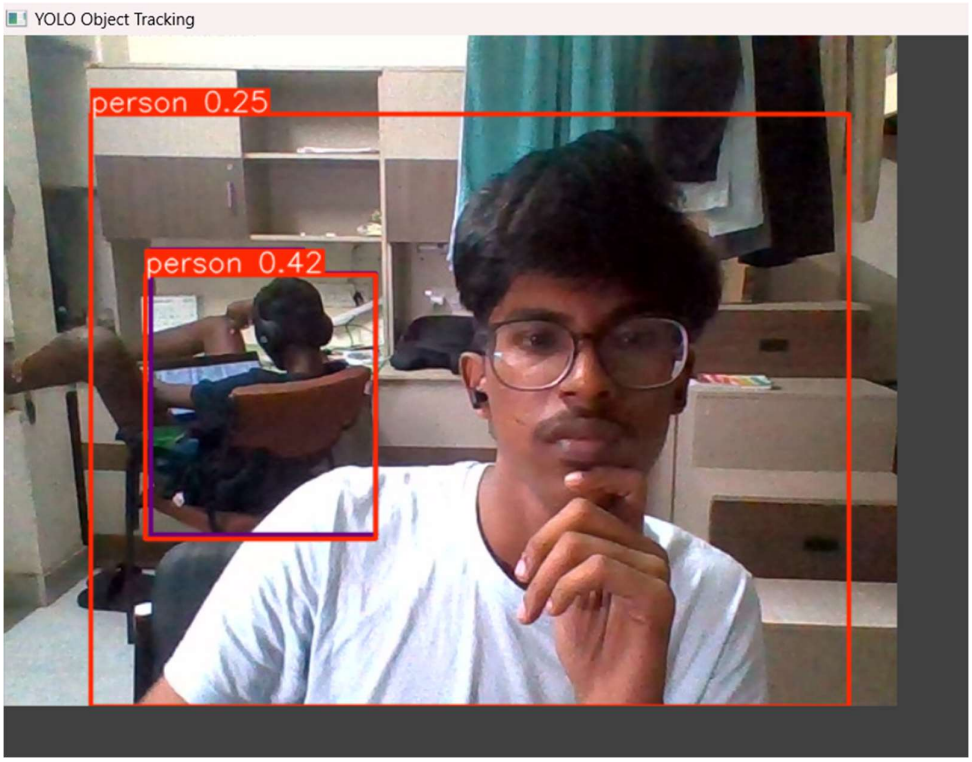


Fig 6.1 Real Time Inference using Webcam.

6.3 Significant Project Outcomes

The project achieved a high level of accuracy and speed. The YOLOv5 model was able to perform real-time detection with accuracy of 0.715. The system was also optimized for deployment in real-world scenarios.

6.4 Project Applicability in Real-World Applications

This object detection system can be applied in several fields:

- **Surveillance**: Real-time detection of objects in security footage.
- **Retail**: Identifying products in stores for inventory management.
- **Autonomous Vehicles**: Detecting pedestrians, vehicles, and obstacles on the road.
- **Traffic Control**: Track vehicle movements to manage traffic flow.
- **Augmented Reality (AR)**: Enhance AR experiences by tracking objects in real-time.
- **Medical Imaging**: Track objects in medical videos for diagnostic purposes.

6.5 Inference

The project demonstrated that YOLOv5, with proper training and fine-tuning, can serve as a powerful tool for real-time object detection in diverse applications.

CHAPTER-7:
CONCLUSIONS AND RECOMMENDATIONS

7.1 Outline

This final chapter summarizes the project's findings and offers recommendations for future work.

7.2 Limitations/Constraints of the System

While the model performed well on both datasets, it faced limitations:

- Small Object Detection: The model showed reduced accuracy when detecting small objects.
- Generalization: The model could be further improved for different real-world environments.

7.3 Future Enhancements

- Improved Data Augmentation: Including more diverse data can help the model generalize better.
- Fine-tuning for Specific Applications: Tailoring the model for specialized use cases (e.g., detecting specific object types).
- Optimizing for Edge Devices: Deploying the model on lightweight devices like mobile phones or drones.

7.4 Inference

The YOLOv5-based object detection system has proven effective for real-time detection tasks. By improving training and model refinement, its applicability can be extended to many fields, providing significant real-world benefits.

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     Publisher: Apress
  3. **"Multiple View Geometry in Computer Vision"**
     Author(s): Richard Hartley and Andrew Zisserman
     Publisher: Cambridge University Press
     Edition: Second Edition (2004)
  4. **"Computer Vision: Models, Learning, and Inference"**
     Author(s): Simon J.D. Prince
     Publisher: Cambridge University Press
     Edition: First Edition (2012)

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     Author(s): Abhijit Bendale and Terrance Boult.
     Journal: ACM Computing Surveys.
     Direct Link: https://dl.acm.org/doi/10.1145/3561381

  2. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks
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     Direct Link: https://www.cs.cmu.edu/~rsalakhu/papers/oneshot1.pdf

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