WASTE MANAGEMENT OF PLASTIC MARINE DEBRIS USING DEEP LEARNING

MINI PROJECT REPORT

Submitted by

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Under the guidance of

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in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

HINDUSTAN
INSTITUTE OF TECHNOLOGY & SCIENCE
(DEEMED TO BE UNIVERSITY)
CHENNAI

NOVEMBER 2022

HINDUSTAN
INSTITUTE OF TECHNOLOGY & SCIENCE
(DEEMED TO BE UNIVERSITY)
CHENNAI

BONAFIDE CERTIFICATE

Certified that this project report **Waste Management of Plastic Marine Debris using Deep Learning** is the bonafide work of **Niranjana A (19113013) & Shreya Kishore (19113016)** who carried out the project work under my supervision during the academic year **2022-2023**.

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ACKNOWLEDGEMENT

First and foremost we would like to thank **ALMIGHTY** who has provided us the strength to do justice to our work and contribute our best to it.

We wish to express our deep sense of gratitude from the bottom of our heart to our guide **Dr.S.Sathyalakshmi, Professor, Computer Science and Engineering**, for her motivating discussions, overwhelming suggestions, ingenious encouragement, invaluable supervision, and exemplary guidance throughout this project work.

We would like to extend our heartfelt gratitude to **Dr. J.Thangakumar, Ph.D., Professor & Head, Department of Computer Science and Engineering** for his valuable suggestions and support in successfully completing the project.

We thank the management of **HINDUSTAN INSTITUTE OF TECHNOLOGY AND SCIENCE** for providing us the necessary facilities and support required for the successful completion of the project.

As a final word, we would like to thank each and every individual who has been a source of support and encouragement and helped us to achieve our goal and complete our project work successfully.

ABSTRACT

Various floating debris in the waterway can be used as one kind of visual index to measure the water quality. The traditional image processing method is difficult to meet the requirements of real-time monitoring of floating debris in the waterway due to the complexity of the environment, such as reflection of sunlight, obstacles of water plants, a large difference between the near and far target scale, and so on. To address these issues, an improved YOLOv5 algorithm is proposed. The system can only detect plastics that are floating and may detect other waste materials as plastic too, so it does not yet have a wide range of applications. The training phase also consists of different augmentation techniques that allows us to exploit the dataset to its fullest potential. The main augmentation techniques used in the training process is random crop collaging. The visualization of training statistics provides many insights such as when to stop training, will further training be beneficial or not. The comparison of the values of the mAP and FPS were made and YOLOv5 gave the highest precision of 93%.

LIST OF FIGURES

LIST OF ABBREVIATIONS

DL	Deep Learning
R-CNN	Region-based Convolutional Neural Network
YOLOv5	You Only Look Once v5

CHAPTER 1

INTRODUCTION

1.1 Overview

The quantification of positively buoyant marine plastic debris is critical to understanding how concentrations of trash gather across the world's oceans and identifying high concentration garbage hotspots in dire need of trash removal. Currently, the most common monitoring method to quantify floating plastic requires the use of a manta trawl. Before analysis, the need for physical removal incurs high costs and requires intensive labor–preventing scalable deployment of a real-time marine plastic monitoring service across the oceans. Without better monitoring and sampling methods, the total impact of plastic pollution on the environment as a whole, and details of impact within specific oceanic regions, will remain unknown. This study presents an automated workflow that utilizes videos and images captured within the epipelagic layer of the ocean as input and produces real-time quantification of marine plastic for accurate quantification and removal.

1.2 Motivation for the project

Plastic waste makes up 80% of all marine pollution and around 8 to 10 million metric tons of plastic end up in the ocean each year. Research states that, by 2050, plastic will likely outweigh all fish in the sea. In the last ten years, we have produced more plastic products than in the previous century. The EPA (Environmental Protection Agency) has stated that basically 100% of all plastics human beings have ever created are still in existence. Plastic generally takes between 500-1000 years to degrade. Even then, it turns into microplastics , without fully degrading . Currently , there are about 50 -75 trillion pieces of plastic and microplastics in the ocean. This plastic either breaks down into microplastic particles (see below), or floats around and ends up forming garbage patches.

1.3 Problem Definition and Scenarios

To Develop real-time detection of different types of trash (plastic, in particular) in the ocean by utilizing transfer learning on different machine-learning object-detection architectures. To Build a fully functional Plastic detection system that can be easily used to train and test object-detection models based on architectures like YOLOv5, Faster-RCNN, SSD-Resnet, Efficient-DET, Tensorflow, etc. Implement our models to work on real-time satellite and camera footage. We wanted to build a generalized object detector capable of identifying and quantifying sub-surface plastic around the world.

1.4 Organization of the report

The report consists of 10 chapters. This report begins with a preface to the motives and the project being undertaken. Following that in the second chapter, exemplifications of affiliated work and literature reviews are bandied. We discuss the objects of the proposed system and its advantages over the subsisting systems in the third chapter of the report. The system design and flowchart are shown in the report's fourth chapter. The project requirements, which include the hardware and software needed to run this system, are discussed in the fifth chapter of the report. A thorough explanation of the modules utilized in the system can be found in Chapter 6. The perpetration and results deduced from executing the inferred system are covered in Chapters 7 and 8.

We discuss the result's conclusion in Chapter 9. The report consists of the contribution of the team in chapter 10 followed by the references section and appendix

1.5 Summary

This project recognizes the usage of Yolov5 (You only look once) in detecting the plastic debris in water bodies. Plastics in water bodies such as rivers or ocean cause a major threat to the marine species and marine environment. The Yolov5 model is used to detect the plastic or any other waste materials in the ocean by looking only once and this model is more accurate than R-CNN and fast R-CNN. This project is based on YOLOv5 detection and Tensorflow Object Detection API models, and it provides an environment where developers can easily prepare, train and test detection models that will identify different types of plastic (and non-plastic) trash in the ocean and on the beach.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The purpose of this chapter is to review the research papers that were taken for this project. The algorithms used for the project will be examined in this chapter. Research papers were extracted from reputed journals.

2.2 Managing Marine Environmental Pollution using Machine Learning

The marine environment has deteriorated to an extent that it has begun to impact human health and the planet itself. The primary cause of this deterioration as identified are, an increasing population, the industrial revolution and the increased use of fossil fuels. While the damage done to the environment cannot be undone, the impact can be lessened by better understanding the ocean and monitoring future pollution using technology. The Industrial Revolution brought about prosperity to humans. Along with prosperity, it also brought about environmental degradation, due to industrial pollution and an unprecedented increase in the population rate. While the increasing population created a stress on the available resources, the industrial pollution led to the deterioration of the air we breathe, the water we drink, and the food we eat. These, in return, affected both the land and the oceans, to the extent that it has manifested in changes to the climate of the Earth, caused the loss of a number of habitats, and created some entirely new norms that have overall increased the chances of destruction of the planet itself.

2.3 Using YOLO v5 for Garbage Classification

At present, people's daily garbage is increasing day by day. How to intelligently classify garbage can save manpower and improve work efficiency. In [2], a garbage classification model based on YOLOv5 object detection network named GC-YOLOv5 is designed. First, according to the common daily garbage category, five typical kinds of garbage were selected, data cleaned, labeled, and constructed a garbage dataset. Second, the GC-YOLOv5 was built and trained on our datasets. Third, in view of the convenience of multi-terminal access in the cloud and the reduction of computing pressure on edge devices, we deploy the garbage classification model in the cloud. The experimental results show that GC-YOLOv5 can accurately identify the garbage's types and find out the location of garbage.

2.4 Improved YOLO Based Detection Algorithm for Floating Debris in Waterway

Various floating debris in the waterway can be used as one kind of visual index to measure the water quality. The traditional image processing method is difficult to meet the requirements of real-time monitoring of floating debris in the waterway due to the complexity of the environment, such as reflection of sunlight, obstacles of water plants, a large difference between the near and far target scale, and so on. To address these issues, an improved YOLOv5s (FMA-YOLOv5s) algorithm by adding a feature map attention (FMA) layer at the end of the backbone is proposed. The mosaic data augmentation is applied to enhance the detection effect of small targets in training. A data expansion method is introduced to expand the training dataset from 1920 to 4800, which fuses the labeled target objects extracted from the original training dataset and the background images of the clean river surface in the actual scene. The comparisons of accuracy and rapidity of six models of this algorithm are completed. The experiment proves that it meets the standards of real-time object detection.

2.5 Research on underwater object recognition based on YOLOv3

In recent years, object recognition and detection technology, which is a very important research direction in the field of computer vision, is widely used in human life. The technology has been relatively mature for the recognition of objects such as people and objects on land. However, due to some conditions, it is relatively rare in the marine field. [5] uses two algorithms that are widely used at present to experiment with underwater image dataset. The experimental results show that the mean Average Precision (mAP) of YOLOv3 algorithm is 6.4% higher than Faster R-CNN, and the recall rate (Recall) is 13.9% higher. Moreover, the detection speed of the YOLOv3 algorithm is 20Fps, which is 12 Fps higher than the speed of Faster R-CNN. The detection speed of the YOLOv3 algorithm basically meets the real-time detection requirements in this experiment.

2.6 Summary

Researching several research papers that are related to this work led to the conclusion stated here. Detailed summaries of each research paper have been provided, along with a description of the advantages and disadvantages of each proposed system.

CHAPTER 3

PROJECT DESCRIPTION

3.1 Overview

In this chapter, the objectives and benefits of the project will be discussed. In addition, the existing system will be evaluated and its drawbacks discussed.

3.2 Objective of the Project work

Create a visualization database based on Deep learning algorithms that will aid in classifying and detecting these plastics using remote sensing data. Understand the potential advantages and limitations of utilizing DL algorithms to classify plastic pollution. The solution should allow data on plastic waste to be more accessible and valuable to citizen scientists, remote-sensing experts, as well as policy makers and regulators. It should enable scientists to better detect plastics utilizing remote sensing data and policy makers to use this information to effectuate change.

3.3 Existing System

Several systems aim to achieve plastic detection. These systems are implementations of relevant computer vision techniques to extract features that are relevant for plastic detection and these systems provide adequate performance. Algorithms such as if Faster RCNNs and yolov3 have been used which are efficient object detection algorithms that make these pipelines perform the task well. The system can only detect plastics that are floating and may detect other waste materials as plastic too, so it does not yet have a wide range of applications.

3.4 Shortcomings of Existing System

The existing systems use outdated object detection algorithms, a majority of the literature that has been reviewed use older algorithms like yolov3 and Faster RCNNs and there have been several advancements in the field of object detection since then. This project uses one of the state of the art object detection algorithms and this guarantees more competent results than existing systems. Since the existing systems can only detect floating debris, it is impossible to identify the waste underwater and the data has to be fed more than once. It takes a longer duration and data breaches may occur.

3.5 Proposed System

YOLO is an acronym that stands for You Only Look Once. We are employing Version 5, which was launched by Ultralytics. It is a novel convolutional neural network (CNN) that detects objects in real-time with great accuracy. This approach uses a single neural network to process the entire picture, then separates it into parts and predicts bounding boxes and probabilities for each component. These bounding boxes are weighted by the expected probability. The method "just looks once" at the image in the sense that it makes predictions after only one forward propagation runs through the neural network. It then delivers detected items after non-max suppression. The system used by the project consists of different components such as the data preparation phase, the training phase, the inference phase and the implementation phase. The data preparation phase is crucial to this project as it is key in tackling one of the main objectives of this project that is combating features. The object detection framework used is the implementation of yolov5 by ultralytics.

YOLOV5 is the smallest version of the YOLOV5 models and this is the model used by the machine-learning pipeline of this project. YOLOV5 has benefits like the bag of freebies and bag of specials that help developers fine-tune models and extract maximum performance from the model and exploit the full potential of YOLOV5. The bag of freebies offered by YOLOV5 are a set of techniques, when used can improve performance without increasing inference cost, whereas the bag of specials offer increases in accuracy with little increase in inference costs. The training phase also consists of different augmentation techniques that allow us to exploit the dataset to its fullest potential. The main augmentation techniques used in the training process is random crop collaging. The training process also uses Wandb visualization for real time visualization of data augmentation, prediction visualization, performance tracking training statistics monitoring.

Fig 3.1: Tensorflow Dashboard

The inference phase of the project consists of analyzing the validation statistics provided by tensorflow and performing detections on unseen data and manually validating the model's prediction on this unseen data. Tensorflow produces visualizations of accuracy metrics on the validation data that is the data that the model is not trained on, since this is a form of unseen data, the models performance on this data gives a decent and representative estimate of how the model might perform on completely unseen data. For this use case, validation accuracy metrics is not sufficient as we need to test if the model performs well on data that is not present in the dataset such as data obtained from different sources located in places different from those of the training dataset.

Fig 3.2 Inference frame 1

The implementation phase consists of implementing the machine learning workflow on actual data that is representative of how the data might actually look like in a real time scenario. The model is made to perform inference on a construction company's advertisement and product description video.

The model's adequate performance on this data tells us that the model is able to generalize its performance to data from different sources and that one of the main objectives is achieved successfully.

Fig 3.3 Inference frame 2

Fig 3.4 Inference frame 3

3.6 Benefits of Proposed System

The proposed system is able to provide acceptable performance on data from a different unseen and unforeseen source therefore it can be interpreted that the model is able to perform detections on the appropriate features.The model's ability to generalize its detection to a more diverse variety of data is a great advantage as an ideal machine learning model should be able to learn the features that is relevant to use case and make appropriate predictions using these features as well as ignore unimportant and non-descriptive features that are irrelevant to the main objective. With the Yolov5 model, plastic debris can be easily detected in the water bodies faster than CNN or fast RNN methodologies and this model is more accurate than the other. Yolov5 gives the output by just looking once as it can locate the wastes using the coordinates in the grids of the input.

3.7 Summary

The purpose of this section is to summarize the proposed system. In this report, we provide a detailed description of the proposed system that will build an efficient plastic detector. Additionally, the section describes the limitations of the current system and how this project aims to overcome them.

CHAPTER 4

SYSTEM DESIGN

4.1 Overview

The architecture of the proposed method will be discussed in this chapter. A flow chart will also be used to illustrate this project's workflow.

4.2 Architecture Diagram

Data preparation is the first module where the complete data used for model training and model building is collected, processed and organized. This is one of the most important modules in the project as the data cleaning and pre-processing for more than 60% of the models performance.

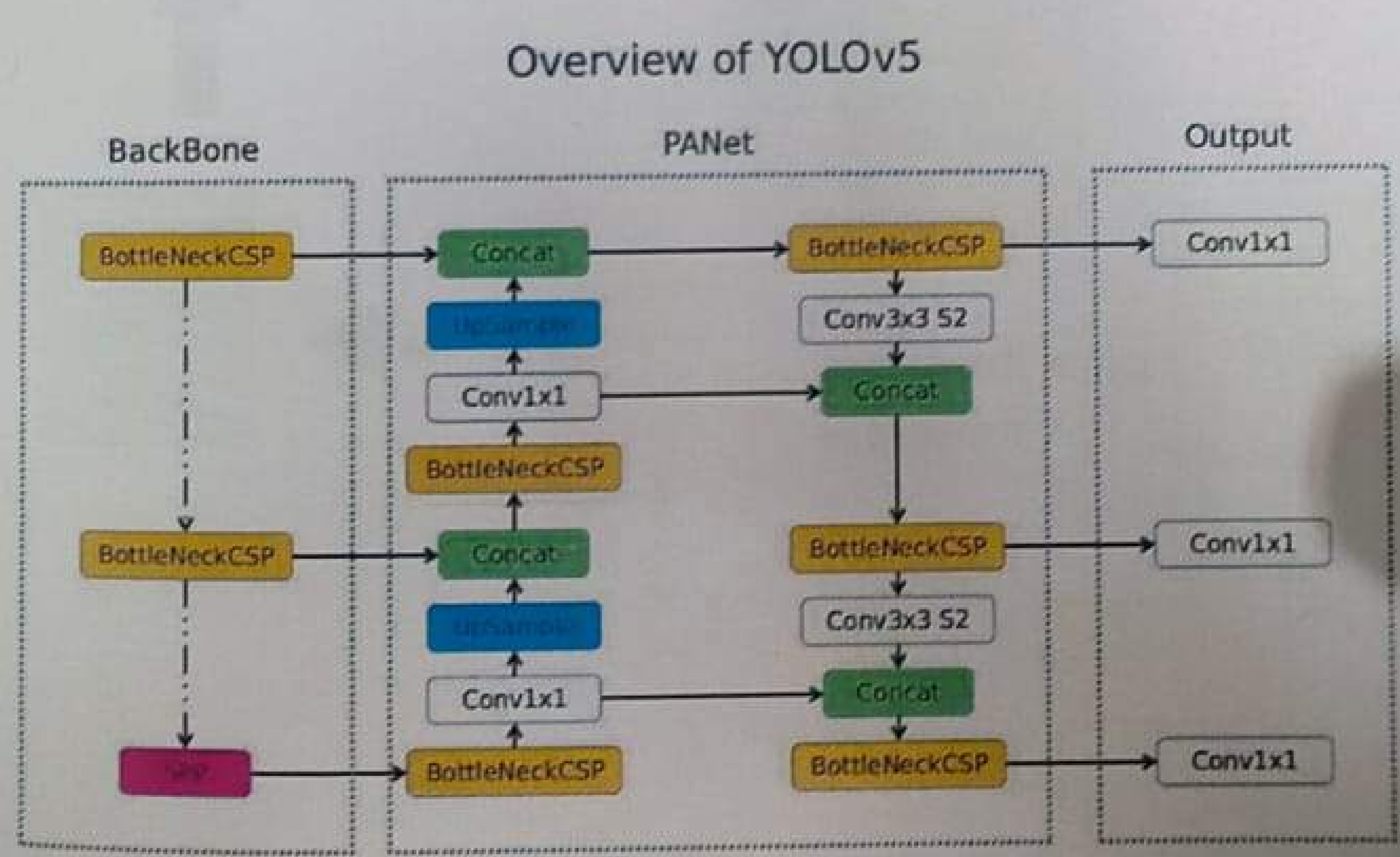

Fig 4.1 System Architecture

The model building module is the module where the data is passed into the model for training and the performance of the model during the training is monitored using the tensorflow visualization platform; this module is crucial and is the first indicator of performance of the model which is the backbone of the whole project.

4.3 Flow Chart

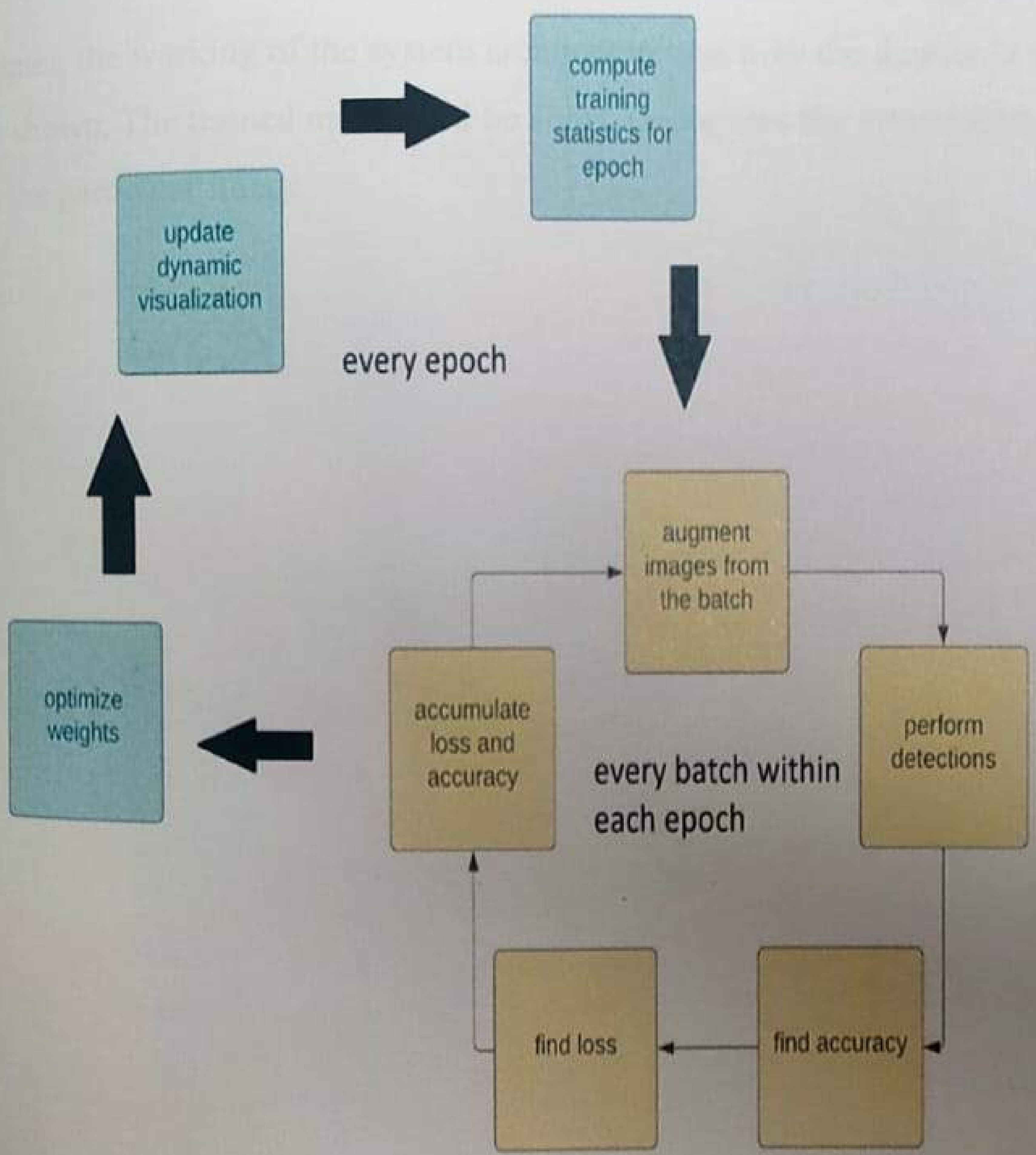

Fig 4.2 Training Process

Visualization is crucial for the training module as it gives us constant and dynamic and real-time feedback about the training statistics and helps us view and understand training statistics that are essential to monitor the training process , the visualization of training statistics provides many insights such as when to stop training, will further training be beneficial or not , etc.

4.4 Summary

In this chapter, the working of the system architecture and how the dataset is used for training is shown. The trained model will be able to recognize the different blood cells present in the particular image.

CHAPTER 5

PROJECT REQUIREMENTS

5.1 Overview

The hardware and software used in this project will be discussed in this chapter, along with its specifications. A brief description of the technology will follow.

5.2 Software Specification

Framework & Libraries

- CUDA
- Keras
- Tensorflow
- Python 3.9.7
- Pyyaml
- PyTorch

5.3 Technologies Used

- Deep Learning
- Computer Vision
- YOLOv5

5.4 Summary

In this chapter, the hardware and software requirements and the technologies used were mentioned.

CHAPTER 6

MODULE DESCRIPTION

6.1 Overview

The objective of this section is to provide a comprehensive overview of all the various modules implemented in the project.

6.2 Data Preparation

A drone might be used to take pictures of the ocean and those images are used as a dataset. Images were resized into 416x416 and converted into the format the YOLOv5 PyTorch required. Data preparation is the first module where the complete data used for model training and model building is collected, processed and organized. This is one of the most important modules in the project as the data cleaning and pre-processing for more than 60% of the models performance.

6.3 Model Building

The model building module is the module where the data is passed into the model for training and the performance of the model during the training is monitored using the tensorflow visualization platform; this module is crucial and is the first indicator of performance of the model which is the backbone of the whole project. Since the main objective of the project is to get the model to work efficiently and perform competently, this module is vital for the proper functioning of the machine-learning pipeline.

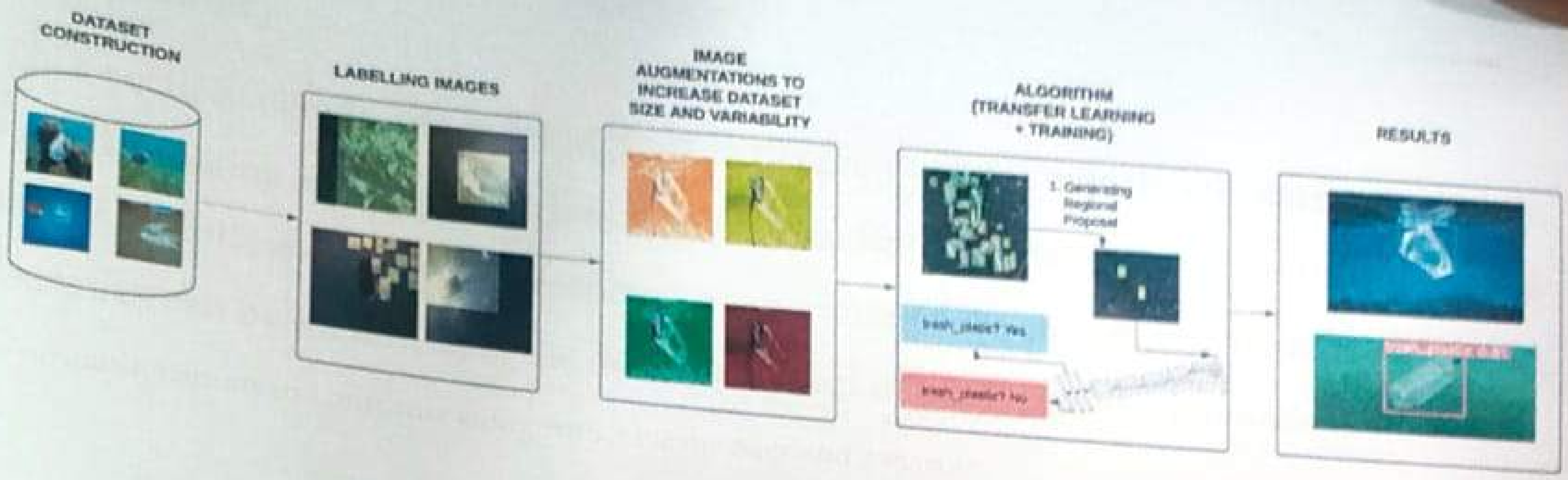

Fig 6.1 Pipeline for Detecting Marine plastic

6.4 Visualization

Visualization is crucial for the training module as it gives us constant and dynamic and real-time feedback about the training statistics and helps us view and understand training statistics that are essential to monitor the training process , the visualization of training statistics provides many insights such as when to stop training, will further training be beneficial or not , etc.

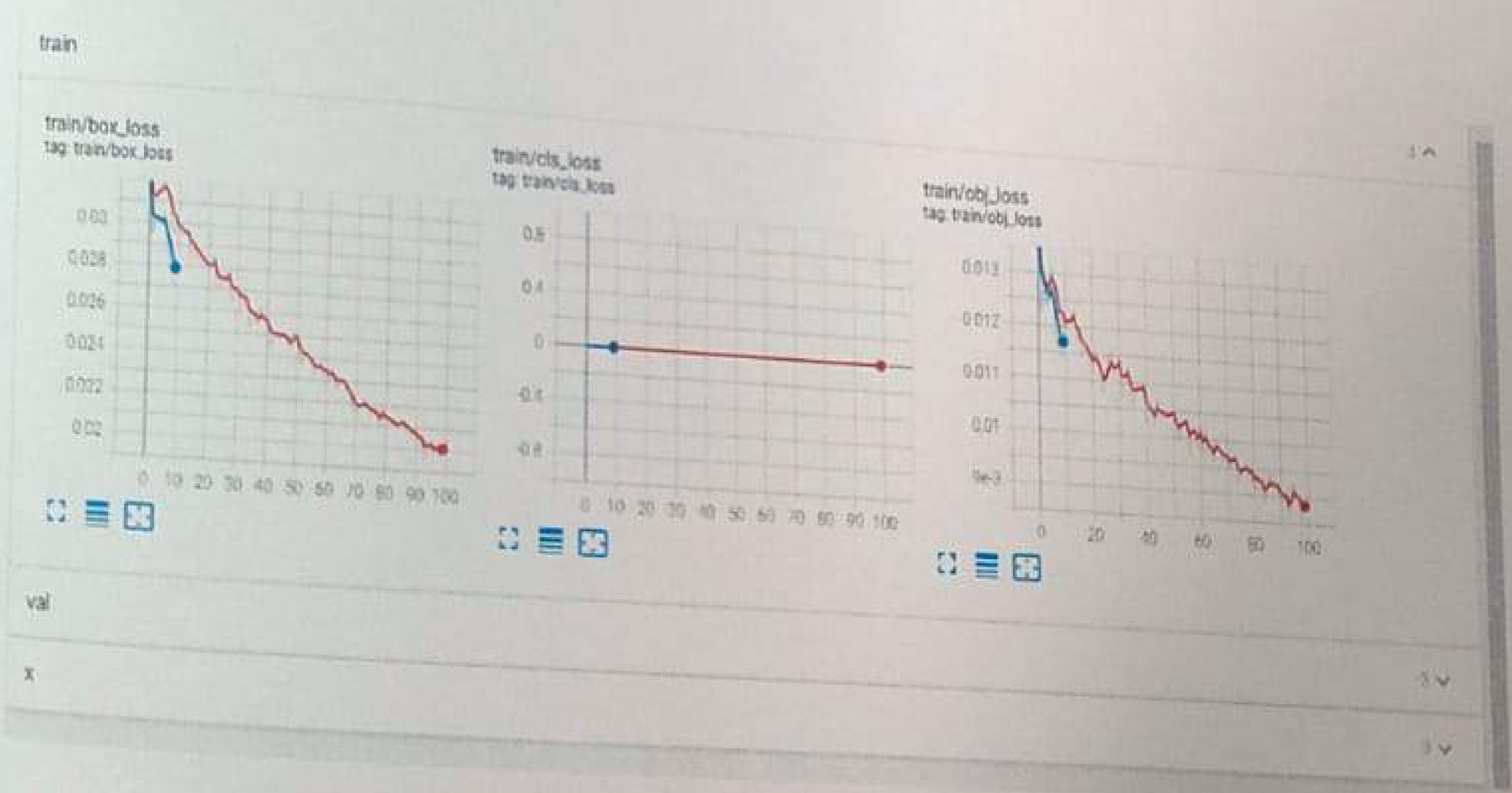

Fig 6.2: Visualization of Training Statistics

6.5 Summary

This section details the workings of different modules which are data preparation, model building and visualization. It can be understood that the module of this system works as follows. By using restricted recognition of the model and the area of interest, varieties can be identified at the deduction level of post-handling methods.

CHAPTER 7

IMPLEMENTATION

7.1 Overview

This chapter provides an in-depth description of the implementation process. Additionally, the chapter describes the interface for visualizing the data, the Tensorflow interface.

7.2 User Interface

The Implementation is done in the training User interface using Google Collab Pro with NVDIA v100 to train the model. It is easy to update profiles and items regularly. It is a Dynamically configurable interface to make the system run without any flaws or errors. Search functions are given to make the user find the desired product. A highly interactive deep-learning environment can be used to document deep-learning pipelines.

The visualization user interface is Tensorflow, which provides an arsenal of graphs and visualizations, and these visualizations are organized in the form of a dashboard for easy access. The users can interact with this visualization and can control the amount of detail the visualizations display.

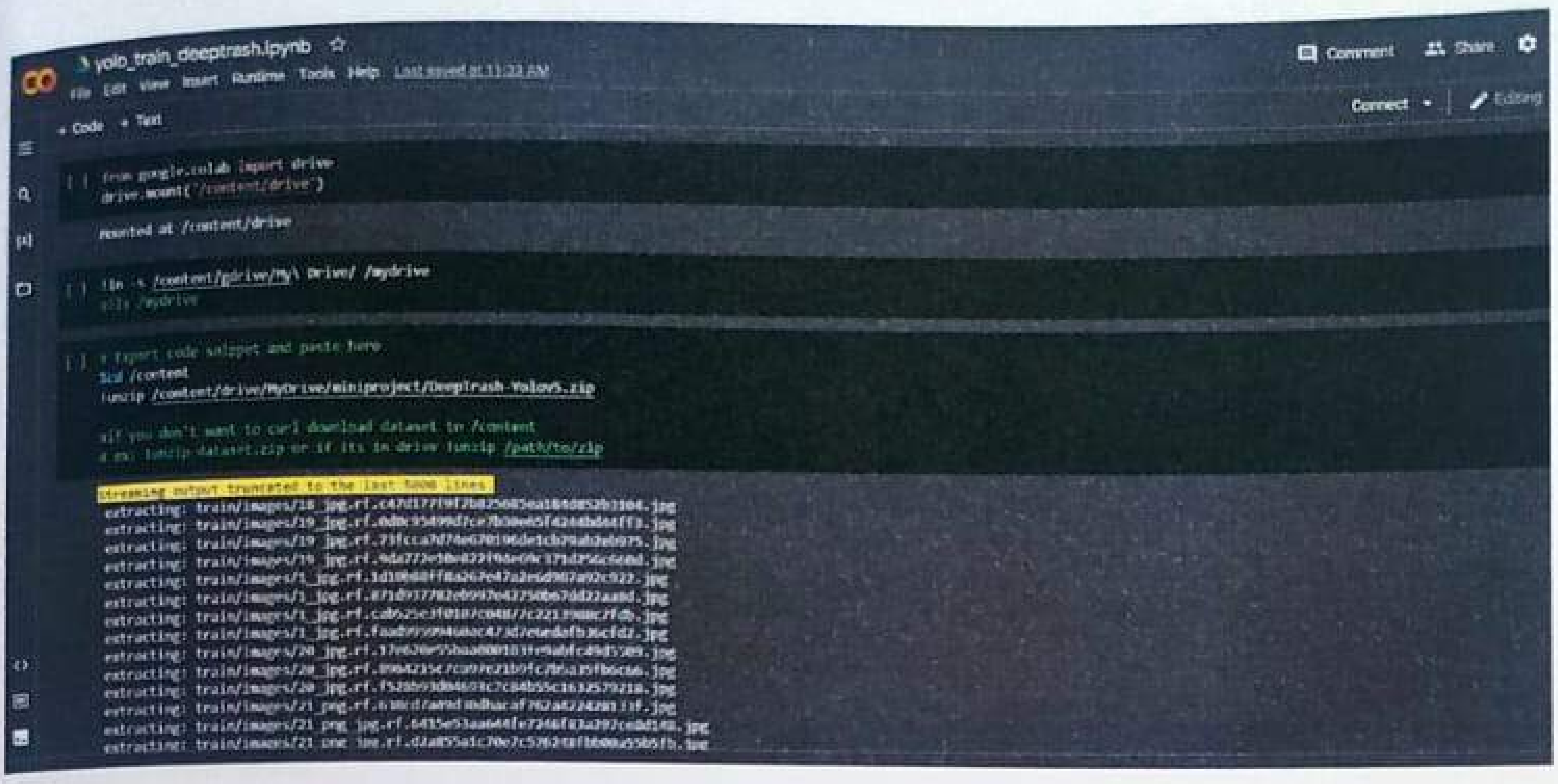

Fig 7.1 Google colab User Interface

7.3 Summary

The purpose of this chapter is to provide a detailed description of the proposed system. In addition to using Google Colab for training testing and validation, tensorflow interfaces are used for the visualization.

CHAPTER 8

RESULT ANALYSIS

8.1 Overview

The results of implementing the project are detailed in this chapter and the effectiveness of the proposed system is discussed.

8.2 Results obtained

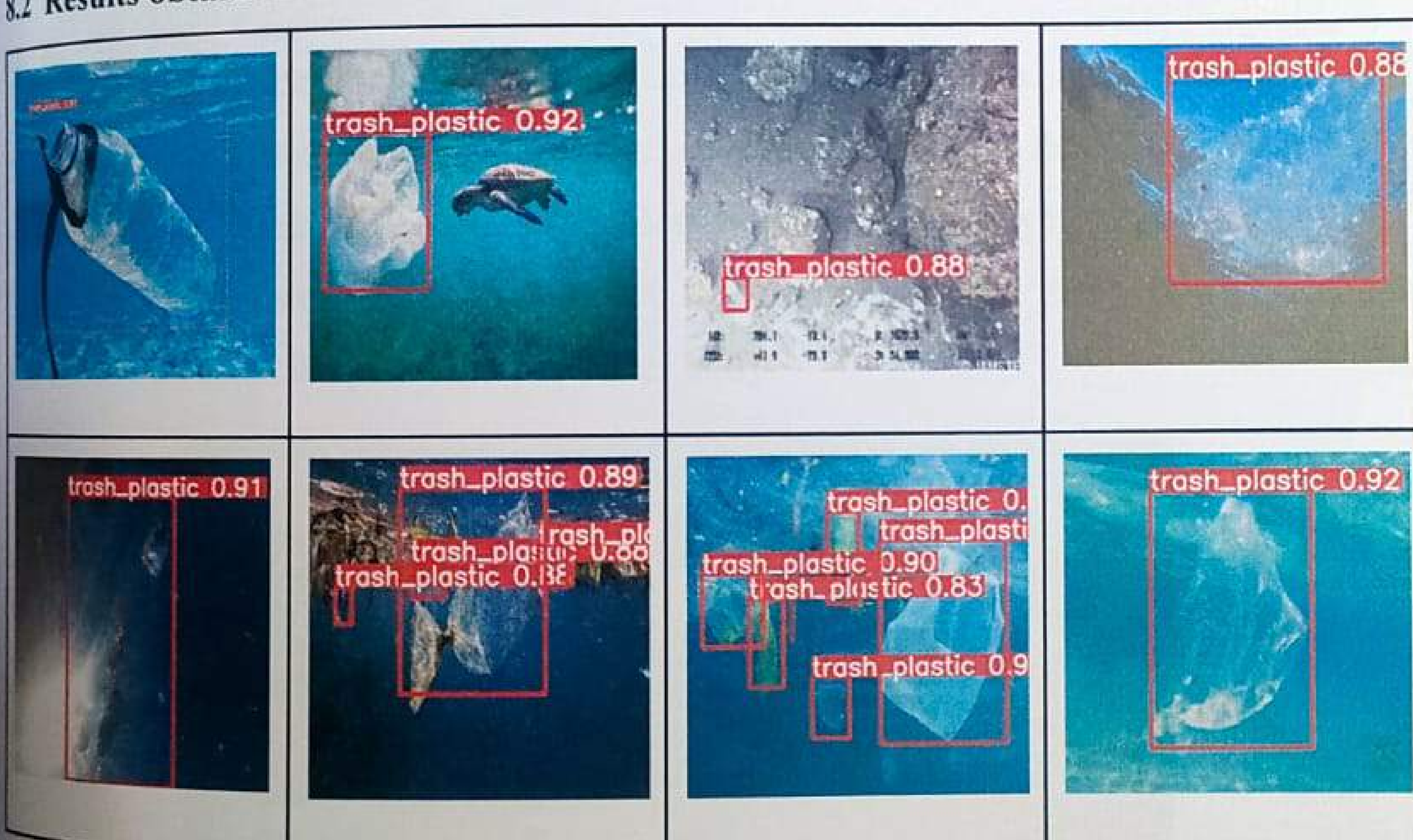

Fig 8.1 Result Image

The dataset was trained using various training methods such as R-CNN, Fast R-CNN, Faster R-CNN and YOLOv5. The values of the precision, Mean-Average-Precision, F1-Score, Inference Speed/FPS were recorded. The comparison of the values of the mAP and FPS were made in Fig 8.2 and YOLOv5 gave the highest precision of 93%.

	mAP	Speed
		FPS
R-CNN	67	0.05
Fast R-CNN	70	0.5
Faster R-CNN	79.3	7
YOLOv5	93	100

Fig 8.2 Performance Comparison

After a lot of experimenting with training methods, data augmentations, and fine-tuning hyperparameters, we finally reached a point where the results were good enough to be used in real-world deployments. YOLOv5: Precision: 96%, Mean-Average-Precision: 93%, F1-Score: 0.89, Inference Speed/FPS :100 . The model successfully detected the plastic in the water body.

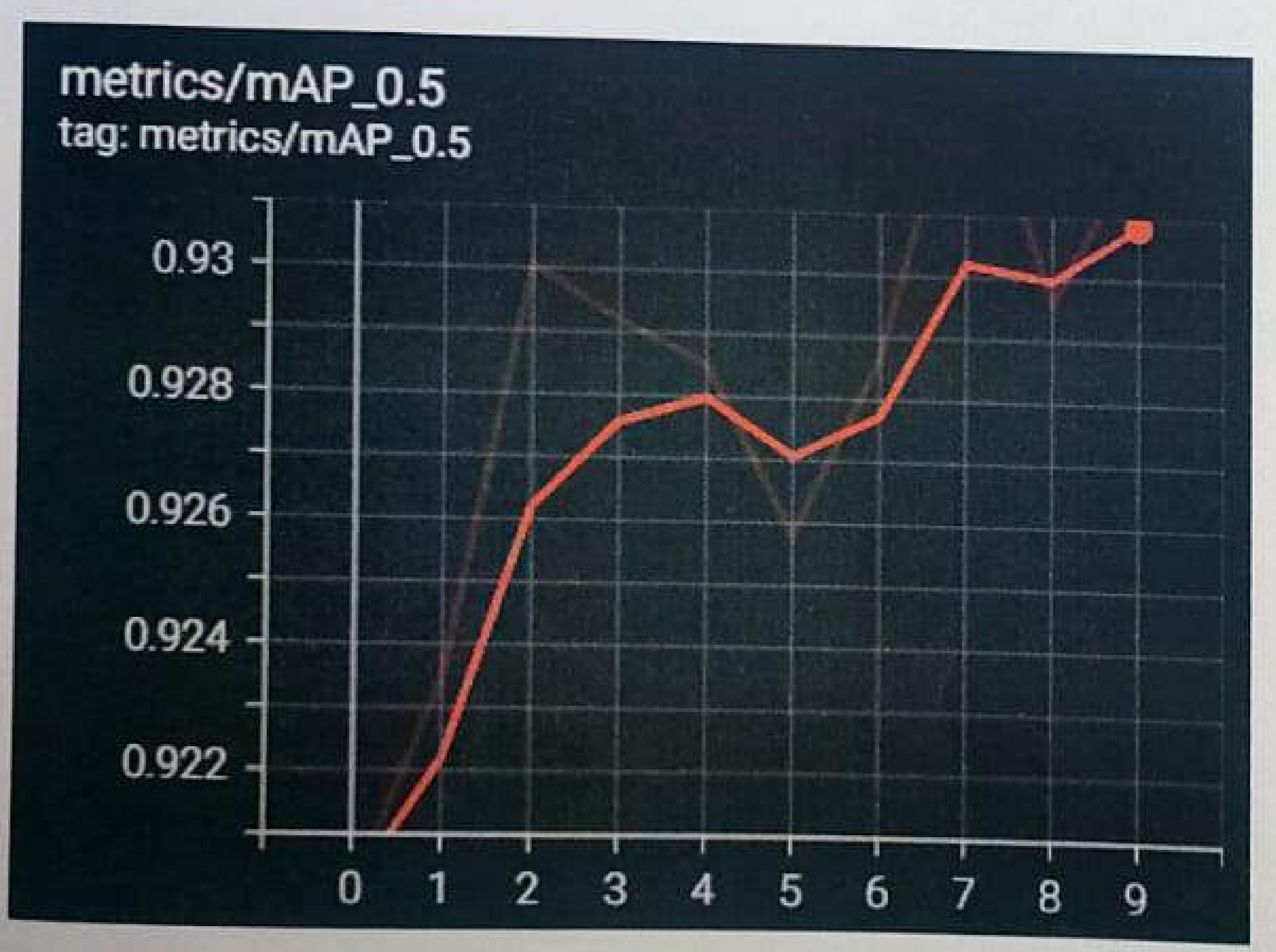

Fig 8.3 Mean Average Precision

9.4 Summary

This section details the conclusions drawn from implementing the project. Based on the analysis of this section, it can effectively and efficiently recognize the person using the given gait data.

CHAPTER 9

CONCLUSION AND FUTURE WORK

9.1 Overview

The results of the project are discussed in this chapter, as well as the conclusions that can be drawn from them. This is followed by a discussion of the possibilities for any future projects that can be derived from this project.

9.2 Conclusion

Thus the plastic debris in the waterways can be detected more accurately using Yolo v5 (You only look once) using the pictures taken by a drone and is more accurate and faster than any other methodologies like CNN, RNN, Fast RNN or Faster RNN. Yolo v5 can also be used to detect any other debris. By this method the most polluted region can be detected.

9.3 Future Work

Certain viewpoints where the work process can be upgraded are available like calibrating of model and discretized variety discovery. The information utilized can be cleaned further and following each of the referenced advances can significantly further develop execution. Alongside some space information, the number of classes can also be increased such as metal detection, oil and e-waste detection can be implemented in further work.

8.3 Summary

The model successfully detects the presence of plastic in ocean in the most efficient way.

CHAPTER 10

INDIVIDUAL TEAM MEMBER's REPORT

10.1 Individual Objective

Niranjana A - To explore different deep learning algorithms by concentrating on various papers , gathering and preprocessing the applicable dataset and analyzing using different models such as R-CNN and Fast R-CNN. To compare the models and find which one gives more accuracy.

Shreya Kishore - To find the best fit model for the proposed system with reference to the inference obtained from the research paper. To compare the models and find which one gives more accuracy and produce a model that would detect the plastic in a more efficient way.

10.2 Role of the Team Members

Niranjana A:

Review the Research Papers & Collected and Preprocessed the dataset. Preparation of the project report.

Shreya Kishore:

Review the Research Papers , Trained the model, Test the Model and analyze the inferences. Preparation of the project report.

10.3 Contribution of Team Members

Niranjana A:

1. Reviewed relevant research papers from previous years to gain an in-depth understanding of existing systems .
2. Analyzed research papers and drawing conclusions.
3. Obtained and preprocessed dataset.
4. Contributed to the project report.

Shreya Kishore:

1. Examined relevant research papers from previous years to gain an understanding of existing systems.
2. Developed a training module and generated the weighted file.
3. Tested the Model and drew inferences.
4. Contributed to the project report.

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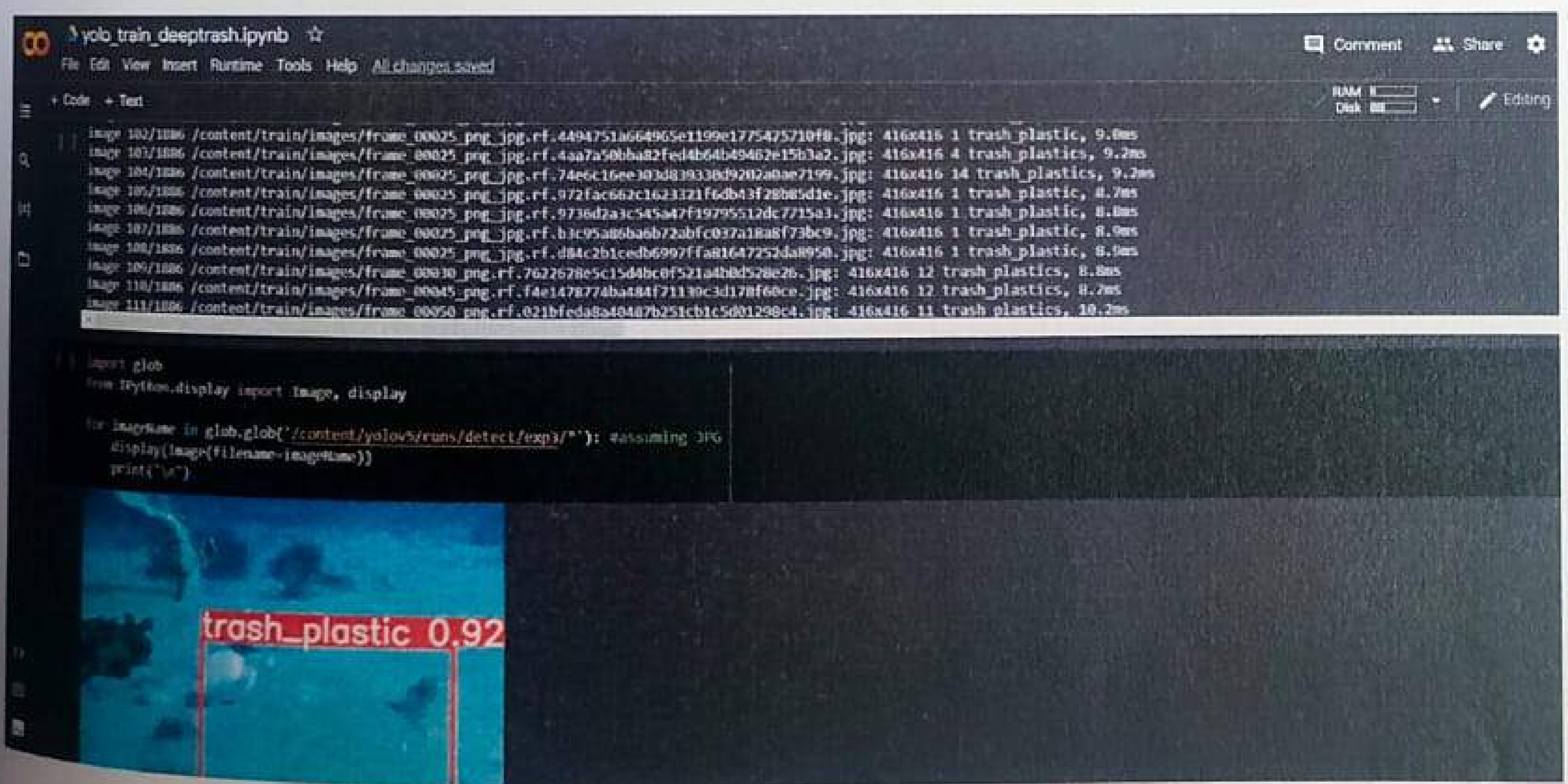
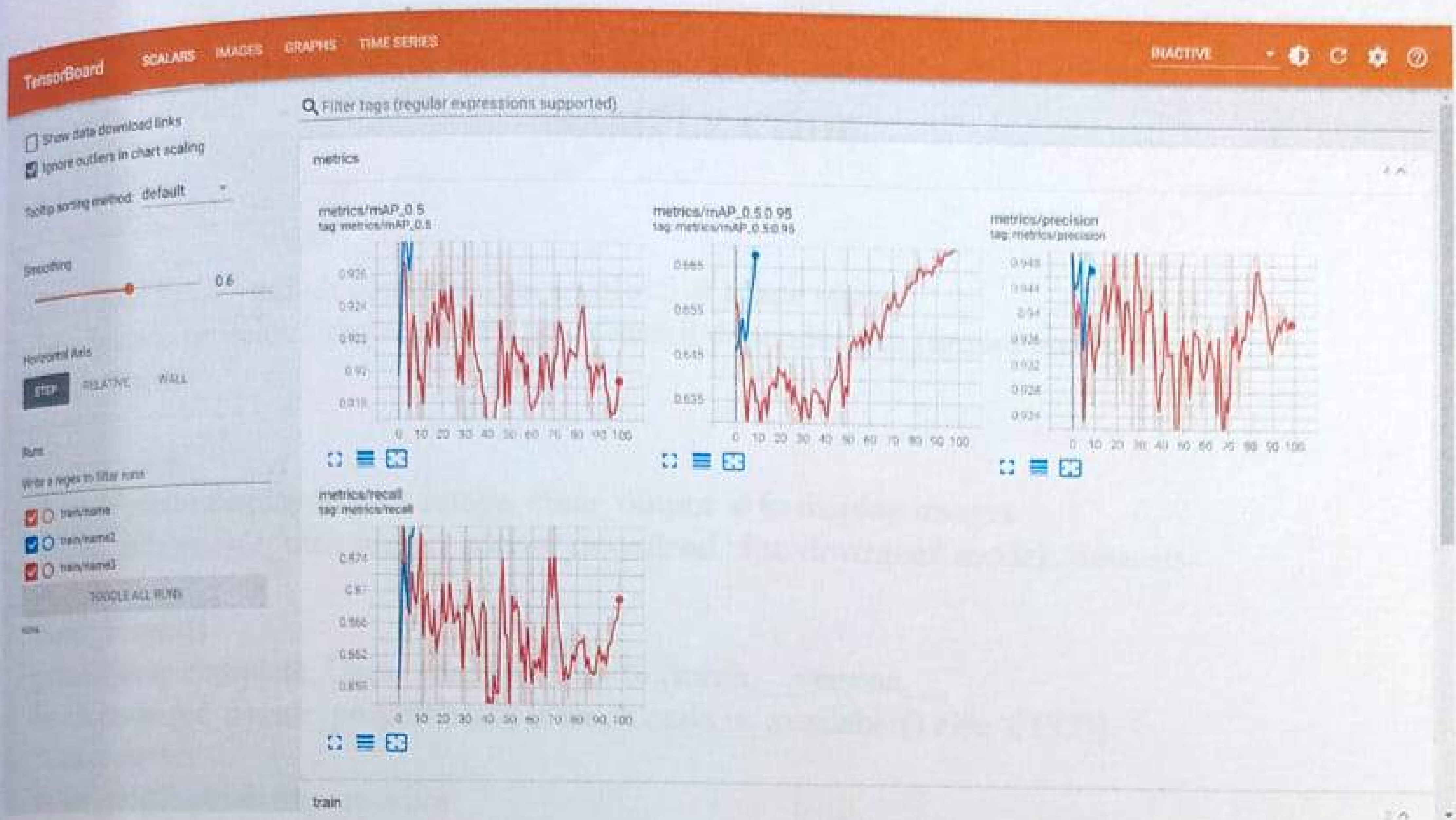
APPENDIX A

SAMPLE SCREEN




TensorBoard
SCALARS
IMAGES
GRAPHS
TIME SERIES
INACTIVE
Filter tags (regular expressions supported)
Show data download links
Ignore outliers in chart scaling
Tooltip sorting method: default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
TOGGLE ALL RUNS
metrics
metrics/mAP_0.5
metrics/mAP_0.5:0.95
metrics/precision
metrics/recall
train

APPENDIX B

SAMPLE CODE

```
!git clone https://github.com/ultralytics/yolov5  # clone repo
!pip install -qr yolov5/requirements.txt  # install dependencies (ignore errors)
%cd yolov5

import torch
from IPython.display import Image, clear_output  # to display images
#from utils.google_utils import gdrive_download  # to download models/datasets

clear_output()
print('Setup complete. Using torch %s %s' % (torch.__version__,
torch.cuda.get_device_properties(0) if torch.cuda.is_available() else 'CPU'))
%cd /content/
from google.colab import drive
drive.mount('/content/gdrive')
!pip install pyyaml
import yaml
with open("data.yaml", 'r') as stream:
  num_classes = str(yaml.safe_load(stream)['nc'])
%cat /content/yolov5/models/yolov5s.yaml
from IPython.core.magic import register_line_cell_magic

@register_line_cell_magic
def writetemplate(line, cell):
  with open(line, 'w') as f:
    f.write(cell.format(**globals()))
%%writetemplate /content/yolov5/models/custom_yolov5s.yaml

# parameters
nc: {num_classes}  # number of classes
depth_multiple: 0.33  # model depth multiple
width_multiple: 0.50  # layer channel multiple

# anchors
anchors:
 - [10,13, 16,30, 33,23]  # P3/8
 - [30,61, 62,45, 59,119]  # P4/16
 - [116,90, 156,198, 373,326]  # P5/32

# YOLOv5 backbone
backbone:
```

```
# [from, number, module, args]
[[-1, 1, Focus, [64, 3]],  # 0-P1/2
 [-1, 1, Conv, [128, 3, 2]],  # 1-P2/4
 [-1, 3, BottleneckCSP, [128]],
 [-1, 1, Conv, [256, 3, 2]],  # 3-P3/8
 [-1, 9, BottleneckCSP, [256]],
 [-1, 1, Conv, [512, 3, 2]],  # 5-P4/16
 [-1, 9, BottleneckCSP, [512]],
 [-1, 1, Conv, [1024, 3, 2]],  # 7-P5/32
 [-1, 1, SPP, [1024, [5, 9, 13]]],
 [-1, 3, BottleneckCSP, [1024, False]],  # 9
]

# YOLOv5 head
head:
 [[-1, 1, Conv, [512, 1, 1]],
  [-1, 1, nn.Upsample, [None, 2, 'nearest']],
  [[-1, 6], 1, Concat, [1]],  # cat backbone P4
  [-1, 3, BottleneckCSP, [512, False]],  # 13

  [-1, 1, Conv, [256, 1, 1]],
  [-1, 1, nn.Upsample, [None, 2, 'nearest']],
  [[-1, 4], 1, Concat, [1]],  # cat backbone P3
  [-1, 3, BottleneckCSP, [256, False]],  # 17 (P3/8-small)

  [-1, 1, Conv, [256, 3, 2]],
  [[-1, 14], 1, Concat, [1]],  # cat head P4
  [-1, 3, BottleneckCSP, [512, False]],  # 20 (P4/16-medium)

  [-1, 1, Conv, [512, 3, 2]],
  [[-1, 10], 1, Concat, [1]],  # cat head P5
  [-1, 3, BottleneckCSP, [1024, False]],  # 23 (P5/32-large)

  [[17, 20, 23], 1, Detect, [nc, anchors]],  # Detect(P3, P4, P5)
 ]
```

APPENDIX C
TEAM DETAILS

S.NO	ROLL NUMBER	TEAM MEMBERS	EMAIL ID	CONTACT NUMBER
1	19113013	Niranjana A	19113013@student.hindustanuniv.ac.in	9384963640
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