CS6811 – Project Work

Third Review

UAV-based Post Disaster Survivor Detection Mechanism using a GAN-aided Ensemble Network

Team Number: 17 (Batch 1)

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Domains: Unmanned Aerial Vehicles, Computer Vision, Ensemble Network

Problem Definition:

Post-disaster scene understanding frameworks are becoming increasingly crucial in search and rescue operations and damage assessment initiatives. The use of Unmanned Aerial Vehicles (UAVs) provides an efficient method to complete the task of scene understanding. However, complex environments present in post-disaster scenarios make it difficult for UAVs to detect humans or objects accurately. Moreover, inefficient object detection mechanisms lead to low accuracy and a long time for object detection tasks. Hence, to mitigate these issues, we propose a UAV-based survivor detection scheme involving a GAN-aided semantic segmentation mechanism. This approach deploys a Generative Adversarial Network (GAN)-based model to denoise and remove occlusion in the images obtained from the UAVs. The framework classifies objects present in the visual scope of the UAV using a semantic segmentation framework based on the images obtained from the UAV, resulting in pixel-level prediction and classification of entities present in the 3D model. Furthermore, an ensemble network consisting of a combination of single-stage and multi-stage detectors is to be used to improve the performance of the survivor detection model. This will help reduce the false negative rate and improve the system's overall accuracy.

Literature Survey:

S.No	Publication Venue and Year	Title	Proposed Work	Limitations
1.	*IEEE Journal on Miniaturization for Air and Space Systems*, vol. 2, no. 4, pp. 209-219 **(2021)**	**UAV-Based Real-Time Survivor Detection System in Post-Disaster Search and Rescue Operations**	❖ This paper proposes a new thermal image dataset consisting of 6447 thermal images designed for survivor detection using UAVs in post-disaster scenarios. ❖ The paper also describes optimal values to prune survivor detection models in order to reduce the complexity of the models. ❖ The model applies knowledge distillation techniques to fine-tune them and improve accuracy. ❖ The performance of several survivor detection models based on YOLOv3 and YOLOv3-MobileNetV1 were compared with and without pruning and fine-tuning.	Older and inferior detection models have been used for survivor detection, thereby resulting in models with high mean average precision (mAP) loss and low accuracy.
2.	*25th IEEE International Conference on Pattern Recognition*	**SyNet: An ensemble network for object detection in UAV images**	With the goal of lowering the high false negative rate of multi-stage detectors and improving the quality	❖ According to the investigation, detecting objects in drone images is more challenging than

	(ICPR), pp. 10227-10234 **(2021)**		of the single-stage detector proposals, the authors of this research propose an ensemble network called SyNet that combines a multi-stage method with a single-stage one.	detecting them in images that were taken from the ground, even with the most advanced object detection algorithms. Hence, the accuracy of the model trained on UAV images is still low compared to models trained on ground images.
3.	*IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 11, pp. 6047-6067 **(2022)**	**Vehicle Detection From UAV Imagery With Deep Learning**	❖ The article provides a review of vehicle detection from UAV imagery using deep learning techniques. ❖ It begins by outlining the various deep learning architectures, including ➢ generative adversarial networks ➢ autoencoders ➢ recurrent neural networks ➢ convolutional neural networks and their contributions to the challenge of improving vehicle detection.	Videos captured in the UAVs are sent to on-ground workstations or to the cloud for processing rather than being implemented on the UAV itself, thereby leading to the absence of a lightweight system for vehicle detection.

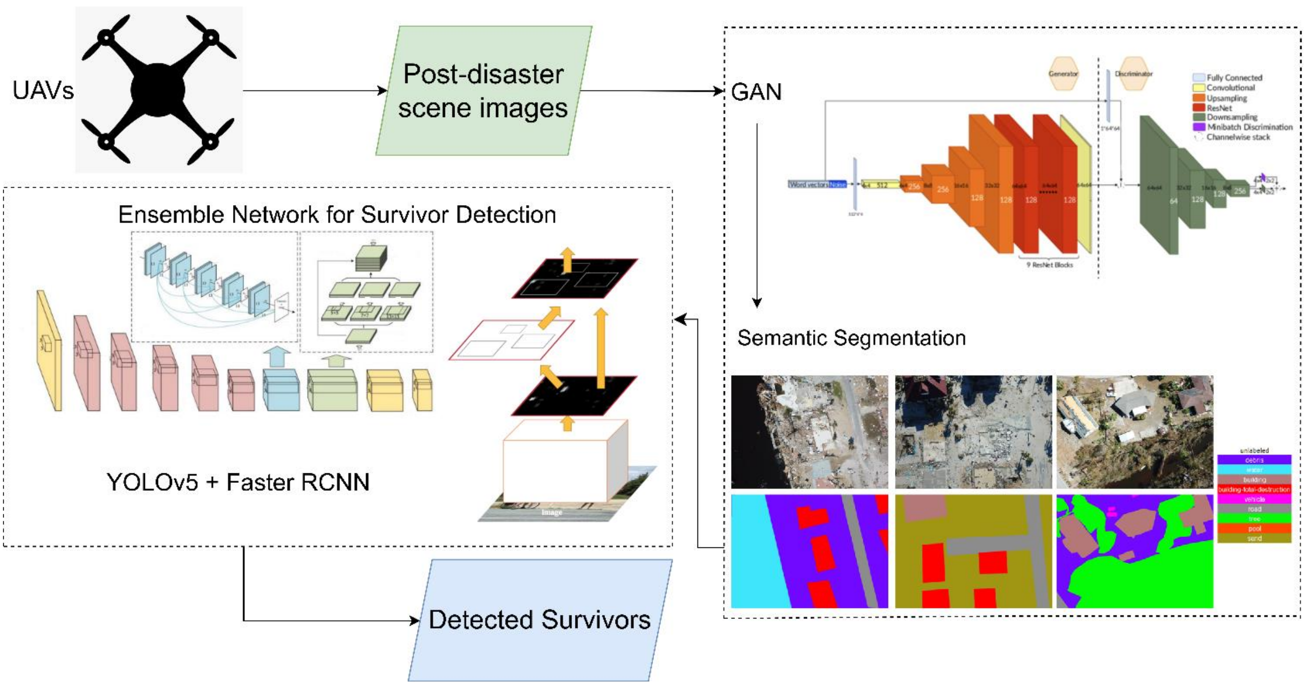
			The paper then focuses on examining various vehicle detection techniques and presents different benchmark datasets and problems that have been discovered, along with possible remedies.	
4.	*IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-13 **(2022)**	**Dense and Small Object Detection in UAV-Vision Based on a Global-Local Feature Enhanced Network**	❖ This paper proposes a global-local feature-enhanced network (GLF-Net) to alleviate issues when detecting small and dense objects using UAVs. ❖ A feature-fusion module has been proposed to tackle the presence of numerous small objects. GLF-Net achieves 86.52% mean Average Precision (mAP) on the RO-UAV dataset.	The scalability of the framework is poor, and the application of GLF-Net on post-disaster UAV images leads to lower mAP, thereby requiring better frameworks.
5.	*IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 1223-1232 **(2021)**	**Unmanned aerial vehicle visual detection and tracking using deep neural networks: A performance benchmark**	❖ This paper executes and compares various UAV detection mechanisms using air-borne UAVs that deploy deep neural networks. ❖ 4 datasets have been used and	❖ Long-distance detection of small UAVs was not taken into consideration. Deep neural networks for re-identification of UAVs were not

			performance has been compared, namely MAV-VID, Drone-vs-Bird, Anti-UAV RGB, and Anti-UAV IR. The performance of 4 models was compared using the datasets mentioned, namely Faster RCNN, SSD512, YOLOv3, and DETR (Detection Transformer). Overall, Faster RCNN performed best.	considered as well.
6.	*UMBC Student Collection* **(2021)**	**RescueNet: A High-Resolution Post Disaster UAV Dataset for Semantic Segmentation**	❖ This paper introduces a high-resolution post-disaster UAV dataset named RescueNet, which contains comprehensive pixel-level annotation of 11 classes for semantic segmentation to assess damage after a natural disaster. The dataset collection and annotation process are discussed, along with the challenges it poses.	❖ RescueNet contains a small number of classes. ❖ As a result, smaller objects like "vehicles" and "pools" make it difficult to get a good segmentation compared to larger objects like buildings and roads. Besides that, since UAV images include only the top view of a scene, it is difficult to assess the actual damage since the horizontal

				view also brings information regarding all sides of a building.
7.	IEEE Access, vol. 9 **(2021)**	**FloodNet: A High-Resolution Aerial Imagery Dataset for Post Flood Scene Understanding**	❖ This paper proposes a new dataset named FloodNet, which contains post-flood images taken from a UAV during the events of Hurricane Harvey. ❖ The images have been labeled pixel-wise to be suitable for semantic segmentation tasks.	❖ Detection of flooded roads and buildings, and distinguishing between natural water and flooded water are challenges faced by the models trained on the FloodNet dataset.
8.	IEEE Access, vol. 10 **(2022)**	**Computer Vision-Based Inspection on Post-Earthquake With UAV Synthetic Dataset**	❖ The paper proposes a novel image recognition pipeline comprising several frameworks for the detection of damage. ❖ Furthermore, the authors provide a synthetic dataset upon which testing was executed.	Synthetic data are prone to errors, which results in low accuracy of trained detection models. Furthermore, a flawlessly prepared synthetic dataset cannot be used to train a computer vision model.
9.	IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 16266-16275 **(2021)**	**Uav-human: A large benchmark for human behavior understanding with unmanned aerial vehicles**	❖ This paper proposes a UAV-Human dataset for human action, pose, and behavior understanding. ❖ The proposed UAV-Human contains ➢ 67,428 multi-modal video sequences	❖ The UAV-Human dataset poses a limitation for attribute recognition because the dataset is captured over a relatively long period of time.

			➢ 119 subjects for action recognition ➢ 22,476 frames for pose estimation ➢ 41,290 frames ➢ 1,144 identities for person re-identification ➢ 22,263 frames for attribute recognition which encourages the exploration and deployment of various data-intensive learning models for UAV-based human behavior understanding.	❖ As a result, the subjects have been diversified with different dressing types and large variations of viewpoints caused by multiple UAV altitudes.
10.	*2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, pp. 2325-2328 **(2021)**	**Attention-Based Semantic Segmentation on UAV Dataset for Natural Disaster Damage Assessment**	❖ This paper proposes and evaluates a novel self-attention segmentation model named ReDNet on a new high-resolution UAV natural disaster dataset named HRUD. ❖ The challenges of semantic segmentation on the HRUD dataset are discussed, along with the excellent performance of the proposed model.	❖ HRUD is a very challenging dataset due to its variable-sized classes along with similar textures among different classes. ❖ Debris, textures of debris, sand, and building with destruction damage make a great impact on the segmentation performance of the evaluated network models.

System Architecture:



Novelty:

A GAN denoiser results in images having lower occlusion and optimal brightness, thereby highlighting the important features of the object. Furthermore, using GAN improves the detection of small and dense objects, which is the case of survivors in images obtained from a UAV. Semantic segmentation on the output obtained from the GAN model leads to a pixel-level prediction of various entities or objects present in the image. The ensemble model, a hybrid architecture consisting of single-stage and multi-stage detectors, overcomes the disadvantages of both frameworks. Deploying an ensemble network comprising the YOLOv5 and Faster R-CNN frameworks improves the performance and efficiency of survivor detection. The overall framework will increase the accuracy and performance of the survivor detection task, thereby resulting in efficient Search-And-Rescue operations.

Expected Outcomes:

- To develop an efficient post-disaster survivor detection framework using UAVs for efficient Search-And-Rescue (SAR) operations.
- To deploy a semantic segmentation mechanism on the 3D model, leading to a pixel-level prediction of various entities or objects in the 3D model. This will improve the detection of survivors present in the post-disaster scene.

- To deploy a Generative Adversarial Network (GAN) framework to improve the detection of survivors, who are generally present as small and dense objects in post-disaster UAV images. A GAN denoiser will result in images having lower occlusion and optimal brightness, thereby highlighting the important features of the object.
- To implement a hybrid single-stage and multi-stage ensemble network for survivor detection on the previously obtained semantic entities. The model will comprise the YOLOv5 and Faster R-CNN mechanisms to combine the benefits of both, thereby decreasing the high false negative rate of multi-stage mechanisms and improving the performance of single-stage detectors.

Modules identified:

Module 1: Semantic Segmentation

Semantic segmentation mechanism for pixel-level prediction and entity classification.

Module 2: GAN-aided Semantic Segmentation pre-processing module

GAN-based occlusion removal mechanism for better survivor detection from UAV images. GAN model incorporated with semantic segmentation for enhanced performance.

Module 3: Ensemble Model

Hybrid single-stage and multi-stage survivor detection model trained on enhanced images obtained from the previous module for efficient Search-And-Rescue operations.

Algorithms:

1. **Algorithm 1: Object Detection using a hybrid Single-Stage and Multi-Stage Ensemble Model**

   Input:

   - **single_stage_model**: A PyTorch model trained with a single-stage detector architecture.
   - **multi_stage_model**: A PyTorch model trained with a multi-stage detector architecture.
   - **images**: A list of images to detect objects in.

- **conf_threshold**: A confidence threshold below which predictions are suppressed.
- **iou_threshold**: An IoU threshold above which overlapping predictions are suppressed.

Output:

- **results**: A list of dictionaries containing the detection results for each image.

Procedure:

1. Initialize an empty list of results.
2. For each image in images, do the following:
    a) Use the single-stage model to detect objects in the image and store the detection results in a list ‘single_stage_results’.
    b) Use the multi-stage model to detect objects in the image and store the detection results in a list ‘multi_stage_results’.
    c) Concatenate the detection results from the single-stage and multi-stage models into a single tensor.
    d) Apply non-maximum suppression to the tensor with confidence threshold conf_threshold and IoU threshold iou_threshold.
    e) Convert the detection results to a dictionary format with keys 'boxes', 'scores', and 'labels', and append the dictionary to results.
3. Return the results list.

2. <u>Algorithm 2: Semantic Segmentation</u>

Input:

- **model**: A PyTorch model trained for semantic segmentation.
- **images**: A list of images to perform segmentation on.
- **batch_size**: An integer specifying the batch size for inference.

Output:

- **results**: A list of dictionaries containing the segmentation results for each image.

Procedure:

1. Initialize an empty list **results**.
2. For each batch of size **batch_size** in **images**, do the following:
    a) Preprocess the images by normalizing and converting them to tensors.

b) Feed the batch of images to the **model** and obtain the segmentation results.
c) Convert the segmentation results to a dictionary format with keys 'mask' and 'class', and append the dictionary to **results**.

3. Return the **results** list.

3. Algorithm 3: GAN-based Occlusion Remover

Input:

- **generator**: A PyTorch generator model trained to remove occlusions.
- **images**: A list of images with occlusions.
- **batch_size**: An integer specifying the batch size for inference.

Output:

- **results**: A list of images with occlusions removed.

Procedure:

1. Initialize an empty list **results**.
2. For each batch of size **batch_size** in **images**, do the following:
   a) Preprocess the images by resizing, normalizing and converting them to tensors.
   b) Feed the batch of images to the **generator** and obtain the occlusion-removed images.
   c) Convert the occlusion-removed images back to numpy arrays and append them to **results**.
3. Return the **results** list.

Preprocessing:

- Resize the input images to the required size for the **generator** model.
- Normalize the pixel values of the images to be in the range [-1, 1].
- Convert the images to tensors.

Occlusion Removal:

- Feed the pre-processed batch of images to the **generator** model.
- The generator model generates occlusion-free versions of the input images.
- Convert the generated occlusion-free images back to numpy arrays.

Implementation:

1. GAN-based occlusion remover:

- A Generative Adversarial Network (GAN) is a model in which two neural networks compete by using deep learning methods to become more accurate in their predictions. GANs typically run unsupervised and use a cooperative zero-sum game framework to learn, where one person's gain equals another person's loss. They are extensively used for several applications like occlusion removal in images.
- For Post-Disaster UAV images, we use the Context-Conditional GAN (CCGAN) to remove occlusion or coverage of entities present in the images through image inpainting.
- In CCGAN, The Generator G is trained to fill in a missing image patch and the Generator G and Discriminator D are conditioned on the surrounding pixels. The model determines if a part of an image is real or fake given the surrounding context.

- We first import all necessary libraries to implement the CCGAN architecture, followed by which the configuration for setting up and training the generator and the discriminator are defined.

```
# number of epochs of training
n_epochs = 15
# size of the batches
batch_size = 16
# name of the dataset
dataset_name = "../input/rescuenet"
# adam: learning rate
lr = 0.00008
# adam: decay of first order momentum of gradient
b1 = 0.5
# adam: decay of first order momentum of gradient
b2 = 0.999
# number of cpu threads to use during batch generation
n_cpu = 4
# dimensionality of the latent space
latent_dim = 100
# size of each image dimension
img_size = 128
# size of random mask
mask_size = 64
# number of image channels
channels = 3
# interval between image sampling
sample_interval = 500
```

- The ImageDataset class is then defined, which enables the loading and usage of a custom dataset to be used for training purposes. Followed by this, the testing and training data loaders are defined for loading the dataset using the ImageDataset class.

```
class ImageDataset(Dataset):
    def __init__(self, root, transforms_=None, img_size=128, mask_size=64, mode="train"):
        self.transform = transforms.Compose(transforms_)
        self.img_size = img_size
        self.mask_size = mask_size
        self.mode = mode
        self.files = sorted(glob.glob("%s/*.jpg" % root))
        self.files = self.files[:-200] if mode == "train" else self.files[-200:]

    def apply_random_mask(self, img):
        """Randomly masks image"""
        y1, x1 = np.random.randint(0, self.img_size - self.mask_size, 2)
        y2, x2 = y1 + self.mask_size, x1 + self.mask_size
        masked_part = img[:, y1:y2, x1:x2]
        masked_img = img.clone()
        masked_img[:, y1:y2, x1:x2] = 1

        return masked_img, masked_part
```

```
transforms_ = [
    transforms.Resize((img_size, img_size), Image.BICUBIC),
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
]
dataloader = DataLoader(
    ImageDataset(dataset_name, transforms_=transforms_),
    batch_size=batch_size,
    shuffle=True,
    num_workers=n_cpu,
)
```

- The generator and the discriminator classes are defined, enabling the creation of the CCGAN model for occlusion removal. The configurations defined earlier are made use of in this stage.

```python
class Generator(nn.Module):
    def __init__(self, channels=3):
        super(Generator, self).__init__()

        def downsample(in_feat, out_feat, normalize=True):
            layers = [nn.Conv2d(in_feat, out_feat, 4, stride=2, padding=1)]
            if normalize:
                layers.append(nn.BatchNorm2d(out_feat, 0.8))
            layers.append(nn.LeakyReLU(0.2))
            return layers

        def upsample(in_feat, out_feat, normalize=True):
            layers = [nn.ConvTranspose2d(in_feat, out_feat, 4, stride=2, padding=1)]
            if normalize:
                layers.append(nn.BatchNorm2d(out_feat, 0.8))
            layers.append(nn.ReLU())
            return layers
```

```python
class Discriminator(nn.Module):
    def __init__(self, channels=3):
        super(Discriminator, self).__init__()

        def discriminator_block(in_filters, out_filters, stride, normalize):
            """Returns layers of each discriminator block"""
            layers = [nn.Conv2d(in_filters, out_filters, 3, stride, 1)]
            if normalize:
                layers.append(nn.InstanceNorm2d(out_filters))
            layers.append(nn.LeakyReLU(0.2, inplace=True))
            return layers

        layers = []
        in_filters = channels
        for out_filters, stride, normalize in [(64, 2, False), (128, 2, True), (256, 2, True)
            layers.extend(discriminator_block(in_filters, out_filters, stride, normalize))
            in_filters = out_filters
```

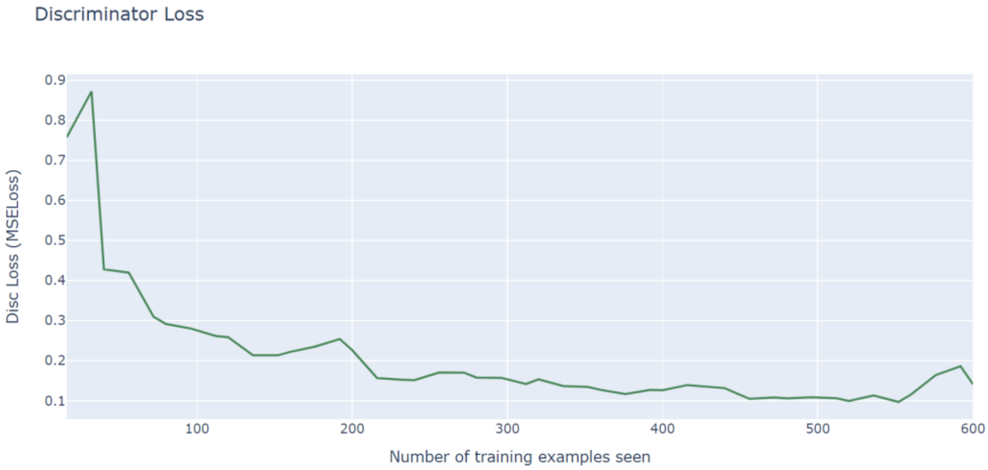
- The CCGAN model is then trained by first instantiating a model using the above declared classes and training the same on the RescueNet dataset for occlusion removal.

```
gen_adv_losses, gen_pixel_losses, disc_losses, counter = [], [], [], []

for epoch in range(n_epochs):

    ### Training ###
    gen_adv_loss, gen_pixel_loss, disc_loss = 0, 0, 0
    tqdm_bar = tqdm(dataloader, desc=f'Training Epoch {epoch} ', total=int(len(dataloader)))
    for i, (imgs, masked_imgs, masked_parts) in enumerate(tqdm_bar):

        # Adversarial ground truths
        valid = Variable(Tensor(imgs.shape[0], *patch).fill_(1.0), requires_grad=False)
        fake = Variable(Tensor(imgs.shape[0], *patch).fill_(0.0), requires_grad=False)

        # Configure input
        imgs = Variable(imgs.type(Tensor))
        masked_imgs = Variable(masked_imgs.type(Tensor))
        masked_parts = Variable(masked_parts.type(Tensor))

        ## Train Generator ##
        optimizer_G.zero_grad()
```

- The training results and performance evaluation are then printed as output to visualize the efficiency of the trained CCGAN model for occlusion removal. The loss of the Generator and the Discriminator during training are plotted, upon which we ascertain that the CCGAN model was trained with minimal training loss of 0.1413. The occlusion-removed images are then stored in the Segmentation folder to be used in the next module.

<u>Results obtained:</u>


Generator Pixel Loss
Gen Pixel Loss (L1 Loss)
0.34
0.33
0.32
0.31
0.3
0.29
0.28
0.27
100
200
300
400
500
600
Number of training examples seen


Discriminator Loss
Disc Loss (MSELoss)
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
100
200
300
400
500
600
Number of training examples seen

2. GAN-aided Semantic Segmentation:

- Semantic Segmentation results in pixel-wise prediction of various entities present in an image. This mechanism generates a color-coding, wherein each entity present in the image is associated with a unique color, thereby making it easy for a detection model to classify between various entities present in the image.
- The mechanism was implemented for post-disaster UAV images, wherein classes of importance, namely car and people, were annotated for semantic segmentation and used to train a SegFormer model.
- SgFormer is a transformer-based framework for semantic segmentation that unifies transformers with lightweight multilayer perceptron (MLP) decoders, thereby improving the performance over regular segmentation mechanisms.

- The necessary libraries were imported to be able to implement the SegFormer framework.

```
import pytorch_lightning as pl
from pytorch_lightning.callbacks.early_stopping import EarlyStopping
from pytorch_lightning.callbacks.model_checkpoint import ModelCheckpoint
from pytorch_lightning.loggers import CSVLogger
from transformers import SegformerFeatureExtractor, SegformerForSemanticSegmentation
from datasets import load_metric
import torch
from torch import nn
from torch.utils.data import Dataset, DataLoader
import os
from PIL import Image
import numpy as np
import random
```

- The images obtained as output from the GAN module are transferred to the GAN folder to be able to make use of the occlusion-removed images for semantic segmentation.

```
from IPython.display import Image
from PIL import Image
import os
from pathlib import Path
path1 = r"/content/drive/MyDrive/Final_Year_Project/Segmentation/Ensemble-1"
os.chdir(path1)

file_path = f"/content/drive/MyDrive/Final_Year_Project/GAN/Ensemble-1/*.jpg"

for i in file_path:
    img = Image.open(i)
    img = img.resize((250,250), Image.ANTIALIAS)
    img.save(path1)
    dataset = Image('/content/drive/MyDrive/Final_Year_Project/Segmentation/Ensemble-1/*.jpg')
```

- The SemanticSegmentationDataset class is defined to load and process the dataset for the semantic segmentation task.

```
class SemanticSegmentationDataset(Dataset):
    """Image (semantic) segmentation dataset."""

    def __init__(self, root_dir, feature_extractor):
        """
        Args:
            root_dir (string): Root directory of the dataset containing the images + annotations.
            feature_extractor (SegFormerFeatureExtractor): feature extractor to prepare images + segmentation maps.
            train (bool): Whether to load "training" or "validation" images + annotations.
        """
        self.root_dir = root_dir
        self.feature_extractor = feature_extractor

        self.classes_csv_file = os.path.join(self.root_dir, "_classes.csv")
        with open(self.classes_csv_file, 'r') as fid:
            data = [l.split(',') for i,l in enumerate(fid) if i !=0]
        self.id2label = {x[0]:x[1] for x in data}

        image_file_names = [f for f in os.listdir(self.root_dir) if '.jpg' in f]
        mask_file_names = [f for f in os.listdir(self.root_dir) if '.png' in f]
```

- The SegFormer model is then defined and implemented to carry out the task of semantic segmentation on the images obtained from the previous module. The SegformerFinetuner class is defined to prune and finetune the parameters used for implementing the model.

```
class SegformerFinetuner(pl.LightningModule):

    def __init__(self, id2label, train_dataloader=None, val_dataloader=None, test_dataloader=None, metrics_interval=100):
        super(SegformerFinetuner, self).__init__()
        self.id2label = id2label
        self.metrics_interval = metrics_interval
        self.train_dl = train_dataloader
        self.val_dl = val_dataloader
        self.test_dl = test_dataloader

        self.num_classes = len(id2label.keys())
        self.label2id = {v:k for k,v in self.id2label.items()}

        self.model = SegformerForSemanticSegmentation.from_pretrained(
            "nvidia/segformer-b0-finetuned-ade-512-512",
            return_dict=False,
            num_labels=self.num_classes,
            id2label=self.id2label,
            label2id=self.label2id,
            ignore_mismatched_sizes=True,
        )

        self.train_mean_iou = load_metric("mean_iou")
        self.val_mean_iou = load_metric("mean_iou")
        self.test_mean_iou = load_metric("mean_iou")
```

- The model is then trained for 300 epochs. The Early Stopping mechanism was incorporated to reduce the chances of overfitting of the model. The model was trained by utilizing the GPU provided by Google Colab using the CUDA library.

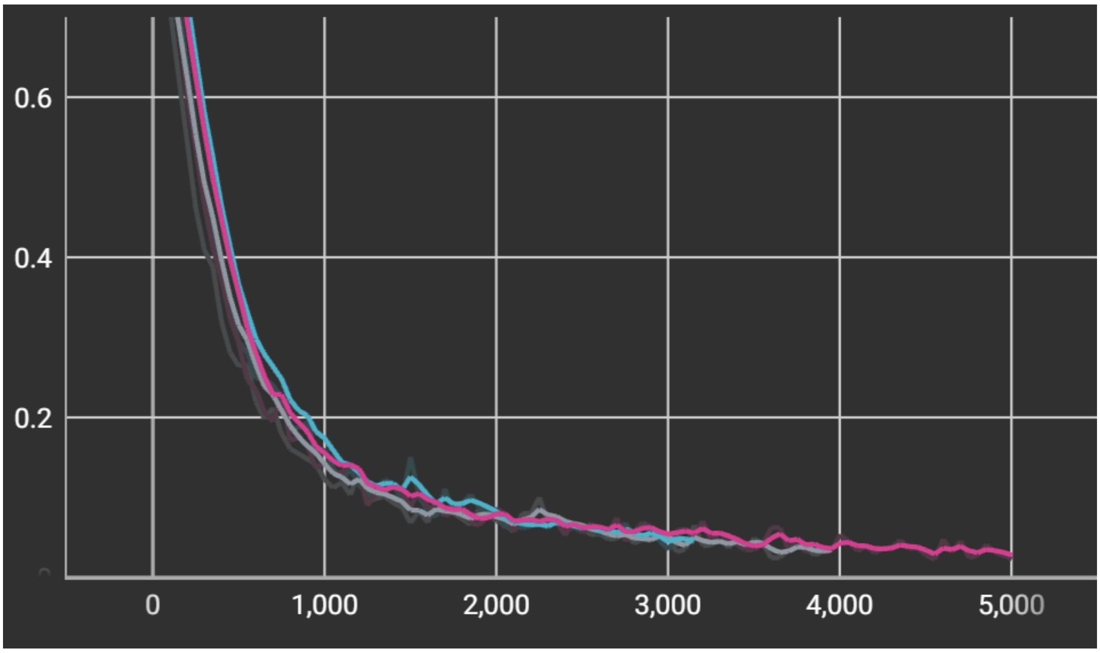
```
trainer = pl.Trainer(
    gpus=1,
    callbacks=[early_stop_callback, checkpoint_callback],
    max_epochs=300,
    val_check_interval=len(train_dataloader),
)
trainer.fit(segformer_finetuner)
```

```
Setting `Trainer(gpus=1)` is deprecated in v1.7 and will be removed in v2.0. Please use
INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda), used: True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False, using: 0 TPU cores
INFO:pytorch_lightning.utilities.rank_zero:IPU available: False, using: 0 IPUs
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False, using: 0 HPUs
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]
INFO:pytorch_lightning.callbacks.model_summary:
  | Name  | Type                             | Params
-----------------------------------------------------------
0 | model | SegformerForSemanticSegmentation | 3.7 M
-----------------------------------------------------------
3.7 M     Trainable params
0         Non-trainable params
3.7 M     Total params
14.860    Total estimated model params size (MB)
```

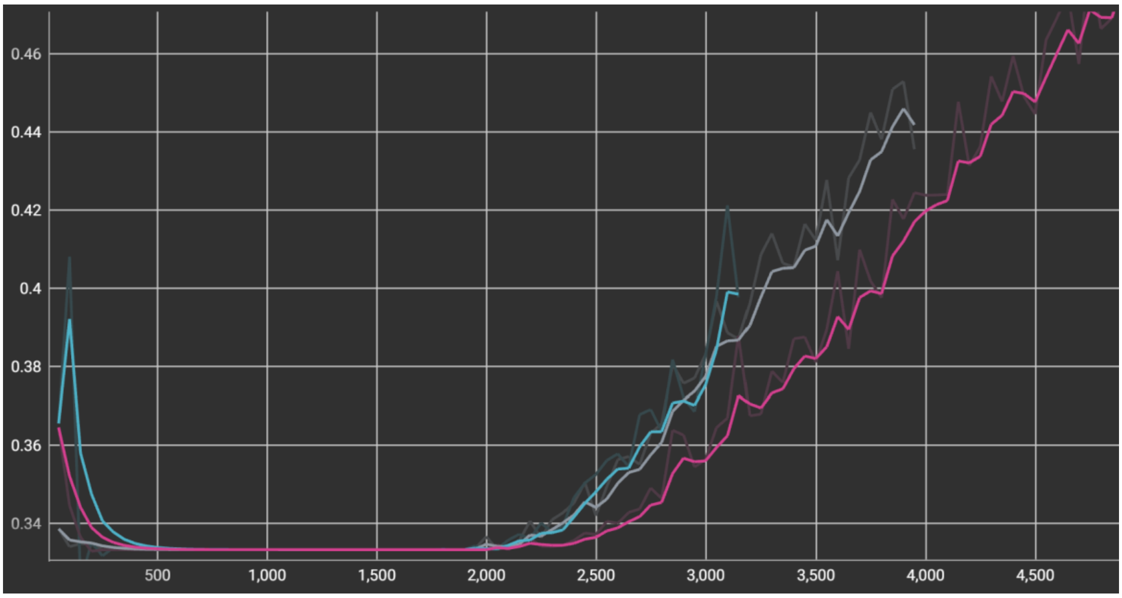
- Tensorboard was instantiated to print the performance evaluation metrics that were witnessed during the training period. The model had minimal training loss, recorded at 0.0233.

<u>Results obtained:</u>

Training loss:

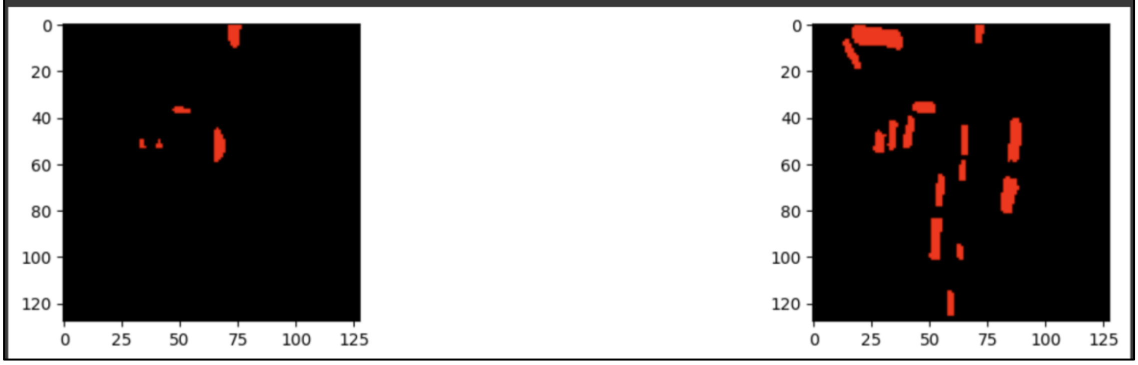


Training accuracy:



- The model's performance was then visualized by running inference on test images using the trained model.

```
n_plots = 4
from matplotlib import pyplot as plt
f, axarr = plt.subplots(n_plots,2)
f.set_figheight(15)
f.set_figwidth(15)
for i in range(n_plots):
    axarr[i,0].imshow(prediction_to_vis(predicted_mask[i,:,:]))
    axarr[i,1].imshow(prediction_to_vis(masks[i,:,:]))
```



- The images obtained as output was saved to the respective folders of YOLOv5 and Faster RCNN models to be trained on enhanced images with entity separation for better performance.

3. Ensemble Model:

- ❖ An ensemble model comprising the YOLOv5 single-stage detector and the Faster RCNN multi-stage detector was implemented.
- ❖ The main advantage of the proposed combination of single-stage and multi-stage detectors is the improved object detection performance over an independent single-stage detector and lower false negative rate than an independent multi-stage detector.
- ❖ Our choice of CNN mechanisms: YOLOv5, being one of the most popular and powerful single-shot detectors, is a stable version of the 'You Only Look Once' family of CNN-based object detection models. Faster RCNN is a very powerful two-stage detector that is widely used for object detection mechanisms.

YOLOv5:

- The YOLOv5 model is instantiated by downloading all dependencies from the official 'ultralytics' github repository.

Installing Dependencies

```
# clone YOLOv5 repository
!git clone https://github.com/ultralytics/yolov5  # clone repo
%cd yolov5
!git reset --hard 064365d8683fd002e9ad789c1e91fa3d021b44f0
```

```
Cloning into 'yolov5'...
remote: Enumerating objects: 15529, done.
remote: Counting objects: 100% (136/136), done.
remote: Compressing objects: 100% (93/93), done.
remote: Total 15529 (delta 49), reused 119 (delta 43), pack-reused 15393
Receiving objects: 100% (15529/15529), 14.59 MiB | 13.31 MiB/s, done.
Resolving deltas: 100% (10577/10577), done.
/content/gdrive/My Drive/Final_Year_Project/YOLOv5/yolov5
HEAD is now at 064365d Update parse_opt() in export.py to work as in train.py (#10789)
```

```
# install dependencies as necessary
!pip install -qr requirements.txt  # install dependencies (ignore errors)
import torch

from IPython.display import Image, clear_output  # to display images
from utils.downloads import attempt_download  # to download models/datasets

# clear_output()
print('Setup complete. Using torch %s %s' % (torch.__version__, torch.cuda.get_device_properties(
```

```
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 184.3/184.3 kB 13.7 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 62.7/62.7 kB 7.5 MB/s eta 0:00:00
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.6/1.6 MB 78.8 MB/s eta 0:00:00
Setup complete. Using torch 2.0.0+cu118 _CudaDeviceProperties(name='Tesla T4', major=7, minor=5, t
```

- The configuration for the YOLOv5 model is defined, wherein various parameters, including the number of classes, batch size, and the number of epochs. Furthermore, The head, backbone, and neck of YOLOv5 are implemented in this stage. The final configuration is then verified.

```
%cd ..
%cat models/yolov5s.yaml
```

```
/content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5
# YOLOv5 🚀 by Ultralytics, GPL-3.0 license

# Parameters
nc: 80  # number of classes
depth_multiple: 0.33  # model depth multiple
width_multiple: 0.50  # layer channel multiple
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 v6.0 backbone
backbone:
  # [from, number, module, args]
  [[-1, 1, Conv, [64, 6, 2, 2]],  # 0-P1/2
   [-1, 1, Conv, [128, 3, 2]],  # 1-P2/4
   [-1, 3, C3, [128]],
   [-1, 1, Conv, [256, 3, 2]],  # 3-P3/8
   [-1, 6, C3, [256]],
```

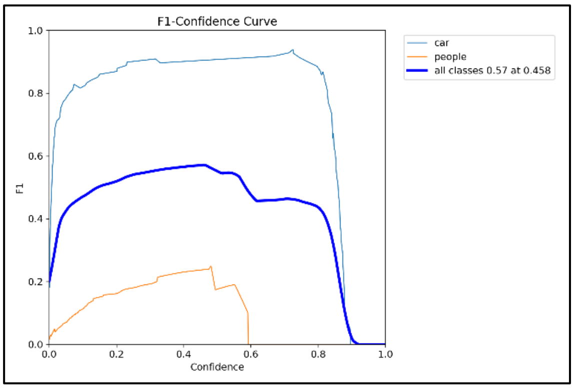
- The YOLOv5 model is then trained with batch size 16 for 492 epochs. The configurations previously defined in custom_yolov5s.yaml are also given as input parameters. In our case, Early stopping was observed as the model performance did not vary over a period of epochs, thereby stopping the training process in the 492nd epoch. The Mean Average Precision (mAP) is calculated for every epoch/iteration and displayed in the output. Finally, the total number of instances that the model visualized under each class is tabulated and presented, and the weights are stored in the yolov5s_results folder as 'best.pt'.

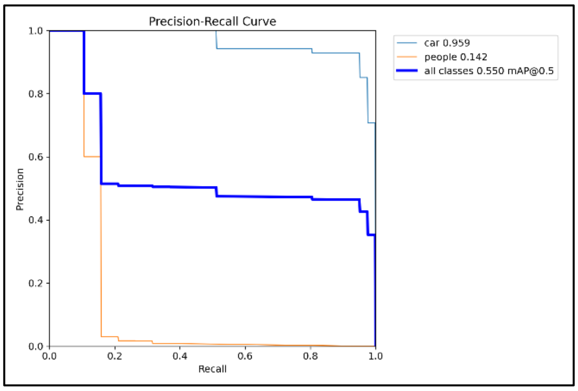
```
     Epoch    GPU_mem   box_loss   obj_loss   cls_loss  Instances       Size
   490/999       1.7G    0.05502    0.02816   0.002194         33        416: 100% 14/14 [00:02<00:00,  5.13it/s]
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 1/1 [00:00<00:00,  3.55it/s]
                   all         10         60      0.681      0.534       0.53      0.264

     Epoch    GPU_mem   box_loss   obj_loss   cls_loss  Instances       Size
   491/999       1.7G    0.05301     0.0274   0.001798         12        416: 100% 14/14 [00:03<00:00,  4.46it/s]
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 1/1 [00:00<00:00,  5.75it/s]
                   all         10         60      0.518      0.567      0.505      0.247

     Epoch    GPU_mem   box_loss   obj_loss   cls_loss  Instances       Size
   492/999       1.7G    0.05517    0.03003   0.002003         23        416: 100% 14/14 [00:02<00:00,  6.20it/s]
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 1/1 [00:00<00:00,  7.62it/s]
                   all         10         60      0.539      0.555      0.498      0.246
Stopping training early as no improvement observed in last 100 epochs. Best results observed at epoch 392, best model saved as best.pt.
To update EarlyStopping(patience=100) pass a new patience value, i.e. `python train.py --patience 300` or use `--patience 0` to disable

493 epochs completed in 0.456 hours.
Optimizer stripped from runs/train/yolov5s_results/weights/last.pt, 14.8MB
Optimizer stripped from runs/train/yolov5s_results/weights/best.pt, 14.8MB

Validating runs/train/yolov5s_results/weights/best.pt...
Fusing layers...
custom_YOLOv5s summary: 182 layers, 7249215 parameters, 0 gradients
                 Class     Images  Instances          P          R      mAP50   mAP50-95: 100% 1/1 [00:00<00:00, 10.73it/s]
                   all         10         60      0.661      0.555       0.55      0.272
                   car         10         41       0.86      0.951      0.959      0.511
                people         10         19      0.462      0.158      0.142     0.0323
Results saved to runs/train/yolov5s_results
```

- Tensorboard is then made use of to visualize the performance of the model. Tesnorboard plots all performance metrics observed while training the model over the range of epochs for which the model was trained. The overall training loss of the model was found to be 0.002 for identifying various classes. The mean average precision (mAP) of the model after 492 epochs as found to be 0.55.

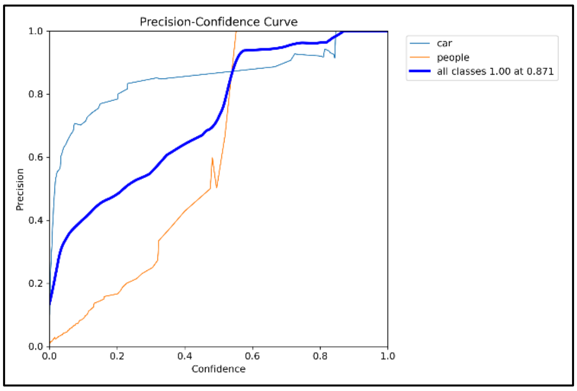
Results obtained:

F1-confidence curve **Precision-Recall curve**

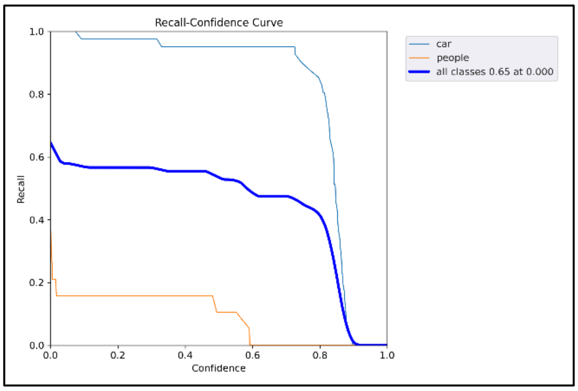




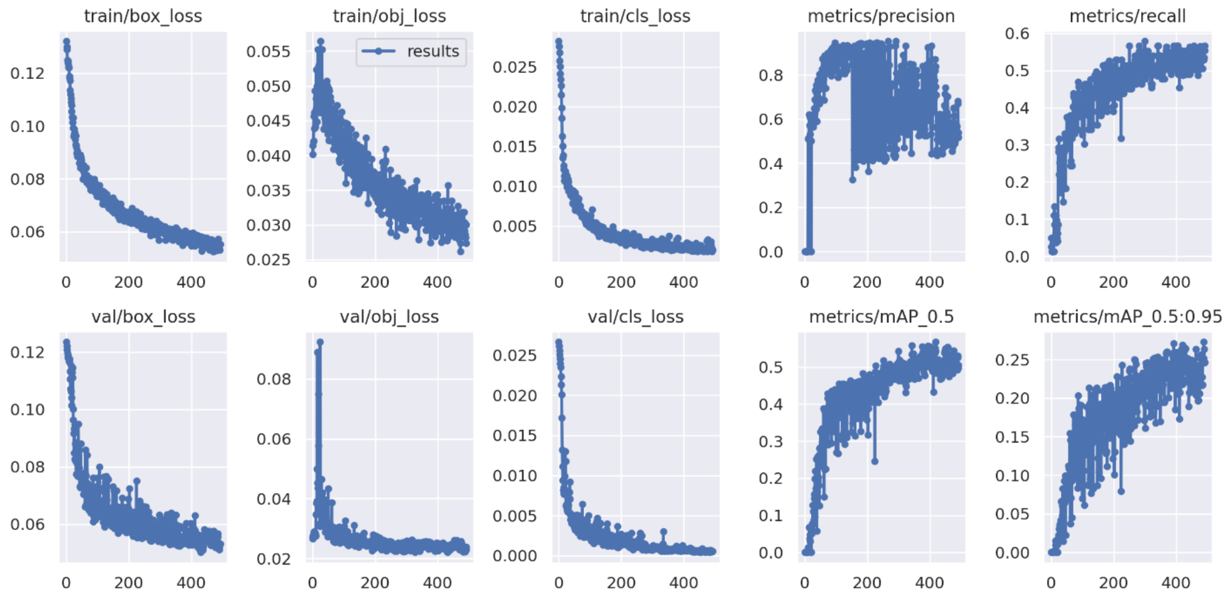
Precision-confidence curve



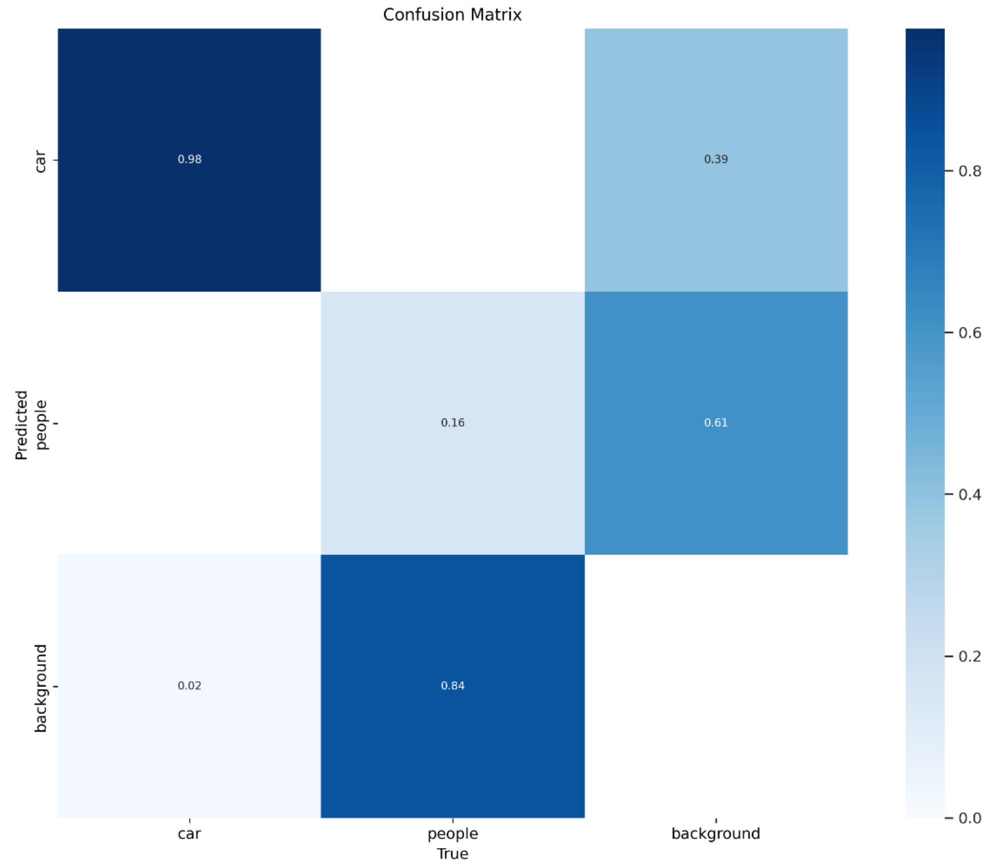
Recall-confidence curve



Performance Metrics:



Confusion Matrix:



- The trained model is then tested by visualizing results obtained when test images are passed through the model. The bounding boxes constructed over detected classes are displayed.

- The images present in the test split are then passed through the trained model loaded with the best weights obtained during the training process. The results are then obtained and visualized.

```
[ ] # %cd /content/yolov5/
    !python detect.py --weights runs/train/yolov5s_results/weights/best.pt --img 416 --conf 0.4 --sou

    detect: weights=['runs/train/yolov5s_results/weights/best.pt'], source=Ensemble-1/test/images, dat
    YOLOv5 🚀 v7.0-72-g064365d Python-3.9.16 torch-2.0.0+cu118 CUDA:0 (Tesla T4, 15102MiB)

    Fusing layers...
    custom_YOLOv5s summary: 182 layers, 7249215 parameters, 0 gradients
    image 1/20 /content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5/Ensemble-1/test/images/10841_j
    image 2/20 /content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5/Ensemble-1/test/images/10845_j
    image 3/20 /content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5/Ensemble-1/test/images/10865_j
    image 4/20 /content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5/Ensemble-1/test/images/10900_j
    image 5/20 /content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5/Ensemble-1/test/images/10910_j
    image 6/20 /content/gdrive/MyDrive/Final_Year_Project/YOLOv5/yolov5/Ensemble-1/test/images/10911_j
```

- The model along with the best weights are then saved in a folder named 'Saved_Models' for it to be used and deployed in the final Ensemble model.

Faster RCNN:

- The Faster RCNN multi-stage CNN model is implemented using Detectron2, which is a computer vision library that allows the implementation of various CNN models through the usage of PyTorch.
- Initially, the GPU instantiated in the Google Colab environment is displayed using the nvidia-smi command.

```
[ ] !nvidia-smi

    Sun Apr 16 12:23:21 2023
    +-----------------------------------------------------------------------------+
    | NVIDIA-SMI 525.85.12    Driver Version: 525.85.12    CUDA Version: 12.0     |
    |-------------------------------+----------------------+----------------------+
    | GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
    | Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
    |                               |                      |               MIG M. |
    |===============================+======================+======================|
    |   0  Tesla T4            Off  | 00000000:00:04.0 Off |                    0 |
    | N/A   42C    P8    10W /  70W |      0MiB / 15360MiB |      0%      Default |
    |                               |                      |                  N/A |
    +-------------------------------+----------------------+----------------------+

    +-----------------------------------------------------------------------------+
    | Processes:                                                                  |
    |  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
    |        ID   ID                                                   Usage      |
    |=============================================================================|
    |  No running processes found                                                 |
    +-----------------------------------------------------------------------------+
```

- The dependencies of Detectron2 are installed to be able to setup Detectron2 and Faster RCNN. The versions of all dependencies are confirmed.

Installing Detectron2 and dependencies

```
[ ]  !python -m pip install 'git+https://github.com/facebookresearch/detectron2.git'

       Downloading omegaconf-2.3.0-py3-none-any.whl (79 kB)
          ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 79.5/79.5 kB 10.0 MB/s eta 0:00:00
     Collecting hydra-core>=1.1
       Downloading hydra_core-1.3.2-py3-none-any.whl (154 kB)
          ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 154.5/154.5 kB 20.0 MB/s eta 0:00:00
     Collecting black
       Downloading black-23.3.0-cp39-cp39-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.7 MB)
          ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.7/1.7 MB 79.8 MB/s eta 0:00:00
     Requirement already satisfied: packaging in /usr/local/lib/python3.9/dist-packages (from det
     Requirement already satisfied: numpy in /usr/local/lib/python3.9/dist-packages (from fvcore<
     Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.9/dist-packages (from f
     Collecting antlr4-python3-runtime==4.9.*
       Downloading antlr4-python3-runtime-4.9.3.tar.gz (117 kB)
          ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 117.0/117.0 kB 15.3 MB/s eta 0:00:00
       Preparing metadata (setup.py) ... done
```

- All libraries required to implement the detectron2 environment and the Faster RCNN model are defined. The libraries required for dataset preparation, visualization of the performance of the model on test images, and training of the model are defined.

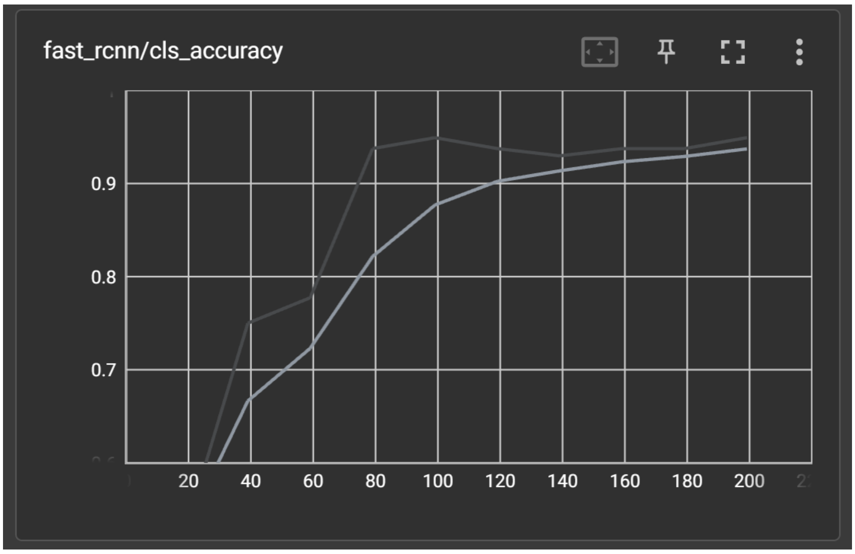
```
[ ]  # COMMON LIBRARIES
     import os
     import cv2

     from datetime import datetime
     from google.colab.patches import cv2_imshow

     # DATA SET PREPARATION AND LOADING
     from detectron2.data.datasets import register_coco_instances
     from detectron2.data import DatasetCatalog, MetadataCatalog

     # VISUALIZATION
     from detectron2.utils.visualizer import Visualizer
     from detectron2.utils.visualizer import ColorMode

     # CONFIGURATION
     from detectron2 import model_zoo
     from detectron2.config import get_cfg

     # EVALUATION
     from detectron2.engine import DefaultPredictor

     # TRAINING
     from detectron2.engine import DefaultTrainer
```

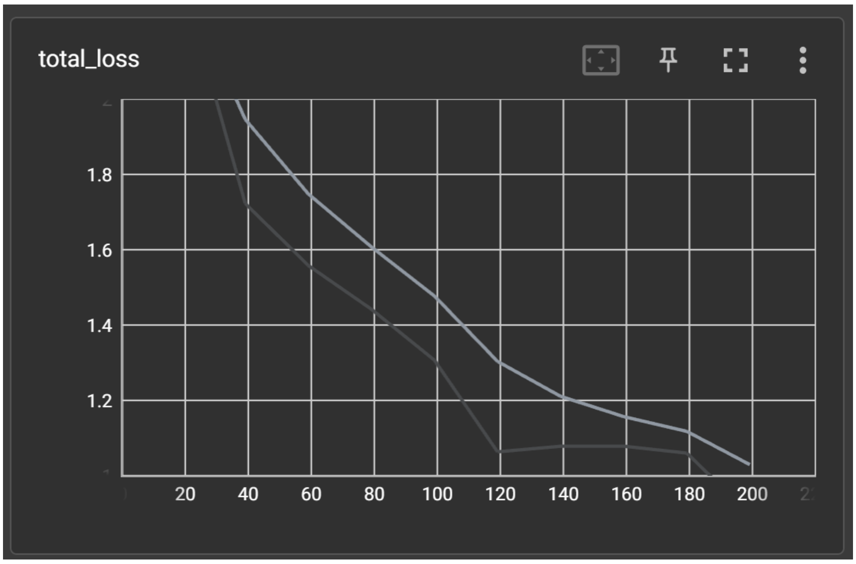
- The Faster RCNN model is then instantiated and trained using the faster_rcnn_X_101_32x8d_FPN_3x architecture present in Detectron2. Other parameters required for training the model are defined as well.

```
[ ] # HYPERPARAMETERS
    ARCHITECTURE = "faster_rcnn_X_101_32x8d_FPN_3x"
    # ARCHITECTURE = "mask_rcnn_R_101_FPN_3x"
    CONFIG_FILE_PATH = f"COCO-Detection/{ARCHITECTURE}.yaml"
    MAX_ITER = 200
    EVAL_PERIOD = 200
    BASE_LR = 0.001
    NUM_CLASSES = 2

    # OUTPUT DIR
    OUTPUT_DIR_PATH = os.path.join(
        DATA_SET_NAME,
        ARCHITECTURE,
        datetime.now().strftime('%Y-%m-%d-%H-%M-%S')
    )

    os.makedirs(OUTPUT_DIR_PATH, exist_ok=True)
```

- Once the model is trained, Tesnorboard is initialized, thereby giving various performance metrics observed during the training process of the Faster RCNN model. Total loss of the model was observed to be 0.89. The accuracy of detecting various classes was found to be 93.75%.

<u>Results obtained:</u>





- The trained model is then tested using the test set and results are visualized.

- The model and its corresponding weights are then saved and stored in the 'Saved_Models' folder.

<u>Final Ensemble Model:</u>

- The final ensemble model is created using the two trained models obtained in the previous steps.

- Both the models are executed for the same image and their respective outputs are visualized.
- The models are then combined using the ensembling technique named 'simple averaging', wherein multiple models are trained independently and their predictions are combined to improve overall performance.

```
# Detect objects in each image using each model
for image in images:
    detection_results = []

    for model in models:
        predictions = model.detect(image)
        detection_results.append(predictions)

    # Ensemble the detection results
    ensemble_predictions = torch.cat(detection_results, dim=0)
    ensemble_predictions = non_max_suppression(ensemble_predictions,

    # Convert the detection results to a dictionary format
    detection_dict = {'boxes': [], 'scores': [], 'labels': []}

    for bbox in ensemble_predictions:
        detection_dict['boxes'].append(bbox[0:4].tolist())
        detection_dict['scores'].append(bbox[5].item())
        detection_dict['labels'].append(int(bbox[6].item()))

    results.append(detection_dict)

return results
```

- The ensembled model is then evaluated using the same image used for the previous models and the outputs are compared. Survivors were detected with an accuracy of 96.4%.

References:

1. J. Dong, K. Ota and M. Dong, "**UAV-Based Real-Time Survivor Detection System in Post-Disaster Search and Rescue Operations**," in *IEEE Journal on Miniaturization for Air and Space Systems*, vol. 2, no. 4, pp. 209-219, 2021
2. Albaba, Berat Mert, and Sedat Ozer, "**SyNet: An ensemble network for object detection in UAV images**," in 25th IEEE International Conference on Pattern Recognition (ICPR), pp. 10227-10234, 2021
3. A. Bouguettaya, H. Zarzour, A. Kechida and A. M. Taberkit, "**Vehicle Detection From UAV Imagery With Deep Learning: A Review**," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 11, pp. 6047-6067, Nov. 2022
4. T. Ye, W. Qin, Y. Li, S. Wang, J. Zhang and Z. Zhao, "**Dense and Small Object Detection in UAV-Vision Based on a Global-Local Feature Enhanced Network**," in *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-13, 2022
5. Rahnemoonfar, Maryam, Tashnim Chowdhury, and Robin Murphy. "**RescueNet: A High-Resolution Post Disaster UAV Dataset for Semantic Segmentation**." *UMBC Student Collection*, 2021

6. T. Chowdhury and M. Rahnemoonfar, "**Attention Based Semantic Segmentation on UAV Dataset for Natural Disaster Damage Assessment**," *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, pp. 2325-2328, 2021
7. M. Rahnemoonfar, T. Chowdhury, A. Sarkar, D. Varshney, M. Yari and R. R. Murphy, "**FloodNet: A High Resolution Aerial Imagery Dataset for Post Flood Scene Understanding**," in IEEE Access, vol. 9, pp. 89644-89654, 2021
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9. Li, Tianjiao, Jun Liu, Wei Zhang, Yun Ni, Wenqian Wang, and Zhiheng Li. "**Uav-human: A large benchmark for human behavior understanding with unmanned aerial vehicles**." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 16266-16275, 2021
10. Isaac-Medina, Brian KS, Matt Poyser, Daniel Organisciak, Chris G. Willcocks, Toby P. Breckon, and Hubert PH Shum. "**Unmanned aerial vehicle visual detection and tracking using deep neural networks: A performance benchmark**." In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 1223-1232, 2021.