LANE SEGMENTATION /SEMATNTIC SEGMENTATION

Objective: The global market for self-driving cars has been on a rise with the market size projected to grow from 20.3 million units in 2021 to 62.4 million units by 2030, a CAGR on 13.3%. Among the many challenges associated with designing self-driving cars, one challenge that we are particularly interested in is designing a machine learning model that can accurately detect road lanes. In this project we are creating an image segmentation model that tries to accurately identify the pixels corresponding to the road from a given dash cam image.

Dataset: The dataset that we will be using in this project is the Cambridge-driving Labeled Video Database (CamVid) which is a collection of frames from videos taken from a front dash cam of cars. The dataset is labelled with 32 categories that includes buildings, trees, sidewalk, etc. but due to computational limitations we will be working with only a single class “road”. So, we will be working with a binary segmentation problem, where road pixels would be indicated by 1 and the remaining pixels in the image would be indicated by 0.

Accuracy Metrics: We used 2 metrics to evaluate our models: Intersection over Union (IoU) and Dice Score, both of which are metrics that quantify the degree of overlap in the true and the predicted image, where IoU is more sensitive to extreme values.

Intersection over Union (IoU): This metric gives the ratio of intersection area of true and predicted image to the union area true and predicted image.

Dice Score: This metric gives the ratio of two times the intersection area of true and predicted image to the sum of areas true and predicted image.

CODE

```
from google.colab import drive
drive.mount('/content/drive')
!unzip drive/My\ Drive/CamVid3.zip
```

```
  inflating: CamVid/val_labels/0016E5_08119.png
  inflating: CamVid/val_labels/0016E5_08121.png
  inflating: CamVid/val_labels/0016E5_08123.png
 extracting: CamVid/val_labels/0016E5_08125.png
  inflating: CamVid/val_labels/0016E5_08127.png
 extracting: CamVid/val_labels/0016E5_08129.png
 extracting: CamVid/val_labels/0016E5_08131.png
 extracting: CamVid/val_labels/0016E5_08133.png
 extracting: CamVid/val_labels/0016E5_08135.png
  inflating: CamVid/val_labels/0016E5_08137.png
  inflating: CamVid/val_labels/0016E5_08139.png
  inflating: CamVid/val_labels/0016E5_08141.png
  inflating: CamVid/val_labels/0016E5_08143.png
  inflating: CamVid/val_labels/0016E5_08145.png
  inflating: CamVid/val_labels/0016E5_08147.png
  inflating: CamVid/val_labels/0016E5_08149.png
  inflating: CamVid/val_labels/0016E5_08151.png
  inflating: CamVid/val_labels/0016E5_08153.png
  inflating: CamVid/val_labels/0016E5_08155.png
  inflating: CamVid/val_labels/0016E5_08157.png
  inflating: CamVid/val_labels/0016E5_08159.png
```

```
!pip install -U segmentation-models-pytorch
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting segmentation-models-pytorch
  Downloading segmentation_models_pytorch-0.3.1-py3-none-any.whl (102 kB)
     |████████████████████████████████| 102 kB 867 kB/s
Collecting efficientnet-pytorch==0.7.1
  Downloading efficientnet_pytorch-0.7.1.tar.gz (21 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.8/dist-packages (from segmentation-models-pytorch) (4.64.1)
Collecting timm==0.4.12
  Downloading timm-0.4.12-py3-none-any.whl (376 kB)
     |████████████████████████████████| 376 kB 2.1 MB/s
Collecting pretrainedmodels==0.7.4
  Downloading pretrainedmodels-0.7.4.tar.gz (58 kB)
     |████████████████████████████████| 58 kB 4.2 MB/s
Requirement already satisfied: pillow in /usr/local/lib/python3.8/dist-packages (from segmentation-models-pytorch) (7.1.2)
Requirement already satisfied: torchvision>=0.5.0 in /usr/local/lib/python3.8/dist-packages (from segmentation-models-pytorch) (0.14.0+c
Requirement already satisfied: torch in /usr/local/lib/python3.8/dist-packages (from efficientnet-pytorch==0.7.1->segmentation-models-py
Collecting munch
  Downloading munch-2.5.0-py2.py3-none-any.whl (10 kB)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.8/dist-packages (from torch->efficientnet-pytorch==0.7.1->seg
Requirement already satisfied: requests in /usr/local/lib/python3.8/dist-packages (from torchvision>=0.5.0->segmentation-models-pytorch)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages (from torchvision>=0.5.0->segmentation-models-pytorch) (1
Requirement already satisfied: six in /usr/local/lib/python3.8/dist-packages (from munch->pretrainedmodels==0.7.4->segmentation-models-p
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.8/dist-packages (from requests->torchvi
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.8/dist-packages (from requests->torchvision>=0.5.0->segmentation-m
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.8/dist-packages (from requests->torchvision>=0.5.0->segmentat
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.8/dist-packages (from requests->torchvision>=0.5.0->segmenta
Building wheels for collected packages: efficientnet-pytorch, pretrainedmodels
  Building wheel for efficientnet-pytorch (setup.py) ... done
  Created wheel for efficientnet-pytorch: filename=efficientnet_pytorch-0.7.1-py3-none-any.whl size=16446 sha256=0448ad8119416d864c523b2
  Stored in directory: /root/.cache/pip/wheels/84/b9/90/25a0195cf95fb5533db96f1c77ea3f296b7cc86ae8ae48e3dc
  Building wheel for pretrainedmodels (setup.py) ... done
  Created wheel for pretrainedmodels: filename=pretrainedmodels-0.7.4-py3-none-any.whl size=60966 sha256=8c180d6945c57a55ff8adb2e65e630e
  Stored in directory: /root/.cache/pip/wheels/ed/fa/b9/5c82b59d905f95542a192b883c0cc0082407ea2f54beb2f9e6
Successfully built efficientnet-pytorch pretrainedmodels
Installing collected packages: munch, timm, pretrainedmodels, efficientnet-pytorch, segmentation-models-pytorch
Successfully installed efficientnet-pytorch-0.7.1 munch-2.5.0 pretrainedmodels-0.7.4 segmentation-models-pytorch-0.3.1 timm-0.4.12
```

```
pip install pytorch-model-summary
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting pytorch-model-summary
  Downloading pytorch_model_summary-0.1.2-py3-none-any.whl (9.3 kB)
Requirement already satisfied: torch in /usr/local/lib/python3.8/dist-packages (from pytorch-model-summary) (1.13.0+cu116)
Requirement already satisfied: numpy in /usr/local/lib/python3.8/dist-packages (from pytorch-model-summary) (1.21.6)
Requirement already satisfied: tqdm in /usr/local/lib/python3.8/dist-packages (from pytorch-model-summary) (4.64.1)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.8/dist-packages (from torch->pytorch-model-summary) (4.4.0)
Installing collected packages: pytorch-model-summary
Successfully installed pytorch-model-summary-0.1.2
```

```
from torch.utils.data import Dataset
from torchvision.transforms import Compose
from torchvision.transforms import Resize
from torchvision.transforms import ToTensor

import os
from PIL import Image
```

```
import numpy as np

import matplotlib.pyplot as plt

from torch.utils.data import DataLoader
from torch.nn import Module, Sequential, Conv2d, ConvTranspose2d, MaxPool2d, MaxUnpool2d, ReLU, BatchNorm2d, Dropout, Sigmoid
from pytorch_model_summary import summary

import torch
from numpy import asarray
import tensorflow as tf

import cv2
import numpy as np
from keras import backend as K

from torchvision.models.segmentation import deeplabv3_resnet101
from torchvision.models.segmentation.deeplabv3 import DeepLabHead
from random import random
from torchvision.transforms import functional as F

import segmentation_models_pytorch as smp

from torchvision.transforms import Normalize
from segmentation_models_pytorch import utils

x_train_dir = '/content/CamVid/train'
y_train_dir = '/content/CamVid/train_labels'
x_val_dir = '/content/CamVid/val'
y_val_dir = '/content/CamVid/val_labels'
x_test_dir = '/content/CamVid/test'
y_test_dir = '/content/CamVid/test_labels'
```

1. CNN model (Baseline)

Baseline CNN: We first created a CNN architecture as a baseline for the lane segmentation problem. The baseline model contains two convolution (num_filters=64, filter_size=3, stride=2, activation=“relu”) and pooling layers (size=2) in the encoder section, and two transpose convolution and unpooling layers in the decoder section. The mean IoU score obtained on the validation set was about 61.85% and the mean dice score was about 63.32%

1.1 Defining the custom dataset

```
from torch.utils.data import Dataset
class CamVidDataset(Dataset):
    def __init__(self, images_dir, masks_dir=None, transforms=None, training_type=None):
        # Here we get names of all the images
        self.image_names = os.listdir(images_dir)

        # Defining the training _type and transforms
        self.training_type = training_type
        self.transforms = transforms

        # Defining the paths of images and masks
        self.images_paths = []
        self.masks_paths = []
        for image_name in self.image_names:
            self.images_paths.append(os.path.join(images_dir, image_name))
            if self.training_type=="train" or self.training_type=="val":
                self.masks_paths.append(os.path.join(masks_dir, image_name.split('.')[0] + '.png'))

    def __getitem__(self, i):

        if self.training_type=="train" or self.training_type=="val":
            image = Image.open(self.images_paths[i])
            mask = Image.open(self.masks_paths[i])

            # preprocessing of mask
```

```
            mask = np.array(mask)
            mask = (mask == 3)
            mask = Image.fromarray(mask)

            # application of transforms
            image = self.transforms(image)
            mask = self.transforms(mask)
            return image, mask

        else:
            # Reading the data
            image = Image.open(self.images_paths[i])

            # application of transforms
            image = self.transforms(image)
            return image

    def __len__(self):
        return len(self.image_names)
```

1.2 Data Exploration

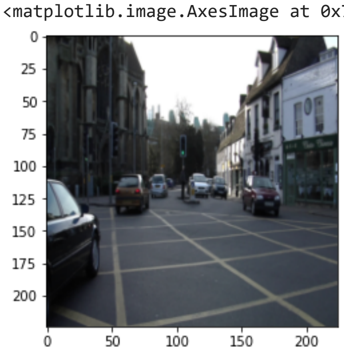
```
# The images resized to 224 x 224
train_transforms = Compose([
    Resize((224, 224)),ToTensor()])
```

```
dataset = CamVidDataset(x_train_dir, y_train_dir, transforms=train_transforms, training_type='train')
image, gt_mask = dataset[0]
image.shape, gt_mask.shape
```

```
(torch.Size([3, 224, 224]), torch.Size([1, 224, 224]))
```

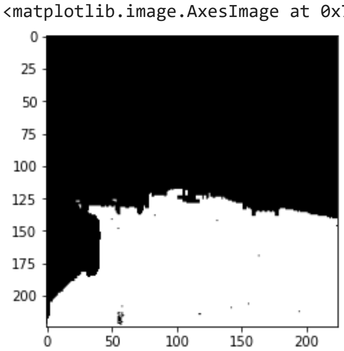
```
# Image
plt.imshow(np.transpose(image, (1, 2, 0)))
```

```
<matplotlib.image.AxesImage at 0x7f3ff68a7520>
```



```
# Mask image
plt.imshow(gt_mask.squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff66f4130>
```



```
# Creating batches
train_transforms = Compose([Resize((224, 224)),ToTensor()]) #resizing
train_dataset = CamVidDataset(x_train_dir, y_train_dir,
    transforms=train_transforms,training_type='train') # creating an instance of custom dataset
train_loader = DataLoader(train_dataset,
```

```
    batch_size=16,num_workers=2) # Load dataloader

for batch_x, batch_y in train_loader:
    break

batch_x.shape, batch_y.shape
```

```
(torch.Size([16, 3, 224, 224]), torch.Size([16, 1, 224, 224]))
```

1.3 Define Model Architecture

```
# Model Architecture

class EncoderDecoder(Module):
    def __init__(self):
        super().__init__()

        # Defining the encoder
        self.encoder_block1 = Sequential(Conv2d(3, 64, 3, stride=2, padding=1),
            ReLU())
        self.pool1 = MaxPool2d(2, return_indices=True)
        self.encoder_block2 = Sequential(
            Conv2d(64, 128, 3, stride=2, padding=1), ReLU())
        self.pool2 = MaxPool2d(2, return_indices=True)

        # Defining the decoder
        self.unpool2 = MaxUnpool2d(2)
        self.decoder_upsample2 = ConvTranspose2d(128, 64, 3, stride=2, padding=1)
        self.decoder_non_linearity2 = ReLU()
        self.unpool1 = MaxUnpool2d(2)
        self.decoder_upsample1 = ConvTranspose2d(64, 64, 3, stride=2, padding=1)
        self.decoder_non_linearity1 = ReLU()

        # Output defined
        self.output_layer = Sequential(
            Conv2d(64, 1, 3, stride=1, padding=1),
            Sigmoid()
        )

    def forward(self, x):
        #Getting input shape for the first blocks and getting pooling incides for pool1
        size_input_encoder_block1 = x.shape
        x = self.encoder_block1(x)
        x, indices_pool1 = self.pool1(x)

        #Getting input shape for the second block and getting pooling incides for pool2
        size_input_encoder_block2 = x.shape
        x = self.encoder_block2(x)
        x, indices_pool2 = self.pool2(x)

        # use pooling indices of pool 2
        x = self.unpool2(x, indices_pool2)
        # use input shape of encoder block 2
        x = self.decoder_upsample2(x, output_size=size_input_encoder_block2)
        x = self.decoder_non_linearity2(x)


        x = self.unpool1(x, indices_pool1)
        x = self.decoder_upsample1(x, output_size=size_input_encoder_block1)
        x = self.decoder_non_linearity1(x)
        x = self.output_layer(x)
        return x


# The model defined
model = EncoderDecoder()
model
```

```
EncoderDecoder(
  (encoder_block1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (1): ReLU()
  )
  (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (encoder_block2): Sequential(
    (0): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
```

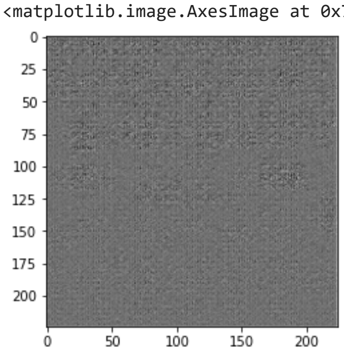
```
      (1): ReLU()
    )
    (pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (unpool2): MaxUnpool2d(kernel_size=(2, 2), stride=(2, 2), padding=(0, 0))
    (decoder_upsample2): ConvTranspose2d(128, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (decoder_non_linearity2): ReLU()
    (unpool1): MaxUnpool2d(kernel_size=(2, 2), stride=(2, 2), padding=(0, 0))
    (decoder_upsample1): ConvTranspose2d(64, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (decoder_non_linearity1): ReLU()
    (output_layer): Sequential(
      (0): Conv2d(64, 1, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): Sigmoid()
    )
  )
```

```
# For batches checking for one iteration
for batch_x, batch_y in train_loader:
    break
print(summary(model, batch_x[1].unsqueeze(dim=0)))
```

```
-------------------------------------------------------------------------------------------
      Layer (type)                          Output Shape         Param #     Tr. Param #
===========================================================================================
          Conv2d-1                    [1, 64, 112, 112]           1,792           1,792
            ReLU-2                    [1, 64, 112, 112]               0               0
       MaxPool2d-3      [1, 64, 56, 56], [1, 64, 56, 56]               0               0
          Conv2d-4                     [1, 128, 28, 28]          73,856          73,856
            ReLU-5                     [1, 128, 28, 28]               0               0
       MaxPool2d-6    [1, 128, 14, 14], [1, 128, 14, 14]               0               0
     MaxUnpool2d-7                     [1, 128, 28, 28]               0               0
 ConvTranspose2d-8                      [1, 64, 56, 56]          73,792          73,792
            ReLU-9                      [1, 64, 56, 56]               0               0
    MaxUnpool2d-10                    [1, 64, 112, 112]               0               0
ConvTranspose2d-11                    [1, 64, 224, 224]          36,928          36,928
           ReLU-12                    [1, 64, 224, 224]               0               0
         Conv2d-13                     [1, 1, 224, 224]             577             577
        Sigmoid-14                     [1, 1, 224, 224]               0               0
===========================================================================================
Total params: 186,945
Trainable params: 186,945
Non-trainable params: 0
-------------------------------------------------------------------------------------------
```

```
# On one image we check the model
output = model(batch_x[1].view(1, 3, 224, 224)).detach().numpy()
plt.imshow(output.squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff69ff160>
```



1.4 Train the model

```
import time
start_time = time.time()

model = model.to("cuda")

# Defining the loss and optimization function
criterion = torch.nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.01)

#Training the model
model.train()
for epoch in range(5):
```

```
    epoch_loss = cnt = 0 #initializing
    for batch_x, batch_y in train_loader:
        batch_x = batch_x.to("cuda").float()
        batch_y = batch_y.to("cuda").float()
        optimizer.zero_grad() #clearing the gradients
        outputs = model(batch_x) #passing batches of images to the models
        loss = criterion(outputs, batch_y) #deriving the loss
        loss.backward() #applying backpropogation
        optimizer.step() #gradients updates
        epoch_loss += loss.item() #summing loss and counts
        cnt += 1

    # Finding out the average losses for all batches
    epoch_loss /= cnt
    print("Training loss for epoch {} is {} ".format(epoch + 1, epoch_loss))


print("Training time for 5 epochs of base CNN %s seconds ---" % (time.time() - start_time))
```

```
Training loss for epoch 1 is 0.6273837426434392
Training loss for epoch 2 is 0.5578117422435594
Training loss for epoch 3 is 0.4909149654533552
Training loss for epoch 4 is 0.4265980292921481
Training loss for epoch 5 is 0.37712207436561584
Training time for 5 epochs of base CNN 19.575265407562256 seconds ---
```

1.5 Testing the model on a single validation image

```
image = Image.open('/content/CamVid/val/0016E5_07987.png')
gt_mask = Image.open('/content/CamVid/val_labels/0016E5_07987.png')
plt.imshow(image)
```

```
<matplotlib.image.AxesImage at 0x7f3ff6642580>
```


```
import time
start_time = time.time()

# Mask preprocessing
gt_mask = np.array(gt_mask)
gt_mask = (gt_mask == 3)
gt_mask = Image.fromarray(gt_mask)

# Resizing
transform = Compose([Resize((224, 224)),ToTensor()])
image = transform(image)
gt_mask = transform(gt_mask)

model.eval()
output = model(image.view(1, 3, 224, 224).to("cuda")).cpu().detach().numpy()

print("Runtime for 1 image of base CNN %s seconds ---" % (time.time() - start_time))
```

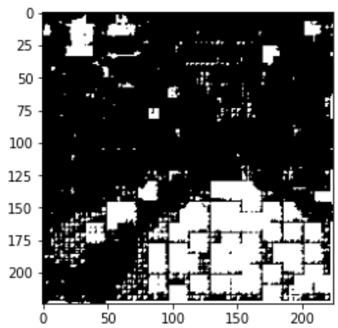
```
Runtime for 1 image of base CNN 0.011220932006835938 seconds ---
```

```
plt.imshow(gt_mask.squeeze(), cmap='gray') # true mask
```

```
<matplotlib.image.AxesImage at 0x7f3ff6608580>
```


```
plt.imshow((output.squeeze() > 0.5).astype(int), cmap='gray') # predicted mask
```

```
<matplotlib.image.AxesImage at 0x7f3ff65d0d60>
```




```
mask = (output.squeeze() > 0.5).astype(int) # Converting thr predicted mask to a flattened numpy array
pred = mask.ravel().copy()

gt_mask = gt_mask.cpu().detach().numpy() # converting the ground truth mask to flattened numpy array
target = gt_mask.ravel().copy().astype(int)

pred_inds = pred == 1 # getting class indices for Lane
target_inds = target == 1

intersection = pred_inds[target_inds].sum()
union = pred_inds.sum() + target_inds.sum() - intersection

#Defining IOP Score
iou = (float(intersection) / float(max(union, 1)))
iou
```

```
0.5141338628664875
```

1.6 Mean IOU Score for validation set

```
valid_transforms = Compose([Resize((224, 224)), ToTensor()]) #preprocessing for valid dataset

valid_dataset = CamVidDataset(x_val_dir,
    transforms=valid_transforms,training_type='valid')

# Finding out the predicted validation masks
valid_masks = []
model.eval()
with torch.no_grad():
    for valid_image in valid_dataset:
        mask = model(valid_image.unsqueeze(0).to('cuda')).cpu().detach().numpy()
        valid_masks.append(mask)
valid_masks = (np.concatenate((valid_masks), axis=0) > 0.5).astype(int)

# Finding the true validation masks

image_names = os.listdir(y_val_dir)
true_masks = []
for image_name in image_names:
  mask_path = os.path.join(y_val_dir, image_name)
  img = Image.open(mask_path)
  img = img.resize((224, 224))
  a = asarray(img)
  b = (a == 3)
  c = 1*b
  true_masks.append(c)
```

```
# Calculating mean IOU Score
T = []

for i in range(len(valid_dataset)):
  p = valid_masks[i].flatten()
  q = true_masks[i].flatten()
  m = tf.keras.metrics.MeanIoU(num_classes=2)
  m.update_state(p, q)
  T.append(m.result().numpy())

np.mean(T)
```

```
0.6185081
```

1.7 Mean Dice Score for validation set

```
def dice_coef(y_true, y_pred, smooth=1):


  intersection=(np.sum(np.array(y_pred[y_true==1])))*2
  dice = intersection / (np.sum(np.array(y_pred)) + np.sum(np.array(y_true)))
  return dice
```

```
T2 = []

for i in range(len(valid_dataset)):
  p2 = valid_masks[i].flatten()
  q2 = true_masks[i].flatten()
  m2 = dice_coef(p2,q2, smooth=1)
  T2.append(m2)

np.mean(T2)
```

```
0.633229649314702
```

2. DeepLabv3

DeepLab V3 is a pre-trained image segmentation model trained on the ImageNet dataset. DeepLab V3 also constitutes an encoder-decoder CNN sections with 4 improvement to the model.

1. Depthwise Separable Convolutions: Instead of using traditional convolution layers, the DeepLabV3 architecture splits the task into depthwise convolutions and pointwise convolutions which significantly reduces the computation time required.
2. Spatial Pyramid Pooling: This layer removes the fixed input size constraint of the input images.
3. Atrous Convolutions: Atrous convolutions provide a way to apply a filter over a larger area of the given image which helps in capturing the broader contextual information.

The mean IoU score obtained on the validation set was 90.89% and the mean dice score was approx 93.00%

2.1 Define custom dataset

```
class CamVidDataset(Dataset):
    def __init__(self, images_dir, masks_dir=None, transforms=None, training_type=None):
        #Here we get the names of all images
        self.image_names = os.listdir(images_dir)
        #Defining the training type and transforms
        self.training_type = training_type
        self.transforms = transforms

        #Defining paths of images and masks
        self.images_paths = []
        self.masks_paths = []
        for image_name in self.image_names:
            self.images_paths.append(os.path.join(images_dir, image_name))
            if self.training_type=="train" or self.training_type=="val":
```

```
            self.masks_paths.append(os.path.join(masks_dir, image_name.split('.')[0] + '.png'))

    def __getitem__(self, i):

        if self.training_type=="train" or self.training_type=="val":
            image = Image.open(self.images_paths[i])
            mask = Image.open(self.masks_paths[i])

            # preprocessing og mask
            mask = np.array(mask)
            mask = (mask == 3)
            mask = Image.fromarray(mask)

            # apply transforms
            image = self.transforms(image)
            mask = self.transforms(mask)
            return image, mask

        else:
            image = Image.open(self.images_paths[i])

            # application of transforms
            image = self.transforms(image)
            return image

    def __len__(self):
        return len(self.image_names)
```

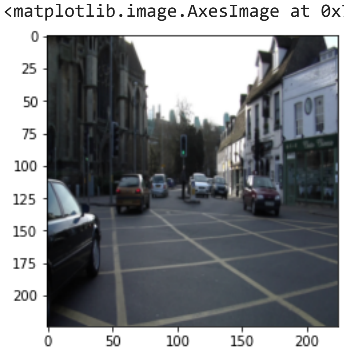
2.2 Data Exploration

```
# Resizing the image >224*224
train_transforms = Compose([Resize((224, 224)),ToTensor()])

dataset = CamVidDataset(x_train_dir, y_train_dir, transforms=train_transforms, training_type='train')
image, gt_mask = dataset[0]
image.shape, gt_mask.shape
```

```
(torch.Size([3, 224, 224]), torch.Size([1, 224, 224]))
```

```
# Image
plt.imshow(np.transpose(image, (1, 2, 0)))
```

```
<matplotlib.image.AxesImage at 0x7f3ff657d6d0>
```




```
# Squeezed mask
plt.imshow(gt_mask.squeeze(), cmap='gray')
```

```
# Creating batches
train_transforms = Compose([Resize((224, 224)),ToTensor()]) #resizing
train_dataset = CamVidDataset(x_train_dir, y_train_dir,
    transforms=train_transforms,training_type='train') #creating instanxe of custom function
train_loader = DataLoader(train_dataset, batch_size=16,
  num_workers=2) # Load dataloader

#Checking on one iteration
for batch_x, batch_y in train_loader:
    break

batch_x.shape, batch_y.shape
```

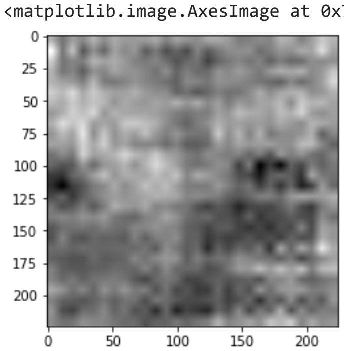
```
(torch.Size([16, 3, 224, 224]), torch.Size([16, 1, 224, 224]))
```

2.3 Define model architecture

```
# Loading pretrained deeplab resnet model
model = deeplabv3_resnet101(pretrained=True)

for parameters in model.parameters():
    parameters.requires_grad = False

model.classifier = DeepLabHead(in_channels=2048, num_classes=1)
```

```
# check for one iteration of loop
for batch_x, batch_y in train_loader:
    break

# check model on one image
model.eval()
output = model(batch_x[1].view(1, 3, 224, 224))['out'].detach().numpy()


plt.imshow(output.squeeze(), cmap='gray') # Displaying output
```

```
<matplotlib.image.AxesImage at 0x7f3ff6337e50>
```



2.4 Train the model

```
import time
start_time = time.time()

model = model.to("cuda") # sending model to GPU

# Loss and optimization function
criterion = torch.nn.BCEWithLogitsLoss()
optimizer = torch.optim.Adam([parameters for parameters in model.parameters() if parameters.requires_grad], lr=1e-3)

# Training the model
model.train()
for epoch in range(5):
    epoch_loss = cnt = 0 #initializing
    for batch_x, batch_y in train_loader:
        batch_x = batch_x.to("cuda").float()
        batch_y = batch_y.to("cuda").float()
```

```
        optimizer.zero_grad()  # clearing the gradients
        outputs = model(batch_x) # passing batches of images to model
        loss = criterion(outputs['out'], batch_y) # deriving the loss
        loss.backward() #backward pass
        optimizer.step() #gradient updates
        epoch_loss += loss.item() # sum loss and get count
        cnt += 1

    # Finding out average losses for all batches
    epoch_loss /= cnt
    print("Training loss for epoch {} is {} ".format(epoch + 1, epoch_loss))

print("--- %s seconds ---" % (time.time() - start_time))
```

```
Training loss for epoch 1 is 0.1655410317623097
Training loss for epoch 2 is 0.08605983043494432
Training loss for epoch 3 is 0.06928741931915283
Training loss for epoch 4 is 0.05794289448986883
Training loss for epoch 5 is 0.05051047630284144
--- 69.34885716438293 seconds ---
```

2.5 Testing model on an image from validation set

```
image = Image.open('/content/CamVid/val/0016E5_07959.png')
gt_mask = Image.open('/content/CamVid/val_labels/0016E5_07959.png')
plt.imshow(image)
```

```
&lt;matplotlib.image.AxesImage at 0x7f3ff629d4c0&gt;
```


```
import time
start_time = time.time()

# Mask preprocessing
gt_mask = np.array(gt_mask)
gt_mask = (gt_mask == 3)
gt_mask = Image.fromarray(gt_mask)

# Resizing
transform = Compose([Resize((224, 224)),ToTensor()])
image = transform(image)
gt_mask = transform(gt_mask)

model.eval()
output = model(image.view(1, 3, 224, 224).to("cuda"))['out'].cpu().detach().numpy()

print("--- %s seconds ---" % (time.time() - start_time))
```

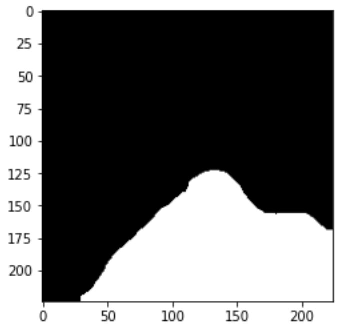
```
--- 0.08929061889648438 seconds ---
```

```
plt.imshow(gt_mask.squeeze(), cmap='gray') # true mask
```

<matplotlib.image.AxesImage at 0x7f3ff625f4c0>

```
plt.imshow((output.squeeze() > 0.5).astype(int), cmap='gray') # predicted mask
```

<matplotlib.image.AxesImage at 0x7f3ff1688d00>



```
mask = (output.squeeze() > 0.5).astype(int) # Converting thr predicted mask to a flattened numpy array
pred = mask.ravel().copy()

gt_mask = gt_mask.cpu().detach().numpy() # converting the ground truth mask to flattened numpy array
target = gt_mask.ravel().copy().astype(int)

pred_inds = pred == 1 # getting class indices for Lane
target_inds = target == 1

intersection = pred_inds[target_inds].sum()
union = pred_inds.sum() + target_inds.sum() - intersection

#Defining IOP Score
iou = (float(intersection) / float(max(union, 1)))
iou
```

0.8828904233800655

2.6 Mean IOU Score for validation set

```
valid_transforms = Compose([
    Resize((224, 224)),
    ToTensor()
])

valid_dataset = CamVidDataset(
    x_val_dir,
    transforms=valid_transforms,
    training_type='valid'
)
```

```
# Obtaining all predicted validation masks
valid_masks = []
model.eval()
with torch.no_grad():
    for valid_image in valid_dataset:
        mask = model(valid_image.unsqueeze(0).to('cuda'))['out'].cpu().detach().numpy()
        valid_masks.append(mask)

valid_masks = (np.concatenate((valid_masks), axis=0) > 0.5).astype(int)
```

```
# Obtaining true validation masks

image_names = os.listdir(y_val_dir)
true_masks = []

for image_name in image_names:
  mask_path = os.path.join(y_val_dir, image_name)
  img = Image.open(mask_path)
  img = img.resize((224, 224))
```

```
    a = asarray(img)
    b = (a == 3)
    c = 1*b
    true_masks.append(c)

T = []

for i in range(len(valid_dataset)):
    p = valid_masks[i].flatten()
    q = true_masks[i].flatten()
    m = tf.keras.metrics.MeanIoU(num_classes=2)
    m.update_state(p, q)
    T.append(m.result().numpy())

np.mean(T)
```

```
0.90893984
```

2.7 Mean Dice Score for validation set

```
T2 = []
for i in range(len(valid_dataset)):
  p2 = valid_masks[i].flatten()
  q2 = true_masks[i].flatten()
  m2 = dice_coef(p2,q2, smooth=1)
  T2.append(m2)
np.mean(T2)
```

```
0.9300489247915121
```

3. U-Net

DeepLab V3 is a pre-trained image segmentation model trained on the ImageNet dataset. DeepLab V3 also constitutes an encoder-decoder CNN sections along with skip connections added between the convolution and transpose convolution layers which helps in recovering fine-grained details in the decoder section.
The base U-Net model outperformed the other 2 models that we had used, and hence we decided to improve the model further to improve its accuracy. Adding image augmentation, model checkpoint, reducing learning rate after a certain number of epochs and increasing number of epochs were the steps taken to improve the model accuracy.

The mean IoU score obtained on the validation set was 97.30% and the mean dice score was 98.04%

3.1 Define custom dataset

```
# custom dataset class with Data augmentation and normalization of images

class CamVidDataset(Dataset):
    def __init__(self, images_dir, masks_dir=None, transforms=None, preprocessing=False, training_type=None):
        # Here we get names of all images
        self.image_names = os.listdir(images_dir)

        # Defining training type,transforms and preprocessing
        self.training_type = training_type
        self.transforms = transforms
        self.preprocessing=preprocessing

        # Definining paths of images and masks
        self.images_paths = []
        self.masks_paths = []
        for image_name in self.image_names:
            self.images_paths.append(os.path.join(images_dir, image_name))
            if self.training_type=="train" or self.training_type=="val":
                self.masks_paths.append(os.path.join(masks_dir, image_name.split('.')[0] + '.png'))

    def __getitem__(self, i):

        if self.training_type=="train" or self.training_type=="val":
            image = Image.open(self.images_paths[i])
```

```
            mask = Image.open(self.masks_paths[i])

            # preprocessing of mask
            mask = np.array(mask)
            mask = (mask == 3)
            mask = Image.fromarray(mask)

            # Introducing data augmentation
            ## random horizontal flip
            if random() < 0.5:
                image, mask = F.hflip(image), F.hflip(mask)

            image = self.transforms(image)
            mask = self.transforms(mask)

            ## apply preprocessing
            if self.preprocessing:
                image = Compose([Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])])(image)
            return image, mask

        else:
            image = Image.open(self.images_paths[i])
            image = self.transforms(image)

            # apply preprocessing
            if self.preprocessing:
                image = Compose([Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])])(image)
            return image

    def __len__(self):
        return len(self.image_names)

train_transforms = Compose([Resize((224, 224)),ToTensor()]) #resizing
train_dataset = CamVidDataset(x_train_dir, y_train_dir,
    transforms=train_transforms,training_type='train')#creating an instance of custom dataset
train_loader = DataLoader(train_dataset, batch_size=16,num_workers=2) # Load dataloader
```

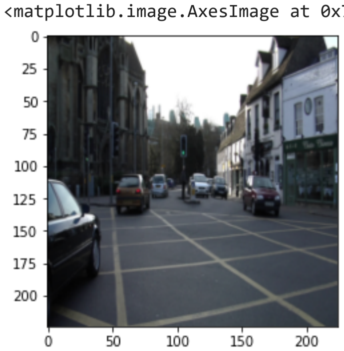
3.2 Data Exploration

```
for batch_x, batch_y in train_loader:
    break
batch_x.shape, batch_y.shape
```

```
(torch.Size([16, 3, 224, 224]), torch.Size([16, 1, 224, 224]))
```

```
plt.imshow(np.transpose(batch_x[0], (1, 2, 0)))
```

```
<matplotlib.image.AxesImage at 0x7f3ff159a0a0>
```




```
plt.imshow(batch_y[0].squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff0c399d0>
```


```
train_dataset = CamVidDataset(x_train_dir, y_train_dir,
    transforms=train_transforms,preprocessing=True,training_type='train')# create instance of custom dataset
#Creating the dataloader
train_loader = DataLoader(train_dataset,
    batch_size=16,num_workers=4)
```

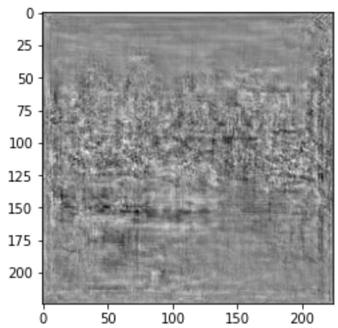
3.3 Define model architecture

```
# Create u-net with a pretrained encoder
model = smp.Unet(encoder_name='resnet18', encoder_weights='imagenet', classes=1, activation='sigmoid')
model
```

```
          (attention1): Attention(
            (attention): Identity()
          )
          (conv2): Conv2dReLU(
            (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention2): Attention(
            (attention): Identity()
          )
        )
        (3): DecoderBlock(
          (conv1): Conv2dReLU(
            (0): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention1): Attention(
            (attention): Identity()
          )
          (conv2): Conv2dReLU(
            (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention2): Attention(
            (attention): Identity()
          )
        )
        (4): DecoderBlock(
          (conv1): Conv2dReLU(
            (0): Conv2d(32, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention1): Attention(
            (attention): Identity()
          )
          (conv2): Conv2dReLU(
            (0): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention2): Attention(
            (attention): Identity()
          )
        )
      )
    )
    (segmentation_head): SegmentationHead(
      (0): Conv2d(16, 1, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): Identity()
      (2): Activation(
        (activation): Sigmoid()
      )
    )
  )
```

```
for batch_x, batch_y in train_loader:
    break
# Running model for one image
model.eval()
output = model(batch_x[1].view(1, 3, 224, 224)).detach().numpy()


# print output
plt.imshow(output.squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff641da00>
```



3.4 Train the model

```
import time
start_time = time.time()

criterion = smp.utils.losses.BCELoss() # Loss function
optimizer = torch.optim.Adam([parameters for parameters in model.parameters() if parameters.requires_grad], lr=1e-3) #Optimizer
metrics = [smp.utils.metrics.IoU(threshold=0.5)] #Evaluation metric

train_epoch = smp.utils.train.TrainEpoch(
    model, loss=criterion, metrics=metrics, optimizer=optimizer,device='cuda',verbose=True,)

# Saving best model and Decrease in LR after 10th epoch added for U-Net model
max_score = 0

for i in range(0, 20):
    print('\nEpoch: {}'.format(i + 1))
    train_logs = train_epoch.run(train_loader)
    if max_score < train_logs['iou_score']:
        max_score = train_logs['iou_score']
        torch.save(model, './best_model.pth')
        print('Model saved!')
    # decreasing learning rate after 10th epoch
    if i+1 == 10:
        optimizer.param_groups[0]['lr'] = 1e-5
        print('Decrease learning rate to 1e-5')

print("--- %s seconds ---" % (time.time() - start_time))
```

```
Epoch: 6
```

```
train: 100%|██████████| 23/23 [00:04<00:00,  4.76it/s, bce_loss - 0.02908, iou_score - 0.9659]

Epoch: 12
train: 100%|██████████| 23/23 [00:04<00:00,  4.86it/s, bce_loss - 0.02536, iou_score - 0.9707]
Model saved!

Epoch: 13
train: 100%|██████████| 23/23 [00:06<00:00,  3.63it/s, bce_loss - 0.02488, iou_score - 0.9713]
Model saved!

Epoch: 14
train: 100%|██████████| 23/23 [00:04<00:00,  4.74it/s, bce_loss - 0.02463, iou_score - 0.9714]
Model saved!

Epoch: 15
train: 100%|██████████| 23/23 [00:06<00:00,  3.81it/s, bce_loss - 0.02431, iou_score - 0.9719]
Model saved!

Epoch: 16
train: 100%|██████████| 23/23 [00:04<00:00,  4.83it/s, bce_loss - 0.02424, iou_score - 0.9722]
Model saved!

Epoch: 17
train: 100%|██████████| 23/23 [00:04<00:00,  4.82it/s, bce_loss - 0.02403, iou_score - 0.9721]

Epoch: 18
train: 100%|██████████| 23/23 [00:04<00:00,  4.92it/s, bce_loss - 0.02388, iou_score - 0.9724]
Model saved!

Epoch: 19
train: 100%|██████████| 23/23 [00:04<00:00,  4.75it/s, bce_loss - 0.02384, iou_score - 0.9724]

Epoch: 20
train: 100%|██████████| 23/23 [00:04<00:00,  4.88it/s, bce_loss - 0.02364, iou_score - 0.9727]
Model saved!
--- 103.19565224647522 seconds ---
```

```
# Loading the best saved point
model = torch.load('./best_model.pth')
```

3.5 Testing the model on a single validation image

```
image = Image.open('/content/CamVid/val/0016E5_07987.png')
gt_mask = Image.open('/content/CamVid/val_labels/0016E5_07987.png')
```

```
plt.imshow(image)
```

```
<matplotlib.image.AxesImage at 0x7f4142819af0>
```

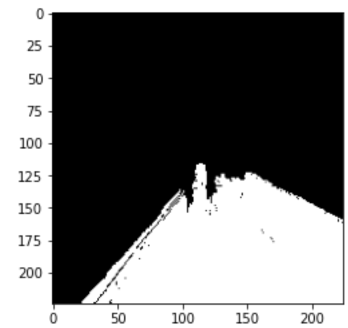

```
import time
start_time = time.time()

# preprocessing of mask
gt_mask = np.array(gt_mask)
gt_mask = (gt_mask == 3)
gt_mask = Image.fromarray(gt_mask)

# Preprocess
transform = Compose([Resize((224, 224)),ToTensor()]) #Resizing
image = transform(image)
image = Compose([Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])])(image)
gt_mask = transform(gt_mask)
```

```
model.eval()
output = model(image.view(1, 3, 224, 224).to("cuda")).cpu().detach().numpy()

print("--- %s seconds ---" % (time.time() - start_time))
```

```
--- 0.02144002914428711 seconds ---
```

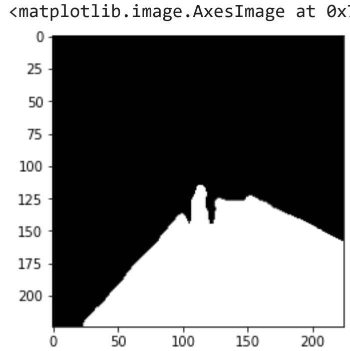
```
# Actual mask
plt.imshow(gt_mask.squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff6526e20>
```




```
# predicted mask
plt.imshow((output.squeeze() > 0.5).astype(int), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff6c45220>
```




```
mask = (output.squeeze() > 0.5).astype(int) # Converting thr predicted mask to a flattened numpy array
pred = mask.ravel().copy()

gt_mask = gt_mask.cpu().detach().numpy() # converting the ground truth mask to flattened numpy array
target = gt_mask.ravel().copy().astype(int)

pred_inds = pred == 1 # getting class indices for Lane
target_inds = target == 1

intersection = pred_inds[target_inds].sum()
union = pred_inds.sum() + target_inds.sum() - intersection

#Defining IOP Score
iou = (float(intersection) / float(max(union, 1)))
iou
```

```
0.9683032939714108
```

3.6 Mean IOU Score for validation set

```
valid_transforms = Compose([
    Resize((224, 224)),
    ToTensor()
])

valid_dataset = CamVidDataset(
    x_val_dir,
    transforms=valid_transforms,
    preprocessing=True,
```

```
    training_type='valid'
)
# Obtaining all predicted validation masks
valid_masks = []
model.eval()
with torch.no_grad():
    for valid_image in valid_dataset:
        mask = model(valid_image.unsqueeze(0).to('cuda')).cpu().detach().numpy()
        valid_masks.append(mask)

valid_masks = (np.concatenate((valid_masks), axis=0) > 0.5).astype(int)


# Obtaining true validation masks

transform = Compose([Resize((224, 224)),ToTensor()])

image_names = os.listdir(y_val_dir)
true_masks = []

for image_name in image_names:
  mask_path = os.path.join(y_val_dir, image_name)
  img = Image.open(mask_path)
  gt_mask = np.array(img)
  gt_mask = (gt_mask == 3)
  gt_mask = Image.fromarray(gt_mask)
  gt_mask = transform(gt_mask)
  true_masks.append(gt_mask)


T = []

for i in range(len(valid_dataset)):
  p = valid_masks[i].flatten()
  q = true_masks[i].flatten()
  m = tf.keras.metrics.MeanIoU(num_classes=2)
  m.update_state(p, q)
  T.append(m.result().numpy())

np.mean(T)
```

```
0.9730491
```

3.7 Mean Dice Score for validation set

```
T2 = []

for i in range(len(valid_dataset)):
  p2 = valid_masks[i].flatten()
  q2 = true_masks[i].flatten()
  m2 = dice_coef(p2,q2, smooth=1)
  T2.append(m2)

np.mean(T2)
```

```
0.9805022089491795
```

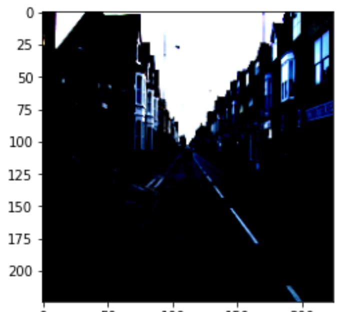
4. Inference on test dataset (applying Model 3 - UNet)

4.1 Obtaining prediction masks for test set

```
test_transforms = Compose([Resize((224, 224)), ToTensor()]) #resize

test_dataset = CamVidDataset(x_test_dir, transforms=test_transforms,preprocessing=True,training_type='test')
```

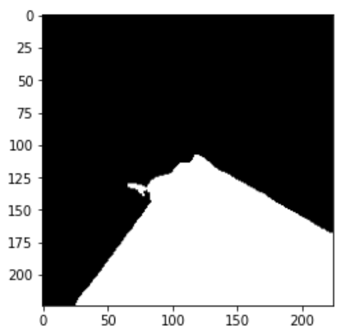
```
# running the model for all images in test dataset
test_masks = []
model.eval()
with torch.no_grad():
    for test_image in test_dataset:
        mask = model(test_image.unsqueeze(0).to('cuda')).cpu().detach().numpy()
        test_masks.append(mask)

test_masks = (np.concatenate((test_masks), axis=0) > 0.5).astype(int)


# display image(original)
test_image = test_dataset[100]
plt.imshow(np.transpose(test_image, (1, 2, 0)))
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data
<matplotlib.image.AxesImage at 0x7f3ff14009a0>
```



```
# display prediction
plt.imshow((test_masks[100]).squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff143d400>
```



4.2 True mask for test set

```
# Obtaining true validation masks

transform = Compose([Resize((224, 224)),ToTensor()]) #resizw
image_names = os.listdir(y_test_dir)
true_masks = []

for image_name in image_names:
  mask_path = os.path.join(y_test_dir, image_name)
  img = Image.open(mask_path)
  gt_mask = np.array(img)
  gt_mask = (gt_mask == 3)
  gt_mask = Image.fromarray(gt_mask)
  gt_mask = transform(gt_mask)
  true_masks.append(gt_mask)
```

4.3 Mean IOU score for test set

```
T = []

for i in range(len(test_dataset)):
```

```
  p = test_masks[i].flatten()
  q = true_masks[i].flatten()
  m = tf.keras.metrics.MeanIoU(num_classes=2)
  m.update_state(p, q)
  T.append(m.result().numpy())

np.mean(T)
```

```
0.91890377
```

4.4 Mean Dice score for test set

```
T2 = []

for i in range(len(test_dataset)):
  p2 = test_masks[i].flatten()
  q2 = true_masks[i].flatten()
  m2 = dice_coef(p2,q2, smooth=1)
  T2.append(m2)

np.mean(T2)
```

```
0.9351180475652184
```

ANOTHER APPLICATION

5. U-Net (Class = 1, Buildings)

5.1 Define custom dataset

```
# Data augmentation and normalization along with custom class

class CamVidDataset(Dataset):
    def __init__(self, images_dir, masks_dir=None, transforms=None, preprocessing=False, training_type=None):
        # Here we write list out name of all images
        self.image_names = os.listdir(images_dir)


        self.training_type = training_type
        self.transforms = transforms
        self.preprocessing=preprocessing

        # deriving paths for images and masks
        self.images_paths = []
        self.masks_paths = []
        for image_name in self.image_names:
            self.images_paths.append(os.path.join(images_dir, image_name))
            if self.training_type=="train" or self.training_type=="val":
                self.masks_paths.append(os.path.join(masks_dir, image_name.split('.')[0] + '.png'))

    def __getitem__(self, i):

        if self.training_type=="train" or self.training_type=="val":
            image = Image.open(self.images_paths[i])
            mask = Image.open(self.masks_paths[i])

            # preprocessing of mask
            mask = np.array(mask)
            mask = (mask == 1)
            mask = Image.fromarray(mask)

            # data augmentation
            ## random horizontal flip
            if random() < 0.5:
                image, mask = F.hflip(image), F.hflip(mask)
```

```
            image = self.transforms(image)
            mask = self.transforms(mask)

            ## apply preprocessing
            if self.preprocessing:
                image = Compose([Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])])(image)

            return image, mask

        else:
            image = Image.open(self.images_paths[i])
            image = self.transforms(image)

            # preprocessing
            if self.preprocessing:
                image = Compose([Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])])(image)
            return image

    def __len__(self):
        return len(self.image_names)
```

```
train_transforms = Compose([Resize((224, 224)),ToTensor()]) #resize
train_dataset = CamVidDataset(
    x_train_dir, y_train_dir,
    transforms=train_transforms,training_type='train')# create instance of custom dataset
train_loader = DataLoader(
    train_dataset, batch_size=16,num_workers=2) # create dataloader for batches
```

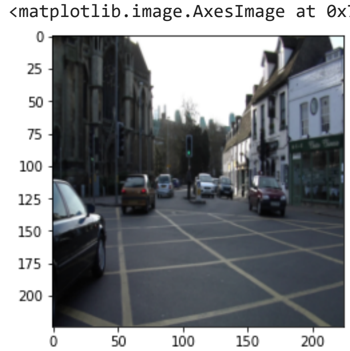
5.2 Data Exploration

```
for batch_x, batch_y in train_loader:
    break
batch_x.shape, batch_y.shape
```

```
(torch.Size([16, 3, 224, 224]), torch.Size([16, 1, 224, 224]))
```

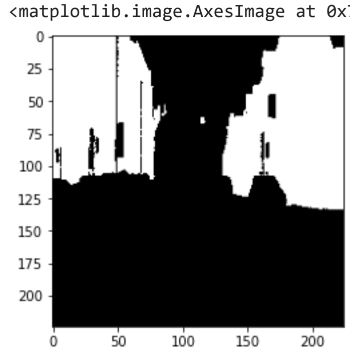
```
plt.imshow(np.transpose(batch_x[0], (1, 2, 0)))
```

```
<matplotlib.image.AxesImage at 0x7f3ff7f44bb0>
```




```
plt.imshow(batch_y[0].squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff7f65ca0>
```



```
# create instance of custom dataset
train_dataset = CamVidDataset(x_train_dir, y_train_dir, transforms=train_transforms,
    preprocessing=True,training_type='train')
# create dataloader
train_loader = DataLoader(train_dataset,
    batch_size=16,num_workers=4)
```

5.3 Define model architecture

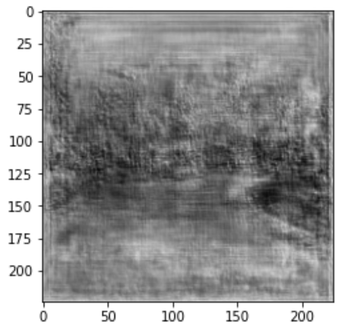
```
# create u net architecture
model = smp.Unet(encoder_name='resnet18',
    encoder_weights='imagenet', classes=1, activation='sigmoid')
model
```

```
          (attention1): Attention(
            (attention): Identity()
          )
          (conv2): Conv2dReLU(
            (0): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention2): Attention(
            (attention): Identity()
          )
        )
        (3): DecoderBlock(
          (conv1): Conv2dReLU(
            (0): Conv2d(128, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention1): Attention(
            (attention): Identity()
          )
          (conv2): Conv2dReLU(
            (0): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention2): Attention(
            (attention): Identity()
          )
        )
        (4): DecoderBlock(
          (conv1): Conv2dReLU(
            (0): Conv2d(32, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention1): Attention(
            (attention): Identity()
          )
          (conv2): Conv2dReLU(
            (0): Conv2d(16, 16, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
            (1): BatchNorm2d(16, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            (2): ReLU(inplace=True)
          )
          (attention2): Attention(
            (attention): Identity()
          )
        )
      )
    )
    (segmentation_head): SegmentationHead(
      (0): Conv2d(16, 1, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): Identity()
      (2): Activation(
        (activation): Sigmoid()
      )
    )
  )
```

```
# runnning forone iteration of loop
for batch_x, batch_y in train_loader:
    break
# running on one image
model.eval()
output = model(batch_x[1].view(1, 3, 224, 224)).detach().numpy()
```

```
plt.imshow(output.squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff8128250>
```



5.4 Train the model

```
# define loss function
criterion = smp.utils.losses.BCELoss()

# define optimizer
optimizer = torch.optim.Adam([parameters for parameters in model.parameters() if parameters.requires_grad], lr=1e-3)

# define evaluation metric
metrics = [
    smp.utils.metrics.IoU(threshold=0.5)
]


# define training epoch
train_epoch = smp.utils.train.TrainEpoch(
    model,
    loss=criterion,
    metrics=metrics,
    optimizer=optimizer,
    device='cuda',
    verbose=True,
)


# Saving best model and Decrease in LR after 10th epoch added for U-Net model
max_score = 0

for i in range(0, 20):
    print('\nEpoch: {}'.format(i + 1))
    train_logs = train_epoch.run(train_loader)

    if max_score < train_logs['iou_score']:
        max_score = train_logs['iou_score']
        torch.save(model, './best_model.pth')
        print('Model saved!')

    # decreasing learning rate after 10th epoch
    if i+1 == 10:
        optimizer.param_groups[0]['lr'] = 1e-5
        print('Decrease learning rate to 1e-5')
```

```
Epoch: 1
train: 100%|██████████| 23/23 [00:04<00:00,  4.85it/s, bce_loss - 0.3497, iou_score - 0.5776]
Model saved!

Epoch: 2
train: 100%|██████████| 23/23 [00:05<00:00,  4.01it/s, bce_loss - 0.1999, iou_score - 0.7225]
Model saved!
```

```
Epoch: 3
train: 100%|██████████| 23/23 [00:04<00:00,  4.81it/s, bce_loss - 0.1579, iou_score - 0.766]
Model saved!

Epoch: 4
train: 100%|██████████| 23/23 [00:05<00:00,  4.47it/s, bce_loss - 0.1366, iou_score - 0.7925]
Model saved!

Epoch: 5
train: 100%|██████████| 23/23 [00:07<00:00,  3.17it/s, bce_loss - 0.1214, iou_score - 0.8121]
Model saved!

Epoch: 6
train: 100%|██████████| 23/23 [00:05<00:00,  3.89it/s, bce_loss - 0.118, iou_score - 0.8182]
Model saved!

Epoch: 7
train: 100%|██████████| 23/23 [00:04<00:00,  4.73it/s, bce_loss - 0.1103, iou_score - 0.8259]
Model saved!

Epoch: 8
train: 100%|██████████| 23/23 [00:06<00:00,  3.79it/s, bce_loss - 0.1036, iou_score - 0.8372]
Model saved!

Epoch: 9
train: 100%|██████████| 23/23 [00:06<00:00,  3.68it/s, bce_loss - 0.09765, iou_score - 0.8471]
Model saved!

Epoch: 10
train: 100%|██████████| 23/23 [00:06<00:00,  3.44it/s, bce_loss - 0.09314, iou_score - 0.8527]
Model saved!
Decrease learning rate to 1e-5

Epoch: 11
train: 100%|██████████| 23/23 [00:04<00:00,  4.60it/s, bce_loss - 0.08654, iou_score - 0.8633]
Model saved!

Epoch: 12
train: 100%|██████████| 23/23 [00:07<00:00,  3.07it/s, bce_loss - 0.08406, iou_score - 0.8687]
Model saved!

Epoch: 13
train: 100%|██████████| 23/23 [00:04<00:00,  4.85it/s, bce_loss - 0.08174, iou_score - 0.8719]
Model saved!

Epoch: 14
train: 100%|██████████| 23/23 [00:04<00:00,  4.83it/s, bce_loss - 0.08037, iou_score - 0.8743]
Model saved!
```

```
# load best saved checkpoint
model = torch.load('./best_model.pth')
```

5.5 Testing the model on a single validation image

```
# get sample data
image = Image.open('/content/CamVid/val/0016E5_07987.png')
gt_mask = Image.open('/content/CamVid/val_labels/0016E5_07987.png')
```

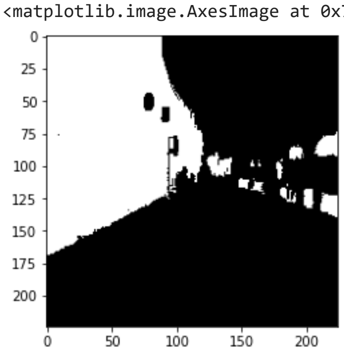
```
plt.imshow(image)
```

```
<matplotlib.image.AxesImage at 0x7f3ff614ec10>
```


```
# preprocess mask
gt_mask = np.array(gt_mask)
```

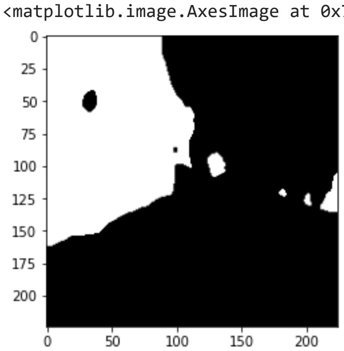
```
gt_mask = (gt_mask == 1)
gt_mask = Image.fromarray(gt_mask)

# apply data pre-processing
transform = Compose([
            Resize((224, 224)),
            ToTensor()
            ])

image = transform(image)

image = Compose([Normalize(mean=[0.485, 0.456, 0.406],
                        std=[0.229, 0.224, 0.225])])(image)

gt_mask = transform(gt_mask)


model.eval()
output = model(image.view(1, 3, 224, 224).to("cuda")).cpu().detach().numpy()


# true mask
plt.imshow(gt_mask.squeeze(), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff60ab520>
```



```
# predicted mask
plt.imshow((output.squeeze() > 0.5).astype(int), cmap='gray')
```

```
<matplotlib.image.AxesImage at 0x7f3ff6084070>
```



```
# convert predicted mask to flattened numpy array
mask = (output.squeeze() > 0.5).astype(int)
pred = mask.ravel().copy()

# convert ground truth mask to flattened numpy array
gt_mask = gt_mask.cpu().detach().numpy()
target = gt_mask.ravel().copy().astype(int)

# get class indices for Lane
pred_inds = pred == 1
target_inds = target == 1

# calculate intersection
intersection = pred_inds[target_inds].sum()

# calculate union
union = pred_inds.sum() + target_inds.sum() - intersection

# get IoU score
```

```
iou = (float(intersection) / float(max(union, 1)))
iou
```

```
0.8831792975970425
```

5.6 Mean IOU Score for validation set

```
valid_transforms = Compose([
    Resize((224, 224)),
    ToTensor()
])

valid_dataset = CamVidDataset(
    x_val_dir,
    transforms=valid_transforms,
    preprocessing=True,
    training_type='valid'
)


# Obtaining all predicted validation masks
valid_masks = []
model.eval()
with torch.no_grad():
    for valid_image in valid_dataset:
        mask = model(valid_image.unsqueeze(0).to('cuda')).cpu().detach().numpy()

        #mask = model(valid_image.unsqueeze(0).to('cuda')).cpu().detach().numpy()
        valid_masks.append(mask)

valid_masks = (np.concatenate((valid_masks), axis=0) > 0.5).astype(int)


# Obtaining true validation masks

transform = Compose([Resize((224, 224)),ToTensor()])

image_names = os.listdir(y_val_dir)
true_masks = []

for image_name in image_names:
  mask_path = os.path.join(y_val_dir, image_name)
  img = Image.open(mask_path)
  gt_mask = np.array(img)
  gt_mask = (gt_mask == 1)
  gt_mask = Image.fromarray(gt_mask)
  gt_mask = transform(gt_mask)
  true_masks.append(gt_mask)


T = []

for i in range(len(valid_dataset)):
  p = valid_masks[i].flatten()
  q = true_masks[i].flatten()
  m = tf.keras.metrics.MeanIoU(num_classes=2)
  m.update_state(p, q)
  T.append(m.result().numpy())

np.mean(T)
```

```
0.8555915
```

5.7 Mean Dice Score for validation set

```
T2 = []

for i in range(len(valid_dataset)):
  p2 = valid_masks[i].flatten()
  q2 = true_masks[i].flatten()
  m2 = dice_coef(p2,q2, smooth=1)
  T2.append(m2)
```

```
np.mean(T2)
    0.8705857404873013
```

CONCLUSION

U-Net model seems to outperform other models in terms of accuracy providing an IoU of 91.89% and Dice score of 93.51% on unseen test set. Along with providing a better accuracy, U-Net also evaluates images 4 times faster than the DeepLab model.

However, the model does seem to overfit a bit, and we would add regularization to generalize the result better. Also, we would be extending our model to mnake predictions on all 32 classes in the future.

0s completed at 5:00 PM