Objective: To create, train and test a Convolutional Neural Network for the task of semantic segmentation using FCN32/FCN16 architecture on Kitti Semantic Segmentation dataset.

1. Introduction:

Convolution Neural Networks (CNN) derive its strength from learning the filters (Kernels) at each layer to extract features from the image and updating the weights iteratively using backpropagation. CNNs were extensively used for image classification tasks where the target is class labels. But for tasks like Image Segmentation where the target is a structured output where every pixel in the image is labeled, the conventional convolution networks had to be modified. Inorder to develop an end-to-end network for Semantic Segmentation, Fully Convolutional Network (FCN) was built in 2015 which achieved better results on PASCAL VOC 2012 dataset. Figure 1 shows the network architecture of FCN32.

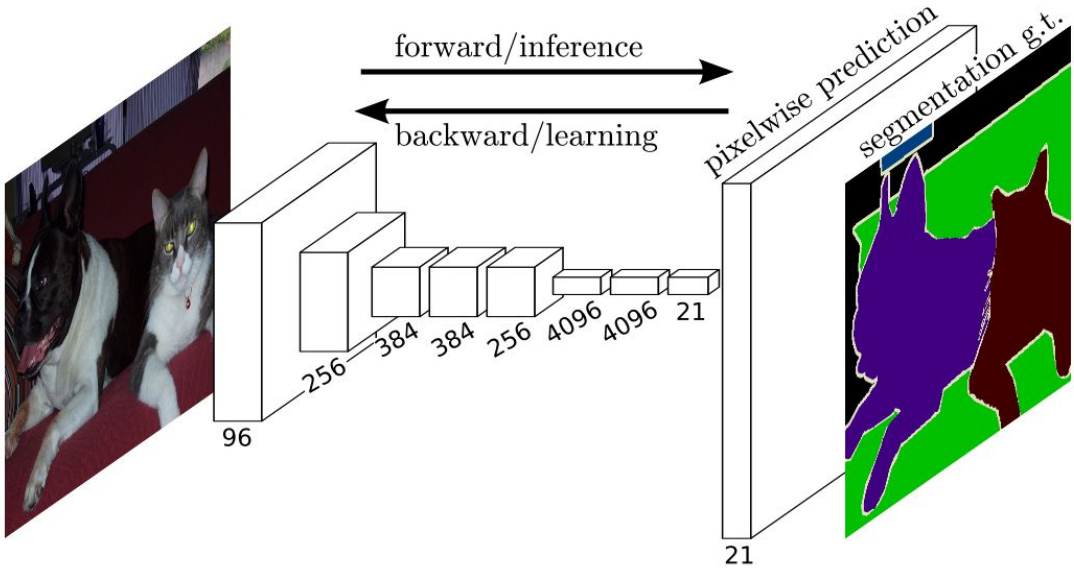


Figure 1: FCN Architecture

I. Classifier to dense FCN:

FCN adopts transfer learning by using pre-trained networks for image classification tasks like VGG-16, AlexNet, GoogLeNet. In this assignment, we are using the pre-trained model of VGG-16 network. We discard the last classifier layer and replace them with convolutional layers. In the last layer, a 1*1 convolution layer with 35 channels to predict the scores of each class at each output location followed by a deconvolution layer to upsample the coarse outputs to pixel dense output.

II. FCN-16 to obtain finer predictions:

By changing the architecture above the pool-5 layer by replacing the existing filters with smaller filters, we get finer predictions. FCN-16 is realized by combining the predictions from both the final layer and the pool4 layer, at stride-16. Figure 2 shows the modifications to original network.

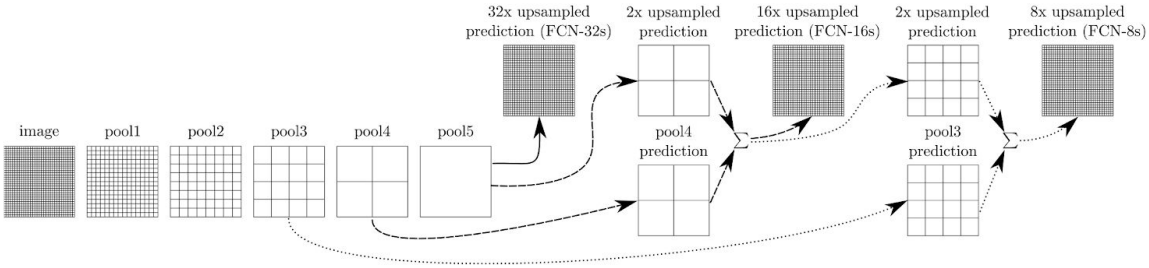


Figure 2: Modified FCN architecture - FCN-16 and FCN-8

2. Summary of the Program:

2.1 Training Information: A brief description of the training process and the parameters are listed below,

a) **Network architecture:** We use pre-trained VGG-16 architecture and convert the last fully connected layers to convolutional layers to get pixel-wise predictions.
b) **Cost function:** Cross entropy loss is used during the training process on training and validation set.
c) **Evaluation metric:** We use pixel level IoU on all the testset images and mIoU (mean IoU) on all testset images to measure the generalization ability of the network.
d) **Preprocessing:** All the input images are resized to 256*516 using BICUBIC interpolation technique and all labels are resized to the same dimension using NEAREST interpolation technique.
e) **Training parameters:** We used SGD and Adam optimizer for training with a learning rate of 0.001, batch size 5, momentum 0.99 and the model is trained for 30-40 epochs.

2.2 Program and dataset information: The code for data loader, training and evaluation is available in the notebook ***FCN_semantic_segmentation.ipynb***. The dataset is available in the ***data_semantics*** folder where we only used 200 training samples and split the data into training, validation and test sets. All the trained models are also included in the zip file ***Models***.

2.3 Source Listing:

A. Data Loader code:

```
class semantic_dataset(Dataset):
    def __init__(self, split = train, transform = None):
        self.split = split
        self.transform = transform
        self.img_list = image_train
        self.mask_list = label_train

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

    def __getitem__(self, idx):
        img = cv2.imread(self.img_list[idx])
        img = cv2.resize(img, (1242, 376))
        mask = None
        if self.split == 'train':
                mask = cv2.imread(self.mask_list[idx],
cv2.IMREAD_GRAYSCALE)
                mask = cv2.resize(mask, (512, 256),
interpolation=cv2.INTER_NEAREST)
            #mask = self.encode_segmap(mask)
            assert(mask.shape == (256, 512))

        if self.transform:
            img = self.transform(img)
            assert(img.shape == (3, 256, 512))
        else :
            assert(img.shape == (256, 512, 3))

        if self.split == 'train':
            return img, mask
        else :
            return img
```

B. Preprocessing and loading data:

```
transformation = transforms.Compose([
          transforms.ToPILImage(),
transforms.Resize((256,512),interpolation=PIL.Image.BICUBIC),
transforms.ToTensor(),
transforms.Normalize(mean = [0.35675976, 0.37380189,
0.3764753], std = [0.32064945, 0.32098866, 0.32325324])
      ])
trainset = semantic_dataset_train(split = 'train', transform =
transformation)
validationset = semantic_dataset_validation(split = 'train',
transform = transformation)
testset = semantic_dataset_test(split = 'train', transform =
transformation)

trainImages = DataLoader(trainset, batch_size = 5, shuffle =
True)
valImages = DataLoader(validationset, batch_size = 5, shuffle
= True)
testImages = DataLoader(testset, batch_size = 1, shuffle =
True)
```

C. FC32 Network:

```
#FC32 architecture
vgg16_mod = vgg16(pretrained=True)
for param in vgg16_mod.features.parameters():
 param.requires_grad = False
class FCN32(nn.Module):
 def __init__(self):
   super(FCN32, self).__init__()
   self.features = vgg16_mod.features
   self.classifier = nn.Sequential(
     nn.Conv2d(512, 4096, 7),
     nn.ReLU(inplace=True),
     nn.Dropout2d(),
     nn.Conv2d(4096, 4096, 1),
     nn.ReLU(inplace=True),
```

```
      nn.Dropout2d(),
      nn.Conv2d(4096, 35, 1),
      nn.ConvTranspose2d(35, 35, 224, stride=32)
    )
  def forward(self, x):
    x = self.features(x)
    x = self.classifier(x)
    return x
fcn = FCN32()
print(fcn)
input = torch.randn(5,3,256,512)
output = fcn(input)
print(output.shape)
```

D. FC-16 architecture

```
#FC16 architecture
vgg16_mod = vgg16(pretrained=True)
for param in vgg16_mod.features.parameters():
 param.requires_grad = False
class FCN16(nn.Module):
 def __init__(self):
   super(FCN16, self).__init__()
   self.features = vgg16_mod.features
   self.classifier = nn.Sequential(
     nn.Conv2d(512, 4096, 7),
     nn.ReLU(inplace=True),
     nn.Conv2d(4096, 4096, 1),
     nn.ReLU(inplace=True),
     nn.Conv2d(4096, 35, 1)
   )
   self.score_pool4 = nn.Conv2d(512, 35, 1)
    self.upscore2 = nn.ConvTranspose2d(35, 35, 14, stride=2,
bias=False)
    self.upscore16 = nn.ConvTranspose2d(35, 35, 16, stride=16,
bias=False)
```

```
 def forward(self, x):
   pool4 = self.features[:-7](x)
   pool5 = self.features[-7:](pool4)
   pool5_upscored = self.upscore2(self.classifier(pool5))
   pool4_scored = self.score_pool4(pool4)
   combined = pool4_scored + pool5_upscored
   res = self.upscore16(combined)
   return res

fcn16 = FCN16()
print(fcn16)
input = torch.randn(5,3,256,512)
output = fcn16(input)
print(output.shape)
```

E. Training:

```
def training(fcn, criterion, optimizer,num_epochs):

 val_loss = []
 train_loss = []
 for epoch in range(num_epochs):
   fcn.train()
   val_running_loss = 0
   train_running_loss = 0
   fcn16.train()
   for i, trainData in enumerate(trainImages, 0):
     imgs, labels = trainData
     labels = labels.type(torch.LongTensor)
     #set the gradient to zero
     optimizer.zero_grad()
     outputs = fcn(imgs)
     loss = criterion(outputs, labels)
     loss.backward()
     train_running_loss += loss.item()
     optimizer.step()

   train_loss.append(train_running_loss)
```

```
    fcn16.eval()
    with torch.no_grad():
      for k, dat1 in enumerate(valImages):
      # Get image, label pair
        inputs1, labels1 = dat1
        labels1 = labels1.type(torch.LongTensor)
      # Predicting segmentation for val inputs
        outputs1 = fcn(inputs1)

        # Compute CE loss and aggregate it
        loss1 = criterion(outputs1, labels1)
        val_running_loss += loss1.item()

    val_loss.append(val_running_loss)
          print("Epochs:  ",  epoch,  "Training  Loss:  ",
train_running_loss, "val_running_loss: ", val_running_loss)
 return train_loss, val_loss

criterion = nn.CrossEntropyLoss()
optimizer    =    optim.Adam(fcn16.parameters(),    lr=0.001,
betas=(0.9,    0.999),    eps=1e-08,    weight_decay=0.0001,
amsgrad=False)
train_loss, val_loss = training(fcn16, criterion, optimizer,
num_epochs=40)
torch.save(fcn16,                                    'drive/My
Drive/CSCI-677-HW5/data_semantics/ModelFCN16_Adam_dropout.pt')
```

F. Calculating Mean IoU and Dice coefficient (F1-score)

(This is calculated using a ***confusion matrix***. Pixel level IoU for each class is used. Complete code is attached at the end.)

```
#Calculating IoU and mean IoU
def get_mean_iou(conf_mat, multiplier=1.0):
 cm = conf_mat.copy()
 np.fill_diagonal(cm, np.diag(cm) * multiplier)
 inter = np.diag(cm)
 gt_set = cm.sum(axis=1)
 pred_set = cm.sum(axis=0)
 union_set =  gt_set + pred_set - inter
 iou = inter.astype(float) / union_set
 mean_iou = np.nanmean(iou)
 return mean_iou
 overall_conf_mat = np.zeros((35, 35))
with torch.no_grad():
 for k, dat1 in enumerate(testImages):
   # Get image, label pair
   inputs1, labels1 = dat1
   # Predicting segmentation for val inputs
   outputs1 = fcn16(inputs1)

   preds = torch.argmax(outputs1, dim=1).detach().numpy()
   gt = labels1.detach().numpy()

   # Compute confusion matrix
        conf_mat   =   confusion_matrix(y_pred=preds.flatten(),
y_true=gt.flatten(), labels=list(range(35)))
   overall_conf_mat += conf_mat

print('DICE                                                score:
{}'.format(np.round(get_mean_iou(conf_mat=overall_conf_mat
,multiplier=2.0), 2)))
print('Mean                        IOU                     score:
{}'.format(np.round(get_mean_iou(conf_mat=overall_conf_mat),
2)))
```

3. Experimental Results:

(Results on all 30 test images along with the code is attached in the end)

FCN-32 is trained with two variations, one with SGD optimizer and the second with Adam optimizer, FCN-16 is trained with Adam optimizer and the performance of each model is evaluated and discussed later.

A. FCN-32 with Adam optimizer:

Result:

Dice score (F1-score): 0.45

Mean IoU score: 0.37

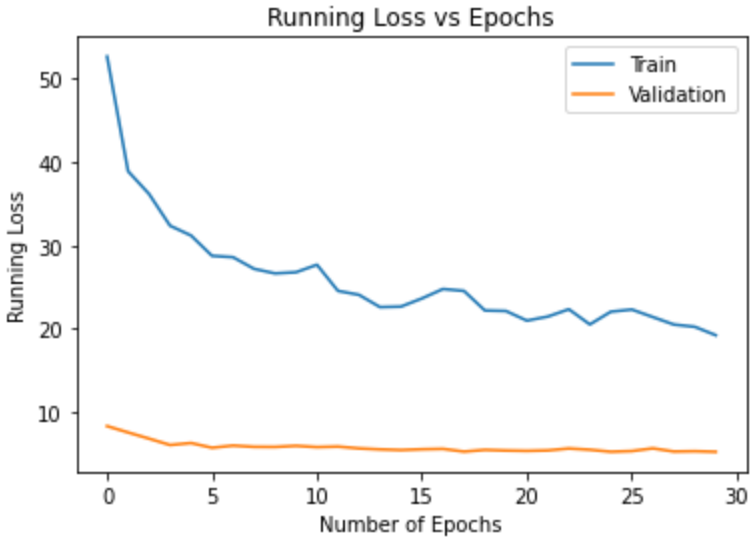
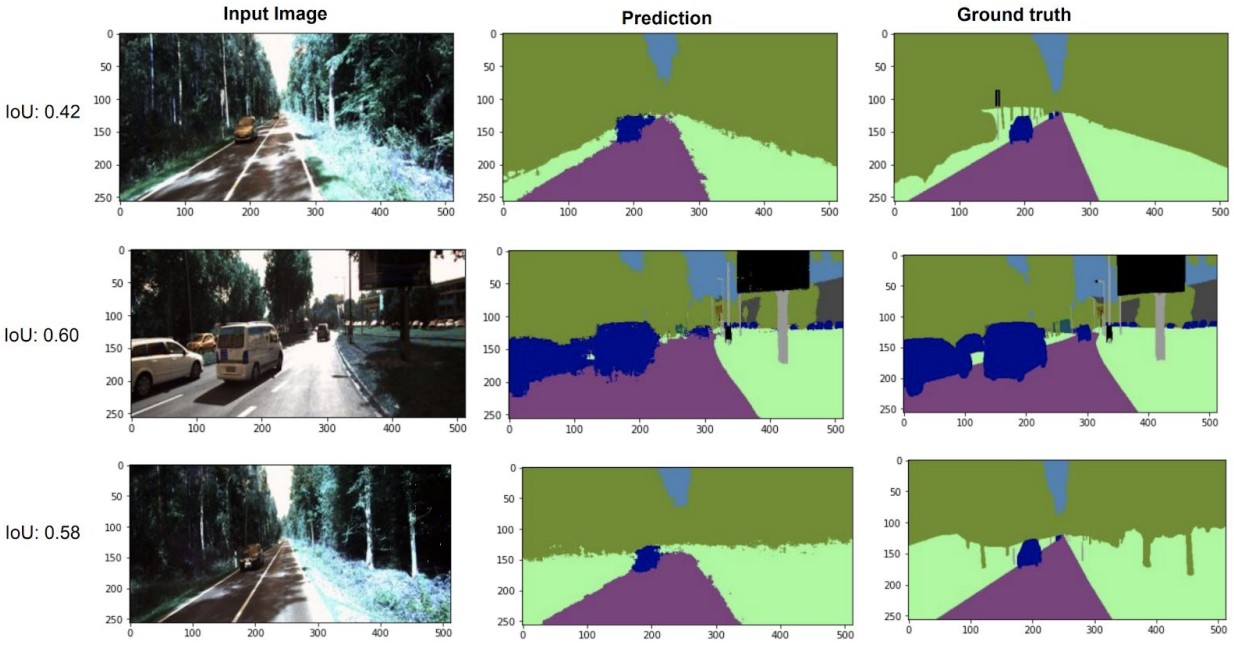


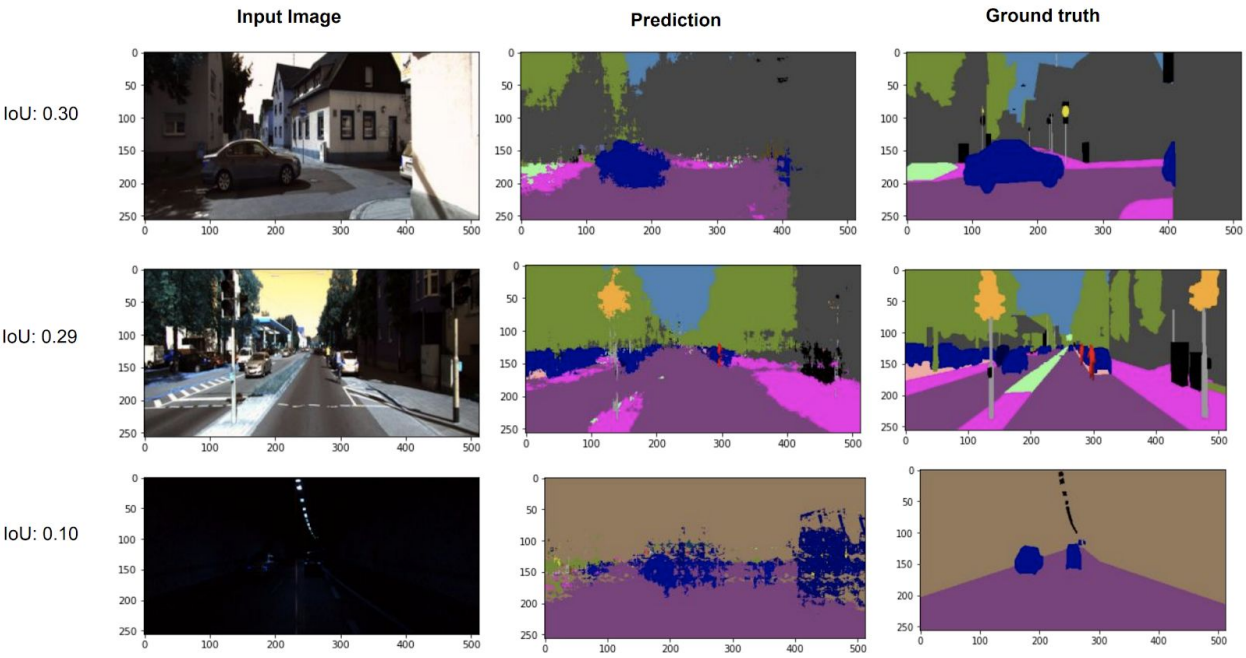
Figure 3: Evolution of training and validation loss on each epoch.

Visualization of results:

(Top 3 successful results: Based on pixel level IoU using confusion matrix)



(Top 3 failed results: Based on pixel level IoU using confusion matrix)



B. FCN-32 with SGD optimizer:

Result:

Dice score (F1-score): 0.35

Mean IoU score: 0.23

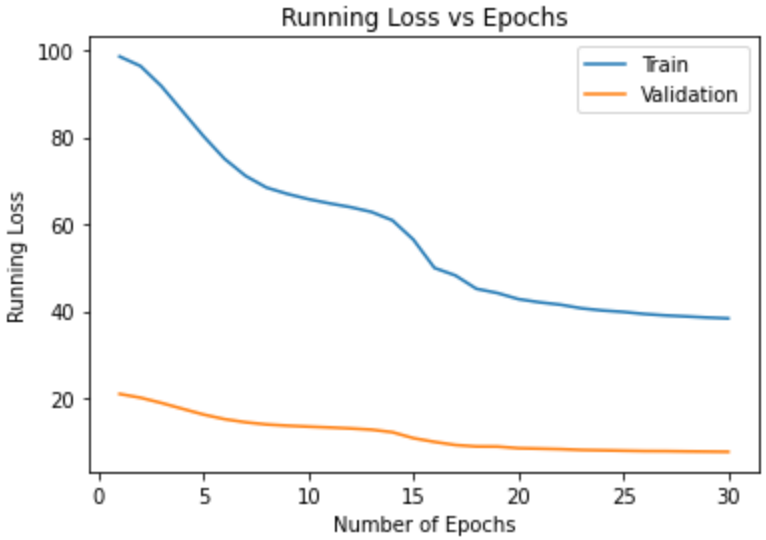
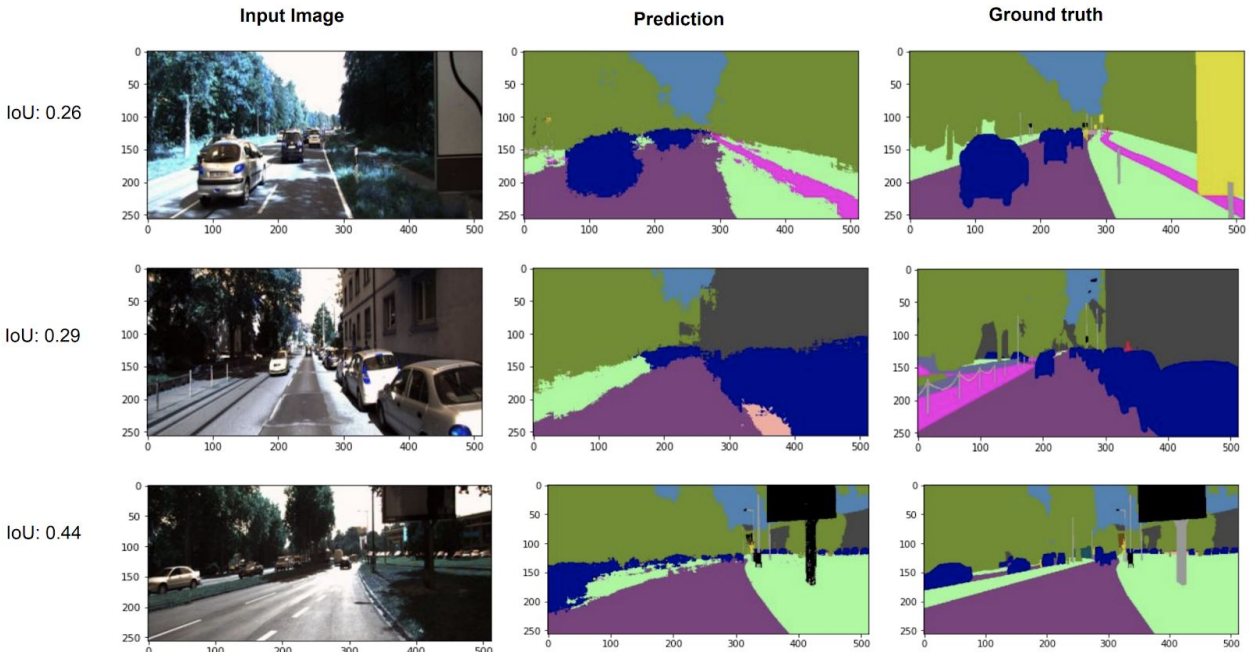
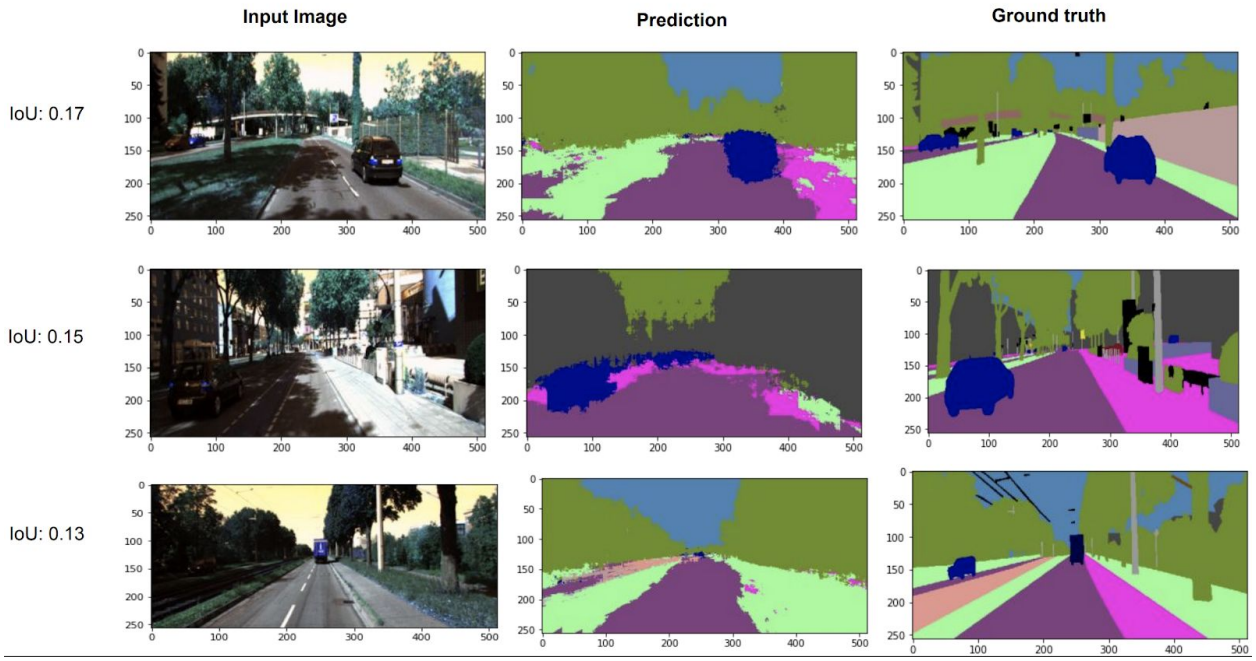


Figure 4: Evolution of training and validation loss on each epoch.

(Successful results with pixel level IoU using confusion matrix)



(Failed results with pixel level IoU using confusion matrix)



C. FCN-16 with Adam optimizer:

Result:

Dice score (F1-score): 0.58

Mean IoU score: 0.43

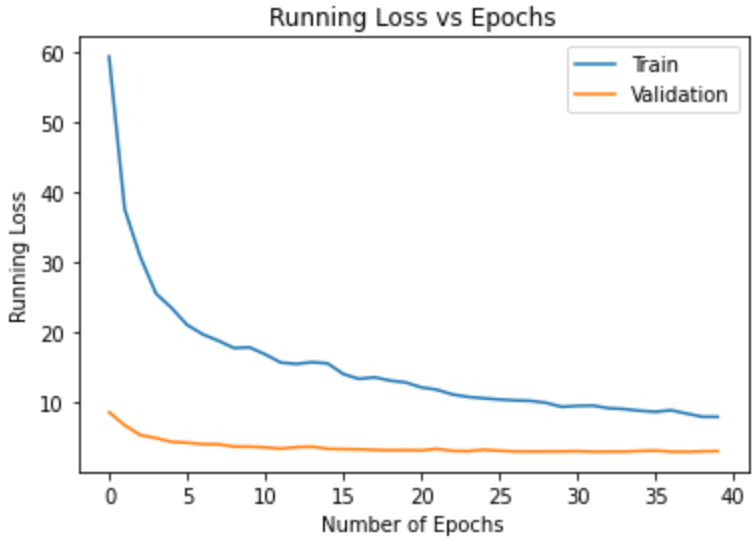
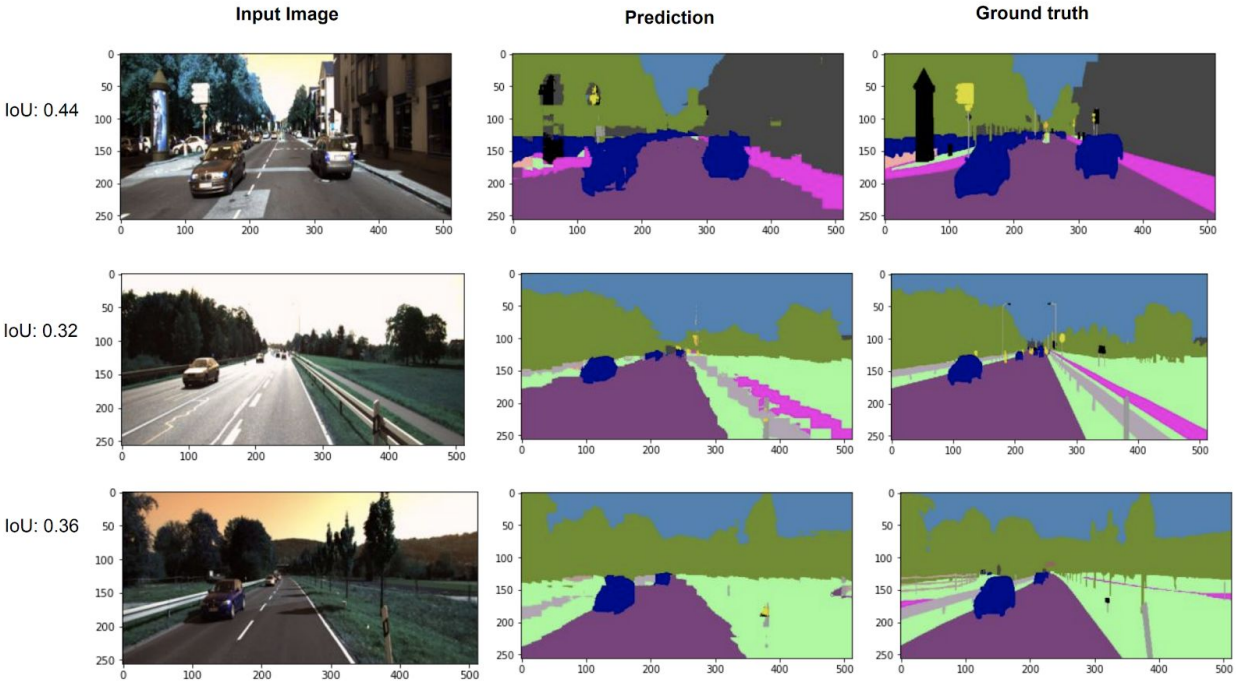
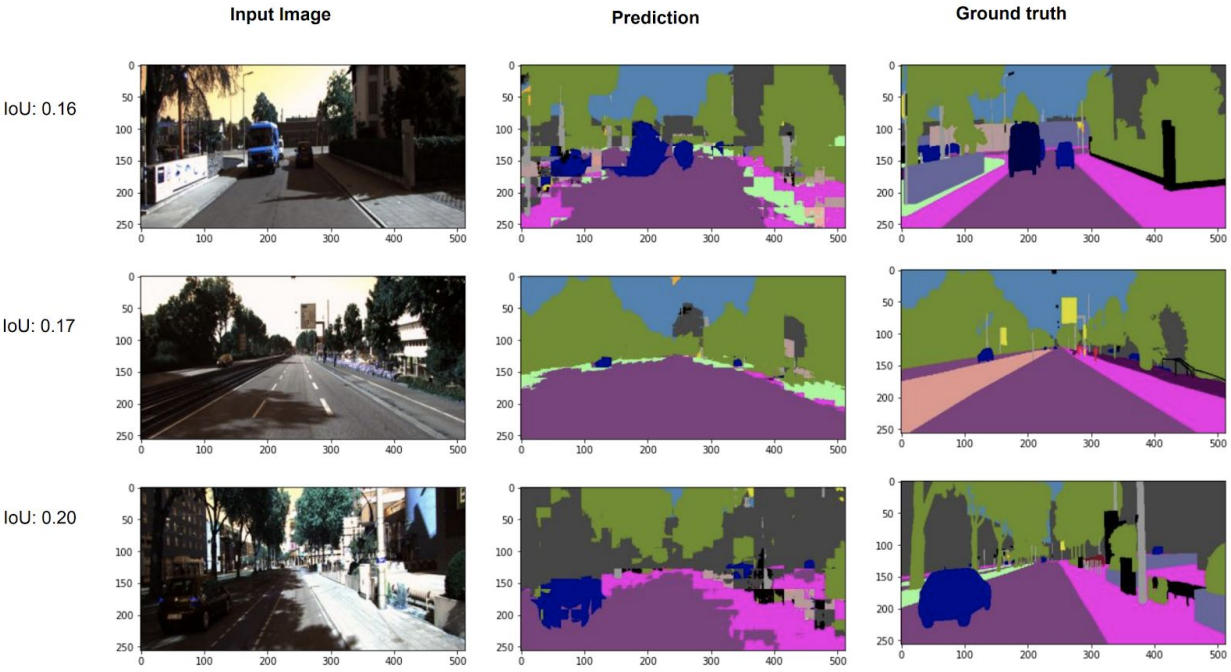


Figure 5: Evolution of training and validation loss on each epoch.

(Successful results with pixel level IoU using confusion matrix: FCN-16)



(Failed results with pixel level IoU using confusion matrix:FCN-16)



4. Discussion on Results:

FCN-32 is trained using Adam and SGD optimizers with a learning rate of 0.001 for 30 epochs. From the above results, it is evident that the results of Adam optimizer is better than SGD optimizer. Observing at the loss curve, we can say that the model trained using SGD optimizer seems to underfit the data. This argument is supported by the low mean-IoU score of 0.23. However, we obtained a better performance for the model trained using Adam optimizer and we got moderate improvement in mean-IoU score (0.37).

FCN-16 is trained using Adam optimizer for 40 epochs. Based on the loss curve, we can say that the model did not overfit the data. We tested the model on the test set and we obtained a best mean-IoU score of 0.43. Since FCN-16 uses upsampled output from the pool-4 layer combined with output from pool-5 layer, we get finer predictions.

Results of semantic segmentation along with the ground truth is shown in the above figures for each model. Few successful results based on the m-IoU score are displayed and to evaluate the shortcomings of the model, few failed examples are also shown. The model is performing extremely well on images which have proper illumination with little or no occlusion. However, the model terribly failed for the images which have shadows in it and have significant occlusions. Also, few examples are shown where the far objects are missed in the predictions.

FCN-16 produced better results by giving finer predictions compared to FCN-32. This can be seen in the visual results where classes like vehicles, vegetation, road, sky were predicted accurately in both FCN-32 and FCN-16. However, classes like traffic lights, sidewalk, and poles are missed in FCN-32 and are predicted correctly in FCN-16.

5. Appendix:

(Complete code with results)

```
from google.colab import drive
drive.mount('/content/drive',force_remount=True)
```

```
Mounted at /content/drive
```

```
import torchvision
import glob
from matplotlib import pyplot as plt
import cv2
from google.colab.patches import cv2_imshow
import os.path as osp
import numpy as np
import torch
from torchvision import transforms, datasets, utils
from torch.utils.data import Dataset, DataLoader
from torchvision.models import vgg16
from torch.optim import lr_scheduler
import torch.optim as optim
import time
import copy
import torch.nn as nn
import PIL
import torch.nn.functional as Func
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

```
#Split the dataset into Train, Validation and Test set
total_image = sorted(glob.glob('drive/My Drive/CSCI-677-HW5/data_semantics/training/in
total_label = sorted(glob.glob('drive/My Drive/CSCI-677-HW5/data_semantics/training/se
image_train, image_rest, label_train, label_rest = train_test_split(total_image, total
image_test, image_val, label_test, label_val = train_test_split(image_rest, label_rest
```

```
class semantic_dataset_train(Dataset):
    def __init__(self, split = 'test', transform = None):
        self.void_labels = [0, 1, 2, 3, 4, 5, 6, 9, 10, 14, 15, 16, 18, 29, 30, -1]
        self.valid_labels = [7, 8, 11, 12, 13, 17, 19, 20, 21, 22, 23, 24, 25, 26, 27,
        self.ignore_index = 250
        self.class_map = dict(zip(self.valid_labels, range(19)))
        self.split = split

        self.transform = transform

        self.img_list = image_train
        self.mask_list = label_train

    def __len__(self):
```

```
        return(len(self.img_list))

    def __getitem__(self, idx):
        img = cv2.imread(self.img_list[idx])
        img = cv2.resize(img, (1242, 376))
        mask = None
        if self.split == 'train':
            mask = cv2.imread(self.mask_list[idx], cv2.IMREAD_GRAYSCALE)
            mask = cv2.resize(mask, (512, 256), interpolation=cv2.INTER_NEAREST)
            #mask = self.encode_segmap(mask)
            assert(mask.shape == (256, 512))

        if self.transform:
            img = self.transform(img)
            assert(img.shape == (3, 256, 512))
        else :
            assert(img.shape == (256, 512, 3))

        if self.split == 'train':
            return img, mask
        else :
            return img


class semantic_dataset_validation(Dataset):
    def __init__(self, split = 'test', transform = None):
        self.void_labels = [0, 1, 2, 3, 4, 5, 6, 9, 10, 14, 15, 16, 18, 29, 30, -1]
        self.valid_labels = [7, 8, 11, 12, 13, 17, 19, 20, 21, 22, 23, 24, 25, 26, 27,
        self.ignore_index = 250
        self.class_map = dict(zip(self.valid_labels, range(19)))
        self.split = split

        self.transform = transform

        self.img_list = image_val
        self.mask_list = label_val

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

    def __getitem__(self, idx):
        img = cv2.imread(self.img_list[idx])
        img = cv2.resize(img, (1242, 376))
        mask = None
        if self.split == 'train':
            mask = cv2.imread(self.mask_list[idx], cv2.IMREAD_GRAYSCALE)
            mask = cv2.resize(mask, (512, 256), interpolation=cv2.INTER_NEAREST)
            #mask = self.encode_segmap(mask)
            assert(mask.shape == (256, 512))

        if self.transform:
            img = self.transform(img)
```

```
            assert(img.shape == (3, 256, 512))
        else :
            assert(img.shape == (256, 512, 3))

        if self.split == 'train':
            return img, mask
        else :
            return img


class semantic_dataset_test(Dataset):
    def __init__(self, split = 'test', transform = None):
        self.void_labels = [0, 1, 2, 3, 4, 5, 6, 9, 10, 14, 15, 16, 18, 29, 30, -1]
        self.valid_labels = [7, 8, 11, 12, 13, 17, 19, 20, 21, 22, 23, 24, 25, 26, 27,
        self.ignore_index = 250
        self.class_map = dict(zip(self.valid_labels, range(19)))
        self.split = split

        self.transform = transform

        self.img_list = image_test
        self.mask_list = label_test

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

    def __getitem__(self, idx):
        img = cv2.imread(self.img_list[idx])
        img = cv2.resize(img, (1242, 376))
        mask = None
        if self.split == 'train':
            mask = cv2.imread(self.mask_list[idx], cv2.IMREAD_GRAYSCALE)
            mask = cv2.resize(mask, (512, 256), interpolation=cv2.INTER_NEAREST)
            #mask = self.encode_segmap(mask)
            assert(mask.shape == (256, 512))

        if self.transform:
            img = self.transform(img)
            assert(img.shape == (3, 256, 512))
        else :
            assert(img.shape == (256, 512, 3))

        if self.split == 'train':
            return img, mask
        else :
            return img


transformation = transforms.Compose([
            transforms.ToPILImage(),
            transforms.Resize((256,512),interpolation=PIL.Image.BICUBIC),
            transforms.ToTensor()
```

```
            transforms.ToTensor(),
            transforms.Normalize(mean = [0.35675976, 0.37380189, 0.3764753], std = [0.
        ])
trainset = semantic_dataset_train(split = 'train', transform = transformation)
validationset = semantic_dataset_validation(split = 'train', transform = transformatio
testset = semantic_dataset_test(split = 'train', transform = transformation)

trainImages = DataLoader(trainset, batch_size = 5, shuffle = True)
valImages = DataLoader(validationset, batch_size = 5, shuffle = True)
testImages = DataLoader(testset, batch_size = 1, shuffle = True)



#FC32 architecture
vgg16_mod = vgg16(pretrained=True)
for param in vgg16_mod.features.parameters():
  param.requires_grad = False
class FCN32(nn.Module):
  def __init__(self):
    super(FCN32, self).__init__()
    self.features = vgg16_mod.features
    self.classifier = nn.Sequential(
      nn.Conv2d(512, 4096, 7),
      nn.ReLU(inplace=True),
      nn.Dropout2d(),
      nn.Conv2d(4096, 4096, 1),
      nn.ReLU(inplace=True),
      nn.Dropout2d(),
      nn.Conv2d(4096, 35, 1),
      nn.ConvTranspose2d(35, 35, 224, stride=32)
    )

  def forward(self, x):
    x = self.features(x)
    x = self.classifier(x)
    return x

fcn = FCN32()
print(fcn)
input = torch.randn(5,3,256,512)
output = fcn(input)
print(output.shape)


#FC16 architecture
vgg16_mod = vgg16(pretrained=True)
for param in vgg16_mod.features.parameters():
  param.requires_grad = False
class FCN16(nn.Module):
  def __init__(self):
    super(FCN16, self).__init__()
    self.features = vgg16_mod.features
    self.classifier = nn.Sequential(
```

```
        nn.Conv2d(512, 4096, 7),
        nn.ReLU(inplace=True),
        nn.Conv2d(4096, 4096, 1),
        nn.ReLU(inplace=True),
        nn.Conv2d(4096, 35, 1)
      )
      self.score_pool4 = nn.Conv2d(512, 35, 1)
      self.upscore2 = nn.ConvTranspose2d(35, 35, 14, stride=2, bias=False)
      self.upscore16 = nn.ConvTranspose2d(35, 35, 16, stride=16, bias=False)

    def forward(self, x):
      pool4 = self.features[:-7](x)
      pool5 = self.features[-7:](pool4)
      pool5_upscored = self.upscore2(self.classifier(pool5))
      pool4_scored = self.score_pool4(pool4)
      combined = pool4_scored + pool5_upscored
      res = self.upscore16(combined)
      return res

fcn16 = FCN16()
print(fcn16)
input = torch.randn(5,3,256,512)
output = fcn16(input)
print(output.shape)
```

```
FCN16(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fals
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fals
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fal
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fal
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

```
      (27): ReLU(inplace=True)
      (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (29): ReLU(inplace=True)
      (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=Fa
    )
    (classifier): Sequential(
      (0): Conv2d(512, 4096, kernel_size=(7, 7), stride=(1, 1))
      (1): ReLU(inplace=True)
      (2): Conv2d(4096, 4096, kernel_size=(1, 1), stride=(1, 1))
      (3): ReLU(inplace=True)
      (4): Conv2d(4096, 35, kernel_size=(1, 1), stride=(1, 1))
    )
    (score_pool4): Conv2d(512, 35, kernel_size=(1, 1), stride=(1, 1))
    (upscore2): ConvTranspose2d(35, 35, kernel_size=(14, 14), stride=(2, 2), bias=
    (upscore16): ConvTranspose2d(35, 35, kernel_size=(16, 16), stride=(16, 16), bi
  )
  torch.Size([5, 35, 256, 512])
```

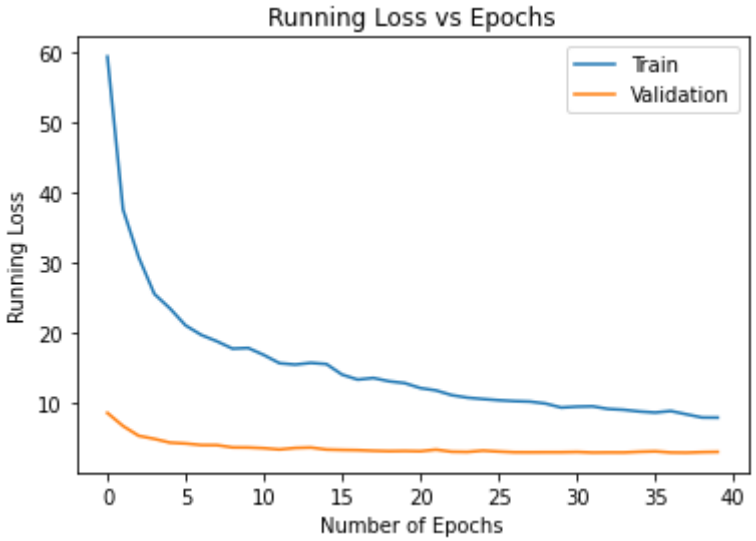
Double-click (or enter) to edit

```
#Do not use
def training(fcn, criterion, optimizer,num_epochs):

  val_loss = []
  train_loss = []
  for epoch in range(num_epochs):
    fcn.train()
    val_running_loss = 0
    train_running_loss = 0
    fcn16.train()
    for i, trainData in enumerate(trainImages, 0):
      imgs, labels = trainData
      labels = labels.type(torch.LongTensor)
      #set the gradient to zero
      optimizer.zero_grad()
      outputs = fcn(imgs)
      loss = criterion(outputs, labels)
      loss.backward()
      train_running_loss += loss.item()
      optimizer.step()

    train_loss.append(train_running_loss)
    fcn16.eval()
    with torch.no_grad():
      for k, dat1 in enumerate(valImages):
      # Get image, label pair
        inputs1, labels1 = dat1
        labels1 = labels1.type(torch.LongTensor)
      # Predicting segmentation for val inputs
        outputs1 = fcn(inputs1)

        # Compute CE loss and aggregate it
```

```
            loss1 = criterion(outputs1, labels1)
            val_running_loss += loss1.item()

        val_loss.append(val_running_loss)
        print("Epochs: ", epoch, "Training Loss: ", train_running_loss, "val_running_loss:
    return train_loss, val_loss

criterion = nn.CrossEntropyLoss()


optimizer = optim.Adam(fcn16.parameters(), lr=0.001, betas=(0.9, 0.999), eps=1e-08, we
train_loss, val_loss = training(fcn16, criterion, optimizer, num_epochs=40)
torch.save(fcn16, 'drive/My Drive/CSCI-677-HW5/data_semantics/ModelFCN16_Adam_dropout.
```

```
Epochs:  0 Training Loss:  59.28895115852356 val_running_loss:  8.55336415767669
Epochs:  1 Training Loss:  37.511099100112915 val_running_loss:  6.691580533981
Epochs:  2 Training Loss:  30.72277069091797 val_running_loss:  5.29584228992462
Epochs:  3 Training Loss:  25.50015300512314 val_running_loss:  4.85788941383618
Epochs:  4 Training Loss:  23.424445688724518 val_running_loss:  4.3232215642929
Epochs:  5 Training Loss:  21.01056444644928 val_running_loss:  4.19649475812912
Epochs:  6 Training Loss:  19.65706741809845 val_running_loss:  3.97957623004913
Epochs:  7 Training Loss:  18.750891357660294 val_running_loss:  3.9666209816932
Epochs:  8 Training Loss:  17.704172015190125 val_running_loss:  3.6421911120414
Epochs:  9 Training Loss:  17.79672572016716 val_running_loss:  3.62778818607330
Epochs:  10 Training Loss:  16.8015516102314 val_running_loss:  3.53162536025047
Epochs:  11 Training Loss:  15.630626678466797 val_running_loss:  3.347768396139
Epochs:  12 Training Loss:  15.435338705778122 val_running_loss:  3.562463164329
Epochs:  13 Training Loss:  15.679339826107025 val_running_loss:  3.624943733215
Epochs:  14 Training Loss:  15.511705696582794 val_running_loss:  3.338151812553
Epochs:  15 Training Loss:  14.003555357456207 val_running_loss:  3.282106667757
Epochs:  16 Training Loss:  13.2979174554348 val_running_loss:  3.249573439356
Epochs:  17 Training Loss:  13.527827441692352 val_running_loss:  3.164175301790
Epochs:  18 Training Loss:  13.056245625019073 val_running_loss:  3.111047983169
Epochs:  19 Training Loss:  12.79800832271576 val_running_loss:  3.135416567325
Epochs:  20 Training Loss:  12.091058164834976 val_running_loss:  3.098386257886
Epochs:  21 Training Loss:  11.756760269403458 val_running_loss:  3.323573887348
Epochs:  22 Training Loss:  11.086442202329636 val_running_loss:  3.029297202825
Epochs:  23 Training Loss:  10.726012796163559 val_running_loss:  2.997289389371
Epochs:  24 Training Loss:  10.530326664447784 val_running_loss:  3.186679244041
Epochs:  25 Training Loss:  10.360094755887985 val_running_loss:  3.054947137832
Epochs:  26 Training Loss:  10.235976576805115 val_running_loss:  2.953990906476
Epochs:  27 Training Loss:  10.16593188047409 val_running_loss:  2.948525965213
Epochs:  28 Training Loss:  9.887732744216919 val_running_loss:  2.956398308277
Epochs:  29 Training Loss:  9.317112028598785 val_running_loss:  2.955011516809
Epochs:  30 Training Loss:  9.44376426935196 val_running_loss:  2.992370307445
Epochs:  31 Training Loss:  9.49117062985897 val_running_loss:  2.909607350826
Epochs:  32 Training Loss:  9.119388341903687 val_running_loss:  2.927274733781
Epochs:  33 Training Loss:  8.997102707624435 val_running_loss:  2.921167880296
Epochs:  34 Training Loss:  8.75710615515709 val_running_loss:  3.020608544349
Epochs:  35 Training Loss:  8.606159165501595 val_running_loss:  3.081506431102
Epochs:  36 Training Loss:  8.827051058411598 val_running_loss:  2.917464941740
Epochs:  37 Training Loss:  8.356737405061722 val_running_loss:  2.896420508623
Epochs:  38 Training Loss:  7.899606853723526 val_running_loss:  2.971041232347
Epochs:  39 Training Loss:  7.882933139801025 val_running_loss:  3.004279553890
```

```
#torch.save(fcn, 'drive/My Drive/CSCI677-Homeworks/data_semantics/Model_3_val_SGD.pt')


#Plotting Running loss vs Epochs
epochList = [i for i in range(0, 40)]
plt.plot(epochList, [x for x in train_loss], label = "Train")
plt.plot(epochList, [y for y in val_loss], label = "Validation")

plt.xlabel('Number of Epochs')
plt.ylabel('Running Loss')
plt.title('Running Loss vs Epochs')
plt.legend()
plt.show()
```




```
#Calculating IoU and mean IoU
def get_mean_iou(conf_mat, multiplier=1.0):
  cm = conf_mat.copy()
  np.fill_diagonal(cm, np.diag(cm) * multiplier)
  inter = np.diag(cm)
  gt_set = cm.sum(axis=1)
  pred_set = cm.sum(axis=0)
  union_set =  gt_set + pred_set - inter
  iou = inter.astype(float) / union_set
  mean_iou = np.nanmean(iou)
  return mean_iou

overall_conf_mat = np.zeros((35, 35))
with torch.no_grad():
  for k, dat1 in enumerate(testImages):
    # Get image, label pair
    inputs1, labels1 = dat1


    # Predicting segmentation for val inputs
    outputs1 = fcn16(inputs1)
```

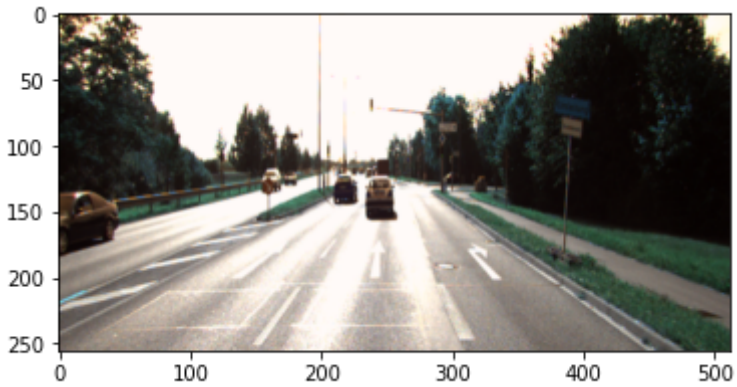
```
    preds = torch.argmax(outputs1, dim=1).detach().numpy()
    gt = labels1.detach().numpy()

    # Compute confusion matrix
    conf_mat = confusion_matrix(y_pred=preds.flatten(), y_true=gt.flatten(), labels=li
    overall_conf_mat += conf_mat

print('DICE score: {}'.format(np.round(get_mean_iou(conf_mat=overall_conf_mat ,multipl
print('Mean IOU score: {}'.format(np.round(get_mean_iou(conf_mat=overall_conf_mat), 2)
```

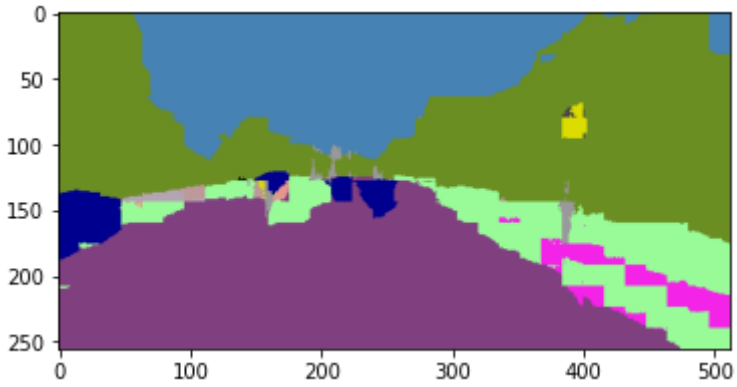
```
DICE score: 0.37
Mean IOU score: 0.28
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:9: RuntimeWarning: 
  if __name__ == '__main__':
```

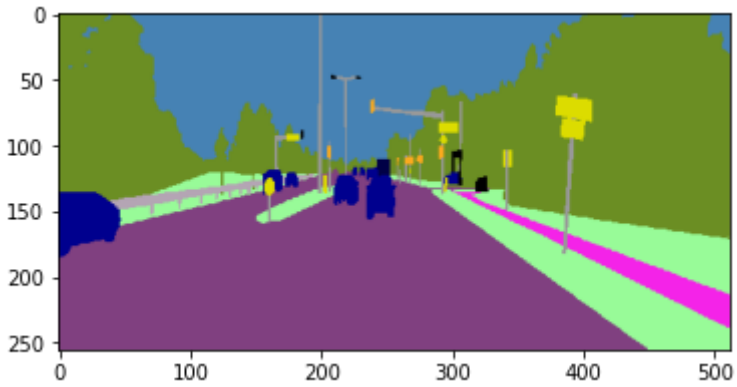
```
class UnNormalize(object):
    def __init__(self, mean, std):
        self.mean = mean
        self.std = std

    def __call__(self, tensor):
        """
        Args:
            tensor (Tensor): Tensor image of size (C, H, W) to be normalized.
        Returns:
            Tensor: Normalized image.
        """
        for t, m, s in zip(tensor, self.mean, self.std):
            t.mul_(s).add_(m)
            # The normalize code -> t.sub_(m).div_(s)
        return tensor


import numpy as np
#Map the labels to colors and display the results
def get_mean_iou(conf_mat, multiplier=1.0):
  cm = conf_mat.copy()
  np.fill_diagonal(cm, np.diag(cm) * multiplier)
  inter = np.diag(cm)
  gt_set = cm.sum(axis=1)
  pred_set = cm.sum(axis=0)
  union_set =  gt_set + pred_set - inter
  iou = inter.astype(float) / union_set
  mean_iou = np.nanmean(iou)
  return mean_iou


def decode_segmap(image, nc=35):

  label_colors = np.array([(  0,  0,  0),
               (  0,  0,  0) , (  0,  0,  0) , (  0,  0,  0), (  0,  0,  0), (111, 74,
               (230, 150, 140) , ( 70,  70,  70) , (102, 102, 156), (190, 153, 153), (180, 165, 1
```

```
                (230,150,140), (  70,  70,  70), (102,102,156), (190,153,153), (180,165,1
                (250,170, 30), (220,220,  0), (107,142, 35), (152,251,152), ( 70,130,18
                (  0,  0, 90), (  0,  0,110), (  0, 80,100), (  0,  0,230), (119, 11, 3

    r = np.zeros_like(image).astype(np.uint8)
    g = np.zeros_like(image).astype(np.uint8)
    b = np.zeros_like(image).astype(np.uint8)

    for l in range(0, nc):
      idx = image == l
      r[idx] = label_colors[l, 0]
      g[idx] = label_colors[l, 1]
      b[idx] = label_colors[l, 2]

    rgb = np.stack([r, g, b], axis=2)
    return rgb

  with torch.no_grad():
    for k, dat in enumerate(testImages):
      inputs, labels = dat
      print("Test set Number: ", k)
      outputs = fcn16(inputs)
      pred = torch.argmax(outputs[0].squeeze(), dim=0).detach().numpy()
      gt = labels[0]

      #Calculate IoU
      preds = torch.argmax(outputs, dim=1).detach().numpy()
      groundTruth = labels.detach().numpy()
      conf_mat = confusion_matrix(y_pred=preds.flatten(), y_true=groundTruth.flatten(),
      IoU = get_mean_iou(conf_mat)
      Dice = get_mean_iou(conf_mat ,multiplier=2.0)
      print("IoU: ",IoU)
      print("Dice: ", Dice)

      unorm = UnNormalize(mean = [0.35675976, 0.37380189, 0.3764753], std = [0.32064945,
      img = unorm(inputs)

      plt.imshow(img[0].permute(1, 2, 0))
      plt.show()
      segmentation = decode_segmap(pred)
      gt_colored = decode_segmap(gt)
      plt.imshow(segmentation)
      plt.show()
      plt.imshow(gt_colored)
      plt.show()
```

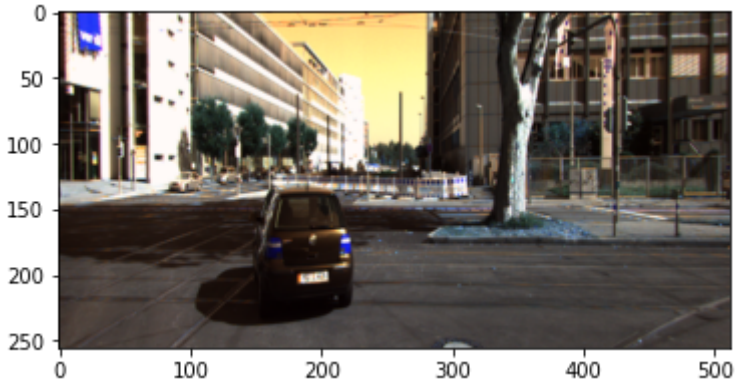
```
Test set Number:  0
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:10: RuntimeWarning:
  # Remove the CWD from sys.path while we load stuff.
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.2994560619263632
Dice:  0.35667136170434527
```

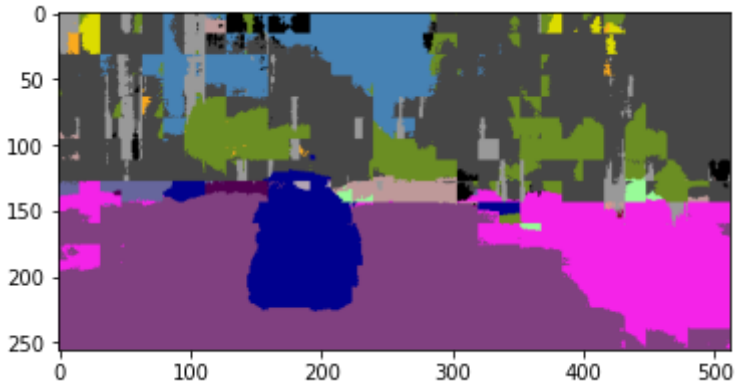


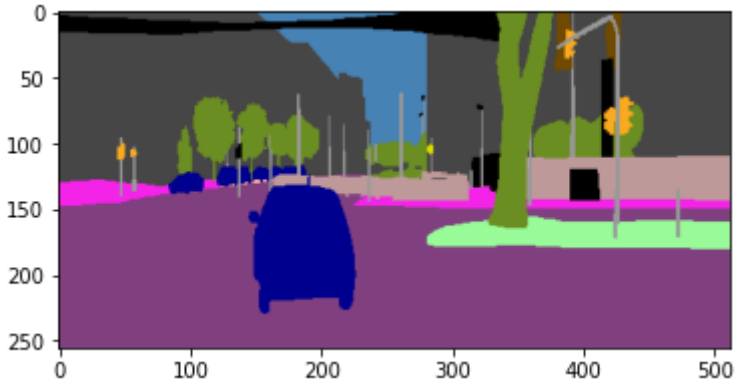




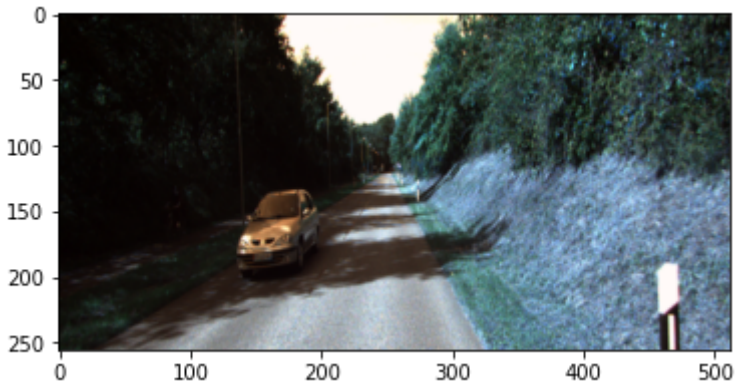

```
Test set Number:  1
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.16395437102933613
Dice:  0.21569265167328563
```

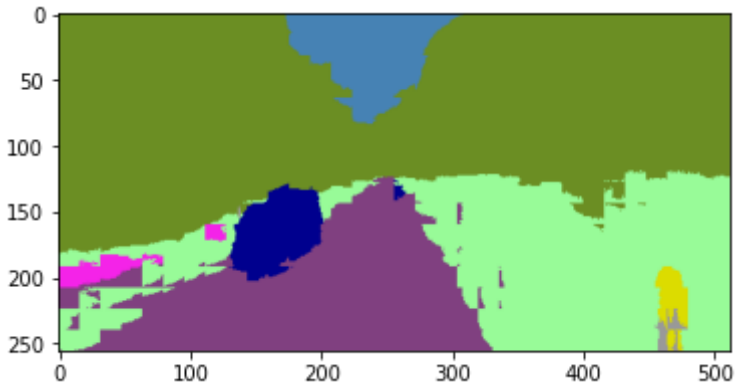


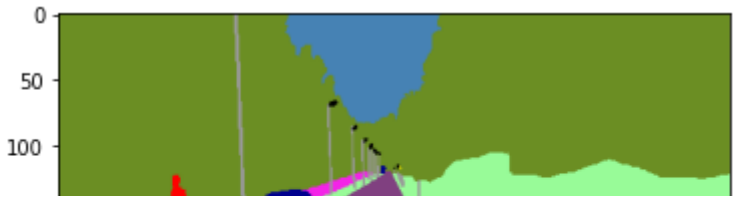


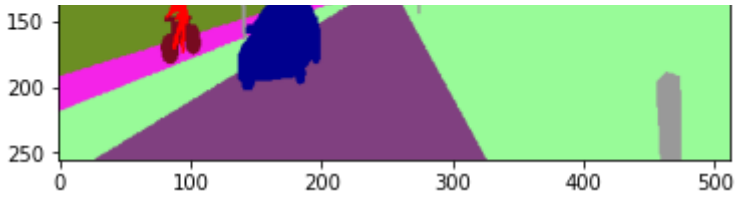


```
Test set Number:  2
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.4302027937450505
Dice:  0.4875077439789489
```

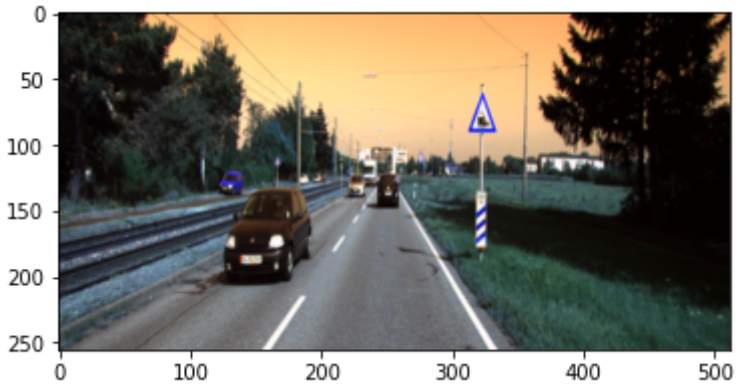


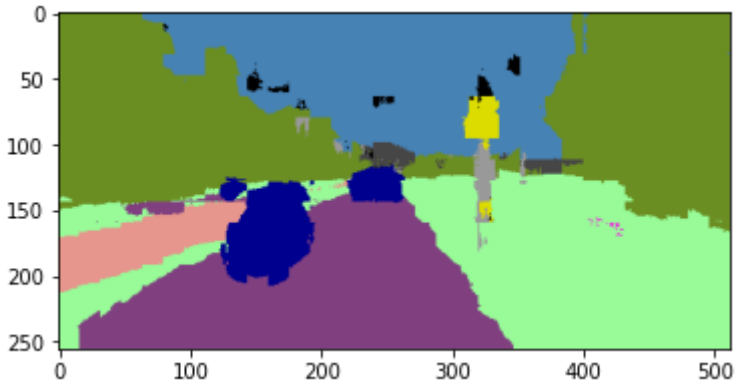


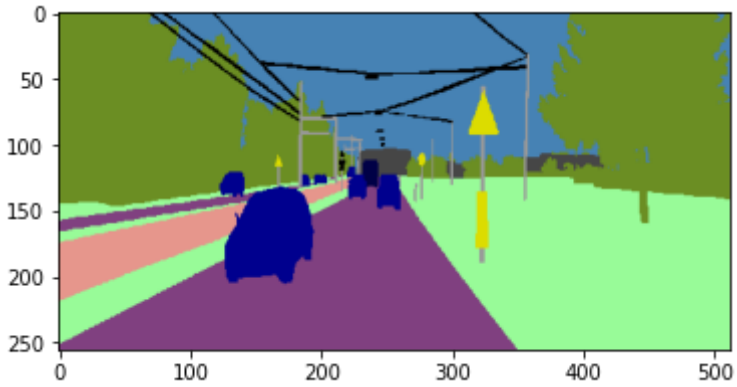




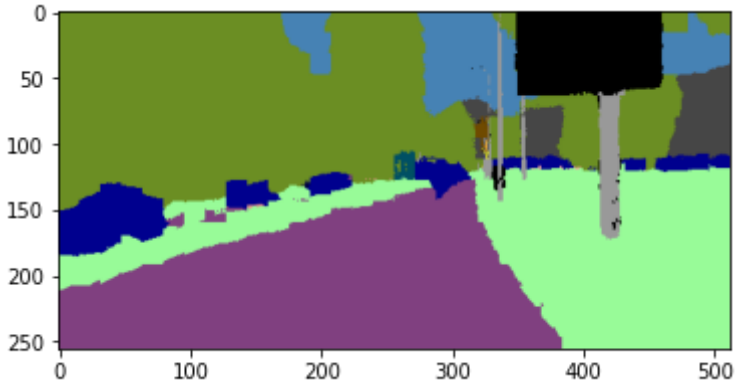
```
Test set Number:  3
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.480692582725838
Dice:  0.5609770772176007
```

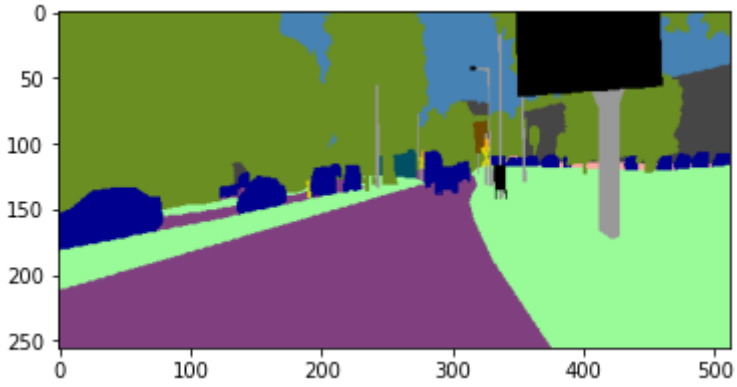




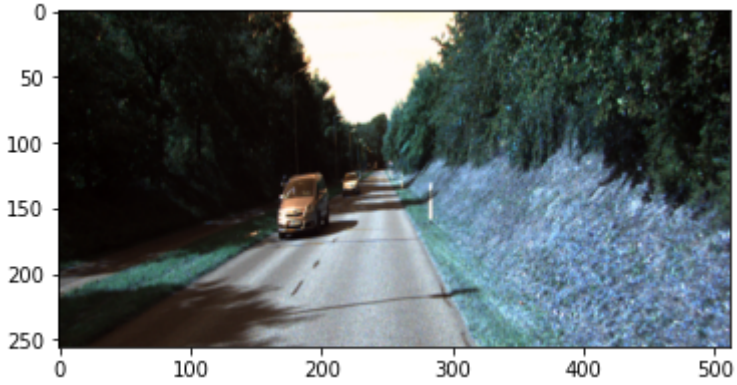


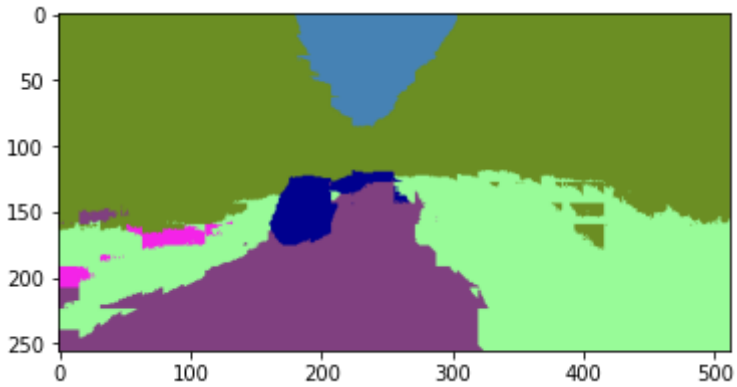
```
Test set Number:  4
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.558094593113312
Dice:  0.633653204353108
```

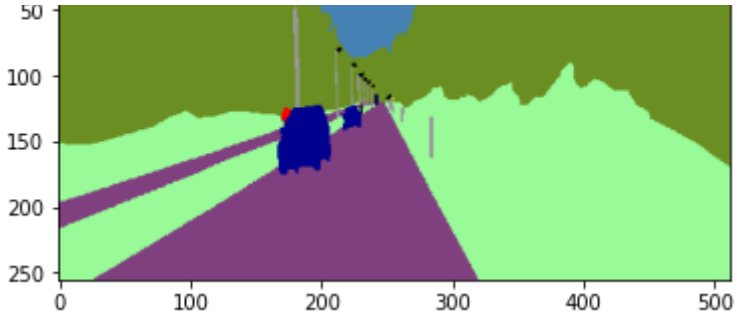




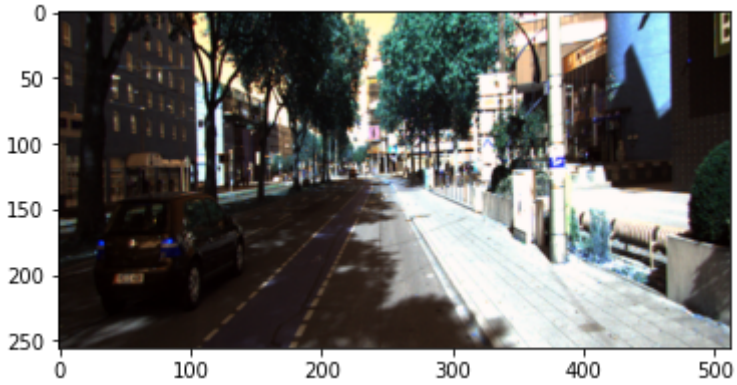
```
Test set Number:  5
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.32771281793950396
Dice:  0.3655345298864862
```

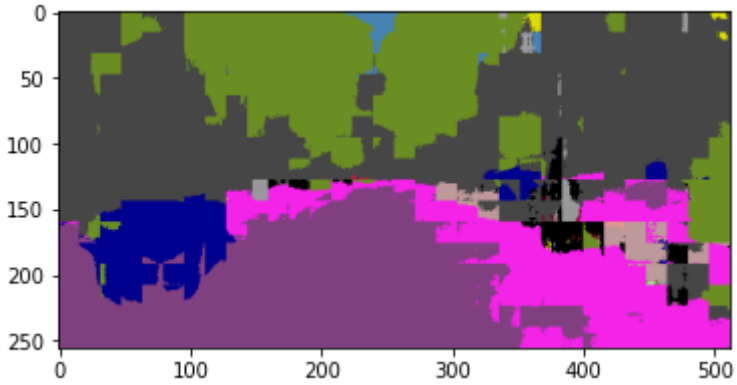


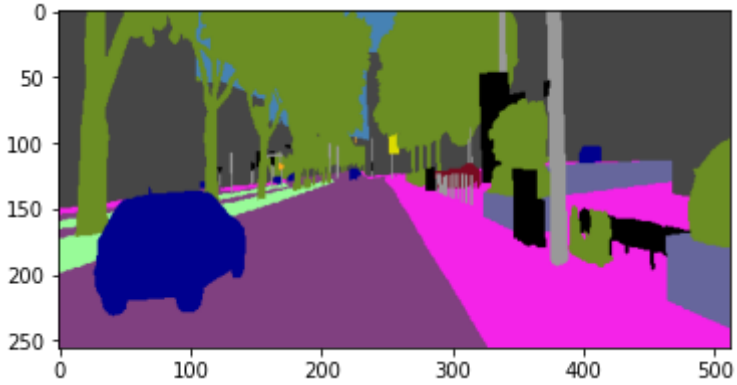




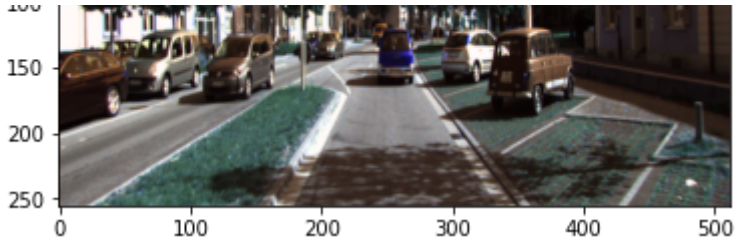
```
Test set Number:  6
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.20680618190206435
Dice:  0.2630828931842847
```

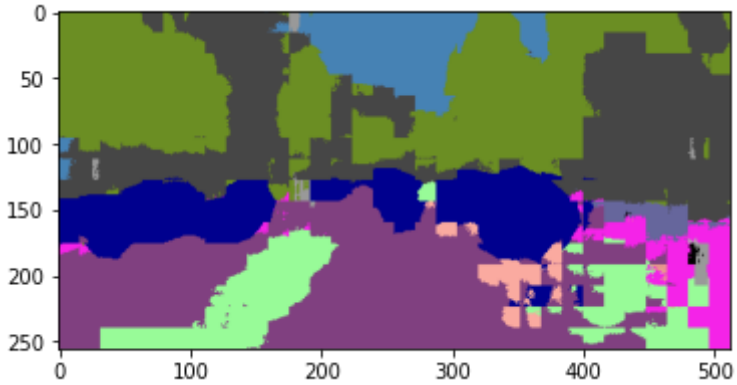


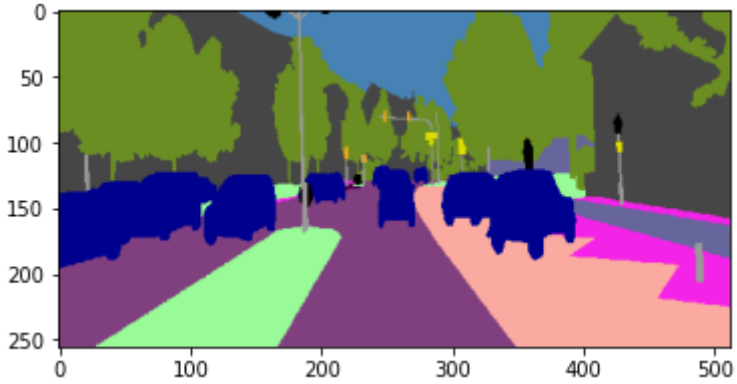




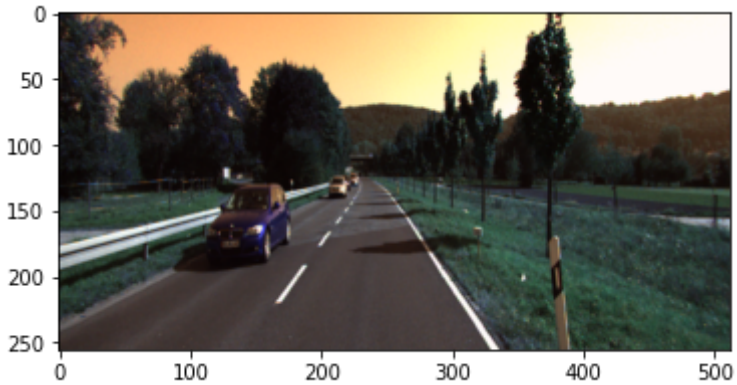
```
Test set Number:  7
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.30699851239735787
Dice:  0.38566679687995015
```

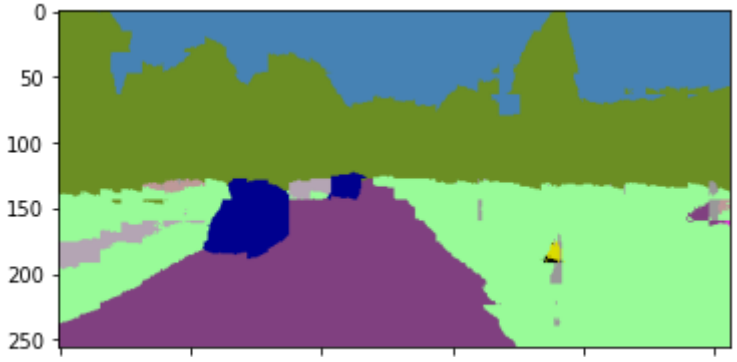


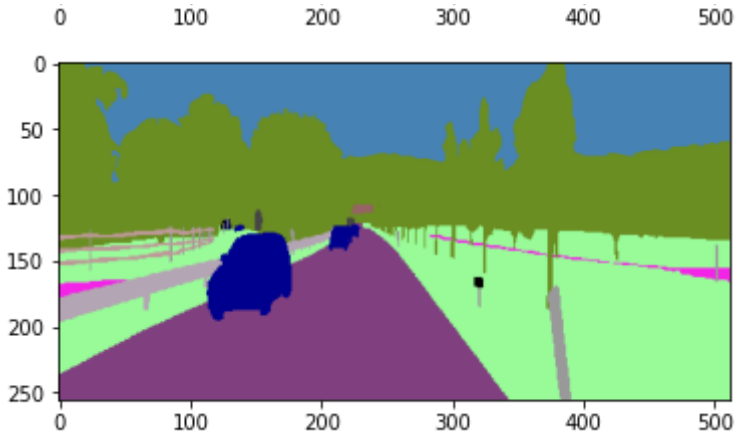




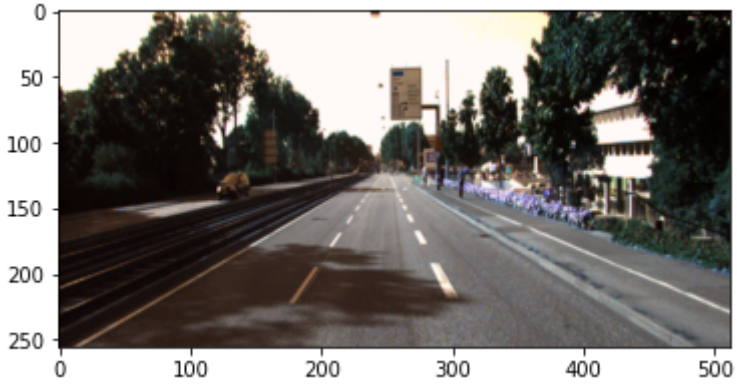
```
Test set Number:  8
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.36153677072828555
Dice:  0.4056605843911772
```

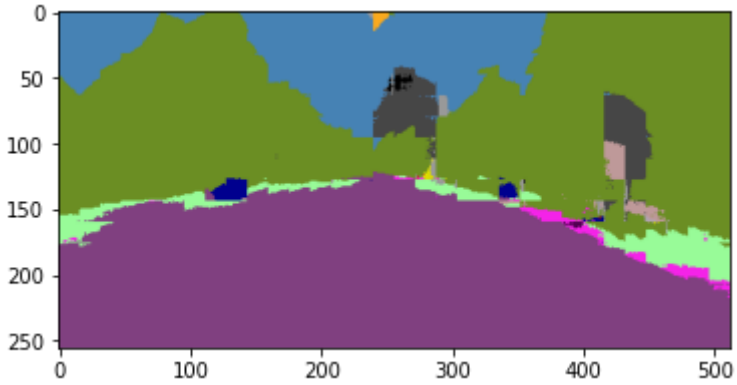


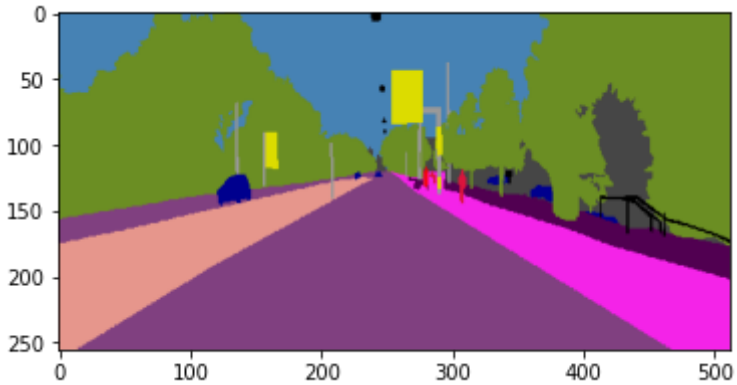




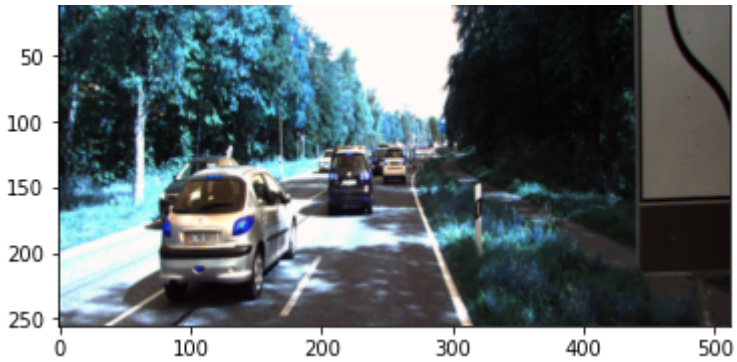
```
Test set Number:  9
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.16616832804771853
Dice:  0.20437211327839633
```

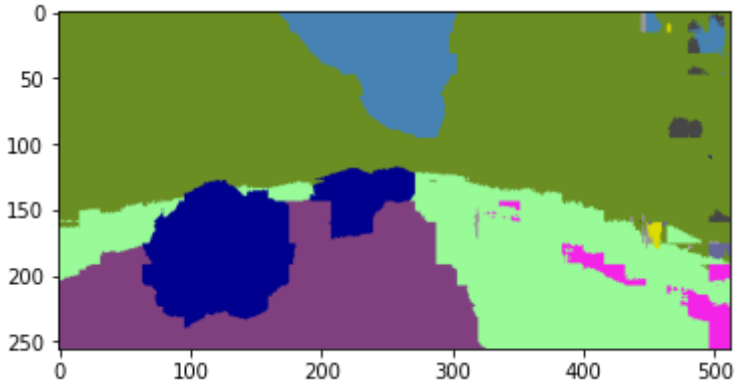


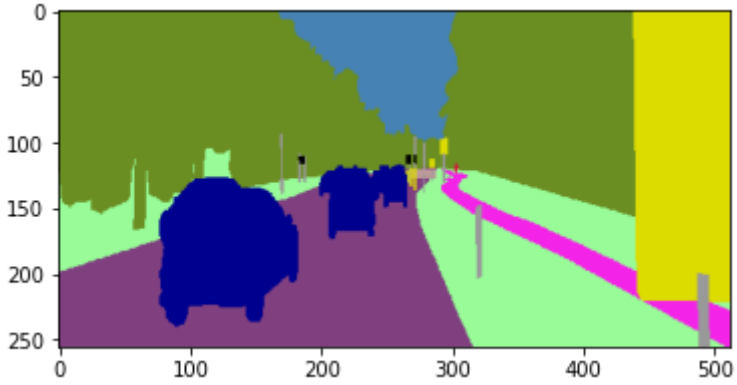




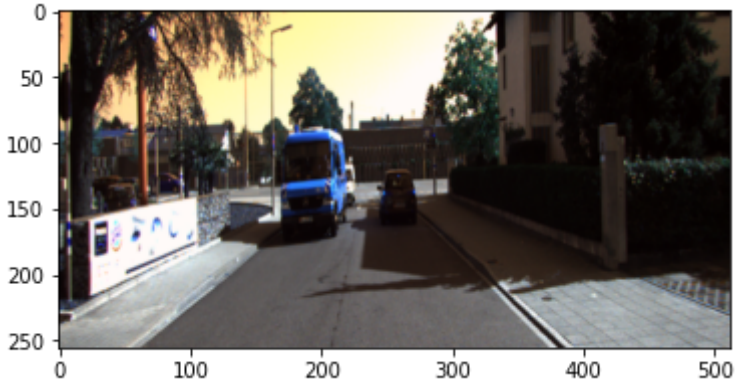
```
Test set Number:  10
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.30941439842409657
Dice:  0.35566833239236034
```

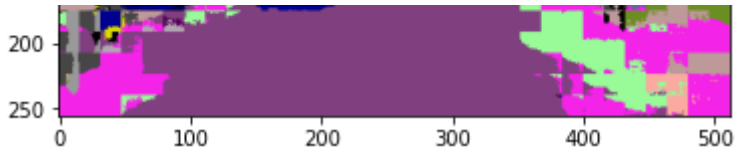


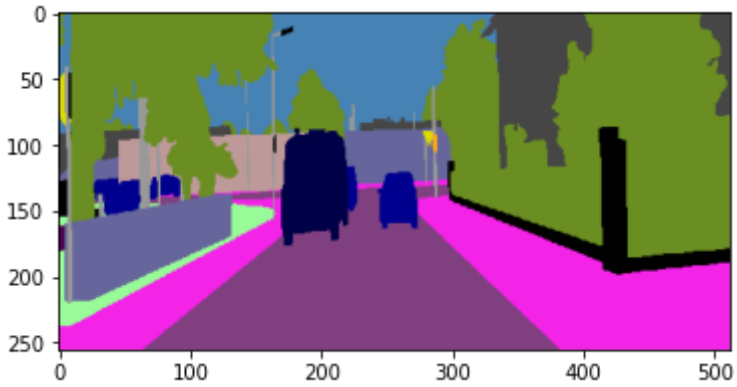




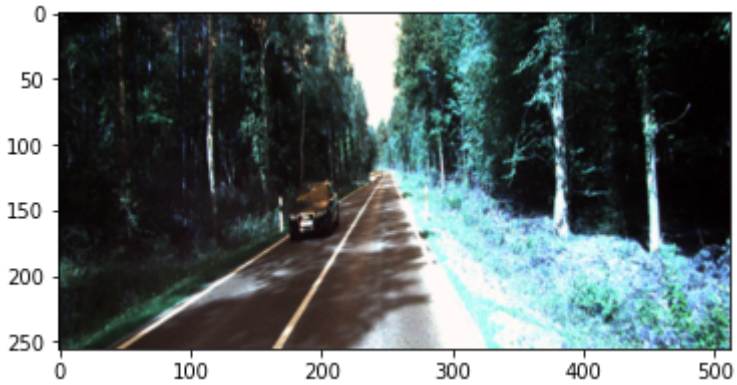
```
Test set Number:  11
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.16434791265206036
Dice:  0.213228998988609
```

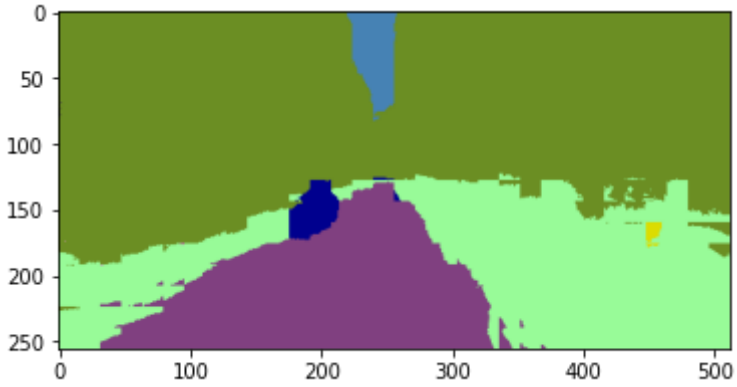


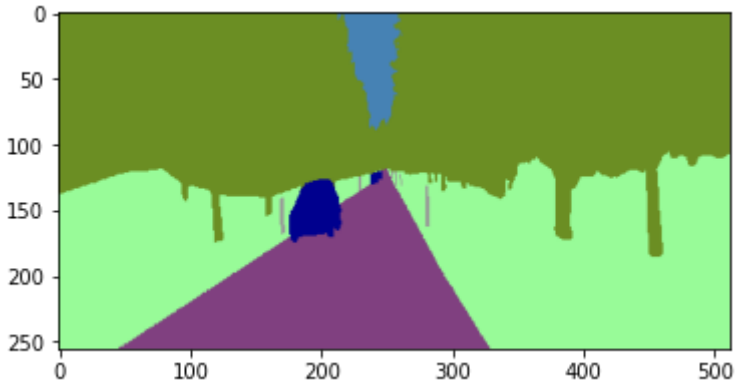




```
Test set Number:  12
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.387273178641238
Dice:  0.43556686956902546
```

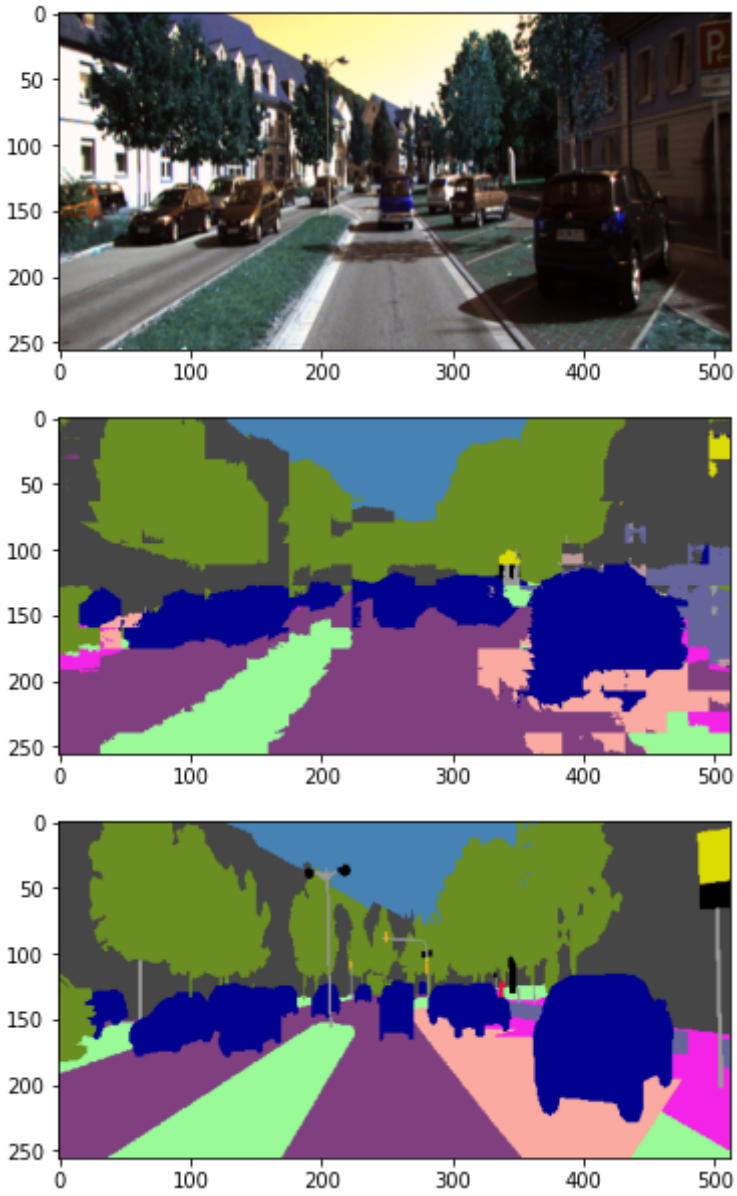




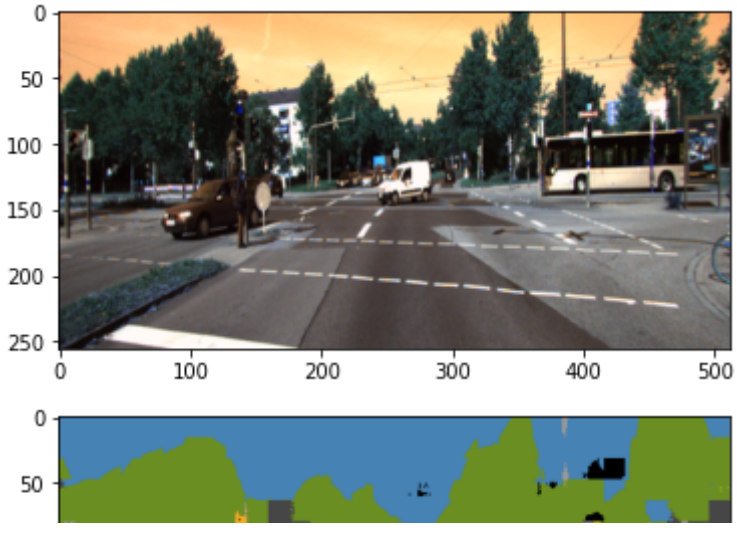


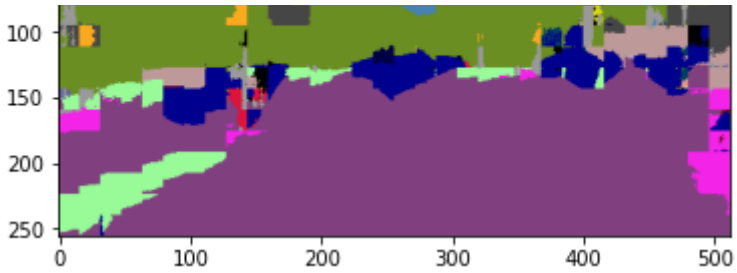
```
Test set Number:  13
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
```

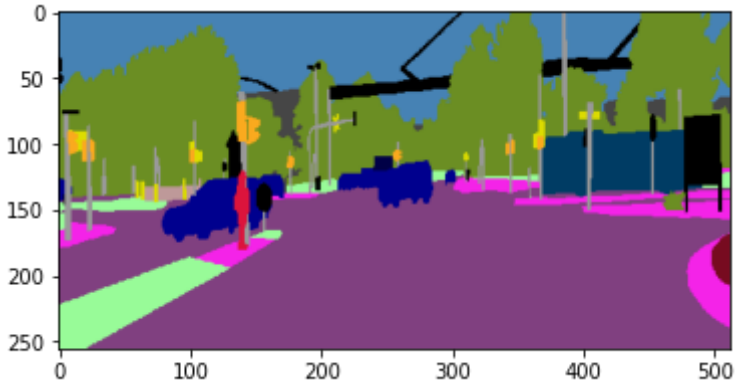
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.33174588345034284
Dice:  0.4039578869473812
```



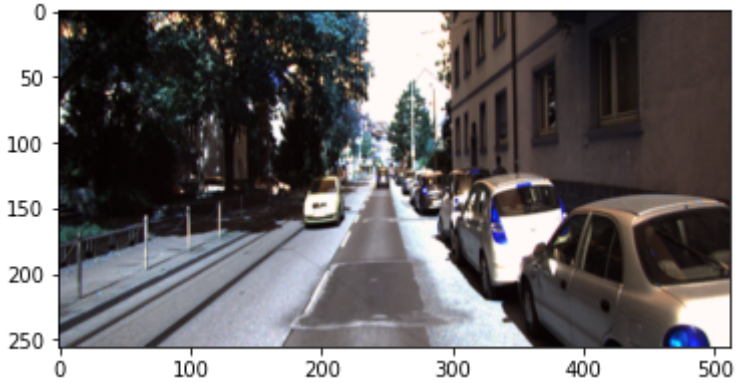
```
Test set Number:  14
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.24364473667441405
Dice:  0.32128596644451046
```

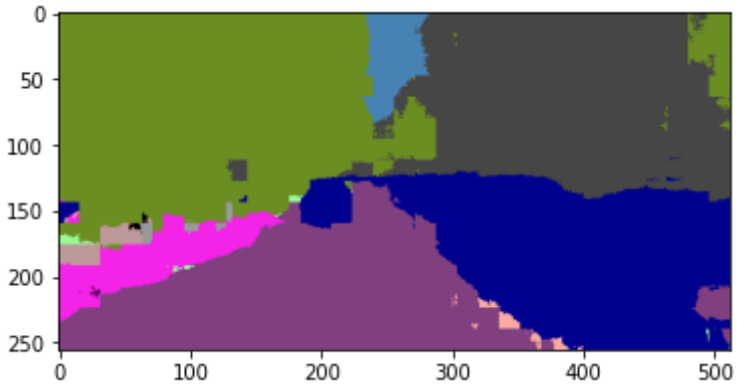


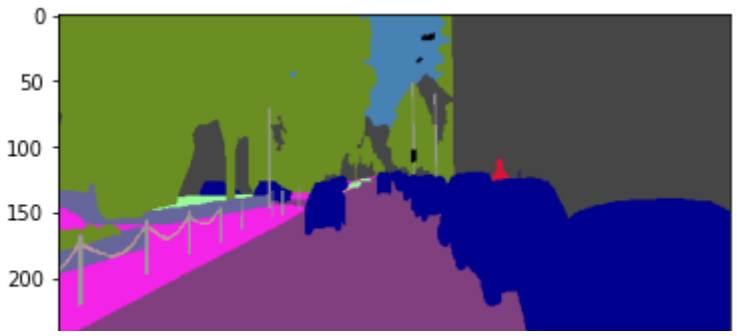




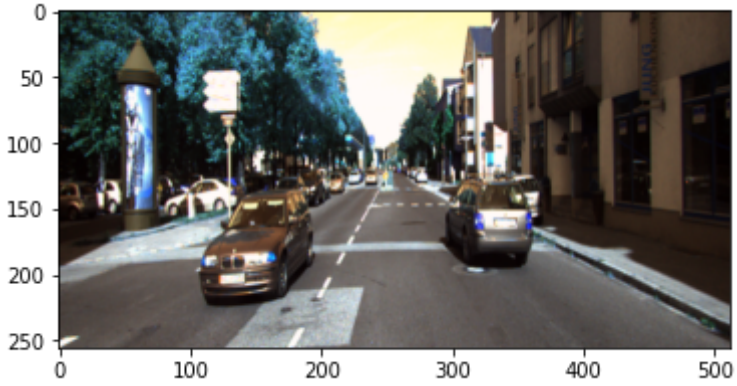
```
Test set Number:  15
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.3371714156819543
Dice:  0.3889251375256572
```

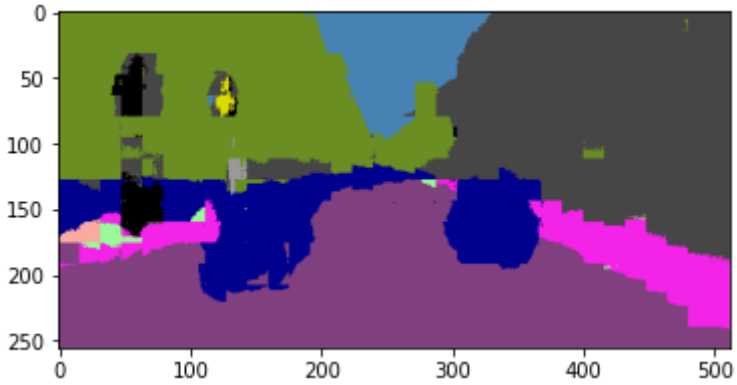


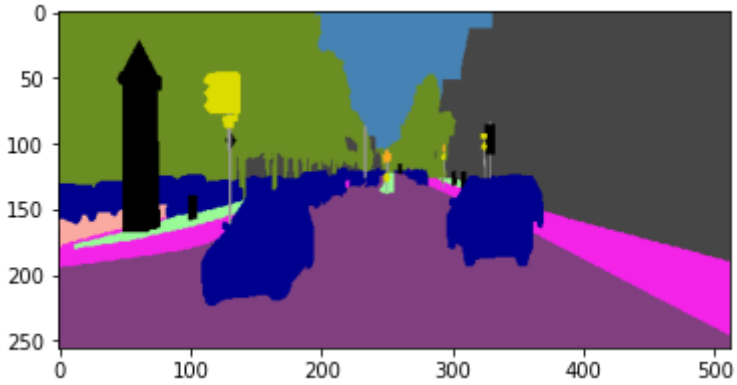




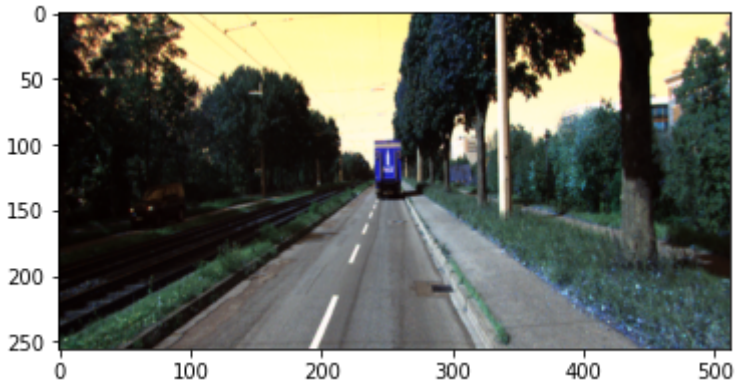
```
Test set Number:  16
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.44335624004307006
Dice:  0.5214470961050112
```

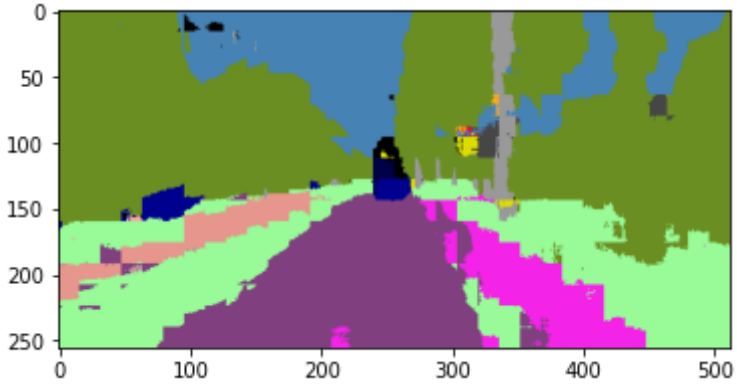


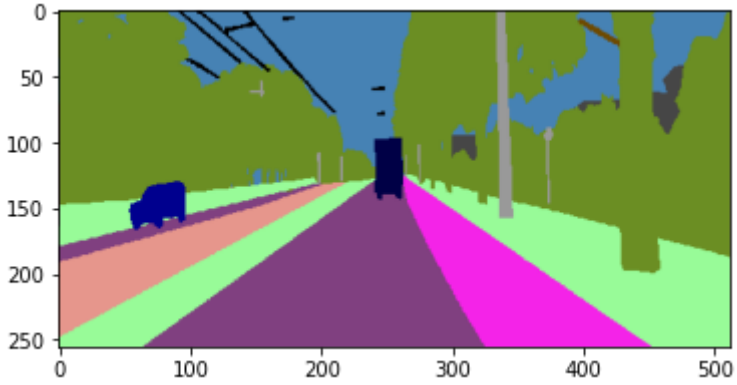




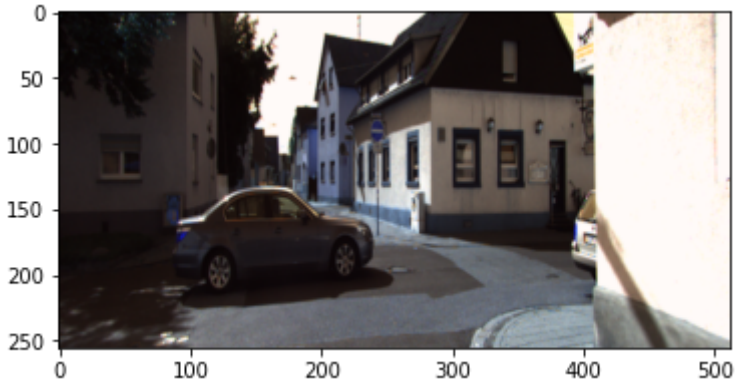
```
Test set Number:  17
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.26893518653329057
Dice:  0.340992803263865
```

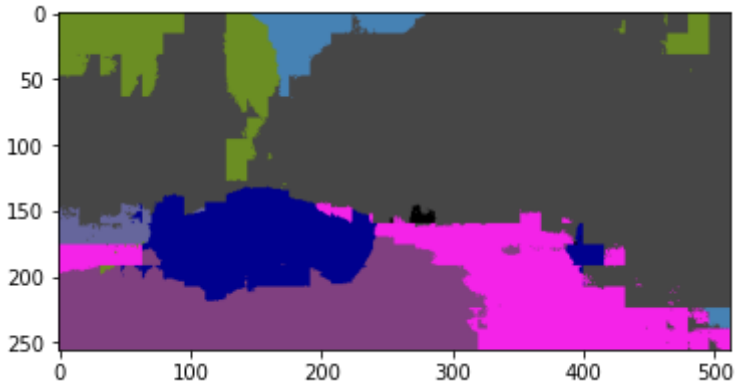


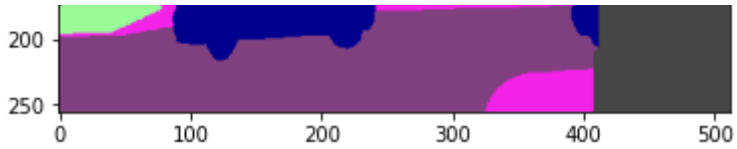




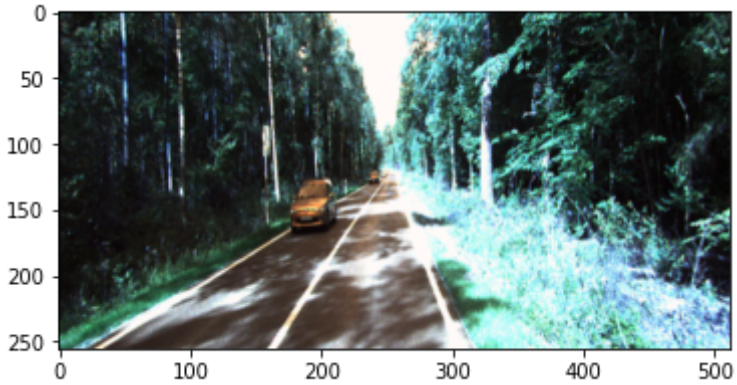
```
Test set Number:  18
IoU:  0.33603373597090974
Dice:  0.4106748131969363
```

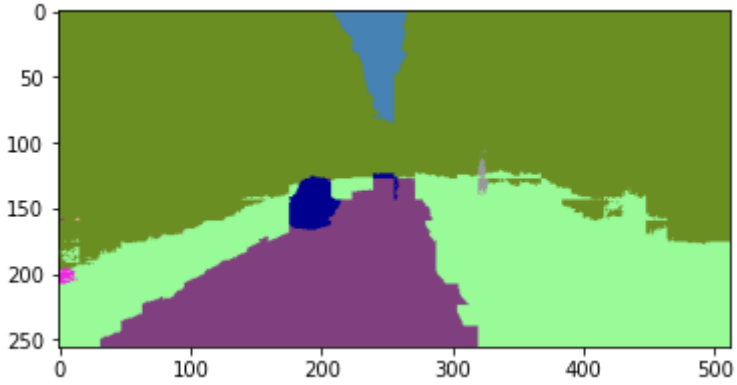


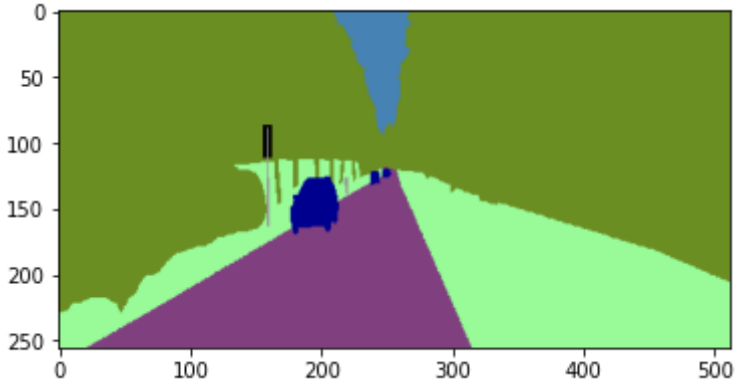




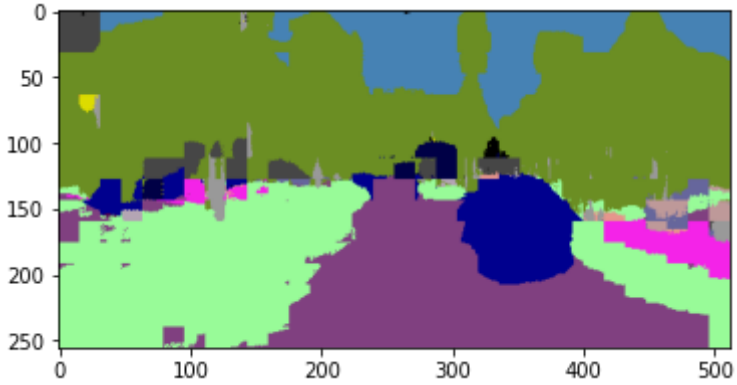
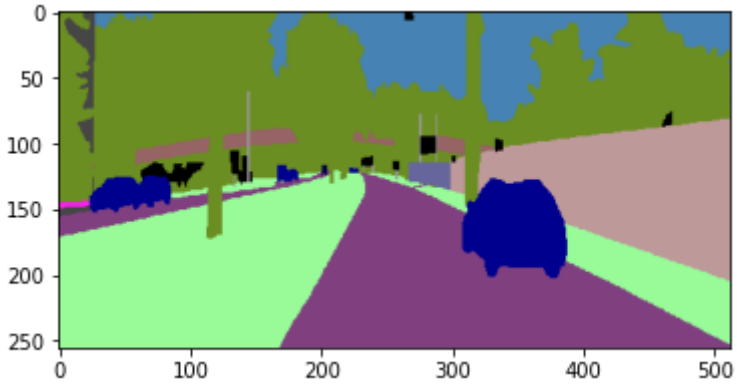
```
Test set Number:  19
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.45357700333428064
Dice:  0.497912989243278
```



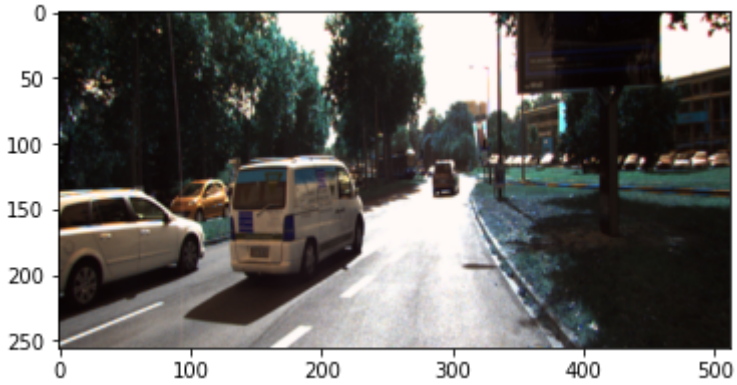
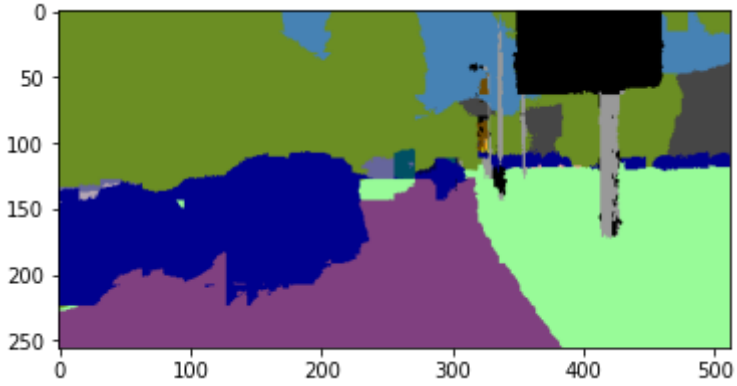


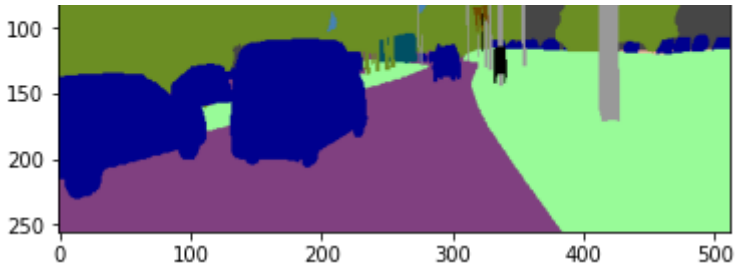


```
Test set Number:  20
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.22430682276647657
Dice:  0.2627560128761261
```

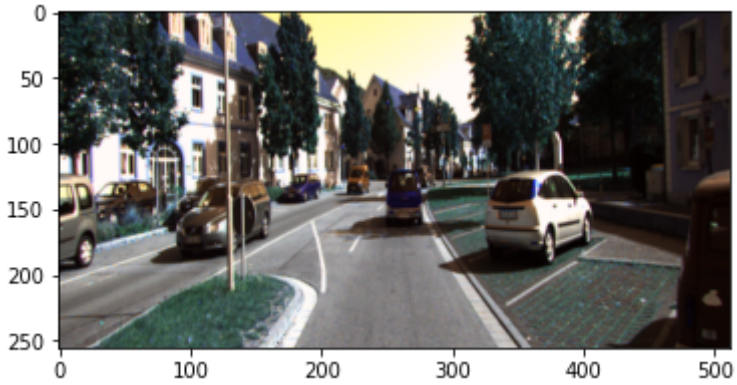




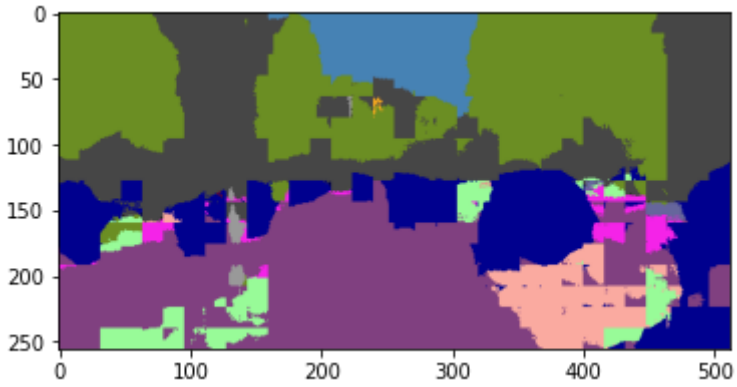
```
Test set Number:  21
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.49505334557847913
Dice:  0.5452795421055631
```

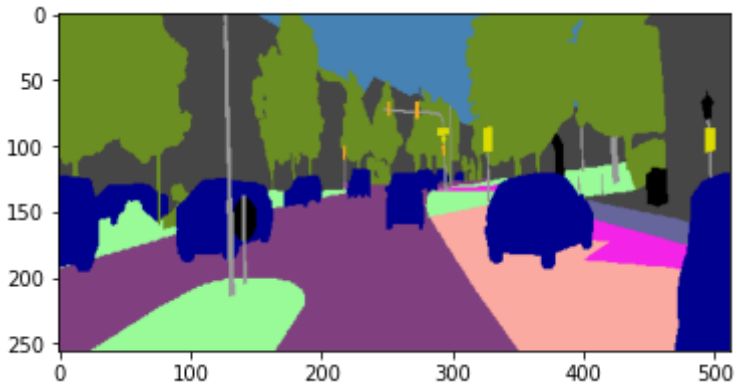



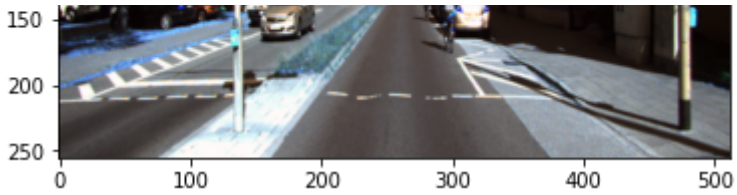
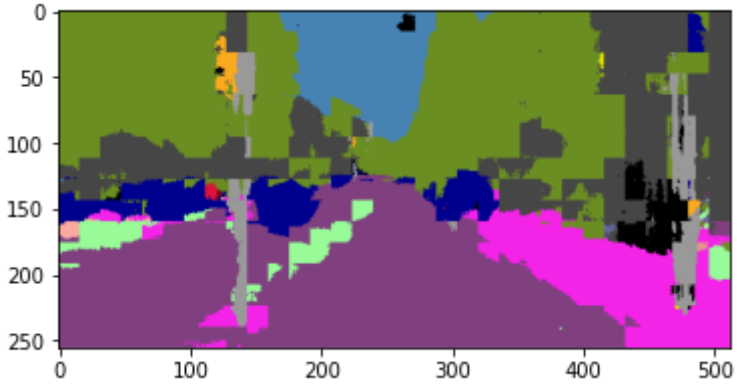
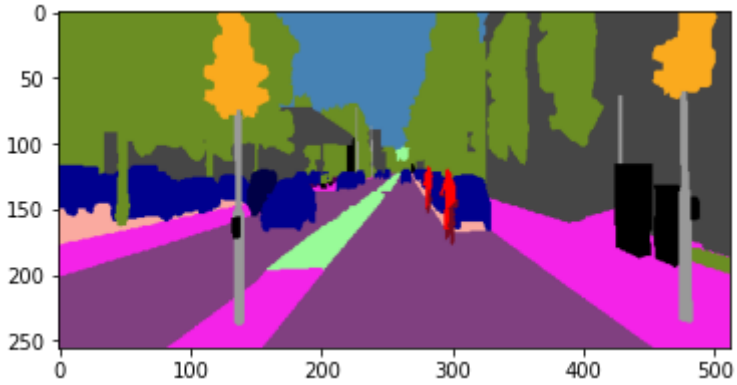
```
Test set Number:  22
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.27982476478884394
Dice:  0.3451869345183699
```



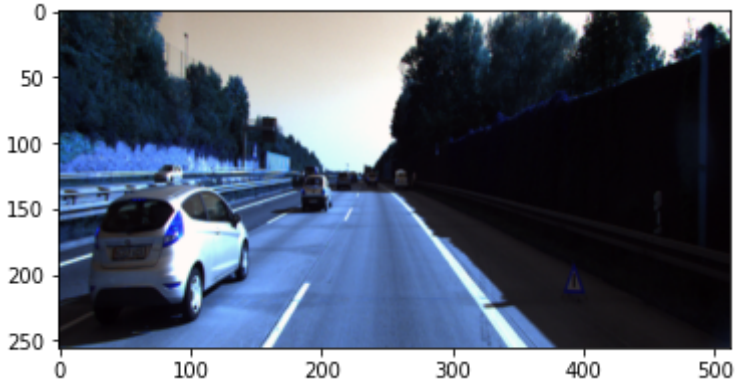
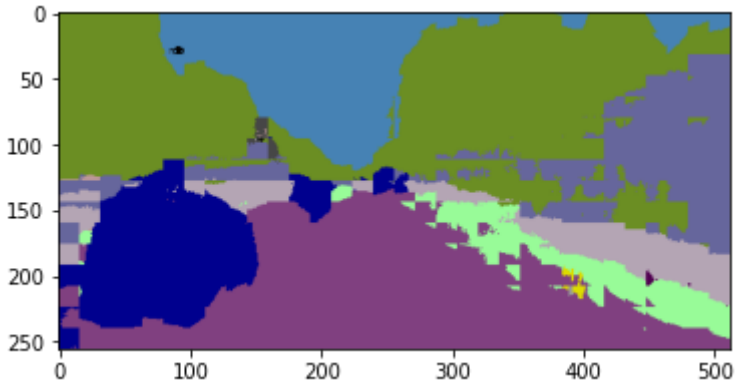


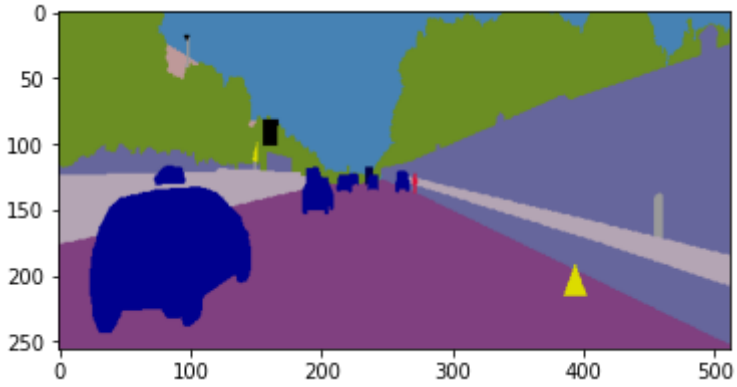


```
Test set Number:  23
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.2538665278997274
Dice:  0.32608584871224455
```

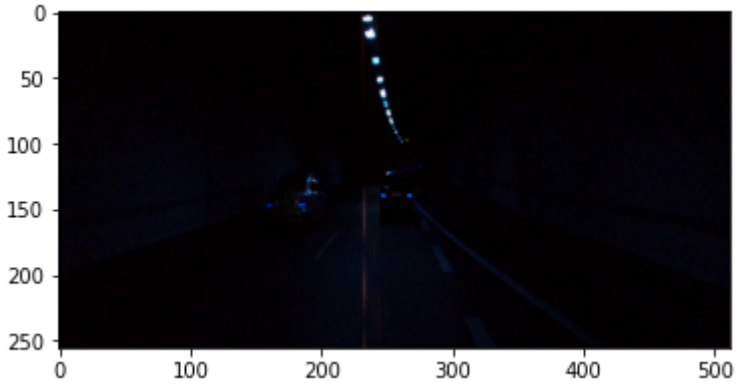




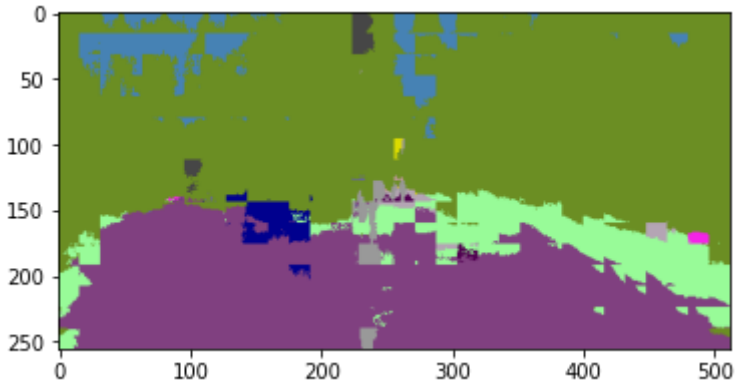
```
Test set Number:  24
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.2850189576481091
Dice:  0.342543047549985
```

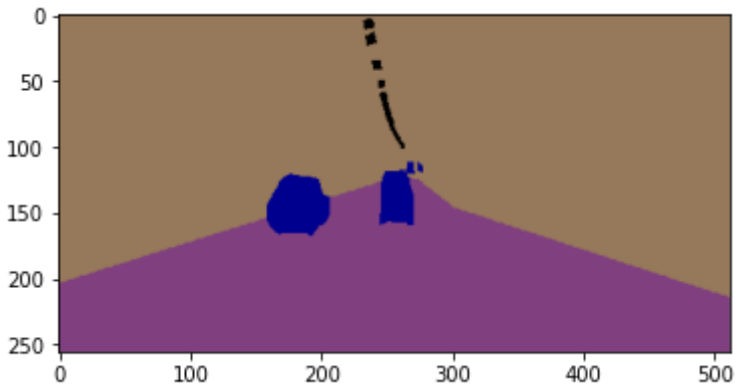





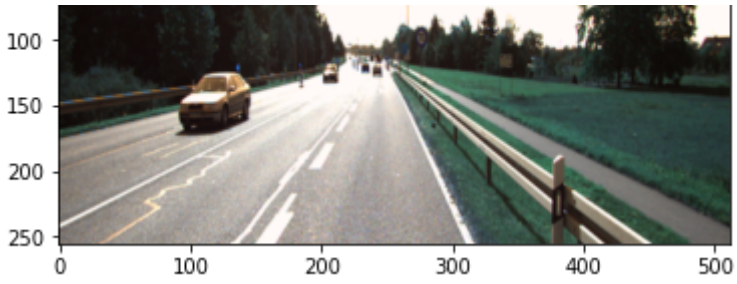
```
Test set Number:  25
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.06177069300187014
Dice:  0.07592515196681485
```

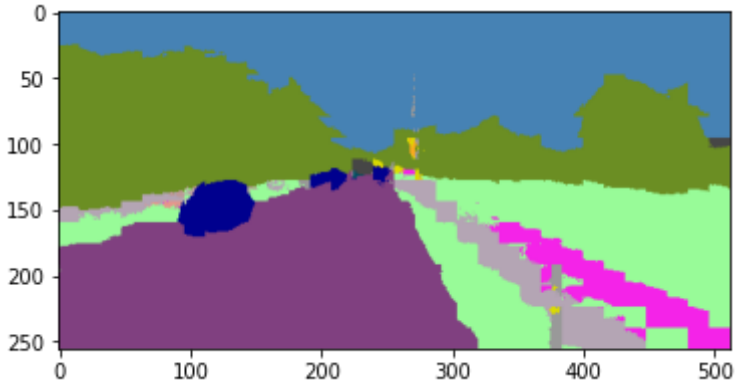


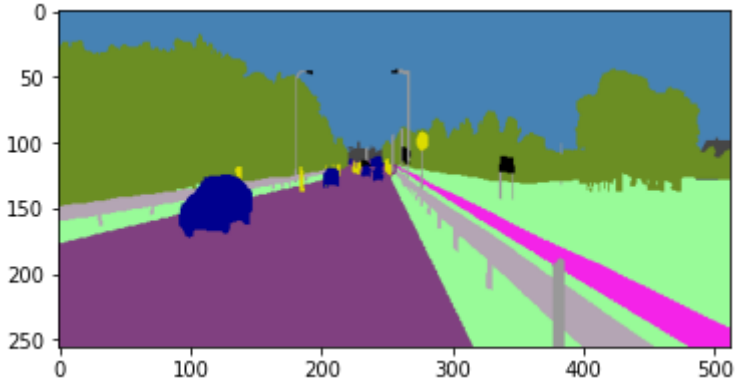




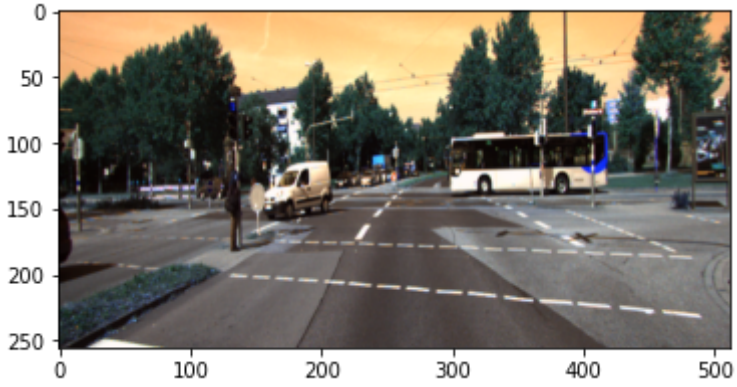
```
Test set Number:  26
IoU:  0.3742639293547273
Dice:  0.4288261269461293
```

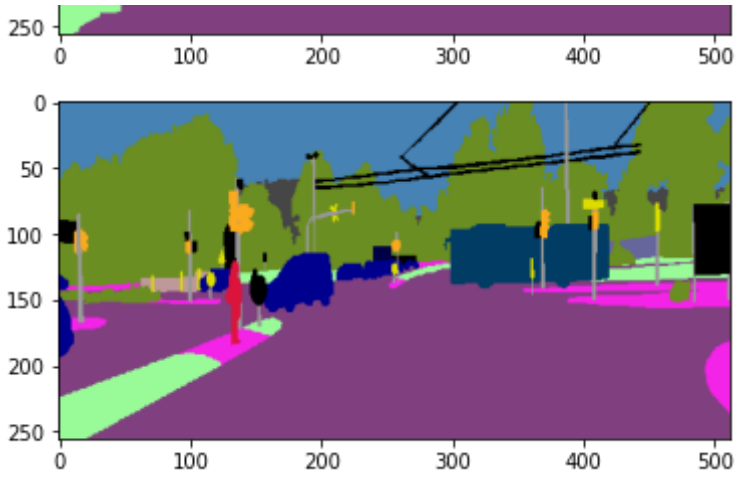




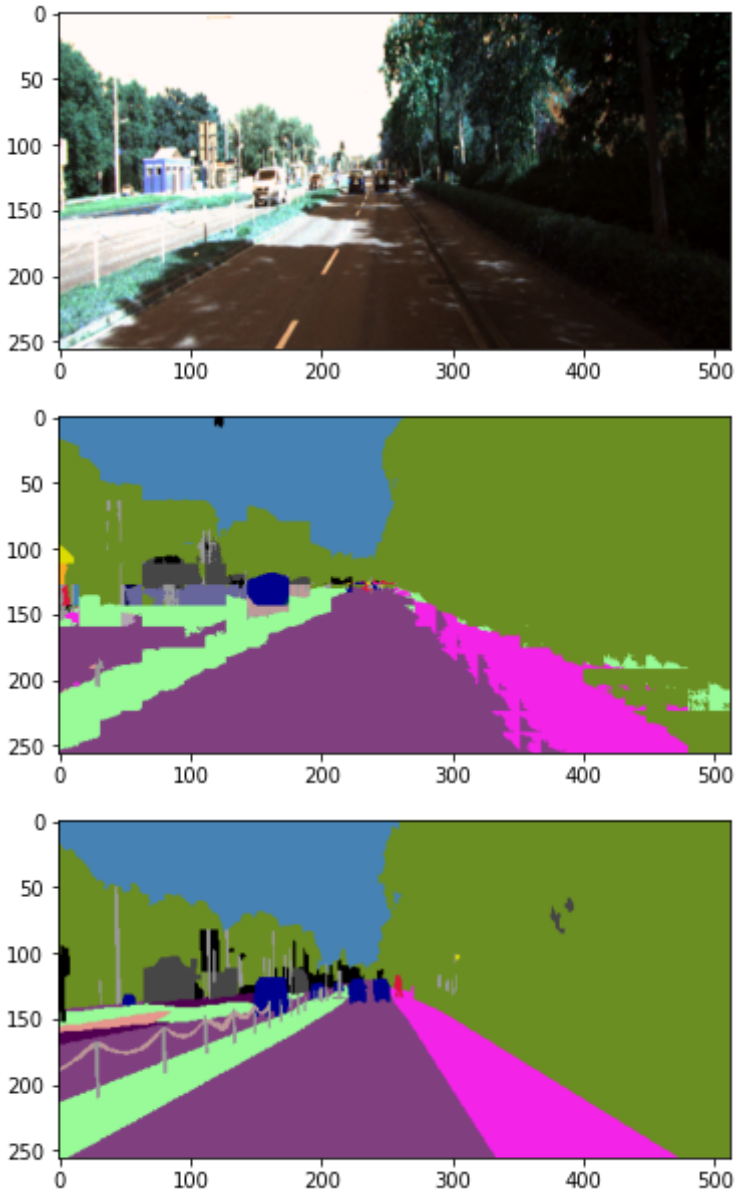


```
Test set Number:  27
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.2424309001515683
Dice:  0.3178963208223133
```

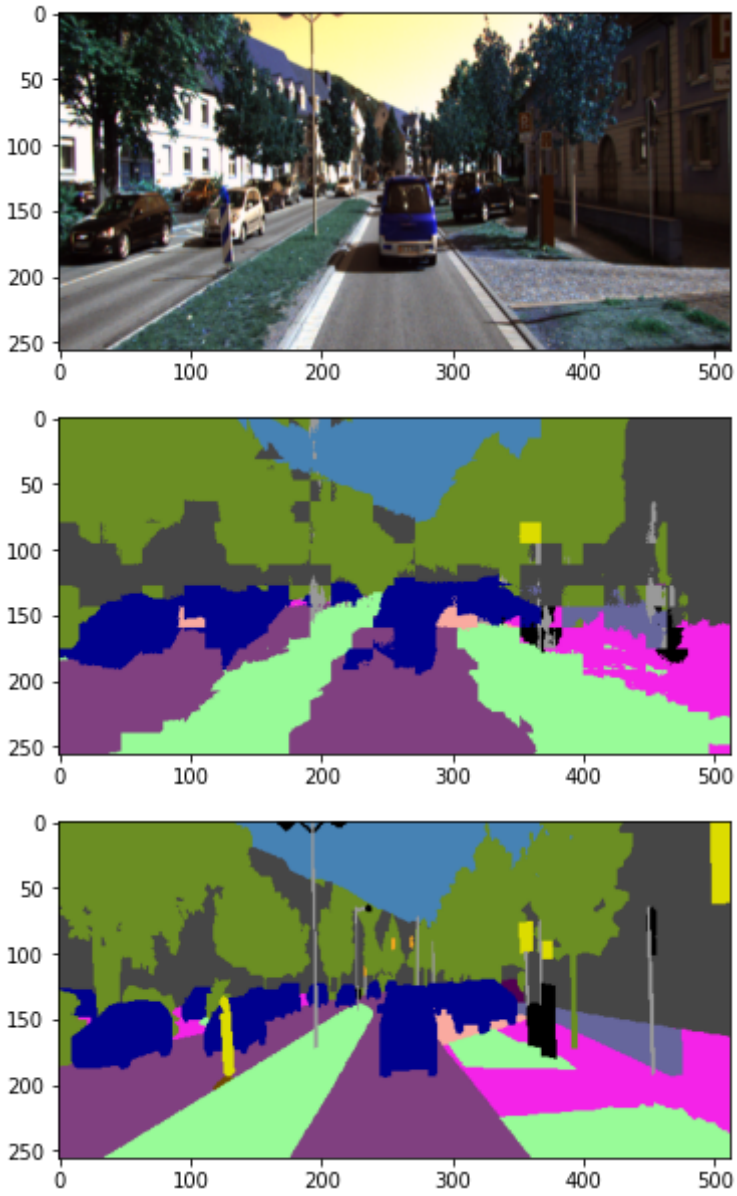




```
Test set Number:  28
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.2476639916627642
Dice:  0.2975545443083053
```



```
Test set Number:  29
Clipping input data to the valid range for imshow with RGB data ([0..1] for floa
IoU:  0.3577634232905005
Dice:  0.44285500528200034
```


0
50
100
150
200
250
0
100
200
300
400
500