Lesson_Three

May 22, 2020

1 Lesson Three: A Guided Walkthrough of a Semantic Segmentation System

Prior to studying this, I recommend reading Jeremy Jordan's overview of semantic image segmentation.

We will be exploring the decisions made throughout the development of a semantic segmentation system. As opposed to exercises, you should run the cells of this notebook and read the provided rationales. This lesson aims to

- Elucidate the process of designing a deep learning system
- Display various best practices
- Showcase the importance of a conceptual understanding of deep learning

Evidently, this code is contained within a Google Colaboratory Notebook. Notebooks are designed for fast experimentation. The code here differs from the source code used in the production system in a number of manners; take a look at the source code to understand how to write code optimized for modularity, readability, and overall robustness.

The semantic segmentation model implemented here is a critical component of Jessii. The model uses **transfer learning**. In transfer learning, a model trained on one task serves as a **backbone** or **encoder** for a model trained on an entirely different task. Jessii uses a U-Net architecture with a EfficientNet encoder trained on ImageNet. This U-Net was trained on competition data stored in the RoboJackets Cloud; it classifies every pixel in an image as a line, barrel, or neither.

Transfer learning is a powerful tool for increasing the performance of a model. The underlying idea is that the current model will inherit useful generalizations from the model used in the encoder. In other words, knowledge of one task will bolster knowledge of another. The decision to use transfer learning was made when a previous U-Net had continuously plateaued at about 60% accuracy during training.

1.1 Environmental Setup

Before anything, we must mount the Drive. Google Colaboratory executes code in a virtual machine, creating its own filesystem. Mounting the Drive allows us to access files within our Drive by shifting it to the allocated virtual machine.

[0]:
```
#Mount Drive
from google.colab import drive
```

```
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

Run `!XYZ` to use Bash commands as if you're working on a separate terminal. We are going to install a library with multiple pretrained segmentation models and Catalyst. These libraries do not come with Google Colab, so we'll use `pip` to install them.

[0]:
```
#Restart runtime after running once

!pip install segmentation-models-pytorch==0.1.0
!pip install -U catalyst
```

```
Requirement already satisfied: segmentation-models-pytorch==0.1.0 in
/usr/local/lib/python3.6/dist-packages (0.1.0)
Requirement already satisfied: pretrainedmodels==0.7.4 in
/usr/local/lib/python3.6/dist-packages (from segmentation-models-pytorch==0.1.0)
(0.7.4)
Requirement already satisfied: torchvision>=0.3.0 in
/usr/local/lib/python3.6/dist-packages (from segmentation-models-pytorch==0.1.0)
(0.6.0+cu101)
Requirement already satisfied: efficientnet-pytorch>=0.5.1 in
/usr/local/lib/python3.6/dist-packages (from segmentation-models-pytorch==0.1.0)
(0.6.3)
Requirement already satisfied: torch in /usr/local/lib/python3.6/dist-packages
(from pretrainedmodels==0.7.4->segmentation-models-pytorch==0.1.0) (1.5.0+cu101)
Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages
(from pretrainedmodels==0.7.4->segmentation-models-pytorch==0.1.0) (4.38.0)
Requirement already satisfied: munch in /usr/local/lib/python3.6/dist-packages
(from pretrainedmodels==0.7.4->segmentation-models-pytorch==0.1.0) (2.5.0)
Requirement already satisfied: pillow>=4.1.1 in /usr/local/lib/python3.6/dist-
packages (from torchvision>=0.3.0->segmentation-models-pytorch==0.1.0) (7.0.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.6/dist-packages
(from torchvision>=0.3.0->segmentation-models-pytorch==0.1.0) (1.18.3)
Requirement already satisfied: future in /usr/local/lib/python3.6/dist-packages
(from torch->pretrainedmodels==0.7.4->segmentation-models-pytorch==0.1.0)
(0.16.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages
(from munch->pretrainedmodels==0.7.4->segmentation-models-pytorch==0.1.0)
(1.12.0)
Requirement already up-to-date: catalyst in /usr/local/lib/python3.6/dist-
packages (20.4.2)
Requirement already satisfied, skipping upgrade: scikit-image>=0.14.2 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (0.16.2)
Requirement already satisfied, skipping upgrade: tqdm>=4.33.0 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (4.38.0)
Requirement already satisfied, skipping upgrade: torch>=1.0.0 in
```

```
/usr/local/lib/python3.6/dist-packages (from catalyst) (1.5.0+cu101)
Requirement already satisfied, skipping upgrade: ipython in
/usr/local/lib/python3.6/dist-packages (from catalyst) (5.5.0)
Requirement already satisfied, skipping upgrade: crc32c>=1.7 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (2.0)
Requirement already satisfied, skipping upgrade: plotly>=4.1.0 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (4.4.1)
Requirement already satisfied, skipping upgrade: torchvision>=0.2.1 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (0.6.0+cu101)
Requirement already satisfied, skipping upgrade: opencv-python in
/usr/local/lib/python3.6/dist-packages (from catalyst) (4.1.2.30)
Requirement already satisfied, skipping upgrade: tensorboard>=1.14.0 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (2.2.1)
Requirement already satisfied, skipping upgrade: numpy>=1.16.4 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (1.18.3)
Requirement already satisfied, skipping upgrade: imageio in
/usr/local/lib/python3.6/dist-packages (from catalyst) (2.4.1)
Requirement already satisfied, skipping upgrade: pandas>=0.22 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (1.0.3)
Requirement already satisfied, skipping upgrade: scikit-learn>=0.20 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (0.22.2.post1)
Requirement already satisfied, skipping upgrade: matplotlib in
/usr/local/lib/python3.6/dist-packages (from catalyst) (3.2.1)
Requirement already satisfied, skipping upgrade: GitPython>=2.1.11 in
/usr/local/lib/python3.6/dist-packages (from catalyst) (3.1.2)
Requirement already satisfied, skipping upgrade: packaging in
/usr/local/lib/python3.6/dist-packages (from catalyst) (20.3)
Requirement already satisfied, skipping upgrade: tensorboardX in
/usr/local/lib/python3.6/dist-packages (from catalyst) (2.0)
Requirement already satisfied, skipping upgrade: deprecation in
/usr/local/lib/python3.6/dist-packages (from catalyst) (2.1.0)
Requirement already satisfied, skipping upgrade: Pillow in
/usr/local/lib/python3.6/dist-packages (from catalyst) (7.0.0)
Requirement already satisfied, skipping upgrade: PyYAML in
/usr/local/lib/python3.6/dist-packages (from catalyst) (3.13)
Requirement already satisfied, skipping upgrade: scipy>=0.19.0 in
/usr/local/lib/python3.6/dist-packages (from scikit-image>=0.14.2->catalyst)
(1.4.1)
Requirement already satisfied, skipping upgrade: PyWavelets>=0.4.0 in
/usr/local/lib/python3.6/dist-packages (from scikit-image>=0.14.2->catalyst)
(1.1.1)
Requirement already satisfied, skipping upgrade: networkx>=2.0 in
/usr/local/lib/python3.6/dist-packages (from scikit-image>=0.14.2->catalyst)
(2.4)
Requirement already satisfied, skipping upgrade: future in
/usr/local/lib/python3.6/dist-packages (from torch>=1.0.0->catalyst) (0.16.0)
Requirement already satisfied, skipping upgrade: traitlets>=4.2 in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (4.3.3)
```

```
Requirement already satisfied, skipping upgrade: pygments in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (2.1.3)
Requirement already satisfied, skipping upgrade: pickleshare in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (0.7.5)
Requirement already satisfied, skipping upgrade: setuptools>=18.5 in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (46.1.3)
Requirement already satisfied, skipping upgrade: prompt-toolkit<2.0.0,>=1.0.4 in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (1.0.18)
Requirement already satisfied, skipping upgrade: decorator in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (4.4.2)
Requirement already satisfied, skipping upgrade: pexpect; sys_platform !=
"win32" in /usr/local/lib/python3.6/dist-packages (from ipython->catalyst)
(4.8.0)
Requirement already satisfied, skipping upgrade: simplegeneric>0.8 in
/usr/local/lib/python3.6/dist-packages (from ipython->catalyst) (0.8.1)
Requirement already satisfied, skipping upgrade: retrying>=1.3.3 in
/usr/local/lib/python3.6/dist-packages (from plotly>=4.1.0->catalyst) (1.3.3)
Requirement already satisfied, skipping upgrade: six in
/usr/local/lib/python3.6/dist-packages (from plotly>=4.1.0->catalyst) (1.12.0)
Requirement already satisfied, skipping upgrade: google-auth<2,>=1.6.3 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(1.7.2)
Requirement already satisfied, skipping upgrade: google-auth-
oauthlib<0.5,>=0.4.1 in /usr/local/lib/python3.6/dist-packages (from
tensorboard>=1.14.0->catalyst) (0.4.1)
Requirement already satisfied, skipping upgrade: protobuf>=3.6.0 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(3.10.0)
Requirement already satisfied, skipping upgrade: markdown>=2.6.8 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(3.2.1)
Requirement already satisfied, skipping upgrade: grpcio>=1.24.3 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(1.28.1)
Requirement already satisfied, skipping upgrade: tensorboard-plugin-wit>=1.6.0
in /usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(1.6.0.post3)
Requirement already satisfied, skipping upgrade: requests<3,>=2.21.0 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(2.23.0)
Requirement already satisfied, skipping upgrade: wheel>=0.26; python_version >=
"3" in /usr/local/lib/python3.6/dist-packages (from
tensorboard>=1.14.0->catalyst) (0.34.2)
Requirement already satisfied, skipping upgrade: absl-py>=0.4 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
(0.9.0)
Requirement already satisfied, skipping upgrade: werkzeug>=0.11.15 in
/usr/local/lib/python3.6/dist-packages (from tensorboard>=1.14.0->catalyst)
```

```
(1.0.1)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.6.1 in
/usr/local/lib/python3.6/dist-packages (from pandas>=0.22->catalyst) (2.8.1)
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in
/usr/local/lib/python3.6/dist-packages (from pandas>=0.22->catalyst) (2018.9)
Requirement already satisfied, skipping upgrade: joblib>=0.11 in
/usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.20->catalyst)
(0.14.1)
Requirement already satisfied, skipping upgrade: cycler>=0.10 in
/usr/local/lib/python3.6/dist-packages (from matplotlib->catalyst) (0.10.0)
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in
/usr/local/lib/python3.6/dist-packages (from matplotlib->catalyst) (1.2.0)
Requirement already satisfied, skipping upgrade:
pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-
packages (from matplotlib->catalyst) (2.4.7)
Requirement already satisfied, skipping upgrade: gitdb<5,>=4.0.1 in
/usr/local/lib/python3.6/dist-packages (from GitPython>=2.1.11->catalyst)
(4.0.5)
Requirement already satisfied, skipping upgrade: ipython-genutils in
/usr/local/lib/python3.6/dist-packages (from traitlets>=4.2->ipython->catalyst)
(0.2.0)
Requirement already satisfied, skipping upgrade: wcwidth in
/usr/local/lib/python3.6/dist-packages (from prompt-
toolkit<2.0.0,>=1.0.4->ipython->catalyst) (0.1.9)
Requirement already satisfied, skipping upgrade: ptyprocess>=0.5 in
/usr/local/lib/python3.6/dist-packages (from pexpect; sys_platform !=
"win32"->ipython->catalyst) (0.6.0)
Requirement already satisfied, skipping upgrade: rsa<4.1,>=3.1.4 in
/usr/local/lib/python3.6/dist-packages (from google-
auth<2,>=1.6.3->tensorboard>=1.14.0->catalyst) (4.0)
Requirement already satisfied, skipping upgrade: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.6/dist-packages (from google-
auth<2,>=1.6.3->tensorboard>=1.14.0->catalyst) (0.2.8)
Requirement already satisfied, skipping upgrade: cachetools<3.2,>=2.0.0 in
/usr/local/lib/python3.6/dist-packages (from google-
auth<2,>=1.6.3->tensorboard>=1.14.0->catalyst) (3.1.1)
Requirement already satisfied, skipping upgrade: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.6/dist-packages (from google-auth-
oauthlib<0.5,>=0.4.1->tensorboard>=1.14.0->catalyst) (1.3.0)
Requirement already satisfied, skipping upgrade: certifi>=2017.4.17 in
/usr/local/lib/python3.6/dist-packages (from
requests<3,>=2.21.0->tensorboard>=1.14.0->catalyst) (2020.4.5.1)
Requirement already satisfied, skipping upgrade: idna<3,>=2.5 in
/usr/local/lib/python3.6/dist-packages (from
requests<3,>=2.21.0->tensorboard>=1.14.0->catalyst) (2.9)
Requirement already satisfied, skipping upgrade:
urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.6/dist-
packages (from requests<3,>=2.21.0->tensorboard>=1.14.0->catalyst) (1.24.3)
```

```
Requirement already satisfied, skipping upgrade: chardet<4,>=3.0.2 in
/usr/local/lib/python3.6/dist-packages (from
requests<3,>=2.21.0->tensorboard>=1.14.0->catalyst) (3.0.4)
Requirement already satisfied, skipping upgrade: smmap<4,>=3.0.1 in
/usr/local/lib/python3.6/dist-packages (from
gitdb<5,>=4.0.1->GitPython>=2.1.11->catalyst) (3.0.4)
Requirement already satisfied, skipping upgrade: pyasn1>=0.1.3 in
/usr/local/lib/python3.6/dist-packages (from rsa<4.1,>=3.1.4->google-
auth<2,>=1.6.3->tensorboard>=1.14.0->catalyst) (0.4.8)
Requirement already satisfied, skipping upgrade: oauthlib>=3.0.0 in
/usr/local/lib/python3.6/dist-packages (from requests-oauthlib>=0.7.0->google-
auth-oauthlib<0.5,>=0.4.1->tensorboard>=1.14.0->catalyst) (3.1.0)
```

The imported statements grab classes, functions, and other objects from either the libraries we just installed or the libraries that come pre-installed with Google Colaboratory.

[0]:
```
#Dependencies

#Handles data
import json
import numpy as np
import matplotlib.pyplot as plt
import cv2
import glob
from operator import itemgetter
import pickle

#Torch utilities
from typing import List
from pathlib import Path
from torch.utils.data import Dataset
import torch

#Data Loader utilities
import collections
from sklearn.model_selection import train_test_split
from torch.utils.data import DataLoader

#Model building and training
import segmentation_models_pytorch as smp
from torch import nn

from catalyst.contrib.nn import DiceLoss, IoULoss
from torch import optim
from torch.optim import AdamW
from catalyst import utils

from catalyst.contrib.nn import RAdam, Lookahead
```

```python
from catalyst.dl import SupervisedRunner

from catalyst.dl.callbacks import DiceCallback, IouCallback, \
  CriterionCallback, AccuracyCallback, MulticlassDiceMetricCallback
```

```
/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning:

numpy.ufunc size changed, may indicate binary incompatibility. Expected 192 from
C header, got 216 from PyObject

/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning:

numpy.ufunc size changed, may indicate binary incompatibility. Expected 192 from
C header, got 216 from PyObject

/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning:

numpy.ufunc size changed, may indicate binary incompatibility. Expected 192 from
C header, got 216 from PyObject
```

Neural network operations often begin with an initialization of random numbers for the parameters. If you run this network multiple times, it will begin with new random numbers (technically psuedorandom). Starting closer or father from the optimal parameter configuration will not only affect how long the network takes to train, but the resultant performance as well. Unlucky parameters can lead to a network getting stuck in a **local minima**. This means the performance will differ between runs.

To prevent this from occuring, we set a specific **seed**- the starting value. Since truly random numbers do not exist, having the random numbers be generated from the same seed will lead to the same results.

[0]:
```python
#Set seed for better reproducibility
SEED = 42
utils.set_global_seed(SEED)
utils.prepare_cudnn(deterministic=True)
```

```
/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning:

numpy.ufunc size changed, may indicate binary incompatibility. Expected 216, got
192

/usr/lib/python3.6/importlib/_bootstrap.py:219: ImportWarning:

can't resolve package from __spec__ or __package__, falling back on __name__ and
__path__
```

1.2 Custom Dataset Creation

Using a custom dataset entails creating a class that inherits PyTorch's Dataset class. We defined the functions **len**() and ___get___item() as they are necessary for PyTorch to execute the training and testing of the system. Note that implementing transformations (but not defining the exact transformations to be used) is typically done during this step.

[0]:
```
#Define and establish a dataset class
class SegmentationDataset(Dataset):
    def __init__(
        self,
        image_arr_path,
        mask_arr_path,
    ) -> None:
        self.images = np.load(image_arr_path)
        self.masks = np.load(mask_arr_path)

    def __len__(self) -> int:
        return len(self.images)

    def __getitem__(self, idx: int) -> dict:
        image = self.images[idx]
        image = np.swapaxes(image, 2, 0)
        image = np.swapaxes(image, 2, 1)
        image = torch.from_numpy(image).float()
        result = {"image": image}

        if self.masks is not None:
            mask = self.masks[idx]
            mask = np.swapaxes(mask, 2, 0)
            mask = np.swapaxes(mask, 2, 1)
            mask = torch.from_numpy(mask).float()
            result["mask"] = mask
        return result
```

It is not explicitly necessary to load the dataset outside of the main training loop, but it enables data exploration and sanity checks. Techniques for data exploration is outside the scope of this notebook, but it should be done when faced with any data science or machine learning task.

[0]:
```
#Load dataset once to enable visualizion prior to model training
dset = SegmentationDataset(image_arr_path="/content/drive/Shared drives/
 ↪Intelligent Ground Vehicle Competition/Previous Year Resources/2019-2020␣
 ↪Season/Software/Collab Notebooks/train_images.npy",
                           mask_arr_path="/content/drive/Shared drives/
 ↪Intelligent Ground Vehicle Competition/Previous Year Resources/2019-2020␣
 ↪Season/Software/Collab Notebooks/train_masks.npy")
```

Pay attention to the shapes of the images, masks, and the length of the dataset,

especially as they change throughout this notebook.

```
[0]: #Show sizes of the image and mask
     out = dset[0]
     out["image"].shape, out["mask"].shape, len(dset)
```

```
[0]: (torch.Size([3, 480, 640]), torch.Size([1, 480, 640]), 592)
```

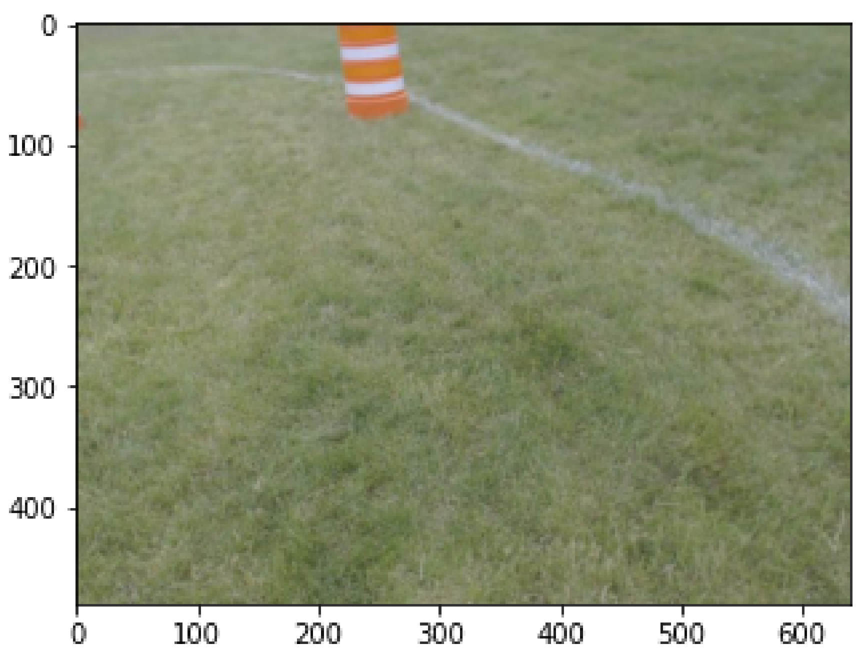
A numpy array is generated by the first line. This array describes an image (as indicated by the key).

Plt.imshow() displays color images, but it requests data in the format of (M, N, 3) where M represents rows and N represents columns with a numerical type. The original image was a numpy array with numerical values of an incompatible type in the form of (3, M, N), requiring us to swap axes and specify the data type. See what happens you comment out any one of lines 2 - 4.

Our original dataset was in BGR form, but plt.imshow() expects RGB data. We used OpenCV for the conversion in line 5. If this were not done, the orange barrel would be blue! Try it for yourself.

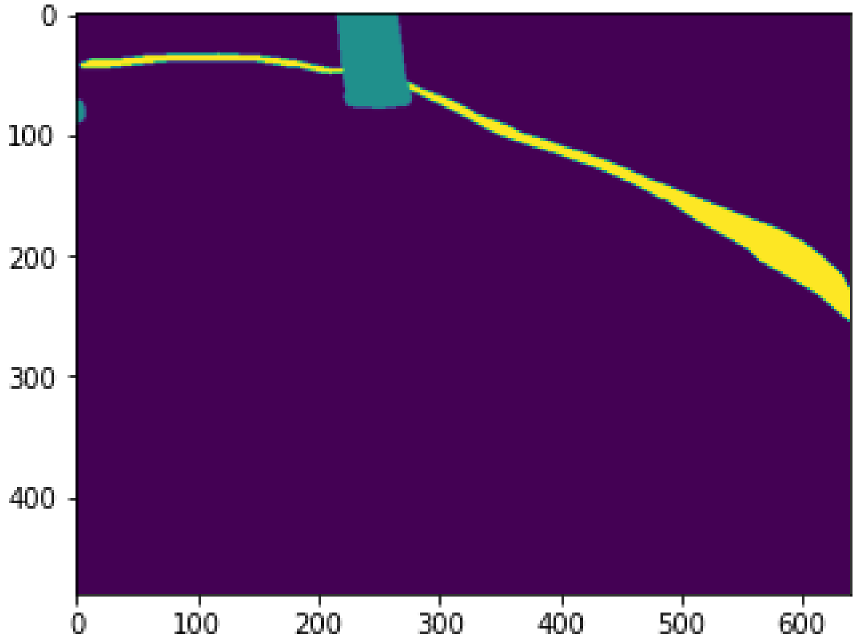
```
[0]: #Show an image
     image = np.asarray(dset[40]['image'])
     image = np.swapaxes(image, 2, 0)
     image = np.swapaxes(image, 1, 0)
     image = image.astype(np.uint8)
     plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
```

```
[0]: <matplotlib.image.AxesImage at 0x7efd7710b550>
```



```
[0]: #Show associated mask
mask = np.squeeze(dset[40]['mask'])
plt.imshow(mask)
```

```
[0]: <matplotlib.image.AxesImage at 0x7efd76894b38>
```



ImageNet is a large dataset used for object detection and an important benchmark utility in the field of machine learning. While lines and barrels like the ones comprising our competition data are not explicitly defined in ImageNet, the hope is that knowledge of many different objects will transfer to knowledge of lines and barrels.

Many encoders could have been used, but EfficientNet was chosen for its high performance and relatively low parameter count.

Always remember to define the device and number of classes!

1.3 Model Architecture Design

```
[0]: #Set up U-Net with EfficientNet backbone pretrained on ImageNet

ENCODER = 'efficientnet-b3'
ENCODER_WEIGHTS = 'imagenet'
DEVICE = 'cuda'
ACTIVATION = None

model = smp.Unet(
```

```
    encoder_name=ENCODER,
    encoder_weights=ENCODER_WEIGHTS,
    classes=3,
    activation=ACTIVATION,
)
```

PyTorch DataLoaders allow us to efficiently iterate over the data while also batching the data, shuffling the data, and calling workers to run the data in parallel. If `num_workers` was set as only 1 instead of 4, there would be a large bottleneck within the system. The ideal number depends on the use case, dataset size, and network size.

1.4 Custom DataLoader Creation

[0]:
```
#Define loaders

def get_loaders(
    images: List[Path],
    masks: List[Path],
    image_arr_path: str,
    mask_arr_path: str,
    random_state: int,
    valid_size: float = 0.1,
    batch_size: int = 12,
    num_workers: int = 4,
    ) -> dict:

    indices = np.arange(len(images))

    train_indices, valid_indices = train_test_split(
      indices, test_size=valid_size, random_state=random_state, shuffle=True
    )

    np_images = np.array(images)
    np_masks = np.array(masks)


    train_dataset = SegmentationDataset(image_arr_path, mask_arr_path)
    train_dataset.images = np_images[train_indices]
    train_dataset.masks = np_masks[train_indices]

    valid_dataset = SegmentationDataset(image_arr_path, mask_arr_path)
    valid_dataset.images = np_images[valid_indices]
    valid_dataset.masks = np_masks[valid_indices]

    train_loader = DataLoader(
      train_dataset,
```

```
      batch_size=batch_size,
      shuffle=False,
      num_workers=num_workers,
      drop_last=False,
    )

    valid_loader = DataLoader(
      valid_dataset,
      batch_size=batch_size,
      shuffle=False,
      num_workers=num_workers,
      drop_last=False,
    )

    loaders = collections.OrderedDict()
    loaders["train"] = train_loader
    loaders["valid"] = valid_loader

    return loaders
```

[0]:
```
#Get loaders

loaders = get_loaders(
    images=np.load("/content/drive/Shared drives/Intelligent Ground Vehicle␣
 ↪Competition/Previous Year Resources/2019-2020 Season/Software/Collab␣
 ↪Notebooks/train_images.npy"),
    masks=np.load("/content/drive/Shared drives/Intelligent Ground Vehicle␣
 ↪Competition/Previous Year Resources/2019-2020 Season/Software/Collab␣
 ↪Notebooks/train_masks.npy"),
    image_arr_path="/content/drive/Shared drives/Intelligent Ground Vehicle␣
 ↪Competition/Previous Year Resources/2019-2020 Season/Software/Collab␣
 ↪Notebooks/train_images.npy",
    mask_arr_path="/content/drive/Shared drives/Intelligent Ground Vehicle␣
 ↪Competition/Previous Year Resources/2019-2020 Season/Software/Collab␣
 ↪Notebooks/train_masks.npy",
    random_state=420,
    valid_size=0.1,
    batch_size=3,
    num_workers=2,
)
```

Here, a lot of numerical operations were rewritten to optimize efficiency and effectiveness. This typically does not need to be done due to the newest release of Catalyst.

[0]:
```
#    Helpful code taken from Joseph Chen
#
```

```python
#    Copyright 2019 Division of Medical Image Computing, German Cancer Research Center (DKFZ), Heidelberg, Germany
#
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#    limitations under the License.

import torch
from torch import nn
import numpy as np

def sum_tensor(inp, axes, keepdim=False):
    axes = np.unique(axes).astype(int)
    if keepdim:
        for ax in axes:
            inp = inp.sum(int(ax), keepdim=True)
    else:
        for ax in sorted(axes, reverse=True):
            inp = inp.sum(int(ax))
    return inp

def softmax_helper(x):
    rpt = [1 for _ in range(len(x.size()))]
    rpt[1] = x.size(1)
    x_max = x.max(1, keepdim=True)[0].repeat(*rpt)
    e_x = torch.exp(x - x_max)
    return e_x / e_x.sum(1, keepdim=True).repeat(*rpt)

class CrossentropyND(nn.CrossEntropyLoss):
    """
    Network has to have NO NONLINEARITY!
    """
    def forward(self, inp, target):
        target = target.long()
        num_classes = inp.size()[1]

        i0 = 1
        i1 = 2
```

```
        while i1 < len(inp.shape):
            inp = inp.transpose(i0, i1)
            i0 += 1
            i1 += 1

        inp = inp.contiguous()
        inp = inp.view(-1, num_classes)

        target = target.view(-1,)

        return super(CrossentropyND, self).forward(inp, target)

def get_tp_fp_fn(net_output, gt, axes=None, mask=None, square=False):
    """
    net_output must be (b, c, x, y(, z)))
    gt must be a label map (shape (b, 1, x, y(, z)) OR shape (b, x, y(, z))) or␣
 ↪one hot encoding (b, c, x, y(, z))
    if mask is provided it must have shape (b, 1, x, y(, z)))
    :param net_output:
    :param gt:
    :param axes:
    :param mask: mask must be 1 for valid pixels and 0 for invalid pixels
    :param square: if True then fp, tp and fn will be squared before summation
    :return:
    """
    if axes is None:
        axes = tuple(range(2, len(net_output.size())))

    shp_x = net_output.shape
    shp_y = gt.shape

    with torch.no_grad():
        if len(shp_x) != len(shp_y):
            gt = gt.view((shp_y[0], 1, *shp_y[1:]))

        if all([i == j for i, j in zip(net_output.shape, gt.shape)]):
            # if this is the case then gt is probably already a one hot encoding
            y_onehot = gt
        else:
            gt = gt.long()
            y_onehot = torch.zeros(shp_x)
            if net_output.device.type == "cuda":
                y_onehot = y_onehot.cuda(net_output.device.index)
            y_onehot.scatter_(1, gt, 1)

    tp = net_output * y_onehot
    fp = net_output * (1 - y_onehot)
```

```
    fn = (1 - net_output) * y_onehot

    if mask is not None:
        tp = torch.stack(tuple(x_i * mask[:, 0] for x_i in torch.unbind(tp,␣
↪dim=1)), dim=1)
        fp = torch.stack(tuple(x_i * mask[:, 0] for x_i in torch.unbind(fp,␣
↪dim=1)), dim=1)
        fn = torch.stack(tuple(x_i * mask[:, 0] for x_i in torch.unbind(fn,␣
↪dim=1)), dim=1)

    if square:
        tp = tp ** 2
        fp = fp ** 2
        fn = fn ** 2

    tp = sum_tensor(tp, axes, keepdim=False)
    fp = sum_tensor(fp, axes, keepdim=False)
    fn = sum_tensor(fn, axes, keepdim=False)

    return tp, fp, fn


class SoftDiceLoss(nn.Module):
    def __init__(self, apply_nonlin=None, batch_dice=False, do_bg=True,
                 smooth=1., square=False):
        super(SoftDiceLoss, self).__init__()

        self.square = square
        self.do_bg = do_bg
        self.batch_dice = batch_dice
        self.apply_nonlin = apply_nonlin
        self.smooth = smooth

    def forward(self, x, y, loss_mask=None):
        shp_x = x.shape

        if self.batch_dice:
            axes = [0] + list(range(2, len(shp_x)))
        else:
            axes = list(range(2, len(shp_x)))

        if self.apply_nonlin is not None:
            x = self.apply_nonlin(x)

        tp, fp, fn = get_tp_fp_fn(x, y, axes, loss_mask, self.square)

        dc = (2 * tp + self.smooth) / (2 * tp + fp + fn + self.smooth)
```

```python
        if not self.do_bg:
            if self.batch_dice:
                dc = dc[1:]
            else:
                dc = dc[:, 1:]
        dc = dc.mean()

        return -dc


class DC_and_CE_loss(nn.Module):
    def __init__(self, soft_dice_kwargs, ce_kwargs, aggregate="sum"):
        super(DC_and_CE_loss, self).__init__()
        self.aggregate = aggregate
        self.ce = CrossentropyND(**ce_kwargs)
        self.dc = SoftDiceLoss(apply_nonlin=softmax_helper, **soft_dice_kwargs)

    def forward(self, net_output, target):
        dc_loss = self.dc(net_output, target)
        ce_loss = self.ce(net_output, target)
        if self.aggregate == "sum":
            result = ce_loss + dc_loss
        else:
            raise NotImplementedError("did not work")
        return result
```

The loss criterion, optimizer, and learning rate configuration requires multiple choices to made based upon the differences between the available options. Cross Entropy Loss will not always be the criterion best suited for the task. However, it is general enough to work for most systems.

[0]:
```python
#Define loss criterion
criterion = {
    "CE": CrossentropyND(),
}

#Configure model optimization
learning_rate = 0.001
encoder_learning_rate = 0.0005
encoder_weight_decay = 0.00003
optimizer_weight_decay = 0.0003
optim_factor = 0.25
optim_patience = 2

optimizer = AdamW(model.parameters(), lr=0.001, betas=(0.9, 0.999), eps=1e-08,
 ↪weight_decay=0.01, amsgrad=False)
```

```
#Use scheduler for improved results
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer,␣
 ↪factor=optim_factor, patience=optim_patience)

num_epochs = 10
device = utils.get_device()

runner = SupervisedRunner(device=device, input_key="image",␣
 ↪input_target_key="mask")
```

1.5 Model Training and Testing

Callbacks are a significant feature of Catalyst that allow the reuse of components of the machine learning pipeline with easy customization. This notebook relies upon the more fundamental use case of metric calculations, but callbacks can be used for more complex affordances.

[0]:
```
#Establish calculations during training through Catalyst callbacks
callbacks = [
        CriterionCallback(
            input_key="mask",
            prefix="loss",
            criterion_key="CE"
        ),
        MulticlassDiceMetricCallback(input_key="mask")
        ]
```

The training loop is where the operations we defined earlier are executed. This is the meat of the system; the cell will run for quite some time in order to finish training the model. To integrate TensorBoard, the logdir parameter is essential.

[0]:
```
#Run training loop
runner.train(
    model=model,
    criterion=criterion,
    optimizer=optimizer,
    scheduler=scheduler,
    loaders=loaders,
    callbacks=callbacks,
    logdir='content/full_model2', #this logdir must be changed with every new␣
 ↪run
    num_epochs=num_epochs,
    main_metric="loss",
    minimize_metric=True,
    fp16=None,
    verbose=True,
)
```

```
1/10 * Epoch (train):   0% 0/178 [00:00<?, ?it/s]

/usr/local/lib/python3.6/dist-packages/efficientnet_pytorch/utils.py:45:
DeprecationWarning:

'saved_variables' is deprecated; use 'saved_tensors'


1/10 * Epoch (train):   1% 1/178 [00:04<14:02,  4.76s/it, loss=1.809]

/pytorch/torch/csrc/utils/python_arg_parser.cpp:756: UserWarning:

This overload of add is deprecated:
        add(Number alpha, Tensor other)
Consider using one of the following signatures instead:
        add(Tensor other, *, Number alpha)


1/10 * Epoch (train): 100% 178/178 [01:19<00:00,  2.25it/s, loss=0.053]
1/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.02it/s, loss=0.131]
[2020-05-06 03:12:32,198]
1/10 * Epoch 1 (_base): lr=0.0010 | momentum=0.9000
1/10 * Epoch 1 (train): dice_0=0.9633 | dice_1=0.0117 | dice_2=0.5902 |
dice_mean=0.5218 | loss=0.2070
1/10 * Epoch 1 (valid): dice_0=0.9830 | dice_1=0.4567 | dice_2=0.7392 |
dice_mean=0.7263 | loss=0.1035
2/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.52it/s, loss=0.042]
2/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  6.94it/s, loss=0.087]
[2020-05-06 03:13:47,599]
2/10 * Epoch 2 (_base): lr=0.0010 | momentum=0.9000
2/10 * Epoch 2 (train): dice_0=0.9899 | dice_1=0.5369 | dice_2=0.8212 |
dice_mean=0.7827 | loss=0.0570
2/10 * Epoch 2 (valid): dice_0=0.9871 | dice_1=0.6465 | dice_2=0.7723 |
dice_mean=0.8020 | loss=0.0754
3/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.53it/s, loss=0.034]
3/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.16it/s, loss=0.062]
[2020-05-06 03:15:02,779]
3/10 * Epoch 3 (_base): lr=0.0010 | momentum=0.9000
3/10 * Epoch 3 (train): dice_0=0.9916 | dice_1=0.7126 | dice_2=0.8468 |
dice_mean=0.8503 | loss=0.0443
3/10 * Epoch 3 (valid): dice_0=0.9880 | dice_1=0.7442 | dice_2=0.7713 |
dice_mean=0.8345 | loss=0.0698
4/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.53it/s, loss=0.033]
4/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.08it/s, loss=0.043]
[2020-05-06 03:16:18,282]
4/10 * Epoch 4 (_base): lr=0.0010 | momentum=0.9000
4/10 * Epoch 4 (train): dice_0=0.9936 | dice_1=0.8940 | dice_2=0.8615 |
dice_mean=0.9164 | loss=0.0350
4/10 * Epoch 4 (valid): dice_0=0.9888 | dice_1=0.8702 | dice_2=0.7936 |
dice_mean=0.8842 | loss=0.0689
```

```
5/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.52it/s, loss=0.030]
5/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.08it/s, loss=0.042]
[2020-05-06 03:17:33,545]
5/10 * Epoch 5 (_base): lr=0.0010 | momentum=0.9000
5/10 * Epoch 5 (train): dice_0=0.9939 | dice_1=0.9067 | dice_2=0.8665 |
dice_mean=0.9224 | loss=0.0328
5/10 * Epoch 5 (valid): dice_0=0.9890 | dice_1=0.9114 | dice_2=0.8091 |
dice_mean=0.9031 | loss=0.0744
6/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.52it/s, loss=0.027]
6/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.05it/s, loss=0.042]
[2020-05-06 03:18:48,028]
6/10 * Epoch 6 (_base): lr=0.0010 | momentum=0.9000
6/10 * Epoch 6 (train): dice_0=0.9942 | dice_1=0.9276 | dice_2=0.8717 |
dice_mean=0.9312 | loss=0.0304
6/10 * Epoch 6 (valid): dice_0=0.9852 | dice_1=0.7874 | dice_2=0.6706 |
dice_mean=0.8144 | loss=0.0824
7/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.53it/s, loss=0.023]
7/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.00it/s, loss=0.024]
[2020-05-06 03:20:02,766]
7/10 * Epoch 7 (_base): lr=0.0010 | momentum=0.9000
7/10 * Epoch 7 (train): dice_0=0.9943 | dice_1=0.9276 | dice_2=0.8752 |
dice_mean=0.9324 | loss=0.0293
7/10 * Epoch 7 (valid): dice_0=0.9903 | dice_1=0.9452 | dice_2=0.8133 |
dice_mean=0.9163 | loss=0.0635
8/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.53it/s, loss=0.021]
8/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.02it/s, loss=0.021]
[2020-05-06 03:21:17,944]
8/10 * Epoch 8 (_base): lr=0.0010 | momentum=0.9000
8/10 * Epoch 8 (train): dice_0=0.9952 | dice_1=0.9630 | dice_2=0.8904 |
dice_mean=0.9495 | loss=0.0240
8/10 * Epoch 8 (valid): dice_0=0.9907 | dice_1=0.9427 | dice_2=0.8233 |
dice_mean=0.9189 | loss=0.0634
9/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.53it/s, loss=0.017]
9/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  6.99it/s, loss=0.021]
[2020-05-06 03:22:32,991]
9/10 * Epoch 9 (_base): lr=0.0010 | momentum=0.9000
9/10 * Epoch 9 (train): dice_0=0.9956 | dice_1=0.9658 | dice_2=0.9006 |
dice_mean=0.9540 | loss=0.0213
9/10 * Epoch 9 (valid): dice_0=0.9904 | dice_1=0.9552 | dice_2=0.8139 |
dice_mean=0.9199 | loss=0.0638
10/10 * Epoch (train): 100% 178/178 [01:10<00:00,  2.53it/s, loss=0.019]
10/10 * Epoch (valid): 100% 20/20 [00:02<00:00,  7.10it/s, loss=0.020]
[2020-05-06 03:23:47,139]
10/10 * Epoch 10 (_base): lr=0.0010 | momentum=0.9000
10/10 * Epoch 10 (train): dice_0=0.9959 | dice_1=0.9723 | dice_2=0.9058 |
dice_mean=0.9580 | loss=0.0197
10/10 * Epoch 10 (valid): dice_0=0.9907 | dice_1=0.9630 | dice_2=0.8243 |
dice_mean=0.9260 | loss=0.0664
```

```
Top best models:
content/full_model2/checkpoints/train.8.pth     0.0634
```

In order to observe how our model does on the test dataset, we have to establish our test dataset, create a DataLoader to generate the predictions of the model, and convert the predictions into a usable format (this often involves usage of Torch's cpu() and numpy() methods).

[0]:
```
#Test model on test dataset
test_data = SegmentationDataset("/content/drive/Shared drives/Intelligent␣
 ↪Ground Vehicle Competition/Previous Year Resources/2019-2020 Season/Software/
 ↪Collab Notebooks/test_images.npy",
                                "/content/drive/Shared drives/Intelligent␣
 ↪Ground Vehicle Competition/Previous Year Resources/2019-2020 Season/Software/
 ↪Collab Notebooks/test_masks.npy")
```

[0]:
```
#Create loader for predictions
infer_loader = DataLoader(
    test_data,
    batch_size=12,
    shuffle=False,
    num_workers=4
)
```

[0]:
```
#Get model predictions on test dataset
predictions = np.vstack(list(map(
    lambda x: x["logits"].cpu().numpy(),
    runner.predict_loader(loader=infer_loader, resume=f"content/full_model2/
 ↪checkpoints/best.pth")
)))

print(type(predictions))
print(predictions.shape)
```

```
<class 'numpy.ndarray'>
(149, 3, 480, 640)
```

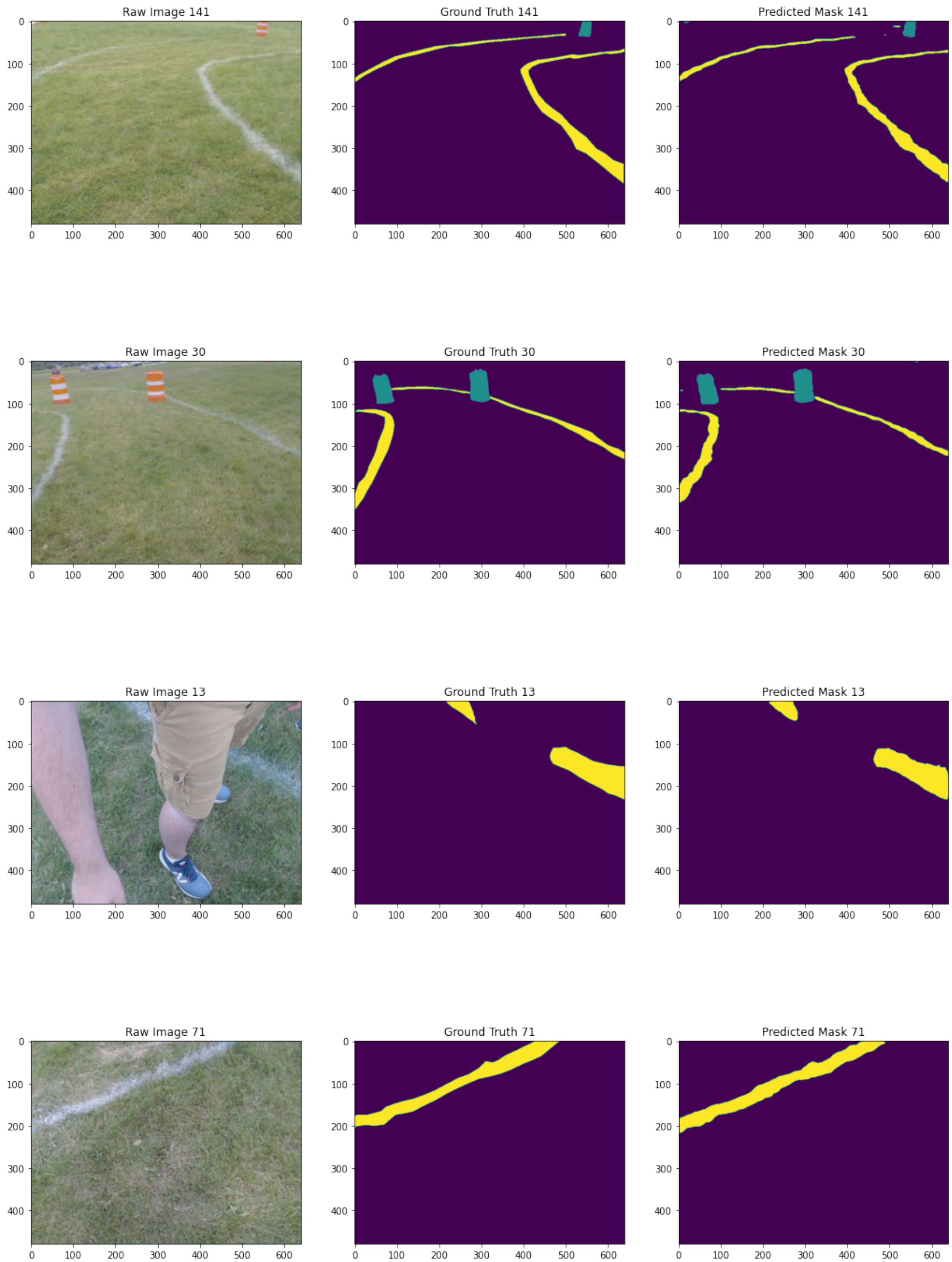
Here, random images will be drawn to showcase the predictions. The results specifically include images 30 and 141 as they are images containing multiple lines and barrels. Hence, they would be strong indicators of performance.

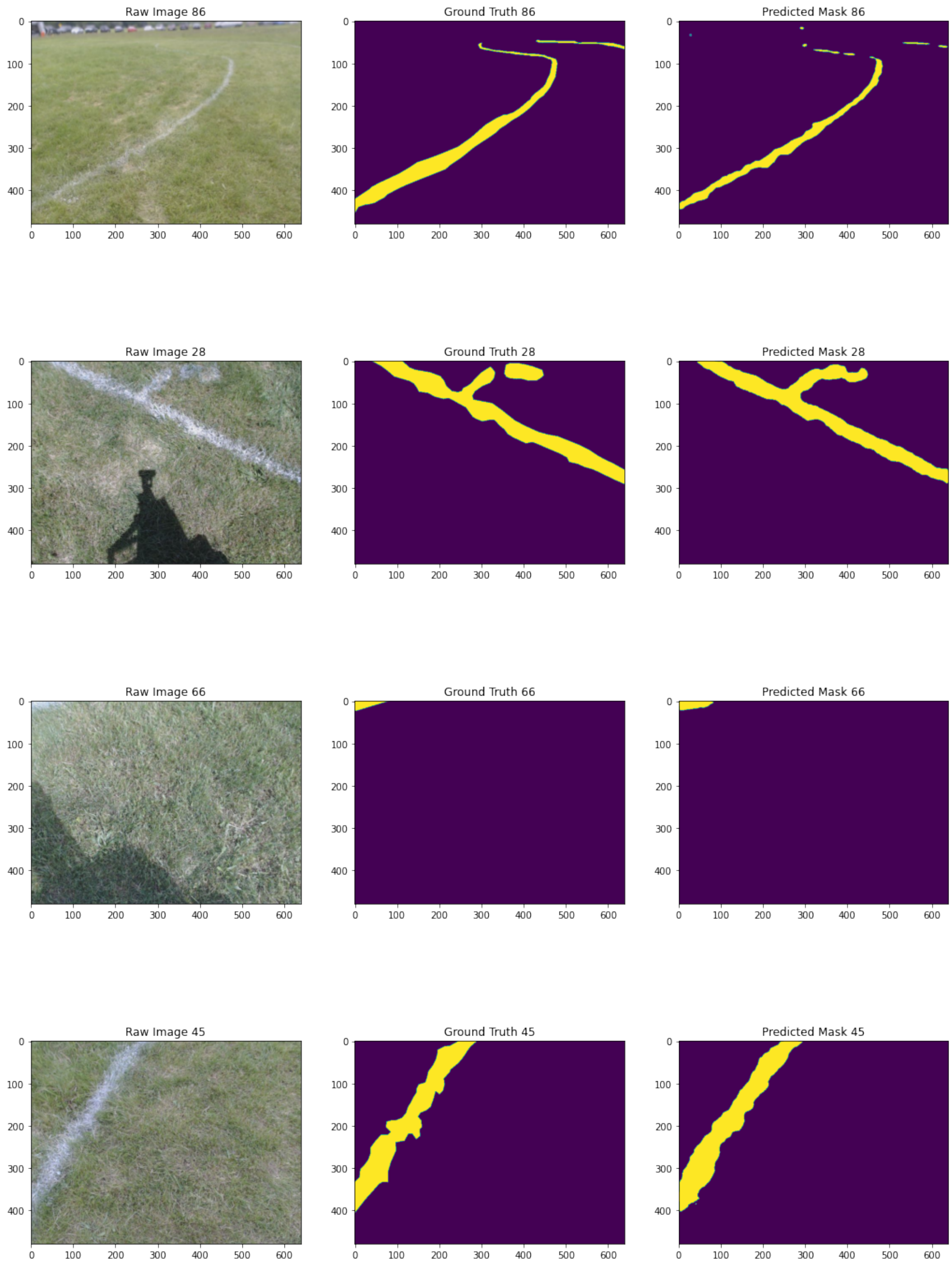
The code shown here differs between notebook and local enviornments. Look here to see what figure generation is like in a local setting.

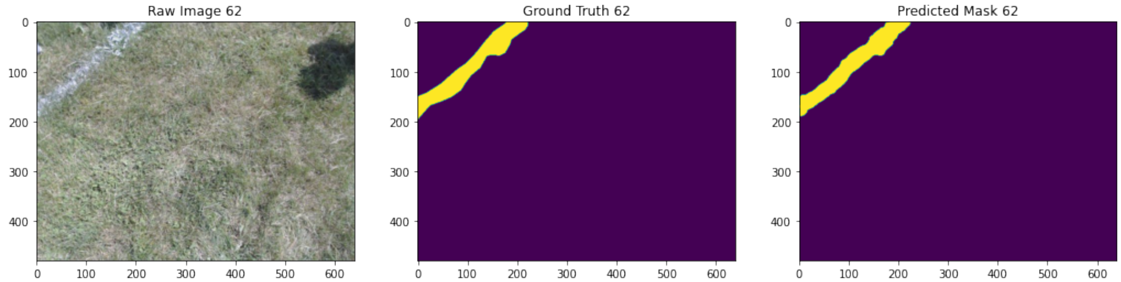
Once again, pay attention to the operations utilized to turn the image and mask arrays into a visible image.

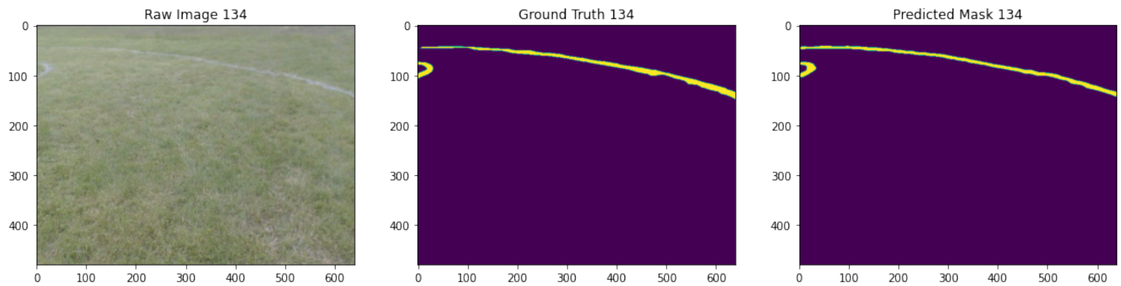
[0]:
```
#Display sample prediction results
pred_results = {}
rand_nums = np.random.randint(low=1, high=148, size=18)
rand_nums = np.insert(rand_nums, 0, 30)
```

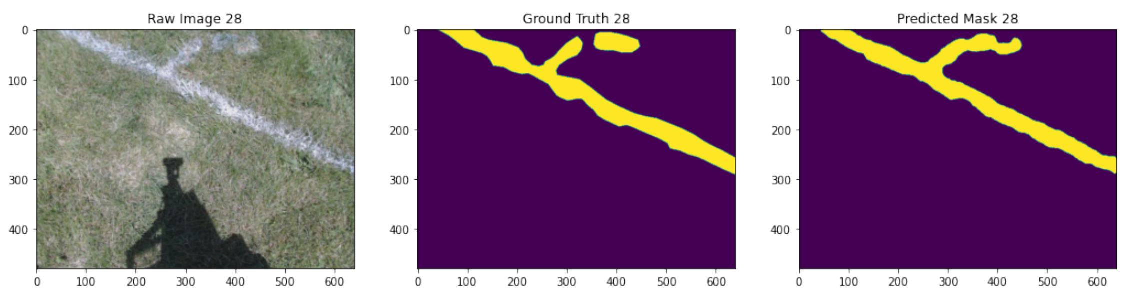
```
rand_nums = np.insert(rand_nums, 0, 141)

for num in rand_nums:00
    #Show image
    image = np.asarray(test_data[num]['image'])
    image = np.swapaxes(image, 2, 0)
    image = np.swapaxes(image, 1, 0)
    image = image.astype(np.uint8)

    #Show mask
    mask = np.squeeze(test_data[num]['mask'])

    #Show predicted mask
    pred_mask = np.asarray(predictions[num])
    pred_mask = np.swapaxes(pred_mask, 2, 0)
    pred_mask = np.swapaxes(pred_mask, 1, 0)
    pred_mask = pred_mask.astype(np.float64)
    pred_mask = np.argmax(pred_mask, axis=2)

    #Add three images to list
    images = []
    images.append(image)
    images.append(mask)
    images.append(pred_mask)

    #Show and plot all three images
    plt.figure(figsize=(30,30))
    columns = 5
    for i, image in enumerate(images):
        image_plot = plt.subplot(len(images) / columns + 1, columns, i + 1)
        if i == 0:
            label = 'Raw Image {}'.format(num)
            image_plot.set_title(label)
            result = plt.imshow(cv2.cvtColor(image, cv2.COLOR_BGR2RGB))
        elif i == 1:
            label = 'Ground Truth {}'.format(num)
            image_plot.set_title(label)
            result = plt.imshow(image)
        elif i == 2:
            label = 'Predicted Mask {}'.format(num)
            image_plot.set_title(label)
            result = plt.imshow(image)
        pred_results[label] = result
```

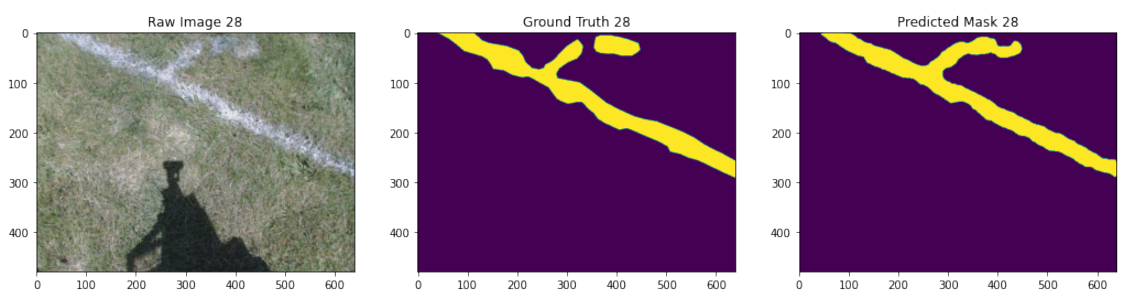

Raw Image 141
Ground Truth 141
Predicted Mask 141
Raw Image 30
Ground Truth 30
Predicted Mask 30
Raw Image 13
Ground Truth 13
Predicted Mask 13
Raw Image 71
Ground Truth 71
Predicted Mask 71

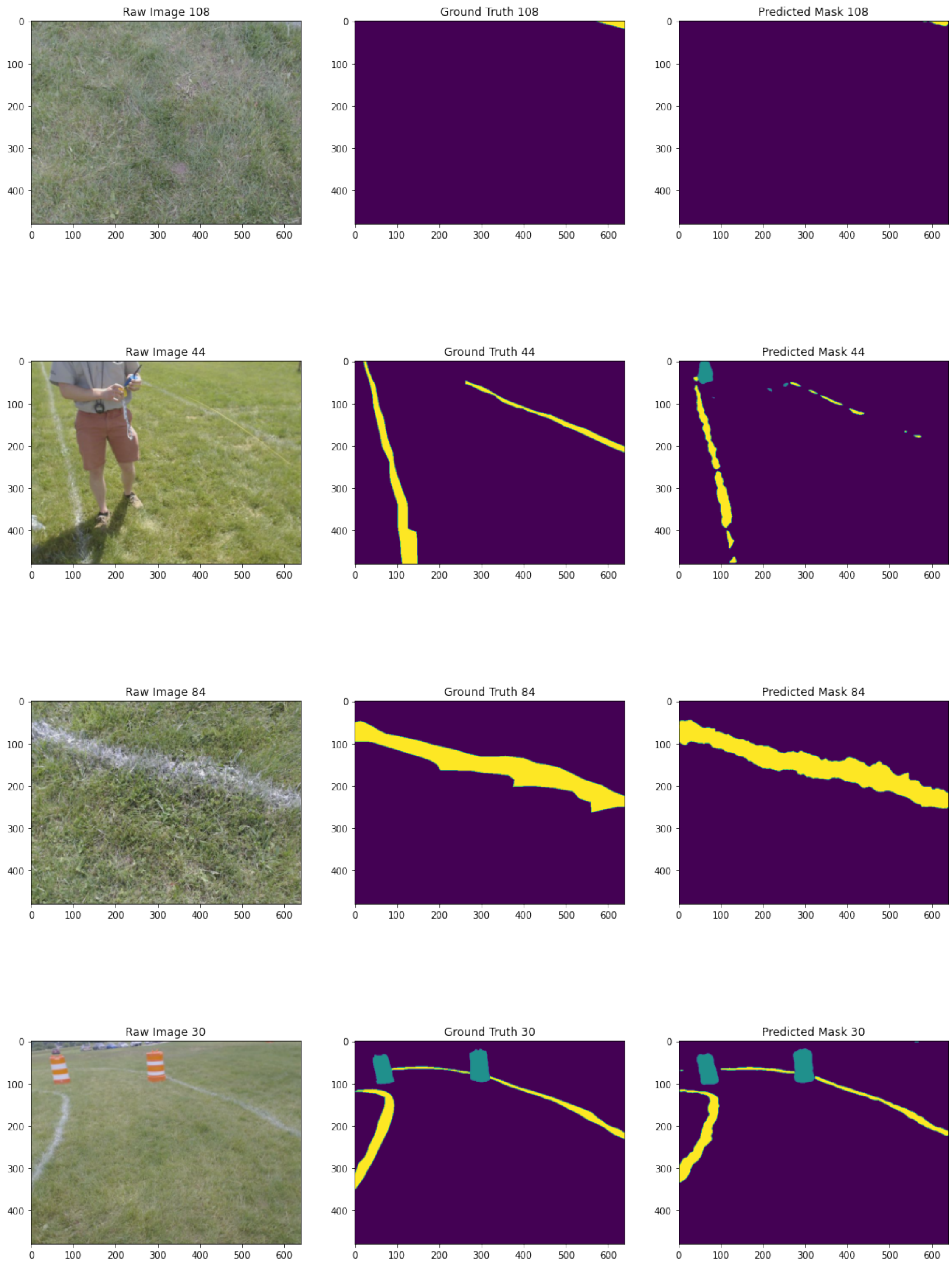

Raw Image 86
Ground Truth 86
Predicted Mask 86
Raw Image 28
Ground Truth 28
Predicted Mask 28
Raw Image 66
Ground Truth 66
Predicted Mask 66
Raw Image 45
Ground Truth 45
Predicted Mask 45

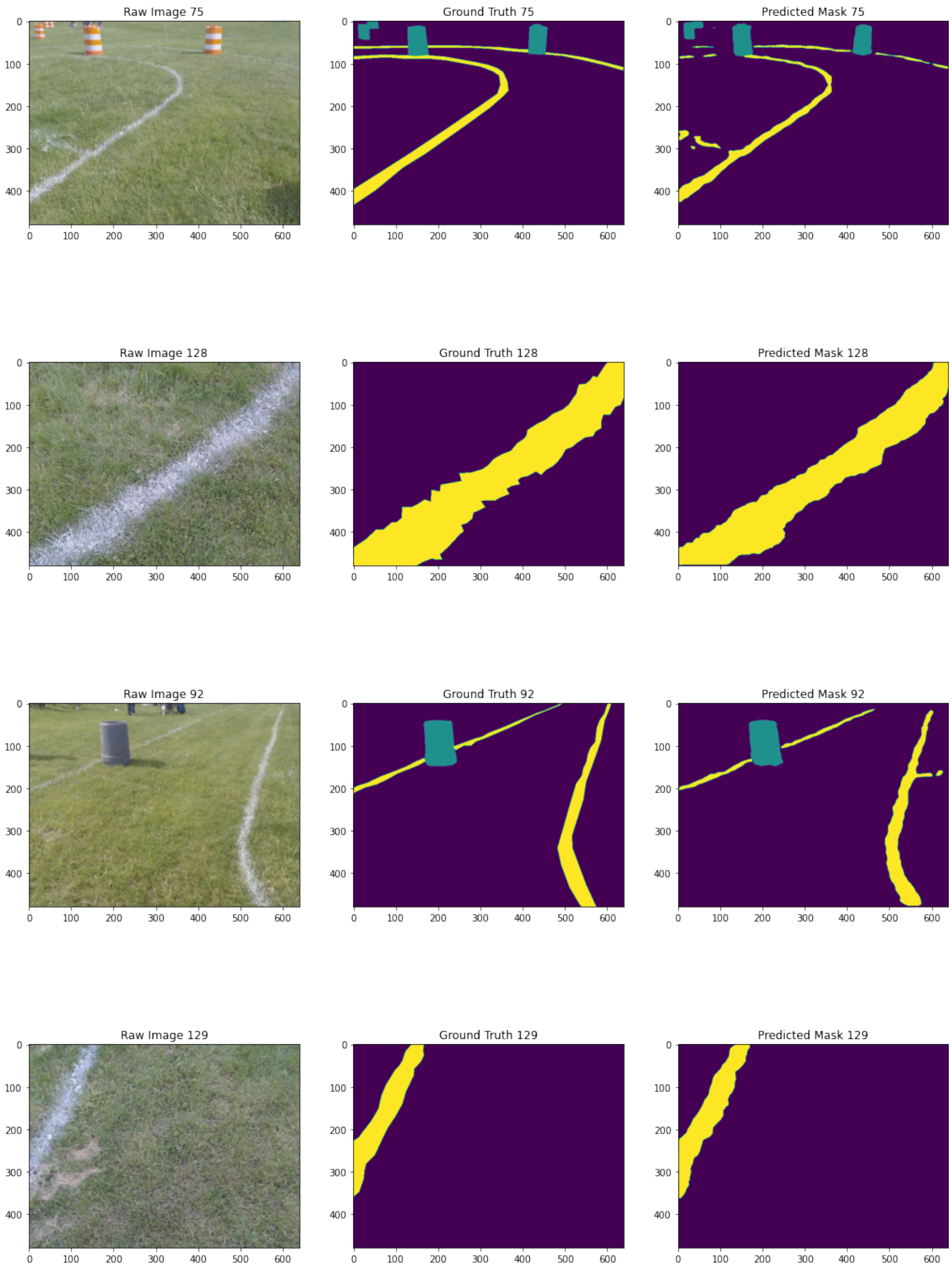

Raw Image 62
Ground Truth 62
Predicted Mask 62


Raw Image 134
Ground Truth 134
Predicted Mask 134


Raw Image 28
Ground Truth 28
Predicted Mask 28


Raw Image 28
Ground Truth 28
Predicted Mask 28


Raw Image 108
Ground Truth 108
Predicted Mask 108
Raw Image 44
Ground Truth 44
Predicted Mask 44
Raw Image 84
Ground Truth 84
Predicted Mask 84
Raw Image 30
Ground Truth 30
Predicted Mask 30



For further exploration, I recommend integrating TensorBoard, adding more metrics, or varying the hyperparameters.