







#### **Born Winner**

Zihang Cheng (z5502944)

Yitong Li (z5504073)

Jinghan Wang (z5286124)

Xianghui Jiang (z5468921)

Xinyi Wu (z5509160)

### Introduction

- Goal of the Project
  - Developing and comparing various computer vision methods
  - Wildlife research
- Methods and Evaluation
  - Six different methods
  - IoU and Accuracy



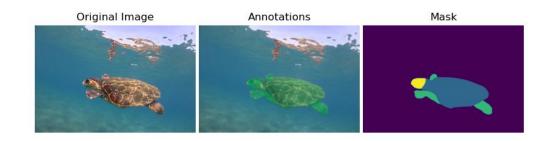
### **Dataset**

#### Original Dataset:

- SeaTurtleID2022 dataset
- 8,729 high-resolution images
- 438 unique sea turtles

#### After splitting the dataset:

- Training Set: 5,303 images
- Validation Set: 1,118 images
- Testing Set: 2,308 images











## Method 1 — Mask R-CNN

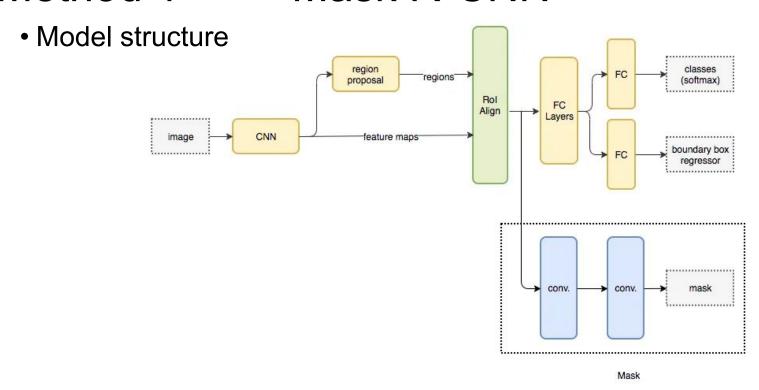


Image source: https://jonathan-hui.medium.com/image-segmentation-with-mask-r-cnn-ebe6d793272



### Mask R-CNN

#### Code Implementation

Backbone

ResNet-50 and FPN (Feature Pyramid Network)

- Classifier and Bounding Box
   Using FastRCNNPredictor
- Mask Predictor
   Using MaskRCNNPredictor
- Data augmentation
- Gradient clipping
- Loss monitoring

```
def get_model_instance_segmentation(num_classes, pretrained=True):
   # Loading the base model
   model = maskrcnn_resnet50_fpn(pretrained=pretrained)
   # Modifying the classifier
   in features = model.roi_heads.box_predictor.cls_score.in_features
   model.roi heads.box predictor = FastRCNNPredictor(in features, num classes)
   # Modifying the mask predictor
   in features mask = model.roi heads.mask predictor.conv5 mask.in channels
   hidden layer = 256
   model.roi heads.mask predictor = MaskRCNNPredictor(
       in_features_mask, hidden_layer, num_classes
   return model
```

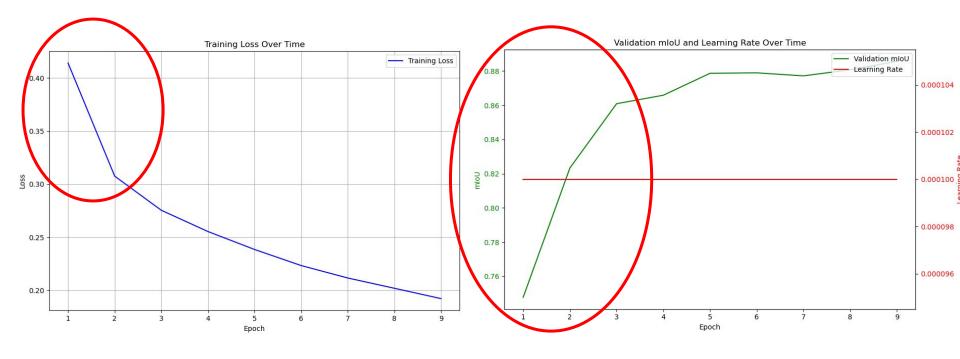


### Results of Mask R-CNN

```
Test Results:
Mean Metrics per Category:
  turtle:
    Mean IoU: 0.9455
    Mean Dice Coefficient: 0.9707
   Mean Accuracy: 0.9764
  flipper:
    Mean IoU: 0.8495
    Mean Dice Coefficient: 0.9066
   Mean Accuracy: 0.9580
  head:
   Mean IoU: 0.8362
    Mean Dice Coefficient: 0.8973
    Mean Accuracy: 0.9146
Average Test Metrics:
  Average Test IoU: 0.8771
  Average Test Dice Coefficient: 0.9249
  Average Test Accuracy: 0.9497
```



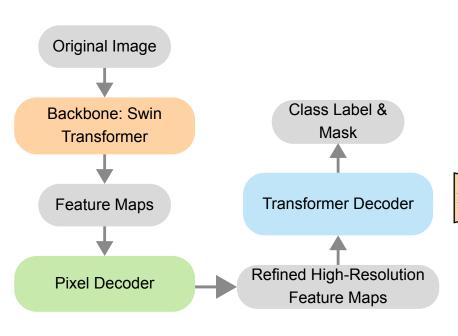
### Results of Mask R-CNN

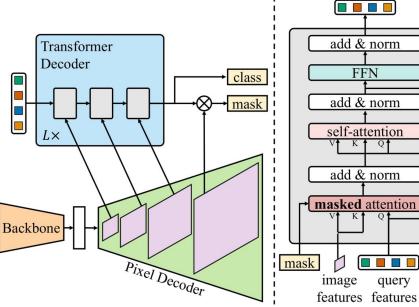




## Method 2 — Mask2Former+Swin

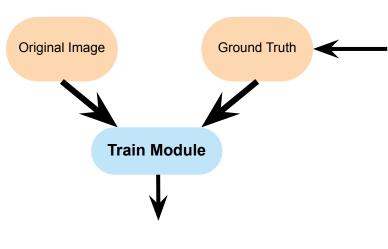
Transformercture







### Mask2Former+Swin Transformer



```
train_ids=[]
 val_ids=[]
 test_ids=[]
 for i, row in data.iterrows():
                                           Split IDs to Different
     if row['split_open'] == 'train':
         train_ids.append(row['id'])
                                                     Lists
     elif row['split_open'] == 'valid':
         val_ids.append(row['id'])
     elif row['split_open'] == 'test':
         test_ids.append(row['id'])
 print(f"TRAIN: {len(train_ids)}, VAL: {len(val_ids)}, TEST: {len(test_ids)}")
TRAIN: 5303, VAL: 1118, TEST: 2308
NUM CLASSES=4
                                                                                     ID
ALL_CLASSES=['backdrop','turtle','head','flipper']
LABEL_COLORS_LIST=np.array([
    [0,0,0],
                                                CLASSES &
    [255, 255, 0].
                                          LABEL COLOR LIST
    [0,0,255],
    [255.0.0]
def generate_mask(img_id):
    coco=COCO("/kaggle/input/seaturtleid2022/turtles-data/data/annotations.json")
    catids=coco.getCatIds()
    annids=coco.getAnnIds(imgIds=img_id, catIds=catids, iscrowd=None)
    anns=coco.loadAnns(annids)
    mask=np.zeros((coco.imgs[img_id]['height'],coco.imgs[img_id]['width']),dtype=int)
    for j in anns:
        putmask=coco.annToMask(j)
        mask=np.maximum(mask.putmask*j['category_id'])
    return mask
```



### Mask2Former+Swin Transformer



Parameters	Purpose	Value	Effect	Apply Value/Not Apply	Methods to Mitigate Negative Impacts
Batch_size	Controls the number of samples processed before model updates, affecting memory usage and generalization.		Capture <b>finer details</b> , improving generalization	16	Use more num_workers to accelerate the process.
		32	Use more memory,and converge more slowly		
num_workers	Control the <b>num of threads</b> to load data in parallel that affects the <b>efficiency</b> .	1	Load data <b>slowly</b> , useful for <b>smaller dataset</b> .	4	To balance memory usage and speed, release memory after each batch with torch.cuda.empty_cache() and gc.collect() to improve efficiency.
		4	Load <b>faster</b> but use more memory.		

```
train_data_loader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    drop_last=False,
    num_workers=4,
    shuffle=True,
    collate_fn=collate_func
)
```

```
del pixel_values
del mask_labels
del class_labels
del pixel_mask
del outputs
gc.collect()
torch.cuda.empty_cache()
```

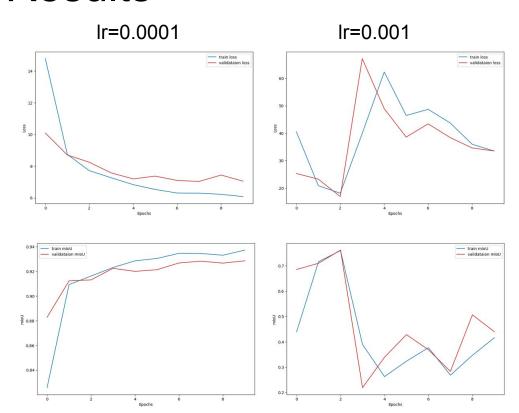
### Mask2Former+Swin Transformer

#### **PARAMETERS**

Parameters	Purpose	Value	Effect	Apply Value/Not Apply	Methods to Mitigate Negative Impacts
Weight Docay	Control <b>overfitting</b> by applying a regularization term that penalizes large weights.	0.0001	Suppress learning fine- grained features	0.0001	Use Data Augmentation to prevent overfitting and improve generalization.
Learning_rate	Determines the step size during gradient descent, impacting convergence speed and stability.	0.001	Cause <b>unstable</b> or poor convergence	0.0001	Add epochs to train, input more features and choose a suitable learning_rate.
			Approach the <b>optimal solution</b> stably, and provide better model performance		

UNSW

### Results



Mean IoU: 0.9104818343361768

Mean accuracy: 0.9502254109612451

Mean IoU of backdrop: 0.9948515956786803

Mean Accuracy of backdrop: 0.9966539178603651

Mean IoU of turtle: 0.9329208801331753

Mean Accuracy of turtle: 0.9742190345788008

Mean IoU of head: 0.861053333626903

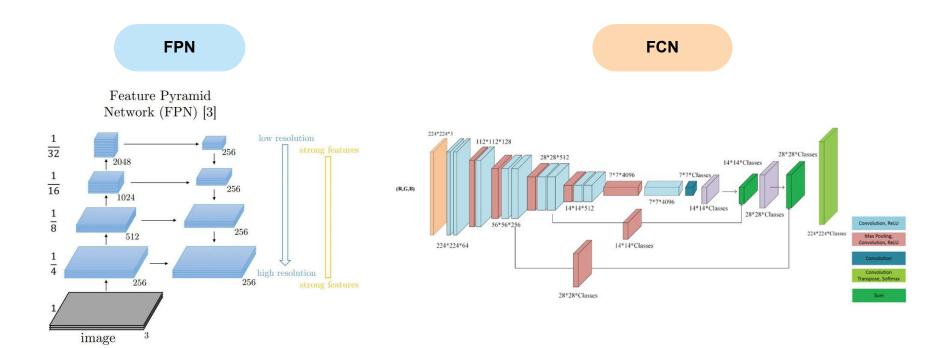
Mean Accuracy of head: 0.9287463721081771

Mean IoU of flipper: 0.8531015279059493

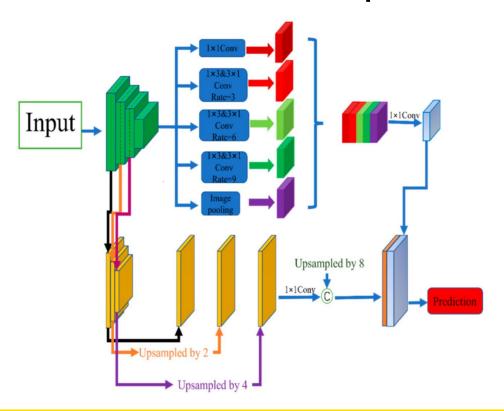
Mean Accuracy of flipper: 0.9012823192976392



# Method 3,4 —— FPN / FCN + Resnet



# Method5——Deeplabv3





1. Backbone:ResNet-50

#### 2.ASPP:

a. a 1x1 convolution

b.3 voids convolution(different expansion rates)

c.A global average pooling layer

3.Output



# Dataset Loader and preprocessing

```
[6]: coco = COCO('/content/drive/MyDrive/annotations.json')
     ds = load_dataset("EnmmmmOvO/SeaTurtleID2022")['train']
     # color:
                       backgtound turtle flipper
     COLOR = np.array([[0, 0, 0], [255, 0, 0], [0, 255, 0], [0, 0, 255]])
     SPLIT = 'split closed'
     device = 'cuda' if torch.cuda.is_available() else 'cpu'
     iou metric = evaluate.load("mean iou")
     TRAIN EPOCHS = 20
     loading annotations into memory...
     Done (t=7.06s)
     creating index...
     index created!
     README.md: 0%
                               | 0.00/656 [00:00<?, ?B/s]
     train-00000-of-00004.parguet: 0%|
                                                   0.00/458M [00:00<?, ?B/s]
     train-00001-of-00004.parquet: 0%|
                                                  | 0.00/483M [00:00<?, ?B/s]
     train-00002-of-00004.parguet: 0%|
                                                  | 0.00/432M [00:00<?, ?B/s]
     train-00003-of-00004.parquet: 0%|
                                                  | 0.00/382M [00:00<?, ?B/s]
     Generating train split: 0%|
                                            | 0/8729 [00:00<?, ? examples/s]
     Downloading builder script: 0%|
                                                | 0.00/12.9k [00:00<?, ?B/s]
[7]: train_dataset = ds.filter(lambda x: x[SPLIT] == 'train')
     valid dataset = ds.filter(lambda x: x[SPLIT] == 'valid')
     test_dataset = ds.filter(lambda x: x[SPLIT] == 'test')
                            | 0/8729 [00:00<?, ? examples/s]
     Filter: 0%|
                            | 0/8729 [00:00<?, ? examples/s]
     Filter: 0%|
                            | 0/8729 [00:00<?, ? examples/s]
[8]: def get mask(id: str | int):
         anns = coco.loadAnns(coco.getAnnIds(imgIds=id, catIds=coco.getCatIds(), iscrowd=None))
         mask = np.zeros((coco.imgs[id]['height'], coco.imgs[id]['width']), dtype=int)
         for ann in anns:
             submask = coco.annToMask(ann)
             mask = np.maximum(mask, submask * ann['category_id'])
         return mask
```

```
[26]: class TurtleDataset(Dataset):
          def __init__(self, dataset, transform=None, rotate=None):
             self.dataset = dataset
                                                                    Apply the same data
             self.transform = transform
              self.rotate = rotate
                                                                    enhancement to the
          def __len__(self):
              return len(self.dataset)
                                                                    picture and the mask
          def getitem (self, index):
              id = self.dataset[index]['id']
              image = np.array(self.dataset[index]['image'])
              mask = np.array(get_mask(id))
              if self.transform:
                 augmented = self.transform(image=image, mask=mask)
                 image = augmented['image']
                 mask = augmented['mask']
              if self.rotate:
                 image = torch.tensor(image).permute(2, 0, 1)
              return image, mask
[12]: train transform = A.Compose([
          A.Resize(256, 256, always_apply=True),
          A. HorizontalFlip(p=0.4),
          A.RandomBrightnessContrast(p=0.15),
          A.Rotate(limit=20),
         A.Normalize(mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0
      ], is check shapes=False, additional targets={'mask': 'mask'})
      image transform = A.Compose([
          A.Resize(256, 256, always_apply=True),
          A.Normalize(mean=(0.485, 0.456, 0.406), std=(0.229, 0.224, 0.225)),
      ], is check shapes=False)
```

# Dataset Loader and preprocessing

Model

```
model = fcn_resnet101(weights=FCN_ResNet101_Weights.DEFAULT).to(device)
model.classifier[4] = nn.Conv2d(512, 4, kernel_size=1)
model = model.to(device)
```

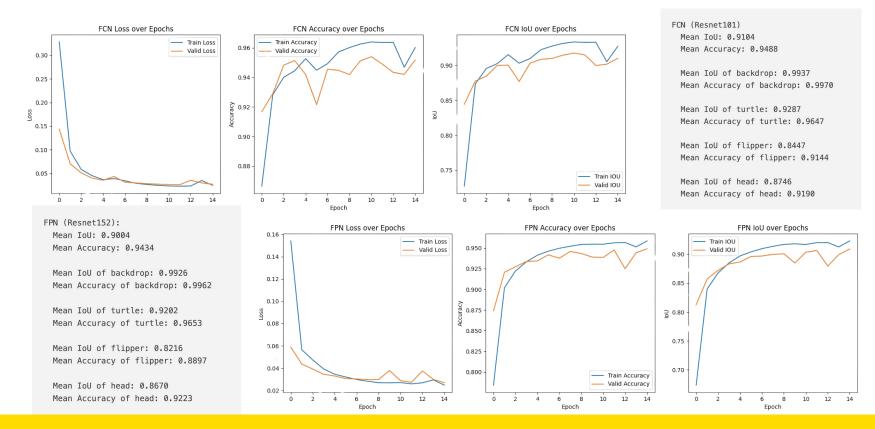
model = FPN(encoder\_name="resnet101", encoder\_weights="imagenet", in\_channels=3, classes=4).to(device)

```
optimizer = optim.AdamW(model.parameters(), lr=1e-4, weight_decay=1e-5)
scheduler = ReduceLROnPlateau(optimizer, mode='min', factor=0.1, patience=5, verbose=True)
criterion = torch.nn.CrossEntropyLoss()
```

Optimizer



### Results





## Pre-training

```
image_transform = transforms.Compose([
          transforms.Resize((512, 512)),
          transforms.ToTensor()
])

mask_transform = transforms.Compose([
          transforms.Resize((512, 512)),
          transforms.ToTensor(),
          transforms.Lambda(lambda x: (x * 255).long())
])
```

a. resize Image andMaskb. Images converted to tensors



### Core code

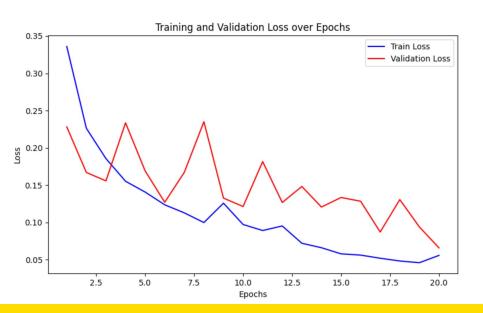
2. Read data, extract the mask

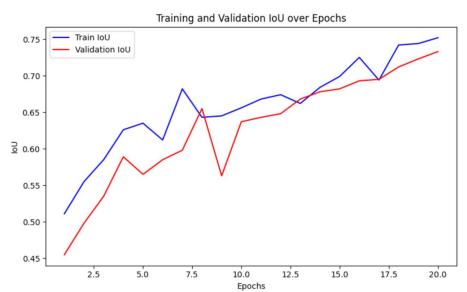
```
class TurtleDataset(Dataset):
   def init (self, image dir, coco, types, image transform=image transform, mask transform=mask transform):
        self.image dir = image dir
        self.coco = coco
        self.image transform = image transform
        self.mask transform = mask transform
        self.images = [img for img in coco.imgs.values() if data type mapping.get(img['file name']) == types]
   def process(self, image id, image):
        mask = np.zeros((image.size[1], image.size[0]), dtype=np.uint8)
        categories = [(1, 1), (2, 2), (3, 3)] # (category id, label)
        for cat id, label in categories:
            ann ids = coco.getAnnIds(imgIds=image id, catIds=cat id, iscrowd=None)
           anns = coco.loadAnns(ann ids)
           for ann in anns:
                mask ann = coco.annToMask(ann)
                mask = np.maximum(mask, mask ann * label)
        return mask
```

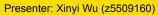
3. classification header= 4 categories (3 categories + 1 background class)



### Results









### Results

```
Test Results:
Mean Metrics per Category:
turtle:
  Mean IoU: 0.7936
  Mean Dice Coefficient: 0.8696
  Mean Accuracy: 0.8933
flipper:
  Mean IoU: 0.6219
  Mean Dice Coefficient: 0.7261
  Mean Accuracy: 0.7274
head:
  Mean IoU: 0.6220
  Mean Dice Coefficient: 0.7113
  Mean Accuracy: 0.7009
Average Test Metrics:
Average Test IoU: 0.7563
Average Test Dice Coefficient: 0.8252
Average Test Accuracy: 0.8289
```

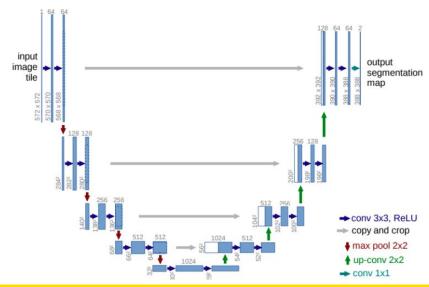


### Method6 - UNet

UNet from Scratch using PyTorch

**Breif** The U-Net is a convolutional neural network architecture

**describle:** designed primarily.



#### UNet from Scratch using PyTorch

#### core code

```
import segmentation_models_pytorch as smp
import torch.optim as optim
import torch.nn as nn

# Define the U-Net model with a pre-trained ResNet34 backbone
model = smp.Unet(
    encoder_name="resnet50",
    encoder_weights="imagenet", # Use ImageNet pre-trained weights
    in_channels=3, # Input channels (RGB)
    classes=4, # Output classes (background, head, body, flippers, activation=None # No softmax applied here; handled by CrossEntropyLoss
)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001) # Adam optimizer
```

### **Unet-Results**





Intersection over Union (IoU):

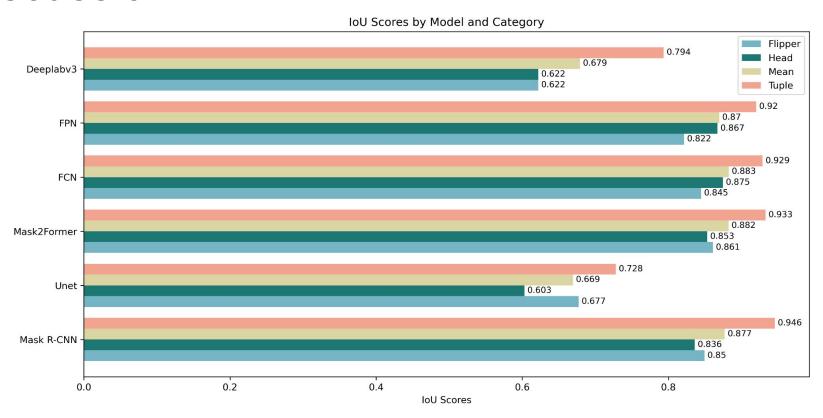
IoU for turtle: 0.728
IoU for flippers: 0.677

IoU for head: 0.603

Overall mean IoU (mIoU): 0.669



### Discussion





## Conclusion

Mask R-CNN	precise object instance segmentation.		
Mask2Former+Swin Transformer	complex and detail-rich segmentation		
FCN	Real-time segmentation		
DeepLab V3	capturing large-scale objects and background information in extensive datasets		
U-Net	Small datasets and large, regular-shaped targets.		
FPN	multi-scale segmentation		

