



Segmentation of images

Anirudh J- EE16BTECH11013

INTRODUCTION:Segmentation

⇒Image Segmentation is the process of partitioning a digital image into multiple segments.

⇒In Deep learning Segmentation is classification of each image pixel.

Types of segmentations implemented :

⇒Semantic segmentation.

⇒Instance segmentation.

Image segmentation

Semantic Segmentation



GRASS, CAT,
TREE, SKY

Instance Segmentation



DOG, DOG, CAT

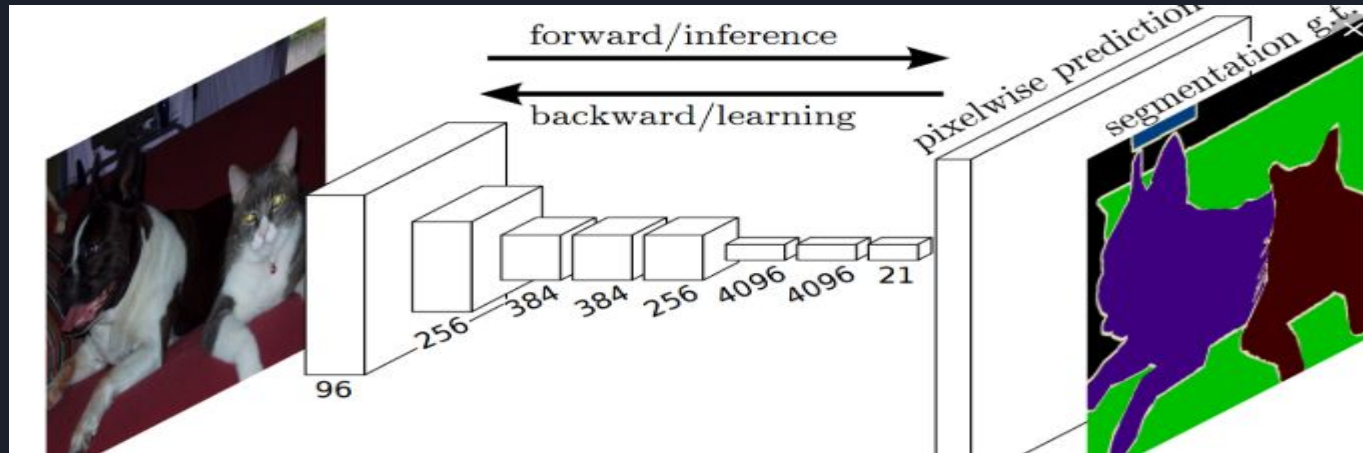
Semantic Segmentation

Implemented two papers for semantic segmentation:

⇒FCN(Fully convolutional Network)

⇒U-Net

FCN(Fully Convolutional Network)



In FCN the gradients doesn't flow upto the first layers of encoder i.e vanishing gradient problem.

Instance Segmentation

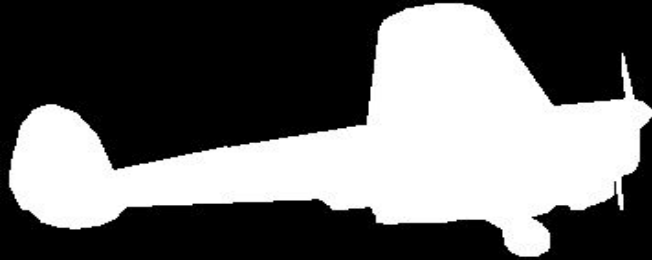
Implemented one paper for Instance segmentation:

- 1) Mask R-CNN(Region Convolutional Neural Network)

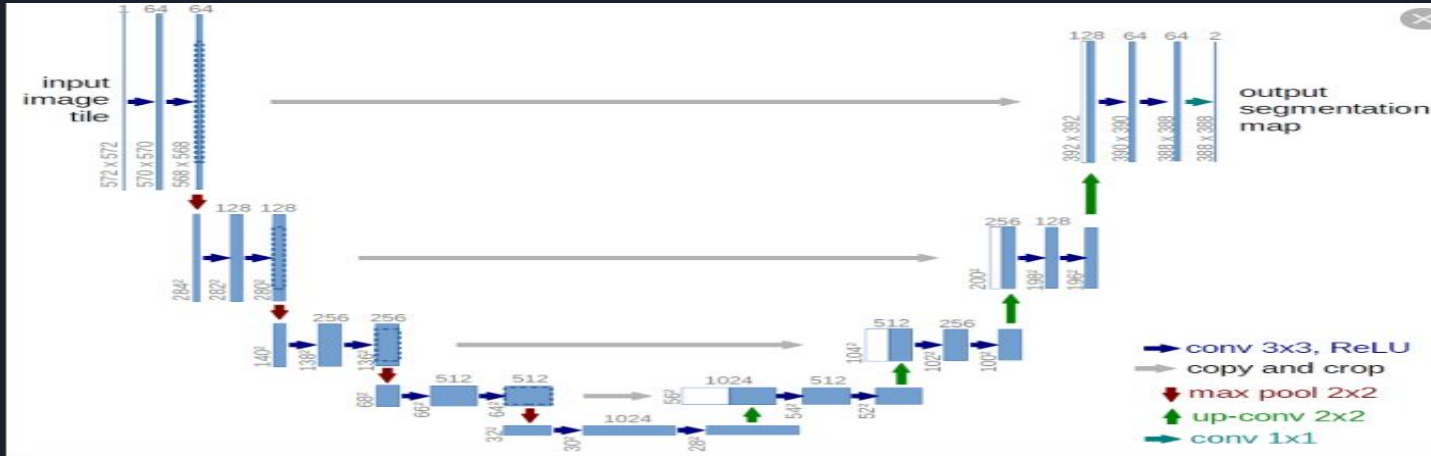
Results of FCN(Fully Convolutional Network)

⇒FCN was able to perform well with binary segmentation i.e Semantic segmentation with two classes.

⇒The following results are by FCN trained by loss function binary cross entropy for 10 epochs.



U-Net



⇒ In UNet there is a healthy gradient flow due to the skip layers in UNet .

⇒ In Unet the gradients directly flows to the encoding layers through skip layers.

⇒ Skip layers preserve the information of image in decoding layers.

How UNet prevents vanishing gradient problem.

Let the model contain four Fully connected layers($L1, L2, L3, L4$).

Let $w1, w2, w3$ be weight matrices between each layer.

Let $A2, A3, A4$ be the activations of layers ($L2, L3, L4$)

Let $\frac{\partial E}{\partial o}$ be ∂o .

$$\implies \partial w1 = (\partial o) * (A4(o)') * (w3) * (A3(L3)') * (w2) * (A2(L2)')$$

\implies This above term may vanish because derivatives of activation functions are less than 1.

\implies To avoid this we are going to add a skip layer from $L4$ to $L2$.

Then $\partial(\text{new } w1) = \partial(w1)$ (Due to back propagation) + $\partial(o)$ (Due to skip layer)

$$\implies \partial(w1) = (\partial o) * (A4(o)') * (w3) * (A3(L3)') * (w2) * (A2(L2)') + (\partial o)$$

In this way we can avoid vanishing gradient problem using skip layers.

This extra gradient is going to be a valid gradient because previously the model is trained for output(O) after adding skip layers it will be trained for $(\text{output}(o) - L2)$.

UNet Results

- ⇒ First Implemented UNet for colouring of grey scale images .
- ⇒ Used Nearest neighbour method in the last layer to see the nearest colour for the pixel in the given set of colours.
- ⇒ The required colours are unique colour pixels in whole dataset.
- ⇒ The UNet is trained for 25 epochs with a batch size of 100 images and with a loss criterion categorical cross entropy.
- ⇒ The optimizer used for UNet is Adam with default momentum.

UNet Results:



⇒The First row are the input grey scale images for UNet.

⇒The Second row are the ground truth images.

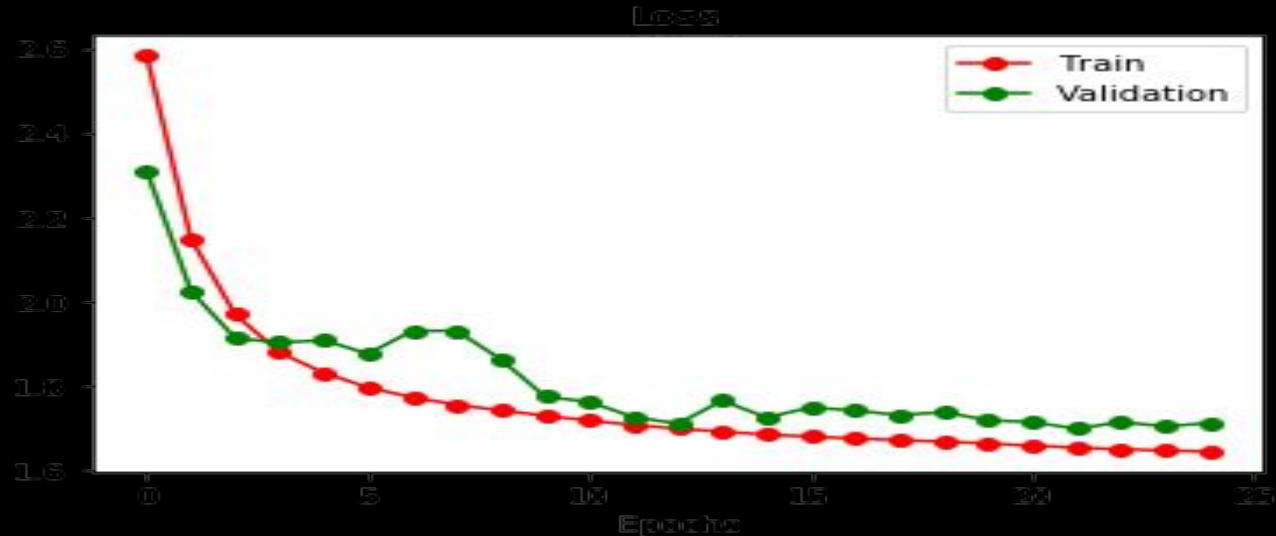
⇒The Third row contains the predicted image of UNet.

⇒The images are of low resolution of 32x32x3.

UNet Results

⇒The below plot is Training and validation loss plotted vs epochs.

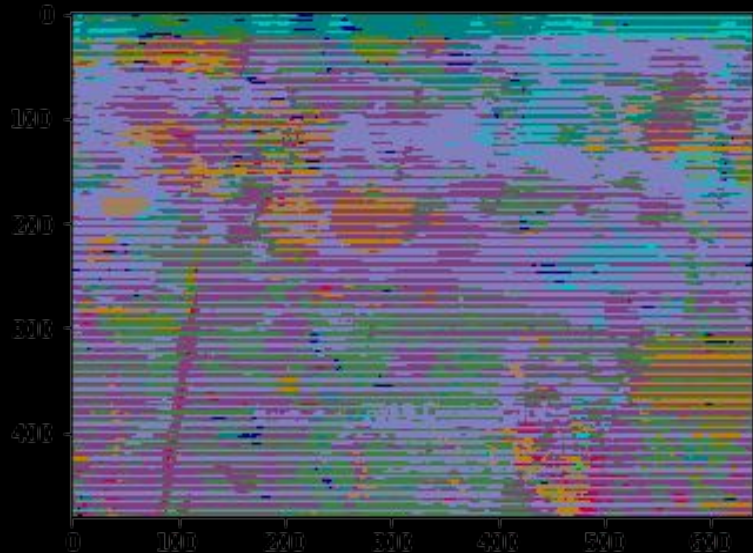
⇒Y-axis represents loss and X-axis represents epochs.



UNet Results on satellite images

⇒The UNet is trained on segmentation of satellite images with categorical cross entropy loss and with Adam as optimizer for 25 epochs.

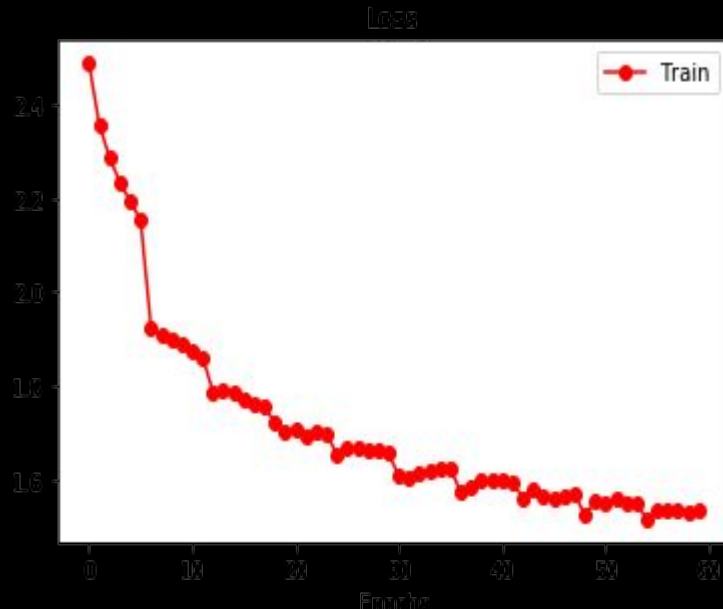
⇒Below image is the predicted image of Unet. The results were very bad on satellite images.



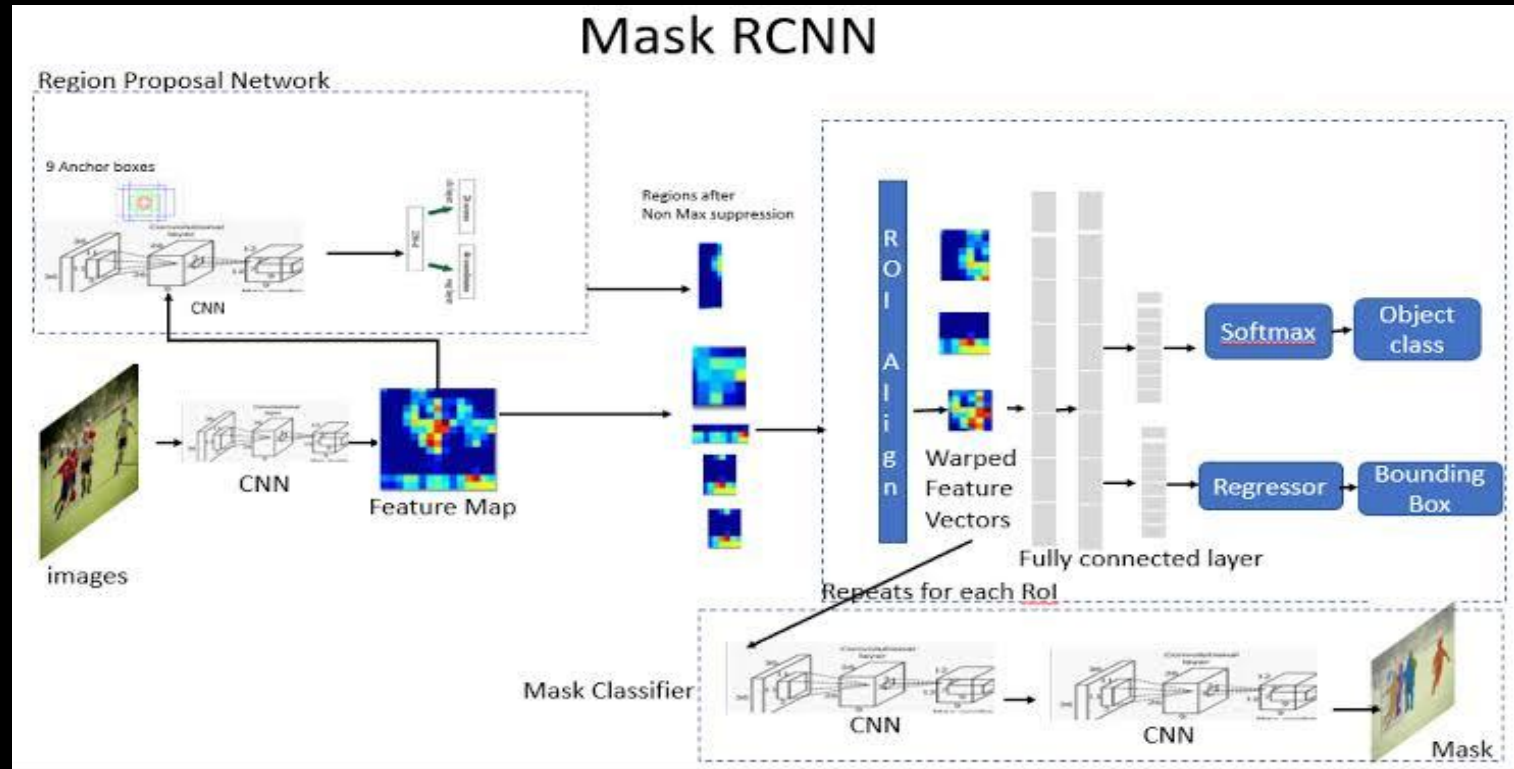
UNet Results

⇒The below plot is Training loss plotted vs epochs.

⇒Y-axis represents loss and X-axis represents epochs.



Instance segmentation using Mask-RCNN



Mask RCNN

⇒The Mask RCNN is trained on Microsoft coco dataset.

⇒The model is trained on ms-coco dataset with three losses
One for bounding box loss, other for mask loss and last is
classification loss.

⇒Each loss uses negative log likelihood as the loss criteria for
training with Adam as optimizer.

Results of Mask RCNN

