

ProjectF2

Team 27

Brain Tumor Detection using Convolutional Neural Networks

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Motivation/Problem

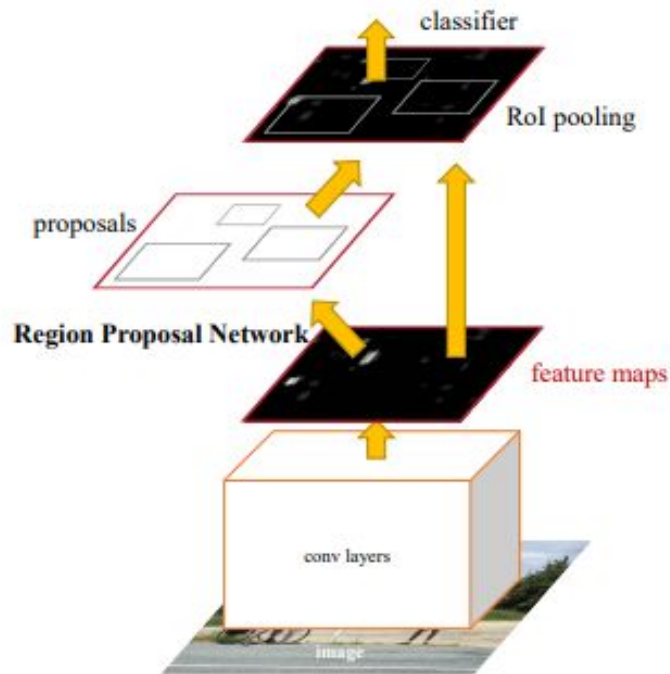
- Affects over 700,000 people within the United States
- Caution and care has to be taken in the accuracy of the diagnosis, treatment, and planning to increase the life expectancy of that patient.
- Radiologists and clinical experts are tasked with detection and identification.
- To reduce the introduction of human error we use Machine Learning for automatic classification.

Task

- Implement CNN model with the ability to detect brain tumors in Images.
- Implement Faster R-CNN for Image segmentation to identify the location of the tumor.

* source - S Ren, K He, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks"

<https://arxiv.org/pdf/1506.01497.pdf>



Faster R-CNN *

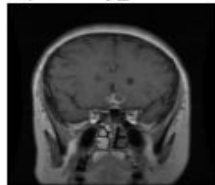
Dataset

- 3,565 raw MRI images found in Kaggle*.
- Each Image is of different sizes.
- Varying tumor location with size and different types.
- 3 different tumor types : Glioma, Meningioma, and pituitary; + 1 for No tumor.
- Resized image shape 3 x 150 x 150

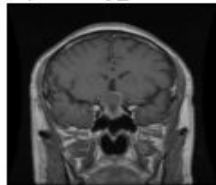
* source : <https://www.kaggle.com/sartajbhuvaji/brain-tumor-classification-mri>

Sample Images

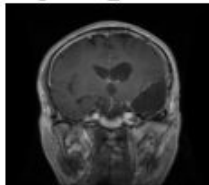
pituitary_tumor



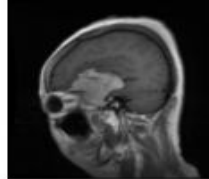
pituitary_tumor



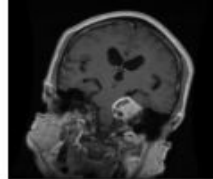
glioma_tumor



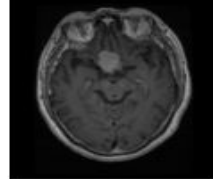
meningioma_tumor



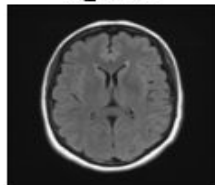
meningioma_tumor



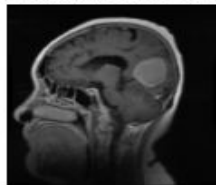
pituitary_tumor



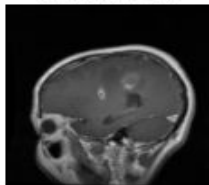
no_tumor



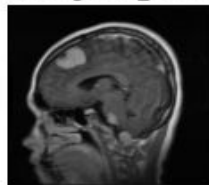
meningioma_tumor



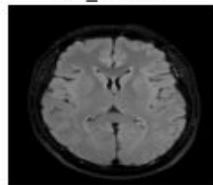
glioma_tumor



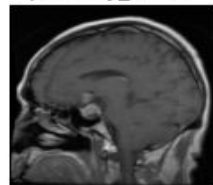
meningioma_tumor



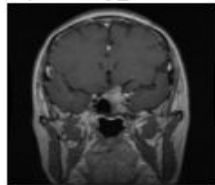
no_tumor



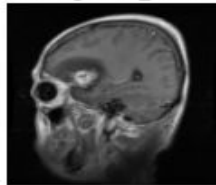
pituitary_tumor



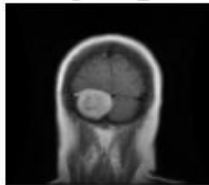
pituitary_tumor



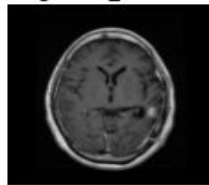
meningioma_tumor



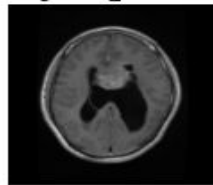
meningioma_tumor



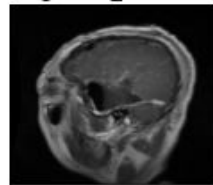
glioma_tumor



glioma_tumor



glioma_tumor



Baseline Model : CNN Parameters

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 150, 150]	336
BatchNorm2d-2	[-1, 12, 150, 150]	24
MaxPool2d-3	[-1, 12, 75, 75]	0
Conv2d-4	[-1, 20, 75, 75]	2,180
BatchNorm2d-5	[-1, 20, 75, 75]	40
MaxPool2d-6	[-1, 20, 37, 37]	0
Conv2d-7	[-1, 32, 37, 37]	5,792
BatchNorm2d-8	[-1, 32, 37, 37]	64
MaxPool2d-9	[-1, 32, 18, 18]	0
Linear-10	[-1, 5184]	53,752,896
Linear-11	[-1, 2592]	13,439,520
Linear-12	[-1, 4]	10,372

Total params: 67,211,224

Trainable params: 67,211,224

Non-trainable params: 0

Input size (MB): 0.26

Forward/backward pass size (MB): 7.37

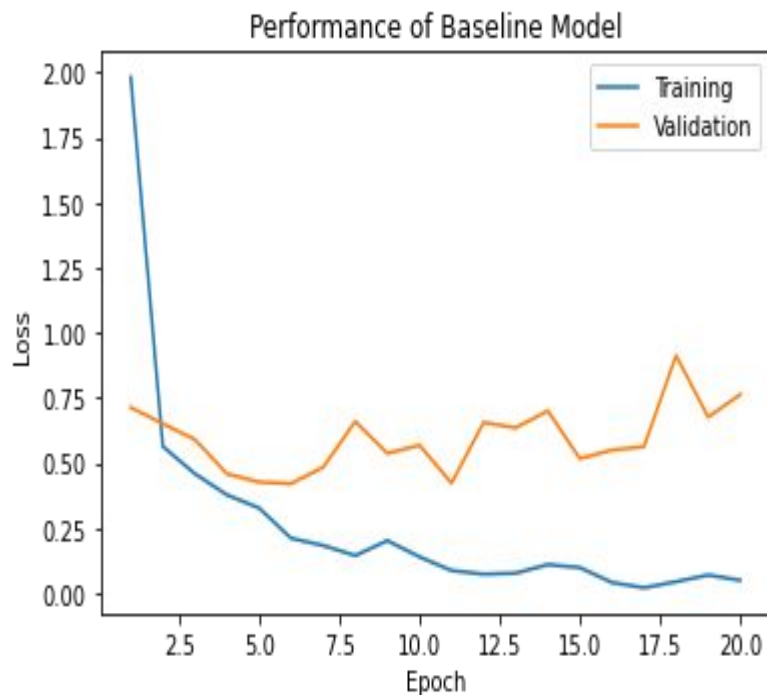
Params size (MB): 256.39

Estimated Total Size (MB): 264.02

```
class Net(nn.Module):
    def __init__(self, num_classes=4):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=12, kernel_size=3, stride=1, padding=1)
        self.bn_1 = nn.BatchNorm2d(num_features=12)
        self.pool = nn.MaxPool2d(kernel_size=2)
        self.conv2 = nn.Conv2d(in_channels=12, out_channels=20, kernel_size=3, stride=1, padding=1)
        self.bn_2 = nn.BatchNorm2d(num_features=20)
        self.conv3 = nn.Conv2d(in_channels=20, out_channels=32, kernel_size=3, stride=1, padding=1)
        self.bn_3 = nn.BatchNorm2d(num_features=32)
        self.fc1 = nn.Linear(in_features=32*18*18, out_features=16*18*18)
        self.fc2 = nn.Linear(in_features=16*18*18, out_features=8*18*18)
        self.fc3 = nn.Linear(in_features=8*18*18, out_features=num_classes)

    def forward(self, x):
        x = self.pool(F.relu(self.bn_1(self.conv1(x))))
        x = self.pool(F.relu(self.bn_2(self.conv2(x))))
        x = self.pool(F.relu(self.bn_3(self.conv3(x))))
        #print(x.shape)
        x = x.view(-1, 32*18*18)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

CNN - Baseline Performance



Test Loss: 2.753260

Test Accuracy of glioma_tumor: 28% (28/100)

Test Accuracy of meningioma_tumor: 83% (96/115)

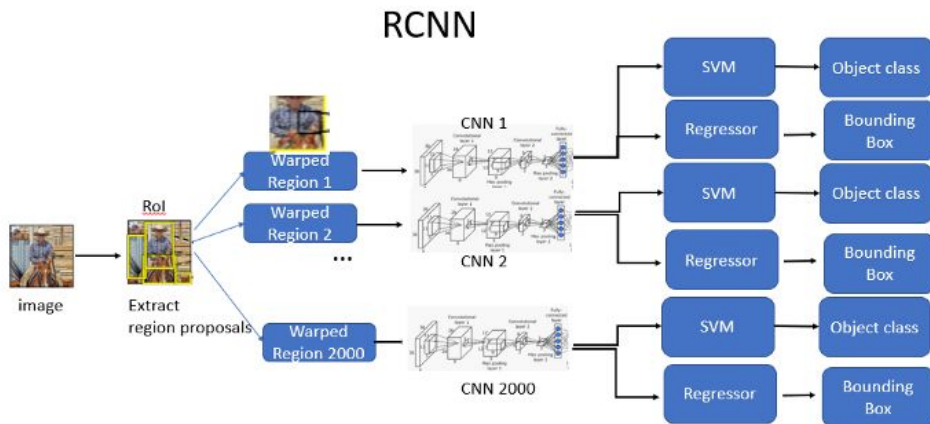
Test Accuracy of no_tumor: 96% (101/105)

Test Accuracy of pituitary_tumor: 62% (46/74)

Test Accuracy (Overall): 68% (271/394)

CNN to Faster R-CNN (1)

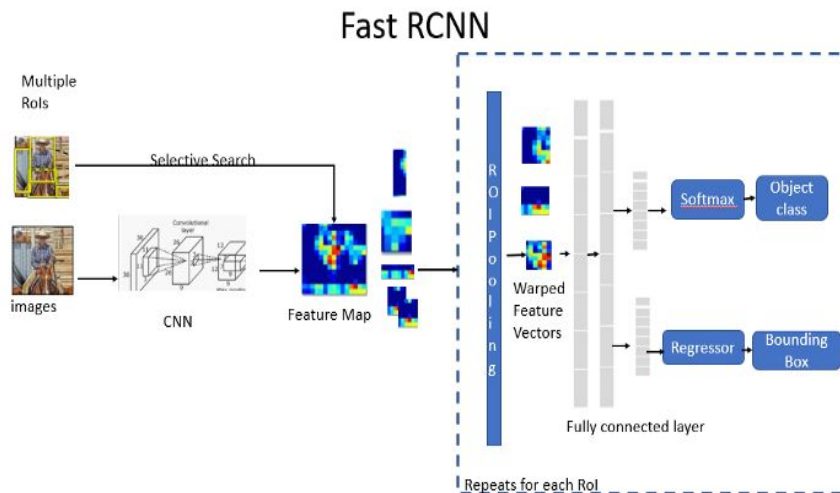
- Convolutional Neural Network - Image classification and object detection.
 - Multiple filters and feature decode layers for Image Classification.
- Regional -CNN (R-CNN) is used for object detection with bounding boxes.
 - Selective Search -> Generate Region Proposals -> CNN -> SVM -> Regressor.



CNN to Faster R-CNN (2)

Disadvantages of R-CNN

- R-CNN slow because of Selective search.
- Region extraction for every region in the image is slow.
- Fast R-CNN uses one ConvNet to extract features for entire image.
- 'RoI Pooling layer' to extract interested regions from feature maps using selective search.
- FC with 2 output layers
 - Softmax for Object Classification.
 - Regressor for defining bounding boxes.

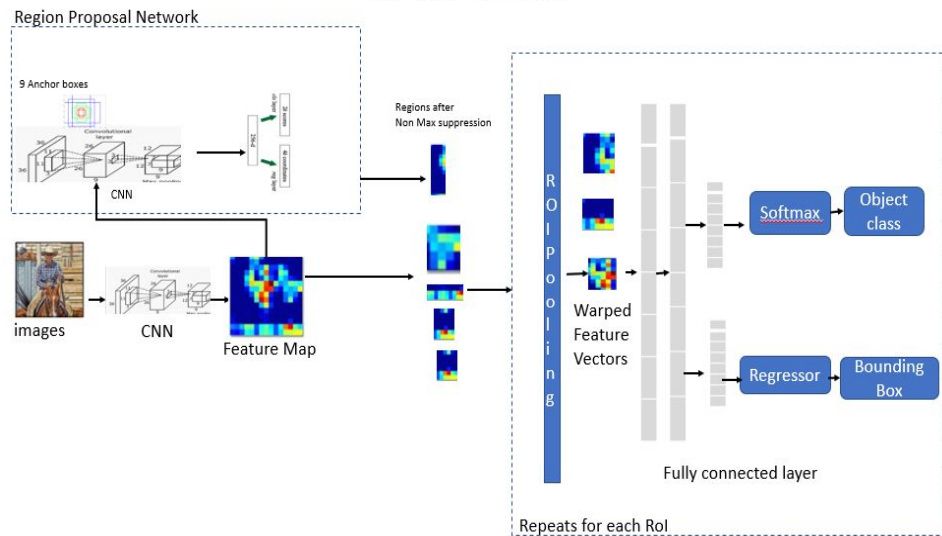


CNN to Faster R-CNN (3)

- Use Region Proposal Network instead of selective search, to generate RoI's.

Faster RCNN

- Image -> Deep CNN -> Feature Maps
- Feature Maps -> RPN -> RoI Bounding Boxes
- Feature Maps & RoI -> Fast R-CNN Detection -> Classification and Bounding Boxes.



Proposed Model : Faster R-CNN

```
#Prediction Function
def predict(classes, data, target, model):
    output = model(data) # get the predictions on the image

    pred_score, pred = torch.max(output, 1)
    amount = torch.max(pred_score)
    pred_class = [classes[i] for i in list(pred.cpu().numpy())]

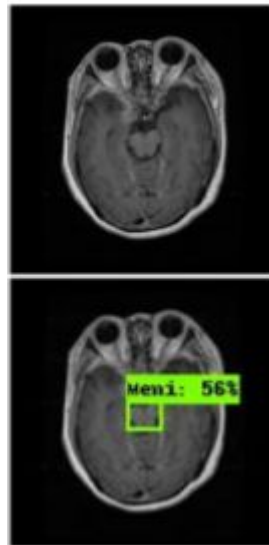
    print(amount)
    #print(pred_class)
    return pred_class, pred_score

#Different color for each class
colors = np.random.uniform(0, 255, size=(len(classes), 3))

# Setting model to evaluate
#device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model.eval()

#Test data
batch_size = 197
test = DataLoader(test_set, batch_size = batch_size)

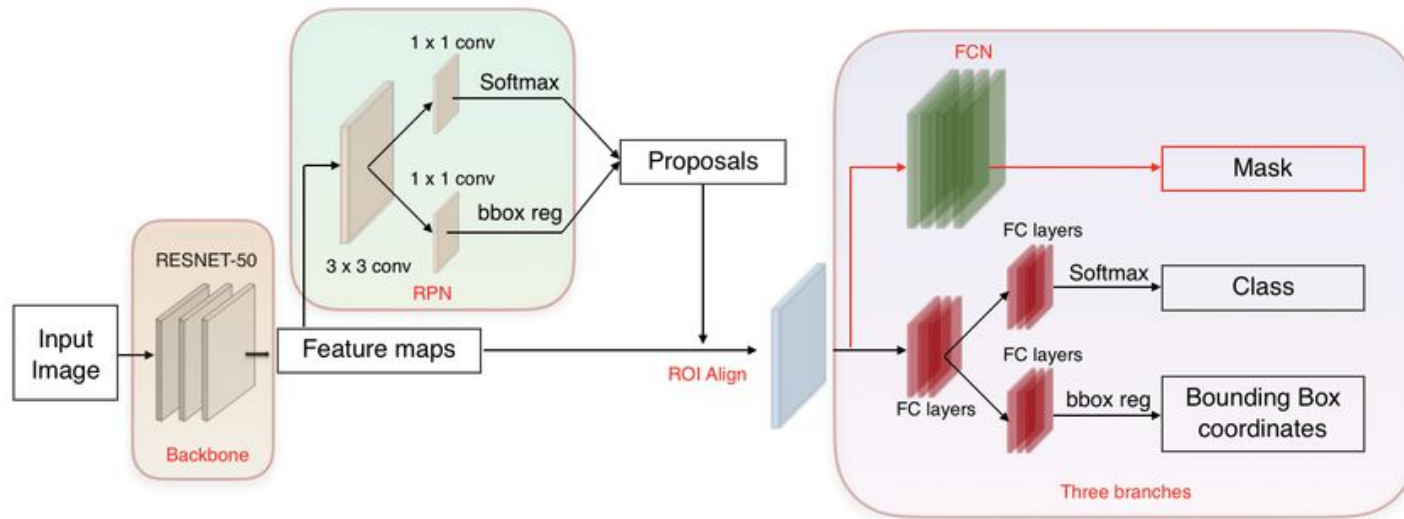
# Iterating over batches of test data
for data, target in test:
    if flag_cuda:
        data, target = data.cuda(), target.cuda()
    pred_class, pred_score = predict(classes, data, target, model)
```



Our Goal

Thank you...

Proposed Model : Mask-RCNN



RPN : Region Proposed Network

RoI : Region of Interest

ResNet-50 : Deep Learning Model 48 with conv layer, 1 MaxPool and 1 AveragePool layer

ResNet-50 won the ILSVRC 2015.

Source :

https://www.researchgate.net/figure/Overview-of-Mask-RCNN-architecture-chosen-to-segment-the-pressure-injury-Proposals-about_fig4_341556236

```

Net(
  (conv1): Conv2d(3, 12, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn_1): BatchNorm2d(12, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (conv2): Conv2d(12, 20, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv3): Conv2d(20, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (bn_3): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (fc): Linear(in_features=43808, out_features=4, bias=True)
)

```

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 150, 150]	336
BatchNorm2d-2	[-1, 12, 150, 150]	24
MaxPool2d-3	[-1, 12, 75, 75]	0
Conv2d-4	[-1, 20, 75, 75]	2,180
Conv2d-5	[-1, 32, 75, 75]	5,792
BatchNorm2d-6	[-1, 32, 75, 75]	64
MaxPool2d-7	[-1, 32, 37, 37]	0
Linear-8	[-1, 4]	175,236

Total params: 183,632

Trainable params: 183,632

Non-trainable params: 0

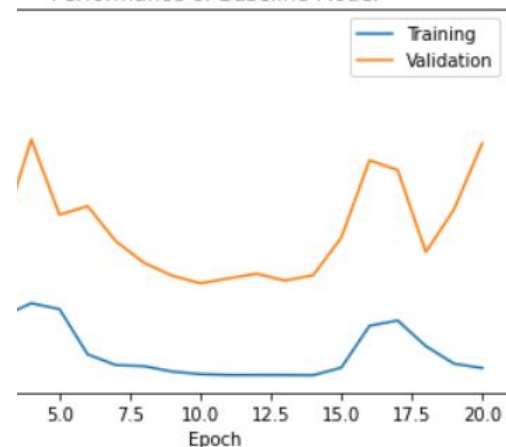
Input size (MB): 0.26

Forward/backward pass size (MB): 8.57

Params size (MB): 0.70

Estimated Total Size (MB): 9.53

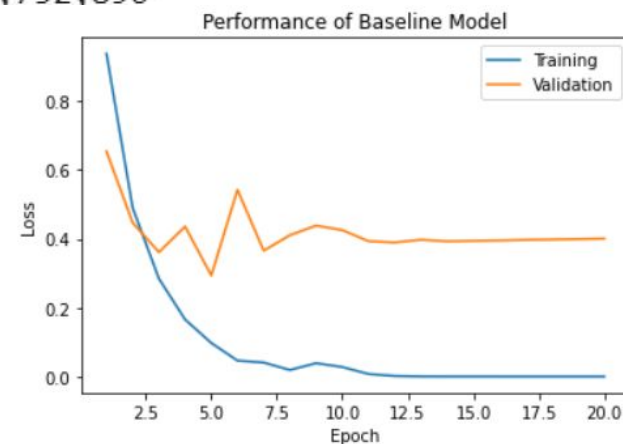
Performance of Baseline Model



Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 150, 150]	336
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Conv2d-3	[-1, 20, 75, 75]	2,180
MaxPool2d-4	[-1, 20, 37, 37]	0
Conv2d-5	[-1, 32, 37, 37]	5,792
MaxPool2d-6	[-1, 32, 18, 18]	0
Linear-7	[-1, 5184]	53,752,896
Linear-8	[-1, 4]	

Total params: 53,781,944
 Trainable params: 53,781,944
 Non-trainable params: 0

Input size (MB): 0.26
 Forward/backward pass size (MB): 4.10
 Params size (MB): 205.16
 Estimated Total Size (MB): 209.51

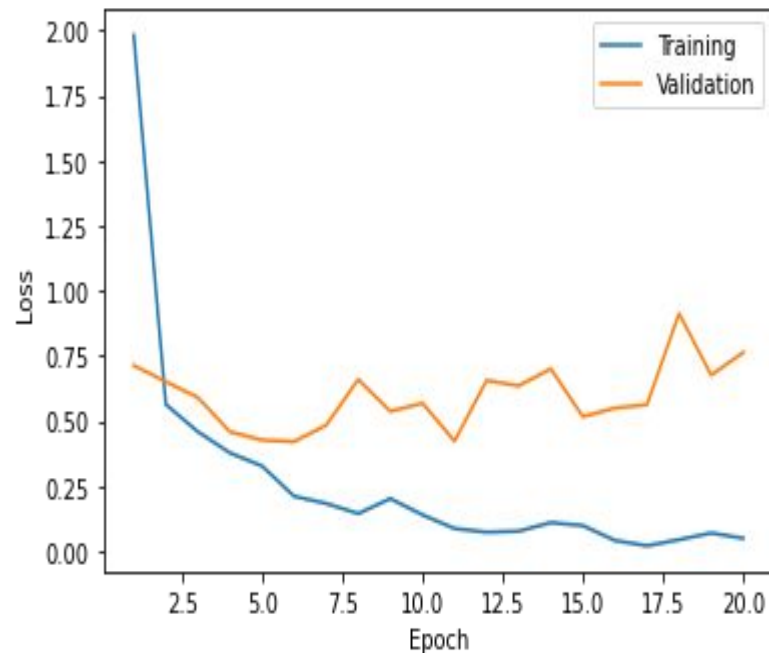


Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 150, 150]	336
BatchNorm2d-2	[-1, 12, 150, 150]	24
MaxPool2d-3	[-1, 12, 75, 75]	0
Conv2d-4	[-1, 20, 75, 75]	2,180
BatchNorm2d-5	[-1, 20, 75, 75]	40
MaxPool2d-6	[-1, 20, 37, 37]	0
Conv2d-7	[-1, 32, 37, 37]	5,792
BatchNorm2d-8	[-1, 32, 37, 37]	64
MaxPool2d-9	[-1, 32, 18, 18]	0
Linear-10	[-1, 5184]	53,752,896
Linear-11	[-1, 2592]	13,439,520
Linear-12	[-1, 4]	10,372

Total params: 67,211,224
 Trainable params: 67,211,224
 Non-trainable params: 0

Input size (MB): 0.26
 Forward/backward pass size (MB): 7.37
 Params size (MB): 256.39
 Estimated Total Size (MB): 264.02

Performance of Baseline Model



Test Loss: 2.623624

Test Accuracy of glioma_tumor: 13% (13/100)
 Test Accuracy of meningioma_tumor: 93% (107/115)
 Test Accuracy of no_tumor: 84% (89/105)
 Test Accuracy of pituitary_tumor: 33% (25/74)

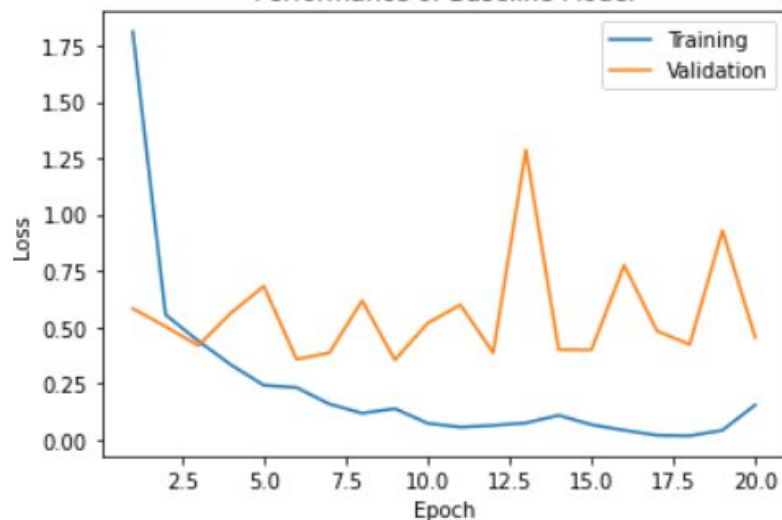
Test Accuracy (Overall): 59% (234/394)

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 150, 150]	336
BatchNorm2d-2	[-1, 12, 150, 150]	24
MaxPool2d-3	[-1, 12, 75, 75]	0
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BatchNorm2d-5	[-1, 20, 75, 75]	40
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Conv2d-7	[-1, 32, 37, 37]	5,792
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Total params: 67,211,224
 Trainable params: 67,211,224
 Non-trainable params: 0

Input size (MB): 0.26
 Forward/backward pass size (MB): 7.37
 Params size (MB): 256.39
 Estimated Total Size (MB): 264.02

Performance of Baseline Model



Test Loss: 2.753260

Test Accuracy of glioma_tumor: 28% (28/100)
 Test Accuracy of meningioma_tumor: 83% (96/115)
 Test Accuracy of no_tumor: 96% (101/105)
 Test Accuracy of pituitary_tumor: 62% (46/74)

Test Accuracy (Overall): 68% (271/394)

Source:

https://www.researchgate.net/figure/The-architecture-of-the-mask-region-convolutional-neural-network-Mask-RCNN-approach-for_fig2_347793558