Semantic Segmentation of Images

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Abstract

In this study, we explore the task of semantic segmentation using different Convolutional Neural Network architectures, specifically focusing on the PASCAL VOC-2012 dataset to classify objects at the pixel level, evaluating their performance using pixel accuracy and Intersection-over-Union (IoU) metrics. Our baseline model is a deep Fully Connected Convolutional Network trained with Xavier weight initialization and optimized using the Adam optimizer. The mean pixel accuracy is 73.77%, and the mean IoU is 0.0665. To enhance the performance, we also try cosine annealing learning rate scheduling, data augmentation techniques (random cropping, flipping), and a weighted loss function to mitigate class imbalance. Additionally, we experiment with a custom architecture integrating dropout layers and transfer learning using ResNet-34. Results indicate that the ResNet-based model outperforms the baseline, with 0.833 pixel accuracy and 0.188 mean IoU. However, our custom architecture showed only marginal improvements over the baseline, suggesting a trade-off between overfitting prevention and information retention.

1 Introduction

Semantic segmentation is important in the AI field today. It enables machines to recognize and interpret the image at a pixel level by assigning a class label to every pixel in an image. This capability is essential for many applications, including but not limited to self-driving, disease detection, remote sensing, etc.

The main goal of this project is to recognize objects from a number of visual object classes in realistic scenes. We build a Convolutional Neural Network to achieve the semantic segmentation task with the PASCAL VOC-2012 dataset, which has pixel-wise annotation. There are 21 categories in the dataset with 20 object categories and 1 background category.

There are two major metrics to measure how good a model is. The first one is the pixel accuracy, which is defined as:

$$\text{Percent correct predictions} = \frac{\text{total correct predictions}}{\text{total number of samples}} \tag{1}$$

The other metrics is called Intersection-Over-Union (IoU): The IoU is the area of overlap between the predicted segmentation and the ground truth divided by the area of union between the predicted segmentation and the ground truth:

$$\text{IoU} = \frac{TP}{TP + FP + FN} \tag{2}$$

where TP, FP, and FN are the numbers of true positive, false positive, and false negative pixels. With these two metrics in hand, the goal of this project is to build a network to reach the accuracy and IoU as high as possible.

2 Related Work

The major part of the code is consistent with the course materials. We also follow the Ronneberger et al. (2015) U-Net architecture while adjusting this architecture to our specific problem.

We also used the ResNet structure found in He et al. (2015) to experiment and improve the result. Not only did we use the architecture of ResNet, we also used the weights using the pytorch ResNet library.

3 Methods

We're using Xavier weight initialization as found in Glorot and Bengio (2010) and batch normalization. This is used to prevent the exploding and vanishing gradient problems. It also leads to quicker convergence.

Xavier weight initialization sets the weights of a layer to random values between the following values:

$\left(-\frac{\sqrt{6}}{\sqrt{n_{\text{in}}+n_{\text{out}}}}\right)$ and $\left(\frac{\sqrt{6}}{\sqrt{n_{\text{in}}+n_{\text{out}}}}\right)$

These random values fit into a uniform distribution. Lastly, another important aspect of our implementation is that we used the Adam gradient descent optimizer.

3.1 Baseline

In the baseline model, we built a fully connected deep convolutional neural network with the RELU activation function. The last layer has 21 out channels, signifying the number of categories we have. We did not apply a softmax or any activation function at the end of our forward function because the softmax is applied within the cross entropy loss function that we implemented. We used Xavier weight initialization as discussed in the Methods section. Our gradient descent optimizer was Adam.

Below is our architecture of the base FCN model:

Table 1: Baseline Structure

Layers	In channel	Out channel	Kernel Size	Stride	Padding	Dilation
Convolutional Layer1	3	32	3	2	1	1
ReLu Layer						
Normalization Layer1	32	32				
Convolutional Layer2	32	64	3	2	1	1
ReLu Layer						
Normalization Layer2	64	64				
Convolutional Layer3	64	128	3	2	1	1
ReLu Layer						
Normalization Layer3	128	128				
Convolutional Layer4	128	256	3	2	1	1
ReLu Layer						
Normalization Layer4	256	256				
Convolutional Layer5	256	512	3	2	1	1
ReLu Layer						
Normalization Layer5	512	512				
DeConvolutional Layer1	512	512	3	2	1	1
ReLu Layer						
Normalization Layer6	512	512				
DeConvolutional Layer2	512	256	3	2	1	1
ReLu Layer						
Normalization Layer7	256	256				
DeConvolutional Layer3	256	128	3	2	1	1
ReLu Layer						
Normalization Layer8	128	128				
DeConvolutional Layer4	128	64	3	2	1	1
ReLu Layer						
Normalization Layer9	64	64				
DeConvolutional Layer5	64	32	3	2	1	1
ReLu Layer						
Normalization Layer10	32	32				
Convolutional Classifier	32	21	1			

3.2 Improvements over Baseline

We made several key improvements to our model, including optimizing the learning rate schedule, applying data augmentations, and addressing class imbalances. These changes enhance generalization and robustness.

3.2.1 Cosine Annealing

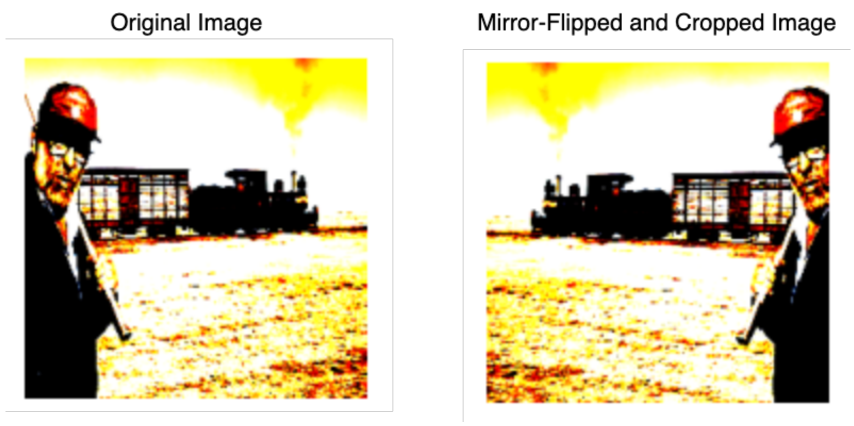
We utilized the cosine annealing learning rate scheduler to adjust the learning rate dynamically over the course of training epochs. This approach helped improve convergence by gradually reducing the learning rate, allowing the model to settle into a better minimum while avoiding sharp drops in performance. Using Cosine Annealing Scheduler, we were able to achieve IOU of 0.0662 and pixel accuracy of 73.6%.

3.2.2 Transformations

We randomly cropped 30% of the images with the fraction of the original image area between 0.9 and 1, and the aspect ratio between $\frac{3}{4}$ and $\frac{4}{3}$. We also randomly flipped mirrors on 30% of the pictures as well as the labels.

Below is an example of applying the image transformations to a sample image. We applied both a mirror flip and a random cropping to this image. However, the chose and transformations are not necessarily done on the same images. 30% of the images are randomly chosen for flipping and

30% are randomly chosen for cropping. Augmenting the data resuled in an IOU of 0.069 and pixel accuracy of 73.71%.



3.2.3 Imbalance problem

To deal with the class imbalance, we implemented the weighted loss function. To obtain the weights, we simply went through each of the training mask and count the number of pixels for each class. To get the class weights we take the inverse of those counts. To prevent division by 0 we add a very small number to each of the counts.

By resolving the issue of class imbalance, we were able to achieve an IOU of 0.064 and pixel accuracy of 74.14%.

3.3 Experimentation

3.3.1 Custom Architecture

We tried different architectures built on the baseline model. We add the dropout layers between the first block of convolutional and deconvolutional sections, which consists of convolutional and normalization layers, with different probabilities of an element to be zeroed. The reason why only adding dropout layers between the first block is to minimize the influence of dropping information. The probability within the convolutional section is set to 0.1, and the probability within the deconvolutional section is set to 0.15. During the experiment, we also followed the similar data augmentation we used above, including randomly cropping and flipping, and tried different learning rates with the Cosine Annealing schedule and class balancing. Table 2 shows the architecture of our experimental network.

Table 2: Experiment Structure

Layers	In channel	Out channel	Kernel Size	Padding	Stride	Dilation	Fraction of Zero
Convolutional Layer1	3	32	3	2	1	1	
ReLu Layer							
Normalization Layer1	32	32					
Dropout Layer							0.1
Convolutional Layer2	32	64	3	2	1	1	
ReLu Layer							
Normalization Layer2	64	64					
Convolutional Layer3	64	128	3	2	1	1	
ReLu Layer							
Normalization Layer3	128	128					
Convolutional Layer4	128	256	3	2	1	1	
ReLu Layer							
Normalization Layer4	256	256					
Convolutional Layer5	256	512	3	2	1	1	
ReLu Layer							
Normalization Layer5	512	512					
DeConvolutional Layer1	512	512	3	2	1	1	
ReLu Layer							
Normalization Layer6	512	512					
Dropout Layer							0.15
DeConvolutional Layer2	512	256	3	2	1	1	
ReLu Layer							
Normalization Layer7	256	256					
DeConvolutional Layer3	256	128	3	2	1	1	
ReLu Layer							
Normalization Layer8	128	128					
DeConvolutional Layer4	128	64	3	2	1	1	
ReLu Layer							
Normalization Layer9	64	64					
DeConvolutional Layer5	64	32	3	2	1	1	
ReLu Layer							
Normalization Layer10	32	32					
Convolutional Classifier	32	21	1				

Metric	**Value**
Test Loss	0.9972
Test IoU	0.1382
Test Pixel Accuracy	0.7855

Table 3: Test Performance Metrics

3.3.2 Transfer Learning with ResNet

We implemented ResNet 34, as described in He et al. (2015), by using the pytorch module and replacing the encoder of our current model. This encoder has 34 convolutional layers and we removed the last two and fit it onto our decoder. This included the architecture and weights from the model. We allowed the model to adjust the ResNet weights during training to fine tune it to our task. The decoder layer weights were still allowed to be adjusted during training. The result was an increase in training, validation, and test accuracy. We kept the Cosine Annealing, class balancing, and image augmentation settings from earlier.

Table 4: ResNet Structure

Layers	In channel	Out channel	Kernel Size	Stride	Padding	Dilation
ResNet Encoder (Removed last 2 layers)	3	512				
DeConvolutional Layer1	512	512	3	2	1	1
ReLu Layer						
Normalization Layer6	512	512				
DeConvolutional Layer2	512	256	3	2	1	1
ReLu Layer						
Normalization Layer7	256	256				
DeConvolutional Layer3	256	128	3	2	1	1
ReLu Layer						
Normalization Layer8	128	128				
DeConvolutional Layer4	128	64	3	2	1	1
ReLu Layer						
Normalization Layer9	64	64				
DeConvolutional Layer5	64	32	3	2	1	1
ReLu Layer						
Normalization Layer10	32	32				
Convolutional Classifier	32	21	1			

Metric	**Value**
Test Loss	0.9150
Test IoU	0.1875
Test Pixel Accuracy	0.8329

Table 5: Test Performance Metrics

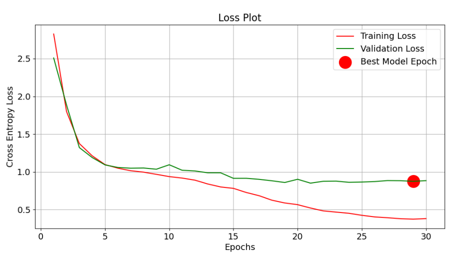


Figure 1: Loss plot from ResNet training

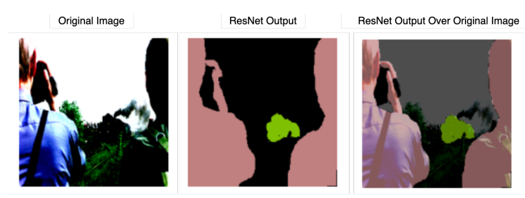


Figure 2: Sample output images from ResNet

3.3.3 U Net

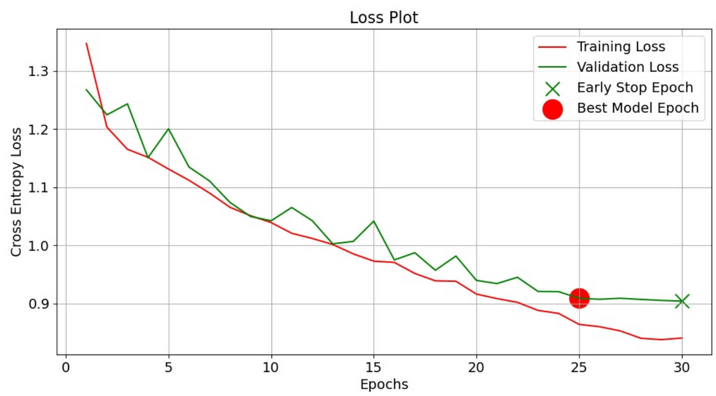
Layers	In Channels	Out Channels	Kernel Size	Stride	Padding	Dilation
Conv1 (Encoder)	3	64	3	1	1	1
Conv2 (Encoder)	64	128	3	1	1	1
Conv3 (Encoder)	128	256	3	1	1	1
Conv4 (Encoder)	256	512	3	1	1	1
Conv5 (Bottleneck)	512	1024	3	1	1	1
UpConv1 (Decoder)	1024	512	2x2	2	0	1
Conv6 (Decoder)	1024	512	3x3	1	1	1
UpConv2 (Decoder)	512	256	2x2	2	0	1
Conv7 (Decoder)	512	256	3x3	1	1	1
UpConv3 (Decoder)	256	128	2x2	2	0	1
Conv8 (Decoder)	256	128	3x3	1	1	1
UpConv4 (Decoder)	128	64	2x2	2	0	1
Conv9 (Decoder)	128	64	3x3	1	1	1
Convolutional Classifier	64	n_class	1x1	-	-	-

Table 6: Layer-wise Description of U-Net Model

Note: Each conv layer represents 2 conv layers which are represented as follows. The in channels and out channels depend on where they are in the network.

Layers	In Channels	Out Channels	Kernel Size	Stride	Padding	Dilation
Conv	input	output	3	1	1	1
BatchNorm	output	output	-	-	-	-
Conv	output	output	3	1	1	1
BatchNorm	output	output	-	-	-	-

We used the standard UNET implementation as directed in the paper with a slight modification of introducing batch norm. All input and output chaneles were maintained as directed in the UNET paper. All the activations were relu, except for the classifier layer having no activation. Batch norm brings regularization to the model. Below are the results -



Metric	Value
Test Loss	0.930
Test IoU	0.083
Test Pixel Accuracy	75.6%

Table 7: Test Performance Metrics

4 Results

Architecture	Pixel Accuracy	Average IoU
Baseline Model	73.77%	0.0665
Cosine Annealing LR Scheduler	73.6%	0.0662
Image Augmentations	73.71%	0.069
Weighted Loss	74.14%	0.064

Table 8: Performance for Models on test sets (Pixel Accuracy and Average IoU)

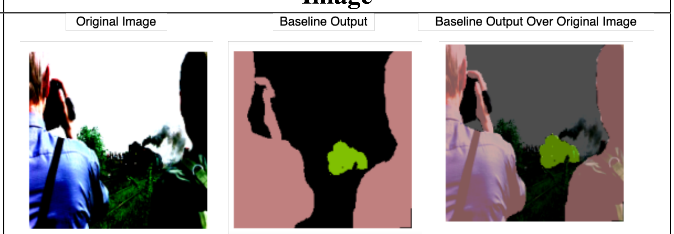
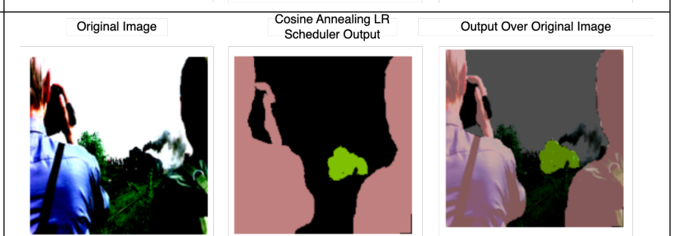
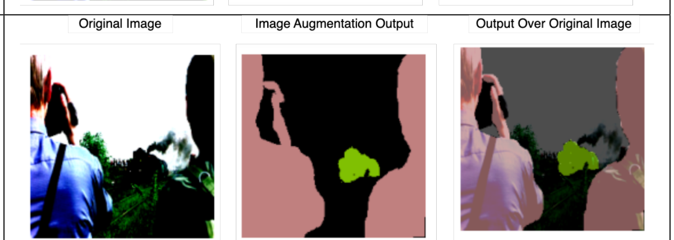
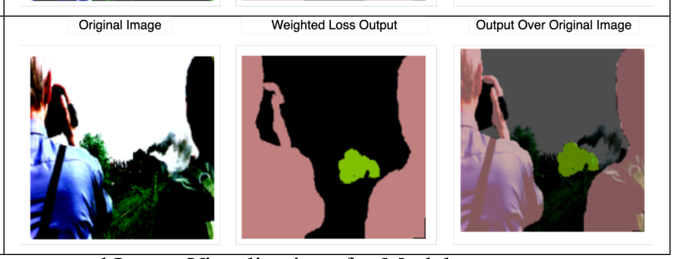
Architecture	Image
Baseline Model	
Cosine Annealing LR Scheduler	
Image Augmentations	
Weighted Loss	

Table 9: Architecture and Image Visualizations for Models

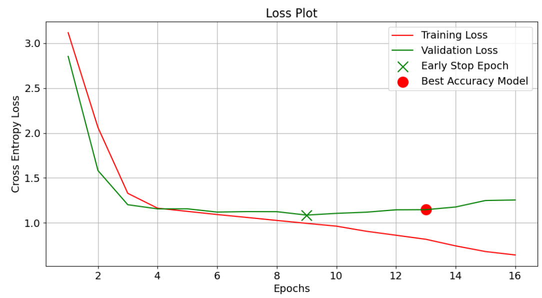
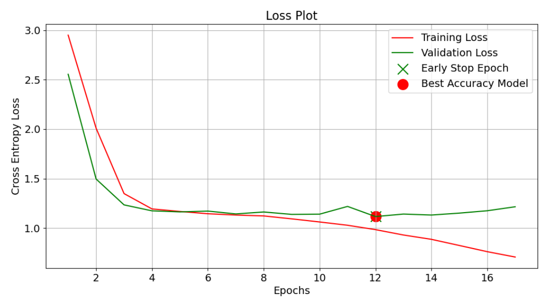
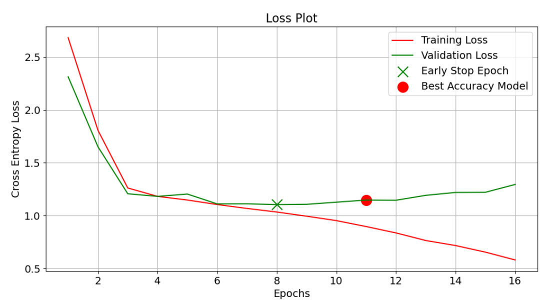
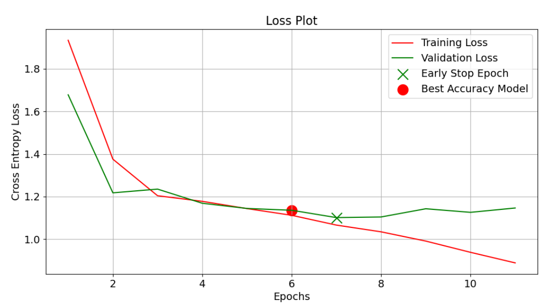
Architecture	Loss
Baseline Model	
Cosine Annealing LR Scheduler	
Image Augmentations	
Weighted Loss	

Table 10: Architecture and Training/Validation Loss for Models

4.1 Discussion on Baseline Model

The baseline model used was a Fully Convolutional Network (FCN) trained on the VOC dataset with cross-entropy loss. This model provided a foundation for evaluating improvements and comparing other architectures. The FCN effectively captured spatial context through convolutional layers, which is important for semantic segmentation.The model showed some drawbacks, such as losing spatial details due to downsampling in deeper layers, slower convergence, and limited generalization.

The baseline model achieved a mean Intersection over Union (mIoU) of 0.066. From the loss plot in 4, the training loss consistently decreased, but the validation loss plateaued early, indicating overfitting after epoch 6, which is marked as the "Early Stop Epoch" (green cross). The best accuracy model (red circle) occurred at epoch 13, where validation loss was slightly lower. This divergence between training and validation losses shows that the model struggled with generalization due to insufficient regularization or data augmentation.

Overall, the baseline model performed reasonably well but had room for improvement in handling class imbalances and preventing overfitting. These results provide a benchmark for comparing the improved baseline and other architectures.

4.2 Discussion on Improving Baseline Model

The first improvement we made was adding a learning rate scheduler, cosine anealing. As we can see in the results there is hardly any improvement. but from the plot we can see that the training loss was a little lower. After this we implemented data augmentation, the 2 augmentations we employed were image cropping and flipping. This did result in model improvements having both better pixel accuracy and higher average IoU. After this we implemented weighted loss to combat class imbalance this made a good improvement in our model taking the pixel accuracy to 77.9 having the most impact on the model.

As we can see from the results section, the improvements that we implemented were necessary but not integral to the larger gains in accuracy that we saw. This point is shown by looking at the masks that were produced for all of the baseline improvements. All of the masks look about the same because the accuracies are very similar. The graphs of the loss functions all look relatively similar as well, where early stopping came into play as our model began to overfit around the 12th epoch.

4.3 Discussion on Experimentation

In our customized architecture, adding the dropout layers between different blocks is supposed to improve the overfitting problem. According to our experimental result, the pixel accuracy and average IoU are similar to the baseline model. This could be because of the trade-off between the benefit of improving overfitting and the loss of throwing information.

Our ResNet model performed quite well compared to our baseline model and other experiments. We used our other model enhancements such as cosine annealing, class balancer, and image augmentations as well. Using the pre-trained weights from ResNet 34 resulted in about a 4% increase in the test accuracy. One thing to note is that allowing the ResNet weights to be changed during training improved the model's performance because it allowed back propagation to slightly fit ResNet's weights to our problem.

UNET model did not perform as well as the other models. Though it did perform better then the baseline model. The main observations were that majority of the learning was completed in very early epochs, no change seemed to affect that even adaptive learning rates did not improve the accuracy by much. Adding batch norm to the layers did help to improve the model a little. We also maintained the weighted loss and image augmentation as removing them reduced the model performance. The model did manage to achieve a test pixel accuracy of 75.6%. We can see from the graph that while the train loss curve was smooth the validation had a lot of changes.

References

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