Artificial Intelligence for Medical Image Analysis Assignment 3

Ujjawal Dewangan

December 15, 2022

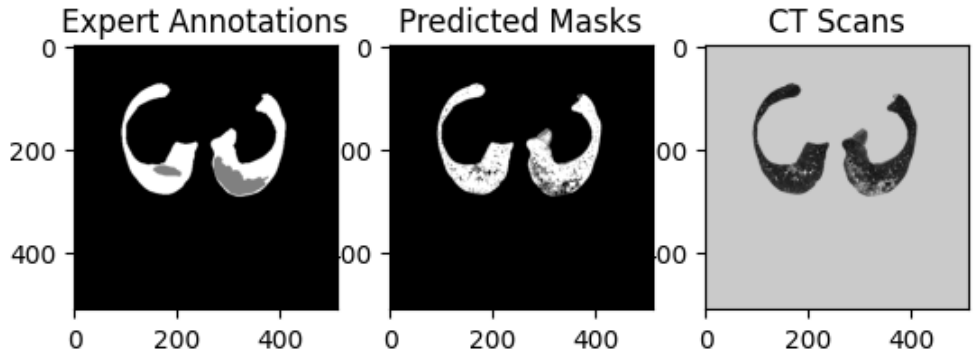
Q1

Task: Split the data(CT slices) into 70% training, 10% validation and 20% testing. Trained a UNet model to segment the given CT slices into background-0, COVID anomaly-1, and normal-2 regions.
Evaluated the performance of segmentation using average dice score, sensitivity, specificity, and accuracy of Anomaly and Normal class.
The following results*(averaged over all the samples)* were obtained:

—	**Anomaly**	**Normal**
Dice Score	0.3562	0.8992
Sensitivity	0.5548	0.8373
Specificity	0.9896	0.9986
Accuracy	0.9902	0.9873

Average evaluation metrics for Anomaly and Normal class.

Sample slice with Expert Annotation(left), Predicted Mask(Middle) and CT Scan(Right)



Q2

Task: Reconstruct CT Scan images from limited angle Sinogram(4x and 8x)
Performed segmentation using UNet model and evaluated the performance as done in question 1.

Repeat Q1 for Reconstructed Images.

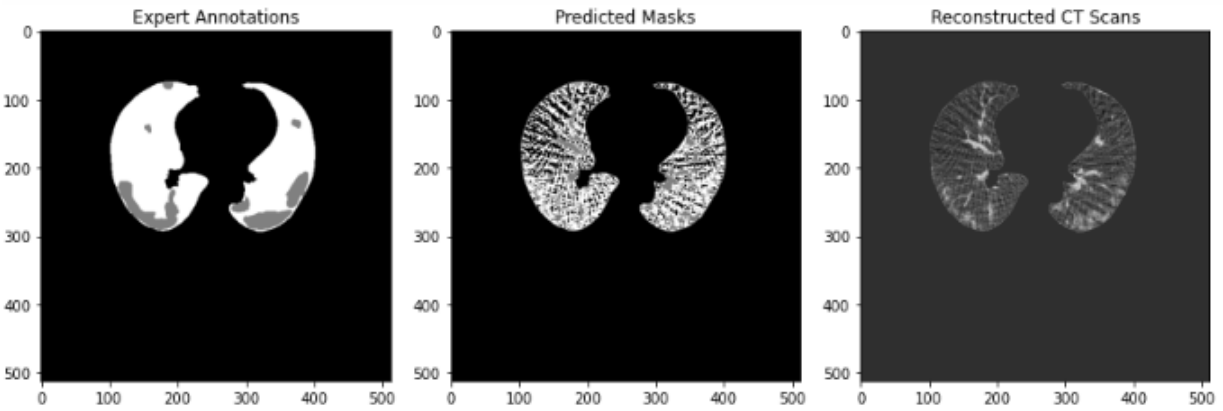
Evaluation of Image Segmentation for Reconstructed CT Scan images.
(i) *4x Reconstruction*

Evaluation

—	Anomaly	Normal
Dice Score	0.2896	0.8764
Sensitivity	0.4459	0.5686
Specificity	0.9634	0.9935
Accuracy	0.9816	0.9907

Average evaluation metrics for Anomaly and Normal class for reconstructed CT Scan images from limited angle Sinogram(4x).

Sample Slice

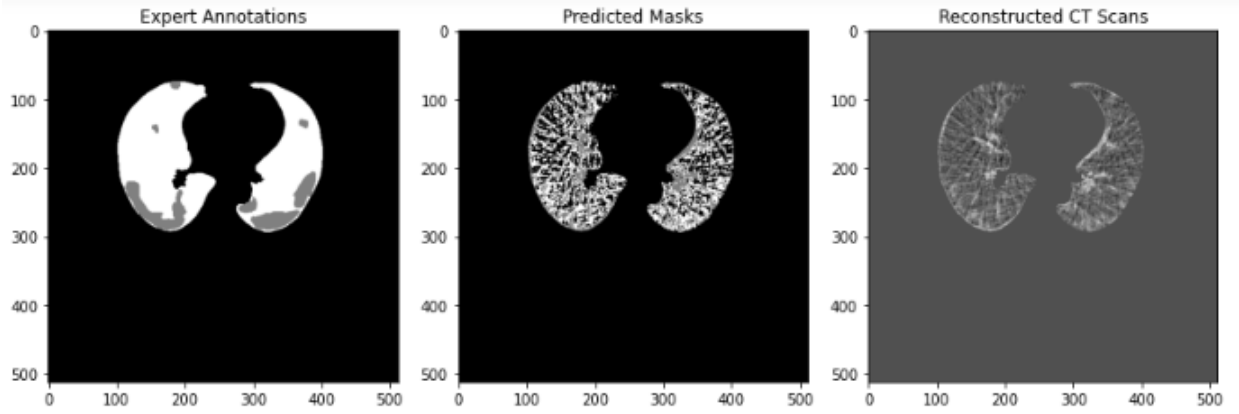


(ii) *8x Reconstruction*
Evaluation

—	Anomaly	Normal
Dice Score	0.2619	0.6932
Sensitivity	0.4012	0.5317
Specificity	0.9609	0.9915
Accuracy	0.9791	0.9901

Average evaluation metrics for Anomaly and Normal class for reconstructed CT Scan images from limited angle Sinogram(8x).

Sample Slice



Q3

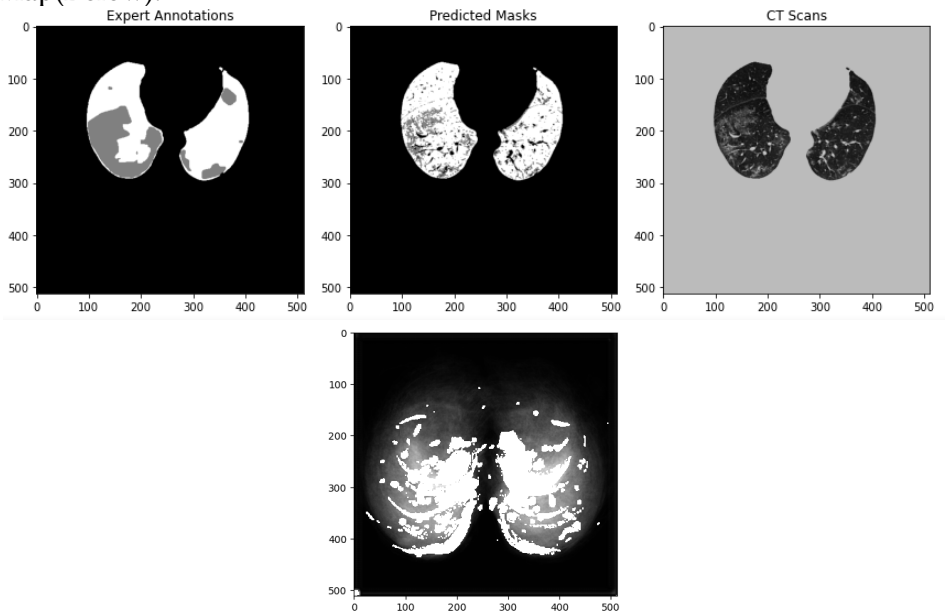
Task: Perturb to the parameters of trained UNet model and calculate all the evaluation metrics for each value of η = [-0.01, -0.001, +0.001, +0.01].

(i) $\eta = -0.01$

—	**Anomaly**	**Normal**
Dice Score	0.4315	0.9525
Sensitivity	0.5630	0.9425
Specificity	0.9856	0.9916
Accuracy	0.9825	0.9932

Average evaluation metrics for Anomaly and Normal class($\eta = -0.01$).

Sample slice with Expert Annotation(left), Predicted Mask(Middle), CT Scan(Right), and Uncertainty Map(Below).

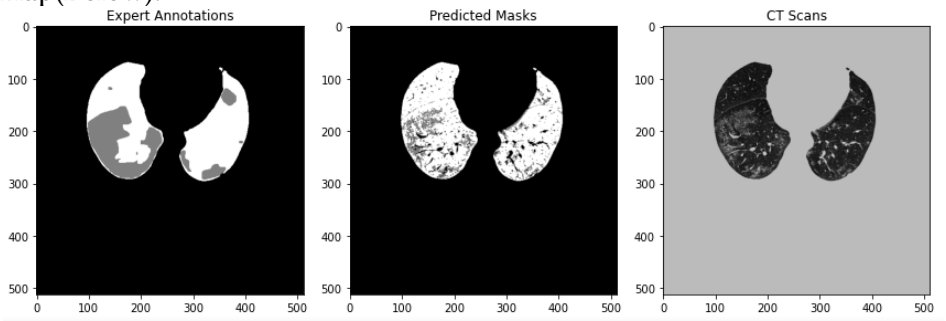


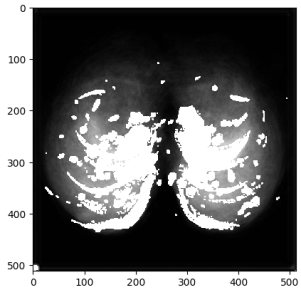
(ii) $\eta = -0.001$

—	**Anomaly**	**Normal**
Dice Score	0.4371	0.9625
Sensitivity	0.5597	0.9384
Specificity	0.9846	0.9966
Accuracy	0.9832	0.9925

Average evaluation metrics for Anomaly and Normal class($\eta = -0.001$).

Sample slice with Expert Annotation(left), Predicted Mask(Middle), CT Scan(Right), and Uncertainty Map(Below).



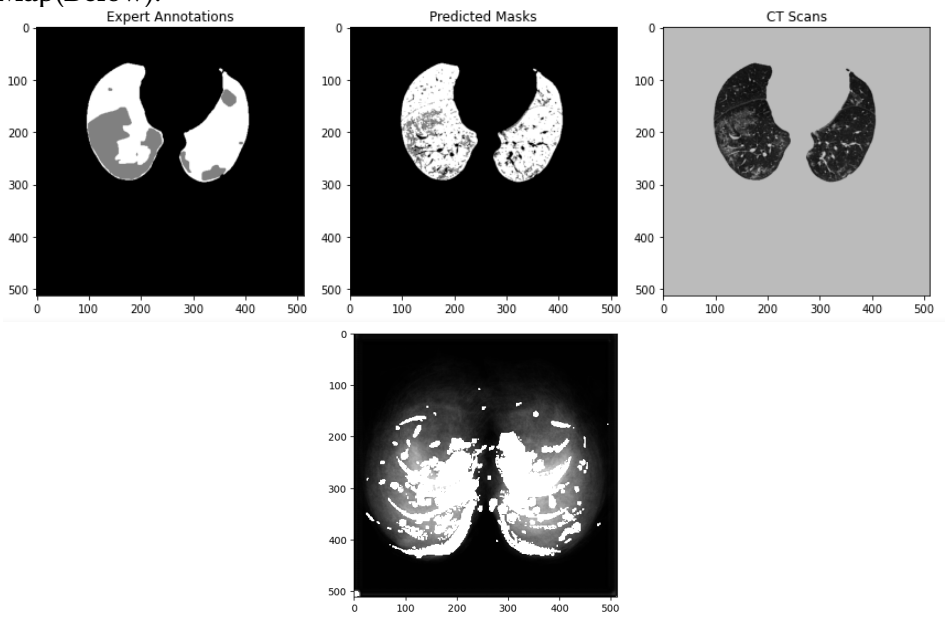


(iii) $\eta = +0.001$

—	**Anomaly**	**Normal**
Dice Score	0.4384	0.9591
Sensitivity	0.5494	0.9326
Specificity	0.9838	0.9897
Accuracy	0.9852	0.9918

Average evaluation metrics for Anomaly and Normal class($\eta = +0.001$).

Sample slice with Expert Annotation(left), Predicted Mask(Middle), CT Scan(Right), and Uncertainty Map(Below).

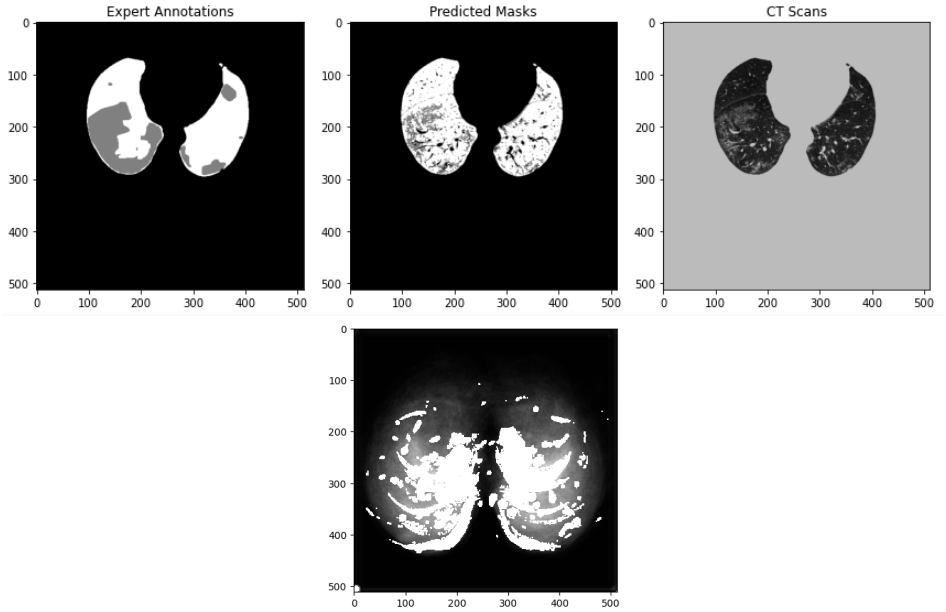


(iv) $\eta = +0.01$

—	**Anomaly**	**Normal**
Dice Score	0.4429	0.9636
Sensitivity	0.5628	0.9364
Specificity	0.9901	0.9928
Accuracy	0.9932	0.9956

Average evaluation metrics for Anomaly and Normal class($\eta = +0.01$).

Sample slice with Expert Annotation(left), Predicted Mask(Middle), CT Scan(Right), and Uncertainty Map(Below).



Observation: The magnitude of the perturbation(η) has a little correlation with the error metrics, as can be seen from the table.