Attention U-Net : Medical Image Segmentation

Design Project ID-34 Neural Networks and Fuzzy Logic

Implementation of the Research Paper - Attention U-Net: Learning Where to Look for the Pancreas

PROBLEM STATEMENT

Existing Problems:

- Manual Segmentation has high error rate.
- o If CT is dense, manual segmentation takes time and is a tedious task.
- Due to this **Automated medical image segmentation** has been extensively studied in the image analysis community as:
 - Accurate and reliable solutions.
 - Support decision making through fast and automatic extraction of quantitative measurements

Examples:

Pancreas Segmentation out of abdomen CT and BP Brachial Plexus Nerve out of ultrasound.

DATASET

Initial Dataset:

- Abdomen CT task to segment pancreas.
- Images in .tcia zip and dicom format.
- Masks in .nii format.
 - Tough to process, load, resize etc.
 - Huge python codes required to convert into uint8, float32 etc.

Final Dataset:

- Ultrasound nerve images(from Kaggle).
 - 5635 samples of images and their masks..
 - 5580 images in test data.
 - .tif format which is easy to work with.
- Mask and images in same folder.
 - Rather than segregating, converted into .npy files.
- Dataset contains two files
 - Xtrain (images).
 - Ytrain (masks)
 - 20% validation data.

DATA PROCESSING

- Original images in dataset consisted of size 420 x 580 pixels.
- Images resized to 96 x 96 pixels.
- Mean Centering & Data Standardization
 - o each feature have a similar range
 - gradients don't go out of control
 - only one global learning rate multiplier

MODEL

Attention U-Net

- Improves model sensitivity and accuracy by attaching attention gates on top of the standard U-Net.
- Automatically learns to focus on target structures of varying shapes and sizes.

Attention gates

- Commonly used in natural image analysis, knowledge graphs and language processing(NLP) for image captioning, machine translation and classification.
- Improve model sensitivity and accuracy for dense label predictions by suppressing feature activation in irrelevant regions.

U-Net

- Built upon the Fully Convolutional Network and modified in a way that it yields better segmentation in medical imaging.
- U-Net architecture is separated in 3 parts:
 - The contracting/downsampling path
 - Bottleneck
 - The expanding/upsampling path

MODEL

Adam Optimizer

- o combining the advantages of two other extensions of stochastic gradient descent:
 - Adaptive Gradient Algorithm.
 - Root Mean Square Propagation.

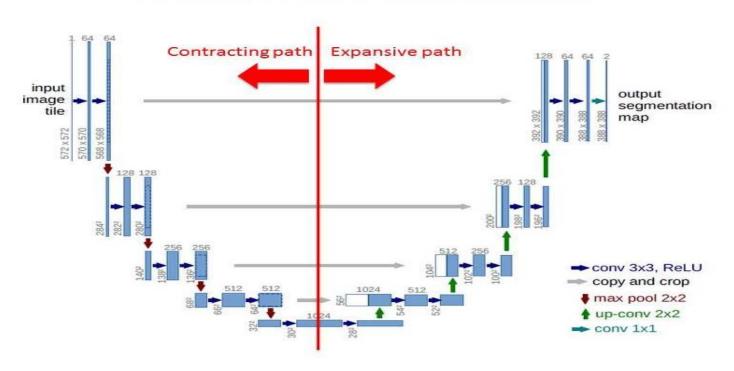
Dice coefficient

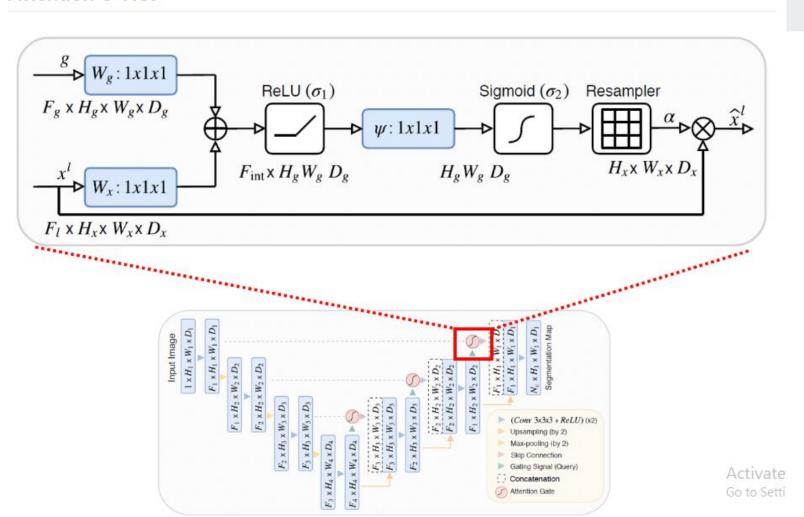
- Statistical tool which measures the similarity between two sets of data.
- Equation:
 - 2 * |X| ∩ |Y| / (|X| + |Y|)
- the range of DSC is between 0 and 1, the larger the better.

Dice Loss

- Dice Loss= 1-(Dice coeff)
- Maximize the overlap between two sets.
- o considers the loss information both locally and globally, which is critical for high accuracy.

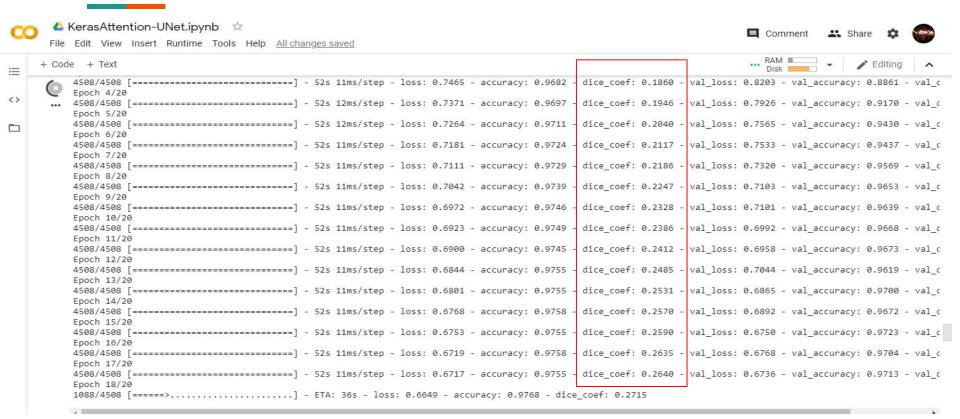
Network Architecture

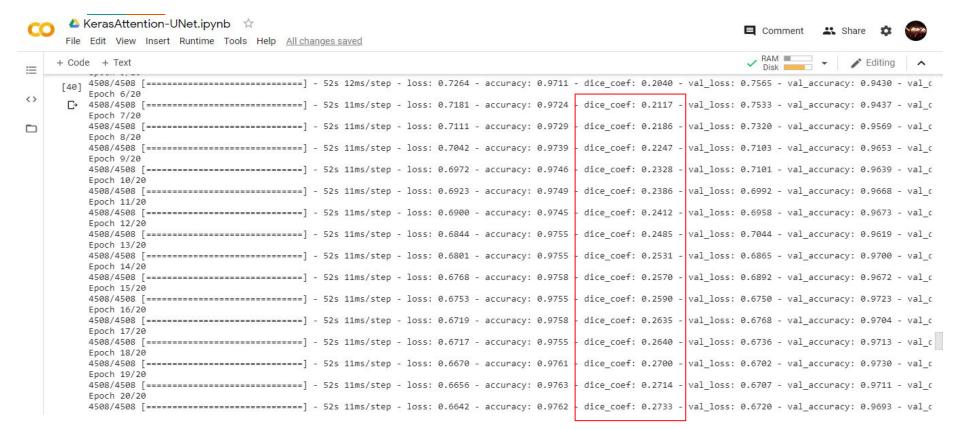


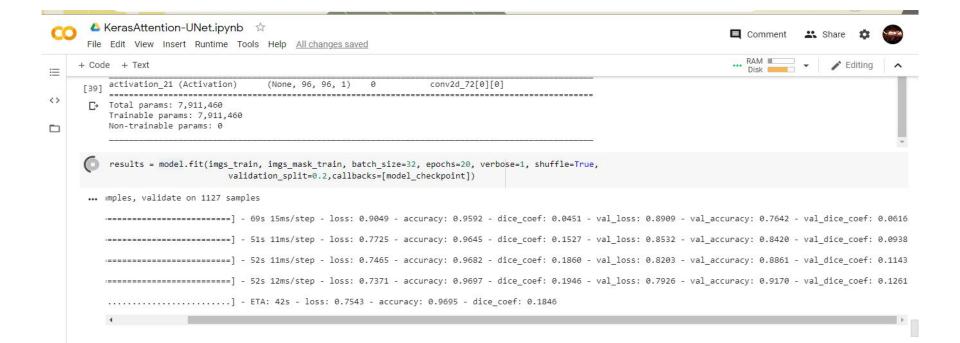


- Measurement and Comparison of performance is done using Dice Coefficient.
- Dice coefficient(Epoch 1)=0.0451
- Dice Coefficient (Epoch 2)=0.2733

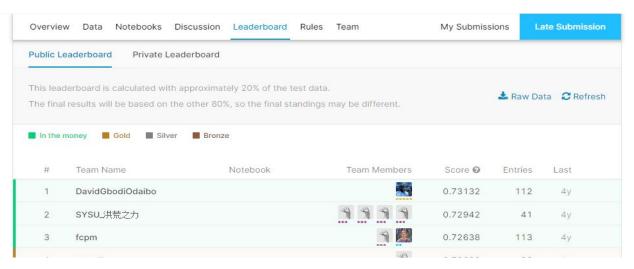


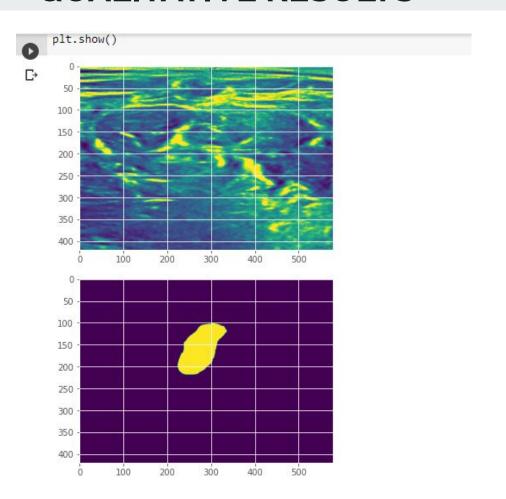






We compared our results with kaggle competition -top 3 entries.





- Kaggle Dataset Entry
- Training Sample:X_train andcorresponding mask Y_train

• Sample Predictions:

