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Ultrasound Nerve Segmentation : A kaggle competition

Final project presentation

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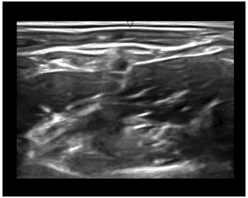
Understanding the Kaggle challenge

We participated in a Kaggle competition called UltraSound Nerve Segmentation.

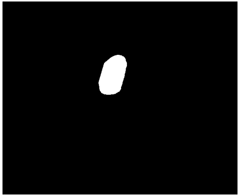
- The goal was : **Build the best performing model to identitfy nerve structures in the neck**.
- Dataset : Ultrasound images from the neck
- Medical goals :
  - Effectively insert a patient's pain management catheter
  - Reduce dependence on narcotics
  - Speed up patient recovery
  - Improve pain management

Datasets

- Large training set of images where nerves were manually annotated by humans.
- Train size = 5635, Test size = 5508
- The dataset contains images with no active regions, some degree of noise and artifacts.
- Identical images possible
- Use of run-length encoding (RLE) on the pixel values for final submission



(a) Image with a nerve



(b) Ground truth mask

Figure: 2 Figures side by side

Evaluation metrics

We used several evaluation metrics :

- **Dice coefficient** : 2 * the Area of Overlap divided by the total number of pixels in both images.
- **Jaccard similarity (IoU)** : intersection over union
- **Recall** : TP/(TP+FN)

U-Net and its variant with 2 heads

Leaderboard score of the classic U-Net : **0.58607**

Leaderboard score of the U-Net variant : **0.68589**

Innovation in the variant of U-Net :

- One auxiliary head (after the encoding part) for predicting the nerve presence in the image
- A weighted loss with binary cross entropy and negative dice coefficient
- Inception blocks

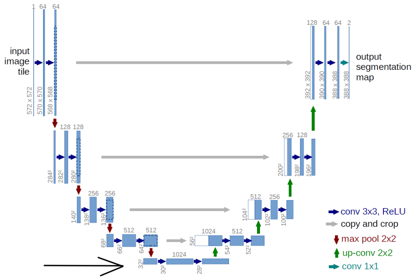


Figure: U-Net with a nerve presence branch at the bottom

R2U-Net

Advantages of R2U-Net over U-Net :

- Residual units help building a more efficient deeper model
- Feature accumulation method helps extract better feature representation in particular low-level features

Score of R2U-Net : **0.51214**

Score of R2U-Net using the probability of nerve presence file : **0.64770**

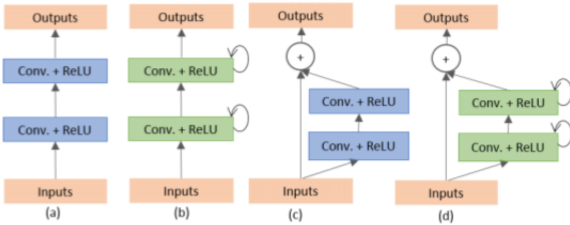


Figure: Different variant of convolutional and recurrent convolutional units (a) Forward convolutional units (d) Recurrent Residual convolutional units

Unet++

Novelty of Unet++ compared to Unet :

- **redesigned skip pathways** (shown in green) : sem link enco-deco
- **dense skip connections** (shown in blue) : improve gradient flow
- **deep supervision** (shown in red) : model pruning and performance

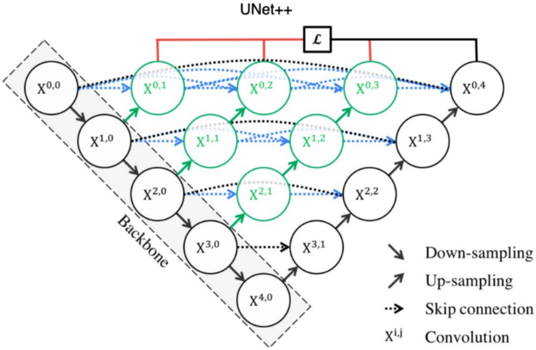


Figure: U-net++ architecture

Unet++

Hyperparameters tuning :

- BatchSize : 32,64,128
- Learning Rate : 1e-5, 1e-4, 2e-4, 3e-4 (value used in original paper)
- Epochs : 20, 50, 70
- Optimizer : Adam, RMSProp

Results for the differents cases

Model	Val Dice Coefficient	Leaderboard
Unet++ no data aug	0.6187	0.63241
Unet++ with data aug	0.0957	0.58086

Table: Unet++ results with and without data augmentation

Attention ResUnet

Attention ResUnet can be seen as a combination of different previously developped models :

- **Unet model** : previously described in this report
- **Attention Gates** : used to perform class-specific pooling, amplify the relevant regions, thus demonstrating superior generalisation, better classification performance.
- **Residual block** : incorporated in this version of Attention-Unet.

Results for the differents cases

Model	Val Dice Coefficient	Leaderboard
AttResNet no data aug	0.0951	0.55389
AttResNet with data aug	RAM crash	RAM crash

Table: AttResNet results with and without data augmentation

Quantitative results

Models	Nb of Parameters	With proba of Nerve presence	Sensitivity	Jaccard Similarity	Dice Coefficient	Leaderboard
U-Net	7,759,521	No	0.6125	0.5833	0.6062	**0.58607**
-	-	Yes	-	-	-	**0.64789**
U-Net incep2 heads	1,865,676	No	0.6078	0.7076	0.5986	**0.58930**
-	-	Yes	-	-	-	**0.68589**
R2U-Net	6,003,009	No	0.6373	0.5988	0.5896	**0.51214**
-	-	Yes	-	-	-	**0.64770**
U-Net++	9,041,601	No	0.6778	0.6635	0.5109	**0.63241**
AttResNet	9,786,857	No	0.4776	0.6690	0.1045	**0.55389**

Table: Model performance with the original dataset

Quantitative results

Models	Sensitivity (validation set)	Jaccard similarity (validation set)	Dice coefficient (validation set)	Dice coefficient (leaderboard)
U-Net inception 2 heads	0.0666	0.5185	0.0942	**0.68311**
U-Net++	0.0634	0.5181	0.0957	**0.62423**

Table: Model performance on the augmented dataset

Qualitative results

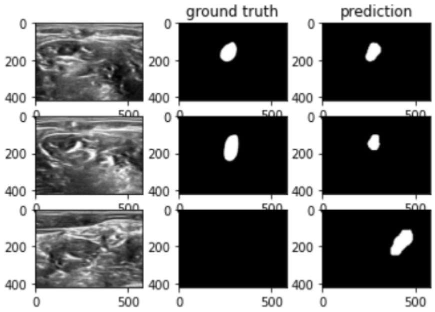


Figure: Images with ground truth masks and predictions from the U-Net with 2 heads model. The dice coefficients are 0.88 for the first image, 0.59 for the second image and 0.0 for the third image

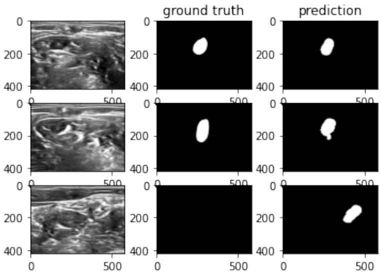


Figure: Images with ground truth masks and predictions from the U-Net++ model. The dice coefficients are 0.89 for the first image, 0.78 for the second image and 0.0 for the third image

Thank You!