Improved Alzheimer's disease (AD) Diagnosis with U-Net Variants Trained on Brain MRI Scans

CS 512 Computer Vision - Spring 2023 - Group 11

Jiaxin Dong A20499780
Toluwani Oyewusi A20425821

1

Introduction

- Alzheimer's disease(AD) is the main cause of dementia.
- Individuals with the AD usually experience difficulties in learning, performance speed, recall accuracy and/or problem solving.
- The hippocampus helps us develop new memories also retrieving old memories.
- The hippocampus is one of the first areas in the brain affected by Alzheimer's disease is the hippocampus.

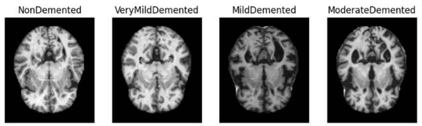
2

Problem statement

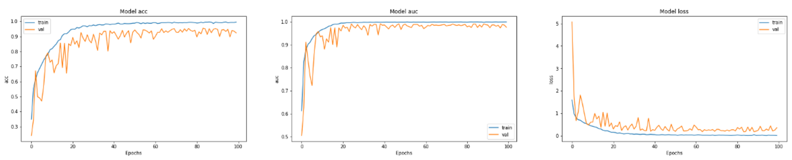
- Develop a deep learning-based approach for the automatic identification and diagnosis of Alzheimer's disease trained on brain MRI scans.
- Preprocess and prepare the dataset for training and evaluation, including standardization, normalization, and data augmentation techniques.
- Implement and train U-Net and its variants, such as U-Net++, on the preprocessed dataset to develop models capable of segmenting regions of interest and classifying Alzheimer's disease.
- Evaluate the performance of the trained models using appropriate metrics.

3

Relative work

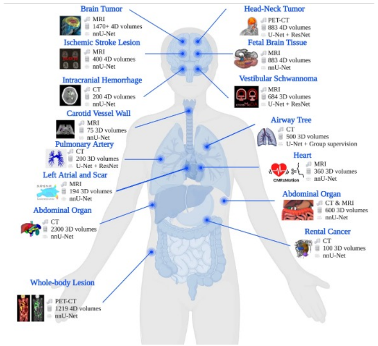


	precision	recall	f1-score	support
NonDemented	0.86	1.00	0.92	639
VeryMildDemented	1.00	1.00	1.00	635
MildDemented	0.91	0.88	0.89	662
ModerateDemented	0.94	0.82	0.88	624
micro avg	0.92	0.92	0.92	2560
macro avg	0.93	0.92	0.92	2560
weighted avg	0.93	0.92	0.92	2560
samples avg	0.92	0.92	0.92	2560



4

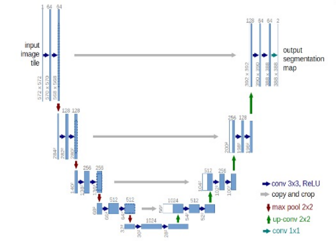
Relative work

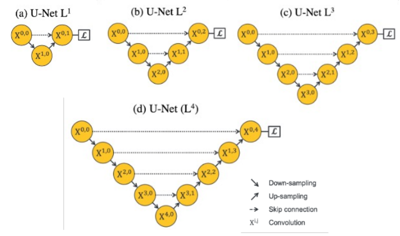


MICCAI 2022

5

Proposed Solution



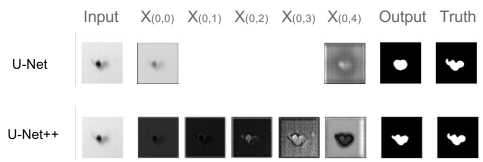


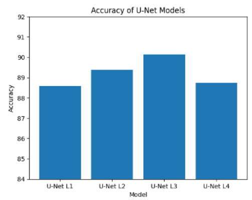
Why up-sampling until 4 level?

6

Proposed Solution

Cell Segmentation

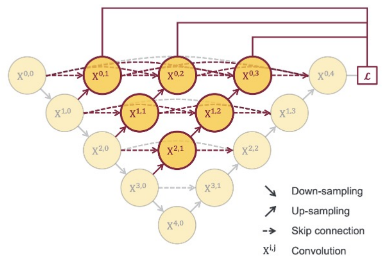




7

Proposed Solution

U-Net++

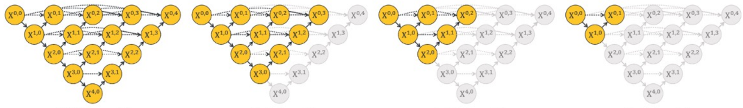


- Redesigned skip pathways
  - Increase feature fusion
  - Dense feature map connections
  - Concatenation for re-usable intermediate representations

8

Proposed Solution

U-Net++



- The use of deep supervision
  - Model pruning for speed-accuracy balance
  - Multi-depth output ensembling

9

Prepare dataset

Folder Structure

- original
  - 100
    - ADNI_002_S_0295_13722_ACPC
      - ADNI_002_S_0295_13722_ACPC_001.jpg
      - …
      - ADNI_002_S_0295_13722_ACPC_189.jpg
    - …
    - ADNI_136_S_0579_116340_ACPC
  - 35
    - …

The label folder is incomplete for a patient as it is missing the right hippocampus data for the brain.

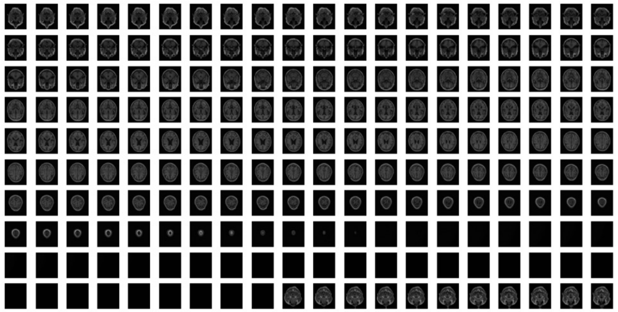
- label
  - 100label
    - ADNI_002_S_0295_13722_ACPC
      - ADNI_002_S_0295_13722_L
        - ADNI_002_S_0295_13722_L_001.jpg
        - …
        - ADNI_002_S_0295_13722_L_189.jpg
      - ADNI_002_S_0295_13722_R
        - ADNI_002_S_0295_13722_R_001.jpg
        - ...
        - ADNI_002_S_0295_13722_R_189.jpg
    - …
    - ADNI_136_S_0579_116340_ACPC
  - 35label
    - …

Data source: Kaggle, MRI Hippocampus Segmentation

10

Prepare dataset

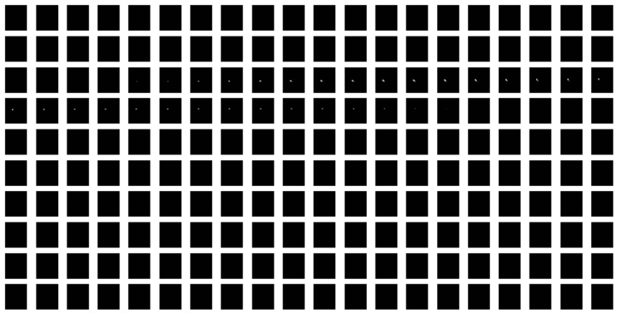
Original (first 200 images)



11

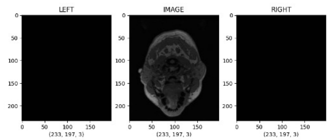
Prepare dataset

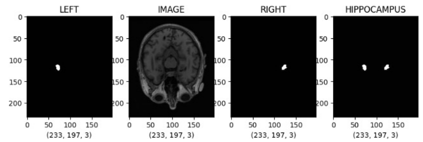
Label (first 200 images)

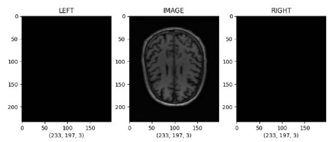


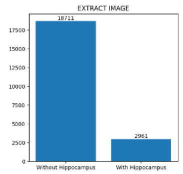
12

Prepare dataset









Model Architectures

U-Net

- Encoder-Decoder structure
- Convolutional blocks with ReLU and batch normalization
- Max-pooling for downsampling
- Upsampling with skip connections

U-Net++

- Encoder-Decoder structure
- Convolutional blocks with ReLU and batch normalization
- Max-pooling for downsampling
- Upsampling with additional nested skip connections
- Dropout rate for regularization
- Deep supervision

Loss Functions

Binary Cross-Entropy Loss (BCE):

Calculates the difference between predicted probabilities and binary ground truth labels, commonly used in binary classification tasks.

Dice Loss:

Measures the overlap between predicted segmentation and ground truth, particularly useful for imbalanced class segmentation tasks.

Combine Loss:

Combination of Binary Cross-Entropy Loss (BCE) and Dice Loss.

Evaluation Metrics

$$IoU = \frac{|A \cap B|}{|A \cup B|} = \frac{TP}{(TP + FP + FN)}$$

$$DSC = \frac{(2 \times Precision \times Recall)}{(Precision + Recall)} = \frac{2TP}{(2TP + FP + FN)}$$

$$Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)}$$

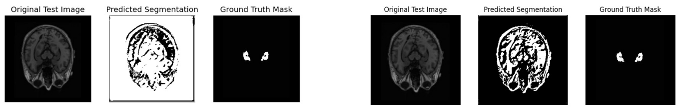
FP: false positive, FN: false negative, TP: true positive, and TN: true negative

Hyper Parameters

Optimizer: Utilize the *Adam* and *SGD* optimizer for updating model weights. Known for its adaptive learning rate and efficient performance on deep learning tasks.

Learning Rate Scheduler: Implement the *Cosine Annealing* and *CyclicLR* learning rate scheduler. *Cosine Annealing* scheduler gradually decrease the learning rate, allowing the model to converge to a better solution.

Regularization Techniques: Apply *dropout layers* within the architecture to prevent overfitting, promoting robustness and generalization to new data.



Results and Evaluate

With the addition of nested skip connections and deep supervision, U-Net++ model is able to learn more detailed feature representations and generalize better on previously unseen data.

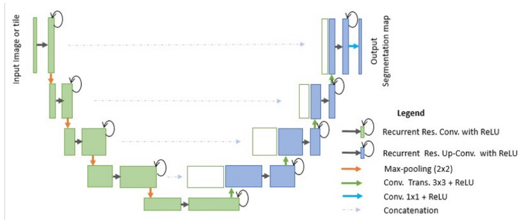
U-Net++ model typically takes more time to train compared to the original U-Net for the same dataset and number of epochs.

This trade-off often leads in enhanced performance, as U-Net++ tends to produce better segmentation results compared to the original U-Net.

	IoU Score	Dice Coefficient	Accuracy
U-Net	0.823	0.8293	85.67
U-Net++	0.8372	0.8385	86.82

Future work

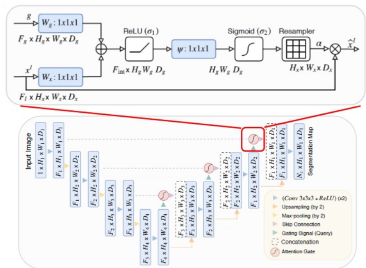
- **R2U-Net**
- Attention U-Net
- Trans U-Net
- 3D U-Net



R2U-Net (Recurrent Residual U-Net), a U-Net variant, incorporates residual and recurrent techniques to enhance segmentation performance.

Future work

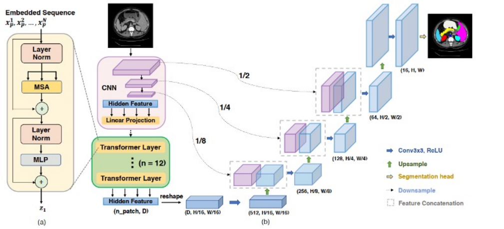
- R2U-Net
- **Attention U-Net**
- Trans U-Net
- 3D U-Net



Attention U-Net enhances the original U-Net architecture by integrating attention gates in skip pathways, improving feature selection.

Future work

- R2U-Net
- Attention U-Net
- **Trans U-Net**
- 3D U-Net

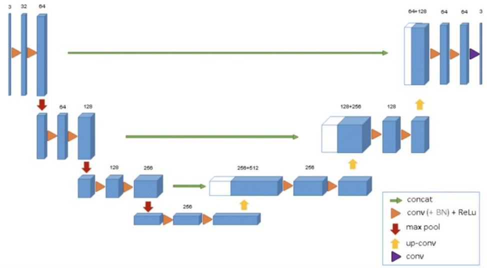


Trans U-Net leverages visual transformers (ViT) to create a powerful, transformer-based architecture for medical image segmentation.

21

Future work

- R2U-Net
- Attention U-Net
- Trans U-Net
- **3D U-Net**



3D U-Net is a 3D extension of the original U-Net architecture designed for volumetric segmentation tasks.

22

Future work

- Collaborate with clinicians and researchers to validate the model in real-world settings
- Explore potential applications in early diagnosis, treatment planning, and monitoring of neurological diseases

23

Any Questions?

24