

# Middle Fusion and Binary Mask Help UNet 2D in Brats Image Segmentation

Medical Imaging & Big Data

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- 1. Data and Pre-Processing**
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## 1. Data and Pre-Processing

- Data Set
- Pre-Processing
- Data Transformation

## 2. Model and Results

## 3. Problem Solution and Results

## 4. Conclusion and Improvements

# 1.1 Data Set

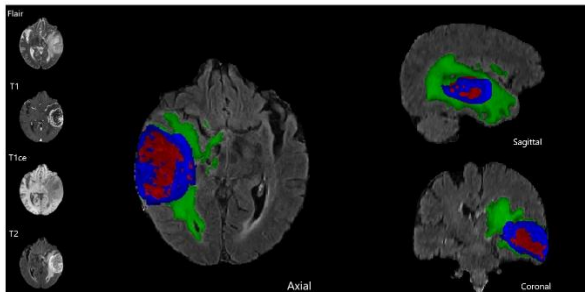


## Image type

4 channel images  
3 dimensional images  
166 brains

## Dataset

Training Set: 82 brains and 1409 slices  
Validation Set: 34 brains and 598 slices  
Test Set: 50 brains and 836 slices



## Objective

Image segmentation in 3 classes using UNet 2D for comparing:

- Early fusion
- Middle fusion

## 1.2 Pre-Processing

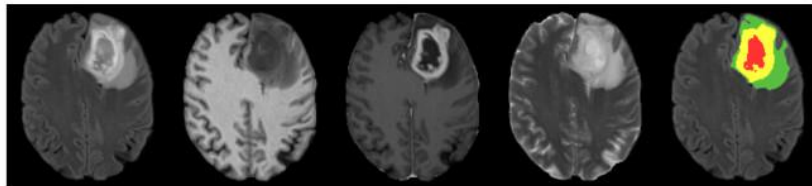
To reduce the computational weight, we used UNet 2D, separating the vertical, frontal and lateral images. The result obtained for the Vertical are generalizable for the other two.

- We used only the slice with tumor ( $>0.5\%$  of tumor in GT).

Idea: the model should also learn to recognize where the tumor is not present.

### Sample Data

Only 40% of data was used for RAM problem



(a) Flair

(b) T1

(c) T1ce

(d) T2

(e) Ground Truth

# 1.3 Data Transformation

Having more images was not possible due to RAM capacity problems.

Despite that we want more variability in the data, since we have only few different brains.

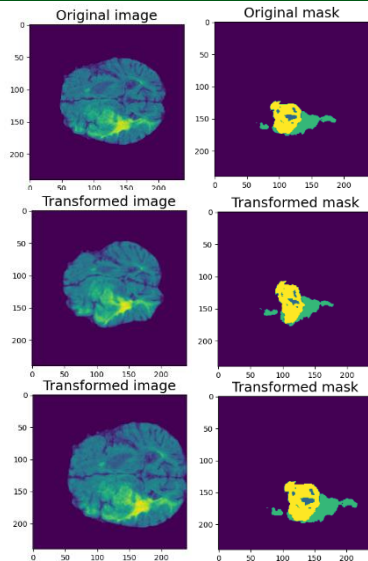


## Data Transformation

### Randomized

- 60% no transformation
- 20% elastic transformation
- 20% grid distortion

Transformation are done to images only in training data



## 1. Data and Pre-Processing

## 2. Model and Results

- UNet
- Results and Problems

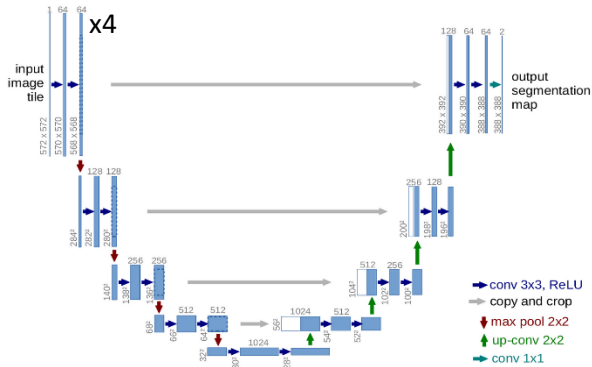
## 3. Problem Solution and Results

## 4. Conclusion and Improvements

Base UNet has 4 input channel and 4 output channel, 3 tumors + 1 brain (not used).  
Middle fusion has the first layer separated for every channel, then it concatenated them on the second layer.

## Hyper-parameters

- Epoch = 100
- Batch size = 5
- Learning rate =  $1e-4$
- Optimizer = Adam
- Decay = 0.1 (every 45/65)
- Loss = cross entropy loss
- Metrics: Accuracy, IoU, Dice





## 2.2 Results and Problems

	Early Fusion	Middle Fusion
Accuracy	0.69	0.61
IoU	0.44	0.37
Dice (1)	0.70	0.69
Dice (2)	0.77	0.68
Dice (3)	0.74	0.63

Early fusion

GT



Prediction



Middle Fusion

GT



Prediction



1. Data and Pre-Processing
2. Model and Results
- 3. Problem Solution and Results**
  - **Problem Solutions**
  - **Problems in Mask Application**
  - **Evaluation**
4. Conclusion and Improvements

## 3.1 Problem Solutions

The problem is both the model did not focus on the brain area and that it use training epochs just to focus on that area.

- Solution 1: crop around the brain (not feasible automatically)
- Solution 2: implement a binary mask to guide the model

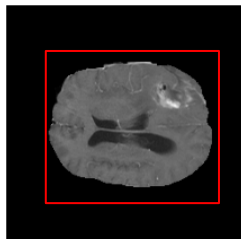
### Application of Solution 2

- Early fusion: mask concatenated to the input as an additional channel
- Middle fusion: mask treated as an additional channel, with its branch

### Middle Fusion Alternative Approach

A branch for only the mask give to much importance to it.

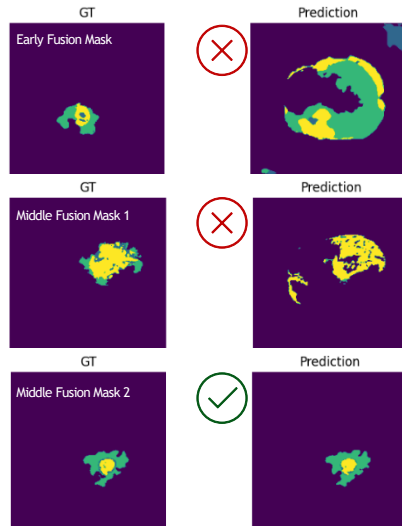
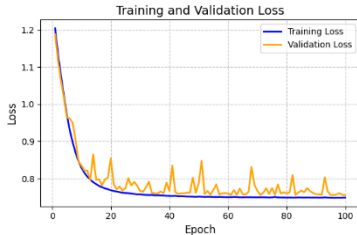
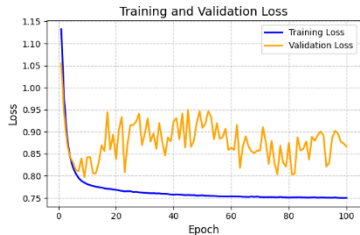
- Middle fusion: mask concatenated to input of every branch (2 channel)



## 3.2 Problems in Mask Application

Both from validation and from prediction is visible how using mask in early fusion and in middle fusion base approach, drove to much attention to it.

Middle fusion alternative approach has the best performance.



### 3.3 Evaluation

	Early Fusion	Middle Fusion	Early Fusion Mask	Middle Fusion Mask 1	Middle Fusion Mask 2
Accuracy	0.69	0.61	0.54	0.28	<u>0.76</u>
IoU	0.44	0.37	0.27	0.16	0.49
Dice (1)	0.70	0.69	0.42	0.17	0.78
Dice (2)	0.77	0.68	0.67	0.31	0.83
Dice (3)	0.74	0.63	0.47	0.54	0.75

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  - **Conclusion and Possible Improvements**

## 4.1 Conclusion and Possible Improvements

Best performing model was by far UNet Middle Fusion with mask using the second approach, it scored best in every metric.

The obtained results are assumed to be generalizable also for the other two direction (lateral, frontal).

### Possible Improvements

- Use all the images
- Use real data augmentation
- Test also late fusion
- Use a Dice based loss function

This experiment could be done using UNet 3D.

Thanks for the attention!  
Questions?