Hippocampus Segmentation for Alzheimer’s induced Dementia Prediction from MRI Images

1905045 - Md. Ishrak Ahsan
1905035 - Farhan Tahmidul Karim

Group ID: A2_4

Problem Definition

But how?

Progressive neurological disorder, affecting thinking, memory, behavior and ability to work

EARLY DIAGNOSIS can help save a lot of patients!!

MRI imaging gives visualization of brain structures allowing **analysis of atrophy pattern**

focusing on **specific brain regions** affected early, like the **hippocampus**, can give significant clues

Image segmentation isolates the regions of interest in MRI scans, facilitating the quantitative analysis

MRI image data driven ML models > Video and voice data [1]

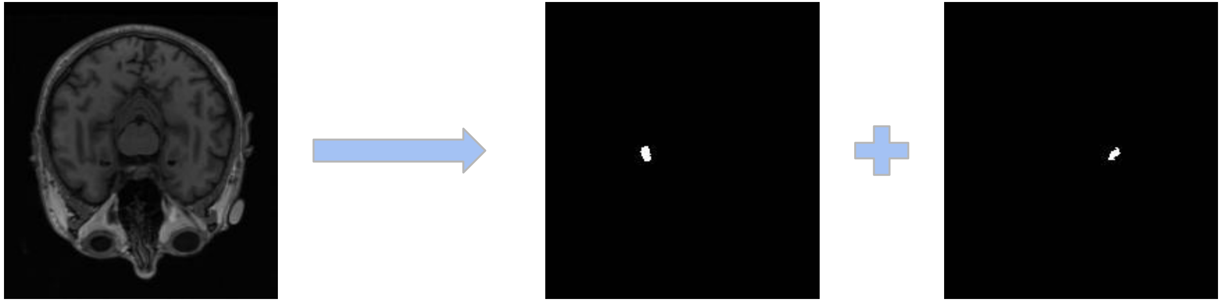
Hippocampus Segmentation-Based diagnosis and classification of MRI Images is effective [3]

U-net style model for AD diagnosis using 3D T1-weighted MRI pays more attention to hippocampus, cortex regions etc. [4]

U-Net Convolutional Network based approach for hippocampus segmentation from 2D brain images segment hippocampus with a good performance [5]

Used Datasets

- **ADNI (Alzheimer's Disease Neuroimaging Initiative) dataset:**
  - Link - https://www.kaggle.com/datasets/sabermalek/mrihs
  - MRI segmentation of Hippocampus gland of dementia patients
  - First part contains MRI images of 100 patients as train data, and the second part contains MRI images of 35 patients as test data
  - Total images - ~25,000 2D MRI slices
  - EADC-ADNI Harmonized Protocol project

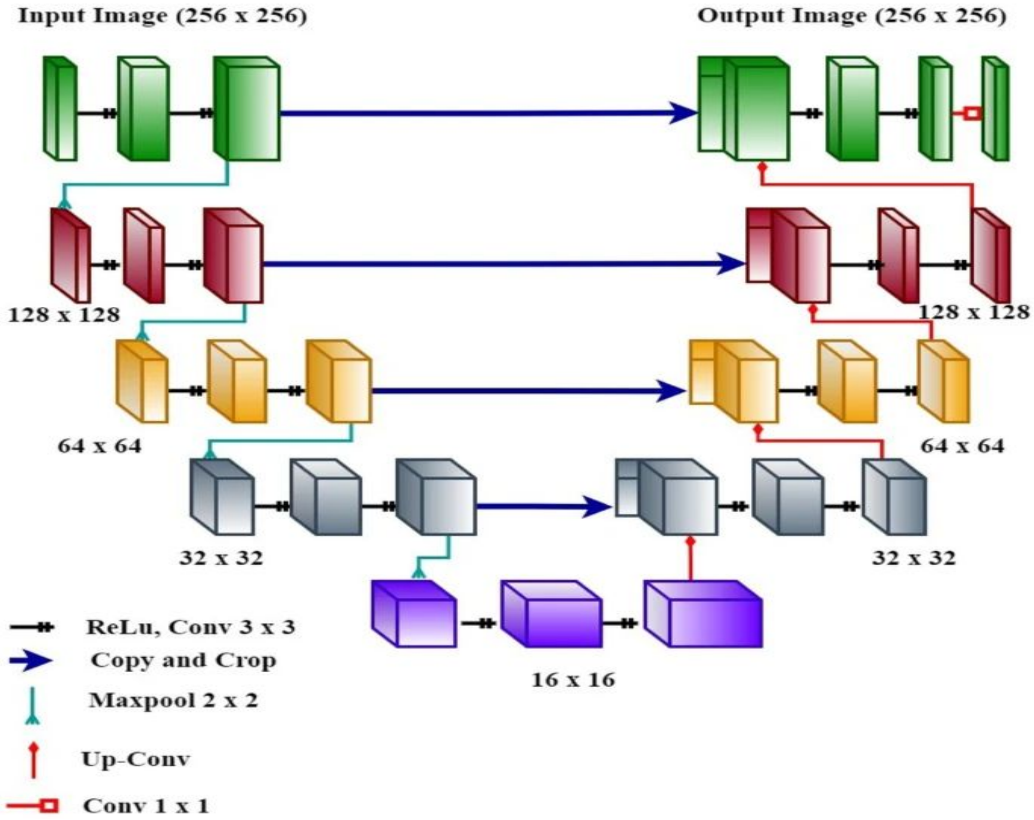


ADNI_002_S_0295_13722_ACPC_068

ADNI_002_S_0295_13722_L_068

ADNI_002_S_0295_13722_R_068

Existing Modified U-Net Architecture



Our Improvements

1. **Swish** Activation Function
    a. We replaced the ReLU activation function with Swish.
    b. ReLU is a commonly used activation function but suffers from the **dying ReLU problem** where neurons output zero for all inputs below 0.
    c. Swish gives **better gradient flow** during backpropagation.
    d. Swish has empirically shown **better performance in tasks like segmentation** due to its flexibility.
2. **SpatialDropout2D**
    a. We replaced standard Dropout with SpatialDropout2D.
    b. In CNN models, standard dropout removes individual neurons (random pixels) independently. This can **disrupt spatial relationships in feature maps**, which are crucial for segmentation.
    c. SpatialDropout2D **preserves spatial information** while providing regularization.
    d. This is particularly effective for segmentation tasks where **spatial coherence** matters.

Our Improvements

3. **Bilinear Interpolation**
    a. We replaced transposed convolutions with bilinear upsampling followed by convolution.
    b. Transposed convolutions can introduce **checkerboard artifacts** due to uneven overlapping during upsampling.
    c. Bilinear interpolation provides **smoother upsampling without artifacts**.
    d. It upsamples the feature maps to the desired resolution using interpolation and then applies convolution to refine the upsampled features.
4. **Combined Loss Function: Binary Cross-Entropy + Dice Loss**
    a. Binary Cross-Entropy Loss measures pixel-wise binary classification error. It works well when the class distribution is balanced.
    b. Dice Loss directly optimizes for the Dice Coefficient, which measures the overlap between predicted and ground truth masks. It is **very effective for class imbalance**, which is common in medical segmentation tasks where the target region (e.g., hippocampus) is small compared to the background.
    c. BCE ensures **pixel-wise accuracy**, and Dice Loss ensures **better overlap** for the segmented regions.

Performance Comparison of U-Net

Model	**Dice Coefficient**	**Jaccard Index**
MultiResUNet	0.897474389	0.87823319367
Modified U-Net	0.8914032548	0.872448485
Our Model	**0.9057411749**	**0.88360496**

- **DIC** = 2 * |A ∩ B| / (|A| + |B|)
- **JI** = |A ∩ B| / |A ∪ B| = DIC / (2 - DIC)

Resources Used

- Platform: Kaggle
- Language: Python
- RAM: 29 GB
- GPU: P100
- VRAM: 16 GB

Any Questions?