

# Medical Image Analysis



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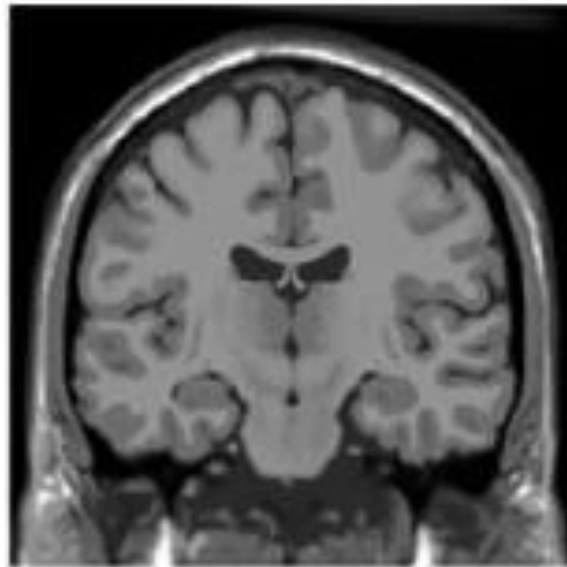
# Random Forest

# MRI Image Analysis

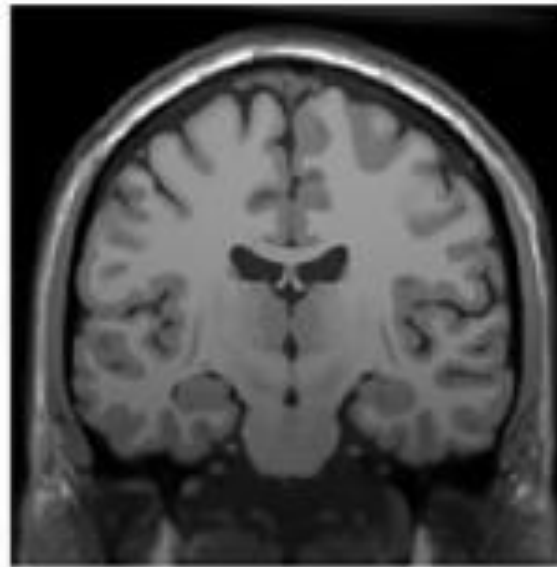
# Preprocessing: Bias field Correction

- Intensity inhomogeneity.
- Very smooth and low-frequency signal that can corrupt MRI images
- Especially from old MRI machines
- Intensity variation among the tissues having same physical property
- Changes the high-frequency component of the image such as contours and edges
- Causes a blurring effect
- May not have a huge effect when seen through the naked eye
- But various image processing and segmentation methods may be affected
- May lead to the detection of lesser number of feature points from the image

# Preprocessing: Bias field Correction



**a) Normal MRI Image**



**b) MRI with a Bias Field Signal**

# Preprocessing: Bias field Correction

- Visible in MRI scanners having higher magnetic field strength such as 1.5 T
- $X_i = X'_i b$ 
  - $X_i$ : observed intensity
  - $X'_i$ : ideal intensity
  - $b$ : bias
  - Ignoring other types of noise
- This is like a multiplicative noise
  - How to handle it?

# Bias field Correction: Filtering

- $X_i = X'_i b$
- $\log X_i = \log X'_i + \log b$
- Bias is treated as low-frequency artifacts
- Use filter on the logarithmic image
  - What is the problem?

# Bias field Correction: Filtering

- $X_i = X'_i b$
- $\log X_i = \log X'_i + \log b$
- Use filter on the logarithmic image
  - It will also remove some important details



# Bias field Correction: Filtering

- Homomorphic filtering

$$\log I(x, y) = \log S(x, y) - LPF(\log S(x, y)) + C_N$$

- $C_N$ : Normalization constant

- Homomorphic Unsharp Masking

$$I(x, y) = S(x, y)/B(x, y) = S(x, y)C_N/LPF(S(x, y))$$

# Bias field Correction: Surface Fitting

- Aim to model the bias field as a parametric surface
  - Usually a polynomial or spline function
- Parametric surface is fitted to a set of image features that contain information about bias field
- Once a surface is generated, the bias field can be acquired by extrapolating all points from the surface
- The correction can be implemented using the estimation of the bias field

# Bias field Correction: Surface Fitting

- The performance of these methods relies heavily on the selection of image features
  - Intensity
  - Gradient
- Intensity-based
  - Assumes that the intensities of one type of tissue do not vary significantly unless they are corrupted by bias field
  - Therefore, the intensity variation inside a region composed of the same type of tissues can be used to estimate the bias field

# Bias field Correction: Surface Fitting

- Gradient-based
  - Assumes that the large bias areas are evenly distributed over the entire image
  - These areas can be corrected for by estimating the local variation of intensity gradients
  - May introduce other adverse information

# Bias field Correction: Other Methods

- Segmentation-based methods
  - Performs alternating bias correction and image segmentation steps
  - Considers that bias correction is commonly served as a necessary preprocessing step for facilitating image segmentation
  - Conversely, accurate segmentation makes the bias correction insignificant
  - Merges the segmentation and bias correction steps into a united framework to simultaneously yielding better results of each step
  - EM-based algorithms
  - FCM-based algorithms

# Bias field Correction: Other Methods

- Histogram-based methods
  - Exploit the image histogram to automatically correct for the bias field in medical images
  - Many of these methods require an initialization or a priori knowledge about the intensity or gradient probability distribution of the imaged structures

# Image Registration: Classical Methods

- Principle Axis Transformation
  - Centroid of brain is calculated based on pixel intensities
  - Moment of inertia matrix is calculated
  - Calculate eigenvector from the above matrix
  - Registration based on the direction of maximum eigenvector
  - Can register images of different modalities, such as PD and T2

# Image Registration: Classical Methods

- Finite Fourier Transform
  - Based on Fourier transform of source and target images
  - Find rotation and translation that best possibly aligns the FT of two images
- Affine transformation
  - Translation
  - Rotation



# Image Registration: DL Methods

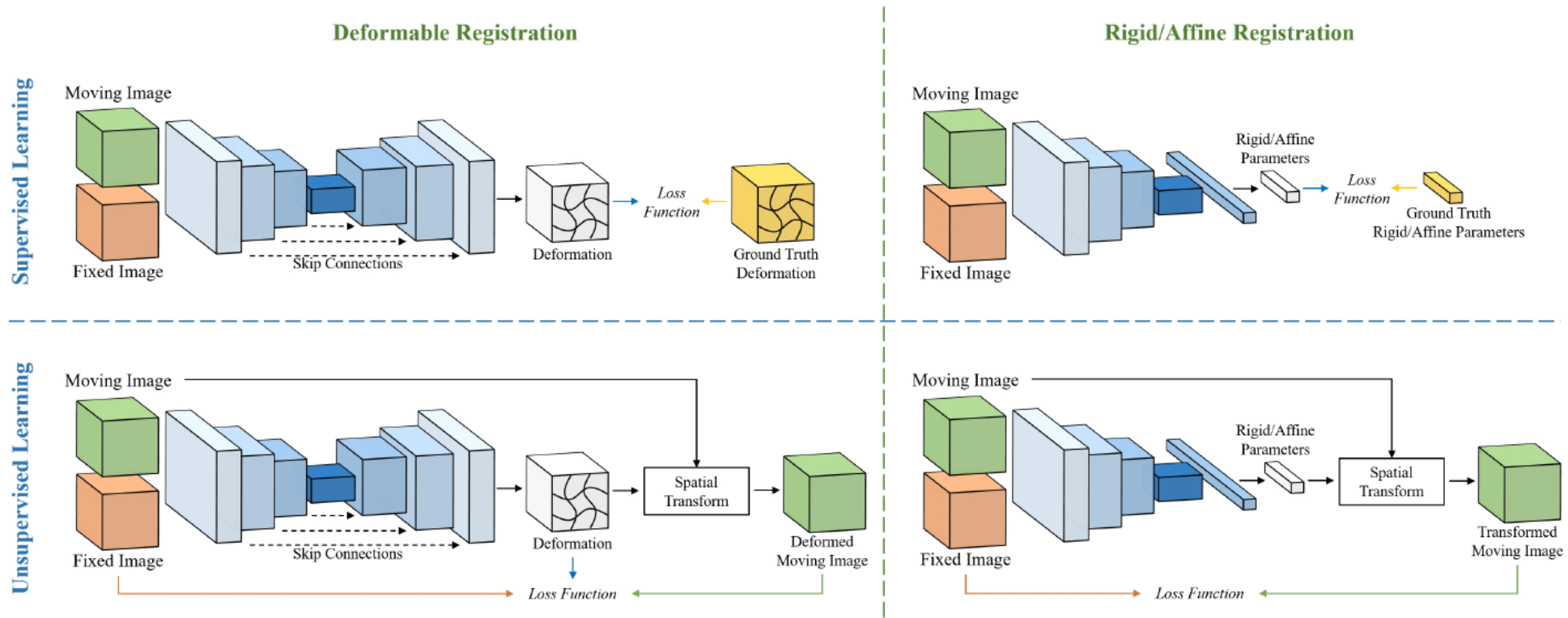


Fig. 2. Overview of learning-based image registration. The top panel depicts the common pipeline for supervised learning in medical image registration, which necessitates ground truth transformations. The bottom panel demonstrates the unsupervised learning pipeline, wherein the network learns to perform registration using only input images. The left panel presents the learning-based DIR pipeline, typically employing an encoder-decoder-style network architecture. The right panel exhibits the learning-based rigid/affine registration, which usually involves only an encoder.

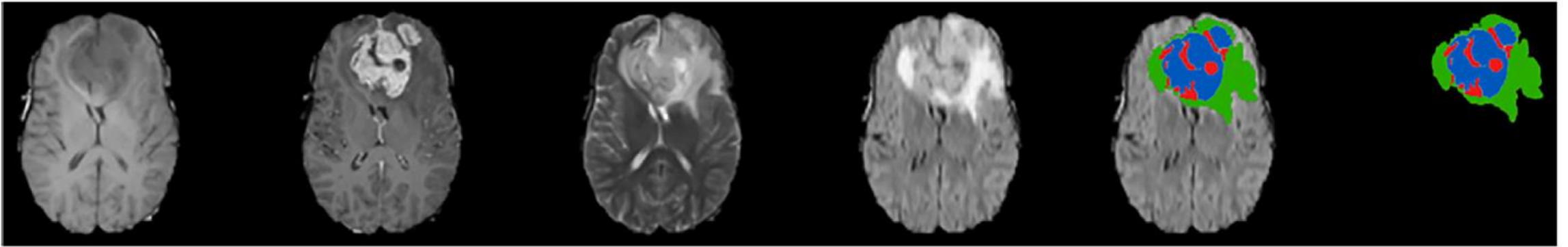
# Additional Pre-processing

- Normalization
  - Gray or color values across multiple images are scaled down to a common set of relative gray values
  - This ensures that variation in acquisition parameters among scanners is accounted for and that similar tissues appear in a common range of values across all images
  - Histogram matching
  - Nonparametric and nonuniform intensity normalization
- Skull Stripping
  - Removes extraneous material not critical for analysis such as the skull, fat, and skin

# Brain Tumor Segmentation

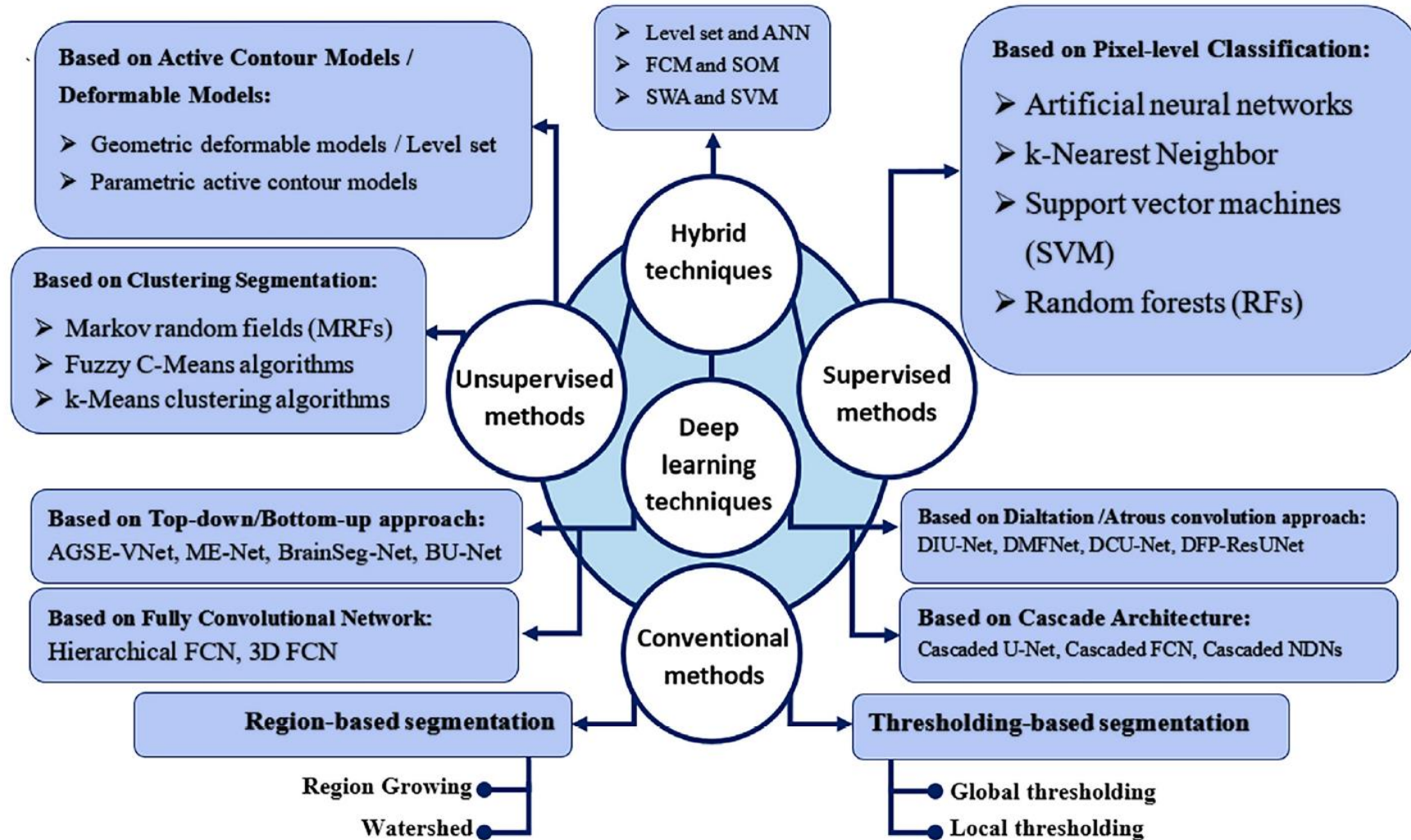
- Gliomas
- Poor prognosis
- Manual segmentation
  - Time consuming
  - Inter rater variability
- Various MR sequences provide complimentary information
  - T1, T2, Flair, post contrast

# Brain Tumor Segmentation

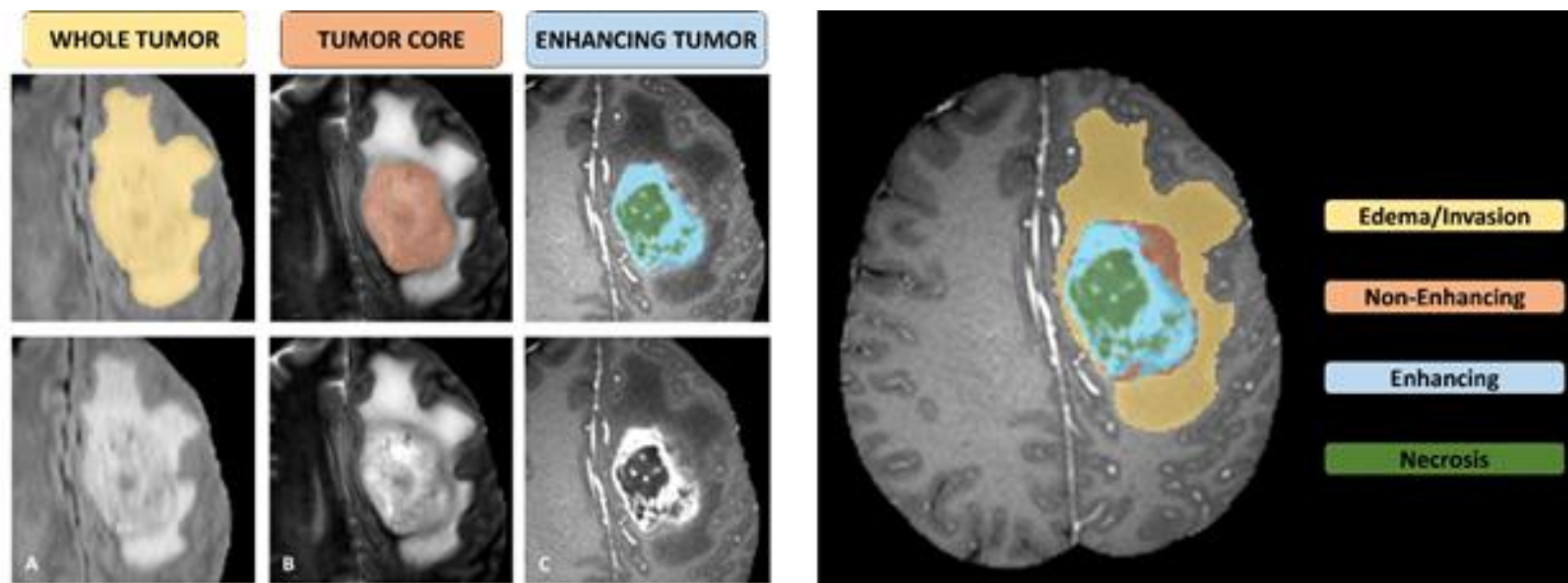


**Figure 2:** Brain tumor segmentation. From left: T1, T1c, T2, FLAIR, and segmented tumor. In segmented image, blue signal is an active region, red signal is necrotic core, and a green level signal is edema. Images are generated by using BraTS 2019 data.

# Brain Tumor Segmentation

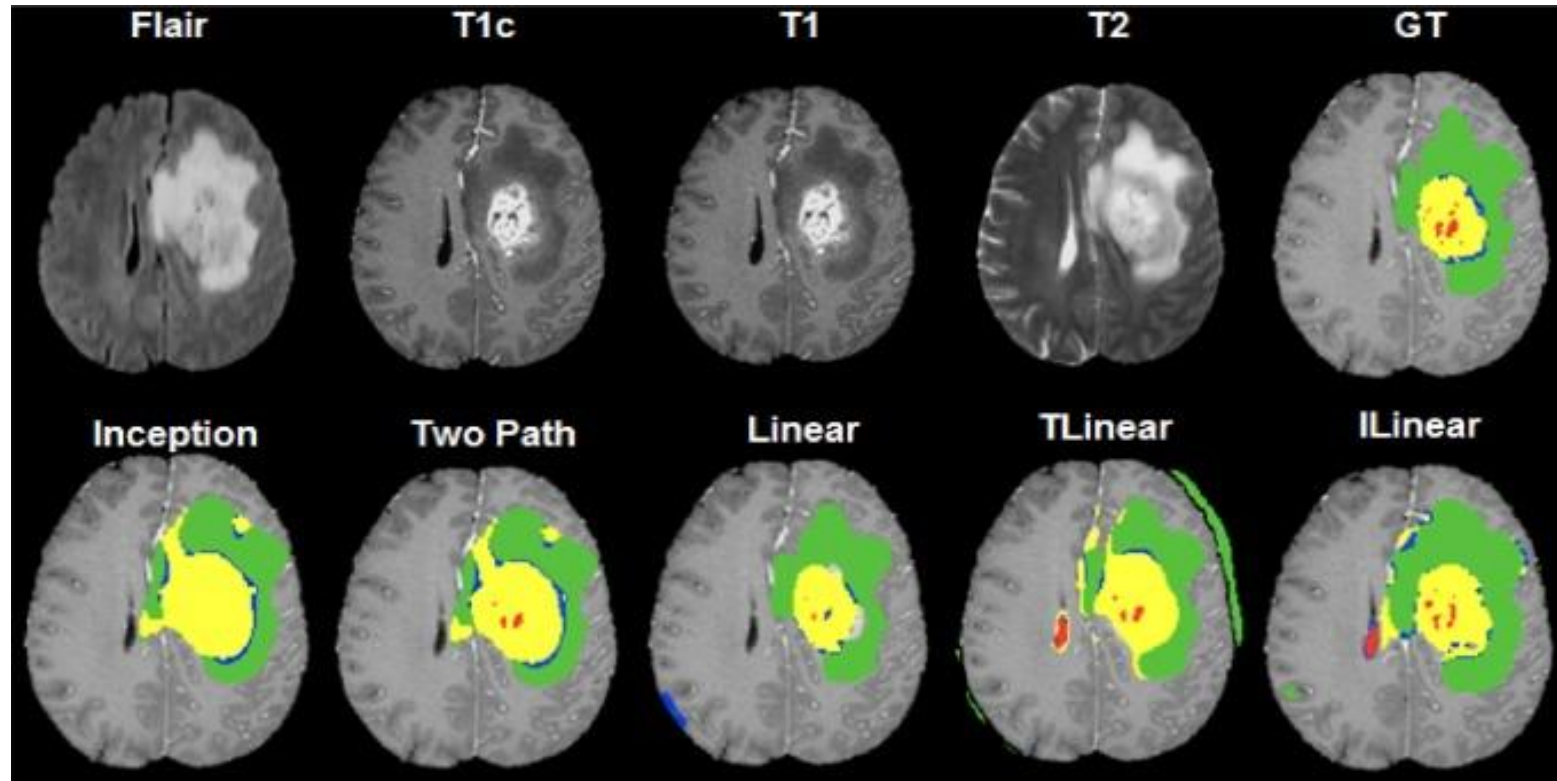


# Brain Tumor Segmentation





# Brain Tumor Segmentation: DL Models



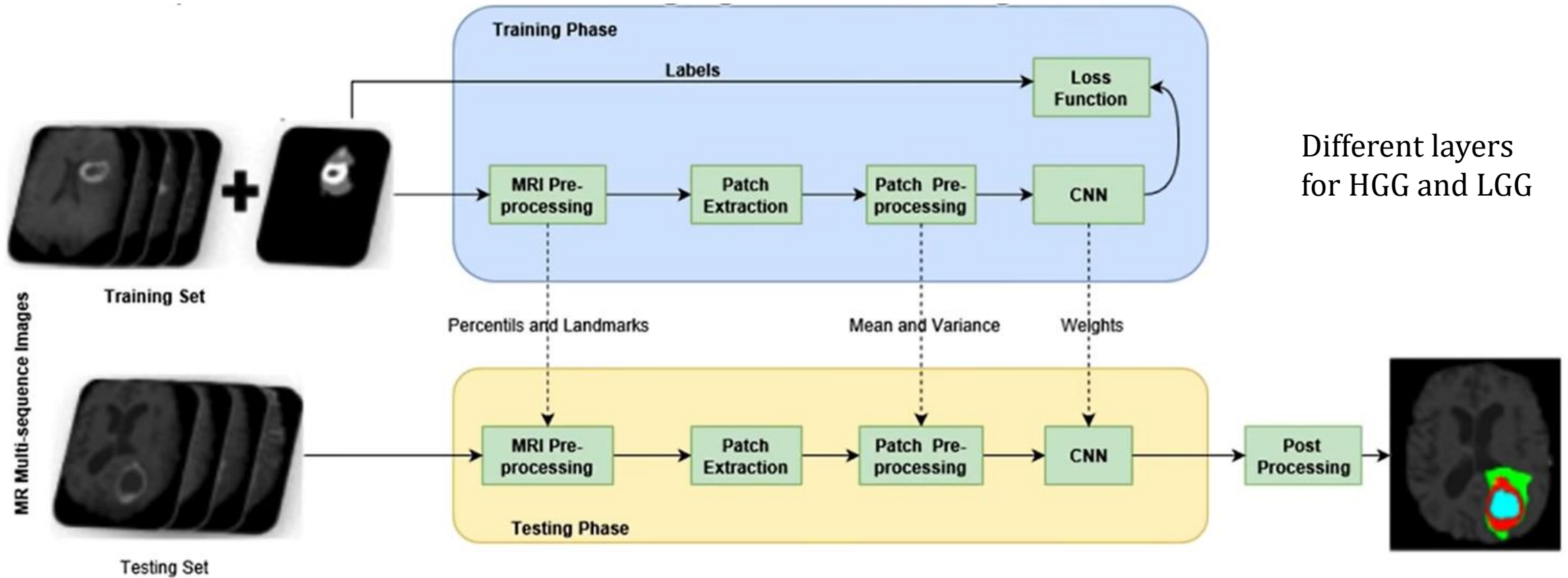
# BraTS Dataset

- Multi-centric, publicly available
- Data of low and high grade glioma
- Each patient's data
  - FLAIR
  - T1 weighted
  - T2 weighted
  - T1 post contrast
  - Ground truth segmentation mask
- Skull stripped, registered, resampled to  $1mm^3$
- Dimension  $240 \times 240 \times 155$  (sagittal, coronal, axial)

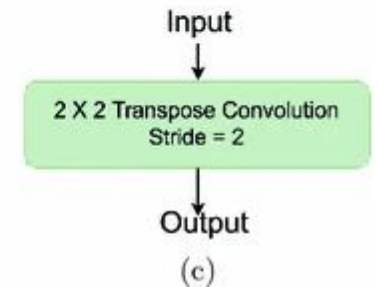
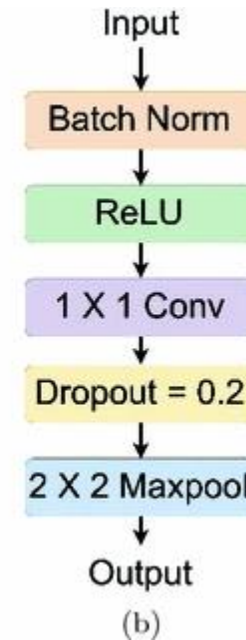
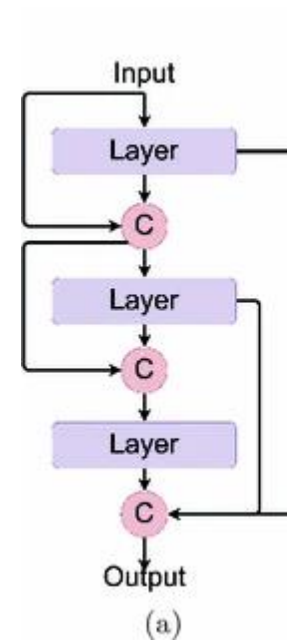
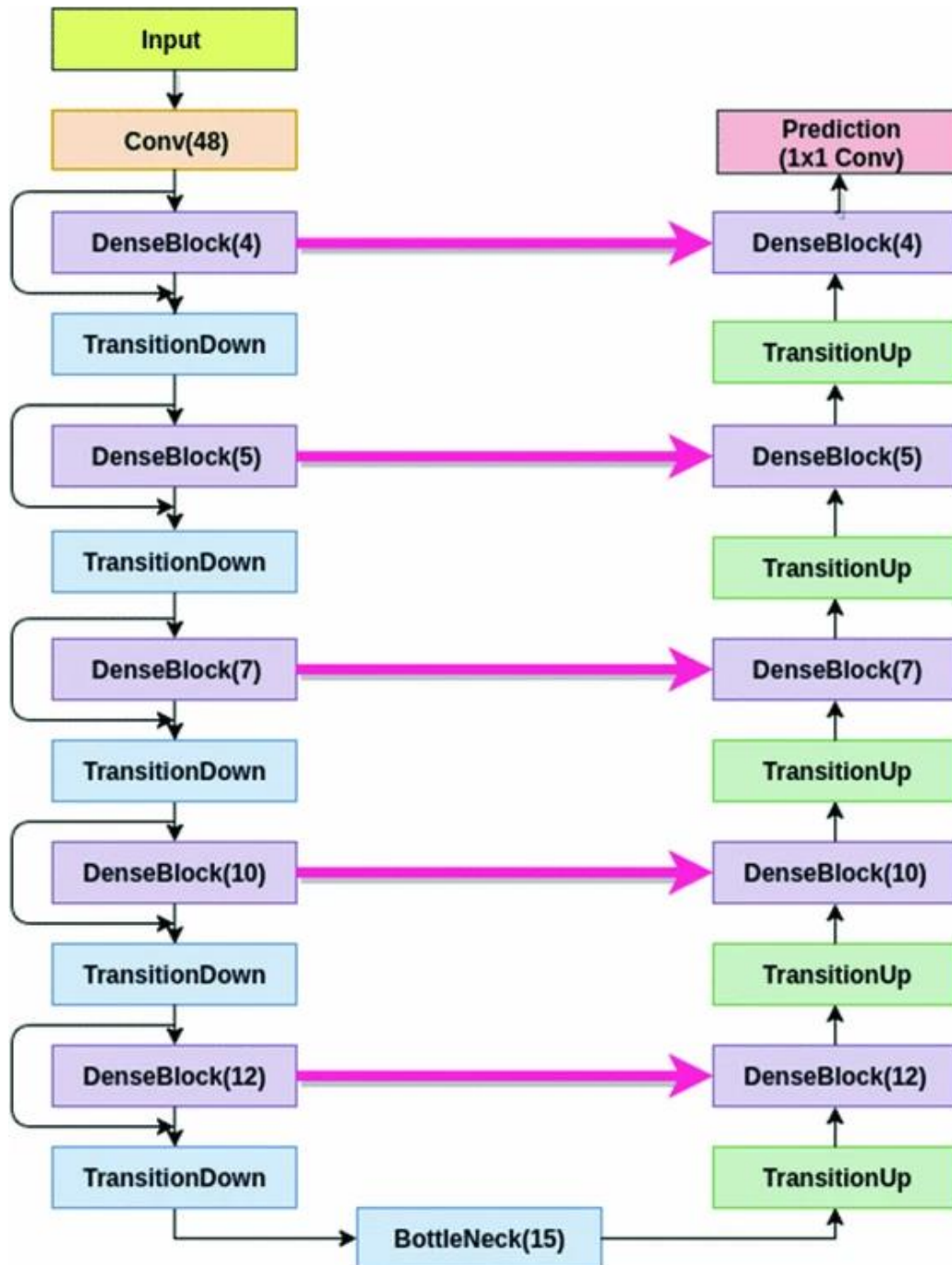


# Brain Tumor Segmentation: DL Models

# Patch-based Segmentation

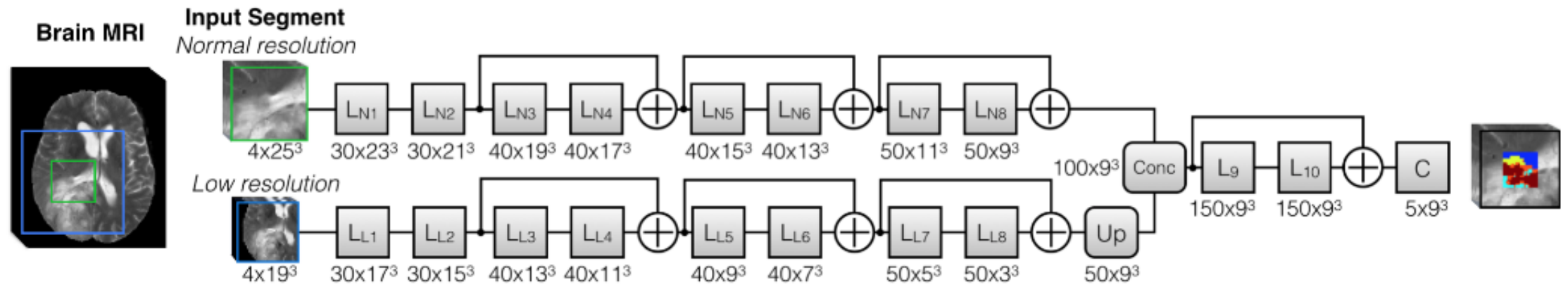


# 2D Tiramisu



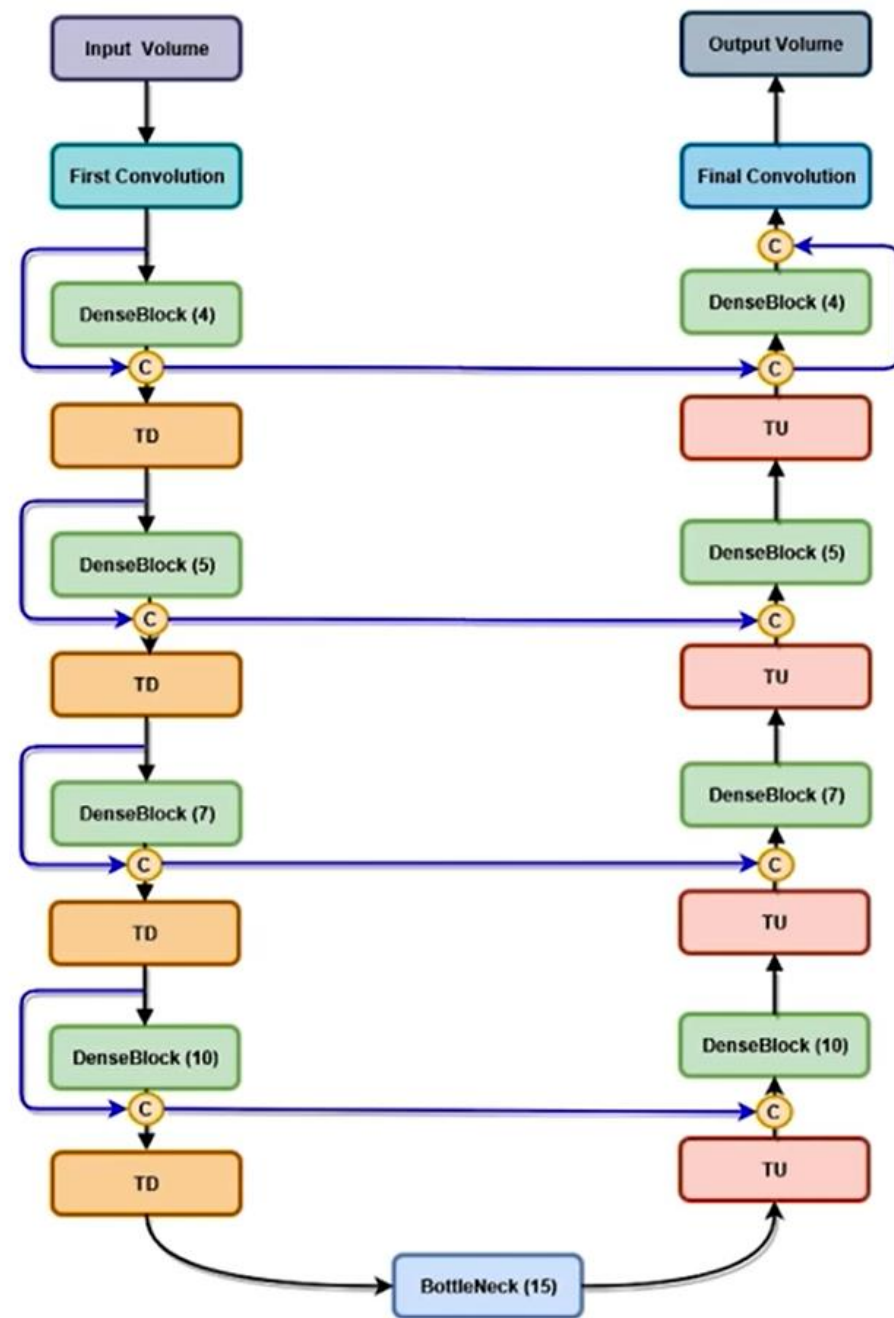
Blocks used in the model. (a) Dense block. (b) Transition down. (c) Transition up

# Deep Medic

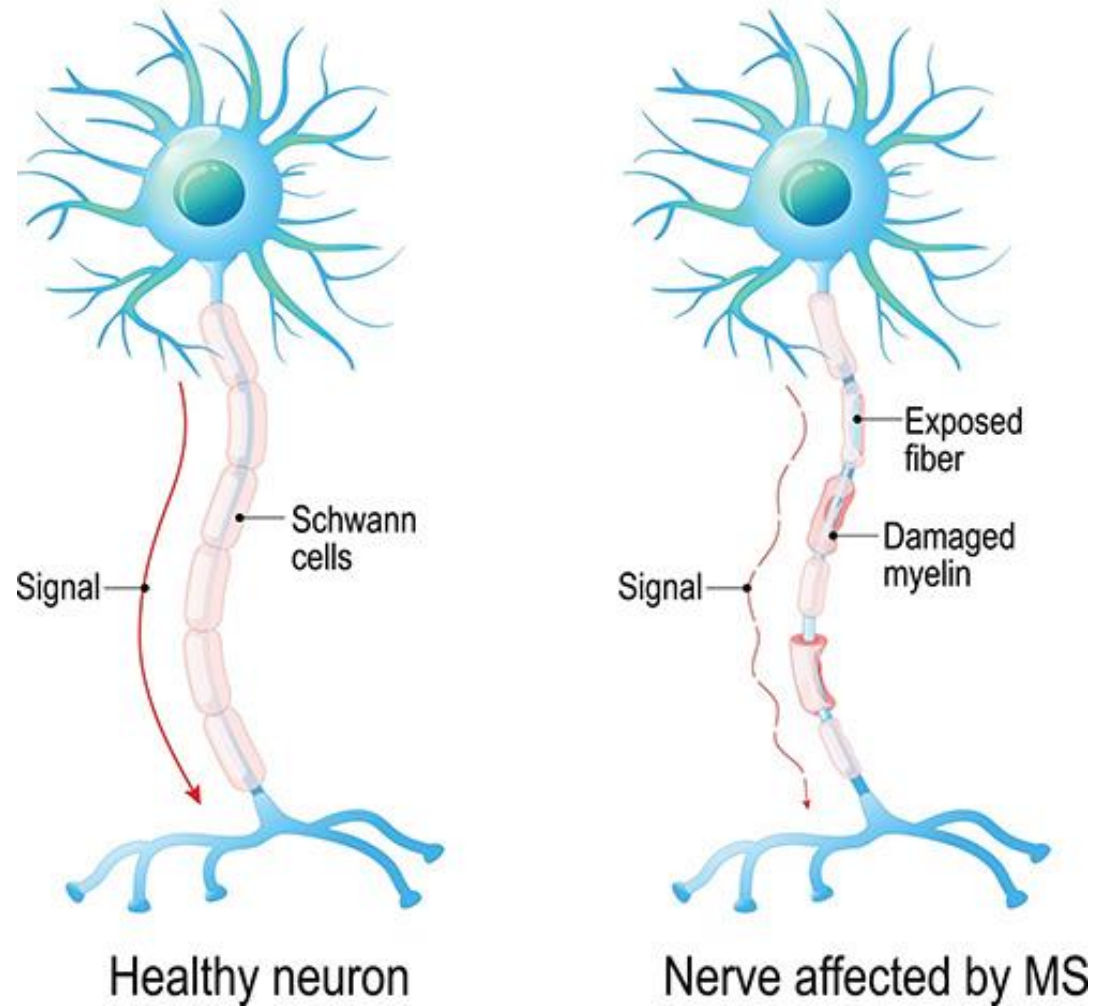


Multi-scale 3D CNN

# 3D Tiramisu



# Multiple Sclerosis Lesion Detection





# Multiple Sclerosis Lesion Detection

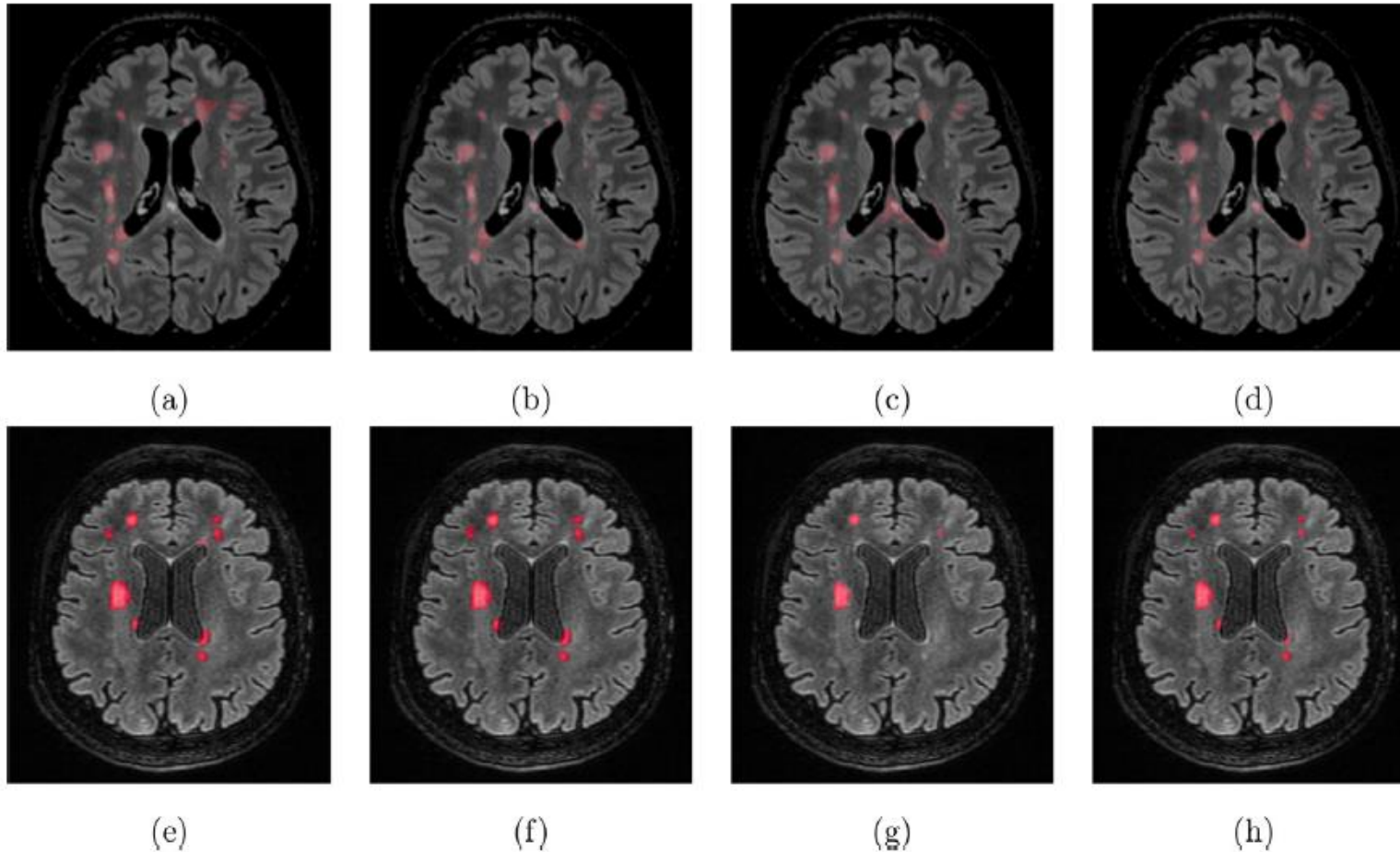
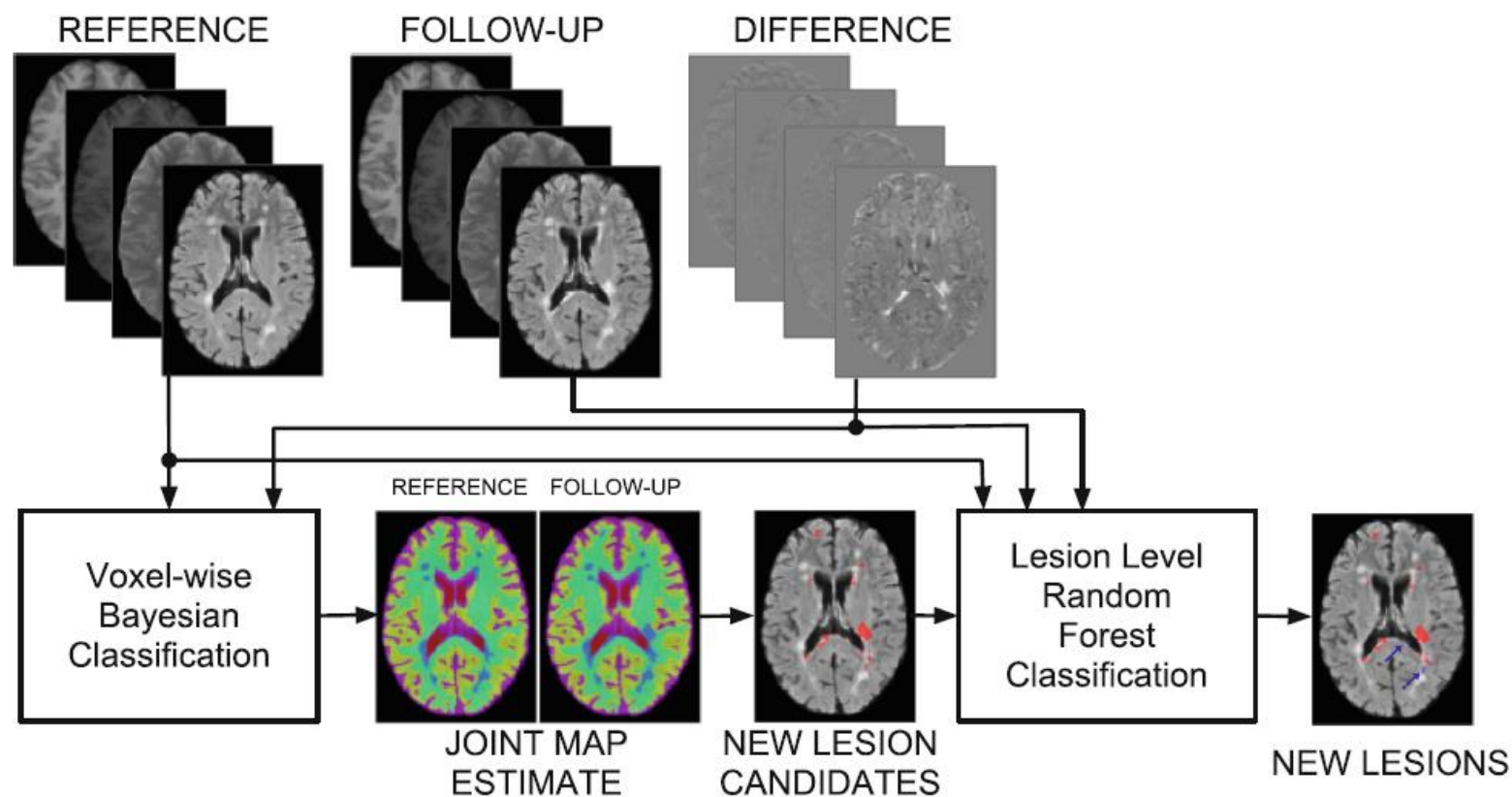


Fig. 1. Illustration of the manual delineations for two MS patients, overlaid on the 3D FLAIR image. First line: patient from center 01, second line: patient from center 03. (a-c, e-f): three out of the seven expert manual delineations of MS lesions, (d,h): consensus segmentation computed from the manual segmentations.

# Multiple Sclerosis Lesion Detection



**Fig. 3.** Automatic detection of new MS lesions. Reference and difference images are input to the Joint Bayesian Classifier, while reference, follow-up and difference images are used for lesion-level classification using a random forest classifier. The image showing the final classification of new lesions shows candidates rejected by the lesion-level classification in blue (additionally shown with blue arrows) while those that are retained are shown in red [8]. (Color figure online)



# Class Imbalance

- More augmentation for underrepresented class
- Focal loss

$$L_F(p_t) = -(1 - p_t)^\gamma \log p_t$$

# Fuzzy C Means Clustering

Minimize

$$J_m = \sum_{i=1}^n \sum_{j=1}^c (u_{j,i})^m \|x_i - C_j\|^2.$$

$$u_{j,i} = \frac{1}{\sum_{k=1}^c \left( \frac{\|x_i - C_j\|}{\|x_i - C_k\|} \right)^{\frac{2}{m-1}}},$$

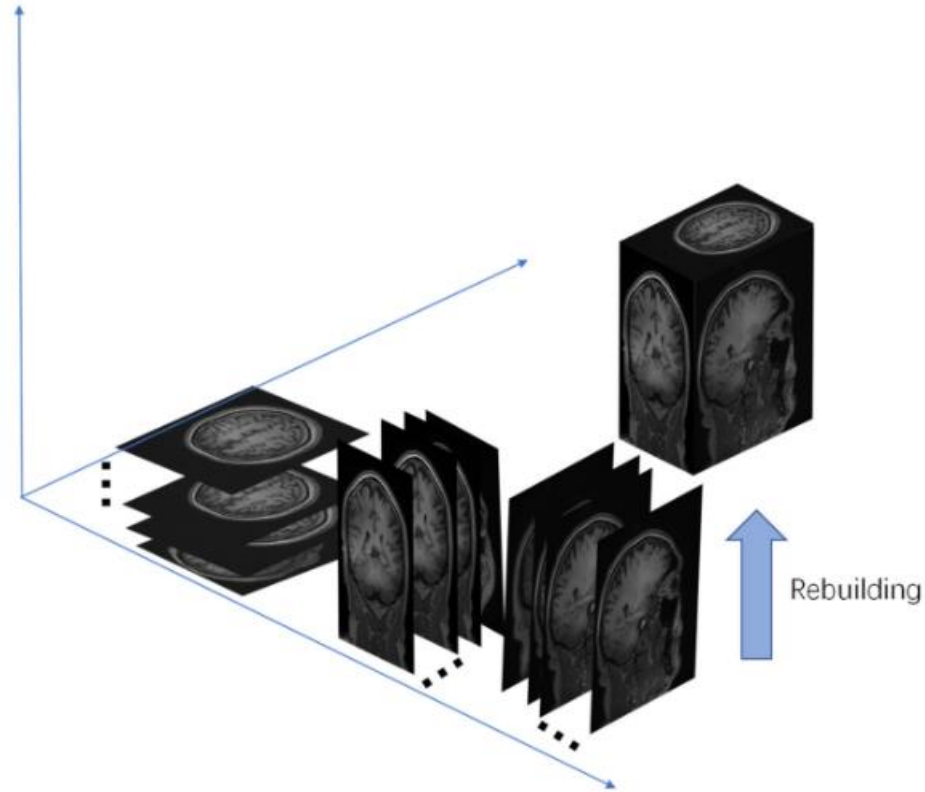
$$C_j = \frac{\sum_{i=1}^n x_i (u_{j,i})^m}{\sum_{i=1}^n (u_{j,i})^m}, \forall j = 1, \dots, c$$

- $m$ : Fuzziness index

# Fuzzy C Means Clustering

<https://in.mathworks.com/help/fuzzy/brain-tumor-segmentation-using-fuzzy-c-means-clustering.html>

# 3D Reconstruction of MRI Images



**Figure 1.** Rebuilding MRI from three plane slices. Number of slices is half that of MRI. Number of slices in three directions is 128 ( $256 \times 150$  pixels), 128 ( $256 \times 150$  pixels), and 75 ( $256 \times 256$  pixels).