A Light Weighted Deep Learning Framework for Multiple Sclerosis Lesion Segmentation

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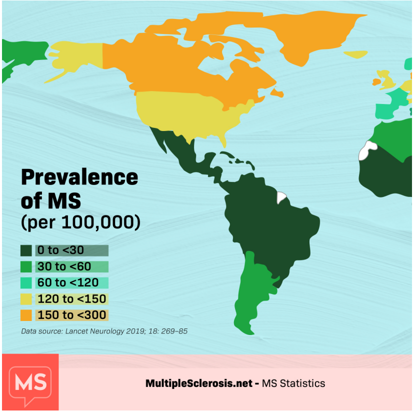
Outline

Introduction

- Multiple Sclerosis is a disabling disease which impacts the brain and the spinal cord which make up the central nervous system, which disturbs the flow of information within the brain, and between the brain and body.
- Magnetic resonance imaging (MRI) is an important tool in diagnosing MS. It can reveal telltale scars, also called lesions, on the brain or spinal cord.
- MRI allows doctors to see lesions in your Central Nervous System(CNS). Lesions show up as white or dark spots, depending on the type of scan.

Prevalence in world wide

- Recent findings from a National MS Society study estimate nearly 1 million people in the United States are living with MS.
- The society also estimates that 2.3 million people live with MS globally.
- As per Times of India in 2014, The crude prevalence of MS in India stands at 8-9 people per 1,00,000.
- It is estimated that the total burden in India is close to 1.8 lakh patients in 2014.



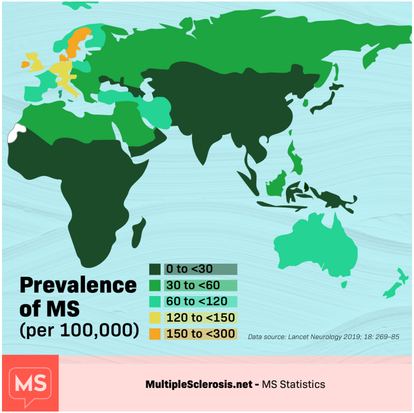


Figure: World distribution of multiple sclerosis : greater prevalence in higher northern and southern latitudes [1]

Motivation

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- Neurology fraternity is growing very slowly and is grossly inadequate to cater to the large population of India
  - Over 90% of the neurology is handled by internal medicine specialists
  - Heavy workload
  - Constant threat to patient safety
- "Computer-aided diagnosis (CAD)" in the field of neuroradiology.

Objective

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To develop a cost effective computer aided diagnosis tool for MS lesion delineation with greater efficacy.

Dataset Description

Data Acquisition

- Widely accessible dataset from MICCAI 2016 [2].
  - Consists of 15 patients in nifti format with manual lesion delineations from seven independent experts.
  - Consists of unprocessed and preprocessed (de-noising, rigidly registered, brain extracted and bias corrected) MRI(T1-w, MPRAGE, FLAIR, T1-w gadolinium enhanced and T2-w/DP contrast enhanced images).

Pre-processing

- Removing Null Samples : $5184 - - > 2834$
- Normalization and Zero-centering: $\hat{x} = (x - \bar{x}) / \left(\sqrt{\sigma^2 + \varepsilon}\right)$
- Data Augmentation : $2834 - - > 11336$

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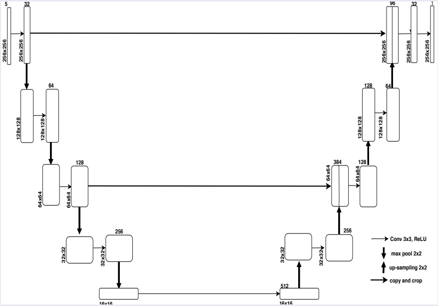
Proposed CNN Architecture



Light Weighted CNN Architecture

- This CNN is more efficient in terms of resources as well as time taken.
- The reason behind this is reduction in the number of convolutional layers in each block and the number concatenations of high resolution feedback from the encoder to decoder.

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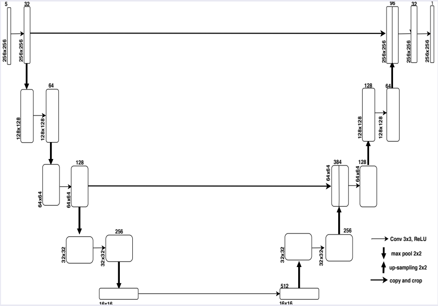

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Parameter Selection

- Kernal-size: $(3, 3)$ with stride $(1, 1)$
- Pool-size: $(2, 2)$ with stride $(2, 2)$
- Weight initialization: *Xavier Uniform initialization*
- Activation: *ReLU*
- Loss: *binary cross entropy*
- Optimizer: $adam\,(lr = 0.001)$
- Batch_size: 32

Evaluation Metrics

- The accuracy of proposed architecture is confirmed with a relative analysis between the extracted lesion and GT
- This analysis is widely used to examine the similarity parameters such as Accuracy, Dice Similairty Co-efficient(DSC), Sensitivity and Specificity.
  - Accuracy $= (T_P + T_N)/(T_P + T_N + F_P + F_N)$
  - DSC $= 2\,(I_{GT} \cap I_S)\,/\,(|I_{GT}| \cup |I_S|)$
  - Sensitivity $= T_P/(T_P + F_N)$
  - Specificity $= T_N/(T_N + F_P)$

Where, I_{GT} is ground truth image, I_S represents segmented image, T_N, T_P, F_N and F_P signifies true negative, true positive, false negative and false positive respectively.

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Plots of evaluation metrics

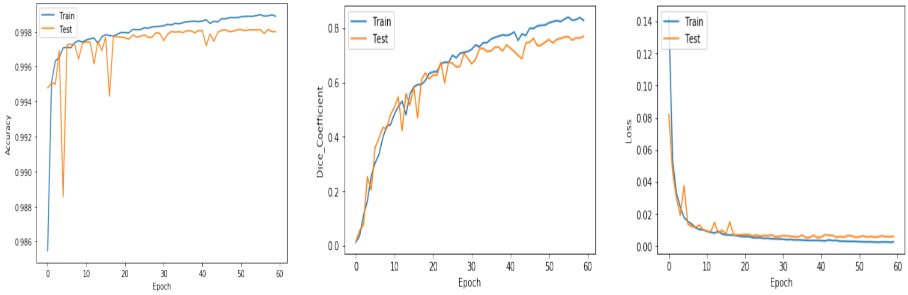

Figure: Plots of Accuracy, Dice Similarity Co-efficient and Loss for MS Lesion Segmentation on MICCAI 2016 dataset.

Performance Comparison

Method	DSC	Sensitivity	Specificity	Accuracy
Proposed	0.76	0.65	0.86	96.79
Andermatt et al[3]	0.63	0.54	0.84	92.07
Valverde et al.[4]	0.64	0.57	0.79	91.44
Birenbaum et al.[5]	0.63	0.55	0.80	91.26
Deshpande et al.[6]	0.60	0.55	0.73	89.81
Jain et al.[7]	0.55	0.47	0.73	88.74
Valcarcel et al.[8]	0.57	0.57	0.61	87.71
Sudre et al.[9]	0.52	0.46	0.66	86.44

Table: Performance Analysis of the Proposed MS Lesion Segmentation Technique

Qualitative Analysis

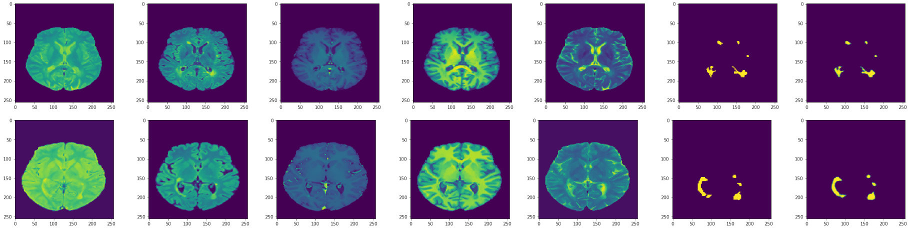

Figure: Comparison between some results obtained by our proposed architecture against the ground truth. From left to right: MPRAGE, FLAIR, T1-w gadolinium enhanced, T1-w and T2-w/DP contrast enhanced and ground truth images respectively and the predicted output.

Conclusion

- Light weighted convolutional neural network(CNN) has been proposed.
- Used for **multiple sclerosis(MS) lesion** segmentation from multimodal magnetic resonance (MR) scans.
- We can envisage a straightforward application on an **independent testing datasets** and further applications for **multi-institutional datasets**

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