SPINAL CORD GRAY MATTER SEGMENTATION USING DEEP CNN ARCHITECTURE

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***Abstract*—Gray matter (GM) tissue change have been related with a wide scope of neurological disorders and were recently found pertinent as a biomarker for inability in amyotrophic lateral sclerosis. The capacity to consequently segment the gray matter is, in this manner, a significant undertaking for present day investigations of the spinal cord. In this work, its anything but an advanced, simple and end-to-end fully-automated human spinal cord gray matter segmentation method utilizing Deep Learning, that works both on in-vivo and ex-vivo MRI acquisitions. We consider our technique in contrast to six freely created strategies on a gray matter segmentation challenge.**

Keywords: Dilated Convolutional Neural Network, Deep Learning, Segmented Spinal cord, Feature Extraction, Training, Testing.

I.INTRODUCTION

Spinal cord plays a crucial part in connecting brain with the body and this spinal cord is tube shaped in structure and is comprised of white matter and gray matter. Gray matter contains numerous sensory tissues. Gray matter (GM) and White matter (WM) tissue changes in the spinal cord (SC) have been associated with an enormous range of neurological problems. For instance, utilizing Magnetic Resonance Imaging (MRI), the inclusion of the spinal cord gray matter (SCGM) region in numerous sclerosis was discovered to be the most grounded correspond of disability in multivariate models including brain GM and WM volumes, FLAIR injury load, SCWM region, age, sex and disease duration. The capacity to consequently evaluate and portray these progressions is, hence, a significant advance in the cutting-edge pipeline to contemplate. The fully-automated segmentation is helpful for longitudinal investigations, where the expansion of gray matter is tedious.

The exact division of the GM remains a challenge. The fundamental properties that make the GM region hard to section are: conflicting powers of the surrounding tissues, image artifacts and pathology-actuated changes in the image contrast.

Additional factors likewise add to the complexity of the GM segmentation task, such as, absence of normalized datasets, contrasts in MRI acquisition conventions, distinctive pixel sizes, various techniques to secure highest quality level segmentations and diverse execution measurements to evaluate segmentation results.

Deep Learning is characterized by a significant shift from conventional handcraft include extraction to a progressive representation learning approach where various levels of consequently found representations are gained from crude data. The study additionally found that Convolutional Neural Networks (CNNs) were more common in the medical image analysis, with Recurrent Neural Networks (RNNs) acquiring prevalence.

In this work, we propose another simple pipeline including a end-to-end learning approach for completely mechanized spinal cord gray matter segmentation utilizing a novel Deep Learning architecture.

The capacity to consequently survey and describe this progression is, accordingly, a significant advance in modern pipeline to consider both the in vivo and ex vivo Spinal Cord. The segmentation result can likewise be utilized for co-registration and spatial standardization to a common space. In addition, the completely computerized segmentation is helpful for longitudinal examinations, where the depiction of grey matter is time consuming.

While ongoing cervical cord cross-section region (CSA) segmentation strategies have accomplished close human execution, accurate segmentation of Gray Matter stays a test. The primary properties that make the gray matter region hard to fragment are: conflicting powers of the encompassing tissues, picture curios and pathology-prompted changes in the picture contract.

Extra factors likewise add to the intricacy of the Gray Matter segmentation task, for example, absence of normalization datasets, contrasts in MRI procurement conventions, distinctive pixel sizes, various techniques to get highest quality level segmentation and diverse execution measurements to evaluate segmentation results. Highlights a few instances of axial MRI obtained at various focuses, exhibiting pictures change ability due factor picture acquisition system and protocols.

Fig 1: Cross section of the spinal cord

II.LITERATURE SURVEY

Claudia Blaiotta et al. "A probabilistic framework to learn normal shaped tissue templates and its application to spinal cord image segmentation". In: Proceedings of the 24th Annual Meeting of ISMRM, Singapore 1449 (2016).

In this paper, they proposed a probabilistic technique for segmentation called "Semi-Supervised BEM", where the MRI signals are assumed to be noticed information used by distorting of a normal shape reference life systems. The noticed image powers are displayed as arbitrary factors drawn from a Gaussian blend circulation, where the parameters are assessed utilizing a variational form of the Expectation-Maximization (EM) calculation. The strategy can be utilized in a fully unsupervised style or by joining training data with manual labels, subsequently the semi supervised scheme.

Feeran Prados et al. "Fully automated grey matter and white matter spinal cord segmentation". In: Scientific Reports 6.June(2016), p.36151.

In this paper, they proposed a strategy called "Joint collaboration for spinal cord gray matter segmentation" (JCSCS), where two existing name combination division techniques were consolidated. The technique depends on a multi-atlas segmentation propagation utilizing registration and segmentation in 2D slice-wise space. In JCSCS, the "Improved Patch-Match Label Fusion"(OPAL) is utilized to identify the spinal cord, where the cord limitation is accomplished by giving an external dataset of spinal cord volumes and their related manual division, after that, the "Similarity and Truth Estimation for Propagated Segmentations" (STEPS) is utilized to fragment the GM in two steps, first the segmentation propagation, and then an agreement division is made by combining best-deformed formats (in light of privately standardized cross-connection).

Esha Datta et al. "Gray matter segmentation of the spinal cord with active contours in MR *images". In: Neuroimage 147 (2017), pp.788-799.*

In this paper, the Morphological Geodesic Active Contour (MGAC) algorithm utilizes an outside spinal cord segmentation tool (Jim, from Xinapse Systems) to assess the spinal cord limit just as a morphological geodesic dynamic form model to fragment the gray matter. The technique has five stages: first, the original image spinal cord is divided with the Jim programming and then a template is enrolled to the subject cord, after that a similar change is applied to the GM layout. The changed gray matter layout is then utilized as an underlying speculation for the dynamic shape calculation.

Adam Porisky et al. "Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support". Vol. 10553. 2017

In the Deep seg approach, based on top of, they utilize a Deep Learning design like the U-Net, where a CNN has a contracting and extending way. The contracting way totals data while the growing way up examples the component maps to accomplish a dense prediction output. To recuperate spatial data misfortune, alternate routes are added between contracting/extending ways of the network. In Deep seg, rather than spending testing layers like in U-Net, they utilize an un-pooling and "deconvolution" approach, for example, in. The network architecture utilized has 11 layers and is pre-trained utilizing 3 convolutional limited Boltzmann Machines. Deep seg additionally utilizes loss function with a weighted amount of 2 distinct terms, the mean square contrasts of the GM and non-GM voxels, adjusting affectability and explicitness. Two models were trained(autonomously), one for the full spinal cord segmentation and another for the GM segmentation.

Ferran Prados et al. "Spinal cord gray matter segmentation challenge". In: Neuroimage 152(2017), pp.312-329.

The "Gray matter segmentation based on Maximum Entropy" (GSBME) calculation is a semi-automatic, supervised segmentation technique for the GM. The GSBME is included three primary stages. First, the image is pre-processed, in this progression the GSBME utilizes the SCT to segment the spinal cord utilizing Prop seg with manual introduction, after that the intensities are standardized and denoised. In the subsequent advance, the images are slice-wise threshold utilizing a sliding window where the ideal edge is found by expanding the amount of GM and WM intensity entropies. In the last stage, an exception indicator disposes of portioned intensities utilizing morphological highlights like edge, whimsy and Hu moments among others.

1. EXISTING SYSTEM:

In existing framework, the problem is analyzed physically by the specialists by utilizing MRI or CT filters. It relies upon the experience and information of the specialist that how effectively he/she will analyze.

2. PROBLEM STATEMENT:

The capacity to consequently portion the gray matter is, thus, a significant task for current investigations of the spinal cord. Gray matter tissue changes have been related with wide scope of neurological problems. Numerous strategies for spinal cord segmentation were proposed before. There is a need to give an enhanced methodology for gray matter segmentation.

3. PROPOSED SOLUTION:

To overcome the current issues, another basic technique highlighting a start to finish learning approach is proposed for completely mechanized spinal cord gray matter segmentation utilizing deep learning design development on deep diluted convolution.

4. OBJECTIVES:

1) To automate human spinal cord gray matter segmentation technique utilizing deep learning, that works both on in-vivo and ex-vivo MRI acquisitions.
2) To identify the gray matter in the scanned images of spinal cord cross section.

III. METHODOLOGY

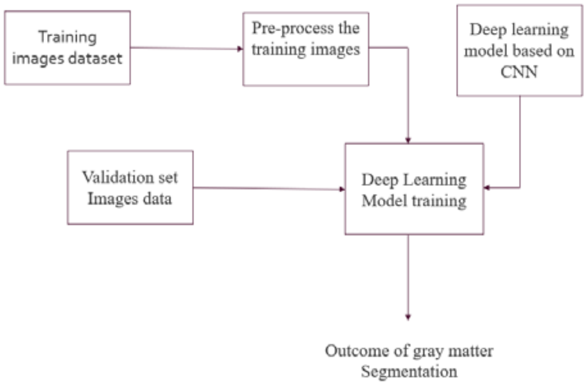

Fig 2: Flow diagram

1. **Description:**

In this methodology the Deep Learning ideas will be utilized to develop a effective and upgraded approach for segmenting the gray matter in a spinal cord. The initial step needs a contribution to begin with, as this is the image of the spinal cord cross area. Dataset of the spinal cord images will be gathered and parted into preparing and approval set of images for the deep learning training and to approve the results of deep learning model.

2. **Dataset Description:**

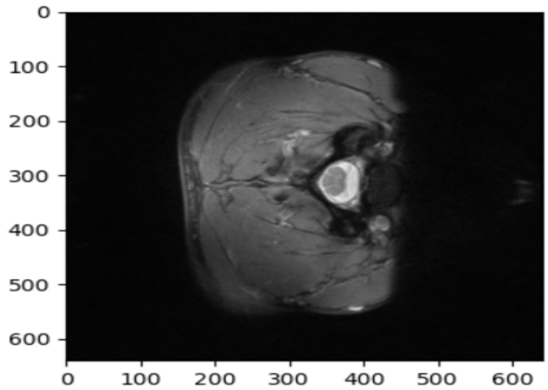

Fig 3: Spinal cord cross section as input data

The Spinal Cord Gray Matter segmentation dataset consists of 100 scanned images of NII (Neuroimaging) file format. The dataset is split between training (80) and test set (20) where the test set hidden. The different MRI systems were used with different acquisition parameters based on a multi-echo gradient echo sequence. Here, the voxel size is not fixed, it varies with patients' data.

3. **Image preprocessing:**

Dataset of spinal cord images will be collected and split into training and validation set of images for the deep learning training and to validate the results deep learning model. These images will be pre-processed for the training purpose, pre-processing like resizing, cropping and so on will be applied.

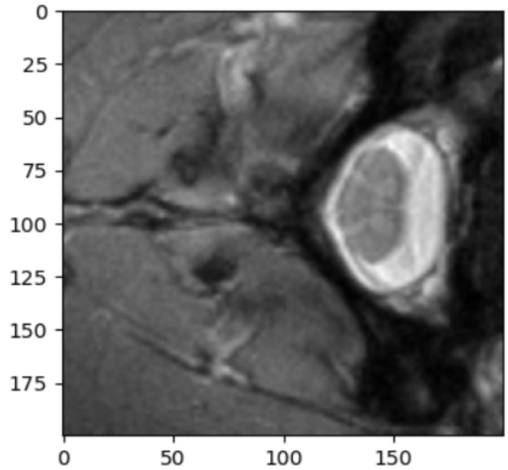

Fig 4: Cropped input image

4. **Feature extraction:**

Gray scale images are taken and converted into reduced variables. Each pixel of the image is taken and converted into matrix for performing convolution. The process runs across all the pixel where convolution matrix is simply multiplied with each pixel matrix. The number of strides is mentioned which refers to shifting of pixel matrix. Max Pooling is used for the system after all variables are obtained by multiplication for better accuracy and extraction of features. The Convolution and Pooling process form an epoch. To improve the system accuracy, number of epochs are performed.

IV. RESULT

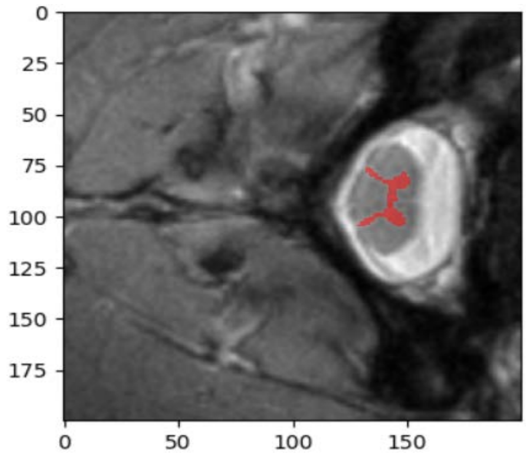

Fig 5: Segmented output

The trained model is used for predicting result. Firstly, the cropping function is applied on the input data to get the cropped region of the image. After loading the model, the segmentation method is used for segmenting the gray matter from the data.

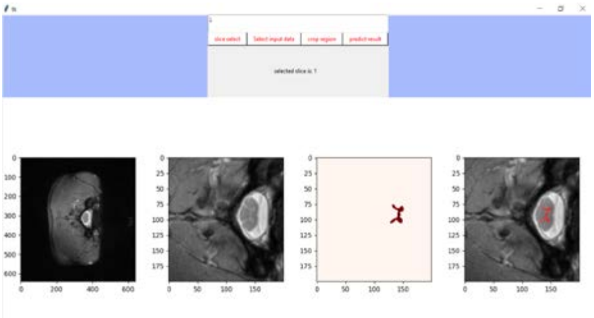

Fig 6: Predicted result

As shown in the figure 6, the selected slice is displayed first. Later, cropped image of the slice, gray matter segmented from the image and segmented gray matter on the actual image are displayed respectively, which can help the beginner level PG students to study gray matter in the spinal cord.

V. PERFORMANCE ANALYSIS

The recent technique in which U-Net architecture is used to segment the gray matter, have accomplished near human execution with the MSE (Mean Square Error) value 0.10, where as our work provides the lowest MSE value i.e., 0.000425 which is nearly equal to zero. If MSE is equal to 0, prediction matches the original result 100%. Hence the performance of our work has more accuracy compared to the recent method.

The performance is also analyzed using PSNR (Peak Signal to Noise Ratio) metrics. 81.8469 dB is the highest value of PSNR obtained. Where, MSE and PSNR metrics are inversely proportional.

VI. CONCLUSION

Most of the recently evolved gray matter segmentation techniques as a rule depend on enrolled layouts/atlases, discretionary distance and similitude measurements or complex pipelines that aren't streamlined in an end-to-end design, neither effective during surmising time. In this work, it is centered around the improvement of a simple Deep Learning strategy that can be trained in a end-to-end design. Dilated convolutions permit us to dramatically develop the responsive field with directly expanding number of parameters, giving a significant parameter decrease while expanding the effective outcomes.

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