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Brain Region Segmentation using CNN and NLM Filter

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Abstract:

Skull stripping (also known as brain region segmentation) is a crucial process in many neuroimaging applications. The accuracy of any existing method is dependent on the registration and the image geometry. If an attempt like this fails, the chances of a future attempt being successful are slim. To go around this problem, researchers turn to the Convolutional Neural Network, or CNN. for operations that do not need precise positioning, such as brain tissue removal. The shape and interconnection of the brain were uncovered by CNN. An open and publicly available benchmark dataset, OASIS is used. CNN's results are improving and becoming closer to those based on ground reality from experts. The objective is also to improve the processes utilized for evaluating parameters by including more calculative aspects into the already used CNN approach.

Keywords— Brain region segmentation, skull stripping, MRI, convolutional neural network.

Introduction:

Segmenting the various parts of the brain is a common enough task that several techniques have been devised for doing so. Discord and Struggle There are two primary challenges in homogeneity. Therefore, noise reduction must occur prior to any further picture processing [1]. An approach for filtering out Rician noise using a non-local mean filter is devised [2]. Rician noise is eliminated by using a novel similarity metric based on that pixel value [3]. Brain area segmentation is performed using a 3D convolutional neural network [4]. There are two methods for training fully convolutional networks, supervised pretraining [5] and patch-wise prediction [6, 7].

CNN was suggested by Mohammad Havaei et al. [6] and is distinct from traditional image processing methods. In the same way, it takes use of both regional characteristics and global context. The study details a 2-stage training process that makes it simple to anticipate tumor labeling. It's 30 times quicker than the current gold standard technology in speed enhancement. When using deep learning, you may expect precise outcomes. The approach is faster and can assess a great deal of information in MRI pictures [7]. Network design is prioritized in brain tumor segmentation, and complicated features are learned from the data. It utilizes both a discriminative and a generative model. Discriminative methods rely heavily on feature extraction to understand the relationship between the input and ground truth images. To isolate tumor cells, generative models are applied. A multimodality glioma segmentation job is performed using a 3D CNN architecture [8]. From MRI scans comes the cube of voxels and patches that serves as the input to the procedure. In order to determine the tissue label from the voxel cube, this article used a convolutional neural network. A 3D Convolutional Neural Network (CNN) is employed for accurate brain lesion segmentation, as suggested by Konstantinos Kamnitsas [9]. Using a dual route design, the input picture may be analyzed concurrently on several scales. It uses a voxel-wise technique to estimate a classification for a whole picture, which means it considers the surrounding area and its context as it works its way through each voxel. The consecutive convolution of the input at the cascaded network accomplishes this and significantly reduces the false positive rate. For glioma segmentation, Deep Convolutional Neural Networks use tiny convolutional kernels [10].

To accommodate more convolutional layers, a smaller kernel is used while maintaining the same receptive field as larger kernels. Although it uses fewer weights than a 5x5 convolutional layer, the effective receptive field of this layer's two 3x3 cascaded convolutional layers is the same. Since a smaller kernel has fewer weights than a larger kernel, over fitting is mitigated by using this technique. For the purpose of segmenting biological images, Olaf Ronneberger [11] created a convolutional network. There are two distinct paths in this design: one that contracts and one that expands symmetrically. The capture context is established by contracting the route, whereas exact localization is achieved by extending the path. This network exceeds the previous best approach (a sliding window convolutional network) for segmentation, and it can be trained from scratch using just a small number of example pictures. This structure employs a ReLU function in both of its 3x3 convolutional layers. At each successive down-sampling stage, the number of feature channels is increased by one. By up-sampling the feature map at each expansion node, we may lower the total number of feature channels. The last layer employs a softmax classifier to sort data into its respective categories. Convolutional layers are used by convolving a signal or picture using kernels to produce feature maps [12]. As part of the training process, the kernels' weights are adjusted adaptively through back propagation to improve the input. There has been a suggestion that the CNN design be used in a cascaded fashion, allowing for more computational flexibility and speed for segmenting medical images. The output of the previous layer is appended to the input of the subsequent layer across the whole network. CNN uses it to get knowledge about context. All convolutional neural networks may be taught to predict the class of a pixel. A more global picture segmentation utilizing super pixels is used to regularize the predictions.

MRI scans are utilized for this study. Rician noise is suppressed in the preprocessing stage by use of a Non-Local Mean (NLM) filter technique. Removing extraneous material, such as the skull, is called "brain area segmentation," and it is a crucial step before moving on to the primary processing in many brain imaging applications. A Convolutional Neural Network is then used to extract the brain from the cleaned-up picture.

Literature Review:

When paired with cutting-edge quantitative image analysis techniques, the large amounts of anatomical and functional data acquired by medical image collection equipment greatly benefit both diagnosis and therapy. Nonetheless, picture artifacts that are unique to a certain imaging modality persist and may have a negative impact on quantitative image analysis; for example, the phenomenon of intensity inhomogeneity in MRIs. Numerous techniques that have been developed to lessen or get rid of the prominence of homogeneities in magnetic resonance imaging (MRI) scans are discussed in this study. The in-homogeneity correction approach is first used to categorize the methods. The next step is a discussion of many methods of analysis, both qualitative and quantitative. Third, important trends, popularity, assessment methodologies, and applications are revealed by an analysis of 60 relevant papers that are sorted and examined according to many parameters. Finally, the findings of the study are used to support a discussion of the analysis's important assessment difficulties and the field's potential for future growth in homogeneity correction [1].

Intensity homogeneity correction techniques for magnetic resonance images have been discussed. Different characteristics were used to categorize the methodologies and validation strategies. An in-depth review of several recent papers added new perspective to the study of intensity in homogeneity correction. Numerous concerns have been raised, showing that intensity in homogeneity correction is far from being an entirely resolved issue. This, together with the development of new MRI techniques and their accompanying applications, ensures that the issue of intensity in homogeneity correction will remain at the forefront of scientific inquiry for the foreseeable future. In addition, validation problems need a lot more focus than they have had in the past [2].

Denoising in synthetic brain MRI is assessed by combining a Non-Local Means (NLM) filter with a suitable fuzzy cluster criteria. Compared to the conventional NLM approach and the wavelet method, experimental findings demonstrate that noise is successfully reduced while picture details are well preserved. Both quantitative and qualitative findings point to an improvement in the quality of MR brain pictures, with artefacts being drastically decreased and continuous edges and fine structure being maintained. Furthermore, the computing time is drastically cut [3].

Using the inherent structural redundancy in a noisy picture, non-local means (NLM) is a patch-based image denoising approach that can recover a better quality version of the original image. In this article, we offer a technique for denoising brain MRI scans that combines non-local methods with fuzzy cluster. Through quantitative and qualitative comparison with the NLM denoising approach and the wavelet method, the author demonstrates that his or her suggested method not only suppresses the noise more efficiently, but also well retains the continuous edge and detailed structure for brain MRI. Furthermore, the calculating time is drastically cut down. Automatically selecting NLM settings based on the medical picture is an issue that needs to be fixed. Using the default settings of the NLM approach, the author achieves satisfactory results in their experiment. Automated parameter choice based on user preferences is a promising area of research for improving picture quality in the future [4].

In this study, we explore how non-local means (NLM) filtering may be used with MRI scans. To compare pixel intensities, a similarity measure is a crucial part of any NLM-based method. The majority of the current similarity metrics used to denoise MRI images were developed on the premise of additive white Gaussian noise contamination. At low signal-to-noise ratios (SNRs), it is well-established that this assumption breaks down, hence it is necessary to find alternate formulations of these measurements that account for the accurate (Rician) statistics of the noise. Thus, the primary advancement of this work is the introduction of a novel similarity measure for NLM filtering of MRI images, which is developed under sound statistical assumptions and is shown to have substantial theoretical benefits over competing formulations. Numerical studies conducted with both in silico and in vivo MRI data [5] prove the effectiveness and practicality of the suggested approach.

The current research suggests two unique NLM-based techniques for improving MR pictures. In particular, two new definitions of the NLM similarity measures were given in this study, both of which account for the genuine Rician statistics of measurement noises. Furthermore, closed form formulas matching to these similarity measures have been obtained for the situation of MRI noise. As a result, it has been shown that the suggested similarity measures have a number of desirable properties for the purpose of denoising MRI pictures. Further, important theoretical links between the similarity measurements have been highlighted. Finally, both virtual and actual trials have shown the suggested algorithm's worth. Results show that the proposed technique outperforms many well-established reference approaches [6] in terms of reconstruction quality.

In many neuroimaging processes, brain extraction from MRI is a necessary step. The state-of-the-art approaches succeed with unenhanced T1-weighted images but fail with other modalities and pathologically modified tissue. This work presents a 3D convolutional deep learning architecture that aims to remedy these drawbacks. Unlike conventional approaches, authors are not restricted to plain T1w scans. Author method, with proper training, can deal with any number of modalities, including contrast-enhanced images. On a difficult clinical data set containing brain tumours (N = 53), the author approach shows superior performance to six commonly used tools with a Dice score of 95.19, demonstrating its applicability to MRI data consisting of four channels: non-enhanced and contrast-enhanced T1w, T2w, and FLAIR contrasts. Moreover, evaluations on three publicly accessible data sets (IBSR, LPBA40, and OASIS) with a combined N = 135 volumes show that the suggested technique at least equals state-of-the-art performance. Although the convolutional neural network (CNN) does not substantially outperform the runner-up technique, it does get the highest average Dice scores on the IBSR (96.32), LPBA40 (96.96), and the tumour data set (95.19). Dice achieves the second-best results (95.02) on the OASIS data, with no statistically significant difference between itself and the top-performing tool. In all datasets, the average specificity measures are shown to be the greatest, while the sensitivity shows findings around the mean. One way to fine-tune the sensitivity of the approach is to play with with the cut-off threshold used to create the binary masks from the CNN's probability output. A trade-off of less specificity is inevitable with this approach, and the decision must be made on a case-by-case basis. With a well-tuned GPU implementation, prediction can be completed in under a minute. Potentially beneficial in large-scale investigations and clinical trials [7].

To extract the brain from MR pictures, the author of this research [8] introduced a 3D convolutional deep learning architecture. The suggested technique solves several issues with prior approaches while still providing at least state-of-the-art performance (Dice score and specificity). The author approach works with contrast-enhanced scans as well as T1w pictures with no modifications. Second, the method may accommodate an infinite variety of modalities with proper training. This was shown using a complex clinical dataset of people with brain tumours. The authors are optimistic that the new method would be beneficial for both large-scale investigations and clinical trials.

Effective visual models, convolutional networks provide feature hierarchies. Author demonstrates that state-of-the-art in semantic segmentation may be surpassed by using just convolutional networks that have been trained end-to-end, pixel-by-pixel. The main idea of the article is to construct "fully convolutional" networks that can train and infer efficiently while processing inputs of arbitrary sizes. The author lays some groundwork by outlining the domain of fully convolutional networks, elaborating on their use in spatially dense prediction problems, and tying in previous work. Using fine-tuning [5, 6], the author converts state-of-the-art classification networks into fully convolutional networks, then applies the networks' previously learned representations to the segmentation task. The author goes on to develop the skip architecture, which merges semantic information from a deep, coarse layer with appearance information from a shallow, fine layer to provide precise and comprehensive segmentations. As shown in [6], the author's fully convolutional network achieves state-of-the-art segmentation on PASCAL VOC (20% relative improvement to 62.2% mean IU on 2012), NYUDv2, and SIFT Flow, with inference times of less than a fifth of a second for a typical picture.

The state-of-the-art classification convnets are a subset of the broader class of models known as fully convolutional networks. Understanding this, researchers have shown that extending classification nets to segmentation and upgrading the design with multi-resolution layer combinations greatly improves the state-of-the-art while also simplifying and speeding up learning and inference [7].

In this research [9], the authors offer a Deep Neural Network-based approach to automated tumour segmentation in the brain (DNNs). The suggested networks are calibrated specifically for magnetic resonance (MR) pictures of glioblastomas of varying grades. Because of their genetic make-up, these tumours may manifest in almost any area of the brain and take on a wide variety of sizes, colours, and textures. As a result of these issues, the author has been looking into a machine learning solution that makes use of a high-capacity, versatile DNN. Here, the authors detail the many model options we've discovered to be crucial for achieving state-of-the-art performance. In particular, the author delves into several Convolutional Neural Network (CNN) designs, which are Deep Neural Networks (DNNs) trained on picture data. The author introduces a new CNN architecture that is a departure from the norm in computer vision. CNN's authors make use of local characteristics and global background details concurrently. Furthermore, author networks employ a convolutional version of a fully connected layer as their last layer, which is 40 times faster than the typical use of CNNs. To address issues arising from asymmetry in tumour labelling, the author also details a two-stage training approach. Finally, the author investigates a cascade architecture where the results of a first CNN are used as input to a second CNN. Author architecture improves above the existing published state-of-the-art while being over 30 times quicker, as shown by results reported on the 2013 BRATS test dataset [10].

Implementation:

The picture once it has been denoised serves as the input for the CNN. In order to separate the different regions of the brain using deep learning, feature extraction is required, as illustrated in Figure 1. Deep learning networks, such as CNN, are used for supervised learning in order to acquire the newly taught characteristics. This paper demonstrates that CNN is capable of producing reliable brain area segmentation.

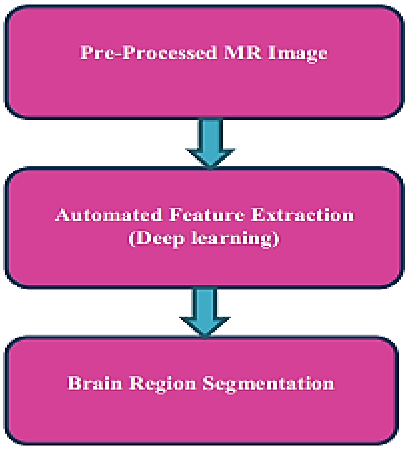

Fig 1. Brain Region Segmentation Steps

Deep nonlinear models that are "human brain inspired" have an architecture that creates complex characteristics at a deeper layer of the network by examining the basic features that were learnt in a lower layer. These characteristics have shown to be particularly useful descriptors in the context of object recognition issues. When these models are being trained, the features are encoded in an iterative fashion during the training phase, and then the learnt weights are modified in order to achieve greater network optimization. Using CNN in a method that requires supervision, the characteristics may be learnt. A trained classifier is given the characteristics that were learnt using a layer-by-layer approach, and it then makes predictions about the labels. The classifier, which is a supervised layer, was trained with the help of a collection of photos together with the label that corresponds to each one. It is expected that the trained network would be able to reliably predict the label for photos that have not yet been seen. In order to perform the process of feature extraction using deep learning, the following implementation phases are required: input generation, creation of the deep network, training of the network, and extraction of the features that were learnt by the network. Figure 2 illustrates the many phases involved in feature extraction using CNN.

CNN is able to learn features directly from a picture, therefore it is not need to handcraft any features. The process is broken down into three stages, which include the creation of input data, the development of the model, and the learning of the parameter values. Therefore, a condensed representation of the picture in the form of image patches is sent to the multilayer convolutional neural network as its source of input data. The supervised deep network is structured in three distinct layers. The input picture is sent to the input layer, which then predicts the label based on the information provided by the input layer. There is always at least one convolutional layer and one pooling layer present in each hidden layer. In the convolutional layer, a dot product is computed using the weights and the input, and then a bias term is added. When examining a grayscale picture, the bias term will always be one. The pooling layer is responsible for down sampling operations, and it cuts down on the amount of connections to the layer that comes after it.

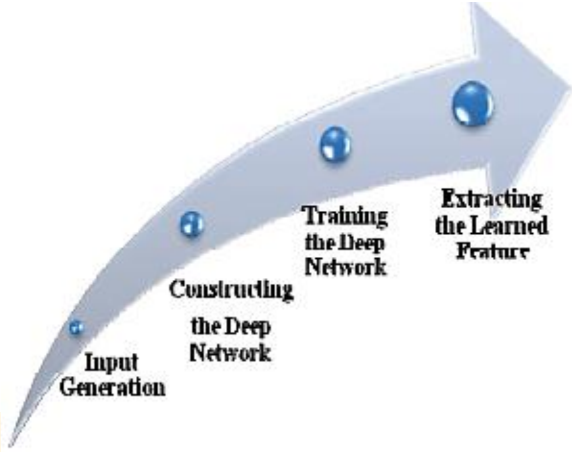

Fig 2. Steps in Feature Extraction using CNN

A conventional back propagation neural network (BPN) should not be confused with a convolutional neural network (CNN) due to the fact that a BPN operates on manually acquired image data, whilst a CNN operates immediately on an image to extract relevant and essential information for segmentation. A convolutional neural network (CNN) is made up of many layers of convolutional processing, pooling processing, and fully connected processing, followed by one layer of classification processing. Convolving the picture with the various filters results in the production of feature maps when the size of the image is provided as an input to the CNN. Each map, on average, has mean or maximum pooling layers serving as its subsampling. The typical range for the subsampling rate is between two and five. After the convolutional layers comes an arbitrary number of fully linked layers, depending on the architecture.

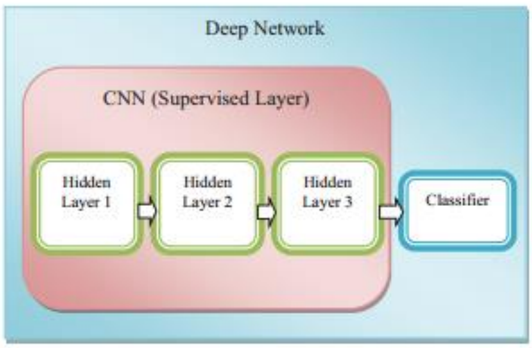

Fig 3. Construction of Convolutional Neural Network

Results:

Input generation, creating the deep network, training the deep network, and finally extracting the learnt features are the phases that make up the implementation. There are three different methods to broadcast CNN. The first approach is to construct and then train a CNN in order to acquire the feature. Utilizing "off-the-shelf CNN features" rather than retraining the CNN is the second option. The third approach is to use CNN for the purpose of refining the findings that were acquired by using a deep learning model. The CNN that is constructed in this study makes use of the first approach. As can be seen in Figure 3, the CNN is built with three distinct layers. Following each hidden layer's one convolutional layer and one pooling layer is a fully connected layer. This sequence repeats for every hidden layer. It does this by combining all of the information learnt by the layer below it in order to determine the broader pattern throughout the picture.

Fig. 4 to 7 shows the result screen shots of different input images.

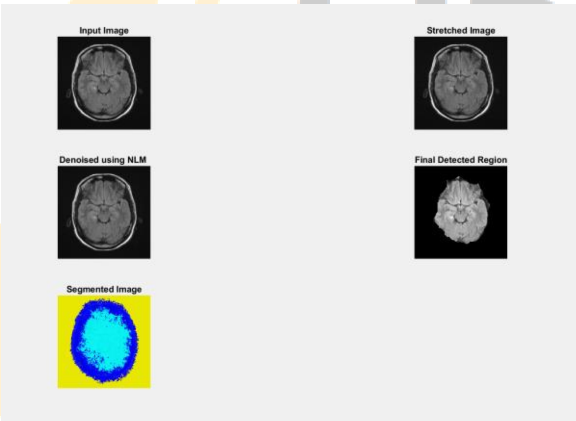

Fig 4. Result for input image 1

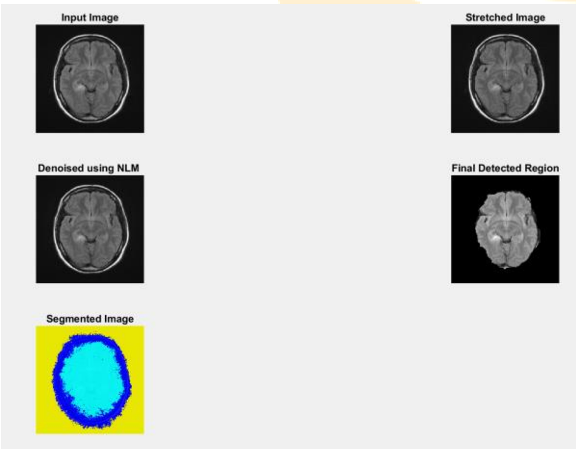

Fig 5. Result for input image 2

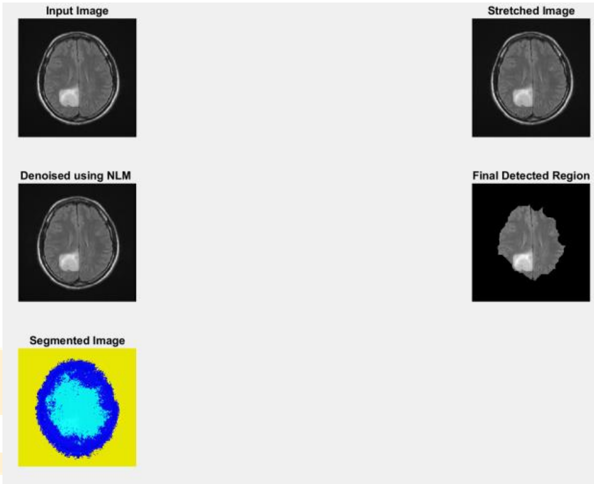

Fig 6. Result for input image 3

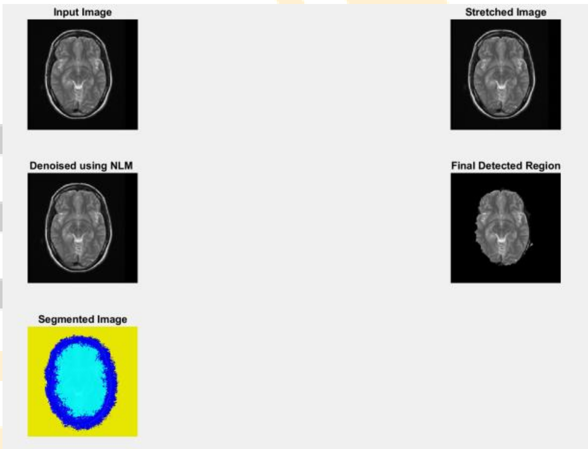

Fig 7. Result for input image 4

Conclusion:

The stage of brain region segmentation or skull stripping is a critical phase that must be finished in order for neuroimaging applications such as surgery, surface reconstruction, image registration, and so on. These applications include imaging of the brain. The degrees of accuracy that may be achieved using any of the presently accessible methods are contingent on the registration as well as the image geometry. When anything of this kind is unsuccessful, there is a far lower chance that it will ever be successful. In order to get around this problem, the Convolutional Neural Network, more often referred to simply as CNN, is used. when it comes to the removal of brain tissue, a process that does not need geometry or registration. CNN made the discovery that the shape of the brain may be determined by its interconnection. We make use of the OASIS database, which offers a standard data collection that is accessible to the general public.

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