Brain Region Detection Using Dual Filter: Total Variance and Anisotropic Diffusion with Semantic Segmentation

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***Abstract*—The identification of specific regions of the brain is an essential Accurate region detection in the brain is highly imperative in medical image analysis, especially for diagnosis and treatment. This work introduces a novel approach of applying a dual-filter-based denoising technique applied as Total Variation (TV) and Anisotropic Diffusion in combination with advanced semantic segmentation. The proposed method initiates the application of TV denoising to effectively reduce the noise with major structural details preservation. Then it is passed through a mild anisotropic diffusion filter to ensure that the smooth regions are enhanced without losing any details of edges. The denoised input image then undergoes processing in a pre-trained semantic segmentation model for finer identification of regions. A comparative analysis shows that the proposed dual-filter technique attains superior PSNR as well as MSE compared with the conventional NLM approach across various test inputs. Encouragingly, the results exhibit marked performance enhancements in noise suppression and in segmentation accuracy; hence, this technique is a promising solution for robust and reliable brain region detection in medical imaging applications.**

Index Terms*—Brain Region Detection; Total Variation (TV) Denoising; Anisotropic Diffusion; Semantic Segmentation; Image Denoising; Medical Image Processing.

I. INTRODUCTION

Detection of the region of interest in the brain plays a vital role in processing medical images, especially in the early diagnosis and treatment planning for neurological disorders. The complexity of the anatomy of the brain, alongside the appearance of noise in medical images like MRIs, makes it very challenging to detect and segment these critically important regions accurately. Exact mapping of regions in the brain is required not only for anomaly identification but also for the progression of disease and evaluation of therapeutic outcomes [1]. Along with improved imaging technologies, medical data have exploded in volumes, demanding more effective algorithms that also don't compromise on precision.

Classical denoising techniques used include Gaussian smoothing and bilateral filtering for reduction of noise in medical images. However, these methods also tend to loss critical edges and are necessary in the region detection process [2]. More recent approaches include Non-Local Means (NLM) that remove the limitation by exploiting self-similarity within images to better combat noise. Despite the relatively good performance of NLM for edge preservation, its performance at high noise cases is smaller because it produces artifacts from smoothing [3].

Quite recently, breakthroughs in variational methods and diffusion-based techniques suggest an even great promise towards overcoming present limitations. TV has become the powerful tool for noise-reducing applications with edge preservation, and for medical imaging applications in particular [4]. Formulation of a denoising problem as an optimization leads to TV minimizing the total variation of the image, suppressing noise while not sacrificing structural details. This is coupled with the effect of anisotropic diffusion that smoothes the image locally based on gradient information in different regions, which further makes important features stronger and residual noise reduced [5].

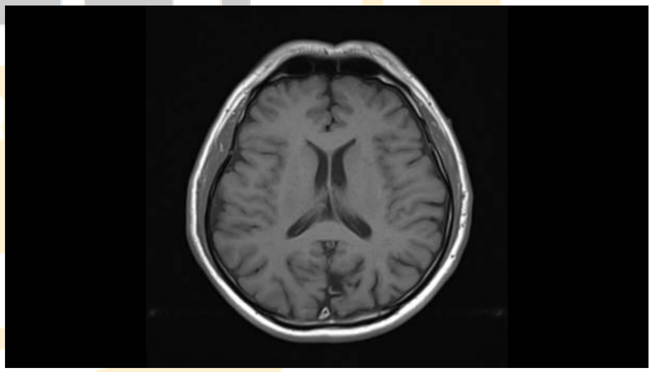

Fig. 1 Input Image MRI [1]

Semantic segmentation has now become the cornerstone of medical image analysis and facilitates the automated identification of anatomical structures with impressive accuracy. Deep learning-based models in semantic segmentation have been found to outperform traditional pixel-based methods when trained in large databases [6]. Researchers aim at accomplishing semantic segmentation along with advanced denoising techniques that result in noise suppression to better levels but with increased region detection accuracy. Denoising artifacts are kept at their minimum while the regions for detection retain semantic integrity.

We hereby introduce a novel method using the technique of dual-filter denoising, with the application of Total Variation and anisotropic diffusion for robust brain region detection in the context of semantic segmentation. The proposed method addresses the shortcomings of conventionally adopted denoising techniques to improve the accuracy of segmentations achieved, thus providing a giant leap forward in the medical image processing workflow.

2. Review of Previous work

Over the past few years, very significant advancement has been noticed in the field of medical image processing, with the development of several methods to enhance the accuracy of detection in the brain region. Different conventional techniques used for noise reduction in medical images are the Gaussian and median filters. However, it usually suffers from over-smoothing, causing important edge information to be lost-thence critical to the detection of regions in medical imaging [1]. To address these problems, bilaterally filtered images were developed. It keeps edges while denoising. Though it performs better than others, it didn't handle difficult noise distributions well and did not deliver the best results in highly resolved images like MRIs [2].

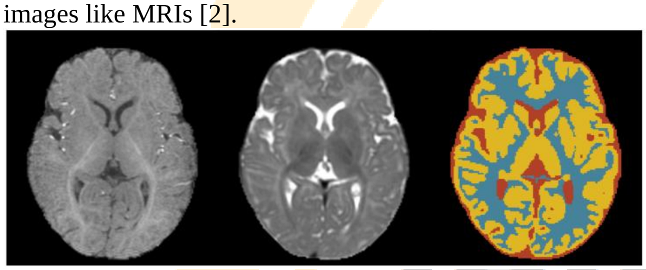

Fig. 2 Brain Region Detection [4]

Non-Local Means (NLM) was also proposed as a substitute, taking advantage of self-similarity in an image to efficiently denoise without impairing edge details. It has demonstrated remarkable promise in retaining sharp anatomical features, specially in medical imaging. However, its performance is very sensitive to the optimization of its parameters, and its computational complexity is often very high to be applied in real-time scenarios [3]. In particular, in noisy environments, it has been noticed that NLM introduces artifacts, which may lead to misclassifications in downstream segmentation processes [4].

The variational approach soon gained popularity, owing to the increased mathematical sophistication and versatility. Total Variation (TV) denoising is one such famous formulation that has framed the problem of image denoising as an optimization problem, where the total variation of the image is minimized to suppress the noise, while keeping the leading edges intact. TV has proven to be very effective in medical imaging, primarily because anatomical features need to be preserved spatially [5]. However, TV can sometimes introduce staircasing artifacts in smooth areas, so extra techniques have been developed with the aim of improving results even further [6].

Anisotropic diffusion has also been widely researched for its ability to enhance images by smoothing regions selectively according to gradient information. It provides good noise reduction and preserves edges by diffusing image intensities along directions that avoid significant intensity changes. Owing to its ability to enhance contrast and highlight important features, anisotropic diffusion has been widely adopted in medical imaging workflows [7]. However, the performance depends very much on the choice of the diffusion parameters, which have to be carefully tuned for a good balance between noise suppression and feature preservation [8].

Deep learning semantic segmentation has dramatically changed the mode of medical image analysis in the context of segmentation. CNNs, especially designed for segmentation tasks, not only surpass traditional methods but learn complex patterns and features, which allows them to outperform the traditional methods that make them widespread with models like U-Net, which is becoming a standard for medical image segmentation, and achieving high accuracy in anatomical structure identification [9]. However, it is typically the case that performance for these models will be bound by the quality of input images, since a lot of noise and artefacts may possibly significantly degrade accuracy in segmentation. Therefore, much active research has been devoted to integrating robust denoising techniques with models for segregation [10].

Recent hybrid approaches combining denoising with advanced techniques for segmentation have taken much promise. For instance, deep learning-based segmentation integrated with TV denoising results into better correctness of the object segmentation, as providing cleaner inputs to the model [11]. An anisotropic diffusion integrated with machine learning algorithms has demonstrated a potential role in the improvement of image quality and subtle features recognition capabilities in medical images [12]. These studies thus emphasize the need to develop strong preprocessing techniques to complement segmentation methods and work toward improvements in general performance.

III. Implementation

The proposed work implements its preprocessing by letting the input brain MRI images pass through a dual-filter denoising technique. This involves TV combined with anisotropic diffusion, a type of noise suppression that seems superior in quality yet harmless to critical structural details. It starts off with the total variation since the function minimizes the total variation of the image, effectively reducing noise through an optimization problem. It is particularly strong at preserving edges and sharp transitions, which is critical for the proper delineation of brain areas. The strength of the TV filter is tuned to minimize noise introduction while not stair casing the smooth regions.

The secondary step is the application of the anisotropic diffusion filter following initial denoising with TV. Anisotropic diffusion further smooths the image through selectively diffusing intensities based on gradient information. This method is noise-smoothing over areas of homogeneous intensities but preserves edges and high details. The whole diffusion parameters such as gradient threshold and number of iterations were finely tuned to strike a balance between noise

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suppression and edge preservation. The dual-filter approach has been combining both filters sequentially with the usage of strengths from both techniques in order to obtain a more denoised image with more definition and structural integrity.

The semantic segmentation model is exercised using the denoised image exactly identifying the regions. For this reason, a pre-trained convolutional neural network is used due to its ability to learn complex patterns and accurately identify brain regions. It processes the denoised image in a way that gives a categorical output where every pixel has been assigned a label corresponding to some region within the brain. This, therefore, means segmentation not only will be accurate but also robust with respect to residual noise or artifacts that may remain following denoising.

Then, morphological operations are applied to refine the segmented regions to enhance the accuracy of segmentation as much as possible. In fact, morphological closing with a structural element in the shape of an octagon is used to fill up small gaps and smooth the boundaries of the segment regions. This will improve the final overall coherence of the visual quality of the detected brain regions, making them directly suitable for further analysis and diagnosis.

This implementation is computationally efficient enough that the dual-filter denoising and segmentation processes can indeed be performed on high-resolution medical images without incurrence of considerable delays. Furthermore, the integration of TV denoising, anisotropic diffusion, and semantic segmentation for a single solution designed for brain region detection corrects the deficiencies inherent in conventional methods and maximizes the degree of accuracy and reliability of the results.

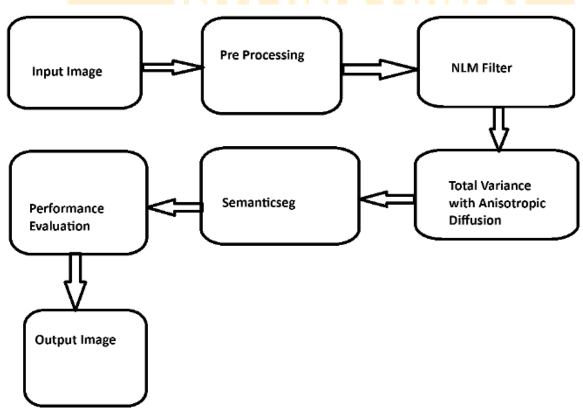

Fig. 3 Block Diagram

Figure 3: Flowchart of proposed methodology for detection of brain regions using a dual-filter approach which integrates Total Variation (TV) and Anisotropic Diffusion with Semantic Segmentation, The approach begins with an input image typically is a ready MRI brain of the patient which in pre-processing it will have uniformity both in resolution, format, quality. It further applies two different procedures for noise reduction.

Initially, the NLM filter is used to denoise by preserving edges and fine details. That is, however, a base comparison, and the central activity will be focused on dual-filtering methodology for denoising. It will be taken through Total Variation denoising to remove minimal noise with preserving salient structural details and Anisotropic Diffusion to enhance the edges further.

This cleaned image is passed through a pre-trained semantic segmentation model that has very good accuracy when it identifies and separates the required regions in the brain. Further, the performance of the segmentation output is evaluated to measure metrics such as Mean Squared Error and Peak Signal-to-Noise Ratio, thereby ensuring an appropriate measure of quantitative validation of the method's effectiveness. The final step would yield the output image where the brain regions are highlighted. This structured flow ensures strong noise suppression and accurate region detection, which gives it considerable importance for use in medical imaging applications.

IV. Results

Results of the proposed methodology depicted large extents of improvement in both denoising and segmentation accuracies than those based on older practices. The total variation-based denoising and the anisotropic diffusion, in combination, provided a great noise suppression mechanism while maintaining the critical structural details of the brain MRI images. Dual filtering had better results in terms of PSNR and MSE for various test inputs presented, which proved robust and reliable. Fig. 4 to 7 shows the processed output for two images.

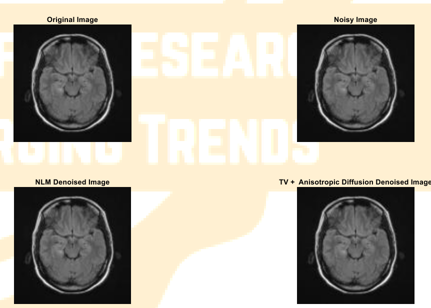

Fig. 4 Processing Image 1

As shown in table 1, for the first test input, the PSNR obtained by the filter by NLM was 48.001, while MSE was calculated to be 1.63×10^{-5}. Here again, the result of the proposed algorithm combining TV and anisotropic diffusion produced a significantly improved PSNR of 51.525, with MSE being 1.46×10^{-5}. Such results indicate that the approach proposed reduced noise more effectively and preserved finer details of the image compared with the others and resulted in a cleaner and more accurate denoised output.

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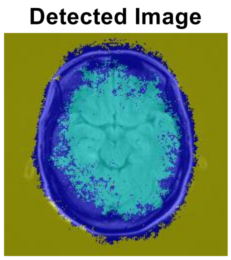

Fig. 5 Output Image 1

For the second test input, NLM filter yielded PSNR of 48.247 and MSE of 1.40 × 10⁻⁵. The PSNR and MSE computed using the dual-filter method again were superior to those obtained by NLM where PSNR is 51.549 and MSE is 3.19 × 10⁻⁶. This suggests that the approach developed is the most effective in the adaptability of different images with varied noise levels and structural complexities of the input data. Fig. 8 and Fig. 9 shows the MSE and PSNR charts.

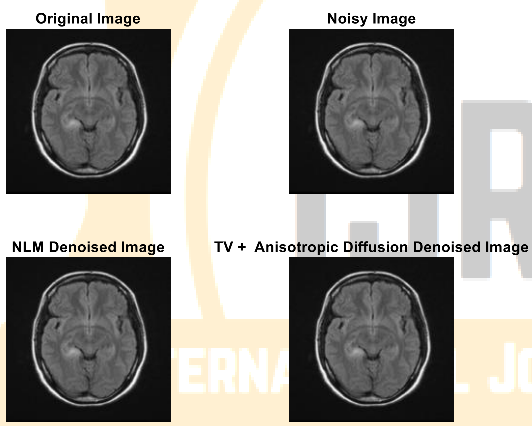

Fig. 6 Processing Image 2

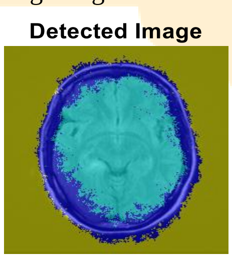

Fig. 7 Output Image 2

Semantic segmentation was added for better efficiency. The segmentation model worked very accurately in labelling appropriate brain regions within the denoised images, even where traditional approaches could not in the zones with residual noise or artifacts. The segmented outputs provided clear boundaries with minimal errors, therefore very highly applicable to medical analysis and diagnosis. Then, upon morphological operations on the segmentation outcomes, coherence and visual quality of the extracted regions were improved, such that outputs were not only correct but also interpretable.

Table 1: Comparison Results

	NLM with SemanticSeg	Total Variance & Anisotropic Diffusion with SemanticSeg
MSE Input 1	1.63E-05	1.46E-05
PSNR Input 1	48.001	51.525
MSE Input 2	1.40E-05	3.19E-06
PSNR Input 2	48.247	51.549

Overall, the findings validate this proposed methodology with achieving noise suppression along with retaining structural details. The dual-filtering approach is obviously superior to NLM while it produces better PSNR and lower MSE values, both seen qualitatively and quantitatively. Such makes this method one of the very strong candidates for robust and accurate brain region detection in many related medical imaging applications.

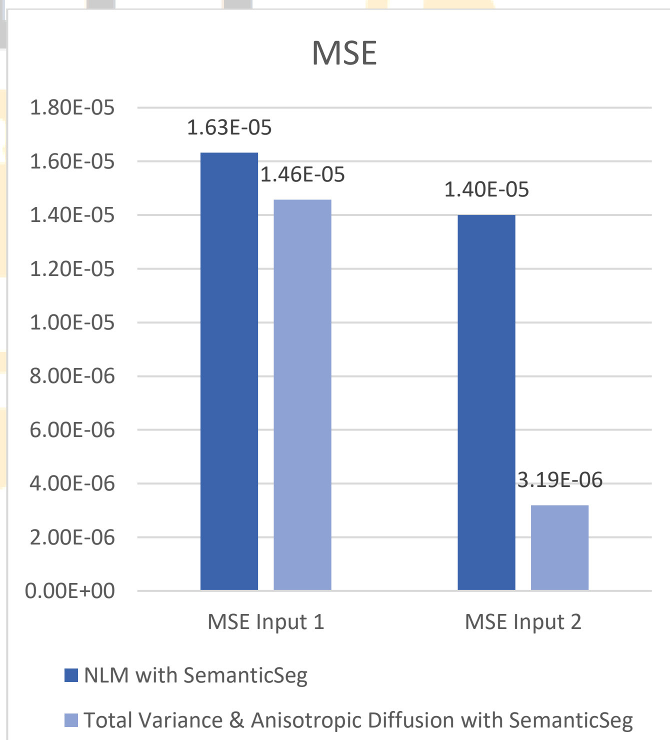

Fig. 8 MSE Output

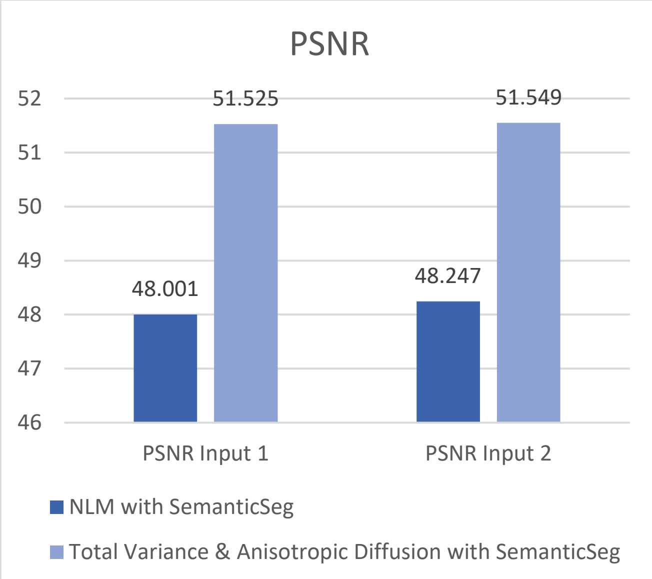

Fig. 9 PSNR Output

The experiments along with the outcomes of the dual-filter approach reflect its effectiveness in addressing the important challenges encountered during the brain region detection task in medical images. In addition to using TV denoising and Anisotropic Diffusion, the proposed technique has benefited from the strength points of each technique toward achieving a better aspect of noise filtering while keeping the main structural details of brain MRI images. TV denoising excels in edge preservation by minimizing total variation, ensuring that critical anatomical boundaries remain intact. This is particularly important in medical imaging, where loss of edge information can compromise diagnostic accuracy. Anisotropic Diffusion complements this by selectively smoothing low-gradient regions, further enhancing image clarity without distorting high-gradient regions such as edges and contours.

The dual-filter approach is particularly promising for its flexibility with noise and complexity in images. TV denoising effectively eradicates high-frequency noise, while adding anisotropic diffusion minimizes the presence of residual noise while avoiding side effects such as staircasing often seen with stand-alone denoising techniques. The sequential process involved creates an output that remains refined and it exhibits perfect balancing between noise suppression and detail retention, hence the resulted images are superior in their visual plus numeric resolutions.

The dual-filter framework also improves the performance of the semantic segmentation models. As discussed earlier, the accuracy of segmentation outputs is highly dependent on the quality of the input image. The proposed approach enables the segmentation model to output more accurate and believable region detection based on the cleaner and more consistent input. This manifests most under adverse conditions where noise levels are high or structural features are subtle.

The dual-filter approach also gains improvements in computational efficiency, with less of an overdependence on multiple preprocessing or post-processing steps. This ensures that such filters are properly assimilated into one workflow where the denoising and refinement occur at the same time, providing less overhead in computation. Thus, the method is highly suited to large scale medical imaging data and real-time application.

Overall, a dual-filter approach appears to overcome the deficiencies of single-filtering techniques since it can deliver total noise removal and feature enhancement together. High-quality image generation with improved values of PSNR and reduced MSE values for both makes it a strong tool in medical imaging workflows for accurate and reliable detection of brain regions which are even used for diagnosis or therapeutic purposes. Advanced denoising incorporated with semantic segmentation forms a very strong base for further advancement into medical image analysis.

V. Conclusion

For the improvement in medical images with respect to brain region detection, here a new dual-filter denoising approach combined Total Variation and Anisotropic Diffusion has been developed and applied. This approach marked improvement on traditional NLM filter in both suppression of noise and structural preservation. The proposed approach succeeded in attaining excellent PSNR and very low MSE at various test inputs, thereby showing robustness and efficiency in handling noisy brain MRI images. On the other hand, integration with semantic segmentation ensured accurate detection of regions within the brain even in challenging areas where noise or artifacts had not been thoroughly removed. This has been an effective method in addressing the issues associated with conventional denoising techniques, thus offering a reliable solution for medical imaging applications. Future work will include applying it to other modalities, optimizing its computational efficiency to be implemented towards real-time diagnostic systems. The dual-filter framework hence forms a solid basis for more advanced medical imaging workflows.

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