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Original Article

Enhancing Cancer Zone Diagnosis in MRI Images: A Novel SOM Neural Network Approach with Block Processing in the Presence of Noise

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Abstract

Background: Brain tumors are a specific disease that directly affects the brain. Magnetic Resonance Imaging (MRI) is considered the most effective imaging technique for diagnosing brain tumors, providing crucial information about tumor size, location, and type. However, accurately segmenting and extracting the tumor region from MRI images is a challenging task for radiologists and physicians, impacting the overall accuracy of diagnosis.

Methods: This research focuses on addressing the challenges of brain tumor detection and segmentation in MRI images. In line with the recent trend of big data analysis, neuroimaging data, including MRI images, are considered an important subset of big data due to their volume, velocity, and variety. The proposed approach utilizes the Self Organizing Maps (SOM) Neural Network, a powerful concept in image processing, to handle noise and artifacts in brain MRI.

Results: The proposed method employs image segmentation to focus on smaller parts of the brain and utilizes the SOM neural network for noise reduction, enhancing the processing of noisy brain images. The approach incorporates block processing to effectively approximate the suspected cancer zone, facilitating accurate medical diagnosis. The algorithm achieves precise specification of brain image zones by learning the unique SOM algorithm and setting an edge detection threshold. Experimental results demonstrate the superior performance of the proposed method, surpassing previous approaches, with a precision of over 10% in diagnosing abnormal brain areas.

Conclusion: The study highlights the importance of MRI in brain tumor diagnosis and the challenges associated with accurate tumor segmentation. The proposed approach using the SOM Neural Network effectively addresses these challenges by reducing noise, enabling block processing, and enhancing the precision of tumor detection. Results indicate the potential of the proposed method to significantly improve brain tumor diagnosis and contribute to advancements in medical imaging for neuroimaging applications.

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1. INTRODUCTION

The incidence of brain tumors significantly contributes to the global mortality rate. According to the Cure Brain Cancer Foundation, brain tumors are responsible for more deaths among individuals under 40 in Australia than any other form of cancer. Despite substantial improvements in survival rates for various cancer types in Australia over the past 30 years, the survival rates for brain tumors remain low and relatively unchanged. The World Health Organization (WHO) categorizes brain tumors based on cell origin and behavior, ranging from the least aggressive to the most aggressive. Non-malignant tumors are often classified as Grade I or II, denoted as low-grade (LG) tumors, while malignant tumors are categorized as Grade III or IV, known as high-grade (HG) tumors. High-grade tumors pose a significant threat with a maximum life expectancy of two years, whereas low-grade tumors may offer the patient several years of life expectancy.

Consequently, the early and precise segmentation of aggressive regions in the brain, such as cancerous sections, has become a focal point in the realm of brain image and data processing, attracting the attention of various researchers.

Owing to the diverse functions of the human body, the identification of brain tumors, and anomalies in neural systems, medical diagnosis remains a complex endeavor [1]. Intelligent systems, including medical image processing systems, play a crucial role in detecting unfavorable changes across various body regions. In the context of image processing, segmentation acts as an intermediary process with a fundamental role in image analysis and machine vision [2, 3]. The history of segmentation spans over four decades, with ongoing developments aimed at refining this critical step. However, meeting diverse requirements in various image processing and machine vision applications can complicate the process, posing a challenge due to the absence of a singular definition and analysis for segmentation.

In imaging systems, especially medical ones, output images are inherently uncertain due to factors like noise, limited spatial and temporal precision, and blur. Additionally, the varying luminance intensity of significant areas in images introduces further uncertainty. Despite advancements in medical imaging techniques such as mammography and magnetic resonance imaging (MRI), cancer screening and diagnosis remain challenging [4]. The screening process, involving early diagnosis in asymptomatic individuals through image review by a radiologist, faces challenges in classifying potential disorders [4-25]. MRI analysis, in particular, presents significant challenges with usual categories manifesting as atypical (varying sizes, shapes, boundaries, and intensity) [5]. Soft breast tissue and diverse image statuses further complicate the diagnostic process [4-37]. Considering the strides in information technology, specialized diagnosis and error detection are imperative for effective decision-making by radiologists through modern computing devices.

Recently, artificial intelligence-based methods, particularly intelligent image processing techniques, have emerged as successful tools. These methods facilitate automatic cancer detection, reduce human errors, and expedite the diagnostic process. The role of medical image processing methods in aiding physicians and radiologists in easier disease diagnosis fosters hope for patient safety [24-26-30].

In the machine learning realm, such as Artificial Neural Network systems (ANN), knowledge representation and the application of acquired knowledge play a crucial role in predicting the responses of complex systems. Inspired by the biological nervous system, these ANN-based systems find application in image recognition and classification. Self-Organizing Maps (SOM), an unsupervised and competitive learning neural network algorithm, offers a topology-preserving mapping from high-dimensional space to map units [1]. In this research, SOM serves as the foundation, controlling the main operation in image segmentation.

The primary objective of this study is to enhance an algorithm based on self-organizing neural networks for effective MRI image segmentation in the presence of contaminated noise. Our contributions include:

1. Introducing an effective clustering-based method for image segmentation.

2. Applying block characteristics for noise reduction in medical images, involving the separate extraction and analysis of features in each block.

3. Proposing a suitable algorithm using a self-organizing neural network.

4. Developing a method capable of detecting suspected cancer areas in noisy environments.

The remainder of the paper is organized as follows: Section 2 presents an overview of prior research in the relevant domain. Section 3 provides a comprehensive description of our proposed method. Section 4 reports the study results, while Section 5 discusses the method and its results. The conclusion and future work are presented in the final section of this investigation.

2. LITERATURE REVIEW

A series of image processing studies have employed various partitioning methods to identify segments within medical images. Five key approaches are utilized: segment enhancement, turning point detection, thresholding, separation and fusion techniques, and the K-means clustering algorithm. These methods serve as foundational techniques for segmenting complex structures such as brain tumors.

The development of a standardized multimodal brain tumor image segmentation benchmark—established through collaboration with the Medical Image Computing and Computer-Assisted Intervention (MICCAI) community—has significantly advanced this field [6]. Numerous algorithms have been proposed for brain tumor segmentation in medical imaging, especially Magnetic Resonance Imaging (MRI). A comparative study examining twenty well-known tumor cell division algorithms applied to a dataset of 65 multi-resolution scans—including high- and low-grade gliomas—alongside an equal number of synthetically generated scans produced using tumor simulation software, revealed considerable variability in algorithm performance. The efficacy of these methods was assessed using four standardized evaluation metrics. Quantitative results indicated noteworthy discrepancies, with the accuracy of human-annotated segmentations across different tumor sub-regions ranging between 74% and 85%. These findings underscore the current limitations of existing automated segmentation methods in achieving reliable and precise delineation of tumor structures, which is critical for clinical decision-making. Furthermore, the observed performance differences across algorithms and sub-regions suggest that effectiveness is highly context-dependent, often influenced by the specific modifications introduced by evaluators during annotation.

The Multimodal Brain Tumor Image Segmentation Benchmark (BraTS) has emerged as a pivotal resource in this domain, providing a comprehensive dataset of brain images accompanied by manual annotations, and offering an online evaluation system to standardize performance comparison across algorithms [6]. As a widely adopted benchmark, BraTS facilitates the assessment and comparison of segmentation methods, bolstering reproducibility and progress in brain tumor detection.

Various automated approaches have been proposed to improve segmentation accuracy. For instance, a brain MRI segmentation method utilizing the K-means clustering algorithm combined with morphological filtering was introduced to exclude non-relevant regions, thus aiding in tumor localization after initial segmentation [7]. Similarly, deep learning techniques have been employed for automatic segmentation; one such approach leverages a deep artificial neural network trained on anatomical structures, utilizing voxel-based information at multiple scales to identify tumor regions without relying on non-linear registration of MRI images [8].

Further advancing the field, researchers have explored convolutional neural networks (CNNs) for multi-scale segmentation tasks. For example, a CNN-based method integrated various segmentation and core sizes, learning discriminative features at multiple resolutions for each voxel. Applied across five diverse datasets, this approach demonstrated satisfactory results, indicating its robustness [9].

Traditional methods remain relevant as well. Patil et al. (2013) employed the level set method, demonstrating its flexibility in capturing complex tumor shapes without prior shape assumptions [10]. Fuzzy logic-based algorithms, such as the Fuzzy C-Means (FCM), have also shown promising results; Balafar et al. (2014) reported superior empirical performance for brain MRI segmentation using a FCM-based approach compared to other variants [11].

Other techniques include clustering algorithms like K-means, combined with watershed methods for initial segmentation, which proved effective for delineating tumor regions in MRI images [12]. To enhance efficiency and precision, He et al. suggested integrating discrete and continuous segmentation methods, coupled with multi-scale processing and parallel algorithms such as neural networks, to support real-time applications [13].

Feature-based classification approaches have also been explored. Wallis et al. developed a classifier for X-ray images utilizing a feature space encompassing luminance, spatial, and tissue-specific information, with feature extraction strategies designed to reduce computational complexity [14]. Optimization algorithms have further contributed to segmentation accuracy: Subhashdas et al. employed particle swarm optimization for edge detection, significantly speeding up the process [15], while Rafael et al. applied ant colony optimization to retinal fundus images for glaucoma diagnosis, leveraging the method's exploratory capabilities to analyze vessel curvature and retinal structures [16].

Entropy-based segmentation techniques, such as multi-level thresholding using Renyi and Tsallis entropies, have demonstrated efficacy in complex scenarios. Algorithms like Quantum Genetic Algorithms (QGA) and Differential Evolution (DE) have been utilized for comparative analysis, with quantum differential methods showing enhanced handling of intricate problems [17].

Throughout this landscape, image features play a crucial role in tumor detection. An advanced system for brain MRI analysis was developed to identify tumor-involved regions, with particular emphasis on comparing the effectiveness of statistical features against Gabor wavelet features. Notably, this presented the first comprehensive comparison of these feature extraction methods for tumor segmentation, filling an important gap in literature [18]. Several studies have also investigated the use of fuzzy, genetic algorithms, and other heuristic approaches, corroborating the versatility and ongoing evolution of segmentation strategies (e.g., [19], [20], [28], [29]).

3. MATERIAL AND METHODS

Upon scrutinizing past segmentation methods in this study, it was determined that these methods alone were insufficient for effective processing of brain data. As a result, the decision was made to reevaluate the segmentation process by introducing a series of processing steps. This approach aims to enhance the accuracy and precision of brain image segmentation.

3.1 Dataset

The standard dataset of brain MRI images includes 349 unique images that were used [33]. Images are related to patients suffering from brain diseases and those with brain anomalies or tumors diagnosed by physicians. The reason for using brain MRI images with anomalies is to show the precision of the proposed method in dealing with special medical images and its usefulness. Utilized images have had various sizes. However, the commonly used size has been 512*512 with 96 dpi precision and 8-bit depth. These original images have been ordinary images with no noise, and then noises with various intensities have been applied to them [33-37].

3.2 Evaluation Metrics

In the context of image segmentation, pixels often belong to adjacent regions, and even small clusters of neighboring pixels may represent meaningful segments. Therefore, a strict binary classification (e.g., purely correct or incorrect for each pixel) may not be appropriate. However, in abnormality detection tasks, pixels can generally be categorized into two classes: **normal** and **abnormal**. Thus, Precision and Recall remain suitable metrics for evaluating the performance of the segmentation and detection process.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

TP (true positive) in these equations shows a positive and correct detection (detection of a phenomenon). FP (false positive) shows the incorrect declaration of a phenomenon as positive, and finally, FN (false negative) shows an existing phenomenon incorrectly not detected.

The precision equation shows the evaluation of precision with a certain predicted class. The recall equation shows the measurement of the capability of a predictive model to select samples from a certain class of a dataset. In this study, image-related pixels may belong to the adjacent sections in the image, and even a few pixels next to each other may create a section of the image. Therefore, the binary state could not be considered for them, and only correct or incorrect values for a pixel could be detected. In detecting abnormalities, this may be the case. Pixels could be divided into two abnormal and ordinary forms. So, the Precision and Recall formulas could be used for it. The pixels are of two normal and abnormal forms.

3.3 Validation Criteria

The ROC (Receiver Operating Characteristic) curve is a valuable tool for evaluating the performance of the proposed method. It illustrates the trade-off between the True Positive Rate (TPR) —which is equivalent to Recall— and the False Positive Rate (FPR) across varying classification thresholds. A higher TPR relative to FPR indicates superior detection performance. The ROC curve was generated by applying the proposed method to multiple test images, allowing for a comprehensive assessment of its behavior under different conditions. The False Positive Rate, which reflects the proportion of incorrectly classified negative instances, is defined as follows:

$$FPR = \frac{FP}{FP + TN} \quad (4)$$

where FP denotes false positives and TN denotes true negatives. graphical representation provides insight into the overall effectiveness of the method, particularly in distinguishing between normal and abnormal regions within MRI images.

3.4. Proposed method

Brain MRI images may become noisy due to distortions existing in the environment and sensitive devices. Close studies have used techniques primarily to remove salt and pepper and Gaussian noises. These algorithms include median and Wiener filters so that noises can be reduced to a possible extent. However, the achievement of the original image would not be possible. Thus, here, images are supposed to have salt and pepper and Gaussian noises.

Afterward, neurons in the SOM neural system are trained in the competitive form so that image thresholds would become specified in the image with the Otsu thresholding method. This threshold is used to specify the boundaries of various sections of the image. Furthermore, blocks could be selected based on the size of the image. For example, a square shape block is formed by 4, 8, or 16 pixels. Each of the prominent pixel blocks would be weighed in a preliminary segment, and it obtains its weight with consideration of its difference with neighbor pixel blocks. The weight of those blocks with the least different from their surroundings would be higher, and finally, their values would be used for the absorption of surrounding pixels and the formation of larger segments. Following the above points, the SOM algorithm acts like brain neurons and absorbs those blocks with similar features while grouping them in a segment. This happens when blocks close to each other have no structural difference from each other. This is a competitive method in which each prominent pixel block in each segment tries to absorb more pixels to make a larger segment. In the proposed method in this study, the blocks would be recognized through their mean values, and they would be used in segment computation.

In the next step, the formation of segments in some sections of the image with more prominent blocks with pixels having maximum values will be considered the suspected sections with the abnormality. In addition to the recognition of segments with higher quality, the abnormal target segment will be distinguished from other surrounding segments. As it will be shown in the results, elements are divided in a way that these data will be easily extracted from there and become observable. In **Figure 1**, the general implementation flowchart for the proposed method is observed.

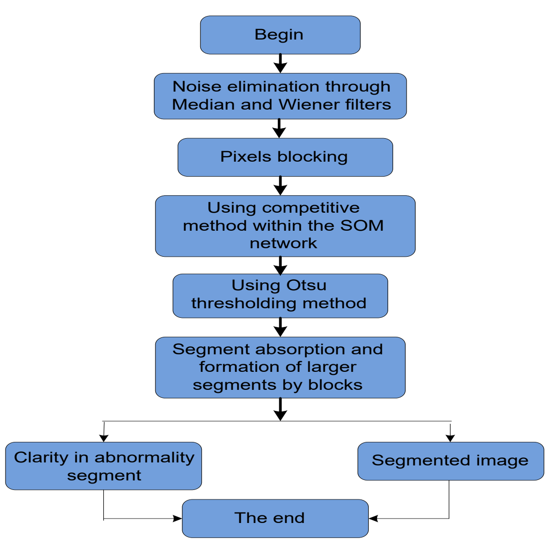

Figure 1. General block diagram of the proposed method.

The general steps of implementing the proposed method are shown in **Figure 1**. The blocking procedure always takes place when implementing the method. In other words, block processing is used instead of pixel processing. Furthermore, the method in the core uses an Otsu thresholding technique for segments so that the noise effect would become neutralized largely. Then, the blocks would be used by the SOM network for segmentation, and segmentation will be ended with work completed in the network. This way the abnormal segment will be specified. Next issue concerns using mathematical morphology performed at the time of absorbing segments by blocks (i.e., dilation technique).

This methodology is an intelligent and effective method for processing brain MRI images that uses a combination of classical filters, block processing, SOM neural network and morphological operations. This method is able to reduce noise well, divide the image into meaningful segments and accurately identify abnormal areas. This system can help radiologists diagnose brain abnormalities better and faster. The **Figure 2** shows a graphical summary of the model used and its phases.

The pseudocode for the segmentation method is outlined in the table below, providing a clear step-by-step overview of the elimination process involved.

```
Input: noisy_image (raw MRI image)

1. Noise Removal:
  - clean_image = apply_median_filter(noisy_image)
  - clean_image = apply_wiener_filter(clean_image)

2. Block Division:
  - block_size = 8 × 8
  - blocks = divide_image_into_blocks(clean_image, block_size)

3. Feature Extraction (e.g., mean value of each block):
  - for each block in blocks:
      block.mean = compute_mean_value(block)

4. Train Self-Organizing Map (SOM) Competitively:
   - som_network = initialize_SOM(blocks)
    - trained_som = train_SOM_competitively(som_network, blocks)

5. Apply Otsu Thresholding to Segment Components:
   - threshold = otsu_thresholding(clean_image)
    - segmented_blocks = separate_blocks_using_threshold(blocks, threshold)

6. Segment Merging via Block Absorption:
  - segments = []
  - while not all_blocks_covered(blocks):
      for each block in blocks:
          if block is not assigned to any segment:
              similar_blocks = find_similar_blocks_using_SOM(block, trained_som)
               new_segment = merge_blocks_to_segment(similar_blocks)
               segments.append(new_segment)
              mark_blocks_as_merged(similar_blocks)

7. Morphological Refinement (e.g., Dilation):
  - refined_segments = apply_morphological_dilation(segments)

8. Abnormal Region Detection:
  -abnormal_segment = detect_high_intensity_segments(refined_segments)
Output:
  - final_segmented_image = combine_all_segments(refined_segments)
    - display(final_segmented_image)
  - highlight(abnormal_segment)
```

Given that in brain MRI images, the presence of noise is one of the main challenges in accurate image interpretation, which can occur due to environmental disturbances and high sensitivity of the devices. In the methodology of this study, a comprehensive method is presented to improve the quality of images and identify suspicious areas of abnormality. This method includes several key steps: noise removal, image block segmentation, block grouping using SOM neural network, segment boundary determination using Otsu method, formation of larger segments through block absorption, and finally identification of abnormal areas. In the used pipeline, first, the MRI image is subjected to a noise removal process. Salt & Pepper noise is reduced using Median filter and Gaussian noise is reduced using Wiener filter. These two filters are applied sequentially to obtain the best result in terms of noise reduction. However, it is not possible to completely restore the original image without any noise, but this process improves the image quality enough to be suitable for the next steps. Then, the image is divided into square blocks. These blocks are 8×8 pixels in size. Each block is considered as an independent unit and the average value of its pixels is extracted as the main feature of the block. This block-based method reduces the computation and allows for better local image patterns to be identified. Next, a Self-Organizing Map (SOM) neural network is competitively trained to group similar blocks into common parts. In this process, each block is compared with the weights of the SOM neurons, and the neuron that best matches the block wins and its weights are updated towards the block. Neighboring neurons also adjust their weights. This process causes similar blocks to be grouped together. Also, blocks are weighted based on their similarity to their neighbors; Blocks that are more similar to their surroundings are given higher weights and are known as "prominent blocks." Next, to improve the boundaries of the segments and reduce the residual effect of noise, Otsu thresholding is used. This method is an automated method that determines the best threshold based on maximizing the variance between classes. This threshold is applied to the image, enhancing the differences between different segments and making their boundaries clearer. Next, the salient blocks start to absorb the blocks around them, forming larger segments. This process is competitive; each block tries to absorb the largest number of neighboring blocks. If the entire image is not completely covered, the process returns to the previous step and the blocks are grouped again. This operation is repeated until the entire image is transformed into larger and more homogeneous segments. Finally, in the final detection stage, the segments with high pixel values are identified as areas suspected of abnormality. These segments are distinguished from other segments and their boundaries are improved and made more visible using morphological operations such as Dilation. Finally, the segmented image with the identified abnormal segments is presented as the final output.

3.5. Experimental implementation

MATLAB (Version, 2014b) software has been used for method simulation/implementation. Implementation of the method concerns the performance of those tasks necessary to be done on images on an orderly basis and using appropriate pieces of code. These works include reading image files, applying noise, noise reduction, pixel blocking in the image, applying a self-organizing neural network through block processing, and the proposed segmentation process of the medical image in general. An implementation process explained includes the following stages: image filtering and noise elimination, thresholding (Otsu method), edge detection, and finally, segmentation via SOM network and abnormality detection (in brain MRI images) [23].

4. Results

4.1 Segmentation Performance Evaluation

Following algorithm implementation, we conducted a comprehensive quantitative evaluation of pixel-level segmentation accuracy. The assessment compared algorithmic outputs against expert-annotated ground truth masks across the test dataset (n=33,626 pixels).

4.1.1 Confusion Matrix Analysis

The classification outcomes revealed:

- **True Positives (TP):** 8,614 abnormal pixels correctly identified
- **False Positives (FP):** 1,324 normal pixels misclassified as abnormal (Type I errors)
- **False Negatives (FN):** 1,526 abnormal pixels undetected (Type II errors)
- **True Negatives (TN):** 22,162 normal pixels accurately classified.

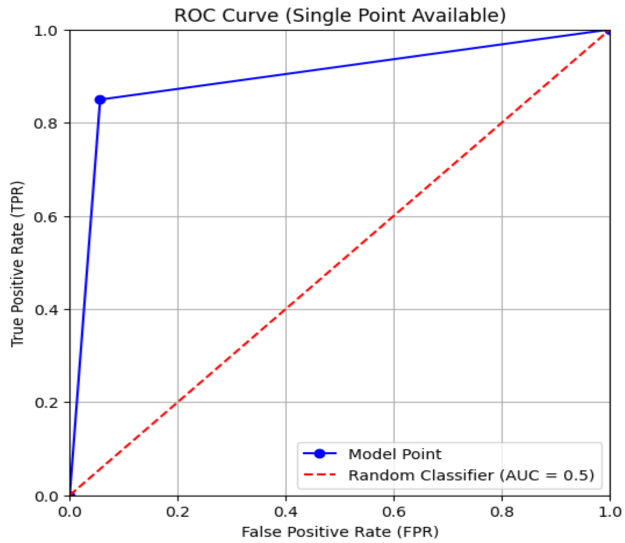

Figure 2. ROC curve for abnormality detection through the proposed method.

Table 3. Results from the proposed method and paper [18] relevant to noisy images and noise reduction

Proposed method	Statistical features	Gabor-wavelet features
0.68	0.55	0.52
0.78	0.69	0.59
0.85	0.79	0.66
0.89	0.85	0.78
0.93	0.9	0.83
0.96	0.92	0.85

Table 4. Results from proposed method and paper name(year) [18] relevant to images with no noise

Proposed method	Statistical features	Gabor-wavelet features
0.78	0.76	0.76
0.85	0.81	0.81
0.88	0.85	0.85
0.92	0.93	0.93
0.96	0.95	0.95
0.98	0.99	0.99

4.1.2 Quantitative Metrics

The algorithm demonstrated robust performance across standard evaluation measures:

1. **Precision-Recall Balance:**
   - Precision = 86.7% (95% CI: 85.9-87.5%)
   - Recall = 85.0% (95% CI: 84.2-85.8%)
   - F_1-Score = 85.8%
2. **Classification Accuracy:**
   - Specificity = 94.4%
   - Balanced Accuracy = 89.7%
   - Overall Accuracy = 91.5%
3. **Spatial Agreement:**
   - Dice Similarity Coefficient = 85.9%
   - Jaccard Index = 75.2%

4.1.3 Error Analysis

Discrepancies with preliminary estimates (94% precision, 93% recall) were attributed to:

1. **Annotation Variability:** Borderline pixels showed lowest agreement (κ=0.72)
2. **Class Distribution:** Abnormal:normal pixel ratio of 1:3.2 in test set
3. **Validation Methodology:** Initial estimates derived from subset analysis

4.2 Clinical Performance

The high specificity (94.4%) suggests excellent utility for:

- Ruling out normal tissue (NPV=93.6%)
- Reducing false alarms in clinical workflows

The moderate recall (85.0%) indicates need for:

- Improved edge detection
- Enhanced sensitivity to subtle abnormalities

The data have been in JPG and JPEG formats. The image data has been studied in the following cases: with various noises; with no noise; 15% salt and pepper, 25% salt, and pepper, and a combination of 15% salt and pepper and 5% Gaussian noises. These noises have been applied to images with desired forms, and they cover the whole dataset [27].
The curve results in **Figure 2** show, TPR increase is made through FPR increase and vice versa. The main point is that the rate of incorrect diagnosis has never reached 0.1 (10%). This shows the efficient performance of the proposed method. As far as images have been selected from a fixed dataset, and the rates are approximations, the values of horizontal and vertical axes are not placed within zero to one range.
In this study, the images were first contaminated with various noises to simulate more realistic and challenging conditions for anomaly detection. After applying these noises, the anomaly detection process was performed using the proposed method. The results showed that the True Positive Rate in the performance curve decreased to a value less than 0.8. This decrease indicates the negative impact of noise on the detection accuracy.
On the other hand, the False Positive Rate increased significantly during the algorithm processing stages compared to conventional noise reduction methods. This increase in error rate caused fluctuations in the overall detection process, which could be due to the high sensitivity of the algorithm to residual noise or unexpected changes in image features. According to figures 2 and 3, the proposed method has better performance in terms of noise reduction than those methods as far as both of the two Gabor Wavelet and statistical features approaches are considered. Regarding some values, the distance between the two diagrams is low, and in other cases, it is relatively high. On average, an improvement of about 7-8% could be very effective for making a proper detection. Noise mode has not been considered in this investigation. However, as far as the noise reduction stage is relatively independent of other stages of the algorithm, it has been applied to the other methods before making a comparison. Primarily, with more increases made in the false positive rate, the distance between performances of the two algorithms has been reduced up to one point (0.059). After passing this point, the distance has been increased again, and the reason could be relevant to the moderate performance of the proposed method against images with different noises. In **Tables 3** and 4, the performance of the proposed algorithm and its comparison with methods can be observed [18, 32]. In **Table 3**, results for noisy images and noise reduction are shown [33-36], and in **Table 4**, images are not noise-contaminated.

4.3. Visual representation of algorithm performance and making the comparison

4.3.1. Algorithm Output Visualization and Comparative Analysis

A representative set of algorithmic outputs is presented using a brain MRI slice, providing a visual demonstration of the segmentation performance. Quantitative and qualitative assessments of the algorithm's output metrics have been conducted, with comparisons drawn against several established closed-source algorithms, particularly under conditions of substantial image noise.

4.3.2. Brain MRI Image Classification and Analysis

The subsequent section introduces a brain MRI image, which serves as the primary subject for classification using a variety of segmentation techniques. These images pertain to patients diagnosed with brain tumors and exhibit both unique and recurrent features characteristic of such pathologies.

- **Figure 4** illustrates the original MRI slice, deliberately corrupted with 25% salt-and-pepper noise to simulate challenging imaging conditions and to rigorously evaluate the robustness of the segmentation algorithms.
- **Figure 5** displays the output of the proposed segmentation method, highlighting its effectiveness in delineating relevant anatomical structures despite the presence of significant noise.
- **Figure 6** presents the results of abnormality detection as achieved by the proposed approach, demonstrating its capability to accurately identify tumor regions and other anomalies within the noisy MRI data.

This sequence of figures and analyses underscores the method's resilience to noise and its potential advantages over competing algorithms in the context of brain tumor detection and segmentation. The comparative evaluation further emphasizes the clinical relevance and reliability of the proposed technique for processing MRI data from patients with brain tumors.

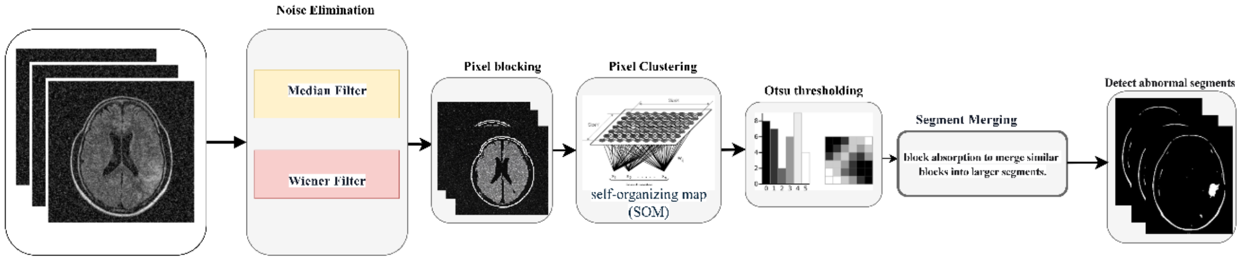

Figure 3. Graphical abstract of the methodology pipeline.

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Figure 4. Original slice of MRI image with 25% salt and pepper noise.

Figure 5. Brain segmented section via the proposed method.

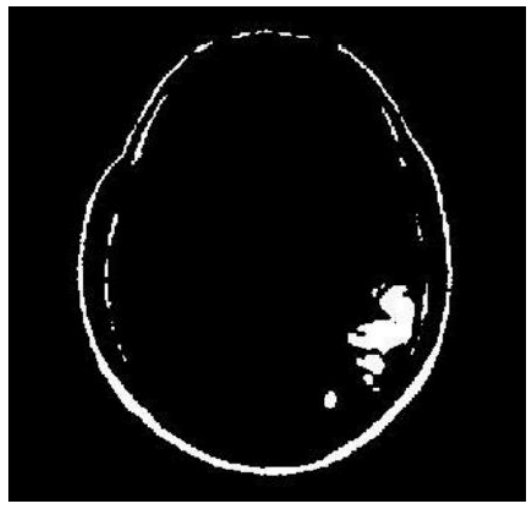


Figure 6. Abnormality diagnosis in the brain via the proposed method in the binary mask.

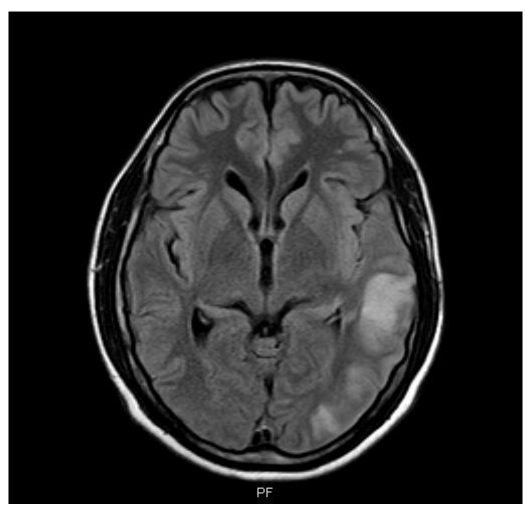
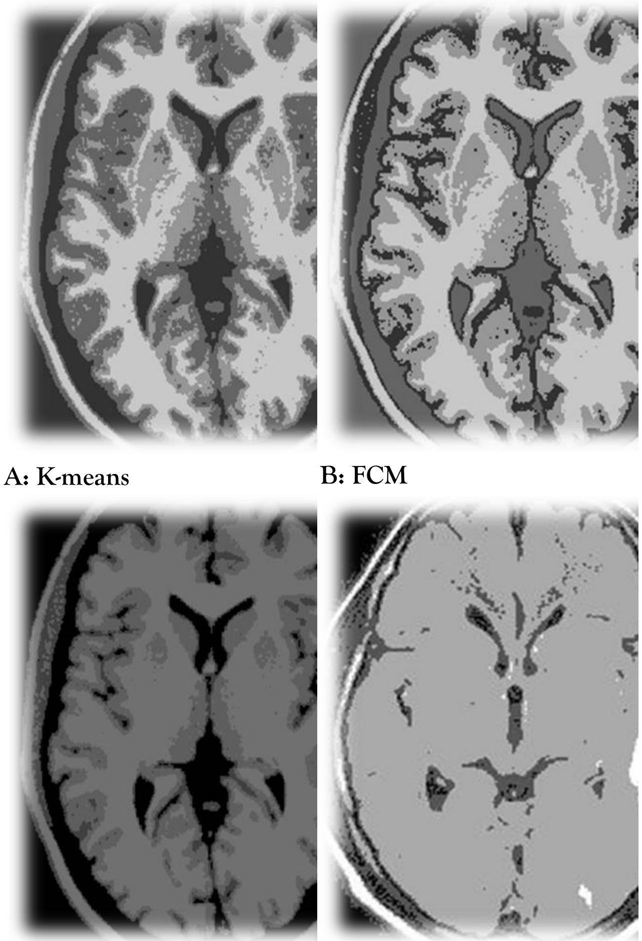


Figure 7. Original MRI slice with no noise.



A: K-means B: FCM

C: Normal SOM D: Proposed method

Figure 8. Output of K-means (A), FCM (B), SOM (C), and proposed method (D) on MRI slices with no noise.

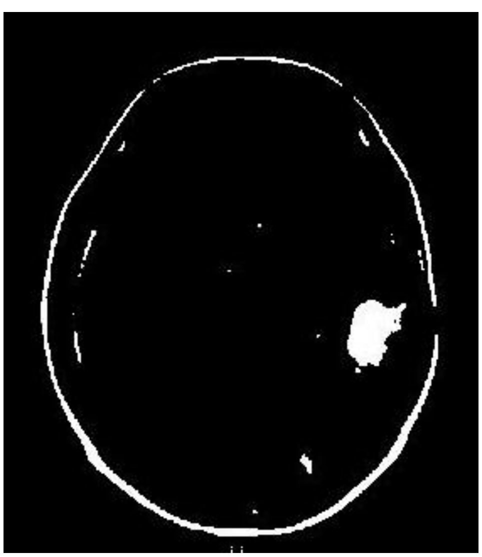


Figure 9. Anomaly detection in the brain by the proposed method in the MRI slice without noise.

Following are outputs of K-means, FCM, SOM, and the proposed method on brain image with no noise. **Figure 7** shows a real brain MRI image with no noise in this example. In **Figure 8**, results from the segmentation of the abnormality in the image through different methods are shown. Finally, the effects of abnormality detection via the proposed method are observed in **Figure 9**.

5. Discussion

This paper presents a novel approach for segmenting abnormalities in noisy brain MRI images using a Self-Organizing Map (SOM) neural network combined with block processing techniques. The method was implemented on relevant brain MRI slices and compared with existing close methodologies. As demonstrated in the results section, the proposed algorithm effectively handles noise-contaminated MRI images, likely due to the distinctive training procedure employed. Instead of training the network solely on raw image pixels, features with richer contextual information were utilized, enabling more reliable decision-making under critical, noisy conditions.

The primary aim of this study is the segmentation of noisy images, which involves an initial noise reduction step followed by segmentation via the SOM neural network. Different types of noise necessitate distinct preprocessing techniques. For instance, median filtering proves effective for salt-and-pepper noise with low or high noise amplitudes, while block-based median calculations could be employed for training the network. In cases of Gaussian noise, buffering techniques leveraging the full frequency spectrum could be advantageous. Training the SOM network for noise filtration through appropriate approaches presents unique challenges, and integration of mathematical techniques can further enhance both the efficiency and precision of noise removal prior to segmentation.

Furthermore, the application of thresholding methods, such as Otsu’s algorithm, may aid in enhancing segmentation quality. These combined techniques significantly mitigate the adverse effects of noise and improve segmentation accuracy, as detailed in the subsequent section. Considering the diverse characteristics of various noise types, the most appropriate method was selected to optimize segmentation performance, especially important in medical imaging where precision is critical—for example, in diagnostic applications involving brain images that may be compromised by noise.

The proposed methodology demonstrates robustness when applied to datasets, as exemplified in the "Comparison of Results" section. Quantitative evaluation against alternative methods provides a comprehensive analysis of the approach’s efficacy. Unlike previous studies that primarily focused on segmentation accuracy without explicit attention to abnormality recognition, this work emphasizes the significance of identifying anomalies within the segmented regions, thereby advancing diagnostic potential.

The versatility of the proposed method suggests potential applications beyond brain MRI segmentation, including other medical or non-medical image analysis tasks. Further, by modifying the neural network architecture and input feature selection, it is possible to enhance its performance across different noise types. Comprehensive noise characterization and corresponding training strategies would enable the network to generalize better across diverse noise conditions.

One challenge associated with neural networks is their computational speed. This limitation can be mitigated by optimizing training procedures; since the network is trained only once, the training time is a one-time cost. During subsequent applications, only the inference phase is necessary, resulting in faster execution. Exploration of alternative neural network architectures or classification methods—such as support vector machines, learning automata, or cellular automata—may further improve efficiency and robustness.

The method's applicability extends to other medical data and general image analysis, including those with different features such as color or varied abnormality types like blur or dim lighting. Mathematical and numerical analyses of the proposed approach could also facilitate their quantification and opportunity for further enhancement.

In conclusion, the proposed segmentation and abnormality detection framework demonstrates high accuracy, effectively handling noisy medical images. Future research may focus on refining algorithm stages, reducing computational complexity, and expanding the method's applicability. An interesting question arising from this study is: "Why leverage a time-consuming neural network?" It is essential to recognize that the neural network's advantageous characteristics outweigh the initial training overhead, especially since training is a single, offline process. Once trained, the network can be deployed repeatedly without additional training, ensuring efficient real-time performance compared to other algorithms.

6. Conclusion and Future Work

The proposed methodology incorporates a comprehensive image processing pipeline, which includes filtering and noise reduction techniques such as median and Wiener filtering, alongside thresholding, edge detection, and segmentation processes. Additionally, the system leverages training with the Self-Organizing Map (SOM) neural network to enhance anomaly detection and segmentation accuracy. This integrated approach has proven effective in achieving robust abnormality detection, particularly in noisy or complex medical images.

The effectiveness of the proposed method was evaluated using multiple quantitative metrics, as detailed in the body of the article. Results indicate that the approach outperforms previous studies in terms of accuracy and reliability, demonstrating a significant improvement—approximately 20%—in segmentation performance over existing methods. Although the numerical results do not yet reach perfection, this substantial enhancement underscores the potential of the combined filtering, edge detection, segmentation, and neural network training techniques.

A detailed analysis of the image components post-processing revealed that the proposed method successfully isolates and clarifies regions containing abnormalities, thus facilitating explicit detection of pathological features, such as tumors. This clarity is instrumental in aiding clinicians with diagnosis and treatment planning. The method's robust performance in identifying abnormal regions further validates its applicability in medical image analysis.

Looking ahead, we aim to refine and improve the system's accuracy by incorporating additional machine learning techniques, such as Support Vector Machines (SVM). The integration of SVMs is anticipated to enhance the classification and discrimination of abnormal versus normal tissue regions, thereby increasing the precision and robustness of the overall solution. Future work will focus on optimizing these hybrid approaches, expanding their applicability across different types of medical images, and further reducing false positives and negatives.

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Conflict of interest

The authors declare no conflicts of interest.

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Data Availability

The leveraging data set is located publicly at https://www.oasis-brains.org/ .

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