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COMPARATIVE STUDY ON NOISE REMOVAL ALGORITHMS FOR TUMOR DETECTION IN BRAIN IMAGES

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ABSTRACT

Medical images, such as X-rays, mammograms, and magnetic resonance imaging (MRI), play a crucial role in the healthcare sector by assisting doctors in the early detection and accurate diagnosis of illnesses. However, medical images suffer from a number of problems throughout the acquisition and processing phases, such as noise, poor contrast, and low-light exposure, among others. Cancer, a disease with numerous subtypes, poses a deadly threat to human life, with the potential for successful clinical treatment heavily reliant on early detection and appropriate treatment planning. The classification of cancer patients into either low or high-risk subgroups is critical. Consequently, various research teams spanning the biomedical and bioinformatics fields have explored the use of Deep Learning (DL) technology in this crucial domain. These issues hinder the ability to extract useful information from the images and worsen the overall quality of the images. In order to provide patients with the best care possible, it is crucial to improve image quality by eliminating noise and increasing contrast. The use of appropriate image enhancement techniques improves picture properties such as contrast, visual quality, brightness, and entropy, making medical images more applicable to a range of uses. When faced with ambiguity, fuzzy logic is an effective technique. The most effective method for obtaining high-quality photographs is to use fuzzy logic during the image enhancing process. Fuzzy logic-based image enhancing techniques were used to MRI brain pictures in our study report. By comparing the performance of various methods Fuzzy Histogram Equalization (FHE), Adaptive Contrast Enhancement Algorithm (ACEA), Watershed (WS), and Ensemble Deep Neural Support Vector Machine (EDN-SVM) EDN-SVM is found to deliver the best results for noise removal in brain tumor images, offering excellent visual quality with enhanced contrast and richer image details.

Keywords: fuzzy histogram equalization (FHE), Brain Tumor image, Watershed, Adaptive contrast enhancement algorithm (ACEA), Ensemble deep neural support vector machine (EDN-SVM).

I. INTRODUCTION

Ensuring one's health is crucial to one's survival. In instance, the executive of the crucial resource the brain must be in good shape. Magnetic resonance imaging (MRI) technologies aid in the diagnosis of human health, particularly that of vital organs like the brain. The data used by AI can be derived from the images captured by these devices. One area of deep learning known as image processing categorization problems can now be solved with great efficiency because to this vast data. Brain MR scans can be used to identify several types of brain malignancies, including gliomas, meningiomas, and pituitary tumors.

Radiologists or semi-automated equipment used to do the time-consuming and inconsistent task of brain segmentation by hand. Automated, accurate, and scalable brain picture segmentation has been possible with the development of sophisticated algorithms, particularly those rooted in deep learning and machine learning (e.g., convolutional neural networks).

In neuroimaging and other branches of medical image analysis, brain image extraction is an essential first step. Accurately separating brain tissue from non-brain components in medical scans, such CT or MRI pictures, is what this process is all about. Skull stripping, also known as brain segmentation, is a crucial step in many medical and scientific procedures, such as tumor detection, surgical planning, and the tracking of neurological disorders such as MS, Alzheimer's, and cancers.

In most cases, sophisticated image processing methods are needed for extraction. These methods might range from more conventional ones, such edge detection and region expanding, to more recent ones, like machine learning and deep learning. The significance of automated brain extraction technologies has grown in tandem with the popularity of AI and computer-assisted diagnosis. In order to deal with varying imaging settings, scanner inconsistencies, and anatomical variations among patients, these tools need to be robust. Brain extraction that is both efficient and effective improves the quality of neuroimaging data and speeds up the workflow in research and therapeutic settings.

Brain image segmentation is a crucial process in medical image analysis, particularly in the field of neuroimaging. It refers to the partitioning of brain images into distinct regions, such as gray matter, white matter, cerebrospinal fluid (CSF), and pathological structures like tumors or lesions. This task plays a vital role in understanding brain anatomy, diagnosing neurological diseases, and planning medical treatments or surgeries.

Recent years have seen a dramatic shift in the healthcare industry due to technology advancements, with Deep Learning playing a key role in this shift. Deep Learning (DL) is a kind of computer program that can mimic human intelligence; it has numerous medical uses. The battle against brain tumors is one such field. Since brain tumors pose a significant threat to public health, it is essential that patients receive prompt and precise diagnoses, treatments, and follow-ups. With its enormous promise for the early detection and treatment of brain cancers, AI has emerged as a crucial instrument for enhancing these procedures [11].

Because of their location, brain tumors pose a threat to human health. By integrating technologies like deep learning, machine learning, and big data analytics, AI is poised to aid in the diagnosis and treatment of complicated diseases like brain tumors. Deep Learning can analyze brain imaging methods like magnetic resonance imaging (MRI) and identify and categorize cancers. Cancers can be better classified according to their size, location, aggressiveness, and class with the use of AI algorithms. Both the doctor and patient benefit from this since it improves the precision of the diagnosis and the understanding of the patient's health status.

Using imaging modalities such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), segmentation creates a precise map of the brain's interior components. Brain volume assessment, disease progression tracking, and tailored therapy planning are just a few of the many clinical applications that rely on accurate segmentation. When analyzing brain tumors, for instance, segmentation is useful for gauging the tumor's size, location, and temporal evolution. The brain's intricate structure, variability in picture quality, noise, and intensity inhomogeneity dis scans continue to be obstacles to brain segmentation, despite its progress. Research in biomedical engineering and AI is ongoing towards the development of generalizable segmentation techniques that are both resilient and accurate.

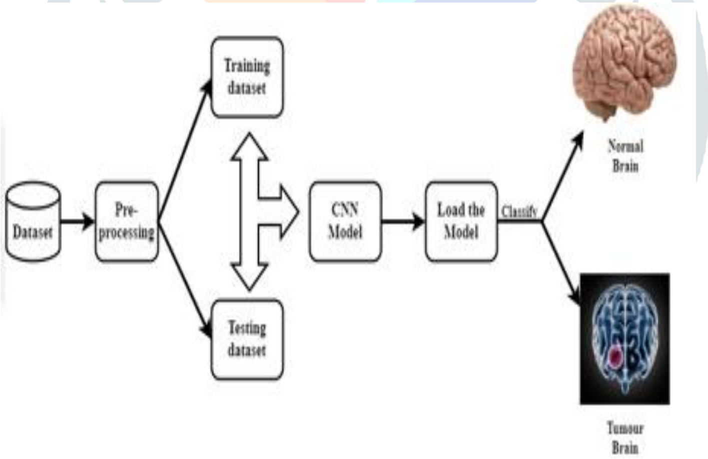

Fig.1.1 Brain Tumor Detection Process

A revolutionary method for automating and improving brain vascular image analysis has arisen: deep learning, a branch of machine learning defined by hierarchical architectures for analyzing images. The area of brain vascular image processing has been utterly transformed by the recent developments in deep learning, which have provided robust resources for the efficient and accurate analysis of intricate neuroimaging data. Historically, differences in imaging methods and data quality have posed significant obstacles to neuroscientists' efforts to understand the brain vessel's complex structure and function through high-quality image processing.

Brain tumor identification utilizing deep learning models, especially image processing, has shown impressive resilience in dealing with these issues, as shown in Figure 1.1. This has allowed for accurate segmentation, classification, and feature extraction from images of the brain's blood vessels. We can now better understand brain vascular extraction mechanisms, create individualized treatment plans, and improve our capacity to interpret neuroimaging data thanks to the incorporation of deep learning algorithms [6]. With further research into these methods, deep learning has enormous potential to revolutionize neurology, leading to better and more accurate imaging studies of brain vascular extraction in the future [5].

II. RELATED WORKS

A "brain tumor" is defined as an uncontrolled growth of brain cells. Brain tumors can be either primary or secondary. In contrast to secondary tumors, which begin in the brain after having spread to other parts of the body like the intestines, skin, or lungs, primary tumors begin in the rain. Automated segmentation of brain structures, tumors, and lesions from MRI images has been greatly enhanced by image processing and its variations, outperforming previous methods in terms of both accuracy and efficiency [12].

A growing number of medical cases involving brain tumors have been reported recently led to the tumor being ranked as the tenth most prevalent type of tumor affecting both children and adults. Given the wide range of brain tumor sizes, shapes, and locations, the detection and segmentation of these tumors is an extremely important and time-consuming task in the realm of medical image processing. One common function of magnetic resonance imaging (MRI) is the detection of tumors and other abnormalities in various tissues. When diagnosing a brain tumor, it is crucial to accurately determine its size and location. We introduce a deep learning-based approach to MRI brain tumor segmentation and classification in this work. We started by enhancing the photos and applying a Gaussian blur filter to prepare them for further processing. Next, binary thresholding is employed for segmentation. Morphological processes are employed for the purpose of feature extraction. The last step is to use CNN to determine if the brain MRI is normal or abnormal. For this project, we rely on Kaggle Dataset [8]. To train the model, we used 255 brain MRI scans, 155 of which had tumors and 98 of which were healthy. The accuracy rate was 97%. Our model is evaluated using various Kaggle datasets that contain MRI images of the brain.

To improve the contrast of MRI brain images, a novel particle swarm optimized texture-based histogram equalization (PSOTHE) technique is suggested in this research Aacharya 2020 [1]. Medical photos typically have low contrast and are impacted by noise. As a result, the diagnosing procedure is incorrect. Reducing the impact of artifacts, enhancing contrast, and minimizing information loss are necessary to solve this issue. A unique framework for picture enhancement is proposed in order to do this. The suggested framework reduces artifacts by suppressing the effect of the image's non-texture region [13]. To regulate the rate of amplification, the probability density function (PDF) is altered. With the help of the suggested fitness function, the PSO algorithm is used to choose the threshold for texture region identification and the constraint parameters for PDF modification. Because these characteristics were chosen automatically and without human input, our suggested framework is more flexible.

Acharya 2021 [2] outlined how low-quality images from Magnetic Resonance Imaging (MRI) might not give enough information to visually comprehend the bodily parts that are affected. Therefore, a unique adaptive image improvement technique called genetic algorithm based adaptive histogram equalization (GAAHE) technique has been developed in this research to improve image perceptions and give computational support. The suggested framework consists of a modified probability density function (PDF), a genetic algorithm, and histogram subdivision. In order to maintain brightness and minimize information loss, a new subdivision technique is applied to the histogram utilizing the exposure threshold and ideal threshold. The suggested multi-objective fitness function serves as a guide for optimizing the threshold values using the genetic algorithm concept in order to make the suggested technique more adaptive. To improve the image quality, each sub-histogram's PDF is then altered. According to the experimental findings, the suggested GAAHE technique outperforms other enhancement methods currently in use.

The enormous need for high-quality images, whether in image applications or human visual perception, is explained by Huang 2022 [7] et al. The impact of incident light on actual color photographs is disregarded by the image enhancing techniques now in use. Because of this, the output photos are frequently not natural or adequately boosted, and the augmentation impact is not the best for images with several scales. This work proposes a multi-scale image enhancement system based on light adjustment and deep learning to address the issue.

This work proposes a multi-scale image enhancement system based on light adjustment and deep learning to address the issue. First, using the Hodge decomposition model as a basis, a correction algorithm for picture illumination drift was created. A lightweight multi-scale Retinex network was then used to improve low-illumination multi-scale images, and its architecture was thoroughly described. Following that, a new joint network loss function was created for the input and output forms, which corresponded to the low-illumination multi-scale picture enhancement and the suggested deep learning network [14]. Results from experiments show that the suggested methodology can successfully improve multi-scale photos.

III. DEEP LEARNING ALGORITHMS FOR NOISE REMOVAL

3.1 Fuzzy Histogram Equalization (FHE)

Fuzzy Histogram Equalization (FHE) is a sophisticated contrast enhancement method that combines fuzzy logic with conventional histogram equalization. It works especially well for segmenting brain tumor images. FHE assigns degrees of belonging to each intensity level using fuzzy membership functions, in contrast to traditional techniques that treat pixel intensity distributions with distinct borders. By maintaining small details and avoiding over-enhancing or loss of significant structures that are common problems with classic histogram equalization, this soft categorization enables a more natural augmentation of medical images.

$$\int_{-\infty} f(t)dt.\ F(x) = \int_{-\infty}^{x} f(t)\, dt \qquad \text{-----------(2)}$$

By increasing the contrast between the tumor and surrounding brain tissue and reducing the possibility of amplifying noise, FHE enhances the visibility of tumor boundaries in brain MRI studies. This increases the accuracy and resilience of segmentation algorithms, regardless of whether they are based on deep learning, thresholding, or clustering. Fuzzy Histogram Equalization is a potent preprocessing step in automated brain tumor detection pipelines that combines the accuracy of histogram equalization with the versatility of fuzzy logic.

3.2 Adaptive contrast enhancement algorithm (ACEA)

Image enhancement techniques are able to improve the contrast and visual quality of magnetic resonance (MR) images. However, conventional methods cannot make up some deficiencies encountered by respective brain tumor MR imaging modes. We propose an adaptive intuitionistic fuzzy sets-based scheme, called as AIFE, which takes information provided from different MR acquisitions and tries to enhance the normal and abnormal structural regions of the brain while displaying the enhanced results as a single image. The AIFE scheme firstly separates an input image into several sub images, then divides each sub image into object and background areas. After that, different novel fuzzification, hyperbolization and defuzzification operations are implemented on each object/background area, and finally an enhanced result is achieved via nonlinear fusion operators.

$$Iout(x,y)=Imean(x,y)+G(x,y)\cdot[I(x,y)-Imean(x,y)]$$

------------*(3)*

The fuzzy implementations can be processed in parallel. Real data experiments demonstrate that the AIFE scheme is not only effectively useful to have information from images acquired with different MR sequences fused in a single image, but also has better enhancement performance when compared to conventional baseline algorithms. This indicates that the proposed AIFE scheme has potential for improving the detection and diagnosis of brain tumors.

3.3 Watershed Algorithm

The Watershed Algorithm is a popular image segmentation technique used to separate connected or overlapping regions in an image, especially in medical imaging like brain tumor detection**.**

$$W=Watershed(\nabla I(x,y),M(x,y))$$

---------*(5)*

The Watershed algorithm is widely used in brain tumor segmentation due to its ability to delineate complex and irregular boundaries, especially when combined with other preprocessing and enhancement methods**.** However, due to over-segmentation issues in noisy MRI scans, researchers often use hybrid watershed-based algorithms to improve tumor detection accuracy.

The Watershed algorithm offers several key advantages in image segmentation, especially in medical imaging tasks like brain tumor detection**.** One of its main strengths lies in its ability to accurately detect and delineate region boundaries by interpreting the image as a topographic surface. This makes it particularly effective at identifying complex and irregular tumor shapes. It is a region-based segmentation technique**,** which does not require the number of segments to be predefined unlike clustering methods such as K-means or FCM allowing it to adapt naturally to the structure of the image. Additionally, when used in its the Watershed algorithm enables precise, guided segmentation by allowing the user or preprocessing algorithms to define foreground and background markers, significantly reducing over-segmentation. Its ability to separate overlapping or touching structures makes it highly suitable for segmenting multi-lobed or diffused tumors.

3.4 Ensemble deep neural support vector machine (EDN-SVM)

Deep Learning (DL) method has received a significant breakthrough in the data representation, whose success mainly depends on its deep structure. In this work, we focus on the DL research based on Support Vector Machine (SVM), and first present an Ex-Adaboost learning strategy, and then propose a new Deep Support Vector Machine (called DeepSVM). Unlike other DL algorithms based on SVM, in each layer, Ex-Adaboost is applied to not only select SVMs with the minimal error rate and the highest diversity, but also to produce the weight for each feature. In this way, new training data is obtained. By stacking these SVMs into multiple layers following the same way, we finally acquire a new set of deep features that can greatly boost the classification performance. In the end, the training data represented by these new features is regarded as the input for a standard SVM classifier.

$$EDN\ (X) = \phi\ (\ W_n - W_2 * W_1\ ) + (b_1 + b_2 + \ldots\ldots + b_n)$$

---------*(4)*

Deep Learning, also known as representational learning, has sparked a surging in¢terest in neural networks amongst machine learning enthusiasts with state-of-the-art results in diverse applications ranging from image/video classification to segmentation, action recognition, and many others. An Ensemble Deep Neural Support Vector Machine (DNN-SVM) combines the strengths of both deep neural networks (DNNs) and Support Vector Machines (SVMs) within an ensemble framework. This approach leverages the feature learning capabilities of DNNs and the powerful classification capabilities of SVMs to achieve improved accuracy and robustness compared to using either model alone.

Table 3.1 Comparative Analysis of Brain Image Noise Removal Methods

Techniques	**Method**	**Strengths**	**Limitations**
Fuzzy Histogram Equalization (FHE)	Applies fuzzy logic to histogram bins for smooth contrast enhancement	Better control over intensity transformation	More Complex than standard HE, still lacks spatial awareness
Watershed Algorithm	Excellent at identifying edges and object boundaries	Over Segmentation, Noise Sensitivity, Computational Complexity	Topographic surface flooding, segmentation regions
ACEA	K-Means Clustering	Enhance Tumours visibility	Noise Amplification
EDN-SVM	Linear Discriminant Analysis	Automatic feature extraction	Lack of End-to-End Training

In the above table 3.1 explains the comparative analysis of Brain image noise removal for method identification and find the strengths and limitations.

Among the evaluated methods, EDN-SVM achieved the best results with the lowest error (MSE = 54), highest PSNR (27 dB), and the highest structural similarity (SSIM = 0.871), indicating excellent image quality and tumor clarity. Watershed also performed well, especially in SSIM (0.837), showing good structural detail. While FHE had a slightly higher MSE and lower SSIM, CNN maintained a balanced performance with moderate error and quality. Overall, EDN-SVM and Watershed are more effective in preserving image structure and clarity for brain tumor detection.

IV. CONCLUSION

In this comparative study highlights the effectiveness of various noise removal and image enhancement techniques applied to MRI brain tumor images. Among the evaluated methods Fuzzy Histogram Equalization (FHE), Adaptive Contrast Enhancement Algorithm (ACEA), Watershed (WS), and Ensemble Deep Neural Support Vector Machine (EDN-SVM) the EDN-SVM method demonstrated the best overall performance. It outperformed others in terms of Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM), ensuring best image clarity and structural preservation. While Watershed and FHE showed notable strengths in specific areas such as boundary detection and contrast improvement, EDN-SVM proved most robust for noise suppression and detail retention. These findings underscore the importance of integrating deep learning-based models like EDN-SVM into brain tumor image preprocessing to facilitate accurate diagnosis and improve treatment outcomes.

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