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Absolute Structure Threshold Segmentation Technique Based Brain Tumor Detection Using Deep Belief Convolution Neural Classifier

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Abstract: Brain tumors are caused by abnormal cells developing in the human brain. The incidence of malignant brain tumors is relatively high and significantly influences humans and society. Magnetic Resonance Imaging (MRI) is an excellent non-invasive technique that produces high-quality brain images without damage. And it makes an adequate diagnosis and is considered the primary technical treatment. This type of method of tumor identification has some problems, there are less efficient for complex tumor stages and increases computation time, and segmentation is an inaccurate and unreliable result. To tackle this problem, this paper proposes Absolute Structure Threshold Segmentation Technique (ASTST) based on Deep Belief Convolution Neural Classifier (DBCNC) using Softmax activation function for brain tumor classification. The proposed method initially starts with the preprocessing step supported by completing the Gaussian and Bilateral Filter(GBF) using the brain images to remove the Noise, enhance the image size and color contrast level and enhance the frequency of the images to find the tumor-affected area. After preprocessing image is trained into Absolute Gabor with Canny Edge Selection (AGCES) technique to identify the edges without affecting the image quality. Then the Similarity Scaling Shapes Feature Selection (S^3FS) method is used to analyze the most delicate features of brain tumors relatively to find the dimension to improve the accuracy. Based on the feature selection, the proposed DBCNC algorithm classifies the brain tumor as malignant or Normal. The proposed method improves prediction accuracy, sensitivity, specificity, and f-measure and minimizes time complexity and false rate.

Keywords: *A brain tumor, Magnetic Resonance Imaging (MRI), feature selection, malignant, preprocessing, segmentation, CNN classification.*

1. Introduction

The brain is the most crucial organ in the human body, controlling other organs' functions and supporting decision-making. It is mainly the control center of the primary nervous system and is responsible for the human body's daily voluntary and involuntary actions. A brain tumor is the leading death cause ratio worldwide. It affects countless people due to unwanted tissue growth in the brain. As brain tumor cells grow, they eventually suck up all the nutrients healthy cells and tissues need, causing brain damage.

Today, doctors manually view MRIs of a patient's brain to determine the location and size of brain tumors. It results in less accurate detection of tumors and is considered time-consuming. MRI brain tumor detection is a complex task due to tumors' complex and varied morphology. This research aims to provide a cost-effective, accurate segmenting of the brain tissue without high time for finding Cancer from collected images.

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The proposed method initially starts with the preprocessing step supported by completing the Gaussian and Bilateral Filter using the brain images to remove the Noise, enhance the image size and color contrast level and enhance the frequency of the pictures to find the tumor-affected area. After preprocessing step, enter the process to edge detection. Before Segmenting, preprocess the images using edge detection based on Absolute Gabor with Canny Edge Selection (AGCES). It isolates Noise from an image and detects edges without affecting the image's edge properties by using thresholds and thresholds to see edges. A canny edge detector first smoothness the image to remove Noise. Gabor filter-sensitive feature edges are detected to the frequency of various image features and rank the features filtered based on maximum successive threshold values.

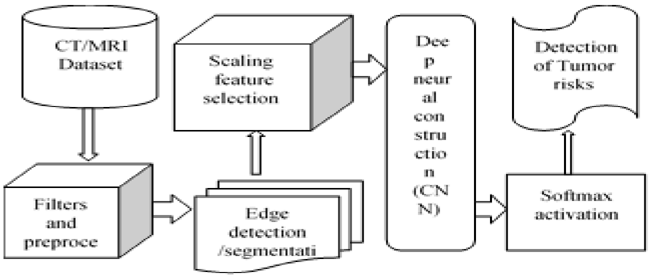

Fig 1. Process of brain tumor detection

The main objective of the research is to improve the brain tumor correctly segmented based on the neural threshold values for improving classification accuracy results. Deep learning-based segmentation is an excellent choice for segmentation, and using this method increases the system's performance compared to other techniques. The figure 1 shows the Process of brain tumor detection to design an Absolute Structure Threshold Segmentation Technique (ASTST) based on Deep Belief Convolution Neuron Classifier using Softmax Neural Network for brain tumor classification. The segmented image is trained into Deep Belief Convolution Neuron Classifier using Softmax Neural Network provides more accurate results better than previous approaches. To design an adaptive Gaussian and Bilateral Filter to enhance the frequency of the Image to find the tumor-affected area. The Absolute Structure Threshold Segmentation Technique approach to image segmentation changes an image's pixels to make the image easier to analyze. To prove higher sensitivity, specificity, f-measure, classification accuracy, and Low false rate with unnecessary timing and less computation time.

Feature selection and classification are essential in the machine learning approach. The features get important for reducing classification burdens. All over the decision are carried out Shape feature dependencies. Scaling objectives and features are soft max defined based on logical redundancy. The feature index returns marginal weights and input to the CNN-neural network. All the training samples are trained and tested in a hidden layer to categorize the result. The searching links remain the timing and neuron weightage class principles to improve the classification accuracy.

The segmentation step using the Adaptive Structure Threshold Segmentation Technique identifies the region based on pixels with similar intensity values. It provides boundaries in images containing solid features on the contrast background. The threshold Segmentation Technique gives a binary output image from the input image. This technique is used to set threshold values for selecting photos. The sum of the individual pixel values, excluding zero-pixel values, is divided by the number of unique pixel values. This function calculates the mean grey value (threshold value) to convert a grayscale image to a binary image. This technique is used for image segmentation, where the regions of interest are extracted from the images and comparing the pixel values to the threshold.

Before classification, using the segmented features for extracting the similarity scaling values based on the shapes (circularity, irregularity, Area, Perimeter, and Shape Index) using Similarity Scaling Shapes Feature Selection (S^3FS). Finally, the classification uses the threshold values in Deep Belief Convolution Neural Classifier using Softmax function (DBCNC). The similar features for the segmenting threshold values based on extracting feature weights get trained into the Softmax Logistic Network. This Segmenting features and extracting features get testing in the classification Deep Belief Convolution Neuron Classifier to improve the accuracy.

For the rest of this research, section 2 discusses the various methods describing brain tumor detection, section 3 discusses the proposed technique and implementation, section 4 discusses the result and discussion, and finally, section 5 describes the conclusion of this research

2. Related work

T. Zhou et al. (2021) proposed unique missing modalities of brain tumor segmentation technique. A correlation model is suggested to depict the latent multi-source correlation since several modalities have a significant link. Different human observers will produce different segmentations of the same image. M. A. Ottom et al. (2022) introduced a unique method for employing deep neural networks (DNN) and data augmentation techniques to segment 2D brain tumors in M.R. images. Deep learning only functions with many data. It can be costly to train it using vast and complicated data models. Much hardware is also required to do complex mathematical computations.

Y. Ding et al. (2022) suggested multi-view Individual deep learning networks for brain tumor segmentation from different perspectives. From a single view, it corresponds to multimodal brain imagery. Like regression, deep neural networks require enormous data to train. Hence, they are not regarded as general-purpose algorithms.

B. Yu et al. (2021) proposed an intensity Lookup Table (LuT) in the adaptive model to adjust the significant contrast of each input MRI image used in subsequent segmentation tasks. Over-segmentation and excessive susceptibility to Noise were the fundamental flaws of traditional image segmentation systems.

Z. Luo et al. (2021) explained a Hierarchical Decoupled Convolution Network (HDC-Net), a compact yet effective pseudo-3D model that can segment 3D volumetric images in a single pass. While segmenting the image, human observers apply high-level knowledge and tackle high-level vision issues like recognition and perceptual completeness.

L. Tan et al. (2021) covered the multimodal brain tumor image segmentation approach based on the ACU-Net network. The network learning may potentially overlook the layers where abstract information is represented since learning can slow down in the intermediate layers of deeper models, which was the only evident disadvantage of U-Net style designs.

Q. Hao et al. (2021) suggested Glioblastoma tumor classification recommendations are based on feature extraction and edge-preserving filtering, spectral phasor analysis, and outcome fusion optimization of data oversampling classification. Spectral-spatial HSV feature extraction and classification based on 2D-CNN and background segmentation based on a fully convolutional network (FCN) was used. The main drawback of spectrum imaging was the need for sophisticated analytic methods. The emission spectra range was frequently wide and included several spectral bands.

N.S. Syazwany et al. (2021) suggested a Multimodal fusion network using a Bi-Directional Feature Pyramid Network (MM-BiFPN). Researchers typically combine all methods in a medical image processing task as inputs to a network for feature extraction, ignoring the intricacies among the other feature extraction methods for each of the four methods. Clinical segmentation tasks already had data transfer from high-resolution maps to low-resolution maps that use encoder/decoder-based models and residual combining.

M. Rahimpour et al. (2022), an augmented CNN model, was developed to perform better than the single sequence CNN model using single-stage MRI data for inference. They proposed a cross-sample filtering strategy to take advantage of multisequence MRI data for training. Overfitting, explosive gradients, and class imbalance presented the most difficulties throughout the model's CNN training. These problems might make the model perform worse.

H. A. Shah et al. (2022) the author described that to improve the quality of the photos, several filters were applied using image enhancement techniques. Deep Convolutional Neural Network (DCNN) EfficientNet-B0 basic model was enhanced using our suggested layers to effectively categorize and detect photos of brain tumors, powerful processing. Deep learning also has a problem with real-world data since it requires a lot of processing power.

C. Ma et al. (2018) discussed that segmenting brain tumors from Magnetic Resonance Imaging (MRI) datasets was critical for Diagnosis, growth rate prediction, and more effective treatment scheduling. However, automation of the process was complex, especially in gliomas, due to severe volume effects and considerable variability in tumor architecture and imaging conditions.

N. Noreen et al. (2020), the author presented that Brain tumors are deadly diseases, and their classification is difficult for radiologists because of the heterogeneity of tumor cells. Recently, a computer-aided diagnosis system has helped detect brain tumors by MRI. Typically, pre-trained models extract features from underlying layers ranging from landscape to medical images. The authors A. Gumaei et al. (2019) suggest a hybrid Regularized Extreme Learning Machine (RELM) and feature extraction approach to create an accurate brain tumor classifier. They first preprocessed Brain images using min-max normalization rules to maximize brain edge and regional contrast. Next, to retrieve features of brain tumors, they used a hybrid approach based on feature extraction.

H. H. Sultan et al. (2019) explained that Brain tumor classification is essential in evaluating the tumor and determining treatment based on its type. Different imaging techniques are used to diagnose brain tumors. However, due to the excellent image quality and lack of ionizing radiation, MRI was the most often used procedure. Deep Learning (DL), a branch of machine learning, has displayed outstanding performance, especially in classification and segmentation problems.

M. I. Razzak et al. (2019) proposed that manually segmenting brain tumors and detecting Cancer from MRI images was tedious, tedious, and time-consuming. Therefore, the accuracy and precision of brain tumor segmentation were important for Diagnosis, treatment planning, and assessment of treatment outcomes. The authors described a novel two-pass ensemble CNN framework for segmenting brain tumors. It used local and global context features together. J. Zhang et al. (2020), the author explained that to diagnose and treat MRI brain tumors, brain tumor segmentation technology was required. Doctors diagnose and measure tumors and formulate strategies for treatment and recovery.

The authors investigated how a recent attention block known as Attention Gate (A.G.) performed in a task requiring segmenting brain tumors and then presented an A.G. Residual U-Net model, AGResU-NET. AGResU-Net integrates the rest of the modules and unifies the U-Net structure. Added a series of persuasive skip-the-link sections.

Z. Huang et al. (2020) illustrated that Diagnosis of brain tumor types usually relies on clinical experience, and computer-assisted Diagnosis increases the accuracy of tumor types. Therefore, a CNN Based on Convolutional Networks (CNNBCN) with improved activation functions was proposed for his MRI classification of brain tumors. The brain tumor classification test loss of the enhanced CNNBCN model was lower than that of the ResNet, DenseNet, and Mobile Net models.

C. Ge et al. (2020) explained that a pairwise Generative Adversarial Network (GAN) model recommends augmenting the training dataset by adding brain M.R. images. Pairwise, GANs can generate synthetic MRIs in different ways. The authors proposed a post-processing strategy that combines the slice-level glioma subtyping results by majority vote. An optimal training strategy was suggested from a two-step course; following the MRI. They used GAN-enhanced MRI to learn glioma function.

M. Li et al. (2019) proposed that by combining a multimodal information fusion brain tumor convolutional neural network detection method called Multi - CNN, the authors investigated the problem of low accuracy in traditional brain tumor detection. From 2D-CNN to multimodal 3D-CNN, brain lesions could be captured under different model properties in more 3D space.

P. Liu et al. (2020) proposed that Brain tumor segmentation from clinical images was a paradigm for clinical Diagnosis and treatment that offers a quantitative and understandable reference. Clinical experience shows that manual segmentation is tedious and time-consuming. Excite V-net (DSSE-V-net) and deep supervised 3D Squeeze were proposed, an encoder/decoder neural network for automatically segmenting brain tumors.

A. M. Alhassan et al. (2020), the author described that the Cancer of the brain has the lowest survival rate of all other types of Cancer. The classification of brain tumors depends on many factors, such as structure, shape, and location. Based on an accurate diagnosis of tumor type, medical professionals were becoming more inclined to provide appropriate treatment to their patients.

P. Afshar et al. (2020), the author proposed that Conditional Radium Fields (CRF) and Heterogeneous Convolutional Neural Networks (HCNN) were used to segment brain tumors utilizing practical deep learning approaches. Get accurate results. Train the HCNN using the image patches. Trained using CRF-Recurrent Regression-based Neural Network (RRNN) image segmentation with HCNN variables fixed. Refine using HCNN and CRF-RRNN image segments.

The author, Y. Ding et al. (2019), explained that UNET was frequently used to segment medical images due to its hierarchical connection during up sampling. They are not suitable for complex medical imaging such as brain MRI. To adopt UNET to get better segmentation performance, many researchers pay attention to the stacking of his UNET. The Stack Multi-Connection Simple Redising_Net architecture (SMCSRNet) was the new design the authors suggested. It is layered with basic blocks called Simple Redising_Net (SRNet).

C. Han et al. (2019), the author described that With CNNs, they used enough annotated training data to do better computer-aided detection. Most medical image datasets were small and sporadic. Generative Adversarial Networks (GANs) can create real or various training images to fill in the missing data and actual image distributions. By combining the data with noise-to-image or image-to-image GANs, the researchers can categorize better.

K. Hu et al. (2019) illustrated that accurate brain tumor segmentation was essential to cancer diagnosis and therapy. The authors suggested an innovative technique for segmenting brain tumors based on Fully Connected Conditional Random Fields (CRF) and Multi-Cascade Convolutional Neural Networks (MCCN).

Z. N. K. Swati et al. (2019) explained that only low-level or high-level characteristics are the primary focus of extraction techniques, and some process attributes are used to fill in the gaps. They needed a feature extraction framework that bridges the gap by encoding/combining low-level features with high-level features without creating features. Deep learning is compelling in feature representation, thoroughly describing low and high-level information, and self-learning feature extraction involves this stage.

Z. A. Al-Saffar et al. (2020), the author proposed that pick a crucial subset of characteristics as the classifier's input. Mutual Information Accelerated Singular Value Decomposition (MI-ASVD) was the technique. An intelligent system was created with an algorithm that classifies MRI brain scans into low-grade and healthy high-grade gliomas. The processes of the proposed system include preprocessing, clustering, tumor dissemination, MI-ASVD, classification, and feature extraction. W. Wang et al. (2020) described that the Brain tumor diagnostic terminals rarely use computer-aided diagnostic technology. It is difficult to rule out the influence of various interfering factors on diagnostic results. The author developed a model suitable for brain tumor feature detection based on CNN combined with nuclear magnetic resonance, Promoting diagnostic technology for the use of computer-assisted diagnostic technology in diagnosing brain tumors. A. Yang et al. (2019) proposed that the medical image feature extraction, analysis of massive data, processing results, and helping doctors make an accurate diagnosis. The method can accurately describe the structural features of shallow layers in tumor images, thus improving the accuracy of delineation of the image region. Two convolutional models, Xception and Dense Net had been constructed to enhance the accuracy of CNN algorithms.

3. Proposed Methodology for Brain Tumor Detection

This proposed methodology explains a detailed description of brain tumor detection using the Absolute Structure Threshold Segmentation Technique (ASTST) based on Deep Belief Convolution Neural Classifier using Softmax function for brain tumor classification. The proposed contains image filtering, Edge detection, feature selection, and classification. The proposed first step is the Gaussian and Bilateral Filter (GBF) technique to remove Noise and enhance quality to find the tumor-affected region.

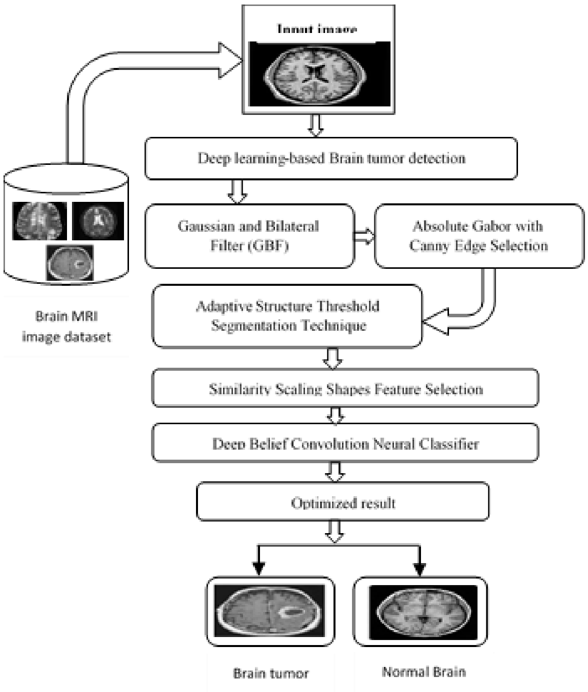

Fig 2. A proposed method for brain tumor detection

Absolute Gabor with Canny Edge Selection (AGCES) algorithm is used to find the edges from filtered brain images. Figure 2 shows the proposed method for brain tumor detection. Edge find images are fed into the Adaptive Structure Threshold Segmentation Technique (ASTST) method is used to find tumor region. Based on the segmentation image, select the essential features for brain tumors using Similarity Scaling Shapes Feature Selection (S^3FS). Finally, the proposed Deep Belief Convolution Neural Classifier using Soft-max function (DBCNC) technique classifies the brain tumor as malignant or normal, as illustrated in figure 2.

3.1 Image preliminaries

The preprocessing was varied through an optimized Gaussian filter, enveloped with Gabor wavelet transform applied on the enhanced tumor-affected region to transfer the noiseless filter at pixels entities into frequency domain pixels. The multi-resolution format kernel of the Gabor wavelet filter is given in the following equation.

$$G(x,y) = g(x,y) * exp\{2\pi j\mu(x * \cos\varphi + y * \sin\varphi)\}$$
(1)

Where $j = \sqrt{-1}$ and $g(x,y)$ is the Gaussian envelope, and it is given in the following equation,

$$g(x,y) = \frac{1}{2\pi\sigma^2} * exp\left\{-\frac{(x^2+y^2)}{2\sigma^2}\right\} \quad (2)$$

Where σ is the standard deviation of the Gaussian envelope, μ is the frequency scale, and φ is the orientation that varies between the angles 0^0 to 180^0. The selection of σ depends on the computation of the Gabor kernel's energy factor and kappa factor.

The energy factor of the Gabor kernel is given as,

$$E[I(x,y)] = \frac{\sum_{x=0}^{P-1}\sum_{y=0}^{Q-1} I(x,y)}{P*Q} \quad (3)$$

The size of the enhanced brain MRI image is denoted as P and Q, respectively.

The kappa factor of the Gabor kernel is given as,

$$K[I(x,y)] = \sqrt{\frac{\sum\sum I(x,y) - \{E[I(x,y)]\}^2}{P*Q}} \quad (4)$$

The standard deviation of the Gabor kernel is defined in the following equation using energy and kappa factor as,

$$\sigma = \begin{cases} 1; if\ K[I(x,y)] \leq 1 \\ \sqrt{2}\ ; else \end{cases} \quad (5)$$

This Gabor kernel can also be written in natural and imaginary terms as depicted in the following equations.

$$G(x,y) = R(x,y) + j\ I\ (x,y) \quad (6)$$

The real term of the Gabor kernel is stated as,

$$R(x,y) = g(x,y) * \cos\ [2\pi\mu(x\cos\varphi + y\sin\varphi)] \quad (7)$$

The imaginary term of the Gabor kernel is stated as,

$$I(x,y) = g(x,y) * \sin\ [2\pi\mu(x\cos\varphi + y\sin\varphi)]$$
(8)

This Gabor kernel is Convolutional multiplied with the enhanced brain MRI image by smoothening using the following equation.

$$I(x,y) = G(x,y) * I\ (x,y), \quad (9)$$

The below education is used to calculate the image smoothing filter (s,y),

$$G_s(x,y) = e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (10)$$

Suppose x and y are the image pixels, and σ is a standard deviation value.

$$N\ \ (ext,y) = \frac{1}{n(x,y)}\sum_{i\in\varphi(x,y)} a_w(x,y)o(i) \quad (11)$$

Adopting the pixel diffraction and noises are removed by this optimization filter for further evaluation of feature selection and classification. These flowing steps progress brain tumor detection through feature evaluation and classification.

3.2 Object projection Canny Edge Selection

To identify the exact boundary region of the tumor area through the canny edge mapping function. This determines the object's length with the same neighboring region by covering the pixel coordination to correct the spatial edges. This finds the same area without loss rate of pixel coordination to segment the object by entity values.

Step 1: To evaluate the Gabor factor→ $GF(i,j) = \frac{1}{2\pi\sigma^2} e^{\frac{i^2+j^2}{2\pi\sigma^2}}$, (12)

to get the magnitude mean rate is estimated to compute using,

$$M(x,y) = \frac{1}{M}\sum_{(x,y)}^{n}\sqrt{Mx(1,2)^2 + My(1,2)^2} \quad (13)$$

Step 2: The average density of the object margin in the disease level is marginalized by the maximum edge covered density region,

$L(1,2) = \frac{C(1,2)}{maxC(1,2)}$, (14) to get the connected component of object pixel is C (i, j)

Step 3: The initialized length of the edge and the magnitude covering the region is mapped to estimate the density level of the edges,

$$P(1,2) = \frac{1}{2}\left(M(1,2) + L(x,y)\right) \quad (15)$$

Step 4; Mapper thresholding function gets the maximum value is,

Step 5: Commute the maximum support if $P(1,2) > T_{max}$

Then P(1,2) is the maximum support of object edges, which is affected by setting T_{max} to get an accurate region.

End if

To average the intensity of the coverage, the edge is,

$$S(\delta \in C_{wat}/J(\delta)) = 1) \geq S(\delta \in C_{cart}/J(\delta) \quad (16)$$

This filters the objects' weight and intensity level of tuberculosis affected region with statistical margins of image structure with disease factor definition. The edge detection improves the margin scalability of the tumor region. This accurately identifies the corrective edges of pixel coordination to detect the object coverage region. Also, this carry ford pixel neighbor is grouped into average mean rate to find the exact boundary region.

3.3 Adaptive Structure Threshold Segmentation Technique

The Adaptive Structure Threshold Segmentation carries over the morphological functions are now applied to the tumor-covered brain MRI image for segmenting the tumor regions in the canny-edged brain image. The following parts are used to obtain the tumor regions in the meningioma brain MRI image.

Erosion function:

$$E[I(x,y)] = Min\{I(x+y) * y \in s\} \quad (17)$$

Where s is the transformation minimum scaling function

The dilation function is carried out to enhance the enlargement of object dependencies to determine the structural dependencies of tumor location. The correlation of enlarged definition was diluted by maximum support to get the structure.

$$D[I(x,y)] = Max\{I(x-y) * y \in s\} \quad (18)$$

A morphological opening function is castoff to decrease optimistic pixels above structural elements s' in brain MRI images of the classified structural region. A morphological closure function is used to reduce bright and dim pixels by the value of the structuring element. The following equations describe these morphological opening and closing operations:

Actual opening on object coverage region,

$$Mor_{ope[\, I\,(x,y)]} = E\,[I\,(x,y)] \quad (19)$$

Image region transformation regret at the closing field

$$Mor_{clo}[I(x,y)] = D[I\,(x,y)] \quad (20)$$

The morphological closing function is subtracted from the morphological opening function, which produces the tumor pixels segmentation in the meningioma brain MRI image. The region gets segregated on transformation function at maximum tumor-covered region.

3.4 Similarity Scaling Shapes Feature Selection

In this stage, the tumor region frequency is identified based on Similarity Scaling Shapes Feature selection relatively compared to the threshold margins. The Linearity Gaussian was used to smooth the feature obstacle shape projected region based on multiplying pixels by real coordination pixel values. That would be in the frequency of the obstacles that were created.

Step 1: Input tumor region boxing object region

Step 2: Read all the images Img→P(x,y)

Step 3: Using Liner scaling-Gaussian filter to pixelate to smooth the Img→i1, i2, i3,

For each I→ image 1..n

$R(x,y) = e^{\frac{s^2(x,y)}{2\sigma^2}}$, have the pixel denomination

To estimate the isotropy $\frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{s^2(x,y)}{2\sigma^2}}$

Step 4: Return the pixel coordination Pc←P(x,y)

Step 5: Reduce the Noise

End

Where the σ runs are the center of the response and Gaussian filters, analyze the distance $R(x,y)$ from the method, preprocessing the image change component is positioned at the center of the image matrix.

A) Shape Stabilization region extraction.

This detection criterion will be applied to all the image's pixels. For the R channel, the anticipated data point of the unit that is being worked on is given through

$$P_{(x,y)}R = \sum_{u=x-2}^{x+2} \sum_{v=y-2}^{y+2} a_{(u,v)R}\, I_{(u,v)R} \quad (21)$$

Where

$a_{(u,v)R}$ = As a result, the anticipated pixel is determined by the linear prediction coefficient for the R channel for the point (u,v). (e(x, y)R)= For the R channel, the difference between the center pixel (I(x, y)R) and the forecasted pixel (P(x, y)R) is given by:

$$e_{(x,y)R} = |I_{(x,y)R} - P_{(x,y)R}| \quad (22)$$

As a result, errors for the G (e(x, y)G) and B (e(x, y)B) channels can be determined. The pixel error under the operation (e(x, y)) is given by

$$e_{(x,y)} = MAX(e_{(x,y)R}, e_{(x,y)y}, e_{(x,y)G}) \quad (23)$$

If e(x, y) is the image is designated as a "detected noisy pixel" if its error is greater than or equal to the optimum error limit, and adaptable vector average filtration is performed.

b) Similarity Scaling Shapes extraction

The proposed Similarity Scaling Shapes Feature Selection (S^3FS) technique is used for selecting tumor features projected region. The extracted features are listed as follows:

$$H_y = \sum_{x,y} \frac{s(x,y)}{1+(x-y)} \quad (24)$$

Homogeneity H_y provides an order value for estimating the closest value of the tumor from the segmented image, which is evaluated in expression. Let us assume $s(x,y)$ is a segmented point of the image axis (x, y).

$$C_c = \sum_{x=0}^{c-1} \sum_{y=0}^{d-1} \frac{(x,y)s(x,y) - m_i x m_i y}{s_d x s_d y} \quad (25)$$

The correlation coefficient C_c is another crucial factor that helps discover the best correlation between each pixel. Here let us assume $m_i x$ and $m_i y$ is a mean value of precise relation with maximum pixel c, d. $s_d x and\ s_d y$ is a standard deviation value to eliminate error. To estimate Standard deviation s_d and Mean valuesm_i,

$$m_i = \left(\frac{1}{c*d}\right) \sum_{x=0}^{c-1} \sum_{y=0}^{d-1} s(x,y) \quad (26)$$

The above equation estimates the mean value m_i from segmented images$s(x,y)$.

$$s_d = \sqrt{\left(\frac{1}{c*d}\right) \sum_{x=0}^{c-1} \sum_{y=0}^{d-1} s(x,y) - m_i} \quad (27)$$

The above equation is used to identify the Standard deviation$s$.

$$E_y = -\sum_{x=0}^{c-1} \sum_{y=0}^{d-1} s(x,y) log_2 s(x,y) \quad (28)$$

The above expression is used to identify the M.R. image entropy for texture data on the image.

$$E_g = \sum_{x=0}^{c-1} \sum_{y=0}^{d-1} s^2(x,y)$$
(29)

Energy is used to detect the similarity of every pixelE_g.

The main feature of this model is that different tumor block sizes of image features can be evaluated to find the best factor for detecting regions from the segmentation images. The essential factors, including homogeneity, area, perimeter, and entropy, were extracted from segmented brain M.R. images using S^3FS.

b) Soft max logical determination

Softmax logical function creates the logical condition to select the features related to creature margins matched with tumor threshold values. The convolution layer is iterated and feature selection is carried out to decide logical evaluations. The actuator attains the threshold weights during the testing phase to select the feature weights. The training function begins with neuron weights after the feed-forward layer before classification is attained through the classifier.

The feed-forward network is optimized with an adaptive forager algorithm for tuning neurons to the closest weight prediction. The logical function adjusts the feature weights to select the importance of the tumor-segmented object region.

The activation function trains remains the f(x)= $\begin{cases} y = 1\ if\ \sum_{i-1}^{n} w_i x_i \geq b \\ y = 0\ otherwise \end{cases}$ where f(x) residues the logistic initiation of neuron accomplished with feature transient values Ft$w_{(t+1)} = w_t - \mathbb{N} \triangle w_t$ and $b_{(t+1)} =$

$b_t - \mathbb{N} \triangle b_{t.}$ The training function considers the threshold margins to select the features.

A fully integrated feed-forward of the neuron is illustrated in the construction of the network. The CNN be fully optimized with feed-forward connective layer 'b' with Feature weights 'W' by carried to evaluate through absolute average weight to avoid error loss.

$net_{i(t)} = \sum_{j=1}^{j} w_{ij} y_{j(t)} + x_{i(t)}, i = 1 \dots j$and $Ti \frac{dy(t)}{dt}$ = - $yi(t) + \varphi(net_i) + x_{i(t)}, i = 1 \dots j$ (28)

The constant τi is biased with frequent neurons to carry the test weight in Net evaluation to get the actual weight w(i) for constructing the convolution layer.

3.5 Deep Belief Convolution Neural Classifier using Soft-max Logistic Network

The selected features are trained with a Logical activation function with an optimized liner softmax function in DBCNN to identify the Leukemia class to categorize the types. Deep Belief Convolution Neural Classifier is an optimized scalar classifier with a decision feed forward classification model. The convolution layers are marginalized with spectral values from the scaled values from feature threshold margins. The pooling layer is depreciated with expanded 16 *16 iteration training for learning feature weights. Each layer marginalizes the segmented cells and counts with match-case scaled features. This attained the Relu soft max defined function with logical activation function to predict cancer-affected cells.

Algorithm

Input: Feature SampleFs, Improved feature rule $N_{i(t)} \dashrightarrow If$

Output: Optimized class feature

Step 1: Compute the maximum weight and rate of feature Max weights

Step 2: Read If dataset values and Fs data values

For each layer class (CFS)

Step 3: Calculate the hidden layer neuron weight to w- as feature class (w)

$$\int_{i=1}^{size(IF)} \sum If(fs).class = w \qquad (29)$$

Nearest feature value (CFS) = nearest feature (WFC)

For each nearest value in the relative connection of the impact ratio, each value f

Step 4: Similarity features are classified based on the risk of the Max feature divided into categories.

Feature selection $WFs = \frac{\int_{x=1}^{size(f)} \sum f(w)==fs(w)}{size(f)}$ (30)

End

Calculate increasing rate $WFs = \frac{\sum_{i=1}^{size(fw)} wfs}{size(wfs)}$ (31)

End

Optimized the Computed Tumor Detection (CTD) = wfc return set maximum values to ascending class by risk.

Step 5: Stop

The input features are trained on the classifier structure and labeled with neural weights representing the class. The input factors help segment sections and learn related features through hidden neurons. An activation function adjusts each neuron to improve classification accuracy by reference. DBCNN classifies the microscopic images based on risk by class of feature weights to improve classification accuracy. This enhances precision, recall, and f-measure and reduces error, false rate, and time complexity.

4. Experimental setup

This section illustrates the different performance measures used to evaluate the proposed method for brain tumor detection. The proposed method for classifying and detecting normal and abnormal MRI images is implemented using Python and the anaconda tool on a system with an i5 processor with 8 G.B. of RAM running on a 64-bit operating system.

Table 1. Deployment parameters

Parameter	***Values***
Simulator language	Python
Simulator Tool	Anaconda
Dataset name	MRI brain tumor
Number of images	253

Table 1 describes the deployment parameters for brain tumor detection. This section can be seen in detail through the following.

4.1 Medical MRI brain dataset

This paper uses MRI brain tumor images collected from the online Kaggle repository. https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection this link has the database. It has two folders with brain and without brain tumors containing 253 MRI brain images.

This dataset includes 155 MR brain images in a folder with a brain tumor and a folder without a brain tumor containing 98 M.R.I brain images. The figure 5 shows affected and non-affected brain M.R.I images from the kaggle repository publicly available images.

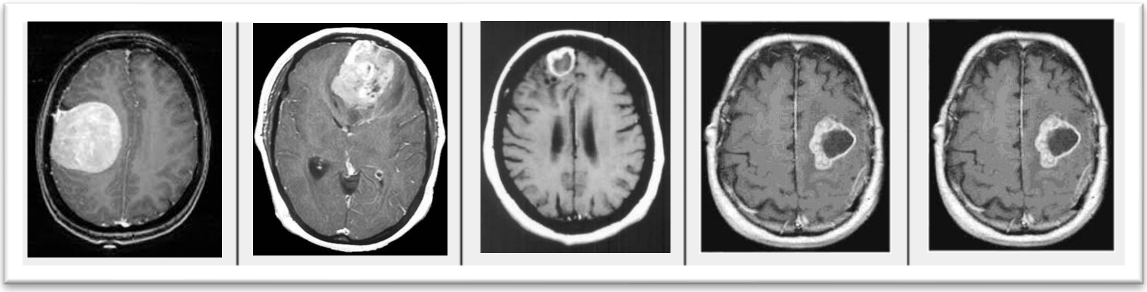

Fig 4. Sample of brain tumor-affected M.R.I images

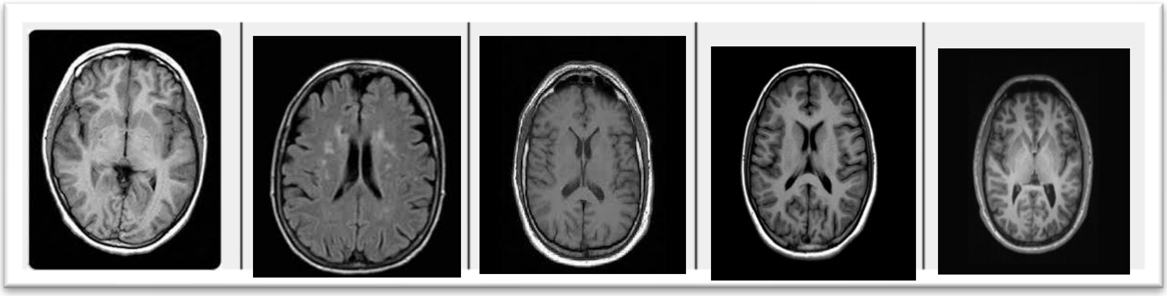

Fig 5. Sample of non-affected brain M.R.I images

4.2 Performance analysis

The performance of the proposed system is analyzed in terms of efficiency, sensitivity, specificity, F-measure, and prediction accuracy by the following equations.

$$\text{Sensitivity} = \sum \frac{T_p}{T_p + F_n} \tag{32}$$

$$\text{Specificity} = \sum \frac{T_n}{F_p + T_n} \tag{33}$$

$$\text{Accuracy} = \sum \frac{T_p + T_n}{T_p + F_n + F_p + T_n} \tag{34}$$

$$\text{F-measure} = \sum 2 * \frac{\text{Sensitivity} * \text{Specificity}}{\text{Sensitivity} + \text{Specificity}} \tag{35}$$

Here we assume T_p is a true positive, T_n is a true negative, F_n is a false negative, and F_p is a false negative.

4.3 Brain tumor detection result

To demonstrate the performance of the proposed brain tumor detection, we compare the proposed method with different existing algorithms, namely Generative Adversarial Networks (GANs), Hierarchical Decoupled Convolution Networks (HDC-Net), and Deep Convolutional Neural Networks (DCNN).

Table 2. Classification result for the proposed and previous method's performance

Classification performance in %				
No brain M.R. images/methods	***GANs***	***HDC-Net***	***DCNN***	***DBCNC***
1	69	73	79	84
2	76	79	83	87
3	80	82	86	90
4	83	87	90	94

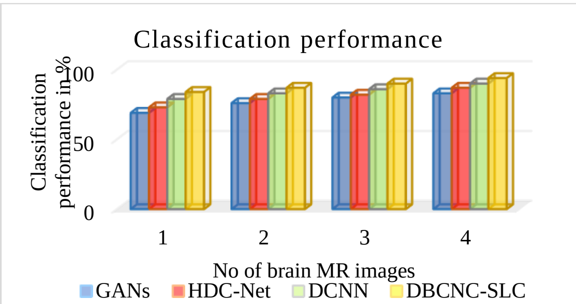

Fig 6. Classification result for the proposed and previous method's performance

The figure 6 and Table 2 depict Brain tumor classification results for the proposed and previous methods' performance. The proposed DBCNC method attained 94% of brain tumor prediction classification performance, the DCNN method attained 90% of classification performance, the HDC-Net process attained 87% of classification performance, and GANs achieved 83% of classification performance.

Table 3: Sensitivity performance for Brain tumor detection

Sensitivity performance in %				
No brain M.R. images/ Methods	**GANs**	**HDC-Net**	**DCNN**	**DBCNC**
1	67	71	77	82
2	74	77	81	85
3	78	81	84	88
4	81	85	88	92

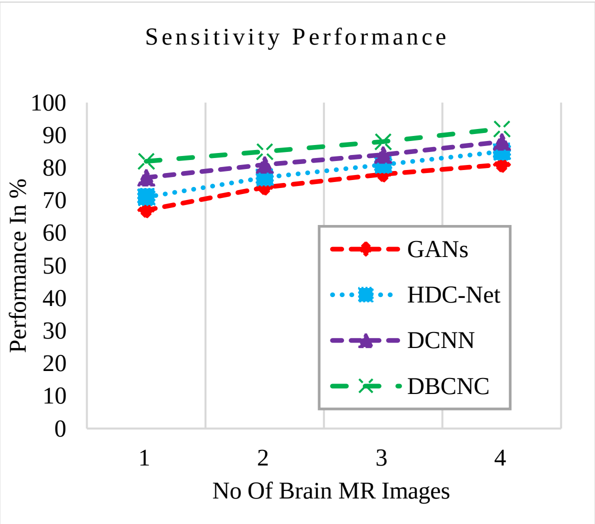

Fig 7. Sensitivity performance for brain tumor detection

The figure 7 and Table 3 show the proposed and existing algorithm performance of sensitivity. The proposed DBCNC method has produced 92% of sensitivity performance to the previous method, namely, GANs, HDC-Net, and DCNN techniques.

Table 4. Specificity performance for brain tumor detection

Specificity performance in %				
No brain M.R. images/ Methods	**GANs**	**HDC-Net**	**DCNN**	**DBCNC**
1	68	72	78	83
2	75	78	82	86
3	79	82	85	89
4	82	86	89	93

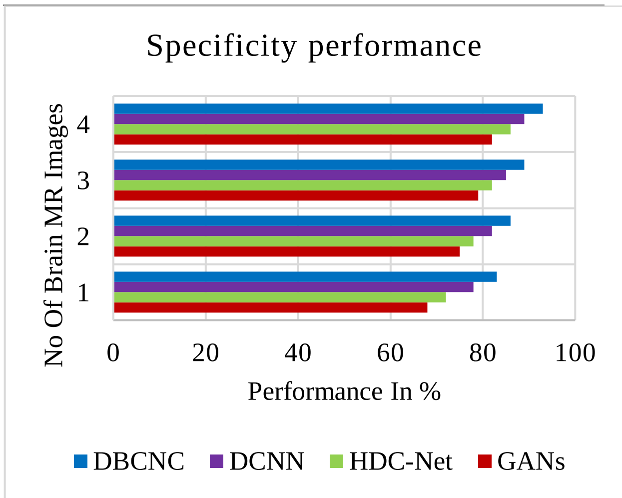

Fig 8. Specificity performance for brain tumor detection

The figure 8 describes the proposed and existing techniques for specificity performance in brain tumor detection. The proposed method achieved a specificity performance has 93% more than previous methods, GANs, HDC-Net, and DCNN techniques.

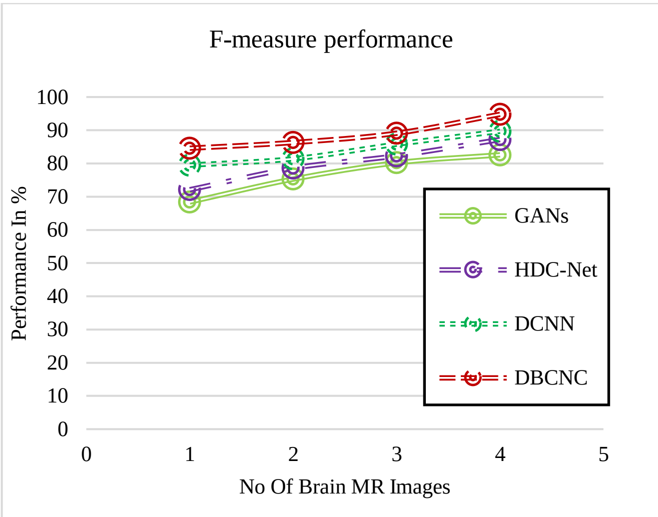

Fig 9. F-measure performance for brain tumor

Figure 9 F-measure performance for brain tumor detection based on Adaptive Structure Threshold Segmentation

Technique (ASTST). The proposed method gives 94.8% of F-measure performance. Also, the existing methods are the GAN method produces 82.6% of F-measure, and the DSCNN method produces 89.7% of F-measure performance. However, the proposed method achieves high performance than other methods.

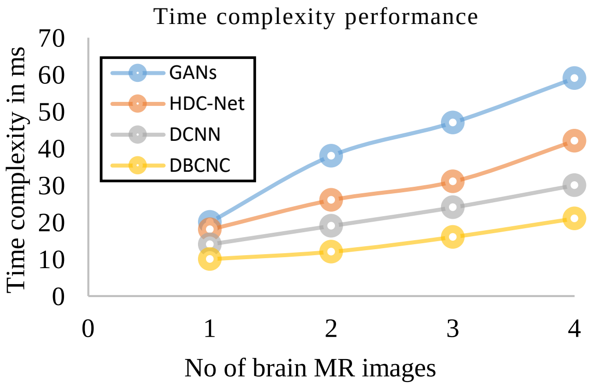

Fig 10. Time complexity for brain tumor detection

The figure 10 shows the proposed and existing methods for time complexity for brain tumor detection. The proposed method produces a time complexity result of 21ms for brain tumor classification, but the existing techniques perform high time complexity.

5. Conclusion

To conclude, this paper presents Absolute Structure Threshold Segmentation Technique (ASTST) based on Deep Belief Convolution Neural Classifier using Softmax function (DBCNC) for brain tumor classification. Initially, the brain M.R.I images are collected from the kaggle repository. The Gaussian and Bilateral Filter technique was performed to remove noise and enhance image quality from the collected dataset. After preprocessing, the optimized Gaussian technique was done by edge detection. Based on the edge detection image, select the essential brain tumor features using S^3FS. Later the proposed DBCNC approach for classifying the brain tumor as malignant or usual. The proposed experimental result was evaluated in python language and the Anaconda tool. The proposed method accomplished result is brain tumor prediction classification has 94%, sensitivity has 92%, specificity performance has 93%, F-measure has 94.8%, and time complexity result is 21ms. The proposed method performed better than GANs, HDC-Net, and DCNN techniques.

Conflicts of interest

The authors declare no conflicts of interest.

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