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Machine-Learning Approach Based Gamma Distribution for Brian Abnormalities Detection and Data Sample Imbalance Analysis

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Abstract: In the recent past artificial intelligence applications in Magnetic Resonance Imaging (MRI) is applied in various clinical researches. However, for analyzing brain tumor without human intervention is considered as a significant area of research because the extracted brain images need to be optimized using segmentation algorithm which should have high resilient towards noise and cluster size sensitivity problem with automatic region of Interest (ROI) detection. In this research, an improved orthogonal gamma distribution based machine-learning approach is used to analyses the under segment and over segments of the brain tumor regions to detect the abnormality with automatic ROI detection. Further data imbalance due to improper edge matching in the abnormality region has been sampled by matching the edge coordinates and the sensitivity, selectivity parameters are measured using machine learning algorithm. The benchmark medical image database has been collected and experimentally analyze to validate the efficiency, accuracy, optimal automatic detection for tumor and non-tumor region and mean error rate of the algorithm using mathematical formulation. This research pays its proficiency in the field of brain abnormality detection and analysis in health care sector without human intermediation.

Keywords: **Magnetic Resonance Imaging, gamma distribution, machine-learning algorithm, brain abnormality.**

1. Introduction:

As indicated by a measurable report distributed by the registry of central brain tumor at United States (CBTRUS), roughly 59,550 individuals were recently diagnosed to have essential benign and essential harmful brain tumors in 2017[1-2]. Besides, in excess of 91,000 individuals, in the United States alone, were living with an essential harmful cerebrum tumor and 367,000 were living with an essential kind brain tumor. A similar report demonstrates that the rate of essential cerebrum tumors, regardless of whether considerate or harmful, is 24 for each 100,000, while middle age at analysis is 47 years [3]. The etiologies of this infection are not clear nor are the purposes behind the expanded number of cases. As of now there are no strategies to anticipate cerebrum tumors, which is the reason early recognition speaks to an imperative factor in tumor treatment. Magnetic

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resonance imaging (MRI) is one of the medicinal image procedure utilized by doctors to enable for determine to have more precision [1]. It protected innovation utilizes unaffected radiations. X-ray also habitually utilized for analyzing image. The MRI the condition cerebrum that seen with high level sensitivity and selectivity [2]. In view of imaging system, scientists presently attempting robotize diagnostics, for a precise and simple data from MRI cerebrum images. Real time image division, and along these lines MRI brain image division for feature analysis is considered as significant area of research. To perform image division, thresholding is the most straightforward technique [3] used for several brain tumor diagnosis.

The brain abnormalities such as injuries, damages, tumors related causes, affects and symptoms are analyzed for recognizing the tumors by using the different image processing, data mining and machine learning techniques [7]. The abnormalities are analyzed using the image cryptography, Computed tomography (CT), Magnetic resonance imaging (MRI),and Electroencephalogram (EEG) related data [8-9]. These data's are capturing the information about the brain with effective manner because it analyze each and every lobe in the brain. Then the remaining section is arranged organized accordingly, section 2 examines the various authors opinion on brain abnormalities detection mechanisms, Section 3 explains Tumor segmentation and analysis using partial derivatives and Orthogonal Gamma Distribution with Machine Learning Approach; section 4 evaluates the efficiency of Orthogonal Gamma Distribution with Machine Learning Approach with existing technique analysis and concludes in section 5.

2. Related Works

In [10] Image segmentation is used in medical field for the identification of brain tumor. MRI is helps to detect brain tumor. The introduced segment method resolve the multi model brain analysis challenges (MICCAI BraTS 2013). The structures isolated here are intensity differences, local neighborhood and texture. The isolated structure is analyzed and classified by applying random forest approach that helps to predict different classes by utilizing various regions.The aim of this research is for accurate classification of tumor cells from the normal cells compare to other methods.

In [11] there are many challenges in the medical image processing with segmentation due to different location shape and other characteristics of the cells. The MRI images are analysed by pre-processing, extraction, and classification and post-processing. In segmentation the classifier algorithms like SVM, AdaBoost and Random Forest (RF) are used. In this paper these three classifiers are compared for their segmentation of brain tumor. These help to use the classifiers based on the accurate segmentation on particular set of data. The future developing classifiers should make segmentation on any level of data sets.

In [12] image processing is for creating the picture view of the different anatomy structure of human body. MRI images are the view of abnormal human brain to identify the tumor cells. These also help to identify the internal structure of human brain and scan them for perfect clarification of cells. The proposed work consists of GLCM feature extraction and wavelet based region segmentation. The morphological filtering method is used for noise removing. The above combination of method is for reduction in complexity and performance improvement with more accuracy in separating the abnormal brain tumor cells for normal cells.

In [14] MRI used to obtain from visualization of different internal body tissues that used to examine brain tumor cell. This paper the MRI segmentation is performed, which is based on different algorithms and threshold method. The segmentation method is for automatic identification of position and boundaries of brain pathology in a highly efficient manner. The method also ensures qualitative analysis of the brain area for separation of tumor cells with high level of sensitivity.

In [15] the image processing are used in the medical field for detection of various abnormal cells in the body. This paper involves the method of fluid attenuated inversion recovery (FLAIR) MRI for automatic detection and prediction of the tumor cells from the normal cells of the brain. [16] The best pixel technique along withs classification of each pixel method is used. The features like intensity, fractal analysis, Gabor textons, and curvatures are analyzed for better segmentation result. The extremely randomized trees (ERT) classifier is collated with support vector machine to classify each super pixel into tumor and non-tumor. The proposed method with the ERT classifiers is to perform segmentation in a high-speed manner and repeated manner to identify the tumor cells in brain.

In [16] Brain tumor cells in the brain leads to cancer, with Gliomas a general brain tumor seen in people which causes death. In this a paper an automatic method of segmentation is designed for identification of gliomas from the brain using MRI image. This is more effective than the other method as the selection of tumor cells are done from histogram and pixel intensity of segmented region. The successful level detection of brain tumor technique provides effective performance with higher noise reduction and accurate segmentation method.

From the survey it is concluded that under segment and over segments of the brain tumor regions to detect the abnormality with automatic ROI detection is considered as significant area of research in brain tumor detection and analysis.

3. METHODOLOGY AND DISCUSSION:

3.1 Tumor segmentation and analysis using partial derivatives:

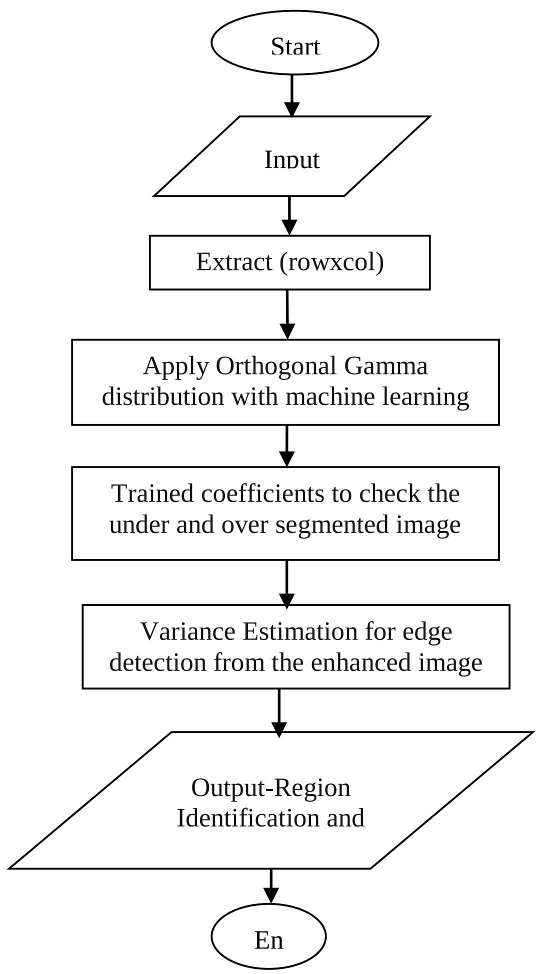

Figure.1 Architectural flow of the orthogonal gamma distribution with machine learning model

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As shown in the Figure.1. Automation can lessen the task of analyzing a vast number of brain tumor samples to avoid misinterpretations by human diagnosis. The proposed technique is completely automated in identifying the tumor region through proper segmentation approach with edge analysis coordinate matching using orthogonal gamma distribution and edge enhancement with identification has been computed using machine learning approach. This edge-based image segmentation coordinate matching with automatic ROI detection has been implemented using orthogonal gamma distribution model with machine learning approach. As this algorithm has self- identification of Region of Interest (ROI) stands distinctive amongst the other techniques such as Li's, chehade and otsu's method.

The brain tumor image as shown in the figure.2. Has been analyzed to facilitate the extracted features for under and over segmentation using fractional derivatives with the help of dataset taken for analysis from (https://openfmri.org/dataset/).

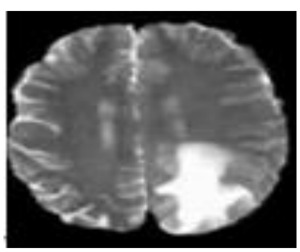

Figure.2. brain Tumor Image

In the existing approaches such as Gaussian distribution on Li's method, chehade and otsu's [20] method have drawbacks when dark peaks of histogram are minuscule in size as shown in the Eq(1) and (2) because these approaches are more generic than orthogonal gamma distribution .

$$\mathbf{C_1 = \sum_{i=0}^{\tau-1} iProb(i)} \quad (1)$$

$$\mathbf{C_2 = \sum_{i=\tau}^{L-1} iProb(i)} \quad (2)$$

C_1 and C_2 are represented as classes dividing pixels based on threshold limit and it fails to reduce the black pixel level at the time segmentation. It proven that Li's approach more better than chehade and otsu's while detecting the black pixel edges by matching the coordinates in the abnormality region during MRI as shown in the Eq(3).

$$\mathbf{P(\partial,\tau) = \sum_{\tau>0}^{L-1} Min\ Value\ P(\partial,\tau)} \ \mathbf{(3)}$$

The above equation shows that Li's method outperforms chehade and Otsu's interms of identifying black pixels by matching the edge coordinates in the background as shown in the Figure.3.

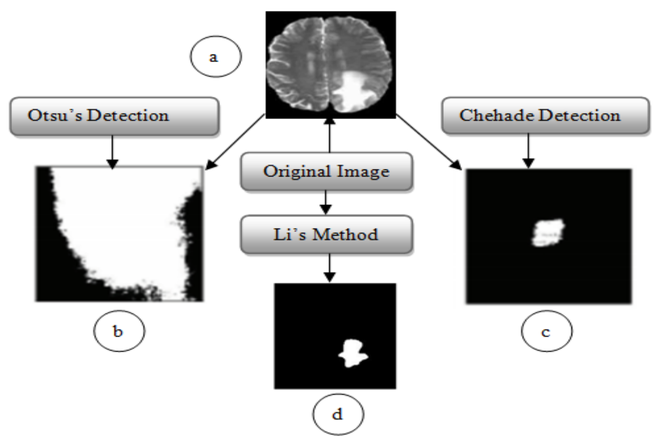

Figure.3. Demonstration of Li's Method (a) original, (b) Otsu's method (c) Chechade method (τ = 222). (D) Li's Method (τ =232) (Data set 1- from https://openfmri.org/dataset/) [21]

Further, the quality of the resultant segmented image is not up to the level to identify the tumors. Because in Otsu's , Li's and Chechade method the class variance sum is considered and variance discrepancy is not calculated for taking optimum threshold limit makes this algorithm not suitable for segmenting images for accurate brain tumor edge diagnosis[22].

3.2 Orthogonal Gamma Distribution with Machine Learning Approach

In our proposed approach, to facilitate the identification of minimum and high level of brain tumor images has been computed using fractional derivatives using orthogonal gamma distribution model for edge analysis and machine learning approach to identify and train the edge coordinates. Initially the fractional derivatives are analyzed for x and y axis of the grey scale image as shown in the Eq(4) &(5).

$$\left.\frac{d^2 \operatorname{Im} g}{dy^2}\right|_{x,y} = \sum_{i=-1}^{1}\left[\operatorname{Im} g(x-i, y-1) - 2\operatorname{Im} g(x-i, y) + \operatorname{Im} g(x-i, y+1)\right] \quad \textbf{(4)}$$

$$\left.\frac{\partial^2 \operatorname{Im} g}{\partial x^2}\right|_{x,y} = \sum_{i=-1}^{1}\left[\operatorname{Im} g(x-1, y-i) - 2\operatorname{Im} g(x, y-i) + \operatorname{Im} g(x+1, y-i)\right] \quad (5)$$

The method applied in any one of direction for getting the edges information and the linear processing is considered in both direction for getting the non-edge details.The pixel intensity has been computed for grey scale, symmetric and non-symmetric values using orthogonal gamma distribution coefficients C_1 and C_2as shown in the Eq(6) &(7),

$$\mathbf{C_1} = \sqrt{\frac{\sum_{j=0}^{\tau}\mathbf{his(img)img^2\, q^2}}{\sum_{j=0}^{\tau}\mathbf{his(img)}}} \quad \textbf{(6)}$$

$$\mathbf{C_2} = \sqrt{\frac{\sum_{j=g}^{255}\mathbf{his(img)img^2\, q^2}}{\sum_{j=g}^{255}\mathbf{his(img)}}} \quad \textbf{(7)}$$

$$\mathbf{\Gamma(x, d\mu, SN)} = \frac{\mathbf{2q}}{\mathbf{d\mu}}\frac{\mathbf{SN^{SN}}}{\mathbf{\Gamma(,SN)}}\left[\frac{\mathbf{qx}}{\mathbf{d\mu}}\right]^{\mathbf{2SN-1}}\mathbf{e}^{\mathbf{-SN(\frac{qx}{d\mu})^2}} \quad \textbf{(8)}$$

Where $\mathbf{\Gamma(x, d\mu, SN)}$in the Eq(8) is defined as gamma (pixel intensity mean distribution and distribution shape). Here the edges are divided with, minimum value that involves towards uniform grey level area based on threshold limit (τ). ‘τ’ has significant part in image processing operations and its applications. In the proposed orthogonal based gamma distribution with machine learning approach, the choice of single threshold τ, criterion to be enlarged is defined as the ratio between different edge response ($\mathbf{eR^2}$) against differnce total response ($\mathbf{tR^2}$) as shown in the Eq(9) and the detailed variance analyses has been computed in the algorithm.1.

$$\tau = \frac{\mathbf{eR^2}}{\mathbf{tR^2}} \quad \textbf{(9)}$$

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Input (i): Brian tumor image of (Rx C);

//*R is the Row and *C is the Column//

Output (O): Enhanced Brian tumor image with proper black pixel reduction;

Begin

For i=0 to ((R-n)-1)

For j=0 to (C-n)-1)

Where n=0 to 255;

Source image= get (MRI data set)

If (variance>min variance)

Min variance ≠variance;

Else

Min variance =variance;

Go to Threshold check (for the values 0 to 255)

Ex (img)= [Ω]= $\{Tu\}^{\tau}$(img){Tu}; (10)

//*Extract (Ex) the over and under segmentation region from the input tumor (Tu) image (img)*//

Return (threshold value);

End

As shown in the algorithm.1 devising heuristics approach has been utilized to analyze the overall distribution of pixel values to match the edge coordinates to avoid data imbalance. The proposed approach used to estimate optimal threshold to remove black pixels present in background images by matching the edge coordinates as shown in the Figure.4.

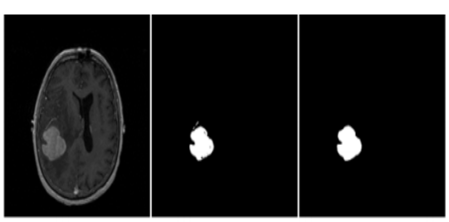

Figure.4.Matched coordinated and malignant area detection (Data set 2- from https://openfmri.org/dataset/)

These orthogonal polynomials are trained using machine learning approach with variance based threshold limit and the difference operators for tumor edge identification and enhancement. The derived features are examined and trained according to feature velocity and position that is depicted in Eq(11) and Eq(12). The effective characteristics of derived features are learned in particular feature space in various direction to select the optimized feature in the tumour for identification and enhancement with reduced data imbalance as shown in the Algorithm.2

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for i=0 to R-1 do

Begin

for j=0 to C-1 do

Begin

Compute the velocities and postion for feature extraction

$$\mathbf{V_e(t+1) = V_e(t) + F_1\big(pbest(i,t) - P_e(t)\big) + F_2(gbest(t) - P_e(t))} \quad \mathbf{(11)}$$

$$\mathbf{P_e(t+1) = P_e(t) + V_e(t+1)} \quad \mathbf{(12)}$$

Repeat this step to reach maximum condition and train selected features..

$$\mathbf{y_j = Af_N\left(\sum_{j=1}^{N_h} \mu(i,j) ax_i\right)} \quad \mathbf{j=1, 2, 3\ldots N_H} \quad \mathbf{(13)}$$

As shown in the above algorithm.2. $\mathbf{ax_i}$, $\mathbf{y_j}$ is input and output of the each neuron for the machine learning activation function $\mathbf{Af_H}$ with the mean distribution μ is neuron weight as shown in the Eq(13). Further network is optimized by updating weight and bias value which minimize error rate.The evaluation of the approach in this research has been analysed based unsupervised method. In the unsupervised evaluation the degree of matching has been computed according to true positive (TP), true negative (TN), False Positive (FP), and False Negative (FN).

4. Experimental Performance Metrics analysis

In this research the Experiments were executed using mathematical formulation and the collected dataset is primarily classified for tumor and non-tumor region .The algorithms are used to train and evaluate MRI slices as shown in the Figure.5 for accurate tumor identification. The data sets consists of 994 MRI image gathered from 30 patients that used to recognize 198 type of seizures. The MRI data has been analyzed , efficiency brain tumor recognition process is evaluated Then the parameters such as accuracy, sensitivity, selectivity, mean square error, optimal tumor matching, and threshold limit and noise factor are discussed in the experimental section as discussed below.

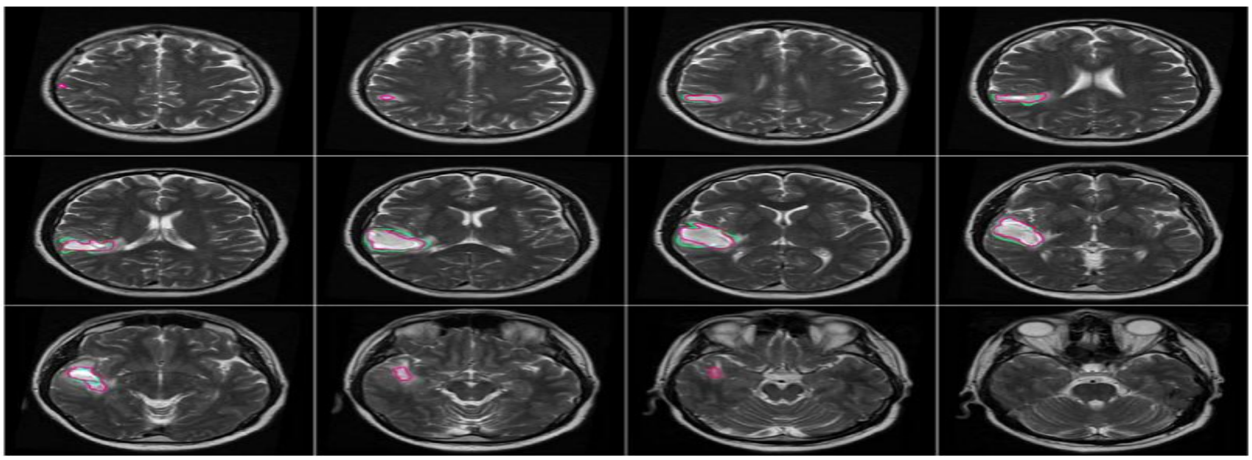

Figure.5.MRI brain images where the pink circle denote the location of tumor region

a) Sensitivity

It is important metric that used to gather brain tumor related features from the segmented MRI image. The collected features are helps to predict whether the features are related to normal or abnormal features.

$$\textbf{Sensitivity} = \frac{\textbf{True Posiitve}}{\textbf{True Posiitve+False negative}} \textbf{ x } \textbf{100}\% \quad \textbf{(14)}$$

b) Specificity

It is used to fetch and retrieve the exact brain tumor features from the gathered brain features that is computed as follows.

$$\textbf{Specificity} = \frac{\textbf{True Positive}}{\textbf{False Positive+True Negative}} \textbf{ x } \textbf{100}\% \quad (15)$$

c) Classification accuracy

Accuracy is the metric how exactly the given features are classified into right manner without making any error.

$$\textbf{Classification Accuracy} = \frac{\textbf{True Positive+True Negative}}{\textbf{True Positive +True Negative+False Positive+False Negative}} \textbf{x100}\% \quad \textbf{(16)}$$

In Orthogonal gamma distribution with machine learning approach (OGDMLA)The edge coordinates are trained to yields the boundaries of all the visible edges in the images by with looped boundaries can be extracted from ROI image which is used to characterize tumor and non-tumor region of the patients. This has been evaluated for 25 MRI data sets based on the extracted features for distinct threshold limit with trained and untrained edge coordinates using machine learning approach. It is found that from and normal liver for 25 patient's evaluation form the datasets. Untrained parameters i.e. data structure values or variable and region covered, are extracted for two different threshold values. However, combination of trained parameter for single threshold values leads to promising classification results and the line separates the graph represents the trained and untrained regions as shown in the Figure.6.

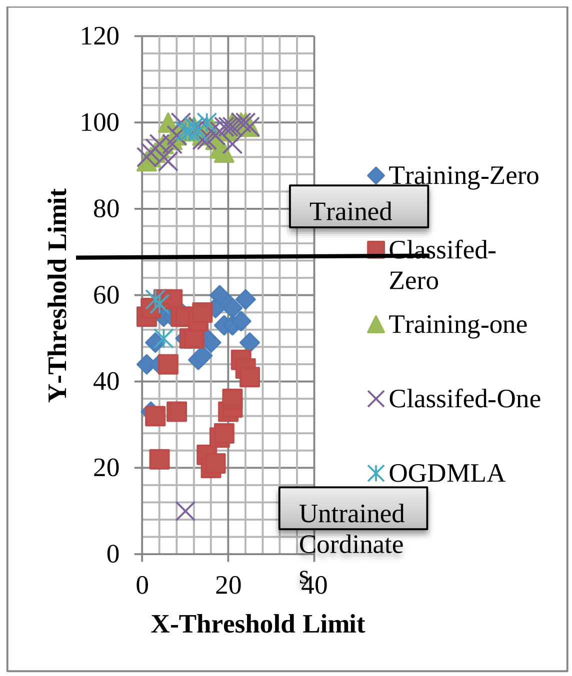

Figure.5. Trained and untrained analysis of brain tumor images

The 25 MRI data sets based on the extracted features for distinct threshold limit with trained and untrained edge coordinates using machine learning approach is compared with Gaussian distribution on Li's method, chehade and otsu's method and It is found that OGDMLA evaluation of trained datasets outperforms

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the existing counterparts as because Gaussian distribution is generic and its uses distinct threshold limits as shown in the Figure.6

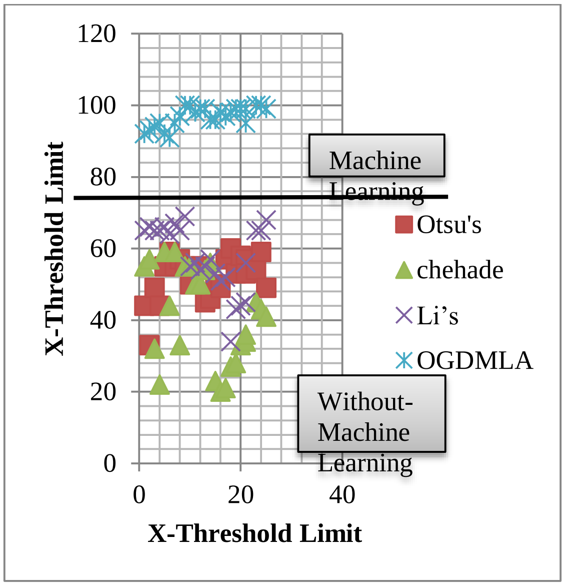

Figure.6. Trained and untrained analysis of brain tumor images with existing counterparts.

d) Peak Signal to noise Ratio (PSNR) and Mean Square Error Rate (MSE)

Table 1: Mean Square Error Rate

Method	MSE	PSNR(dB)
Li's and	3.88	8.37
chehade	2.22	11.33
otsu's	0.10	21.22
OGDMLA	0.03	45.56

As shown in the Table.1 the metrics MSE and PSNR can be used to find the trained image quality of the MRI dataset.The MSE characterizes the collective squared error among the input and output image, whereas PSNR as shown in the Eq(17) signifies a degree of error. The minimum MSE value , lower is the error. Whereas in the Eq(18) $I(i, j)$ is the input image and $O(i, j)$ is the output image with graphical repesentaoin is shown the Figure.7.

$$\mathbf{PSNR} = \mathbf{10log_{10}}(\frac{\mathbf{R^2}}{\mathbf{MSE}}) \quad \mathbf{(17)}$$

$$\mathbf{MSE} = \frac{\mathbf{1}}{\mathbf{ab}}(\sum_{i=0}^{a-1} \mathbf{I(i,j)} - \sum_{j=0}^{b-1} \mathbf{O(i,j)})^{\mathbf{2}} \quad \mathbf{(18)}$$

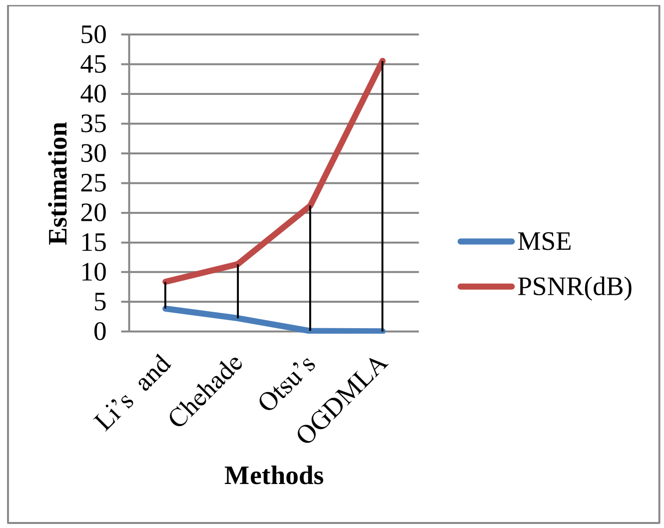

Figure.7. Comparative analyses on brain tumor diagnosis methods for MSE and PSNR

d) Sensitivity, Specificity and Accuracy

According to the above results, it clearly shows that introduced OGDMLA method attains effective entropy value due to trained edge coordinate matching leads to improve overall efficiency of recognition process for tumor slices and reduce the data imbalance in detection. Then the accuracy, specificity and sensitivity value of the OGDMLA approach is computed as follows.

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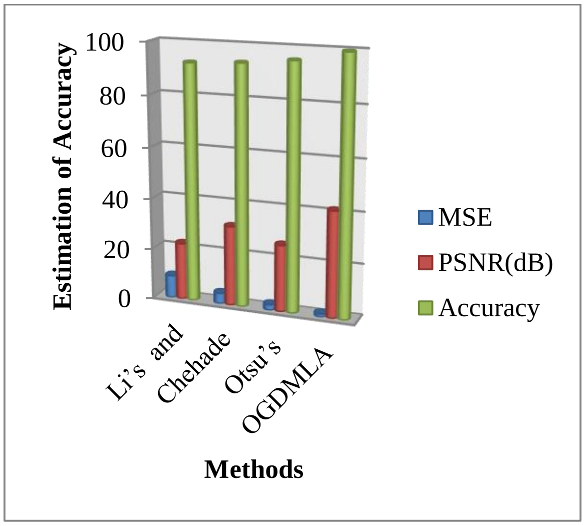

Figure.8. Sensitivity and Specificity Comparative Analysis

The resultant image is shown in figure 8, the prominent feature of OGDMLA model is recognize the edges of tumors from segmented region. As Specificity used to identify how exactly recognize the non-tumor region which are correctly segmented and sensitivity specifies the tumor region of the MRI slices. In order to estimate the region of tumors, an edge tracing to match the coordinated was initiated. As data were trained using machine learning approach using threshold limit the matched edge coordinates around the tumors are estimated accurately as shown in the Figure.9 because lowers value of error rate indicate better performance identifying the spot of the characterize tumor region

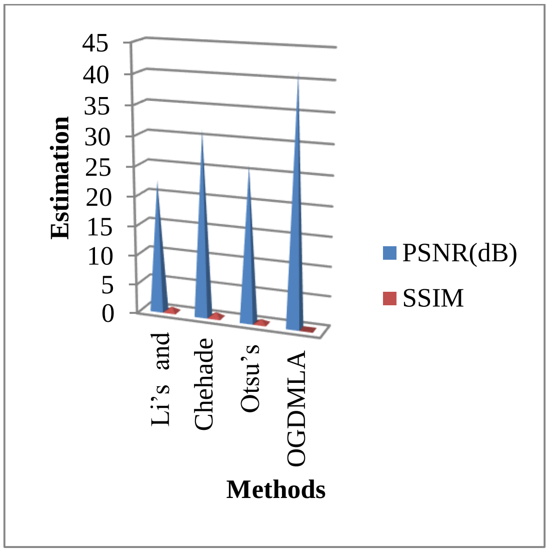

Figure.9. Comparative analyses on brain tumor diagnosis methods for Accuracy Vs MSE Vs PSNR

For quantitative comparisons, variance is generally used to find in what way each pixel varies from the neighboring pixel whereas PSNR and the Structural similarity Index (SSIM) parameters are considered for analysis and remarkably the proposed OGDMLA shows variance distributions with a low value as represented in the figure.10.

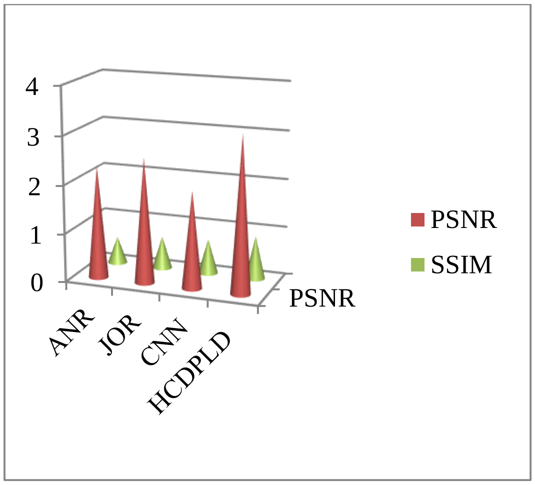

Figure 10: PSNR and SSIM analysis

The benchmark medical image database has been collected and experimentally analyze to validate the accuracy, sensitivity, selectivity, mean square error, optimal tumor matching, and threshold limit and noise factor are discussed in the experimental section as discussed below.
using mathematical formulation shows OGDMLA is more profienct than existing couterparts.

5.Conclusion:

Accurate brain tumor analysis plays a vital role in health care sector. The proposed technique is completely automated in identifying tumor images based on training the edge-based image segmentation coordinates using orthogonal gamma distribution with machine learning approach. The significant features of OGDMLA are self- identification of ROI with enhanced imaging segmentation approach using edge coordinate matching stands unique amongst the other techniques. The experimental analysis has been recorded for various datasets and gives prominent performance for the detection of tumor status of the patients pays promising implication in the treatment plan. Hence, precise detection of tumors in the suspected cases can well define a therapeutic strategy with a favorable disease prognosis. Furthermore, the proposed OGDMLA is potential and favorable in the field of real time medical image diagnosis in health care sector. Further research in future extension will be carried out to accelerate real-time medical applications computation using machine learning techniques in medical internet of things (MIoT).

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