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Machine Learning Approach-Based Gamma Distribution for Brain Tumor Detection and Data Sample Imbalance Analysis

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ABSTRACT Recently, artificial intelligence applications in magnetic resonance imaging have been applied in several clinical studies. The analysis of brain tumors without human intervention is considered a significant area of research because the extracted brain images need to be optimized using a segmentation algorithm that is highly resilient to noise and cluster size sensitivity problems and automatically detects the region of interest (ROI). In this paper, an improved orthogonal gamma distribution-based machine-learning approach is used to analyze the under- segments and over-segments of brain tumor regions to automatically detect abnormalities in the ROI. Further data imbalances due to improper edge matching in the abnormal region is sampled by matching the edge coordinates and sensitivity, and the selectivity parameters are measured using the machine learning algorithm. The benchmark medical image database was collected and analyzed to validate the efficiency and accuracy of the optimal automatic detection in tumor and non-tumor regions. The mean error rate of the algorithm was determined using a mathematical formulation. The system is evaluated based on experimental results that showed the method of orthogonal gamma distribution with the machine learning approach attained an accuracy of 99.55% in detecting brain tumors. This research contributes to the field of brain abnormality detection and analysis without human intervention in the health care sector.

INDEX TERMS Magnetic resonance imaging, gamma distribution, machine-learning algorithm, brain abnormality.

I. INTRODUCTION

According to a report published by the Registry of Central Brain Tumors in the United States (CBTRUS), in 2017, roughly 59,550 patients were recently diagnosed to have benign and malignant brain tumors [1], [2]. Moreover, in excess of 91,000 individuals in the United States were living with a harmful cerebrum tumor, and 367,000 were living with an benign brain tumor. A similar report stated that the rate of cerebrum tumors, regardless of whether they were benign or malignant was 24 in each 100,000, and the median age at diagnosis was 47 years [3]. The etiologies of this infection are not clear, which easily spreads from more number of patients. Currently, there are no strategies for anticipating cerebrum tumors, which is the reason that early recognition is an imperative factor in tumor treatment. Magnetic resonance imaging (MRI) is one of the medical imaging procedures utilized by doctors to improve the accuracy of diagnoses [4]. This tumor detection methodology utilizes unaffected radiation. X-rays are also utilized to analyze images. MRIs conducted of the cerebrum are highly sensitive and selective [5]. In imaging systems, scientists are studying robotized diagnostics and MRIs to predict disease in an effective manner. Real-time image division, such as MRI brain image division for feature analysis, is considered a significant area of research. To perform image division, thresholding is the most straightforward technique [6] used to diagnose several brain tumors.

Brain abnormalities, such as injuries, damage, tumor-related causes, affects, and symptoms, have been analyzed for tumor recognition by using image processing, data mining, and machine learning techniques [7]. Abnormalities are analyzed using image cryptography, computed tomography (CT), MRI, and electroencephalogram (EEG) related data [8], [9]. These techniques capture information data in an effective manner because they analyze every lobe in the brain.

The rest of this paper is organized as follows: section 2 reviews the relevant literature on the mechanisms used to detect brain abnormalities; section 3 explains tumor segmentation and analysis using partial derivatives and orthogonal gamma distribution with machine learning approach; section 4 evaluates the efficiency of using orthogonal gamma distribution with machine learning approach compared with existing techniques; section 5 concludes the paper.

II. RELATED WORKS

As reported in [10], image segmentation has been used in the medical field for the identification of brain tumors. MRI helps to detect brain tumors. The introduced segment method was shown to resolve challenges present in multi-model brain analysis (MICCAI BraTS 2013). The structures isolated here were intensity differences, local neighborhoods, and texture. The isolated structure was analyzed and classified by applying a random forest approach, which helps to predict different classes by utilizing various regions. The aim of this research is the accurate classification of tumor cells as distinct from the normal cells compared with other methods.

As reported in [11], there are many challenges in medical image processing with segmentation because of the locations, shapes, and other characteristics of the cells. MRI images are analyzed by pre-processing, extraction, and classification and post-processing. In segmentation, classifier algorithms such as SVM, Adaboost, and random forest (RF) are used. In this paper, these three classifiers were compared for their segmentation of brain tumors. These helped to use the classifiers based on the accurate segmentation of a particular set of data. The future development of classifiers should facilitate the segmentation of any data set.

As described in [12], image processing is conducted to create a picture of the anatomical structure of the human body. MRI images provide views of the abnormal human brain to identify tumor cells. These also help to identify the internal structure of the human brain and scan it to detect cells clearly. The proposed work consists of Gray Level Co-occurrence Matrix (GLCM) feature extraction and wavelet-based region segmentation. The morphological filtering method is used for noise removal. The above combination of methods is used to reduce complexity and improve accuracy in separating abnormal brain tumor cells from normal cells.

In [13], MRI was used to visualize internal body tissues that are used to examine brain tumor cells. In this paper, MRI segmentation was performed based on different algorithms and threshold methods. The segmentation method was used for the automatic identification of the position and boundaries of brain pathology in a highly efficient manner. This method can also be used to conduct a qualitative analysis of the brain area for the separation of tumor cells having high levels of sensitivity.

As discussed in [14], image processing is used in the medical field to detect abnormal cells in the body. In this paper, the method of fluid attenuated inversion recovery (FLAIR) was applied with MRI for the automatic detection and prediction of tumor cells and normal cells in the brain [15]. The best pixel technique and the classification of each pixel method was used. Features such as intensity, fractal analysis, Gabor textons, and curvatures were analyzed to ensure improved segmentation results. The extremely randomized tree (ERT) classifier was collated with a support vector machine to classify each super pixel as tumor or non-tumor. The proposed method of using ERT classifiers performed segmentation rapidly and repeatedly to identify tumor cells in the brain.

As reported in [16], tumor cells in the brain lead to cancer. Gliomas, which is a general brain tumor, causes death. In this paper, an automatic segmentation method was designed for the identification of gliomas using MRI. This method was more effective than the other method, as tumor cells were selected from the histogram and pixel intensity of the segmented region. This technique successfully detected brain tumors, and it provided effective performance with higher noise reduction and an accurate segmentation method.

Based on this review of the relevant literature, it is concluded that under-segments and over-segments of brain tumor regions can be used to detect abnormalities. Automatic ROI detection is considered a significant area of research in brain tumor detection and analysis.

III. METHODOLOGY AND DISCUSSION

A. TUMOR SEGMENTATION AND ANALYSIS USING ORTHOGONAL GAMMA DISTRIBUTION IN THE MACHINE LEARNING MODEL

As shown in Figure 1. automation can lessen the task of analyzing a vast number of brain tumor samples to avoid misinterpretation by human diagnosis. The proposed technique is automated in identifying the tumor region through a proper segmentation approach with edge analysis. Coordinate matching using orthogonal gamma distribution and edge enhancement with identification were computed using the machine learning approach. This edge-based image segmentation [17] coordinate matching with automatic ROI detection was implemented using an orthogonal gamma distribution model with a machine learning approach. Because this algorithm self-identifies the region of interest (ROI) [18] it is distinctive among other techniques, such as Li's method, Chehade's method, and Otsu's method.

Figure 2 shows the image of a brain tumor. It has been analyzed to facilitate the extracted features for under- and over-segmentation using fractional derivatives with the help of a dataset obtained from MPI-Leipzig_Mind-Brain-Body (https://legacy.openfmri.org/dataset/ds000221/). The data set consists of a structural and resting situation of brain details [19] that were captured by an fMRI image by using machine learning techniques to examine the tumor condition.

The existing approaches, such as Gaussian distribution in L's method, Chehade's method, and Ots's [20] method, have drawbacks. In the histogram, dark peaks are minuscule as shown in the image, which was derived by Eqs. (1) and (2).

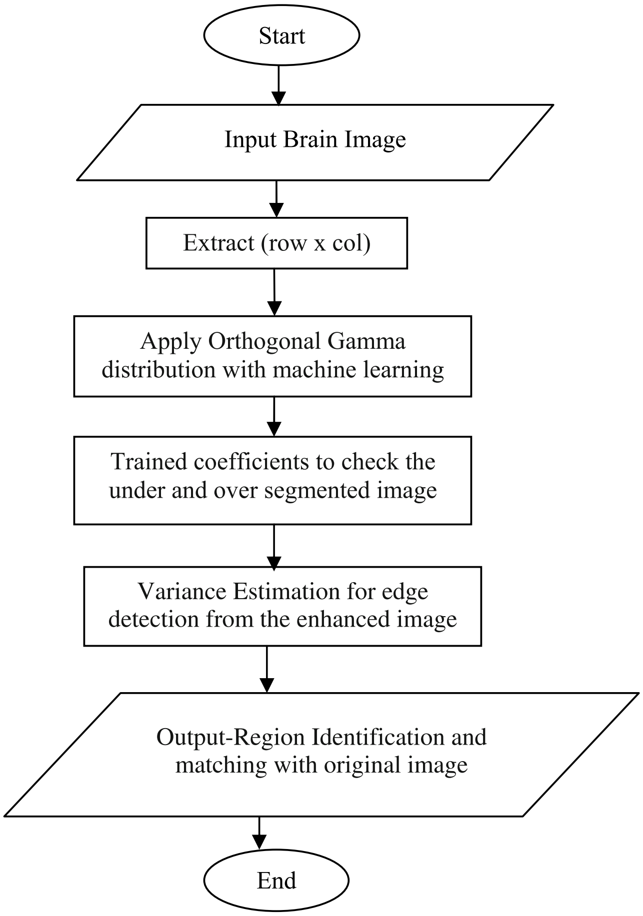

FIGURE 1. Architectural flow of the orthogonal gamma distribution in the machine learning model.

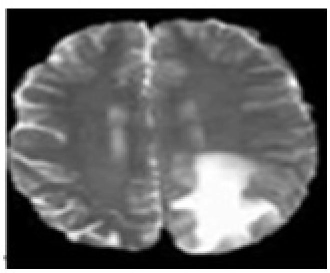

FIGURE 2. Brain tumor image.

These approaches are more generic compared with orthogonal gamma distribution.

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

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

where C_1 and C_2 are classes dividing pixels based on the threshold limit, and it fails to reduce the black pixel level at the time of segmentation. The problem is the probability of pixel i. It was proven that L's method was better than Chehade's method and Ots's method in detecting the black pixel edges by matching the coordinates in the abnormal region during MRI, as shown in Eq. (3).

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

The above equation shows that Li's method outperforms Chehade's method and Ots's method in identifying black pixels by matching the edge coordinates in the background, as shown in Figure 3.

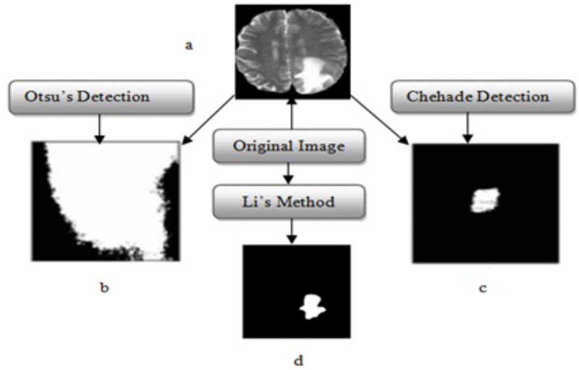

FIGURE 3. Demonstration of Li's Method (a) original image, (b) Ots's method (c) Chechade's method ($\tau = 222$. (D) L's Method ($\tau = 232$) (Data set 1- from MPI-Leipzig_Mind-Brain-Body (https://legacy.openfmri.org/dataset/ds000221/) [21].

Furthermore, the quality of the resulting segmented image is not sufficient to identify tumors. In Otsu's method, L's method, and Chechad's method, the sum of class variance sum is considered, and variance discrepancy is not calculated for the optimal threshold limit. Therefore, this algorithm (Ots's, Li's, and Chechade's methods) is not suitable for segmenting images for the accurate diagnosis of brain tumor edge.

B. ORTHOGONAL GAMMA DISTRIBUTION WITH MACHINE LEARNING APPROACH

In our proposed approach,to facilitate the identification of minimum and high-level brain tumor images, they have been computed using fractional derivatives based an orthogonal gamma distribution model. This approach uses edge analysis and machine learning approach to identify and train the edge coordinates. Initially, the fractional derivatives are analyzed for the x and y axis of the gray scale image, as shown in Eqs. (4) and (5).

$$\left.\frac{d^2 Img}{dy^2}\right|_{x,y} = \sum_{i=1}^{l} [Img\,(x-i, y-1) - 2Img\,(x-i, y) + Img(x-i, y+1)] \tag{4}$$

$$\left.\frac{d^2 Img}{dx^2}\right|_{x,y} = \sum_{i=-1}^{l} [Img\,(x-1, y-i) - 2Img\,(x, y-i) + Img(x+1, y-i)] \tag{5}$$

The method is applied in any direction to obtain edge information. The linear processing is considered in both directions

Algorithm 1

Input (i): Brian tumor image of (Rx C)
//∗ R is the Row and ∗ C is the Column//
Output (O): Enhanced brain 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 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)

$$\mathbf{Ex(img)} = [\boldsymbol{\Omega}] = \{\mathbf{Tu}\}^{\tau}(\mathbf{img})\{\mathbf{Tu}\}; \tag{10}$$

//∗ Extract (Ex) the over and under segmentation region from the input tumor (Tu) image (img)∗//
Return (threshold value);
End

to obtain the non-edge details. The pixel intensity is computed for gray scale, symmetric, and non-symmetric values using orthogonal gamma distribution coefficients C_1 and C_2, as shown in Eq. (6) and (7):

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

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

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

where **Γ (x, d$\boldsymbol{\mu}$, SN)** in Eq. (8) is defined as gamma (pixel intensity, mean distribution, and distribution shape). Here the edges are divided by minimum values that involve the uniform gray level area based on threshold limit (τ), which has a significant role in image processing operations and its applications. In the proposed approach, which combines orthogonal-based gamma distribution with the machine learning approach, the choice of the single threshold τ, the criterion to be enlarged, is defined as the ratio between different edge response (**eR**^{2}) and difference total response (**tR**^{2}) as shown in Eq. (9). The detailed variance analyses are computed in the algorithm 1.

$$\tau = \frac{\mathbf{eR}^2}{\mathbf{tR}^2} \tag{9}$$

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

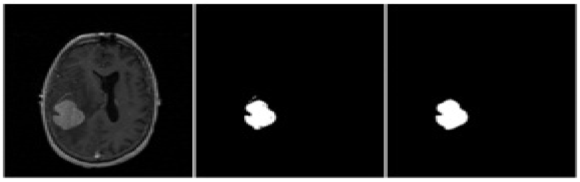

FIGURE 4. Matched coordinated and malignant area detection (Data set 2- from MPI-Leipzig_Mind-Brain-Body data set).

These orthogonal polynomials are trained using the machine learning approach with a variance-based threshold limit and difference operators for tumor edge identification and enhancement. The derived features are examined and trained according to feature velocity and position using Eq. (11) and Eq. (12). The effective characteristics of the derived features are trained in a specific feature space. The optimized feature that is used to identify the tumor enhancement process reduces the data imbalance, as shown in algorithm 2.

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

Algorithm 2

for i = 0 to R-1 do
Begin
for j = 0 to C-1 do
Begin
Compute the velocities and position for feature extraction

$$\mathbf{V_e}\,(\mathbf{t}+1) = \mathbf{V_e}\,(\mathbf{t}) + \mathbf{F}_1\,(\mathbf{pbest}\,(\mathbf{i},\mathbf{t}) - \mathbf{P_e}\,(\mathbf{t})) + \mathbf{F}_2(\mathbf{gbest}\,(\mathbf{t}) - \mathbf{P_e}\,(\mathbf{t})) \tag{11}$$

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

Repeat this step to reach maximum condition and train selected features

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

IV. EXPERIMENTAL PERFORMANCE METRICS ANALYSIS

In this research, the experiments were executed using mathematical formulations and the collected dataset is primarily classified according to tumor and non-tumor regions. The algorithms are used to train and evaluate MRI slices as shown in Figure 5 for accurate tumor identification.

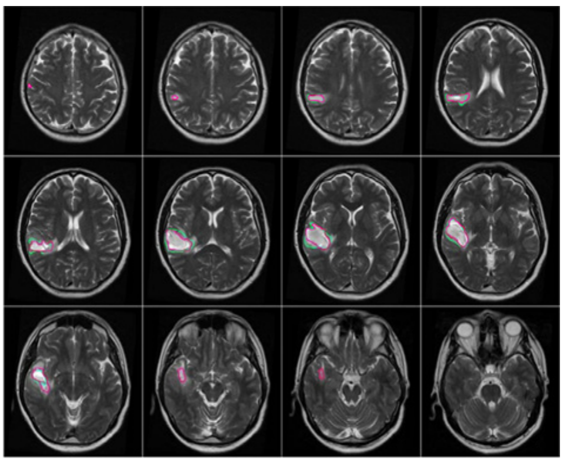

FIGURE 5. MRI brain images where the pink circle denotes the location of the tumor region.

The data sets consist of a 994 MRI image gathered from 30 patients that are used to recognize 198 types of seizures. The MRI data has been analyzed, and the efficiency of the brain tumor recognition process is evaluated. Parameters such as accuracy, sensitivity, selectivity, mean square error, optimal tumor matching, threshold limit, and noise factor are explained in the experimental section, which is below.

A. SENSITIVITY

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

$$\mathbf{Sensitivity} = \frac{\mathbf{True\ Posiitve}}{\mathbf{True\ Posiitve} + \mathbf{False\ negative}} \times \mathbf{100\%} \tag{14}$$

B. SPECIFICITY

This metric is used to retrieve the exact brain tumor features from the gathered brain features, which are computed as follows:

$$\mathbf{Specificity} = \frac{\mathbf{TruePositive}}{\mathbf{FalsePositive} + \mathbf{TrueNegative}} \times \mathbf{100\%} \tag{15}$$

C. CLASSIFICATION ACCURACY

Accuracy is the metric how exactly the given features are classified into the right manner without making any error, (16), as shown at the bottom of the next page. In orthogonal gamma distribution with the machine learning approach (OGDMLA), the edge coordinates are trained to yield the boundaries of all the visible edges in the images by using the boundaries derived from the ROI region of the image. From the extracted region, the tumor and the non-tumor conditions of the patient are characterized effectively. The brain tumor detection system was evaluated for 25 MRI data sets based on the extracted features for distinct threshold limits with trained and untrained edge coordinates using the machine learning approach. The brain tumor was examined using 25 patient details in the dataset. The untrained parameters, i.e., data structure values or variables and the region covered were extracted for two different threshold values. The combination of trained parameters for single threshold values led to promising classification results, and the line separating the graph represents the trained and untrained regions, as shown in Figure.6.

The 25 MRI data sets based on the extracted features of the distinct threshold limit with trained and untrained edge coordinates using the machine learning approach were compared

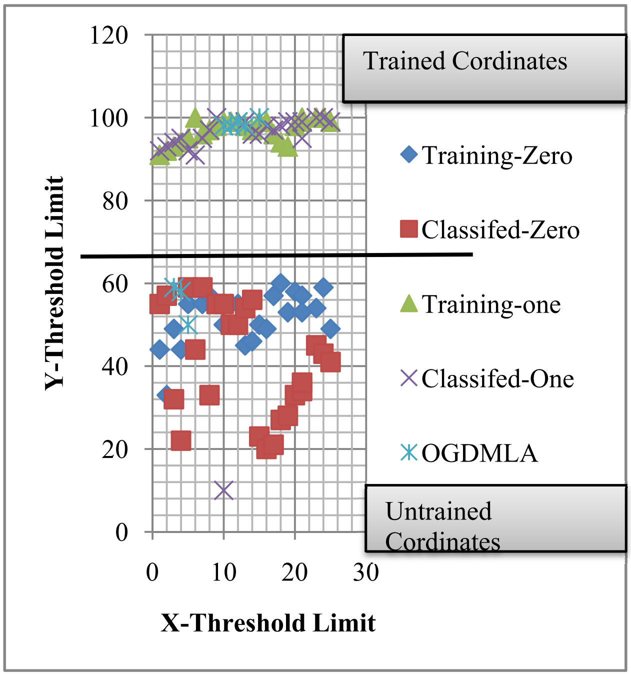

FIGURE 6. Trained and untrained analysis of brain tumor images in terms of using threshold value.

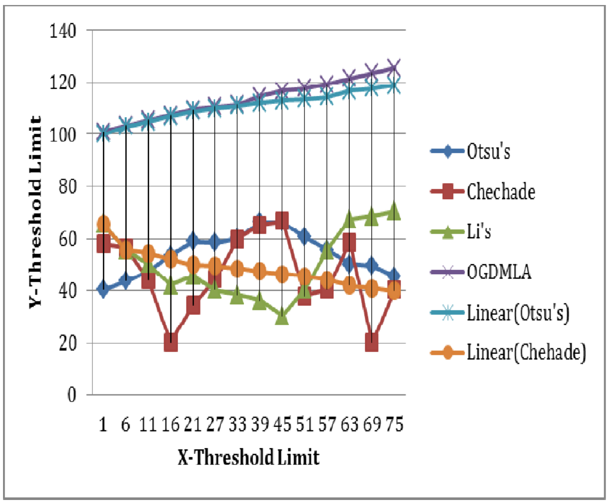

FIGURE 7. Trained and untrained analysis of brain tumor images.

with the Gaussian distribution in L's method, Chehade's method, and Ots's method. The results showed that that the OGDMLA evaluation of the trained datasets outperformed their existing counterparts, indicating that the Gaussian distribution is generic, and its use is distinct (Figure 7).

D. PEAK SIGNAL TO NOISE RATIO (PSNR) AND MEAN SQUARE ERROR RATE (MSE)

As shown in Table 1, the metrics MSE and PSNR were used to find the trained image quality of the MRI dataset. The 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

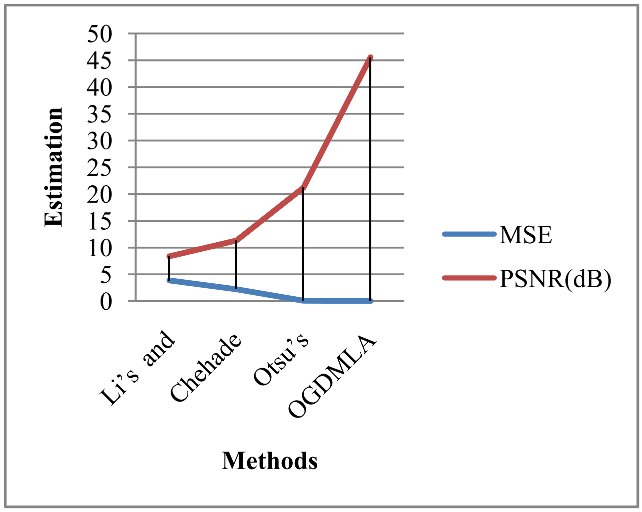

FIGURE 8. MSE and PSNR.

characterizes the collective squared error among the input and output image, whereas the PSNR, as shown in Eq. (17), signified a degree of error. The lower the MSE value is, the lower the error. Conversely, in Eq. (18), I (i, j) is the input image, and O (i, j) is the output image, as shown graphically in Figure 8.

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

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

E. SENSITIVITY, SPECIFICITY, AND ACCURACY

The results clearly showed that the introduced OGDMLA method attained effective entropy values. The trained edge coordinate matching led to the improved overall efficiency of the recognition process in the tumor slices and reduced the data imbalance in detection. The accuracy, specificity, and

$$\textbf{Classification Accuracy} = \frac{\textbf{True Positive} + \textbf{True Negative}}{\textbf{True Positive} + \textbf{True Negative} + \textbf{False Positive} + \textbf{False Negative}} \times 100\% \tag{16}$$

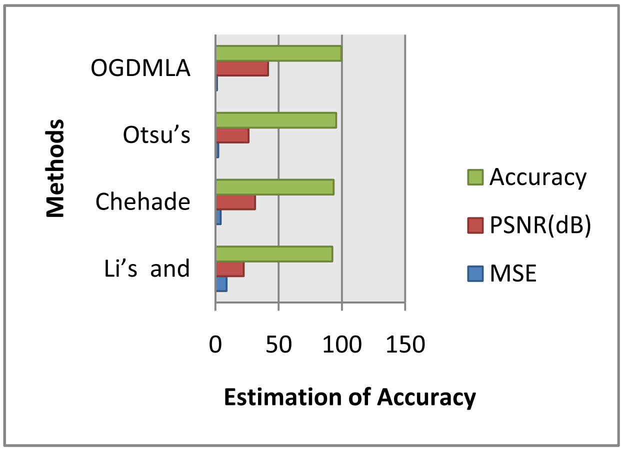

FIGURE 9. Accuracy vs MSE vs PSNR.

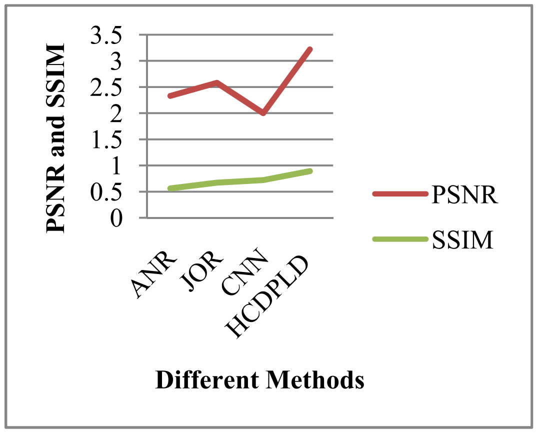

FIGURE 11. PSNR and SSIM analysis of different classifiers.

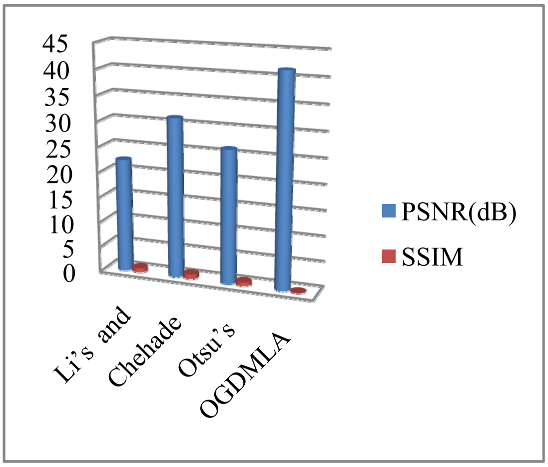

FIGURE 10. Comparative analyses of brain tumor diagnostic methods PSNR and SSIM.

sensitivity value of the OGDMLA approach were computed as follows:

The resulting image is shown in Figure 8. The prominent feature of the OGDMLA model is that it recognized the edges of tumors in the segmented region. Specificity was used to identify the non-tumor regions, which were correctly segmented. Sensitivity specified the tumor regions in the MRI slices. To estimate the tumor regions, edge tracing to match the coordinates was initiated. The data were trained using the machine learning approach based on the threshold limit. The matched edge coordinates around the tumors were estimated accurately, as shown in Figure 10 The lower error rate indicated better performance in identifying the spots characterizing the tumor region.

For quantitative comparisons, variance is used to determine the ways in which each pixel varies from t neighboring pixels. PSNR and structural similarity index (SSIM) parameters were used in the analysis. Remarkably in the proposed OGDMLA, the variance distributions had low values, as shown in Figure 11.

The benchmark medical image database was collected and experimentally analyzed to validate the accuracy, sensitivity, selectivity, mean square error, optimal tumor matching, and threshold limit. The mathematical formulation showed that OGDMLA was more proficient compared with its existing counterparts.

V. CONCLUSION

Accurate brain tumor analysis plays a vital role in the 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 the machine learning approach. The significant features of OGDMLA are the self-identification of ROI with an enhanced imaging segmentation approach using edge coordinate matching stands, which is unique among the other techniques. The experimental analysis was recorded for various datasets and showed a satisfactory performance in the detection of tumor status of patients, which has promising implications for treatment plans. Hence, the precise detection of tumors in suspected cases can be used to define a therapeutic strategy with a favorable disease prognosis. Furthermore, the proposed OGDMLA has potential for the field of real-time medical image diagnosis in the health care sector. Further research will be carried out to accelerate real-time medical applications and computation using machine learning techniques in the medical internet of things (MIoT).

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Authors' photographs and biographies not available at the time of publication.