International Conference on Neural Nexus and Synergy:Innovation in Emerging Technologies
Vol. 1. (2024). PP.199-213. SNIST

Integrating VGG-16 And CNN For Brain Tumor Detection

Seelam Keerthi , Yeruva Pravalika , Dugyala Srinitha , Dr G Yogesh

UG Student , Dept of Computer Science , Sreenidhi Institute Of Science And Technology , Hyderabad seelamkeerthi2002@gmail.com

UG Student , Dept of Computer Science , Sreenidhi Institute Of Science And Technology , Hyderabad
Yeruvapravalika12@gmail.com

UG Student , Dept of Computer Science , Sreenidhi Institute Of Science And Technology , Hyderabad
dugyalasrinitha111@gmail.com

Assistant Professor,Dept of Computer Science, Sreenidhi Institute Of Science AndTechnology , Hyderabad
yogeshg@sreenidhi.edu.in

Abstract—**Advancements in medical technology have significantly altered the landscape of healthcare, especially in diagnostic capabilities. This project focuses on leveraging Convolutional Neural Network (CNN) technology, specifically the VGG16 architecture, for the detection of brain cancer. CNNs are renowned for their prowess in analyzing visual data, making them ideal for scrutinizing Brain Magnetic Resonance Imaging (MRI) datasets to identify tumors accurately. Brain tumor segmentation, a challenging task in medical image processing, is further complicated by the potential for errors in manual analysis. To overcome this hurdle, we propose an automated solution that combines VGG16 for feature extraction with a custom CNN tailored specifically for brain tumor detection. The objective is to minimize reliance on manual classification while maximizing prediction accuracy. The project utilizes 2D MRI images to extract brain tumors, acknowledging the vast variability in tumor appearance and the nuanced differences between tumor and normal tissues. By integrating VGG16 and a custom CNN in a two-step process, the approach ensures robust feature extraction and precise classification. To validate the efficacy of our method, experiments are conducted using a diverse dataset containing tumors of varying sizes, locations, shapes, and image intensities. The results underscore the potential of our developed model to deliver reliable and automated brain tumor detection, addressing a critical requirement in the medical domain.**

Keywords: CNN, Medical Imaging Analysis, segmentation, VGG - 16 Model

I. INTRODUCTION

Scientific imaging methods allow for non-invasive examination of the body, while medical photography employs diverse techniques to capture images for diagnostic and treatment purposes, significantly impacting healthcare. Picture segmentation, a crucial step in image processing, is particularly vital in medical imaging. It aids in identifying tumors or lesions, improves computer-assisted diagnostic systems, and enhances the accuracy of subsequent analysis by increasing sensitivity and specificity.

As cited in [3], brain and other nervous system cancers rank as the tenth leading cause of death globally. The five-year survival rates for individuals with brain cancer stand at 34% for men and 36% for women. Additionally, the World Health Organization (WHO) reports that approximately 400,000 individuals worldwide are grappling with brain tumors, resulting in 120,000 deaths in recent years [4].Moreover, an estimated 86,970 new cases of primary malignant and nonmalignant brain and other central nervous system (CNS) tumors are projected to be diagnosed in United States in 2019.

When abnormal cell growth occurs in the brain, it leads to the formation of a brain tumor. These tumors are broadly classified as either benign or malignant. Malignant tumors, originating from brain tissue, exhibit rapid growth and invasive tendencies, potentially impacting nearby tissues and spreading to other regions of the brain. Primary tumors, which originate within the brain, and secondary tumors, known as brain metastasis tumors, which spread from elsewhere in the body, are the two main types of malignant brain tumors. On the other hand, benign brain tumors are characterized by slow growth and consist of a mass of cells within the brain.

Large volumes of data present one of the most significant challenges in medical image processing. Additionally, tumors may have Consequently, early detection of brain tumors offers substantial benefits in terms of treatment options and survival rates. However, due to the extensive number of MRI images generated in clinical practice, manually segmenting tumors or lesions is a laborious and time-consuming task. Magnetic Resonance Imaging (MRI) is commonly utilized for detecting lesions or cancers in the brain. Given that brain tumor segmentation from MRI scans typically involves poorly defined soft tissue boundaries, accurately segmenting brain tumors becomes exceedingly challenging.

II. LITERATURE REVIEW

Medical image processing, particularly when it comes to brain tumor identification, is hampered by the need to handle massive amounts of data. Treatment choices and survival rates for brain tumors are significantly improved by early detection. Nevertheless, the tedious and intricate process of manually segmenting tumors or lesions from the several MRI images produced in clinical practice takes time. A typical method for identifying brain tumors or lesions is magnetic resonance imaging, or MRI. It is difficult to precisely define the boundaries of soft tissues when segmenting brain tumors using MRI data. The goal of precise segmentation research is shared by researchers worldwide; neural network-based techniques are gaining traction and demonstrating promising outcomes.

In order to improve computation time, Devkota et al. [7] developed a thorough segmentation method that makes use of the spatial FCM algorithm and mathematical morphological operations. Even still, the results show an 86.6% classifier accuracy and a 92% cancer detection rate, even though the suggested remedy has not been evaluated. Yantao et al. [8] used a segmentation strategy based on histograms. There were issues in two modalities—FLAIR and T1—with regard to the brain tumor segmentation task as a threeincludes tumor with necrosis, tumor with edema, and normal-class classification (which tissue). Using the FLAIR modality's region-based active contour model, abnormal regions were found. Using the OK-method technique, edema and tumor tissues were identified within the aberrant regions based on contrast-enhanced T1 modality, yielding a Dice coefficient and sensitivity of 73.6% and 90.3%, respectively.

Badran et al. [9] used adaptive thresholding in conjunction with the Canny edge detection model to extract the Region of Interest (ROI) from a collection of 102 photos using region identification techniques. After preprocessing the photos, two neural network sets were applied, one using Canny edge detection and the other using adaptive thresholding. After the photos were divided, level numbers were assigned, and the Harris method was used to extract features. The neural network was then applied to two tasks: distinguishing between several types of malignancies and identifying regions that were either healthy or harbored tumors. When the outcomes of these two models were compared, the Canny edge detection method showed better accuracy. Pei and associates.[10] proposed an improved texture-based tumor segmentation technique in longitudinal MRI by utilizing tumor development patterns as new features. After extracting textures and intensity data, label maps were used to forecast cellular density and help with modeling tumor progression. The Dice Similarity Coefficient (DSC) with tumor cellular density was used to evaluate the model's performance, and the result was a score of 0.819302.

A model that combines learning vector quantization with a probabilistic neural network model was described by Dina et al. [11]. A dataset of 64 MRI pictures was used to evaluate the model's performance, of which 18 were used for validation and the remaining images for training. After the images were smoothed using Gaussian filtering, the updated PNN approach was able to reduce processing time by 79%.

Principal Component Analysis (PCA) was used by Othman et al. in their probabilistic neural network-based segmentation technique for feature extraction and dimensionality reduction [12]. This method involved first converting MRI pictures into matrices, then classifying the data using a probabilistic neural network. Performance analysis was then carried out with a test dataset of 15 subjects and a training dataset of 20 subjects. The accuracy was calculated using the spread value, which ranged from 73% to 100%.

By applying deformable models and fuzzy clustering to target regions, Rajendran et al. [13] used an improved probabilistic fuzzy C-means model with extra morphological operations and obtained 95.3% and 82.1%, respectively, in terms of ASM and Jaccard index. LinkNet network was utilized by Zahra et al. [14] for tumor segmentation. At first, they used a single LinkNet network for segmentation, applying it to all seven datasets. They presented a technique for CNN to automatically segregate the most frequent forms of brain tumors, removing the requirement for preprocessing stages and doing so without taking the viewing angle of the pictures into account. A Dice score of 0.79 was attained for several structures, compared to 0.73 for a single network.

III. Proposed Methodology

We provide a novel approach to brain tumor detection and segmentation that combines two different techniques. The first method divides the tumor into segments with Fuzzy C-Means (FCM) and then classifies it with conventional machine learning techniques.The second strategy, on the other hand, uses deep learning methods especially for tumor identification. Better results are obtained using FCM-based segmentation, especially for noisy clustered datasets [15]. It maintains more information even though it takes longer to execute.

A. Using Conventional Classifiers for Tumor Segmentation and Classification: A Proposed Methodology

In our first prospective model, we used a knowledge-acquisition algorithm to categorize and detect brain tumors, and then we compared classifiers within our model framework. Skull stripping, filtering and enhancement, segmentation using a fuzzy C-means algorithm, morphological operations, tumor contouring, feature extraction, and classification using conventional classifiers are the seven steps of our proposed brain image segmentation system. Our investigation produced results that were satisfactory. These are the main phases of our suggested model (Fig. 1), which will be discussed in the sections that follow.

The suggested technique for classification using traditional classifiers is shown in Fig. 1. 1) Skull Stripping: Since the MRI picture's background usually contains no useful information and greatly increases processing time, skull removal is an essential stage in medical image processing. In this study, we used a three-step procedure to remove the skull component from MRI pictures.

These three actions are as follows:

a) Otsu Thresholding: To remove the skull, we first used Otsu's Thresholding approach, which divides the image into the foreground and background by automatically calculating the edge value. The threshold used in this method is selected to minimize the intra-class variance, which is expressed as a weighted sum of the variances between the two classes.

b) Connected Component Analysis: To exclude the skull component, we used region analysis to separate the brain region alone after our skull stripping procedure.

2) *Filtering and Enhancement*:

Improving MRI picture quality while lowering noise is crucial for better segmentation accuracy, especially as brain MRI images are more prone to noise than other types of medical images. In this work, we used Gaussian blurring with filtering to improve segmentation performance by lowering Gaussian noise that is frequently seen in brain MRI images.

3) Fuzzy C-Means clustering method segmentation: We used this technique to divide up the data such that each piece of information may be assigned to two or more clusters. We now have a fuzz clustered segmented image, which guarantees better segmentation quality.

4) Morphological Operation: Rather than concentrating on the skull section, we targeted the brain component in order to isolate the tumor. We used morphological operations on our photos to do this. First, poorly related regions in the MRI picture were separated by erosion, creating several unconnected regions.

Thereafter, dilation was used.

5) Tumor Contouring: An intensity-based method called thresholding is now used to extract tumor clusters. With a dark background, the tumor site is emphasized in the final photograph.

6) Features Extraction: Two feature sets were extracted in order to aid in categorization. Texture-based characteristics were extracted from segmented MRI images, including dissimilarity, homogeneity, energy, correlation, and ASM. It was also possible to retrieve statistically based features such as centroid, implied entropy, skewness, kurtosis, and trending deviation.

7) Traditional Classifiers: K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naive Bayes, Random Forest, and Support Vector Machine are the six classic machine learning classifiers that we used to assess the accuracy of our suggested model in tumor identification.

8) Assessment Phase: Our model successfully isolates the Region of Interest (ROI) and separates the tumor component by utilizing several region-based segmentation methods and comparing them with our suggested segmentation strategy. An example that is representative of the full procedure is shown in Figure 5. We used six classification techniques after tumor segmentation and feature extraction. Notably, with an accuracy of 92.42%, VGG16 produced the best results.

B. Proposed Approach using CNNs

In medical image processing, convolutional neural networks (CNNs) are frequently used as researchers attempt to create models for more accurate tumor identification. Building a model that could accurately identify cancers from 2D brain MRI pictures was our main goal. We choose CNN for our model despite the fact that a fully-connected neural network would also be able to detect cancers because of its benefits in parameter sharing and connection sparsity.

We present and implement a tumor detection system based on a five-layer convolutional neural network. The most noteworthy result in tumor detection is produced by this composite model, which consists of seven phases including hidden layers. The suggested methodology is provided below with a brief explanation.

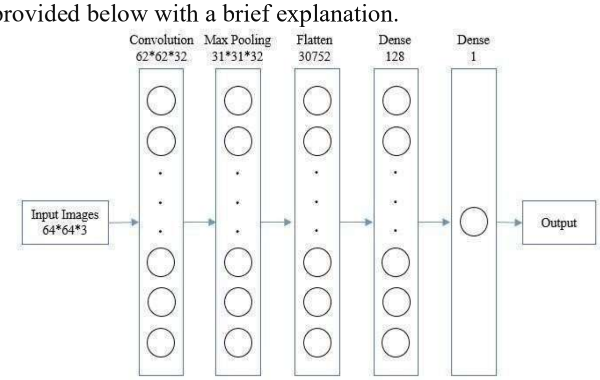


Fig. 2: 5-Layer Convolutional Neural Network-Based

Tumor Detection Methodology

because of its better convergence results. The second completely connected layer is the last layer in the model, coming after the first dense layer. In this case, the activation function is the sigmoid function, which keeps the total number of nodes at one. The goal of this choice is to improve execution time by using less processing power. Although the sigmoid function may hinder learning in deep networks, we reduce this danger by scaling the sigmoid function and lowering the node count to make this deep network's maintenance easier.

To put it briefly, Fig

We demonstrate how to separate the tumor from 2D brain MRI and compare our proposed machine learning and deep learning classification models to bolster our proposed model. With VGG-16, we obtained 92.42% accuracy, while

TABLE I. HYPERPARAMETER VALUE OF CNN MODEL

Stage	**Hyper-parameter**	**Value**
	Batchsize	32
	Epoch	10
	Steps per epoch	80

We build an input shape of 64643 for the MRI scans, starting with a convolutional layer, to provide consistent dimensions throughout all images. The 32 convolutional filters, each with a size of 3*3, are then integrated across 3channel tensors to generate a convolutional kernel, which is then applied to the input layer. ReLU is used as the activation function to guarantee that it has no effect on the output.

In order to lower the number of parameters and the network's processing time, we progressively reduce the spatial dimension of the representation in our ConvNet design. Overfitting can occur when working with brain MRI pictures, and the Max Pooling layer is a useful countermeasure. In the model, we use MaxPooling2D to handle spatial data that corresponds to our input image. The dimensions of this convolutional layer are 31*31*32. The input photographs are downscaled in both spatial dimensions, as specified by a tuple of two values for vertical and horizontal scaling, because the pool size is 2,2

After the pooling layer, a map of pooled features is generated. This is where flattening becomes important since we need to convert the whole matrix containing the input photos into a single column vector in order to process the data further. After that, the data is put into the neural network to be processed further. Dense1 and Dense-2, two nearly related layers, were used to symbolize the dense layers. The produced vector is used as the input for this layer of the neural network processing process in Keras, where the dense feature is implemented. 128 nodes make up the buried layer. In order to achieve optimal performance, we chose a comparatively small number of nodes, taking into account the computational resources required by our model. Thus, we get the optimum result with 128 nodes. ReLU is used as the activation function

International Conference on Neural Nexus and Synergy:Innovation in Emerging Technologies
Vol. 1. (2024). PP.199-213. SNIST

Algorithm 1: Evaluation process of CNN model

```
loadImage();
dataAugmentation();
splitData();
loadModel();
for each epoch in epochNumber do
    for each batch in batchSize do
        ŷ = model(features);
        loss = crossEntropy(y, ŷ);
        optimization(loss);
        accuracy();
        bestAccuracy = max(bestAccuracy, accuracy);
return
```

Fig. 4. Algorithm of the performance evaluation

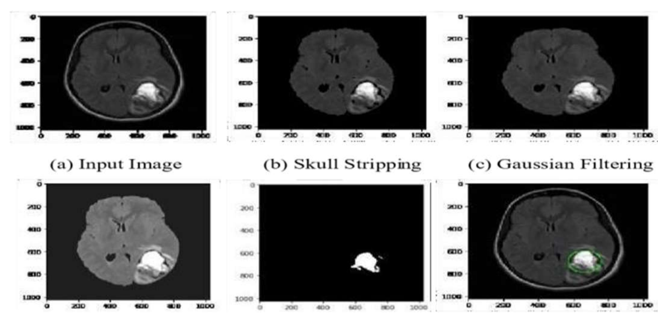
Working Flow Devised for Proposed Methodology

1. Load the input dataset
2. Adding a Convolution Layer with 32 convolutional filter
3. Passing the Convolutional kernel into the Max Pooling layer
4. Pooled feature map is used to get the single column vector
5. Processing of the vector in dense layer with 128 nodes
6. Final dense layer applying Sigmoid as the Activation function
7. Validation stage and Performance evaluation

Figure 3 shows how the suggested CNN Model operates.

We constructed the model and used the Adam optimizer with binary cross-entropy as the loss function to assess the model's tumor recognition capability. The algorithm used to evaluate the model's performance is shown in Figure 4. Table I contains a complete list of all hyperparameter values. A precision of almost 97.87% was reached.

Stage	Hyper-parameter	Value
Intializiation	Bias	Zero
	Weights	uniform
Training	Learning rate	0.001
	Decay	0
	Epsilon	None



(a) Input Image (b) Skull Stripping (c) Gaussian Filtering

I. EXPERIMENTAL RESULTS

International Conference on Neural Nexus and Synergy:Innovation in Emerging Technologies
Vol. 1. (2024). PP.199-213. SNIST

B. Image processing approaches for segmentation.

with CNN, we obtained 97.87% accuracy.

A. Trial Dataset We used the BRATS dataset [16] to evaluate the efficacy of our proposed model. Class-0 and class-1 represent MRI images of tumors and non-tumors, respectively. Tumor and non-tumor categorized MRI scans are designated as class-1 and class-0, respectively. Each image is an MRI obtained using a variety of modalities, including T1, T2, and FLAIR. By dividing the dataset in training and test photos by 70:30 for basic machine learning classifiers, we achieved the best results. For CNN, we divided the dataset in both 70:30 and 80:20 formations and compared the outcomes.

We successfully segmented tumors without losing any subtle information by applying our suggested methods. Since the function of the skull differs from that of the segmented brain tumor, its removal was essential for tumor segmentation. We also measured the tumor's diameter, convex hull area, and approximate null and ambiguous areas during this procedure. We were able to classify the pictures as normal or abnormal by extrapolating these qualities from the segmented MRI. The values of several features taken from the segmented MRI are shown in Table II.

We used statistical variables extracted from the photos, such as mean, entropy, centroid, standard deviation, skewness, and kurtosis, in addition to dissimilarity, homogeneity, energy, correlation, and ASM, for classification. Six common machine learning classifiers are presented in Table-III, with VGG-16 exhibiting the most noteworthy performance with an accuracy of 92.42%. In terms of specificity and precision, Naïve Bayes produced the greatest results; however, when compared to other performance measures, the difference with VGG-16 was small and insignificant. Successful feature extraction is indicated by additional performance indicators. We used six classifiers: VGG-16, Random Forest, Naïve Bayes, Multilayer Perceptron, Logistic Regression, and KNN. Of these, VGG-16 produced the greatest accuracy. Table-III shows the classifier performance and the confusion matrix..

Table II: Highlighted Aspects of Divided Tumor

Classifiers	Accuracy	Recall	Specificity	Precision	Dice Score	Jaccard Index
KNN	86.33	0.946	0.324	0.952	0. 947	0.948
Logistic Regression	86.54	0.943	0.234	0.234	0.965	0.832
Multilayer Perception	87.45	**1.650**	0	0.687	0.856	0.234
Naïve Bayes	74.59	0.656	**0.515**	**0.559**	0.670	0.780
Random Forest	85.35	0.655	0.567	0.587	0.686	0.562
VGG -16	**95.42**	0.684	0.828	0.635	**0.659**	**0.521**

Image No	Contrast	Dissimilarity	Homogeneity	Energy	Correlation	ASM	Label
1	241.18	1.24	1.21	0.79	0.39	0.79	1
2	94.36	0.63	0.78	0.88	0.94	0.98	1
3	367.39	1.68	0.98	0.97	0.82	0.95	1
4	335.59	2.34	0.94	0.92	0.90	0.86	1
5	169.37	0.82	0.98	0.96	0.96	0.93	0
6	578.59	2.44	0.95	0.93	0.97	0.85	0

TABLE III. CONFUSION METRICS OF THE CLASSIFIERS

A 2D magnetic resonance imaging (MRI) input image was chosen from the dataset. In order to properly capture the MRI features, the input image was first subjected to skull stripping (Fig. 1b) and then image enhancement (Fig. 1c). After that, noise was removed using a Gaussian filter (Fig. 1d) before the FCM segmentation method (Fig. 1e) and tumor contouring (Fig. 1f) were applied to define the Region of Interest (ROI), which is the tumor in Brain MRI. The tumor was classified using a variety of common machine learning algorithms following tumor segmentation.

C. Classification Using Machine Learning

We can differentiate between tumorous and non-tumorous MRI scans thanks to these characteristics. For classification, we used both statistical and texture-based characteristics. Precision and specificity, two texture-based metrics, differed from VGG-16 and other performance measures just slightly and insignificantly. Successful feature extraction is highlighted by additional performance indicators. Six classifiers were used in our approach: VGG-16, Random Forest, Naïve Bayes, Multilayer Perceptron, KNN, and Logistic Regression. VGG16 showed the highest accuracy. Table III provides specifics on the classifier performance and confusion matrix.

The next aspect assesses the performance – VGG-16 yielded the most favorable outcomes

$$\text{Accuracy}= \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

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

$$speficity = \frac{TN}{TN+FP} \quad (3)$$

$$precision(PPV) = \frac{TP}{TP+FP} \quad (4)$$

D. Categorization Making use of CNN

The suggested five-layer method shows a notable improvement in tumor identification. Convolution, max pooling, flattening, and two thick layers make up this CNN model. Before training the model, data augmentation was done because of CNN's translation invariance. A performance evaluation based on dataset division was carried out in two circumstances. The model's accuracy was 92.98% with a 70:30 split ratio and 99.01% during training. The accuracy in the second scenario was 97.87% and the training accuracy was 98.47% since 80% of the photos were used for training. Thus, our suggested model performs best when the split is 80:20. An overview of the suggested method's performance on CNN can be found in Table IV. Using our five-layer CNN model, we achieved an astonishing 97.87% accuracy. In contrast to our CNN model with five layers, we explored with alternative layer configurations, but the differences in the results were not statistically significant. Batch size, steps per second, processing time, and technique complexity all rose as the number of layers increased. Furthermore, we did not fine-tune the model because the accuracy plateaued after we initially set the dropout amount at 0.2. As a result, without using dropout, this model obtained the maximum accuracy.

TABLE IV. PERFORMANCE OF THE PROPOSED CNN MODEL

No	Training Image	Testing Image	Splitting Ratio	Accuracy (%)
1	152	65	70 : 30	92.98
2	174	43	80 : 20	**97.87**

The accuracy of our model during training and validation, as determined by the Keras callback function, is shown in Figure 6. We assessed the accuracy of the training and validation data over a range of epoch counts. After nine epochs, it was found that the model reached its maximum accuracy in both training and validation.

Fig. 6. Accuracy of the proposed CNN model.

E. Performance Comparison

Finally, we compared our suggested classification techniques with CNN and traditional machine learning classifiers. We also compared our findings to those of other research projects that made use of the same dataset. Seetha et al. [17] reported 97.5% accuracy using CNN and 83.0% accuracy using VGG-16-based categorization. CNN-based categorization and machine learning were both outperformed by our suggested method. Furthermore, our Dice score was 96%, whereas Mariam et al. [18] obtained roughly 95% dice coefficient.

TABLE V. PERFORMANCE COMPARISON

Methodology	Accuracy(%)
Seetha et al[17]	97.5
Proposed CNN Model	**97.87**

CONCLUSION AND FUTURE WORK

Because medical images can be very complicated, it is important to segment them when processing medical images. Our study concentrated on the use of MRI and CT scan images to segment brain tumors. Brain cancers are best classified and segmented using magnetic resonance imaging (MRI). In this work, we applied Fuzzy C-Means clustering, which has demonstrated efficacy in tumor cell prediction, to tumor segmentation. After segmentation, we classified the data using a Convolutional Neural Network in addition to conventional classifiers. The outcomes of several conventional classifiers, such as K-Nearest Neighbor, Logistic Regression, Multilayer Perceptron, Naive Bayes, Random Forest, and Support Vector Machine, were used and contrasted in the traditional classifier section. With an accuracy of 92.42%, VGG-16 outperformed the other conventional classifiers.

In order to improve our results even further, we applied CNN, which achieved a 97.87% accuracy rate using an 80:20 split ratio of 217 photos, of which 80% were training images and 20% were test images. In the future, we hope to investigate 3D brain scans for more accurate brain tumor segmentation. Managing a larger dataset is difficult, but our goal is to curate a dataset that emphasizes abstraction and is specific to the features of our country. This plan will help us finish our work more quickly.

References

[1] Dina Salama, Hany Kasban, and Mohsen El-bendary (2015). "A Comparative Study of Medical Imaging Techniques." International Journal of Intelligent Systems and Information Science, 4, 37–58.

[2] In J. Clerk Maxwell's "A Treatise on Electricity and Magnetism," third edition, volume 2. Clarendon Press, Oxford,

[3] "Evaluation of Image Segmentation Performance using Objective Methods," D. Surya Prabha and J. Satheesh Kumar, Indian Journal of Science and Technology, Vol. 9(8), February 2016.

[4] Cancer.Net Editorial Board, "Brain Tumor: Statistics," November 2017 (accessed January 17, 2019)

[5] On the topic of Advanced Brain Tumor Segmentation from MRI Images, Kavitha Angamuthu Rajasekaran and Chellamuthu Chinna Gounder conducted research in 2018.

[6] "General Information About Adult Brain Tumors." NCI. 14 April 2014. On July 5, 2014, the original content was archived. accessed on June 8, 2014. Date of access: January 11, 2019

[7] "Mathematical Morphological Reconstruction for Early Stage Brain Tumor Detection through Image Segmentation," By B. Devkota, Abeer Alsadoon, P.W.C. Prasad, A. K. Singh, and A. Elchouemi, presented at the 6th International Conference on Smart Computing and Communications, ICSCC 2017, December 7-8, 2017, Kurukshetra, India.

[8] The Technical Writer's Handbook, M. Young. 1989; University Science, Mill Valley, CA.

[9] Yantao Song, Ji, Zexuan, Sun, Quansen, and Zheng Yuhui (2016). "A Novel Model for Brain Tumor Segmentation from Multi-Modality MRI Using a Level-Set-Based Approach." DOI: 10.1007/s11265-016-11884 in Journal of Signal Processing Systems, volume 87, issue one.