# Brain tumor segmentation and classification Using mrimages

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**ABSTRACT**
Brain tumors impact the brain and spinal cord, making them one of the most severe cancers. Many computer vision techniques have been proposed to aid early diagnosis and reduce surgical intervention. However, these approaches struggle with segmentation and classification of brain tumors in magnetic resonance imaging (MRIs). A new automated brain tumor detection and classification method is proposed in this research. The system includes augmentation, segmentation, and classification. These parts finish the system. An MRI picture is corrected during the enhancing phase using Adaptive Histogram Equalization (AHE). U-NET was needed to distinguish aberrant cells from healthy brain tissue to complete segmentation. The brain tumor's HGG or LGG status was determined using 3D-CNN. To validate the Brats-2015 dataset-based system, many tests were run. The system achieved segmentation accuracy rates of 97% and 99% using 5-fold and 10-fold methods, respectively, resulting in a Dice Similarity Coefficient (DSC) accuracy rate of 99.8%.

**Keywords**: classification, image processing, medical image, segmentation, neural network

**INTRODUCTION**
Due to the fact that brain tumors can be fatal at more advanced stages, detecting and categorizing them is a work that is both crucial and required. The development of an effective treatment approach and the arrival at an accurate diagnosis are both of the utmost importance. On the other hand, manual segmentation is a method that is not only time-consuming but also difficult, prone to human error, and even occasionally subjective [1]. The numerous characteristics of brain tumors, such as their location, form, size, and consistency, are among the factors that contribute to this condition. According to projections, the annual tumor incidence rate in Turkey was around 100,000 cases in the year 2018 [2]. Meningiomas, gliomas, astrocytomas, and ependymal tumors are some of the several types of brain tumors that may be found and classified [3]. On the other hand, gliomas are the most prevalent kind of brain tumor, with 5909 cases being documented by the National Cancer Statistics Unit of the Turkish Ministry of Health. This particular patient population has a mortality rate of 86%.
In addition, tumors of the central nervous system (CNS) rank as the tenth most frequent malignancies that cause death in males, with an incidence of 5.2% per 100,000 persons. In spite of this, the incidence of central nervous system malignancies among women was only 4.1% per 100,000 individuals [2]. According to the categorization system used by the World Health Organization (WHO), brain tumors can be divided into two distinct categories: high-grade glioma (HGG) and low-grade glioma (LGG) [4]. Computer vision techniques and medical imaging are two methods that may be utilized in the classification of these disorders. Through the use of several imaging modalities, medical professionals are able to identify and assess malignancies at various stages of their metastatic dissemination. There are many different types of image capture modalities, some examples of which are positron emission tomography (PET), computed tomography (CT), and magnetic resonance imaging (MRI). In spite of this, magnetic resonance imaging (MRI) is still widely accepted as the most comprehensive and frequent method for routinely evaluating illnesses. This is done in order to precisely diagnose tumors and offer suitable assistance for surgical treatments and radiation planning according to the kind of tumor [5].
When magnetic resonance imaging (MRI) pictures are recorded in three dimensions, a Region of Interest (ROI) that is solely focused on the tumor is created [6]. As a consequence of this, several initiatives have been proposed in order to acquire and categorize the tumor using an automated method. By utilizing Deep Learning (DL) and Artificial Intelligence (AI) approaches, it is possible to automate the process of determining the type of tumor that is present. There have been several applications of these methods in a wide range of sectors, the most prominent of which being medicine. It was found that their use in the field of bioinformatics and the analysis of medical pictures to provide assistance with the identification and diagnosis process was rather successful. It is now much simpler for individuals to monitor the efficacy of

treatment and to increase the accuracy of diagnostics thanks to the advancements made possible by digital libraries [7].
Additionally, deep learning is a significant tool in a variety of medical domains, including as pathology, brain tumors, and lung cancer, among others. In this regard, the manual process of processing pictures of brain tumors may be finished image by image, and it takes at least twelve minutes for each tumor to be processed. In addition, the semi-automatic can work for somewhere between three and five minutes [8]. It is for this reason that this work provides a novel technique for the automated segmentation and categorization of brain tumors, which makes use of magnetic resonance imaging. In order to improve the contrast of the magnetic resonance (MR) pictures, adaptive histogram equalization (AHE) was performed to them. More specifically, the 3D Convolutional Neural Network (3D-CNN) was utilized for the purpose of classification in this investigation, whilst the U-Net method was utilized for the purpose of segmentation. The application of computer vision (CV) on medical pictures is extremely beneficial to the early identification of a wide variety of diseases [9]. By assisting physicians in the analysis of the crucial metrics and traits, it enables them to classify patients in a more expedient and accurate manner [10]. The creation of an automated system for the detection of brain tumors has proven to be an issue that has been persistently difficult to solve over the course of many years. Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Clustering Mean (FCM), Random Forest (RF), and Convolutional Neural Network (CNN) are some of the approaches that have been developed for the purpose of brain tumor classification utilizing magnetic resonance (MR) data. The study demonstrated how classification may be accomplished through the utilization of Discrete Wavelet Transform (DWT) and Convolutional Neural Networks (CNN). For the experimental investigation, there were a total of five datasets examined [11]. An accuracy of 94.07 was achieved by the utilization of neural network and KNN algorithms in order to identify and categorize abnormalities that were associated with brain tumors [12].
An approach to detecting brain cancers through the utilization of a multiclassifier was presented[13]. This approach involved selecting features based on entropy. In the evaluation that was conducted using 5-10 cross-validation, the model attained accuracy rates of 84.7% and 99% respectively. In a dataset consisting of fivefolds, the accuracy of the model was 87%, but in a dataset consisting of tenfolds, it was 99%. The performance of the model is going to be determined by the multiclassifier that is getting used. It was possible to achieve an accuracy of 92.03% through the utilization of gray level co-occurrence matrix (GLCM) applications for segmentation and classification applications [14]. An investigation was conducted using a fusion technique that was based on NSCT, and the results showed that the accuracy of segmentation and classification was 96% [15]. The findings of the research provided an explanation of how to improve MR images by utilizing three distinct methods. The Otsu approach, which employs discrete wavelet transform for computation and pixel thresholding for segmentation, was applied for the purpose of classification.
The classification was successful in meeting a criterion for flair modulation that was 84%. As a result of processing MRI pictures with BWT and SVM algorithms for de-noise imaging and skull stripping, the approach described by Bahadure et al. [16] is able to obtain an accuracy rate of 95%. Wang et al. [17] introduced a hybrid CNN-KNN model for classification, which had a prediction accuracy of 96%. This model was used for classification. The segmentation of brain tumors is recommended to be done using a novel u-net model. u-net optimization and data augmentation are both combined in this approach through the utilization of the Adam optimizer. It was determined that the Dice Similarity Coefficient (DSC) for the whole tumor was 86% [18]. Generative adversarial networks (GAN) were used in an end-to-end application that was recommended for the purpose of MRI image segmentation of brain tumors [19]. This application achieved a DSC of 82%.
A deep neural network (DNN) was utilized in order to generate a segmented magnetic resonance imaging (MRI) image that was divided into various patches [1]. The overall accuracy that was achieved for Brats-2015 was 95% on average. In point of fact, there are a number of challenges involved in the classification and segmentation of brain tumors. According to the findings, the high segmentation rates were caused by a number of different aspects, such as the modality of the input picture, the approach for feature extraction, and the technique for image enhancement. As a consequence of this, the machine learning approach does not have access to sufficient data to accurately detect the tumor [20].

**MRI Segmentation and Classification Framework**

The proposed framework proposes to manage a wide variety of procedures, including the segmentation and classification of brain tumors, to name just two of them. For the former, it is necessary to have an accurate rate of tumor detection, while for the latter, it is necessary to have an accurate rate of categorizing the types of tumors. The pre-processing, segmentation, and classification processes are the three primary components that make up this system. Figure 1 depicts the architecture of the proposed system as well as the primary procedures involved in its implementation.

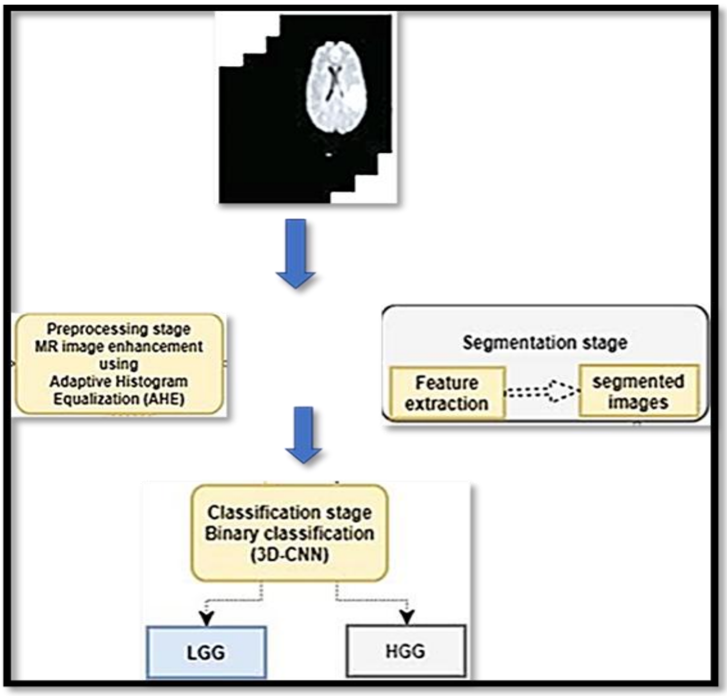


**Fig 1.** Proposed flow schematic diagram for brain tumour classification and segmentation

**Preprocessing**

The data from the MRI is shown in MHA format, which is a medical image format that is utilized by the Insight Segmentation and registration toolkit as well as other graphic visualization applications that are relevant to healthcare. Since this is the case, in an effort to enhance the digital approach and the quality of the pictures. There is a correlation between the amount of contrast augmentation and the image quality. The end effect is that every single magnetic resonance imaging (MRI) scan has issues with lesser contrast or clarity, and this is true independent of the equipment or shooting strategy that was used. These issues are addressed by employing pre-processing approaches for the purpose of diagnosis and improvement. These methodologies make use of Adaptive Histogram Equalization (AHE), which acts on tiny data sections (tiles) rather than the complete image. The precise dimensions of a local window are analysed by the HE mapping function in order to get the increased density value for each individual window. The phrase "local operation" is an excellent way to express it. During the course of the implementation procedure, there were five stages. Examine the grayscale image that has been presented and determine the frequency with which each conceivable value appears in the pixels that are next to it. It is necessary to compute the cumulative probability of being associated with a superior subset of these values, as well as the possibility of a value that is not found anywhere else. When everything is said and done, the maximum potential value is the sum of all the different outcomes that might occur when each beginning value is replaced with the value that corresponds to it.

**Tumor Segmentation Based On U-NET**

A fully convolutional neural network (CNN) architecture serves as the foundation for the United Network (U-Net) approach, which is frequently utilized for the purpose of biological image segmentation. In the process of segmentation, the primary purpose is to separate the necrotic core, active cells, and edema from the healthy brain tissues that are associated with the tumor. Prior to the use of convolutional methods, the input MRI borders were initially zero-padded. As a result of the utilization of zero-padding, the resolution of the input size and the resolution of the output size possess the same level of precision. We will then be able to forecast all of the pixel labels simultaneously through the process of forward propagation of the data, which will eliminate the requirement for mirroring or the overlap-tile approach. Furthermore, the updated U-NET is made up of five convolutional blocks inside its structure. A three-by-three filter that has a value of one in both directions and two convolutional layers that are activated using rectified linear unit (RELU) are the components that make up each block. Activation like this helps to increase the number of characteristics from one to ten thousand twenty-four. In addition, a batchnormalization regularization approach is employed between every two convolutional layers in order to improve the accuracy of the network and make it easier for U-Net training to take place. During the down-sampling process, the max-pooling technique makes use of a stride. A deconvolution layer is included at the beginning of each and every up-sampling block. The up-sampling approach involves increasing the size of features by a factor of two, which results in a reduction of features by a factor of half. Through the utilization of the U-net model, the images were successfully classified as background, edema, necrotic, non-enhancing, or enhancing. Without supervision, the Neural Network Methodology is being used. A metric known as balanced cross-entropy is utilized throughout the training process [21]. The Dice Similarity Coefficient (DSC) was selected as the statistic to be used for determining correctness. Within the initial version of U-NET, the default optimizer that was utilized was known as stochastic gradient descent (SGD), and its purpose was to minimize the cost function with regard to the parameters that were supplied. The RMSProp optimizer is used to make adjustments to the weight parameter for the suggested U-NET, which operates at a learning rate of 0.001.

**Tumor classification based on 3D-CNN**

As input for the classification step, the result from the previous phase will be applied, and the segmented pictures will be superimposed over the MRI scans that have been pre-processed. Through the process of attaching the segmentation results to the dataset, the neural network is able to get access to more data. Additionally, by combining pixels from many layers, 3D convolutional layers make it possible for the neural network to identify distinctive characteristics that are seen throughout the training process. The output of the final 3D convolutional layer may then be flattened. The Sigmoid activation function is utilized by the solitary neuron that makes up the output layer of the neural network. The outcome is restricted to the range of values between 0 and 1, which represents the probability that the input is a member of the HGG with LGG class. The Rectified Linear Unit (RELU) activation function is utilized in the training process before the convolutional layers of the network are learned. In order to prevent overfitting to the highly distinguishable traits that are present in the training dataset, the model incorporates a number of different algorithms for identifying the kind of tumor. There are three dropout levels, and each one has a dropout rate of twenty percent. This guarantees that the lack of particular qualities from the testing dataset will not have a major influence on the predictions that the model makes with regard to those attributes. Training the suggested neural network is accomplished by the utilization of a supervised technique, which is dependent on the output of the neural network. The cost function of the network is referred to as cross-entropy. Within the context of this evaluation, we made use of assessment performance [22]. The Adam algorithm is an optimizer that is utilized to reduce the weights that are associated with a certain parameter using the Adam method. Totaling one hundred training iterations, the cross-validation models were put through their paces.

**Evaluation performance**

I necrosis, II edema, III non-enhancing tumor, and IV enhancing tumor are the four area-labels that make up a whole tumor. Necrosis is the first area-label, followed by edema, and then enhancing tumor. The validation of these four area designations was accomplished through the use of seven performance metrics. In the course of the segmentation phase, the suggested system was evaluated using DSC in order to determine its level of accuracy and sensitivity. Accuracy, Sensitivity, Specificity, DSC, FNR, and FPR were the seven metrics that were utilized in order to assess and compute the classification phase [23]. Those pixels that did not include any tumor were referred to as True Negative (TN), whereas those that contained the entire tumor were referred to as True Positive (TP) for values ranging from 1 to 7. While the False Negative (FN) group comprises areas that were not recognized and categorized by the proposed approach, the False Positive (FP) category includes malignancies that were incorrectly diagnosed. Both of these categories are referred to as "false negatives." The detail of the performance review is provided in the following paragraphs:

$$\text{Sensitivity} = TP/(TP+FN) \quad (1)$$

$$\text{Specificity} = TP/(TN+FP) \quad (2)$$

$$\text{Accuracy (ACC)} = TP+TN/(TP+TN+FP+FN) \quad (3)$$

$$FPR = 1-\text{Sensitivity} \quad (4)$$

$$FPR = 1-\text{Specificity} \quad (5)$$

$$JSI = TP/(TP+FN+FP) \quad (6)$$

$$DSC = 2TP/(FP+2TP+FN) \quad (7)$$

**RESULTS AND DISCUSSIONS**

For the purpose of evaluating the proposed framework for segmentation and classification tasks, the Brats-2015 dataset [24] was utilized in a variety of different experimentations. There are 218 instances that fall under the HGG category in the Brats-2015 dataset, whereas there are 52 instances that fall under the LGG category. A comprehensive review of the brain tumors that were included in the Brats-2015 dataset is shown in Table 1. Therefore, the outputs of segmentation and classification procedures are assessed in terms of accuracy, sensitivity, specificity, and other significant features in the following subsections.

**Table 1.** Brats-2015Dataset

| No. of cases | Cases (HGG) | Cases (LGG) | Total images |
|---|---|---|---|
| 270 | 218 | 52 | 42.470 |

The Se Sequences were created by utilizing Time to Echo (TE) and Repetition time (TR). An adaptive histogram equalization approach was utilized to enhance the contrast in order to improve the overall quality of the pictures that were produced for the purpose of more precise segmentation and classification. The approach has effectively proven its potential to improve the images, as illustrated in Figure 2.

**Segmentation results**

During the segmentation step, the data was separated into two distinct groups: the training group and the testing group. When adopting the paper technique, twenty percent of the total was utilized for experimental testing, while eighty percent was used for training. The findings are shown in Table 2, along with a comparison to any previous research investigations. The suggested research was successful in achieving a DSC average segmentation accuracy of 99.6%, as well as a sensitivity of 99.2% and a specificity of 99.4 percent. using the examination of significant characteristics, the segmentation algorithm was able to identify the location of the tumor. This was made possible by the effective augmentation of picture contrast that was achieved using the picture optimization technique. U-NET operates on a per-pixel basis and is completely automated in its operation. Compatibility with the input photos is ensured, and the requirements of the algorithm are satisfied, thanks to the addition of zero padding to the images. At the end of the day, this strategy not only enhances comprehension but also makes it possible to extract all of the characteristics in a more exact and comprehensive manner. This table presents a comparison with three current studies that have been conducted on the segmentation of brain tumors.


**Fig 2.** Proposed adaptive histogram equalization(AHE)usingMRimages.A- Original images, B- (AHE) images

**Table 2.** Comparison With Existing Studies Of Segmentation

| Result | DSC | SE | SP |
|---|---|---|---|
| **Proposed** | 99.6 | 99.2 | 99.4 |
| **[1]** | 95 | 95 | 95.2 |
| **[18]** | 86 | - | - |
| **[19]** | 82 | - | - |

Using deep neural networks (DNN), the approach that was developed by Amine et al. [1] places a restriction on the amount of information that can be recovered by the DNN. This restriction is imposed by the partitioning of MRI images into areas, which is accomplished by the utilization of both techniques. The utilization of the U-NET segmentation neural network throughout the entirety of the picture resulted in an improvement in the level of comprehension of the segmentation process. The information that was given above was collected by utilizing the segmentation approach that was greatly improved. The severe working conditions of the MRI equipment also result in pictures that are characterized by a high degree of similarity. This is another characteristic of the images that are created. As a result of the employment of data augmentation technology by Dong et al. [18], the segmentation paradigm became more complicated. This was a consequence of the utilization of the technology. In addition, the quality of the segments that were created was poor since it was necessary to control the imposed variability rather than giving priority to the distinctive qualities of the inputs. This resulted in a compromise of the quality of the segments that were formed. Although Chen et al. [19] attempted to obtain a high degree of accuracy in tumor segmentation by using Multi-Layer Perceptron-based post-processing with two current architectural techniques, namely Deep Medic and U-NET, they were not successful in accomplishing this goal.

**Classification results**

Following this, the succeeding section provides an illustration of the outcomes of the classification step in relation to operational KPIs. To put the classification strategy into action, the cross-validation method is utilized in conjunction with the three-dimensional convolutional neural network (CNN) for binary classification. In this method, the tumor is categorized as either 0 (LGG) or 1 (HGG). Fivefold and tenfold validation were the two cross-validation approaches that were utilized in order to evaluate the results of the testing in question. The approaches that were utilized in order to carry out the calculation of the mean classification performance metrics are presented in Table 3. These methodologies include accuracy, specificity, sensitivity, DSC, and JSI. In addition, this table presents a comparison of the findings obtained from the suggested approach with those obtained from other methodologies that are considered to be state-of-the-art technologies. Because of this, the suggested approach produced good outcomes in contrast to other methodologies that were already in use with relation to categorizing techniques. The application of 10-fold cross-validation resulted in a considerable improvement in the accuracy of the prediction of tumors. Based on this conclusion, it appears that increasing the amount of training data that is accessible to the neural network contributes to an improvement in its ability to extract information. As a result, the properties of the inputs are more accurate, and they are able to analyze the MRI pictures that are included in the testing dataset in a substantially more efficient manner.

**Table 3.**

| **Result** | **DSC** | **SE** | **SP** | **JSI** | **ACC** |
|---|---|---|---|---|---|
| Proposed – 5-fold | 97.5 | 97.2 | 98.4 | 95.5 | 96.5 |
| Proposed -10-fold | 99.2 | 99.4 | 96.8 | 98.4 | 98.6 |
| 5 -fold[12] | 85 | 92.02 | 88.2 | - | 90.2 |
| 10 – fold[12] | 99.8 | 99.2 | 99.4 | - | 99.9 |
| [25] | - | 95.9 | 96.8 | - | 96.5 |

The suggested technique performed better than the methods that are currently considered to be state-of-the-art for classifying brain tumors, particularly in situations when there was insufficient exposure to training data. As an illustration of this characteristic, consider the fact that the accuracy drops to a lower amount when the number of pleats is decreased from ten to five. Due to the huge drop in the number of training instances that occurs as a consequence of this size reduction, the neural network's capacity to extract distinguishing properties is greatly hindered. It was established by Amine et al. [15] that the effectiveness of the classifier was dramatically reduced as the number of pleats dropped. This limitation on the dependability of the technology is especially relevant when it is applied in applications that are used in the real world and the training dataset does not contain any MRI pictures.

CNN, which is used for feature extraction, and KNN, which is used for classification, are the two algorithms that are combined in Srinivas and Rao's [26] experiment to create the approach that they suggest. KNNs are a type of indolent learning that use the training data to evaluate classification. They are used to determine the classification. In addition, this strategy is limited since it is necessary to categorize and train all of the data before making any predictions. As a result, the approach that was suggested has demonstrated an excellent capacity to extract distinguishing traits, even in circumstances when the collection of training instances is limited. In addition, the incorporation of segmentation results into the 3D-CNN has resulted in an enhancement of the neural network's capability to gather precise information, which has enabledit to enhance its performance in a manner that is both consistent and superior.

## CONCLUSION

Within the scope of this article, a novel method for the segmentation and classification of brain lesions is provided. It is possible to precisely determine the HGG and LGG grades of the tumor by the utilization of MRI modalities. For the purpose of enhancing contrast in magnetic resonance imaging (MRI) images, this research proposes a comprehensive approach for performing adaptive histogram equalization (AHE). Additionally, a technique of segmentation that is totally automated and makes use of the U-NET algorithm was developed. By providing a method that is both reliable and effective in segmenting the whole tumor zone, our strategy outperforms the accuracy of manually demarcated ground truth. It is advised that a revolutionary fully-automatic three-dimensional CNN that has good accuracy be used for classification. Through the utilization of four distinct modalities of magnetic resonance imaging (MRI) pictures, this approach integrates the output of the segmentation model as input for the convolutional neural network. The dataset from Brats-2015 was utilized in the studies that were conducted out. The validation was performed with the help of a framework that utilized both 5-fold and 10-fold cross-validation. Through the implementation of the notion that has been proposed, the process of developing a brain tumor segmentation and classification model that is patient-specific and does not require human verification is simplified. Clinical duties such as diagnosis, patient monitoring, and action planning are reduced in complexity as a result of this discovery. For the purpose of validating the method, the following phase will include applying the framework that was recommended to the private dataset.

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