CONTENT-BASED TUMOR IMAGE RETRIEVAL SYSTEM FOR MRI BRAIN TUMOR IMAGES USING CONVOLUTIONAL NEURAL NETWORK

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Abstract

The MRI has established excellent proficiency in detecting tumors, with vast numbers of MRI tumor images formed each day globally. The content-based tumor image retrieval (CBTIR) system has shown significant potential in medical image analysis This paper proposes a CBTIR method using ResNet50 for a hasty and precise image retrieval process. We tried several popular ResNet models, which were resolute as the optimal option. The CE-MRI data set is used for the assessment of the proposed work and results in retrieval precision values of 98.33% with Euclidean distance metrics compare to other state-of-art conventional methods.

keyword: Content-based image retrieval, CNN, MRI, Tumor images, Tumor retrieval

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1. Introduction

In recent decades, medical imaging technology has reached unimaginable development and they are more convenient for analyzing clinical data and planning treatment. Due to these rapid developments, the clinics produced a vast amount of data every day which will create a delay in the clinical process. For that, in medical imaging, researchers have shown interest in the content-based image retrieval system (CBIR), such as MRI, X-ray, and CT[1]. It might be difficult for radiologists to manually retrieve an MRI from a large imaging data collection of images with comparable structures or appearances. The obtainability and ability of the radiotherapist who reviews and retrieves the tumor images of the pertinent from the stored data will regulate this. For a sizable volume of stored data, this manual retrieval process is inefficient, difficult to repeat, and time-consuming. To solve this issue, automated CBIR could index archival images with the least amount of radiologists' involvement. In this study, we concentrate on tumor retrieval. Based on the image represented by the radiotherapist, the CBIR system extracts the exact tumor images. The radiotherapist fetched the exact or similar images and their diagnosis history from the repository for the new case. The three forms of brain tumors with the greatest proportion are included in the CE-MRI dataset [2] used in this investigation. Glioma, meningioma, and pituitary tumor incidence rates are around 45%, 15%, and 15%, respectively, of all brain tumors in clinical practice.

The CBIR system has two furthermost important processes they are feature extraction and distance measurement. Different variety of approaches was used for the feature extraction process one of them is traditional machine-learning approaches. It divides the features into two categories. The first kind is called a local feature [3] and is based on the texture characteristics of the image and intensity levels. These features include first-order statistics and second-order statistics obtained from shape, wavelet transform, Gabor, gray-level co-occurrence matrix (GLMC), and other factors. Because many forms of brain tumors have a related aspect and type that might differ in some factors such as boundaries, consistency, dimensions, and shape, these qualities are low-level and have little representational capacity. The global features are extracted in the other types. such as BoW [4], Fisher vector[5], and scale-invariant feature transformation [6], and they are also used to extract the statistical features from the images.

Researchers have proposed several methods to retrieve images from a large dataset or repository. Rao et al. [7] have developed an image retrieval method using a deep learning neural network (DLNN). They used the Brownian motion weighting DLNN (BMWDLNN) as a classifier and the Canny steerable texture filter (CSTF). Primarily, noises that appeared in the images are removed by using Modified Kuan Filter (MKF) and enhancing the contrast of the image. Then, the features of the images are taken out via CSTF. They achieved a 0.9981 average precision rate for the tested images. Sampathila et. al[8] have been proposed a method to retrieve tumor images by using the e K-Nearest Neighbour algorithm and achieved the average accuracy of 95.5% test results for the OASIS open-source repository images.

Kumar and Raman [9] developed a CBIR system to retrieve medical images by using a gray-Level Co-Occurrence Matrix (GLCM), Discrete Wavelet Transform (DWT), and the principal component analysis (PCA). The test results were obtained from different types of medical images and achieved 99 % accuracy. Deepak et. al[10] developed a methodology to retrieve MRI tumor images by using GoogleNet. The test results were obtained by using Figshare datasets and attained a 97.3 precision rate. Swati, Zar Nawab Khan, et al.[11] established a system to retrieve the MR brain images by using a deep convolutional neural network(DCNN) VGG19 and applying closed-form metric learning(CFML) to calculate the similarity among the query and repository images. The test results were obtained by using the CE-MRI image dataset and achieved 96.13 % of the mean average precision value compared to the existing methods. Cheng, Jun, et al[12] have been developed a methodology to retrieve brain tumor images by using the adaptive spatial division method, fisher kernel basis, and CFML algorithm. The test results were obtained using 3064 MRI brain tumor images and achieved mean average precision of 94.68% compared to state-of-art methods. Retrieval of the brain tumor images is a little bit difficult task. Here we proposed a content-based tumor image retrieval (CBTR) methodology for the tumor image retrieval from the extensive repository using a DCNN ResNet50 with Euclidean distance metrics for similarity measurement.

The remaining particulars of the paper are ordered as follows. The proposed work was deliberated in Section II. The performance of the CBTIR system and outcomes are shown in Section

III. Finally, Section IV contains the conclusion of the CBTIR system.

2. Methodology

We proposed a CBTIR system for similar tumor image retrieval from the repository. In this work, we use a transfer learning concept and Euclidean distance to calculate the similarity among the repository image and query image. ResNet50 is a pre-trained CNN used to extract the MRI tumor image features. ResNet50 is a variant of the ResNet model that has one max and average pool layer with 48 convolution layers. It is a widely used ResNet model. ResNets were initially applied to the image recognition task and then also used for image classification, object recognition, and localization. Figure 1 shows the structure of ResNet50.Using this ResNet50 we retrieved the brain tumor images from the datasets.

Figure 2 represents the proposed work respectively. As mentioned in above figure 2 the goal of the CBTIR system is to extract images from a repository that are similar to a given query image. Initially, we process the training repository to extract the image features. Then the extracted features are stored in a repository. After that, we process the test dataset and extract the features of the query image. These features are compared with the features already extract from the training datasets. This process is known as similarity measurement. The similarity among these features is calculated by the different types of similarity measure and distance measure algorithms such as histogram similarity, similarity matrix, visual similarity [13] and Euclidean distance, Manhattan distance, and confusion matrix[14]. In our proposed work we use Euclidean distance metrics for better accuracy in a tumor retrieval system (TRS).

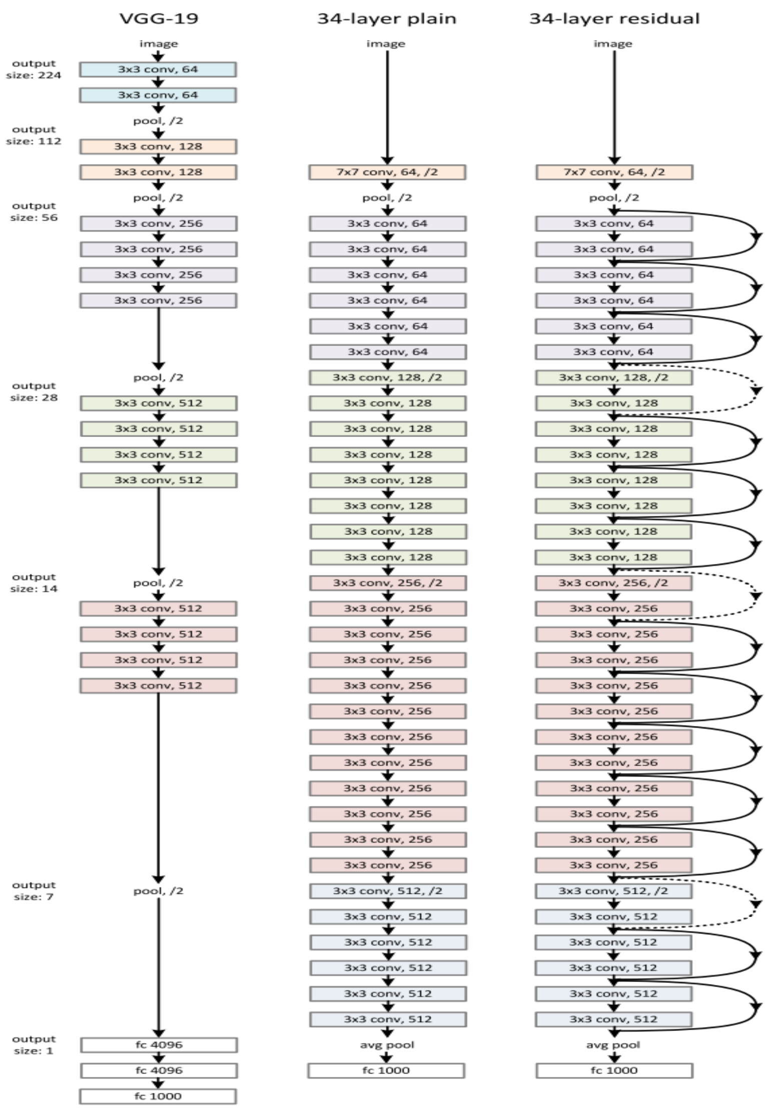


Figure 1 The architecture of the ResNet50

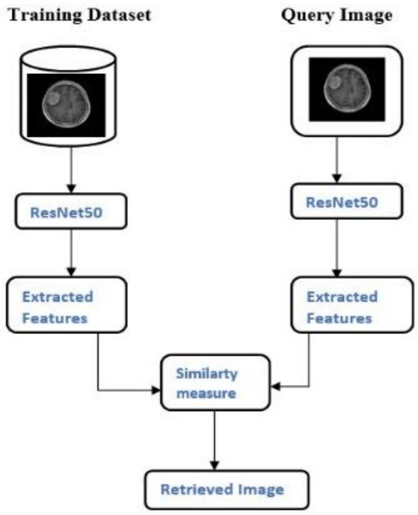


Figure 2: The framework of the proposed work

3. Results and discussion

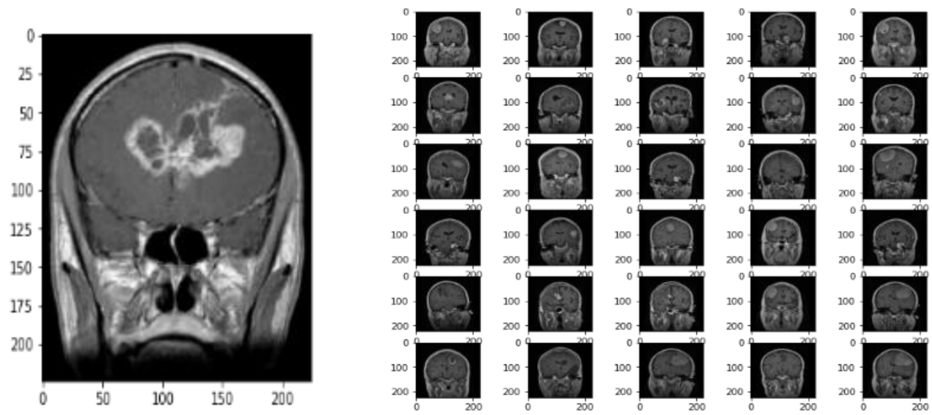
In our proposed work we use a transfer learning concept using all variants of the ResNet models and test the results with the CE-MRI dataset[2]. We test our proposed work with all resnet models such as resnet 50, resnet 50 v2, resnet 101, resnet 101v2, resnet152, and resnet152v2 with Euclidean distance metrics (ED) to know which model gives a better outcome for the CBTIR system. CBTIR system retrieves the tumor images by using the resnet model. This model automatically extracts the features in the images for both training and testing images. In this process, similarity measure is most important to retrieve similar images from the repository it will be done by using Euclidean distance metrics. Generally, the similarity is calculated in the range of 0 to 1 [0,1] and is known as the similarity score. The key deliberations of similarity are given below:

S = 1 if P = Q

S= 0 if P ≠ Q

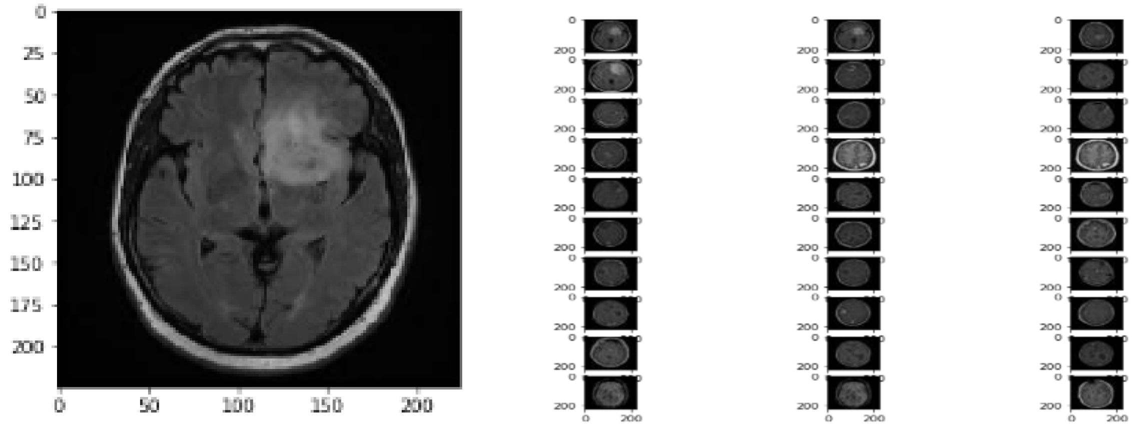
Where P and Q are two substances, S denotes similarity.ED is one of the simple and best distance-measure techniques When data is compressed or constant. The ED among the points is the length of the trail linking them. The distance among the points will be given by the theorem of Pythagorean.

For the initial level, our work is set to retrieve 30 images then it will be set to 100,300 and 1000 in a single time. Figure 3 shows the outcome of the resnet50 model in this figure a represents the query image and b represents the retrieved images which are similar to the user query image. In this model, we retrieved 30 similar images for test purposes. The resnet50 model retrieved 30 similar shapes of MRI brain tumor images out of 30 images at the same time it does not retrieve a single exact tumor image that matches the query image.



(a) Query image (b) Retrieved Tumor Images

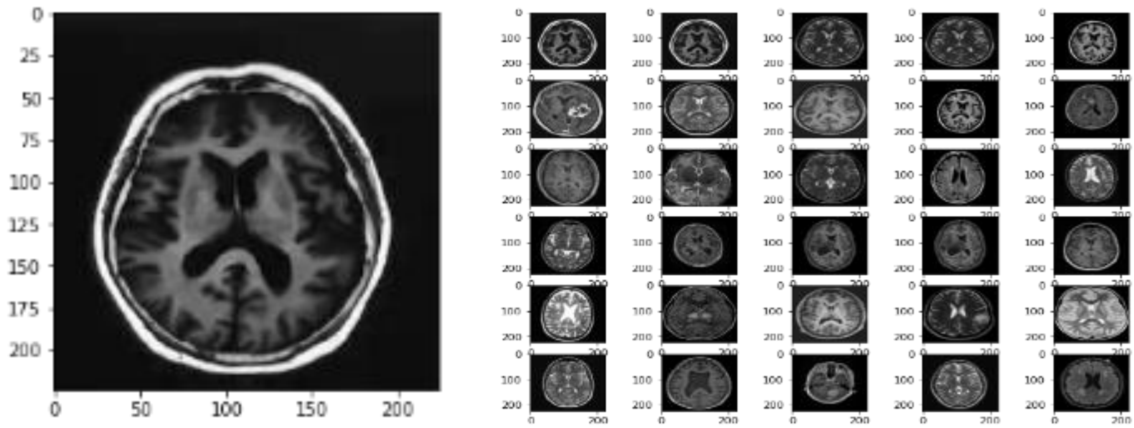
Figure 3: Visual representation of the proposed work ResNet50



(a) Query image (b) Retrieved Tumor Images

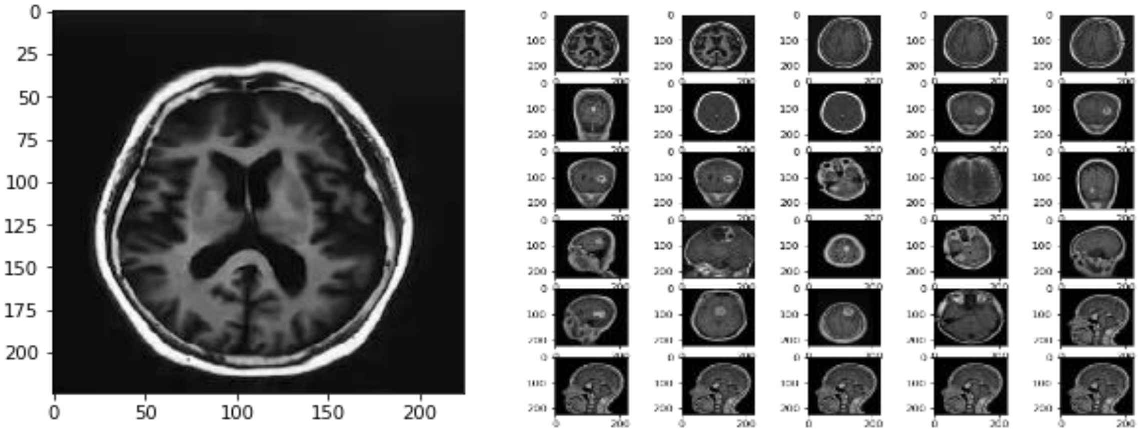
Figure 4: Visual representation of ResNet101 outcome for proposed work

Figure 4 shows the visual representation of the outcome of the resnet101 model. In this figure a represents the query image and b represents the retrieved tumor images. For this proposed work we retrieve 30 images similar to the query image chosen by the user. In these 30 images, the resnet101 model retrieved the 3 exact tumor images and 27 similar shapes MRI brain images.



(a)Query image (b) Retrieved Tumor Images

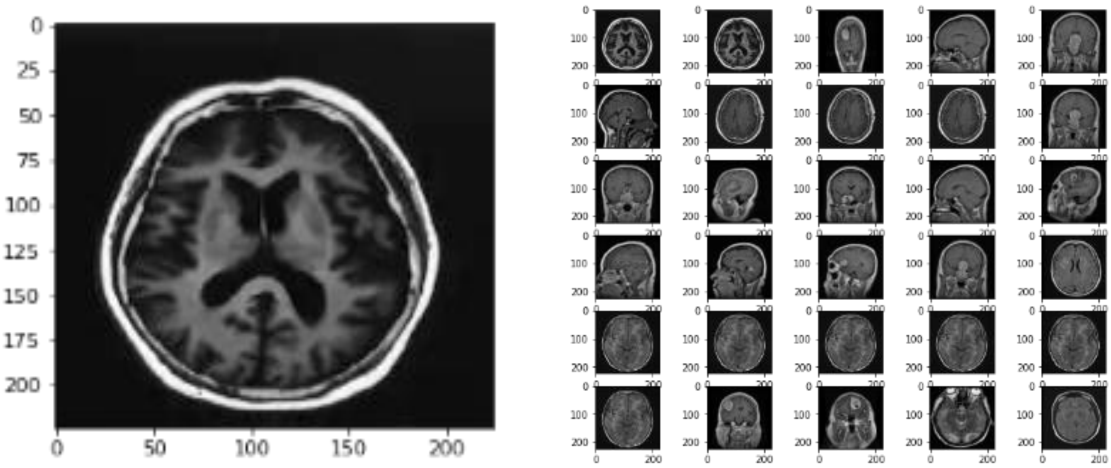
Figure 5: Visual representation of ResNet152 outcome for proposed work



(a)Query image (b) Retrieved Tumor Images

Figure 6: Visual representation of ResNet101V2 outcome for proposed work

Figure 5 shows the visual representation of the outcome of the resnet152 model. In this figure a represents the query image and b epitomizes the retrieved tumor images. For this proposed work we retrieve 30 images similar to the query image chosen by the user. In these 30 images, the resnet152 model retrieved more than a number of exact images which has a similar shape compared to the query image. Figure 6 shows the visual representation of the outcome of the resnet101V2 model. In this figure a represents the query image and b epitomizes the retrieved tumor images. For this proposed work we retrieve 30 images similar to the query image chosen by the user. In these 30 images, the resnet101V2 model retrieved the two exact images and other images are not similar to the query image. From this, we conclude that the resnet101V2 model is not appropriate for the retrieval system.



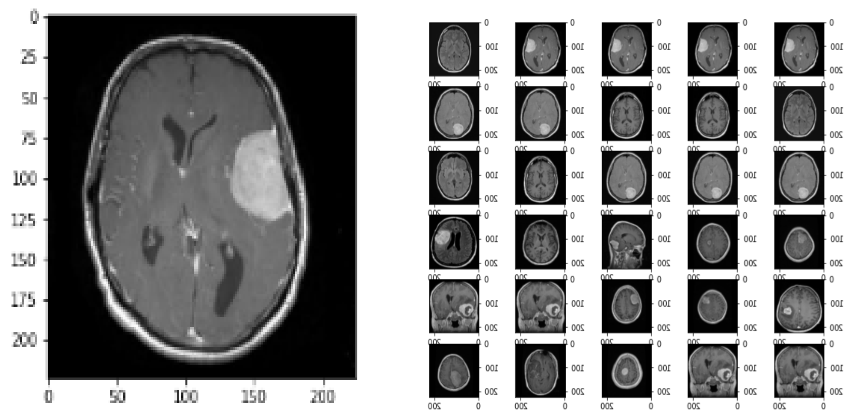
(a)Query image (b) Retrieved Tumor Images

Figure 7. Visual representation of ResNet152V2 outcome for proposed work

Figure 7 shows the visual representation of the outcome of the resnet152V2 model. In this figure a represents the query image and b epitomizes the retrieved tumor images. For this proposed work we retrieve 30 images similar to the query image chosen by the user. In these 30 images, the resnet152V2 model retrieved the two exact images 11 similar images and other images that are not similar to the query image. From this, we conclude that the resnet152V2 model is not suitable for the retrieval system. As well as Figure 8 shows the outcome of the resnet50v2. This model retrieves 25 similar tumor images out of 30 retrieval images. Compare to other resnet models it will give better results.

To prove the best resnet model for retrieval is need a precision value beyond visual representation. Here we call to measure the precision value for each resnet model using the following equation[15]. Table 1 and Figure 9 show the precision value for each model.

$$precision(p) = \frac{No.of.releveant\ images\ retrieved}{No.of\ images\ retrieved}$$



(a) Query image (b) Retrieved Tumor Images

Figure 8: Visual representation of ResNet50V2 outcome for proposed work

Table1: Retrieval Precision value

Model	Precision
ResNet50	0.9833
ResNet101	0.833
ResNet152	0.73
ResNet50V2	0.8333
ResNet101V2	0.006
ResNet152 V2	0.4333

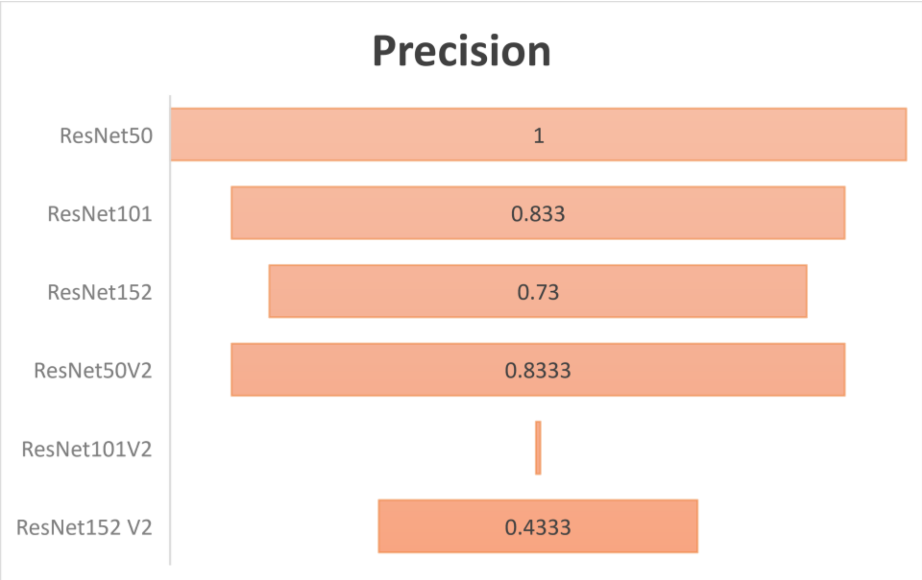


Figure 9: Diagrammatic representation of the proposed work.

From the above-shown Table 1 and figure, we conclude that resnet50 gives a better outcome for the CBTIR system compared to the rest of the resnet models. We use Euclidean distance as a similarity measure for all the resnet models tested here.

4. Conclusion

In this paper, we developed a CBTIR system for the retrieval of tumor images from the vast repository. Due to the acquisition process and availability of a vast amount of images in the medical repository retrieval of a particular image is a more critical task. The redundancy of the images needs to be reduced. Nowadays image retrieval is an essential task. There are a large number of CBIR methods developed by researchers in that all methodologies deep learning methods have a good reach due to the faster retrieval of the images from the large repository. Based on this survey we implemented the automatic CBTIR system by using CNN and ResNet50 models with Euclidean distance matrics and compared our method with all ResNet models to achieve the fastest retrieval system. In the future, we will implement our method to achieve more accurate tumor images with a grade level and produce the fastest retrieval of the images compared to the present results.

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