



Classification of Brain MRI into Benign and Malignant using Convolutional Neural Network

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Abstract: One of the most deadly, prevalent, and aggressive disease, brain tumors have an extremely low life expectancy at the highest grade. Early detection and prompt treatment are therefore crucial in order to avoid the spread of such diseases. In this method, anomalies in the brain are examined using MRI. It takes a lot of time to manually investigate the categorization of brain tumors, and human error is always a possibility. Because of this, doing an accurate analysis quickly is crucial. This method presents a highly accurate Convolutional Neural Network (CNN) algorithm-based automated brain tumor classification algorithm. The segmentation of the brain portion begins with a thresholding technique, which is then followed by a morphological operation. Brain MRI data is classified into benign and malignant conditions using CNN algorithms.

Index Terms - MRI, Brain tumor, Deep learning, vgg16, machine learning.

I. INTRODUCTION

It was noted in the 20th century that sickness rates are rising quickly. The brain is a working organ with billions of cells that is the most important and diverse part of the human body. One of the factors that impairs the brain's ability to operate properly is a brain tumor. Neurological tissue is growing unchecked and alone inside or around the brain [1,2]. The name of the brain tumor is based on the type of cell from which the tissue develops. Primary and secondary tumors are the two categories of tumors. Primary tumors are those that start inside of an organ and spread there, whereas secondary tumors are those that start in one region of the body and spread to another. The growth might be both malignant and benign. Malignant (cancerous) and benign (noncancerous) tumors are two further classifications for the tumor. Noncancerous and not progressing, benign tumors are.

They start in the brain and develop slowly and less aggressively. Additionally, they are unable to spread to another area of the body. Malignant tumors, on the other hand, progress and are cancerous. They had erratic borders and swiftly spread. Both primary and secondary cancers are possible [3-5]. It is more crucial to get an early diagnosis of a brain tumor. The study of the diagnosis of individuals with brain malignancies depends heavily on brain MRI. Due to their ability to deliver very detailed information on the structure and abnormalities of the brain, MRIs have a significant influence on medical image processing and analysis [6-8].

Based on the visual confirmation of a brain tumor's presence in brain MRI, radiologists assess the anomalies of the brain. But when a large amount of MRI data needs to be evaluated, there is a chance of misclassification. Another reason for a misdiagnosis might be that human eyesight becomes less sensitive with experience, often when only a few slices are damaged. It takes a lot of time to use this strategy. Consequently, an effective approach for the study and classification of brain anomalies is required. Early detection will make it easier to repair the harm and give the patient the best care possible as soon as possible. In hospitals and clinics nowadays, MRI is often utilized for medical diagnosis, particularly in brain imaging. Soft-tissue contrast and MRI's noninvasive nature are advantages. There is no ionizing radiation used in MRI. Because it is a non-radioactive, non-aggressive, and painless technique, MRI is employed in brain imaging.

In this paper, the brain MRI classification into benign and malignant using CNN algorithm is presented. The paper is organized as Section II gives an overview of the recent development in the brain MRI classification using the machine and deep learning algorithms with its pros and cons. Section III presents the architecture of the proposed methodology for brain MRI classification using a deep learning algorithm. Section IV describes the experimental results in a qualitative and quantitative manner. Conclusion and Future work are presented in section V.

II. LITERATURE SURVEY

In recent years, artificial intelligence algorithms such as Machine Learning (ML) and deep learning (DL) were mostly used for classification.

A Fuzzy C-Mean (FCM) approach was published by Saleck et al. [9] to determine the mass of the brain tumor. By choosing the pixel intensities and generally clustering them into two, this strategy aimed to solve the problem of estimating the number of clusters in the FCM. In this method, the features for estimating the threshold value are extracted using the Gray Level Co-Occurrence Matrix (GLCM) texture feature extraction technique. The system's performance is assessed using metrics for sensitivity, specificity, and accuracy.

Brain MRI categorization into malignant vs benign and low-grade versus high-grade gliomas was proposed by Vijay Wasuleet. al. [10]. The supervised SVM and K-Nearest Neighbor (KNN) algorithms were used in this study to classify the features that had been retrieved using the GLCM technique. Both the standard and clinical Brats 2012 dataset were used to evaluate the system. The system's accuracy for the clinical database is 96% and 86% for SVM and KNN, respectively, whereas it is 85% and 72.50% for SVM and KNN for the standard database.

The categorization of brain MRIs made using the AdaBoost algorithm was described by Ravindra Sonavane et al. [11]. Anisotropic diffusion filtering and an edge detection algorithm are used to first eliminate the undesirable portions of the brain MRI using the brain skull skipping approach. Additionally, the DWT deconstructed filter image was used to extract the features. Finally, the AdaBoost method was used to classify the features.

Brain tumor categorization and detection using KNN was suggested by K. Sudharani et al. [12]. The trials were run for various k values. The distance between the training sample and the testing sample is calculated using the Manhattan distance measure. LabView is used to implement this approach.

The hybrid strategy of SVM and FCM for the categorization of brain MRI was proposed by Parveen et al. [13]. Using image enhancement methods like contrast enhancement and mid-range stretch, the MRI is enhanced early in the process. For skull skipping, thresholding with morphological operation is utilized. The FCM clustering technique is used to segregate the brain tumor portion from the background. The features from the brain MRI are extracted using the Grey Level Run Length Matrix (GLRLM), and then they are classified using SVM. For linear, quadratic, and polynomial kernels, the suggested approach attained accuracy of 91.66%, 83.33%, and 87.50%, respectively.

Later, many researchers proposed ensemble classifiers combinations of various ML algorithms to attain high accuracy. The ensemble classifier was suggested by Amasyali et al. [14] to increase the approach's accuracy. They chose the classifiers based on two criteria: accuracy and execution time. In these trials, the accuracy of 11 machine learning classifiers and 12 distinct ensemble techniques has been compared.

J. Seetha et al. [15] suggested utilizing the CNN classifier to categorize brain tumors. In this method, the brain tumor is separated out using the FCM algorithm, the features are extracted using GLCM, and the features are classified using SVM and Deep Neural Network algorithms. This method demonstrates minimal complexity and quick computing, but accuracy is worse. Consequently, a new technique, CNN-based normal and tumorous brain MRI categorization, is added to this approach. To cut training time, the ImageNet pretrained model is employed. With this method, the training accuracy was 97.5%.

S. Deepak et al. [16] extracted the characteristics from brain MRI using a transfer learning methodology. This essay is centered on the three classes of meningioma, glioma, and pituitary tumors. The characteristics from the input brain MRI are extracted using the GoogLeNet transfer learning model. SVM and KNN algorithms were used to classify the deep CNN feature that was retrieved. For fivefold cross-validation, this method's accuracy was 98%.

Using deep learning, Muhammad Sajjad et al. [17] proposed a method for classifying multigrade brain tumors. This method first segments the brain tumor using the CNN model, augments the segmented data with various parameters to increase the training samples, and then trains the model using the VGG-19 CNN model that has already been pretrained. With the augmented data, the accuracy of this system increased to 90.67% from the initial 87.38%.

Javaria Amin et al. [20], proposed brain MRI classification into the tumor and non-tumor region through image fusion technique. First, structural and texture information of MRI sequences T1C, T1, Flair, and T2 are combined for brain tumor detection. The fusion approach is carried out by using the Daubechies wavelet kernel of Discrete Wavelet Transform (DWT). The fusion process provides a more informative tumor as compared to an individual sequence. After this, the partial differential diffusion filter (PDDF) is applied over the fused image to remove noise. Global thresholding method segment the brain MRI into the background (non-tumor) and foreground (tumor) region. This approach is performed on five publicly available datasets i.e., BRATS 2013, BRATS 2015, BRATS 2018, Brats challenge, BRATS 2012 image dataset, and 2013 BRATS Leader Board Dataset. The method got good accuracy on the fused images such as 0.97, 0.98, 0.96, 1.00, and 0.97 on BRATS 2012 Image, BRATS 2013 Challenge, BRATS 2013 Leader board, BRATS 2015 Challenge, and BRATS 2018 Challenge datasets respectively.

According to the literature study, GLCM and GLRLM algorithms are used to extract texture characteristics for the majority of brain MRI classification tasks that use machine learning methods. Some of the methods CNN utilizes to categorize normal and abnormal brain MRI results.

III. METHODOLOGY

Because of the complexity and variety of malignancies, MRI brain tumor detection is challenging. The tumor is recognized in brain MRI using a thresholding technique, and the brain MRI is graded as normal or abnormal using a convolutional neural network in this method.

3.1 Dataset

The clinical database of brain MRI is used in this method. There are both normal and aberrant MR images in the database. Table I shows the complete database distribution for normal and abnormal. After splitting training and testing data, the database comprises raw images that have been pre-processed and segmentation and augmentation algorithms.

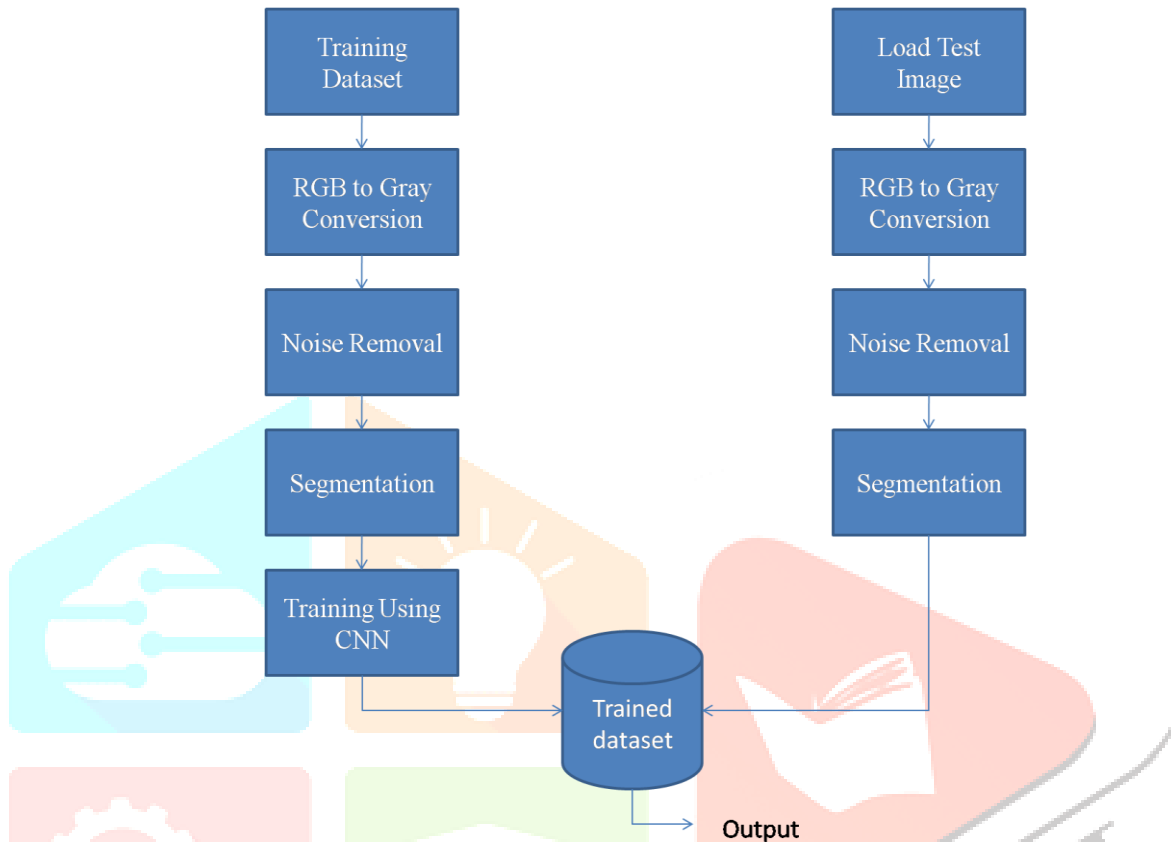


Figure.1. Flow diagram of the proposed system

TABLE I. DATABASE DISTRIBUTION NORMAL ABNORMAL CLASSIFICATION

Table Head	Database Distribution		
	Total Images	Training Images	Testing Images
Normal	273	212	61
Abnormal	194	163	31

3.2 Pre-processing

The patient data text is included in the raw, noisy database images. To begin with, the images are in RGB color format. The weighted average approach is used to convert the RGB color to grayscale. Rician and salt and pepper noise have the most significant impact on medical imaging. In salt and pepper noise, the median filter is effective. The median filter is employed to reduce noise at an earlier stage to obtain accuracy during the judgment phase. Low contrast is another issue with medical images. The power-law transformation can help low-contrast images. It is expressed mathematically as.

$$S = Cr^\gamma \tag{1}$$

where r specifies the input image's intensities and is called gamma, resulting in gamma transformation. The value varies between 0 and 1. The resulting image has a gray level of S. Constant is represented by the C.

3.3 MRI Segmentation and tumor identification

The segmentation process is crucial for separating the brain from the skull. The brain portion is segmented using thresholding in this method.

$$f_{g(x,y)} = \begin{cases} 1 & I(x,y) > T \\ 0 & \text{else} \end{cases} \tag{2}$$

The pixel's grayscale value is I(x, y), while the binary image is f g(x, y). Using the thresholding procedure, the tumor component is discovered. The colored MRI image is first transformed to grayscale using the weighted average approach. The grayscale image is transformed to binary using median filtering and thresholding. Morphological filters such as erosion and dilation are used for the binary image to achieve smoother borders. The contour approach is used in the tumor detection procedure. The number of binary items is tallied first using the contour approach, and then the most prominent object is chosen as a tumor.

3.4 Classification of brain MRI into normal and abnormal

The clinical information is utilized to classify brain MRI into normal and pathological categories. Table I contains the dataset's specifics. The dataset is split into 80:20 training and testing. This categorization approach divides brain MRI into normal and pathological categories using the CNN algorithm.

IV. RESULTS

The system is written in Python and uses the Keras package. The Google Colab cloud platform is used for the training. The suggested system's findings are given through qualitative and quantitative analysis. The suggested approach divides brain MRI into normal and pathological categories using the CNN algorithm. In Fig.5.1, the CNN training progress for brain MRI categorization into normal and abnormal is illustrated.

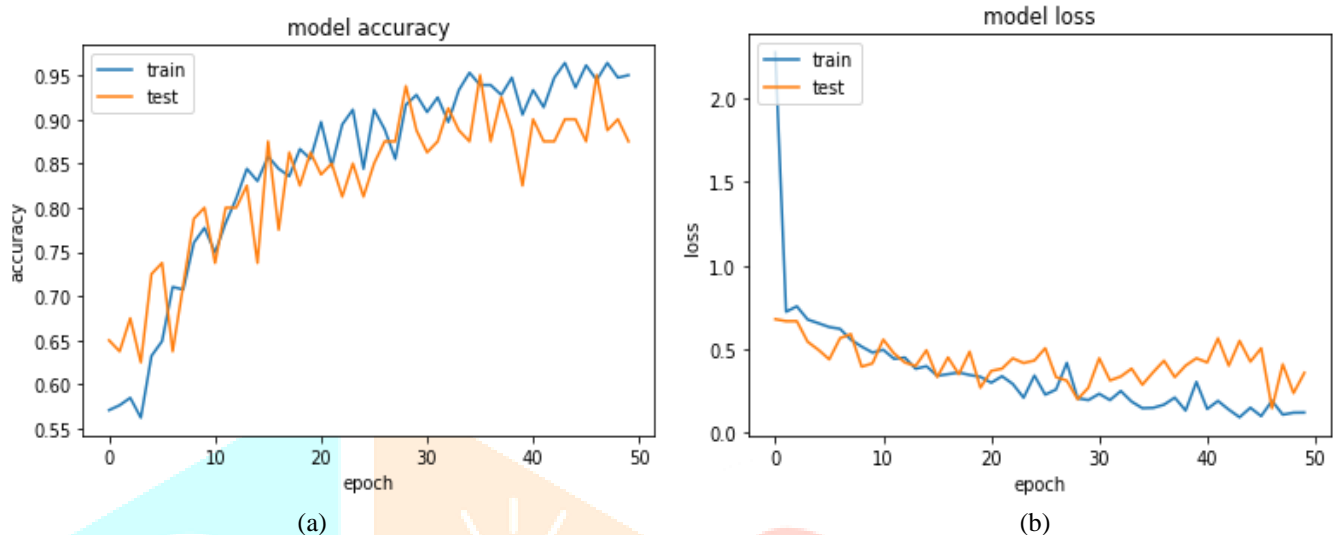


Figure.2. Performance of CNN for classification of brain MRI into normal and abnormal (a) Accuracy (b) Loss

The result of the brain tumor detection on the abnormal and normal images is shown in Fig.6.2 and Fig.6.3, respectively.

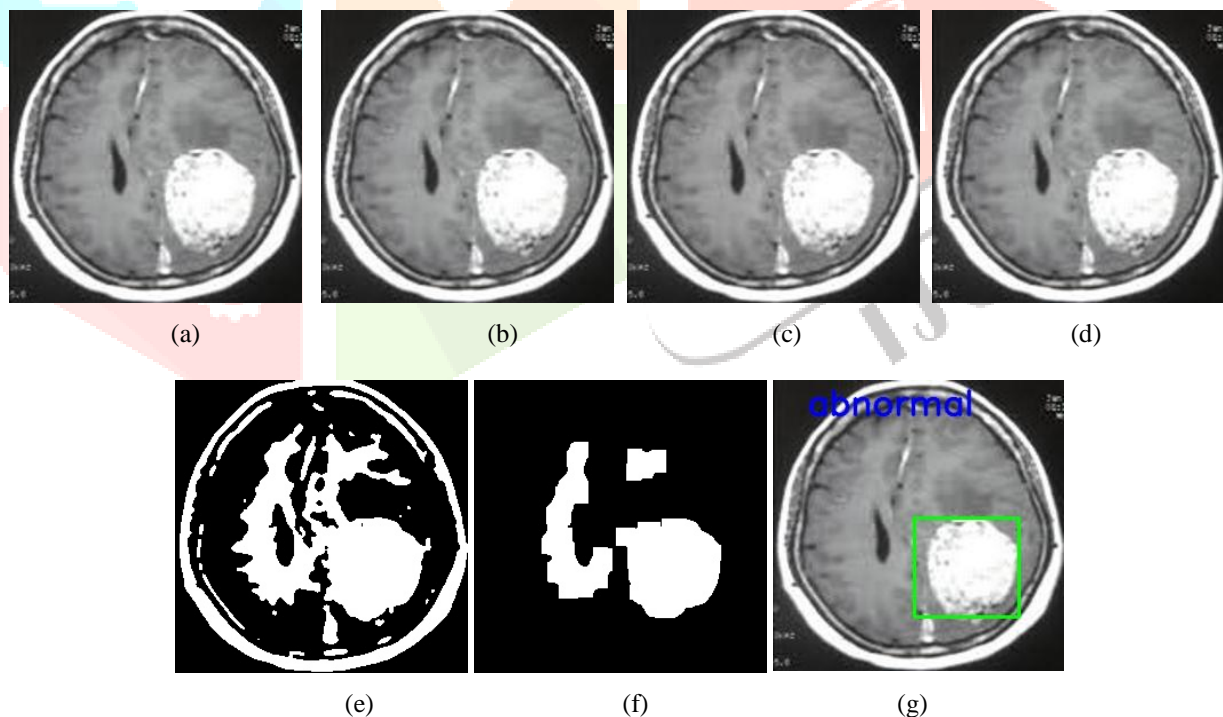
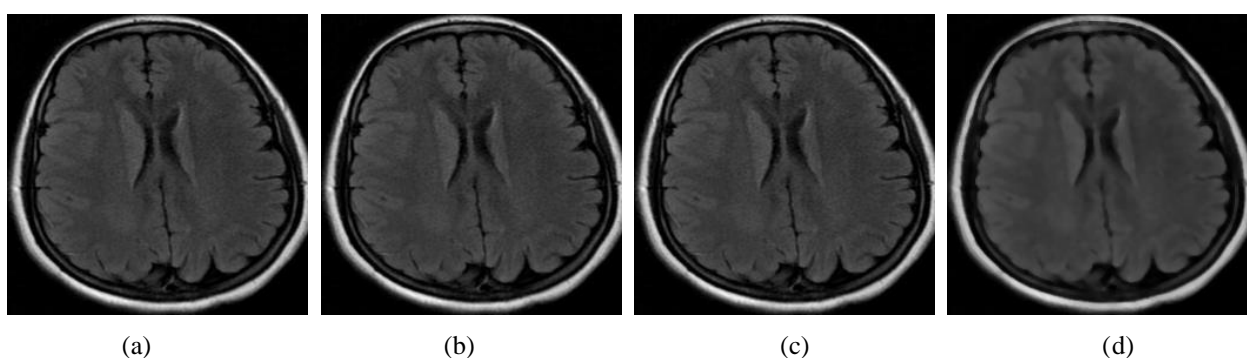


Figure 3. Flowchart of the system (a) Input abnormal Brain MR image (b) Resized image (c) grayscale image (d) filtered image (e) Segmented image (f) image after the morphological operation (g) Output



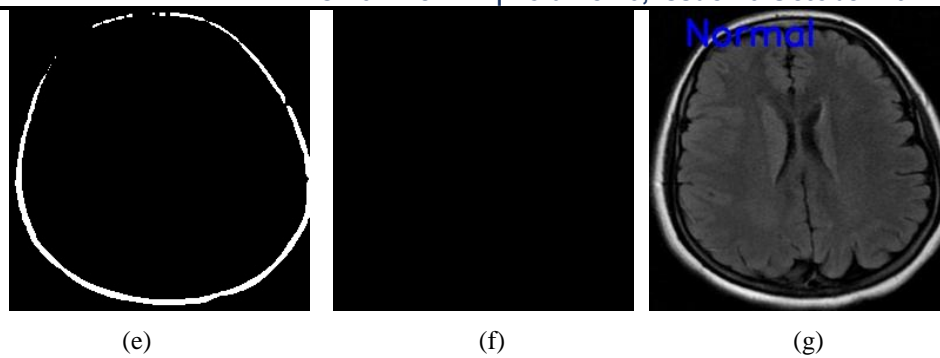


Figure 4 Flowchart of the system (a) Input normal Brain MR image (b) Resized image (c) grayscale image (d) filtered image (e) Segmented image (f) image after the morphological operation (g) Output

The qualitative analysis of the proposed system shows promising results. For the first approach, i.e., analysis of brain MRI classification into normal and abnormal, the CNN performs better on unknown testing samples.

V. CONCLUSION

The findings of this study show that the applied strategy is effective in classifying human brain images into normal and abnormal as a summary of this project contribution, a completely automatic procedure for brain MRI classification from MR anatomical images as described. This system offers categorization of brain MRI into normal and abnormal. The first method utilized the CNN algorithm, which produced an accuracy of 0.8750 after 50 epochs. In the future, this approach can be implemented for the further subclass of the brain cancer stages like glioma and meningioma. The limited dataset is one of the hurdles in implementing a real-time system, and hence in the future, the model needs to train on a more significant number of samples.

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