Brain Tumor Detection Using MRI Images

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Abstract. Brain tumors are a severe medical disease that can have serious consequences in terms of morbidity and death. For efficient therapy and improved patient results, early identification of brain tumors is essential. MRI scans allow us to find brain tumors.The doctor will be able to see the abnormal growth on these MRI pictures and determine if the tumor has impacted the brain or not. MRI images can be used to detect typical tissue development and blood clots in the nervous system. The symmetrical and asymmetrical shapes of the brain are examined to identify any abnormalities at the initial stage in the diagnosis of brain tumors.In many of the research papers, machine learning and deep learning algorithms are used to identify brain cancers. The detection of a brain tumor may be carried out much more quickly and precisely when these methods are applied to MRI pictures, which facilitates patient treatment. In the suggested research, a conscious artificial neural network (ANN) and a convolution neural network (CNN) is employed to detect the presence of a brain tumor, and their performance is evaluated. The accuracy of the CNN is almost 95.43%, whereas the accuracy of the ANN model is 91.48%, according to training and testing findings. For the provided dataset, CNN appears to be the most accurate method for identifying brain lesions.

Keywords: MRI images, Convolution Neural Network (CNN), Image Classification, Brain Tumor, Artificial Neural Network (ANN)

1 Introduction

The brain is the most essential organ in the human body. The majority of people believe it to be the center of the human organism. Almost every vital physiological process is governed by the brain. It is believed that the brain controls hormones, movement, and knowledge for image processing to extract the required properties from visual input so that a machine can make an accurate diagnosis [4]. Pre-processing (image enhancement, noise reduction, etc.), segmentation, feature extraction, and classification are the most common digital image processing steps

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used to automate the partial or complete detection of brain tumors. In this research, we propose combining CNN and ANN models for MRI brain lesion detection. Using an MRI image dataset, the proposed models are trained and evaluated, and their precision, sensitivity, specificity, and computational efficiency are compared. This study's findings could enhance the accuracy and efficacy of brain tumor detection systems, leading to improved patient outcomes and more effective treatment.

2 Literature Survey

In a study that was conducted not too long ago on brain tumors, the researchers separated the tumors using a combination of uncontrolled and supervised algorithms. While the algorithm learns from the automated procedures of projection on labeled input data and adapts its response each time based on training and testing to improve its efficiency, supervised methods require the participation of humans in order to classify the data accurately.[4]

While the algorithm learns from the automated procedures of projection on labeled input data and adapts its response each time based on training and testing to improve its effectiveness, [5]As a result, accurate and automated brain tumor segmentation will significantly influence tumor detection and therapy. Medical data analysis is extremely challenging. This methodology comprises a number of steps, including preprocessing with median and sharpening filters, image enhancement with histogram equalization, and image segmentation with thresholding.[6]

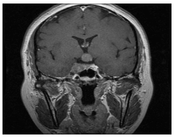
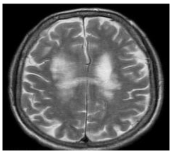
The approach of image subtraction can be analyzed to measure the tumor's location.The precise location and extent of a suspected brain tumor can be determined through radiologic evaluations. MRI imaging provides a detailed description of brain tissue. It is typically non-invasive and painless. No ionizing radiation is emitted. MRI is among the greatest clinical imaging modalities, therefore. Several segmentation approaches have been proposed. However, segmenting MRI brain images remains a difficult challenge due to their complexity. [7] CNN's apps and website first recognized handwritten numbers in 1998 [8].

CNN-based categorization method for MRI-observable brain tumors was developed [9]. Most of the time, this is done by using a CNN to extract features and a fully connected network to classify them. With an f score of 97.3, the model is right about 96.08% of the time. Only early detection and diagnosis can eliminate a tumor. Undiagnosed brain tumors may become deadly (cancerous). Image processing methods have been developed in recent years for precise and efficient computer-aided cerebrum cancer diagnosis. Algorithms analyze MRI images. Morphological analysts can locate cells in tumor scans. [10]

3 Dataset

Brain tumor categorization MRI dataset was available on Kaggle which was created by Sartaj Bhuvaji and consists of a total of 3,264 MRI images of the brain, with both tumor and non-tumor cases.[11] The dataset is divided into two classes: 1) images with a tumor and 2) images without a tumor as shown in table 1. The dataset was preprocessed by merging different tumor classifications (glioma, meningioma, and pituitary tumor) into a single "tumor" class to increase the size of the tumor class dataset as the purpose of this model is to classify between tumor and no tumor while keeping a separate "no tumor" class. The dataset contained 2,764 tumor images and 500 non-tumor images. The dataset was split into training (80%) and testing (20%) sections. As MRI images are not always clear; visualization errors can sometimes degrade image quality. Poor image distortion and resolution cause these errors.

Table 1. Table captions should be placed above the tables.

Classification	MRI Image	Number of Images in Dataset
Tumor		2764
No Tumor		500

This could lead to flawed analysis. As a result, various image preparation methods can be used to improve image robustness and neural network usability. We resized the images and reduced their dimensionality. To facilitate learning, the images have been scaled to an image breadth of 128px, image height of 128 px, and with 3 channels.

4 Methodology

How the model predicts the output:

1. Initially, the model will receive input in the form of MRI pictures.
2. Then, the model will preprocess the data, as in this study, images are shrunk to the (128*128*3)size.
3. Afterwards the model will extract the image's characteristics .
4. Using the characteristics extracted from the image, the model will then decide whether or not the tumor is present.

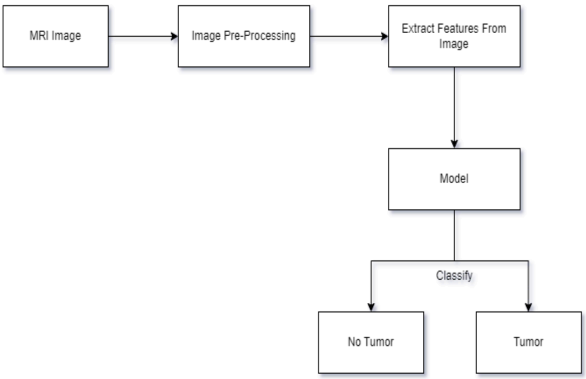


Fig. 1. General Flow Diagram of the Model

We have created two models. The ANN model comes in first, followed by the CNN Model.

4.1 ANN Model:

The form and operation of biological neural networks in the human brain serve as inspiration for the design of artificial neural networks (ANNs). An ANN processes input data through many layers of linked nodes, or "neurons," which process the data using mathematical operations before passing it to the following layer. ANNs may learn to spot patterns and make predictions based on fresh, unused data through a process of training on labeled data. There are primarily 3 types of layers in an ANN. 1. Input Layer: This layer receives input data, which is then forwarded to the subsequent layer in the sequence. 2. Hidden Layers: These layers are in charge of extracting patterns and characteristics from the data. 3. Output Layers: These layers create an output in response to an input.

As shown in Fig.2 , In the proposed ANN model, the input to the model is an MRI picture with dimensions (128 * 128 * 3), followed by two dese layers with 1000 neurons each with RELU as the activation function, and an output layer with a sigmoid activation function.

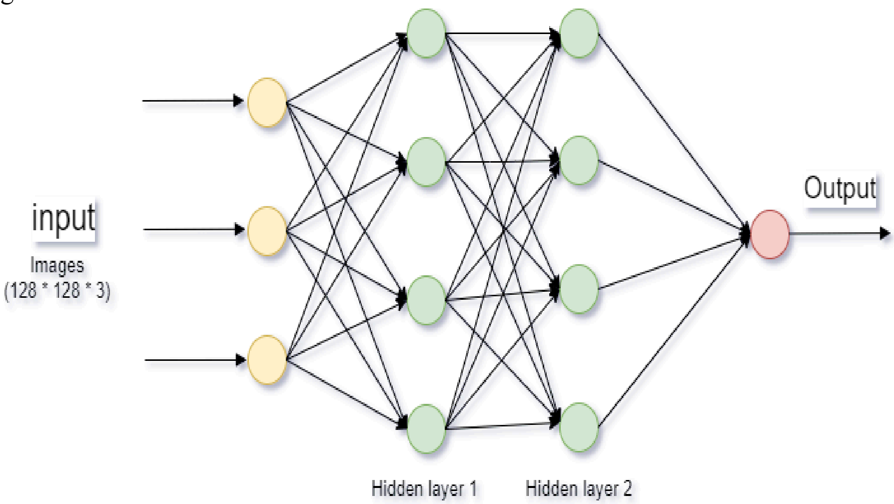


Fig. 2. ANN Model Architecture

4.2 CNN Model:

For deep learning algorithms, a CNN (convolution neural network) is a specific kind of network design that is used for tasks like image recognition and pixel data processing. CNNs operate on input pictures by applying a number of operations on the pixel values. The study presented here proposes a CNN model with two convolution layers, two max-pooling layers, one flatten layer and two dense layers. The recommended design accepts input images as (128 * 128 * 3) pixels in size. The first convolution layer has a Rectified Linear Unit (RELU) as the activation function and 32 filters with a 3*3 kernel size. The second convolution layer's parameters, which include 64 filters, are the same as those for the first in the model. Following each convolution layer, a max-pooling layer is added, followed by further calls to dense layers again with a RELU activation function. and output layer with a sigmoid activation function. The detailed architecture of the CNN model is shown in Fig. 3.

Convolutional Layer: The convolutional layer, the fundamental building block of a CNN, performs the majority of computations. The convolution procedure involves a kernel or filter within this layer traveling over the receptive fields of the image and determining if a feature is present. Over a number of cycles, the kernel goes over the whole image. After each iteration, a dot product between the pixels that came in and the filter is found. A feature map or convolved feature is the final result of the series of dots. In the end, the image is turned into numbers in this layer. This gives CNN a way to understand the image and find patterns in it.

Pooling Layer: The pooling layer is similar to the convolutional layer, it moves a kernel or filter across the image. But, unlike the convolutional layer of convolutional, the pool Input parameter count is decreased by the pooling layer, and some information is also lost. On the plus side, this layer makes CNN easier to use and less complicated.

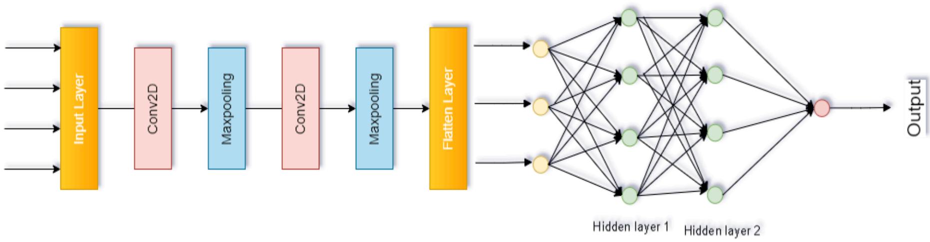


Fig. 3. CNN Model Architecture

5 Result

Using a Google Colab notebook, which allows the use of well-known Python tools like TensorFlow and Keras, the ANN model and the CNN model was trained. A matplotlib.pyplot library is used to create the precision and loss graphs. Fig. 4 for the ANN model displays the model's validation accuracy during the assessment phase as well as training period accuracy. The ANN model's 10th epoch ultimate accuracy is 94.44%, while its value accuracy is 91.48%.

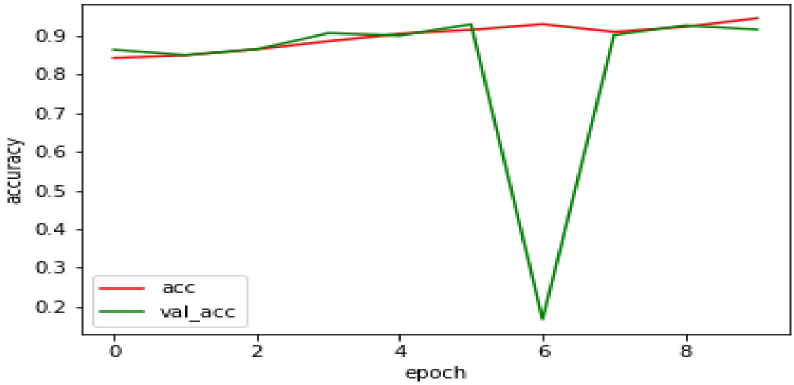


Fig. 4. ANN Model Accuracy

The training set loss value and testing phase validation loss are shown in Fig. 5. The ANN model's loss at the 10th period is 15.6%, and the testing phase's value loss is 24.4%.

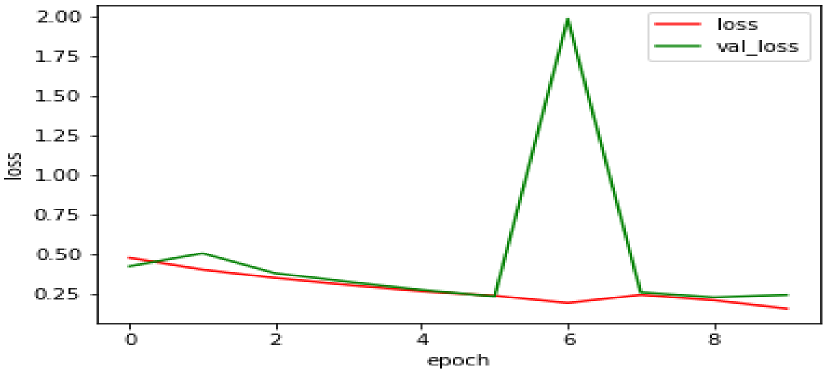


Fig. 5. ANN model Loss

Fig.6 for the CNN model displays the model's value accuracy during the assessment phase as well as training period accuracy. The CNN model's 15th-period ultimate accuracy is 99.66%, while its value accuracy is 95.43%.

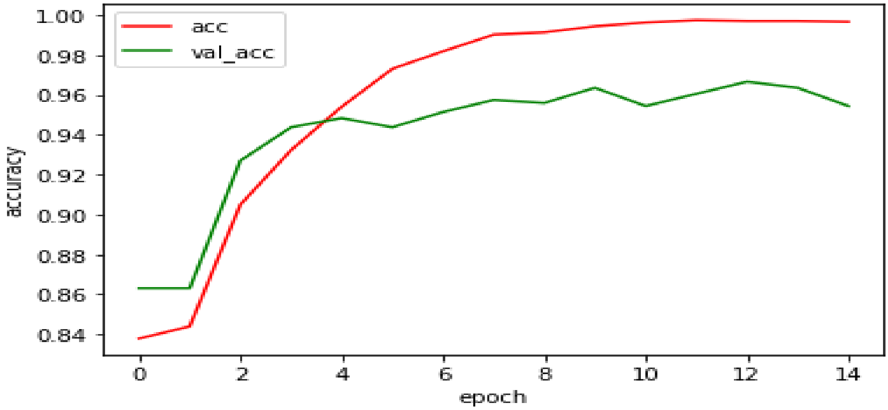


Fig. 6. CNN model Accuracy

The training set loss value and testing phase validation loss are shown in Fig. 7. The CNN model's loss at the 15th period is 6.5%, and the testing phase's value loss is 20.2%

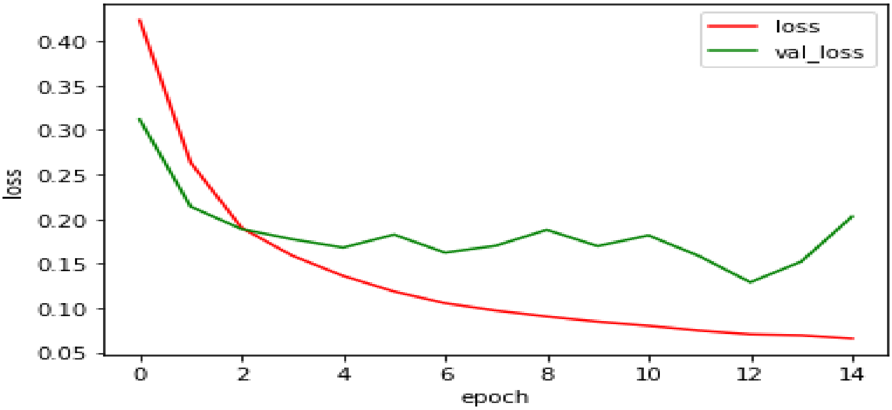


Fig. 7.CNN model Loss

6 Conclusion

This study article suggests using a CNN model to divide MRI pictures of brain tumors into two groups: those with tumors and those without. The suggested technique had the highest degree of precision for identifying and classifying MRI images. Before the convolutional neural network is applied, these pictures have undergone certain processes like preprocessing and scaling. 3,264 brain MRI images were used for training and confirmation. including 2764 pictures of tumors and 500 photographs without tumors. The precision of the CNN model is almost 95.43% compared to the ANN model's 91.48% value accuracy. Because they improve image clarity, reduce noise, and clear unwanted backgrounds, enhancement, and filtering are crucial. In the end, CNN appears to be the most accurate technique for forecasting the development of brain tumors in the sample. This research demonstrates how a CNN network can classify and spot brain cancers more accurately using performance evaluation metrics and curve analysis. Convolutional neural networks' design was given in this study, which also showed how well they performed when used to analyze a modified database of images. Additional studies may improve the suggested model's design, and a sizable database will be used to rate the model's reliability and effectiveness.

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