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Brain Tumor Detection using CNN

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ABSTRACT: The human brain is the major controller of the humanoid system. The abnormal growth and division of cells in the brain lead to brain tumor, and the further growth of brain tumor leads to brain cancer. Training, testing and validation datasets are used. Based on our machine, we will predict whether the subject has a brain tumor or not. The resultant outcomes will be examined through various performance examined metrics that include accuracy, sensitivity and specificity. It is desired that the proposed work would exhibit a more exceptional performance over its counterparts.

KEYWORDS: Brain tumor, Medical Imaging, Deep Learning, Convolutional Neural Network, Optimizers

I. INTRODUCTION

Our study deals with automated brain tumor detection and classification. The main reason for detection of brain tumors is to provide aid to clinical diagnosis. The aim is to provide an algorithm that guarantees the presence of a tumor by combining several procedures to provide a fool proof method of tumor detection in MR brain images. The focus of this project is MR brain images tumor extraction and its representation in simpler form such that it is understandable by everyone. The resultant image will be able to provide information like size, dimension and position of the tumor, and its boundary provides us with information related to the tumor that can prove useful for various cases, which will provide a better base for staff to decide the curing procedure. To lower the chances of death, the tumor region must first be identified. Computed Tomography (CT scan) and Magnetic Resonance Imaging (MRI) are used to monitor patients physically. Because MRI images reveal the structure, size, and location of the tumor in the brain, they will make it so much easier to diagnose the tumor and plan the surgical procedure to remove it. In a variety of medical cancer diagnosis and therapy, machine learning-based automatic defect diagnosis in medical imaging became a hot research topic. Its significance in MRI brain tumor detection is crucial because it identifies irregular tissues that must be examined when chemotherapy is planned. Automatic digital and electronic sickness detection and treatment based on medical vision analysis, according to a recent survey, might be a powerful device in which it would minimize radiologist work.

Deep Learning is a branch of machine learning that deals with artificial neural networks modelled after the structure and brain function.

In our study, we used the Convolutional Neural Network architecture to detect and classify brain tumors with demonstrated accuracy. For image classification, image processing, face identification, and other applications, convolutional neural networks evaluate densely connected data. It's a specialised 3D structure with specialised NN for analysing the RGB layers of a picture. Also, we assess the performance of CNN with different optimizer such as Adam. We created a GUI-based user interface in which we can upload MRI scans and get the results whether there is a tumor or not.

II. RELATED WORK

In the present day, the field of Medical Imaging diagnosis using AI has gained a lot of importance, and it is the need of the hour to overwhelm the burden of health professionals. Most researchers have proposed various approaches to medical diagnosis earlier, and some of them are listed below.

B. Devkota et al. [1] suggested a computer-aided detection (CAD) method for detecting aberrant tissues using Morphological procedures. Among the several segmentation procedures available, morphological opening and closure operations are recommended because they need less processing time while extracting tumor regions with minor defects.

AstinaMinz et al. [2] used the AdaBoost gadget mastering method to build an effective automated classification

solution for brain images. The suggested system is divided into three parts. Pre-processing removed noise from the datasets and transformed photos to grayscale. The pre-processed picture includes median filtering and thresholding segmentation.

Mukambika et al. [3] proposed a method for determining whether or not a tumor is present at a later stage. The Level set technique, discontinuous wavelength transformations (DWT), and K-method segmentation algorithms are all part of their planned work, which is a comparative evaluation of tumor identification approaches utilizing MR images. The feature extraction process is then followed by SVM classification.

Shikha Gitte et al. [4] described various techniques to classify brain tumors, therapies improving patient's quality of life.

III. PROPOSED SYSTEM

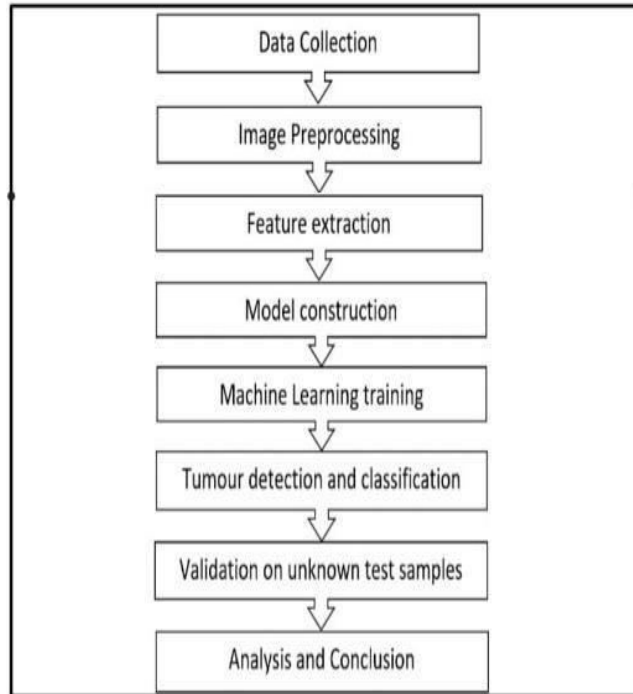
Our project deals with brain tumor detection and classification. Normally the anatomy of the brain is analyzed by MRI scans or CT scans. The main idea of proposed system is to identify the tumor and to do the detailed diagnosis of that tumor which will be used in the treatment of tumor patient. The MRI images are fitted into the CNN model. We will train the neural network model with all the training data for many cycles where each cycle is called as an epoch. If we increase the number of epochs while training the model the accuracy of the algorithm and the model increases. Finally the model produces an output as whether the MRI image is having a brain tumor or not.

Convolutional Neural Network

. Creative models depend on hand-crafted features and prejudicial models associated with classical learning techniques. In contrast to generative modelling approaches, discriminative models (CNN) are utilised in brain tumor segmentation because they rely on extracting a large variety of low-level image qualities and explicitly modelling the link between these features and the label of a single voxel. Convolutional neural networks are used to evaluate densely related data in picture classification, image processing, face recognition, and other applications. It's a three-dimensional framework that examines RGB layers in an image applying particular neural networks. It examines one image at a time, recognizing and collecting crucial parts and utilizing them to characterize the image, unlike other algorithms

IV. WORKFLOW

The workflow is an image processing technique for brain tumor identification and localization. Pre-processing, edge detection, and segmentation are among the phases of the method. The pre-processing stage involves converting the original image to grayscale and, if necessary, removing noise. After that, image enhancement methods are used to improve the appearance. Edge detection is then performed using Sobel and Canny algorithms. Finally, in the MRI images, segmentation is used to emphasize the tumor using morphological operations towards the afflicted region.



V. OPTIMIZERS

Optimizers are techniques or approaches that adjust the characteristics of your neural network, such as weights and learning rate, to decrease losses.

Adam Optimizer

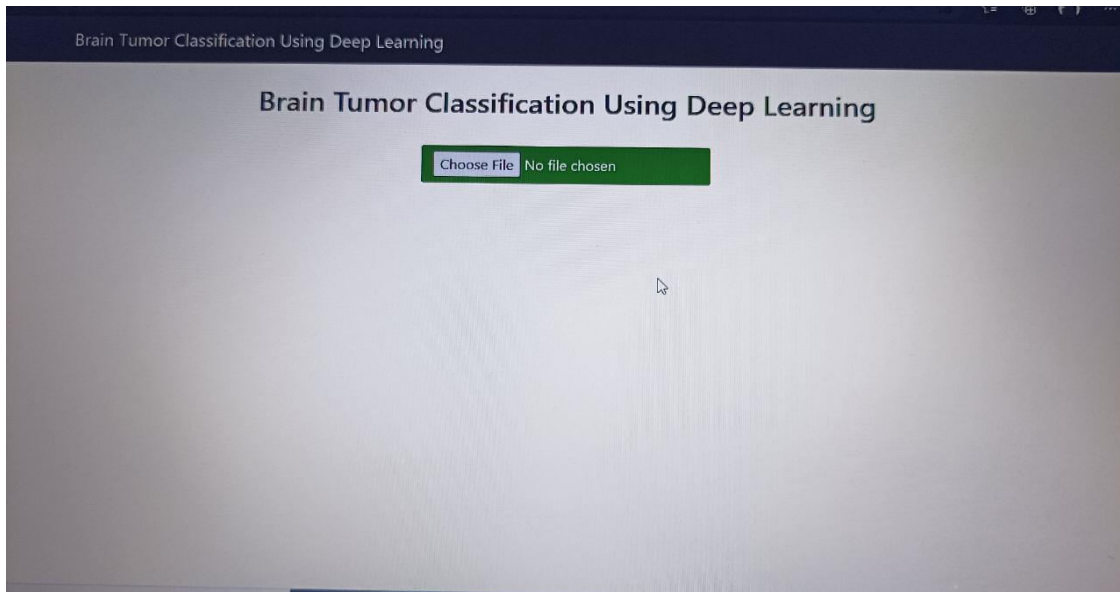
Adaptive moment estimate is the source of the word Adam. To update network weights during training, this optimization approach further develops stochastic gradient descent (SGD). Unlike SGD, Adam optimizer changes the learning rate for each network weight individually rather than maintaining a single learning rate throughout the training.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \left[\frac{\delta L}{\delta w_t} \right] \quad v_t = \beta_2 v_{t-1} + (1 - \beta_2) \left[\frac{\delta L}{\delta w_t} \right]^2$$

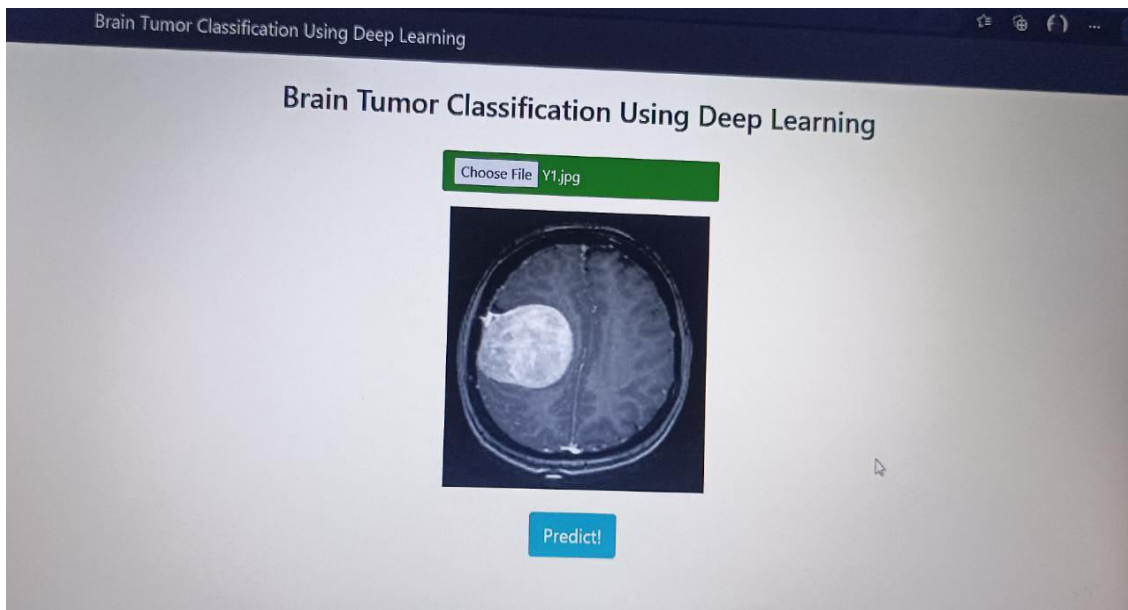
The Adam optimizer's operation is represented above. The decay rates of the average of the gradients are represented by B1 and B2

VI. RESULTS AND DISCUSSION

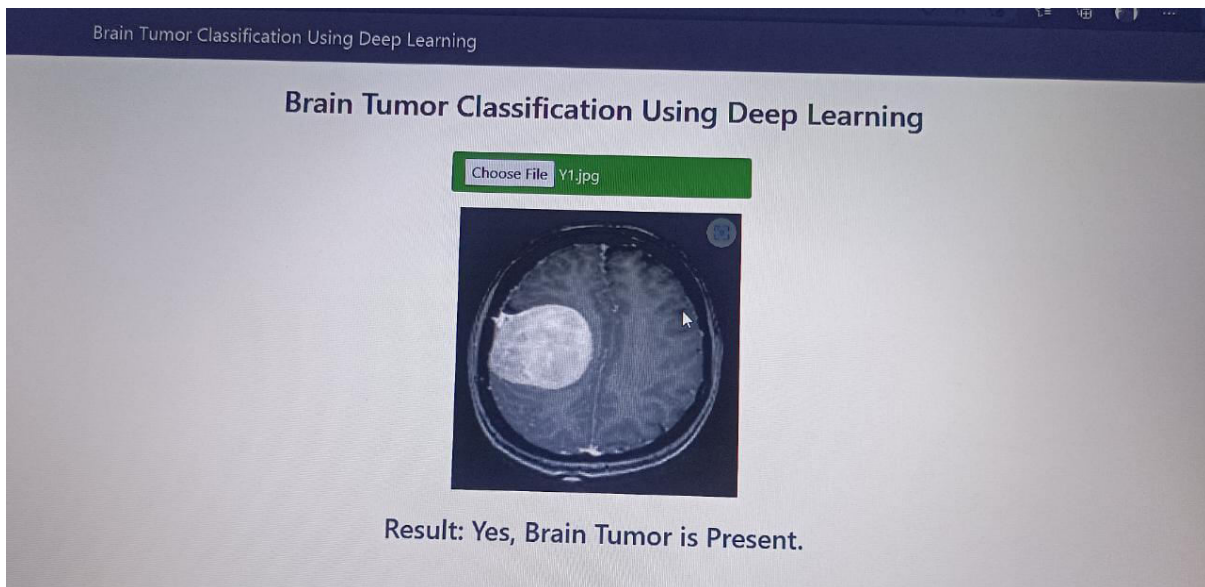
We used CNN with several optimizers to identify the tumor in the brain, and we compared the suggested approaches to some existing models. According to the findings, the new frame workout performs and improves the prior techniques. The best results of the created approach are obtained by comparing the findings to existing work in the literature. Our suggested approach has predictive value in identifying tumors in patients with brain tumors. Doctors and clinics will benefit from the suggested paradigm. A confusion matrix is a matrix that is being used to judge the effectiveness of classification techniques on a number of experimental data.



1. User Interface



2. MRI scan uploaded



3. Brain Tumor is present

Model Training

We used three different optimizers in this project, i.e., ADAM, RMS Prop, and SGD. Among the three optimizers, ADAM produces the best accuracy results.

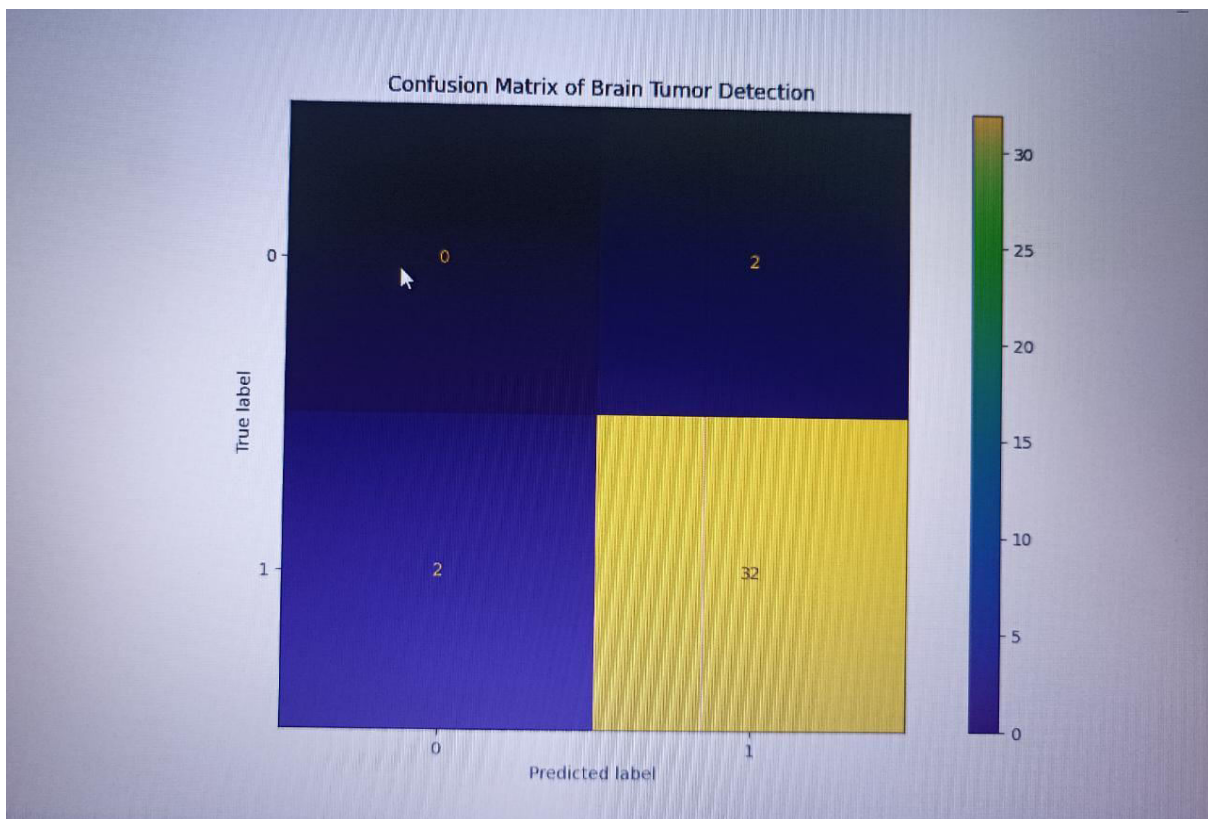
- Model with Adam optimizer training result, confusion matrix, accuracy, summary classification reports:

Adam optimizer training results :

```
Run and Debug
Terminal
Epoch 24/50
5/5 [=====] - 8s 2s/step - loss: 0.0280 - accuracy: 0.9789 - val_loss: 0.9169 - val_accuracy: 0.9167
Epoch 25/50
5/5 [=====] - 8s 2s/step - loss: 0.0230 - accuracy: 0.9789 - val_loss: 0.9257 - val_accuracy: 0.9167
Epoch 26/50
5/5 [=====] - 8s 2s/step - loss: 0.0220 - accuracy: 0.9789 - val_loss: 0.9615 - val_accuracy: 0.9167
Epoch 27/50
5/5 [=====] - 8s 2s/step - loss: 0.0250 - accuracy: 0.9718 - val_loss: 0.9974 - val_accuracy: 0.9167
Epoch 28/50
5/5 [=====] - 8s 2s/step - loss: 0.0312 - accuracy: 0.9718 - val_loss: 1.0294 - val_accuracy: 0.9167
Epoch 29/50
5/5 [=====] - 8s 2s/step - loss: 0.0202 - accuracy: 0.9930 - val_loss: 1.0529 - val_accuracy: 0.9167
Epoch 30/50
5/5 [=====] - 8s 2s/step - loss: 0.0192 - accuracy: 1.0000 - val_loss: 1.0749 - val_accuracy: 0.9167
Epoch 31/50
5/5 [=====] - 8s 2s/step - loss: 0.0222 - accuracy: 1.0000 - val_loss: 1.1104 - val_accuracy: 0.8889
Epoch 32/50
5/5 [=====] - 8s 2s/step - loss: 0.0209 - accuracy: 0.9859 - val_loss: 1.1411 - val_accuracy: 0.8889
Epoch 33/50
5/5 [=====] - 8s 2s/step - loss: 0.0245 - accuracy: 0.9930 - val_loss: 1.1676 - val_accuracy: 0.8889
Epoch 34/50
5/5 [=====] - 8s 2s/step - loss: 0.0283 - accuracy: 0.9789 - val_loss: 1.1667 - val_accuracy: 0.8889
Epoch 35/50
5/5 [=====] - 8s 2s/step - loss: 0.0198 - accuracy: 1.0000 - val_loss: 1.1639 - val_accuracy: 0.8889
Epoch 36/50
5/5 [=====] - 8s 2s/step - loss: 0.0233 - accuracy: 1.0000 - val_loss: 1.1832 - val_accuracy: 0.8889
Epoch 37/50
5/5 [=====] - 8s 2s/step - loss: 0.0249 - accuracy: 0.9859 - val_loss: 1.2104 - val_accuracy: 0.8889
Epoch 38/50
5/5 [=====] - 7s 1s/step - loss: 0.0320 - accuracy: 0.9789 - val_loss: 1.2562 - val_accuracy: 0.8889
Epoch 39/50
5/5 [=====] - 7s 1s/step - loss: 0.0198 - accuracy: 0.9930 - val_loss: 1.3140 - val_accuracy: 0.8889
Epoch 40/50
```

```
PS C:\Users\DELL\Desktop\Datasets> & C:/Users/DELL/AppData/Local/Programs/Python/Python311/python.exe C:/Users/DELL/Desktop/Datasets/...
py
Epoch 1/50
5/5 [-----] - 16s 2s/step - loss: 5.0659 - accuracy: 0.8380 - val_loss: 55.6557 - val_accuracy: 0.9444
Epoch 2/50
5/5 [-----] - 9s 2s/step - loss: 3.4038 - accuracy: 0.9577 - val_loss: 36.7766 - val_accuracy: 0.9444
Epoch 3/50
5/5 [-----] - 8s 2s/step - loss: 2.6387 - accuracy: 0.9437 - val_loss: 24.3385 - val_accuracy: 0.9444
Epoch 4/50
5/5 [-----] - 8s 2s/step - loss: 0.8843 - accuracy: 0.9507 - val_loss: 17.4290 - val_accuracy: 0.9444
Epoch 5/50
5/5 [-----] - 8s 2s/step - loss: 0.7057 - accuracy: 0.9718 - val_loss: 12.1232 - val_accuracy: 0.9444
Epoch 6/50
5/5 [-----] - 8s 2s/step - loss: 0.7471 - accuracy: 0.9648 - val_loss: 8.2230 - val_accuracy: 0.9444
Epoch 7/50
5/5 [-----] - 9s 2s/step - loss: 0.8335 - accuracy: 0.9366 - val_loss: 5.2826 - val_accuracy: 0.9444
Epoch 8/50
5/5 [-----] - 8s 1s/step - loss: 0.0417 - accuracy: 0.9789 - val_loss: 3.7348 - val_accuracy: 0.9444
Epoch 9/50
5/5 [-----] - 7s 1s/step - loss: 0.3186 - accuracy: 0.9718 - val_loss: 2.7248 - val_accuracy: 0.9444
Epoch 10/50
5/5 [-----] - 8s 1s/step - loss: 0.1040 - accuracy: 0.9789 - val_loss: 2.1752 - val_accuracy: 0.9444
Epoch 11/50
5/5 [-----] - 9s 2s/step - loss: 0.2313 - accuracy: 0.9789 - val_loss: 1.8835 - val_accuracy: 0.9444
Epoch 12/50
5/5 [-----] - 7s 1s/step - loss: 0.0636 - accuracy: 0.9789 - val_loss: 1.6247 - val_accuracy: 0.9444
Epoch 13/50
5/5 [-----] - 7s 1s/step - loss: 0.1993 - accuracy: 0.9718 - val_loss: 1.4682 - val_accuracy: 0.9444
Epoch 14/50
5/5 [-----] - 7s 1s/step - loss: 0.0162 - accuracy: 0.9859 - val_loss: 1.3519 - val_accuracy: 0.9444
Epoch 15/50
5/5 [-----] - 7s 1s/step - loss: 0.1436 - accuracy: 0.9648 - val_loss: 1.3079 - val_accuracy: 0.9444
Epoch 16/50
```

Adam optimizer Model Confusion matrix:



VII. CONCLUSION

The identification of brain tumours is critical in the medical sector. In our study, we used deep learning using a CNN model to identify brain cancers and MRI images to assess alternative optimizers. The results show that the Adam optimizer surpasses other optimizers by a percentage of 98.8 percent accuracy and other criteria. In this paper, we detected a brain tumor in the brain with the help of CNN. We have tested different optimizers. We created a GUI-based user interface in which we can upload MRI scans and get the results whether there is a tumor. This work can be extended in the future, and we can find the tumor percentage in the brain, find the size of the tumor in the brain, and find which stage of tumor the patient is by testing the MRI scans.

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