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A METHODOLOGY TO IDENTFY BRAIN TUMOR USING DEEP LEARNING TECHNIQUES

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ABSTRACT: Patients suffering from brain tumors are some of the most prevalent and aggressive, and in the latter stages of the disease, they have a very low life expectancy. The planning stage of surgical procedures is very important if the goal is to provide patients a higher quality of life throughout the course of their lives. Imaging techniques such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are often used in the process of locating malignancies in various parts of the body, including the brain, lungs, liver, breast, and prostate. In this particular instance, magnetic resonance imaging (MRI) scans are carried out in order to examine the patient's brain in search of signs of cancer. On the other hand, since an MRI gets so much information at once, it is difficult to differentiate between a tumor and something that isn't a tumor at the same time. This approach has a lot of drawbacks, the most notable one being that it can only produce accurate quantitative data for a constrained selection of photographs. There are also a great deal of additional restrictions associated with it. It is feasible that automated systems that can be relied on in a trustworthy manner might aid in the prevention of suicide. It is difficult to automatically classify brain tumors since the region and structure around a tumor may be somewhat variable. This is one reason why brain tumors can be so dangerous. In this article, fresh techniques to the early identification of malignant brain tumors are explained. CNNs are put to use in order to classify the data (Convolutional Neural Networks). According on the site of the tumor, this section classifies gliomas, meningiomas, pituitary tumors, and other types of tumors that are not malignant. The architectural design of the system's deeper levels is predicated on the use of tiny kernels as the building blocks. This is a reference to the very little amount of mass that the neuron has. The fact that CNN's accuracy in test results was 99.5% puts it in a class by itself above all other methods used by the present generation. In addition to this, it is simple to understand and much simpler to put into practice.

Keyterms: [CNN, MRI, tumours.]

1. INTRODUCTION

Imaging technology has advanced to the point that it is now possible to perform diagnostic scans of the human body without the requirement for invasive surgical procedures [2]. This category encompasses a broad variety of imaging modalities that may be used for both diagnostic and therapeutic purposes. In the end, the use of medical imaging may be able to lead to improvements in both the health and well-being of the general population. The effectiveness of the segmentation stage [5], an essential and fundamental step in the processing of images, is contingent on the subsequent processing that is performed on the image. Through the process of picture segmentation in medical image processing [2], tissues and lesions may be recognised, the machine's vision can be enhanced, and a high-quality output can be produced for future diagnostic work. The identification of tumors or lesions has long been a challenge in the field of medical imaging; however, recent advancements in computer diagnostics (CAD) technology have made it feasible to improve sensitivity and specificity. According to [3,] the 5-year survival rate for men and women diagnosed with cancer of the brain and nerve system was respectively 34% and 36%. According to projections made by the World Health Organization (WHO), more than 120,000 individuals would lose their lives to brain tumors in this year alone [4]. In 2019, around 86,000 Americans will be diagnosed with primary CNS tumors, including malignant and nonmalignant [5]. .. A tumor develops when regularly occurring cells in the cortex of the brain begin to proliferate in an inappropriate manner.

There are two types of tumors: malignant and non-malignant. When a malignant brain tumor develops, it quickly and aggressively spreads into the tissue that is around it. There is a potential threat to the central nervous system posed by the spread of this sickness. In contrast to primary tumors, secondary tumors are cancerous tumors that have traveled to the brain from another section of the body. Primary tumors originate in one area of the body. In a benign brain tumor, the total number of brain cells will steadily increase during the course of the disease. Recent years have seen a rise in their use in various computer systems, such as neural networks and support vector machines (SVMs).

The use of DL models, such as KNN and SVM surface frameworks, which can explain complicated connections without the need of a significant number of nodes, is a new development in machine learning (SVM). The fields of medical image analysis and healthcare information systems are also included in the bioinformatics industry. A patient's life expectancy and the number of treatment choices that are open to them may both considerably improve if they get a diagnosis of a brain tumor at an earlier stage.

Problem statement

It is difficult and time consuming to manually segment tumors or lesions from a large number of MRI images that have been obtained in the course of medical practice. When looking for tumors or lesions in the brain, magnetic resonance imaging (MRI) is the imaging method of choice. Since it often involves a significant amount of data, brain tumor segmentation using magnetic resonance imaging (MRI) is one of the most essential aspects of medical image processing. When soft tissues are present, it may be difficult for tumors to accurately define the borders of their territory. To effectively differentiate between brain tumors requires a significant investment of both time and labor.

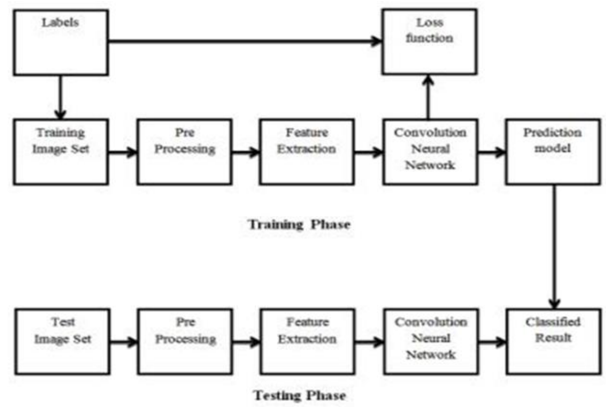
In this paper explains new strategies for early brain tumour detection. CNNs categorise data (Convolutional Neural Networks). This section divides gliomas, meningiomas, pituitary tumours, and other nonmalignant tumours by location. Deeper system tiers are built from small kernels. Neurons have relatively little mass. CNN's 99.5 percent accuracy puts it beyond all other approaches utilised today. It's easy to learn and implement.

2. RELATED WORK

It's possible that the method to segment a brain tumor on an MRI will be challenging and time-consuming. Researchers from all around the world are investigating and modeling a variety of different approaches in an attempt to optimize segmented return on investment (ROI). Because it produces better results than other methods, neural network segmentation is gaining popularity among an increasing number of people. As shown in [1], fuzzy segmentation may be applied to differentiate between parts of the brain that have tumors and those that do not contain tumors. It is possible to recover wavelet information (WW) by using multi-layer discrete wavelet transforms on occasion (DWT). A high level of precision in the diagnosis of brain tumors is attainable with the use of DNN. This classification method is evaluated in comparison to others, such as KNN, LDA, and SMO, which are all examples of classification algorithms[3]. A classification of brain tumors using DNN has an accuracy rate of 96.97 percent, according to the study. On the other hand, both its complexity and its performance fall short of expectations. Researchers in [2] have created a novel technique for modeling the formation of tumors, which has the potential to be used to the study of the progression of cancers in human beings. Gliomas[1]om and other solid tumors will be treated by focusing on their individual margins, which will ensure that the bulk of the tumor is not drastically altered. The construction of a system for simulating the progression of tumors makes use of both discrete and continuous methodologies. The atlas-based registration that is used in the proposed method makes it possible to properly and discreetly segment brain images that include tumors. In the third chapter, AdaBoost and multifractal feature extraction are used in order to find and segment brain tumors. Finding out how tumor tissue in the brain is structured may be accomplished by the use of the MultiFD feature extraction method. It is possible to utilise AdaBoost classification algorithms [3] to determine whether or not brain tissue contains cancerous cells. To put it another way, this is a really challenging task. The projection-based method is used while carrying out the categorizing process. You can figure out where you are heading with the help of this strategy as well. It is unnecessary to regularize LIPC in light of the information presented above. The amount of attention to detail that was put into this is incredible. In this paper, the seeded tumor segmentation method and the CellularAutomata (CA) graph slice methodology are analyzed and contrasted. Choosing choice 2 is the path that will lead to the best results. Brain tumors have the potential to be segmented accurately when both the initial selection and the VOI are chosen appropriately. This study has been expanded to include the segmentation of tumor slices. As a direct consequence of this, it is not very complicated. On the other hand, there is still a problem with accuracy. According to reference, these methods are referred to as "multimodal brain tumor segmentation methodologies." [6] It is possible that the performance of the current approach might be enhanced by combining a number of different segmentation strategies. In spite of the difficulties, the reference [7] provides a wealth of information on the process of segmenting brain tumors. In the course of conducting this study, a wide variety of research approaches were applied, each of which was subjected to extensive testing to validate its accuracy, reliability, and validity. Helps in the diagnosis of brain cancer by employing a combination of hybrid feature selection and ensemble classification. There is a wide range of software and processes that may be used to develop decision rules. Some examples of these include GANNIGMAC, decision trees, and C libraries. To make the process of decision-making more straightforward, you may want to think about using a mixed method to choose the features. [10] makes use of a method known as adaptive histogram equalization (AHE) in order to get better contrast. A surgical treatment is necessary in order to remove the tumor from the patient's brain. After that, an operation known as a Gabor function will be used to remove any aberrant brain cells. Using a fuzzy with (KNN) classification method, problems on a brain MRI might potentially be identified (MRI). Playing this game might be a difficult ordeal. Despite this, there is still a lack of clarity around the issue. Utilizing a convolutional neural network allowed for the very first time the classification of brain cancers[4]. In order to categorize brain tumors in a manner that is completely novel, this research takes use of a convolutional neural network.

3. CNN CLASSIFICATION FOR BRAIN TUMOR IDENTIFICATION

The design and implementation of neural networks are used in the process of developing a computer model of the human brain. Neural networks may be used for a wide variety of tasks, including pattern matching, pattern approximation, pattern grouping, and vector quantization, to name just a few of those potential applications. Interoperability between neurons may be broken down into three categories: basic, moderate, and advanced. In this section, we went into further depth on recurrent neural networks, feedback neural networks, and feedforward neural networks. There are a number of different kinds of feedforward neural networks, in addition to single-layer and multi-layer feedforward neural networks. In order to conceal the hidden layer, a single-layer network is used. Input and output may also be separated into two distinct levels as an alternative, which results in improved performance. The output of the system as a whole is composed of Layers 1 through 3, which are all interconnected and function as such. If your feedback system operates via a series of closed loops, we call it a "recurrent network." Traditional neural networks aren't equipped to handle the challenge of scaling photographs, thus they can't be used to solve this problem. Convolutional neural networks may be used to scale images in many ways. Convolutional neural networks have input and output layers that are made up of the ReLU, pooling, and fully connected layers, respectively. The process of concatenating many images is what convolutional layers do to create a single composite picture. The ReLU layer is in charge of activating each component once it has been loaded. There is no need for any further pooling levels. It is entirely up to us to choose whether or not we will make use of this. When downsampling, the pooling layer is often employed. The probabilities obtained from the previous layers are utilized in the final layer to generate a class or label score, the value of which may vary anywhere from 0 to 1. This concept is referred to as being "full-connected." Brain tumors are able to be categorized with the use of convolutional neural networks, as seen in Figure 1. Pretesting and posttesting are the two categories that make up this testing. Brain scans, for instance, may have labels superimposed on them so that researchers can more efficiently sort through an extremely large number of pictures. Preprocessing, feature excision, and loss function classification are the first steps that need to be taken before constructing a prediction model. To get started, you need give your picture collection a name. Resizing an image allows for the modification of its proportions prior to the processing of the image. In conclusion, a convolutional neural network is the tool of choice for performing automated classification of brain cancers. ImageNet kindly supplied the brain imaging dataset that was used in this investigation. One of the models that has previously undergone training is referred to as Image Net. In order to begin from square one, each successive layer has to be instructed (i.e. from the initial layer to the final layer). Because of this, a significant amount of time is lost. This change will have an effect on the outcomes of the experiment. During the categorizing process, pre-trained models that make use of brain datasets are used so that this issue is not encountered. Only the last layer of our CNN solution will be trained using Python. There is no need to instruct all of the layers all at once. As a consequence of this, the suggested approach for automatically classifying brain tumors requires just a little amount of processing effort, despite the fact that it carries out very effectively. Here is an example of how to compute the amount of the loss. A class score is given to every pixel in the raw picture by use of a scoring system. It is possible to assess the quality of a set of variables by doing an analysis using a loss function on the full set of variables. It is important to us to see how closely the induced scores correspond to the ground truth labels in the training data. Increased accuracy will result from the loss function being calculated in the suitable manner. When the loss function is increased, the accuracy suffers. When the loss function has a low metric, accuracy is also improved significantly. It is essential to construct a loss function before moving on to the development of the strategy. When calculating the slope of the loss function, it is possible to make use of many different assessments of the gradient value.



4. CNN ALGORITHM CLASSIFICATION

Put in place in your application the necessary library components. It is possible that the variety of data that may be used for training models would significantly improve if step 3 included the use of data augmentation rather than the collection of actual data. In order to load the data, you will first need to specify the path to the data collecting. Have the ability to recognise photos and the tags that accompany them. On the basis of the data that is currently available, tumors may be broken down into the following four categories: gliomas, meningiomas, pituitary tumors, and those who do not have tumors. If required, identify and define CNN for the whole of the training. There is a possibility that using a rectified linear unit (RELU) would shorten the amount of time needed for training. In order to provide the neural network feedback, a loss is implemented during training. The accuracy of the exam may be determined by tallying the number of correct guesses made in comparison to the total number of incorrect predictions. After you have done studying the output that has been labeled, you will be able to decide whether or not your original prediction was correct.

5. EXPERIMENTAL RESULTS

We gathered non-tumor as well as tumor pictures from a variety of online sources for our collection of MRI scans, which comprise both tumor and non-tumor images. utilizes data from publicly accessible sources to represent real-world patient cases and tumor pictures, such as Radiopaedia and the Brain Tumor Image Segmentation Benchmark (BRATS). Examples of such sources include. Convolutional neural networks have the potential to provide accurate diagnoses of

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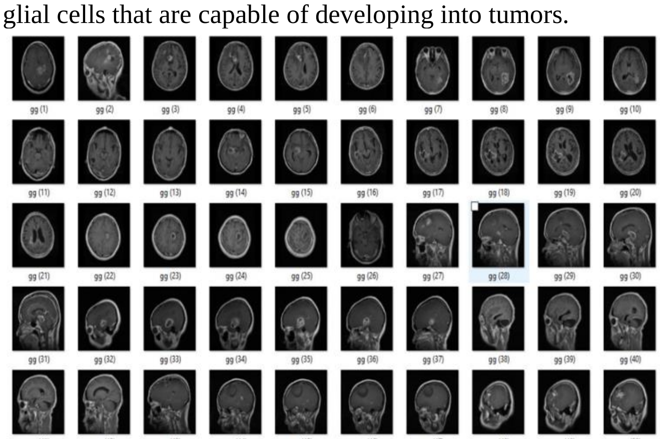
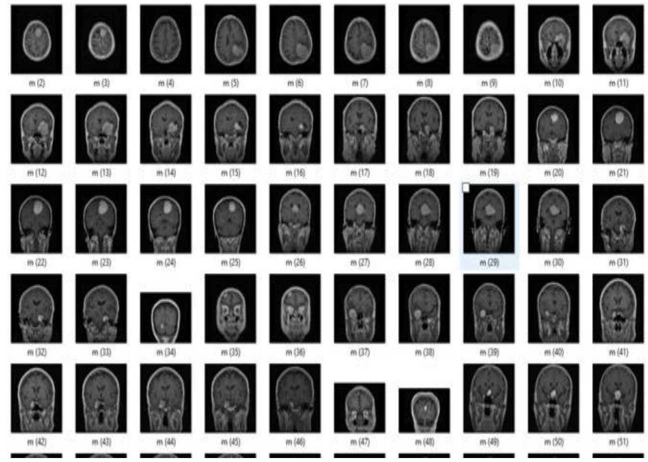
brain malignancies far more quickly than was previously possible. Utilizing Python scripts, the simulation is carried out in its entirety. The accuracy of this approach may be calculated, and then it is compared to any and all of the other methods that are now available. The efficiency of the method for classifying brain tumors may be evaluated based on training, validation accuracy, and validation loss. The diagnosis of brain cancers is performed with the use of SVM-based classification technology, which is currently accessible in imaging. To find out takes a significant amount of time and is not particularly accurate. There is no need for any additional feature extraction procedures in order to use the CNN-based classification approach that was presented. The value of the CNN function can only be obtained from the CNN website. In Figures 2, 3, 4, and 5, scans of the brain are categorized as either showing tumors or not showing any evidence of tumors. As a direct consequence of this, accuracy is maintained despite a reduction in both calculation time and complexity. Figures 6, 7, 8, and 9 provide evidence of the reliability of the classification (right to left in these images). If a person has a tumor in their brain, then the likelihood score is much greater than if their brain is normal. As a consequence of this, the likelihood that it is the brain in its most frequent form is lower than it is with other representations. When contrasted with the normal brain, the brain affected by the tumor possesses the greatest likelihood score value. Training Information and Resources Regarding Glioma Gliomas are cancerous growths that may develop in either the brain or the spinal cord, and they always result in the patient's death. Gliomas are thought to originate from the sticky support cells known as glial cells, which surround and assist nerve cells in their activity. However, this theory has not been verified. There are primarily three different types of glial cells that are capable of developing into tumors.



B. Training with Meningioma Tumor

As a result, it originates in the cranial or spinal canals. In terms of benign primary brain tumors, meningiomas are the most prevalent form. Higher-grade meningiomas, on the other hand, are very uncommon.To make a precise diagnosis, surgeons may remove a bit of tumour tissue during surgery. Thereafter, the tumour tissue should be examined by a neuropathology specialist.

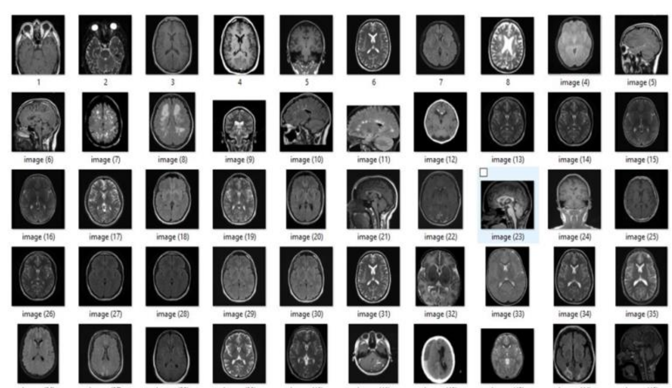


C. Training with a Pituitary Tumor Dataset

Pituitary tumors are growths that develop on the pituitary gland, which is a small gland that sits close to the brain and has the ability to change the amount of hormones that are produced by the body. This picture demonstrates how much the tumor has shrunk over time (microadenoma). Pituitary tumors are the medical name for cancers that begin in the pituitary gland. Pituitary tumors may affect both men and women. Both cancerous and noncancerous tumors are both conceivable outcomes of the potential for tumor development.

D. Non Tumor Data Set Training

The person does not have a brain tumor, check the dataset below



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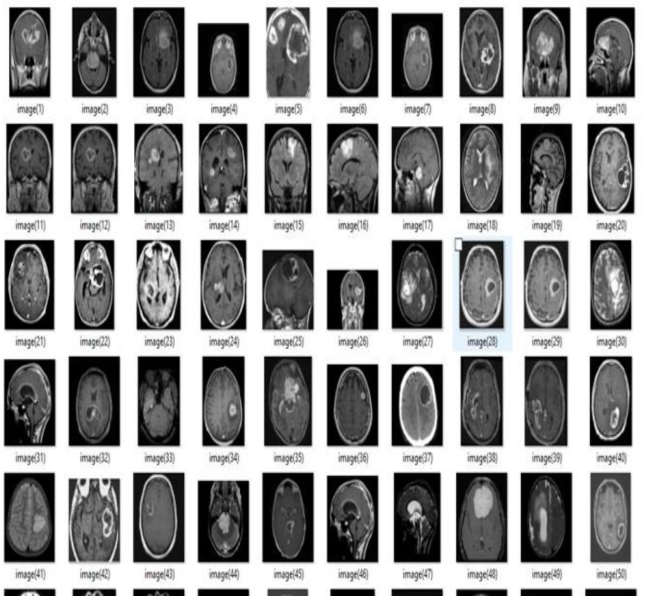
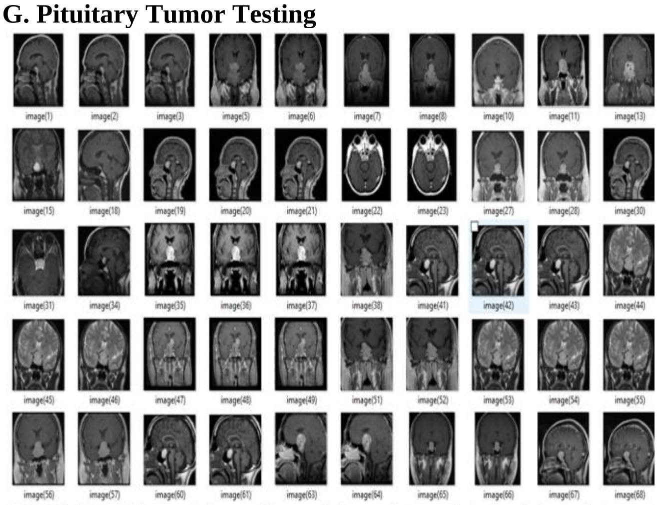
E. Testing of a Glioma Tumor Data Set

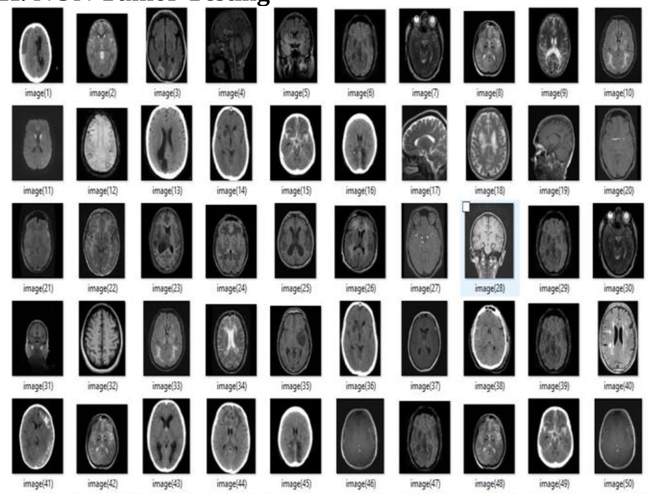


F. Meningioma Tumor Testing

G. Pituitary Tumor Testing



H. NON Tumor Testing

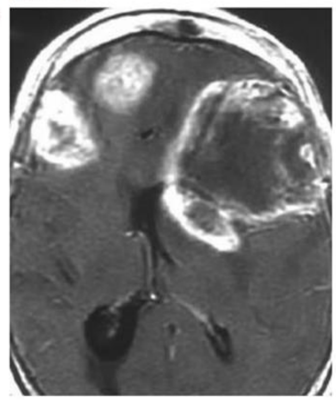


I. Test Cases

Test case-1 check if the person is affected by Glioma tumor. here it will provide it as an input image of the Glimo tumor test case

```
lab, img = predict(BrainTumorClassifier,'./data/Testing/glioma_tumor/image(5).jpg')
print(lab)
img
```

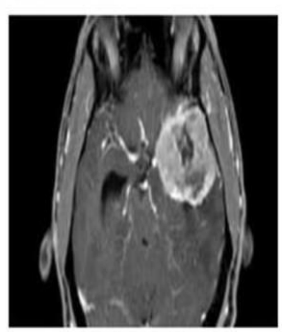
```
glioma tumor
```



Test case-2 checks if the person is affected by meningioma tumor. here it will provide an image of a meningioma test case as input

```
lab, img = predict(BrainTumorClassifier,'./data/Testing/meningioma_tumor/image(5).jpg')
print(lab)
img
```

```
meningioma tumor
```



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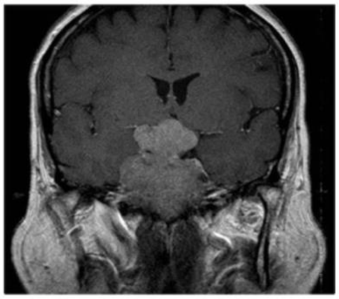
Test case-3 check if the person is affected by a pituitary tumor. here it will provide it as an input image of the pituitary test case

```
lab, img = predict(BrainTumorClassifier,'./data/Testing/pituitary_tumor/image(6).jpg')
print(lab)
img
```

```
pituitary tumor
```

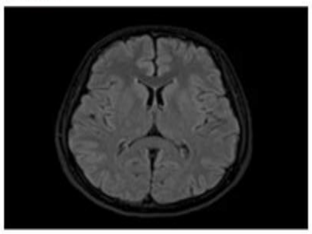


Test case-4

check if a person is affected by a tumor without a tumor. Here, it provides an image of a tumor-free test case as input.

```
lab, img = predict(BrainTumorClassifier,'./data/Testing/no_tumor/image(100).jpg')
print(lab)
img
```

```
no tumor
```



Test Accuracy and Validation loss

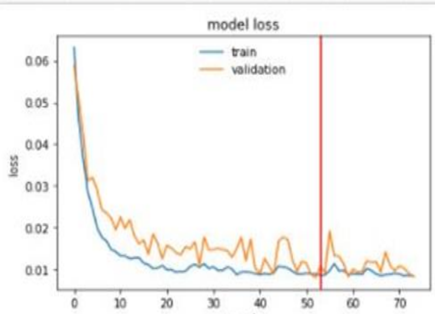
```
net = Network()
optimizer = optim.Adam(net.parameters(), lr=1.0E-3)

BrainTumorClassifier = Model(net, optimizer, RMSE, device)
BrainTumorClassifier.train(train_data=(data.train_inputs, data.train_outputs),
                           val_data=(data.val_inputs, data.val_outputs),
                           epochs=200, patience=20, batch_size=100)
```

```
nce: 7
        Epoch: 67/200,  Epoch duration: 107s,  Train Loss: 0.00858,  Val Loss: 0.00939 - No improvement -> Remaining pati
ence: 6
        Epoch: 68/200,  Epoch duration: 121s,  Train Loss: 0.00878,  Val Loss: 0.0142 - No improvement -> Remaining patie
nce: 5
        Epoch: 69/200,  Epoch duration: 117s,  Train Loss: 0.0089,  Val Loss: 0.011 - No improvement -> Remaining patienc
e: 4
        Epoch: 70/200,  Epoch duration: 129s,  Train Loss: 0.00914,  Val Loss: 0.00973 - No improvement -> Remaining pati
ence: 3
        Epoch: 71/200,  Epoch duration: 125s,  Train Loss: 0.00894,  Val Loss: 0.0109 - No improvement -> Remaining patie
nce: 2
        Epoch: 72/200,  Epoch duration: 122s,  Train Loss: 0.00857,  Val Loss: 0.0103 - No improvement -> Remaining patie
nce: 1
        Epoch: 73/200,  Epoch duration: 109s,  Train Loss: 0.00866,  Val Loss: 0.00918 - No improvement -> Remaining pati
ence: 0

Early stopping after 20 epochs of no improvements

Train finished successfully :)
```

```
BrainTumorClassifier.evaluate(test_data=(data.test_inputs, data.test_outputs))
```

```
Test accuracy:99.6%
Correct predictions: 488, Wrong predictions: 2
```

```
BrainTumorClassifier.plot()
BrainTumorClassifier.save(path="./", checkpoint_name="module")
```




```
Checkpoint saved successfully :)
```

CONCLUSION

Automated brain tumor categorization systems that are accurate, rapid, and sophisticated at cheap cost are the goals of this research effort. Feature extraction and algorithmic classifications have long been used in the categorization of brain tumors. This job is predicted to be somewhat tough. On the other hand, the computation takes a long time and the results are inaccurate. Using convolutional neural networks, the suggested system can classify more accurately while using less computing time. Other displays include brain tumors and normal pictures, as well as results of classification.. Using feedforward layers sequentially, CNN is a deep learning technique. In addition, Python scripting is used in the system. The photos are classified using an image network database. It is a model that has already been tested. When attempting to extract the depth, breadth, and height of the individual pixels from the CNN data set As a result, a loss function based on gradient descent is applied to obtain great precision. There is a calculation for training accuracy, validation accuracy, and loss of validation accuracy. 99.6 percent of the time this instruction is right. Accordingly, both the accuracy and loss of validation are quite high.

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