MRI Based Brain Tumor Classification Using Convolutional Neural Network

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APPROVAL

Approval

This thesis titled on "**MRI Based Brain Tumor Classification Using Convolutional Neural Network**", submitted by **Mou Afroz Tona (ID: 192-35-463)** to the Department of Software Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Software Engineering and approval as to its style and contents.

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DECLARATION

This statement states that **Mou Afroz Tona** completed the thesis titled **"MRI Based Brain Tumor Classification Using Convolutional Neural Network"** under the guidance of **Mr. Md. Rittique Alam,** Lecturer, Department of Software Engineering, Daffodil International University. Additionally, it declares that neither this paper nor any component of it has been submitted to another institution for the conferment of a degree.

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Before I end, I must do my parents justice by properly thanking them for their enduring love and tolerance.

ABSTRACT

Purpose: It's a crucial and difficult task to define a brain tumor in the process of medical imaging. If the brain tumor can be classified, it might be quite important in improving the patient's likelihood of survival while undergoing therapy, and This project's main objective is to create a model for detecting brain tumours.that can be seen on 2D MRI imaging.

Research gap: If there are no MRI sequences, MRI images of the brain produced by convolutional neural networks may be incorporated into deep learning models.

Problem statement: In the paper, only a 2D image and CNN are used.

Objective: The major objective is to determine whether there is a brain tumor or not, the brain is in good condition. For the purpose of enhancing performance and streamlining the classification process of medical images, the proposed system has been investigated based on CNN and deep learning classifiers.

Methodology: Here, preprocess the data set,split it into two sections,train the model,and finally evaluate the accuracy.

Result: Comparative data demonstrates that the proposed model’s accuracy was higher than that of the previously used method in detecting and classifying tumors.

Conclusion: In this study, it was shown that it is possible to plan treatment for patients with brain tumors by analyzing MRI images produced using a deep learning method based on CNN.

Keywords- CNN, brain tumor, deep learning, classification, artificial intelligence.

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List of Nomenclatures

CNN	Convolutional neural network
MRI	Magnetic resonance Imaging
ANN	Artificial Neural Network

CHAPTER 1

Introduction

1.1 Overview

A review of medical images has played a vital role in this difficult subject of study for the past 20 years. There are a ton of applications for this topic that concern both humans and animals. Research with regard to diagnosis and patient care greatly benefits from the use of medical images. It can get the radiology department of a hospital’s biomedical picture. Even a biological photograph is different from other medical images. There are different kinds of machines in radiology unit of a hospital, such as positron emission tomography, computed tomography, X-ray, magnetic resonance angiography, etc. There are some problems with the constructed images that are used by biomedical imaging, such as low lighting, blurriness, noise, or sharpness. To get over this problem, it should have some fun. Two varieties of brain tumors exist: primary and secondary tumors. fundamental image processing methods to improve the image quality. These photos have undergone processing to calculate the tumor, see the tumor in 3D and 4D space, and categorize the type, stage, and location of the tumor. These four are highlighted topics for researchers in medical image processing. The major organ is thought to be the brain, which is protected by the scalp. An average human brain is 1260 cubic millimeters in size and weighs 1.3-1.5 kg.

1.2 Brain Tumor

The term "brain tumor" refers to an unnatural cell proliferation in the tissues of the brain. Brain tumors come in two different subtypes: benign (lacking cancer cells) and malignant (having rapidly proliferating cancer cells). Primary brain tumors are some of them, since they develop in the brain. Some illnesses are metastatic, starting elsewhere in the body and progressing to the brain. The World Health Organization disseminates fresh research and papers on patient statistics, tumor types, and tumor types. Tumors may endanger life if they are not identified and treated right away.

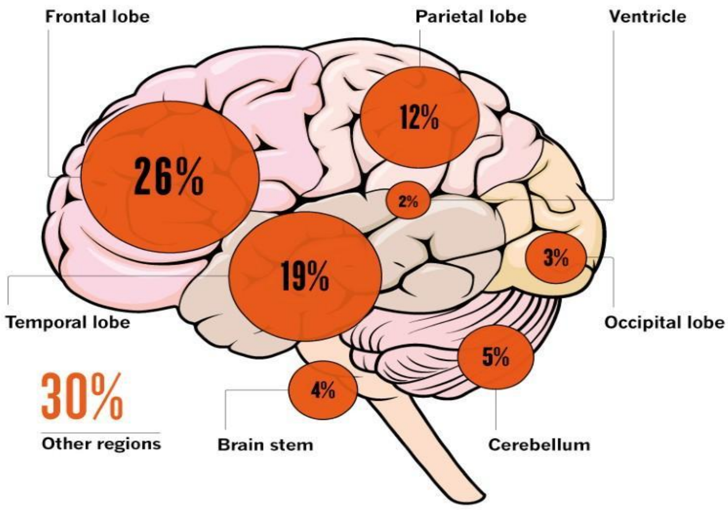

Figure 1.1: Breaking down the epidemiology of brain cancer (google 2018)

1.3 Brain tumor classification

Brain tumors can be classified as either primary or secondary. The brain clink that causes primary tumors and after first affecting one organ, the secondary tumor spread to other ones.

1.3.1 Glioma Tumor

The majority of initial brain tumors occur as gliomas. The spinal cord and brain include glial cells that are becoming cancerous, which is why they are growing. We can identify gliomas by their various histological and malignant grades. A Glioma patient can live less than 14 months. There are two types of gliomas. Glioblastoma multiforme (GBM) is the most prevalent glioma kind. The WHO has categorized gliomas into four classes, with grades 1 and Glial cells can be found in the brain and spinal cord.

1.3.2 Malignant Tumor

A malignant, invasive type of brain tumor is a high caliber glioma. When cancerous cells proliferate and grow in bulk, malignant tumors are created. Cancer cells may infiltrate adjacent tissue, as opposed to benign tumors. In a process known as metastasis, they may potentially separate from tumors and disperse throughout the body.

- This type of tumor develops quickly.
- Generally, you need surgery,
- Radiotherapy
- A small number of patients can be alive.

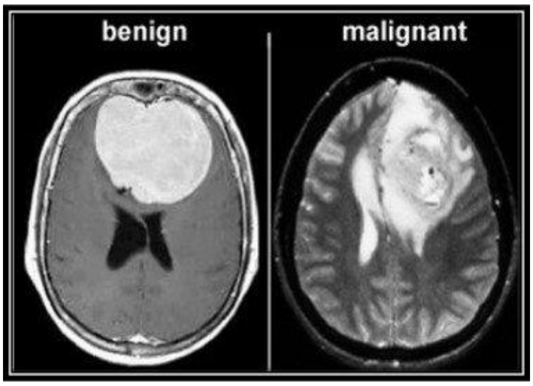

Figure 1.2: Malignant Tumor (Right) and Benign (glioma) Tumor (left).(Google 2019)

1.4 Motivation

MRI is the main tool for diagnosing brain tumors. That helps with analysis, monitoring, and surgery planning. Brain tumor structural MRI picture segmentation and processing by hand is a tedious effort that takes time that is currently limited to skilled neuroradiologists. As a result, brain tumor identification and therapy will be significantly influenced by a mechanical and effective brain tumor division. It may also lead to the early identification and treatment of neurological disorders. For the purpose of assisting radiologists in providing crucial details like the size, location, and shapes includes (increasing both the core and entire tumor areas), They can segment lesions using an automated method. This will increase the effectiveness and significance of therapy.

Table 1.1: Survival rate according to age caused by brain tumor

Species of tumor	**Rate of Relative Survival at Five Years**		
	Age		
	20-44	45-54	55-64
low-grade, widespread astrocytoma	73%	46%	26%
Astrocytoma that is anaplastic	58%	29%	15%
Glioblastoma	22%	9%	6%
Oligodendroglioma	90%	82%	69%
Anaplastic oligodendroglioma	76%	67%	45%
Ependymoma/anaplastic ependymoma	92%	90%	87%
Meningioma	84%	79%	74%

According to figures from the past ten years, in 2012, there were 14.1 million new cancer cases believed to have occurred globally. There were 6.7 million women and 7.4 million males among them. By 2035, this figure is projected to rise to 24 million. Lung cancer, which made up 13% of all newly diagnosed instances of cancer in 2012, was the most prevalent type of cancer overall. We therefore sought to examine these statistics and contribute to the study of images in medicine.

1.5 Objective

The thesis paper's primary goals are-

1. To do obtain brain tumor datasets, gathering them is the first step in creating a medical image.
1. To do selecting features, segmenting data, filtering, or deleting the skull.
2. To do created a model by us that can carry out all of the essential and significant activities required to locate a tumor and its characteristics.
3. To do described in the research, which uses convolutional neural networks as a foundation without requiring human participation, is effective and efficient at classifying and diagnosing brain tumors.
4. To, compared, and the model with the best sensitivity, accuracy, and other performance measures was chosen.

1.6 Thesis Contribution

- The paper conducted a statistical evaluation that closely examined 50 research articles from various backgrounds to understand the state of segmentation strategies for brain tumors. Image processing and neural network approaches are also included in this statistical analysis of tumor segmentation. Both the various kinds of pre-processing techniques and practically all segmentation approaches are covered.

- In order to categorize and divide up brain tumors, a novel deep learning model is put forth.
- A variety of CNN-based layers that were trained on the most current dataset make up the segmentation model that is being recommended. To get better results, A median filter is used for preprocessing, and the global threshold approach is used for postprocessing.
- To enhance the effectiveness of the suggested strategy, many training samples are used.
- To address class unbalance difficulties in the proposed model, batch normalization is applied, and overfitting issues are avoided by using the focal loss function.
- On a GoogleNet model that has been previously trained to classify brain tumors, transfer learning techniques are used in the suggested framework.
- The suggested method for segmenting and classifying brain tumors is computationally efficient and produces results that are more accurate and trustworthy than cutting-edge techniques.

1.7 Thesis structure

Based on the study we conducted, our thesis book has seven chapters. We'll go over the foundation of the chapters in a little more detail after that.

- **Chapter 1: Introduction** The purpose, our aim, and the contribution of our thesis will all be briefly discussed in this chapter.
- **Chapter 2: Related Works** It'll discuss a few related projects that have already been completed and discuss their method of operation, benefits, and drawbacks.

- **Chapter 3: Brain Tumor segmentation techniques: A Static Analysis** This part includes an evaluation of the data as well as several charts, figures, and tables, some of which are depicted, followed by descriptions of the contents.
- **Chapter 4: Background study** The methods for processing images, The topics of discussion will include both conventional machine learning and deep learning classifiers.
- **Chapter 5: Proposed methodology** This chapter, explains our recommended method for categorizing tumors using traditional machine learning to identify tumor classifiers and detect the tumor Convolutional neural networks areimage processing techniques.
- **Chapter 6: Experimental Results and Evaluation** It will address the experimental findings, our suggested algorithm for performance evaluation, and performance measurements in the chapter.
- **Chapter 7: Conclusion** It'll talk about the work's shortcomings as well as potential improvements and future work.

1.8 Summary

The topic of brain tumors and its subfields are briefly discussed in the chapter. The various forms of brain tumors and their characteristics have been covered. It gave a succinct explanation of our work's purpose and motive. The contribution of our thesis and its format were briefly described in the final section.

CHAPTER 2

Literature Review

2.1 Overview

There are numerous subfields in the examination of medical images, which is a very large area of study. We looked at previous research on the categorization of brain tumors. Brain tumors on MRI scans are automatically segmented in the majority of the research that has been done. The categorization of the tumor must proceed through several gradations after segmentation. But in the preliminary research investigations, Malignant and benign tumors are the focus of the classification strategy.

So, This part includes a presentation of medical imaging as well as related work on the model and data collection, including information on its features, advantages, and research limitations.

2.2 Reviews of the relevant literature

Yumin Dong et al. have introduced hybrid quantum-classic convolutional neural network (HQC-CNN) algorithm to identify brain tumors and measure their size,The experimental outcomes demonstrate that the enhanced HQC-CNN excels on the brain tumor MRI dataset with more accuracy and fewer parameters, attaining a classification success rate of 97.85%. Tumors are automatically segmented in the majority of the research that has been done [1]. Sanjiban Sekhar Roy et al., Loveleen Gaur et al., Chenjie Ge et al., S. Suganyadevi et al., Shahabedin Nabavi et al., Zhihua Liu et al., Lei Tong et al., Martin Kocher et al., and Maximilian I et al. proposed CNN to identify brain tumors and measure their size. Finally, Despite a wide diversity of applicable imaging modalities and computational tools, most approaches may achieve high diagnostic accuracies of 80–90%. Sahar Gull et al. have implemented the fully convolutional neural network (F-CNN) algorithm to identify brain tumors and measure their size. The highest batch accuracy, minimum batch accuracy, and maximum batch accuracy of the suggested approach are 95%, 96.50%, and 98%, respectively. For the BRATS 2018 dataset, the BRATS 2019 dataset, and the BRATS 2020 dataset, the suggested method achieves average accuracy levels of 96.50%, 97.50%, and 98.00%, respectively,in order to split brain tumors. Similarly,for the BRATS 2018 dataset, the BRATS 2019 dataset, and the BRATS 2020 dataset, the proposed technique exhibits average accuracies of 96.49%, 97.31%, and 98.79%, respectively,for classifying brain tumors. On the BRATS2 datasets, the calculation time and error rate are both 3.02%. FOUZIA ALTAF et al., JUN HUANG et al., Sumbal Rasheed et al., Zohaib Salahuddin et al., and Lars Heiliger et al. have implemented CNN and RNN, and according to the published information gathered from the SEER (Surveillance, Epidemiology, and End Results) research from the National Cancer Institute, GBM accounts for 50.8% of all CNS malignant tumors. Yin Dai applies CNN and Artificial Neural networks (ANN) . Finally, When compared to the prior state-of-the-art models, our strategy improved accuracy on average by 10.1% and 1.9%, respectively, in the two multimodal medical picture classification datasets.Momina Masood has proposed Mask-RCNN and Over the Figshare dataset, the proposed method produced average accuracy and dice scores of 95.9% and 0.955 for ResNet-50 and 96.3% and 0.959 for DenseNet-41, respectively. For regression layer localization of the brain tumor area, the suggested method's mean average precision (mAP) is 0.949. M.O. Khairandish et al. and J. Seetha et al. have implemented CNN and SVM for tumor classification. These two suggested techniques have successfully distinguished between malignant and benign tumors from MRI scans with a classification accuracy of 97.5% , respectively. Mobeen Ur Rehman et al., Chenjie GE et al., Sourabh Hanwat et al., Song Wu et al., Hao Tang et al., and Jianxin

Zhang et al. proposed U-Net with 2D CNN, VGG16, Res18, and DnCNN, AGResU-Net, to detect brain cancer and measure its size. The suggested approach greatly outperforms current methods by, on average, 16.32%, 8.45%, and 6.24%, respectively, in terms of DSC. Tongxue Zhou et al., Wei Ji algorithm et al., and Stefanus Tao Hwa Kieu et al. also proposed the VGGNet, GoogleNet , Residual Net, and DenseNet algorithms. And By boosting the tumor core, whole tumor, and tumor core, respectively, the suggested technique achieves average Dice scores of 0.7831, 0.8739, and 0.7748, according to the experiments with the testing set of BraTS 2017 data. Other projects have also been completed, including Changhee HAN1 et al., Varun A. Kelkar et al., Hai Tang et al., Samaneh Kazemifar et al., and Shahabedin Nabavi et al., who proposed the method GAN to identify brain tumor classification. This method achieves the highest sensitivity of 97.48%, compared to the 93.67% best-performing traditional DAs. Jyoti Islam et al., Debadyuti Mukherkjee et al., Qingyun Li et al., Isabella Castiglioni et al., and Changhee Han et al. have introduced Deep Convolutional Generative Adversarial Networks (DCGANs) and AGGrGAN, PGGAN architecture,MUNIT, SimGAN, and ResNet-50 architecture. In PGGAN, the accuracy (actual vs. synthetic) is 79.5%. (tumor vs. non-tumor) is 87.5%. In MUNIT, accuracy (real vs. synthetic) is 77.0%, and (tumor vs. non-tumor is 92.5%. In SimGAN, accuracy (real vs. Synthetic) is 76.0%, and accuracy (tumor vs. non -tumor) is 94.0%. Muhammad Usman Saeed et al. developed MobileNetV2 for the categorization of brain tumors using an algorithm. According to the experiments, the model generated dice coefficient scores for WT, TC, and ET on BraTS 2020 of 91.35%, 88.13%, and 83.26%, on BraTS 2019 of 91.76%, 91.23%, and 83.19%, and on BraTS 2018 datasets of 90.80%, 86.75%, and 79.36%, respectively.Ching-Hsin Wang et al. have proposed the pix2pix algorithm and the ensemble model's dice results obtained by averaging the outputs of eight models with different parameter configurations with regard to At 0.7847, 0.9053, and 0.8373, respectively, ET, WT, and TC. K. Shankar et al. introduce the AGO algorithm to classify brain tumors. The suggested technique successfully retrieved the image with little noise and 72% PSNR. Erena Siyoum Biratu et al. implemented Convolutional Neural Networks, Deep Convolutional Neural Networks, Long Short-Term Memory (LSTM), Recurrent Neural Networks, Deep Autoencoders,Deep Neural Networks, and Generative Adversarial Networks (GANs) algorithm An example of a deep learning model is convolutional neural networks (CNNs), which are frequently employed in brain tumor classification tasks and have produced significant results. Akram Belazi et al. introduced block-based permutation, pixel-based substitution algorithms, and the resulting 99.6% and 33.4%, respectively, for NPCR and UACI scores are remarkably comparable to those anticipated. Furthermore, 99.6179% and 33.4784%, respectively, are the averages for the NPCR and UACI. For the radiologist to effectively decide on a patient's course of therapy, binary classification is insufficient. To solve these problems, deep learning-based techniques have recently been implemented. As a result, we suggested a model that is more effective at spotting brain cancers and is based on deep convolutional networks.

2.3 Summary

In this chapter, It analyzed 50 research articles in total and spoke about how they functioned. This study of the literature demonstrates that there have been various published research studies looking at the segmentation and detection of brain tumors.Some efforts yielded significant results while using conventional techniques, whereas others did not. However, after reviewing these studies,due to the network's memory use and learning strategy, we can say that deep learning beats conventional classifiers.

CHAPTER 3

Methodology

3.1 Overview

There is a model we've put forth for finding aberrant cells in brain MRIs. Using a convolutional neural network, it has attempted to find the tumor. It will first go over the suggested segmentation method for identifying the tumor. Next, It'll talk about applying a machine learning algorithm to detect tumors.

3.2 Proposed approach

Our suggested approach uses CNNs, which add the dilation rate as a new hyper-parameter to the mix. In order to achieve dilation, zeros are added between the filter elements. Using a convolutional neural network (CNN), made to wring the most information possible from each image. Since 5*5 is the most compact filter that can catch it, a 5*5 convolution layer is used to extract the up/down, left/right, and center from the image, which enables more precise attributes to be captured by the network. It utilizes the identical CNN architecture as shown but does not apply any dilations to the convolution layers (set dilation_rate = 1) to assess effectiveness against the fundamental CNN. The introduction and application of identifying tumors using an artificial neural network with five layers. The consolidated model, which has seven steps, including the buried layers, provides the most accurate results for finding tumors. Convolutional, flattening, pooling, and the hidden layers are layers that are entirely connected together with the output and input layers.

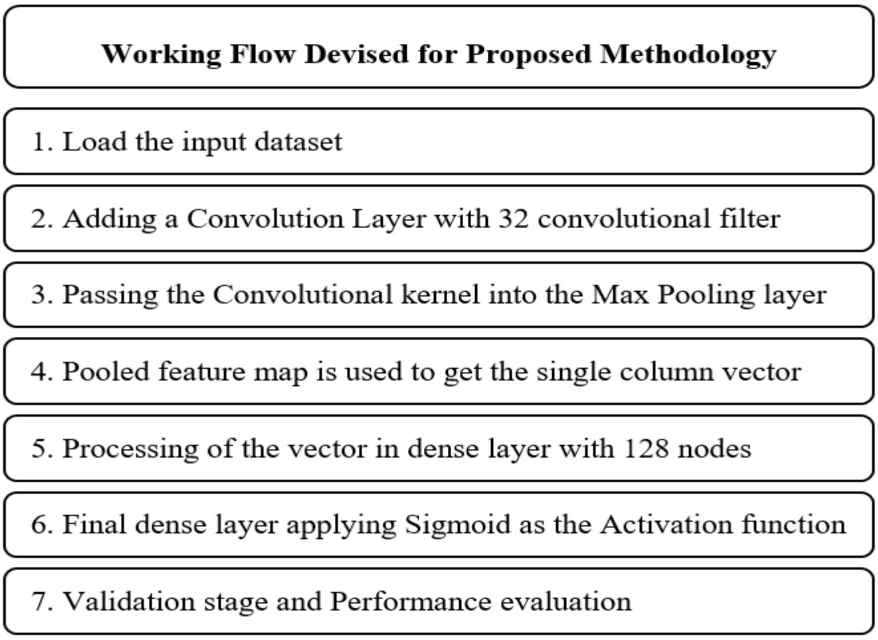

Figure 3.1: The suggested five-layer CNN Model's operational flow. Google(2019)

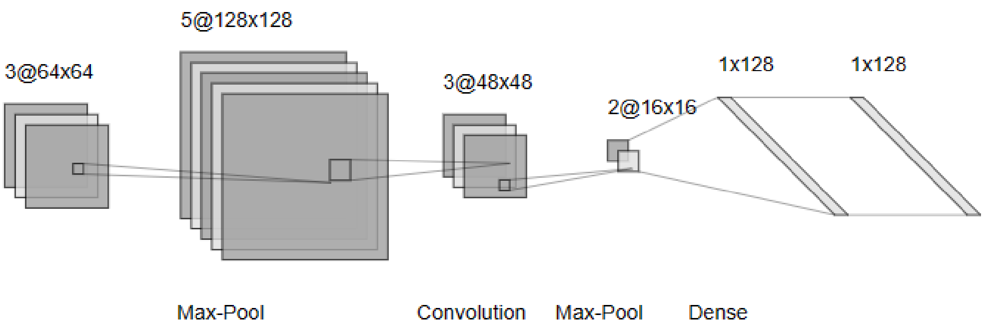

Figure 3.2: The proposed model architecture of the Dilated CNN displays all of the convolutional, flattening,pooling, and Dense layers as well as the forms of the input and output tensors that correspond to each layer.

3.2.1 Convolutional Layer

The foundation for a CNN model is a convolutional layer. The only required elements are input data, a feature map, and a filter. Assume the input will be a color image represented by a 3D pixel matrix. Accordingly,the three dimensions of the input :a width, height, and depth, which are equivalent to RGB in an image. The identical 5*5 filters are used by three distinct convolution layers, and the dilation rate of the feature maps is constructed exclusively using the layers.

The input volume is 128*128*3 with a 3*3 filter size, or 128 pixels wide, 128 pixels high, and 3 pixels deep. Then, for a total of three times three weights, or 27 weights, there will be weights applied to a 3*3*3 region of the input volume for each neuron in the convolutional layer.

The three hyperparameters are stride, zero-padding, and depth, which we shall assess. Our model's input volume measures 128*128*3, whereas the filter measures 3*3, with three as the final geographical extent. Each of the three convolution layers uses the ReLU activation function. Additionally, the names of the dilated CNN models include d1, d2, and d3, which are the dilation rates, Using the rates of dilation (d1 = 4, d2 = 2, d3 = 1), a CNN model might be represented as CNN (4, 2, 1).

3.2.2 Max Pooling Layer

With the use of the Max Pooling pooling technique, a feature map is down sampled (pooled), which decides what the feature map's patch's maximum value should be. The convolutional layer is typically followed by its application. It increases a small amount of translation invariance and suggests that the values of the bulk of pooled outputs are not significantly affected by slightly modifying the image's size. The contamination of over-fitting can be costly when working with brain MRI images, and Ideal for this view is the Max Pooling layer. Therefore, for the suggested model, MaxPooling2D was employed for our input image. I have had a straightforward pool size of 2*2 and Max Pooling layers to maintain a simple model's reliance on the dilation rate parameter and model architecture. The pool size used by all three of the pooling levels, MaxPool1, MaxPool2, and MaxPool3, is 2 *2. The pool size, which can be downscaled both vertically and horizontally, is (2, 2), or a tuple of two integers because the incoming photographs were split into their two spatial dimensions.

3.2.3 Flatten Layer

The pooling layer results in the creation of a map of pooled features. After pooling, One of the most critical layers is the flatten layer since processing requires that we convert the entire input picture matrix into a single column vector. Along with the addition of a form layer that is fully connected (512), 101 of the nodes are dropped. The results are made nonlinear by using the activation process of ReLU. The final layer and the two completely linked layers, FC1 and FC2. 101 of the nodes in the preceding layer are removed in order to avoid overfitting once more. With the aid of the Adam optimizer, the binary cross entropy loss is reduced through training the model to do so.

3.2.4 Fully Connected Layer

The dense layer was represented by denser layers, denser-1 and denser-2, both fully connected. When processing a neural network using Keras, the dense function is used,and this layer's input is the generated vector..

The hidden layer contains 128 nodes. It kept the number of dimensions, or nodes, as low as possible because they are inversely related to the equipment needed on computers to fit our model, and from this point of view, the most important result is produced by 128 nodes. ReLU has a better convergence performance, hence, it is employed as the process of activation.

As the final layer of the model, following the first dense layer, the second fully linked layer was applied. We needed to use less computer resources so that a larger amount could speed up execution because,in this layer, it used a single node of the sigmoid function as the activation function. As the activation function, the sigmoid, is used, there is the potential that deep networks won't learn as well. As a result, we reduce the sigmoid function, which results in a deep network with a considerably smaller number of nodes and easier management.

3.3 Dataset

This study didn't directly include any people, and the data was either generated artificially via simulators or is anonymous. To preserve uniformity across the dataset, it has chosen slices from a variety of MRI scans and used the necessary preprocessing procedures to turn the pictures into a standard JPEG format. The information is divided into four groups, including No Tumor”, “Glioma Tumor”, “Meningioma Tumor”, and “Pituitary Tumor”. A variety of publicly accessible sources are used to curate the photos for the model's training and testing. Kaggle offers an open dataset that compiles 2870 MRI scans of the brain in total, divided into two folders (tumor detected—"yes" and "no"). 2870 MRI scans of tumors and 80% of MRI scans of normal tissue make up the training set. 20% of testing photos are also available for performance analysis. The dataset developed by NAVONEEL CHAKRABARTY, MD MOSARROF HOSSEN, Sartaj Bhuvaji, and Joykumer had From 233 individuals with three different types of brain tumors, 3064 T1-weighted contrast-enhanced pictures were collected. These tumors included 708 slices each of meningiomas, gliomas, and 930 slices each of pituitary tumors. It is only applied when evaluating the CNN model.

Image pre-processing comes after that. In order to ensure that each image is a specific category and that only the brain's main area is given full attention, it attempt to exclude any irrelevant data that may have surrounded the primary MRI brain image. The aforementioned preprocessing was performed using a technique that is quite popular: employing a contour's extreme points. We must generate a broad dataset when preparing the data for training because deep learning methods are heavily data-driven. As a result,Sets that are unbalanced and other skewed picture qualities in a certain class will cause the model to become biased, leading to incorrect classification. There are two fundamental problems with the dataset from brain MRI: both the size of the information and the fact that there isn't a single best anatomical shape for the human brain. By enhancing the photographs over a set of parameters using the Keras Image Data Generator,we introduce a small amount of unpredictability into the images. The model is trained using a generalized dataset throughout the entire procedure. The image is scaled between [0, 1], rotated arbitrarily between [-15, +15], has its height and width changed by no more than 10% of the image's dimensions, has its shear range increased by 0.1, and has its brightness varied between [0.5, 1.5] boundaries. The enhancement techniques used include Reducing the image's size to a range between [1./255], changing the image's maximum height and width, a rotation range of 30, a [-1,128,128,3] reshape range, and a shear range of 9.

Image Pre-processing **Algorithm 1**

Input a raw image

Output a cropped picture

1: iteration = 1, 2,..., Nimagesdo
2: ImageGray ← Grayscale (ImageInput)
3: ImageBinary ← (Binary, threshold [45-255], ImageGray)

Opening

4: ImageBinary ← Erosion (ImageBinary)
5: ImageBinary ← Dilation (ImageBinary)
6: ImageContour ← Contour(ImageBinary)
7: ImageMask ← Extremes (ImageContour)
8: ImageOutput ← Crop(ImageBinary, ImageMask)

end for

Sets for training and validation are created from the data after being prepared and using the augmentation procedures previously discussed. Training is done on the practise set each model using back propagation, and the validation's precision is obtained after each epoch (a single iteration across the entire practice set). Checkpoints are established based on the correctness of the validation. The ideal weights are saved at these checkpoints, so they can be used for model inference or additional training in the future. In Algorithm 2, there is discussion of the sequential flow.

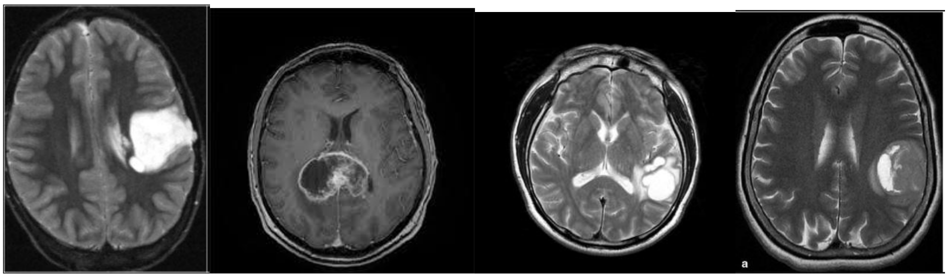

Figure 3.3 : After image preprocessing of brain tumor.

CNN Classifier Algorithm, **Version 2**

Input Picture Dataset

Output Brain tumor classifier with training

1: SAMPLE TRAINING

2: initialize a neural network at random

3: Accuracy ← 0

4: **for** epoch = 1, 2,...., Nepochs do

5: **for** image = 1, 2,..., Nbatch_size do

6: Imagedata ← Resize (Image)

7: Imagedata ← Augmentation (Imagedata)

8: Image data is sent to the hidden layers by input layer u(t), which receives it.

Hidden layers

substantial dilation_rate Unfined features

diminutive dilation_rate better qualities

Diagnosed outcomes are returned by output layer w(t).

Determine the error rate e(t).

Back_propagation is used to update weights.

Using Adam_Optimizer to minimize e(t)

end for

CHECK-POINT MODEL

Determine validation accuracy by using the validation set.

if Validation_Accuracy ≥ Accuracy, **then**

Verification model, Save Weights

Best_Weights ← Weights

end if

end for

3.4 Summary

This chapter describes the suggested methods for classifying brain tumors With an appropriate illustration and explanation, it is clearly explained how to classify aberrant tissues and detect them using different processes.

CHAPTER 4

Background study

4.1 Medical Image

The ability to see internal structures is called medical imaging and is used in clinical diagnosis, therapy, and disease surveillance. Nuclear medicine, Radiology, optical imaging, and image-guided intervention are all subsets of imaging techniques.

4.2 Important aspects of the medical image process

In contemporary medicine, medical image analysis is essential. It can be challenging to analyze and diagnose an illness based solely on an image; thus, computer-aided diagnostic techniques have been employed to shed light on potential disease mechanisms. Depending on the modalities and demands of the doctors, medical images can be colored or grayscale. Using a magnetic field, MRI images are produced. The image data is made up of various series, each with a distinct amount of contrast. This is a detailed discussion of a few medical imaging techniques.

4.2.1 Magnetic resonance imaging

A technique that creates a sequence of finely detailed images of various body parts using radio waves, a strong magnet, and a computer. The idea behind MRI devices is the same as that of electromagnets, which create a magnetic field by running an electrical current through a large coil. The coil is engulfed in liquid helium (at a temperature of about 273 °C) to make it superconducting, which eliminates electrical resistance. The two basic MRI image types are T1 and T2-weighted images, usually referred to as T1 and T2 images.

4.2.1.1 T1-weighted MRI

With quick TE and TR times, T1-weighted pictures are created. The picture's contrast and brightness are mostly determined by the tissue's T1 properties.

- WM appears rarely cheerful.
- Bright-looking fat and cartilage
- Edema, CSF, tumor, and GM all seem dark.

4.2.1.2 T2-weighted MRI

A T2-weighted picture is a fundamental pulse sequence used in (MRI) that displays variations in the T2 relaxation time of different tissues.

- CSF, tumors, and fats are bright.
- Cartilage, fat, and WM appear dark.
- GM seemed optimistic.

4.3 Medical Image Analysis

The possibility of utilizing artificial intelligence for a variety of radiological imaging jobs,like diagnosis, risk assessment,detection, prognosis, and therapy, in addition to the quick identification of new diseases, has increased dramatically as a result of advances in both imaging and computing. Utilizing methods for machine learning, the system then decides how to best organize these image attributes in order to classify the image or calculate some measure for the specific image region. There are several different methods that each have their own benefits and drawbacks. Many radio microphone characteristics are unified into one value using such machine learning algorithms as a tumor hallmark that could be linked to the possibility of a clinical condition.

4.4 Image processing for classification

Region segmentation of interest from an object is one of the most difficult and demanding tasks, and it is ambitious to segment an MRI of the brain's tumor Segmenting brain tumors from MRI images is among the hardest problems in medical image processing. since it frequently demands a substantial volume of data. Additionally, the margins of the tumors may be poorly delineated by soft tissue. The precise segmentation of malignancies in the human brain is therefore a highly challenging task. Image analysis involves dissecting an image into its constituent parts in order to obtain usable information from it. Finding shapes,counting objects, eliminating noise,spotting edges, and computing statistics for texture analysis or image quality are just a few illustrations of the different types of jobs that can be carried out during picture analysis.

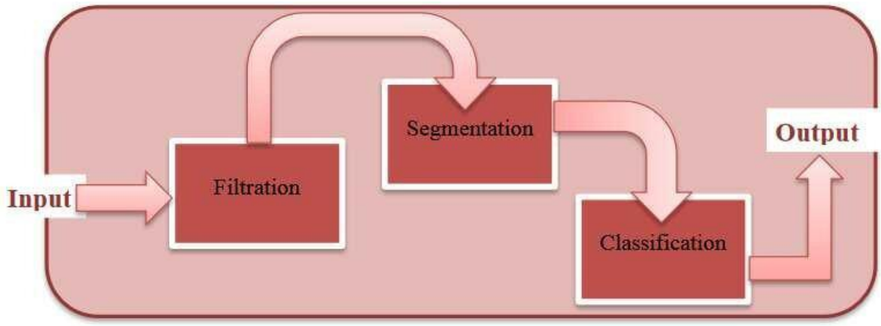

Figure 4.1: Image preprocessing steps for brain tumors (Google 2018)

4.4.1 Image Filtration

The first step in preprocessing a picture is called "image filtration and denoising". Denoising is the process of removing induced noise from images that may have crept in during the capture, transmission, or compression process. To produce better and more accurate results, this technique improves and raises the image quality.

4.4.2 Image segmentation

By dividing a computer image into more manageable chunks known as image segments, a technique called image segmentation can be used to simplify the image's complexity and make each segment more accessible for processing or analysis. Because it isolates the objects of interest for later processing, such as description or recognition, segmentation is a critical step in the image recognition method. Thresholding is a notable example straightforward techniques for segmenting images because it determines a cutoff point for classifying pixels into two categories.

4.4.3 Image classification

The process of categorizing and identifying sets of vectors or pixels included in a picture in accordance with image classification refers to the application of specified rules. It is possible to use one or more spectral or textural factors to generate the classification law. There are three categories for categorizing images:

- classified images under supervision
- Image categorization without supervision
- Analysis of objects in images

Convolutional neural networks (CNNs) are a type of neural network., and it is used most frequently for image categorization issues.

4.5 Deep Learning

"Deep learning" is a subfield in machine learning, and neural networks with three or more layers are considered to be neural networks. Despite the fact that they are unable to match the capacities of the human brain, in order to allow it to learn," these neural networks try to mimic behavior using huge amounts of data. Even an approximate outcome can be produced by a single-layer neural network. But more covert layers can aid in enhancing and optimizing accuracy.

4.5.1 Artificial Neural Network

The underlying technology of deep learning techniques is neural networks, referred to as "simulated neural networks (SNNs)" or "artificial neural networks (ANNs)", which is a division of machine learning. Input, a concealed layer, or among the layers is an output layer that makes up a node layer in artificial neural networks (ANNs). Each node or synthetic neuron has connections with the others, and each one has an associated threshold and weight. As soon as a node is turned on, Whenever a node's output rises above the threshold value set for that node, the network begins passing data to the level below. The following tier of the network does not receive any further data.

4.5.2 Using Neural Networks for Image

While the recognition or discovery of item categories can be accomplished using neural networks, the process of uniquely identifying an object will be more difficult. A set of features taken from every image must be inputted into a traditional neural network. Working with picture pixels is a DNN, or deep neural network. A matrix that has the color information for each pixel in an image can be used to represent it. The neural network's input data comes from the matrix. The images' tiny dimensions make it simple and quick to aid in learning by determining how many input vectors there are and how big the vector is. A function of activation is another name for the transfer function that is employed. Various procedures are used in artificial neural network image processing, including:

- **Image preprocessing:** Preprocessing is important to make image data ready for model input. For example, convolutional neural networks' fully linked layers required that all of the photos be organized in identical-sized arrays. Model preprocessing may also reduce the amount of time needed for model training and accelerate model inference.
- **Feature extraction or Data reduction:** a group of pixels having similar spectral, spatial, an object is a thing with shape, color, size, texture, etc.(also known as a segment) in the object-based technique used by Feature Extraction to categorize pictures. Traditional classification techniques are pixel-based,

which means that each pixel's spectral information is used to categorize imagery.

- **Segmentation:** Tools for segmenting and categorizing data offer a method for extracting features from pictures based on objects. These objects are made using an image segmentation technique in which segments are formed by grouping together pixels with similar spectral properties that are close to one another.
- **Recognition:** Computers can interpret and categorize what they "see" in images and videos thanks to a computer vision technique known as image recognition**.** This primary task, It is commonly known as"image classification" or "image labeling," is an important step in addressing various issues with machine learning based on computer vision.

  Classification, identification, authentication, diagnostics, optimization, and approximation issues are successfully solved by processing images using artificial neural networks.

4.5.3 Convolutional Neural Network (CNN)

A subclass of neural networks called convolutional neural networks (also known as CNNs or ConvNets) was developed that excels at handling input with a grid-like architecture, such as photographs. A digital image is a representation of binary visual data. Pixel values are used to specify that pixels are arranged in a grid-like layout, with each pixel having a different brightness and color. Among deep, feed-forward artificial neural networks, CNNs are a subset that don't require much pre-processing (connections between nodes don't create cycles) and use a multi-layer perceptron version.

1.Why CNN differs from a straightforward neural network: Contrary to regular neural networks, convolutional neural networks possess a distinct architecture**.** In conventional neural networks, an input is changed by being routed via a number of layers of secrecy. Numerous neurons make up each layer,which are each completely interconnected with every neuron in the layer above them. Additionally, the behavior of neurons inside a single layer is independent of one another, and none of their relationships are exchanged. The output layer is the final fully connected layer, which reflects the predictions. Full images are difficult for regular neural networks to scale to. A little differently are convolutional neural networks. In order to arrange the layers, the three dimensions of width, height, and depth are first taken into consideration. Furthermore, only a small percentage of the neurons in the layers above and below are interconnected. Following that, the results will be compiled into a single probability score vector and arranged in accordance with the depth dimension.

Additionally, Convolution is performed by CNNs while multiplying matrices.

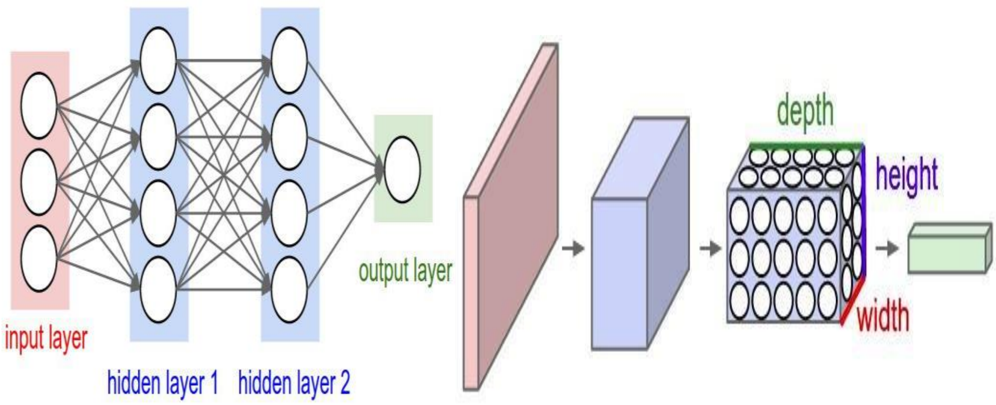

Figure 4.2:A convolutional neural network and a basic neural network

(Google 2019)

The figure 4.5, A typical three-layer neural network is shown on the left. In contrast, a CNN is depicted on the right side of the diagram, where its neurons are arranged in three measurements: width, height, and depth.

2. The Convolution Operation: A convolutional operation refers to the process of reestimating one input as the average of its surrounding inputs, weighted. We use the weighted average of neighbor values., which we have weighted based on the neighbor values, to determine the value of the current input or pixel. F*g stands for the convolution operation between f and g. The two functions' combined integral is how it is defined. after one of them has been moved and reversed. This particular integral transform is what this operation is.

The convolution process makes use of three elements.

- **Input Image:** An image explicitly serves as the input.
- **Feature director:** The term "kernel" or "filter" is frequently used to describe the feature detector. As a feature detector, a 5*5 or 7*7 matrix may occasionally be employed.
- **Feature map:** The term "activation map" may also be used to describe the feature map. Since it also maps out the locations of specific types of features inside the image, it is known as a feature map.

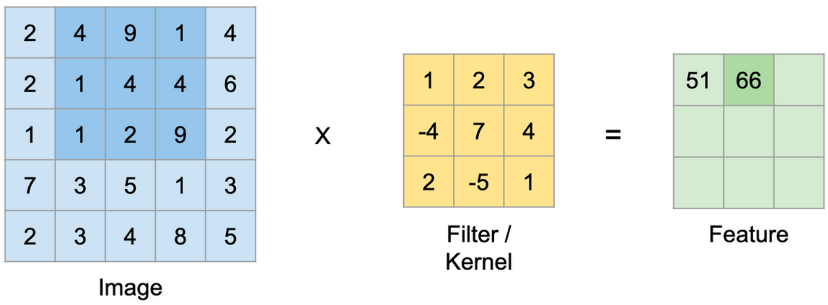

Figure 4.3: The Convolution Operation.(google 2020)

3. The Convolution Arithmetic: Here, it is demonstrated how several elements can alter the qualities of an image as it is output.

$$O = I - F + 2P \quad \text{------------------------} (4.1)$$

4. Layer's Used to Build a CNN Model: Several layers make up a basic CNN, each of which turns the activation levels of one volume of data into another using a differentiable function. When creating CNN structures, layers fall into three main kinds:

- **Convolutional Layer:** One of a CNN's most important layers is the convolutional layer. and where the bulk of the computing occurs, is also its primary computational component. A feature map, a filter, and input data are the only elements required. Consider a color image as the input,whose 3D pixel matrix is made out of.

  A common 3X3 filter, for instance, would be 5*5*3 in size on a ConvNet's first layer (i.e., considering that images have three depth channels, they are five pixels wide by three pixels high). The forward pass involves the convolution of a filter applied to the input volume's width and height for each, and anywhere there is a filter, calculated dot products exist between entries and input. A 2-dimensional activation map is produced by moving the filters throughout the input volume's width and height, displaying how each filter responds at each spatial position. Filters that activate when they detect specific visual elements, such as an edge or a particular orientation, will be intuitively recognized by the network.

  When these activation maps are stacked along the depth dimension, an output volume is produced.

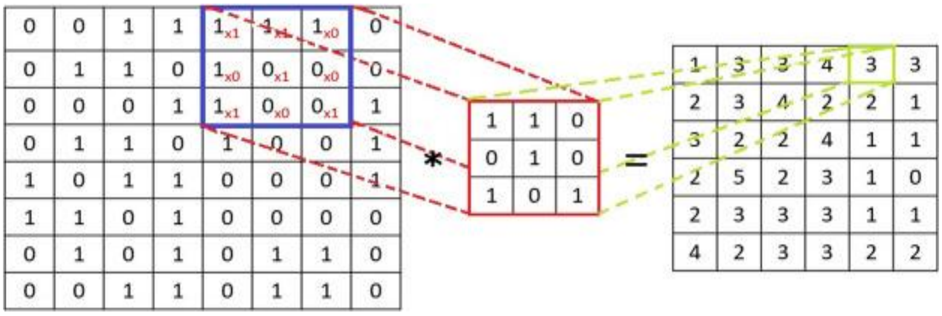

Figure 4.4:CNN's Convolution Operation (Google 2017)

-Parameter Sharing: Each neuron in a particular feature map shares weights in the procedure known as parameter sharing.

-Local Connectivity: Instead of a neural network, which has fully connected neurons, local connectivity refers to the idea that Only a part of each neuron's connections to the input image are present.

These characteristics aid in lowering the total system's parameter count and improving calculation efficiency. The convolution layer's output volume is governed by three hyperparameters. These conditions are:

-Depth: The first layer's input volume's depth corresponds to the color channels of the input picture. The red, green, and blue channels are represented by a depth of 3 when a color input image is used. The depth is 1 if the image is grayscale or black and white.

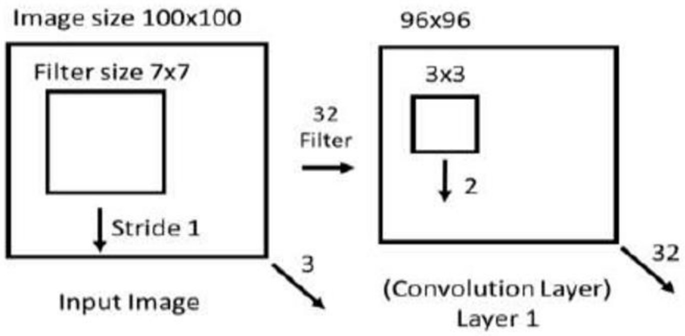

Figure 4.5: 3 to 32 depth changes with 32 filters.(Google 2021)

-Stride: When you walk or run, you take a long step known as a stride. Running athletes can exert up to five times their body weight at each step.

-Zero Padding: Making the input sequence's size equal to a power of two is commonly accomplished using the zero padding technique. To increase the number of samples to the next larger power of two, I append zeros to the end of the input sequence with zero padding.

- **Pooling Layer:** Another CNN component is the pooling layer. After the convolutional layer, the pooling layer is frequently placed. The representation's spatial dimension is gradually reduced in order to reduce the quantity of parameters and calculations throughout the network and, consequently, avoid overfitting. The Pooling Layer individually resizes each spatial slice of input depth. There is no effect of pooling on the depth dimension of the input volume.

0	0	0	0	0	0
0	35	19	25	6	0
0	13	22	16	53	0
0	4	3	7	10	0
0	9	8	1	3	0
0	0	0	0	0	0

Figure 4.6: The input is zero-padded (the padding quantity is 1) (Google 2019)

By utilizing a variety of strategies to summarize the input's subregions, the process of pooling is completed, for example, by using the subregions' average, maximum, or least value. These methods are referred to as pooling activities.

Different Kinds of Pooling Functions: Layer pooling contains a couple symmetric aggregation functions, including:

- **Max Pooling:** A pooling business is Max Pooling, which determines a feature map's maximum value for patches, then creates a downscaled (pooled) feature map using that data.

- **Average Pooling:** The downsampling (pooling) of a feature map employs the average value for each patch, which is calculated as part of the pooling operation known as average pooling.
- **Weighted Average Pooling:** According to how far away its center pixel is, It establishes the weight for the neighborhood.
- **L2 Norm Pooling:** It gives back sum of the square roots of the rectangle neighborhood. Most ConvNet topologies use Max Pooling to reduce the cost of computation.

5. Activation Function: An activation function controls the level of activation in a neuron. By utilizing simpler mathematical procedures,throughout the prediction process, it will decide whether the neuron's network input is significant or not.

- **Commonly Used Activation Functions:** The deep learning business uses a variety of activation functions. Here, it'll briefly go over a few activation mechanisms that are frequently used.

  -Sigmoid: Mathematical functions having sigmoid curves or curves like a "S" are known as sigmoid functions. It changes every value within the range into a number between 0 and 1.

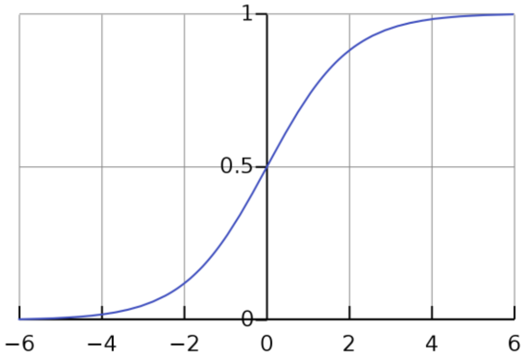

Figure 4.7:The logistic curve of the sigmoid function (google 2019)

-Tanh/Hyperbolic Tangent: The result of Y = tanh (X) is the hyperbolic tangent of the components of X. Arrays are handled element-by-element using the tanh function. The function accepts inputs that are both real and complicated. Every angle is measured in radians**.**

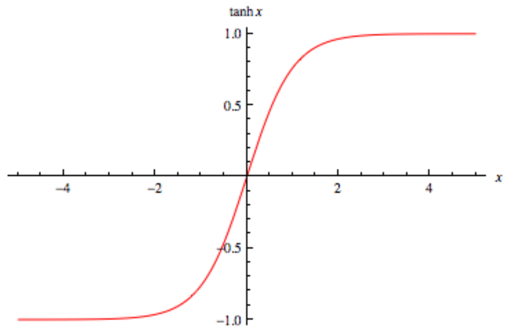

Figure 4.8: Activation Curve of the Hyperbolic Tanh Function.(google 2017)

-ReLU (Rectified Linear Unit): A deep learning model's non-linearity property and the problem of vanishing gradients are introduced by the activation function, rectified linear unit (ReLU). The persuasive aspect of its case is interpreted. In deep learning, one of the most often employed activation functions is it.

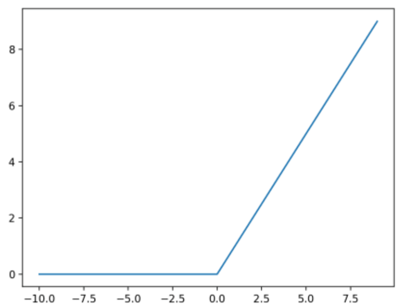

Figure 4.9: Activation function of ReLU (google 2015)

-Leaky ReLU: The function is modified by when the input is less than zero, the Leaky ReLU (LReLU or LReL) is used to enable slight negative values. When the apparatus is saturated and not in use, A slight gradient that is not zero is allowed by the leaky rectifier.

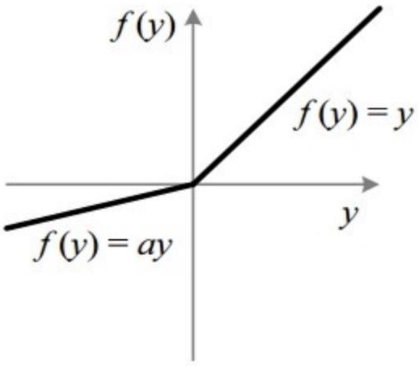

Figure 4.10: Activation function of leaky Relu (Google 2017)

6. Regularization Function: Regularization is the process of reducing the adjusted loss function and preventing either overfitting or underfitting by calibrating it using machine learning algorithms.

7. Hyper-parameters of CNN architecture: There are many hyper-parameter types in the suggested model. Here is a quick explanation of the hyper-parameters.

- **Bias:** By including a constant (i.e., the specified bias) in the input, bias enables you to move the activation function. The function of a constant in a linear function, which effectively causes the line to be transposed by the constant value, can be compared to the role of bias in neural networks.
- **glorot_uniform:** The initializer's name is Xavier Normal. Samples are drawn from a consistent distribution within the boundaries of [-limit, limit].
- **Learning rate:** The most crucial hyperparameter in a neural network is the learning rate. Any optimization algorithm, including Adam, Gradient Descent, and RMSprop, can contain it. For example, import RMSprop from TensorFlow. Learning_rate = 0.001; RMSprop; Keras.Optimizers

- **Beta_1 and Beta_2:** The factors beta1 and beta2 determine how quickly these moving averages decay, which represent the gradient's and the moving average's exponentials and the gradient squared as determined by the method.
- **Epsilon:** For the implementation to avoid any division by zero, it is a very small integer.
- **Dropout or Decay weight:** An additional major component of CNN's. As a mask, the Dropout layer is used, removing the contributions of some neurons to the following layer while preserving the operation of every other neuron.
- **Amsgrad:** A gradient-based optimization approach is called the Adaptive Gradient Approach (Adagrad). The parameters determine how the learning rate is altered component-by-component by including prior knowledge from observations.
- **Epoch:** One cycle of training data is used to train the entire A neural network within an epoch. Every epoch, only one use of each piece of data is made.
- **Batch Size:** The quantity of samples handled in a batch before a model update is called a batch's size. The training dataset's total iterations, or "epochs," are added up to determine the total number of epochs.

4.6 Summary

Each problem that is pertinent to our thesis work is briefly summarized in this chapter, along with details on how they work, their advantages and disadvantages, etc. Prior to going into the outline of the fundamental CNN architecture and many hyper-parameters, it made an effort to explain the basics of image processing.

CHAPTER 5

Experimental Results and Evaluation

5.1 Overview

It'll go into great detail about the results of our suggested methods. The classification of the tumor as a tumor or not can be done using an artificial convolutional neural network. Following that, the models' performance will be compared using the performance evaluation approach. Additionally, It compares our model's categorization capabilities to those of the current model.

5.2 Experimental setup

For image processing, It combined the google colab with a number of Python tools, including Numpy, Pandas, OpenCV, etc. It utilized Scikit-Learn for the conventional classifiers. Python 3.6 was used here. Tensorflow and the Keras framework were used to train and test models with CNN. It used Google Colab's dedicated GPU, which is available.

5.3 Dataset Acquisition

The segmentation of brain tumors is done using the integrated dataset, which is the industry standard, and it was employed in our analysis. The Society for Computer-Assisted Intervention and Medical Image Computing is the origin of the moniker "BRATS," which stands for "Brain Tumor Segmentation Dataset in Multimodal Modes." The dataset distinguishes between tumors and non-tumors and is labeled. The dataset is composed of two parts:the practice and testing sets. All of the photos fall into one of three categories: T1-weighted, FLAIR (Fluid Attenuated Inversion Recovery), or both. Each set includes two classes. The first is for MRIs that detect tumors (class

1), and the second is for MRIs that do not detect tumors (class 0). 30 testing photos are also available for performance analysis.

3064 T1-weighted images with contrast were drawn from 233 patients with brain tumors. There are three main types, totaling 3064 images, that were included in the dataset created by NAVONEEL CHAKRABARTY, MD MOSARROF HOSSEN, Sartaj Bhuvaji, and Joykumer. These tumors included pituitary tumors (930 slices), gliomas (1426 pieces), and meningiomas (708 slices). It is only used for the CNN model's evaluation.

5.4 Performance Measures

The performance matrices must be discussed to be able to assess how accurate our model is. In this section,It will go over the performance metrics that is use to assess the model. Some terms pertaining to the performance measures must be familiarized.

5.4.1 Confusion Matrix

One of the easiest measures to understand is the confusion matrix when assessing a model's accuracy and correctness. It is employed in classificatory issues where the output may include two or more different classes. Four parameters that make up the confusion matrix are listed below-

- **True Positive (TP):** The quantity of accurately categorized tumor images.
- **True Negative (TN):** The quantity of correctly identified non-tumor images.
- **False Positive (FP):** The quantity of images that are falsely identified as tumors when they are not.
- **False Negative (FN):** The quantity of tumor pictures that were mistakenly classified as non-tumor.

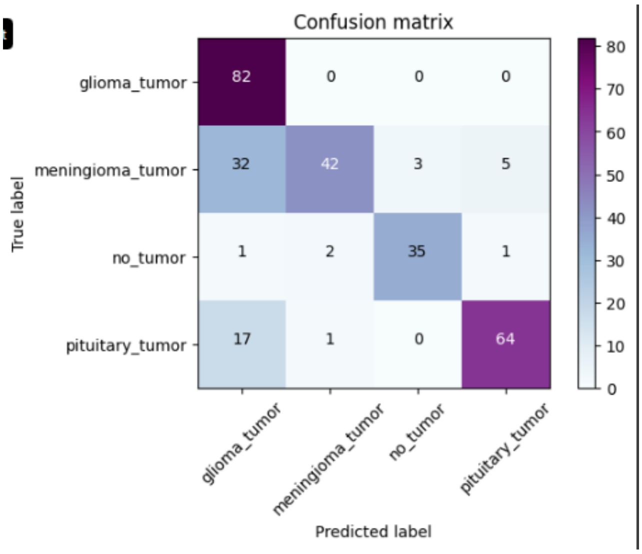

Figure 5.1: Confusion matrix for CNN model

5.4.2 Accuracy

The performance matrix with the highest usage rate is this one for figuring out How often does the classifier predicts correctly. According to mathematics, accuracy is calculated as the proportion of accurately predicted images to all images, and it is symbolized by the following:

$$\text{Accuracy} = \frac{Correct\ Prediction}{Total\ number\ of\ images} = \frac{T\ P + T\ N}{T\ P + T\ N + F\ P + FN} \text{---------(5.1)}$$

5.4.3 Precision

When two or more measurements are compared, precision shows how much agreement there is between them and assesses how much information a number can convey through its digits. Accuracy has no bearing on it. The ratio of correctly classified tumor pictures (TP) to incorrectly categorized or misclassified tumor images (TP + FP) is known as precision. Higher Precision results from a lower FP. In cases with a higher precision rate, the model is more efficient.

$$\text{Precision} = \frac{TP}{TP+FP} \text{----------(5.2)}$$

5.4.4 Recoll:

It measures how many photographs were obtained successfully. The proportion of correctly classified tumor pictures recalled to those that require forecasting. The terms hit rate,sensitivity, and true positive rate are also used to refer to recall. Because fewer tumor images are mistakenly labeled as non-tumors, recall increases as False negatives decrease.

$$\text{Recoll} = \frac{TP}{TP + FN} \text{———————————(5.3)}$$

5.4.5 F-Score:

It measures the correctness of the test and is the precision and recall harmonic means, respectively. At 1 (100% recall and precision), at its highest, the F-score; at 0, it is at its best. F-Score is characterized as-

$$\text{F-Score} = 2*\frac{Precision * Recall}{Precision + Recall} = \frac{2TP}{2\,TP + FP + FN} \text{————(5.4)}$$

5.4.6 Specificity:

The model's True Negative Rate (TNR), a statistical indicator used in the binary classification test, is a measure of specificity. We may use this as a performance evaluation because our categorization is binary (tumor or nontumor). It is the proportion of correctly classified non-tumor pictures (TN) to incorrectly categorized or misclassified non-tumor images (TN + FP). Higher specificity or selectivity means a smaller false positive (FP).

$$\text{Specificity} = \text{TNR} = \frac{TN}{TN + FP} \text{———————————(5.5)}$$

Table 5.1: Comparing the three CNN models for accuracy, precision, recall, and F-measure

Model	Accuracy	Precision	Recall	F-score
CNN 1	86	85.53	78.24	78.74

CNN 2	94	93.80	93.68	93.68
CNN 3	96	95.10	95.08	95.09

5.5 Hyper-parameter settings

The values of the hyper-parameters are discussed here that were used to implement the CNN model throughout the initialization and training phases. In the graph below, these details are shown:

Table 5.2:Value of the hyper-parameter for the suggested CNN Model

Stage	Hyper-parameter	Value
Initialization	Bias	Zero
	Weights	glorot_uniform
	Learning rate	0.001
Training	Beta_1	0.9
	Beta_2	0.999
	Epsilon	None
	Decay	0.0
Training	Epoch	100
	Batch_size	32
	steps_per_epoch	98

5.6 Experimental Results

This paragraph will go over the outcomes of the experiment obtained using the indicated techniques. This part is divided into three subsections, each of which will be fully discussed.

5.6.1 Classification using Convolutional Neural Networks:

In the subsection that follows, it will present the experimental findings together with other traits and evaluations. In Experiments I and II, employing a five-layer model based on split ratios of 70:30 and 80:20, it demonstrated accuracy while adjusting the learning rate and epoch. Later, it will examine the results of employing a CNN model with five, six, and seven layers.

5.6.1.1 Experiment-I

This section's dataset is divided into 80:20 ratios in order to train the five-layer CNN model that is being suggested. The relationship between the model's accuracy, learning rate, epochs, and time to train is shown in Table 5.3. Our greatest accuracy is 99% The splitting ratio is equal to 100 with a learning rate of 0.001 and a training period of 1185 seconds.

Table 5.3: Training Period and Three-Model Proposed Model's Accuracy

Learning Rate	**Epochs**	**Time to train (sec)**	**Accuracy (%)**
	10	934	88%
o.oo1	71	759	92%
	97	1184	**96%**
	100	**1197**	99%

0.005	10	934	88%
	71	**759**	92%
	97	1185	96%
	100	1197	**99%**
0.01	10	934	88%
	71	759	92%
	97	**1185**	96%
	100	1197	**99%**

5.6.1.2 Experiment-III (Five-layer Architecture)

Additionally, it has presented a number of experimental findings based on various hyper-parameters and splitting ratios to support the case for the five-layer CNN model that has been proposed. A five-layer CNN model's effectiveness based on splitting ratios of 80:20 and 80:20 is displayed in Table 5.4. According to the model in table 5.4, When the batch size is 32, the epoch is 66, and the splitting ratio is 80:20, the accuracy reaches a maximum of 99.43%.

Table 5.4: Performance of the suggested CNN five-layer model

Convolution Layer	Max Pooling	Split Ratio	Batch Size	Epoch	Accuracy (%)
				11	79.80
				13	82.58
				50	92.97
				66	94.25
				85	93.77
				11	90.72
128*128*64	64*64*32	80:20	32	13	93.72
				50	98.54
				66	99.43
				85	98.98
				11	73.34
				13	78.38
				50	94.87
				66	97.08
				85	98.45

5.7 Model Validation

5.7.1 CNN Model 1

The suggested CNN model employing the dataset is split into three graphical representations, which are shown in the below figures. 80:20 is the splitting ratio in the figures. The loss curve was first noticed earlier in the era when the training and validation curves overlapped. In the figure, The accuracy for training is 83%, and for validation it is 77.25%. Again, The losses for training and validation are, respectively, 0.41 and 0.63. As a result, while this is bad for the model, the validation rate has never been proportionate to model correctness.

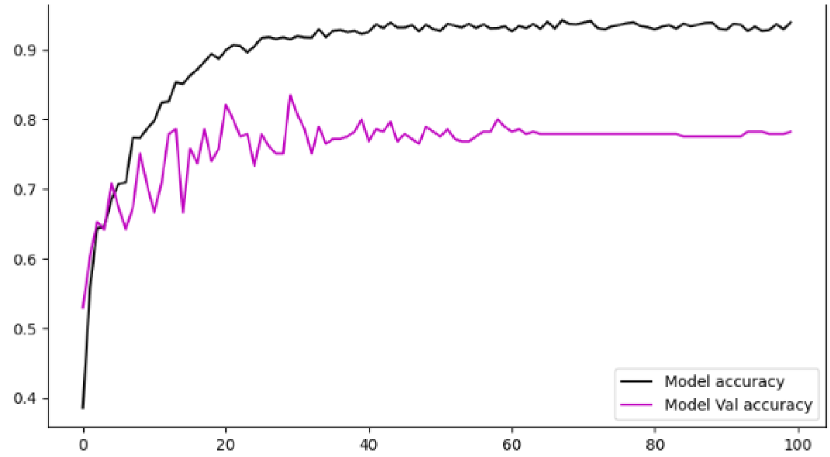

Figure 5.2: The accuracy curve of the model is based on an 80:20 split ratio.

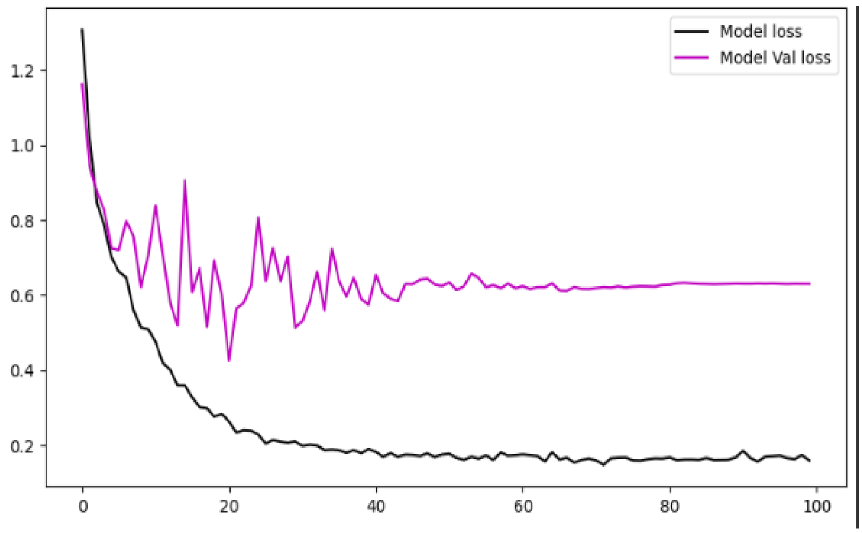

Figure 5.3: 80:20 split ratio-based model loss curve

5.7.2 Model 2

In the figure, The accuracy during validation is 93.68%, while the accuracy during training is 100%. The training loss is once again 0.00022, and the validation loss is 0.83. As a result, while this is not bad for the model, the validation rate has been proportionate to model correctness.

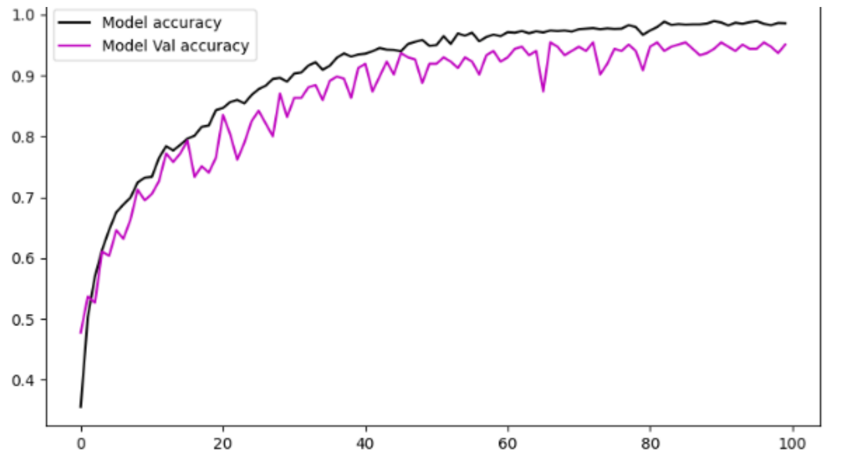

Figure 5.4: The accuracy curve of the model is based on an 80:20 split ratio.

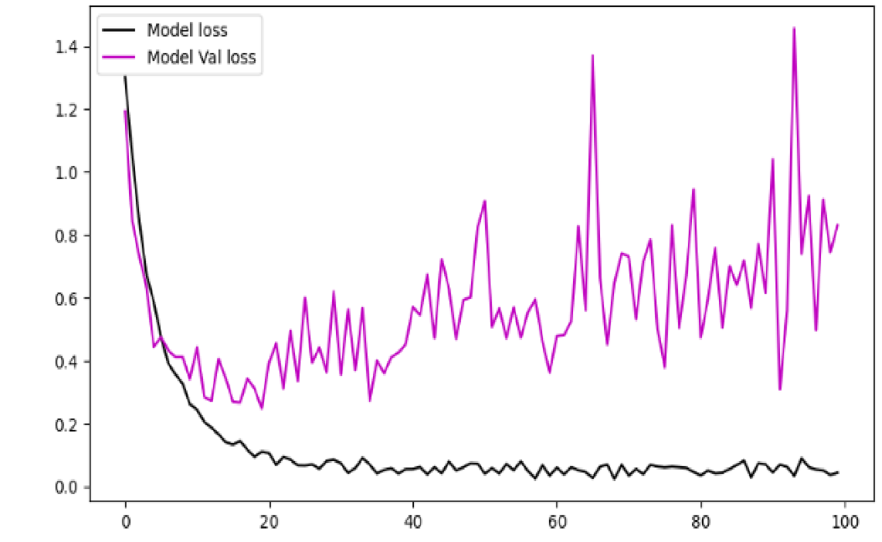

Figure 5.5: 80:20 split ratio-based model loss curve

5.7.3 Model 3

The figure shows the accuracy of the training and validation are 100% and 95%, respectively. Again, The loss for training is 0.003, while the loss for validation is 0.19. Thus, it can be concluded that the best result is produced by this model.

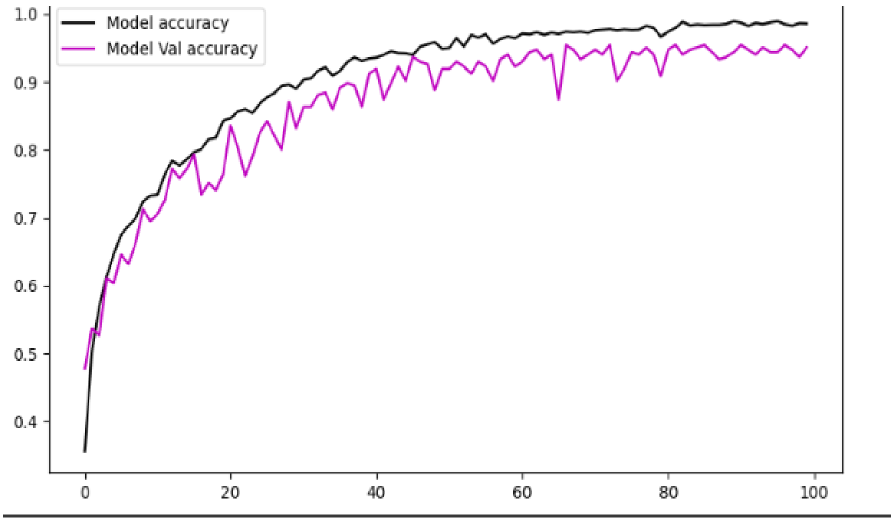

Figure 5.6: The accuracy curve of the model is based on an 80:20 split ratio.

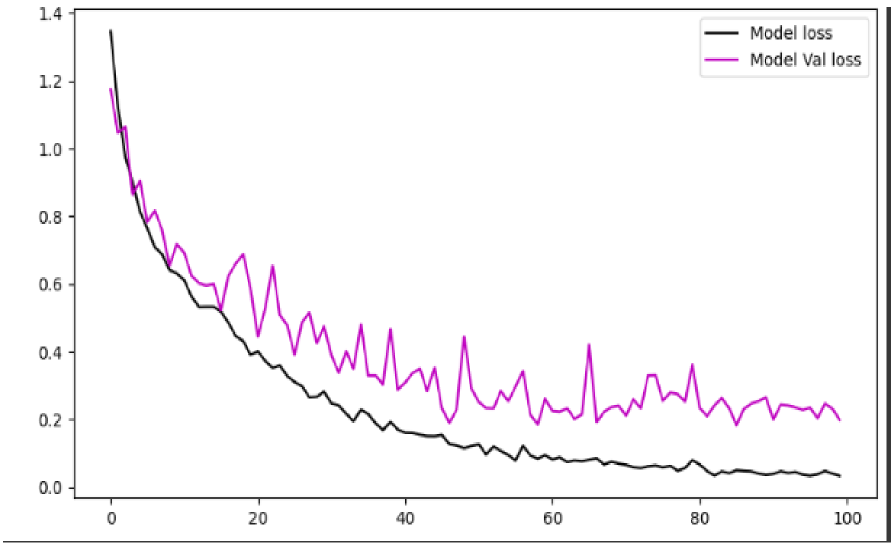

Figure 5.7: 80:20 split ratio-based loss curve model

5.8 Performance comparison

In this section, to compare the current model with the five-layer CNN model methodology that has been suggested. The contrast between the proposed models and the ones already in use is shown in To compare the findings of seven relevant research articles using different approaches and the same dataset to CNN's suggested model.

Table 5.5: Performance evaluation of the suggested CNN model in contrast to the current models

No	Paper Name	Year	Method	Accuracy
1	An Efficient Optimal Key Based Chaos Function for Medical Image Security	2020	AGO algorithm	72%
2	Learning Calibrated Medical Image Segmentation via Multi-rater Agreement Modeling	2021	GoogLenet, ResNet and VggNet architectures	86%
3	Combining Noise-to-Image and Image-to-Image GANs: Brain MR Image Augmentation for Tumor Detection	2022	Generative Adversarial Networks (GANs)	93%
4	GAN-based synthetic brain PET image generation	2019	(DCGANs)	71%
5	**Proposed model**	**2023**	**CNN**	**96%**

5.9 Summary

The performance matrices, along with a brief explanation and the hyper-parameter values that gave us the best results for the suggested CNN model, are presented below. Following that, a representation of the results of each stage of the tumor classification is shown. After providing adequate justification, it later displayed all of the experimental and empirical findings. It've compared our suggested models to the existing ones and vice versa to arrive at this conclusion.

CHAPTER 6

Conclusion and Future Works

6.1 Conclusion

Utilizing core image processing approaches based on a variety of hard and soft computing methodologies, a brain tumor analysis using automated identification from MR imaging and CT images has been carried out. Deep learning techniques must be incorporated into our work in order to use CNN to detect brain tumors. The results of CNN were compared to the model with the best accuracy. Additionally, the work we've done offers a general technique for finding tumors and extracting different aspects of them.

For the full dataset, parallelization, and best performance, a high-speed computer platform is necessary. Despite its best efforts to accurately identify tumors, Occasionally, especially when the tumor was misidentified, this was not achievable during the course of our investigation. So, it will make an effort to work on both those pictures and the whole dataset. So that it may obtain a more accurate and superior outcome, it will attempt to employ additional deep learning techniques in the future.

6.2 Limitation

This section outlines the limitations of our thesis work, and intends to address them in subsequent publications.

- Perhaps in an effort to improve accuracy, it tested out more conventional classifiers.
- only engaged in 2D image work.

6.3 Future Works

To better comprehend how the network functions inside and how effective the dilatancy rate variable is, experimental studies might be performed on additional datasets in future publications. Besides,

- There is a possibility of adding more photos. The model is taught more effectively with more photos.
- For greater accuracy, more conventional classifiers can be used.
- Not least among other possibilities is the potential for future testing of more deep learning variants.

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