Brain Tumor Detection Using Convolutional Neural Network

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ABSTRACT

One of the most important and challenging problems in the area of medical image processing is the segmentation of brain tumors since manual categorization with human assistance may lead to incorrect prognosis and diagnosis. Also, handling a lot of data manually becomes a tiresome process. It takes a lot of time and accuracy for a human to manually locate a brain tumor. It might have an impact on the patient's appropriate medical care. Again, it can take a very long time because there are so many image datasets involved. Brain tumor cells and cells from normal tissue resemble one another quite a bit. It can be difficult to spot tumor regions in images of brain tumors because they can develop in a number of ways and because, in some cases, they mimic normal tissues. Thus, the need for a highly accurate automated tumor detection system exists. In this study, we presented a CNN algorithm followed by deep learning techniques to segment brain cancers from 2D magnetic resonance brain images (MRI). To properly train the model, we have gathered a wide variety of MRI scans with different tumor types, sizes, locations, forms, and image intensities. In contrast, the deep convolutional layers automatically separate noteworthy and accurate features from the input space to typically preceding layers of neural networks. Python is utilized to implement our suggested approach because it is a strong programming language for speedy work and supports "TensorFlow" and "Keras". A freely accessible dataset of 766 patient MRI brain images served as the classifier's training and testing data. Our CNN-based approach will help doctors quickly and accurately locate brain tumors in MRI images, speeding up the course of treatment.

Keywords: Brain Tumor, Deep Learning, CNN.

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LIST OF ABBREVIATION

Abbreviation	Full Name
IARC	International Agency of Research on Cancer
CT	Computed Tomography
MRI	Medical Reasoning Imaging
PET	Positron Emission Tomography
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
ECOC-SVM	Error-Correcting Output Codes Support Vector Machine
VGG	Visual Geometry Group
ReLU	Rectified Linear Unit
DWT	Discrete wavelet Transform
PDDF	Partial Differential Diffusion Filter
CUDA	Compute Unified Device Architecture
OpenCL	Open Computing Language
CNN-LSTM	Convolutional Neural Network Long Short-Term Memory
HG	High Grade
LG	Low Grade
FCM	Fuzzy c-means
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
SOM	Self -Organization Map
MLP	Multi-Layer Perceptron
DNN	Deep Neural Networks
PCA	Common Principal Component Analysis

CHAPTER ONE

Introduction

1.1 Overview

Medical imaging refers to a variety of techniques that may be used as constrained internal viewing methods [1]. Medical imaging encompasses a variety of figure modalities and approaches to figure the human frame for conduct and diagnostic purposes, and as a result, it plays a crucial role in receiving performances for the enhancement of everyone's physical well-being. The most complex and important area of digital image processing is the arranging of medical images. When it comes to medical embodiment categorization issues, cancer finding or tumor identification are two of the most outstanding ones. And according to statistics on the mortality rate due to brain tumors, this cancer kind is the most concerning and worrying in a person's body. The International Agency for Research on Cancer (IARC) estimates that each year, more than 1,000,010 persons worldwide receive a brain tumor diagnosis, with the morality rate steadily rising. The medium-most destructive cause of cancer-related death in children and adults under 30 years old is a brain tumor [2]. The use of modern technology by doctors to detect brain tumors is making the condition much more agonizing for those who are affected. CT (Computerized Tomography) and MRI (Medical Reasoning Imaging) scanning are the two practical techniques for resolving the unusualness in distinct bodily qualities. A growing need for efficient and objective grading of vast amounts of medical data has led to greater interest in the MRI-emerging medical image experiment due to brain tumor lessons. Tools for distorted computerized quantification and then visualization are required for the exploration of this multiple limit of the image form. Therefore, by eliminating the need for manual technology of vast quantities of data, instinctive brain tumor identification from MRI pictures hopes to play a decisive role in this incident.

1.2 Brain Tumor

Brain tumors are brought on by the development of aberrant cells in the brain, claim Ilhan et al. Brain tumors can take many different forms. Brain tumors can be either cancerous (malignant), benign (benign), or pre-malignant. Cancerous tumors can be divided into two distinct types: primary tumors that start in the brain and secondary tumors, also known as brain transference cancers, that have spread from another region. [3].

1.3 Classification of Brain Tumor

Brain tumors fall into two different kinds. A benign tumor is a form of tumor that is considered to be non-cancerous, and a malignant tumor is also referred to as a tumor that is cancerous.

1.3.1 Benign Tumor

The formation of benign, non-cancerous brain tumors inside a cluster of cells that, under a microscope, do not show the typical characteristics of cancer is characterized as a clump of homogeneous cells that aren't adhering to the laws of division of cells and expansion [4]. All of these traits apply to benign tumors:

- The majority of benign growths are discovered using CT or MRI scans of the brain.
- They often have a boundary or edge that can be detected on CT scans, they grow gently, and they don't move to other organs or affect neighboring tissues.
- Since benign tumors have the potential to destroy brain cells and other skull structure, The word "benign" could be misleading.

1.3.2 Malignant Tumor

The brain tumors called Malignant are cancerous because they take on cancer tissues and typically lack a clear border. Since they spread quickly and target nearby brain tissues, they are expected to serve as a permanent damage [5]. These are all characteristics of a malignant tumor that is cancerous.

- Rapidly spreading cancer that affects the spine and brain in other areas.
- A grade 3 or grade 4 malignant (cancerous) brain tumor is different from a grade 1 or grade 2 tumor are typically categorized as benign that means non-cancerous tumor.
- These are typically serious and frequently increase the risks to life.

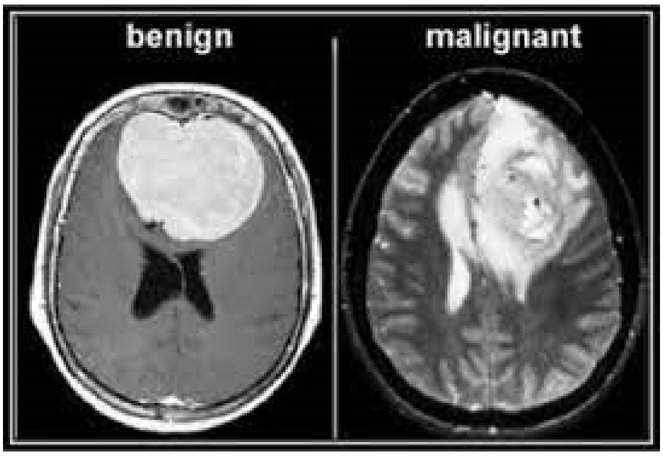


Figure 1.1: Malignant Tumor (right) and Benign Tumor (left). [6]

1.4 Motivation

We chose brain tumor categorization and detection that is associated with the region of analysis of medical imaging after taking into consideration the existing statistics rate of deaths which is caused by brain tumors. Medical image tumor detection takes time and relies on human judgment. Before making decisions that will alter the course of therapy, radiologists along with other experienced medical professionals who expertise in this field analyze the outcomes of CT, PET, and MRI scans. The process as a whole wastes time. Analysis of automated medical embodiment can assist in reducing the workload of humans and the time and effort required to complete tasks that are more appropriately performed by machines.

Figure 1.2 illustrates how brain cancer causes more human deaths than other types of cancer. Early brain tumor detection can help to reduce the number of deaths in this area. Analyze pictures automatically will be very helpful for facilitating quicker communication as patient care can be extended to other domains treating information technology. All of the developed nations in the entire world are introduced to the analysis of automated medical images. Analysis of automated medical images hasn't been well embraced in Bangladesh, though.

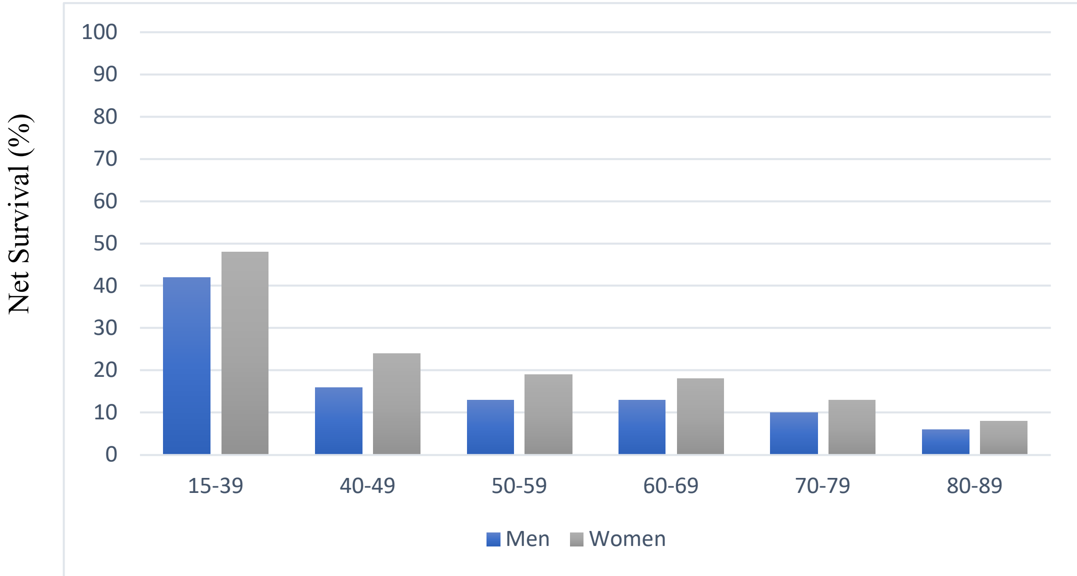


Figure 1.2: Newly found cases and survival rate which is caused by brain tumor. [7]

We all want to create a model that will work effectively and practically in Bangladesh. If we look at the figures for the past ten years as a whole, we can see that in 2012 there were estimated to be 14.1 million cases of cancer worldwide. Men made up 7.4 million of them, while women made up the remaining 6.7 million. Near 2035, it is anticipated that this number will rise to 24 million. The most prevalent cancer overall, according to the classification of malignancies, was lung cancer, which accounted for 13% of all new cases identified in 2012 [8]. Due to the study of all these statistics, we must participate in the analysis of medical images.

1.5 Objectives

The major objective of our study is to develop a simulator that can identify brain tumors in medical images and search for their characteristics. The first step in using medical pictures is dataset gathering because it is difficult and rare to obtain datasets for brain tumors. Most searchers concentrated on task-specific tasks such segmentation, feature selection, skull removal, or filtering. In this experiment, we tried to create a representation that can carry out all the essential and fundamental tasks needed to identify a tumor's properties. Without much assistance from humans, we developed an effective and efficient strategy that works with both conventional classifiers and convolutional neural networks to help detect and segment tumors. Finally, we compared all of the empirical findings to determine which pattern offers the best depiction of sensitivity, accuracy, and different performance indicators over time.

CHAPTER TWO

Literature Review

2.1 Overview

In recent years, several medical image processing techniques have been used to portray a wide variety of activities. Medical image processing has attracted researchers from a variety of fields, including machine learning, computer vision, and image processing. We have all read through a few of the older articles in an effort to identify the most effective and modern techniques used there. We will attempt to go into detail about these documents and their operational procedures that relate to our project in this section.

2.2 Reviews of The Related Papers

Two distinct approaches are suggested by N. Sravanthi et al. for segmenting a tumor on an MRI picture and identifying the type of tumor. The current approach used a variety of image processing techniques to identify brain tumors. A brain's CT scan image is first acquired, and pre-processing techniques are applied to it. Segmentation was the extent of the methods employed to reveal the brain cancer. We segment the pre-processed image and then further extract shape from the segmented image. In this project, segmentation refers to the division of an image into various segments. The image should then be categorized based on the features used in the extraction. [9]

Artificial neural networks were utilized by Borase et al. to identify tumor blocks and categorize the different types of tumors. For the testing and training phases, they used MRI images. For pre-processing and noise removal, high pass filter is used. For segmentation, a region-growing approach is employed. Following segmentation, the same distinct region label is given to every connected collection of pixels with the same gray-level values. For classification, artificial neural networks are employed. Clustering using K-means may be a better option for preliminary processing the images. To make the image smaller, erosion is used, while dilation is utilized to bring back a portion of the tumor that has been removed due to erosion. By contrasting the actual image with the dilated image, the tumor is removed. Erosion is used to reduce any noise that remains in the image of the tumor that has been removed. [10]

An algorithm was developed by Shehzad et al. to identify brain tumors in MRI images and determine their location. The intended algorithm promises to find and remove tumors of any shape, size, severity, or location. MRI scans are converted to grayscale images. A Gaussian low pass filter is used to blur the image, and the blurred image is then superimposed on the original image. A median filter is used to reduce noise. Elongation and erosion were used to calculate the morphological gradient. A morphological gradient image and a processed image have been added to the image for improvement. The filter image's mean and standard deviation are used to calculate the value of the threshold. By analyzing each pixel's value to the threshold value, image binaries are produced. The picture is thinned by performing erosion once again, then dilation is performed once more to bring the tumor's excised (via erosion) portion back. By contrasting the actual image with the enlarged version, the tumor is eliminated. Erosion is used to reduce any noise that may have remained in the tumor image after extraction. It is determined where the tumor is located. [11]

Mahmoud Khaled et al. suggested a dual-phase multi-model for automatically identifying brain tumors from magnetic resonance images using convolutional neural networks. Convolutional neural networks (CNN) are used in the error-correcting output codes support vector machine (ECOC-SVM) technique. AlexNet and two additional CNN models, VGG-16 and VGG-19, were used and evaluated during the tumor identification phase. Convolutional layers and kernels (weights) have been applied upon the input image to produce a feature map. The versatility, ability to prevent over-fitting by using a dropout layer, and ability to train more quickly by applying a rectified linear unit (ReLU) are the reasons why the AlexNet model was chosen. Using error-correcting codes, the approach (ECOC) converts binary classifiers towards multi-class classifications. The highest possible accuracy for detection of 99.55 percent was reached using AlexNet. [12]

Javaria Amin et al. suggested a technique for categorizing brain cancers using DWT and convolutional neural network fusion of MRI sequences. Discrete wavelet transformations (DWT) and Daubechies wavelet kernel are applied in the fusion process to produce a more informative tumor region when compared to a single MRI signal. After the fusion process, noise is removed using a partial differential diffusion filter (PDDF). PDDF is utilized to lessen noise. The global threshold maintaining is used for precise tumor region segmentation on enhanced images. The images with segments are fed through a 23-layer CNN structure that has been recommended for categorizing brain cancers. With fused images, such as 0.97 ACC on BRATS 2012 Image, 0.98 ACC on BRATS 2013 Challenge, 0.96 ACC on BRATS 2013 Leader board, 1.00 ACC on BRATS 2015 Challenge, and 0.97 ACC on BRATS2018 Challenge datasets, the technique yields the best results. [13]

A technique for detecting brain cancer using hyperspectral images and Parallel K-Means Clustering (Serial Code Profiling, OpenMP, CUDA, and OpenCL Algorithms) was developed by Emanuele Torti et al. The delineation of tumor borders, which is of paramount relevance, is where the K-means method first appeared. The program divides the incoming data into K distinct clusters, each with a predetermined K value. Based on the similarity of the features, data are grouped together. According to experimental findings, the CUDA version can process data 150 times faster than a sequential method. The creation of a real-time categorization system is made possible by the outstanding result found in this study. [14]

Cascaded Framework for Brain Tumor Classification, an approach to CNN-LSTM, was suggested by Iram Shahzadi et al. by utilizing a cascade of CNN with an LSTM network to classify 3D MR images of brain tumors into HG and LG gliomas. In order to classify the 3D brain tumor volumes into HG and LG glioma, features from pre-trained VGG-16 were extracted and fed into an LSTM network. The findings demonstrated that, in comparison to features taken from ResNet and AlexNet, those from VGG-16 provided superior classification accuracy. With fewer samples, this method has generated results that are equivalent, and it has an accuracy rate of 84% when using VGG-16. [15]

Borase et al. suggested utilizing an artificial neural network to distinguish tumor blocks and classify the different types of tumors. For the testing and training phases, they used MRI images. For pre-processing and noise removal, high pass filter is used. For segmentation, a region-growing approach is employed. Following segmentation, the same distinct region label is given to every connected collection of pixels with the same gray-level values. For classification, artificial neural networks are employed. The algorithm for clustering using K-means might be a better option for pre-processing the images. Erosion usually used to narrow the picture, while dilation is utilized to bring back a portion of the tumor that has been removed due to erosion. By contrasting the actual image with the dilated image, the tumor is removed. Erosion is used to reduce any noise that remains in the image of the tumor that has been removed. [17]

A Deep Convolutional Neural Networks Model-based Brain Tumor Detection in Brain MRI Images was proposed by Md. Abu Bakr Siddique et al. Noise removal, bias correction, skull stripping, and intensity normalization were all used as preprocessing steps. After that, a sizable dataset of brain MRI images, both with and without tumors, is used to train the deep CNNs model. In the train process, the model's parameters are optimized to reduce the loss function. Sensitivity, accuracy, and specificity are criteria used to identify brain tumors after evaluation. [18]

Andronicus A. Akinyelu and colleagues used machine learning to categorize the diagnosis of brain tumors. MRI image acquisition from the database for the purpose of finding brain tumors. Apply preprocessing next to enhance the image data. subsequently used segmentation to distinguish the tumor from healthy brain tissue. Then, to enhance intensity features, Feature Extraction is used. For the classification of MR brain pictures, machine learning algorithms are utilized. [19]

Soheila Saeedi et al. employed convolutional deep learning methods and selected machine learning approaches for MRI-based brain tumor identification. retrieved 3264 MRI brain scans from a database. used a number of convolutional layers with the CNN algorithm. After this approach, a hierarchical network with eight convolutional layers and four pooling layers was added, and machine learning was used to classify brain tumors. For the classification of MR brain pictures, machine learning algorithms are utilized. Maximum detection precision between 95.63% and 96.47%. [20]

The automatic diagnosis of human brain tumors in MRI images using template-based K means and an improved fuzzy C means clustering algorithm was proposed by Md. Shahariar Alam et al. 40 photos of brain tumors taken from a database. used TK-means, FCM algorithm, and artificial neural network (ANN) for a number of convolution layers. Following these methods, triangle inequality is used to reduce the amount of distances and enable data points to be connected to many clusters by various layers of interconnected nodes. [21]

Multi-Classification of Brain Tumor Images Using Deep Neural Network was proposed by Hossam H. Sultan, Nancy M. Salem, and Walid Al-Atabany. 3064 and 516 images containing 233 and 73 individuals are included in the datasets. CNN and genetic algorithms were used to optimize the CNNs' hyperparameters. Following those techniques, CNNs with deep learning skills and genetic strength are combined. 96.13% is the highest possible detection accuracy. [22]

Using deep learning, Sidra Sajid, Saddam Hussain, and Amna Sarwar presented tumor detection and segmentation in MR images. Used BRATS 2013 dataset. Minimizing the error or loss function is a feature of the CNN algorithm. This program demonstrates the use of artificial neural networks for modeling and neuronal connectivity training. Maximum tumor area enhancement detection accuracy of 0.07, 0.65, and 0.67. [23]

A technique to find brain tumors was proposed by Mr. T. Sathies and others. SVM Classifier is utilized. Hospitals, research facilities, and other healthcare facilities are used as public databases. used K-means The support vector machine algorithm for CNN hyperparameter optimization. SVM classifier is used as a step after those methods, which also comprise classification and regression analysis, to separate the data point. Give accurate results with a 90% accuracy rate. [24]

Automated Brain Tumor Detection and Identification Using Probabilistic Neural Network Techniques was the idea put out by Dina et al. Six classes made use of 64 MRI scans. segmentation was done using a probabilistic neural network algorithm. following the application of a Gaussian filter, the image has been blurred to remove noise and adjacent pixels with gradient-direction values. provide results with complete accuracy. [25]

Diagnose Brain Tumor Using Fuzzy C Means Along with Intelligent Optimization Techniques was proposed by N. Nandha Gopal and Dr. M. Karnan. 42 photos of the brain from the KG hospital were taken from a database. used the Particle Swarm Optimization Algorithm, Genetic Algorithm, and Fuzzy C Means to get the best solution. Following such procedures, backpropagation is used to update the network's weights and reduce the difference between expected and actual outputs. Maximum precision is 98.6%. [26]

Brain Tumor Detection Using Shape Features and Machine Learning Algorithms was proposed by Dena Nadir George et al. A database of 174 MRI pictures was used. The best solution was achieved using the Adaptive Threshold, C4.5 decision tree, detection, Region, and Multi-Layer Perceptron algorithm. These algorithms then take the best possible answer to the problem and allow for the possibility of partial membership of data points to different clusters. Maximum precision is 95%. [27]

Brain Tumor Segmentation with Deep Learning was proposed by Havaei M et al. BraTS 2015 was the dataset utilized for this experiment. used CNN algorithm to process data at several scales. In order to detect and segment brain tumors with high accuracy, this system includes various processing routes. achieved a tumor segmentation dice similarity coefficient of 0.87. [28]

A New Architecture for Automatic Detection of Brain Tumors Using DCNN was proposed by AHMED S. MUSALLAM et al. 394 MRI images make up the dataset for the proposed model. DCNN, or deep convolutional neural network. The proposed model achieved a 97.72% accuracy. [29]

An architecture for detecting brain tumors based on machine learning algorithms like ANN and K-NN was proposed by Komal Sharma et al. The proposed model was tested against a dataset of 212 MRI images. k-nearest neighbors (k-NN), self-organization maps (SOM), and artificial neural networks (ANN). The proposed model achieved 98.6% accuracy at its highest level. [30]

An architecture of combining tissue segmentation and neural networks for brain tumor detection was proposed by Selvaraj Damodharan et al. The MRI picture collection includes 20 brain MRI scans, 10 of which are images with tumors while the remaining 10 are tumor-free. In this research, K-NN classification is utilized. The findings indicate that over 80% of the results are accurate. [31]

Brain Tumor Detection Using Deep Learning Techniques was proposed by Prof. Kavita et al. On the Kaggle website, Navoneel Chakrabarty offers the dataset that was used. 253 MRI pictures total, 98 of which are of a non-cancerous type, and 155 of which are of a cancerous type. Algorithm for fuzzy C-Means clustering. It was discovered that the accuracy was 92%. [32]

P A method for brain tumor detection from MRI images using deep learning techniques was proposed by Gokila Brindha et al. A dataset of 2065 MRI scans of brain tumors is included in this study. In total, 1085 photographs of tumors and 980 images of non-tumors are taken, along with 186 images for validation and 207 images for testing. In this research, the ANN and CNN algorithms are utilized. It achieves a 97% testing accuracy. [33]

A method for classifying and characterizing brain tumor MRI images using gray scaled segmentation and DNN was put forth by Tampere ammattikorkeakoulu et al. Ten MRI scans, both with and without tumors, were used in this thesis. The DNN algorithm is used to categorize and characterize brain tumors. 90% of the classifications are accurate. [34]

Deep Convolutional Neural Networks Model-based Brain Tumor Detection in Brain MRI Images was proposed by Md. Abu Bakr Siddique et al. There are 253 different sized raw photos in total. The pictures were gathered from brain MRI image databases on Kaggle. Based on the existence of tumors, the dataset is divided into the YES and NO classes. The remaining 98 photos are of normal brains, leaving 155 photographs with brain tumors overall. The CNN algorithm is used. The model's overall classification accuracy of 96% is supported by the results. [35]

An Artificial Neural Network Approach for Brain Tumor Detection Using Digital Image Segmentation was proposed by Kamal Kant Hiran et al. They made use of 186 brain MRIs and more than 120 other forms of brain and central nervous system imaging. To convert a grayscale or color image into a binary image, they employed an artificial neural network (ANN), and they discovered accuracy of more than 80% and superior segmentation results. [36]

Brain Tumor Detection Based on Multimodal Information Fusion and Convolutional Neural Network was proposed by Mingli et al. Each of the 1000 remaining photos in the ImageNet collection has 1000 items. They were able to identify the two-dimensional brain tumor and the original single mode brain tumor using multimodal information fusion and convolution neural network detection, which assign a degree of membership between the data point and the cluster. This is a substantial advancement. [37]

Development of Automated Brain Tumor Identification Using MRI Images was suggested by T.M. Shahriar Sazzad et al. 120 T1-weighted contrast-enhanced pictures from 3 patients make up the dataset that was used. To account for the greatest amount of variation in the data and transforms, they employed the PCA feature selection approach. They discovered that results are often 97.34% accurate. [38]

Brain Tumor Detection Using Deep Neural Network and Machine Learning Algorithm was proposed by Masoumeh Siar et al. They used the BRATS 2012 dataset as well as two datasets comprising 19 MRI FLAIR images. For the objective of classifying and recognizing photos, they utilized the CNN algorithm. On the test data, the proposed method's accuracy rose to 99.12%. [39]

Proposed Brain Tumor Detection Using Image Processing by Suresha D. et al. In this paper, it has been estimated that 33% of these will pose a threat. ABTA estimates that there are already 700,000 cases and that 16,700 people will pass away from brain and spinal cord cancers in 2017.For classification and regression analysis, they employed the SVM technique, which is effective with both linearly and non-linearly separable data. The system requires less training set, aids in tumor diagnosis more quickly, and produces reliable findings.[40]

Tumor Detection Using Threshold Operation in MRI Brain Images was proposed by Natarajan P et al. the 20-year period covered by the National Cancer Institute statistics (NCIS) dataset. They used the high pass filter, histogram equalization, and grayscale imaging techniques. They succeeded in detecting a brain tumor in MRI scans.[41]

By utilizing gray scaled segmentation and DNN, Tampereen et al. proposed classifying and characterizing brain tumor MRI images. 140 MRI pictures, both tumor and non-tumor, were used in total. For the purpose of providing predicting value and image results, they applied the DNN algorithm. The maximum accuracy found was 90%.[42]

The idea of Brain Tumor Detection by Using Artificial Neural Networks was put up by Hussna Elnoor Mohammed Abdalla. The back propagation technique and artificial neural network (ANN) were employed in this thesis's step-by-step brain tumor detection. Maximum sensitivity and accuracy were found to be 97.9% and 99%, respectively.[43]

Brain Tumor Segmentation using Deep Learning was proposed by Havaei et al. 220 training examples and 191 testing instances from the dataset were used in this study. They discovered a maximum accuracy of 90% using the CNN algorithm.[44]

Xiaohua Wang and others suggested a multi-model ensemble method for segmenting brain tumors that is based on deep learning. In this study, 285 3D MRI dataset volumes were employed, and the segmentation results were obtained using the CNN technique. They were successful in segmenting the brain tumor's 3D MRI volume in under a second.[45]

Hyeonjin Kim Chang and others suggested Glioma classification using deep learning in traditional MRI scans. The CNN method was used to extract characteristics from the dataset of 120 MRI images and to identify patterns in the growth of glioma tumors. They had a 92.8% maximum accuracy.[46]

Proposed State-of-the-Art CNN Optimizer for Brain Tumor Segmentation in Magnetic Resonance Images by Muhammad Yaqub et al. They were used Bra Ts2015 databases and used CNN and ANN algorithm. They were able to obtain 97.9% accuracy.[47]

Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks was proposed by Hao Dong et al. They made use of the BRATS 2015 datasets, which included 54 cases of low-grade brain tumors and 220 cases of high-grade brain tumors. The accuracy in this paper, which used the DCNN algorithm, was 97.72% overall and 99% at its highest.[48]

Goswami, Anurag suggested conducting an analysis of image segmentation techniques for MRI images used to detect brain tumors. They made use of the BRATS2015 databases, which contained 54 low grade gliomas and 220 patient multimodal scans. The CNN algorithm, which has 100% accuracy, was used in that study.[49]

Proposed Computer-Aided Brain Tumor Diagnosis: Performance Assessment of Deep Learner CNN Using Augmented Brain MRIs. Tahreem Yasir et al. They used the 255 negative and 255 positive MRIs of brain tumors from the 2020(BR35H) dataset. For performing brain tumor diagnostics, CNN algorithm was utilized. They discovered maximum and average accuracy of 100%.[50]

2.3 Summery

In this chapter, we analyzed 40 research articles in total and spoke about how they work. This literature review reveals that there had been numerous research works published on the segmentation and identification of brain tumors. Traditional classifiers were used by some researchers, whereas deep learning techniques were used by others. Using conventional methods, some works produced meaningful results while others did not. However, after reviewing these works, we can assert that deep learning outperforms classical classifiers due to their utilization of memory in the network and learning mechanism. We summarize all the above work in the below table-

Data Set	Algorithm	Result & Findings
Three types of tumor (meningioma, glioma, pituitary) and normal brain image.	CNN	A maximum accuracy was 99.13%.
They used RIDER Neuro MRI database.	CNN	Maximum accuracy was 99.55% .
Dataset of BRATS 2012	DWT,CNN	Maximum 0.97 Accuracy achieved.
Vivo hyperspectral human brain image database.	K-Means, OpenMP	Accuracy of the classification is 92.45%.
Experimental evaluation 80 of malign tumors.	NS-CNN	An average success of 95.62%.
A dataset of 66 brain MRIs.	DNN ,DWT	The accuracy was 93.4% .
2015 BRATS dataset.	CNN, LSTM	Maximum accuracy of 84%.
Dataset of 186 brain MRIs.	ANN	Maximum accuracy of 80%.
1000 objects, each having 1000 images.	CNN	Average accuracy of 94.8%.
The dataset contains 120 T1-weighted contrast-enhanced images.	PCA	The accuracy of proposed method is 97.34%.
19 MRI FLAIR and BRATS 2012 dataset.	DNN	The accuracy was 99.12%.
A database of 40 brain tumor images.	ANN, FCM	Maximum accuracy of 98%
The datasets include 233 and 73 patients with a total of 3064 and 516 images.	CNN,GA-CNN	The model achieved an overall classification accuracy of 96.13%.
BRATS 2013 dataset.	CNN	Maximum accuracy of 95.5%.
Images collected hospitals, laboratories.	SVM	Maximum accuracy was 96.98%
A group of 64 MRI images were	PNN	Maximum accuracy was 100%
270 MRI images are used.	SVM	Accuracy was 97.56%.
42 image from the KG hospital database.	Fuzzy Means,	The accuracy was 98.87%.

dataset used by the NCIS	GI,HE,HPF	Accuracy was 95.78%.
A dataset of 394 MRI images.	DCNN	Maximum accuracy of 97.72%.
The A dataset of 212 MRI Images.	ANN, k-NN	Maximum accuracy of 98.6%.
Contain 174 MRI Images.	MLP	The maximum accuracy was 95% .
contains 20 brain MRI images.	K-NN	The accuracy was 80%.
This dataset has bn used 253 MRI images.	Fuzzy Means	The accuracy was 92% .
2065 MRI images of brain tumor.	ANN ,CNN	It obtains a testing accuracy of 97%.
Total 10 MRI images of tumor and normal	DNN	Accuracy of 90%.
Kaggle datasets	CNN	Maximum accuracy of 96%.
140 brain tumor MRI image from internet	DNN	Maximum accuracy was 93,18%
Database Whole Brain Atlas website that collected from the Harvard University.	BPA,ANN	The proposed algorithm reaches accuracy about 99%.
Dataset of MICCAI Society	MLA,CNN	Has maximum accuracy of 97.01%
Containing 3264 MRI brain images.	CNN	A maximum accuracy was 96.47%.
Contains 220 training & 191 testing cases.	CNN	Accuracy was 90%.
The dataset consists of 285 MRI images.	CNN	Fast segmentation achieved
Used a dataset of 210 glioma tumors.	CNN	The model has accuracy of 92.8%.
BRATS 2015 databases.	CNN,ANN	This method got 97.9% accuracy.
BRATS 2015 datasets.	DCNN	Maximum accuracy of 97.72%.
The training database of BRATS 2015.	CNN	Maximum accuracy was 96.13%
255 negative & positive MRIs of tumor.	CNN	Average accuracy of 98.8%.

Table 2.1: Dataset, Algorithm and Result of different report

CHAPTER THREE

Methodology

3.1 Overview

We have put out a methodology for identifying abnormal cells in brain MRI. Many images processing algorithms, including CNN, Max Pooling, and Data Augmentation, have been used to try and detect the tumor. We will talk about how different image processing algorithms can be used to find tumors. Following that, we'll introduce the suggested model and go into great detail on all the layers involved in using CNN to detect brain tumors.

3.2 Dataset

Brain tumors come in more than 120 different types, each having a different origin, location, size, and tumor tissue composition. From among these, we have considered three main types of malignant tumors. The first is a type of Grade IV primary malignant brain tumor that develops from astrocytes, which are cells with a star-like form that normally start in the cerebrum and nourish nerve cells. A sarcoma tumor can be graded from 1 to IV. This tumor also grows in connective tissues like blood vessels. The next malignant brain tumor is Metastatic Bronchogenic Carcinoma, which arises as a result of a lung tumor termed Bronchogenic Carcinoma. Several human brain MRIs, 493 regular images, and 273 abnormal images make up the data collection.

3.3 Materials, Methods

For the proposed framework that makes use of a brain tumor dataset for the classification and detection of brain cancers, we present a number of deep convolution neural network topologies in this section. Using enhanced MRI slices from a dataset of brain tumor, we investigate and assess the well-known CNN. Transfer learning techniques are applied to these pre-trained CNN networks to acquire rich and discriminative visual characteristics. In the subsections, the core ideas of the suggested framework are investigated.

3.4 Convolution Neural Network (CNN)

Kunihiko Fukushima introduced the convolutional neural network's fundamental concept for the first time in the 1980s. [51]. CNNs, sometimes referred to as convolutional neural networks, are a subtype of neural network that are particularly effective at identifying and classifying images. Because of the accuracy of their picture classification, convolutional neural networks dominate computer vision approaches. CNNs, A subclass of deep, feed-forward artificial neural networks uses a particular kind of multi-layer perceptron that only requires little pre-processing (connections between nodes do not form a cycle in CNNs). ConvNet designs explicitly assume that the input images allows us to incorporate particular features within the architecture. As a result, they significantly lower the number of parameters in the network and increase the forward function's implementation efficiency. ConvNets' constituent neurons have biases and weights that can be taught. Each neuron does a dot product, some

input processing, and, if desired, a non-linearity to follow. From the unprocessed image pixels in one end to the class ranks at the other, the complete network retains a single distinguishable scoring function. Additionally, the final layer contains a loss function.

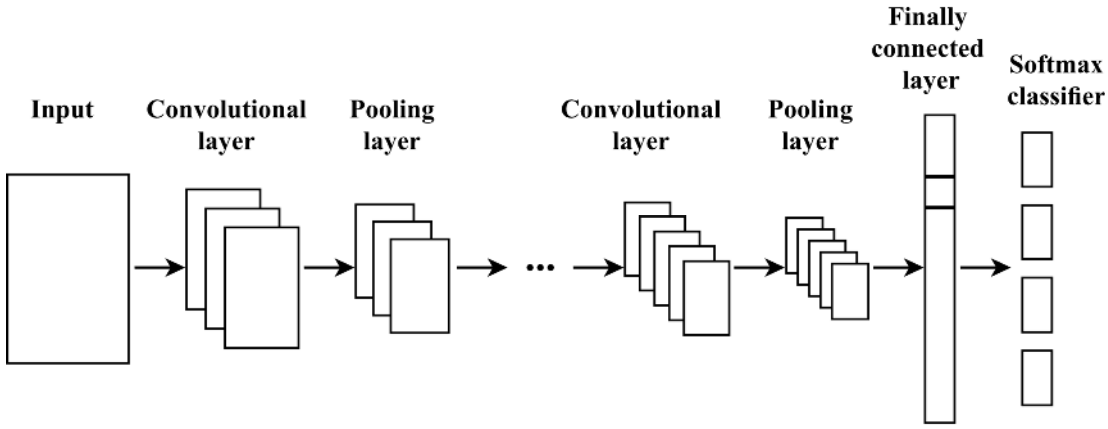


Figure 3.1: Structure of CNN.[52]

3.5 Classification Using Convolution Neural Network

CNN is frequently utilized in the field of processing medical images. Over the years, numerous researchers have sought to create a model that can more accurately detect cancers. We worked hard to create an illustration that can accurately classify the tumor from 2D brain MRI scans. It is a member of a group of deep neural networks used to interpret visual information. We opt to employ a CNN for our model regardless of being aware that a fully connected neural network may be able to identify tumors due to parameter sharing and connection sparsity. The demonstration and application of a five-layer convolutional neural network for cancer detection. With the pooled model, which comprises of seven phases, including the hidden layers, we get the most accurate tumor detection results. In spite of both the input and output layers, the hidden layers consist of a single convolutional layer, single pooling layer, single flattens layer, and two layers that are fully interconnected.. In order to employ CNN to locate a brain tumor, we separated the entire working procedure into seven parts. Fig. 3.1 shows the seven-step working flow diagram. The dimensions of five hidden layers are displayed in Fig. 3.2, which illustrates the 5-Layer CNN technique for tumor identification. The layer and its characteristics will be discussed in the section after this one.

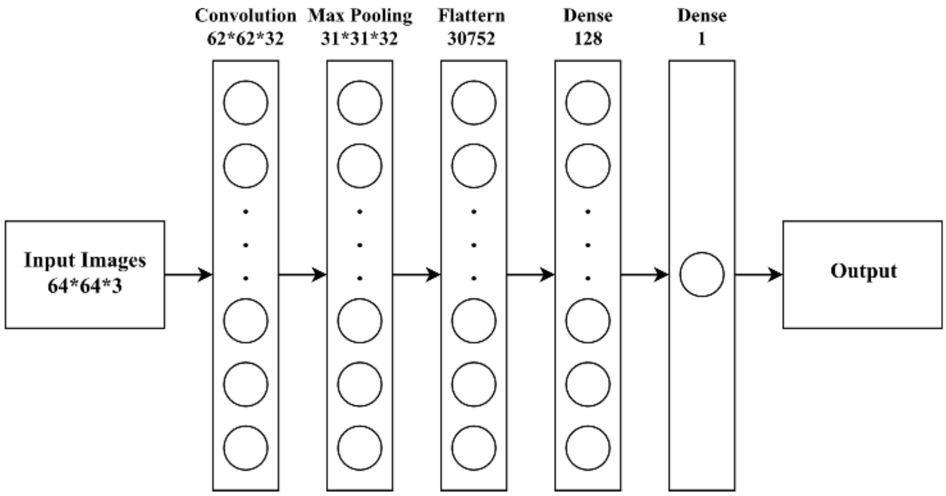


Figure 3.2: Brain tumor identification using a suggested 5-layer convolution neural network.[23]

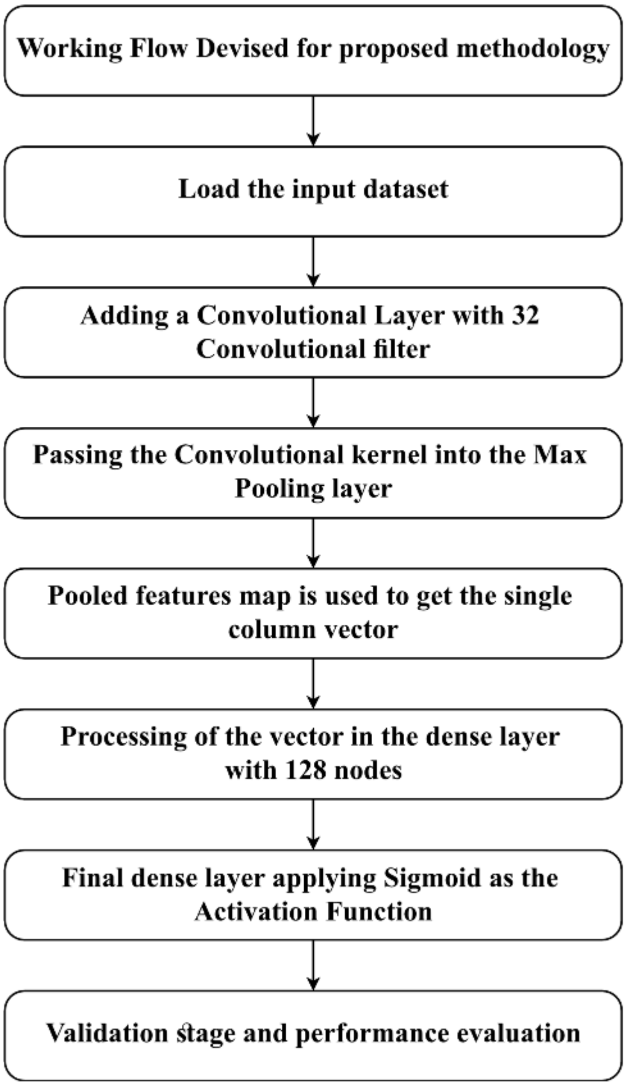


Figure 3.3: Workflow of the Five Layers Proposed CNN model.

3.6 Convolution Layer

A convolutional layer serves as the basis of a CNN model. A convolutional layer is used as the first layer to construct the original shape for the MRI pictures, which is 64*64*3, bringing every image into the exact same dimension. Using 32 convolutional filters, each measuring 3*3, three channels of tensor support, and the combined images into one aspect, we produced a convolutional kernel which is convoluted with the input layer. Utilized as an activation function is the Rectified Linear Unit (ReLU). 64 pixels on each side, 64 pixels across, and 3 pixels depth make up the input volume. The input volume is 64*64*3, the size of filter is 3*3, and. As a result, the input volume's 3*3*3 region will have weights for every single neuron in the convolutional layer, totaling 27 weights (3*3*3 + 1 weight for the bias parameter). We will evaluate three hyper parameters: depth, stride, and zero-padding. Our model's spatial extent, or filter size, is 3, having an input region dimension of 64*64*3 and its filter size of 3*3. To achieve Zero Padding with a stride of 1, we did not employ padding in the border. Due to stride being set to 1, the pooling layers may complete the entire spatial down sampling., whereas the CONV layers just modify the depth of the input volume. Now, the layer's dimensions, which are 62, 62, and 32, respectively, are obtained using the convolutional layer. The layer named max pooling was comprising the second layer, following the convolutional layer.

3.7 Activation Functions

In order to get the response that's needed from the input functions, activation mechanisms are often added into the neural network. Both the sigmoid as well as hyperbolic tangent activation functions are particularly pertinent among the possible activation functions for neural networks. The sigmoid function produces an output in a range of 0 and 1 from an input that can range from 1 to -1[54]. Using the hyperbolic tangent function, a value between 1 and 1 is returned. Because of this functionality, these two functions are used less frequently in CNN networks. When using these functions, there is frequently a lack of image data due to the use of numerous values in matrix images, rendering the device ineffective. [55]

3.7.1 Sigmoid

The range of the input value that the Sigmoid function can accept is 0 to 1. It returns 1 for large positive numbers and 0 for huge negative numbers. The sigmoid function is represented mathematically by [56]:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

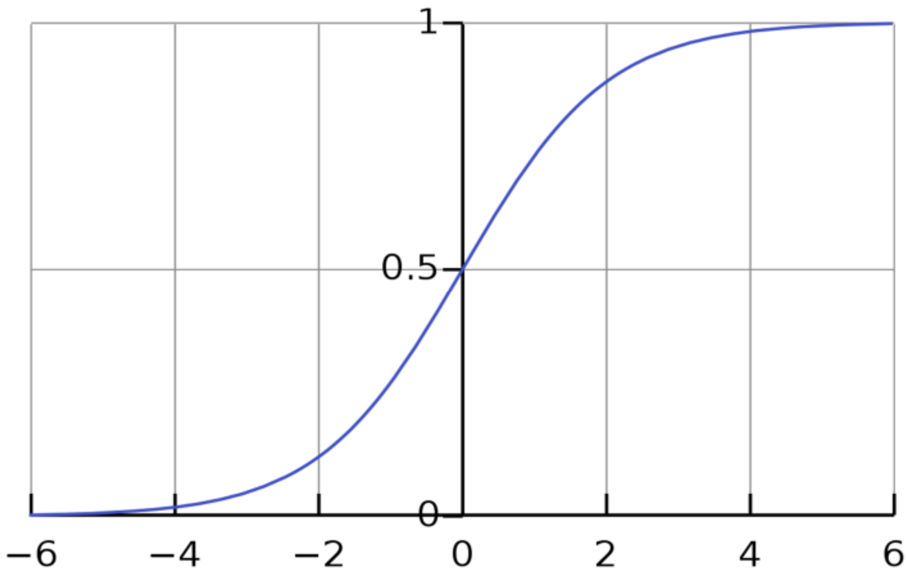


Figure 3.4: Sigmoid function curve.[57]

The sigmoid function has the following benefits:

- The output numbers don't "jump" because of the smooth gradient it offers.
- Every neuron's output is normalized.
- It makes exact forecasts possible.

The sigmoid function has the following drawbacks:

- This results in the "vanishing gradient" issue. No effect is had by extremely low or high input quantities. As a consequence, the network can start to resist learning new information or move too slowly to make precise forecasts.
- The results are not centered at zero.

3.7.2 ReLU

One of the recently introduced activation characteristics is the unit having linear rectified ReLU functionality. An all-inclusive activation-based function is ReLU. Its purpose is to give the network nonlinear behavior. In 2012, Krizhevsky et al. added this function. Every negative value in each pixel of the image is changed to zero by this function, as shown in Formula 1. The convolution neural network's nonlinear training is described by ReLU as a nonlinear component (Convolution is a multiplying linear technique and concatenating the components to sum them up) [58]. The CNN uses this function the most frequently among the activation functions.

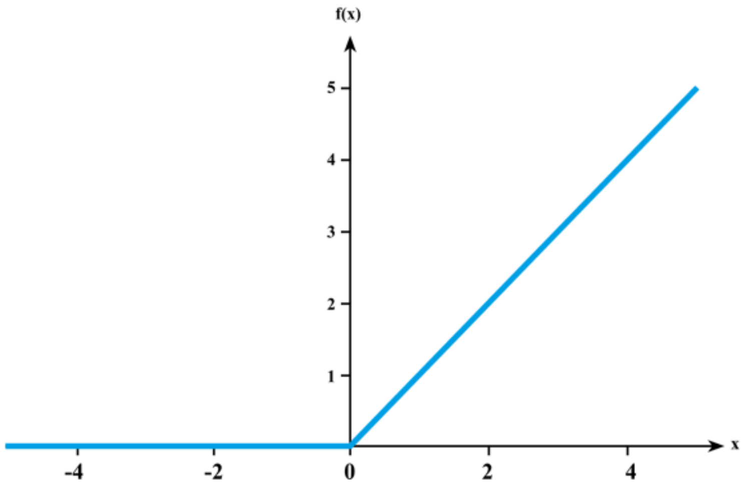


Figure 3.5: Curve of ReLU.[59]

The ReLU function has the following benefits:

- The positive zone of the gradient isn't saturated.
- Calculating the threshold criteria is simple.
- It Has a lower training error rate and performs more quickly than sigmoidal as well as hyperbolic tangent functions.

The ReLU function has the following drawback:

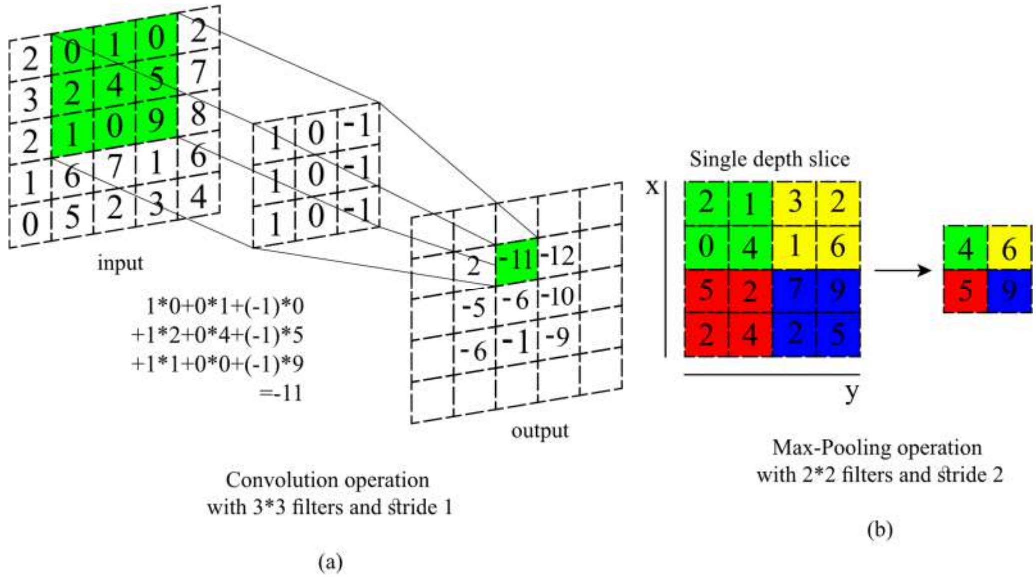
- The outputs of this function are always positive and lack a zero center.

3.8 Max Polling Layer

The primary goal of the pooling layer is to gradually shrink the representation's spatial size in order to lessen the amount of parameters and computing labor required in the network. To prevent over-fitting, the parameters must be reduced in size. It may individually operate on and enlarge each of the depth slices of the input utilizing the max pooling layer. When working with brain MRI pictures, the contamination of over-fitting can be expensive, and Max Pooling layer is ideal for this perception. Therefore, we chose MaxPooling2D as our input image for the suggested model. This convolutional layer has the following measurements: 31*31*32. Using the equation, the size of input is 62* 62* 32. (which is the sigmoid function's mathematical version),

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

We produced an output volume with the dimensions 31*31*32 in order to calculate the size of the maximum pooling layer. The pool size is (2, 2) as a result of the input photos being split into both



spatial dimensions, which results in a tuple of two values for the vertical and horizontal downscaling factors.

Figure 3.6: Illustration of convolutional operation and max-pooling operation are shown in (a) and (b), respectively. [60]

3.9 Flatten Layer

The pooled feature map is produced following the pooling layer. The layer called flatten, which comes after pooling, is among the most crucial ones since processing necessitates that we turn the entire input picture matrix into a single column vector. The Neural Network then receives it for processing after that. The size of this layer is 31*31*32, or 30752.

3.10 Fully Connected Layer

The dense layer was represented by two layers that are completely connected, Dense-1 and Dense-2. The resulting vector acts as an input for this layer when Keras processes the neural network using the dense function.

The hidden layer contains 128 nodes. We kept it as low as practical as the quantity of nodes is directly proportional to the amount of computer power required to fit our model. According to this viewpoint, the result produced by 128 nodes is the most significant. Because ReLU performs better in terms of convergence, it is employed as the activation function. The second layer that was entirely connected was employed for the model's final layer after the initial dense layer. Since there is only one node overall at this layer, we utilized the sigmoid function as the activation function to reduce the demand on the computer's resources and speed up execution. The selection of the sigmoid as the activation function can make it more difficult for deep networks to learn. the complexity of the sigmoid function more manageable and compact, we also lowered the total amount of nodes within this deep network. We successfully identify a tumor from an MRI picture using our five-layer CNN model. Figure 3.2 shows the five-layer CNN model's whole operating process. Before the input dataset can be imported, every image in the input image must be the same size. We implemented a Convolution layer containing 32 convolutional filters utilizing ReLU as a function of activation after the input layer. Max pooling layer uses the employer design from CNN.

The vector of single column produced by the Max pooling layer is flattened to create the pooled map of features. Finally, we build a dense layer of 128 nodes, which our model defines to as two layers that are completely interconnected. The final dense layer's activation function is the sigmoid function. We developed the model and evaluated the accuracy of tumor detection utilizing the Adam optimizer and the binary cross-entropy as a loss function. We built an algorithm (Algorithm-1) and evaluated its performance in identifying brain tumors. Our CNN model's performance was assessed using the following algorithm:

Algorithm :

```
loadImage ();
dataAugmentation ();
splitData();
laodData();
for each epoch in epochNumber do
for each batch in batchSize do
ˆy = model(features);
loss = crossEntropy(y, ˆy);
optimization(loss);
Accuracy = (1 - loss) * 100%;
end
end
```

3.11 Data Augmentation

However, it's not actually all that big of a deal. However, it is not always necessary to perform this work. Before starting any data processing, we must decide whether our work needs to be preprocessed. For instance, a standardized method for mean-normalizing photographs has been adopted in the categorization of photos and is based on the mean of the trained data. Numerous research has shown that the optimal preprocessing method is average normalization. Mean-normalization, on the other hand, can harm the network and result in less accurate outputs even though it is used to optimize the images. The absence of average normalization is likely to be advantageous for any task involving really small fluctuations in variables, including color, appearance, overall form, and semantic distinctions in the image. The enhancement of uniform performance, on the other hand, is intimately tied to data augmentation, both in terms of network generalization and absolute accuracy. This is done in a variety of tasks, from high-level classification to low-level optimization. The kind of data augmentation used as a result needs to be considered.

3.12 Summery

The suggested approaches for categorizing and recognizing brain tumors are described in this chapter. With the aid of a clear diagram and an explanation, the segmentation of the abnormal cells and the detection utilizing two different procedures are extensively explained.

CHAPETR FOUR

Result and Discussion

This section outlines the findings of our suggested tumor detection method using various brain MRI scans. Python (3.10.9) was used to implement the suggested method. We made use of 767 MRI scans of the brain.

4.1 Result

The GUI use interface which will show after the program start is shown in figure 4.1

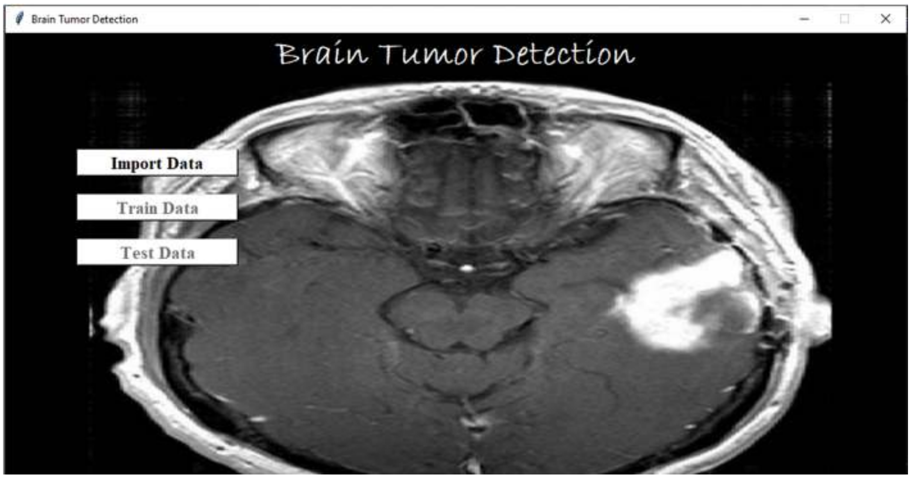


Figure 4.1: GUI for user

There are three buttons. They are-

1. Import Data
2. Train Data
3. Test Data

4.1.1 Important Data

Initially Import Data button is active. By clicking this button, the user will import the data that is stored in the program directory. After import, the data the user will have a prompt message which will show after successful import. Once import is completed the import button will disable and the Train Data will active.

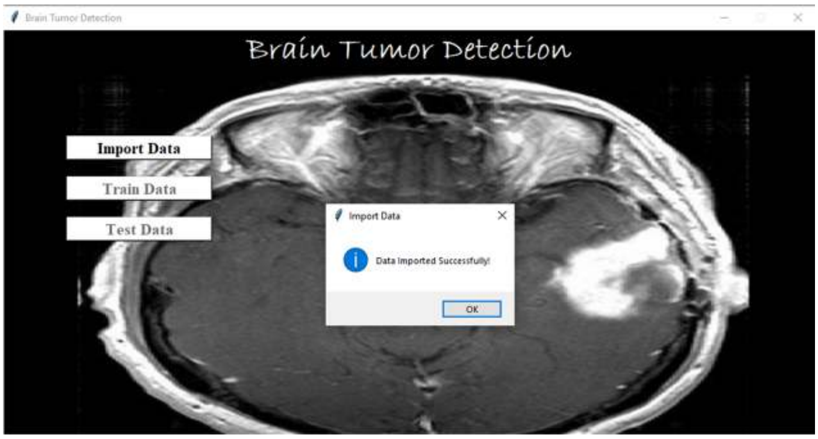


Figure 4.2: Successful import

4.1.2 Train Data

When user click on the Train Data button, The model will start to train itself. The model will take the data store in the train folder so that it can train itself. We trained the model using a different algorithm in the training section. At first the 2D Convolution is completed then the Max Pooling and after that we make the multidimensional array that was made by the previous step to a single dimensional array using Flatten. The Dense method is used to train the model nonlinear relationship between images. The Sigmoid function is used to map the value between 0 and 1 for easy comparison. The epoch will optimize the result of the training dataset. After all of this the model is fully trained and ready for test. All of this are shown in figure 4.3 and figure 4.4. Immediate after the training competition training button is deactivate and Test Data button is activated.

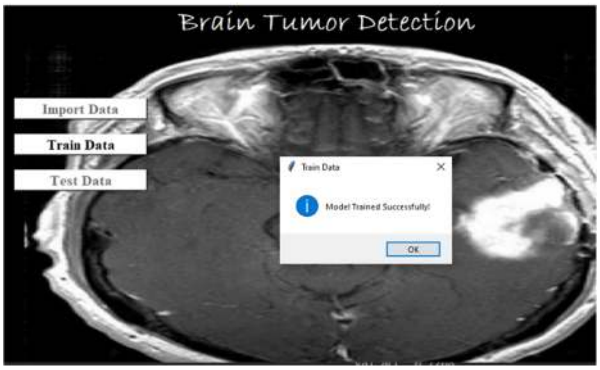


Figure 4.3: Trained successful

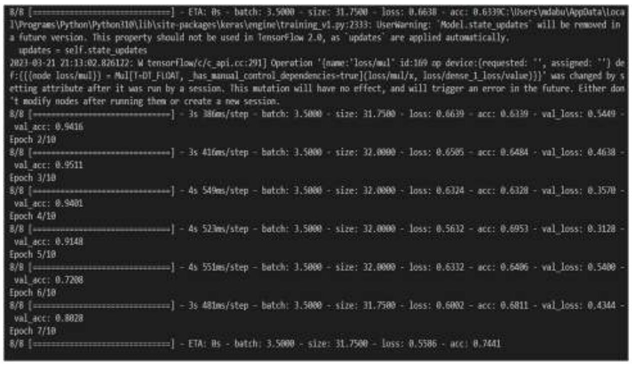


Figure 4.4: Terminal while training

4.1.3 Test Data

After clicking in the Test Data button, a list direction will show for select an image for test. This is shown in the figure 4.5. After selecting the image, the image will show to the user for confirmation.

This is shown in figure 4.6. After cancelling the dialog box, the mode will start testing the image according to the training. The test result will show Tumor if the predicted answer is greater than 0.5. Else it will show Normal in a message box. This is shown figure 4.7.

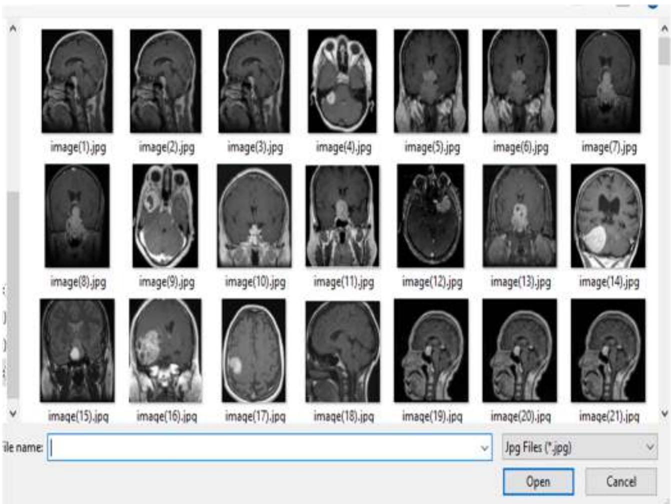


Figure 4.5: Selection menu

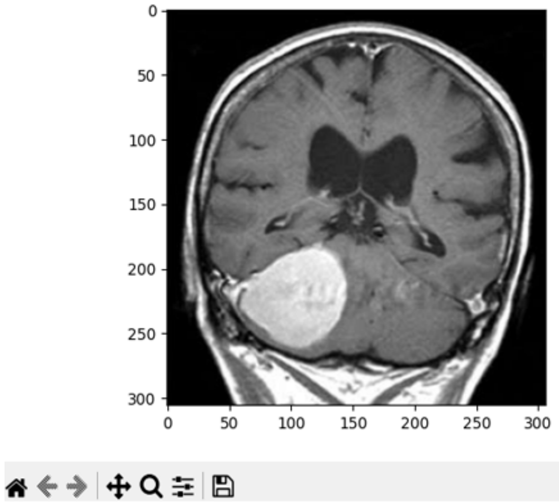


Figure 4.6: Selected image

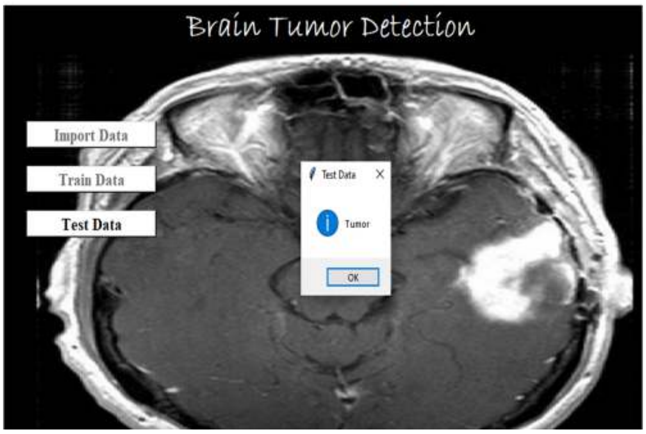


Figure 4.7: Brain tumor

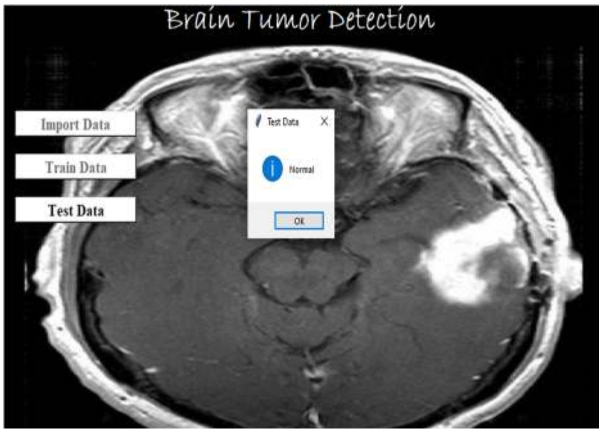


Figure 4.8: Normal brain

In our method of finding the Brain Tumor the epoch plays a significant role. More the epoch more the accuracy. Epoch is process of deep learning where the trained dataset is passed to the model for optimizing the outcome of model. The testing accuracy of machine will increase after each epoch.

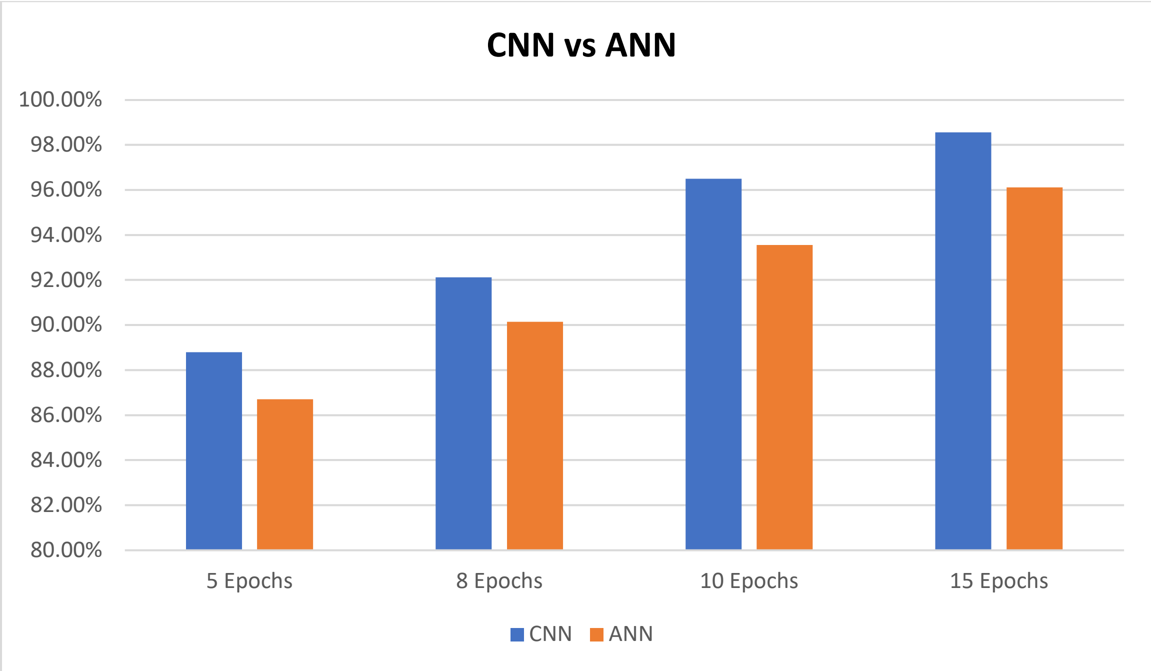


Figure 4.9: CNN vs ANN according to Epochs bar chart

We have shown the bar chart for accuracy comparison between CNN and ANN according to the number of epochs in the above figure 4.9. Here we were checked each model for 767 images. For number of epochs the models was came with different outcome. The chart shows the comparison of CNN vs ANN according to the increased Epochs. We were using 10 epochs for our models which gives us accuracy of 96.5% for CNN and 93,56% for ANN. which means the mode gives 755 correct outputs among 767 MRI brain images in CNN whereas in ANN gives 740 correct output.

4.2 Discussion

Our method gives better outcomes than many ANN. Day by Day detection process is increased in the term of its accuracy. Moreover, increased accuracy get acceptance among the people. High accuracy means high chances of finding accurate result. In ANN we get maximum of 96.12% whereas in our proposed CNN method we get total of 98.56%. So, our proposed methodology is better because of higher accuracy in CNN than ANN.

4.3 Summery

We were used CNN model to evaluate the proposed methods. We had used 10 epochs to get the accuracy. In sort we get 98.56% accuracy among 767 images which is better than ANN which was 96.12%.

CHAPTER FIVE

Conclusion and Future Work

5.1 Conclusion

Using a variety of both soft and hard computing techniques, we have examined the effectiveness of automated algorithms for MRI image-based diagnosis of brain tumors in this work. We also employed CNN to find brain tumors in order to incorporate deep learning in our study. Our study presents a universal strategy for feature extraction and tumor detection. Parallelization and the utilization of a high-speed computing platform are necessary for the algorithm to be most effective when applied to the complete dataset. Despite our best efforts, there were still a few cases during our trial where it was either impossible to accurately detect malignancies or the tumor was misinterpreted. As a result, we'll try to work with both those photographs and the entire dataset. We'll attempt to use better deep learning algorithms in the future in an effort to produce results that are better and more precise.

5.2 Limitations

The limits of our work are stated in this part, and we plan to address them in our further studies.

• There are only 493 images in the MRI dataset.

• Focused solely on 2D visuals.

• To improve accuracy, we may have attempted more conventional classifiers.

• Tumor types could not be identified.

5.3 Future Works

Future work on our project has greater potential for development or investigation.

1. The first option is to increase the number of images. The model is taught more effectively the more photos there are.

2. Secondly, in the future, we intend to work on 3D photos.

3. Thirdly, to boost accuracy, more conventional classifiers can be used.

4. Fourthly, following the discovery of the tumor, we will attempt to categorize it as benign or malignant.

5. At last, other deep learning method modifications may be investigated in the future.

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