Brain Tumor Identification using Deep Learning Models

BY

Fahim Yusuf

ID: 183-15-2239

AND

Md. Omar Faruq Fahim

ID: 183-15-2270

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Md. Sabab Zulfiker

Lecturer (Senior Scale)

Department of CSE

Daffodil International University

Co-Supervised By

Tania Khatun

Assistant Professor

Department of CSE

Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

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APPROVAL

This Project titled "**Brain Tumor identification using Deep Learning Model**", submitted by Fahim Yusuf, ID No: 183-15-2239, MD. Omar Faruq Fahim, ID No: 183-15-2270 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 12th September 2022.

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Al Amin Biswas — **Internal Examiner**
Senior Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Dewan Md. Farid — **External Examiner**
Professor
Department of
United International University

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Md. Sabab Zulfiker, Senior Lecturer, Department of Computer Science and Engineering** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Md. Sabab Zulfiker
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Co-Supervised by:

Tania Khatun

Tania Khatun
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Fahim

Fahim Yusuf
ID: - 183-15-2239
Department of CSE
Daffodil International University

Md. Omar Faruq Fahim
ID: - 183-15-2270
Department of CSE
Daffodil International University

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ABSTRACT

Determining the amount of the tumor may be a particularly difficult process among all of them; the brain tumor is the toughest one. Brain tumors account for 85% to 90% of all primary central nervous system (CNS) tumors. One of the discrete methods that emerged as a first-line, radiation-free method of diagnosing brain tumors is magnetic resonance imaging (MRI). When it comes to picture identification, deep learning has made significant progress. Work on transitioning from convolutional neural networks (CNN) and visual geometry group (VGG-16) alternative autoencoders has found countless applications in the realm of medical image analysis, propelling it forward quickly. In radiology, the skilled physician externally evaluated clinical images for the identification, depiction, and observation of illnesses. In this study, machine learning and classifications using convolution neural networks (CNNs) are offered as a technique for automatically detecting brain tumors. Small kernels are responsible for designing the deeper architecture. There is a minor weight assigned for the neuron. In comparison to all other methods, it has been found that VGG-16 achieves a high rate of accuracy with a minimal level of complexity. The increased accuracy will facilitate effective medical care and other institutions that work with brain tumors or any other related diseases.

Keywords: Brain Tumor, MRI, CNN, VGG-16.

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CHAPTER 1

Introduction

1.1 Introduction

The brain, which has billions of cells, is one of the body's essential organs. Uncontrolled cell division produces the aberrant cell group, which is also known as a tumor. The two forms of brain tumors are low grade and high-grade tumors. A benign brain tumor is one that is of low grade. A high-grade tumor is also referred to as malignant. Cancerous tumors are not benign tumors. As a result, it doesn't spread to other brain regions. The cancerous tumor, however, is a malignant tumor. Because of this, it easily and quickly spreads to other parts of the body with arbitrary boundaries, making it dangerous. It results in instant death, according to medical specialists. Clinical professionals must help patients access more effective e-health care systems because it results in immediate mortality. Health care systems are useful in a variety of medical fields. Biomedical imaging technologies based on computer vision are becoming more important as they give radiologists recognition data for solving treatment-related issues more effectively. There are numerous medical imaging techniques and approaches, including X-rays, MRIs, ultrasounds, and computerized tomography (CT), which have a significant impact on how patients are diagnosed and treated. In particular, an MRI image can be used to track a tumor's progression using modeling. MRI images contain more data than CT or ultrasound images do. A magnetic resonance imaging (MRI) image may be used to detect irregularities in brain tissue and offer detailed information on brain anatomy. Due to their efficiency and capability to generate detailed images, MRIs are being considered for brain tumor identification [5]. It entails a non-invasive, radioactive material free examination. This is as well as least dangerous imaging method [6]. Because although the MRI has a low brightness level [7]. we must enhance it all to achieve better the visual effect. Since it became possible to produce and load medical images to the computer, Scholars have actually provided distinct automated methods for discovering and cataloging brain cancers utilizing MRI scans of the brain. Contrarily, because to their success in recent years, Convolutional Neural Network (NN) and Visual Geometry Group (VGG-16) are the most frequently used techniques. DL (Deep Learning) models have currently solved an AI mixing pattern because their underground design successfully addresses complex connections without needing numerous hubs, unlike shallow structures like CNN and VGG-16. In contrast to other health informatics fields like medical image analysis, medical informatics, and bioinformatics, they expanded swiftly to reach the state of the art as a result.

1.2 Motivation

A primary tumor is one that has its origins either in the spinal cord or brain. At this time, there are projected to be 25,050 adults in the US with primary malignant tumors of the brain and spinal cord, including 14,170 men and 10,880 women. Less than 1% of individuals will experience this sort of tumor in their lives. 85 to 90 percent of all primary central nervous system (CNS) malignancies are brain tumors. In 2020, it is anticipated that 308,102 individuals will receive a primary brain or spinal cord tumor diagnosis worldwide. In addition, 4,170 kids under the age of 15 will receive a brain or CNS tumor diagnosis this year in the US. The remainder of this article discusses adult primary brain tumors. Learn more about pediatric brain tumors. Brain metastases or secondary brain tumors exist in addition to primary brain tumors. This is when the tumor first appeared during body and then metastasized toward the brain. Leukemia, lymphoma, melanoma, breast, kidney, and lung cancers are the most typical tumors that spread to the brain. Only primary adult brain tumors are covered in this manual. The 10th biggest cause of death for both sexes is cancer of the neurological system, including the brain. According to estimates. It is anticipated that primary malignant brain and CNS tumors would claim the lives of 18,280 persons in the US this year (10,710 males and 7,570 women). In 2020, primary CNS and brain tumors are expected as the primary cause of death for 251,329 people worldwide.

The 5-year survival rate illustrates the proportion, patients with tumors who survive for at least five years is found. Percentage refers to the number out of 100. Nearly 36% of Americans with malignant brain or CNS tumors survive for at least five years after diagnosis. The survival rate after 10 years is about 31%.

1.3 Rationale of the Study

For the purpose of tumor identification, a variety of studies have been conducted, some of which are addressed here: To accurately identify brain tumors, the paper "Basis Function (RBF) classifier, Masoumeh Siar and Mohammad Teshnehlab's "Decision Tree (DT) CNN Soft max classifier" was applied. Their research was broken down into three stages: Preprocessing MRI pictures is the first stage. Post-processing, which includes segmentation, morphological procedures, feature extraction, etc., is the second stage. The third step is to put the feature of picture patterns for tumor detection into practice [8]. In their 2018 discussion of the proposed work, Remi Y, Cédric Balsat YE, and Verset L classified high grade gliomas. Astrocytoma is the glioma that affects both adults and children the most frequently. Both low-grade and high-grade gliomas contain different types of astrocytes.

The CNN used in this work is entirely automatic. CNN implementation was done with Python. The framework of Anaconda, which builds the BRATS database using TensorFlow and a neural organization network, was used to implement the AI concept. This improves segmentation accuracy and provides the features needed to process larger datasets. The 2015 photos from the BRATS database were compared to the segmentation analysis of MRI brain tumor results. The parameter used to describe the precision of automatic segmentation is the dice coefficient [9]. A multimodal brain tumor segmentation technique, or new brain tumor segmentation, has been developed by Bjoern H. M. The plan integrated various segmentation methods to deliver superior performance. However, complexity levels are considerable [10]. For the purpose of diagnosing brain tumors, Huda S. proposed hybrid ensemble classification with feature selection. The decision rules are produced using the GANNIGMAC, decision Tree, and bagging C-based wrapper techniques [11]. The research of J Seetha, which was presented, suggested using MRI scans to identify brain tumors. The MRI check often produces a ton of data, making it quite time consuming to manually compare tumors to non-tumors. Despite the fact that it only provides precise quantitative measurements for a select few images. As a result, automated classification methods that can be trusted become necessary to lower the human fatality rate. The automatic classification of brain tumors is frequently highly complicated because to significant spatial and anatomical inconsistencies of surrounding tumorous parts of the brain. As a result, a programmed cerebrum tumor identification strategy based on Convolutional Neural Network (CNN) classification was proposed [12].

1.4 Research Questions

- What is the Brain tumor status globally?
- What are the associated factors with brain tumor?
- Which algorithm perform well and why?

- What is image processing?
- How does CNN, VGG-16 work?

1.5 Research Objective

- To find out the Brain tumor status.
- To identify the associated factors.
- Finding the best performing algorithm.
- Making awareness to reduce the percentage of brain tumor in every year.
- Giving message with the effect of lacking knowledge on brain tumor causes to peoples.
- To increase the knowledge on brain tumor preventing factors.

1.6 Report Layout

This research paper's contents are:

I. In the first chapter we discuss about the motivation, rational study and objectives.

II. In the second chapter we discus about the related work and research summary.

III. Research methodology, data collection and preparation, Research Subject and Instrumentation and discuss about the applied model in the Chapter 3.

IV. The experimental evaluation and numerical result of the study are discussed in Chapter 4.

V. The fifth chapter offer the summary, conclusion and future work.

CHAPTER 2

Background Study

2.1 Related Works

Brain tumors are incredibly unstable and possibly fatal in the absolute lack of innovative solutions due to the complexity of the issues. [13] Because tumors have the potential to spread widely and to aggravate the patient's condition, medical sciences are working in this area. Like us all, medical science has been using technology for many years, and as a result, with its assistance, the field of medical science is able to produce the greatest results at the right time. Patients' quality of life is improved, and their life expectancy rises as a result of early disease detection and effective treatment. Brain tumors come in two flavors: benign and malignant. So, deep neural networks were the most significant practical method here (DNN). CNNs are used in Siar, et al. [14] paper named "Brain tumor detection using deep neural network and machine learning algorithm." which is published in 9th international conference on computer and knowledge engineering. With CNN, images were initially used. The acquired images are classified using the SoftMax fully connected layer, which has a classification accuracy of 98.67%. The accuracy of the Decision Tree (DT) and Radial Basis Function (RBF) classifiers, which have a combined accuracy of 94.24 percent and 97.34 percent, respectively, was utilized to assess the performance of CNN. Additionally, they employed the benchmarks of sensitivity, specificity, and precision to assess the precision of the criterion.

The outcomes of the network accuracy test on the images reveal that among the classifiers used by CNN, the SoftMax classifier had the highest degree of accuracy.

They also developed a brand-new strategy for tumor diagnosis from brain imaging based on combining the feature extraction technique with CNN. The proposed approach provides test data accuracy of 99.12%. The importance of a doctor's accurate tumor diagnosis and patient treatment has increased along with the value of a doctor's diagnosis. One of the deadliest diseases, the brain tumor demands prompt and precise detection techniques; typically, the method of finding and diagnosing relies on the expertise radiologists and experts in neurology workable picture evaluation. Abdalla et al. [15] said in a paper named "Brain tumor detection by using artificial neural network." Which was presented in International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE) that one of the most severe diseases that calls for quick and precise diagnostic techniques is the brain tumor. The detection and diagnosis process are typically based on the radiologists' and neurospecialists judgment regarding the quality of the images, which takes time and is subject to human mistake. It was done following the gathering of picture data, at various stages of the Computer Aided Detection System (CAD), after the acquisition of image data, according to a summary from another research paper (MRI). The MRI pictures were preprocessed in the first phase, enhanced and made more analytically acceptable after post processing, and then threshold was used takes time and is susceptible to human error. using the mean gray level approach. The second stage extracts feature from the images using statistical feature analysis. Based on the spatial gray level dependency matrix, the Haraticles characteristic (SGLD) is used to produce the features from equations, and the best feature is then selected to pinpoint the tumor's location. In the third stage of ANN development, the supervised feed forward back propagation neural network was used as a way for automatically determining if the photos being studied are tumors or not.

2.2 Research Summary

The health care industry has a ton of information on hand. Early disease prediction is possible with the proper application of reliable data mining categorization methodology. Machine learning and data mining have legitimate applications in the medical field. The vast majority of it is correctly implemented. The study looks at a list of risk factors that are tracked by brain tumor monitoring systems. The proposed strategy for detecting, segmenting, and categorizing brain tumors appears to be extremely accurate and productive [16]. Automatic or semi-automatic processes were required to achieve this level of precision. According to the research, segmentation and classification can be done automatically using a method that depends on CNN and works in small 3x3 kernels.

CNN is a machine learning technique that makes use of neural networks with results classification layers. These involved a variety of mechanisms at different levels, including feature extraction, segmentation, average filtering, preprocessing, CNN, and VGG-16. Significant relationships and patterns from the data can be identified through classification and identification using data mining techniques. These data mining and machine learning methods are useful for early-stage brain tumor identification and prevention. The brain is a crucial component of the nerve system of humans since it regulates all bodily functions [17]. The primary cause of death is a brain tumor. The unusual brain cells are where the tumor develops. Malignant, benign, and cancerous tumors are the three main categories of tumors. The preprocessing, segmentation, feature extraction, and classification steps are used in this study by the author [18]. The tumor segment is detected using a set of criteria, and it is also classified using a (SVM) classifier. Investigating the sort of tumor at earlier stages is the major goal to assist the healthcare provider.

Extraction of features CNN using segmentation, classification, identification, data collecting, pre-processing, and average filtering. Pre-processing of the data collected during data collection, which removes noisy data, is the method used in this study. The average filtering follows. Following that, the segmentation technique is used for pixels-based detection. Following that, different features were extracted, including PSNR, MEAN, ENTROPY, SD, etc. CNN for utilized MRI image they use T1 and FLAIR. They also use Multi FD for extracting the brain tumor tissue-texture. They using Neural Networks and support vector Machine for better performance.

They also use Anaconda framework in AI. Also, TensorFlow. They also try multi-model brain tumor segmentation, which, in order to obtain great efficiency, combines many segmentation techniques. But the complexity of it is high. They recognize that neural networks are particularly useful for data clustering, approximation, pattern matching, optimization algorithms, and classification techniques. They boast that the Neural Network is divided into three sorts. They are feed-forward, recurrent, and feedback networks. There are two layers in the feed forward neural network: single layer and multilayer. The hidden layer is not apparent in a single layer network. It only has input and output layers, though. The multilayer has three layers in total as well. The input layer, hidden layer, and output layer are these. The technique is divided into two phases: training and testing, according to the CNN-based brain tumor classification system. In order to create a classification models, pre - processing step, extraction of features, and classification using the Loss function are done during the training phase.

In this article, the author examines, reviews, and describes how Magnetic Resonance Imaging (MRI) and Artificial Neural Network (ANN) approaches are used to identify brain tumors. After collecting the MRI image data, it was completed by the Computer

Aided Detection System (CAD) in a number of processes. Pre- and post-processing of MRI images was done in the initial stage in order to enhance and make them more suitable for analysis. The mean gray level approach was used in the second phase to segment the MRI images using a threshold. The Particles based on the dependency matrix for the spatial gray levels (SGLD) was chosen as the top characteristic to identify tumor localization in the second stage, which extracts features from images using statistical feature analysis.

This categorization is used to categorize various kinds of brain tumors, including aberrant and normal MR pictures. There is an advantage to employing this differential deep-CNN for image analysis of a pixel directed pattern using contrast calculations. They employed a dataset of 25,000 brain MRI scans, both aberrant and normal. Compared to the 2D CNN version, their suggested design produces the most specific feature map to distinguish between LG and HG gliomas. When compared, their Deep-CNN provides high-speed and accurate detection and classification capabilities. The basic structure a CNN are convolutional layers, pooling layers, and fully convolutional layers linked layers.

CHAPTER 3

Research Methodology

3.1 Introduction

Deep learning (DL) algorithms for interpreting magnetic resonance imaging (MRI) images and predicting brain tumors have seen rapid development in cancer research. We discovered a significant disparity between the high accuracy, interpretability, and explanation of DL models. As a result, we present an explanation-driven model for deep learning using a convolutional neural network (CNN) [19].

3.2 Data Collection Procedure

Data has collected from Kaggle. The place where data scientists spend their evenings and weekends is called Kaggle. To address issues using predictive analytics, machine learning, and data science it is a crowdsourced platform that draws, trains, educates, and tests several data scientists over the world. Around 536,000 of its users are active, and it receives about 150,000 submissions each month. was initiated in Melbourne, Australia Max Levchin, PayPal, Index, Hal Varian, Google's Chief Economist, and Khosla Ventures were among the investors who helped Kaggle collect about $11 million when it first arrived in Silicon Valley in 2011. Google ultimately purchased Kaggle in March 2017. On Kaggle, enthusiasts for data science from all around the world fight for rewards and to advance in the rankings. Just 94 people are Kaggle Grandmasters left as of this moment [20]. Data is always the prior issue to have some result in any field of work. To complete this process in deep learning we needed the datasets and we collected it from the kaggle website. Kaggle is big data warehouse the main challenge was to find the best outfit datasets for our purpose. So, we deeply looked into the website and other’s reference papers that we have studied for our research summery. We also looked into the UCI machine learning repository, which houses a paper warehouse and one of the biggest datasets. However, UCI was unable to assist us with the datasets, and we emailed more resources from the articles we had discovered without success before turning to Kaggle Data Warehouse for assistance in locating the datasets.

3.3 Data preparation

One of our study project's most difficult tasks is data collection. But the main challenge was to applied the algorithm. As we are not using framework, we have used the raw python coding to do that the data must need to prepare and specified folder to access the datasets. There are numerous numbers of cluster datasets which we have cleaned and integrate for our purpose at last the datasets was ready to apply the algorithms.

3.4 Research Subject and Instrumentation

The vastly increased size of data in technological advancements necessitates more complex and refined instruments. Although progressions in Deep Learning technology have invented large data acquisition much cautiously is still assuredly obliging there is also consistent the requirement for new methodologies and instruments that can help transform this data into valuable information and knowledge. The concept and techniques maintain the legacy of providing the user with a knowledge and application of the theory and practice of uncovering hidden patterns in massive data sets. Our research topic is "Brain Tumor Identification using Deep Learning Models" and in this paper, we are using CNN model, VGG-16 model, Microsoft Excel. Python3.5.

3.5 Used Deep Learning Models:

To classify brain tumors, we used two different deep learning models. One is Convolutional Neural Network (CNN) and another is Visual Geometry Group-16 (VGG-16). Here is a brief discussion about those.

a) **Convolutional Neural Network (CNN):**

Convolutional neural networks, or CNNs, are a deep learning technique that are frequently used for object and picture recognition and categorization [21]. As a result, Deep Learning employs a CNN to recognize objects in a picture. ConvNet requires far less pre-processing than some other classification models. While simple sorting techniques are still efficient, with sufficient training, they can gain knowledge of additional features such as ConvNet [22]. CNNs are widely used in a wide range of tasks and functions, including voice recognition in natural language processing, motion detection, image analysis challenges, computer vision, and auto car sensing system. CNNs are extensively used for the deep learning because of their substantial contribution to all of these rapidly developing and expanding fields.

Let's first discuss some fundamentals, such as what an image is and how it is displayed, before moving on to CNN's operation. Although all an RGB image is simply a matrix of pixel values, a RGB image and a grayscale image are identical, however contains a single plane. For further explanation, see this picture.

a

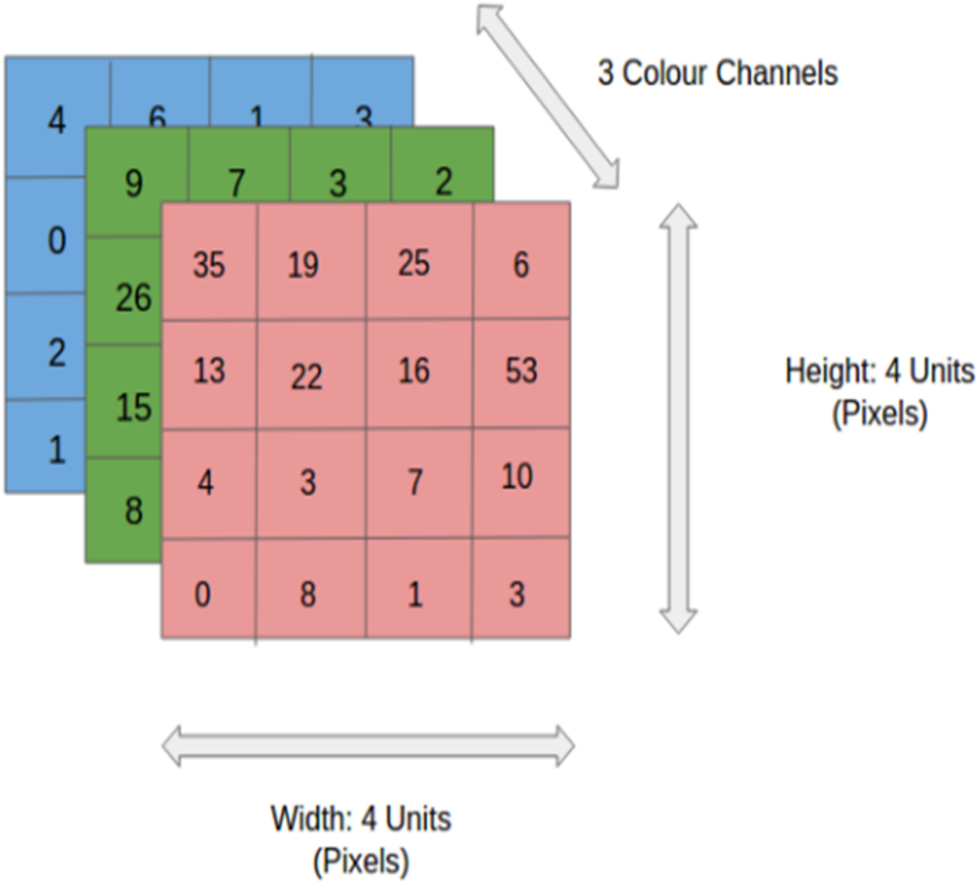

Figure 3.5.1: CNN RGB Image

Let's keep things straightforward by only using grayscale photographs to demonstrate how CNNs work.

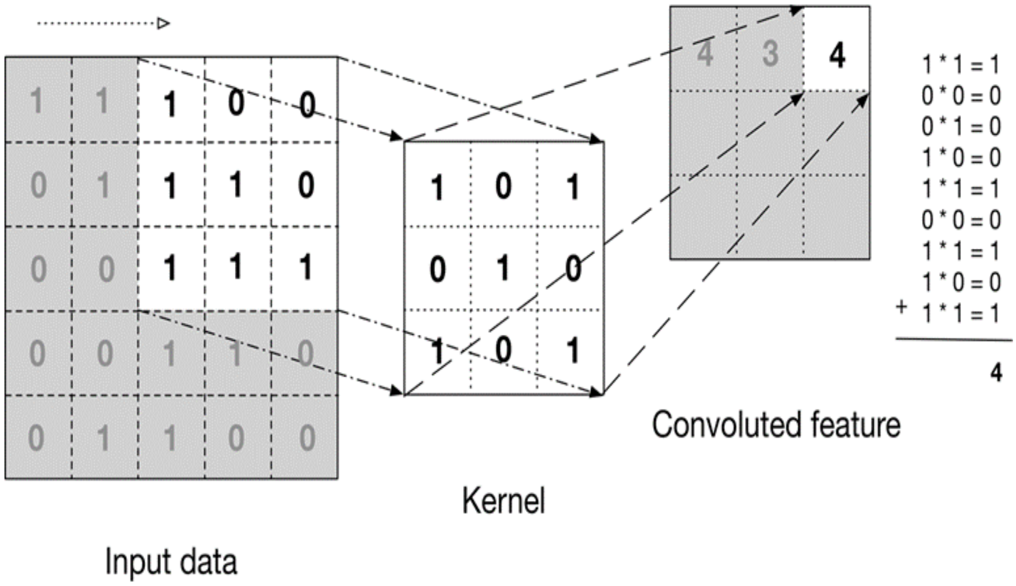

Figure 3.5.2: CNN work procedure

There is a convolution, as shown in the graphic above. A filter or kernel (3x3 matrix) is applied to the input picture to produce the convolved feature. This convolved function is being passed across to the layer following table.

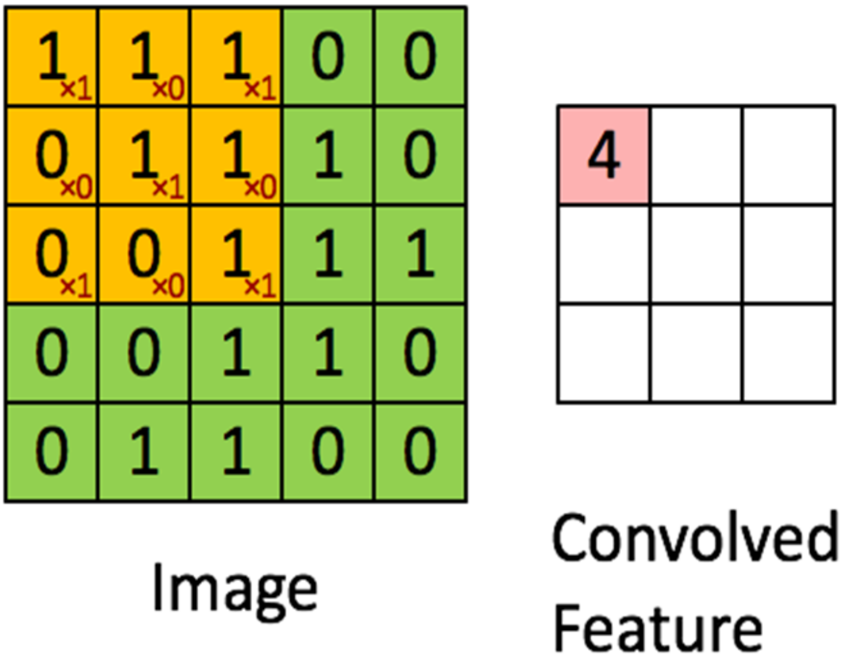

Figure 3.5.3: Convolved feature

See this animation to learn more about how the RGB color channel functions.

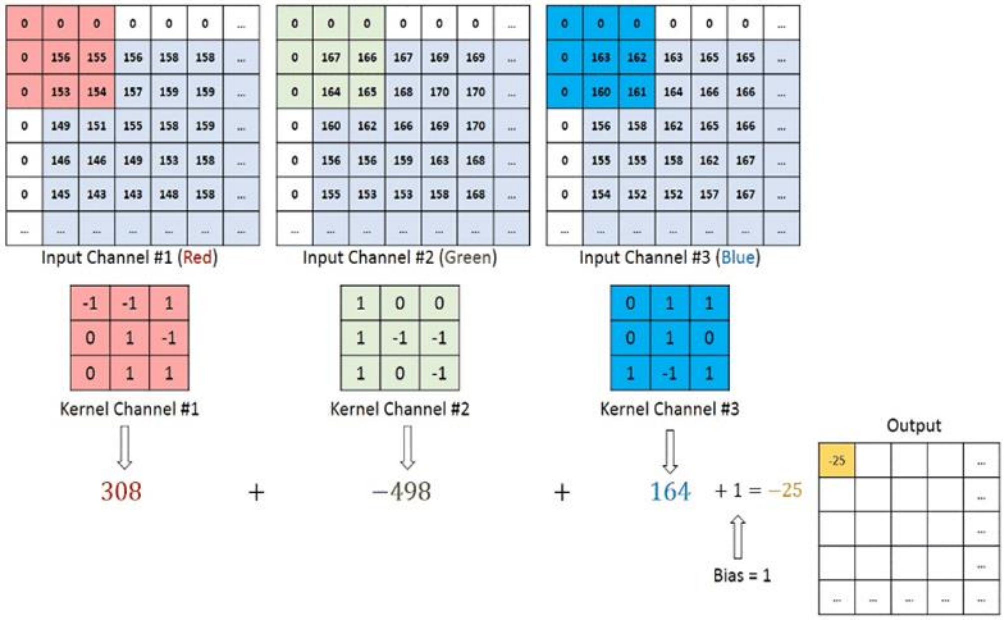

Figure 3.5.4: RGB color

Convolutional neural networks are made of artificial neurons that are stacked in layers. Similar to their biological counterparts, artificial neurons are mathematical constructs that compute the activation value from the weighted sum of a set of inputs. When an image is fed into a ConvNet, each layer generates a set of activation functions, which are subsequently transferred to the following layer.

Horizontal or diagonal edges are fundamental characteristics that are frequently retrieved by the first layer. After receiving this output, the subsequent layer looks for more complex features, such as corners and numerous edges. The network may eventually be able to distinguish things, faces, and other subtle details as we probe deeper.

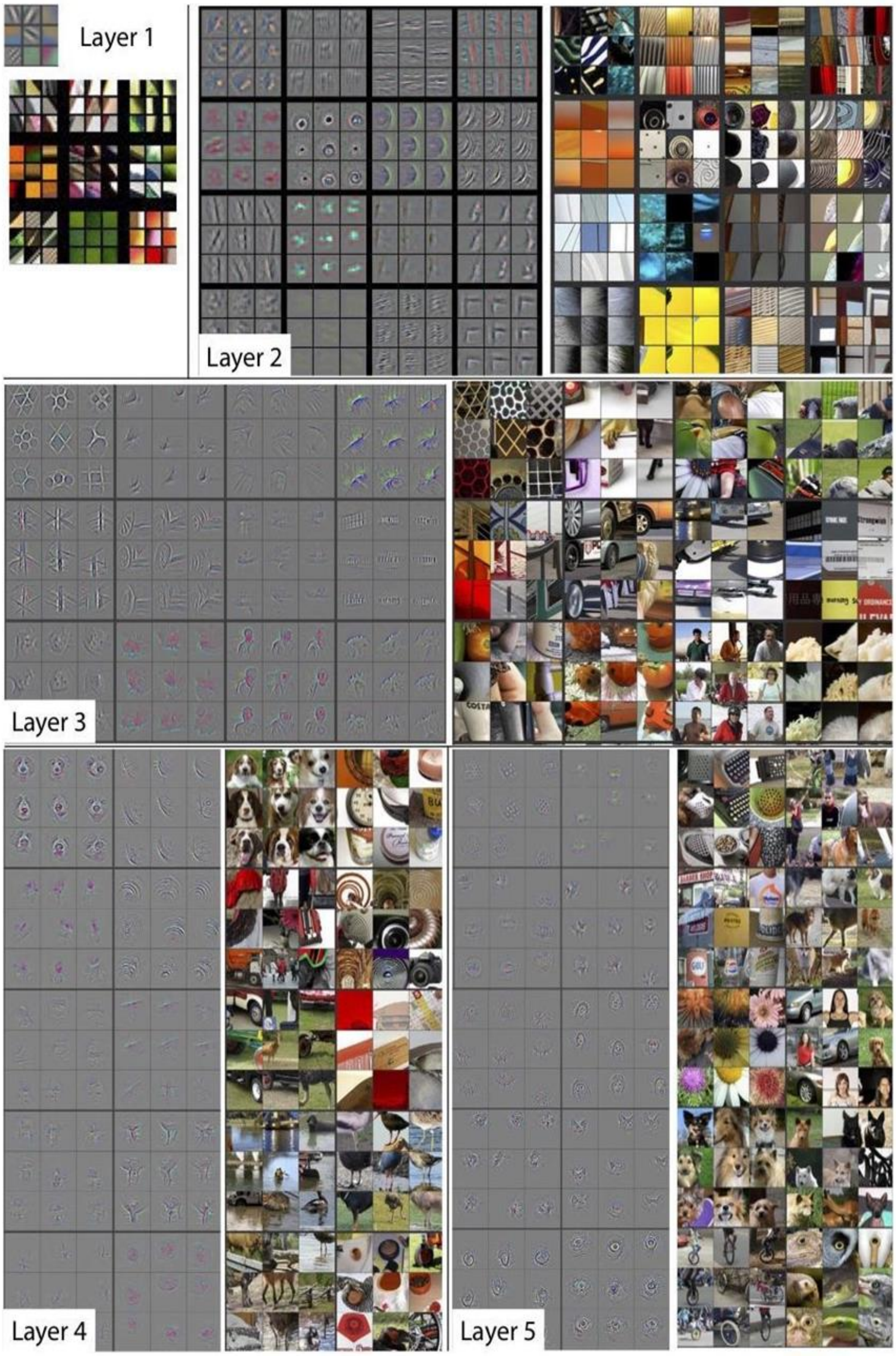

Figure 3.5.5: Classification layer

The classification layer produces a number of optimism ratings (numbers between 0 and 1) based on the activation map of the last convolution layer, indicating how likely it is for the image to belong to a "class". The last layer's output, for example, can be the likelihood assuming the input image contains any of the cats, dogs, or horses detected by the ConvNet.

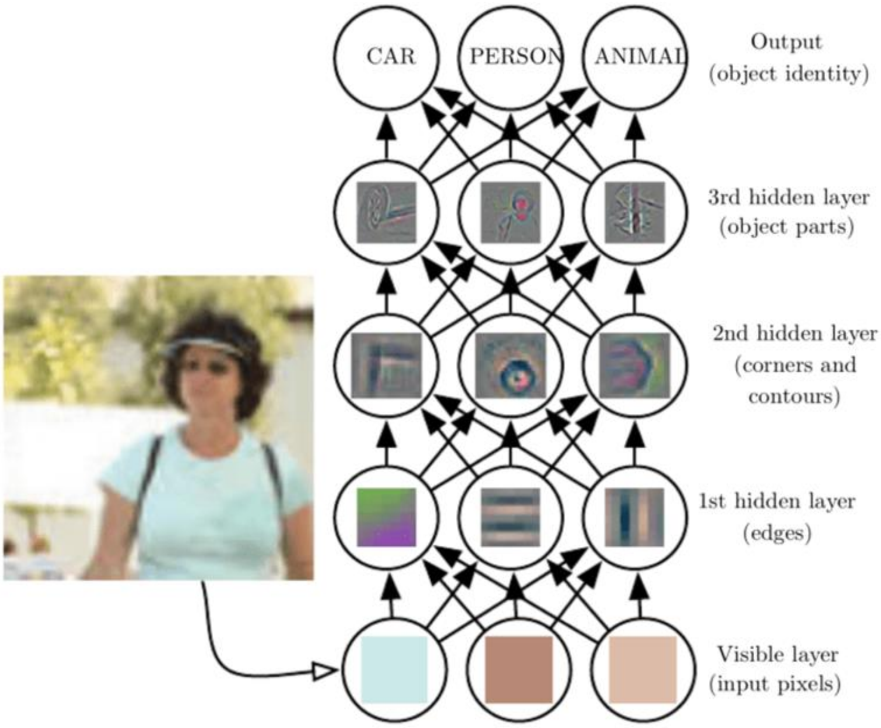

Figure 3.5.6: Final layer

Similar to the convolutional layer, the pooling layer is in charge of reducing the spatial size of the convolutional feature. Lowering the dimensions will result in less CPU processing power being essential for processing the data. Pooling comes in two flavors: average pooling and maximal pooling. I've just tried Max Pooling once, but so far, I haven't encountered any issues.

Similar to the convolutional layer, the pooling layer is in charge of reducing the spatial size of the convolutional feature. Lowering the dimensions will result in less CPU processing power being essential for processing the data. Pooling comes in two flavors: average pooling and maximal pooling. I've just tried Max Pooling once, but so far, I haven't encountered any issues.

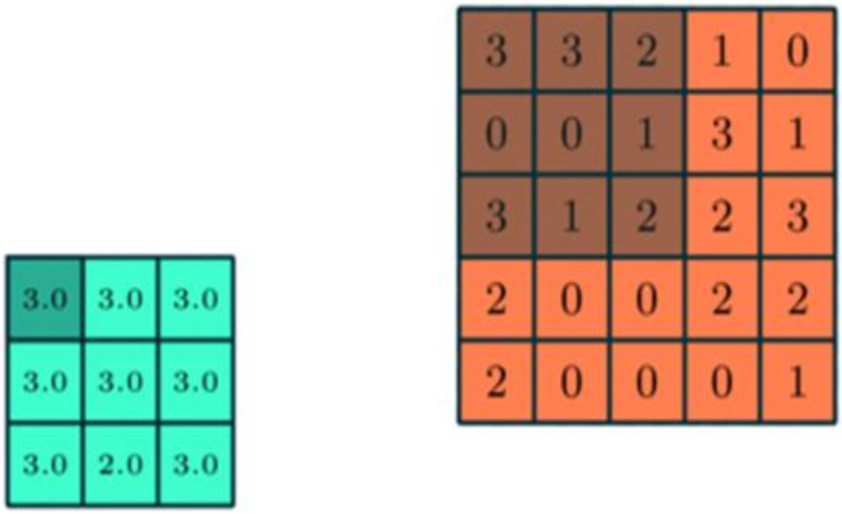

Figure 3.5.7: Polling Layer

As a result, in Max Pooling, we select a portion of the image that the kernel has covered in order to find the maximum value of a pixel. Max Pooling also acts as a sound deadener. Along with entirely rejecting the noisy activations, de-noising and dimensionality reduction are also carried out.

The mean of all the values in the image's area that the Kernel has covered, on the other hand, is what is obtained via average pooling. Only reducing dimensionality can reduce noise with average pooling. Therefore, we may say that Max Pooling significantly outperforms Average Pooling.

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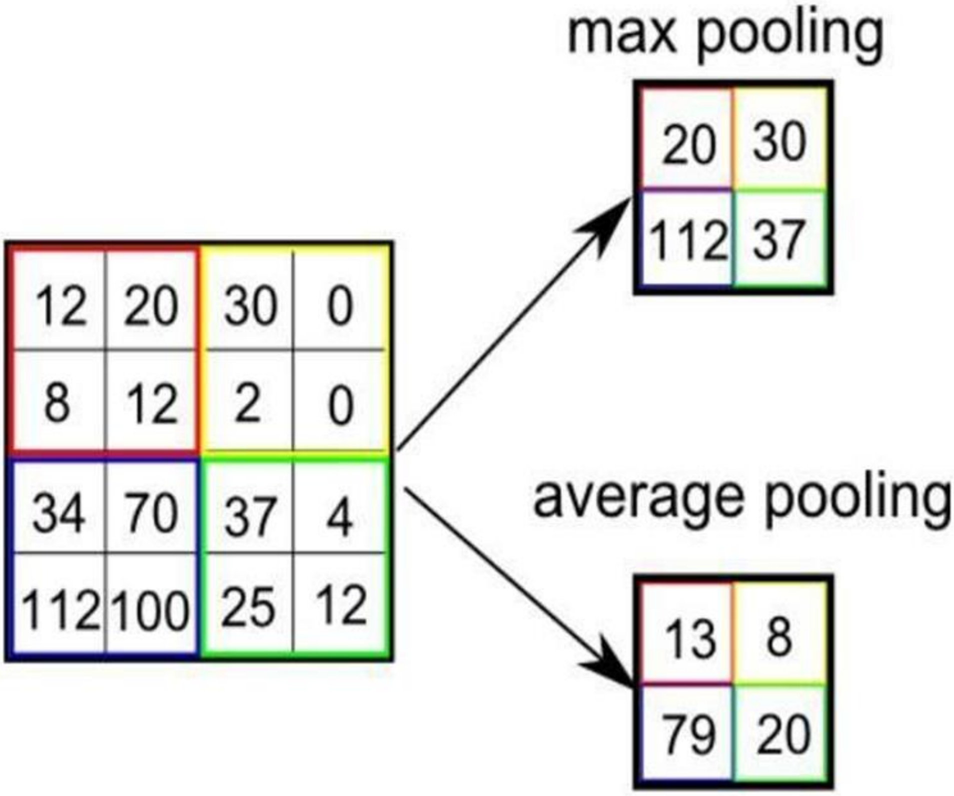

Figure 3.5.8: Polling image

b) Visual Geometry Group-16 (VGG-16):

VGG-16 refers to a 16-layer convolutional neural network. On over a million images from ImageNet's collection, a pre-trained version of the network has been trained [23]. VGG is composed of two fully connected layers, which are recommended by a softmax activation function for the output layer [24]. Using a trained network, images may be categorized many animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories. Because of this, the network has amassed extensive a variety of picture representations with features. VGG16 is an image segmentation and object recognition algorithm that classifies 1000 images into 1000 different categories with 92.7% accuracy. It is a well-established image classification method that is simple to integrate into transfer learning. Although this model is very simple, tasteful, and easy to do using, it isn't without drawbacks. This model's total quantity of parameters reached 138M, and its size exceeds 500MB. Because the compared to similar is longer, the model's application is severely limited, hugely in edge computing. Second, there is no specific method for dealing with the issue of vanishing or exploding gradients. This problem was resolved in GoogLeNet by using inception modules, and in ResNet by using skip connections.

Vgg architecture:

Vgg offers two models: the vgg-16 and the vgg-19. In this blog, our dataset will be classified using vgg-16. Vgg-16 is primarily composed of convolution, pooling, and fully linked layers. The input size of the corresponding network is 224 by 224 [25].

- Convolution layer: filters are used in this layer to draw out features from images. The stride and kernel size are the most crucial variables.
- The pooling layer's task is to shrink a network's spatial extent in order to scale back on processing and parameterization.
- Fully connected: in a straightforward neural network, these connections to the preceding layers are all fully connected.

Given figure shows the architecture of the model:

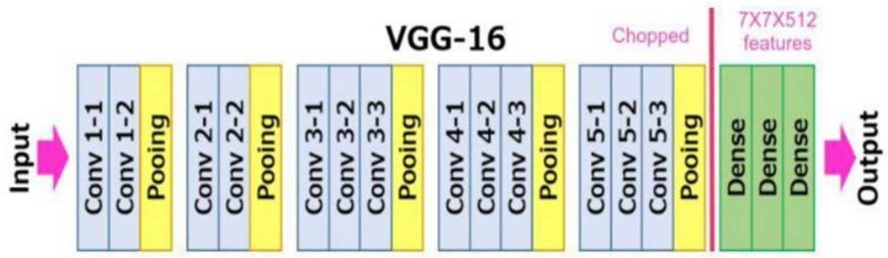

Figure 3.5.9: vgg-16 layer

Source Import a pre-trained model using PyTorch, remove the final fully connected layer or add an additional fully connected layer at the end depending on our needs and then run the model to perform transfer learning.

3.6 Implementation Procedure:

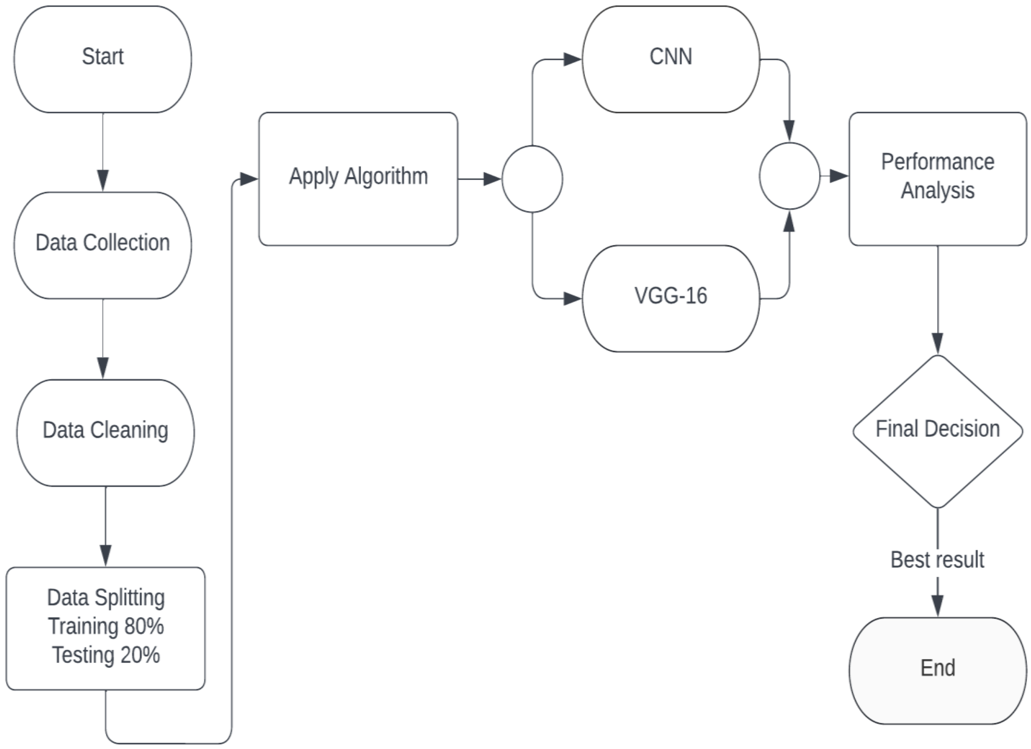

Figure 3.6.10: Research Methodology Flow chart

In this process first, we make a clear diagram to show us the path that how we are going to do our work. The path is clean that is seen in the diagram first we start the process then collected the data from Kaggle. Why Kaggle? We have tried to find the real dataset from various institution but we have failed then we plan if we can work on the demo datas we will have the experience to work on the real that's why we didn't stop/limit ourselves we keep working as per the flowchart diagram.

After collected the datasets, the data was not ready to apply the algorithms so we have clean and filter the datasets which is known as the preprocessing of data. Then we splitting the data sets into two parts: testing and training, respectively. The training (80%) percentage of the data and the rest (20%) of the data as testing dataset. After completing the process, we have applied two algorithms one is CNN and another one is VGG -16 to find out the associated factors that is causes the brain tumor and the accuracy of the result. Between these two algorithms VGG-16 perform better which is shown in the flowchart.

CHAPTER 4

Experimental Results & Discussion

4.1 Introduction

The preceding section we discussed the dataset and dataset processing techniques. This section will explain the results of some models that use the processed data. CNN and VGG-16 have been used, and the results are being analyzed to determine which approach provides the best accuracy.

4.2 Confusion Matrix

The confusion matrix is a tool for summing up the efficiency of a classification algorithm. If our dataset comprises more than two classes or fewer observations in certain classes than others, classification accuracy alone may be misleading. By creating a confusion matrix, we can gain a better understanding of the classification model's achievements and failures. This is the table of confusion matrix:

Table 4.2.1: Confusion Matrix

		Predicted	
		No Tumor	**Tumor**
Actual	**No Tumor**	True Negative (TN)	False Positive (FP)
	Tumor	False Negative (FN)	True Positive (TP)

The following performance metrics are obtained from the segmentation and classified results.

Table 4.2.2: CNN confusion matrix

		Predicted	
Actual		No Tumor	Tumor
	No Tumor	529	50
	Tumor	15	221

Table 4.2.3: VGG-16 confusion matrix

		Predicted	
Actual		No Tumor	Tumor
	No Tumor	556	23
	Tumor	16	220

The proportion of accurately predicted data points among all data points is defined as accuracy. The official definition of accuracy is as follows:

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100\%$$

Binary classification accuracy can also be assessed in terms of positives and negatives.as shown below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\%$$

The sensitivity of a machine-learning algorithm demonstrates how effectively it can recognize positive attributes. The true positive rate, also known as sensitivity, can be computed as follows:

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$

The percentage of true negatives that the model correctly detects is known as specificity. Calculating specificity involves doing the following:

$$Specificity = \frac{TN}{TN + FP} \times 100\%$$

The proportion of True Positives to All Positives is known as precision. The following is a formula for calculating precision:

$$Precision = \frac{TP}{TP + FP} \times 100\%$$

A machine learning statistic that can be applied in classification models is the F1 score. The following can be used to calculate the F1 score:

$$F1\ score = \frac{2TP}{2TP + FP + FN} \times 100\%$$

Table 1 describes the performance of each algorithm. The best method for our model has been chosen based on the performance and correctness of these algorithms. Based on this accuracy, sensitivity, specificity, and precision F1-Score, it is clear that VGG-16 performs the best. After taking everything into account, this algorithm can be utilized to optimize model performance.

Table 4.2.4: Performance evaluation

No	**Model Name**	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**F1-score**
1	CNN	92.02 %	**93.64** %	91.74 %	81.54 %	87.17 %
2	VGG-16	**95.21** %	93.22 %	**96.02** %	**90.53** %	**91.85** %

4.2 Descriptive Analysis

After all this process of the application algorithm, we have got our result that can see that the F1 score, precision, sensitivity, and specificity have a huge kind of value. Whereas the f1 score is made of two basic features, precision and recall, both determined as percentages and combined as harmonic mean to assign a single number that is easy to understand and performs well in the accuracy matrix, vgg-16 obtained the best result. As you can see in the table the CNN has below or no portion of the larger part that's why CNN performs less. We have tried multiple folding in epoch, and we have got that vgg-16 is the best for our dataset. VGG-16 shows the highest Accuracy 95.21%, in Specificity VGG-16 shows 96.02%, in Precision VGG-16 shows 90.53%, and in F1-score VGG-16 shows 91.85%. All of those are greater than CNN. On the other hand, in Sensitivity CNN shows 93.64%.

CHAPTER 5

Conclusions & Future work

5.1 Conclusions

Due to the intricacy of the images and the dearth of anatomical models that accurately represent the various deformations in each component, segmenting medical images is a difficult problem. The initial cluster size and cluster centers can be successfully managed using the suggested strategy. BWT approaches, which have lower accuracy and processing speed, are used for segmentation. This work suggests a technique to divide the brain tissue that requires barely any human intervention. The major objective of this suggested approach is to let human experts or neurosurgeons quickly identify the patients. According to the experimental results, the accuracy is 98.5 percent higher than that of cutting-edge technologies. The methods' computational time, system complexity, and memory space needs may all be further decreased. The same method can be used to identify and examine various disorders found in other body parts (kidney, liver, lungs, etc.). Future research can use various classifiers that employ optimization methodology to increase accuracy by combining more efficient segmentation and extraction algorithms with real-time images and clinical cases and a larger data set that includes a variety of scenarios.

5.2 Future Work

As we have some limitations for the work to clear the dataset and further apply more algorithms. But as we have not experienced it. So, looking for further indeed that how can we applied more algorithms to get the best accuracy. And this can help mankind to solve this problem of "Brain Tumor" disease all over the world not only in this country. And this holds hardily determination that we can perform much better accuracy by using the algorithm then we can serve it all over the world mostly.

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