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Thème

A new version of deep learning segmentation to detect brain tumor In An IOT system

Présenté par :

Friki Imed Salah Eddine

Bekaddour Abdel Madjid

Dirigé par :

Dr.Bouarara Hadj Ahmed

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ABSTRACT

Abstract

With the development of the field of artificial intelligence, especially deep learning, and the spread of cancerous tumors frequently. That is why we have proposed a solution using various deep learning tools to deal with different problems related to the detection, diagnosis and location of brain tumors. This solution consists of several parts : 1) Receiving data by diagnostic tools such as MRI. 2) Data augmentation methods were used. 3) Using four models for Transfer Learning, represented by : Xception, VGG16, ResNet50, InceptionV3 For tumor detection. 4)We proposed a segmentation model called UNet_Model_Verstion_Updated to locate the tumor. The results obtained represent empirical evidence of the benefit derived from using deep learning and computer vision to help clinicians make a decision and remove brain tumors.

Keywords : MRI, data augmentation,models for Transfer Learning,segmentation model UNet_Model_Verstion_Updated.

Résumé

Avec le développement du domaine de l'intelligence artificielle, en particulier l'apprentissage en profondeur, et la propagation fréquente des tumeurs cancéreuses. C'est pourquoi nous avons proposé une solution utilisant divers outils d'apprentissage profond pour traiter différents problèmes liés à la détection, au diagnostic et à la localisation des tumeurs cérébrales. Cette solution se compose de plusieurs parties : 1)Réception des données par des outils de diagnostic tels que l'IRM. 2) Des méthodes d'augmentation des données ont été utilisées. 3) Utilisation de quatre modèles d'éducation au transfert, représentés par : Xception, VGG16, ResNet50, InceptionV3 Pour la détection des tumeurs. 4)Nous avons proposé un modèle de segmentation appelé UNet_Model _Verstion_Updated pour localiser le tumeur. Les résultats obtenus représentent une preuve empirique du bénéfice tiré de l'utilisation de l'apprentissage en profondeur et de la vision par ordinateur pour aider les cliniciens à prendre des décisions et à retirer des tumeurs cérébrales.

Mots clés : IRM, augmentation de données, modèles d'apprentissage par transfert, modèle de hachage UNet_Model_Verstion_Updated.

الملخص

مع تطور مجال الذكاء الاصطناعي وخاصة التعلم العميق وانتشار الأورام السرطانية بشكلمع تطور مجال الذكاء الاصطناعي وخاصة التعلم العميق وانتشار الأورام السرطانية بشكل متكرر. لهذا السبب اقترحنا حلاً باستخدام أدوات التعلم العميق المتنوعة لمعالجة المشكلات المختلفة المتعلقة باكتشاف أورام المخ وتشخيصها وتحديد موقعها. يتكون هذا الحل من عدة أجزاء : ١)استقبال البيانات بأدوات التشخيص مثل التصوير بالرنين المغناطيسي ٢). تم استخدام طرق زيادة البيانات. ٣)اكاستخدام استخدام أربعة نماذج نقل التعلم، ممثلة في ResNet و VGG-16 و InceptionV3 Xception. ٤)اقترحنا نموذج تجزئة يسمى UNet Model Verstion updqted لتحديد موقع الورم.

تمثل النتائج التي تم الحصول عليها دليلاً تجريبياً على فائدة استخدام التعلم العميق ورؤية الكمبيوتر لمساعدة الأطباء على اتخاذ القرارات وإزالة أورام المخ.

الكلمات المفتاحية: MRI، UNet Model Verstion updqted نماذج نقل التعلم ،زيادة البيانات

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IMED

Dedicate

I dedicate my dissertation work to my family and many friends. A special feeling of gratitude to **my loving Parents**, whose words of encouragement and push for tenacity ring in my ears. I also dedicate this dissertation to my brothers **youcef** and **zakaria** who have supported me throughout the process. I will always appreciate all they have done,

A special thanks to my supervisor **Dr. Hadj Ahmed Bouarara**, who have supported me and stood by me when things looked bleak.

ACRONYMS

ACRONYMS

MRI : *Magnetic resonance imaging*
DL : *Deep Learning.*
ML : *Machine Learning.*
AI : *Artificial Intelligence.*
CNN : *Convolutional Neural Network.*
CV : *Computer Vision.*
ReLu : *Rectified Linear Unit.*
OF : *Overfitting.*
UF : *Underfitting.*
IOT :*Internet Of Things.*
WSNs :*Wireless Sensor Networks.*

Table des matières

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LISTE DES TABLEAUX

TABLE **Page**

TABLE DES FIGURES

Chapitre 1

Introduction

The tumor is a mass of irregular cells called the primary brain tumor inside the brain, uncontrolled growth of tissue cells results in a tumor that may be benign or malignant/cancerous. Brain cancer is among the different causes of an increase in mortality rate in the world. The death rate, due to a brain tumors, has increased to 300 in the last few decades.

Medical imaging analysis has been commonly involved in basic medical research and clinical treatment, e.g. computer-aided diagnosis, medical record data management, medical robots, and image-based applications. Medical image analysis provides useful guidance for medical professionals to understand diseases and investigate clinical challenges to improve healthcare quality. Among various tasks in medical image analysis, brain tumor segmentation has attracted much attention in the research community, which has been continuously studied. Despite the tireless efforts of researchers, as a key challenge, accurate brain tumor segmentation remains to be solved, due to various challenges such as location uncertainty, morphological uncertainty, low contrast imaging, annotation bias, and data imbalance. With the promising performance made by powerful deep learning methods, several deep learning-based methods have been applied to brain tumor segmentation to extract feature representations automatically and achieve accurate and stable performance.

Automatic segmentation and classification of medical images play an important role in diagnostics, growth prediction, and treatment of brain tumors. An early tumor brain diagnosis implies a faster response in treatment, which helps to improve the patient's survival rate. Location and classification of brain tumors in large medical image databases, taken in routine clinical tasks by manual procedures, have a high cost both in effort and time. An automatic detection, location, and classification procedure is desirable and worthwhile.

1.1 Motivation

-With advances in medicine, more and more surgeries depend on technology, In recent years, robotic technology has been introduced into a wide range of medical fields, and With the arrival of 5g, the latest wireless communication technology featuring ultra high speed, super-low latency, and massive connectivity, which will allow calculations to be made remotely, makes it possible to connect several million objects per km^2, and offers an even shorter reaction time, or latency, and significantly better image quality than previous networks, thus limiting the risk of error by providing more information to medical teams.
-This new era of 5G will bring together improved connectivity, cloud-based storage, and an array of connected devices and services. Extensive computing capability combined with virtual system architecture will open up a mobile internet of things (IoT). Advanced digital networks will bring together a system that connects billions of devices and sensors enabling advances in health care.
-Helps manipulators and doctors perform operations and analyze remotely using intelligent programs.
-Decision Support : helps manipulators and doctors to make the decision.
- The machines have become powerful, which has facilitated instance calculations «thanks for gaming».

1.2 Problematic

Research in the domain of biomedical image analysis has been one of the most challenging and promising areas in recent years due to an increase in brain tumors, during our work we encountered some problems :

1. Machine learning :
   - Classic machine learning techniques cannot process voluminous data (big data).
   - Does not allow to make a better features extraction
   - The features extraction step is done manually.
   - Does not give satisfactory results.
   - does not allow the segmentation.
2. Deep learning :
   - Many models are proposed in the literature.
   - Classic segmentation techniques have a problem requiring too much human intervention.
   - There are too many hyperparameters to fix.
   - The feature extraction step takes a long time to calculate the lack of data.

1.3 Organization Work

Organization of work Our thesis consists of four chapters :

- **Chapter One :**
  In the first chapter we will present the techniques used in this memoir which is the use of Deep learning and Convolutional neural networks , their different architectures of models and their different fields of application.
- **Chapter two :**
  deals with the nature of bio informatics and the spread of cancerous tumors and their types, as well as Image segmentation.
- **Chapter Three :** We will talk about future work and provide an in-depth explanation of the project.
- **Chapter Four :** Experimental validation of our work and discussion of our conclusions and highlighting future research work to improve our models.

CHAPITRE 2

DEEP LEARNING

"We're making this analogy that AI is the new electricity."..... Andrew Ng

2.1 Introduction

Deep learning is an ambiguous term, as it has gone through several different meanings throughout the years.
Deep learning is a form of machine learning that enables computers to learn from experience and understand the world in terms of a hierarchy of concepts. Because the computer gathers knowledge from experience, there is no need for a human computer operator formally to specify all of the knowledge needed by the computer
Deep Learning is a subset of machine learning, which is in itself a subfield of AI.
The figure below is a visual representation of the relationship between AI, ML and DL.

2.2 Why deep learning :

Deep learning, with its remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends too complex to be noticed by humans or computer techniques. A trained neural network can be considered an "expert" in the category of information it has been given to analyse. This expert can then be used to provide new projections of situations of interest and response.
Other benefits include :

— Storage of information on the whole network : information such as in traditional programming is stored on the whole network, not on a database.

— Ability to work with incomplete knowledge : after training, the data can produce an output even with incomplete information.
— Fault tolerance : the corruption of one or more cells.
— Having a distributed memory : for Ann to be able to learn, it is necessary to determine the instances and teach the network according to the desired output by showing these instances to the network. The success of the network is directly proportional to the instances selected and if the event cannot be shown to the network in all its aspects, the network may produce a false output.
— Ability to make machine learn : Artificial neural networks learn from events and make decisions by commenting on similar events.
— Parallel processing capability : artificial neural networks have a numerical strength that can perform more than one job at the same time. [35]

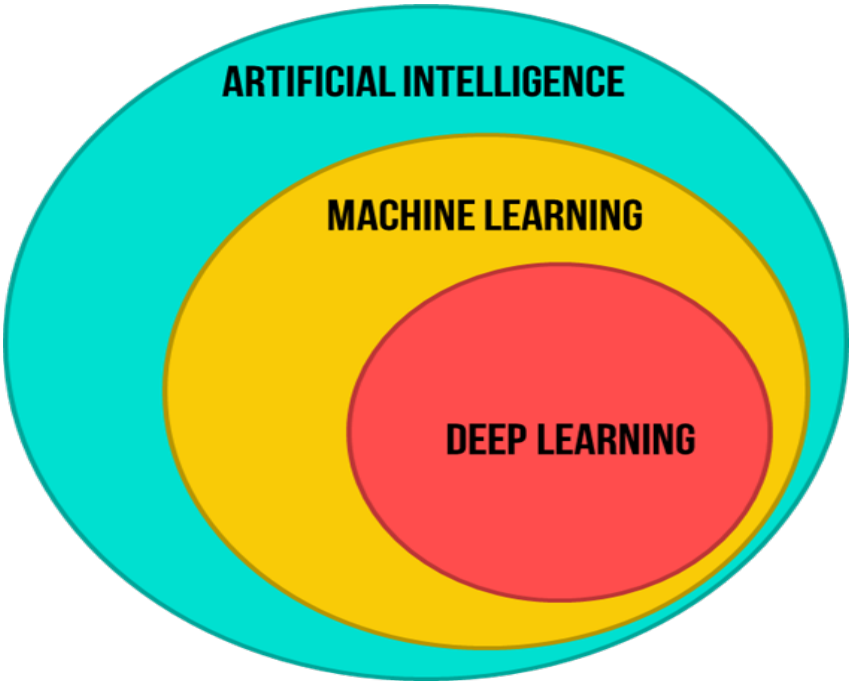

FIGURE 2.1: Relationship between AI, ML and DL

[35]

2.3 Convolutional neural networks :

In recent years, the convolutional neural network (CNN) has emerged as the prevalent model for the machine learning and computer vision. deep CNNs are widely used in a broad range of real-life applications, such as image classification, object detection and image segmentation.
The name “convolutional neural network” indicates that the network employs a mathematical

operation called convolution. Convolution is a specialized kind of linear operation. Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.
The typical use of convolutional networks is on classification tasks, where the output to an image is a single class label.

2.3.1 Overall architecture

CNNs are comprised of three types of layers. These are convolutional layers, pooling layers and fully-connected layers. When these layers are stacked, A simplified CNN architecture for MNIST classification is illustrated in Figure 2.2.

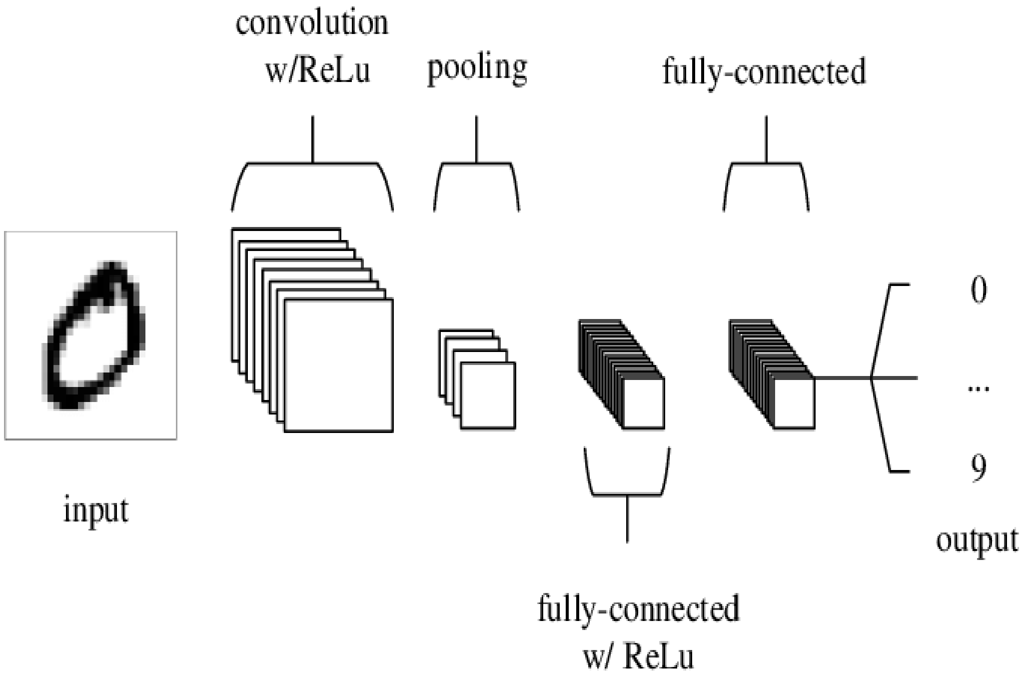

FIGURE 2.2: Architecture of CNN

[36]

The basic functionality of the example CNN above can be broken down into four key areas.

— As found in other forms of ANN, the input layer will hold the pixel values of the image.

— The convolutional layer will determine the output of neurons of which are connected to local regions of the input through the calculation of the scalar product between their weights and the region connected to the input volume. The rectified linear unit (commonly shortened to ReLu) aims to apply an 'elementwise' activation function such as sigmoid to the output of the activation produced by the previous layer.

— The pooling layer will then simply perform down sampling along the spatial dimensionality of the given input, further reducing the number of parameters within that activation.

— The fully-connected layers will then perform the same duties found in standard ANNs and attempt to produce class scores from the activations, to be used for classification. It is also suggested that ReLu may be used between these layers, as to improve performance[36]

2.3.2 edge detection :

The edge detection on the images is so important for image processing. It is used in a various fields of applications ranging from real-time video surveillance and traffic management to medical imaging applications.
the role of edge detection is very crucial as it is the preliminary or fundamental stage in pattern recognition.
Edges characterize object boundaries and are therefore useful for segmentation and identification of objects in a scene.
The idea that the edge detection is the first step in vision processing has fueled a long term search for a good edge detection algorithm[9].

FIGURE 2.3: Edge detection using Sobel filters

[9]

1. More edge detection :
   — The Sobel filter, shown in figure below. And the advantage of this Sobel filter is it puts a little bit more weight to the central row, the central pixel, and this makes it maybe a little bit more robust.
   — The Scharr filter as well.

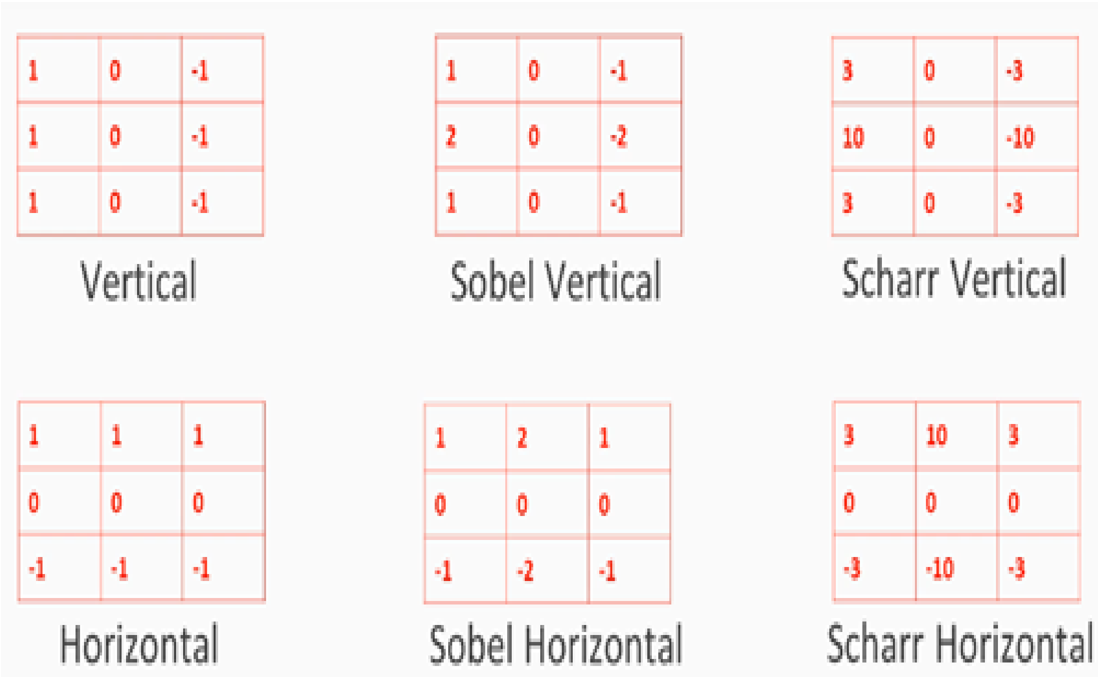

FIGURE 2.4: Types of filters

[34]

— These 2 filters in figure are representing vertical edge filters. You can flip them 2 by 90 degrees to get the horizontal edge filters.

2.3.3 Padding :

Convolutional operation often requires padding when part of the filter extends beyond the input image or feature map. Standard approaches include zero padding (extend with zeros), reflection padding (reflect the input values across the border axis) and replication padding (extend by replicating the values along borders) padding (extend by replicating the values along borders). Among them, the most commonly used scheme is zero padding, as was adopted by. Padding basically extends the area of an image in which a convolutional neural network processes. The kernel/filter which moves across the image scans each pixel and converts the image into a smaller image. In order to work the kernel with processing in the image, padding is added to the outer frame of the image to allow for more space for the filter to cover in the image. Adding padding to an image processed by a CNN allows for a more accurate analysis of images[26].

— Type of Padding

1. The valid convolutions : No padding", its mean
   N.N F.F $\rightarrow$ (N F +1)(N F +1)
2. The Same convolutions : Dimension of input matrix = dimension of output matrix
   (N.N)(F.F) $\rightarrow$ ((N +2P F)/S)+1((N +2P F)/S)+1

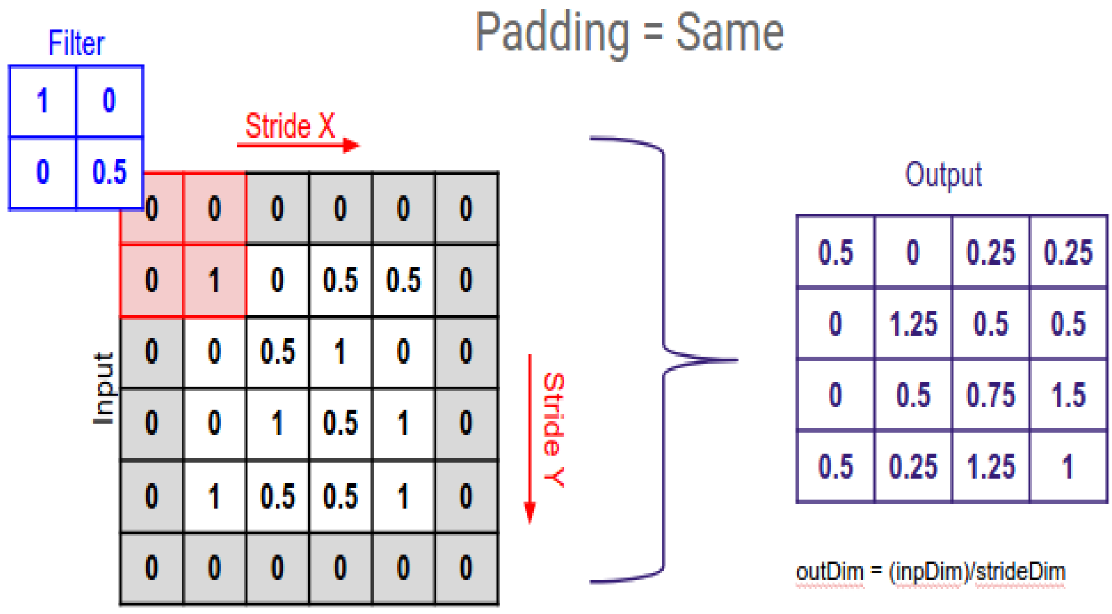

FIGURE 2.5: ConvNet application using a single padding.

[26]

Through this equation we find this rule to achieve the same convolutions :
P = (F 1)/2

3. Strided convolutions : It's helpful for save time but the quality decreases
(N.N)(F.F) = ((N +2P F)/S)+1((N +2P F)/S)+1

2.3.4 Pooling :

Pooling layers aim to gradually reduce the dimensionality of the representation, and thus further reduce the number of parameters and the computational complexity of the model.
The pooling layer operates over each activation map in the input, and scales its dimensionality using the "MAX" function. In most CNNs, these come in the form of max-pooling layers with kernels of a dimensionality of 2×2 applied with a stride of 2 along the spatial dimensions of the input. This scales the activation map down to 25 of the original size - whilst maintaining the depth volume to its standard size.
Due to the destructive nature of the pooling layer, there are only two generally observed methods of max-pooling. Usually, the stride and filters of the pooling layers are both set to 2×2, which will allow the layer to extend through the entirety of the spatial dimensionality of the input. Furthermore overlapping pooling may be utilised, where the stride is set to 2 with a kernel size set to 3. Due to the destructive nature of pooling, having a kernel size above 3 will usually greatly decrease the performance of the model.

It is also important to understand that beyond max-pooling, CNN architectures may contain general-pooling. General pooling layers are comprised of pooling neurons that are able to perform a multitude of common operations including L1/L2-normalisation, and average pooling. However, this tutorial will primarily focus on the use of max-pooling.

2.4 Activation functions :

Activation Functions are specially used in artificial neural networks to transform an input signal into an output signal which in turn is fed as input to the next layer in the stack. In an artificial neural network, we calculate the sum of products of inputs and their corresponding weights and finally apply an activation function to it to get the output of that particular layer and supply it as the input to the next layer[38]. Some examples of some of the popular activation

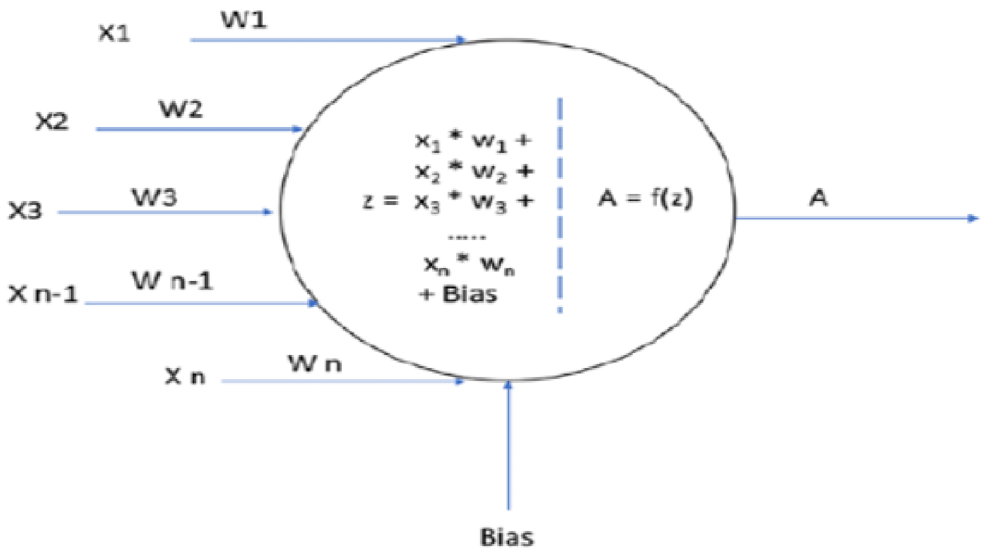

FIGURE 2.6: Activation function on a single neuron

[38]

functions used in neural networks for classification and detection tasks are given as follows :

2.4.1 Sigmoid Activation Function :

It is the most widely used activation function as it is a non-linear function. Sigmoid function transforms the values in the range 0 to 1. It can be defined as :

$$f(x) = 1/e - x$$

Sigmoid function is continuously differentiable and a smooth S-shaped function. The derivative of the function is :

$$f'(x) = 1 - sigmoid(x)$$

Also, sigmoid function is not symmetric about zero which means that the signs of all output values of neurons will be same. This issue can be improved by scaling the sigmoid function.

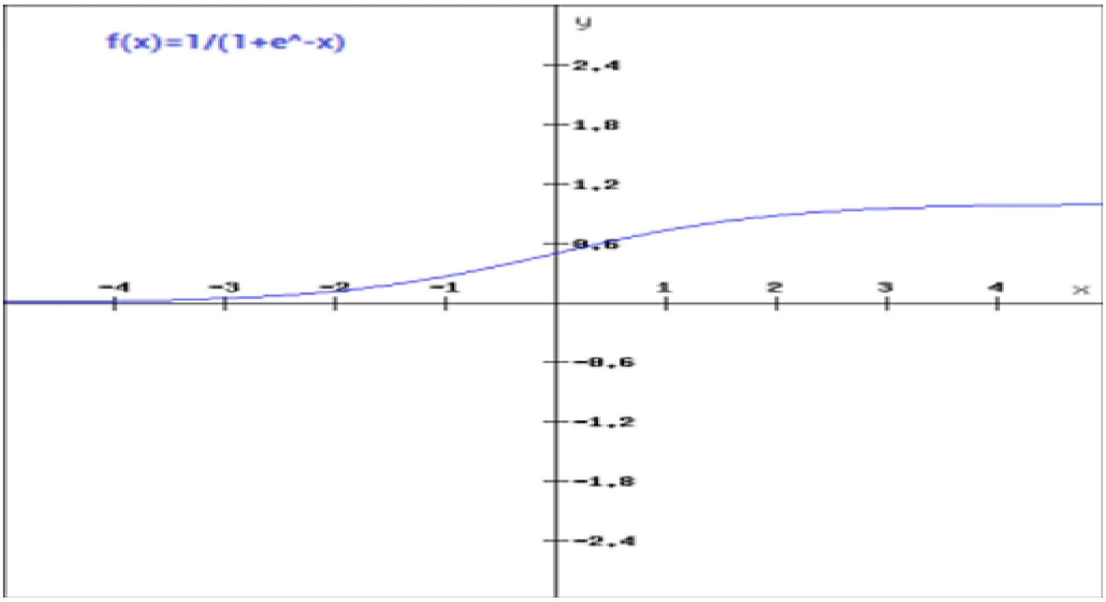

FIGURE 2.7: Sigmoid function

[38]

2.4.2 Tanh Function

It is Hyperbolic Tangent function. Tanh function is similar to the sigmoid function but it is symmetric to around the origin. This results in different signs of outputs from previous layers which will be fed as input to the next layer. It can be defined as :

$$f(x) = 2sigmoid(2x) - 1$$

Tanh function is continuous and differentiable, the values lies in the range -1 to 1. As compared to the sigmoid function the gradient of tanh function is more steep. Tanh is preferred over sigmoid function as it has gradients which are not restricted to vary in a certain direction and also, it is zero centered[38].

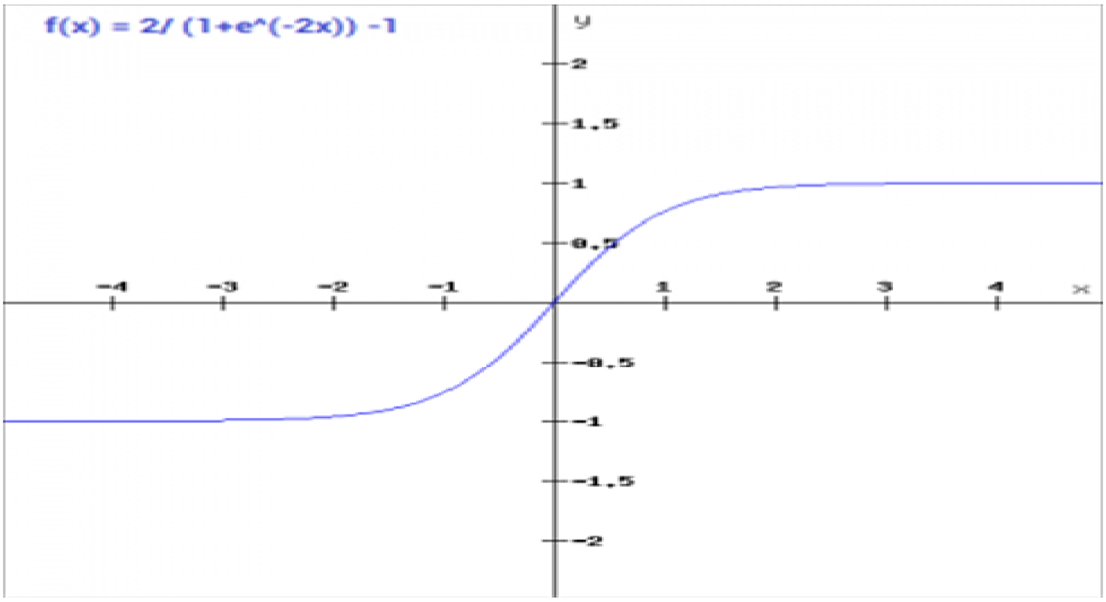

FIGURE 2.8: Tanh Function

[38]

2.4.3 ReLU Function :

ReLU stands for rectified liner unit and is a non-linear activation function which is widely used in neural network. The upper hand of using ReLU function is that all the neurons are not activated at the same time. This implies that a neuron will be deactivated only when the output of linear transformation is zero. It can be defined mathematically as :

$$f(x) = max(0, x)$$

ReLU is more efficient than other functions because as all the neurons are not activated at the same time, rather a certain number of neurons are activated at a time. In some cases, the value of gradient is zero, due to which the weights and biases are not updated during back-propagation step in neural network training[38].

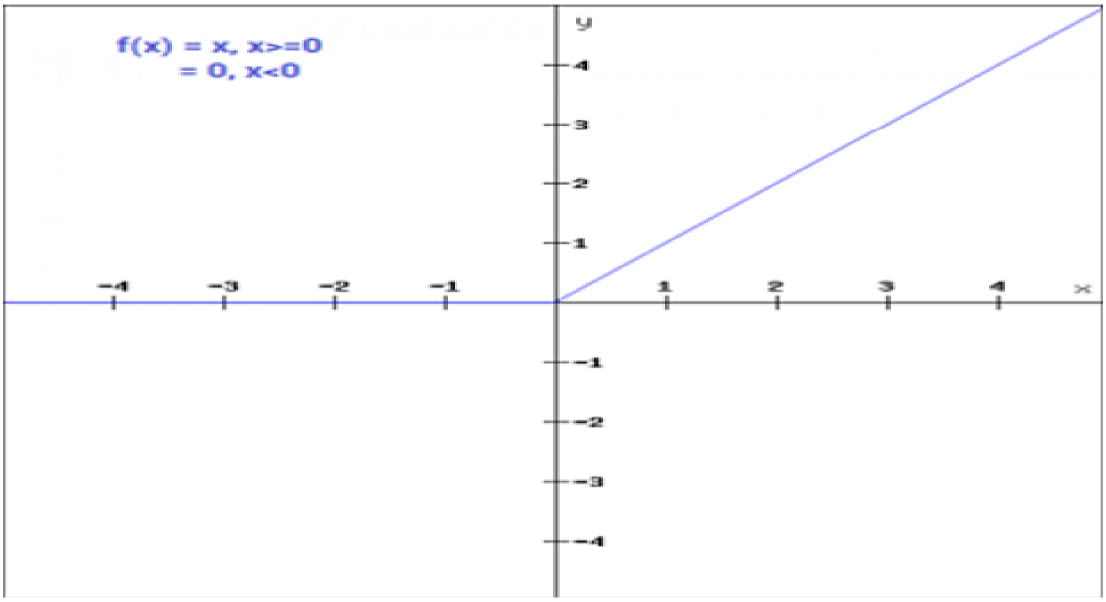

FIGURE 2.9: ReLU Function

[38]

— Unité linéaire rectifiée Leaky (Leaky ReLU) :
The Leaky ReLU activation function is similar to the ReLU function with one key difference : it allows a small positive gradient when the unit is inactive[7].A Leaky ReLU is calculated as follows : (x)=max (x,).

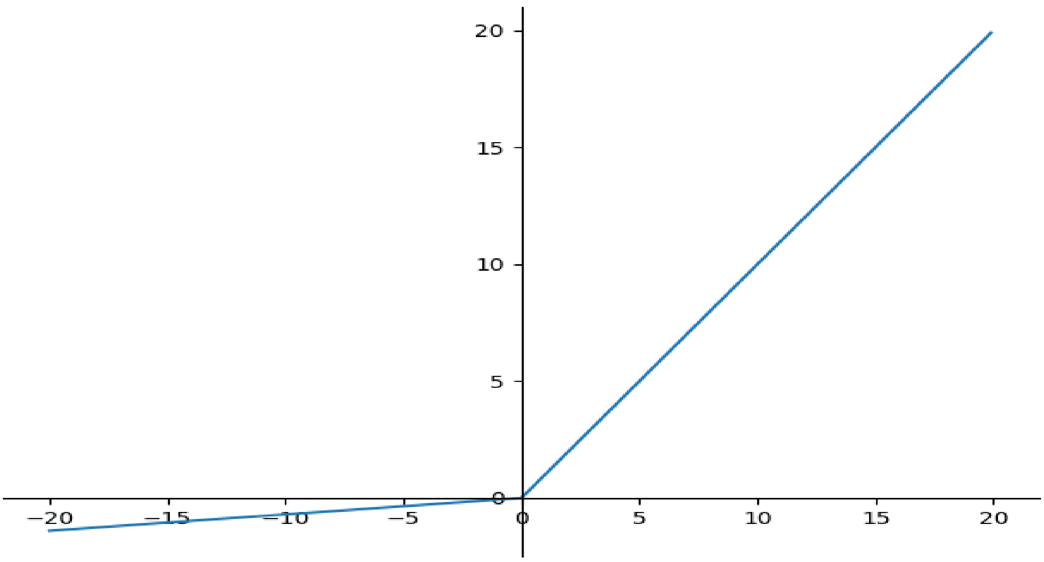

FIGURE 2.10: Leaky ReLU Function

[38]

2.4.4 SOFTMAX ACTIVATION FUNCTION :

Softmax function is a combination of multiple sigmoid functions. As we know that a sigmoid function returns values in the range 0 to 1, these can be treated as probabilities of a particular class' data point. Softmax function unlike sigmoid functions which are used for binary classification, can be used for multiclass classification problems. The function, for every data point of all the individual classes, returns the probability. It can be expressed as :

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

When we build a network or model for multiple class classification, then the output layer of the network will have the same number of neurons as the number of classes in the target[38].

2.5 Optimization Methods :

The most important part of the model training is the optimizer. Let's imagine the structure of a model. The structure created by defining the sequence of layers with the number of neurons, activation functions and the shape of input and output is initialized with random weights at the beginning. The weights that determined the influence of a neuron on the next neuron or the final output are updated by the network during the learning process. In short, a network with random weights and a defined structure is the starting point for a model. The network takes a training sample and uses its values as inputs to the neurons in the first layer, which then produce an output with the defined activation function. The output then becomes an input to the next layer, and so on. The output of the last layer would be the prediction for the training sample. This is where the loss function comes into play. The loss function helps the network understand how well or poorly the current set of weights performed on the training sample. The next step for the model is to reduce the loss. How does the network know what steps or updates it needs to make to the weights to reduce the loss? The optimizer helps it understand this step. The optimizer function is a mathematical algorithm that uses derivatives, partial derivatives, and the chain rule in the calculation to understand how much the network will change in the loss function by making a small change to the weights of the neurons. The change in the loss function, which would be an increase or decrease, helps to determine the direction of change needed in the weight of the connection.

To summarize, we can say that the optimizer uses the score obtained by the loss function to adjust the value of the weights a bit, in a direction that will lower the loss score, as shown in Figure bellow. The optimizer implements what is called the backpropagation algorithm : the central algorithm of deep learning[15].

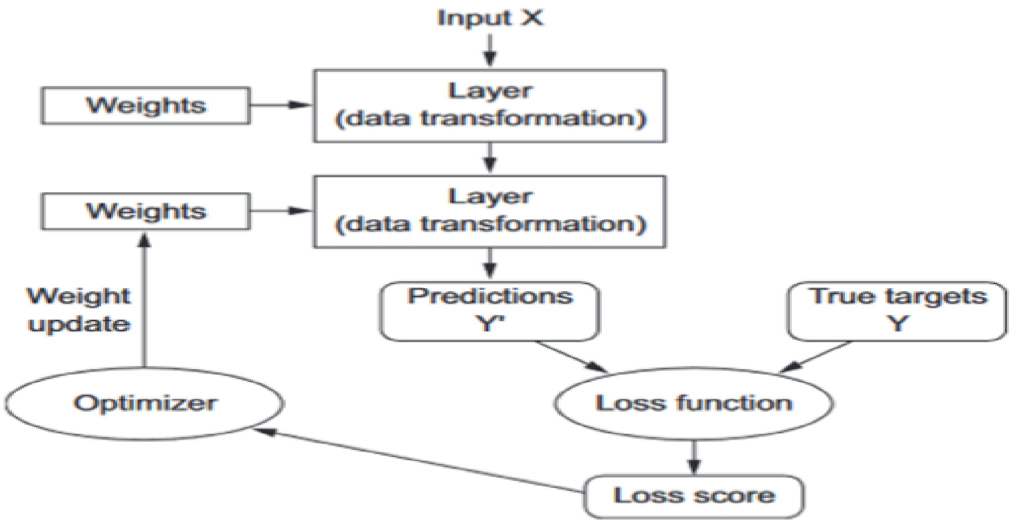

FIGURE 2.11: The loss score is used as a feedback signal to adjust the weights.

[15]

2.5.1 Stochastic Gradient Descent (SGD) :

SGD performs an iteration with each training sample (i.e., after the pass of every training sample, it calculates the loss and updates the weight). Since the weights are updated too frequently, the overall loss curve would be very noisy. However, the optimization is relatively fast compared to others.
The formula for weight updates can be expressed in a simple way as follows :

$$Weights = Weights – learningrate * Loss$$

Where learning rate is a parameter we define in the network architecture. Say, for learning rate =0.01.
For updates with every training sample, we would need to use batch-size=1 in the model training function. To reduce high fluctuations in the SGD optimizations, a better approach would be to reduce the number of iterations by providing a mini-batch, which would then enable averaging the loss for all samples in a batch and updating the weights at the end of the batch. This approach has been more successful and results in a smoother training process. Batch size is usually set in powers of 2 (i.e., 32, 64, 128, etc.)[15].

2.5.2 Adam :

Adam, which stands for Adaptive Moment Estimation, is by far the most popular and widely used optimizer in DL. In most cases, you can blindly choose the Adam optimizer and forget about the optimization alternatives. This optimization technique computes an adaptive learning rate for each parameter. It defines momentum and variance of the gradient of the loss and leverages a combined effect to update the weight parameters. The momentum and variance together help smooth the learning curve and effectively improve the learning process[15].
The math representation can be simplified in the following way :

$$Weights = Weights–(MomentumandVariancecombined)$$

2.5.3 Other Important Optimizer :

There are many other popular optimizers that can also be used for different DL models like :
— Adagrad
— Adadelta
— RMSProp
— Adamax
— Nadam
Each of the optimization techniques has its own pros and cons. A major problem which we often face in DL is the vanishing gradient and saddle point problem. You can explore these problems in more detail while choosing the best optimizer for your problem. But for most use cases, Adam always works fine[15].

2.6 Architectural innovations in CNN

Different improvements in CNN architecture have been made from 1989 to date. These improvements can be categorized as parameter optimization, regularization, structural reformulation, etc. However, it is observed that the main thrust in CNN performance improvement came from the restructuring of processing units and the designing of new blocks. Most of the innovations in CNN architectures have been made in relation to depth and spatial exploitation. Depending upon the type of architectural modifications, CNNs can be broadly categorized into seven different classes, namely; spatial exploitation, depth, multi-path, width, feature-map exploitation, channel boosting, and attention-based CNNs. The taxonomy of CNN architectures is pictorially represented in Fig. 12. Architectural details of the state-of-the-art CNN models, their parameters, and performance on benchmark datasets are summarized in Table 1[19].

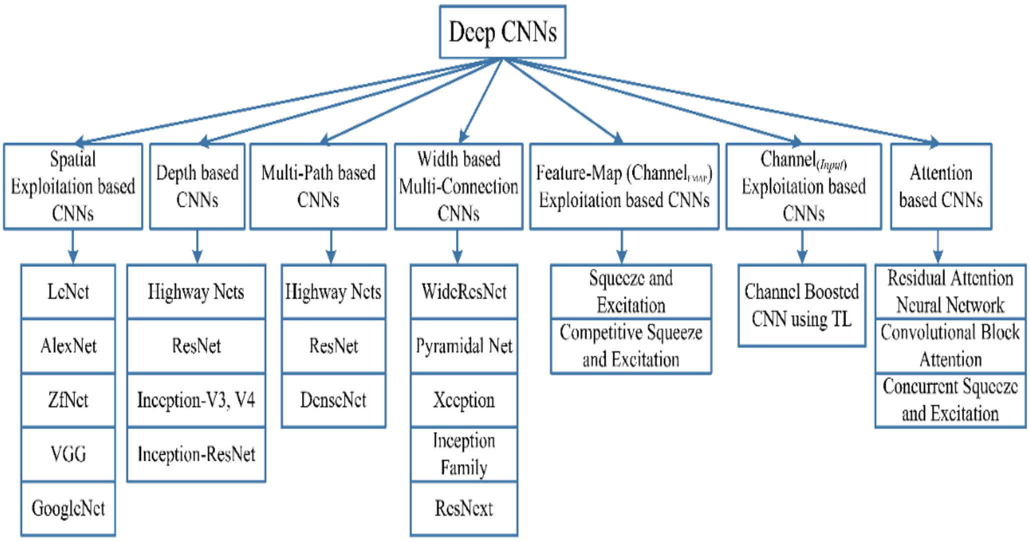

FIGURE 2.12: Taxonomy of deep CNN architectures showing seven different categories.

[19]

2.7 Different Models of Cnn for Images Classification

2.7.1 LeNet-5

LeNet-5 is a gradient-based learning CNN structure and first successfully applied in handwritten digital character recognition, introduced by Yan LeCun as shown in figure bellow, has 7 weighted (trainable) layers. Among them, three (C1, C3, C5) convolutional layers, two (S2, S4) average pooling layers, one (F6) fully connected layer and one output layer[41].

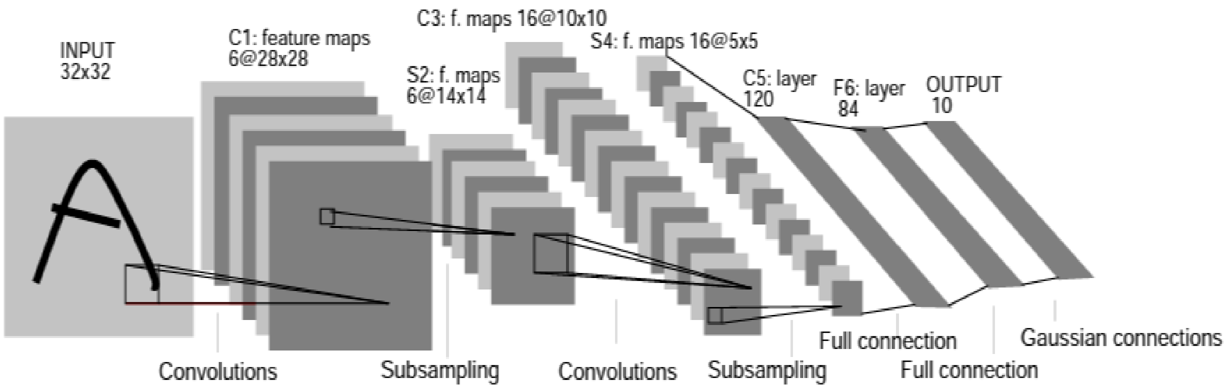

FIGURE 2.13: architecture of Lenet-5.

[41]

2.7.2 AlexNet

In 2012 Krizhevky et al. designed a large deep CNN, called AlexNet to classify ImageNet [10] data. The architecture of AlexNet is same as LeNet-5 but much bigger. It is made up of 8 trainable layers. Among them, 5 convolutional layers (conv layer) and 3 fully connected layers are there. Using rectified linear unit (ReLU)[41].

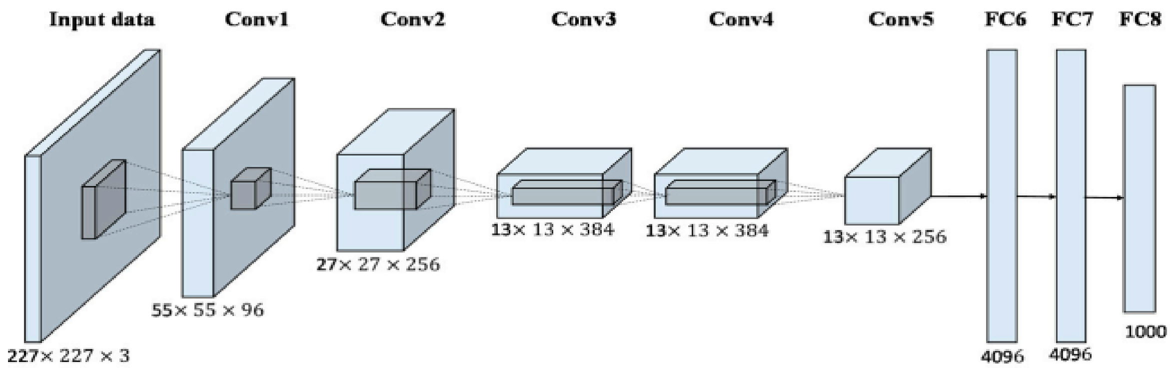

FIGURE 2.14: architecture of AlexNet .

[41]

2.7.3 VGGNet

The Visual Geometry Group network (VGGNet) is a deep neural network with a multilayered operation. The VGGNet is based on the CNN model and is applied on the ImageNet dataset. Simonyan and Zisserman used deeper configuration of AlexNet, and they proposed it as VGGNet. They have used small filters of size 3 × 3 for all layers and made the network deeper keeping other parameters fixed. They have used total 6 different CNN configurations : A, A-LRN, B, C, D (VGG16) and E (VGG19) with 11, 11, 13, 16, 16, 19 weighted layers respectively[41].

— **VGG16 :**

VGG-16 model is one of the simple architecture of CNN which uses less hyperparameter. This model uses filter size 3 × 3 throughout the architecture and also it uses 1 stride in the convolution layer and stride 2 for the pooling layer with the same padding. It consists of 16 layers including the convolution layer to softmax that is why it is named VGG-16. The last layer of the VGG16 model is replaced by two FC layer with softmax activation instead of 10 FC layer with [33],And the detailed layer by layer configuration of the VGG-16 model is pictured in figure bellow

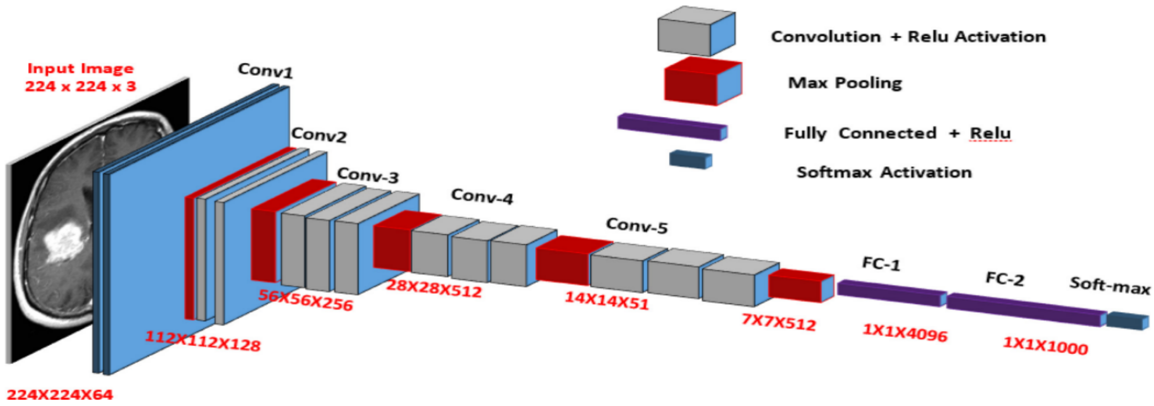

FIGURE 2.15: VGG-16 CNN model architecture layer wise.

[41]

— **VGG19 :**
Has 19 weight layers consisting of 16 convolutional layers with 3 fully connected layers and same 5 pooling layers. In both variation of VGGNet there consists of two Fully Connected layers with 4096 channels each which is followed by another fully connected layer with 1000 channels to predict 1000 labels. Last fully connected layer uses softmax layer for classification purpose.

2.7.4 Residual Network (ResNet) :

The winner of ILSVRC 2015 was the Residual Network architecture, ResNet. Resnet was developed by Kaiming He with the intent of designing ultra-deep networks that did not suffer from the vanishing gradient problem that predecessors had.
ResNet is developed with many different numbers of layers ; 34, 50,101, 152, and even 1202. The popular ResNet50 contained 49 convolution layers and 1 fully connected layer at the end of the network. The total number of weights and MACs for the whole network are 25.5M and 3.9M respectively.
The basic block diagram of the ResNet architecture is shown in Fig. 18. ResNet is a traditional feed forward network with a residual connection. The output of a residual layer can be defined based on the outputs of$(l-1)th$ which comes from the previous layer defined as :

$$xl-1.(xl-1)$$

is the output after performing various operations (e.g. convolution with different size of filters, Batch Normalization (BN) followed by an activation function such as a ReLU on $xl-1$).The final output of residual unit is xl which can be defined with the following equation :

$$xl = F(xl-1)+xl-1$$

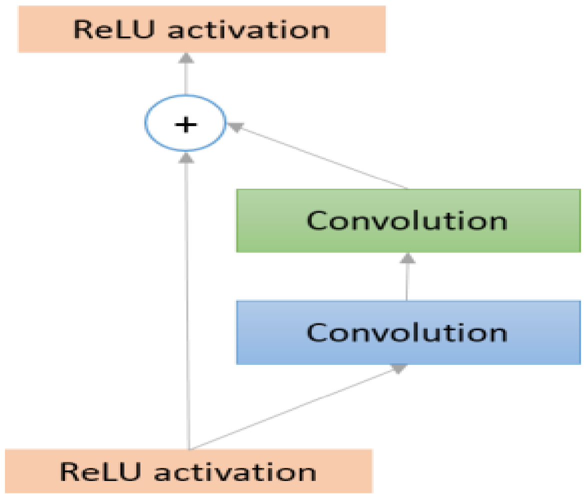

FIGURE 2.16: basic diagram of residual block.

[3]

The residual network consists of several basic residual blocks. However, the operations in the residual block can be varied depending on the different architecture of residual networks. The wider version of residual network was proposed by Zagoruvko el at.In 2016. Another improved residual network approach known as aggregated residual transformation was proposed in 2016. Recently, some other variants of residual models have been proposed based on the Residual Network architecture [68, 69, and 70]. Furthermore, there are several advanced architectures that have been proposed with the combination of Inception and Residual units. The basic conceptual diagram of Inception-Residual unit is shown in the following Figure 2.17.

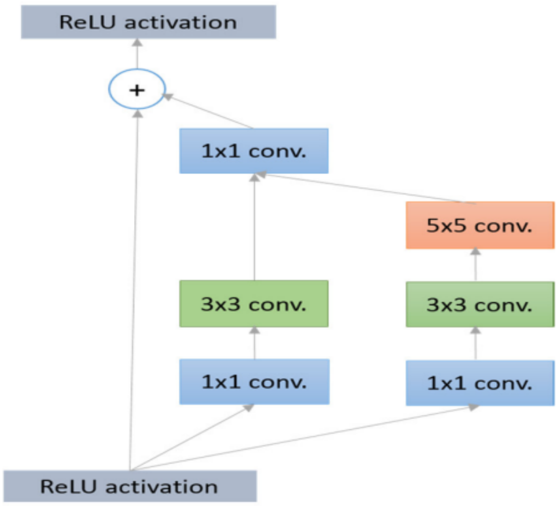

FIGURE 2.17: the basic block diagram for inception Residual unit.

[3]

Mathematically, this concept can be represented as : xl Where the symbol refers the concentration operations between two outputs from the 3×3 and 5×5 filters. After that, the convolution operation is performed with1×1 filters. Finally, the outputs are added with the inputs of this block of xl-1. The concept of Inception block with residual connections is introduced in the Inception-v4 architecture. The improved version of the Inception-Residual network were also proposed[3].

2.7.5 GoogLeNet (2014) :

GoogLeNet, the winner of ILSVRC 2014, was a model proposed by Christian Szegedy of Google with the objective of reducing computation complexity compared to the traditional CNN. The proposed method was to incorporate Inception Layers that had variable receptive fields, which were created by different kernel sizes. These receptive fields created operations that captured sparse correlation patterns in the new feature map stack[21].

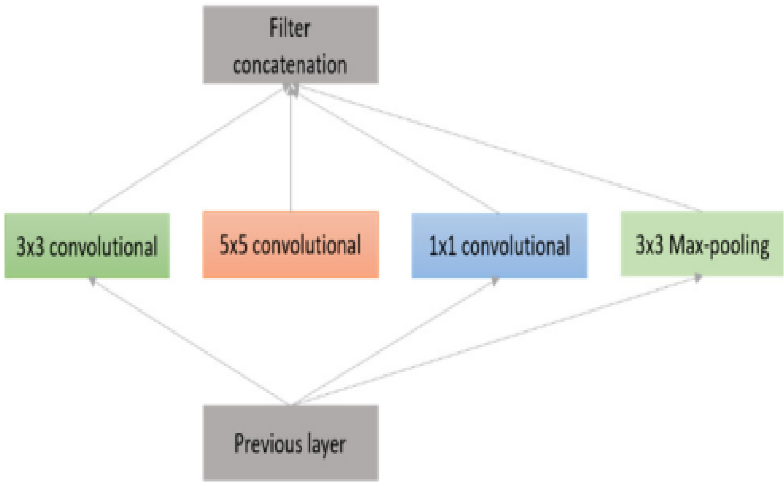

FIGURE 2.18: Inception layer : Naïve version.

[21]

The initial concept of the Inception layer can be seen in Figure 16. GoogLeNet improved state of-the-art recognition accuracy using a stack of Inception layers, seen in Figure 17. The difference between the naïve inception layer and final Inception Layer was the addition of 1x1 convolution kernels. These kernels allowed for dimensionality reduction before computationally expensive layers. GoogLeNet consisted of 22 layers in total, which was far greater than any network before it. Later improved version of this network is proposed in[3]. However, the number of network parameters GoogLeNet used was much lower than its predecessor AlexNet or VGG. GoogLeNet had 7M network parameters when AlexNet had 60M and VGG-19 138M. The computations for GoogLeNet also were 1.53G MACs far lower than that of AlexNet or VGG.

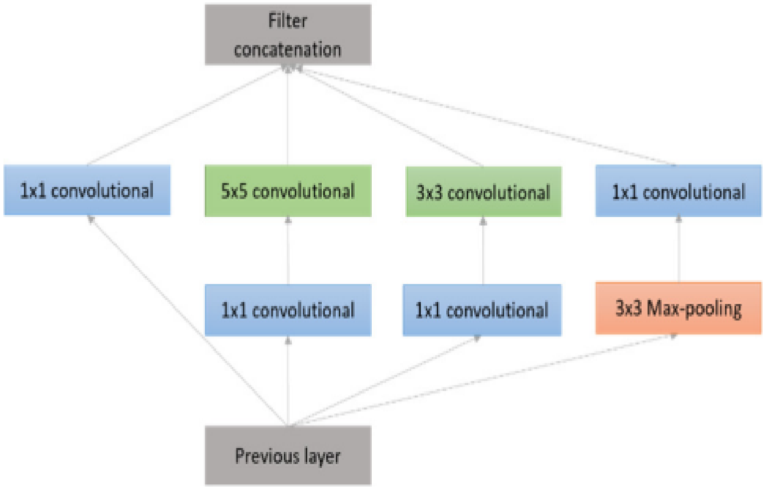

FIGURE 2.19: Inception Layer with dimension reduction.

[21]

Architecture name	Year	Main contribution	Parameters	Depth	Category
LeNet	1998	First popular CNN architecture	0.060M	7	Spatial exploitation
VGG	2014	Homogenous topology-Small kernel size	138M	19	Spatial exploitation
GoogLeNet	2015	Split transform merge -Introduces block	4M	22	Spatial exploitation
Inception-V3	2015	Replace large size filters with small filters	23.6M	-	Depth
ResNet	2016	residual learning and identity mapping based skip connection	6.8M	152	Spatial exploitation
Xception	2017	depth wise convolution	22.8M	36	Width
denseNet	2017	Cross-layer information flow	25.6M	190	Multi-path

TABLE 2.1: Performance comparison of the recent architectures of different categories. Top 5 error rate is reported for all architectures.

[19]

2.7.6 Different Models of Cnn for Images Segmentation :

2.7.6.1 U-Net :

The U-Net has an encoder decoder structure, with jump connections between the corresponding encoding and decoding layers that allow the network to retain low-level functionality for final prediction. U-Net is a convolutional neural network developed for biomedical image segmentation at the Department of Computer Science, University of Freiburg, Germany[39]. Its architecture is based on the fully convolutional network, it has been modified and extended to work with fewer training images and to allow more accurate segmentation. Segmentation of a 512×512 image takes less than a second on a recent GPU. The network consists of a contracting part and an expanding path, which gives it a "U" shaped architecture. The contracting part is a typical convolution network which consists of repeated application of convolutions, each followed by a rectified linear unit (ReLU) and a maximum pooling operation. During contraction, spatial information is reduced while feature information is increased. The expansive path combines geographic and spatial feature information through a sequence of upward convolutions and concatenations with high-resolution features from the contracting path, so the U-Net architecture is separated into 3 parts :

1. The contraction / subsampling path
2. Bottleneck
3. The extension / oversampling channel

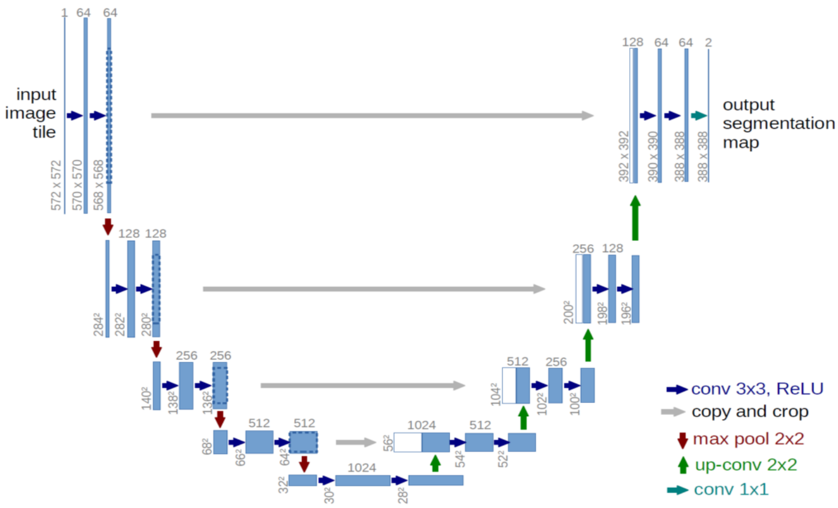

FIGURE 2.20: The U-net architecture.

[39]

CHAPITRE 3

BIOINFORMATICS AND COMPUTER VISION IN TUMORS

"We are together - and we will go through this, together

3.1 Introduction

Informatics and Internet technologies have become very common in today's healthcare system. The emergence of the web around the world has affected the way health-related information is distributed and accessed through cyberspace. The Internet is rapidly gaining importance, not only for healthcare professionals, but also for patients, by enabling them to search for information health [42]. So in this chapter we will see a definition bioinformatics and the components ofbioinformatics and The value of Bioinformatics in ML and Tumor image segmentation.

3.2 Bioinformatics

Bioinformatics is the combination of biology and information technology[4].The term bioinformatics was coined by Paulien Hogeweg in 1979 for the study of informatics processes in biotic systems. It was primary used since late 1980s has been in genomics and genetics, particularly in those areas of genomics involving large-scale DNA sequencing. Bioinformatics can be defined as the application of computer technology to the management of biological information. Bioinformatics is the science of storing, extracting, organizing,analyzing, interpreting and utilizing information from biological sequences and molecules.It has been mainly fueled by advances in DNA sequencing and mapping techniques. of biological information. Bioinformatics is the science of storing, extracting, organizing,analyzing, interpreting and utilizing information from biological sequences and molecules.It has been mainly fueled by advances in DNA sequencing and mapping techniques.

3.3 The components of bioinformatics

The discipline encompasses any computational tools and methods used to manage, analyze and manipulate large sets of biological data. Essentially, bioinformatics has three components :

- The creation of databases, allowing the storage and management of large biological data sets
- The development of algorithms and statistics to determine relationships among members of large data sets
- The use of these tools for the analysis and interpretation of various types of biological data, including DNA, RNA and protein sequences, protein structures, gene expression profiles, and biochemical pathways[4].

3.4 The value of Bioinformatics in ML

The Bioinformatics focuses on the development of algorithms and software for the transfer, storage, analysis, and development of genomics databases[1]. Machine learning (ML) belongs to the branch of computer science that provides self-learning capability to the machines without explicit programming. The ML algorithms are being extensively used for the tasks of prediction, classification, and feature selection in bioinformatics. The ML approaches are very good for solving problems such as distinguishing between DNA sequences and classification of DNA sequences. Currently, the ML in bioinformatics has become significant due to the advent of deep learning[20].

3.5 Tumor :

An abnormal mass of tissue that forms when cells grow and divide more than they should or do not die when they should. Tumors may be benign (not cancer) or malignant (cancer). Benign tumors may grow large but do not spread into, or invade, nearby tissues or other parts of the body. Malignant tumors can spread into, or invade, nearby tissues. They can also spread to other parts of the body through the blood and lymph systems. Also called neoplasm[14]

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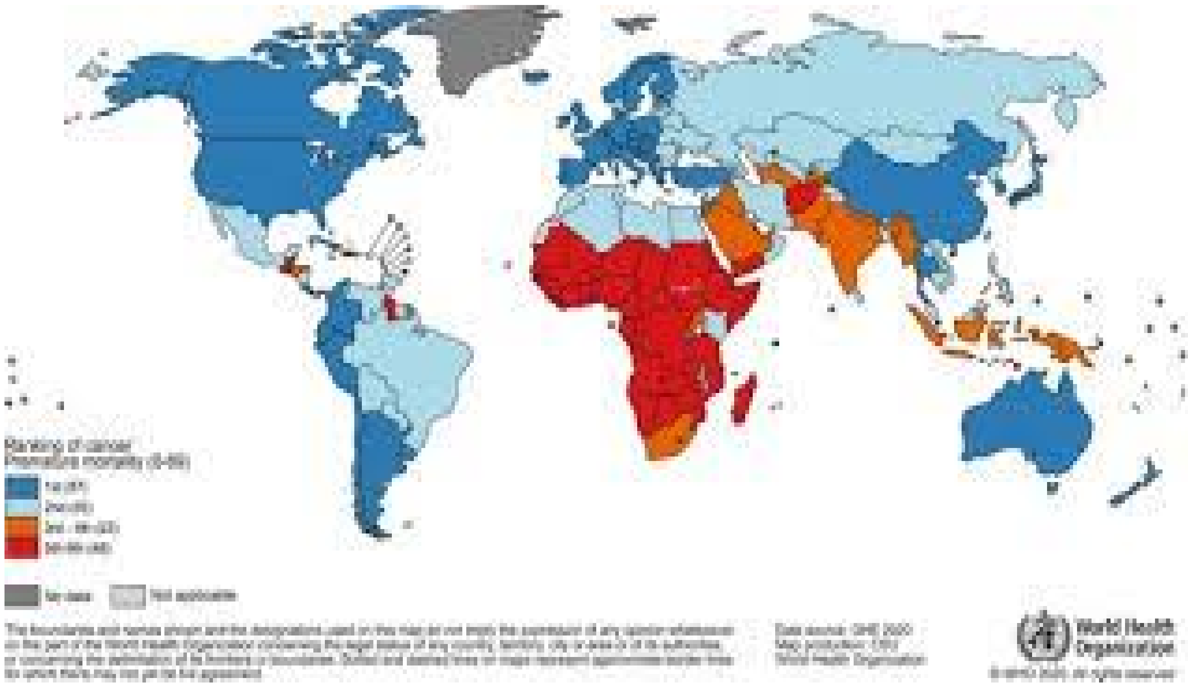


FIGURE 3.1: Global Cancer Statistics 2020 : GLOBOCAN Estimates of Incidence and Mortality Worldwide for 36 Cancers in 185 Countries

[12]

3.5.1 Tumor in Africa

Cancer care in Africa has greatly improved over the last 10 years. By 2017, 71% of African countries, up from 46% in 2013, had operational national cancer control programmes, and the oncology workforce has increased steadily. However, care and services vary widely, sometimes within the same country or region – frome institutions offering state-of-the-art care to basic services that can be hard to access. Many patients in Africa are diagnosed with advanced cancers and do not complete their care. There are several reasons for this, cost being the main one : patients frequently must pay out of pocket to access care, incurring expenses that can be financially catastrophic. Poor referral systems that may not support timely pathways to care or adequate treatment, palliative or supportive services. Geographical inequities also exist in terms of Access to care[12].

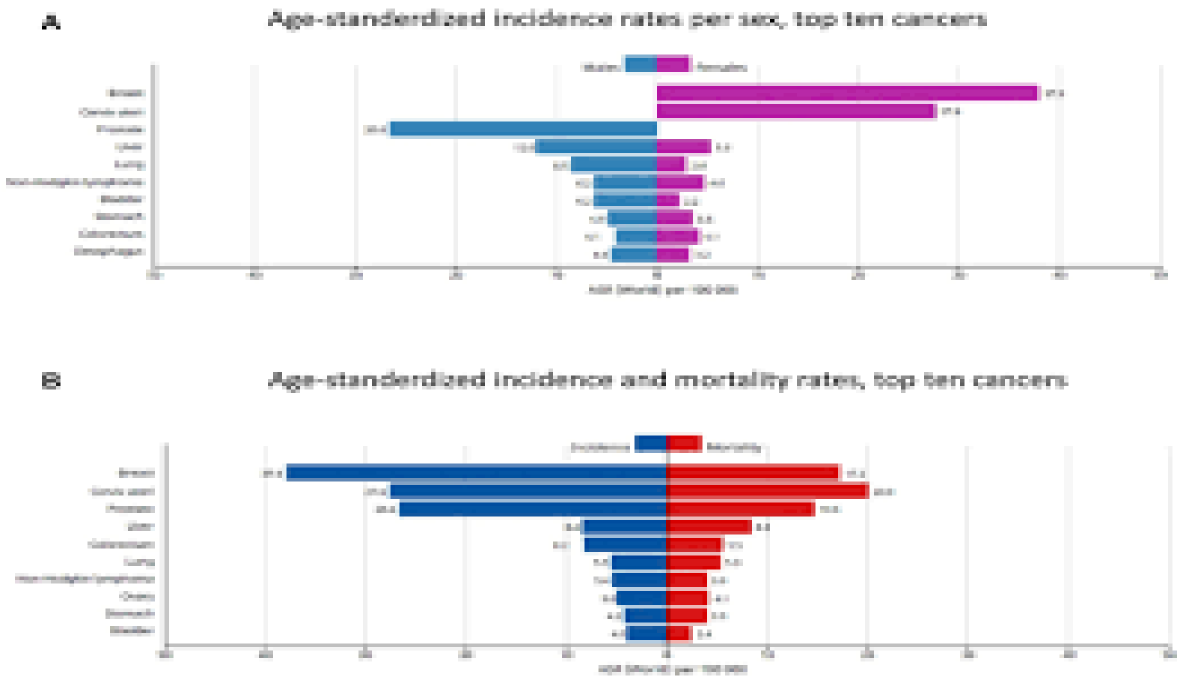


FIGURE 3.2: The top 10 cancers in African patients. (A) Age-standardized incidence rates per sex, (B) Age-standardized incidence and mortality rates. Reproduced from “The Global Cancer Observatory, Africa Globocan 2018

[12]

3.5.2 Tumor and robotics

The field of medicine has also been invaded by robots. They weren’t there to replace the doctors and Nurses but to help them in their routine work with them accurate tasks. Medical Robots Promise- J that really took off in the ’90s. where Then, it has a wide range of medical applications Featured : laboratory robotics, telesurgery, and surgery- Cal training, telesurgery, telemedicine and Tele-consulting, rehabilitation, deaf assistance Blind people and hospital robots. medical robots Assisting in surgeries for patients with heart attacks and Made it possible to adjust the exact millimeters of prosthetic limbs. However, there are many challenges In the wide application of robotics in The medical field, mainly due to issues such as Safety, accuracy, cost and reluctance to accept it Technique. Medical robots include a number of of devices used in surgery and medical training, Rehabilitation therapy, prosthetics and assistance[5]. The types of cancers for which we can use robotic surgery include gastrointestinal and gastrointestinal cancers, colorectal cancer, gynecological cancer, head and neck cancer, lung cancer, and urinary tract cancer.

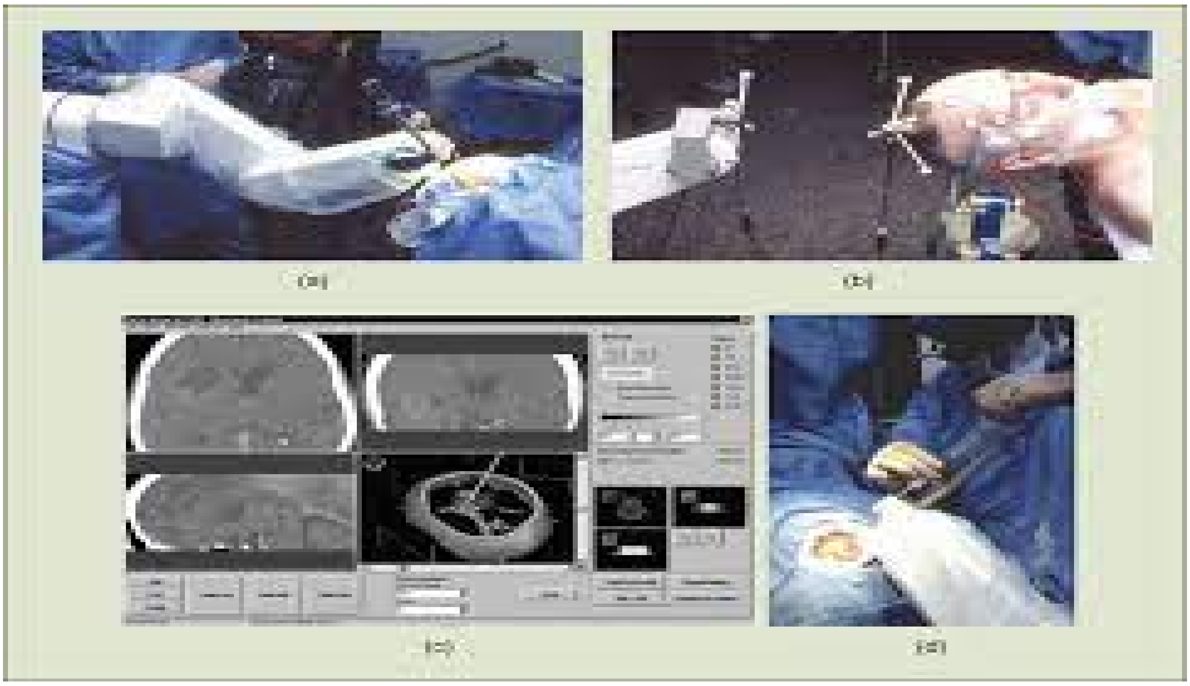


FIGURE 3.3: Neuromate robot in brain surgery.(a) The robotic arm holding an aspiration needle. (b) Robot-to-patient registration with optically tracked fiducials. (c) Screenshot from CT-based treatment planning. (d) Surgeon performing the aspiration. (Images courtesy of Integrated Surgical Systems.)[

[5]

3.5.3 Diagnosis :

The pathologist is forever trying to improve upon the accuracy of the diagnosis. In order that a method may fulfill the latter purpose it must be rapid, provide good staining differential qualities.

Several imaging tests are used to conduct a diagnosis for brain tumors. These include :

— Neurological Examination
— PET Scan
— Cerebral Angiogram
— MRI
— MRI Spectroscopy
— MRI Contrast
— Perfusion MRI
— Functional MRI[14]

3.6 Types of Tumors

It existe different types of tumors such as :

3.6.1 Brain tumor :

A brain tumor is defined as an abnormally growing cluster of cells within the brain. Glioblastoma is a tumor in the malignant group that can develop in the brain and spinal cord, consisting of glia that supports nerve cells. Glioblastoma is mostly sporadic, except in rare cases, Turcot syndrome or Li-Fraumeni syndrome[22]. It is one of the most dangerous and fatal diseases for humans, it must be detected, diagnosed, and cured in the early stages. It occurs in almost every part of the human body but the human brain is the part where the tumor is the most. Brain tumors can be considered dangerous since the majority of persons die in 9–12 months of identification. Brain tumors occur in about 40,000–50,000 individuals each year, of which 20% are children[14]. And according to [10] Brain cancer is classified based on the level of cancerous growth present. There are two major types LGG(Low-Grade Glioma) and HGG (high-grade gliomas). Low grade gliomas are benign tumors (grade I or II). All low-grade gliomas eventually progress to high grade glioma and death. GBM(Glioblastoma) is the most common type of HGG, it is the most aggressive cancer that begins within the brain and is the most common type of malignant brain tumor among adults. It is usually aggressive, which means it can grow fast and spread quickly. Although there is no cure, there are treatments to help ease symptoms. The conventional method for medical resonance brain image classification and tumor detection is by human inspection. There is a need to have a fast and reliable method to classify if the tumor present is cancerous(LGG or HGG).

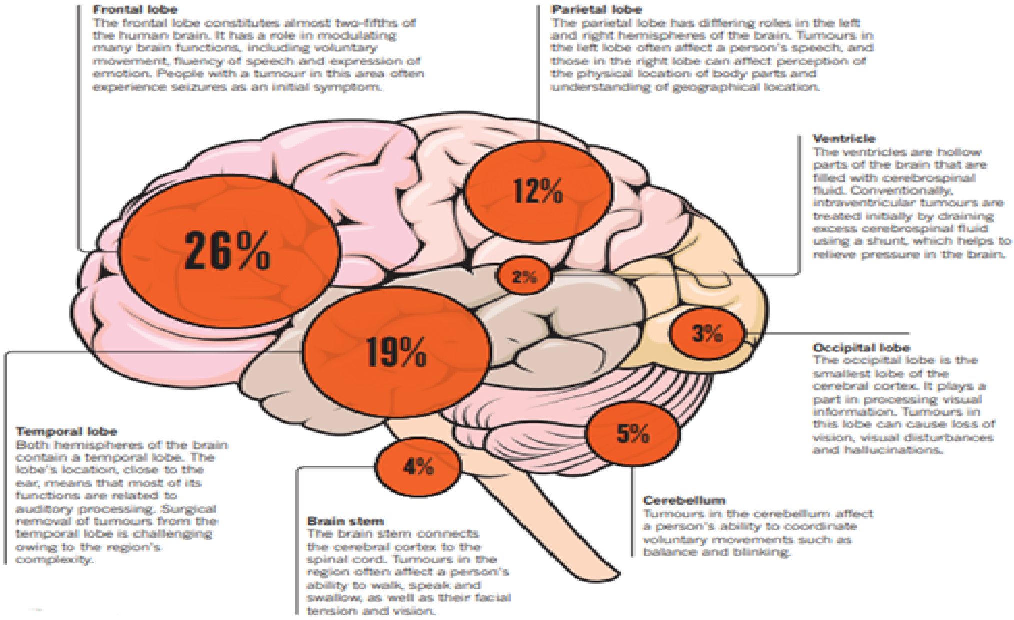


FIGURE 3.4: tumor pourecentages and we notice that it's not 100% percent because some tumores neurologist did not identified them emplacement yet)[

[29]

- **Brain tumor treatement**

  The common types of treatments used for a brain tumor are many and the treatment options and recommendations depend on several factors :
  - The size, type, and grade of the tumor
  - Whether the tumor is putting pressure on vital parts of the brain
  - If the tumor has spread to other parts of the CNS or body
  - Possible side effects
  - The patient's preferences and overall health

  Treatment options include those described below, such as surgery, radiation therapy, chemotherapy, and targeted therapy[32].
- **Surgery :**

  Surgery is the removal of the tumor and some surrounding healthy tissue during an operation. It is usually the first treatment used for a brain tumor. It is often the only treatment needed for a low-grade brain tumor. Removing the tumor can improve neurological symptoms, provide tissue for diagnosis and genetic analysis, help make other brain tumor treatments more effective, and, in many instances, improve the prognosis of a person with a brain tumor.
- **Radiation therapy :**

  Radiation therapy is the use of high-energy x-rays or other particles to destroy tumor cells.

— **Therapies using medication :**

Treatments using medication are used to destroy cancer cells. Medication may be given through the bloodstream to reach cancer cells throughout the body. When a drug is given this way, it is called systemic therapy. Medication may also be given locally, which is when the medication is applied directly to the cancer or kept in a single part of the body[32].

3.6.2 lung cancer

Lung cancer occurs when cells divide in the lungs uncontrollably. This causes tumors to grow. These can reduce a person's ability to breathe and spread to other parts of the body. Lung cancer is the third most common-Trusted Source cancer and the main cause Trusted Source of cancer-related death in the United States. It is most common in males, and in the U.S., Black males are around 15% more likely to develop it than white males. Smoking is a major risk factor, though not everyone who develops lung cancer has a history of smoking. Lung cancer can be fatal, but effective diagnoses and treatments are improving the outlook. The two main types of lung cancer are small cell lung cancer and non-small cell lung cancer, depending on how they appear under a microscope. Non-small cell lung cancer is more common than small cell lung cancer[16].

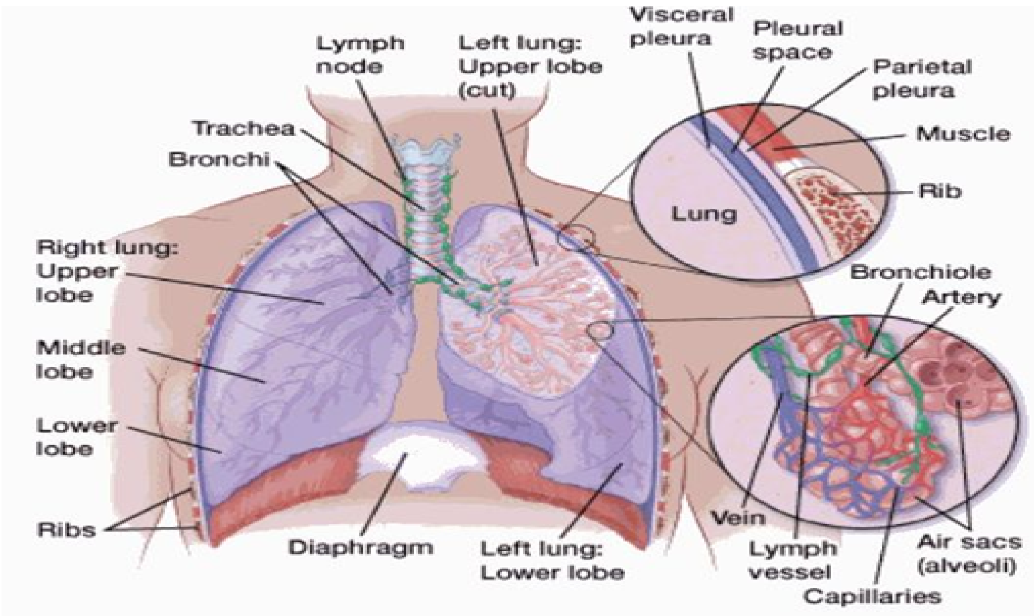


FIGURE 3.5: anatomy of lung)[

[29]

1. **treatment for lung cancer**
   In the past 10 years there's been a lot of progress in lung cancer treatments. People are usually given more than one treatment at a time and you might have several courses of treatment[16].
   The outcome of lung cancer has gradually improved over recent years. Survival is closely related to stage of disease. If the cancer is detected and treated at an early stage, more people will survive for longer.The main treatments for lung cancer are :

2. **Surgery**
   There are a few different types of surgery. The surgeon might remove a section of your lung or your whole lung[16].

3. **Drug therapies :**

   chemotherapy :
   This is medication that attacks cancer cells. They may be delivered straight into your bloodstream through a drip or you might have injections or tablets.
   - targeted treatments : These are medicines, such as erlotinib, gefitinib and crizotinib, that stop the genetic mutations that cause some types of lung cancer. They can be very effective.
   - immunotherapies :
   These are medicines that work on the immune system in the body to enhance its response to cancer cells. An example is pembrolizumab, which can be used on its own or in combination with chemotherapy to treat metastatic NSCLC.

4. **Radiotherapy :** This treatment uses high-energy X-rays to destroy cancer cells. This can be both curative and palliative – helping to manage symptoms[13].

3.6.3 Prostate cancer :

The prostate is a walnut sized gland located between the bladder and external urinary sphincter through which the urethra passes. The primary function of the prostate is to produce a slightly alkaline fluid that protects spermatozoa from the acidic environment found within the vaginal tract[13].

Prostate cancer accounts for 7% of newly diagnosed cancers in men globally. Annually, >1.2 million new cases are diagnosed and prostate cancer-related deaths exceed 350,000, making the disease one of the leading causes of cancer-associated death in men. In the USA, men of African or Caribbean descent have a twofold higher relative risk of early, more aggressive disease than white men. For some groups, such as Ashkenazi Jews and those of Icelandic descent, the risk of early, more aggressive disease is linked to germline mutations in genes such as BRCA2. For others, the reasons for disparities in prostate cancer incidence and/or mortality are not known.

Prostate cancer is the second most common cancer in men. Genetic mutations in basal or luminal prostate epithelial cells are considered the primary driver of disease. Early diagnosis can result in favourable outcomes and high long-term survival but prognosis for men with castration-resistant metastatic disease is relatively poor[27].

- **Diagnosis :**
  Digital rectal examination (DRE), serum prostate-specific antigen (PSA) level measurement and MRI are standard diagnostic tools for detecting prostate cancer. Both DRE and PSA findings can be abnormal in the absence of prostate cancer or normal despite the presence of prostate cancer. A prostate biopsy is indicated for abnormal DRE results and a definitive diagnosis depends on histopathological verification. Prostate cancer aggressiveness is graded according to histological tumour features using the Gleason grade system, which was updated in 2014 to improve differential prognoses. The new Gleason grade group system, together with PSA levels and clinical tumour stage, is recommended for patient risk classification, owing to its superiority in predicting risk of potentially lethal disease.
- **Prostate Cancer Treatment :** Treatments for prostate cancer that has not spread elsewhere in the body are surgery or radiation therapy (RT), with or without hormone therapy. Active surveillance is also an option for men who have a low risk of their cancer spreading[30].

3.6.4 Lymph node

A small bean-shaped structure that is part of the body's immune system. Lymph nodes filter substances that travel through the lymphatic fluid, and they contain lymphocytes (white blood cells) that help the body fight infection and disease. There are hundreds of lymph nodes found throughout the body. They are connected to one another by lymph vessels.

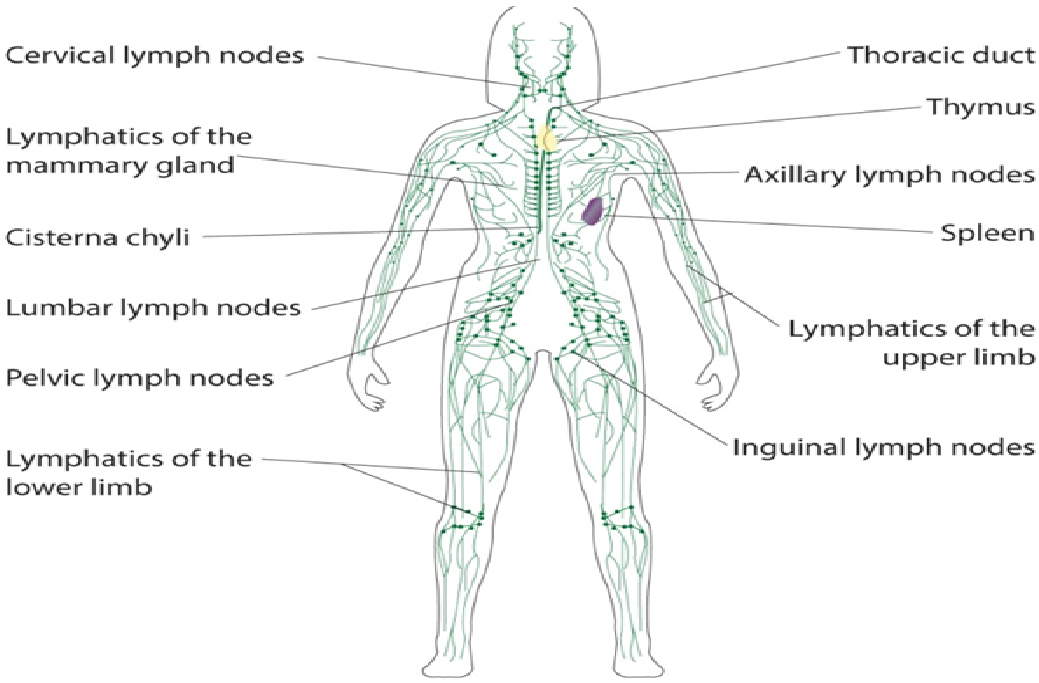


FIGURE 3.6: the complet system lymphatic

[17]

Lymph nodes are part of the lymph system, a network of organs, nodes, ducts, and vessels that support the body's immune system. Nodes are little filters throughout the body. The cells in lymph nodes help to destroy infection, such as from a virus, or harmful cells, such as cancer cells[8] Cancer can start in the lymph nodes. This is called lymphoma. There are several types of lymphomas, such as non-Hodgkin lymphoma. Cancer cells can also spread to the lymph nodes from a cancer in any part of the body. This is called metastatic cancer. Cancer cells break off from a tumor in the body and travel to an area of lymph nodes. The cancer cells often travel to nodes near the tumor first[8]

The cancer in lymph nodes can be treated with :

— Surgery
— Chemotherapy
— Radiation

3.7 Histopathology using in dealing with cancers

Histopathology is widely used to study the manifestation of diseases. Histopathology is the branch of pathology that deals with microscopic examination of tissues. The thin tissue specimen collected from patients' body has to be converted to slides to make them feasible for microscopic examination. The above figure depicts the manual process of finding cancer through scanned images. This laborious process involves 5 stages :

— Tissue fixation : Tissues have the tendency to destroy and destruct themselves under the action of certain enzymes, to prevent such action it needs to be fixed. Collected tissue specimens are fixed using formalin. It terminates ongoing biochemical reactions providing mechanical strength and stability to the treated tissues.
— Specimen transfer to cassettes : The fixed tissue are then transferred to cassettes (special containers for tissue)
— Tissue processing : In this stage the tissue is prepared for sectioning (slicing). The tissue is first dehydrated and then cleared followed by infiltrating the tissue in an embedding agent like paraffin wax. Solidification paraffin wax solidifies provides a support matrix for tissue specimen and now it can be sectioned .
— Sectioning : The tissue specimen can now be sectioned at different thickness and placed over a slide .
— Staining : Most cells are transparent, and appear almost colorless when unstained. Wide range of histochemical stains is therefore used to provide contrast to tissue sections, making tissue structures more visible and easier to evaluate[6].

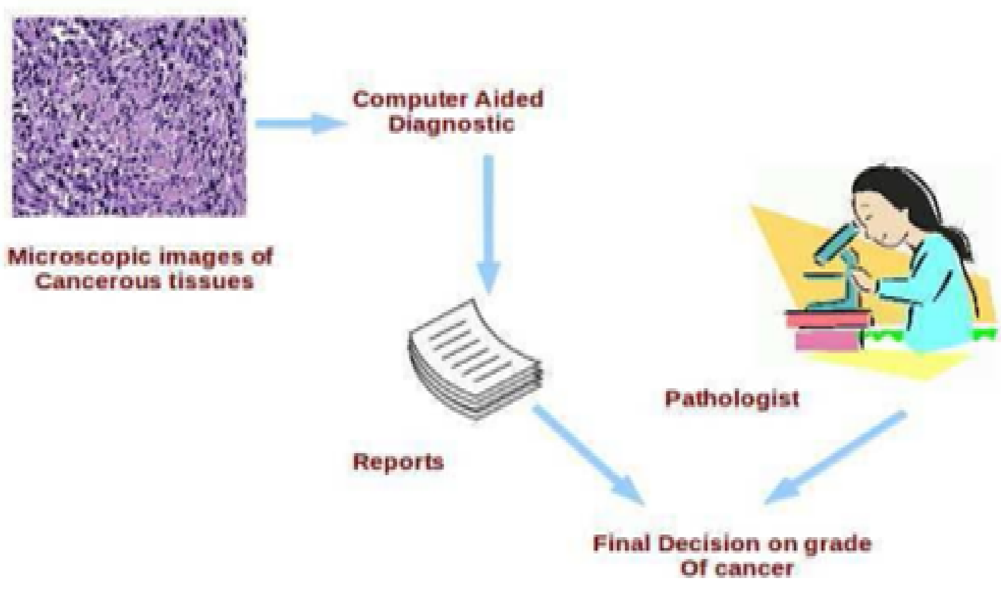


FIGURE 3.7: image segemntation of histopathological tissue

[6]

3.8 Image segmentation

To segment an image means, to find its homogeneous regions and its contours, these two latter are assumed to be relevant, i.e. the regions must correspond to the parts significant real-world objects, and the contours at their apparent boundaries. Let " be the domain of the image and ' ' the function which associates a value f(x,y) with each pixel[23].

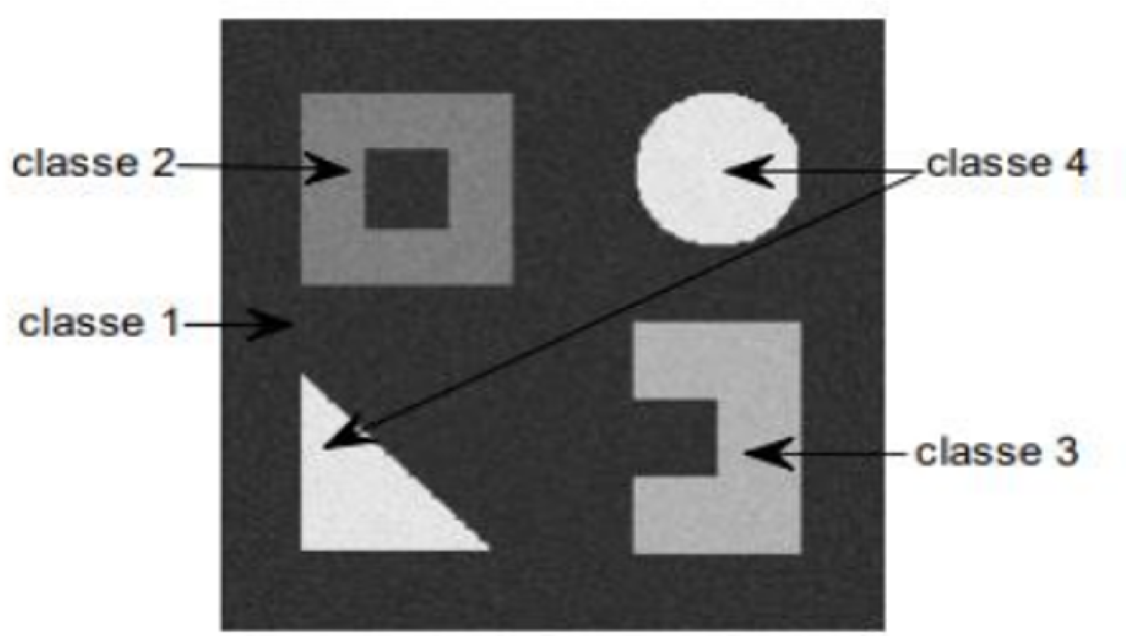


FIGURE 3.8: segmentation of an image into 4 classes

[23]

3.8.1 The objectives of segmentation

The goal of segmentation is to cut the image into several regions, in which the pixels are Check a certain criterion of homogeneity, such as gray level or color, and there are very Several methods allow this haircut, the effectiveness of which depends above all on the image.They Seeks to :

- Provide homogeneous fields
- Study and interpretation of anatomical structures.
- Accurately define areas.
- Noise Reduction[25]

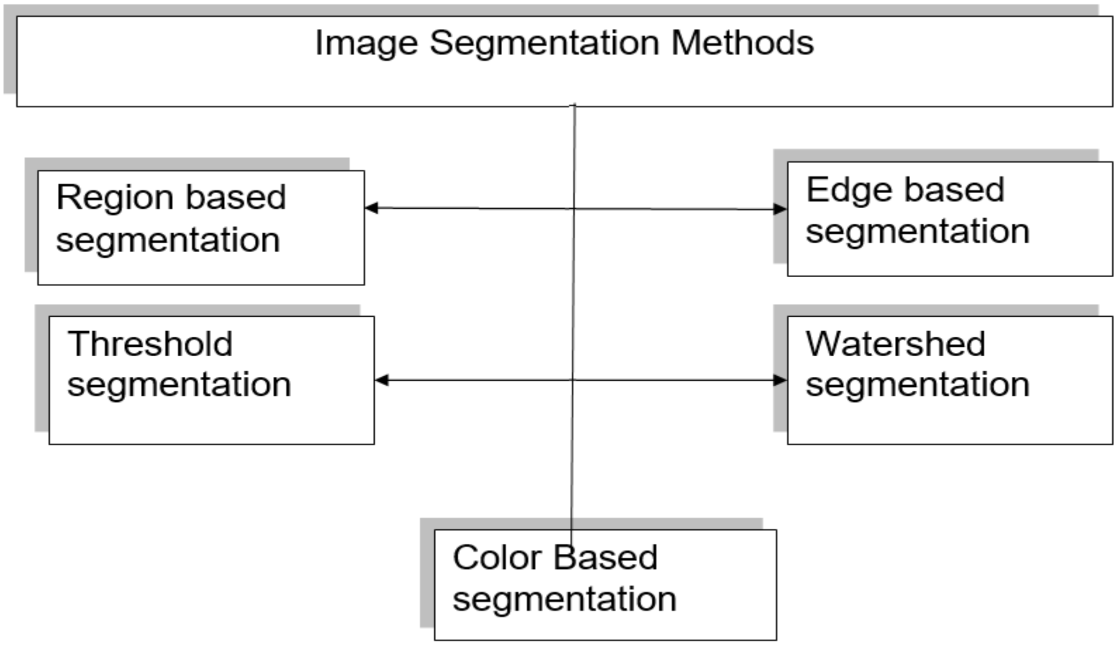


FIGURE 3.9: TYPES OF IMAGE SEGMENTATION

3.8.2 Edge-Based Segmentation

Segmentation can also be done by using edge detection techniques. In this technique, the frontier is identified to the segment. It is detected to identify the discontinuities in the image. Edges of the region are traced by identifying the pixel value and it is compared with the neighboring pixels. The edge-based segmentation there is no need for the detected edges to be closed. These methods have problems with images that are :

- Edge-less
- Very noisy
- Boundary that is very smooth
- Texture boundary[23]

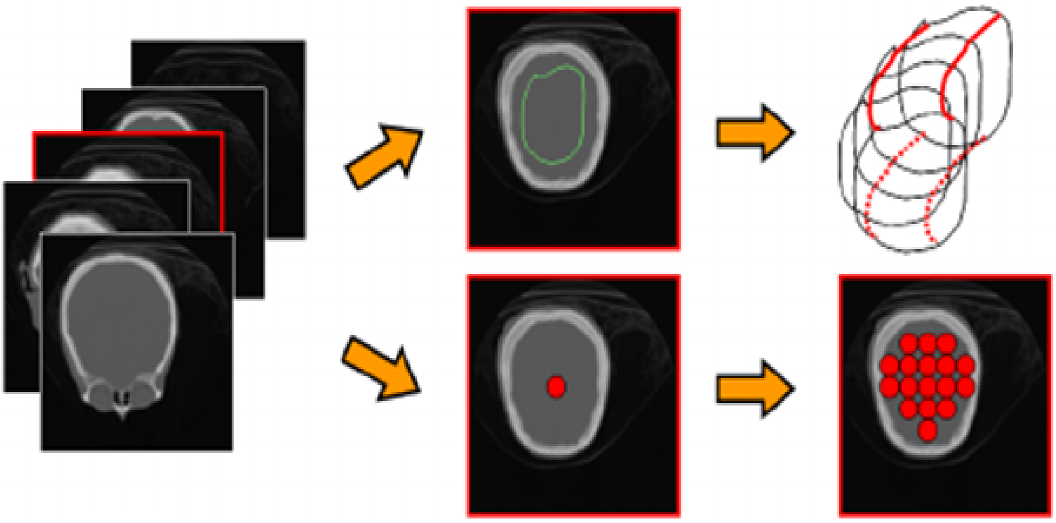


FIGURE 3.10: Conventional segmentation methods. Top row : edge-based method. Bottom row : region-based method

[25]

Algorithm :

- Step1 : Smooth the input image with a Gaussian filter.
- Step2 : Compute the gradient and angle images.
- Step3 :Apply maximum suppression to the gradient magnitude image.
- Step4 : Use double thresholding and connectivity analysis to detect and link edges.

Advantage :

- The approach had to do with the way humans segment images.
- Works well in frames with good contrast between object and background .

Disadvantage :

- Not working correctly in images with smooth transitions and low contrast
- Sensitive to noise.
- Robust edge linking is not trivial[37].

3.8.3 Region-Based Segmentation

Locale developing may be a simple region-based picture division strategy. It is additionally classified as the pixel-based picture division method. The fundamental objective of division is to the division of the picture into districts. A few division strategies such as "Thresholding" accomplish this objective by looking at for the boundaries between locales based on discontinuities in gray levels or color properties[40].

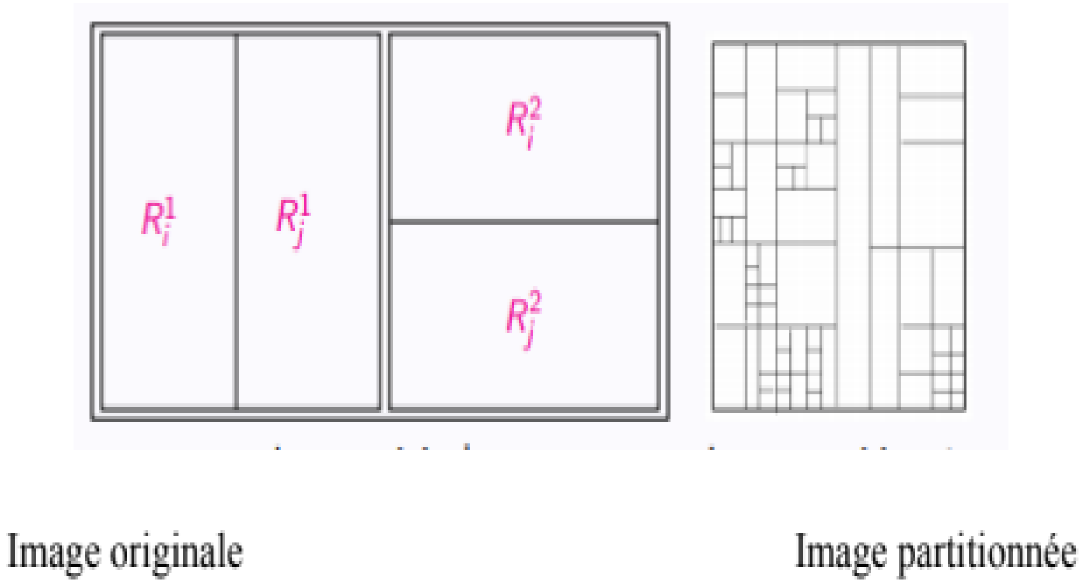


FIGURE 3.11: segmentation based on regions

[23]

- **Region growing Algorithm :**
  - Step1 : Starts with a set of seeds (starting pixels)
    - Predefined seed
    - All pixels as seeds
    - Randomly chosen seeds
  - Step2 : Region growing intensity steps (bottom-up method)
    - Find starting points
    - Include nearest pixels with similar features (Gray level, texture, color)
    - A similarity measure must be selected
- **Advantage :**
  - Region developing strategies can accurately partitioned the regions.

— Region developing strategies can give the first images.
— We can select the numerous criteria at the same time.

— **Disadvantage :**

— The computation is solid, Dismissal matter the time or power.
— Excessive or variance escalation may result in excessive cleavage.
— This strategy may not recognize the shading of the genuine[40]

3.8.4 Watershed Segmentation

The presented the watershed change as a implies to isolating covering objects. A watershed is shaped by „flooding an picture from its nearby minima and shaping dams where waterfronts meet. When recreating this prepare for picture division, two approaches are utilized. One finds bowl at that point watersheds by taking a set of complement. One computes a total segment of the picture into bowls and subsequently refined the watersheds by boundary location. To be more express utilize the expression 'watershed transform' to represent a labeling of the picture. All focuses of a given catchment bowl have the same special name. A uncommon name, particular from all the names of the catchment bowls, is relegated to all focuses of the watersheds[24].

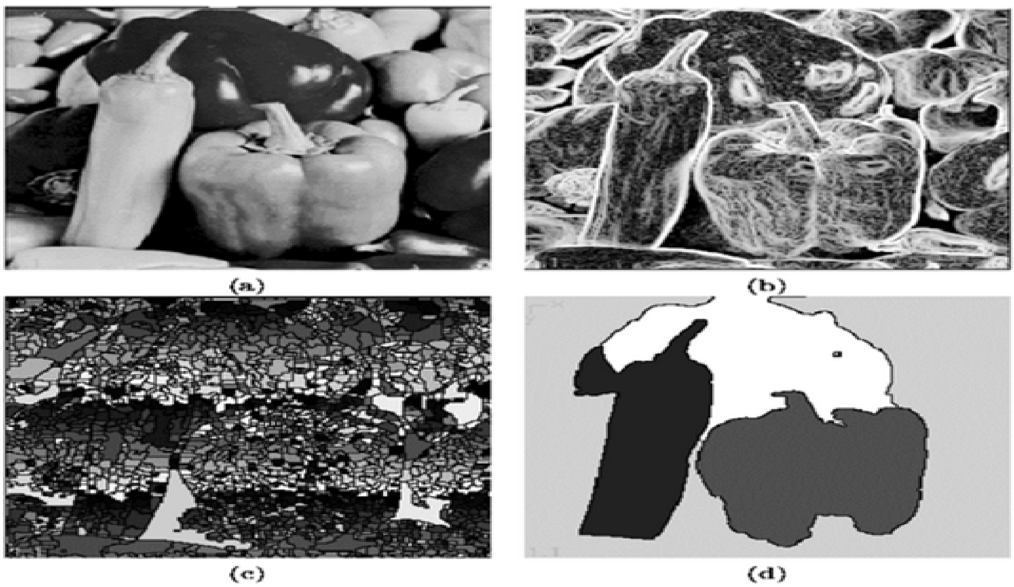


FIGURE 3.12: An example of watershed segmentation :a) Original image ; b) Gradient image ; c) Watershed segmentation without using region markers (oversegmentation) ; d) Watershed segmentation using region markers.0

[25]

- **Watershed algorithm :**
  - Step1 : Let g(x, y) be the input image (often a gradient image).
  - Step2 : Let M1...MR be the coordinates of the regional minima.
  - Step3 : Let C (Mi) be a set consisting of the coordinates of all points belonging to the catchment basin associated with the regional minimumMi.
  - Step4 : Let T[n] be the set of coordinates (s,t) where g(s ,t)<t T[n] =(s, t) | g (s, t) < n.
- **Advantage :**
  - The coming about boundaries frame closed and associated regions.
  - The boundaries of the coming about districts continuously compare to contours.
  - The union of all the districts shapes the whole picture locale.
- **Disadvantage**
  - Most normal pictures it produces intemperate over division[24].

3.8.5 Threshold Based Segmentation

Thresholding is one of the only approaches for picture division based on concentrated levels. The Threshold-based procedure works on the explanation that the pixels falling inside the certain extend of escalated values. Speaks to one class and remaining pixels within the picture speaks to the another lesson. Thresholding can be actualized either locally or universally. For worldwide thresholding brightness edge esteem is to be chosen. To portion the picture into the protest and the background. It produces a parallel picture from given input picture. The pixels satisfying limit test are considered as protest pixels with twofold esteem „1 and another pixels are treated as background pixels with parallel esteem „0. Where T could be a predefined limit[2].

FIGURE 3.13: An example of threshold based segmentation :a) Original image ; b) Segmentation result.

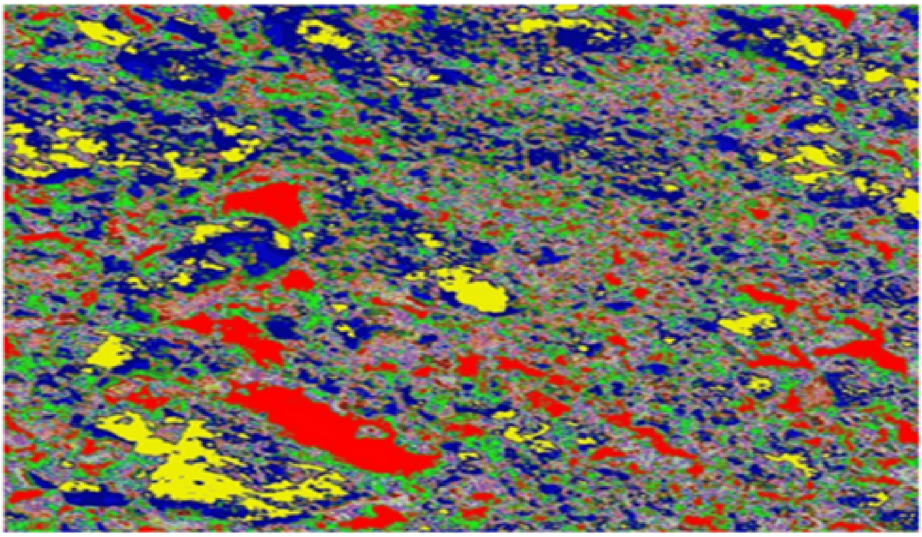
[25]

- **Algorithm :**
  - Step1 : Select an initial estimate for the global threshold, T.
  - Step2 : Segment the image using T.
  - Step3 : This will produce two groups of pixels. The G1 consisting of all pixels with intensity values >T. The G2 consisting of pixels with values T.
  - Step4 : Compute the average (mean) intensity values m1, m2 for the pixels in G1 and G2, respectively.
  - Step5 : Compute a new threshold value : T=1/2(m1+m2)[2]
- **Advantage :**
  - Do not require past data of the image.
  - The computationally expensive.
  - The Quick and straightforward for implementation
  - Can be utilized in genuine time Applications[2].
- **Disadvantage :**
  - Neglects spatial data of an image.
  - Highly clamor sensitive.

— Selection of limit is significant, the off-base choice may result into over or beneath segmentation.

3.8.6 Clustering Based color Image Segmentation

In cluster based division, information is combined into bunches. The information with comparative highlights will drop into one bunch. The information clusters are being distinctive from each other. The k-means calculation is commonly utilized for deciding the organization of the information. This unsupervised clustering approach features a solid partiality to induce caught into nearby minima. Creating an ideal arrangement. It makes clustering entirely dependent on the essential cluster centers dispersion. Think about to recognize adjust input parameters for getting ideal or problematic clustering results.



(b)

FIGURE 3.14: k-means clusters (b) of a raw soil image.

[25]

— **Algorithm :**

- — Step1 : Choose the number k of clusters, either randomly or based on several heuristics.
- — Step2 : Generate k clusters and determine the cluster center.
- — Step3 : allocate each pixel in the image to the clusters. That minimizes the distance between the pixel and the cluster center.
- — Step4 : Re-compute cluster center by averaging all of the pixels in the cluster.

  - Step5 : Repeat steps 2 and 3 until the meeting is attained[18].
- **Advantage :**
  - When k is little, K-means is computationally faster.
  - It may create clenched clusters than various leveled clustering
  - The clusters are globular[11].
- **Disadvantage :**
  - Difficult to anticipate k with settled number of clusters.
  - Does not work well with a non-globular cluster[11].

3.9 Conclusion

In this chapter, we saw general concepts about bioinformatics, cancerous tumors, their types, diagnosis, and image segmentation. And a quick overview of the different segmentation technologies in general.

CHAPITRE 4

NEW VERSION OF DEEPLEARNING SEGMENTATION TO DETECT BRAIN TUMOR IN AN IOT SYSTEM

"I want to live in an AI-powered society." Andrew Ng

4.1 Introduction

This chapter shows a prototype for the final project, in which we need the IOT and 5G system. To detect the presence of the tumor and know its location from a distance The objectives of the project are to help the doctor make a decision and remove the tumor In this letter, we rely on two units, namely classification and segmentation to detect brain tumor.

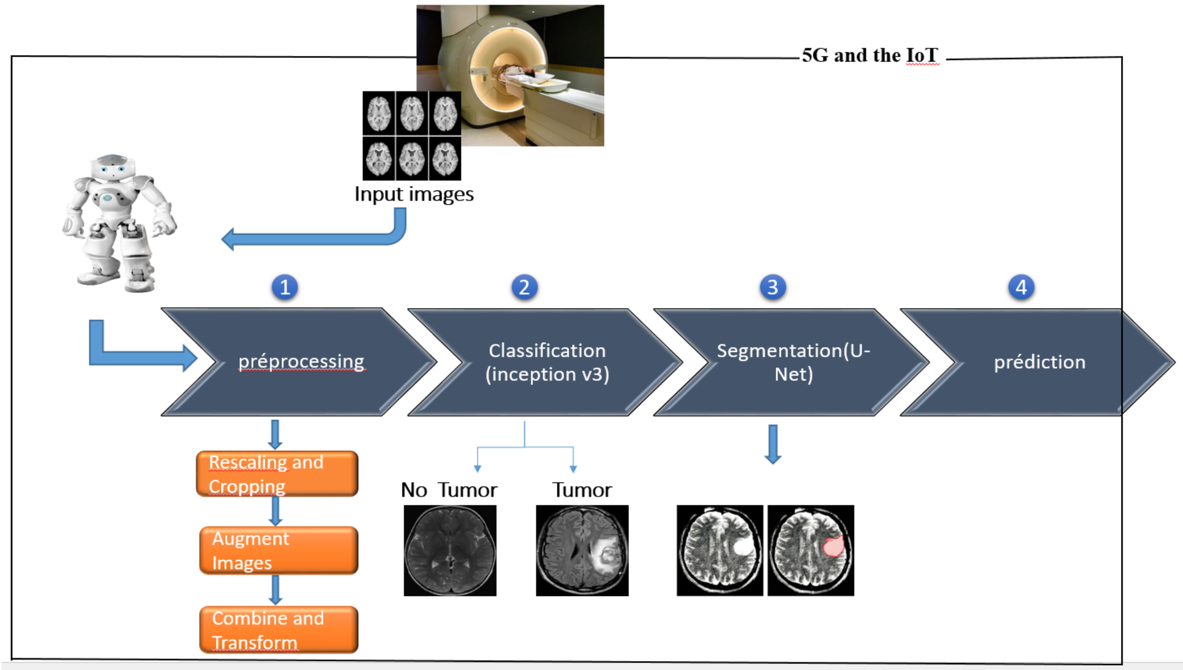


FIGURE 4.1: new version of deep learning segmentation to detect brain tumor in an IOT system. [25]

4.2 Image preprocessing

— To train a network and make predictions on new data, your images must match the input size of the network. If you need to adjust the size of your images to match the network, then you can rescale or crop your data to the required size.

— You can effectively increase the amount of training data by applying randomized augmentation to your data. Augmentation also enables you to train networks to be invariant to distortions in image data. For example, you can add randomized rotations to input images so that a network is invariant to the presence of rotation in input images.

— For more advanced preprocessing operations, to preprocess images for regression problems, or to preprocess 3-D volumetric images, you can start with a built-in datastore. You can also preprocess images according to your own pipeline by using the transform and combine functions.

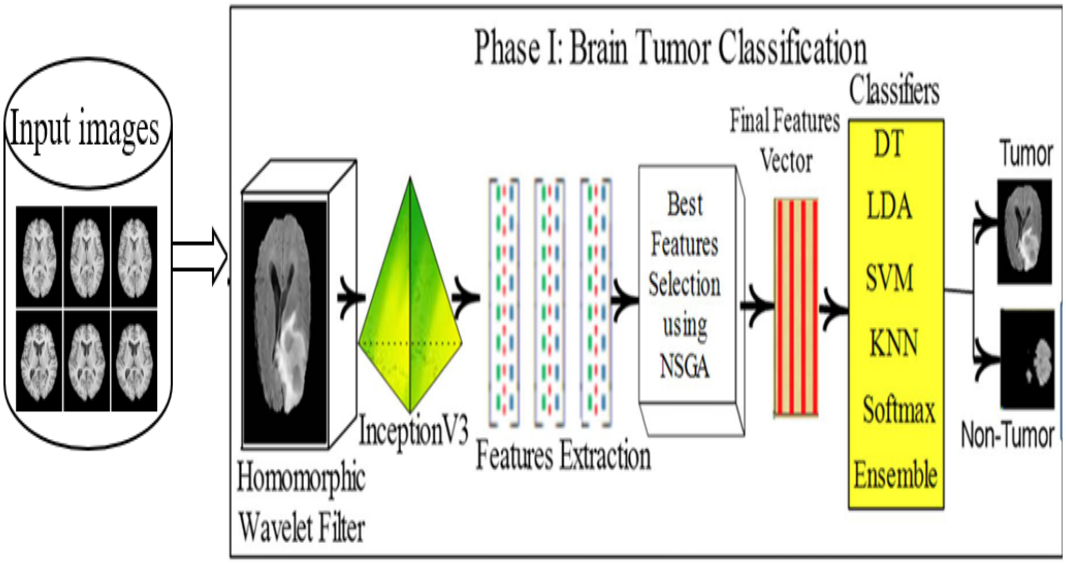


FIGURE 4.2: Brain tumor classification.

[25]

4.3 Brain tumor classification

4.3.1 Extracted deep features using pre trained inceptionv3 architecture :

Deep learning is widely utilized in artificial intelligence applications, such as speech recognition and computer vision. However, with more interest in the area of deep learning, classification into corresponding categories is a major problem. This problem might be solved through transfer learning because accurate models and architecture are built in in a time-saving manner. In this process, learning is performed through already learned patterns to solve different problems instead of using features learning from scratch. Transfer learning uses pre-trained models that are learned on huge amount of data for problem-solving. Thus, this work utilizes an inceptionv3 pre-trained transfer learning model.

4.4 Brain tumor segmentation

The most common deep learning-based methods in the field of medical image segmentation are U-Net and Fully Convolutional Network (FCN). Among them, U-net has proved to be the most reliable technique in terms of performance. The U-net architecture has a U-symmetrical structure where the left side performs encoder task and the right side of the architecture performs decoder task. Another specification in this architecture is that the encoder concatenates the corresponding layer of the decoder. This characteristic allows the resultant feature map to have both low-level and high-level features. Further, the model performance is improved by integrating features from different levels while preserving the location information.

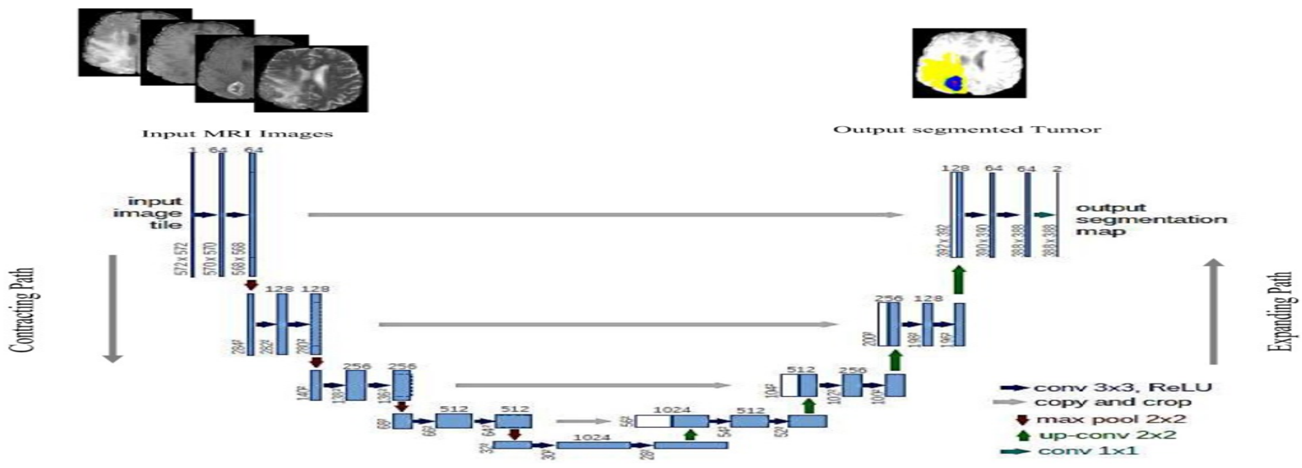


FIGURE 4.3: Brain tumor segmentation.

[25]

We made some changes to the content of U-Net to improve the performance of the model in terms of accuracy, loss function and also time gain, we got another model which we called the updated UNet Model Verstion, and we compared the obtained model with U-Net we got the same accuracy 0.99 and with However, the new model was much better in loss function compared to U-Net, as well as in terms of number of parameters. UNet Model Verstion is lower than U-Net which makes the new model faster in terms of time.

4.5 Remote surgical operation thanks to 5G and IoT technology

4.5.1 What is 5G Network

— 5G is the fifth generation of mobile networks. With Internet speeds up to ten times faster than 4G and latency in the millisecond range, the new mobile communications standard will deliver on many promises in the areas of healthcare.
— 5G allows haptic applications to take life, in combination with haptic data communication protocols, bilateral teleoperation control schemes and haptic data processing.

4.5.2 What is IoT ? (Internet of Things)

- IoT is the new technological revolution that aspires to connect all the everyday physical objects to the Internet.
- The objective is the development of a huge global network of uniquely things which can share information amongst each other and complete scheduled tasks.
- IoT brings multiple advantages in many scientific areas, such as in Medicine.
- IoT is part of M2M (Machine-to-Machine), which consists in making connected objects communicate with each other without human intervention.

4.6 The Impact of IoT and 5G Technology in Telesurgery

4.6.1 Research Objectives

- Highlight the weaknesses in the conventional surgery operation.
- Demonstrate the new emerging technologies for telesurgery .
- Specify the motivation and the potential solutions for proper transition from surgery to telesurgery.

4.6.2 What is "Telesurgery" ?

- "Telesurgery" or "Remote Surgery" is an innovative trend of surgery which promises to replace or help supportively the conventional method of surgery operation.
- Telesurgery makes use of wireless technologies and robotic systems so as to allow surgeons to operate on patients from distance.

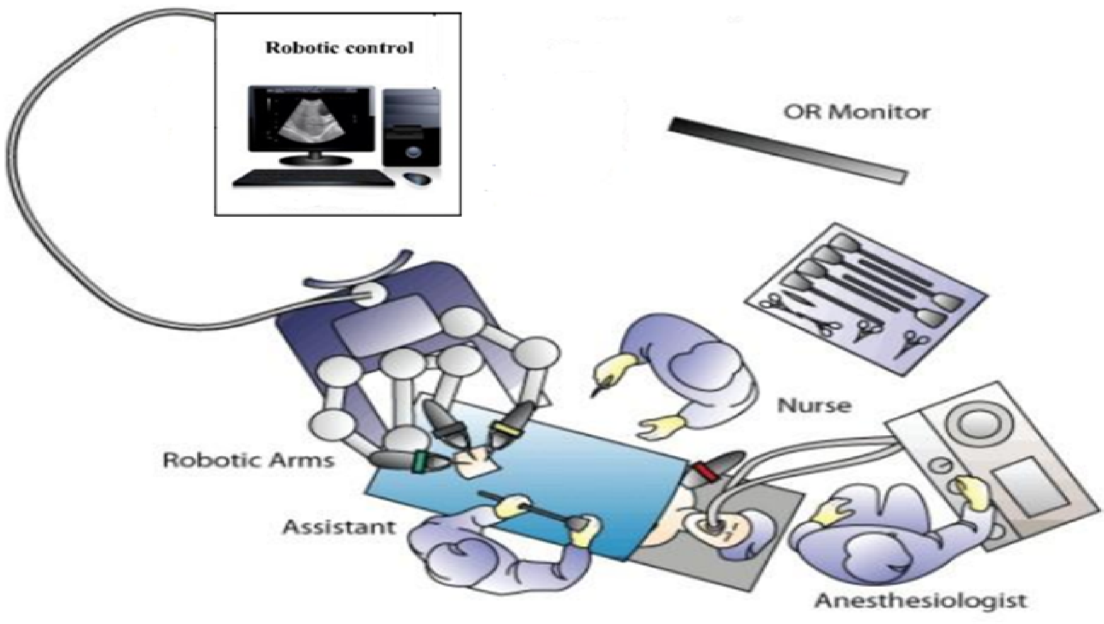


FIGURE 4.4: A telesurgery operation room.

4.7 Benefits and Limitations

4.7.1 Benefits for surgeons

— Close-up views of areas that they are not able to see during open surgery.
— Greater dexterity and control.
— Enhance their surgical accuracy.
— Reduce their anxiety.
— Eliminate potential daily shortage of surgeons.

4.7.2 Benefits for patients

— High-quality surgery services to patients worldwide, even in medically underserved areas.
— Minimization of the surgery operating costs.
— Shorter hospital stay.
— Less pain and risk of infection.
— Less blood loss and transfusions.
— Smaller incisions for minimal scarring.

4.7.3 Limitations

- Need for global network development.
- Equipment acquisition and maintenance is not an easy decision (from legal/ethical and economical aspects).
- Many countries worldwide, do not still have the proper infrastructure to fully support the parallel use of the necessary creative technologies for telesurgery.
- Billing issues on distributing operation fees and facility fees among the participating medical centers.
- Concerns about patients' health privacy.

4.8 Proposed approach

The proposed approach is the integration of the following emerging technologies :

4.8.1 Internet of Things (IoT)

- IoT is the new technological revolution that aspires to connect all the everyday physical objects to the Internet.
- The objective is the development of a huge global network of uniquely things which can share information amongst each other and complete scheduled tasks.
- IoT brings multiple advantages in many scientific areas, such as in Medicine.

4.8.2 Wireless Sensor Networks (WSNs)

- WSN is composed of a large number of small sensor nodes with limited resources and densely deployed in an environment.
- The purpose of WSN is to interconnect all the IoT-based devices (e.g. of a patient) in order to deliver useful information wherever is needed, such as in a medical center.

4.8.3 5G Network

- 5G allows haptic applications to take life, in combination with haptic data communication protocols, bilateral teleoperation control schemes and haptic data processing.

4G vs 5G :

- 4G theoretical maximum speed is up to 100Mbps, 5G one is up to 10Gbps (100 times faster) .
- 5G promises to significantly reduce latency, which means faster load times and improved responsiveness.

4.8.4 Future Directions

- Legal and ethical issues should be studied.
- Patients' health privacy and their personal sensitive data which are collected in remote cloud servers.

4.9 Pseudocode for segmentation phase using CNNs

Input :Brain CT scan ; IMGi : the number of images in the training dataset. Output : Segmented brain images.

1. Start :
2. remove the noise in the non-brain regions
3. Do
4. training data augmentation
5. For i=1 to IMGi
6. INITIALIZE numpy (array) Size [X,Y,Z]
7. augmented mask=Transfoms(spatial)
8. mask=mask[0]
9. return (augmented image[0],mask(IMGi)])
10. ENDFor
11. Normalize Image
12. path_size=ShapeArray([1 :])
13. Augmented = Transform(Gaussian_Noise)
14. Assigning labels to patches
15. For each i in IMGi
16. N_samples = length(SelfLabels)
17. CountDiC=dict(unique,counts)
18. labels=[]
19. For each label in SelfLabels
20. Append(Patches)->(n_samples/Count Labels)
21. Return labels
22. End For
23. End For
24. Update labels

25. returns :Sample(labels)
26. While(iter<-IMGi)
27. End

4.10 U-Net approach with pre/Post-processing

1. For each of 1800 Training RGB images :
   — Rescale RGB image such
     that largest dimension is 250 pixels
   — Im_hsi=convert RGB image to HSI image
   — I_orig =I channel of Im_hsi
   — Normalize I_orig to values between 0 and 1
   — apply histogram equalization to I channel of im_hsi
   — Train_img[channels 0 , 1 , 2] =convert im_hsi to RGB
   — Train_img [channel 3] = I_orig
   — Train_img[channel 4]=2D Gaussian with 125 pixel Full Width Half Maximum
   — Horzontally Flip,Vertically Flip,rotate 180 images to 7200)
   — White-Pad Train_img and flipped/rotated versions to 342x342 pixels
   — add Train_img and flipped/rotated versions to training set
2. Train U-Net with 10000 iterations selected from the 7200 training images (this corresponds to just over 1 epoch)
3. Initialize Threshold as 0,5
4. For each of 1800 Training Image :
   — Predict the skin lesion Image
   — Apply Binary Fill Holes
   — Use gradient descent to optimize threshold value that maximizes Jaccard Index
5. For each test data set image,use optimized threshold to get skin lesion area.
6. Apply Binary fill holes

4.11 Transfer Learning

Many computer vision researchers have used these datasets to train their algorithms. This training can take several weeks and a large number of GPUs. We can frequently get open source weights since someone else has already completed this effort and gone through the arduous high-performance research procedure. Following that, we can utilize them as excellent initialization parameters for our own neural network. That is, we can utilize transfer learning to transfer information from some of these massive public datasets to our frozen problem[31].

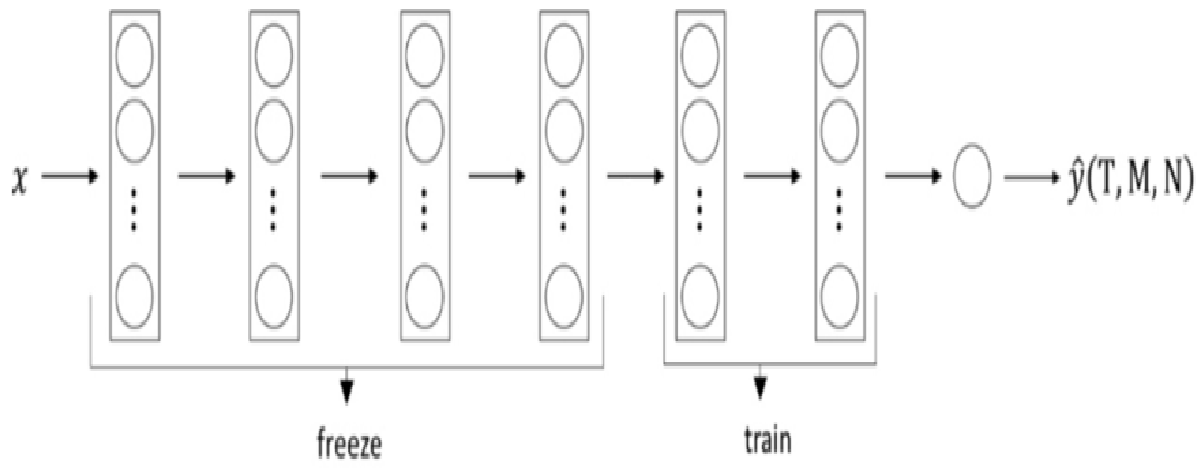


FIGURE 4.5: Transfer Learning Technique.

[31]

So, in Figure 4.5, we'll calculate the activation function and save all of the previous layers' weights on our disk, train the softmax layer just with our own issues with the new output, and sometimes use SoftMax to alter the final layers. It allows us to save time and speed up training by eliminating the requirement to compute forward and backward propagation because we already know optimum weights.

4.12 Data augmentation

Most computer vision jobs might benefit from extra data, and data augmentation is a common strategy for enhancing the accuracy of any algorithm and improving the performance of computer vision systems[28]. In computer vision, we have numerous data augmentation methods. Some of them are shown in Figure 4.6.

FIGURE 4.6: Different augmentation methods

[28]

4.13 Conclusion

In this chapter, we highlight the U-Net segmentation model and its changes as well as a transfer learning method where transfer learning is used to improve situational generalization, help improve outcomes and improve Neural network acceleration.

CHAPITRE 5

RESULT, DISCUSSION AND EXPERIMENTATION

"The world as we have created it is a process of our thinking. It cannot be changed without changing our thinking" Albert Einstein

This chapter presents the results, achieved to assess the effectiveness of our solution to the issue of Classification and Segementation Brain Tumor. By explaining the different tools used in the practice, We worked in order to reach our goals. To validate the results, we used a supervised group Measurements such as : recall, precision, f-measurement, precision, loss function, to enhance the results Obtained, a comparative study between models for Transfer Learning classification and model segmentation In terms of accuracy and loss is also the number of parameters, but before we validated our models, we made A series of experiments to choose the best hyperparameters and optimizers in order to improve model performance.

5.1 Implementation tools

To implement and optimize proposed models, we now have an easy-to-use open source deep learning framework that aim to streamlining the implementation of large and complex models.

5.1.1 TensorFlow

TensorFlow is an end-to-end open source machine learning platform. It offers a comprehensive and flexible ecosystem of tools, libraries, and community resources that allow researchers to advance in the field of machine learning, and developers to easily create and deploy applications that use this technology. is a symbolic math library that uses dataflow and differentiable programming to perform various tasks focused on training and inference of deep neural

networks . it was built to run on multiple CPUs or GPUs and even mobile operating systems.
uses of TensorFlow :

- Image Recognition.
- Video Detection.
- Voice Recognition.
- Text-based applications.

5.1.2 Kears

Keras is an API designed for humans. Keras follows best practices to reduce cognitive load : it provides consistent and simple APIs to solve a variety of problems, reduces the number of user actions required for common use cases, and provides clear, actionable error messages. It also has extensive documentation and guides for developers.
An example of some of the buildings in Keras (image classification)

1. VGG16
2. ResNet50
3. Xception

5.1.3 Sklearn

Scikit-Learn is a major library of the Python programming language that is used in machine learning projects. Scikit-Learn focuses on machine learning tools including mathematical, statistical, and general-purpose algorithms that form the basis of many machine learning technologies. Scikit-Learn is very important in many different types of algorithm development for unsupervised and supervised learning. It is built on some technologies such as NumPy, Pandas, and Matplotlib. The functionality that scikit-learn provides include :

- Regression, including Linear and Logistic Regression.
- Classification.
- Clustering.
- Model selection
- Preprocessing

5.2 Programming language used

5.2.1 Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. The built-in high-level data structures, along with dynamic typing and dynamic binding, make them very attractive for rapid application development, Python's simple and easy-to-learn syntax emphasizes readability and thus reduces the cost of program maintenance.

Python supports modules and packages, which encourages code reuse and program modularity. The comprehensive Python compiler and standard library are available in source or binary form free of charge for all major platforms, such as google colab.

5.3 Evaluation measures

5.3.1 Confusion matrix

A confusion matrix provides a summary of the predictive results in a classification problem. Correct and incorrect predictions are summarized in a table with their values and broken down by each class.

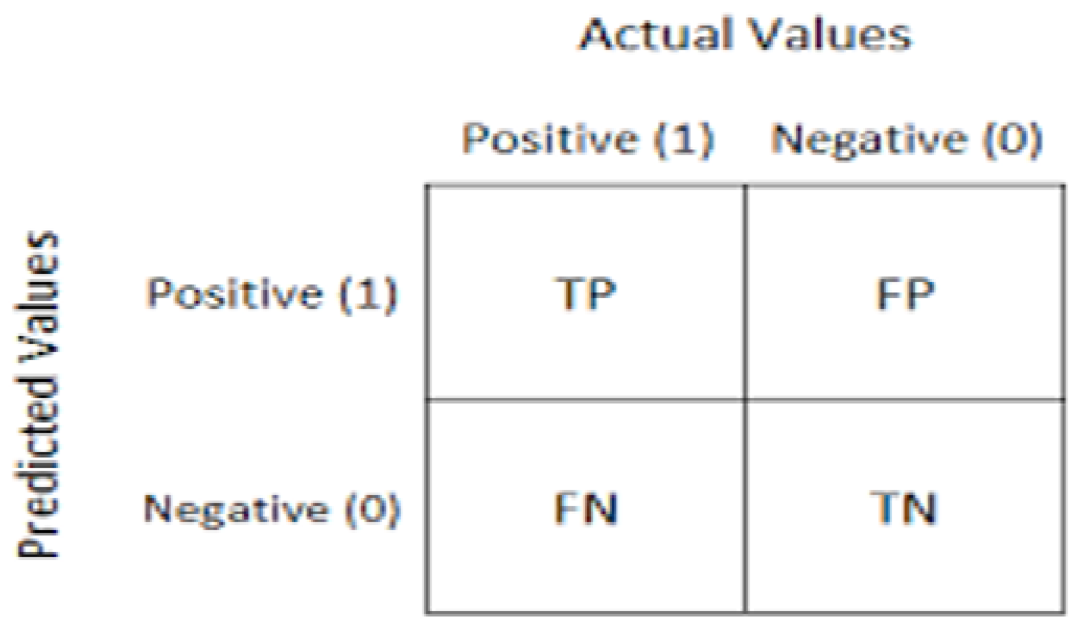


FIGURE 5.1: Confusion matrix. Figure reproduced from [10]

The confusion matrix consists of Key terms : TP, TN, FP, and FN. Terminology :

- **TP (True Positives) :**
  Cases where the prediction is positive and true compared to the true value.
- **TN (True Negatives) :**
  Situations where the prediction is negative, and is true compared to the true value.
- **FP (False Positive) :**
  Situations in which the prediction is positive, and false compared to the true value.
- **FN (False Negative) :** Situations in which the prediction is negative but false compared to the true value.

5.3.2 Precision

Accuracy is the ratio between the number of correctly classified positive samples to the expected total positive Notes.

$$Precision = TP/((TP + FP))$$

5.3.3 Recall

The recall is the ratio between the number of positive samples correctly classified as positive to the total number of positive samples.

$$Recall = TP/((TP + FN))$$

5.3.4 F1 score

F1 Score is the weighted average of Precision and Recall.

$$F1 = 2x((PrecisionxRecell))/((PrecisionxRecell))$$

5.4 Experiments and implementation

5.4.1 Transfer Learning for brain tumor Classification

We used four models for Transfer Learning, represented in :

— Xception
— VGG16
— ResNet50
— InceptionV3

1. ResNet50 : We have done several experiments with different optimizers, learning rate and batch size.
   — **Optimizers :**
   In the following figure, we have an experiment with seven types of optimizers SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax ,Nadam .

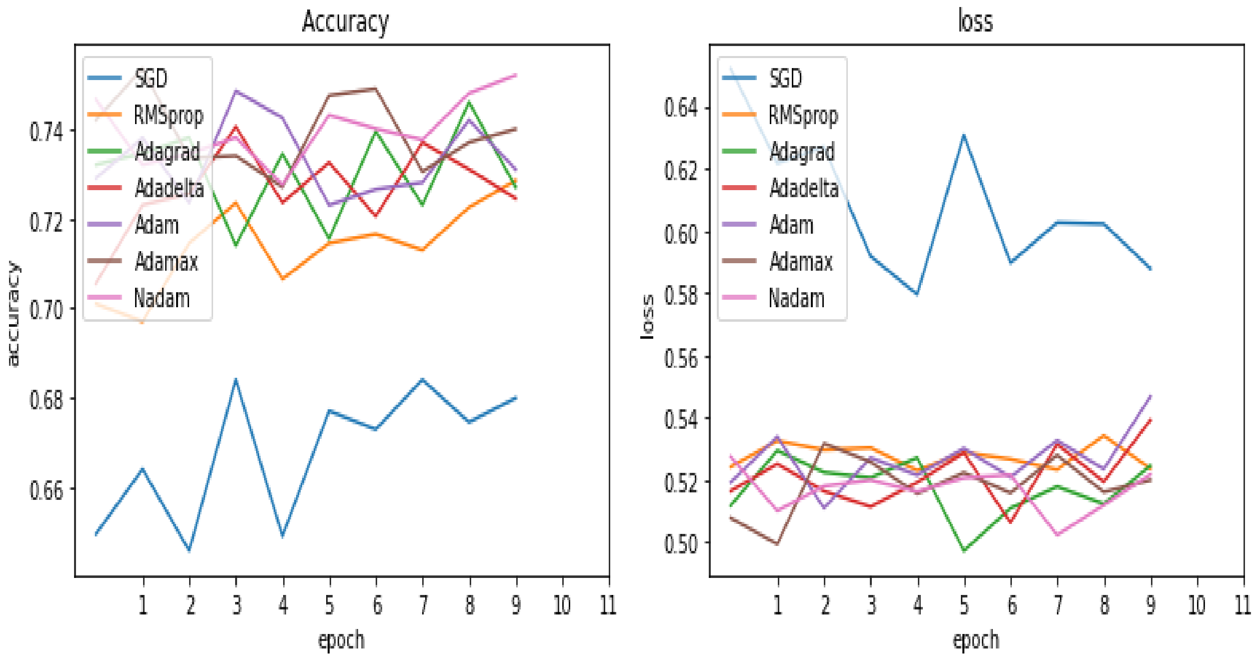


FIGURE 5.2: The accuracy and the loss function with different optimizers ResNet50

We note that Nadam Optimizer It gives good results compared to optimizers others.

— **Learning Rate :**

here we have the experimentation of the different values of Learning Rate.

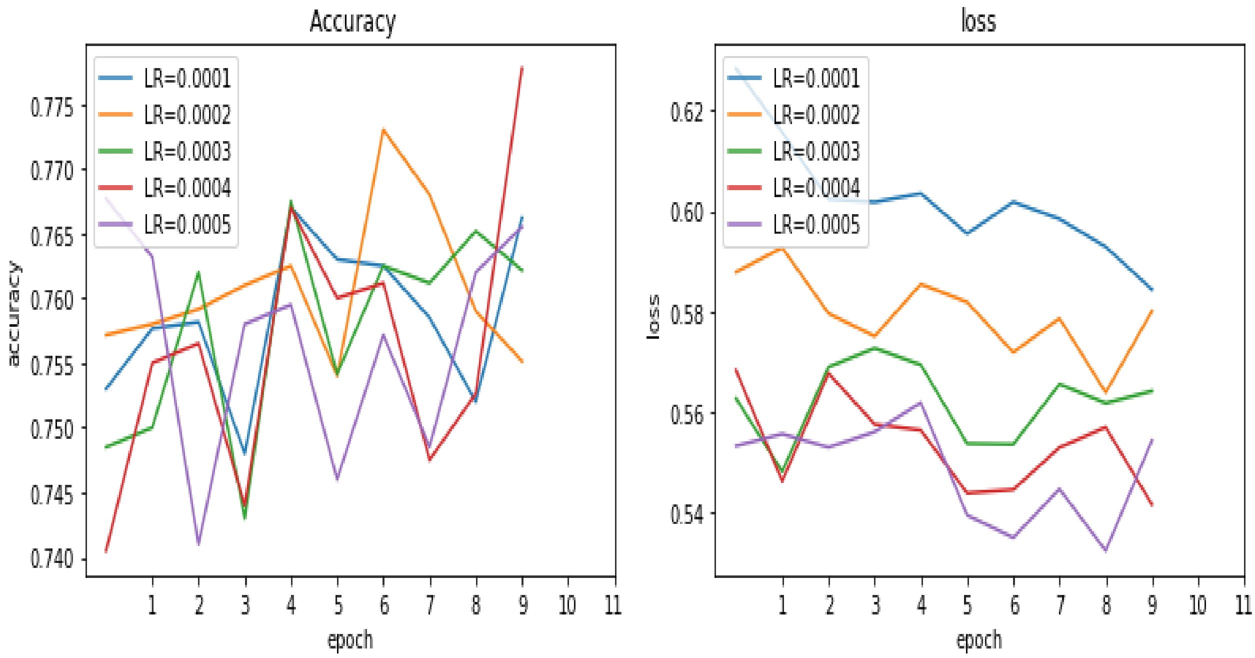


FIGURE 5.3: The accuracy and the loss function with different values of learning rate ResNet50

We note that the learning rate= 0.0004 gives good results compared to other values of learning rate.

— **Batch Size :**

here we have the experimentation of batch size with a different values Batch Size.

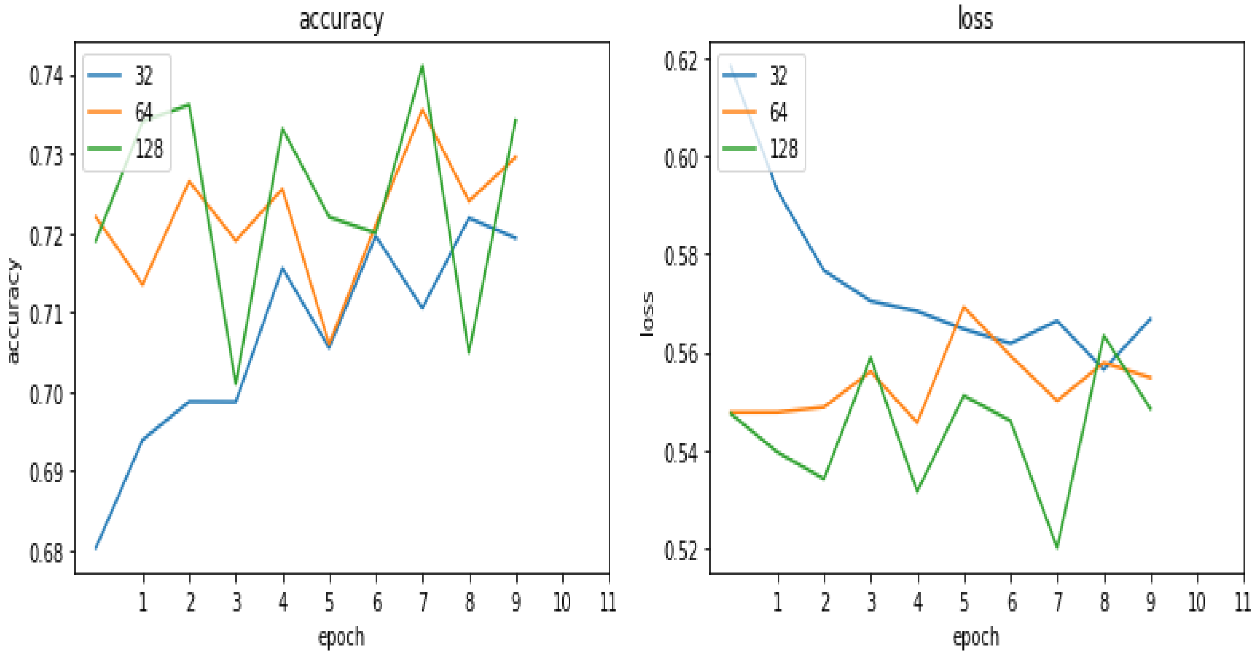


FIGURE 5.4: The accuracy and the loss function with different batch size ResNet50

After the comparison, the batch-size with the value 128 gives the best result

— **Final result :**

The Curve represents the precision and the loss function for our model after the experimentation

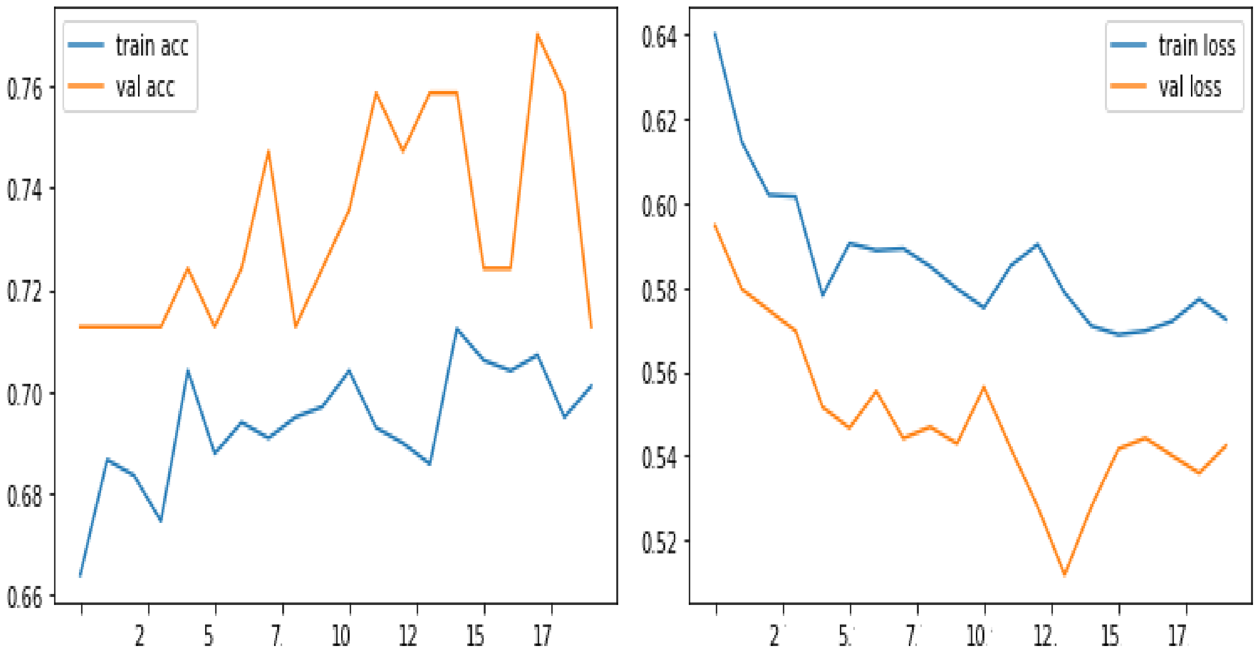


FIGURE 5.5: Validation results through The accuracy and the loss function ResNet50

we obtain the result in table :

Accuracy	Loss function
0.71	0.57

TABLE 5.1: The accuracy and loss function after the experimentation ResNet50.

— **Final configuration**

After experiments, we come to the parameters configuration in Table

Optimizers	Learning Rate	Batch Size	number of Epochs	model
Nadam	0.0004	128	20	ResNet50

TABLE 5.2: The Final configuration ResNet50.

— Confusion matrix
Compute Confusion Matrix to evaluate the accuracy of a classification.

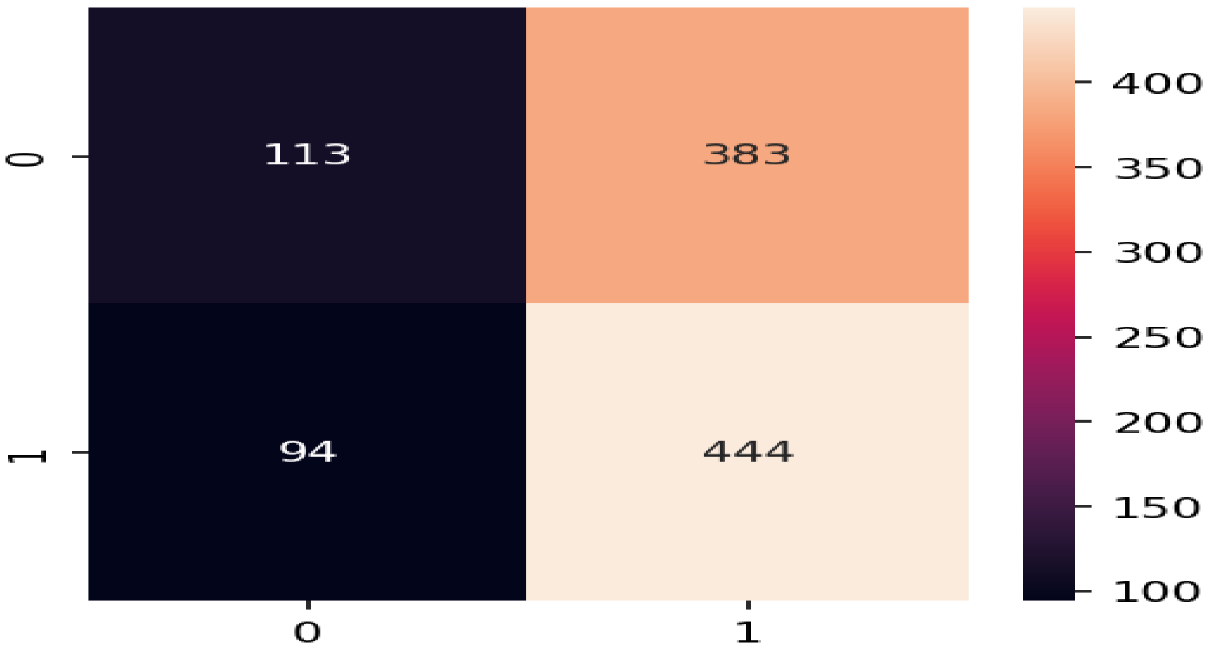


FIGURE 5.6: Confusion matrix model ResNet50

Number of images being tested 1034 of which 496 no tumor (0) and 538 tumor (1)

— True positive = 113
— True negative = 444
— False positive =383
— False negative =94

2. VGG16 We have done several experiments with different optimizers, learning rate and batch size.
   — **Optimizers :**
   In the following figure, we have an experiment with seven types of optimizers SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax ,Nadam .

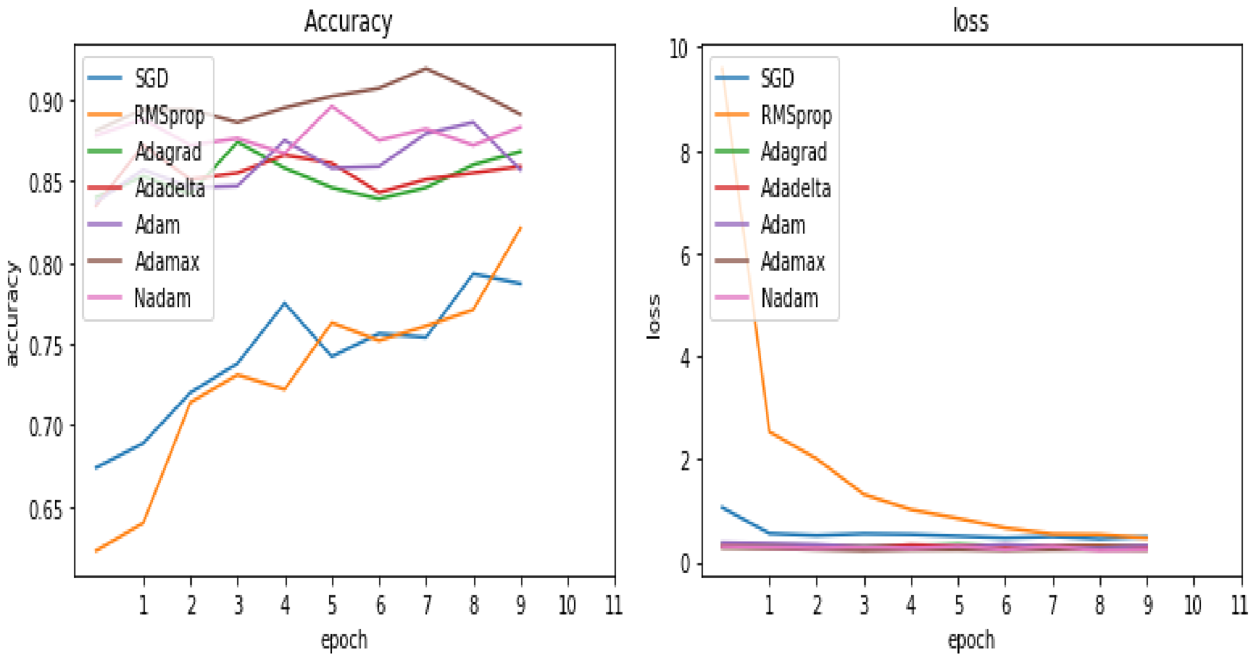


FIGURE 5.7: The accuracy and the loss function with different optimizers VGG16

We note that Adamax Optimizer It gives good results compared to optimizers others.

— **Learning Rate :**

here we have the experimentation of the different values of Learning Rate.

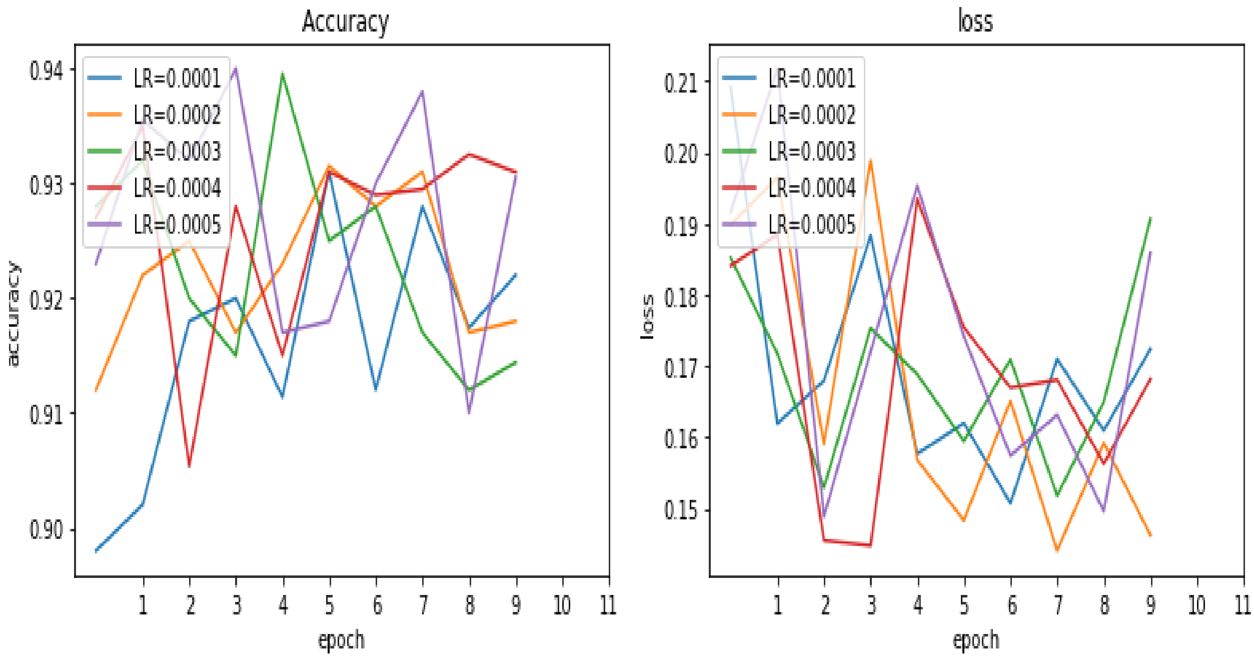


FIGURE 5.8: The accuracy and the loss function with different values of learning rate VGG16

We note that the learning rate= 0.0005 gives good results compared to other values of learning rate.

— **Batch Size :**

here we have the experimentation of batch size with a different values Batch Size.

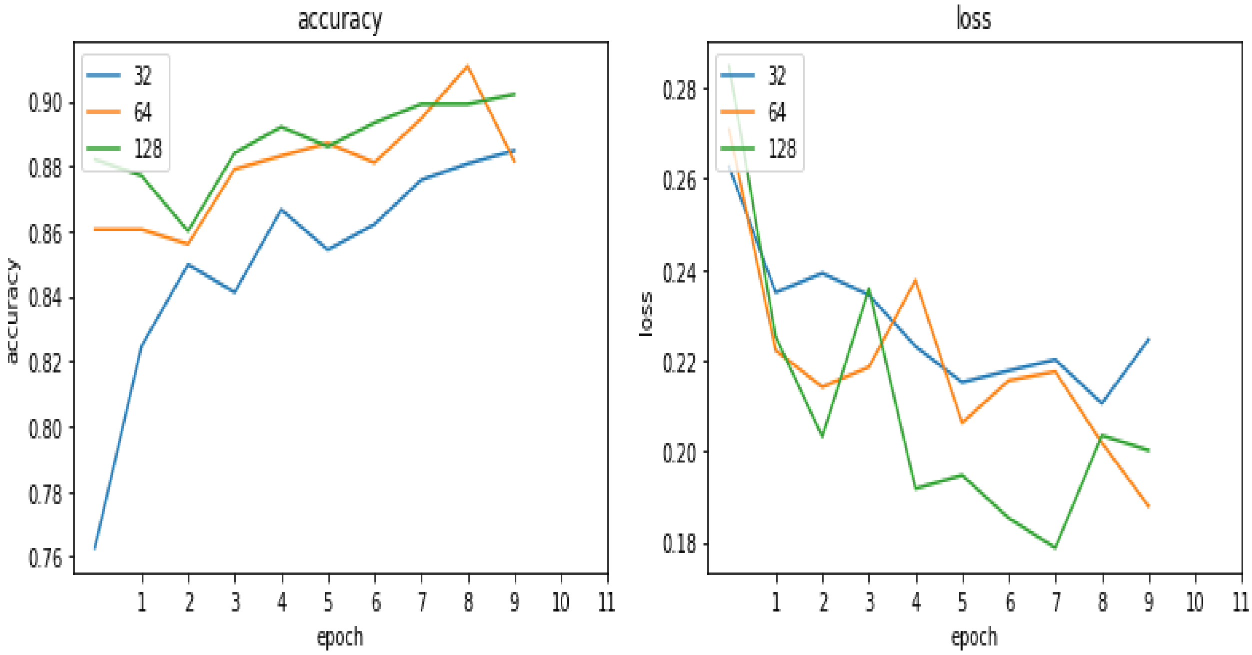


FIGURE 5.9: The accuracy and the loss function with different batch size VGG16

After the comparison, the batch-sise with the value 64 gives the best result

— **Final result :**

The Curve represents the precision and the loss function for our model after the experimentation

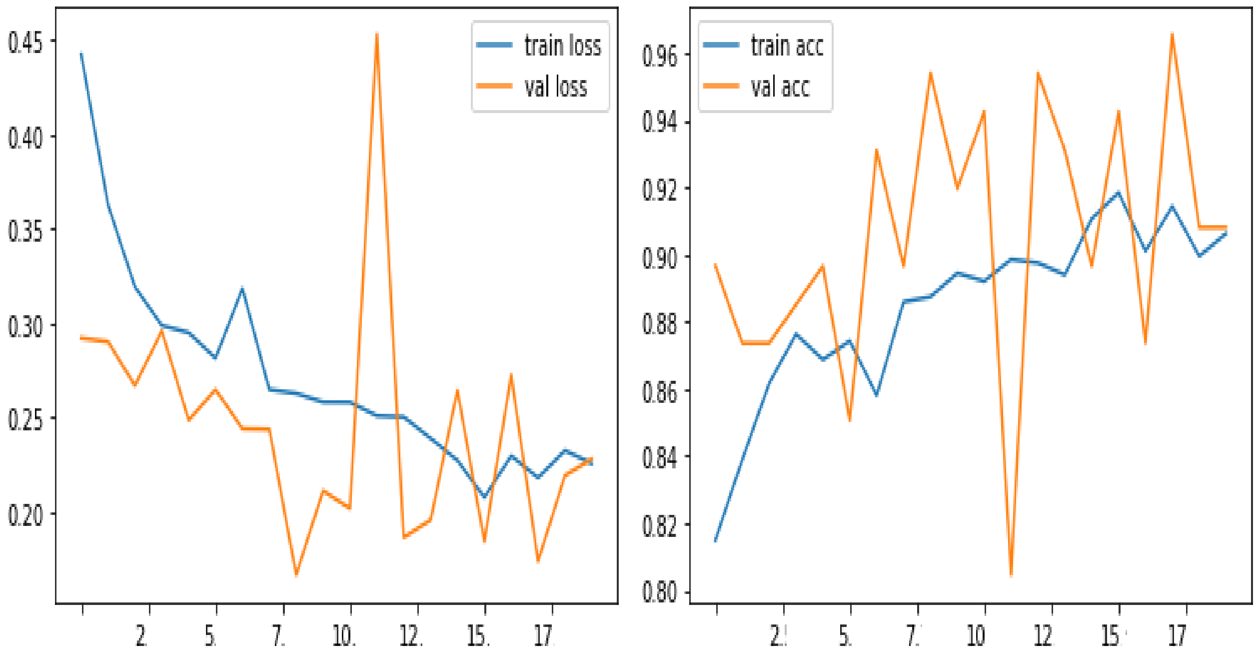


FIGURE 5.10: Validation results through The accuracy and the loss function VGG16

we obtain the result in table :

Accuracy	Loss function
0.92	0.20

TABLE 5.3: The accuracy and loss function after the experimentation VGG16.

— **Final configuration**

After experiments, we come to the parameters configuration in Table

Optimizers	Learning Rate	Batch Size	number of Epochs	model
Adamax	0.0005	64	20	VGG16

TABLE 5.4: The Final configuration VGG16.

— **Confusion matrix**
Compute Confusion Matrix to evaluate the accuracy of a classification.

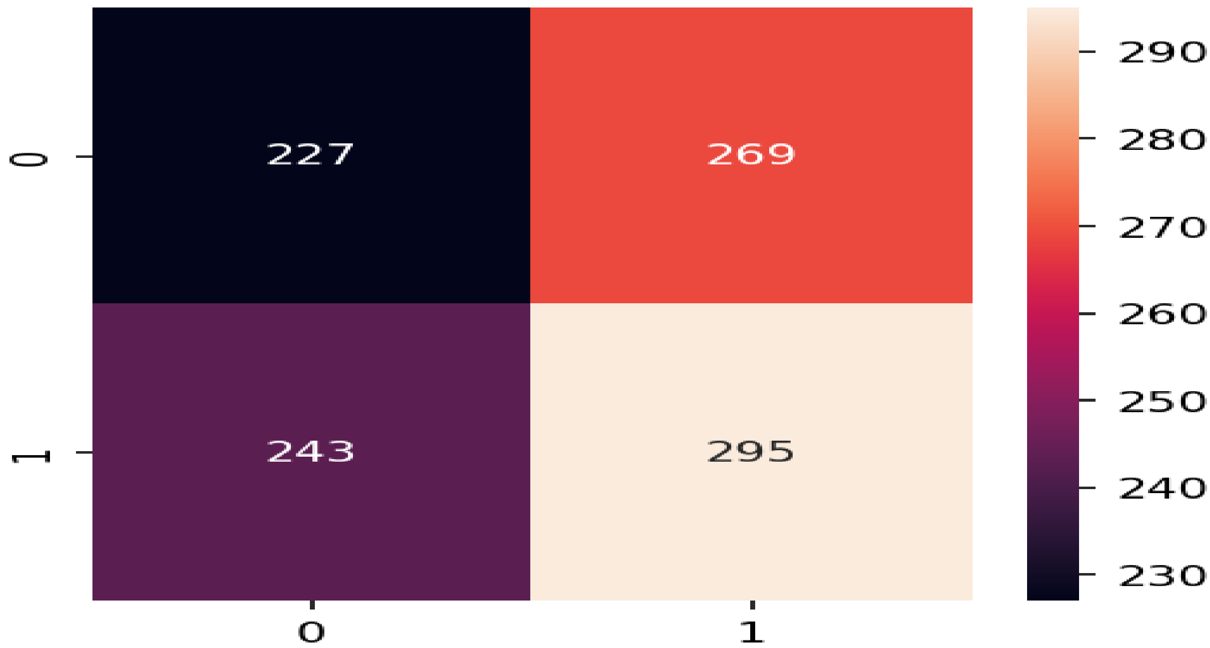


FIGURE 5.11: Confusion matrix model VGG16

Number of images being tested 1034 of which 496 no tumor (0) and 538 tumor (1)

— True positive = 227
— True negative = 295
— False positive =269
— False negative =243

3. Xception We have done several experiments with different optimizers, learning rate and batch size.
   — **Optimizers :**
   In the following figure, we have an experiment with seven types of optimizers SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax ,Nadam .

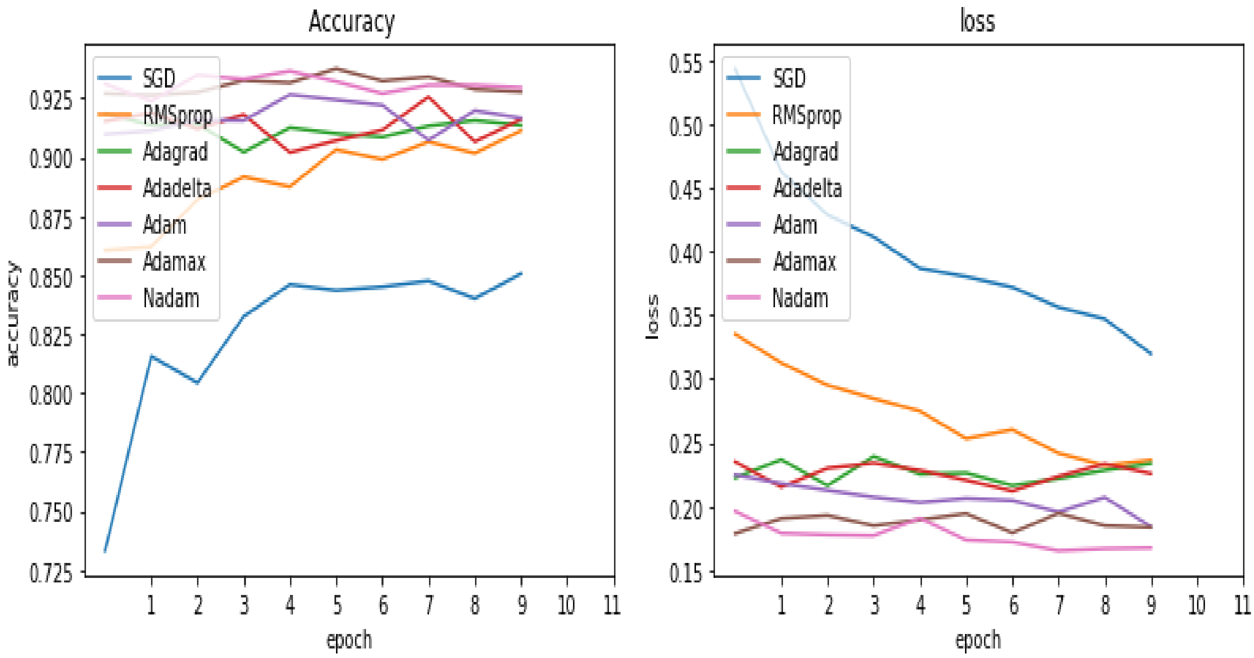


FIGURE 5.12: The accuracy and the loss function with different optimizers Xception

We note that Nadam Optimizer It gives good results compared to optimizers others.

— **Learning Rate :**

here we have the experimentation of the different values of Learning Rate.

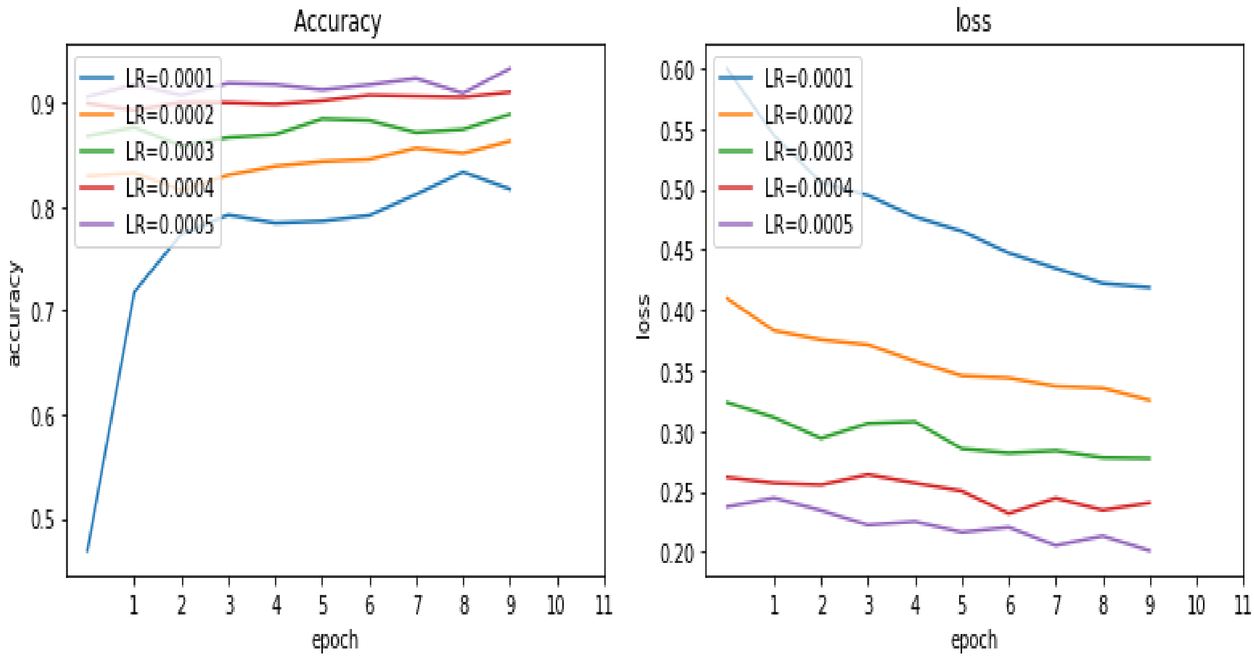


FIGURE 5.13: The accuracy and the loss function with different values of learning rate Xception

We note that the learning rate= 0.0005 gives good results compared to other values of learning rate.

— **Batch Size :**

here we have the experimentation of batch size with a different values Batch Size.

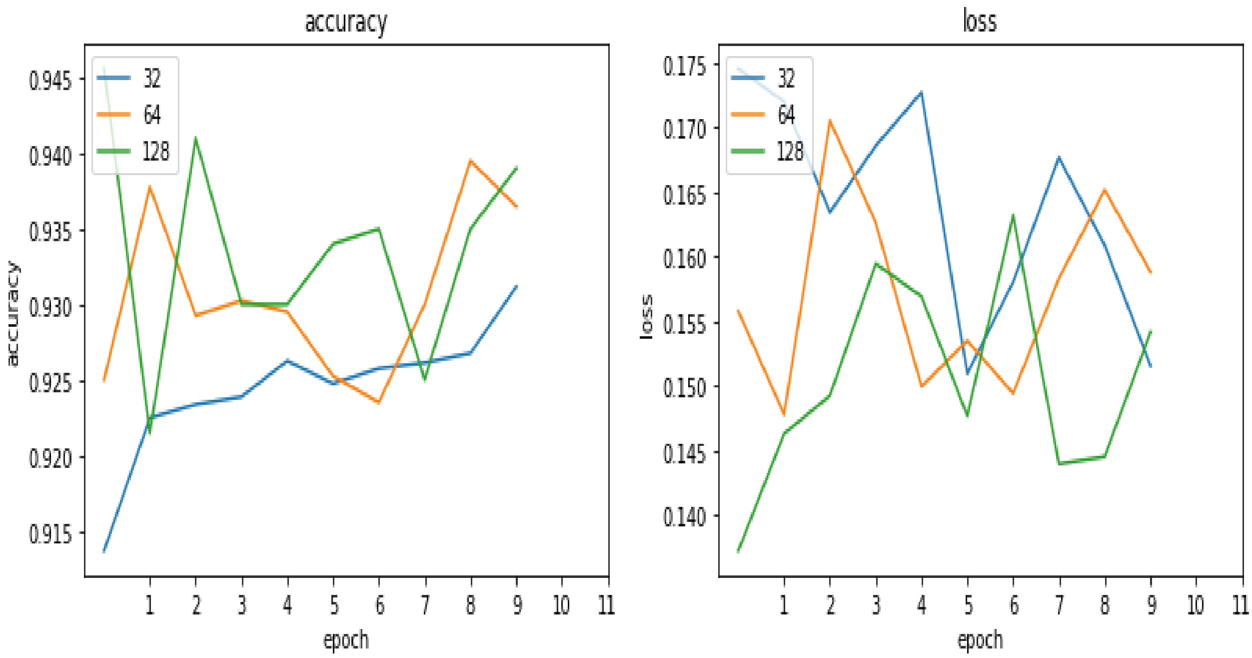


FIGURE 5.14: The accuracy and the loss function with different batch size Xception

After the comparison, the batch-sise with the value 128 gives the best result

— **Final result :**

The Curve represents the precision and the loss function for our model after the experimentation

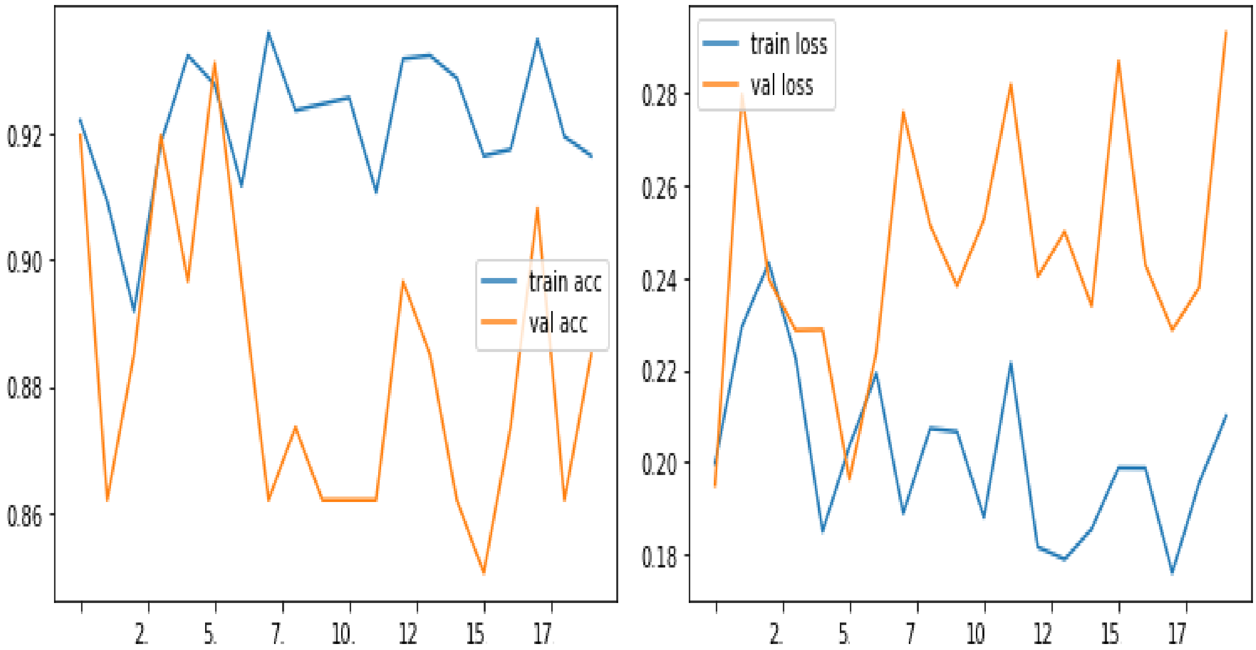


FIGURE 5.15: Validation results through The accuracy and the loss function Xception

we obtain the result in table :

Accuracy	Loss function
0.93	0.17

TABLE 5.5: The accuracy and loss function after the experimentation Xception.

— **Final configuration**
After experiments, we come to the parameters configuration in Table

Optimizers	Learning Rate	Batch Size	number of Epochs	model
Ndama	0.0005	128	20	Xception

TABLE 5.6: The Final configuration Xception.

— **Confusion matrix**

Compute Confusion Matrix to evaluate the accuracy of a classification.

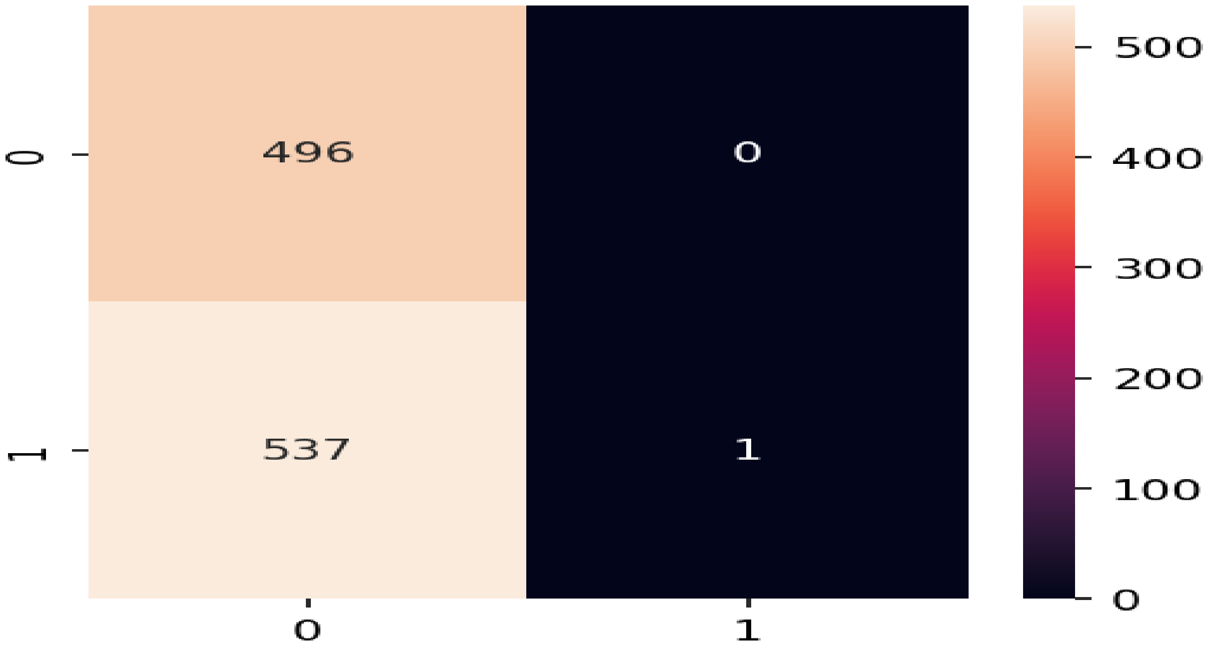


FIGURE 5.16: Confusion matrix model Xception

Number of images being tested 1034 of which 496 no tumor (0) and 538 tumor (1)

— True positive = 496

— True negative = 1

— False positive =0

— False negative =537

4. inceptionV3 We have done several experiments with different optimizers, learning rate and batch size.

   — **Optimizers :**

   In the following figure, we have an experiment with seven types of optimizers SGD, RMSprop, Adagrad, Adadelta, Adam, Adamax ,Nadam .

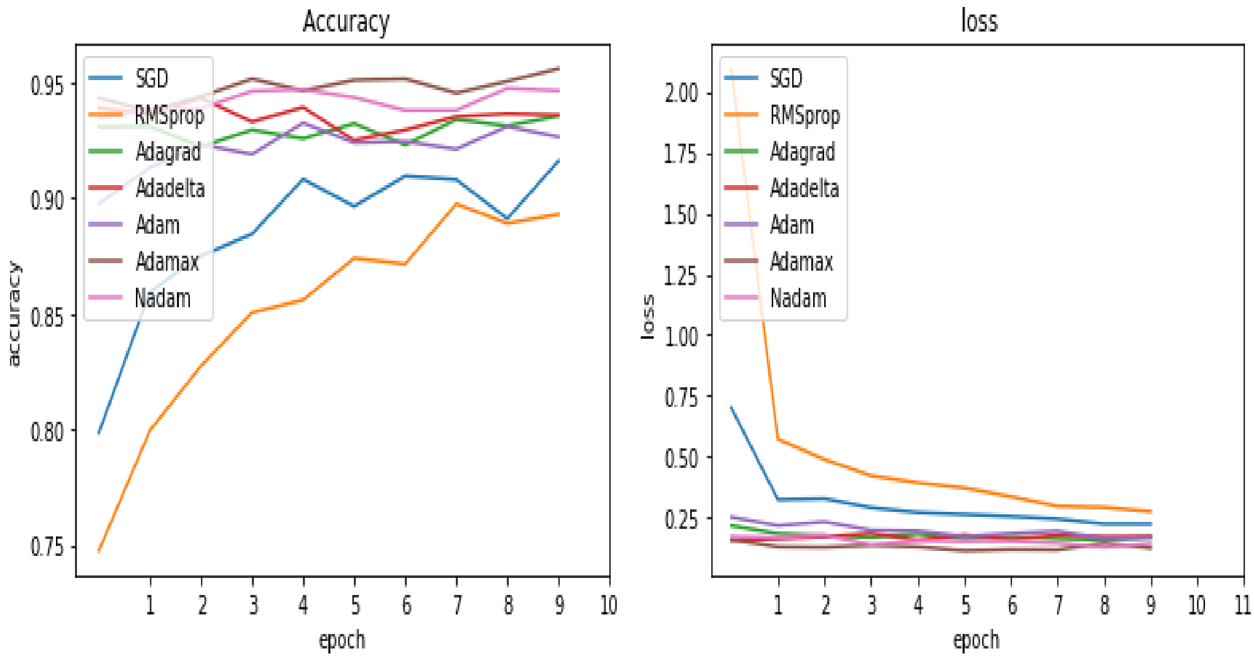


FIGURE 5.17: The accuracy and the loss function with different optimizers InceptionV3

We note that Adamax Optimizer It gives good results compared to optimizers others.

— **Learning Rate :**

here we have the experimentation of the different values of Learning Rate.

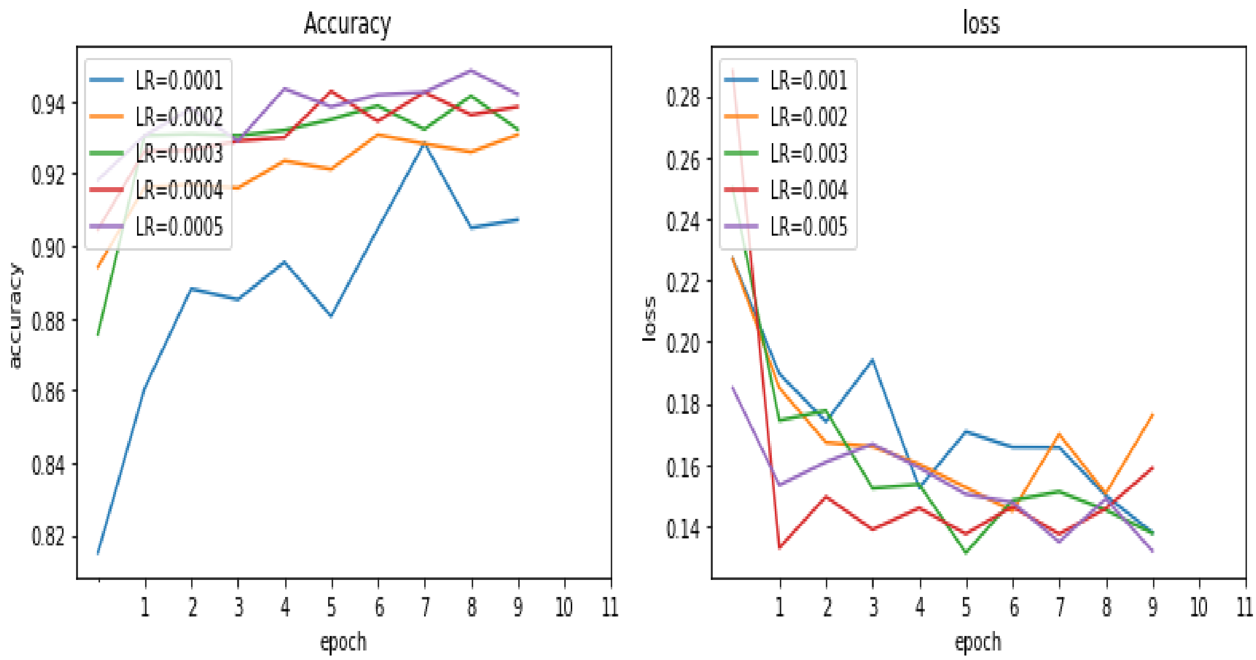


FIGURE 5.18: The accuracy and the loss function with different values of learning rate InceptionV3

We note that the learning rate= 0.0005 gives good results compared to other values of learning rate.

— **Batch Size :**

here we have the experimentation of batch size with a different values Batch Size.

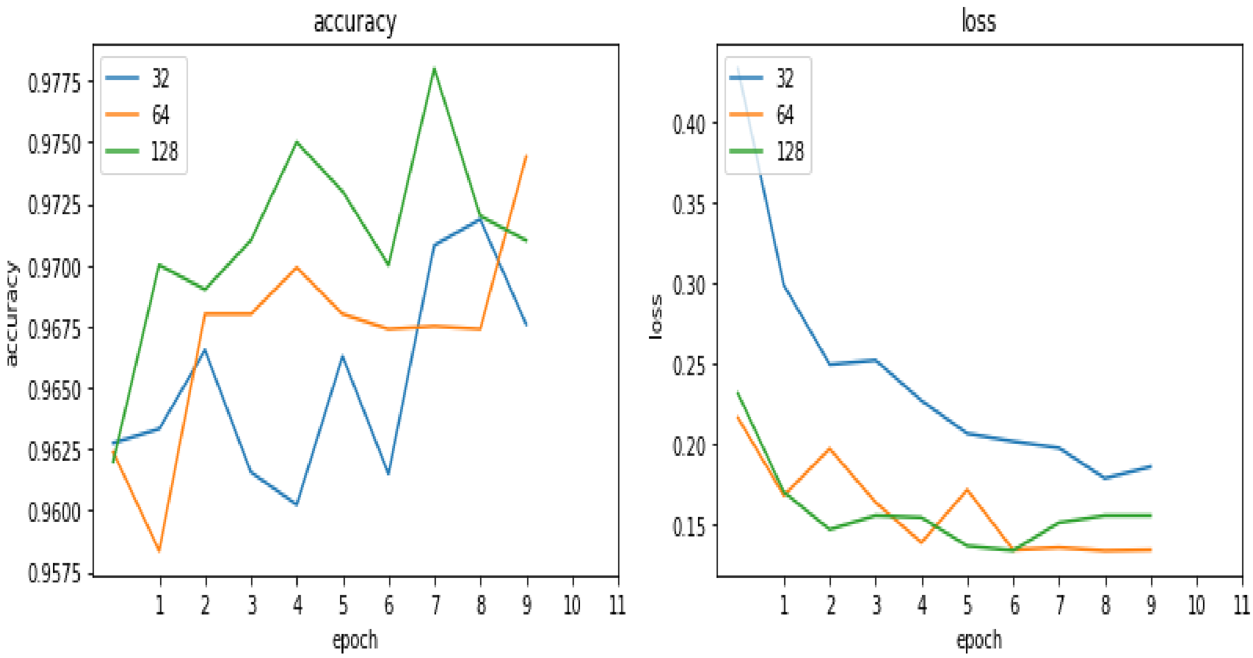


FIGURE 5.19: The accuracy and the loss function with different batch size InceptionV3

After the comparison, the batch-sise with the value 64 gives the best result

— **Final result :**

The Curve represents the precision and the loss function for our model after the experimentation

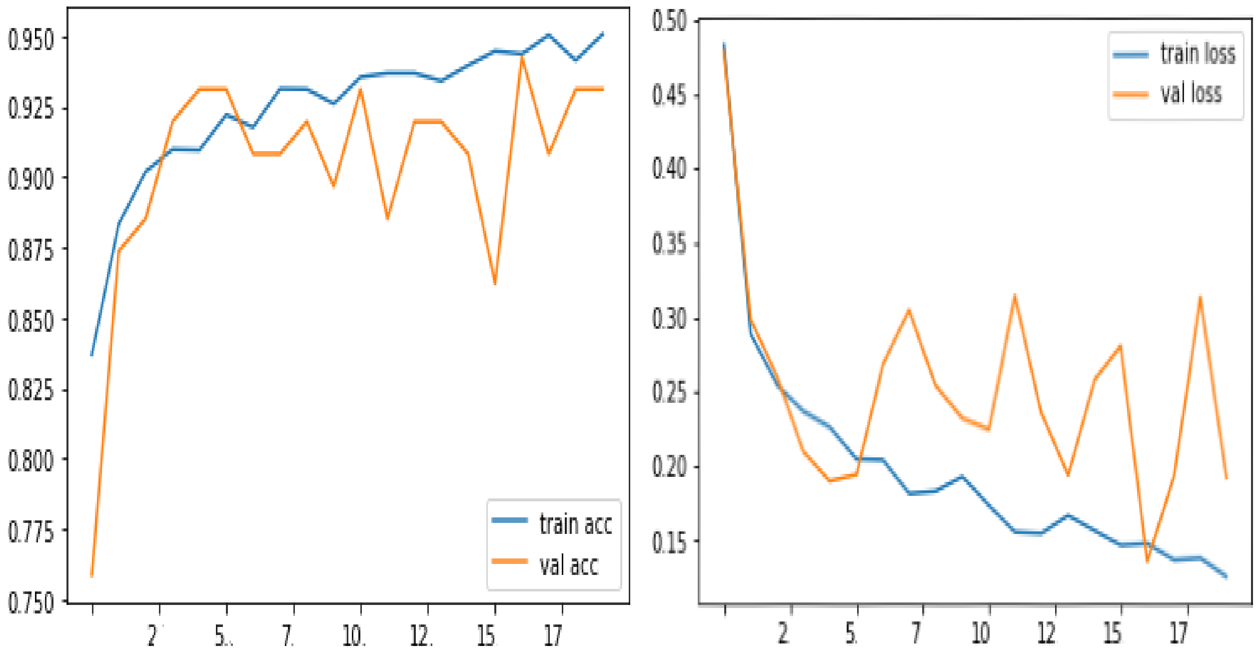


FIGURE 5.20: Validation results through The accuracy and the loss function InceptionV3

we obtain the result in table :

Accuracy	Loss function
0.95	0.12

TABLE 5.7: The accuracy and loss function after the experimentation InceptionV3.

— Final configuration
  After experiments, we come to the parameters configuration in Table

Optimizers	Learning Rate	Batch Size	number of Epochs	model
Adamax	0.0005	64	20	InceptionV3

TABLE 5.8: The Final configuration InceptionV3.

— **Confusion matrix :**
Compute Confusion Matrix to evaluate the accuracy of a classification.

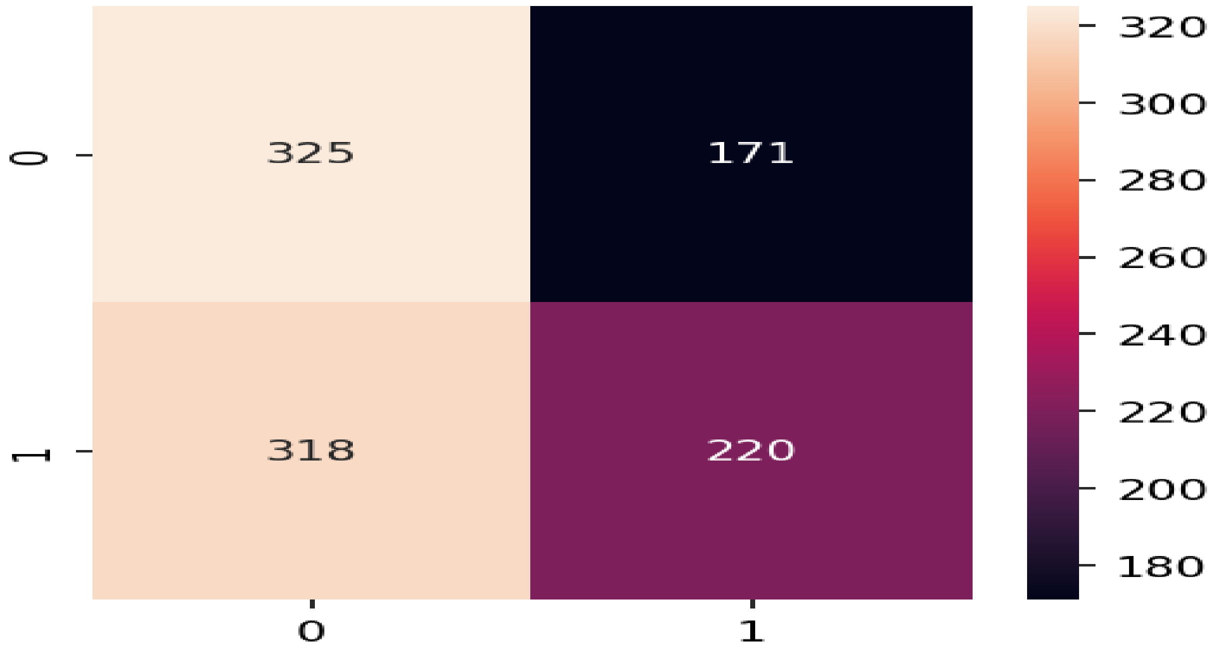


FIGURE 5.21: Confusion matrix model InceptionV3

Number of images being tested 1034 of which 496 no tumor (0) and 538 tumor (1)

— True positive = 325

— True negative = 220

— False positive =171

— False negative =318

5.4.2 Comparison between models for Transfer Learning :

We try to compare the predictions of VGG-16, InceptionV3, Xception and ResNet50 in shapes. Within the range of these numbers, which is an estimate for pre-trained networks, we note a slight difference, which is that InceptionV3 is the best.

Training VGG-16 takes a very long time compared to others, due to the number of layers and parameters. The following table 5.9 and Figure 5.22 show the performance of each model. Figure

5.5 and 5.10 and 5.15 and 5.20 show the precision and loss function of VGG-16, InceptionV3, Xception and ResNet50

	Precision	Recall	F1 score	number of parameters
InceptionV3	0.535	0.535	0.52	23,903,010
Xception	0.74	0.50	0.325	20,863,529
Vgg16	0.50	0.505	0.505	117,483,329
ResNet50	0.545	0.53	0.485	23,589,761

TABLE 5.9: Performance measures of models for Transfer Learning.

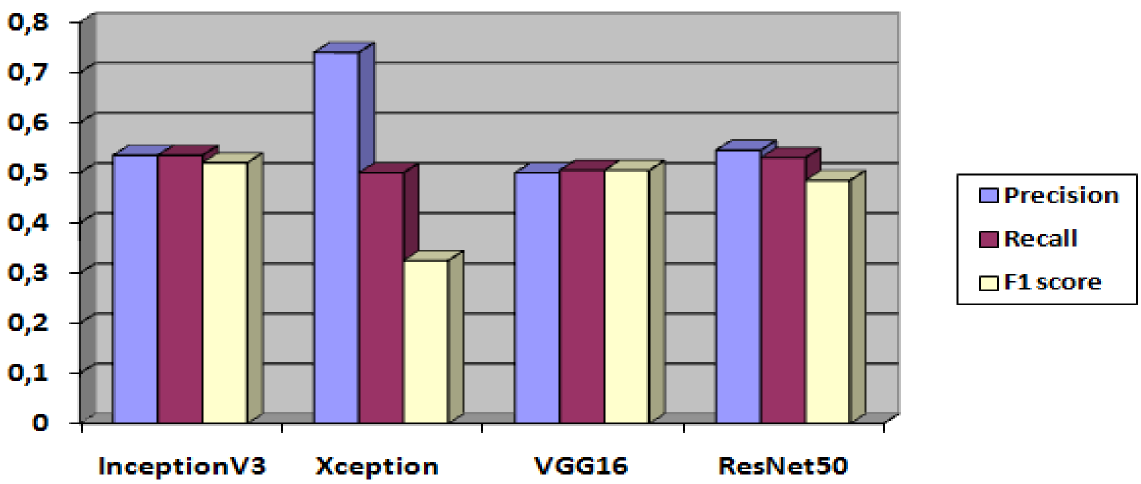


FIGURE 5.22: Performance measures of models for Transfer Learning.

5.4.3 Comparison of models in terms of the number of parameters

In the table 5.10 and Figure 5.23 below , we have a comparison of the following models in terms of number the of parameters.

	Trainable parameters	Non-trainable parameters	Total parameters
InceptionV3	2,100,226	21,802,784	23,903,010
Xception	2,049	20,861,480	20,863,529
Vgg16	102,768,641	14,714,688	117,483,329
ResNet50	2,049	23,587,712	23,589,761

TABLE 5.10: Comparison of models in terms of the number of parameters.

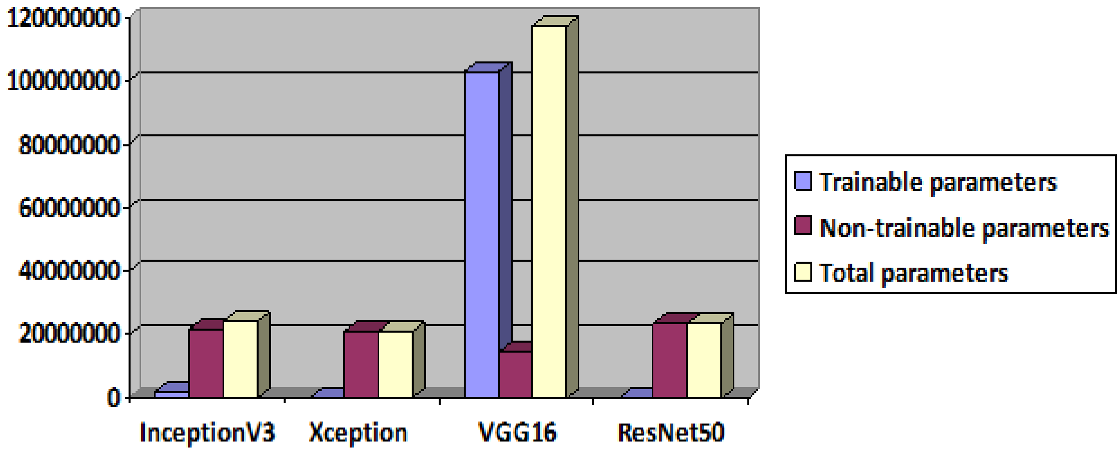


FIGURE 5.23: Comparison of models in terms of the number of parameters.

5.4.4 segmentation

1. UNet Model Verstion Updated

   After we made some modifications to the content UNet Model to improve Accuracy and Loos and win time , We get the following results .

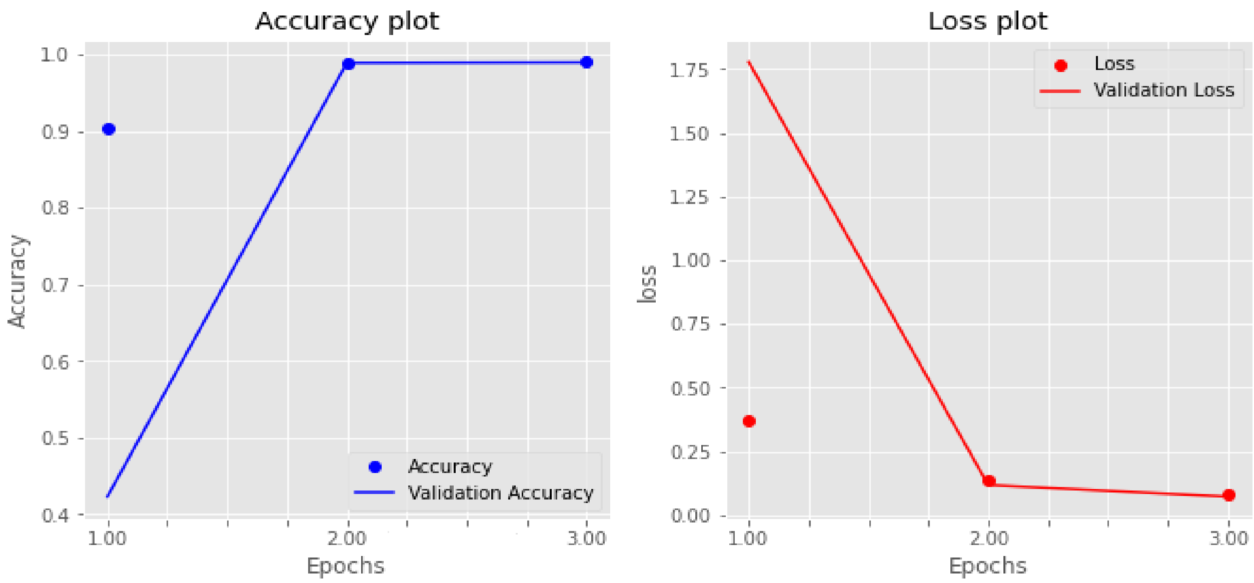


FIGURE 5.24: Validation results through The accuracy and the loss function UNet Model Verstion Updated.

we obtain the result in table :

Accuracy	Loss function
0.99	0.08

TABLE 5.11: The accuracy and loss function after the experimentation UNet Model Verstion Updated.

2. UNet Model

   The Curve represents the precision and the loss function for UNet model

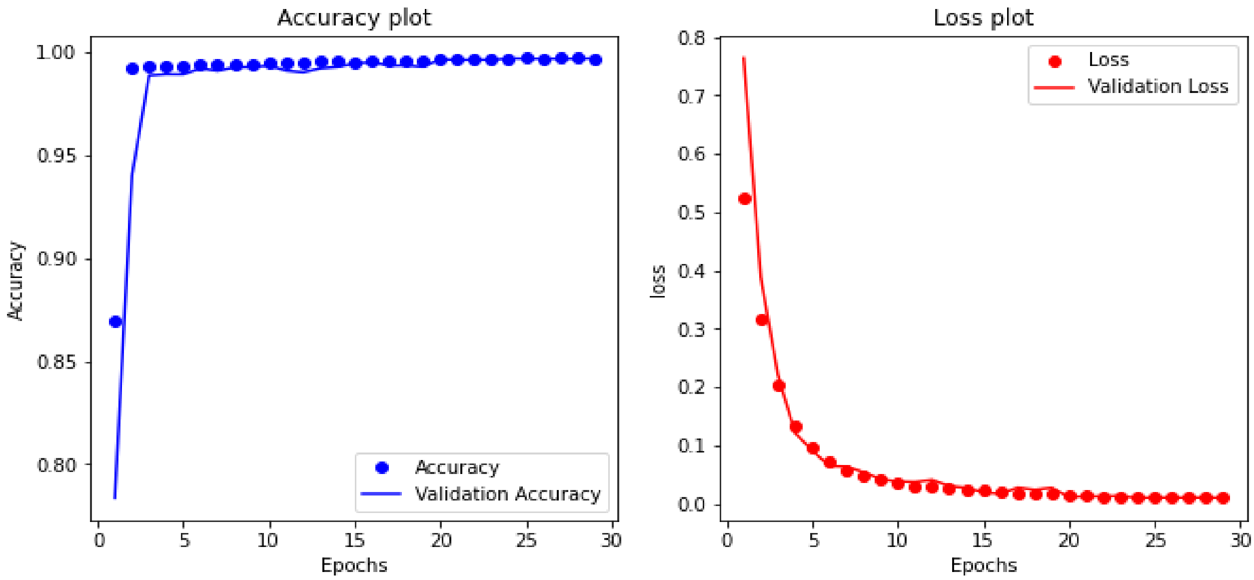


FIGURE 5.25: Validation results through The accuracy and the loss function UNet model.

we obtain the result in table :

Accuracy	Loss function
0.99	0.31

TABLE 5.12: The accuracy and loss function after the experimentation UNet model.

5.4.5 Comparison between UNet Model Verstion Updated and UNet Model

— Configuration
Configuration UNet Model Verstion Updated and UNet Model (Optimizers , Learning Rate, Batch Size, number of Epochs, number of Epochs)

model	Optimizers	Learning Rate	Batch Size	nb of Epochs	nb of parameters
UNet Verstion Updated	Adam	0.001	32	3	31,106,529
UNet	Adam	0.001	32	30	34,619,777

TABLE 5.13: Configuration UNet Model Verstion Updated and UNet Model.

— Validation results
Comparison between Validation results of UNet Model Verstion Updated and UNet Model

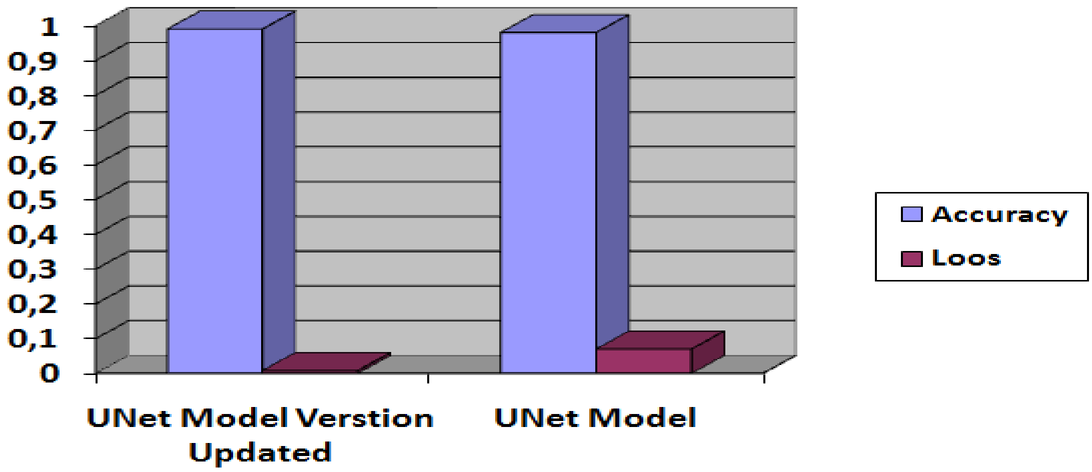


FIGURE 5.26: The accuracy and loss function of UNet Model Verstion Updated and UNet Model.

— Comparison of models in terms of the number of parameters :
In the table 5.14 and Figure 5.27 below , we have a comparison of the UNet Model Verstion Updated and UNet Model in terms of number the of parameters

	Trainable parameters	Non-trainable parameters	Total parameters
UNet Model Verstion Updated	31,100,513	6,016	31,106,529
UNet Model	34,607,681	12,096	34,619,777

TABLE 5.14: Comparison of the UNet Model Verstion Updated and UNet Model in terms of the number of parameters..

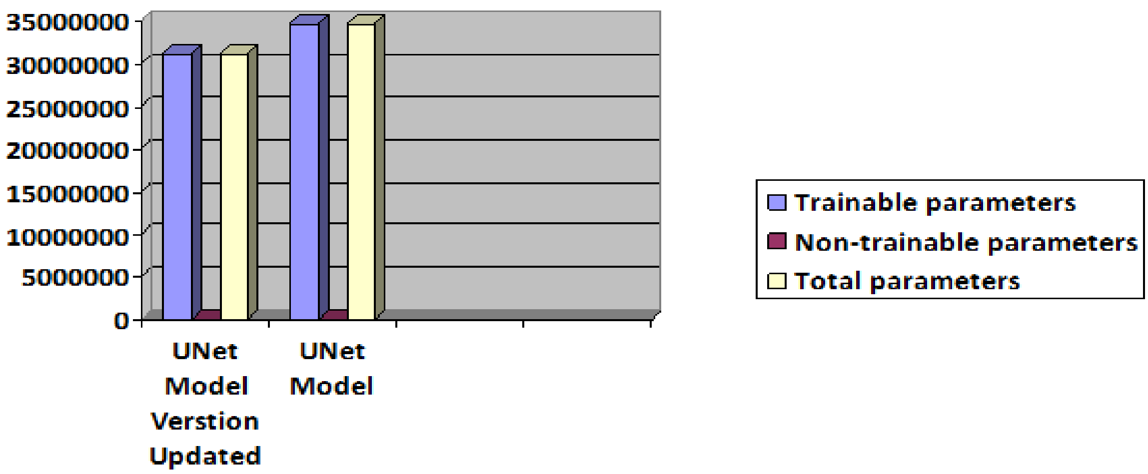


FIGURE 5.27: Comparison of the UNet Model Verstion Updated and UNet Model in terms of the number of parameters.

5.4.6 Visualising the predictions

We gave 100 images to make a prediction. We got the following results.

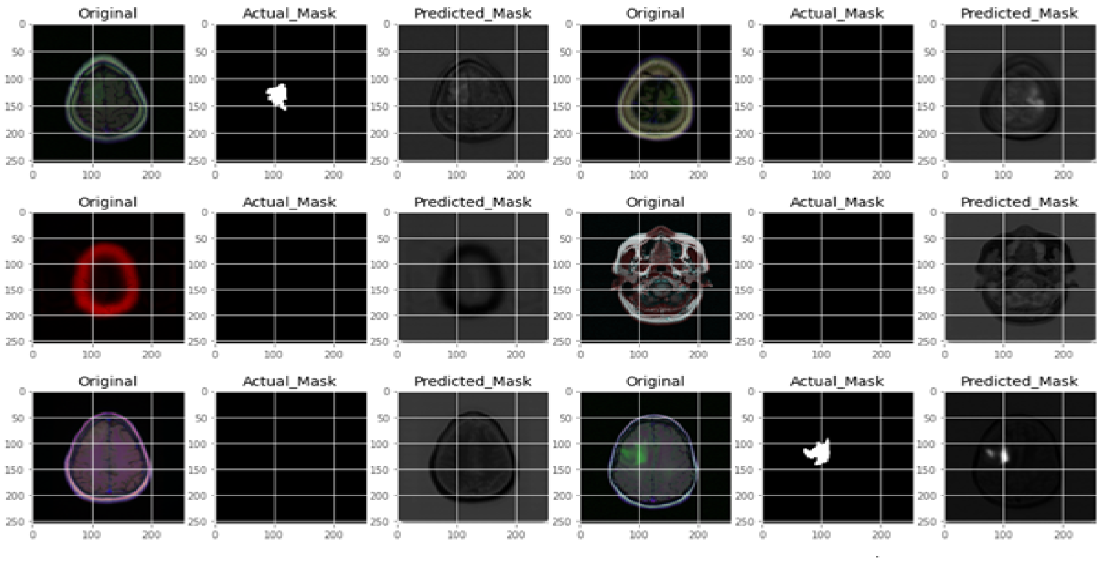


FIGURE 5.28: some predictions UNet Model Verstion Updated

5.5 Conclusion

In this chapter we have detailed the evaluation measures used in our work, Discuss and interpret the results obtained, Detail the stages of implementation of our work, Carry out a comparative study between the models for Transfer Learning , moreover, we did a comparative between the models of segmentation .

General conclusion

The aim of this thesis is to help doctors discover brain tumors, make a decision, and in the future reach to remote tumor removal using some technologies such as 5G and IOT , to link the field of medicine and artificial intelligence. To do this work, we used a convolutional neural network as a method, and this choice of method is justified by the simplicity and efficiency of its methods. We had to first define the concept of deep learning and how to apply it to our research topic. We addressed two topics, classification and segmentation in brain tumors, both of which use different techniques. We focus on transferring learning technology to speed up neural network formation, as well as data augmentation to prevent data scarcity for better models. The results we obtained confirm the effectiveness of our approach. This work is still open for further improvements in this area.

Future work :

After our findings during this thesis, some new research doors have been opened Detailed below :

- We will integrate our model in the environment of the Internet of Things and the field of robotics to perform the operation remotely and without human intervention and generalize this technology to all cancerous tumors
- We will test our solution with Arduino to implement it in real life.
- Add security in 5G and encrypt photos to keep data.
- This technology can be combined with radiation therapy to identify and destroy cancer cells.

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