Figures University of Zawia

Faculty of Engineering

Electrical and Electronic Department

Communication Engineering Section

Zawia - Libya

MSc thesis

Brain Tumor Classification by Using Gray Scaled Deep Neural Network

A thesis submitted to the faculty of engineering, University of Zawya in Fulfillment of the Requirements for Degree of Master of Science in the Department of Electrical and Electronic Engineering

Presented By: ***Wafa Hadi Dradi***

Supervisor Name: ***Dr. Ali Al-Amouri***

Fall 2020

الملخص:

الدماغ البشري هو مركز الجهاز العصبي.وهو مجموعة من الخلايا البيضاء مثل االخلايا العصبية والخلايا الدبقية والاوعية الدموية والانسجة الليمفاوية ،والزيادة غير المنضبطة لهذه الخلايا الموجودة بشكل غير طبيعي في جزء مختلف من الدماغ تكون مايعرف بالورم .

يعد تحديد ورم الدماغ مهمة صعبة حقًا في المراحل المبكرة من الحياة. ولكن الآن أصبح متقدمًا مع العديد من خوارزميات التعلم الآلي والتعلم العميق، حيث أصبحت قضية التحديد التلقائي لورم المخ ذات أهمية كبيرة .

ومن أجل الكشف عن ورم دماغ المريض ، نأخذ في الاعتبار بيانات المرضى مثل صور التصوير بالرنين المغناطيسي لدماغ المريض .

يعد اكتشاف منطقة الورم المصابة واستخراجها من صور الرنين المغناطيسي (MRI) مصدر قلق أساسي ، وهي مهمة شاقة وتستغرق وقتًا طويلاً يؤديها اختصاصيو الأشعة أوالخبراءالسريريون .

حيث تعتمد دقة التصوير بالرنين المغناطيسي على خبرة الطبيب فقط. لذلك ، يصبح استخدام التكنولوجيا بمساعدة الكمبيوتر ضروريًا للغاية للتغلب على هذه القيود.

كما يعد التحليل الدقيق لصور ورم الدماغ خطوة أساسية في تحديد حالة المريض. ومع ذلك ، فإن تراكم المعرفة الطبية الشخصية للأطباء ، والاختلافات في مستويات الخبرة ، والتعب البصري يمكن أن يؤثر على التحليل الصحيح لنتائج الصور

في هذه الأطروحة ، يتم تقديم مثال لاكتشاف تشوهات الدماغ باستخدام تطبيق الشبكة العصبيةاللالتفافية (cnn).

كما تم استخدام نماذج التعلم العميق على نطاق واسع لتحليل الصور الطبية على مدى السنوات القليلة الماضية.

في هذه الاطروحة قد قمنا بتدريب نوعين من الشبكة العصبية الاصطناعيةالالتفافية وهي

(Alexa net&Googlnet) لتصنيف صور MRl تلقائيًا إلى فئات الأمراض العادية ، والأوعية الدموية الدماغية ، والأورام ، والأمراض التنكسية ، والالتهابات. قمنا أيضًا بمقارنة أداء تصنيفهم بالنماذج المدربة. حصلنا على أفضل دقة تقييم (98.67٪ مع نموذج googlenet ، و 97.33٪ مع Alexnet) للنماذج المدربة. نموذجنا جاهز للاختبار باستخدام صور التصوير. بالرنين المغناطيسي الضخمة لتشوهات الدماغ. ستساعد نتيجة النموذج أيضًا الأطباء على التحقق من صحة نتائجهم بعد قراءة صور التصوير بالرنين المغناطيسي باليد.

Abstract

Brain disorders may cause loss of some vital functions such as thinking, speech and movement. Therefore, early detection of brain disease may assist in getting the best treatment in time. One common way to diagnose these disorders is magnetic resonance imaging (MRI) technology. Manual diagnosis of brain abnormalities takes a long time and subtle changes are difficult to perceive on (MRI)images, especially in the early stages of the abnormalities.

In this thesis, a method to detect brain defects using a neural network application is Introduit. Appropriate selection of features and classifiers to obtain higher performance a challenging task. Hence, deep learning models have been widely used for medical image analysis over the past few years. In this thesis, we trained AlexNet models, a Googlenet to automatically classify MRI images into the categories of normal diseases, cerebrovascular, neoplastic, degenerative diseases, and inflammations. We also compared their rating performance with trained models. We got the best rating accuracy (98.67% with the Googlenet model, 97.33% with Alexnet) for the trained models. Our model is ready for testing with massive MRI images of brain abnormalities. The model result will also help clinicians validate their results after hand reading the MRI images.

Dedication

To everyone who taught me letters in this mortal world.

To the pure spirit of my father.

To my dear mother.

To my dear husband and sons and daughters.

To all my loved family members.

To my colleagues and colleagues ,who have had a great impact on all obstacles and difficulties.

To all my honorable teachers who did not hesitate to extend a helping hand to me.

We ask God to make it a beacon for every student of knowledge.

ACKNOWLEDGMENTS

First of all I would like to specify to my supervisor **Dr. Ali . Al amorai** sincere thanks and gratitude for his intensive supervision, guidance and continuous help during the study and the preparation of this research, great thanks wishing from god to pless him

I would like to express my deep thanks to my husband**, yousef alharabi,** for his patience, encouragement and lending a helping hand in completing this work.

Finely I would like to express my thanks and gratitude to my friends for their support and help during my study and research, and my special thanks to my family,for encouragement and patience during my study.

Table of Contents

List of Figures

List of Tables

Acronyms

HG	High Grade
LG	Low Grade
SVM	Support vector machine
MRI	Magnetic Resonance Imaging
DICOM	DICOM Digital Imaging and Communications in Medicine
DBN	deep belief network
FCM	Fuzzy C Means
DNN	Deep Neural Network
CNN	convolutional neural networks
DWT	discrete wavelet transform
RELU Layer	Rectified Linear Unit
RGB	RED ،GREEN& BLUE
DIP	Digital Image Processing
CV	CORSS VILDATION
ML	Machine Learning
DL	Deep Learning
N/A	Not Available
TP	true positive
TN	true negative
FP	False positives
FN	false negative
ACC	Accuracy
REC	Recall
PREC	Precision

CHAPTER ONE

INTRODUCTION

1.1 Introduction

Brain tumor is a mass or accumulation of biological cells in the brain. These cells are classified as abnormal cells that differ from the cure brain cells. These cells grow and increase in size inside the rigid skull that encloses the brain.[1] Detection of these tumors from brain is very difficult at the regions where a tumor is overlapped with dense brain tissues.

Visual detection of these abnormal tissues may result in misdiagnosis of volume and location of unwanted tissues due to human errors caused by visual fatigue[2]. The brain is a complex human body organ and works through billions of cells. Brain tumors are caused due to the uncontrolled growth of cells. These cells might affect normal brain activities and also destroy normal cells. Gliomas are a primary type of brain tumors. It contains IV grades (I, II: High Grade (HG) and III, IV: Low Grade (LG)) [3] . Despite major developments in the medical field like surgical procedure, chemotherapy and radiotherapy, still malignant brain tumor cases are untreatable. According to reports[3] Brain tumor is nothing but any mass that results from an abnormal and an uncontrolled growth of cells in the brain. Its threat levels depend upon the combination of factors like the type of tumor, its position, its size and its state of growth. Brain tumors can be malignant (malignant) or non- malignant (benign).[4] The early detection of any type of disease is a key stone in the cure of patient that increases the survival possibilities. This is also true in the case of brain tumor. The early detection reduces the danger on the life of patients and increases their hopes of being cured to 90%. However, early detection of the tumor is a process that involves the intervention of expert people in all evaluation process of the patien.[1] This study of brain Images is helpful in brain tumor diagnosis processTumor and cancer is a harmful and death-defying disease for humanLife. And effort to reveal the importance of the imageClassification in the world of the Biocomputing field .image classification technique is efficiently improving the process of diseaseDiggram.it is a process in which images are labeled into numerous predefined classes .Several techniques has been introduced for image

Classification like SVM .Boltzman.fuzzy C-mean.Random forest and many others. This study will a model in which deep neural network technique is used with grey scaled segmentation technique combination of these two techniques is giving better result in minimum computational time.

1.2- Problem Statement

The main problem in tumor detection using 2D or 3D medical images is the unavailability of a robust and reliable method. Classification of human brain tumors types (i.e. malignant and benign) is performed using conventional methods used object recognition. Finding a dataset that consists of benign and malignant image dataset is also consider a serious research issue because no freely dataset is available An efficient and accurate tumor detection system using brain MRI images to identify which slices or images consists of tumors. Also the lack of a training dataset make it more complicated task. Once the tumor is detection in the brain region then it is easy to isolate/segment and identify the type of brain tumors. A serious issue in this research domain is training and guidance about the various diseases, modalities and software that are used for the analysis of medical images.

1.3-Objectives of this Research .

The main objectives of the thesies can be summinzed as follows:

- To develop a dataset that consists of normal and tumors images, which will be used for the training and validation of our proposed method.
- To develop a technique, which will be able to automatically detect whether an image consists of brain tumor or not.
- To use a Convolution neural network (CNN) model will be used for the feature extraction and classification of MRI image either it contains tumor or not.

1.4 Significance of the Study

Processing DICOM volumetric image is a challenging and time consuming task, volumetric data consist of many DICOM slices and each slices has an importance (more or less) in the disease study. It is crucial to study all the slices at same time, an automatic system is needed to separate the normal slices with no tumor and abnormal slices with tumor. In a study where the whole thousands of DICOM images exist, it is difficult for the radiologist to study each single slice of the DICOM. This automatic detection of tumor slices make it easy for the radiologist, surgeons in treatment planning and surgeries. Early and efficient diagnosis of tumor can save a life, tumors if not treated on time maybe life threatening. Convolution Neural Networks is a deep learning technology used to understand and learn patterns in a digital image. CNN models are trained on image for various application such as tumor detection, tumor type recognition, skin cancer detection, blood cancer detection.

1.5-Scope of study

The proposed research work is to develop a method based on machine learning, image processing and deep learning for detection of tumor in a digital MRI image. Image processing techniques are used to enhance the image quality, segment region of interest from an image, image information such as texture, geometry are used for advance image processing. Machine learning based system assists us to develop automatic system for the diagnosis of various abnormalities, CNN is deep learning technology for image data. A CNN model has two parts e.g. features extractor and classifier. To develop a system, which will automatically recognize whether a brain MRI image consist of tumor or not. The CNN must trained on normal brain MRI and tumor MRI images. CNN learns from images of both these classes, once the system is trained it can be used to classify an image into normal image or tumor image. The develop system will be evaluated with the validation data, machine learning classification performance parameters will be used to compute the performance of the CNN model.

1.6- Related Works

Different classification methods in brain tumor dectaction have been developed over the last few years. Most of the methods involve segmentation, feature extraction and classification process to classify brian tumors.

The study of cancerous tumor has attracted the attention of many researchers around the world. Hundreds of researches are being published yearly that discuss issues related to t he brain tumor.

There are number of researches have been developed for early detection of brain tumor. The following paragraphs discuss some of these researches.

(Mustafa Rashid Ismael) [5] Network classifier, the proposed classification system trains each layer separately, and controls.

The release of every neuron into the crypt orchid layer, reduces over fitting. This can be accomplished because The Soft max function (within the Softmax classifier) is designed for multi-class logistics Regression compared to the x-function (used by the back propagation neural network Classifier) restricted to two-class logistic regression. This suggested system could be helpful A tool for radiologists as a second opinion for diagnosing a tumor

(J. Seetha1As.Selvakumar2) [6] Raja. The main goal of this research work is to design efficient automatic brain tumor classification with high accuracy, performance and low complexity. In the conventional brain tumor classification is performed by using Fuzzy C Means (FCM) based segmentation texture and shape feature extraction and SVM and DNN based classification are carried out. The complexity is low. But the computation time is high meanwhile accuracy is low.Further to improve the accuracy and to reduce the computation time, a convolution neural network based classification is introduced in the proposed scheme

(Naz, Saeeda, and Ibrahim A. Hameed)[7]. Modified probabilistic neural network technique implemented in this work. the processing time to approximately 79%. Training result of 100% was also obtained in this research. Discrete cosine transform based brain tumor classification was presented by (Sridhar & Krishna,). Authors also presented a neural network based brain tumor classification and presented a comparison between results. The tumor detection based on radial basis neural networks and regression based neural networks was presented in (Thara & Jasmine,)[8]. The use of different types of ANN based tumor detection techniques were also presented in (Subashini & Sahoo,)[9], (Amsaveni & Singh,)[10]. Unsupervised artificial neural network for brain tumor detection was also proposed by (S. Goswami & Bhaiya,)[11]. Many other researchers have also focused and studied the brain tumor detection based on different approaches and new techniques. we explored two important clinical tasks: brain lesions classification and detection. We proposed end-to-end trainable approaches based on state -of the- art deep convolutional neural networks. And implemented a novel pooling operator: l2-norm unit which can effectively generalize the network, and make the learned model more robust. The applicability, model accuracy and generalization ability have been evaluated by using a set of publicly available datasets. As the future work we will further investigate the automatic segmentation of tumor regions based on the detection results(, Prof.-Dr.-Helmert-Strae)[12]. The network (CNN) trains a set of examples in an unsupervised manner.The layers then act as a feature detector on the input. after this Learning step, to perform the classification, it can be DBN More training in a supervised way. The system mainly includes three steps which are pre-treatment, classification and post-processing. A DBN The (Deep Faith Network) based classification method is used to identify a brain tumor on MRI images that can yield more results Accurately.(Sapra, Pankaj, Rupinderpal Singh, and Shivani Khurana)[13] The paper proses a method for classification of tumor in a brain image. The main objective of this step is to differentiate the different abnormal brain images based on the optimal feature set. This classification is performed on proton Magnetic Resonance Spectroscopy images. (Mohsen, Heba, et al)[14] we proposed an efficient methodology which combines the discrete wavelet transform (DWT) with the Deep Neural Network (DNN) to classify the brain MRIs into Normal and 3 types of malignant brain tumors: glioblastoma, sarcoma and metastatic bronchogenic carcinoma The new methodology architecture resemble the convolutional neural networks (CNN) architecture but requires less hardware specifications and takes a convenient time of processing forlarge size images (256 * 256). In addition using the DNN classifier shows high accuracy compared to traditional classifiers. The good results achieved using the DWT could beem ployed with the CNN in the future and compare the results(Badža, Milica M., and Marko Č. Barjaktarović. ".)[15]fore definitive brain surgery. The improvement of technology and machine learning can help radiologists in tumor diagnostics without invasive measures. A machine-learning algorithm thathas achieved substantial results in image segmentation and classification is the convolutional neural network (CNN). We present a new CNN architecture for brain tumor classification of three tumor types. The developed network is simpler than already-existing pre-trained networks, and it was testedon T1-weighted contrast-enhanced magnetic resonance images The performance of the network was evaluated using four approaches: combinations of two 10-fold cross-validation methods and two databases. The generalization capability of the network was tested with one of the 10-fold methods,subject-wise cross-validation

1.7 Methodology

In biomedical image processing and computer visions systems reliable and features extraction method plays an important role in disease diagnosis and patient treatment plans. To understand we consider that image is our data which is meaningless for user who don’t have medical background, this image data is processed in such a way that some special kind of information points are extracted. These features are used by classifiers to develop a method that allow us to detect and recognize various kind of disease and abnormalities in the human body. Image features are stored in feature vector that are labeled and passed to classifier for training. Images features are numerical values and the vector used to store these features is called features vector. The mechanism of

Normal and tumor containing image classification system is similar to the object recognition problem in computer vision and machine learning.

Our proposed approach is summarized into the following steps:

1) Incorporating stand-of-the-art CNN model based features extraction.
2) Classification of MRI images using matlab program.

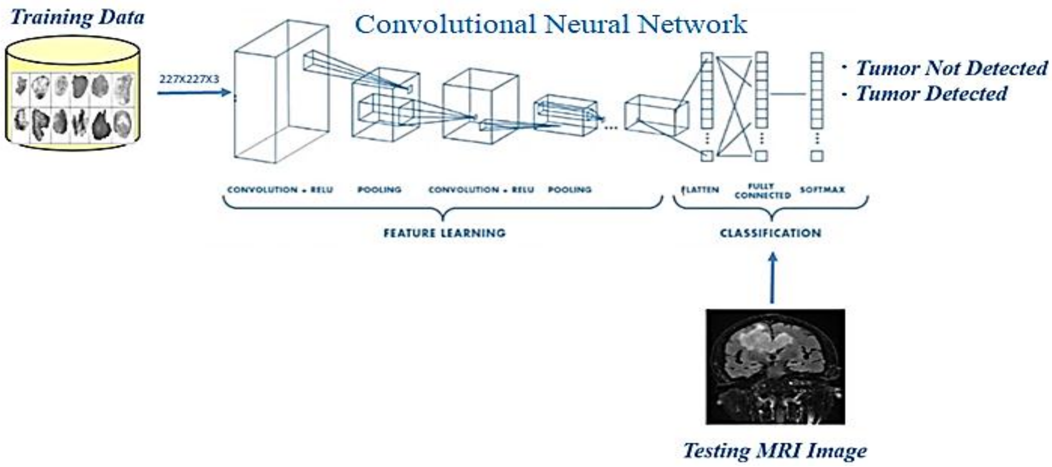


Fig (1.1), our proposed framework for the detection of tumor in MRI images.

1.8 Thesis Organization

The study is evaluating in the form of different chapters. Thesis structure is given below.

Chapter One Introduction tells about research topic, its aims and objective and importance of this whole study .

Chapter Two Convolutional Neural Network .

Chapter Three Digital Image Processing Techniques .

Chapter Four Experimental results and discussions articulate the implementation is presented. Discuss the analysis of researcher of this study with the help of final results.

Chapter Five The conclusion of the whole work and future recommendation has been Introduced

CHAPTER TWO

Convolutional Neural Network

2.1- Introduction

Convolutional Neural Network are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to over fitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. However, CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme[16].

Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing. [17]

2.2- Convolutional Layer

each convolutional layer within a neural network should have the following attributes[18]:

- Input is a tensor with shape (number of images) x (image width) x (image height) x (image depth).
- Convolutional kernels whose width and height are hyper-parameters, and whose depth must be equal to that of the image. Convolutional layers convolve the input and pass its result to the next layer. This is similar to the response of a neuron in the visual cortex to a specific stimulus.

Each convolutional neuron processes data only for its receptive field. Although fully connected feed forward neural networks can be used to learn features as well as classify data, it is not practical to apply this architecture to images. A very high number of neurons would be necessary, even in a shallow (opposite of deep) architecture, due to the very large input sizes associated with images, where each pixel is a relevant variable. For instance, a fully connected layer for a (small) image of size 100 x 100 has 10,000 weights for *each* neuron in the second layer.

The convolution operation brings a solution to this problem as it reduces the number of free parameters, allowing the network to be deeper with fewer parameters. For instance, regardless of image size, tiling regions of size 5 x 5, each with the same shared weights, requires only 25 learnable parameters. In this way, it resolves the vanishing or exploding gradients problem in training traditional multi-layer neural networks with many layers by using back propagation[19].

A convolution is how the input is modified by a filter. In convolutional networks, multiple filters are taken to slice through the image and map them one by one and learn different portions of an input image. Imagine a small filter sliding left to right across the image from top to bottom and that moving filter is looking for, say, a dark edge. Each time a match is found, it is mapped out onto an output image.

There is an image of a brain tumor and the shown matrix is used as a convolution to detect dark edges. As a result, we see an image where only dark edges are emphasized.

Note that an image is 2D (dimensional) with width and height. If the image is colored, it is considered to have one more dimension for R.G and B color. For that reason, 2D convolutions are usually used for black and white images, while 3D convolutions are used for colored images.[20]

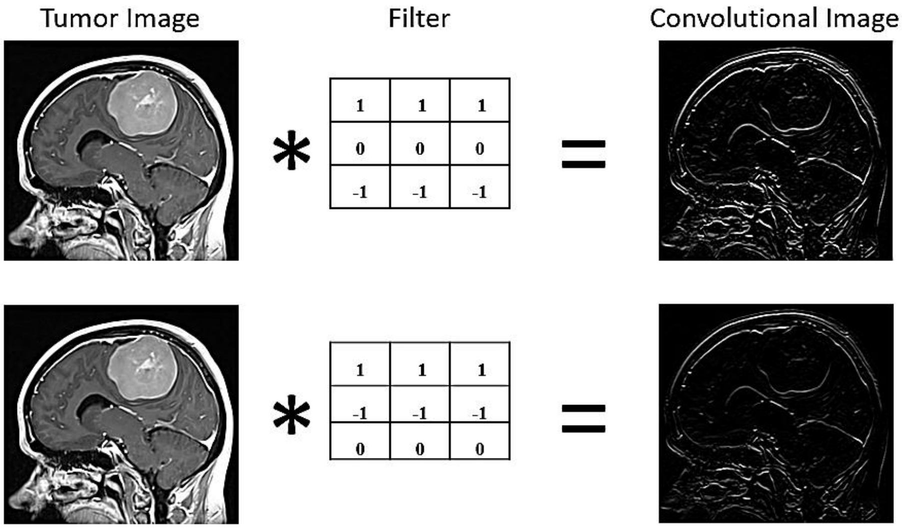


Fig (2.1), Applying Convolutional Filter on MRI Images.

2.3- Pooling Layer in CNN.

Convolutional networks may include local or global pooling layers to streamline the underlying computation. Pooling layers reduce the dimensions of the data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer. Local pooling combines small clusters, typically 2 x 2. Global pooling acts on all the neurons of the convolutional layer. In addition, pooling may compute a max or an average. *Max pooling* uses the maximum value from each of a cluster of neurons at the prior layer. *Average pooling* uses the average value from each of a cluster of neurons at the prior layer [21]

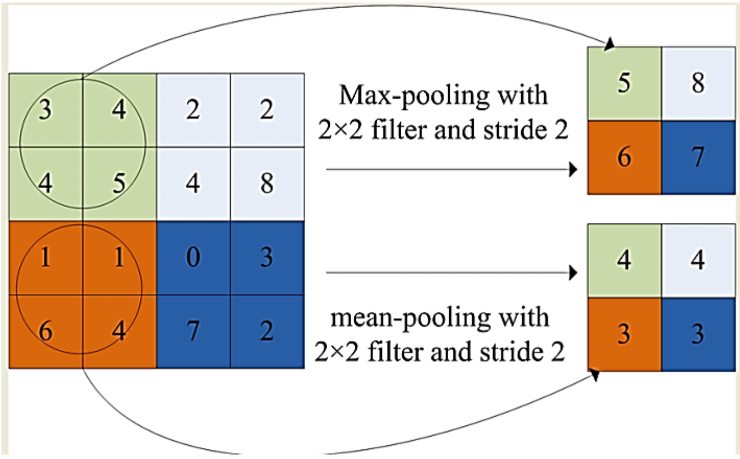


Table (2.1), Applying Max, Mean Pooling on Matrix.

2.4- RELU Layer in CNN (Rectified Linear Unit)

ReLU is the abbreviation of rectified linear unit, which applies the non-saturating activation function.

$$f\ (\chi) = \max(0, x) \quad \dots\dots\dots\dots..(2.1)$$

It effectively removes negative values from an activation map by setting them to zero.[16] It increases the nonlinear properties of the decision function and of the overall network without affecting the receptive fields of the convolution layer. Other functions are also used to increase nonlinearity, for example the saturating hyperbolic tangent

$f(x) = \tanh(x)$……………………….....(2.2)

$f(x) = |\tanh(x)|$ ………………………..(2.3)

and the sigmoid function

$\alpha(x) = (1+e^{-x})^{-1}$………………………...(2.4)

ReLU is often preferred to other functions because it trains the neural network several times faster without a significant penalty to generalization accuracy.[22]

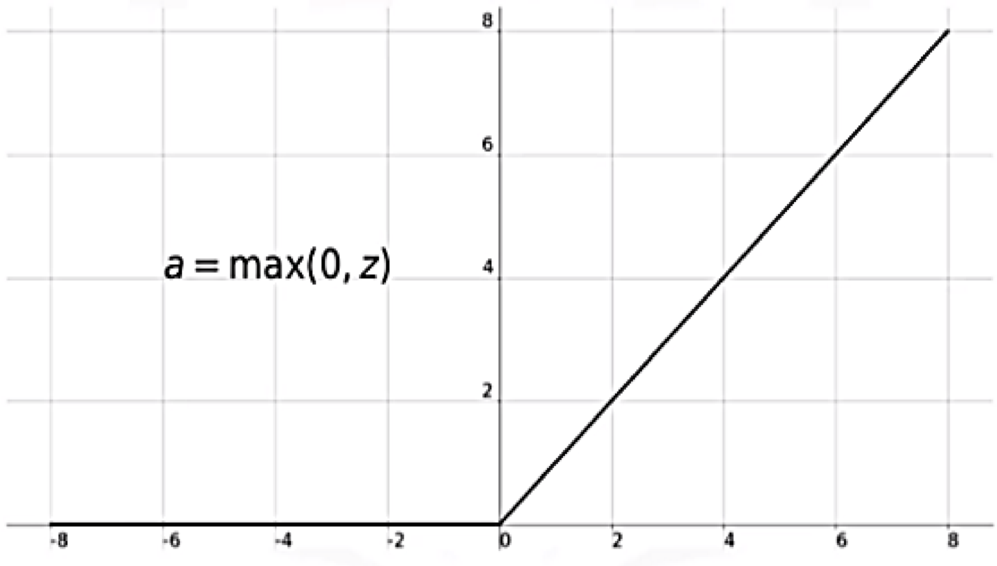


Fig (2.3) RELU Activation in Cnn

The rectified linear unit, or ReLU, function is the most widely used activation function when designing networks today. In addition to it being nonlinear, the main advantage of using the ReLU, function over the other activation functions is that it does not activate all the neurons at the same time. According to the plot here Table(2.2), if the input is negative it will be converted to 0, and the neuron does not get activated. This means that at a time, only a few neurons are activated, making the network sparse and very efficient. Also, the ReLU function was one of the main advancements in the field of deep learning that led to overcoming the vanishing gradient problem[23].

Input Matrix

55	-2	51	24
86	25	75	-63
25	-12	02	35
95	15	-25	44

⟶

RELU Activation

55	0	51	24
86	25	75	0
25	0	02	35
95	15	0	44

Table (2.2), Applying RELU Activation function on a Matrix.

2.5 -Fully Connected Layer in CNN.

After several convolutional and max pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular (non-convolutional) artificial neural networks. Their activations can thus be computed as an affine transformation, with matrix multiplication followed by a bias offset (vector addition of a learned or fixed bias term) see Table(2.3) [24]

Input Matrix

55	2	51	24
86	25	75	63
25	12	02	35
95	15	25	44

Fully Connected

55
86
25
95
2
25
12
15
51
75
02
25
24
63
35
44

Table (2.3), Fully Connected Layer on a Matrix.

2.6 –Dropout layers in CNN.

Have very specific function in neural network , it is prone to over fitting. One method to reduce over fitting is dropout. At each training stage, individual nodes are either "dropped out" of the net with probability 1-*p* or kept with probability *P*, so that a reduced network is left; incoming and outgoing edges to a dropped-out node are also removed. Only the reduced network is trained on the data in that stage. The removed nodes are then reinserted into the network with their original weights. In the training stages, the probability that a hidden node will be dropped is usually 0.5; for input nodes, this should be much lower, intuitively because information is directly lost when input nodes are ignored. At testing time after training has finished, we would ideally like to find a sample average of all possible 2^n dropped-out networks; unfortunately this is unfeasible for large values of *n*. However, we can find an approximation by using the full network with each node's output weighted by a factor of p, so the expected value of the output of any node is the same as in the training stages. This is the biggest contribution of the dropout method: although it effectively generates 2^n neural nets, and as such allows for model combination, at test time only a single network needs to be tested[25].

2.7-Softmax Layer in CNN .

A Softmax function is a type of squashing function. Squashing functions limit the output of the function into the range (0 ، 1). This allows the output to be interpreted directly as a probability.The softmax function takes as input avector X of K real numbers and normalizes it into aprobability distribution .Consisting of K probabilities proportional to the exponential sof the input number، Similarly, softmax functions are multi-class sigmoids, meaning they are used in determining probability of multiple classes at once. It is important to note that a softmax layer must have the same number of nodes as the output later. The Softmax function is computed using the relationship defined by the formula:- [26].

$$f(x_i) = \frac{exp\ (x_i)}{\sum_{j=1}^{k} exp(x_j)} \quad \ldots\ldots\ldots\ldots\ldots..(2.5) \quad \text{for } j = 1\ldots k$$

A neural network may be attempting to determine if there is a dog in an image. It may be able to produce a probability that a dog is, or is not, in the image, but it would do so individually, for each input. A softmax layer, allows the neural network to run a multi-class function. This example is figured below:

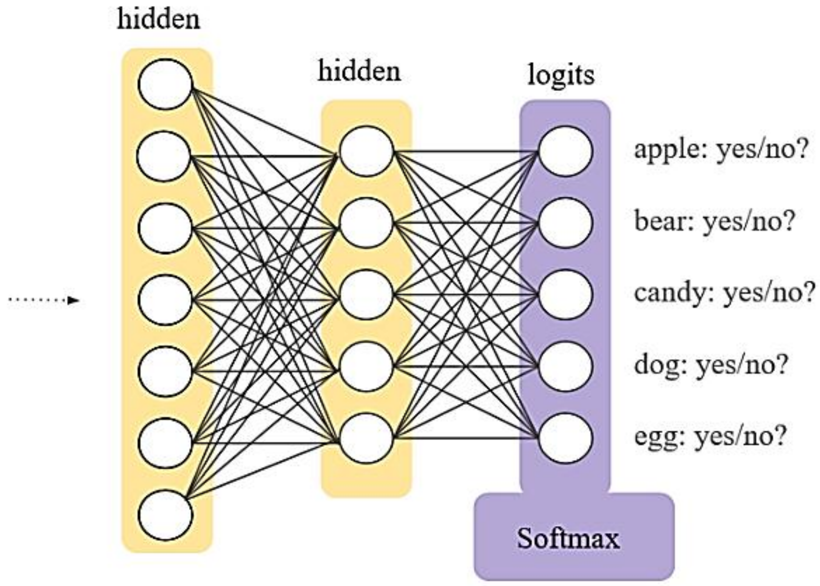


Fig (2.4)Applying Softmax layers.

In those situations, candidate sampling can be an effective workaround. With candidate sampling, a softmax layer will limit the scope of its calculations to a specific set of classes. For example, when determining if an image of a bowl of fruit has apples, the probability does not need to be calculated for every type of fruit, just the apples. Additionally, a softmax layer assumes that `there is only one member per class, and in situations where an object belongs to multiple classes(yes=1,no=0)

2.8-Forward Pass

Convolutional neural networks is a type of feed forward neural networks in which a forward pass of training is computed with no loops in neuron connections; the next layers must only be connected to previous layers. When movingto a convolutional or fully connected layer, aset of weights and bias is applied to all of the connected neurons from the previous layer inorder to sum them together. This canbe seen as applying a certain weight to a certain pixel and adding a bias. [21].

2.9 –Alexnet

In 2012 Alex Krajevsky proposed a deep convolutional neural network.

Alex Net has eight neural network layers and five convolutional and Three are fully connected (see Fig 2.5)[27] This laid the groundwork forCNN, a conventional convolutional layer followed by an activation function followed by the maximal assembly process (sometimes Deleted to preserve image spatial resolution). AlexNet was the first to implement corrected linear units (ReLUs) as energizing functions.

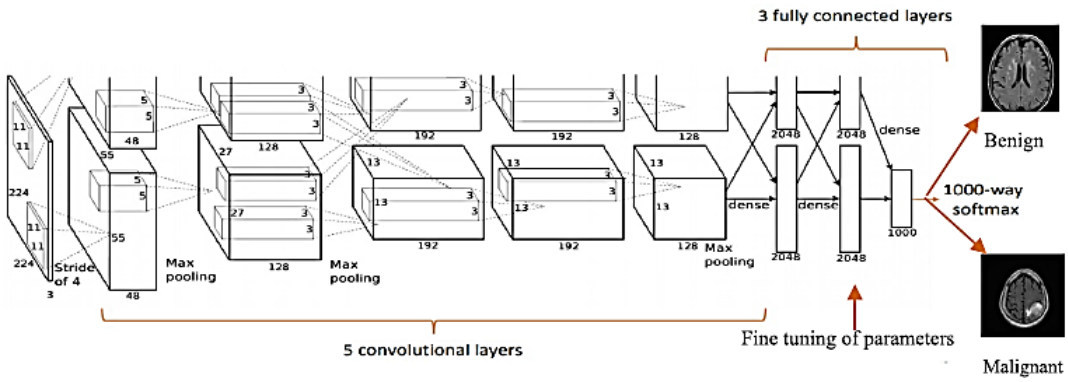


Fig (2.5) AlexNet

CHAPTER THREE

Digital Image Processing Techniques

3.1- Introduction.

Image processing is one of the most important and useful sciences in our daily life. It is employed extensively in our daily life , scanners, printers ,Our mobile cameras, TVs, computers, and many other applications are using digital image processing to present us the visual effects that we see all around us. Image processing is the mathematical representation and treatment of the image to obtain and modify its features or to ameliorate its characteristics .Pre-treatment mainly includes those processes which are usually necessarily prior to the main objective analysis And extract the required information and engineering corrections on the actual original image. These improvements It includes data correction for irregularities and unwanted atmospheric noise, and removal and transformation of the non-constituent image of the brain Data so that it is properly reflected in the original image. But the main difficulties with image processing are: 1) noise, 2) low-contrast blur, 3) field bias) incidence Varying intra-tissue intensity), 4) effect of partial size. Photo filter and The improvement stage is the most obvious part of medical image processing. This pre-treatment is used to reduce the image Noise, highlighting important parts, or displaying clear portions of digital images [8]. Other techniques may be used Medical image processing of coherent echo signals before image creation and some images are suspended from the clip thus Noises may occur. The optimization stage includes improving accuracy; Brightness improvement. These are used for Noise suppression and imaging of spectral parameters. After this stage, the medical image is converted to a standard image without it Noise, cinematic artifacts, and posters[28]

3.2- RGB image

The human retina has three different types Types of receptors or optic sticks. These rods can sense three different types of waves The frequencies that correspond to the colors red, green, and blue. Then all the other colors The brain is constructed by mixing the intensities of these three major colors. In RGB images, The colors are made from a combination of the intensity of these three colors in every single pixel. The human visual system is more complex and different from digital systems. Humans can extract More useful information from pictures and get details of the colors that look as well Not important for digital computers[1]

3.3- RGB to gray image conversion

Color images can be converted To gray scale images. It can be a conversion Made using the proposed equation.

$$Iy = 0.333Fr + 0.5Fg + 0.1666Fb \ldots\ldots\ldots\ldots(3.1)$$

Where Fr, Fg, and Fb is the density of R(RED), G(GREEN) and B(BLUE)The component respectively and I is the equivalent gray intensity RGB image level image[32]Then the gray scale images are represented by the intensity values. Where Gray scale images have many shades of gray in between black and white. The pixel value is represented in a specific range between 0 and 1 (minimum And maximum) and between varying degrees of Gray that ranges from 0 to 255. Image pixels It is stored in binary, quantitative form.[29]

3.4 Mean Normalization

The mean along each of the features (dimensions of images) of training samples is computed and subtracted from each of the images. This way the whole training set is turned into organized data . Thus the brightness of the whole training set is normalized with respect to each dimension. This is done by[3.2].

$$X' = X - \mu \quad \text{.........(3.2)}$$

Where X' is the normalized data, X is the original data and μ is the mean vector across all the features of X.[30]

The flowchart of the proposed Research flow diagram is shown in fig (3.1).

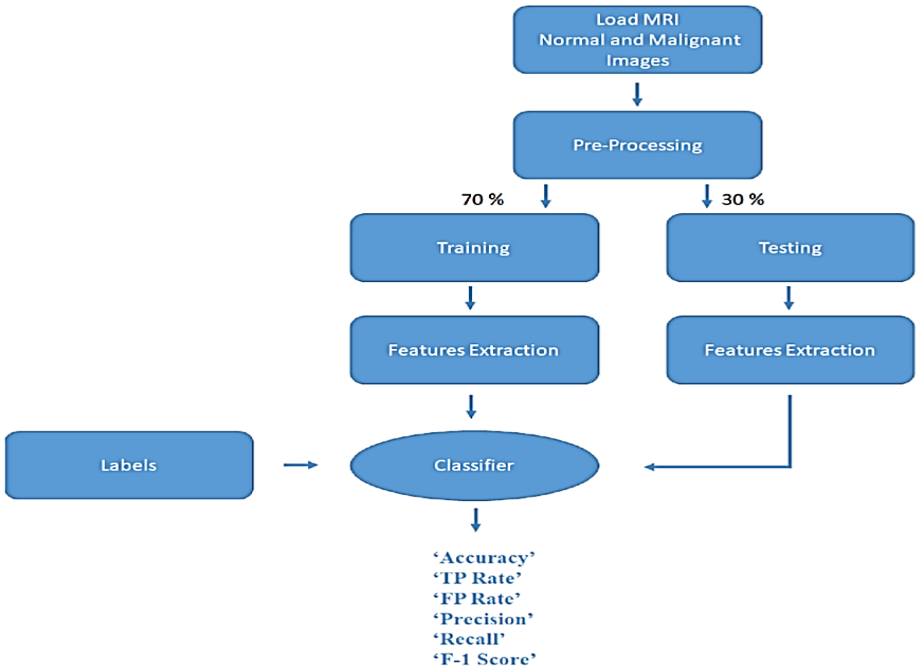


Fig (3.1), Our Proposed Research Flow diagram

We upload and insert normal and malignant MRI images. Then we adjust the dimensions of each image specifically first, then convert the pixel values from(0،255), transform them between (-1، 0) or(-1 ، + 1). Then we allocate a simple segment with which we test the model 30% and the greater part 70% for training (this is a common Prostiger.

Then the feature extraction in general means reducing image dimensions. In other words, we need before we start the model on an image, try to extract the most important features that enter / contribute significantly to the classification process, and therefore if we enter the image as it is, the model will give all the image details importance and thus we will be in the end In front of a problem called over fitting, meaning that the model saves the pictures without what he understands how to distinguish between them, so that if we give him a new picture I don’t see it, the error rate will be large because he knows things that are unnecessary.

Therefore, we need to create a feature extraction in order to reduce the insignificant features that have nothing to do with identifying or classifying the disease Then we give image data or any other data and the corresponding data from the label, for example, the first image represents a patient and the second is healthy, so the label gives 1 to the patient’s image and the label to the second image 0. What is required from the label is that it is extracted from the image so that he can distinguish it, for example, so that it gives 1 out put propolety for the first image.

When we do a test for the model, we block the label, we only give it Data (imge) and we give it a signal to predict the label for this image in case it is healthy or infected. Based on the prediction, we measure the accuracy of the model based on the strength, degree, or accuracy of the prediction approaching the true value.

CHAPTER FOUR

Experimental Results and discussions

4.1- Introduction

This chapter will present the Introduced Methods in this Thesis. All practical results by applying a neural network will be tabulated, discussed and evaluated.

In the proposed system 200 different brain images(normal & Abnormal) was used. All of these images have been graded based on the expertise of specialists and carefully separated.

The brain MRI images used in this work were downloaded from Radiopedia database. We used the entire data set, all brain images have equal sizes of 256 x 256 pixels and T2 in the axial plane. . The brain image consists of a different number of slices. In Figure 4.1, different slices of brain images are shown. We obtained a total of 200 images slidesl from this dataset.

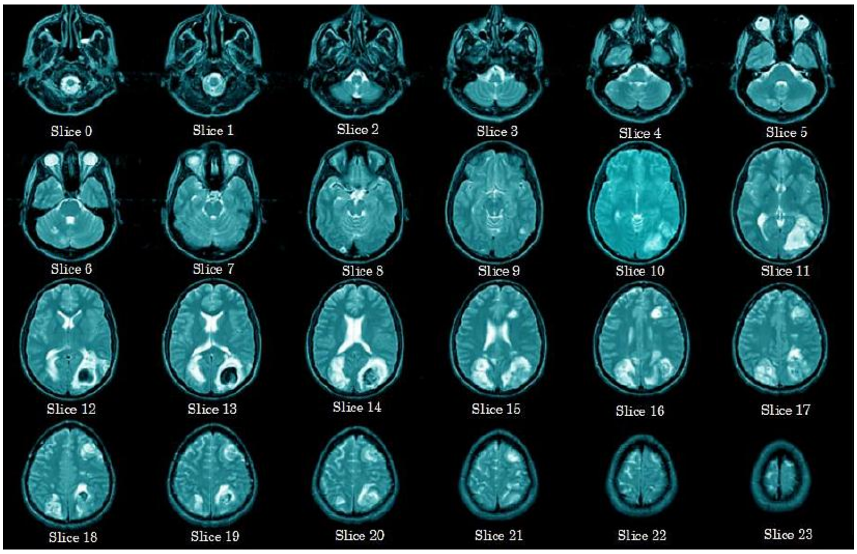


Figure (4.1): Sample of our database images

In this work, all database images will be processed using convolutional neural network techniques to classify these images. The goal of classification and treatment is to provide an automated decision system that can assist drugs in making their final decisions about a brain tumor at its various stages. It is also needed to help in the early detection of the brain tumor; the thing that can reduce the number of brain tumor caused death cases.

Table (4.1) : Programming/Simulation Parameters:

Programming Evironment	MATLAB R2018a
Tool Boxes	(Digital Image Processing **DIP)**, (CORSS VILDATION **CV),** **(**Machin Learning**ML**)and(Deep Learning **DL**)
Datasets	Radiopedia
No of classes	2 (Tumor and Normal)
Features Extraction Time	N/A(Not Available)
Training Time	N/A((Not Available)
Average Time of testing image	N/A((Not Available)
Classifier	Deep Learning
Experimental Evaluation Parameters	Confussion Matrix

4.2 -Comparision Parameters

- Comparison of Accuracy based on confusion matrix with different cross-validation
- Comparison of our proposed technique with some of the updated state-of-the-art techniques.

Action steps When using an infected image and un-infected image, they are the same etc.

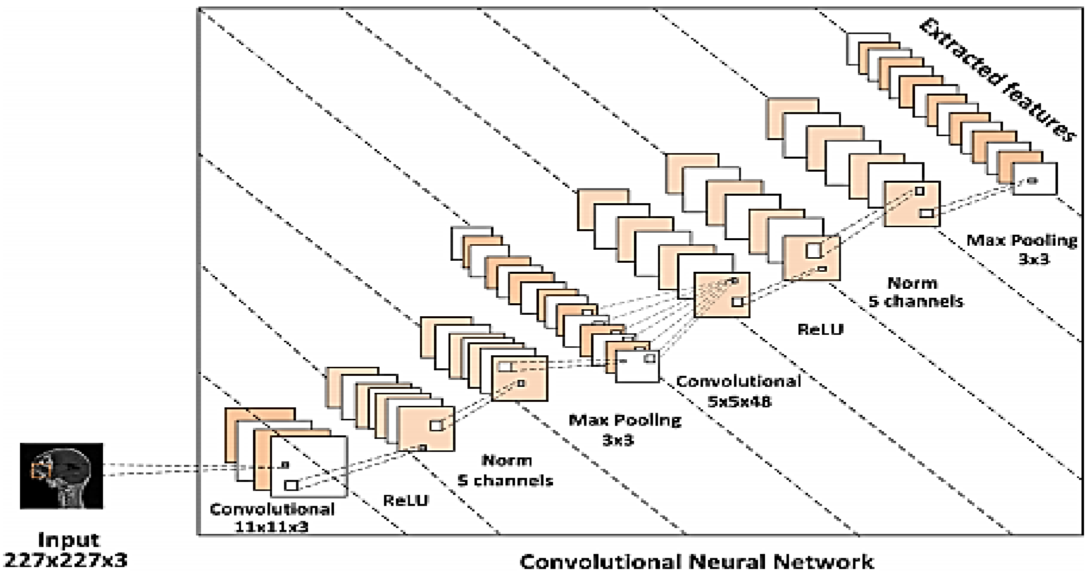


Fig (4.2)Convolutional neural network

From the image above, we can see that the CNN architecture is simply: Image passes through Convolution, Pooling, and Fully Connected twice, which is CNN architecture (see fig (4.2))**.**

Step one :Convolution layer

The Convolution process is to compare the original image with a specific image. Feature Detector (filter) We have done a Convolution process (symbol⊗). The Convolution process is 3 x3. The arrays are multiplied and then added (0 * 0 + 0 * 0 + 0 * 1 + 0 * 1 + 1 * 0 + 0 * 0 + 0 * 0 + 0 * 1 + 0 * 1) = 0

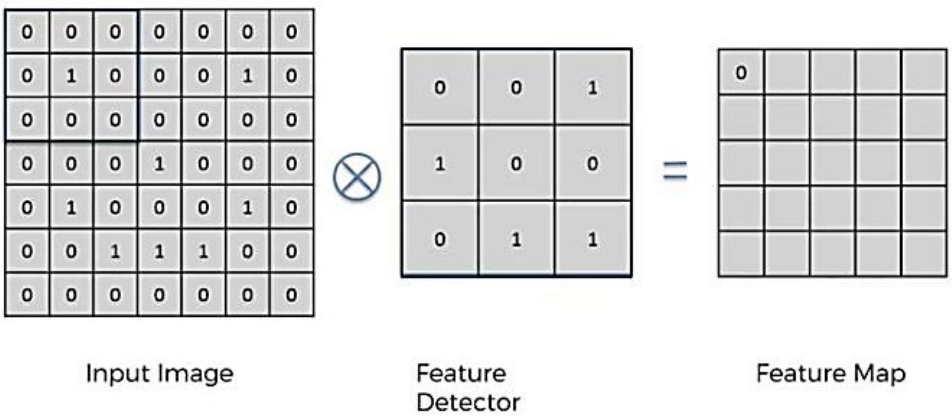


Fig (4.3) Input Image& Feature Detector

Every time one step moves(Means the filter is sliding pixel by pixel), we can calculate the result of the entire matrix, As follows:

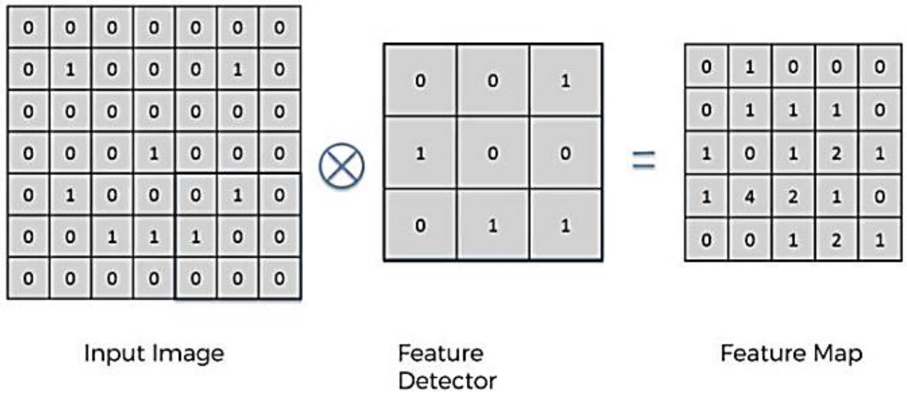


Fig (4.4)The result of feature Map

The feature detector (Filter) in the middle will randomly generate several types. The purpose of the feature detector is to help us extract some features (such as: shape) in an image, just like the human mind judging whether this image is also based on shape.

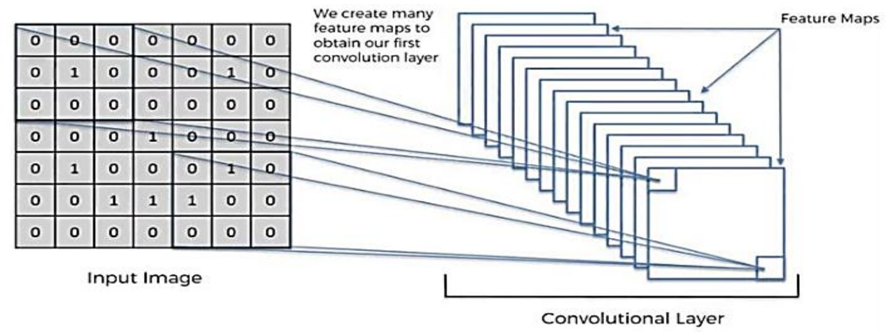


Fig (4.5)The feature Map

We used Relu (Activation Function) function to remove negative values, which can better improve the look of the image.

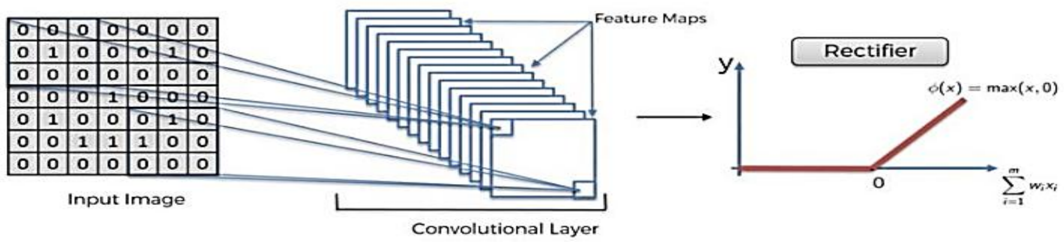


Fig (4.6)The Activation Function

Black = negative. White = positive value

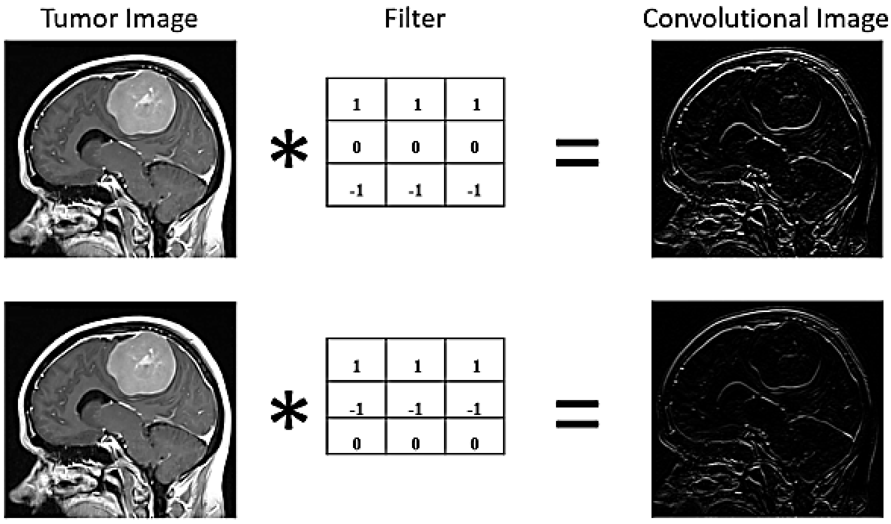


Fig (4.7), Applying Convolutional Filter on MRI Images

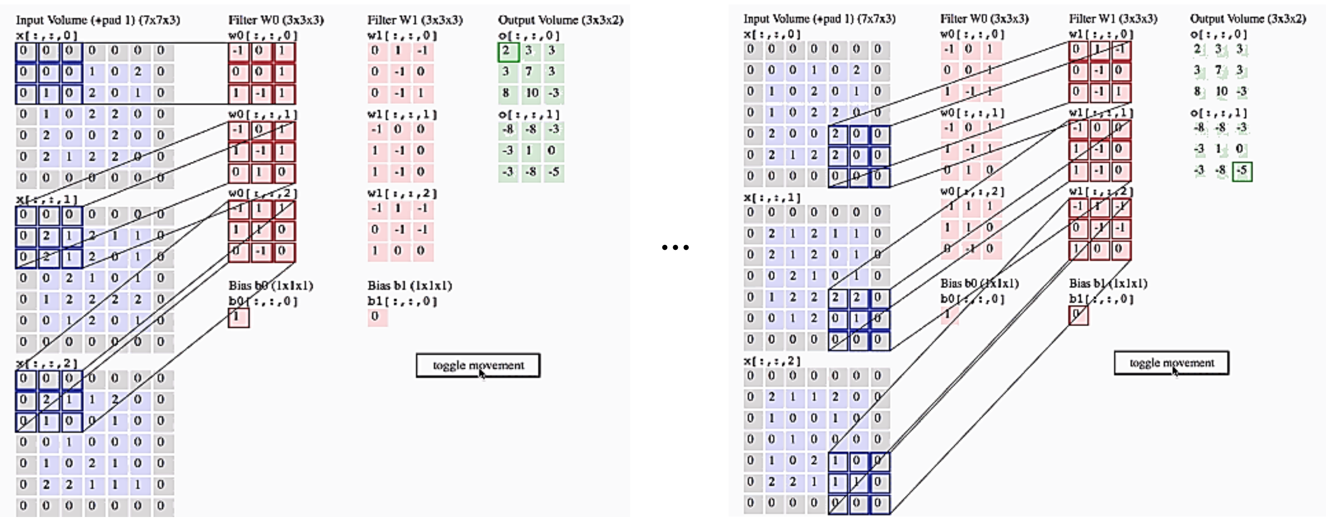


Fig (4.8) Convolution layer& Feature Detector

Step two:

Layer pooling After convolutional layers, the pooling layer is usually between CNN layers. Constantly reducing the number of dimensions to reduce parameters and calculation times in the network. This shortens the training time and controls overdoing.

The most common type of event is the maximum pool, the maximum value in each window. Select windows. This reduces the size of the feature map and preserves important information

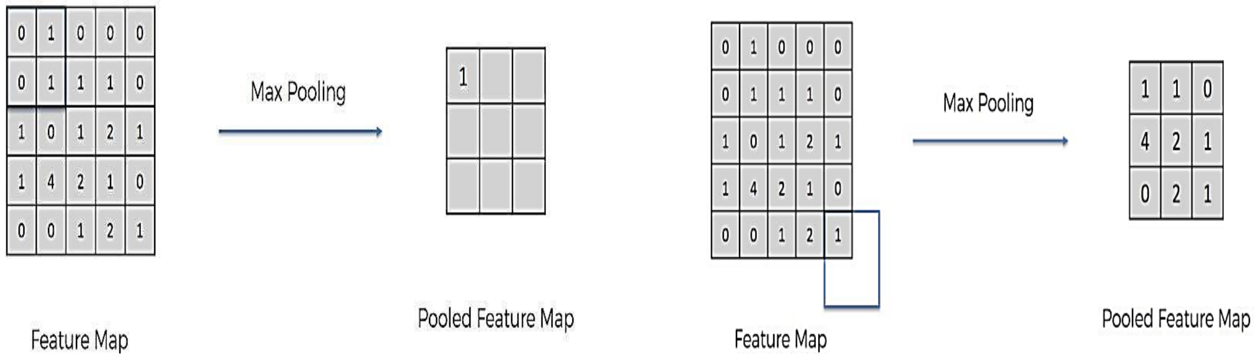


Fig (4.9) Layer pooling

The main advantage of Max Pooling is that when the image is converted by a few pixels, it will not affect at all, and it has good anti-noise function. (giving additional pixeis at the boundary of the data . sometimes filter does not perfectiy fit the input image then we will be using padding, (giving additional pixeis at the boundary of the data . sometimes filter does not perfectiy fit the input image then we will be using padding , We added a column of zeros on the right and a row from the bottom to fit the dimensions of the input image)

Step Three:

Fully connected layer In this layer, the fully connected part is the settlement of previous results and the connection to the underlying neural network (For horizontal borders and edges).

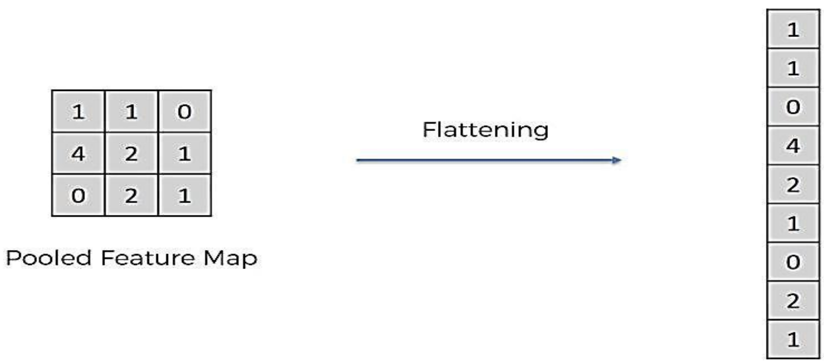


Fig (4.10) Fully connected layer

In the final stage, we compared the original image that the network was trained on (ALexnet & googlenet)[31] and the resulting image to predict whether it is infected or not infected and calculate the efficiency of the two networks.

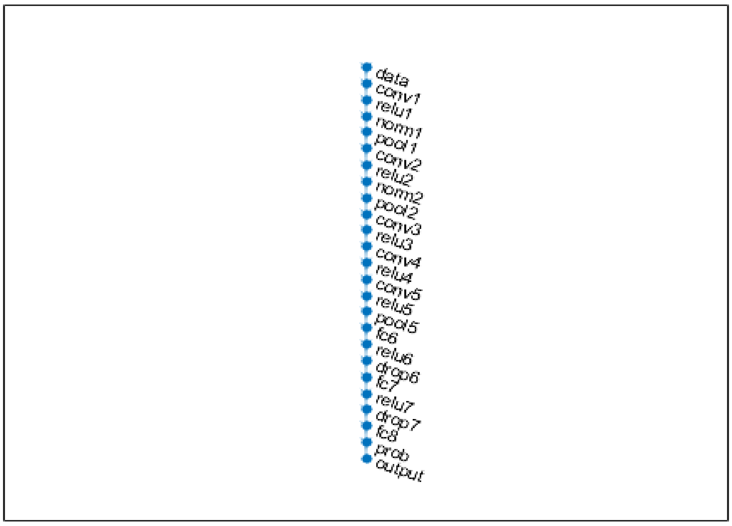


Fig. (4.11). AlexNet Network results (Tumer Image)

Fig. (4.12).Anlysis GoogleNet Network results (Tumer Image)

4.3-CNN Classification Results

Performance of the proposed classifier is measured in terms of confusion matrix, TP Rate, FP Rate, Precision, Recall and F-Measure as[17] :-

$$\text{Sensitivity} = \frac{TP}{TP+FN} \ \ldots\ldots.. \qquad (4.1)$$

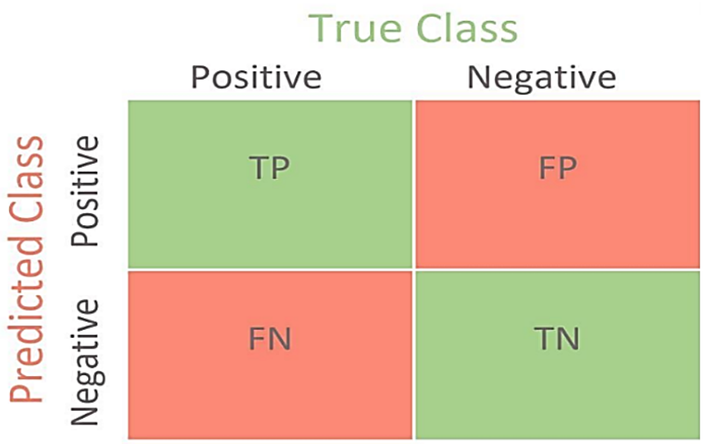
$$\text{Specificity} = \frac{TN}{TP+FN} \ldots\ldots\ldots \qquad (4.2)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \ldots.. \ (4.3)$$

Where, true positive (TP) represents number of images correctly classified true cases, true negative (TN) represents number of correctly classified false cases. False positives (FP) show incorrectly classified false cases and false negative (FN) is incorrectly classified true cases. Sensitivity is the probability that classification test is true, given that the proposed classifier correctly classify the tumor to its respective category malignant or benign. Specificity is the probability that a classification test is false, given that the proposed classifier incorrectly classifies the tumor to its respective category malignant or benign. Accuracy is the probability that the proposed classifier correctly performs on the said MR

Datasets. The Alexnet CNN and Googlenet CNN classifier achieves classification accuracies of 97.33% and 98.67% for the dataset consisting of 200 patients. The proposed algorithm based on CNN features is the most feasible learning model for feature selection over a higher dimension space. The experimental results show that CNN (Features + Classification) gives higher performance in feature selection, optimization, and tumor classification. Hence the proposed method improves the classification accuracy by minimal optimization of the feature sets

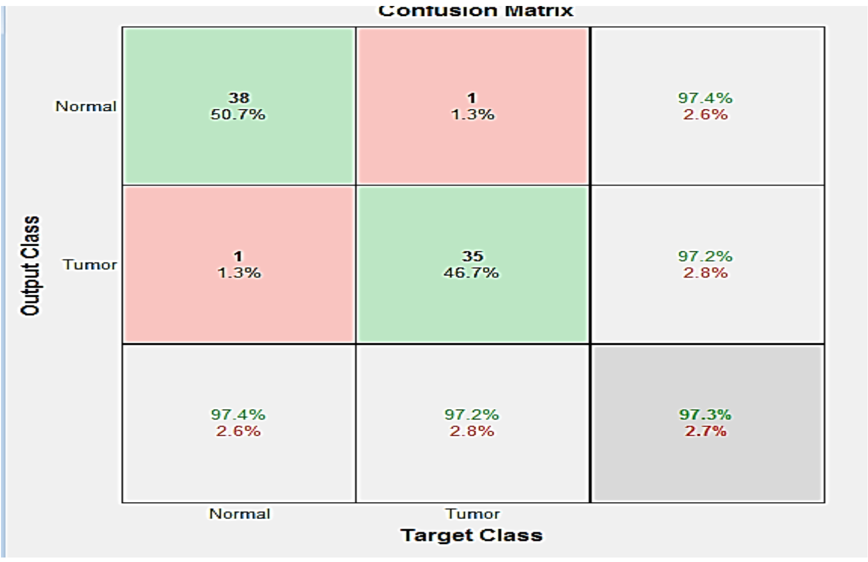
Table (4.2) Predicted Class



where true positives (*TP*) are the correctly classified positive cases, true negatives (*TN*) are the correctly classified negative cases, false positives (*FN*) are the incorrectly classified positive cases, and false negatives (*FP*) are the incorrectly classified negative cases.

We fill in the cells in class Predicting values (true positive TP), (true negative TN),(False positives FP),(False negative FN) after displaying the detection results.

Table(4.3) Confusion Matrix of Alexnet CNN Model.



TP= 38 **FP=1** **TN= 35** **FN= 1**

Table (4.4) Detailed Accuracy by Class of Alexnet CNN model

Name	Formula	Value
Accuracy	$ACC = \frac{TP + TN}{TP + TN + FN + FP}$	97.33%
Recall	$SN = \frac{TP}{TP + FN}$	97.435%
Precision	$PREC = \frac{TP}{TP + FP}$	97.435%
F1-Score	$F_1 = \frac{2.PREC.REC}{PREC + REC}$	97.3%

- **Accuracy**

This measures how much of the text was predicted correctly (both as belonging to acategory and not belonging to the category) from the text in the corpus.

$$ACC = \frac{TP + TN}{TP + TN + FN + FP}$$

ACC=[(38+35)/ (38+1+1+35)] = 0.973333*100= 97.33%

- **Recall**

This measures how the text was predicted correctly as belonging to given category out of all the text that should have been predicted as belonging to the category .

The more data we feed into our classifiers, the better recall will be**.**

$$SN = \frac{TP}{TP + FN}$$

REC= 38/(38+1)= 0.97435*100=97.435%

- **Precision**

This measures how well the text was predicted as belonging to given category out of all of the text that was predicted(correctly and incorrectly) as belonging to the category.

$$PREC = \frac{TP}{TP + FP}$$

PREC= 38/(38+1)=0.97435*100=97.435%

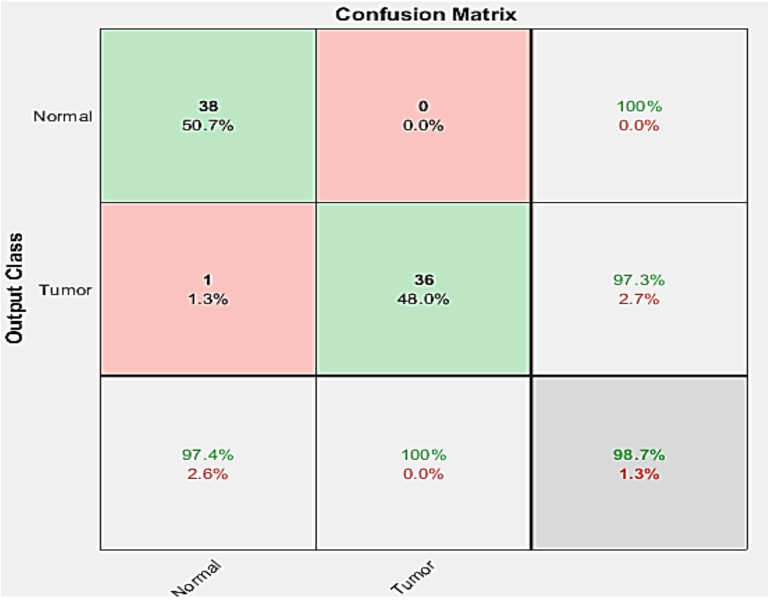
- **F1-Score**

Is the product of(2* Precision* Recall) divided by the sum of Recall and Precision**.**

$$F_1 = \frac{2.PREC.REC}{PREC + REC}$$

F1=(2*0.97435*0.97333)/(0.97435+0.97333)= 0.93*100= 97.3%

Table(4.5) : Confusion Matrix of Googlenet CNN Model.



TP=38 FP= 0 TN= 36 FN= 1

Table(4.6) Detailed Accuracy by Class of googlenet CNN model.

Name	Formula	Value
Accuracy	$ACC = \dfrac{TP + TN}{TP + TN + FN + FP}$ (38+36)/(38+1+0+36)=0.9866*100	98.66%
Recall	$SN = \dfrac{TP}{TP + FN}$ =(38/(38+1))=0.97435*100	98.67%
Precision	$PREC = \dfrac{TP}{TP + FP}$ = 38/(38+0)= 1*100	100%
F1-Score	$F_1 = \dfrac{2.PREC.REC}{PREC + REC}$ =2(1)*(0.9866)/(1+0.9866)=0.999	99.9%

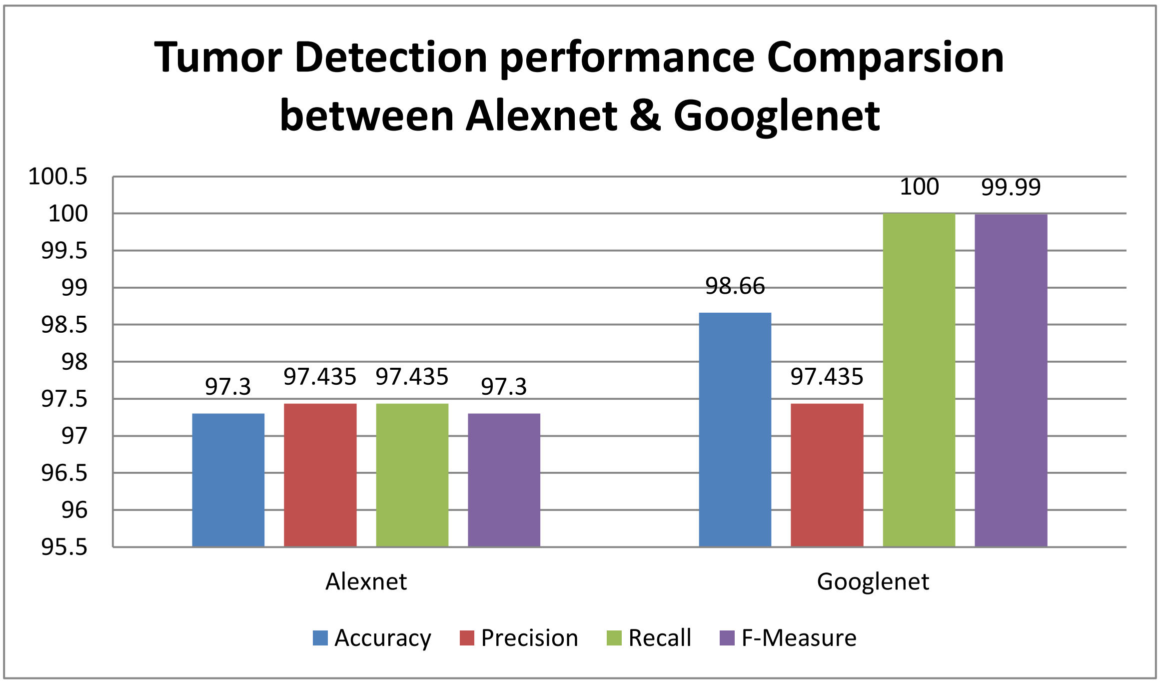


Fig (4.13) Comparison of Alexnet and GoogLeNet Results.

Here in this practical work(comparison of Alexnet and GoogLeNet Results, we have used information of200 images in which 100 images are Abnormal MRI brain images and 100 images are Normal MRI brain images. GoogLeNet Results as follows: Accuracy = 98.67%, Precision =

98.67% , Recall = 98.67% and F-Measure =98.67 .All those values are achieved through suggested method.and : Accuracy = 97.3%, Precision = 97.435%, Recall = 97.435% and F-Measure =97.33 The graph of benchmarking is shown in figure above (4.3).

4.4 Discussion of the Results .

Here we experimental Results about heality and offected imaes As mentioned in early stage of these thesis the objective is to develop an automatic tumor detection in a MRI slices system. The accurty of the system is depending the number of MRI slices are depend it may increase or decrease. Our experimental procedure two state-of-the-art (Alexnet and GooLeNet) CNN model were investigated, as discussed above a CNN model has two major responsibilities features extraction and classification. The layers from the input to ***n-2*** are responsible for features extraction. Features are extracted from the CNN last fully connected layer which is also known as the n-2 layer. Both models have different input sizes and number of layer. The GoogleNet was updated and compared with alexnet model with mentaining the difference in number of layers. GoogLeNet is 144 layer model while alexnet model is 25 layers model(It gives constant efficiency up to 30 layers), which is the maximum (. Transfer learning were done on the data obtained from the largest medical imaging repository (Radiopedia) http://mouldy.bic.mni.mcgill.ca/brainweb. Classification comparison was performed using Confusion Matrix. The model is base on calculated true positive rate, false positive rate, and precision and recall building the accuracy of the classifier. Table 6 shows the results of each classifier and comparison among these two models.

Table(4.7) : CNN comparison with other classifiers

Classifier	Accuracy	No. Layer
Alexnet	97.33%	constant efficiency up to 30layer
GoogLeNet	98.67%	144layer

The results shows our updated Googlene CNN model performance better than Alexnet with ≈1.5%. This as result of the googlenet model is 144 layers which makes it less time efficient compare to alexnet model.

We finally have obtained the results from different classifiers. We compared the performance Alexnet and GoogLeNet CNN model on our data. In term of accuracy googlenet model performs better.

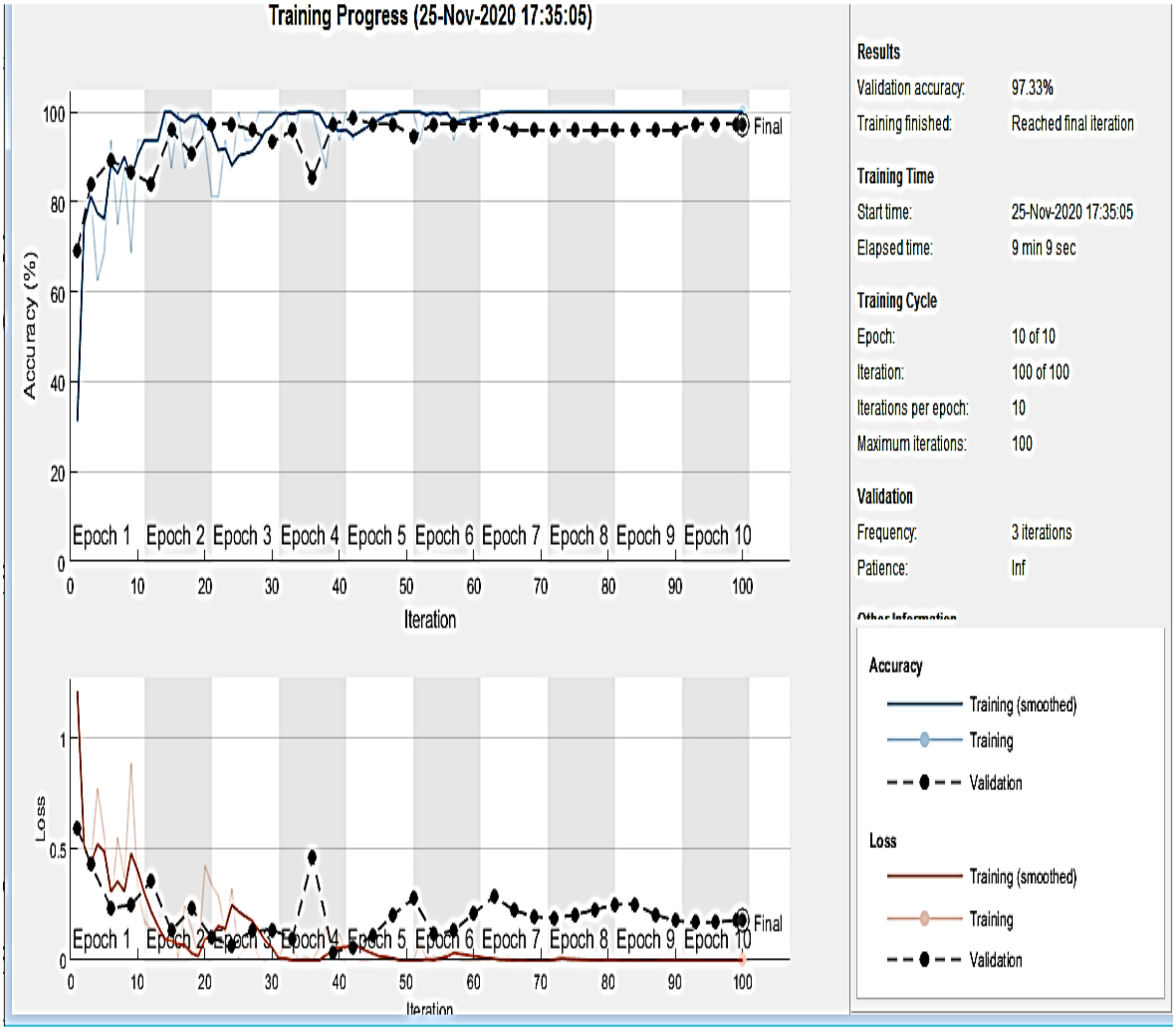


Fig (4.14)Training Progress about Alexnet

Performance validation graph showed in figure(4.13) represents that how close test value is to the trained value. This graph represents that when the test value and train value are almost close to each other and these two lines are close to the validation value in the best value line then performance will be the best.

the figure (4.13) shown evident low loss rates comparing with high accuracy of both validation and training data(97.33%).

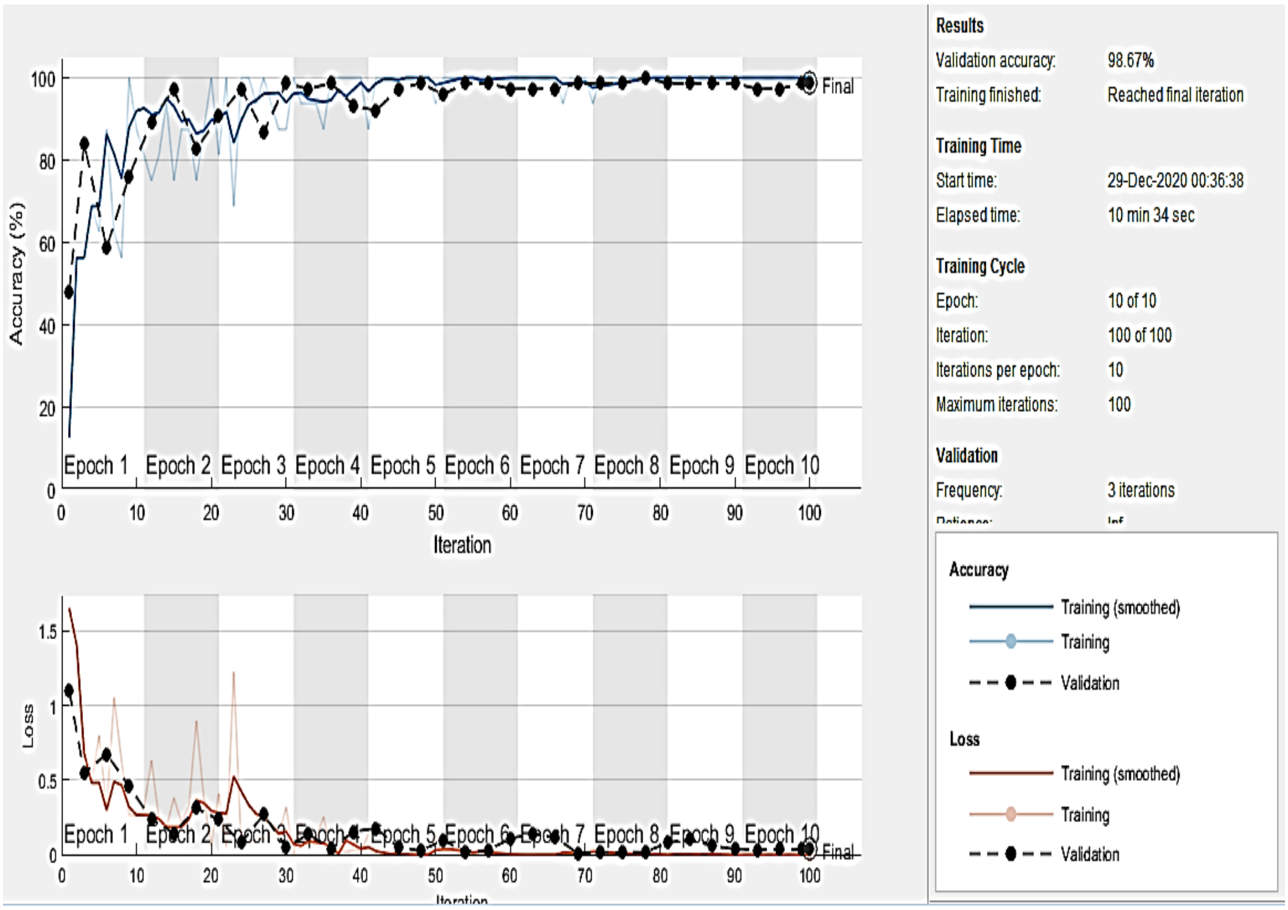


Fig (4.14)Training Progress about Googlenet

The graphs in figure (4.14) shown that when the test value and train value are almost close to each other and two lines were close to the validation value that lead to the best high

In this case the loss rates were low and accuracy was high in both validation and training data that leads to the best reuslts (98.67%).

4.5-Concluding notes:

- CNN accepts input image of height x width x dimension where the dimension indicates.The image is either RGB or grayscale, and is processed into specific classes. Technically speaking, image entry.
- The CNN model layer passes input data for training and testing over a series of wrapping layers.With filter details, grouping, fully connected layers, and softmax function to classify an object with itProbability values are between 0 and 1.
- The wrapping layer extracts the features of the input image that the warp method maintains the relationship between pixels by learning the features of the image.
- Number of filters spread in the warp layer allow to discover more features but cost more training time.
- The aggregation layer reduces the number of parameters by keeping sub-sampling important information.
- The fully connected layer which resembles a neural network has transformed the feature matrix map into a vector. Set the feature vector together to create a model using the softmax process That is used to classify the desired object.

In this work, the design and implementation of a tumor detection system using two CNN models is considered. Digital image processing and Deep Learning technologies enable us to develop an automatic system for the diagnosis/detection of various kind of diseases and abnormalities. The tumor detection system may include image enhancement, segmentation, data augmentation, features extraction and classification, all these steps are discussed in details in the above sections. To work on CNNs, powerful GPU based system are required to speed up the process, lot of processing is carried out and also lot of RAM is required to process the images for testing. CNNs has also some options such as optimization technique selection, Number of Epoch, Batch size, iteration and learning rate. These options are tuned to get the optimal results from the CNN model. Learning rate is used to update the weights and bias in training phase, learning rate changes the weights. One Epoch is when the model see all images in training, as the training data maybe of very big sizes, the data in each Epoch is divided into batch sizes. Every epoch has a training and test session, after each Epoch the weights are updated according to the learning rate, optimization algorithms are used to update the learning of a CNN adaptively. When the best weight for training are computed, the model is said to be trained. All the experimental work is carried out in MATLAB package.

CHAPTER FIVE

Conclusion And Recommendation

5.1 Conclusion

The most Important concluding remarks obtained in this work can be summarized as following, The design of Computer Aided Diagnosis System for the detection of tumor in a MRI images using Deep Learning CNN is considered. This method is founas the most safe and efficient method. The tumor slice detection using CNN include filtering, features extraction, classification/matching has shown that this method is reliable for detection of tumor in MRI in nase of speed and accuracy. Training of CNN is done with different parameters, the parameters of the CNN are tuned to select the best parameters for our model to achieve higher accuracy and time efficiency. The implementation of our proposed method for detection of tumor slices has done. The Proposed method achieve an average accuracies of 97.33% on alexnet model and 98.67% on googlenet model.

5.2 Recommendation

The results show that there is a room for further enhancement in the proposed identification system. In this respect, our experiments show that CNNs can be used to develop automatic diagnosis systems for medical applications. New CNNs models with many hidden layers and advance architecture are developed which may increase the accuracy and reduce the execution time. As another future work, developing technologies would enable us that the proposed methods could be used in hospitals and diagnostic radiology units. The efficiency can be improved using parallel processing e.g. graphical processor units are co-processors used as general purpose unit, the GPU can work with CPU in parallel to solve a problem or make computing more efficiently.

Although the proposed method shows a good performance, there is still room for further improvement. It is shown that the proposed method shows a better performance than other methods for the tumor detection system. However, still some image are falsely detected as tumor slices. In the future, we may be able to use other CNN models to resolve the issues faced.

REFERENCES

[1] AL-Antout, Abdulhamid. *Brain Tumor Detection and Classification Using Neural Network*. Diss. Near East University, 2017.

[2] Mahajani, Prachi Gadpay leand Prof PS. "Detection and Classification of Brain Tumor in MRI Images."

[3] Amin, Javaria, et al. "Brain tumor detection using statistical and machine learning method." *Computer methods and programs in biomedicine* 177 (2019): PP 69-79.

[4] Chithambaram, T., and K. Perumal. "Brain Tumor Detection and Segmentation in MRI Images Using Neural Network." *International Journal* 7.3 (2017).

[5] Ismael, Mustafa Rashid. "Hybrid Model-Statistical Features and Deep Neural Network for Brain Tumor Classification in MRI Images." (2018).

[6] Seetha, J., and S. Selvakumar Raja. "Brain tumor classification using convolutional neural networks." *Biomedical & Pharmacology Journal* 11.3 (2018): 1457.

[7] Naz, Saeeda, and Ibrahim A. Hameed. "Automated techniques for brain tumor segmentation and detection: A review study." *2017 International Conference on Behavioral, Economic, Socio-cultural Computing (BESC)*. IEEE, 2017.

[8] Thara, K. S., and K. Jasmine. "Brain tumour detection in MRI images using PNN and GRNN." *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*. IEEE, 2016.

[9] Subashini, M. Monica, and Sarat Kumar Sahoo. "Pulse coupled neural networks and its applications." *Expert systems with Applications* 41.8 (2014): 3965-3974.

[10] Amsaveni, V., and N. Albert Singh. "Detection of brain tumor using neural network." *2013 Fourth International Conference on*

Computing, Communications and Networking Technologies (ICCCNT). IEEE, 2013.

[11] Goswami, Suchita, and Lalit Kumar P. Bhaiya. "Brain tumour detection using unsupervised learning based neural network." *2013 International Conference on Communication Systems and Network Technologies*. IEEE, 2013..

[12] Rezaei, Mina, Haojin Yang, and Christoph Meinel. "Deep neural network with l2-norm unit for brain lesions detection." *International Conference on Neural Information Processing*. Springer, Cham, 2017.

[13] Sapra, Pankaj, Rupinderpal Singh, and Shivani Khurana. "Brain tumor detection using neural network." *International Journal of Science and Modern Engineering (IJISME) ISSN* (2013): 2319-6386.

[14] Mohsen, Heba, et al. "Classification using deep learning neural networks for brain tumors." *Future Computing and Informatics Journal* 3.1 (2018):P 68P-71

[15] Badža, Milica M., and Marko Č. Barjaktarović. "Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network." *Applied Sciences* 10.6 (2020): 1999.

[16] Furaha, Damien, and Kumar Ujjwal. "Convulational Neural Networks and simple Multi-Layer Percepton for Image classification.")

[17] Mehrotra, Rajat, et al. "A Transfer Learning approach for AI-based classification of brain tumors." *Machine Learning with Applications* 2 (2020): 100003)

[18] O'Shea, Keiron, and Ryan Nash. "An introduction to convolutional neural networks." *arXiv preprint arXiv:1511.08458* (2015)

[19] Pashaei, Ali, Hedieh Sajedi, and Niloofar Jazayeri. "Brain tumor classification via convolutional neural network and extreme learning machines." *2018 8th International conference on computer and knowledge engineering (ICCKE)*. IEEE, 2018.

[20] Kim, Suhyun. "A Beginner’s Guide to Convolutional Neural Networks (CNNs)." *Towards Data Science*.).

[21] Paul, Justin S., et al. "Deep learning for brain tumor classification." *Medical Imaging 2017: Biomedical Applications in Molecular, Structural, and Functional Imaging*. Vol. 10137. International Society for Optics and Photonics, 2017.

[22] Abd-Ellah, Mahmoud Khaled, et al. "Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks." *EURASIP Journal on Image and Video Processing* 2018.1 (2018): 97.)

[23] Kesgin, H. Toprak, et al. "Bankrupcy Risk Forecast Based on Company Balance Sheet Data Using Machine Learning." *2019 4th International Conference on Computer Science and Engineering (UBMK)*. IEEE, 2019.

[24] Ker, Justin, et al. "Deep learning applications in medical image analysis." *Ieee Access* 6 (2017): 9375-9389.

[25] Srivastava, Nitish. "Improving neural networks with dropout." University of Toronto 182.566 (2013):

[26] Nwankpa, Chigozie, et al. "Activation functions: Comparison of trends in practice and research for deep learning." *arXiv preprint arXiv:1811.03378* (2018).

[27] Silaparasetty, Vinita. "Deep Learning Projects Using TensorFlow 2.")

[28] Roy, Sudipta, et al. "A review on automated brain tumor detection and segmentation from MRI of brain." *arXiv preprint arXiv:1312.6150* (2013).

[29] Kumar, Tarun, and Karun Verma. "A Theory Based on Conversion of RGB image to Gray image." *International Journal of Computer Applications* 7.2 (2010): 7-10.

[30] Padmavathi, K., and K. Thangadurai. "Implementation of RGB and grayscale images in plant leaves disease detection–comparative study." *Indian Journal of Science and Technology* 9.6 (2016): 1-6.

[31] Pal, Kuntal Kumar, and K. S. Sudeep. "Preprocessing for image classification by convolutional neural networks." *2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*. IEEE, 2016.