Diagnosing Cancer Using Deep-Learning Models

Supervised By

Dr. Manal Mohsen Tantawi
TA. Hadeer Elsaadawy

Member name	Department
El Bara Mohamed Mahmoud	Computer Science
Islam Hesham Hussein	Computer Science
Eslam Yahiya Abd El Aziz	Computer Science
Ahmed Magdy Ali	Computer Science
Islam Mohamed Zakaria	Computer Science

Agenda

- **Problem Definition**
- Project Motivation
- Project Objective
- Related Work
- Proposed Methodology
- Dataset
- Results
- Conclusion and Future Work
- Tools
- References

Problem Definition

- In the past, there was no way to diagnose tumors resulting in many deaths.
- As technology advances, X-rays have emerged, allowing scientists to speculate the presence of the tumor and act accordingly.
- Neuroimaging: In the late 1940s, which outlined tumors at the time of surgery, and then tagged the fluorescein with radioactive iodine, which allowed visualization of the tumors before surgery
- Until the emergence of MRI, which in turn led to the development of methods of treatment of patients and contribute to the medical field through computer-aided diagnosis(CAD).

MRI Definition

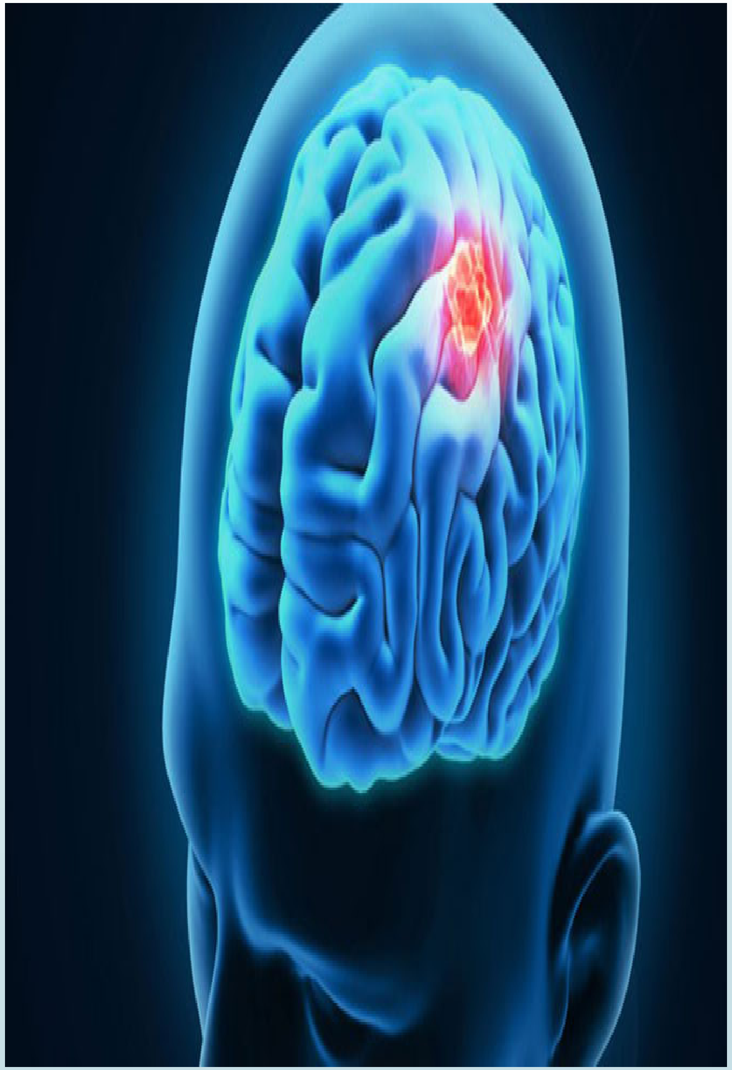
- Magnetic resonance imaging is a medical imaging technique that uses a magnetic filed and computer generated radio waves to create detailed images of the organs and tissues in your body.
- MRI is the most frequently used imaging test of the brain often performed to help diagnose tumors , stroke and brain injury from trauma.

Agenda

- Problem Definition
- **Project Motivation**
- Project Objective
- Related Work
- Proposed Methodology
- Dataset
- Results
- Conclusion and Future Work
- Tools
- References

Motivation

- Brain tumor detection is an important task in medical image processing. Early diagnosis of brain tumors plays an important role in improving treatment possibilities and increases the survival rate of the patients.
- Due to the level of complexity in both the Human brain and the MRI Scanners there are many issues that may occur that increases the misdiagnoses of tumor.
- Misdiagnosis occur due to technical reasons related to image quality resulting in human error.
- (CAD) systems are developed to overcome these restrictions as it improves radiologists' performance in discriminating between normal and abnormal tissues.



Agenda

- Problem Definition
- Project Motivation
- **Project Objectives**
- Related Work
- Proposed Methodology
- Dataset
- Results
- Conclusion and Future Work
- Tools
- References

Objectives

- The Project aims to Implement the techniques of Deep learning for diagnosis tumors.
- Deep learning implementation aims to provide an accurate diagnosis for brain tumor by processing (MRI) Scans
- The Project is designed to be scalable and to be used for diagnosis of other malignant tumors

Agenda

- Problem Definition
- Project Motivation
- Project Objective
- **Related Work**
- Proposed Methodology
- Dataset
- Results
- Conclusion and Future Work
- Tools
- References

Related Work

References	Dataset	Preprocessing	Features & Classifiers	Accuracy
o Isin et al. [1] (2016)	**BRATS 2013** o 274 mri scan of patients with gliomas(both high and low grades) . o 110 scans are available with unknown grades and unknown ground truths for testing.	o Noise removal o Skull-stripping o Intensity base correction	o **Features :-** o Discrete wavelet transforms (DWT) o Textons o Multifractal Brownian motion o First order statistical o Raw intensities o Local image textures o Intensity gradients o Edge based o **Classifiers :-** o NN o SVM o AdaBoost o KNN o SOM o RFs o CRF o CC	67%
o Zacharaki et al. [2] (2017)	o 98 patient(52 woman - 46 men) age (17 - 83) 4 had multiple tumors	o Noise Reduction o Inhomogeneity correction o rigid intra subject registration using the public software (FSL)	o **Features :-** o forward selection method o subset selection method o **Classifiers :-** o SVM o RFs o Leave-one-out	98.2%
o Sudha et al. [3] (2014)	o 42 (25 abnormal 17 normal) testing data 30 (12 abnormal)	o Noise removal o Intensity base correction	o **Features :-** o FFNN o MLP o BPN o **Classifiers :-** o GLCM & GLRM AND Fuzzy Entropy Measure	96%

References	Dataset	Preprocessing	Features & Classifiers	Accuracy
o Roy et al. [4] (2019)	o Whole Brain Atlas: MR brain image o o The EASI MRI Home. MR brain image	o Dimension construction method o Transform MRI into gray-scale using weighted summation of R,G,B components.	**Classifiers :-** o K-means	94.4%
o Akkus et al. [5] (2017)	BRATS 2016 o 220 subjects with high grade and 54 subjects with low-grade for training. o 53 subjects with mixed grades for testing	o Registration o skull-stripping o intensity base correction o Intensity Normalization o noise removal	o **Classifiers :-** o DSC o CNN o SVM o RFs o CSF o GM o WM	90%
o Cheng et al. [6] (2015)	o Brain tumor dataset o 233 patient with 3064 image (708 meningioma's – 1426 gliomas – 930 pituitary tumor).	o Intensity normalization.	o **Features :-** o intensity histogram o **Classifiers :-** o BoW o GLCM o SVM o SRC o (1-3-715-45)NN	91.14%
o Thillaikkarasi et al. [7] (2018)	o Small dataset	o Smoothing using LoG o CLAHE	o **Features :-** o SGLDM o **Classifiers :-** o SVM	84%

References	Dataset	Preprocessing	Features & Classifiers	Accuracy
o Zhao et al. [8] (2016)	**BRATS 2013** o 35 patient.	o intensity base correction o Intensity Normalization	**Classifiers :-** o FCNN o CRF	82%
o Gubta et al. [9] (2015)	o 78 MRI brain tumor	o Morphological Opening o Noise Removal o gradient magnitude	**Classifiers :-** o CNN o HSV o SVM o Naive Bayes	91.49%
o Kaur et al. [10] (2014)	o 70 MRI from local govt. hospital	o image resizing o Noise removal o morphological operations like dilation and erosion	**Classifiers :-** o Thresholding based methods o Region growing based methods o Neural network methods o Fuzzy methods o FVT	99.59%
o Seetha et al. [11] (2018)	**BRATS 2015** o 80 MRI brain tumor	o intensity base correction o Intensity Normalization	**Classifiers :-** o NN o SVM o KNN o FCM o DWT o DNN o LDA o SMO	97.5%
o Kalapala et al. [12] (2015)	o 1100 image slices (833 abnormal slices and 267 normal slices) of 150 abnormal patient volumes were considered in this work.	o Normalization	**Classifiers :-** o SVM o LS	98.92%

References	Dataset	Preprocessing	Deep-Learning Models	Accuracy
o Ari et al. [13] (2018)	o 16 patient : 9 patient used for training and 7 patient used for testing	o Noise removal	o CNN o ELM o ELM-LRF o AlexNet	97.18%
o Banerjee et al. [14] (2018)	o 285 patient : 210 hgg and 75 lgg	o Noise Reduction	o PatchNet o SliceNet o VolumeNet o VggNet o ResNet o Anfc-IH o NB o LR o MIP o SVM o CART o KNN	97.18%
o Sobhaninia et al. [15] (2018)	o 233 patient with 3064 image (708 meningioma's – 1426 gliomas – 930 pituitary tumor). 900 for training and 200 for testing.	o Intensity normalization.	o LinkNet	79%
o Lin et al. [16] (2016)	**BRATS 2015** o (213)patient 18 has been removed because of incomplete or impropriate feature disclosure	o Resize to 60*60 o Intensity normalization.	o LeNet-5	(74 – 85)%

References	Dataset	Preprocessing	Deep-Learning Models	Accuracy
o Iqbal et al. [17] (2017)	o 36 patient	o Noise removal	o SVM o FFNN o ELM o EC	91.17%
o Zhang et al. [18] (2017)	o 274 patient : 220 hgg and 54 lgg	o Noise Reduction	o VGG o U-Net o ResNet	87%
o Soltaninejad et al. [19] (2018)	**BRATS 2017** o 46 patient 220 hgg and 75 lgg	o Intensity normalization.	o VGG	86%

Related Work Analysis

We Concluded that :

- Preprocessing techniques like noise removal and intensity normalization Increases the accuracy

- VGG, SVM and Res-Net Models could Achieve the Best Results

Agenda

- Problem Definition
- Project Motivation
- Project Objective
- Related Work
- **Proposed Methodology**
- Dataset
- Results
- Conclusion and Future Work
- Tools
- References

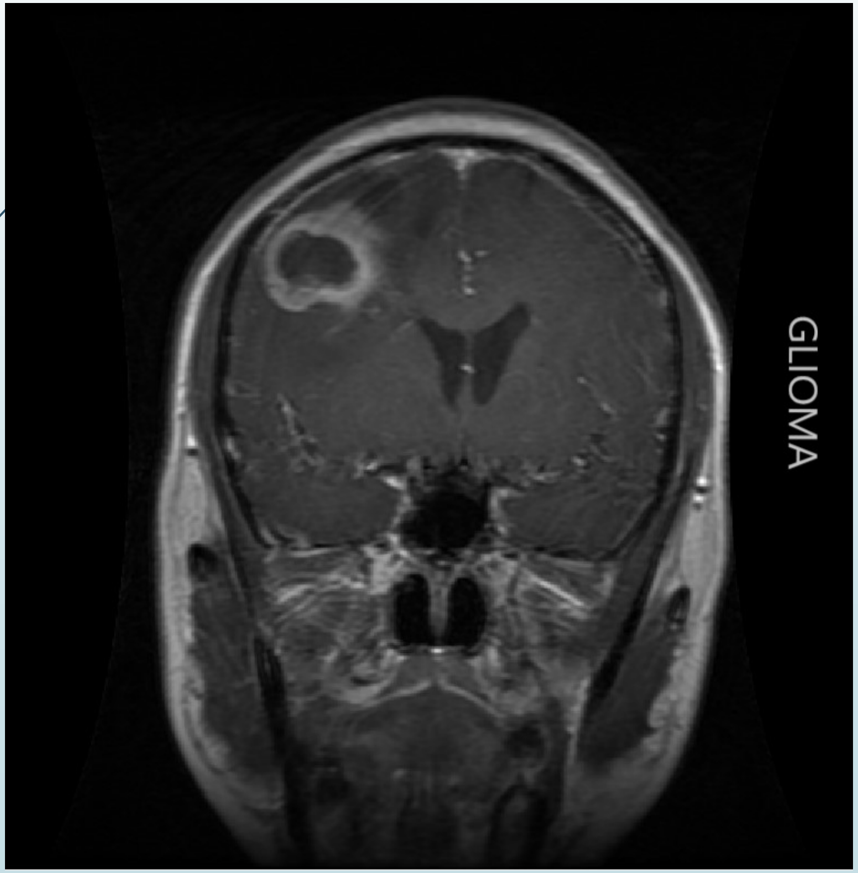
Preprocessing Steps:

- Resizing
- Noise removal using median filter
- Intensity Normalization

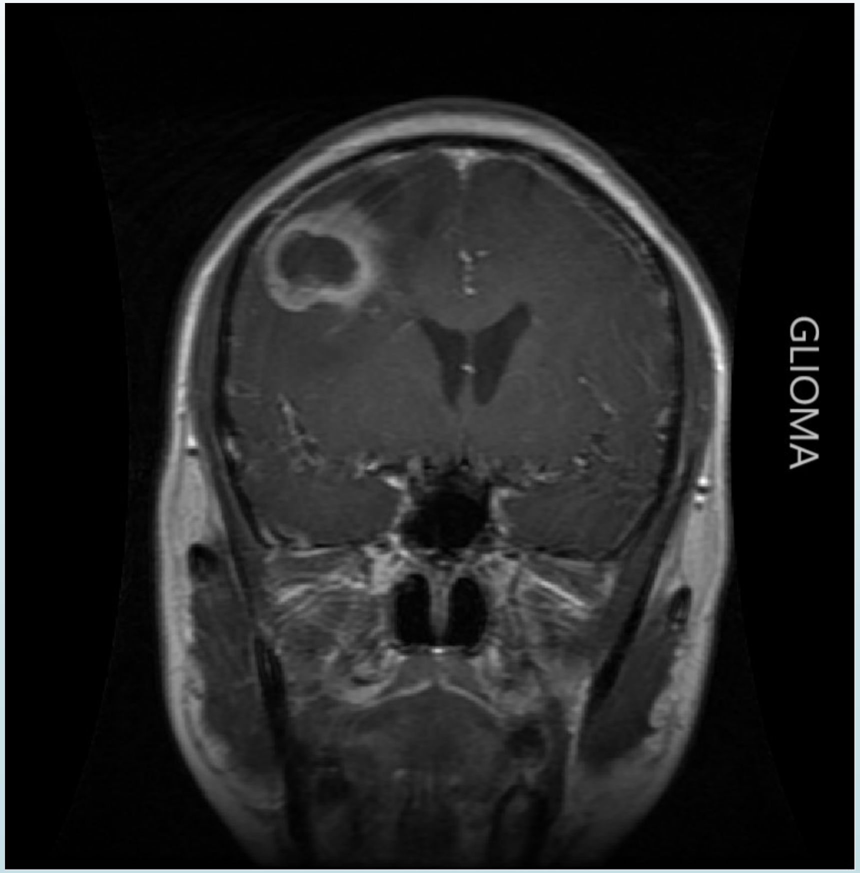
1-Resizing

Initially, All Images are Resized by 224x224

BEFORE Resizing

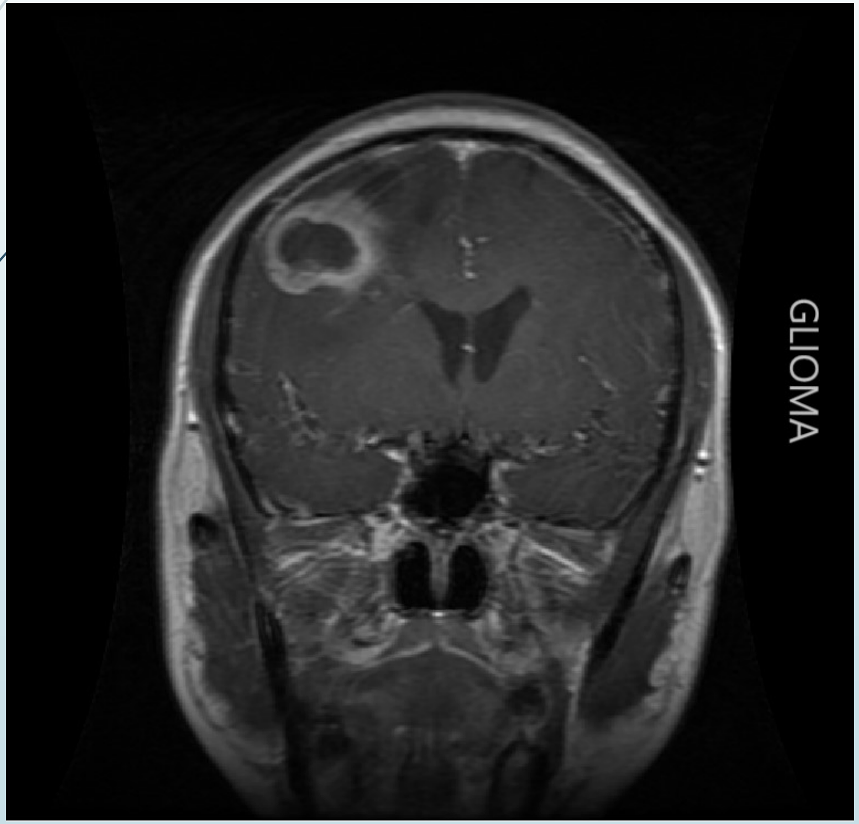


AFTER Resizing

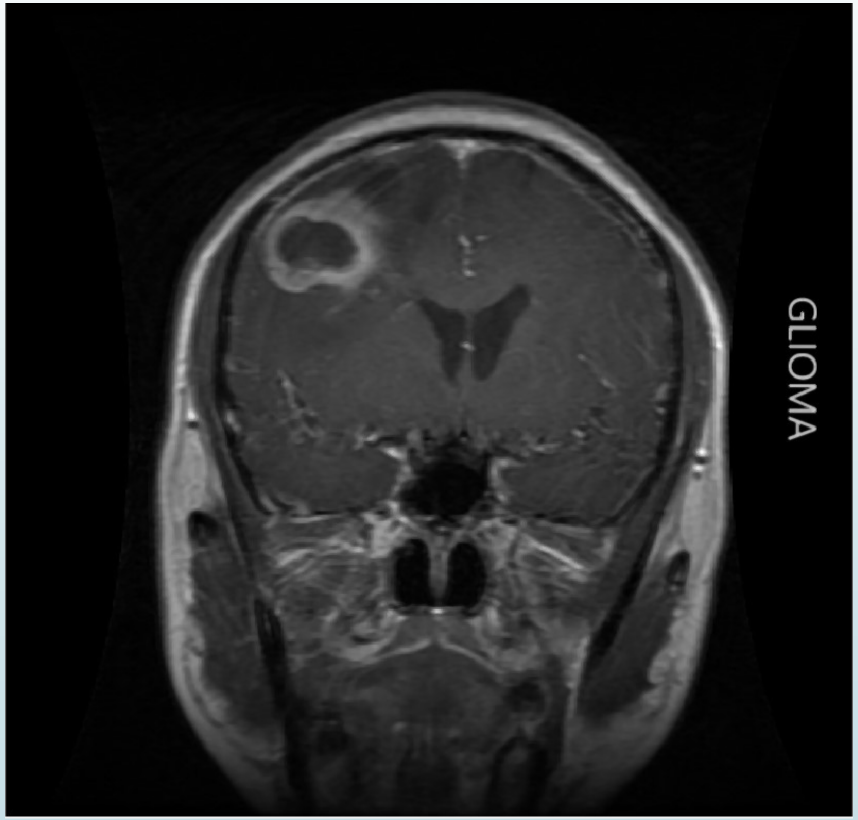


2-noise removal using median filter

BEFORE Noise Removal

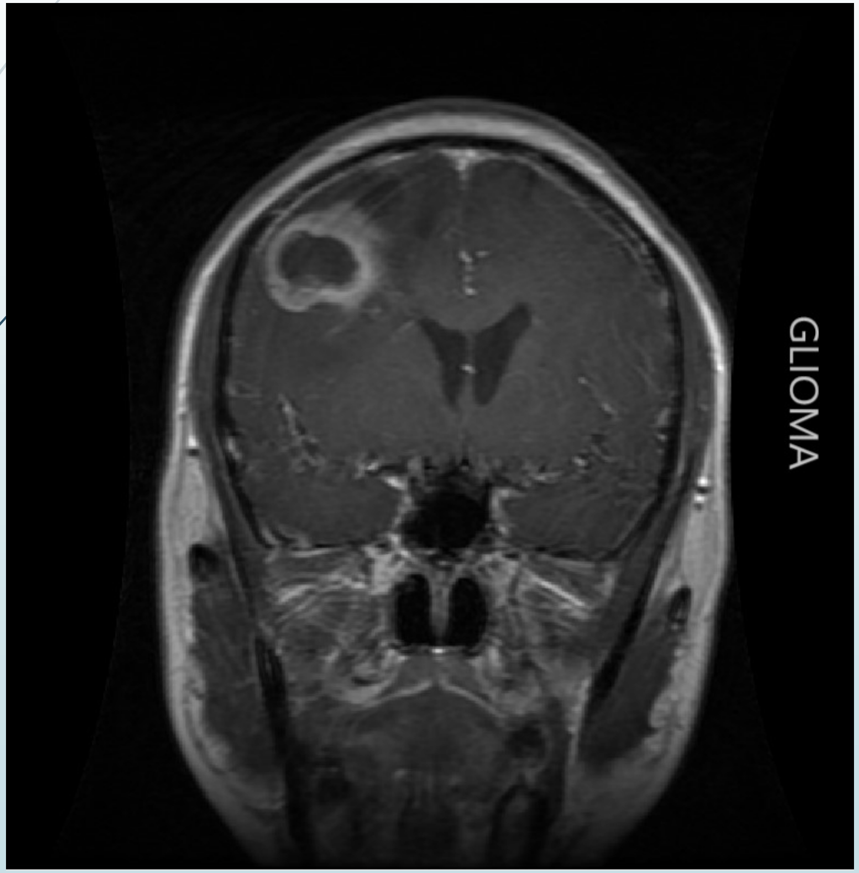


AFTER Noise Removal

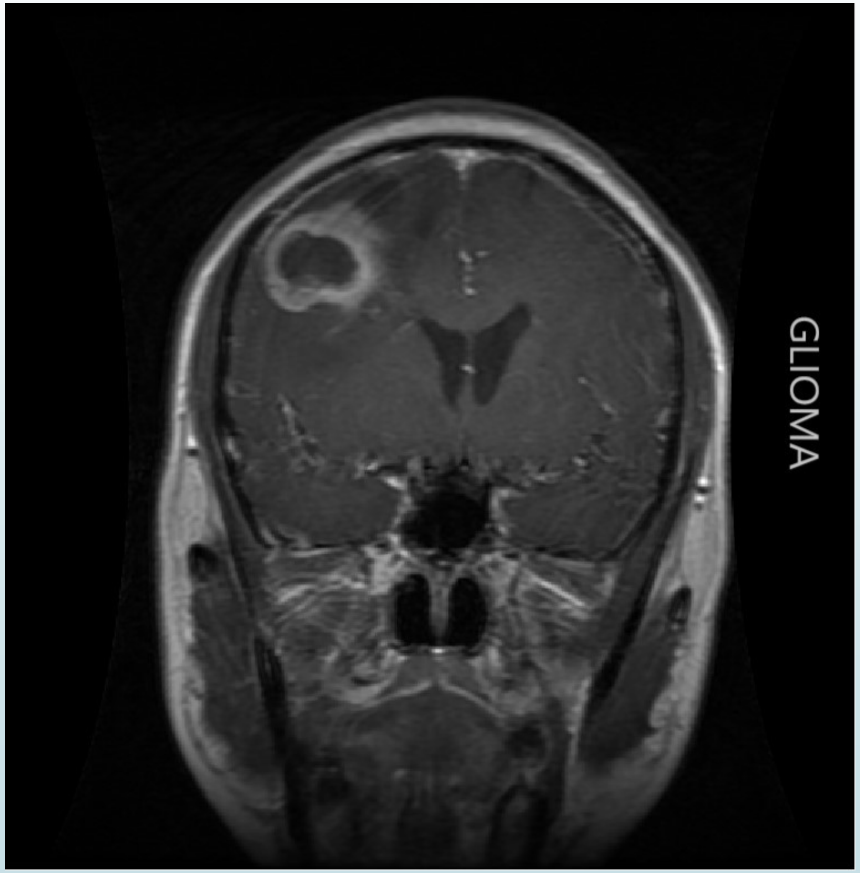


3- Intensity normalization

BEFORE Normalization



AFTER Normalization



Classification:

- We have utilized **two different Approaches** to compare the results and get the best one
  - **First Approach:** multi stage classification:
    - **First stage:** View Classification
    - **Second stage :** tumor Classification
  - **Second Approach :** single stage classification

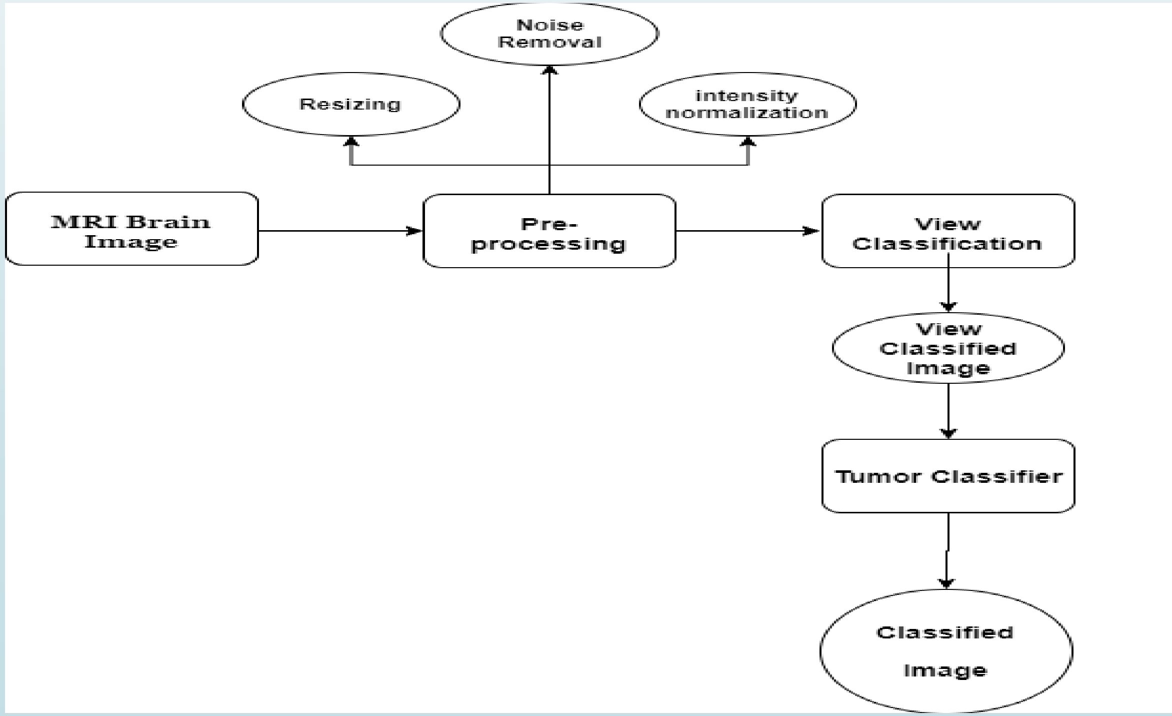
Multi stage Classification

1- View Classification:

- The feature is extracted from the enhanced image
  The feature is selected from the extracted features based on the image view.

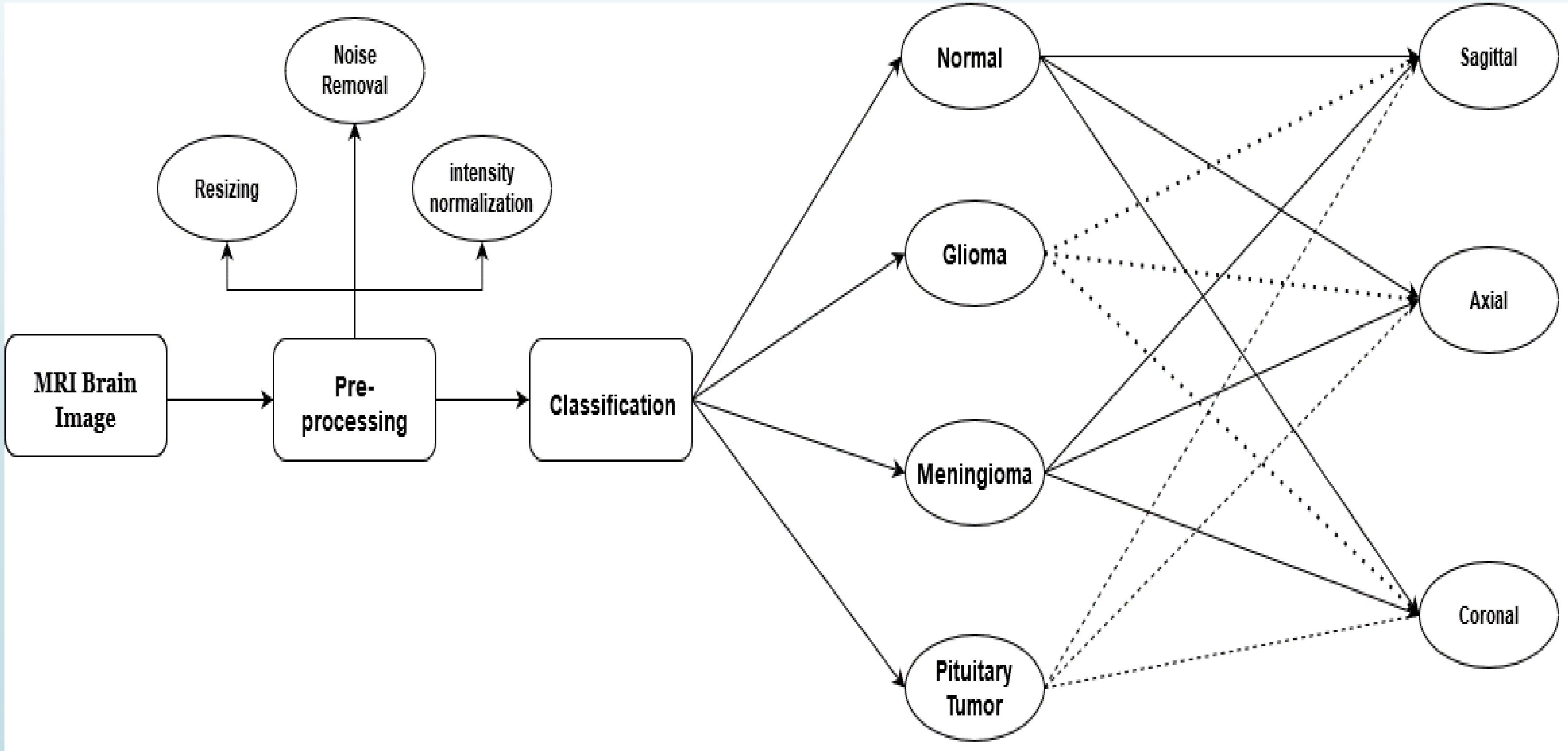
2-Tumor Classification:

- After deciding the view of the image we use another model to classify if the imag
- is normal or abnormal then if it is abnormal the model decides what kind
- of tumor found in the image.



Single Stage Classification

- The features are extracted from the enhanced image
- The feature is selected from the extracted features based on the tumor features and image view.
- Then, the selected feature can be given to the RES-NET classifier to classify the given image.



Classification Techniques:

Traditional Techniques:

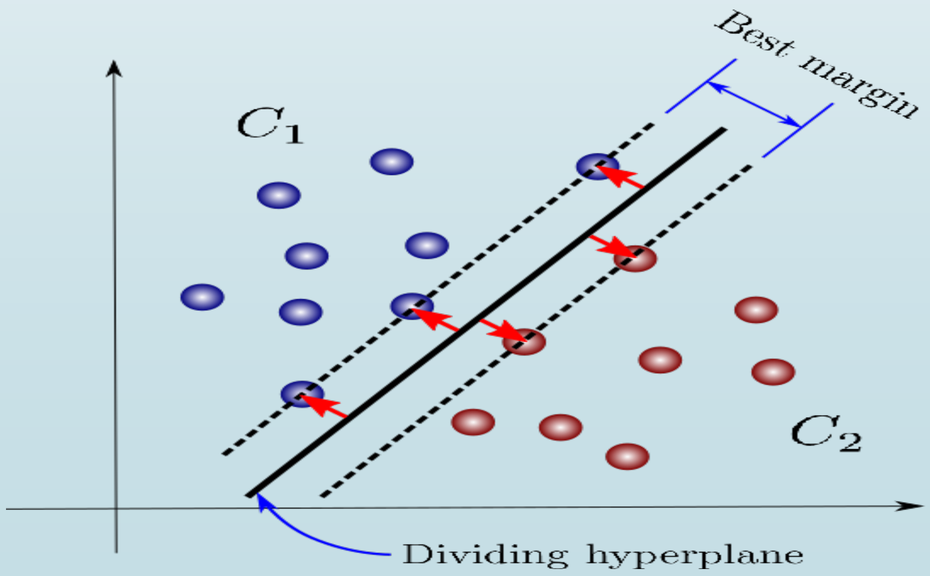
- Support Vector Machine (SVM)

Deep Learning Techniques :

- VGG-16
- VGG-19
- Resnet50

Traditional Technique :

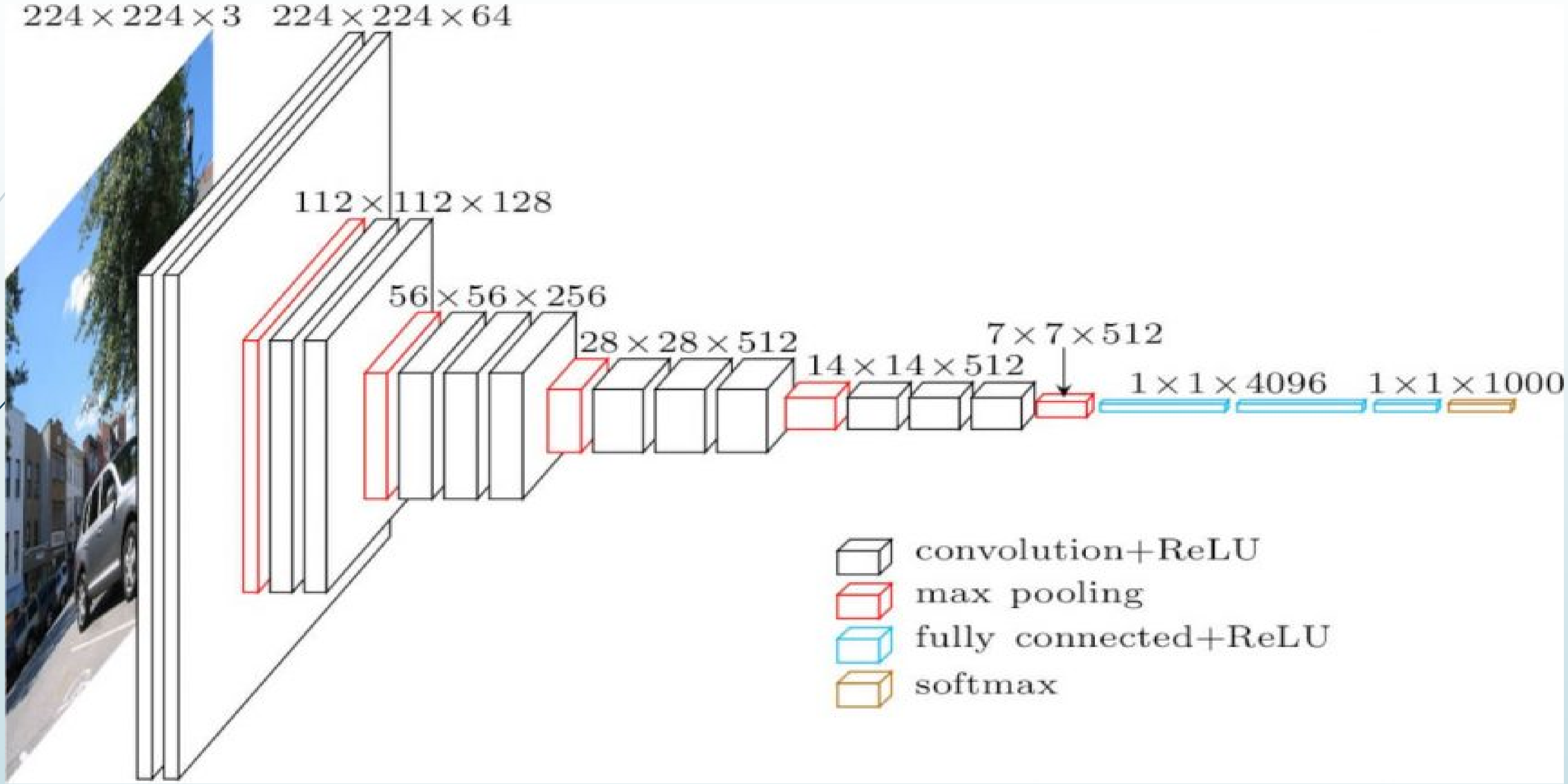
- SVM
  - SVM are supervised learning models with associated learning algorithms that analyze data.
  - Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other
  - An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on the side of the gap on which they fall.



Deep Learning Techniques:

VGG-16

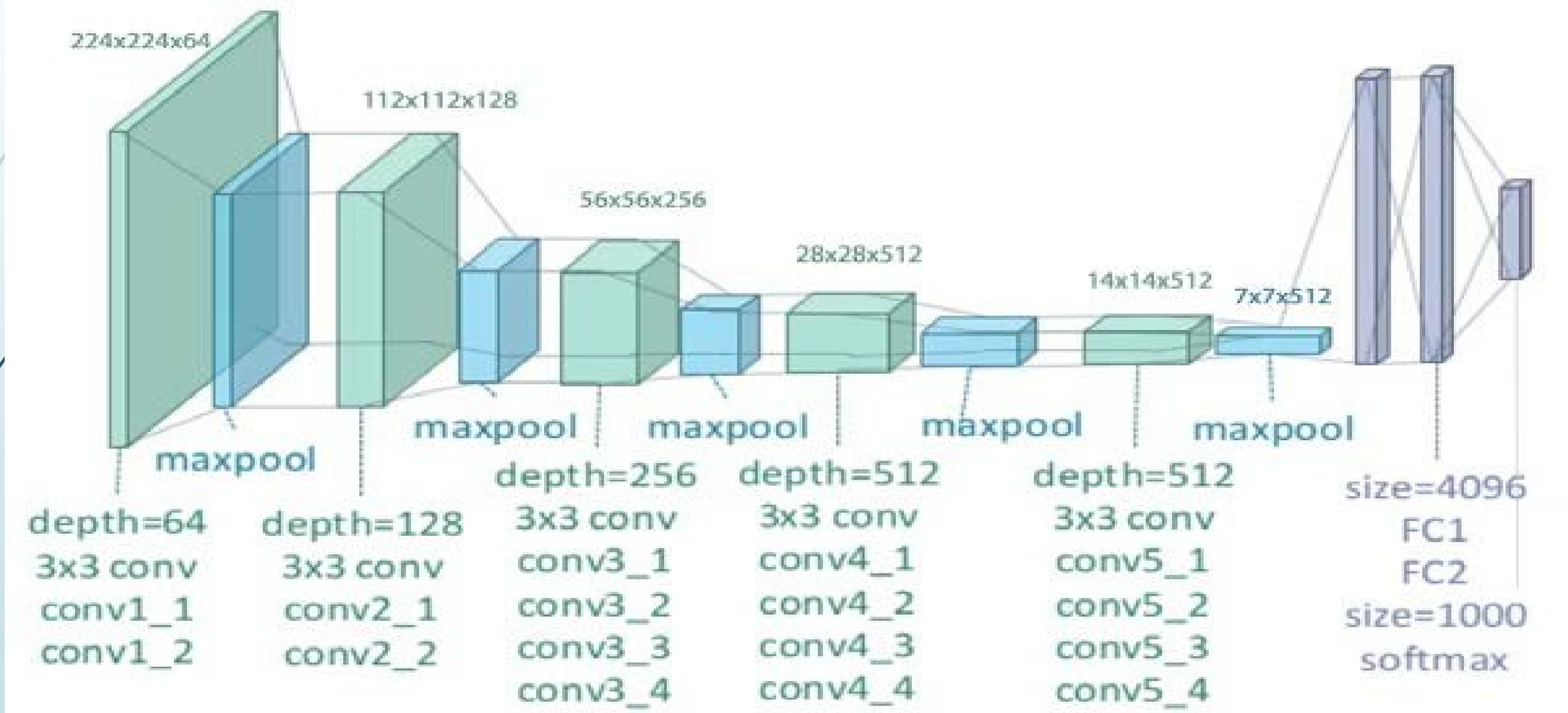
- The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional layers, where the filters were used with a very small receptive field: 3×3 .In one of the configurations, it also utilizes 1×1 convolution filter, which is a linear transformation of the input channels (followed by non-linearity). The convolution stride is 1 pixel.
- Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max-pooling is performed over a 2×2-pixel window, with stride 2.
- Three Fully-Connected (FC) layers follow a stack of convolutional .the first two have 4096 channels each, the third 1000 channels. The final layer is a soft-max layer to classify image into 1 of 12 classes .
- All hidden layers are equipped with the rectification (ReLU) non-linearity.



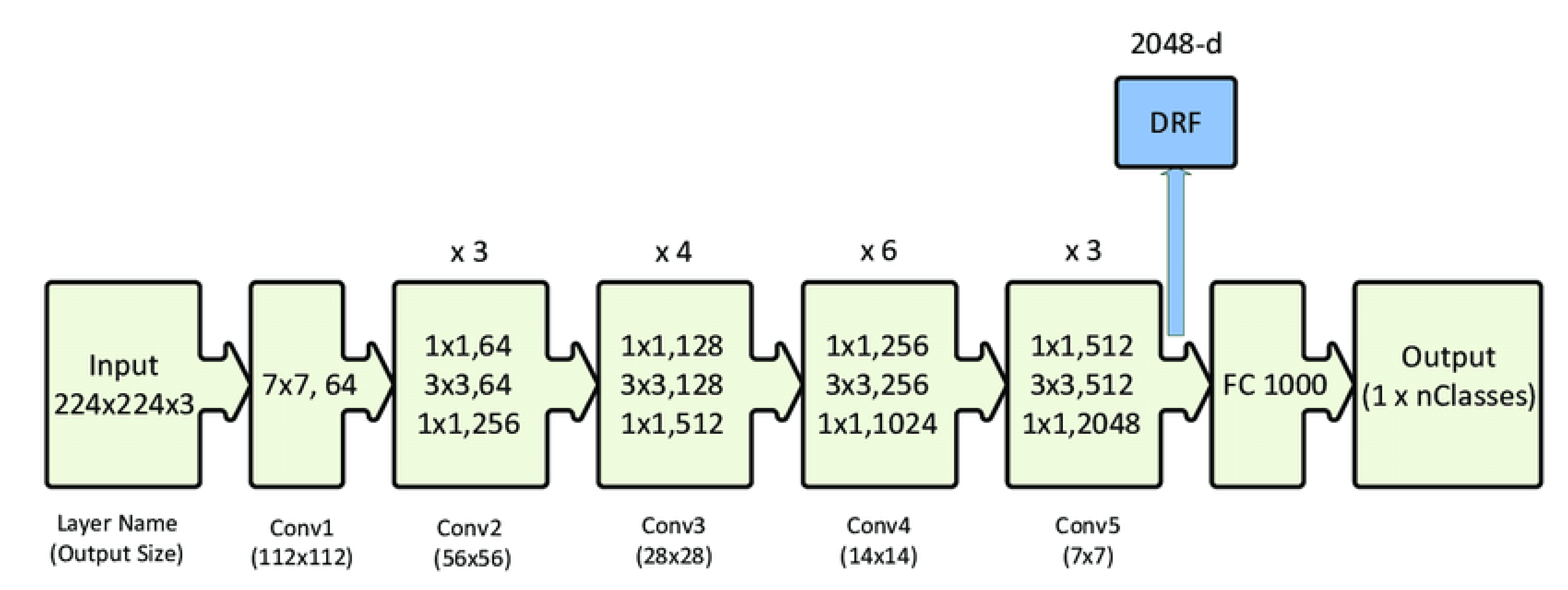
224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
7 × 7 × 512
1 × 1 × 4096
1 × 1 × 1000
convolution+ReLU
max pooling
fully connected+ReLU
softmax

➢ VGG-19

- The number 19 stands for the number of layers with trainable weights. 16 Convolutional layers and 3 Fully Connected layers.
- utilizes the Architectural style of:
  - [CONV-RELU-CONV-RELU-POOL]x16,[FC-RELU]x3,FC,SOFTMAX
- UNTIL Fully Connected layer, ReLU, Dropout, Fully Connected, SoftMax, Classification output
- **Convolutions:** is the functional operation of performing concatenation of Functional Curves
- **ReLU :** Convolution is a linear operation. Therefore, we need a non-linearity.
- **Max Pooling:** Pooling retains the most important information.
- **A Fully Connected Layer** : is a traditional Multilayer Perceptron (MLP)
- **SoftMax** act as a regularizer over a distribution

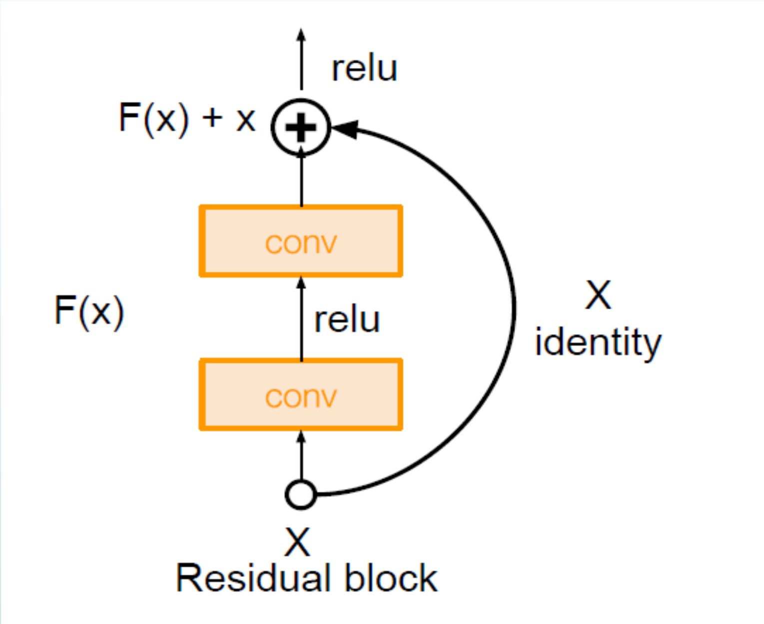

224x224x64
112x112x128
56x56x256
28x28x512
14x14x512
7x7x512
maxpool
maxpool
maxpool
maxpool
maxpool
depth=64
3x3 conv
conv1_1
conv1_2
depth=128
3x3 conv
conv2_1
conv2_2
depth=256
3x3 conv
conv3_1
conv3_2
conv3_3
conv3_4
depth=512
3x3 conv
conv4_1
conv4_2
conv4_3
conv4_4
depth=512
3x3 conv
conv5_1
conv5_2
conv5_3
conv5_4
size=4096
FC1
FC2
size=1000
softmax

➢ Resnet50



2048-d
DRF
x 3
x 4
x 6
x 3
Input
224x224x3
7x7, 64
1x1,64
3x3,64
1x1,256
1x1,128
3x3,128
1x1,512
1x1,256
3x3,256
1x1,1024
1x1,512
3x3,512
1x1,2048
FC 1000
Output
(1 x nClasses)
Layer Name
(Output Size)
Conv1
(112x112)
Conv2
(56x56)
Conv3
(28x28)
Conv4
(14x14)
Conv5
(7x7)

- Full ResNet architecture:
- -Stack residual blocks
- -Every residual block has two 3x3 conv layers
- Batch Norm Layer
- -Additional conv layer at the beginning
- -No FC layers at the end
- (only FC 1000 to output
- classes).



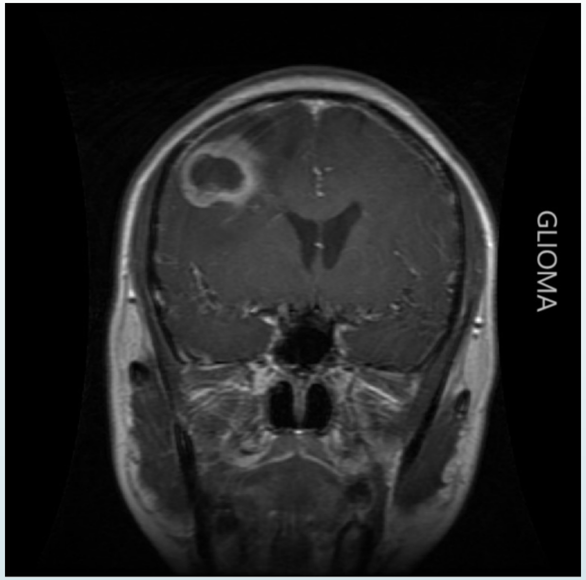
Agenda

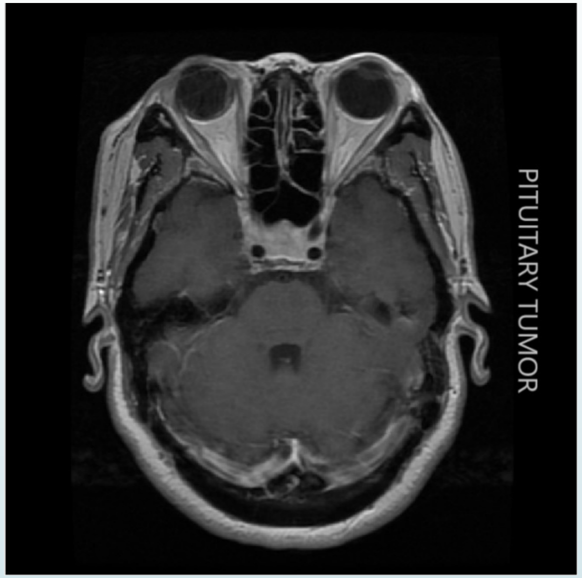
- Problem Definition
- Project Motivation
- Project Objective
- Related Work
- Proposed Methodology
- **Dataset**
- Results
- Conclusion and Future Work
- Tools
- References

Dataset and sampling

- To ensure accurate results , The Dataset is acquired from
  - Hospital
- The dataset for brain tumor comprises of :

  233 patient with 3064 image, classified as following
  - 708 meningioma's
  - 1426 glioma's
  - 930 pituitary tumor
- At the first we only have an abnormal dataset. the challenge we must get a normal dataset.
- We start to search online in the first on Kaggle, google and a lot of searching sites but we did not find it.
- After that we try to get it from an Egyptian hospital like (57357, alfa scan, techno scan) but for patient privacy they refused.
- We are sending a lot of mail for an outside hospital until one of them respond with a dataset for a normal dataset and its software called mango





708 meningioma's

1426 gliomas

930 pituitary tumor

Agenda

- Problem Definition
- Project Motivation
- Project Objective
- Related Work
- Proposed Methodology
- Dataset
- Conclusion and Future Work
- Demo
- Tools
- References

Results

- We used multiple CNN Architecture like VGG-16, VGG-19, Res-Net 50 and SVM. We started with SVM and after getting the best results we could got from it we tried VGG-16, VGG19, and Res-Net 50. The results we got from them was better than we got from SVM.
- We tried 2 approaches:

1- Multi Stage Classification

2- Single Stage Classification

Multi-Stage Classification

- First stage was designed for classifying views, second stage contains 4 classes designed for classifying tumor. We achieved total accuracy from 84% up to 94% and the best accuracy we got from Res-Net.

Single-Stage Classification

- At Second approach we **used single stage classification**. We used 12 class each class consist of view (Axial, Coronal, Sagittal) and state of MRI (Normal, Glioma, Meningioma, Pituitary Tumor). We achieved total accuracy from 89% up to 95% from different trials on dataset (changing train and test) and the best accuracy we got from Res-Net.
- After word we decided to be used Res-Net model as our model for implementing our project.
- By trying some data augmentation techniques (Zoom, Rotate, Fill) and changing hyperparameters (optimizer, learning rate, epochs). We achieved accuracy up to 97%.

Traditional Techniques Results

SVM	98% For Classifying Views

Deep Learning Techniques Results

ResNet-50	84% up to 94% 2-stage classification
VGG-16	79% up to 84% on Abnormal
VGG-19	80% up to 85% on Abnormal
ResNet-50	97% On the Whole Data

Observations on the proposed Methodologies

After many trials of the proposed methodologies by changing hyper parameters, we found that the **single stage method led to achieving slightly higher accuracy than that multi stage method.**

Multi Stage Performance:

View Classification accuracy: 99%
tumor classification accuracy : 94%

Single Stage Accuracy:

Classification accuracy: 97%

Agenda

- Problem Definition
- Project Motivation
- Project Objective
- Related Work
- Proposed Methodology
- Dataset
- Results
- **Conclusion and Future Work**
- Tools
- References

Conclusion

- In this project, the computer-based techniques for automatic classification of MR images as normal or abnormal using different classifier.
- We worked on dataset we collected from multiple sources (Kaggle, some outside hospitals that respond to us).
- We resized Images to 224x224 image resolution and tried training the models with RGB images. Then we normalized and removing noise using median filter for images because MR images are too sensitive for noise. Finally, we start our training. The performances of the classifiers in terms of statistical measures such as loss rate and accuracy are analyzed.
- We trained some Deep Learning models like VGG-16, VGG-19 and Res-Net, and tried a machine learning method SVM. The results indicated that RES-Net approach yielded the better performance when compared to other classifiers as we achieved accuracy of 97% while other classifiers achieved accuracy ranged between 93% to 95%.
- With each model we used we tried different hyper parameter like changing learning rate, optimizers and various numbers of epochs.
- We used different data augmentation techniques to increase and balance our dataset to achieve higher accuracy

Future Work

- We aim to try to increase the dataset to improve accuracy and we will get MR image for a breast cancer and lung cancer and more cancer types to add more functionality for our software like make a segmentation for MR image to know the exact cancer place. Also, trying to make a marketing for software and get a sponsor to be real world project.
- Another aspect that may improve the performance is to involve more complicated image preprocessing procedures. MR images is susceptible to noise, so inhomogeneity correction and noise removal algorithms can be applied before feature extraction.

Agenda

- Problem Definition
- Project Motivation
- Project Objective
- Related Work
- Proposed Methodology
- Dataset
- Results
- Conclusion and Future Work
- Tools
- References

Tools

- **MATLAB**
  - For preprocessing
- **Python**
  - For Models Implementations and gui

References

1) Ali IúÕna, Cem Direkoglub, Melike ùahc. Review of MRI-based brain tumor image segmentation using deep learning methods. Procedia Computer Science(2016).

2) Evangelia I. Zacharaki, Sumei Wang, Sanjeev Chawla, Dong Soo Yoo, Ronald Wolf, Elias R. Melhem, Christos Davatzikos. MRI-BASED CLASSIFICATION OF BRAIN TUMOR TYPE AND GRADE USING SVM-RFE. IEEE International Symposium on Biomedical Imaging(2014).

3) B.Sudha, P.Gopikannan, A.Shenbagarajan, C.Balasubramanian. Classification of Brain Tumor Grades using Neural Network. Proceedings of the World Congress on Engineering(2014).

4) Sudipta Roy a, Debnath Bhattacharyya, Samir Kumar Bandyopadhyay, Tai-Hoon Kim. Heterogeneity of human brain tumor with lesion identification, localization and analysis from MRI. Elsevier(2019).

5) Zeynettin Akkus, Alfiia Galimzianova, Assaf Hoogi, Daniel L. Rubin, Bradley J. Erickson. Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions. J Digit Imaging (2017).

6) Jun Cheng, Wei Huang, Shuangliang Cao, Ru Yang, Wei Yang, Zhaoqiang Yun, Zhijian Wang, Qianjin Feng. Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition. PLoS ONE(2015).

7) R. Thillaikkarasi, S. Saravanan. An Enhancement of Deep Learning Algorithm for Brain Tumor Segmentation Using Kernel Based CNN with M-SVM. Journal of Medical Systems (2019).

8) Xiaomei Zhao, Yihong Wu, Guidong Song, Zhenye Li, Yong Fan and Yazhuo Zhang. Brain Tumor Segmentation Using a Fully Convolutional Neural Network with Conditional Random Fields. Chinese Academy of Sciences(2016).

9) Geetika Gupta, Rupinder Kaur, Arun Bansal, Munish Bansal. Analysis and Comparison of Brain Tumor Detection and Extraction Techniques from MRI Images. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering(2014).

10) Mandhir Kaur, Rinkesh Mittal. An Efficient Scheme for Brain Tumor Detection of MRI Brain Images Using Euclidean Distance With FVT. JOURNAL OF EMERGING TECHNOLOGIES IN WEB INTELLIGENCE(2014).

11) J. Seetha, S. Selvakumar Raja. Brain Tumor Classification Using Convolutional Neural Networks. Biomedical & Pharmacology Journal(2018).

12) Vidyasagar, Bhujangarao, Madhu. Qualitative Analysis of Brain tumor MRI. The International Daily journal(2015).

13) Ali ARI, Davut HANBAY. Deep learning based brain tumor classification and detection system. Turkish Journal of Electrical Engineering & Computer Sciences(2018).

14) Subhashis Banerjee, Sushmita Mitra. Brain Tumor Detection and Classification from Multi-Channel MRIs using Deep Learning and Transfer Learning. IEEE(2018).

15) Zahra Sobhaninia, Safiyeh Rezaei, Alireza Noroozi, Mehdi Ahmadi, Hamidreza Zarrabi, Nader Karimi, Ali Emami, Shadrokh Samavi. Brain Tumor Segmentation Using Deep Learning by Type Specific Sorting of Images. Department of Electrical and Computer Engineering(2018).

16) Yuehao Pan, Weimin Huang, Zhiping Lin, Wanzheng Zhu, Jiayin Zhou, Jocelyn Wong, Zhongxiang Ding. Brain Tumor Grading Based on Neural Networks and Convolutional Neural Networks. Society. IEEE Engineering in Medicine and Biology Society(2016).

17) Sajid Iqbal1, M. Usman Ghani, Tanzila Saba, Amjad Rehman. Brain tumor segmentation in multi-spectral MRI using convolutional neural networks (CNN). EMS Microscopy Acadmy(2018).

18) Jiachi Zhang, Xiaolei Shen, Tianqi Zhuo, Hong Zhou. Brain Tumor Segmentation Based on Refined Fully Convolutional Neural Networks with A Hierarchical Dice Loss. Key Laboratory for Biomedical Engineering(2017).

19) Mohammadreza Soltaninejad, Lei Zhang, Tryphon Lambrou, Guang Yang, Nigel Allinson, and Xujiong Ye. MRI Brain Tumor Segmentation using Random Forests and Fully Convolutional Networks. MICCAI(2017).

20) Parasuraman Kumar, B. VijayKumar. Brain Tumor MRI Segmentation and Classification Using Ensemble Classifier. International Journal of Recent Technology and Engineering(2019).

Any Questions ?!

THANK YOU