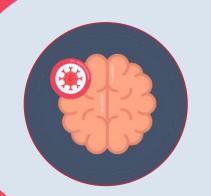
## Final Project Deep Learning:

Brain Tumors Detection Using Convolutional Neural Network.





#### **IBM Machine Learning Professional Certificate**

Course 05: Deep Learning & Reinforcement Learning | Brain Tumors Detection

By ARPAN SANKESH



### Contents

- Dataset Description
- Main objectives of the analysis.
- EDA, Data Cleaning, Feature Engineering
- Training deep learning models.
- ML analysis and findings.
- Models flaws and advanced steps.

## Data Description Section

### ntroduction

percent or air primary central vervous systemicins) tumors. Every year, around 11,700 people are diagnosed with a brain tumor. The 5-year survival rote for people within cancerous brain of CNS tumor is approximately 34 percent for men and 50 percent for women. Brain rumors one classified as:

Truditary Tumor, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the line expectancy of the patients. The best technique to detect brain tumors is magnetic resonance imaging (mrt). A mage amount or image data is generated through the scans. These images ore examined by the

rodiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties.

Application of automated has consistently

shown higher accuracy than manual classification.

Hence, proposing a system performing detection and classification by using Deep Learning Algorithms using

would be helpful to doctors around the world

#### What is Brain Tumor?

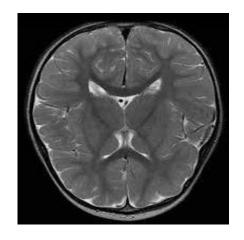
A brain tumor occurs when abnormal cells form within the brain. There are two main types of tumors: cancerous (malignant) tumors and benign tumors. Cancerous tumors can be divided into primary tumors, which start within the brain, and secondary tumors, which have spread from elsewhere, known as brain metastasis tumors. All types of brain tumors may produce symptoms that vary depending on the part of the brain involved. These symptoms may include headaches, seizures, problems with vision, vomiting and mental changes. The headache is classically worse in the morning and goes away with vomiting. Other symptoms may include difficulty walking, speaking or with sensations. As the disease

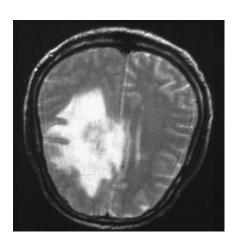


Brain metastasis in the right cerebral hemisphere from lung cancer, shown on magnetic resonance imaging .

**Quick explanation of the dataset** 

• YES – tumor, encoded as 1





dd ataset for this problem is Brgin MRI Images which will be used for Brain Tumor

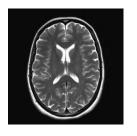
consists of MRI scans of two classes:

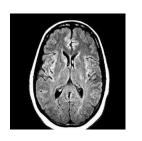
• NO - no tumor, encoded as 0

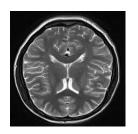
#### Quick explanation of the dataset

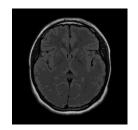
Folder	Description
No	The folder no contains 1500 Brain MRI Images that are nortumorous
Yes	The folder yes contains 1500 Brain MRI Images that are tumorous

No Tumor Samples

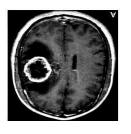




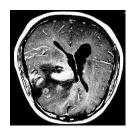


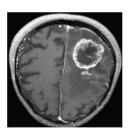


**Tumor Samples** 









# Main Objective of the analysis:

In thisanalysis we will explore the MRI Brain images

dataset in more details to approach a robust deep learning model aims to help doctors over the world in brain tumors diagnosis.

The selected model should be robust enough to detect tumors in the brain since there is no room for many errors in this delicate field.

# Exploratory Data Analysis (EDA) + Feature Engineering Section

## **Exploratory Data Analysis**

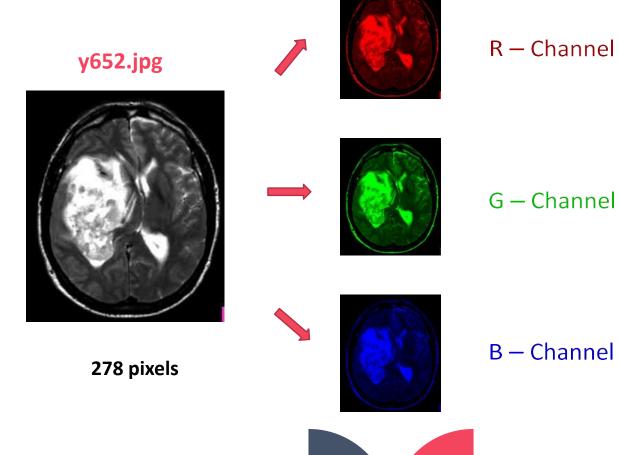
- Identifying images types and dimension:

• Images type : JPG

Dimensions : (width, height, 3)324

Image sample: "y652.jpg" pixels

• (324, 278, 3)



## Exploratory Data Analysis Here we will compare between the classes

	image_label	image_width	image_height
0	no0	630	630
1	no1	198	150
2	no10	225	225
3	no100	217	232
4	no1000	194	259
1495	no995	221	228
1496	no996	225	225
1497	no997	225	225
1498	no998	225	225
1499	no999	168	300
1500 rows × 3 columns			

No-Tumor images information

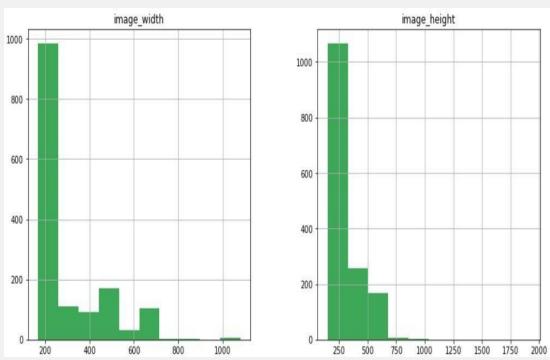
y0 y1	348 630	287
	630	
v10		587
y10	879	766
y100	630	630
y1000	336	264
y995	334	283
y996	354	303
y997	348	297
y998	1200	1059
y999	316	270
	y1000  y995 y996 y997 y998	y1000 336 y995 334 y996 354 y997 348 y998 1200

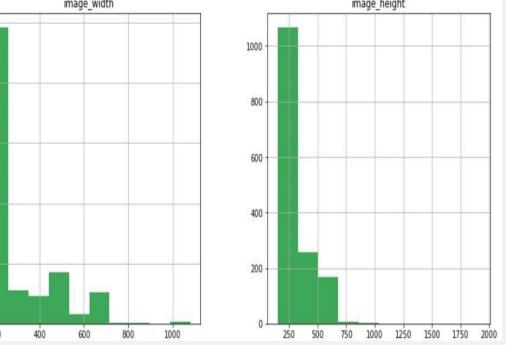
Tumor images information

## **Exploratory Data Analysis**

Here we compare between images widths and heights in both classes







image\_width image height 800 200 200 1250 1000

No-Tumor images [width, height] distribution

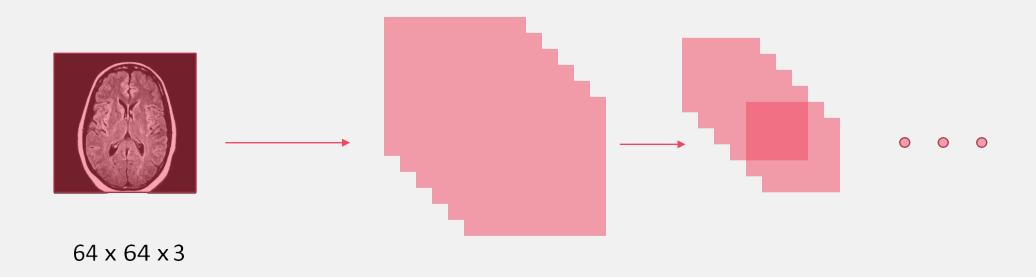
Tumor images [width, height] distribution

## **Feature Engineering**

#### **Images Resizing**

Since we have images with different dimensions, we must uniform all the dimensions due to the architecture of deep learning models :

- Input shape = 64 pixels
- After reshaping every image, we store them in a NumPy array



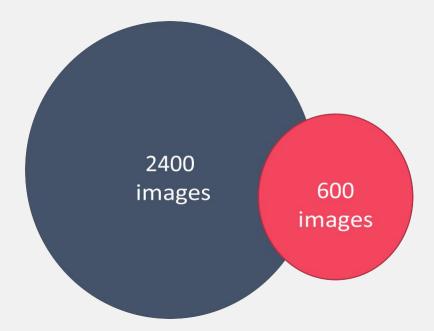
## **Feature Engineering**

#### **Dataset Splitting**

As we mentioned before in this presentation, we have in total 3000 images from this point we are going to split these images into two sets 80% for training set and 20% testing set

Training set: 2400 images

Testing set: 600 images





# Machine Learning Analysis & Findings

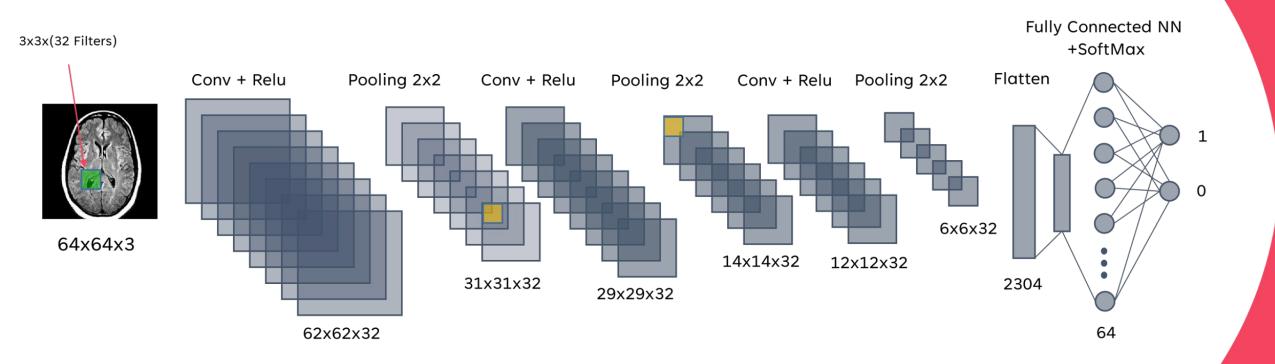
### Machine Learning Analysis & Findings

In the following slides we will compare between 2 different convolutional neural networks (CNN) one is based on Binary Cross Entropy and sigmoid function and the second one is based on Categorical Cross Entropy and SoftMax function for the final prediction layer.

These two models aim to classify MRI brain images to distinguish between the images that contain tumors and those that don't, for the sake of helping doctors in the diagnostic processes in the healthcare sector.

## **Machine Learning Analysis**

Model 01: CNN Categorical Cross Entropy Based & SoftMax Function.





# Machine Learning Analysis

Model 01: CNN Binary Cross Entropy Based & SoftMax Function.

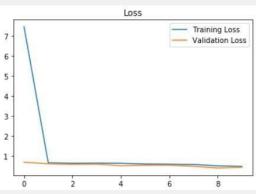
## Model 01 architecture & total number of parameters

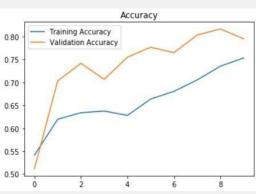
dense_7 (Dense)	(None, 2)	130
activation_19 (Activation)	(None, 2)	0
 Total params: 176,290		
Trainable params: 176,290		
Non-trainable params: 0		



## Machine Learning Findings Model 01 Training

```
Epoch 1/10
75/75 [===================] - 1s 15ms/step - loss: 7.4719 - accuracy: 0.5412 - val loss: 0.6770 - val accuracy: 0.511
Epoch 2/10
75/75 [=================] - 1s 8ms/step - loss: 0.6492 - accuracy: 0.6196 - val loss: 0.6024 - val accuracy: 0.7033
Epoch 3/10
75/75 [====================] - 1s 8ms/step - loss: 0.6263 - accuracy: 0.6338 - val loss: 0.5744 - val accuracy: 0.7417
Epoch 4/10
75/75 [====================] - 1s 8ms/step - loss: 0.6339 - accuracy: 0.6375 - val loss: 0.5849 - val accuracy: 0.7067
75/75 [=====================] - 1s 8ms/step - loss: 0.6251 - accuracy: 0.6279 - val loss: 0.5065 - val accuracy: 0.7550
75/75 [==================] - 1s 8ms/step - loss: 0.5902 - accuracy: 0.6637 - val loss: 0.5243 - val accuracy: 0.7767
75/75 [=====================] - 1s 8ms/step - loss: 0.5813 - accuracy: 0.6804 - val loss: 0.5312 - val accuracy: 0.7650
75/75 [==================] - 1s 8ms/step - loss: 0.5651 - accuracy: 0.7054 - val loss: 0.4740 - val accuracy: 0.8033
75/75 [====================] - 1s 7ms/step - loss: 0.4967 - accuracy: 0.7354 - val loss: 0.3874 - val accuracy: 0.8167
```



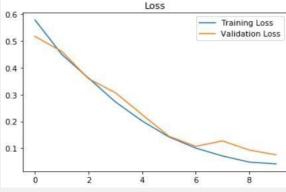


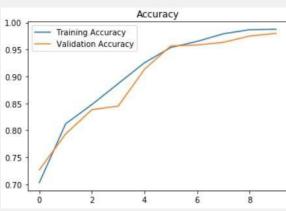
Set	Accuracy	Losses
Training	73.54 %	0.4967
Validation	81.67 %	0.3874

## **Machine Learning Findings**

**Model 02 Training** 

```
Epoch 1/10
Epoch 2/10
75/75 [====================] - 1s 8ms/step - loss: 0.4501 - accuracy: 0.8121 - val loss: 0.4612 - val accuracy: 0.7933
Epoch 3/10
Epoch 4/10
75/75 [======================] - 1s 8ms/step - loss: 0.2731 - accuracy: 0.8867 - val loss: 0.3073 - val accuracy: 0.8450
Epoch 5/10
75/75 [=====================] - 1s 8ms/step - loss: 0.2017 - accuracy: 0.9254 - val loss: 0.2255 - val accuracy: 0.9133
Epoch 6/10
75/75 [====================] - 1s 8ms/step - loss: 0.1421 - accuracy: 0.9538 - val loss: 0.1444 - val accuracy: 0.9567
Epoch 7/10
75/75 [======================] - 1s 8ms/step - loss: 0.1005 - accuracy: 0.9650 - val loss: 0.1069 - val accuracy: 0.9583
Epoch 8/10
Epoch 9/10
Epoch 10/10
```





Set	Accuracy	Losses
Training	98.75 %	0.0414
Validation	98.00 %	0.0755

# Models flaws and strengths and advanced steps

## Models' strengths and flaws

The first CNN model which is based on Categorical Cross Entropy as loss function and SoftMax for final Models Strengths and Flaws: prediction layer was not that accurate where it is achieved 73% on the training set and 81% on the validation set, since we deal with very sensitive field which is tumors diagnosis, we were required to improve our model, so we change the loss function into Binary Cross Entropy and sigmoid function for final prediction layer which is achieved high accuracy compared to the first one which achieved 98.75 % on the training set and 98.0 % on the validation set.

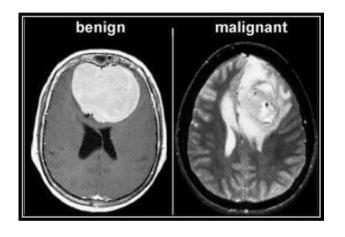
One of main flaws in these models is inability to detect the type of tumor, whether it is Benign Tumor or Malignant Tumor in addition of that it is unable of detecting the location of the tumor which is considered unexplainable model from this point we can improve our model by adding these features in advanced steps in the future.

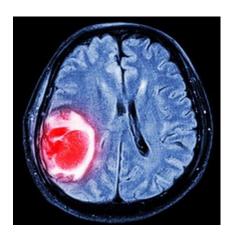
### Advanced

#### further suggestions:

In addition of detecting the tumors in the MRI Images we can provide more additional features :

- Classification of tumor type, whether benign or malignant
- Using advanced object detection algorithm to detect the boundaries of the tumor.
- Deploying the model on smartphone platforms to ease the access of the model to the specialists.





## Thank you

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Deep Learning and Reinforcement Learning

