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

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IBM

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- Main objectives of the analysis.
- EDA, Data Cleaning, Feature Engineering
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- Models flaws and advanced steps.

Data Description Section

Introduction

A Brain tumor is considered as one of the aggressive diseases, among children and adults. Brain tumors account for 85 to 90 percent of all primary Central Nervous System(CNS) tumors. Every year, around 11,700 people are diagnosed with a brain tumor. The 5-year survival rate for people with a cancerous brain or CNS tumor is approximately 34 percent for men and 36 percent for women. Brain Tumors are classified as: Benign Tumor, Malignant Tumor, Pituitary Tumor, etc. Proper treatment, planning, and accurate diagnostics should be implemented to improve the life expectancy of the patients. The best technique to detect brain tumors is Magnetic Resonance Imaging (MRI). A huge amount of image data is generated through the scans. These images are examined by the radiologist. A manual examination can be error-prone due to the level of complexities involved in brain tumors and their properties.

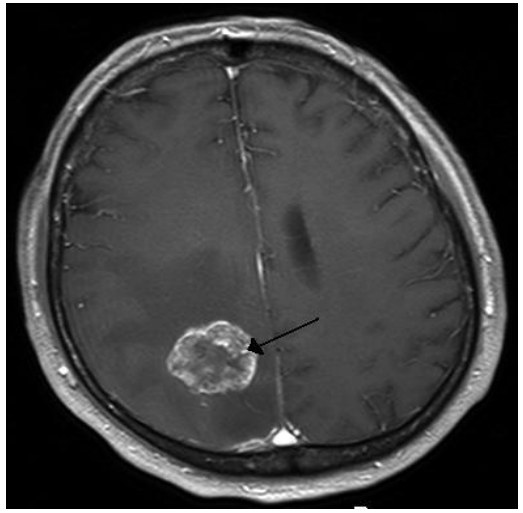
Application of automated classification techniques using Machine Learning(ML) and Artificial Intelligence(AI) has consistently shown higher accuracy than manual classification.

Hence, proposing a system performing detection and classification by using Deep Learning Algorithms using Convolution-Neural Network (CNN), Artificial Neural Network (ANN), and Transfer-Learning (TL) would be helpful to doctors around the world.

Dataset Description

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 progresses, unconsciousness may occur.



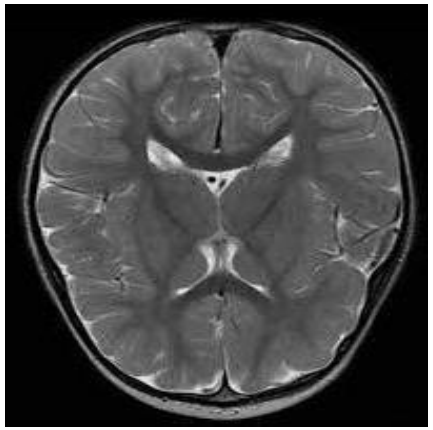
Brain metastasis in the right cerebral hemisphere from lung cancer, shown on magnetic resonance imaging .

Dataset Description

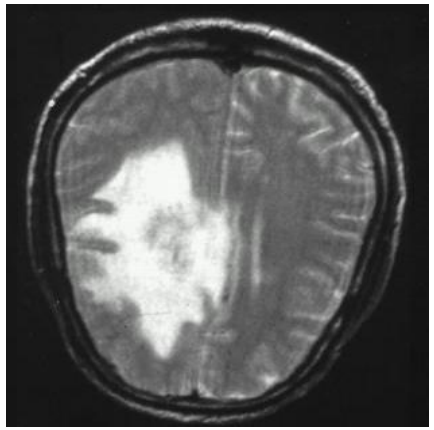
Quick explanation of the dataset

The dataset for this problem is Brain MRI Images which will be used for Brain Tumor Detection. It consists of MRI scans of two classes:

- NO - no tumor, encoded as 0
- YES - tumor, encoded as 1



0



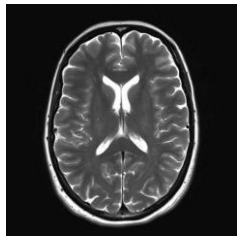
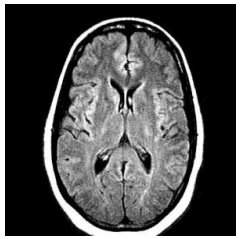
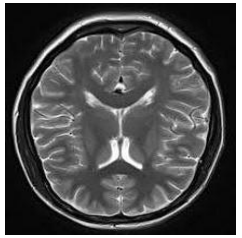
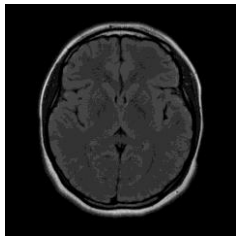
1

Dataset Description

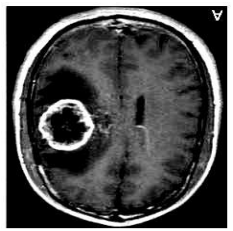
Quick explanation of the dataset

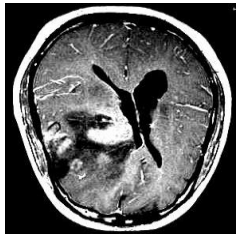
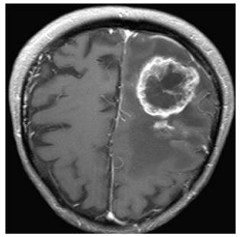
Folder	Description
No	The folder no contains 1500 Brain MRI Images that are non-tumorous
Yes	The folder yes contains 1500 Brain MRI Images that are tumorous

No Tumor Samples

Tumor Samples



Main Objective of the analysis:

In this analysis 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.

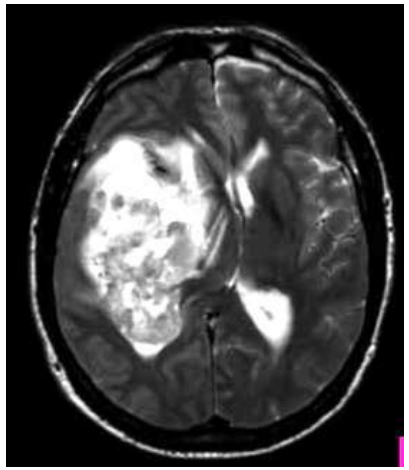
Exploratory Data Analysis (EDA) + Feature Engineering Section

Exploratory Data Analysis

- Identifying images types and dimension:

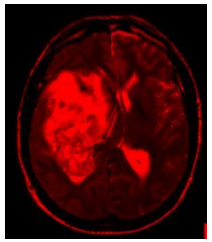
- Images type : JPG
- Dimensions : (width, height, 3)
- Image sample: “y652.jpg”
  - (324, 278, 3)

y652.jpg

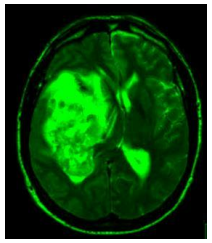


324 pixels

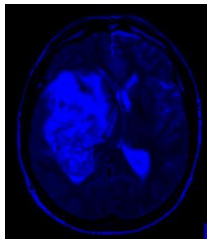
278 pixels



R – Channel



G – Channel



B – Channel

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

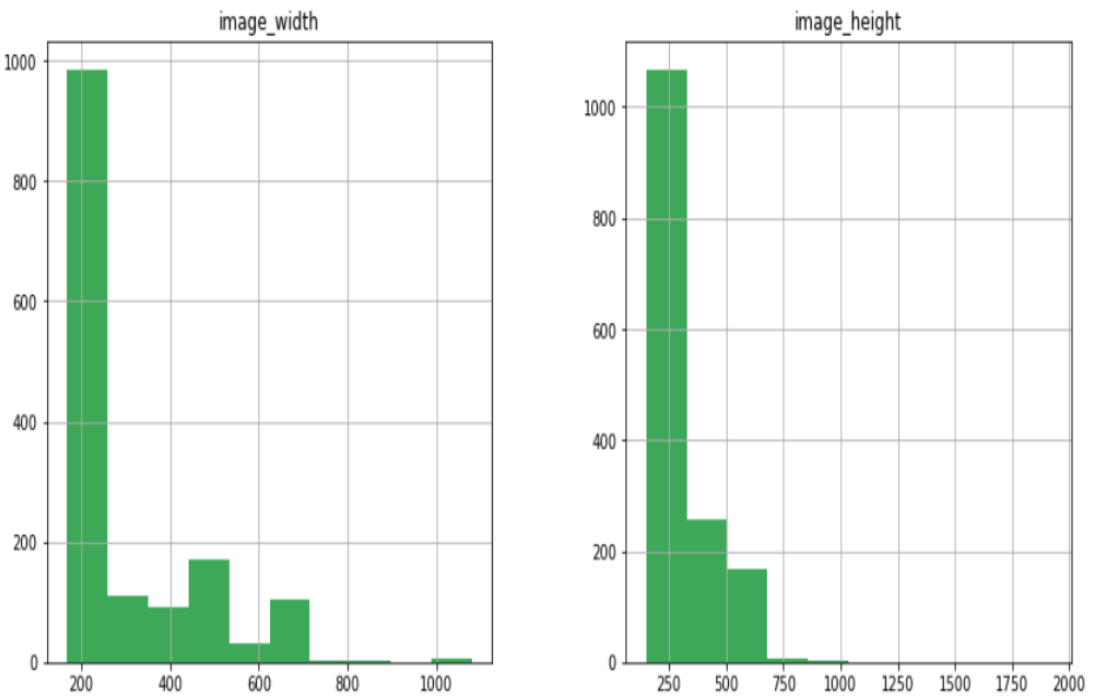
	image_label	image_width	image_height
0	y0	348	287
1	y1	630	587
2	y10	879	766
3	y100	630	630
4	y1000	336	264
...	...	...	...
1495	y995	334	283
1496	y996	354	303
1497	y997	348	297
1498	y998	1200	1059
1499	y999	316	270

1500 rows × 3 columns

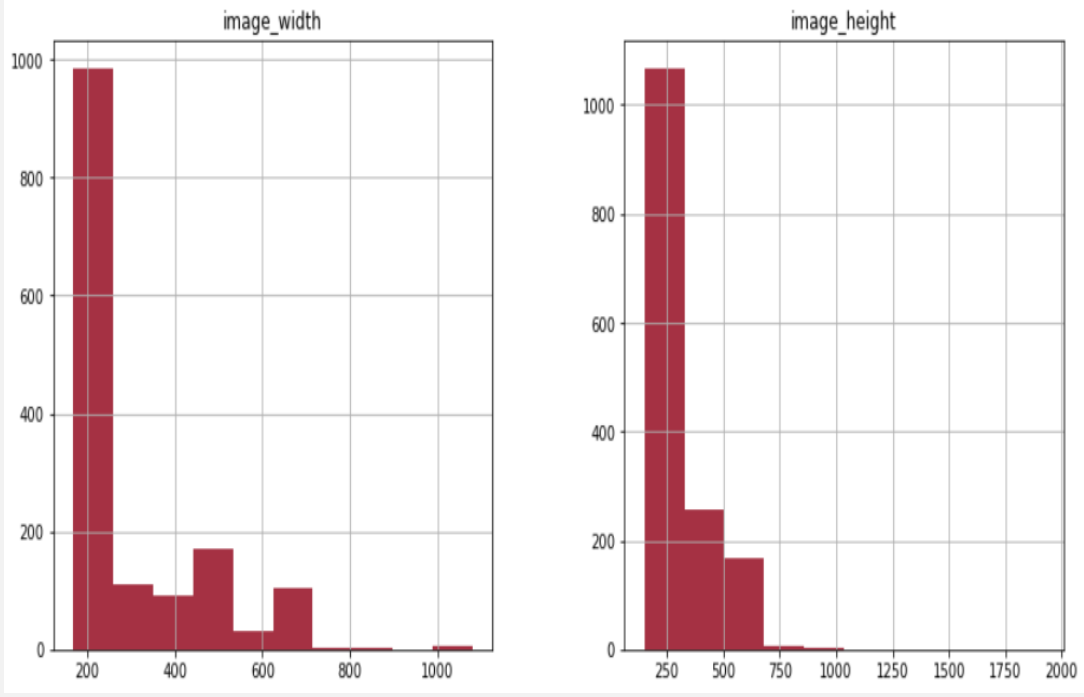
Tumor images information

Exploratory Data Analysis

Here we compare between images widths and heights in both classes



No-Tumor images [width, height] distribution



Tumor images [width, height] distribution

Exploratory Data Analysis

	image_width	image_height
count	1500.000000	1500.000000
mean	398.853333	350.455333
std	206.095229	193.916053
min	167.000000	175.000000
25%	294.000000	247.500000
50%	342.000000	283.000000
75%	380.000000	353.000000
max	1427.000000	1275.000000

No-Tumor Images Statistics

	image_width	image_height
count	1500.000000	1500.000000
mean	306.702667	299.980667
std	141.918226	148.211275
min	168.000000	150.000000
25%	225.000000	214.000000
50%	238.000000	227.000000
75%	400.000000	368.000000
max	1080.000000	1920.000000

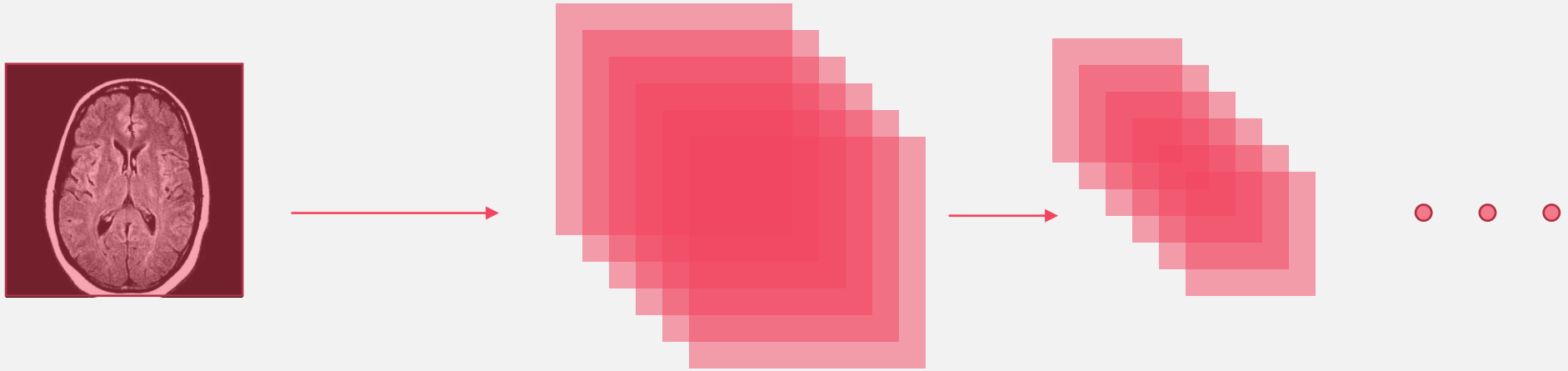
Tumor images Statistics

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



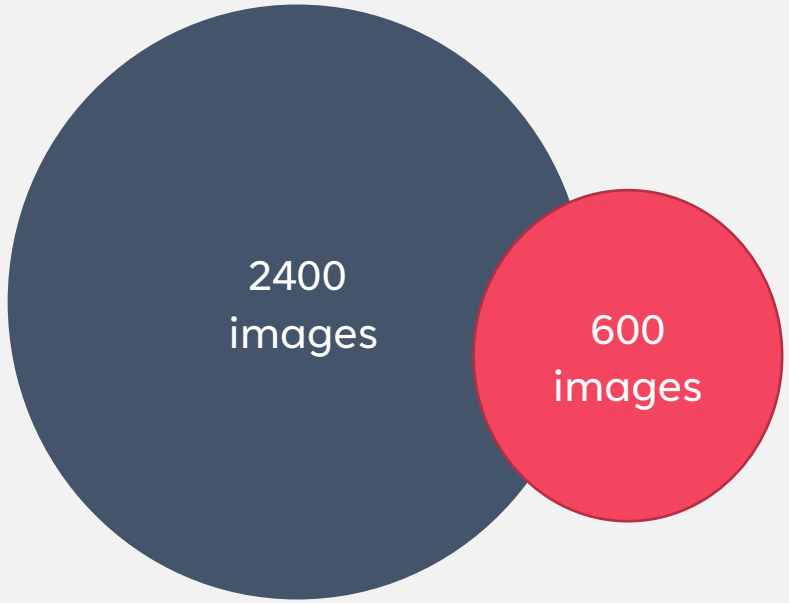
64 x 64 x 3

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

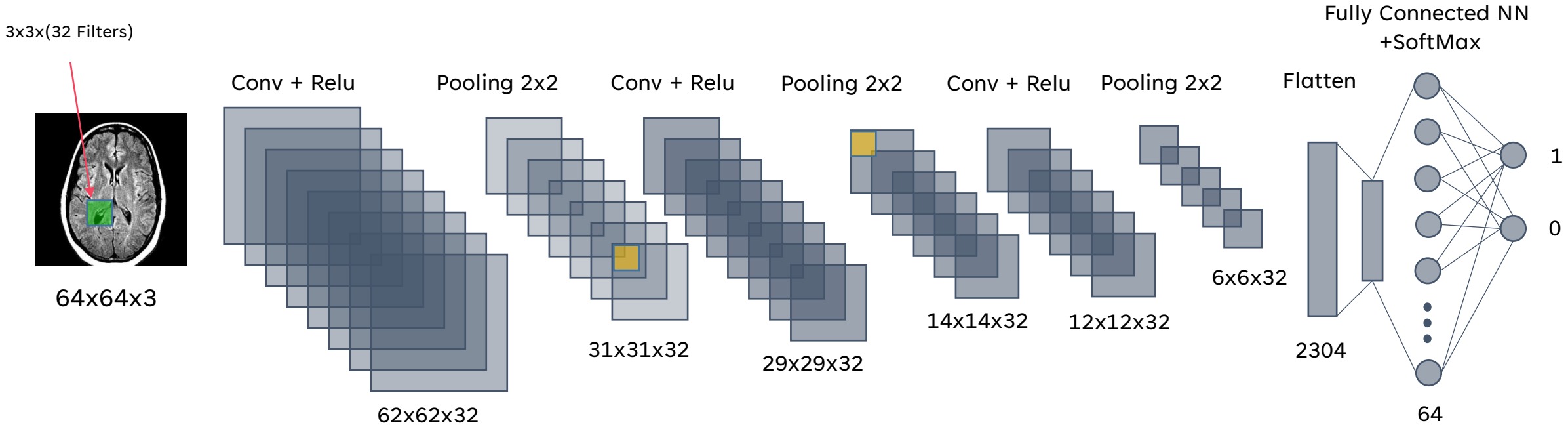
Machine Learning Analysis & Findings

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.

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 62, 62, 32)	896
activation_15 (Activation)	(None, 62, 62, 32)	0
max_pooling2d_9 (MaxPooling2	(None, 31, 31, 32)	0
conv2d_10 (Conv2D)	(None, 29, 29, 32)	9248
activation_16 (Activation)	(None, 29, 29, 32)	0
max_pooling2d_10 (MaxPooling	(None, 14, 14, 32)	0
conv2d_11 (Conv2D)	(None, 12, 12, 64)	18496
activation_17 (Activation)	(None, 12, 12, 64)	0
max_pooling2d_11 (MaxPooling	(None, 6, 6, 64)	0
flatten_3 (Flatten)	(None, 2304)	0
dense_6 (Dense)	(None, 64)	147520
activation_18 (Activation)	(None, 64)	0
dropout_3 (Dropout)	(None, 64)	0

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

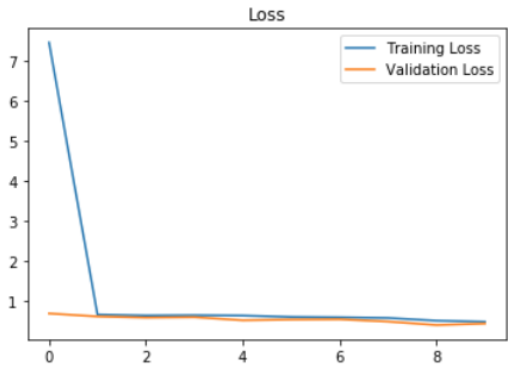
Machine Learning Findings

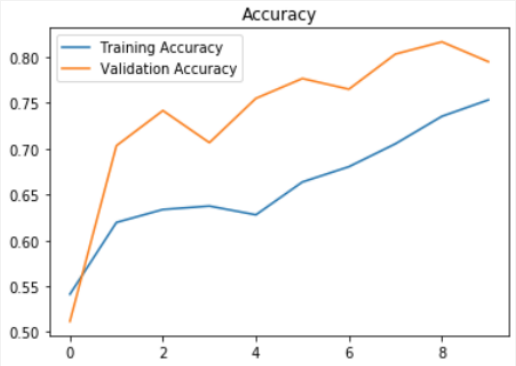
Model 01 Training

```
model_1.fit(x_train, y_train, batch_size=32, verbose=True, epochs=10,
            validation_data=(x_test, y_test), shuffle=False)

model_1.save("BrainTumorCategorical10Epochs.h5")
```

```
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
Epoch 5/10
75/75 [==============================] - 1s 8ms/step - loss: 0.6251 - accuracy: 0.6279 - val_loss: 0.5065 - val_accuracy: 0.7550
Epoch 6/10
75/75 [==============================] - 1s 8ms/step - loss: 0.5902 - accuracy: 0.6637 - val_loss: 0.5243 - val_accuracy: 0.7767
Epoch 7/10
75/75 [==============================] - 1s 8ms/step - loss: 0.5813 - accuracy: 0.6804 - val_loss: 0.5312 - val_accuracy: 0.7650
Epoch 8/10
75/75 [==============================] - 1s 8ms/step - loss: 0.5651 - accuracy: 0.7054 - val_loss: 0.4740 - val_accuracy: 0.8033
Epoch 9/10
75/75 [==============================] - 1s 7ms/step - loss: 0.4967 - accuracy: 0.7354 - val_loss: 0.3874 - val_accuracy: 0.8167
Epoch 10/10
75/75 [==============================] - 1s 7ms/step - loss: 0.4699 - accuracy: 0.7533 - val_loss: 0.4243 - val_accuracy: 0.7950
```

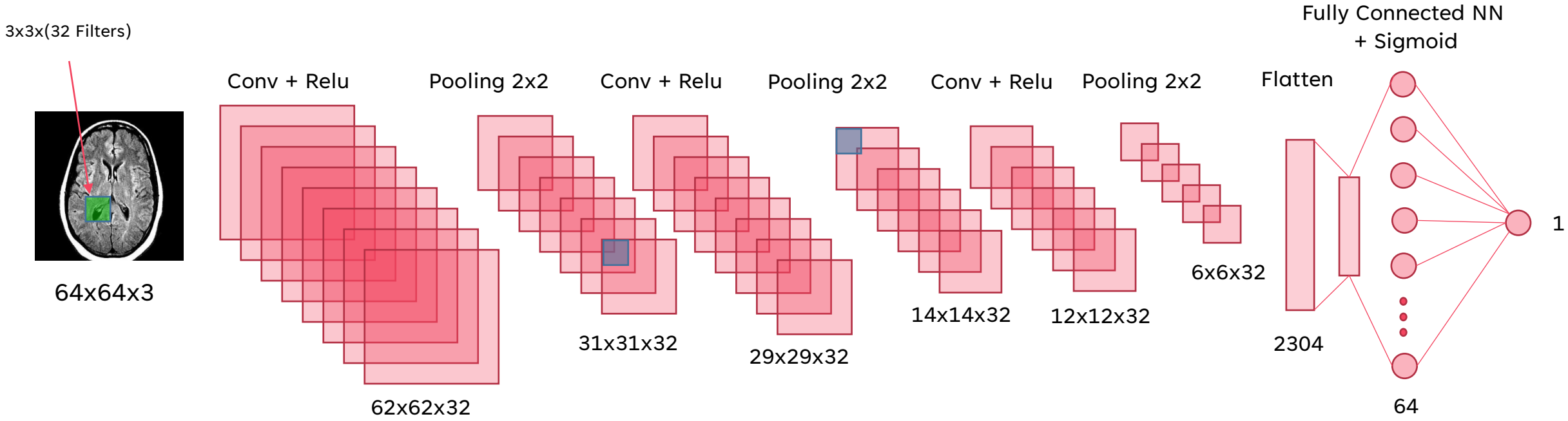




Set	Accuracy	Losses
Training	73.54 %	0.4967
Validation	81.67 %	0.3874

Machine Learning Analysis

Model 02 : CNN Binary Cross Entropy Based & Sigmoid Function.



Machine Learning Analysis

Model 02 : CNN Binary Cross Entropy Based & Sigmoid Function.

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 62, 62, 32)	896
activation_12 (Activation)	(None, 62, 62, 32)	0
max_pooling2d_9 (MaxPooling2	(None, 31, 31, 32)	0
conv2d_10 (Conv2D)	(None, 29, 29, 32)	9248
activation_13 (Activation)	(None, 29, 29, 32)	0
max_pooling2d_10 (MaxPooling	(None, 14, 14, 32)	0
conv2d_11 (Conv2D)	(None, 12, 12, 64)	18496
activation_14 (Activation)	(None, 12, 12, 64)	0
max_pooling2d_11 (MaxPooling	(None, 6, 6, 64)	0
flatten_3 (Flatten)	(None, 2304)	0
dense_3 (Dense)	(None, 64)	147520
activation_15 (Activation)	(None, 64)	0
dropout_3 (Dropout)	(None, 64)	0

Model 02 architecture & total number of parameters

dense_4 (Dense)	(None, 1)	65
activation_16 (Activation)	(None, 1)	0

Total params: 176,225

Trainable params: 176,225

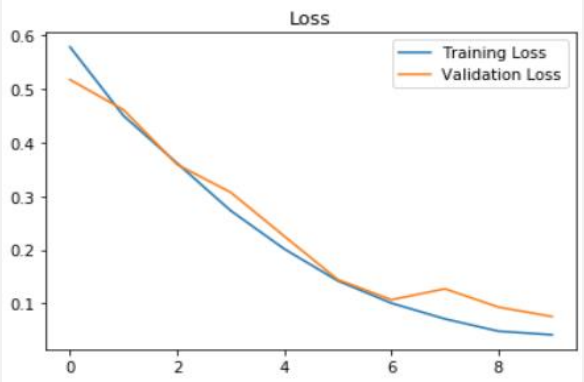
Non-trainable params: 0

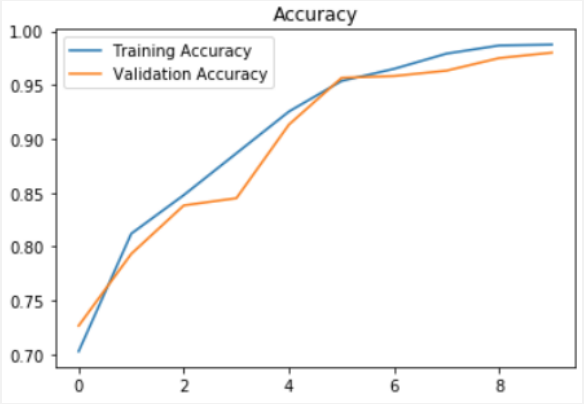
Machine Learning Findings

Model 02 Training

```
model_2.fit(x_train, y_train, batch_size=32, verbose=True, epochs=10,
            validation_data=(x_test, y_test), shuffle=False)
```

```
Epoch 1/10
75/75 [==============================] - 1s 16ms/step - loss: 0.5786 - accuracy: 0.7029 - val_loss: 0.5175 - val_accuracy: 0.7267
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
75/75 [==============================] - 1s 8ms/step - loss: 0.3616 - accuracy: 0.8479 - val_loss: 0.3592 - val_accuracy: 0.8383
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
75/75 [==============================] - 1s 9ms/step - loss: 0.0711 - accuracy: 0.9792 - val_loss: 0.1272 - val_accuracy: 0.9633
Epoch 9/10
75/75 [==============================] - 1s 9ms/step - loss: 0.0481 - accuracy: 0.9867 - val_loss: 0.0930 - val_accuracy: 0.9750
Epoch 10/10
75/75 [==============================] - 1s 8ms/step - loss: 0.0414 - accuracy: 0.9875 - val_loss: 0.0755 - val_accuracy: 0.9800
```





Set	Accuracy	Losses
Training	98.75 %	0.0414
Validation	98.00 %	0.0755

Models flaws and strengths and advanced steps

Models' strengths and flaws

Models Strengths and Flaws:

The first CNN model which is based on Categorical Cross Entropy as loss function and SoftMax for final 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.

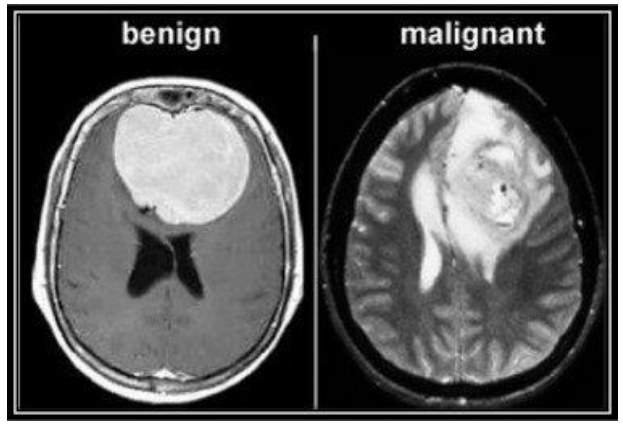
One of main flaws in these models is inability to detect the type of tumor, whether it is Benign Tumor or Malignant Tumor in addition of that it is unable of detecting the location of the tumor which is considered unexplainable model from this point we can improve our model by adding these features in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

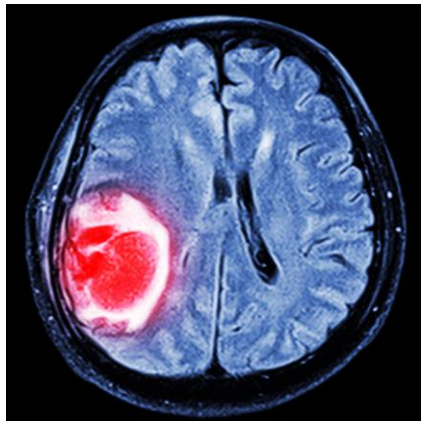
Advanced steps

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

IBM Machine Learning Professional Certificate

Deep Learning and Reinforcement Learning

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