Brain Tumor Classification in MRI Images

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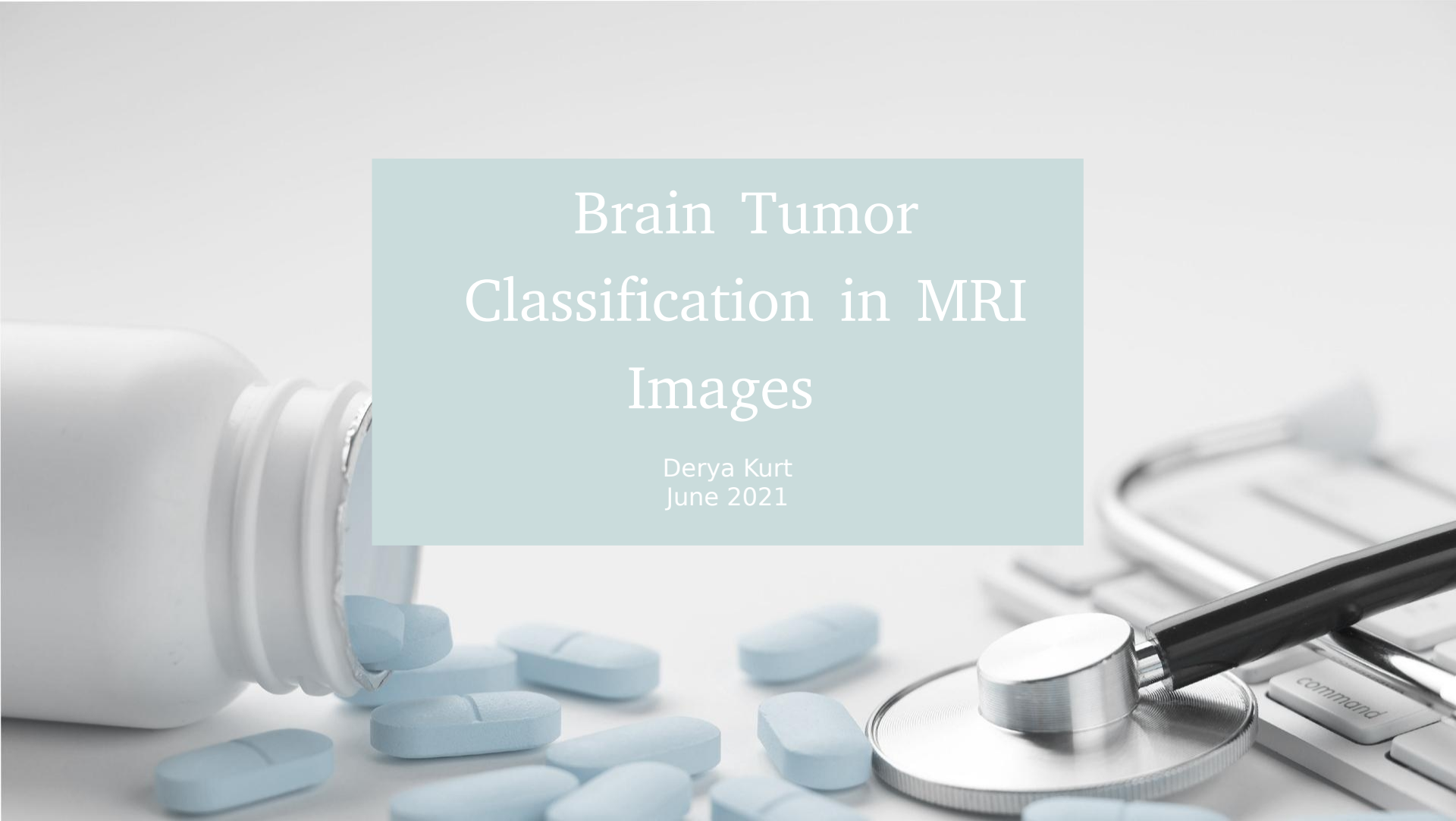
June 2021



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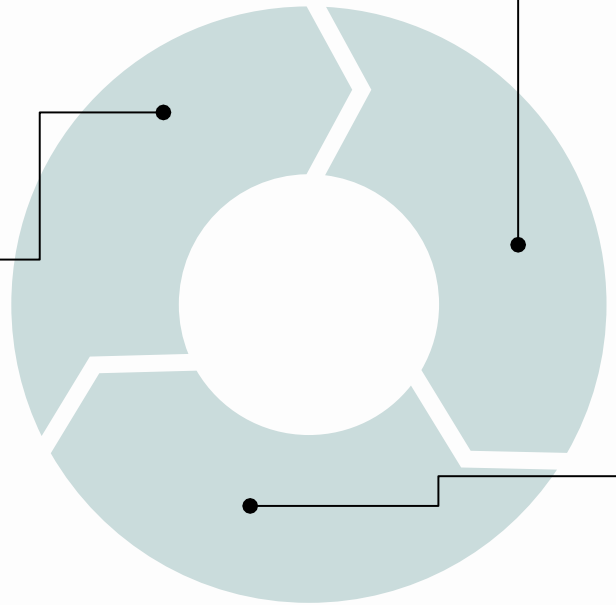
INTRODUCTION

BRAIN TUMOR



NEW CASES PER YEAR

84.000

PRIMARY TUMOR TYPES

Meningioma

Pituitary

Glioma

SURVIVAL RATE FROM MALIGNANT TUMORS

36 %

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PROBLEM STATEMENT

PROBLEM STATEMENT

Magnetic Resonance Imaging (MRI)

Most common technique for tumor diagnosis

Limitations of MRI

-Time Consuming during MRI Analysis

-Accuracy depends on radiologists experience

Objective

Develop a Deep Learning approach to detect and classify Brain Tumor in a short time

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DATA AND PREPROCESSING

DATA OVERVIEW

2,870

MENINGIOMA	GLIOMA	PITUITARY	NO TUMOR
822	826	827	395

DATA PREPROCESSING

IMAGE PROCESSING

SIZE Different Image Shapes (250 X 250) (130 X 130) (512 X 512) (300 X 236)
Images Resized to 150 X15

COLOR RGB ---> GRAYSCALE

PIXEL VALUE Normalized to [0,1]

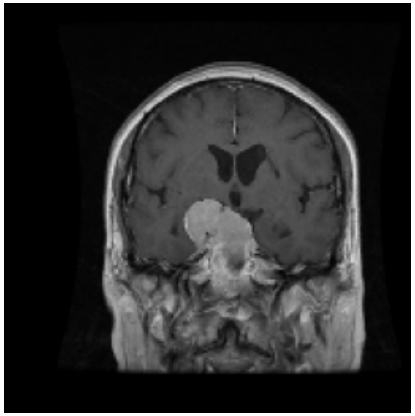
CLASS LABELS ['glioma', meningioma, no tumor, pituitary'] **LabelEncoder()** → [0, 1, 2, 3]

	OneHotEncoding
Glioma	[1 0 0 0]
Meningioma	[0 1 0 0]
No Tumor	[0 0 1 0]
Pituitary	[0 0 0 1]

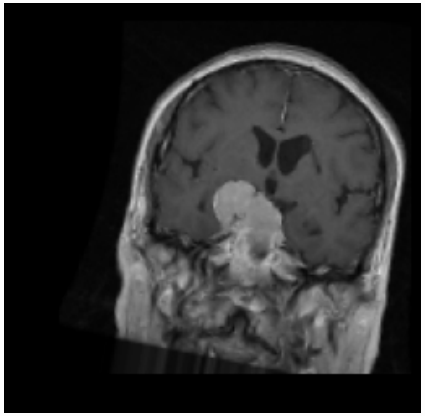
DATA PREPROCESSING

DATA AUGMENTATION

- Avoids Overfitting
- Shear - Zoom - Width & Height Shift - Horizantal - Flip Rotation



Original Image



Augmented Image

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CLASSIFICATION METHODS AND MODELS

Multi-Class Classifiers Method

CNN Model Architecture

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 150, 150, 64)	640
max_pooling2d_10 (MaxPooling	(None, 75, 75, 64)	0
conv2d_11 (Conv2D)	(None, 75, 75, 128)	73856
max_pooling2d_11 (MaxPooling	(None, 38, 38, 128)	0
conv2d_12 (Conv2D)	(None, 38, 38, 128)	147584
max_pooling2d_12 (MaxPooling	(None, 19, 19, 128)	0
conv2d_13 (Conv2D)	(None, 19, 19, 128)	147584
max_pooling2d_13 (MaxPooling	(None, 10, 10, 128)	0
conv2d_14 (Conv2D)	(None, 10, 10, 128)	147584
max_pooling2d_14 (MaxPooling	(None, 5, 5, 128)	0
flatten_2 (Flatten)	(None, 3200)	0
dense_4 (Dense)	(None, 512)	1638912
dense_5 (Dense)	(None, 4)	2052

Total params: 2,158,212
Trainable params: 2,158,212
Non-trainable params: 0

5 – Convolutional Layer
5 – MaxPooling Layer
1 - Fully Connected Layer
Output Layer with 4 classes

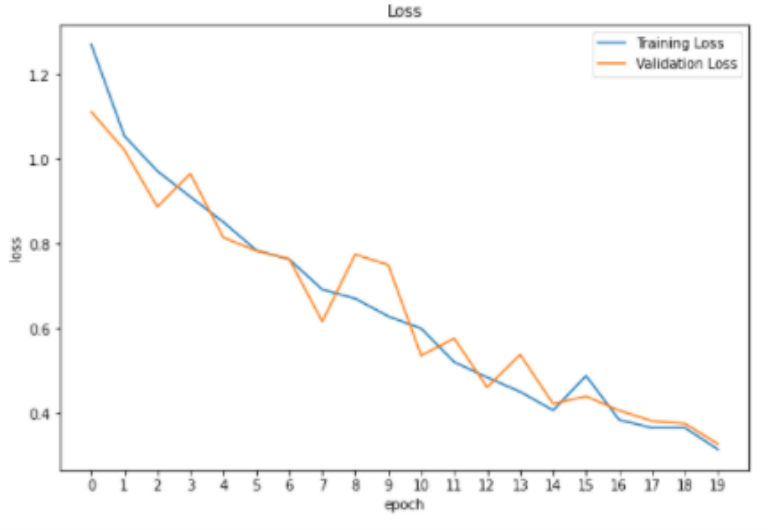
Multi-Class Classifiers Method

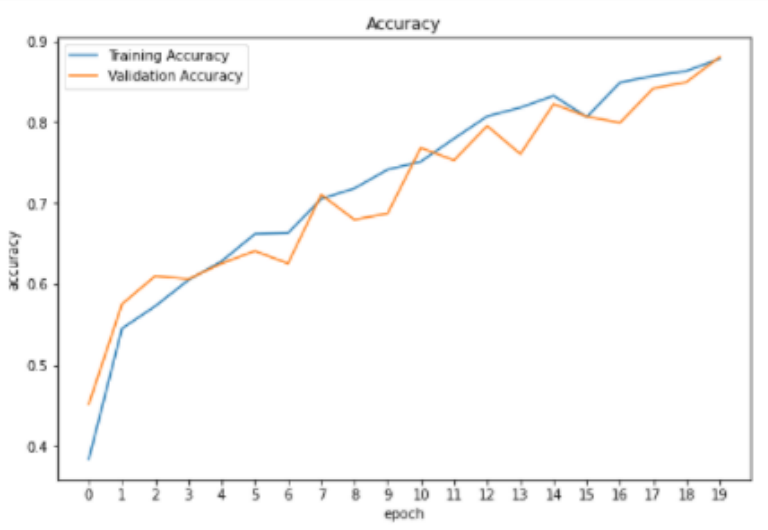
Model Compiling		Model Training CALLBACKS
OPTIMIZER	ADAM	**EARLYSTOPPING**
LEARNING RATE	0.01	Stop training when the monitored metric validation set accuracy stops improving
LOSS FUNCTION	CATEGORICAL CROSSENTROPY	**MODELCHECKPOINT**
METRICS	ACCURACY	Save the model weights at the maximum of the monitored quantity

Multi-Class Classifiers Method

CNN Multiclass Model Evaluation

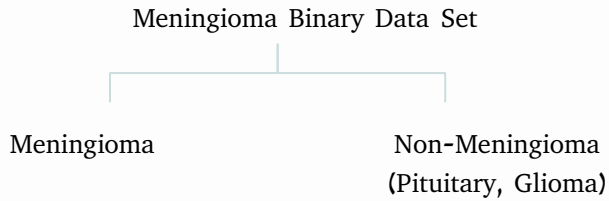
Validation Accuracy - **0.8803** Test Accuracy - **0.8815**





Binary-Classifiers Method

Meningioma Binary Classifier



Model Architecture

Same architecture with Multiclass CNN Model:

5 – Convolutional Layer

5 – MaxPooling Layer

1 - Fully Connected Layer

Output Layer with 2 classes

Model Compiling

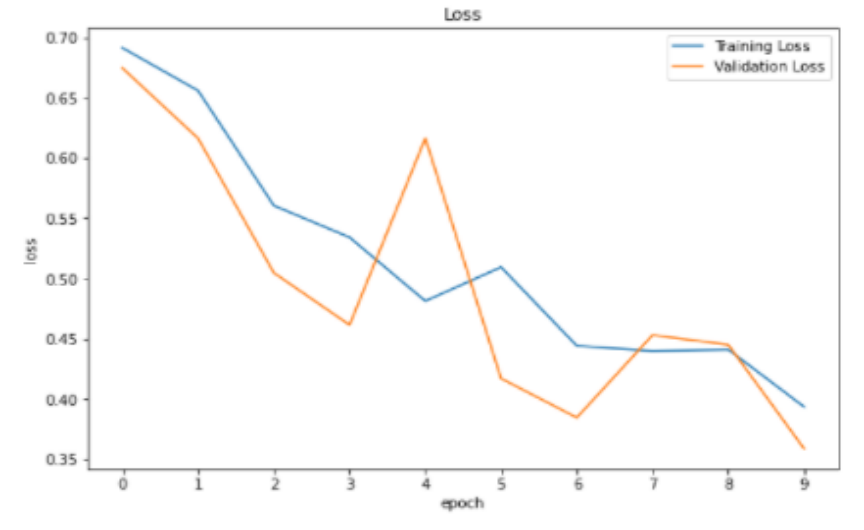
Same paramaters with Multiclass CNN Model

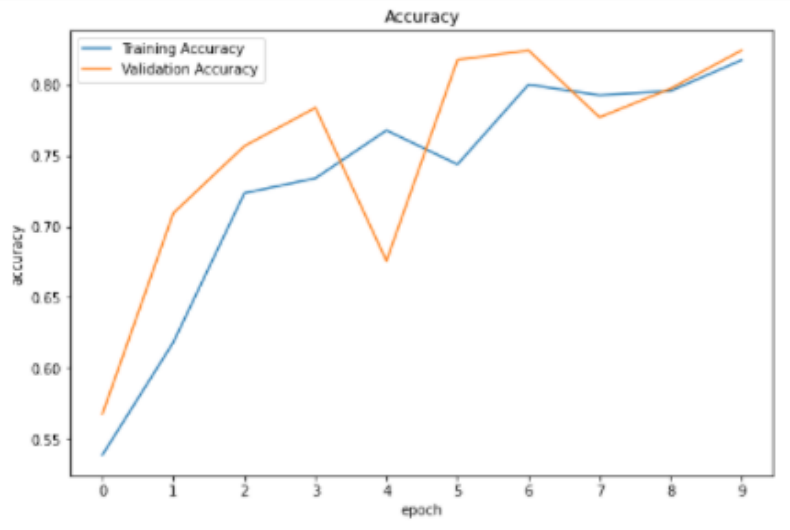
Model Training

Binary-Classifiers Method

Meningioma Binary Model Evaluation

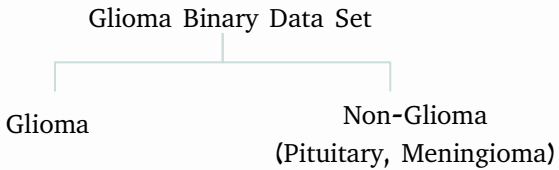
Validation Accuracy - **0.8243** Test Accuracy - **0.8061**





Binary-Classifiers Method

Glioma Binary Classifier



Model Architecture

3 – Convolutional Layer
3 – MaxPooling Layer
1 - Fully Connected Layer
Output Layer with 2 classes

Model Compiling

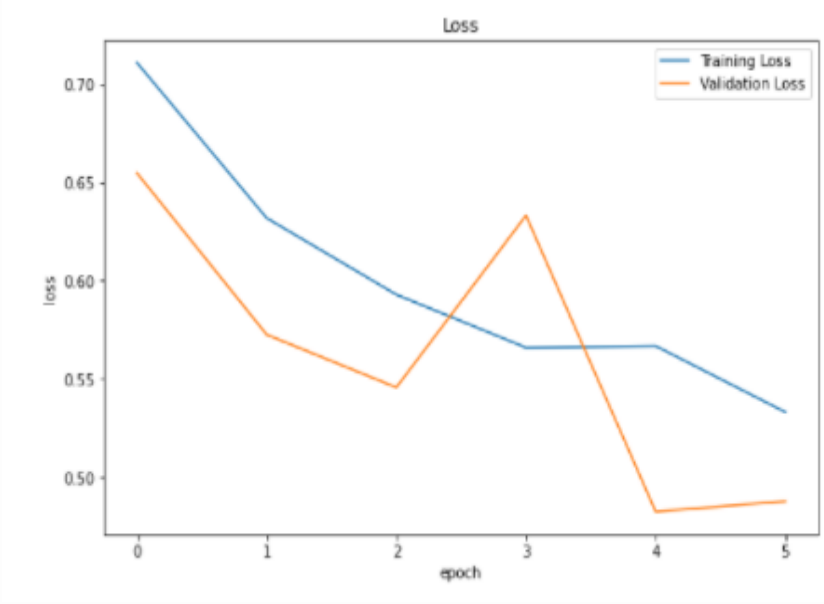
Model Training

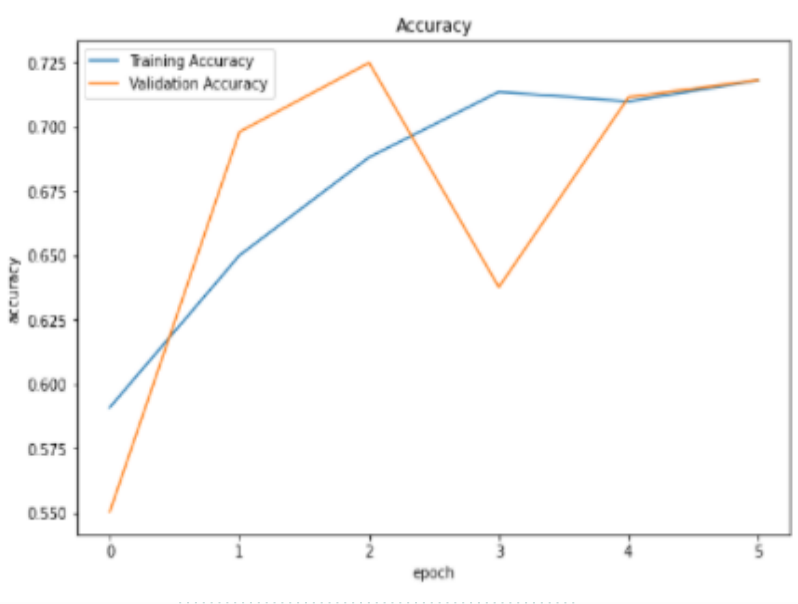
Same paramaters with Multiclass CNN Model

Binary-Classifiers Method

Glioma Binary Model Evaluation

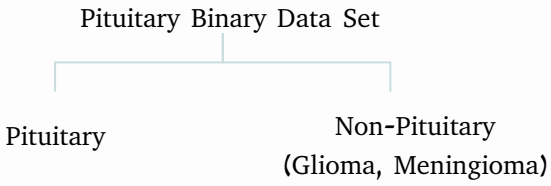
Validation Accuracy - **0.7181** Test Accuracy - **0.7289**





Multiple Binary-Classifiers Method

Pituitary Binary Classifier



Model Architecture

Same structure with Glioma Binary Model

3 – Convolutional Layer

3 – MaxPooling Layer

1 - Fully Connected Layer

Output Layer with 2 classes

Model Compiling

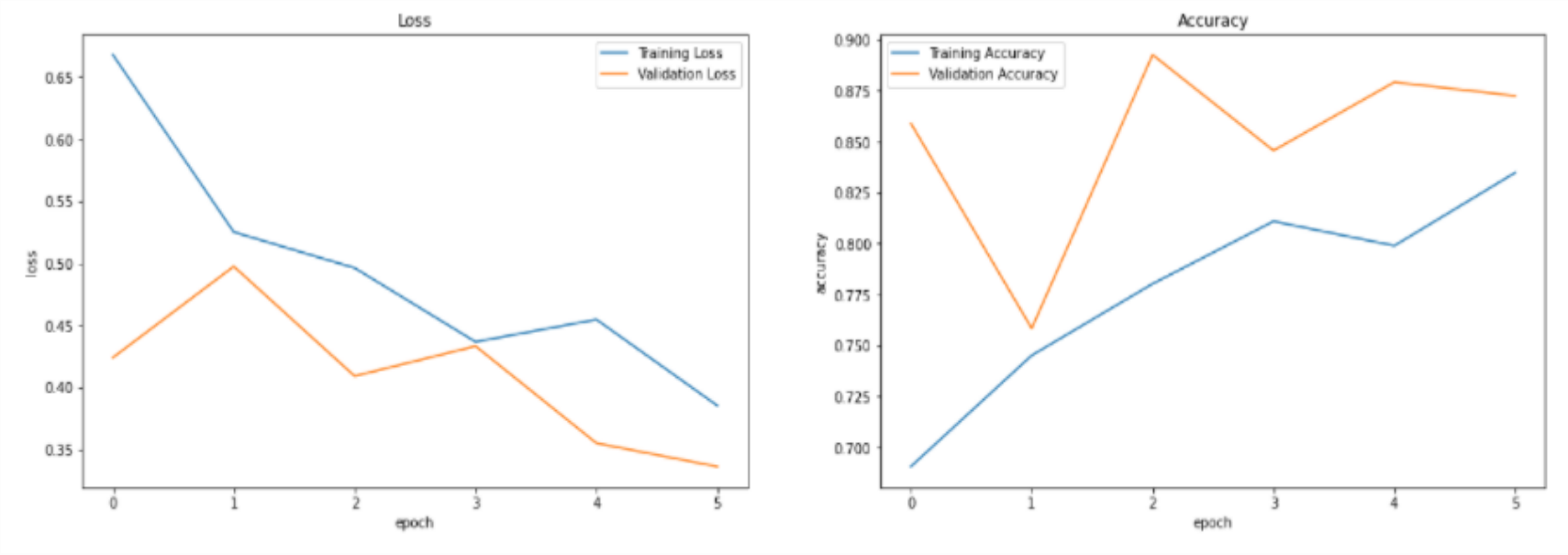
Same paramaters with Multiclass CNN Model

Model Training

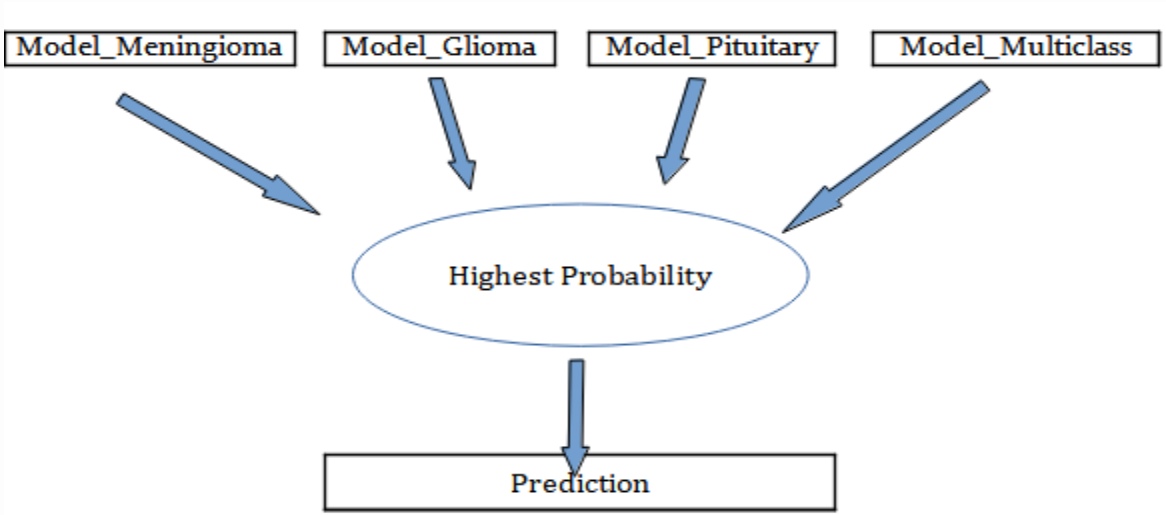
Binary-Classifiers Method

Pituitary Binary Model Evaluation

Validation Accuracy - **0.8275** Test Accuracy - **0.8675**



Ensemble Method




```
path='C:/Users/laptop/Desktop/BRAIN_TUMOR_STUDY/brain-tumor-classification-mri/Training/MultiClass/meningioma_tumor/m2 (15
img_process(path)
```

	multi_glioma	multi_meningioma	multi_no	multi_pituitary	model_meningioma	model_pituitary	model_glioma	Highest predicted class	True Class
0	0.043286	0.956708	4.925593e-08	0.000006	0.890799	0.993142	0.848486	pituitary	meningioma

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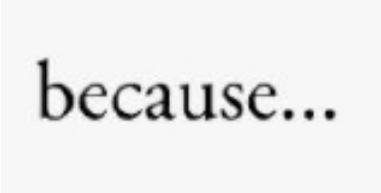
MODEL EVALUATION

Model Evaluation

Evaluation Metrics



RECALL

Capturing Tumor Highly Important For Treatment

PRECISION

Avoid improper treatment to a patient with no disease or differeet type of tumor

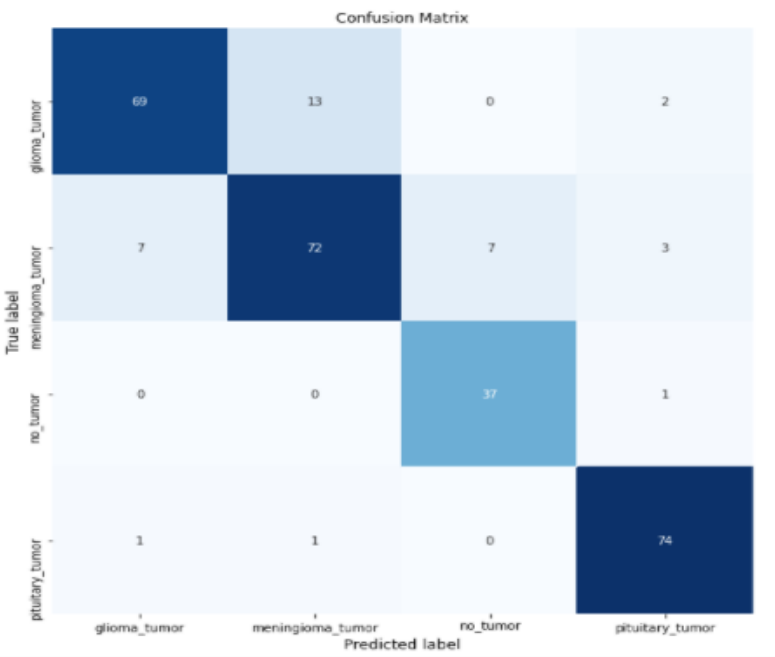
$$\text{Recall} = \frac{\text{correctly detected tumor (TP)}}{\text{all actual tumor (TP + FN)}}$$

$$\text{Precision} = \frac{\text{correctly detected tumor (TP)}}{\text{all tumor predicted (TP + FP)}}$$

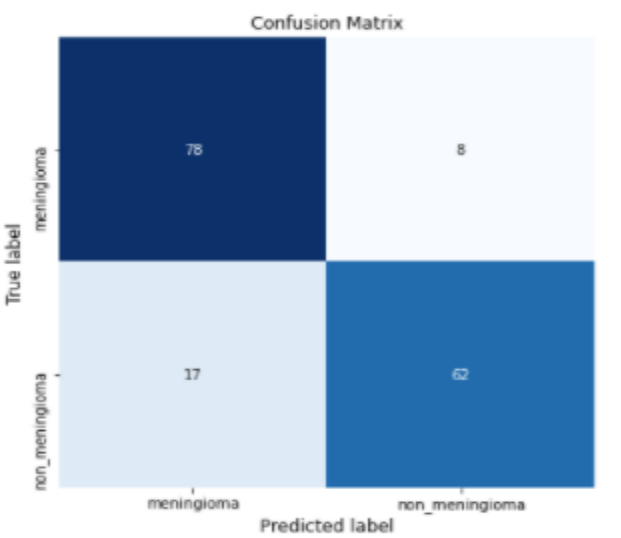
MODEL EVALUATION

Confusion Matrices

MULTICLASS MODEL



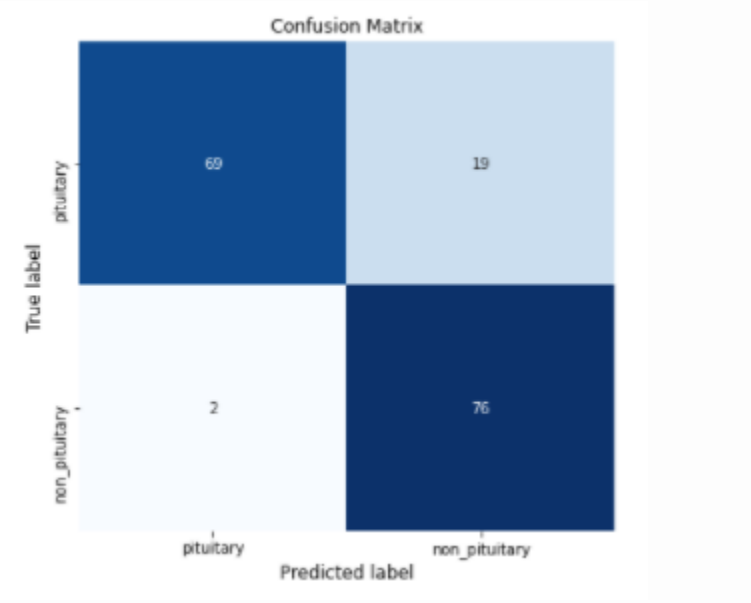
MENINGIOMA BINARY MODEL



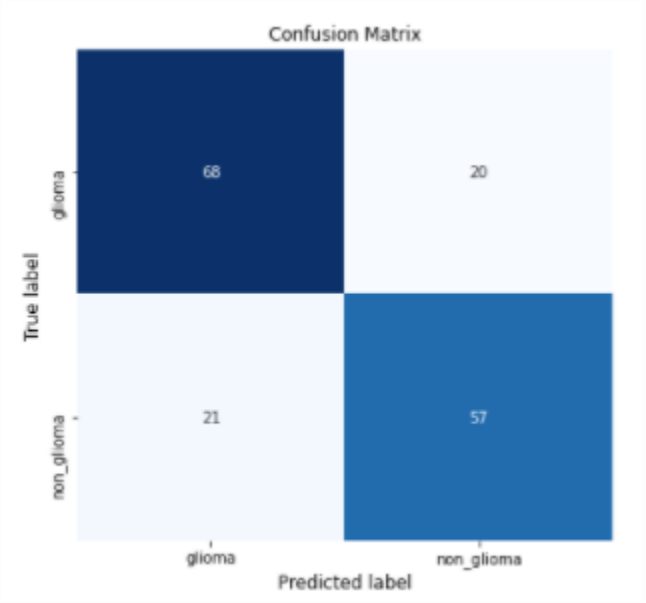
MODEL EVALUATION

Confusion Matrices

PITUITARY BINARY MODEL

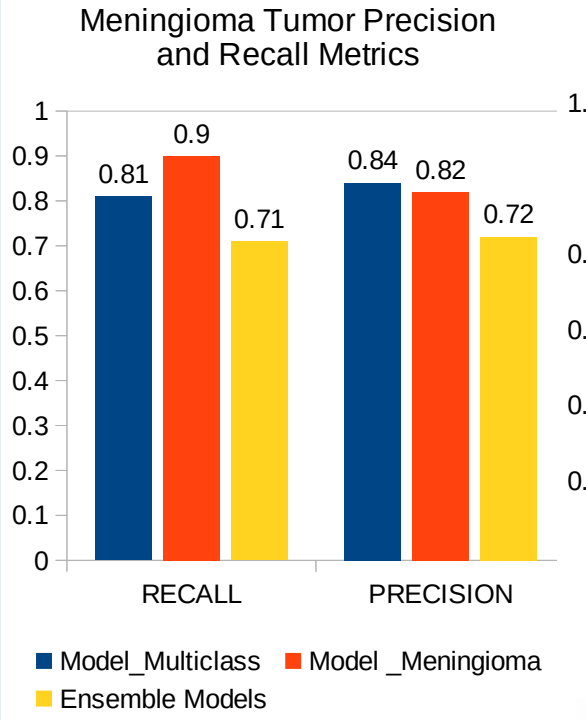


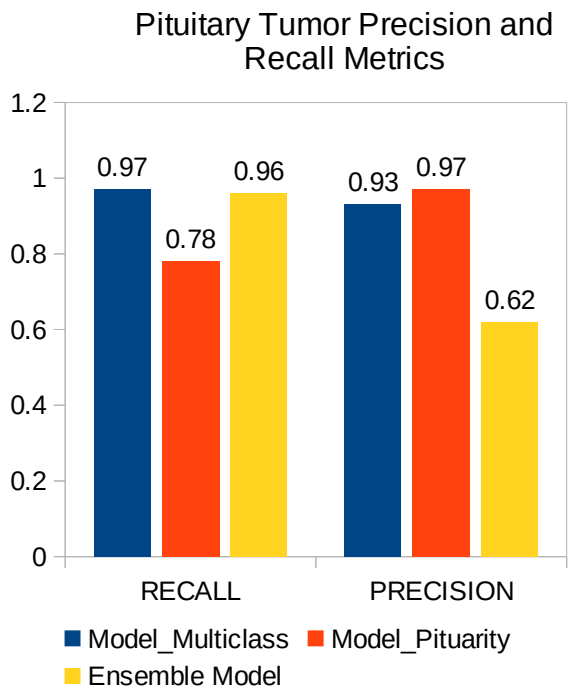
GLIOMA BINARY MODEL

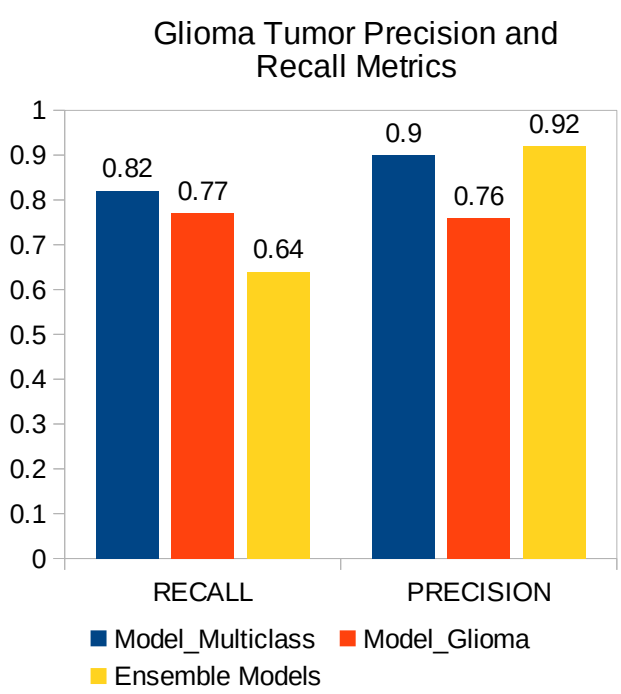


MODEL EVALUATION

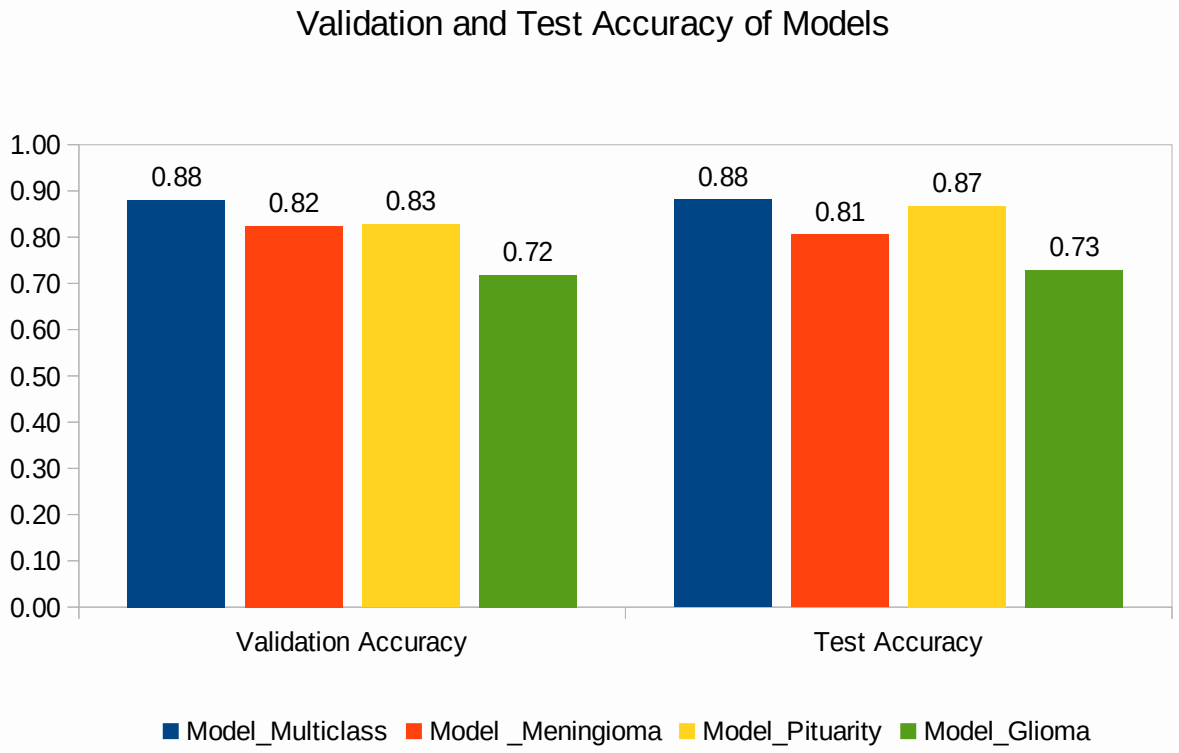
Recall and Precision Comparisons







MODEL EVALUATION



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CONCLUSION

CONCLUSION

The highest Prediction and Recall of each tumor:

Meningioma Tumor Classification: **Recall:** Model_Meningioma - 0.91 **Precision:** Multiclass Model - 0.84

Pituitary Tumor Classification: **Recall:** Multiclass Model – 0.97 **Precision:** Model_Pituitary- 0.97

Glioma Tumor Classification: **Recall:** Multiclass Model – 0.82 **Precision:** Multiclass Model - 0.92

Almost all models with 90% precision and recall scores.

Multiclass CNN model with the highest either recall or precision score.

The highest Test Accuracy:

Multiclass CNN model with Test Accuracy 0.8815.

The Multiclass Model has the highest precision, recall and test accuracy.

07

RECOMMENDATION

RECOMMENDATION

Since Multiclass Model results almost 90% accuracy in detecting and classifying brain tumor we would recommend to use Multiclass Model.

08

FUTURE WORK

FUTURE WORK

To build more robust deep learning model by

- using more images
- applying GridSearch for hyperparameter optimization
- using GPUs to reduce training time