

# RSNA-MICCAI BRAIN TUMOR RADIO GENOMIC MGMT CLASSIFICATION

(METHYLGUANINE METHYLTRANSFERASE)

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# PROBLEM STATEMENT

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- Aim to study the Brain Tumor MRI images and classify for MGMT promoter methylation status
- MRI scan images are **quite different** from our traditional **RGB images**
- First preprocess the images data, then fit it to several baseline models to **investigate the utility of AI**

# INTRODUCTION

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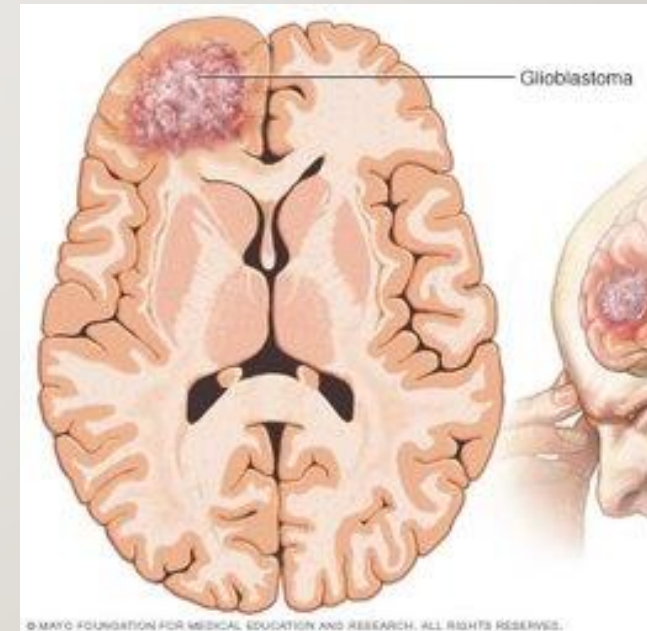
- ❑ The brain is the most **complex part of the human body**.
- ❑ Brain tumor is an **uncontrolled development of brain cells** in brain cancer
- ❑ Brain Tumors can be **malignant or benign**.

Benign Tumor	Malignant Tumor
Slow rate of growth	Rapid rate of growth
Non invasive (Capsule covered)	Invasive (No capsule) Highly spreadable
Metastasis – Absent	Metastasis – Present (Spread in organs)
Hemorrhage and Necrosis – Absent	Hemorrhage and Necrosis - Present

# WHAT IS GLIOBLASTOMA?

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- ❑ **Glioblastoma is an aggressive type of cancer that can occur in the brain. (Grade IV tumor GBM)**
- ❑ **Frontal Lobe is most common but can occur Brainstem, Cerebellum**
- ❑ **Treatments:**
  - ❑ **Surgery**
  - ❑ **Radiation**
  - ❑ **Chemotherapy**





# MGMT PROMOTER METHYLATION?

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- MGMT - Methylguanine Methyltransferase it is an enzyme which removes the molecule to synthesize chemo drug, helps in DNA repair for cancer cell
- **Methylated MGMT associated with improved outcome** in glioblastoma
- It is a favorable **prognostic factor and a strong predictor** of responsiveness to chemotherapy.
- Help in therapy decision making

# MOTIVATION

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- Currently, genetic analysis of cancer requires **surgery to extract a tissue sample**.
- Then it takes **several weeks** to determine the genetic characteristics of the tumor.
- An automatic model to **detect the presence of MGMT** promoter methylation might **help faster** treatment and avoid surgery for test

# DATASET

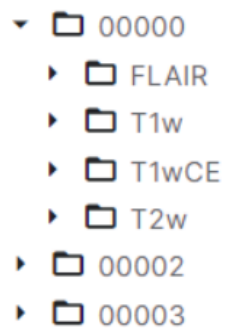


**Images are in DICOM format.**



**Three cohorts of multi-parametric MRI (mpMRI) scans:**

1. Training Data
2. Validation Data
3. Test Data



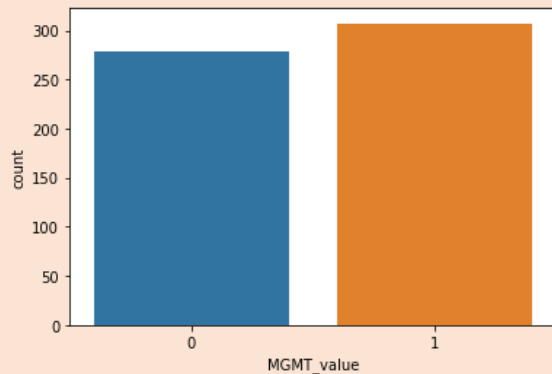
**Four subfolders within cohorts:**

1. Fluid Attenuated Inversion Recovery (FLAIR)
2. T1-weighted pre-contrast (T1w)
3. T1-weighted post-contrast (T1WCE)
4. T2-weighted (T2)



# PREDICTION OF GENETIC CHARACTERISTIC OF GLIOBLASTOMA

- ❑ The MGMT promoter methylation status data is defined as a binary label (0: unmethylated, 1: methylated)
- ❑ 307 Positive Cases (Methylated)
- ❑ 278 Negative Cases (Unmethylated)
- ❑ 585 Total Patients



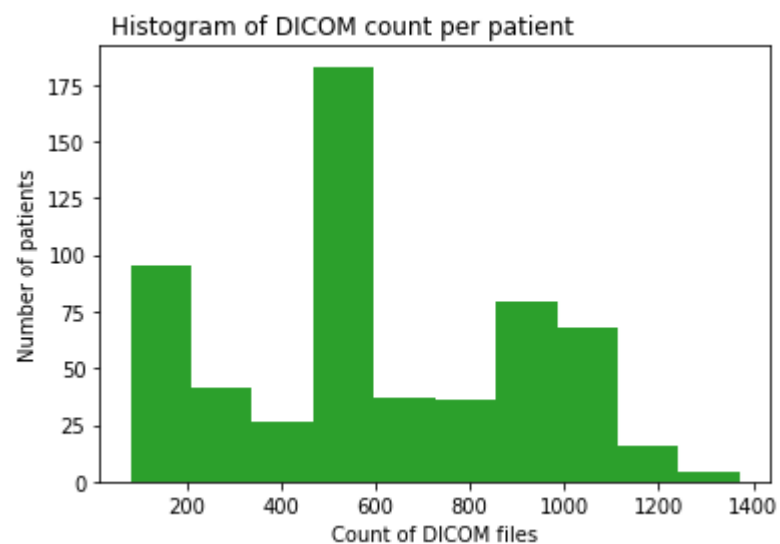
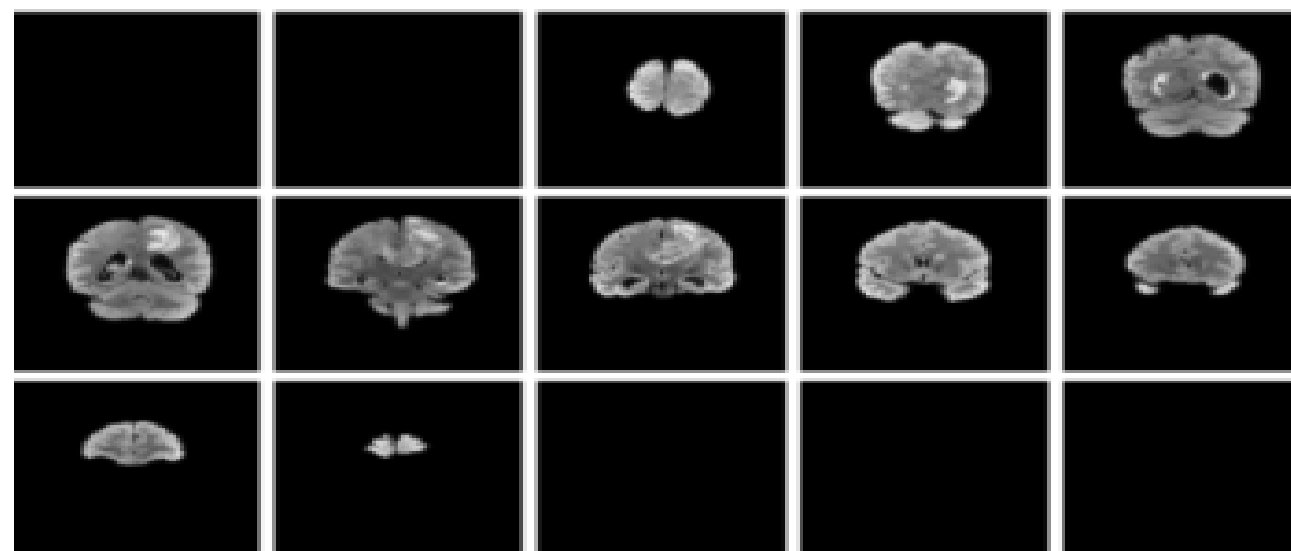
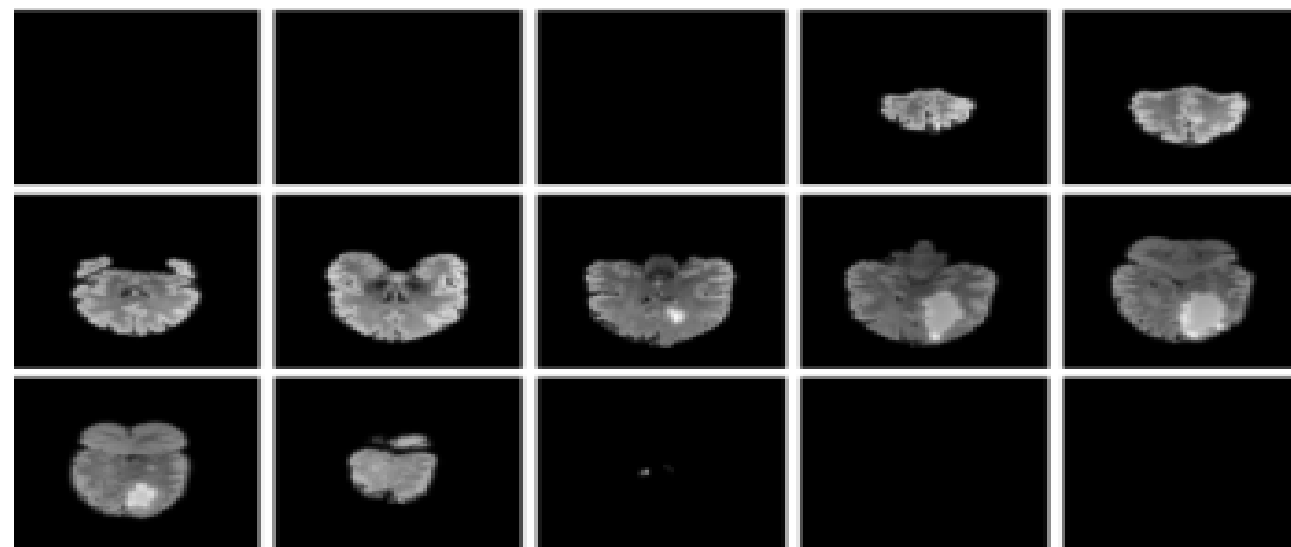
BraTS21ID		MGMT_value
2	3	0
6	9	0
10	17	0
11	18	0
12	19	0
...	...	...
569	837	0
571	839	0
579	1004	0
583	1009	0
584	1010	0

278 rows × 2 columns

BraTS21ID		MGMT_value
0	0	1
1	2	1
3	5	1
4	6	1
5	8	1
...	...	...
577	1002	1
578	1003	1
580	1005	1
581	1007	1
582	1008	1

307 rows × 2 columns

Each patient has  
**several scans for  
each MRI Type (4  
types).**



# EXPLORATORY DATA ANALYSIS

87 Patients have Similar count of images in subfolder

Total number of patients: 585

Total file count: 348641

	BraTS21ID	MGMT_value	imfolder	path	FLAIR_count	T1w_count	T1wCE_count	T2w_count	allsame
0	0	1	00000	../input/rsna-miccai-brain-tumor-radiogenomic-...	400	33	129	408	False
1	2	1	00002	../input/rsna-miccai-brain-tumor-radiogenomic-...	129	31	129	384	False
2	3	0	00003	../input/rsna-miccai-brain-tumor-radiogenomic-...	129	33	129	408	False
3	5	1	00005	../input/rsna-miccai-brain-tumor-radiogenomic-...	400	28	129	424	False
4	6	1	00006	../input/rsna-miccai-brain-tumor-radiogenomic-...	129	32	129	408	False
...	...	...	...	...	...	...	...	...	...
580	1005	1	01005	../input/rsna-miccai-brain-tumor-radiogenomic-...	23	23	23	23	True
581	1007	1	01007	../input/rsna-miccai-brain-tumor-radiogenomic-...	124	124	124	124	True

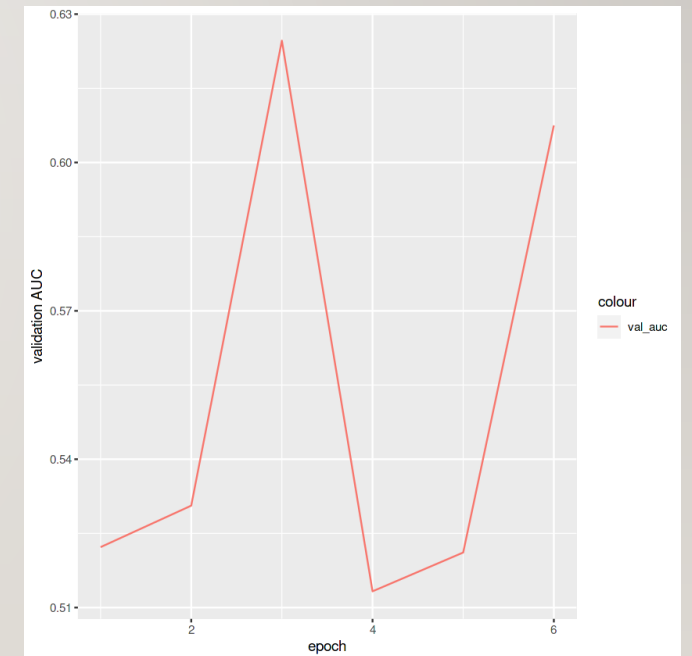
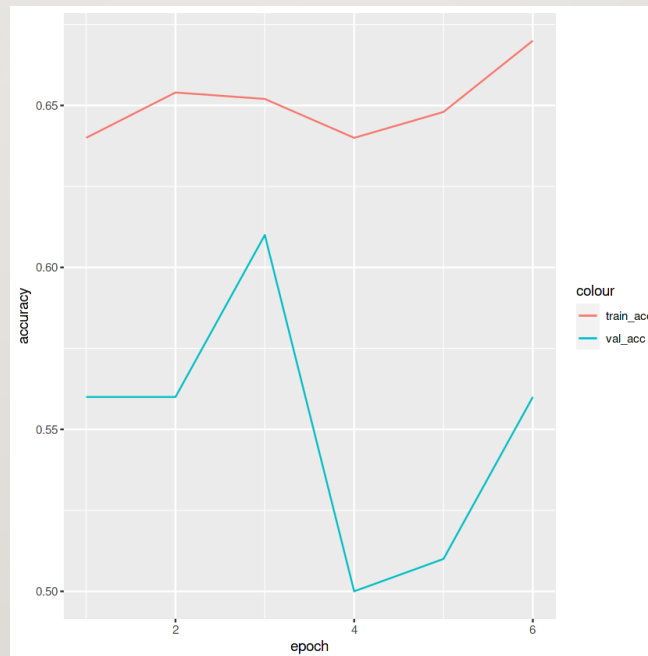
# BASELINE MODEL

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- A simple solution
  - For each patient, we consider 4 sequences (FLAIR, T1w, T1Gd, T2), and for each of those sequences take a slice randomly.
  - Use CNN to perform Classification
- Convolutional Neural Network
  - ResNet50 [4]
  - EfficientNet [5]

# RESULTS WITH CNN – WITH MORE IMAGES

- Very poor results with random selection of images
- Lets consider more images
- Still poor results
- Validation Accuracy ~55%
- Training Accuracy ~ 65%
- Validation AUC ~ 0.55

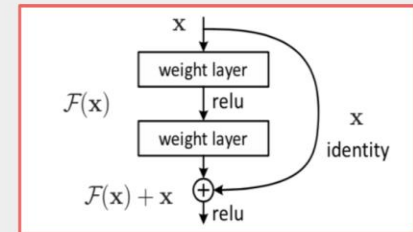




# RESNET50

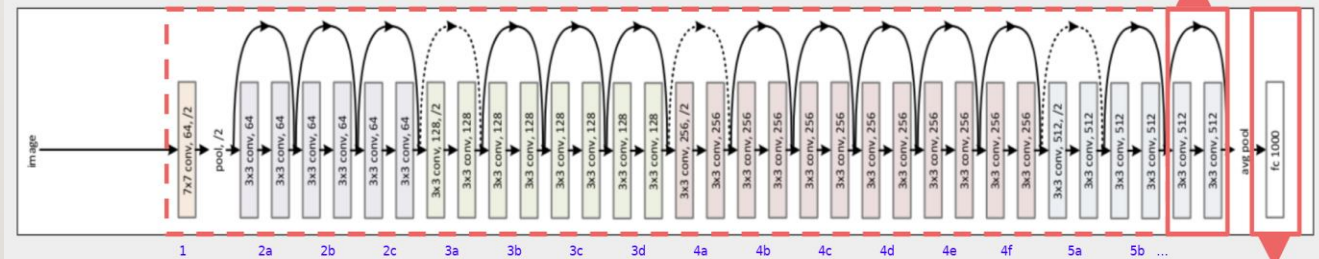
- Deep Learning model for image classification of the Convolutional Neural Network.
- 50 layers deep
- Deep neural networks are susceptible to vanishing gradients
- Resnet used skip connection to propagate information over layers

## Retrain ResNet50

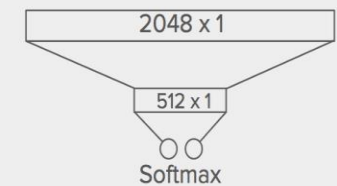


Residual Learning Block

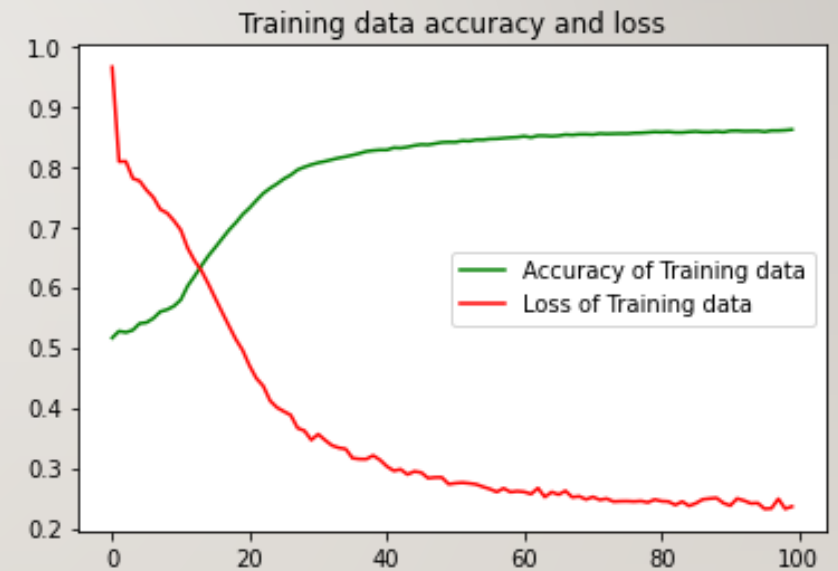
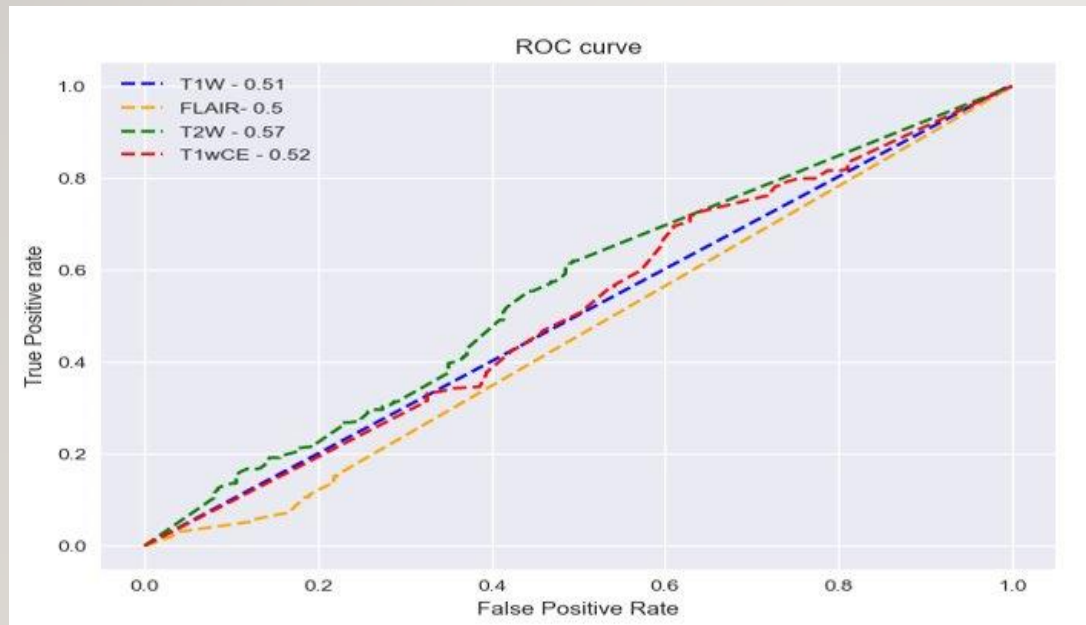
ResNet50 Diagram



Re-architect fully-connected layers

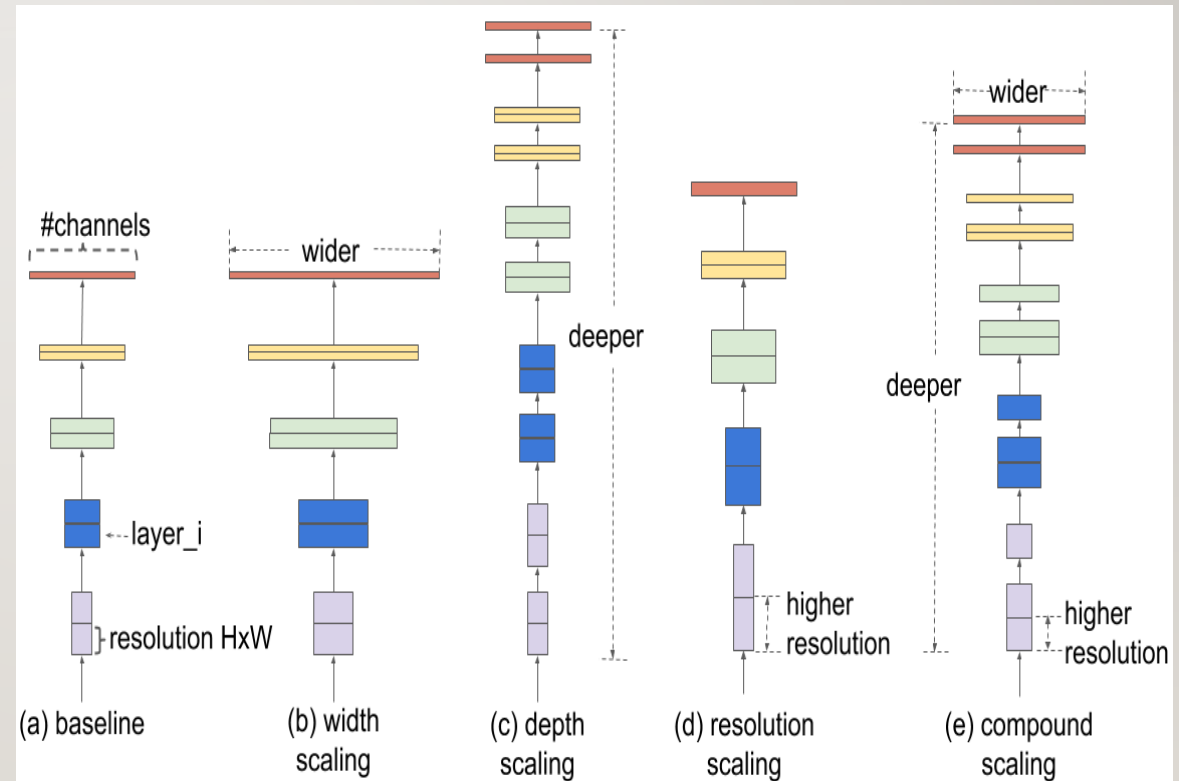


# EXPERIMENTAL ANALYSIS [RESNET50]



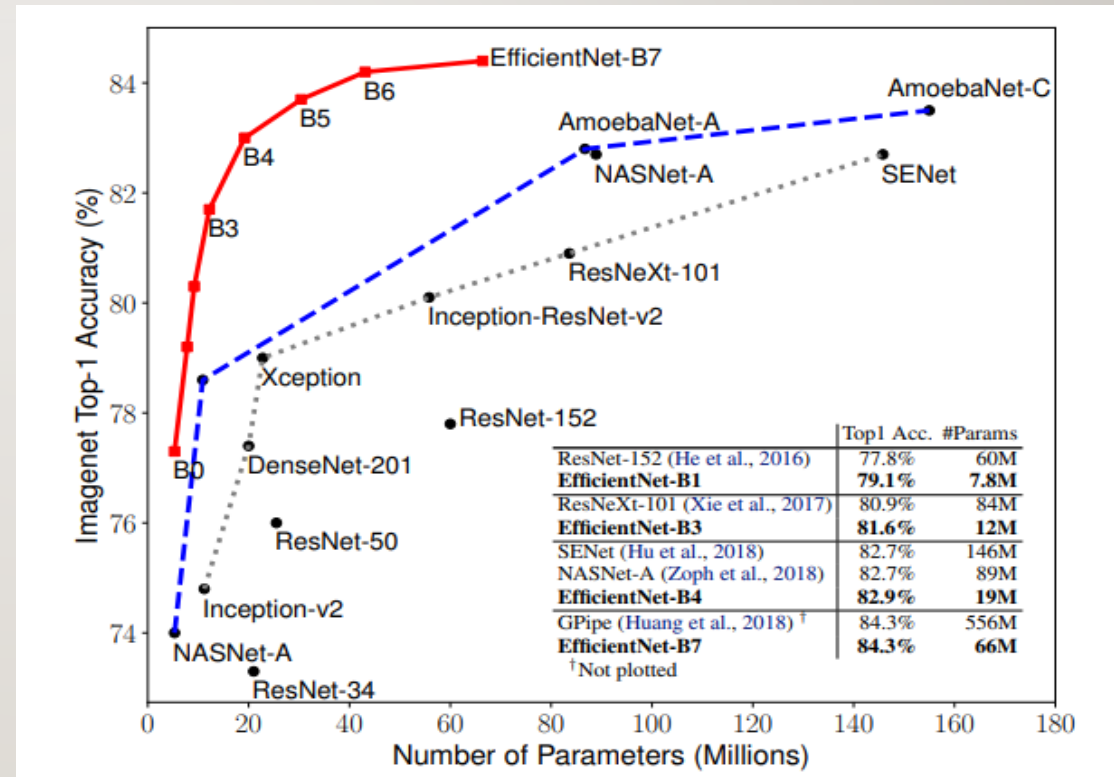
# EFFICIENTNET

- EfficientNet, as the name suggests are very efficient computationally.
- Achieved state of art result on ImageNet dataset which is 84.4% top-1 accuracy.
- Model scaling is about scaling the network depth (more layers), width (more channels per layer), resolution (input image)



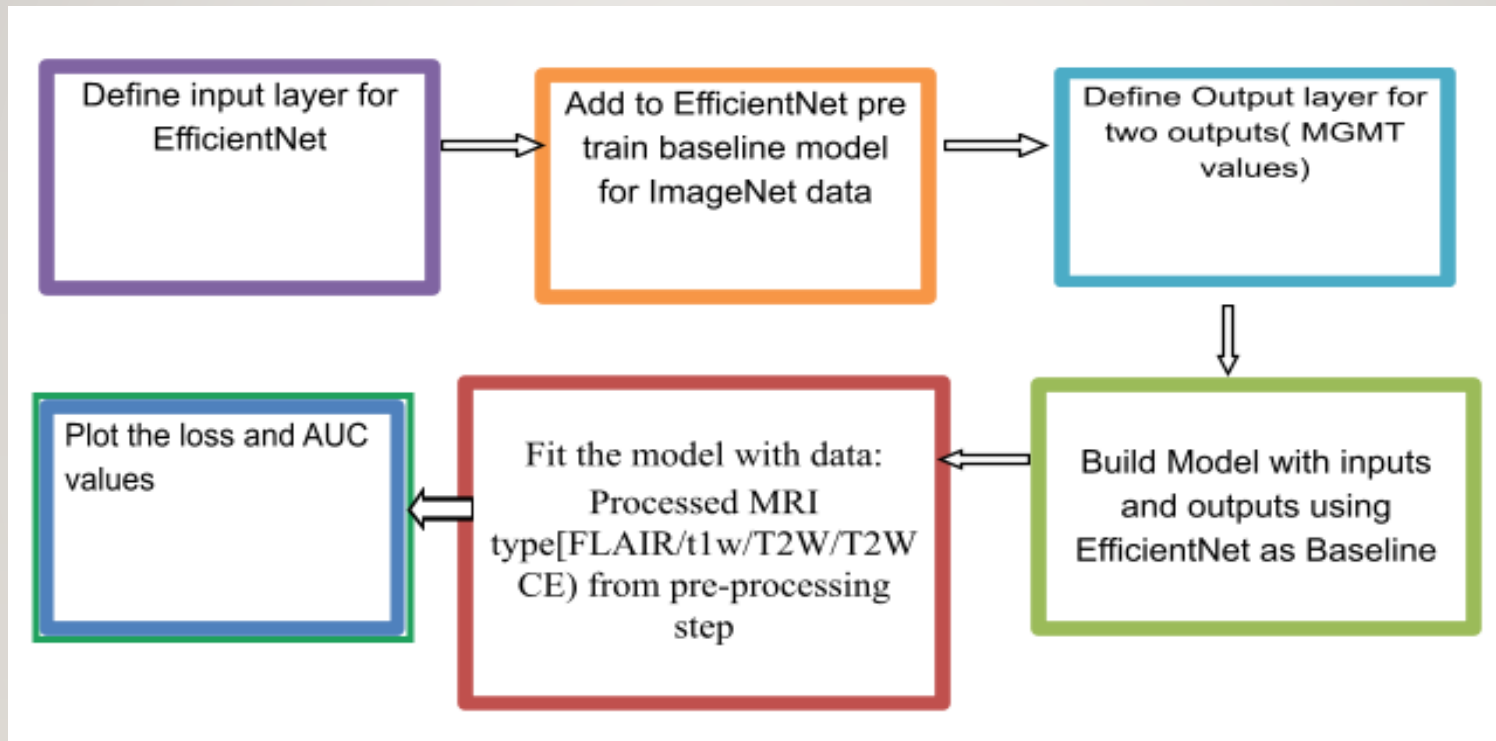
# WHY EFFICIENTNET ?

- EfficientNets has large activations which cause a larger memory footprint because
- Use similar FLOPs as ResNet to give better Accuracy
- FLOPs, simply means the total number of floating point operations required for a single forward pass. The higher the FLOPs, the slower the model and hence low throughput.





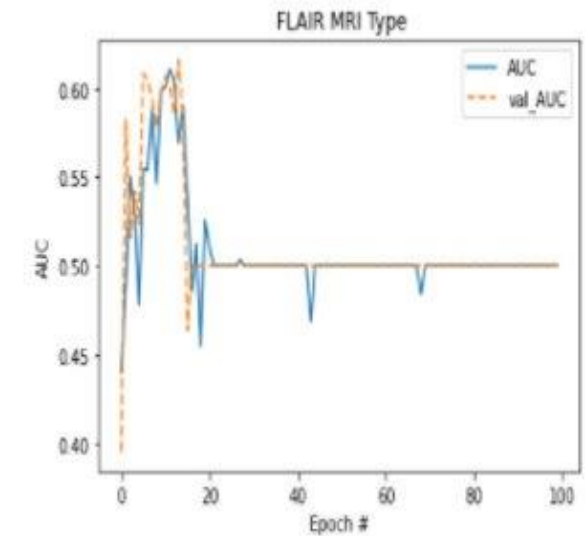
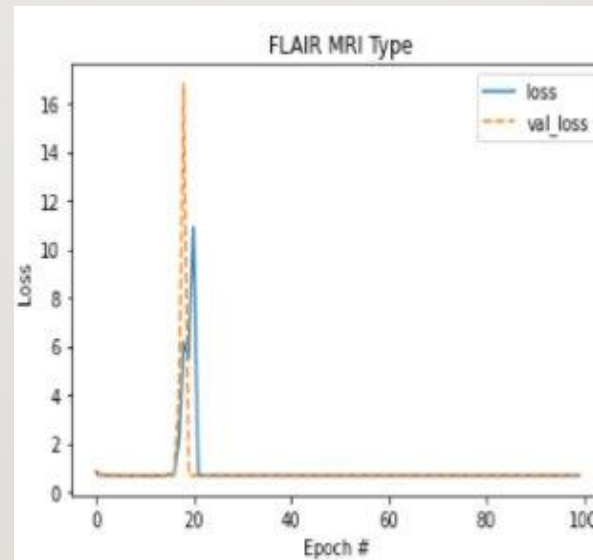
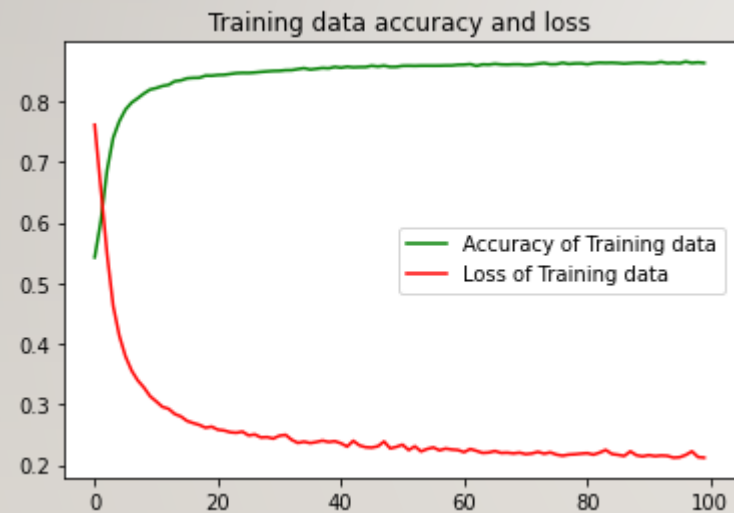
# WORKFLOW OF DEEP LEARNING MODEL ARCHITECTURE



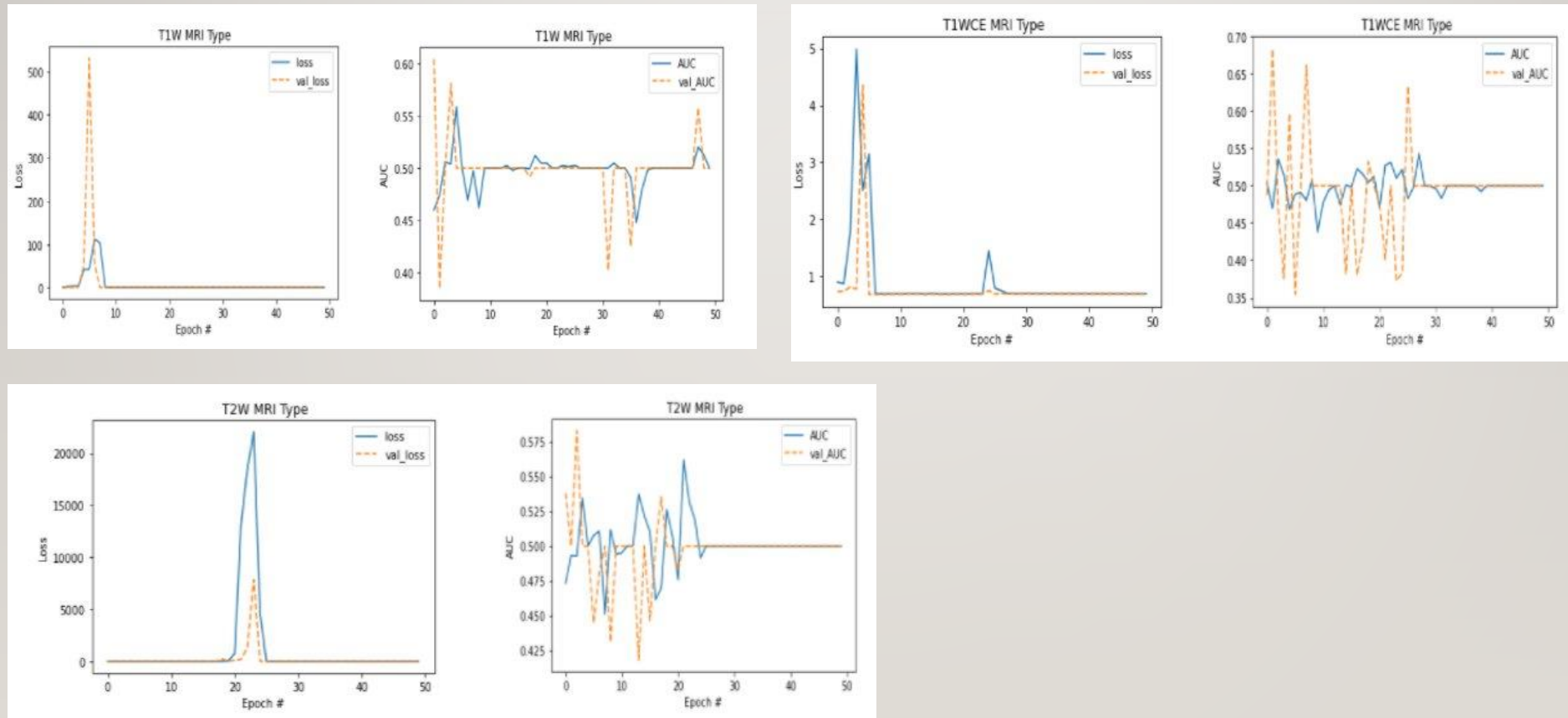


# EXPERIMENTAL ANALYSIS [EFFICIENTNET]

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# EXPERIMENTAL ANALYSIS [EFFICIENTNET]



# TEST RESULTS

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MRI Type	Test Accuracy	Test AUC
FLAIR	0.7551	0.458
T1w	0.822	0.29
T1Gd	0.59	0.91
T2W	0.9125	0.7842

# CONCLUSION AND FUTURE WORK

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## Conclusion

- MRI images are very different from non-medical images
- Pre-trained models for ImageNet may not be as good as baseline
- Unique pre processing may require

## Future Work

- Additional, higher quality pre-processed data
- Apply sequence model like LSTM along with CNN
- Use VGG 16 /19 DenseNet or other Pretrained Models



\*Image Source - <https://memegenerator.net/instance/72296984/waiting-skeleton-near-computer-still-waiting-for-my-neural-network-to-train>



# REFERENCES

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- [2] Ker J, Singh SP, Bai Y, Rao J, Lim T, Wang L (2019) Image thresholding improves 3-dimensional convolutional neural network diagnosis of different acute brain hemorrhages on computed tomography scans. *Sensors* 19(9):2167
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**THANK YOU**