# Clinical background

A malignant tumor in the brain is a life-threatening condition. Known as glioblastoma, it's both the most common form of brain cancer in adults and the one with the worst prognosis, with median survival being less than a year. The presence of a specific genetic sequence in the tumor known as MGMT promoter methylation has been shown to be a favorable prognostic factor and a strong predictor of responsiveness to chemotherapy.

Currently, genetic analysis of cancer requires surgery to extract a tissue sample. Then it can take several weeks to determine the genetic characterization of the tumor. Depending upon the results and type of initial therapy chosen, a subsequent surgery may be necessary. If an accurate method to predict the genetics of the cancer through imaging (i.e., radiogenomics) alone could be developed, this would potentially minimize the number of surgeries and refine the type of therapy required.

In this competition we  will predict the genetic subtype of glioblastoma using MRI (magnetic resonance imaging) scans to train and test your model to detect for the presence of MGMT promoter methylation.

The organizers provided the participants with two sets of data, training and test, consisting of MRI images. The images are sorted by patient. For each patient, several images of four different scan types (FLAIR, T1w, T1wCE, T2) are available. The training set contains scans of 1010 patients.

# Result summarization

The methods submitted by the participating teams for task 2 will be evaluated based on the area under the ROC curve (AUC), accuracy, FScore (harmonic mean of the precision and recall) and Matthew's Correlation Coefficient of the classification of the MGMT status as methylated and unmethylated. The AUC is a metric that measures the overall discriminatory capacity of a model for all possible thresholds and allows for comparing the performance of the entries by each participant, even though it has no straightforward clinical meaning and does not guarantee the model is calibrated. The AUC will be used as the reference metric to rank the participants in the leaderboard of task 2.

* **ROC curve**: It plots TPR vs. FPR at different classification thresholds. AUC ranges in value from 0 to 1. A model whose predictions are 100% wrong has an AUC of 0.0; one whose predictions are 100% correct has an AUC of 1.0.

* **Matthews Correlation Coefficient**: For binary classification, there is another (and arguably more elegant) solution: treat the true class and the predicted class as two (binary) variables, and compute their *correlation coefficient* (in a similar way to computing correlation coefficient between any two variables). The higher the correlation between true and predicted values, the better the prediction. This is the *phi-coefficient*

(φ), rechristened Matthews Correlation Coefficient (MCC) when applied to classifiers. Computing the MCC is not rocket science:

# Winning approach

On the contrary of what top solutions look like, the winner's final solution was one of the very first baselines he started with. There was no model ensembling, no complex/big models, and no sophisticated training techniques. So it's very curious to know why some more complex ideas are not working.

- 3D CNN
- Resnet10
- Binary Cross Entropy loss
- Adam optimizer
- 15 epochs
- LR: epoch 1->10; lr = 0.0001 | epoch 10 to 15 lr=0.00005
- Batch size: 8 (the bigger, the worse)
- Used a small trick to build the 3D images. Let's call it "The best central image trick".
- One epoch takes around 1 minute and 20 seconds using an RTX 3090.

"The best central image trick": Each independent case has a different number of images for all the MRI (Magnetic resonance imaging) scans. Using all the scans will confuse the model to learn the spatial dependence of the brain pixels that are not useful in our case. What people did was take the central image (the image in the middle). Nevertheless, using the biggest image as a central image (the image that contains the largest brain cutaway view) will slightly improve the performance.

Things that didn't work include ensembling and network pre-trained on brain images.

# Other approaches

My approach is simple, using a CNN-LSTM architecture to do the classification task. For the CNN part I used EfficientNet B0 and I trained the LSTM part from scratch. All 4 types of MRI image sequences (FLAIR, T1w, T1wCE, T2w) are used as inputs.

All images were converted into PNG format and DICOM images were removed.

The chosen CNN model for image features extraction task is a pre-trained EfficientNet B0 model. Since the input image has 4 channels, each corresponding to an MRI image type, a 2D convolution is applied to map the 4-channel image into a 3-channel feature map to fit the input shape of the pre-trained EfficientNet model.

# Remarks - Conclusions

**What's interesting about the second model is that the complexity is higher due to the addition of an LSTM network. Nevertheless, the simpler solution proposed by the winner outperformed this one.**

**This is even more interesting when we consider other than even more complex approaches such as Visual Transformers obtained even worse performances. 0.60054.**

**Another interesting comment is the lack of straightforward clinical meaning extracted from the winners results. Where none of them applied clinical reasons to fine tune their experiments. Thus, the challenge was based mostly on experimental criteria and wasn't able to give explanations for the behavior of the networks**

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**This is particularly relevant as this is a medical discipline. AI has to be explainable as there are strong ethical and moral reasons why decisions have to be based on reason and, to this day, it is still up to humans to make the final decision.**

# Extra information

**Links**

https://www.kaggle.com/competitions/rsna-miccai-brain-tumor-radiogenomic-classification

Presentation paper: https://arxiv.org/abs/2107.02314

Results comments:
https://www.rsna.org/education/ai-resources-and-training/ai-image-challenge/brain-tumor-ai-challenge-2021
Images in png: https://www.kaggle.com/jonathanbesomi/rsna-miccai-png