

# Liver tumour detection and segmentation

Mounir [redacted]

Si-belkacem KETIR

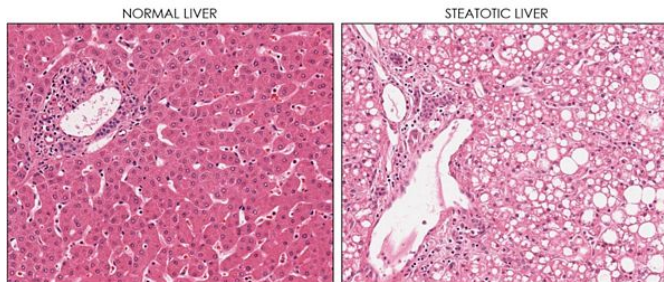
Mahmoud [redacted]

Fodé [redacted]

# Introduction

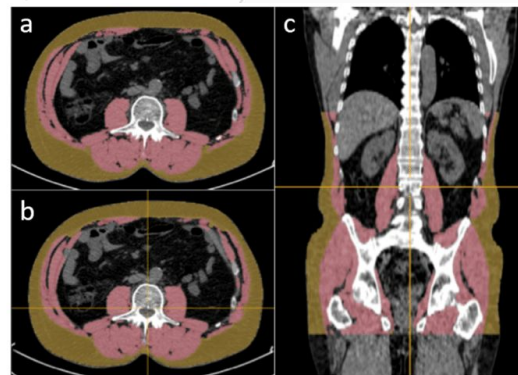
## Problem Statement:

“How can we automate the classification and segmentation of liver tumors from CT images while ensuring precision and clinical reliability?”



## Challenges :

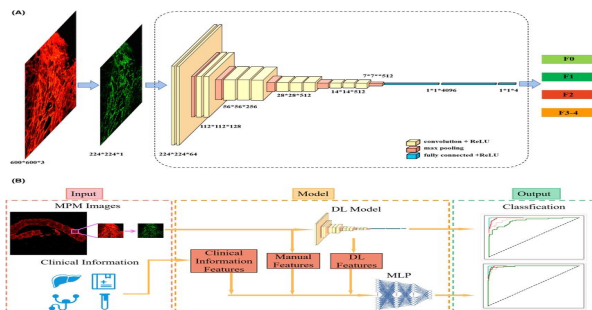
- CT image Variability
- Tumor Complexity
- Clinical Accuracy



# Approach and Methodology

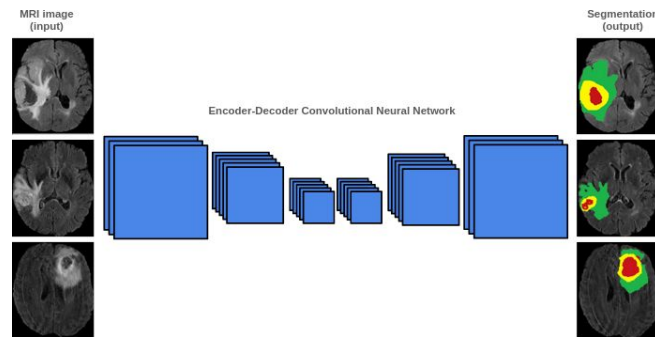
## Approach

- Classification: Using VGG16 to identify healthy vs pathological livers.
- Segmentation: Using U-Net to precisely localize tumors

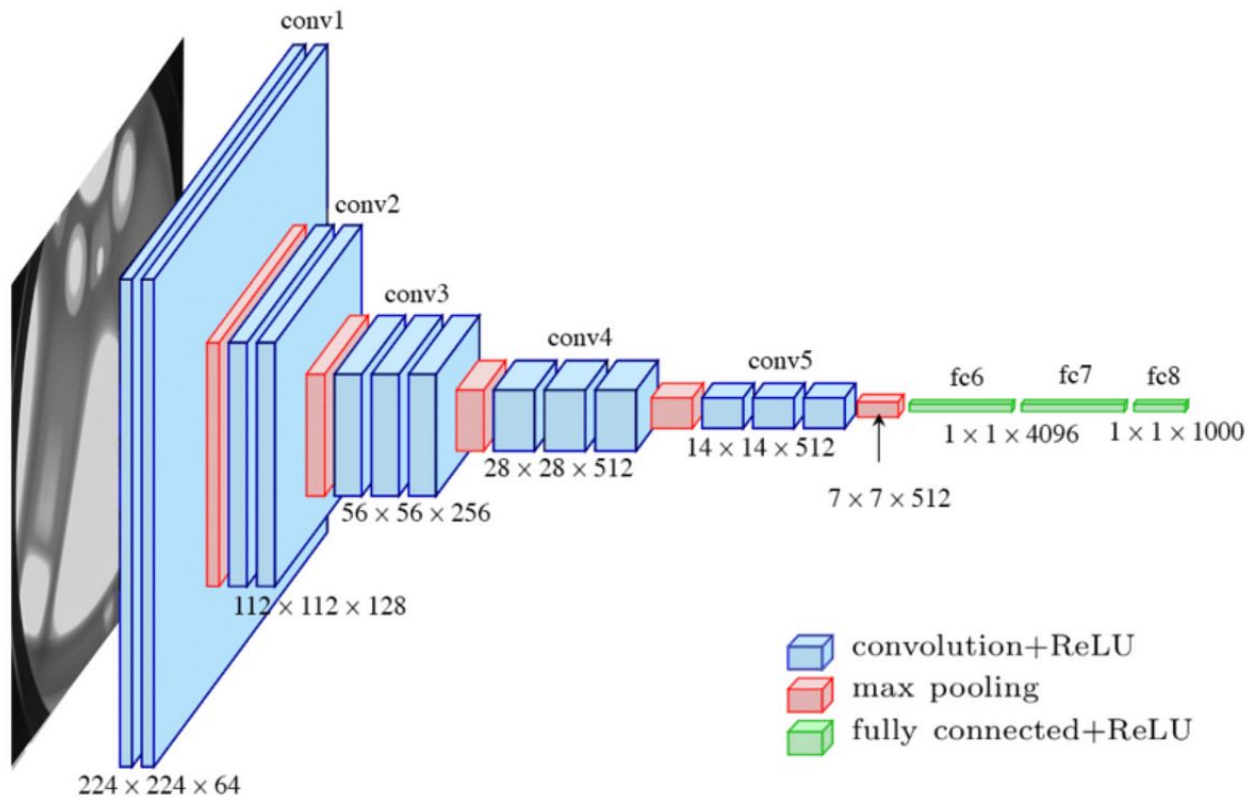


## Expected Impact

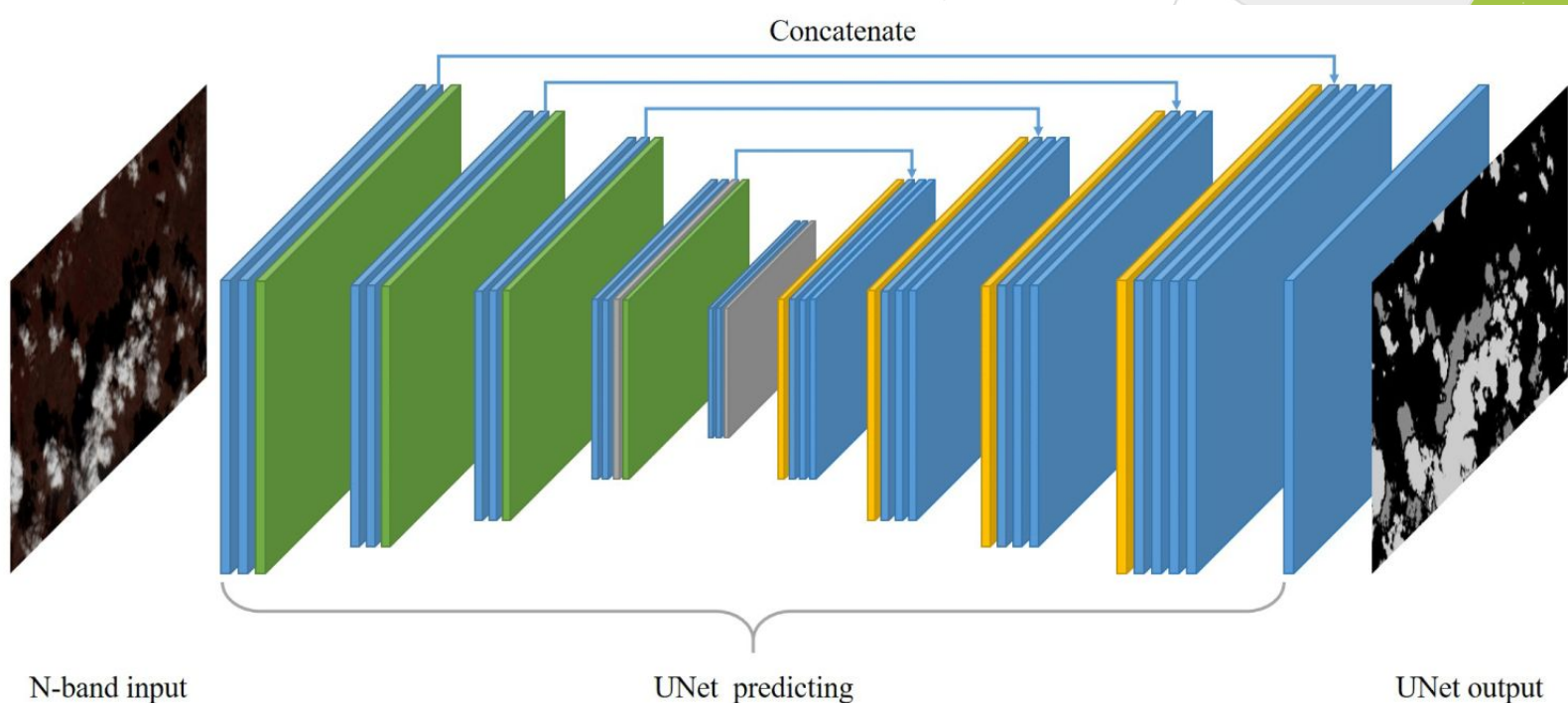
- Reducing analysis time for radiologists
- Improving diagnostic accuracy and reproducibility



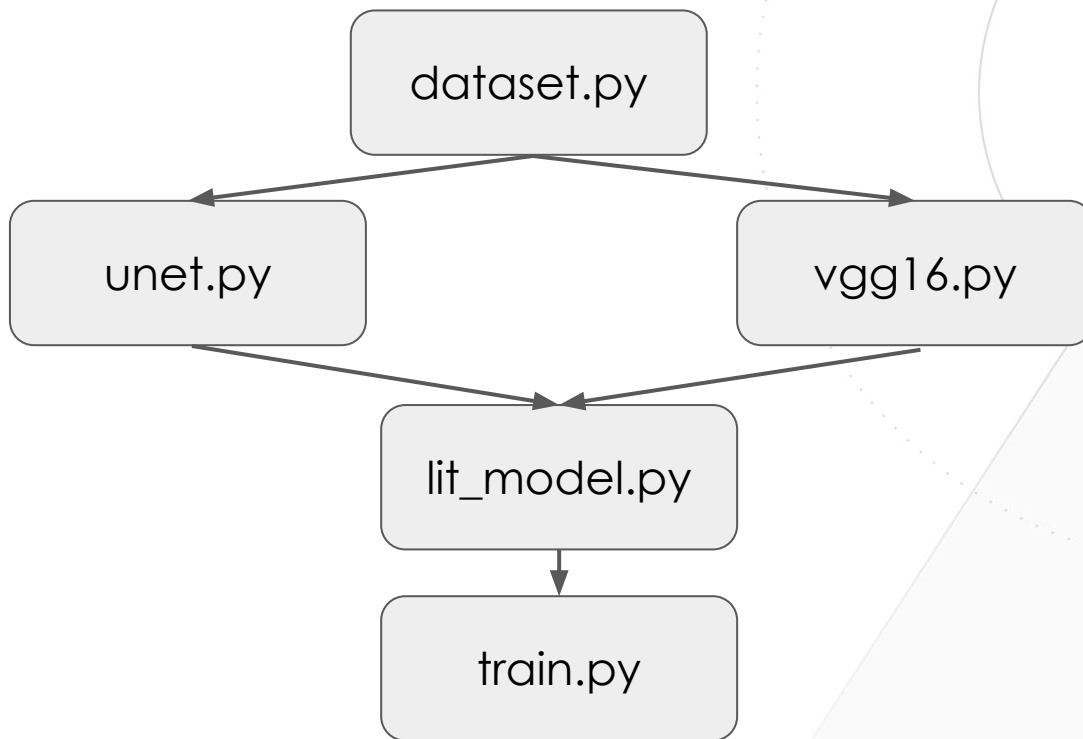
# Architecture VGG16



# Architecture U-Net

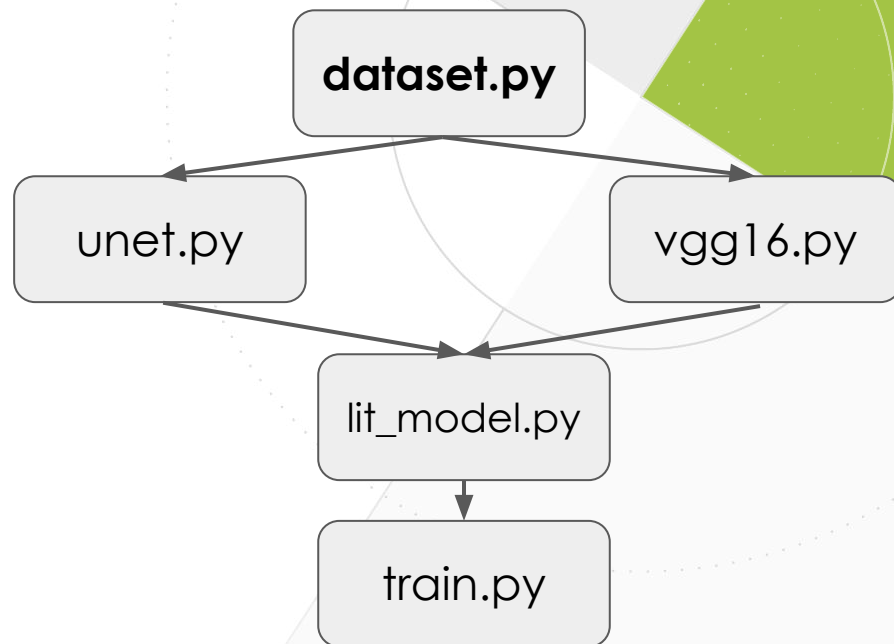


# Work and implementation



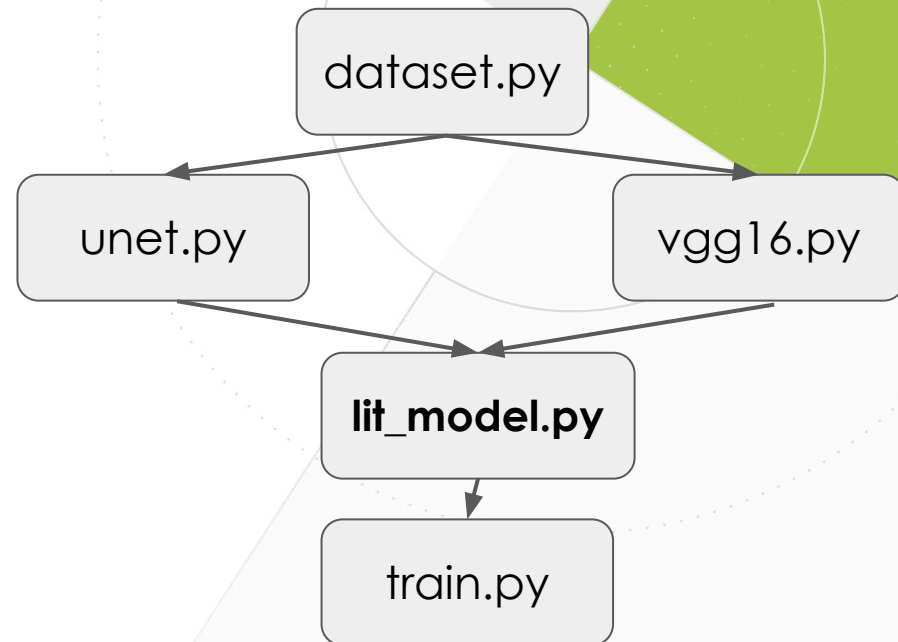
# datasete.py

- Load data
- Data preprocessing
- Awakening the data
- Prepare for the training
- Sending the data



# lit\_model.py

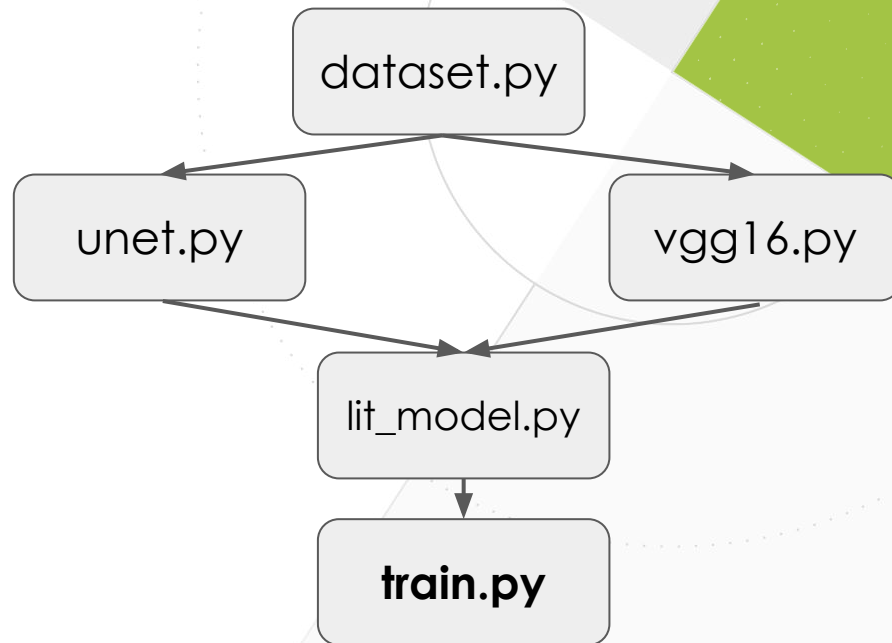
- Import the models (classification or segmentation)
- Set the Adam optimization
- Dice score for segmentation
- Accuracy for classification





# Train.py

- Set the epochs, batch size
- Inherit the model from lit\_model
- Stock the weights in ModelCheckpoint file
- Start the training



**lit\_model.py**

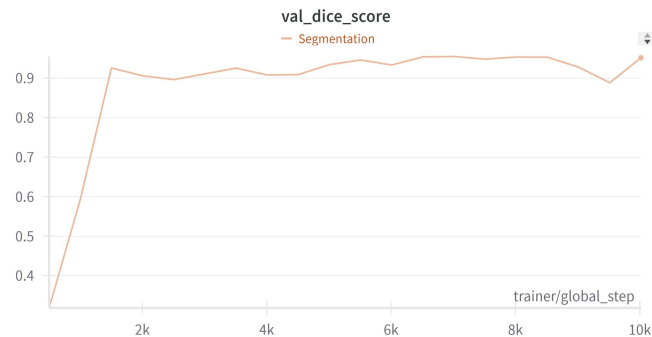
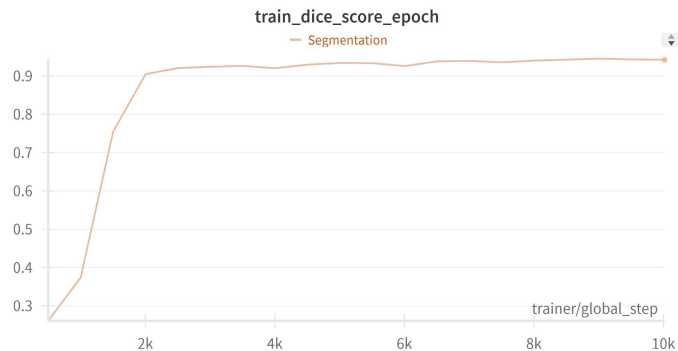
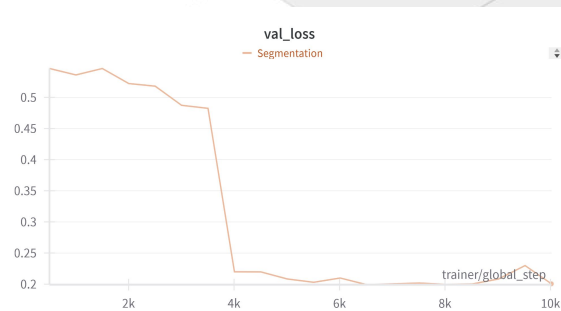
**predict\_classification.py**

- Load ModelCheckpoint
- Load test dataset
- Preprocessing data
- Classification
- Getting the class predicted.

**predict\_segmentation.py**

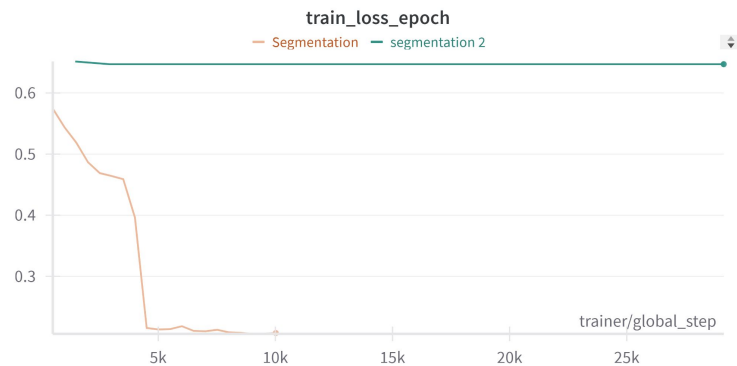
- Load ModelCheckpoint
- Load the test dataset
- Preprocessing data
- Segmentation
- Predicts the mask

# U-Net Segmentation Model Performance

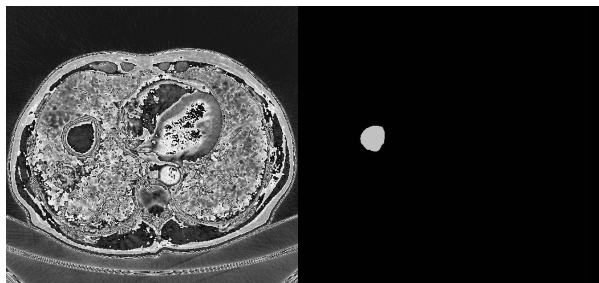


# U-Net Segmentation Model Performance

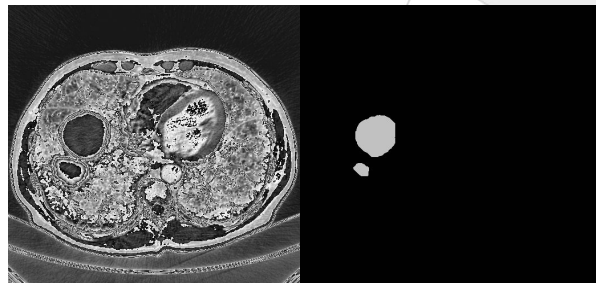
Trouble : Our first attempt was a failure



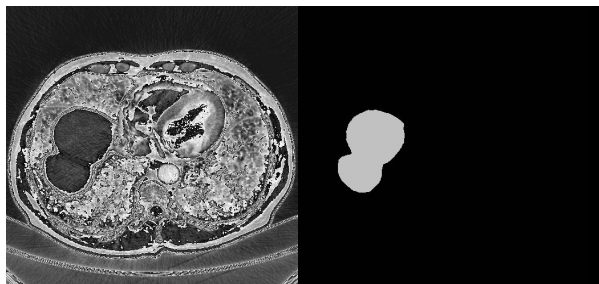
# Experimental Results of Our Segmentation Model



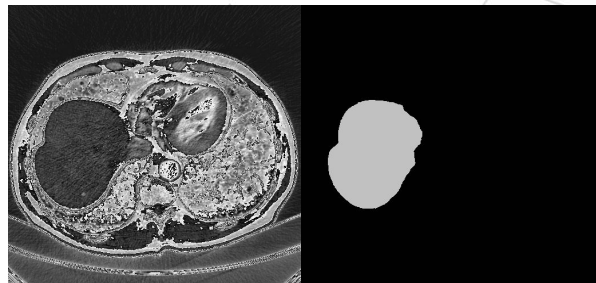
*Small tumor*



*Two tumors*



*Tumor with a complex shape*



*Large tumor*

# VGG16 CLASSIFICATION MODEL PERFORMANCES

train\_loss\_step

— classification

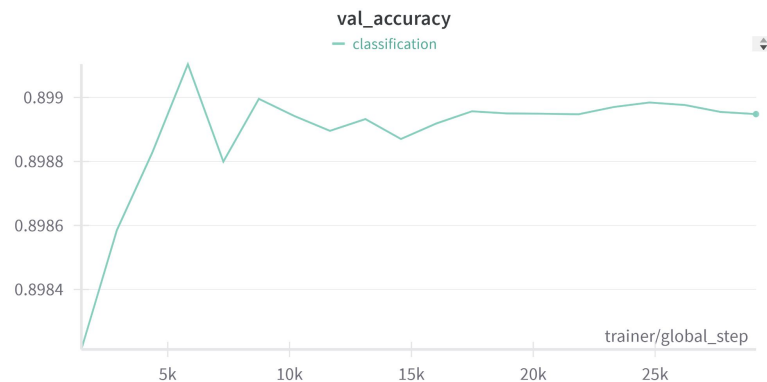
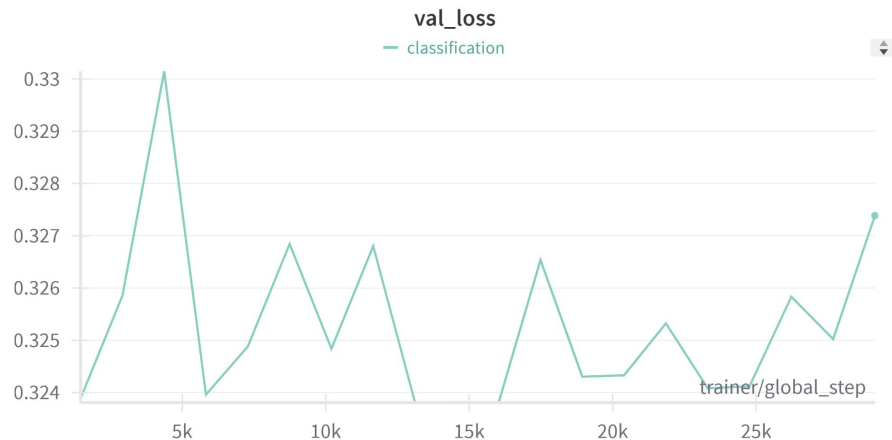


train\_accuracy\_step

— classification



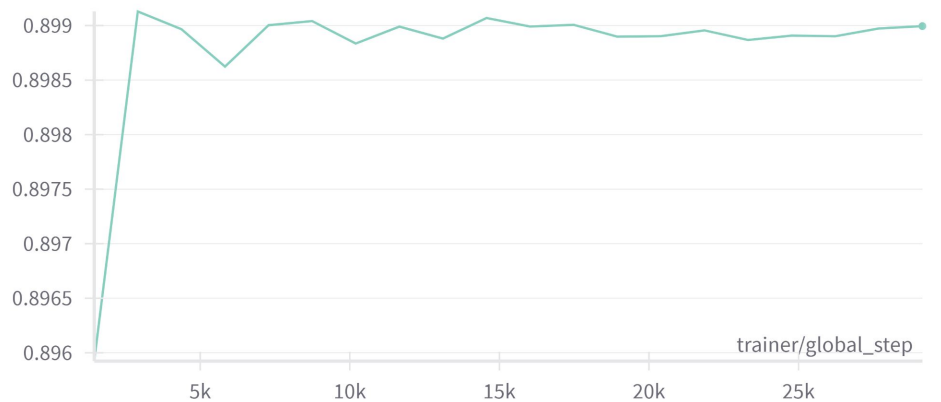
# VGG16 CLASSIFICATION MODEL PERFORMANCES



# VGG16 CLASSIFICATION MODEL PERFORMANCES

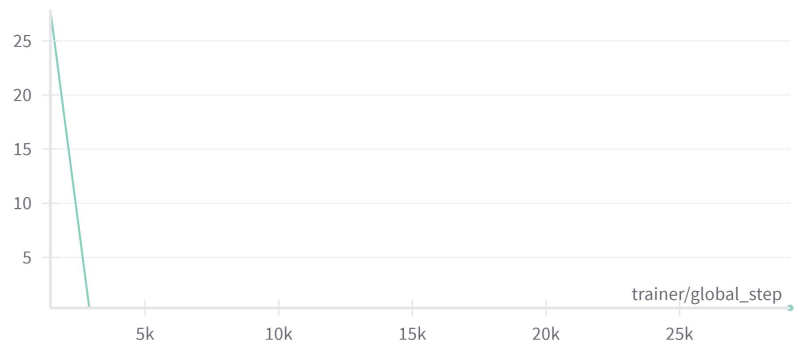
train\_accuracy\_epoch

— classification



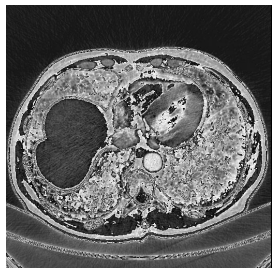
train\_loss\_epoch

— classification





# VGG16 CLASSIFICATION MODEL PREDICTION



VGG 16  
ARCHITECTURE



softmax



p0

p1

p2

ARGMAX

backgro  
und

**Tumor**

**No  
tumor**

# VGG16 CLASSIFICATION MODEL PREDICTION

$2.2259520 \times 10^{-8}$  ← background  
 8  
 0.89969039 ← tumor  
 0.10030963 ← no tumor

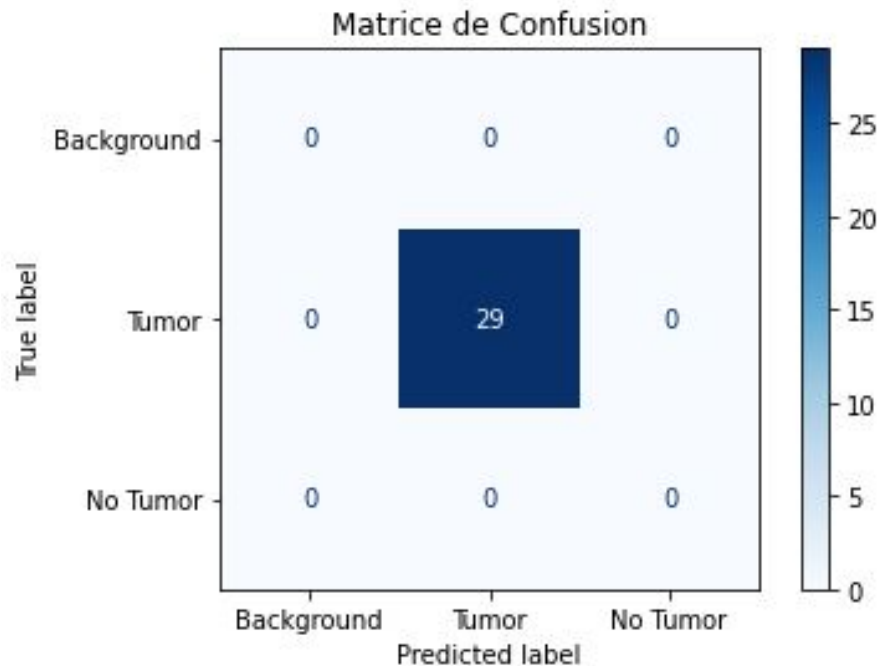


Image 20: Classe prédite = 1, Probabilités =  $[2.2259520 \times 10^{-8} \ 8.9969039 \times 10^{-1} \ 1.0030963 \times 10^{-1}]$

# Conclusion

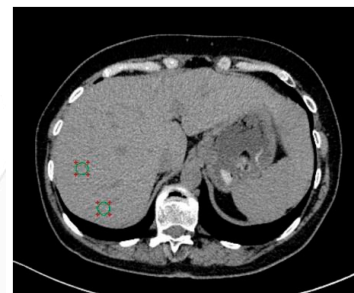
## What We Learned:

- The importance of AI in medical imaging and computer vision applications.
- How CNNs like VGG16 and U-Net are applied in real-world medical challenges.
- The complexity of handling medical datasets (preprocessing, annotation, and AI training).



## Difficulties Encountered:

- **Managing dataset quality:** CT scans come with varying resolutions and annotations.
- **Tuning deep learning models:** Balancing accuracy, training time, and overfitting.



# Thank you for your attention !