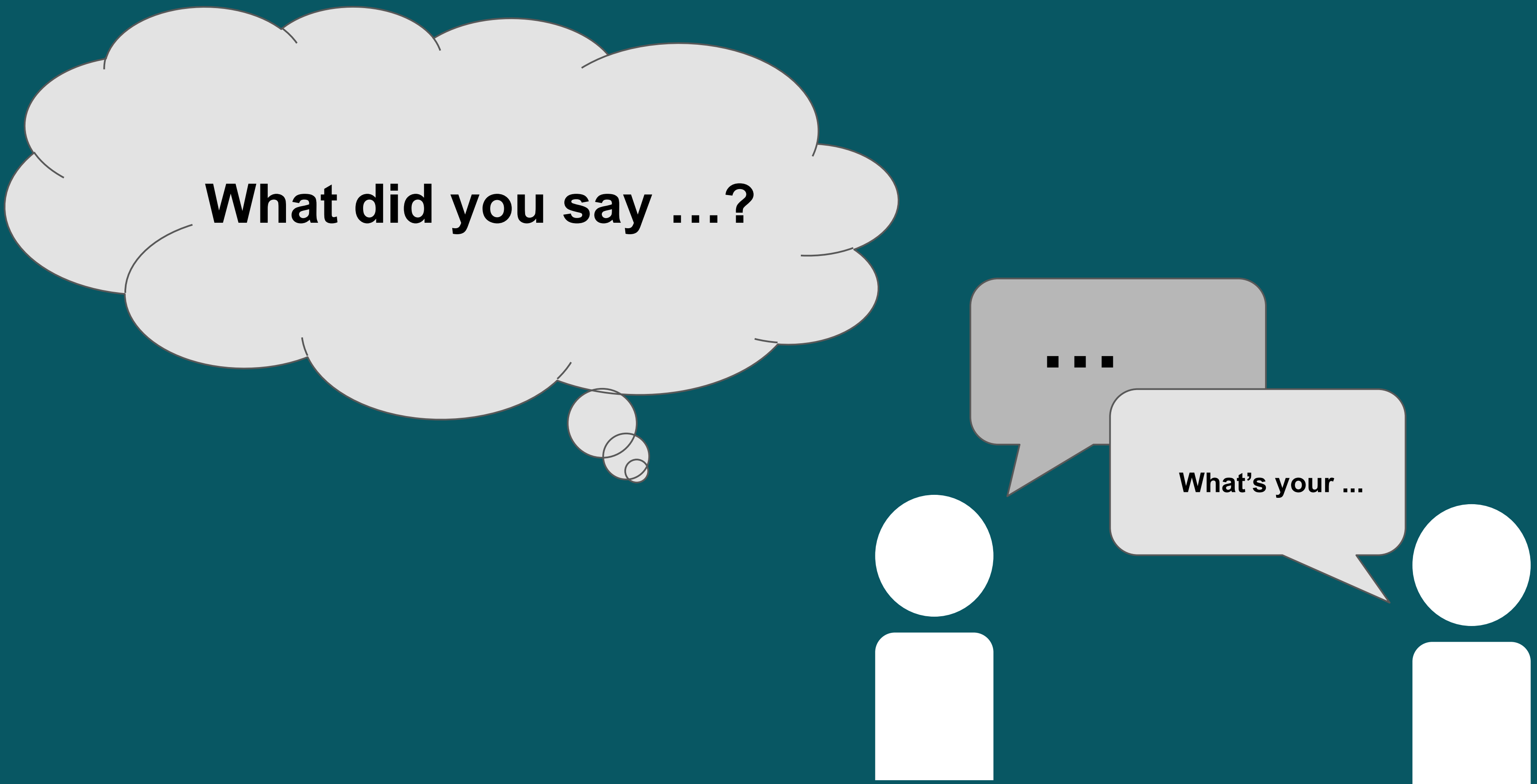
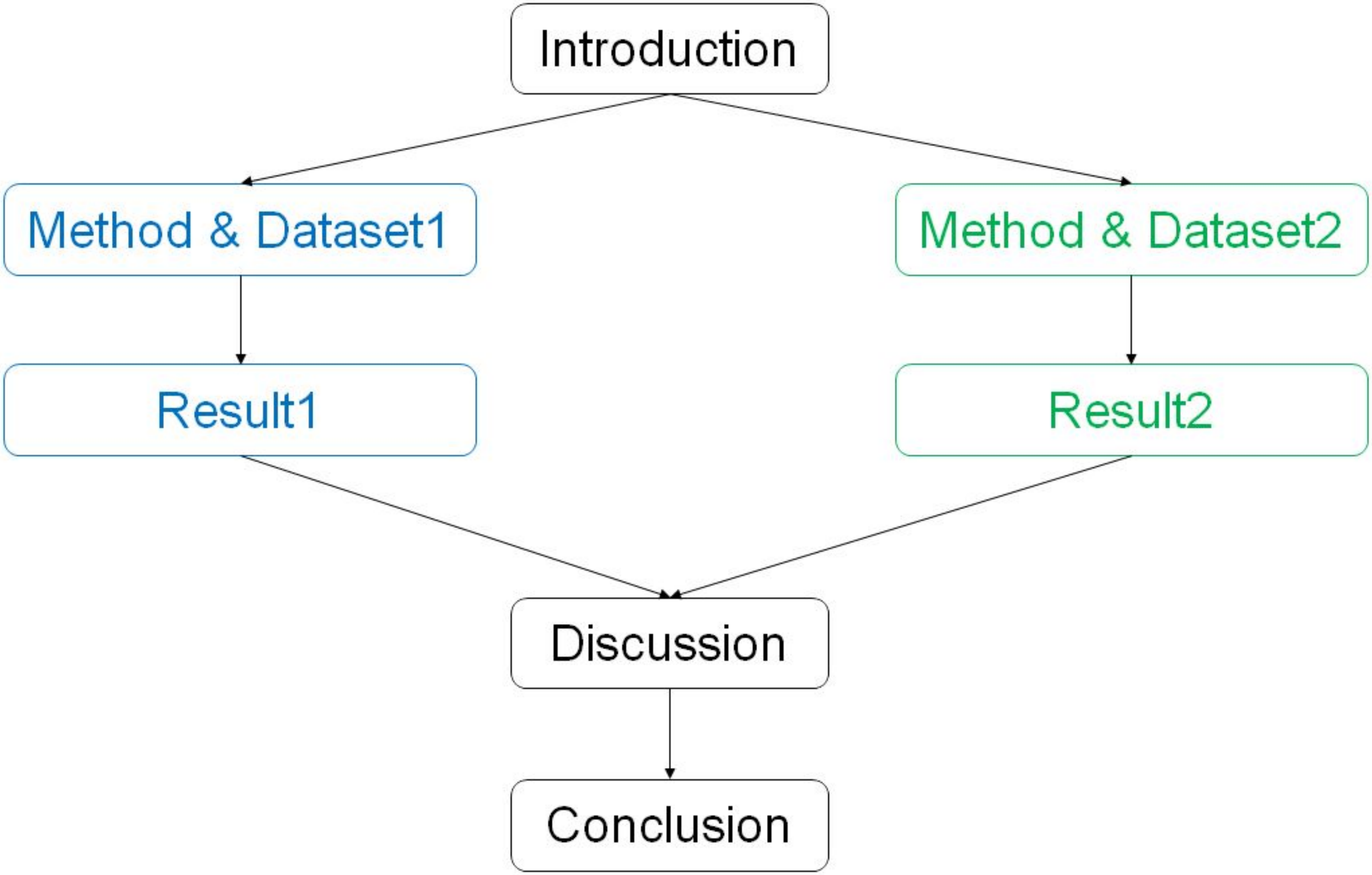
Graduation Work

B3 Suzuki Takahiro

please ask a question loudly and slowly



Presentation flow



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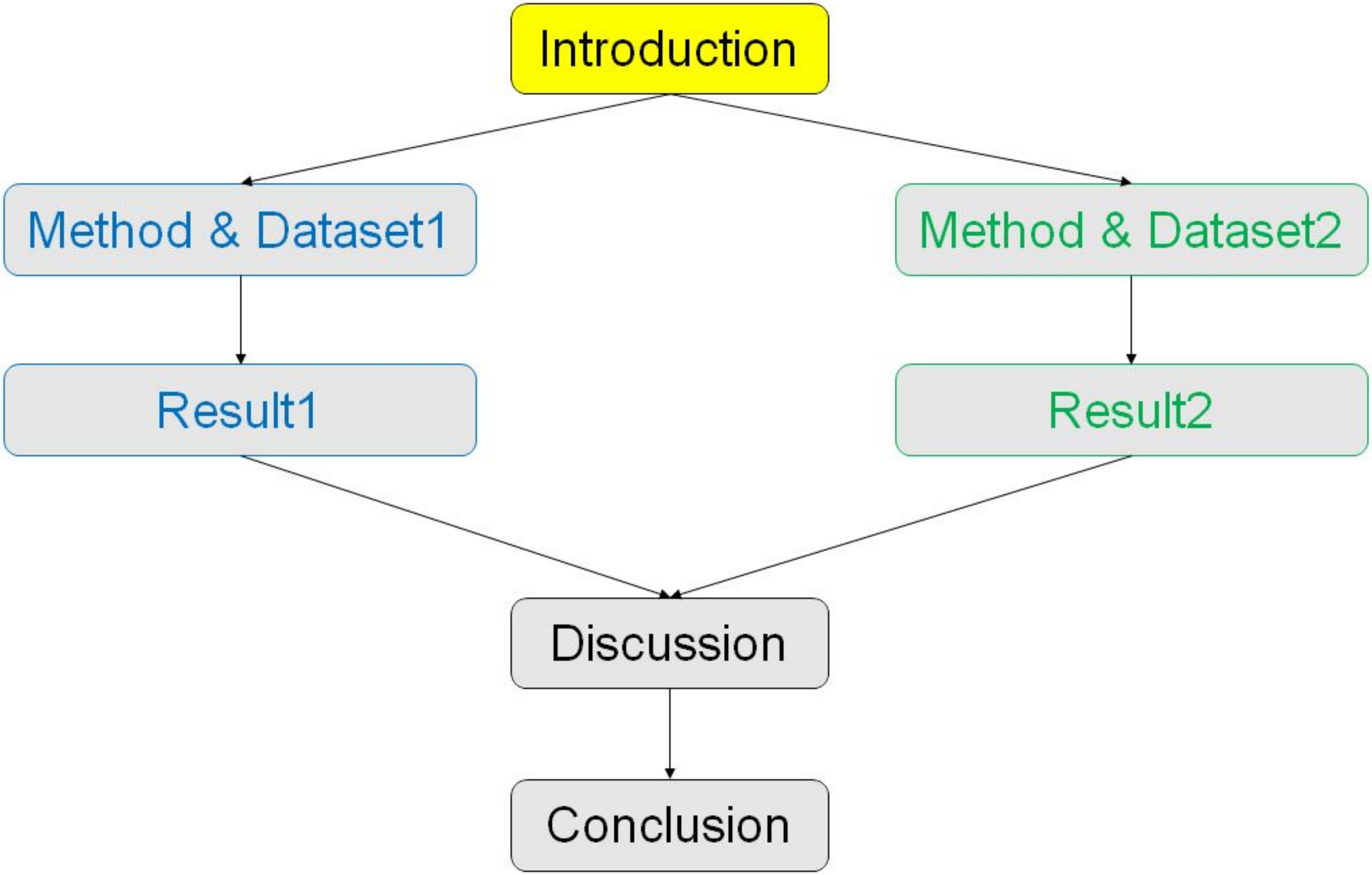


Introduction

- Research theme

Automatic diagnosis of glioma

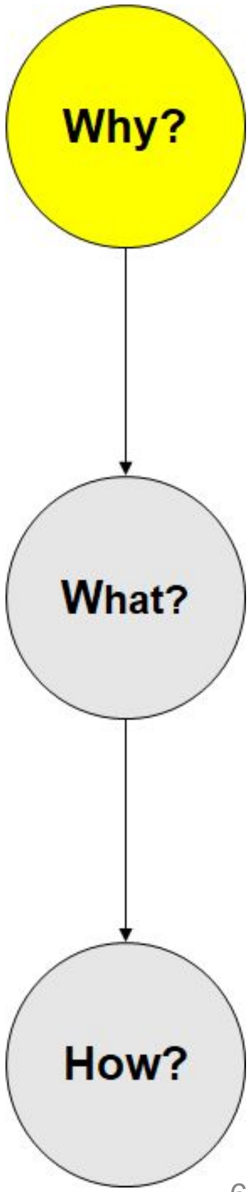
Introduction

❑ Why this theme?

- ➢ Fear of cancer
- ➢ Interest in machine learning

❑ Why glioma?

- ➢ Clearness of presence
- ➢ Findability of MRI datasets

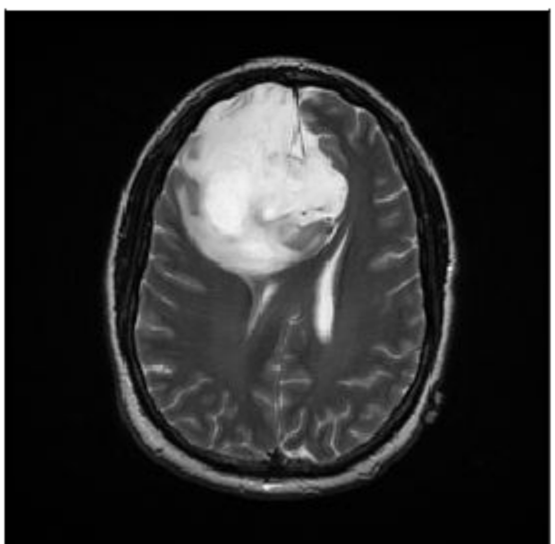


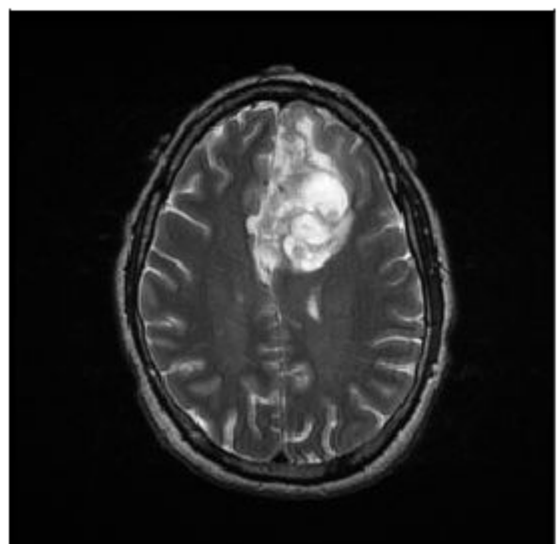
Introduction

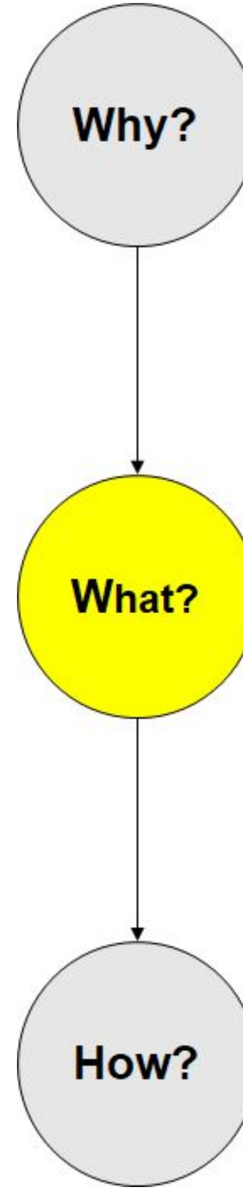
❑ What glioma?

➢ Kind of malignant brain tumor

➢ Canceration of glial cells







Introduction

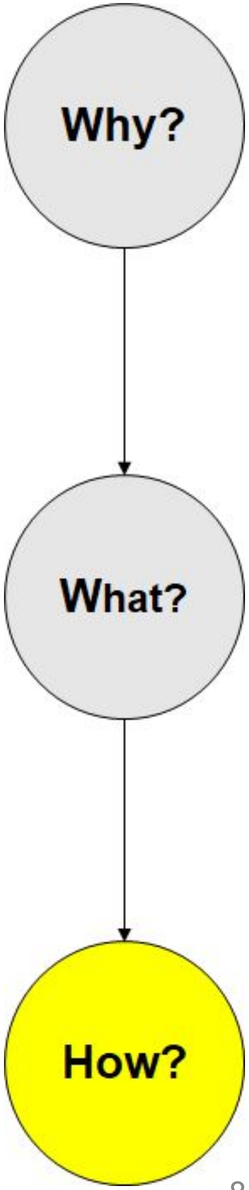
❑ How archive “automatic diagnosis”?

➢ By Deep Learning

- VGG16
- Original CNN

➢ By Classical Machine Learning

- SVM
- RandomForest
- Gradient Boosting



Introduction

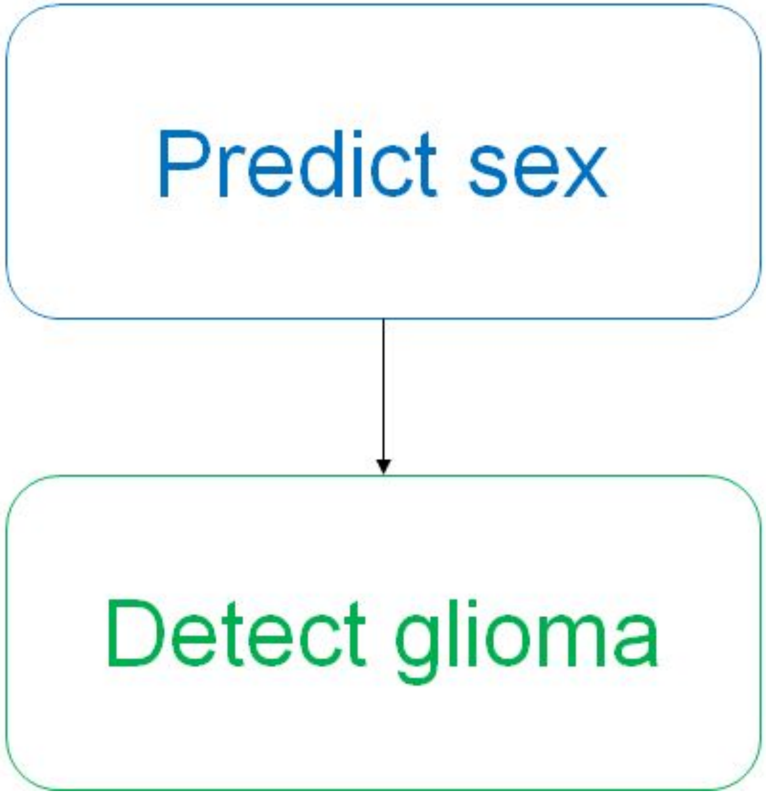
Study flow

1. Predict sex

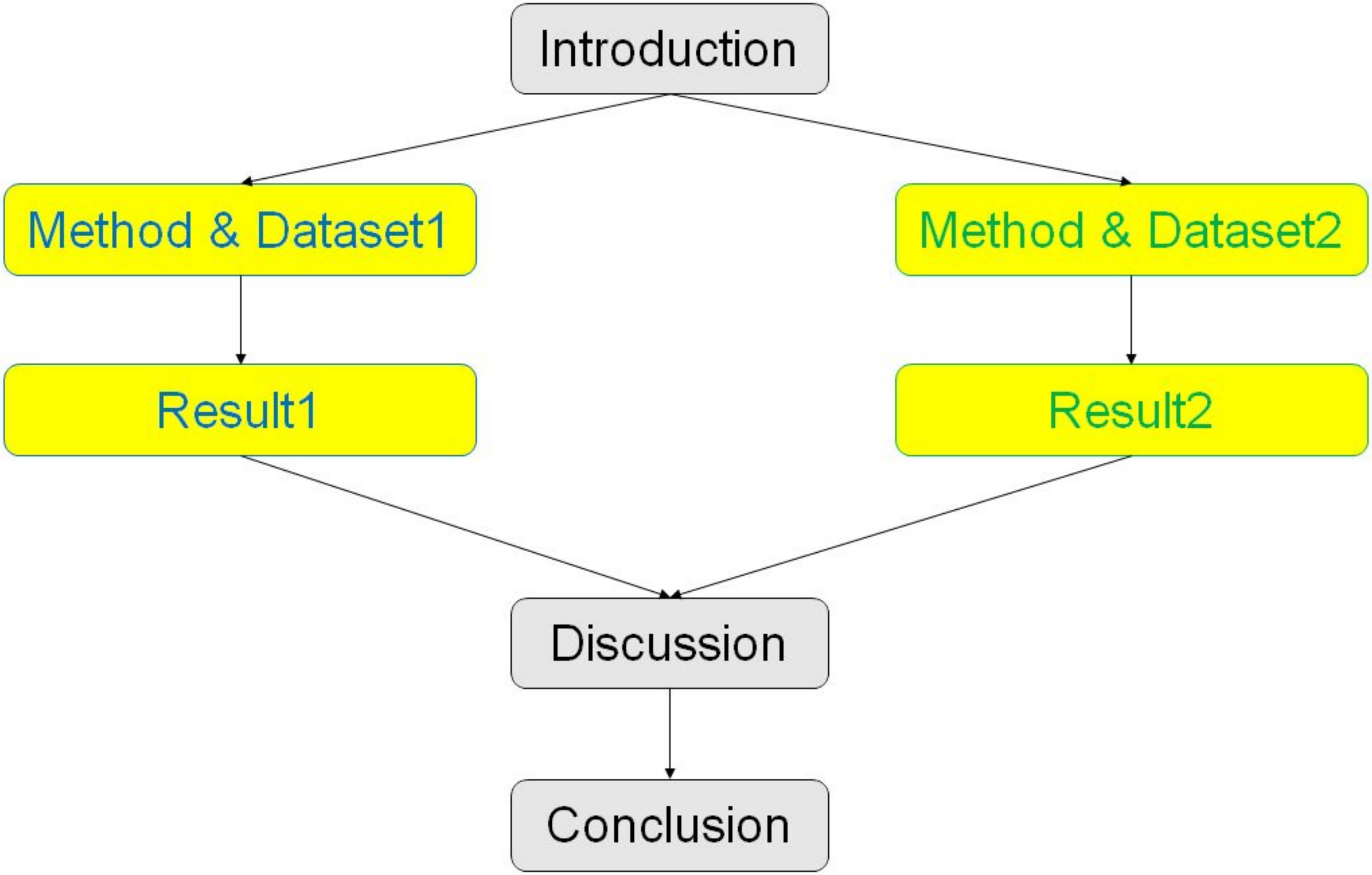
➢ Learn how to Machine Learning

2. Detect glioma

➢ Pursue detection rate

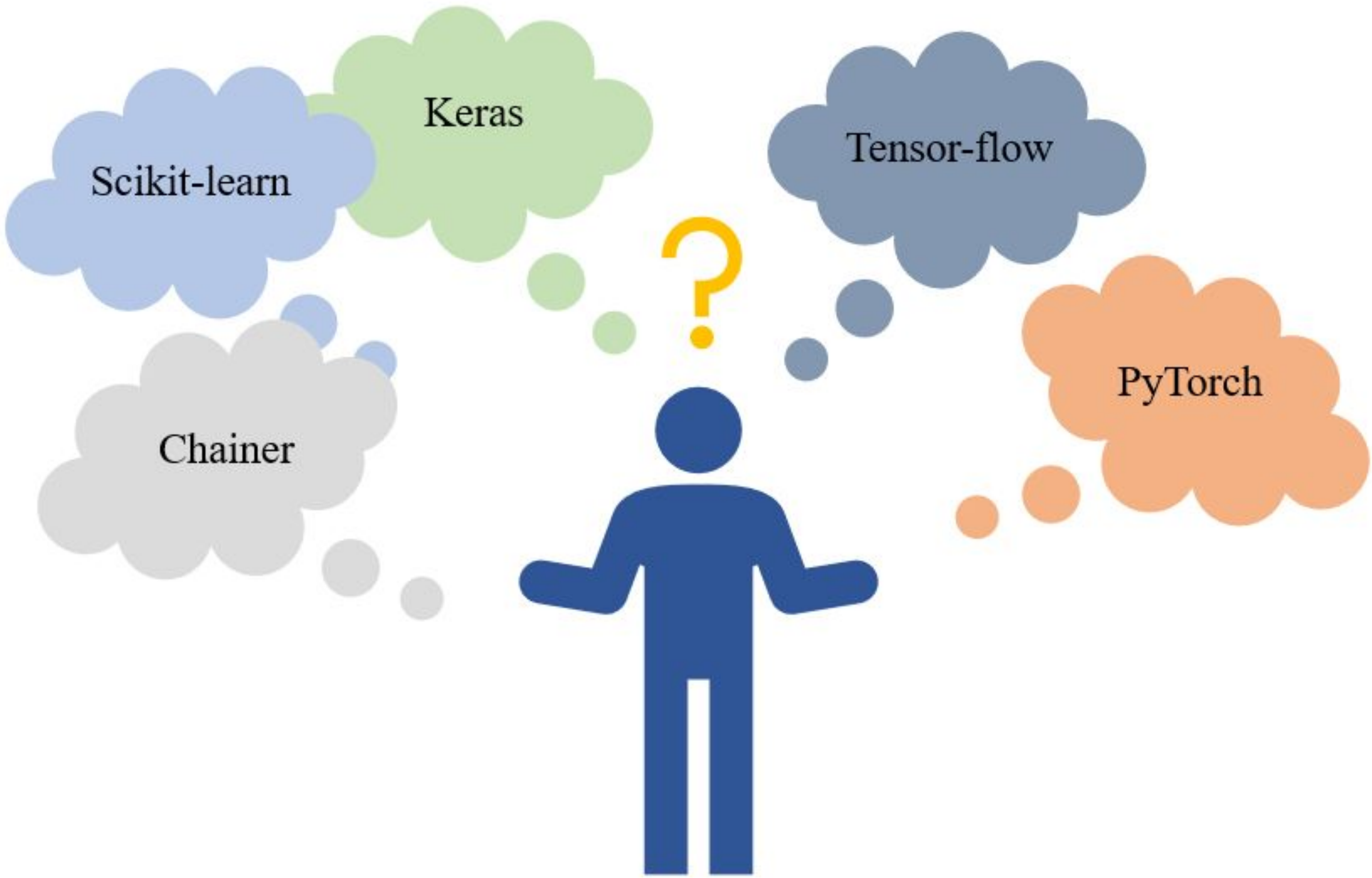


Presentation flow



Method & Dataset

❑ Library for Deep Learning



Method & Dataset

- Library for Deep Learning

PyTorch

Method & Dataset

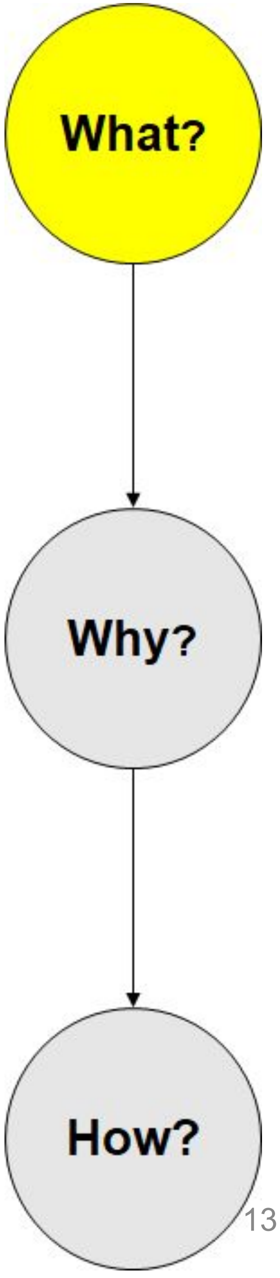
❑ What PyTorch?

➢ Deep Learning framework

❑ What PyTorch character?

➢ Make GPU available more easily

➢ Based on “Define by Run” policy



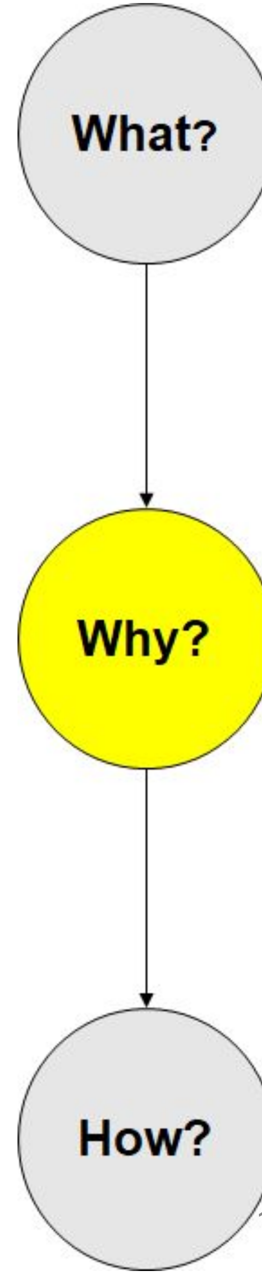
Method & Dataset

❑ Why PyTorch?

➢ <u>Receive advice from Mr. Nakamura easily</u>

➢ More flexible than other framework

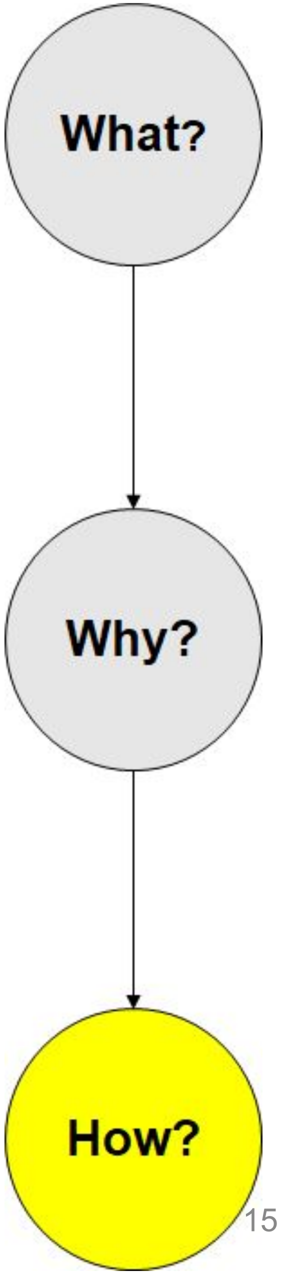
➢ have a easy-to-understand book



Method & Dataset

❑ How use PyTorch?

1. Pre-processing, post-processing
2. Creating Dataset
3. Creating DataLoader
4. Creating a network model
5. Definition of forward
6. Definition of loss function
7. Setting the optimization method
8. Implementation of learning and verification
9. Infer with test data

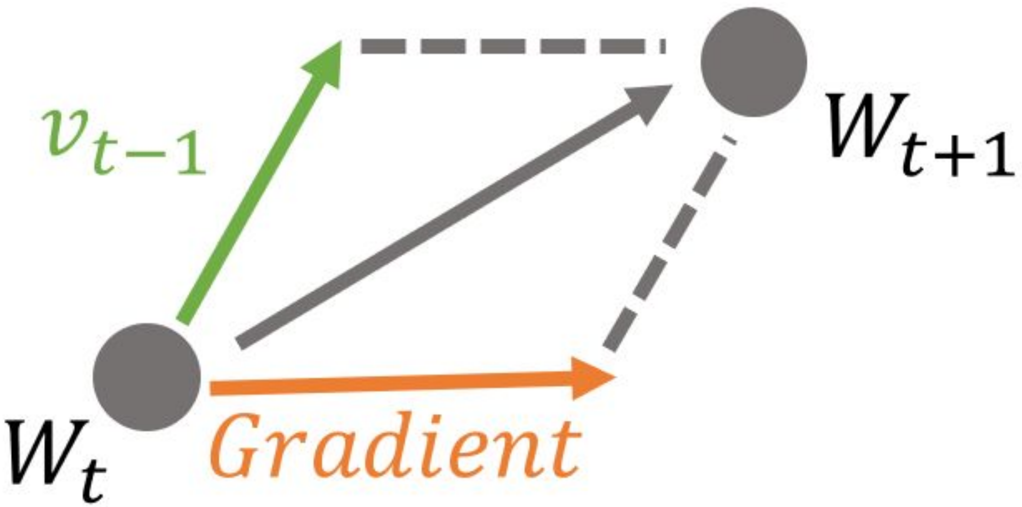


Method & Dataset

❑ Momentum

➢ Method of optimization for updating parameters

➢ Consider not only the direction of the gradient but also that of momentum



$$\mathrm{v} \leftarrow \alpha \mathrm{v} - \eta \frac{\partial L}{\partial W}$$

$$\mathrm{W} \leftarrow \mathrm{W} + \mathrm{v}$$

Method & Dataset

❑ AdaGrad

➢ Method of optimization for updating parameters

➢ At first learn “strongly”, and then learn “weakly”

➢ Adjusting the learning rate adaptively for each parameter

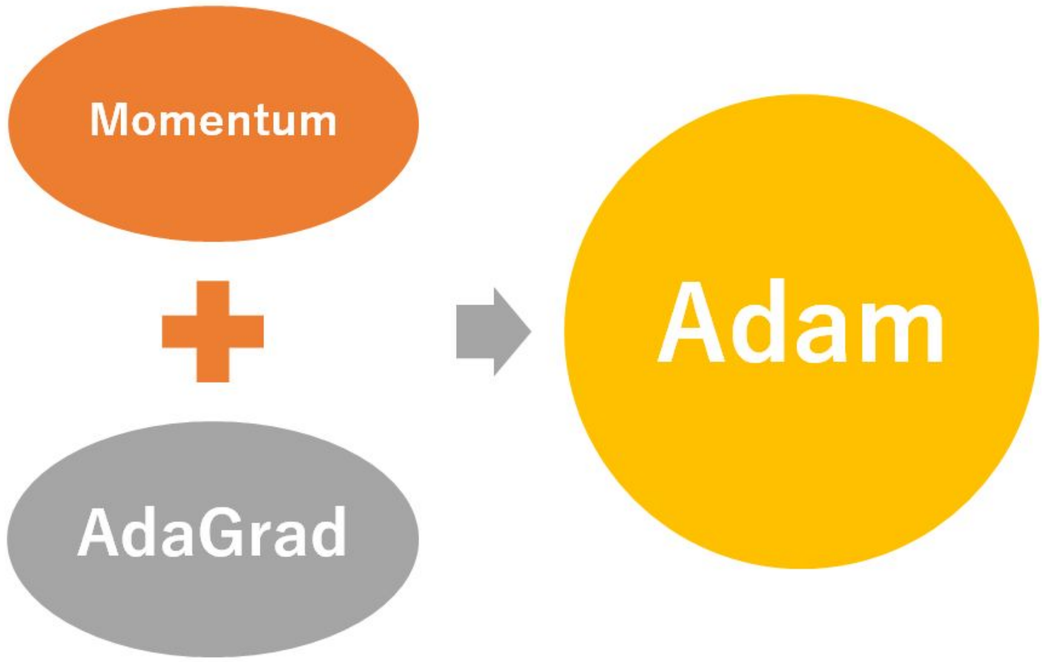
$$h \leftarrow h + \frac{\partial L}{\partial W} \odot \frac{\partial L}{\partial W}$$

$$\mathrm{W} \leftarrow \mathrm{W} - \eta \frac{1}{\sqrt{h}} \frac{\partial L}{\partial W}$$

Method & Dataset

❑ Adam

- ➢ Method of optimization for updating parameters
- ➢ Naively, hybrid method of Momentum and AdaGrad

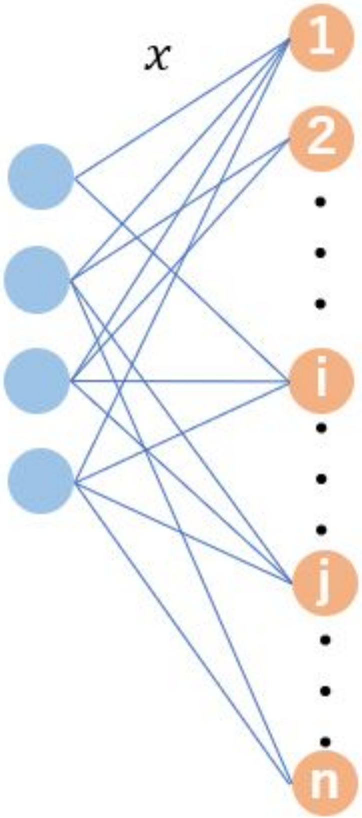


Method & Dataset

❑ Softmax function

$$y_i = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}}$$

- $0 < y_i < 1$
- $y_1 + \cdots + y_n = 1$



Method & Dataset

- **Cross entropy error function**

$$E = \sum_{k=1} -t_k \log y_k$$

$$\boldsymbol{t} = [t_1\ t_2\ \cdot\ \cdot\ \cdot\ t_k\ \cdot\ \cdot\ \cdot\ ] : \mathrm{one-hot\ label}$$

$$\boldsymbol{y} = [y_1\ y_2\ \cdot\ \cdot\ \cdot\ y_k\ \cdot\ \cdot\ \cdot\ ] : \mathrm{output\ of\ network}$$

Method & Dataset

❑ Dataset

1. **IXI Dataset**

    - IXI : **I**nformation e**X**traction from **I**mages
    - https://brain-development.org/ixi-dataset/

2. **LGG-1p19qDeletion from TCIA (Simply call this dataset TCIA)**

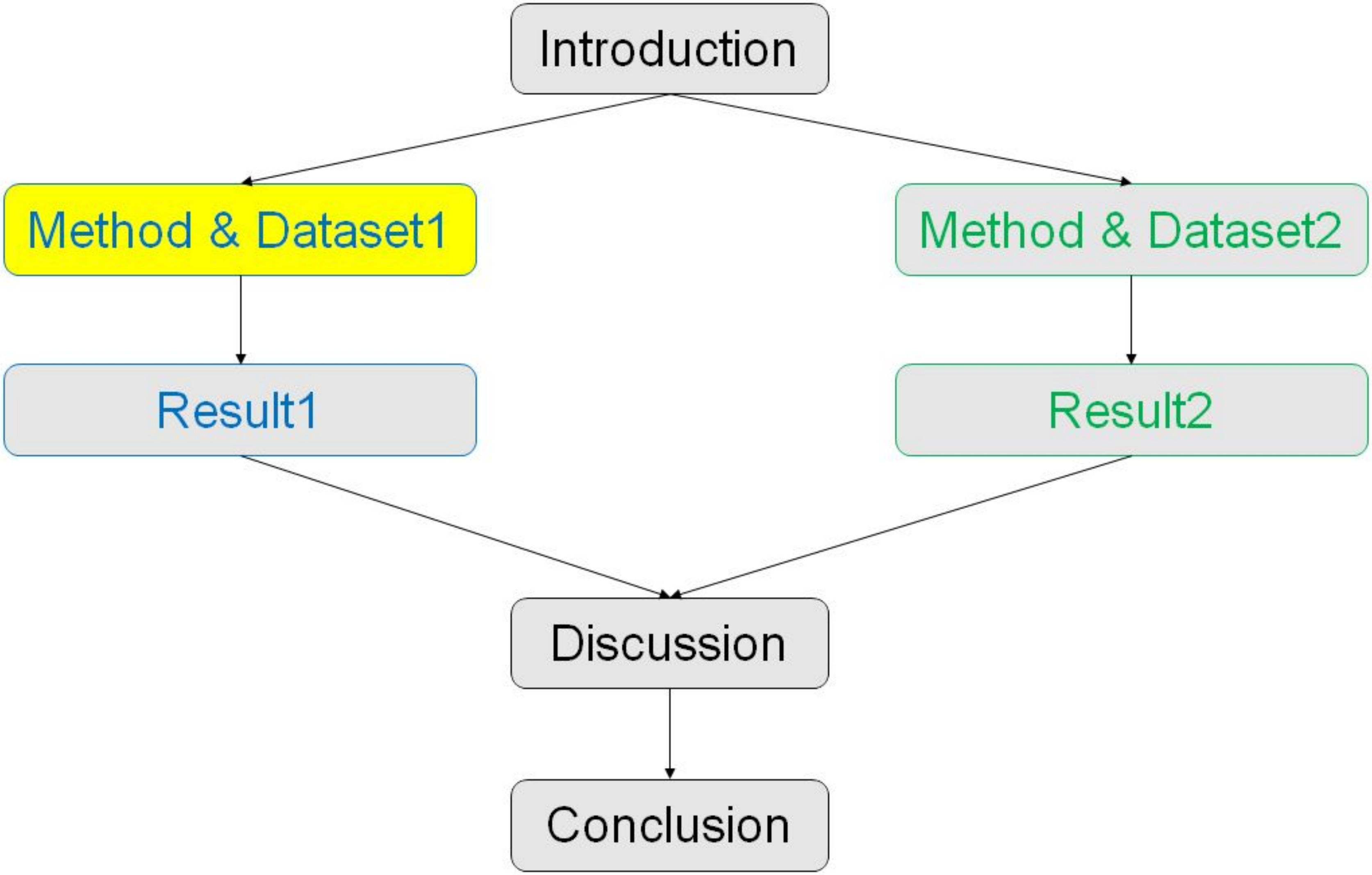
    - TCIA : **T**he **C**ancer **I**mage **A**rchive
    - https://www.cancerimagingarchive.net/

Method & Dataset

❑ Dataset detail

	State	Size	Attached Label
IXI	Normal	585	Weight, Height, Age, Sex, etc.
TCIA	Glioma	159	Grade(悪性度), Weight, Age, Sex, etc.

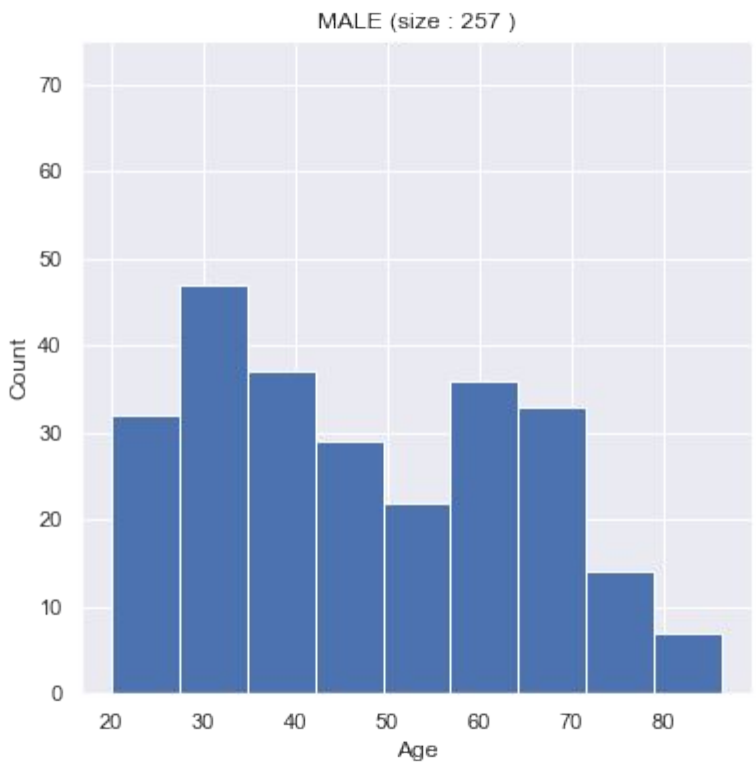
Presentation flow

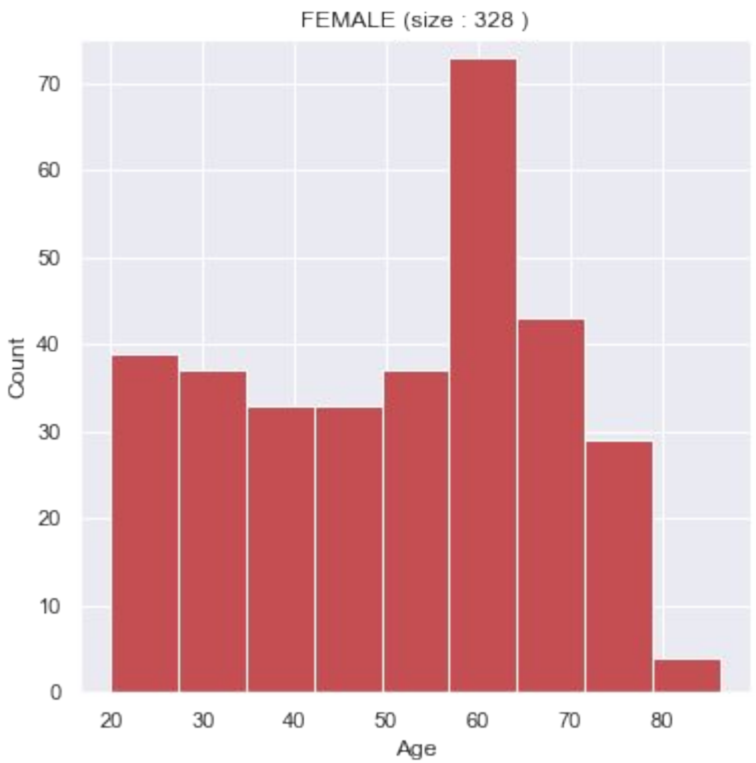


Method & Dataset

❑ Step1- Predicts sex

- **Dataset**
  - IXI dataset only





Method & Dataset

- **Step1- Predicts sex**
  - **What problems?**

1. MRI data is a three-dimensional image

→ MRI data has spatial information

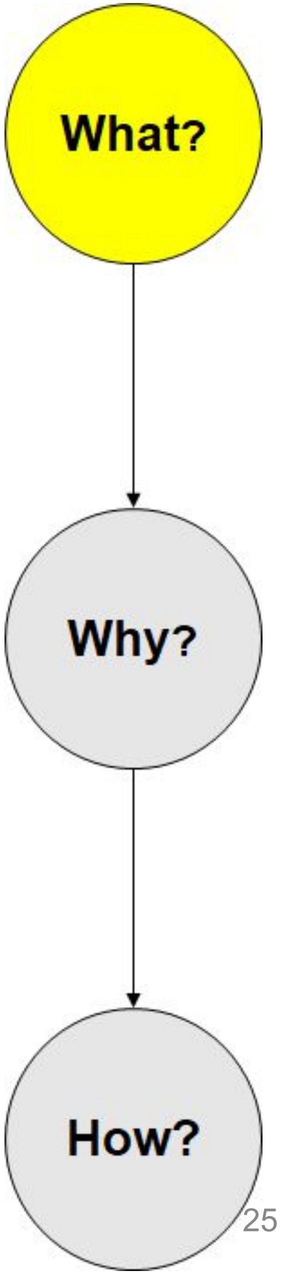
↔ Machine Learning method (not deep) requires one-dimensional data(probably ...)

→ Adopt Deep Learning method(3D CNN) only

2. Deep Learning needs a lot of time and memory

→ I have temporal and memory constraints

→ Use small size data type and shallow structure



Method & Dataset

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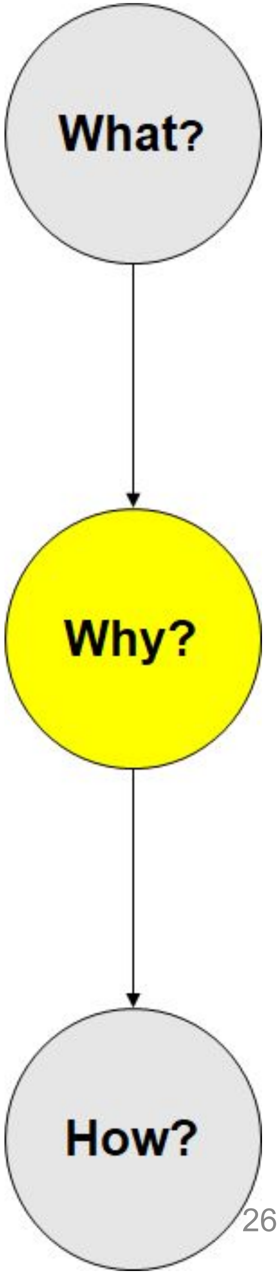

Method & Dataset

❑ **Step1- Predicts sex**

How resolve problems?

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→ MRI data has spatial information

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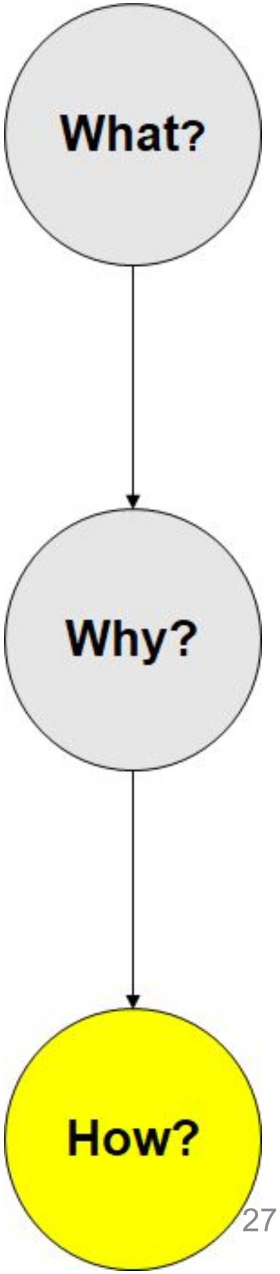


Method & Dataset

❑ Step1- Predicts sex

Method

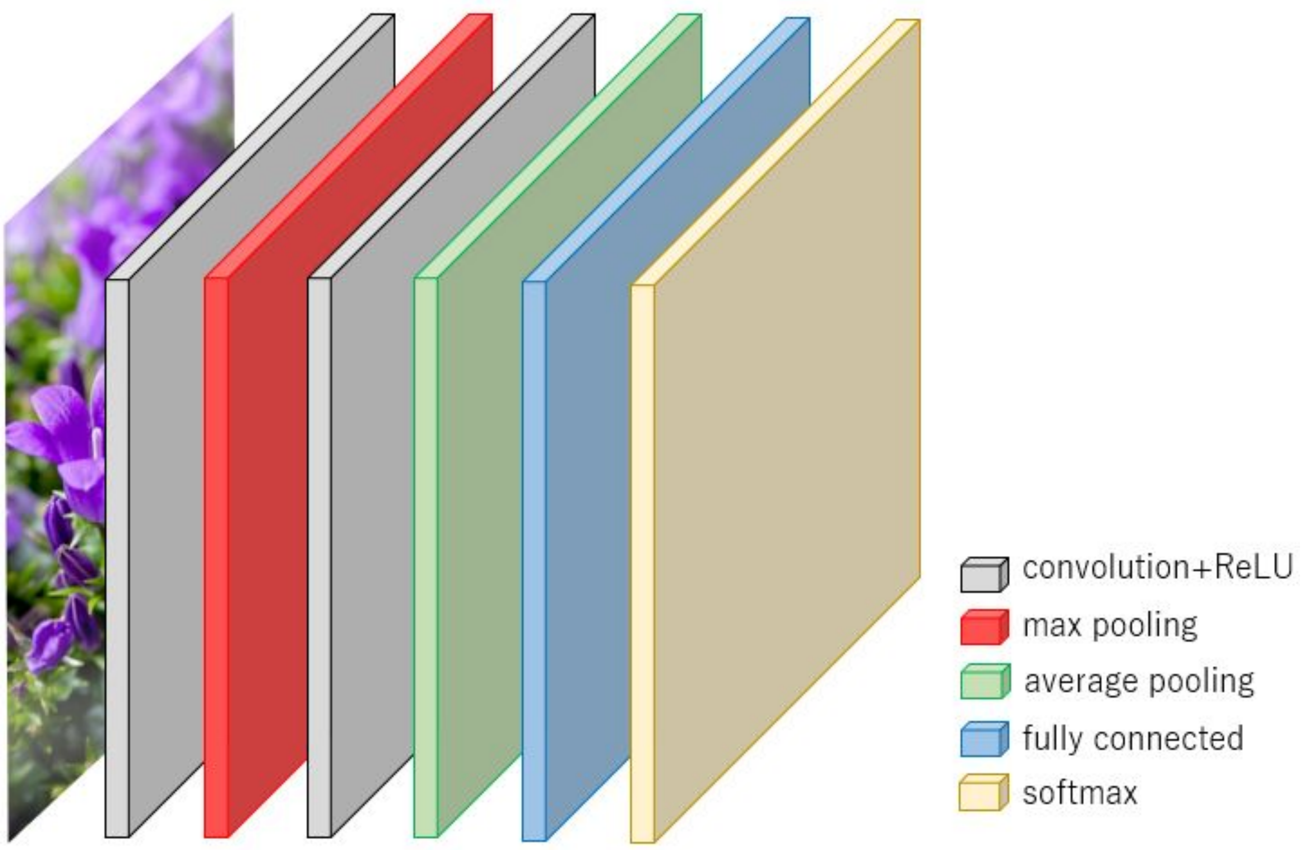
1. Original 3D CNN
   - Call this CNN “3D ConvNet”

2. Original 3D CNN -version 2-
   - Call this CNN “3D ConvNet v2”

Method & Dataset

- **Step1- Predicts sex**

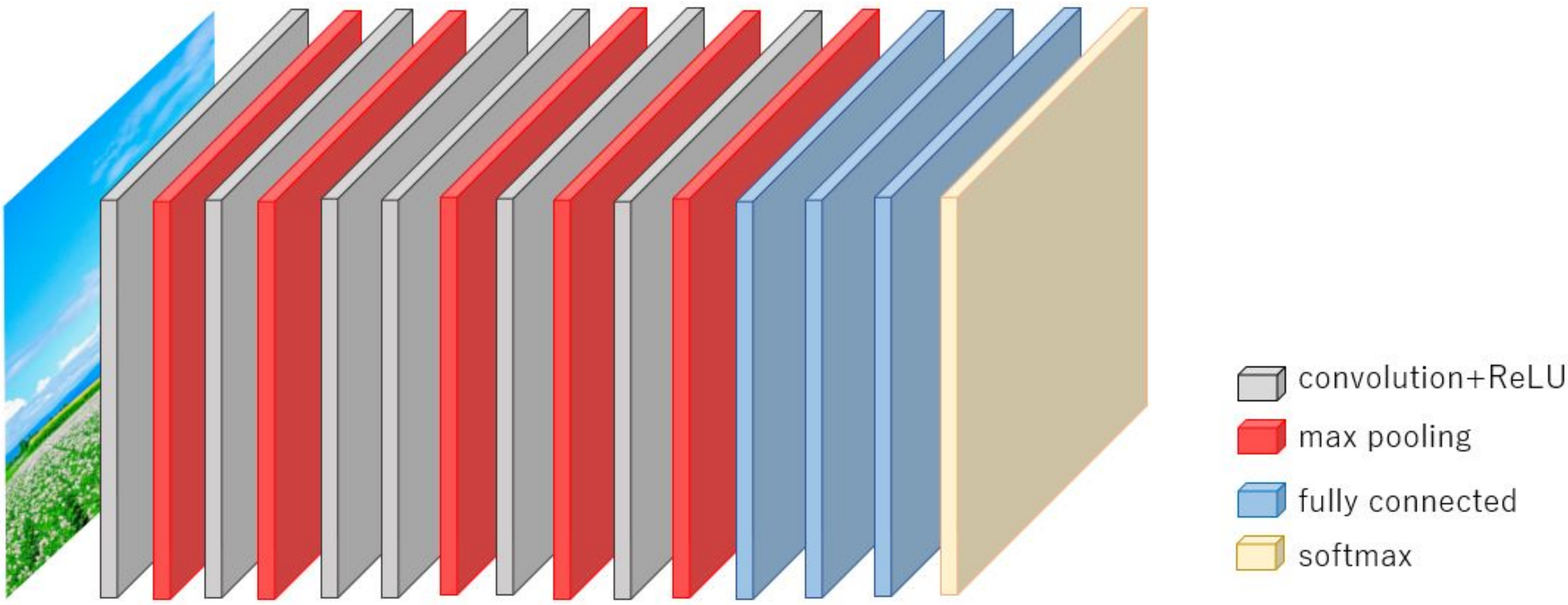
  - **Method Detail(3D ConvNet)**



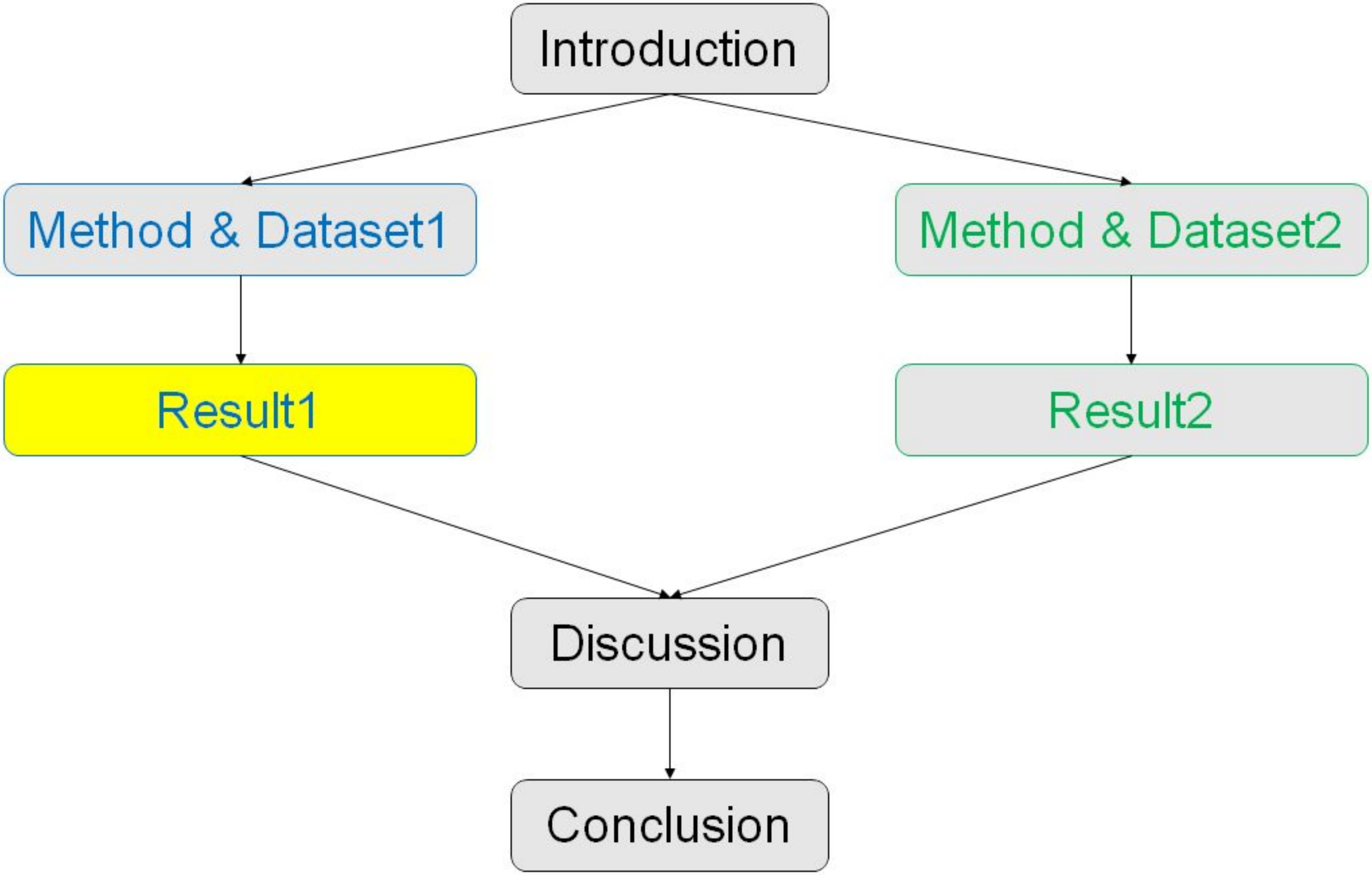
Method & Dataset

❑ **Step1- Predicts sex**

- **Method Detail(3D ConvNet v2)**



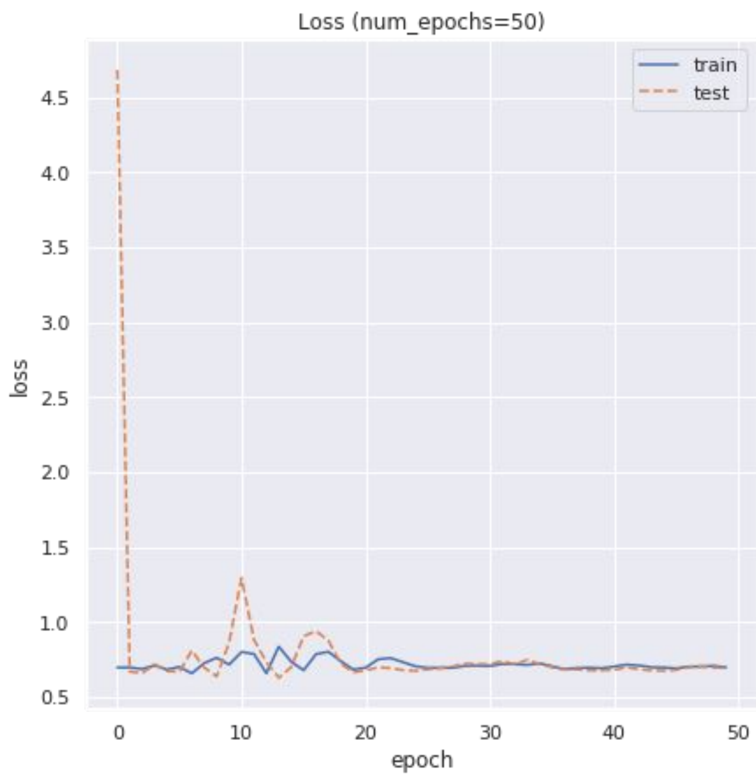
Presentation flow

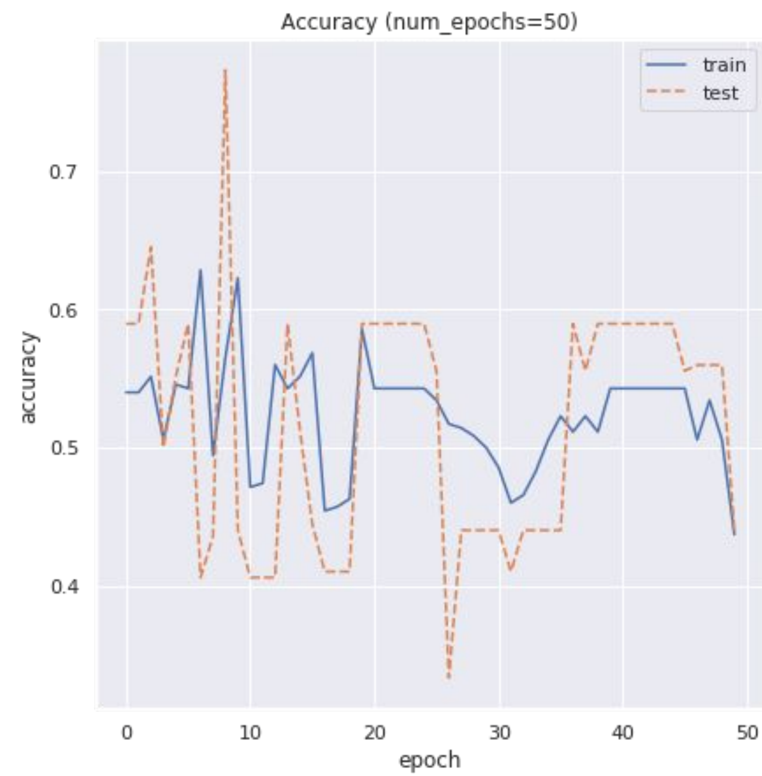


Result

❑ Step1 - Predicts sex

- 3D ConvNet
  - 50 epoch

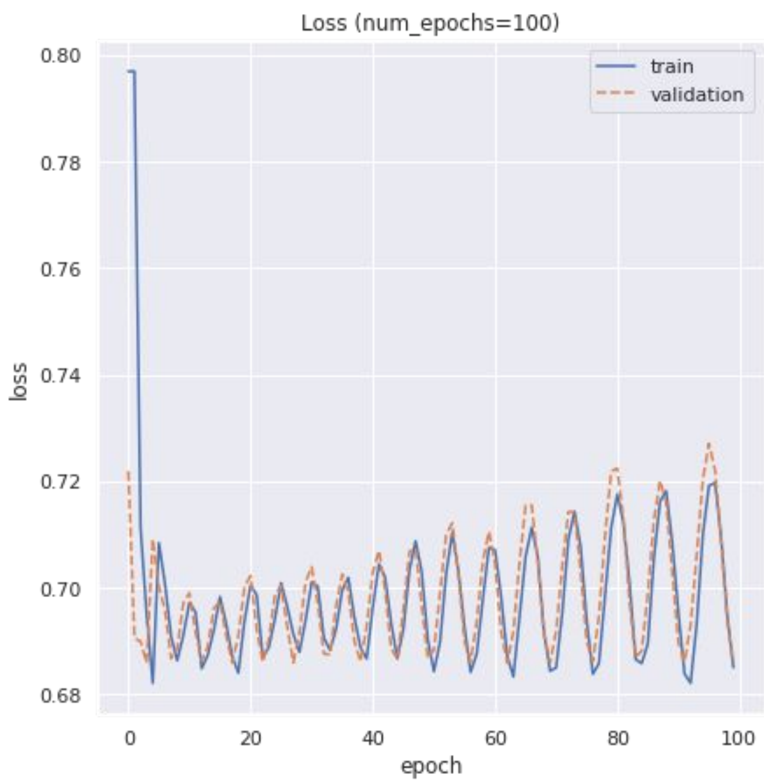


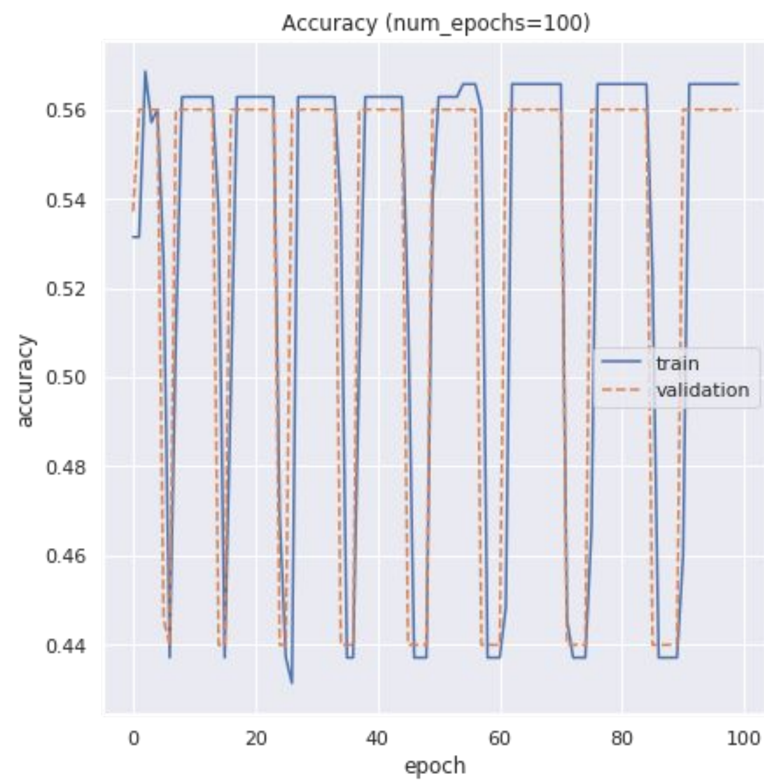


Result

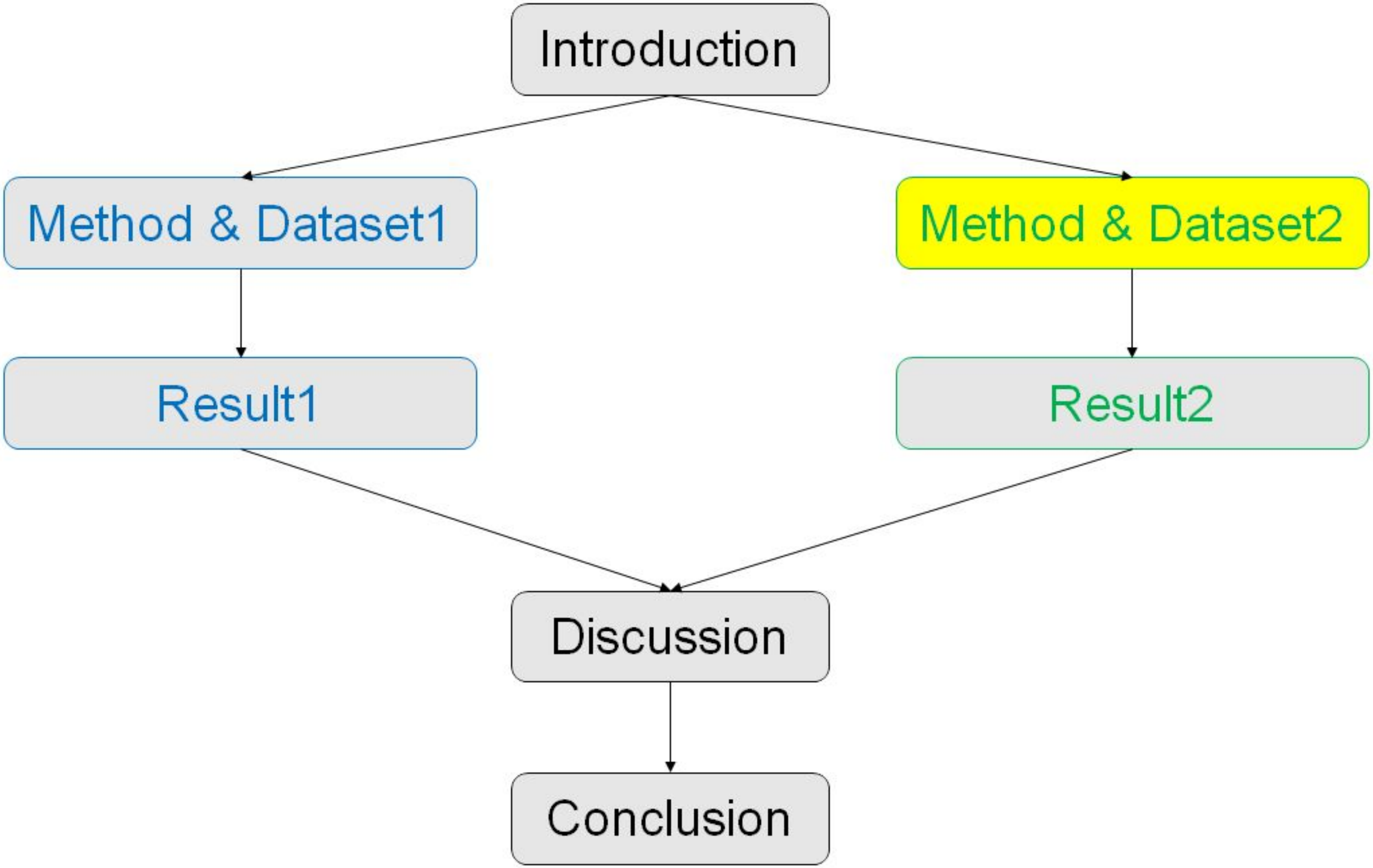
❏ Step1 - Predicts sex

- 3D ConvNet v2
  - 100 epoch





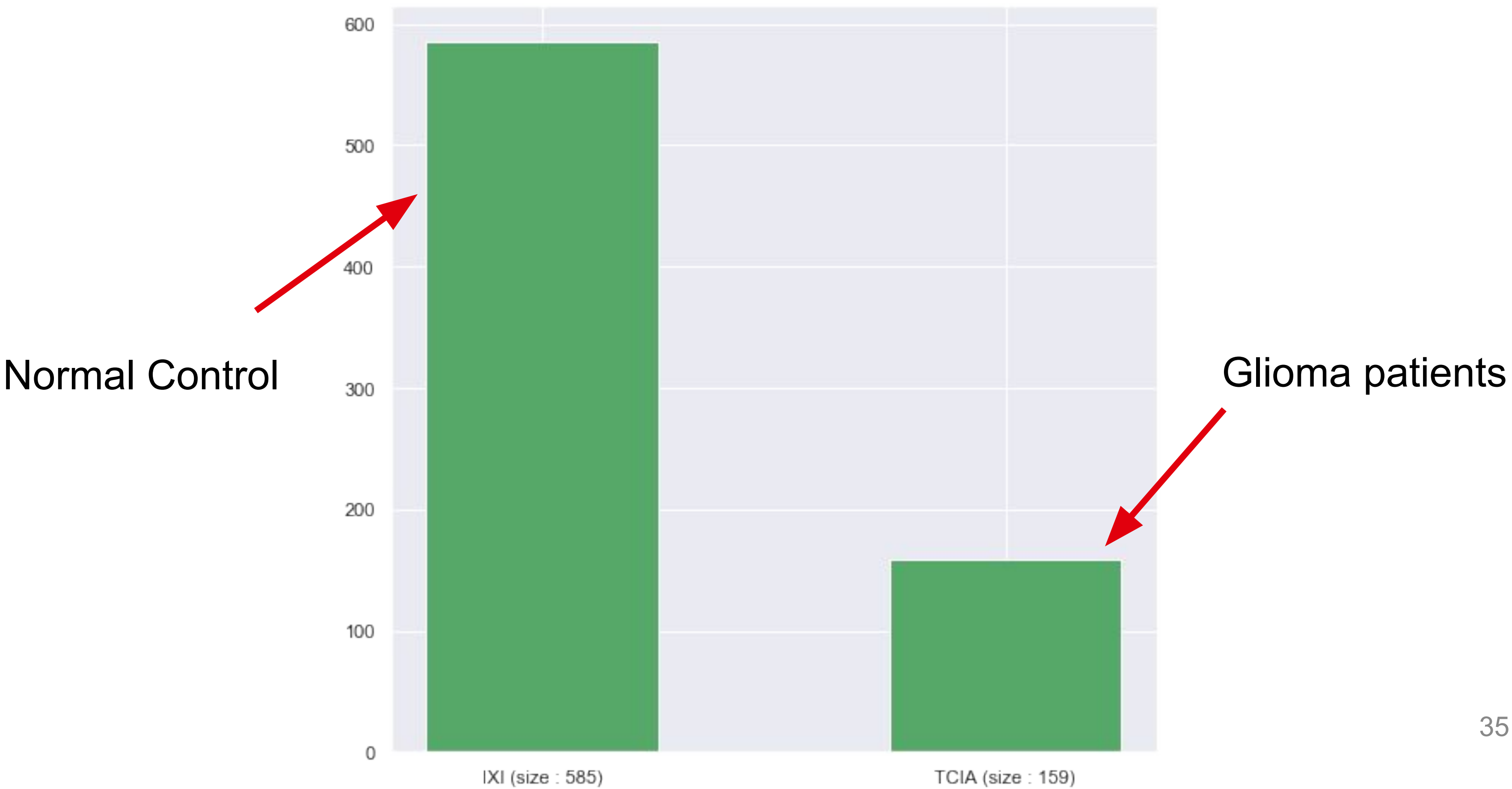
Presentation flow



Method & Dataset

❏ Step2 - Detect glioma

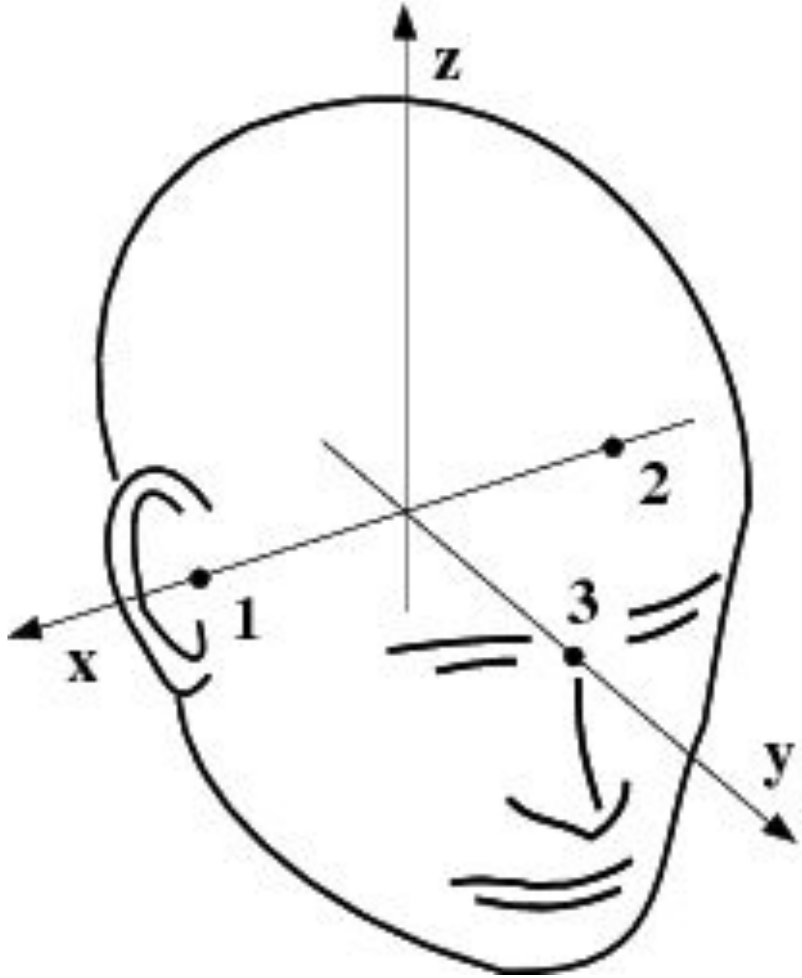
- Dataset



Method & Dataset

❑ **Step2 - Detect glioma**

 Confirmation - Definition of MRI coordinate system -



Method & Dataset

- **Step2 - Detect glioma**
  - **What problems?**

1. TCIA images have lower size in z-axis direction than IXI

→ Must input same shape data to CNN
→ Must compress IXI images in some way
→ Give up using IXI images

2. Each TCIA image have diverse number of z-axis image

→ Must input same shape data to CNN
← The location of glioma differs in each patient
← Must manually reduce the number of image
→ Use 2D-images along z-axis from TCIA

Method & Dataset

- **Step2 - Detect glioma**
  - **What problems?**

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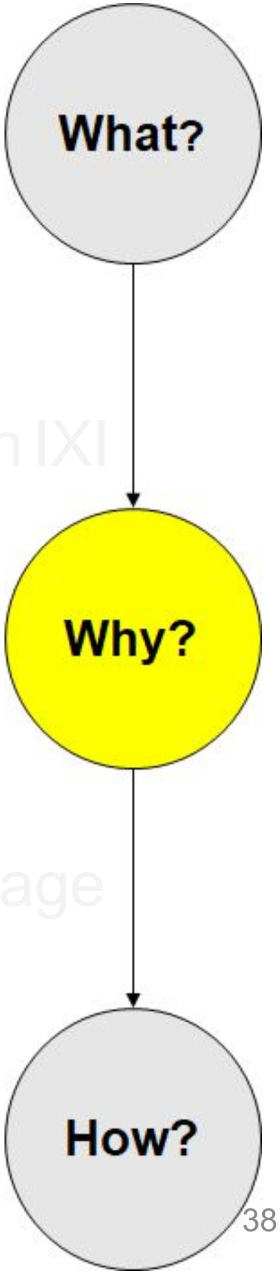

Method & Dataset

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← The location of glioma differs in each patient

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→ Use 2D-images along z-axis from TCIA

Method & Dataset

❑ Step2 - Detect glioma

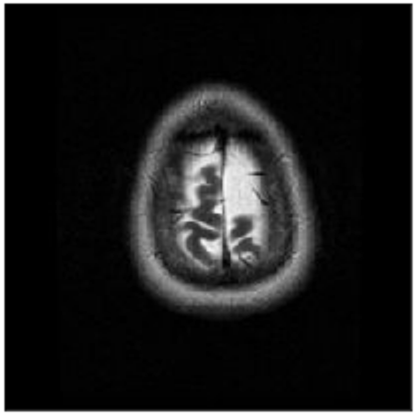
- Mean of each label

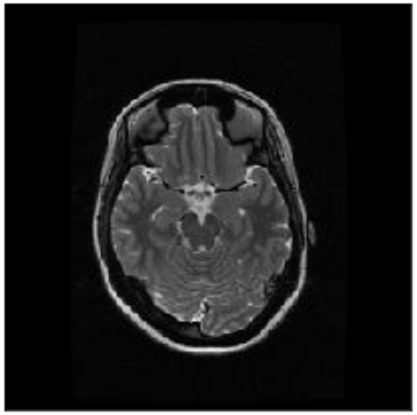
label	mean
0	normal control
1	glioma
2	black image
3	unused image

Method & Dataset

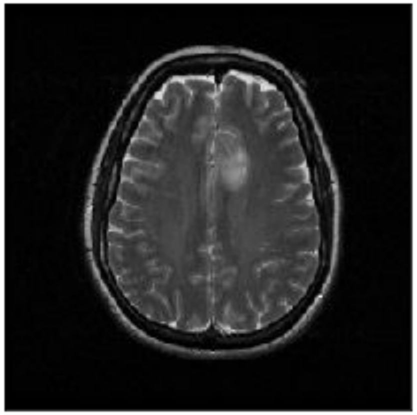
- **Step2 - Detect glioma**
  - **Example of each label**

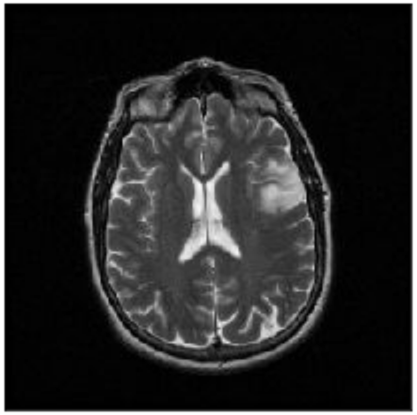
label : 0





label : 1



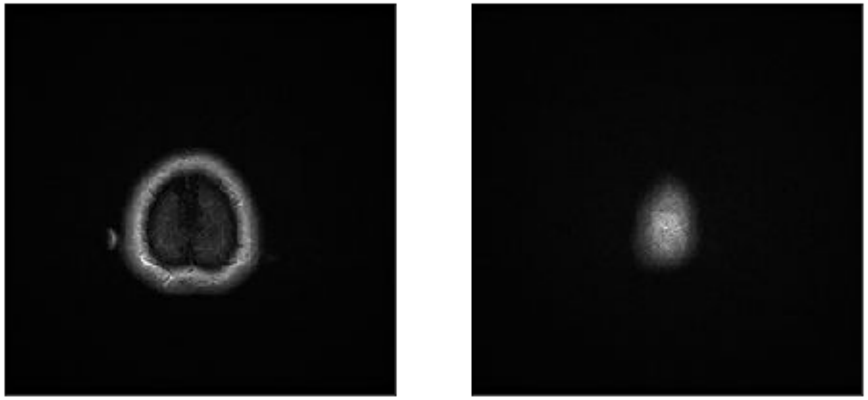


Method & Dataset

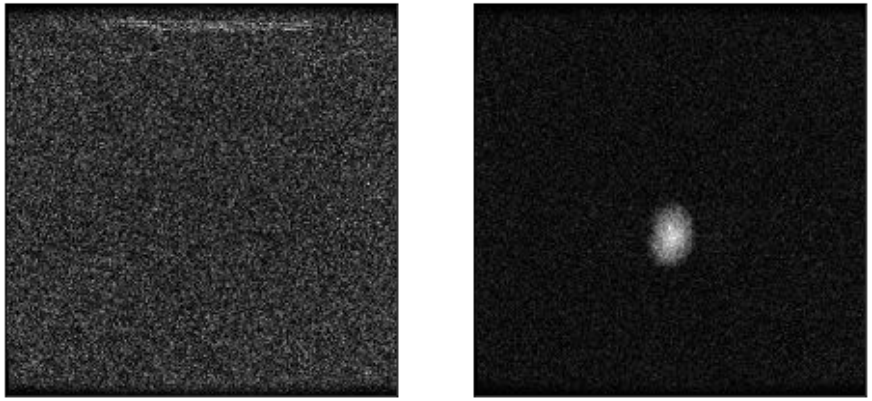
❑ Step2 - Detect glioma

- Example of each label

label : 2



label : 3



Method & Dataset

❑ Step2 - Detect glioma

▯ Dataset

- Number of images on each label

label	number of images
0	5166
1	1868
2	731
3	222

Method & Dataset

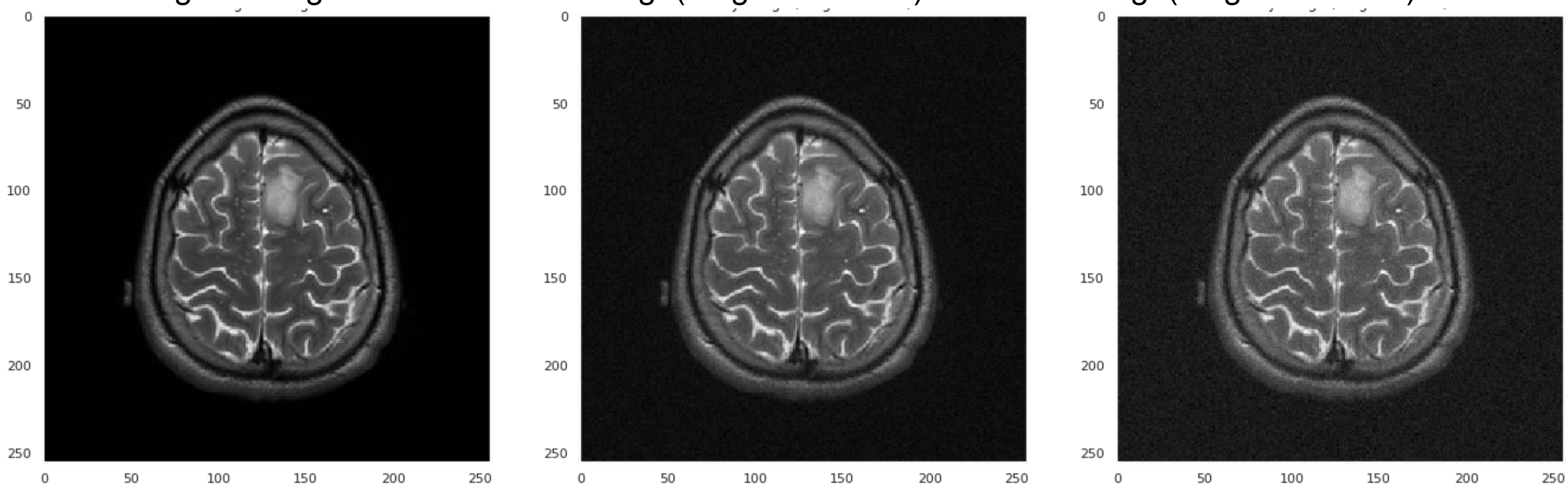
❑ Step2 - Detect glioma

▯ Dataset

○ Add Gaussian noise to training data

ex)

original image | noise image(magnitude = 29) | noise image(magnitude = 50)



Method & Dataset

❑ Step2 - Detect glioma

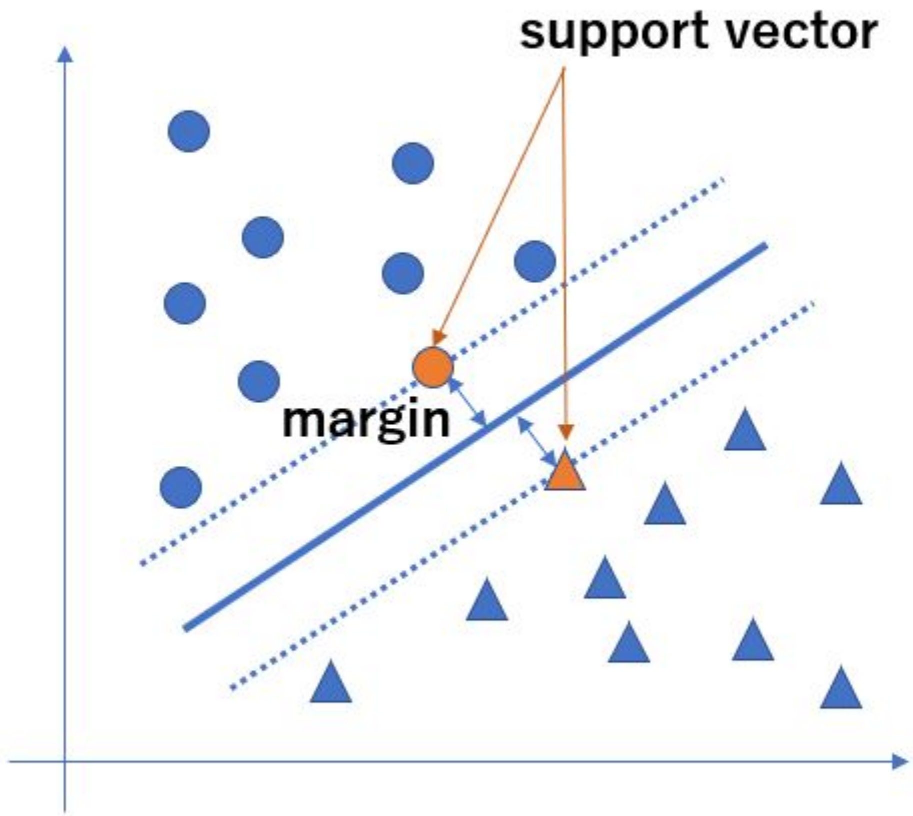
Method

1. SVM(**S**upport **V**ector **M**achine)
2. Random Forest
3. Gradient Boosting
4. VGG16(relearning based on fine tuning)
5. Original CNN
   - Call this CNN 2D ConvNet

Method & Dataset

❑ Step2 - Detect glioma

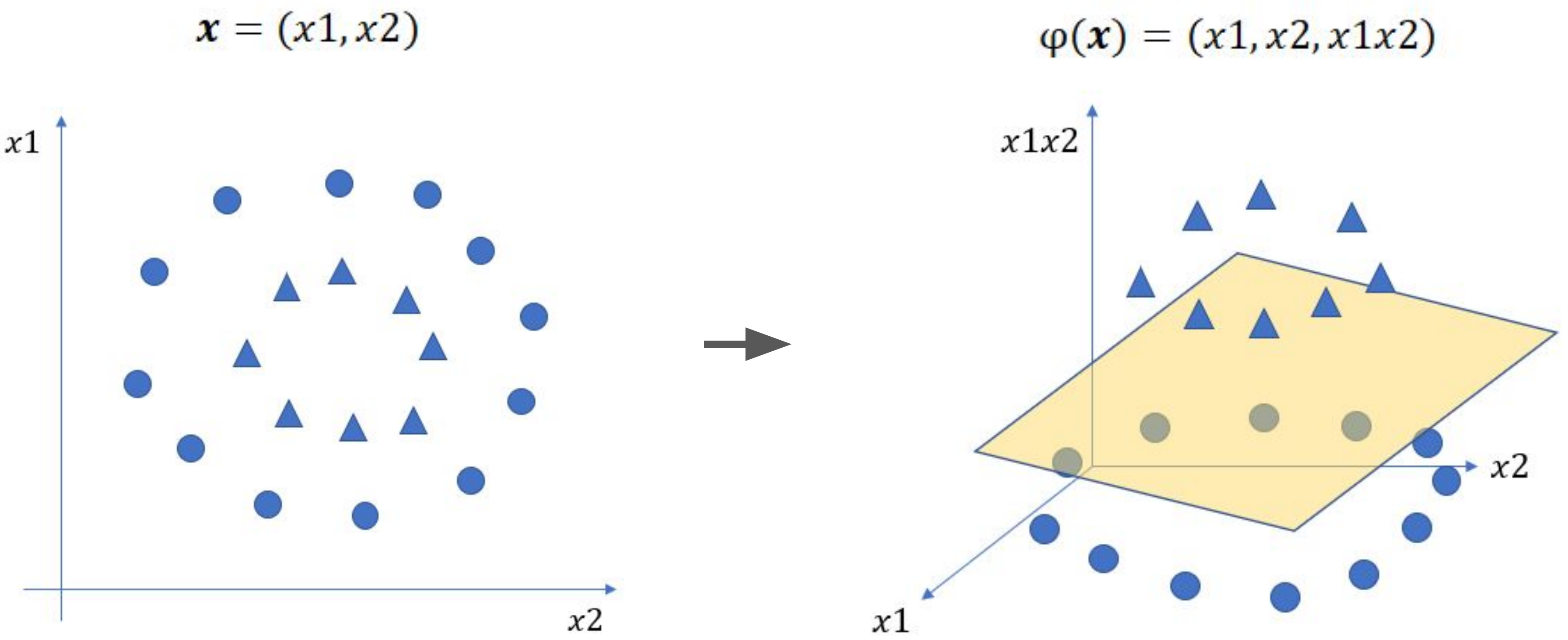
Method Detail(SVM)



Method & Dataset

❑ Step2 - Detect glioma

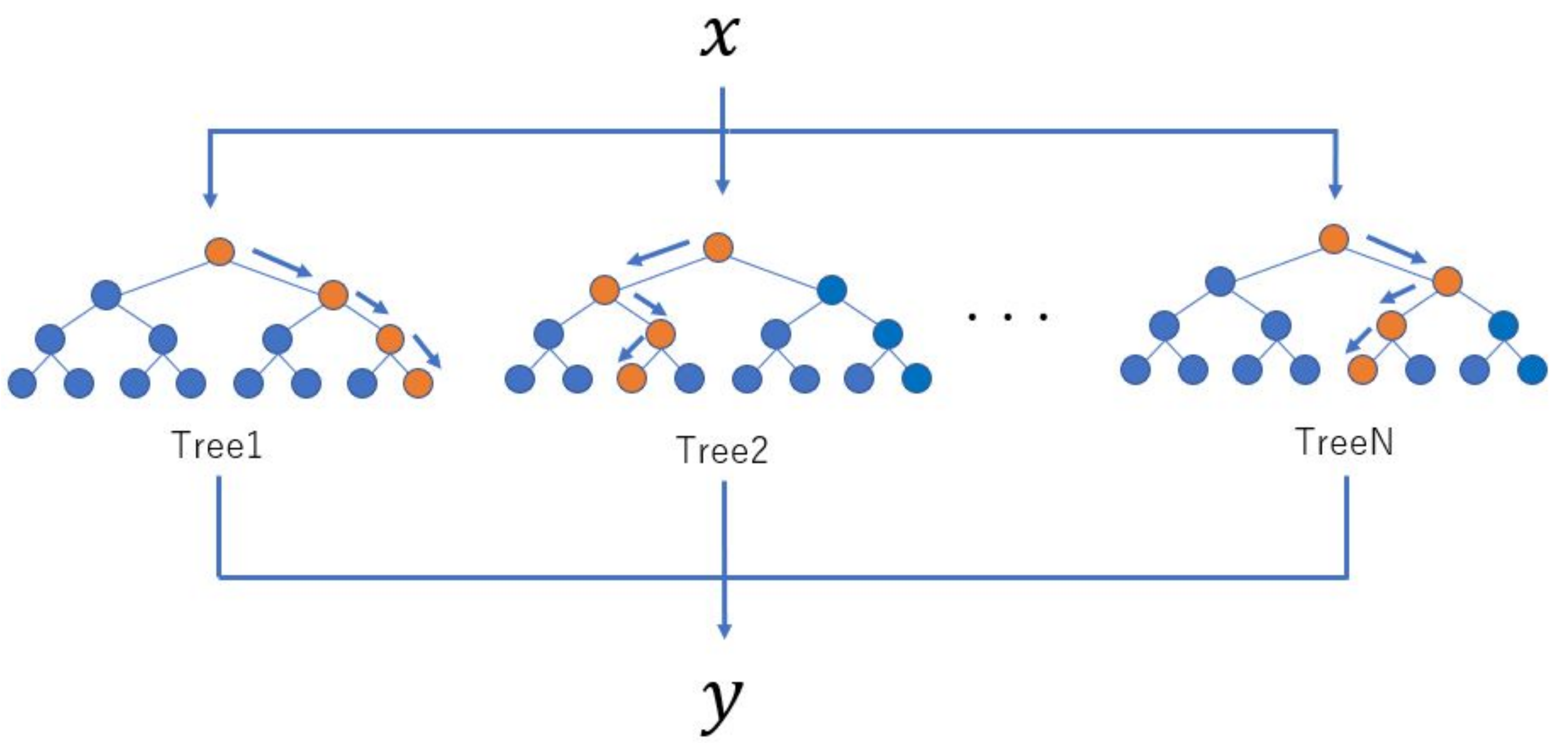
Method Detail(SVM)



Method & Dataset

❑ Step2 - Detect glioma

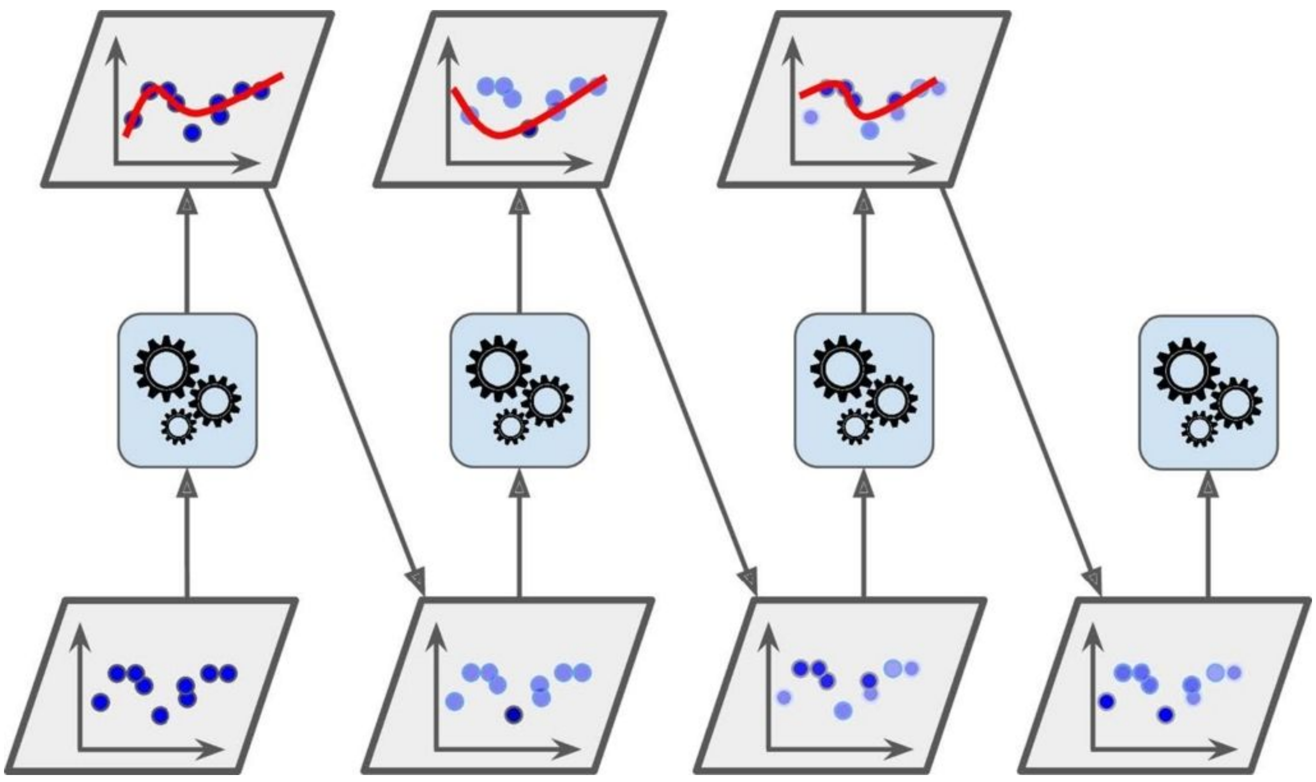
▯ Method Detail(Random Forest)



Method & Dataset

- Step2 - Detect glioma

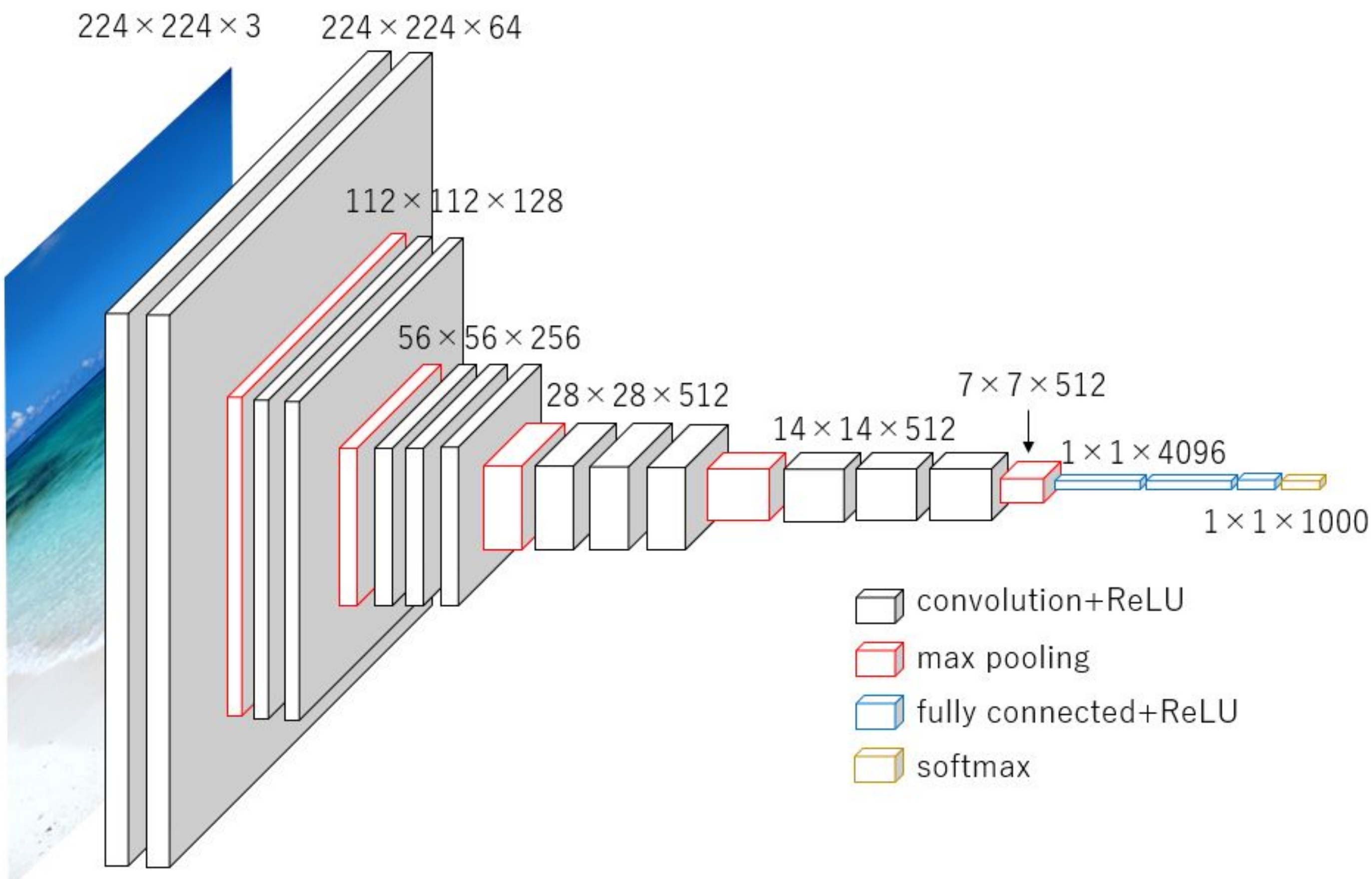
  - Method Detail(Gradient boosting)



Method & Dataset

❑ Step2 - Detect glioma

▯ Method Detail(VGG16)



Method & Dataset

❑ Step2 - Detect glioma

▯ Method Detail(Fine tuning)

○ Method of building model using pre-trained network

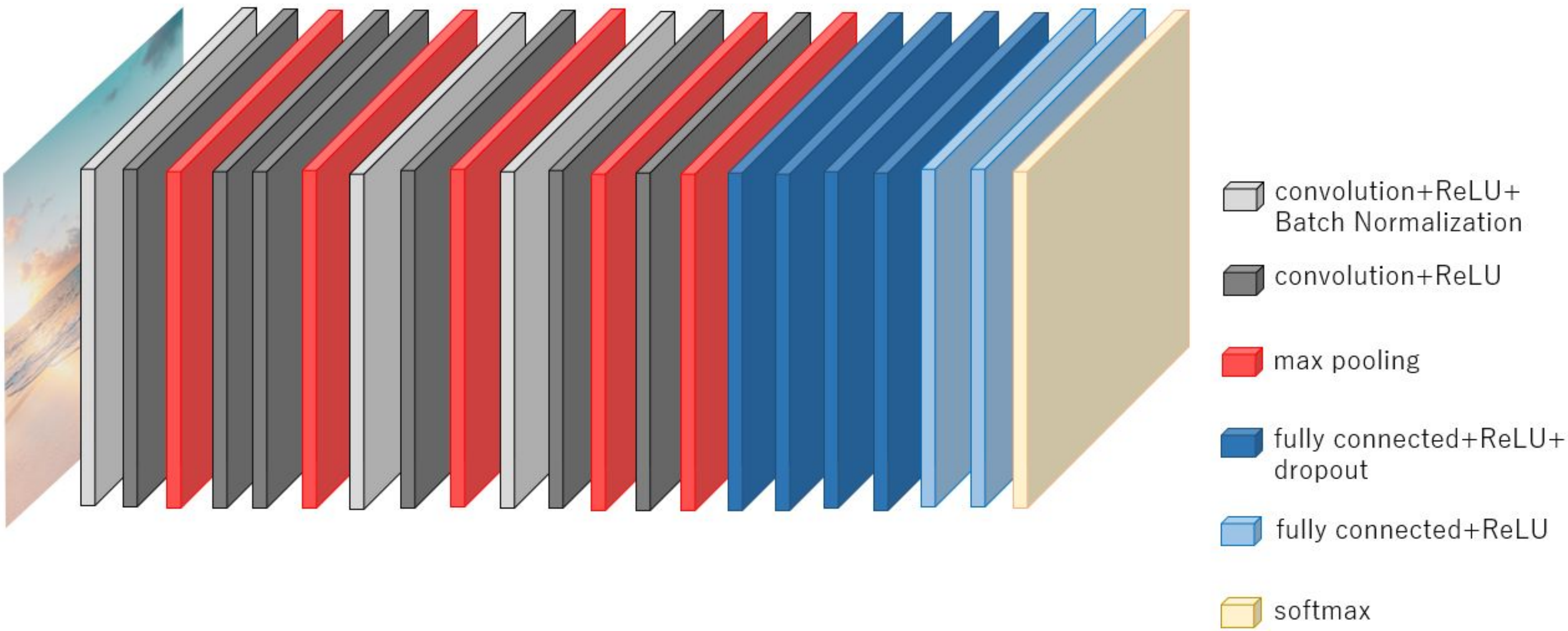
→ We have **only** to change the input and output layer

○ Retrain **all** parameters

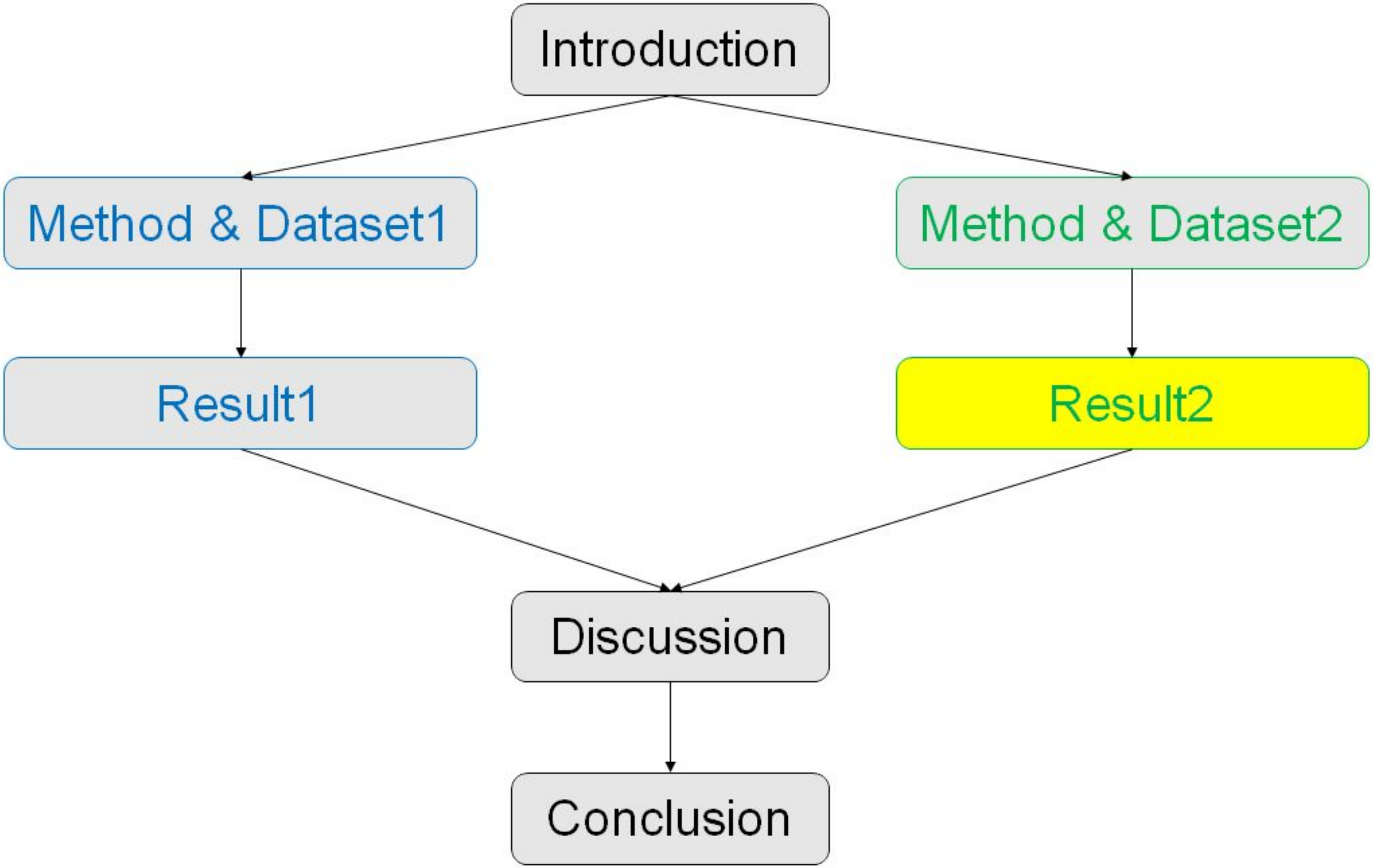
Method & Dataset

❑ Step2 - Detect glioma

Method Detail(2D ConvNet)



Presentation flow



Result

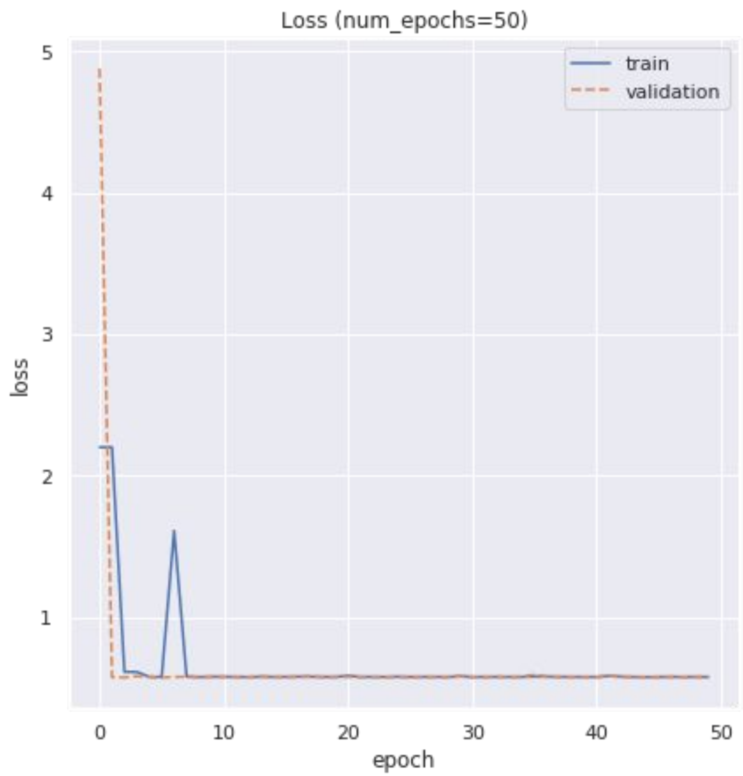
❑ Step2 - Detect glioma

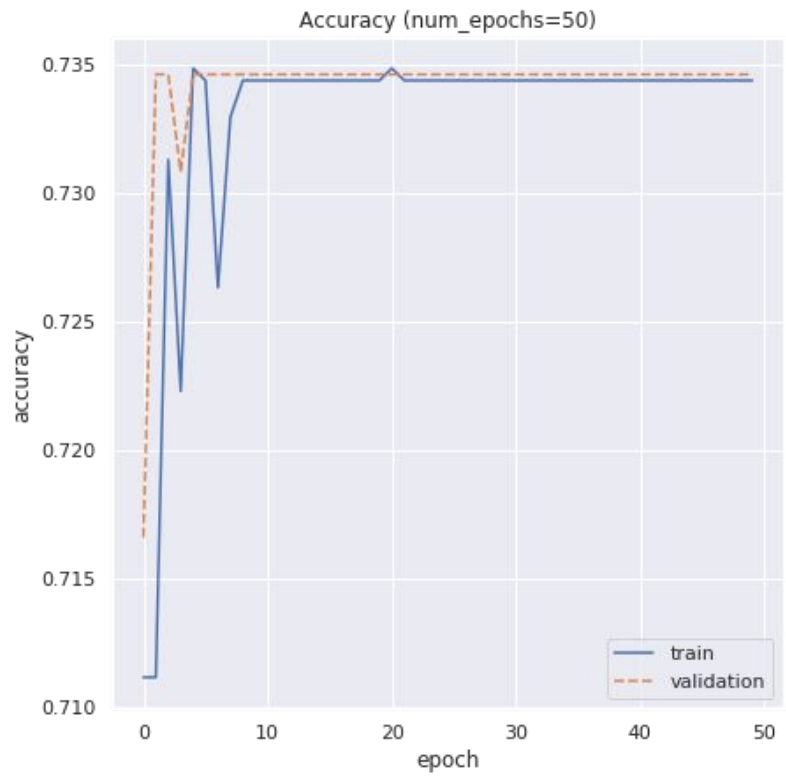
- Comparison with each classical Machine Learning method

	Train score	Val score	Test score
Random Forest	99%	88%	89%
Gradient Boosting	96%	88%	87%
SVM	84%	81%	82%

Result

- **Step2 - Detect glioma**
  - VGG16
    - 50 epoch



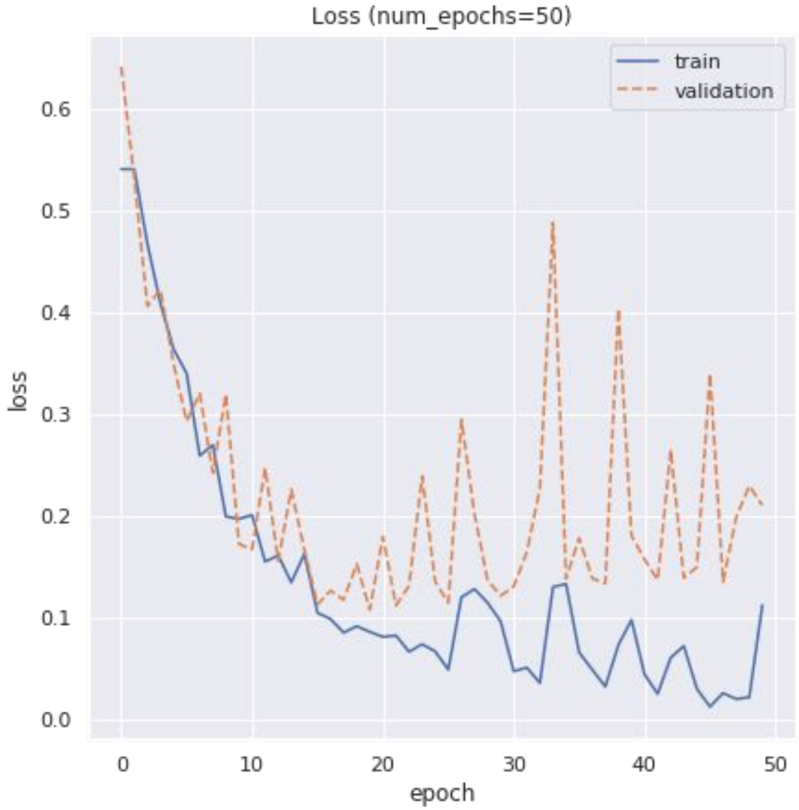


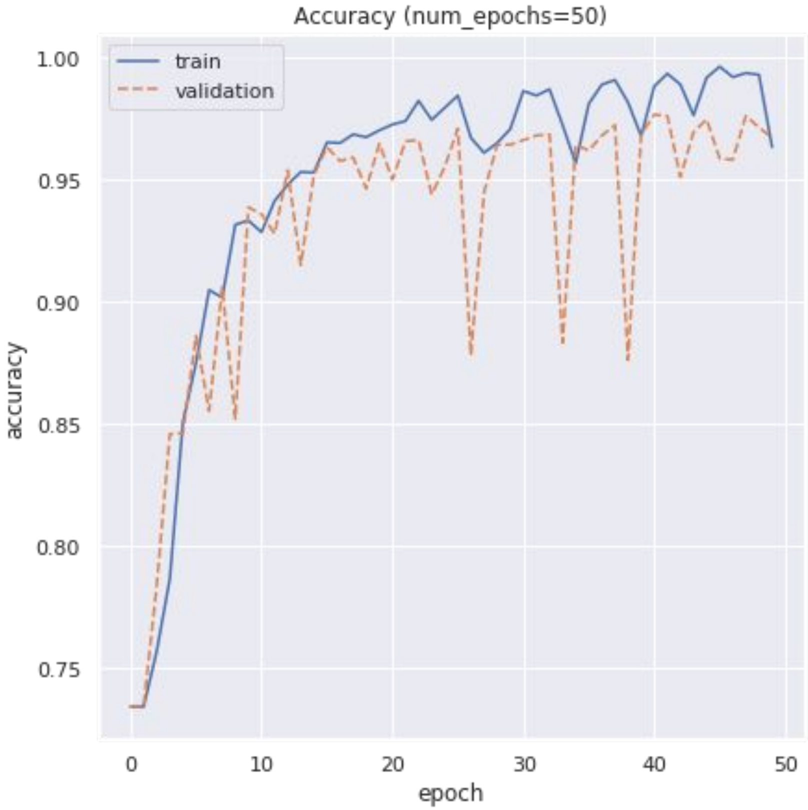
Result

Result

❑ Step2 - Detect glioma

- 2D ConvNet
  - ○ 50 epoch

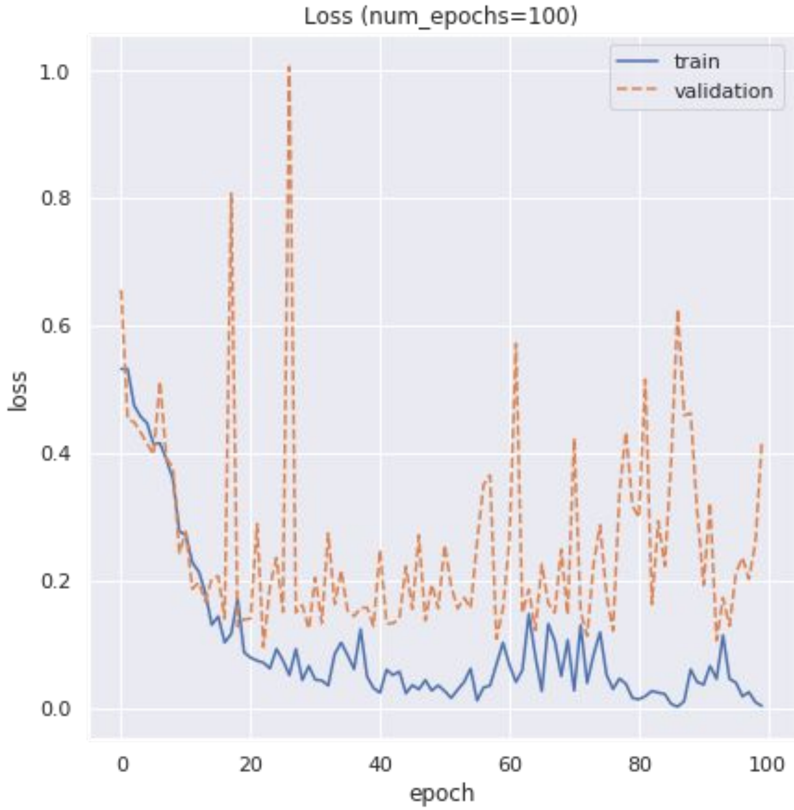


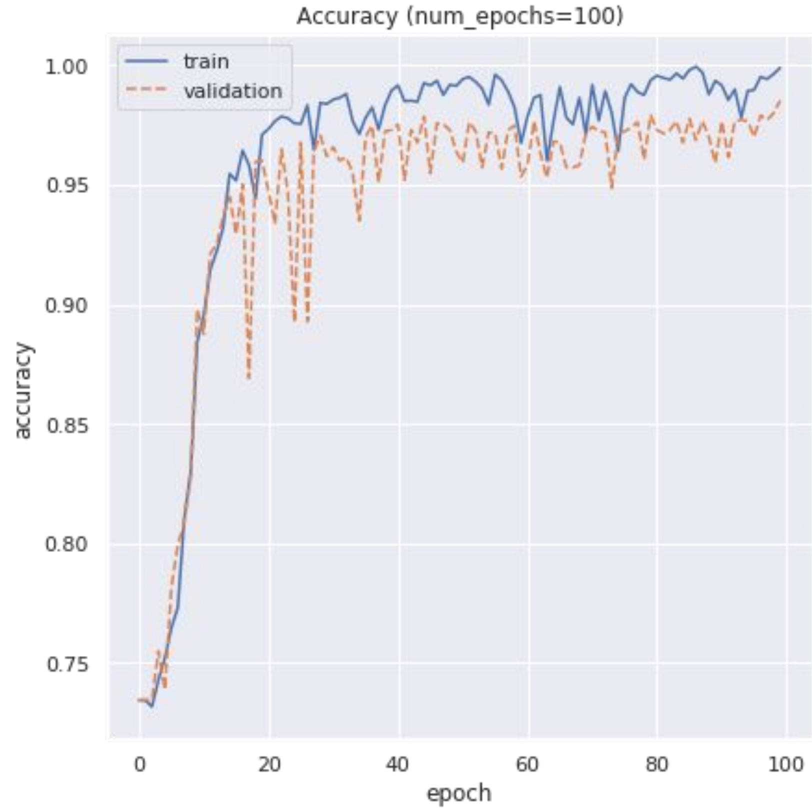


Result

❑ Step2 - Detect glioma

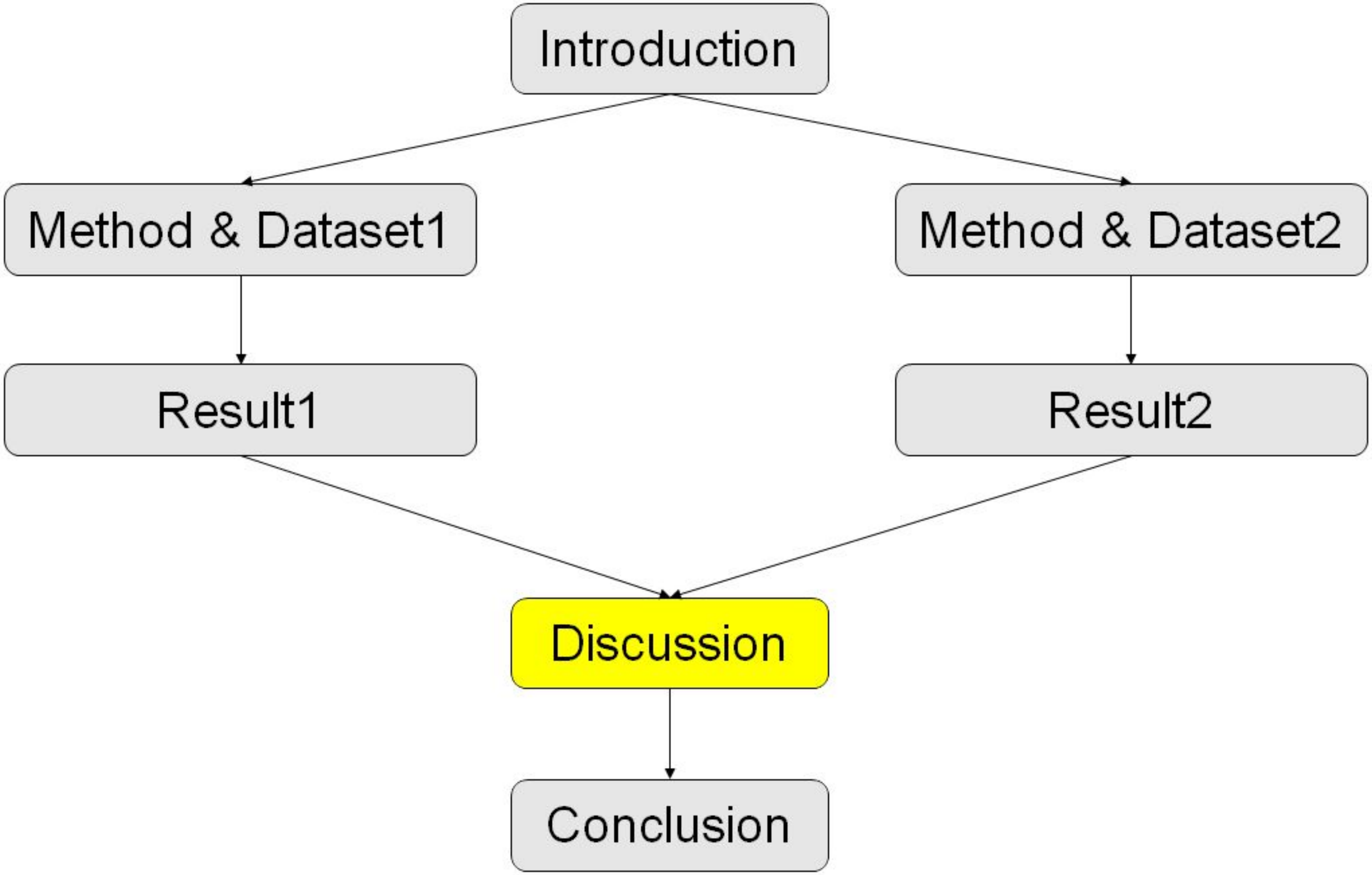
- 2D ConvNet
  - 100 epoch





Result

Presentation flow



Discussion

❑ Step1 - Predicts sex

- Why **can't** predict sex accurately?
    - 3D ConvNet's input is only MRI data and label

      → Volume of men's brain is larger than that of women's

      → Volume of young people's brain is larger than that of elderly people's

      → Input age data as well

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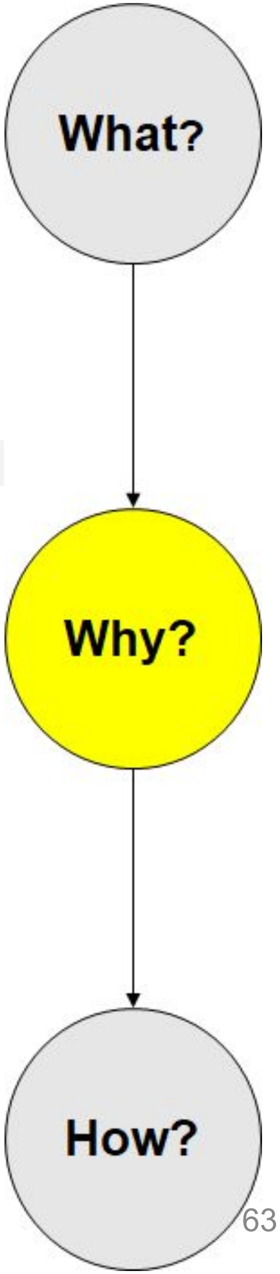

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Discussion

❑ Step2 - Detect glioma

- Why VGG16 **can’t** surpass classical Machine Learning accuracy?

Discussion

Step2 - Detect glioma

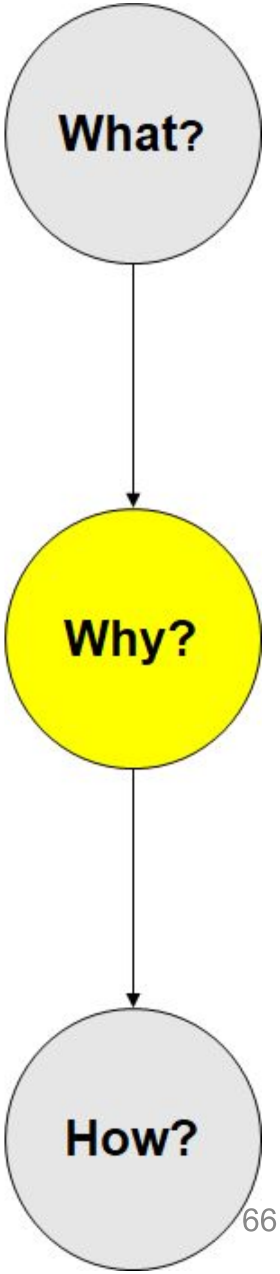
- Why VGG16 **can't** surpass classical Machine Learning accuracy?

1. I should have standardize input images

   → VGG16 requires standardized inputs

   ← I forgot it …

   → Standardize input images



Discussion

❑ Step2 - Detect glioma

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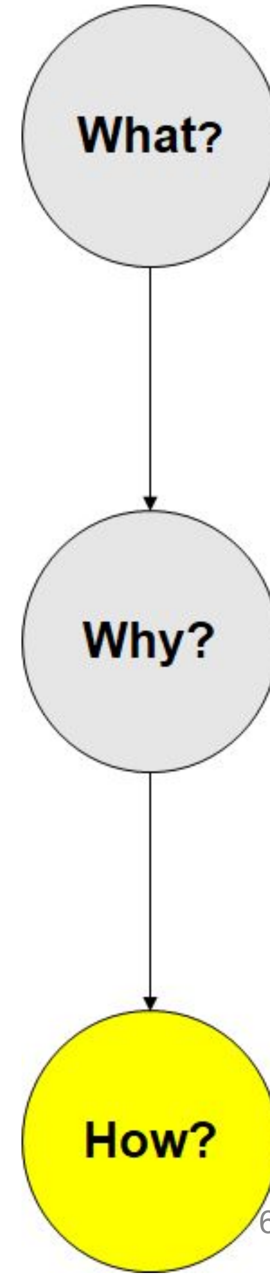

Discussion

❑ Step2 - Detect glioma

- Why VGG16 **can't** surpass classical Machine Learning accuracy?

2. Dataset I used and dataset used for pretraining is differ in characters

→ Dataset I used is gray scale images

← Dataset used for pretraining has RGB channel

→ Dataset I used consists of brain image only

← Dataset used for pretraining consists of daily images (I think ...)

→ Use another pre-trained model

Discussion

❑ Step2 - Detect glioma

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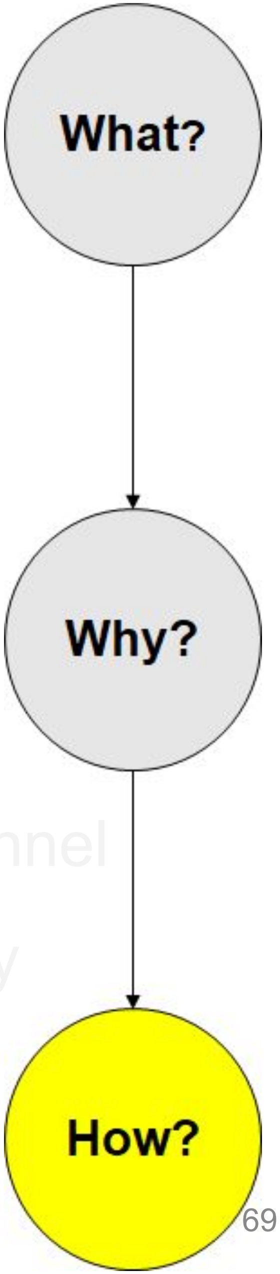
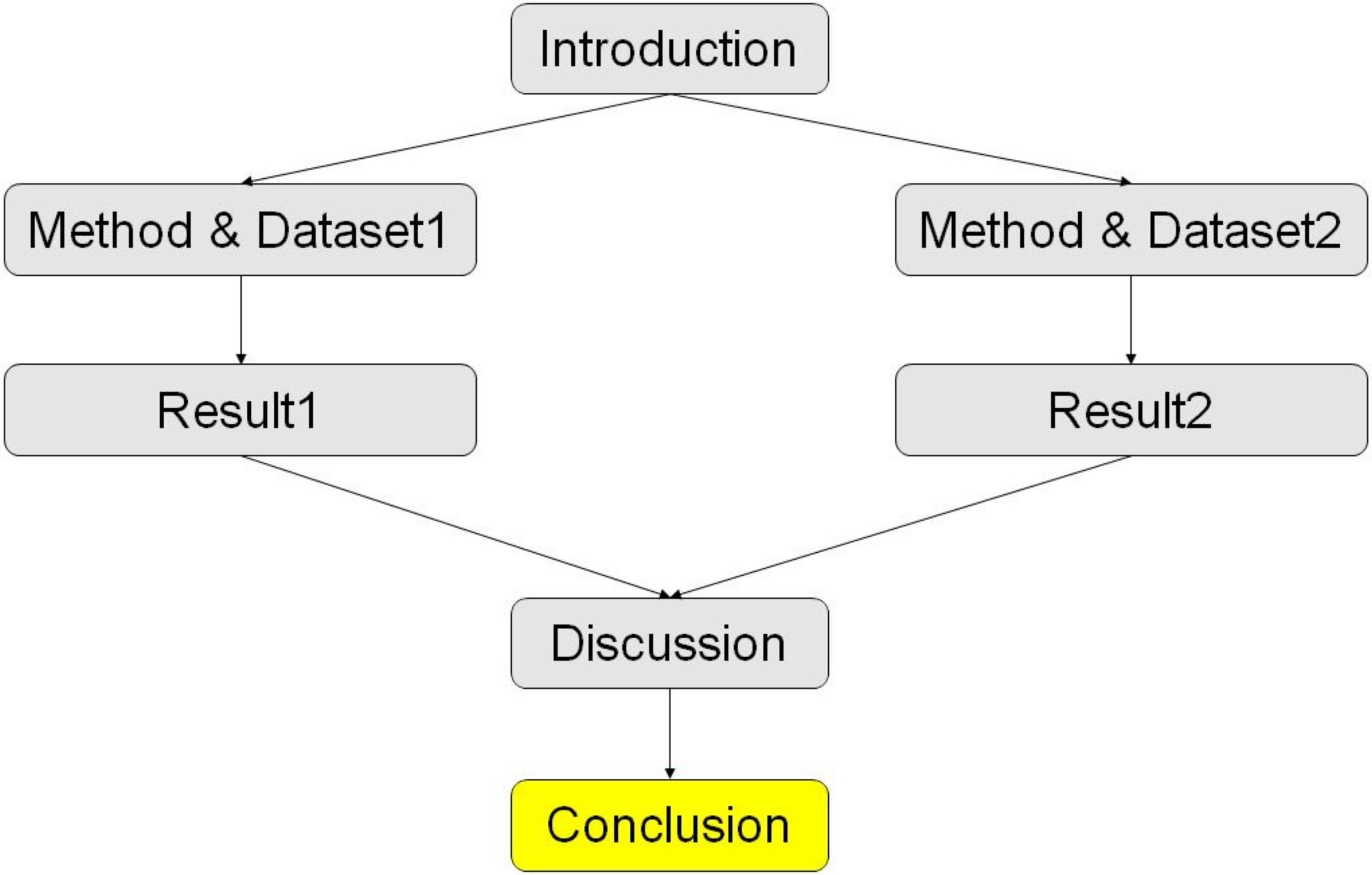


Presentation flow



Conclusion

❑ About Machine Learning

➢ I can learn Machine Learning in detail
  - I don’t feel like doing without such opportunity…
  - I wander I reduce what I don’t know now

➢ I keenly realize the gap between theory and reality
  - Restriction of memory size, time, and data structure

❑ About Automatic diagnosis

➢ In the case of glioma, high detection accuracy is achieved
  - This is a easy case, not hard case
  - I hope we’re able to detect many kinds of illness easily