

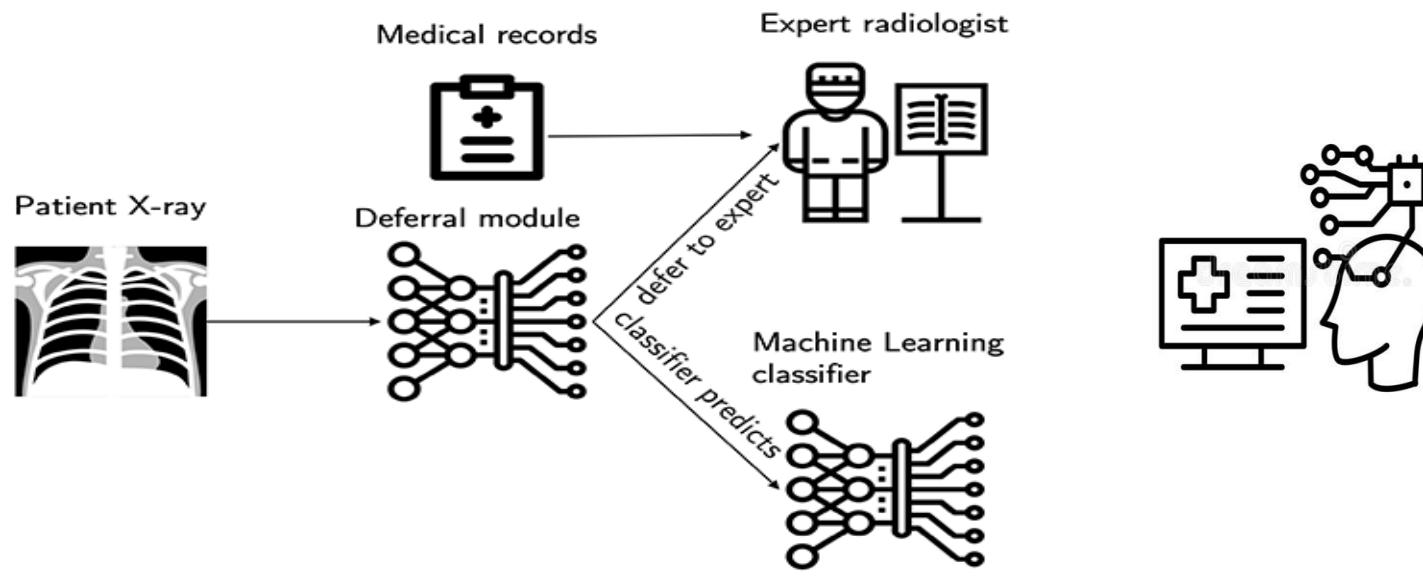
# Medical Diagnosis System (MDA)

Supervised by:  
Dr. Hany Aly Elghaish

# Overview

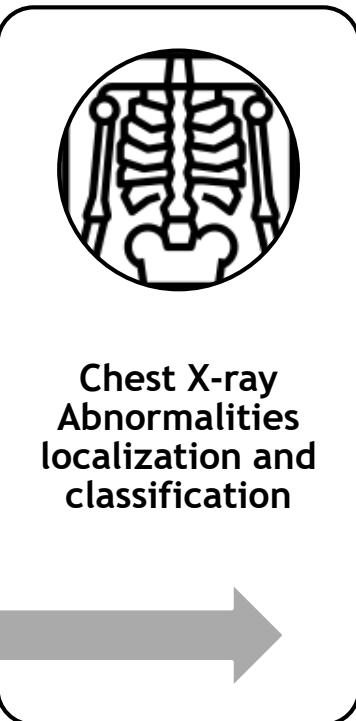
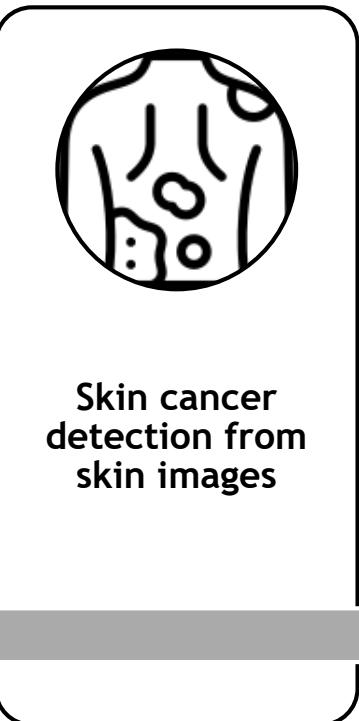
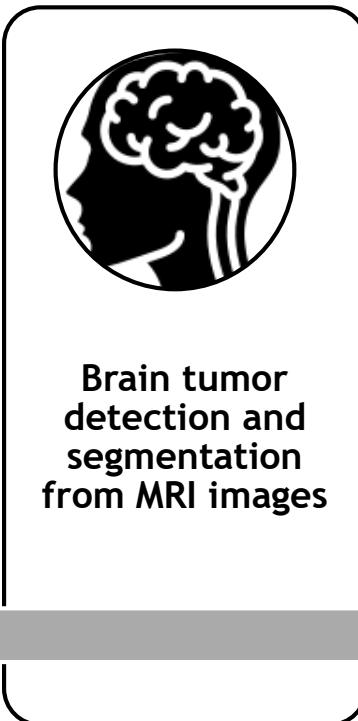
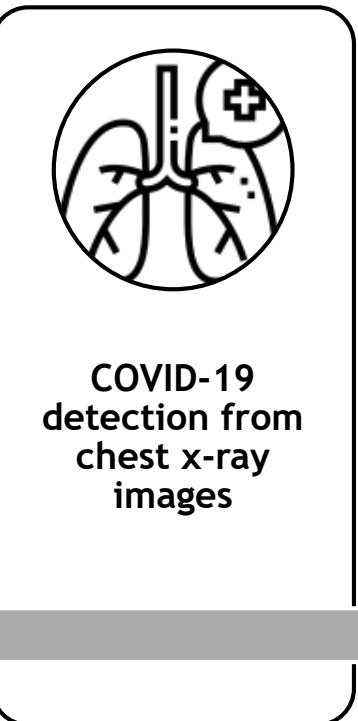
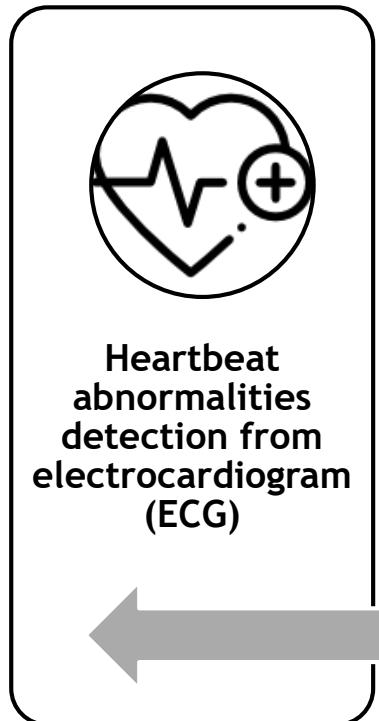
## ► Project Idea:

The project idea is to Provide medical services using AI to help doctors in hard cases and assist enhance patient experiences and health outcomes.



# Overview

## ► Offered Services:



# Overview

## Heartbeat abnormalities detection from electrocardiogram (ECG):

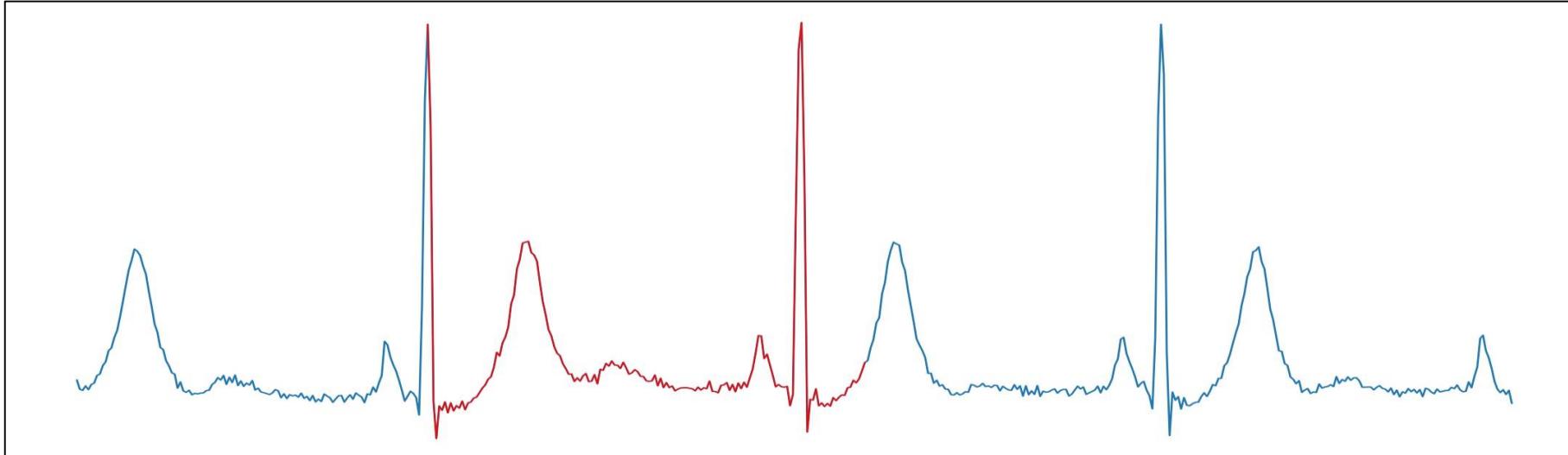
Model can classify between five cases of heartbeats:

- Normal beat نبضة طبيعية
- Supraventricular premature beat الخدج فوق البطيني
- Premature ventricular contraction beat تقلص بطيني سابق لأوانه
- Fusion of ventricular beat اندماج ضربات البطين
- Unclassifiable beat نبضة غير معروفة



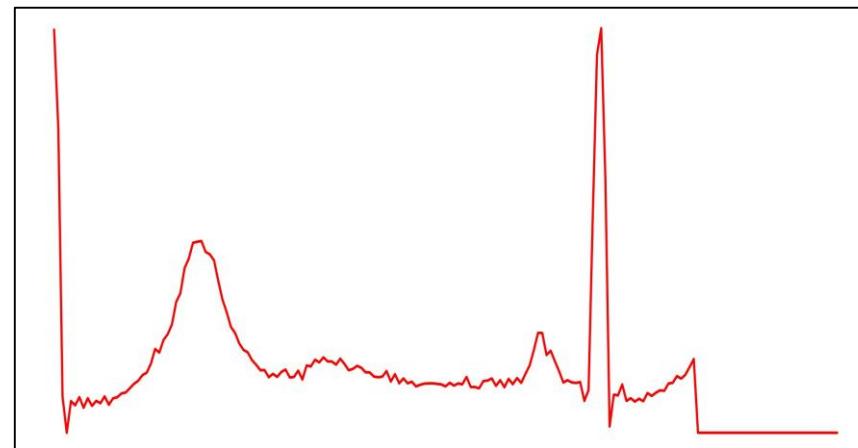
# Overview

- ▶ End user view of the heartbeat abnormalities service



.dat file  
Hardware

Normal beat, 90%

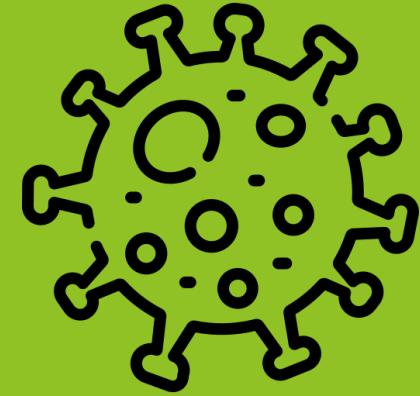


# Overview

## COVID-19 detection from chest x-ray images :

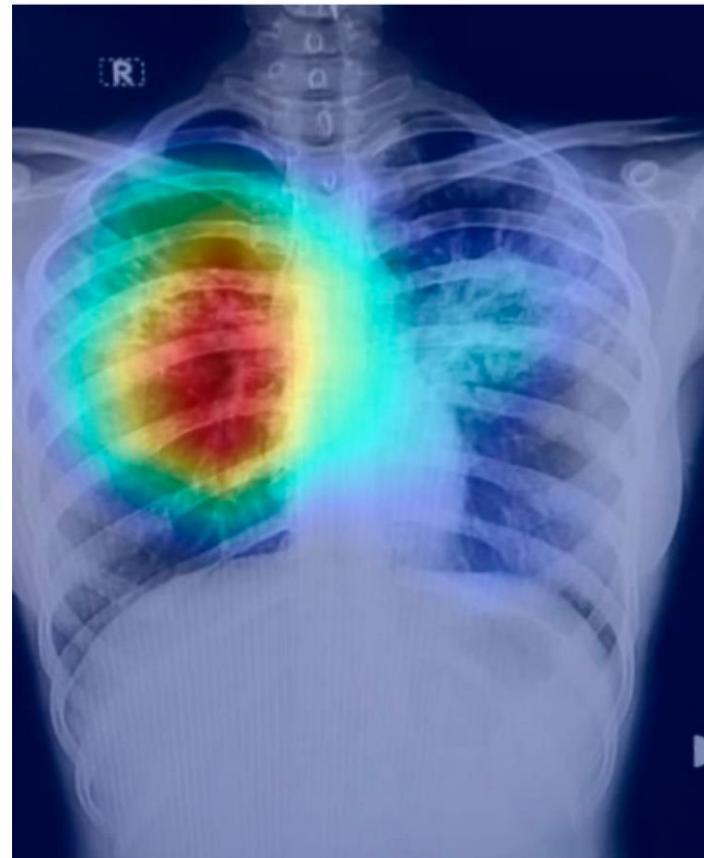
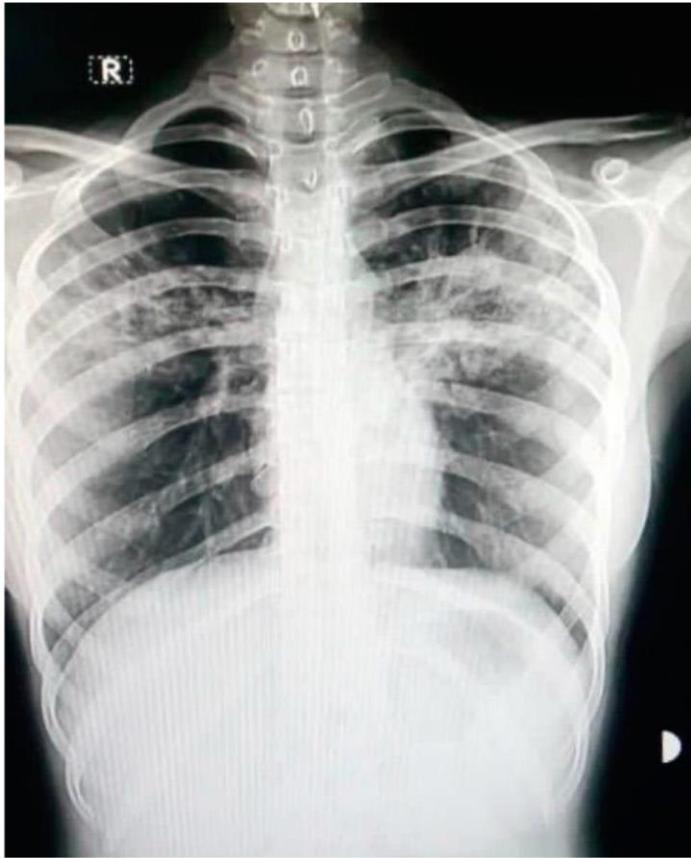
Model can classify between three cases :

- COVID-19 كوفيد-19
  - Pneumonia التهاب رئوي
  - Normal طبيعي



# Overview

- ▶ End user view of the covid-19 detection service



Covid-19, 90%

# Overview

# Brain tumor MRI classification:

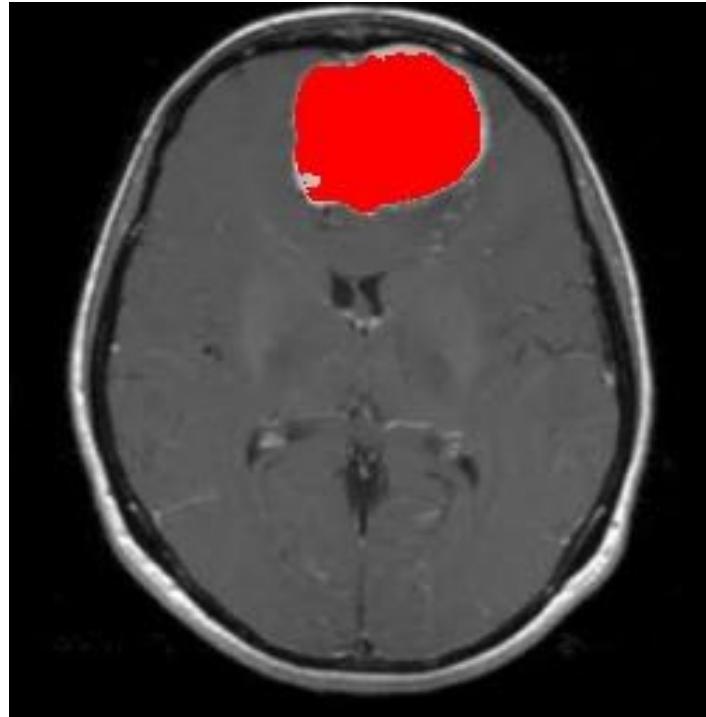
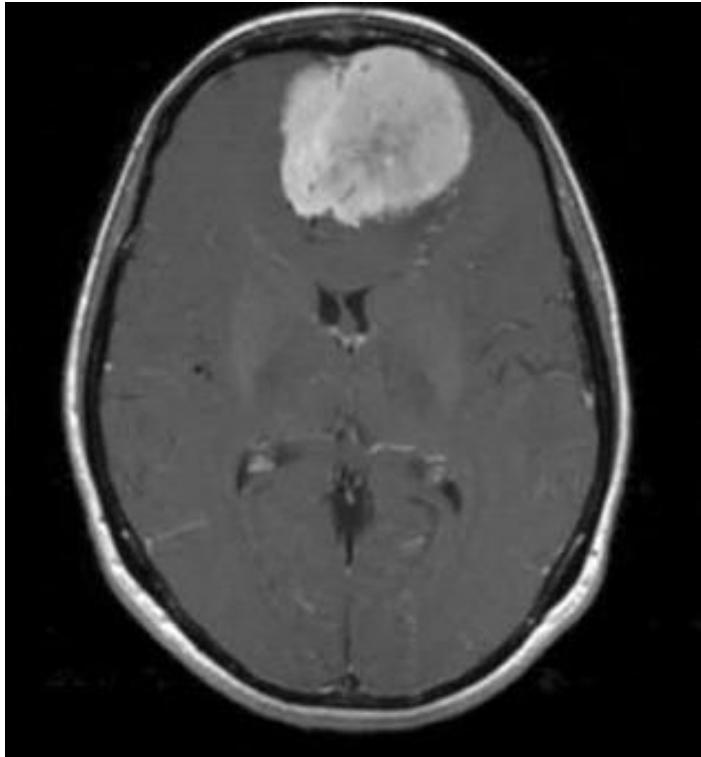
Model can classify between four cases :

- Glioma ورم دبقي
  - Meningioma ورم سحائي
  - No tumor طبيعي
  - Pituitary ورم الغدة النخامية



# Overview

- ▶ End user view of the brain tumor detection and segmentation service



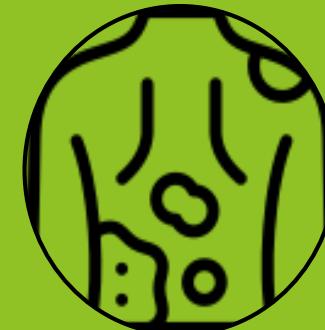
Glioma, 90%

# Overview

## Skin cancer detection from skin images:

Model can classify between two cases:

- **Malignant**      ورم خبيث
- **Benign**      ورم حميد



# Overview

- ▶ End user view of the skin cancer detection service



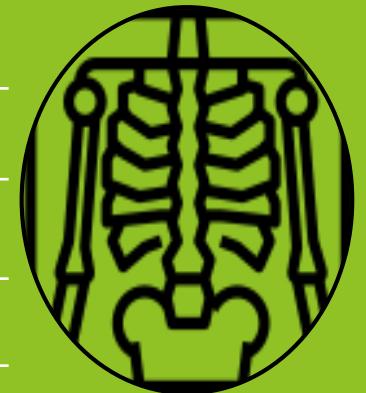
malignant, 90%

# Overview

## Chest X-ray Abnormalities localization and classification:

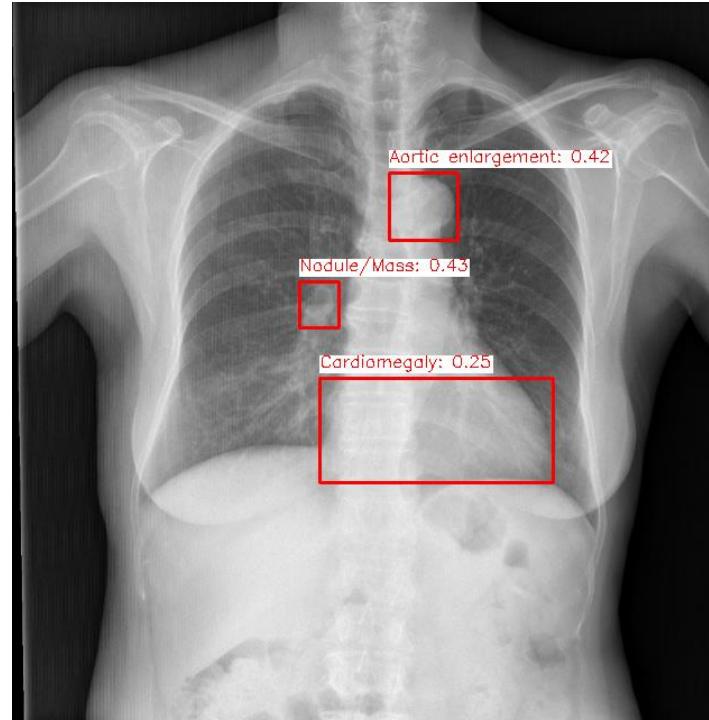
Model can localize and classify between 14 cases of chest abnormalities:

- Aortic enlargement
- Atelectasis
- Calcification
- Cardiomegaly
- Consolidation
- Pleural thickening
- Pleural effusion
- Lung opacity
- ILD
- Infiltration
- Nodule/Mass
- Other lesion
- Pneumothorax
- Pulmonary fibrosis
- No finding

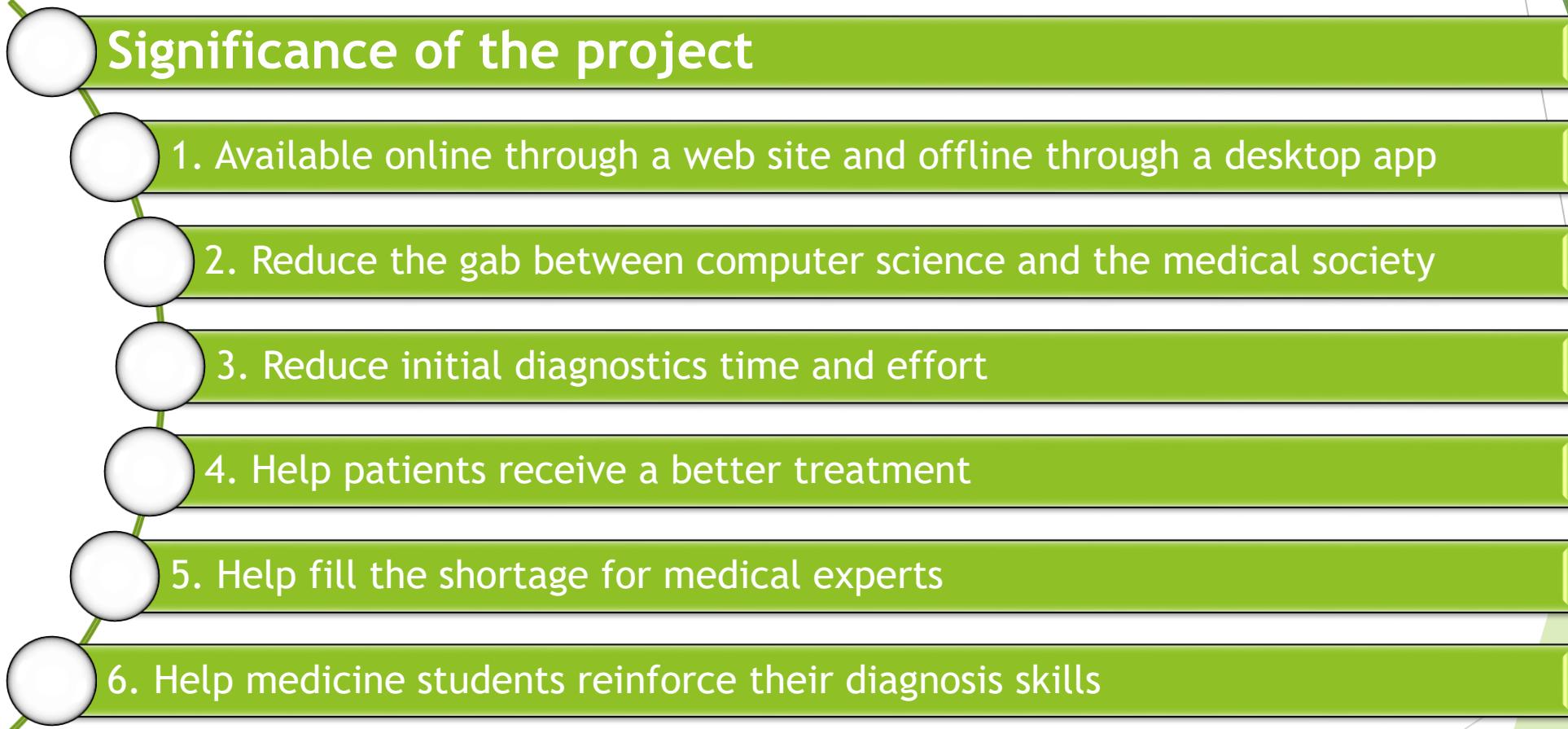


# Overview

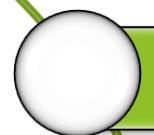
- ▶ End user view of the chest abnormalities detection and localization



# Overview



# Overview



## Scope of the project

1. The proposed system is a prototype as a proof of concept

2. The proposed system based on AI models will be deployed in a desktop application and a web application

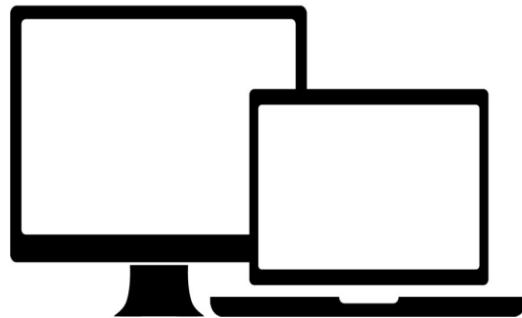
3. The proposed system is developed for public use and not for a specific org

4. A hardware system for real time analysis of ECG signal will be developed

# System operation

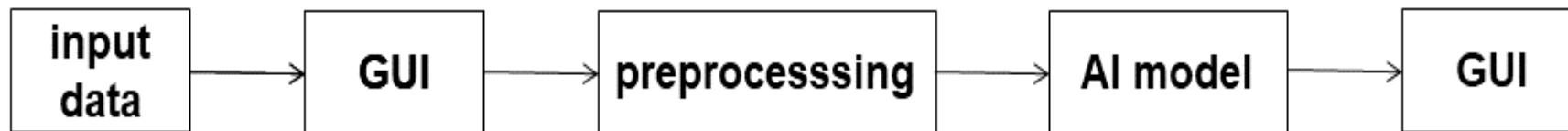
# System operation

- Our services will be deployed in a desktop application and as well as a web site.



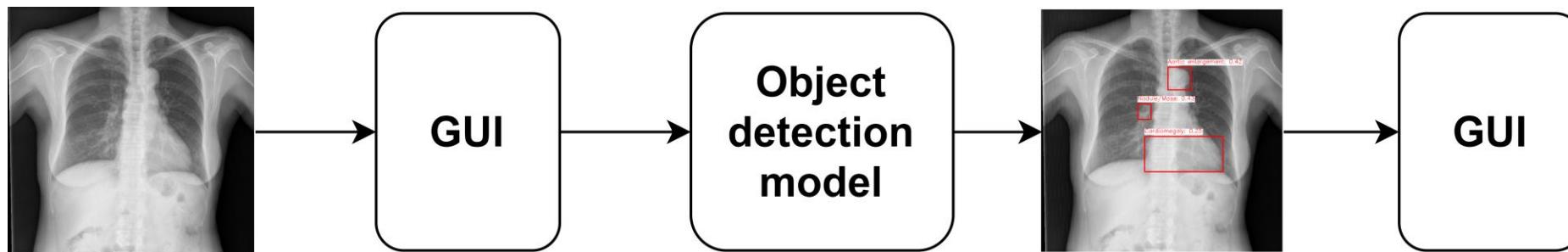
# System operation

- ▶ Skin cancer detection service diagram:



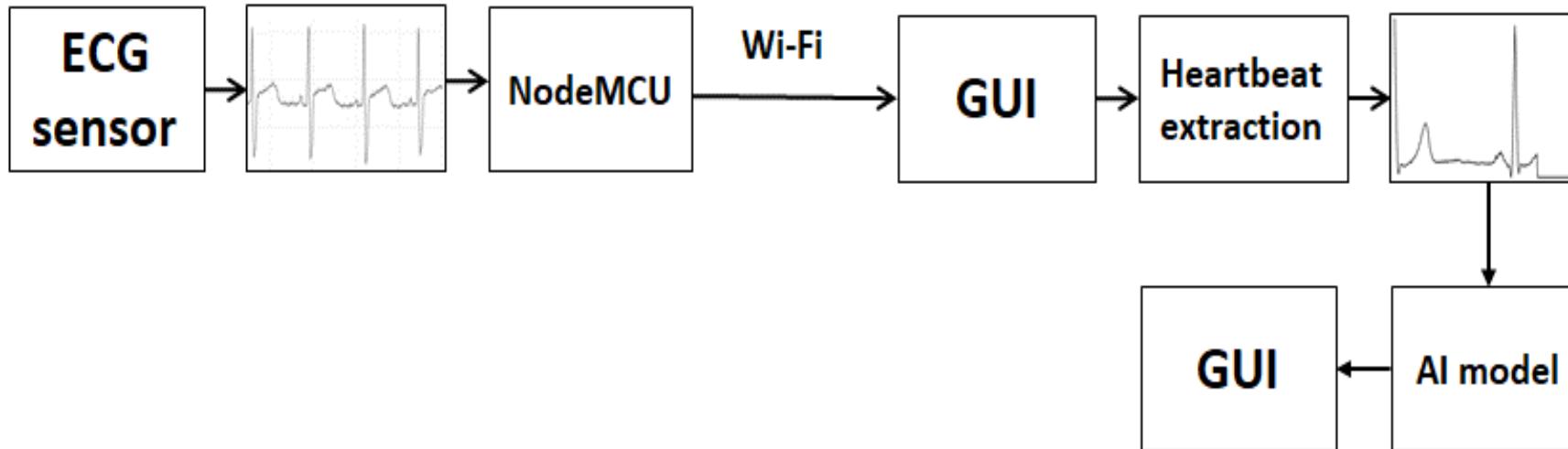
# System operation

- chest x-ray abnormalities localization service diagram:



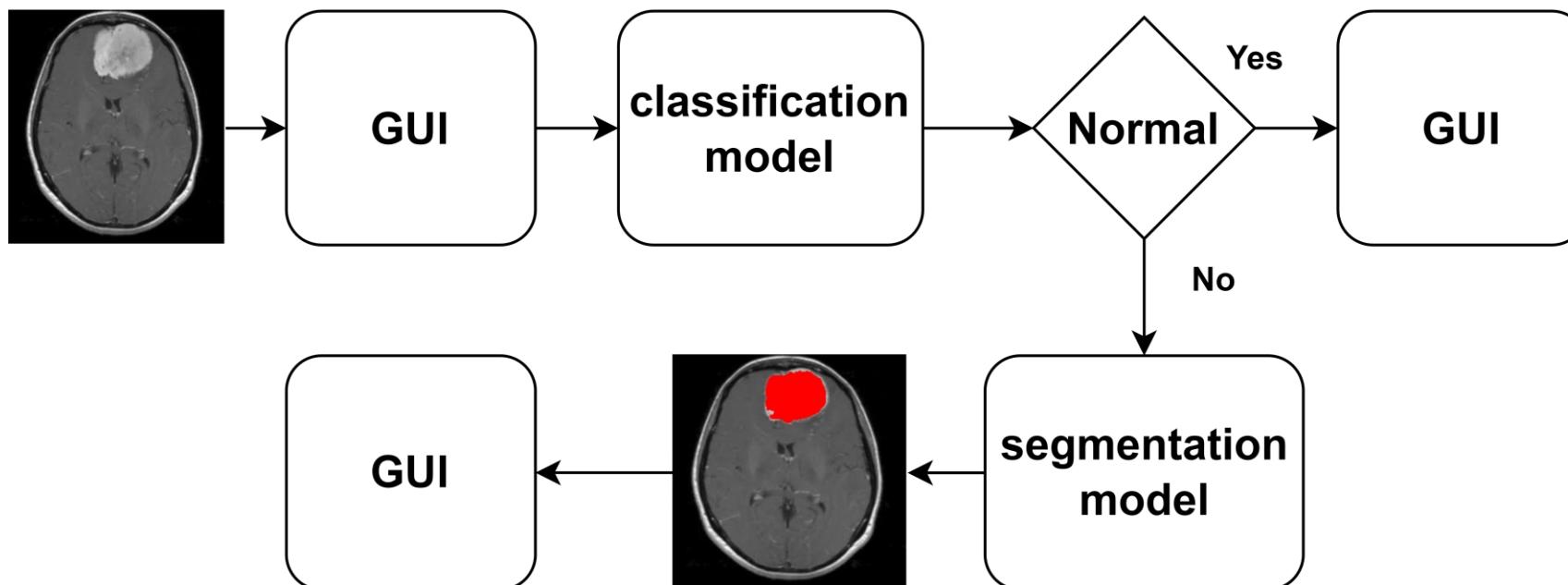
# System operation

- ▶ Real time heartbeat abnormalities service diagram:



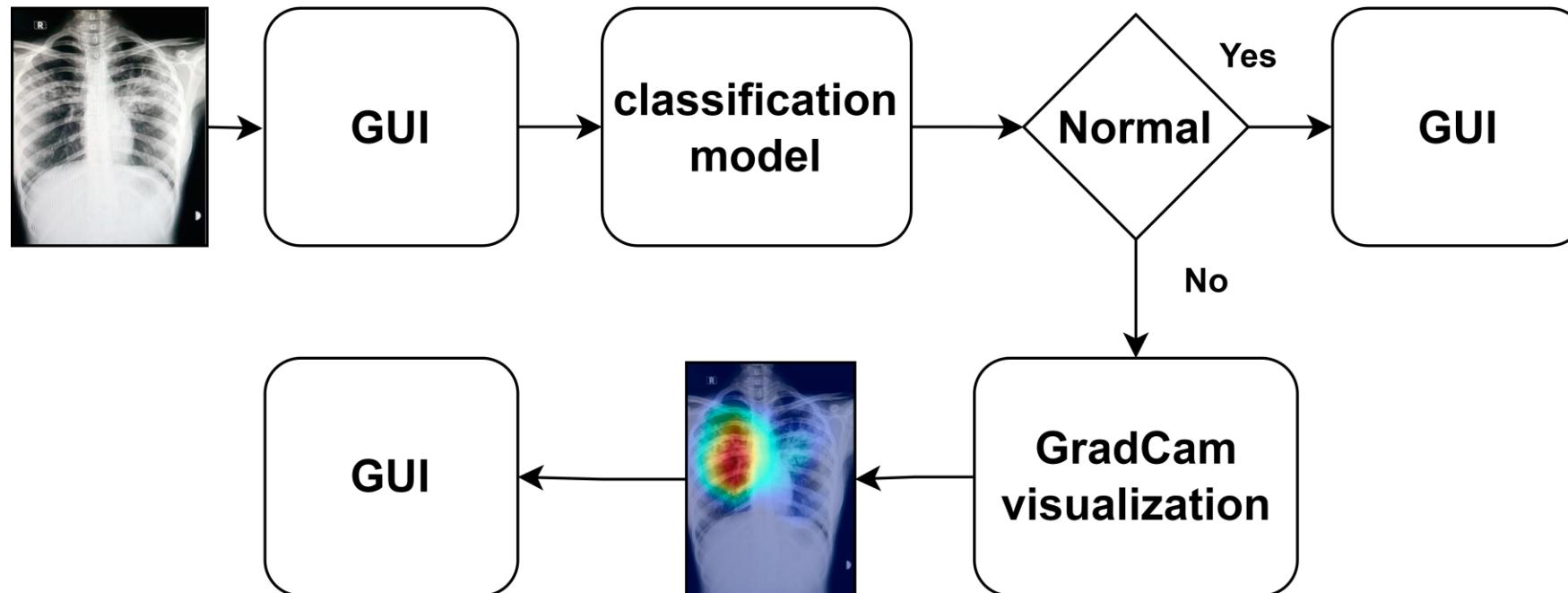
# System operation

- ▶ Brain tumor detection and segmentation service diagram:



# System operation

- ▶ Covid-19 detection service diagram:

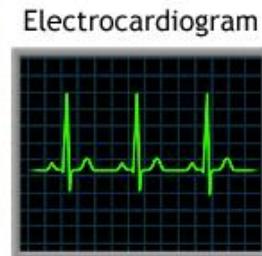
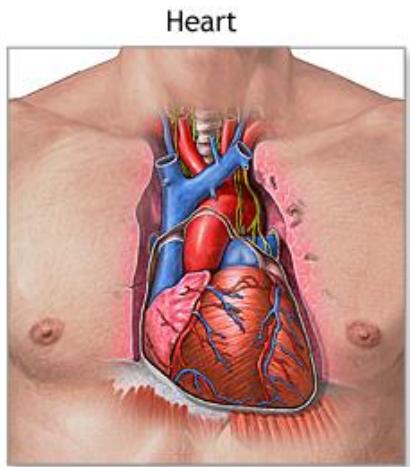


# Experiments

# Heartbeat abnormalities detection from ECG

## ► What is electrocardiogram

a simple test that can be used to check your heart's rhythm and electrical activity via sensors attached to the skin to detect the electrical signals produced by your heart each time it beats

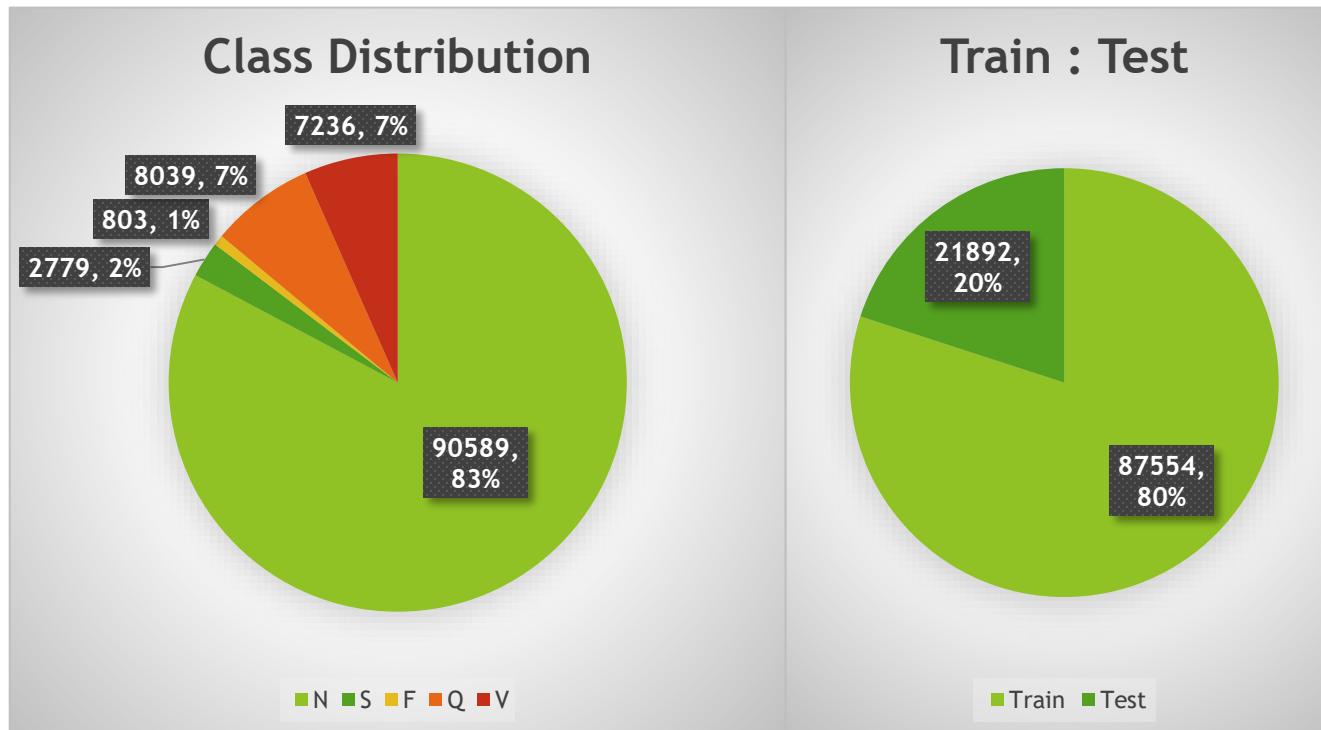


# Heartbeat abnormalities detection from ECG

## ► Dataset description

### The MIT-BIH Arrhythmia Database

Class distribution						
	N	S	F	Q	V	total
train	72471	2223	641	6431	5788	87554
test	18118	556	162	1608	1448	21892
						109,446



N: Normal beat  
S: Supraventricular premature beat  
V: Premature ventricular contraction  
F: Fusion of ventricular and normal beat  
Q: Unclassifiable beat

# Heartbeat abnormalities detection from ECG

## ► Dataset description

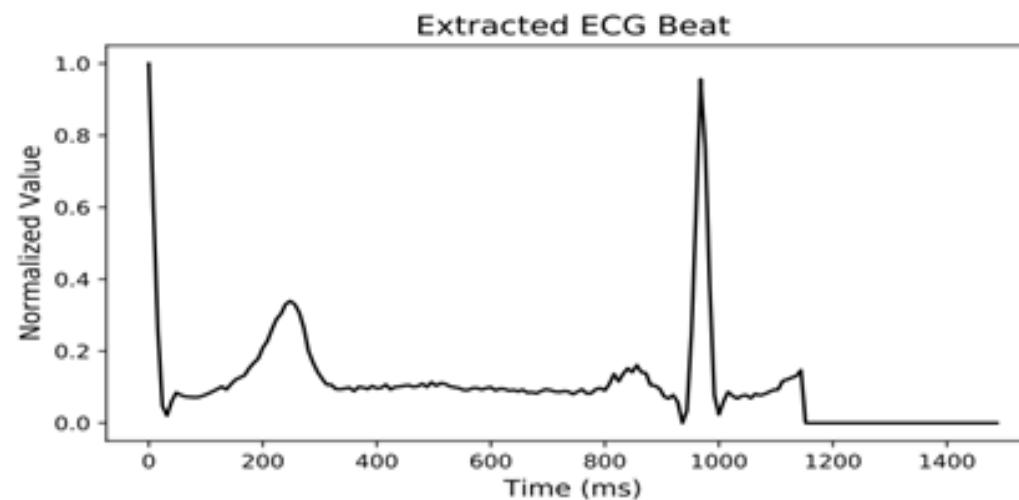
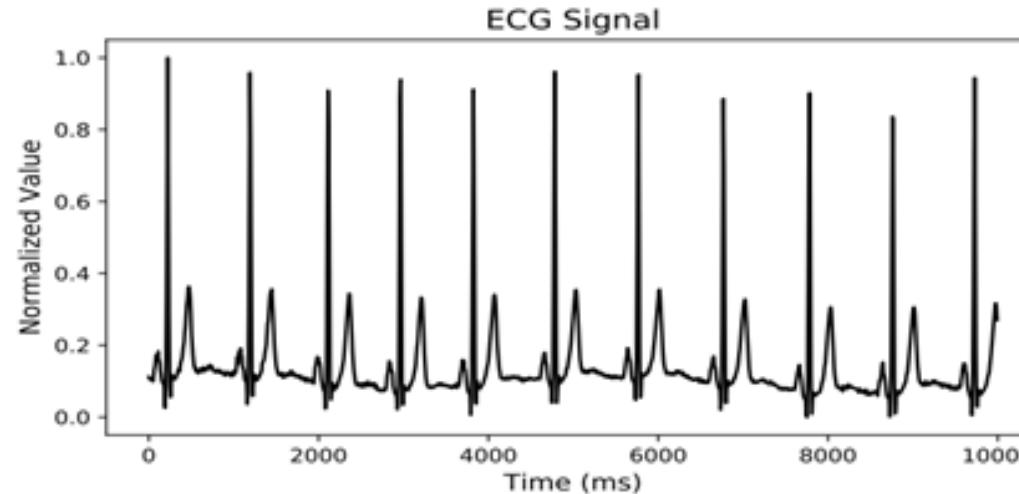
### Data source

- **Deaconess Medical Center:** This hospital provided the facilities and resources for the collection of the data.
- **Massachusetts Institute of Technology:** This University provided the expertise and technical support for the collection of the data.
- **National Institutes of Health:** This agency provided the funding for the collection of the data.
- **American Heart Association:** This non-profit organization provided the medical expertise and oversight for the collection of the data.

# Heartbeat abnormalities detection from ECG

## ► Dataset description

Heartbeat extraction



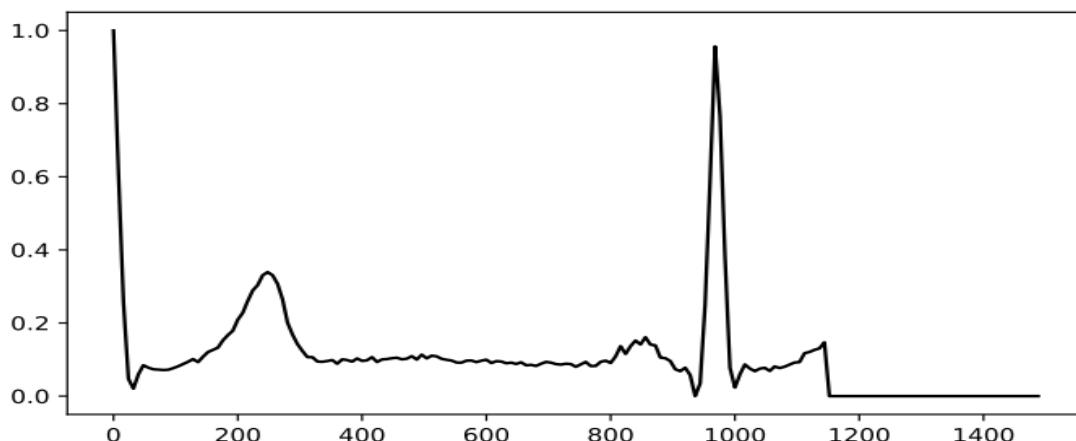
# Heartbeat abnormalities detection from ECG

## ► Dataset description

### CSV format

	0	1	2	3	4	5	6	7	8	9	...	178	179	180	181	182	183	184	185	186	187
0	1.000000	0.758264	0.111570	0.000000	0.080579	0.078512	0.066116	0.049587	0.047521	0.035124	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.908425	0.783883	0.531136	0.362637	0.366300	0.344322	0.333333	0.307692	0.296703	0.300366	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.730088	0.212389	0.000000	0.119469	0.101770	0.101770	0.110619	0.123894	0.115044	0.132743	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	1.000000	0.910417	0.681250	0.472917	0.229167	0.068750	0.000000	0.004167	0.014583	0.054167	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.570470	0.399329	0.238255	0.147651	0.000000	0.003356	0.040268	0.080537	0.070470	0.090604	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

### Image format



# Heartbeat abnormalities detection from ECG

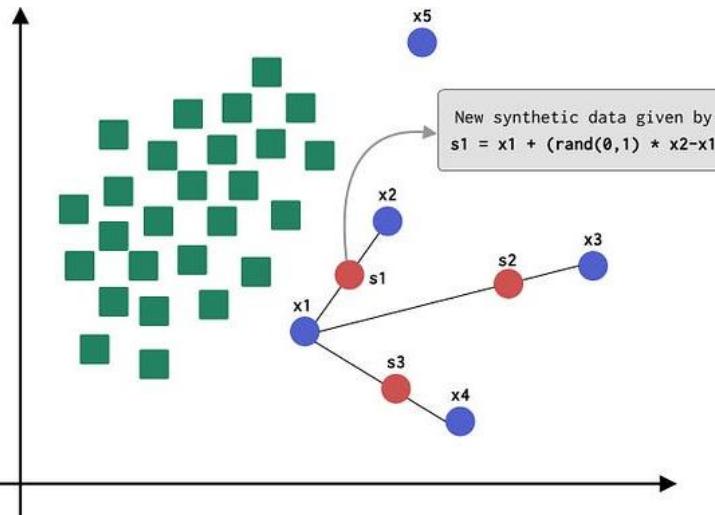
## ► Reference paper for result comparison

M. Kachuee, S. Fazeli, and M. Sarrafzadeh, “Ecg heartbeat classification: A deep transferable representation,” in 2018 IEEE International Conference on Healthcare Informatics (ICHI), 2018, pp. 443–444.

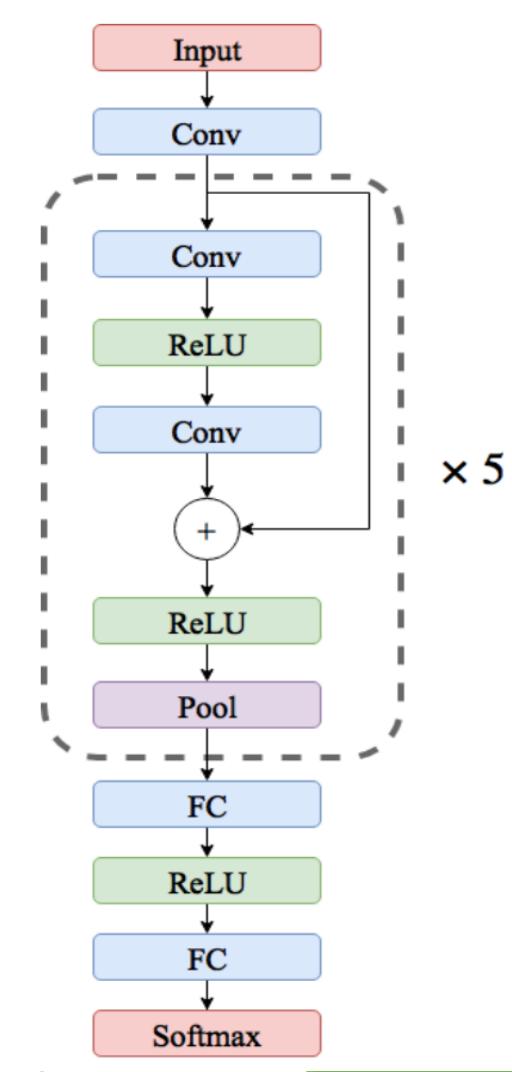
1-D convolution

93.4% accuracy

Low recall on some classes  
oversampling



		Predicted Label				
		N	S	V	F	Q
True Label	N	0.97	0.01	0.0	0.0	0.0
	S	0.08	0.89	0.0	0.0	0.0
V	N	0.02	0.0	0.96	0.0	0.0
	S	0.08	0.0	0.05	0.86	0.0
F	N	0.0	0.0	0.0	0.0	0.98
	S	0.0	0.0	0.0	0.0	0.0



# Heartbeat abnormalities detection from ECG

## ► 2-D convolution Experiments summary

version	Model architecture	Notes	Results accuracy	Notes on results	Reference accuracy
Version 1	VGG 16	<ul style="list-style-type: none"><li>• RGB images</li><li>• Each class has a different color</li><li>• 640 sample from each class</li></ul>	100%	Classes are distinguished by color	
Version 2	2 convolution blocks 3 fully connected	<ul style="list-style-type: none"><li>• Gray images</li><li>• 640 sample from each class</li></ul>	80.25% : 81%	Low number of samples for each class	
Version 3	3 convolution blocks 2 fully connected	<ul style="list-style-type: none"><li>• Gray images</li><li>• 640 sample from each class</li></ul>	84.58% : 91%	Low number of samples for each class	93.4%
Version 4	VGG 16	<ul style="list-style-type: none"><li>• 3 channel gray images</li><li>• 640 sample from each class</li></ul>	76.56%		
Version 5	ResNet50	<ul style="list-style-type: none"><li>• 3 channel gray images</li><li>• 640 sample from each class</li></ul>	96.56%		

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution

Feature extraction

- 1D-CNN
- Adaptive kernel size convolution (AKSC)
- Adaptive feature recalibration (AFR)

Temporal dependency

- Long-short time memory (LSTM)
- Multi-head attention

classification

- Fully connected layers

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (feature extraction)

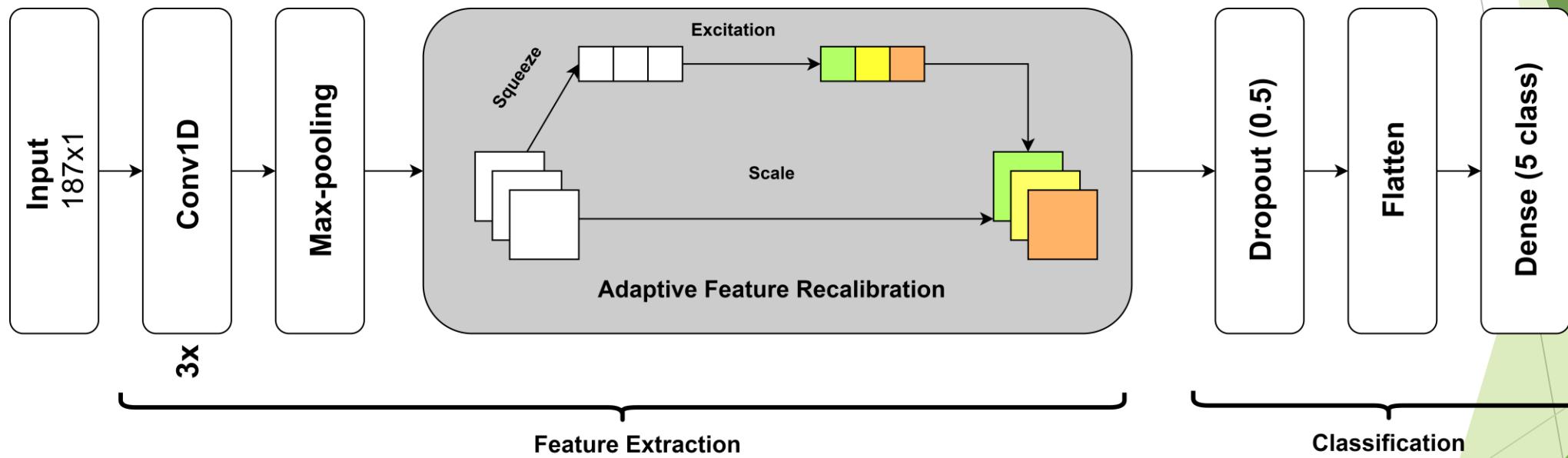
	Model description	Notes	Result	Reference accuracy
CNN-1	3x { Conv1D BatchNormalization MaxPooling1D } flatten 3x fully connected	Dataset as it is	98.63% accuracy 90% recall	93.4 accuracy
		Reduce the N class to 6000 sample	92.83% accuracy 92.77% recall	
		oversample to 20000	93.34% accuracy 93.20% recall	
CNN-2	3x Conv1D MaxPooling1D flatten 1x fully connected	Oversample to 20000	93.35% accuracy 93.23% recall	

CNN-2 has less parameters

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (feature extraction)

Adaptive feature recalibration (AFR)

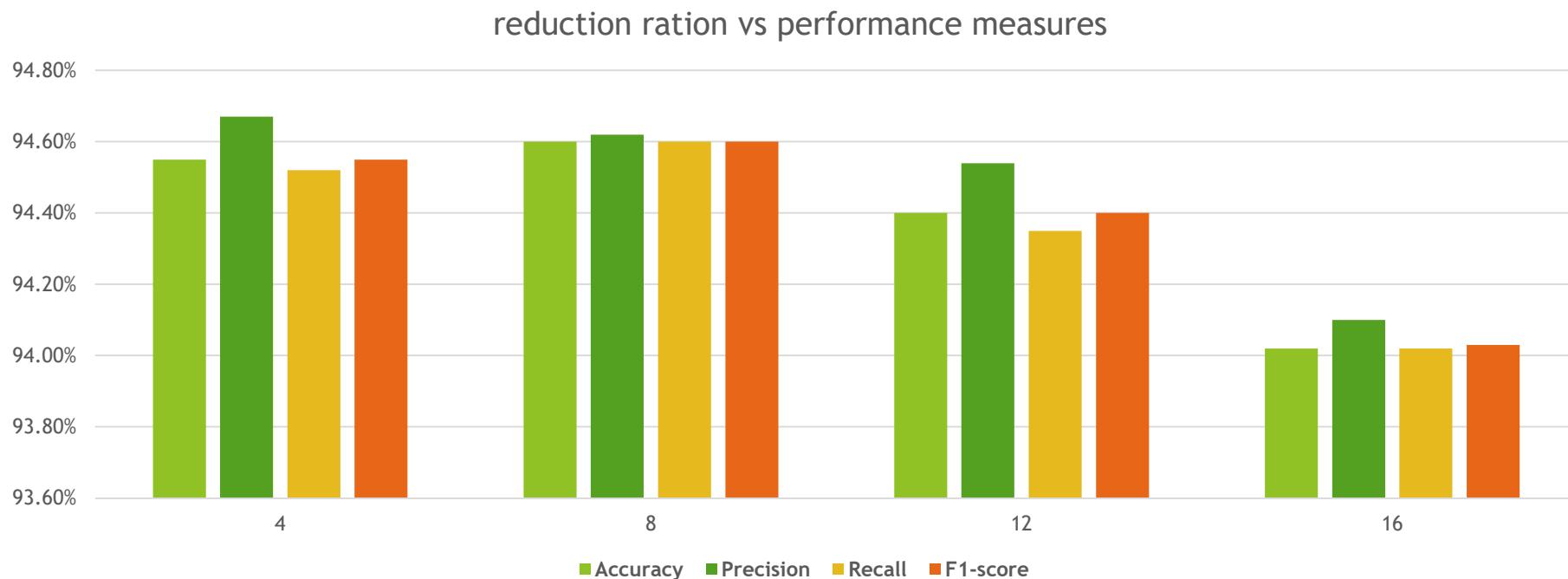


Hyper-parameters:  
Reduction ration

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (feature extraction)

Adaptive feature recalibration (AFR)



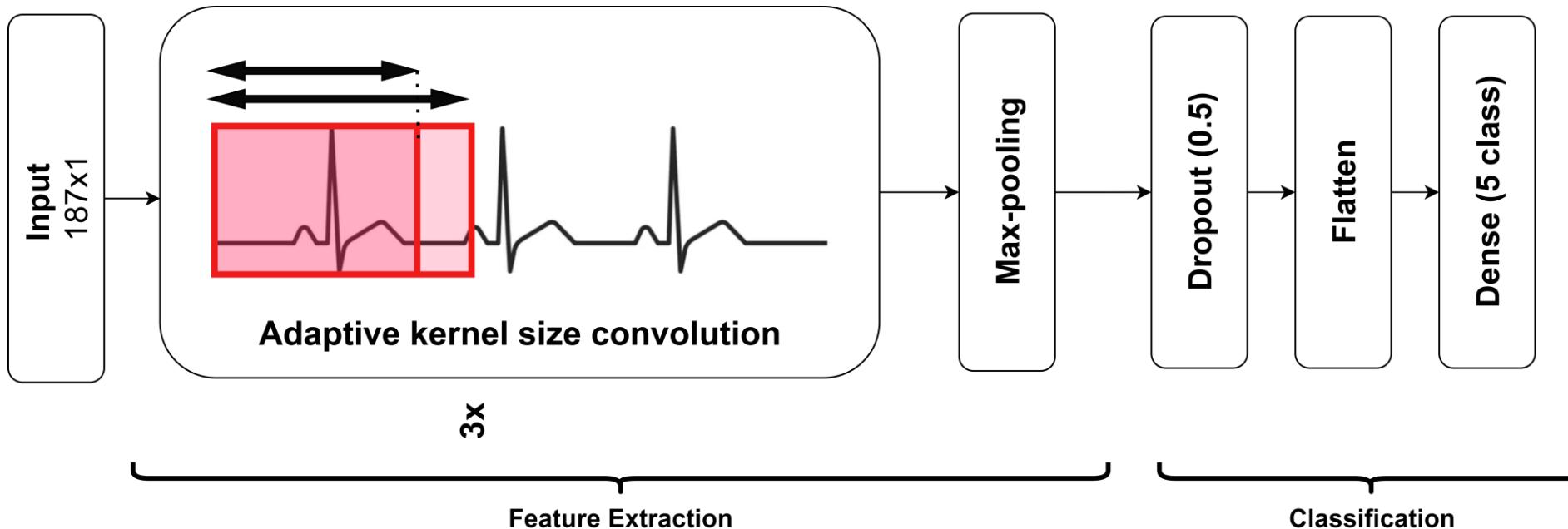
Reduction ratio	Accuracy	Precision	Recall	F1
8	94.60%	94.62%	94.60%	94.60%

Ref	93.4%
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# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (feature extraction)

Adaptive Kernel Size Convolution (AKSC)

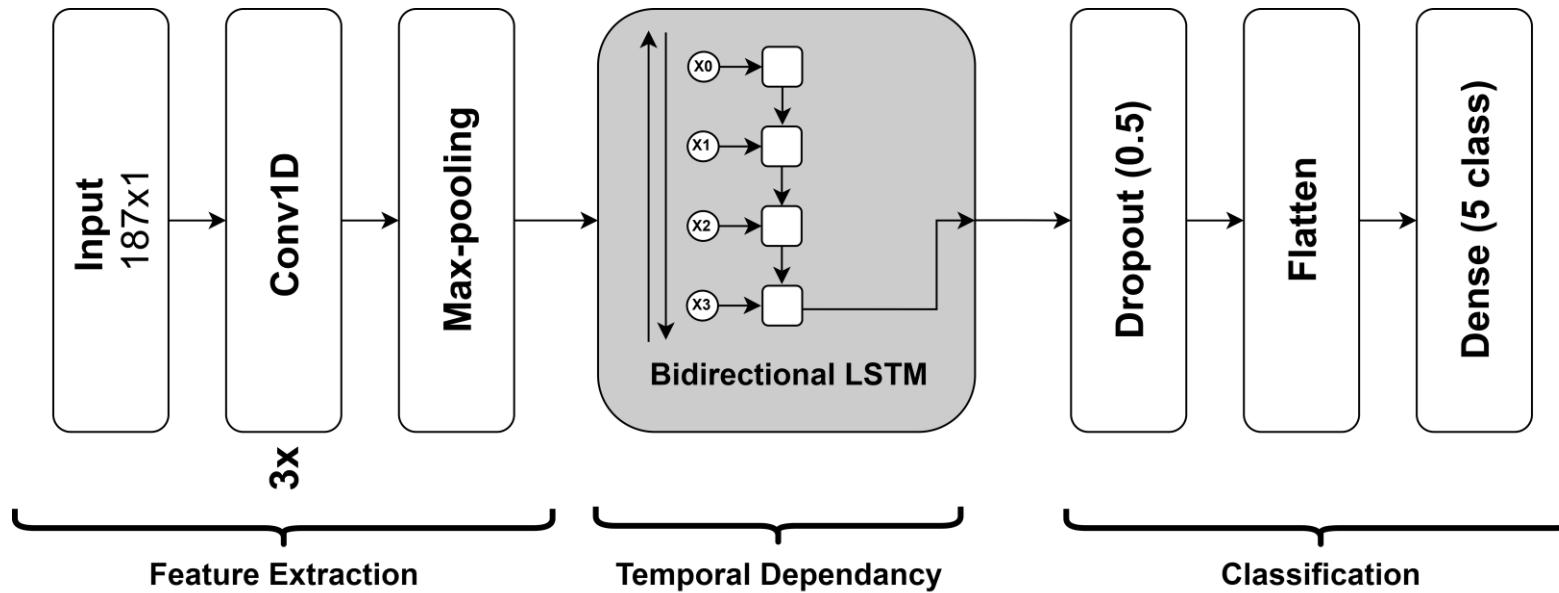


	Accuracy	precision	Recall	F1
Proposed	93.80%	93.80%	93.80%	93.80%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

Long-Short Time Memory (LSTM): Bi-directional

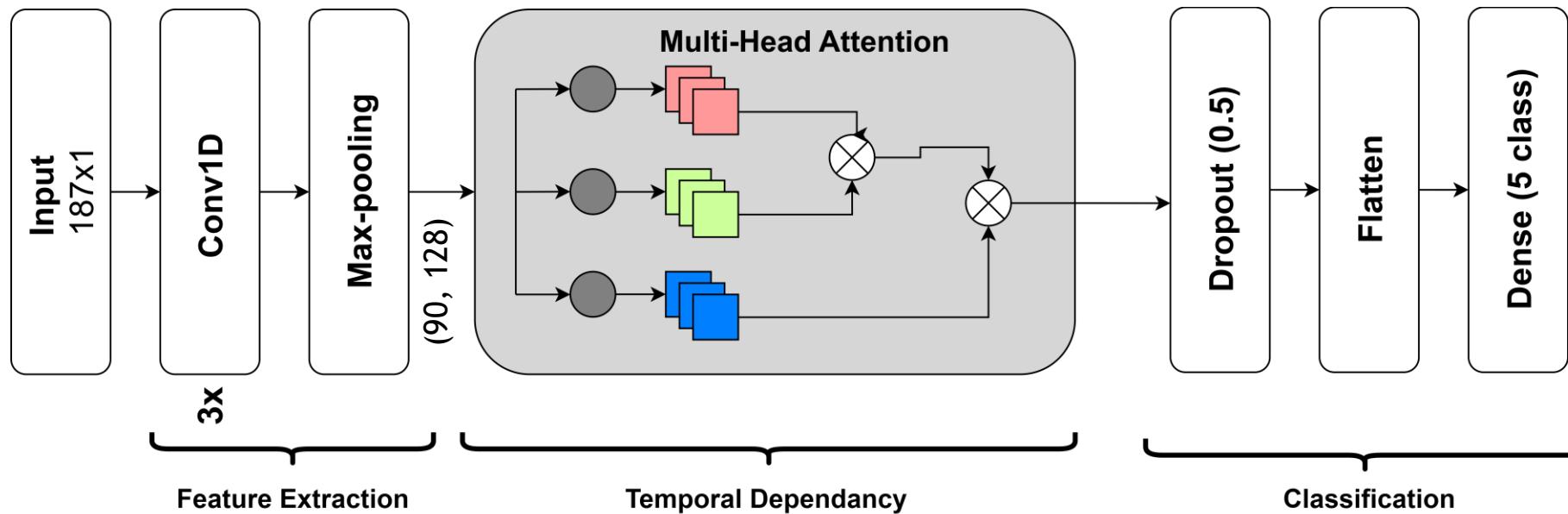


	Accuracy	Precision	Recall	F1
proposed	94.98%	95.16%	94.95%	95.55%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

Multi-head attention (MHA): single branch



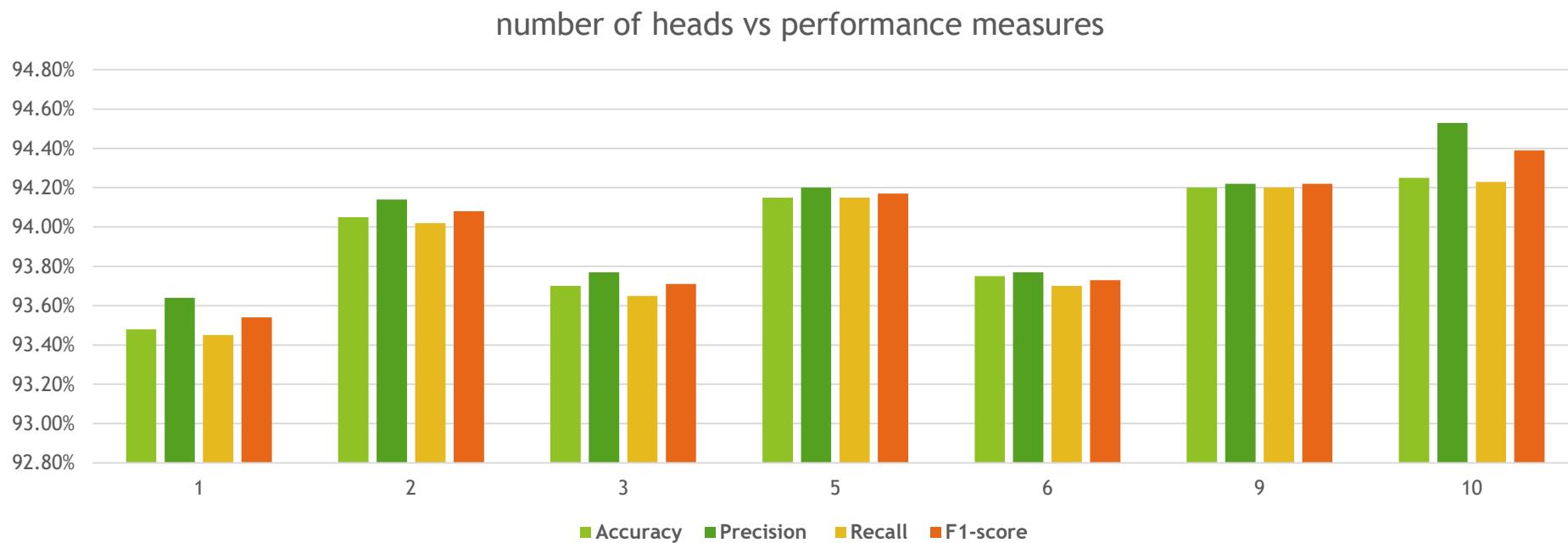
Hyper-parameters:  
no. of heads

no. of heads should be dividable by the  
no. features

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

Multi-head attention (MHA): single branch

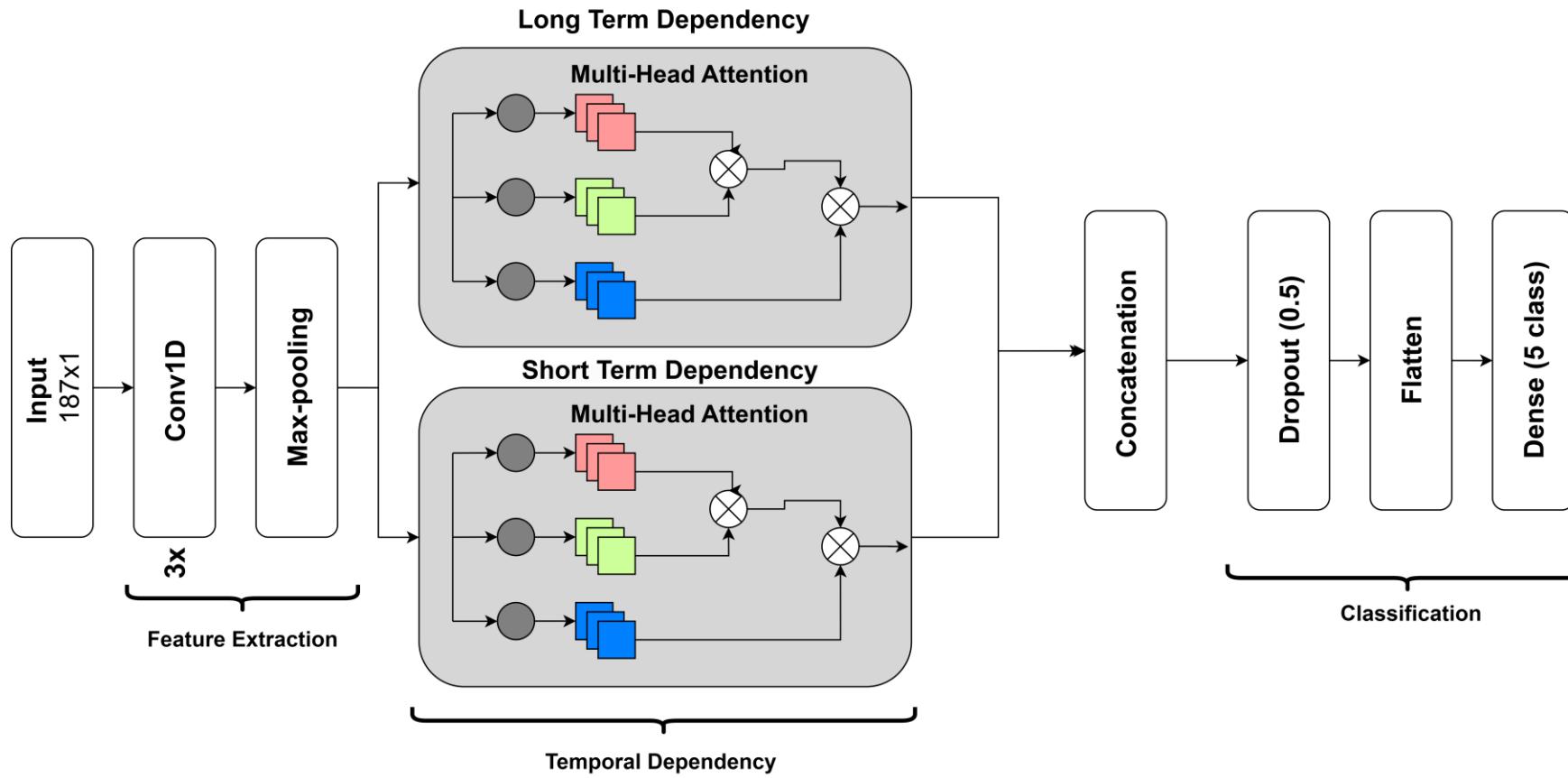


No. of heads	Accuracy	Precision	Recall	F1
10	94.25%	94.53%	94.23%	94.39%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

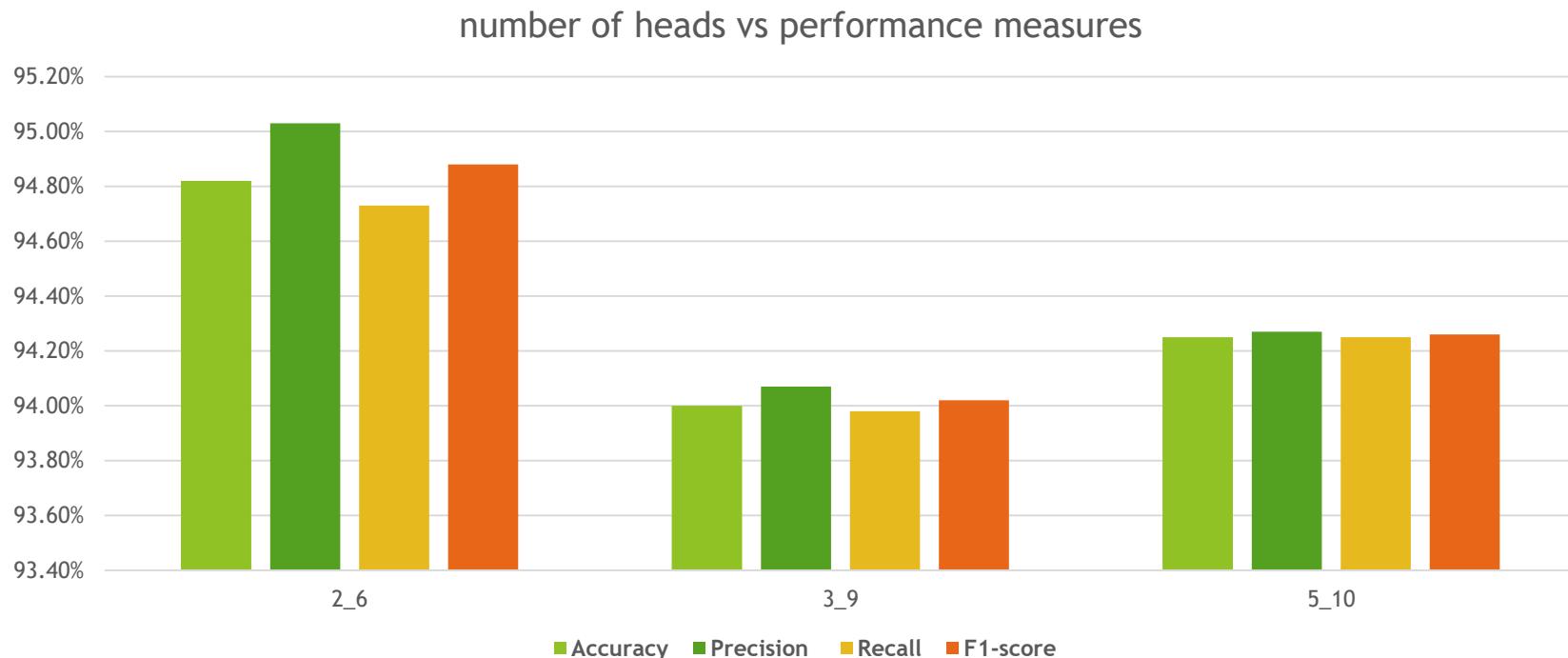
Multi-head attention (MHA): parallel branches



# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

Multi-head attention (MHA): parallel branches

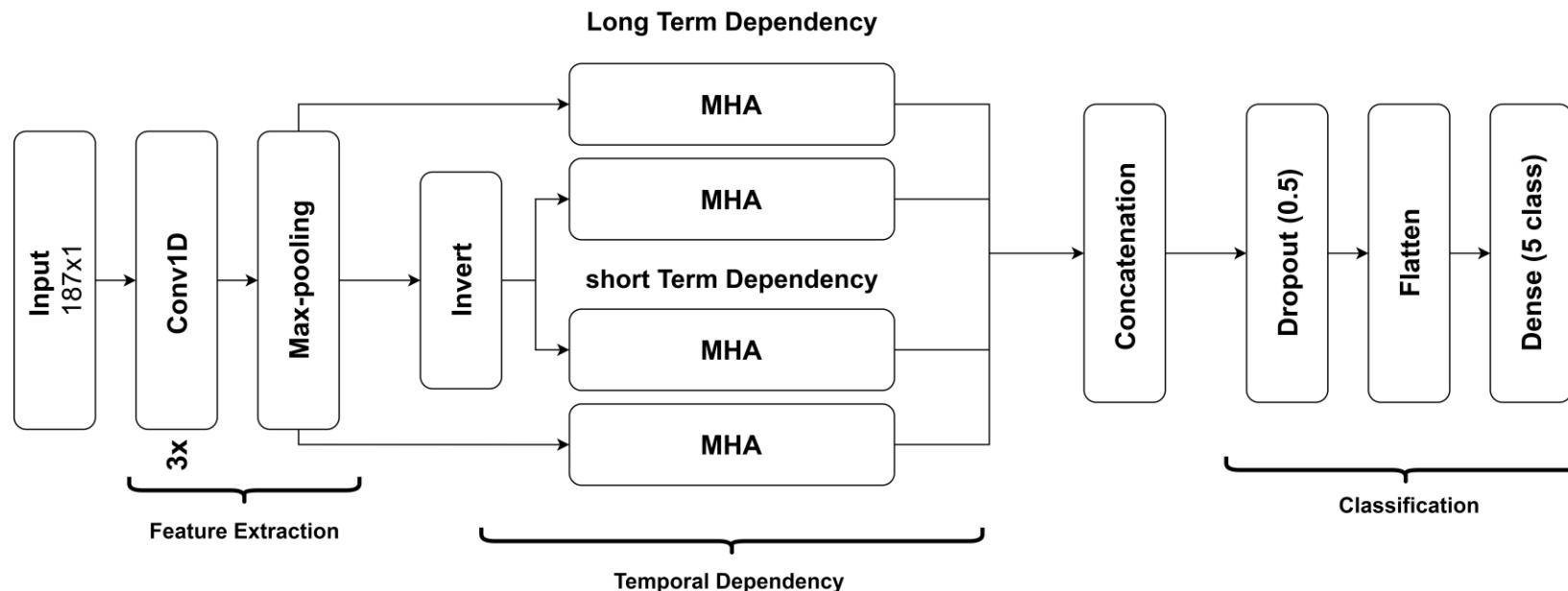


No. of heads	Accuracy	Precision	Recall	F1
2_6	94.82%	95.03%	94.73%	94.88%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

Multi-head attention (MHA): Bi-directional parallel branches

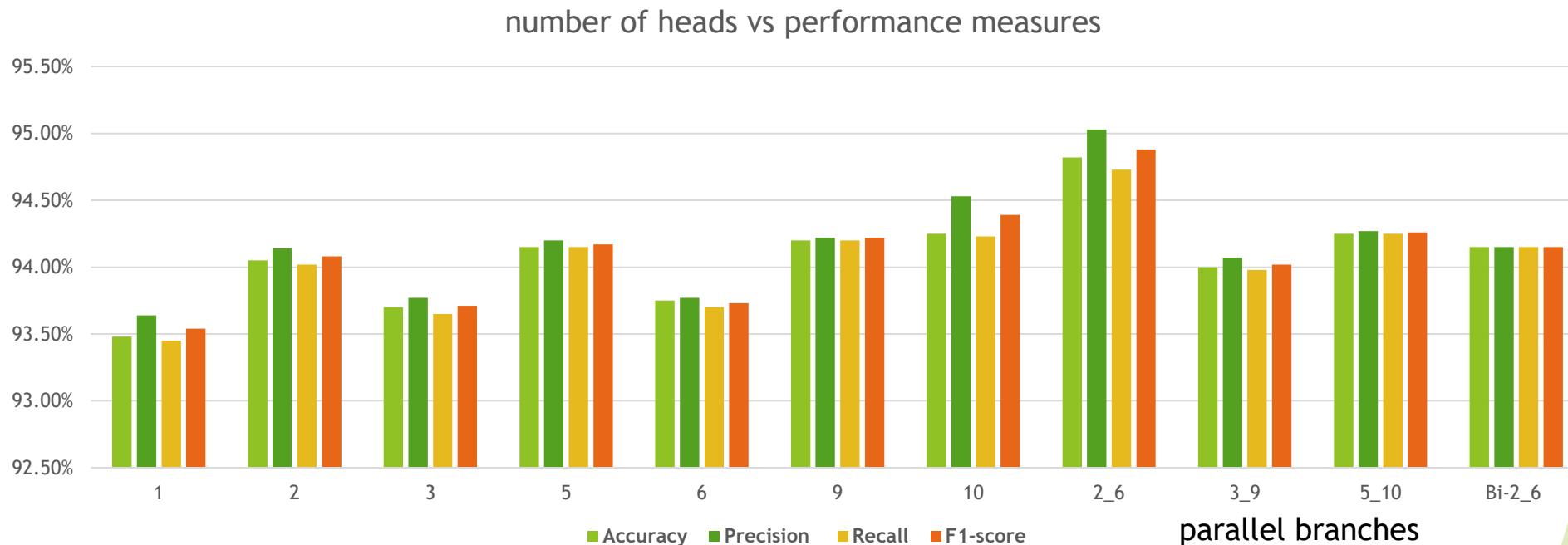


No. of heads	Accuracy	Precision	Recall	F1
2-6	94.15%	94.15%	94.15%	94.15%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments (temporal dependency)

Multi-head attention (MHA): Experiments summary

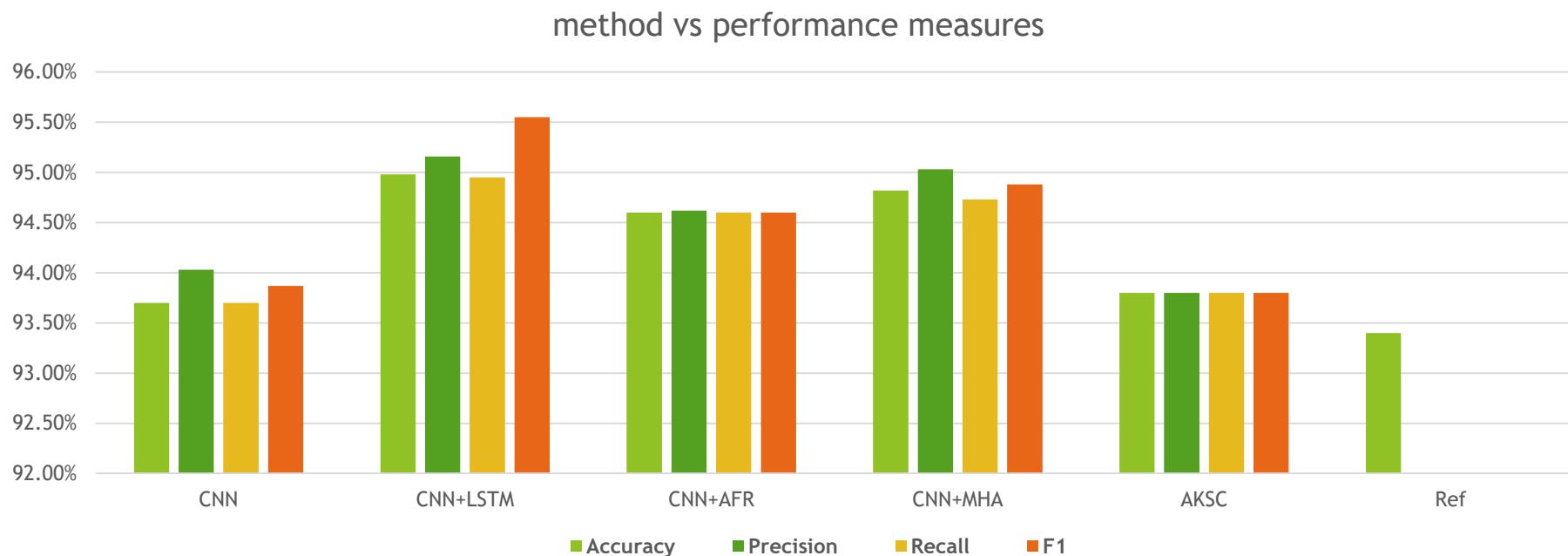


No. of heads	Accuracy	Precision	Recall	F1
2-6	94.82%	95.03%	94.73%	94.88%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

Experiments summary with over sampling



	Accuracy	Precision	Recall	F1
CNN+LSTM	94.98%	95.16%	94.95%	95.55%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

Cross entropy loss VS weighted cross entropy loss VS focal loss

Prediction      Actual

$\hat{y}$	$y$
0.7	1
0.2	0
0.1	0

- Cross entropy loss

$$\text{Loss} = - \sum_{i=1} y_i \cdot \log \hat{y}_i$$

$$w_0 = 1 / 72471$$

$$w_1 = 1 / 2223$$

$$w_2 = 1 / 5788$$

$$w_3 = 1 / 641$$

$$w_4 = 1 / 6431$$

$$\text{sum} = 0.002025$$

- Weighted cross entropy loss

$$\text{Loss} = - \sum_{i=1} w_i \cdot y_i \cdot \log \hat{y}_i$$

$$w_0 = w_0 / \text{sum} = 0.00684$$

$$w_1 = w_1 / \text{sum} = 0.22214$$

$$w_2 = w_2 / \text{sum} = 0.08541$$

$$w_3 = w_3 / \text{sum} = 0.77094$$

$$w_4 = w_4 / \text{sum} = 0.07667$$

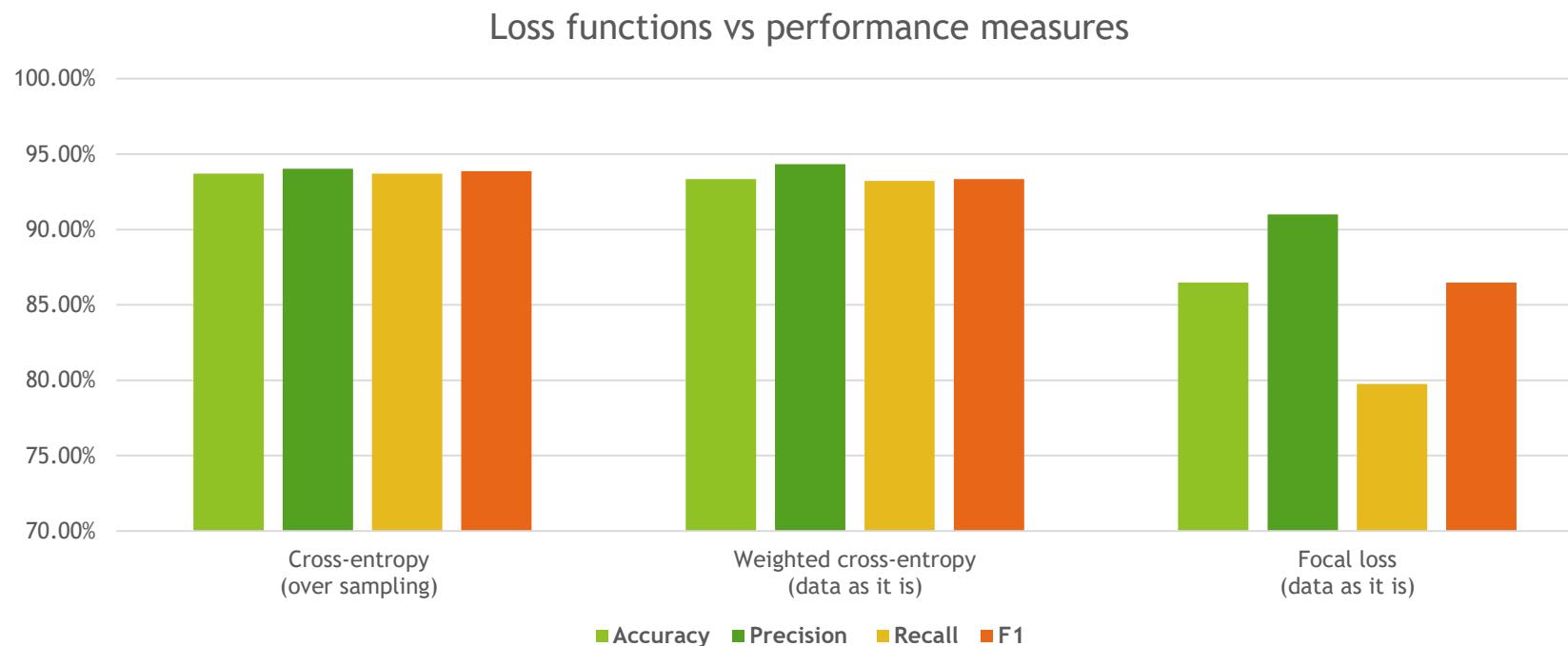
- Focal loss

$$\text{Loss} = - \sum_{i=1} \alpha_i \cdot (1 - \hat{y}_i) \gamma \cdot \log \hat{y}_i$$

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

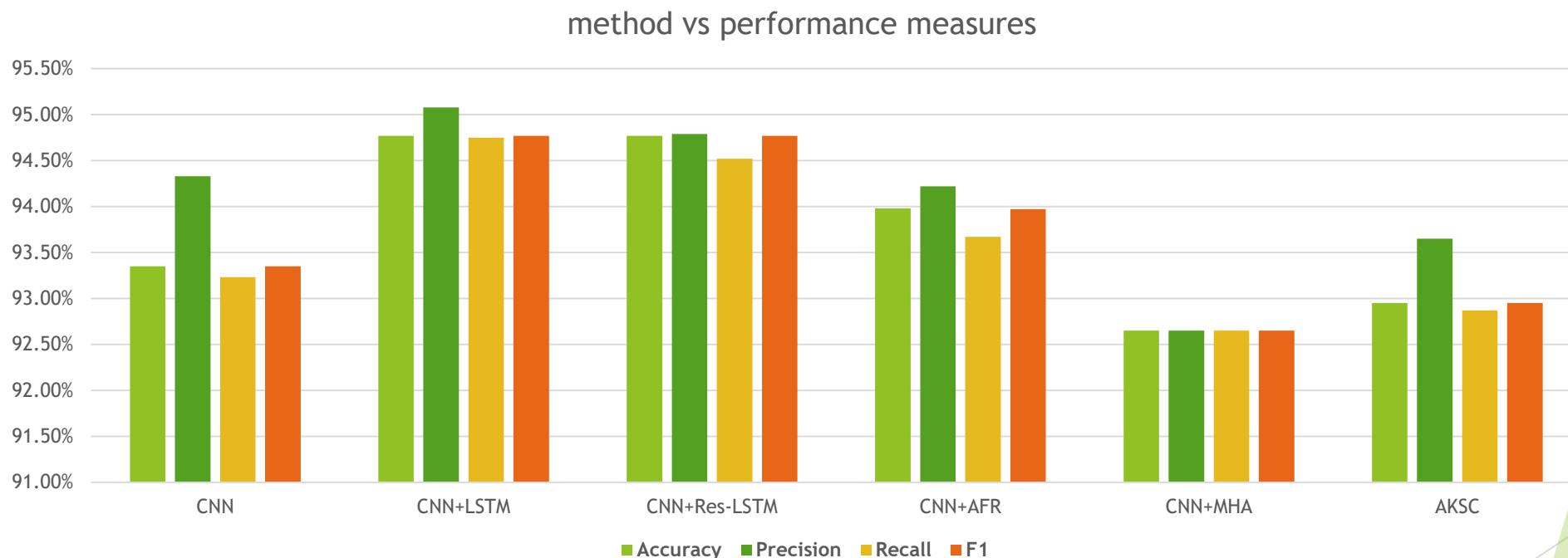
Cross entropy loss VS weighted cross entropy loss VS focal loss



# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

Experiments summary with weighted cross-entropy

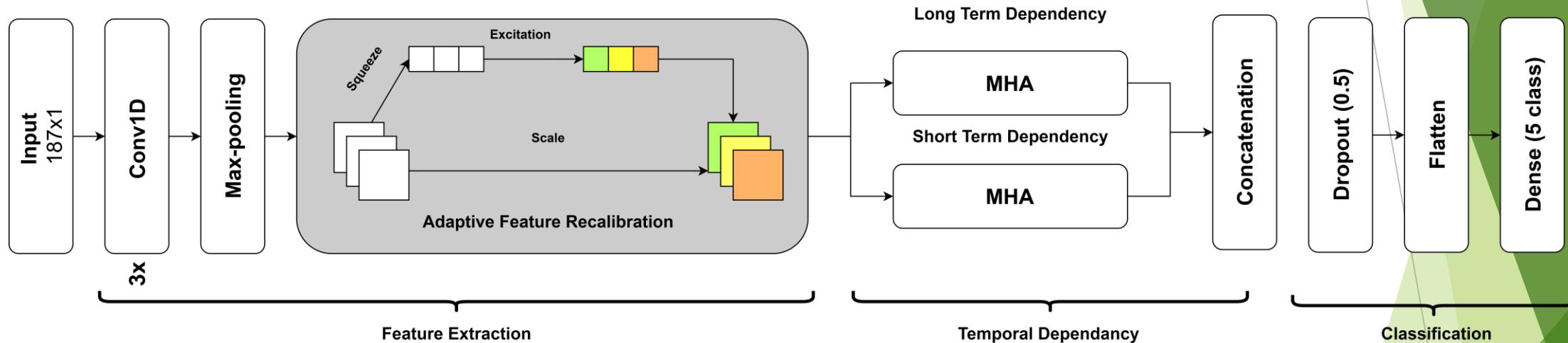


	Accuracy	Precision	Recall	F1
CNN+ Bi-LSTM	94.77%	95.08%	94.75%	94.77%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

CNN+AFR+MHA

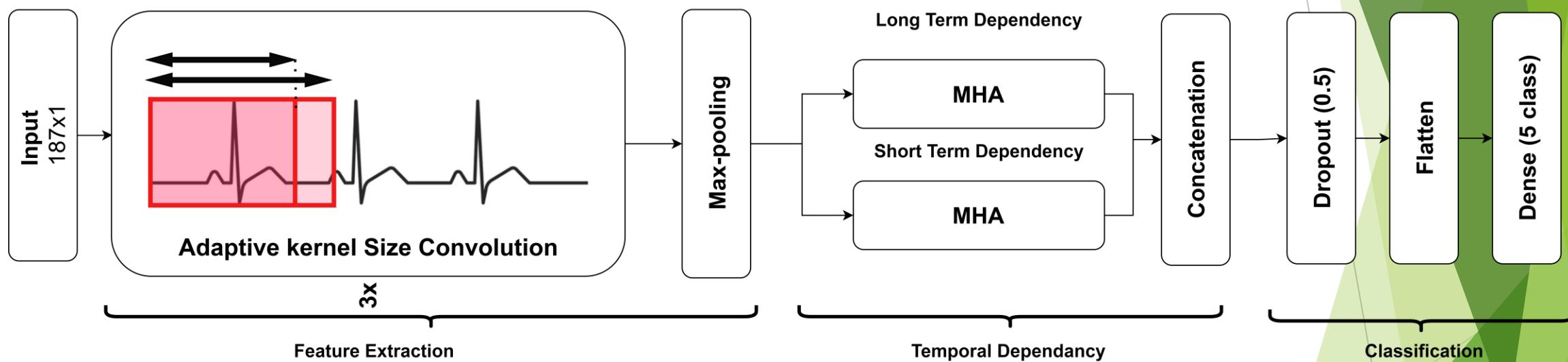


	Accuracy	Precision	Recall	F1
CNN+AFR+ MHA	93.45%	93.67%	93.27%	93.45%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

AKSC+MHA

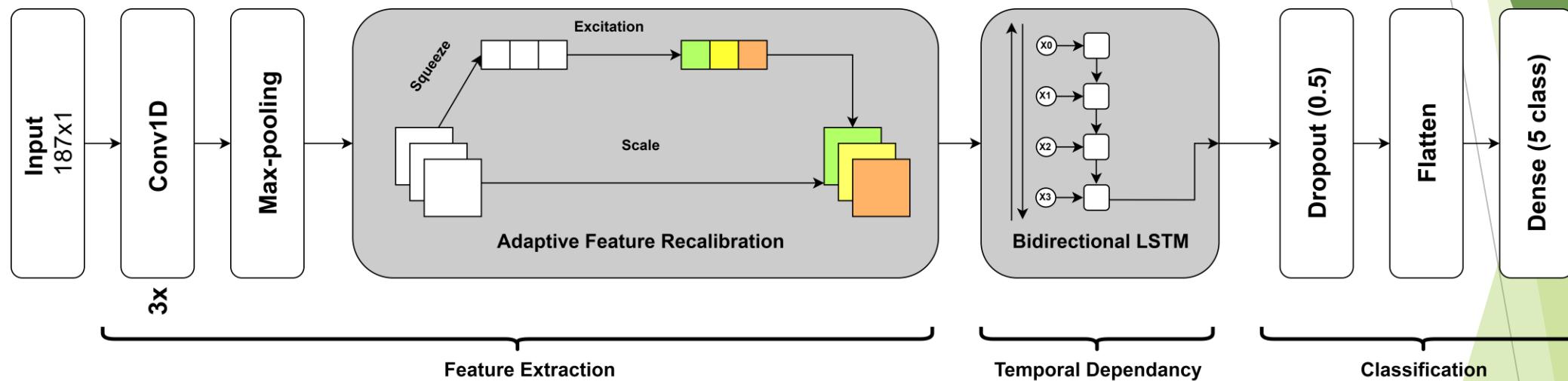


	Accuracy	Precision	Recall	F1
AKSC+MHA	92.68%	93.04%	92.22%	92.67%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

CNN+AFR+Bi-LSTM

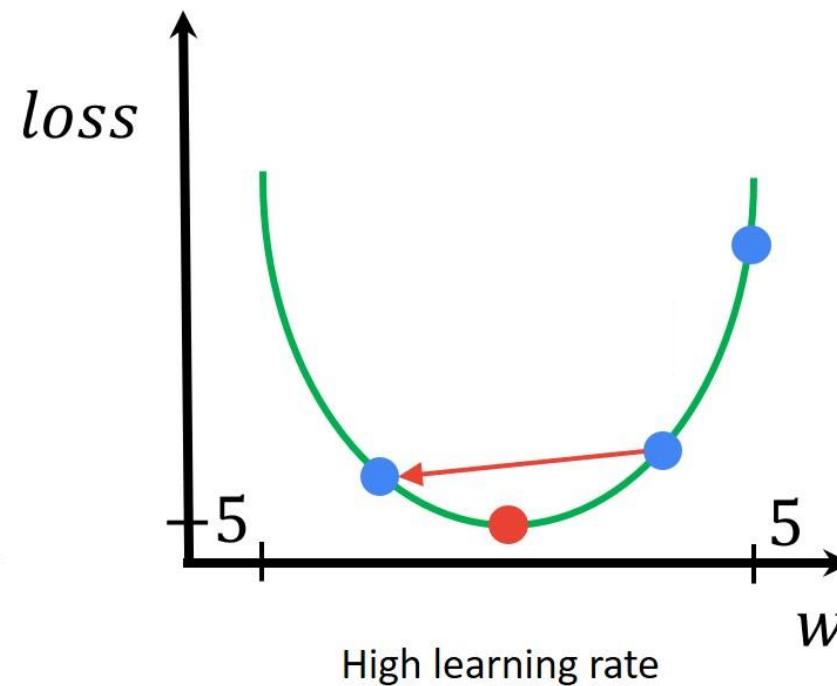
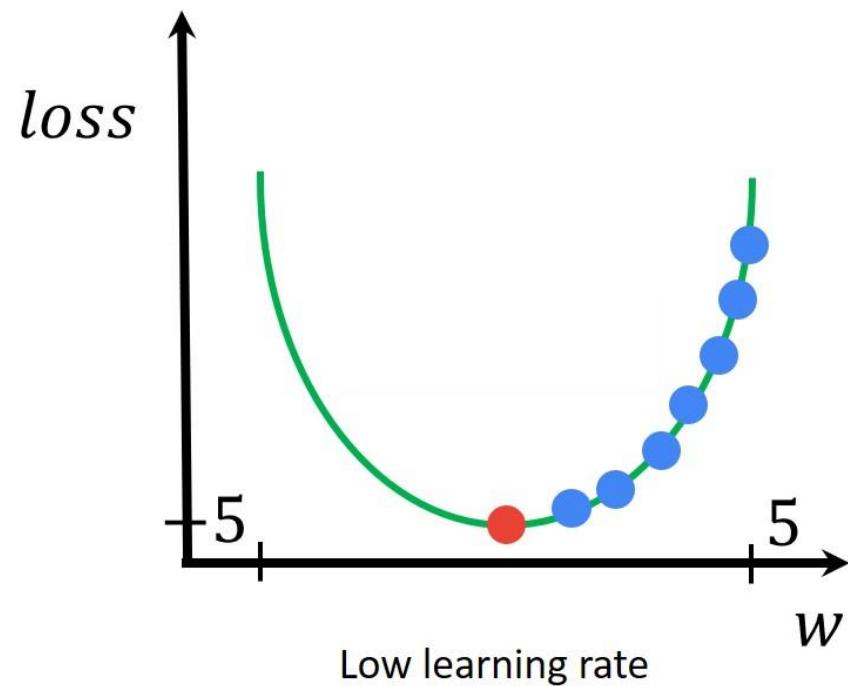


	Accuracy	Precision	Recall	F1
CNN+AFR+ Bi-LSTM	94.88%	95.09%	94.82%	94.88%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

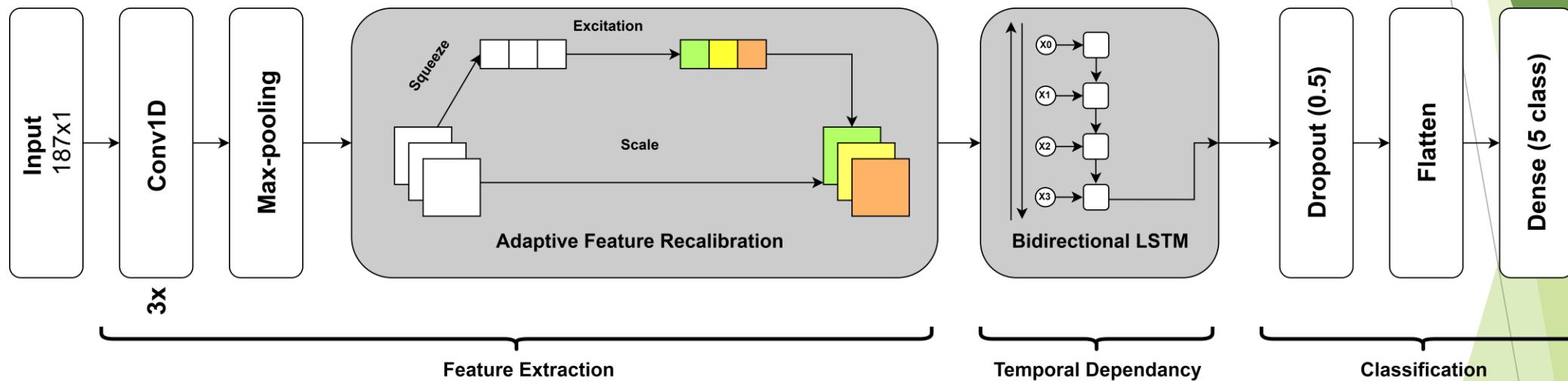
Reducible learning rate



# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

CNN+AFR+Bi-LSTM+RLR

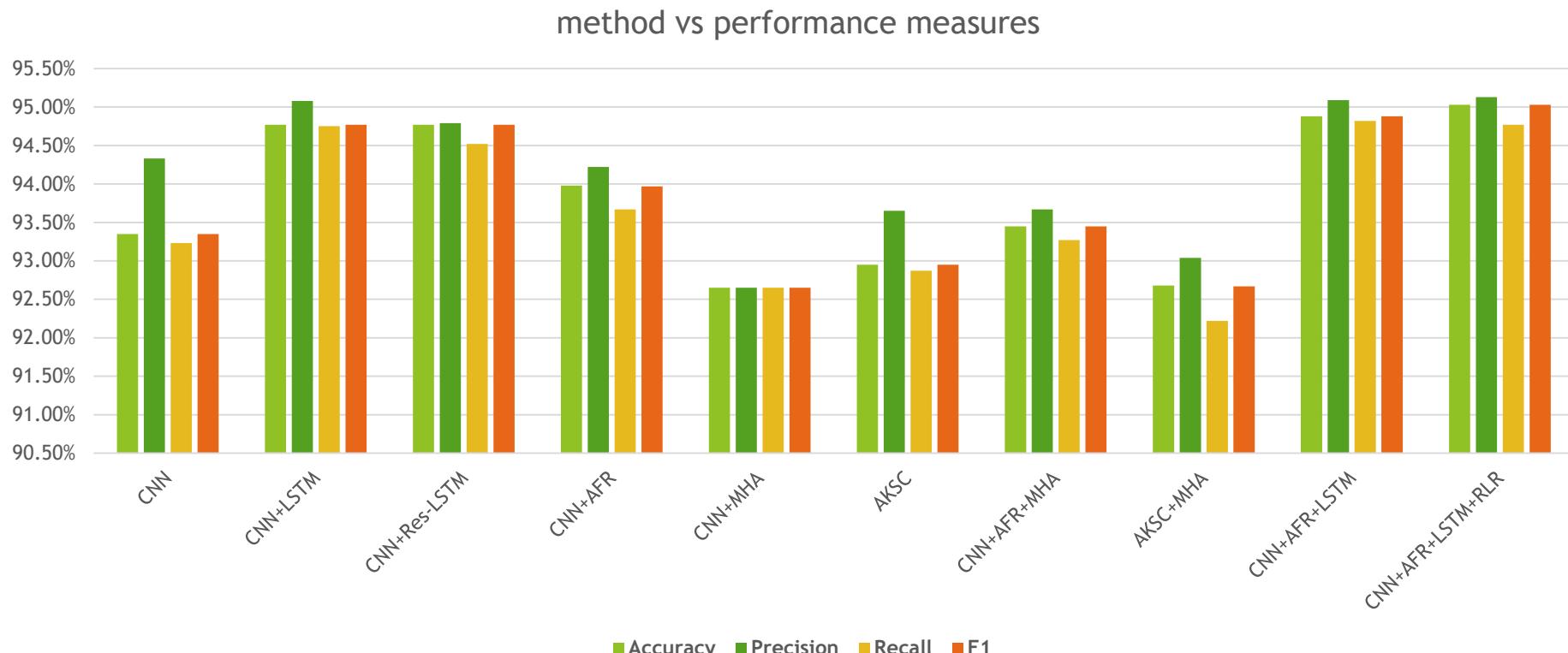


	Accuracy	Precision	Recall	F1
CNN+AFR+ Bi-LSTM+RLR	95.10%	95.10%	95.00%	95.10%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

Experiments summary with weighted cross-entropy

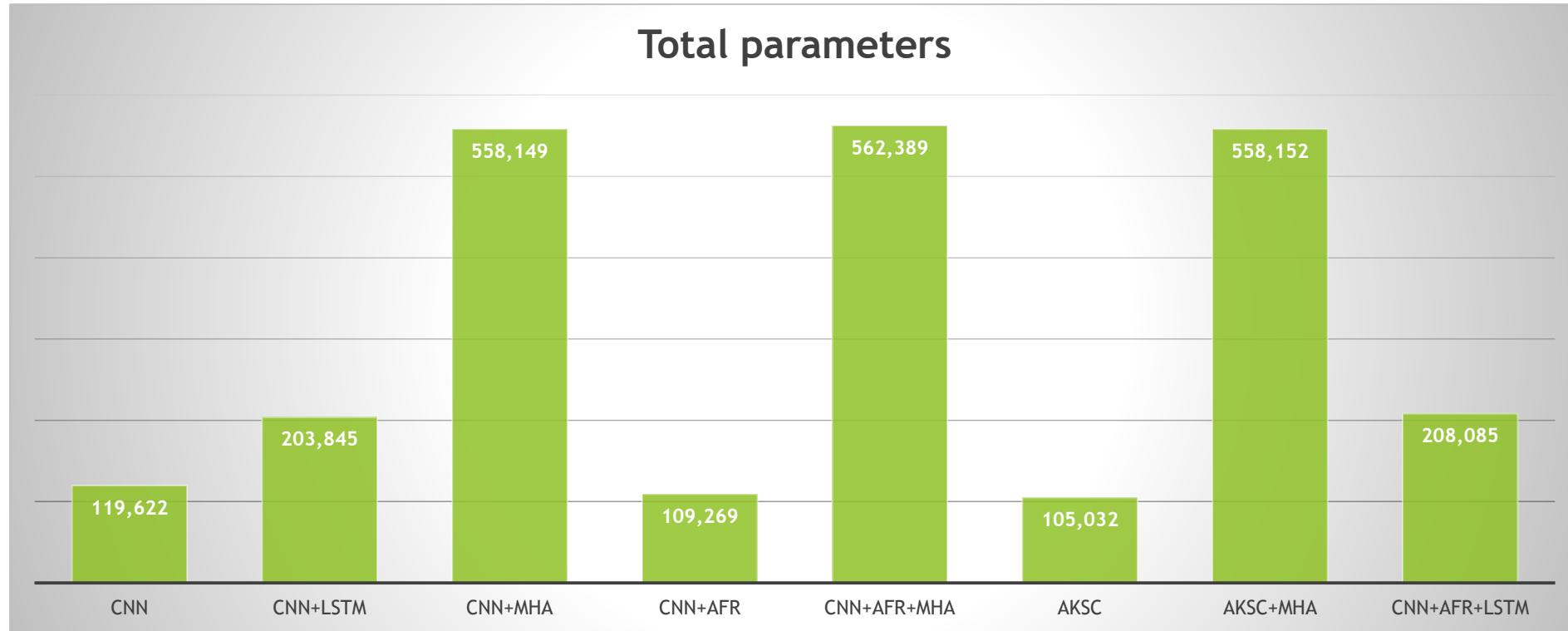


	Accuracy	Precision	Recall	F1
CNN+AFR+ Bi-LSTM+RLR	95.10%	95.10%	95.00%	95.10%
Ref	93.4%			

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

Total parameters



# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

Training time



### NVIDIA T4 GPU

Architecture: Turing

CUDA Cores: 2,560

Tensor Cores: 320

Memory Size: 16 GB GDDR6

Memory Bandwidth: 320 GB/s

Memory Interface: 256-bit

Max Power Consumption: 70 Watts

PCIe Interface: PCIe 3.0 x16

Form Factor: Single-slot, Full-height

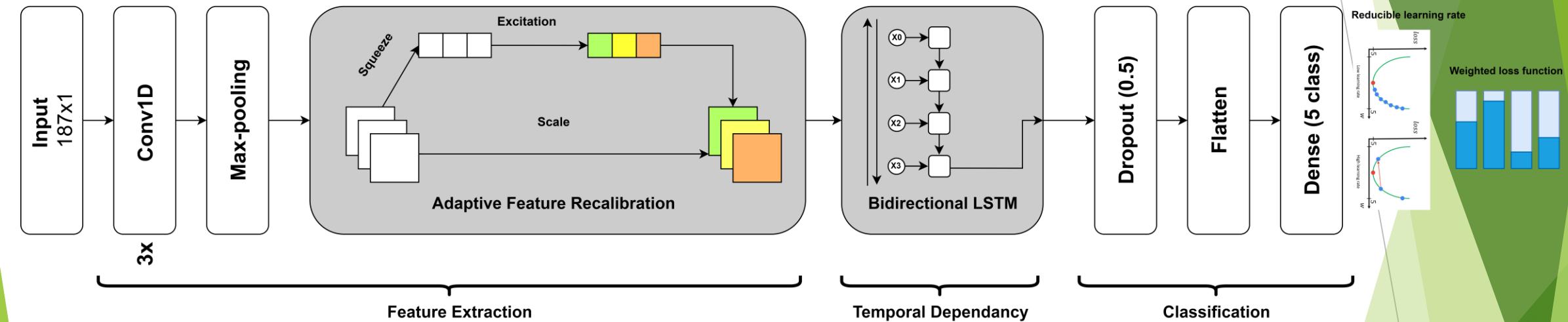
Compute Capability: 7.5

*GPU Boost Clock: 1,590 MHz*

# Heartbeat abnormalities detection from ECG

## ► 1-D convolution Experiments

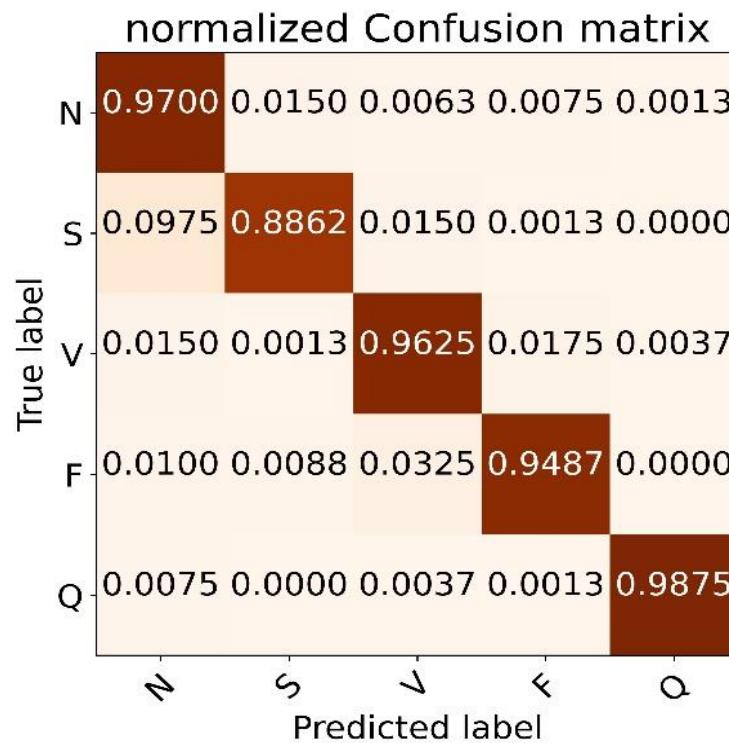
Best results: CNN+AFR+Bi-LSTM+RLR+WLF



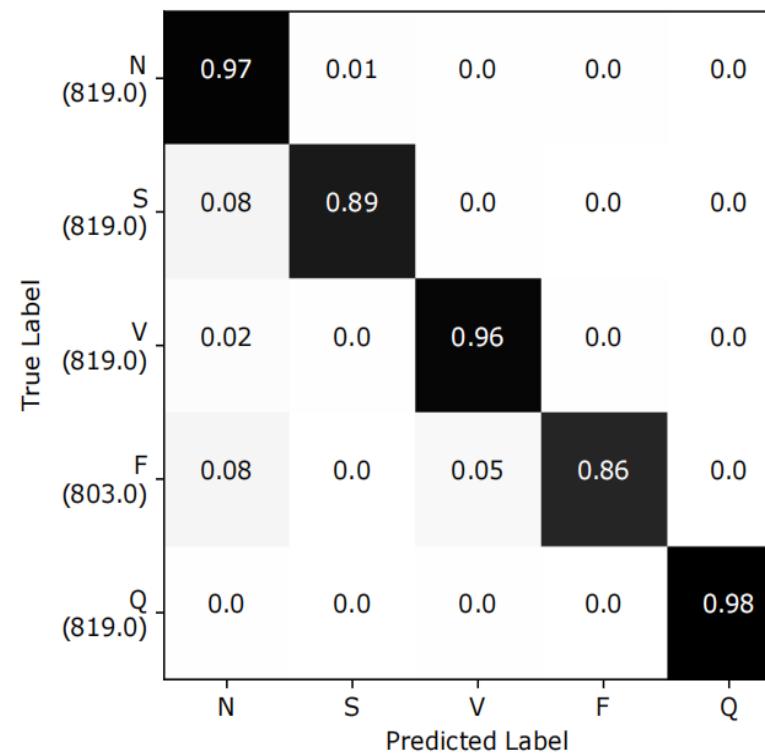
# Heartbeat abnormalities detection from ECG

## ► Performance

### Confusion matrix



Ours



Ref

# Heartbeat abnormalities detection from ECG

## ► Performance

### Classification report

index	Class name	Precision	Recall	F1-score	Support
0	N	0.8818	0.97	0.9238	800
1	S	0.9726	0.8862	0.9274	800
2	V	0.9436	0.9625	0.953	800
3	F	0.9718	0.9487	0.9602	800
4	Q	0.995	0.9875	0.9912	800
accuracy				0.9510	4000
macro avg		0.9511	0.9510	0.9511	4000
weighted avg		0.9511	0.9510	0.9511	4000

# Heartbeat abnormalities detection from ECG

## ► Result Comparison

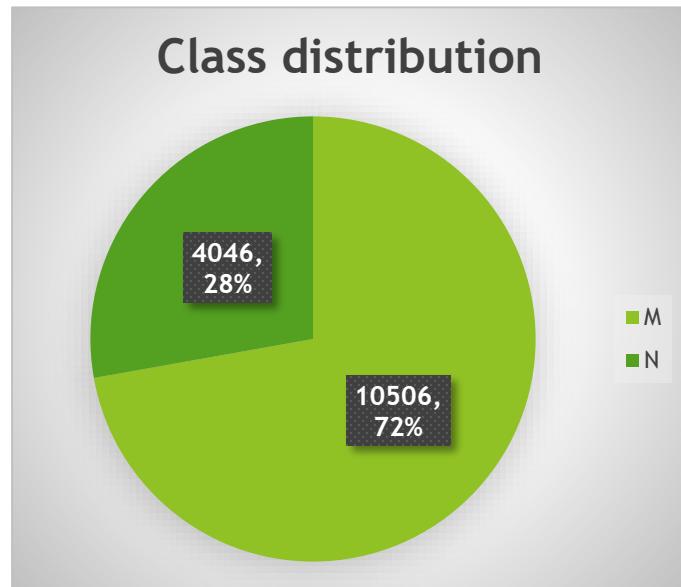
	Architecture	Temporal dependency	Handling data imbalance	Remarks	Accuracy	Macro F1
Resampling the test data to 800						
[1]	Residual CNN	-	Oversampling	Low recall on S,F classes	93.4%	
Ours	CNN+AFR	Bi-LSTM	Weighted loss	Good recall	95.10%	
Test data as it is						
[2]	CNN	-	Oversampling	Low recall on S,F classes	93.47%	
[3]	SVM	-	-	Low recall		82%
Ours	CNN+AFR	Bi-LSTM	Weighted loss	Good recall	97.11%	85.48%

- [1] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, “Ecg heartbeat classification: A deep transferable representation,” in 2018 IEEE International Conference on Healthcare Informatics (ICHI), 2018, pp. 443-444.
- [2] Pirova, D., Zaberzhinsky, B., & Mashkov, A. (2020). Detecting heart 2 disease symptoms using machine learning methods. Proceedings of the Information Technology and Nanotechnology (ITNT-2020), 2667, 260-263.
- [3] Walsh, P. (2019). Support Vector Machine Learning for ECG Classification. In CERC (pp. 195-204).

# Heartbeat abnormalities detection from ECG

## ► Method validation

PTB Diagnostic ECG Database



M	N
4046	10506

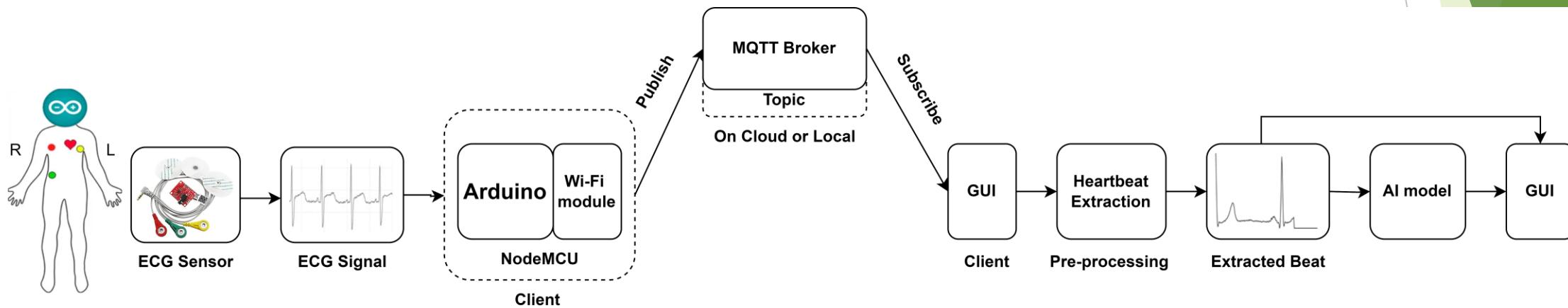
M: myocardial infarction      الذبحة القلبية  
N: normal      طبيعي

	Method	Accuracy	precision	Recall
Proposed	CNN+AFR+ Bi-LSTM+RLR	99.79%	99.82%	99.66%
[1]	Transfer learning Res-CNN	95.9%	95.1%	95.2%

# Heartbeat abnormalities detection from ECG

## ► Real time diagnosis of ECG signal

Over all diagram

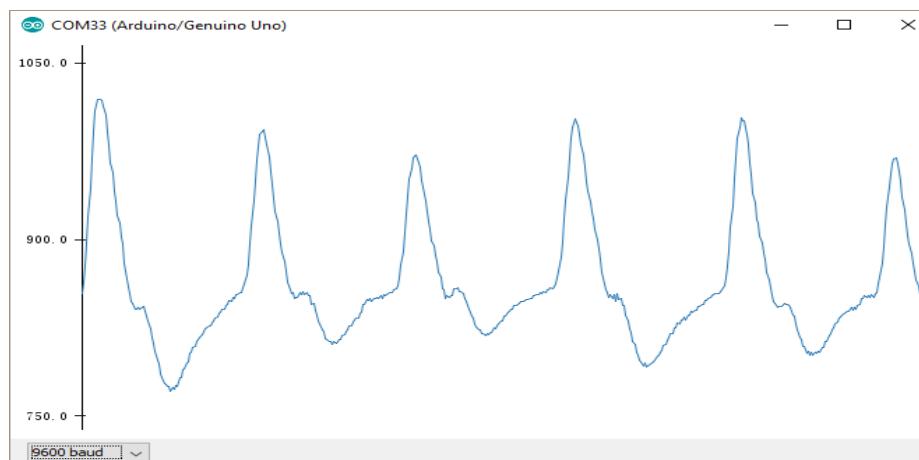
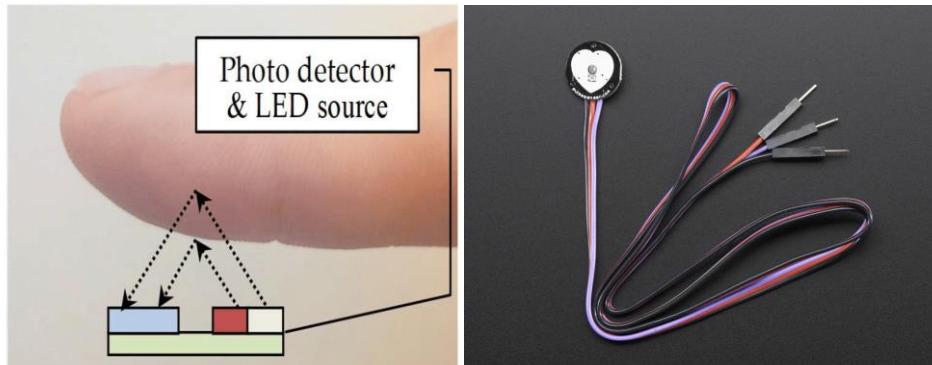


# Heartbeat abnormalities detection from ECG

## ► Real time diagnosis of ECG signal

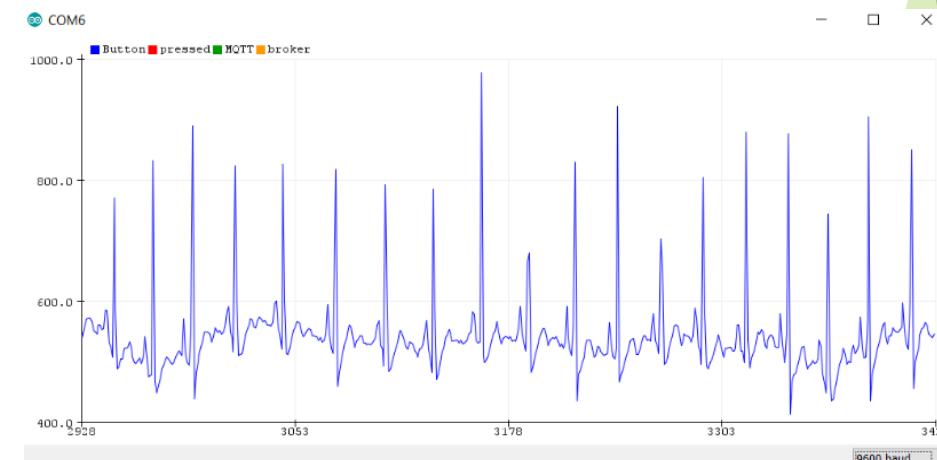
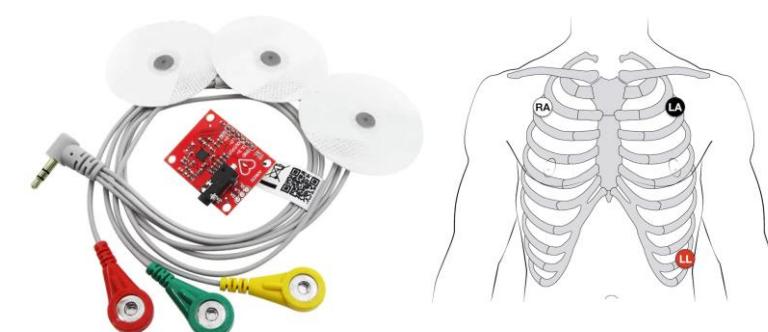
### Sensors

- ppg



Unsuitable output

- AD8232

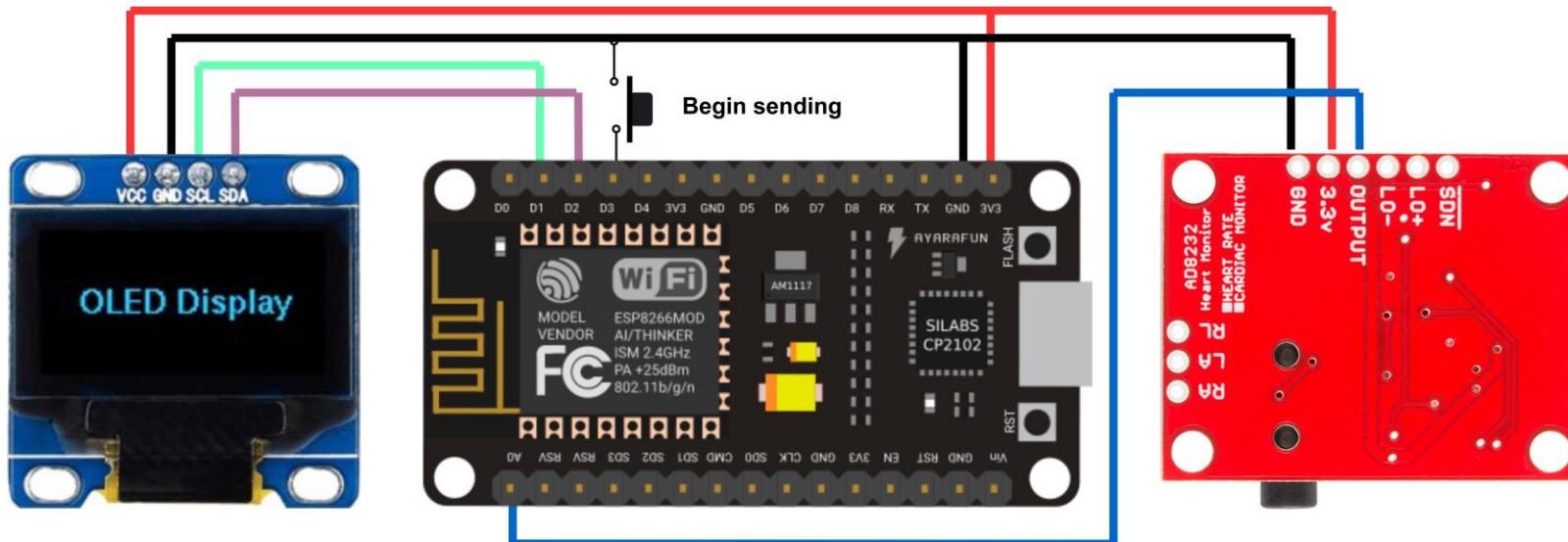


Suitable output

# Heartbeat abnormalities detection from ECG

- ▶ Real time diagnosis of ECG signal

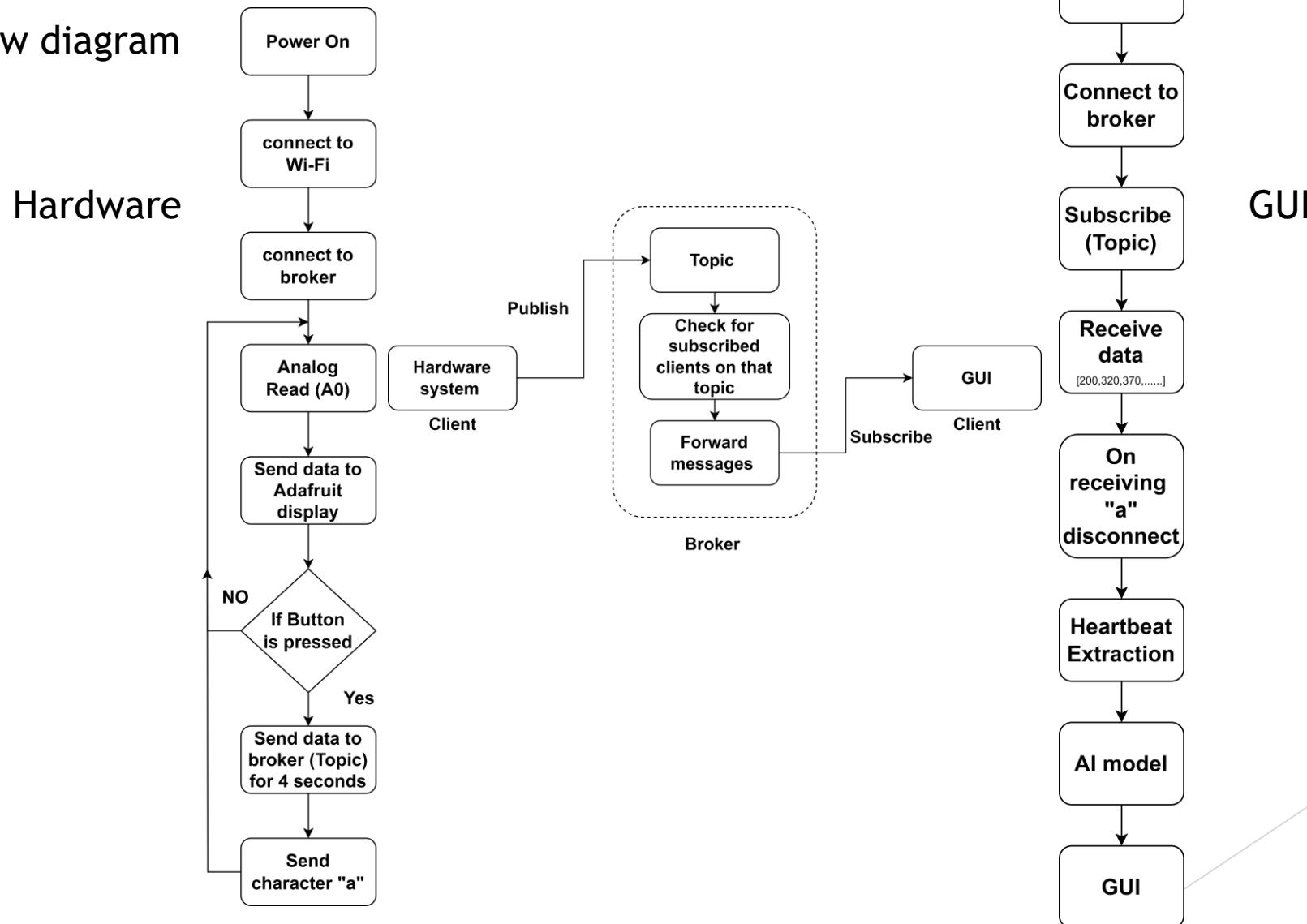
Connection diagram



# Heartbeat abnormalities detection from ECG

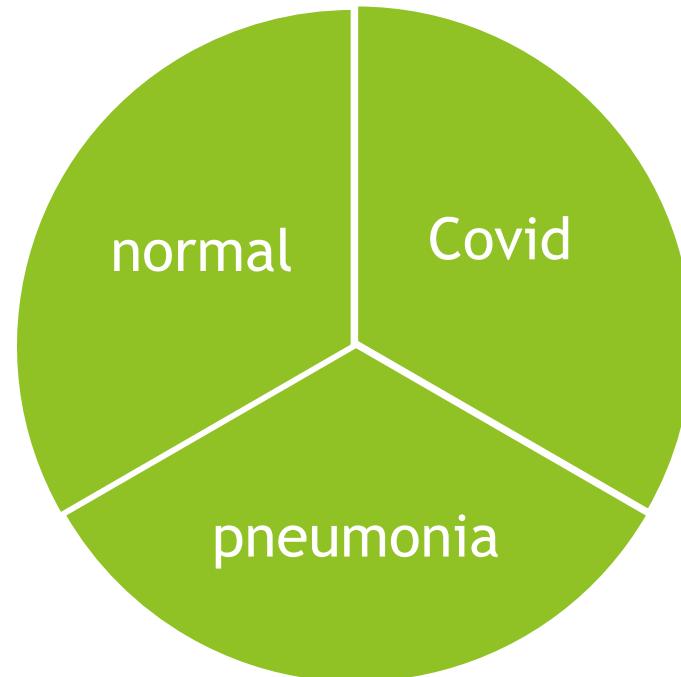
## ► Real time diagnosis of ECG signal

Flow diagram

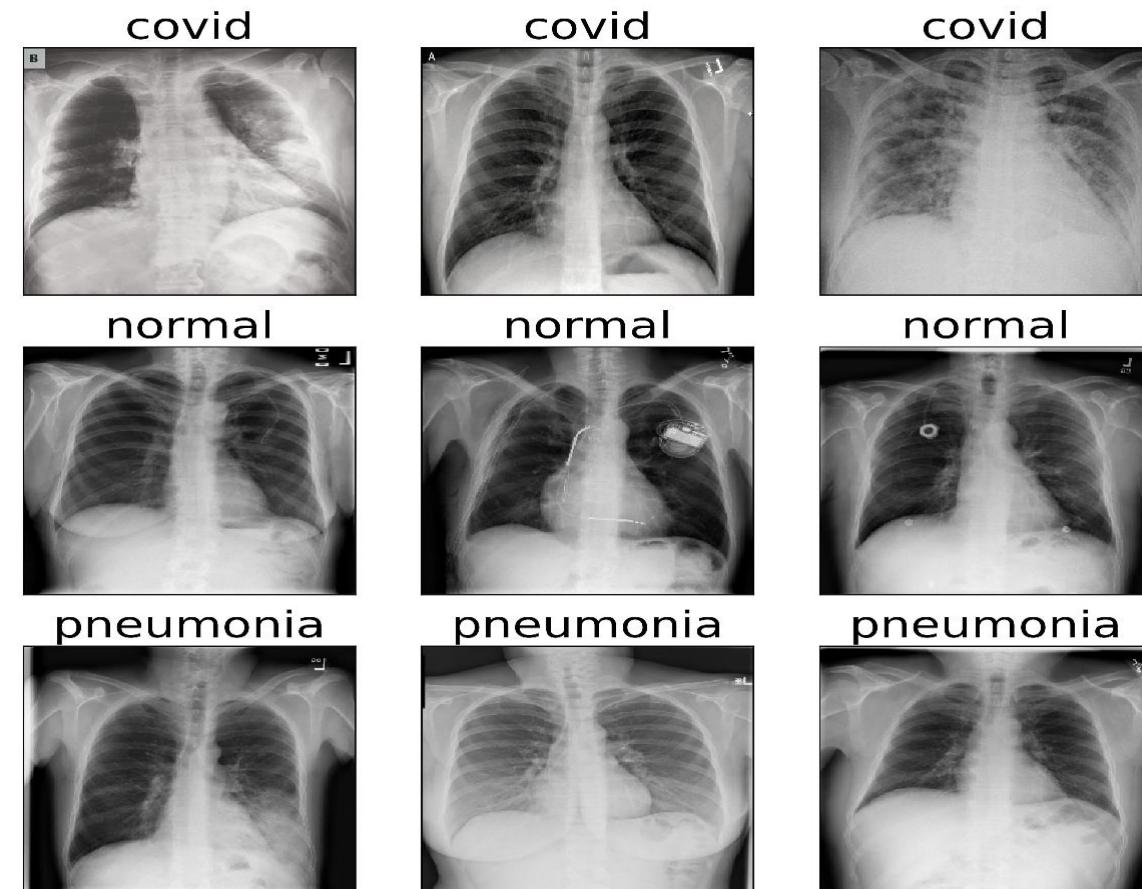


# COVID-19 detection

## ► Dataset description



2313 sample for each class  
6939 samples in total  
RGB images



# COVID-19 detection

## ► Dataset description

Data source

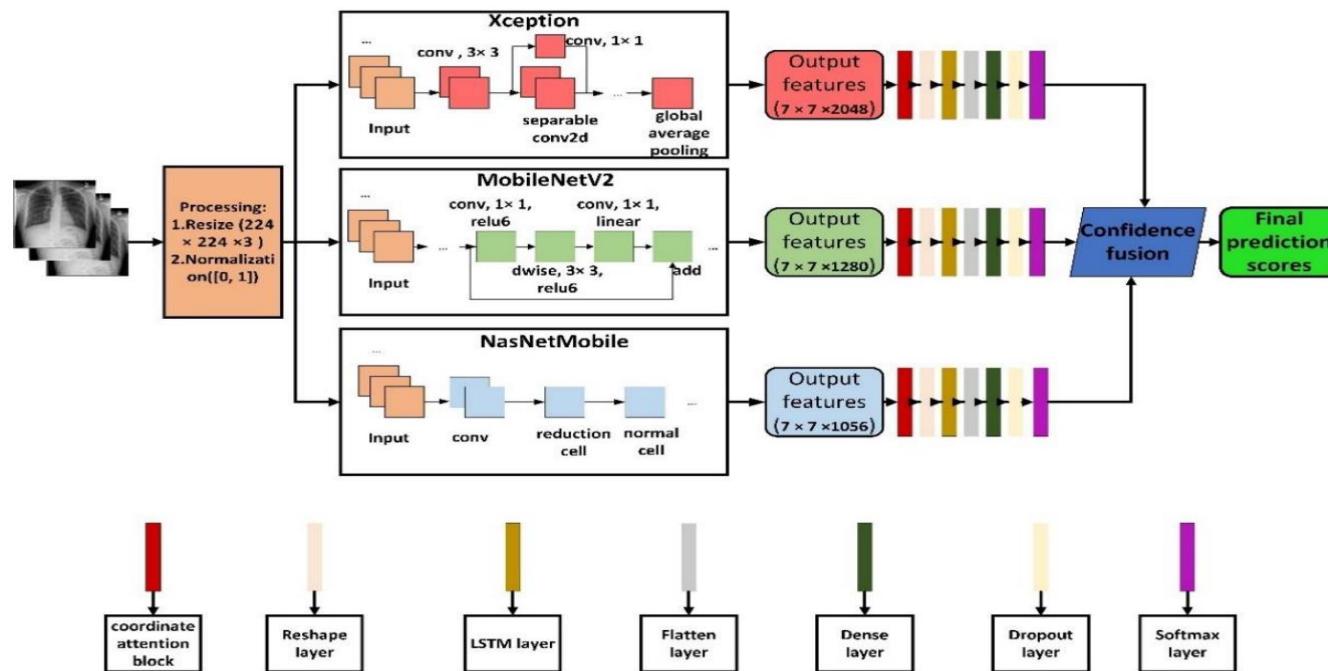
**Radiopedia.org:** A free, open-access, peer-reviewed, and collaborative radiology resource

**Italian Society of Medical and Interventional Radiology**

# COVID-19 detection

## ► Reference paper for result comparison

- [1] W. Wang, S. Liu, H. Xu, and L. Deng, “COVIDX-LwNet: A lightweight network ensemble model for the detection of COVID-19 based on chest X-ray images,” Sensors (Basel), vol. 22, no. 21, p. 8578, 2022.



95.56% Accuracy  
Complicated model  
Massive no. of parameters (71million)

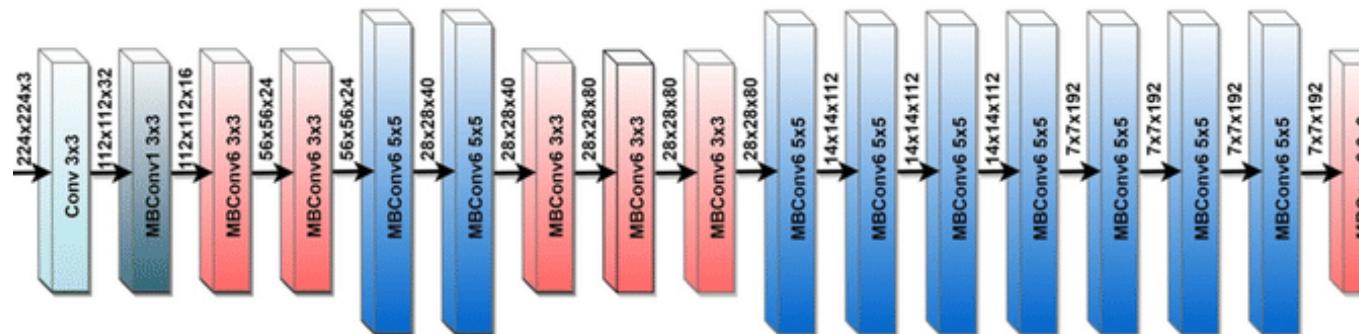
# COVID-19 detection

## ► Reference paper for result comparison

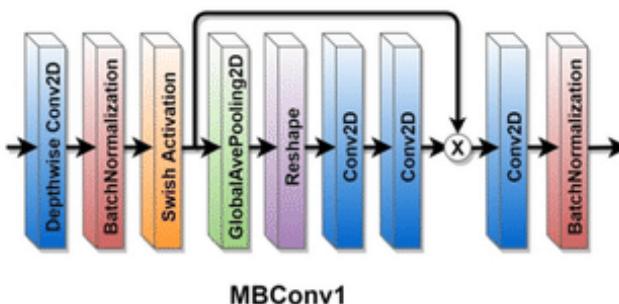
- [2] E. Cengil and A. Çınar, “The effect of deep feature concatenation in the classification problem: An approach on COVID-19 disease detection,” Int. J. Imaging Syst. Technol., vol. 32, no. 1, pp. 26-40, 2022.

EfficientNet-b0  
94.7% Accuracy

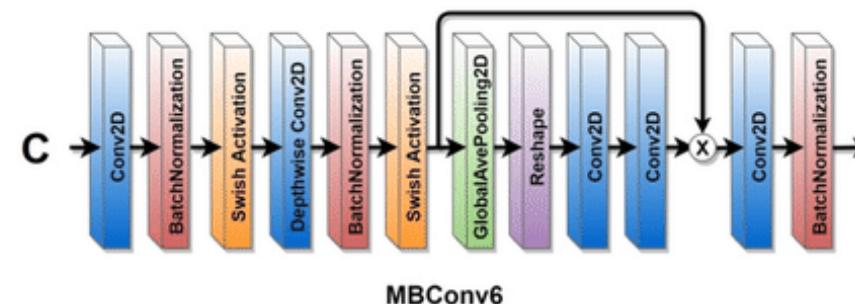
A



B

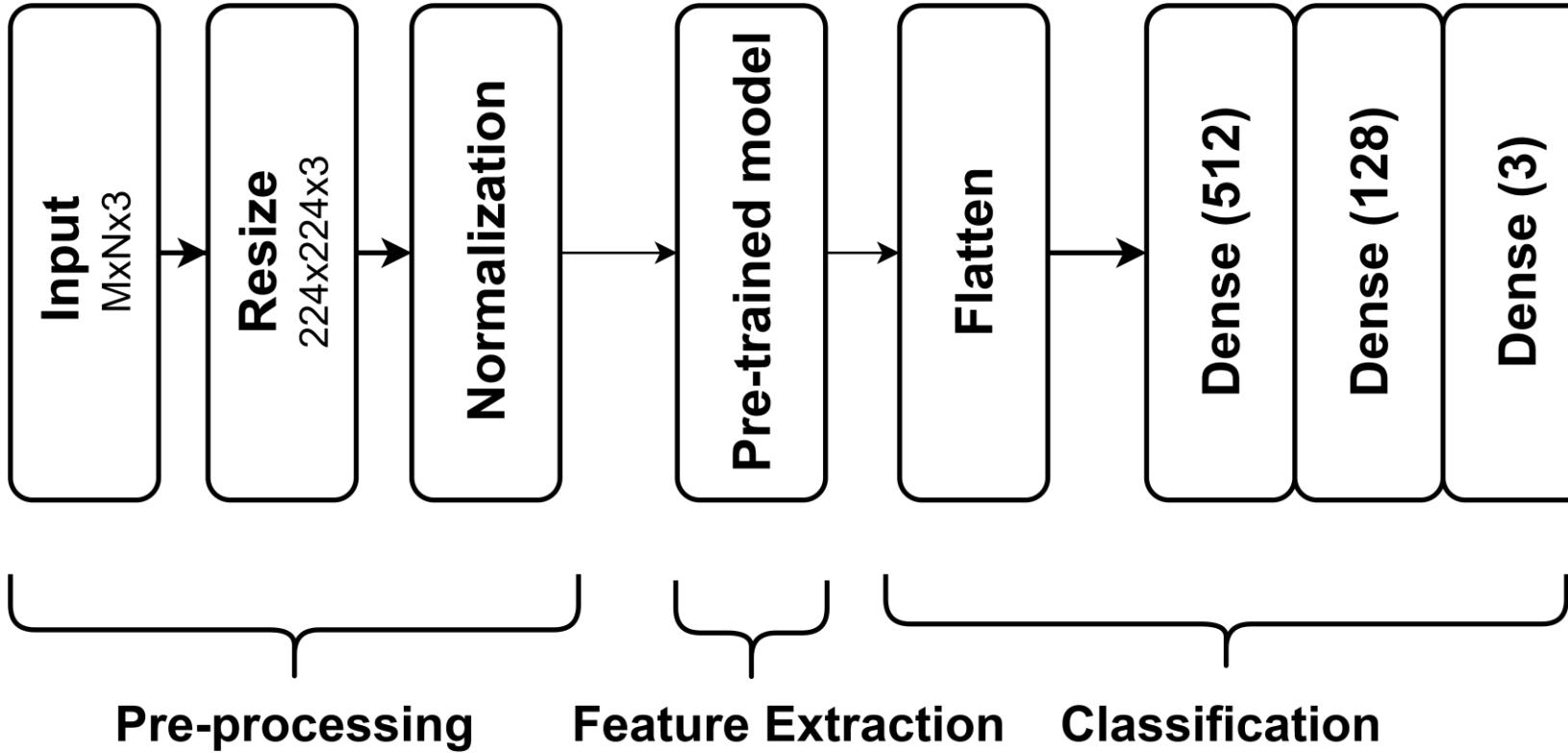


C



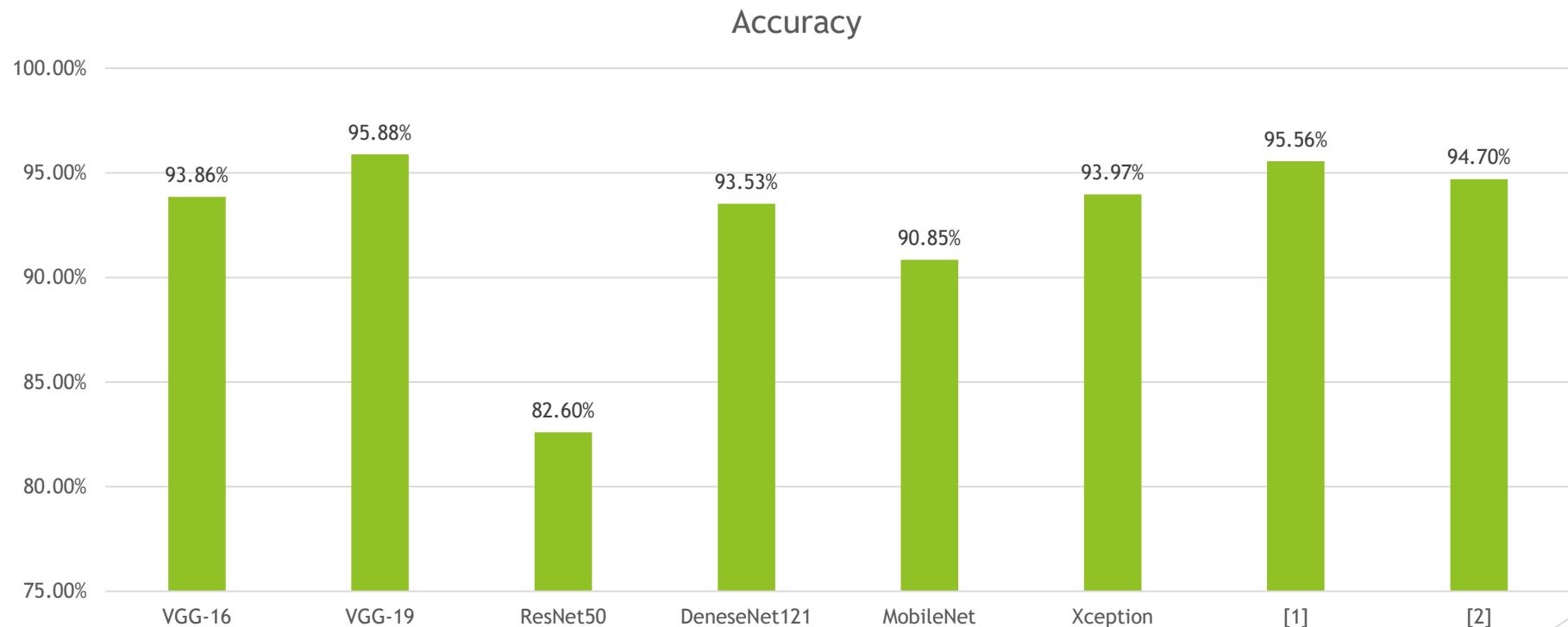
# COVID-19 detection

## ► Pre-trained models



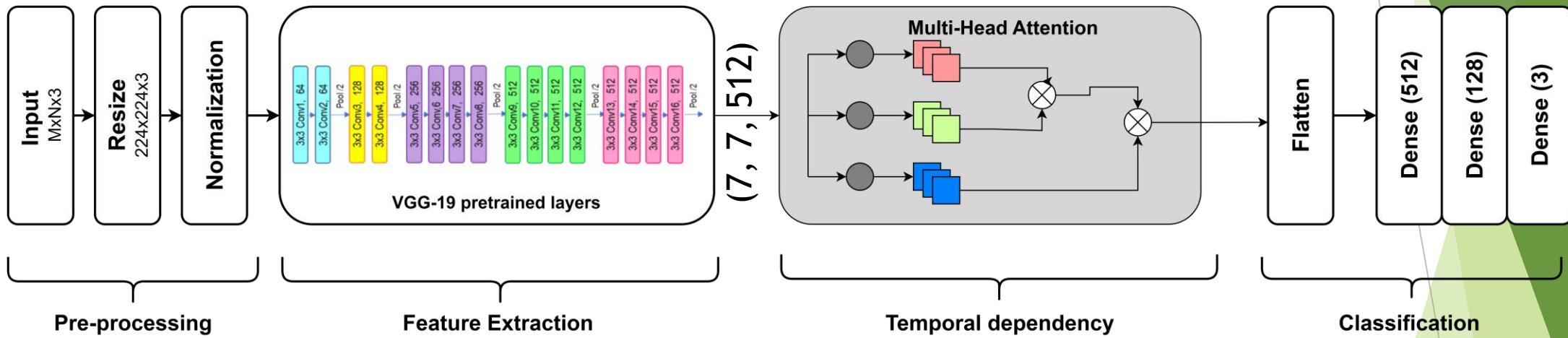
# COVID-19 detection

## ► Pre-trained models



# COVID-19 detection

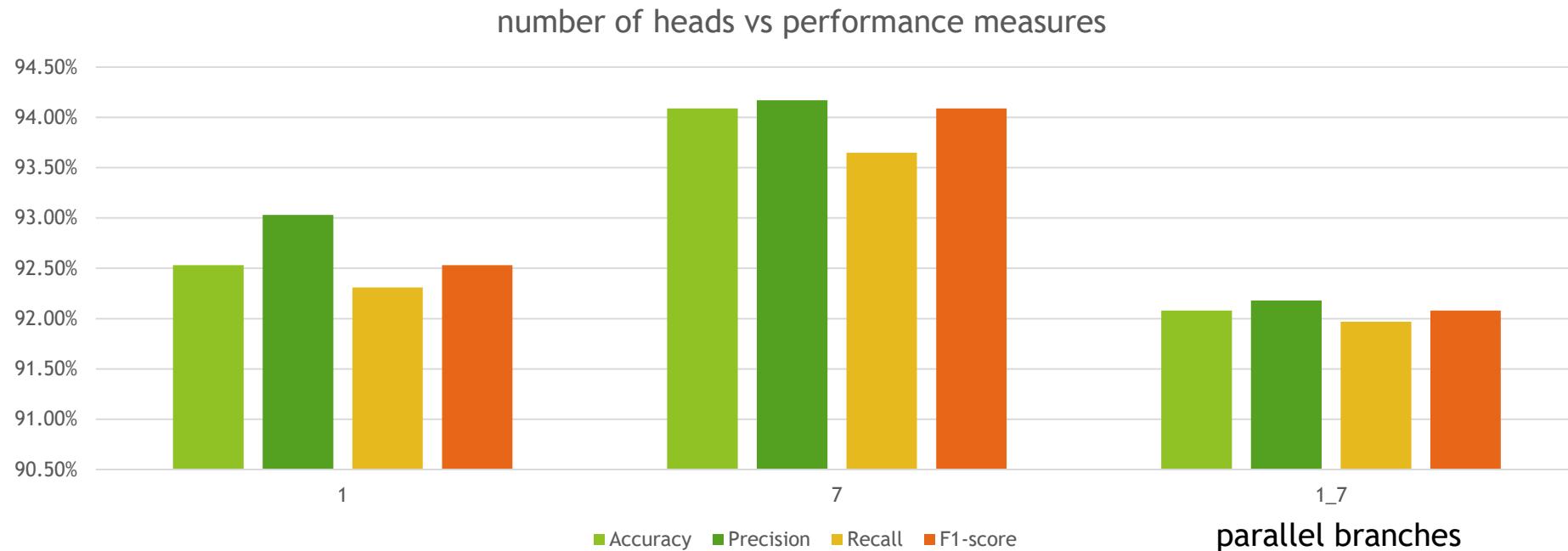
## ► VGG-19 + Multi-head attention (MHA)



Hyper-parameters:  
No. of heads

# COVID-19 detection

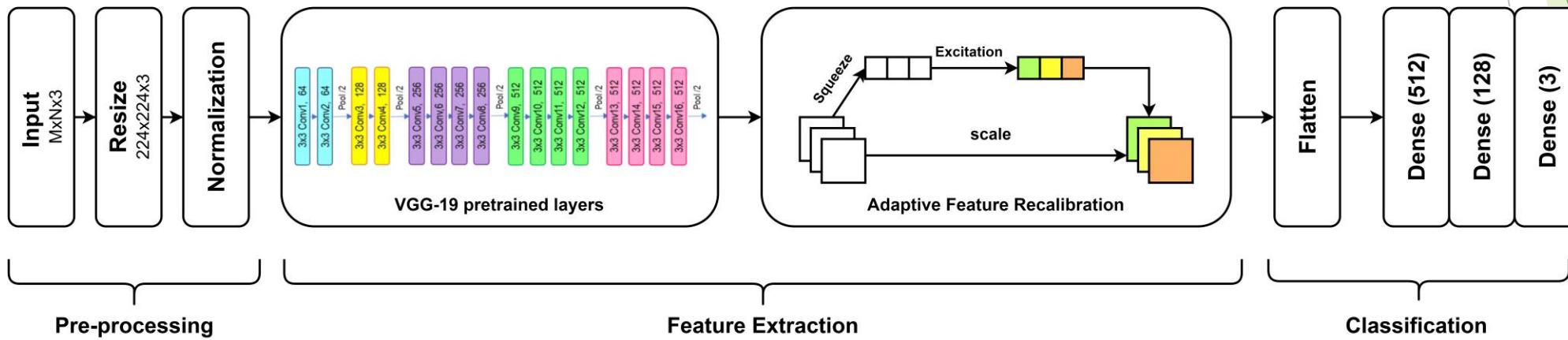
## ► VGG-19 + Multi-head attention (MHA)



No. of heads	Accuracy	Precision	Recall	F1
7	94.09%	94.17%	93.65%	94.09%
[1]	95.56%			
[2]	94.7%			

# COVID-19 detection

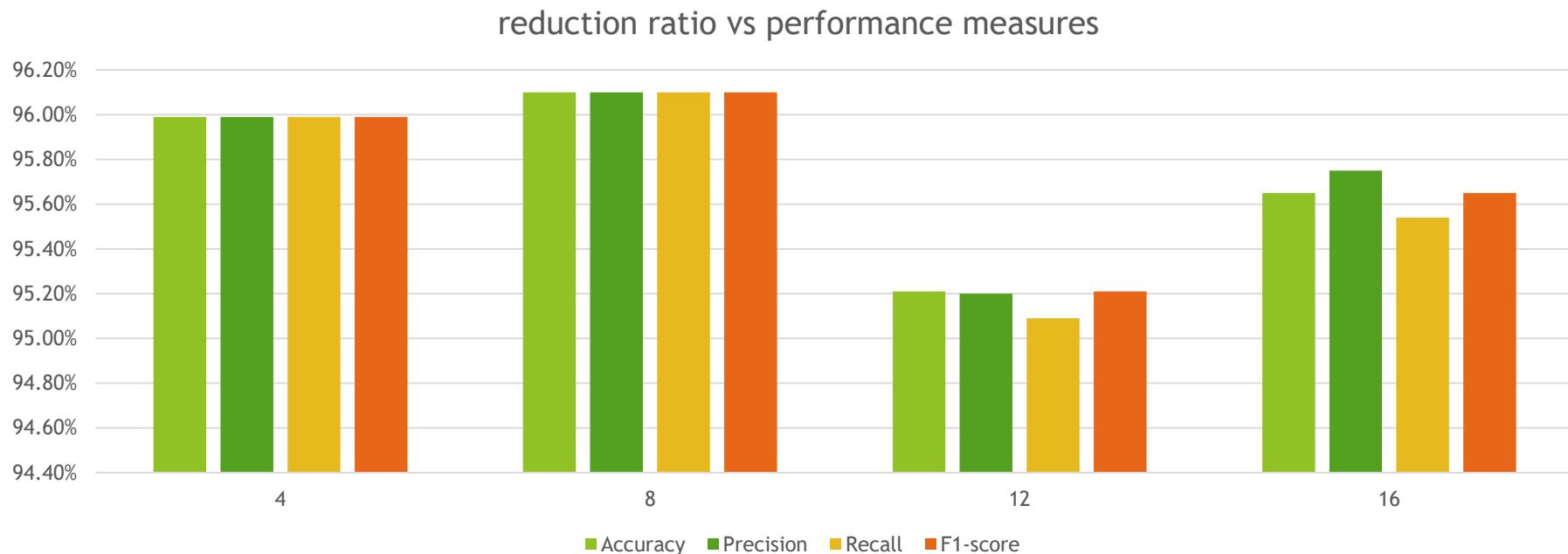
- ▶ VGG-19 + Adaptive feature recalibration (AFR)



Hyper-parameters:  
Reduction ration

# COVID-19 detection

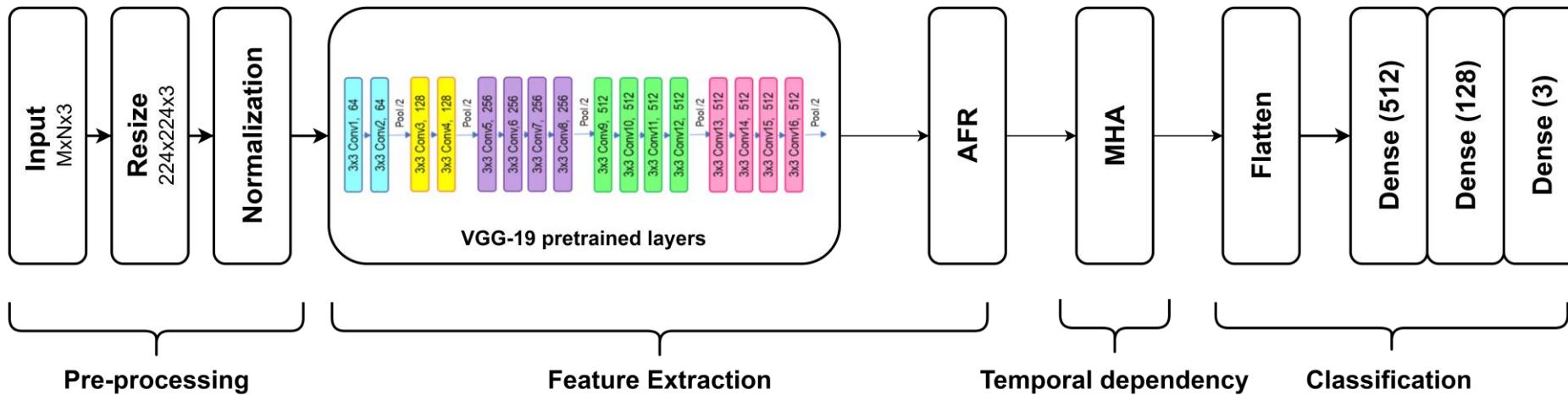
## ► VGG-19 + Adaptive feature recalibration (AFR)



Reduction ratio	Accuracy	Precision	Recall	F1
8	96.10%	96.10%	96.10%	96.10%
[1]	95.56%			
[2]	94.7%			

# COVID-19 detection

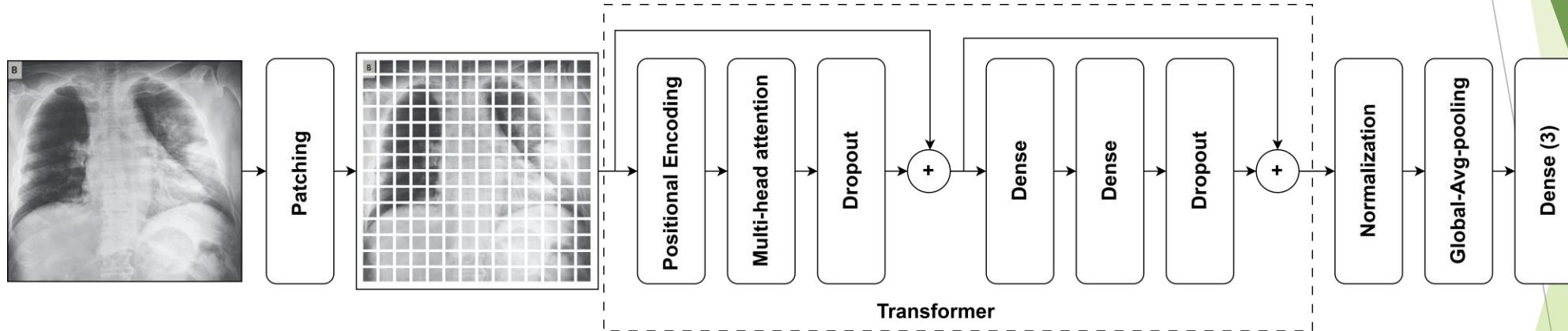
## ► VGG-19+AFR+MHA



	Accuracy	Precision	Recall	F1
Proposed	92.20%	92.48%	91.86%	92.20%
[1]	95.56%			
[2]	94.7%			

# COVID-19 detection

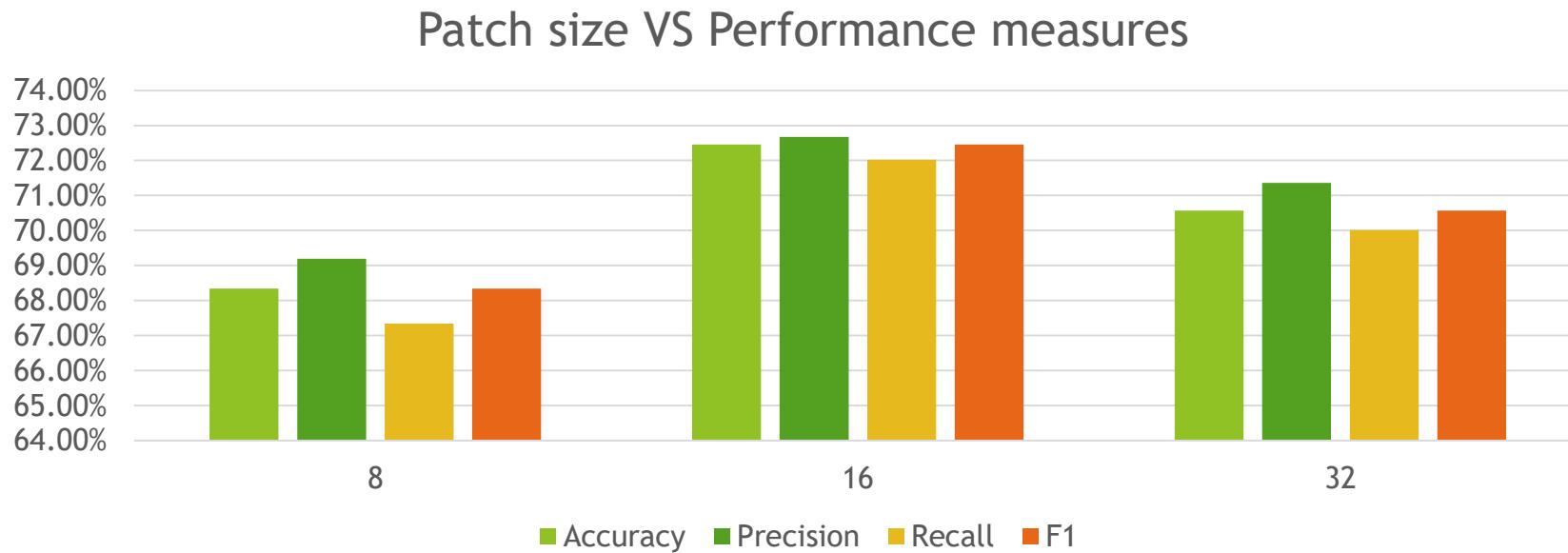
## ► Vision transformer model (ViT)



Hyper-parameters:  
Patch size (no. of patches)

# COVID-19 detection

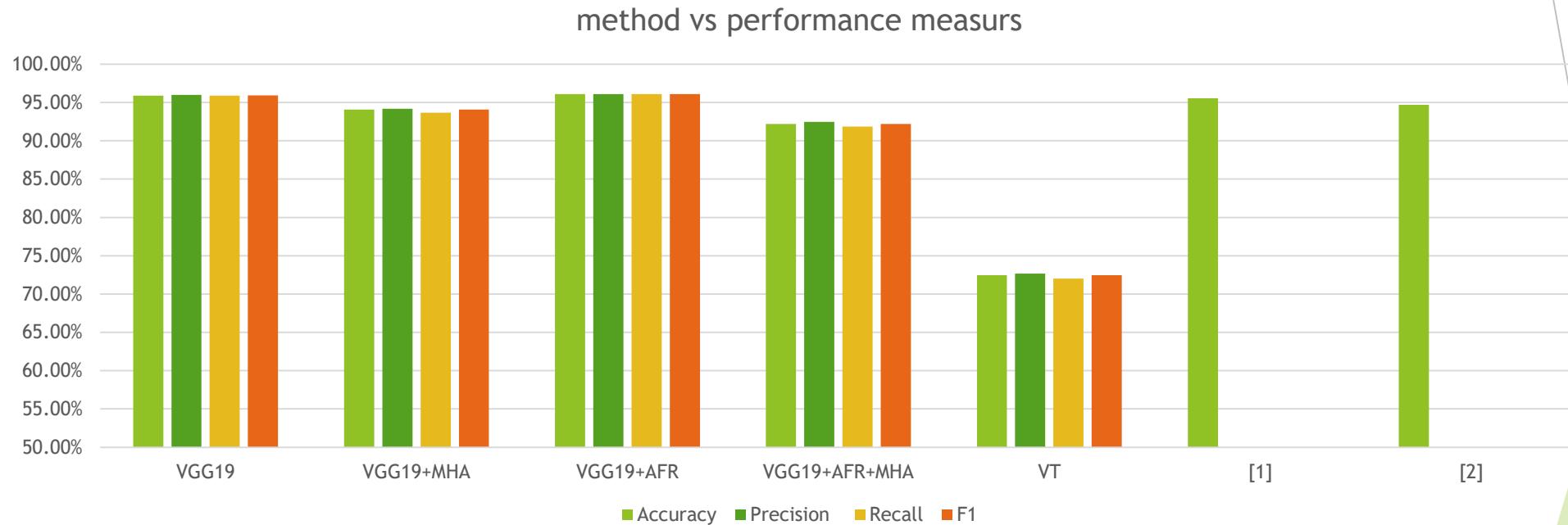
## ► Vision transformer model (ViT)



Patch size	Accuracy	Precision	Recall	F1
16	72.46%	72.67%	72.02%	72.46%
[1]	95.56%			
[2]	94.7%			

# COVID-19 detection

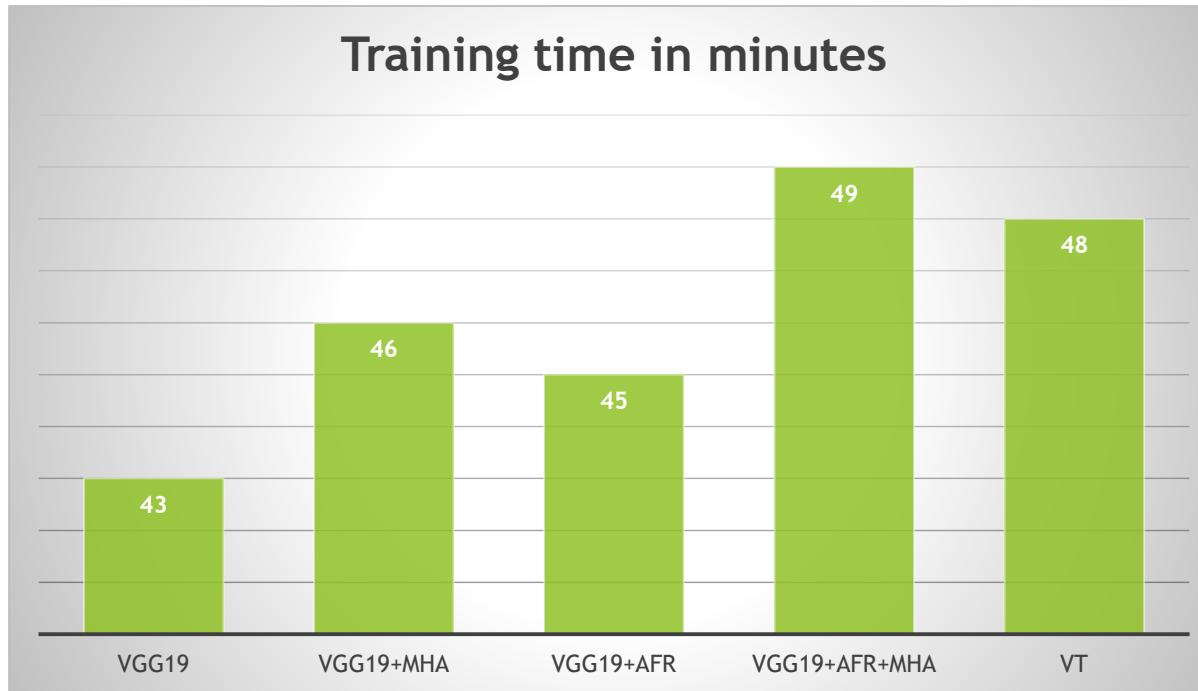
## ► Experiments summary



	Accuracy	Precision	Recall	F1
VGG-19+AFR	96.10%	96.10%	96.10%	96.10%
[1]	95.56%			
[2]	94.7%			

# COVID-19 detection

## ► Training time



## NVIDIA T4 GPU

Architecture: Turing

CUDA Cores: 2,560

Tensor Cores: 320

Memory Size: 16 GB GDDR6

Memory Bandwidth: 320 GB/s

Memory Interface: 256-bit

Max Power Consumption: 70 Watts

PCIe Interface: PCIe 3.0 x16

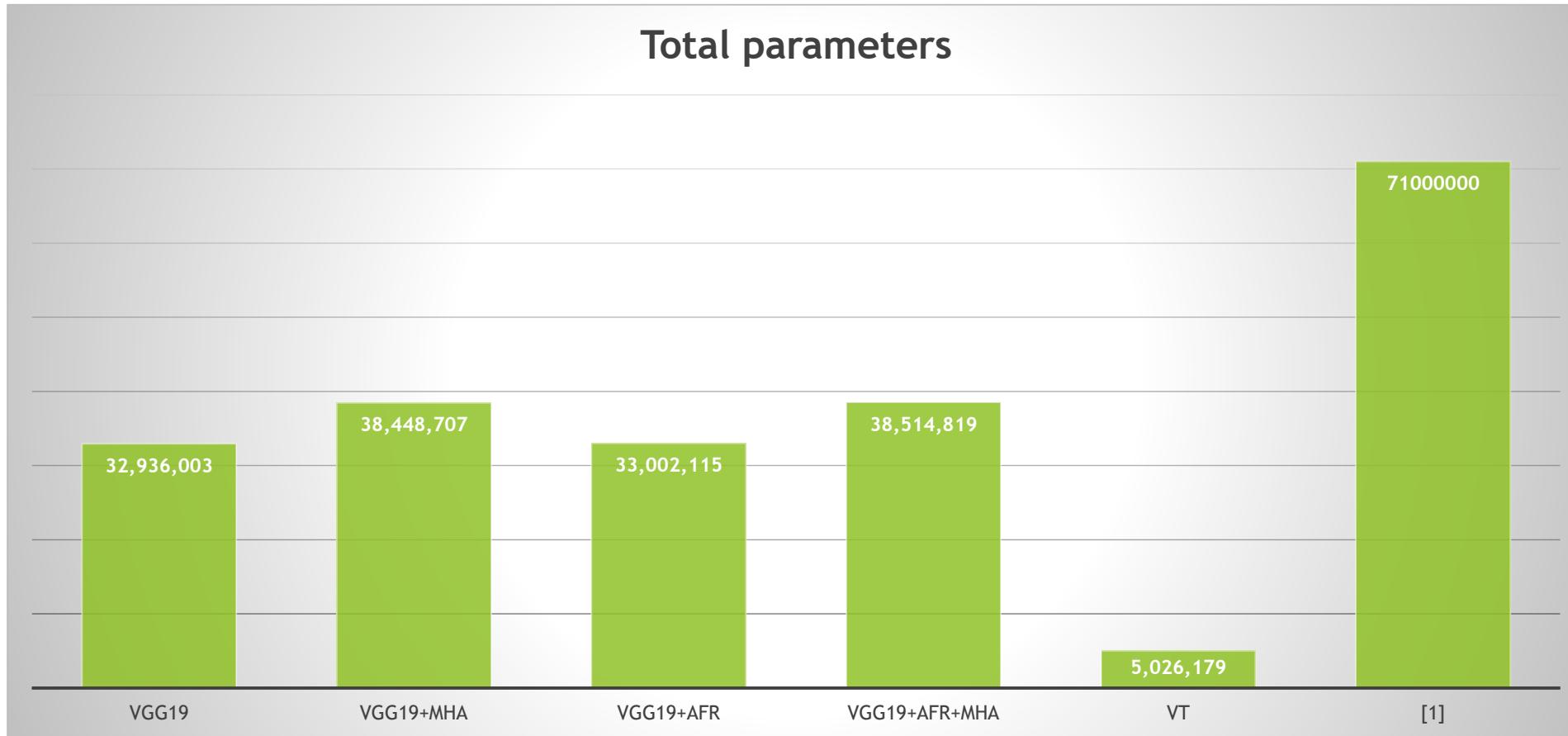
Form Factor: Single-slot, Full-height

Compute Capability: 7.5

*GPU Boost Clock: 1,590 MHz*

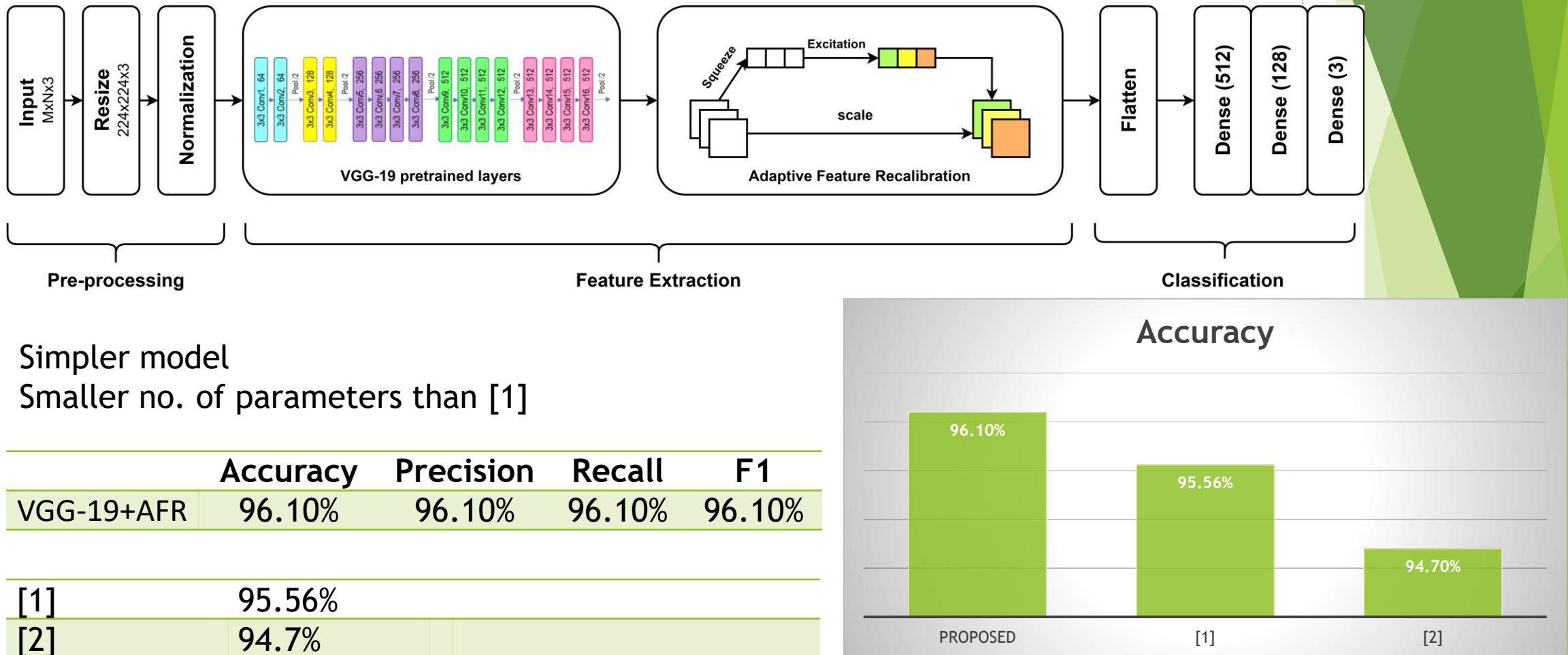
# COVID-19 detection

## ► Total parameters



# COVID-19 detection

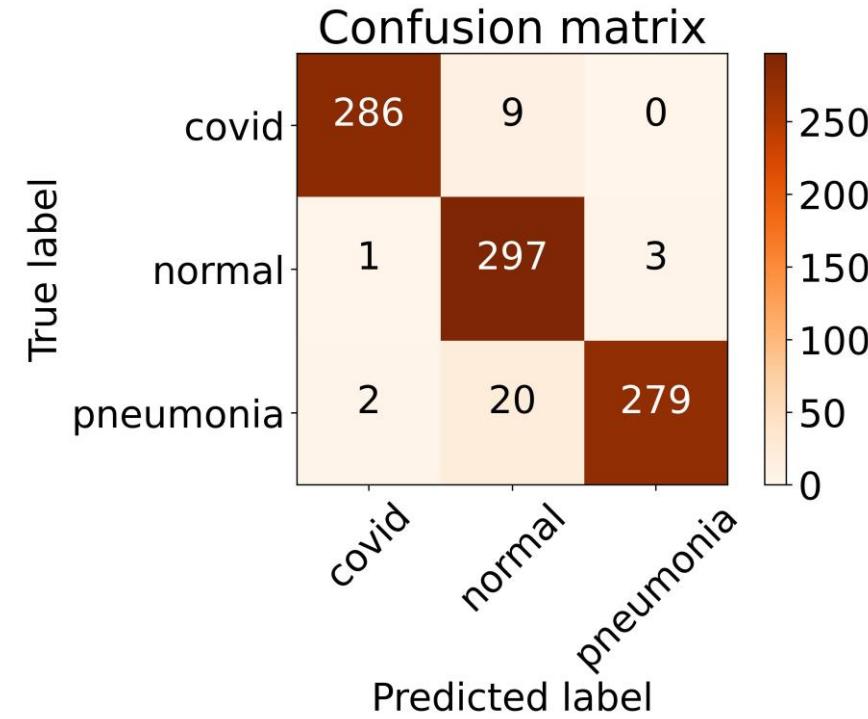
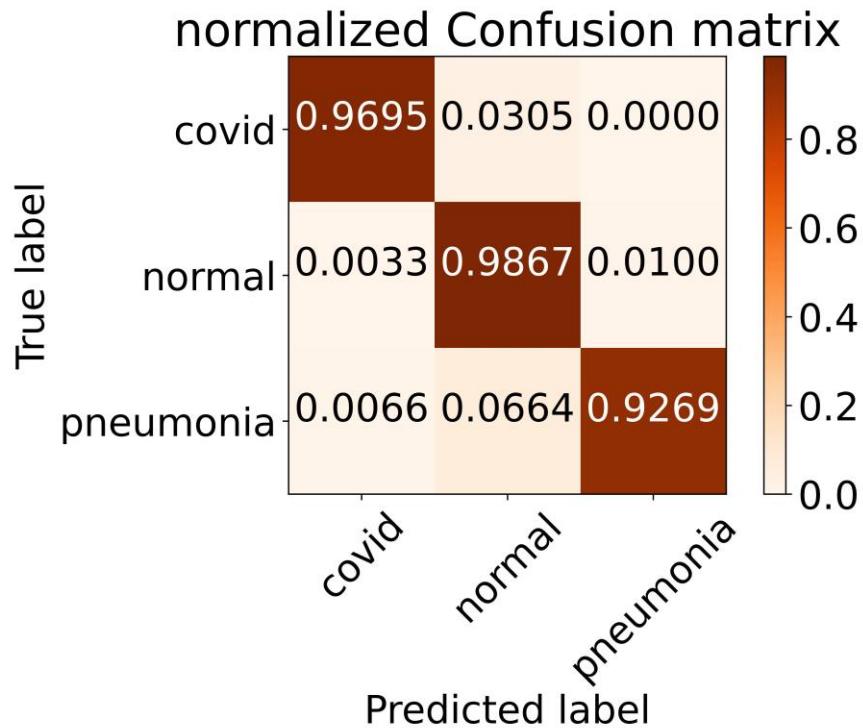
## ► Best results



# COVID-19 detection

## ► Performance

Confusion matrix



# COVID-19 detection

## ► Performance

### Classification report

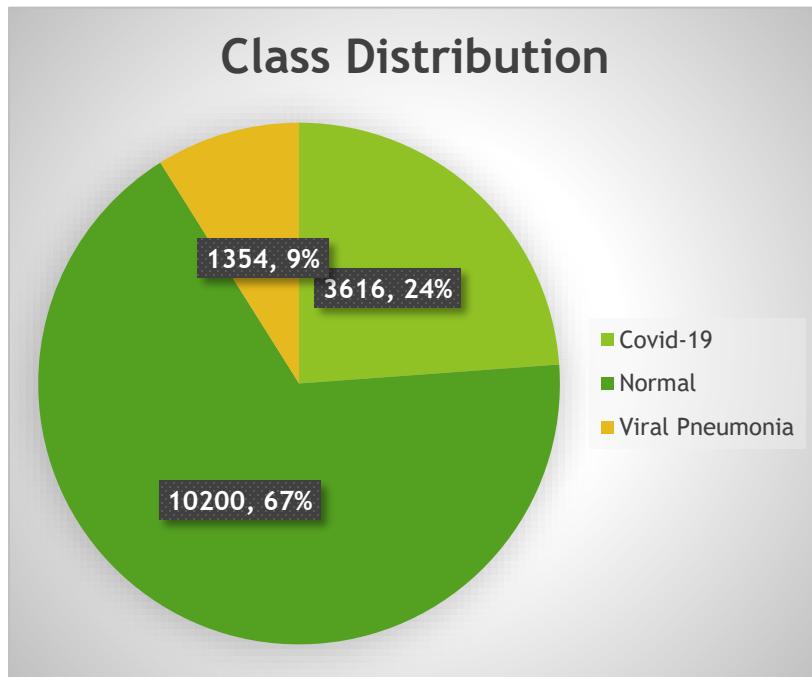
index	Class name	Precision	Recall	F1-score	Support
0	Covid-19	0.9896	0.9695	0.9795	295
1	Normal	0.911	0.9867	0.9474	301
2	pneumonia	0.9894	0.9269	0.9571	301
accuracy				0.9610	897
macro avg		0.9633	0.9610	0.9613	897
Weighted avg		0.9632	0.9610	0.9612	897

# COVID-19 detection

## ► Method validation

COVID-19 Radiography Database

Covid-19	Normal	Viral Pneumonia
3616	10.2 k	1354



# COVID-19 detection

## ► Method validation

COVID-19 Radiography Database

	Handling data imbalance	Train : Test	Model	Accuracy	Recall	Precision	F1-score	Kappa
[1]	Augmentation	70% : 30%	CovidDetNet	98.40%	96.66%	97.00%	96.82%	95.0%
Ours	Weighted loss		VGG-19+AFR	98.22%	97.37%	98.08%	97.72%	96.29%
[2]	Augmentation	90% : 10%	AlexNet	97.59%	95.45%	98.55%	96.9%	
Ours	Weighted loss		VGG19+AFR	98.02%	97.54%	98.08%	97.81%	95.89%

- [1] N. Ullah et al., “A novel CovidDetNet deep learning model for effective COVID-19 infection detection using chest radiograph images,” Appl. Sci. (Basel), vol. 12, no. 12, p. 6269, 2022.
- [2] T. D. Pham, “Classification of COVID-19 chest X-rays with deep learning: new models or fine tuning?,” Health Inf. Sci. Syst., vol. 9, no. 1, 2021.

# COVID-19 detection

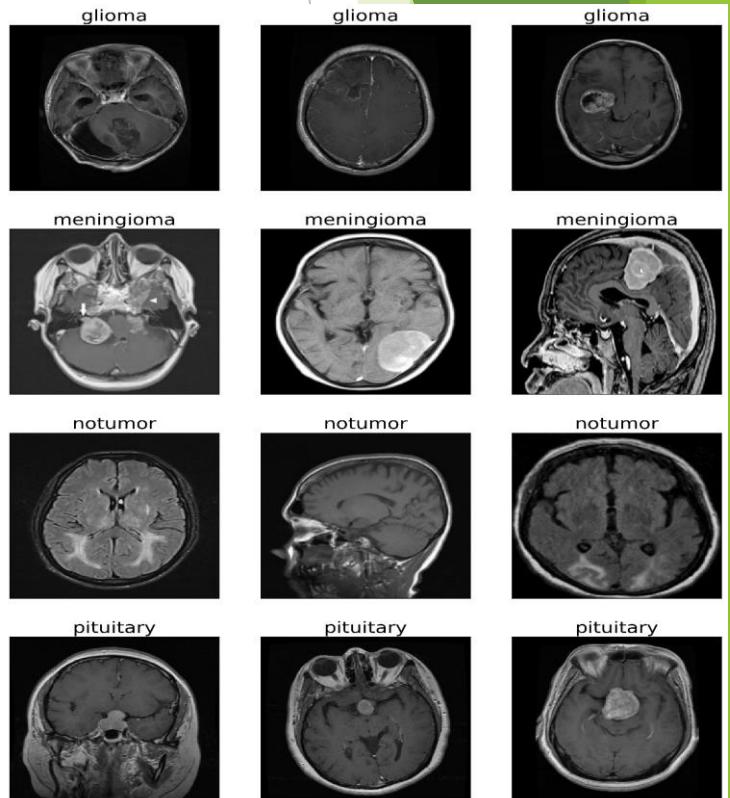
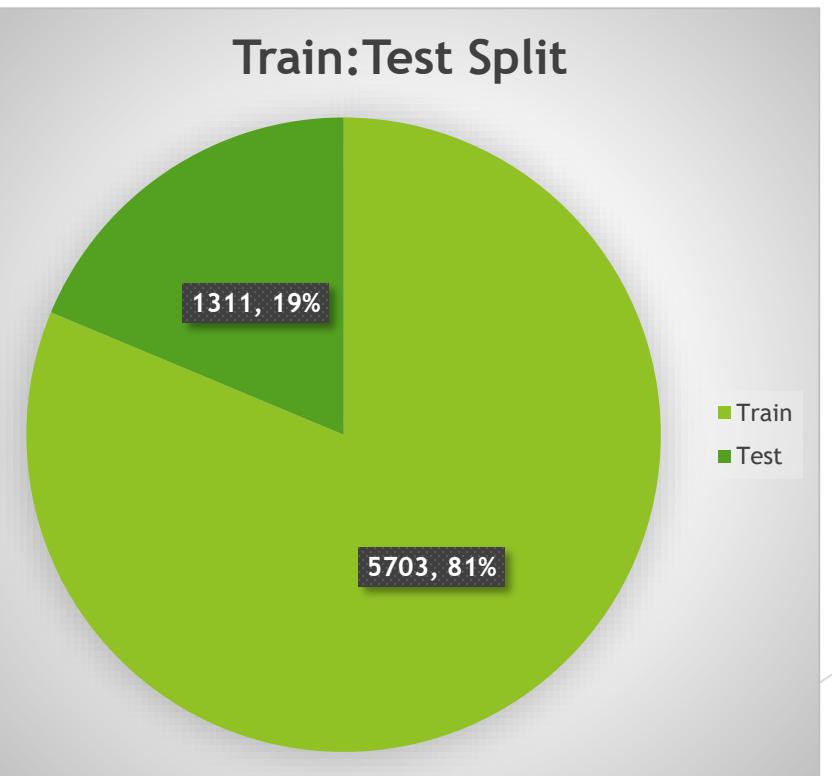
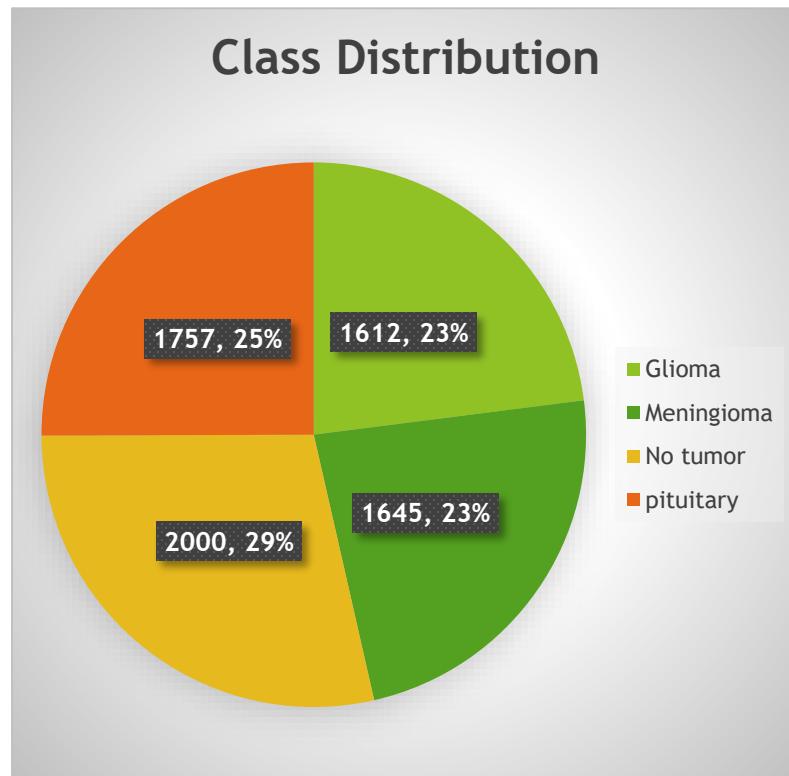
## ► Online testing

Covid-19	Normal	Pneumonia
8 samples	8 samples	8 samples
All correctly diagnosed	1 misdiagnosed	All correctly diagnosed

# Brain tumor classification

## ► Dataset description

	glioma	meningioma	no tumor	pituitary	total
train	1312	1339	1595	1457	5712
test	300	306	405	300	1311



# Brain tumor classification

## ► Dataset description

### Data source

**Indian Institute of Technology Bombay (IIT Bombay)** : A public research university and technical institute in India

**University of California, San Francisco (UCSF)**: A part of the University of California system as its Medical Department and is dedicated entirely to health science and life science

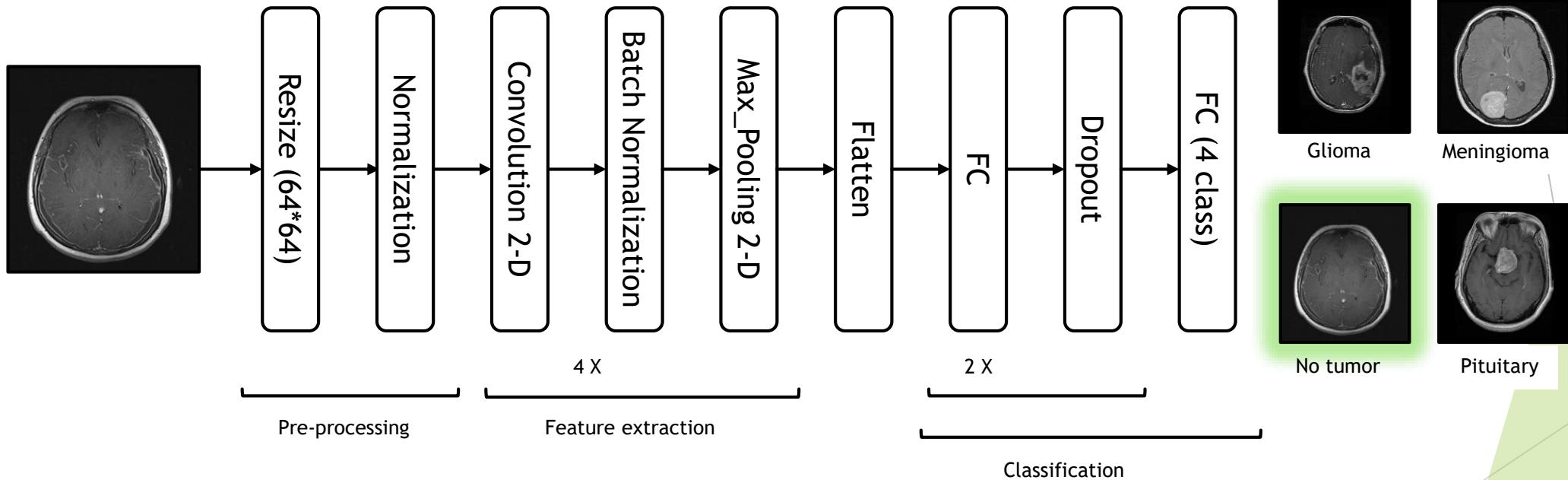
# Brain tumor classification

## ► Experiments summary

version	Model	Notes	Result accuracy
CNN-1	6x { Conv2D BatchNormalization MaxPooling2D } 3 fully connected	Dataset as it is	96.26%
		augmentation	97.03%
CNN-2	4x { Conv2D BatchNormalization MaxPooling2D } 3 fully connected	augmentation	99.16%

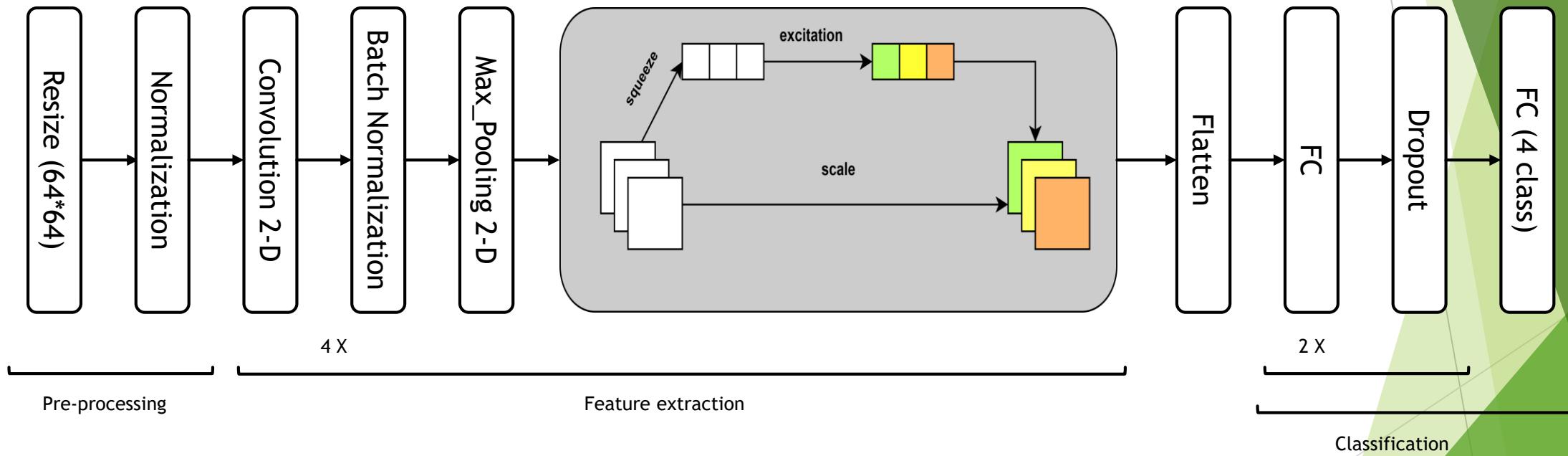
# Brain tumor classification

## ► CNN architecture



# Brain tumor classification

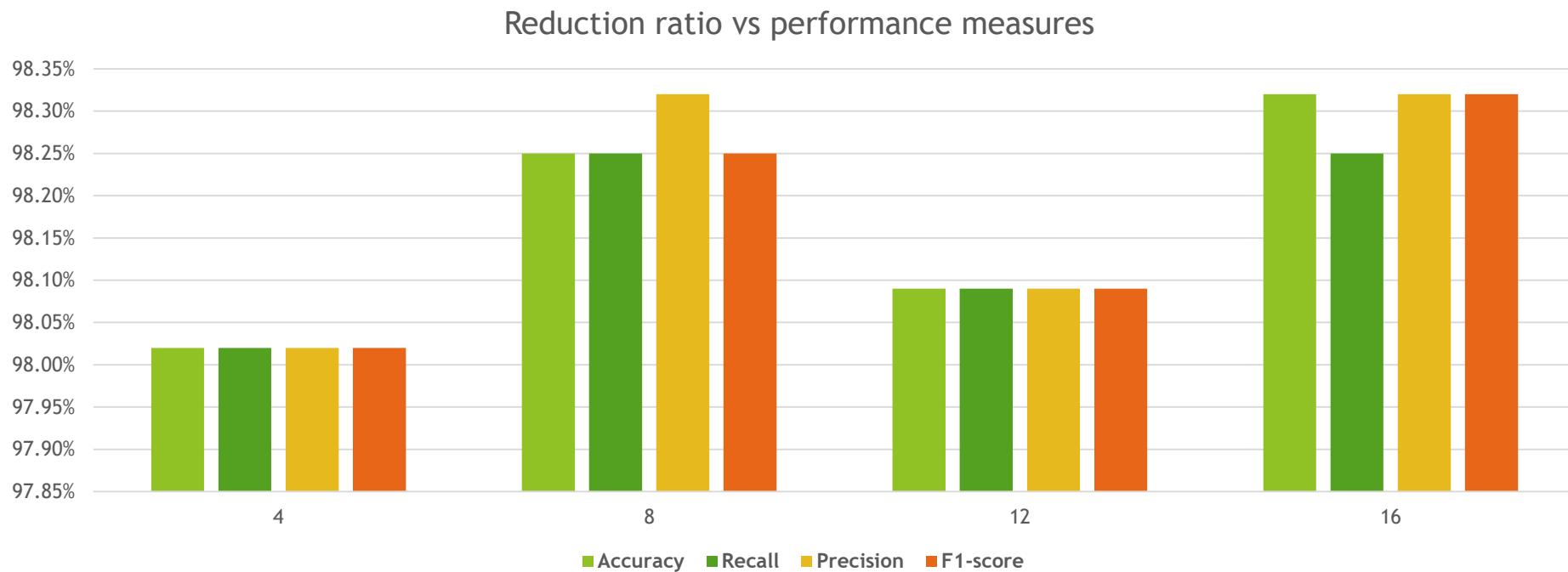
## ► CNN+ Adaptive Feature Recalibration (AFR)



Hyper-parameters:  
Reduction ration

# Brain tumor classification

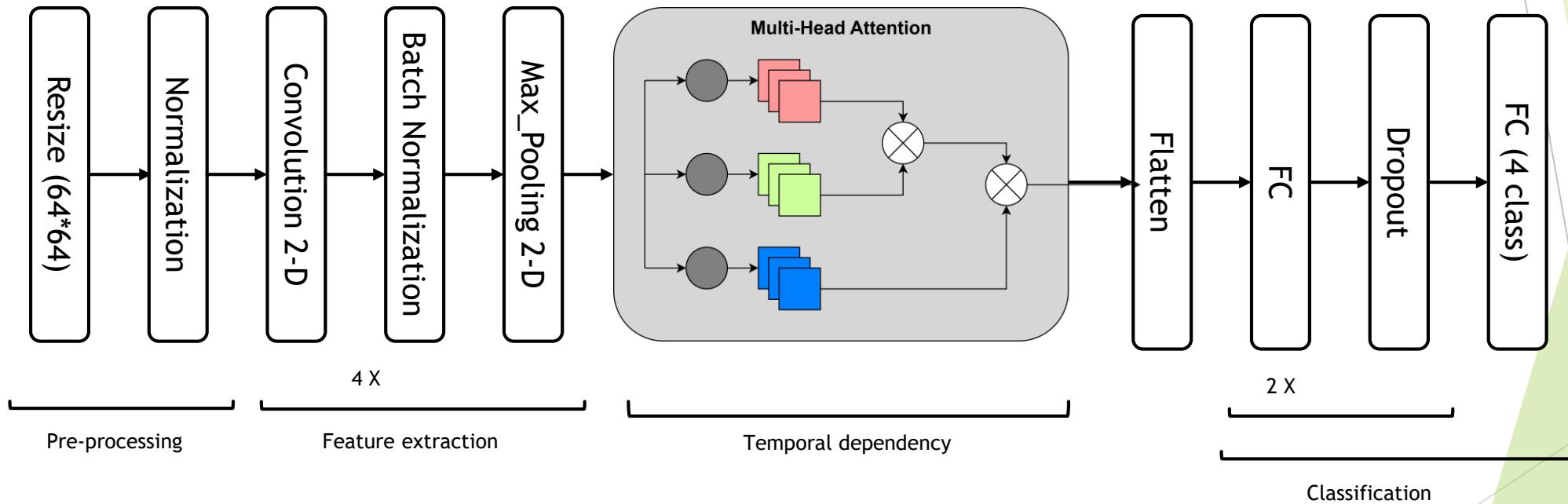
## ► CNN+ Adaptive Feature Recalibration (AFR)



Reduction ratio	Accuracy	Precision	Recall	F1
16	98.32%	98.32%	98.25%	98.32%

# Brain tumor classification

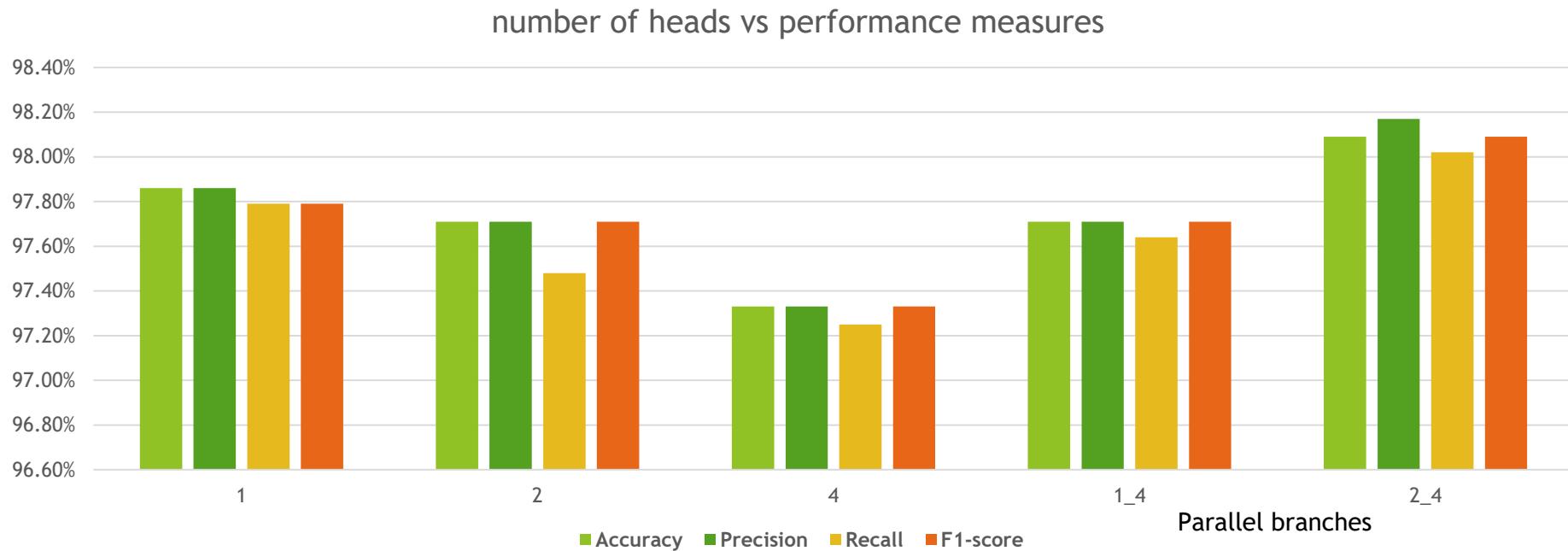
## ► CNN+ Multi-head Attention (MHA)



Hyper-parameters:  
No. of heads

# Brain tumor classification

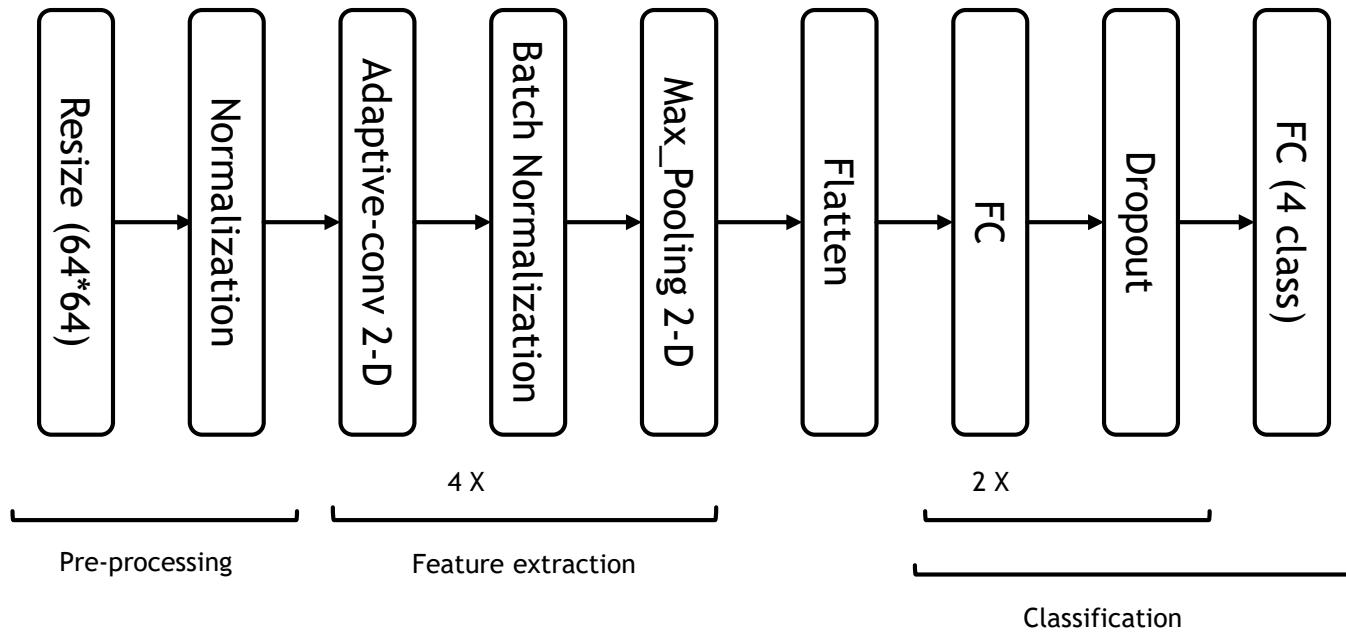
## ► CNN+ Multi-head Attention (MHA)



No. of heads	Accuracy	Precision	Recall	F1
2-4	98.09%	98.17%	98.02%	98.09%

# Brain tumor classification

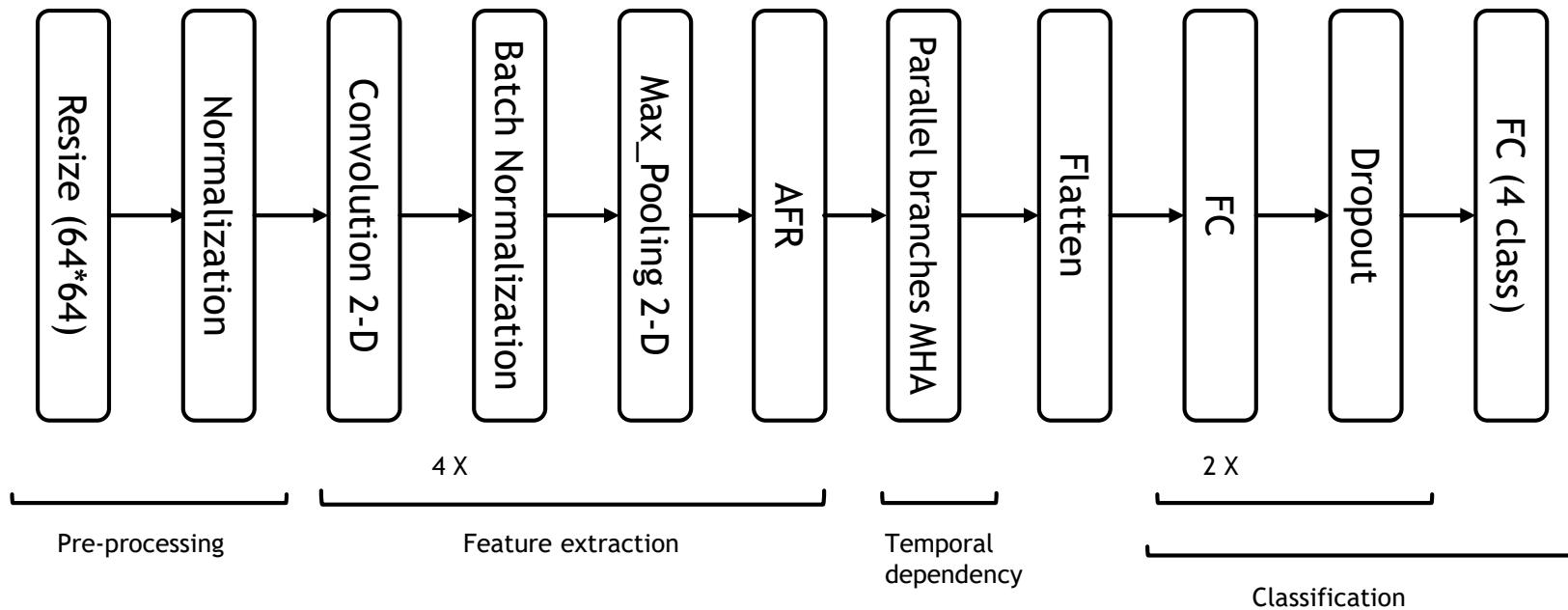
## ► Adaptive Kernel Size Convolution (AKSC)



Accuracy	precision	Recall	F1
98.17%	98.17%	98.17%	98.17%

# Brain tumor classification

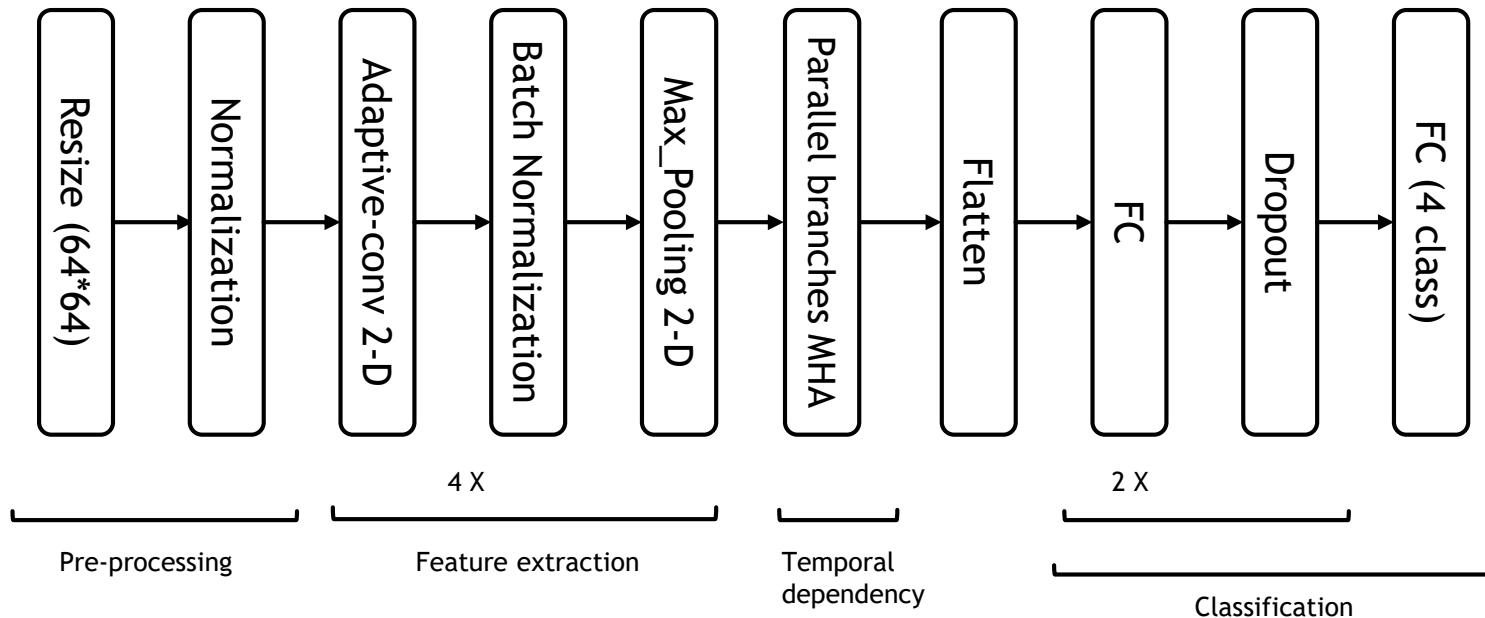
## ► CNN+AFR+MHA



Accuracy	precision	Recall	F1
96.19%	96.24%	95.58%	96.19%

# Brain tumor classification

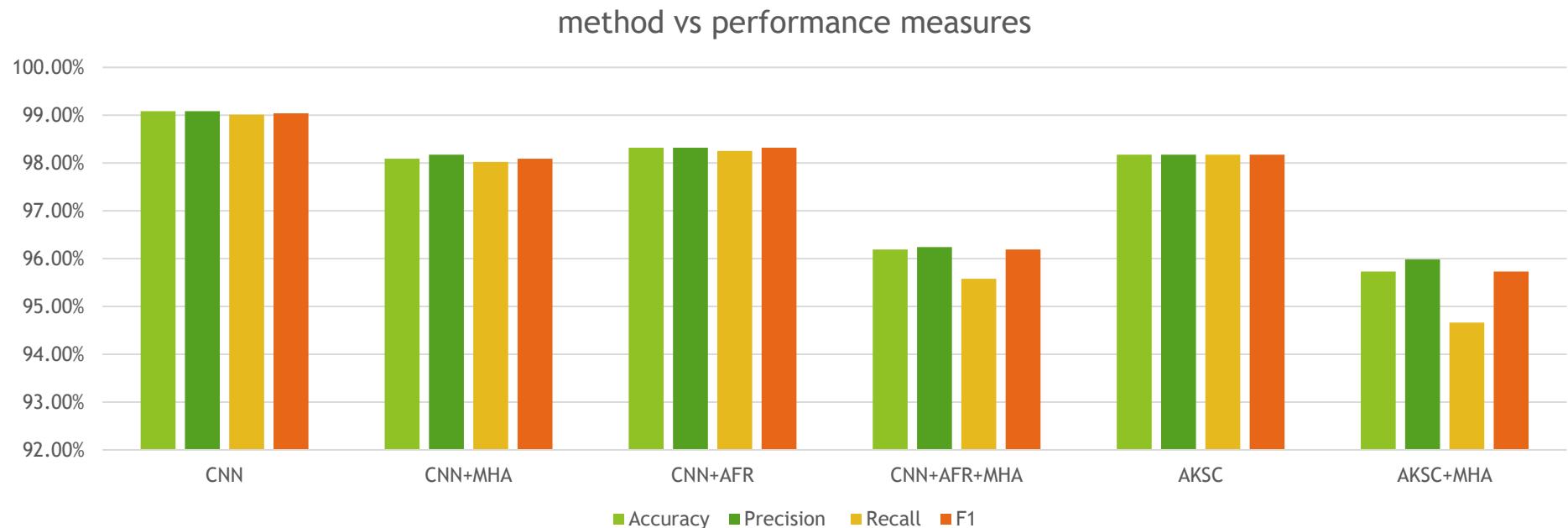
## ► AKSC+MHA



Accuracy	precision	Recall	F1
95.73%	95.98%	94.66%	95.73%

# Brain tumor classification

## ► Experiments summary



---

Accuracy	precision	Recall	F1
----------	-----------	--------	----

---

99.08%
--------

99.08%
--------

99.01%
--------

99.04%
--------

# Brain tumor classification

## ► Training time



## NVIDIA T4 GPU

Architecture: Turing

CUDA Cores: 2,560

Tensor Cores: 320

Memory Size: 16 GB GDDR6

Memory Bandwidth: 320 GB/s

Memory Interface: 256-bit

Max Power Consumption: 70 Watts

PCIe Interface: PCIe 3.0 x16

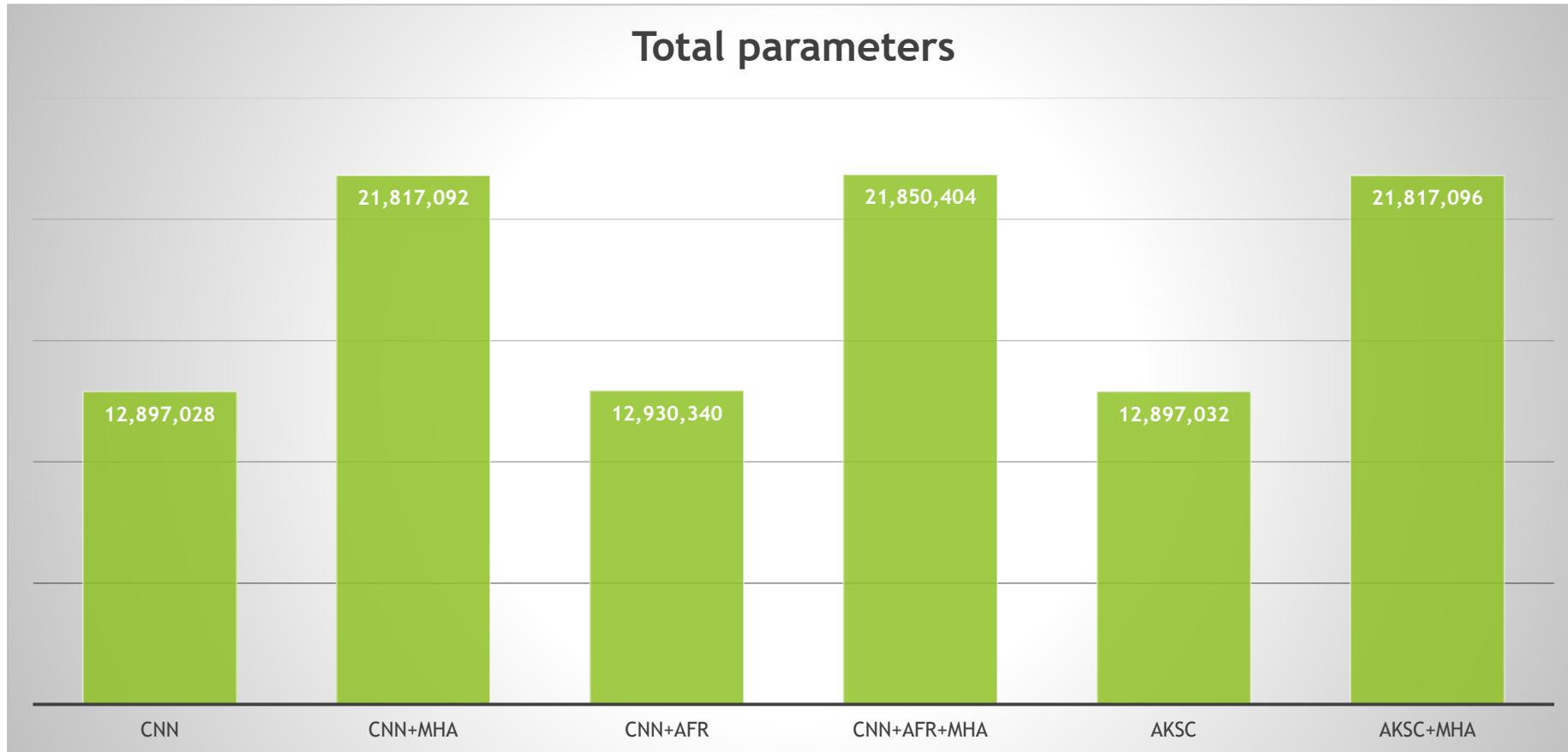
Form Factor: Single-slot, Full-height

Compute Capability: 7.5

*GPU Boost Clock: 1,590 MHz*

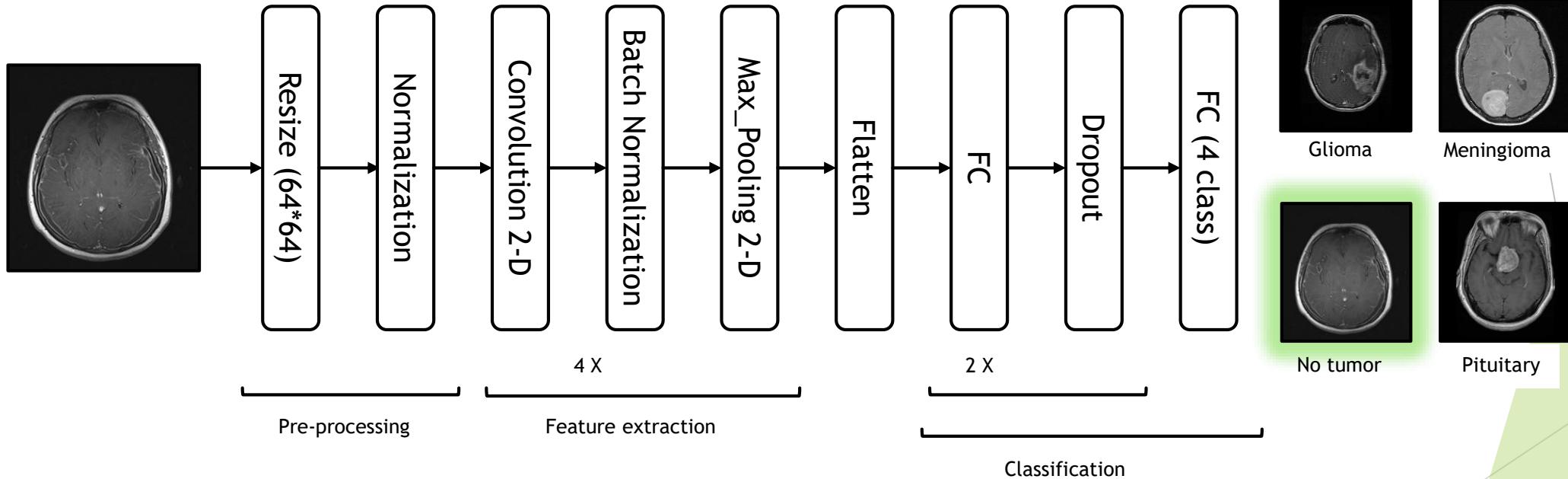
# Brain tumor classification

## ► Total parameters



# Brain tumor classification

## ► Best results

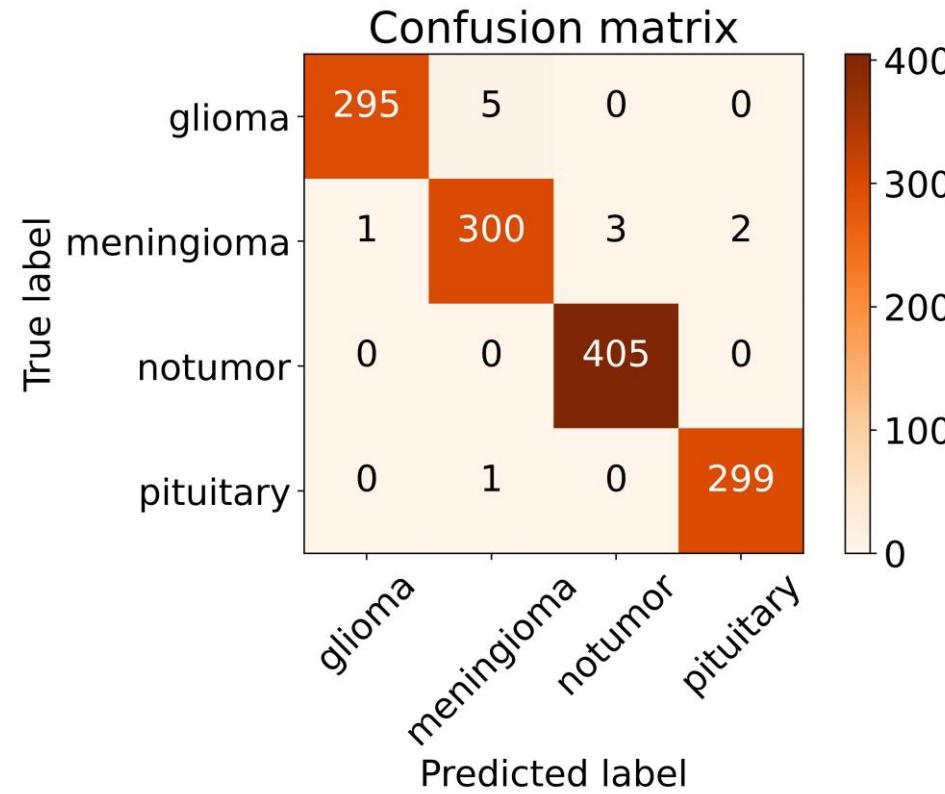
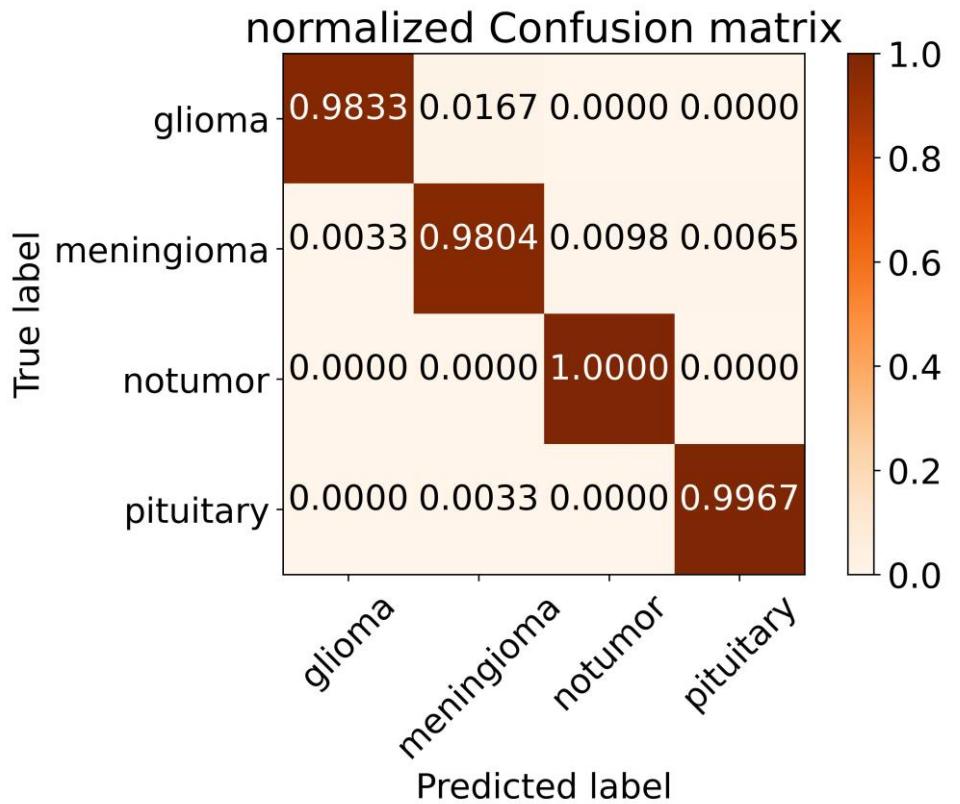


99.16% accuracy

# Brain tumor classification

## ► Performance

### Confusion matrix



# Brain tumor classification

## ► Performance

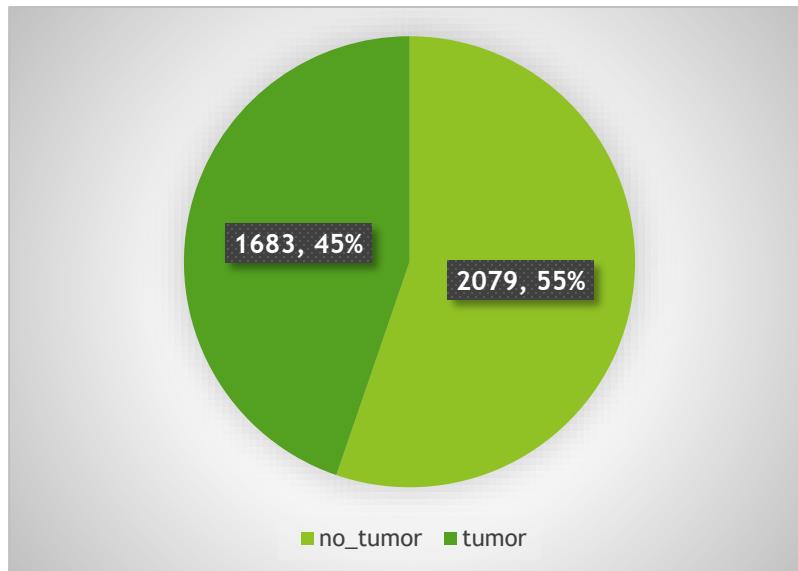
### Classification report

index	Class name	Precision	Recall	F1-score	Support
0	Glioma	0.9966	0.9833	0.9899	300
1	Meningioma	0.9804	0.9804	0.9804	306
2	No tumor	0.9926	1	0.9963	405
3	Pituitary	0.9934	0.9967	0.995	300
accuracy				0.9908	1311
macro avg		0.9908	0.9901	0.9904	1311
Weighted avg		0.9909	0.9908	0.9908	1311

# Brain tumor classification

## ► Method validation

Brain Tumor Dataset



- [1] D. Santos and E. Santos, “Brain tumor detection using Deep Learning,” bioRxiv, p. 2022.01.19.22269457, 2022.

	Model	Accuracy	precision	Recall	F1
<b>Proposed</b>	CNN	98.14%	98.22%	98%	98.10%
[1]	MobileNetV2	89%			

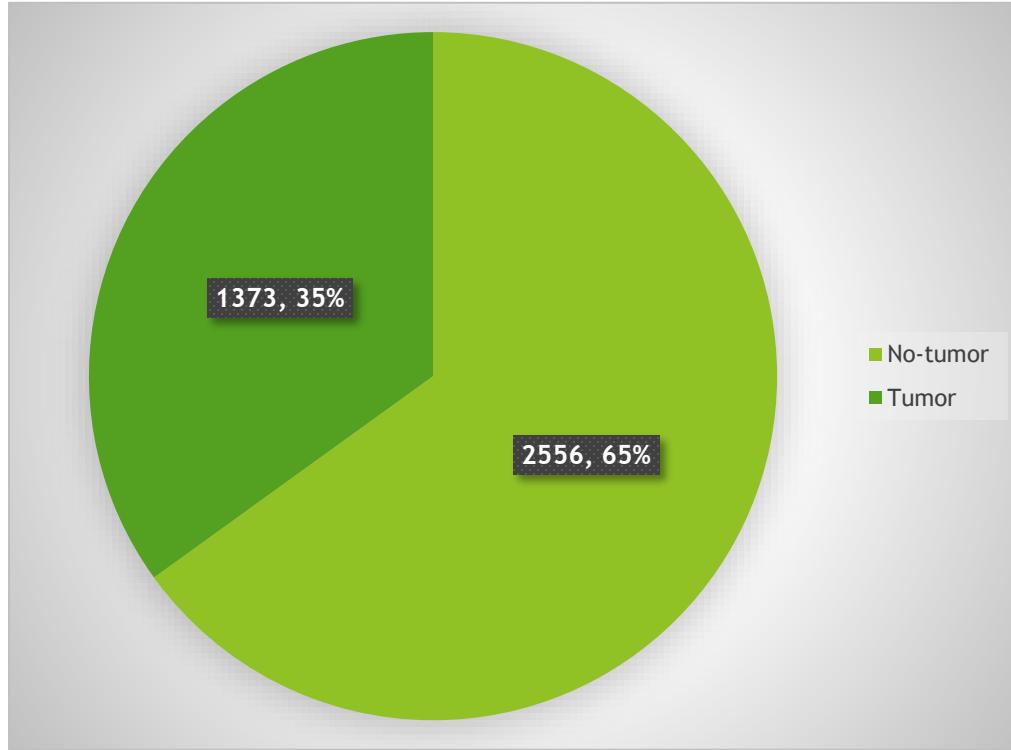
# Brain tumor detection

## ► Online testing

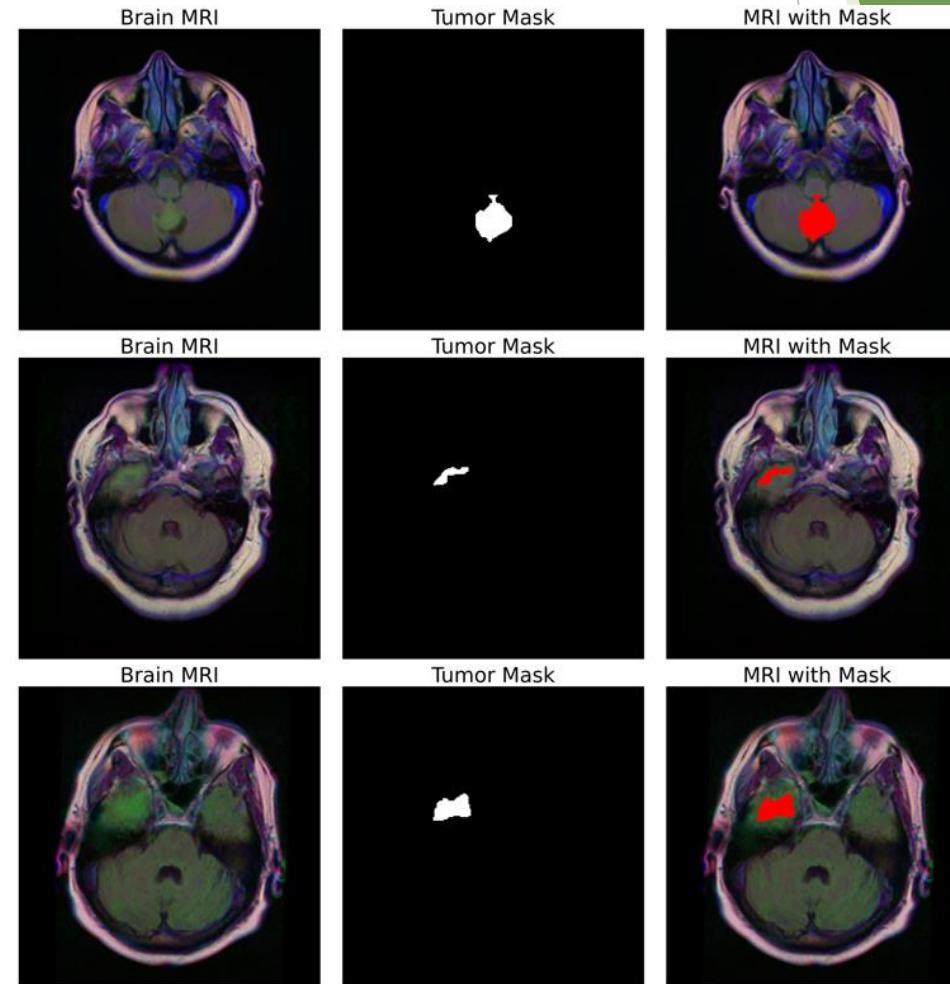
Meningioma	Normal	Glioma	Pituitary
8 samples	8 samples	8 samples	8 samples
1 misdiagnosed	All correctly diagnosed	All correctly diagnosed	All correctly diagnosed

# Brain tumor segmentation

## ► Dataset description



RGB Images



# Brain tumor segmentation

## ► Dataset description

Data source

- **The Cancer Imaging Archive (TCIA):** A public repository of medical images and associated metadata.
- **The German Cancer Research Center (DKFZ):** A research institute that specializes in cancer research.
- **The University of Pennsylvania:** A research university that has a strong track record in medical imaging research.

# Brain tumor segmentation

## ► Segmentation performance measures



- Intersection over union

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

A diagram illustrating the components of IoU. It shows four colored regions: 'True Positives' (blue), 'False Negatives' (yellow), 'False Positives' (red), and 'Area of Union' (the combined area of blue and red).

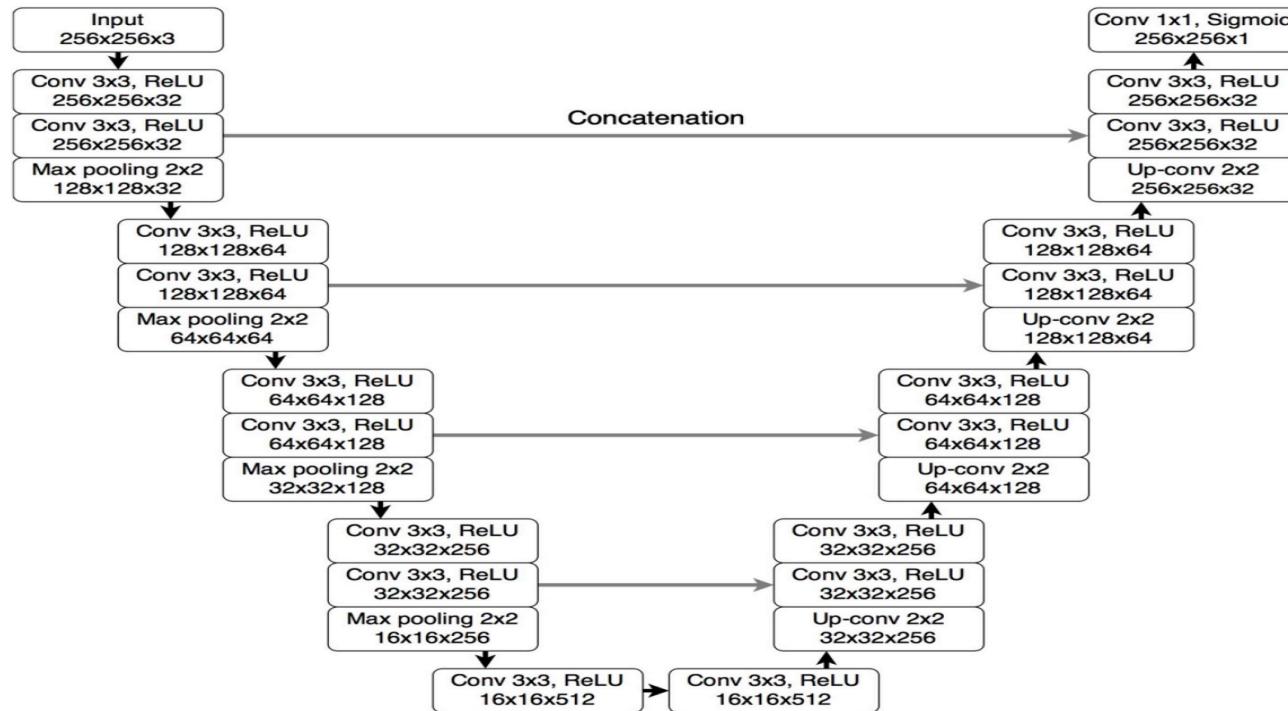
- Dice coefficient

$$\frac{2 \times \text{Intersection}}{\text{True Positives} + \text{False Positives}}$$

A diagram illustrating the Dice coefficient using two overlapping circles. One circle is blue and the other is orange. Their overlapping area represents the 'Intersection', while the sum of their individual areas represents the 'True Positives' and 'False Positives' combined.

# Brain tumor segmentation

- ▶ Reference paper for result comparison

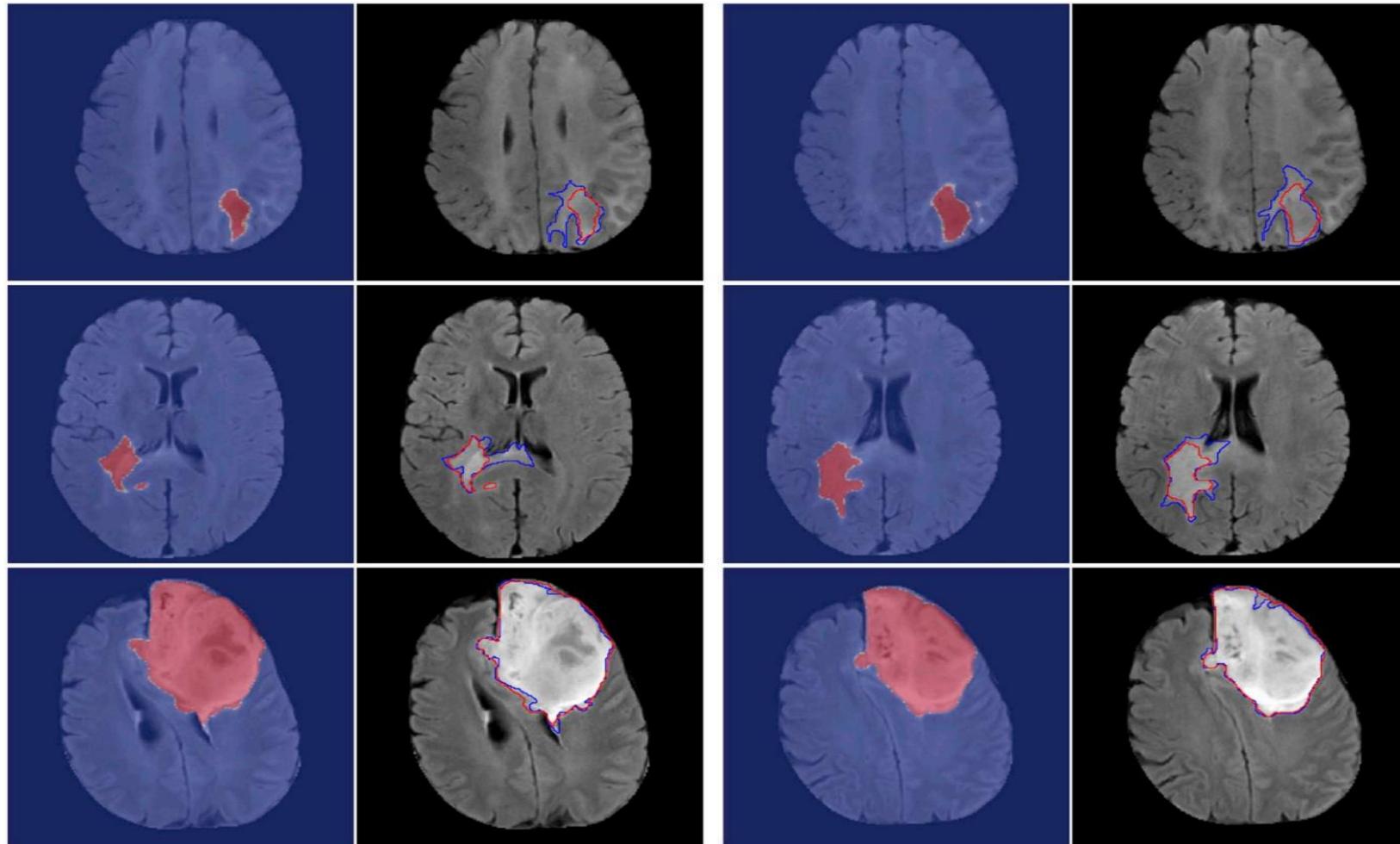


Dice coefficient score: 82%

- [1] M. Buda, A. Saha, and M. A. Mazurowski, “Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm,” Comput. Biol. Med., vol. 109, pp. 218-225, 2019.

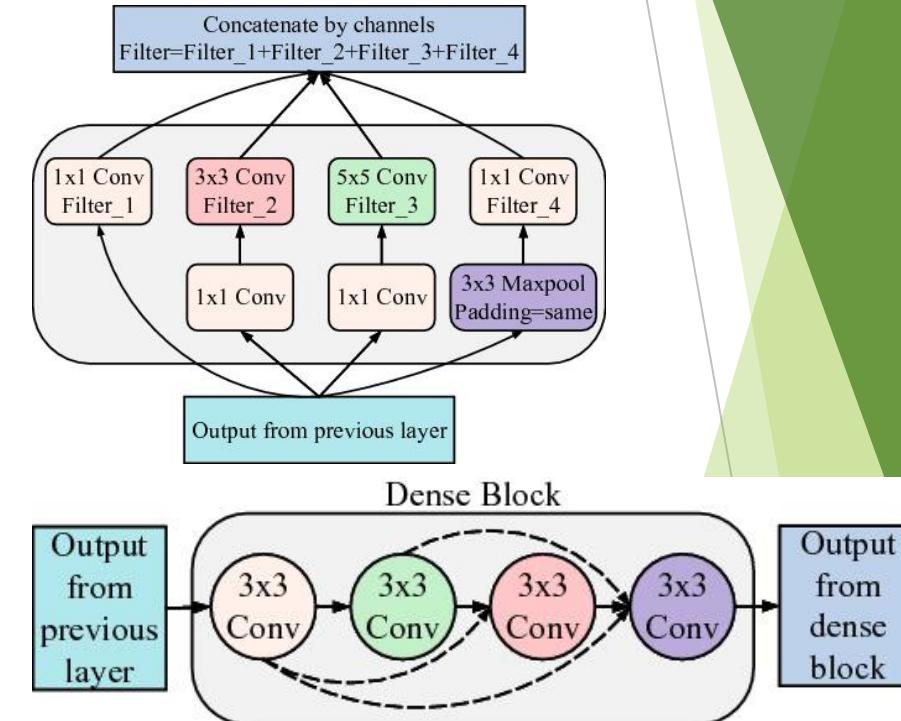
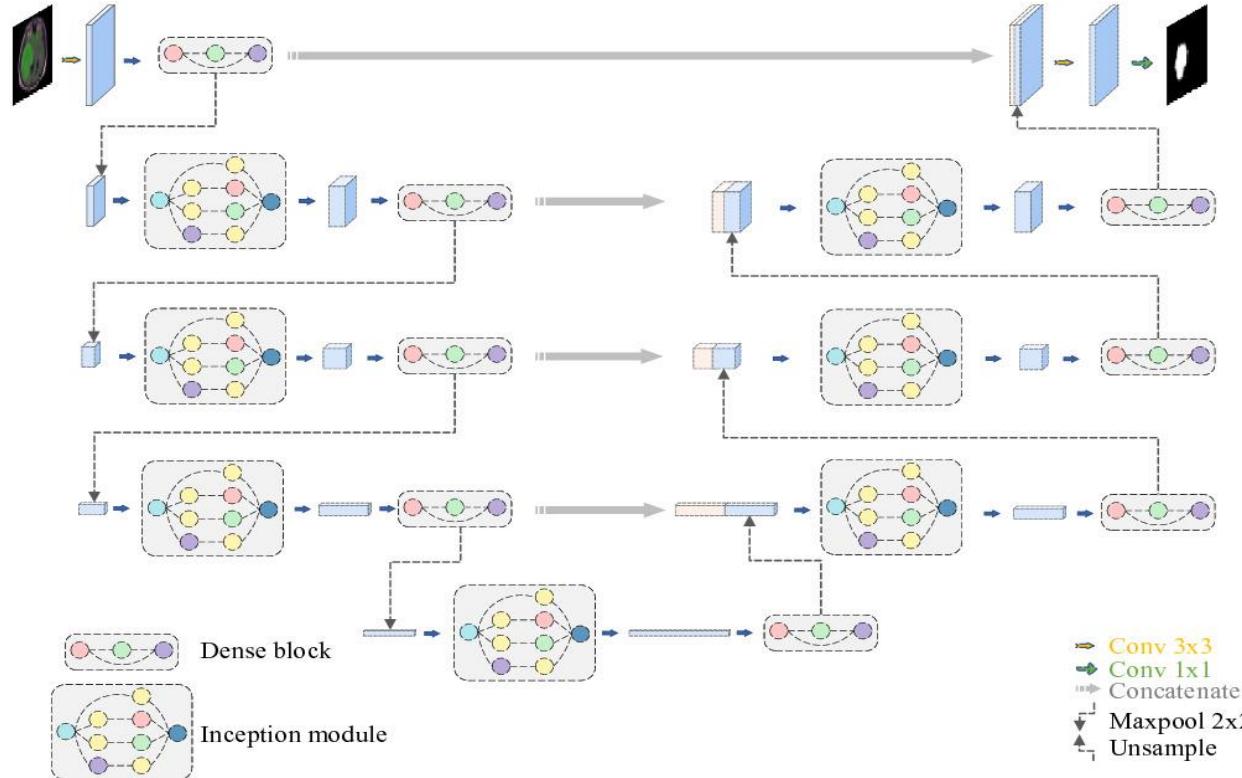
# Brain tumor segmentation

- ▶ Reference paper for result comparison



# Brain tumor segmentation

## ► Reference paper for result comparison

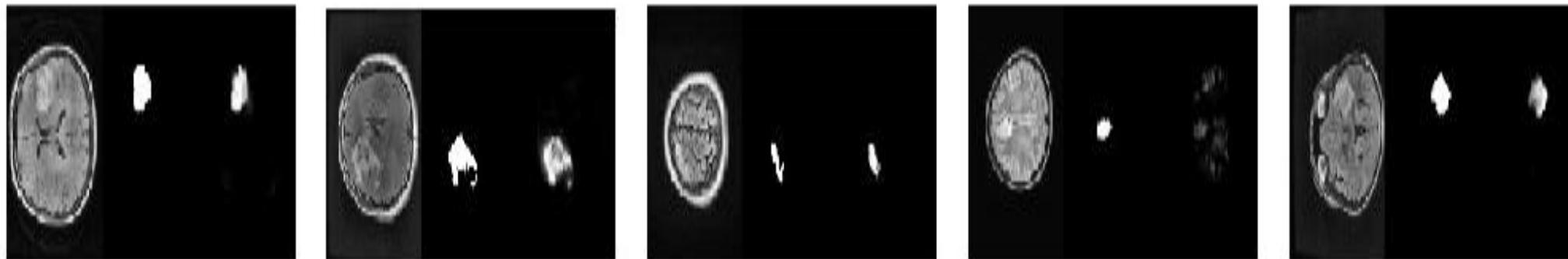


- [2] L. Yi, J. Zhang, R. Zhang, J. Shi, G. Wang, and X. Liu, “SU-net: An efficient encoder-decoder model of federated learning for brain tumor segmentation,” in *Artificial Neural Networks and Machine Learning – ICANN 2020*, Cham: Springer International Publishing, 2020, pp. 761–773.

# Brain tumor segmentation

- ▶ Reference paper for result comparison

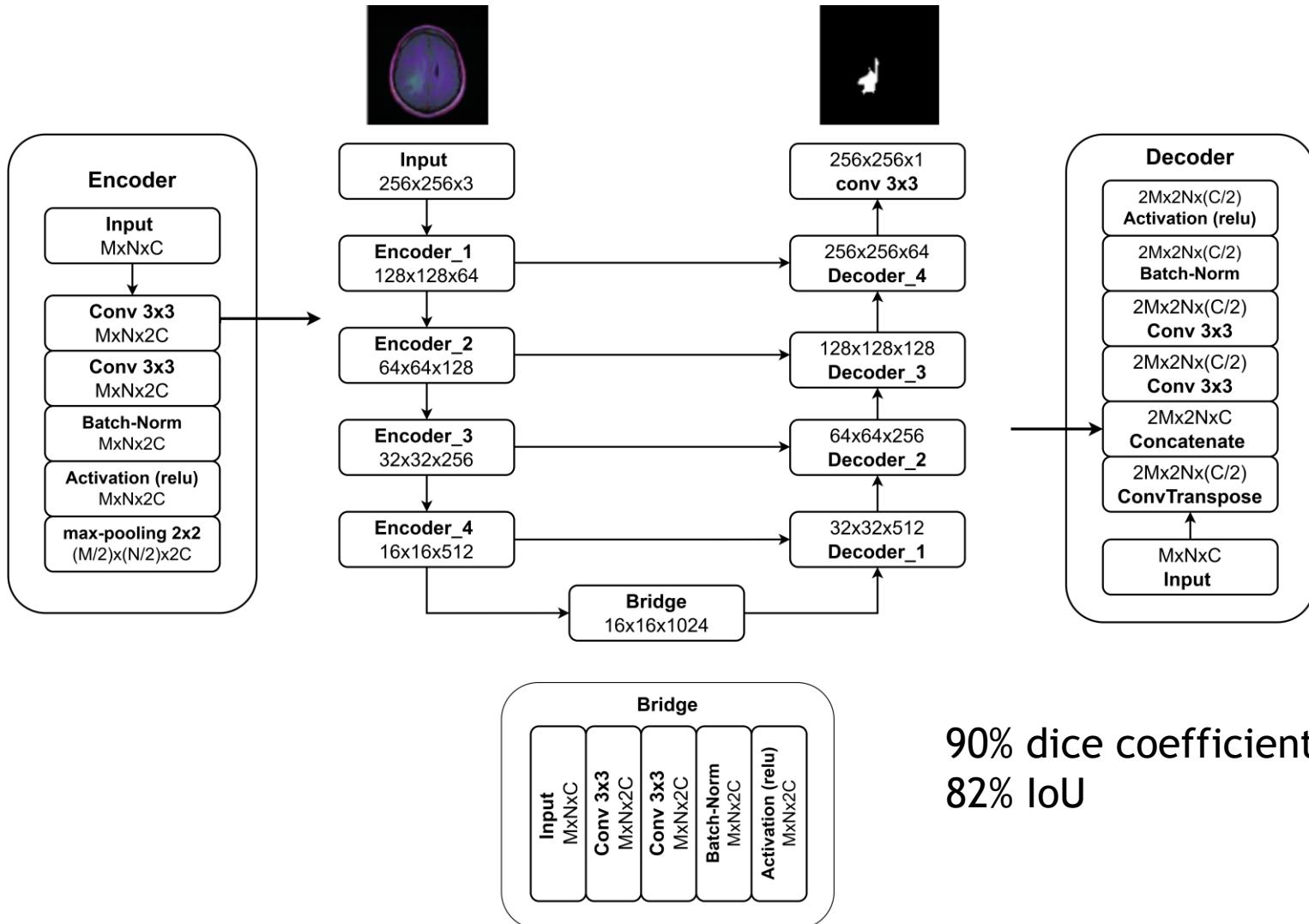
78.5 Dice coefficient



- [2] L. Yi, J. Zhang, R. Zhang, J. Shi, G. Wang, and X. Liu, “SU-net: An efficient encoder-decoder model of federated learning for brain tumor segmentation,” in *Artificial Neural Networks and Machine Learning – ICANN 2020*, Cham: Springer International Publishing, 2020, pp. 761–773.

# Brain tumor segmentation

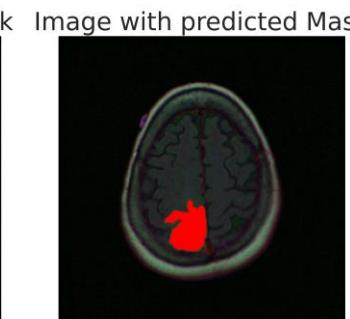
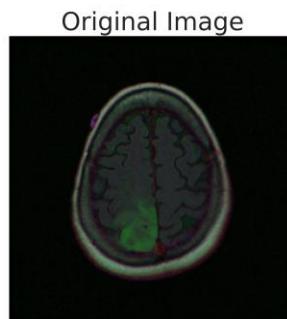
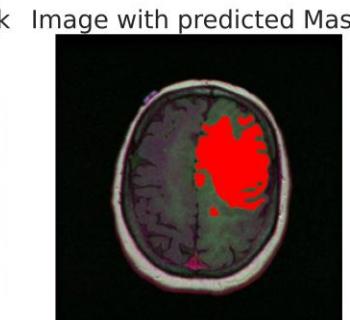
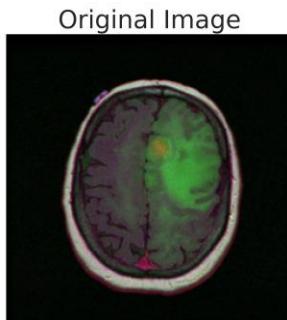
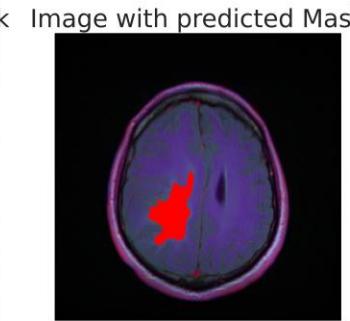
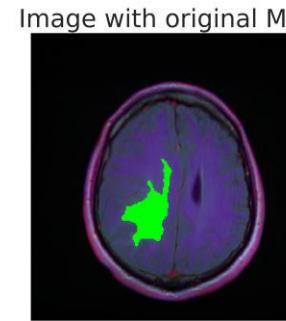
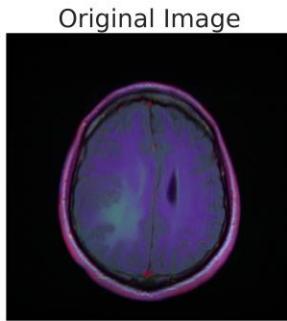
## ► Proposed U-Net model



# Brain tumor segmentation

## ► Proposed U-Net model

### Predictions

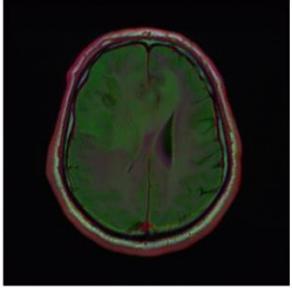


# Brain tumor segmentation

## ► Proposed U-Net model

### Predictions

Original Image



Original Mask



Prediction

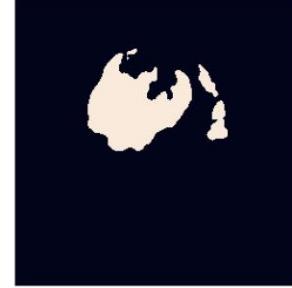


Image with original Mask

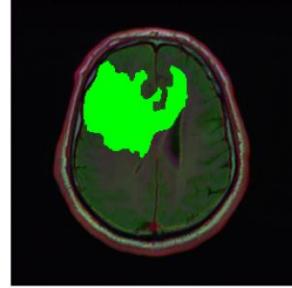
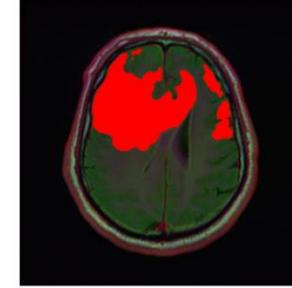
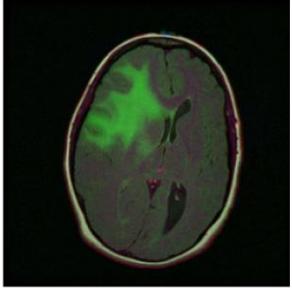


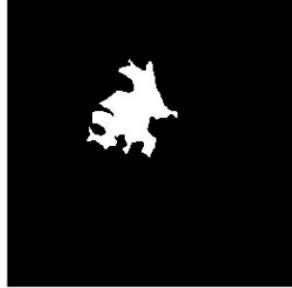
Image with predicted Mask



Original Image



Original Mask



Prediction

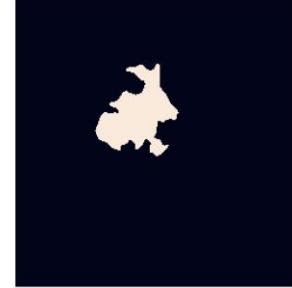


Image with original Mask

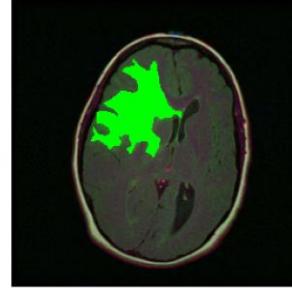
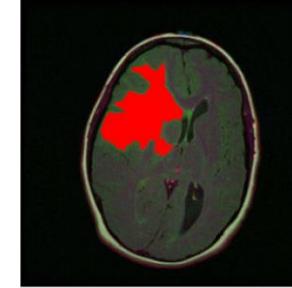
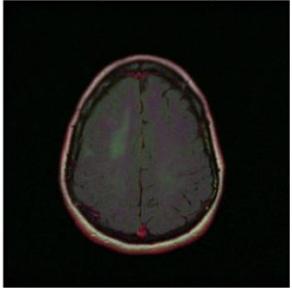


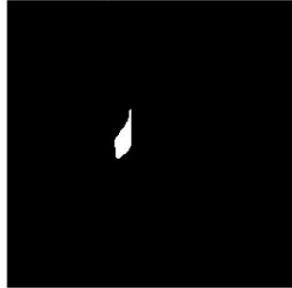
Image with predicted Mask



Original Image



Original Mask



Prediction

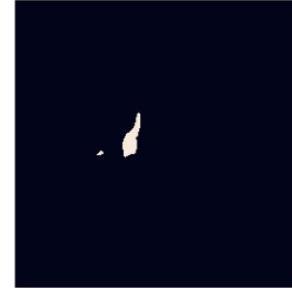


Image with original Mask

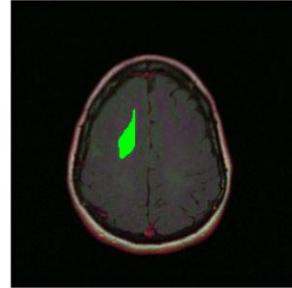
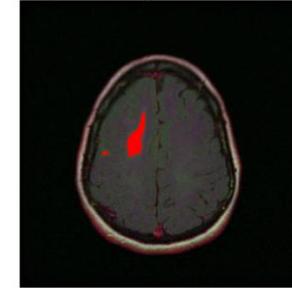
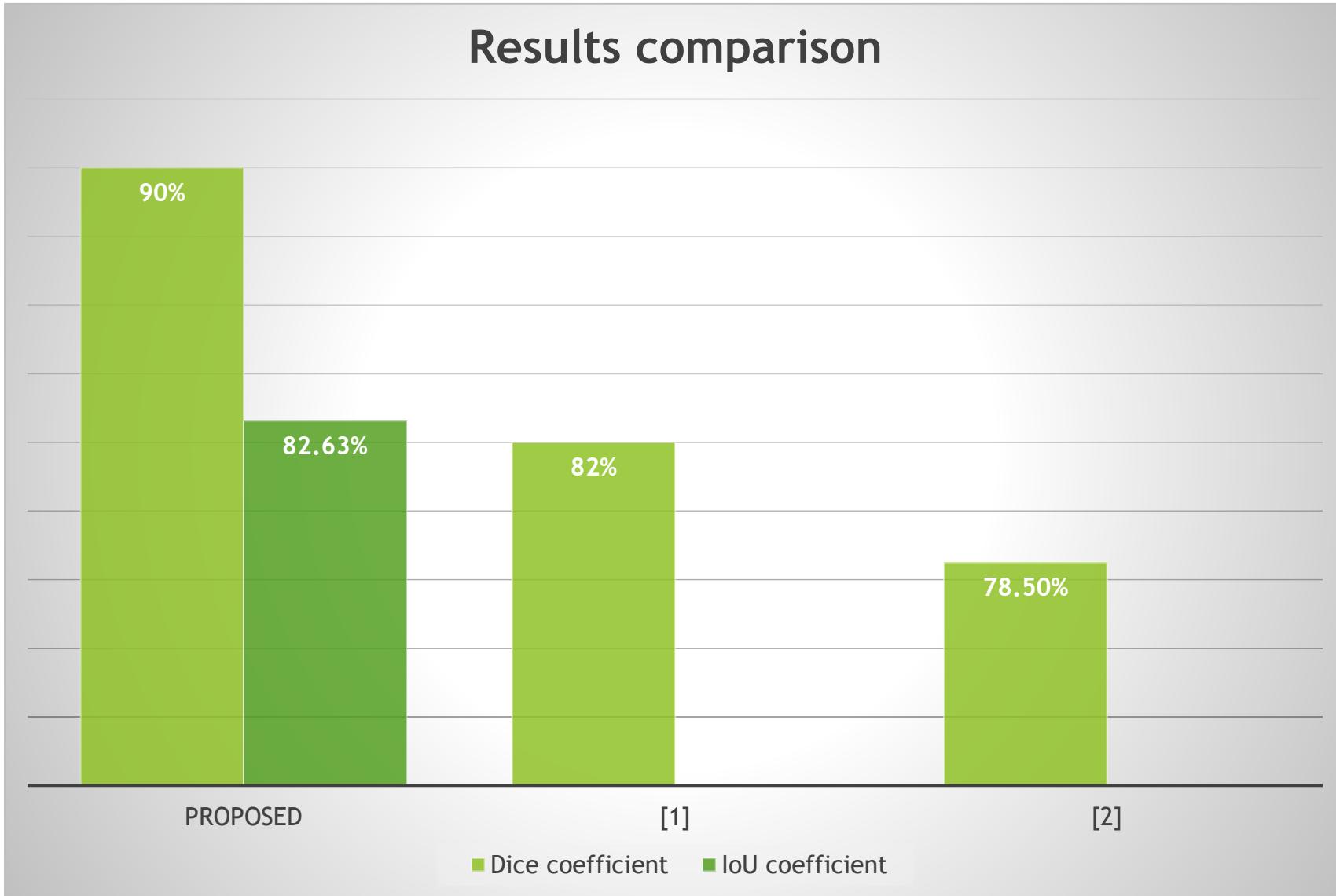


Image with predicted Mask



# Brain tumor segmentation

## ► Result comparison

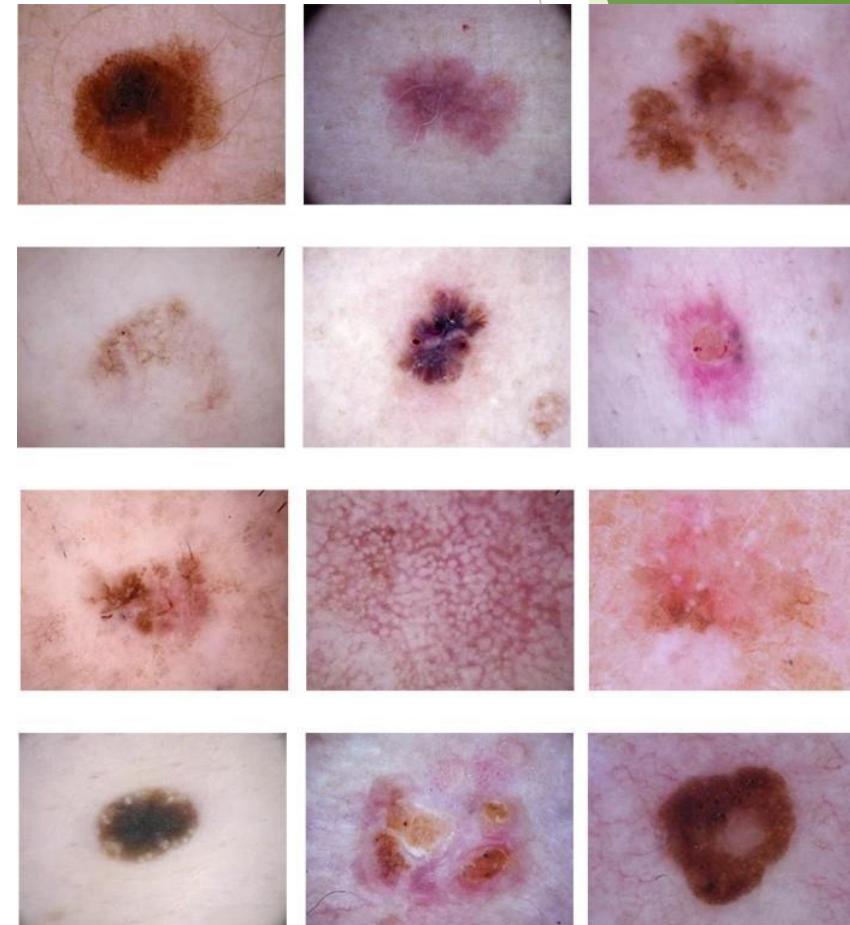
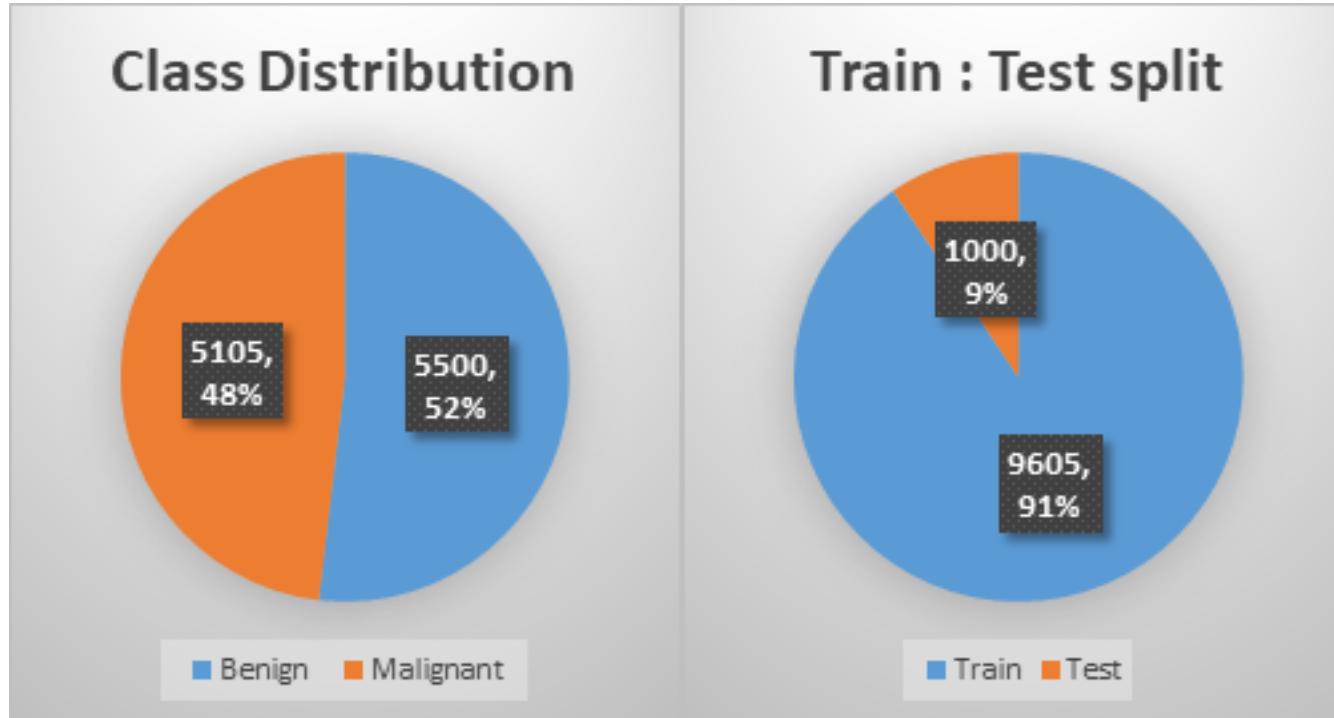


# Skin cancer detection

## ► Dataset description

HAM10000 dataset

	Malignant	Benign	Total
Train	4605	5000	9605
Test	500	500	1000



# Skin cancer detection

## ► Dataset description

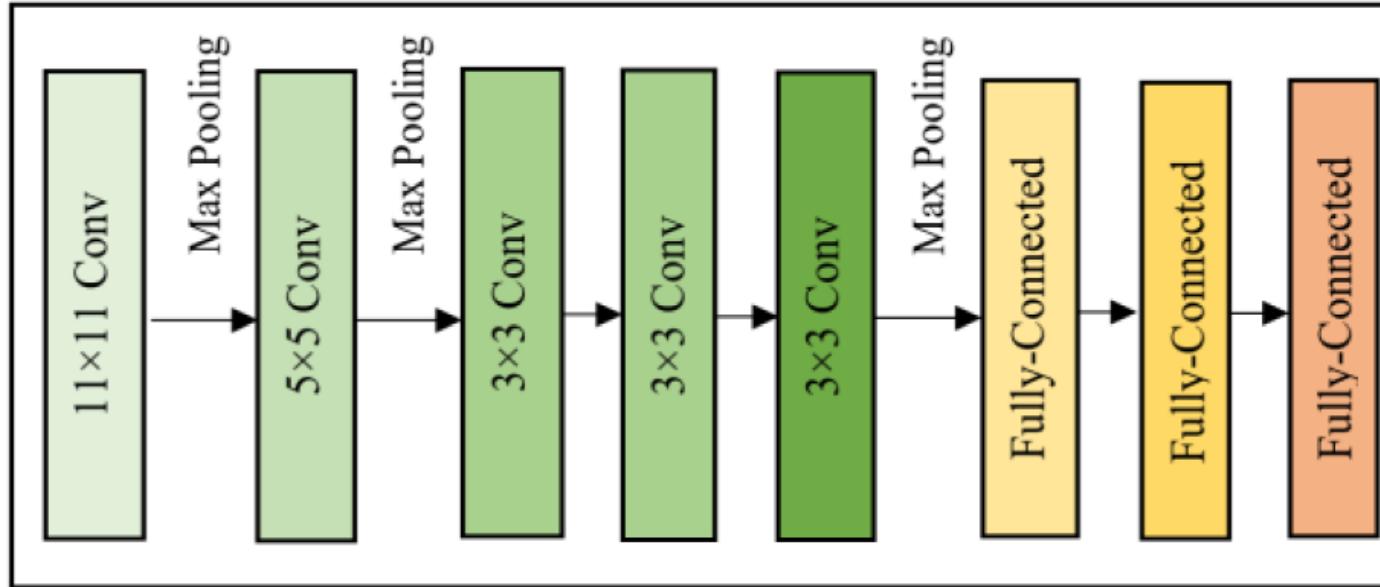
### Data source

- **Austrian Society for Dermatology and Venereology (ÖGDV)**: A professional organization for dermatologists and venereologists in Austria
- **German Society for Dermatology and Venereology (DDG)**: A professional medical society in Germany that focuses on dermatology and venereology
- **European Academy of Dermatology and Venereology (EADV)** : An international organization that represents dermatologists and venereologists in Europe

# Skin cancer detection

## ► Reference papers for result comparison

- [1] A. A, “A deep learning approach to skin cancer detection in dermoscopy images,” J. Biomed. Phys. Eng., vol. 10, no. 6, pp. 801–806, 2020.

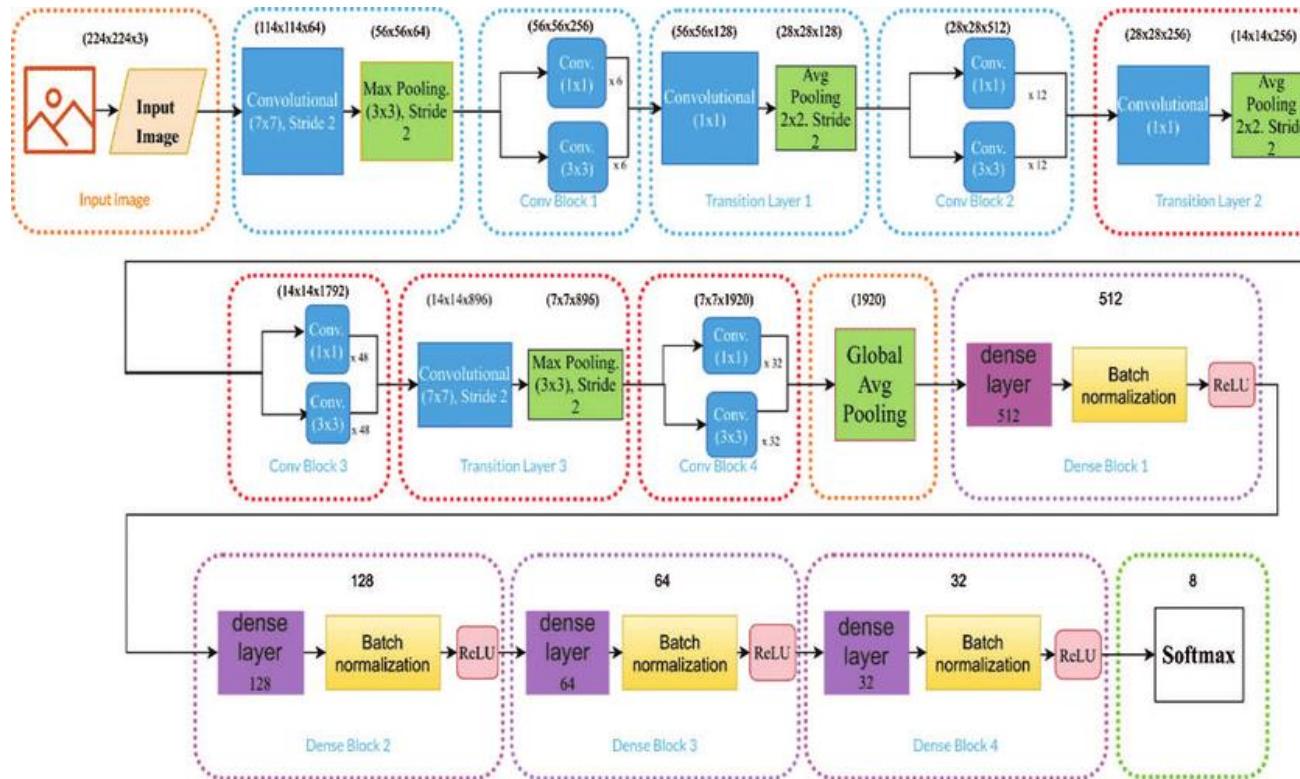


AlexNet pre-trained model  
84% accuracy

# Skin cancer detection

## ► Reference papers for result comparison

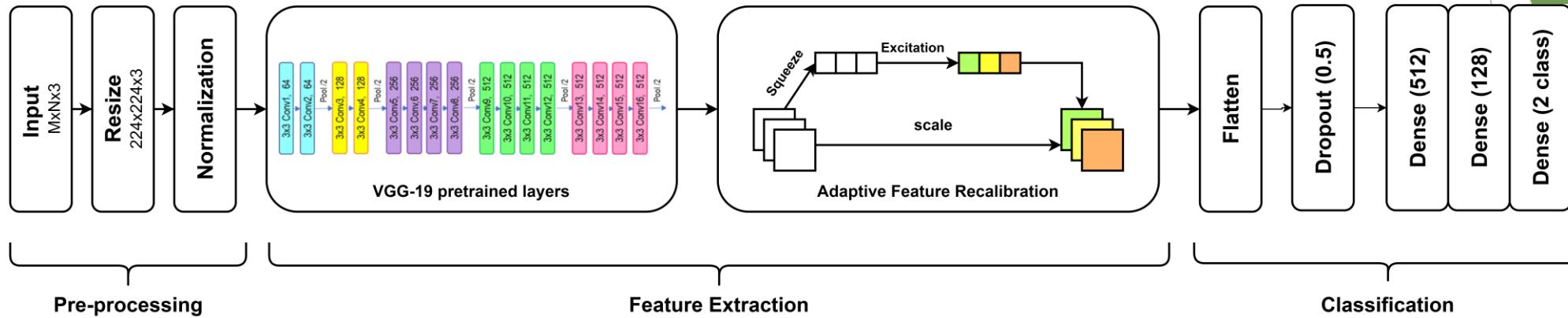
- [2] M. Upadhyay, J. Rawat, and S. Maji, “Skin cancer image classification using deep neural network models,” in Evolution in Computational Intelligence, Singapore: Springer Nature Singapore, 2022, pp. 451-460..



DenseNet201 pre-trained model  
93% accuracy

# Skin cancer detection

## ► VGG-19+Adaptive feature recalibration (AFR)



	Accuracy	precision	Recall	F1
<b>Proposed</b>	92.10%	93.58%	90.40%	92.10
[1]	84%		81%	
[2]	93%	93%	92%	93%

# Skin cancer detection

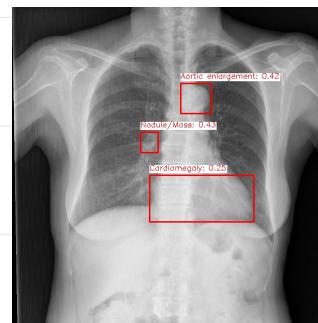
## ► Online testing

Malignant	Benign
8 samples	8 samples
All correctly diagnosed	1 misdiagnosed

# Chest x-ray abnormalities localization

## ► Dataset description

image_id	class_name	x_min	y_min	x_max	y_max
1c32170b4af4ce1a3030eb8167753b06	Pleural thickening	627.0	357.0	947.0	433.0
0c7a38f293d5f5e4846aa4ca6db4daf1	ILD	1347.0	245.0	2188.0	2169.0
47ed17dcbb2cbeec15182ed335a8b5a9e	Nodule/Mass	557.0	2352.0	675.0	2484.0
d3637a1935a905b3c326af31389cb846	Aortic enlargement	1329.0	743.0	1521.0	958.0
afb6230703512afcc370f236e8fe98806	Pulmonary fibrosis	1857.0	1607.0	2126.0	2036.0
7c1add6833d5f0102b0d3619a1682a64	Lung Opacity	600.0	1332.0	903.0	1523.0
18a61a07e6f5f13ebfee57fa36cd8b6f	Pulmonary fibrosis	393.0	283.0	822.0	643.0



# Chest x-ray abnormalities localization

## ► Dataset description

Class name	Class ID	Class frequency
Aortic enlargement	0	7162
Atelectasis	1	279
Calcification	2	960
Cardiomegaly	3	5427
Consolidation	4	556
Interstitial lung disease (ILD)	5	1000
Infiltration	6	1247
Lung Opacity	7	2483
Nodule/Mass	8	2580
Other lesion	9	2203
Pleural effusion	10	2476
Pleural thickening	11	4842
Pneumothorax	12	226
Pulmonary fibrosis	13	4655
No finding	14	10k

# Chest x-ray abnormalities localization

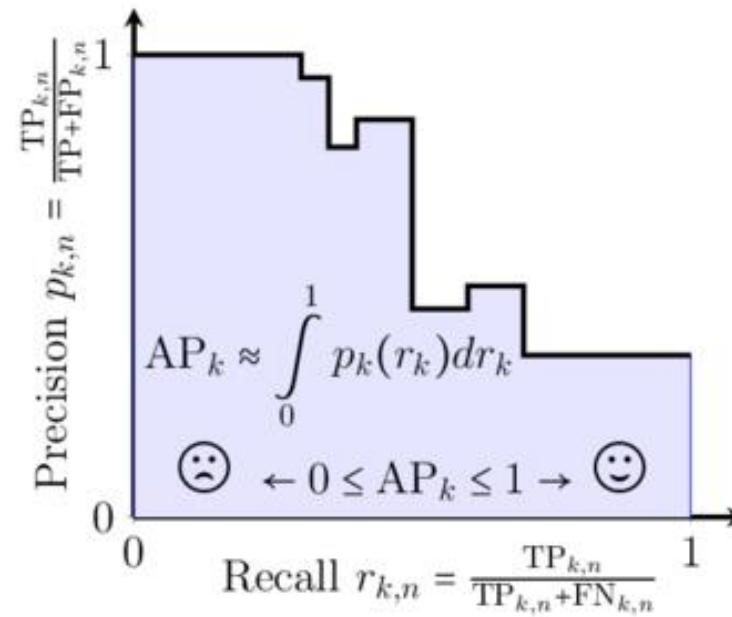
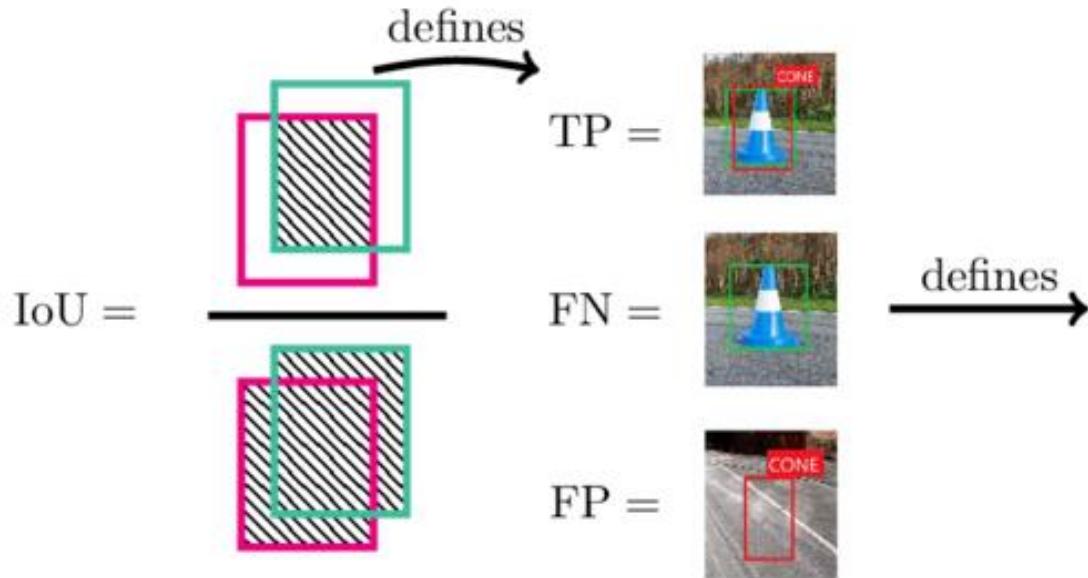
## ► Data source

- **the Hospital 108:** A large military hospital in Hanoi, Vietnam
- **the Hanoi Medical University Hospital:** A large public hospital in Hanoi, Vietnam

# Chest x-ray abnormalities localization

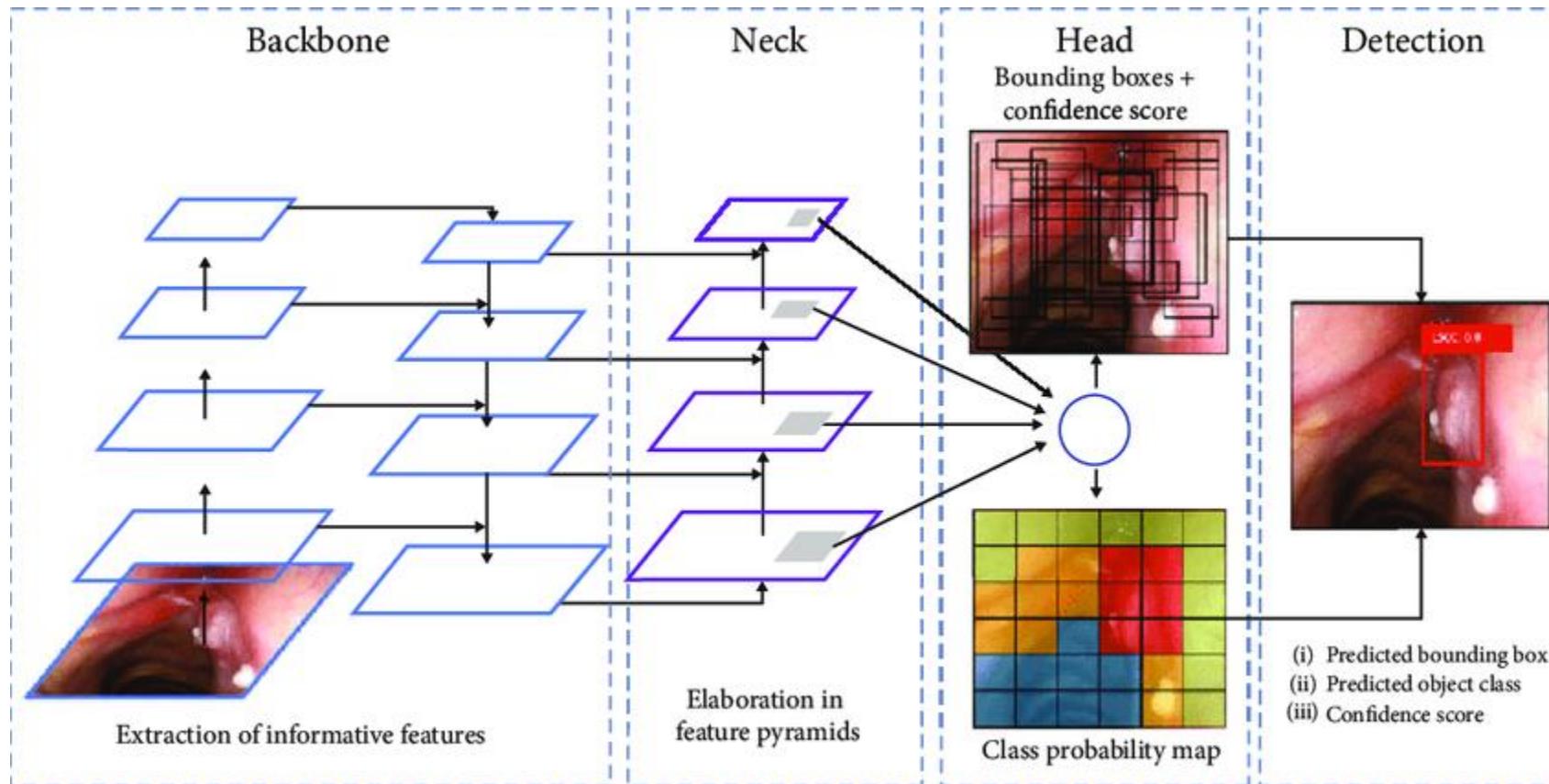
## ► Performance measures for object detection

Mean average precision (mAP)



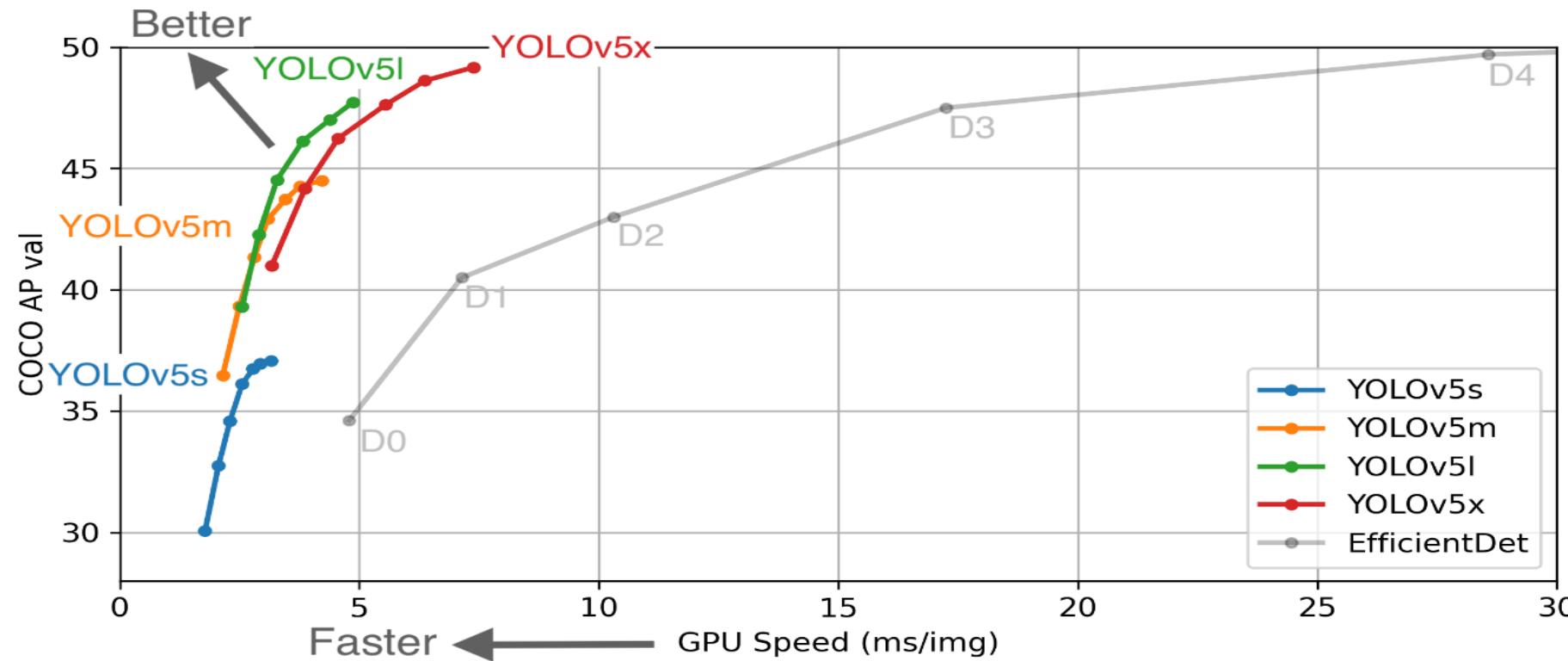
# Chest x-ray abnormalities localization

## ► object detector architecture



# Chest x-ray abnormalities localization

## ► YOLO v5 versions



# Chest x-ray abnormalities localization

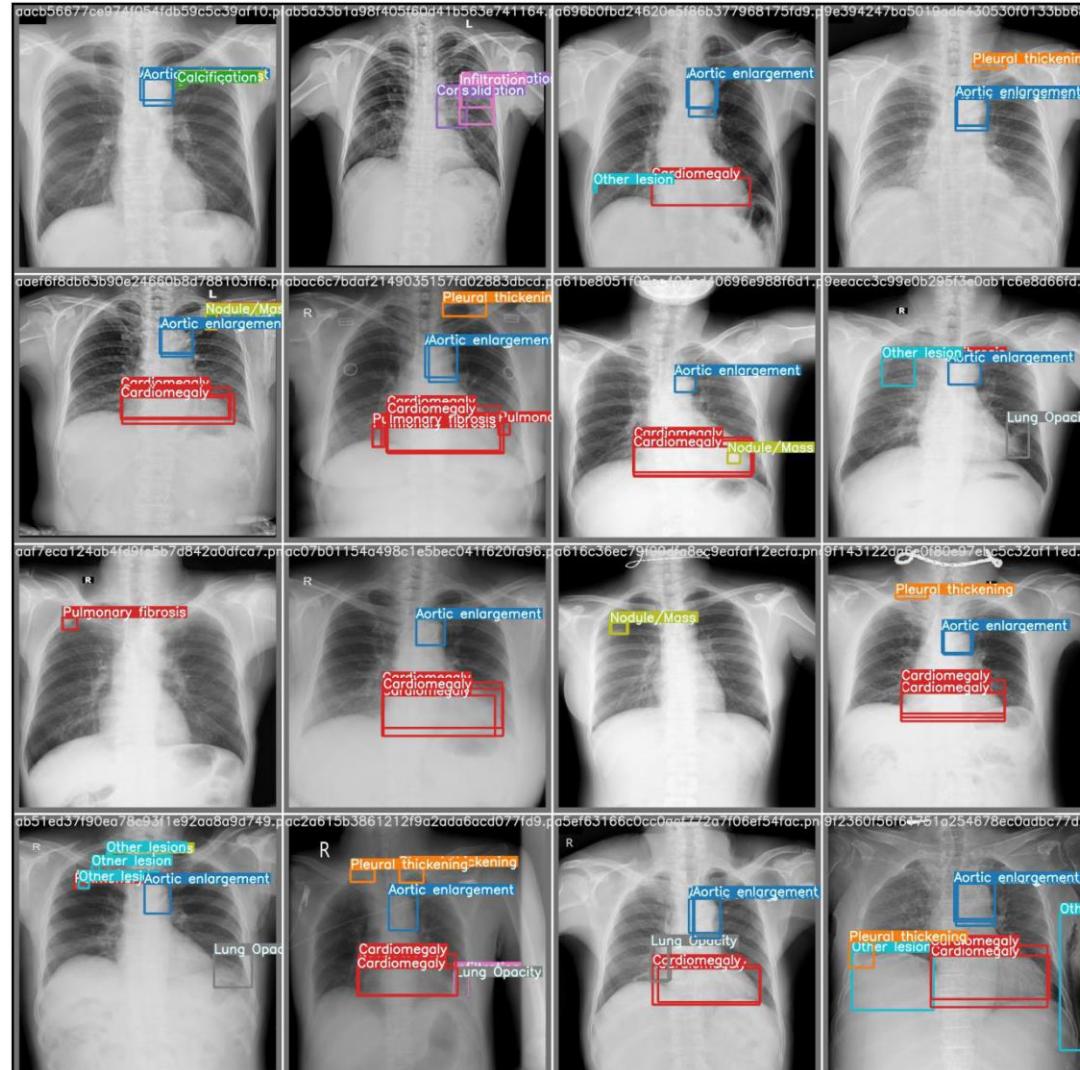
## ► Results

	model	Mean average precision (mAP0.5)
[1]	Detectron 2	0.235
[2]	ResNet50 - FPN	0.246
Ours	Yolo v5x	0.312

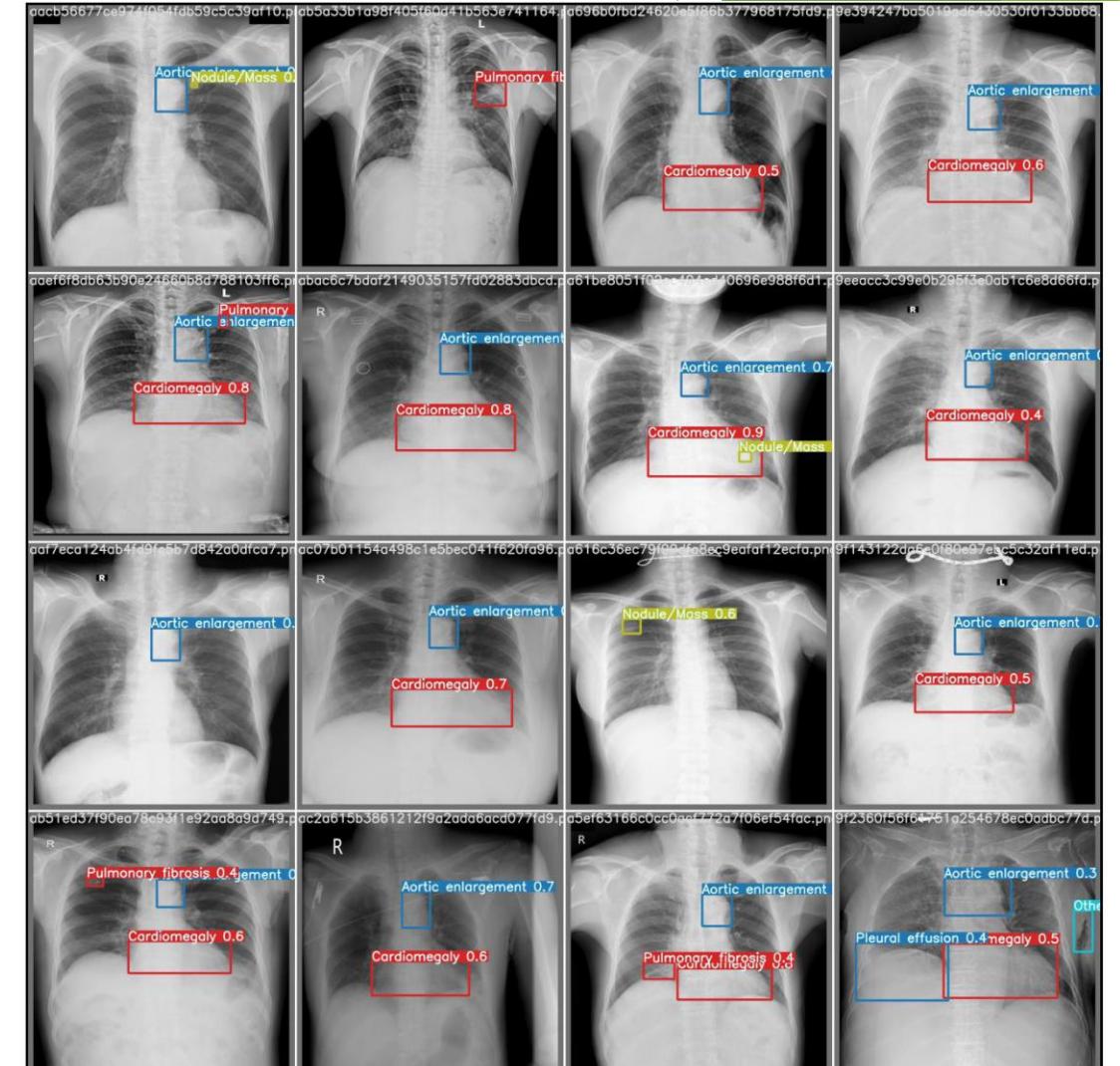
- [1] Talius, E., & Sayana, R. Zero-Shot Object Detection for Chest X-Rays.
- [2] V. Parikh, J. Shah, C. Bhatt, J. M. Corchado, and D.-N. Le, “Deep learning based automated chest X-ray abnormalities detection,” in Lecture Notes in Networks and Systems, Cham: Springer International Publishing, 2023, pp. 1-12.

# Chest x-ray abnormalities localization

## ► Results



prediction



Actual

# Chest x-ray abnormalities localization

## ► Online testing

