Medical Diagnosis System (MDA)

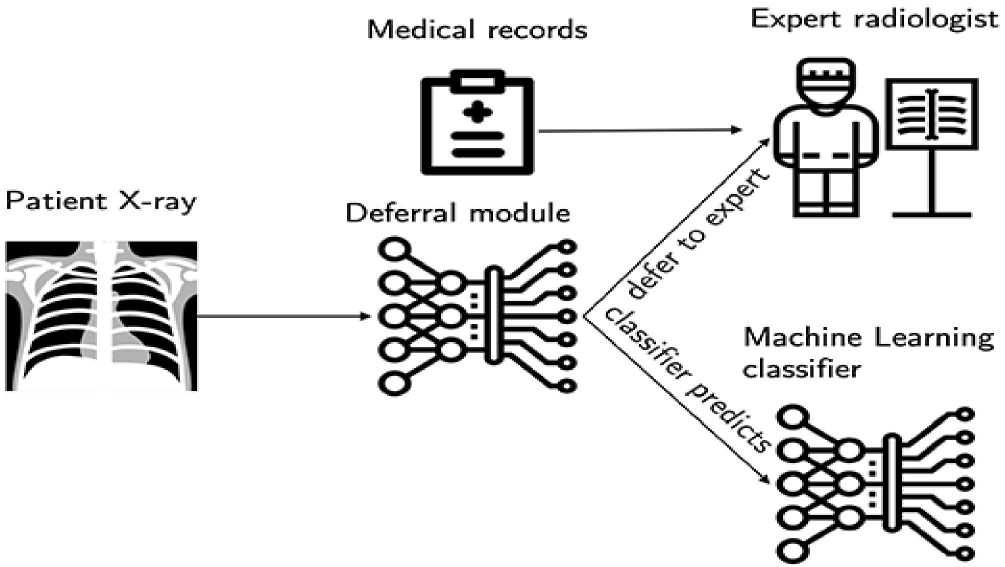
Supervised by:

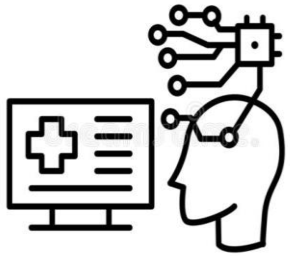
Dr. Hany Aly Elghaish

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.

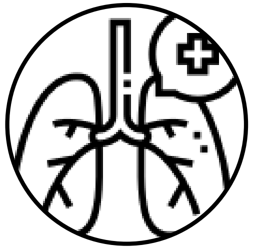




Overview

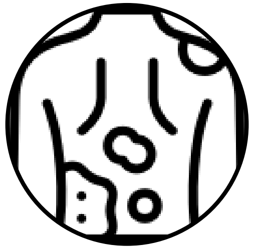
- <u>Offered Services:</u>

Heartbeat abnormalities detection from electrocardiogram (ECG)

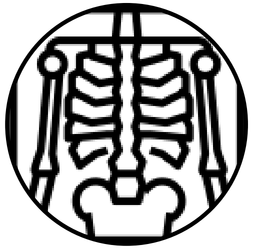


COVID-19 detection from chest x-ray images

Brain tumor detection and segmentation from MRI images



Skin cancer detection from skin images



Chest X-ray Abnormalities localization and classification

Overview

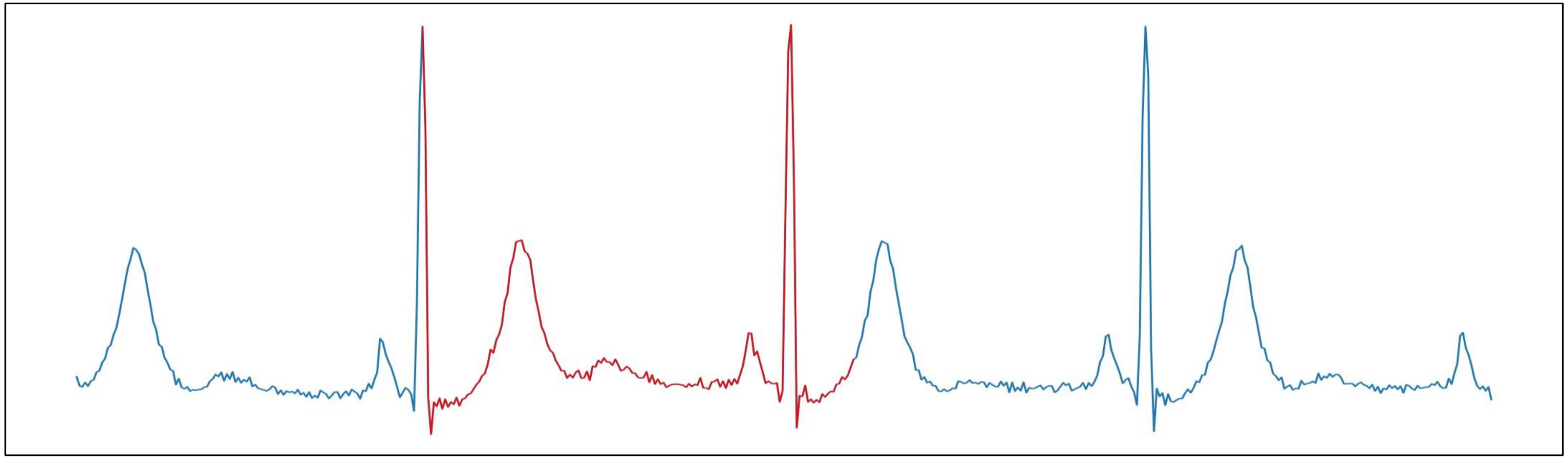
<u>Heartbeat abnormalities detection from electrocardiogram (ECG):</u>

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

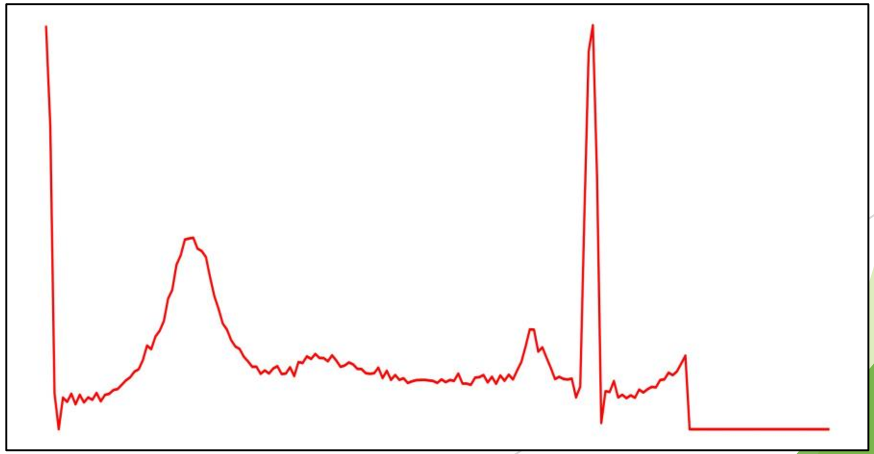
Overview

- End user view of the heartbeat abnormalities service



.dat file
Hardware

Normal beat, 90%



Overview

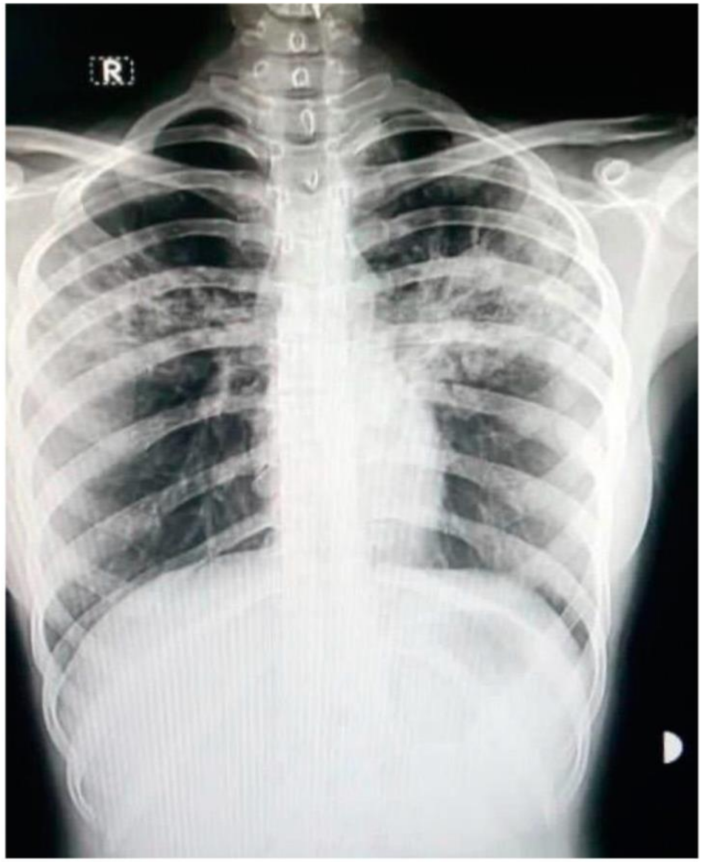
COVID-19 detection from chest x-ray images :

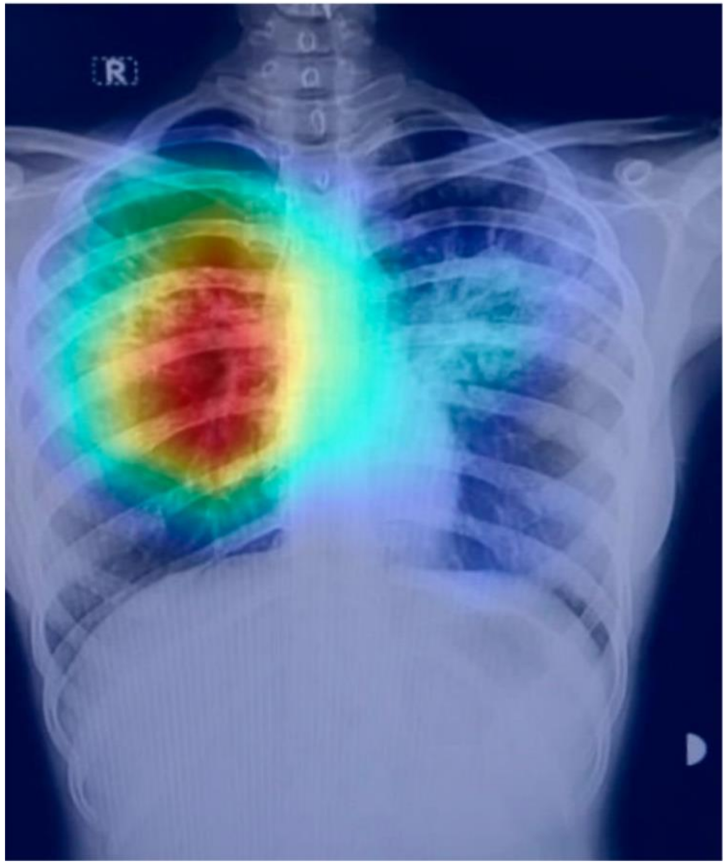
Model can classify between three cases :

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

Overview

- End user view of the covid-19 detection service





Covid-19, 90%

Overview

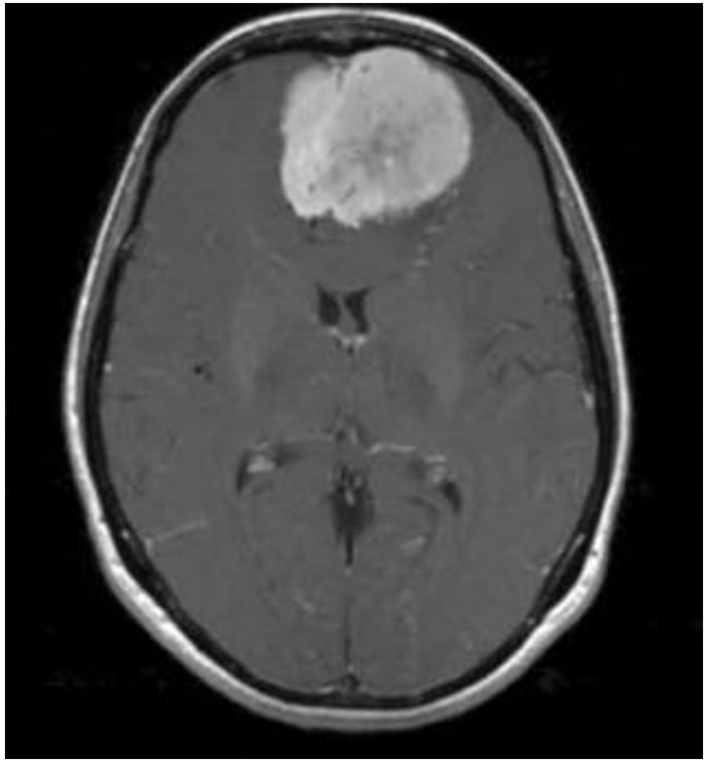
Brain tumor MRI classification:

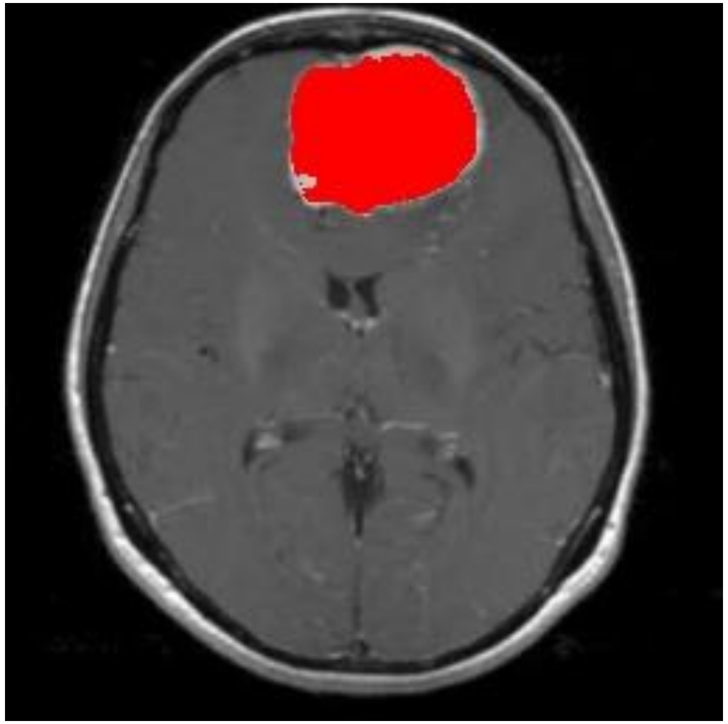
Model can classify between four cases :

- 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

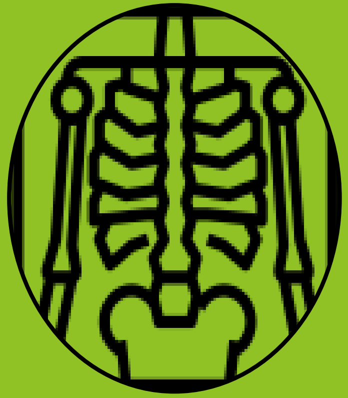
malignant, 90%

Overview

Chest X-ray Abnormalities localization and classification:

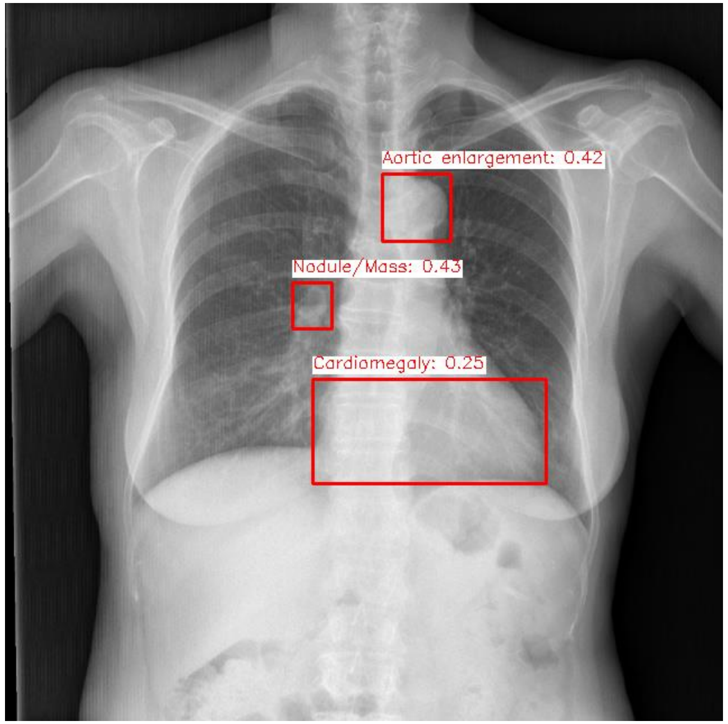
Model can localize and classify between **14 cases** of chest abnormalities:

- 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

Significance of the project

1. Available online through a web site and offline through a desktop app
2. Reduce the gab between computer science and the medical society
3. Reduce initial diagnostics time and effort
4. Help patients receive a better treatment
5. Help fill the shortage for medical experts
6. Help medicine students reinforce their diagnosis skills

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

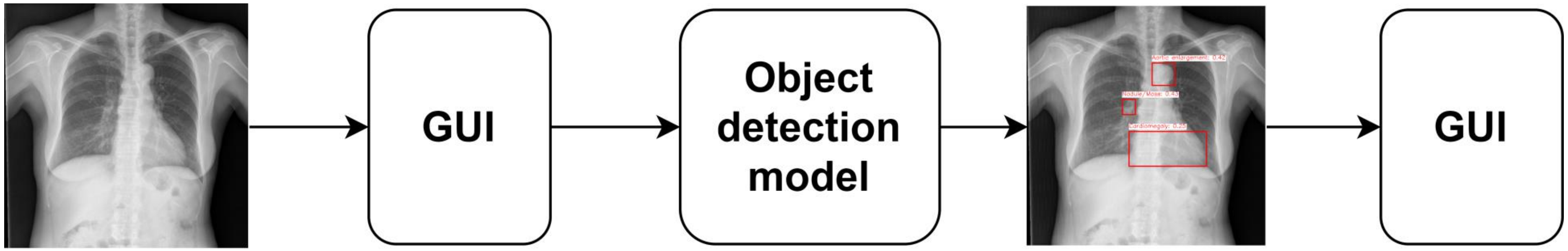
- Our services will be deployed in a desktop application and as well as a web site.

System operation

- Skin cancer detection service diagram:

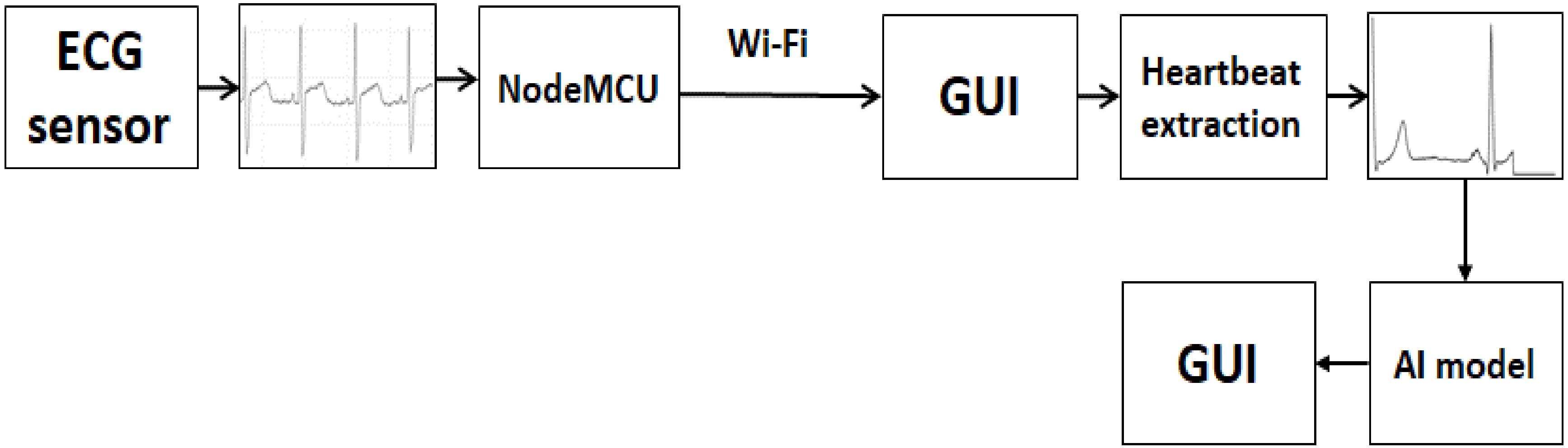
System operation

- chest x-ray abnormalities localization service diagram:



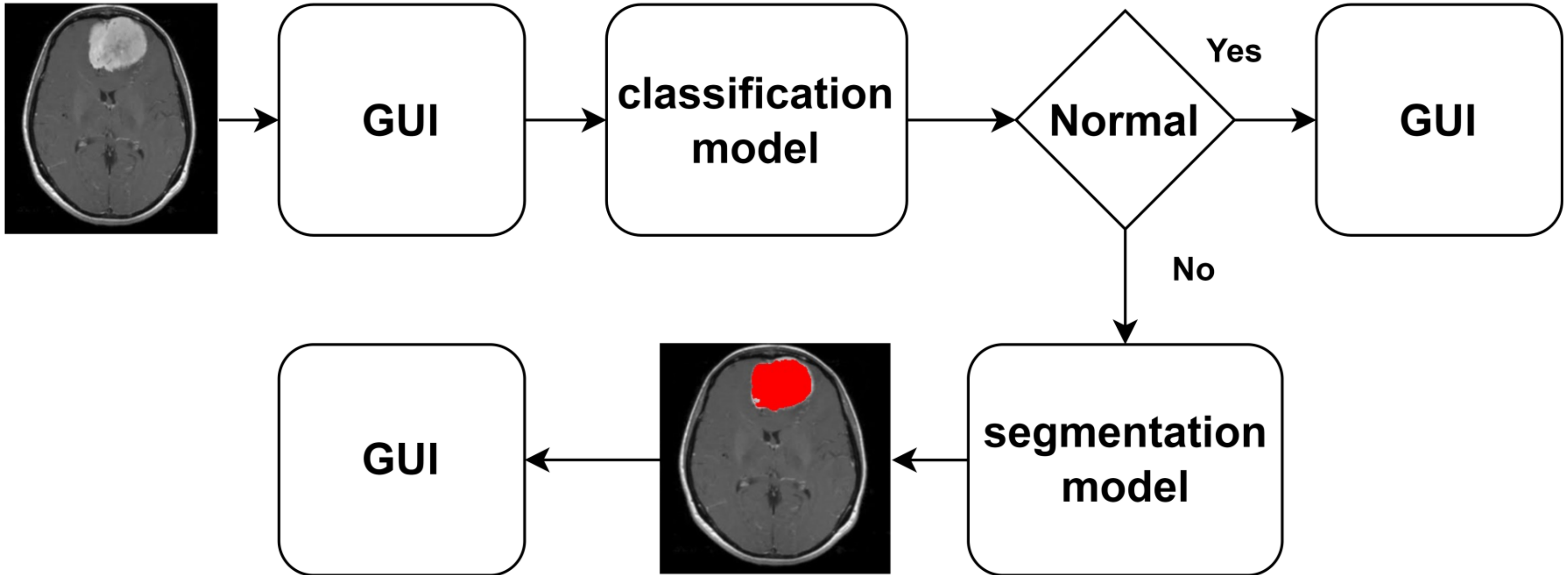
System operation

- Real time heartbeat abnormalities service diagram:



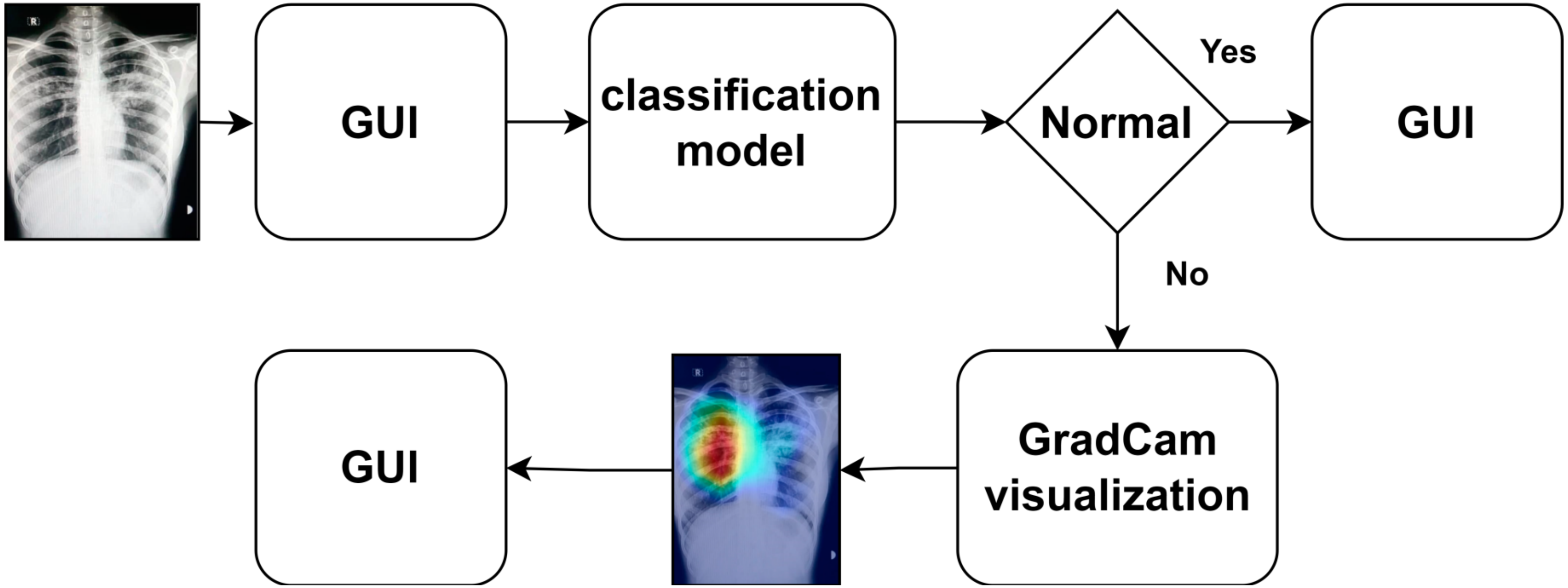
System operation

- Brain tumor detection and segmentation service diagram:



System operation

- Covid-19 detection service diagram:

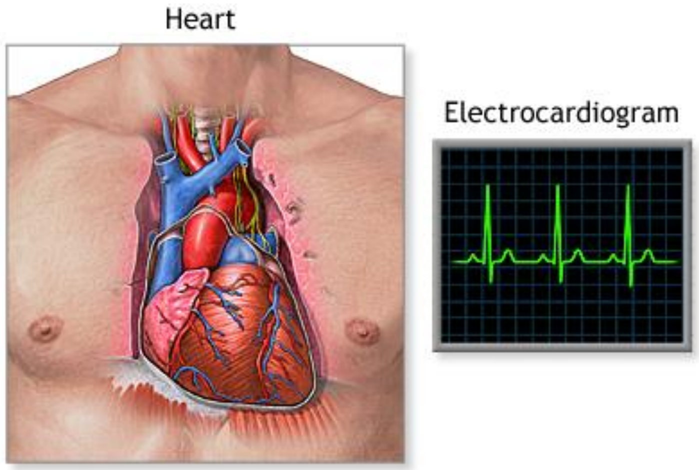


Experiments

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

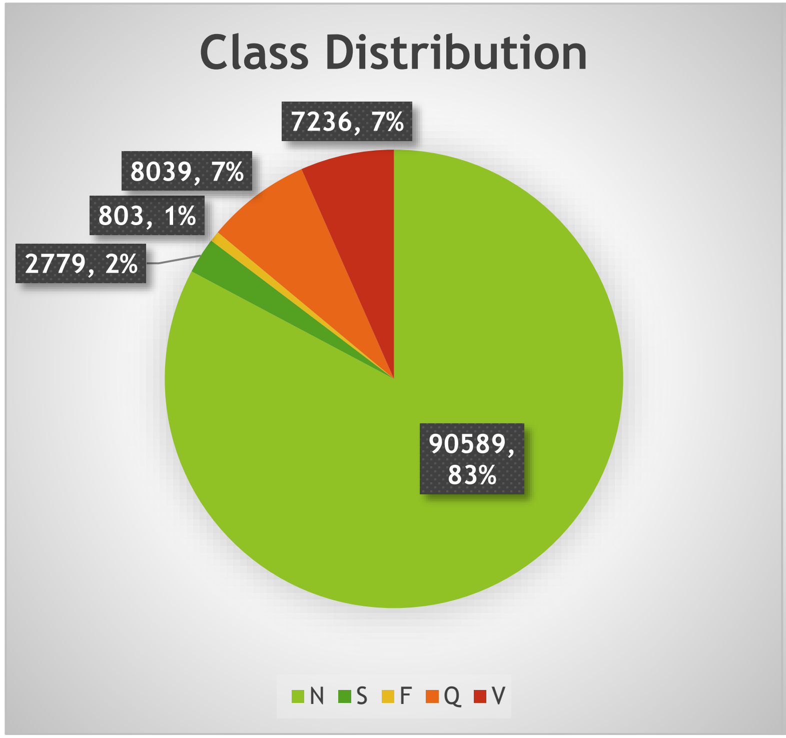


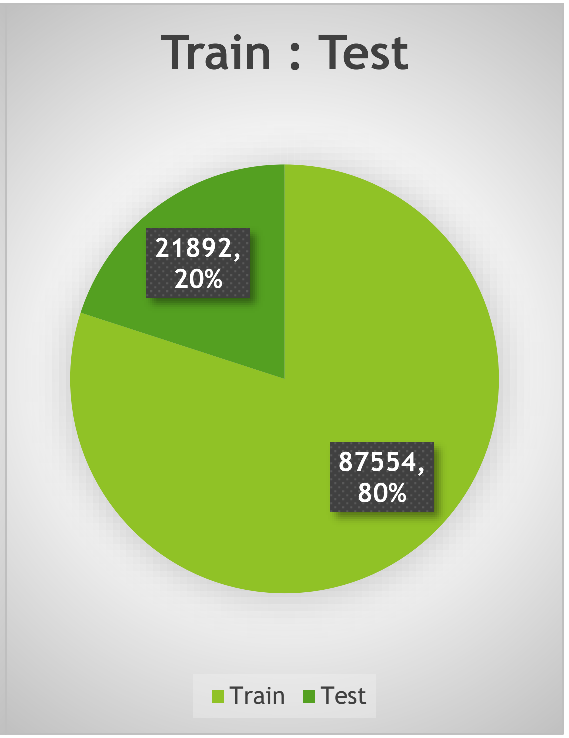
Heartbeat abnormalities detection from ECG

- **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

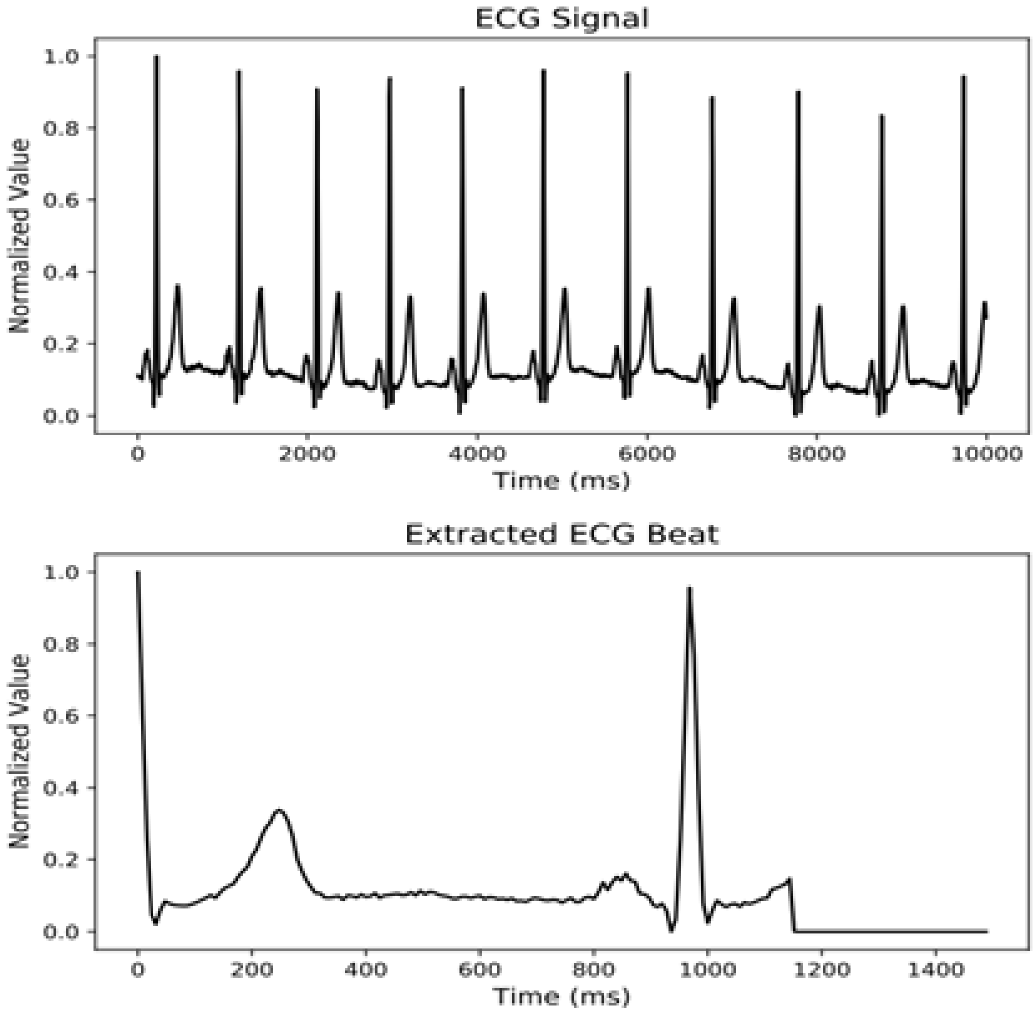
Data source

- **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

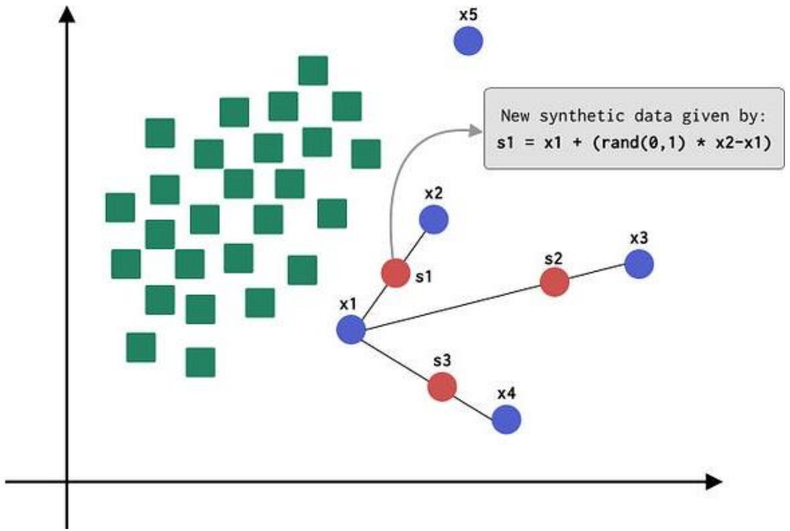
	0	1	2	3	4	5	6	7	8	9	...	178	179	180	181	182	183	184	185	186	187
0	1.000000	0.758264	0.111570	0.000000	0.080579	0.078512	0.066116	0.049587	0.047521	0.035124	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.908425	0.783883	0.531136	0.362637	0.366300	0.344322	0.333333	0.307692	0.296703	0.300366	...	0.0	0.0	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

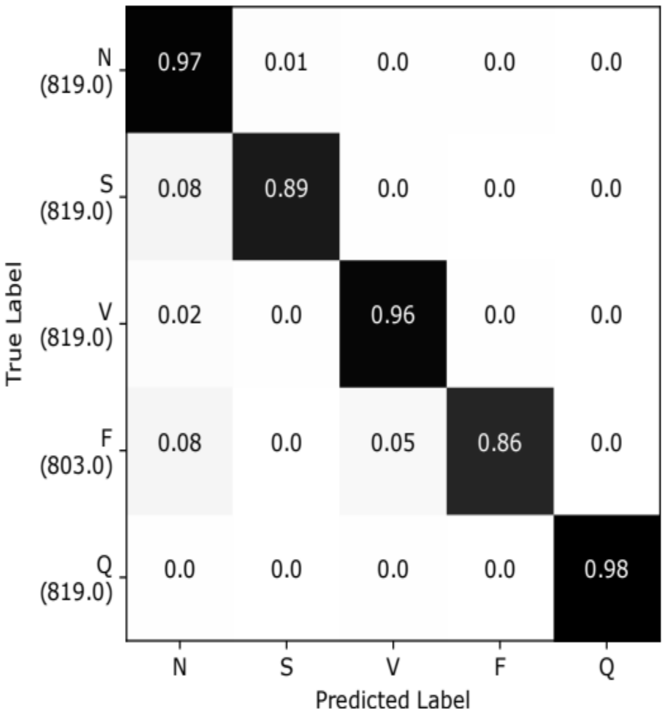
Heartbeat abnormalities detection from ECG

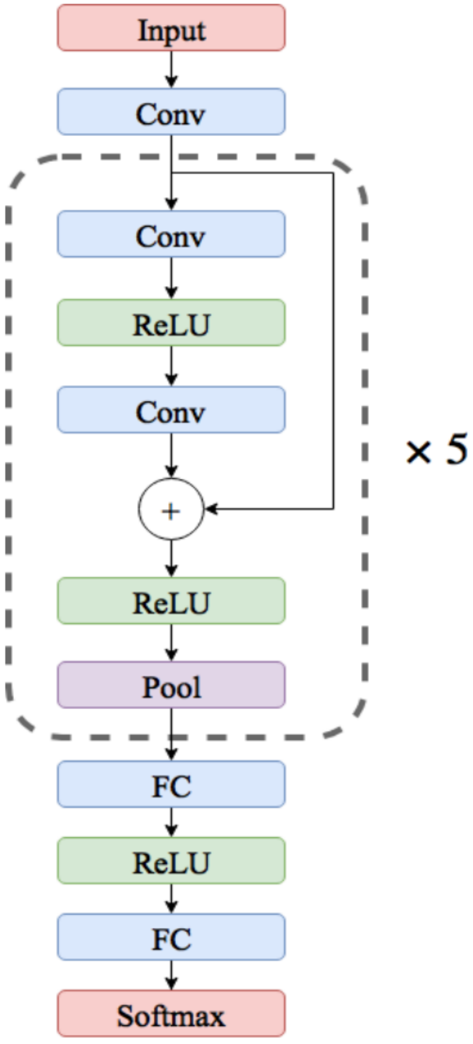
Reference paper for result comparison

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







Heartbeat abnormalities detection from ECG

- **1-D convolution**

Feature extraction	Temporal dependency	classification
• 1D-CNN • Adaptive kernel size convolution (AKSC) • Adaptive feature recalibration (AFR)	• Long-short time memory (LSTM) • Multi-head attention	• 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

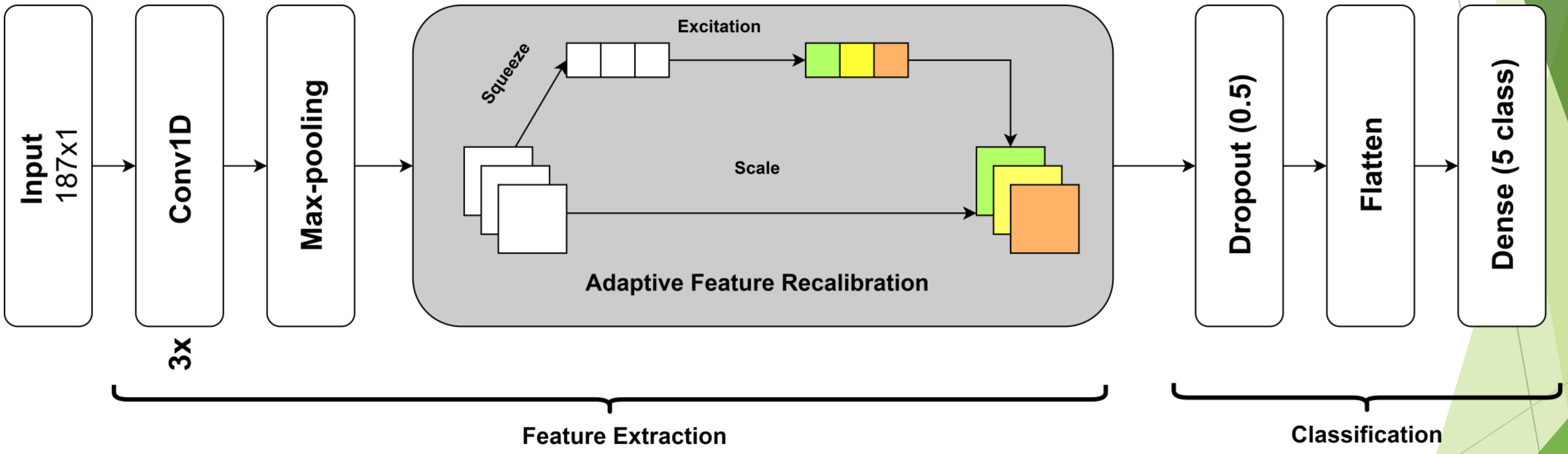
		Reduce the N class to 6000 sample	92.83% accuracy 92.77% recall	
		oversample to 20000	93.34% accuracy 93.20% recall	
CNN-2	3x Conv1D MaxPooling1D flatten 1x fully connected	Oversample to 20000	93.35% accuracy 93.23% recall	

CNN-2 has less parameters

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (feature extraction)**

Adaptive feature recalibration (AFR)

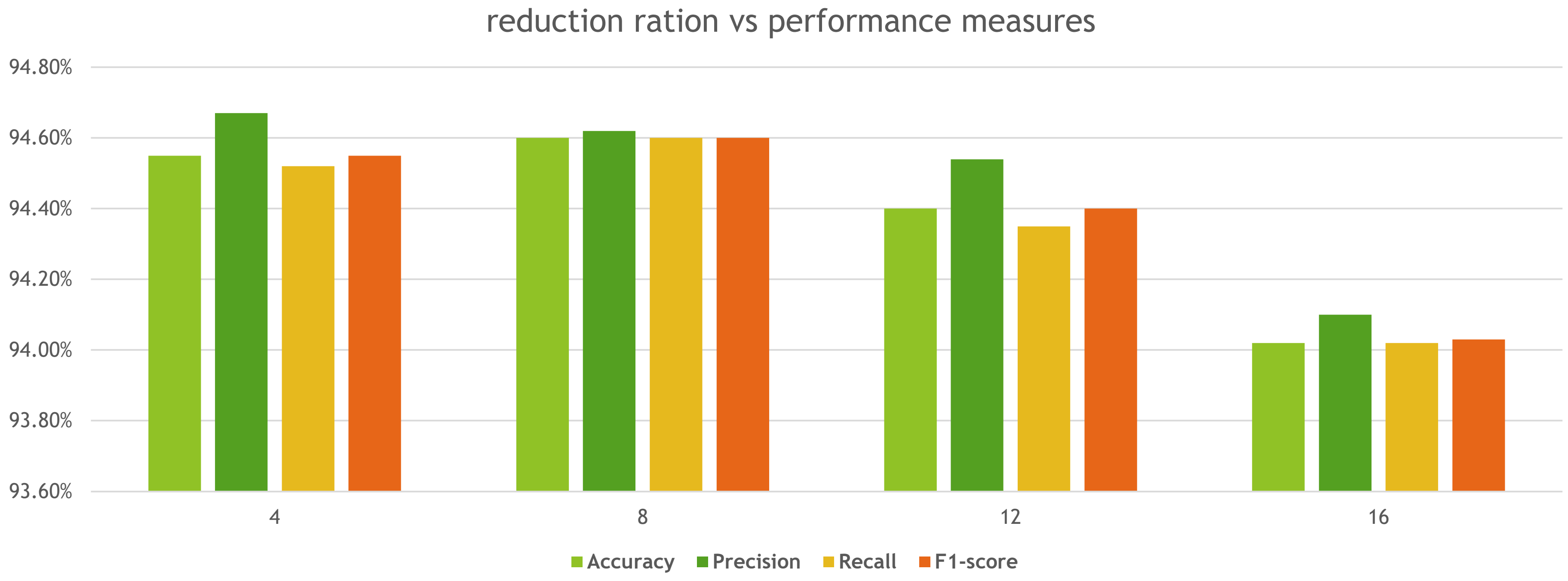


Hyper-parameters:
Reduction ration

Heartbeat abnormalities detection from ECG

▶ 1-D convolution Experiments (feature extraction)

Adaptive feature recalibration (AFR)

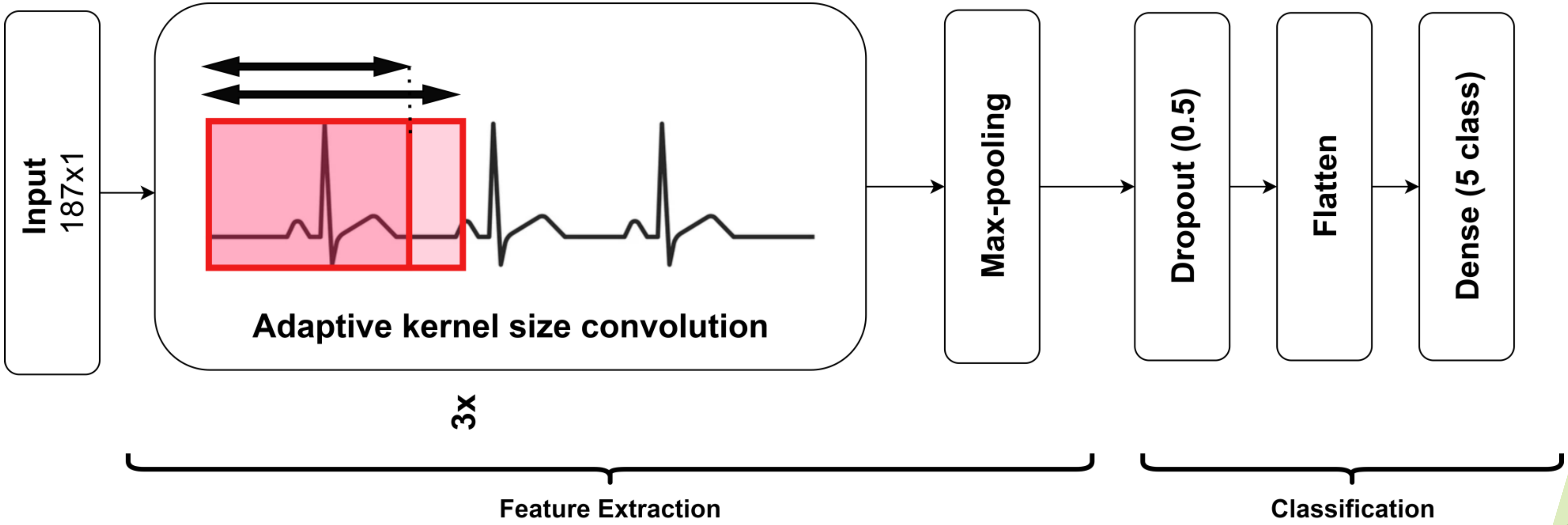


Reduction ratio	Accuracy	Precision	Recall	F1
8	94.60%	94.62%	94.60%	94.60%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (feature extraction)**

Adaptive Kernel Size Convolution (AKSC)

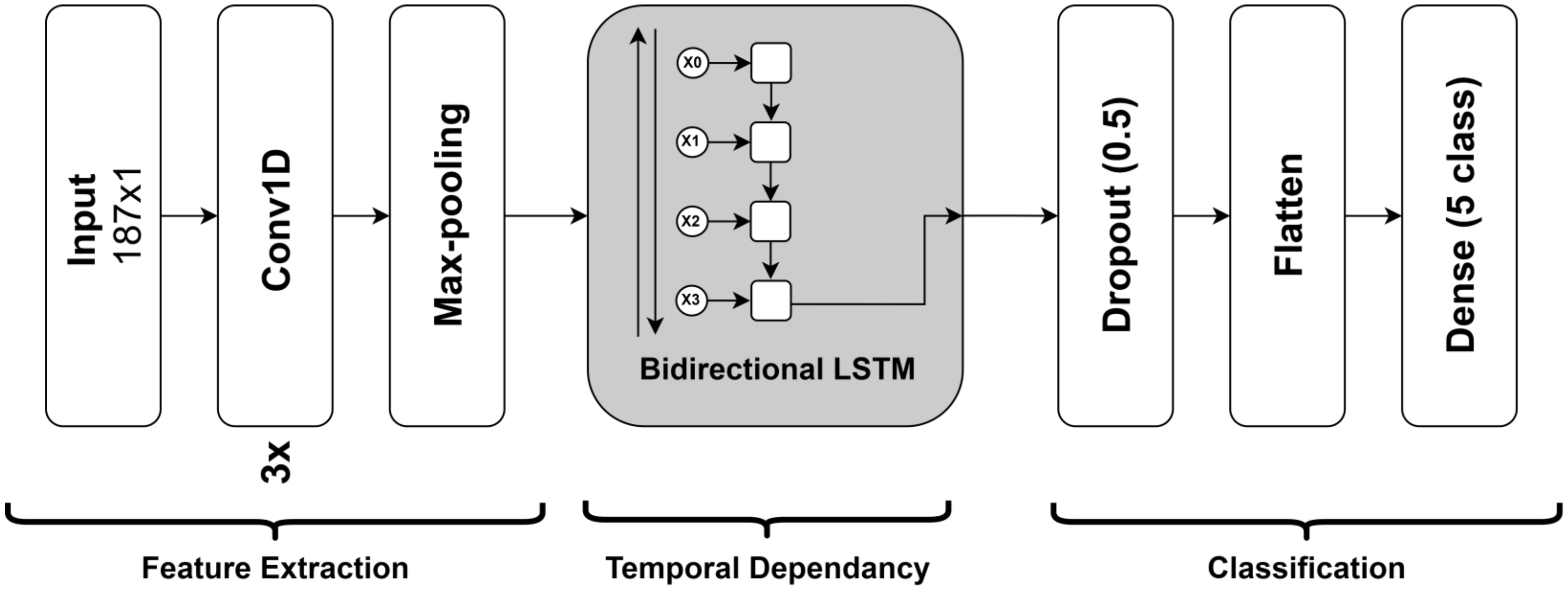


	Accuracy	precision	Recall	F1
Proposed	93.80%	93.80%	93.80%	93.80%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (temporal dependency)**

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

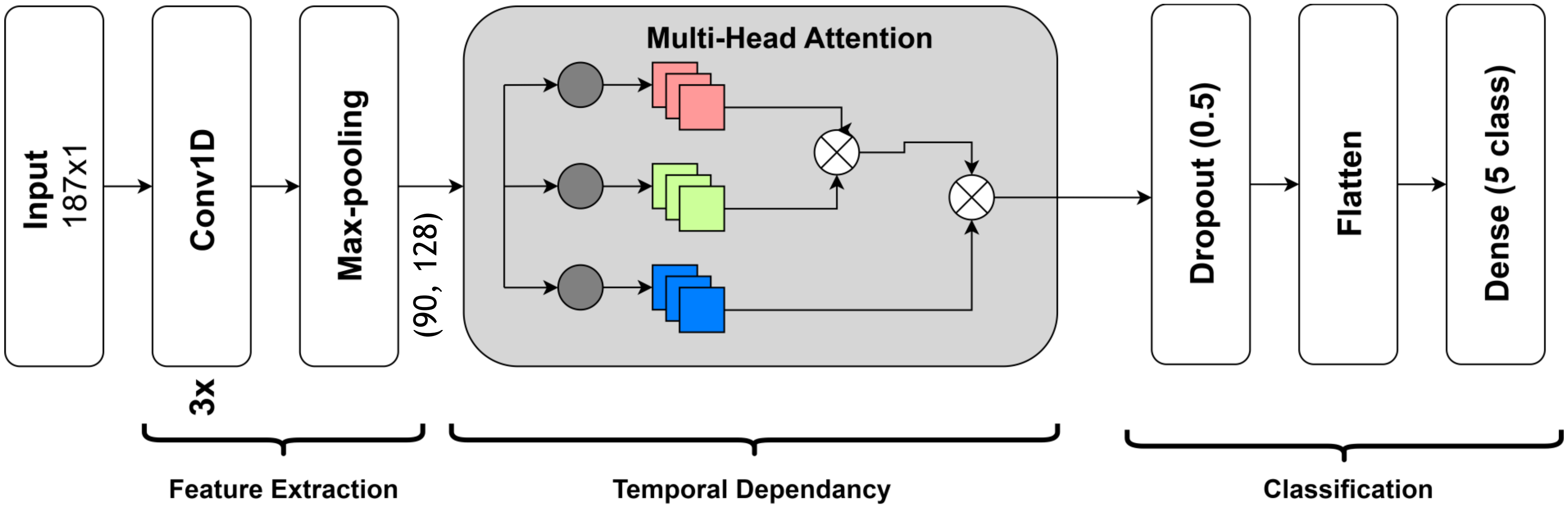


	Accuracy	Precision	Recall	F1
proposed	94.98%	95.16%	94.95%	95.55%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (temporal dependency)**

Multi-head attention (MHA): single branch



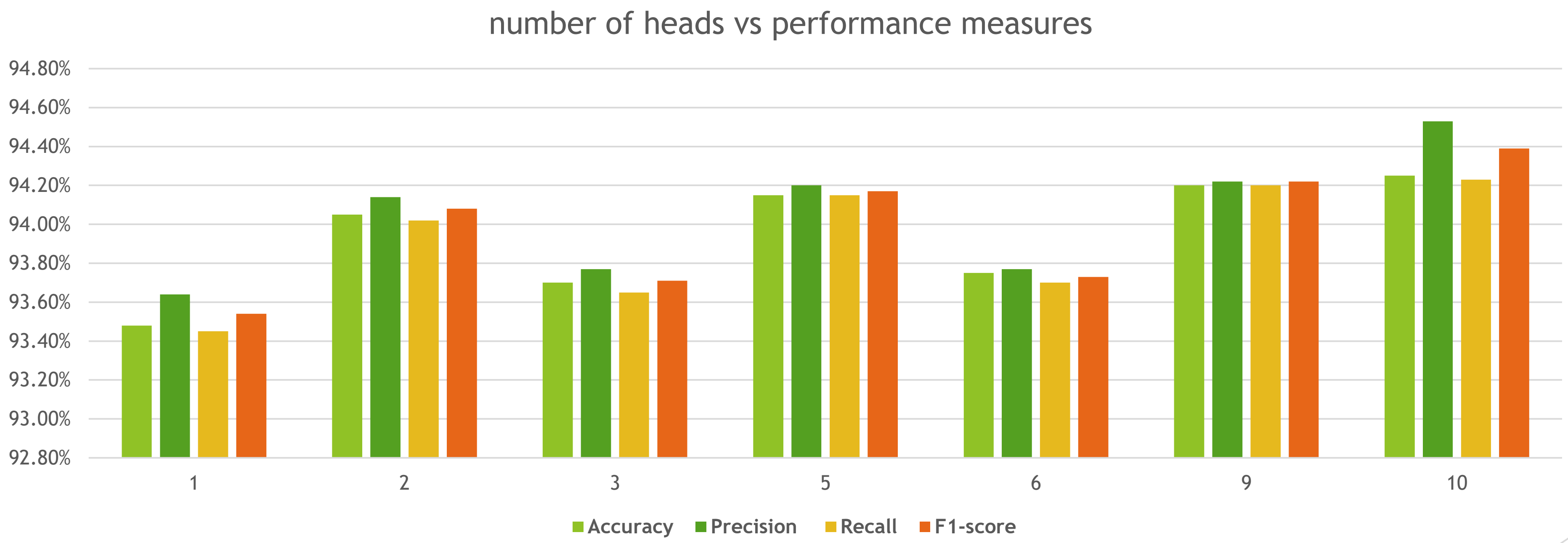
Hyper-parameters:
no. of heads

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

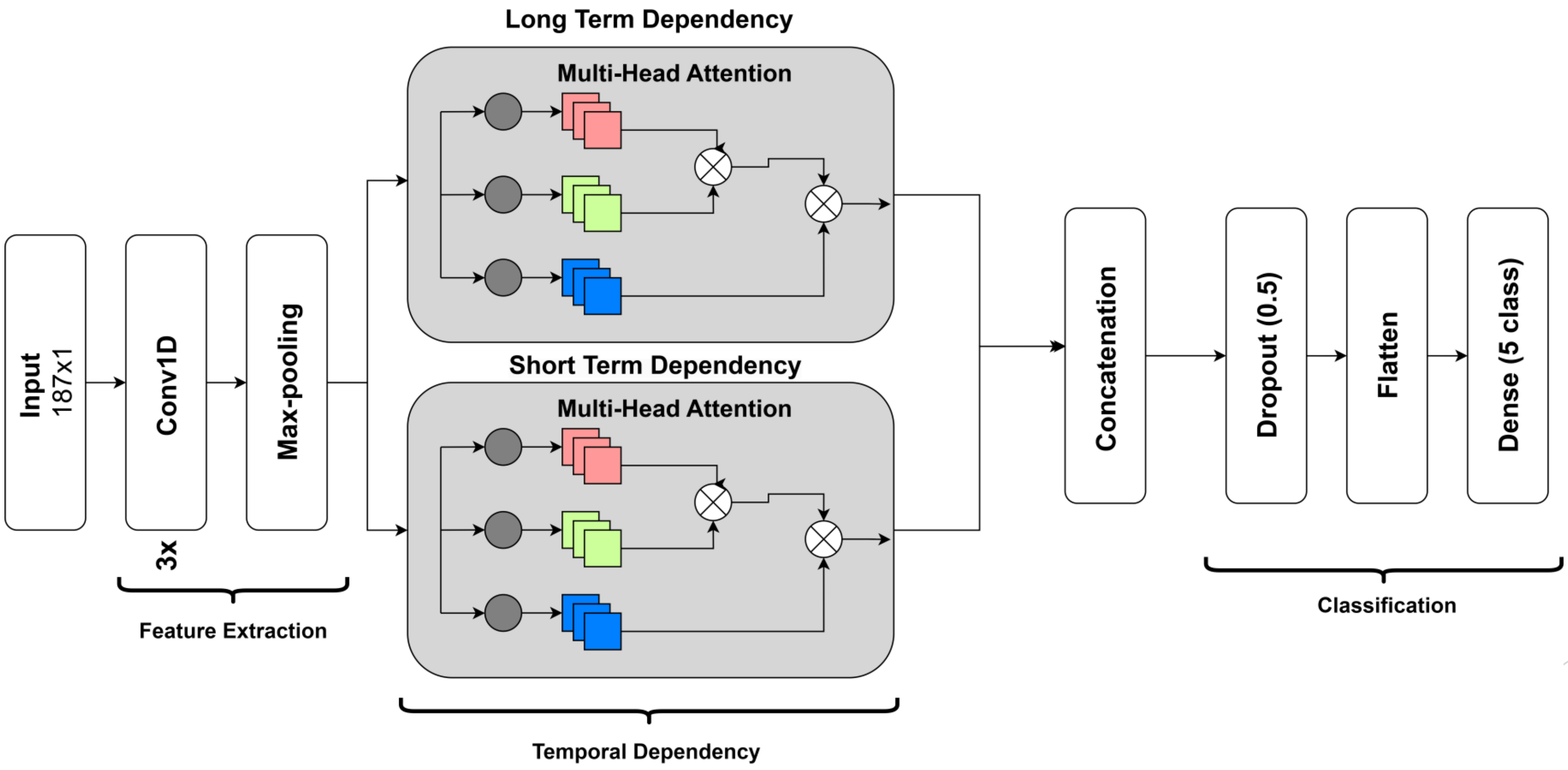


No. of heads	Accuracy	Precision	Recall	F1
10	94.25%	94.53%	94.23%	94.39%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (temporal dependency)**

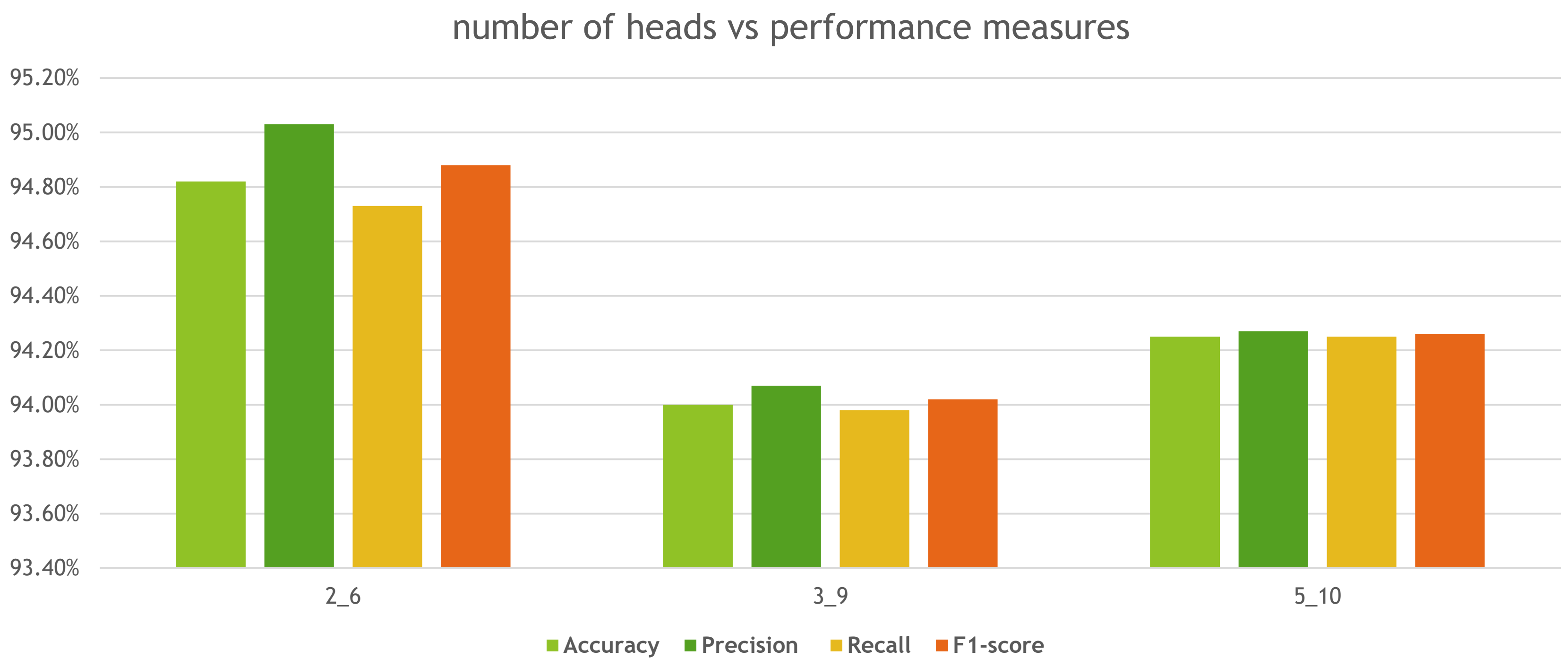
Multi-head attention (MHA): parallel branches



Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (temporal dependency)**

Multi-head attention (MHA): parallel branches

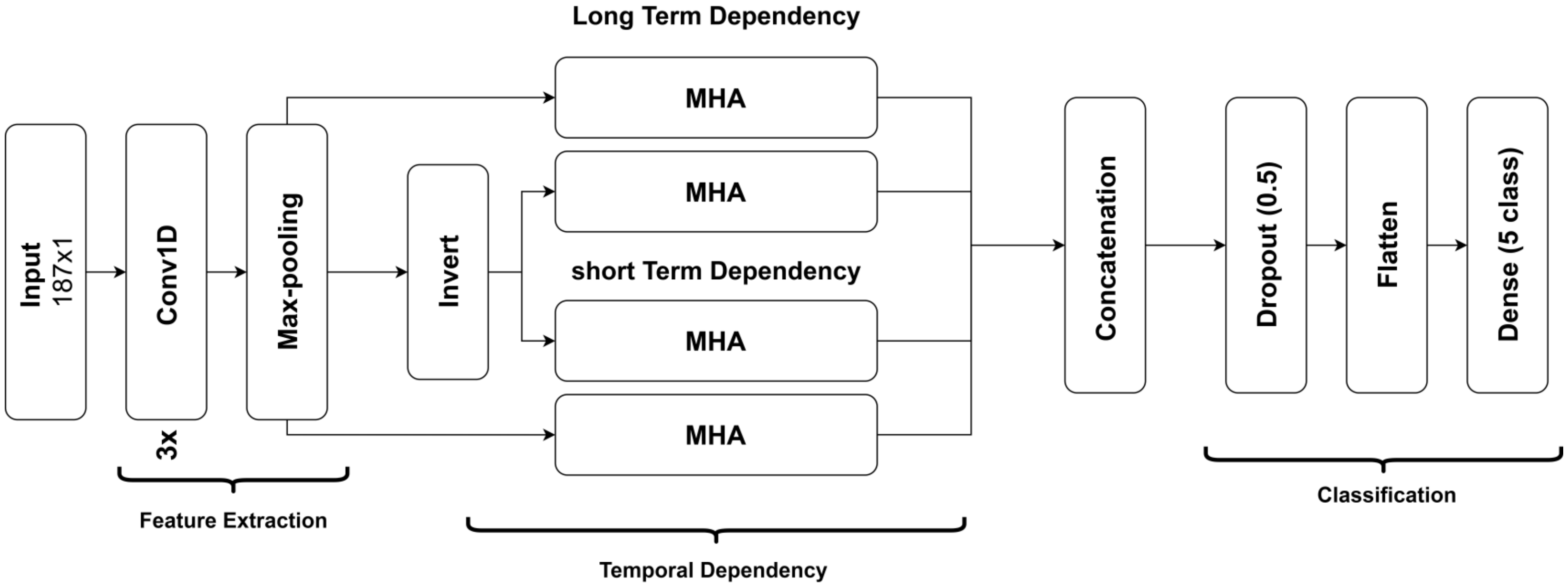


No. of heads	Accuracy	Precision	Recall	F1
2-6	94.82%	95.03%	94.73%	94.88%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments (temporal dependency)**

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

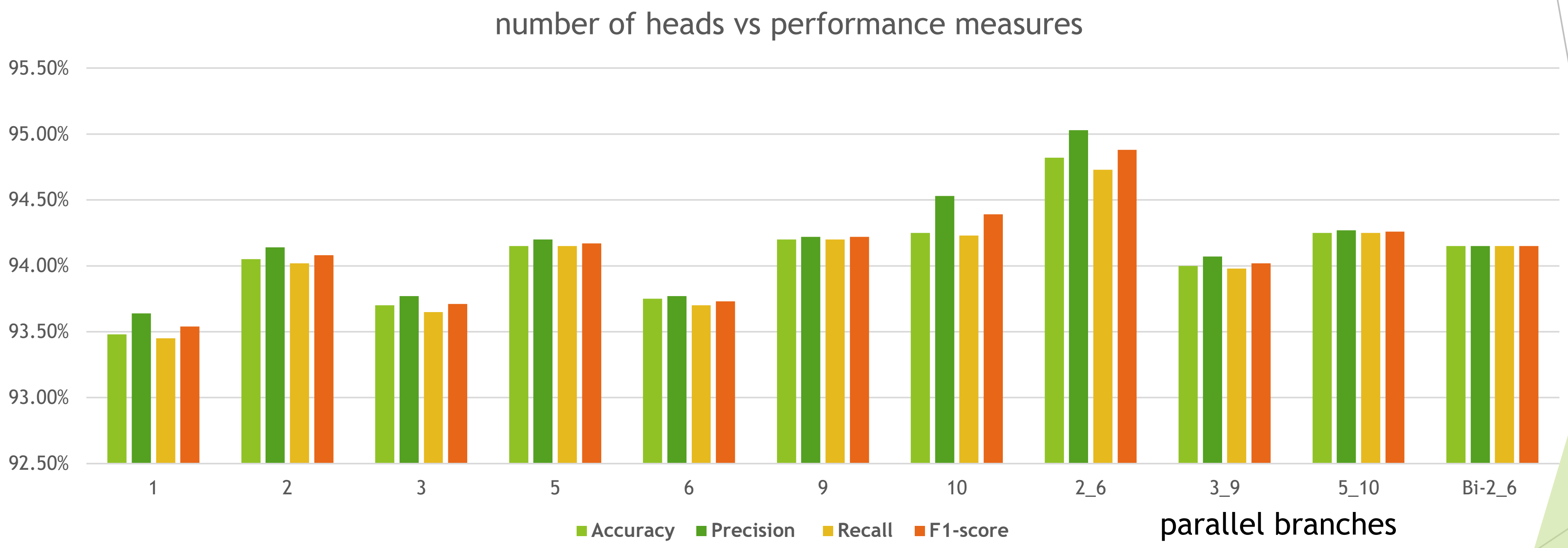


No. of heads	Accuracy	Precision	Recall	F1
2-6	94.15%	94.15%	94.15%	94.15%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

1-D convolution Experiments (temporal dependency)

Multi-head attention (MHA): Experiments summary

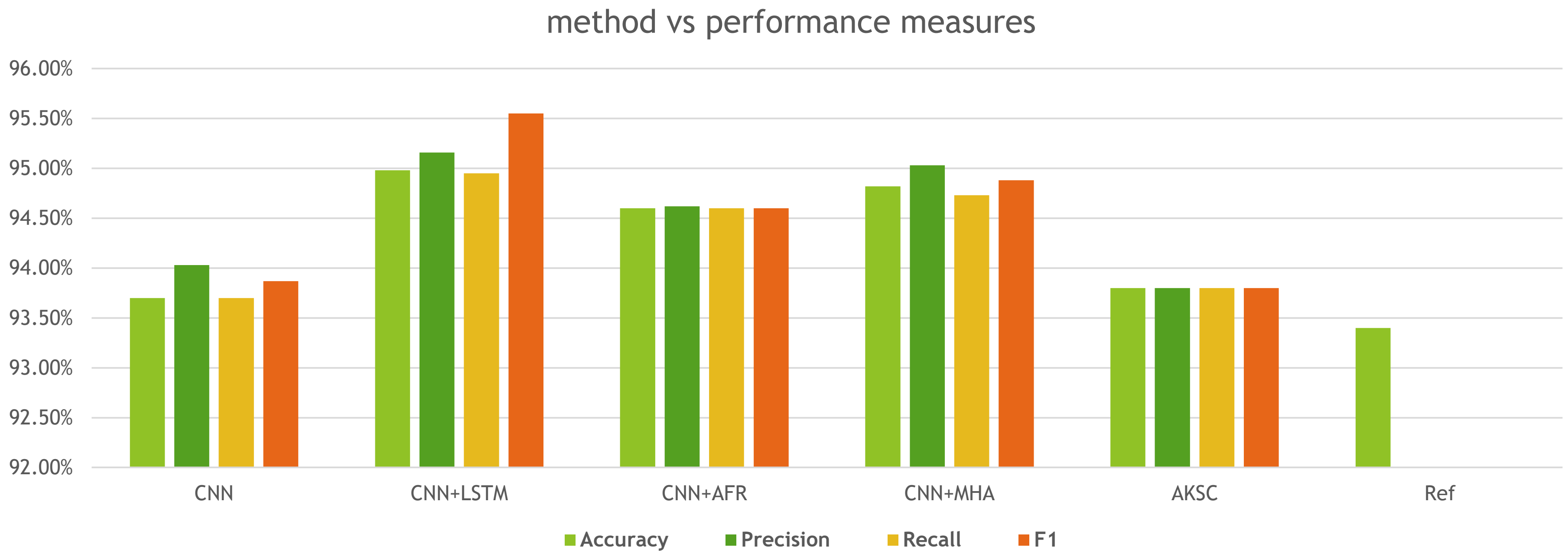


No. of heads	Accuracy	Precision	Recall	F1
2-6	94.82%	95.03%	94.73%	94.88%
Ref	93.4%			

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

ŷ
0.7
0.2
0.1

Actual

y
1
0
0

- Cross entropy loss

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

- Weighted cross entropy loss

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

- Focal loss

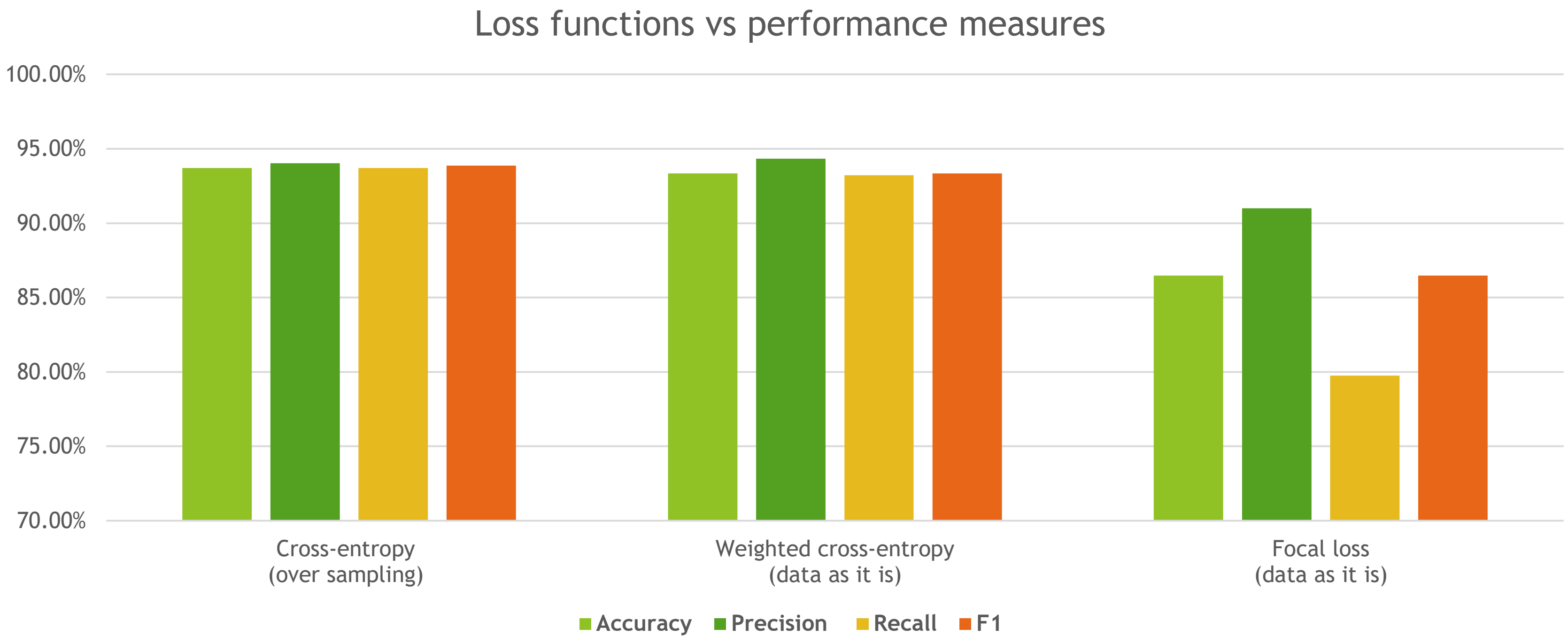
$$\text{Loss} = -\sum_{i=1} \alpha_i \cdot (1-\hat{y}_i)^{\gamma} \cdot \log \hat{y}_i$$

w_0 = 1 / 72471
w_1 = 1 / 2223
w_2 = 1 / 5788
w_3 = 1 / 641
w_4 = 1 / 6431
sum = 0.002025
w_0 = w_0 / sum = 0.00684
w_1 = w_1 / sum = 0.22214
w_2 = w_2 / sum = 0.08541
w_3 = w_3 / sum = 0.77094
w_4 = w_4 / sum = 0.07667

Heartbeat abnormalities detection from ECG

1-D convolution Experiments

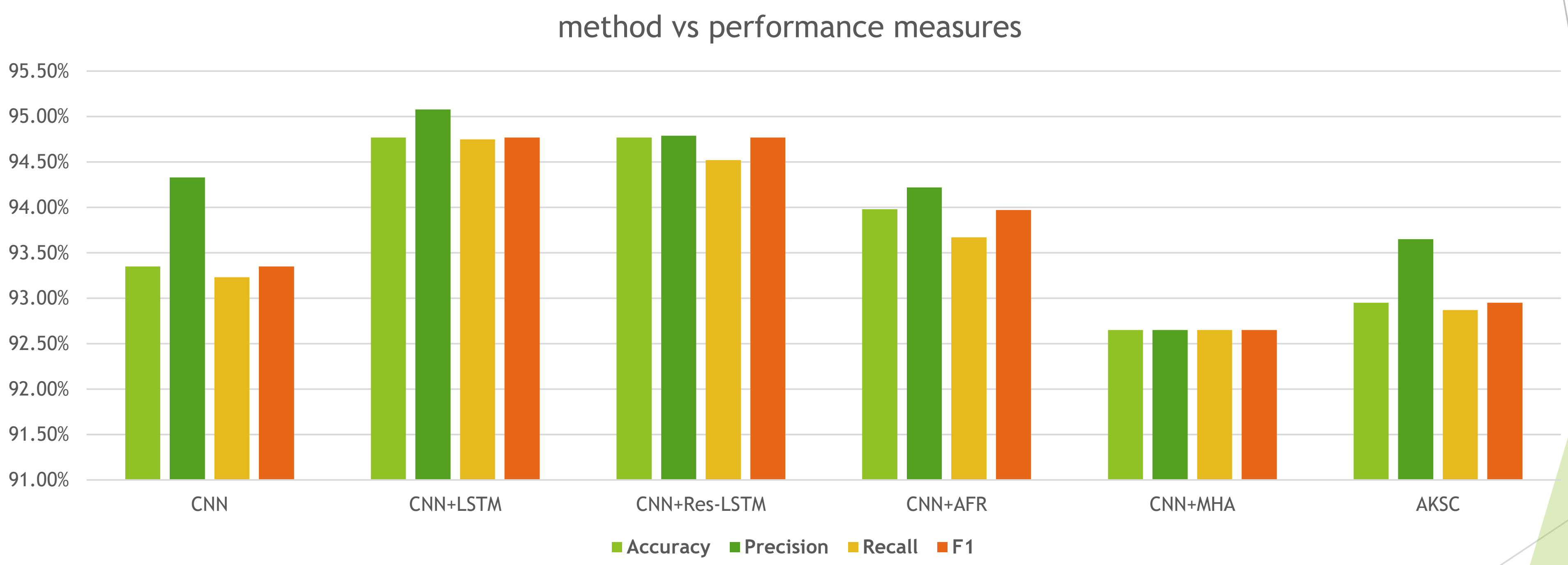
Cross entropy loss VS weighted cross entropy loss VS focal loss



Heartbeat abnormalities detection from ECG

1-D convolution Experiments

Experiments summary with weighted cross-entropy

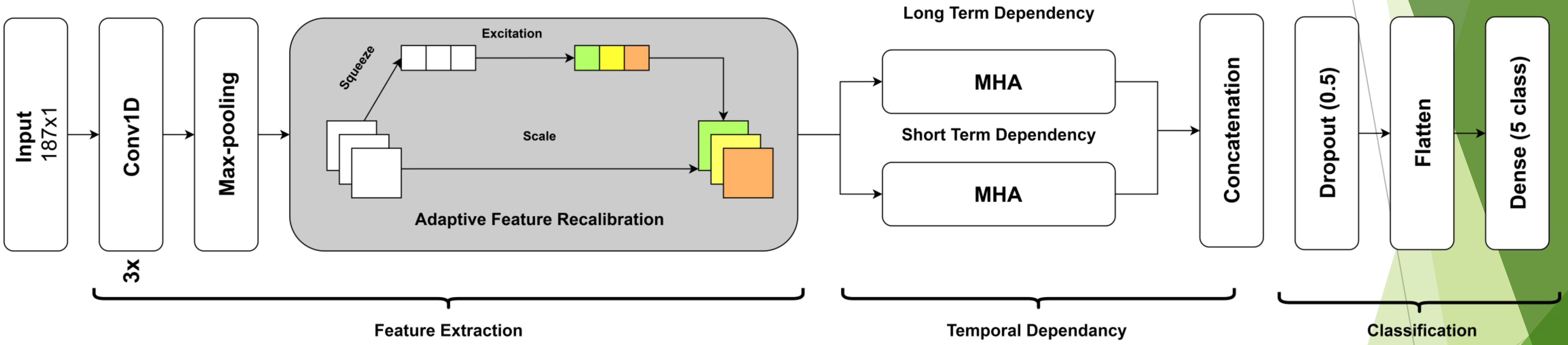


	Accuracy	Precision	Recall	F1
CNN+ Bi-LSTM	94.77%	95.08%	94.75%	94.77%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

1-D convolution Experiments

CNN+AFR+MHA

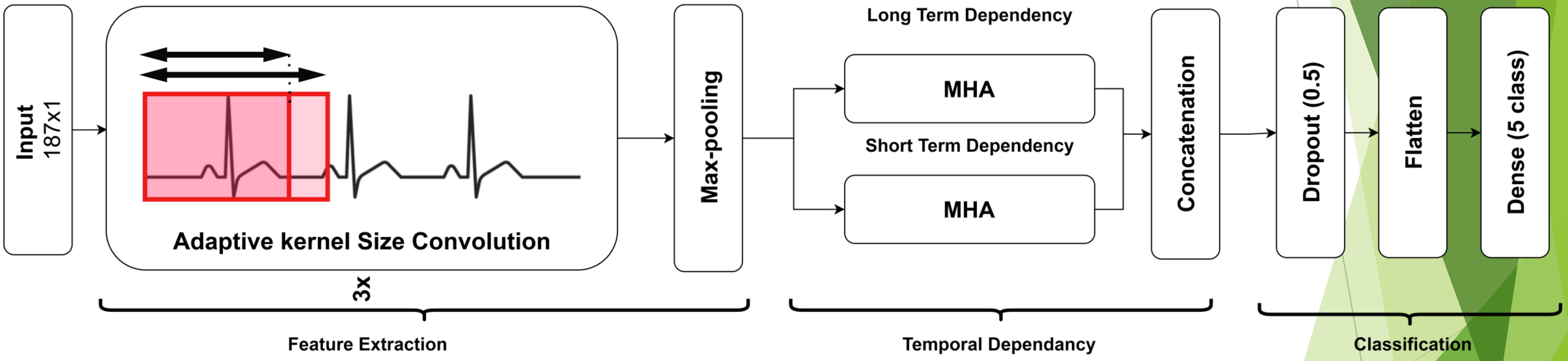


	Accuracy	Precision	Recall	F1
CNN+AFR+MHA	93.45%	93.67%	93.27%	93.45%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments**

AKSC+MHA

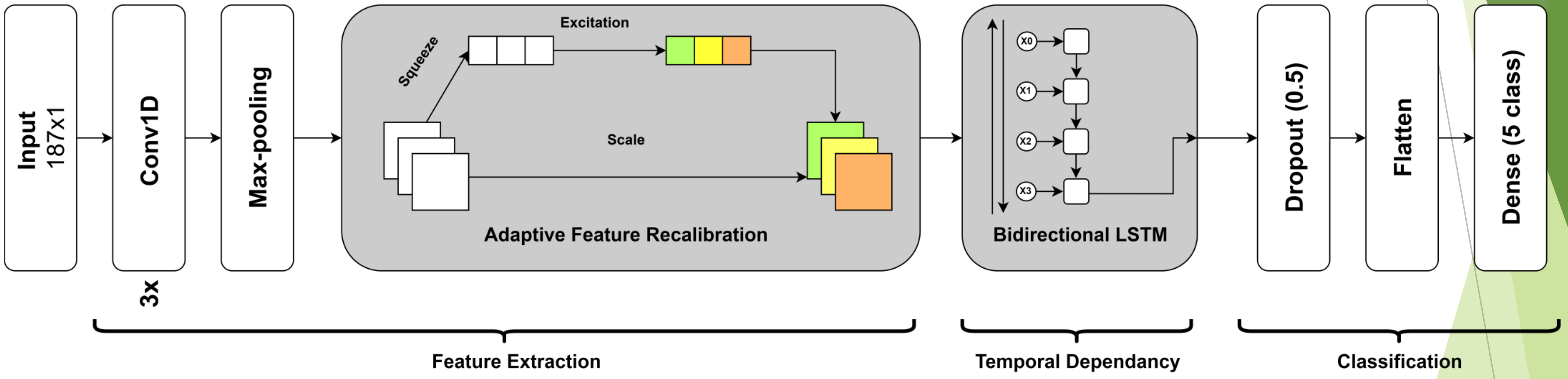


	Accuracy	Precision	Recall	F1
AKSC+MHA	92.68%	93.04%	92.22%	92.67%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

1-D convolution Experiments

CNN+AFR+Bi-LSTM

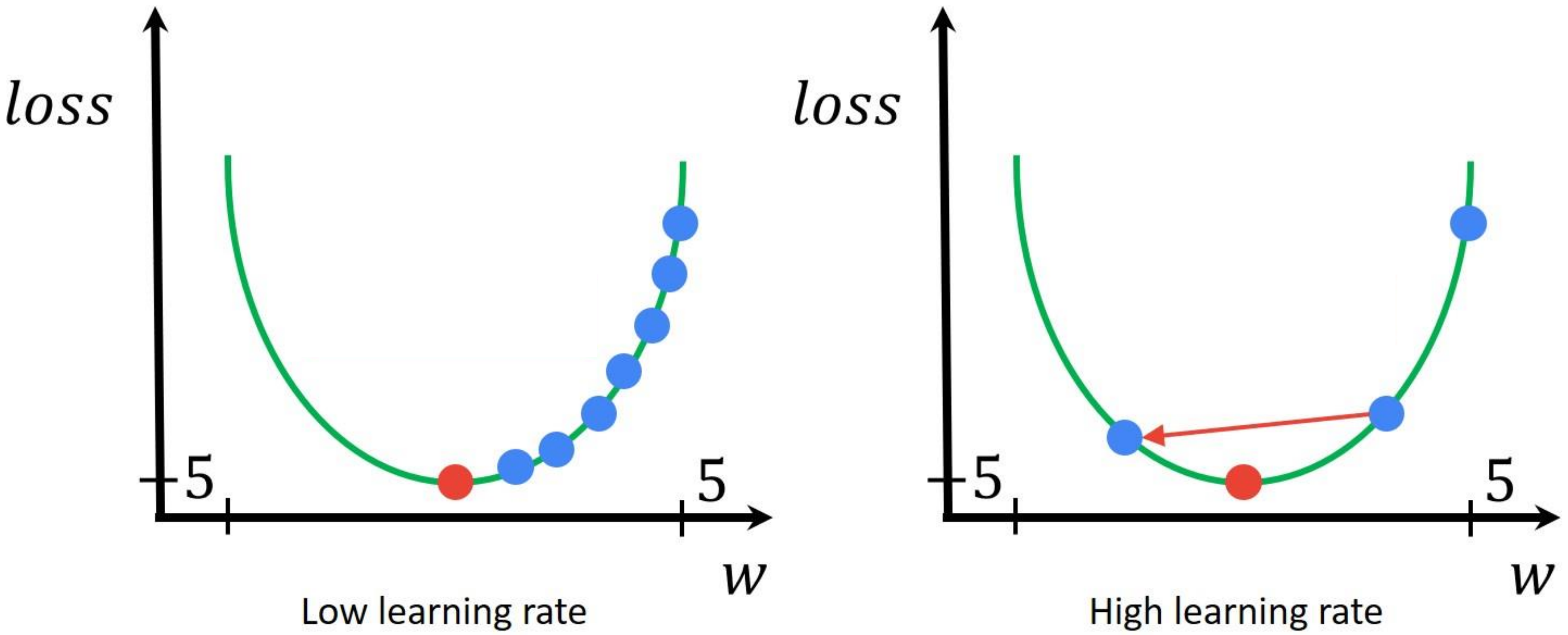


	Accuracy	Precision	Recall	F1
CNN+AFR+ Bi-LSTM	94.88%	95.09%	94.82%	94.88%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments**

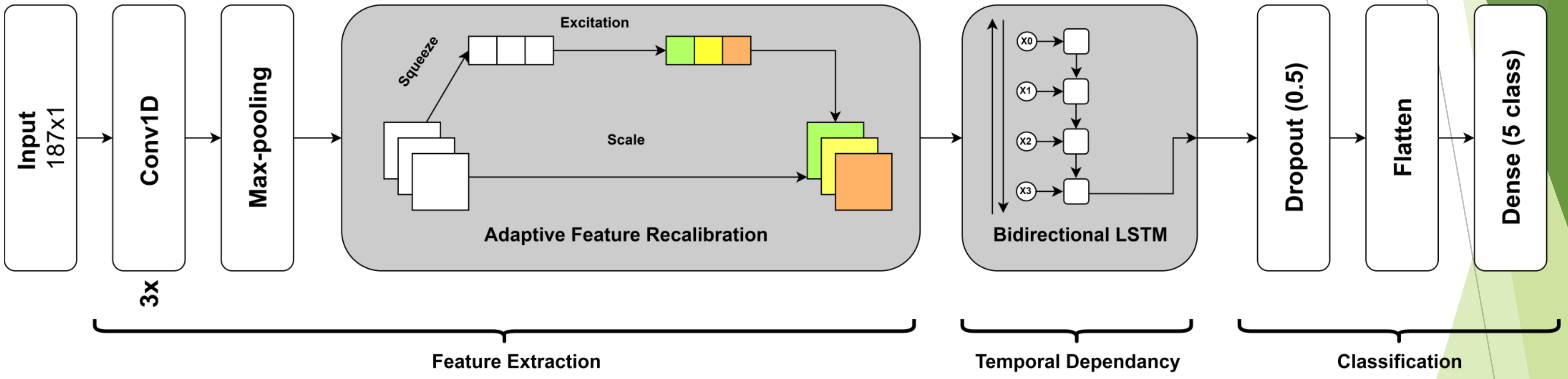
Reducible learning rate



Heartbeat abnormalities detection from ECG

1-D convolution Experiments

CNN+AFR+Bi-LSTM+RLR

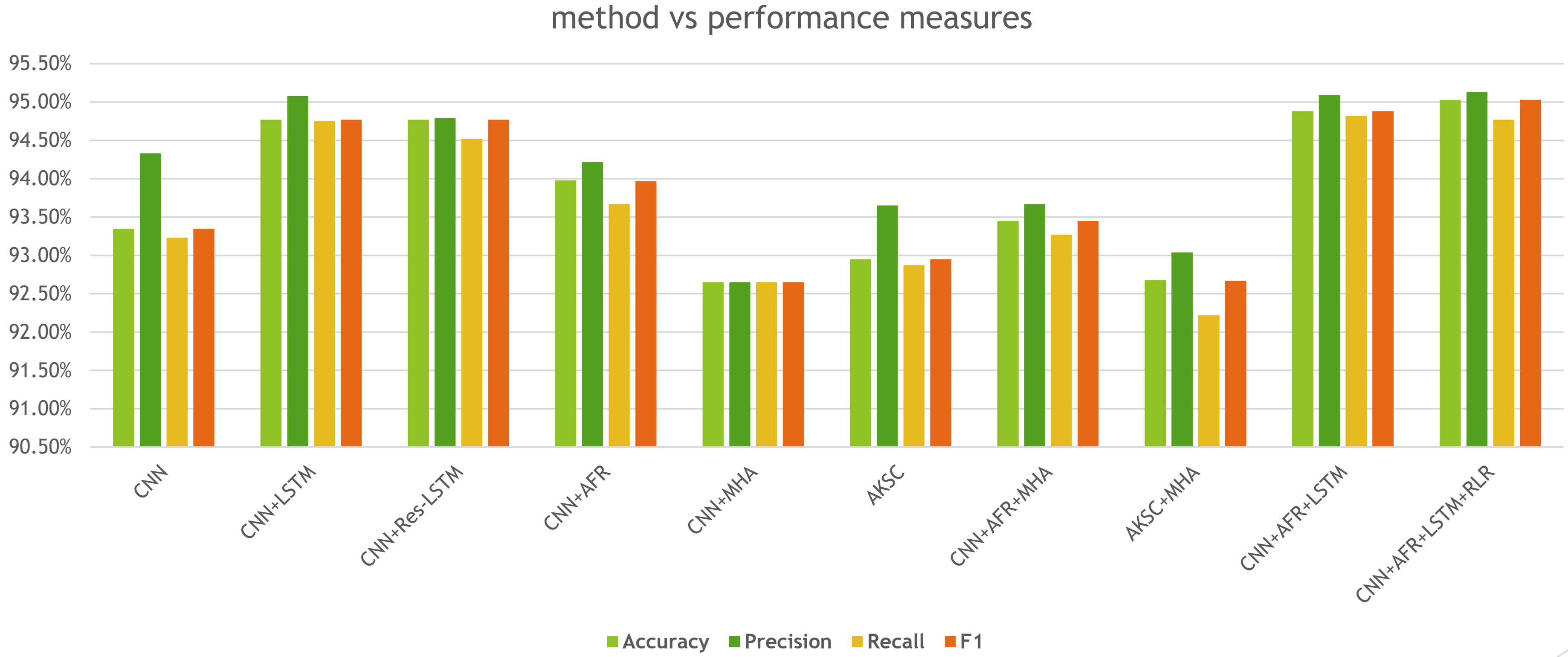


	Accuracy	Precision	Recall	F1
CNN+AFR+ Bi-LSTM+RLR	95.10%	95.10%	95.00%	95.10%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

1-D convolution Experiments

Experiments summary with weighted cross-entropy

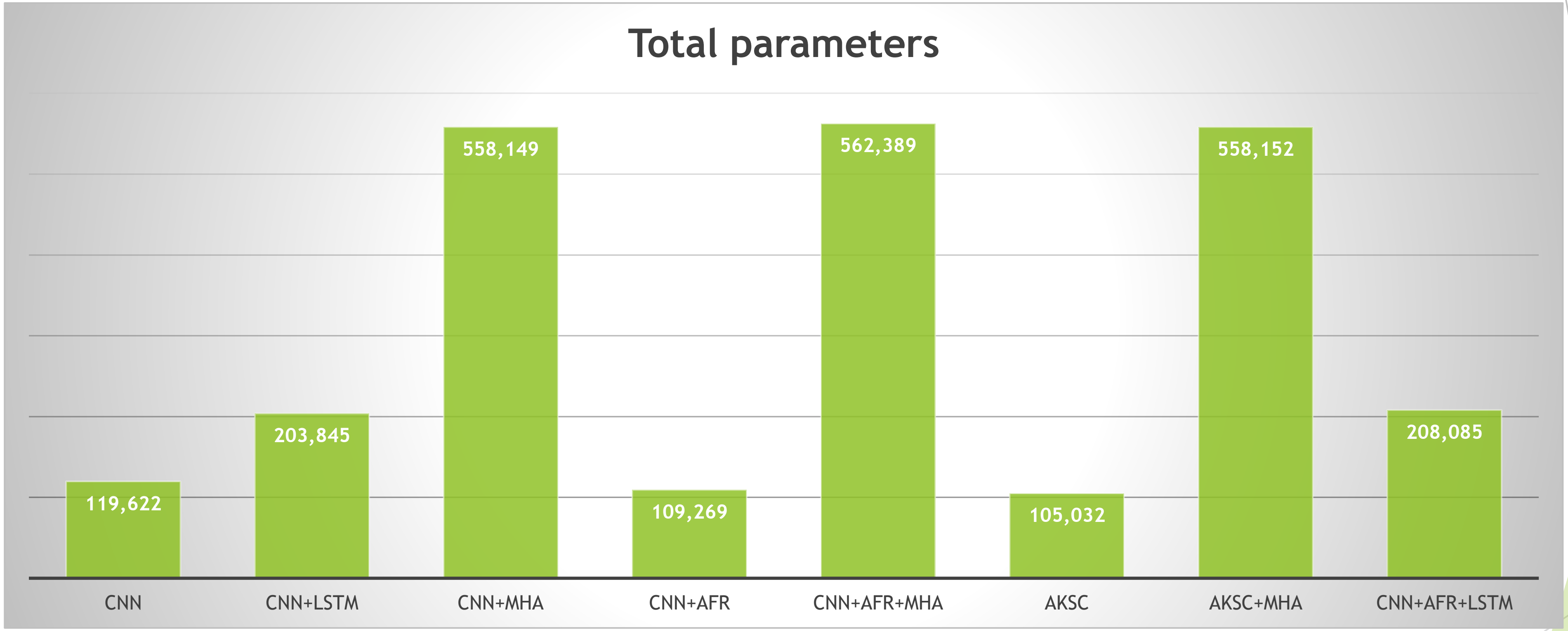


	Accuracy	Precision	Recall	F1
CNN+AFR+ Bi-LSTM+RLR	95.10%	95.10%	95.00%	95.10%
Ref	93.4%			

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments**

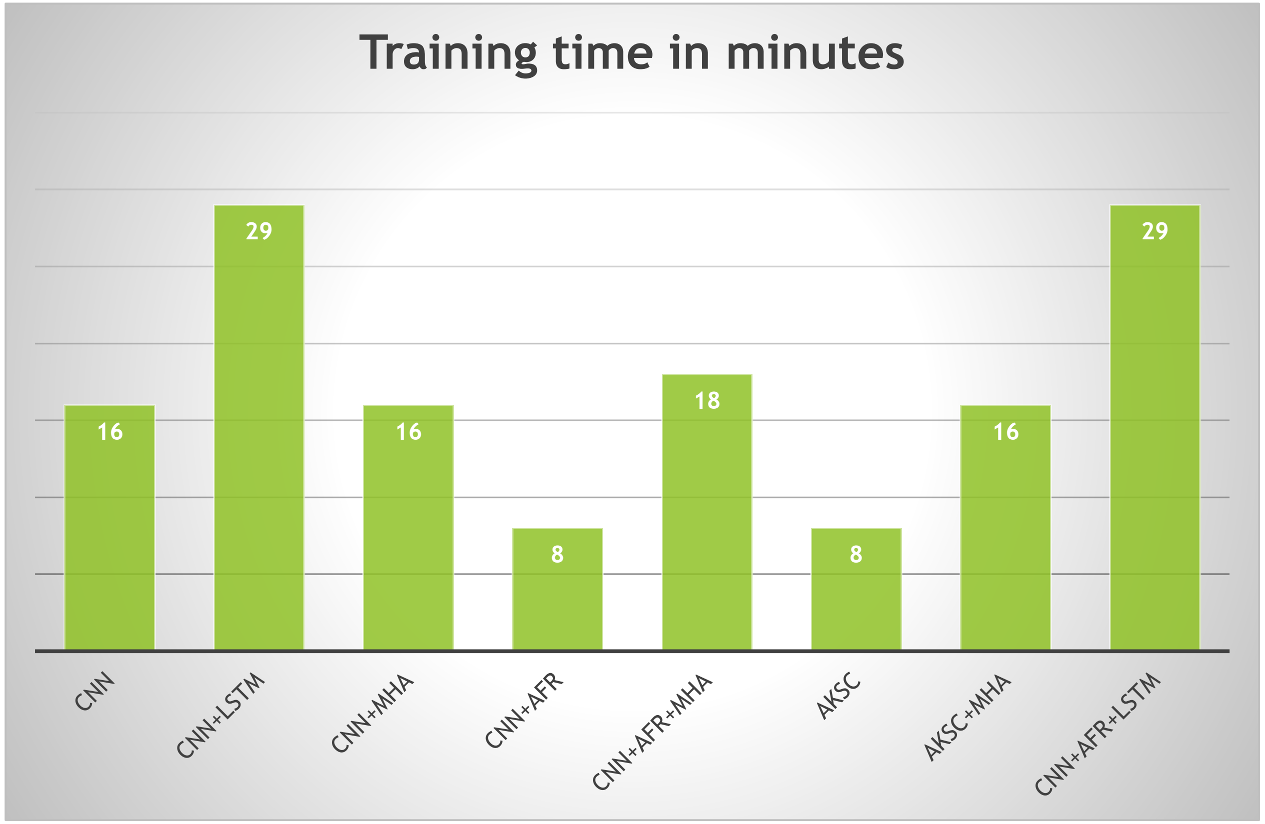
Total parameters



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

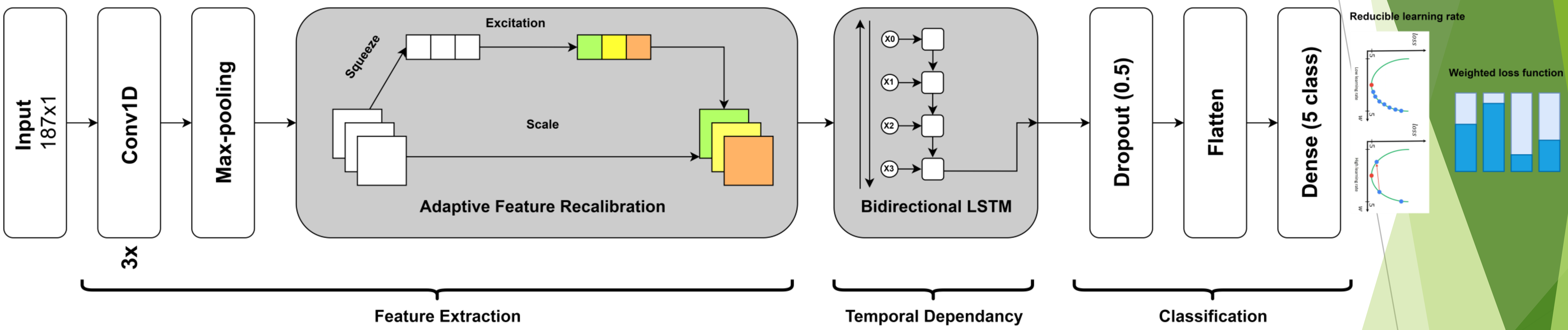
Compute Capability: 7.5

GPU Boost Clock: 1,590 MHz

Heartbeat abnormalities detection from ECG

- **1-D convolution Experiments**

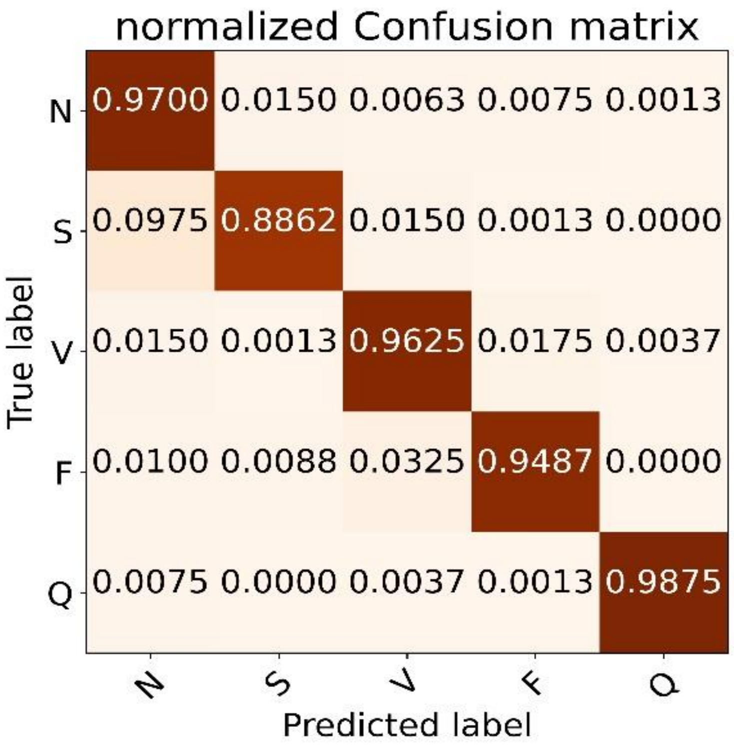
Best results: CNN+AFR+Bi-LSTM+RLR+WLF



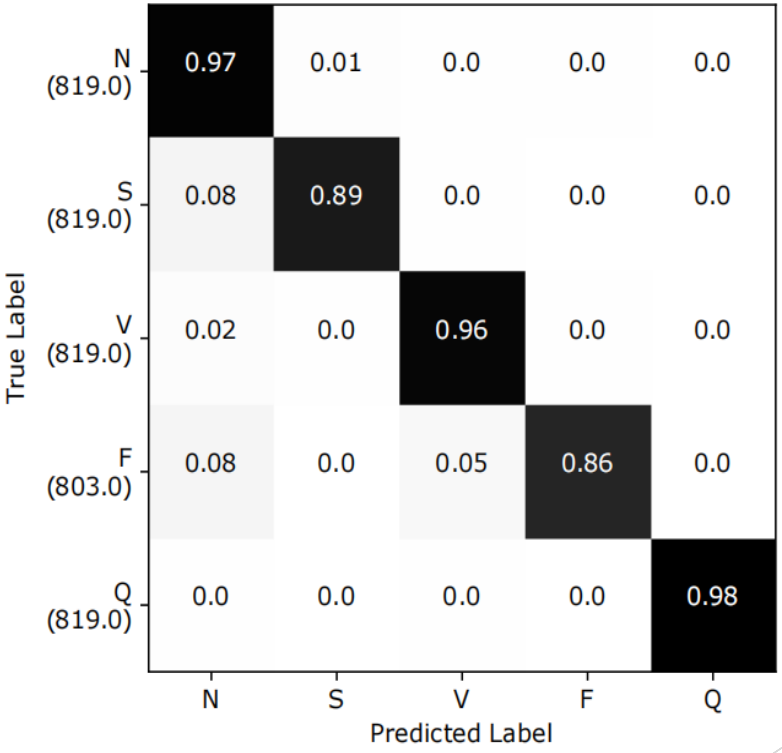
Heartbeat abnormalities detection from ECG

- **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.

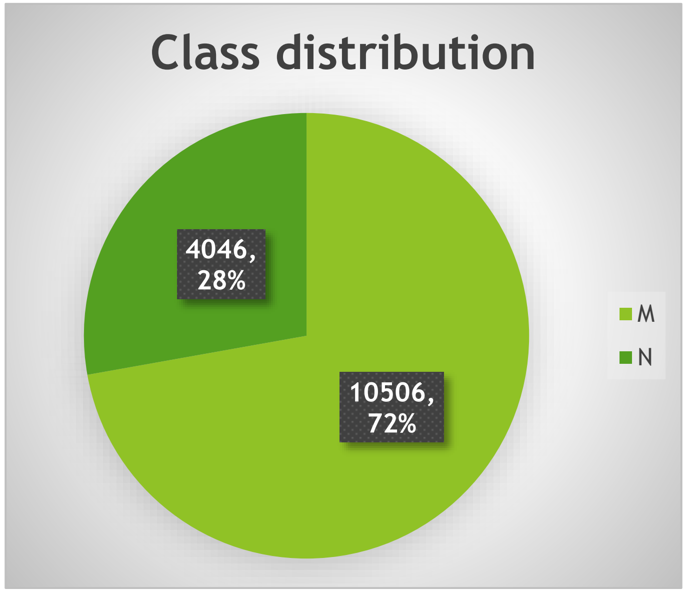
[2] Pirova, D., Zaberzhinsky, B., & Mashkov, A. (2020). Detecting heart 2 disease symptoms using machine learning methods. Proceedings of the Information Technology and Nanotechnology (ITNT-2020), 2667, 260-263.

[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

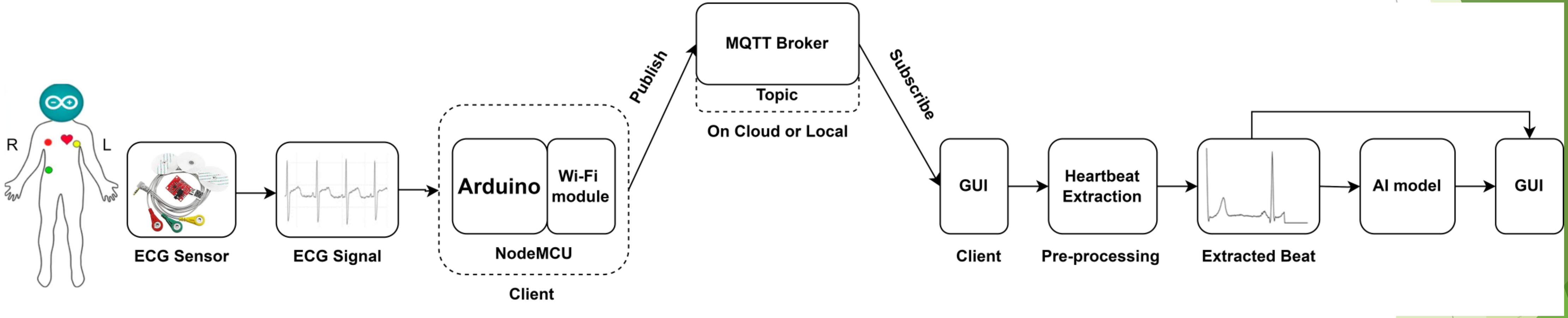
M: myocardial infarction الذبحة القلبية
N: normal طبيعي

	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

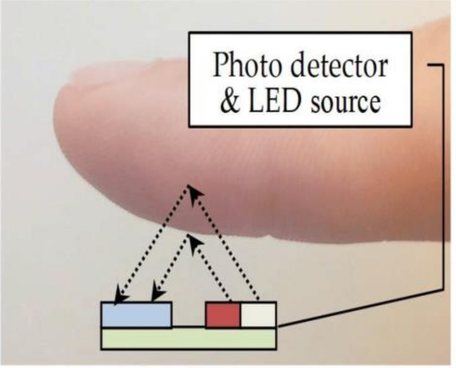


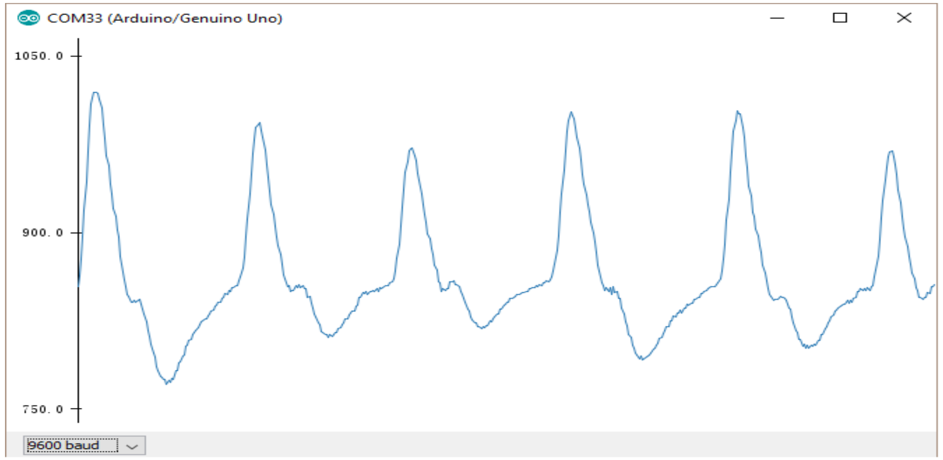
Heartbeat abnormalities detection from ECG

- **Real time diagnosis of ECG signal**

Sensors

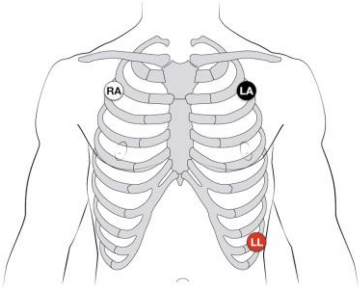
- ppg

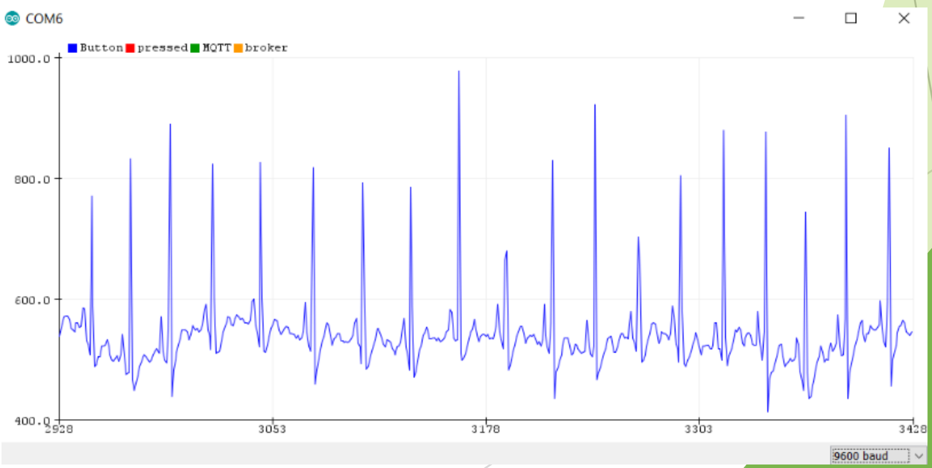




Unsuitable output

- AD8232



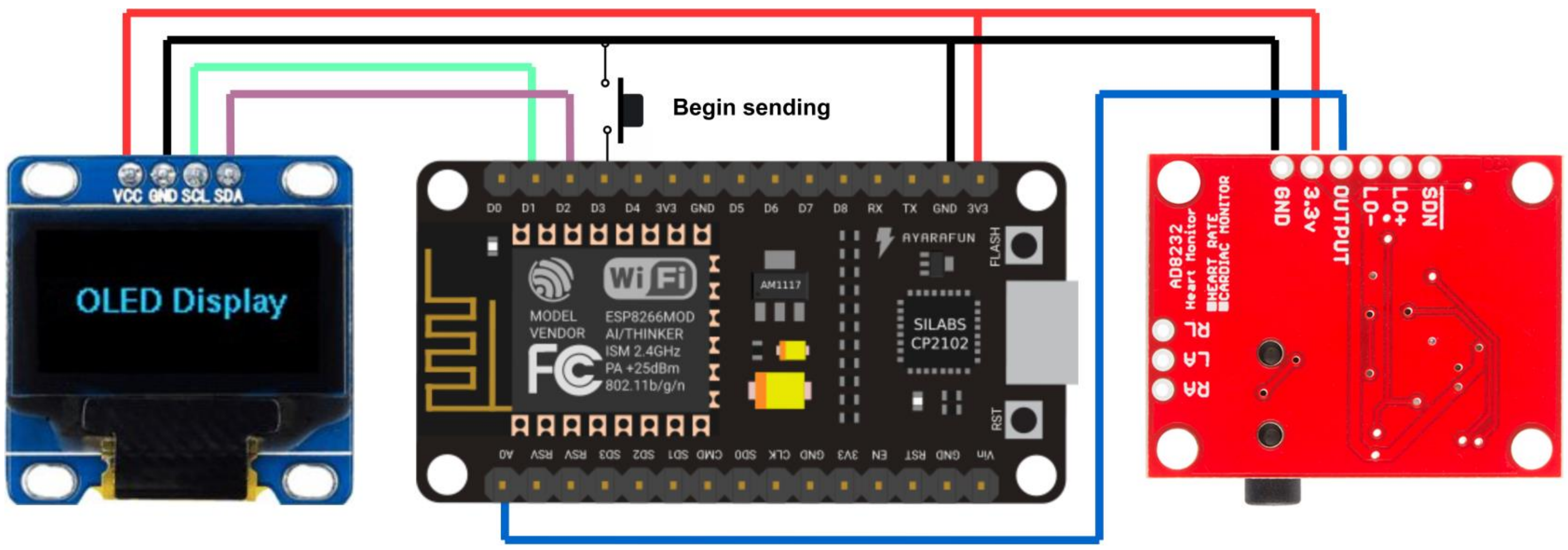


Suitable output

Heartbeat abnormalities detection from ECG

- **Real time diagnosis of ECG signal**

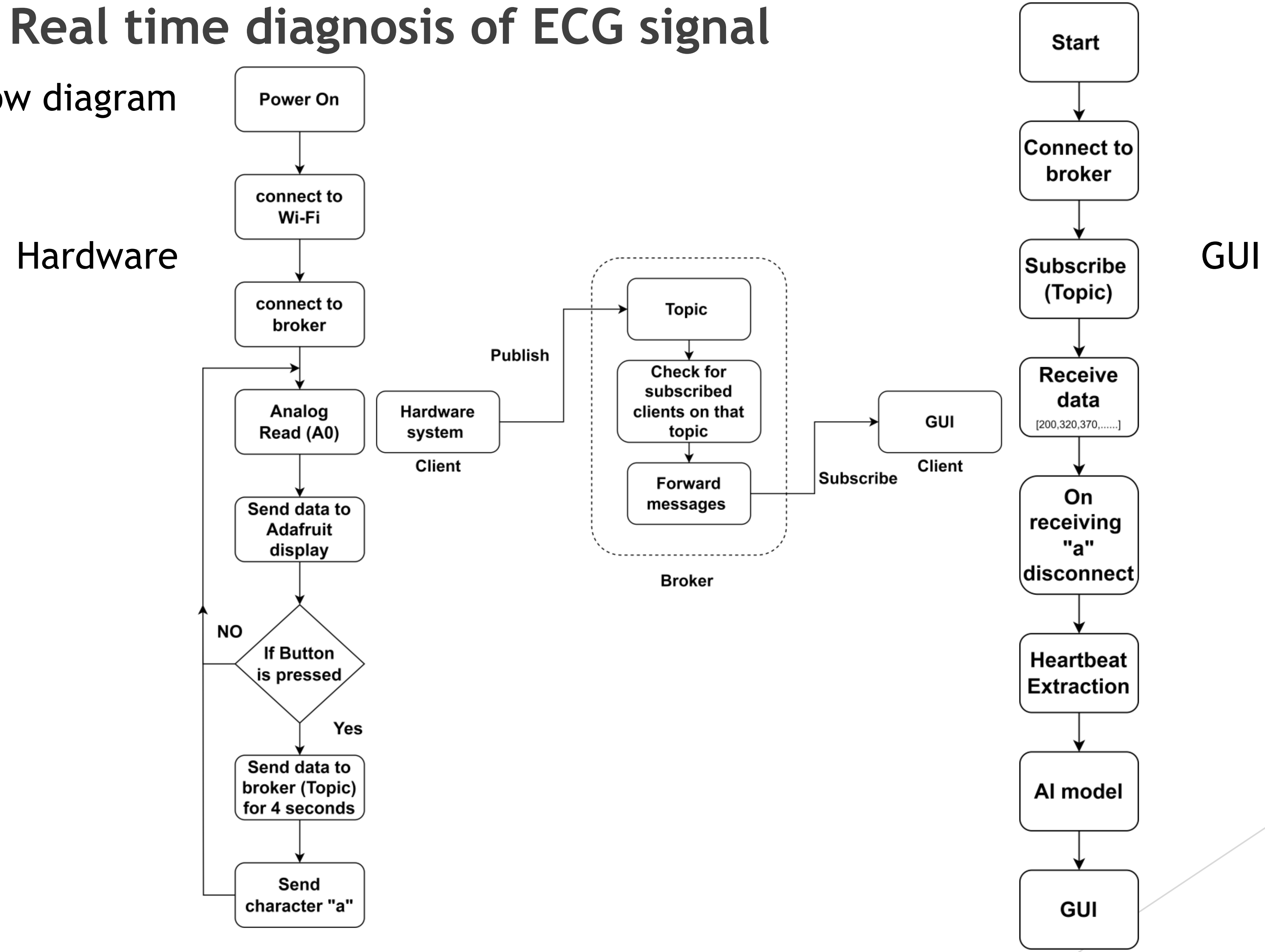
Connection diagram



Heartbeat abnormalities detection from ECG

- **Real time diagnosis of ECG signal**

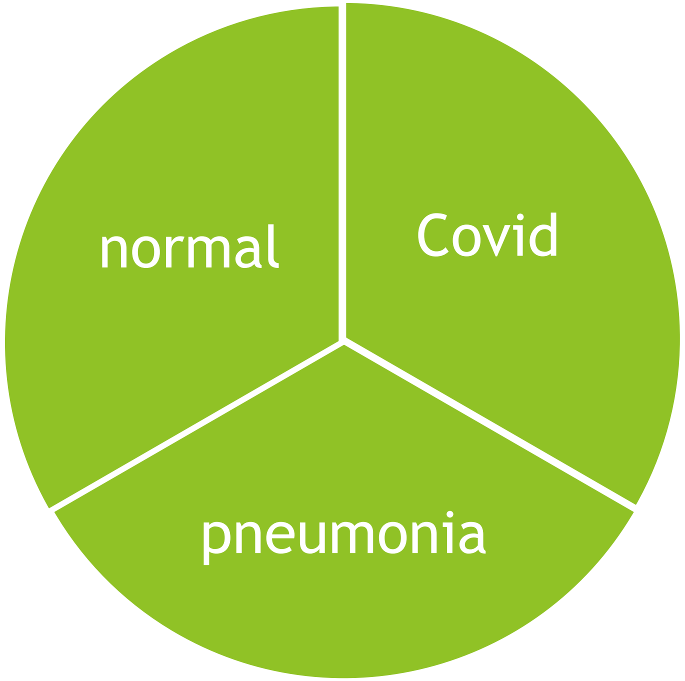
Flow diagram

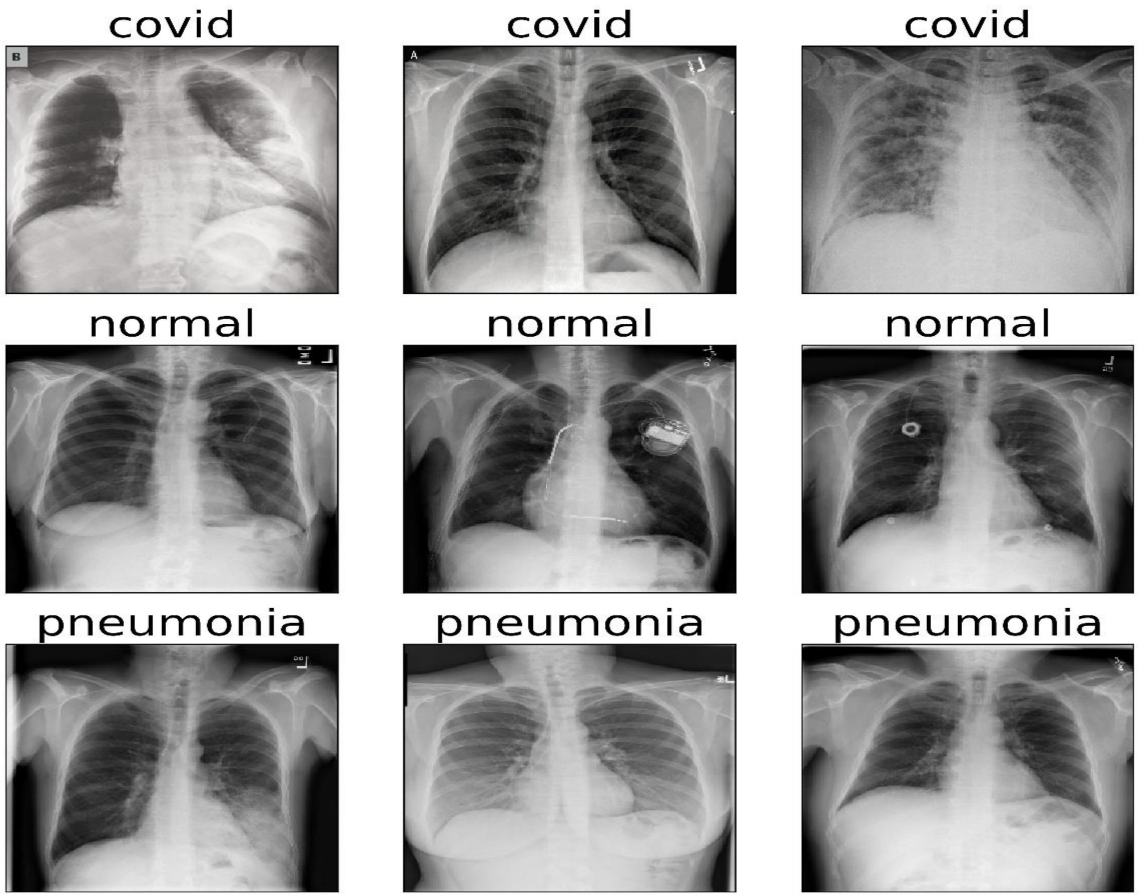


COVID-19 detection

- **Dataset description**

2313 sample for each class
6939 samples in total
RGB images





COVID-19 detection

- **Dataset description**

Data source

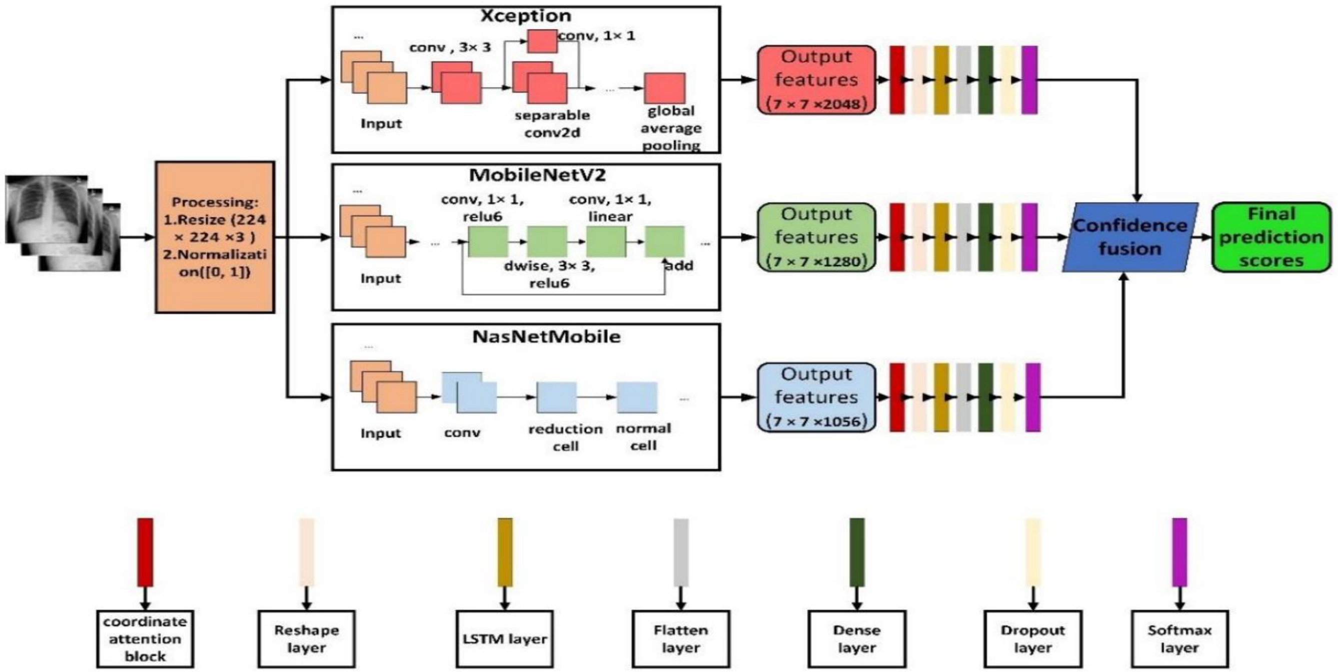
Radiopedia.org: A free, open-access, peer-reviewed, and collaborative radiology resource

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.



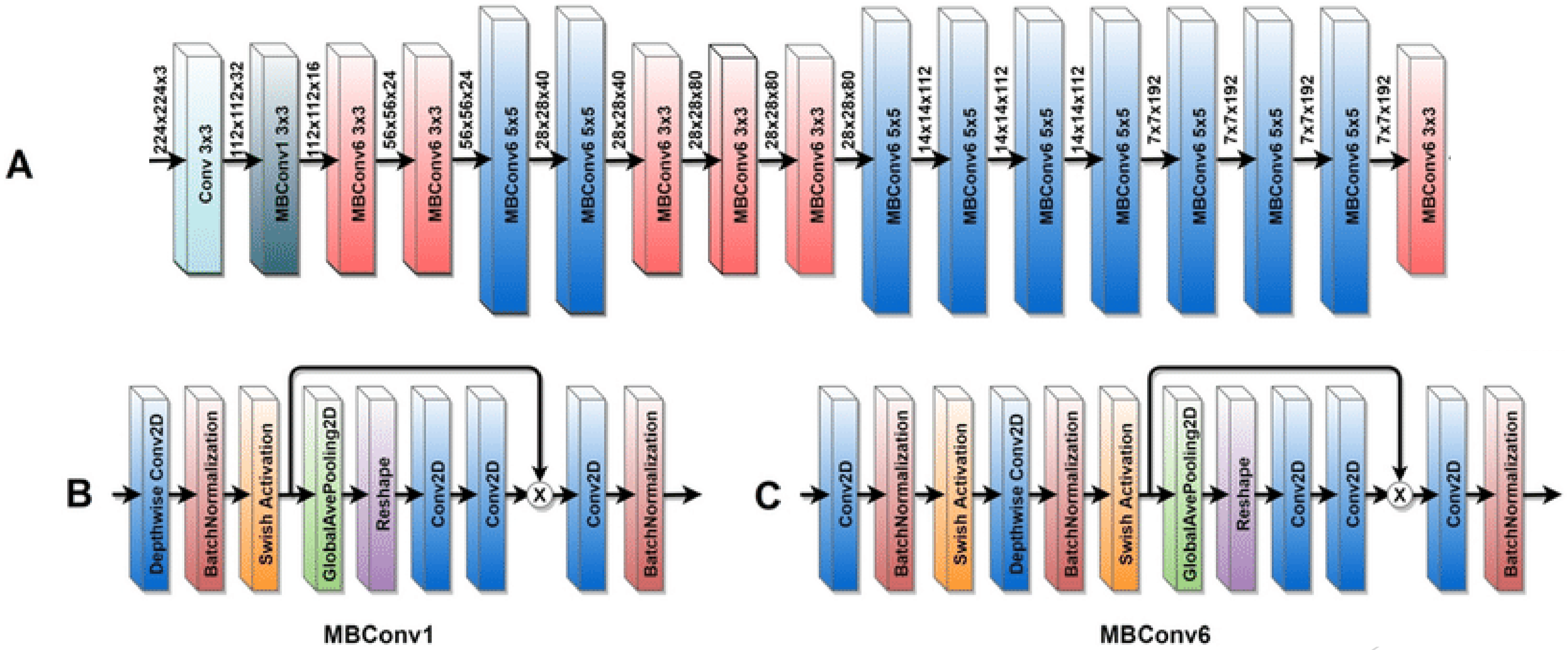
95.56% Accuracy
Complicated model
Massive no. of parameters (71million)

COVID-19 detection

- **Reference paper for result comparison**

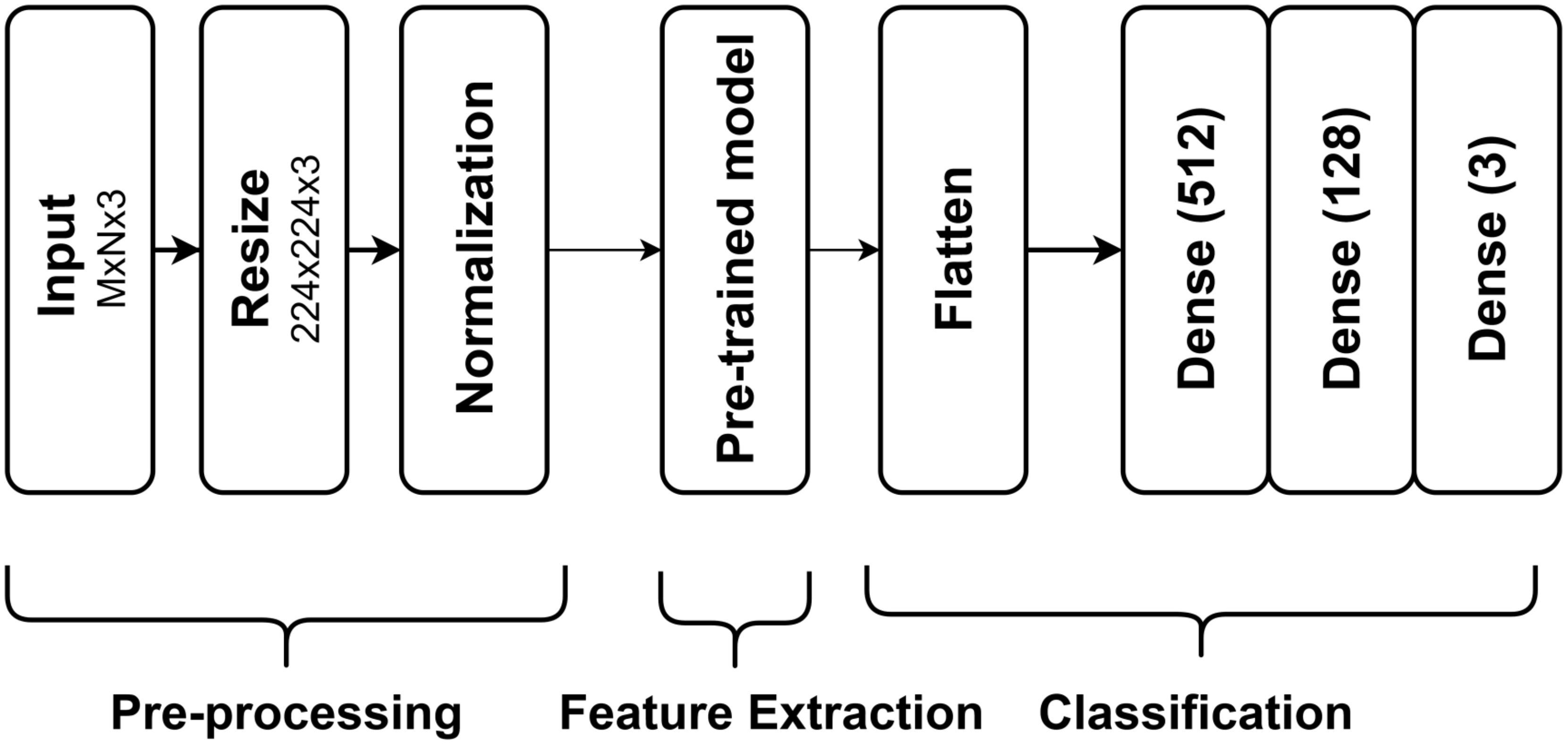
[2] E. Cengil and A. Çınar, “The effect of deep feature concatenation in the classification problem: An approach on COVID-19 disease detection,” Int. J. Imaging Syst. Technol., vol. 32, no. 1, pp. 26–40, 2022.

EfficientNet-b0
94.7% Accuracy



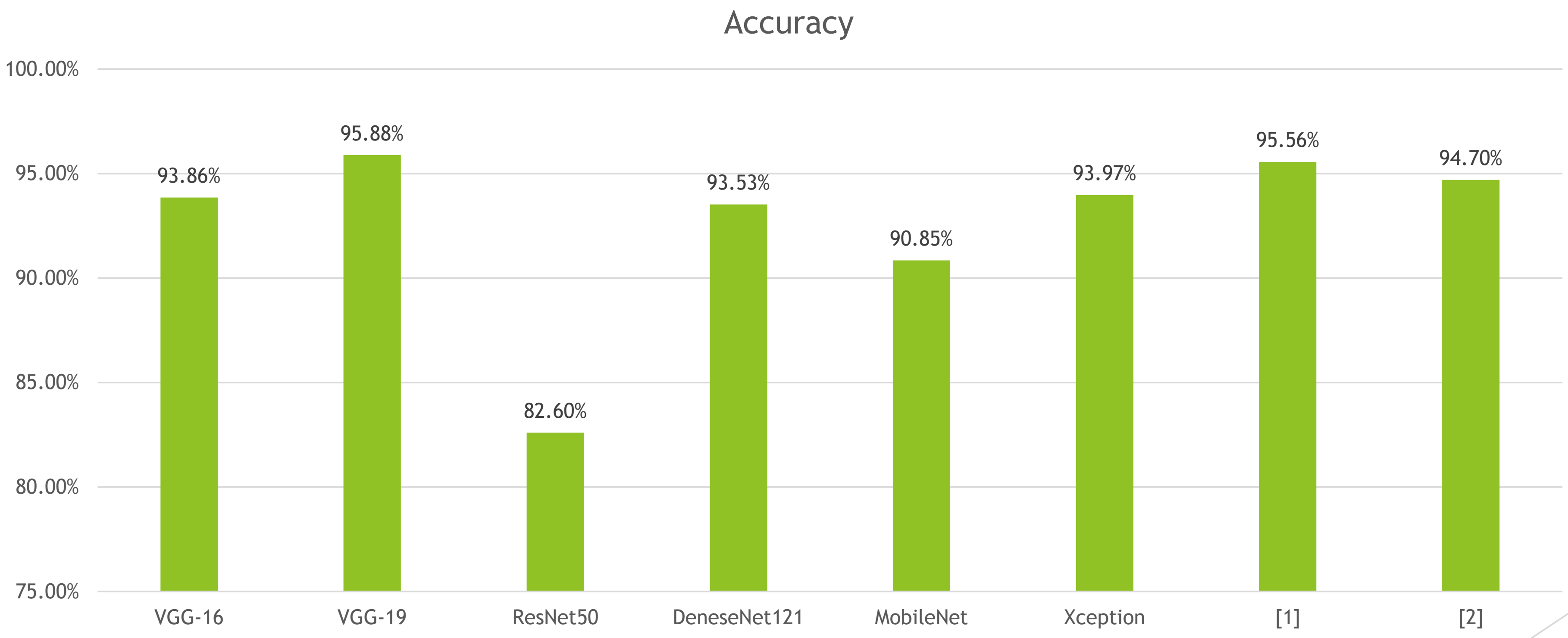
COVID-19 detection

- Pre-trained models



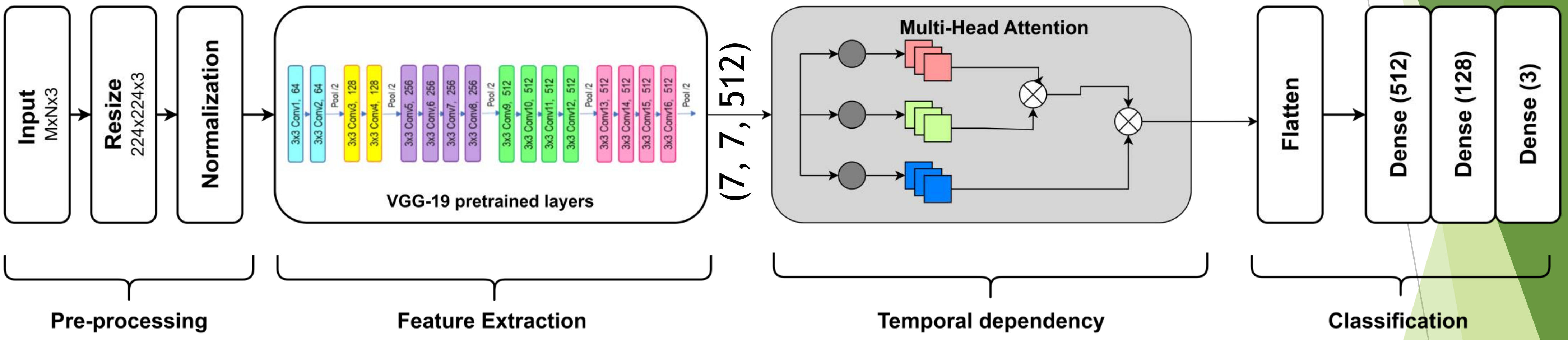
COVID-19 detection

- **Pre-trained models**



COVID-19 detection

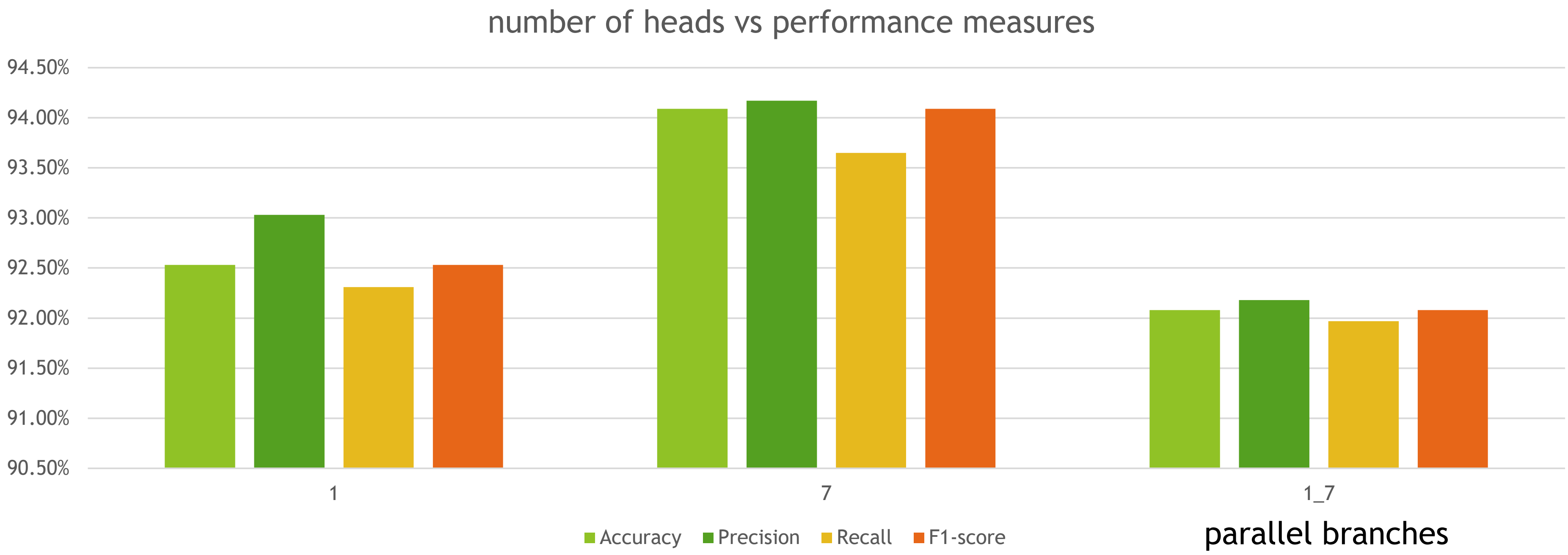
- **VGG-19 + Multi-head attention (MHA)**



Hyper-parameters:
No. of heads

COVID-19 detection

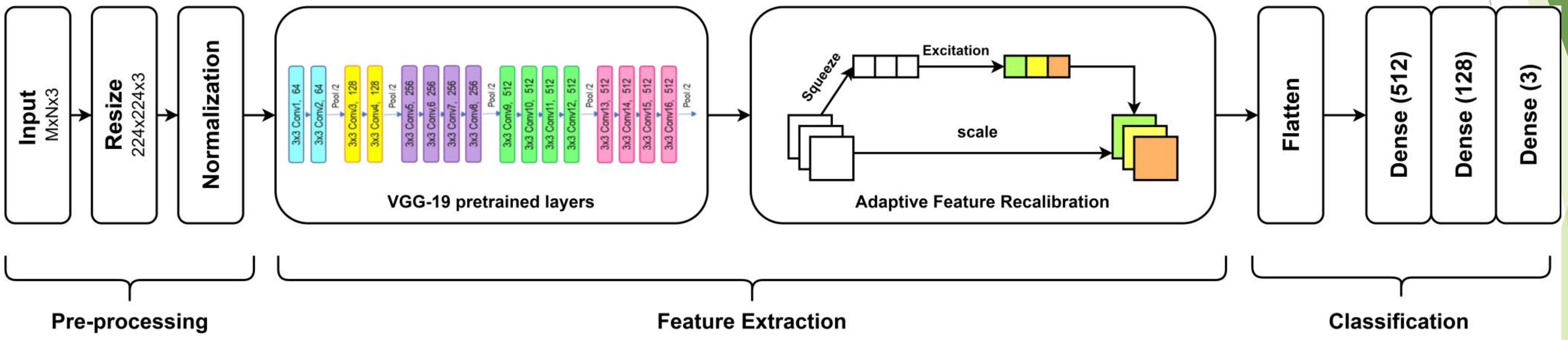
- **VGG-19 + Multi-head attention (MHA)**



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

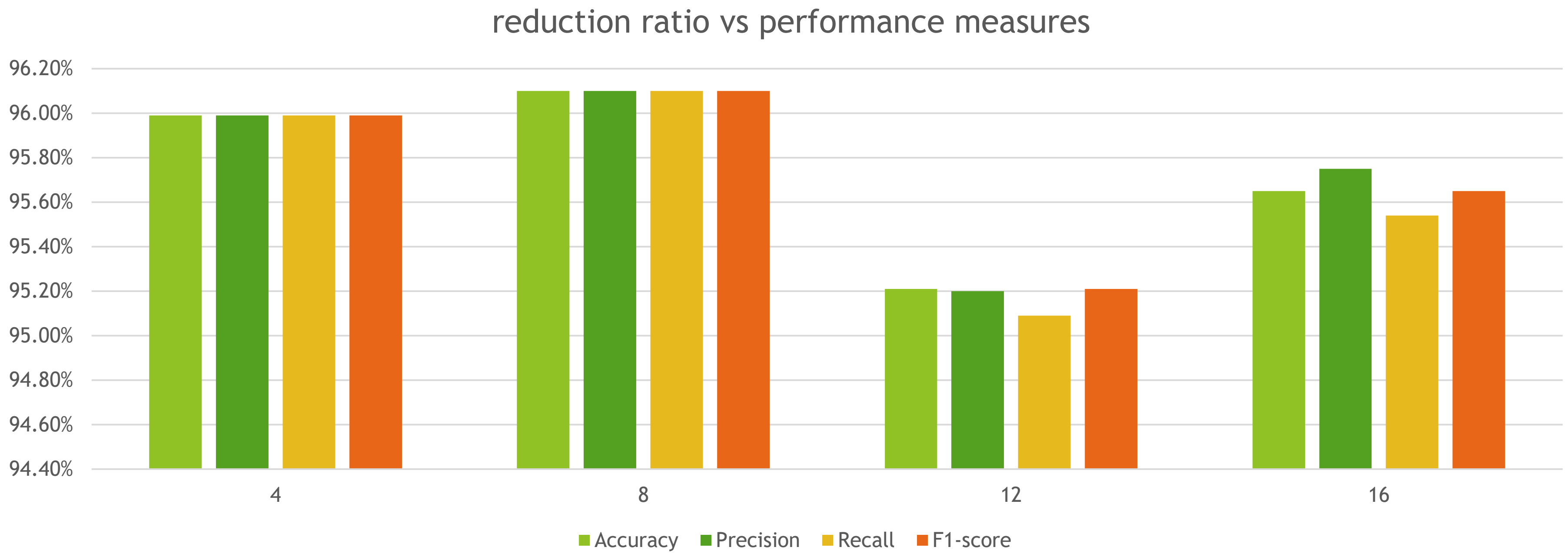
- **VGG-19 + Adaptive feature recalibration (AFR)**



Hyper-parameters:
Reduction ration

COVID-19 detection

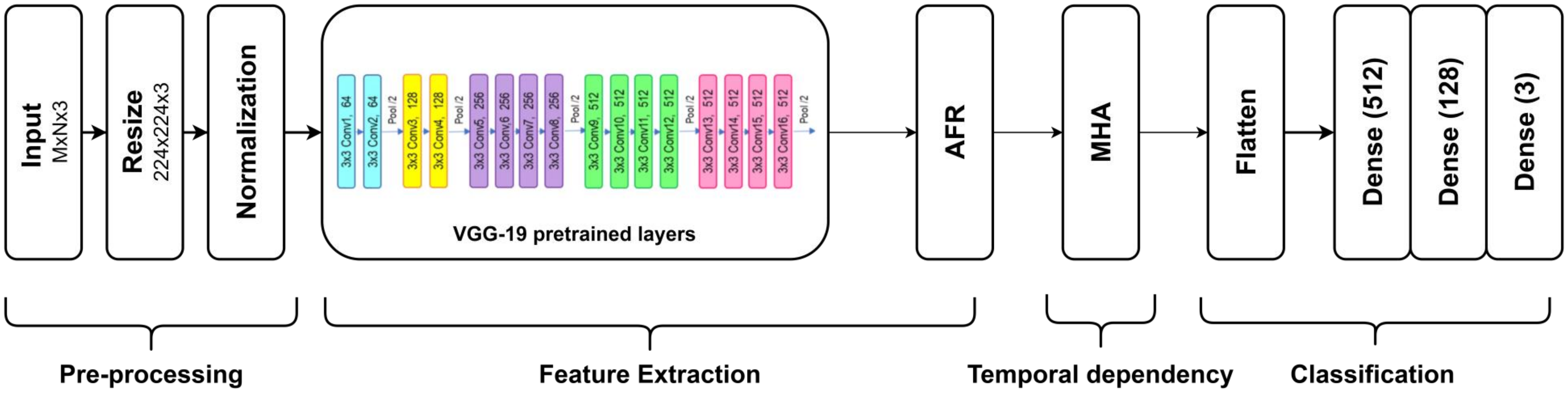
- **VGG-19 + Adaptive feature recalibration (AFR)**



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**

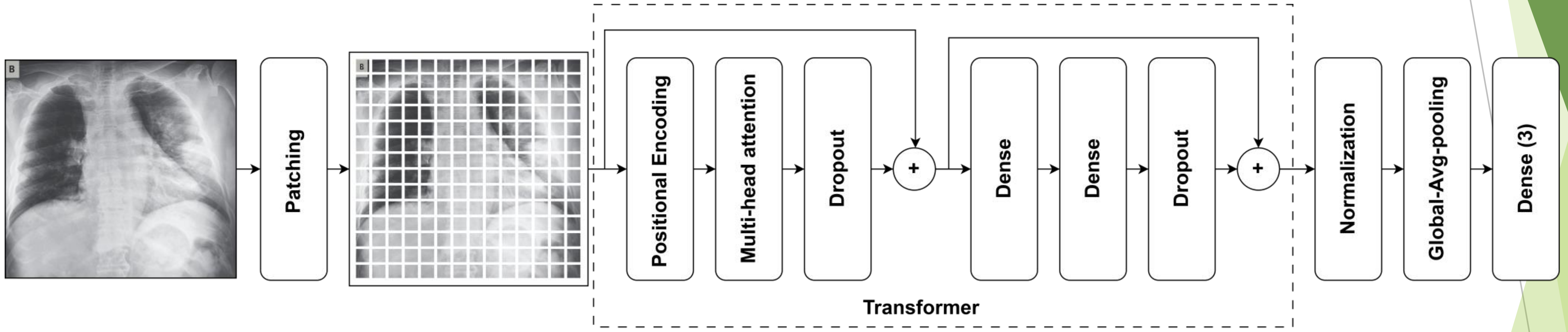


	Accuracy	Precision	Recall	F1
Proposed	92.20%	92.48%	91.86%	92.20%

[1]	95.56%			
[2]	94.7%			

COVID-19 detection

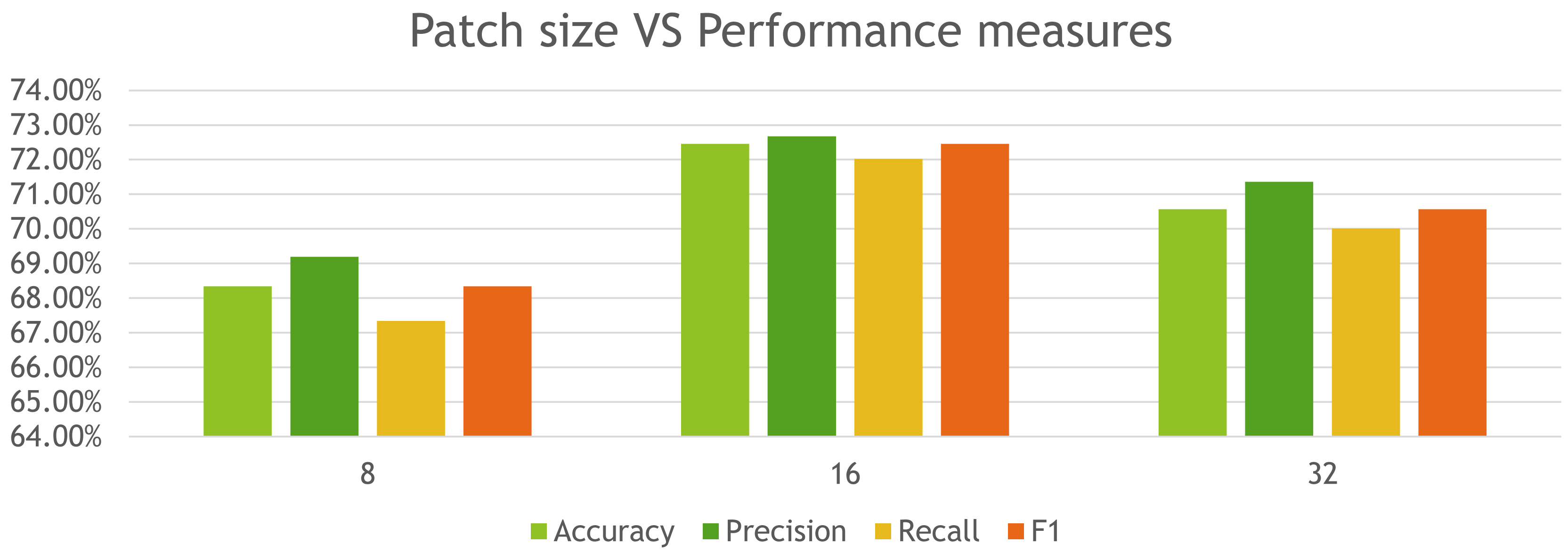
- **Vision transformer model (ViT)**



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

COVID-19 detection

- **Vision transformer model (ViT)**

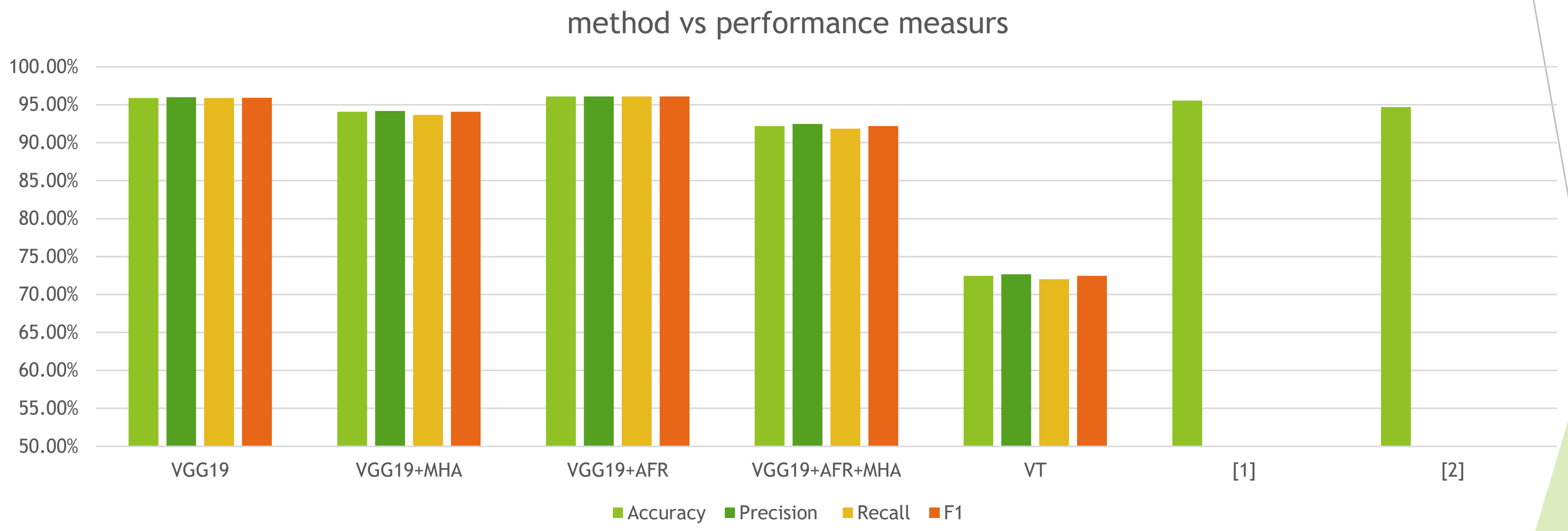


Patch size	Accuracy	Precision	Recall	F1
16	72.46%	72.67%	72.02%	72.46%

[1]	95.56%			
[2]	94.7%			

COVID-19 detection

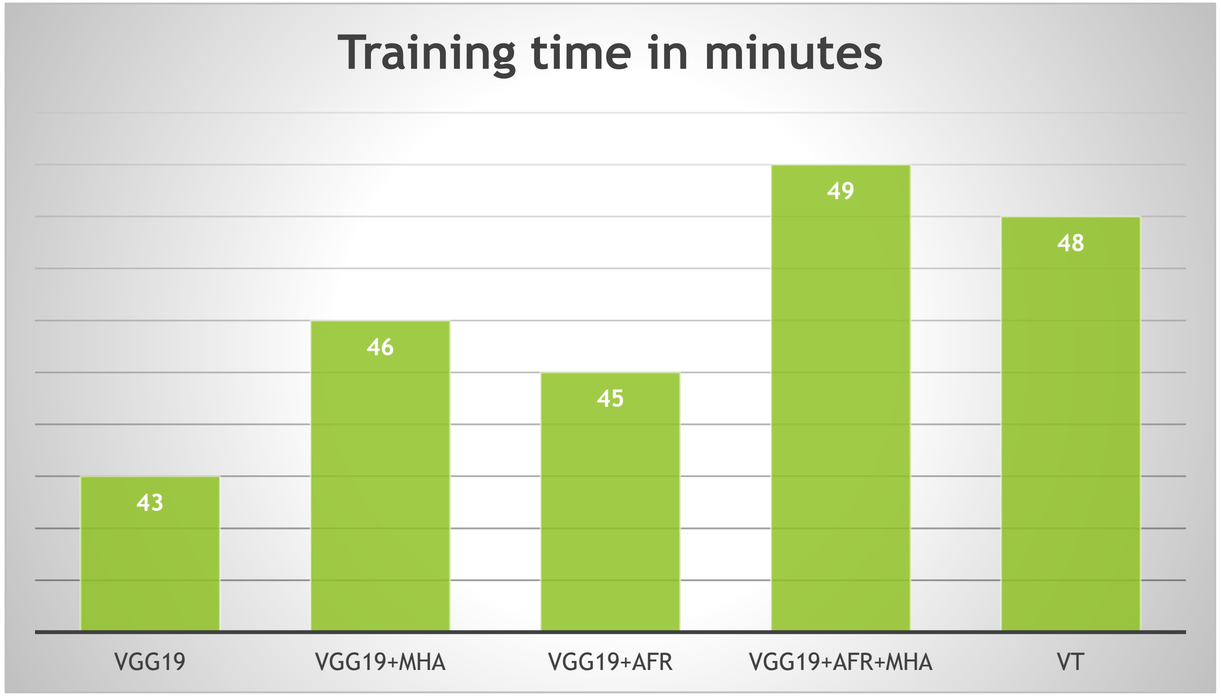
- **Experiments summary**



	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

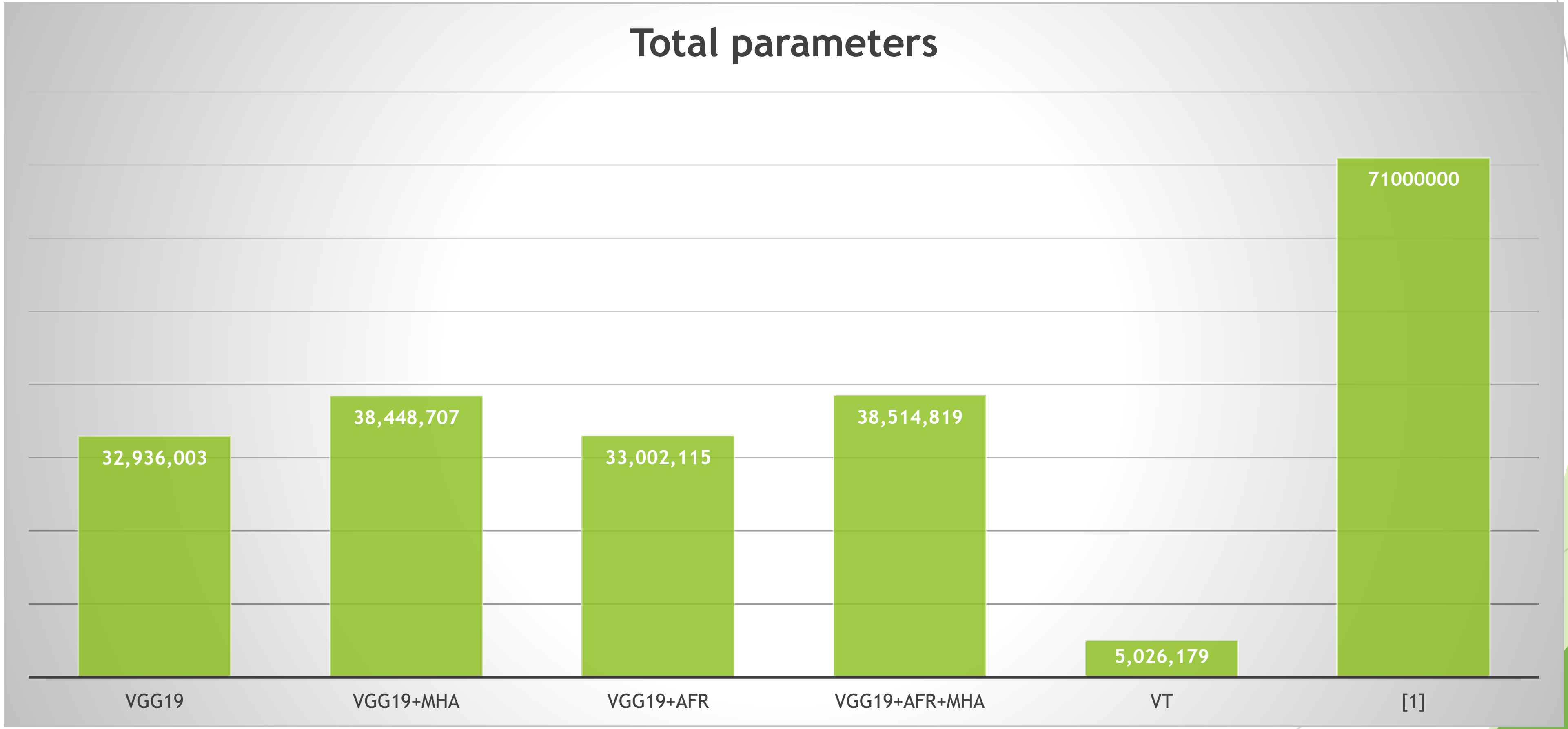
Form Factor: Single-slot, Full-height

Compute Capability: 7.5

GPU Boost Clock: 1,590 MHz

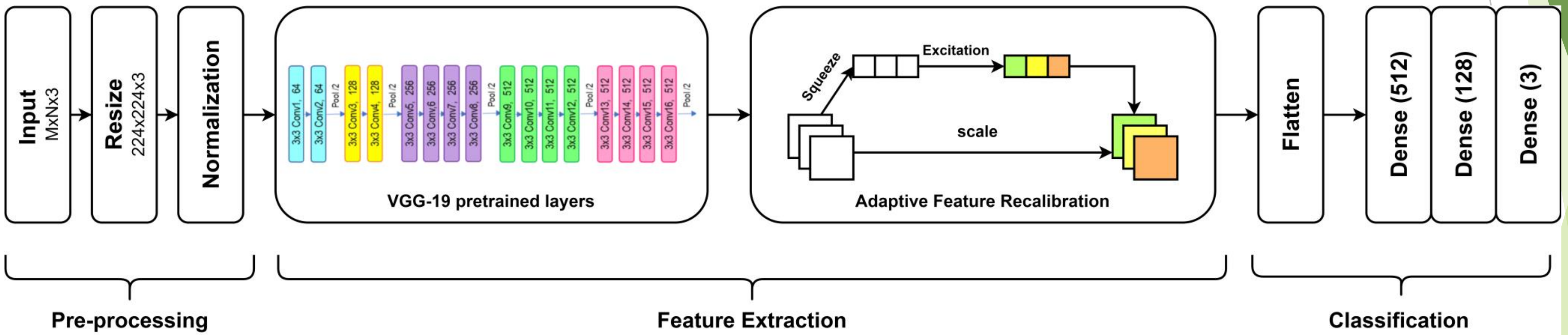
COVID-19 detection

- Total parameters



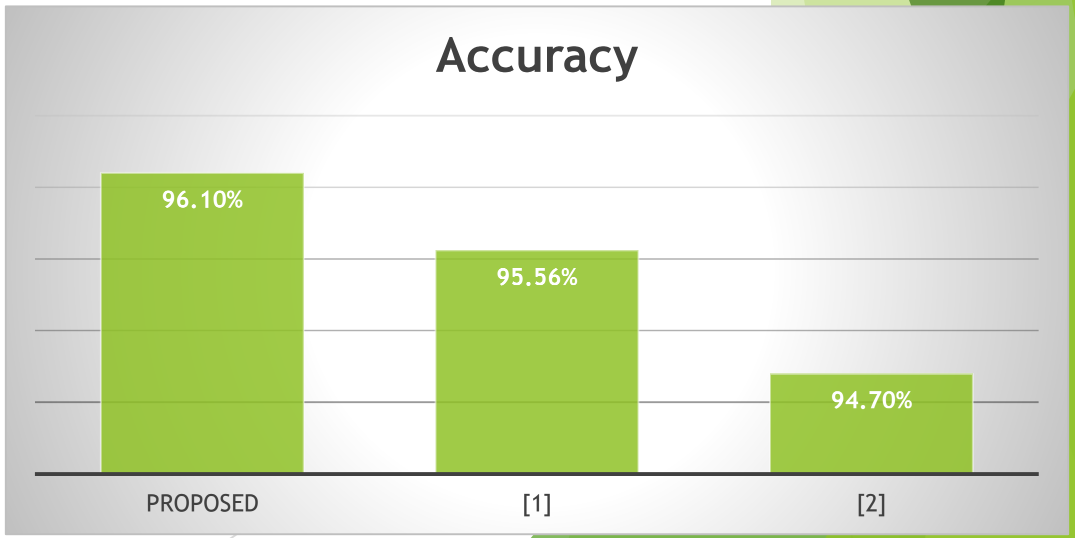
COVID-19 detection

- Best results



Simpler model
Smaller no. of parameters than [1]

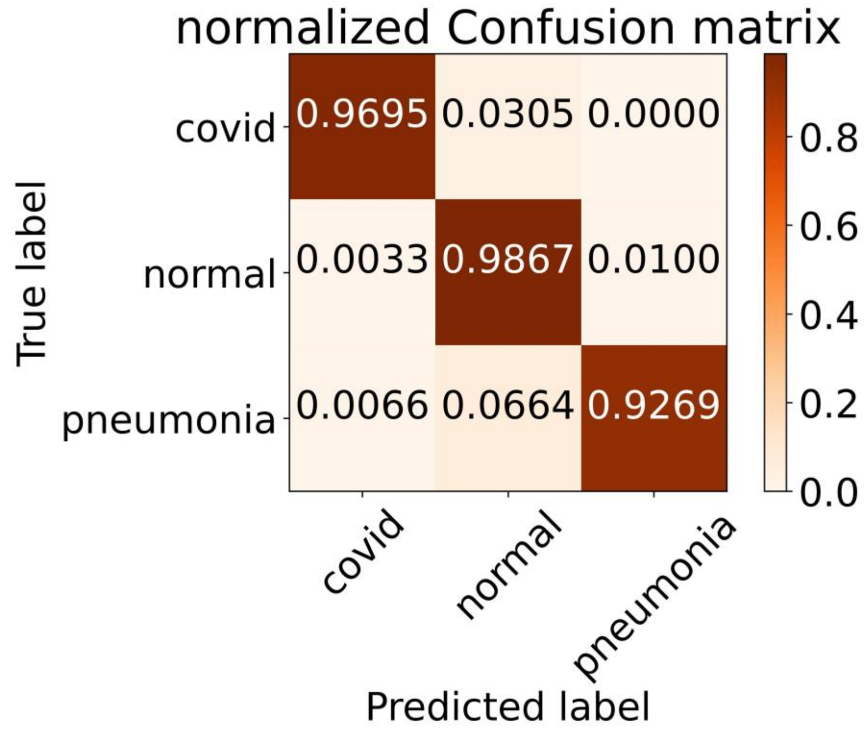
	Accuracy	Precision	Recall	F1
VGG-19+AFR	96.10%	96.10%	96.10%	96.10%
[1]	95.56%			
[2]	94.7%			

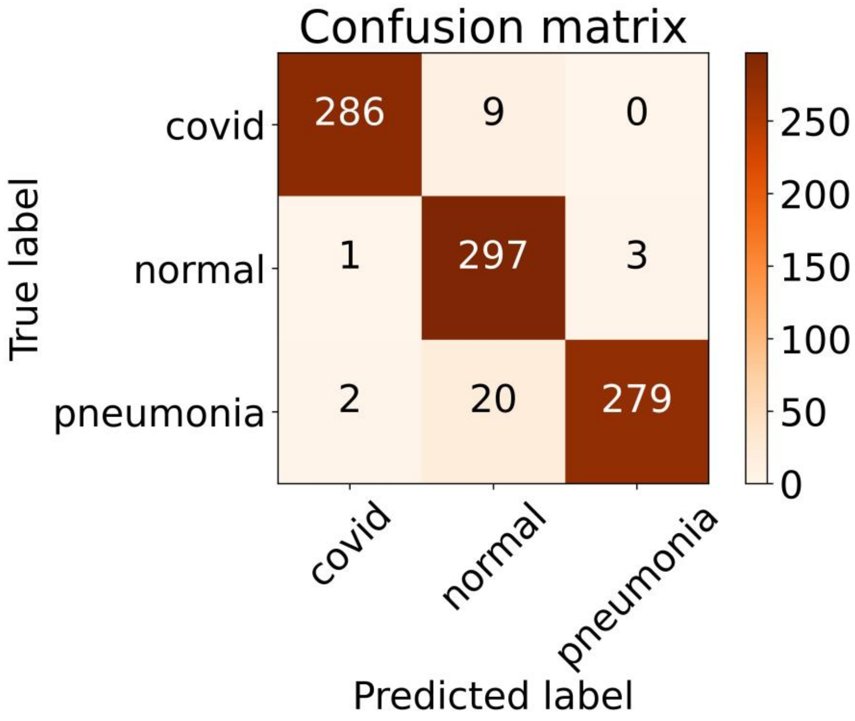


COVID-19 detection

- **Performance**

Confusion matrix





COVID-19 detection

- **Performance**

Classification report

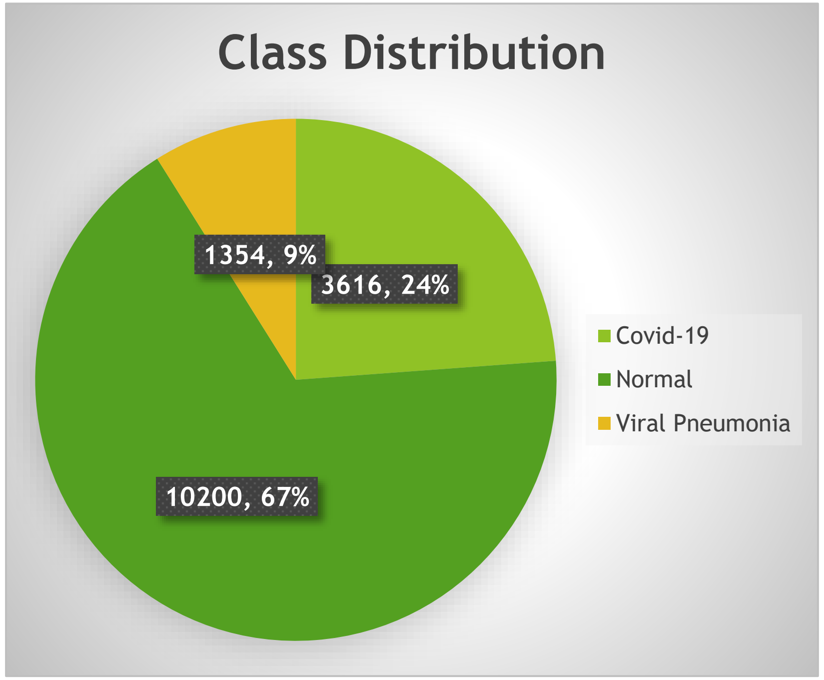
index	Class name	Precision	Recall	F1-score	Support
0	Covid-19	0.9896	0.9695	0.9795	295
1	Normal	0.911	0.9867	0.9474	301
2	pneumonia	0.9894	0.9269	0.9571	301
accuracy				0.9610	897
macro avg		0.9633	0.9610	0.9613	897
Weighted avg		0.9632	0.9610	0.9612	897

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

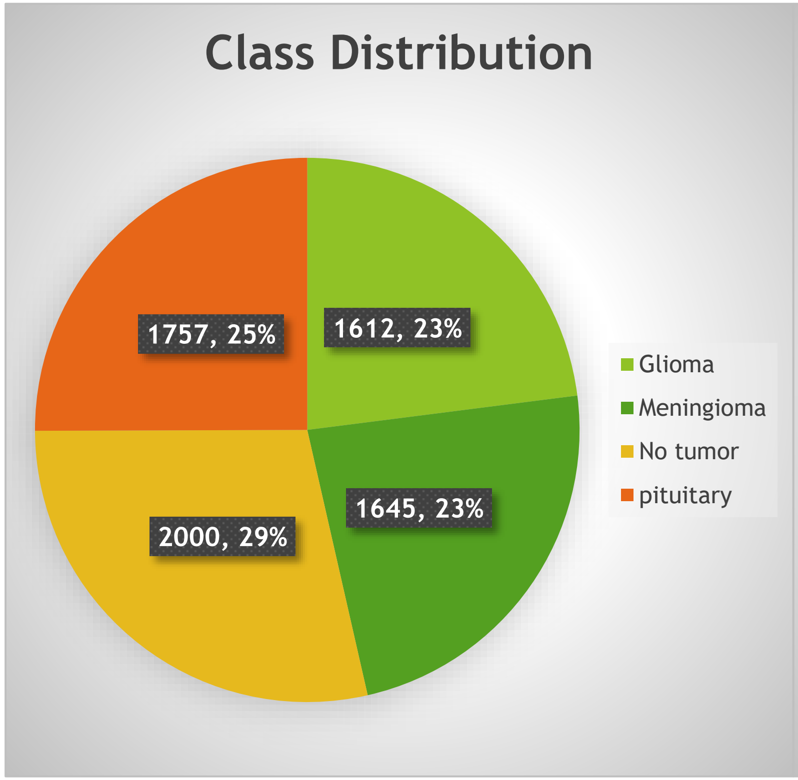
- **Online testing**

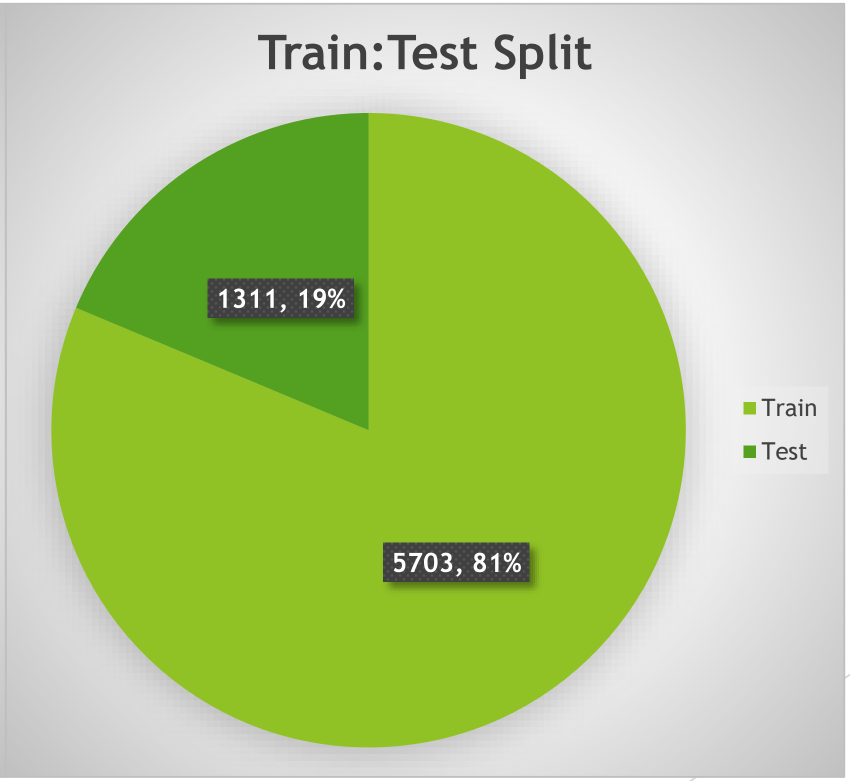
Covid-19	Normal	Pneumonia
8 samples	8 samples	8 samples
All correctly diagnosed	1 misdiagnosed	All correctly diagnosed

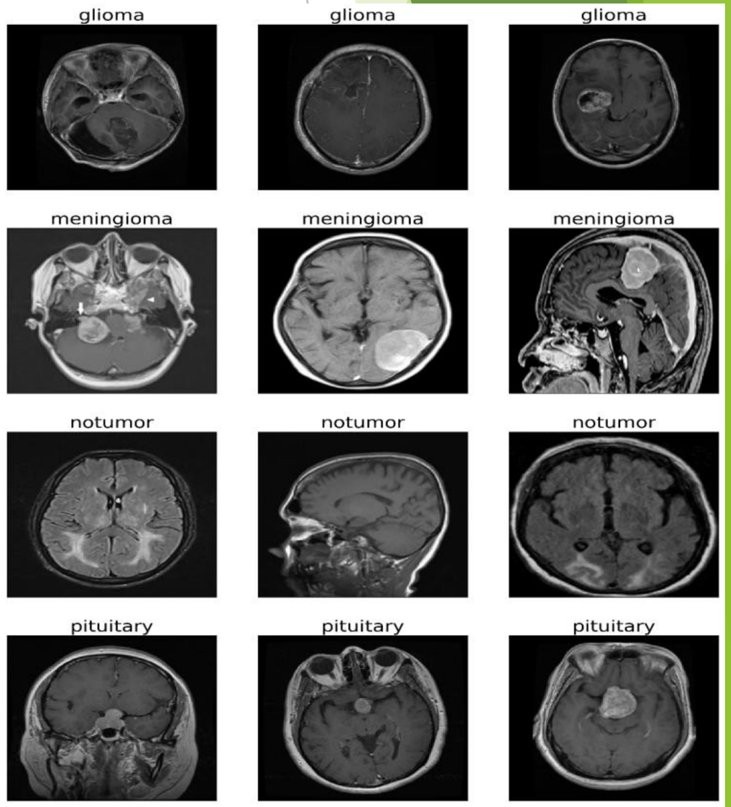
Brain tumor classification

- **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

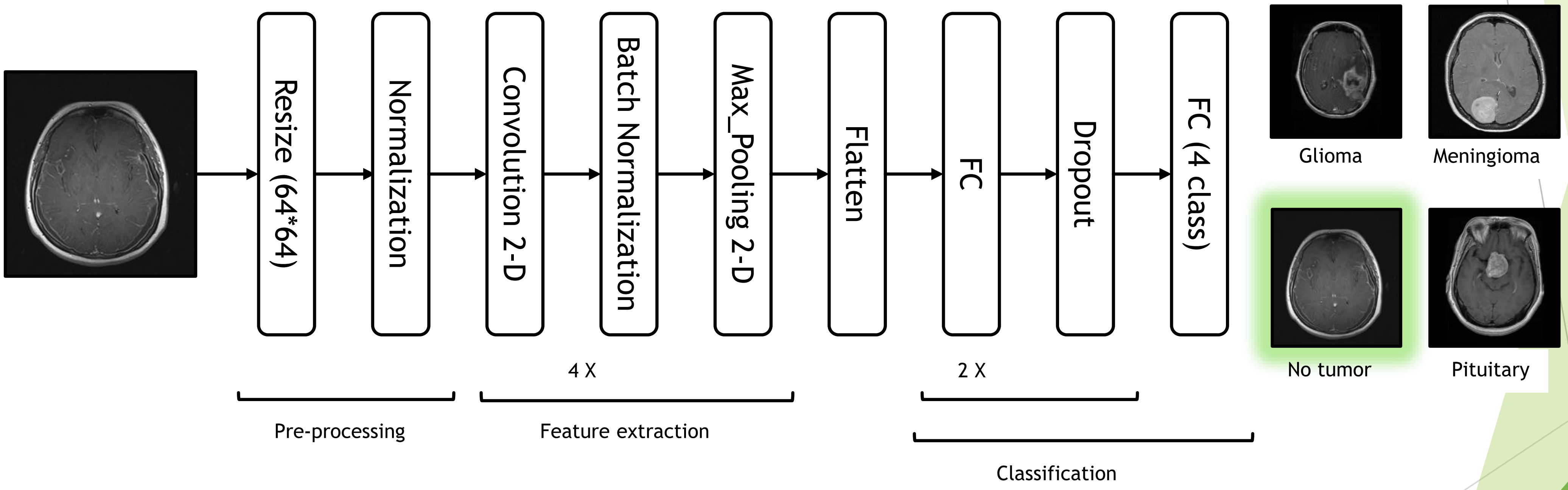
Brain tumor classification

- **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

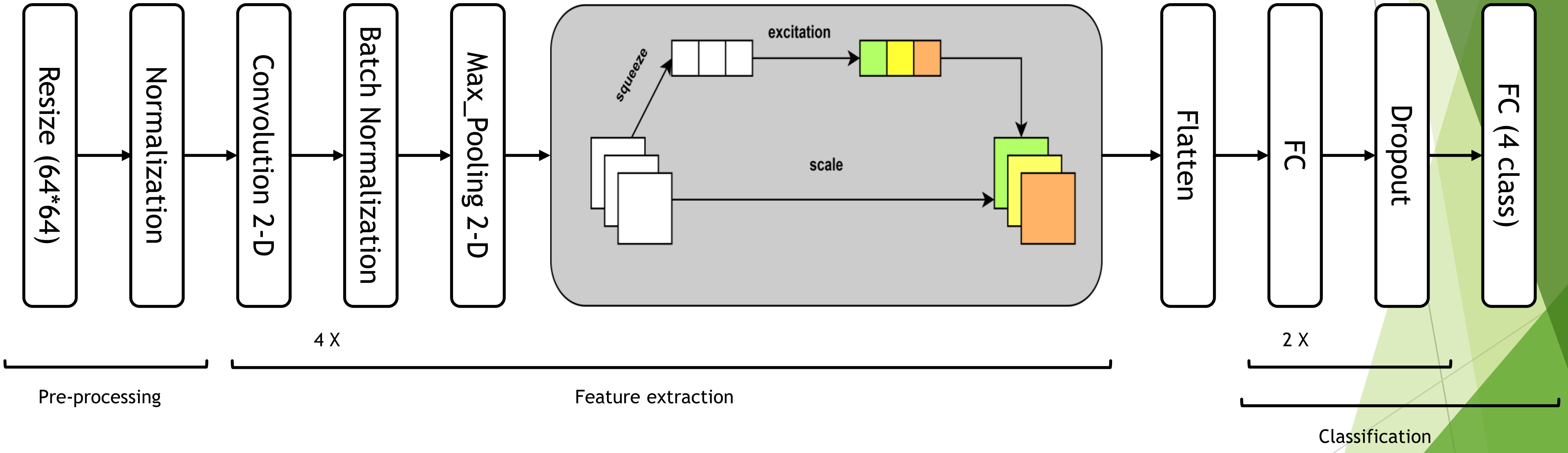
- CNN architecture



99.16% accuracy

Brain tumor classification

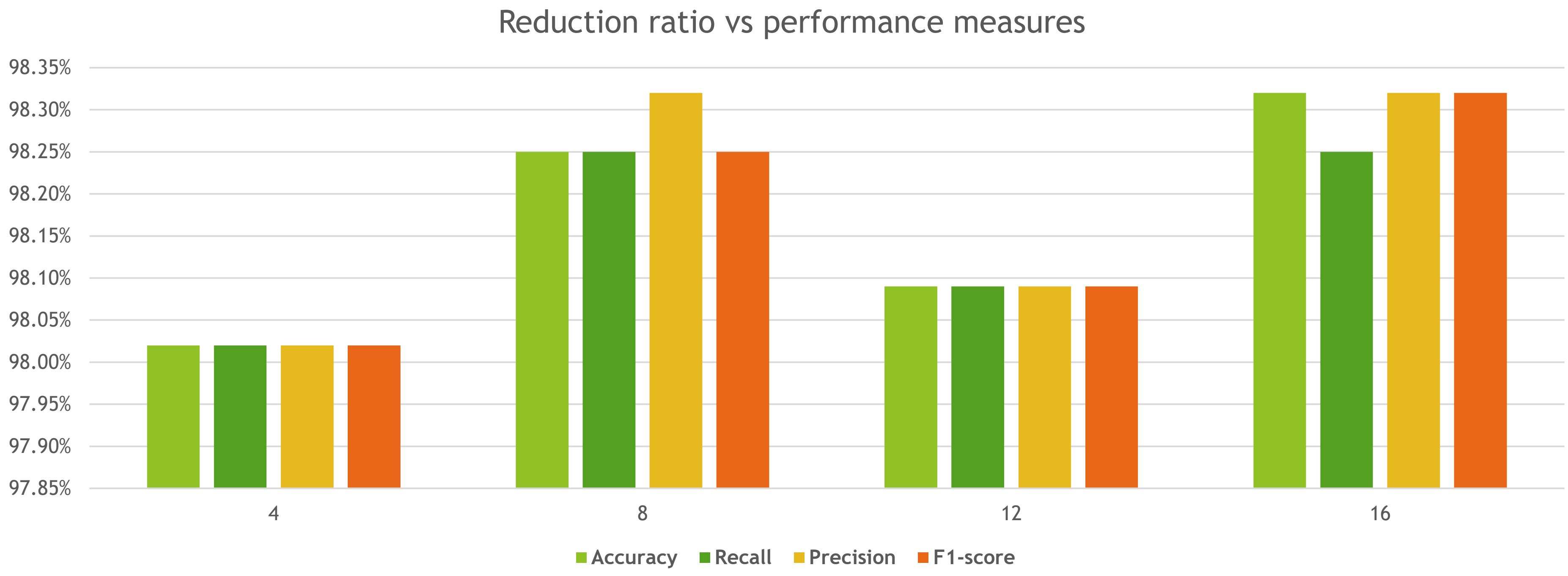
- **CNN+ Adaptive Feature Recalibration (AFR)**



Hyper-parameters:
Reduction ration

Brain tumor classification

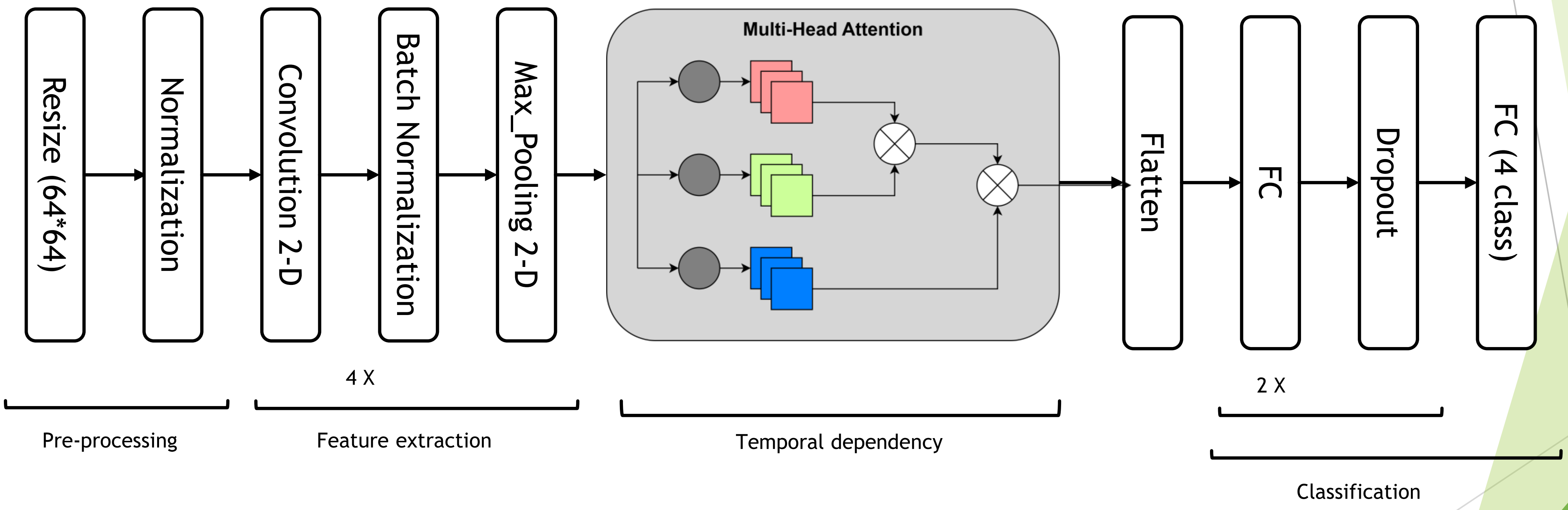
- **CNN+ Adaptive Feature Recalibration (AFR)**



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

Brain tumor classification

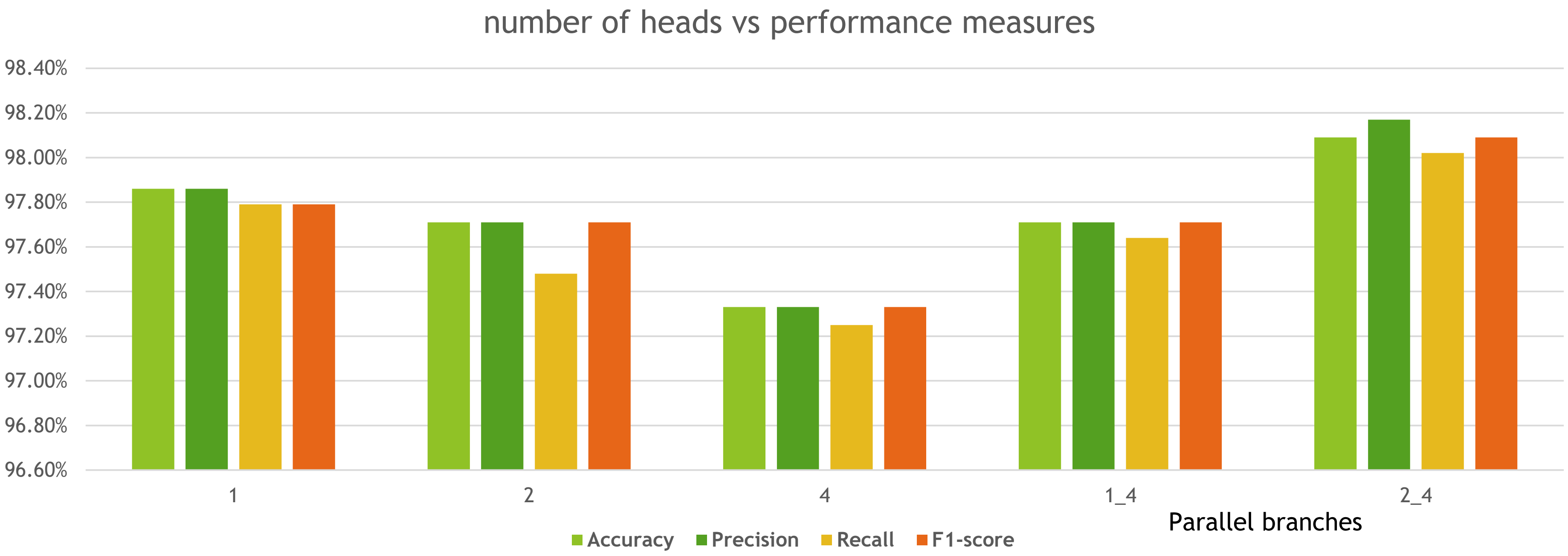
- **CNN+ Multi-head Attention (MHA)**



Hyper-parameters:
No. of heads

Brain tumor classification

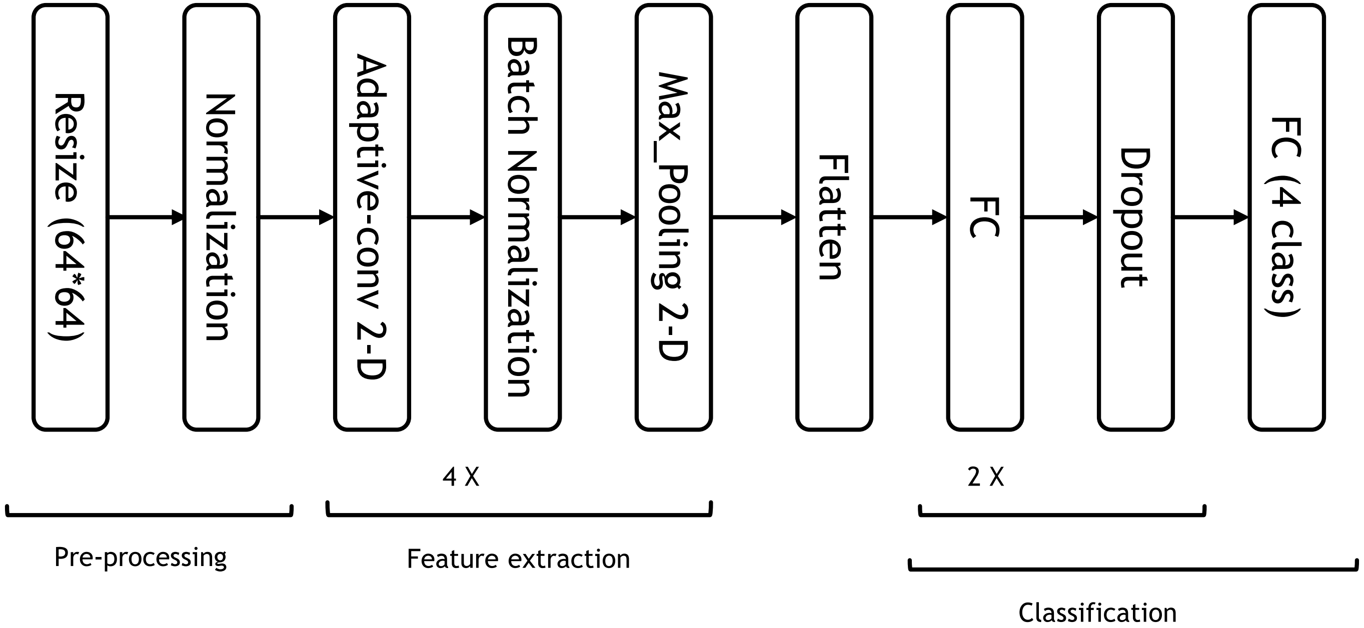
- **CNN+ Multi-head Attention (MHA)**



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

Brain tumor classification

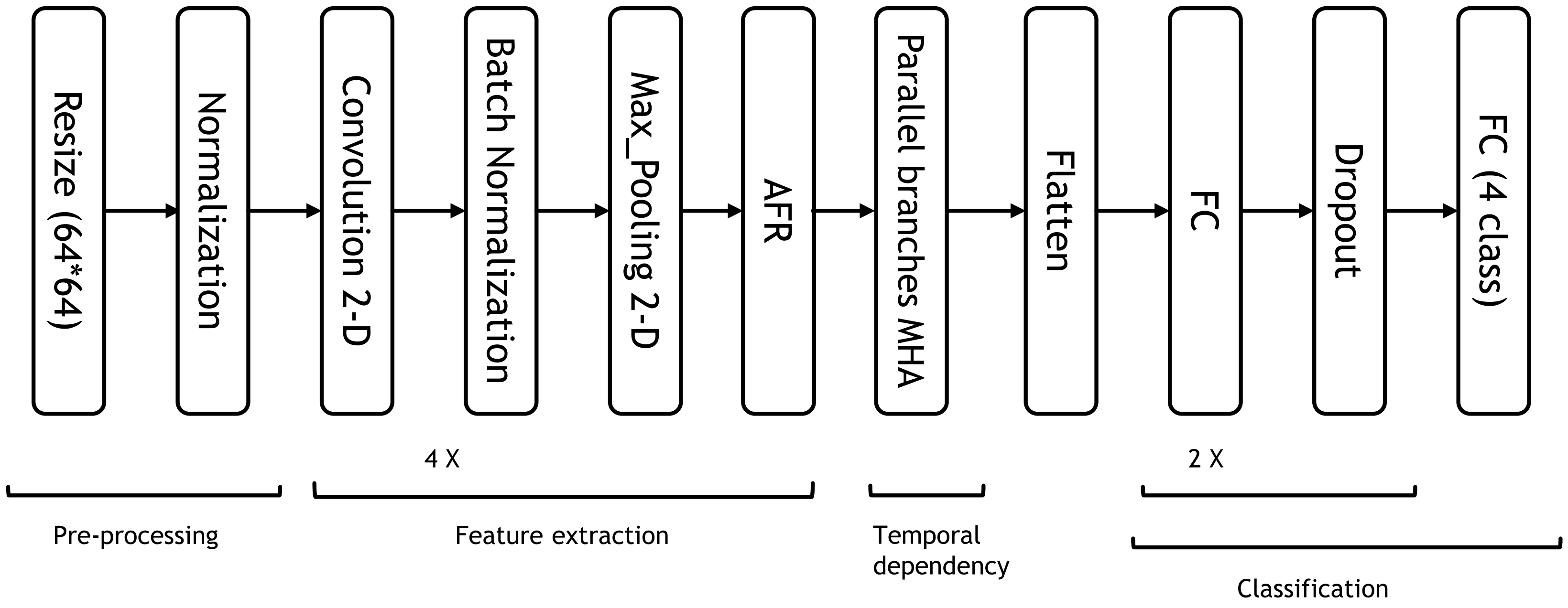
- **Adaptive Kernel Size Convolution (AKSC)**



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

Brain tumor classification

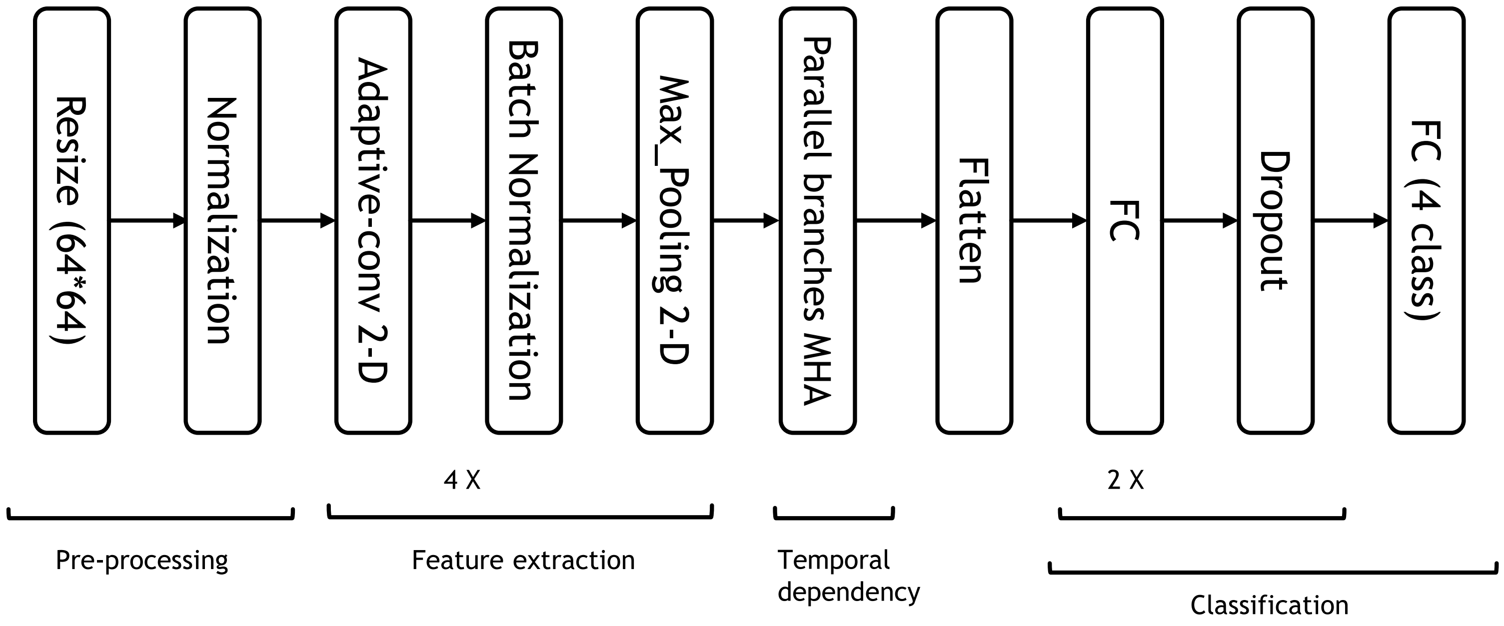
- **CNN+AFR+MHA**



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

Brain tumor classification

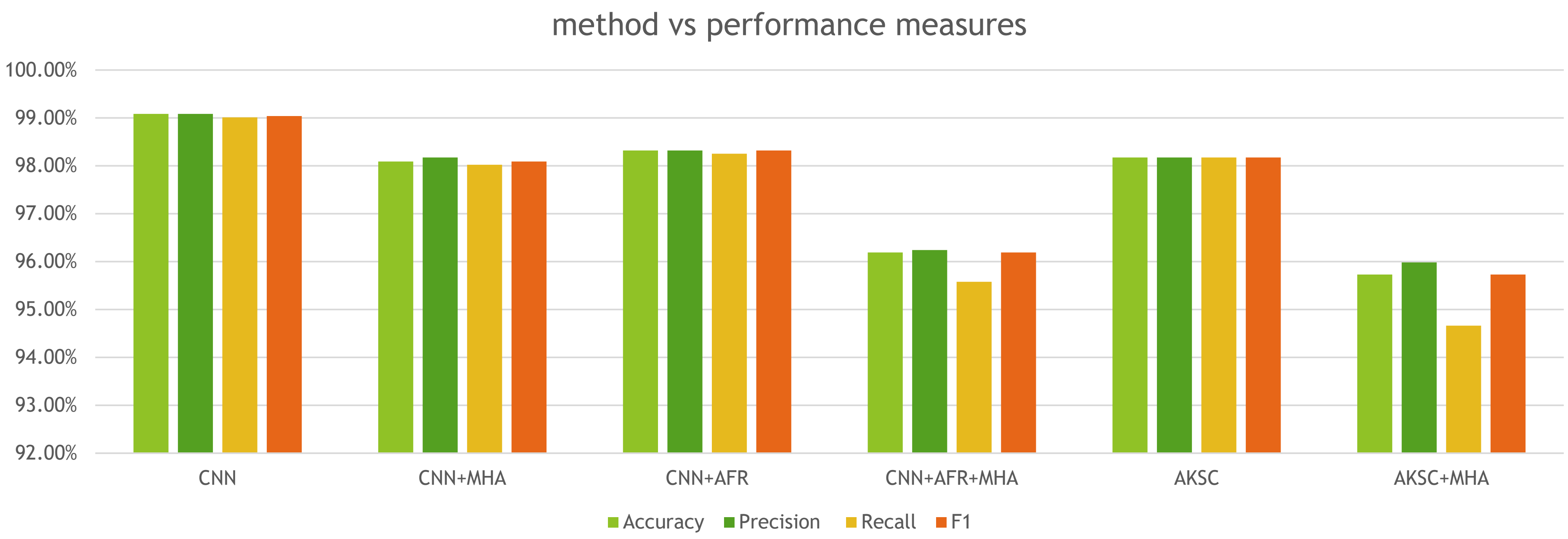
- **AKSC+MHA**



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

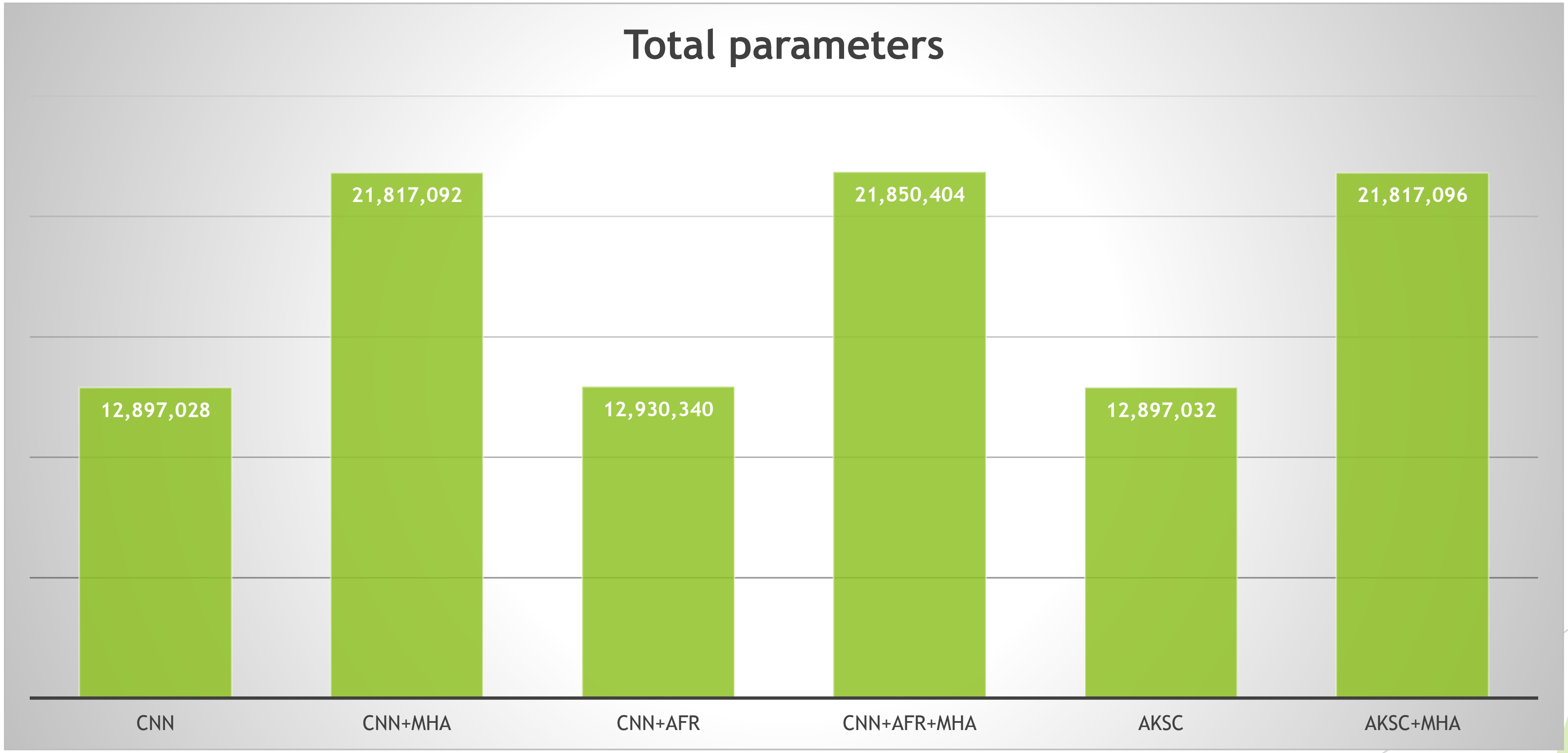
Form Factor: Single-slot, Full-height

Compute Capability: 7.5

GPU Boost Clock: 1,590 MHz

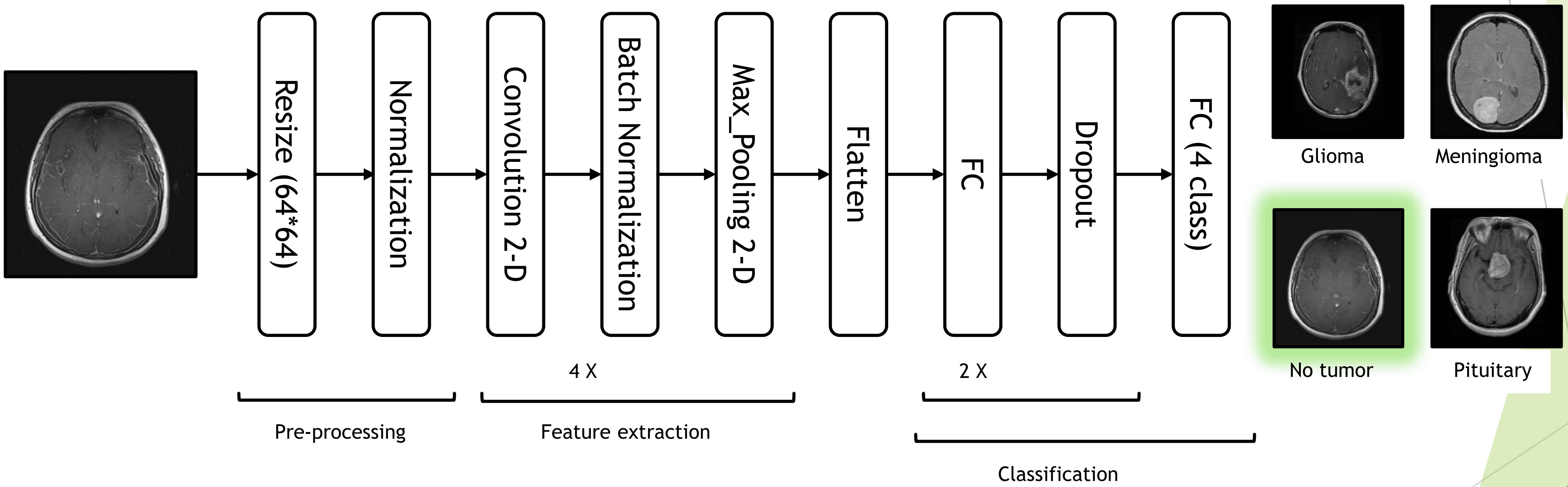
Brain tumor classification

- **Total parameters**



Brain tumor classification

- **Best results**

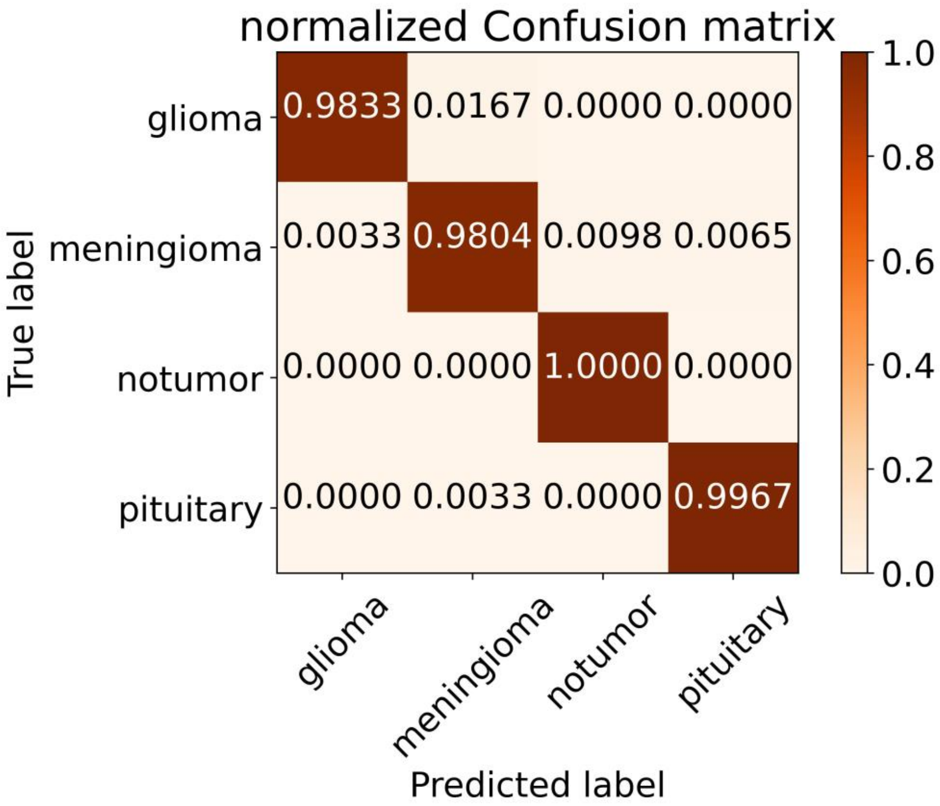


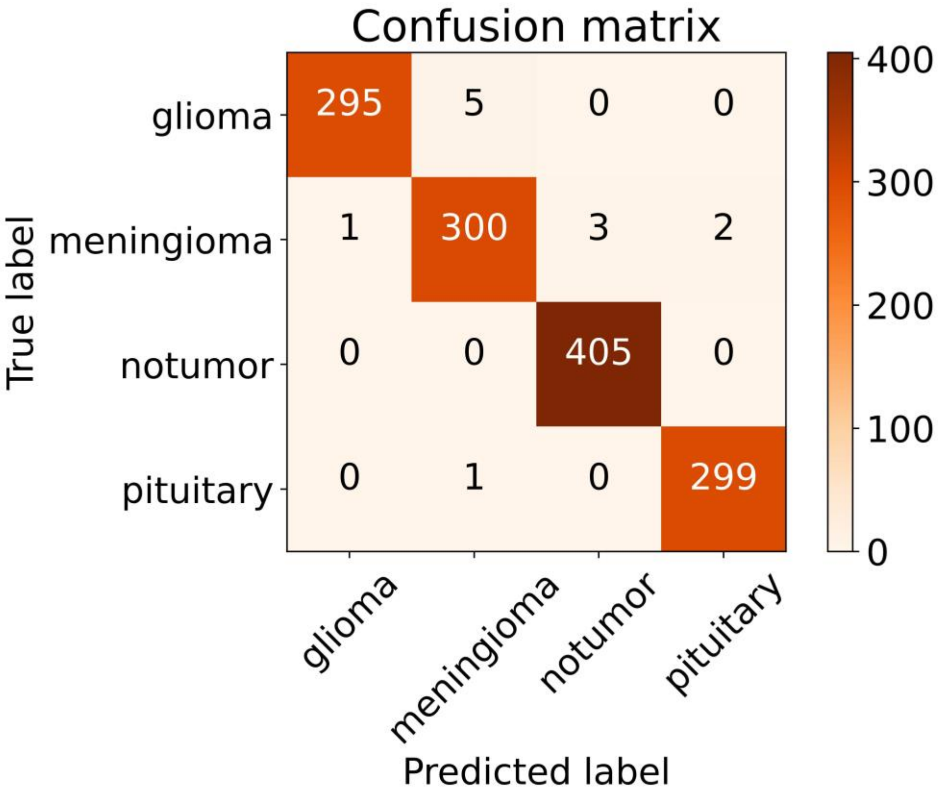
99.16% accuracy

Brain tumor classification

- **Performance**

Confusion matrix





Brain tumor classification

Performance

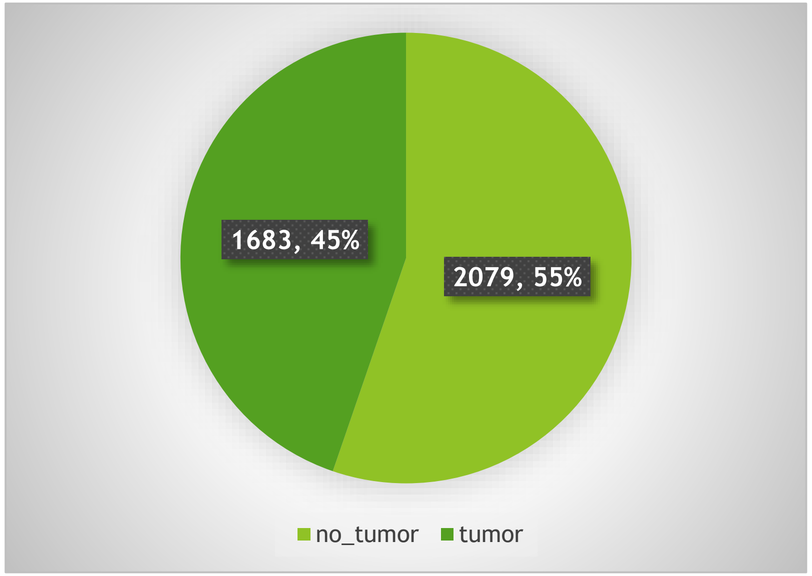
Classification report

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
Proposed	CNN	98.14%	98.22%	98%	98.10%
[1]	MobileNetV2	89%			

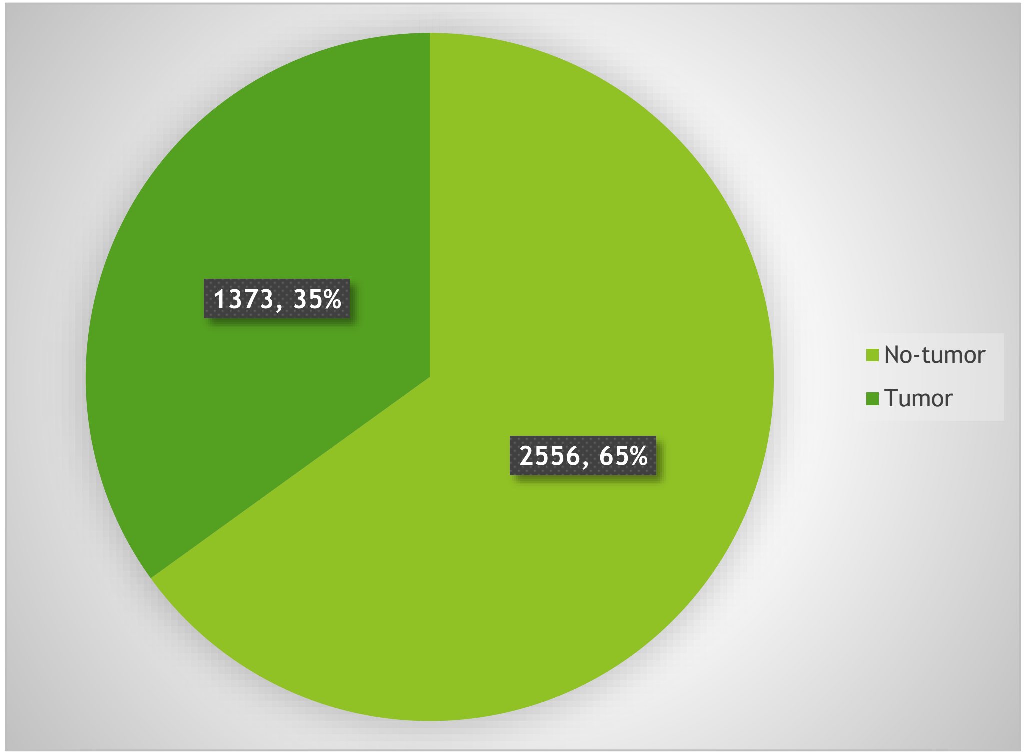
Brain tumor detection

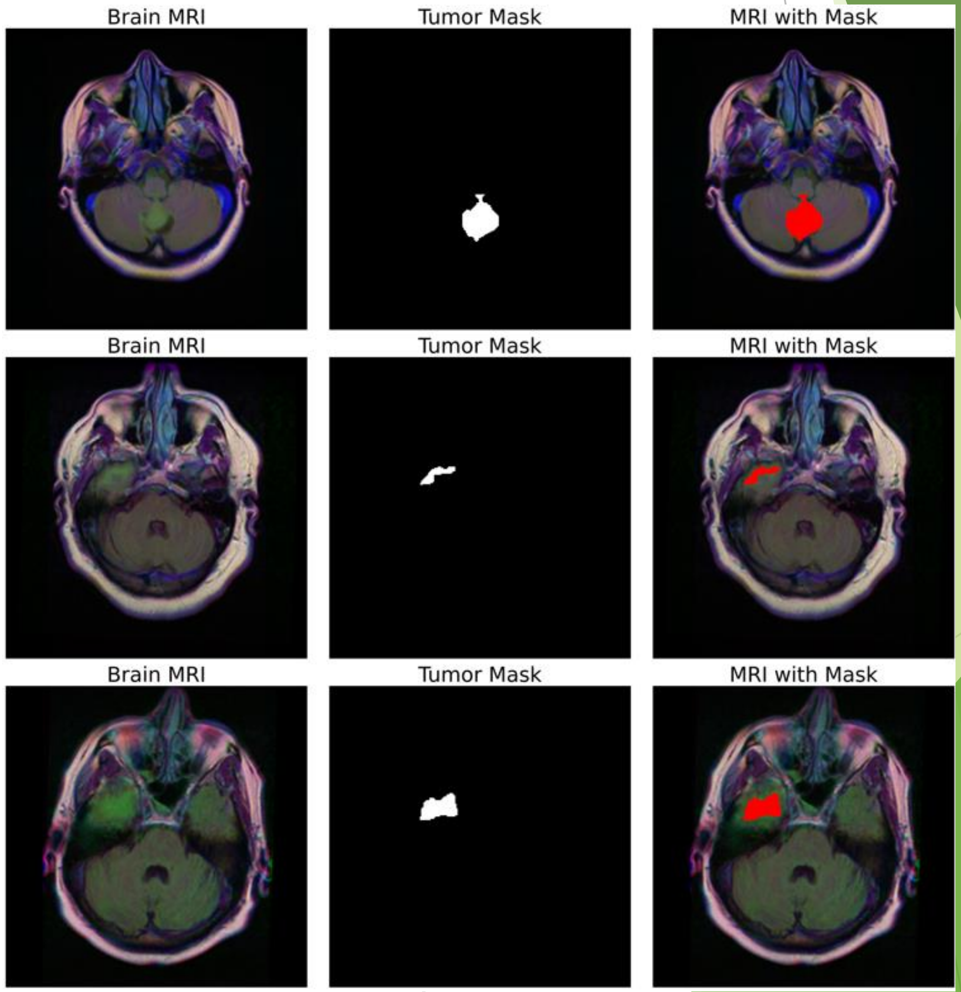
- **Online testing**

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

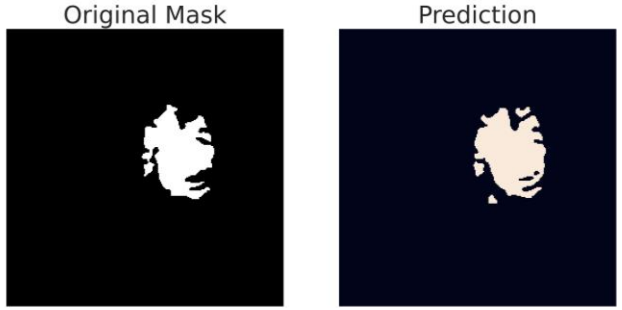
- **Dataset description**

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.

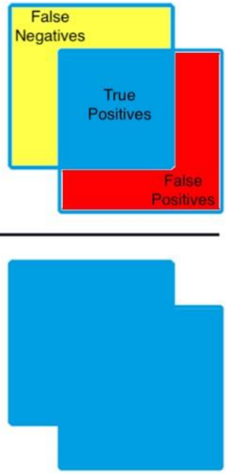
Brain tumor segmentation

- **Segmentation performance measures**

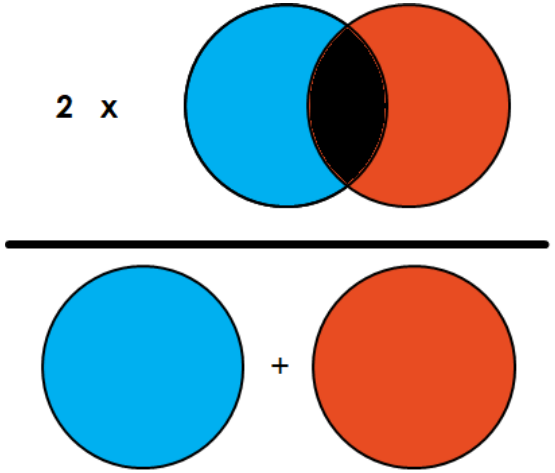


- Intersection over union

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

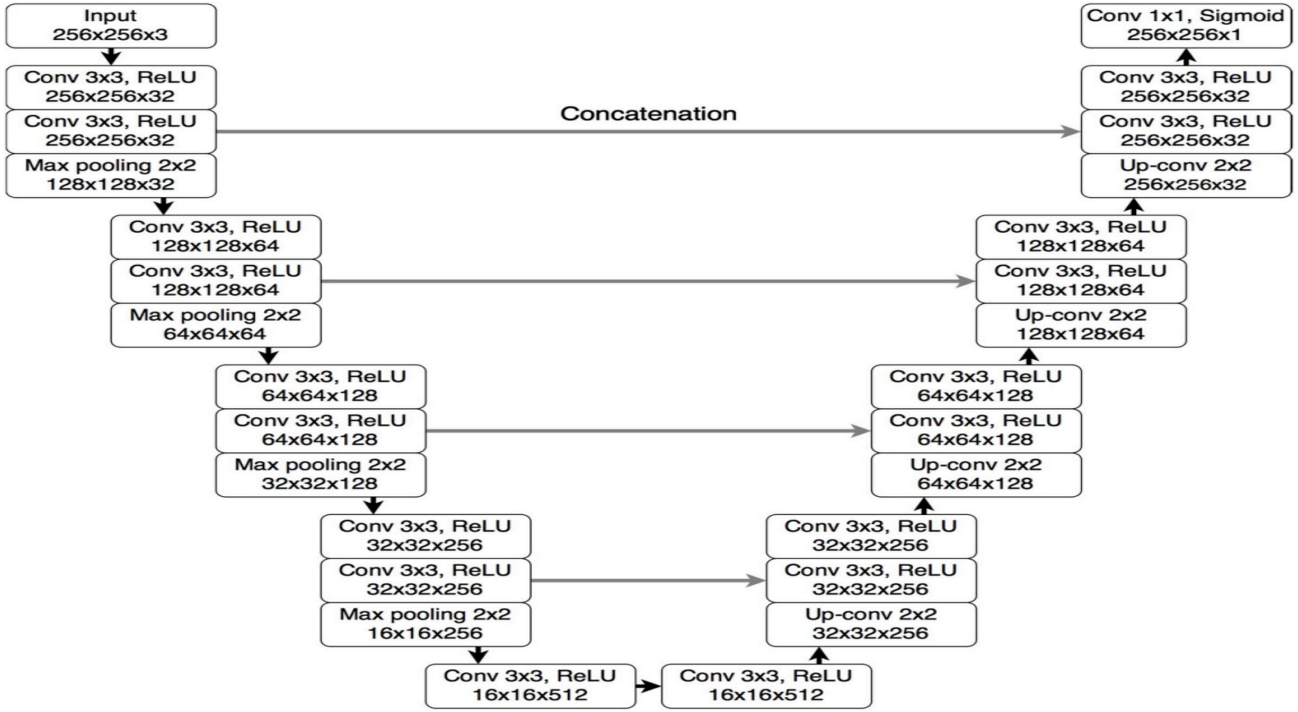


- Dice coefficient



Brain tumor segmentation

- **Reference paper for result comparison**

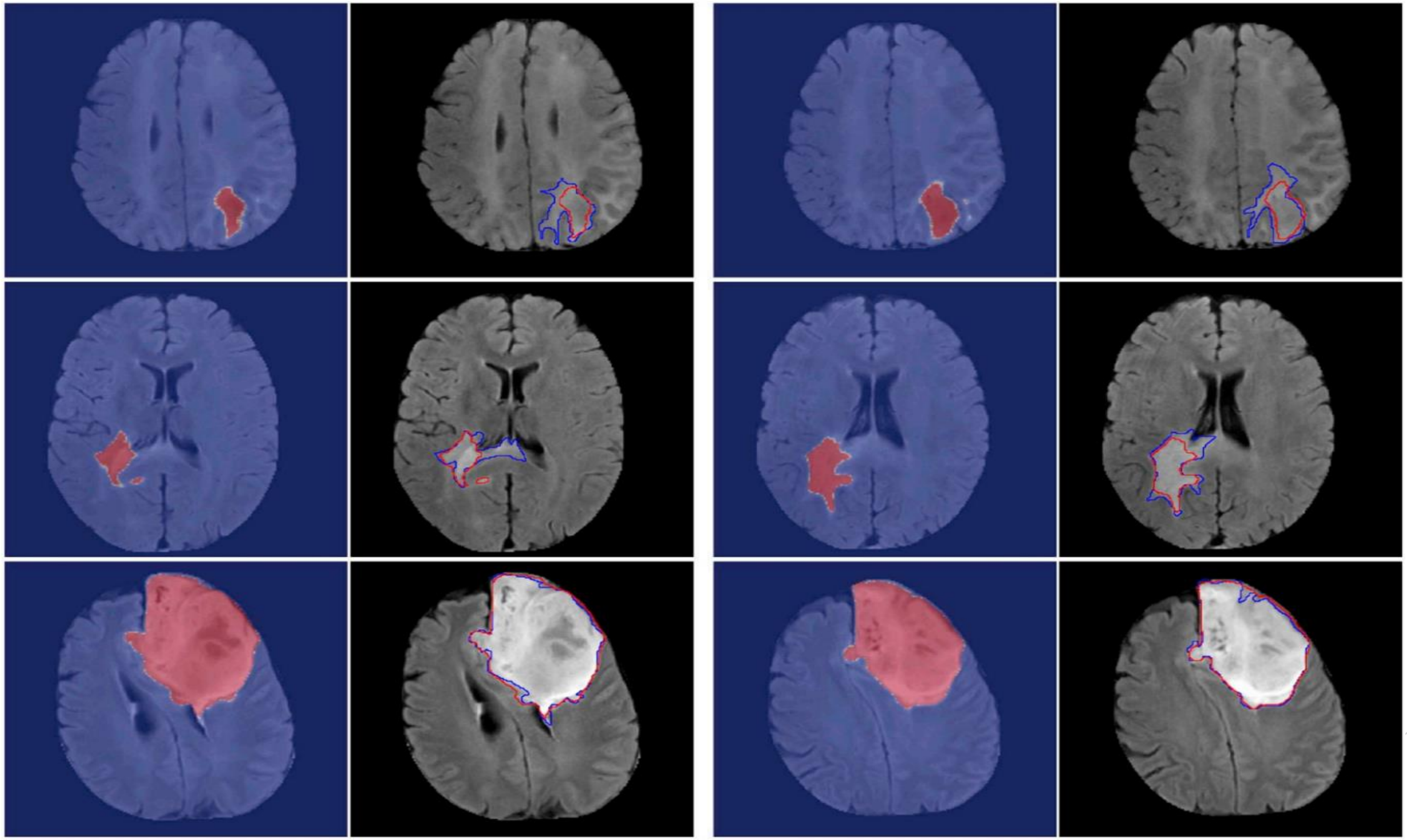


Dice coefficient score: 82%

[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.

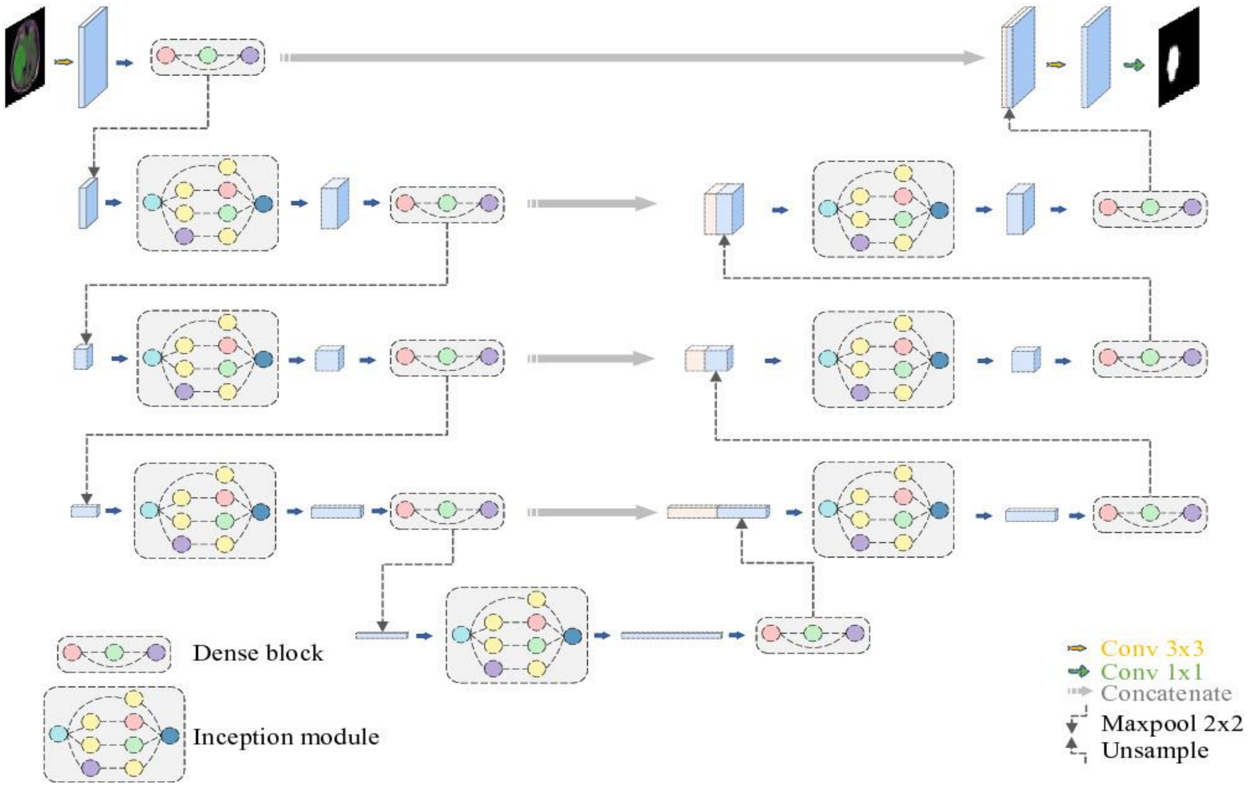
Brain tumor segmentation

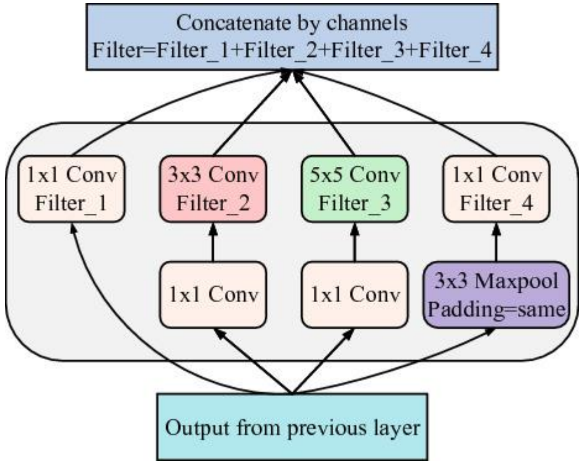
- **Reference paper for result comparison**

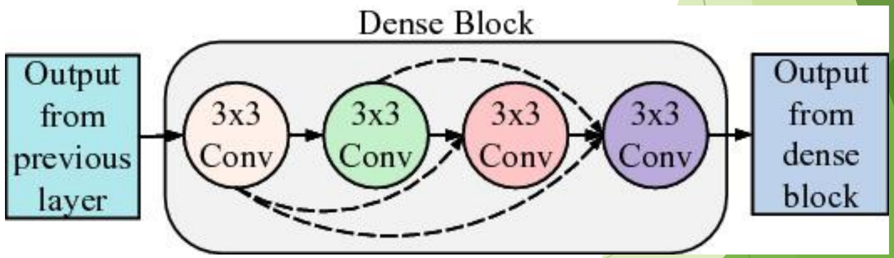


Brain tumor segmentation

- **Reference paper for result comparison**





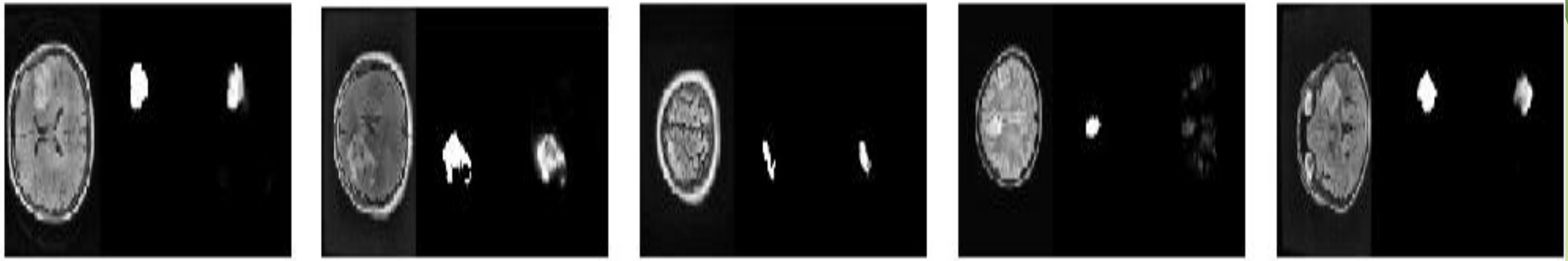


[2] L. Yi, J. Zhang, R. Zhang, J. Shi, G. Wang, and X. Liu, “SU-net: An efficient encoder-decoder model of federated learning for brain tumor segmentation,” in *Artificial Neural Networks and Machine Learning – ICANN 2020*, Cham: Springer International Publishing, 2020, pp. 761–773.

Brain tumor segmentation

- **Reference paper for result comparison**

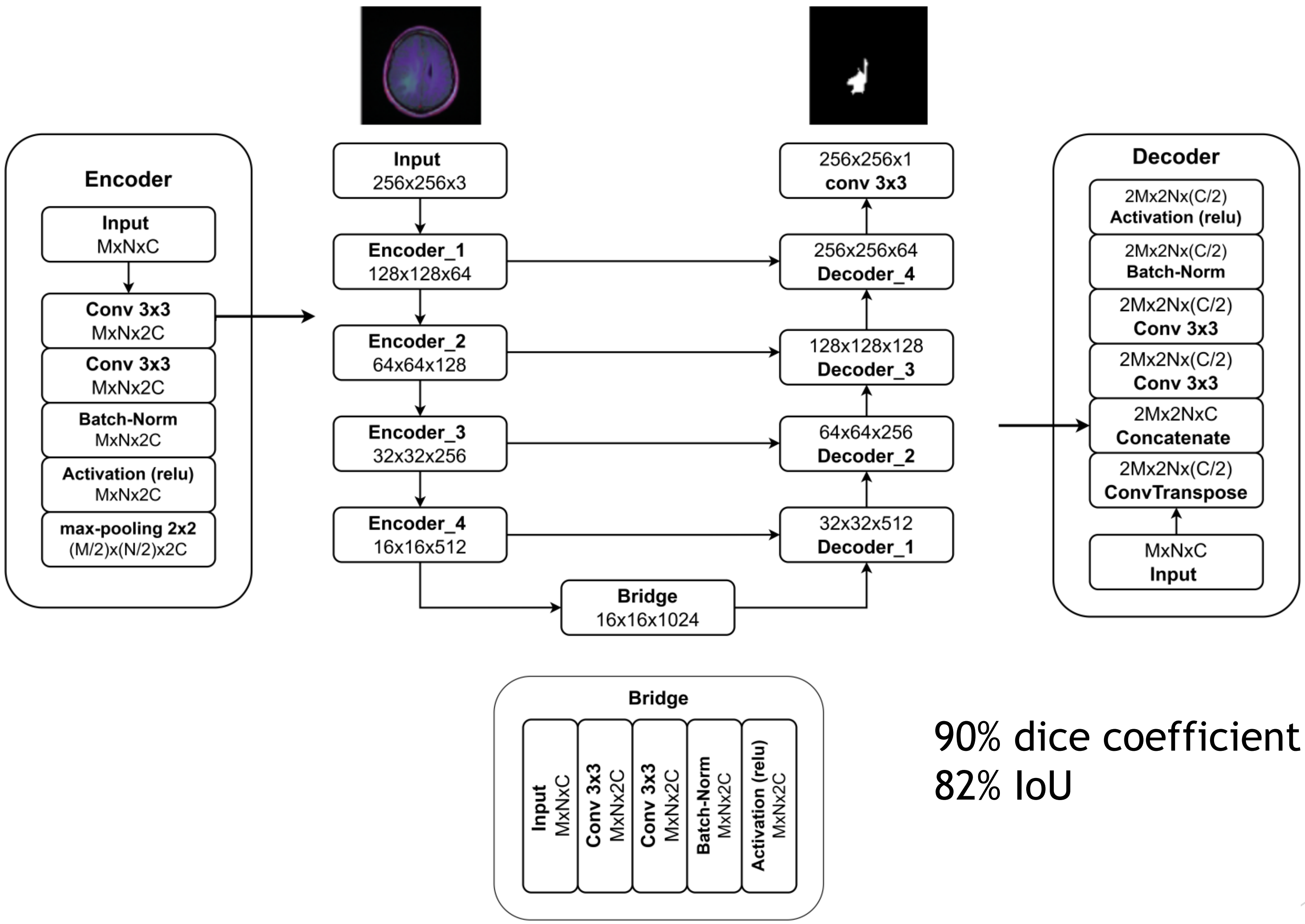
78.5 Dice coefficient



[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**

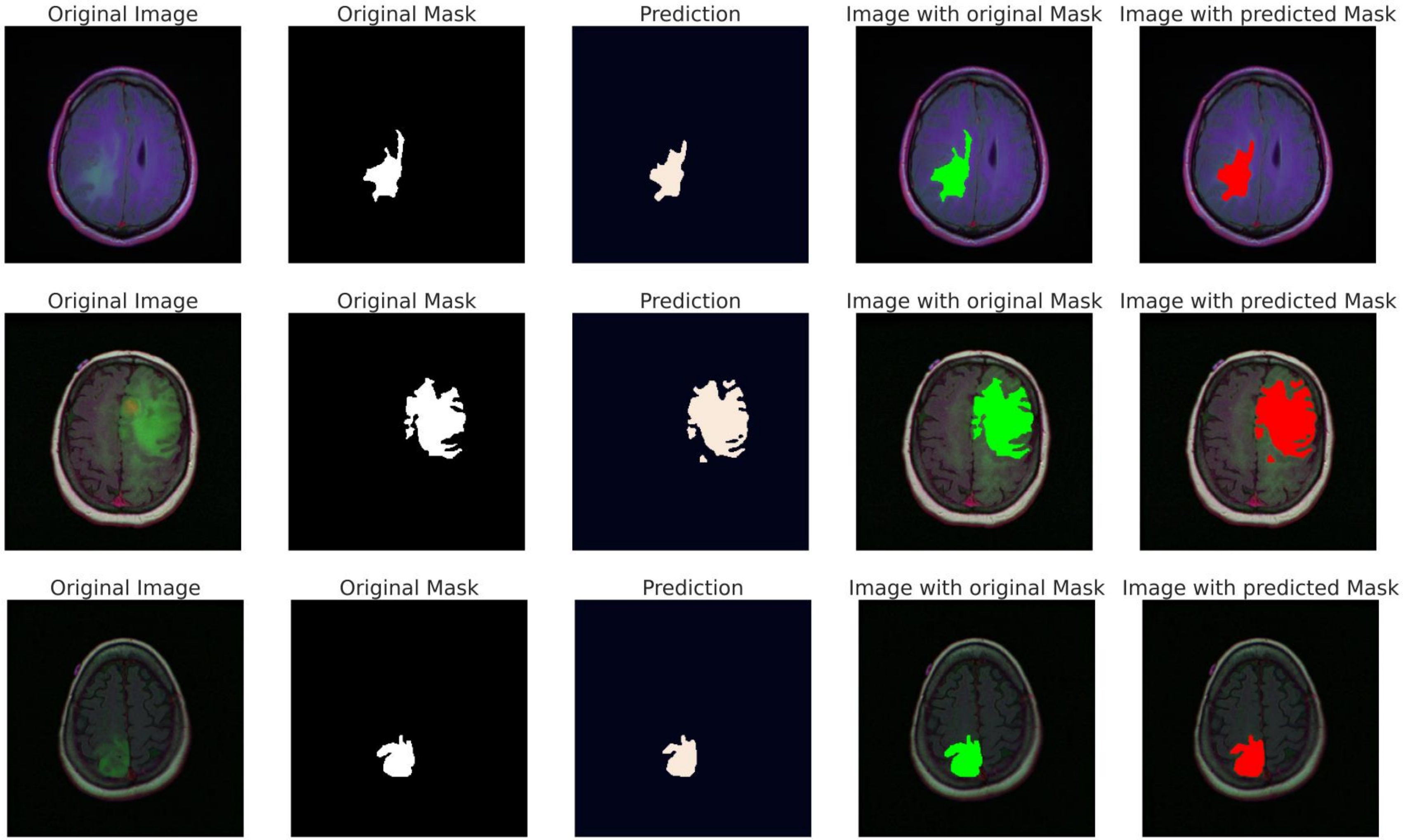


90% dice coefficient
82% IoU

Brain tumor segmentation

- **Proposed U-Net model**

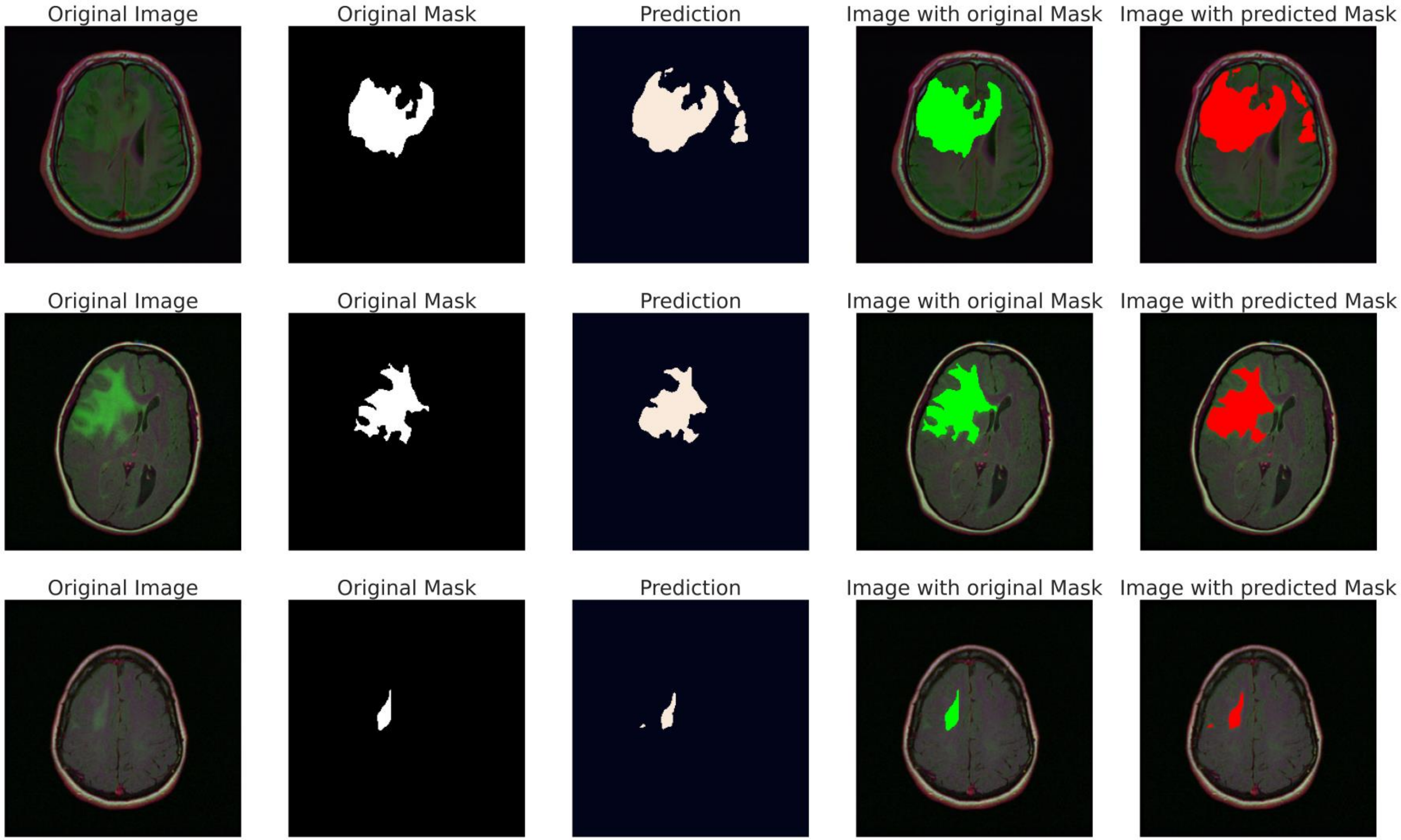
Predictions



Brain tumor segmentation

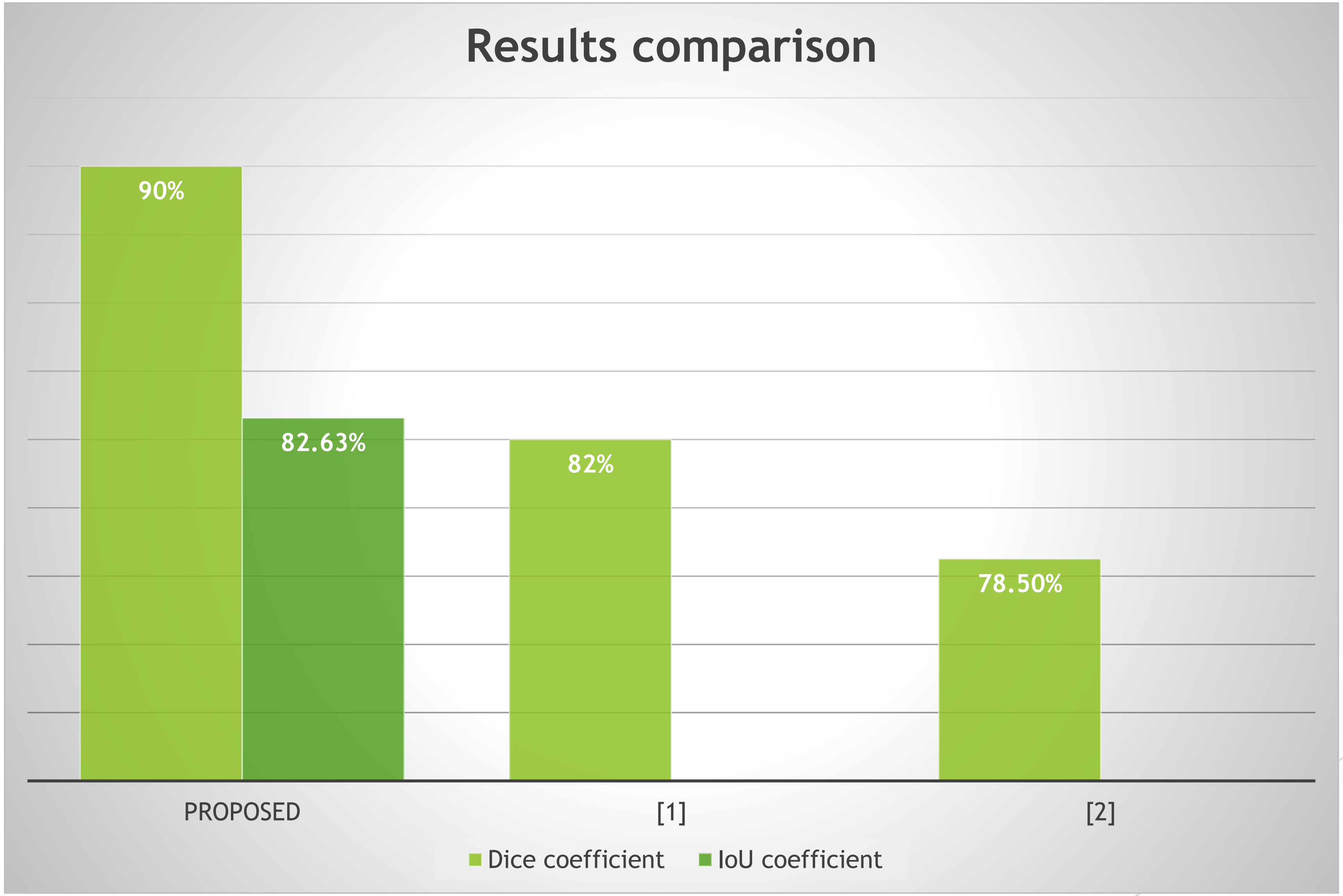
- **Proposed U-Net model**

Predictions



Brain tumor segmentation

- **Result comparison**

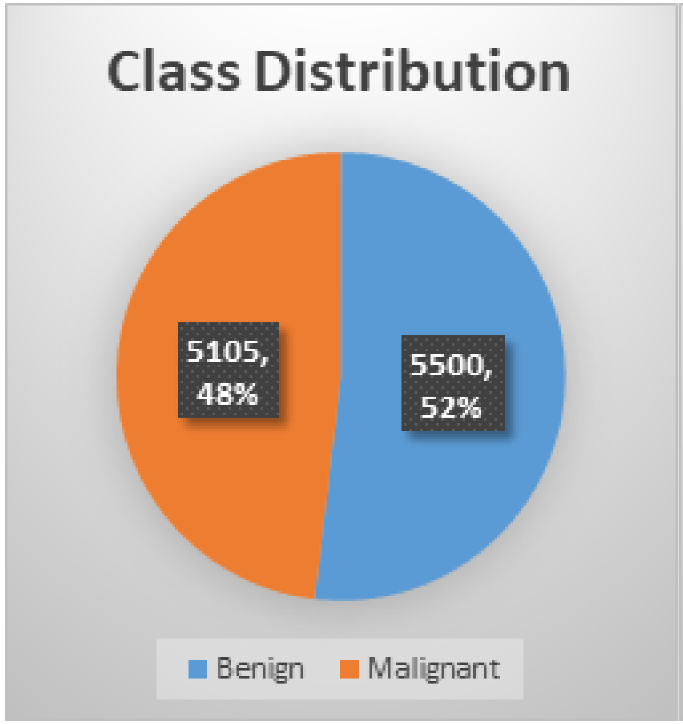


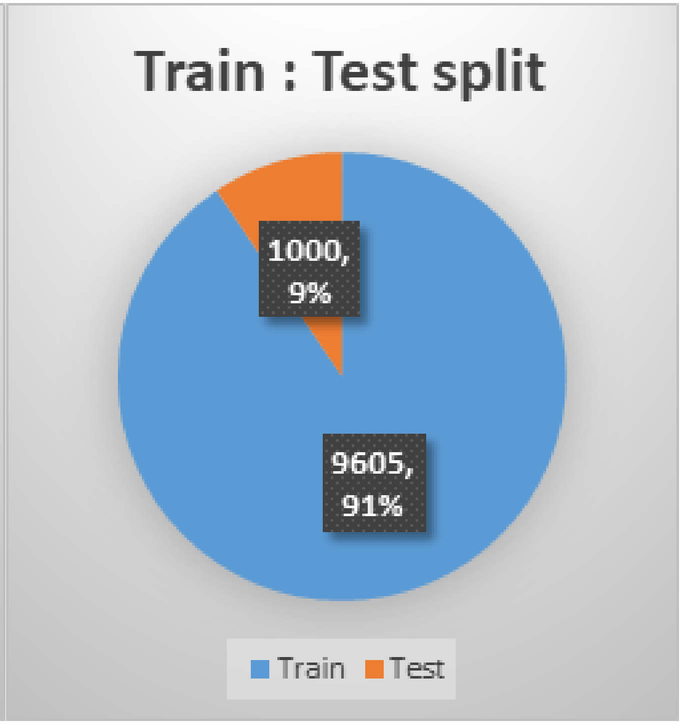
Skin cancer detection

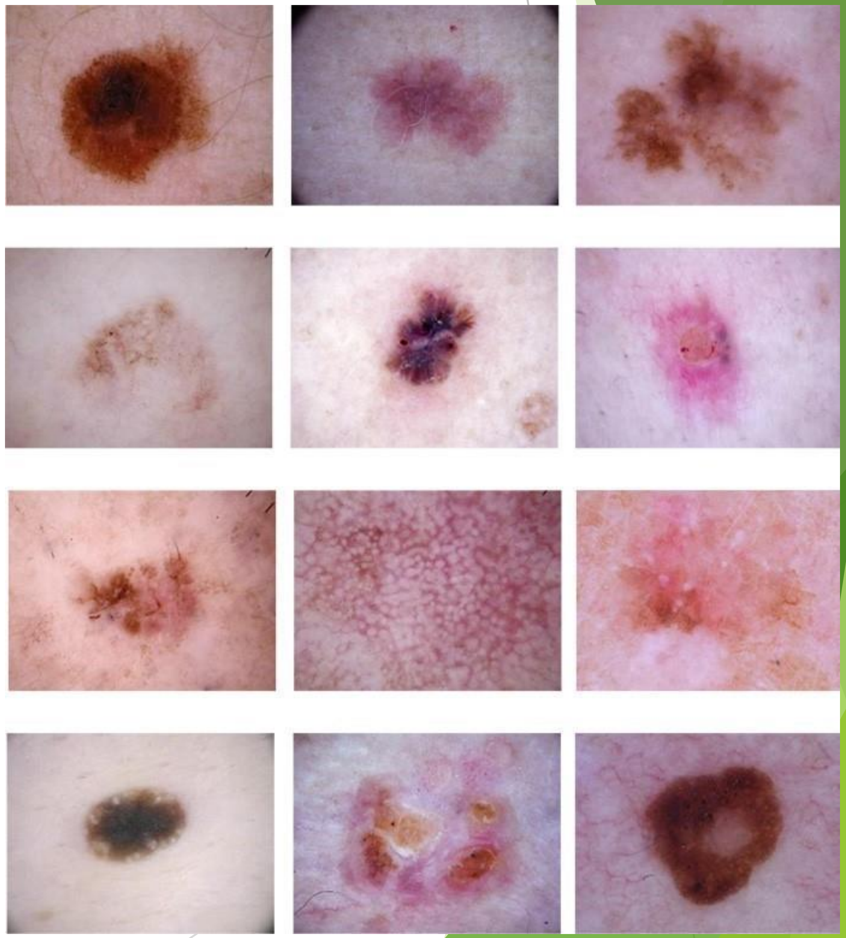
▶ Dataset description

HAM10000 dataset

	Malignant	Benign	Total	
Train	4605	5000	9605	10605
Test	500	500	1000	







Skin cancer detection

▶ Dataset description

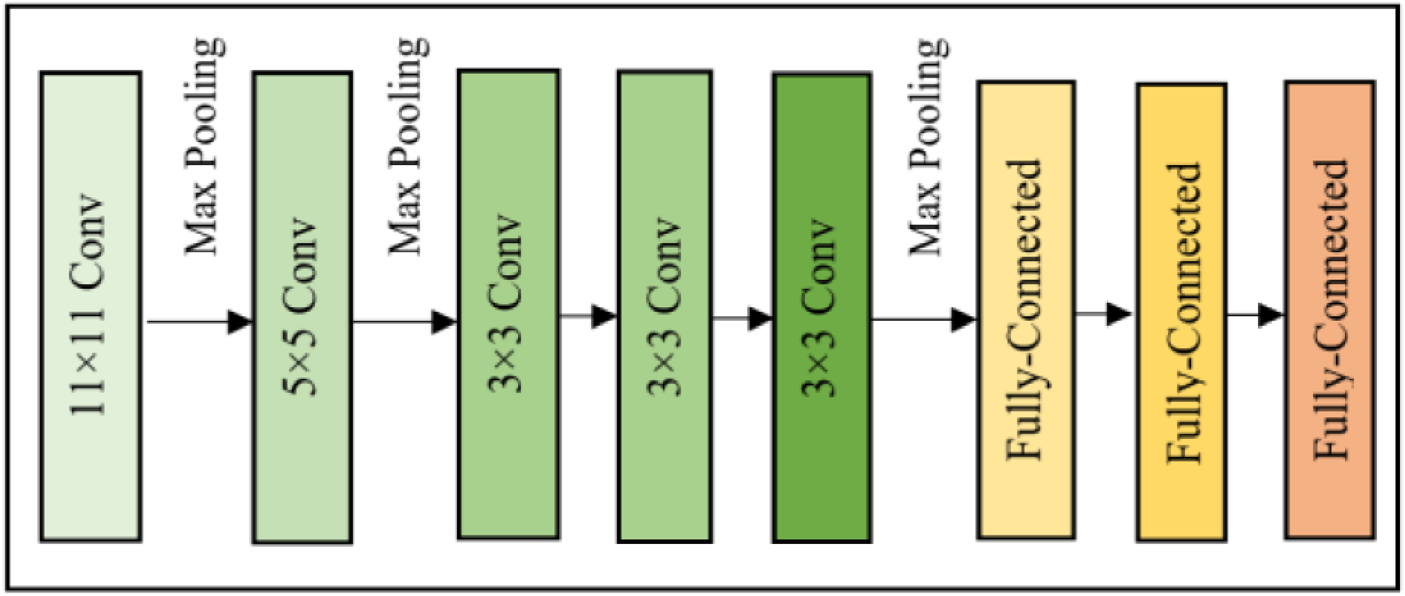
Data source

- **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.

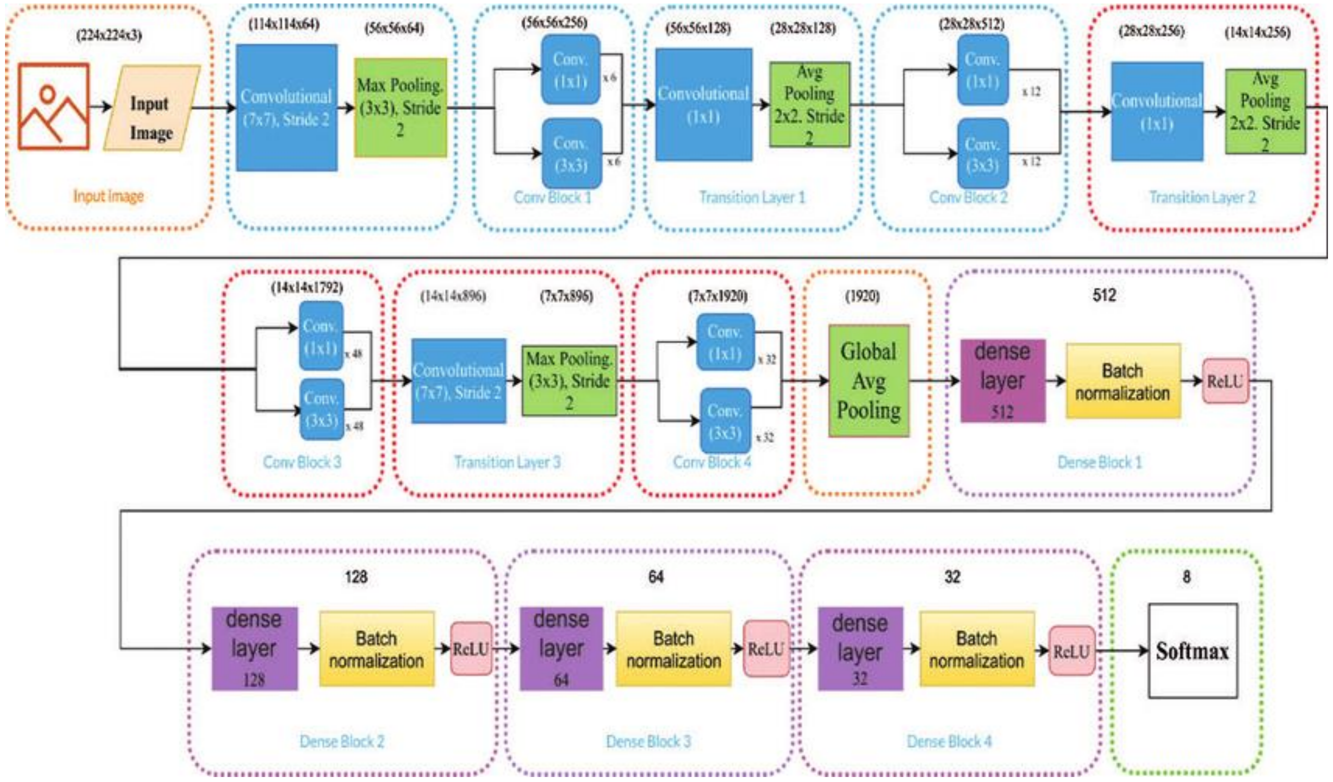


AlexNet pre-trained model
84% accuracy

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..

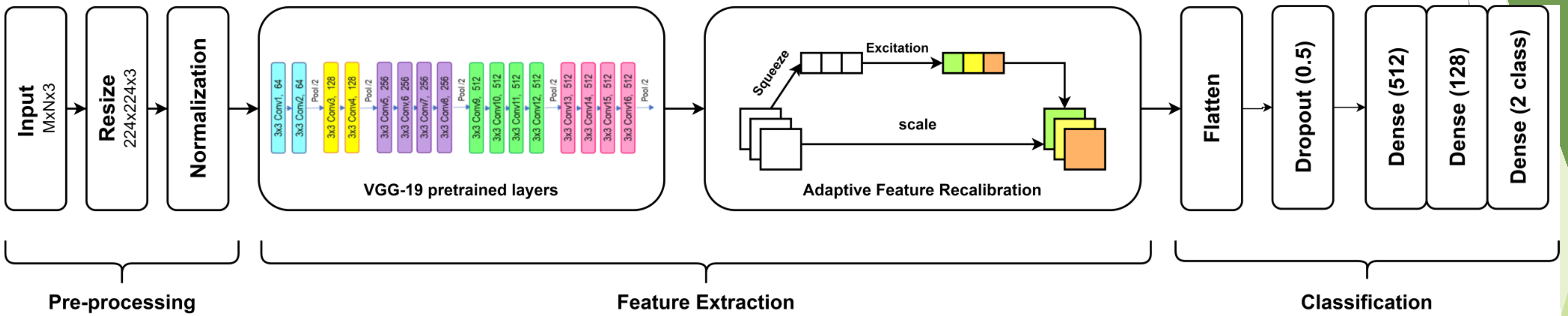


DenseNet201 pre-trained model

93% accuracy

Skin cancer detection

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



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

Skin cancer detection

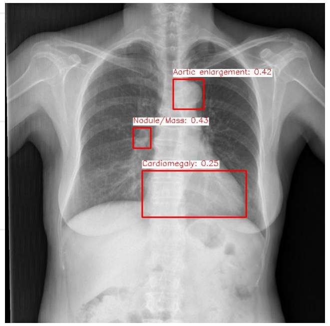
- **Online testing**

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
47ed17dcb2cbeec15182ed335a8b5a9e	Nodule/Mass	557.0	2352.0	675.0	2484.0
d3637a1935a905b3c326af31389cb846	Aortic enlargement	1329.0	743.0	1521.0	958.0
afb6230703512afc370f236e8fe98806	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

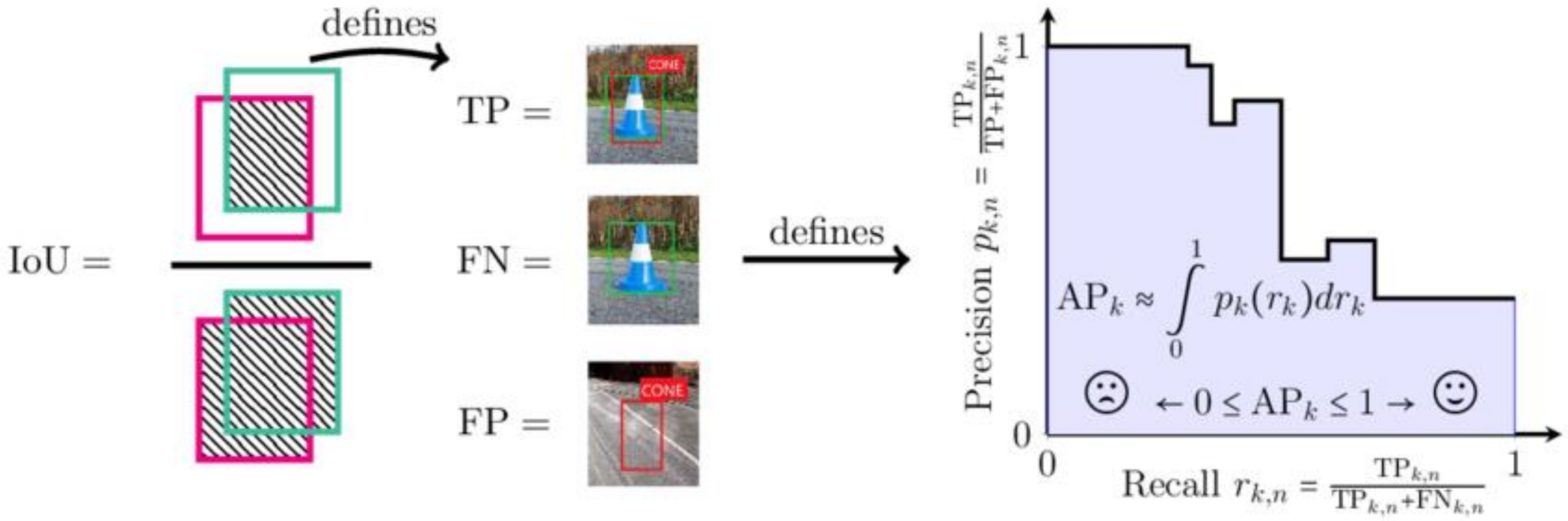
- Data source

- **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

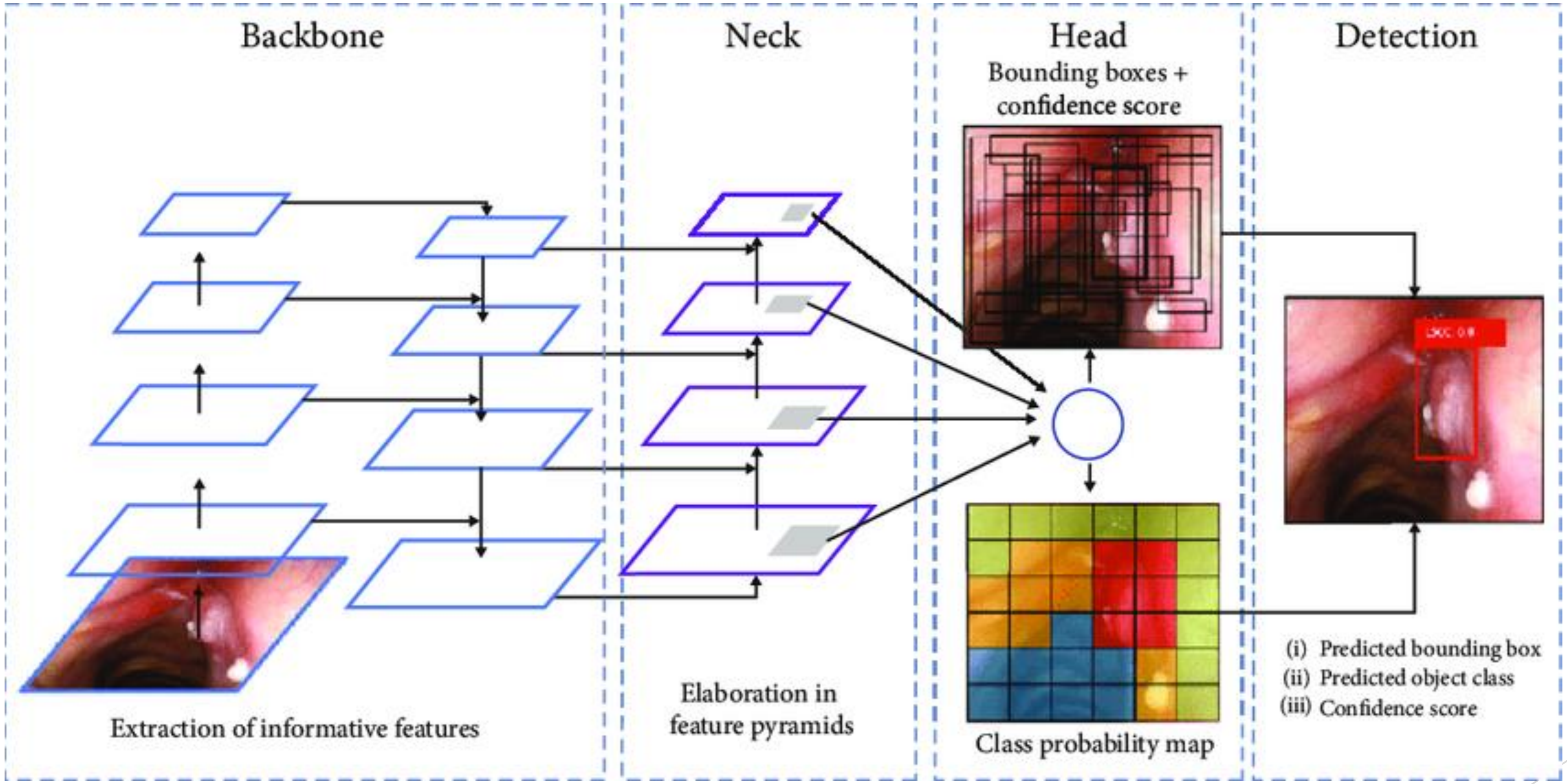
- **Performance measures for object detection**

Mean average precision (mAP)



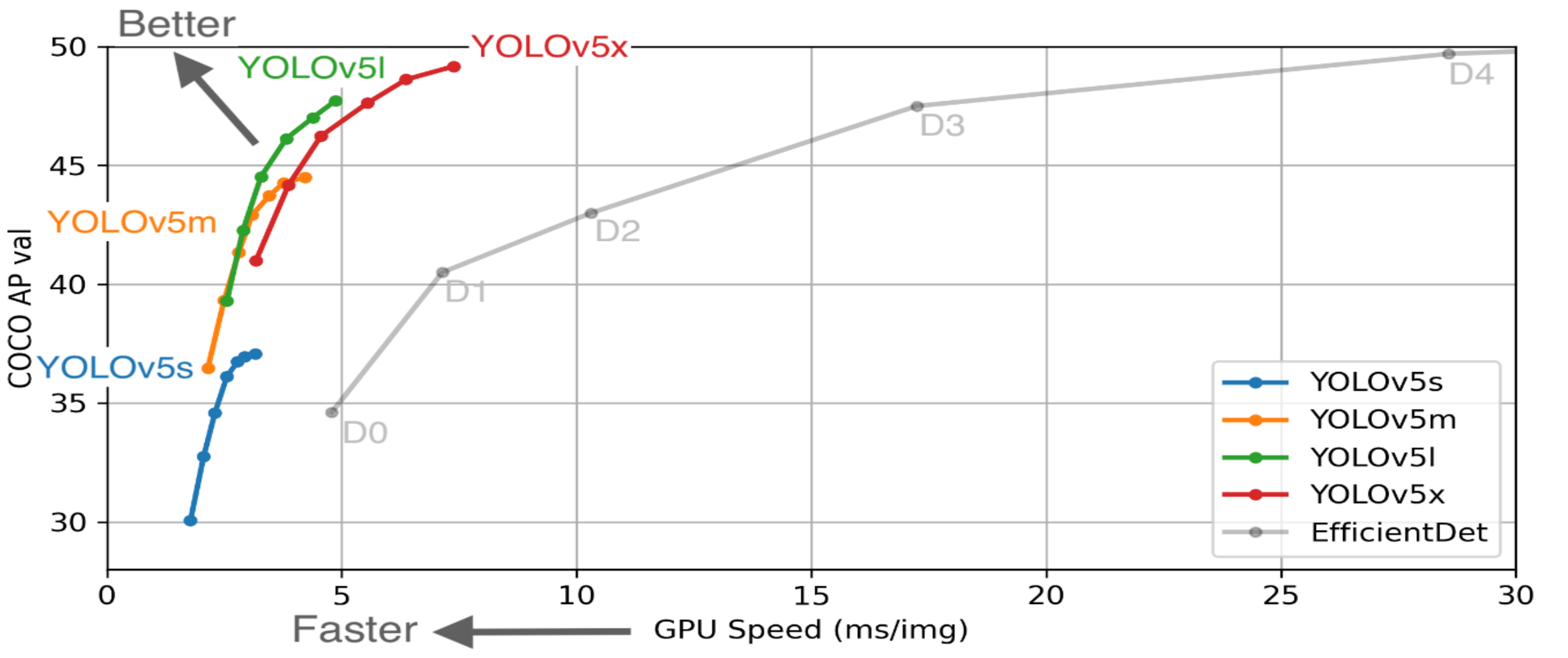
Chest x-ray abnormalities localization

- **object detector architecture**



Chest x-ray abnormalities localization

- **YOLO v5 versions**



Chest x-ray abnormalities localization

- **Results**

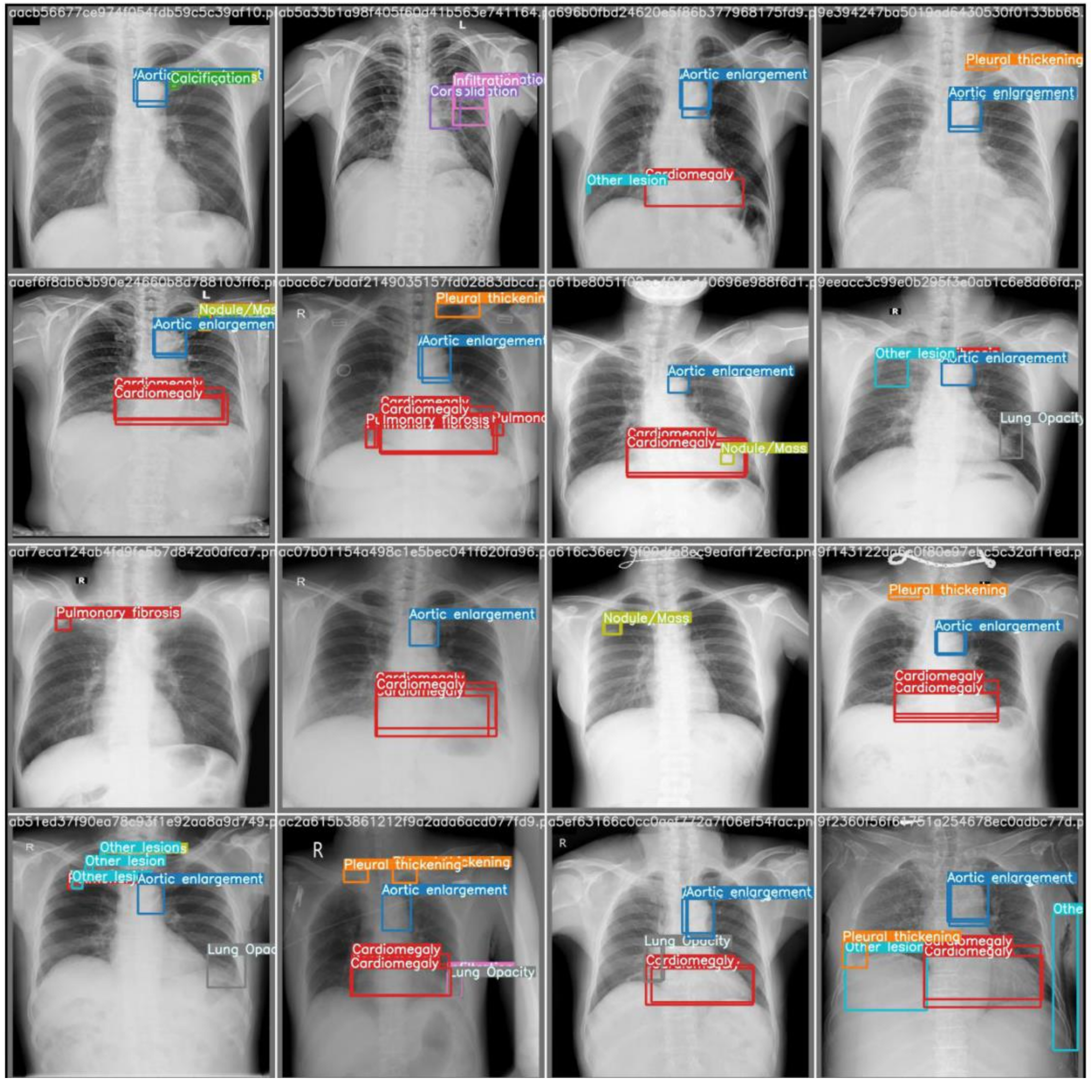
	model	Mean average precision (mAP0.5)
[1]	Detectron 2	0.235
[2]	ResNet50 - FPN	0.246
Ours	Yolo v5x	0.312

[1] Talius, E., & Sayana, R. Zero-Shot Object Detection for Chest X-Rays.

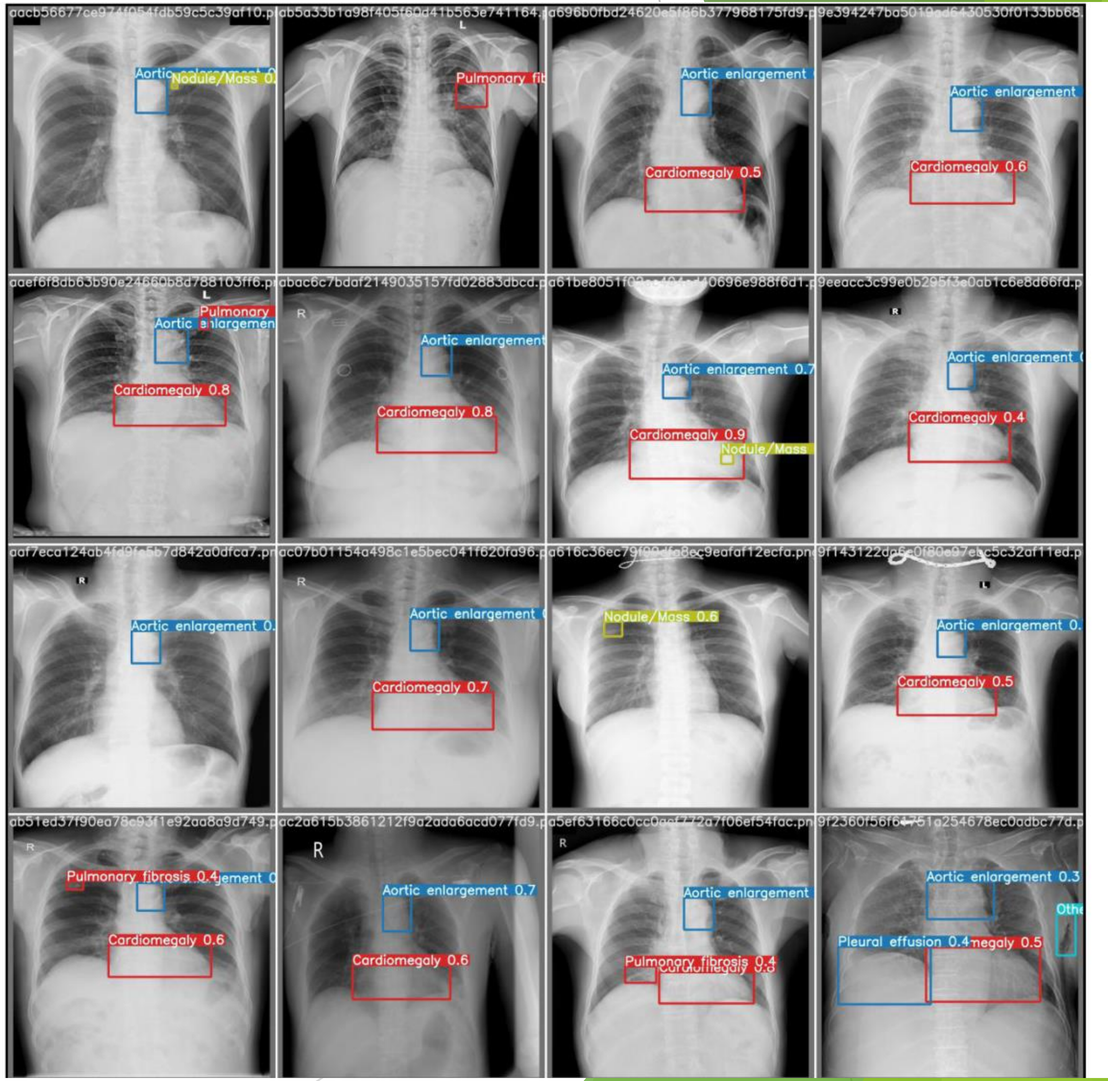
[2] V. Parikh, J. Shah, C. Bhatt, J. M. Corchado, and D.-N. Le, “Deep learning based automated chest X-ray abnormalities detection,” in Lecture Notes in Networks and Systems, Cham: Springer International Publishing, 2023, pp. 1–12.

Chest x-ray abnormalities localization

- **Results**



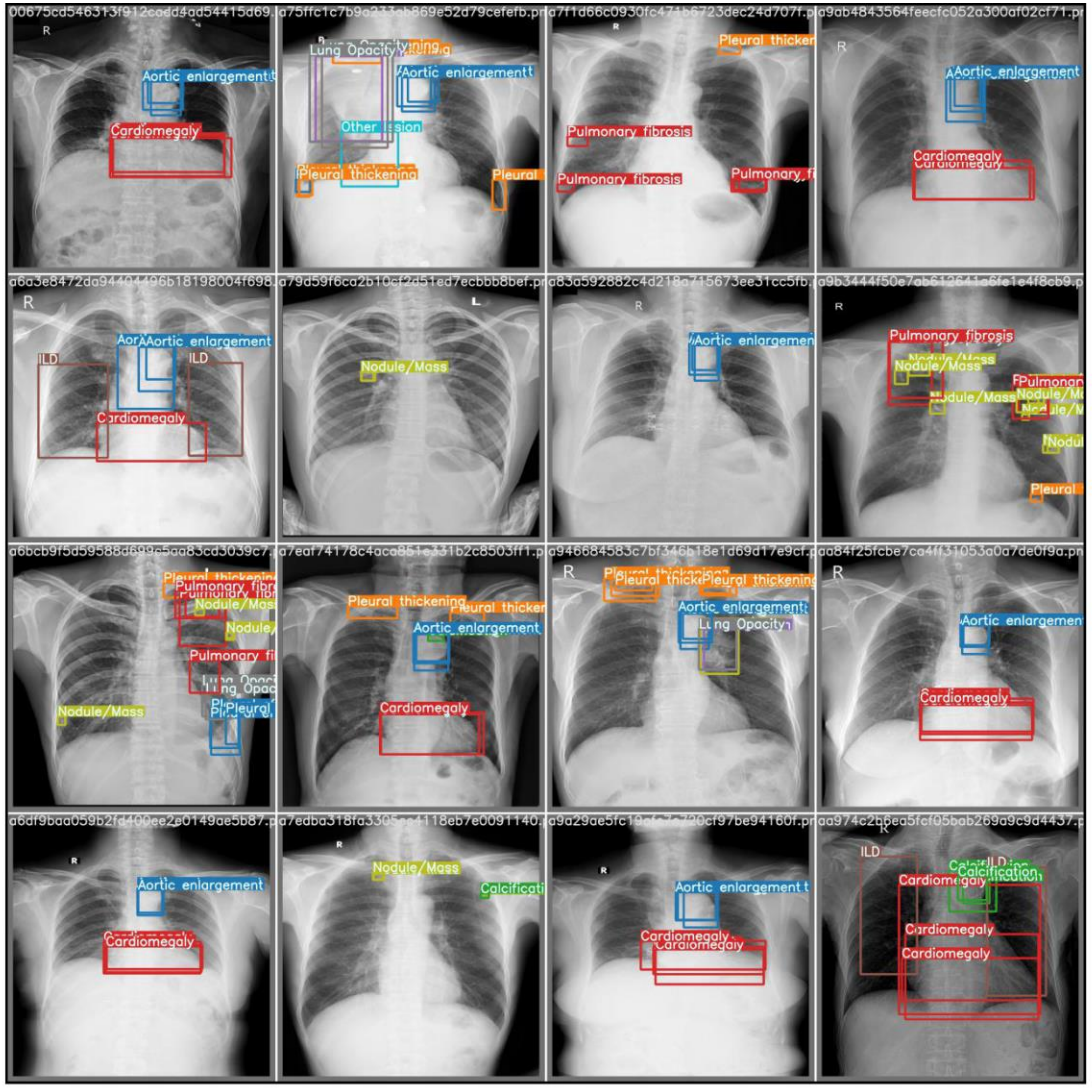
prediction



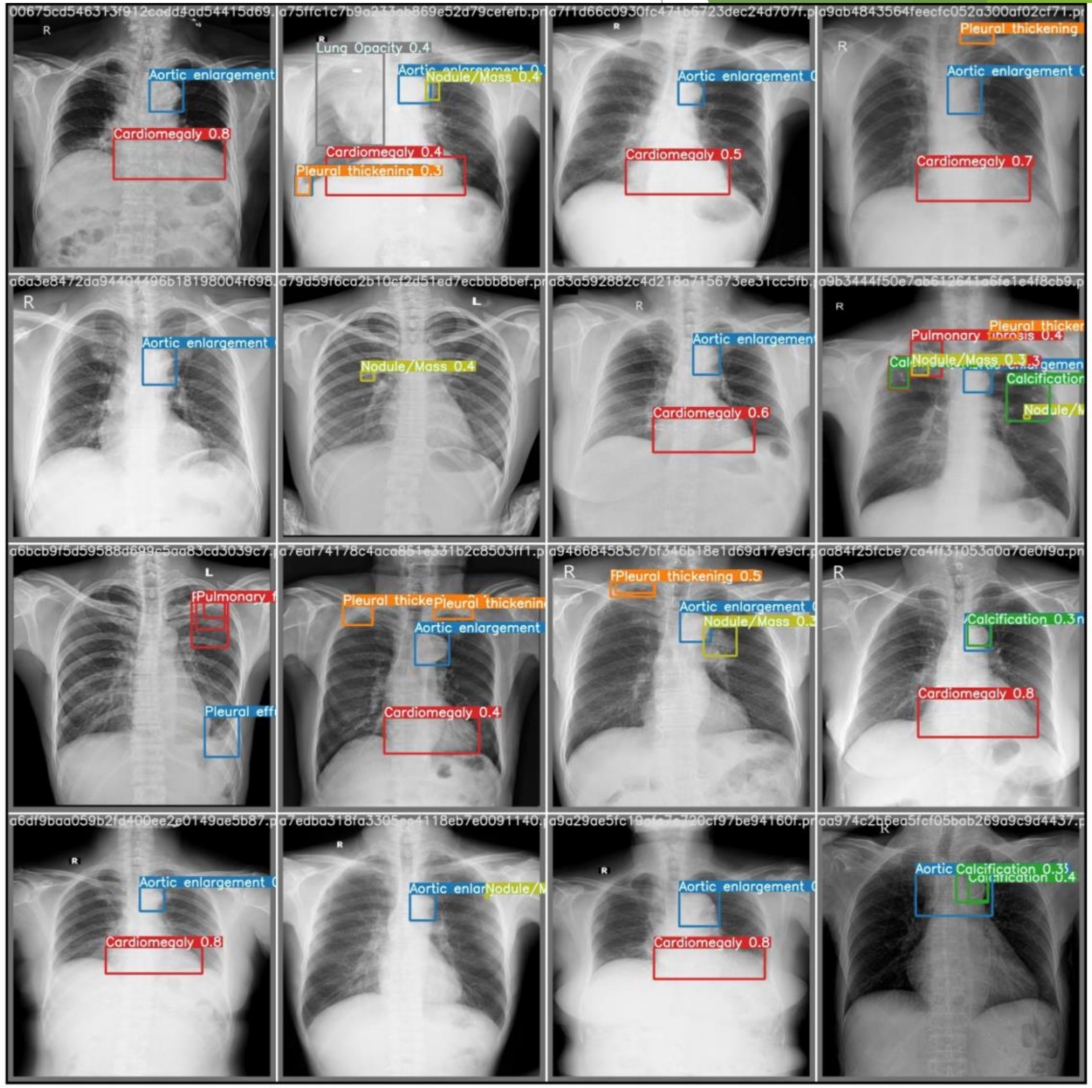
Actual

Chest x-ray abnormalities localization

- **Online testing**



prediction



Actual