

Detection and Risk Measurement of Silent Atrial Fibrillation in ECG Using Diverse AI Techniques

Yonsei Medical Convergence Challenge

2024.01.26.

Yonsei University

4조

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Severance

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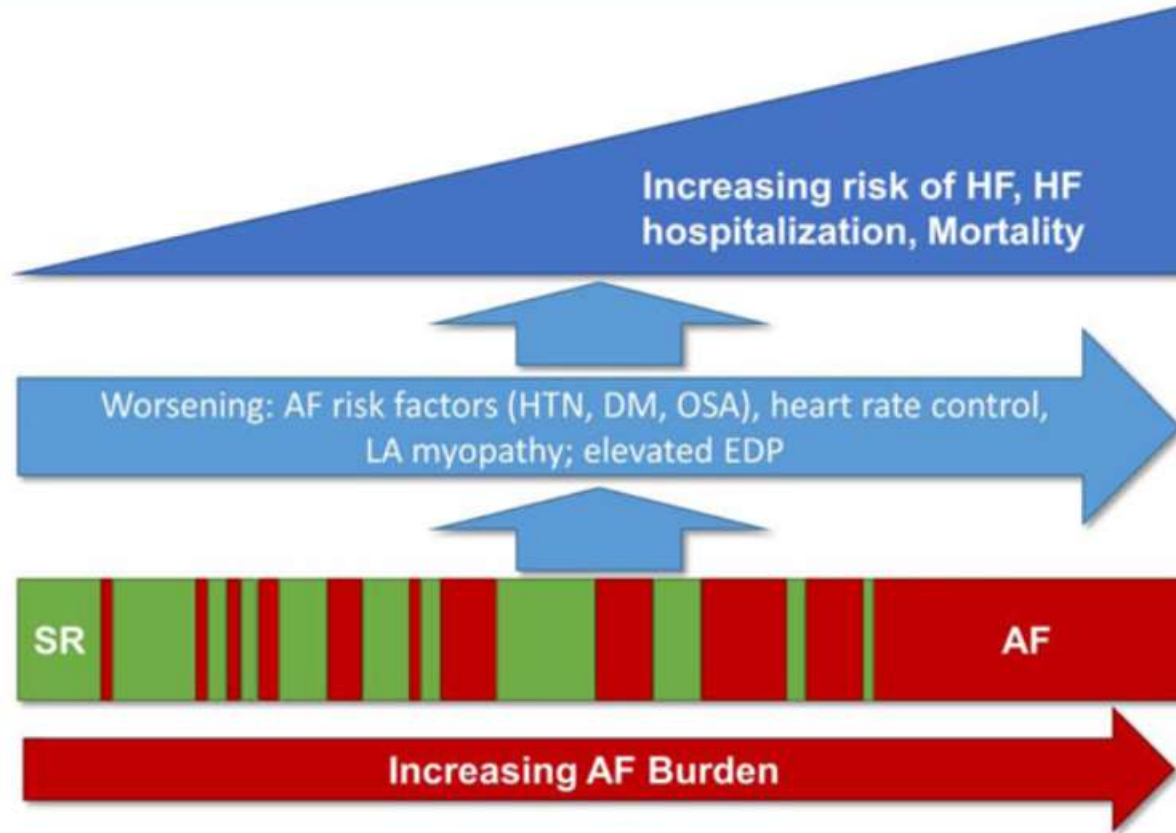











그림 2. AF related risk factors and association between HF, AFB

• AF related Outcomes

Clinical Presentation		AF-related OUTCOMES		
	Asymptomatic or Silent (!)	AF-Related Outcome	Frequency in AF	Mechanism(s)
	Symptomatic Palpitations, dyspnoea, fatigue, Chest tightness/pain, poor effort tolerance, dizziness, syncope, disordered sleep, etc. Haemodynamically unstable • Syncope • Symptomatic hypotension • Acute HF, pulmonary oedema • Ongoing myocardial ischaemia • Cardiogenic shock Haemodynamically stable	Death 	1.5 - 3.5 fold increase	Excess mortality related to: • HF, comorbidities • Stroke
		Stroke 	20-30% of all ischaemic strokes, 10% of cryptogenic strokes	• Cardioembolic, or • Related to comorbid vascular atheroma
		LV dysfunction / Heart failure 	In 20-30% of AF patients	• Excessive ventricular rate • Irregular ventricular contractions • A primary underlying cause of AF
		Cognitive decline / Vascular dementia 	HR 1.4 / 1.6 (irrespective of stroke history)	• Brain white matter lesions, inflammation, • Hypoperfusion, • Micro-embolism
		Depression 	Depression in 16-20% (even suicidal ideation)	• Severe symptoms and decreased QoL • Drug side effects
		Impaired quality of life 	>60% of patients	• Related to AF burden, comorbidities, psychological functioning and medication • Distressed personality type
		Hospitalizations 	10-40% annual hospitalization rate	• AF management, related to HF, MI or AF related symptoms • Treatment-associated complications

Introduction – Atrial fibrillation Burden and Silent AF

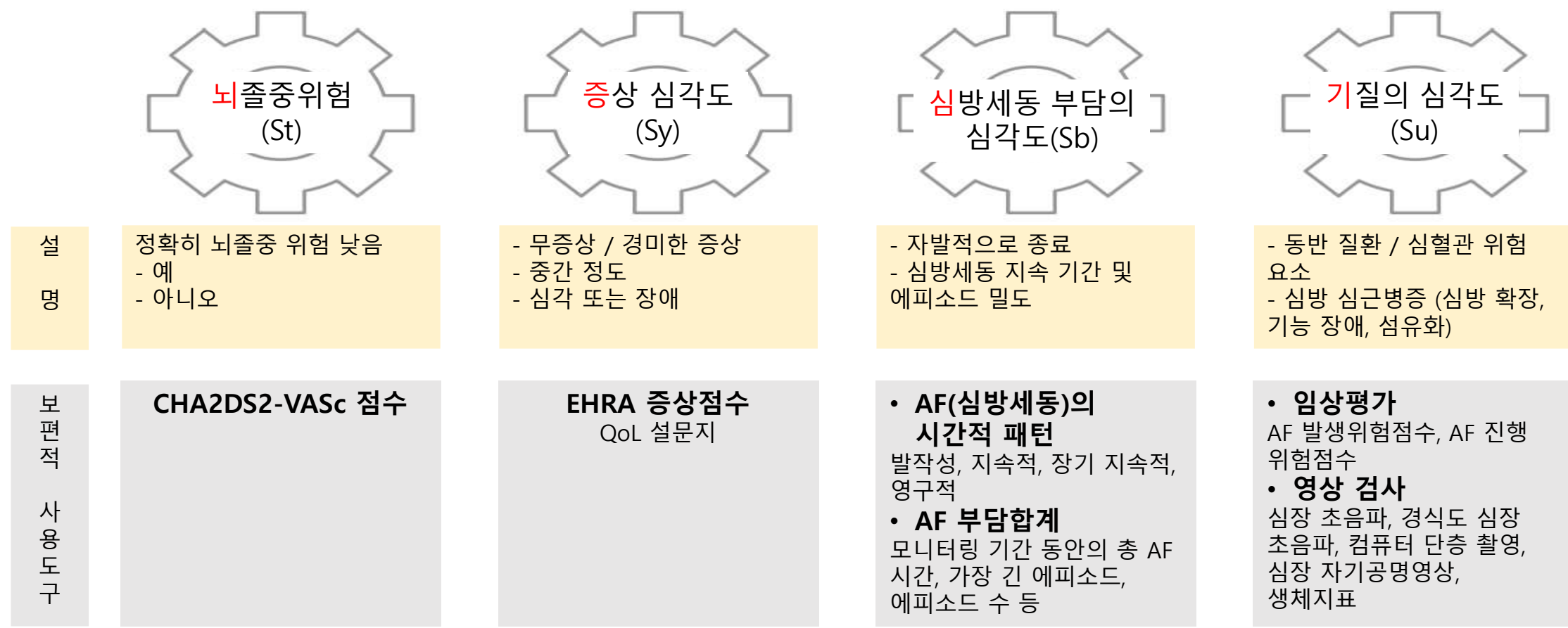


그림 1. AF의 구조화된 특성화의 예로서 4S-AF 체계.
 AF = 심방 세동; CHA2DS2-VASc = 울혈성 심부전, 고혈압, 75세 이상, 당뇨병, 뇌졸중, 혈관 질환, 65-74세, 성별 카테고리(여성); CT = 컴퓨터 단층 촬영; EHRA = 유럽 심장 리듬 협회; LA = 왼쪽 심방; MRI = 자기 공명 영상; QoL = 삶의 질; TOE = 경식도 심장 초음파; TTE = 경흉부 심장 초음파.

Fourier transform

<Hyperparameters>

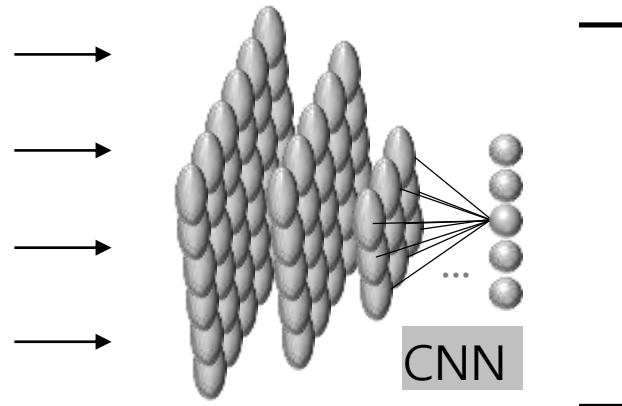
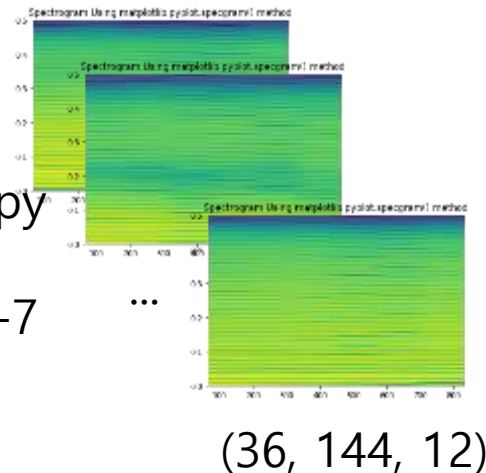
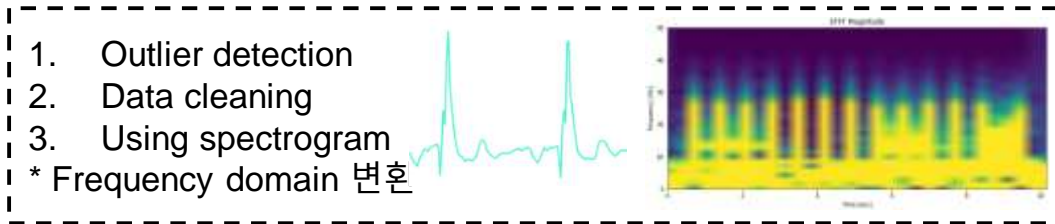
Lead: 8 or 12

Loss: MSE or Cross-Entropy

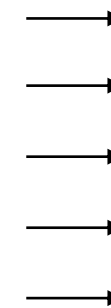
Learning Rate: $1e-1 \sim 1e-7$

Dropout: $0.2 \sim 0.8$

Fourier Sampling Frequency,
number per segment: 100,
70~100



Hyperparameter adjustment



Classification

Rhythm
Classification into
“SR”, “SBRAD”,
“STACH”, “AFIB”,

Model evaluation & Visualization

Figure 1. 본 Study에서 진행된 1번째 Deep learning analysis의 흐름도. 본격적인 “돌보기” AI의 적용에 앞서 일차적으로 Rhythm을 4개로 진단하는 First-Step Classification이다. Fourier 변환을 거친 (36, 144, 12)의 3차원 데이터에 대해 CNN을 적용하였다. 이때 마지막 Layer에 Softmax + Cross-Entropy Loss를 사용하는 것보다 Sigmoid + Mean-Squared Error를 사용하는 것이 더 효과적이었다.

<Hyperparameters>

Lead: 8 or 12

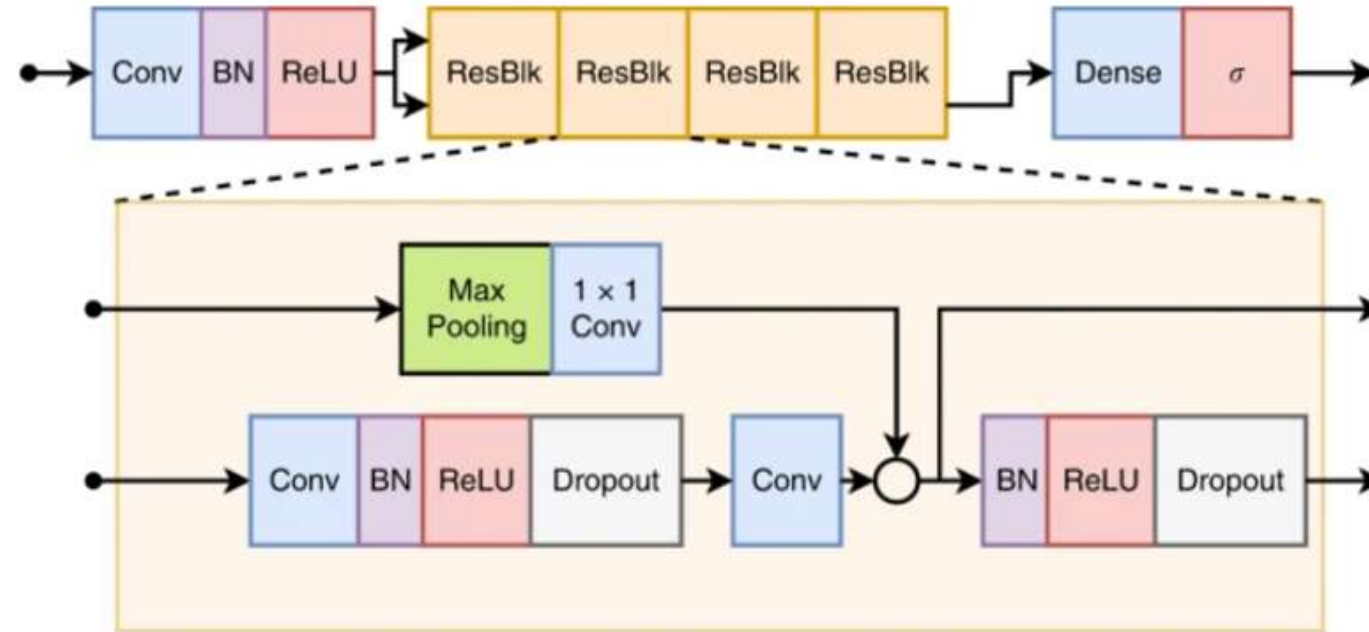
Loss: MSE or Cross-Entropy

Learning Rate: $1e-1 \sim 1e-7$

Dropout: 0.2 ~ 0.8

Block: 3 ~ 5

Fig. 3: (DNN architecture).



The unidimensional residual neural network architecture used for ECG classification.

Figure 1. 본 Study에서 진행된 2번째 Deep-learning Analysis의 흐름도. 본격적인 “돌보기” AI의 적용에 앞서 일차적으로 Rhythm을 4개로 진단하는 First-Step Classification이다. 12개의 Lead에 대한 5000개의 Point를 2차원으로 나열한 데이터에 대해 Resnet1D 모델을 적용하여 분류하였다. 이때 마지막 Layer에 Softmax + Cross-Entropy Loss를 사용하는 것보다 Sigmoid + Mean-Squared Error를 사용하는 것이 더 효과적이었다.

Method using Fourier Transform + 2D Convolution

- ECG는 여러 심박/파동의 중첩, 좋은 성능
- 하지만 Visualization (Interpretable AI) 면에서 부족

Method using 1D Convolution with Residual Block

- 데이터수가 적은 상황에서 충분한 학습이 안 이루어질 수도 있음
- Visualization 면에서 좋음

➔ Let's Compare These Two Models for **First-step Classification** into four labels => (SR, SBRAD, STACH, AFIB)

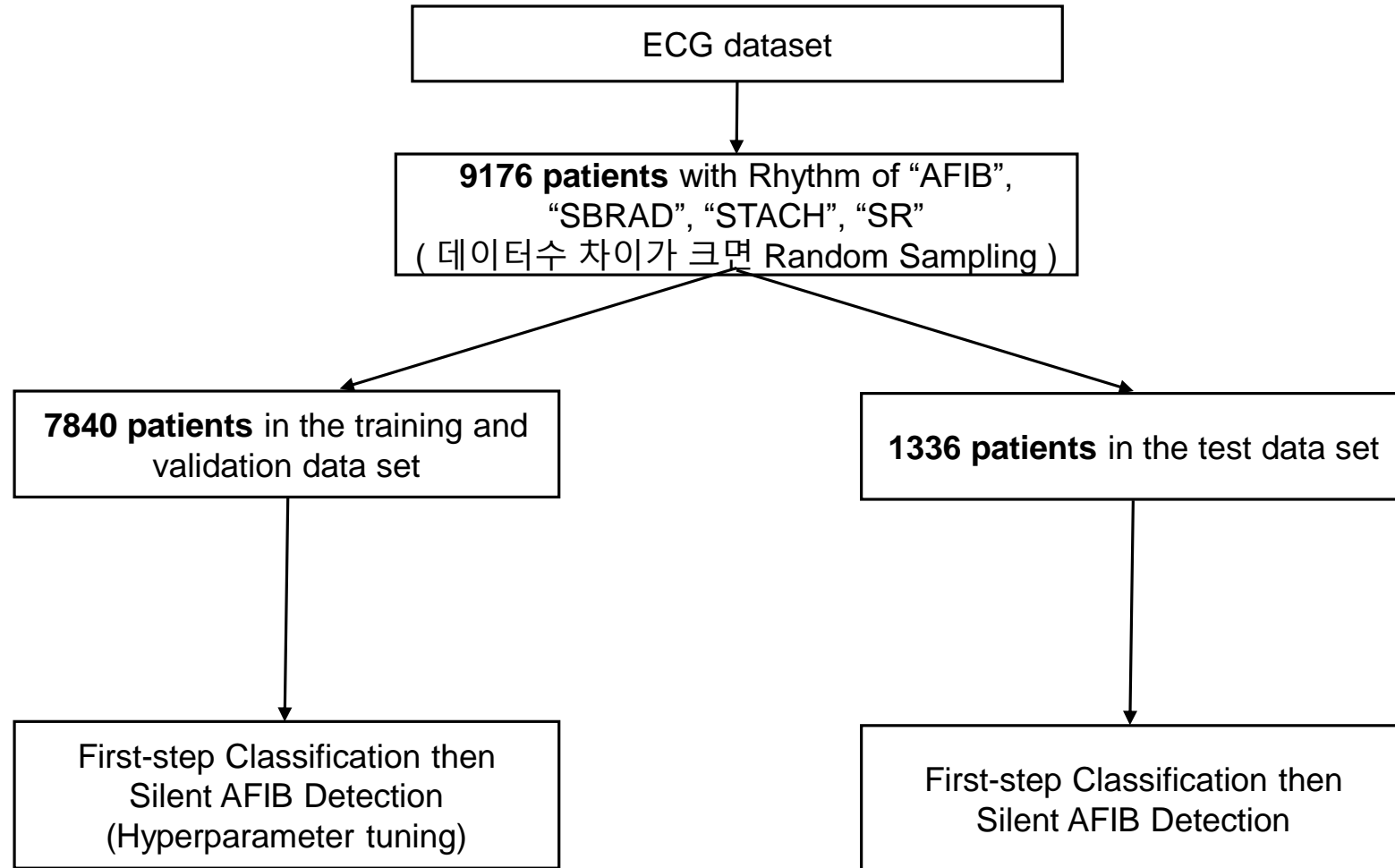


Figure 2. 환자 처리 및 분석 흐름도. 세브란스 데이터와 PTB 데이터를 합쳐 이 중 Rhythm이 SR, AFIB, SBRAD, STACH 에 속하는 9176 명의 환자를 추출하였다. 이때 SR과 다른 데이터의 불균형을 고려하여 Max / Min이 3~4 정도가 되도록 Random Sampling 하였으며 이후 이들을 Train + Val / Test Dataset으로 나누어 분석하였다.

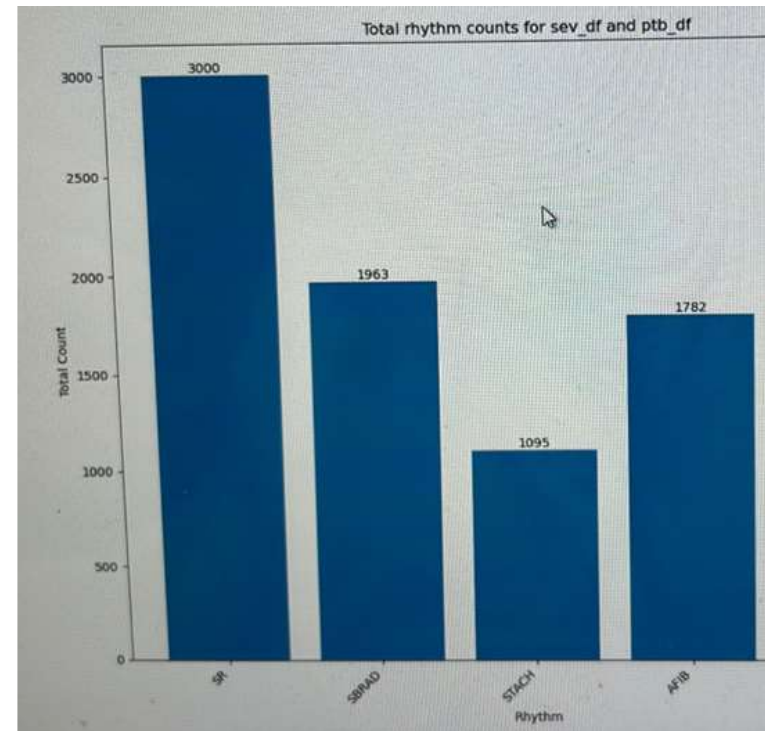
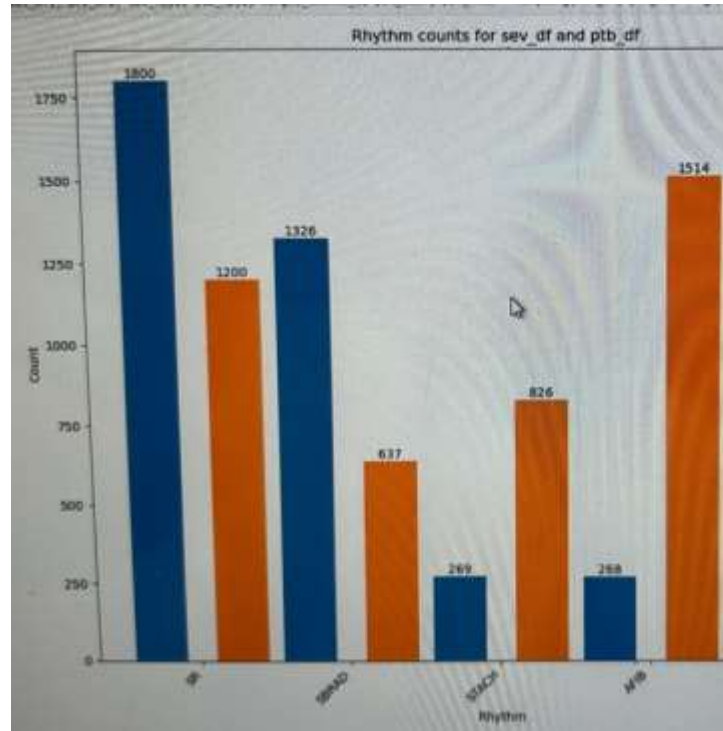


Figure 2. Train + Val 환자 처리 및 분석 흐름도. 세브란스 데이터와 PTB 데이터를 합쳐 이 중 Rhythm이 SR, AFIB, SBRAD, STACH 에 속하는 9176 명의 환자를 추출하였다. 이때 SR과 다른 데이터의 불균형을 고려하여 Max / Min 이 3~4 정도가 되도록 Random Sampling 하였으며 이후 이들을 Train + Val / Test Dataset으로 나누어 분석하였다.

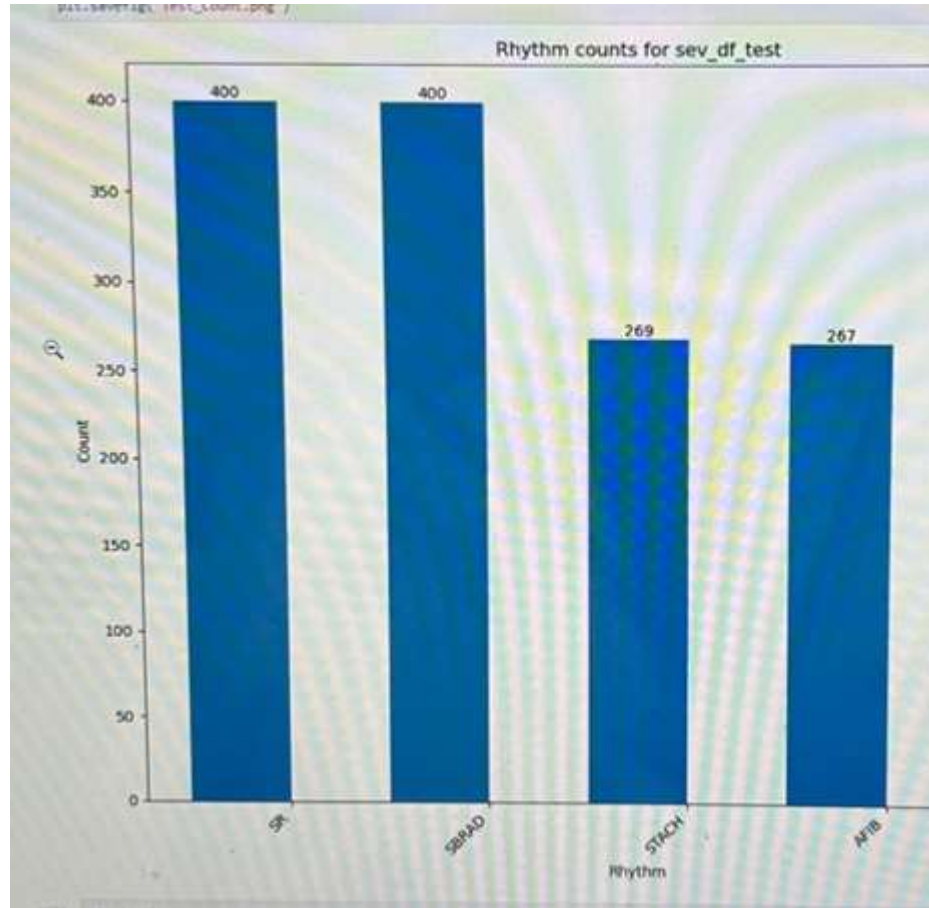
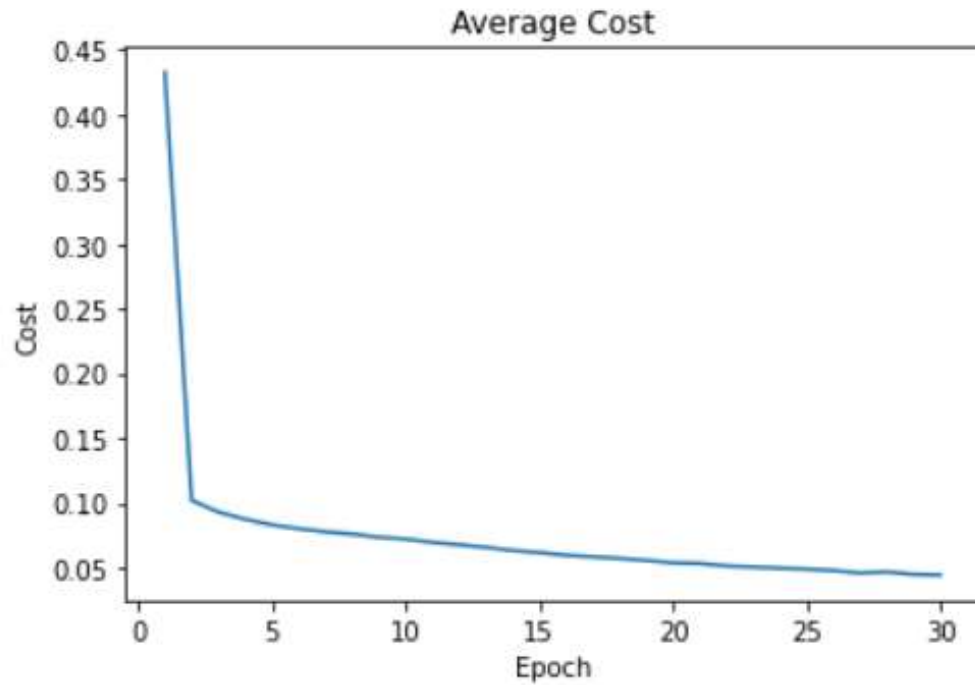


Figure 2. Test 환자 처리 및 분석 흐름도. 세브란스 데이터와 PTB 데이터를 합쳐 이 중 Rhythm이 SR, AFIB, SBRAD, STACH 에 속하는 9176 명의 환자를 추출하였다. 이때 SR과 다른 데이터의 불균형을 고려하여 Max / Min 이 3~4 정도가 되도록 Random Sampling 하였으며 이후 이들을 Train + Val / Test Dataset으로 나누어 분석하였다.)

Table 1. Data set characteristics

Characteristics	Training and validation	Test
Number of patients	7840	1336
Age (mean \pm SD)	62.5 \pm 15.7	65.5 \pm 11.4
Weight (mean \pm SD) (PTB)	69.6 \pm 16.9	-
Height (mean \pm SD) (PTB)	166.7 \pm 10.3	-
Sex		
Male (n)	3827	693
Female (n)	4013	643

Model 1.



$$Accuracy = \frac{(TP + PN)}{(TP + TN + FP + FN)}$$

Accuracy 93 (AFIB)
 96 (SBRAD)
 87 (SR)
 98 (STACH)

Mean ± SD 92.66 ± 4.21

Figure 6. Cost-Epoch plot 및 Model 1의 accuracy and Mean (±SD)

Model 1.

<AUPRC>

0.83 (AFIB)
0.98 (SBRAD)
0.80 (SR)
0.98 (STACH)

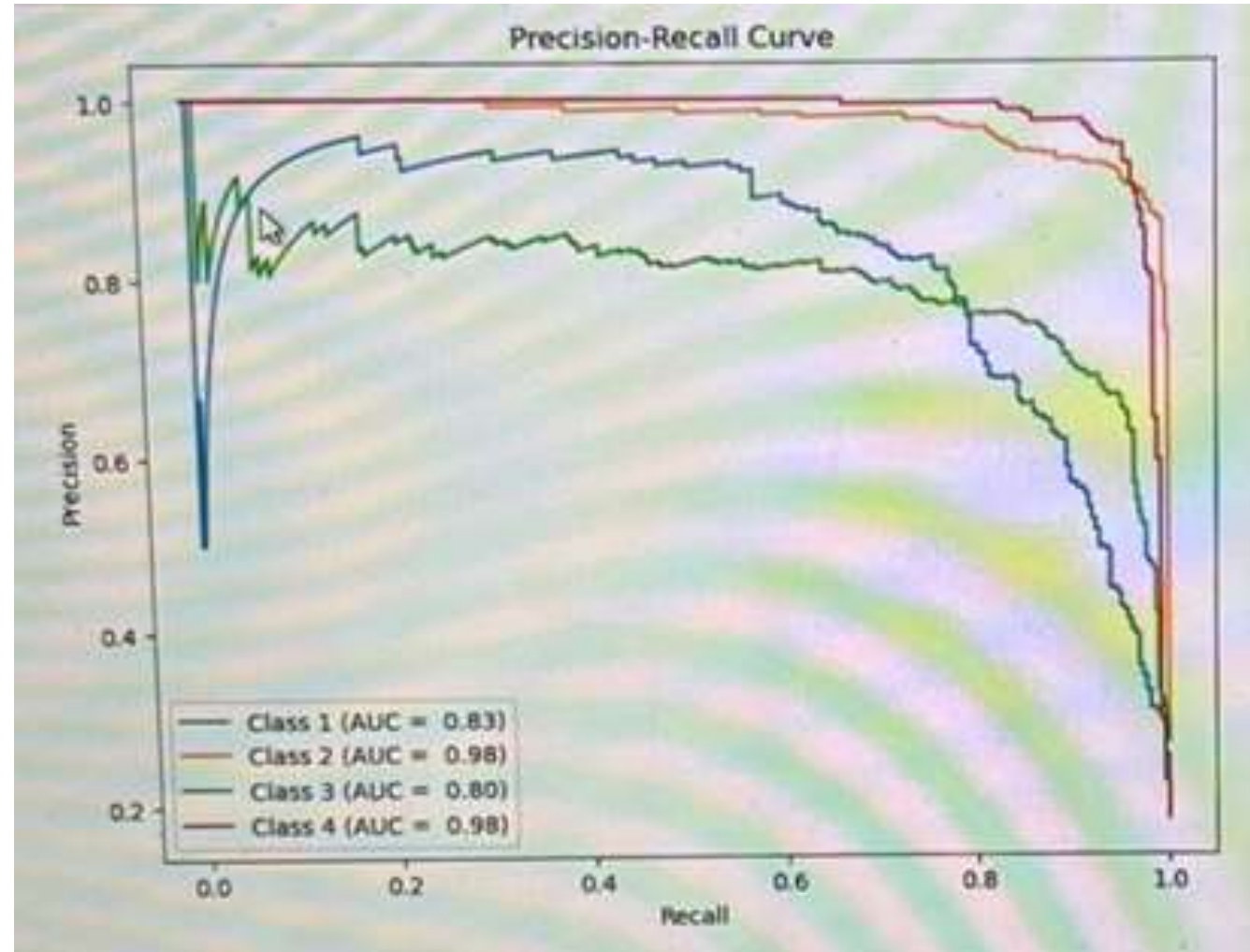


Figure 8. PR curve 및 AUPRC (area under PR curve) 값. Data imbalance가 있을 경우 AUROC가 높게 나오는 경향이 있어 AUPRC 값을 도출함.

Model 1.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	191	27
	Negative (0)	76	1188

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	398	56
	Negative (0)	2	1026

Model 1

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	369	168
	Negative (0)	31	914

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	249	8
	Negative (0)	20	1205

Figure 7. confusion metrics

Model 1.

True

AFIB SBRAD SR STACH

Pred

AFIB

191

0

7

15

SBRAD

25

398

20

0

SR

38

0

369

4

STACH

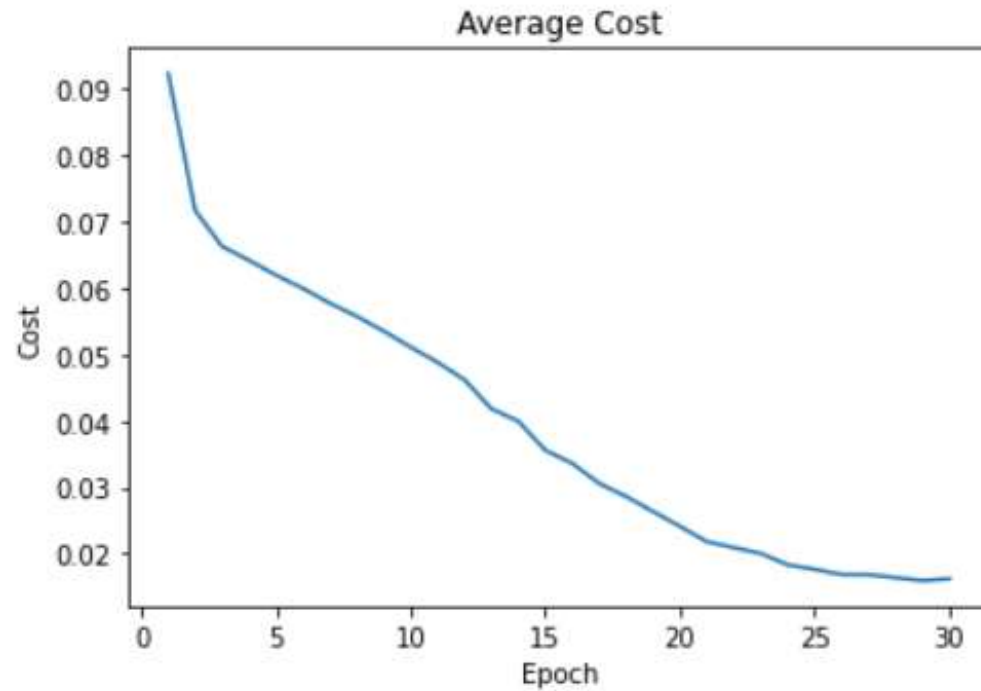
4

0

3

249

Model 2.



$$Accuracy = \frac{(TP + PN)}{(TP + TN + FP + FN)}$$

Accuracy 74 (AFIB)
 73 (SBRAD)
 47 (SR)
 80 (STACH)

Mean ± SD 72.31 ± 13.74

Figure 9. Cost-Epoch plot 및 Model 2의 accuracy and Mean (±SD)

Model 2.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	41	158
	Negative (0)	226	1057

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	94	94
	Negative (0)	306	988

Model 2

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	269	658
	Negative (0)	131	424

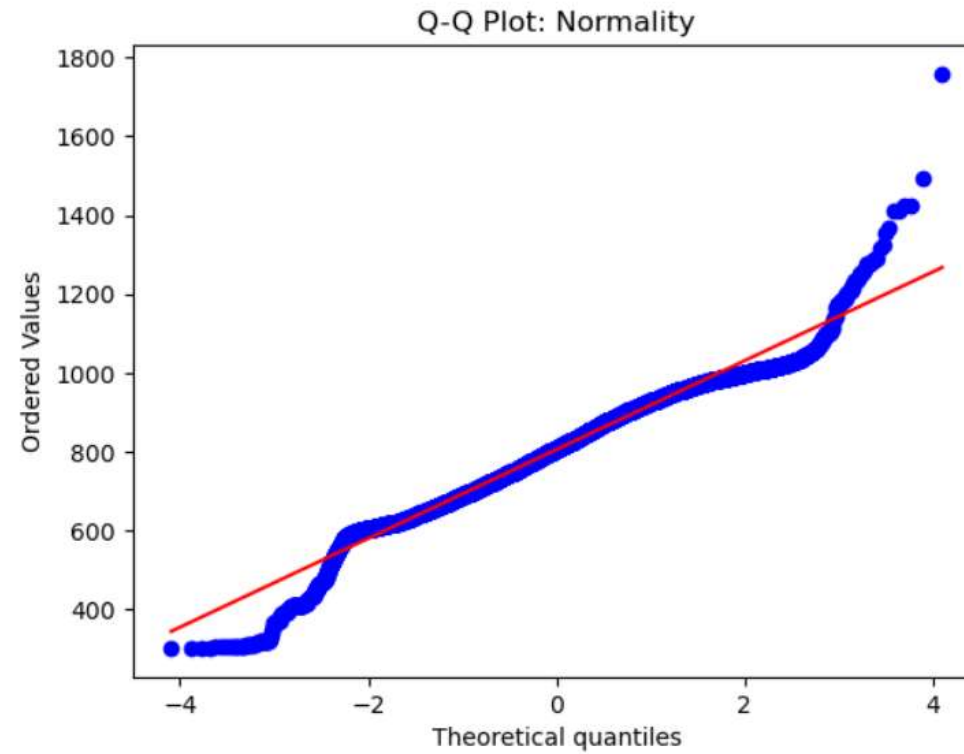
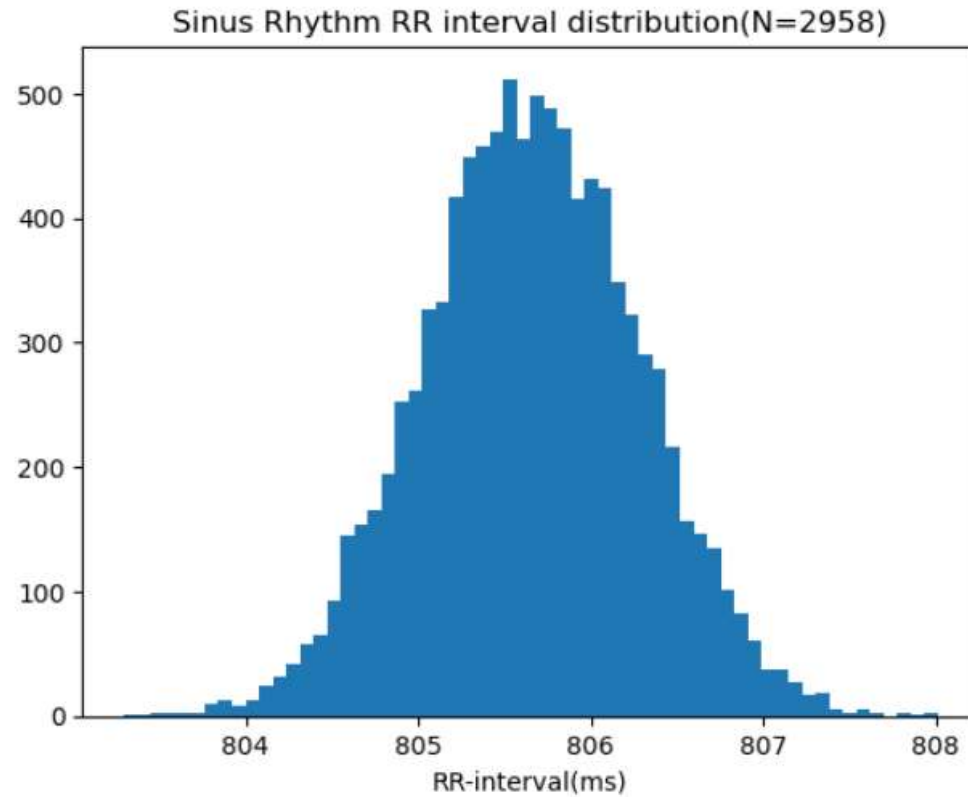
		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	47	67
	Negative (0)	222	1146

Figure 7. confusion metrics

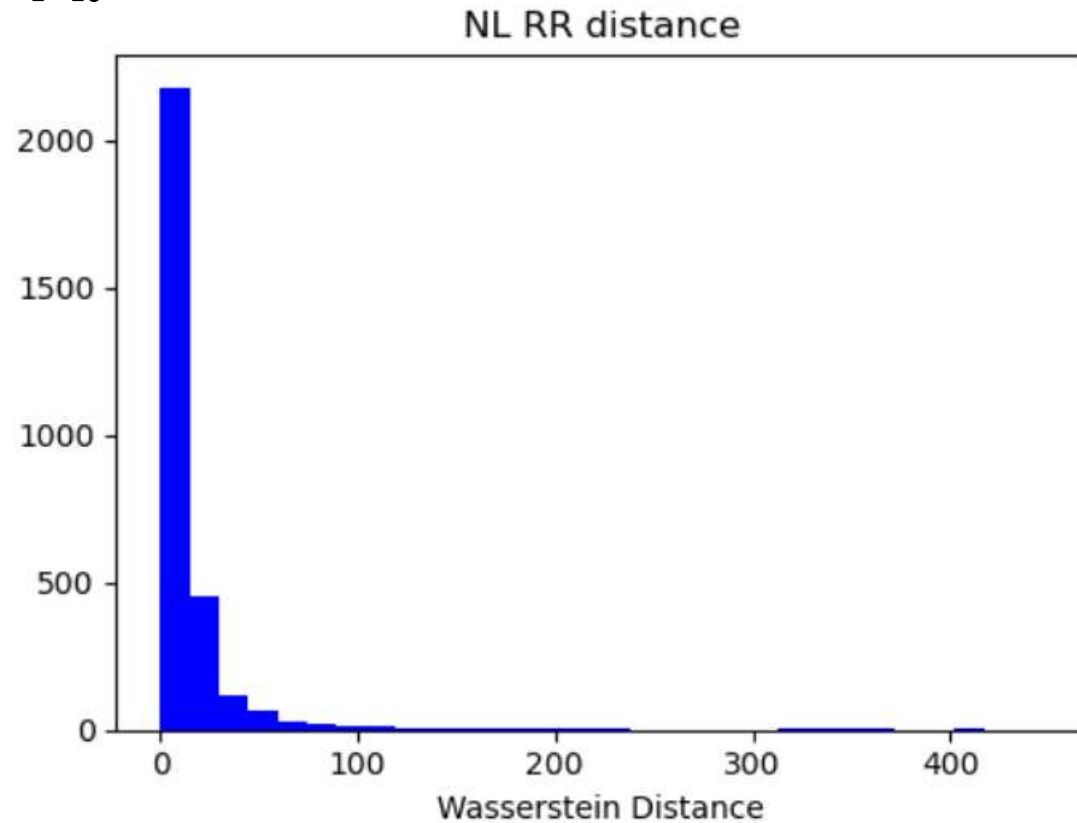
Model 1.

		True			
		AFIB	SBRAD	SR	STACH
Pred	AFIB	41	46	51	41
	SBRAD	20	94	43	8
	SR	178	226	269	164
	STACH	15	20	24	47

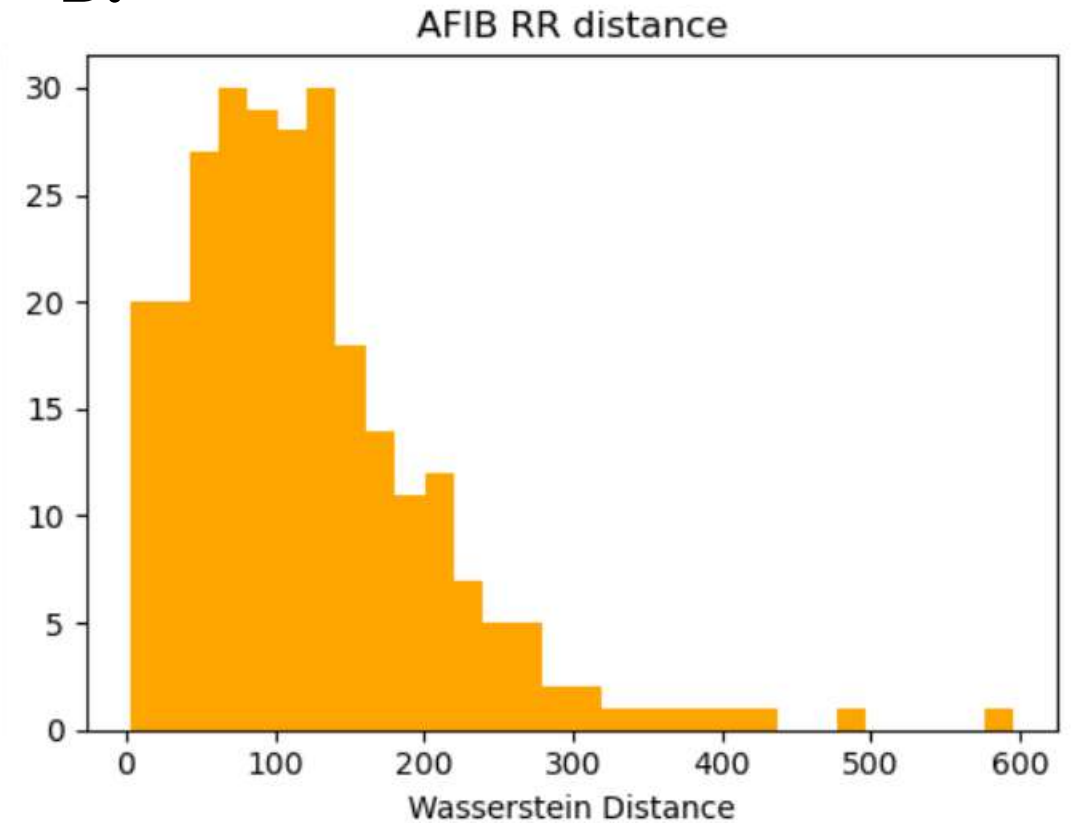
Distribution of RR interval



A.



B.



Lead II에서 RR간격 표본 추출을 통해 구한 Wasserstein distance의 분포 비교 정상 vs 환자. 각 환자별로 Lead II에서 RR 간격(이웃한 R Peak 사이의 시간차) 배열을 구한 뒤 $n=3$, 3번 복원 추출하여 구한 벡터에 대해 Wasserstein Distance를 구함. 환자군에 대해 반복

패널 (A): rhythm이 SR인 집단에 대한 Wasserstein distance 분포도.

패널 (B): AFIB가 나타나는 집단에 대한 Wasserstein distance 분포도. SR rhythm에 비해 Wasserstein Distance가 더 큰 경향이 나타난다. RR간격 집단 내의 차이는 SR rhythm에 비해 AFIB가 더 크다고 볼 수 있고 이는 AFIB의 ECG 소견 중 하나인 irregularly irregular pulse 와 대응된다.

SR/AFIB Discriminator Score 공식

4개의 판단 항목에 대한
label sum (비정상 : 1)

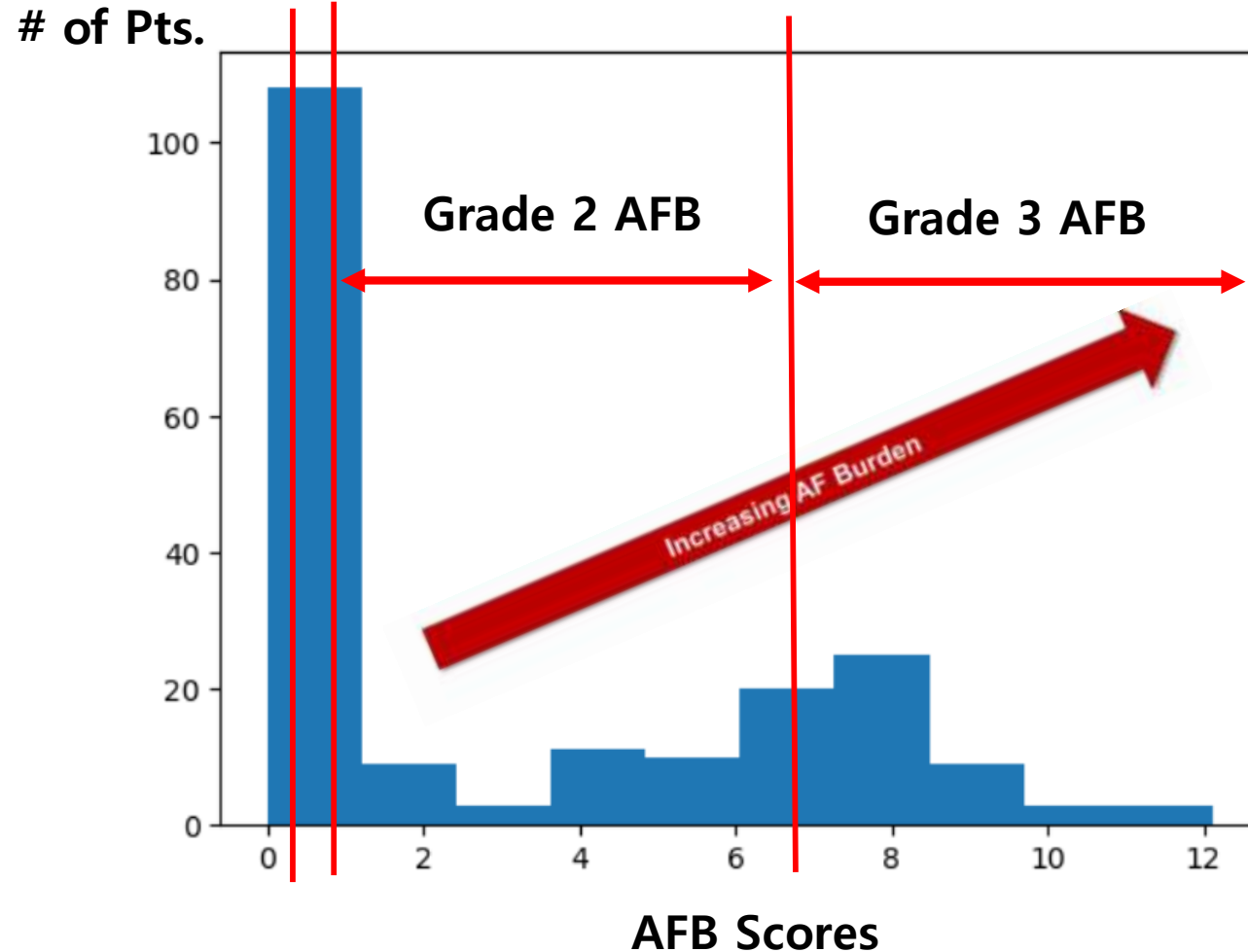
PR_interval P_wave QRS_Dur Axis	X	RR 간격 벡터 <div style="background-color: #c8e6c9; padding: 5px; display: inline-block;">RR_vector</div>	=	$ \begin{bmatrix} SC_{1,1} & \cdots & SC_{1,n_beat} \\ \vdots & \ddots & \vdots \\ SC_{4,1} & \cdots & SC_{4,n_beat} \end{bmatrix} $
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Score matrix

$$\text{Score} = \sum \sum sc_{i,j}$$

Scoring distribution of AFB

'Afib diagnosed Cases(n=201) scoring distribution'



25th Percentile : AFB scores < 0.01

→ grade 1 AFB : No tx needed

50th Percentile : 0.8565

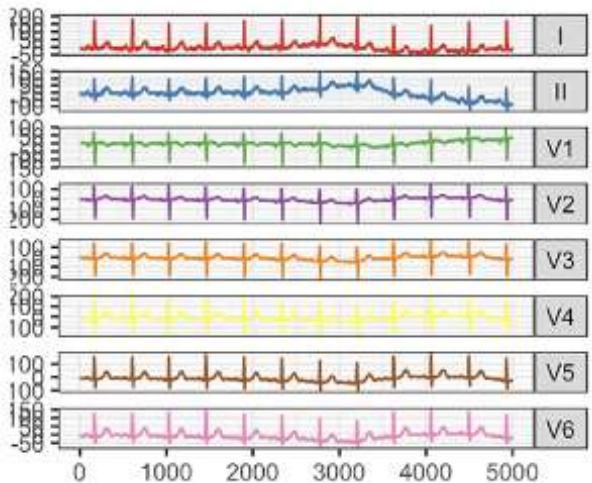
→ grade 2 AFB : **Regular f/u**

75th Percentile : 6.63

→ grade 3 AFB : **Tx as Afib**

	Description		Score
P	Scoring stratification by analyzing each wave	1. Overall abnormal findings	0 / 1
PR		2. Conduction disturbance	0 / 1
RR		3. Hypertrophy	0 / 1
QRS		4. Ischemic heart disease	0 / 1
Axis		5. ST/T change	0 / 1

Table 2. Scoring system for evaluating likelihood of AFB



Sum each lead's likelihood of AFB

$$\sum W(t_i) * P(isPW, isPR, isQRS, isAxis)$$

→ analysed by beat, beat-to-beat

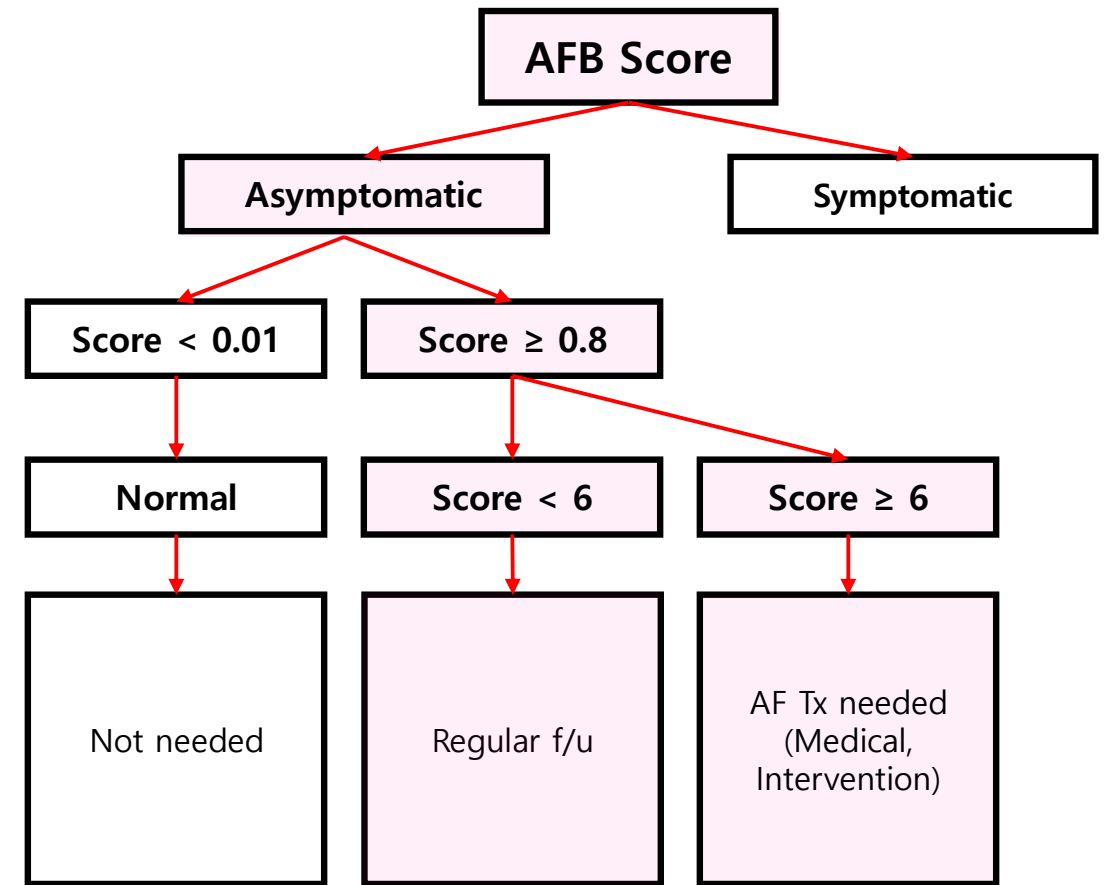


Figure 4. Decision flow. AFB Scoring system에 따른 환자의 관리 제언, 환자 내 반복적 AFB에 따른 예후 분석 등 후속 연구가 필요.

✓ Strength

- Macroscopic, microscopic analysis of Af, Saf
- Using 2 kinds of mechanisms of model for detecting Arrhythmia

✓ Limitations

- Need for further validation of microscopic beat analysis scoring system
- Interpretation of SAF Scores and risk, comorbidities

- ✓ 김동현 : First-step classification에 사용되는 2개의 모델 학습 + Visualization 담당, 모델2 제작함, 논문 검색
- ✓ 변유경 : 사전논문 찾고 임상해석함, ppt 제작, 참고문헌 정리
- ✓ 이승준 : 모델2 제작함, 논문 검색
- ✓ 이승환 : study baseline 특성 찾고 결과 해석함, 논문 검색, 모델2 제작함, ppt 제작
- ✓ 조나현 : 모델2 가르치고 AF detection함, 모델2 제작함 , 논문 검색

Steinberg, B. A. et al. (2021). Atrial Fibrillation Burden and Heart Failure: Data from 39,710 Individuals with Cardiac Implanted Electronic Devices. *Heart Rhythm*, 18(5), 709–716. doi: 10.1016/j.hrthm.2021.01.021

Henri_Gruwez, H. et al. (2023). Detecting Paroxysmal Atrial Fibrillation From an Electrocardiogram in Sinus Rhythm: External Validation of the AI Approach. *JACC: Clinical Electrophysiology*, 9(8), 1771-1782. doi: 10.1016/j.jacep.2023.04.008

Hindricks, G. (2021). 2020 ESC Guidelines for the diagnosis and management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS): The Task Force for the diagnosis and management of atrial fibrillation of the European Society of Cardiology (ESC) Developed with the special contribution of the European Heart Rhythm Association (EHRA) of the ESC. *European Heart Journal*, 42(5), 373–498. doi: 10.1093/eurheartj/ehaa612

Khurshid, S. et al. (2022). ECG-Based Deep Learning and Clinical Risk Factors to Predict Atrial Fibrillation. *Circulation*, 145(2), 122-133. doi: 10.1161/CIRCULATIONAHA.121.057480.

Agrawal, A. et al. (2022). ECG-iCOVIDNet: Interpretable AI model to identify changes in the ECG signals of post-COVID subjects. *Comput Biol Med.*, 146, 105540. doi: 10.1016/j.compbimed.2022.105540

Thank You

For Listening