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ECG: SAFE OR NOT?

Binary ECG Classification: Normal vs. Abnormal

WHY THIS STUDY?

The electrocardiogram (**ECG**) is the main non-invasive tool to monitor the electrical activity of the heart and detect arrhythmias, ischemia, or other abnormalities.

Automating the classification between 'normal' and 'abnormal' traces allows us to:

- Reduce reporting times
- Support cardiologists by reducing workload
- Improve the timely detection of at-risk patients

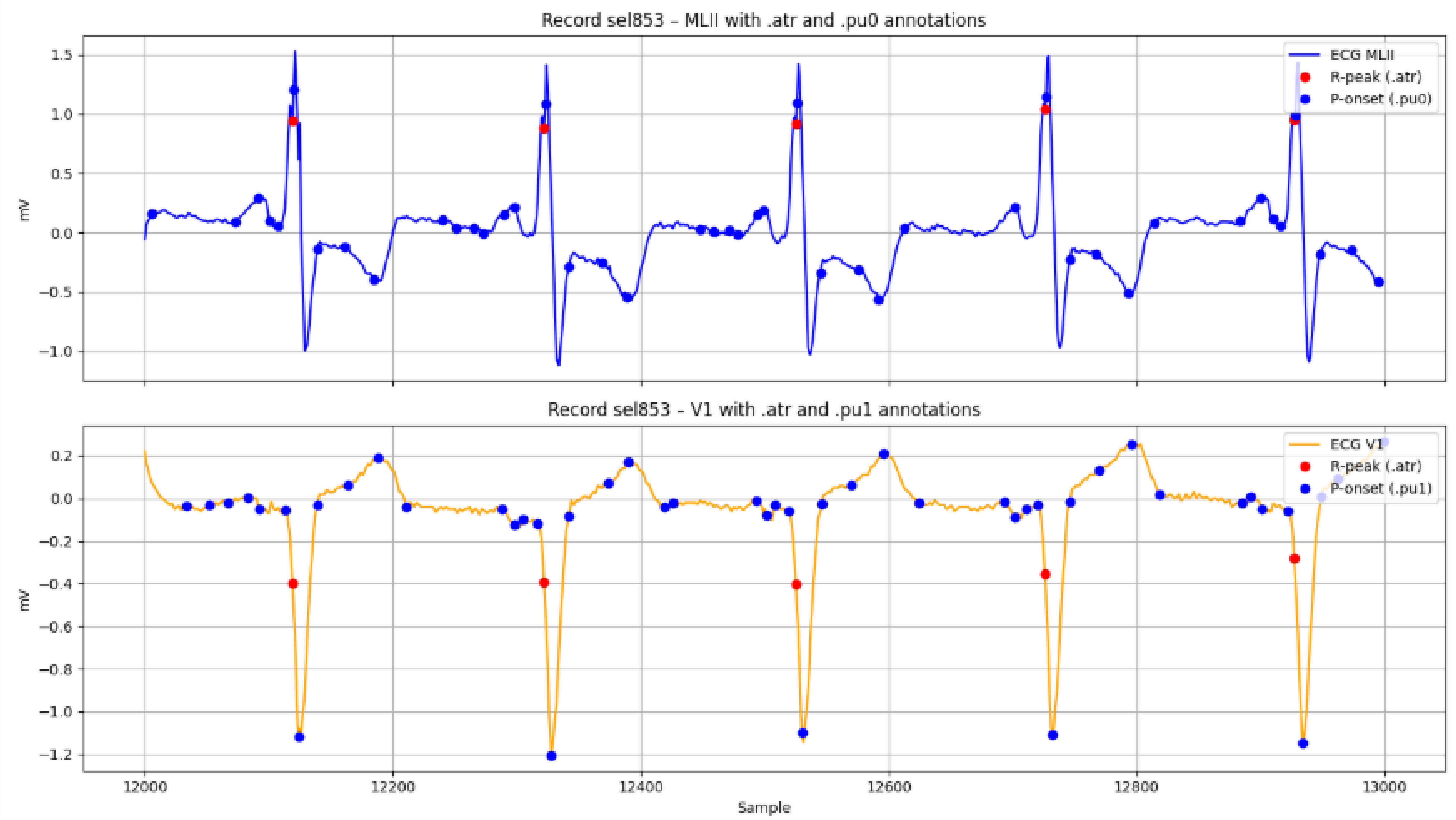
Our work fits into this context, proposing a deep learning model to assist clinicians and ensure more consistent diagnostic outcomes.”

QT - DATABASE

- **105** patients included in the database
- 2 leads: **MLII** (Modified Lead II) & **V1** (Precordial lead)
- **15** minutes per signal, sampled at 250 Hz (~225,000 samples per lead)
- File Types (up to 9 per record):
  - *.hea* → Header file (metadata)
  - *.dat* → ECG signals
  - *.atr, .man, .qt1, .qt2, .q1c, .q2c, .pu, .pu0, .pu1* → Annotations (manual & automatic)

For our analysis we mainly focused on ***.dat, .atr*** and ***.pu*** files.

VISUALIZATIONS



DATA PREPARATION

- **Record removal**

  For the patients (105) the file .atr was not always available (24 missing) so we removed those ones. (**81**)

- **Beat Annotation Symbols (.atm file)**

  N → Normal beat (**N**)
  All other letters (e.g., L, R, A, etc.) → Abnormal Beats (**A**).

  Non-letter symbols (such as /, +, ~, ", and |) do not represent beats and are therefore ignored.

```
Record: sel104

--- Original (.atr) ---
Unique symbols: ['+', '/', 'N', 'V', 'f']
Total annotations: 1113
First 6 symbols: ['/', '/', '/', '/', '/', 'f']
```

```
--- Filtered (.atm) ---
Unique symbols: ['A', 'N']
Total annotations: 349
First 6 filtered symbols: ['A', 'A', 'A', 'A', 'A', 'A']
```

Symbol	Description	Label to Use
N	Normal beat	Normal
L	Left bundle branch block beat	Abnormal
R	Right bundle branch block beat	Abnormal
A	Atrial premature beat	Abnormal
a	Aberrated atrial premature beat	Abnormal
J	Nodal (junctional) beat	Abnormal
S	Supraventricular premature beat	Abnormal
V	Premature ventricular contraction (PVC)	Abnormal
F	Fusion of ventricular and normal beat	Abnormal
e	Atrial escape beat	Abnormal
j	Nodal escape beat	Abnormal
f	Fusion of paced and normal beat	Abnormal
s	Supraventricular escape beat	Abnormal
Q	Unknown beat	Abnormal
/	Non-beat marker (e.g., segment boundary)	Ignore
+	Rhythm change annotation	Ignore
~	Signal artifact or noise	Ignore
"	Comment (not a beat)	Ignore
|	Isolated marker	Ignore

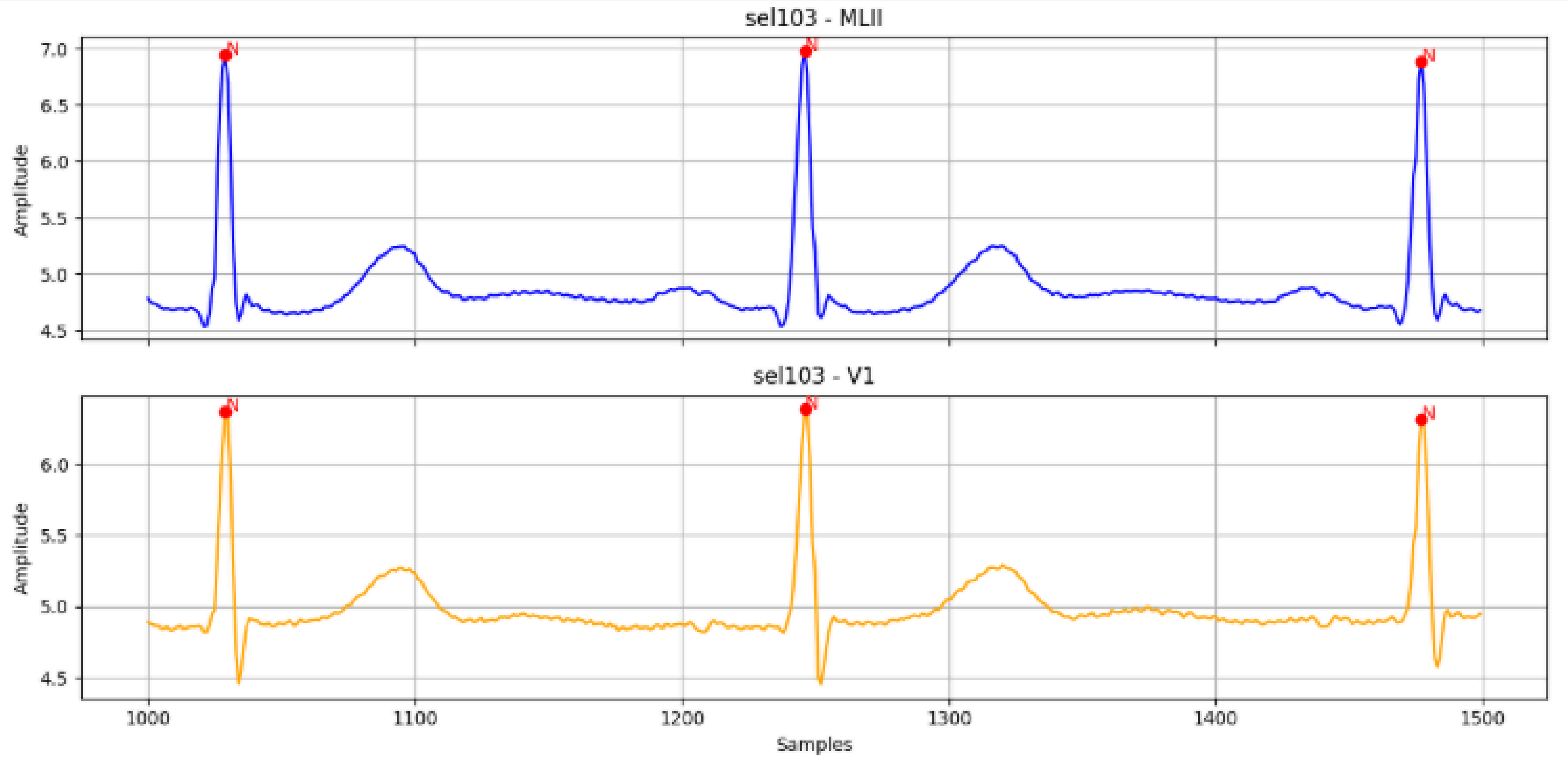
- **Windows creation**

In this step, we segment each ECG recording into 2-second windows and assign a label to each window based on the R-peaks it contains.

For each window:

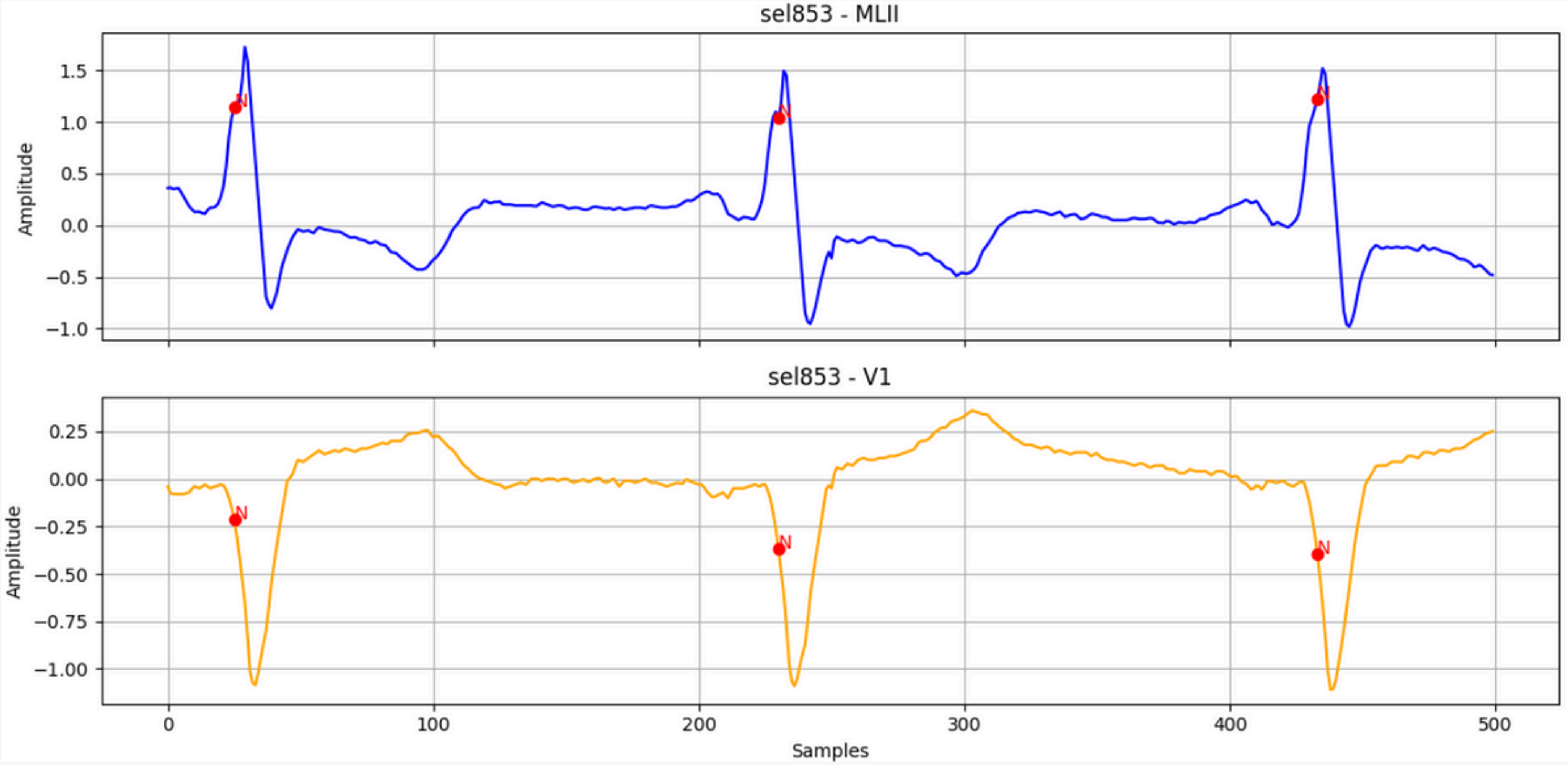
- We detect the R-peaks using .atr annotations.
- We match each R-peak to its corresponding label (N for normal, or any other symbol marked as abnormal) from the .atm file.
- If at least one abnormal beat is found in the window, the entire window is labeled as Abnormal; otherwise, it is labeled as Normal.

	record	window_start	window_end	label	r_peaks
0	sel102	54000	54500	Abnormal	[54125, 54265, 54475]
1	sel103	0	500	Normal	[14, 184, 399]
2	sel103	500	1000	Normal	[608, 819]
3	sel103	1000	1500	Normal	[1029, 1246, 1477]
4	sel103	1500	2000	Normal	[1697, 1905]
5	sel103	2000	2500	Normal	[2113, 2324]
6	sel103	2500	3000	Normal	[2532, 2745, 2973]
7	sel103	3000	3500	Normal	[3200, 3429]
8	sel103	3500	4000	Normal	[3649, 3875]
9	sel103	4000	4500	Normal	[4091, 4316]
10	sel103	4500	5000	Normal	[4550, 4772, 4984]



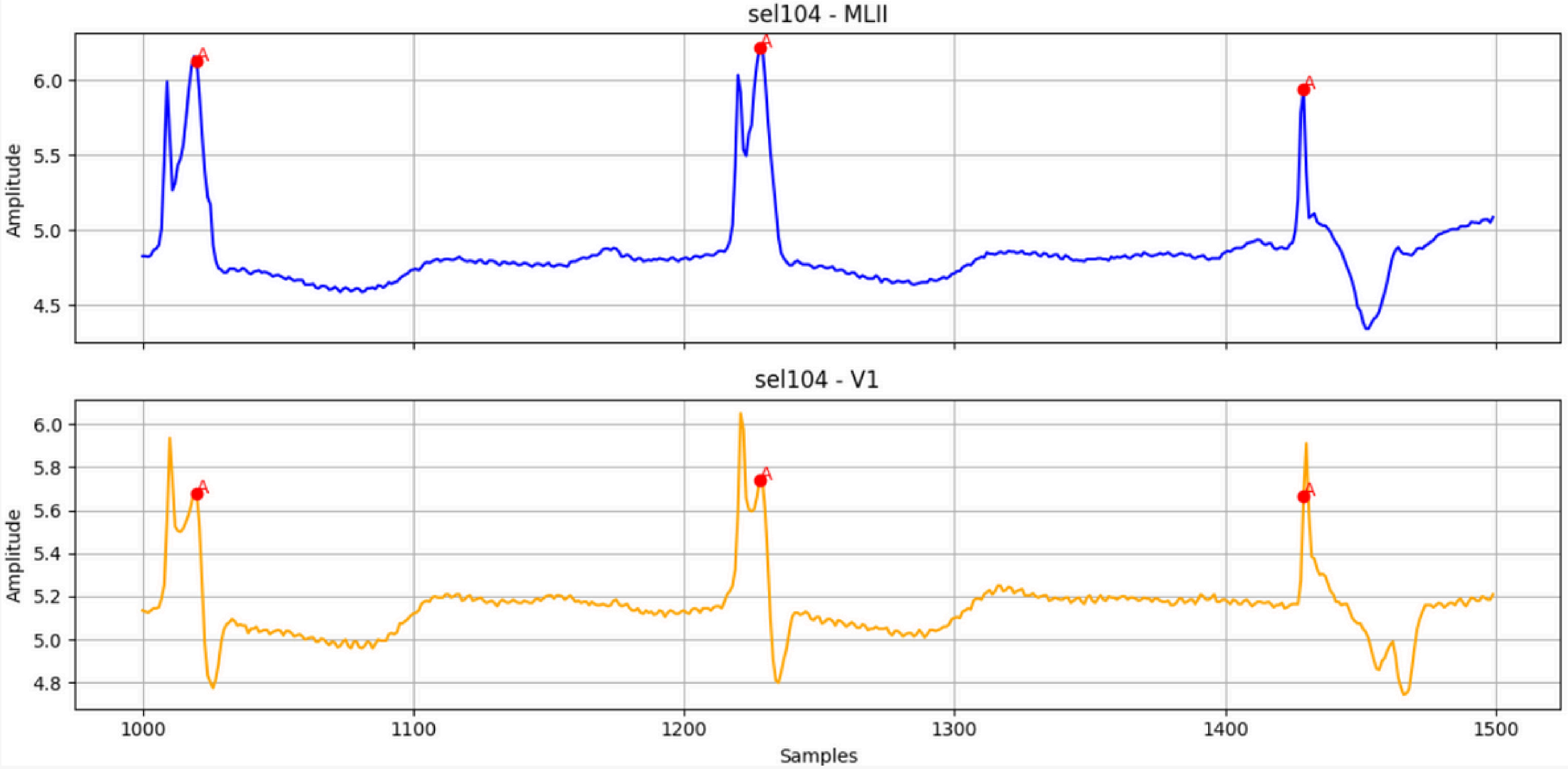

```
R-peak positions: [1029, 1246, 1477]
Labels of the peaks: ['N', 'N', 'N']

Final label for this window: Normal
```



Label: **Normal**

Label: **Abnormal**



DATASET SPLITTING

label	
Normal	32343
Abnormal	3347

To properly evaluate the model’s performance and avoid data leakage, the dataset is divided into three subsets:

1. **Training Set (80%)**

This subset is used to train the model, helping it learn patterns in the data. The model's parameters are updated based on this data.

2. **Validation Set (10%)**

This subset helps tune model hyperparameters and monitor generalization performance.

3. **Test Set (10%)**

This portion will be used only for final evaluation and remains untouched during training and validation.

Z-SCORE NORMALIZATION on ECG Signals:

- **Training Data**:
  - Flatten all windows → fit `StandardScaler` → compute **μ, σ per channel** (MLII, V1)
  - **Reshape** back to (35'690, 500, 2)

- **Validation** & **Test**:
  - Apply **same** μ, σ to ensure → **No DATA LEAKAGE** ✓

- **Outcome**:
  - Each channel in every window: **mean = 0, std = 1**

- **Signal Cleaning:**
  - **Notch filter** 50 Hz to remove power-line noise
  - 0.5–40 Hz band-pass **Butterworth filter** to retain ECG frequencies

Why this way?

- Preserves pathological amplitude differences *within* a window
- Avoids inter-patient amplitude bias

Training Set Balancing

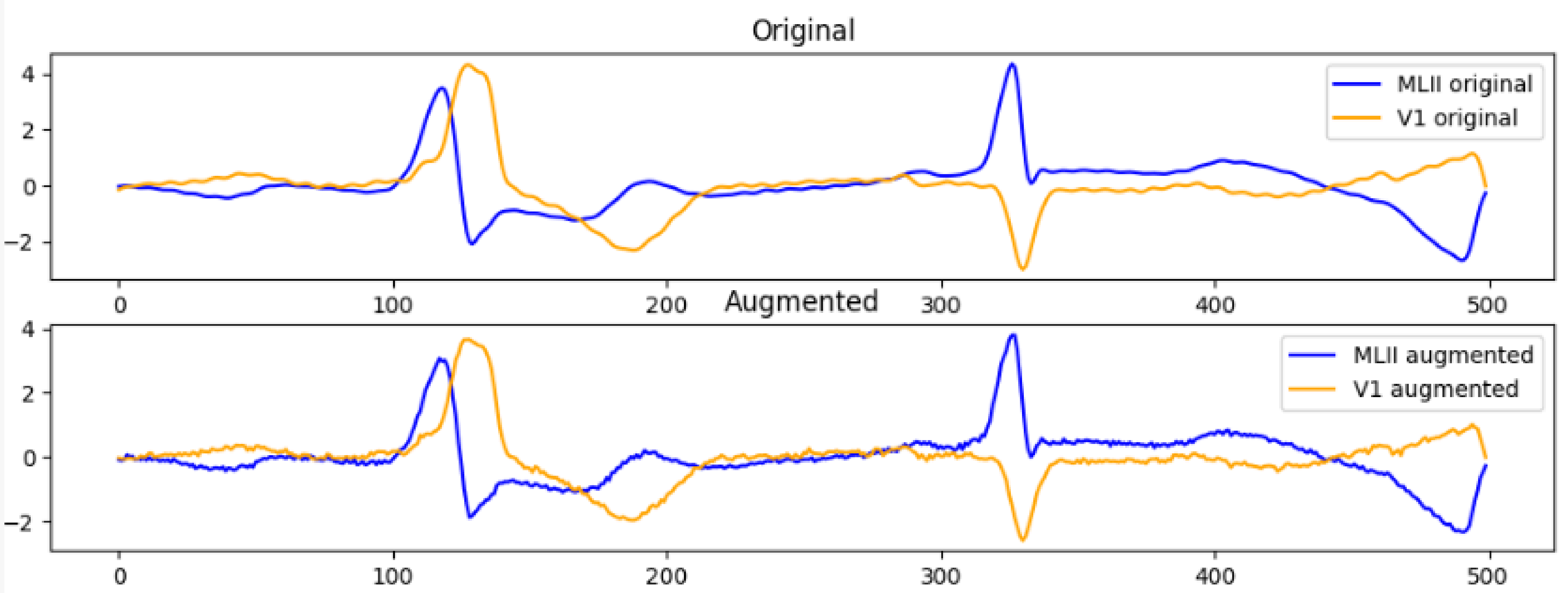
```
label
Normal      32343
Abnormal     3347
```

The original dataset was highly imbalanced, with a large majority of normal beats compared to abnormal ones. To address the imbalance in the training set, we perform two key steps:

. **OVERSAMPLING** with **Data Augmentation**

We generate synthetic abnormal samples by applying random transformations to the original abnormal windows:

- **Jittering**: Adding small Gaussian noise to simulate sensor variability.
- **Scaling**: Randomly amplifying or attenuating the signal to introduce realistic variation.



2. **UNDERSAMPLING cutting** normal windows

We performed **random undersampling** of the normal beats to match the number of abnormal samples.

The final training set is **perfectly balanced**, containing an equal number of normal and abnormal windows (50% each).

This strategy helps prevent bias during model training and ensures fair learning across classes.

```
Original Abnormal: 2692
Original Normal: 26220
Total abnormal: 2692 original + 8076 augmented = 10768
Balanced training set: 21536 total | Normal=10768, Abnormal=10768

Final balanced training distribution:
 -> Normal: 10768 windows (50.00%)
 -> Abnormal: 10768 windows (50.00%)
Total windows: 21536
```

HYPERPARAMETER OPTIMIZATION

To improve model performance, we used **Keras Tuner** to automatically search for the best CNN configuration.

Key steps:

- **Input shape**: ECG windows of **500 samples × 2 channels**

- **Hyperparameters optimized**:
  - Number of convolutional filters
  - Kernel size
  - Dense layer units
  - L2 regularization strength
  - Dropout rate
  - Learning rate

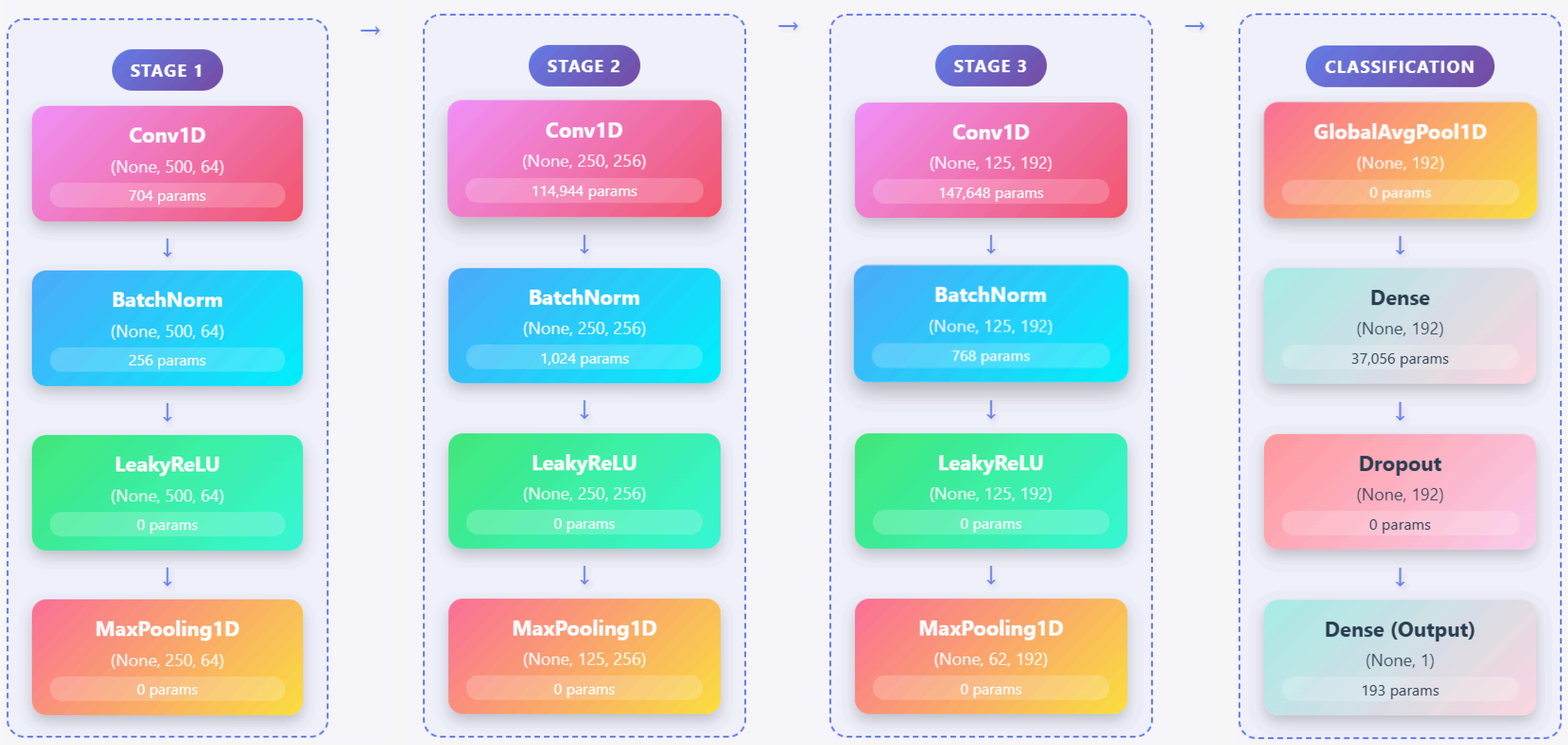
- **Optimization objective**: **Maximize validation recall** (focus on minimizing false negatives)

- **Search method**: **Random Search** over **30 trials** with early stopping.

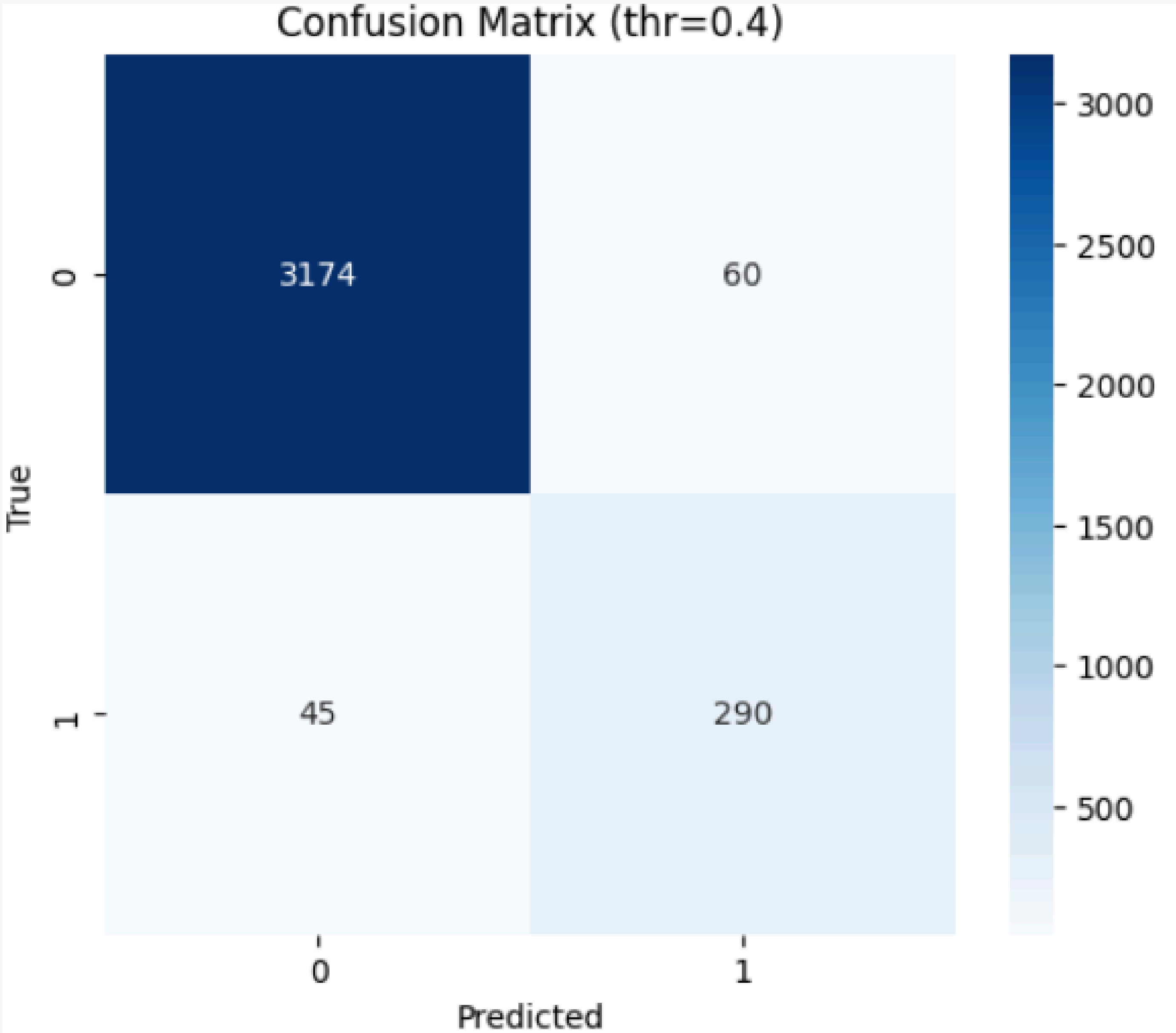
```
Trial 28 summary
Hyperparameters:
conv1_filters: 64
conv1_kernel: 5
conv2_filters: 256
conv2_kernel: 7
conv3_filters: 192
conv3_kernel: 3
dense_units: 192
l2: 1.5409404207370287e-05
dropout: 0.2
lr: 0.009644270859916792
Score: 1.0
```

input_shape = (500, 2)

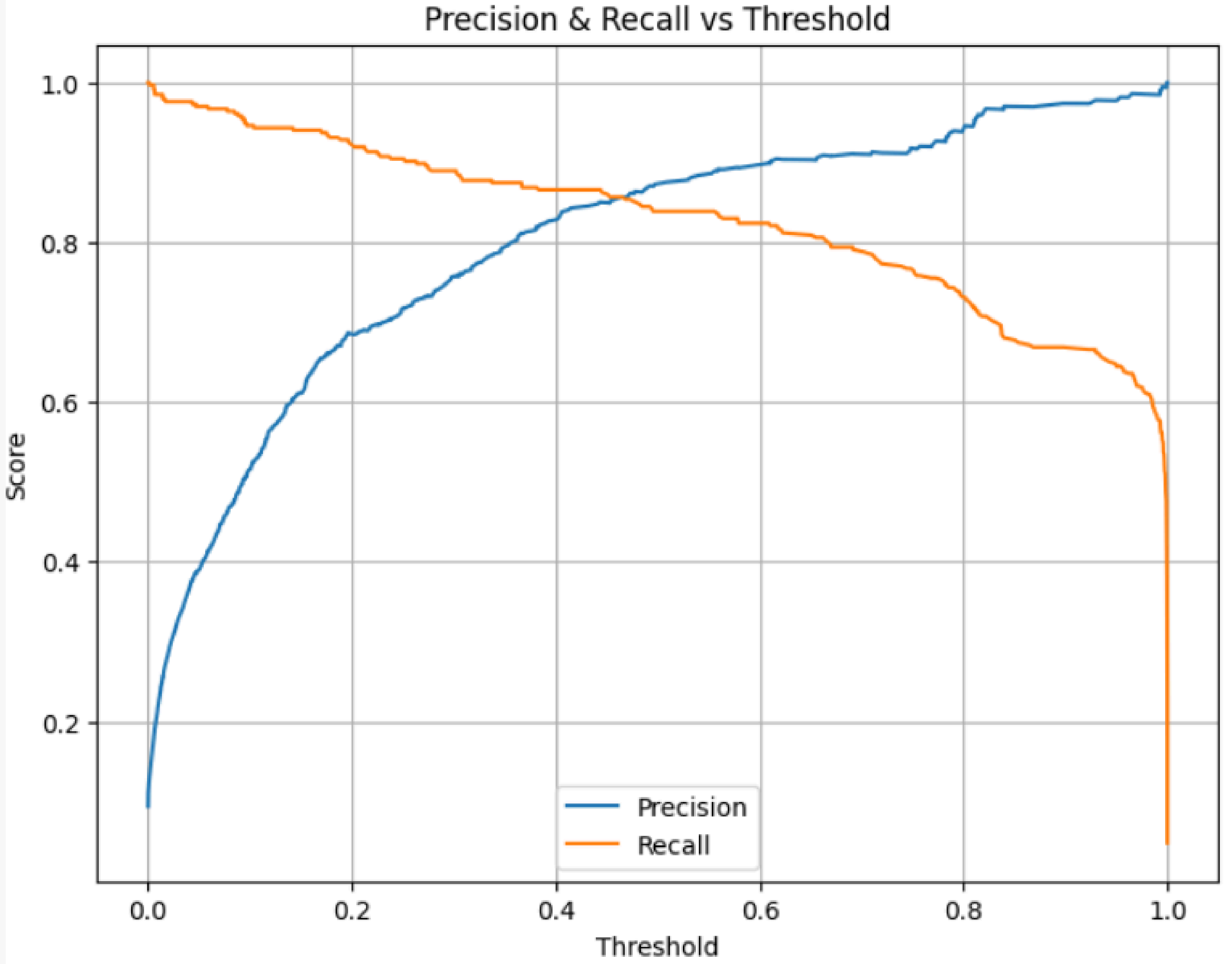
1D CNN - ARCHITECTURE



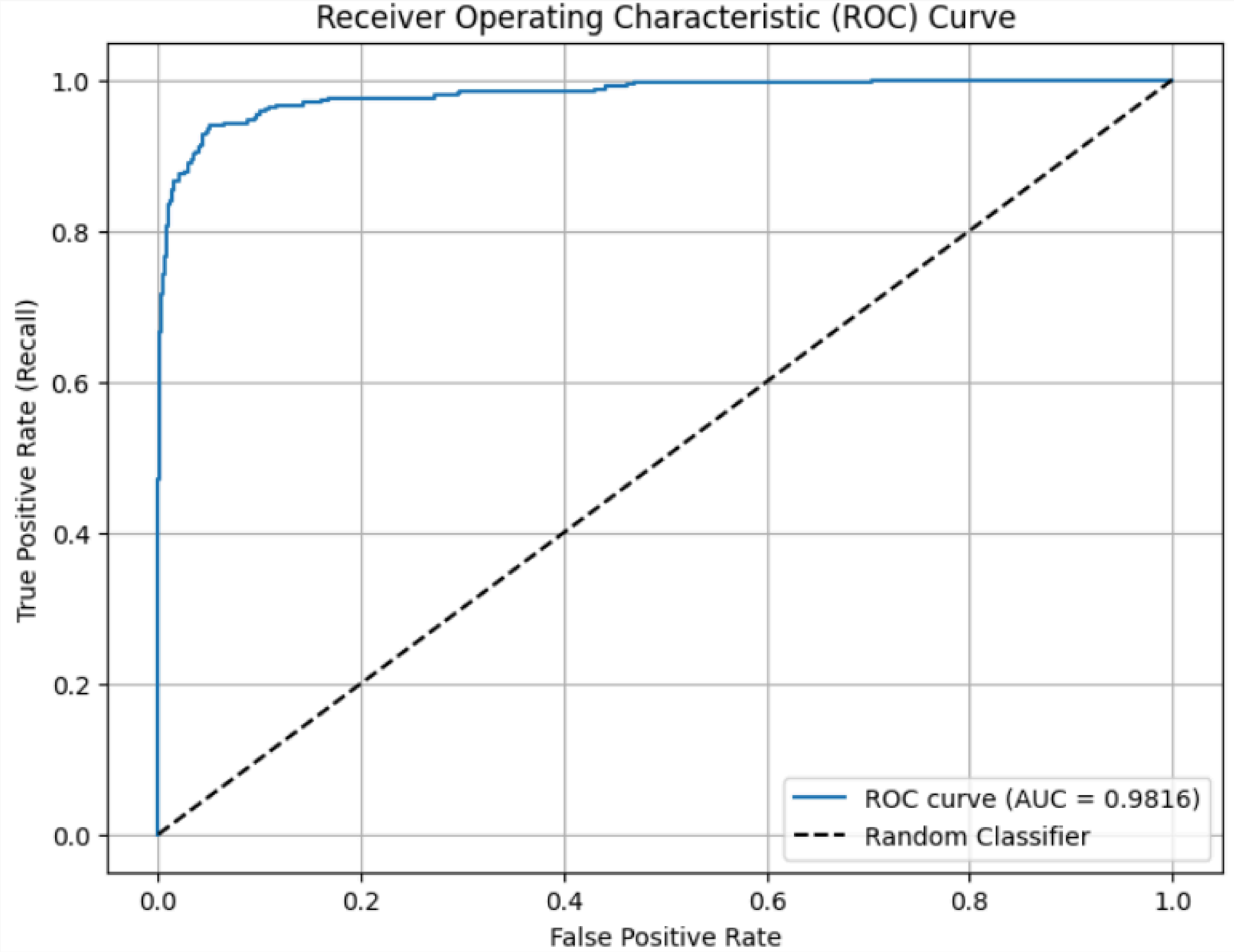
MODEL EVALUATION: TEST SET RESULTS



	precision	recall	f1-score
Normal	0.99	0.98	0.98
Abnormal	0.83	0.87	0.85



ROC - CURVE


Receiver Operating Characteristic (ROC) Curve
True Positive Rate (Recall)
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.9816)
Random Classifier

ADVANTAGES AND DISADVANTAGES of the study

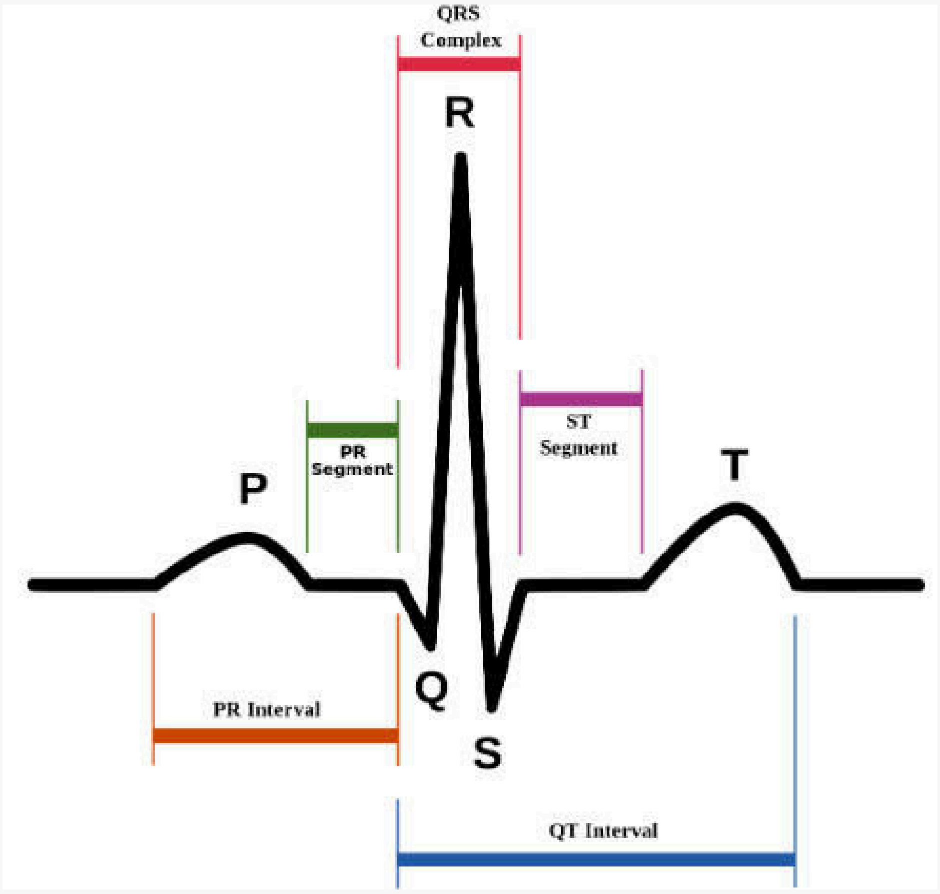
- Dual-lead ECG input with expert-verified labels
- Targeted data augmentation instead of simple duplication
- Hyperparameter tuning for optimal performance
- Ground truth derived from cardiologist annotations

- Limited number of anomalous samples
- Fixed windows spanning only 2–3 heartbeats
- Binary classification; lacks multiclass anomaly differentiation

FUTURE DEVELOPMENTS?

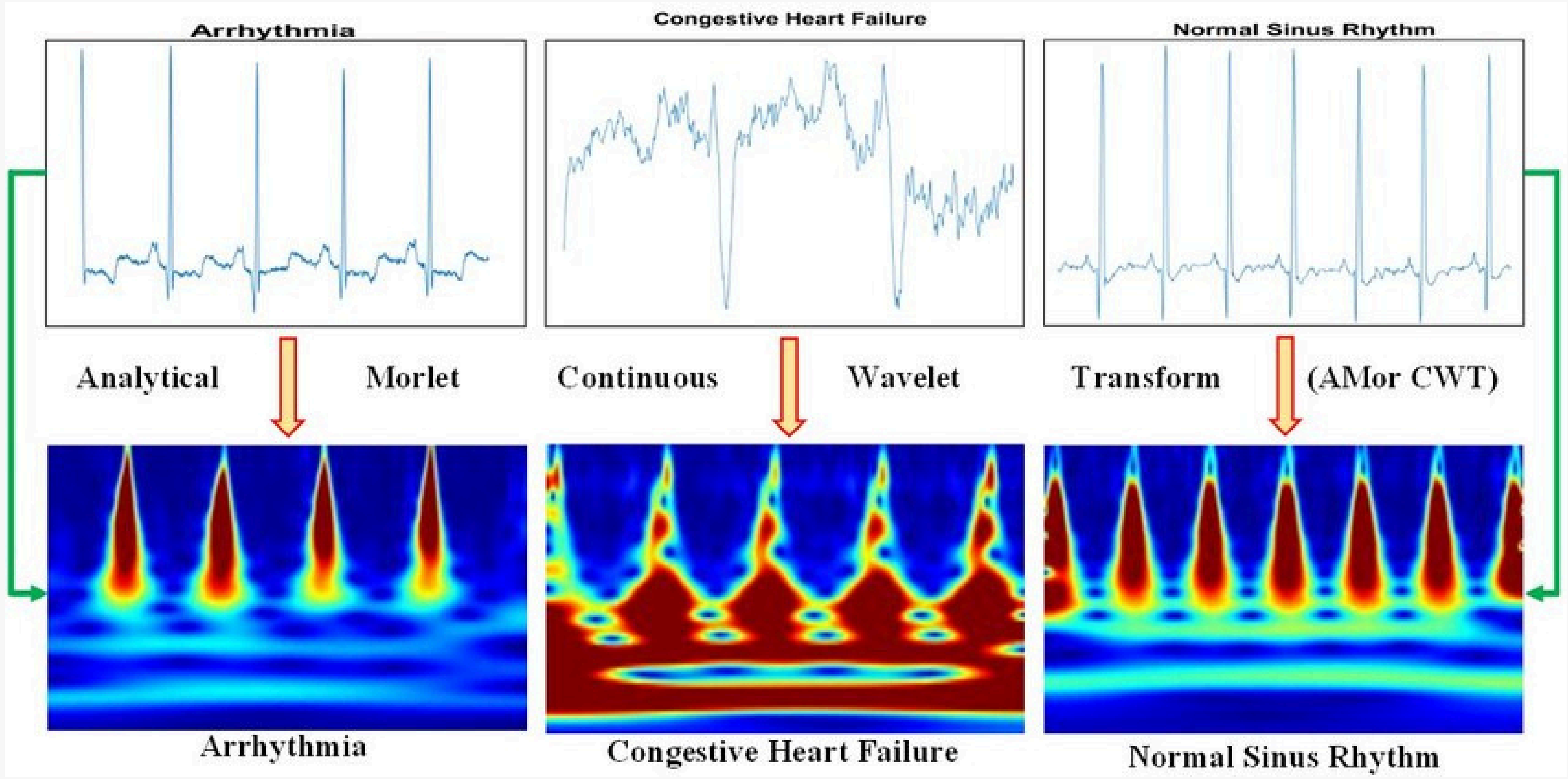
- **Multiclass classification**

Differentiate specific arrhythmia types (e.g., extrasystoles, fibrillation, tachycardia) instead of just “normal vs. abnormal.”



- Using **CWT-based scalograms**

Convert ECG segments into time-frequency scalogram images and feed them to a CNN, explicitly capturing non-stationary arrhythmia features (e.g., fibrillation bursts, prolonged pauses) that pure time-domain methods miss.



Thank you!