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# Artificial Intelligence for Automated Cardiac Defibrillation in Embedded Systems

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 Inn'Pulse, Grasse, France

Find out more!

Linktree\*



## What is Cardiac Arrest?

In cardiac arrest the heart suddenly stops pumping blood effectively, due to a disruption in its electrical activity, leading to a loss of circulation and unconsciousness.

Immediate intervention is needed by:

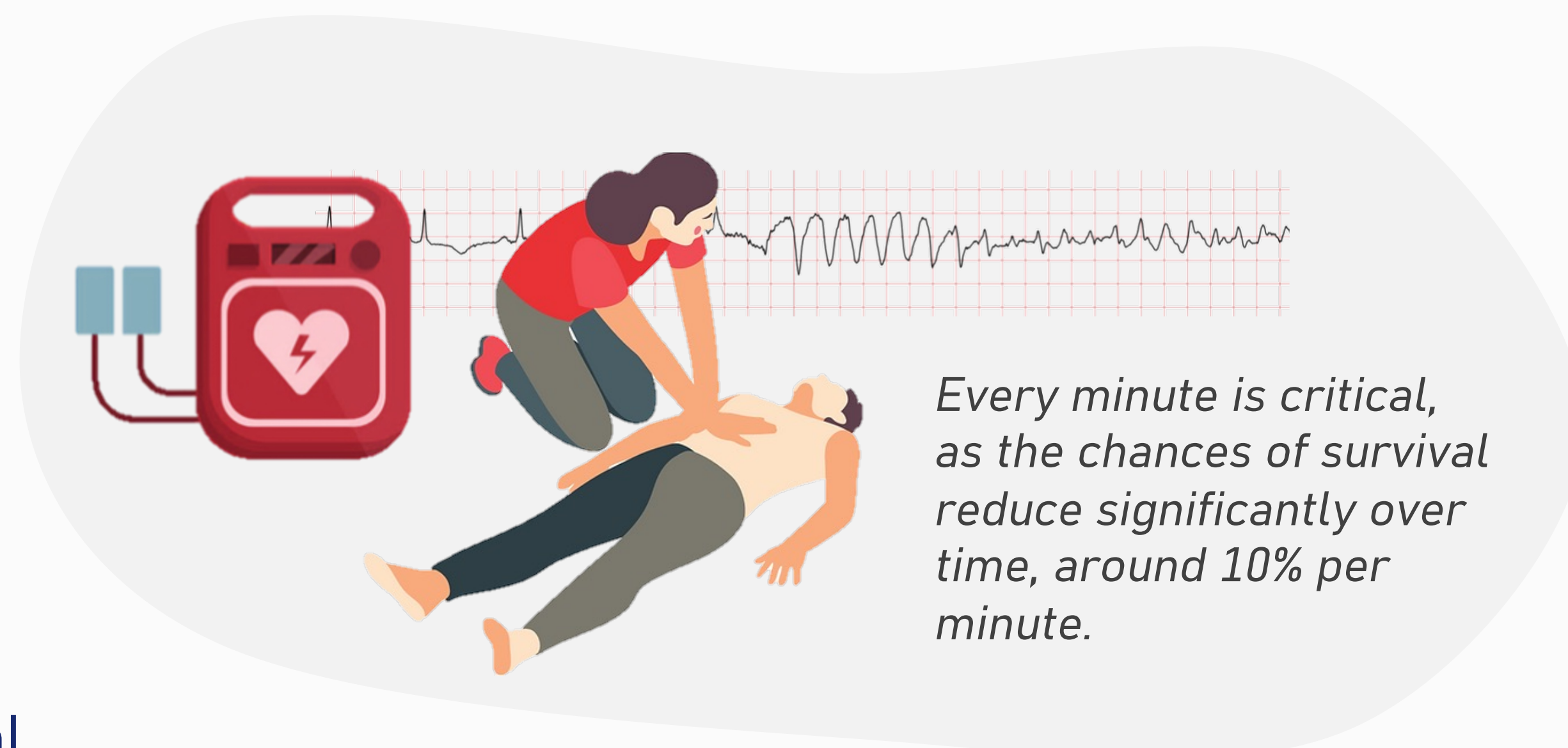
- Performing CPR to maintain blood flow
- Defibrillation to reset the heart's electrical system

Automated External Defibrillators (AEDs) analyze the patient's Electrocardiogram (ECG) to identify cardiac arrest and apply an electrical shock to the heart.

**300 000**  
cardiac arrests per year in Europe

**10%**  
survival rate

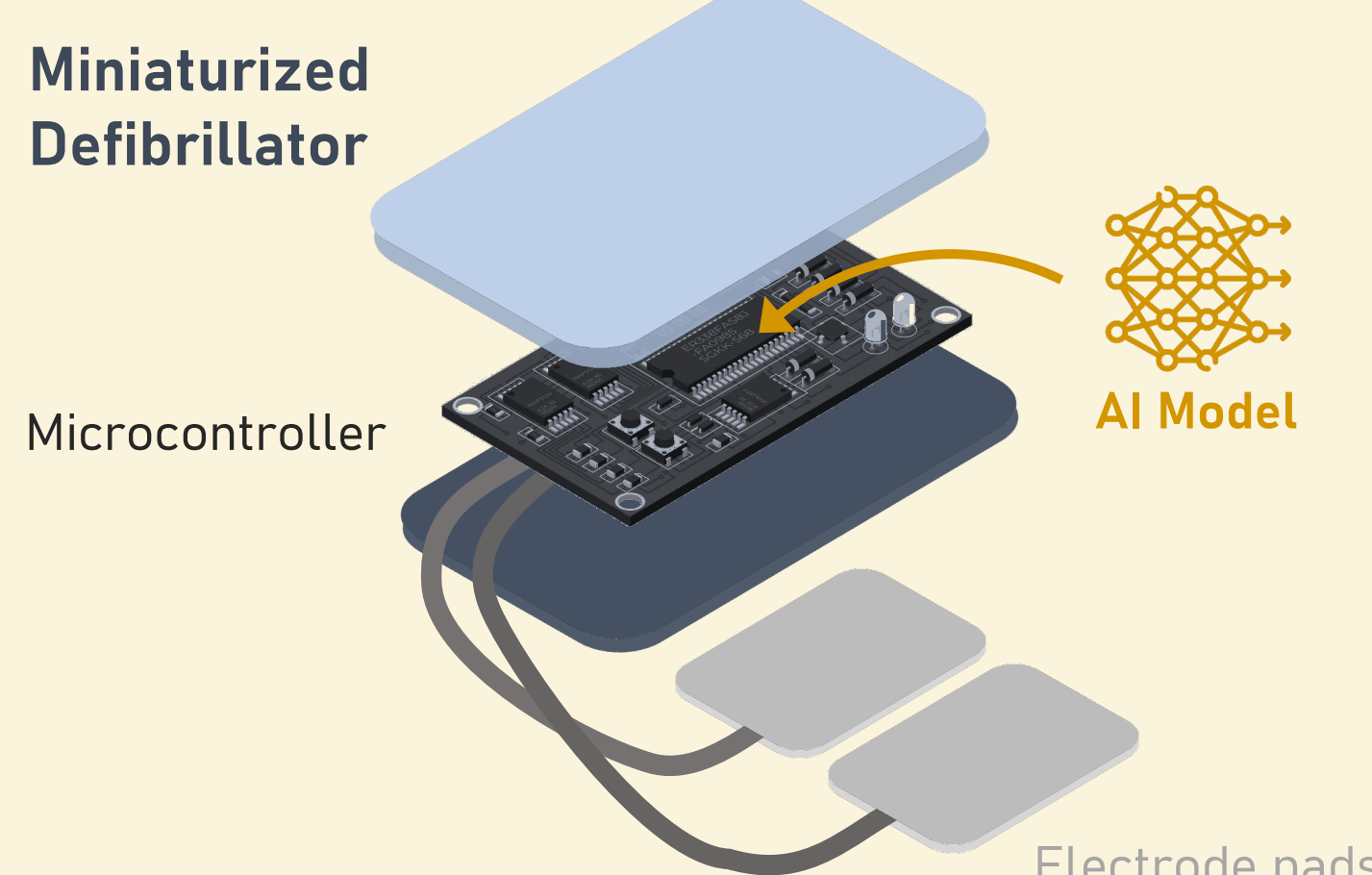
**~10 min**  
for emergency medical services to arrive



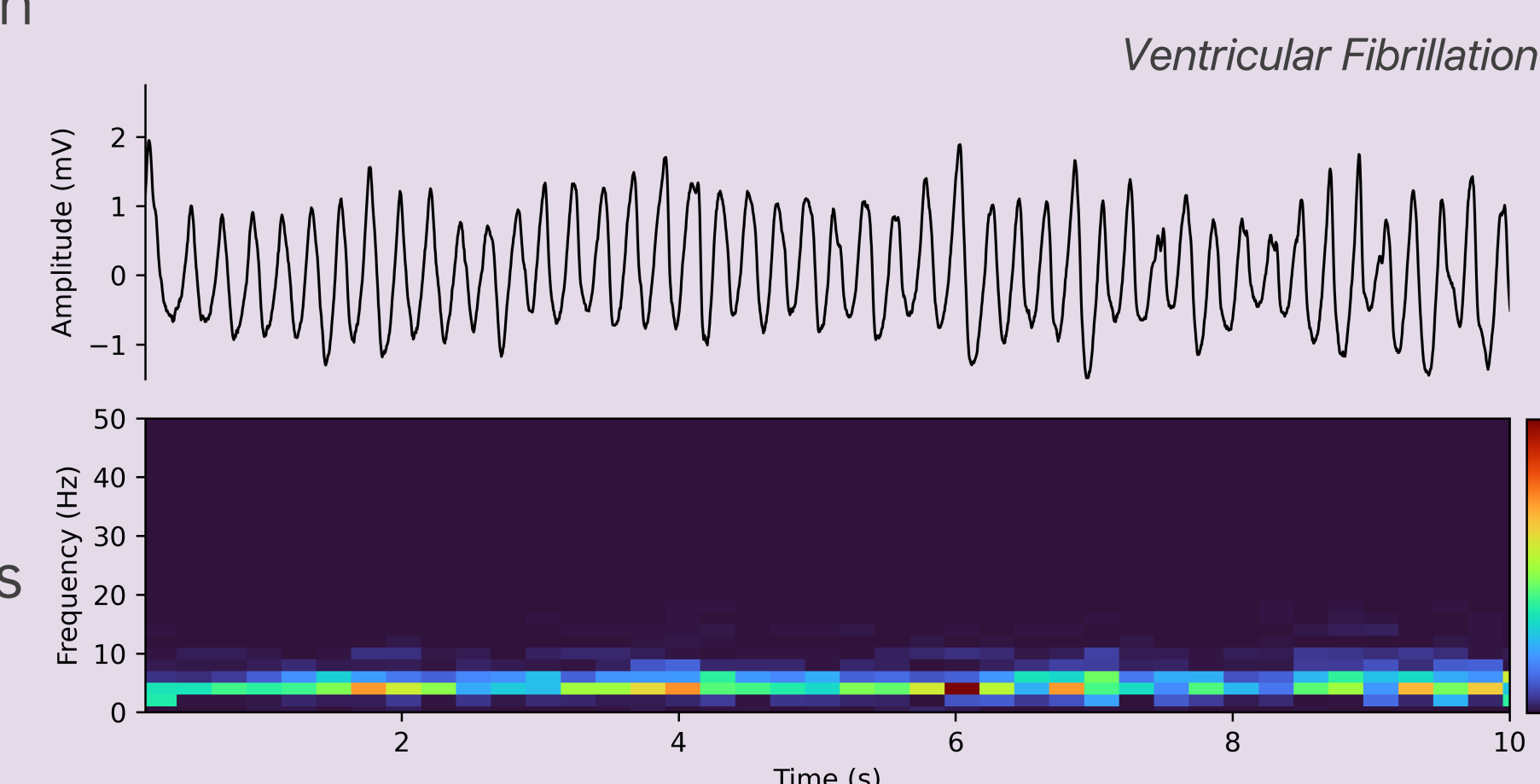
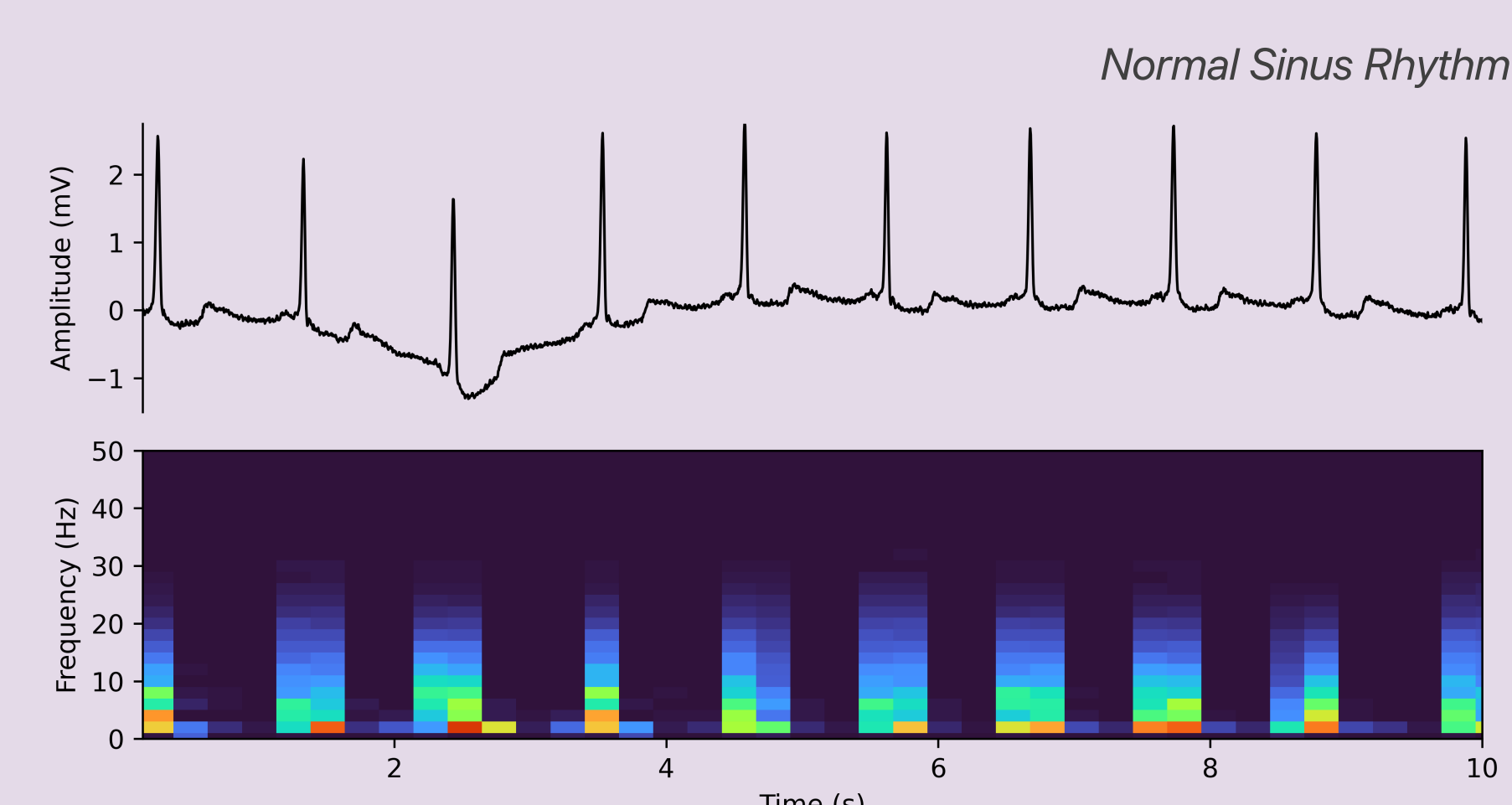
## AI to the Rescue!

AI algorithms can analyze ECG signals in **real time** and perform rapid decision-making. Given the diversity of ECG morphologies, rhythms, and artifacts, finding a model that generalizes well and avoids false predictions is crucial.

Such a model can then be deployed in a **microcontroller** adapted for ECG acquisition and shock delivery, which also imposes resource-related constraints.



## Data Representation Types

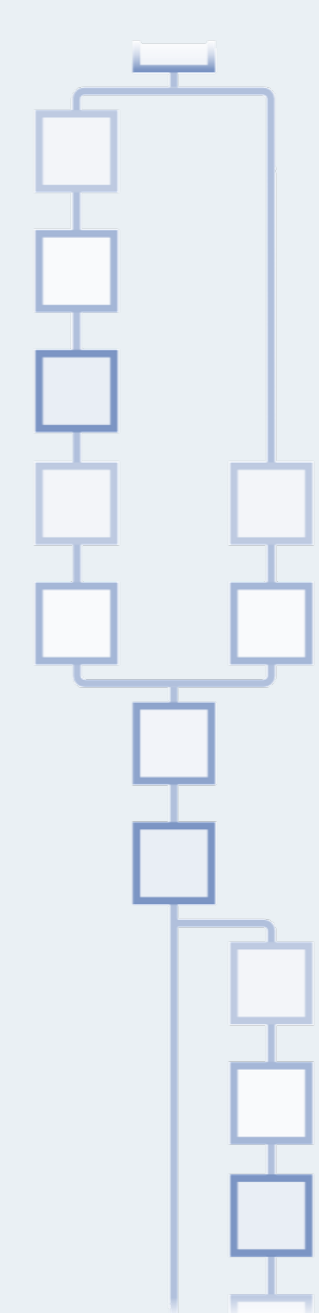


The ECG can be represented in various ways, providing different information or being adapted for certain network architectures (1D vs 2D).

The **time series** provides morphological details, whereas the **spectrogram** describes its frequency content.

## Deep Learning Architectures for Embedded Systems

Different **resource-efficient** neural network architectures have been used for embedded systems. When choosing the architecture, one should consider how it impacts the implementation requirements.



- ResNet**  
Network with skip connections
- EfficientNet**  
Scaling width, depth, and resolution
- DenseNet**  
Dense connections between blocks
- MobileNet**  
Depthwise separable convolutions
- WRNs**  
Wider networks with fewer layers

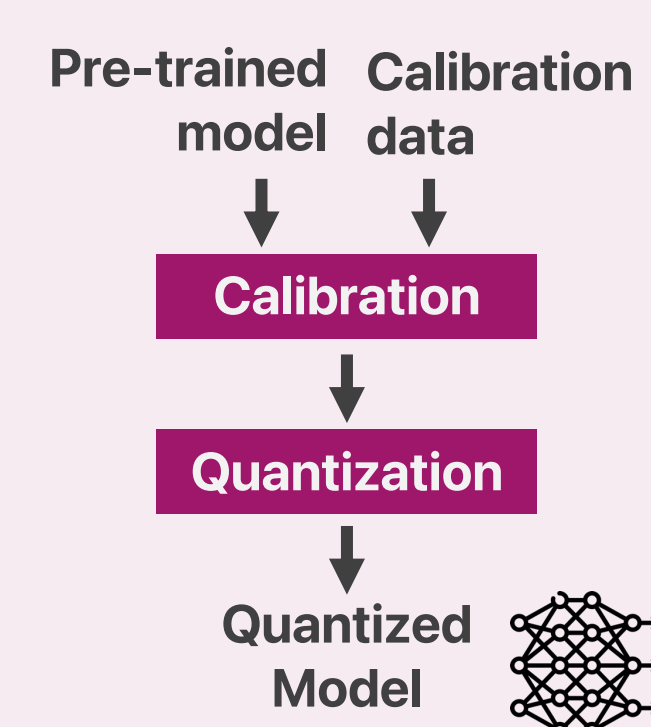
## Model Quantization

**32 bits**  
↓  
**8 bits**

For an embedded system implementation, decreasing the number of bits to represent the weights and activations comes with multiple advantages:

- Reduce model size
- Faster inference
- Lower memory requirements
- Minimal loss of information

### Post Training Quantization



## Experiments and Preliminary Results

### Data summary

129 patients from 4 PhysioNet databases (VFDB, CUDB, MITDB, AFDB)  
 Over 15 rhythm types and conditions  
 938h of ECG recordings (1:100 positive)

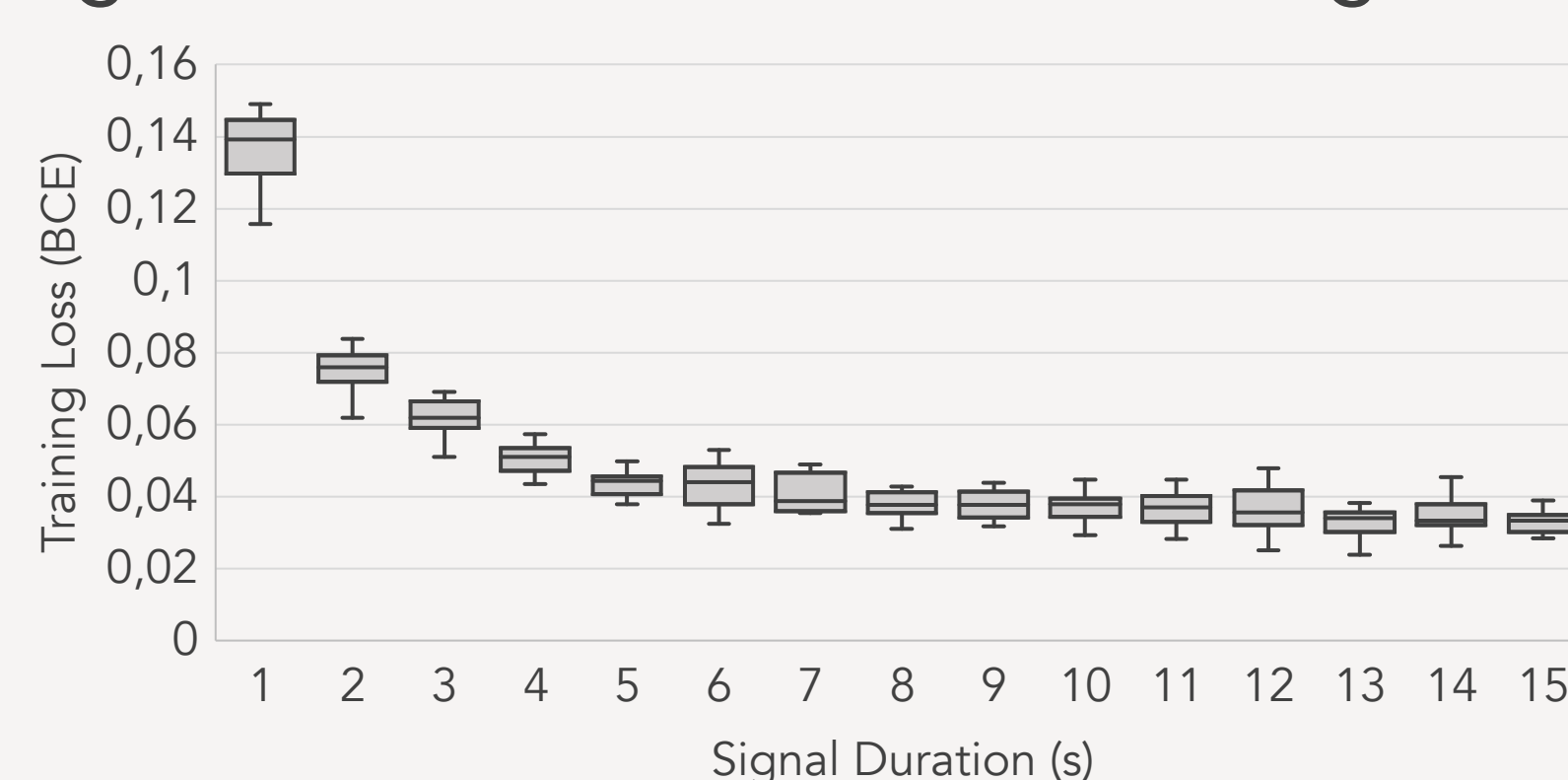
### Preprocessing

Resampling to 100 Hz  
 Segmentation according to available annotations  
 Standard Scaling  
 Label aggregation (binary targets)  
 Patient-based data split

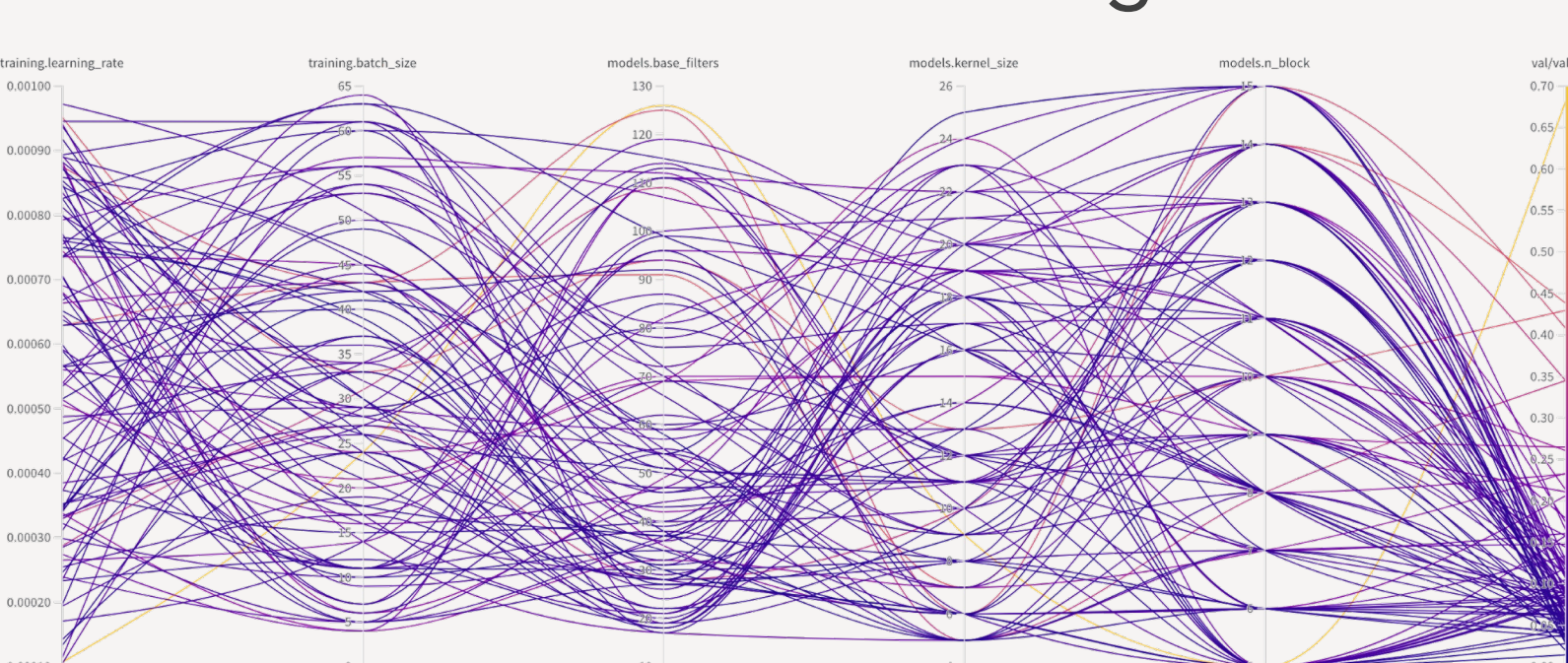
### Training

Sliding window approach  
 Weighted sampling (ensure data balance)  
 Time series data augmentation  
 Binary cross-entropy loss function  
 AdamW optimizer

### 1. Signal duration affects model training



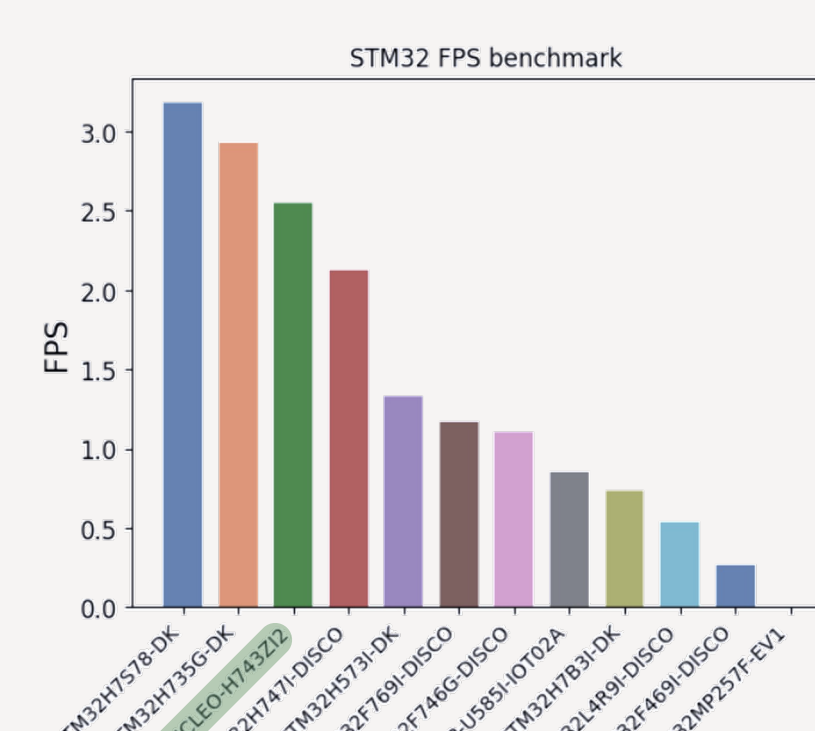
### 2. Bayesian hyperparameter optimization helps define architecture and training



### 3. Quantization does not degrade performance

	Floating point model (32 bits)	Quantized model (8 bits)
Accuracy	97,2%	96,9%
Sensitivity	97%	97%
FPR	3%	3%

### 4. Benchmarking on STM32 boards (Cube.AI)



MACCs | 55M  
 Flash weights | 55,6 KiB  
 RAM activations | 153,4 KiB  
 Inference time | 392.7 ms  
 FPS | 2,5

MACCs: Multiply-Accumulate Operations  
 FPS: frames per second

\*results for ResNet1D model in NUCLEO-H743ZII board