

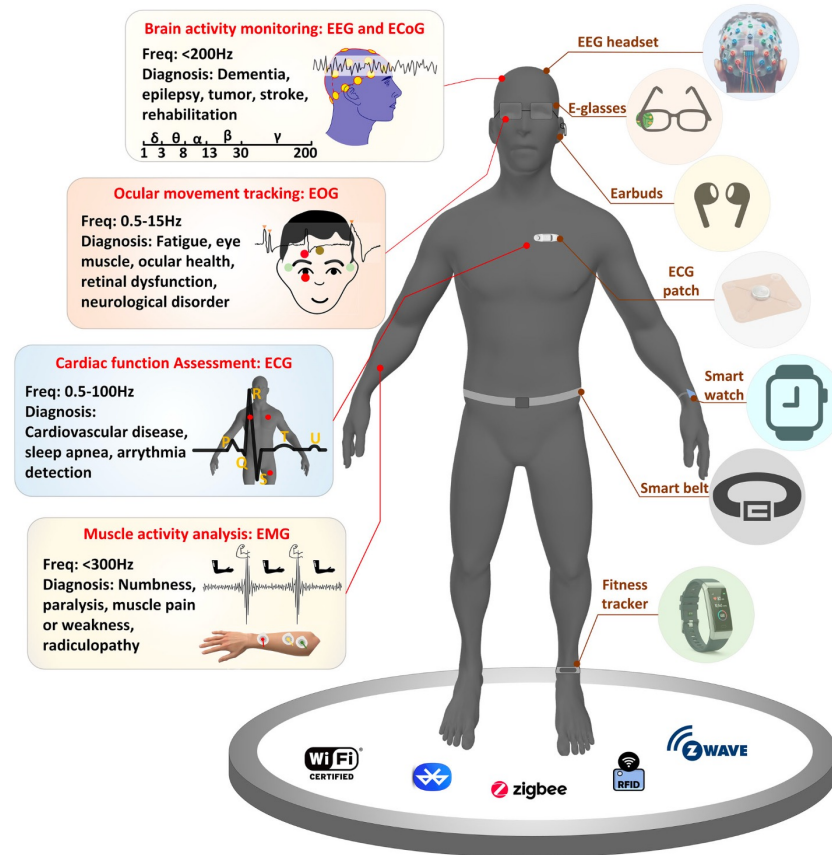
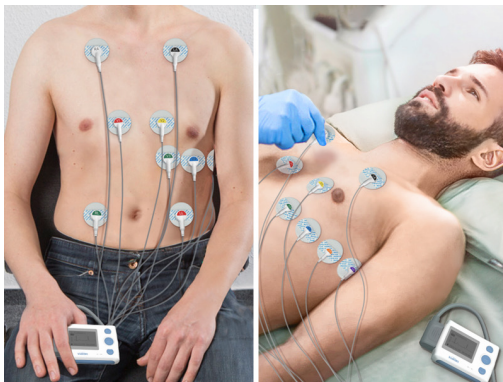
Biomedical Signal Feature Extraction: From Classical Signal Processing to AI/DL-Based Methods

電信所博一 郭承諺 Tony

指導教授：蘇炫榮

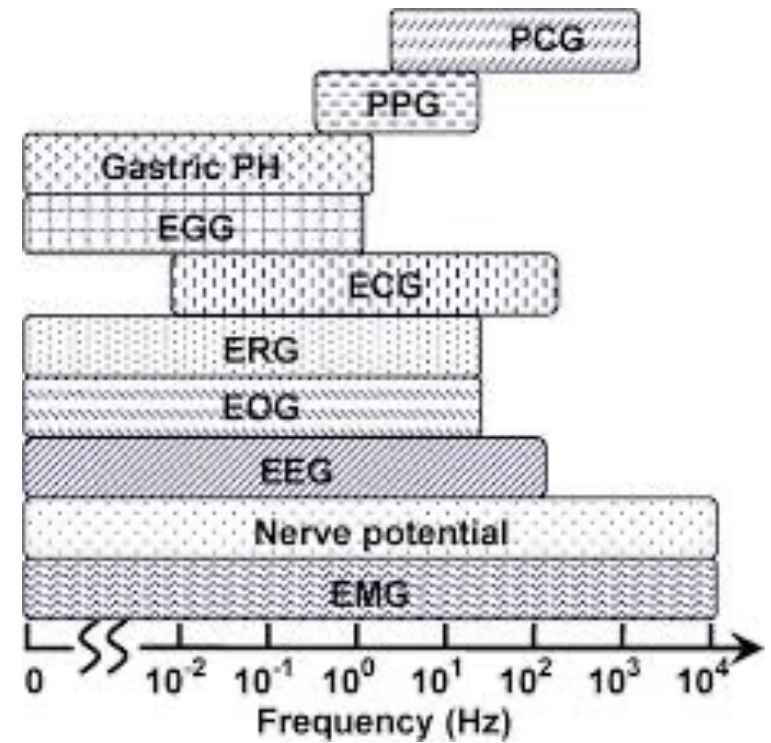
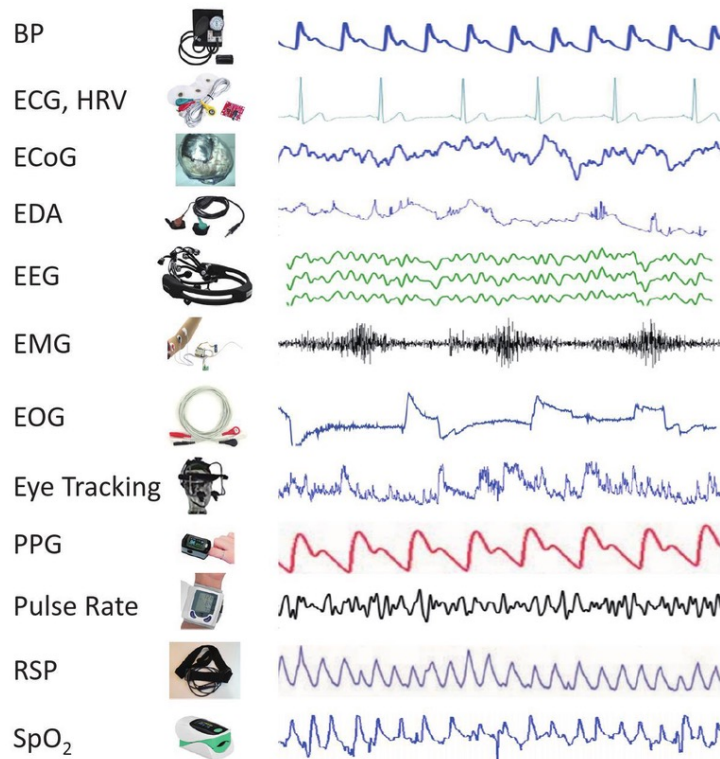
2026/06/08

Biomedical Signal-Enabled Human Healthcare Monitoring

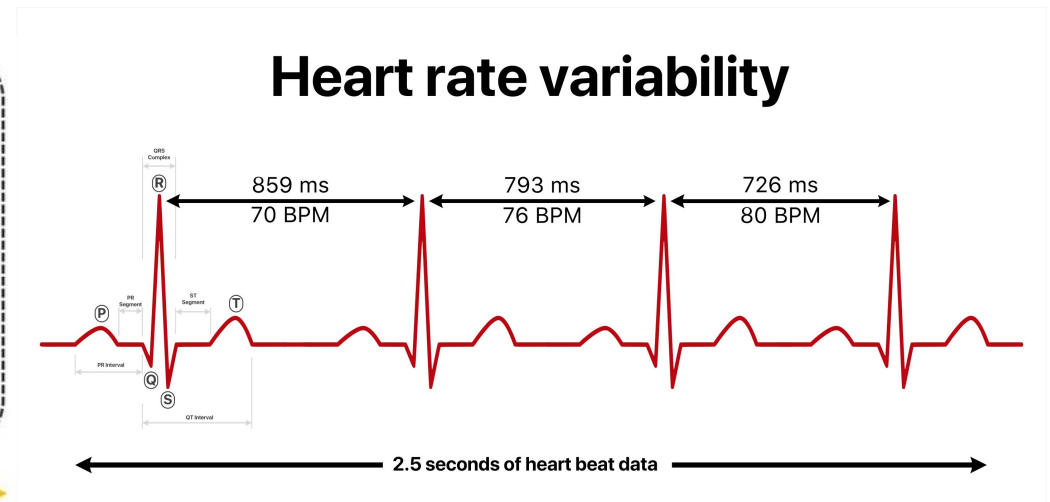
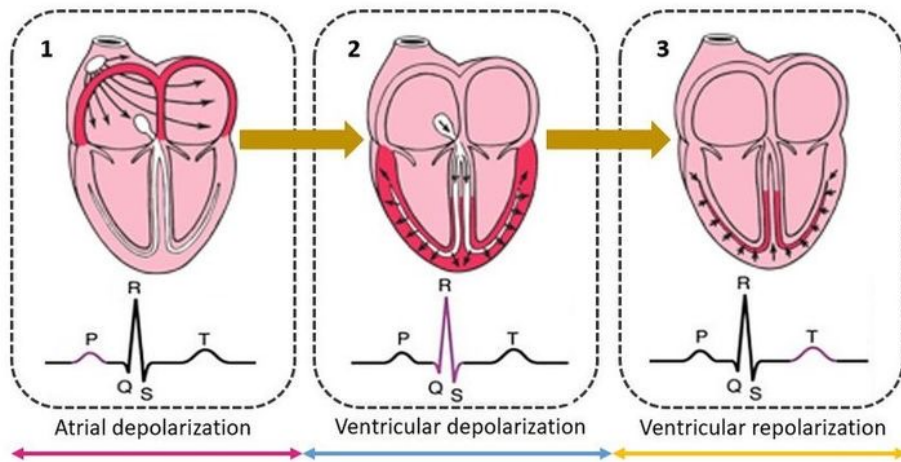


Lou, Z., Wang, R., Belmekki, B. E. Y., & Alouini, M. S. (2026). Towards bioelectric signal-enabled human healthcare monitoring: state-of-the-art, design strategies, challenge, and future. *npj Biomedical Innovations*, 3(1), 7.

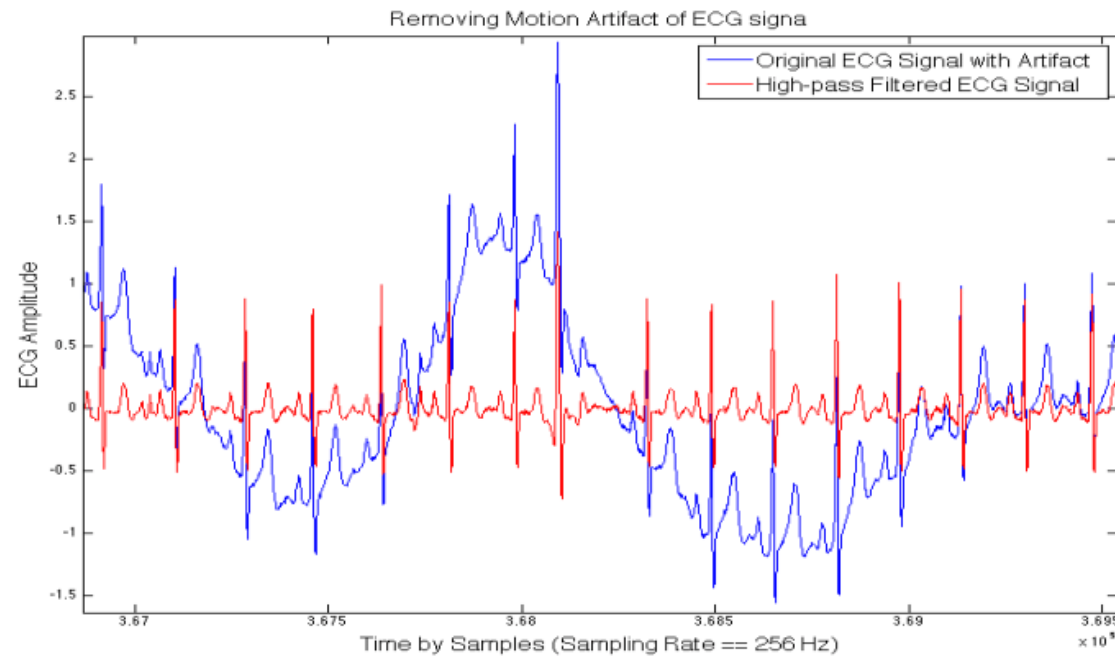
Type of Biomedical Signal



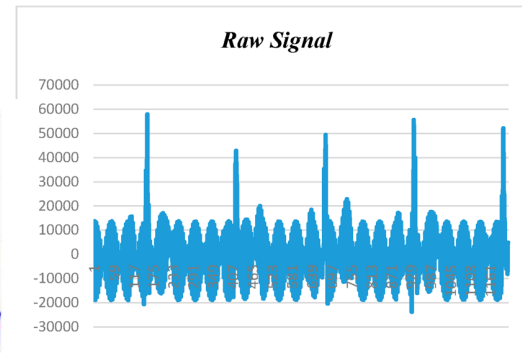
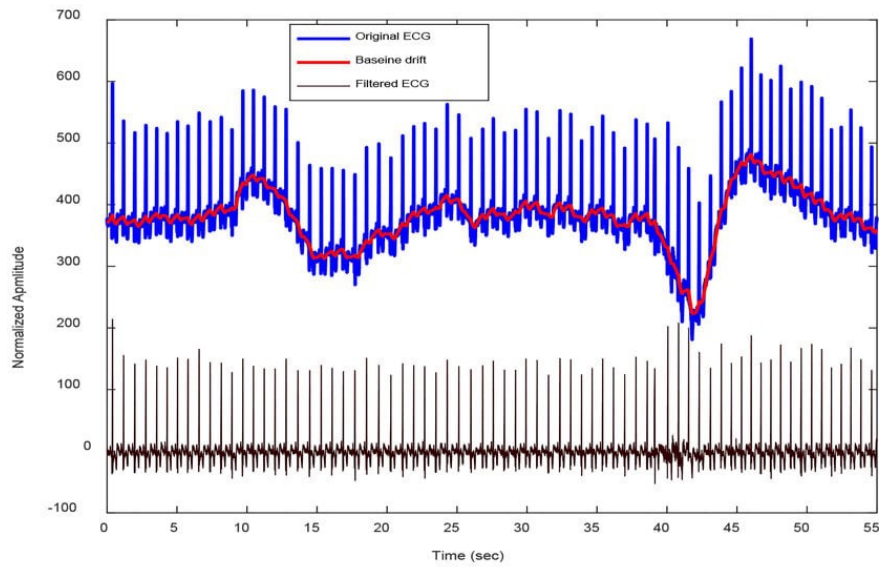
Examples of Biomedical Signal Analysis - Calculating Heart Rate Variability



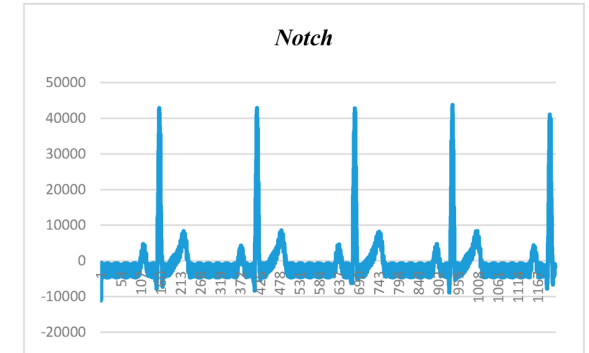
Challenges of Noise, Baseline Drift, and Motion Artifacts



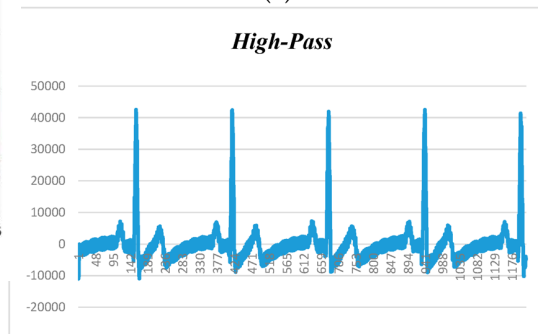
Example of Biomedical Signal Pre-Process – ECG MLII Led Signal



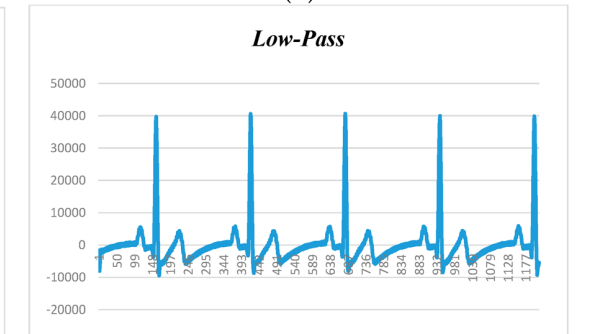
(a)



(b)

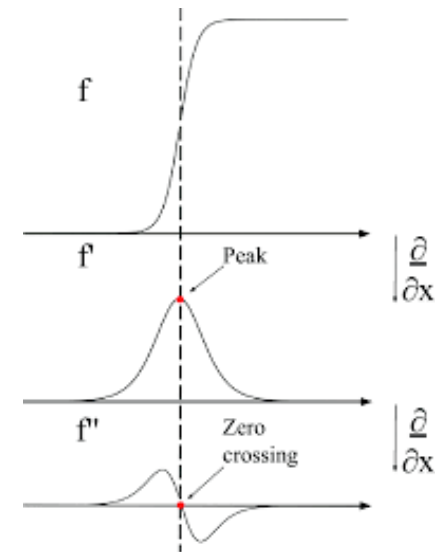
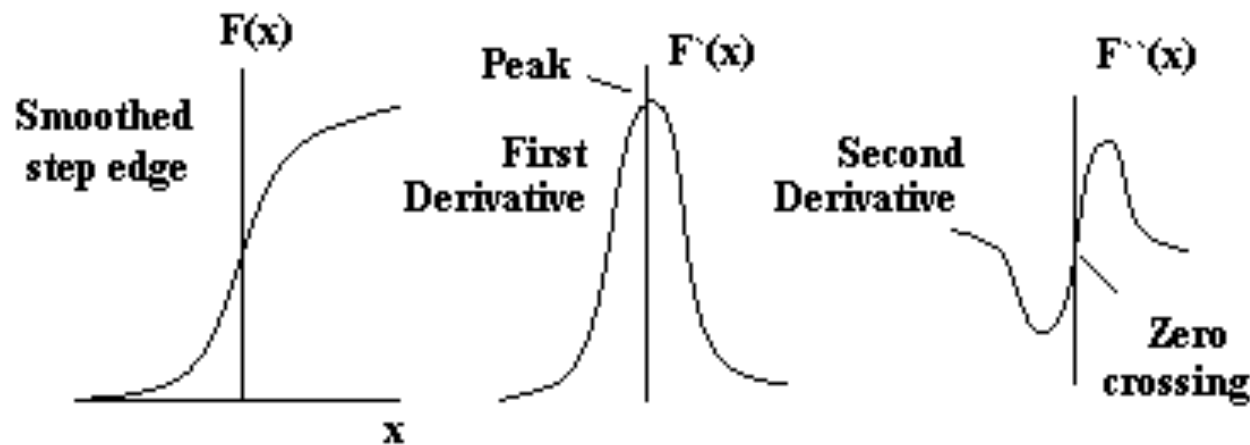


(c)

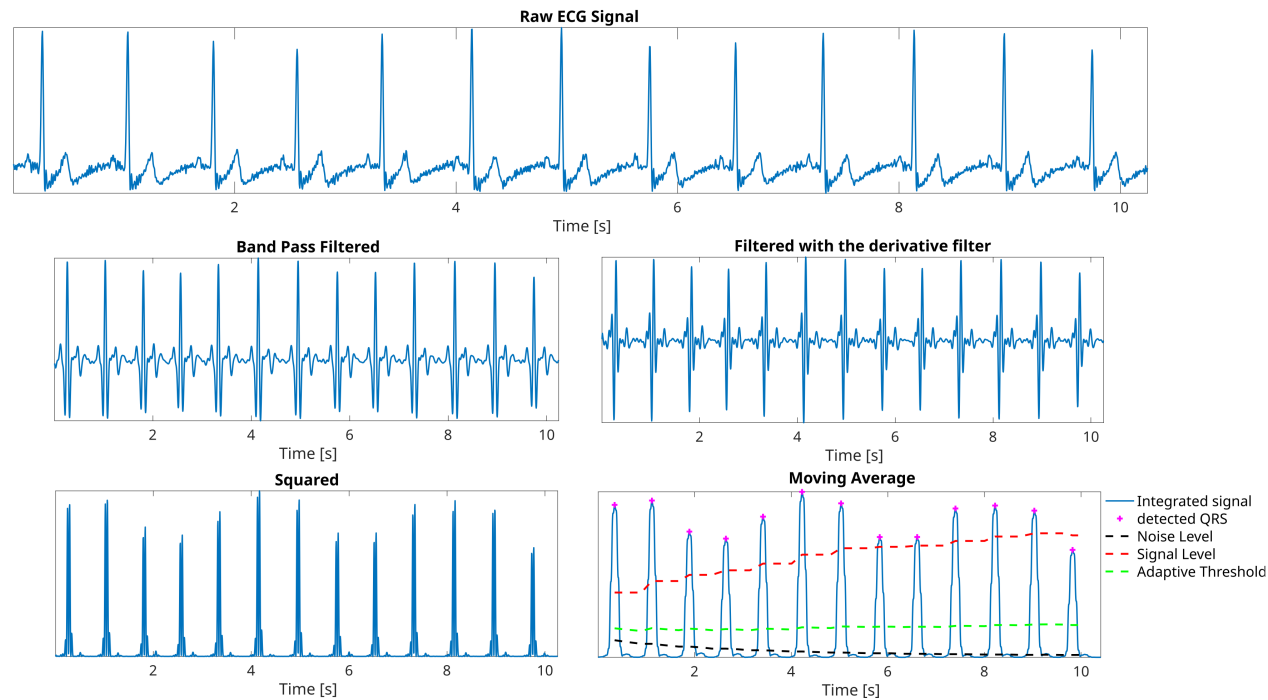


(d)

Classical Peak Detection Using Gradient and Derivative Methods



The Classic ECG Feature Extraction Algorithm - Pan-Tompkins Algorithm



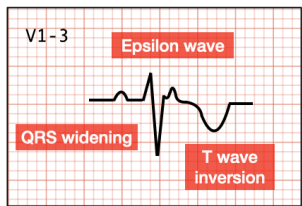
Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. *IEEE transactions on biomedical engineering*, (3), 230-236.

General Classical Techniques Used Across Biomedical Signals

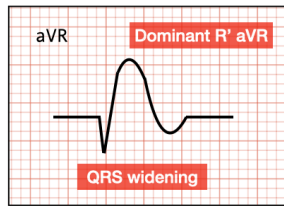
1. Filtering
2. Baseline Removal
3. Smoothing
4. Windowing and Segmentation
5. Derivative and Gradient-Based Methods
6. Energy and Envelope Methods
7. Threshold-Based Detection
8. Peak and Valley Detection
9. Template and Correlation Methods
10. Time-Domain Features
11. Frequency-Domain Features
12. Time-Frequency Features

More Abnormal ECG Patterns

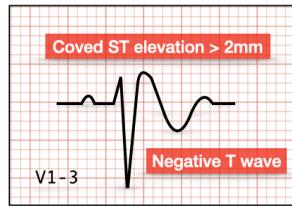
Rule-based algorithms are not easy to model all patterns.



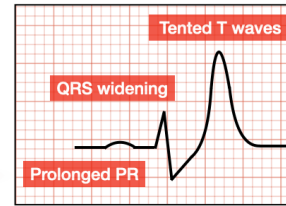
Arrhythmogenic Right Ventricular Dysplasia



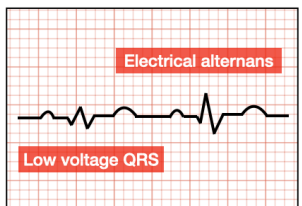
Sodium channel blockade



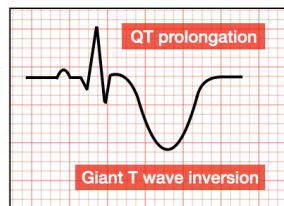
Brugada Syndrome



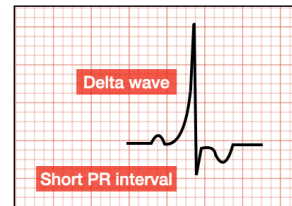
Hyperkalaemia



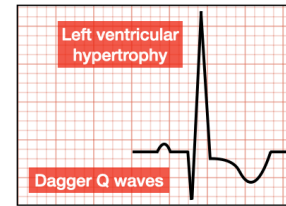
Massive pericardial effusion



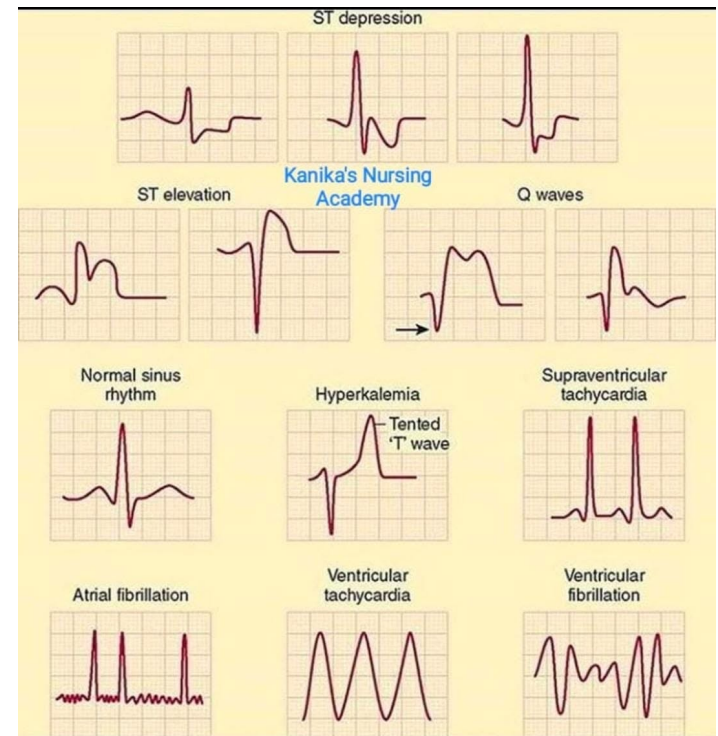
Intracranial haemorrhage



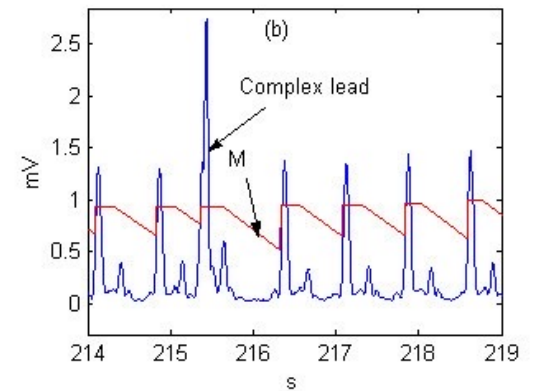
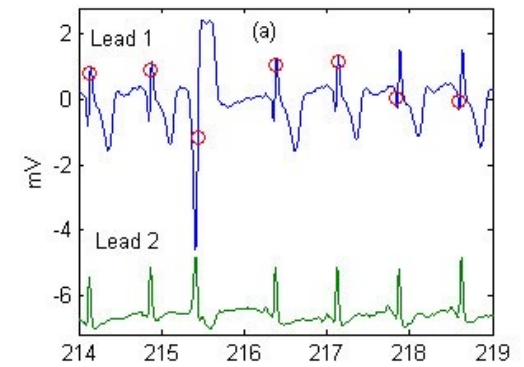
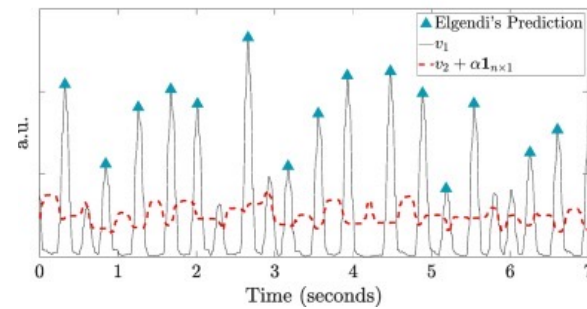
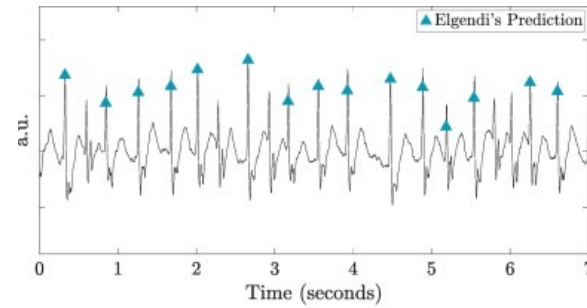
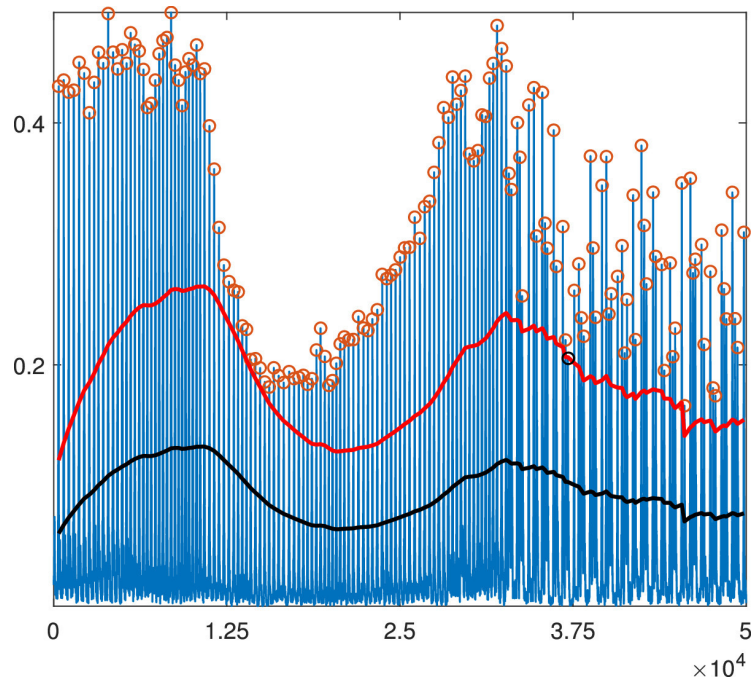
Wolff-Parkinson-White Syndrome



Hypertrophic Cardiomyopathy



Adaptive Detection Algorithm for ECG Signal



From Handcrafted Features to AI-Based Analysis

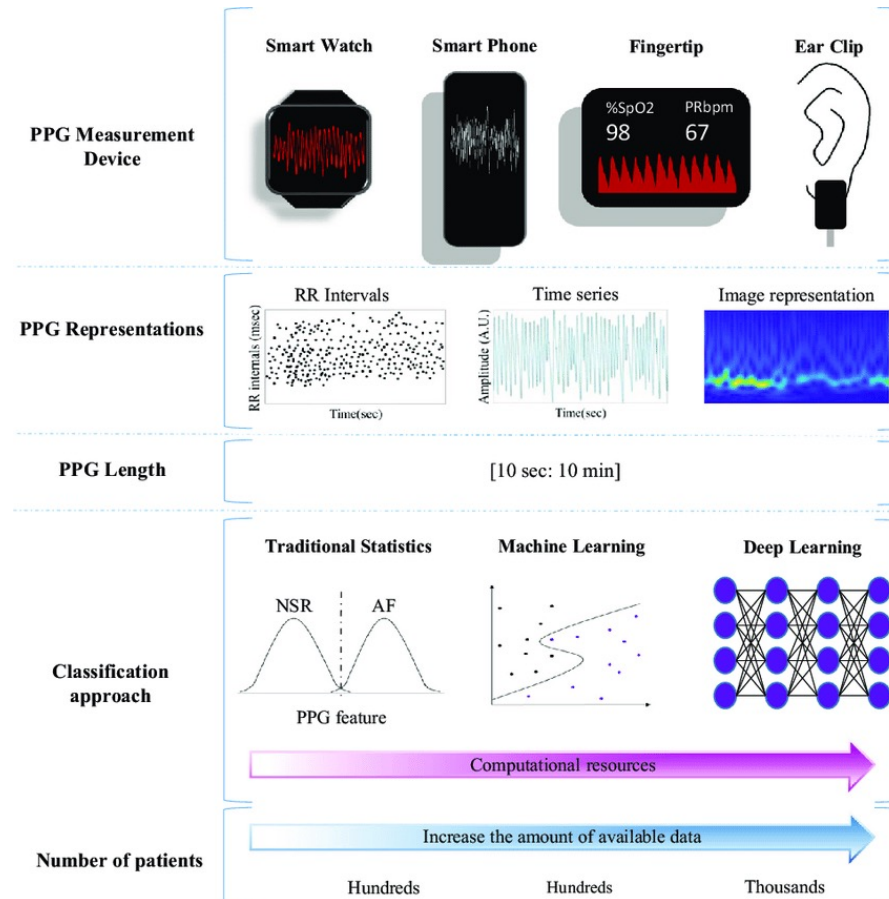
Machine learning methods use handcrafted biomedical features as input and learn a mapping from features to clinical or physiological targets.

Types	ECG	PPG	Use Case
Time-domain features	RR interval 、 QRS duration 、 PR interval 、 QT interval	pulse interval 、 rise time 、 decay time 、 pulse width	HR 、 HRV 、 arrhythmia 、 BP
Frequency-domain features	LF 、 HF 、 LF/HF 、 PSD	pulse variability spectrum 、 respiratory modulation	HRV 、 autonomic function
Morphological features	R amplitude 、 ST level 、 T-wave shape	systolic peak 、 diastolic peak 、 dicrotic notch 、 pulse area	BP estimation 、 vascular condition

ML Classification (1/2)

Task	Input Feature	Output
ECG beat classification	RR interval 、 QRS width 、 R amplitude 、 morphology	normal / PVC / APC / LBBB / RBBB
Arrhythmia detection	beat interval variability 、 QRS features 、 rhythm features	AF / non-AF 、 normal / abnormal
PPG signal quality classification	amplitude 、 noise index 、 peak consistency	good / poor signal
Hypertension risk classification	PPG morphology 、 demographic features	normal / prehypertension / hypertension
Sleep or respiration event detection	ECG-derived respiration 、 HRV 、 PPG modulation	normal / apnea event

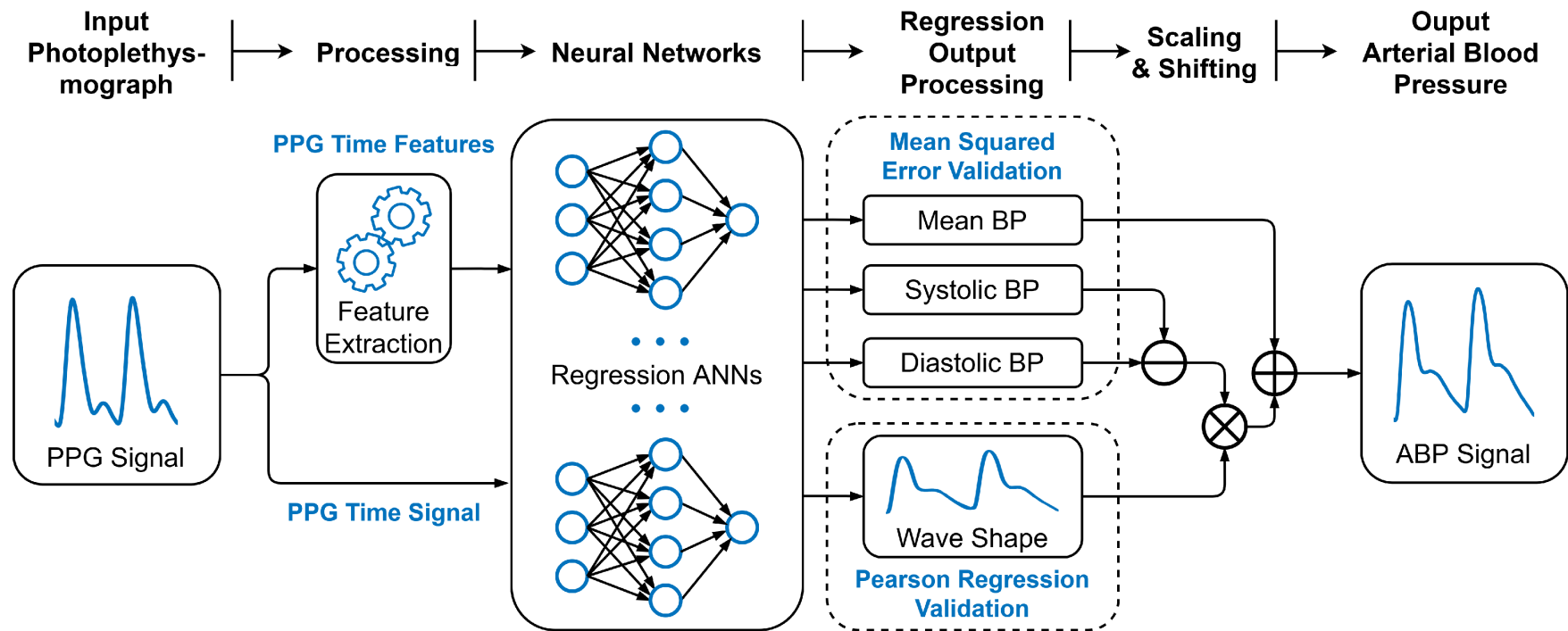
ML Classification (2/2)



ML Regression (1/2)

Task	Input Feature	Output
Cuffless BP estimation	PTT 、 PAT 、 PPG morphology 、 ECG/PPG features	SBP / DBP
Heart rate estimation	peak interval 、 spectral peak	HR
Respiratory rate estimation	PPG amplitude modulation 、 ECG-derived respiration	RR
Stress / autonomic index	HRV time-domain + frequency-domain features	stress score
Signal quality score	noise 、 baseline drift 、 peak consistency	SQL score

ML Regression (2/2)



Deep Learning and AI Methods: CNN, RNN/LSTM, Transformer, and Segmentation

Deep learning shifts the focus from handcrafted feature extraction to automatic representation learning.

Traditional ML:

Raw signal -> handcrafted features -> classifier/regressor

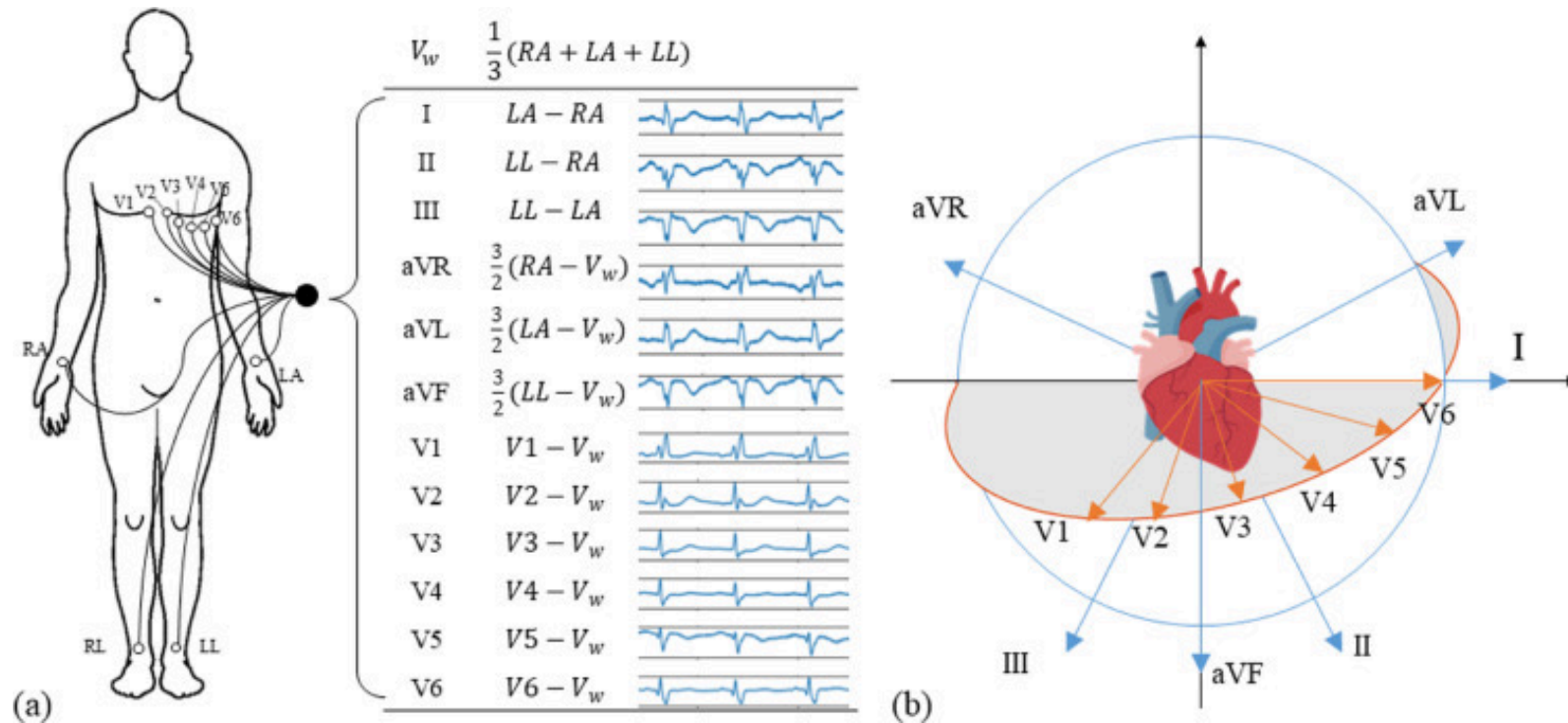
Deep Learning:

Raw or minimally processed signal -> neural network -> learned features -> output

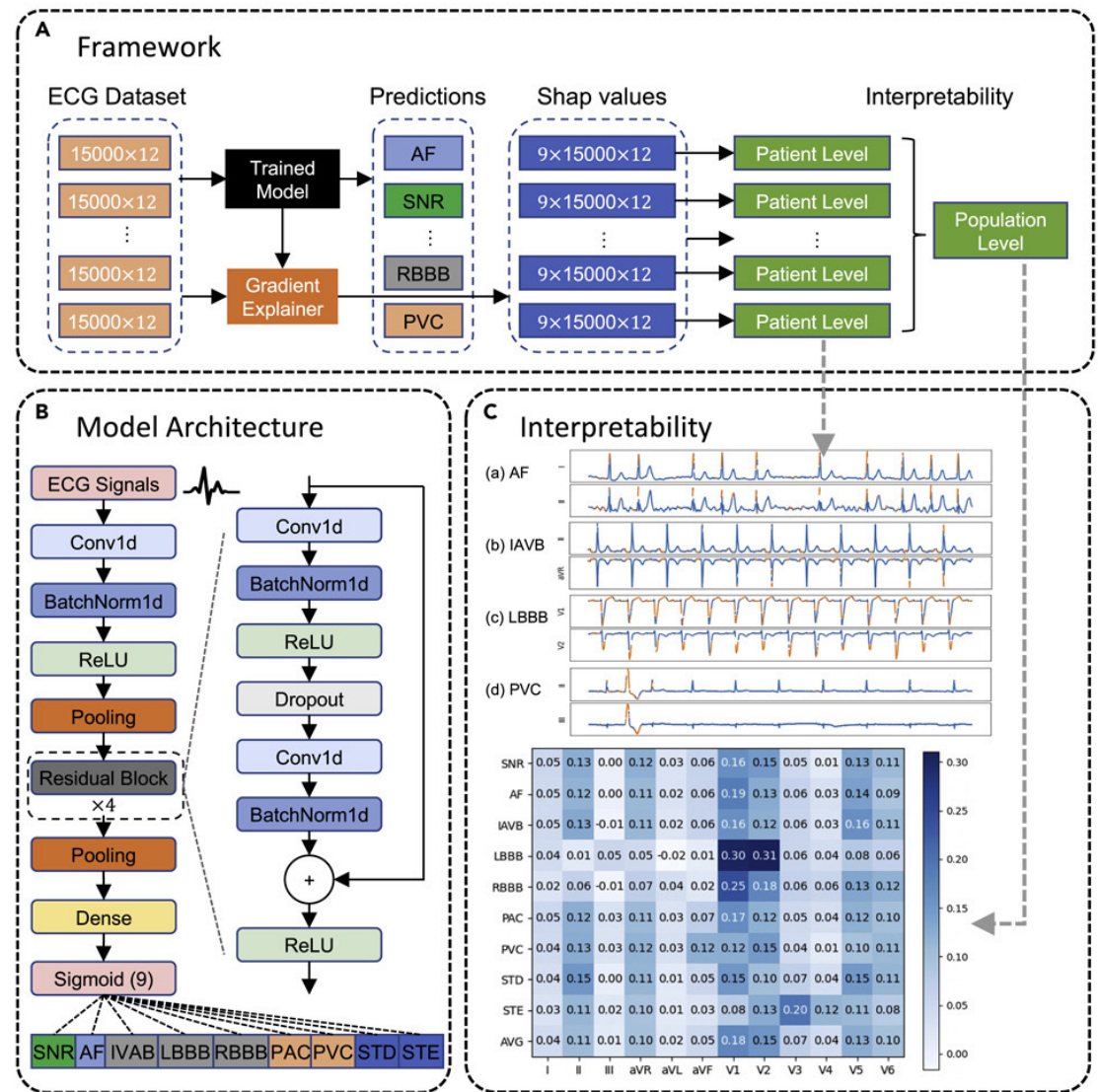
Comparison of DL Methods for ECG and PPG Analysis

DL Method	ECG / PPG Applications	Advantages	Key Strength
CNN / 1D-CNN	ECG arrhythmia detection, abnormal beat classification, PPG pulse morphology analysis, PPG signal quality assessment	Good at learning local waveform patterns such as QRS complexes and PPG pulse shapes, relatively efficient for implementation	Learns morphology
RNN / LSTM / GRU	ECG rhythm analysis, atrial fibrillation detection, long-term ECG monitoring, PPG pulse-to-pulse trend analysis	Good at modeling temporal relationships across beats, pulses, or signal windows	Learns temporal patterns
Transformer	Long ECG sequence analysis, multi-lead ECG classification, long-term PPG monitoring, BP or respiratory-related analysis	Strong ability to capture long-range dependencies and relationships across signal segments	Learns global relationships
Segmentation-Based Models / U-Net	ECG R-peak detection, QRS segmentation, PPG systolic peak detection, pulse foot or diastolic notch detection	Useful for precise peak, fiducial point, or waveform-region localization	Provides precise localization

Multi-lead varied-length ECG



Automatic diagnosis of 12-lead electrocardiogram



Zhang, D., Yang, S., Yuan, X., & Zhang, P. (2021). Interpretable deep learning for automatic diagnosis of 12-lead electrocardiogram. *Iscience*, 24(4).

Traditional Signal Processing vs ML vs DL

Method	Main Idea	Advantages	Limitations	Suitable Applications
Classical Signal Processing	使用濾波、微分、window、threshold、local max & min 等規則式方法找 peak 或特徵	運算量低、可解釋、容易 debug、適合即時系統、不需要大量資料	對雜訊、個體差異、參數設定敏感，複雜波形下可能失效	ECG R-peak detection、PPG peak detection、HR & HRV、wearable real-time monitoring
Traditional ML Classifier / Regression	先取手工特徵，再用 SVM、Random Forest、XGBoost、Regression 等模型分類或估測	可整合多個特徵，可處理非線性關係，模型通常比 DL 輕量	依賴 feature quality；如果 peak detection 錯，後面模型也會錯	Arrhythmia classification、BP estimation、signal quality assessment、risk prediction
Deep Learning / AI	從 raw signal 或 preprocessed waveform 自動學習特徵	可處理複雜與高雜訊訊號，能做 end-to-end classification、regression、segmentation	需要大量標註資料、運算量高、記憶體需求大、可解釋性較低	Large-scale ECG diagnosis、PPG BP estimation、artifact detection、R-peak & fiducial segmentation
Hybrid Method	傳統訊號處理 + ML/DL + physiological rules	兼具可解釋性與 AI 適應能力，實務上最常見也最穩定	系統設計較複雜，需要調整 pipeline	Wearable devices、clinical monitoring、edge AI biomedical systems

Conclusions

- Biomedical signal analysis has evolved from classical signal processing to machine learning and deep learning, moving from rule-based feature extraction toward data-driven representation learning.
- Classical methods are efficient and interpretable, while traditional ML improves classification and regression by using handcrafted physiological features from ECG or PPG signals.
- For embedded systems, hybrid designs are often more practical, combining lightweight signal processing with ML or DL while balancing accuracy, memory, power, and real-time constraints.