

Politecnico di Torino

2026

From Morphology to Physiology: Limits of Data-Driven Learning and Physics-Informed Neural Networks for Cuffless Blood Pressure Estimation

Federico Delrio

Recent advances in deep learning have demonstrated remarkable performance in the analysis of cardiovascular biosignals, particularly in tasks involving electrocardiogram (ECG) pattern recognition and intra-subject prediction. Convolutional and recurrent neural networks are able to accurately detect morphological features such as P waves, QRS complexes, and T waves, achieving state-of-the-art results when trained and evaluated on data originating from the same subjects. These capabilities have been further confirmed in real-world scenarios through the development of PulsECG, a custom wearable device designed for simultaneous ECG and photoplethysmogram (PPG) acquisition, where neural networks exhibit strong intra-subject blood pressure estimation performance under controlled conditions.

However, this thesis shows that such performance does not reliably extend to inter-subject and cross-database scenarios. When models are required to generalize across different individuals, their accuracy degrades substantially, revealing a strong dependence on subject-specific signal morphology rather than on underlying physiological mechanisms. This limitation is not confined to blood pressure estimation: similar generalization failures emerge in stress detection tasks, where subjective labels and individual autonomic responses further exacerbate model ambiguity and performance saturation.

Through extensive experimental analysis, this work argues that purely data-driven approaches implicitly learn individual signal signatures instead of causal physiological relationships, leading to over-optimistic results under improper evaluation protocols and to inherent performance ceilings under subject-wise validation. To address this fundamental issue, the thesis introduces Physics-Informed Neural Networks (PINNs) as a principled modeling framework that integrates cardiovascular hemodynamics with neural representations. By embedding one-dimensional blood flow equations, Windkessel boundary conditions, and physiologically constrained

parameters into the learning process, the proposed PINN framework aims to regularize the solution space and reduce degeneracy in the ECG–PPG–blood pressure mapping .

Experimental results on large-scale clinical databases demonstrate that, while current data availability and subject metadata are insufficient to achieve fully generalized and calibration-free blood pressure estimation, physics-informed models produce physiologically consistent arterial pressure waveforms and exhibit improved robustness compared to purely data-driven baselines. This thesis concludes that reliable inter-subject generalization in cuffless blood pressure monitoring is not yet attainable with existing datasets alone. Nevertheless, it establishes a methodological foundation upon which future systems, leveraging ECG and PPG together with easily accessible non-invasive subject information, including anthropometrics (age, sex, height, weight), short-term physiological states (e.g., hydration level, bladder filling), and lifestyle-related factors (such as recent alcohol or caffeine consumption) known to modulate blood pressure dynamics, can build. In this perspective, Physics-Informed Neural Networks emerge as a necessary step toward interpretable, personalized, and generalizable cardiovascular monitoring.