DA 221(M) Project Presentation

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Physics-informed neural networks for modeling physiological time series for cuffless blood pressure estimation

Researchers propose physics-informed neural network (PINN) models for cuffless blood pressure estimation using minimal ground truth data. PINNs incorporate known cardiovascular relationships via Taylor's approximation. In a case study on bioimpedance data, PINNs outperform state-of-the-art time series models, achieving high correlations (systolic: 0.90, diastolic: 0.89) and low error (systolic: 1.3 ± 7.6 mmHg, diastolic: 0.6 ± 6.4 mmHg) while reducing required training data by a factor of 15. This approach could significantly advance AI algorithms for interpreting physiological data in precision medicine with minimal training data.

Physics informed Machine learning

Physics-informed Machine Learning (PIML) integrates mathematical physics models and observational data for coherent learning, even in uncertain, high-dimensional scenarios. Key advantages include: (1) Ensuring physical and scientific consistency in ML models.

(2) Highly data-efficient training, requiring fewer data points.

(3) Accelerated training process leading to faster convergence.

(4) Enhanced generalizability for unseen scenarios.

(5) Improved transparency and interpretability, making models more trustworthy and explainable.

Strategies used to incorporate Physics knowledge in Machine learning

Observational bias leverages multi-modal data to capture underlying physical principles, exposing deep neural networks directly to training data, which can be obtained from various sources including direct observations, simulations, maps, and extracted physics data.

Learning bias enforces prior knowledge through soft penalty constraints, augmenting loss functions with terms based on the physics of the process. Physics-informed neural networks (PINN) embed partial differential equations (PDEs) into the loss function using automatic differentiation, while other approaches include statistically constrained GAN and physics-informed auto-encoders.

Inductive biases incorporate prior knowledge through hard constraints imposed on neural networks. Examples include Hamiltonian NN, which respects conservation laws, Lagrangian Neural Networks for arbitrary Lagrangians, and DeepONets for PDE agnostic physical problems.

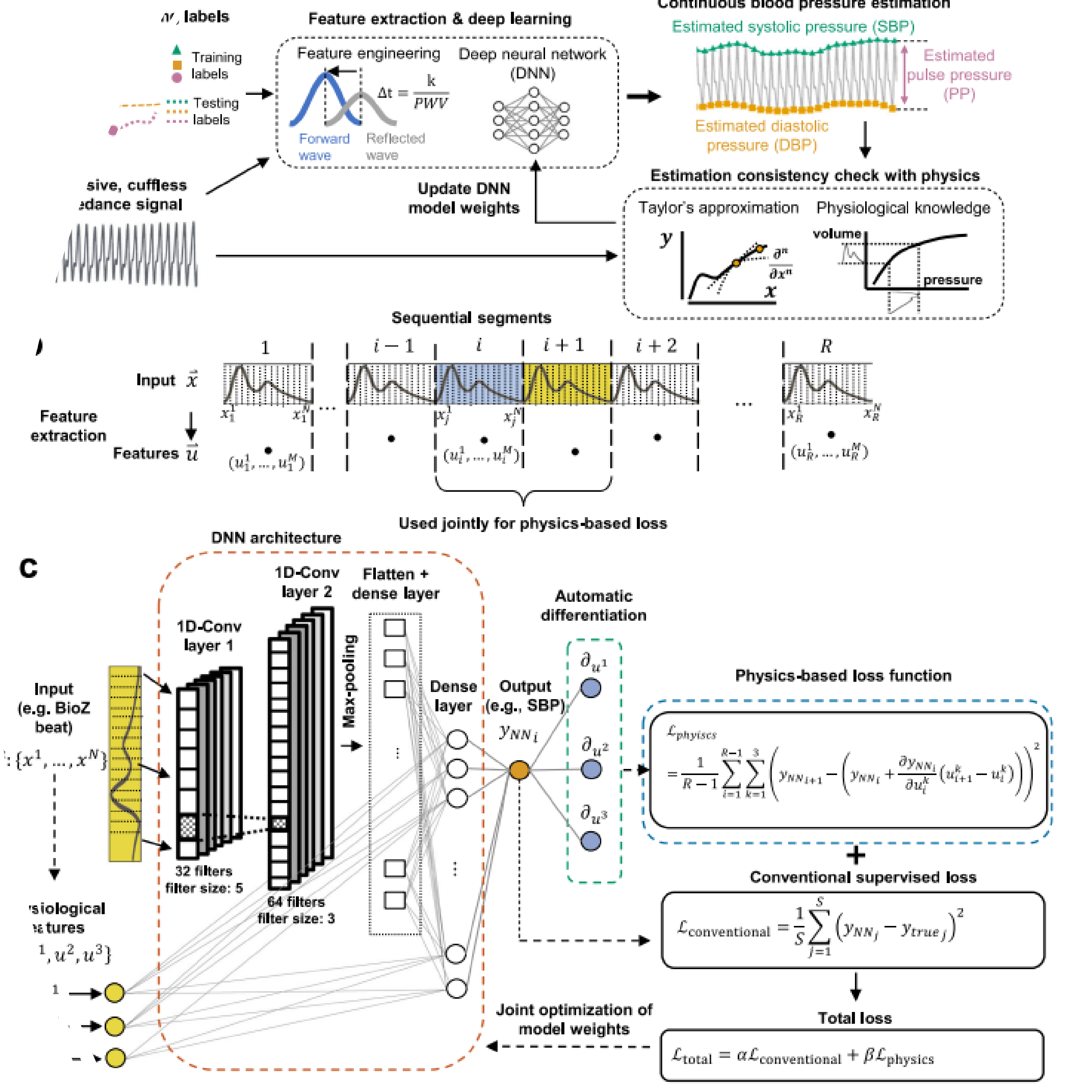
Method being used

- The process involves utilizing a DNN model to estimate continuous systolic, diastolic, and pulse pressure values from time series measurements like bioimpedance (BioZ). Taylor's approximation is applied to physiological features extracted from BioZ, with blood pressure guiding neural network training. Sequential segmented BioZ data is indexed, and a feature set is extracted. The PINN architecture includes CNN layers to extract information from segmented BioZ, and outputs are concatenated with physiological features to estimate BP (yNN). Taylor's polynomial is constructed for each input segment, evaluated at the next segment, and compared with neural network predictions to calculate a physics-based loss. This, along with a conventional loss, trains the PINN models.

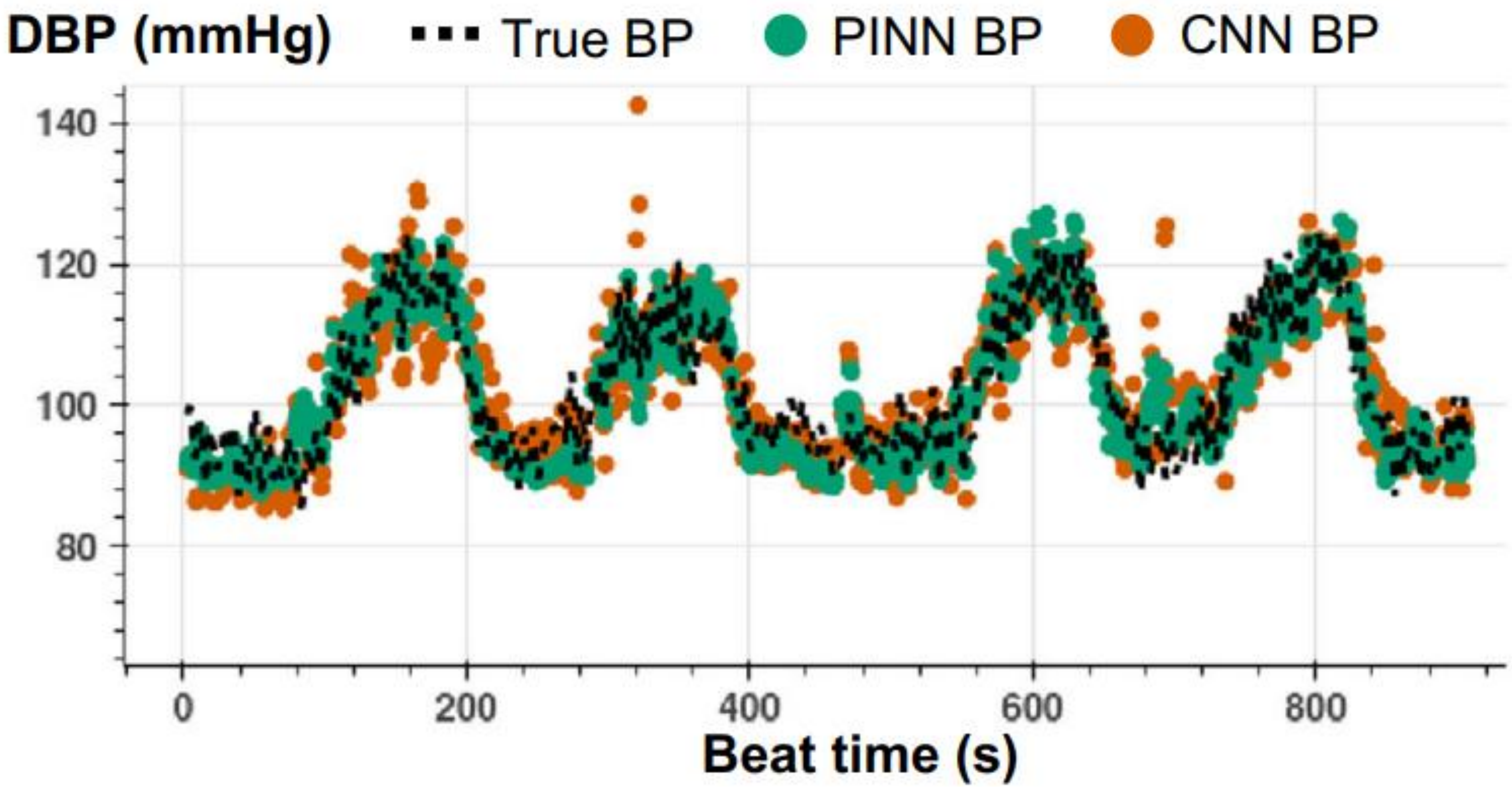
Hemodynamic relationships
- Systolic (SBP) and diastolic blood pressure (DBP) represent maximum and minimum pressure points respectively.
- SBP occurs during systole when the heart ejects blood into the aorta.
- Pulse pressure (PP) is the difference between SBP and DBP.
- Changes in PP and SBP are proportional to volumetric changes based on arterial wall compliance.
- Blood pressure pulse wave velocity (PWV) is related to arterial wall characteristics and pressure changes.
- PWV Equation: $PWV = \sqrt{(Eh/D\rho)}$, where D is artery diameter, h is wall thickness, ρ is blood density, and E is arterial elastic modulus.
- Understanding these dynamics aids in cardiovascular health assessment and personalized management strategies.

Model Architecture

The proposed model integrates deep neural networks (DNNs) with physics principles to estimate continuous blood pressure values from time series bioimpedance (BioZ) measurements. Physiological features from BioZ are used in Taylor's approximation to guide DNN training with blood pressure data. The model architecture includes convolutional neural network (CNN) layers for BioZ feature extraction, and outputs are combined with physiological features to predict blood pressure. A physics-based loss function, derived from Taylor's polynomial, supplements conventional loss for training PINN models. This approach enhances accuracy and interpretability while reducing data requirements for precise blood pressure estimation.



Some results of the Authors



- Green depicts PINN + CNN
- Orange depicts only CNN model