Physic-Informed Neural Networks for Medical Data

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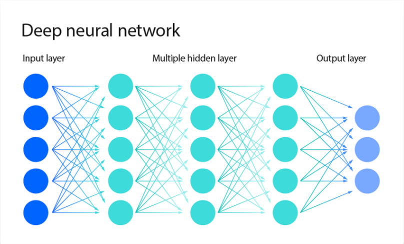
27/03/2025

Outline

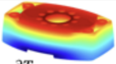
Outline

Physics-Informed Neural Networks



+

Physics Knowledge



$$\rho c \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T)$$

=

PINN

$$\mathcal{L}_{supervised} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_{true})^2$$

+

$$\mathcal{L}_{unsupervised}$$

Outline

Motivations

- Limited labeled data in biomedical settings

Motivations

- Non-invasive diagnostic tools

Contents lists available at ScienceDirect

ELSEVIER

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

Physics-informed neural network for fast prediction of temperature distributions in cancerous breasts as a potential efficient portable AI-based diagnostic tool

Olzhas Mukhmetov [a], Yong Zhao [a], Aigerim Mashekova [a], Vasilios Zarikas [b,c], Eddie Yin Kwee Ng [d,*], Nurduman Aidossov [a]

PINN + thermograms from IR cameras + 3D breast models from 3D scanner

Mammography: exposing patients to ionizing radiation

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Mammography: exposing patients to ionizing radiation

PINN + thermograms from IR cameras + 3D breast models from 3D scanner

"The comparison validates the PINN model as an accurate and fast method for thermal modeling and breast cancer diagnostic tool as the PINN simulation is found to be around 12 times faster than its Finite Element Analysis counterpart."

Outline

Cuffless blood pressure estimation

ARTICLE OPEN

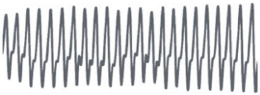
Check for updates

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

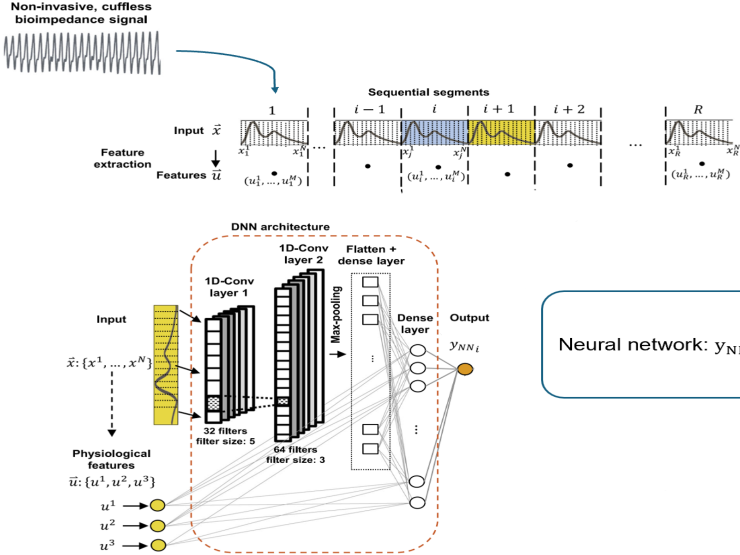
Kaan Sel[1], Amirmohammad Mohammadi[2], Roderic I. Pettigrew[3] and Roozbeh Jafari[1,2,3]

(a) (b)

Non-invasive, cuffless bioimpedance signal

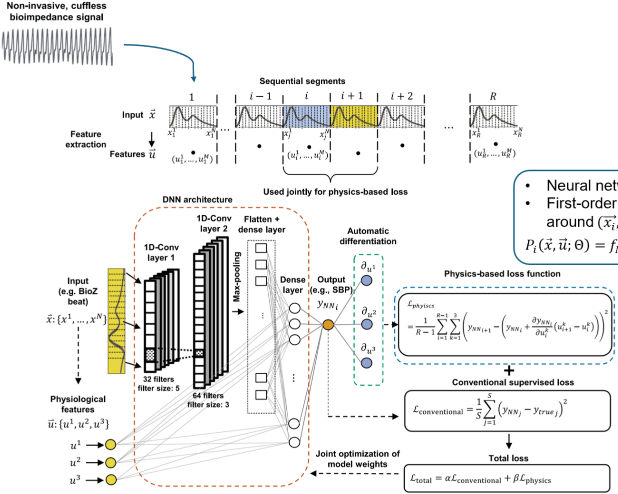


Cuffless blood pressure estimation



Neural network: $\mathrm{y_{NN}} = f_{NN}(\vec{x}, \vec{u}; \Theta)$

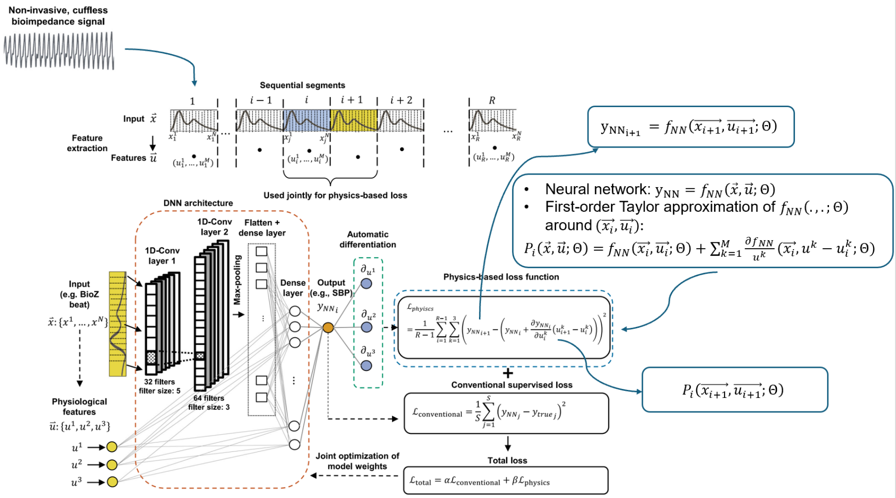
Cuffless blood pressure estimation



- Neural network: $y_{NN} = f_{NN}(\vec{x}, \vec{u}; \Theta)$
- First-order Taylor approximation of $f_{NN}(.,.;\Theta)$ around $(\vec{x_i}, \vec{u_i})$:

$$P_i(\vec{x}, \vec{u}; \Theta) = f_{NN}(\vec{x_i}, \vec{u_i}; \Theta) + \sum_{k=1}^{M} \frac{\partial f_{NN}}{u^k}(\vec{x_i}, u^k - u_i^k; \Theta)$$

Cuffless blood pressure estimation



Tumor growth forecasting

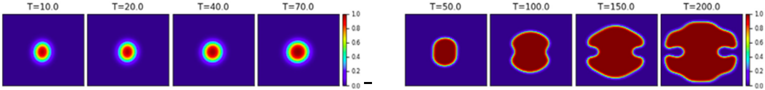
Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

TGM-Nets: A deep learning framework for enhanced forecasting of tumor growth by integrating imaging and modeling

Qijing Chen [a], Qi Ye [b,c], Weiqi Zhang [d,c], He Li [e], Xiaoning Zheng [a,*]

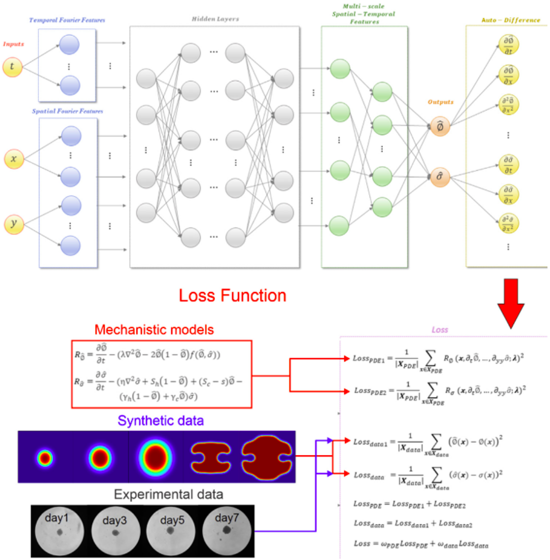


Tumor growth forecasting

The tumor growth dynamics are described by the following phase-field equations:

$$
\begin{aligned}
\frac{\partial \phi}{\partial t} &= \lambda \nabla^2 \phi - 2\phi(1-\phi) f(\phi, \sigma) \\
\frac{\partial \sigma}{\partial t} &= \eta \nabla^2 \sigma + S_h(1-\phi) + S_c \phi - (\gamma_h(1-\phi) + \gamma_c \phi)\sigma \\
f(\phi, \sigma) &= M(1 - 2\phi - 3m(\sigma)) \\
m(\sigma) &= m_{ref} \left(\frac{\rho + A}{2} + \frac{\rho - A}{\pi} \arctan\left(\frac{\sigma - \sigma_l}{\sigma_r} \right) \right)
\end{aligned}
\tag{1}
$$

Tumor growth forecasting



Tumor growth forecasting

- k_s, k_t: variance controlling hyperparameters.
- Weight matrices: $B^s \sim \mathcal{N}(0, k_s^2)$ and $B^t \sim \mathcal{N}(0, k_t^2)$.
- The spatial and temporal Fourier features are then computed as:

$$\gamma^s(x) = \begin{pmatrix} \cos(2\pi B^s x) \\ \sin(2\pi B^s x) \end{pmatrix}, \quad \gamma^t(t) = \begin{pmatrix} \cos(2\pi B^t t) \\ \sin(2\pi B^t t) \end{pmatrix}$$

Other applications

- Myocardial perfusion MRI quantification
- COVID-19 transmission dynamics analysis

Outline

Limitations

- PINNs are subject-specific due to personalized biological characteristics.
- PINNs still require certain assumptions in the model.
- In some applications, training PINNs requires dedicated hyperparameter tuning.

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References

- K. Sel et. al, *Physics-informed neural networks for modeling physiological time series for cuffless blood pressure estimation*, **npj Digit. Med. 6**, 2023.
- Q. Chen et. al, *TGM-Nets: A deep learning framework for enhanced forecasting of tumor growth by integrating imaging and modeling*, **Eng. Appl. Artif. Intell. 126**, 2023.
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