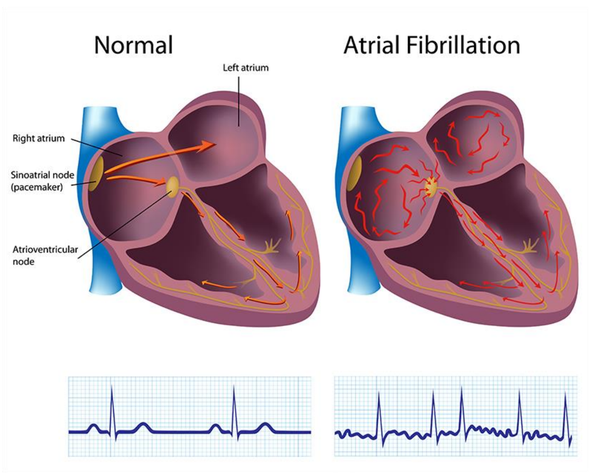
Cardiac Activation Mapping for Atrial Fibrillation Diagnosis and Treatment using Physics-Informed Neural Networks

Abstract

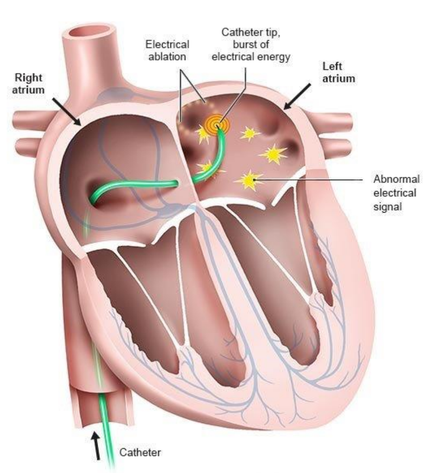
we propose a physics-informed neural network (PINN) for cardiac activation mapping that incorporates the underlying wave propagation dynamics of cardiac electrical activity. Benchmarking against traditional interpolation and Gaussian process regression, the PINN model demonstrated improved diagnostic accuracy, paving the way for improved procedural efficiency and patient outcomes in atrial fibrillation diagnostics.

Introduction

Atrial fibrillation, the most common cardiac arrhythmia, affects 2.7–6.1 million people in the U.S.[1]. Electrical activation mapping is a standard diagnostic and treatment procedure, where activation times are recorded at multiple atrial sites to generate electro-anatomic maps. Common interpolation methods, reconstruct wave propagation patterns but neglect the physics of wave dynamics, potentially leading to unrealistic conduction velocities. Physics-based approaches[2] improve realism by incorporating wave dynamics but often assume constant conduction velocities, limiting accuracy and applicability. We propose a physics-informed neural network (PINN) for cardiac activation mapping that integrates wave propagation physics, addressing limitations of interpolation-based and physics-based techniques.



SOURCE: [3]



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Methodology

Physics-Informed Neural Networks (PINNs) solve PDEs by embedding the equation residual and boundary conditions into the training process. For cardiac activation mapping, the Eikonal equation[5] is expressed in residual form as:

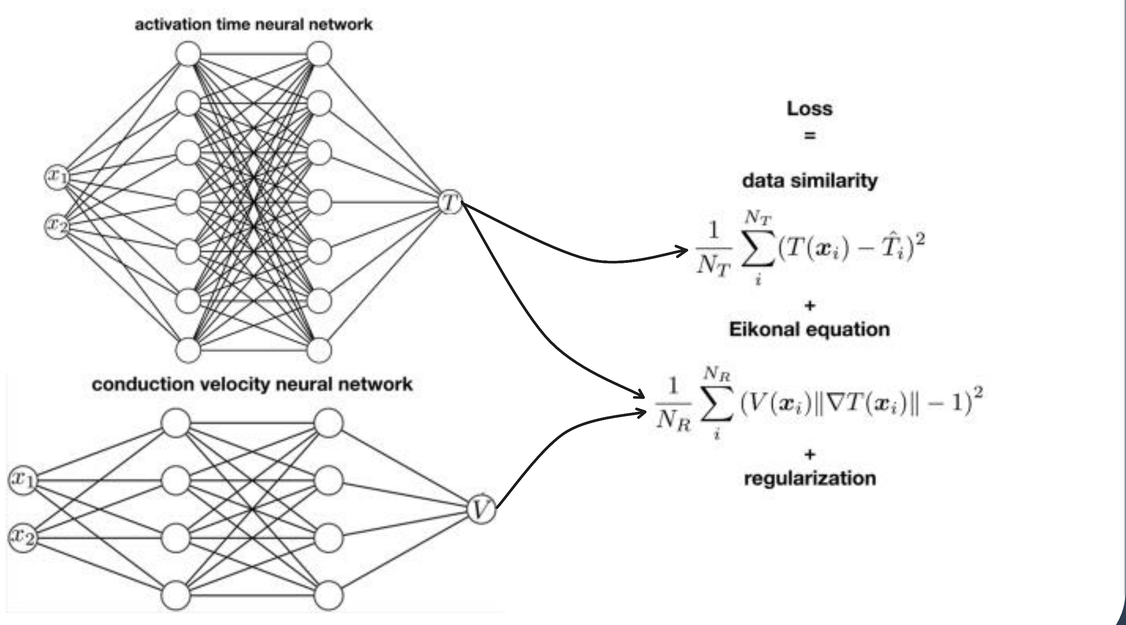
$$R(x) := V(x) \parallel \nabla T(x) \parallel -1 = 0$$

where $T(\mathrm{x})$ is the activation time, $V(\mathrm{x})$ is the conduction velocity, and $\nabla T(\mathrm{x})$ is the activation time gradient. Neural networks NN_T and NN_V approximate $T(\mathrm{x})$ and $V(\mathrm{x})$:

$$T(\mathrm{x}) \approx \mathrm{NN}_T(\mathrm{x}, \theta_T), \qquad V(x) \approx V_{max} \cdot \sigma(\mathrm{NN}_V(\mathrm{x}, \theta_V))$$

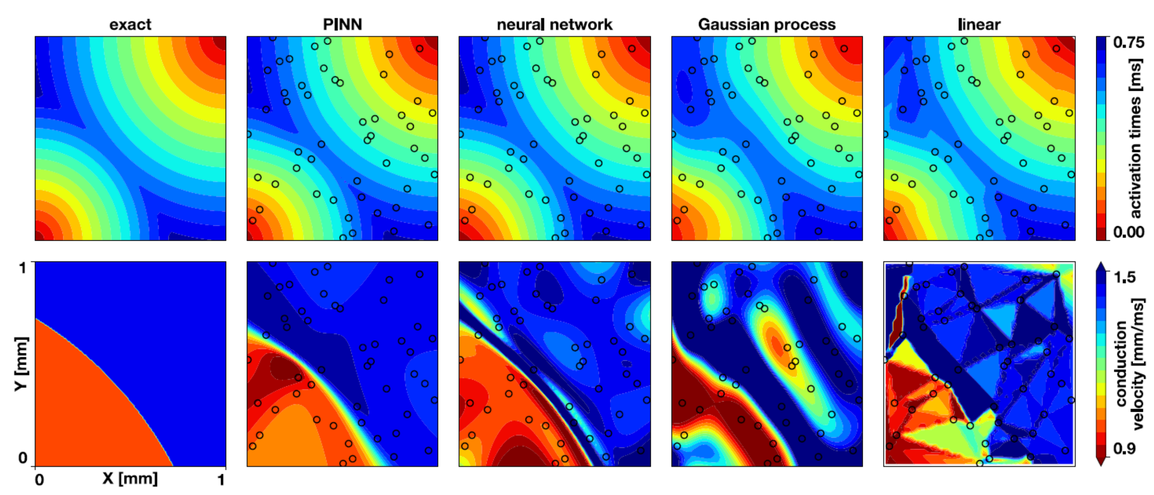
where σ is a sigmoid function ensuring $V(\mathrm{x})$ remains positive and bounded within physiological limits. The loss function minimizes discrepancies between predictions and physical constraints:

$$L(\theta_T, \theta_V) = \frac{1}{N_T}\sum_{i=1}^{N_T}\left(T(x_i) - \widehat{T}_i\right)^2 + \frac{1}{N_R}\sum_{i=1}^{N_R} R(x_i)^2 + \alpha_{TV}\frac{1}{N_R}\sum_{i=1}^{N_R}|\nabla V(x_i)| + \alpha_{L2}\sum_{i=1}^{N_\theta}\theta_{T,i}^2$$

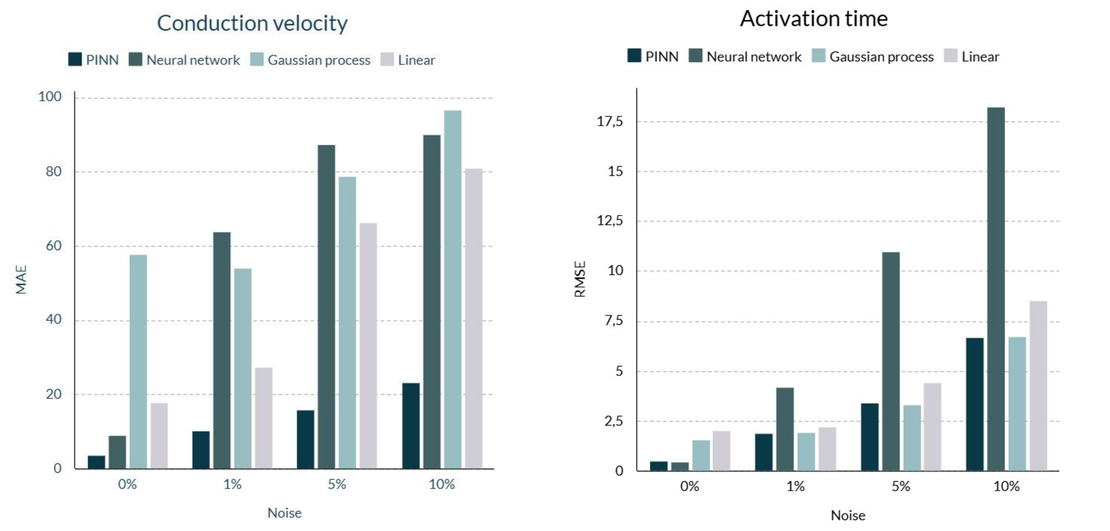


Results

To evaluate the effectiveness of the PINN framework, we designed a synthetic benchmark problem where the activation times and conduction velocity analytically satisfy the Eikonal equation. We evaluated the performance of all four methods.



We introduce Gaussian noise with a standard deviation of 1, 5, and 10% of the maximum value of activation time and run all methods 30 times with the same datasets. We illustrate the results quantitively in the bar chart below:



The PINN outperforms traditional methods, achieving lower error in both activation times and conduction velocity. Incorporating wave propagation physics into neural network training enables more accurate and physically consistent predictions of cardiac activation mapping, significantly enhancing its performance.

Conclusion and Future Work

We introduced a PINN-based framework for cardiac activation mapping, excelling in predicting activation times and conduction velocities while accurately modeling wavefront dynamics. However, it currently lacks anisotropy modeling and clinical validation. Future work will address these gaps by incorporating fiber orientation data, uncertainty quantification, and real-world testing. This approach shows strong potential for improving arrhythmia diagnosis and treatment.

References

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Team Members:
Mohamed Gad[1]
Mazen Atlam[1]
Sherif Elgendy[1]
Anas Elsheikh[1]
Ahmed Abdelghafar[1]

Under The Supervision of:
Dr. Ahmed S. A. Mohamed[2]

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Find Team Members' Portfolios on:

[1]Department of Systems and Biomedical Engineering, Faculty of Engineering, Cairo University
[2]Department of Engineering Mathematics and Physics, Faculty of Engineering, Cairo University