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Physics-Informed Deep Learning Surrogates for Aneurysm Blood Flow Simulation

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1. Introduction

Abdominal Aortic Aneurysms (AAA) can affect blood flow patterns in ways that impact disease progression and rupture risk. Accurately simulating blood flow in an AAA is crucial for understanding hemodynamics, but current methods face significant challenges. Four-dimensional flow MRI can non-invasively measure blood velocities, yet it suffers from limited resolution and accuracy in complex cardiovascular flows. On the other hand, fluid structure interaction (FSI) numerical modeling requires detailed patient-specific boundary conditions (e.g. inlet flow profiles, outlet pressures, mechanical behavior of arterial wall) that are often hard to obtain, and running high-fidelity FSI is computationally expensive and time-consuming. These limitations motivate the exploration of physics-informed deep learning techniques as an alternative for vascular flow modeling. In this work, we apply Physics-Informed Neural Networks (PINNs) and Physics-Informed Deep Operator Networks (PI-DeepONets) to predict velocity and pressure fields of steady (Cruz-González et al. 2025) and unsteady flows in an idealized 3D AAA model. The long-term goal is to apply these methods to realistic AAA geometry and moving arterial walls. Our approach is particularly relevant in the field of biomedical engineering, where simulating blood flow is critical for understanding cardiovascular diseases.

2. Methods

2.1 Physics-Informed Neural Networks

PINNs (Raissi et al. 2019) are deep neural networks trained to satisfy physical laws expressed as partial differential equations (PDEs) in addition to any observational data. Here we design a PINN that outputs the blood flow field (velocity and pressure) given spatial coordinates (x, y, z) for steady flow or spatial coordinates and time t for unsteady one. During training, the PINN's loss function integrates terms enforcing the Navier–Stokes equations at collocation points across the 3D domain, initial and boundary conditions, and optionally, available data points. Best practice techniques such as non-dimensionalization, loss balancing, Fourier feature embedding, among others, are employed to improve performance and accuracy in flow predictions.

2.2 Physics-Informed DeepONets

Whereas PINNs learn only one solution at a time, Deep Operator Networks (Lu et al. 2021) take a different approach by learning the mapping (operator) from problem input functions to solution functions. In our context, a DeepONet is trained to map the inlet velocity and outlet pressure boundary conditions of the Navier-Stokes system to the resulting 3D velocity and pressure fields throughout the aneurysm. By training on a family of simulated examples (multiple CFD-generated flow solutions under varying boundary conditions), the DeepONet learns to generalize across different flow

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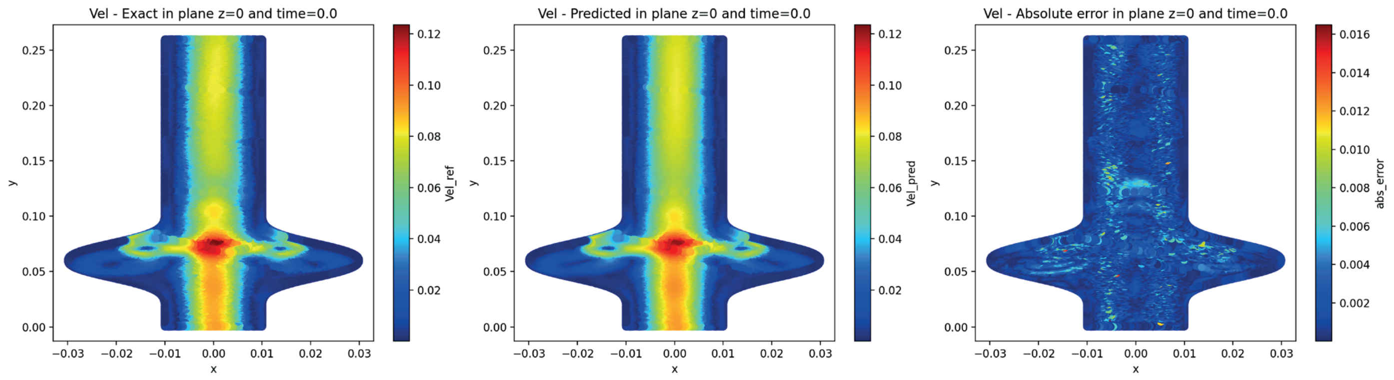

Figure 1. Magnitude of the velocity in plane z=0 at t=0 for unsteady flow. Ground Trust using CFD (left), Predicted using PINNs (middle), Absolute Error (right). The 3rd period of CFD modelling was used.

scenarios. We further use the PI-DeepONet (Wang et al. 2021) by incorporating the Navier-Stokes equations into its training loss, similar to PINN methodology. Once trained, it can instantly produce a new flow field for any novel set of boundary conditions within the learned range.

3. Results and discussion

We evaluated PINN, DeepONet, and PI-DeepONet models on benchmark cases and compared their predictions to high-fidelity CFD simulations using ANSYS modeling steady and unsteady flow in an idealized 3D AAA model. All approaches achieved good agreement with the CFD ground truth, successfully reproducing the flow patterns and pressure fields (see Fig. 1. and its complementary results in Tab. 1.).

Through a series of test cases, we identified the scenarios where each approach excels. The PINN can predict the flow with minimal or no data, relying on known physics alone, useful for instance when patient-specific measurements are sparse. The DeepONet requires a training dataset of flow solutions; hence it leverages prior CFD simulations or experiments. Once trained, it is extremely fast for performing new predictions. The PI-DeepONet incorporates the use of known physics in training to reduce data requirements and improve reliability, while retaining rapid evaluation. We observed that PI-DeepONet outperformed the standard DeepONet when data were limited, and it preserved the physical phenomena better in the extrapolation scenarios. In summary, these approaches offer an alternative way to study vascular flow simulation, with complementary advantages and limitations.

Table 1. Relative L^2 error in plane z=0 at different time steps.

Time step	Magnitude of velocity	Pressure
t=0	5.2026e-2	2.4218e-2
t=0.5	6.2435e-2	4.0259e-2
t=0.9	8.5025e-2	4.2667e-2

4. Conclusions

This study demonstrates that physics-informed deep learning can significantly enhance vascular flow simulations for aortic aneurysms, offering accurate results with improved efficiency. By integrating the 3D Navier–Stokes equations into neural network training, we showed that patient-specific blood flow in an AAA can be predicted with appropriate speed, and with the flexibility to incorporate whatever clinical data are available. The proposed methodology is not meant to replace traditional CFD or imaging; rather, it augments the toolkit for cardiovascular hemodynamics by providing fast, physics-respecting surrogate. Looking forward, this work serves as a starting point for deeper integration of AI in cardiovascular modeling. Future research will involve applying our PINN / PI-DeepONet framework to more anatomically realistic geometries and patient-specific data.

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Conflict of Interest Statement

None.

Contributor Roles

OLCG: Conceptualization, Methodology, Software, Visualization, Formal analysis, Writing original draft. BG: Funding acquisition, Conceptualization, Methodology, Formal analysis, Writing review and editing. VD: Funding acquisition, Conceptualization, Methodology, Formal analysis, Writing-review and editing.

Data, software, code availability

The data and code that support the findings of this study are available from the corresponding author upon reasonable request.

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