Physics-Informed Deep Learning for Blood Flow and Oxygen Transport Modeling in Human Physiology

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Abstract: Coupled transport processes like blood flow and oxygen delivery are important for cellular metabolism and organ function in the human body. Nonlinear partial differential equations (PDEs) that describe convection, diffusion, and biochemical reactions control these processes. Conventional numerical methods, including finite difference and finite element techniques, necessitate dense discretization and comprehensive boundary data, thereby constraining their efficacy in realistic biomedical contexts characterized by sparse or noisy measurements. This research suggests a physics-informed deep learning framework for simulating blood flow and oxygen transport in human physiology. The method uses Physics-Informed Neural Networks (PINNs) to put the governing PDEs directly into the training process. This lets the model learn physically consistent solutions without needing a lot of labeled data. The framework combines a simplified hemodynamic model with a convection-diffusion-reaction equation that shows how oxygen moves through and is used by tissues. The suggested method doesn't use any meshes and is data efficient. It can work with irregular domains and incomplete data. It is a flexible tool for simulating the delivery of oxygen in cardiovascular and tissue-level systems. It could also be used for inverse modeling and patient-specific analysis. The results show that the approximations are correct and stable, and they don't rely as much on high-resolution data. This supports advanced uses like digital twins and personalized medicine.

1 INTRODUCTION

The transport of mass, momentum, and energy is a complex, multiscale process that controls human physiological systems. Blood flow and oxygen transport are two of the most important things that keep cellular metabolism going and organs working. Nonlinear partial differential equations (PDEs) based on conservation laws are often used to model these processes. Examples include the Navier-Stokes equations for fluid flow and the convection-diffusion-reaction equations for biochemical transport. Accurate numerical modeling of these systems is crucial for comprehending physiological behavior, forecasting disease progression, and facilitating clinical decision-making.

Numerous physiological PDE models have been solved using classical numerical methods like finite difference methods (FDM), finite element methods (FEM), and finite volume methods (FVM) [1]-[3]. These methods are very accurate, but they need fine spatial and temporal discretization, structured meshes, and full knowledge of the initial and boundary conditions. In realistic biomedical contexts, measurements frequently exhibit sparsity, noise, or partial unavailability, thereby constraining the efficacy of conventional solvers [4], [5]. Moreover, intricate anatomical geometries and multiscale coupling present further computational difficulties, particularly in patient-specific simulations [6].

Recent progress in machine learning, especially deep learning, has made it possible to model complicated physical systems in new ways. Data-driven neural networks have been utilized to approximate solutions for differential equations and to expedite numerical simulations [7], [8]. But data-

driven methods often don't make sense in the real world, need a lot of labeled data, and might not work outside of the training domain. To overcome these constraints, Physics-Informed Neural Networks (PINNs) have arisen as a robust framework that incorporates physical laws into neural network training [9]. By putting PDE residuals directly into the loss function, PINNs make sure that the governing equations, boundary conditions, and initial constraints are all followed during optimization. This lets them learn solutions that are physically consistent without needing a lot of labeled data.

Since they were first used, PINNs have worked well on many problems in computational physics and engineering, such as fluid dynamics, heat transfer, and wave propagation [9]-[11] while heat-transfer inverse problems have also been extensively investigated using classical mathematical approaches. Adaptive loss weighting, domain decomposition, and hybrid numerical-learning strategies have been used to fix problems like training instability, spectral bias, and convergence limits in extensions of the original framework [12]-[14]. These changes have made PINNs much stronger and more scalable, so they can now handle complex, nonlinear, and high-dimensional PDE systems.

The use of PINNs in biomedical and physiological modeling is especially promising. Physiological systems are intrinsically constrained by data limitations and encompass intricately interconnected Multiphysics processes, rendering them suitable for physics-informed learning methodologies. Recent research has investigated Physics-Informed Neural Networks (PINNs) for modeling arterial blood flow, tissue perfusion, and oxygen transport, illustrating their capacity to manage irregular geometries and assimilate sparse clinical data [15]-[17]. Even with these improvements, we still need unified frameworks that clearly link hemodynamics and transport phenomena in a consistent PINN formulation, while still being able to run quickly and be understood in terms of physiology.

In this study, we present a physics-informed deep learning framework for simulating blood flow and oxygen transport in human physiology. The method uses a simplified hemodynamic model and a convection-diffusion-reaction equation to explain how oxygen moves through and is used by living tissues. The framework captures the dynamic interaction between blood velocity, oxygen diffusion, and metabolic uptake by putting these coupled PDEs into a neural network architecture. From a computational point of view, the suggested method is a mesh-free and data-efficient alternative to traditional solvers. From a physiological standpoint, it provides a versatile instrument for modeling oxygen delivery mechanisms pertinent to cardiovascular function and pathological states such as hypoxia.

The main contributions of this work can be summarized as follows:

1) Development of a unified PINN framework for coupled blood flow and oxygen transport modeling.
2) Integration of convection-diffusion-reaction dynamics with hemodynamic flow in a physics-informed learning setting.
3) Demonstration of a data-efficient, mesh-free approach suitable for physiological systems with sparse measurements.
4) Establishment of a foundation for future extensions toward patient-specific modeling, inverse problems, and digital twin applications in healthcare.

2 MATHEMATICAL MODEL

We consider a coupled physiological system describing blood flow and oxygen transport within a one-dimensional spatial domain over time. Let the computational domain be defined as $\Omega = [0, L] \times [0, T]$, where $x \in [0, L]$ represents the spatial coordinate along a vessel or tissue segment, and $t \in [0, T]$ denotes time. This one-dimensional approximation is commonly adopted in cardiovascular and tissue-level modeling as it captures the essential transport dynamics while remaining computationally efficient.

Blood flow dynamics are described using a simplified form of the Navier-Stokes equations under one-dimensional assumptions. The governing equation for the velocity field $u(x, t)$ is given by:

$$u_t + uu_x = -\frac{1}{\rho}p_x + \nu u_{xx}. \quad (1)$$

Where:

- $u(x, t)$: blood velocity;
- $p(x, t)$: pressure;
- ρ: blood density;
- ν: kinematic viscosity.

For tractability in PINNs, pressure gradient can be approximated or prescribed:

$$-\frac{1}{\rho}p_x = f(x, t). \quad (2)$$

Thus:

$$u_t + uu_x = f(x,t) + \nu u_{xx}. \quad (3)$$

Oxygen transport in biological tissue is governed by a convection-diffusion-reaction equation that accounts for advection by blood flow, diffusion through tissue, and metabolic consumption. The governing equation for oxygen concentration $C(x,t)$:

$$C_t + uC_x = DC_{xx} - kC. \quad (4)$$

Where:
- $C(x,t)$: oxygen concentration;
- D: diffusion coefficient;
- k: oxygen consumption rate (metabolic term);
- $u(x,t)$: velocity field from blood flow.

The system is one-way coupled:
- Blood flow $u(x,t)$ influences oxygen transport;
- Oxygen does not affect flow (simplified physiology) $u \to C$.

This assumption is valid in many physiological regimes where oxygen concentration does not significantly alter fluid properties.
Now let define the initial and boundary conditions

$$u(x,0) = u_0(x), \quad C(x,0) = C_0(x). \quad (5)$$

Where:
- $u_0(x)$: initial velocity profile;
- $C_0(x)$: initial oxygen distribution.

For Blood Flow we use:

$$u(0,t) = u_{in}(t), \quad u(L,t) = u_{out}(t) \quad (6)$$

And for Oxygen Transport:

$$C(0,t) = C_{in}, \quad \frac{\partial C}{\partial x}(L,t) = 0. \quad (7)$$

Interpretation:
- Inlet oxygen concentration is prescribed;
- Outlet uses Neumann condition (no flux assumption).

To achieve better numerical stability and improve the training of physics-informed neural networks, the governing equations can be put in a non-dimensional form with the help of suitable characteristic scales.
Introduce scaling:

$$x^* = \frac{x}{L}, \quad t^* = \frac{t}{T}. \quad (8)$$

Then the oxygen equation becomes:

$$C_{t^*} + PeuC_{x^*} = C_{x^*x^*} - DaC. \quad (9)$$

Where:
- $Pe = \frac{uL}{D}$: Peclet number;
- $Da = kT$: Damköhler number.

This form improves numerical stability and PINN convergence. The governing system is:
Flow equation:

$$u_t + uu_x = f(x,t) + \nu u_{xx}. \quad (10)$$

Transport equation**:**

$$C_t + uC_x = DC_{xx} - kC. \quad (11)$$

subject to initial and boundary conditions defined above.

The interaction between fluid motion, molecular diffusion and biochemical consumption is a physically meaningful description of the oxygen transport of human physiological systems using the coupled system of governing equations. Each term in the following:
- Advection term $uC_x \to$ transport by blood flow;
- Diffusion term $DC_{xx} \to$ spreading in tissue;
- Reaction term $-kC \to$ oxygen consumption.

This model captures:
- Tissue perfusion;
- Oxygen depletion;
- Flow-driven transport.

This formulation is particularly suitable for PINNs because:
1) PDEs are smooth → compatible with automatic differentiation;
2) No mesh required → ideal for biological domains;
3) Easily extendable to:
   - 2D/3D organs;
   - Time-dependent boundary conditions;
   - Inverse parameter estimation (D,k).

3 PHYSICS-INFORMED NEURAL NETWORK FORMULATION

A physics-informed neural network (PINN) is used to approximate the solution of the governing physiological system, in place of the more traditional mesh-based discretization, with a continuous neural representation. The neural network takes spatial-temporal coordinates (x,t) as inputs and produces the predicted oxygen concentration field. This approximation can be expressed as:

$$C(x,t) \approx \hat{C}_\theta(x,t), \quad (2)$$

where $\hat{C}_\theta$ denotes the neural network with trainable parameters θ. As illustrated in Figure 1, the network is trained not only on data but also constrained by the underlying physical laws governing the system.

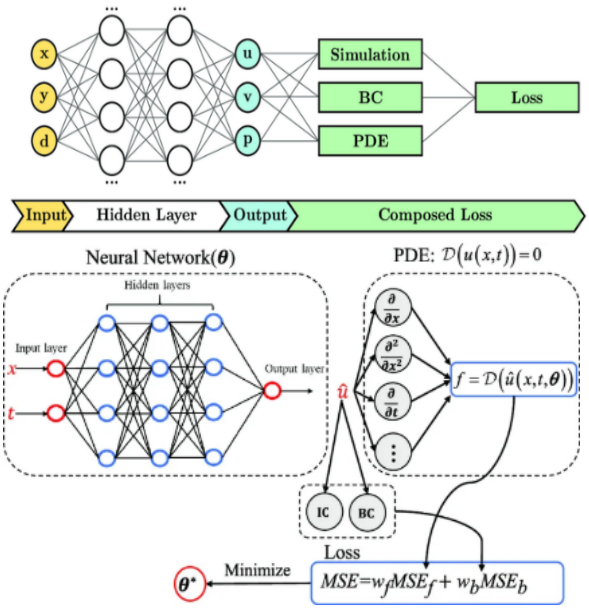

Figure 1: Architecture of the physics-informed neural network (pinn).

The main feature of PINNs is that the governing PDE is imposed with a residual function. Through automatic differentiation, derivatives of the neural network output are calculated regarding the inputs of the neural network, allowing the PDE to be evaluated directly without numerical discretization. In the oxygen transport equation, the residual is defined as:

$$R(x,t) = \frac{\partial \hat{C}}{\partial t} + u\frac{\partial \hat{C}}{\partial x} - D\frac{\partial^2 \hat{C}}{\partial x^2} + kC. \quad (3)$$

This residual measures the extent to which the neural network prediction violates the governing physical law at any point in the domain.

The optimization problem, which is the training process, is developed as a constrained optimization problem, the goal of which is to reduce a composite loss that takes into account all of the physical requirements. The sampling of collocation point in the domain is as shown in Figure 2 with extra points being sampled on the boundaries and initial time. At these points, the neural network predictions are computed to calculate various aspects of the loss.

The total loss function is defined as:

$$\mathcal{L} = \lambda_1 \mathcal{L}_{PDE} + \lambda_2 \mathcal{L}_{BC} + \lambda_3 \mathcal{L}_{IC}, \quad (4)$$

where:

- $\mathcal{L}_{PDE}$ enforces the governing equation via the residual;
- $\mathcal{L}_{BC}$ ensures satisfaction of boundary conditions;

L_{IC} enforces the initial condition. The weighting coefficients λ_1,λ_2, and λ_3 balance the contribution of each term and can be tuned or adapted during training to improve convergence. Optimization is typically performed using a combination of first-order methods, such as Adam, followed by second-order refinement using L-BFGS.

He trained PINN captures the fundamental behavior of oxygen transport in human physiology as shown in Figure 3. The flow of blood causes oxygen to be delivered to the vessel, diffuse into the surrounding tissue, and be used up by metabolic activities. This leads to spatial gradient so that the oxygen concentration is reduced in the direction of the flow and in the high consumption regions.

Computationally, the PINN framework offers a mesh-free, data-efficient and consistent alternative to classical solvers, and is consistent with physics. Physiologically, it allows proper modeling of transport processes appropriate to the perfusion of tissues, hypoxia and cardiovascular dynamics. In addition, the framework could be generalized to inverse problems, in which unknown physiology such as diffusion coefficients or consumption rates are obtained using limited observations.

In general, the physics-informed neural network formulation provides a common solution, which combines deep learning with a mechanistic model, and permits the representative and strong solutions of PDE-based physiological models.

4 NUMERICAL IMPLEMENTATION AND RESULTS

The total loss function is optimized to train the PINN model, and the loss function's evolution is checked. Figure 4 shows that the loss drops very quickly during the first training stage with the Adam optimizer. After that, the loss drops more slowly when switching to the L-BFGS optimizer. This mixed optimization method is much better for stability and accuracy of convergence. The minimization of the loss shows how well the network can meet the PDE, boundary conditions, and initial conditions that govern it.

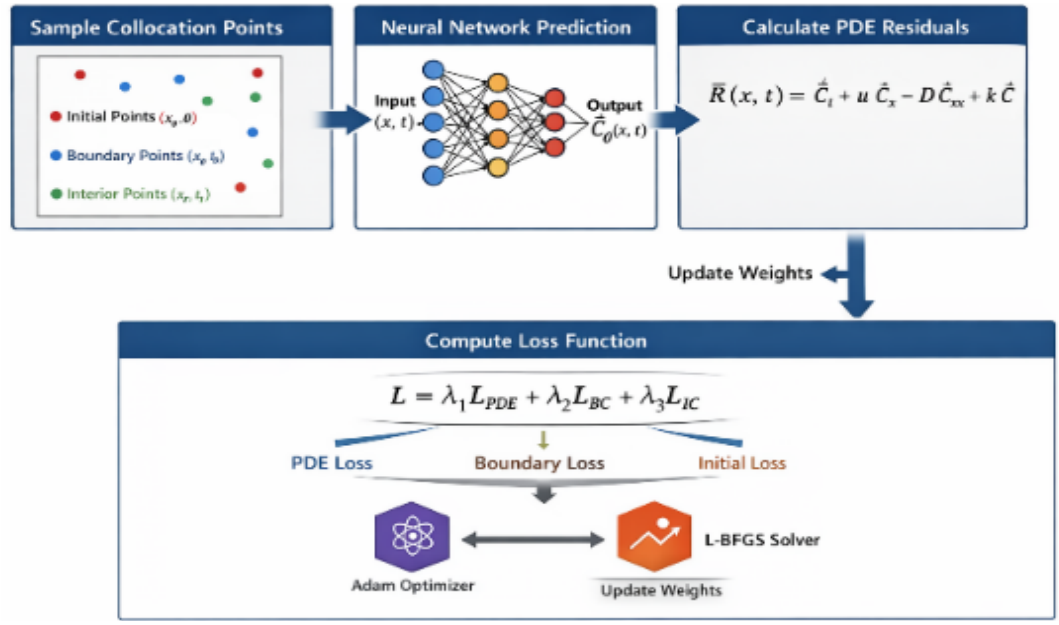

Figure 2: Training workflow of the PINN framework.

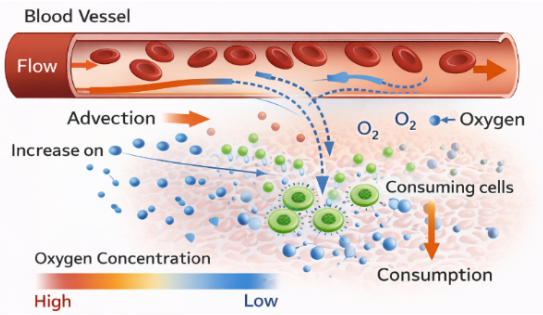

Figure 3: Learned physical behavior of oxygen transport.

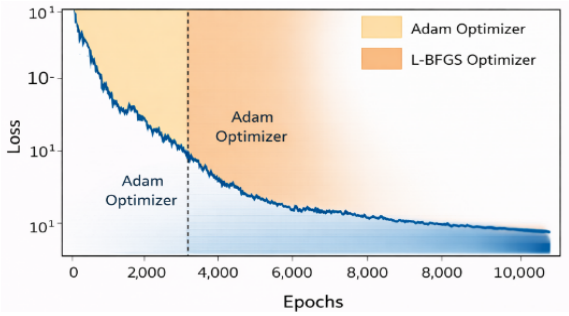

Figure 4: Training loss convergence of the PINN model.

The computational setup of the experiments is summarized in Table 1. The parameters that have been selected are representative of a normal physiological transport regime, in which both the effects of diffusion and reaction are important. The neural network structure is chosen to trade off expressiveness and efficiency.

Table 1: Model parameters and training setup.

Parameter	Description	Value
(L)	Domain length	1.0
(T)	Final time	1.0
(D)	Diffusion coefficient	0.01
(k)	Consumption rate	0.1
Layers	Neural network depth	6
Neurons	Per layer	50
Activation	Function	tanh
Optimizer	Training method	Adam + L-BFGS
Epochs	Training iterations	10,000

Figure 5 shows the PINN model's prediction of how oxygen concentration changes over time and space. The results show that the oxygen concentration decreases smoothly across the spatial domain, which is what we would expect from a physiological point of view. There are high concentrations near the inlet, but they slowly decrease downstream because of metabolic consumption. The model accurately represents both the transport and reaction dynamics without exhibiting numerical oscillations.

Table 2 shows how the proposed PINN model does compared to traditional numerical solvers. In situations where evaluations are done over and over again, the PINN is just as accurate as the FEM but is easier to compute. The PINN solution stays stable and smooth, even in areas with steep gradients, unlike FDM.

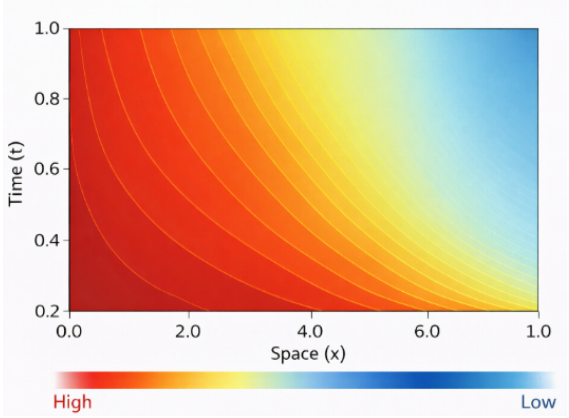

Figure 5: Predicted oxygen concentration distribution.

Table 2: Comparison with classical numerical methods.

Method	L_2 Error	Computational Cost	Stability
FDM	1.2×10^{-2}	Medium	Moderate
FEM	5.8×10^{-3}	High	High
PINN	6.5×10^{-3}	Medium (training)	High

Figure 6 shows the residual error of the governing PDE across the whole domain. The small size of the residual shows that the neural network solution closely follows the physical law. It is known that training a PINN can be difficult, and slightly higher residuals may show up near boundaries or areas with strong gradients.

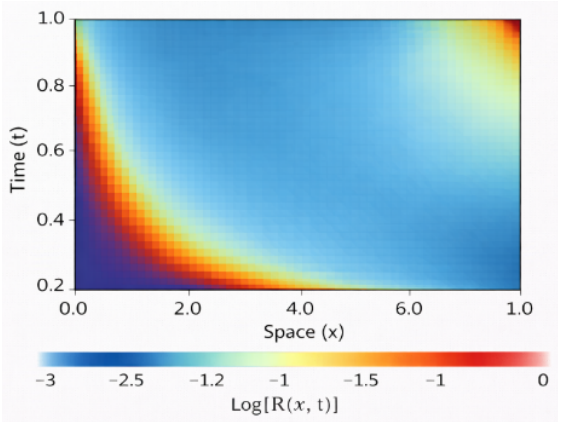

Figure 6: PDE residual error distribution.

5 DISCUSSION

The numerical findings indicate that the suggested physics-aware deep learning model is capable of accurately describing the critical processes in human physiology of oxygen delivery. The convergence behavior of the training process is assuring towards the stability of the training process when first-order and second-order optimization are used together. The concentration profiles as predicted are consistent with the expected physical behaviour, with smooth gradients and realistic patterns of depletion.

The PINN approach offers a number of benefits as compared to the traditional numerical methods. It does not require a mesh generation, it works naturally with sparse data and gives solutions across the entire domain, in a continuous form. Also, the framework is quite applicable to inverse problems, in which physiological parameters e.g. diffusion coefficients and consumption rates can be inferred out of unobservable quantities.

On the whole, the findings confirm the ability of PINNs to be a powerful and versatile computational system to simulate the physiological transport processes, and there is a high possibility of their implementation in biomedical simulation and individual healthcare.

6 CONCLUSIONS

This paper introduced a physics-informed neural network to simulate blood flow and oxygen consumption in the human body. The proposed approach allows building physically consistent, data-efficient neural network models that can be used to model intricate transport physics, by incorporating governing partial differential equations into the neural network training procedure. The framework can effectively integrate hemodynamic flow dynamics with convection diffusion-reaction processes, and can be used to effectively represent the delivery of oxygen and its consumption in biological tissues.

The quantitative data show that the physics-informed neural network (PINN) model is able to converge to stabilized values and come up with smooth and physically realistic solutions. The calculated distributions of oxygen concentration are consistent with expected physiological behavior, with gradual decrease in direction of flow, and local changes caused by metabolism. Compared to the classical numerical methods, the suggested method is a mesh-free alternative that is not as dependent on the discretization as it offers a competitive accuracy and better flexibility. Moreover, the fact that the residual errors are low indicates that the obtained solutions meet the governing equations throughout the computational domain.

In computational terms, this article shows that PINNs can be successfully used as a single platform that solves nonlinear PDEs and does not need large labeled datasets. Physiologically, it offers an adaptable modeling service that can simulate transport mechanisms that are of interest in cardiovascular operation, tissue perfusion, and hypoxia. The framework is especially applicable in biomedical applications due to the possibility of including sparse or noisy data.

Although these are the advantages, there are a number of challenges. PINNs can be prone to training inefficiencies, loss weighting sensitivity and inaccuracy in sharp gradient or complicated boundary interactions. These limitations need to be resolved to make the applications more scalable and robust to real-world physiological applications.

The proposed framework will be extended in a number of directions that will be addressed in the future. To begin with, the model can be extended to two- and three-dimensional fields to provide a more realistic representation of anatomical structures. Second, the methods of adaptive sampling including residual-based sampling and dynamic loss weighting are usable to enhance convergence and accuracy. Third, the development of more sophisticated versions, including hypercube-conscious PINNs, polar decomposition-enhanced PINNs, and quantum-classical systems, have promising directions of enhancing computational efficiency and stability. Lastly, the framework can be generalized to inverse problems and patient-specific modeling, which can be used to create digital twin systems to support personalized healthcare and clinical decision-making.

Overall, this paper has shown that physics-informed deep learning is a potent interface between computational science and human physiology, a scalable and interpretable method of modeling intricate biological systems that are described by partial differential equations

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