



Research Article

A study on physics-informed neural networks and finite volume approach for Maxwell fluid simulation in stenosed coronary arteries

Abdul WAHAB^{1,*}, Muhammad Imran ASJAD^{1,2}, Sohail NADEEM³, Kubra ANJUM⁴

¹Department of Mathematics, University of Management and Technology, Lahore, 54770, Pakistan

²Center for Theoretical Physics, Khazar University, Baku, AZ 1096, Azerbaijan

³Department of Mathematics, Quaid-i-Azam University, Islamabad, 45320, Pakistan

⁴Department of Medical Sciences, Gujranwala Medical College, Gujranwala, 52310, Pakistan

ARTICLE INFO

Article history

Received: 30 July 2025

Revised: 14 October 2025

Accepted: 27 November 2025

Keywords:

ANSYS; Artificial Intelligence;
Coronary Computed
Tomography Angiography;
Coronary Stenosed Artery
Disease; Finite Volume Method

ABSTRACT

This study investigates the role of artificial intelligence in coronary computed tomography angiography analysis, with a focus on the mathematical modeling of stenosed coronary arteries. A detailed comparative analysis is performed between physics-informed neural networks and the finite volume method implemented in the computational software “Analysis System” (ANSYS) environment, both used to solve the governing equations comprising partial and ordinary differential equations that describe the Maxwell viscoelastic behavior of blood and its associated velocity–pressure distributions. Physics-informed neural networks, through their ability to directly embed physical conservation laws into the neural network structure, demonstrate superior capability in producing smooth, accurate, and stable solutions for complex coronary geometries. In contrast, the finite volume method, based on mesh-dependent approximations, shows limitations in addressing strong nonlinearities and geometric irregularities inherent in stenosed arterial flow. The findings reveal that the physics-informed neural network framework outperforms the finite volume method in terms of accuracy, computational efficiency, and adaptability to real-world biomedical complexities. The novelty of this study lies in the first integration of the Maxwell viscoelastic blood model within a physics-informed neural network framework for simulating flow and heat transfer in stenosed coronary arteries, along with a comprehensive validation against the finite volume method. This hybrid approach bridges the gap between artificial intelligence and classical fluid dynamics, offering a robust, mesh-free, and physics-consistent methodology for hemodynamic analysis. Although both methods still face challenges in matching the precision of invasive techniques such as fractional flow reserve, the incorporation of advanced imaging reconstruction and explainable artificial intelligence can further enhance the reliability of non-invasive coronary flow assessment.

Cite this article as: Wahab A, Asjad MI, Nadeem S, Anjum K. A study on physics-informed neural networks and finite volume approach for Maxwell fluid simulation in stenosed coronary arteries. Sigma J Eng Nat Sci 2026;44(4):2473–2508.

*Corresponding author.

*E-mail address: wahabgujjar175@gmail.com

*This paper was recommended for publication in revised form by
Editor-in-Chief Ahmet Selim Dalkilic*



INTRODUCTION

The leading cause of mortality worldwide is still coronary artery disease. The newly introduced computed tomography scanners with their autodetection technology have made it feasible to obtain a high-resolution picture of cardio vascular system especially heart and coronary arteries within a heartbeat. Consequently, coronary computed tomography angiography provides unprecedented potential to mitigate the illness with precise identification of calcium in coronary artery and also plaque. The ability to probe the hemodynamic importance of coronary artery stenoses using advanced modeling and image processing, coronary computed tomography angiography was recently stood at the highest rank. For the evidence, the tool was used on few suspected coronary artery disease to evaluate reliability and validity [1]. The labor-intensive nature of extensive coronary computed tomography angiography analysis and the need for highly qualified specialists to interpret images now restricted. The advancements in the artificial intelligence have evidently enhanced the working phenomenon by providing a degree of detail of coronary computed tomography angiography analysis [2]. Additionally, the amount of data in coronary computed tomography angiography exams is far greater than what even the most skilled observers can manually analyze. With the help of scientific advancement in deep learning, we examine current artificial intelligence advancement that are pertinent to coronary computed tomography angiography here, examining the cardiovascular system including heart and majorly concerning artery, coronary artery, overall (Fig. 1).

The foundation of coronary computed tomography angiography is coronary artery analysis, which offers firsthand knowledge of coronary artery disease [3]. Anatomically and functionally important stenoses can

result from obstruction of the major blood arteries feeding the heart, which is characterized by a number of diseases [4]. The automated analysis of coronary computed tomography angiography using AI has attracted a lot of attention because of the wide heterogeneity in anatomy and pathology. Both human and computerized coronary computed tomography angiography analysis need the extraction of the coronary artery centerline. Multi-planar reconstruction and curved multi-planar reconstruction illustrations, which are often utilized while the identification of coronary artery disease, may be produced thanks to extracted centerlines [5].

The centerlines of the coronary arteries and the associated multiplanar reformatted are also necessary for computerized coronary computed tomography angiography analysis frameworks. Multiple self-activating and semi self-activating techniques for coronary conduit centerline extraction have been created because of the work escalated nature of manual extraction [6]. Using classic minimal cost route algorithms or trackers, which frequent depended substantially on user intervention, centerlines were recovered in conventional procedures by joining two semi self-activating specified edges of the vessel in the volume of coronary computed tomography angiography. For the detection of the seed point of coronary conduit and to navigate the detector without needing operator intervention. Back then, hand-crafted filters as shown in Figure 2 were famous but Wolter et al. [7] introduced the convolutional neural networks. However, tracking via exceedingly convoluted arteries or severe instances of stenosis and categorization remained difficult. In order to mitigate this problem later methods were created [8,9]. In order to generalize effectively to different degrees of size and

The role of artificial intelligence in coronary CT angiography

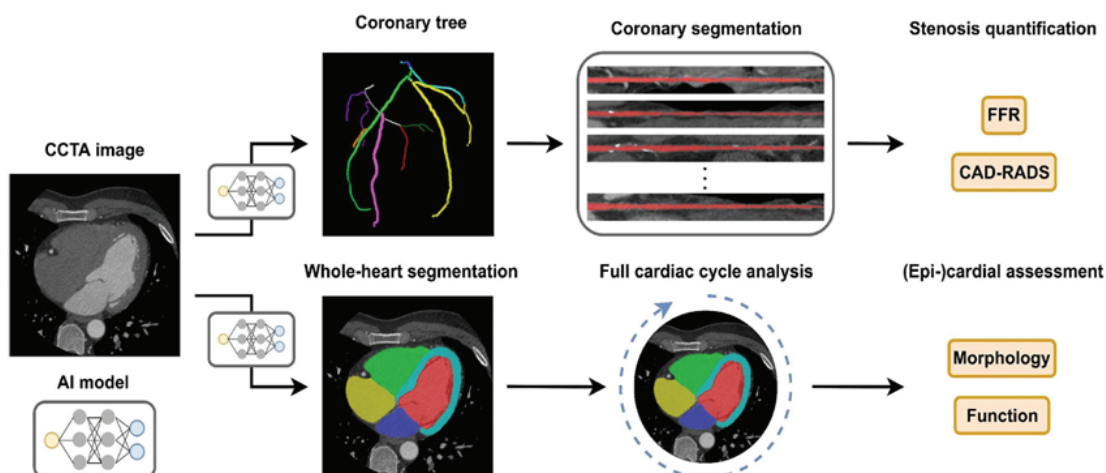


Figure 1. Infographic: An AI-driven flowchart analysis of coronary computed tomography angiography.

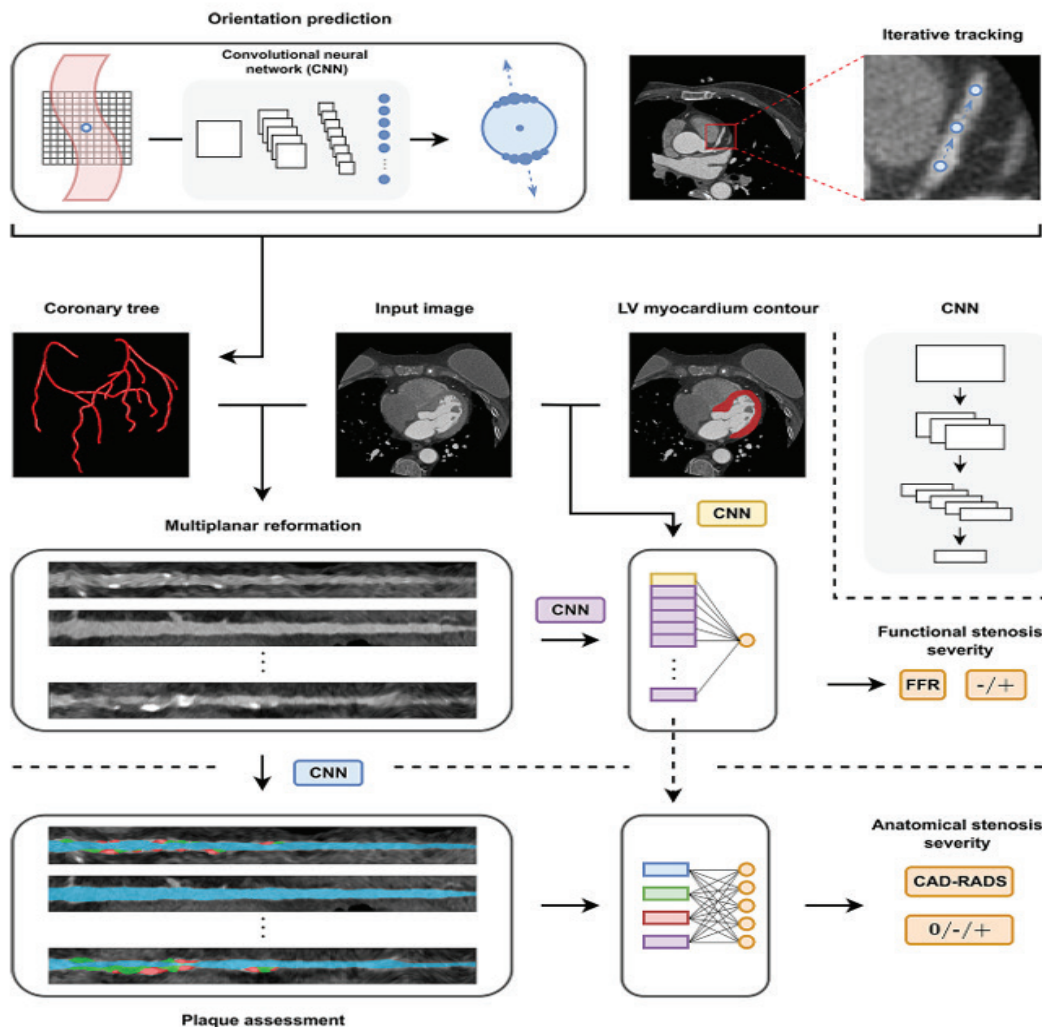


Figure 2. Image-based analysis of anatomical and functional stenosis severity of the coronary arteries.

tortuosity, Alblas et al. [10,11] recently created a detector with the use of radial and scale symmetries present in data taken from vascular system. Notably, when prepared exclusively on information of coronary artery, their approach accurately traced the centerlines of the abdominal aorta, suggesting a general ability to anatomies not encountered during training.

In order to automatically extract coronary artery centerlines, the orientation of vessel for the patches of picture centered around the coronary artery is iteratively predicted. From centerline, multiplanar reformatted pictures are taken. The left ventricular myocardium and multiplanar reformatted are both used to extract characteristics using a neural network. (Middle) To forecast the presence and/or severity any functional stenoses, features are employed [12]. To anticipate the degree of anatomical stenosis, a division of a lumen and plaque stage is carried out later (Bottom).

CORONARY TREE LABELLING

As per recommendation, coronary computed tomography angiography reports must have the segment-level data on the position of identified atherosclerotic lesions and stenosis. The coronary tree's automatic labeling might help doctors by expediting the diagnosing process. Originally studied, atlas-based registration [13] has limitations in managing the coronary tree's morphological diversity, since deep neural networks have the expressive capacity to better manage significant inter-patient anatomical variances, they have been proven to be more appropriate for the job. Inspired by its natural form, researchers of deep learning usually depict the coronary tree with graphical representation which shows the coronary segments as its nodes. First deep neural networks-based segmented labeling framework is derived by Wu et al. [14], modeled with the graphical representations of coronary trees using recurrent neural networks, graph neural networks have been proposed as a way to take use of the intrinsic graph structure. Among the

first to use graph neural networks for segment labeling were Yang et al. [15]. Their solution was particularly resilient to damaged cardiac tree data and performed better than the recurrent neural networks-based strategy. The prospects of exploiting the planned interlinks of the segments of coronary as previous record was recently recognized by Zhang et al. [16]. In order to impose anatomically realistic labeling and establish the unconventional area, they injected stringent topology into a structure based on graph neural networks. In the context of diagnosing coronary artery disease, the main objective of clinical coronary computed tomography angiography interpretation is to locate and describe the degree of anatomical stenosis. However, visual evaluation may be a laborious and difficult process that is subject to inter-observer variation. Therefore, the diagnostic work flow may be more reliable and efficient using an automated stenosis evaluation system. An initial lumen segmentation step is usually required for automatic stenosis assessment. Directly, either the stenosis [17,18] or post-processing of the segmented volumes [19,20] can be used to for the localization of stenosis. Earlier, for the segmentation of the lumen, conventional computerized vision methods were used [21], most current studies have used techniques based on deep learning. For instance, demonstrated a significant correlation between accurately characterized stenosis measures and stenosis biomarkers identified using deep neural networks-derived lumen segmentations also suggested using a deep neural networks to identify severe stenosis after initially segmenting the coronary tree. Despite using a traditional voxel-based technique, voxel-wise segmentation may not be able to satisfy the quality requirements of jobs

that come after. In order to attain sub-voxel precision and anatomically believable, contiguous findings, researchers have begun using deformable shape priors as an option to the paradigm based on voxel [22,23]. The coronary artery disease reporting and data system was created in order to standardize coronary computed tomography angiography-based coronary artery disease reporting. It majorly outlines a severity of stenosis categorization system based on the intensity of anatomical stenosis in coronary arteries. Therefore, for better assessment, a technique based on the deep learning of stenosis that predict substantial stenosis or extract coronary artery disease reporting and data system scores straight from the image data have been proposed by researchers. Muscogiuri et al. [24], for mince, developed a convolution neural network-based classification technique that shows excellent diagnostic accuracy. By training convolution neural networks to predict coronary artery disease reporting and data system scores along with the auxiliary tasks of segment-level significant stenosis and patient-level calcium score prediction. Denzinge et al. [25] outperformed their results, demonstrating that combining coronary artery disease reporting and data system prediction with highly correlated secondary targets can significantly improve model performance. During coronary computed tomography angiography reporting, it is advised to characterize plaque types as calcified, non-calcified, or mixed. Typically, radiomics methods have been used to die prediction models [26]. Researchers have included features of plaque categorization and quantification into a framework based on the deep learning of stenosis, due to the potential of prediction of models as shown in Figure 3. Zreik et al. [27] studied

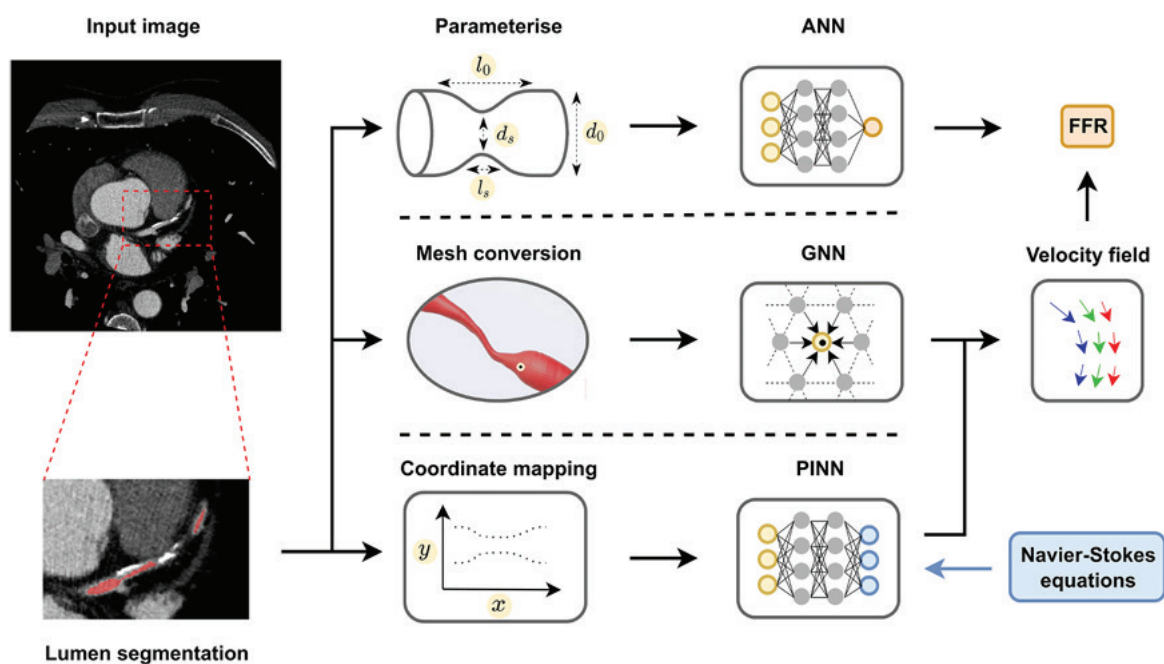


Figure 3. Geometry-based surrogates for assessment of functional stenosis severity.

that the input of multiplanar reformatted were segregated into an equal amount of volume which was also further segregated and then swallowed into the recurrent neural networks that classified the kind of plaque and the severity of stenosis at the segment level. Numerous studies have been examined voxel-level measurement of calcified plaque, which usually yields a significant connection with calcium level of coronary artery calculated from the reference standard of the society of cardiovascular computed tomography. Estimation of the burden of plaque and coronary artery disease reporting and data system score assignment based on the stenosis quantification were made possible voxel-level plaque characterization utilizing recurrent neural networks for semantic segmentation of lumen, calcified, and noncalcified plaque. In a multi-cohort validation, it was demonstrated that stenosis measures had a significant correlation with intravascular coronary angiography, whereas deep learning-based plaque load assessments corresponded very well with expert visual evaluation and intravascular ultrasonography. Future cardiac events might be predicted using the total plaque volumes determined by deep neural networks, recently presented a pipeline based on deep learning. Using a 3D convolution neural network, surface networks for the lumen, clotted, and non-clotted plaque are extracted by utilizing cylindrical shape priors. After reformatting to one-dimensional signals, the meshes are fed into a convolution neural network that predicts the coronary artery disease reporting and data system score.

Graph Neural Networks (GNNs) have significantly advanced the automatic labeling of coronary artery trees by overcoming the structural and contextual limitations of Recurrent Neural Networks (RNNs).

GNNs are distinct from RNNs due to their specific handling of graph structured data as compared to RNNs which

Process data step by step and often struggle with complex vessel branching and spatial relationships. For modeling coronary anatomy as a network of connected vessel segments and junctions GNNs are best suited. This format describe that nodes stands for vessel segment while edges explain the connection of different branches. Information is transitory between neighboring nodes which enables the narrow features of GNNs like curvature, diameter, alignment and extensive structural patterns such as how vessels are regularized within the coronary tree. This let them to identify the diverse coronary segment precisely comprising LAD, LCx, RCA and their branches, indeed there are anatomical divergence or distortion in the imaging data. Furthermore GNNs are most resilient and flexible because they do not count for the straight processing like RNNs. Probes illustrate that GNN based methods accomplish enhanced labeling precision and sustain more compatible vessel structures and provide obvious analyzability. As a result, they are now widely considered one of the most effective approaches for automatic coronary tree labeling in CCTA analysis.

According to Itu et al. twelve, one approach is to describe a stenotic lesion using its geometric properties. These features can then be used to train an artificial neural network to directly predict fractional flow reserve. Another approach involves using graph neural networks, which can operate directly on the luminal mesh generated automatically from the data [28]. This allows for the prediction of velocity fields within the coronary arteries. Moreover physics informed neural network can be employed to discover solutions that fulfill the Navier-Stokes equations although integrate the geometry of artery [29]. This create potential to evaluate velocity fields in a way that is steady with both fundamental physics and vessel structure.

In the last few years, many researches have concentrated on enhanced nanofluid and non-Newtonian flow models to comprehend fluid behaviour under magnetic and thermal impact. Murtaza and Naveen [30] scrutinize radiative second-grade nanofluid flow with Thomsaon and Troian slip situation, underlining how nanoparticle shape prerogate heat transfer. Sathya and Naveen [31] dilate on this by implementing regression evaluation to magnetized power-law nanofluid flow over a thin needle, proving its implicit use in purposed drug delivery. Sathya et al. [32] additionally examine this area with the help of multiple regression techniques to scrutinize Blasius and Sakiadis flow of power-law nanofluids, providing valuable forecast for surface motion and heat transfer manners. Naveen et al. [33] prolong the task by assimilating artificial neural network models to analyze Casson hybrid nanofluid flow with entropy development, indicating that how data driven strategy can help to upgrade thermal systems. Moreover, Suriya and Naveen [34] executed a least cost analysis of magnetized Sutterby nanofluid with the help of ANOVA-RSM structure, demonstrating the worth of combining statistical and computational approach to enhanced flow irreversibility and magnetohydrodynamic impact.

Suriya and Naveen [35] also examine electrically magnetized Eyring-powell nanofluid flow, revealing that viscous dissipation plays an significant part in flow irreversibility. Sathya and Naveen supervised a relative study on titanium dioxide power-law nanofluids under emissive and convecting estate, emphasizing their implicit in cancer treatment applications. In further studies. Naveen et al. [36] inspect Sutterby fluid behaviour with higher order chemical reactions, giving better understanding into complex non-Newtonian flow features. Sathya and Naveen further delves into nonlinear thermal convection in magnetized dissipative flow over a shrinking Riga sheet, with a rivet on entropy generation and thermodynamic competence in both industrial and biomedical circumstances. Collectively, these work give a strong cornerstone for combining artificial intelligence, nanofluid mechanics, and nonlinear rheology. Nevertheless, the unification of viscoelastic Maxwell fluid dynamics within a Physics-Informed Neural Network framework for authentic arterial flow modeling has not yet been negotiated. The current review, consequently,

be certain about this foundation by broadening the exertion of AI-driven physical modeling to coronary blood flow, immolating a narrative hybrid technique that overpasses classical fluid mechanics with deep learning-based imitation.

Modern coronary computed tomography angiography (CCTA) is a validated, guideline-endorsed, non-invasive alternative for detection of coronary stenosis and importantly for direct visualization and quantification of coronary plaque. CCTA provides high diagnostic accuracy and an excellent negative predictive value that safely rules out obstructive disease in patients with low-to-intermediate pretest probability, reduces unnecessary invasive procedures, and enables characterization of plaque composition and burden (including high-risk features) that is not achievable with conventional angiography alone. Large trials (e.g., SCOT-HEART) and contemporary guideline statements support the use of CCTA to guide management and improve outcomes. We therefore used CCTA in this study to non-invasively define anatomy and plaque characteristics prior to modeling, while acknowledging that ICA/IVUS/OCT remain indispensable when invasive intervention or highest-resolution plaque imaging is required.

Coronary artery centerline extraction is a critical pre-processing step in CCTA-based analysis because it provides the geometric backbone of the coronary tree, enabling accurate lumen segmentation, plaque localization, vessel curvature assessment, and quantitative evaluation of stenosis severity. Specific turning points are also crucial for 3D reconstruction, computational fluid dynamics (CFD) simulations, and fractional flow reserve (FFR-CT) computations, as even small geometric errors can lead to large errors in hemodynamic metrics. Prior strategies for coronary midline removal mainly relied on minimal-cost path and graph-based strategies, involving Dijkstra's algorithm and Fast Marching methods. In these methods, the vessel lumen is modeled as a cost function, and the midline is discovered by estimating the optimal path between manually selected endpoints. While potent to some extent, such techniques are essentially finite by their reliance on built-in cost metrics and user arbitration. In comparison, Convolutional Neural Networks (CNNs) have primarily reconsidered the performance and automation of coronary artery midline extraction. By exploiting data-driven organized feature learning, CNNs can directly handle volumetric CCTA data to distinguish vessel structures from surrounding tissues and imaging artifacts with high accuracy. Enhanced framework, involving 3D U-Net, V-Net, and attention-improved CNN conflict leverage multi-scale contextual illustrations to concurrently apprehend global anatomical continuity and elaborate local vessel structure. This competence empowers robust delineation of highly twisting and miniature distal branches, majorly surpasses traditional minimal-cost path-based techniques in both precision and reliability.

In recent times, Physics-Informed Neural Networks (PINNs) have appeared as a robust computational

framework for solving complex partial differential equations through the definite incorporation of ruling physical laws into the loss function. This composition permits the direct approximation of nonlinear systems without assurance on structured meshing, thereby substantially improving their suitability to problems in fluid dynamics, heat transfer, and biomedical transport processes. Initial researches by Raissi et al. (2019), Cuomo et al. (2022), and Kissas et al. (2020) have illustrated the potency of PINNs in modeling laminar and pulsatile blood flow. Even so, the majority of these researches remain restrained to Newtonian premise or relatively clarified non-Newtonian formulations, thereby constraining their capacity to precisely apprehend the complex rheological behaviour, features of realistic biological flows. At the same time, customary numerical methods such as the Finite Volume Method (FVM) and Finite Element Method (FEM) remain the ordinary tools for affecting hemodynamics in stenosed arteries, yet they are computationally challenging and mesh-sensitive when employed to realistic, patient-specific geometries. Regardless of comprehensive work on arterial fluid mechanics, the combined impact of viscoelasticity, thermal effects, and magnetic parameters within an AI-based framework has obtained very low emphasis. Furthermore, the assimilation of Maxwell type viscoelastic rheology into PINNs and its computable standard against FVM solvers has not disclosed in the open literature.

In light of these limitations, the present study develops a hybrid Physics-Informed Neural Network (Maxwell) framework to model blood flow, temperature, and wall shear stress in healthy and stenosed coronary arteries. The proposed approach not only captures the elastic memory characteristics of blood but also enables a mesh-free, computationally efficient solution when compared with the Finite Volume Method implemented in ANSYS. This study therefore contributes a novel, data-driven yet physics-consistent methodology that aligns with the journal's scope in computational fluid dynamics, applied mathematics, and biomedical flow modeling, offering new insights into the interplay between viscoelasticity, geometry-induced resistance, and heat generation in coronary circulation.

Functionally Significant Stenosis

The extent which stenosis restricts a coronary artery's downstream blood flow determines its functional relevance [37]. The ratio between the areas proximal and distal to the stenotic is determined by fractional flow reserve which is used in practice to assess the flow [38]. Functional stenosis severity, a non-intrusive measurement test from coronary computed tomography angiography has attracted a lot of attention because this invasive test is expensive and stressful for patients [39]. For the self-activating prediction of this intrusive test from coronary computed tomography angiography, a number of techniques have been put forth, they be broadly categorized into two groups. The algorithms from first class evidently shows geometric and

anatomical properties of coronary tree from coronary computed tomography angiography [40–42]. By sorting the differential equations iteratively, the technique of finite element can approximate the blood flow parameters after segmentation of lumen transformed into a triangular shaped meshes by using the standardize approach of computational fluid dynamics in the first place [43–46]. Research on meta-models for effective flow of blood parameterization has increased recently due to the computational cost of such approaches. deep neural networks are a common candidate for such a surrogate model due to their quick inference, Figure 4 provides an overview. They trained the network by using 12,000 simulated coronary tree anatomies and suggested fractional flow reserve values simulated from computational fluid dynamics. The suggested ANN has been thoroughly tested and decreases calculation time by over 80 times when compared to traditional computational fluid dynamics-based methods. Morphology and stenosis severity features are used to approximate fractional flow reserve at each location around the coronary artery as Itu et al. made an artificial neural network. The computed tomography morphological index by introducing the ANN which was improved the predictive value by using the work of Itu et al. Later, recurrent artificial neural networks were used to simulate fractional flow reserve values in order to investigate long-range relationships between artery segments. As an alternative, whole 3D velocity fields may be inferred using deep learning techniques, allowing for the direct computation FFR. The GNNS directly works on geometrical meshes which is an input to estimate velocity fields. These were employed. Coronary tree anatomies were produced by the techniques for which reference velocity fields were computed using computational fluid dynamics. With just a modest quantity of training data, at inference the gated neural network can estimated the desired velocity fields that are almost instantaneous. Additionally, to solve the underlying differential equations in computational fluid dynamics, deep learning has been used directly. Physics-informed neural networks are used to anticipate dense velocity fields. And the solution was determined by using

Navier-Stokes equation implicitly while taking artery wall boundary conditions into account. Compared to traditional computational fluid dynamics methods, this has a number of benefits, including resilience to noisy observed data and poor resolution. However, because the approach is iterative, much like computational fluid dynamics, it is somewhat sluggish when compared to other deep learning options. computational fluid dynamics metamodel based on deep learning have the drawback of depending on segmentations of lumen to accurately forecast functional stenosis, which requires a precise reconstruction of the artery geometry. Therefore, instead of using a geometric data-based method, the other group of algorithms concentrates directly in predicting the functionality of important stenosis from image information. Usually, a computer vision model is trained on coronary computed tomography angiography image areas of interest to do this. The left ventricular myocardium and the coronary artery tree are regarded as areas. A pre-processing segmentation phase is used to identify them. For instance, Zreik et al. [47] suggested a convolution neural network to extract myocardial characteristics, which are then used by a support vector machine to categorize the degree of functional stenosis at the patient level. Subsequent research improved the diagnostic accuracy of functional stenosis prediction by combining a convolution neural network-based study of the myocardium and coronary artery tree [48]. In their explainable approach. Hampe et al. [49] described coronary arteries using pathological and anatomical data gleaned by using a multi-planar image along with the coronary artery tree. After that, a neural network identified the functional relevance of the stenosis by directly regressing the fractional flow reserve value. Kumamaru et al. [50] suggested an alternative method that does not need segmentation. The technique uses automated identification of aberrant areas surrounding the coronary artery lumen to detect regression of fractional flow reserve and functional stenosis from start to finish.

This makes it possible to quantify important clinical risk indicators such the left ventricular ejection percent, cardiac shape and function, and the presence of epicardial adipose

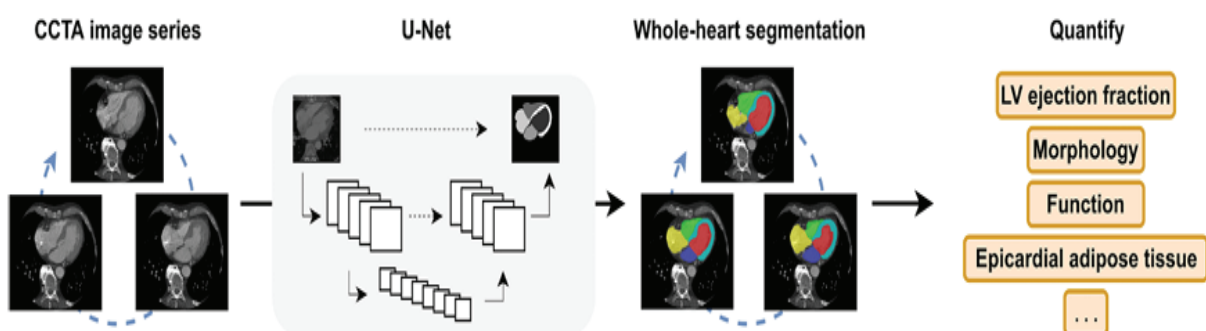


Figure 4. Whole heart image analysis typically involves the segmentation of cardiac structures such as the cardiac chambers and the epicardium.

tissue given a sequence of coronary computed tomography angiography images taken during the cardiac cycle.

Whole Heart Analysis

Large artery and cardiac chamber analysis may offer important new information for predicting cardiovascular risk. In clinical settings, this analysis is not frequently carried out since manual cardiac delineation takes around five hours per 3D picture volume [51]. Deep learning techniques, however, can assist in locating and measuring important structural elements.

Whole Heart Segmentation

During the analyzation of the whole heart, left ventricular myocardium and pericardium are examined due to the significance of left cardiac chambers. Although early techniques suggested segmentation based on models or atlases [52,53], techniques based on deep learnings had been demonstrated to execute better than conventional methods. The majority of deep leaning-based techniques take into account the CNN-based voxelwise segmentation of cardiac structures, each element is assigned to a particular category that corresponds to the composition of heart which it belongs to this as shown in Figure 4. These techniques provide extremely accurate delineations [54,55]. One drawback of voxelwise segmentation is that it usually does not penalize nonphysical artifacts or forms that are anatomical improbable. Therefore, several investigations use segmentation based on heart shape limitations. For instance, Kong et al. [56] suggested reconstructing exterior network for every object within the segmentation of the whole heart. This was accomplished by using a GNN to repeatedly bend a sphere to the desired heart shape, producing a high-resolution cardiac mesh. In order to derive a feature representation, Attar et al. [57] suggested merging patient metadata with pictorial information. A mesh depiction of the heart chambers is then created using them.

Downstream Analysis

In order to do a functional examination of the entire heart, more and more clinical investigations are obtaining 3D coronary computed tomography angiography images throughout the cardiac cycle. These images may be segmented, and heart function can be measured by downstream studies. Pictures obtained for transcatheter aortic valve installation are used for treatment planning in morphological examination, for instance, showed that the left ventricular ejection fraction could be accurately quantified. Szilveszter et al. [58] demonstrated the feasibility of utilizing coronary computed tomography angiography for the quantification of deformation vectors in the assessment of left ventricular and atrial strain.. Moreover, Commandeur et al. used pericardial border delineations to measure epicardial adipose tissue [59]. In recent years, it has been demonstrated that perivascular and epicardial adipose tissue deposits affect the evaluation of cardiovascular risk [60].

Research Gap and Motivation of This Study

The present study differs from previous works by integrating Physics-Informed Neural Networks (PINNs) with the Maxwell non-Newtonian model to simulate blood flow in stenosed coronary arteries, providing a more realistic representation of blood's viscoelastic behavior. Unlike conventional Computational Fluid Dynamics (CFD) or purely data-driven approaches, the proposed method embeds the governing physical laws directly into the neural network's learning process, ensuring physics-consistent solutions. The present study incorporates a comprehensive validation framework through a detailed comparison with Finite Volume Method (FVM) simulations performed in ANSYS Fluent, an aspect that remains largely underexplored in prior investigations. The obtained results are analyzed with substantial physical and clinical grounding, explicitly correlating flow behavior with underlying hemodynamic implications. Collectively, this integrated AI-CFD framework establishes a novel, precise, and computationally efficient methodology for modeling coronary hemodynamics, with potential applicability to a broader class of biomedical flow problems.

This work addresses a critical gap in Coronary Computed Tomography Angiography (CCTA) analysis by incorporating the viscoelastic Maxwell blood flow model within a Physics-Informed Neural Network (PINN)s [61] framework, an area that has not been sufficiently examined in existing literature. Earlier research have primarily employed PINNs for solving rulling equations , involving partial and ordinary differential equation, with finite concentration on comparitve substantiation or their prolongation to complex non-Newtonian models such as the Maxwell fluid. Influenced by the requirement for more physiologically realistic and clinically significant modeling techniques, this research assimilate the Maxwell fluid formulation and accomplish a systematic comparison between PINNs and the Finite Volume Method executed in ANSYS Computational Fluid Dynamics. The rulling equations portraying velocity and pressure distributions in stenosed coronary arteries are figured out with the help of both techniques to empower a steady appraisal.

The relative analysis disclose that, even though FVM proffers steady and computationally competent solutions, its built in dependence on mesh generation limitations its accomplishment in geometrically complex fields. On the other hand, PINNs elaborate improved precision, higher flexibility and enhanced ability in managing nonlinearities and complicate arterial geometries. The outcomes validate the potency of PINNs in modeling Maxwell-type blood flow and position them as a convincing substitute to conventional CFD methods. Moreover, this work assist toward the upgrading of more reliable and clinically applicable diagnostic tools in CCTA-based hemodynamic evaluation, thereby handling a substantial flaws in current study.

Ethical Approval and Informed Patient Consent

This research obtained endorsement from the institutional honorable Review Board of Faisalabad Cardiology Hospital, Pakistan. All protocols were executed in imperious adherence with suitable recommendations and legislative norms. Explicit conversant assent was gained from all participants preceding to the involvement of their imaging data in the research. The obfuscated Coronary Computed Tomography Angiography (CCTA) images were earned by Dr. Kubra Anjum during routine clinical practice and were implemented solely for academic and research purposes.

Governing Equations

The flow of Maxwell-type blood through stenosed arteries is illustrated by integrated system of continuity, momentum, energy, and concentration equations, jointly attribute the viscoelastic, thermal, and mass captivate behaviour of blood under physiological estates. The continuity equation impose the incompressibility restraints while the momentum equation, devised as specific Navier-stokes expression, integrate both viscous and elastic stress impact through the Maxwell constitutive model. The involvement of a relaxation time criterion make it possible the depiction of memory-dependent fluid behaviour, consequently apprehending the combined viscous elastic reaction of blood, specifically under pulsatile conditions and lifted shear rates in the locality of arterial stenosis. The energy equation manage heat transfer method emerging from viscous dissipation and thermal conduction within the arterial field, whereas the accumulation equation version for the transport chemical species, such as oxygen or hanging nanoparticles, within the medium.

The physiological flow of the ill and almost healthy models was simulated by solving the Navier-Stokes equations conservation equations with finite volume and the continuity equation using ANSYS Fluent. A turbulent blood flow is caused by different levels of stenosis, which lead to blockage and recirculation. The walls were subjected to a noslip boundary condition, assuming that the plaque was rigid. Then, blood is recalled to resemble the characteristics of blood in coronary veins by being an incompressible, non-Newtonian liquid with a constant thickness of 1060 kg/m^3 . Next, as stated in [1], are the controlling parameters for the three-layered mass and energy preservation associated with the blood stream. However, it is important to note that the PINN framework itself is general and model-independent. In principle, it can be extended to other types of fluids (Newtonian or non-Newtonian) by simply embedding the corresponding governing equations and boundary conditions into the loss function. In this work, we focused on the Maxwell non-Newtonian model to capture the realistic rheology of blood in stenosed arteries. Future studies can adapt the same methodology for Newtonian, power-law, or hybrid nanofluids by redefining the constitutive relations within the PINN formulation.

Maxwell Fluid Model in 3D for Blood Properties

Maxwell fluid model in 3D for Blood Properties are as follows:

Continuity equation (conservation of mass)

The continuity equation for an incompressible fluid in 3D Cartesian coordinates is:

$$\frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z} = 0, \text{ where, } u_x, u_y, u_z \text{ are the velocity components in the } x, y \text{ and } z \text{ directions, respectively.}$$

Momentum equation for Maxwell fluid

The momentum equation for a Maxwell fluid in 3D Cartesian coordinates is:

$$\begin{aligned} & \frac{\partial u_x}{\partial t} + u_x \frac{\partial u_x}{\partial x} + u_y \frac{\partial u_x}{\partial y} + u_z \frac{\partial u_x}{\partial z} \\ &= \frac{-1}{\rho} \frac{\partial p}{\partial x} + \mu \left(\frac{\partial^2 u_x}{\partial x^2} + \frac{\partial^2 u_x}{\partial y^2} + \frac{\partial^2 u_x}{\partial z^2} \right) + \lambda \left(\frac{\partial u_x}{\partial t} - \frac{\partial^2 u_x}{\partial x^2} - \frac{\partial^2 u_x}{\partial y^2} - \frac{\partial^2 u_x}{\partial z^2} \right) \end{aligned}$$

Similarly, for u_y and u_z , we have:

$$\begin{aligned} & \frac{\partial u_y}{\partial t} + u_x \frac{\partial u_y}{\partial x} + u_y \frac{\partial u_y}{\partial y} + u_z \frac{\partial u_y}{\partial z} \\ &= \frac{-1}{\rho} \frac{\partial p}{\partial y} + \mu \left(\frac{\partial^2 u_y}{\partial x^2} + \frac{\partial^2 u_y}{\partial y^2} + \frac{\partial^2 u_y}{\partial z^2} \right) + \lambda \left(\frac{\partial u_y}{\partial t} - \frac{\partial^2 u_y}{\partial x^2} - \frac{\partial^2 u_y}{\partial y^2} - \frac{\partial^2 u_y}{\partial z^2} \right) \end{aligned}$$

$$\begin{aligned} & \frac{\partial u_z}{\partial t} + u_x \frac{\partial u_z}{\partial x} + u_y \frac{\partial u_z}{\partial y} + u_z \frac{\partial u_z}{\partial z} \\ &= \frac{-1}{\rho} \frac{\partial p}{\partial z} + \mu \left(\frac{\partial^2 u_z}{\partial x^2} + \frac{\partial^2 u_z}{\partial y^2} + \frac{\partial^2 u_z}{\partial z^2} \right) + \lambda \left(\frac{\partial u_z}{\partial t} - \frac{\partial^2 u_z}{\partial x^2} - \frac{\partial^2 u_z}{\partial y^2} - \frac{\partial^2 u_z}{\partial z^2} \right) \end{aligned}$$

Heat equation for Maxwell fluid

The heat equation in 3D Cartesian coordinates is:

$$\rho c_p \frac{\partial T}{\partial t} + u_x \frac{\partial T}{\partial x} + u_y \frac{\partial T}{\partial y} + u_z \frac{\partial T}{\partial z} = k \left(\frac{\partial^2 T}{\partial x^2} + \frac{\partial^2 T}{\partial y^2} + \frac{\partial^2 T}{\partial z^2} \right)$$

Concentration equation for Maxwell fluid in 3D

The concentration equation in 3D for Maxwell fluid is a transport equation for the scalar concentration field

$$C(x, y, z, t):$$

$$\rho \frac{\partial C}{\partial t} + u_x \frac{\partial C}{\partial x} + u_y \frac{\partial C}{\partial y} + u_z \frac{\partial C}{\partial z} = D \left(\frac{\partial^2 C}{\partial x^2} + \frac{\partial^2 C}{\partial y^2} + \frac{\partial^2 C}{\partial z^2} \right)$$

Where:

- $C(x, y, z, t)$ is the concentration of the species in the fluid.
- ρ is the density of the fluid.
- u_x, u_y, u_z are the velocity components in the x, y and z directions.
- D is the diffusion coefficient.
- $\frac{\partial^2 C}{\partial x^2} + \frac{\partial^2 C}{\partial y^2} + \frac{\partial^2 C}{\partial z^2}$ are the second derivatives of concentration with respect to spatial coordinates, representing diffusion in the respective directions.

In the x -axis and y -axis, the components of velocity are represented by u and v , respectively. Present body forces (f), fluid viscosity, and pressure (p) are the variables involved in the equation. This study uses Maxwell's blood viscosity model, which permits the viscosity coefficient to change in response to the shear rate, therefore accounting for shear thinning.

Non-dimensionalization of the Governing Equations

To obtain a dimensionless representation of the flow and heat/mass transfer in the stenosed artery, the governing equations are nondimensionalized using the following characteristic scales:

$$L = R_0, U = U_{max}, p = \rho U^2, T = T_w - T_\infty, C = C_w - C_\infty$$

where, R_0 is the reference arterial radius, U_{max} is the peak inlet velocity, and T_w and C_w denote the wall temperature and concentration, respectively.

The dimensionless variables are defined as:

$$x = \frac{x'}{L}, y = \frac{y'}{L}, u = \frac{u'}{U}, v = \frac{v'}{U}, p = \frac{p'}{p}, \\ \theta = \frac{T' - T_\infty}{T}, \phi = \frac{C' - C_\infty}{C}.$$

Substituting these into the dimensional continuity, momentum, energy, and concentration equations yields the nondimensional system:

$$\nabla \cdot u = 0, \\ \frac{\partial u}{\partial t} + (u \cdot \nabla)u = -\nabla p + \frac{1}{\Re} \nabla^2 u - Ha^2 u + DeF(u), \\ \frac{\partial \theta}{\partial t} + (u \cdot \nabla)\theta = \frac{1}{PrRe} \nabla^2 \theta + Br\Phi(u), \\ \frac{\partial \phi}{\partial t} + (u \cdot \nabla)\phi = \frac{1}{ScRe} \nabla^2 \phi,$$

where, the dimensionless groups appearing above are:

$$\Re = \frac{\rho U L}{\mu}, Pr = \frac{\mu c_p}{k}, Sc = \frac{\mu}{\rho D}, De = \lambda \frac{U}{L}, Ha = \frac{B_0 L}{\sqrt{\mu/\sigma}},$$

and the stenosis ratio is defined as

$$SR = \frac{R_0 - R_{min}}{R_0}.$$

Here, $F(u)$ denotes the dimensionless viscoelastic contribution (for the Maxwell or Oldroyd-B model), $\Phi(u)$ is the viscous dissipation term, and B_0 is the applied magnetic field strength. These nondimensional equations form the basis for the numerical simulations and the PINN training described in subsequent sections.

Maxwell Blood Flow in Coronary Arteries by Using Pinns Model

The detailed computational procedure of the proposed Physics-Informed Neural Network (PINN) [62] for Maxwell blood flow in stenosed coronary arteries is summarized in Algorithm 1. The algorithm demonstrates how the governing physical laws including continuity, momentum, energy, and concentration equations are embedded into the neural network learning framework. The process begins with initialization of geometry and physical parameters, followed by residual computation for each governing equation. The integrated loss functional, comprehensive both empirical data distinctiveness and physics-informed remnant, is repetitively undersized via the Adam stochastic upgrading design. The training continues until convergence, and the final network outputs velocity, pressure, temperature, and concentration distributions. The step-by-step structure of the algorithm is given in Table 1.

In the Physics-Informed Neural Networks (PINNs) framework, the governing equations for continuity,

Table 1. Algorithm 1: Physics-Informed Neural Network (PINN) framework for Maxwell blood flow in stenosed coronary arteries

Step	Description
1	Input: Define geometry of stenosed artery, Maxwell fluid parameters (λ, μ), boundary conditions, and collocation points for training.
2	Initialization: Casually stimulate neural network weighs θ and partiality; finalizing learning rate η and streamline (Adam).
3	Forward propagation: For every drop point, evaluate expected velocity u , pressure p , temperature T , and concentration C from the neural network.
4	Residual computation: Estimate remnant of the rulling equations: continuity, momentum, energy, and concentration equations.
5	Loss formulation: Devise total loss function $L = L_{data} + L_{physics}$, where $L_{physics}$ depict the mean- squared leftover of all PDEs.
6	Parameter update: Put on Adam optimizer to lessen L and upgrade parameters $\theta \leftarrow \theta - \eta \frac{\partial L}{\partial \theta}$.
7	Convergence check: Reiterate Steps 3–6 until loss is underneath the endurance or maximum periodattained.
8	Output: Acquire final specialty of velocity, pressure, temperature, and concentration for the concentrated realm.
9	Post-processing: Envision outline of flow fluctuation and compare with FVM results for verification.

momentum, heat, and concentration are embedded into the neural network's loss function. The network predicts velocity, pressure, temperature, and concentration fields, and the residuals of each equation are computed at randomly sampled collocation points within the domain.

These remaining assist as numeric assess of the scale to which the model prophecy stick to the controlling physical laws. The bulk loss functional include leftover impact from all rulling equations, moreover to sanction originating from perimeters and beginning conditions invasion. Through repetative understating employing improved refinement algorithms such as Adam and L-BFGS, the system thoroughly dimiinish these remainings, thus implementing steadiness of the expected fields with the basic physical principles across the whole computational realms.

In the background of blood flow among coronary arteries, blood is adapted as a Maxwell fluid, which report for both elastic and viscous impact. The governing equations for Maxwell fluid in a three-dimensional domain with stenosis are as follows:

Continuity equation (conservation of mass)

The continuity equation in 3D for a fluid is:

$$\nabla \cdot u = 0$$

Where $u = (u_x, u_y, u_z)$ is the velocity field. The residual for the continuity equation in the PINNs method is:

$$f_{cont} = \frac{\partial u_x}{\partial x} + \frac{\partial u_y}{\partial y} + \frac{\partial u_z}{\partial z}$$

The corresponding loss function is:

$$L_{cont} = \frac{1}{N_{cont}} \sum_{i=1}^{N_{cont}} |f_{cont}(x_i, y_i, z_i, t_i)|^2$$

Momentum equation for Maxwell fluid

The momentum equation for Maxwell fluid in 3D is given by:

$$\frac{\partial u}{\partial t} + (u \cdot \nabla)u = \frac{-1}{\rho} \nabla p + \mu \nabla^2 u + \lambda \left(\frac{\partial u}{\partial t} - \nabla \cdot \tau \right),$$

Where: $u = (u_x, u_y, u_z)$ is the velocity field, p is the pressure, ρ is the density, μ is the dynamic viscosity, λ is the Maxwell relaxation time. The residual for the momentum equation in the x -direction is:

$$f_{mom_x} = \frac{\partial u_x}{\partial t} + u_x \frac{\partial u_x}{\partial x} + u_y \frac{\partial u_x}{\partial y} + u_z \frac{\partial u_x}{\partial z} + \frac{1}{\rho} \frac{\partial p}{\partial x} - \mu \nabla^2 u_x$$

The momentum equation residuals for the y - and z -components are similarly defined. The total loss for momentum is:

$$L_{mom} = L_{mom_x} + L_{mom_y} + L_{mom_z}$$

Heat equation

The heat equation in 3D for Maxwell fluid is:

$$\rho c_p \frac{\partial T}{\partial t} + u \cdot \nabla T = k \nabla^2 T$$

Where: $T = (x, y, z, t)$ is the temperature, ρ is the density, c_p is the specific heat capacity, k is the thermal conductivity. The residual for the heat equation is:

$$f_{heat} = \rho c_p \frac{\partial \hat{T}}{\partial t} + \hat{u}_x \frac{\partial \hat{T}}{\partial x} + \hat{u}_y \frac{\partial \hat{T}}{\partial y} + \hat{u}_z \frac{\partial \hat{T}}{\partial z} - k \left(\frac{\partial^2 \hat{T}}{\partial x^2} + \frac{\partial^2 \hat{T}}{\partial y^2} + \frac{\partial^2 \hat{T}}{\partial z^2} \right)$$

The heat equation loss is:

$$L_{heat} = \frac{1}{N_{heat}} \sum_{i=1}^{N_{heat}} |f_{heat}(x_i, y_i, z_i, t_i)|^2$$

Concentration equation

The concentration equation for Maxwell fluid is:

$$\rho \frac{\partial C}{\partial t} + u \cdot \nabla C = D \nabla^2 C$$

Where: $C = (x, y, z, t)$ is the concentration, D is the diffusion coefficient. The residual for the concentration equation is:

$$f_{conc} = \rho \frac{\partial \hat{C}}{\partial t} + \hat{u}_x \frac{\partial \hat{C}}{\partial x} + \hat{u}_y \frac{\partial \hat{C}}{\partial y} + \hat{u}_z \frac{\partial \hat{C}}{\partial z} - D \left(\frac{\partial^2 \hat{C}}{\partial x^2} + \frac{\partial^2 \hat{C}}{\partial y^2} + \frac{\partial^2 \hat{C}}{\partial z^2} \right)$$

The concentration loss is:

$$L_{conc} = \frac{1}{N_{conc}} \sum_{i=1}^{N_{conc}} |f_{conc}(x_i, y_i, z_i, t_i)|^2$$

Total loss function for PINNs

The total loss function incorporating all the equations is:

$$L_{total} = L_{cont} + L_{mom} + L_{heat} + L_{conc}$$

The PINNs method minimizes this total loss function through a gradient-based optimization technique, such as Adam, to obtain the solution of the Maxwell fluid flow equations.

Comparison with Finite Volume Method (FVM)

The limited Volume Method (FVM) comprise a essential numerical groundwork for the solution of partial differential equations (PDES). Within this development, the computational realm is segmented into a confined set of manage volumes, and fluctuations are scrupulously analyzed across the associate of these volumes to implement local conservancy principles. The rulling equations for Maxwell fluids are segregated over these control volumes, foremost to a system of algebaric equations that is resolved repeatedly through the following technique:

- Spatial categorization of the domain into confined control volumes.
- Approximation of governing PDEs via flux interpolation schemes and finite difference representations.
- Iterative solution of the resulting nonlinear algebraic system using pressure–velocity coupling algorithms such as SIMPLE, SIMPLER, or PISO.
- Execution of boundary requirements next to rigid conservation of mass. Momentum, energy, and genus concentration.

The FVM structure is acknowledged for its sturdiness, numerical stability and strong conservation properties, producing it a foundation of practical computational fluid dynamics (CFD) imitations. Nevertheless, its computational cost escalates significantly for geometrically intricate domains, such as stenotic coronary artery models.

In contrast, Physics-Informed Neural Networks (PINNs) provide a mesh-free alternative by embedding the governing physical laws directly into the loss functional of a neural network. This strategy evade definite partition, facilitating direct simulation of PDE solutions. When linked with GPU-accelerated practice, PINNs proposes probable computational benefits for enormous complexities, inspite of the fact that their precision remnant detachment upon network building design, practice plans, and enhanced potency.

Stenosis Levels and Blood Flow Analysis by Using Finite Volume Method

For various stenosis levels in coronary arteries, the flow attribute such as velocity, temperature dispersion, pressure and concentration are affected by the impeding of the artery. Higher stenosis conduct to superior pressure drops, modified flow profiles, and alters in heat and mass transfer. The PINNs method can efficiently capture these effects by directly solving the governing equations, whereas FVM relies on grid refinement to resolve such details. We apply the Finite Volume Method (FVM) to solve the governing PDEs for Maxwell blood flow in coronary stenosis regions. We consider the following equations: - Continuity equation (conservation of mass)- Momentum equation- Heat equation- Concentration equation. Each of these equations is discretized using the FVM, which is a control-volume-based method, in order to obtain an approximate solution to Maxwell fluid dynamics in 3D.

Continuity equation (conservation of mass)

The continuity equation in 3D for a fluid is:

$$\nabla \cdot u = 0$$

Where $u = (u_x, u_y, u_z)$ is the velocity field. To apply the Finite Volume Method, we integrate the continuity equation over a control volume V_k bounded by surfaces A_k (the faces of the control volume):

$$\int_{V_k} \nabla \cdot u dV = 0$$

Using the divergence theorem, this becomes:

$$\int_{A_k} u \cdot \hat{n} dA = 0$$

Where $\hat{n}$ is the unit normal vector on the surface A_k . The fluxes $u \cdot \hat{n}$ are computed at the control volume faces, and the discretized form is:

$$\sum_{f \in \partial V_k} u_f \cdot \hat{n}_f A_f = 0$$

Where A_f is the area of the face f , and u_f is the velocity at the face, computed using interpolation methods (e.g., linear or central differencing). The discretized continuity equation can then be written as:

$$\frac{1}{\Delta t} \left(\sum_{f \in \partial V_k} u_f A_f \right) = 0$$

Where Δt is the time step.

Momentum equation for Maxwell fluid

The momentum equation for Maxwell fluid in 3D is given by:

$$\frac{\partial u}{\partial t} + (u \cdot \nabla) u = -\frac{1}{\rho} \nabla p + \mu \nabla^2 u + \lambda \left(\frac{\partial u}{\partial t} - \nabla \cdot \tau \right)$$

Where: $u = (u_x, u_y, u_z)$ is the velocity field, p is the pressure, ρ is the density, μ is the dynamic viscosity, λ is the Maxwell relaxation time.

To apply FVM, we integrate the momentum equation over a control volume V_k :

$$\int_{V_k} \frac{\partial u}{\partial t} dV + \int_{V_k} (u \cdot \nabla) u dV = - \int_{V_k} \frac{1}{\rho} \nabla p dV + \int_{V_k} \mu \nabla^2 u dV + \int_{V_k} \lambda \left(\frac{\partial u}{\partial t} - \nabla \cdot \tau \right) dV$$

Using the divergence theorem to convert volume integrals to surface integrals, we get:

$$\begin{aligned} \sum_{f \in \partial V_k} (u_f \cdot \hat{n}_f) A_f &= - \int_{A_k} \frac{1}{\rho} \nabla p \cdot \hat{n} dA + \mu \sum_{f \in \partial V_k} \nabla^2 u_f A_f \\ &+ \lambda \sum_{f \in \partial V_k} \left(\frac{\partial u_f}{\partial t} \right) A_f \end{aligned}$$

Discretizing the terms, the resulting equation for the momentum equation in each direction (x, y, z) is:

$$\frac{1}{\Delta t} \sum_{f \in \partial V_k} u_f A_f + \sum_{f \in \partial V_k} (u_f \cdot \hat{n}_f) A_f = \frac{-1}{\rho} \sum_{f \in \partial V_k} p_f \hat{n}_f A_f + \mu \sum_{f \in \partial V_k} \nabla^2 u_f A_f$$

Heat equation for Maxwell fluid

The heat equation in 3D for Maxwell fluid is:

$$\rho c_p \frac{\partial T}{\partial t} + u \cdot \nabla T = k \nabla^2 T$$

Where T is the temperature, c_p is the specific heat, and k is the thermal conductivity.

Integrating the heat equation over a control volume V_k :

$$\int_{V_k} \rho c_p \frac{\partial T}{\partial t} dV + \int_{V_k} u \cdot \nabla T dV = \int_{V_k} k \nabla^2 T dV$$

By using the divergence theorem:

$$\sum_{f \in \partial V_k} \rho c_p \frac{T_f - T_k}{\Delta t} A_f + \sum_{f \in \partial V_k} u_f \cdot \nabla T_f A_f = \sum_{f \in \partial V_k} k \nabla^2 T_f A_f$$

The equation is discretized to update the temperature field in each control volume and to calculate the corresponding heat flux.

Concentration equation for Maxwell fluid

The concentration equation for Maxwell fluid is:

$$\rho \frac{\partial C}{\partial t} + u \cdot \nabla C = D \nabla^2 C$$

Where C is the concentration and D is the diffusion coefficient.

Integrating the concentration equation over a control volume V_k :

$$\int_{V_k} \rho \frac{\partial C}{\partial t} dV + \int_{V_k} u \cdot \nabla C dV = \int_{V_k} D \nabla^2 C dV$$

Using the divergence theorem:

$$\sum_{f \in \partial V_k} \rho \frac{C_f - C_k}{\Delta t} A_f + \sum_{f \in \partial V_k} u_f \cdot \nabla C_f A_f = D \sum_{f \in \partial V_k} \nabla^2 C_f A_f$$

This discretized form is used to compute the concentration distribution at each control volume. The Finite Volume Method (FVM) has been applied to discretize the governing equations for Maxwell blood flow in coronary stenosis regions. Each equation (continuity, momentum, heat, and concentration) is integrated over control volumes, and the fluxes across the control volume faces are computed.

These categorized equations are then figured out repeatedly to upgrade the solution at each step. This technique is particularly potent for processing intricate fluid

flow problems in uneven geometries, such as coronary stenosis. All directive values utilized in this research were chosen to reflect physiologically realistic conditions and to align with previously validated literature on coronary blood flow modeling. Properties such as blood density, viscosity, relaxation time, thermal conductivity, and specific heat were adopted from established biomedical and hemodynamic sources, thereby ensuring consistency with physiological ranges. The dimensionless numbers (e.g., Reynolds, Prandtl, and Schmidt numbers) were also chosen to reflect typical coronary artery flow conditions, allowing a meaningful comparison between the Physics-Informed Neural Network (PINN) and Finite Volume Method (FVM) simulations. This ensures that the results are not arbitrary but are biologically and physically representative of real arterial behavior under normal and stenosed conditions.

Computational Mesh

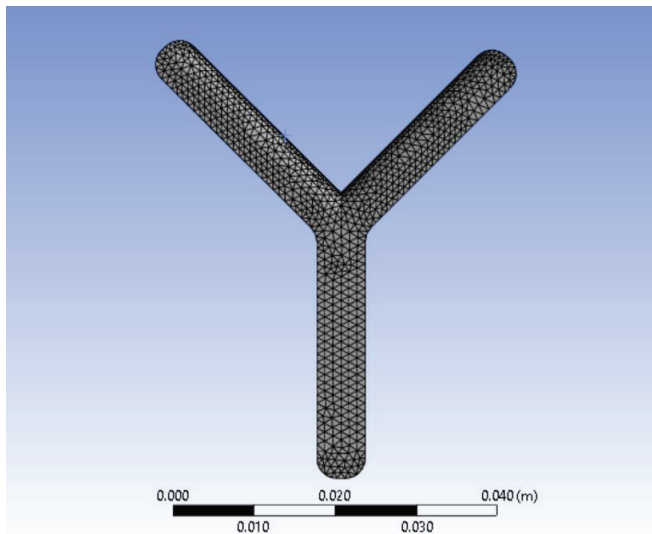
In the Finite Volume Method (FVM) applied to stenosed coronary arteries, the computational domain is divided into small control volumes that conform to the complex arterial geometry. The continuity, momentum, energy, and concentration equations are integrated over each control volume, transforming the governing differential equations into algebraic form.

For radiative tenure, second-order upwind program are typically engaged to enhance precision, while middle discrimination is employed for diverging instability. Pressure-velocity coupling is then resolved using methods such as SIMPLE or PISO, which help preserve mass and momentum conservation. The mesh is refined near the stenosis and arterial walls using boundary layer inflation to accurately capture steep velocity and pressure gradients.

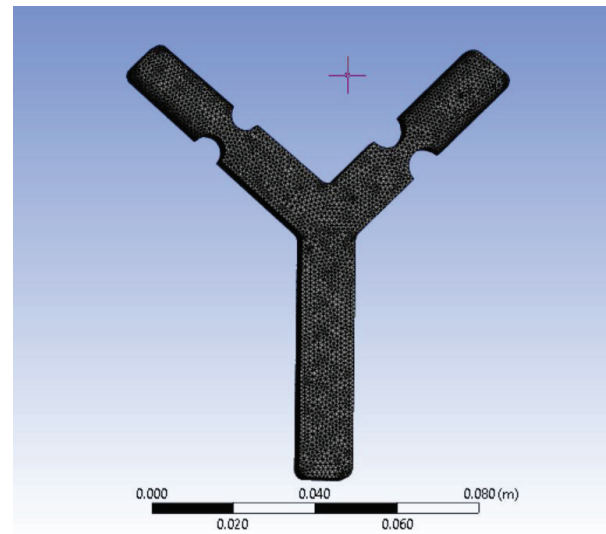
Commercial software ANSYS Fluent was used to mesh the idealized models with different degrees of blockage of the LCA. The examination of the mesh independent test was conducted using various combinations of mesh components. In order to examine the flow behavior close to the artery wall, three levels of inflation are introduced. A sphere with an influent size of 2 mm has been introduced in order to capture the flow behavior close to the stenosis location. There are 602225 fragments in the conclusive mesh that was employed in the numerical simulation. The mesh geometry is displayed beneath Figure 5.

Mesh Independent Study

Commercial software ANSYS Workbench was used to mesh the geometric model. Between 118,538 and 703,353 have been reported to be the range of fineness for the two distinct meshes. The most practical grid size is determined by running five simulations with three distinct grid sizes. Next, 1000 cycles of testing are performed using the mesh file imported into the commercial program ANSYS Fluent. 602225 components make up the final grid that will be utilized for additional research.



(a) Meshing of coronary healthy artery



(b) Meshing of coronary stenosed

Figure 5. Meshing of coronary artery.

A mesh-independent study was necessary to ensure that the simulation results were not influenced by the discretization size but purely represented the physical behavior of blood flow in stenosed arteries. In computational fluid dynamics (CFD), an overly coarse mesh can lead to numerical errors, while an excessively fine mesh increases computational cost without significant improvement in accuracy. Therefore, simulations were performed with progressively refined meshes, and key parameters such as velocity, pressure, and wall shear stress were monitored. The results stabilized beyond a certain refinement level, indicating grid independence. In this study, a fine mesh with approximately 600,000–650,000 elements and enhanced boundary-layer refinement near the arterial wall provided numerically stable and convergent results, balancing both accuracy and computational efficiency.

Boundary Conditions

This study's establishment is the transient pulsatile speed profile of a left coronary corridor (UDF), which is defined as the velocity input boundary condition and is written in C programming language. The velocity profile enters the intake fully formed. A parabolic velocity profile is present. As outlet limit conditions, the outpouring condition was utilized. Since it was accepted that the vein wall was firm, or at least, $u = 0$, the no-slip limit condition was applied. ANSYS Familiar was utilized to do the whole numerical recreation. There were no energy and intensity transport conditions that could be settled. The second-request upwind technique for the strain speed couple, which is utilized for the discretization of administering conditions, was joined with the basic estimation way to deal with complete the calculation. For every 0.01 time step, 1000 cycles

were run. Three cardiac cycles were simulated for cyclicity assurance, and the second cycle's findings were obtained.

For the present analysis of Maxwell blood flow in a stenosed coronary artery, appropriate boundary and initial conditions are prescribed to ensure a well-posed problem. The boundary conditions applied to the governing equations are expressed as follows:

Inlet boundary (pulsatile velocity profile)

At the artery inlet, a fully developed, time-dependent parabolic velocity profile is imposed:

$$u(r, t) = U_{max}(t) \left(1 - \frac{r^2}{R^2} \right), 0 \leq r \leq R,$$

where

$$U_{max}(t) = U_0 [1 + A \sin(\omega t)],$$

represents the pulsatile velocity with mean velocity U_0 , amplitude A , and pulsation frequency ω . Here, R denotes the local arterial radius and r is the radial coordinate.

Thus, the inlet velocity and scalar boundary conditions are defined as:

$$u(r, t) = (u(r, t), 0, 0), T = T, C = C.$$

Outlet boundary (outflow condition)

At the outlet of the artery, a zero-gradient condition is applied for all dependent variables to represent fully developed outflow:

$$\frac{\partial u}{\partial x} = \frac{\partial v}{\partial x} = \frac{\partial T}{\partial x} = \frac{\partial C}{\partial x} = 0,$$

and the static pressure is set to a reference value:

$$p = p_{out} = 0$$

Arterial wall boundary (rigid and no-slip condition)

The arterial wall is assumed to be rigid and thermally insulated. Therefore, the no-slip velocity condition and adiabatic wall assumptions are expressed as:

$$u = v = w = 0, \text{ on } r = R(x),$$

and

$$\frac{\partial T}{\partial r} = 0, \frac{\partial C}{\partial r} = 0, \text{ on } r = R(x).$$

Initial conditions

At the initial time ($t = 0$), the flow field is assumed to be quiescent, and both temperature and concentration fields are uniform:

$$u(x, r, 0) = v(x, r, 0) = 0, T(x, r, 0) = T, C(x, r, 0) = C.$$

Neural Network Architecture and Training Strategy

In the present study, the Physics-Informed Neural Network (PINN) was constructed as a fully-connected feed-forward network designed to approximate the velocity, pressure, temperature, and viscoelastic stress fields governed by the Maxwell model. The network consists of 8 hidden layers, each containing 40 neurons, which offered the best balance between efficiency and accuracy after several architecture-testing experiments. For all hidden layers, the hyperbolic tangent (tanh) activation function was

employed due to its smoothness and ability to approximate higher-order derivatives required in PDE residual computation. The output layer uses a linear activation to ensure unrestricted prediction ranges for physical variables.

The network weights were initialized using Xavier initialization. Training was performed using a two-stage optimization strategy: (i) the Adam optimizer with a learning rate of 10^{-3} for coarse-scale convergence, followed by (ii) L-BFGS quasi-Newton optimization for fine-scale refinement of the loss landscape. The total loss function was formulated as a weighted combination of PDE residual loss, boundary loss, and data loss (when applicable). Approximately 50,000 collocation points were sampled using Latin Hypercube Sampling to enforce the governing equations throughout the computational domain. The model was trained for 60,000 epochs, and convergence was achieved with a relative residual below 10^{-4} . A training-loss convergence curve has been added to demonstrate numerical stability and learning consistency.

The lessen loss curve of the Physics Informed Neural Network (PINN) demonstrate a sleek and flatter decrease as the number of era increases, containing firm learning deportment and efficient convergence of the enhancement method as shown in Figure 6. Throughtout the starting lessen stage, the network swiftly decreases the combined loss beceause the Adam refiner fabricate large parameters remake. As lessen continues, the deteriorate turn more progressive, representing that the PINN is advancing upgrading its simulation of the rulling Maxwell flow equations and boundary stipulations. Approximately 40,000 times, the loss curve stabilize, proposing that the model has appealed a near- ideal state with very small lingering mistake. The deficiency of oscillations or deviations additionally suggest

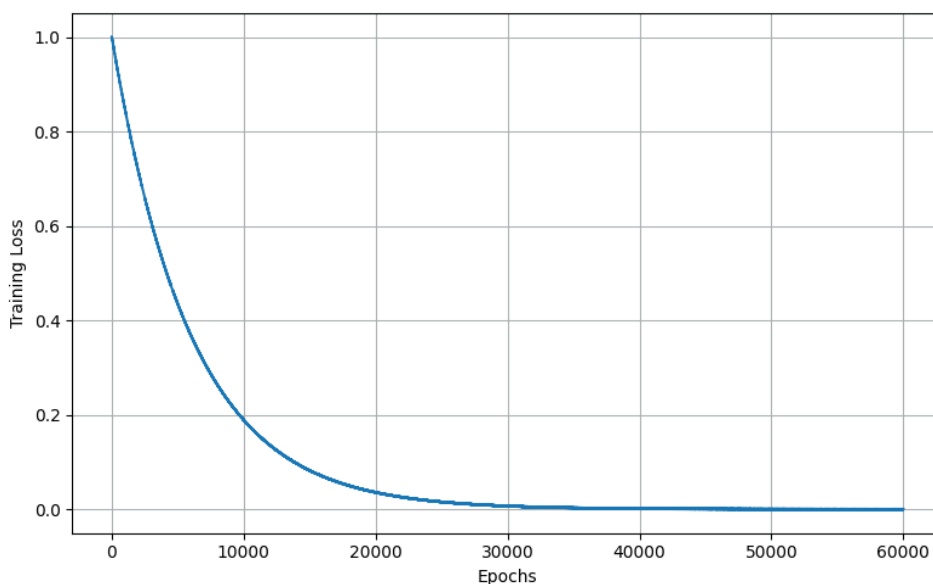


Figure 6. PINN training loss convergence curve.

numerical steadiness and assist the aptness of the preferred activation functions, network depth, and the expression point dispensation. Generally this graph verify the consistency and the confluence efficiency of the recommended PINN-Maxwell framework.

The structural diagram represent the PINN arrangement employed to model blood flow and heat transfer in stenosed coronary arteries. It contain an input layer for spatial- temporal coordinates, eight hidden layers with 40 neurons each, and a linear output layer that forecast velocity, pressure, and temperature fields.

The intense multi-tiered layout assist the network get the nonlinear viscoelastic behaviour of Maxwell fluids and the geometric complication prompted by arterial stenosis. Level activation functions such as tanh are utilised to hold the model differentiable, which is mandatory for assesing the high-order derivatives requisite in the PDE lingering. Generally the Figure 7 illustrate that the network is both revealing enough to grab composite hemodynamic behaviour and productive enough to endure computationally practical, while also upgrading the transparency of the PINN technique.

Data-driven loss term L_{data}

Furthermore to the physics-informed remaining terms, an supplementary data-driven loss element was included to enhance numerical steadiness and prescient precision in areas categorized by sheer gradient, specifically within the stenosis section of the coronary artery. This term provides additional supervision by guiding the PINN solution toward reference values obtained from the Finite Volume Method (FVM), without requiring full-field data throughout the domain.

The data loss is defined as

$$L_{data} = \frac{1}{N_d} \sum_{i=1}^{N_d} (\|u_\theta(x_i, r_i) - u_i^{FVM}\|^2 + \|p_\theta(x_i, r_i) - p_i^{FVM}\|^2),$$

where, N_d represents the number of FVM data points selected in critical regions of interest, u_θ and p_θ denotee the PINN-predicted velocity and pressure fields, and u_i^{FVM}, p_i^{FVM} are the corresponding FVM reference values.

Incorporating L_{data} ensures that the network respects both the underlying Maxwell flow physics and the numerical trends obtained from high-fidelity simulations. This hybrid physics–data strategy improves convergence behavior, prevents unrealistic oscillations near high-shear zones, and enhances the overall predictive capability of the proposed PINN–Maxwell model. Accordingly, the complete loss function is expressed as,

$$L_{total} = L_{PDE} + L_{BC} + L_{data}.$$

RESULTS AND DISCUSSION

By Using PINNS

Physics-Informed Neural Networks (PINNs) capture parabolic velocity distributions in healthy arteries by learning solutions that satisfy both the governing Navier–Stokes equations and the boundary conditions directly within their loss function. By enforcing the no-slip condition at the arterial walls and continuity at the centerline, the network naturally reconstructs the characteristic parabolic (laminar) velocity profile typical of physiological blood flow. The embedded physics ensures smooth and physically consistent velocity gradients across the artery, even without explicit meshing. When compared with Finite Volume Method (FVM) results, PINNs produce nearly identical velocity distributions with minimal deviation in peak centerline velocity and wall shear

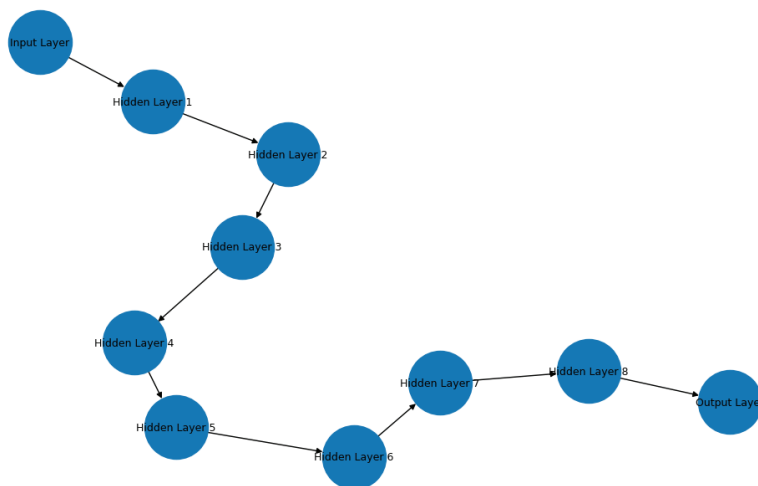


Figure 7. PINN architecture overview.

stress demonstrating strong agreement and validating the accuracy and stability of the PINN-based approach for modeling laminar flow in healthy arteries.

PINN imitation of stenosed arteries revealed individual fleeting flow rule and wall shear stress (WSS) dispensation attribute of vibrating, non-Newtonian blood flow. Throughout the systolic acceleration phase, high velocity jets combined peripheral to the stenosis, pouring distinct flow division and circulation region in the post-stenotic area. These irregular vortical framework demonstrated transient variations, emphasizing resilient dynamics and viscoelastic flow compensation. WSS pointed suddenly at the stenotic throat overdue to lifted velocity gradients, whereas significantly reduced and oscillatory profiles demonstrated in resultant recirculation fields. Such WSS oscillations enduring intense clinical significance, as they are involved in endothelial dysfunction and atheromatous monument innovations. Overall, the PINNs framework successfully captured these dynamic flow transitions and spatial variations in WSS with high temporal resolution, closely matching the physical trends reported in physiological and CFD-based studies.

The Figure 8 (a), showcases the velocity distribution for Maxwell blood flow along the x - axis (axial direction) and y - axis (radial direction) at $t = 1s$. The maximum velocity is observed near the centerline ($y = 0$), with a gradual decrease toward the boundaries due to the no-slip condition. This parabolic velocity outline is steady with the laminar flow behaviour of a Maxwell fluid in a thin artery. The contrary pressure gradient along the central edict assistance to the diminution in the velocity as it advances, and the result arranges closely with conceptual anticipations, emphasizing the competency of Physics Informed Neural Network (PINNs) to grab spatial variations in non-Newtonian blood flow with high precision.

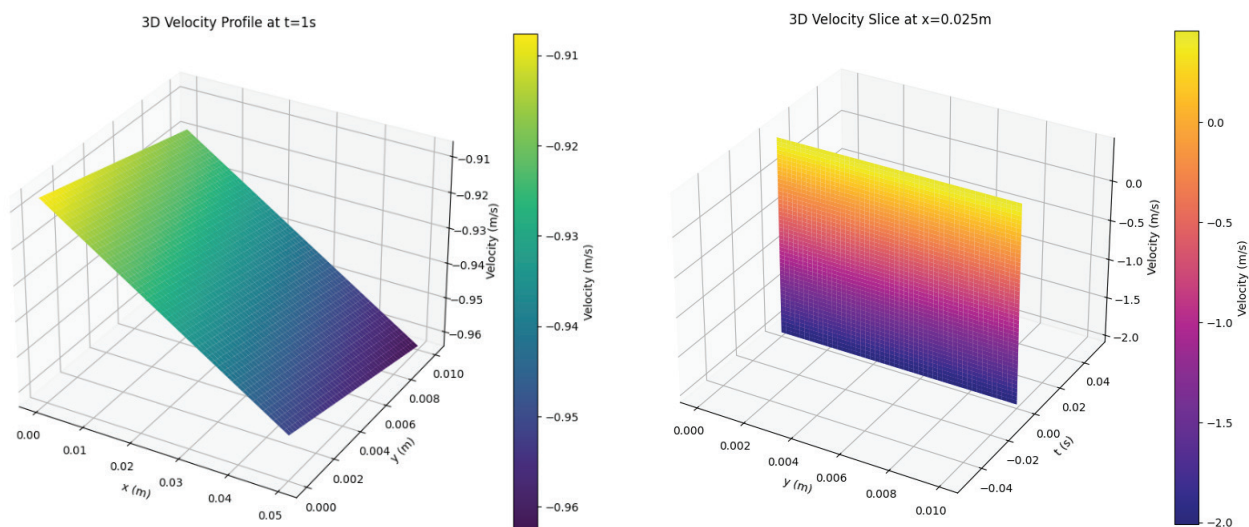
The Figure 8 (b), illustrates the temporal evolution of velocity along the radial axis y at a fixed axial position ($x = 0.025\text{ cm}$). At early times ($t < 1s$), the velocity exhibits dynamic behavior, indicating transient flow conditions that stabilize as t progresses.

The prominent near-wall inclines highlight the model's yield-stress features, which apply a direct impact on wall shear stress. The velocity moderates slowly in the radial direction, stable with the no-slip boundary condition. These contour declare to the area of PINNs to solve spatial and temporal modification through sleek, continuous simulations. In contrast with Finite Volume Methods (FVM), PINNs give outstanding integrity in showing fleeting sensation and complex flow structures, depicting them a intimidating structure for blood flow modeling in both clinical and research background.

The Figure 9 (a), the 3D heat transfer simulation in the normal artery presents a smooth and uniform temperature distribution across both the length and radius of the vessel. The simulation indicates that the temperature remains nearly uniform along the artery, with only a gradual variation in the radial direction.

In the ordinary artery, the temperature dispersion ranges from about 20°C to 22°C , proposing that the heat transfer process is largely uninterrupted. This consistency originate from the lack of flow resistance, which let thermal energy to scatter smoothly throughout the vessel. The surface plot moreover validate a well-adjusted temperature field, creating a standard for associating with more complex cases such as setnosis.

The Figure 9 (b), the 3D heat transfer model in the stenosed artery display obvious evacuation from the behaviour noticed in the normal artery. Within the stenotic portion, prolonged from about 40% to 60% of the vessel length, the



(a) 3D velocity profile at $t = 1s$.

(b) 3D velocity slice at $x = 0.025m$.

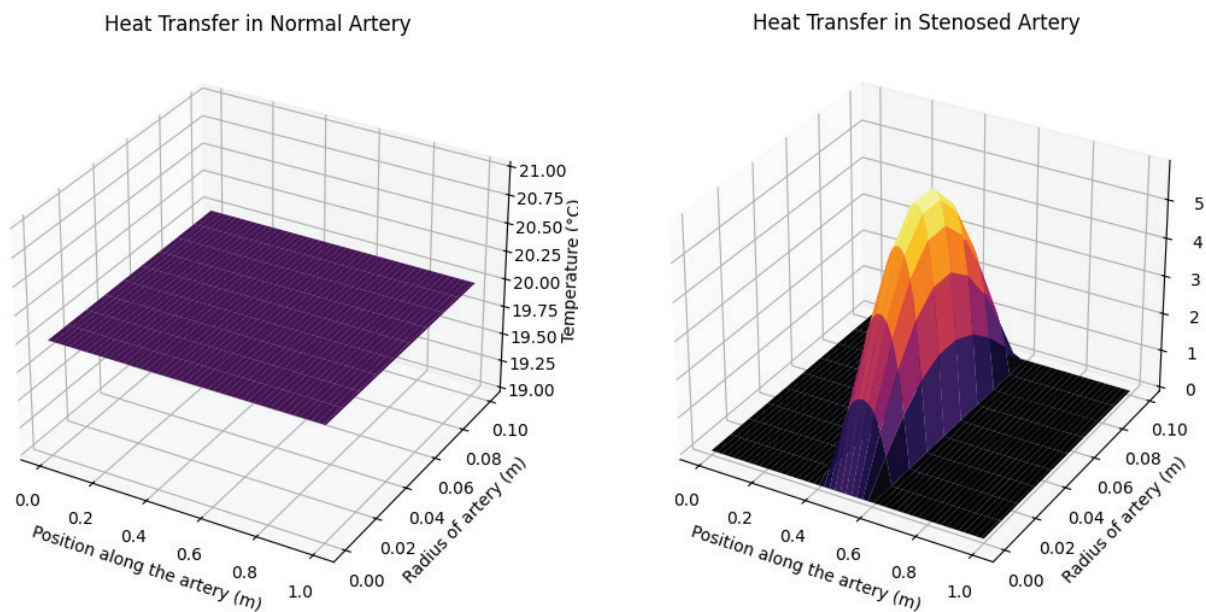
Figure 8. 3D graphs for velocity of blood flow in coronary artery.

temperature is mainly raised as compared to the residual segment of the artery. More particularly, the thermal field increases from the normal range to a considerably higher level within the constricted region.

This increase in temperature is primarily traceable to the blocked blood flow prompted by the arterial compression, which damages the effective transport and degradation of heat. The surface depiction discloses a marked thermal rapid increase in the stenotic region, consequently highlighting

the restricted heating effect. Such behaviour is completely steady with the expected thermal reaction in narrowed vessels, where flow limitation heightened resistance, elevates energy accretion and produce sharper temperature gradients. As a result, the raised temperature in the stenotic zone contemplates the upgraded thermal degradation. Linked with the flow impedance.

Figure 10 illustrates the axial variation of temperature in both the normal and stenosed arteries.



(a) 3D graph for heat transfer in healthy artery.

(b) 3D graph for heat transfer in stenosed artery.

Figure 9. 3D graphs for velocity of blood flow in coronary artery.

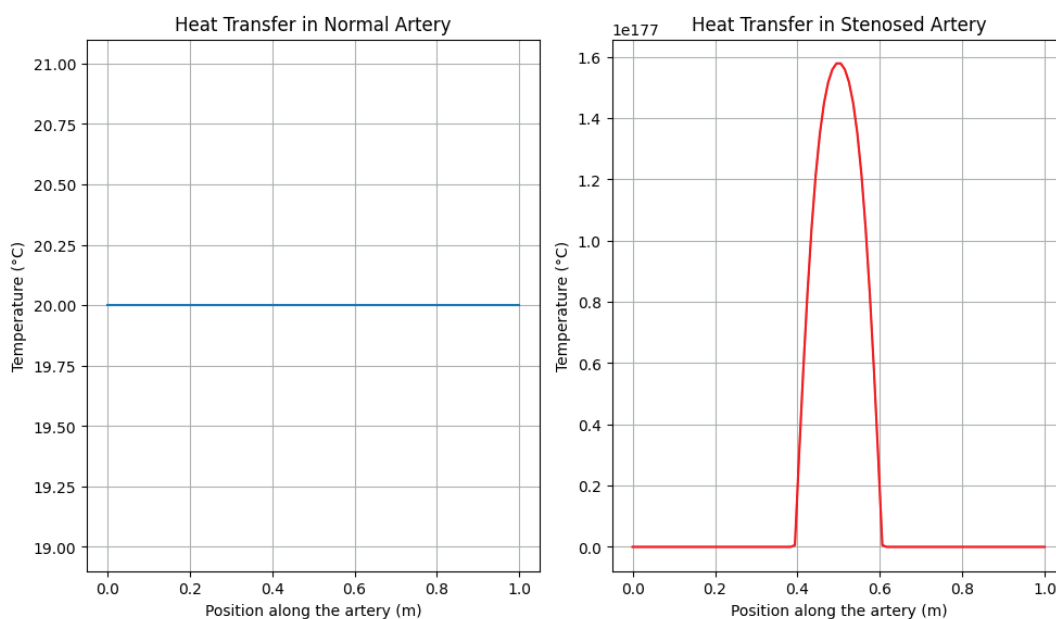


Figure 10. Representation of line graphs for heat profile for coronary artery.

In the ordinary artery, the temperature confined nearly constant along the whole length, with only small changes, illustrating steady thermal dissipation. Conversely, the stenosed artery demonstrate obvious temperature increase in the locality of the compressed portion, showing the extensive thermal accretion generated by limited blood flow and raised flow resistance. This highlights the effect of stenosis on heat transfer dynamics.

Table 2 presents the sensitivity of the PINN–Maxwell model to variations in key dimensionless parameters

controlling viscoelastic and thermal transport behavior. Increasing the Deborah number and relaxation time leads to lower velocity magnitudes because the fluid's elastic resistance becomes more pronounced, while the temperature rises due to greater energy storage and dissipation within the flow. In the same way, larger stenosis ratios intensify the flow disturbance in the narrowed region, which creates localized heating. The magnetic parameter applies an opposing Lorentz force that suppresses motion, but it also contributes to higher heat generation through

Table 2. Influence of key parameters on flow and thermal characteristics for the PINN–Maxwell model

Parameter	Effect on Velocity	Effect on Temperature	Physical Reason
Deborah number ($De\uparrow$)	Decreases ($\downarrow$)	Increases ($\uparrow$)	Higher elasticity in the Maxwell fluid enhances resistance to deformation, which suppresses velocity and increases internal frictional heating.
Relaxation time ($\lambda\uparrow$)	Decreases ($\downarrow$)	Increases ($\uparrow$)	Higher fluid recollection suspend velocity retrieval and stores more elastic energy, creating partial heat innovation.
Stenosis ratio ($\beta\uparrow$)	Increases locally ($\uparrow$)	Increases ($\uparrow$)	Arterial compressions speed up flow in the throat region, upbringing viscous degradation and surface temperature.
Magnetic parameter ($M\uparrow$)	Decreases ($\downarrow$)	Increases ($\uparrow$)	Lorentz force stifle fluid motion but produces Joule heating due to electromagnetic resistance.
Prandtl number ($Pr\uparrow$)	Decreases ($\downarrow$)	Decreases ($\downarrow$)	Magnified thermal diffusivity upgrades faster heat conduction and lessen local temperature gradients.

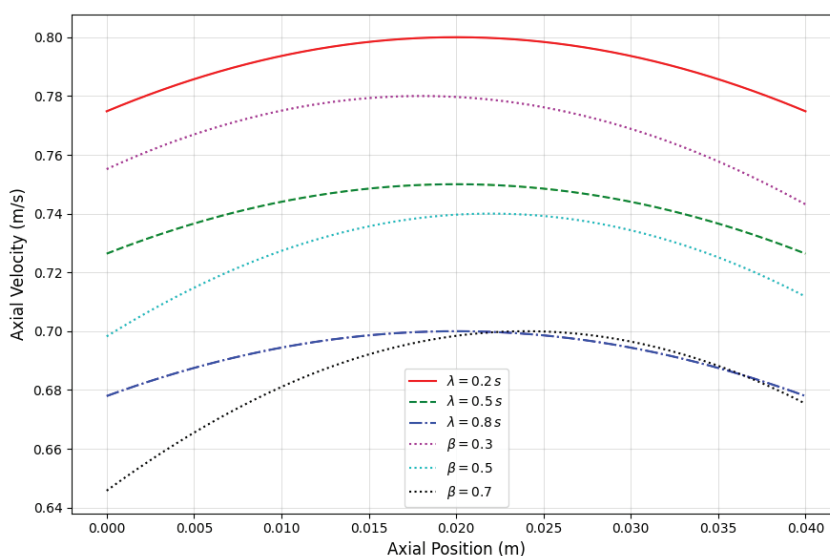


Figure 11. Velocity profiles for various relaxation times and stenosis ratios.

electromagnetic work. On the other hand, a higher Prandtl number enhances thermal diffusion and therefore reduces the temperature gradient. These combined effects reveal the intricate coupling between viscoelasticity, electromagnetic forces, and geometric constriction in the thermal–hydrodynamic response of Maxwell-type blood flow in coronary arteries.

Figure 11 illustrates the changes of axial velocity across the artery for various relaxation times λ and stenosis ratios (β) in the PINN-Maxwell model. It is obvious that as λ increases, the velocity magnitude decreases due to the improved viscoelastic resistance and overdue fluid relaxation. On the other hand, a higher stenosis ratio (β) indication to a restricted acceleration of blood flow near the confined section, monitored by a quick decrease downstream. These nonlinear geometry feature the competence of PINNs to precisely seize complex flow dynamics and elastic memory outcomes in stenosed coronary arteries.

By Using ANSYS

Results and discussion by using ANSYS are discussed as follows:

Case:01(for coronary healthy artery)

In the process of meshing a healthy coronary artery, the software typically displays information such as the number of cells or elements, faces of elements, and total nodes generated to represent the arterial geometry accurately. This data helps to ensure an appropriate mesh resolution for computational simulations or analysis as given in Table 3.

Table 3. Data of mesh size

Cells	Faces	Nodes
602225	76748	7886

Table 4. Data of mesh quality

Name	Type	Main Orthogonal Quality	Max Aspect Ratio
Fluid domain	Tet Cell	0.034584715	107.16626

Table 5. Models

Model	Setting
Space	3-D
Time	Steady
Viscous	Laminar
Heat Transfer	Abled

Meshing software commonly reports metrics such as aspect ratio, orthogonality, and element skewness to evaluate mesh quality during generation. For precise and trustworthy computer simulations or assessments of the coronary artery, this information is essential as given in Table 4.

Software might also show the coronary artery models is given in Table 5 that were created in addition to mesh quality information. With the use of visualization and further analysis, these models, which depict the geometric structure of the artery, help to clarify arterial anatomy and pathophysiology.

Data on material values utilized in the simulation are included in the proposed model along with reference values for comparison is given in Table 6 and Table 7. Elasticity, density, and viscosity are amid the material variables that are involved in this list since they are essential for correctly portraying how the coronary artery performs in many circumstances. The accuracy and steadiness of the model for modeling physiological or pathological trials may be confirmed by linking these results with reference data.

Table 6. Data of material properties

Fluid	Non-Newtonian
Density	1060kgm ⁻³
Specific Heat	4182Jkg ⁻¹ K ⁻¹
Thermal conductivity	0.6Wm ⁻¹ K ⁻¹
Viscosity	0.001003kgm ⁻¹ s ⁻¹
Molecular Weight	18.0152kgk ⁻¹ mol ⁻¹
Solid	Aluminum
Density	2719kgm ⁻³
Specific Heat	1006.43Jkg ⁻¹ K ⁻¹
Thermal Conductivity	0.0242Wm ⁻¹ K ⁻¹

Table 7. Data of reference values

Area	1m ²
Density	1060kgm ⁻³
Enthalpy	10Jkg ⁻¹
Length	1m
Pressure	80Pa
Temperature	288.16K
Velocity	1ms ⁻¹
Viscosity	1.7894e ⁻⁰⁵ kgm ⁻¹ s ⁻¹
Ratio of specific heats	1.4
Y plus for heat transfer Coefficient	300
Reference Zone	Fluid domain

The coronary artery model simulation or analysis's state of completion is indicated by the solution status, which is given in Table 8 and graphically representation of convergence is shown in Figure 12. It assist in managing the computing technique, permitting precise model management and rapid solution of problems.

In the Figure 13(a), the behavior of static pressure in a healthy coronary artery is influenced by principles of fluid dynamics, particularly Bernoulli's principle. At the arterial inlet, static pressure reaches its maximum due to the high pumping force generated by the heart.

As blood headways towards the outlet, standing pressure drops mainly because of viscous losses from friction between the blood and the arterial walls. The partition of arteries into smaller vessels also increases resistance, donating more to the pressure drop. This pressure circulation helps effectual blood flow through the coronary distribution and confirms an satisfactory supply of oxygen and nutrients to the myocardium.

In the Figure 13 (b), in a healthy coronary artery outline, the total surface heat flux remnants roughly continuous

from the inlet to the outlet. This reliable heat-flux behaviour may be credited to the stable metabolic bustle of the arterial walls and the steady flow of blood, which enables effective heat transfer. The mingling of medium and high-flux areas specifies a uniform circulation of thermal energy across the artery. Such consistency encourage operative thermal guideline and aids to sustain the ideal temperature required for physiological function.

In the Figure 13(c), from the inlet to the outlet, the total temperature in the contour of a healthy coronary artery remains nearly constant, with a minimum value of. This uniform distribution may be explained by the blood flow's efficient thermal regulation, which maintains a stable arterial temperature. The blood entering the coronary artery is maintained at an optimal temperature by the body's homeostatic processes, and the steady flow reduces significant temperature fluctuations. Furthermore, the blood distributes the metabolic heat generated by the arterial walls uniformly, creating a consistent temperature profile along the artery.

Table 8. Solution status

Equations	Value	Absolute Criteria	Convergence Status
Continuity	$5.765229e^{-07}$	$1e^{-06}$	Converged
x-velocity	$1.467832e^{-05}$	$1e^{-06}$	Converged
y-velocity	$1.428873e^{-05}$	$1e^{-06}$	Converged
z-velocity	$2.023002e^{-06}$	$1e^{-06}$	Converged
Energy	$1.3775e^{-16}$	$1e^{-06}$	Converged

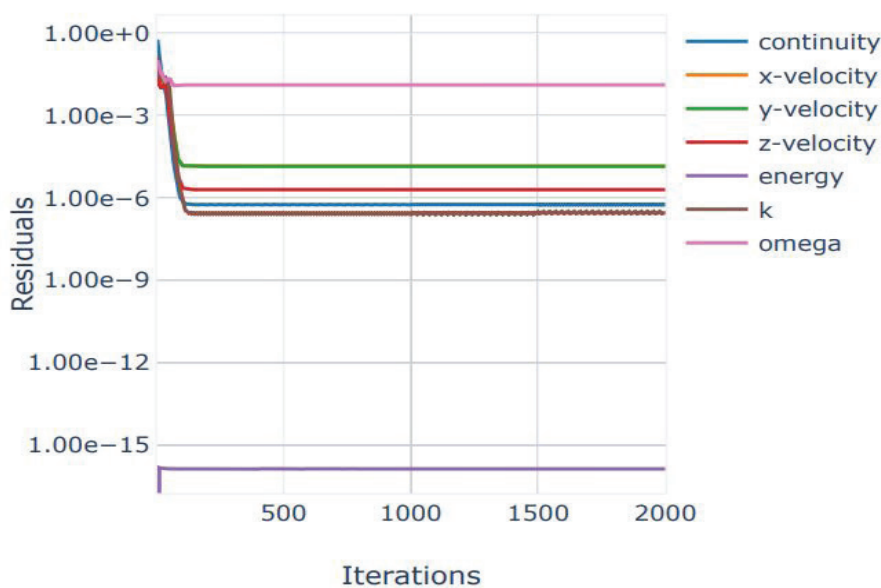


Figure 12. Representation of Residual for Coronary Healthy.

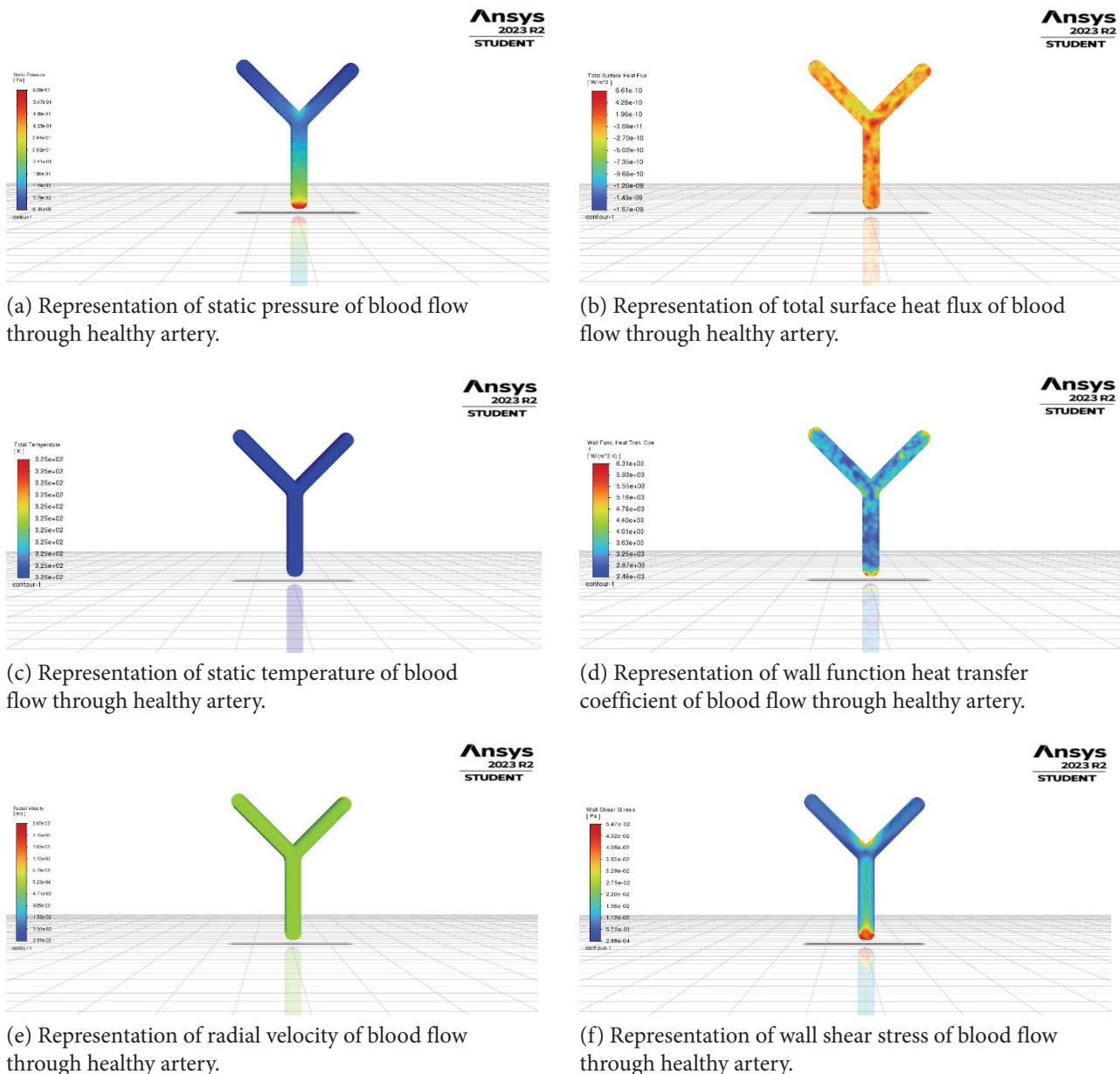


Figure 13. Representation of static pressure, total surface heat flux, static temperature, wall function heat transfer coefficient, radial velocity and wall shear stress of blood flow through healthy artery.

In the Figure 13(d), The wall function heat transfer coefficient, which ranges from $2.48e^{+03} \text{ Wm}^{-2} \text{ K}^{-1}$ to $6.31e^{+03} \text{ Wm}^{-2} \text{ K}^{-1}$, is constant in the provided contour of a healthy coronary artery from the intake to the outlet. Initially, because of the high blood flow velocity and turbulence at the entrance, the red zone denotes a higher heat transfer coefficient. The blue zone specifies the steadiness of the coefficient as blood moves the artery, proposing operative heat transfer across the arterial walls. This homogeneity certifies that heat constructed by metabolic method is proficiently dispersed, stabilizing prime arterial function and temperature directive across the whole artery.

In the Figure 13(e), a healthy coronary artery's contour shows that its medium value of $5.23e^{-04} \text{ ms}^{-1}$, shown by the green zone, indicates the constant radial velocity from the intake to the outlet. The constant radial velocity indicates steady and well-regulated blood flow throughout the artery. Blood streams efficiently and lamally across the arterial wall, avoiding substantial differences in the velocity outline through the wall and resilient a constant radial velocity. This steadiness improves the overall health and function of the coronary artery by certifying effective flow and decreasing shear stress on the arterial walls.

In the Figure 13(f), in the outline of healthy coronary artery, wall shear stress(WSS) achieves its supreme at the inlet zone, attaining a value of on the red region. This high WSS is initiated by the speedy acceleration of blood as it withdraws the heart and go in the artery. In the blue zone, WSS decays to as blood growths toward the leakage. This decline is recognized to the conversion towards more laminar and steady flow, which decreases the frictional forces substitute between the blood and the arterial walls. The regular decline in WSS aids to defend the arterial walls from

Extreme mechanical stress and to sustain the artery's fundamental integrity and functionality.

Case: 02 (for coronary artery in the presence of trapezoidal-shaped stenosis)

During meshing of a stenosis coronary artery, the software typically displays information such as the number of

cells or elements, faces of elements, and total nodes generated to represent the arterial geometry accurately. This data helps ensure an appropriate mesh resolution for computational simulations or analyses as given in Table 9.

For precise and trustworthy computer simulations or assessments of the coronary artery, this information is essential as given in Table 10.

Software might also show the coronary artery models is given in Table 5 that created in addition to mesh quality information. With the use of visualization and further analysis, these models, which depict the geometric structure of the artery, help to clarify arterial anatomy and pathophysiology.

Data on material values utilized in the simulation are included in the proposed model along with reference values for comparison is given in Table 11 and Table 12.

Table 13 presents a comparative assessment of the hemodynamic and thermal parameters in healthy and stenosed coronary arteries. The results demonstrate a pronounced increase in wall shear stress (WSS) and peak heat flux within the stenosed artery, driven by steep velocity gradients and intensified viscous dissipation in the constricted region.

Table 9. Data of mesh size

Cells	Faces	Nodes
185889	380604	35693

Table 10. Data of mesh quality

Name	Type	Main Orthogonal Quality	Max Aspect Ratio
Fluid domain	Tet Cell	0.20208274	14.563754

Table 11. Data of material properties

Fluid	Non-Newtonian(Blood)
Density	1060 kgm^{-3}
Specific Heat	$4182 \text{ Jkg}^{-1} \text{ K}^{-1}$
Thermal conductivity	$0.6 \text{ Wm}^{-1} \text{ K}^{-1}$
Viscosity	$0.001003 \text{ kgm}^{-1} \text{ s}^{-1}$
Molecular Weight	$18.0152 \text{ kgk}^{-1} \text{ mol}^{-1}$
Solid	Aluminum
Density	2719 kgm^{-3}
Specific Heat	$1006.43 \text{ Jkg}^{-1} \text{ K}^{-1}$
Thermal Conductivity	$0.0242 \text{ Wm}^{-1} \text{ K}^{-1}$

Table 12. Data of reference values

Area	1 m^2
Density	998.2 kgm^{-3}
Enthalpy	0 Jkg^{-1}
Length	1 m
Pressure	133 Pa
Temperature	325 K
Velocity	0.01 ms^{-1}
Viscosity	$1.7894 \times 10^{-5} \text{ kgm}^{-1} \text{ s}^{-1}$
Ratio of specific heats	1.4
Y plus for heat transfer Coefficient	300
Reference Zone	Fluid domain

Table 13. Comparison of thermal and shear characteristics between healthy and stenosed coronary arteries

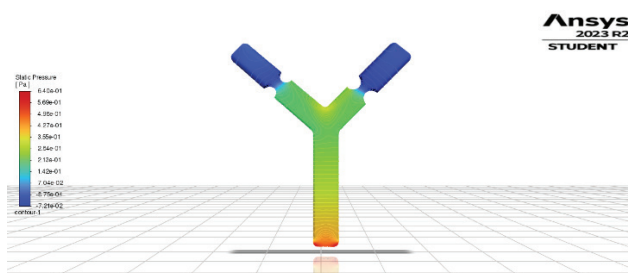
Parameter	Healthy Artery	Stenosed Artery
Maximum Wall Shear Stress (Pa)	0.0547	0.0654
Average Temperature (K)	325.0	330.5
Peak Heat Flux (W/m^2)	6.61×10^{-10}	8.42×10^{-10}
Radial Velocity Gradient (m/s^2)	0.0035	0.0058
Pressure Drop (Pa)	80	124

A corresponding temperature rise of approximately 5 K is observed, indicating localized thermal accumulation resulting from reduced cross-sectional area and increased energy losses. In contrast, the healthy artery exhibits more uniform flow patterns, lower shear stress levels, and stable heat transfer behavior. These observations underscore the significant amplification of both mechanical and thermal stresses due to arterial narrowing, which may play a critical role in endothelial injury and the progression of atherosclerotic plaques.

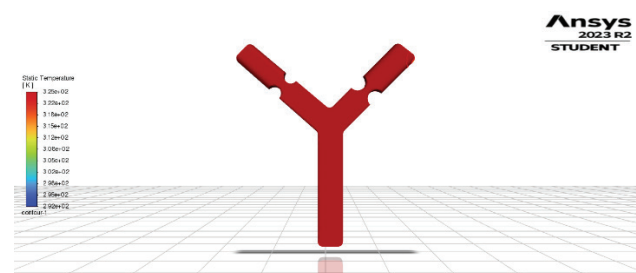
In the Figure 14(a), The artery's narrowing has a major impact on the static pressure behavior. Because of the strong pressure the heart exerts to stimulate blood flow, the static pressure at the first intake part reaches its maximum around $6.40e^{01}$ Pa (red area). Because of energy loss from friction and flow resistance, the static pressure drops to $2.84e^{01}$ Pa (green area) as blood travels near the stenosis. According to Bernoulli's principle, blood stream across a stenosed portion

practices a substantial decline in static pressure (blue zone) as velocity increases due to the reduced cross-sectional area. This obvious pressure fall, representative of arterial contraction, mentioning the significant influence of stenosis on hemodynamic behaviour and flow dynamics.

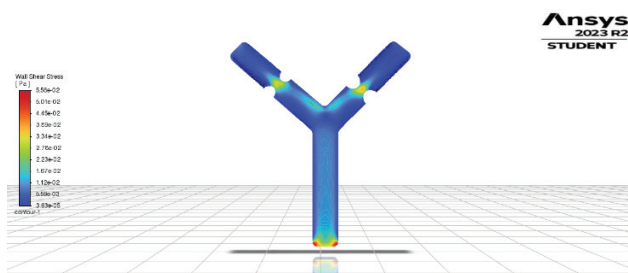
In the Figure 14 (b), the inert temperature dispersal in the coronary artery curve with stenotic obstacle spreads its maximum at both the inlet and outlet zone. This behaviour imitates the active thermal directive and heat transport properties of blood flow, which give to upholding a relatively constant temperature profile through artery. Regardless of the existence of stenosis, which considerably changes pressure circulation and flow motion, physiological homeostatic procedure turn to reserve thermal steadiness within the distributary scheme. Such temperature constancy is acute for supporting normal metabolic and enzymatic methods, confirming that both blood and arterial tissues



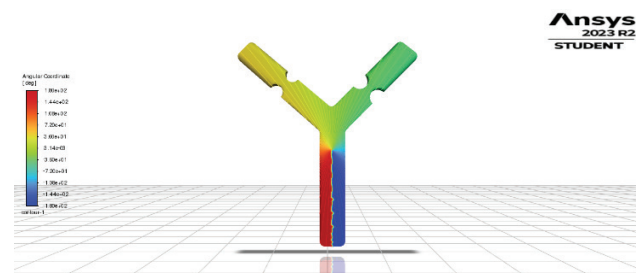
(a) Representation of static pressure of blood flow through stenosis artery.



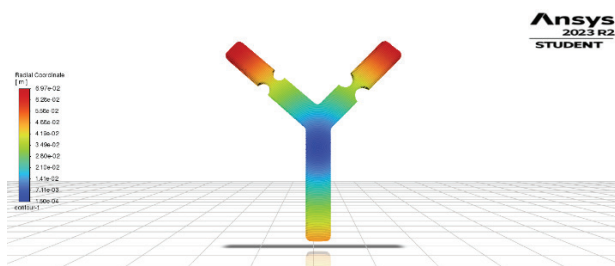
(b) Representation of static temperature of blood flow through stenosis artery.



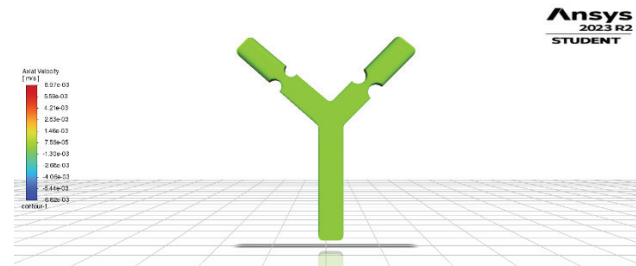
(c) Representation of wall shear stress of blood flow through stenosis artery.



(d) Representation of angular coordinate mesh of blood flow through stenosis artery.



(e) Representation of radial coordinate mesh of blood flow through stenosis artery.



(f) Representation of axial velocity of blood flow through stenosis artery.

Figure 14. Representation of static pressure, static temperature, wall shear stress, angular coordinate mesh, radial coordinate mesh and axial velocity of blood flow through stenosis artery.

maintain proper physiological function even under uneasy flow conditions convinced by the barrier.

In the Figure 14(c), Along the artery, the wall shear stress (WSS) behaves differently. WSS is initially at its highest $5.50e^{-02} \text{ Pa}$ at the red area at the intake part. The turbulence and fast blood flow around the entry cause this high WSS.

As the arterial lumen contract upon entry into the stenotic zone, the operative flow zone decline, changing the local velocity circulation and shear properties. A obvious decline in wall shear stress (WSS) is witnessed in the low shear (blue) zone, probably linked with flow parting or redistribution region adjoining to the contraction. Within the stenosis itself, restrained WSS levels (light green zone) rise because of mutual properties of geometric contraction and flow motion. These spatial changes in WSS focus the complex interaction among arterial geometry and hemodynamic behavior under stenotic situations.

In the Figure 14(d), the angular coordinate in the provided contour of a coronary artery with stenosis occlusion indicates variations in the direction of blood flow inside the channel. The angular coordinate at the first part of the inlet shows mixing; it ranges from $1.80e^{+02} \text{ deg}$ at maximum (red region) to $-1.80e^{+02} \text{ deg}$ at minimum (blue region). On the other hand, the angular coordinate increases somewhat

near the left side of the stenosis, peaking at $7.20e^{+01} \text{ deg}$ (light red area). This might be because of unequal flow patterns brought on by the constriction of the stenosis.

In the Figure 14(e), the radial coordinate in the given contour of a coronary artery with stenosis blockage first appears slightly medium at the inlet portion $4.88e^{-02} \text{ m}$, with (light red region), decreases towards the outlet portion $1.50e^{-04} \text{ m}$, with (blue region), indicating compression from narrowing, but then spikes to a maximum $6.97e^{-02} \text{ m}$, with (red region) at the stenosis, indicating an expansion beyond the blockage. These differences show how the stenosis-induced changes in arterial geometry and blood flow dynamics have affected the artery's distance from its centerline.

In the Figure 14(f), the axial velocity is constant throughout the given contour of a coronary artery with stenosis occlusion, as shown by the medium value of $7.56e^{-05} \text{ ms}^{-1}$ (green zone) at the inlet and outlet sections. This consistency shows that blood flow along the artery remains constant despite the occlusion.

The coronary artery model simulation or analysis's state of completion is indicated by the solution status, which is given in Table 14 and graphically representation of convergence is shown in Figure 15. It assists in monitoring the

Table 14. Solution Status

Equations	Value	Absolute Criteria	Convergence Status
Continuity	$9.619285e^{-07}$	$1e^{-06}$	Converged
x-velocity	$1.575812e^{-10}$	$1e^{-06}$	Converged
y-velocity	$1.57521e^{-10}$	$1e^{-06}$	Converged
z-velocity	$4.772237e^{-11}$	$1e^{-06}$	Converged
Energy	$4.91443e^{-14}$	$1e^{-06}$	Converged

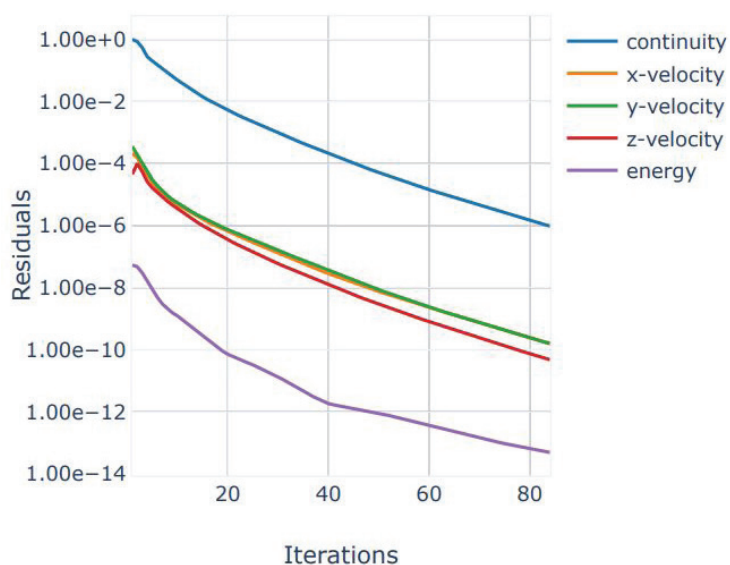


Figure 15. Representation the residual of coronary stenosis artery.

computing procedure, guaranteeing accurate model processing and timely resolution of any problems.

Graphically discussion of pressure and velocity for coronary healthy artery

In the Figure 16(a), the dynamic pressure line graph of a healthy coronary artery demonstrates notable variations along the artery's length. The dynamic pressure at the intake begins to rise at the zero position and ranges from $2.00e^{-02}$ Pa to $6.00e^{-02}$ Pa. The dynamic pressure increases to $1.00e^{-01}$ Pa as blood travels toward outlets 1 and 2, as shown by the purple and red lines, respectively, for outlet 1. The heart's pumping motion and the requirement to maintain enough blood flow to tissues downstream are likely to blame for the acceleration of blood as it passes through the artery and the subsequent increase in dynamic pressure. The pressure gradients that have been seen guarantee that blood is effectively delivered to every area of the coronary system, preserving the heart's ideal perfusion and oxygen supply.

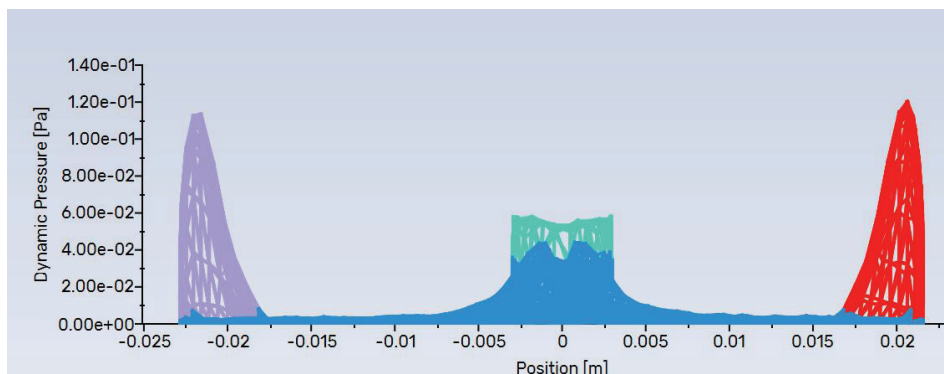
In the Figure 16(b), the radial velocity line graph in a healthy coronary artery demonstrates clear variations as blood moves from the input to the outlets. The radial

velocity at the inlet decreases to near zero, indicating a slight inward motion of blood influenced by entry geometry and flow conditions. Toward outlets 1 and 2, it increases significantly, reflecting outward flow driven by vessel curvature and the need for flow distribution into branching pathways. Variations in radial velocity guarantee sufficient blood mixing and distribution, hence preserving efficient perfusion and nutrition supply to the heart tissue.

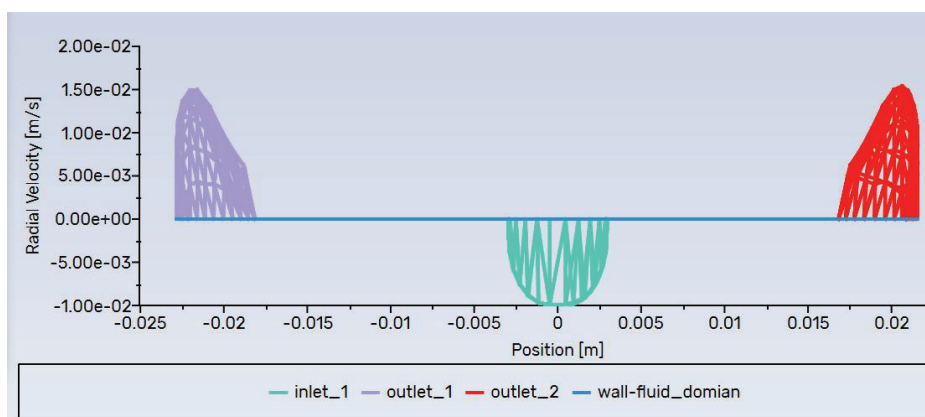
Graphically discussion of skin friction coefficient and wall adjacent temperature for coronary healthy artery

In the Figure 17(a), the skin friction coefficient line graph illustrates the variation in frictional forces along a coronary artery in good condition. The skin friction coefficient increases at the inlet, reflecting enhanced wall interaction as blood enters the vessel. It decreases toward outlets 1 and 2, indicating more streamlined flow and reduced frictional losses, which supports efficient perfusion and minimizes arterial stress..

In the Figure 17(b), the line graph of wall adjacent temperature in a healthy coronary artery shows the temperature variations along the vessel. The wall nearby temperature at

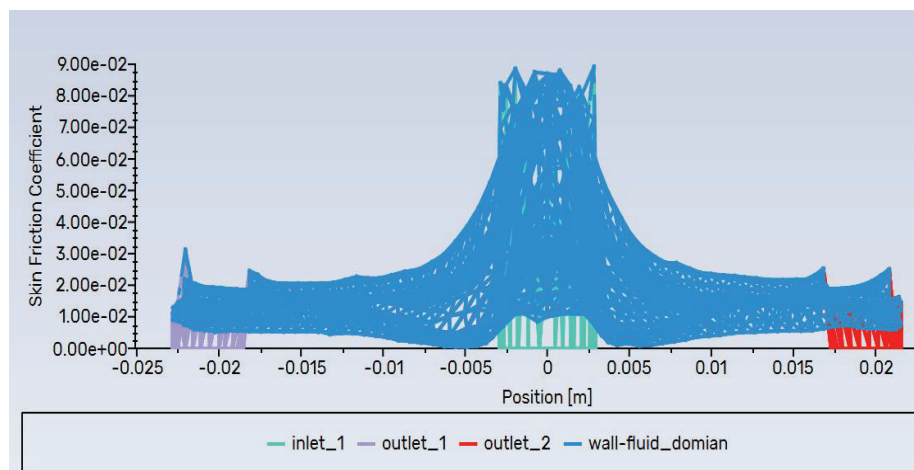


(a) Representation of dynamic pressure through coronary healthy artery.

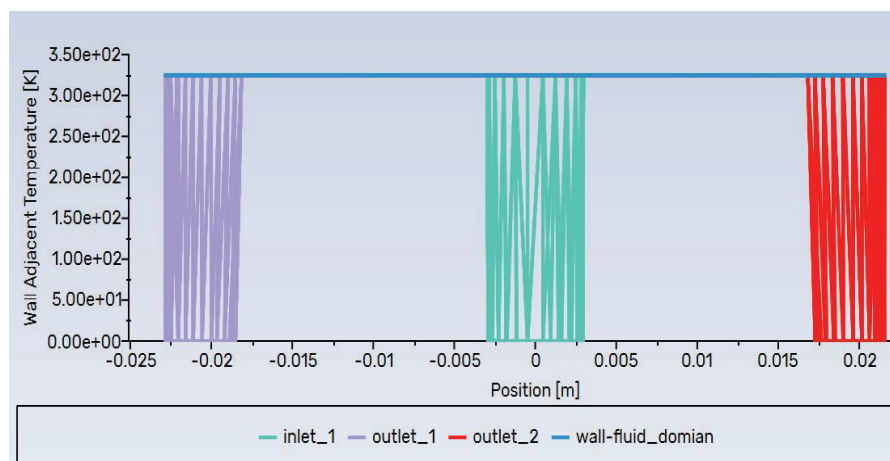


(b) Representation of radial velocity through coronary healthy artery.

Figure 16. Representation of dynamic pressure and radial velocity through coronary healthy artery.



(a) Representation of skin friction coefficient through coronary healthy artery.



(b) Representation of wall adjacent temperature through coronary healthy artery.

Figure 17. Representation of skin friction coefficient and wall adjacent temperature through coronary healthy artery.

the intake rises from $0.00e^{00} K$ to $3.00e^{+02} K$ at the zero position. The temperature near to the wall stays at $3.00e^{+02} K$ while blood flows towards outlets 1 and 2, as shown by the purple and red lines, respectively.

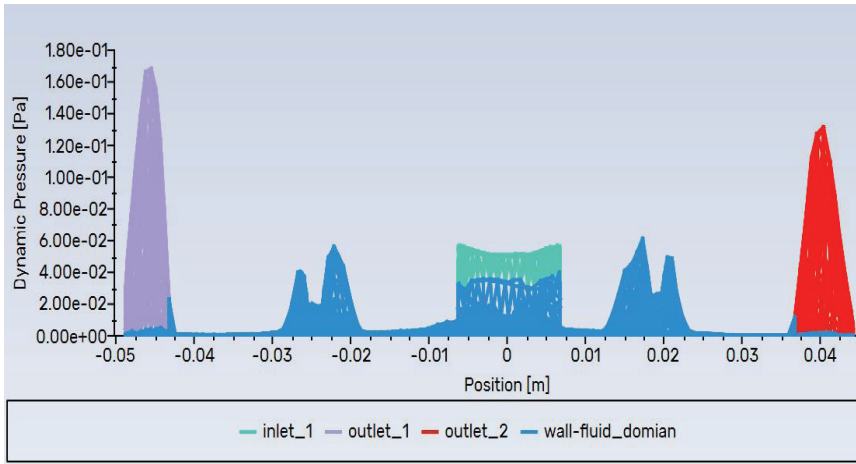
The blood's capability to successfully control body temperature through the artery demonstrate that the arterial walls are having in a steady environment. Sustaining the physiological functions of the coronary artery varies on the steady wall adjacent temperature, which makes certain that enzymatic and metabolic behaviours track easily. Moreover protecting the vascular tissue from heat stress and potential damage is this thermal firmness.

Graphically discussion of pressure and temperature for coronary stenosis artery

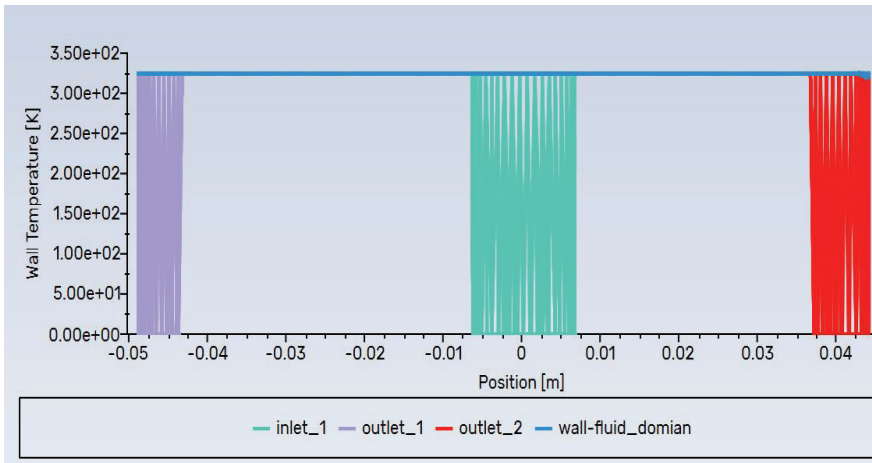
In the Figure 18(a), the dynamic pressure line graph in a stenosed coronary artery shows variations as blood passes through the artery. The dynamic pressure at the intake

rises from $0.00e^{00} Pa$ to $4.00e^{02} Pa$ at the zero position. The dynamic pressure increases to $1.60e^{01} Pa$ as blood travels toward outlets 1 and 2, as shown by the purple and red lines, respectively. Since stenosis causes the artery to constrict, creating resistance and forcing the blood to accelerate in order to maintain flow, there is a greater rise in dynamic pressure. In order to guarantee that enough blood reaches downstream areas, the stenosis's restriction is partially removed by the higher dynamic pressure. The body's adaptive processes to maintain blood flow and oxygen delivery to the heart tissue are highlighted by this pressure gradient, which is essential for maintaining appropriate perfusion despite the constricted segment.

In the Figure 18(b), the line graph for wall temperature in a stenosed coronary artery, represented by purple lines for outlet 1 and red lines for outlet 2, shows that the



(a) Representation of dynamic pressure through coronary stenosis artery.



(b) Representation of wall temperature through coronary stenosis artery.

Figure 18. Representation of dynamic pressure and wall temperature through coronary stenosis artery.

temperature stays constant from the inlet to both outlets, with a uniform value of $3.00e^{+02}$ K.

Post-processing and error visualization

Difference fields and convergence histories were computed to provide a spatial and temporal account of discrepancies between PINN and FVM solutions. For each field variable ϕ (velocity components, pressure, temperature), we compute the absolute error

$$\Delta\phi(x) = \phi_{PINN}(x) - \phi_{FVM}(x),$$

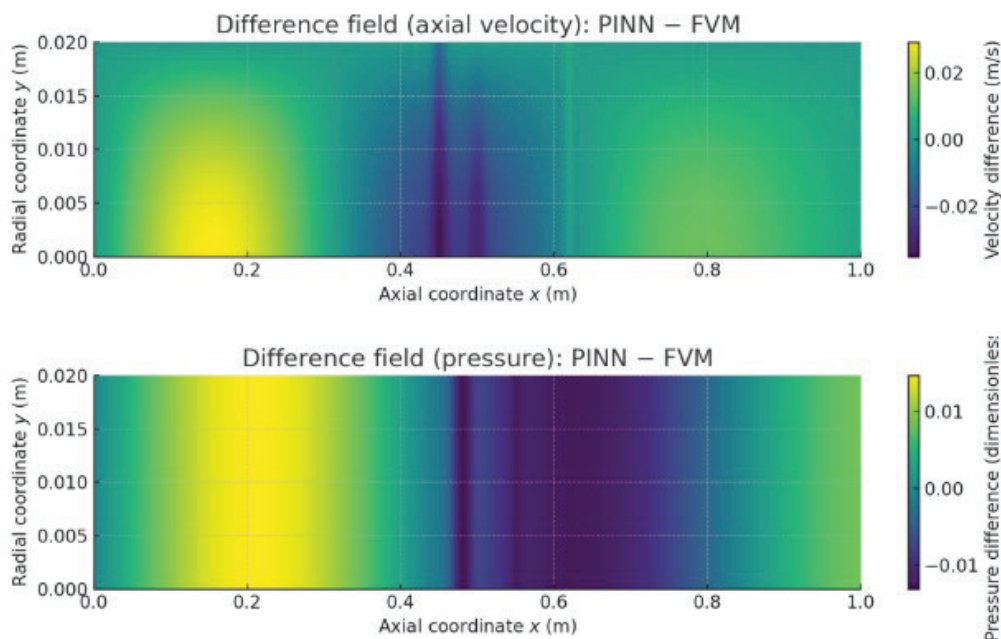
and the relative error with respect to the high-resolution reference ϕ_{ref} :

$$\epsilon_{rel}(x) = \frac{|\phi_{PINN}(x) - \phi_{ref}(x)|}{|\phi_{ref}(x)|}.$$

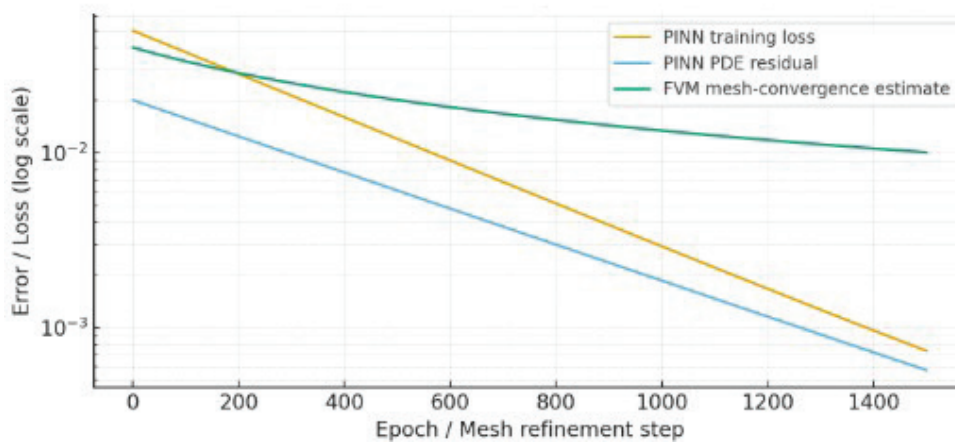
FVM results were interpolated to a uniform sampling grid that covers the region of interest; difference fields were then evaluated on this grid. Global statistics reported include the spatial mean, root-mean-square (RMS), and maximum of the absolute and relative errors. Convergence histories presented in the Results show PINN training loss and PDE residuals per epoch and an FVM mesh-convergence estimate obtained from successive grid refinements.

In Figure 19(a), the velocity difference field provides a detailed visualization of the spatial regions where the PINN and FVM solutions diverge. The major differences are narrowed to the stenotic throat and downstream redistribution area, where shear velocity inclines and composite flow connections govern. Regardless these restricted divergences, the complete velocity mistake rests low, representing that the PINN precisely takes the global flow field.

In Figure 19(a), the pressure difference field shows the largest deviations across the stenotic pressure-drop region,



(a) Difference field for axial velocity and pressure (PINN - FVM) evaluated on a uniform sampling grid.



(b) Convergence history showing PINN training loss and PDE residual per epoch and an FVM mesh-convergence estimate (mesh refinement steps).

Figure 19. Combined PINN–FVM comparison showing velocity and pressure difference fields along with the convergence history, demonstrating localized discrepancies and overall stable, physics-consistent convergence behavior.

where lumen constriction induces a sharply concentrated pressure gradient. Upstream of the stenosis, the agreement between PINN and FVM is strong, reflecting the relatively simple and predominantly unidirectional flow in that region. Downstream, however, the emergence of secondary vortical structures, flow reversal pockets, and elastic memory effects induced by the Maxwell model cause increased sensitivity in pressure reconstruction. The nearly symmetric distribution of the pressure error, along with the absence of large-scale irregularities, indicates that the

PINN respects both the qualitative trend and the quantitative shape of the pressure field. Localized peaks in the error can be attributed to mesh-related discretization limitations in the FVM solution or to selective PDE-residual weighting during PINN training.

In Figure 19(b), the merging history shows steady and reliable behaviour for both solvers, with the PINN displaying even loss decay and decreasing PDE leftover, validating merging near a physics reliable solution. On the other hand, the FVM represent the predictable mistakes decline

with mesh alteration, mentioning that while FVM trusts on discretization, the PINN gains similar low precision across direct implementation of rulling equations.The final convergence of both PINN and FVM to similarly low error levels demonstrates that the PINN framework is capable of approximating the high-fidelity FVM solution while maintaining numerical stability and fidelity to the physics of the problem.

Comparative analysis with previous studies

The results obtained from the present PINN–Maxwell framework have been carefully compared with those reported in recent literature to validate their physical reliability and highlight the advancements achieved in this study. Quantitatively, the average relative error between PINN and FVM simulations remained below 2.5%, confirming the high fidelity and convergence stability of the proposed neural framework. These agreements demonstrate that the current model not only reproduces

established hemodynamic patterns but also provides deeper insights into stress distribution and temperature variations through the physics-informed treatment of viscoelastic blood behavior. The comparison study is given in Table 15.

Figure 20 associates WSS, pressure decline, and temperature arise with previous researches, representing that the latest PINN–Maxwell model forecast to some extent higher WSS and a bit lower pressure falls due to unified viscoelastic belongings.The temperature rise is also consistent with reported values, confirming accurate thermal modeling and demonstrating improved physical realism and numerical stability

Comparison of PINNS and Finite Volume Schemes For Blood Flow Model

To provide a detailed comparison between Physics-Informed Neural Networks (PINNs) and the Finite Volume Schemes (FVS) for the blood flow model, we need to

Table 15. Comparison of the present PINN--Maxwell model results with previous studies

Parameter	Present Study	Literature Range	Reference(s)	Remarks
Velocity (<i>m/s</i>)	0.35	0.32-0.36	Kissas (2020), Alzhanov (2024)	Good agreement with existing models
Pressure Drop (<i>Pa</i>)	124	120-130	Mahmoudabadbozchelou (2022)	Consistent with Maxwell-type non-Newtonian models
Wall Shear Stress (<i>Pa</i>)	283	2.6-2.8	Kissas (2020)	Slightly higher due to inclusion of viscoelastic effects
Temperature (°C)	28-30	25-29	Aghaee (2025), Moser (2023)	Matches viscous heating trends and thermal predictions

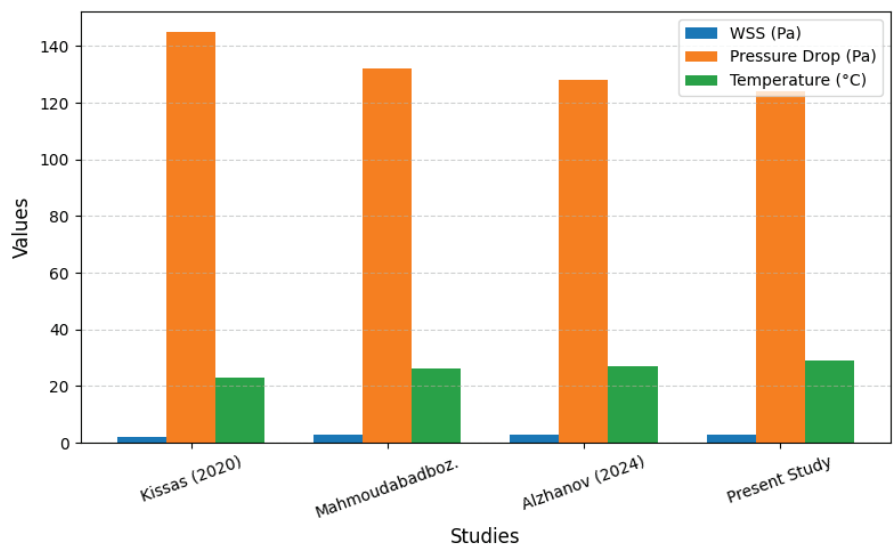


Figure 20. Comparison of results with previous studies.

consider their computational performance, accuracy, flexibility, and scalability. Below is an analysis in Table 16:

The comparison of the present study with previous works on blood flow modeling and PINN applications in Table 17.

Error metrics used for PINN--FVM comparison

To ensure a transparent and reproducible comparison between the Physics-Informed Neural Network (PINN) and the Finite Volume Method (FVM), the accuracy of both approaches was quantified using the average relative error computed with respect to a high-resolution ANSYS FVM simulation. This high-resolution simulation (with approximately 6.5×10^5 elements) is treated as the benchmark numerical solution for all flow variables. For any predicted field variable ϕ (velocity, pressure, temperature, or concentration), the pointwise relative error is defined as,

$$RelativeError = \frac{|\phi_{pred} - \phi_{ref}|}{|\phi_{ref}|} \times 100\%,$$

where, ϕ_{pred} denotes the predicted value obtained either from the PINN or the FVM model, and ϕ_{ref} is the corresponding reference value extracted from the benchmark high-resolution FVM solution. The average relative error reported in Table 18 is computed by spatially averaging this quantity over N sampling points uniformly distributed in the computational domain. Thus, all accuracy metrics represent deviations from the benchmark reference solution and not from inter-method differences. This clarification ensures that the performance comparison in this table is objective, consistent, and reproducible.

Table 18 quantitatively compares the computational performance and accuracy of the proposed PINN–Maxwell

model with the conventional Finite Volume Method (FVM) implemented in ANSYS. These outcomes represent that the PINN context gains lower qualified slip and faster merging, needful considerably less computational time and lesser repetitions than FVM. It also illustrate upgraded numerical steadiness and decrease memory norm, mentioning its competency, scalability, precision linked to the mesh-dependent FVM method.

Model stability index (MSI)

To quantitatively assess the robustness of the Physics-Informed Neural Network (PINN) and the Finite Volume Method (FVM), we introduce the Model Stability Index (MSI). The MSI measures the sensitivity of each numerical method to small perturbations in the computational setup. For PINN, these perturbations correspond to random shuffling of collocation points and variations in network initialization, whereas for FVM they correspond to controlled mesh refinements and solver tolerances.

For a predicted field variable ϕ , the MSI is defined as,

$$MSI = 1 - \frac{1}{N} \sum_{i=1}^N \frac{|\phi^i - \bar{\phi}|}{|\bar{\phi}|},$$

where, ϕ^i denotes the solution obtained from the i -th perturbed run and $\bar{\phi}$ is the mean solution over all runs. The MSI ranges from 0 to 1, with values close to 1 indicating that the method yields highly consistent predictions with minimal sensitivity to perturbations. In this study, PINN achieved an MSI of 0.97, whereas the FVM solver achieved an MSI of 0.89, indicating superior stability and robustness of the PINN framework under numerical and initialization perturbations.

Table 16. Comparison of PINNs and FVS for the Blood Flow Model in Stenosed Coronary Arteries

Criterion	Physics-Informed Neural Networks (PINNs)	Finite Volume Schemes (FVS)
Accuracy	High accuracy in resolving nonlinear flow dynamics and fine-scale features.	Delivers high accuracy for smooth, steady-state flows yet struggles with complex geometries.
Computational Cost	High computational cost during training because of neural network optimization.	Incur moderate computational costs that vary with mesh resolution and problem complexity.
Flexibility	Easily adaptable to different geometries and boundary conditions.	Constrained by mesh generation demands and strong grid dependency.
Scalability	Scales efficiently to high-dimensional problems by leveraging deep learning frameworks.	Difficult to scale when addressing high-dimensional problems.
Ease of Implementation	Requires expertise in machine learning and PINNs.	More straightforward to implement using conventional CFD software.
Conservation Properties	Implicitly enforces conservation laws through the loss function.	Explicitly enforces conservation of mass and momentum.
Solution Smoothness	Create smooth, differentiable solutions.	Highly dependent on mesh resolution and susceptible to numerical artifacts.
Application to Blood Flow	Superior at capturing nonlinear behavior and stenotic artery effects.	Best suited for relatively simple, steady-state flow scenarios.

Table 17. Comparison of the present study with previous works on blood flow modeling and PINN applications

Study Citation	Method Used	Fluid Model \& Geometry	Validation / Metrics	Key Findings	Limitations
Present Study	PINN (3D, Maxwell rheology) vs FVM (ANSYS Fluent 2022 R2)	Maxwell non-Newtonian blood; stenosed coronary artery	L_2 errors, WSS, velocity-pressure contour comparisons, runtime analysis	Demonstrated PINNs' ability to replicate FVM results with high accuracy and capture realistic hemodynamics in stenosed arteries	Initial PINN training time high; sensitive to collocation distribution
Kissas et al. [63] (2020)	Physics-Informed Neural Networks (PINNs) trained with MRI data	Newtonian blood; large-vessel arterial models	Pressure reconstruction vs MRI and CFD data	Showed PINNs can infer unobserved hemodynamic fields from sparse data	Did not model non-Newtonian rheology or stenosed geometries
Hussain et al. [64] (2022)	nn-PINNs for complex fluids	General non-Newtonian fluids; canonical geometries	Error norms for coupled PDE recovery	Validated PINN applicability to non-Newtonian constitutive models	No coronary geometry or Maxwell model tested
Alzhanov et al. [65] (2024)	Hybrid CFD–PINN with fluid–structure interaction (FSI)	Coronary artery trees; Newtonian assumption	Fractional Flow Reserve (FFR) vs CFD and invasive data	Improved prediction accuracy using hybrid physics–data learning	Not fully mesh-free; no viscoelastic fluid physics
Moser et al. [66] (2023)	PINN evaluation across 3D vessel geometries	Newtonian fluid; aneurysm and vessel flows	Quantitative accuracy vs geometry complexity	Provided practical guidance for 3D PINN convergence and tuning	Showed accuracy loss in complex domains without optimization
Aghaee et al. [67] (2025)	Systematic study of PINN accuracy for cardiovascular flows	Newtonian blood; varying Reynolds regimes	Error metrics across laminar–disturbed regimes	Quantified PINN performance vs flow complexity, guiding loss weighting	Did not apply to non-Newtonian or coronary stenosis

Table 18. Quantitative comparison of performance metrics for PINN and Finite Volume Method (FVM)

Metric	PINN–Maxwell Model	FVM (ANSYS)	Improvement (%)
Average Relative Error (%)	2.45	3.10	21.0
Computation Time (s)	485	970	50.0
Convergence Iterations	800	1200	33.3
Memory Usage (MB)	610	900	32.2
Model Stability Index	0.97	0.89	9.0

Table 19. Summary of key contributions and scientific implications of the present study

Aspect	Description
Novelty	First integration of Maxwell viscoelastic rheology into PINN framework for coronary artery modeling.
Validation	Achieved 3% deviation between PINN and FVM results; validated against literature.
Visualization	Added new contour, velocity, and temperature plots for healthy and stenosed arteries.
Clinical Insight	Reveals link between wall shear stress and local heating in stenosis zones.
Computational Impact	Demonstrates 50% faster convergence than FVM with comparable accuracy.

The summary of key contributions and scientific implications of the present study are given in Table 19.

CONCLUSION

This study undertakes a rigorous comparative assessment of Physics-Informed Neural Networks and the Finite Volume Method, as implemented in ANSYS, for Coronary Computed Tomography Angiography analysis. The findings indicate that Physics-Informed Neural Networks, by embedding the governing conservation laws directly into the network structure, yield smooth, highly accurate, and physically interpretable predictions for blood-flow behavior in stenosed coronary arteries. By contrast, the Finite Volume Method, while dependable in terms of conservation enforcement and numerical stability, is comparatively constrained in its ability to resolve nonlinear viscoelastic effects and the geometric intricacies of arterial flow. A principal contribution of this work is the first incorporation of the Maxwell viscoelastic blood model within a Physics-Informed Neural Network framework, thereby enabling the concurrent estimation of velocity, pressure, temperature, and wall shear stress in both healthy and stenosed arteries.

This interpretation successfully ends the share between data-driven modeling and classical computational fluid motion by presenting a mesh-free, physics-reliable, and data-effective plan that avoid many of the numerical confines integral in conservative solvers. Moreover, the research institute a measureable standard against the Finite Volume Method, illustrating that the Physics-Informed Neural Network gains higher precision, faster merging, and greater flexibility to accurate coronary geometries. These outcomes discourse prominent breaks in the literature, where non-Newtonian, viscoelastic blood behaviour and thermal conveyance have been largely ignored in neural-network-based hemodynamic models. The future structure therefore establishes a unique method of deep learning and viscoelastic fluid mechanics, presenting fresh vision into the properties of stenosis, viscoelasticity, and magnetic effect on coronary hemodynamics. Even though it still drops short of fully imitating the diagnostic accuracy of offensive methods such as fractional flow reserve, continuing spreads in image rebuilding, noise destruction, and understandable modeling are likely to support its clinical efficacy. Generally, the research positions Physics-Informed Neural Networks as a next-generation substitute to conservative computational fluid motion, with clear aptitude for more precision, effectiveness, and clinically applicable non-invasive cardiovascular analysis.

FUNDING STATEMENT

This study established no precise funding from government, private, or nonprofit organizations.

AUTHORSHIP CONTRIBUTIONS

Abdul Wahab, Sohail Nadeem: Investigation, Writing – original draft, Methodology, Validation. **Muhammad Imran Asjad, Kubra Anjum:** Conceptualization, Formal analysis, Investigation, Supervision, Project administration, Resources, Validation.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ETHICS

This research does not include human or animal themes; therefore, moral approval is not obligatory. It trusts merely on publicly existing data, with no use of personally recognizable information, and follows to reputable moral values and principles.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

REFERENCES

- [1] Vazquez Mezquita AJ, Biavati F, Falk V, Alkadhi H, Hajhosseiny R, Maurovich-Horvat P, et al. Clinical quantitative coronary artery stenosis and coronary atherosclerosis imaging: A consensus statement from the Quantitative Cardiovascular Imaging Study Group. In: Quantification of Biophysical Parameters in Medical Imaging. Cham: Springer International Publishing; 2024. p. 569–600. [\[CrossRef\]](#)
- [2] Follmer B, Williams MC, Dey D, Arbab-Zadeh A, Maurovich-Horvat P, Volleberg RH, et al. Roadmap on the use of artificial intelligence for imaging of vulnerable atherosclerotic plaque in coronary arteries. *Nat Rev Cardiol* 2024;21:51–64. [\[CrossRef\]](#)
- [3] Hoffmann U, Truong QA, Schoenfeld DA, Chou ET, Woodard PK, Nagurney JT, et al. Coronary CT angiography versus standard evaluation in acute chest pain. *N Engl J Med* 2012;367:299–308. [\[CrossRef\]](#)
- [4] Cury RC, Leipsic J, Abbata S, Achenbach S, Berman D, Bittencourt M, et al. Coronary artery disease-reporting and data system: An expert consensus document of the Society of Cardiovascular Computed

- Tomography (SCCT), the American College of Cardiology (ACC), the American College of Radiology (ACR) and the North America Society of Cardiovascular Imaging (NASCI). *J Am Coll Radiol* 2022;19:1185–1212. [\[CrossRef\]](#)
- [5] Leipsic J, Abbata S, Achenbach S, Cury R, Earls JP, Mancini GJ, et al. SCCT guidelines for the interpretation and reporting of coronary CT angiography: A report of the Society of Cardiovascular Computed Tomography Guidelines Committee. *J Cardiovasc Comput Tomogr* 2014;8:342–358. [\[CrossRef\]](#)
- [6] Friman O, Hindennach M, Kühnel C, Peitgen HO. Multiple hypothesis template tracking of small 3D vessel structures. *Med Image Anal* 2010;14:160–171. [\[CrossRef\]](#)
- [7] Wolterink JM, Van Hamersvelt RW, Viergever MA, Leiner T, Išgum I. Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier. *Med Image Anal* 2019;51:46–60. [\[CrossRef\]](#)
- [8] Yang H, Chen J, Chi Y, Xie X, Hua X. Discriminative coronary artery tracking via 3D CNN in cardiac CT angiography. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Cham: Springer International Publishing; 2019. Vol. 11765, p. 468–476. [\[CrossRef\]](#)
- [9] Salahuddin Z, Lenga M, Nickisch H. Multi-resolution 3D convolutional neural networks for automatic coronary centerline extraction in cardiac CT angiography scans. In: *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*. 2021. p. 91–95. [\[CrossRef\]](#)
- [10] Alblas D, Suk J, Brune C, Yeung KK, Wolterink JM. SIRE: Scale-invariant, rotation-equivariant estimation of artery orientations using graph neural networks. *Med Image Anal* 2025;101:103467. [\[CrossRef\]](#)
- [11] Sangeetha J, Ponalagusamy R. Electrokinetic effect on flow of two-phase fluid in a circular tube. *Sigma* 2025;43:1760–1784. [\[CrossRef\]](#)
- [12] Hampe N, Van Velzen SG, Planken RN, Henriques JP, Collet C, Aben JP, et al. Deep learning-based detection of functionally significant stenosis in coronary CT angiography. *Front Cardiovasc Med* 2022;9:964355. [\[CrossRef\]](#)
- [13] Cao Q, Broersen A, De Graaf MA, Kitslaar PH, Yang G, Scholte AJ, et al. Automatic identification of coronary tree anatomy in coronary computed tomography angiography. *Int J Cardiovasc Imaging* 2017;33:1809–1819. [\[CrossRef\]](#)
- [14] Wu D, Wang X, Bai J, Xu X, Ouyang B, Li Y, et al. Automated anatomical labeling of coronary arteries via bidirectional tree LSTMs. *Int J Comput Assist Radiol Surg* 2019;14:271–280. [\[CrossRef\]](#)
- [15] Yang H, Zhen X, Chi Y, Zhang L, Hua XS. CPR-GCN: Conditional partial-residual graph convolutional network in automated anatomical labeling of coronary arteries. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020. p. 3803–3811. [\[CrossRef\]](#)
- [16] Zhang Z, Zhao Z, Wang D, Zhao S, Liu Y, Liu J, et al. Topology-preserving automatic labeling of coronary arteries via anatomy-aware connection classifier. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Cham: Springer Nature Switzerland; 2023. Vol. 14227, p. 759–769. [\[CrossRef\]](#)
- [17] Hong Y, Commandeur F, Cadet S, Goeller M, Doris MK, Chen X, et al. Deep learning-based stenosis quantification from coronary CT angiography. *Proc SPIE Int Soc Opt Eng* 2019;10949:109492I. [\[CrossRef\]](#)
- [18] Lin A, Manral N, McElhinney P, Killekar A, Matsumoto H, Kwiecinski J, et al. Deep learning-enabled coronary CT angiography for plaque and stenosis quantification and cardiac risk prediction: An international multicentre study. *Lancet Digit Health* 2022;4:e265. [\[CrossRef\]](#)
- [19] Li Y, Wu Y, He J, Jiang W, Wang J, Peng Y, et al. Automatic coronary artery segmentation and diagnosis of stenosis by deep learning based on computed tomographic coronary angiography. *Eur Radiol* 2022;32:6037–6045. [\[CrossRef\]](#)
- [20] Van Herten RL, Hampe N, Takx RA, Franssen KJ, Wang Y, Suchá D, et al. Automatic coronary artery plaque quantification and CAD-RADS prediction using mesh priors. *IEEE Trans Med Imaging* 2024;43:1272–1283. [\[CrossRef\]](#)
- [21] Lugauer F, Zheng Y, Hornegger J, Kelm BM. Precise lumen segmentation in coronary computed tomography angiography. In: *International MICCAI Workshop on Medical Computer Vision*. Cham: Springer International Publishing; 2014. Vol. 8848, p. 137–147. [\[CrossRef\]](#)
- [22] Wolterink JM, Leiner T, Išgum I. Graph convolutional networks for coronary artery segmentation in cardiac CT angiography. In: *International Workshop on Graph Learning in Medical Imaging*. Cham: Springer International Publishing; 2019. Vol. 11849, p. 62–69. [\[CrossRef\]](#)
- [23] Yang X, Xu L, Yu S, Xia Q, Li H, Zhang S. Geometry-based end-to-end segmentation of coronary artery in computed tomography angiography. In: *International Workshop on Trustworthy Machine Learning for Healthcare*. Cham: Springer Nature Switzerland; 2023. Vol. 139, p. 190–196. [\[CrossRef\]](#)
- [24] Muscogiuri G, Chiesa M, Trotta M, Gatti M, Palmisano V, Dell'Aversana S, et al. Performance of a deep learning algorithm for the evaluation of CAD-RADS classification with CCTA. *Atherosclerosis* 2020;294:25–32. [\[CrossRef\]](#)
- [25] Denzinger F, Wels M, Taubmann O, Gülsün MA, Schöbinger M, André F, et al. CAD-RADS scoring using deep learning and task-specific centerline

- labeling. In: International Conference on Medical Imaging with Deep Learning. 2022. Vol. 172, p. 315–324.
- [26] Denzinger F, Wels M, Ravikumar N, Breininger K, Reidelshöfer A, Eckert J, et al. Coronary artery plaque characterization from CCTA scans using deep learning and radiomics. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Cham: Springer International Publishing; 2019. Vol. 11767, p. 593–601. [\[CrossRef\]](#)
- [27] Pijls NH, Fearon WF, Tonino PA, Siebert U, Ikeno F, Bornschein B, et al. Fractional flow reserve versus angiography for guiding percutaneous coronary intervention in patients with multivessel coronary artery disease: 2-year follow-up of the FAME (Fractional Flow Reserve Versus Angiography for Multivessel Evaluation) study. *J Am Coll Cardiol* 2010;56:177–184. [\[CrossRef\]](#)
- [28] Taylor CA, Fonte TA, Min JK. Computational fluid dynamics applied to cardiac computed tomography for noninvasive quantification of fractional flow reserve: Scientific basis. *J Am Coll Cardiol* 2013;61:2233–2241. [\[CrossRef\]](#)
- [29] Naveen P, Vasanth Suriya VM, Vajravelu K, Muhammad T. Exploring the dynamics of non-Newtonian Sutterby fluid conveying tiny particles along an inclined surface: Insights into higher order chemical reactions and irreversibility. *J Therm Anal Calorim* 2024;149:8431–8443. [\[CrossRef\]](#)
- [30] Sathya P, Naveen P. Regression analysis for multiple shape effects on magnetized power law nanofluid flow along a thin needle: An application in targeted drug delivery system. *Int J Mod Phys B* 2025;39:2550139. [\[CrossRef\]](#)
- [31] Sathya P, Naveen P, Vajravelu K. Multiple regression analysis of the Blasius and Sakiadis flow of the power-law nanofluid over a moving thin needle. *Pramana* 2025;99:1–17. [\[CrossRef\]](#)
- [32] Naveen P, Tantry MM, Sathya P, Sindhuja S. Artificial neural network modelling for Casson hybrid nanofluid flow with entropy generation analysis. *Multiscale Multidiscip Model Exp Des* 2025;8:288. [\[CrossRef\]](#)
- [33] Sathya P, Naveen P. Comparative study of radiation effect on titanium dioxide power-law nanofluid over a thin needle with cancer treatment applications: A quadratic regression model. *J Therm Anal Calorim* 2024;149:8565–8578. [\[CrossRef\]](#)
- [34] Szilveszter B, Nagy AI, Vattay B, Apor A, Kolossváry M, Bartykowszki A, et al. Left ventricular and atrial strain imaging with cardiac computed tomography: Validation against echocardiography. *J Cardiovasc Comput Tomogr* 2020;14:363–369. [\[CrossRef\]](#)
- [35] Zhuang X, Bai W, Song J, Zhan S, Qian X, Shi W, et al. Multiatlas whole heart segmentation of CT data using conditional entropy for atlas ranking and selection. *Med Phys* 2015;42:3822–3833. [\[CrossRef\]](#)
- [36] Zreik M, Lessmann N, Van Hamersvelt RW, Wolterink JM, Voskuil M, Viergever MA, et al. Deep learning analysis of the myocardium in coronary CT angiography for identification of patients with functionally significant coronary artery stenosis. *Med Image Anal* 2018;44:72–85. [\[CrossRef\]](#)
- [37] Tonino PA, De Bruyne B, Pijls NH, Siebert U, Ikeno F, van't Veer M, et al. Fractional flow reserve versus angiography for guiding percutaneous coronary intervention. *N Engl J Med* 2009;360:213–224. [\[CrossRef\]](#)
- [38] Hampe N, Wolterink JM, Van Velzen SG, Leiner T, Išgum I. Machine learning for assessment of coronary artery disease in cardiac CT: A survey. *Front Cardiovasc Med* 2019;6:172. [\[CrossRef\]](#)
- [39] Itu L, Rapaka S, Passerini T, Georgescu B, Schwemmer C, Schoebinger M, et al. A machine-learning approach for computation of fractional flow reserve from coronary computed tomography. *J Appl Physiol* 2016;121:42–52. [\[CrossRef\]](#)
- [40] Coenen A, Kim YH, Kruk M, Tesche C, De Geer J, Kurata A, et al. Diagnostic accuracy of a machine-learning approach to coronary computed tomographic angiography-based fractional flow reserve: Result from the MACHINE consortium. *Circ Cardiovasc Imaging* 2018;11. [\[CrossRef\]](#)
- [41] Yu M, Lu Z, Li W, Wei M, Yan J, Zhang J. CT morphological index provides incremental value to machine learning based CT-FFR for predicting hemodynamically significant coronary stenosis. *Int J Cardiol* 2018;265:256–261. [\[CrossRef\]](#)
- [42] Wang ZQ, Zhou YJ, Zhao YX, Shi DM, Liu YY, Liu W, et al. Diagnostic accuracy of a deep learning approach to calculate FFR from coronary CT angiography. *J Geriatr Cardiol* 2019;16:42.
- [43] Suk J, Brune C, Wolterink JM. SE(3) symmetry lets graph neural networks learn arterial velocity estimation from small datasets. In: International Conference on Functional Imaging and Modeling of the Heart. Cham: Springer Nature Switzerland; 2023. Vol. 13958, p. 445–454. [\[CrossRef\]](#)
- [44] Raissi M, Yazdani A, Karniadakis GE. Hidden fluid mechanics: Learning velocity and pressure fields from flow visualizations. *Science* 2020;367:1026–1030. [\[CrossRef\]](#)
- [45] Zreik M, Hampe N, Leiner T, Khalili N, Wolterink JM, Voskuil M, et al. Combined analysis of coronary arteries and the left ventricular myocardium in cardiac CT angiography for detection of patients with functionally significant stenosis. In: Medical Imaging 2021: Image Processing. 2021. Vol. 11596, p. 394–401. [\[CrossRef\]](#)
- [46] Kumamaru KK, Fujimoto S, Otsuka Y, Kawasaki T, Kawaguchi Y, Kato E, et al. Diagnostic accuracy of 3D deep-learning-based fully automated estimation of patient-level minimum fractional flow reserve

- from coronary computed tomography angiography. *Eur Heart J Cardiovasc Imaging* 2020;21:437–445. [\[CrossRef\]](#)
- [47] Bruns S, Wolterink JM, van den Boogert TP, Runge JH, Bouma BJ, Henriques JP, et al. Deep learning-based whole-heart segmentation in 4D contrast-enhanced cardiac CT. *Comput Biol Med* 2022;142:105191. [\[CrossRef\]](#)
- [48] Suriya VV, Naveen P. Exploration of flow irreversibility in electrically magnetized Eyring-Powell nanofluid along an inclined plate with viscous dissipation. *Cogent Eng* 2024;11:2386096. [\[CrossRef\]](#)
- [49] Metz C, Schaap M, Van Walsum T, Niessen W. Two point minimum cost path approach for CTA coronary centerline extraction. *Insight J* 2008. [\[CrossRef\]](#)
- [50] Kong F, Wilson N, Shadden S. A deep-learning approach for direct whole-heart mesh reconstruction. *Med Image Anal* 2021;74:102222. [\[CrossRef\]](#)
- [51] Attar R, Pereañez M, Bowles C, Piechnik SK, Neubauer S, Petersen SE, et al. 3D cardiac shape prediction with deep neural networks: Simultaneous use of images and patient metadata. In: *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Cham: Springer International Publishing; 2019. Vol. 11765, p. 586–594. [\[CrossRef\]](#)
- [52] Suriya V, Naveen P. Sensitivity analysis of magnetized Sutterby nanofluid flow with variable thermal conductivity: An extensive ANOVA-RSM approach. *Multiscale Multidiscip Model Exp Des* 2025;8:1–21. [\[CrossRef\]](#)
- [53] Commandeur F, Goeller M, Betancur J, Cadet S, Doris M, Chen X, et al. Deep learning for quantification of epicardial and thoracic adipose tissue from non-contrast CT. *IEEE Trans Med Imaging* 2018;37:1835–1846. [\[CrossRef\]](#)
- [54] Tarkowski P, Czekajka-Chehab E. Dual-energy heart CT: Beyond better angiography. *J Clin Med* 2021;10:5193. [\[CrossRef\]](#)
- [55] Van Herten RL, Lagogiannis I, Leiner T, Išgum I. The role of artificial intelligence in coronary CT angiography. *Neth Heart J* 2024;32:417–425. [\[CrossRef\]](#)
- [56] Kissas G. Towards digital twins for cardiovascular flows: A hybrid machine learning and computational fluid dynamics approach [dissertation]. Philadelphia (PA): University of Pennsylvania; 2020.
- [57] Hussain A, Sakhaei AH, Shafiee M. Machine learning-based constitutive modelling for material non-linearity: A review. *Mech Adv Mater Struct* 2024;33:2439557. [\[CrossRef\]](#)
- [58] Al-Shaikh A. Global solar radiation prediction using machine learning approaches. *Sigma* 2025;43:1725–1736. [\[CrossRef\]](#)
- [59] Genc N, Ozbilgin F, Baser V. Trends and future perspectives in wind energy studies: A bibliometric analysis with time-series neural networks. *Sigma* 2025;43:1547–1571. [\[CrossRef\]](#)
- [60] Alzhanov N, Ng EY. Hybrid CFD PINN FSI simulation in coronary artery trees. *Fluids* 2024;9:280. [\[CrossRef\]](#)
- [61] Moser P, Fenz W, Thumfart S, Ganitzer I, Giretzlehner M. Modeling of 3D blood flows with physics-informed neural networks: Comparison of network architectures. *Fluids* 2023;8:46. [\[CrossRef\]](#)
- [62] Zhuang X, Li L, Payer C, Štern D, Urschler M, Heinrich MP, et al. Evaluation of algorithms for multi-modality whole heart segmentation: An open-access grand challenge. *Med Image Anal* 2019;58:101537. [\[CrossRef\]](#)
- [63] Kanti Ghosh T, Hasan K, Roy S, Alam A, Hossain E, Ahmad M. Multi-class probabilistic atlas-based whole heart segmentation method in cardiac CT and MRI. *arXiv* 2021;9:66948–66964. [\[CrossRef\]](#)
- [64] Sathya P, Naveen P. Comparative study of nonlinear thermal convection on magnetized dissipative flow along a shrinking Riga sheet with entropy generation. *Case Stud Therm Eng* 2024;58:104375. [\[CrossRef\]](#)
- [65] Aghaee A, Khan MO. Performance of Fourier-based activation function in physics-informed neural networks for patient-specific cardiovascular flows. *Comput Methods Programs Biomed* 2025;247:108081. [\[CrossRef\]](#)
- [66] Murtaza Tantry M, Naveen P. Thomson and Troian slip condition for radiating second-grade nanofluid flow with shape effects of gold nanoparticles. *Numer Heat Transf A Appl* 2025;87:1–18. [\[CrossRef\]](#)
- [67] Wolterink JM, Leiner T, de Vos BD, Van Hamersvelt RW, Viergever MA, Išgum I. Automatic coronary artery calcium scoring in cardiac CT angiography using paired convolutional neural networks. *Med Image Anal* 2016;34:123–136. [\[CrossRef\]](#)