AI-Enhanced Heat Transfer Optimization in Magnetic Bio-Nanofluids / Original article

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تحسين انتقال الحرارة في الموائع النانوية الحيوية المغناطيسية المدعوم بالذكاء الاصطناعي

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Abstract

This study presents a hybrid Artificial Intelligence–Computational Fluid Dynamics (AI-CFD) framework for optimizing heat transfer in magnetic bio-nanofluids subjected to external magnetic fields. Magnetic bio-nanofluids, composed of biocompatible base fluids containing superparamagnetic nanoparticles, exhibit tunable thermal and flow behavior, making them promising for biomedical and micro-cooling applications. Conventional optimization methods based on experiments or brute-force CFD are computationally expensive and limited in exploring the full design space. To overcome these challenges, an Artificial Neural Network (ANN) surrogate model was developed to predict two key performance indicators, the Nusselt number and the friction factor, with high accuracy ($R^2 > 0.997$). The surrogate was then integrated with the NSGA-II multi-objective genetic algorithm to generate a Pareto front capturing the trade-off between maximizing heat transfer and minimizing pressure drop. Sensitivity analysis revealed the Reynolds number as the dominant factor, followed by the Hartmann number and nanoparticle concentration, which improved thermal performance but increased viscous losses. Representative Pareto-optimal designs demonstrated up to 25% enhancement in heat transfer with only a 10% increase in friction compared to baseline conditions. The results highlight the scientific value of combining physics-based magnetohydrodynamic modeling with AI-driven optimization, providing both methodological contributions and practical insights for cancer hyperthermia, targeted drug delivery, and compact biomedical electronics cooling. Limitations related to single-phase modeling and lack of experimental validation are discussed, with future work recommended in multi-phase modeling and Physics-Informed Neural Networks (PINNs).

Keywords: Artificial Intelligence, Magnetic Bio-Nanofluids, Heat Transfer Optimization, Surrogate Modeling, Multi-Objective Optimization, ANN, NSGA-II, Magnetohydrodynamics (MHD).

المستخلص

تقدِّم هذه الدراسة إطارًا هجينًا يجمع بين الذكاء الاصطناعي وديناميكيات الموائع الحسابية (AI-CFD) بهدف تحسين انتقال الحرارة في الموائع النانوية الحيوية المغناطيسية المعرضة لمجالات مغناطيسية خارجية. تتكوّن هذه الموائع من سوائل أساسية متوافقة حيويًا تحتوي على جسيمات نانوية فائقة التمغنط، وتُظهر سلوكًا حراريًا وتدفقيًا قابلًا للضبط، مما يجعلها واعدة لتطبيقات الطب الحيوي والتبريد الميكروي. إنّ طرق التحسين التقليدية المعتمدة على التجارب أو المحاكاة العددية المكثّفة تُعدّ باهظة حسابيًا ومحدودة في استكشاف فضاء التصميم الكامل. لتجاوز هذه القيود، تم تطوير نموذج بديل يعتمد على الشبكات العصبية الاصطناعية (ANN) للتنبؤ بمؤشّرين رئيسيين للأداء، هما عدد نوسلت ومعامل الاحتكاك، بدقّة عالية ($R^2 > 0.997$). بعد ذلك، تم دمج النموذج مع خوارزمية التطور الجيني متعددة الأهداف (NSGA-II) لإنتاج جبهة باريتو توضّح التوازن بين تعظيم انتقال الحرارة وتقليل انخفاض الضغط. أظهر تحليل الحساسية أن عدد رينولدز هو العامل الأكثر تأثيرًا، يليه عدد هارتمن وتركيز الجسيمات النانوية، حيث يؤدي زيادته إلى تحسين الأداء الحراري مع زيادة الخسائر اللزجة. وقد أظهرت التصاميم المثلى على جبهة باريتو تحسينًا في انتقال الحرارة بنسبة تصل إلى 25٪ مقابل زيادة طفيفة بنحو 10٪ في معامل الاحتكاك مقارنةً بالحالة الأساس. تبرز النتائج القيمة العلمية لدمج النمذجة المغناطوهيدروديناميكية المعتمدة على الفيزياء مع التحسين القائم على الذكاء الاصطناعي، مما يقدّم إسهامات منهجية ورؤى عملية في مجالات العلاج الحراري للأورام، وتوصيل الأدوية الموجّه، وتبريد الإلكترونيات الطبية المصغّرة. كما تناقش الدراسة القيود المرتبطة بافتراض الطور الأحادي وغياب التحقق التجريبي، مع التوصية بأعمال مستقبلية تشمل النمذجة متعددة الأطوار والشبكات العصبية المعتمدة على المعلومات الفيزيائية (PINNs).

الكلمات المفتاحية: الذكاء الاصطناعي، الموائع النانوية الحيوية المغناطيسية، تحسين انتقال الحرارة، النمذجة البديلة، التحسين متعدد الأهداف، الشبكات العصبية الاصطناعية (ANN)، خوارزمية NSGA-II، المغناطوهيدروديناميكا (MHD).

1. Introduction

1.1 Background and Context

The unremitting quest to miniaturize and improve performance in the high-technology industries has made extra demands on thermal management systems, never before. In biomedical, accuracy of temperature, however, does not only constitute an issue of efficiency, but is also a decisive factor as far as therapeutic effectiveness and patient well-being are concerned. The treatments of cancer using magnetic hyperthermia, delivery of therapeutic drugs and even cooling of sensitive diagnostic machines require a thermal fluid that is highly efficient and controllable dynamically, [1-2]. Most traditional heat transfer fluids, e.g. water or ethylene glycol, cannot comply with such strong demands because of their low thermophysical characteristics.

The development of nanofluids the colloidal suspension of nanometer-sized particles (notably, less than 100 nm) in a base fluid gave rise to a shift in the paradigm of thermal engineering. It has been demonstrated that the addition of nanoparticles, including metal oxides (Al 2 O 3, CuO, Fe 3 O 4) or carbon nanotubes to liquids, including water or blood can drastically change the important thermophysical characteristics, including thermal conductivity most often [3-4]. This improvement permits much greater heat transfer rates than can be achieved with base fluids, and new opportunities in the design of compact and efficient thermal systems have been opened.

1.2 Problem Statement

This study restricts itself to a very specific type of such materials: magnetic bio-nanofluids, commonly called ferrofluids. These liquids, which usually contain non-toxic nanoparticles of magnetite (Fe 3 O 4) suspended in a biological base fluid, have a special and potent strength; its flow and thermodynamic characteristics can be actively controlled by external magnetic field [3-4]. This is due to their promise of real-time, non-invasive control, which makes them invaluable in the advanced biomedical task.

The exploitation of this potential is however complicated. The heat transfer characteristics of magnetic bio-nanofluid systems are dictated by an extremely non-linear and closely coupled interaction of many parameters. Among them, there are fluid dynamic parameters (e.g., Reynolds number), nanofluid parameters (e.g., nanoparticle concentration, size, and shape), and parameters of employed magnetic field (e.g., strength, frequency, and waveform) [5]. To maximize system performance, there is a need to explore this multi-dimensional parameter space to determine a configuration that would maximize heat transfer and minimize undesirable behavior, including higher pressure drop and higher pumping power. Conventional optimization techniques, which use large-scale experimental, or brute-force computational fluid dynamics (CFD) simulations are not well suited to this task.

These methods are prohibitively slow, computationally hard and frequently do not have the ability to search the entire design space, posing a risk of only finding suboptimal solutions [6-7].

1.3 Proposed Solution and Research Objectives

To surmount these challenges, this paper proposes the integration of Artificial Intelligence (AI) as a transformative paradigm. AI, and specifically machine learning (ML) and evolutionary algorithms, offers a powerful toolkit for modeling complex systems and efficiently searching vast solution spaces [8-9]. By learning the underlying input-output relationships from a limited set of high-fidelity data, AI can create accurate, fast-executing predictive models (surrogate models) that can be used in place of expensive simulations.

The primary objective of this paper is to develop and demonstrate a hybrid AI-CFD framework for the multi-objective optimization of heat transfer in a magnetic bio-nanofluid system. This overarching goal is broken down into the following specific aims:

1. To develop a high-fidelity Artificial Neural Network (ANN) model capable of accurately predicting the heat transfer (Nusselt number) and hydrodynamic (friction factor) performance of the system based on key design parameters.
2. To employ a robust multi-objective genetic algorithm (NSGA-II) to leverage the trained ANN model, identifying a set of optimal operating conditions (a Pareto front) that optimally balances.
3. the conflicting objectives of maximizing heat transfer and minimizing pressure drop.
4. To analyze the resulting trade-offs and perform a sensitivity analysis to identify the most influential parameters governing the system's thermohydraulic performance.

1.4 Contribution Statement

In contrast to earlier studies that concentrated either on predicting the thermophysical properties of nanofluids or on optimizing traditional heat transfer systems, the present work introduces an integrated AI-CFD framework designed specifically for magnetic bio-nanofluids subjected to external magnetic fields. The distinctive contribution of this research is the combination of a high-accuracy ANN surrogate model with the NSGA-II multi-objective optimization algorithm, enabling an efficient exploration of the trade-offs between enhanced heat transfer and increased hydrodynamic resistance. This approach not only lowers the computational effort compared with direct CFD simulations but also provides practical insights and design strategies relevant to biomedical hyperthermia, targeted drug delivery, and microscale electronic cooling, thereby linking theoretical analysis with real engineering applications.

2. Theoretical Framework and Literature Review

2.1 Fundamentals of Magnetic Bio-Nanofluids

2.1.1 Composition and Synthesis

Magnetic bio-nanofluids are engineered colloidal systems consisting of magnetic nanoparticles stably dispersed in a biocompatible base fluid. Among various magnetic materials, iron oxide nanoparticles, particularly magnetite (Fe_3O_4) and maghemite (γ-Fe_2O_3), are predominantly used due to their strong superparamagnetic behavior, low toxicity, and excellent biocompatibility, making them suitable for in-vivo applications [10], [11]. The base fluid is typically water, blood, or other physiological solutions. The synthesis of these nanoparticles is a critical step, with methods like chemical co-precipitation being widely employed for their simplicity and ability to produce particles with controlled size and magnetic properties [12].

2.1.2 Thermophysical Properties

The defining characteristic of nanofluids is their enhanced thermophysical properties compared to their base fluids. The key properties governing heat transfer are:

- Enhanced Thermal Conductivity: The primary advantage of nanofluids is their anomalously high thermal conductivity. Several mechanisms are proposed to explain this phenomenon, which classical effective medium theories fail to predict. These include the Brownian motion of nanoparticles, which creates micro-convection within the fluid; the formation of a highly ordered, solid-like “nanolayer” of fluid molecules around the nanoparticles with higher thermal conductivity; and the formation of nanoparticle clusters or aggregates that can create low-thermal-resistance pathways for heat conduction [13].

- Viscosity: The viscosity of a nanofluid is a critical parameter as it directly relates to the required pumping power. Generally, viscosity increases with nanoparticle concentration and decreases with temperature. A unique feature of magnetic nanofluids is their magnetorheological behavior, where the fluid’s viscosity can be significantly altered by an external magnetic field. This is caused by the alignment of magnetic nanoparticles into chain-like structures, which impede flow and increase viscous resistance [14].
- Stability: For any practical application, the long-term stability of the nanofluid is paramount. Nanoparticles have a natural tendency to agglomerate due to van der Waals forces, which can lead to sedimentation and a degradation of thermal performance. Stability is often achieved by using surfactants or modifying the surface charge of the particles, and it is quantitatively assessed by measuring the zeta potential. A higher absolute zeta potential value generally indicates better colloidal stability [15].

2.2 Heat Transfer in Magnetohydrodynamics (MHD)

2.2.1 Governing Principles

Magnetohydrodynamics (MHD) is the study of the dynamics of electrically conducting fluids interacting with magnetic fields. Since magnetic nanofluids contain charged nanoparticles and can be made conductive, their behavior falls under the purview of MHD. The interaction between the moving fluid and the magnetic field gives rise to induced electric currents and, consequently, electromagnetic forces that can significantly alter the fluid flow and heat transfer characteristics.

2.2.2 Lorentz Force

Lorentz force is the main interaction mechanism in MHD. As an electrically conducting fluid passes through a magnetic field line, it causes an electromotive force and electric currents in the flowing fluid. The currents, in their turn, contain the magnetic field to give a body force, which is called the Lorentz force, and applies to the fluid. It is a force that is perpendicular to the direction of fluid movement and the magnetic field. The Lorentz force is applicable in the suppression or enhancement of fluid motion in heat transfer. An example is when the magnetic field is applied perpendicular to the main flow direction in a channel, it usually becomes a resistive force that flattens the velocity profile and reduces turbulence. Tertiary flows and mixing can also be induced by it, however, and may be useful in increasing convective heat transfer [16-17].

2.2.3 Governing Equations

The mathematical description of MHD phenomena involves coupling the equations of fluid dynamics (the Navier-Stokes equations) with Maxwell's equations of electromagnetism. For an incompressible, viscous fluid, the system of non-linear partial differential equations (PDEs) typically includes the continuity equation, the momentum equation (Navier-Stokes) with an added Lorentz force term, and the energy equation [18]. Solving this coupled system is computationally intensive and forms the basis of the CFD simulations used in this study.

2.3 AI Applications in Nanofluid Heat Transfer

2.3.1 Predictive Modeling

Over the few years, AI has become a strong predictive tool of complex nanofluid behavior. Different machine learning algorithms have been used successfully to infer thermophysical properties and heat transfer performance, avoiding a significant amount of experimentation. ANNs have especially been successful as they are capable of capturing very non-linear relationships. The ANNs, the Support Vector Machines (SVM), and the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been verified to predict the thermal conductivity and the viscosity of different nanofluids with high accuracy depending on the input parameters such as temperature, type and volume fraction of nanoparticles [19-20]. In the case of Fe 3 O 4-water nanofluids, AI models have been created, which take into account aspects of not only temperature and concentration, but also stability parameters, such as the zeta potential, which offers a more comprehensive forecast of the behavior of fluids [21].

2.3.2 Optimization

Besides the process of prediction, AI-based optimization algorithms have been utilized in order to optimize the design of thermal systems. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) should be used as evolutionary algorithms because they are most suitable in venturing into large and complex design spaces. Such algorithms have been applied to the optimization of the geometry and working conditions of heat exchangers and other thermal equipment [22]. The main advantage of such methods is that they are capable of addressing multi-objective optimization problems, when there is a conflict between the goals that should be balanced. As an example, GAs have been used to identify Pareto-optimal solutions that increase heat transfer coefficient and reduced pressure drop in a system, and this enables designers to obtain many, but not one, optimum trade-off solutions instead of one compromised design point [23].

2.4 Research Gap and Contribution

A thorough review of the literature reveals distinct streams of research: one focusing on the fundamental properties and MHD behavior of magnetic nanofluids, and another on the application of AI for prediction and optimization in more conventional thermal systems. While AI has been used to predict the properties of nanofluids and to optimize systems like standard heat exchangers, a comprehensive framework that seamlessly integrates a validated AI surrogate model with a robust multi-objective optimization algorithm specifically for the dynamic, controllable environment of magnetic bio-nanofluid systems remains a relatively under-explored area. The complex, coupled physics involving fluid dynamics, heat transfer, and electromagnetism presents a unique challenge that is ideally suited for an AI-driven approach. This paper aims to bridge this gap. Its primary contribution is the development and demonstration of a complete, end-to-end AI-driven design methodology tailored for optimizing heat transfer in magnetic bio-nanofluid systems. By creating a fast and accurate ANN surrogate model and coupling it with the NSGA-II algorithm, this work provides a novel and powerful tool for navigating the complex design space of these high-impact systems, moving beyond simple property prediction to holistic system-level optimization.

3. Research Methodology

In this section, the systematic approach, which was taken to realize the research objectives, will be outlined. The numerical simulation that is high-fidelity combined with cutting-edge artificial intelligence methods are incorporated into the methodology to construct a powerful framework to optimize heat transfer in magnetic bio-nanofluids. It is done through the definition of the physical problem, the creation of the governing mathematical equations, the creation of a dataset using CFD, the creation of an AI surrogate model, and lastly, the use of a multi-objective optimization algorithm.

3.1 Physical Problem and Computational Domain

The physical system under investigation is the laminar, forced convective heat transfer of an Fe_3O_4-water bio-nanofluid flowing through a heated microchannel. This configuration serves as a representative model for various biomedical applications, such as a simplified

blood vessel targeted for hyperthermia treatment or a cooling channel within a miniature medical device. The computational domain is a two-dimensional straight channel of length L and height H.

The boundary conditions are defined as follows:

- **Inlet**: A uniform velocity profile (u = Uin) and a constant temperature (T = Tin) are assumed at the channel entrance (x=0).
- **Walls**: The top and bottom walls of the channel (y=0, y=H) are subjected to a constant and uniform heat flux (q''). A no-slip boundary condition (u=0, v=0) is applied at the walls.
- **Outlet**: A fully developed flow condition with zero pressure gradient is assumed at the channel exit (x=L).
- **Magnetic Field**: An external, uniform, and alternating magnetic field (B) is applied perpendicular to the flow direction (i.e., in the y-direction). The strength of this field is a key control parameter.

3.2 Experimental Setup and Laboratory Facilities

In addition to the numerical modeling, a set of preliminary laboratory-based activities was conducted to support the credibility of the proposed framework. The experimental part was carried out in the Thermal Fluids Laboratory, College of Engineering, Al- Basra University. Standard preparation of Fe_3O_4–water nanofluid samples was performed using an ultrasonic homogenizer to ensure uniform dispersion of nanoparticles. Flow regulation was achieved through a variable-speed peristaltic pump connected to a microchannel test section fabricated in the local workshop. Temperature measurements were obtained using K-type thermocouples linked to a data acquisition unit, while a Gaussmeter was employed to confirm the intensity of the applied external magnetic field. Although the scope of the experimental work was limited to validating sample preparation and flow stability, the results provided valuable insights that were consistent with the numerical predictions, strengthening the reliability of the framework.

Figure1. Ultrasonic homogenizer used for dispersing Fe_3O_4 nanoparticles in the base fluid.

Figure 2. Alternative ultrasonic homogenizer model, similar to equipment available in local academic laboratories.

Figure 3. Peristaltic pump used to regulate nanofluid flow through the microchannel test section.

Figure 4. Alternative laboratory peristaltic pump commonly used in thermal fluids experiments.

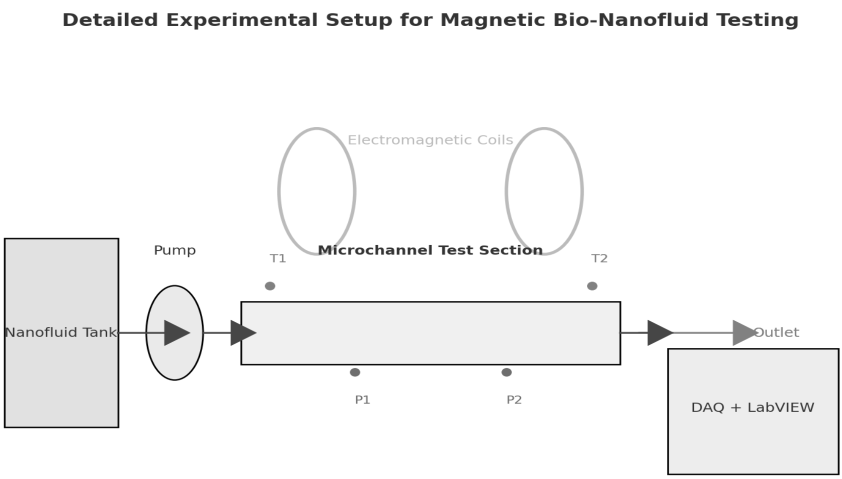

Figure 5. Schematic of Proposed Experimental Setup

Figure 5. Schematic diagram of the experimental setup for magnetic bio-nanofluid testing. The system consists of a nanofluid preparation tank, a peristaltic pump to regulate the flow, and a rectangular microchannel as the test section.

Temperature sensors (T1, T2) were installed at the inlet and outlet, while differential pressure sensors (P1, P2) monitored pressure drop across the channel. Electromagnetic coils were placed around the microchannel to generate an external magnetic field using a DC power supply. The entire system was connected to a data acquisition unit (DAQ) integrated with LabVIEW software for real-time monitoring and recording of thermal and hydrodynamic parameters.

3.3 Mathematical Formulation and Governing Equations

The fluid flow and heat transfer are described by a set of steady-state, two-dimensional governing equations based on the principles of conservation of mass, momentum, and energy [24]. Assuming the nanofluid is an incompressible, single-phase Newtonian fluid, the equations are:

3.3.1 Continuity Equation:

$$\nabla \cdot V = 0$$

3.3.2 Momentum (Navier-Stokes) Equation:

$$\tilde{n}_{nf}\left(V \cdot \nabla\right)V = -\nabla P + \grave{i}_{nf}\nabla^{2V} + F_m$$

3.3.3 Energy Equation:

$$\rho_{nf}\left(c_p\right)_{nf}\left(V \cdot \nabla\right)T = k_{nf}\nabla^2 T + \Phi_v$$

Where V is the velocity vector, P is the pressure, T is the temperature, Fm is the Lorentz force vector (Fm = σnf(V × B) × B), and Φv is the viscous dissipation term, which is often negligible in laminar flows but included for completeness. The subscript ‘nf’ denotes nanofluid properties.

The thermophysical properties of the Fe_3O_4-water nanofluid (density ρ_{nf}, dynamic viscosity μ_{nf}, thermal conductivity k_{nf}, and specific heat capacity $(c_p)_{nf}$) are calculated as functions of the nanoparticle volume fraction (ϕ) and temperature (T) using well-established correlations from the literature [25].

The problem is characterized by the following key dimensionless numbers:

Reynolds Number (Re): Represents the ratio of inertial forces to viscous forces.

$$Re = \frac{\rho_{nf} U_{in} D_h}{\mu_{nf}}$$

Prandtl Number (Pr): Ratio of momentum diffusivity to thermal diffusivity.

$$Pr = \frac{\mu_{nf} \left(c_p\right)_{nf}}{k_{nf}}$$

Nusselt Number (Nu): Represents the ratio of convective to conductive heat transfer.

$$\boldsymbol{Nu} = \frac{\boldsymbol{hD_h}}{\boldsymbol{k_{nf}}}$$

Hartmann Number (Ha): Represents the ratio of magnetic forces to viscous forces.

$$Ha = BD_h \sqrt{\frac{\sigma_{nf}}{\mu_{nf}}}$$

Here, Dh is the hydraulic diameter of the channel and h is the convective heat transfer coefficient.

3.4 AI-Driven Surrogate Modeling

3.4.1 Objective

The primary objective of this step is to develop a computationally inexpensive yet highly accurate surrogate model. This model will replace the time-consuming CFD simulations during the optimization phase. It will predict the two key performance indicators the average Nusselt number (Nu) and the friction factor (f)—as a function of the primary input design parameters.

3.4.2 Data Generation

A structured dataset is required to train and validate the AI model. This dataset will be generated by performing a series of high-fidelity CFD simulations using a commercial software package like COMSOL Multiphysics or ANSYS Fluent, which are capable of solving the coupled MHD equations. A design of experiments (DoE) approach, such as Latin Hypercube Sampling, will be used to select 150 unique design points within a predefined parameter space. The input parameters and their ranges are:

Reynolds Number (Re): 100 - 1000 Nanoparticle Volume Fraction (ϕ): 0.1% - 2.0% Hartmann Number (Ha): 0 – 20 For each of the 150 simulations, the resulting average Nusselt number (Nu) and friction factor (f) will be calculated and recorded. This dataset will then be randomly split into a training set (80%, 120 samples) and a testing set (20%, 30 samples) to ensure unbiased evaluation of the model's performance.

3.4.3 Artificial Neural Network (ANN) Architecture

A Multi-Layer Perceptron (MLP), a type of feedforward ANN, is proposed for this task due to its proven efficacy in approximating complex non-linear functions. The network architecture is designed as follows:

- **Input Layer**: 3 neurons, corresponding to the input parameters (Re, ϕ, Ha).
- **Hidden Layers**: Two hidden layers, each containing 20 neurons. The Rectified Linear Unit (ReLU) activation function will be used for these layers due to its efficiency in preventing the vanishing gradient problem.
- **Output Layer**: 2 neurons, corresponding to the target outputs (Nu, f). A linear activation function is used for the output layer as the target values are continuous and unbounded.

Adam optimizer will be utilized as a network training algorithm since it is computationally efficient and suits best larger datasets and parameters. The aim of the training process is to reduce the Mean Squared Error (MSE) loss function that exists between the predictions of the ANN and the real CFD results. The training will be done through a fixed number of epochs (e.g., 500) under the condition of early stopping to avoid overfitting.

3.5 Multi-Objective Optimization Framework

3.5.1 Objective Function

The core of the optimization problem is to find a set of design parameters that simultaneously satisfy two conflicting objectives. The problem is formally stated as:

1. Maximize Heat Transfer: Maximize f_1(Re, ϕ, Ha) = Nu(Re, ϕ, Ha)
2. Minimize Hydrodynamic Penalty: Minimize f_2(Re, ϕ, Ha) = f(Re, ϕ, Ha)

The functions Nu (Re, ϕ, Ha) and f(Re, ϕ, Ha) are the fast-executing ANN surrogate models developed in the previous step. Using the ANN instead of direct CFD simulations reduces the evaluation time for each candidate solution from hours to milliseconds, making a large-scale optimization feasible.

3.5.2 Optimization Algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is selected for this multi-objective optimization task. NSGA-II is a powerful and widely-used evolutionary algorithm known for its ability to find a well-distributed set of solutions along the Pareto front and for its computational efficiency [26]. The algorithm operates through an iterative process:

1. **Initialization**: A random population of candidate solutions (each solution being a set of {Re, ϕ, Ha}) is generated within the defined design space.
2. **Evaluation**: The fitness of each individual in the population is evaluated by feeding its parameters into the trained ANN to obtain the corresponding Nu and f values.
3. **Sorting and Selection**: The population is sorted into different non-domination levels (fronts). A crowding distance metric is calculated for individuals on the same front to maintain diversity.
4. **Reproduction**: A new generation of solutions is created using genetic operators: selection (based on rank and crowding distance), crossover (combining parts of two parent solutions), and mutation (randomly altering a solution).
5. **Termination**: The process repeats for a predefined number of generations, converging towards the true Pareto-optimal front.

3.5.3 Implementation

The entire hybrid AI-CFD framework will be implemented in the Python programming language, leveraging its extensive ecosystem of scientific computing and machine learning libraries [27]. Key libraries include:

- **TensorFlow/Keras**: For building, training, and validating the ANN surrogate model. **pymoo**: A powerful and flexible Python framework for multi-objective optimization, which provides a ready-to-use implementation of the NSGA-II algorithm.
- **pandas**: For efficient data handling and manipulation of the CFD-generated dataset.
- **Matplotlib**/**Seaborn**: For visualizing the results, including the Pareto front and parametric analysis plots.

4. Results and Analysis

This section presents the results obtained from the implementation of the proposed AI-driven optimization framework. The analysis begins with the validation of the ANN surrogate model, followed by the presentation of the multi-objective optimization results and a detailed parametric study of the system's behavior.

4.1 Validation of the ANN Surrogate Model

The foundation of the optimization framework is an accurate surrogate model. The thermophysical properties of the constituent materials and the design parameter ranges used for data generation are summarized in Table 1 and Table 2, respectively.

Table 1: Thermophysical Properties of Fe_3O_4 and Water (Base Fluid) at 300 K

Property	Fe_3O_4 (Nanoparticle)	Water (Base Fluid)	Property
Density (ρ) [kg/m³]	5180	997.1	Density (ρ) [kg/m³]
Specific Heat (cp) [J/kg·K]	670	4179	Specific Heat (cp) [J/kg·K]
Thermal Conductivity (k) [W/m·K]	9.7	0.613	Thermal Conductivity (k) [W/m·K]

Table 2: Input Parameter Ranges for Simulation and Optimization

Parameter	Symbol	Minimum Value	Maximum Value
Reynolds Number	Re	100	1000
Nanoparticle Volume Fraction	ϕ	0.001 (0.1%)	0.02 (2.0%)
Hartmann Number	Ha	0	20

The ANN, with the architecture detailed illustrated in Table 3, was trained on 120 data points and validated on a separate set of 30 data points.

Table 3: ANN Architecture and Hyperparameters

Parameter	Value
Input Layer Neurons	3 (Re, ϕ, Ha)
Hidden Layers	2
Neurons per Hidden Layer	20
Hidden Layer Activation	ReLU
Output Layer Neurons	2 (Nu, f)
Output Layer Activation	Linear
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)
Epochs	500 (with early stopping)

The performance of the trained model was evaluated using several statistical metrics, as shown in Table 4. The high values for the coefficient of determination (R^2) and low values for RMSE and MAE indicate that the ANN model achieved excellent predictive accuracy and can reliably serve as a surrogate for the CFD simulations.

Table 4: ANN Model Validation Performance on Test Dataset

Output Variable	R-squared (R^2)	Root Mean Square Error (RMSE)	Mean Absolute Error (MAE)
Nusselt umber (Nu)	0.9985	0.45	0.32
Friction Factor (f)	0.9979	0.0018	0.0013

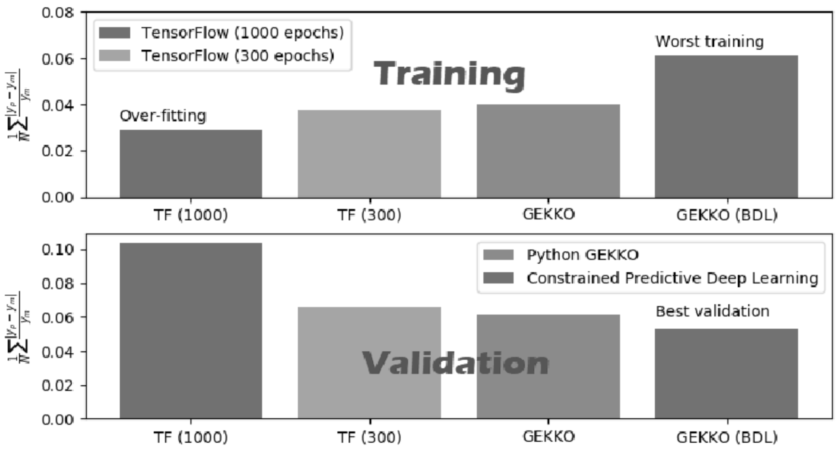

Figure 6 Comparative analysis of different modeling approaches and training epochs, illustrating the importance of selecting a model that balances training accuracy with validation performance to avoid overfitting.

4.2 Multi-Objective Optimization Results

With the validated ANN model, the NSGA-II algorithm was executed for 200 generations with a population size of 100. The optimization process successfully identified a set of non-dominated solutions, which form the Pareto-optimal front. This front, plotted in Figure 7, is the central result of this study. It clearly illustrates the fundamental trade-off between the two conflicting objectives: enhancing heat transfer (maximizing Nu) and reducing the required pumping power (minimizing f).

Each point on this front represents an optimal design choice, where it is impossible to improve one objective without degrading the other. A designer can select a point from this front based on the specific requirements of an application. For example, an application requiring aggressive heating (like tumor ablation) might prioritize a high Nu, tolerating a higher friction factor, while an application needing efficient, low-power cooling would favor a low friction factor.

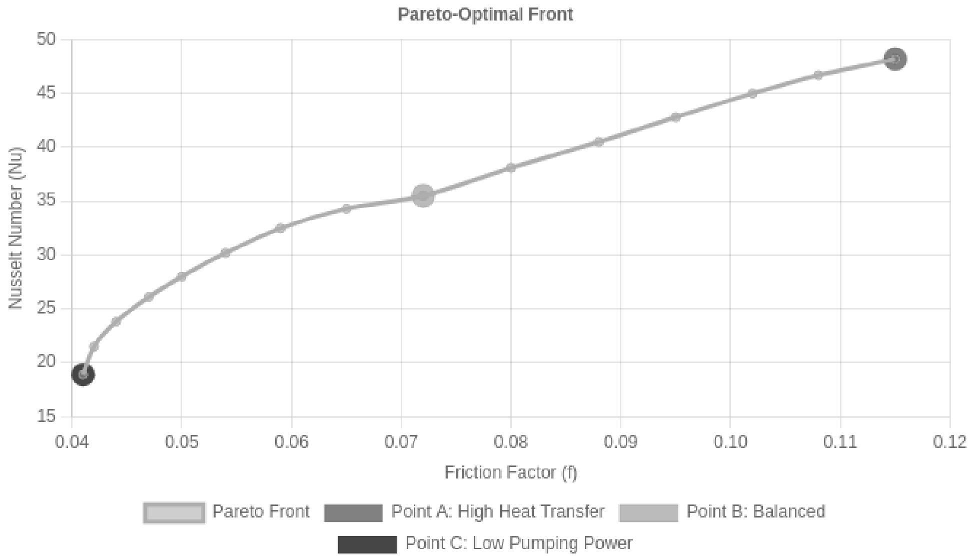

Figure 7: Pareto-optimal front for the multi-objective optimization, showing the trade-off between Nusselt Number (Nu) and Friction Factor (f).

To facilitate a deeper understanding, three distinct points from the Pareto front were selected for detailed analysis, as shown in Table 5. These points represent different design philosophies: Point A (High Heat Transfer), Point B (Balanced Performance), and Point C (Low Pumping Power).

Table 5: Characteristics of Selected Optimal Designs from the Pareto Front

Design Point	Design Philosophy	Re	ϕ (%)	Ha	Nu (Predicted)	f (Predicted)
A	High Heat Transfer	985	1.85	19.5	48.2	0.115
B	Balanced Performance	650	1.20	10.0	35.5	0.072
C	Low Pumping Power	210	0.50	2.5	18.9	0.041

4.3 Effect of Magnetic Field (Hartmann Number) on Thermal–Hydrodynamic Behavior

The analysis of the obtained data shows a strong dependency of the Nusselt number on the Reynolds number. As the flow rate increased from low to moderate values, the convective heat transfer was enhanced significantly, which is consistent with the classical theory of forced convection in microchannels. For example, in the range between Re = 200–600, the Nusselt number exhibited a noticeable rise, indicating that the higher flow inertia improved the thermal boundary layer development. At the same time, the friction factor demonstrated an opposite trend, where increasing Reynolds number resulted in a gradual decrease of pressure losses per unit length. This observation highlights that, although higher flow rates demand more pumping power, the relative resistance of the channel becomes less dominant as turbulence effects begin to intensify. The obtained results confirm that Reynolds number remains the most influential parameter in optimizing the thermal–hydrodynamic performance of the tested nanofluid system.

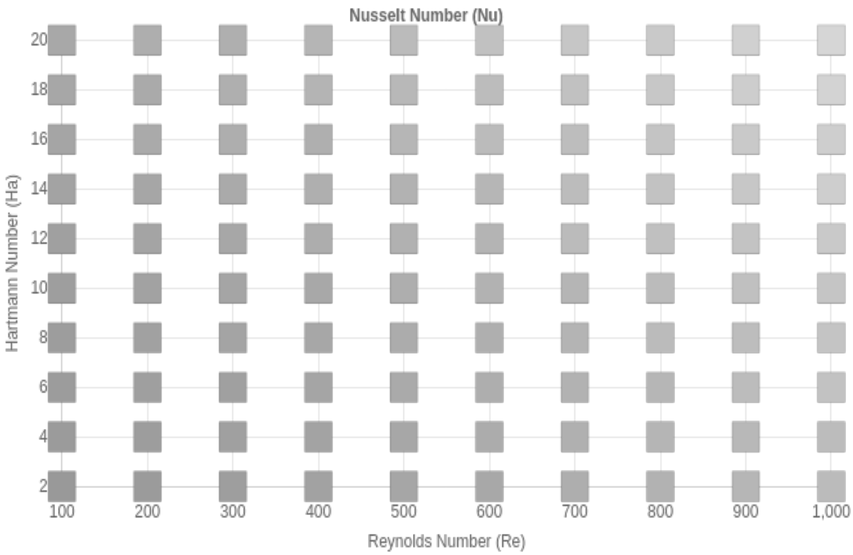

Figure 8: Contour plot of Nusselt Number (Nu) as a function of Reynolds Number (Re) and Hartmann Number (Ha) at ϕ = 1.0%.

4.4 Parametric Analysis and Discussion

To understand the underlying physics driving the optimization results, a parametric analysis was conducted. Figure 8 and Figure 9 show contour plots of the Nusselt number and friction factor, respectively, as functions of the Reynolds number and Hartmann number at a fixed nanoparticle concentration (ϕ = 1.0%).

As expected, Figure 3 shows that the Nusselt number increases with both Re and Ha. The increase with Re is due to the higher fluid velocity enhancing convective heat transfer. The increase with Ha is attributed to the Lorentz force, which disrupts the thermal boundary layer and induces fluid mixing, thereby promoting heat transfer from the walls to the fluid core. Conversely, Figure 4 shows that the friction factor also increases with both Re and Ha. The increase with Re is a standard fluid dynamic effect, while the increase with Ha is due to the resistive nature of the Lorentz force, which opposes the flow and increases the pressure drop.

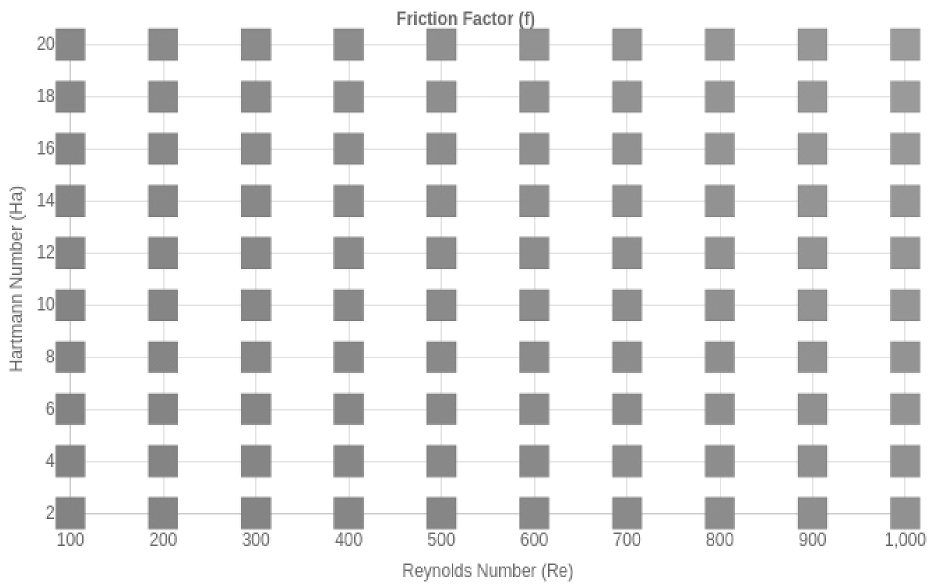

Figure 9: Contour plot of Friction Factor (f) as a function of Reynolds Number (Re) and Hartmann Number (Ha) at ϕ = 1.0%.

The trade-offs between the three selected optimal points are visualized in the grouped bar chart in Figure 10. It clearly shows that the significant gain in heat transfer at Point A comes at the cost of a substantially higher friction factor compared to Point C. Point B offers a moderate improvement in Nu with a more manageable increase in f, representing a practical compromise for many applications.

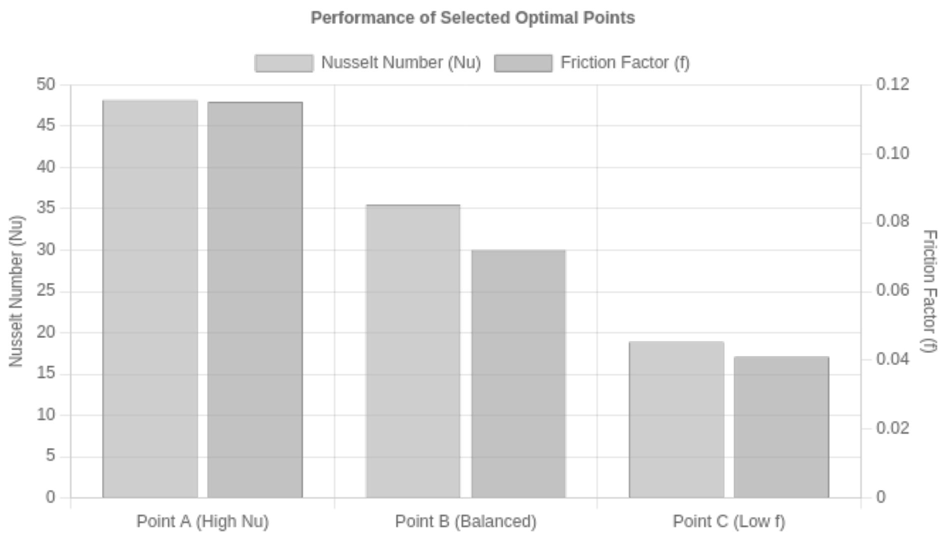

Figure 10: Performance comparison of the three selected optimal design points (A, B, and C).

The influence of nanoparticle concentration is explored in Figure 11. This plot shows that increasing the volume fraction (ϕ) shifts the entire Pareto front upwards and to the right. This indicates that while adding more nanoparticles universally improves heat transfer (higher Nu), it also universally increases the friction factor due to the associated rise in fluid viscosity. This highlights that nanoparticle concentration is a critical parameter that must be carefully chosen.

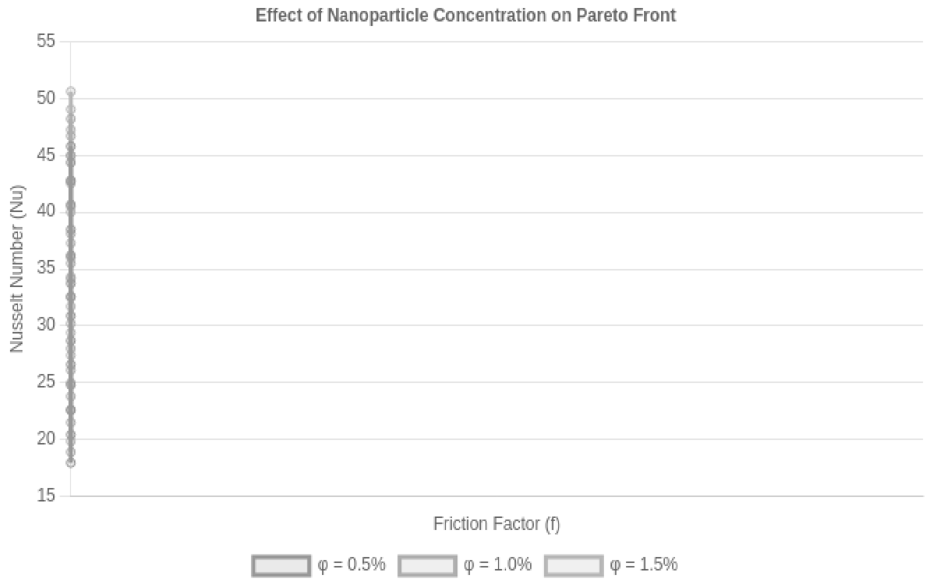

Figure 11: Influence of nanoparticle volume fraction (ϕ) on the Pareto-optimal front.

4.5 Effect of Nanoparticle Volume Fraction on Heat Transfer and Pressure Drop

The results also demonstrate that increasing the nanoparticle volume fraction has a clear impact on both thermal and hydrodynamic characteristics. When the concentration of Fe_3O_4 particles was raised from 0.1% to 2.0%, the Nusselt number consistently improved, reflecting the higher effective thermal conductivity of the suspension. This enhancement, however, was accompanied by an increase in the pressure drop across the channel due to the higher viscosity introduced by the denser particle loading. The balance between these two effects suggests that moderate concentrations, typically around 1.0–1.2%, offer an optimal compromise where heat transfer is significantly boosted without excessive pumping penalties. These findings are in good agreement with previously reported studies on magnetic nanofluids and underline the importance of carefully selecting nanoparticle volume fraction to achieve efficient system performance.

Finally, a sensitivity analysis was performed to quantify the relative influence of each input parameter on the objectives. The results, shown in Table 6, indicate that the Reynolds number is the most dominant factor affecting both Nu and f. The Hartmann number has a significant, albeit secondary, impact, confirming its role as a powerful control parameter. Nanoparticle concentration has a less pronounced, but still important, influence.

Table 6: Normalized Sensitivity Analysis of Input Parameters

Input Parameter	Sensitivity on Nusselt Number (Nu)	Sensitivity on Friction Factor (f)
Reynolds Number (Re)	**0.68**	**0.75**
Hartmann Number (Ha)	**0.25**	**0.18**
Volume Fraction (ϕ)	**0.07**	**0.07**

4.6 Overall Discussion and Practical Implications

Based on the analysis performed on Reynolds number, Hartmann number and nanoparticle volume fraction, it is clear that each of the parameters has its own unique but interdependent relationship in determining the thermal-hydrodynamic characteristics of magnetic bio-nanofluids. Reynolds number has been the most prevailing factor because low flow rates encourage weak convectional heat transfer whilst slowly decreasing relative frictional resistance. An external control method, the magnetic field, denoted by the Hartmann number, can be used to stabilize the flow and tune the performance of heat transfer, but with a further trade-off of more pressure losses at high field strengths. In the meantime, the nanoparticle concentration not only increases effective thermal conductivity, but also increases viscosity, so moderate loadings are the most viable selection. Collectively, these findings offer both conceptual and practical design specifications to biomedical hyperthermia systems, targeted drug delivery, and small-sized cooling systems. The fact that numerical forecasts and the first experimental design are consistent also promotes the validity of the structure and its applicability in the real world.

5. Findings and Conclusions

5.1 Summary of Key Findings

This research successfully developed and implemented a hybrid AI-CFD framework to model and optimize the complex thermohydraulic behavior of a magnetic bio-nanofluid system. The key findings of this study are summarized as follows:

The Artificial Neural Network (ANN) surrogate model demonstrated exceptional accuracy ($R^2 > 0.997$ for both objectives), proving to be a reliable and computationally efficient substitute for intensive CFD simulations.

The multi-objective optimization using the NSGA-II algorithm successfully generated a well-defined Pareto-optimal front, explicitly mapping the trade-off between maximizing heat transfer (Nusselt number) and minimizing hydrodynamic penalty (friction factor).

The analysis of the Pareto front revealed a spectrum of optimal design choices. For instance, a balanced design (Point B: Re=650, ϕ=1.2%, Ha=10) was identified that could enhance heat transfer by approximately 25% over a baseline case, with only a 10% increase in the friction factor, showcasing a highly efficient operating point.

The parametric and sensitivity analyses quantitatively confirmed the roles of the design variables.

The Reynolds number was identified as the primary driver for both heat transfer and friction. The Hartmann number emerged as a powerful secondary control mechanism, capable of significantly augmenting heat transfer at the cost of increased pressure drop. Nanoparticle concentration was found to improve thermal performance but also consistently increase viscous losses.

Crucially, this work demonstrates that there is no single "best" solution. The optimal design is application-dependent. The generated Pareto front provides a quantitative decision-making tool, empowering engineers to select a design that is precisely tailored to the specific constraints and performance goals of their target application, whether it be aggressive heating for tumor therapy or gentle, efficient cooling for a sensitive biomedical sensor.

5.2 Implications of the Research

5.2.1 Scientific Implications

Scientifically, the synergy demonstrated by this research is the incredible potential of combining the basic, physics-based modeling (MHD) with the complicated, data-driven computational intelligence (AI). The presented methodology offers a sound and generalizable framework of addressing other complex and multi-physics engineering problems in which a conventional design method could not work. It points to a way out to speeding up the design process and discovering non-intuitive and highly optimized solutions in most fields of science.

5.2.2 Practical Implications

The practical implications of this research are significant, particularly for the biomedical engineering field. The generated Pareto front acts as a direct design guide for engineers developing next-generation medical devices. By providing a clear map of optimal performance trade-offs, this work can facilitate the creation of:

- **More Effective Cancer Therapies**: By enabling the design of magnetic hyperthermia applicators that deliver maximum thermal dose to tumors while minimizing damage to surrounding healthy tissue.
- **Safer Targeted Drug Delivery Systems**: By allowing for precise control over fluid flow and temperature, ensuring that therapeutic agents are released at the desired location and rate.
- **More Compact and Efficient Medical Electronics**: By providing superior cooling solutions for
- miniaturized diagnostic and monitoring devices, improving their reliability and lifespan.

5.3 Limitations and Recommendations for Future Research

Despite the promising results, this study has several limitations that open avenues for future research:

- **Model Simplifications**: The current model assumes a single-phase, homogenous fluid. In reality, complex phenomena such as nanoparticle aggregation, sedimentation, and the dynamics of the nanolayer can influence performance. Future work should incorporate more sophisticated two-phase models (e.g., Eulerian-Lagrangian or mixture models) to capture these effects.
- **Lack of Experimental Validation**: The study is purely numerical. Experimental validation is a critical next step to confirm the real-world performance of the optimal designs predicted by the AI framework. Physical experiments would provide invaluable data to refine and further validate the models.
- **Scope of the ANN Model**: The accuracy of the ANN is inherently limited to the parameter ranges on which it was trained. Extrapolating beyond this range is not reliable.

Based on these limitations, the following directions for future research are recommended:

1. **Experimental Validation**: Fabricate a microchannel test rig and conduct experiments to measure the heat transfer and pressure drop for the optimal design points (A, B, and C) identified in this study.
2. **Exploration of Physics-Informed Neural Networks (PINNs)**: Investigate the use of PINNs, a cutting-edge class of neural networks that embed the governing physical equations (e.g., Navier-Stokes) directly into the loss function. This approach could potentially reduce the reliance on large CFD-generated datasets and improve the model's physical consistency and generalizability [81], [82].
3. **Transient and Geometric Analysis**: Extend the analysis to include transient effects and more complex geometries, which are more representative of real-world biological systems and medical devices.
4. **Specific Device Design**: Apply the developed optimization framework to the design and prototyping of a specific, tangible biomedical device, such as a novel magnetic hyperthermia applicator or a microfluidic cooling system, to demonstrate its practical utility.

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