

ARTIFICIAL NEURAL NETWORK–BASED MODELING OF MHD BLOOD–CU–AL₂O₃ HYBRID NANOFLUID FLOW OVER A STRETCHING SHEET FOR BIOMEDICAL APPLICATIONS

Kaseeswara Reddy Dondeti¹, Kotte Amaranadha Reddy^{2*}

¹Department of Mathematics, School of Advanced Sciences, Kalasalingam Academy of Research and Education, Krishnankoil, Srivilliputtur, Virudhunagar, Tamilnadu, India - 626126. Email: kaseeswarareddy1986.kr@gmail.com

²Department of Mathematics, School of Advanced Sciences, Kalasalingam Academy of Research and Education, Krishnankoil, Srivilliputtur, Virudhunagar, Tamilnadu, India - 626126.

*Corresponding author: Kotte Amaranadha Reddy, Email: amar.anil159@gmail.com

ABSTRACT:

Machine learning techniques employ new techniques to solve complicated issues and optimize methods for understanding through large data sets. In fluid dynamics, there is currently a continuous and rising interest for the use of nano particles in a variety of medical fields. Artificial neural networks (ANNs) help medical devices work more efficiently by minimizing heat transfer through circulation control of hybrid nanofluids. ANN was also used to look into the inspiration for magnetohydrodynamic hybrid nanofluid flow through a stretching sheet in the presence of thermal radiation and porous medium. In this model used blood mixed with Cu-Al₂O₃ nanoparticles. The PDE is transformed into an ODE by using the appropriate self-similarity variables. The dimensionless equations are solved using the MATLAB software in the Bvp4c scheme. Furthermore, in the results section, noticed that the velocity outlines decreased, and, on the other hand, there was an increasing tendency on the energy outlines to increase the magnetic field parameter. Graphs and tables explain how operational factors affect fluid flow efficiency. Hybrid nanofluids have a higher heat transfer rate compared to nanofluids. Consequently, the latest study's originality, its impact on technology and mathematical information, and its potential to inspire young scientists and also these kinds of models to play an important role in biomedical systems. In addition, magnetic field interactions with tiny fluids may be tuned utilizing ANNs to create desired magnetic implications, hence improving the efficiency of MHD compressors and biomedical industry.

KEYWORDS: Thermal radiation, Hybrid nanofluid, ANN model, Porous medium, MHD.

INTRODUCTION

The broad spectrum of machinery products generated in many sectors and connected to numerous engineering uses is essential to modern living. Nonetheless, the item's effectiveness and efficacy play a difficult function. The caliber of the final product determines this efficacy. Enhancing heat has been recognized as a significant obstacle in the field of temperature distribution techniques by scientists and companies in the past few decades. Due to their insufficient thermal conductivity, popular heat-transferring liquids such as water, gasoline, ethylene glycol, petrol, and engine oil reduce the quantity of improvement in heat transfer that may be achieved. In 1995, Choi introduced small atoms, which ranged in size from one to one hundred nanometers, to the basic liquids in order to boost the thermal effectiveness of the fluids. They referred to this dispersion of colloidal matter termed nanofluids (NFs) in their research document. Isolating tiny particles with high electrical conductivity from an initial liquid with lesser conductivity significantly improves the fluid's characteristics [1]. Because of the aforementioned, nanofluid is finding widespread usage in a wide variety of industries and fields, including biomedicine, heat transfer, renewable energy sources, and heating elements. Additionally, NFs have shown that they possess better thermal characteristics than conventional coolant, making them a promising alternative over conditioning components in gadgets, power stations, and autos and also recent research efforts to improve the thermal performance in tiny fluids heating processes have highlighted the wide range of possibilities for this technology [2, 3]. These applications include cooling devices in complex electronics and aviation thermal control, as well as processes for the movement of big vehicles and the production of electricity. The new inquiry is predicated on the potential benefits of both hybrid and nanofluids, in contrast to previous examinations that employed conventional fluids during the item's manufacturing. This happens as a result of the scattered nanomaterials in the foundational fluid having a greater conductance.

Artificially intelligent technology is a branch of computer engineering that aims to solve issues, adapt to new environments, make decisions, gain knowledge, and communicate with humans. A number of domains, including but not limited to automation, vision, pattern identification, finding information, language processing, healthcare computation, machine learning, visual processing, information extraction, data representation, among other domains, provide applications for artificial intelligence. The ANN, which constitutes one of more often used methods, represents neural processes in order to operate in a manner that is analogous to that human mind. It

proves to be quite useful in addressing many complex physical technical difficulties. As a consequence, it works in a variety of mechanical networks, such as engines with combustion, cooling systems, and temperature equipment. To calculate heat conductivity utilizing ANN, researchers studied the impact of particle dimensions, heat, and particle fractions. Their results demonstrate that ANN can accurately estimate the heat conductivity within the Cu-Al₂O₃ mixed nanofluid. When it comes to determining the fundamental connects that exist among information obtained from complicated structures or simulations of different levels of difficulty, scientists and technologists from a variety of areas are utilizing the potential of artificial intelligence. One popular machine learning tool for solving a variety of engineering challenges is the ANN, a non-linear framework. An ANN is a network of linked neurons that can learn from its inputs and apply what it has learned to new situations. There is a lot learning hope that ANN may solve problems in areas like efficiency and identification of patterns [4].

During the study of magneto hydrodynamics, often known as MHD, liquid, magnetism, and a field are all components that work together to examine the evolution of devices. The movement of MHD has been the subject of a number of researches both practical as well as conceptual, owing to the fact that it serves applications in manufacturing [5, 6]. For a variety of industrial reasons, including power generation, building airplanes, and nuclear power plant cooling. When it comes to biological science, MHD is a hot topic. Magnetohydrodynamic (MHD) movement has been the subject of an exhaustive amount of theory and experimentation in a wide variety of domains, including geothermal power, manufacturing, and physical processes. The MHD fluxes that are involved with the movement of heat have received a significant amount of interest from the experts. This is as a result of its uses in a wide variety of commercial industries, including the cooling of radioactive power plants, electric-powered transportation for missions to space, planes, diamond development in fluids, microelectronic components and many more [7,8,9,10].

To the best of the authors' knowledge, limited studies have addressed the combined effects of magnetohydrodynamic (MHD) forces, hybrid nanoparticles, heat generation/absorption, and thermal radiation on blood-based nanofluid flow over a stretching sheet within an artificial neural network (ANN) framework. Therefore, the present investigation develops a mathematical and computational model for the transport characteristics of blood-based Cu-Al₂O₃ hybrid nanofluid under the influence of an applied magnetic field and thermal effects. The governing equations describing the fluid motion and energy transport are initially formulated as nonlinear partial differential equations and subsequently transformed into a system of nonlinear ordinary differential equations through appropriate similarity transformations. The resulting boundary-value problem is solved numerically using the MATLAB bvp4c technique, and the generated numerical data are employed to construct and validate an ANN model for predicting the flow and thermal characteristics. Blood is considered the base fluid, while Cu and Al₂O₃ are incorporated as hybrid nanoparticles to enhance the thermal transport properties of the working fluid. The model further accounts for heat source/sink, thermal radiation, and magnetic-field effects, allowing the influence of these parameters on velocity, temperature, skin-friction, and heat-transfer characteristics to be systematically evaluated. The numerical outcomes are presented through graphical and tabular analyses, while the ANN predictions are compared with the numerical results to establish the reliability and predictive performance of the proposed machine-learning approach. The developed framework offers a computationally efficient means of examining complex blood-based hybrid nanofluid transport phenomena and may provide useful theoretical insights for potential biomedical engineering applications, particularly in thermal management, medical devices, and other systems involving controlled fluid flow and heat transfer.

2. Mathematical model

A two-dimensional heat-transfer problem for a blood-based Cu-Al₂O₃ hybrid nanofluid flowing over a stretching sheet is considered in the present investigation. The mathematical formulation incorporates the effects of the porous medium and thermal radiation together with the velocity and energy transport mechanisms. Blood is selected as the base fluid, while Cu and Al₂O₃ are dispersed as two distinct nanoparticle components to form the hybrid nanofluid, and the corresponding thermophysical properties are listed in Table 1. The velocity components u and v are defined along the x - and y -directions, respectively. The stretching velocity of the surface is assumed to vary linearly with the streamwise coordinate and is expressed as $U=u_w=ax$, where a denotes the stretching rate. The temperatures of the stretching surface and the ambient fluid are denoted by T_w and T_∞ , respectively. Accordingly, the present model is formulated to investigate the combined influence of magnetic effects, thermal radiation, porous-medium characteristics, and heat source/sink on the flow and thermal behavior of the blood-based hybrid nanofluid.

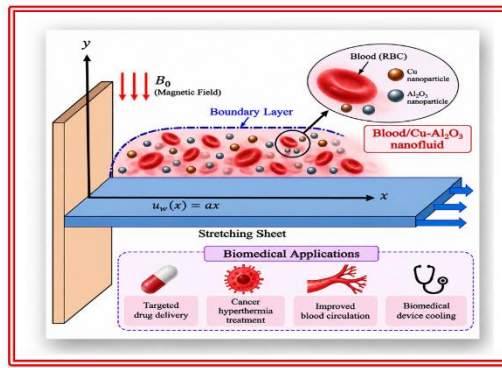


Fig 1. Flow geometry.

The governing flow equations are constructed as [11, 12, 13, 14, 15]

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} = 0, \quad (1)$$

$$u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} = \frac{\mu_{hnf}}{\rho_{hnf}} \left(\frac{\partial^2 u}{\partial y^2} \right) - \frac{\mu_{hnf}}{\rho_{hnf}} \frac{u}{K^*} - \frac{\sigma_{hnf}}{\rho_{hnf}} (B^2 u), \quad (2)$$

$$u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} = \frac{k_{hnf}}{(\rho c_p)_{hnf}} \left(\frac{\partial^2 T}{\partial y^2} \right) + \frac{1}{(\rho c_p)_{hnf}} \frac{16T_\infty^3}{3k^*} \frac{\partial^2 T}{\partial y^2} + \frac{\sigma_{hnf} B^2}{(\rho c_p)_{hnf}} u^2 + \frac{Q_0}{(\rho c_p)_{hnf}} (T - T_\infty).$$

(3)

The corresponding B.Cs. are:

$$\begin{aligned} u_w(x) = U = ax, v = 0, T = T_w, \quad \text{at } y = 0 \\ u \rightarrow 0, T \rightarrow T_\infty \quad \text{as } y \rightarrow \infty. \end{aligned} \quad (4)$$

The self-similarity variables are defined as:

$$u = axf'(\eta), v = -\sqrt{av_f} f(\eta), \theta(\eta) = \frac{T - T_\infty}{T_w - T_\infty}, \eta = y \sqrt{\frac{a}{v_f}}.$$

(5)

The properties of *hnf* thermophysical characteristics are

$$\begin{aligned} \psi_1 = \frac{\mu_{hnf}}{\mu_f}, \psi_2 = \frac{\rho_{hnf}}{\rho_f}, \psi_3 = \frac{(\rho c_p)_{hnf}}{(\rho c_p)_f}, \psi_4 = \frac{k_{hnf}}{k_f}, \psi_5 = \frac{\sigma_{hnf}}{\sigma_f}. \\ \left. \begin{aligned} \psi_1 &= \frac{1}{(1-\phi_1)^{2.5} (1-\phi_2)^{2.5}}, \\ \psi_2 &= \left\{ (1-\phi_2) \left[(1-\phi_1) + \phi_1 \left(\frac{\rho_{s_1}}{\rho_f} \right) \right] + \phi_2 \frac{\rho_{s_2}}{\rho_f} \right\}, \\ \psi_3 &= (1-\phi_2) \left[(1-\phi_1) + \phi_1 \left(\frac{(\rho c_p)_{s_1}}{(\rho c_p)_f} \right) \right] + \phi_2 \frac{(\rho c_p)_{s_2}}{(\rho c_p)_f}, \\ \psi_4 &= \frac{k_{s_1} + 2k_{bf} - 2\phi_2(k_{bf} - k_{s_2})}{k_{s_2} + 2k_{bf} + \phi_2(k_{bf} - k_{s_2})} \times \frac{k_{s_1} + 2k_f - 2\phi_1(k_f - k_{s_1})}{k_{s_1} + 2k_f + \phi_1(k_f - k_{s_1})}, \\ \psi_5 &= \frac{\sigma_{s_2} + 2\sigma_{nf} - 2\phi_2(\sigma_{nf} - \sigma_{s_2})}{\sigma_{s_2} + 2\sigma_{nf} + \phi_2(\sigma_{nf} - \sigma_{s_2})} \times \frac{\sigma_{s_1} + 2\sigma_f - 2\phi_1(\sigma_f - \sigma_{s_1})}{\sigma_{s_1} + 2\sigma_f + \phi_1(\sigma_f - \sigma_{s_1})}. \end{aligned} \right\} \quad (6)$$

Non-dimensional equations are

$$\frac{\psi_1}{\psi_2} f''' + \left(ff'' - (f')^2 \right) - \frac{\psi_1}{\psi_2} Kf' - \frac{\psi_5}{\psi_2} Mf' = 0, \quad (7)$$

$$\theta'' \left(\psi_4 + \frac{4}{3} Rd \right) Pr + \psi_3 Pr f \theta' + \psi_5 MEc (f')^2 + Q\theta = 0. \quad (8)$$

$$f(0) = 0, f'(0) = 1, \theta(0) = 1$$

$$f'(\infty) = 0, \theta(\infty) = 0. \quad (9)$$

$Q = \frac{Q_0}{a(\rho C_p)_f}$	Heat absorption/generation parameter
$M = \frac{\sigma_f B^2}{\rho_f a}$	Magnetic parameter
$Pr = \frac{v_f (\rho c_p)_f}{k_f}$	Prandtl number
$Rd = \frac{4\sigma^* T_\infty^3}{k^* k_f}$	Radiation parameter
$Ec = \frac{U^2}{c_p (T_w - T_\infty)}$	Eckert number
$K = \frac{\nu_f}{aK^*}$	Porosity parameter

The dimensional form of Cf and Nu are

$$C_f = \frac{\tau_w}{\rho_f U^2} \quad (10)$$

Where shear stress τ_w is $\tau_w = \mu_{hmf} \left. \frac{\partial u}{\partial y} \right|_{y=0}$

$$Nu = \frac{xq_w}{k_f (T_w - T_\infty)} \quad (11)$$

Where heat flux q_w is $q_w = -k_{hmf} \left. \frac{\partial T}{\partial y} \right|_{y=0}$

The dimensionless Eqs. are

$$Re_r^{1/2} C_f = \psi_1 f''(0), \quad (12)$$

$$Re_r^{-1/2} Nu_r = -\psi_4 \theta'(0). \quad (13)$$

Where Re_r is the local Reynolds number.

3. Numerical method

Using the Bvp4c method involved within MATLAB solver, the model solves the extremely nonlinear connected ODE system that includes equations (7-8) together with boundary conditions (9). Equations 7–8 are initially converted into a set of connected first-order equations before the start of the process. The Bvp4c method is widely used in research and engineering assignments to deal with ODEs, especially when the specific nature of the problem is unknown prior to time and an adaptable strategy is necessary to maintain accuracy and efficacy. The numerical findings are presented for a variety of outputs for the factors examined in this study.

4. Design of artificial neural network (ANN) modeling

The ANN is a computer model designed to simulate the anatomical and functional properties of the nervous system of humans. The suggested research has the purpose of analyzing the information for the many aspects that

contribute to the reaction of optimal thermal transfer percentage, also known as the Nusselt number. Considering knowing that it is a method that uses machine learning with a variety of jobs, our goal is to evaluate the information. A neural network is built on a number of principles, which serve as its foundation.

Structures of neurons

The nerve cells constitute the fundamental building blocks of a neural network; they take in data, process it using a weighted total, implement a function of activation and finally provide an output. Nevertheless, a typical neural network architecture consists of three primary layers: (i) input phases, which capture incoming data; (ii) invisible layers, that operate as a bridge connecting input and output, collecting characteristics and trends; and (iii) layers for output, that generate the output.

Elements and prejudice

The connections among cells are nothing more than variables that the neural network learns throughout training, known as weights. Additionally, bias serves as an extra variable that helps the algorithm to predict the autonomous outcome.

The roles of activation

This presents the non-linear nature associated with the approach, which makes it possible to acquire knowledge about a connection.

In addition to reverse propagation and feed forward

The method by how data is transferred between the first layers of input into the final layer of output is referred to as feed forward. In this procedure, the weighted total and stimulation function are applied to every cell in every level. Back-propagation describes the method through which an algorithm trains to alter its weights and prejudices depending on the amount of error that exists among the previous forecast and the real value.

Training as well as learning

The term "epoch" refers to a period of time that runs across the whole of the information. Additionally, the training rates serve as a hyper parameter which is responsible for controlling the phase length throughout the optimization process [16-20].

The project of ANN and the purpose of the Levenberg technique to the construction of an ANN approach, which is presented in Figs 2. Fig 2 displays the results of the examination of skin friction through a region agent of the situations of ANN result nodes. Different parameters are determined beginning the input data from the network. We trained the algorithm using 70% of the information, validated it using 15%, and tested its forecasts with 15%. Tests of the skin friction coefficient and heat transfer rate have been carried out on the machine learning algorithm throughout the training stage, verification, and evaluation phases. The results of these tests are shown in Figs 3-5 and Figs 6-8. So, it involves replicating the complex connection that occurs between the components that constitute input and those that determine the output, it gives programs everything required. The results of the machine learning algorithm are very similar to the characteristics that were generated by computers. The following is an incredible occurrence.

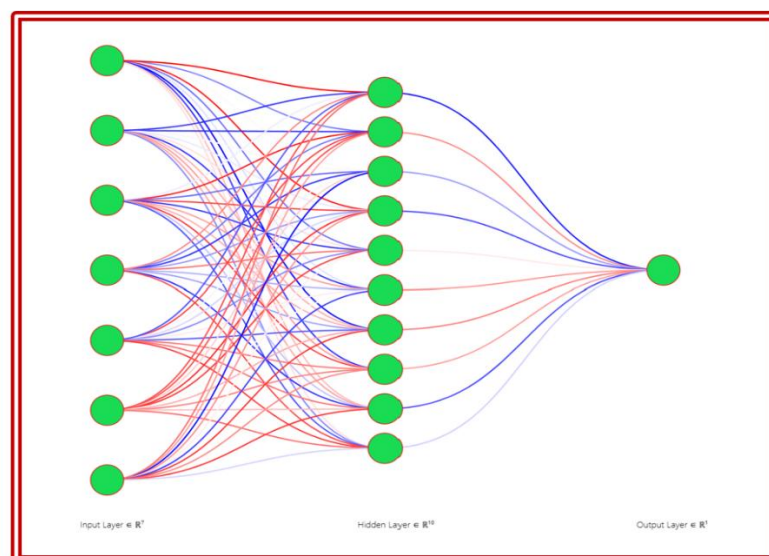


Fig 2. Project of ANN.

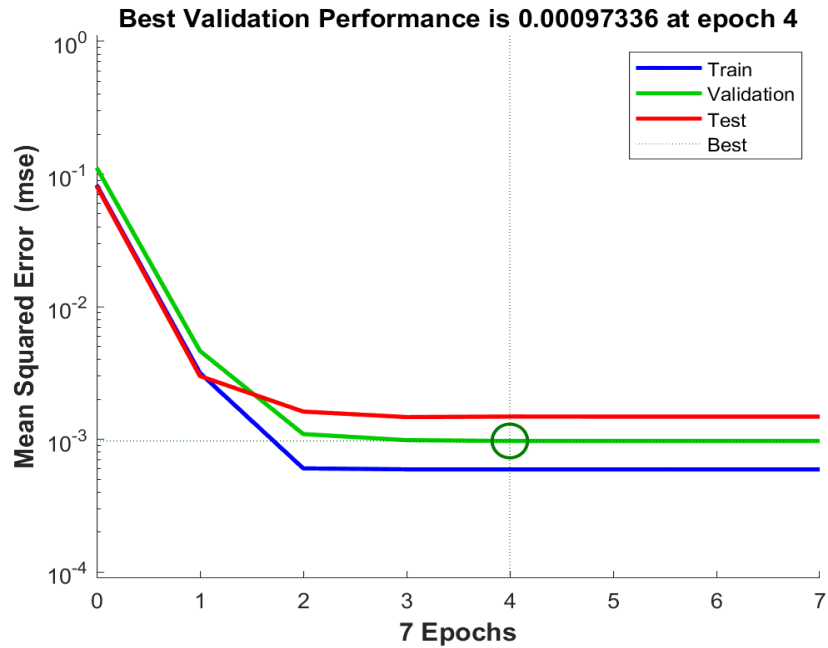


Fig 3. ANN performance for skin friction.

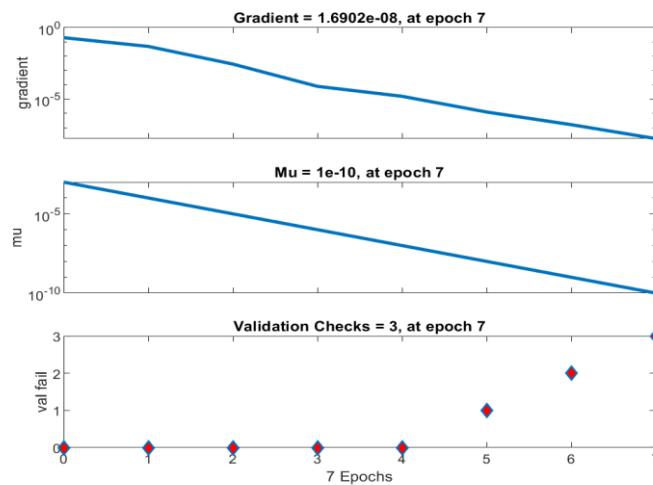


Fig 4. ANN training state for skin friction.

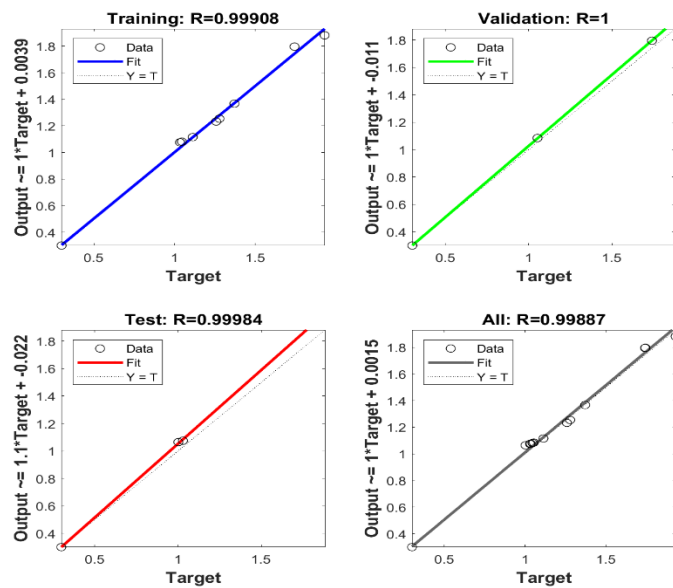


Fig 5. Graphical illustration for skin friction.



Fig 6. ANN performance for Nusselt number.

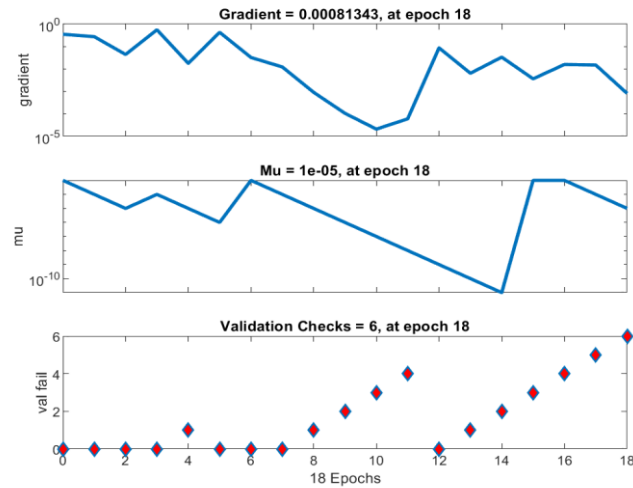


Fig 7. ANN training state for Nusselt number.

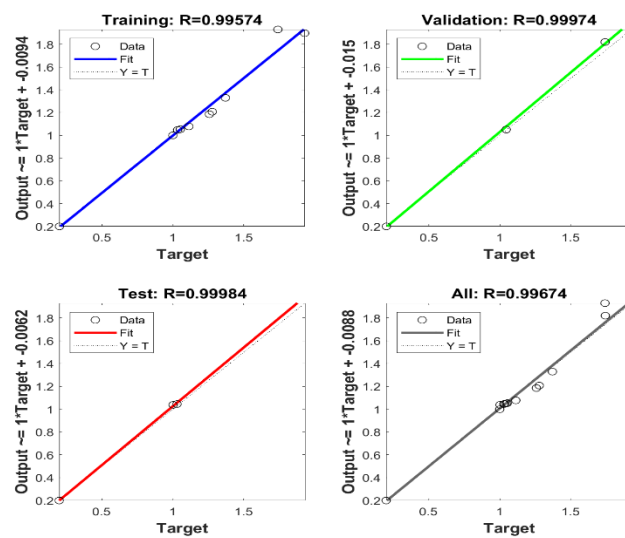


Fig 8. Graphical illustration of the Nusselt number.

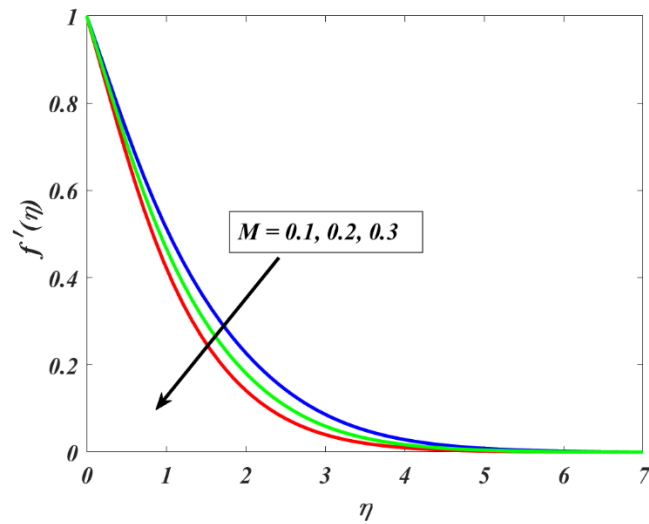


Fig 9. Representation of M on $f'(\eta)$.

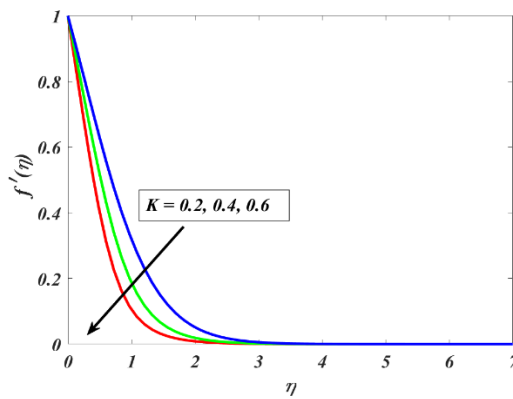


Fig 10. Representation of K on $f'(\eta)$.

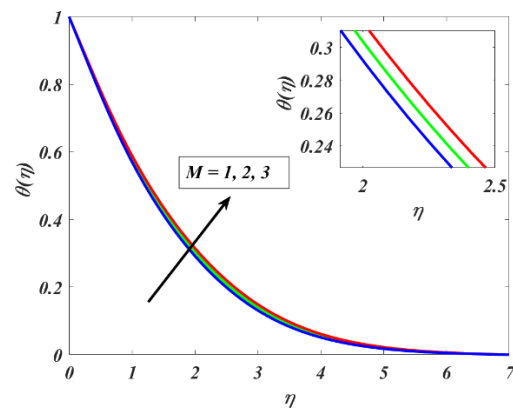


Fig 11. Representation of M on $\theta(\eta)$.

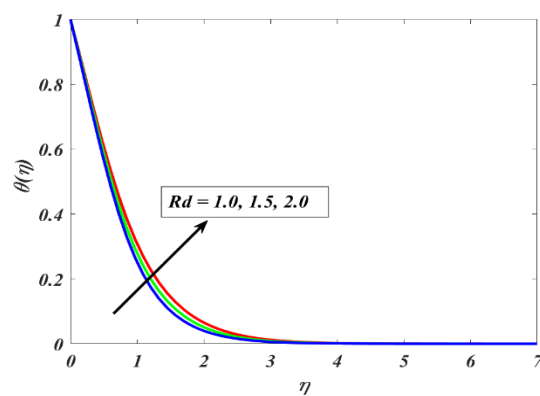


Fig 12. Representation of Rd on $\theta(\eta)$.

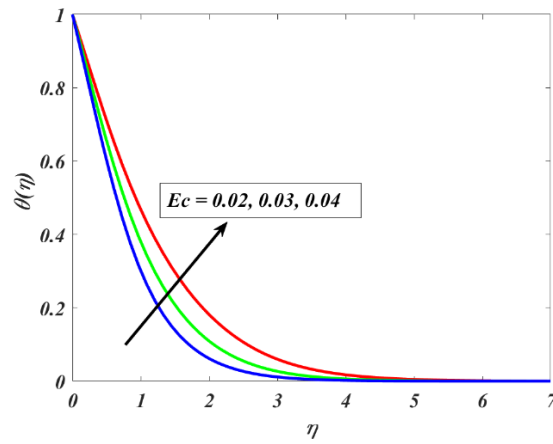


Fig 13. Representation of Ec on $\theta(\eta)$.

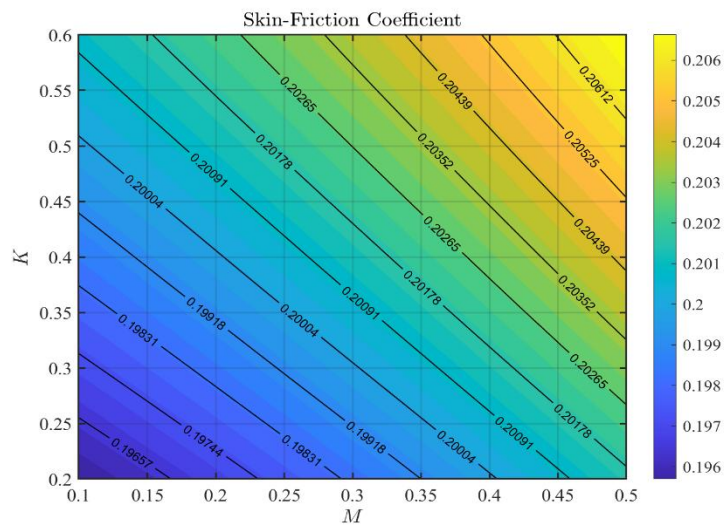


Fig 14. Impacts of K and M on $C_f Re_r^{1/2}$.

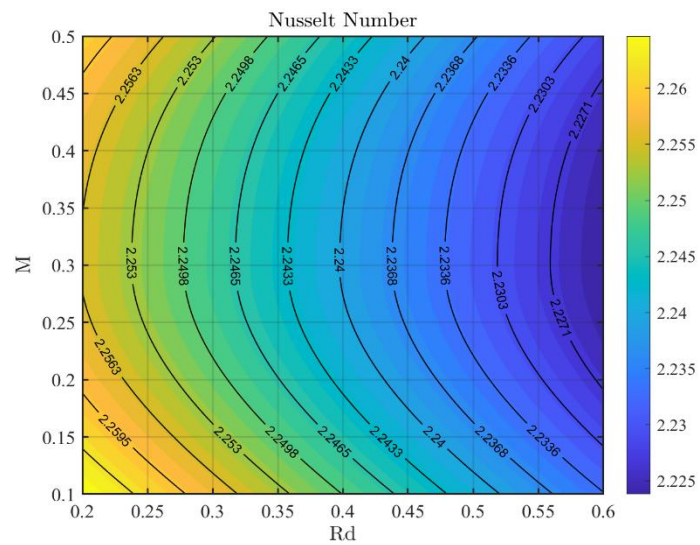


Fig 15. Impacts of M and Rd on $Nu_r Re_r^{-1/2}$.

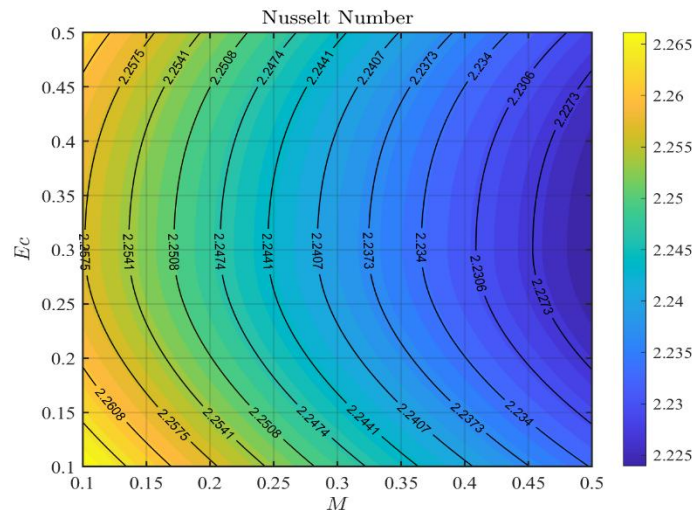


Fig 16. Impacts of Ec and M on $Nu_r Re_r^{-1/2}$.

Table 1: Hybrid nanoparticles of thermo physical properties [21-22].

Property	Blood	Cu	Al_2O_3
Density ρ (kgm^{-3})	1050	8933	3970
Specific heat C_p ($Jkg^{-1}K^{-1}$)	3617	385	765
Thermal conductivity k ($Wm^{-1}K^{-1}$)	0.52	401	40
Electrical conductivity σ (Sm^{-1})	0.43	59.6×10^6	35×10^6

5. RESULTS AND DISCUSSION

Employing the assistance that is offered by the MATLAB algorithm in accordance towards the Bvp4c approach, it is possible to get numerical solutions to the dimensionless equations (7) through (8), as well as the boundary equation (9). The assessment that was carried out utilized many of all of the numerical information that had been collected from the non-dimensional factors. The exact findings may be acquired from Tables 2, the conclusions from both examinations were found to be fairly precise according to the conclusions.

Fig 9 shows that M influences the velocity plot. The velocity graph shows a decreasing tendency for larger M numbers, indicating that M is growing. Physically, increasing M produces a Lorentz force that slows the flow of the fluid. Because the Lorentz force faces movement of fluids, the rate of flow falls due to increasing opposition, subsequent in a decrease in the field of momentum. Boosting the K values enhances the velocity outline, as seen in Fig 10. Practically, boosting the K numbers makes a porous material more challenging to flow over, slowing the movement of liquids. As an obvious and instantaneous result, the size of the outer border barrier is reduced.

Fig 11 depicts the effect of M on the energy profile. It directs that increasing the M factor increases the energy contour. The inclusion of M within an electrically magnetic substance provides a frictional Lorentz force, which accounts for this amplification. The force generated includes the potential to increase the fluid's heat. As a result, the temperature profile has improved. The characteristics of the Rd parameter temperature profile are shown in Fig 12. From a physics perspective, any generating operating above zero will generate thermal radiation. When electromagnetic waves travel through hotter regions, they induce molecular spin, a process which subsequently in turn generates kinetic energy. This illustration shows how a rise in energy could lead to a rise in heat transfer. A higher thermal barrier is the outcome of a rise in Rd , which causes a larger quantity of heat to be transmitted into the liquid. The total rate of absorption drops as the amount of energy increases, causing the temperature increase. Fig. 13 illustrates the influence that the Ec has on the energy plot. Due to this assertion, raising the Ec values improves the energy profile. Ec is accountable for the formation of frictional forces, that are the actual source of the increase in fluid temperature.

Fig 14 depicts the influence of K and M on the skin friction profile. The skin friction factor decreases as K rises. Similarly, increasing K alters the resistance associated with the porous medium and leads to a higher wall shear response in the present formulation. The highest skin-friction values therefore occur in the upper-right region of the contour diagram, corresponding to simultaneously larger M and K , while the lower-left region represents the minimum skin-friction levels. The smooth and almost linear progression of the contours also indicates a systematic interaction between the magnetic and porous-medium effects. Figs. 15 and 16 show the influence of Ec , Rd , and M on the $Nu_r Re_r^{-1/2}$ pattern. It demonstrates that the $Nu_r Re_r^{-1/2}$ increases with higher levels of Rd and magnetic

field. The maximum heat-transfer rate occurs at lower R_d , whereas higher radiation parameter values reduce the Nusselt number.

Table 2. Impacts of various parameters on $-f''(0)$ and $-\theta'(0)$ in comparison with existed published work. Ref. (Al-Zubaidi et al., 2023) [23].

M	K	Ec	$-f''(0)$ Al-Zubaidi et al. [23]	Present work	$-\theta'(0)$ Al-Zubaidi et al. [23]	Present work
0.1			0.195773	0.195708	2.2673	2.26752
0.3			0.198929	0.198423	2.24989	2.24926
0.5			0.201617	0.201603	2.23387	2.23383
	0.2		0.197417	0.197426	2.2673	2.26600
	0.4		0.200324	0.200381	2.24989	2.24974
	0.6		0.20282	0.202813	2.23387	2.23371
		0.1	0.138557	0.138046	4.00117	4.00110
		0.3	0.138611	0.138582	3.9913	3.99125
		0.5	0.138665	0.138638	3.99708	3.99653

6. CONCLUSION

This research provides a mathematical framework to examine the flow and heat transfer properties of a blood-based Cu-Al₂O₃ hybrid nanofluid. The governing equations for the velocity and temperature fields are translated into an appropriate boundary-value problem and computationally solved via the MATLAB bvp4c solver program. Under the specified physical parameters, this numerical approach yields correct answers to the relevant velocity and temperature variations. The numerical results are then evaluated to determine the influence of the key controlling factors on the flow and thermal properties. The differences in physical amounts are provided in suitable visualizations and tabular data to allow for a full evaluation of the findings.

The main findings are:

- The framework for artificial neural networks uses minimal processing resources, converges quickly, and does not require the linearization process.
- Through the use of neural systems and machine learning, it is possible to get precise predictions about the physical world.
- Velocity profile declined for the larger values of the M and K parameter values.
- The energy profile enhanced with an increasing the R_d parameter.
- The $C_f Re_r^{1/2}$ slowly enhanced for the improving values of the K parameter.
- The $Nu_r Re_r^{-1/2}$ outline enhanced, for the rising values of the M and R_d .

The suggested model sheds light on the flow and heat-transfer properties of blood-containing hybrid nanofluids in the presence of magnetic and heat influences. Incorporating Cu-Al₂O₃ nanoparticles improves blood temperature transport, indicating the possibility for enhanced biological heat transfer uses. The combination of computational simulations with an artificial neural network provides a powerful prediction framework for studying complicated mixed nanofluid systems and advancing biomedical engineering uses.

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REFERENCES

1. S. Jakeer, M. Lakshmi Rupa, S. R. Reddissekhar Reddy, and A. M. Rashad, "Artificial neural network model of non-Darcy MHD Sutterby hybrid nanofluid flow over a curved permeable surface: Solar energy applications," *Propuls. Power Res.*, vol. 12, no. 3, pp. 410–427, 2023, doi: 10.1016/j.jppr.2023.07.002.
2. Pooja, M. N., Gunisetty Ramasekhar, and S. K. Narasimhamurthy. "Artificial neural network-based prediction of Casson tri-hybrid nanofluid flow over a curved stretching surface: Application to drug delivery." *Multiscale and Multidisciplinary Modeling, Experiments and Design* 8, no. 8 (2025): 351.
3. N. S. M. Hanafi, W. A. W. Ghopa, R. Zulkifli, S. Abdullah, Z. Harun, and M. R. A. Mansor, "Numerical simulation on the effectiveness of hybrid nanofluid in jet impingement cooling application," *Energy Reports*, vol. 8, pp. 764–775, Nov. 2022, doi: 10.1016/J.EGYR.2022.07.096.
4. Tian, Shaopeng, Noreen Izza Arshad, Davood Toghraie, S. Ali Eftekhari, and Maboud Hekmatifar. "Using perceptron feed-forward Artificial Neural Network (ANN) for predicting the thermal conductivity of graphene oxide-Al₂O₃/water-ethylene glycol hybrid nanofluid." *Case Studies in Thermal Engineering* 26 (2021): 101055.
5. Azmi, et al. *J. of Mechanical*, and 2019., "A review on thermo-physical properties and heat transfer applications of single and hybrid metal oxide nanofluids," 103.53.35.75. doi.org/10.15282/jmes.13.2.2019.28.0425.

6. G. Ramasekhar, "Scrutinization of BVP Midrich method for heat transfer analysis on various geometries in the presence of porous medium and thermal radiation", *J. Nanofluids*, 13 (2024), 100-107. <https://doi.org/10.1166/jon.2024.2130>.
7. R. Chandra Sekhar Reddy, and Gunisetty Ramasekhar. "Enhanced Heat Transfer Analysis on MHD Hybrid Nanofluid Flow Over a Porous Stretching Surface: An Application to Aerospace Features." *East European Journal of Physics* 4 (2023): 286-293.
8. M. Ramzan, F. Ali, N. Akkurt, A. Saeed, P. Kumam, and A. M. Galal, "Computational assesment of Carreau ternary hybrid nanofluid influenced by MHD flow for entropy generation," *J. Magn. Magn. Mater.*, vol. 567, no. October 2022, p. 170353, 2023, doi: 10.1016/j.jmmm.2023.170353.
9. Joshi, Vimal K., Gunisetty Ramasekhar, Laltesh Kumar, Salman Saleem, and Kushal Sharma. "Neural network approach to mhd micropolar bioconvective flow under hall and thermal radiation effects in porous media." *International Communications in Heat and Mass Transfer* 172 (2026): 110599.
10. G. Rasool, A. J. Chamkha, T. Muhammad, A. Shafiq, and I. Khan, "Darcy-Forchheimer relation in Casson type MHD nanofluid flow over non-linear stretching surface," *Propuls. Power Res.*, vol. 9, no. 2, pp. 159–168, 2020, doi: 10.1016/j.jprr.2020.04.003.
11. S. Tian, N. I. Arshad, D. Toghraie, S. A. Eftekhari, and M. Hekmatifar, Using perceptron feed-forward Artificial Neural Network (ANN) for predicting the thermal conductivity of graphene oxide-Al₂O₃/water-ethylene glycol hybrid nanofluid, *Case Stud. Therm. Eng.*, 26(2021), 101055. <https://doi.org/10.1016/j.csite.2021.101055>.
12. Ramesh, K., A. S. Warke, K. Kotecha, and K. Vajravelu. "Numerical and artificial neural network modelling of magnetorheological radiative hybrid nanofluid flow with Joule heating effects." *Journal of Magnetism and Magnetic Materials* 570 (2023): 170552.
13. Qu, Yiran, Dheyaa J. Jasim, S. Mohammad Sajadi, Soheil Salahshour, Alireza Rahmanian, and Sh Baghaei. "Artificial neural network modeling of thermal characteristics of WO₃-CuO (50: 50)/water hybrid nanofluid with a back-propagation algorithm." *Materials Today Communications* 38 (2024): 108169.
14. Alhadri, Muapper, Jawad Raza, Ubaidullah Yashkun, Liaquat Ali Lund, Chemseddine Maatki, Sami Ullah Khan, and Lioua Kolsi. "Response surface methodology (RSM) and artificial neural network (ANN) simulations for thermal flow hybrid nanofluid flow with Darcy-Forchheimer effects." *Journal of the Indian Chemical Society* 99, no. 8 (2022): 100607.
15. Khan, Imad, and M. Waleed Ahmed Khan. "Artificial neural networking for computational assessment of ternary hybrid nanofluid flow caused by a stretching sheet: implications of machine-learning approach." *Engineering Applications of Computational Fluid Mechanics* 18, no. 1 (2024): 2411786.
16. S. Tian, N. I. Arshad, D. Toghraie, S. A. Eftekhari, and M. Hekmatifar, "Using perceptron feed forward Artificial Neural Network (ANN) for predicting the thermal conductivity of graphene oxide-Al₂O₃/water-ethylene glycol hybrid nanofluid," *Case Stud. Therm. Eng.*, vol. 26, no. May, p. 101055, 2021, doi: 10.1016/j.csite.2021.101055.
17. S. Jakeer, M. L. Rupa, S. R. R. Reddy, A. M. Rashad, Artificial neural network model of non-Darcy MHD Sutterby hybrid nanofluid flow over a curved permeable surface: Solar energy applications, *Propuls. Power Res.*, 12 (2023), 410–427. <https://doi.org/10.1016/j.jprr.2023.07.002>.
18. S. Tian, N. I. Arshad, D. Toghraie, S. A. Eftekhari, and M. Hekmatifar, "Using perceptron feed-forward Artificial Neural Network (ANN) for predicting the thermal conductivity of graphene oxide-Al₂O₃/water-ethylene glycol hybrid nanofluid," *Case Stud. Therm. Eng.*, vol. 26, no. May, p. 101055, 2021, doi: 10.1016/j.csite.2021.101055.
19. M. Alhadri et al., "Response surface methodology (RSM) and artificial neural network (ANN) simulations for thermal flow hybrid nanofluid flow with Darcy-Forchheimer effects," *J. Indian Chem. Soc.*, vol. 99, no. 8, p. 100607, 2022, doi: 10.1016/j.jics.2022.100607.
20. Bartwal, Ritu, Sawan Kumar Rawat, Moh Yaseen, Manish Pant, and Anju Saini. "Artificial intelligence based analysis of heat transfer of a ternary hybrid nanofluid flow over a bidirectional stretching surface." *Chemical Papers* (2026): 1-35.
21. Khashi'ie, Najiyah Safwa, Norihan Md Arifin, Ioan Pop, and Nur Syahirah Wahid. "Flow and heat transfer of hybrid nanofluid over a permeable shrinking cylinder with Joule heating: A comparative analysis." *Alexandria Engineering Journal* 59, no. 3 (2020): 1787-1798.
22. Ramasekhar, Gunisetty, N. Bala Kishore, C. Rekha, B. V. S. N. Lakshmi, A. Divya, Maddina Dinesh Kumar, and Nehad Ali Shah. "Heat transfer analysis of non-Newtonian hybrid nanofluid flow over a stretching surface using an artificial neural network." *Discover Nano* 21, no. 1 (2026): 319.
23. Al-Zubaidi, A., Hajar Abutuqayqah, Bilal Ahmad, Sadaf Bibi, Tasawar Abbas, and S. Saleem. "Analysis of slip condition in MHD nanofluid flow over stretching sheet in presence of viscous dissipation: Keller box simulations." *Alexandria Engineering Journal* 82 (2023): 26-34. <https://doi.org/10.1016/j.aej.2023.09.055>.