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Use of artificial neural network optimization for MHD and non-Newtonian peritoneal Jeffery nanofluid dynamics on female reproductive health

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Abstract

The dynamics of peritoneal fluid has vital applications in various physiological functions, particularly in female reproductive physiology, which modulates the transport of gametes within the fallopian tubes. This research aims to study the interactive operating factors of peritoneal fluid flow, heat transfer, and mass transport under various physiological and pathological conditions. In this regard, the Jeffrey fluid model is applied to examine the non-Newtonian behavior of peritoneal fluid and its responses to thermal and magnetic influences. The study extends to consider thermophoresis and Brownian motion of nanoparticles in nanofluids with the purpose of enhancing thermal conductivity and optimizing fluid properties toward better reproductive health. Magnetic field effects on fluid dynamics, using magnetohydrodynamics, are also explored in relation to possible therapeutic interventions for endometriosis and tubal factor infertility. Numerical solutions and graphical interpretations are used to illustrate the impact of salient parameters such as Grashof numbers, Brownian motion, and shear-dependent viscosity on the fluid behavior. The results deepen the current understanding of the mechanics of peritoneal fluids and provide potential improvements in fertility treatments and biomedical applications. The proposed model can be applied to develop a non-invasive diagnostic technique for detection of endometriosis, to optimize infertility treatments and to design biomedical devices for peritoneal fluid manipulation in female reproductive therapy.

Keywords Two-phase model, Jeffrey (non-Newtonian) model, Artificial neural networks, MHD, Application of female reproductive health

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Introduction

In the recent past, many studies have been conducted on peritoneal fluid flow, these studies have served as a tool in research across diverse fields. The rhythmic contractions of the smooth muscles of different tubular structures aid in the movement of different fluids, food and other contents, this process is termed as peristalsis. This process has its physiological uses in various systems of the body like Urinary system, Lymphatic system, Respiratory system, Gastro-intestinal system. To add on to these much research has also been carried out on its implication in the Female reproductive system. Study conducted in [1–3], had pioneered the theoretical study of peristaltic transport, whereas [4, 5] had examined the peristalsis in female reproductive system and its significant role in gamete transportation. Peritoneal fluid surrounds reproductive organs like ovaries, fallopian tubes and uterus. Figure 1(a) shows the ovaries, the bilateral fallopian (uterine) tubes, the uterus, and their relationship within the pelvic cavity. The fluid functions as a medium of transmission for peristaltic waves. Figure 1(b) shows the peritoneal cavity (visceral and parietal peritoneum) in the female pelvis, with the potential space for peritoneal

fluid, and how the reproductive organs lie within/adjacent to it. In the Female reproductive system, peristalsis is mainly observed in the transport of the gametes through the fallopian tubes.

However, the transport of these gametes depends on various factors like the flow of peritoneal fluid and conditions like tubal factor infertility. Many studies have been conducted on the various conditions that affect the peritoneal fluid flow [4, 8, 9]. Tubal factor infertility refers to the damage of the fallopian tubes. When the fallopian tubes are blocked or damaged the normal reproductive process is hindered. The normal flow of the peritoneal fluid flow can be disrupted by conditions like pelvic inflammatory disease (PID), endometriosis, tubal blockages, or scarring. These conditions can alter the volume, quality, and composition of the fluid. Recent studies have explored the heat transmission characteristics for both Newtonian and non-Newtonian fluids [10–12]. Peritoneal fluid is a non-Newtonian fluid. Heat and mass transfer in peritoneal fluid plays a significant role in ensuring normal biological health. This fluid is involved in maintaining a constant temperature which is essential for cellular function. Temperature changes can affect the

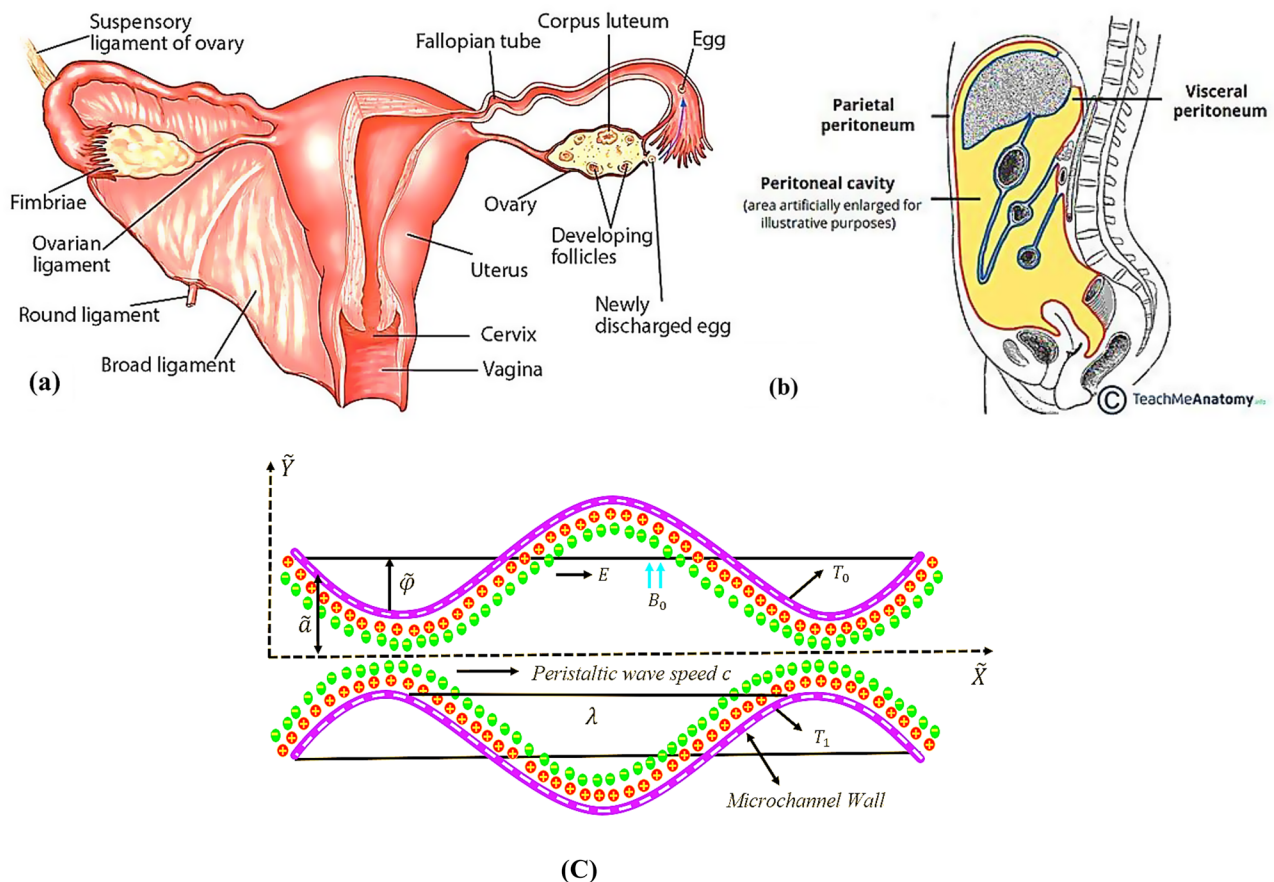


Fig. 1 (a) Anatomical overview of the female reproductive system [6]. (b) Schematic representation of the peritoneal cavity and fluid distribution around reproductive organs [7]. (c). Geometry of the fluid flow problem

metabolic activity of these cells potentially determining the success of fertilization and implantation. However, the property of low thermal conductivity in the base fluids is considered a limitation of heat transmission.

Common heat transfer fluids like water, ethylene glycol, propylene glycol, mineral oil, silicone oil, molten salts, air, and thermal oil have less thermal conductivity as compared to that of solids [13]. Choi [14] discovered that adding a certain number of nano sized particles into base fluids enhances thermal conductivity. This offers improved efficiency with lower energy consumptions, emissions and cost [15]. Particles of diameter size from 1 to 100 nm are termed as nanoparticles. When these nano sized particles are induced in the base fluids, they are called as nanofluids. Nanofluids like Cu /Water Nanofluid, Al_2O_3 /Water Nanofluid, ethylene glycol nanofluid, oil nanofluid have various applications like in cooling systems, heat exchangers, HVAC etc. Research has been carried out on the various applications that can be carried out using nanofluids such as, nanofluid for the storage of solar thermal energy [16], the application of nanofluids in industrial food processes [17], dynamics of nanofluid for exponential heat and for inclined magnetic field [18], the optical properties of nanofluids and its application in splitting of spectral beam [19]. In the context of heat and mass transfer studies, the basic characteristics of nanofluids depend on a few parameters such as the Brownian motion parameter (Nb) and the thermophoresis parameter (Nt), and some other distinct physical effects of the fluid were studied in [20–45]. When the nanoparticles collide with the base fluid it leads to randomness in the motion of the nanoparticles this in turn enhances the ability to conduct heat of the fluid. The quantification of this effect is called as Brownian motion parameter (Nb). The Thermophoresis parameter (Nt) calculates the impact of the particles moving from hotter regions to cooler regions on the ability of the nanofluid to conduct heat [46–50].

Another method termed as magnetohydrodynamics (MHD) is the analysis of the changes in the fluid dynamics and heat exchange properties of the fluid by conducting the fluids under the influence of magnetic fields. Both these methods have the same goal of optimizing fluid dynamics and thermal management. Research has been conducted on the dynamics of fluids under the magnetic field's effect more importantly on their behaviour in reproductive organs or under certain conditions like endometriosis or infertility [51, 52]. Many MHD parameters like fluid conductivity, flow rates and magnetic field strength are crucial in defining the properties of fluids. In most case Peritoneal fluid follows non-Newtonian characteristics however it can exhibit Newtonian or non-Newtonian characteristic based on the surrounding conditions. In the recent past many studies have also

been conducted on MHD peristalsis by varying different parameters [53–65]. The peritoneal fluid exhibits higher viscosity at reduced shear rates; this can also be observed in the yield stress fluid models.

The Jeffery Fluid model is responsible for the shear-thinning or shear-thickening behaviour depending on the conditions of the fluid flow. This model considers the relaxation/retardation time ratio, which influences fluid behavior. Shear thinning occurs when retardation time is the dominant factor and effective viscosity falls with shear rate. Shear-thickening happens when relaxation time is prioritized, since effective viscosity increases with shear rate. This model is used for fluids that have shear-dependant viscosity. Numerous studies have used this model to understand the fluid dynamics in different environments. For example, many studies have employed this model to describe the characteristics of blood flow in small vessels, polymer solutions and the fluid dynamics of the peritoneal fluid under different circumstances [66, 67]. This model is used in systems in which the Newtonian principles fall short by using the shear-dependant viscosity. Studies have been conducted on how the interaction of magnetic fields with non-Newtonian fluid together influence the flow of fluid [68]. For conditions like endometriosis, using the Jeffery fluid model aids in the understanding of the fluid dynamics of peritoneal fluid, this fluid follows the characteristics of a non-Newtonian fluid in most cases. The rheological properties of the fluid are determined by various physiological and pathological conditions. Studies have shown that changing the characteristics of the fluid influences the success rate of reproductive process such as fertilization and embryo implantation [69, 70]. This model is also used by research to understand how shear-dependant viscosity of the peritoneal fluid under different magnetic field strengths and flow conditions determine the transport of vital nutrients, cells in the reproductive organs [71, 72]. The Jeffrey fluid model is ideal for peritoneal fluid because it accounts for both relaxation and retardation times, capturing fundamental viscoelastic features with a simple constitutive relation. Casson models, for example, are better suited to yield-stress fluids (such as blood), whereas Maxwell and Oldroyd-B models emphasise elastic effects but need more mathematical complexity. The Carreau model largely explains shear-thinning behaviour; however, it does not explicitly include fluid memory effects. The model also aids in examining the effects of peristalsis in the reproductive tract and how magnetic fields on interaction with non-Newtonian fluids influence these properties. Hence this model plays a significant role in better understanding fertility related issues and for developing potential treatments for conditions like endometriosis [73]. These crucial insights enable the opportunity to design therapeutic interventions which includes

magnetic field-based treatments specific for tubal factor infertility and nanoparticles enhanced drug delivery systems to the female reproductive tract.

Artificial neural network (ANN) is an interconnection of algorithms that process information in response to an external input. This model is inspired by the function of brain and the nervous system, and how it handles information. Recently, much research has been conducted on the working of ANN and its various applications [74–76]. Apart from its various applications ANN model is recently being applied in the field of medicine. Research has shown that ANN model can be used in early detection of diseases, classification of medical images and analysis, patient monitoring and prognosis [77–83]. ANN model is also being deployed in various studies related to the peritoneal fluid. Research has shown that the use of ANN model in predicting fluid absorption rates can increase the treatment efficiency [84]. In recent years the research discusses about the use of ANN models to forecast patient prognosis and improve healthcare delivery [85].

The coupling of MHD forces with shear dependent viscosity in the Jeffery fluid model produces significant competing non-linear effects on its flow behaviour. The Lorentz force opposes the fluid motion, specifically at high Hartmann numbers (Mn), which causes wall shear stress amplification. On the other hand, the Jeffery fluid model's shear thinning property reduces viscosity under high shear gradients imposed by Lorentz forces, which partially counteracts the magnetic field's resistive effect in cases when the retardation dominates. In cases of low shear rates in the centre of channel, the fluid exhibits Newtonian like behaviour with an elevated viscosity, whereas near the walls the viscosity drops significantly since the shear rates are high and MHD effects are the strongest. This significant interplay creates a complex distribution of velocity and stress which linear models cannot capture, which necessitates the need of the coupled numerical ANN approach which is modelled in this study.

The prior studies conducted have modelled peritoneal fluid with the help of Newtonian approaches or a simple non-Newtonian model, but they have not simultaneously incorporated the Jeffery fluid model in specific, the MHD effects, nanofluid dynamics and machine learning based optimization. In addition, most of the current models lack a detailed ANN based surrogate modelling for real time prediction of heat and mass transfer coefficients specific in electrokinetic biofluid environments. This study aims to fill the current gap by developing an integrated computational framework which couples nonlinear partial differential equations governing Jeffery nanofluid flow under MHD influence with ANN for

robust and accurate prediction of the critical physiological parameters. The key novelty of the proposed study is:

- Simultaneous coupling of Jeffery viscoelasticity along with electroosmotic effects in peritoneal flow.
- Integration of ANN optimization to develop surrogate model for Nusselt and Sherwood numbers with high correlation ($R^2 \approx 0.99995$).
- Direct application into female reproductive health, in specific to endometriosis and tubal factor infertility with machine learning model.

Problem formulation

Figure 1(c) shows a schematic diagram of the model's flow configuration. A 2D electroosmotic fluid flow involving non-Newtonian Jeffery fluid through a microchannel with a width of $2\bar{a}$ and $\bar{Y} = \bar{h}(\bar{X}, \bar{t})$ as the bottom and top walls, respectively is considered. A peristaltic wave propagation induces motion in the medium at c along the microchannel. The temperature and concentration fields of the upper and lower channel walls are maintained at T_0 , C_0 , T_1 and C_1 , respectively. The geometry of the microchannel is mathematically given by

$$\bar{Y} = \bar{h}(\bar{X}, \bar{t}) = 1 + \frac{LK\bar{X}}{\bar{b}} + \bar{b}\sin\left(\frac{2\pi(\bar{X} - c\bar{t})}{\lambda}\right) \quad (1)$$

Here, $\bar{X}$, $\bar{a}$, $\bar{b}$, c , λ and $\bar{t}$ are axial coordinate, half width of the channel, amplitude and speed of the wave, wavelength, and time, respectively.

The fundamental equations in the laboratory reference frame for a Jeffery fluid in electro-magnetohydrodynamic are defined as [78]:

$$\frac{d\bar{U}}{d\bar{X}} + \frac{d\bar{V}}{d\bar{Y}} = 0, \quad (2)$$

$$\begin{aligned} & \rho \left(\frac{d}{d\bar{t}} + \bar{U} \frac{d}{d\bar{X}} + \bar{V} \frac{d}{d\bar{Y}} \right) \bar{U} \\ &= -\frac{d\bar{p}}{d\bar{X}} + \frac{d}{d\bar{Y}} \bar{\tau}_{XY} \\ &+ \frac{d}{d\bar{X}} \bar{\tau}_{XX} - \sigma B_0^2 \bar{U} \\ &+ g\rho\beta_f(T - T_0) + g\rho\omega^*(C - C_0) + \rho_e E_x, \end{aligned} \quad (3)$$

$$\rho \left(\frac{d\bar{V}}{d\bar{t}} + \bar{U} \frac{d\bar{V}}{d\bar{X}} + \bar{V} \frac{d\bar{V}}{d\bar{Y}} \right) = -\frac{d\bar{p}}{d\bar{Y}} + \frac{d}{d\bar{X}} \bar{\tau}_{XY} + \frac{d}{d\bar{Y}} \bar{\tau}_{YY} - \sigma B_0^2 \bar{V} \quad (4)$$

$$\rho c_p \left(\frac{d\bar{T}}{dt} + \bar{U} \frac{d\bar{T}}{d\bar{X}} + \bar{V} \frac{d\bar{T}}{d\bar{Y}} \right) = k \left(\frac{d^2\bar{T}}{d\bar{X}^2} + \frac{d^2\bar{T}}{d\bar{Y}^2} \right) + \left(\frac{d\bar{U}}{d\bar{X}} \bar{\tau}_{XX} + \frac{d\bar{V}}{d\bar{Y}} \bar{\tau}_{YY} + \left(\frac{d\bar{U}}{d\bar{Y}} + \frac{d\bar{V}}{d\bar{X}} \right) \bar{\tau}_{XY} \right) \quad (5)$$

$$\left(\frac{d\bar{C}}{dt} + \bar{U} \frac{d\bar{C}}{d\bar{X}} + \bar{V} \frac{d\bar{C}}{d\bar{Y}} \right) = D_m \left(\frac{d^2\bar{C}}{d\bar{X}^2} + \frac{d^2\bar{C}}{d\bar{Y}^2} \right) + \frac{k_t D_m}{T_m} \left(\frac{d^2\bar{T}}{d\bar{X}^2} + \frac{d^2\bar{T}}{d\bar{Y}^2} \right) \quad (6)$$

Here, $\bar{U}$ is the velocity along $\bar{X}$ -direction, $\bar{V}$ is the velocity along $\bar{Y}$ -direction, ρ_e is the electrical charge density, $\bar{p}$ represents pressure, ρ is the fluid density, E_x represents the axial electric field, c_p represents specific heat, k shows the thermal conductivity, k_t represents the ratio of thermal diffusion, D_m is the mass diffusivity co-efficient, T_m represents mean temperature, $\bar{T}$ is the temperature, and $\bar{C}$ is the concentration field. The Cauchy stress tensor formulation for the Jeffrey fluid, as represented by Hayat et al. [71], is expressed as:

$$S = -pI + \tau,$$

$$\tau = \frac{\mu}{1 + \lambda_1} \left(\dot{\gamma} + \lambda_2 \frac{d\dot{\gamma}}{dt} \right) \quad (7)$$

In the above expression, S denotes the extra stress tensor, p stands for pressure, I is the identity tensor, d/dt is the total derivative, μ is the dynamic viscosity, λ_1 and λ_2 denote the respective ratio of relaxation to retardation time and retardation time, and $\dot{\gamma}$ stands for shear-rate.

Similarly, the Rivlin-Erickson tensor $\bar{A}_n$ defines the following:

$$\bar{A}_1 = \left(\nabla \hat{V} \right) + \left(\nabla \hat{V} \right)^T$$

where $\hat{V} = [\bar{U}(\bar{X}, \bar{Y}, \bar{t}), \bar{V}(\bar{X}, \bar{Y}, \bar{t}), 0]$, and

$$\bar{A}_n = \frac{d\bar{A}_{n-1}}{d\bar{t}} + \bar{A}_{n-1} \left(\nabla \hat{V} \right) + \left(\nabla \hat{V} \right)^T \bar{A}_{n-1}, n \geq 2 \quad (8)$$

In a microchannel, the Poisson equation is formulated as follows:

$$\nabla^2 \bar{\varphi} = -\frac{\rho_e}{\varepsilon} \quad (9)$$

Here, ρ_e , ε , and $\bar{\varphi}$ represent total charge density, dielectric permittivity, and electric potential.

The translational transformation between a fixed coordinate system $(\bar{X}, \bar{Y})$ and a moving coordinate system $(\bar{x}, \bar{y})$ is as follows:

$$\bar{x} = \bar{X} - c\bar{t}, \bar{y} = \bar{Y}, \bar{u}(\bar{x}, \bar{y}) = \bar{U}(\bar{X}, \bar{Y}, \bar{t}) - c, \bar{v}(\bar{x}, \bar{y}) = \bar{V}(\bar{X}, \bar{Y}, \bar{t}), \bar{p}(\bar{x}, \bar{y}) = \bar{P}(\bar{X}, \bar{Y}, \bar{t}), T(\bar{x}, \bar{y}) = \bar{T}(\bar{X}, \bar{Y}, \bar{t}) \quad (10)$$

The given transformations are used in Eqs. (2-6), and non-dimensional variables are defined as follows:

$$x = \frac{2\pi\bar{x}}{\lambda}, y = \frac{\bar{y}}{a}, u = \frac{\bar{u}}{c}, v = \frac{\bar{v}}{c\delta}, \delta = \frac{a}{\lambda}, t = \frac{2\pi c\bar{t}}{\lambda},$$

$$p = \frac{2\pi\bar{p}a^2}{\lambda\mu c}, a = \frac{2\pi\bar{a}}{\lambda}, b = \frac{b_1}{d_1}, h = \frac{\bar{h}}{a},$$

$$\varepsilon = \frac{b}{a}, \psi = \frac{\bar{\psi}}{ca}, u = \frac{\partial\psi}{\partial y}, v = -\frac{\partial\psi}{\partial x}, \Phi = \frac{ez_v}{T_{av}K_B} \bar{\Phi},$$

$$m_e = \frac{a}{\lambda_D}, U_{HS} = -\frac{E_1\varepsilon}{c\mu}, f = \frac{\bar{q}}{ca}, \Theta = \frac{\bar{Q}}{ca},$$

$$\lambda_1 = \frac{\alpha_1 c}{a\mu}, \lambda_2 = \frac{\alpha_2 c}{a\mu}, \lambda_D = \frac{1}{ez_v} \sqrt{\frac{T_0\varepsilon K_H}{2n_0}}, \text{Pr} = \frac{\mu c_p}{k}, Ec = \frac{c^2}{c_p T_0},$$

$$Br = EcPr, \theta = \frac{T - T_0}{T_0}, \Upsilon = \frac{C - C_0}{C_0},$$

$$Nt = \frac{\tau T_0 D_T}{\nu T_m}, Nb = \frac{\tau C_0 D_B}{\nu},$$

$$Mn = \sqrt{\frac{\sigma}{\mu}} B_0 a, Gr_T = \frac{\rho_f \beta_f g T_0 d^2}{c\mu}, Gr_C = \frac{\rho_f \beta_f g C_0 d^2}{c\mu}.$$

Here, x is the non-dimensional axial coordinate, y is the non-dimensional transverse coordinate, m_e is the electroosmosis parameter, p is the non-dimensional pressure, λ_D is the Debye length, α is the peristaltic wave number, Θ is the dimensionless volume flow rate, θ is the dimensionless temperature, Ω is the dimensionless concentration, U_{HS} is the Helmholtz-Smoluchowski velocity, ψ is the non-dimensional shear stress, Br is the Brinkmann number, Re is the Reynolds number, Pr is the Prandtl number, ε is the amplitude ratio, S is the non-dimensional shear stress, Nt is the non-dimensional thermophoresis parameter, Nb is the Brownian motion parameter, Ec is the Eckert number. The relation of the velocity and the stream function ψ is defined as follows:

$$u = \frac{\partial\psi}{\partial y}, v = -\frac{\partial\psi}{\partial x} \quad (11)$$

Equation (2) is identically satisfied. Furthermore, from Eqs. (3)–(6), by invoking the long-wavelength approximation ($\frac{a}{\lambda} \ll 1$), which implies negligible axial gradients compared to transverse gradients, and the low-Reynolds-number assumption ($Re \ll 1$), under which inertial effects are negligible relative to viscous forces, and by neglecting higher-order terms in the small parameters, the governing equations reduce to the following expression:

$$\frac{\partial p}{\partial x} = \frac{1}{1+\lambda} \frac{\partial^3 \psi}{\partial y^3} - \frac{Mn^2 + S^2}{1+\Omega^2} \left(\frac{\partial \psi}{\partial y} + 1 \right) + Gr_T \theta + Gr_C \Upsilon + me^2 U_{HS} \Phi \quad (12)$$

$$\frac{\partial p}{\partial y} = 0 \quad (13)$$

$$\frac{\partial^2 \theta}{\partial y^2} + Nb \frac{\partial \theta}{\partial y} \frac{\partial \Omega}{\partial y} + Nt \left(\frac{\partial \theta}{\partial y} \right)^2 + Br \left(\frac{1}{1+\lambda} \right) \left(\frac{\partial^2 \psi}{\partial y^2} \right)^2 = 0 \quad (14)$$

$$\frac{\partial^2 \Upsilon}{\partial y^2} + \frac{Nt}{Nb} \frac{\partial^2 \theta}{\partial y^2} = 0 \quad (15)$$

Correspondingly, the constructed boundary assumptions are

$$\frac{\partial^2 \psi}{dy^2} = 0, \theta = 0, \phi = 0, \Upsilon = 0 \text{ at } y = 0 \quad (16a)$$

$$\begin{aligned} \frac{\partial \psi}{\partial y} + \frac{1}{\sigma} \frac{\partial^2 \psi}{\partial y^2} &= 1, \theta = 1, \phi = 1, \Upsilon = 1 \text{ at } \\ y = h &= 1 + \frac{LKx}{b} + \omega \cos \left[\frac{2\pi}{\lambda} (x - t) \right] \end{aligned} \quad (16b)$$

The Poisson equation ($\nabla^2 \bar{\phi} = -\frac{\rho_e}{\epsilon}$) is used to describe the electric potential in the microchannel. The net charge density ρ_e follows the Boltzmann distribution, which is given by the following relation:

$$\rho_e = -z_v e (\bar{n}^- + \bar{n}^+) \quad (17)$$

Here, the anions ($\bar{n}^-$) and cations ($\bar{n}^+$) are defined through ρ_e of the Boltzmann equation are as follows:

$$\bar{n}^\pm = n_0 e^{\left(\pm \frac{e z_v}{T_{av}} \bar{\phi} \right)} \quad (18)$$

where n_0 is the bulk concentration, z_v is the charge balance, K_B is the Boltzmann constant, e is the electronic charge, and T_{av} is the average temperature. Applying Debye-Huckel linearization approximation [12], Eq. (9) becomes:

$$\frac{d^2 \phi}{dy^2} = m_e^2 \phi. \quad (19)$$

Here, m_e is the electroosmotic parameter. The analytical solution of the above Eq. (19) subjected to boundary conditions (16a, 16b) is obtained as follows:

$$\phi(y) = \frac{\cosh(m_e y)}{\cosh(m_e h)} \quad (20)$$

The wall shear stress (skin-friction co-efficient), heat transfer co-efficient (Nusselt number) and mass transfer

co-efficient (Sherwood number) in non-dimensional form is given by

$$C_f = h' \frac{\partial^2 \psi}{\partial y^2} \Big|_{y=h} \quad (21)$$

$$Nu = h' \frac{\partial \theta}{\partial y} \Big|_{y=h} \quad (22)$$

$$Sh = h' \frac{\partial \Upsilon}{\partial y} \Big|_{y=h} \quad (23)$$

The nonlinear system of Eqs. (12–15), together with the boundary conditions (16a–16b), governing the stream function, temperature, concentration, skin-friction coefficient, Nusselt number, and Sherwood number, is solved analytically using built-in symbolic computation routines in MATLAB. The coupled equations of ordinary differential equations were defined and solved with the help of inbuilt dsolve function which gives the exact solutions of closed form under the given boundary conditions. Temperature equation was solved first and then the solution was further applied to obtain the concentration profile. The expressions that resulted were then further inserted in the momentum equation which too was solved analytically. This method does not involve numerical discretization and iteration and provides accurate and continuous domain solutions. Traditional numerical analysis concepts such as order of accuracy, truncation error, and residual convergence do not apply in this context when working with analytical solutions. The solutions obtained are exact within the assumptions of the governing equations and boundary conditions, eliminating discretization-induced errors. Solutions for the parameter combinations were generated as the training data for the ANN model.

Graphical results and discussion

This section aims to elucidate the derived equations with their graphical representation. The equations for velocity, temperature and concentration which were derived have been solved by numerical method. The equations solved are illustrated as graphs based on variations of key parameters like the Brownian motion parameter (Nb), the thermophoretic parameter (Nt), and the non-uniformity parameter (K), thermal Grashoff number (Gr_T), concentration Grashoff number (Gr_C), Jeffrey fluid parameter (λ), porous parameter (σ), and Hall parameter (Ω). These include characterization of their impact on the distribution of nanoparticles, heat transfer, and overall behaviour of the system. These plots allow us to understand the behaviour of our system and how we can use them to improve our thermal and mass transfer

processes. The computer program MATLAB served to be the best tool to facilitate the illustration of the numerical results obtained for the model that is to be plotted.

Validation of the results

The justifications for the concentration, temperature and velocity profile for fluid flow have been taken from the conclusions by comparing the obtained results ($Mn = 0.1, \lambda = 0.01, \Omega = 0.1, K = 0.5$) with Srinivas et al. [23] ($Mn = 0, \lambda = 0, \Omega = 0, K = 0$) as shown in Fig. 2(a-c). Both the current findings and the findings of the previous results are in the same phase. This confirms the reliability of the present scheme and demonstrates that it can be used to predict results for cases for which no published data are available.

Velocity profile

The graphical representation of the solutions of velocity was calculated by solving and analyzing it up-to second order. The graphs were produced through variations in the following parameters: $Gr_T, Gr_C, K, \lambda, Mn, Nb, Nt, \Omega$ and σ . In two dimensions, these plots are analysed to examine the effect of axial velocity on peritoneal fluid flow through the fallopian tube via Fig. 3((a)-(i)), not the flow of blood, as peritoneal fluid provides the physiological medium for the transportation of gametes and the delivery of nutrients in the reproductive environment. From Fig. 3(a), the graph signifies that as Gr_T rises, velocity also rises because it symbolizes increased buoyancy forces from a higher temperature difference, thus boosting fluid motion. From Fig. 3(b), it is seen that as the increase in Gr_C , velocity rises because buoyancy forces become higher with concentration differences, increasing convection currents and fluid velocity.

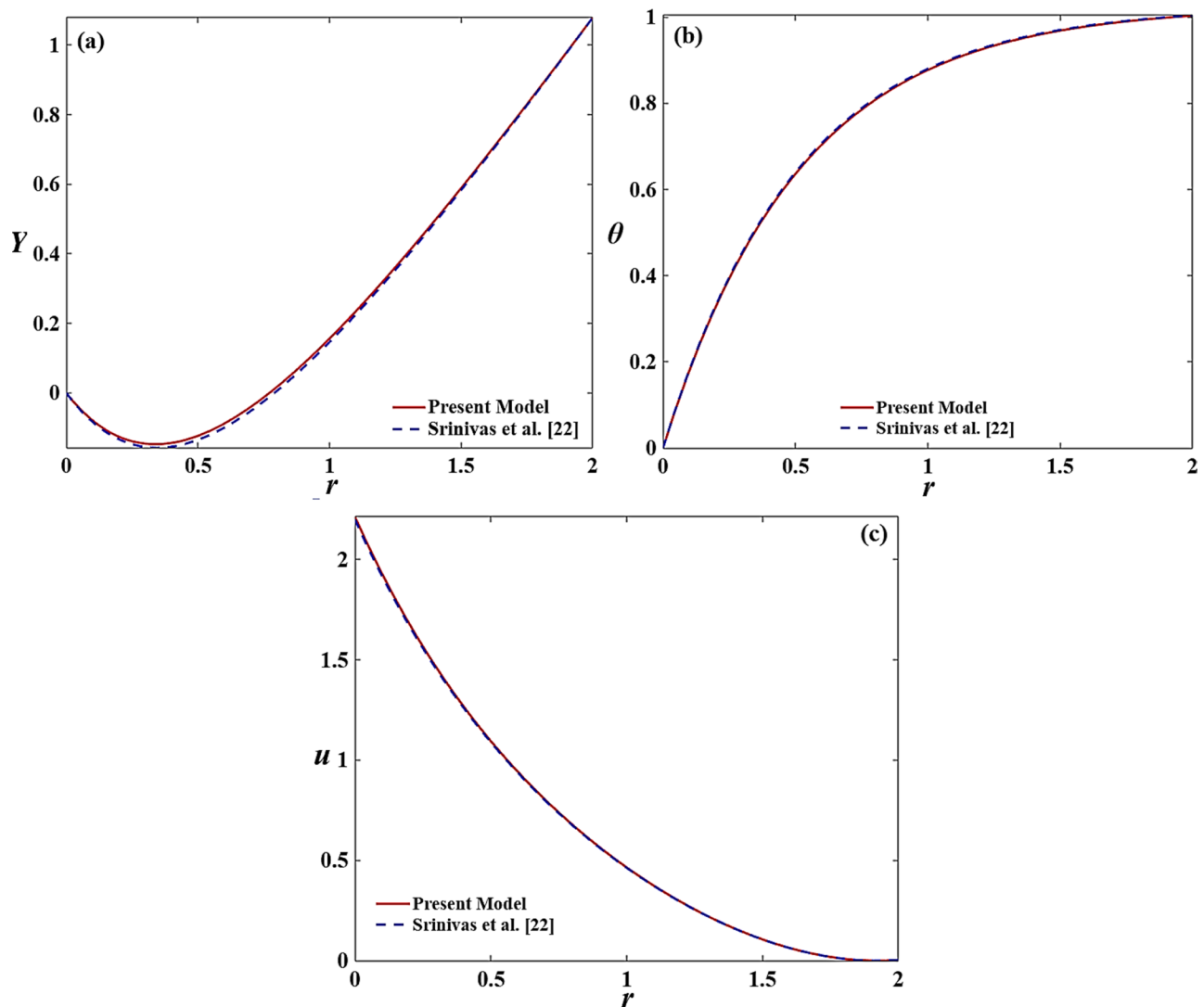


Fig. 2 Validation of the results with Srinivas et al. [23] work

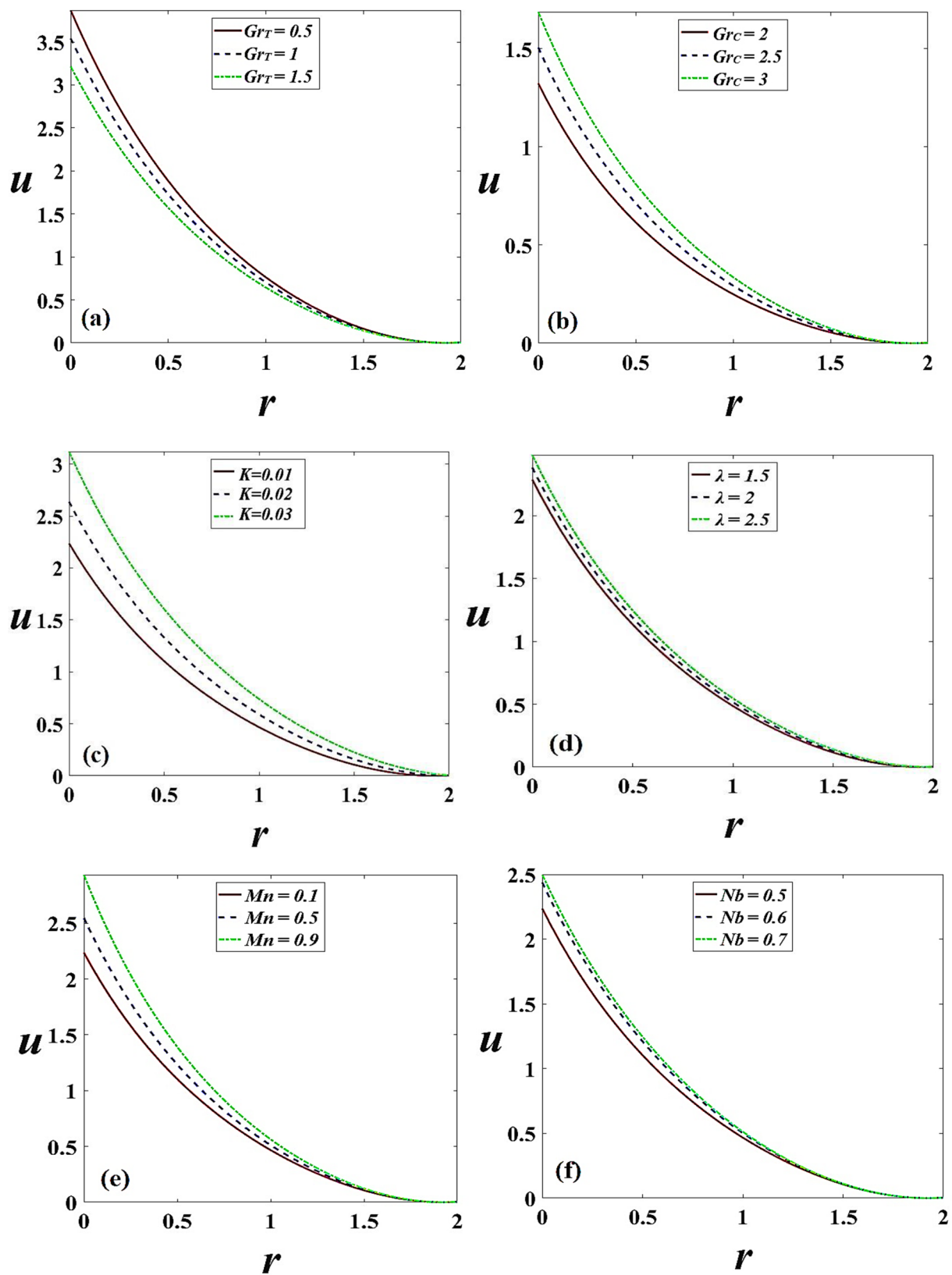


Fig. 3 Variation of velocity distribution for diverse values of (a) Gr_C (b) Gr_T (c) K (d) λ (e) Mn (f) Nb (g) Nt (h) Ω (i) σ

Elevated peritoneal temperature and altered biochemical compositions can result from localized inflammation in the female reproductive system, especially endometriosis. Gamete transport may be disrupted and failure to fertilize could arise from these heat and concentration gradients' enhanced convection-driven fluid movements in the fallopian tubes or peritoneal cavity. Figure 3(c) depicts that increase in K increases the velocity because efficient heat transfer reduces thermal gradients, which ultimately boosts the overall flow velocity in a system. Improved geometric modulation may allow for better mobility of gametes or secretions inside the fallopian tubes, resulting in more effective fluid transfer. Raising the Jeffery parameter λ minimizes viscoelastic retardation, flow resistance, and increases velocity, as seen in Fig. 3(d). Endometriosis alters the rheological properties of peritoneal and tubal fluids as a result of inflammation, elevated cytokines, and increased protein content. Such changes can affect the viscoelastic properties of reproductive fluids, prevent normal sperm transport and contribute to endometriosis-related subfertility. On the other hand, raising the magnetic parameter Mn decreases velocity because of increased resistive (Lorentz) forces, as seen in Fig. 3(e). From a physiological perspective, this may be seen as an increased internal resistance or an external regulatory impact that could impede effective reproductive transport processes and inhibit fluid motility. Recent research suggests that therapies based on magnetic fields might be used in reproductive medicine. Methods such as pulsed electromagnetic field therapy and repeated transcranial magnetic stimulation have demonstrated potential in reducing endometriosis pain and inflammation. Additionally, preclinical and clinical trials for targeted treatment and pain management are exploring magnetic hyperthermia and stimulation devices. Increasing the Brownian motion parameter Nb causes random particle movement to rise, improving thermal diffusion but disrupting coherent flow, which lowers velocity (Fig. 3(f)). Random nanoparticle fluctuations generated by Nb disrupt coherent fluid layers, increasing effective viscosity and microscopic momentum exchange. This additional resistance lowers velocity by impeding bulk momentum transmission. Coordinated gamete transport may be impacted by microscopic agitation in the peritoneal or tubal fluid caused by elevated suspended biological components in the female reproductive system. Boosting the thermophoresis parameter Nt enhances heat transfer and decreases fluid temperature, resulting in reduced velocity, as seen in Fig. 3(g). Temperature gradients and particle dispersion changes in the peritoneal cavity may have an impact on sperm motility and overall reproductive success in inflammatory conditions such as endometriosis. Figure 3(h) shows that higher Ω values promote fluid relaxation during stress, leading to decreased

internal resistance and increased velocity. This might be due to differences in the microstructural or biochemical makeup of the female reproductive system's reproductive fluids, which alters their relaxation properties and influences sperm and ovum transport. On the other hand, Figure 3(i) demonstrates that increasing the porosity parameter σ results in greater flow resistance due to blockage, which lowers velocity and increases energy dissipation. From a physiological perspective, this might be caused by issues such as adhesions, tissue thickening, or inflammatory deposits that raise the reproductive canal's structural resistance and impede the efficient passage of fluid and gametes.

Temperature profile

The two-dimension plot for the temperature profile was plotted to study the effects of Nb , Nt and K . Figure 4(a) shows that increasing the thermophoresis parameter Nt causes the temperature to rise. The mobility of suspended biological components in reproductive fluids can be impacted by temperature differences. Enhanced thermophoretic effects may modify the local heat fields in the fallopian tubes or peritoneal cavity, thereby affecting cellular activity and fertilization circumstances. Figure 4(b) indicates that improving the Brownian motion parameter, Nb , optimizes heat transfer through boosting spontaneous nanoscale mobility. Elevated inflammatory cells or biochemical particles, as seen in endometriosis, can worsen micro-level agitation and thermal diffusion in a biological context, altering the local thermal milieu necessary for oocyte function and sperm survival. Increasing the heat transfer coefficient K results in faster and more consistent temperature dispersion, as Figure 4(c) illustrates. Sustaining optimal conditions for conception and the early stages of embryo development requires efficient temperature regulation in the reproductive system. Implantation success and reproductive efficiency may be impacted by any modifications to the properties of heat distribution.

Concentration profile

A two-dimensional plot of the concentration profile is presented to examine the effect of Nb , Nt and K . The concentration function Υ in Figure 5(a) drops as Nb rises, indicating more uniform particle dispersion due to microscopic agitation. This might be linked to increased protein, inflammatory cell, or biochemical mediator mixing in the peritoneal cavity of reproductive fluids. Excessive particle activity, such as in inflammatory situations like endometriosis, may alter the biochemical environment required for conception, whereas mild homogeneity may allow for balanced transport. As the nanoparticles move to cooler zones, a higher Nt decreases the concentration at the core region, as seen in Fig. 5(b). Within the

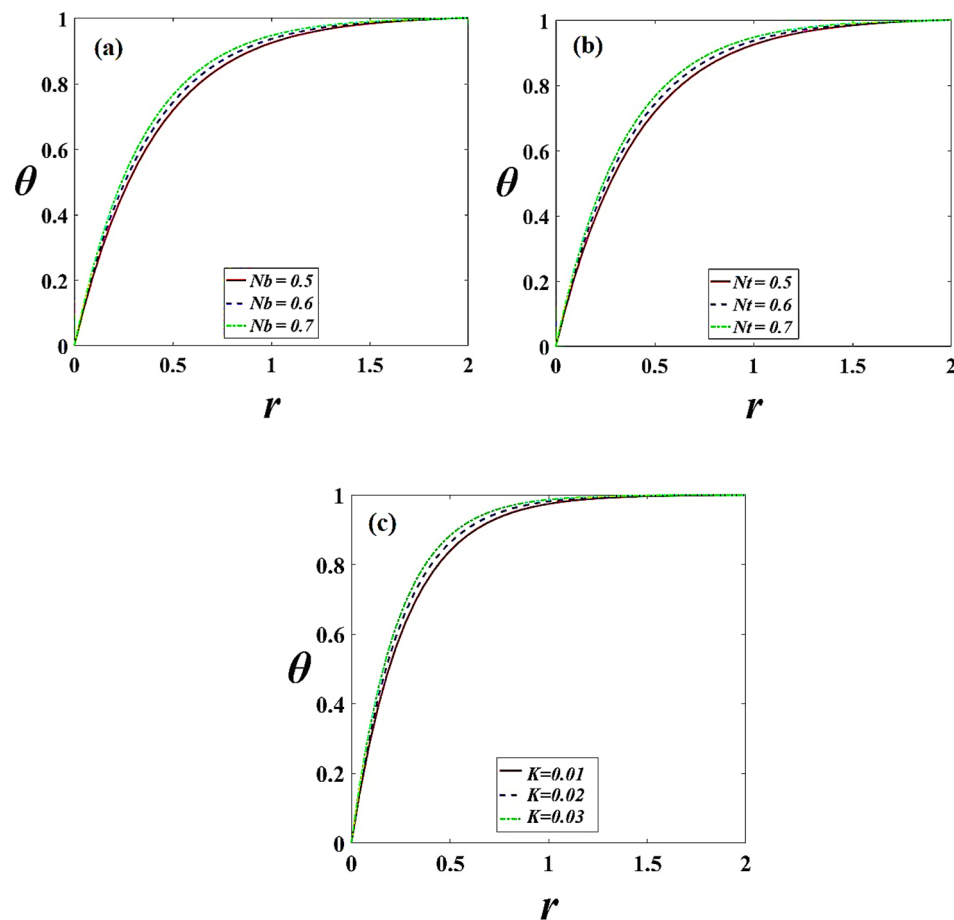


Fig. 4 Variation of temperature distribution for diverse values of (a) Nb (b) Nt (c) K

reproductive canal, temperature gradients may induce cytokines or suspended biological components to redistribute, which might change sperm-oocyte contact zones and local cellular communication. Figure 5(c) shows that increasing K decreases concentration gradients and improves transfer. Although pathological changes in form or flow may redistribute inflammatory chemicals, decreasing fertility outcomes, increased geometric modulation or fluid transport efficiency may allow for improved distribution of nutrients and signaling molecules in the reproductive system.

ANN model predictions

An ANN model was trained to predict the values of Nu , Sh and C_f . The nonlinear physiological relationships among MHD parameters, nanofluid dynamics, and heat/mass transfer coefficients necessitate the need for machine learning approaches, for which the ANN model was developed. The feed forward neural network

was designed with following specifications. The input layer consisted of three neurons which corresponds to each input parameters (Nt , Nb for Nu and Sh , Nt , Nb and Mn for C_f). There were two hidden layers, each of which contained 15 and 10 neurons, respectively. Both of these layers utilized tangent sigmoid activation functions (tansig) to incorporate nonlinear relationships between parameters. The reason behind choosing two hidden layers of 15 and 10 neurons was through a course of experiment and by judging the performance. Various network structures with differing levels of layers and neurons were experimented and this structure gave the most optimal results in terms of prediction accuracy and computation efficiency. Bayesian Regularization was also used to achieve the best generalization so that the architecture choice becomes less sensitive. The default tansig (hidden layers) and purelin (output layer) activation functions of ANN yielded a consistent result and are well-adapted to nonlinear regression problems that

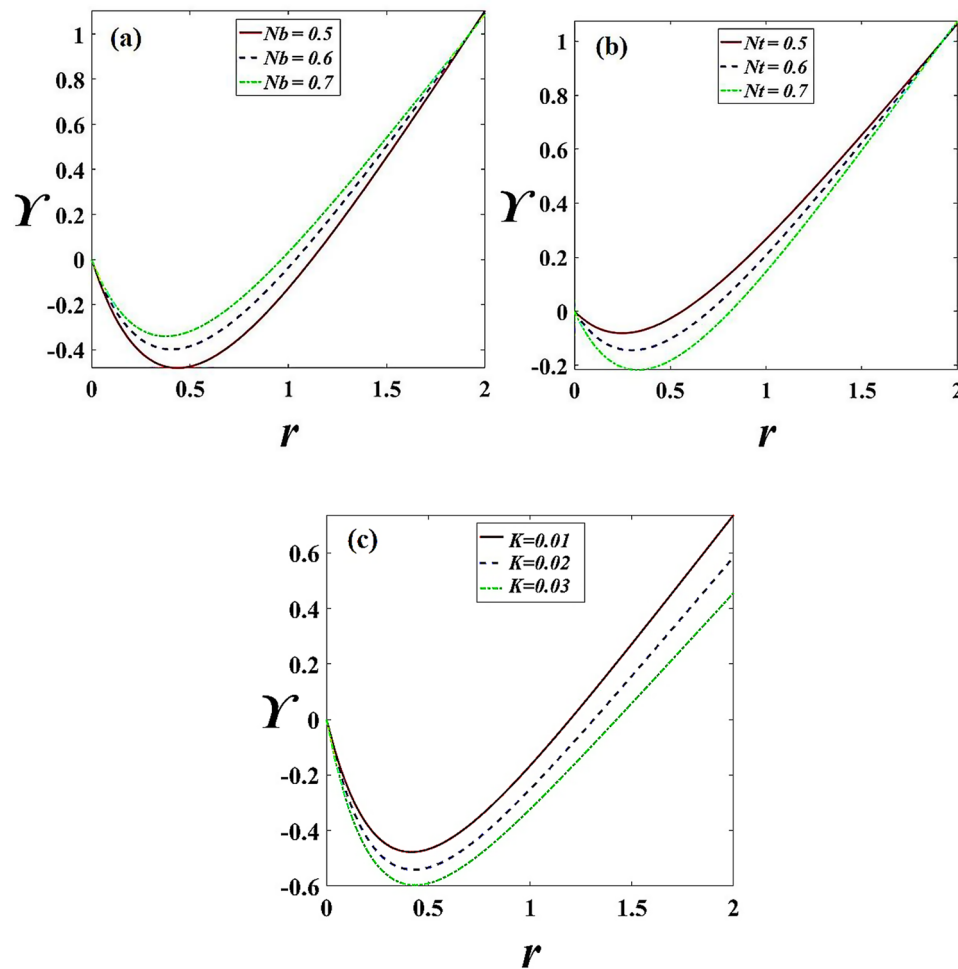


Fig. 5 Variation of concentration distribution for diverse values of (a) Nb (b) Nt (c) K

are smooth. Other activation functions, such as ReLU-type nonlinearities, had also been initially tried but not shown to give much more accurate or faster convergence on the current dataset, implying not much sensitivity to the choice of activation function. The output layer contained one neuron, which utilized linear activation function (purelin) to cover regression results obtained in Nu , Sh , and C_f . Training data consisted of 240 parameters and was generated by using numerical solutions for different ranges of parameters. Data was then split and 70% was assigned to training, 15% to validation, and 15% to testing. Likewise, one potential form of loss function was the mean squared error function. One such function, which prevents overfitting during model development, is Bayesian regularization. The prototype was trained using Bayesian Regularization (trainbr) for Nu and Sh , along with Levenberg-Marquardt (trainlm) on C_f , and

a maximum of 1000 epochs were utilized, and model validation was done using validation data. Hence, it was ensured that generalization error between different data sets was negligible, and the network was designed such that it corresponded to the validation error achieved during the design. For each of these physiological parameters, the required features were sent as the input to the ANN model. For Nu and Sh , the features which determined the values were Nt and Nb respectively. But for C_f , along with Nt and Nb , Mn was also another feature which determined the final output. Each of these models were trained with hidden layers and finally the predicted output was obtained. The results which were obtained from the ANN model has been elucidated in the upcoming subsections. The model has shown a high correlation of the predicted and the target values on unseen validation and test data sets, which was verified by low mean

squared error and regression plots, which showed sufficient interpolation in the trained parameter space. Due to the limited size of the dataset used, although k-fold cross-validation is generally preferred, it was not adopted here to avoid extensive data fragmentation as it would not yield in enhancing the overall performance of the ANN model. There was a little extrapolation testing done by extending the input parameters outside their training range. The ANN was able to make constant predictions close to the boundaries; but the accuracy declined steadily with data inputs that were far beyond the trained domain, which is expected given the known limitations of data-driven models. At this point, scalars like Nusselt number are targets of the study. Nonetheless, the identical ANN structure can be easily expanded to create line-by-line velocity, temperature and concentration profile comparisons, when the appropriate datasets are present. This is an extension that will be incorporated in future works to enhance validation. Bayesian Regularization (trainbr) was used to deal with overfitting and is an algorithm that automatically regulates the complexity of a model and enhances generalization. Also, dataset splitting (70/15/15) was utilized to monitor the validation, which maintained the same consistency of the model with no explicit early stopping.

Nusselt number

The ANN model designed to predict the Nusselt number showed good accuracy across a wide range of input parameters of thermophoretic (Nt) and Brownian

motion (Nb) parameters based on the Table 1. The predicted Nu values closely matched the reference solutions, with maximum deviations as low as 0.0002, indicating a prediction accuracy exceeding 99.9% from Table 1. The model effectively captured the nonlinear thermal behavior of the nanofluid system, particularly the consistent physical trend of decreasing Nusselt number with increasing Nt . This observation agrees well with the expected influence of thermophoresis, that is the rate of heat diffusion near the channel walls reduces because the nanoparticles are driven away from the hot regions.

Quantitative performance metrics further substantiated the model's accuracy, yielding a coefficient of determination (R^2) of approximately 0.99995 and an average relative deviation below 0.01%. These results confirm the ANN's capability to replicate complex thermal dynamics within the flow domain, validating its utility as a reliable surrogate model for real-time heat transfer prediction in biomedical and microscale systems.

The Nu regression plot, which is illustrated in Fig. 6(a), exhibits near-perfect alignment of predicted and target values along the 45° reference line, with an $R \approx 0.99995$. Data points merge into a single visual band, confirming negligible bias and no systematic deviation. This is because Nu varies smoothly and monotonically with parameters like Nt and Nb , so the ANN can accurately capture the mapping without oscillations. The performance (MSE vs. epoch) from Fig. 6(b) curve shows rapid convergence for training and testing datasets, with both the curves nearly overlapping. This overlap signifies excellent generalization; the model did not overfit or underfit. The fast drop in MSE also suggests that the heat transfer behaviour is inherently easier to approximate. The error histogram depicted in Fig. 6(c), is sharply peaked at zero with symmetric, extremely narrow tails (error magnitudes in the order of 10^{-4}). The symmetrical distribution means errors are random rather than biased toward over- or under-prediction.

Sherwood Number

The ANN developed for Sherwood number estimation also performed very well in predicting wall mass transfer rates under varying conditions of Nb and Nt , as shown in Table 2. Both the gradual and sudden variations in the Sherwood number were well reproduced by the model in all parameter regions, including those where the non-linear or non-monotonic behavior of the mass transfer profile was particularly strong. Most predictions had an error margin within 1%, although many individual outputs exhibited much smaller errors than this value. The Sherwood number is non-monotonic due to conflicting effects of Nb and Nt on mass transfer. Initially, stronger Brownian motion encourages random mixing, amplifying

Table 1 ANN model predictions for Nusselt number (Nu) with Nt and Nb as the features

Nt	Nb	Nu Target Value	ANN Prediction
0.1	0.8	0.1677	0.167513256
0.2	0.8	0.1415	0.141686935
0.3	0.8	0.1174	0.11747858
0.4	0.8	0.096	0.095949334
0.5	0.8	0.0776	0.077513398
0.6	0.8	0.0621	0.062083111
0.7	0.8	0.0492	0.049306562
0.8	0.8	0.0386	0.038754051
0.9	0.8	0.0301	0.030018491
1	0.8	0.0233	0.022752723
0.8	0.1	0.1677	0.167782908
0.8	0.2	0.1415	0.142020224
0.8	0.3	0.1174	0.117720118
0.8	0.4	0.096	0.096037442
0.8	0.5	0.0776	0.077466038
0.8	0.6	0.0621	0.061965835
0.8	0.7	0.0492	0.049204635
0.8	0.8	0.0386	0.038754051
0.8	0.9	0.0301	0.030197341
0.8	1	0.0233	0.023171828

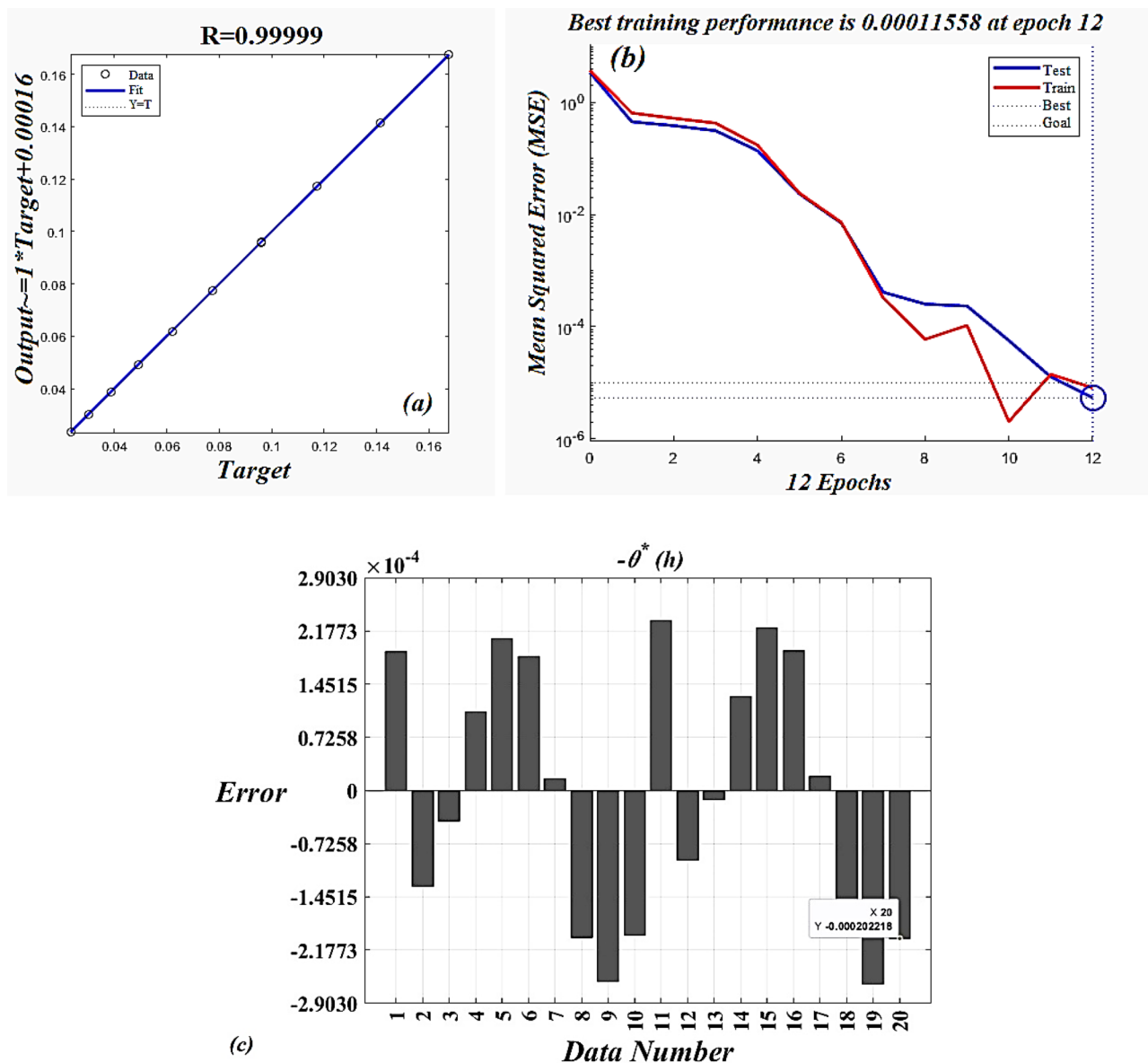


Fig. 6 (a) Regression line plotted for ANN model predictions for Nu (b) mean squared error (MSE) vs number of epochs on training performance (c) error obtained between actual and predicted values of Nu

concentration gradients near the wall and increasing the Sherwood number. Nonetheless, if thermophoretic processes take a turn, nanoparticles relocate beyond the wall to calmer places, reducing the concentration gradient and lowering mass transfer. Thus, the interplay of improved mixing and particle migration produces a spike followed by a decrease in the Sherwood number, resulting in the observed non-monotonic trend.

In the process, the ANN generalizes rather well over the combined effects of the thermophoretic and Brownian diffusion mechanisms, along with the kinetics of chemical reactions. This marks the strength of ANN in modeling species transport in an electrokinetically driven bio-microfluidic environment. The predictive performance was further confirmed by the high R^2 value (~ 0.99995) with the mean squared error (MSE) in

Table 2 ANN model predictions for Sherwood number (Sh) with Nt and Nb as the features

Nt	Nb	$Sh_{\text{Target Value}}$	ANN Prediction
0.1	0.8	-0.021	-0.022935784
0.2	0.8	-0.0354	-0.031783943
0.3	0.8	-0.044	-0.046101921
0.4	0.8	-0.48	-0.293336596
0.5	0.8	-0.485	-0.484015334
0.6	0.8	-0.0466	-0.048861153
0.7	0.8	-0.043	-0.039829582
0.8	0.8	-0.086	-0.052457591
0.9	0.8	-0.0339	-0.037532733
1	0.8	-0.0292	-0.027423131
0.8	0.1	-1.3414	-1.340387964
0.8	0.2	-0.5658	-0.567680387
0.8	0.3	-0.313	-0.311353452
0.8	0.4	-0.1921	-0.209431577
0.8	0.5	-0.1242	-0.126861394
0.8	0.6	-0.0828	-0.084188386
0.8	0.7	-0.0562	-0.065110512
0.8	0.8	-0.0386	-0.052457591
0.8	0.9	-0.0268	-0.037538646
0.8	1	-0.0187	-0.017578812

the order of 6.11×10^{-4} . Altogether, these results point toward the robustness of the ANN model in estimating the mass transport phenomena with great accuracy and computational efficiency.

The Sh regression plot in Fig. 7(a) also aligns closely with the 45° ideal line, but with slightly more spread than Nu . This is due to localized nonlinearities and non-monotonic changes in Sh , driven by complex interactions of thermophoresis, Brownian motion, and chemical reaction effects. The high correlation ($R^2 \approx 0.99995$) still indicates excellent accuracy. The Sh performance curves from Fig. 7(b) remain very well aligned between training and testing sets. Convergence is a little slower compared to Nu because the ANN needs to fit sharper transitions in the mass transfer profile, but no divergence is observed, which indicates that the network generalizes well. The histogram of Sh errors from Fig. 7(c) remains concentrated around zero but with marginally wider tails compared to Nu . These wider tails capture small under/

overshoots in regions where Sh changes abruptly. Symmetry of the error reflects that deviations are not systematically skewed.

Wall shear stress

The ANN model was built to predict the Wall Shear Stress (C_f), using input variables like Nt , Nb , and Mn to include magnetohydrodynamic effects. Indeed, the model showed very accurate predictions of the wall shear stress in various flow regimes as taken from Table 3. Moreover, it has successfully captured the influence of both Lorentz forces and the dynamics of nanoparticles on the shear profile, showing both attenuated and enhanced stress zones in alignment with the physical expectations.

Although there were minor deviations in certain high-gradient regions, such as $C_{f_Target} = -3.9718$ vs. $C_{f_Predicted} = -2.4943$, the overall predictions of the simulation matched the reference data. Most of the outputs had an absolute error within ± 0.01 , further confirming the model's accuracy. The ANN was thus effective at distinguishing between subtle variations in wall shear stress and more pronounced transitions, exhibiting a level of sensitivity and reliability that is well-suited for biomedical applications with wall-driven flow dynamics.

The C_f regression plot from Fig. 8(a). shows strong alignment with the target line but with visibly larger deviations at certain extreme values (e.g., $C_{f_Target} = -3.9718$ vs. $C_{f_Predicted} = -2.4943$). These discrepancies arise from parameter zones where MHD and electroosmotic effects induce steep jumps in wall shear stress, conditions that are inherently harder for a data-driven model to insert perfectly. Performance curves for C_f from Fig. 8(b). show slightly higher final MSE values compared to Nu and Sh , but the curves for training, testing, and validation still remain close together upto 9 epochs, confirming the absence of overfitting. The C_f error histogram from Fig. 8(c). is wider and slightly skewed compared to Nu and Sh . The skewness is caused by asymmetric extreme events in C_f , ex: intense negative shear peaks caused by Lorentz force dominance. Despite this, the bulk of errors remain within ± 0.01 , indicating the model is still highly accurate in most regions.

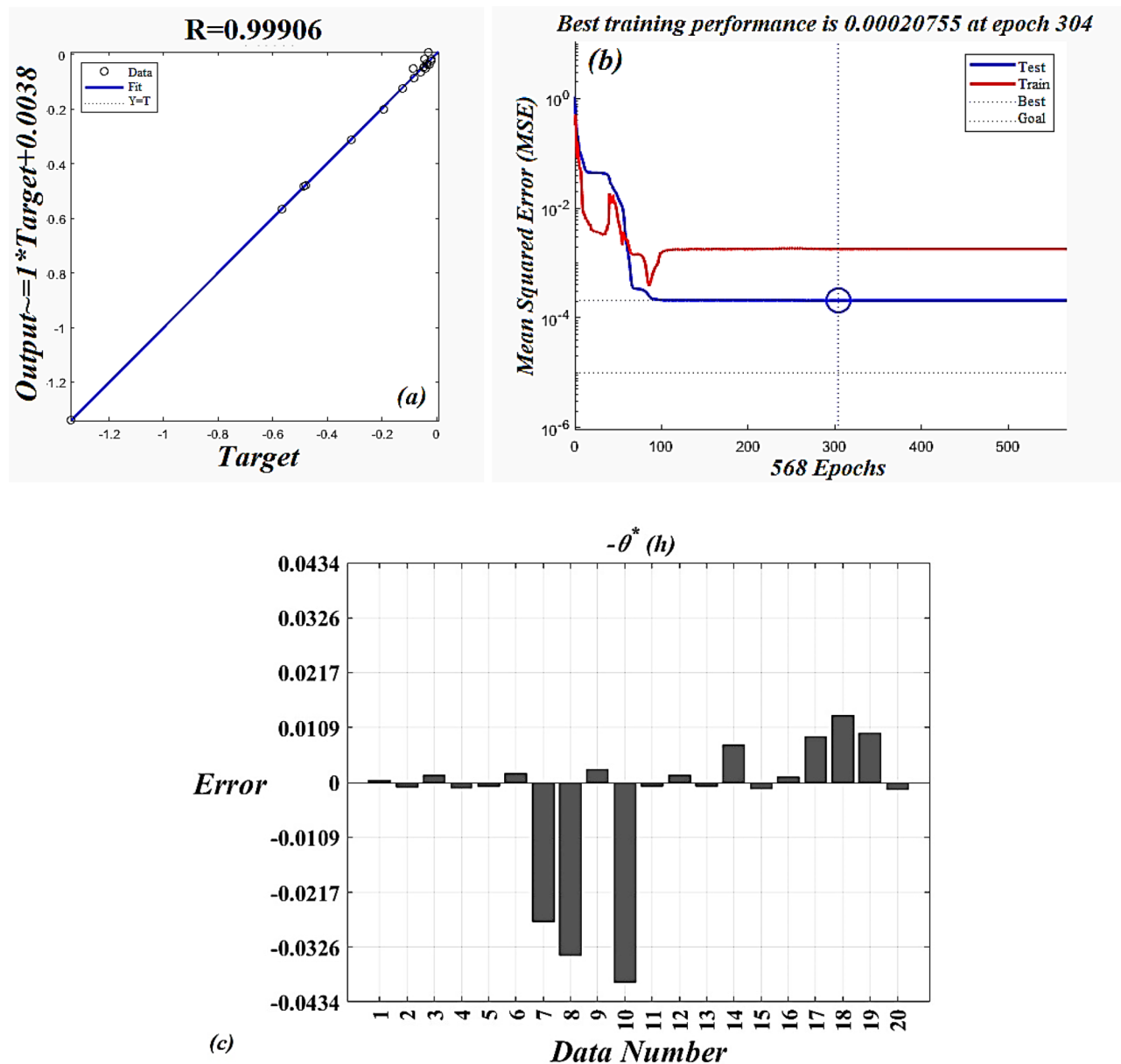


Fig. 7 (a) Regression line plotted for ANN model predictions for Sh (b) mean squared error (MSE) vs number of epochs on training performance (c) error obtained between actual and predicted values of Sh

Conclusion

This review identifies the importance of peritoneal fluid flow in the reproductive cycle due to its role in gamete transport within the fallopian tubes. Studying heat and mass transfer within this medium, which is non-Newtonian in nature, draws attention to the importance of thermal regulation in cellular function and fertilization. Additional thermal conductivity promoters in base fluids prove to be useful in enhancing energy efficiency and biological stability. Magnetohydrodynamics (MHD) and the

Jeffery fluid model were applied to optimize the dynamics of fluid flow, which can handle pathologies such as endometriosis and infertility. The key observations drawn from the study are as follows:

- Increasing Nb , Nt , and k correlates with the higher fluid temperatures.
- Concentration profile portrays that Nt , Nb , and K are indirectly related to the nanoparticle concentration.

Table 3 ANN model predictions for wall shear stress (C_f) with Nt , Nb and Mn as the features

Nt	Mn	Nb	C_f Target Value	ANN Prediction
0.1	0.5	0.8	-3.9718	-2.49433
0.2	0.5	0.8	-4.0817	-4.08564
0.3	0.5	0.8	-5.6331	-5.62385
0.4	0.5	0.8	-2.5187	-2.51692
0.5	0.5	0.8	-2.9222	-2.92337
0.6	0.5	0.8	-2.9478	-2.9509
0.7	0.5	0.8	-2.9006	-2.90335
0.8	0.5	0.8	-2.8272	-2.83006
0.9	0.5	0.8	-2.7413	-2.75364
1	0.5	0.8	-2.6488	-2.63886
0.8	0.5	0.1	-1.4403	1.254923
0.8	0.5	0.2	-3.5381	-3.58693
0.8	0.5	0.3	-8.9899	-9.00315
0.8	0.5	0.4	-0.2193	-0.24008
0.8	0.5	0.5	-1.9014	-1.90738
0.8	0.5	0.6	-2.4046	-2.40771
0.8	0.5	0.7	-2.6638	-2.66486
0.8	0.5	0.8	-2.8272	-2.83006
0.8	0.5	0.9	-2.9416	-2.94663
0.8	0.5	1	-3.0273	-3.06319
0.8	0.1	0.8	-2.651	-2.60735
0.8	0.2	0.8	-2.6739	-2.76439
0.8	0.3	0.8	-2.7114	-2.71838
0.8	0.4	0.8	-2.7628	-2.74509
0.8	0.5	0.8	-2.8272	-2.83006
0.8	0.6	0.8	-2.9032	-2.91162
0.8	0.7	0.8	-2.9897	-2.98881
0.8	0.8	0.8	-3.0853	-3.09424
0.8	0.9	0.8	-3.1887	-3.27591
0.8	1	0.8	-3.2985	-3.29783

- Nt causes a decrease in nanoparticle concentration toward the center with uniformly stable concentration throughout the fluid.
- Increasing Mn , Nb , Nt results in a decrease of velocity while increasing in Gr_T , Gr_C , λ , and σ directly relates to velocity.

Future studies can investigate the introduction of nanoparticles into reproductive health for possible novel treatments of infertility due to abnormalities in peritoneal fluid. Further refinement in the understanding of peristaltic flow with different boundary conditions can be investigated using advanced techniques in computer

modelling. Experimental validation of MHD effects on fluid dynamics may also contribute to non-invasive diagnostic techniques for early detection and intervention for reproductive disorders. The use of machine learning techniques like Physics-informed neural networks (PINNs) and transfer learning could significantly enhance predictive capabilities for a broad parametric range. Additionally, the ANN model can extend to include the line plot comparisons of velocity, temperature and concentration profiles for a better comprehensive validation beyond the scalar outputs as the future scope of this study.

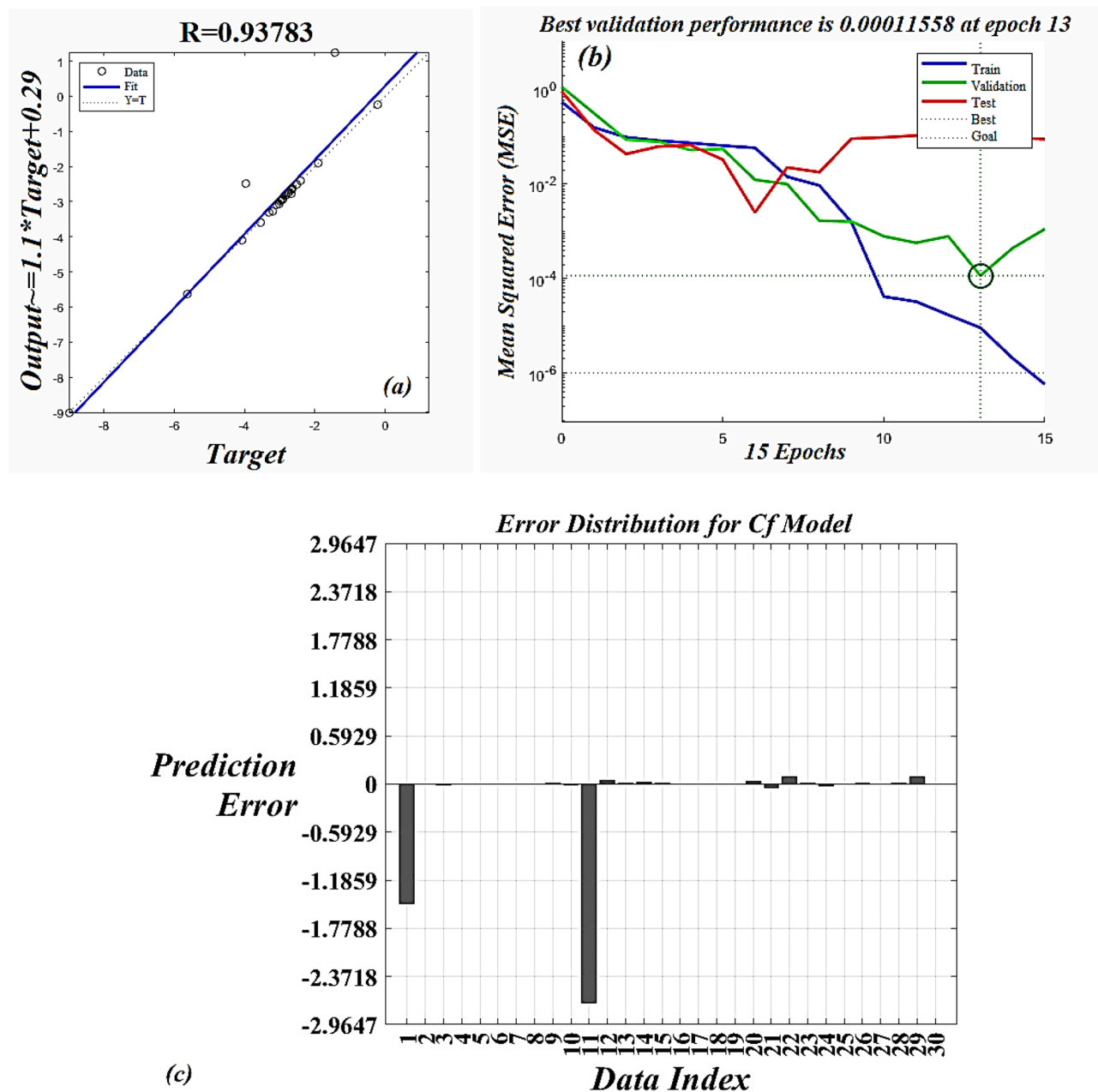


Fig. 8 (a) Regression line plotted for ANN model predictions for C_f (b) mean squared error (MSE) vs number of epochs on training performance (c) error obtained between actual and predicted values of C_f

Abbreviations

$\bar{X}$	Dimensional axial co-ordinate
$\bar{Y}$	Dimensional transverse co-ordinate
$\bar{U}$	Dimensional velocity along $\bar{X}$ -direction
$\bar{V}$	Dimensional velocity along $\bar{Y}$ -direction
T	Dimensional temperature
C	Dimensional concentration
P	Dimensional pressure
Ψ	Non-dimensional shear stress
x	Non-Dimensional axial co-ordinate
y	Non-Dimensional transverse co-ordinate
u	Non-Dimensional velocity along $\bar{X}$ -direction
v	Non-Dimensional velocity along $\bar{Y}$ -direction
θ	Non-Dimensional temperature
Ω	Non-Dimensional concentration

$\bar{p}$	Non-Dimensional pressure
ψ	Non-dimensional shear stress
ρ_e	Electrical charge density
$\bar{p}$	Pressure
ρ	Fluid density
E_0	Axial electric field
c_p	Specific heat
k	Thermal conductivity
k_t	Ratio of thermal diffusion
D_B	Brownian Diffusion Coefficient
D_T	Thermophoretic Diffusion Coefficient
D_m	Mass diffusivity co-efficient
T_m	Mean temperature
A_n	Rivlin-Erickson tensor
m_e	Electroosmosis parameter

λ_D	Debye length
α	Peristaltic wave number
U_{HS}	Helmholtz-Smoluchowski velocity
Br	Brinkmann number
Re	Reynolds number
Pr	Prandtl number
σ	Porous parameter
ε	Amplitude ratio
Nt	Non-dimensional thermophoresis parameter
Nb	Non-dimensional Brownian motion parameter
Ec	Eckert number

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Author contributions

Author contributions: K.D.A.; V.D.; J.U.V.: Conceptualization, Methodology, Software, Formal analysis, Validation; Writing – original draft. S.V.: Writing – original draft, Data curation, Investigation, Visualization, Validation. U.K.: Conceptualization, Writing – original draft, Writing – review & editing, Supervision, Resources. N.S.K., J.N.: Validation, Investigation, Writing – review & editing, Formal analysis; Project administration; Funding acquisition, software.

Data availability

All data available within the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

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References

- Fung YC, Yih CS. Peristaltic transport. *J APPL Mech.* 1968;35(4):669–75. <https://doi.org/10.1115/1.3601290>.
- Lyons RA, Saridogan E, Djahanbakhch O. The reproductive significance of human fallopian tube cilia. *Hum Reproduction Update.* 2006;12(4):363–72. <https://doi.org/10.1093/humupd/dml012>.
- Halbert SA, Tam PY, Blandau RJ. Egg transport in the rabbit oviduct: the roles of cilia and muscle. *Science.* 1976;191(4231):1052–53. <https://doi.org/10.1126/science.1251215>.
- Shaw JLV, Dey SK, Critchley HOD, Horne AW. Current knowledge of the aetiology of human tubal ectopic pregnancy. *Hum Reproduction Update.* 2010;16(4):432–44. <https://doi.org/10.1093/humupd/dmp057>.
- Gupta S, Agarwal A, Krajcir N, Alvarez JG. Role of oxidative stress in endometriosis. *Reprod Biomed Online.* 2006;13(1):126–34. [https://doi.org/10.1016/S1472-6483\(10\)62026-3](https://doi.org/10.1016/S1472-6483(10)62026-3).
- Human reproductive system – uterine tubes. Iowa State University Pressbooks.
- Peritonealcavity–TeachMeAnatomy. <https://teachmeanatomy.info/abdomen/areas/peritoneal-cavity/>.
- Kędzia W, Machnik G, Kondera-Anasz Z. Total oxidative status of peritoneal fluid in women with endometriosis. *Gynecol Obstet Invest.* 2005;60(2):82–86.
- Coughlan C, Ledger W, Wang Q, Liu F, Demiroglu A, Gurgan T, et al. Recurrent implantation failure: definition and management. *Reprod Biomed Online.* 2014;28(1):14–38. <https://doi.org/10.1016/j.rbmo.2013.08.011>.
- Mahian O, Kolsi L, Amani M, Estellé P, Ahmadi G, Kleinstreuer C, et al. Recent advances in modeling and simulation of nanofluid flows-part I: fundamentals and theory. *Phys Rep.* 2019;790:1–48. <https://doi.org/10.1016/j.physrep.2018.11.004>.
- Nield DA, Kuznetsov AV. The Cheng–minkowycz problem for natural convective boundary-layer flow in a porous medium saturated by a nanofluid. *Int J Heat Mass Transf.* 2009;52(25–26):5792–95. <https://doi.org/10.1016/j.jheatmasstransfer.2009.07.024>.
- Solangi KH, Kazi SN, Luhur MR, Badarudin A, Amiri A, Sadri R, et al. A comprehensive review of thermo-physical properties and convective heat transfer to nanofluids. *Energy.* 2015;89:1065–86. <https://doi.org/10.1016/j.energy.2015.06.105>.
- Choi SUS. Enhancing thermal conductivity of fluids with nanoparticles. *Developments Appl Non-Newtonian Flows, ASME Fed.* 1995;231(MD-66):99–105.
- Sher Akbar N, AboueiMehrizi A, Maimona Rafiq MBH, Bilal Habib M, Muhammad T. Peristaltic flow analysis of thermal engineering nano model with effective thermal conductivity of different shape nanomaterials assessing variable fluid properties. *Alex Eng J.* 2023;81:395–404. <https://doi.org/10.1016/j.aej.2023.09.027>.
- Dai J, Zhai Y, Li Z, Wang H. Mechanism of enhanced thermal conductivity of hybrid nanofluids by adjusting mixing ratio of nanoparticles. *J Mol Liq.* 2024;400:124518. <https://doi.org/10.1016/j.molliq.2024.124518>.
- Paul UK, Shahriar Mohtasim MS, Golam Kibria MG, Das BK. Nano-material based composite phase change materials and nanofluid for solar thermal energy storage applications: featuring numerical and experimental approaches. *J Energy Storage.* 2024;98:113032. <https://doi.org/10.1016/j.est.2024.113032>.
- Bianco V, Cascetta F, Nardini S. Application of nanofluids in industrial processes. The case of food processing. *Therm Sci Eng Prog.* 2024;53:102726. <https://doi.org/10.1016/j.tsep.2024.102726>.
- Mahendra DL, Viharika JU, Ramanjini V, Makinde OD, Vishwanatha UB. Entropy analysis on the bioconvective peristaltic flow of gyrotactic microbes in Eyring–Powell nanofluid through an asymmetric channel. *J Indian Chem Soc.* 2023;100(3):100935. <https://doi.org/10.1016/j.jics.2023.100935>.
- Viharika JU, Khan U, Muhammad T. Implementation to cardiovascular disorders under the action of magnetohydrodynamics in a non-Newtonian peristaltic blood flow of nanofluid. *Z Angew Math Mech.* 2024;104(3):e202300716. <https://doi.org/10.1002/zamm.202300716>.
- Dhinakaran V, Anuradha KD, Viharika JU, Khan U, Abdullah N, Elattar S. Effectiveness of heat source/sink and Lorentz force constraints in a non-Newtonian peristaltic arterial blood hybrid nanofluid past an overlapping stenotic artery. *Case Stud Therm Eng.* 2025;65:105577. <https://doi.org/10.1016/j.csite.2024.105577>.
- Viharika JU, Mahendra DL, Ramanjini V, Khan U, Modassir Hussain S. Irreversibility analysis for peristaltic transport flow of a Phan–Thien–Tanner nanofluid past an asymmetric channel with Lorentz forces. *Z Angew Math Mech.* 2025;105(5):e70040. <https://doi.org/10.1002/zamm.70040>.
- Nabwey HA, Rashad AM, Khan WA, Abdelrahman ZM, AbdElnaem S, Hawsah MA. Heat and mass transfer of Oldroyd-B and Jeffery–Williamson ternary-hybrid nanofluids over a stretching sheet in a porous medium. *J Por Media.* 2024;27(11):25–49. <https://doi.org/10.1615/JPorMedia.2024052406>.
- Srinivas ANS, Haseena C, Sreenadh S. Peristaltic transport of nanofluid in a vertical porous stratum with heat transfer effects. *BioNanoSci.* 2019;9(1):117–30. <https://doi.org/10.1007/s12668-018-0571-y>.
- Nabwey HA, Rashad AM, Mahdy AEN, Shaaban SM. Thermal conductivity and thermophoretic impacts of micropolar fluid flow by a horizontal absorbent isothermal porous wall with heat source/sink. *Mathematics.* 2022;10(9):1514. <https://doi.org/10.3390/math10091514>.
- Goud BS, Krishnan D, Durgaprasad P, Dharmalaiah G. Numerical simulations of radiative three-dimensional stretching regime by hybridized (ag–CuO/Water) flow with chemical reaction and heat absorption. *J Therm. Anal. Calorim.* 2025;150(17):13489–514. <https://doi.org/10.1007/s10973-025-14512-1>.
- Reddy NN, Shankar Goud B, Maaitah H, Mustafa MY. Slip-induced variations in MHD nanofluid (Cu–Al₂O₃) flow over a permeable stretching sheet with dissipation and thermal radiation: role of Dufour and Joule heating effects. *Int J Multiling Thermofluids.* 2025;29:101320. <https://doi.org/10.1016/j.ijft.2025.101320>.
- Lutera JN, Raja Shekar MR, Shankar Goud B. Investigating MHD flow of Al₂O₃/H₂O nanofluid with thermophoresis, magnetic and chemical reaction past an exponentially moving surface. *Next Res.* 2025;2(2):100298. <https://doi.org/10.1016/j.nexres.2025.100298>.
- Jubair S, Ali B, Mahmood Z, Rafique K, Kumar A, Emam W. Investigating thermal conduction dynamics in ternary Carreau–Yasuda nanofluids under convective boundary conditions and exponential heat source/sink effects. *Energy Exploration Exploit.* 2025;43(2):608–30. <https://doi.org/10.1177/01445987241276261>.
- Jubair S, Ali B, Rafique K, Ahmad Ansari M, Mahmood Z, Kumar A, et al. Couple-stress nanofluid flow comprised of titanium alloy subject to hall current and Joule heating effects: numerical investigation. *AIP Adv.* 2024;14(11). <https://doi.org/10.1063/5.0235980>.
- Jubair S, Yang J, Ali B, Bin-Mohsin B, Abd El-Wahed Khalifa H. Analyzing the impact of non-Newtonian nanofluid flow on pollutant discharge

- concentration in wastewater management using an artificial computing approach. *Appl Water Sci.* 2025;15(1). <https://doi.org/10.1007/s13201-024-02333-w>.
31. Ali B, Liu S, Liu H. An application of artificial neural network toward the mathematical modeling of MHD tangent hyperbolic nanofluid across a vertical stretching surface. *J Por Media.* 2024;27(10):49–72. <https://doi.org/10.1615/JPorMedia.2024051939>.
 32. Ali B, Ishtiaq U, Popa I-L, Abd El-Wahed Khalifa H, Kumar A, Irfanul Haque Siddiqui MI. Numerical modelling and deep learning-based analysis of unsteady micropolar nanofluid flow with heat radiation over a Riga plate. *J Radiat Res Appl Sci.* 2025;18(2):101512. <https://doi.org/10.1016/j.jrras.2025.101512>.
 33. Ali B, Zhou Y-T, Jubair S, Hameed Tariq M, Kumar A, Irfanul Haque Siddiqui MI. Entropy optimization and Prandtl-eyring non-Newtonian fluid flow with second-order slip conditions past a curved Riga sheet; numerical simulation. *Int J Therm Sci.* 2025;214:109916. <https://doi.org/10.1016/j.jijthermalsci.2025.109916>.
 34. Alshaheri AA, Ibrahim Mohamed Tahir M, Basyaruddin Abdul Rahman M, Begum T, Saleh TA. Synthesis, characterisation and catalytic activity of dithiocarbamate Schiff base complexes in oxidation of cyclohexane. *J Mol Liq.* 2017;240:486–96. <https://doi.org/10.1016/j.molliq.2017.05.081>.
 35. Kataria HR, Mittal AS. Velocity, mass and temperature analysis of gravity-driven convection nanofluid flow past an oscillating vertical plate in the presence of magnetic field in a porous medium. *Appl Therm Eng.* 2017;110:864–74. <https://doi.org/10.1016/j.applthermaleng.2016.08.129>.
 36. Kataria HR, Mittal AS. Mathematical model for velocity and temperature of gravity-driven convective optically thick nanofluid flow past an oscillating vertical plate in presence of magnetic field and radiation. *J Educ Chang Niger Math Soc.* 2015;34(3):303–17. <https://doi.org/10.1016/j.jnnms.2015.08.005>.
 37. Sheikhholeslami M, Kataria HR, Mittal AS. Radiation effects on heat transfer of three dimensional nanofluid flow considering thermal interfacial resistance and micro mixing in suspensions. *Chin J Phys.* 2017;55(6):2254–72. <https://doi.org/10.1016/j.cjph.2017.09.010>.
 38. Hojman SA. Geometrical unification of gravitation and electromagnetism. *Eur Phys J Plus.* 2019;134(10). <https://doi.org/10.1140/epjp/i2019-13006-4>.
 39. Patel HR, Mittal AS, Darji RR. MHD flow of micropolar nanofluid over a stretching/shrinking sheet considering radiation. *Int Commun Heat Mass Transf.* 2019;108:104322. <https://doi.org/10.1016/j.icheatmasstransfer.2019.104322>.
 40. Mittal AS, Patel HR. Influence of thermophoresis and Brownian motion on mixed convection two dimensional MHD Casson fluid flow with non-linear radiation and heat generation. *Physica A.* 2020;537:122710. <https://doi.org/10.1016/j.physa.2019.122710>.
 41. Mittal AS, Kataria HR. Three dimensional CuO–Water nanofluid flow considering Brownian motion in presence of radiation. *Karbala Int J Mod Sci.* 2018;4(3):275–86. <https://doi.org/10.1016/j.kijoms.2018.05.002>.
 42. Patel H, Mittal A, Nagar T. Fractional order simulation for unsteady MHD nanofluid flow in porous medium with solet and heat generation effects. *Heat Transf.* 2023;52(1):563–84. <https://doi.org/10.1002/htj.22707>.
 43. Patel H, Mittal A, Nagar T. Effect of magnetic field on unsteady mixed convection micropolar nanofluid flow in the presence of non-uniform heat source/sink. *Int J Ambient Energy.* 2024;45(1). <https://doi.org/10.1080/01430750.2023.2266748>.
 44. Mittal AS, Kori V. Impact of Dufour-Soret diffusion and chemical reactivity on darcy-forchheimer MHD nanofluid flow over a variable-thickness elastico-viscous sheet. *Int J Appl Comput Math.* 2025;11(2). <https://doi.org/10.1007/s40819-025-01948-0>.
 45. Mittal AS, Kori V. HAM-Based analysis of MHD maxwell nanofluid flow with melting heat effects and zero mass flux conditions. *Int J Appl Comput Math.* 2025;11(4). <https://doi.org/10.1007/s40819-025-01948-0>.
 46. Akbar Y, Chen C, Iqbal J, Mao X. Intelligent modeling of thermal transport in peristaltic flow of nanofluid through porous media using response surface and neural networks. *Int Commun Heat Mass Transf.* 2026;174:110901. <https://doi.org/10.1016/j.icheatmasstransfer.2026.110901>.
 47. Akbar Y, Li K, Iqbal J, Yang X, Mao X. Thermodynamic analysis of nanofluid with aggregated and non-aggregated nanoparticles. *Int J Heat Fluid Flow.* 2026;118:110205. <https://doi.org/10.1016/j.jijheatfluidflow.2025.110205>.
 48. Iqbal J, Akbar Y. Tensor flow-based deep learning framework for thermodynamic and entropy generation analysis of dihydrogen oxide-based nanofluids. *Int J Soc Res Methodol Hydrogen Energy.* 2026;201:152947. <https://doi.org/10.1016/j.jijhydene.2025.152947>.
 49. Iqbal J, Akbar Y, Alam MM. Thermal enhancement and energy minimization using Powell–eyring nanofluid flow in PTSC for solar-powered aircraft: a combined RSM, ANN, and sensitivity analysis. *J. Therm. Anal. Calorim.* 2026;151(2):1717–41. <https://doi.org/10.1007/s10973-025-15104-9>.
 50. Iqbal J, Abbasi FM, Alam MM. Machine learning computations for MHD bio-convection peristaltic transport of non-Newtonian nanofluid flow containing gyrotactic microorganisms with porous medium. *J Por Media.* 2025;28(11):1–28. <https://doi.org/10.1615/JPorMedia.2025057165>.
 51. Rippe B, Stelin G. Simulations of peritoneal solute transport during CAPD. Application of two-pore formalism. *Kidney Int.* 1989;35(5):1234–44. <https://doi.org/10.1038/ki.1989.115>.
 52. Strandell A, Lindhard A. Why does hydrosalpinx reduce fertility? *Hum Reproduction Update.* 2002;8(5):515–20.
 53. Khan AA, Ellahi R, Vafai K. Peristaltic transport of a Jeffrey fluid with variable viscosity through a porous medium in an asymmetric channel. *Adv Math Phys.* 2012, Article ID 169642, 2012:1–15. <https://doi.org/10.1155/2012/169642>.
 54. Rashidi MM, Vishnu Ganesh N, Abdul Hakeem AK, Ganga B. Buoyancy effect on MHD flow of nanofluid over a stretching sheet in the presence of thermal radiation. *J Mol Liq.* 2014;198:234–38. <https://doi.org/10.1016/j.molliq.2014.06.037>.
 55. Sheikhholeslami M, Abelman S, Ganji DD. Numerical simulation of MHD nanofluid flow and heat transfer considering viscous dissipation. *Int J Heat Mass Transf.* 2014;79:212–22. <https://doi.org/10.1016/j.jijheatmasstransfer.2014.08.004>.
 56. Rana SB, Pal R. Effects of variable viscosity and thermal conductivity on MHD flow of a nanofluid over a flat plate with suction/injection. *J Magnetism Magnetic Mater.* 2018;448:118–26.
 57. Mahmood MAA. Thermal radiation effect on MHD flow and heat transfer analysis of Williamson nanofluid over a stretching sheet with constant wall temperature. *Journal of Physics: Conference Series.* 2017, 012034, 890.
 58. Mittal AS, Patel HR, Darji RR. Mixed convection micropolar ferrofluid flow with viscous dissipation, Joule heating and convective boundary conditions. *Int Commun Heat Mass Transf.* 2019;108:104320. <https://doi.org/10.1016/j.icheatmasstransfer.2019.104320>.
 59. Mittal AS. Analysis of water-based composite MHD fluid flow using HAM. *Int J Ambient Energy.* 2021;42(13):1538–50. <https://doi.org/10.1080/01430750.2021.91611648>.
 60. Mittal AS. Study of radiation effects on unsteady 2D MHD Al 2 O 3 -water flow through parallel squeezing plates. *Int J Ambient Energy.* 2022;43(1):653–60. <https://doi.org/10.1080/01430750.2019.1662843>.
 61. Kataria HR, Mistry M, Mittal A. Influence of nonlinear radiation on MHD micropolar fluid flow with viscous dissipation. *Heat Transf.* 2022;51(2):1449–67. <https://doi.org/10.1002/htj.22359>.
 62. Kataria H, Mittal AS, Mistry M. Effect of nonlinear radiation on entropy optimised MHD fluid flow. *Int J Ambient Energy.* 2022;43(1):6909–18. <https://doi.org/10.1080/01430750.2022.2059000>.
 63. Mittal AS. Effects of magnetic field and chemical reaction on a time dependent Casson fluid flow. *Appl Appl Math: Int J.* 2024;19(3).
 64. Patel H, Mittal A, Darji R. Study of micropolar MHD ferrofluid flow with nonlinear stretching sheet. *Therm Adv.* 2025;3:100032. <https://doi.org/10.1016/j.thradv.2025.100032>.
 65. Nabwey HA, Mushtaq M, Nadeem M, Ashraf M, Rashad AM, Alshber SI, et al. Note on the numerical solutions of unsteady flow and heat transfer of Jeffrey fluid past stretching sheet with Soret and Dufour effects. *Mathematics.* 2022;10(24):4634. <https://doi.org/10.3390/math10244634>.
 66. Chhabra RP, Richardson JF. Non-Newtonian flow and applied rheology. Oxford: Elsevier; 2008.
 67. Bird RB, Armstrong RC, Hassager O. In: Dynamics of polymeric liquids. Vol. 1. *Fluid Mechanics.* Wiley; 1987.
 68. Sadeghy K, Sharifi M. Magnetohydrodynamic flows of non-Newtonian fluids. *J Nonnewton Fluid Mech.* 2004;123(1):1–9.
 69. D'Hooghe TM, Debrock S, Hill JA, Meuleman C. Endometriosis and subfertility: is the relationship resolved? *Semin Reprod Med.* 2003;21(2):243–54.
 70. Oosterlynck DJ, Meuleman C, Sobis H, Vandeputte M, Koninckx PR.
 71. Hayat T, Ali N. Peristaltic motion of a Jeffrey fluid under the effect of a magnetic field in a tube. *Commun Nonlinear Sci Numer Simul.* 2008;13(7):1343–52. <https://doi.org/10.1016/j.cnsns.2006.12.009>.
 72. Steinleitner A, Lambert H, Kazensky C, Danks P. Peritoneal fluid from endometriosis patients affects reproductive outcome in an in vivo model. *Fertil Steril.* 1990;53(5):926–29. [https://doi.org/10.1016/S0015-0282\(16\)53533-X](https://doi.org/10.1016/S0015-0282(16)53533-X).
 73. Burney RO, Giudice LC. Pathogenesis and pathophysiology of endometriosis. *Fertil Steril.* 2012;98(3):511–19. <https://doi.org/10.1016/j.fertnstert.2012.06.029>.

74. Gómez-Torres MJ, Acien P, Campos A, Velasco I. Embryotoxicity of peritoneal fluid in women with endometriosis. Its relation with cytokines and lymphocyte populations. *Hum Reproduction*. 2002;17(3):777–81. <https://doi.org/10.1093/humrep/17.3.777>.
75. Illera MJ, Juan L, Stewart CL, Cullinan E, Ruman J, Lessey BA. Effect of peritoneal fluid from women with endometriosis on implantation in the mouse model. *Fertil Steril*. 2000;74(1):41–48. [https://doi.org/10.1016/S0015-0282\(00\)00552-5](https://doi.org/10.1016/S0015-0282(00)00552-5).
76. Jianini BTGM, Giorgi VSI, da Broi MG, de Paz CCP, Rosae, Ferriani RA, et al. Peritoneal fluid from infertile women with Minimal/Mild endometriosis compromises the meiotic spindle of metaphase II bovine oocytes: a Pilot study. *Reprod. Sci*. 2017;24(9):1304–11. <https://doi.org/10.1177/1933719116687658>.
77. Rodríguez JDD, Pérez A, Lozano JA. Sensitivity analysis of k-fold cross validation in prediction error estimation. *IEEE Trans Pattern Anal Mach Intell*. 2010;32(3):569–75. <https://doi.org/10.1109/TPAMI.2009.187>.
78. Akbar Y, Andaç Batur Çolak AB, Huang S, Alshamrani A, Alam MM. Intelligent computing for the electro-osmotically modulated peristaltic pumping of blood-based nanofluid. *Numer Heat Transf, Part A: Appl*. 2026;87(1). <https://doi.org/10.1080/10407782.2024.2377698>.
79. Weiss R, Karimijafarbigloo S, Roggenbuck D, Rödiger S. Applications of neural networks in biomedical data analysis. *Biomedicines*. 2022;10(7):1469. <https://doi.org/10.3390/biomedicines10071469>.
80. Akbar Y, Iqbal J, Chen C. Numerical and ANN-based prediction of thermal enhancement in PTSC for solar-powered aircraft wings. *Int Commun Heat Mass Transf*. 2026;174:110933. <https://doi.org/10.1016/j.icheatmasstransfer.2026.110933>.
81. Iqbal J, Abbasi FM, Alam MM. Significance of thermal transport analysis through an artificial intelligence stochastic approach for MHD peristaltic propulsion of Reiner–philippoff fluid. *J. Therm. Anal. Calorim*. 2025;150(23):19157–74. <https://doi.org/10.1007/s10973-025-14865-7>.
82. Iqbal J, Abbasi FM, Alam MM, Akbar Y. Thermal and energy optimization of hybrid nanofluid flow in parabolic trough surface collectors (PTSCs) using statistical modeling, neural networks, and sensitivity analysis for solar-powered aircraft. *Phys Fluids*. 2025;37(8). <https://doi.org/10.1063/5.0279425>.
83. Iqbal J, Abbasi FM. “Optimization of heat transfer via response surface methodology (RSM), sensitivity analysis, and application of machine learning for radially magnetized reiner-philippoff hybrid nanofluid”. In: *Advances in heat transfer*. Vol. 60. Elsevier; 2025. p. 153–86.
84. Ahmed FE. Artificial neural networks for diagnosis and survival prediction in colon cancer. *Mol Cancer*. 2005;4(1):29. <https://doi.org/10.1186/1476-4598-4-29>.
85. Abiodun OI, Jantan A, Omolara AE, Dada KV, Mohamed NA, Arshad H. State-of-the-art in artificial neural network applications: a survey. *Heliyon*. 2018;4(11):e00938. <https://doi.org/10.1016/j.heliyon.2018.e00938>.

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