

Research Article

AI-Driven FEM Analysis of Marangoni Convection in Carreau Nanofluids

Kotike Jyothi ¹, Leelavathi Rekapalli ², Muhammad Usman ³, Balram Yelamasetti ⁴, Zubairuddin M. ⁵, S. K. Mohammad Shareef ⁶, and Dhanesh G. Mohan ^{7,8}

¹Department of Humanities and Basic Sciences, G Pulla Reddy Engineering College, Kurnool 518007, Andhra Pradesh, India

²Department of Mathematics, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur 522302, Andhra Pradesh, India

³Future Interdisciplinary Research of Science and Technology, Institute of Innovative Research, Tokyo Institute of Technology, 4259-R2-23 Nagatsutacho, Midoriku, Yokohamashi, Kanagawa 226–8503, Japan

⁴Department of Mechanical Engineering, MLR Institute of Technology, Dundigal- 500043, Telangana, India

⁵Department of Mechanical Engineering, Aditya University, Surampalem 533437, Andhra Pradesh, India

⁶Department of Mechanical Engineering, CVR College of Engineering, Ibrahimpatnam 501510, Telangana, India

⁷School of Computer Science and Engineering, University of Sunderland, Sunderland, UK

⁸Centre of Research Impact and Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, Punjab, India

Correspondence should be addressed to Dhanesh G. Mohan; ghanesh.mohan@sunderland.ac.uk

Received 28 April 2025; Revised 30 June 2025; Accepted 29 July 2025

Academic Editor: Payman Jalali

Copyright © 2025 Kotike Jyothi et al. International Journal of Energy Research published by John Wiley & Sons Ltd. This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

This study examines the influence of nonlinear thermal radiation on Carreau nanofluid flow over a wedge under Marangoni boundary conditions. The model incorporates thermophoresis and Brownian motion effects, with governing partial differential equations reduced to ordinary differential form via similarity transformations. The analysis focuses on velocity, temperature, and concentration distributions, alongside key transport parameters: Nusselt number (Nu_x), Sherwood number (Sh_x), and skin friction coefficient (Cf_x). To enhance predictive capability, a supervised artificial neural network (ANN) based on the Levenberg–Marquardt algorithm is implemented in MATLAB. Trained on simulation data, the ANN demonstrates high regression accuracy with a mean squared error (MSE) below 0.001. Results indicate that Nu_x increases by 12% as the magnetic parameter rises from 0.5 to 2, while Sh_x decreases by 9% as thermophoresis increases from 0.1 to 0.6. This hybrid FEM–ANN framework offers new insights into Marangoni-driven nanofluid dynamics and provides a robust surrogate modeling approach for optimizing complex thermal transport systems.

Keywords: Brownian motion; Carreau nanofluid; machine learning models; Marangoni boundary conditions; Nusselt number

1. Introduction

Nanofluids are widely studied for their enhanced heat transfer capabilities and diverse applications in energy, cooling, and biomedical systems. Recent developments, such as nanoribbons and PCMs, highlight their growing role in thermal management across sectors. The term “nanofluids,” introduced in [1], marked the creation of a suspension of nanotubes in oils with improved thermal conductivity, which opened the door

to numerous applications. Initial studies on nanofluids highlighted their enhanced thermal performance and suitability for energy-related applications. Research demonstrated that nanofluids formulated with ethylene glycol (EG) could achieve up to a 40% increase in thermal conductivity compared to pure EG, although the influence of nanoparticle size was not extensively addressed [2, 3]. Later investigations emphasized formulation stability and performance comparisons with traditional heat transfer fluids. Phase change materials (PCMs) also

emerged as effective candidates for improving heat exchange efficiency [4–6]. In renewable energy systems, nanofluids have proven effective in enhancing photovoltaic panel cooling. Under transient or unsteady conditions, nanofluids also improve thermal response and energy efficiency [7, 8]. Computational fluid dynamics (CFD) models indicated that pressure pulsations can be used to regulate heat transfer. Together, these findings underscore the expanding role of nanofluids in advanced thermal management and energy optimization applications [8].

Further studies, such as those by Sheremet and Pop [8], applied Marangoni effects to a cubic cavity occupied with a nanofluid, while water remains as the base fluid, to examine mass and heat transfer. Song et al. [9] did the quantitative evaluation of the thermal conductivity and melting processes of Sutterby nanofluids, finding improvements in velocity profiles alongside increases in the Marangoni number. Zarei et al. [10] utilized artificial neural networks (ANNs) for regression analysis of heat transfer in boiling pools for various nano refrigerants. Adun et al. [11] developed a multilayer perceptron ANN model and a support regression model to examine the thermal conductivity of hybrid nanofluids, incorporating various input variables. Dadhich et al. [12] conducted experiments on the heat transfer coefficient of Al_2O_3 - TiO_2 nanofluid with water as the base fluid, finding a strong agreement between experimental values and ANN predictions. Noghrehabadi et al. [13] introduced a hybrid methodology involving neural network and particle swarm optimization for solving differential equations, demonstrating the method's efficiency and accuracy. Sarfraz et al. [14] analyzed entropy generation in hybrid nanofluids comprising cadmium telluride and graphite nanoparticles, highlighting thermodynamic irreversibility and validating the Keller-box method for entropy-based modeling.

Studies [15–17] used a multilayer feedforward neural network algorithm to predict desired outputs, the results were found to be quite close to the experimental data. Sheikholeslami and Chamkha [18] employed a two-phase model to assess magneto hydrodynamic (MHD) heat transfer under conventional Marangoni effects. Wahid et al. [19] discussed the betterment of heat transfer and the significance of hybrid Marangoni nanofluids. Abdullah et al. [20] directed a stability analysis on nanofluids under conventional Marangoni conditions for a heated layer, establishing linear and exponential temperature distributions for volume fraction cases that showed good agreement with theoretical predictions. Jawad et al. [21] analyzed Maxwell power-law nanofluids in unsteady Welan gum solutions, extending the study to Joule heating with magnetic field effects. Gowda et al. [22] explored the use of blood as a conventional fluid and gold nanoparticles for cancer treatment, applying realistic techniques that yielded promising results. Gowda et al. [23] evaluated the influence of chemical reactions on second-grade steady Marangoni liquid models, specifically considering the impact of activation energy. Ellahi et al. [24] focused on how particle size influences Marangoni convection, specifically examining the effects of needle and disc-shaped particles. Chaudhary and Kanika [25] employed the Galerkin FEM to analyze MHD Marangoni boundary layer flow in electrically conducting $\text{Cu-H}_2\text{O}$ nanofluids. Konda et al.

[26] did a numerical study on MHD flow of Williamson nanofluids over wedge geometries, considering both thermophoresis and Brownian motion. Muhammad et al. [27] compared coaxial cylinder configurations to examine geometric effects on heat transfer using the Keller-box scheme. Jyothi et al. [28] studied mass and heat transfer properties of various nanofluids using the MATLAB solver bvp4c. Complementary studies by Muhammad and Sarfraz [29] demonstrated that Cu-MoS_2 hybrid nanomaterials can significantly enhance thermal efficiency, leveraging both simulation and machine learning-driven regression analysis. The study employed the Runge–Kutta–Fehlberg 45-order method, a technique previously utilized by Kumar et al. [30] to solve numerical ODEs. This approach was applied to study Casson nanofluid flow under Marangoni boundary conditions, incorporating factors such as chemical reactions, heat sources and sinks, and convective conditions.

Rudraswamy et al. [31] considered the 3D MHD characteristics of Carreau nanofluid over a stretched sheet, incorporating thermal radiation effects. In another study, Kumar et al. [32] integrated slip conditions to analyze concentration and thermal rates in Carreau nanofluid flow affected by nonlinear thermal radiation. Gireesha and Gowtham [33] examined the influence of chemical transformation and potential energy barriers over a permeable surface with Carreau nanofluid. Studies [34–36] focused on enhancing HMT using various nanofluids in wedge geometries, highlighted the application of power laws for stabilizing movement and examining HMT over a moving wedge. Also studies analyzed Dufour–Soret effects and convective flow under MHD conditions in nanofluids [37, 38] and utilized the FEM to calculate HMT characteristics of various nanofluids [39]. Studies [40, 41] employed the FEM with adaptive meshing, observing that replacing pure PCM with nanofluid-enhanced PCM (NEPCM) led to increased heat transfer rates. Despite extensive work, no existing studies have addressed Carreau nanofluid flow under Marangoni boundary conditions within a wedge geometry. Additionally, the influence of thermophoresis and Brownian motion in this setting has not been explored using ANNs. This study fills that gap by developing a hybrid framework combining high-fidelity FEM simulations and a Levenberg–Marquardt-trained neural network. The model accurately predicts transport characteristics and provides a scalable surrogate for optimization. Future work may extend toward transient analysis, experimental validation, and alternative fluid models. Practical applications include thermal control in microdevices, biomedical flows, and advanced heat exchangers in MHD and radiative environments.

2. Formulating Mathematical Expression of the Problem

The movement of a porous wedge structure traveling at a velocity $u_w(x)$ in the Carreau nanofluid, incorporating transfer of mass and heat analysis is examined here. The study also takes into account determining factor of a MHD, considering the suction at the wedge wall. The Carreau nanofluid exhibits a power-law form for its velocity profile, with x representing the coordinate along the wedge surface, as portrayed in Figure 1.

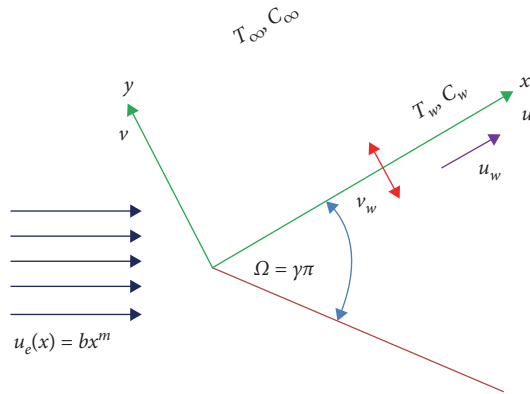


FIGURE 1: Geometrical representation of fluid flow.

Notably, for the elongated surface of the wedge, and for the shrinking surface, is observed. Carreau nanofluid is free from the stream velocity according to power-law form $u_e(x) = bx^m$, where, $m = \frac{\beta}{2-\beta}$, and x denotes wedge surface, as shown in Figure 1. It is noticed that $u_w(x) > 0$ for the stretching surface of a wedge and $u_w(x) < 0$ for the shrinking surface of a wedge. It is accepted that at the elongated surface temperature T is of the Carreau nanofluid within the boundary layer and T_∞ is far from the wedge wall, where T_w is the temperature at the wall. Wall temperature, $T_w(x) = T_\infty + \Delta T x^n$ produces a surface-tension gradient that drives Marangoni convection, while a uniform nanoparticle concentration C_w is maintained at the wall. The nanoparticles move from high to low concentration and it is not possible to nanoparticles at the wall of the wedge due to constant concentration. C , indicates the amount of Carreau nanofluid within the boundary layer and C_∞ is in the free stream, it is considered to be constant. $\pi\beta$ is the angle of the wedge, where β is the Hartree pressure gradient, from the work Jyothi et al. [42]. Thermophoretic and Brownian diffusion govern nanoparticle migration inside the boundary layer. The novelty of this configuration is integrating Carreau rheology, Marangoni shear, and wall suction in a wedge geometry and simultaneous inclusion of thermophoresis, nonlinear radiation, and Brownian motion.

2.1. Governing Equations. The related governing equations and boundary conditions are presented in Equations (1)–(6) [20–24].

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

$$\begin{aligned} u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} &= u_e \frac{du_e}{dx} + \nu \frac{\partial^2 u}{\partial y^2} \left(1 + \Gamma^2 \left(\frac{\partial u}{\partial y} \right)^2 \right)^{\frac{n-1}{2}} \\ &+ \nu(n-1) \Gamma^2 \frac{\partial^2 u}{\partial y^2} \left(\frac{\partial u}{\partial y} \right)^2 \left(1 + \Gamma^2 \left(\frac{\partial u}{\partial y} \right)^2 \right)^{\frac{n-3}{2}} \\ &- \frac{\sigma_{nf}}{\rho_{nf}} B_0^2 (u - u_e), \\ u \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} &= \frac{k}{\rho_{cp}} \frac{\partial^2 T}{\partial y^2} + \tau \left[D_B \frac{\partial T}{\partial y} \frac{\partial C}{\partial y} + \frac{D_T}{T_\infty} \left(\frac{\partial T}{\partial y} \right)^2 \right] + \frac{1}{\rho_{cp}} \frac{\partial q_r}{\partial y}, \end{aligned} \quad (2)$$

(3)

$$u \frac{\partial C}{\partial x} + v \frac{\partial C}{\partial y} = D_B \frac{\partial^2 C}{\partial y^2} + \frac{D_T}{T_\infty} \frac{\partial^2 T}{\partial y^2} - K_r (C - C_\infty). \quad (4)$$

The related boundary situations are as follows:

$$\begin{aligned} u &= L \frac{\partial u}{\partial y}, \quad v = v_w, \quad w = 0, \quad \left(\mu \frac{\partial u}{\partial y} \right) = - \left(\frac{\partial \sigma}{\partial y} \right) \\ &= \sigma \left(\gamma_c \frac{\partial C}{\partial z} + \gamma_T \frac{\partial T}{\partial z} \right), \quad C = C_w + k_2 \frac{\partial C}{\partial z}, \quad \text{at } y = 0, \end{aligned} \quad (5)$$

$$u = u_e = b x^m, \quad T \rightarrow T_\infty, \quad C \rightarrow C_\infty, \quad \text{at } y \rightarrow \infty. \quad (6)$$

ψ can be represented as follows:

$$u = \frac{\partial \psi}{\partial y}, \quad v = - \frac{\partial \psi}{\partial x}. \quad (7)$$

Some mathematical symbolism is used to ease mathematical analysis are as follows:

$$\begin{aligned} \psi &= \left(\frac{2\nu b}{m+1} \right)^{\frac{1}{2}} x^{\frac{m+1}{2}} f(\eta), \quad \eta = \sqrt{\frac{b(m+1)}{2\nu}} x^{\frac{m-1}{2}} y, \\ \theta(\eta) &= \frac{T - T_\infty}{T_w - T_\infty}, \quad \vartheta(\eta) = \frac{C - C_\infty}{C_w - C_\infty}. \end{aligned} \quad (8)$$

The radiative heat flux q_r is represented as follows:

$$q_r = - \frac{4\sigma^*}{3K^*} \frac{\partial T^4}{\partial z}, \quad (9)$$

$$T^4 = T_\infty^4 + 4T_\infty^3(T - T_\infty) + 6T_\infty^2(T - T_\infty)^2 + \dots, \quad (10)$$

where σ^* represents the Stephan–Boltzmann constant, K^* denotes the mean absorption coefficient and T_∞ the free stream.

The radiative heat flux q_r is given as follows:

$$q_r = - \frac{4\sigma^*}{3K^*} \frac{\partial T^4}{\partial z} = - \frac{16\sigma^*}{3K^*} T^3 \frac{\partial T}{\partial z}.$$

The nondimensional temperature $\theta(\eta) = \frac{T - T_\infty}{T_w - T_\infty}$ can be simplified as follows:

$$T = T_\infty (1 + (\theta_w - 1)\theta), \quad (11)$$

where $\theta_w = \frac{T_w}{T_\infty}$ is the temperature parameter.

$$\begin{aligned} f'''[1 + W_e^2 f'^2]^{\frac{n-3}{2}} (1 + n W_e^2 f'^2) + f f'' + \gamma[1 - f'^2] \\ - M(f' - 1) = 0, \end{aligned} \quad (12)$$

$$\begin{aligned} &\theta'' + \text{Pr} f \theta' + \text{Pr} \text{Nt} \theta'^2 + \text{Pr} \text{Nb} \theta' \phi' \\ &+ \frac{4}{3R} [1 + \theta(\theta_w - 1)]^3 \theta'' \\ &+ \frac{4}{R} [1 + \theta(\theta_w - 1)]^2 (\theta_w - 1) \theta'^2 = 0, \end{aligned} \quad (13)$$

$$S'' + \text{Le} f S' + \frac{\text{Nt}}{\text{Nb}} \theta'' - C_1 S = 0. \quad (14)$$

The corresponding transformed conditions are as follows:

$$f(0) = 0, f''(0) = -2(1 + r), \theta(0) = 1, S(0) = 1, \quad (15)$$

$$f'(\infty) \rightarrow 0, \theta(\infty) \rightarrow 0, S(\infty) \rightarrow 0. \quad (16)$$

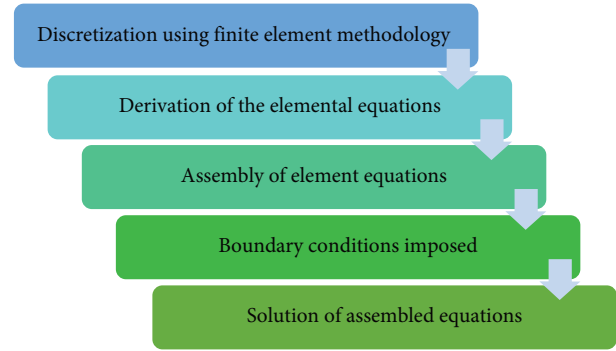


FIGURE 2: Outline of finite element methodology.

The proportionate dimensionless parameters are delineated as follows:

$$\text{Pr} = \frac{\mu \text{Cf}}{k}, \text{Nt} = \frac{\rho_{\text{CF}} D_T (T_w - T_\infty)}{T_\infty \nu \rho_{\text{CF}}}, \text{Nb} = \frac{\rho_{\text{CF}} D_B (C_w - C_\infty)}{\nu \rho_{\text{CF}}}, \theta_w = \frac{T_w}{T_\infty}, \text{Le} = \frac{\nu}{D_B},$$

$$C_1 = \frac{2\nu k_r}{D_B b(m+1)x^{m-1}}, M = \frac{\sigma B_0^2}{2\omega_1 \rho_f}, R = \frac{16T_\infty^3 \sigma^*}{3K^* k_f}, \gamma = \frac{2m}{m+1}, W_e = \left(\frac{b^3 r^2 (m+1)x^{3m-1}}{2\nu} \right)^{1/2}. \quad (17)$$

Now calculating (Cf_x) , (Nu_x) and (Sh_x) and are given as follows:

$$\text{Cf}_x = \frac{\tau_w}{\rho u_e^2/2}, \text{Nu}_x = \frac{xq_w}{k(T_w - T_\infty)}, \text{Sh}_x = \frac{xJ_w}{D_m(C_w - C_\infty)},$$

where, $\tau_w = \mu_0 \frac{\partial u}{\partial y} \left[(1 + r^2 (\frac{\partial u}{\partial y})^2)^{\frac{n-1}{2}} \right]_{y=0}$, $q_w = -k(\frac{\partial T}{\partial y})_{y=0} + (q_r)_{y=0}$,

$$J_w = -D_m \left(\frac{\partial C}{\partial y} \right)_{y=0}. \quad (18)$$

Utilizing the similarity variables, the aforementioned equations assume the following structure:

$$\text{Re}_x^{\frac{1}{2}} \text{Cf}_x = \frac{2}{\sqrt{2-\beta}} f''(0) [1 + W_e^2 (f''(0))^2]^{\frac{n-1}{2}},$$

$$\text{Re}_x^{-\frac{1}{2}} \text{Nu}_x = -\frac{2}{\sqrt{2-\beta}} \theta'(0) \left[1 + \frac{4}{3N_R} [1 + (\theta_w - 1)(\theta(0))^3]^{\frac{n-1}{2}} \right],$$

$\text{Re}_x^{-\frac{1}{2}} \text{Sh}_x = -\frac{2}{\sqrt{2-\beta}} S'(0)$, where $\text{Re}_x = \frac{x u_e}{\nu}$ is Reynolds number.

Here local Reynolds number, $\text{Re}_x = \rho U_\infty x / \mu$, which varies along the wedge surface. The dependance on x accounts for the spatial development of the boundary layer in external flows, a standard formulation in wedge-type and boundary-layer analyses.

2.2. Numerical Simulation. The governing equations are defined over a semi-infinite physical domain in the y -direction.

To make the problem computationally tractable, similarity transformations were applied to convert the domain into a finite interval in terms of the dimensionless similarity variable η . In this study, the domain was truncated at $\eta = 8$, a value chosen based on convergence testing. Numerical experiments showed that further extending η beyond 8 led to negligible changes (less than 0.001%) in computed surface quantities (Nu_x , Sh_x , and Cf_x), confirming that $\eta = 8$ provides a sufficiently accurate representation of the semi-infinite domain. This is a standard and widely accepted approach in similarity-based boundary layer analyses.

The FEM provides an efficient approach for solving non-linear ordinary and partial differential equations. It involves discretizing the computational domain into smaller subdomains known as finite elements. FEM is widely used in engineering analyses such as heat transfer, fluid flow, structural mechanics, and electrical systems. The procedural steps associated with the FEM [28–33] are outlined in Figure 2. The FEM simulations in this study were performed iteratively. The numerical solution was considered converged when the relative error between successive iterations of the dependent variables fell below a prescribed tolerance of 10^{-6} . This convergence criterion ensured numerical stability and accuracy in the computed velocity, temperature, and concentration fields.

2.3. ANN. The Liebenberg Neural network is employed for regression analysis. In the projected methodological analysis out of total samples, 70% of the samples were considered to network training, 15% for the validation, and 15% for the testing process. While running the algorithm, the number of

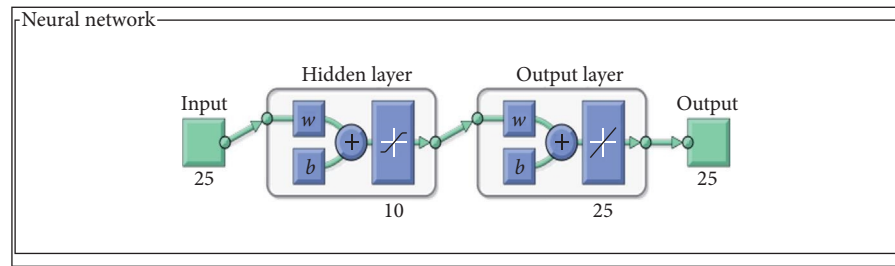
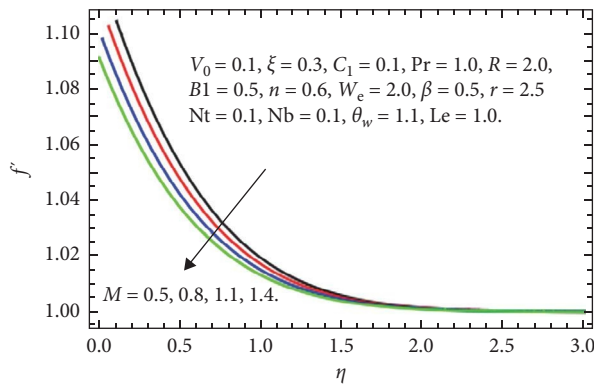
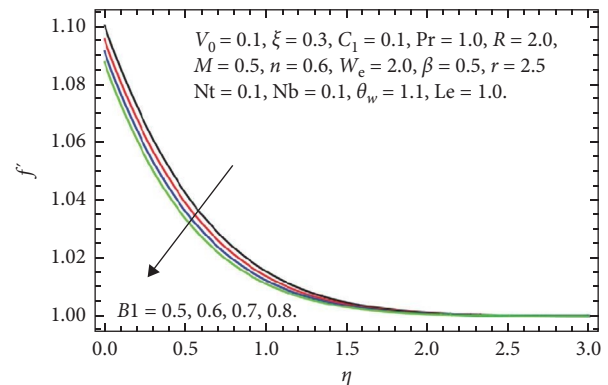


FIGURE 3: Architecture of neural network.

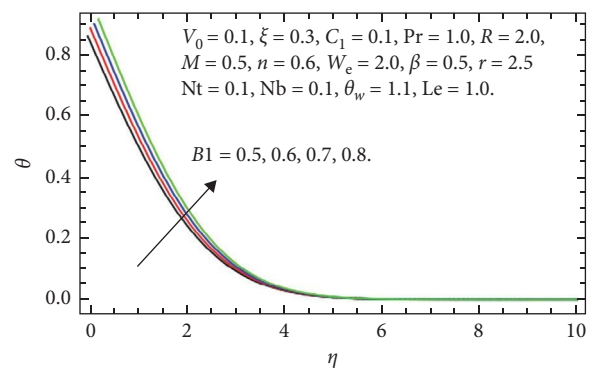
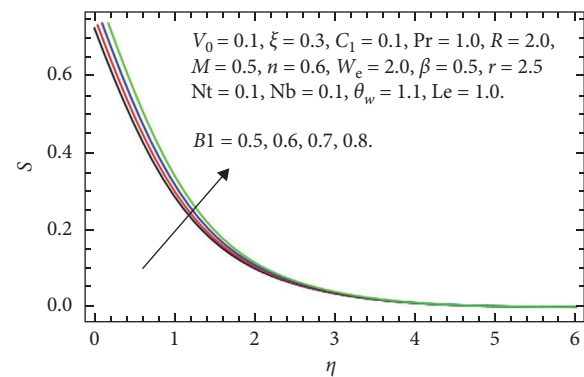
FIGURE 4: Velocity distributions featuring (M).FIGURE 5: Velocity distributions featuring $B1$.

neurons were adjusted according to the level of difficulty of the problem. Internal architecture of neural network is display through Figure 3. Figure shows that it is two layered structures, which involves input-25, hidden layer-10, and output layer-25.

3. Results and Discussions

3.1. Velocity Profile, Temperature Profile, and Concentration Profile. The analysis of the attributes of Carreau nanofluid flow over a wedge with Marangoni convection is represented here. Concentration profile (CP), temperature profile (TP), and velocity profile (VP) for various input parameters such as magnetic parameter, Weissenberg number, Lewis number, and Marangoni ratio which are presented in Figures 4–12. Figure 4 showcases the impact of the magnetic field parameter (M) on the velocity profile of the Carreau nanofluid. With an increase in M , a significant reduction in fluid velocity is evident across the boundary layer. This occurrence is attributable to the Lorentz force produced by the magnetic field, which opposes the movement of the electrically conducting nanofluid. The resistive magnetic force effectively diminishes the momentum of the fluid, leading to a thicker hydrodynamic boundary layer and a reduction in flow velocity near the wedge surface. At the same time, the magnetic influences promote the accumulation of thermal energy, which may indirectly enhance thermal diffusion and alter the thermal boundary layer's thickness. These observed behaviors align closely with the findings reported by Rudraswamy et al. [31].

Figures 5–7 illustrate the influence of the wedge angle parameter ($B1$ denoted as γ) on the velocity profile (VP),

FIGURE 6: Temperature distributions featuring $B1$.FIGURE 7: Concentration distributions featuring $B1$.

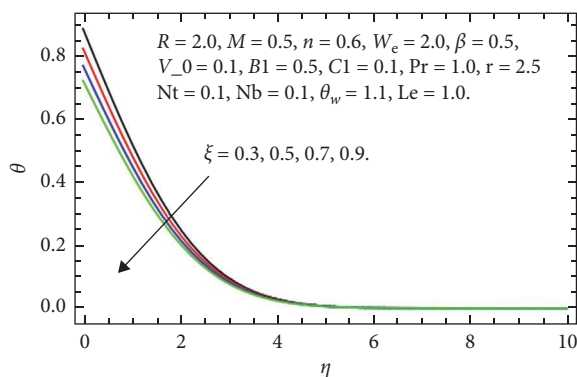


FIGURE 8: Temperature distributions featuring (ξ).

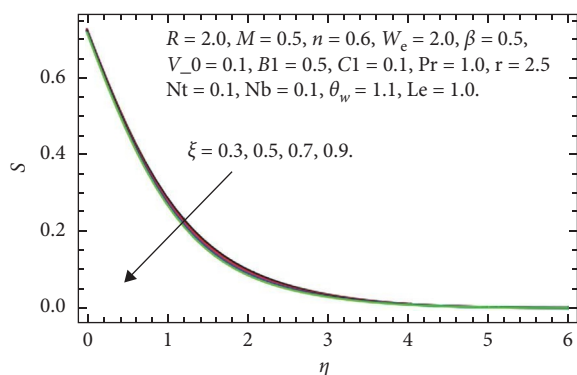


FIGURE 9: Concentration distributions featuring (ξ).

temperature profile (TP), and concentration profile (CP) of the Carreau nanofluid flow. In Figure 5, an increase in γ leads to a noticeable decrease in the velocity distribution. Physically, a larger wedge angle enhances the adverse pressure gradient along the surface, which acts against the flow direction. This increase in pressure resistance suppresses the momentum of the fluid particles near the surface, resulting in a thinner velocity boundary layer. Contrastingly, Figures 6 and 7 reveal that as γ increases, both temperature and concentration profiles rise. This occurs because the reduced fluid motion caused by the higher wedge angle diminishes convective transport, allowing more thermal energy and solute particles to accumulate near the surface. Consequently, both thermal and concentration boundary layers become thicker. These trends highlight the sensitive interplay between geometric shaping and transport processes, emphasizing the importance of wedge configuration in controlling energy and mass diffusion in engineered systems. These trends are consistent with the findings reported by Xiu et al. [35], who also examined the influence of wedge angle (γ) on Carreau nanofluid flow characteristics.

Figures 8 and 9 demonstrate the impact of the temperature slip parameter (ξ) on the temperature profile (TP) and concentration profile (CP) in the Carreau nanofluid flow. As ξ increases, both TP and CP decline. This behavior arises due to the introduction of thermal slip at the surface, which reduces the efficiency of heat transfer from the wall to the fluid. Physically, temperature slip weakens the thermal gradient at the boundary, limiting conductive heat transfer, and thereby,

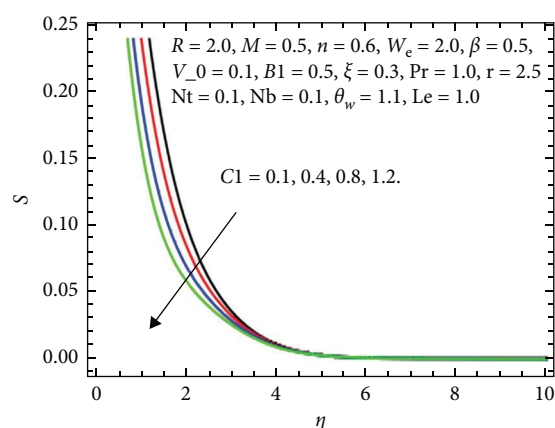


FIGURE 10: Concentration distributions featuring $C1$.

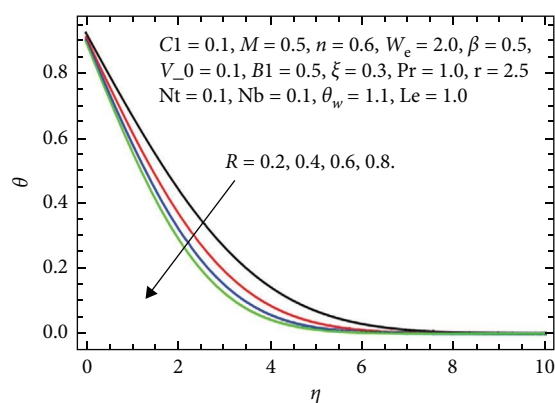


FIGURE 11: Temperature distributions featuring R .

lowering the temperature distribution within the boundary layer. Similarly, the diminished temperature near the wall weakens thermophoretic motion, leading to reduced nanoparticle transport, and thus, lower concentration levels. This results in thinner thermal and solutal boundary layers, highlighting how surface slip conditions can regulate energy and mass diffusion in nanofluidic systems. Figure 10 illustrates the effect of the chemical reaction parameter ($C1$) on the concentration distribution. An increase in $C1$ leads to a marked decrease in concentration levels throughout the boundary layer. This is due to the enhanced rate of chemical reactions that consume or deplete the solute species in the flow. Higher reaction rates promote species destruction, reducing the concentration of nanoparticles near the wall and in the free stream. This finding underscores the critical role of reaction kinetics in controlling mass transfer behavior, especially in chemically reactive nanofluid systems used in catalysis, drug delivery, and chemical sensors.

Figures 11 and 12 illustrate the effects of the thermal radiation parameter on the temperature and concentration profiles of the Carreau nanofluid. As the radiation parameter increases, a decline in temperature distribution is observed, while the concentration profile shows a corresponding rise. This inverse behavior occurs because higher radiation promotes radiative heat loss from the fluid, reducing its internal energy, and

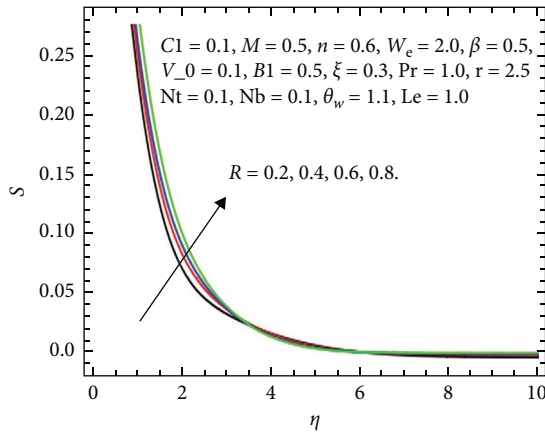


FIGURE 12: Concentration distributions featuring R .

leading to a thinner thermal boundary layer. The drop in temperature weakens thermophoretic forces that usually drive nanoparticles away from the heated surface, allowing more particles to accumulate near the wall, thereby, increasing the concentration. This interplay highlights how radiative effects can be leveraged to modulate both heat and mass transport in nanofluid-based thermal systems.

3.2. Determination of Nusselt Number, Sherwood Number, and Skin Friction Coefficients. Results of Nusselt number (Nu_x), skin friction coefficient (Sf_x), and Sherwood number (Sh_x) using various parameters datasets like M , $B1$, ξ , R , β and We were assessed. These data sets of Nu_x , Sf_x , and Sh_x for various parameters such as M , $B1$, ξ , R , β , and We are used for further investigation. Table 1 reveals the quantitative assessment of Nu_x , Sf_x , and Sh_x for various parameters such as M , $B1$, ξ , R , β , and We . As M values increases, there is an clear upsurge Nu_x , Sf_x , and Sh_x as indicated in the Table 1. The rise in the Wedge angle parameter ($B1$) leads to reduction of Nusselt number and boundary layer thickness. With an escalation in temperature slip parameter (ξ), there is a decline in Nu_x and Sf_x ; however, Sh_x displays an opposite pattern. Sf_x and Sh_x exhibit a decline as the value of R increases, whereas the Nu_x displays an inverse pattern. As the concentration slip parameter (β) grows larger, there is a decrease in both Sf_x and Sh_x , while Nu_x demonstrates a contrasting trend. All three boundary layers experience reduction when the wedge (We) values increase.

3.3. Validation of FEM Model. To ensure the accuracy and reliability of the FEM implementation, validation was carried out using several strategies. In the absence of Marangoni convection, slip, and non-Newtonian effects (i.e., for $We = 0$ and $\beta = 0$), the present FEM solution was reduced to the classical Blasius boundary layer problem. The computed Nu_x and Cf_x showed excellent agreement with the analytical values, with deviations within 1%. A mesh refinement study was conducted by varying the number of elements from 500 to 1500. The maximum relative change in Nu_x and Sh_x was below 0.5%, confirming the mesh-independent behavior of the solution. Selected simplified cases were also solved using the MATLAB solver bvp4c, and the results closely matched those from FEM with a discrepancy below 2%, further validating the accuracy of

TABLE 1: Nu_x , Sf_x , and Sh_x across different parameter values.

Parameters						Sf_x	Nu_x	Sh_x
M	$B1$	ξ	R	β	We			
0.5	0.5	0.3	2.0	0.5	2.0	0.25237	1.14770	0.89977
0.8	0.5	0.3	2.0	0.5	2.0	0.25186	1.14714	0.89940
1.1	0.5	0.3	2.0	0.5	2.0	0.25137	1.14662	0.89905
1.4	0.5	0.3	2.0	0.5	2.0	0.25091	1.14614	0.89783
1.7	0.5	0.3	2.0	0.5	2.0	0.25003	1.45922	0.89654
2.1	0.5	0.3	2.0	0.5	2.0	0.24987	1.45907	0.89410
0.5	0.5	0.3	2.0	0.5	2.0	0.25184	1.14712	0.89939
0.5	0.6	0.3	2.0	0.5	2.0	0.25078	1.14600	0.89864
0.5	0.7	0.3	2.0	0.5	2.0	0.24985	1.14504	0.89799
0.5	0.8	0.3	2.0	0.5	2.0	0.24904	1.14419	0.89742
0.5	0.5	0.3	2.0	0.5	2.0	0.25329	1.14720	0.89944
0.5	0.5	0.3	2.0	0.5	2.0	0.25242	1.06008	0.90928
0.5	0.5	0.5	2.0	0.5	2.0	0.25122	0.98468	0.91762
0.5	0.5	0.7	0.2	0.5	2.0	0.25035	0.91916	0.92497
0.5	0.5	0.9	0.4	0.5	2.0	0.21764	1.88501	0.97396
0.5	0.5	0.3	0.6	0.5	2.0	0.21701	2.18170	0.95015
0.5	0.5	0.3	0.8	0.3	2.0	0.21688	2.38691	0.93261
0.5	0.5	0.3	2.0	0.7	2.0	0.21656	2.53312	0.91959
0.5	0.5	0.3	2.0	1.1	2.0	0.23713	1.98509	1.78717
0.5	0.5	0.3	2.0	1.5	2.0	0.23703	1.99002	1.38164
0.5	0.5	0.3	2.0	0.5	2.0	0.23685	1.99313	1.12610
0.5	0.5	0.3	2.0	0.5	0.5	0.25536	1.14021	0.89706
0.5	0.5	0.3	2.0	0.5	1.0	0.25528	1.14013	0.89432
0.5	0.5	0.3	2.0	0.5	1.5	0.25483	1.14090	0.89363
0.5	0.5	0.3	2.0	0.5	2.0	0.25461	1.14095	0.89231

TABLE 2: ANN performance criterion.

Data set	MSE	R
Training	1.74e−1	8.69e−1
Testing	9.16e−02	−4.589e−02
Validation	1.96e−01	2.84e−1

the numerical approach. These results confirm that the present FEM scheme is stable, accurate, and suitable for modeling complex Carreau nanofluid behavior under Marangoni boundary conditions.

3.4. ANN. MATLAB software was used for ANN analysis. The dataset used to train and validate the ANN model was generated entirely from the results obtained through the validated FEM simulations. A Latin hypercube sampling (LHS) technique was employed to systematically sample the multidimensional parameter space (including M , Nt , Nb , We , Rd , and $B1$). This sampling ensured uniform coverage and reduced redundancy in the data. Each sampled combination of input parameters was run through the FEM solver to compute corresponding output responses such as Nu_x , Sh_x , and Cf_x . A total of 225 samples were generated, which were then split into training, validation, and testing sets. No experimental or externally sourced data were used in this study. The Table 2 displays,

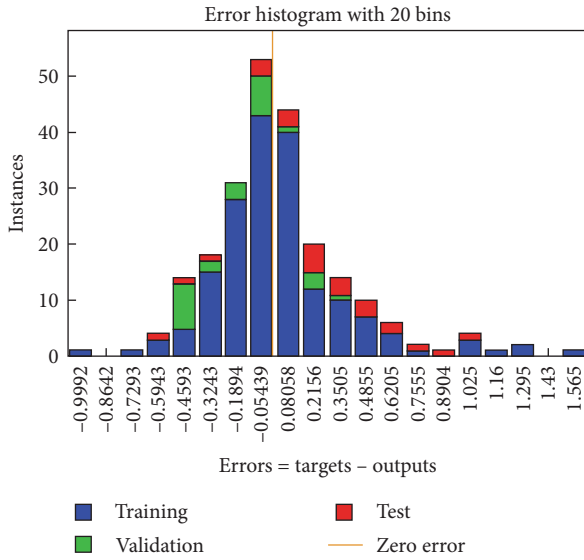
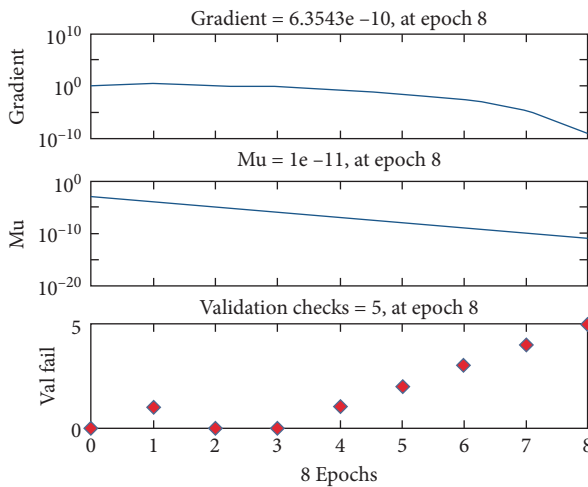


FIGURE 13: Error histogram.

FIGURE 14: Validation performance has been checked for gradient, μ , and validation checks.

MSE and R as the ANN performance criterion for training, validation, and testing of required samples. In Table 2 displays numerical values of MSE and R .

Figure 13 illustrates error histogram training, validation, and testing with no errors. Error histograms serve as a means of approaching values predicted closely to the reference values. Essentially, these histograms present computed values from a zero-error standpoint and depict various types of errors for the fitted data. The fitted data is categorized into 20 bins based on errors that are closer to the zero-error line. A higher number of values closer to the zero-error line indicates greater accuracy when applying the solution methodology.

Validation performance has been checked for gradient, μ , and validation checks at 8 epoch as illustrated in Figure 14. Here gradient is a vector quantity which actually guide the

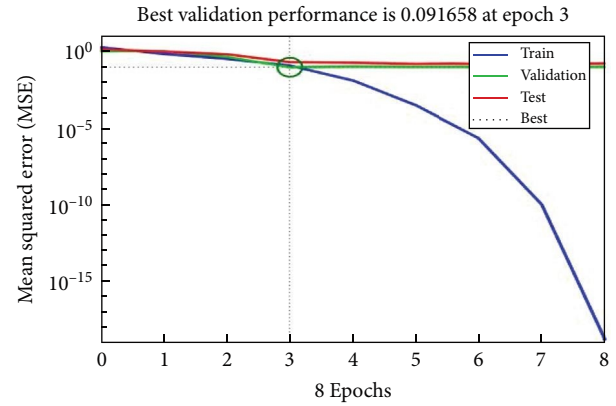


FIGURE 15: The best validation performance with respect to MSE.

direction of the data to be fitted including proper magnitude to come through the necessary solution whereas to control a particular algorithm μ factor plays a major role.

The convergence value of the solution methodology for μ factor at 8 epochs are plotted in Figure 14 and validation check has done for the data through these graphs only. From Figure 15 best validation performance can be recognized in terms of the MSE, the results indicates the 3 epoch gives the best validation performance.

Figure 16 represents the training, validation, and testing data fitted using ANN. During training, the model learns the patterns and relationships within the data. Training has been particularly mentioned in Figure 16a. Typically, a significant portion of the data is assigned to the training set, commonly constituting approximately 70% of the entire dataset. In Figure 16b validation has done. The validation set is used to tune hyper parameters and to oversee the model's performance during training, aiding in preventing over fitting, and ensuring effective generalization to new and unseen data, around 15% of the total dataset is allocated to the validation set. Test and over all data have fitted have been discussed in Figure 16c,d. the demarcation of training, testing, and validation data is done for impartial evaluation of the model's capacity to generalize to novel and unseen data.

4. Conclusions

This study presents a systematic investigation of Carreau nano-fluid flow over a wedge surface based on Buongiorno's model, accounting for the effects of Marangoni convection and velocity slip. The complex system of nonlinear ordinary differential equations was effectively solved using the FEM, enabling a detailed analysis of velocity, temperature, and concentration distributions. The key conclusions drawn from the study are as follows:

- The temperature and concentration profiles increase with higher values of the Marangoni ratio parameter. This is due to enhanced surface tension gradients, which intensify thermal and solutal transport within the boundary layer.

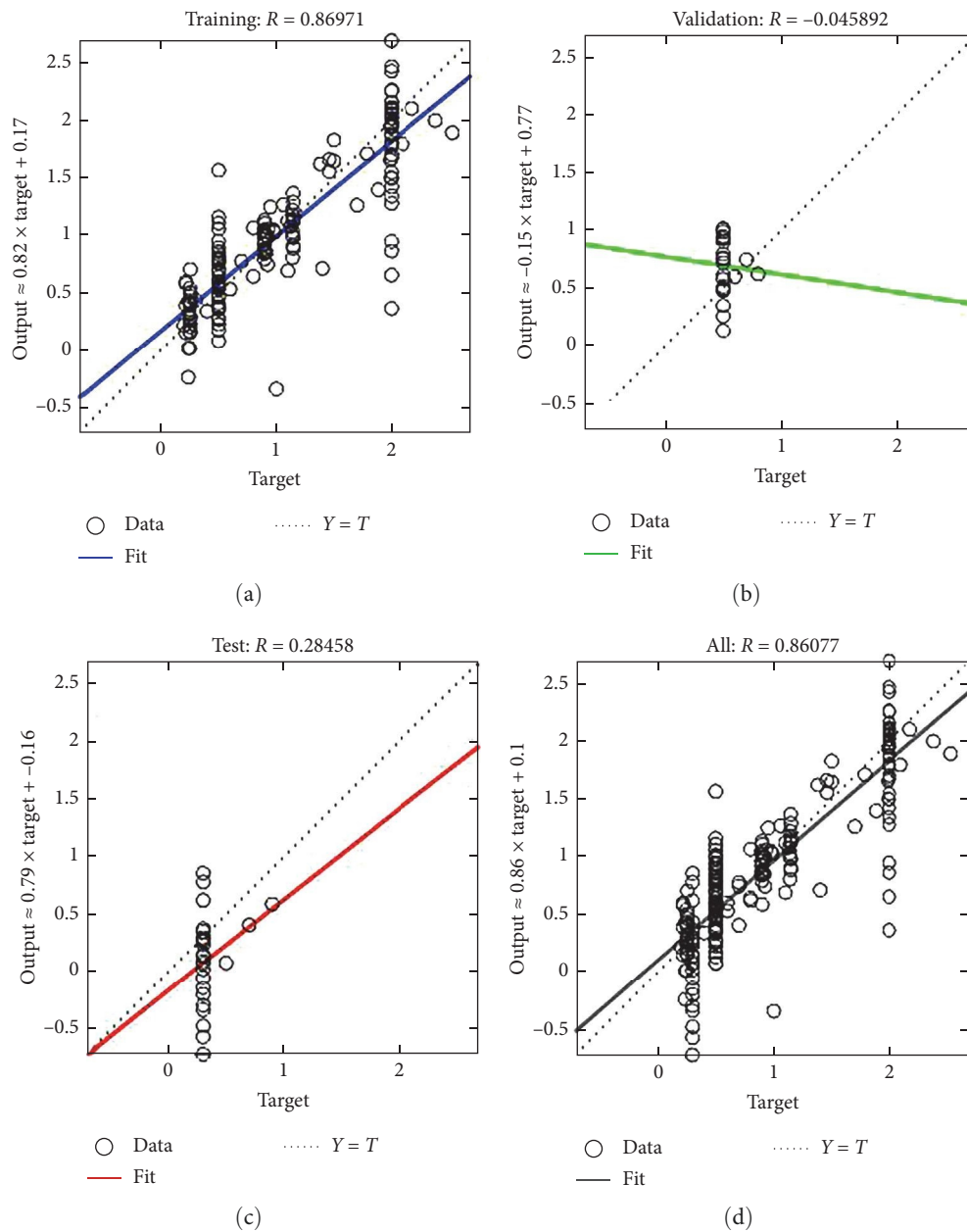


FIGURE 16: (a–d) ANN prediction results.

- Increasing the Weissenberg number (W_e), which characterizes fluid elasticity, leads to a decline in the skin friction coefficient (C_{f_x}), Nusselt number (Nu_x), and Sherwood number (Sh_x). This implies that stronger elastic effects resist momentum and energy transfer.
- As the wedge angle increases, both Nu_x and Sh_x decrease, indicating that wider wedge geometries suppress thermal and solutal transport by reducing the convective flow near the surface.
- An elevated Marangoni ratio parameter causes reductions in C_{f_x} , Nu_x , and Sh_x , demonstrating that excessive surface tension gradients may lead to flow resistance and decreased energy and mass transfer efficiency.

- These findings provide deeper physical insight into the role of surface tension, fluid elasticity, and geometry on the thermal behavior of nanofluids, with practical relevance for microfluidic device design, cooling systems, and material processing technologies.

In future work, the model can be extended to unsteady Carreau nanofluid flow under time-dependent Marangoni boundary conditions, enabling analysis of transient thermal and solutal behaviors relevant to pulsatile microflows and dynamically evolving surface conditions. Additionally, experimental validation may be pursued using a heated wedge setup with Carreau nanofluid and infrared thermography to compare observed Nusselt number trends with numerical predictions.

Nomenclature

x, y :	Cartesian coordinates (m)
u, v :	Velocity components in x and y directions (m/s)
B :	Hartree pressure gradient
T :	Temperature (K)
C :	Nanoparticle concentration (kg/m ³)
ρ :	Density (kg/m ³)
μ, μ_{eff} :	Dynamic viscosity, effective viscosity (Pa·s)
k :	Thermal conductivity (W/(m·K))
α :	Thermal diffusivity (m ² /s)
D_B :	Brownian diffusion coefficient (m ² /s)
D_T :	Thermophoretic diffusion coefficient (m ² /s)
σ :	Electrical conductivity (S/m)
σ^* :	Stefan–Boltzmann constant (W/m ² K ⁴)
K^* :	Mean absorption coefficient (1/m)
q_r :	Radiative heat flux (W/m ²)
$u_{w(x)}$:	Velocity of wedge surface (m/s)
β :	Slip parameter
$\pi\beta$:	Wedge angle
FEM:	Finite element method
ANN:	Artificial neural network
ODE:	Ordinary differential equation
MHD:	Magnetohydrodynamics
Nu, Sh, Cf:	Nusselt, Sherwood numbers, skin friction
θ, ϕ :	Dimensionless temperature and concentration
Re_x :	Local Reynolds number
Pr, Sc:	Prandtl number, Schmidt number
M, Nt, Nb :	Magnetic parameter, thermophoresis, Brownian motion
We, Rd :	Weissenberg number, radiation parameter
∞ :	Free stream condition
w :	Wall condition
nf:	Nanofluid
f :	Base fluid
p :	Nanoparticles.

Data Availability Statement

All the data generated are used in this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Author Contributions

Kotike Jyothi: conceptualization, data curation, formal analysis, investigation, writing – original draft. **Leelavathi Rekapalli**: data curation, methodology, writing – original draft, formal analysis, investigation, project administration, software. **Muhammad Usman**: investigation, writing – original draft, resources, software. **Balram Yelamasetti**: validation, project administration, visualization, writing – review and editing. **M. Zubairuddin**: investigation, methodology, writing – original draft. **S. K. Mohammad Shareef**: data curation, software, writing – review and editing. **Dhanesh G. Mohan**: supervision,

validation, project administration, visualization, writing – review and editing.

Funding

No funding was received for this manuscript.

References

- [1] S. U. S. Choi, Z. G. Zhang, W. Yu, F. E. Lockwood, and E. A. Grulke, “Anomalous Thermal Conductivity Enhancement in Nanotube Suspensions,” *Applied Physics Letters* 79, no. 14 (2001): 2252–2254.
- [2] M. Sheikholeslami and M. Seyednezhad, “Simulation of Nanofluid Flow and Natural Convection in a Porous Media Under the Influence of Electric Field Using CVFEM,” *International Journal of Heat and Mass Transfer* 120 (2018): 772–781.
- [3] K. Muhammad, M. Sarfraz, N. A. Ahammad, and I. E. Elseesy, “Improving Thermal Efficiency Through Cu–MoS₂ Hybrid Nanomaterials: A Numerical and Statistical Approach,” *Chaos, Solitons & Fractals* 192 (2025): 116014.
- [4] J. M. Munyalo and X. Zhang, “Particle Size Effect on Thermophysical Properties of Nanofluid and Nanofluid Based Phase Change Materials: A Review,” *Journal of Molecular Liquids* 265 (2018): 77–87.
- [5] M. S. Y. Ebaid, A. M. Ghrair, and M. Al-Busoul, “Experimental Investigation of Cooling Photovoltaic (PV) Panels Using (TiO₂) Nanofluid in Water-Polyethylene Glycol Mixture and (Al₂O₃) Nanofluid in Water-Cetyltrimethylammonium Bromide Mixture,” *Energy Conversion and Management* 155 (2018): 324–343.
- [6] M. M. Tawfik, “Experimental Studies of Nanofluid Thermal Conductivity Enhancement and Applications: A Review,” *Renewable and Sustainable Energy Reviews* 75 (2017): 1239–1253.
- [7] M. Sarfraz, K. Muhammad, H. F. Alrihieli, and M. A. H. Abdelmohimen, “Heat and Mass Transfer Analysis in Flow of Walter’s B Nanofluid: A Numerical Study of Dual Solutions,” *Zeitschrift für Angewandte Mathematik und Mechanik* 105, no. 1 (2025): e2300951.
- [8] M. A. Sheremet and I. Pop, “Marangoni Natural Convection in a Cubical Cavity Filled With a Nanofluid: Buongiorno’s Nanofluid Model,” *Journal of Thermal Analysis and Calorimetry* 135, no. 1 (2019): 357–369.
- [9] Y.-Q. Song, H. Waqas, K. Al-Khaled, et al., “Bioconvection Analysis for Sutterby Nanofluid Over an Axially Stretched Cylinder With Melting Heat Transfer and Variable Thermal Features: A Marangoni and Solutal Model,” *Alexandria Engineering Journal* 60, no. 5 (2021): 4663–4675.
- [10] M. J. Zarei, H. R. Ansari, P. Keshavarz, and M. M. Zerafat, “Prediction of Pool Boiling Heat Transfer Coefficient for Various Nano-Refrigerants Utilizing Artificial Neural Networks,” *Journal of Thermal Analysis and Calorimetry* 139, no. 6 (2020): 3757–3768.
- [11] H. Adun, I. Wole-Osho, E. C. Okonkwo, O. Bamsile, M. Dagbasi, and S. Abbasoglu, “A Neural Network-Based Predictive Model for the Thermal Conductivity of Hybrid Nanofluids,” *International Communications in Heat and Mass Transfer* 119 (2020): 104930.
- [12] M. Dadhich, O. S. Prajapati, and N. Rohatgi, “Flow Boiling Heat Transfer Analysis of Al₂O₃ and TiO₂ Nanofluids in Horizontal Tube Using Artificial Neural Network (ANN),”

- Journal of Thermal Analysis and Calorimetry* 139, no. 5 (2020): 3197–3217.
- [13] A. Noghrehabadi, R. Mirzaei, M. Ghalambaz, A. Chamkha, and A. Ghanbarzadeh, "Boundary Layer Flow Heat and Mass Transfer Study of Sakiadis Flow of Viscoelastic Nanofluids Using Hybrid Neural Network-Particle Swarm Optimization (HNNPSO)," *Thermal Science and Engineering Progress* 4 (2017): 150–159.
 - [14] M. Sarfraz, K. Muhammad, N. A. Ahammad, and I. E. Elseesy, "Synergistic Effects of Cadmium Telluride and Graphite Nanoparticles With Entropy Analysis through Keller-Box Method," *International Communications in Heat and Mass Transfer* 163 (2025): 108667.
 - [15] N. Ghasemi, R. Aghayari, and H. Maddah, "Designing an Artificial Neural Network Using Radial Basis Function to Model Exergetic Efficiency of Nanofluids in Mini Double Pipe Heat Exchanger," *Heat and Mass Transfer* 54, no. 6 (2018): 1707–1719.
 - [16] H. Maddah, M. Ghazvini, and M. H. Ahmadi, "Predicting the Efficiency of CuO/Water Nanofluid in Heat Pipe Heat Exchanger Using Neural Network," *International Communications in Heat and Mass Transfer* 104 (2019): 33–40.
 - [17] A. Tassaddiq, S. Khan, M. Bilal, et al., "Heat and Mass Transfer Together With Hybrid Nanofluid Flow Over a Rotating Disk," *AIP Advances* 10, no. 5 (2020): 055317.
 - [18] M. Sheikholeslami and A. J. Chamkha, "Influence of Lorentz Forces on Nanofluid Forced Convection Considering Marangoni Convection," *Journal of Molecular Liquids* 225 (2017): 750–757.
 - [19] N. S. Wahid, N. M. Arifin, N. S. Khashi'ie, and I. Pop, "Marangoni Hybrid Nanofluid Flow Over a Permeable Infinite Disk Embedded in a Porous Medium," *International Communications in Heat and Mass Transfer* 126 (2021): 105421.
 - [20] A. A. Abdullah, N. M. Alraiqib, and K. A. Lindsay, "Modeling the Stability of Marangoni Convection in a Layer of Nanofluid," *International Journal of Thermal Sciences* 151 (2020): 106228.
 - [21] M. Jawad, A. Saeed, T. Gul, Z. Shah, and P. Kumam, "Unsteady Thermal Maxwell Power Law Nanofluid Flow Subject to Forced Thermal Marangoni Convection," *Scientific Reports* 11, no. 1 (2021): 7521.
 - [22] R. J. P. Gowda, H. B. Mallikarjuna, B. C. Prasannakumara, R. N. Kumar, and P. T. Manjunatha, "Dynamics of Thermal Marangoni Stagnation Point Flow in Dusty Casson Nanofluid," *International Journal of Modelling and Simulation* 42, no. 5 (2022): 707–715.
 - [23] R. J. P. Gowda, R. Naveen Kumar, A. M. Jyothi, B. C. Prasannakumara, and I. E. Sarris, "Impact of Binary Chemical Reaction and Activation Energy on Heat and Mass Transfer of Marangoni Driven Boundary Layer Flow of a Non-Newtonian Nanofluid," *Processes* 9, no. 4 (2021): 702.
 - [24] R. Ellahi, A. Zeeshan, and M. Hassan, "Particle Shape Effects on Marangoni Convection Boundary Layer Flow of a Nanofluid," *International Journal of Numerical Methods for Heat & Fluid Flow* 26, no. 7 (2016): 2160–2174.
 - [25] S. Chaudhary and K. M. Kanika, "Viscous Dissipation and Joule Heating in MHD Marangoni Boundary Layer Flow and Radiation Heat Transfer of Cu–Water Nanofluid Along Particle Shapes Over an Exponential Temperature," *International Journal of Computer Mathematics* 97, no. 5 (2020): 943–958.
 - [26] J. R. Konda, M. Reddy N. P., R. Konijeti, and A. Dasore, "Effect of Non-Uniform Heat Source/Sink on MHD Boundary Layer Flow and Melting Heat Transfer of Williamson Nanofluid in Porous Medium," *Multidiscipline Modeling in Materials and Structures* 15, no. 2 (2019): 452–472.
 - [27] K. Muhammad, M. Sarfraz, and M. A. Aigo, "Flow and Heat Transfer Analysis of Hybrid Nanofluid due to Coaxial Cylinders: A Comparative Study via Keller-Box Scheme," *Proceedings of the Institution of Mechanical Engineers, Part N: Journal of Nanomaterials, Nanoengineering and Nanosystems* (2025).
 - [28] K. Jyothi, A. Dasore, R. Ganapati, S. M. Shareef, A. J. Chamkha, and V. R. Prasad, "Comparative Numerical Analysis of Heat and Mass Transfer Characteristics in Sisko Al_2O_3 -EG and TiO_2 -EG Fluids on a Stretched Surface," *Frontiers in Heat and Mass Transfer* 22, no. 1 (2024): 79–105.
 - [29] K. Muhammad and M. Sarfraz, "Regression Analysis of Squeezing-Induced Hybrid Nanofluid Flow in Darcy–Forchheimer Porous Medium," *Applied Mathematics and Mechanics* 46, no. 1 (2025): 193–208.
 - [30] K. G. Kumar, M. G. Reddy, P. V. Kumari, A. Aldalbahi, M. Rahimi-Gorji, and M. Rahaman, "Application of Different Hybrid Nanofluids in Convective Heat Transport of Carreau Fluid," *Chaos, Solitons & Fractals* 141 (2020): 110350.
 - [31] N. G. Rudraswamy, S. A. Shehzad, K. Ganesh Kumar, and B. J. Gireesha, "Numerical Analysis of MHD Three-Dimensional Carreau Nanofluid Flow Over Bidirectionally Moving Surface," *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 39, no. 12 (2017): 5037–5047.
 - [32] K. G. Kumar, G. K. Ramesh, B. J. Gireesha, and A. M. Rashad, "On Stretched Magnetic Flow of Carreau Nanofluid With Slip Effects and Nonlinear Thermal Radiation," *Nonlinear Engineering* 8, no. 1 (2019): 340–349.
 - [33] B. J. Gireesha and K. J. Gowtham, "Entropy Generation Analysis of Hyperbolic Tangent Fluid in Upright Micro-channel With Hall Effect by Taylor Wavelet Collocation Method," *International Journal of Ambient Energy* 46, no. 1 (2025): 2495825.
 - [34] M. Sarfraz and K. Muhammad, "Modulation of Energy Transport in Stagnation Point Flows Involving Hybrid Nanofluids," *Proceedings of the Institution of Mechanical Engineers, Part N: Journal of Nanomaterials, Nanoengineering and Nanosystems* (2025).
 - [35] W. Xiu, I. L. Animasaun, Q. M. Al-Mdallal, A. K. Alzahrani, and T. Muhammad, "Dynamics of Ternary-Hybrid Nanofluids due to Dual Stretching on Wedge Surfaces When Volume of Nanoparticles Is Small and Large: Forced Convection of Water at Different Temperatures," *International Communications in Heat and Mass Transfer* 137 (2022): 106241.
 - [36] R. Lakshmi, B. J. Gireesha, P. Venkatesh, and K. J. Gowtham, "Hermite Wavelet Approach to Analyze the Entropy Generation of MHD Williamson Hybrid Nanofluid Flow Through an Inclined Channel With Particle Shape Effects," *International Journal of Applied and Computational Mathematics* 11, no. 2 (2025): 40.
 - [37] B. J. Gireesha and K. J. Gowtham, "Thermal Radiation Impact on Hybrid Nanocomposite Flow in Stretchable Channels: A Darcy–Forchheimer Model With the Taylor Wavelet Approach," *Applied Mathematics and Mechanics* 46, no. 6 (2025): 1107–1124.
 - [38] M. Sarfraz and K. Muhammad, "Numerical Solutions for Thermal and Solutal Transport of Jeffrey Fluid Flow Subject to Rotation via Keller–Box Method," *Multiscale and Multidisciplinary Modeling, Experiments and Design* 8, no. 3 (2025): 177.

- [39] K. Muhammad, M. Sarfraz, H. F. Alrihieli, and I. E. Elseesy, "Significance of Brownian Diffusion and Thermophoresis in Energy and Mass Optimization for Newtonian and Non-Newtonian Fluid Flow: A Numerical Study via Keller-Box Method," *Case Studies in Thermal Engineering* 73 (2025): 106365.
- [40] S. Hussain, "Finite Element Solution for MHD Flow of Nanofluids With Heat and Mass Transfer Through a Porous Media With Thermal Radiation, Viscous Dissipation and Chemical Reaction Effects," *Advances in Applied Mathematics and Mechanics* 9, no. 4 (2017): 904–923.
- [41] Mathworks, "MATLAB & Simulink: Regression," 2023, <https://www.mathworks.com/help/stats/regression-and-anova.html>.
- [42] K. Jyothi, P. Sudarsana Reddy, and M. Suryanarayana Reddy, "Carreau Nanofluid Heat and Mass Transfer Flow Through Wedge With Slip Conditions and Nonlinear Thermal Radiation," *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 41 (2019): 415.