Machine learning-assisted prediction of thermal-hydraulic behaviour in additively manufactured microchannels using hybrid nanofluids and surface roughness correlation

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Abstract. This research explores the thermal and hydraulic behaviour of straight microchannel heat sinks (MCHS) fabricated using Direct Metal Laser Sintering (DMLS) and cooled with hybrid nanofluids containing Al_2O_3 and CuO nanoparticles. The combined use of these nanoparticles improved the fluid's thermophysical properties, while the natural rough surfaces formed during additive manufacturing promoted passive convection. Experiments were conducted with nanofluid concentrations of 0.02% and 0.05% for Reynolds numbers ranging from 23 to 125, under heat fluxes of 20 to 40 W/cm². At a 0.05% concentration and a 30 W/cm² heat flux, the Nusselt number increased by 12.9%, the surface temperature decreased by 13.8%, and the pressure drop rose by a moderate 6.4%. The performance evaluation criteria (PEC > 1) confirmed that the heat transfer benefit outperformed the hydraulic penalty. The experimental data were further applied to machine learning regression models, including polynomial regression, random forest, Gradient boosting and decision tree. Among them, the Gradient boosting model achieved the highest prediction accuracy, with R^2 values above 0.94. The findings highlight that integrating hybrid nanofluids, additive manufacturing, and predictive modelling can lead to compact and energy-efficient cooling systems for modern power and electronic devices.

1 Introduction

As the miniaturization of high-power electronic devices continues, heat flux levels are becoming too high to be handled by conventional air and liquid cooling methods. Therefore, microchannel heat sinks (MCHS) have attracted interest as a solution due to their small and large surface-area-to-volume ratio [1]. However, manufacturing metallic microchannels using conventional machining is hampered by tool accessibility, accuracy and geometric

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flexibility [2]. To overcome this, additive manufacturing (AM), particularly Direct Metal Laser Sintering (DMLS), can be utilized to manufacture complex channel structures layer by layer, using alloys such as AlSi10Mg. However, the process, as a consequence of using non-fused powders and various layers, produces rough surface textures due to the different levels of fusion achieved [3]. While usually considered an imperfection, such textures can cause disturbances in boundary layers, which assist in convective heat transfer [4].

In parallel, the advent of nanotechnology has been found to increase cooling performance through the extension of nanofluids. Nanofluids are augmented with nanoparticles [5]. Hybrid nanofluids, which may consist of combinations such as Al_2O_3 and CuO, tend to favour thermally transmitting and convective behaviours due to increased Brownian motion and dispersion, showing Nusselt's numbers of 25-30% higher than usual under laminar flow conditions [6,7]. The combined effects of AM ruggedness and hybrid nanofluids on microscale heat transfer have not yet been investigated, providing a future dual benefit of wall-induced flow disturbances and those of nanoparticle-led heat enhancements.

In addition to experimental research, machine learning (ML) has emerged as a data-driven approach for modelling nonlinear correlations between heat transfer responses and operating factors. Even with small experimental datasets, regression-based machine learning algorithms have demonstrated remarkable predictive accuracy [8], enabling practical estimation of convective performance and nanofluid behaviour in microscale domains [9]. However, the integration of machine learning with experimental research using AM-fabricated microchannels and hybrid nanofluids remains limited.

This study addresses the research gap by integrating an experimental-computational framework that links AM microchannels, hybrid nanofluids, and ML-based prediction. Straight AlSi10Mg microchannels were fabricated by DMLS and characterized by SEM for surface morphology. Al_2O_3-CuO hybrid nanofluids at 0.02% and 0.05% volume concentrations in a water-EG (60:40) base fluid were tested under heat fluxes of 20-40 W/cm² and Reynolds numbers of 23 to 125. Performance parameters, including surface temperature, Nusselt number, friction factor, Pressure drop, and performance enhancement criteria, are evaluated. Additionally, Polynomial, Gradient Boosting, Random Forest, and Decision Tree regression models were employed on the dataset for predictive modelling. The novelty of this work lies in establishing the synergetic enhancement resulting from AM-induced surface roughness and hybrid nanofluid cooling, validated through machine-learning-assisted predictions for compact electronic cooling applications.

2 Experimental methodology

2.1 Microchannel fabrication and surface characterization

A straight microchannel heat sink was fabricated by DMLS on an EOS M290 system with AlSi10Mg alloy powder (k=110 W/mK, particle size 25-70 μm). The design consisted of 11 parallel channels (0.5 mm width, 0.3 mm fins) within a 10 × 10 × 8 mm³ block, printed with a 60 μm layer thickness in an argon-purged environment (<10 ppm O_2). Post-fabrication involved heat treatment at 284 °C for 90 min under argon improved metallurgical bonding and reduced surface asperities. Surface characterization using a 3D optical profilometer showed mean roughness values of Ra = 0.62 ± 0.04 μm (top face), 0.67 ± 0.05 μm (side walls), and 0.59 ± 0.03 μm (bottom face), resulting in an average Ra of 0.6 μm. The geometric specifications, SEM morphology, the fabricated MCHS, and the surface profile are presented in Figure 1(a-d).

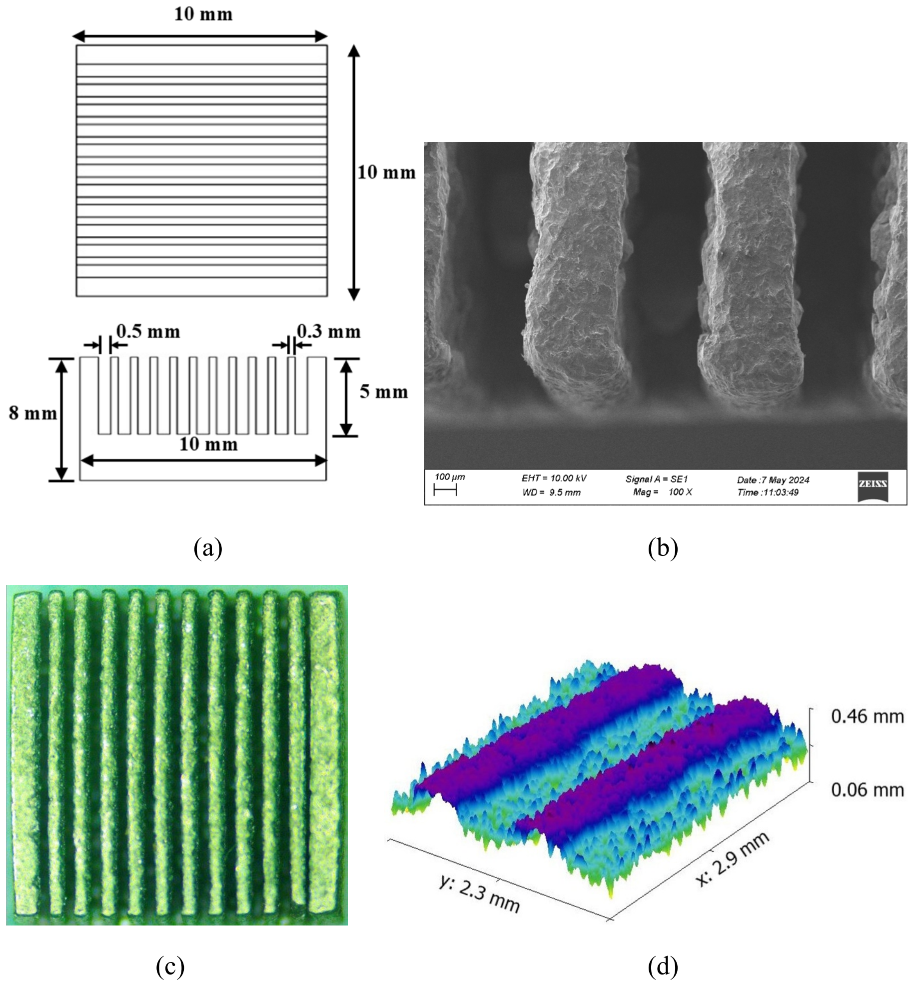


Fig. 1. (a) Geometric specifications of the MCHS, (b) SEM morphology of the microchannel surface, (c) Fabricated AM microchannel, and (d) Microchannel Surface roughness spectral image.

2.2 Hybrid nanofluid preparation and stability

Hybrid nanofluids were prepared by dispersing Al_2O_3 and CuO nanoparticles (mean diameter < 40 nm, spherical) in a 60:40 water-EG base fluid at 0.02% and 0.05% volume concentrations with equal mass fractions. A two-step method involving magnetic stirring for 120 minutes and ultrasonic probe sonication for 90 minutes ensured uniform dispersion. No surfactant was added to maintain base fluid properties. Zetapotential analysis confirmed stability, with measured values exceeding $\pm$30 mV. Representative stability results for the 0.05% hybrid nanofluid are shown in Figure 2.

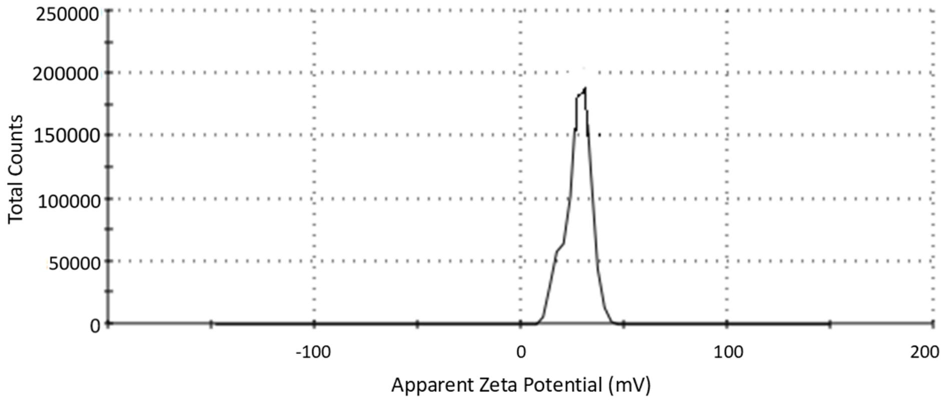
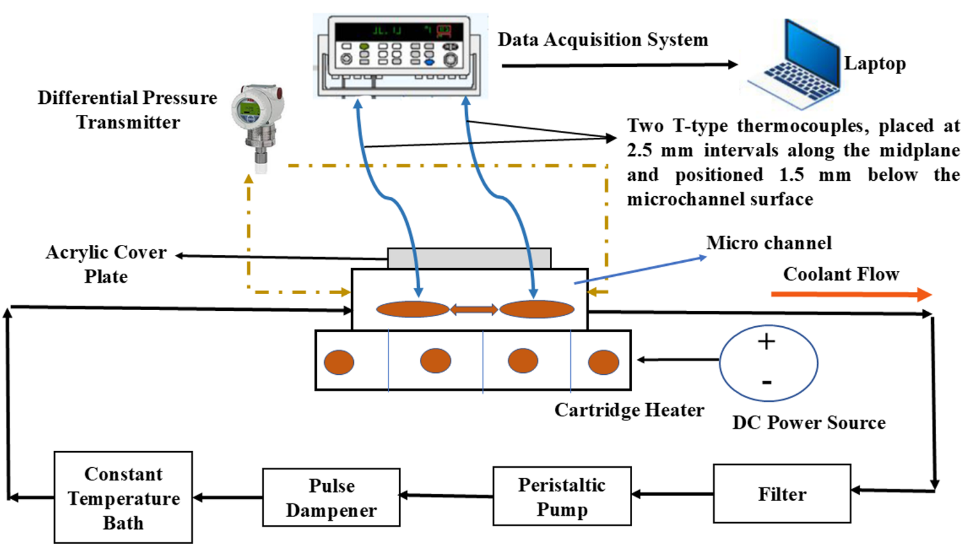


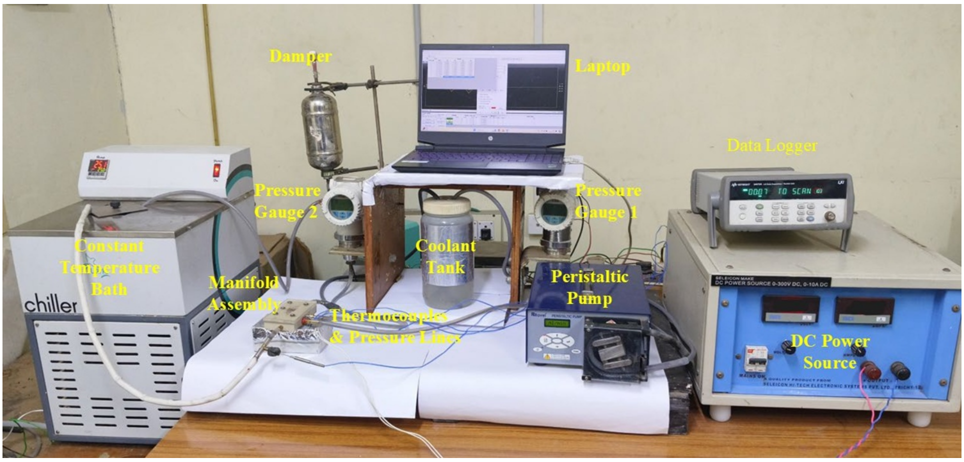
Fig. 2. Zeta potential analysis of 0.05% Al_2O_3-CuO hybrid nanofluid.

2.3 Experimental setup and operating conditions

The experimental facility consisted of a closed-loop cooling circuit with a peristaltic pump (0-999 ml/min) that delivered flow rates corresponding to a Reynolds number (Re) of 23-125. The microchannel block was mounted on a cartridge-heated base to impose uniform heat fluxes of 20, 30, and 40 W/cm^2. Thermal contact was ensured with thermal grease, and heat losses were minimized with glass wool insulation. T-type thermocouples recorded inlet, outlet and wall temperatures, while differential pressure transducers measured pressure difference across the channels. A data acquisition system logged real-time measurements. The experimental setup's schematic is shown in Figure 3 a and b.



(a)



(b)

Fig. 3. (a) Schematic diagram showing flow loop and measurement points (b) Photograph of test setup.

3 Machine learning framework

Machine learning is a data-driven approach used to model the complex, nonlinear relationship between thermal-hydraulic performance and flow and operating parameters. Channel type, Reynolds number, heat flux, and nanofluid concentration were selected as the input parameters in this research. Surface temperature and the Nusselt number were the output variables. Four types of regression models were tested: Polynomial Regression, Gradient Boosting (GBR) Regression, Random Forest (RF) Regression and Decision Tree Regression. Polynomial regression is used as a reference nonlinear model. Decision tree regression provided a basic, rule-based approach. The RF method uses multiple decision trees to reduce the risk of overfitting by averaging their outputs. GBR provides a successive build-up of decision trees, with each tree attempting to correct the error produced by the previous tree to improve prediction accuracy.

The dataset was split into an 80/20 ratio for training/testing. Cross-validation was employed to optimize the model parameters and ensure the reliability of the results. Prediction performance was analyzed using the coefficient of determination (R^2) and root mean square error (RMSE) as defined in Eq. (1) and Eq.(2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

Where y_i represents the experimental value, $\hat{y}_i$ and $\hat{y}$ denotes the predicted value and the mean of experimental values, respectively. These metrics enabled an objective comparison of model accuracy in predicting microchannel thermal-hydraulic behaviour.

4 Data reduction and uncertainty

4.1 Data reduction

The heat transfer rate was computed as,

$$Q = \dot{m}C_p(T_{out} - T_{in}) \quad (3)$$

The average heat transfer coefficient,

$$h_{avg} = \frac{Q_{actual}}{A_s \times (T_{wall} - T_{coolant})} \quad (4)$$

Where A_s = surface area, T_{wall}= wall temperature, and $T_{coolant}$= coolant bulk temperature.

Average Nusselt number,

$$Nu_{avg} = h_{avg} \times D_h \ / \ k_{coolant} \quad (5)$$

Reynolds number,

$$Re = \ \rho_{coolant} \times V_a \times \ D_h \ / \ \mu_{coolant} \quad (6)$$

Friction factor,

$$f = 2 \times \Delta p \times D_h / (L \times \rho_{coolant} \times {V_a}^2) \quad (7)$$

Performance evaluation factor,

$$PEC = (Nu_{Hnf}/Nu_{base-fluid})/\left(f_{Hnf}/f_{base-fluid}\right)^{(1/3)} \quad (8)$$

4.2 Uncertainty analysis

Uncertainties were estimated using the Kline-McClintock [10] method. Temperature measurements had an error of $\pm$0.5°C, a flow rate error of ±2%, and a pressure drop error of $\pm$1.5%. The combined uncertainties were $\pm$2.75% for the Nusselt number and $\pm$3% for the pressure drop, within acceptable limits for microchannel experiments.

5 Results and discussion

Figure 4-8 presents the experimental results for surface temperature, Nusselt number, pressure drop, friction factor, and performance evaluation criteria, as functions of Reynolds number at heat fluxes of 20, 30, and 40 W/cm². In all cases, the Al_2O_3-CuO hybrid nanofluids outperformed the base water-ethylene glycol mixture, with the 0.05% volume concentration showing the most pronounced effect. A 13.8% reduction in wall temperature was achieved compared to the base fluid at Re = 125 and a heat flux of 30 W/cm² (Figure 4). This improvement is attributed to enhanced thermal conductivity and micro-scale convection driven by nanoparticle dispersion and the intrinsic DMLS surface roughness (R_a = 0.6μm). The post-processing ensured that the surface roughness improved near-wall mixing without imposing excessive hydraulic resistance.

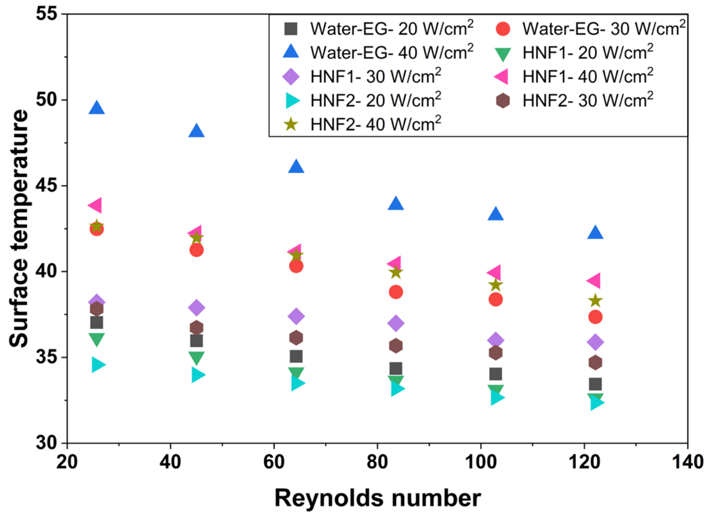


Fig. 4. Variation of surface temperature with Reynolds number for various coolants. (Higher Re and nanoparticle concentration decrease surface temperature through increased convective heat transfer).

As demonstrated in Figure 5, the Nusselt number improved for all fluids, with the hybrid nanofluid showing an increase of 12.9% at 30 W/cm². Further, flow expansion was limited by pressure losses, excessive heat loss, insufficient thermal growth, and varying viscosity. The pressure drop (Figure 6) increased slightly with the Reynolds number and particle loading in the fluid, reaching a maximum increase of 6.4% over the base fluid at low flow rates. Engineering connotations of this order of increase will be satisfactory for compact cooling devices, as a slight increase of 5-10% in pumping capacity will easily overcome the extra resistance without significant energy conservation consequences.

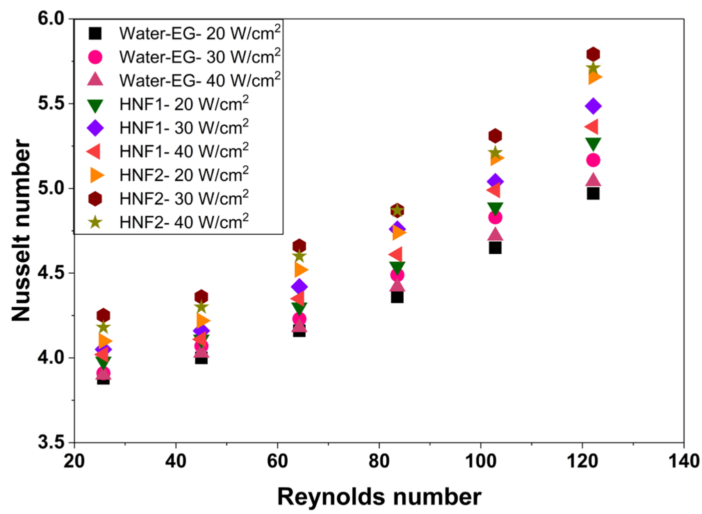


Fig. 5. Plot of Nusselt number vs Reynolds number for various fluids and heat fluxes. (An increase in Re leads to higher Nu, showing an enhancement of about 12.9% for the 0.05% hybrid nanofluid).

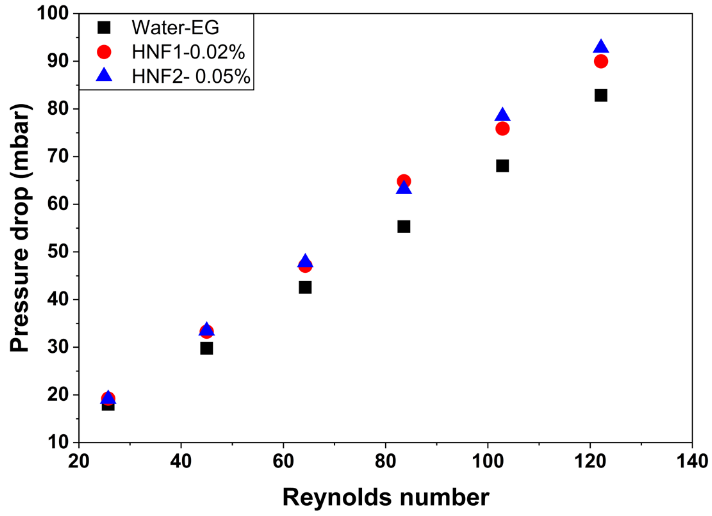


Fig. 6. The graph shows the relationship between pressure drop and Reynolds number for various fluids. (The pressure drop increases moderately because of higher viscosity and particle-wall interactions).

Additionally, the friction factor, calculated from Eq. (7), followed the anticipated decreasing trend with increasing Re (Figure 7); however, it remained slightly higher for nanofluids due to their enhanced viscosity. The PEC, obtained from Eq.(8) (Figure 8), consistently exceeded unity (1.00-1.10), confirming that the thermal benefit outweighed the hydraulic loss. The 0.05% hybrid nanofluid operating at 30W/cm^2 demonstrated the most favourable thermal-hydraulic balance. Overall, the results highlight the combined influence of additive-manufactured surface textures and the thermophysical behaviour of hybrid nanofluids, in which surface-induced flow disturbances and nanoparticle dispersion jointly enhance heat transfer while maintaining acceptable flow resistance.

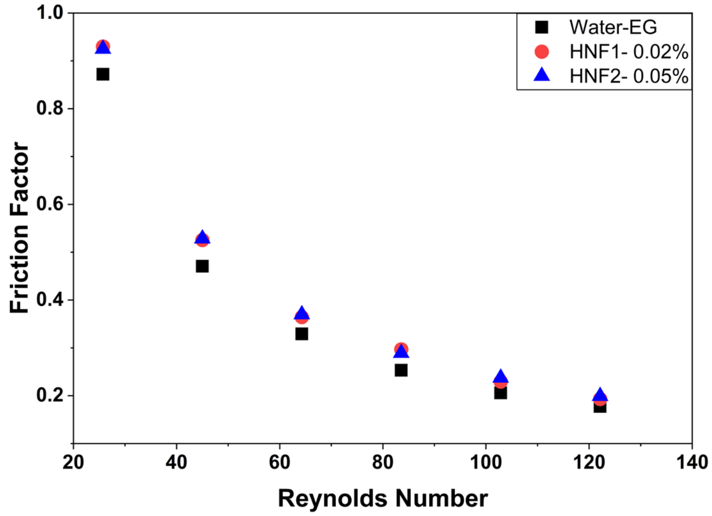


Fig. 7. Variation of friction factor with Re. (As Re increases, the friction factor decreases, but values remain comparatively higher for nanofluids because of their increased viscosity).

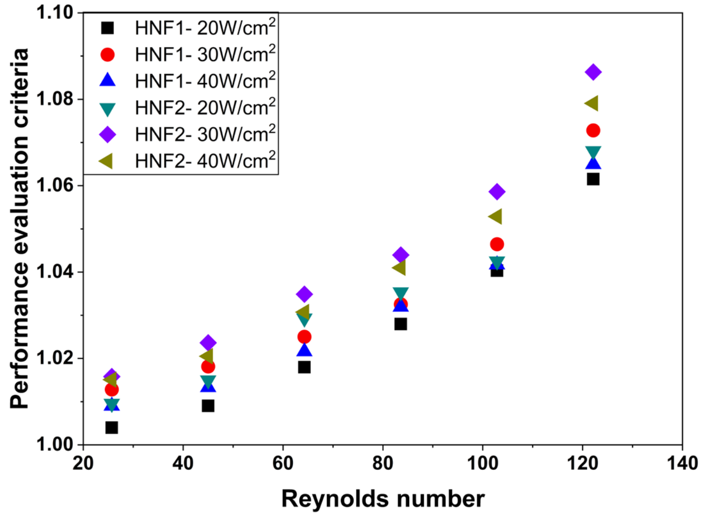


Fig. 8. Performance evaluation criteria as a function of Reynolds number. (PEC > 1 indicates that the improvement in heat transfer surpasses the associated rise in flow resistance).

To complement the experimental investigations, four regression algorithms, Polynomial Regression, Decision Tree, Random Forest, and Gradient boosting were developed to predict the thermal-hydraulic performance of DMLS-fabricated microchannels using mass flow rate, heat flux, and nanofluid concentration as inputs, and surface temperature and Nusselt number as outputs (Figure 9 - Figure 13). All models effectively reflected experimental trends with R^2 values above 0.90, while ensemble methods, especially Gradient Boosting, delivered the best accuracy ($R^2 > 0.94$) owing to their strength in capturing nonlinear interactions. Pair plots and scatter plots (Figure 9 – Figure 12) showed clear correlations among parameters and close agreement between predicted and measured values, confirming reliable performance. Furthermore, beyond 40 training data points, the learning curve (Figure 13) demonstrated that the model was stable and had sufficient information to generalize from the 54-sample dataset. While additional training data may increase the model's accuracy, it is clear that Gradient Boosting models can be quite stable even when trained on relatively few data points, making them suitable for small experimental datasets common in heat transfer research, as outlined in Table 1.

Table 1. Performance analysis of machine learning models in predicting Nusselt number and surface temperature.

Model	**Hyperparameters**	**CV folds**	**Metrics**	**Nusselt number**	**Surface temperature**
Polynomial Regression	Degree=3	5	RMSE	0.045	0.901
			R^2	0.988	0.901
Decision Tree Regression	max_depth = 6	5	RMSE	0.107	0.865
			R^2	0.937	0.908
Random Forest Regression	n_estimators = 100, max_depth = 8	5	RMSE	0.094	0.831
			R^2	0.952	0.915
Gradient Boosting Regression	n_estimators = 200, learning_rate = 0.05, max_depth = 4	5	RMSE	0.045	0.660
			R^2	0.989	0.946

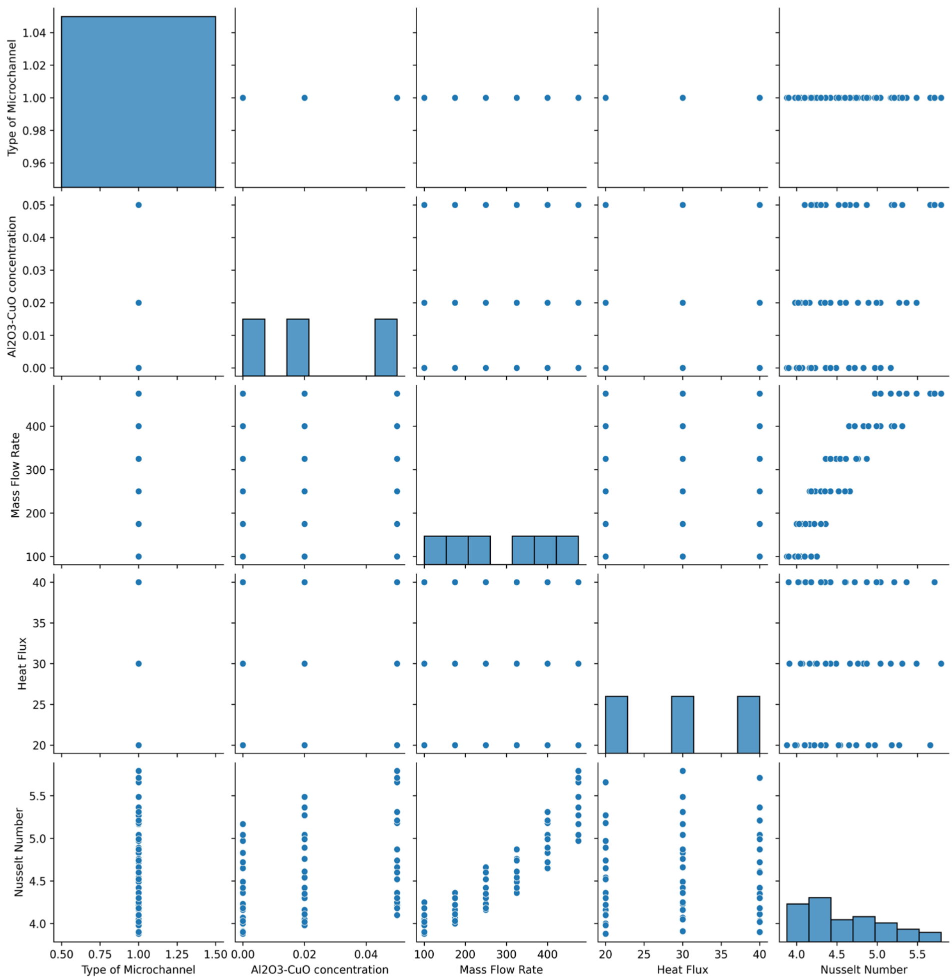
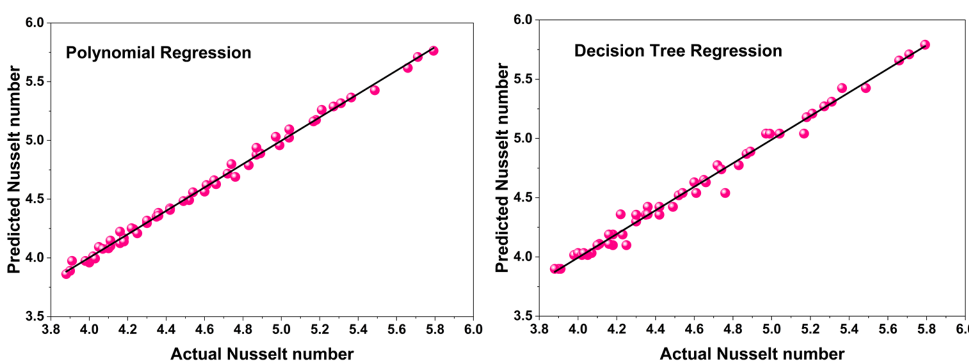


Fig. 9. Pair plot for Nusselt number distribution (Positive correlation observed between Nusselt number and Reynolds number).



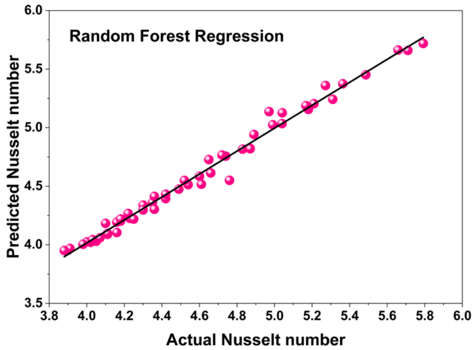


Fig. 10. Predicted vs experimental Nusselt number (Close alignment along the regression line demonstrates higher model accuracy).

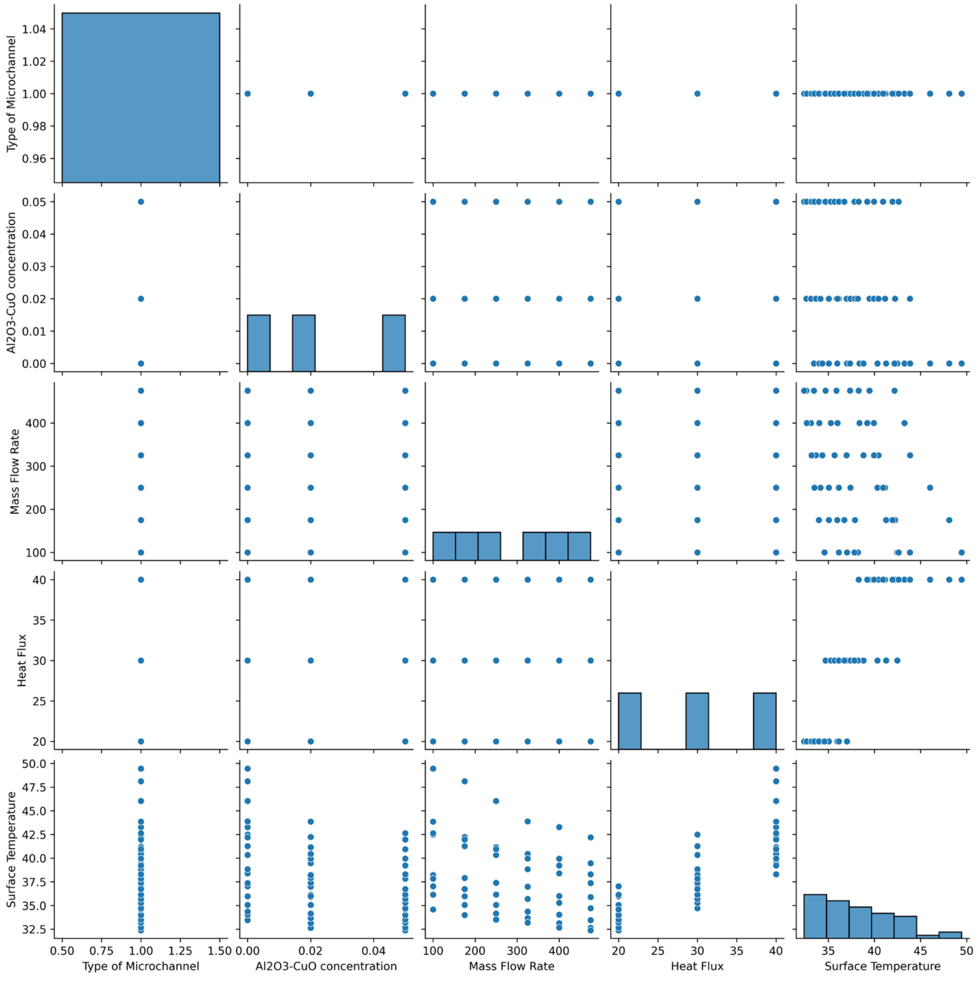


Fig. 11. Pair plot for Surface temperature (Inverse correlation was observed between Reynolds number and Surface temperature).

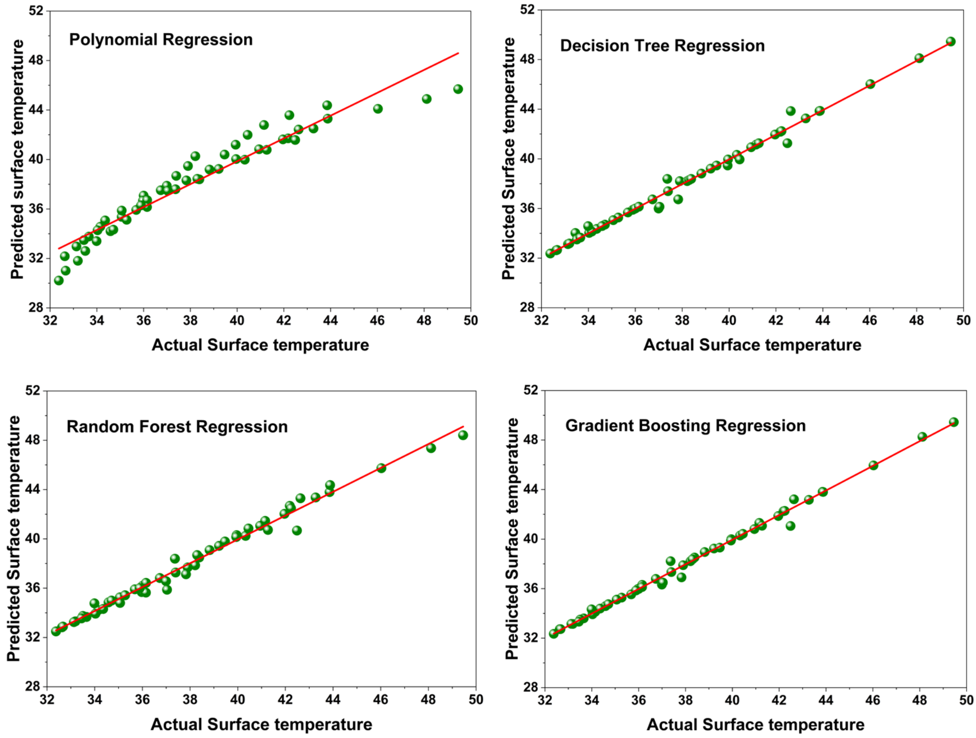


Fig. 12. Predicted vs experimental surface temperature (Minimal scatter indicates consistent predictive fidelity across all models).

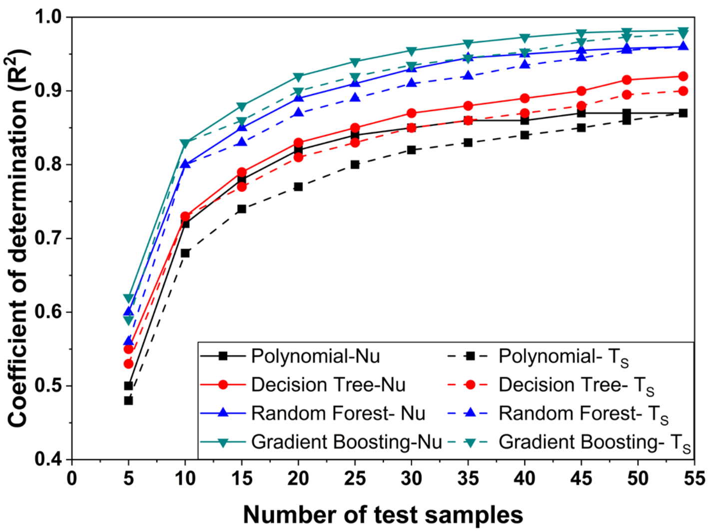


Fig. 13. Learning curves for predicting Nusselt number and surface temperature (Gradient Boosting shows better convergence for 54 data samples, indicating good data efficiency).

6 Conclusion

The research showed that straight microchannel by Direct Metal Laser Sintering had better thermal-hydraulic performance when working with Al_2O_3-CuO hybrid nanofluids. The combination of the surface roughness created by additive manufacturing, and the improved thermophysical properties of the nanofluids resulted in 13.8% decrease in surface temperature and a 12.9% increase in the Nusselt number, while only a 6.4% increase in the pressure drop occurred at 0.05% concentration, and 30 W/cm² heat flux. The indicates that the performance evaluation criteria (PEC > 1) show that there is an acceptable trade-off between heat transfer enhancements, and pumping penalty, and therefore it would be practical to operate these compact cooling systems efficiently. Reesults from machine learning support this observation and, as expected, the best prediction model for the thermal behaviour over different floe rates and concentrations was achieved by Gradient Boosting Regression (R^2 > 0.94).

While the outcomes are promising, limitations such as the small dataset and the exclusion of temperature-dependent properties or nanoparticle deposition effects remain. Future work should address these aspects through extended testing, in-situ visualization, and larger datasets to strengthen model generalization and enable adaptive cooling solutions for advanced thermal management applications.

This research was carried out in the Research Laboratory of the Department of Mechanical Engineering, National Institute of Technology, Tiruchirappalli.

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