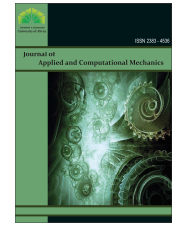




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Research Paper

Advanced Machine Learning Driven Optimization of Radiator Heat Exchanger Performance for Automotive Applications

Faizan Ahmed^{1,2}, Hiren Mewada³, Nayeemuddin Mohammed⁴

¹ Department of Mechanical Engineering, Prince Mohammad Bin Fahd University, Al Khobar 31952, Saudi Arabia

² Center of Environment and Water Solutions (CEWS), Prince Mohammad Bin Fahd University, Al Khobar 31952, Saudi Arabia

³ Department of Electrical Engineering, Prince Mohammad Bin Fahd University, Al Khobar 31952, Saudi Arabia

⁴ Department of Civil Engineering, Prince Mohammad Bin Fahd University, Al Khobar 31952, Saudi Arabia

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✉ Corresponding author: F. Ahmed (fahmed@pmu.edu.sa)

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Abstract. In this research, response surface methodology (RSM) based experimental investigation coupled with three machine learning techniques namely, Bagging (Bootstrap Aggregating), Categorical Boosting (CatBoost) and Random Forest (RF) are employed to optimize and model the performance of a radiator. Model development is performed by collecting experimental data by varying hot water flow rate (0.5-2.5 l/min), cold air velocity (1-5 m/s) and feeding temperature (50-60 °C). The best radiator effectiveness was figured out to be 71.9%. The model RSM was found to be capable of predicting effectiveness with a coefficient of determination (R^2) of 0.966 as compared to Bagging, CatBoost and RF techniques with an R^2 of 0.99, 0.99 and 0.98, respectively. The Mean Squared Error (MSE) of Bagging, CatBoost and RF techniques were found as 6.242, 2.876 and 8.837, respectively while the Root Mean Squared Error (RMSE) for Bagging, CatBoost and RF techniques were found as 2.498, 1.696 and 2.973, respectively. The CatBoost model emerged as the best model because it had the highest coefficient of determination, along with the lowest mean square error and root mean square error. SHapley Additive exPlanations (SHAP) analysis indicated that the ML models relied most heavily on feed temperature (mean |SHAP| of 10.23, 9.65 and 6.67 for Bagging, RF and CatBoost, respectively), whereas ANOVA of the RSM model identified air velocity and water flow rate as the statistically significant factors. The reasons for this difference are discussed. This research highlights the importance of a data-driven approach to optimizing and modeling radiators.

Keywords: Optimization, Response surface methodology, Machine learning, Modeling, Radiator heat exchanger.

1. Introduction

Heat exchangers have become a critical component in a wide range of heating and cooling systems such as automotive radiators, heating, ventilation, and air conditioning (HVAC) units, cooling systems and industrial process plants. Radiators are superior in comparison to the classic tube heat exchangers because of their compact design, excellent heat transfer effectiveness, easy maintenance and adaptability [1]. Radiators promote thermal exchange between the hot fluid and ambient air through increased surface area and improved flow channels, keeping operating temperatures within safe and effective bounds [2]. Modern radiators are frequently made out of materials with high thermal conductivity. The materials used are typically copper or aluminum and are typically in fin and tube, or plate-fin design configuration to maximize convective heat transfer. Moreover, machine learning-driven prediction combined with RSM optimization has recently proven effective for energy-related systems [3]. However, the thermal performance of the radiator is highly sensitive to various operating factors such as flow rate, feeding temperature, geometry and flow configuration. In complex applications such as electronic and automotive cooling systems, the performance of a radiator affects overall energy effectiveness, system dependability, and thermal stability under different operating conditions [4]. Some researchers optimized a wavy fin-and-elliptical tube heat exchanger using CFD simulation combined with a radial basis function and a multi-objective genetic algorithm [5], and a similar approach was applied to optimize the thermal and flow characteristics of a plate heat exchanger [6]. In another study, iron oxide nanofluid was the most efficient nanofluid in a heat exchanger that used several nanofluids to enhance the transfer of heat. The nanofluids resulted in a decrease of 10.1% in pressure and 21.9% increase in heat transfer. For performance prediction of heat exchangers, empirical Nusselt correlations have also been developed [7].

Some scientists developed a model that has been validated across various radiator types and applications. Their results lead to improvement in design of radiators [8]. A newly developed model for radiator, namely, extended heat transfer model overcomes the limitations of the standard models at low water flow rates. It provides excellent predictions of heat output from radiators for a variety of operating conditions [9]. Few scholars developed an analytical model for the automotive radiators, considering the



difference between the heat transfer coefficient in the water side of the radiator and the air side. The model accounts for the variation in the flow regime and the model is able to accurately predict the thermal output of round and oval tube radiators without any empirical correlation [10]. This method is an acceptable substitute for extensive testing of the design of heat exchangers and has been validated against experimental designs [11]. Plate-fin heat exchangers have also been optimized for heat dissipation in thermoelectric coolers [12]. Some scientists fabricated and tested a novel polymeric hollow fiber heat exchanger for automobiles; it performed 20% better and weighed 30% less than a conventional aluminum radiator, with a greater air-side pressure drop but similar liquid-side pressure losses [13]. Similarly, researchers modelled the thermal conductivity of MWCNT/water nanofluids as a function of temperature and particle concentration using response surface methodology (RSM), verified the model by analysis of variance (ANOVA), and obtained maximum thermal conductivity at 60 °C with an R^2 of 0.98; the nanofluid showed great potential for solar thermal and hybrid photovoltaic/thermal applications [14]. RSM with CCD has also been used to design and optimize a concentrated solar powered flash desalination system [15], and the integration of renewable energy into thermal desalination technologies has been reviewed [16]. Experimental and computational analysis has likewise been combined to optimize seawater treatment processes [17]. Artificial neural networks have been employed to predict the heat transfer and thermo-hydraulic performance of a solar air-heater tube with high accuracy, providing an effective design tool for thermal engineers [18]. Another study examined heat pipes filled with nanofluids at different inclination angles and filling levels [19], while a TiO_2 nanofluid doped with Al_2O_3 was shown to synergistically enhance the thermal performance of a closed two-phase thermosyphon [20].

Similarly, RSM was used in another study that involved semi-circular heat pipes integrated with V-grooved absorbers. These absorbers enhanced the heat transfer and effectiveness [21]. Deep learning with a multilayer perceptron has been used to optimize mixed convection heat transfer of MWCNT–water nanofluid [22]. Multi-layer perceptron and radial basis function networks were also developed to predict heat transfer in a mini-channel heatsink with alumina/water nanofluid, where the optimized radial basis function network achieved errors below 2% and outperformed the multi-layer perceptron, showing that artificial neural networks can reduce experimental burden [23]. Therefore, the development of accurate prediction models and optimization methods is essential to increase energy effectiveness, reduce operational costs and ensure reliable heat management in dynamic application environments [24, 25]. This work is directed towards the design and test of hybrid optimization and performance prediction of radiators. A central composite design-based experimentation is performed for obtaining training and validation data sets. The characteristic variables are also changed like the hot and cold fluid flow rates, and the feed temperatures in the design of experiments. At each setting of the factors, the effectiveness of the radiator is then measured. The underlying polynomial regression model and best factor levels are obtained by a response surface methodology. In addition, the nonlinearities are compared to each other, and the reliability of the predictions is also compared to using machine learning (ML) techniques: Bagging, Categorical Boosting (CatBoost) and Random Forest (RF). Performance measure such as R^2 , Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are used to evaluate and compare all the developed models. This research highlights the importance of data driven approach for optimization and modeling of radiator heat exchanger systems.

1.1. Objectives of this study

The main objectives of this study are:

- To experimentally investigate and optimize the performance of radiator heat exchanger by utilizing RSM with central composite design (CCD) approach.
- To develop predictive models based on advanced ML techniques namely, Bootstrap Aggregating, CatBoost and RF.

1.2. Research gap and novelty

Very few simplistic models are developed on radiator heat exchanger. Furthermore, the traditional modelling approaches are still largely based on empirical correlations, and the commonly used analytical models have the drawback of being too simple to describe the complex nonlinear relationship among the important operating parameters. Only a handful of past studies have addressed the importance of using artificial intelligence to develop prediction models for radiators. There is a lack of integrated frameworks that integrate RSM with advanced ML techniques, namely Bootstrap Aggregating, Categorical Boosting, and RF, to design, analyze, optimize, and accurately predict the performance of automotive radiators. Most prior studies have not considered the interaction between statistical design-of-experiments modeling and ML methods for predicting and optimizing radiator performance.

This study aims to fill this gap by developing a hybrid modeling approach that integrates RSM- CCD with advanced ML techniques to predict and optimize radiator performance. The goal is to verify and justify that ensemble models have greater prediction accuracy and robustness, especially under complex and variable input conditions. The overall contributions of the paper are as follows:

- Prior studies used a single ML model or a single optimization framework. This paper presents an integrated approach using RSM with optimized Bagging, CatBoost, and RF models.
- The ML models' performance highly depends on the combination of hyperparameters. Manual tuning does not guarantee optimal performance. Therefore, the grid search algorithm identifies the optimal parameter combination.
- To address overfitting, the proposed approach used 5-fold cross-validation ensuring model stability. CatBoost performed best overall, with consistent R^2 scores across folds and the lowest MSE and RMSE.
- This method enables high-precision modeling, enhances energy efficiency, and promotes intelligent thermal management strategies for automotive applications.

2. Experimental Setup

The experimental setup of the radiator heat exchanger is shown in Fig. 1(a). The system comprises three parts: the base unit, the radiator heat exchanger unit and the data monitoring computer interface system. The base unit consists of the hot water tank with an integrated electric heater (1), pressure regulator (2), pump (3), bypass valves (4, 5), flow sensors (6, 7) and flow valves (8, 9). The radiator heat exchanger unit consists of the tunnel housing the fan (10) and radiator (11), flow valves (12), thermocouples at the water inlet and outlet (13, 14), thermocouples at the air inlet and outlet (15, 16), and the air velocity sensor (17).

The radiator is stationed in the center of the tunnel. Additionally, fins are attached on the outer surface of radiator to enhance heat transfer. The hot fluid inlet and exit temperatures are measured by two thermocouples placed at inlet and exit of the radiator during the operation. Two other thermocouples are also located at the inlet and exit of the tunnel so that cold fluid inlet and exit temperatures can be measured during the tunnel operation. A velocity sensor is also positioned at the exit of the tunnel to measure the air velocity. A suction type of fan is mounted at the inlet of the duct to suck air and move it through the tunnel. As the air moves inside the tunnel, it flows over the radiator tubes, exchanges heat with the hot fluid and then exits the tunnel from the



other end. This facility allows for examining the heat transfer while the fluids move in orthogonal direction in a crossflow pattern. The hot fluid in this arrangement is water while the cold fluid is air. The two fluids are non-mixing types during the operation. The hot fluid circulates within the tubes of the radiator, and the cold air circulates over the surface of the radiator tubes. Thus, the heat transfer between the two fluids occurs in the surface of the radiator by means of convection mode of heat transfer. The engineering application considered in this study is the automotive engine cooling circuit shown in Fig. 1(b). The coolant absorbs heat from the engine block and is circulated by the water pump through the thermostat to the radiator, where the heat is rejected to the ambient air drawn through the radiator core by the cooling fan. Inside the radiator, the hot coolant flows through the tubes while the air flows across the aluminum fins in a perpendicular direction, forming a crossflow heat exchanger in which both fluids are unmixed. The thermal performance of the radiator governs the engine operating temperature and depends on the coolant flow rate set by the water pump, the air velocity set by the vehicle speed and fan operation, and the coolant inlet temperature set by the engine load. The experimental facility and the process are represented in the schematic of Fig. 2. Table 1 shows the specification of the experimental setup, grouped by function of each component.

The experiments were performed by varying hot water flow rate, cold airflow rate, and feeding temperatures. The water pump and the fan were controlled by means of the supervisory control and data acquisition (SCADA) computer interface that allowed data monitoring and recording. The water pump speed and fan speed were varied through the interface to achieve variations in the flow rates of both fluids. The feeding temperatures were varied by means of an electric heating element placed inside the heating tank. The effectiveness of the heat exchanger was the targeted output from the system. Using RSM and Design Expert software, various combinations of input factor settings were tested, as suggested by the software and subsequently the targeted output was computed using measurements from various temperature sensors and flow sensors corresponding to both the fluids.

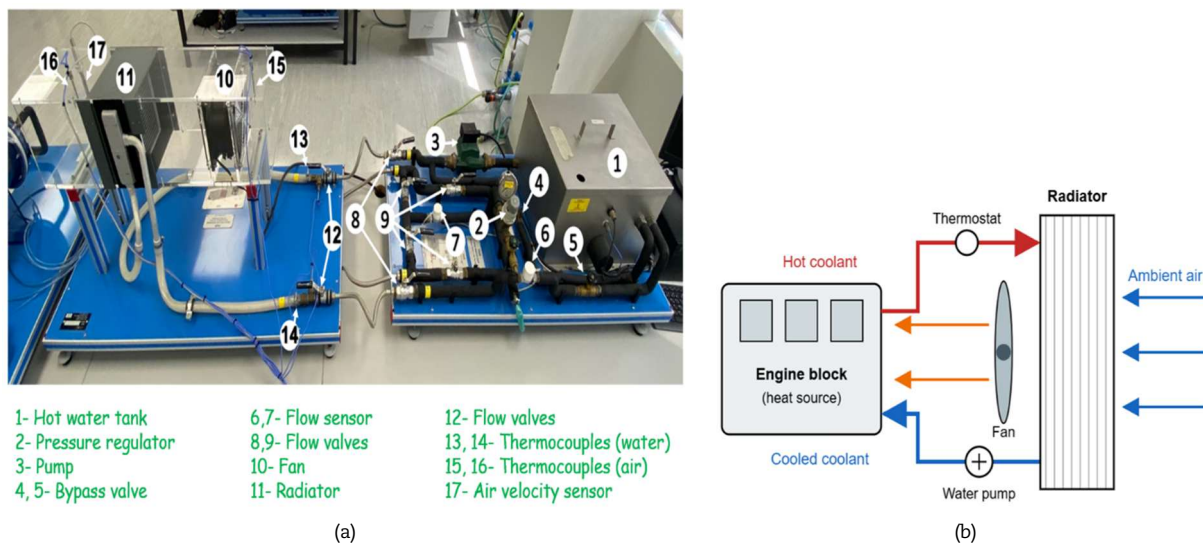


Fig. 1. Configuration of the considered system: (a) Experimental setup of the radiator heat exchanger with its main components; (b) Schematic of the automotive engine cooling circuit, showing the engineering application of the radiator.

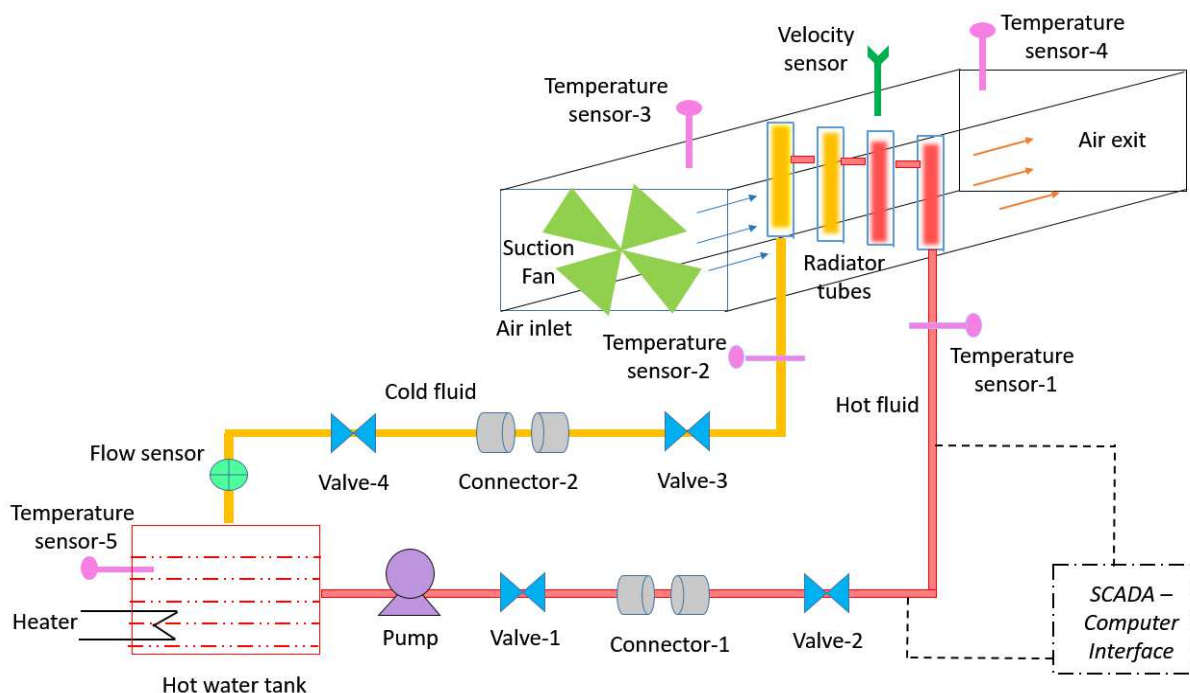


Fig. 2. Schematic of process and facility.



Table 1. Specifications of the experimental setup (grouped by function).

S. No	Subsystem	Component / Parameter	Specification
1	Water circuit	Feed tank	Stainless steel, 30 L, 3000 W (input)
2	Water circuit	Water pump	0–3 L/min
3	Water circuit	Regulation valve	0.7 bar (maximum pressure)
4	Water circuit	Flow valves (base unit)	6 valves
5	Water circuit	Valves (heat exchanger unit)	2 valves
6	Water circuit	Connecting tubes	4 tubes
7	Heat exchanger	Duct material	Poly-methyl methacrylate (PMMA)
8	Heat exchanger	Fin material	Aluminum
9	Heat exchanger	Heat transfer area	35,000 mm ²
10	Heat exchanger	Dimensions	800 × 200 × 200 mm
11	Air side	Fan flow rate	0–500 m ³ /h
12	Instrumentation	Flow sensors	2 sensors; range: 0–5 L/min; accuracy: ±1.25%
13	Instrumentation	Thermocouples	4 sensors (Type-J); range: 0–550 °C; accuracy: ±1.5 °C
14	Instrumentation	Air velocity sensor	0–6 m/s

3. Methodology

In this study, RSM and ML techniques namely, Bagging, CatBoost and RF techniques were employed for the design of experiments, modeling, analysis, optimization and prediction of radiator effectiveness.

3.1. Response surface approach

Inside the domain of RSM, CCD method with randomized option, polynomial analysis and quadratic design model is employed. RSM with CCD is a statistical technique which adopts systematic approach for modelling and analysing a problem involving several independent variables that affect a response of interest. It is applied to optimise processes, by studying the interaction of multiple input variables and a desired output (response), especially second order models of the response surface, which can be used to determine optimum settings for the input variables. In the present study there are three independent variables namely: Water flow rate, air velocity and feeding temperature. The dependent variable is radiator effectiveness. Eq. (1) is employed to calculate the number of experimental runs for the design of experiments and analysis of dependent variables. Eq. (2) is a polynomial quadratic equation, which is employed to develop the model in actual and coded terms:

$$N = 2^k + 2k + n_c \quad (1)$$

where, N is the number of experimental runs, k is the number of factors and n_c is the number of centers, one also has:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_k x_k + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{kk} x_k^2 + \beta_{12} x_1 x_2 + \beta_{(k-1)k} x_{k-1} x_k \quad (2)$$

where,

y is the predicted response variable or dependent variable;

β_0 is the intercept (constant term) form;

β_1, β_2 to β_k are the linear effect coefficient of factor x_1, x_2 , to x_k ;

β_{11}, β_{22} to β_{kk} are the quadratic effect coefficient of factor;

β_{12}, β_{13} to $\beta_{(k-1)k}$ are the interaction effect coefficient between factors;

x_1, x_2 to x_k are the independent variables;

k is the number of factors in the model.

Equation (3) represents the effectiveness of radiator heat exchanger. However, based on the properties of the hot and cold fluid, Eq. (4) or Eq. (5) serves for computation of the radiator effectiveness:

$$\varepsilon = \frac{Q_{actual}}{Q_{maximum}} \quad (3)$$

If $m_h C_{p,h} < m_c C_{p,c}$:

$$\varepsilon = \frac{T_{h,i} - T_{h,o}}{T_{h,i} - T_{c,i}} \quad (4)$$

If $m_c C_{p,c} < m_h C_{p,h}$:

$$\varepsilon = \frac{T_{c,o} - T_{c,i}}{T_{h,i} - T_{c,i}} \quad (5)$$

where,

Q indicates heat transmission, W;

ε represents effectiveness;

m_h and m_c are flow rates (hot/cold fluid), kg/s;

$C_{p,h}$ and $C_{p,c}$ are specific heats (hot/cold fluid), J/kgK;

$T_{h,i}$ and $T_{c,i}$ are inlet temperatures (hot/cold fluid), °C;

$T_{h,o}$ and $T_{c,o}$ are exit temperatures (hot/cold fluid), °C.

3.2. Machine learning approaches

The methodologies of the three ML techniques namely, Bagging, CatBoost and RF are presented in the following sub sections.



3.2.1. Bagging technique

ML with Bootstrap aggregating, also known as bagging, is an ensemble learning technique that decreases variance, overfitting, and error while increasing accuracy and stability of ML models. In this technique, a separate model is trained on each subset, then, these individual predictions are combined into the final prediction using majority vote for classification or averaging for regression. Equations (6), (7) and (8) illustrate the concepts of the bootstrap aggregating Bagging method. The Bagging technique involves generating numerous training subsets by randomly selecting data points with replacement from the same original dataset. To make the model more robust and to make the model generalizable, M different bootstraps samples are used which have redundant data across samples. A base estimator (x), such as a decision tree, is trained separately on each resampled dataset. The combination of all results produces the final ensemble forecast. Figure 3 illustrates the detailed process of Bagging ML technique [26]:

$$S = \{(Y_i, X_i): i = 1, \dots, n\} \quad (6)$$

$$S_m^* = \{(Y_i^*, X_i^*): i = 1, \dots, n^*\}, \quad m = 1, \dots, M. \quad (7)$$

$$\hat{f}(x) = \frac{1}{M} \sum_{m=1}^M \hat{f}_m(x) \quad (8)$$

3.2.2. CatBoost technique

CatBoost is an ML technique that enables computers to learn from data in order to draw reliable conclusions or predictions. The "Cat" in "CatBoost" indicates that CatBoost can work with both numbers and categories. CatBoost can be used for a variety of tasks such as estimating price, detecting patterns, and gaming. It has extensive network as depicted in Fig. 4. Equation (9) provides training dataset for CatBoost while Eq. (10) aims to construct a strong predictor:

$$S = \{(x_i, y_i)\}_{i=1}^n \quad (9)$$

$$\widehat{F}_t(x) = \widehat{F}_{t-1}(x) + \eta f_t(x) \quad (10)$$

3.2.3. Random Forest technique

RF is a versatile technique that works on a wide range of problems in data science such as classification, regression, non-linear, non-parametric and high dimensional, numerical and categorical variables with no special requirements for the data used. It does not involve any distribution assumptions or standardizing of the input features. Figure 5 illustrates the framework of RF technique. Equation (11) enables predicting experimental data using RF technique:

$$\hat{f}(x) = \frac{1}{M} \sum_{m=1}^M f_m(x) \quad (11)$$

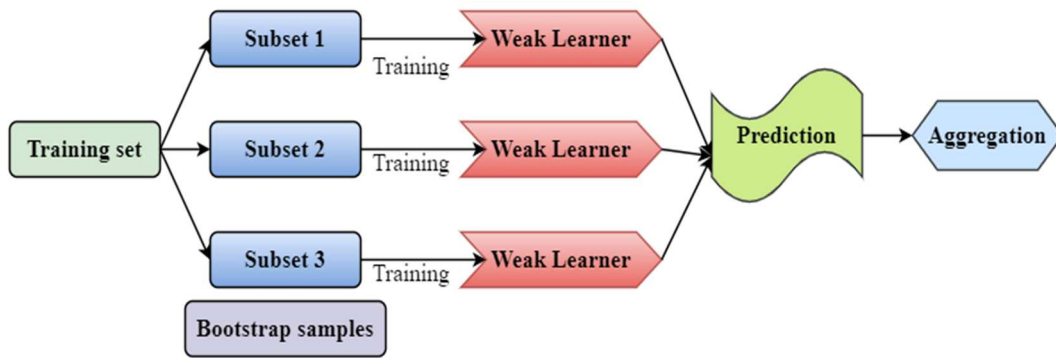


Fig. 3. Bagging technique of ML.

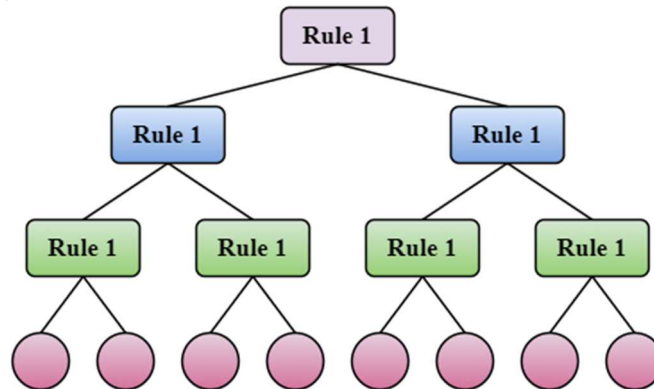


Fig. 4. CatBoost method of ML.



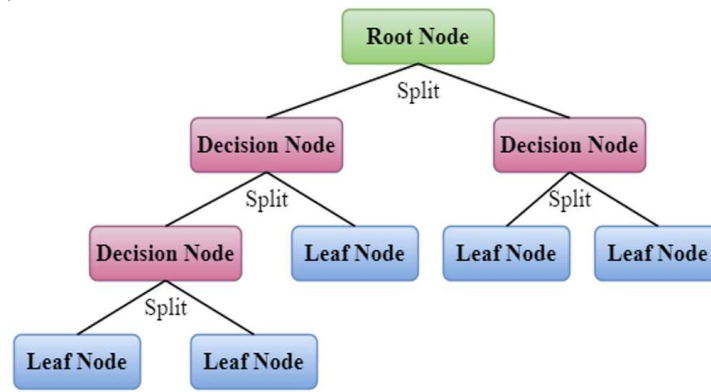


Fig. 5. RF method of ML.

4. Results and Discussion

4.1. Response surface approach

The statistical analysis of the results obtained by ANOVA is shown in Table 2. In this analysis, the terms A, B and C denote water flow rate (l/min), air velocity (m/s) and feed temperature (°C), respectively. According to the model, the F-value is determined to be 22.11, which implies that the model is significant. The probability of the F value being this large due to noise is only 0.02%. The p-value for the model is < 0.050. This means that the model is significant. Further, the significant model terms are A, B, and AC. The p-values greater than 0.05 indicates the model terms are not significant. Furthermore, the lack of fit F-value is 1.89 which is not significant with respect to the pure error. The ANOVA results indicate that the linear terms A and B and the interaction term AC have p-values below 0.05 and are therefore statistically significant for the response variable, whereas the remaining terms are not significant at the 95% confidence level. The regression model is reliable and is suitable for the experiment data. Factor B had the greatest sum of squares (2760.70), F-value (135.03) and p-value (< 0.0001) and thus was the most important factor affecting the response [27]. Factor A was also found to be significant (F value of 43.39, p value of 0.0003). In contrast, the main effect of feed temperature (factor C) was not significant (F value of 0.0021, p value of 0.9647) within the investigated range of 50–60 °C. However, factor C was retained in the model to preserve model hierarchy, since its interaction with water flow rate (AC) was significant. Also, the term AC was statistically significant with p value 0.0249 depicting significant synergistic effect of factors A and C. The AB and BC interactions were not significant at the 95% confidence level (p value of 0.0894 and 0.1305, respectively), although AB was significant at the 90% level. All quadratic terms (A², B² and C²) have high p-values (0.1633, 0.2146 and 0.4710) suggesting that they are not statistically significant. The residual sum of squares was relatively small (143.11) and the Lack-of-Fit Test was not significant (F value of 1.89, p value of 0.3813) which shows that the model fits the data well. When there is a difference between the actual results it is from pure experimental errors and not from failing of the model. Hence the regression is statistically sound, and the impact of the regression is the highest for the factors A and B. The non-significant lack of fit further confirms the validity of the prediction model in the investigated design space [28].

The model can be written in terms of coded factors as shown in Eq. (12) and can be used to predict the response at a set level of each factor. The default coding is that a high value is coded as +1, while a low value is coded as -1. The coded equation can be used for comparison of the factors' coefficients to determine the relative influence of the factors. The levels for each factor are to be expressed in the units used in the experiment. The factors are scaled by their units when they are used in calculating the coefficients. Equation (13) presents the model in terms of actual values for various factors:

$$Response = 41.70 + 8.06A - 14.22B + 0.0567C - 3.15AB + 4.55AC + 2.74BC + 2.10A^2 + 1.84B^2 - 1.03C^2 \quad (12)$$

$$Response = 48.13302 - 43.53115A - 22.55933B + 2.34029C - 1.57500AB + 0.90950AC + 0.27375BC + 2.09763A^2 + 0.459442B^2 - 0.041041C^2 \quad (13)$$

Table 2. ANOVA results.

Source	Mean square	Degree of freedom	Sum of squares	F-value	p-value	
Model	452.08	9	4068.68	22.11	0.0002	significant
A	887.03	1	887.03	43.39	0.0003	
B	2760.70	1	2760.70	135.03	< 0.0001	
C	0.0438	1	0.0438	0.0021	0.9647	
AB	79.38	1	79.38	3.88	0.0894	
AC	165.44	1	165.44	8.09	0.0249	
BC	59.95	1	59.95	2.93	0.1305	
A ²	49.60	1	49.60	2.43	0.1633	
B ²	38.07	1	38.07	1.86	0.2146	
C ²	11.87	1	11.87	0.5805	0.4710	
Residual	20.44	7	143.11			
Lack of Fit	23.62	5	118.11	1.89	0.3813	not significant
Pure Error	12.50	2	25.00			
Cor Total		16	4211.79			



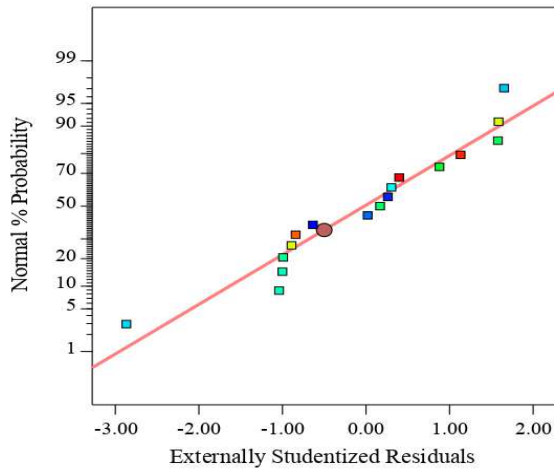


Fig. 6. Normal plot of externally studentized residuals.

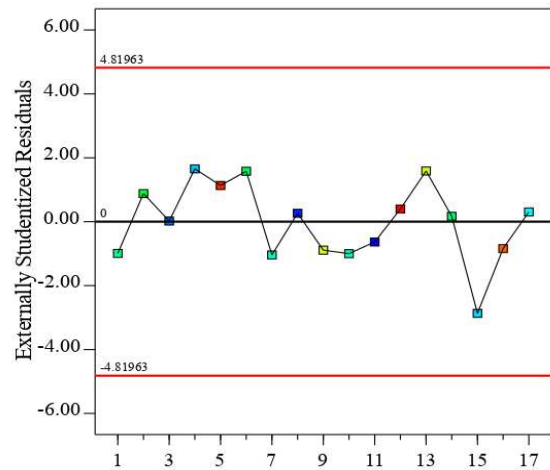


Fig. 7. Variation of residuals with experimental runs.

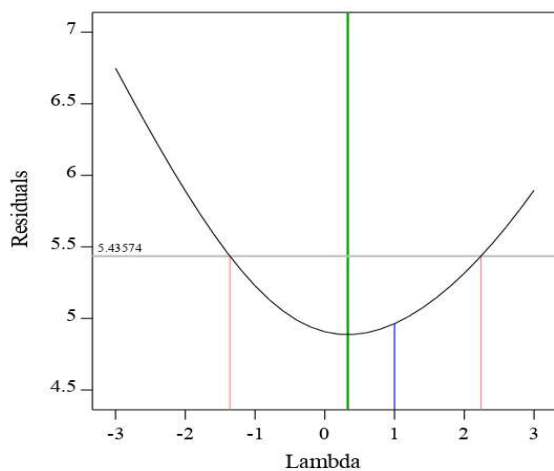


Fig. 8. Box-Cox transformation plot.

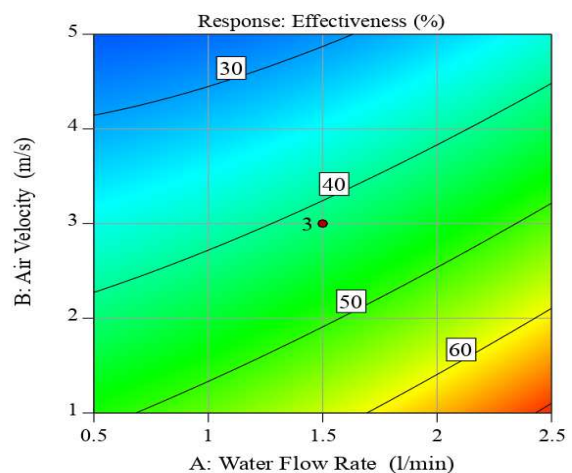


Fig. 9. Contour plot of effectiveness.

Figure 6 shows the normal probability plot of externally studentized residuals for the test of the normality of the residuals assumed in the regression model. The data points align close to the theoretical line, which are typical for residuals of a normal distribution. It confirms that the residuals appear to be normally distributed, thus confirming the normality assumption required for regression diagnostics. There is no significant departure from linearity, nor any obvious outliers or influential points. Figure 7 represents the externally studentized residuals and their variation with each experiment. This plot is useful to identify any patterns, drifts, and time-related effects that might indicate non-randomization or the presence of unaccounted variables. The residual distribution is centered at zero. There are no apparent cycles or systematic structure through the experimental runs. Further, all data points lie within control limits (± 4.81963). This confirms that there are no statistically significant outliers or influential observations distorting model predictions. Additionally, consistency in the experimental procedure over time is implied by the consistent distribution of residuals along the run sequence. The lack of curvature or clustering validates that the residuals show independence and that the experimental design's randomization is sufficient [29].

Box Cox plot for power transformation ($\lambda = 0.3$) is presented in Fig. 8 and is a useful tool for reducing the variance and improving normality of the regression model's residuals. The horizontal axis contains the range of lambda (λ) values considered for potential transformation. The vertical axis contains the residual sum of squares (RSS). There is a minimum point in the curve near $\lambda \approx 0.3$ indicating that the ideal transformation value yields minimal residual variance. The green vertical line indicates the best predicted value of λ . The blue line indicates the commonly used choice for $\lambda = 1$ (no transformation) and the red lines indicate the 95% confidence interval boundaries. The relatively flat shape of the curve near the minimum indicates that the model will be somewhat resistant to small changes in λ . According to the Box-Cox plot, a minor adjustment (λ between 0.3 and 1) may slightly enhance the fit of the model to the data.

Figure 9 shows the contour plot of trends of the interaction between air velocity and water flow rate on the system effectiveness. It appears that more water flow leads to better contact and interactivity within the system. Hence, increasing the water flow rate increases effectiveness across all levels of air velocity. But, at the same flow rate of water, the higher the air velocity the lower the effectiveness and it is thought that the reason for this is reduction in residence time and reduction in phase interaction. The two factors clearly interact since the highest effectiveness (around 60%) occurs at lower air velocities (1.0-2.0 m/s) and higher water flow rates (2.0-2.5 l/min). On the other hand, even large increases in water flow rate do not yield a meaningful improvement in performance at high air velocities (> 4.0 m/s) suggesting that excessive air speed becomes the limiting factor.

The 3D surface plot is shown on Fig. 10. It demonstrates the interaction effect between the air velocity and the flow rate of water on effectiveness. With highest values (about 70%) at the upper end of the water flow range (2.0-2.5 l/min), the surface gradient indicates that effectiveness increases significantly with increasing water flow rates. However, effectiveness is negatively affected by rising air velocity, especially in combination with decreasing water flow rates. As shown by the surface curvature, high water flow reduces the negative effects of moderate air velocities but at very high air velocities (over 4.0 m/s) and regardless of water flow rate, the effectiveness is quite limited.



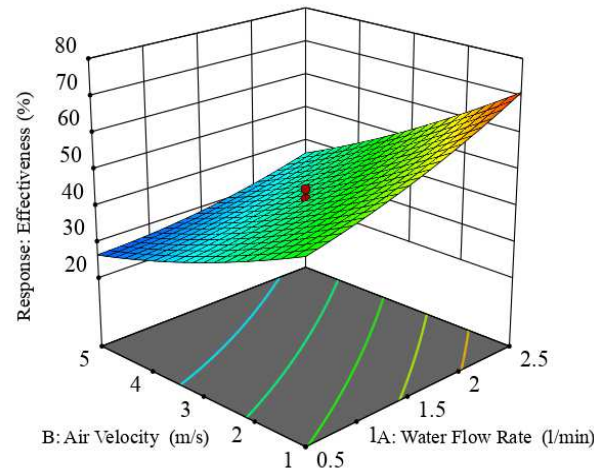


Fig. 10. 3D surface plot of effectiveness.

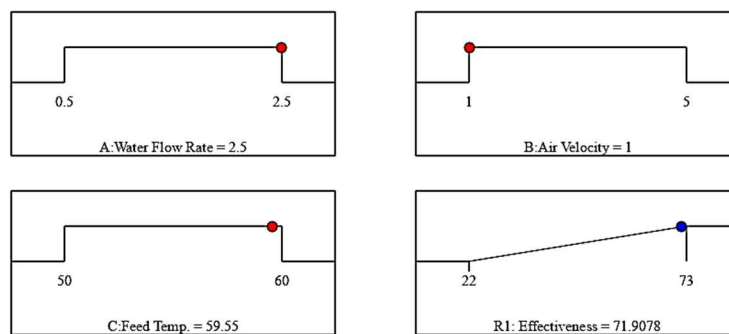


Fig. 11. Ramp plot for optimization.

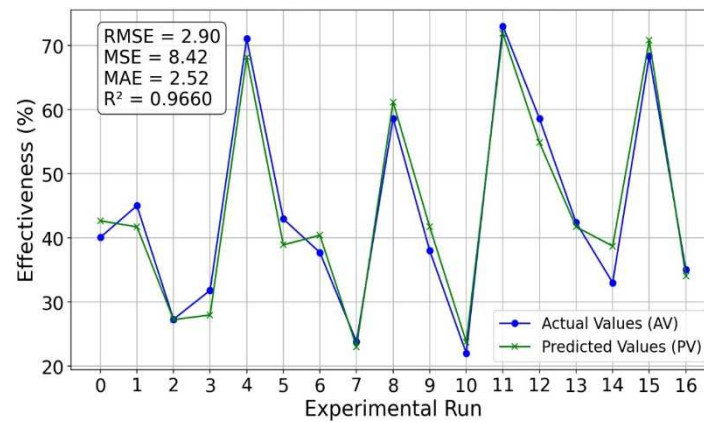


Fig. 12. Variation of actual and predicted effectiveness using RSM.

The optimal process parameter combination is presented in the ramp plot shown in Fig. 11. The optimal solution selected based on the obtained high effectiveness value of 71.91% is the water flow rate of 2.5 l/min, air velocity of 1.0 m/s and feeding temperature of 59.5 °C. The desirability value of 0.979 indicates good optimization as it is close to the ideal value of 1.0. This combination was determined to be the best solution out of total 72 solutions. It means that this combination is superior in terms of balancing all the elements that are examined. The response trend shows a sharp rise in effectiveness with increasing water flow rates and higher feed temperatures. However, keeping air velocity within its lower range reduces the detrimental effects on effectiveness. These results provide a strong guideline for process design and scale-up, confirming that the best operating conditions are obtained by optimizing water flow and feed temperature while reducing air velocity.

Figure 12 displays the comparison of actual experimental data with predicted values of RSM model. The R^2 value is determined to be 0.9660. The MSE is determined to be 8.42, Mean Absolute Error (MAE) is determined to be 2.52, while the RMSE was determined as 2.90. Adequate Precision is the adequate value which should be greater than 4. In the present model, an obtained ratio of 14.106 indicates an adequate signal and thus, it can be used to navigate the design space.

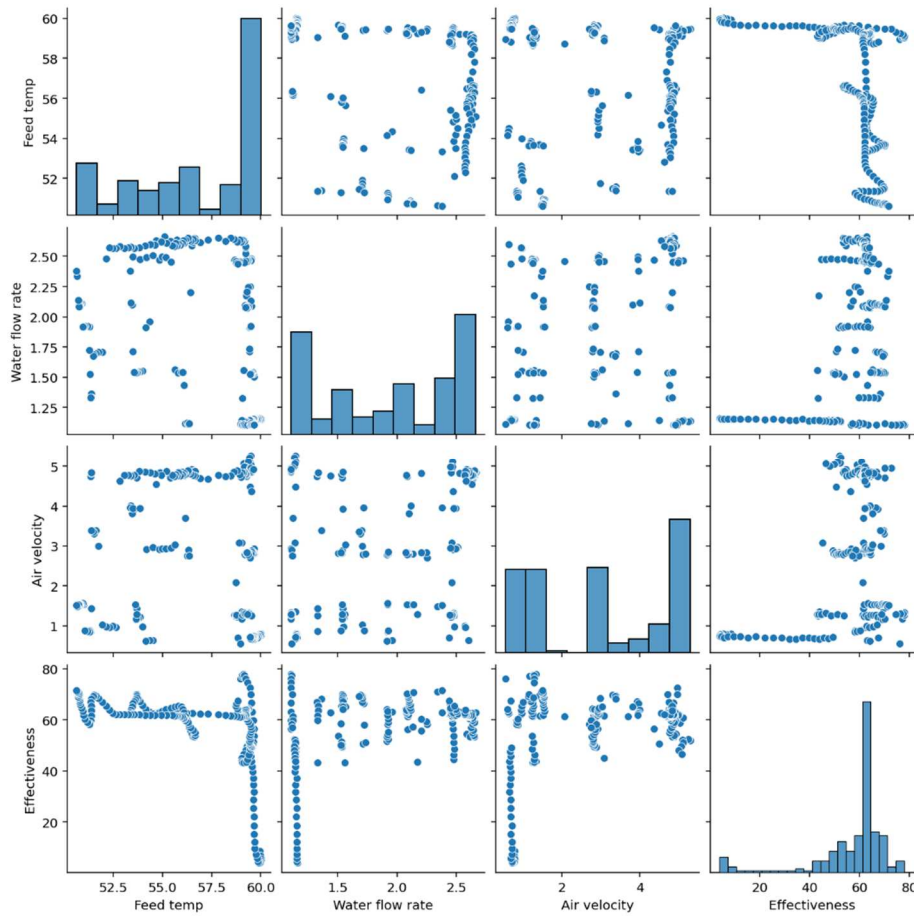
4.2 Machine learning approach

The relationship between the process parameters and effectiveness was examined using a scatter plot matrix (Fig. 13). The diagonal elements show the discrete factor levels of the central composite design. The off-diagonal plots show a clear decrease in effectiveness with increasing air velocity and an increase with water flow rate, whereas no distinct trend is visible for feed temperature, in agreement with the ANOVA results. The scatter around these trends reflects the interaction effects between the factors, which motivates the use of multivariate RSM and ML models [30, 31].



Table 3. Initial range of model hyperparameters and selected optimal value.

Model	Parameter	Range	Optimal Value
Bagging	n_estimators	[30, 200]	192
	max_samples	[0.60, 1.00]	0.8845
	max_features	[0.60, 1.00]	0.6795
	estimator__max_depth	[4, 16]	11
	estimator__min_samples_leaf	[1, 5]	3
CatBoost	iterations	[100, 400]	148
	depth	[4, 10]	4
	learning_rate	[0.01, 0.20]	0.0827
	l2_leaf_reg	[1, 10]	3
RF	n_estimators	[50, 300]	70
	max_depth	[4, 16]	8
	min_samples_split	[2, 10]	8
	min_samples_leaf	[1, 5]	3

**Fig. 13.** Scatter diagram for the input and output variables.

Model performance depends heavily on hyperparameter configuration [32]. The model training phase covers two major steps: (a) tuning of hyperparameters using Grid search optimization and (b) 5-fold cross-validation. Before passing the data to the model, we pre-process it using Z-score normalization, which sets the mean to 0 and the variance to 1. This normalization ensures that all parameters are in the same range. To obtain the optimal model parameters, a traditional grid-search approach is used with MSE as the objective function. We explored the model hyperparameters over continuous and discrete ranges. Table 3 lists the initial parameter ranges and the corresponding optimal values obtained. The optimal combination of hyperparameters was tested using an out-of-fold test dataset. This ensured unbiased performance estimates across folds.

4.2.1. Bagging technique

During the training phase, the black and red point markers were found to be hardly deviating from each other when there is no significant difference among the sample indices. The errors of prediction are symmetrical about zero with only some evident outliers. In addition, the prediction errors are low, as the model shows an MSE of 3.0233 and an RMSE of 1.7388. Second, the error distribution follows a Gaussian curve, with an error mean of 0.0809 and a standard deviation of 1.7417. This indicates that residuals are centered close to zero with low variation [33]. The model is highly accurate and robust during training and testing without significant evidence of under fitting or overfitting as illustrated in Fig. 14.



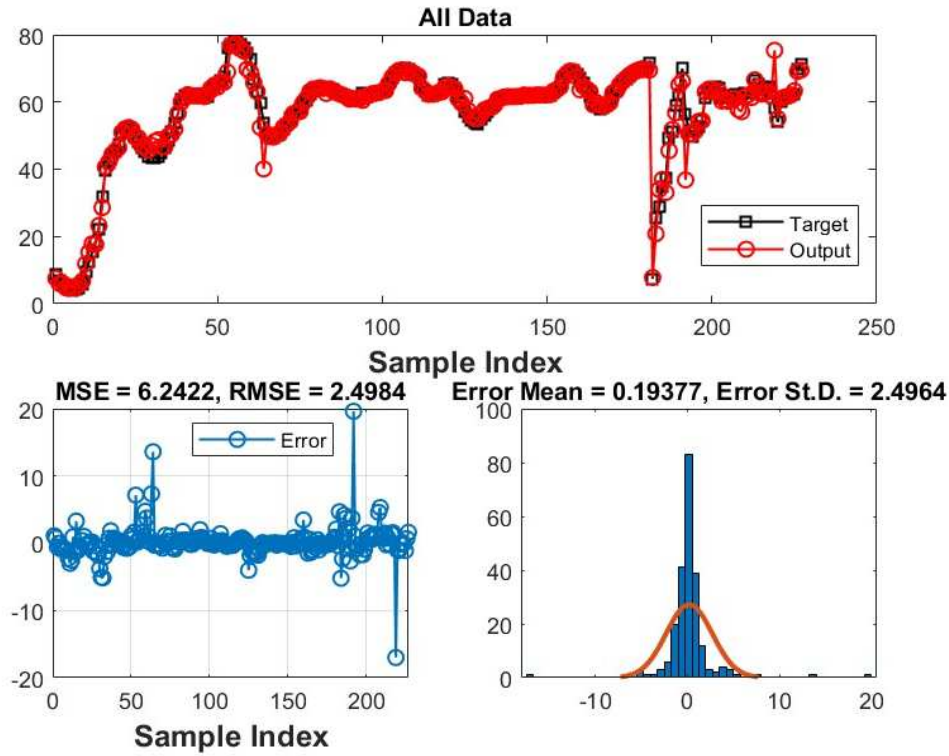


Fig. 14. All data performance of Bagging technique.

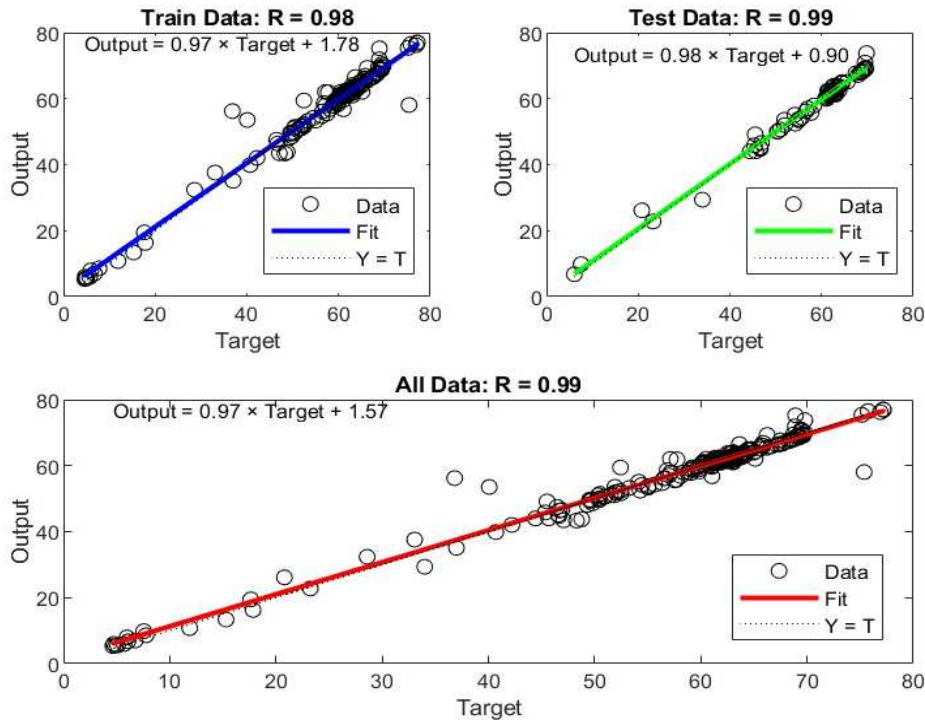


Fig. 15. Regression plot of Bagging technique.

The regression plots in Fig. 15 evaluate the prediction capability of the generated model during training, testing and over all the datasets. In training phase, the regression analysis showed a very strong linear relationship between predicted and actual values (R value of 0.98). The regression line was close to ideal $Y = T$ reference with no bias. $\text{Output} = 0.97 \times \text{Target} + 1.78$ indicates that the model captures the trend without much bias, which is the fitted linear equation for training data. In testing phase, the testing showed slightly better generalization performance (R value of 0.99) and a regression equation of $\text{Output} = 0.98 \times \text{Target} + 0.90$ demonstrates how close the prediction is to the ideal value. The best-fit equation was $\text{Output} = 0.97 \times \text{Target} + 1.57$. It shows that the model has good predictive power over the entire dataset with little overfitting (high correlation values for all subgroups). The close fit of the regression lines to the unity line ($Y = T$) at all stages verifies that the model accurately predicted the target variable [34].



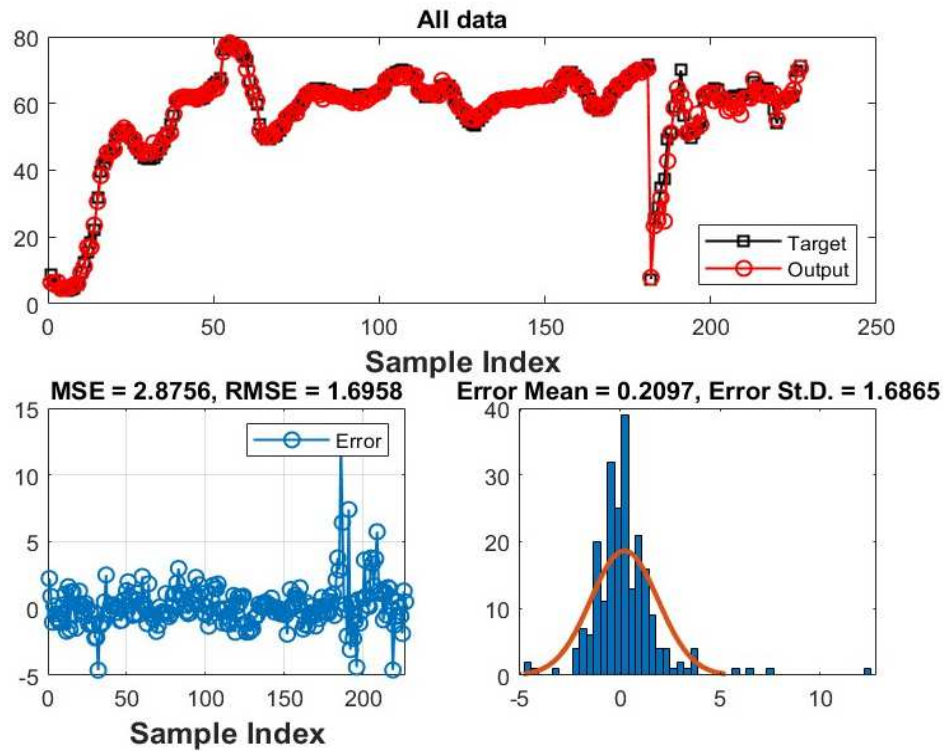


Fig. 16. All data performance of CatBoost technique.

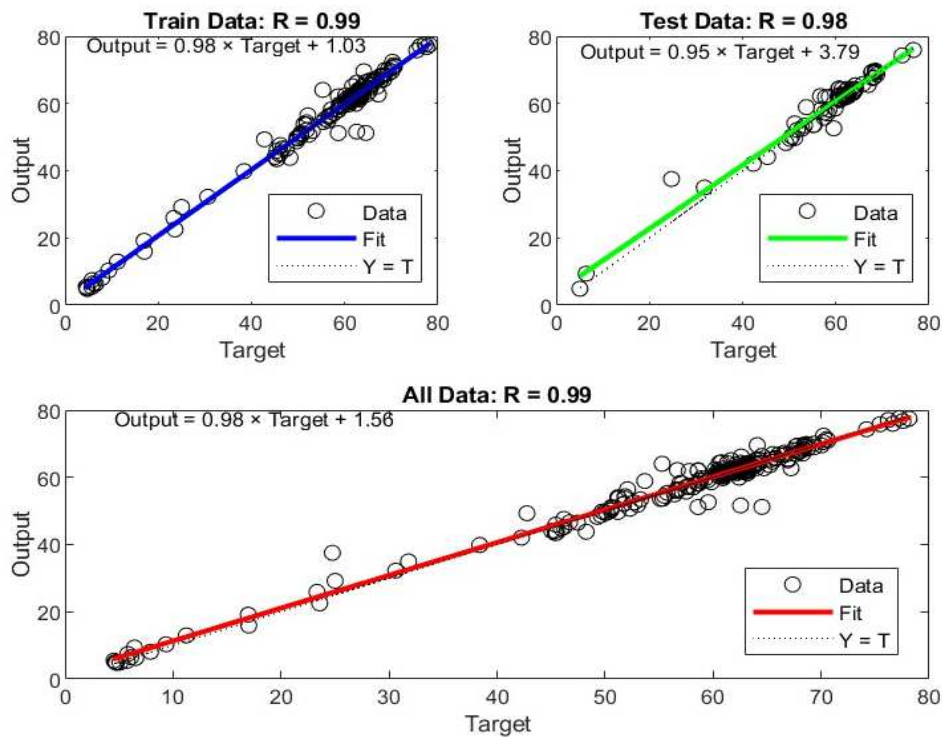


Fig. 17. Regression analysis of CatBoost technique.

4.2.2. CatBoost technique

Using the CatBoost technique, the model was acquainted with the training data and the training indicated high correlation between the two datasets. It demonstrates that the model understands the underlying data patterns well. A strong model generalization was observed during training as the predicted values fit the trend of real values with minimal deviation. The residuals are mostly within ± 2 units, which mainly vary around the zero-error baseline. Suggesting a small residual range implies low prediction deviation with high fidelity learning capacity. In addition, the low MSE and RMSE also indicate a low average prediction error [35]. In addition, there is no systemic bias as the model either overestimates or underestimates significantly, because the error mean is close to zero. The bell-shaped distribution of residues is very similar to the overlaid Gaussian curve, suggesting that they are almost normalized. This observation supports the basic principle of regression analysis and indicates that the errors of the model are random and homoscedastic, which increases the statistical reliability of the model as shown in Fig. 16.



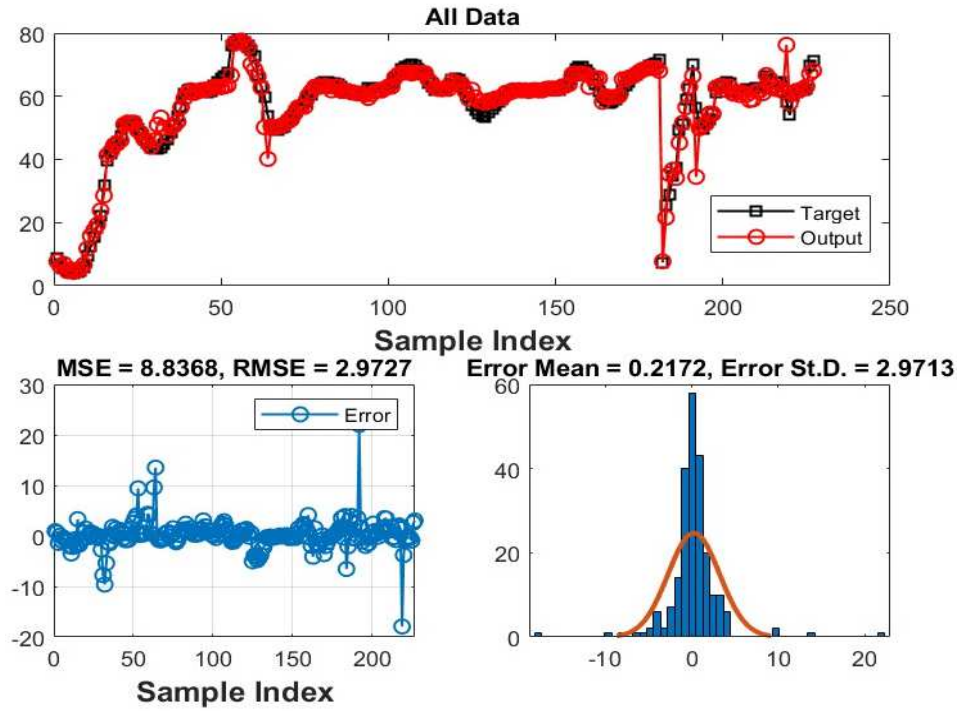


Fig. 18. All data performance of RF technique.

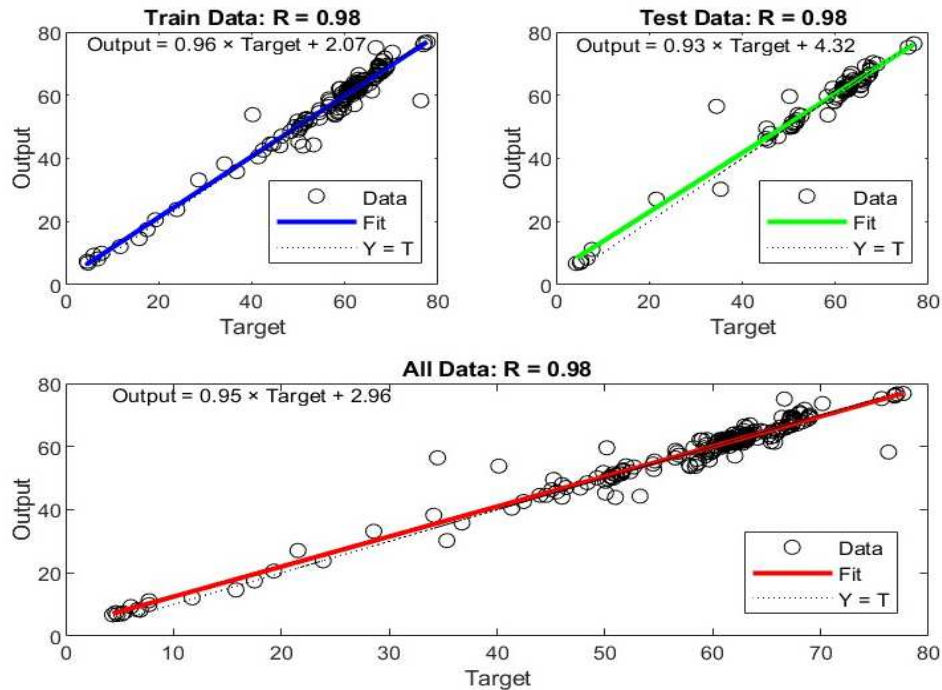


Fig. 19. Regression analysis of RF technique.

The regression plots in Fig. 17 evaluate the prediction capability of the generated model during training, testing and over all the datasets. The regression analysis revealed a very strong linear relationship between the predicted and actual values (R value of 0.99) in training phase. The regression line was close to ideal $Y = T$ reference with no bias. $\text{Output} = 0.98 \times \text{Target} + 1.03$ indicates that the model captures the trend without much bias, which is the fitted linear equation for training data. In testing phase, the testing showed slightly better generalization performance (R value of 0.98) and a regression equation of $\text{Output} = 0.95 \times \text{Target} + 3.79$ demonstrates how close the prediction is to the ideal value. The best-fit equation was $\text{Output} = 0.98 \times \text{Target} + 1.56$. It shows that the model has good predictive power over the entire dataset with little overfitting (high correlation values for all subgroups) [36]. The close fit of the regression lines to the unity line ($Y = T$) at all stages verifies that the model accurately predicted the target variable.

4.2.3 Random Forest technique

Figure 18 reflects the accuracy and generalization capability of the RF technique. The model performs exceptionally well in training. It indicates that the predicted values are in line with the actual targets. This behaviour shows that the RF framework can



model the complex nonlinear patterns in the data. The randomness technique that has been built in the model makes it perform equally well during the test phase using unknown data and the risk of overfitting is low. When the entire data set was used to test this model, the R^2 was high and the prediction error was low. The model remains stable across all iterations and is suitable for predictive modeling with high precision outcomes in complex and multi-dimensional datasets [37].

The regression plots in Fig. 19 evaluate the prediction capability of the generated model during training, testing and over all the datasets. In training phase, the regression analysis revealed a very strong linear relationship between the predicted and the actual values (R value of 0.98). The regression line was close to ideal $Y = T$ reference with no bias. Output = $0.96 \times \text{Target} + 2.07$ indicates that the model captures the trend without much bias, which is the fitted linear equation for training data. In testing phase, the testing showed slightly better generalization performance (R value of 0.98) and a regression equation of Output = $0.93 \times \text{Target} + 4.32$ demonstrates how close the prediction is to the ideal value. The best-fit equation was Output = $0.95 \times \text{Target} + 2.96$. It shows that the model has good predictive power over the entire dataset with little overfitting (high correlation values for all subgroups). The close fit of the regression lines to the unity line ($Y = T$) at all stages verifies that the model accurately predicted the target variable [38].

Figure 20 illustrates the comprehensive heat-map visualization of key performance indicators, namely RMSE, MSE, and R^2 , for the RSM-based model and the three applied ML models for predicting the performance of radiator effectiveness [39]. The results indicated that all four models performed similarly in predicting radiator effectiveness, with only marginal variation in the coefficient of determination. However, the CatBoost model is reported as the best among the four models because it has the highest R^2 , along with the lowest MSE and root mean square error.

A comparison between conventional heat transfer models and proposed machine learning approach is presented in Table 4. The comparison indicates that conventional correlations remain valuable for fundamental design calculations and physical interpretation, whereas machine learning approaches provide an advanced predictive framework for complex operating environments. Therefore, ML should not be considered a replacement for heat transfer theory; rather, it serves as a complementary modelling strategy that can capture nonlinear interactions beyond the limitations of traditional regression-based correlations. The integration of physics-based understanding with data-driven prediction can provide a more flexible approach for optimization and intelligent control of automotive heat exchanger systems.

4.3. Discussion and limitation

The model stability was analyzed using a cross-validation algorithm. Figure 21 shows an overall comparison of all models using performance metrics on the test dataset.

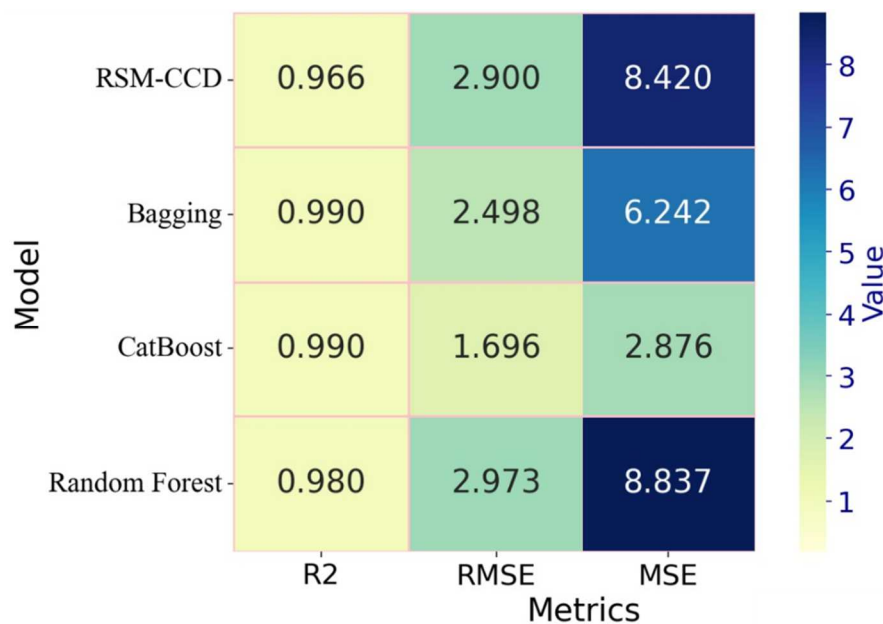


Fig. 20. Heat-map comparison of key performance indicators on all data.

Table 4. Comparison between conventional heat transfer models and proposed machine learning approach.

Aspect	Conventional heat transfer correlations / theoretical models	Proposed ML approach
Modelling basis	Physics equations, dimensionless parameters, empirical datasets	Data-driven nonlinear learning
Input requirements	Requires assumptions regarding geometry, flow regime and thermal properties	Uses experimentally measured operating parameters
Relationship representation	Usually fixed mathematical form	Learns complex nonlinear relationships
Adaptability	Limited outside correlation development range	Higher adaptability within trained operating conditions
Interaction effects	Often require additional formulations	Automatically captures parameter interactions
Model development effort	Requires derivation or experimental correlation development	Requires representative training data
Application suitability	Fundamental design and preliminary sizing	Prediction, optimization and real-time decision support



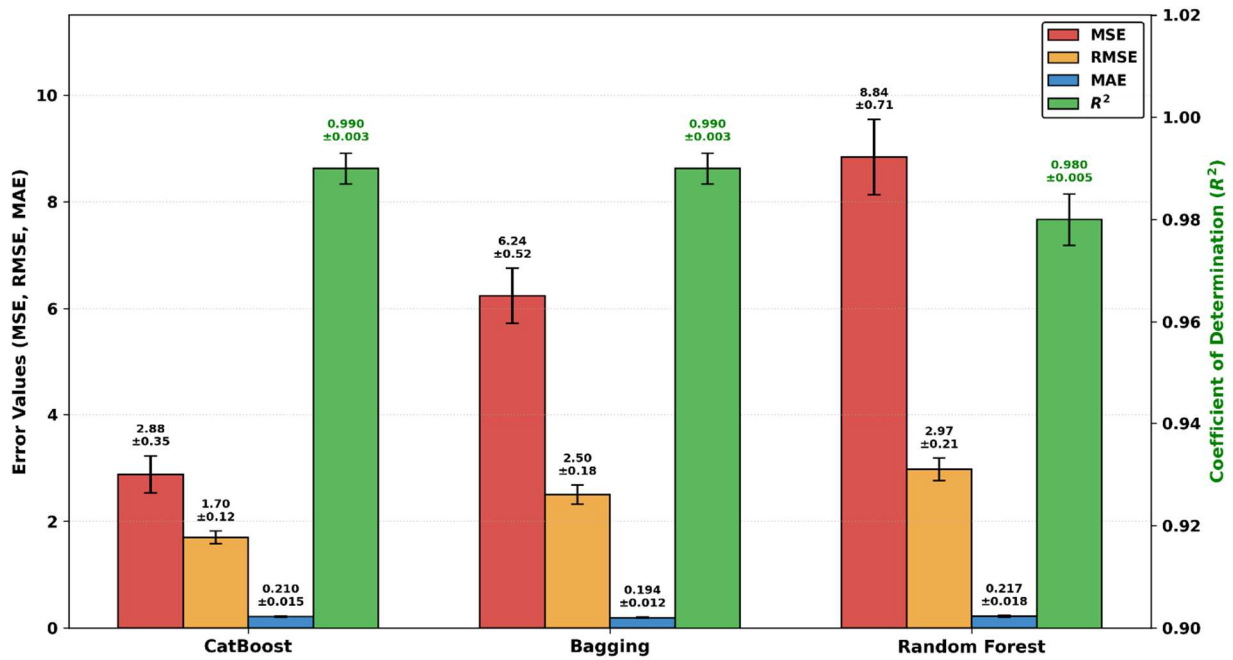


Fig. 21. Comparison of all parameters on Test dataset using average for all folds.

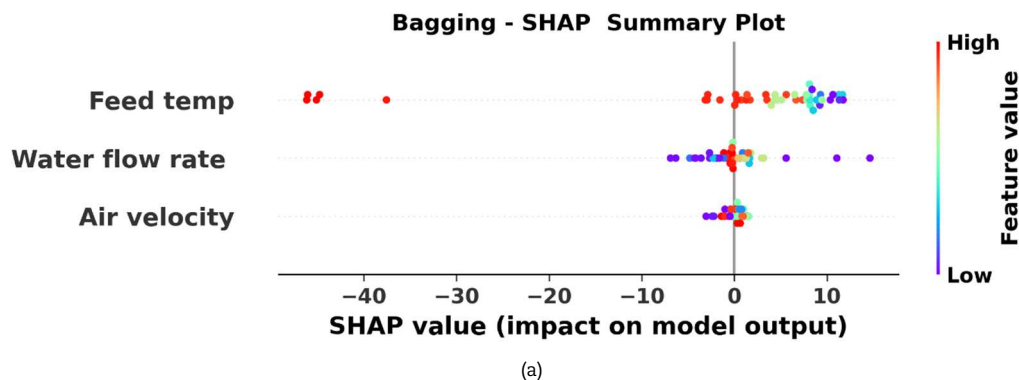
Bagging and RF have higher average error performance, with MSE of 6.242 ± 0.52 and 8.837 ± 0.71 , and RMSE of 2.498 ± 0.18 and 2.973 ± 0.21 . In contrast, CatBoost showed lower MSE and RMSE of 2.876 and 1.696 . Additionally, CatBoost had the highest average R^2 score among all models, though the range was narrow. Feature attribution for the three ML models was evaluated using SHapley Additive exPlanations (SHAP), as shown in Fig. 22. In all three models, feed temperature received the largest mean |SHAP| values (10.23 , 9.65 and 6.67 for Bagging, RF and CatBoost, respectively), followed by water flow rate and air velocity. This ranking differs from the ANOVA results of the RSM model, in which air velocity (F value of 135.03 , $p < 0.0001$) and water flow rate (F value of 43.39 , p value of 0.0003) were the dominant significant factors, while the main effect of feed temperature was not significant (p value of 0.9647) and its influence appeared only through the AC interaction (p value of 0.0249).

The two analyses answer different questions. ANOVA quantifies the variance in effectiveness explained by each factor under a controlled, orthogonal experimental design. SHAP, in contrast, quantifies how strongly a trained model relies on each input to produce its predictions. It also distributes interaction effects, such as the AC interaction, among the participating features. With a limited dataset, tree-based ensembles can exploit associations between an input and the response that do not correspond to a causal main effect. SHAP attributions should therefore be interpreted as a description of model behaviour rather than of the underlying heat transfer physics. From a physical standpoint, the RSM findings are consistent with ε -NTU theory. Air is the minimum heat-capacity fluid, so increasing air velocity reduces NTU, thereby lowering effectiveness. Inlet temperature affects effectiveness weakly, through temperature-dependent fluid properties. Accordingly, the RSM model is recommended for physical interpretation and optimization of operating conditions, while the ML models are recommended for prediction within the investigated domain.

Water flow rate has a moderate influence on predictions and interacts with feed temperature, consistent with the significant AC term in the ANOVA. CatBoost is more sensitive to water flow rate than the Bagging model. Increasing air velocity raises the air-side Reynolds number and convective heat transfer coefficient, but it also increases the air heat-capacity rate and shortens the residence time of air in the fin matrix; the net effect is a reduction in effectiveness at higher air velocities.

The high R^2 scores for all models obtained in the study are based on a bounded experimental design. The application of the developed model beyond the investigated parameter bound has certain limitations:

- The tree-based model uses orthogonal hyperrectangle feature space division. For values beyond the range, it assigns a constant value within each leaf node. Therefore, the tree-based model may fail to explore non-linear trends and flatten the output to the nearest training leaf.



(a)

Fig. 22. Analysis of directional impact of parameters using SHAP using, (a) Bagging, (b) RF, (c) CatBoost, (d) Feature importance comparison of all models using mean |SHAP| values.



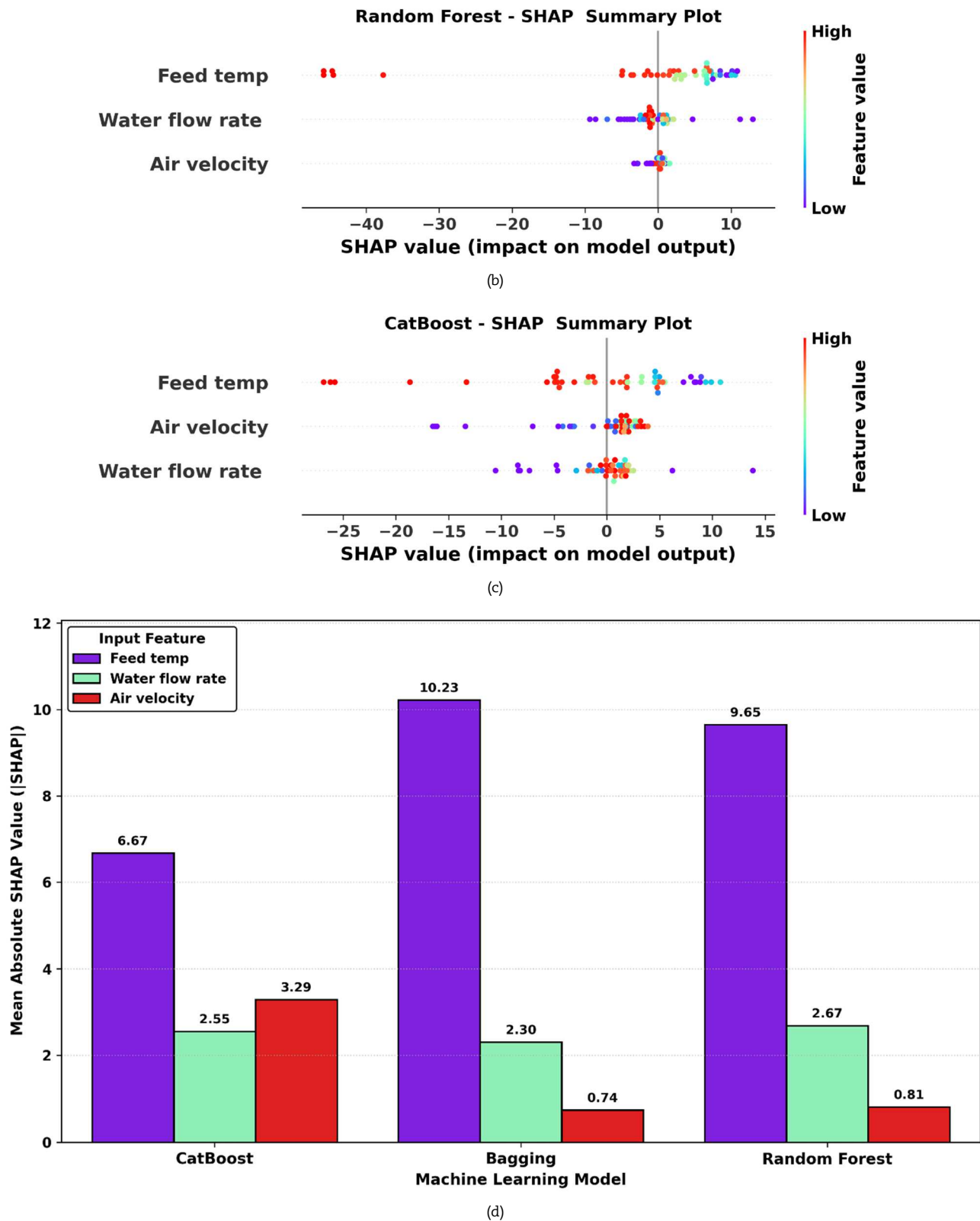


Fig. 22. Continued.

- The RSM model used a second-order polynomial representation. A further exploration of RSM beyond the empirical design boundaries can yield non-physical or severely inflated values.
- The present experimental design is validated for operational interpolation within the study domain. An initial boundary condition is required to use them in field applications. These models can be integrated with physics-informed networks, allowing physical consistency and stability for out-of-bound values.
- Feature attributions from the ML models did not fully agree with the ANOVA results of the controlled experiment. Future work will use a larger dataset and physics-informed constraints to improve the physical consistency of ML-based feature attribution.



5. Conclusion

In this study, the optimization and performance prediction of a typical radiator heat exchanger has been optimized and predicted through the RSM along with three ML techniques i.e., Bagging, CatBoost and RF. Experimental investigations were undertaken, and mathematical models were developed based on statistical and ML methods. The highest radiator effectiveness was 71.9%. The results showed that the RSM model fit well with the experimental data, with an R^2 of 0.966 and low errors (MSE: 8.42, RMSE: 2.9). CatBoost performed best among the ML models with an excellent R^2 value of 0.99 and the lowest MSE and RMSE, followed by RF, which had an R^2 value of 0.98. Cross-model evaluation confirms its stability and generalization. ANOVA of the RSM model showed that air velocity and water flow rate are the significant factors governing radiator effectiveness, consistent with effectiveness-NTU theory, while feed temperature acts mainly through its interaction with water flow rate. SHAP analysis indicated that the ML models relied most strongly on feed temperature; this difference reflects the distinction between model-based feature attribution and experimentally determined factor significance. Consequently, the RSM model is recommended for physical interpretation and optimization, and the ML models for performance prediction within the studied range. The results show that all four models can predict radiator heat exchanger performance, and the CatBoost model is the best performer, with the highest accuracy and the lowest error metrics. Future studies could employ more sophisticated multi-objective optimization methods and incorporate computational fluid dynamics with AI to further optimize thermal performance. Further, real-time monitoring systems using smart control algorithms could be explored to optimize radiator performance.

Author Contributions

F. Ahmed conceptualized and planned the research, designed and conducted the experiments, validated the results, and wrote the original draft of the manuscript; H. Mewada developed the machine learning methodology, prepared the visualizations, and reviewed and edited the manuscript; N. Mohammed developed the software implementation of the models, performed the formal analysis, prepared the visualizations, and contributed to writing the original draft. The manuscript was written through the contribution of all authors. All authors discussed the results, reviewed, and approved the final version of the manuscript.

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Conflict of Interest

The authors declare no personal or financial competing interests that affect this work.

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Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

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ORCID iD

Faizan Ahmed  <https://orcid.org/0000-0002-4792-2139>

Hiren Mewada  <https://orcid.org/0000-0002-3579-8708>

Nayeemuddin Mohammed  <https://orcid.org/0000-0002-7757-936X>



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