

Article

Prediction of Boiling Heat Transfer Coefficient for Micro-Fin Using Mini-Channel

Tomihiko Kinjo ^{1,2,*}, Yuichi Sei ³ , Niccolo Giannetti ², Kiyoshi Saito ⁴ and Koji Enoki ^{2,*} 
¹ Japan Aerospace Exploration Agency, 3-1-1 Yoshinodai, Sagamihara 252-5210, Kanagawa, Japan

² Department of Mechanical and Intelligent Systems Engineering, The University of Electro-Communications, Tokyo 182-8585, Japan; giannetti.n@gmail.com

³ Department of Informatics, The University of Electro-Communications, 1-5-1 Chofugaoka, Chofu, Tokyo 182-8585, Japan; seiuny@uec.ac.jp

⁴ Department of Applied Mechanics and Aerospace Engineering, Waseda University, 3-4-1 Okubo, Shinjuku, Tokyo 169-8555, Japan; saito@waseda.jp

* Correspondence: kinjoh.tomihiko@jaxa.jp (T.K.); enoki.koji@uec.ac.jp (K.E.)

Abstract: The prediction of the heat transfer coefficient commonly relies on the development of new empirical prediction equations when operating conditions and refrigerants change from the existing equations. Creating new prediction equations is expensive and time-consuming; therefore, recent attention has been given to machine learning approaches. However, machine learning requires a large amount of data, and insufficient data can result in inadequate accuracy and applicability. This study showed that using mini-channel data as highly relevant data for the micro-fin heat transfer coefficient yields high prediction accuracy, even when the experimental dataset of interest is limited. In the proposed method, we added dimensionless numbers assumed to significantly influence heat transfer coefficients calculated from experimental data to the training dataset. This allowed efficient learning of the characteristics of thin liquid films present in mini-channels and micro-fins. By combining distinctive physical mechanisms related to heat transfer coefficients with DNN/GPR/Fine-tuning, the proposed method can predict 96.7% of the data points within $\pm 30\%$ deviation. In addition, it has been confirmed that the dryout quality and post-dryout heat transfer coefficients were predicted with high accuracy. Additionally, we utilized visualization techniques to investigate the contents of the black-box machine learning models.

Keywords: heat transfer; two-phase flow boiling; deep learning; fine-tuning; dryout



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1. Introduction

1.1. Motivation to Predict Heat Transfer Coefficients for Micro-Fins

Heat control systems utilizing boiling two-phase flow are employed in cooling power generation facilities and electronic devices. Additionally, two-phase flow boiling technology is being considered in space applications such as communication satellites and lunar exploration. Heat control techniques using boiling two-phase flow leverage the latent heat of vaporization during the phase change of the liquid and provide a heat transfer performance that is generally two orders of magnitude higher than systems that transport heat using only liquid. This results in smaller temperature increases, contributing to the miniaturization and energy efficiency of the system. Moreover, in renewable energy and energy saving, high performance and miniaturization of heat exchangers are recognized as critical efforts to improve heat pumps' efficiency and enhance the use of renewable energy for achieving carbon neutrality.

Heat pump technology uses a compressor and exchanges heat with the external environment through a heat exchanger. This technology can yield four or five times as much heating or cooling rate as the electrical power input to the compressor. A heat pump consists of several components: the compressor, expansion valve, and heat exchanger.

Among these, the performance of the heat exchanger, which exchanges heat with the external environment, is particularly critical. The requirements for improving the performance of heat exchangers include (1) enhancement of heat transfer performance and (2) downsizing of the heat exchanger. To meet these needs, research is being conducted on methods such as mini-channel technology, which involves reducing the diameter of the tubes, and micro-fin technology, which involves fine grooving. Predicting the heat transfer coefficient of two-phase flow in the boiling state is particularly important in downsizing heat exchangers. Consequently, many studies have reported the heat transfer coefficients of boiling two-phase flow. These studies categorized the two-phase state into representative flow patterns to predict appropriate heat transfer coefficients. However, predicting boiling heat transfer is challenging due to several factors. The mixture of gas and liquid with different properties undergoes a phase change while flowing, requiring predictions to be made according to the flow state. Additionally, phenomena such as post-dryout, where the heat transfer coefficient changes abruptly under high-quality conditions, complicate accurate predictions of heat transfer coefficients. In the post-dryout, the heat transfer coefficient decreases significantly, causing a rapid increase in the temperature of the heat exchanger. Therefore, predicting dryout quality is crucial in design. Numerous experimental verifications are necessary to predict these characteristics accurately. Furthermore, it has been found that these phenomena depend on the properties of the refrigerant and the operating conditions. Therefore, appropriate design and efficient operation require designers to accurately estimate boiling heat transfer coefficient. This presents a significant challenge in development.

Thus, our research group has investigated prediction techniques for boiling heat transfer coefficients using deep learning to address these issues. Prediction methods utilizing artificial intelligence consider the heat transfer coefficients obtained under multiple conditions as big data, offering a promising alternative to traditional methods. Focusing on mini-channels, we examined the prediction of heat transfer coefficients using deep learning for different refrigerants and various operating conditions. Our results demonstrated that this approach achieves higher accuracy than existing studies. Moreover, while conventional deep learning predictions typically cannot evaluate the uncertainty of the obtained results, Sei et al. propose a novel method that combines deep neural networks (DNN) and Gaussian Process Regression (GPR). This method can accurately predict heat transfer coefficients and their uncertainties [1].

Therefore, it has been confirmed that deep learning allows for highly accurate predictions of boiling heat transfer coefficients. Our research group is now focused on predicting heat transfer coefficients for micro-fins as the next goal. By developing prediction techniques for micro-fins and mini-channels, we aim to contribute to a wide range of industrial applications.

1.2. Flow Boiling in Micro-Fins and Mini-Channels

Micro-fins have higher heat transfer coefficients than smooth tubes of the same inner diameter, primarily due to the higher surface area provided by the fins. The micro-fin features involve fine grooves inside the tube, with design parameters including the number of fins, fin depth, and fin angle. Previous studies have reported that the surface tension effect results in thinner liquid films within the grooves and around the fins and that liquid is supplied along the grooves up to the tube's top, contributing to enhanced heat transfer. In low mass flow regions, even when there is a flow where the gas and liquid phases are separated vertically, a liquid film still exists between the fins at the top of the tube. The presence of this liquid film enhances the heat transfer because surface tension causes a meniscus liquid film to form on the sides of the fins. However, an annular flow develops at high mass flow rates, forming a uniformly distributed liquid film around the tube circumference. As a result, the heat transfer enhancement is known to be smaller than in low mass flow regions [2–4]. Previous research suggests that the state of the liquid around

the fins significantly affects heat transfer coefficients, especially in terms of the relationship between surface tension and inertial forces.

In this study, we considered leveraging data from mini-channels, previously predicted with high accuracy [1], to predict the boiling heat transfer coefficient of micro-fins. The mechanism proposed for improving heat transfer coefficients in both mini-channels and micro-fins involves boiling facilitated by thin liquid films, as illustrated in Figure 1. In mini-channels, slug flow predominates in regions with low flow rates and low qualities. In these regions, the effect of surface tension becomes significant, and the thinning of the liquid film surrounding the gas plug increases the heat transfer coefficient via evaporative heat transfer due to liquid film conduction (liquid film conduction evaporation) [5–8]. Similarly, in the case of micro-fins, the state of the liquid film around the fins is crucial for evaluating heat transfer characteristics. Therefore, the relationship between surface tension and inertial forces around the fins is important. Additionally, the complex interaction between surface tension and inertial forces complicates the prediction of post-dryout heat transfer coefficient and dryout quality.

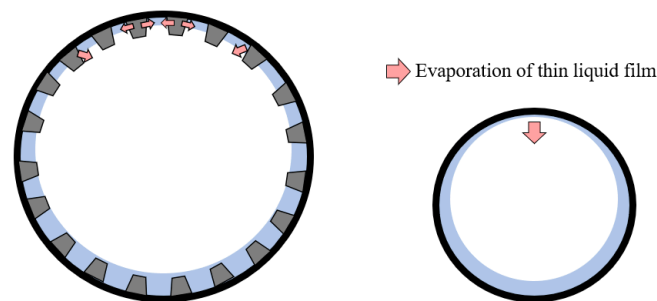


Figure 1. Images of boiling by thin liquid films in mini-channels and micro-fins.

The most common and widely used approach for predicting the heat transfer coefficient of micro-fins is based on data obtained from several experiments conducted within the geometric and operational ranges of the micro-fins and the refrigerant and operating conditions. Cavallini et al. [9] proposed a heat transfer prediction model based on experimental data obtained by other researchers using HCFC22, HCFC123, R134a, and CFC12. They introduced the Bond number to account for the effect of surface tension, but the number of fins and fin depth was limited. Additionally, the Cavallini model has been modified by many researchers to include additional refrigerants and operating conditions. Diani et al. [10] conducted R1234ze(E) experiments and modified the predictive model to a wider range of refrigerants. Further, Tang et al. [11] collected 2221 data points from previous studies and proposed a new predictive model capable of accommodating new refrigerants by modifying the Cavallini model. The data encompassed seven refrigerants: R22, R410A, R407C, R134a, R1234yf, R1234ze(E), and CO₂. Although the predictive model accurately predicts the heat transfer coefficient, it defines the point of sharp decrease in heat transfer coefficient as the onset of post-dryout and excludes data points beyond this point from the prediction target.

From the above, it is clear that when operating conditions or refrigerants differ from those in existing prediction equations, it is generally necessary to conduct evaluations based on a wide range of experimental conditions and modify the prediction equations accordingly. Constructing prediction equations requires a significant amount of time. Additionally, many existing prediction equations do not include heat transfer coefficients beyond the onset of post-dryout, making it difficult to predict post-dryout heat transfer coefficients and dryout quality.

1.3. Predicting Heat Transfer Coefficients Using Machine Learning

In natural language processing, collecting a sufficiently large volume of training data when building custom services is often challenging. Therefore, achieving sufficient accuracy with limited collected training data can be difficult. One solution is fine-tuning pre-trained large language models (LLMs) with fewer additional data, used to improve prediction accuracy [12]. Similarly, in predicting boiling heat transfer coefficients, developing models with high prediction accuracy requires gathering a large amount of training data, a challenge for most industrial applications. Qiu et al. [13] used data from previous studies to predict heat transfer coefficients for circular or square mini-channels. They reported that prediction models predict high accuracy only when they contain learning data included in the target data. Additionally, Zhu et al. [14] explored the application of deep learning to predict heat transfer coefficients for pin fins used in aircraft, addressing the difficulty of acquiring a large amount of experimental data. They proposed a method using transfer learning, a form of pre-training in deep learning, which resulted in improved prediction accuracy. Thus, it is known that constructing predictive models using deep learning can be achieved much more quickly. However, acquiring the necessary experimental data still demands a significant amount of time. Furthermore, achieving high prediction accuracy is difficult when the desired experimental data is insufficient.

1.4. Objective of Study

This study developed a deep learning model that achieves high prediction accuracy for the heat transfer coefficient of micro-fins, including post-dryout, using a relatively small amount of data. The proposed approach involves conducting pre-training based on data from mini-channels, which are highly relevant to the heat transfer coefficient of micro-fins and fine-tuning the pre-trained model using the target data. Furthermore, we added dimensionless numbers assumed to significantly influence heat transfer coefficients calculated from experimental data to the training dataset. By applying fine-tuning, the model can learn the features (weights) of the data based on a related dataset before training on the target dataset, thereby improving learning accuracy, particularly when the target dataset is limited. In natural language processing, fine-tuning using relevant data is commonly employed, but its application to predicting heat transfer coefficients is limited. Furthermore, we propose a novel approach that utilizes mini-channel data to predict the heat transfer coefficients of micro-fins, combining physical mechanisms with DNN/GPR/Fine-tuning.

This approach allows for predictions based on a small amount of data for new refrigerants or missing operating conditions, leading to significant reductions in time costs. Additionally, due to the limited experimental data available for post-dryout heat transfer coefficients in previous studies, post-dryout data was included in the evaluation as part of the prediction target.

2. Preliminaries

2.1. Deep Neural Networks

Prediction methods employing artificial intelligence may be suitable alternatives to traditional methods, leveraging target data gathered from various conditions as big data [15]. Previous research has recognized the application of deep learning in analyzing heat flow phenomena in two-phase fluids, emphasizing categorizing flow patterns and forecasting heat transfer coefficient during boiling processes.

Figure 2 illustrates part of the computational process of a node. As an example, it focuses on the x node in the (j) layer, specifically the β th node $x_{\beta}^{(j)}$, and represents the calculation process for the next layer. For the node $x_{\beta}^{(j)}$, the input data carried over from the previous layer is combined with weight coefficients w and bias. Further, an activation function F is applied, and the output result is propagated to the next layer.

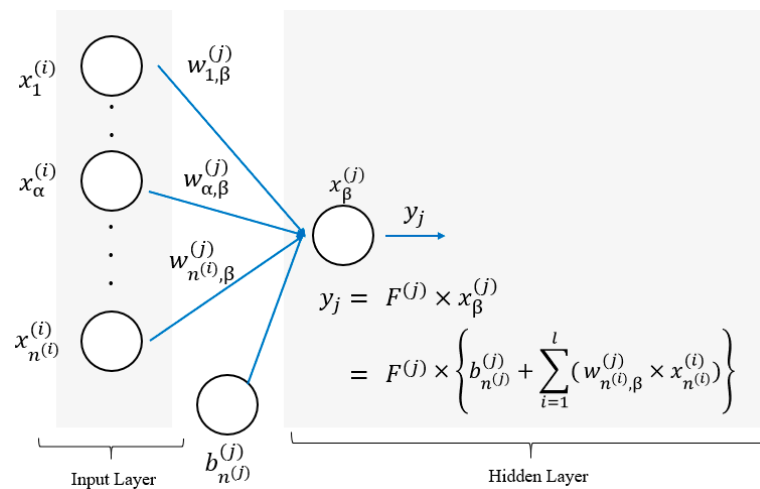


Figure 2. Calculation process of node.

Figure 3 illustrates the overall structure of the ANN used to predict the heat transfer coefficient. Each layer of the DNN is represented by l th and denoted as $L^{(l)}$. The input layer is $L^{(0)}$, and the output layer is $L^{(L)}$. Thus, the DNN has $L + 1$ layers.

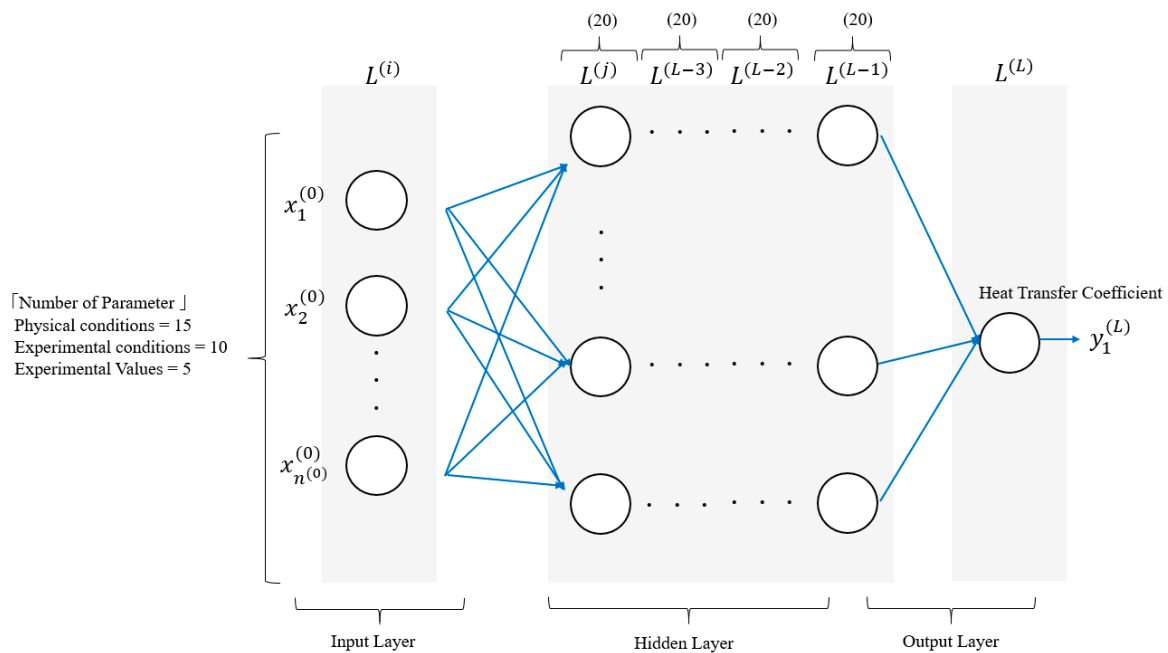


Figure 3. Overall structure of deep neural networks.

Let $N_i^{(l)}$ represent the weight between nodes and let $L^{(l)}$ and $n^{(l)}$ represent the number of nodes of layer $L^{(l)}$. Layer $L^{(l)}$ contains nodes $N_1^{(l)}, N_2^{(l)}, \dots, N_{n^{(l)}}^{(l)}$. Let $N_i^{(l)}$ represent the weight between nodes and let $L^{(l)}$ and $n^{(l)}$ represent the number of nodes of layer $L^{(l)}$. Layer $L^{(l)}$ contains nodes $N_1^{(l)}, N_2^{(l)}, \dots, N_{n^{(l)}}^{(l)}$. Let $w_{ij}^{(l)}$ represent the weight between nodes $N_i^{(l-1)}$ and $N_j^{(l)}$, and $b_j^{(l)}$ represent the bias connected to node $N_j^{(l)}$. Nodes of layer $L^{(l)}$ share an activation function $F^{(l)}$. The input and output values of node $N_i^{(l)}$ are $x_i^{(l)}$ and $y_i^{(l)}$, respectively. The loss function is defined by where B represents the DNN batch size, and $\hat{y}_i$ and t_i represent the predicted heat transfer coefficient and the true value of the i th

target sample, respectively. We set the number of epochs to 200, B represents the DNN batch size to 10, and repeat time to 10. These values are calculated by

$$x_i^{(l)} = \sum_{j=1}^{n^{(l-1)}} y_j^{(l-1)} w_{ji}^{(l)} + b_i^{(l)} \quad (1)$$

$$y_i^{(l)} = F^{(l)} \left(x_i^{(l)} \right) \quad (2)$$

$$F^{(l)} = \frac{1}{B} \sum_i \left(\frac{\hat{y}_i - t_i}{t_i} \right)^2 \quad (3)$$

2.2. Gaussian Process Regression

GPR is a fully probabilistic model used in various research fields [16]. GPR can be used for supervised learning. It receives x as its input and returns $y = f(x)$. GPR aims to generate accurate values of $f(x)$. Moreover, GPR can return the corresponding uncertainty of the predicted value.

Generally, it is not possible to evaluate the uncertainty of the results obtained from predictions using deep learning. However, the authors propose a novel method for predicting heat transfer coefficients by combining DNN and GPR. DNN and GPR can predict heat transfer coefficients with high accuracy, but the uncertainties of the predicted heat transfer coefficients are also high [1].

2.3. Fine-Tuning

Pre-training is one method to improve the accuracy of deep learning. Pre-training includes techniques such as transfer learning and fine-tuning, which propose to use network information learned from different data to construct a new model. In transfer learning, only the output layer of a pre-trained model is retrained without changing the weights of the other layers, thereby constructing a new model. Fine-tuning, on the other hand, initializes the weights of a pre-trained model and retrain the entire model to construct a new one. In this study, we constructed a prediction model focusing on fine-tuning.

3. Databases and Methods

3.1. Databases

Databases containing horizontal flow data on boiling flow were utilized, comprising two types of data: mini-channel and micro-fin. The mini-channel dataset comprises 1111 points, while the micro-fin dataset comprises 4583 points. Table 1 summarizes the mini-channel databases, including five experimental conditions. Table 2 summarizes the micro-fin databases, including five experimental conditions. Furthermore, Figure 4 shows the distribution of the mini-channel databases. Figure 5 shows the distribution of the micro-fin databases.

Table 1. Summary of the mini-channel databases.

Source	Fluid	Work Conditions	N
Wambsganss et al. [17]	R113	$x = 0.01\text{--}0.71$, $P_{sat} = 0.12\text{--}0.16$, $D = 2.92$, $G = 50\text{--}300$, $q = 8.8\text{--}90.8$	72
Tran et al. [18]	R12	$x = 0.20\text{--}0.77$, $P_{sat} = 0.83$, $D = 2.46$, $G = 66.3\text{--}300$, $q = 7.5\text{--}59.4$	59
Kew et al. [19]	R141b	$x = 0.00\text{--}0.90$, $P_{sat} = 0.10$, $D = 2.87$, 3.69 , $G = 188\text{--}212$, $q = 9.7\text{--}90$	67
Bao et al. [20]	R11	$x = 0.01\text{--}0.64$, $P_{sat} = 0.29\text{--}0.47$, $D = 1.95$, $G = 167\text{--}560$, $q = 52\text{--}125$	81
	R123	$x = 0.01\text{--}0.68$, $P_{sat} = 0.35\text{--}0.51$, $D = 1.95$, $G = 167\text{--}452$, $q = 39\text{--}125$	80
Kuwahara et al. [21]	R134a	$x = 0.01\text{--}0.66$, $P_{sat} = 0.88$, $D = 0.84$, $G = 552$, $q = 15.6$	15
Saitohet et al. [22]	R134a	$x = 0.22\text{--}0.91$, $P_{sat} = 0.41$, $D = 0.51$, 1.12 , 3.1 , $G = 150\text{--}300$, $q = 12\text{--}29$	75

Table 1. Cont.

Source	Fluid	Work Conditions	N
Yamashita et al. [23]	CO2	$x = 0.01\text{--}0.85$, $P_{sat} = 5.00$, $D = 1.02$, $G = 300\text{--}1000$, $q = 30\text{--}50$	62
Li et al. [24]	R32	$x = 0.28\text{--}0.86$, $P_{sat} = 1.28$, $D = 2.00$, $G = 200$, $q = 4\text{--}24$	44
	R1234yf	$x = 0.22\text{--}0.92$, $P_{sat} = 0.51$, $D = 2.00$, $G = 100\text{--}400$, $q = 6\text{--}24$	91
Enoki et al. [8]	R410A	$x = 0.05\text{--}0.95$, $P_{sat} = 1.09$, $D = 1.00$, $G = 30\text{--}400$, $q = 2\text{--}24$	287
Yokoyama et al. [25]	NH3	$x = 0.03\text{--}0.78$, $P_{sat} = 0.43$, $D = 1.00$, $G = 100$, $q = 20$	132
Wu et al. [26]	R32	$x = 0.13\text{--}0.65$, $P_{sat} = 1.28$, $D = 2.00$, $G = 300$, $q = 10$	14
Longo et al. [27]	R1234ze(E)	$x = 0.11\text{--}0.74$, $P_{sat} = 0.31$, $D = 4.00$, $G = 200$, $q = 20$	15
	R600a	$x = 0.06\text{--}0.26$, $P_{sat} = 0.55$, $D = 1.10$, $G = 400$, $q = 35$	5
Sempertgui et al. [28]	R1234ze(E)	$x = 0.04\text{--}0.29$, $P_{sat} = 0.60$, $D = 1.10$, $G = 500$, $q = 25\text{--}35$	12
Total			1111

Table 2. Summary of the micro-fin databases.

Source	Fluid	Work Conditions	N
Diani et al. [29]	R1234yf	$x = 0.19\text{--}0.99$, $P_{sat} = 0.78$, $D = 3.64$, $G = 190\text{--}940$, $q = 10\text{--}50$	94
Celen et al. [30]	R134a	$x = 0.22\text{--}0.77$, $P_{sat} = 0.49\text{--}0.61$, $D = 8.62$, $G = 190\text{--}381$, $q = 10$	47
Diani et al. [31]	R1234ze(E)	$x = 0.16\text{--}0.98$, $P_{sat} = 0.58$, $D = 2.64$, $G = 375\text{--}940$, $q = 10\text{--}50$	93
Diani et al. [10]	R1234ze(E)	$x = 0.20\text{--}0.99$, $P_{sat} = 0.58$, $D = 3.64$, $G = 190\text{--}940$, $q = 10\text{--}50$	96
Padvan et al. [32]	R410A, R134a	$x = 0.10\text{--}1.00$, $P_{sat} = 0.76\text{--}2.42$, $D = 8.15$, $G = 80\text{--}600$, $q = 14.7\text{--}44.2$	296
Kuo et al. [33]	R22	$x = 0.16\text{--}0.81$, $P_{sat} = 0.60$, $D = 9.32$, $G = 100\text{--}300$, $q = 6\text{--}14$	24
Yang et al. [34]	R410A	$x = 0.09\text{--}0.97$, $P_{sat} = 1.09$, $D = 6.52$, $G = 100\text{--}300$, $q = 10\text{--}20$	66
Kondou et al. [35]	R134a	$x = 0.15\text{--}0.91$, $P_{sat} = 0.77$, $D = 5.45$, $G = 150\text{--}300$, $q = 10$	14
Kondou et al. [36]	R1234ze(E)	$x = 0.14\text{--}0.95$, $P_{sat} = 0.30\text{--}1.10$, $D = 5.37\text{--}5.45$, $G = 200\text{--}387$, $q = 10$	88
Jige et al. [37]	R32	$x = 0.02\text{--}0.99$, $P_{sat} = 1.28$, $D = 3.61$, $G = 50\text{--}400$, $q = 5\text{--}20$	593
Jige et al. [38]	R32	$x = 0.01\text{--}1.00$, $P_{sat} = 1.28$, $D = 2.18\text{--}3.14$, $G = 50\text{--}400$, $q = 2.5\text{--}40$	1609
Bandarra Filho et al. [39]	R134a	$x = 0.06\text{--}0.88$, $P_{sat} = 0.35$, $D = 8.92$, $G = 100\text{--}500$, $q = 5$	87
Longo et al. [40]	R245fa	$x = 0.18\text{--}0.99$, $P_{sat} = 0.18$, $D = 4.5$, $G = 100\text{--}300$, $q = 30$	26
Jiang et al. [41]	R22	$x = 0.10\text{--}0.90$, $P_{sat} = 0.35\text{--}0.94$, $D = 8.96$, $G = 250$, $q = 12.5$	27
Honda et al. [42]	R744	$x = 0.16\text{--}1.00$, $P_{sat} = 4.50$, $D = 3.26$, $G = 190\text{--}770$, $q = 10\text{--}30$	126
Longo et al. [43]	R32	$x = 0.05\text{--}0.90$, $P_{sat} = 0.93\text{--}1.47$, $D = 4.50$, $G = 200\text{--}600$, $q = 12\text{--}51$	88
Spindler et al. [44]	R134a	$x = 0.11\text{--}0.83$, $P_{sat} = 0.57$, $D = 8.92$, $G = 25\text{--}150$, $q = 1\text{--}15$	90
Mancin et al. [45]	R134a	$x = 0.20\text{--}0.99$, $P_{sat} = 0.77$, $D = 3.64$, $G = 190\text{--}755$, $q = 10\text{--}50$	54
Yoshida et al. [46]	R22	$x = 0.50$, $P_{sat} = 0.40\text{--}0.59$, $D = 11.88$, $G = 50.1\text{--}507$, $q = 5\text{--}30$	38
		$x = 0.06\text{--}1.00$, $P_{sat} = 0.37\text{--}0.64$, $D = 6.41$, $G = 100\text{--}250$, $q = 28.15\text{--}49.29$	197
Zhao et al. [47]	R161		
Jin Kim et al. [48]	R744	$x = 0.02\text{--}0.78$, $P_{sat} = 3.05\text{--}3.97$, $D = 4.5$, $G = 212\text{--}530$, $q = 15\text{--}45$	72
Wang et al. [49]	R245fa, R22, R141b, R161	$x = 0.04\text{--}1.00$, $P_{sat} = 0.15\text{--}0.64$, $D = 6.41\text{--}8.72$, $G = 100\text{--}306.6$, $q = 7\text{--}49.29$	412
Iizuka et al. [50]	R410A	$x = 0.20\text{--}0.98$, $P_{sat} = 1.08$, $D = 6.7\text{--}6.8$, $G = 100\text{--}300$, $q = 5\text{--}20$	346
Total			4583

3.2. Physical Properties

The 30 physical properties listed in Tables 1 and 2 were used to influence heat transfer. Table 1 displays the data for the mini-channel, while Table 2 shows the data for the micro-fin. Where x is the mass quality, P_{sat} is the saturation pressure [MPa], D is the inner diameter [mm], G is the mass flux [$\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$], q is the heat flux [$\text{kW}\cdot\text{m}^{-2}$]. Thus, the databases are appropriate for evaluating our proposed algorithm. The physical property values were calculated using REFPROP Ver. 10.0 [51] provided by NIST.

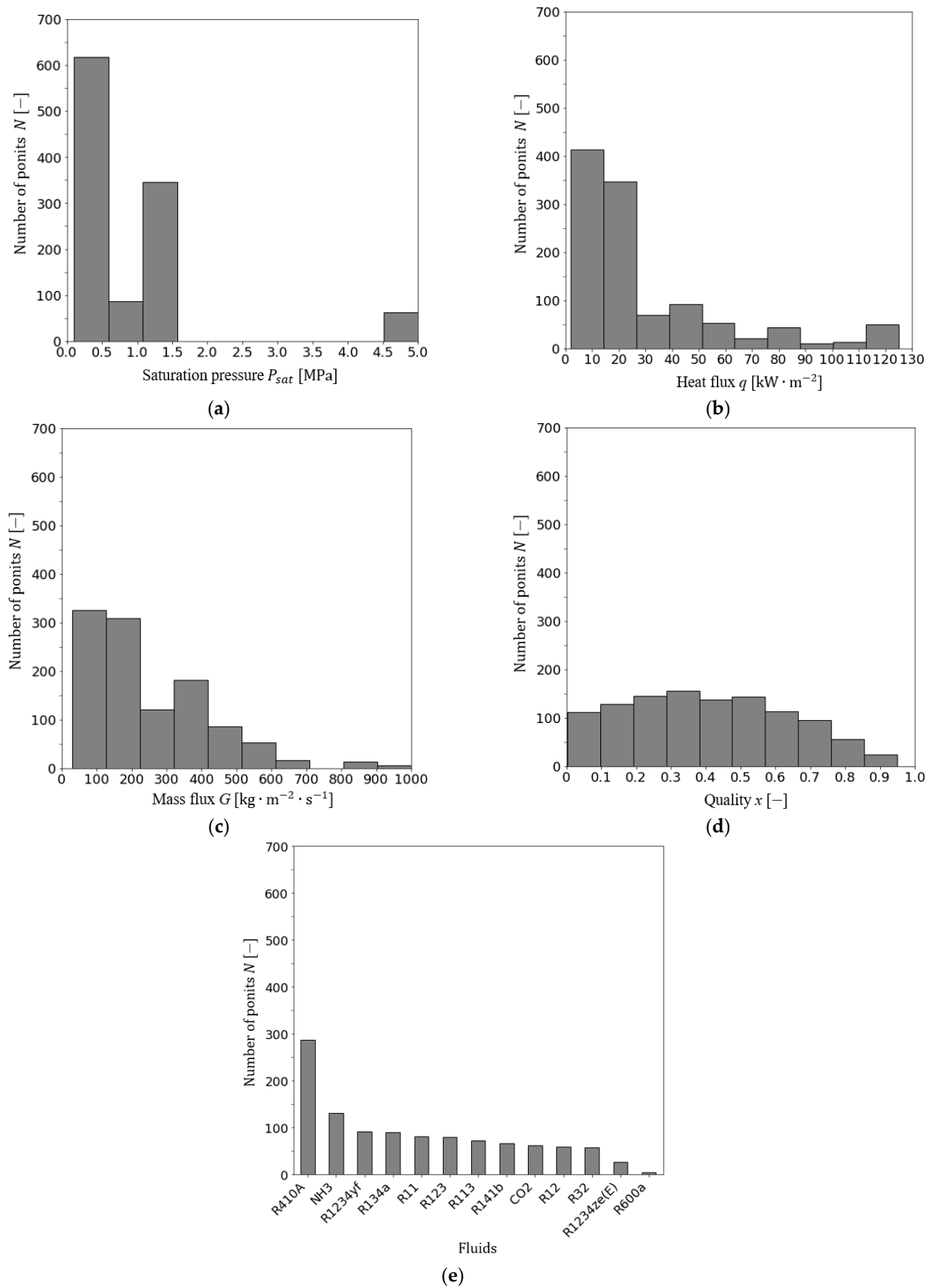


Figure 4. Distribution of the mini-channel database: (a) saturation pressure, (b) heat flux, (c) mass flux, (d) quality, (e) work fluids.

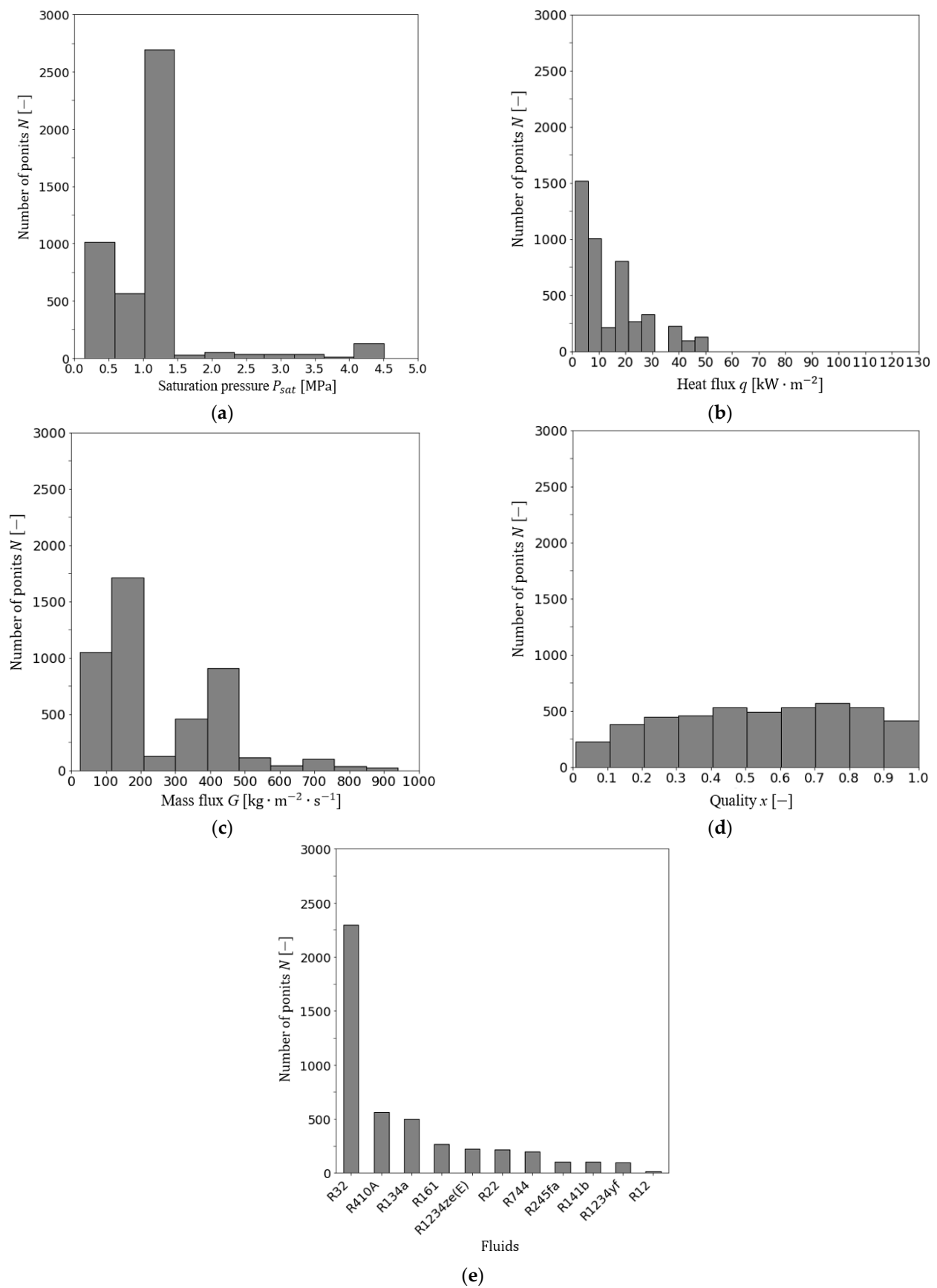


Figure 5. Distribution of the micro-fin database: (a) saturation pressure, (b) heat flux, (c) mass flux, (d) quality, (e) work fluids.

3.3. Method

A summary of each learning method is presented in Table 3. This paper compares three types of learning methods for predicting heat transfer coefficients: (1) deep learning only (Case 1), (2) a combination of deep learning and GPR (Case 2) [1], and (3) the proposed method, which involves building a pre-trained model followed by fine-tuning with deep learning and GPR (Case 3, present). Each proposed method follows a two-phase structure consisting of a training phase and a prediction phase. Figures 6 and 7 illustrate the training and prediction phases of the proposed learning approach. In the training phase, preliminary training is conducted based on standardized mini-channel data. Subsequently, fine-tuning (Case 3) is performed based on micro-fin data. Finally, in the prediction phase, the trained model is used to evaluate uncertainty using GPR, and predictions are adjusted to minimize uncertainty (variance), resulting in the output of predicted values for micro-fin heat transfer coefficients.

Table 3. Summary of methods.

	Case 1	Case 2	Case 3 (Present)
DNN	✓	✓	✓
GPR	-	✓	✓
Pre-training	-	-	✓
Consideration of physical mechanisms	-	-	✓
Visualization	-	-	✓

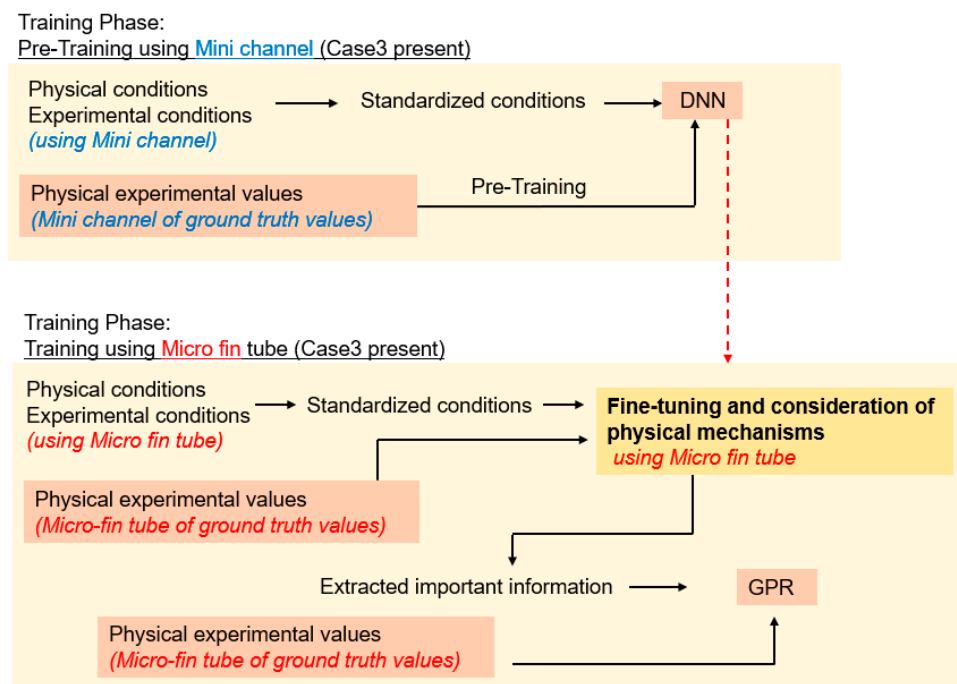


Figure 6. Pre-training and Fine-tuning, with consideration of physical mechanisms (Case 3, Present).

Furthermore, in the dataset, in addition to refrigerant properties and experimental conditions, common dimensionless numbers have been added to the prediction equations for the heat transfer coefficient to evaluate various phenomena consistently [52]. Dimensionless numbers provide a unified way to evaluate physical phenomena regardless of operating conditions and refrigerant properties, and they are used to describe the governing conditions of each force. Figure 8 illustrates the overview of the Proposed Method Incorporating Dimensionless Numbers. The additional dimensionless numbers are the

Bond number Bo , the Froude number Fr , the Weber number We , and the Reynolds numbers Re_V and Re_L , which are shown in Equations (4)–(8).

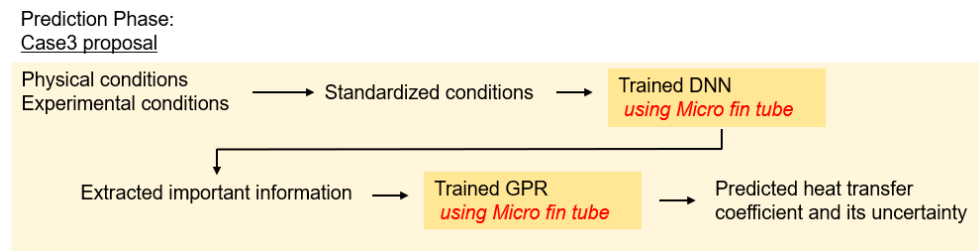


Figure 7. Prediction using micro-fins and consideration of physical mechanisms (Case 3, Present).

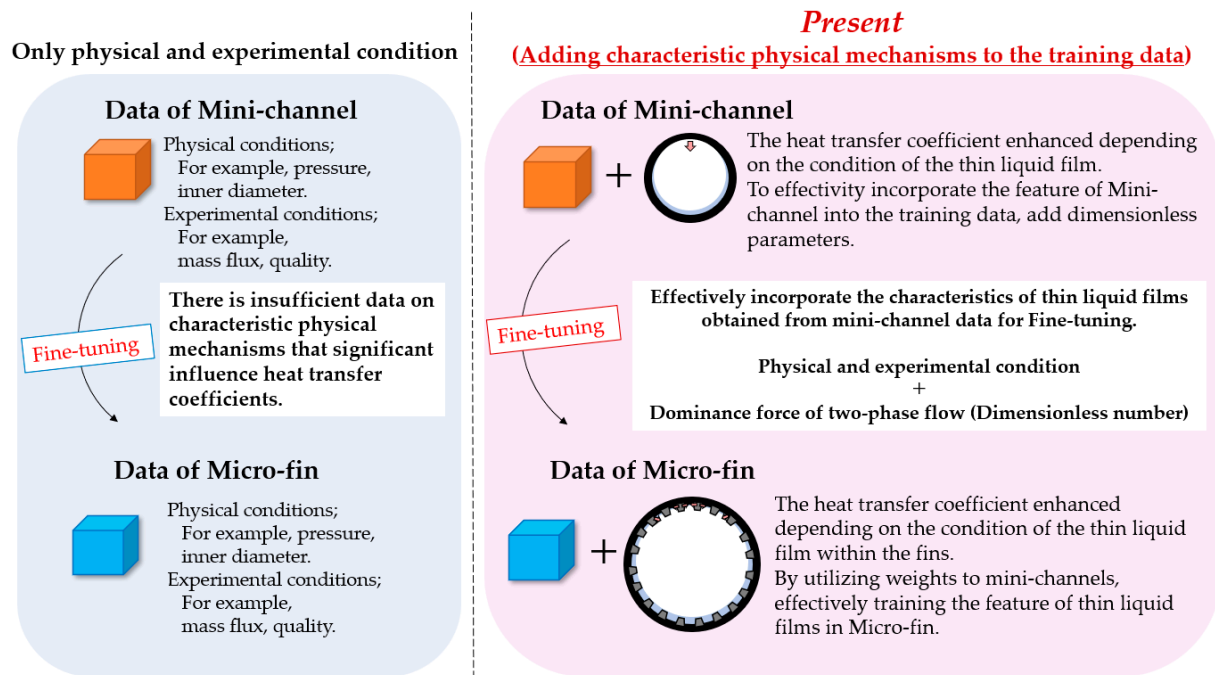


Figure 8. Overview of the Proposed Method Incorporating Dimensionless Numbers.

G is the mass flux [$\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$], ρ_L is the liquid density [$\text{kg}\cdot\text{m}^{-3}$], ρ_V is the vapor density [$\text{kg}\cdot\text{m}^{-3}$], g is the gravity [$\text{m}\cdot\text{s}^{-2}$], d is the inner diameter [mm], σ is surface tension [$\text{mN}\cdot\text{m}^{-1}$], μ_L is the liquid viscosity [$\mu\text{Pa}\cdot\text{s}$], μ_V is the vapor viscosity [$\mu\text{Pa}\cdot\text{s}$], ρ_m is average density [$\text{kg}\cdot\text{m}^{-3}$]. Here, the Bo , Fr , and We numbers represent the relationship between the forces acting on the two-phase flow inside the tube, including inertia, volume force, and surface tension. The Bo number represents the ratio of volume force to surface force, the Fr number represents the ratio of inertia force to volume force, and the We number represents the ratio of inertia force to surface tension. When inertia force dominates, the effects of mass velocity and quality are significant, whereas when surface tension dominates, the effects of mass velocity and quality are diminished. Additionally, the Re number represents the ratio of inertia force to viscous force. By considering the Re number, it is possible to determine whether viscous or inertia force predominates, thus allowing the flow patterns of two-phase flow to be evaluated according to the operational conditions.

$$Bo = \frac{(\rho_L - \rho_V)gd^2}{\sigma} \quad (4)$$

$$Fr = \frac{G^2}{\rho_L(\rho_L - \rho_V)gd} \quad (5)$$

$$We = \frac{G^2 d}{\rho_m \sigma}, \quad \rho_m = \frac{1}{\left(\frac{x}{\rho_V} + \frac{1-x}{\rho_L}\right)} \quad (6)$$

$$Re_V = \frac{G x d}{\mu_V} \quad (7)$$

$$Re_L = \frac{G(1-x)d}{\mu_L} \quad (8)$$

Figure 9 illustrates the structure of the learning process through fine-tuning. Fine-tuning involves using the weights of a pre-trained model as the initial values (in this paper, based on the mini-channel data) and constructing a new model by re-training the entire model using the micro-fin data. In the training process, a prediction function $f(x)$ is learned, where x represents the input data, and $f(x)$ returns the predicted heat transfer coefficient and the corresponding uncertainty. In the prediction process, based on the target input x^* , the heat transfer coefficient and the uncertainty are output.

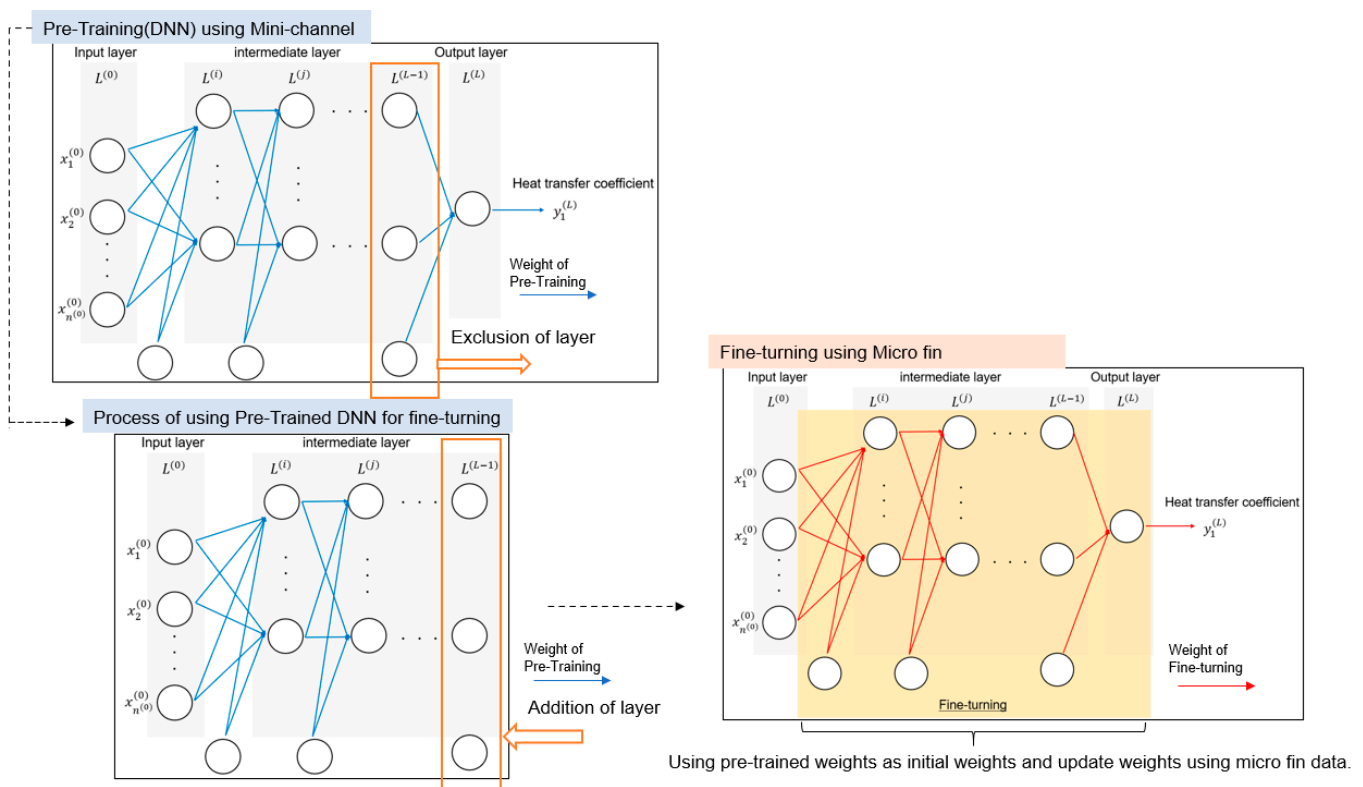


Figure 9. Model structure of training phase using pre-training and fine-tuning, with consideration of physical mechanisms (Case 3, Present).

There are three steps in the training phase. In the first step, a DNN performs preliminary training using standardized mini-channel data. The training data consists of physical conditions, experimental conditions, and the corresponding heat transfer coefficients. Equation (9) shows the method for standardizing the mini-channel training data $X_c = \{x_{c1}, \dots, x_{cn}\}$ and the micro-fin training data $X_f = \{x_{f1}, \dots, x_{fn}\}$. The training data uses 30 different physical quantities, and because their values vary significantly, standardization of the data is performed as preprocessing to improve the model's accuracy.

Here, x_i represents the i th sample of the training dataset. x_i comprises 30 conditions (15 physical conditions, ten experimental conditions, and five experimental values). Let x_{ij} represent the value of the j th condition of the i th sample. For each i and j , we calculate the value. For each i and j , $\text{Mean}(\cdot)$ and $\text{Std}(\cdot)$ represent the mean and standard deviation of $\cdot$. Here, let us denote the standardized mini-channel data as $\hat{X}_c = \{\hat{x}_{c1}, \hat{x}_{c2}, \dots, \hat{x}_{cn}\}$

and $\hat{x}_{ci} = \{\hat{x}_{ci,1}, \hat{x}_{ci,2}, \dots, \hat{x}_{ci,30}\}$, respectively. Similarly, denote the micro-fin data as $\hat{X}_f = \{\hat{x}_{f1}, \hat{x}_{f2}, \dots, \hat{x}_{fn'}\}$ and $\hat{x}_{fi} = \{\hat{x}_{fi,1}, \hat{x}_{fi,2}, \dots, \hat{x}_{fi,30}\}$, respectively.

$$\hat{x}_{ij} \leftarrow \frac{x_{ij} - \text{Mean}(\{x_{1j}, \dots, x_{nj}\})}{\text{Std}(\{x_{1j}, \dots, x_{nj}\})} \quad (9)$$

In the second step of the training phase, before fine-tuning based on micro-fin data, the weight $w_{1,1}^{(\mathcal{L})}, w_{2,1}^{(\mathcal{L})}, \dots, w_{L-1,1}^{(\mathcal{L})}$ and $b_1^{(\mathcal{L})}$ are initialized. The weights are connected to the final layer of the DNN, which was trained based on mini-channel data. After that, the DNN model, with the weights connected to the final layer initialized, is retrained (fine-tuning) using micro-fin data based on the L^{L-1} .

In the third step of the training phase, GPR is trained based on the output of layer L^{L-1} of the fine-tuning model and the corresponding heat transfer coefficient y . We do not use the final output value of the fine-tuning model but instead use y^{L-1} .

In the prediction phase, the samples needed to determine the heat transfer coefficient are first standardized based on Equation (10).

$$\hat{x}_{ij}^* \leftarrow \frac{x_{ij}^* - \text{Mean}(\{x_{1j}, \dots, x_{nj}\})}{\text{Std}(\{x_{1j}, \dots, x_{nj}\})} \quad (10)$$

Continuing, the GPR outputs the predicted heat transfer coefficient and the corresponding uncertainty for the target sample based on y^{L-1} . The training and prediction processes are repeated q times, where q is a predefined hyperparameter.

Finally, the results obtained from the repeated iterations (q times) are compared. The output results may include low and high uncertainty outcomes at this stage. Therefore, a procedure is carried out to consider the uncertainty of each result and aggregate their weights accordingly.

Here, assume that the true value t_i of the j th sample and the predicted value y_{ij} of the i th sample in the j th round follow a normal distribution. The probability that the predicted value y_{ij} occurs is shown in Equation (11).

Hence, v_{ij} represents the variance of the normal distribution of the i th sample in the j th turn. Furthermore, the probability for $j = 1, \dots, q$ is shown for each case in Equation (12).

$$p(y_{ij}) = \frac{1}{\sqrt{2\pi v_{ij}}} \exp\left(-\frac{1}{2v_{ij}} (t_i - y_{ij})^2\right) \quad (11)$$

$$\prod_{j=1}^q p(y_{ij}) = \left(\prod_{j=1}^q \frac{1}{\sqrt{2\pi v_{ij}}}\right) \exp\left(-\sum_{j=1}^q \frac{1}{2v_{ij}} (t_i - y_{ij})^2\right) \quad (12)$$

The value of x_i that maximizes Equation (12) is the most likely. When the following Equation (13) is satisfied, Equation (12) is maximized. Let $\hat{y}_i$ represent the most likely value of

$$\sum_{j=1}^q \frac{1}{2v_{ij}} (t_i - y_{ij}) = 0 \quad (13)$$

t_i that maximizes Equation (11). In this case, we have

$$\hat{y}_i \leftarrow \frac{\sum_{j=1}^q y_{ij}/v_{ij}}{\sum_{j=1}^q 1/v_{ij}} \quad (14)$$

The resulting variance can be obtained based on the propagation of the error formula [53]. Consider a function $z = f(t_1, t_2, \dots, t_q)$, where the variance of t_i is v_i . The variance $v(z)$ of z is represented by

$$v(x) = \sum_{j=1}^q \left(\frac{\partial z}{\partial t_j} \right)^2 v_j \quad (15)$$

Therefore, in our case, we have

$$\hat{v}_i \leftarrow 1 / \sum_{j=1}^q 1 / v_{ij} \quad (16)$$

Based on the above, the predicted heat transfer coefficients, optimized to minimize uncertainty through each learning phase, are output as the results. The overall algorithm of the learning process is presented in Algorithm 1.

Algorithm 1. Algorithm for predicting heat transfer coefficients of target samples

- 1: **Input:** Dataset of mini-channel; Training dataset $X_c = \{x_{c1}, \dots, x_{cn}\}$,
corresponding heat transfer coefficient $y_c = \{y_{c1}, \dots, y_{cn}\}$, target samples
 $T_c = \{t_{c1}, \dots, t_{cm}\}$
Dataset of micro-fin Training dataset $X_f = \{x_{f1}, \dots, x_{fn}\}$,
corresponding heat transfer coefficient of $y_f = \{y_{f1}, \dots, y_{fn}\}$, target samples
 $T_f = \{t_{f1}, \dots, t_{fm}\}$
 - 2: **Output:** Predicted heat transfer coefficients $\hat{Y} = \{\hat{y}_1, \dots, \hat{y}_n\}$, and corresponding uncertainty
 $\hat{V} = \{v_1, \dots, v_n\}$
 - 3: /** Standardization */
 - 4: **for** $j = 1, \dots, 30$ **do**
 - 5: **for** $i = 1, \dots, n$ **do** /** Standardize X_c */
 - 6: $\hat{x}_{ij} \leftarrow \frac{x_{ij} - \text{Mean}(\{x_{1j}, \dots, x_{nj}\})}{\text{Std}(\{x_{1j}, \dots, x_{nj}\})}$
 - 7: **end for**
 - 8: **for** $i = 1, \dots, n'$ **do** /** Standardize X_f */
 - 9: $\hat{x}_{ij} \leftarrow \frac{x_{ij} - \text{Mean}(\{x_{1j}, \dots, x_{nj}\})}{\text{Std}(\{x_{1j}, \dots, x_{nj}\})}$
 - 10: **end for**
 - 11: **for** $i = 1, \dots, m$ **do** /** Standardize T_c */
 - 12: $\hat{t}_{ij} \leftarrow \frac{t_{ij} - \text{Mean}(\{x_{1j}, \dots, x_{nj}\})}{\text{Std}(\{x_{1j}, \dots, x_{nj}\})}$
 - 13: **end for**
 - 14: **for** $i = 1, \dots, m'$ **do** /** Standardize T_f */
 - 15: $\hat{t}_{ij} \leftarrow \frac{t_{ij} - \text{Mean}(\{x_{1j}, \dots, x_{nj}\})}{\text{Std}(\{x_{1j}, \dots, x_{nj}\})}$
 - 16: **end for**
 - 17: **end for**
 - 18: Create an empty array y_s and v_s
 - 19: **for** $i' = \{1, \dots, q\}$ **do**
 - 20: Initialize and train the DNN model M_D based on $\hat{X}_c$ and y_c . □
 - 21: Initialize weight parameters $w_{i1}^{(\mathcal{L})}$ and $b_1^{(\mathcal{L})}$ leading to the M_D output of $(\mathcal{L}, \hat{T})$ layer.
 - 22: Train the fine-tuning model M_F based on initialized weight M_D and $\hat{X}_f$ and y_f . □
 - 23: Initialize and train the GPR model M_G based on M_F output of $(\mathcal{L} - 1, \hat{T})$ layer and y .
 - 24: y_{pred} and $v_{pred} \leftarrow M_G \text{ predict}(M_F \text{ output of layer } (\mathcal{L} - 1, \hat{T}))$
 - 25: Substitute y_{pred} and v_{pred} in y_s and v_s , respectively.
 - 26: **end for**
 - 27: **for** $i = 1, \dots, m$ **do**
 - 28: $\hat{y}_i \leftarrow$ Equation (14) using y_s and v_s
 - 29: $\hat{v}_i \leftarrow$ Equation (16) using v_s
 - 30: **end for**
 - 31: **return** $\hat{Y}$ and $\hat{V}$
-

4. Evaluation

The error of heat transfer coefficients between the predicted values at the output layer and the actual values was evaluated using the standard deviation (*SD*) and mean squared error (*MSE*). Equation (17) represents the *SD*, while Equation (18) is the mean squared error. Here, α_i^{exp} denotes the heat transfer coefficient of the test data, and α_i^{cal} represents the predicted heat transfer coefficient. *R20* and *R30* are the ratios of the number of data points within $\pm 20\%$ and $\pm 30\%$ deviation, respectively, from each predicted value to the total number of data points.

We conducted tenfold cross-validation for training and prediction. The data points in the databases were randomly divided into ten datasets. Nine sets were used as training data for deep learning. The remaining dataset was used to predict the heat transfer coefficient based on the trained deep learning model. This process was repeated ten times using the tenfold cross-validation method, and the average value of the predicted heat transfer coefficients was calculated as α^{cal} by machine learning.

$$SD = \sqrt{\frac{1}{N} \sum_i^N \left(\frac{\alpha_i^{cal} - \alpha_i^{exp}}{\alpha_i^{exp}} \right)^2} \quad (17)$$

$$MSE = \frac{1}{N} \sum_i^N \left(\alpha_i^{cal} - \alpha_i^{exp} \right)^2 \quad (18)$$

5. Results and Discussion

5.1. Prediction Accuracy Depends on Learning Conditions

Prediction accuracy was evaluated for each learning condition, and the results were compared. Table 4 shows the prediction results for each learning condition. Additionally, Figure 10 illustrates the relationship between predicted values α_i^{cal} and training values α_i^{exp} for each learning condition. *R20* and *R30* represent the ratios of the number of data points within $\pm 20\%$ and $\pm 30\%$ deviation, respectively, from each predicted value α_i^{cal} to the total number of data points.

Table 4. MSE and percentages of *SD*, *R20*, and *R30* per prediction condition.

	DNN, Case 1	DNN + GPR, Case 2	Fine-Tuning and Consideration of Physical Mechanisms, Case 3 (Present)
<i>SD</i>	21.9	19.8	18.7
<i>R20</i>	88.2	93.0	93.5
<i>R30</i>	94.5	96.2	96.7
<i>MSE</i>	5.1	2.4	2.3

The prediction results confirmed that those of fine-tuning (Case 3) exhibited the highest accuracy in terms of *SD*, *R20*, *R30*, and *MSE*. Additionally, fine-tuning allowed for accurate prediction of HFO refrigerants, which are relatively new, indicating that high-accuracy prediction can be achieved regardless of the refrigerant type. The improved prediction accuracy with fine-tuning is attributed to its ability to utilize the weights of the pre-trained model as initial values and retrain the entire model, effectively incorporating the feature of micro-fins. Using the weights of mini-channels as initial values in Case 3, the features of micro-fin heat transfer coefficients were more effectively captured than learning from micro-fin data. Furthermore, to evaluate accuracy in predicting under operating conditions, we assessed predictive accuracy using heat flux and mass flux conditions. Table 5 shows the prediction results under heat flux conditions. Table 6 shows the results under mass flux conditions. From the results, it is confirmed that high accuracy in prediction is achieved regardless of the operating conditions. Furthermore, Figure 11 illustrates the relationship

between MSE and variance by the proposed method. The variances can be considered as uncertainties, and it is observed that as variance increases, MSE also increases. In the proposed method, prediction accuracy is improved by minimizing both the predicted error and its uncertainties in each prediction phase.

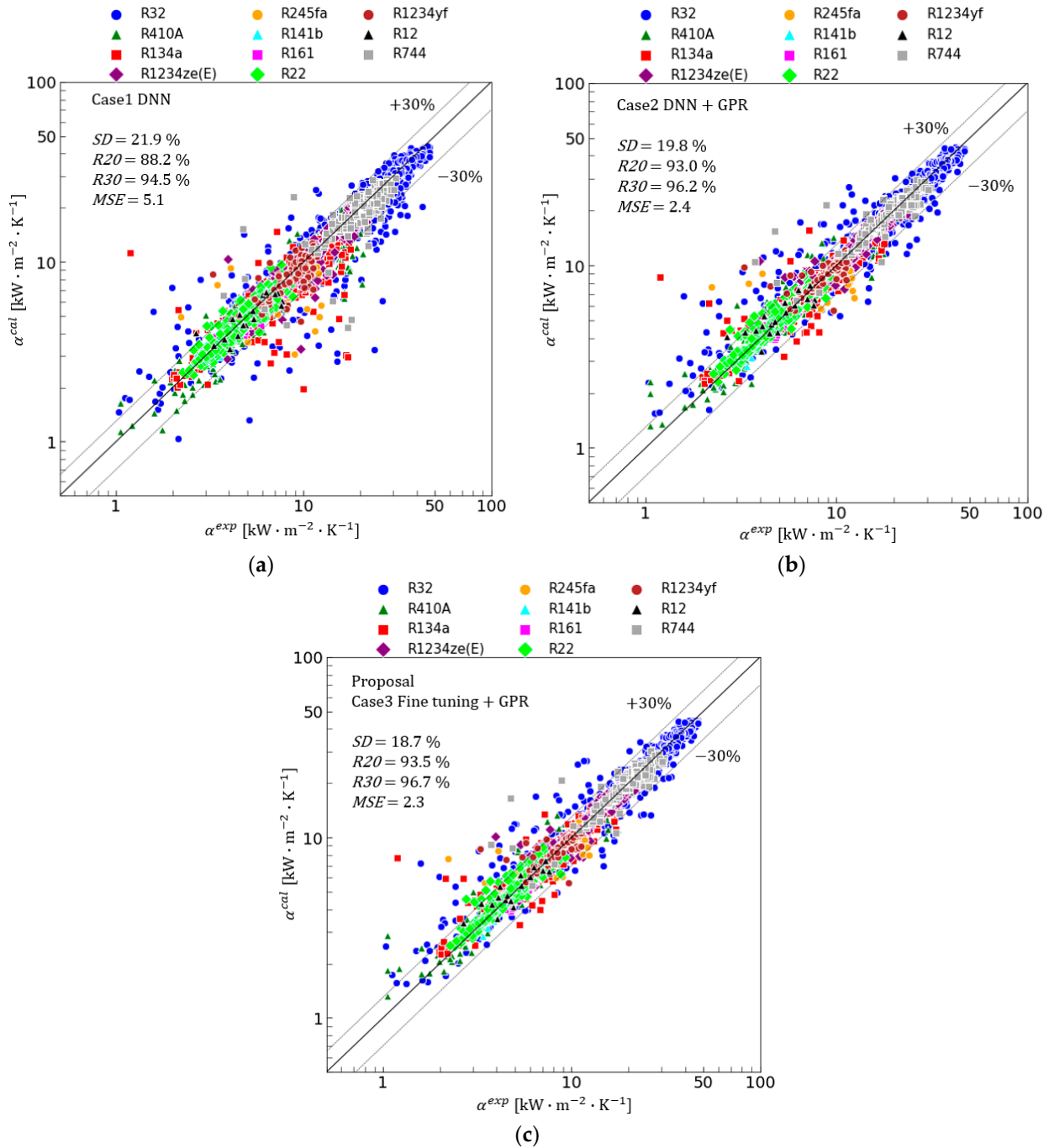


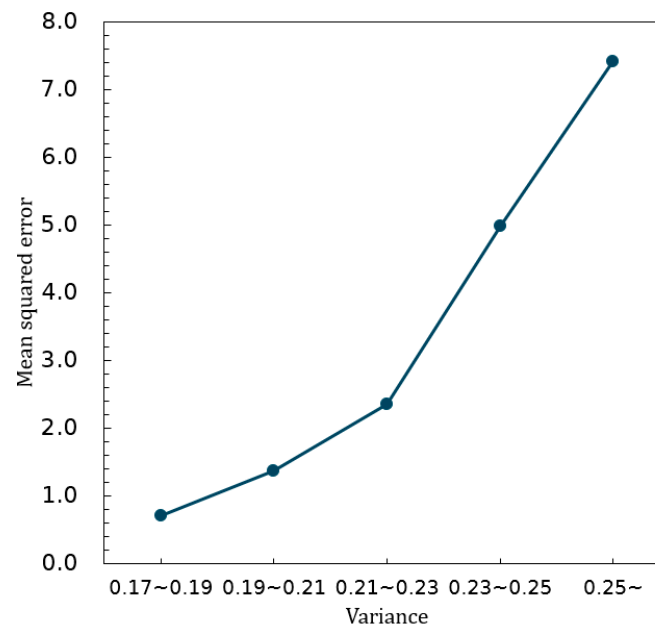
Figure 10. Comparison of predictions and experimental data: (a) Results of DNN (Case 1); (b) Results of DNN + GPR (Case 2); (c) Results of fine-tuning and consideration of physical mechanisms (Case 3).

Table 5. MSE and percentages of SD, R20, and R30 per heat flux condition in Case 3.

Heat Flux [$\text{kW}\cdot\text{m}^{-2}$]	SD [%]	R20 [%]	R30 [%]	MSE
0~5.0	18.6	93.0	96.4	2.7
5.0~20.0	19.3	93.7	97.0	2.7
20.0~30.0	16.6	93.1	96.2	2.2
35.0~50.0	12.1	94.3	96.4	0.6

Table 6. MSE and percentages of SD, R20, and R30 per mass flux condition in Case 3.

Mass Flux [$\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$]	SD [%]	R20 [%]	R30 [%]	MSE
0~250	20.5	92.3	96.2	2.5
250~500	15.0	95.9	97.8	1.9
500~750	8.6	96.2	98.7	1.0
750~1000	16.5	94.0	96.4	2.7

**Figure 11.** Variance (uncertainty) vs. mean squared error.

To visualize the contribution of each feature to the prediction accuracy for each model, SHAP (SHapley Additive exPlanations) was utilized to evaluate the importance of features, representing the impact of each feature on the model's predictions for the training data [54]. Figure 12 illustrates the differences in feature importance attributed to the training data. It compares the SHAP results for Case 3 (which utilized pre-training with mini-channel data) and Case 2 (which used micro-fin data). Figure 12 shows that the importance of a feature depends on the training data. When mini-channel data is used as training data, features such as surface tension, heat flux, latent heat, and liquid thermal conductivity are highly important. Conversely, when micro-fin data is used, features such as mass flux, quality, Fr number, Re number, and fin height are more important. Mini-channels exhibit slug flow, primarily in regions characterized by low flow rate and low quality, where the effect of surface tension becomes significant. This results in a thinner liquid film surrounding the gas plug, which enhances evaporative heat transfer coefficients due to heat conduction. Also, micro-fins show high importance in groove shape features, mass flux, quality, and Fr number. Figure 13 depicts the importance of features during the training

process of Case 3, including pre-training and fine-tuning. In fine-tuning, the weights from pre-training with mini-channel data are used as initial values, and new weights are trained using micro-fin data. Thus, the features of Case 3 fine-tuning (using micro-fins) exhibit stronger contributions from parameters such as inner diameter, quality, mass flux, and We number than features related to groove shapes such as fin count. In particular, the contributions of inner diameter and We number increased as a result of fine-tuning with micro-fin data, indicating their enhanced relevance in predicting heat transfer coefficients. It has been reported that the heat transfer coefficients of mini-channels depend on the mass flux. In low mass flux, the liquid film between the fins at the top of the tube and the formation of meniscus liquid film on the side of the fins due to surface tension improve heat transfer enhancement. However, in high mass flux, the liquid film formed around the tube circumference is uniform, resulting in a smaller heat transfer enhancement than in low mass flux regions. Therefore, the relationship between surface tension and inertia forces around the fins is crucial for predicting micro-fin heat transfer coefficients. Thus, we assumed that the initial weights of fine-tuning were influenced by training from mini-channel data with high weights on surface tension during pre-training, training to higher contributions of features such as We number and inner diameter, which indicate the relationship between surface tension and inertia forces. Consequently, this contributed to the improvement in prediction accuracy of fine-tuning.

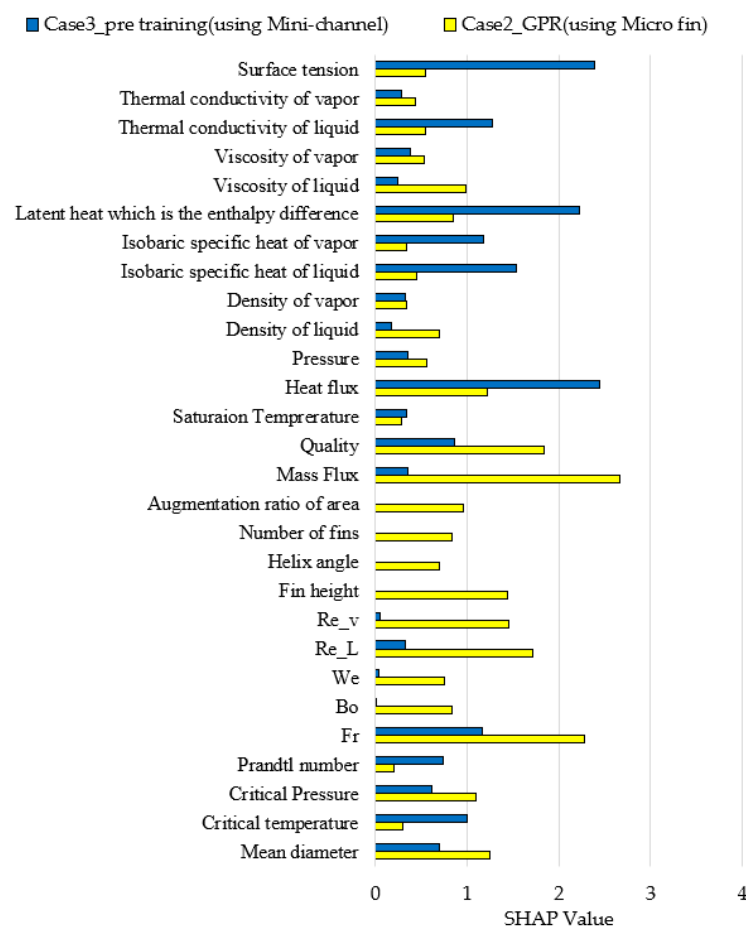


Figure 12. Impact on model output (for micro-fin vs. mini-channel data).

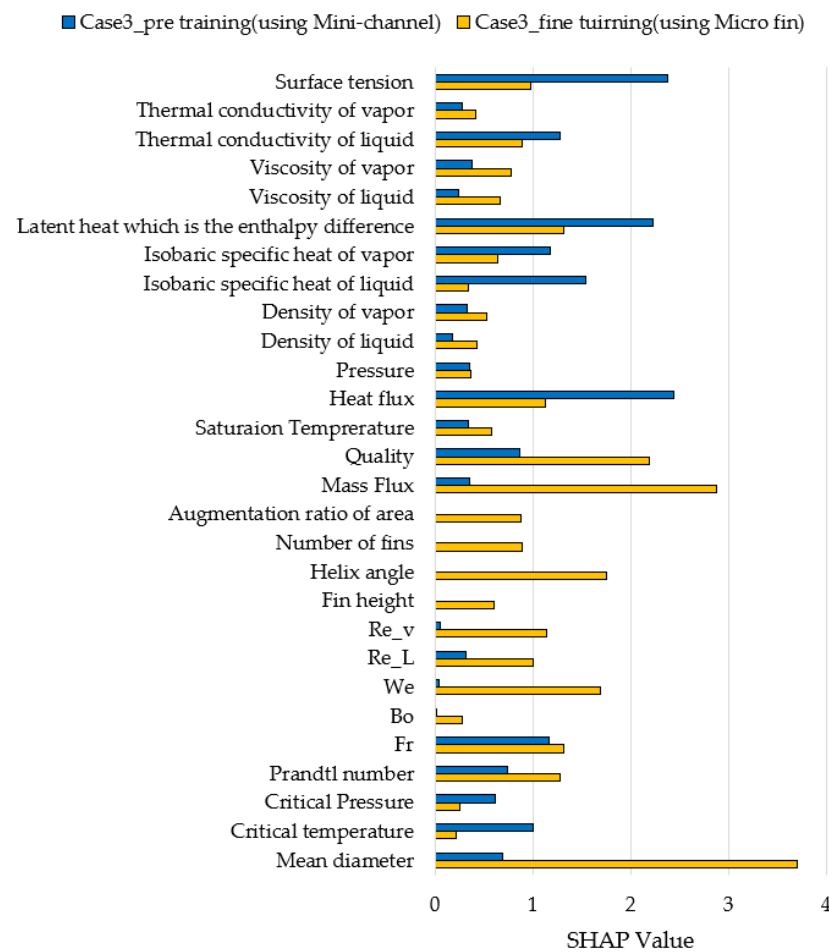


Figure 13. Impact on Case 3 model output (pre-training vs. fine-tuning and consideration of physical mechanisms).

5.2. Prediction Accuracy with Less Learning Data

To verify the effect of the number of training data points on prediction accuracy, we reorganized the training data for micro-fins and conducted verification. From the micro-fin data, we selected data based on tubes having a diameter below 7 mm and inclusion of refrigerants in smooth tube data. This reorganization resulted in reducing the number of micro-fin data points to 1002. Thus, we conducted preliminary training using 1111 data points from smooth tubes and then performed training using the 1002 micro-fin data points.

Figure 14 illustrates the relationship between predicted values α_i^{cal} and training values α_i^{exp} for each learning condition. Additionally, Table 7 presents the results of SD , $R20$, and $R30$ for each condition. From the results, while the SD value was comparable to existing methods, all other evaluation metrics surpassed those of the proposed method. Furthermore, as a comparison with existing prediction equations, we evaluated using Diani et al. [10] models. Diani et al. proposed a highly accurate prediction model for the heat transfer coefficient of micro-fin using R1234ze(E). However, including multiple refrigerants such as R1234yf, R410A, R32, and R134a, the ratio of the number of data points within $\pm 30\%$ is $R30 = 68\%$. Hence, the efficacy of our proposed method in developing prediction models for multiple refrigerants is confirmed.

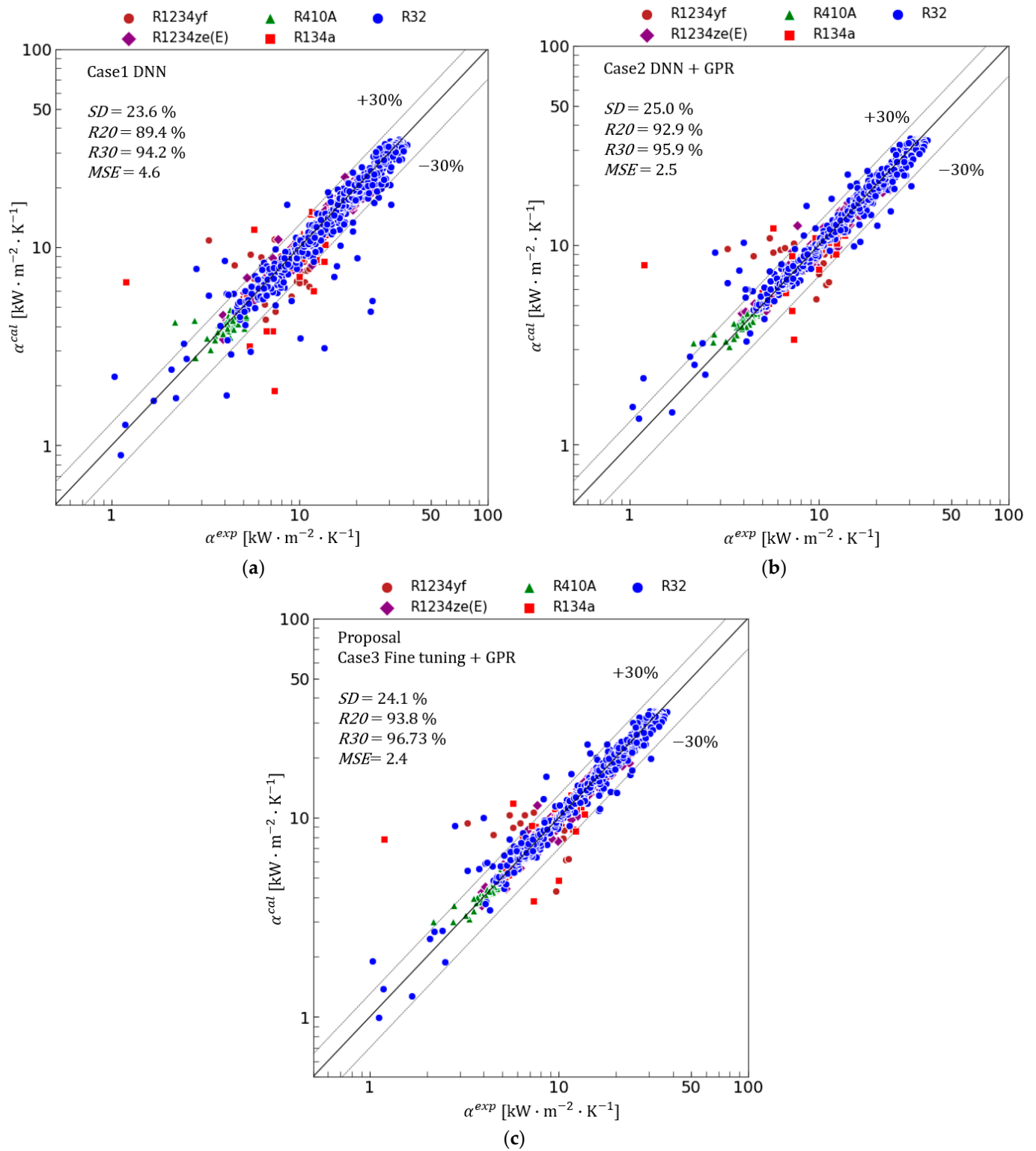
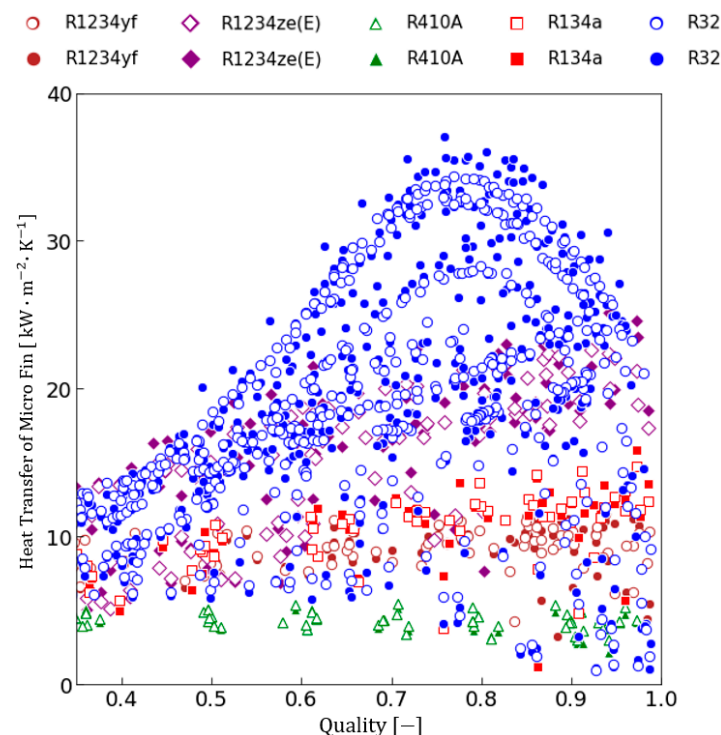


Figure 14. Comparison of predictions and experimental data (mini-channel data > micro-fin data): (a) Results of DNN (Case 1); (b) Results of DNN + GPR (Case 2); (c) Results of fine-tuning and consideration of physical mechanisms (Case 3).

Table 7. MSE and percentages of SD, R20, and R30 per prediction condition (mini-channel data > micro-fin data).

	DNN, Case 1	DNN + GPR, Case 2	Fine-Tuning and Consideration of Physical Mechanisms, Case 3 (Present)
<i>SD</i>	23.6	25.0	24.1
<i>R20</i>	89.4	92.9	93.8
<i>R30</i>	94.2	95.9	96.3
<i>MSE</i>	4.6	2.5	2.4

Figure 15 displays the results comparing predicted values α_i^{cal} (open symbols) and training values α_i^{exp} (closed symbols) near the post-dryout region across a range of qualities from 0.4 to 1.0. The training data for R32 reveals a decrease in heat transfer coefficient due to post-dryout when the quality is approximately 0.8 or higher. Correspondingly, the predicted values also show a decrease in heat transfer coefficient under conditions where the quality is 0.8 or higher, indicating that the model can predict the decrease in heat transfer coefficient due to post-dryout. In this evaluation, the data for post-dryout is not included in the mini-channel data. From this result, it can be inferred that the proposed method accurately predicts the decrease in heat transfer coefficient based on quality for post-dryout data despite the limited experimental data available, thus confirming the effectiveness of this approach.

**Figure 15.** Comparison of prediction (open) and experimental (closed) heat transfer coefficients.

6. Conclusions

This study developed a deep learning model that achieves high prediction accuracy for the heat transfer coefficient of micro-fins, including post-dryout, using a relatively small amount of data. The proposed approach involves conducting pre-training based on data from mini-channels, which are highly relevant to the heat transfer coefficient of micro-fins and fine-tuning the pre-trained model using the target data. Furthermore, we added dimensionless numbers assumed to significantly influence heat transfer coefficients

calculated from experimental data to the training dataset. We propose a novel approach that utilizes microchannel data to predict the heat transfer coefficients of micro-fins, combining physical mechanisms with DNN/GPR/fine-tuning.

In the experiments, 4584 data points for micro-fin heat transfer coefficients and 1111 data points for mini-channel heat transfer coefficients were used to develop the prediction model, considering 16 types of refrigerants. Three predicting conditions were evaluated: a model using only a deep neural network (DNN), a model combining DNN with GPR, and the proposed fine-tuning approach.

- (1) In our proposed method, we verified the attainment of high accuracy by introducing dimensionless numbers presumed to exert significant influence on calculated heat transfer coefficients from data. It has been reported that heat transfer coefficients in mini-channels improve as the liquid film thins, and similarly, microfins enhance heat transfer coefficients by facilitating the formation of thin liquid films between fins. Thus, we represented the predominant influence of phase interactions crucial to heat transfer coefficients using dimensionless numbers added to the training dataset. Consequently, by reutilizing the physical insights derived from data in mini-channels as weights, we effectively fine-tuned predictions of microfin characteristics based on thin liquid films.
- (2) The results predict that the proposed method using fine-tuning with pre-training on mini-channel data outperformed other methods solely trained on micro-fin data in prediction accuracy. Additionally, under conditions where the training data was reduced compared with pre-training data (mini-channel > micro-fin), the proposed method showed equivalent results to existing methods only in terms of the standard deviation (SD) but outperformed in all other evaluation metrics. Furthermore, the proposed method accurately predicted the decrease in heat transfer coefficients according to the quality of post-dryout data with limited experimental data, confirming the effectiveness of this approach. Hence, it has been confirmed that high heat transfer coefficients not only before dryout obtained from experimental data, but also dryout quality and post-dryout heat transfer coefficients, can be predicted with high accuracy.
- (3) We employed SHAP for visualizing the opaque black box of machine learning models. Our findings revealed that fine-tuning mini-channel data to predict heat transfer coefficients for microfins showed significant influence from mini-channels where surface tension played a crucial role. This influence was observed to affect the initial weights of the fine-tuning process, emphasizing the substantial contribution of features related to surface tension and inner diameter in elucidating the relationship.
- (4) For future work, we plan to expand the scope of prediction by incorporating flow patterns, different geometries, and gravity directions into the training data. This will allow us to extend the prediction capabilities to conditions and environments where experimental data acquisition is challenging. Furthermore, we plan to continue considering improvements to further enhance prediction accuracy through data augmentation and proposing novel prediction models. By doing so, we aim to support the prediction of heat transfer coefficients and contribute to the development of efficient, innovative technologies.

Author Contributions: K.E., Y.S. and T.K.: methodology, Y.S.: software, Y.S. and T.K.: validation, T.K.: investigation, T.K.: data curation, K.E.: Writing—original draft, T.K.: Writing—review and editing, T.K., Y.S., K.E., N.G. and K.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Acronyms

ANN	Artificial Neural Network
Bo	Bond number
DNN	Deep Neural Networks
Fr	Froude number
GPR	Gaussian Process Regression
LLMs	Large Language Models
MSE	Mean Squared Error
Re	Reynolds number
R_{20}	Ratios of the number of data points within $\pm 20\%$
R_{30}	Ratios of the number of data points within $\pm 30\%$
Std	Standard deviation
SD	Standard deviation
SHAP	SHapley Additive exPlanations
We	Weber number

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