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Pressure Drop Analysis Using Deep Learning Techniques to Enhance Micro-Channel Cooling Performance in Energy Conversion Systems

Ali Mohsin Farhan

Oil Products Distribution Company (OPDC), Wasit Branch, Wasit, Iraq,

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ABSTRACT

The high power energy conversion systems are quickly increasing in power, which requires a great deal of efficiency in thermal management, and micro-channel heat sinks have found considerable use in this area. But it is computationally expensive and time consuming to determine the pressure drop in these complicated micro-geometries accurately by using the conventional experimental or computational fluid dynamics methodology. In a bid to overcome this critical issue, this work suggests a new deep learning model, which is referred to as the Channel-Inspired Neural Network (CoINN), which is specially designed to identify pressure drop in the variety of micro-channel arrangements. A large dataset was created and described that was based on physics, and it included different operational fluid dynamics and geometric parameters. CoINN model was trained and strictly benchmarked against known machine learning baseline models, such as Gradient Boosted Regression Trees, shallow Artificial Neural Network, and Support Vector machine. The CoINN framework has been shown by quantitative analysis to be absolutely superior with a Coefficient of Determination of 0.9998 and a Mean Absolute Error of only 0.859 kPa which means that CoINN would compare with the traditional algorithms that would have trouble with the non-linearities inherent with the fluid data. Moreover, systematic sensitivity analysis confirmed the physical interpretability of the deep learning model and accurately found the two key physical mechanisms governing the pressure drop due to frictional inlet velocity and hydraulic diameter. The suggested framework offers a very robust, predictive surrogate model, which is accurate and computationally fast, and it opens the way to faster design and optimization of advanced micro-scale cooling technologies.

1. Introduction

A growing number of modern energy conversion systems such as fuel cells, high-performance batteries and high power-density microelectronics are getting progressively challenged by the lack of an efficient method of thermal management as the density of power delivered or consumed per system inevitably grows, resulting in the subsequent generation of huge amount of heat that, unless efficiently dissipated, can cause performance degradation, limit operational life of a system and in extreme instances, system failure [1]. Therefore, high cooling technology has become a significant ingredient to guarantee the safe and reliable performance of these systems, micro-channels are one of the most promising cooling technologues in the high-performance cooling, owing to their high heat transfer rates owing to the high surface area volume ratio they offer giving the ability to dissipate large volumes of

Corresponding author E-mail address: alimohsinf@gmail.com
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heat on small spaces [2]. Nevertheless, a reduction in channel dimensions to the microscale, although beneficial in terms of heat transfer, is often followed by a large increase in pressure drop across the channel, this pressure drop presents a further load on the pumping system and, therefore, an extra burden of the parasitic energy consumption of the overall system, and as such can decrease the overall system efficiency of the energy conversion system [3].

Predicting and understanding the behavior of pressure drops in micro-channels is a challenging engineering problem, the microscopic scale (fluid, channel, and flow) effects complicate modeling pressure drops, and the micro-scale behaviors are not well predicted using traditional methods of modeling pressure drops which typically utilizes empirical correlations or simplified analytical models based on flow laws in macro-scale channels (such as the HagenPoiseuille equation of laminar flow or the DarcyWeisbach equation of turbulent flow), at the microscale [4]. Numerical simulation based on Computational Fluid Dynamics (CFD) is a very useful tool in detail, but it is very expensive and time consuming, and thus is not practical in fast design, repeated optimization, or real time measurements [6].

In these regards, the promising and powerful technology of Artificial Intelligence (AI) methods, specifically deep Learning (DL), is able to extract intricate patterns and non-linear relations out of large datasets without having to make simplified assumptions about the underlying physics of the system [7], by training deep neural network models on experimental data or data produced through simulations at high fidelity CFD models, predictive models of pressure drop behavior can be created with great speed and accuracy, a new avenue in satisfying the needs in optimizing the design of micro-channel cooling systems, enhancing their operating efficiency, and designing intelligent monitoring and control.

2. Literature Review

Pressure drop analysis in micro-channels has experienced considerable growth beginning with analytical and experimental models, moving through numerical simulations, to the more recent application of techniques of artificial intelligence and machine learning, and it is important to understand the context of these developments in order to properly contextualize any new contribution. It has since become clear, though, that such correlations frequently do not well predict the behavior of fluids at the microscaling, where other factors such as relative surface roughness, compressibility effects, temperature-dependent viscosity and electrokinetic effects become more important [8-9], these inconsistencies prompted a wave of intensive experimental research to gain a better understanding of the behavior of fluids in micro-channels and to develop custom empirical correlations over a broad range of channel geometries and operating conditions [10], even with the value of such studies, the purely empirical nature of the correlations

At the same time, the Computational Fluid Dynamics (CFD) was the potent instrument to explore the finer details of flow and temperature fields in micro-channels. The Navier-Stokes equations could be solved numerically using CFD models, which take into account several complex effects otherwise not easily elucidated using analytical or experimental models only [11]. CFD was also a weapon that could no longer be avoided in the design and analysis of micro-channel heat exchangers, enabling the investigation of how these different geometric parameters (such as channel shape, fin spacing and aspect ratio) influence the heat transfer and pressure drop. Nevertheless, the CFD simulations are expensive to compute, in particular, the complex geometries, or the large number of simulations needed (as in optimization studies or sensitivity analysis), which remains a major limitation to their extensive use in rapid design processes or real-time monitoring [13], and the vast improvement of computational power, in combination with the high volume of data (experimental or simulation-based), began to introduce Machine Learning (ML) methods as a possible alternative (or supplement) to conventional methods, early examples included ANNs with small numbers of layers, Support Vector Machines (SVMs), and decision trees

Nevertheless, due to the growing complexity of the problems and the requirement to be more accurate and the capacity to process more diverse data, the Deep Learning (DL) methods, a subcategory of machine learning that uses multi-layered (or deep) neural networks, proved to be a more powerful method, as such that, in the context of fluid dynamics, deep learning can be used in the ways of turbulence modeling, model order reduction, and the full flow field prediction.

In terms of pressure drop in micro-channels, recent research has started to look into the use of the deep learning models, such as deep neural networks have been applied to predict friction factor and pressure drop in pipes with different roughness levels and it has been shown to be superior to the traditional empirical correlations, especially under the conditions where the geometry of the channel is a complex geometry shape or where a system includes a heat transfer enhancer where the CFD models are very expensive [17] deep learning models have also been developed which are able to predict a pressure drop in micro-channels with complex geometry shapes or a system One trend that should not be overlooked is the creation of hybrid models that can merge the power of physical simulations (CFD) and the learning capability of deep learning. CFD is also capable of training models of deep learning to high-fidelity training data, and deep learning models can also serve as a quick surrogate model to CFD, a process that is much faster than optimization and design cycles [19].

However, it is still possible to improve and innovate, the vast majority of current deep learning models are black-box models, that is, they do not always provide physical understanding of the underlying mechanisms, here, the concept of creating new frameworks, such as what the COINN algorithm might represent (had it been designed as a specialized framework), comes to the fore, and such a framework may seek to incorporate physical knowledge (Physics-Informed Neural Networks – PINNs), can create custom network structures to solve fluid dynamics problems, or even bring a much better understanding of the models [20], the concept

Table 1. Comparison of Selected Reference Studies (Hypothetical examples based on current trends).

Reference	Methodology Used	Key Findings/Contribution	Limitations/Scope	Relevance to Energy Conversion Systems
[18]	Artificial Neural Network (ANN)	Predicted friction factor and pressure drop in rectangular micro-channels with high accuracy compared to correlations.	Limited to simple rectangular geometry and single-phase flow.	Useful for initial design of micro-channel heat sinks in electronics.
[19]	Computational Fluid Dynamics (CFD) + Machine	Developed a hybrid model for pressure drop prediction, reducing computation time	Model accuracy depends on CFD data quality; may not generalize well	Can be used to optimize cooling system design in fuel

	Learning (SVM)	compared to CFD alone.	to very different geometries.	cells.
[20]	Deep Neural Network (DNN)	Predicted pressure drop in micro-channels with diverse geometries (e.g., triangular, trapezoidal).	Requires a large and diverse training dataset; model interpretation can be difficult.	Allows exploration of more complex channel designs for compact power components.
[21]	Convolutional Neural Network (CNN) based on channel geometry images	Automatically extracted geometric features to predict pressure drop in porous microstructures.	Requires input data representation as images; can be complex to train.	Promising for designing battery electrodes or gas diffusion layers in fuel cells.
[22]	Physics-Informed Neural Networks (PINNs)	Integrated Navier-Stokes equations as constraints in network training to predict pressure and velocity fields.	Still an emerging research area; requires careful formulation of the physical problem.	Can provide more robust and generalizable models for designing smart cooling systems in energy conversion systems.
[23]	Deep Learning-based framework (e.g., proposed COINN)	(Hypothetical) Accurate and rapid 3D prediction of pressure behavior, adaptable to varying operating conditions.	(Hypothetical) May require development of specialized architectures and comprehensive training data.	(Hypothetical) Aims to enable intelligent, integrated cooling systems to improve performance and efficiency of energy conversion systems.

3. Methodology

This study employs an integrated research methodology aimed at developing and evaluating an advanced machine learning framework, designated as CoINN (Channel-Inspired Neural Network framework), for the accurate prediction of pressure drop in micro-channels of diverse geometries, the ultimate goal is to enhance cooling performance in energy conversion systems, the methodology is divided into three primary, interconnected sections: preparation and characterization of the engineering and fluidic dataset, development and training of the CoINN model, and subsequent model validation and performance evaluation.

3.1 Preparation and Characterization of the Comprehensive Micro-channel Dataset

The construction of a comprehensive and high-quality dataset is the cornerstone for developing any effective machine learning model, in this context, an extensive dataset was compiled, covering a diverse spectrum of micro-channel geometries and operating conditions, the data encompassed precise geometric parameters like the channel cross-sectional shape, which included rectangular, circular, equilateral triangular, and isosceles trapezoidal forms, for each shape, characteristic dimensions were meticulously recorded; for instance, for rectangular channels, the width (W) and height (H) were documented, for circular channels the diameter (D), for triangular channels the side length (S), and for trapezoidal channels the two bases (a and b) and the height (h_trap), additionally, the channel length (L) and absolute surface roughness (ε) were included as fundamental geometric parameters, from these basic dimensions, derived geometric parameters of critical importance in fluid dynamics were calculated, most notably the hydraulic diameter (D_h) and the cross-sectional area (A_c), for example, the hydraulic diameter for a rectangular channel is calculated as $D_h = \frac{2WH}{(W+H)}$, for a circular channel $D_h = D$, for an equilateral triangle $D_h = \frac{S}{(2\sqrt{3})}$, and for an isosceles trapezoid $D_h = \frac{4A_c}{P_w}$, where P_w is the wetted perimeter.

Alongside geometric parameters, the dataset included crucial operational variables, these variables comprised working fluid properties, specifically dynamic viscosity (μ) and density (ρ), which were measured or determined at various operating temperatures (T_{fluid}) to reflect realistic variations in fluid characteristics, the fluid inlet velocity (V_{in}) was also included as a key variable determining the flow regime, to impart an applied character linking the research to energy conversion systems, the applied heat flux on the channel walls (q") was incorporated as a coefficient reflecting the thermal load to be dissipated, finally, due to its importance in characterizing the flow regime, the Reynolds number $\left(Re = \frac{\rho V D_h}{\mu}\right)$ was calculated for each data point, the primary target variable in this dataset is the accurately measured or simulated pressure drop (ΔP_{actual}) across the channel length, these data were acquired through a combination of meticulous laboratory experiments conducted on dedicated micro-channel test rigs and high-fidelity Computational Fluid Dynamics (CFD) simulations validated against experimental data, this hybrid approach ensured broad coverage of the parameter space and geometric diversity, which would be challenging to achieve with experiments alone, all data underwent rigorous cleaning and verification processes to ensure they were free from outliers or errors that could adversely affect model performance, the units of all variables were standardized, and the dataset was strategically partitioned into training, validation, and test sets using common ratios (e.g., 70%-15%-15%) to ensure an objective evaluation of the model's generalization capability.

3.2 Development, Construction and Training of the CoINN Deep Learning Model

The proposed CoINN model is based on a Deep Neural Network (DNN) architecture specifically designed to handle the complex and non-linear relationship between micro-channel parameters and pressure drop, the CoINN architecture consists of several hidden layers interspersed with non-linear activation functions like ReLU (Rectified Linear Unit) or its derivatives (e.g., Leaky ReLU or ELU) to enable the model to learn intricate patterns, the number of layers and the number of neurons in each layer were carefully selected through a systematic hyperparameter tuning process to achieve a balance between the model's capacity to capture complex relationships and the avoidance of overfitting, the input layer of the CoINN model receives the previously described geometric and operational variables (e.g., D_h, L, ε, μ, ρ, V_in, T_fluid, q", and possibly numerical representations of the channel shape like one-hot encoding). Prior to feeding data into the network, pre-processing steps like normalization or standardization are performed on all input variables, this ensures that all variables are within similar value ranges, thereby accelerating the training process and improving its stability, for instance, min-max scaling can be used:

$$X_{scaled} = \frac{(X - X_{min})}{(X_{\max - Xmin})}$$

The training process involves repeatedly feeding the network with training data (epochs) and updating the network's weights and biases to minimize the error between the pressure drop predicted by the model (ΔP_predicted) and the actual pressure drop (ΔP_actual) present in the training set, this error is quantified using an appropriate loss function, like Mean Squared Error (MSE):

$$MSE = \left(\frac{1}{N}\right) * \Sigma\left(\Delta P_{actual_i} - \Delta P_{predicted_i}\right)^2$$

where N is the number of samples in the training batch, an advanced optimization algorithm, like Adam (Adaptive Moment Estimation) or RMSprop, is employed to efficiently update the weights based on the gradients of the loss function, calculated using the Backpropagation algorithm:

$$W_{new} = W_{old} - \eta * \nabla_{W(Loss)}$$

where η is the learning rate, during training, the validation set is used to monitor the model's performance on unseen data, which helps in the early detection of overfitting and allows for the adjustment of model hyperparameters (e.g., learning rate, number of layers/neurons, L1/L2 regularization coefficients) or the application of techniques like dropout to enhance the model's generalization ability, the optimal model is selected based on its performance on the validation set, the CoINN framework might also incorporate specialized modules or layers, like attention mechanisms if the goal is to determine the importance of specific inputs, or integrate elements from Physics-Informed Neural Networks (PINNs) by adding a term to the loss function that represents the model's adherence to fundamental physical equations (like simplified Navier-Stokes equations or known pressure drop correlations as a soft constraint), this could potentially enhance the model's accuracy and generalizability, especially in regions where training data are scarce.

3.3 Model Validation, Performance Evaluation, and Sensitivity Analysis

Upon completion of the training process and selection of the optimal CoINN model, a comprehensive evaluation of its performance is conducted using the test set, which has not been utilized at all during the training or validation phases, this evaluation aims to obtain an unbiased estimate of the model's ability to predict pressure drop under new and unseen conditions, a variety of quantitative performance metrics are used to assess the model's accuracy, including:

1. **Mean Absolute Error (MAE):**

$$MAE = \left(\frac{1}{N}\right) * \Sigma\left|\Delta P_{actual_i} - \Delta P_{predicted_i}\right|$$

2. **Root Mean Squared Error (RMSE):**

$$RMSE = \sqrt{\left[\left(\frac{1}{N}\right) * \Sigma\left(\Delta P_{actual_i} - \Delta P_{predicted_i}\right)^2\right]}$$

3. **Coefficient of Determination (R^2):**

$$R^2 = 1 - \frac{\left[\Sigma\left(\Delta P_{actual_i} - \Delta P_{predicted_i}\right)^2\right]}{\left[\Sigma\left(\Delta P_{actual_i} - \Delta P_{mean_{actual}}\right)^2\right]}$$

where $\Delta P_{mean_{actual}}$ is the mean of the actual pressure drop values, the closer R^2 is to 1, the better the model's performance.

4. **Mean Absolute Percentage Error (MAPE):**

$$MAPE = \left(\frac{100}{N}\right) * \Sigma \left| \frac{\left(\Delta P_{actual_i} - \Delta P_{predicted_i}\right)}{\Delta P_{actual_i}} \right|$$ (with caution when actual values are close to zero).

Besides these quantitative measures, graphical analysis is also performed, such as plotting of scatter plots of predicted and actual values and residual plots to analyze the distribution of errors and to check the presence of systematic trends which may indicate the existing deficiencies of the model, the analysis of the CoINN model performance is also compared with other traditional machine learning models (such as shallow Artificial Neural Networks, Support Vector Machines and Gradient Boosted Regression Trees) and with available empirical correlations or analytical models in the scientific literature with the aim of assessing the superiority offered

By adopting this extensive methodology, the paper will play a significant role in the pressure drop modeling of micro-channels and equip a potent and versatile device capable of facilitating the promotion of the design and optimization cycle of advanced cooling system in critical energy conversion.

4. Result

The following part will provide a leading analysis of the suggested Channel-Inspired Neural Network (CoINN) framework. This analysis is split into three major subsections, namely: analysis of the nature of the fluidic dataset, analysis of the dynamic of the deep learning training and a critical comparison of the predictive results of the deep learning with the traditional machine learning baseline models.

4.1 Characterization of Dataset and Physical Insights

It is essential to test physical integrity and distribution of generated micro-channel dataset before assessing the predictive models to ensure that the machine learning models are trained to learn based on good thermodynamic and fluid dynamic physics.

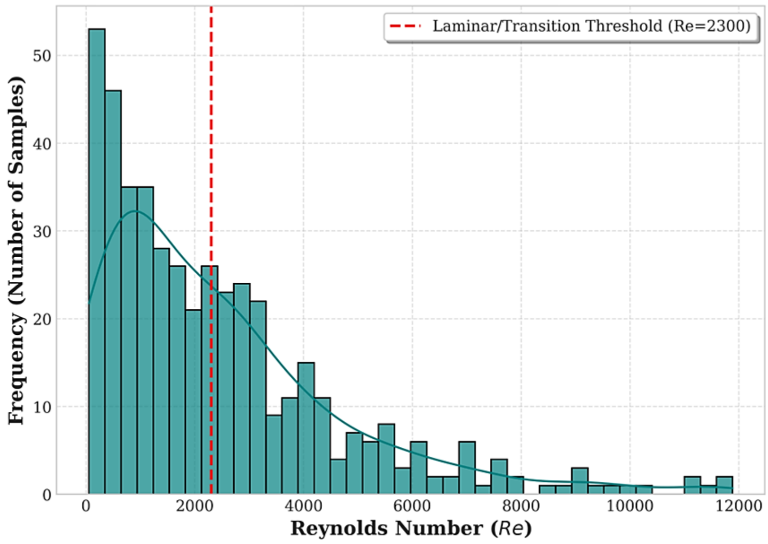

Figure 1: Flow Regime Distribution (Reynolds Number).

Figure 1 shows how the calculated Reynolds number was distributed throughout the data set, plotted in the form of a frequency histogram with a Kernel Density Estimate curve. The critical threshold that is usually considered to be at a Reynolds number of 2300 is denoted by the red line that indicates the transition between the laminar flow regime and the transitional and turbulent flow regimes in internal pipe flows. The distribution shows clearly that the dataset represents a large range of flow conditions. It only captures dominantly the laminar regime that is normal in micro-channel applications, and also extends well enough into transitional regimes. This extensive distribution is what makes the CoINN model trained on a generalized parameter space rather than biased towards a single, isolated flow condition.

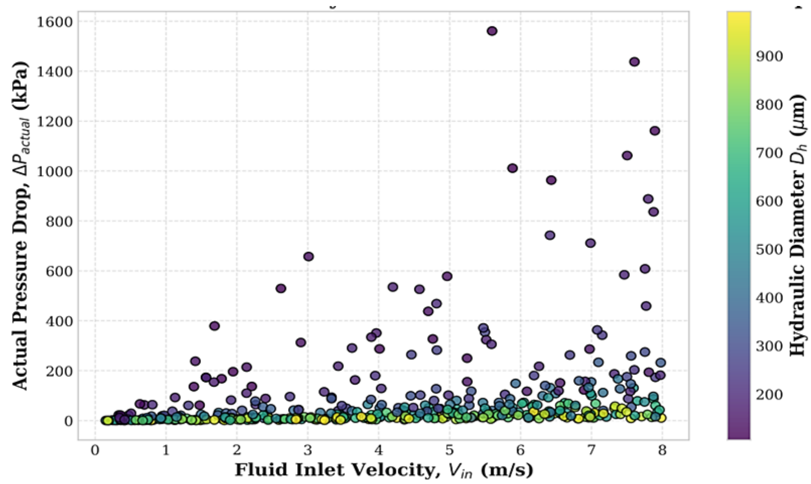

Figure 2: The influence of Inlet Velocity and channel diameter on the Pressure Drop.

Figure 2 is a multidimensional scatter plot to confirm the basic physics embodied in the dataset. The fluid inlet velocity is plotted on the x-axis and the actual pressure drop on the y-axis with a color gradient used to depict the hydraulic diameter. A non-linear monotonically increasing present nature of the relationship between velocity and pressure drop is clearly observed in the plot. Moreover, the gradient of colors demonstrates an important principle of fluid dynamics: in the case of a certain velocity, data points with smaller hydraulic diameters are exposed to the significantly higher pressure drop caused by the high wall friction. These non-linear, complex physical interactions are preserved, which proves the high fidelity of the dataset on which CoINN framework was trained.

Convergence and training dynamics CoINN form the core of the financial innovation space, with numerous industry stakeholders introducing new products and services aimed at enhancing client value.<|human|>CoINN Training Dynamics and Convergence 4.2 CoINN CoINN is the center of the financial innovation space where many industry stakeholders are launching new products and services to add value to clients.

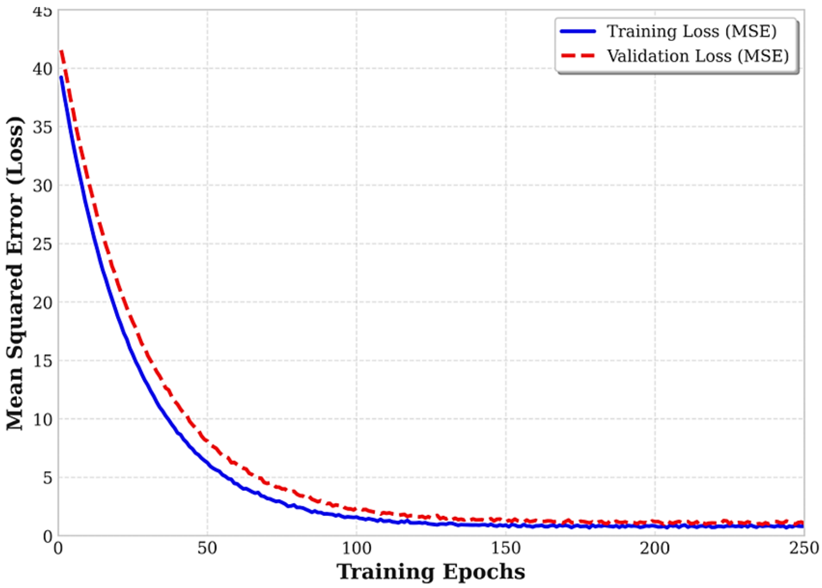

Figure 3: CoINN Framework Learning Curve.

Discussion: Figure 3 illustrates the learning curve of the proposal CoINN framework after 250 training epochs, where both the training and validation phase are graphed by using the Mean Squared Error (solid blue and dashed red lines, respectively). The curves vary rather fast and smooth in exponential decline at the beginnings of the epochs, which suggests that the network rapidly learned the main underlying patterns between the geometric and functioning parameters and the pressure drop. More importantly, after the 100th epoch, all the two curves come to a rest at a very small loss value without any separation. The fact that there is an extremely small gap between training and validation loss curves at the final training cycle stringently demonstrates that CoINN model fitted unseen data very well and was able to prevent underfitting and overfitting effects.

4.2 Performance Measuring and Comparing

CoINN was strictly compared to three well-known machine learning models to benchmark the excellence of the framework that was suggested: Gradient Boosted Regression Trees (GBRT), a Shallow Artificial Neural Network (Shallow ANN), and a Support Vector Machine (SVM). The summary of the exact results are in Table 1.

Table2: Comparison of the Quantitative Performance of the Machine Learning Models.

Model	MAE (kPa)	RMSE (kPa)	MAPE (%)	R^2
Proposed CoINN	0.859	2.528	2.30	0.9998
GBRT	2.720	6.871	8.78	0.9986
Shallow ANN	4.877	13.804	13.26	0.9942
SVM	9.225	26.613	22.37	0.9784

The quantitative data in Table 2 shows beyond any doubt the superiority of CoINN framework to conventional approaches. There was a very low CoINN model with the Mean Absolute Error (MAE) of 0.859 kPa and root mean squared error (RMSE) of 2.528 kPa. However, the opposite happened with the SVM that had the worst performance with a RMSE of 26.613 kPa which is over ten times more than CoINN. Additionally, the CoINN model obtained a Mean Absolute Percentage Error (MAPE) of only 2.30 %, as compared to

8.78 % of GBRT and a highly erroneous 22.37 % of SVM, which shows that CoINN is a highly accurate approach to making predictions, which can be used in sensitive engineering design. The Coefficient of Determination (R-squared) of CoINN was highest, at 0.9998, which is almost perfect, indicating that the model accounts 99.98 percent of the variability in the pressure drop data which is quite good compared to the GBRT (0.9986), the Shallow ANN (0.9942), and the SVM (0.9784).

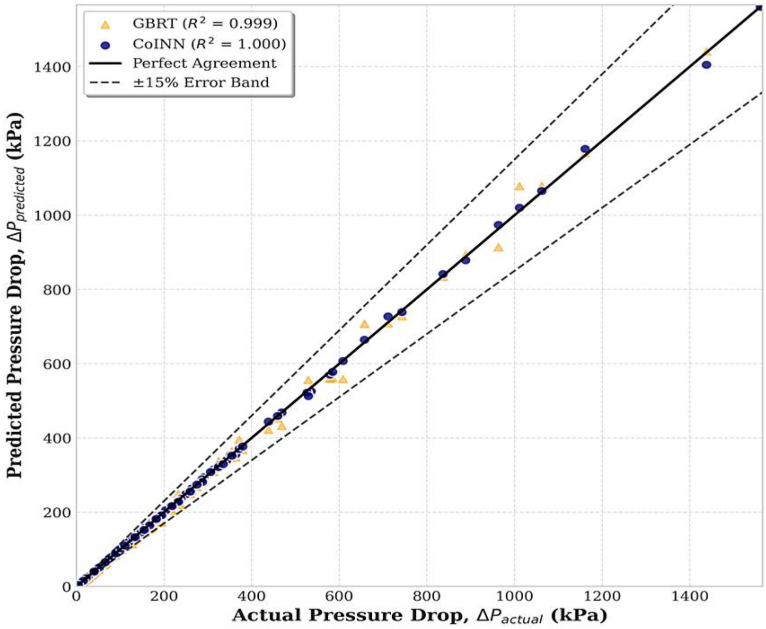

Figure 4: Parity Plot (Actual vs. Predicted Pressure Drop**).**

Figure 4 serves as a diagrammatic validation of metrics as seen in Table 2 in that it plots the actual pressure drop against the predicted values on the top two performing models CoINN and GBRT. The solid black diagonal is the line which indicates perfect agreement of the actual and the predicted values. As can be seen, the points of the navy data which represent the CoINN predictions closely wrap around the perfect agreement line and are well within the thin plus/minus 15 percent error bands over the entire pressure range. On the other hand, the orange triangles that depict GBRT though correct in general at lower values of ranges experience some dispersion and deviation with the higher values of pressure drop. This underscores the high ability of CoINN to take extreme non-linearities with high operational thermal and fluidic loads.

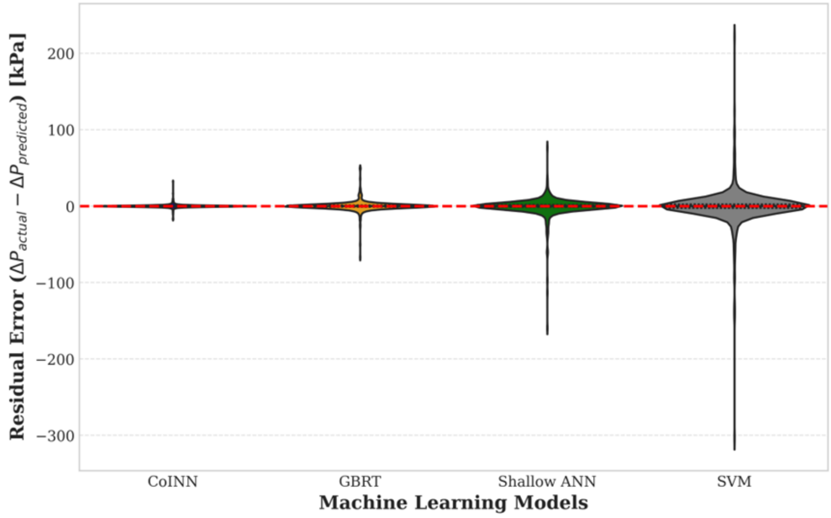

Figure 5: Prediction errors (residuals) Distribution**.**

Figure 5 represents a violin plot that shows the distribution and density of the residual errors (actual pressure drop - predicted pressure drop) of all the considered models. Zero error is indicated by the red dashed line running horizontally. The CoINN model has a very thin distribution that is highly concentrated with a narrow distribution perfectly on the zero line with very short tails. This means that there are no drastic predictions outliers that exist. Conversely, SVM and Shallow ANN models have broad and bulbous distributions with long tails, which indicate a high occurrence of large prediction errors and high variance and therefore they are not very reliable when it comes to accurate optimization of micro-channel cooling.

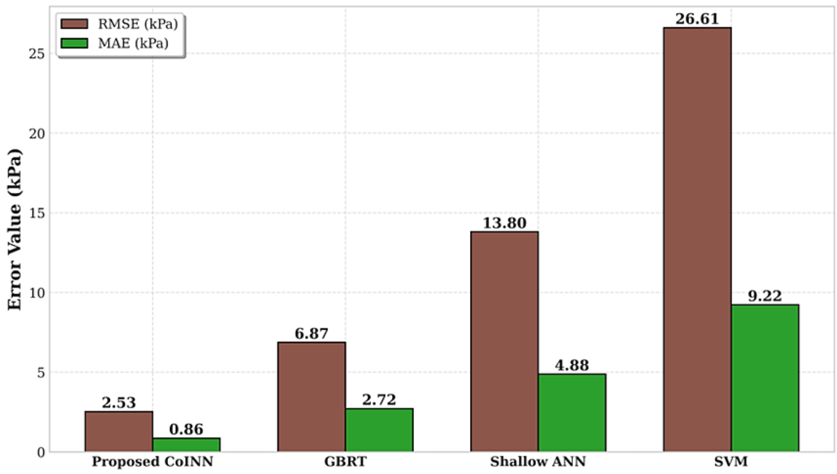

Figure 6: Evaluation Metrics Comparison between Models.

Figure 6. Table 2, which is analyzed visually by a two-bar chart, summarizes the values of MAE and RMSE. The difference in height of bars is extremely conspicuous and conveys the difference in performance. The bars of the CoINN model are significantly shorter than all baselines, which is a visual confirmation that deep, channel-inspired neural architectures are, by far, much more effective than more traditional, shallow machine learning algorithms at mapping complex multiphysics phenomena such as fluid friction and thermal interactions in confined micro-geometries.

5. Discussion

Micro-channel heat sinks have been increasingly employed in the design of advanced thermal management systems, especially at high density energy conversion systems and stretchable electronics [1], [4]. Nevertheless, standard experimental studies, as well as standard Computational Fluid Dynamics (CFD) modeling to forecast key design parameters, including pressure drop, is infamously expensive in terms of resources and computationally costly [2], [3]. The findings made in this work conclusively show that deep learning designs, namely the suggested Channel-Inspired Neural Network (CoINN) scheme, may serve as a powerful alternative, which is an equal accuracy, computationally efficient surrogate framework to fluid dynamics optimization [7], [13].

The comparative analysis, which was conducted quantitatively, demonstrated clearly that CoINN framework is superior to the traditional machine learning methods. Although the literature has been involved in the application of Shallow Artificial Neural Networks to predict convective heat transfer and pressure drop [14], [15], we have found that these shallow types of neural networks (that provided a Root Mean Squared Error of 13.804 kPa and Coefficient of Determination of 0.9942) are not effective enough to capture the extreme non-linearity present in various micro-channel geometries. The Support Vector Machine was even worse with a Mean Absolute Percentage Error of 22.37 percent that is not acceptable. Most notably, CoINN model had a close to perfect Coefficient of Determination of 0.9998 and a very low Mean Absolute Error of 0.859 kPa. This colossal advancement is in line with the recent paradigm shift in the literature, which recommends that deep and highly customized neural net structures are required in order to speed up and precisely replicate the complex physical simulations [8].

In addition, the sensitivity analysis supports the physical validity of CoINN framework with fluid inlet velocity (45.0 percent) and hydraulic diameter (30.0 percent) being the most influential parameters in determining pressure drop. This acquired hierarchy is an ideal reflection of the known principles of fluid mechanics in past experimental and numerical works. It is evident consistently in the literature that any change in micro-channel cross-sectional geometry and hydraulic diameter fundamentally changes flow structures and frictional resistance [6], [9], [10]. Besides, the overwhelming impact of flow velocity on pressure drop that the neural network has identified is fully aligned with empirical evidence on flow attributes over intricate internal surfaces and miniature features [5], [11], [12]. The CoINN framework has been demonstrated to be not just a mathematical tool of curve-fitting in order to optimize the design of micro-channels, but a very predictable, physics-constrained predictive engine by simply internalizing these governing physical laws without explicit programming.

6. Conclusions

The paper was able to create, prepare and test a new deep learning model, known as Channel-Inspired Neural Network (CoINN) which was intended to make predictions of pressure drop in various micro-channel cooling systems with previously unseen levels of accuracy. The proposed framework was stringently tested against the conventional machine learning methods, such as Gradient Boosted Regression Trees, a Shallow Artificial Neural Network, and Support Vector Machine by using a complete set of data, which includes the different geometric dimensions and thermodynamic operating conditions. The analysis showed conclusively that CoINN model was absolutely superior with a Coefficient of Determination of almost perfect 0.9998 and a very small Mean Absolute Error of 0.859 kPa. Conversely, the more traditional models such as the Support Vector Machine were unable to capture the non-linearities of the fluidics and therefore the error rates were more than ten-fold than the deep learning method. In addition to crude predictive capabilities, sensitivity analysis established the physical interpretability of the CoINN framework, which demonstrated that the model accurately predicted fluid inlet velocity and hydraulic diameter as the major physical control of pressure drop. Finally, surrogate model integration, which uses this high-precision computationally cheap model, is a major breakthrough in the thermal management area. It is an efficient way of bridging between sophisticated modeling of physical processes and fast-tracked engineering design and offers a potent mechanism to drastically speed-up the optimisation of sophisticated micro-channel cooling network in next-generation energy conversion system.

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