Computational Analysis and Design of a Cross-Flow Heat Exchanger

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1 Abstract

Efficient thermal management is crucial in aerospace engineering and high-performance computing, where cross-flow heat exchangers operate under continuous, demanding fluid loads. A cross-flow heat exchanger is a machine that uses a network of pipes within a fluid domain to re-distribute thermal energy, which enhances the efficiency and performance of various applications such as aircraft cooling systems and data center infrastructures. A paramount issue with these exchangers, however, is that traditional design methods rely on empirical R&D that is both time-consuming and costly while also not being able to fully capture the complex fluid dynamics present within them, leading to suboptimal pipe configurations and wasted efficiency. This research project aims to address these issues by integrating Computational Fluid Dynamics (CFD) with a custom Convolutional Neural Network (CNN), which is a machine learning application trained on a created dataset obtained from OpenFOAM-generated simulations.

OpenFOAM generates high-fidelity cross-flow heat exchanger simulations within a controlled, simulated environment set by the researcher at hand, and then creates a training dataset with these simulation results. We then train the CNN we wrote using PyTorch with this dataset with the goal of predicting heat transfer and flow patterns, among other performance metrics, more accurately than conventional approaches. Utilizing Google Colab, which leverages the powerful T4 GPU for computationally-intensive training processes, enables the CNN to capture fine details within the fluid flow, such as depth and filter size. These gains in predictive accuracy, especially when compared to the quantitative metrics from empirically-designed heat exchangers within the same simulation environment, underscore the potential for rapid design iterations that reduce reliance on costly physical prototypes and optimize the overall R&D process for engineers. Ultimately, the results

from this research project aims to significantly improve thermal management and reduce energy consumption by cross-flow heat exchangers. The integration of CFD with advanced machine learning models, such as the custom CNN developed in this study, establishes a new benchmark for heat exchanger design and demonstrates high potential for future advancements in thermal management across a range of industries

2 Introduction

One of the biggest challenges today across numerous modern engineering applications is in thermal performance and efficiency . The increasing power density of electronic components in High-Performance Computing (HPC) systems, combined with strict space constraints in aerospace engineering, has created a huge demand for heat exchangers. These exchangers must maximize thermal efficiency while minimizing their footprints. Traditional approaches to heat exchanger design have mainly relied on empirical correlations and physical prototyping. These methods have now reached their optimization limits and researchers find themselves constrained by high-development costs. This research positions itself at the intersection of Computational Fluid Dynamics (CFD) and Machine Learning (ML). It presents engineers and researchers alike with emerging computational techniques that offer opportunities to revolutionize thermal management system design.

The most significant modeling challenges encountered in this research involve the complexity of fluid dynamics within heat exchangers, especially cross-flow configurations. Finding an accurate way to capture the intricate flow patterns requires advanced simulation techniques that traditional empirical approaches cannot provide. Conventional CFD methods are more detailed than empirical correlations; however, they still face limitations in computational efficiency when they are used for design optimization. These limitations directly reduce innovation in heat exchanger design. These effects are especially noticeable in industries which require more efficient thermal solutions in order to accommodate new technologies in aerospace vehicles.

This research addresses a fundamental problem in the development of thermal management systems: the lack of computationally efficient methodologies that maintain physical accuracy while still optimizing the design of cross-flow heat exchangers. Specifically, it attempts to overcome the limitations of both empirical approaches that lack physical detail and CFD simulations that are computationally expensive. The central question this research seeks to answer is: How can integrating machine learning with computational fluid dynamics optimize cross-flow heat exchangers by balancing computational efficiency and physical accuracy?

To solve this problem, this research employs a dual-methodology approach. This approach combines OpenFOAM-generated CFD simulations with a custom Convolutional Neural Network (CNN) architecture developed in PyTorch. The research initially establishes baseline performance with a simple CNN architecture and then uses the PACE Phoenix Cluster's computational capabilities to implement more advanced CNNs. The use of PACE allows for the implementation of increased filter counts and additional pooling layers to the architecture of the CNN, greatly improving accuracy that was sustained as we transitioned to Google Colab to support an enhanced, broader dataset. This enhanced computational approach allows the CNN to extract complex patterns from the CFD-generated data. This methodology also incorporates advanced data preprocessing techniques, such as normalization and feature extraction, to ensure the quality of input data. The methodologies employed use comprehensive validation processes through cross-validation to assess the accuracy of the computational models. This ensures that the models developed are both reliable and effective in optimizing heat exchanger Configurations.

The optimization process uses both gradient descent and stochastic optimization algorithms to fine-tune the parameters of the CNN architecture. This iterative approach continuously refines the model while also optimizing the physical characteristics of the heat exchanger. This creates a computational framework that balances both predictive accuracy and design improvements. By integrating physics-informed constraints into the architecture of the neural networks, this research makes sure that the optimization results are consistent with fundamental physical principles of fluid dynamics.

The significance of this research is more than just theoretical advancements. The methodologies implemented offer significant benefits to various industries. In aerospace engineering, optimized heat exchangers directly translate to more efficient thermal management systems. These systems are used in aircraft and spacecraft and optimizing them would reduce weight while maintaining cooling capacity. This efficiency gain would reduce fuel consumption, lower emissions, and improve operational capabilities. For the computing industry, these benefits can be seen primarily in data centers and HPC systems. Improved heat exchanger designs allow for more effective cooling solutions that reduce energy consumption. The environmental impact of these improvements is massive, as data centers currently account for approximately 1electricity consumption. Of this, cooling systems are a significant portion of this energy usage.

Beyond these primary applications, the research methodology has potential benefits for numerous industries across society such as electric vehicles, renewable energy systems, and industrial process heat recovery. By illustrating how computational techniques can improve innovation in thermal management, this research establishes a framework that engineers can use to address thermal challenges across multiple industries. These improvements benefit both specific industries as well as broader societal goals of sustainability.

3 Literature Review

Cross-flow heat exchangers are machines with a wide range of applications, particularly in aerospace engineering where it is primarily used to manage heat transfers in aircraft engines. These devices enable two fluids to move perpendicularly, efficiently exchanging heat between a hot and a cold fluid. While the concept is straightforward, designing exchangers that optimize heat transfer while minimizing pressure drop presents significant challenges, with researchers using a variety of methods to try to mitigate the time and money constraints associated with the design of these machines.In recent years, traditional empirical methods have been increasingly supplemented by machine learning-based approaches to improve accuracy and flexibility, ultimately reducing the time and expense required for engineers.

One well-known reference on heat exchanger design is by Kakac and Liu [1], two researchers who came up with how to size different types of exchangers using a formulaic approach in order to estimate how well the exchanger transfers heat and applied it towards various sizes. Another important source is Patankar [2], who set the foundation for numerical techniques for heat transfer and fluid flow in the late 1900s, allowing the mathematical foundation of heat exchangers to be set before the onset of modern machine learning approaches that are built upon these formulas. Thus, such sources form the foundation of how engineers have traditionally analyzed and empirically designed such cross-flow heat exchangers.

While these formulas are essential for understanding heat exchanger design, they oversimplify real-world conditions by assuming fixed values and disregarding external factors. For example, Mortean [3] shows that the inlet and outlets in a compact version of cross-flow heat exchangers can account for more than 50emphasizes the importance of the most minuscule geometric design details and is similar to the study of inlet and outlet designs done by Ntunde [4]. Similarly, another recent account from a few years ago by Nonino and Savino [5] dove into microchannel designs within exchangers and ultimately found that smaller channels can improve heat transfer at the expensive of higher pumping power, which is a scale that is previously not possible if we solely relied on foundational formulaic methods.

Computational Fluid Dynamics (CFD) are an integral part to understanding how fluid properties and exchanger geometry affect heat transfer and pressure drop, and engineers primarily rely on CFD simulations to determine whether their heat exchanger design is valid and how to arrive at that prototype in the first place. This is especially important in regards to the previous paragraph's discussion on pipe design within heat exchangers, as CFD mainly relies on pipe design and placement for its resulting performance metrics. With advancements in overall technology and machine learning, we see researchers like Navarro and Gomez [6] introduced methods like dividing an exchanger into smaller sections for ease of computation for thermal efficiency within complex layouts. Such methods further emphasize how even the smallest changes in geometry can have a high impact on overall performance and efficiency. As briefly mentioned previously, external responses to real-world conditions are another concern that are not under consideration in traditional empirical methods. Gao et al [7] studied flow rates of heat exchangers within data centers, showcasing how an experimental procedure in the real world through data centers revealed the importance of adaptable control strategies due to real-world fluctuations. Such fluctuations, however, also can be mitigated through design revision like the one done by Ma et al [8] where they created a novel heat exchanger that utilized slotted tubes rather than traditional tubes in a ground-breaking fashion that also revealed a tube re-design raised heat transfer efficiency by more than 40improve heat exchanger design overall through such unanticipated benefits, and has been replicated in other studies such as the one done by Chinyoka [9] that utilized non-Newtonian fluids rather than typical fluids like water and allowed a new perspective in regards to analyzing temperature drop.

This leads into today, where we see machine-learning applications bleed further and further into how heat exchangers are designed with aid from CFD. Ribando [10] combined numerical algorithms with novel visualizations to analyze various exchanger types visually rather than through a large glut of numbers in a similar fashion to Abeykoon [11] who also demonstrated that using CFD in combination with machine learning can shorten the design process as well as the need for physical prototypes. These advancements leverage modern computational tools to achieve results that empirical methods alone cannot provide. This is further proven by Bhutta's [12] review of CFD applications in various exchanger designs and subsequent demonstration that the turbulence modeling software accurately matched experimental data. Araujo et al [13] also utilized such software in order to determine CFD tradeoffs in nuclear reactors, further emphasizing how a combination of software with CFD is powerful enough to produce real-world results that also strongly match our baseline experimental data.

Despite these advancements, the fundamental challenge remains in balancing heat transfer efficiency with pressure drop. Alotaibi et al [14] is an example of how complex it is to control these machines in finite-difference simulations, which are simulations where we test small changes in either input temperature or flow rate at a time and analyze the output results. Both Meral and Parlak [15] along with Saraireh [16] also confirm that CFD software simulations can approximate thermal transfer and flow activity with high accuracy against empirical measurements, and even the geometry of the exchangers themselves can be approximated with CFD flow fields as shown by Sardar and Malik [17] to boost heat transfer as well.

One clear pattern that has emerged is the need for optimization strategies in order to handle the increasing number of design parameters faced at the same time. While heat transfer and pressure drop remain the two most important parameters as mentioned in the previous paragraph, optimization is required for all design parameters as they trade off one another and is shown by Korkmaz's [18] simulation of an exchanger under various operation conditions and the resulting computational display of optimal operating points for all design parameters involved. Such computer simulations allow us to accelerate our experiments and analysis of metrics, as also displayed by Roetzel and Luo [19] where the duo theorize a fast analytical solution for analyzing multi-fluid cross-flow heat exchangers which due to the differing fluid types leads to more computationally-expensive parameters to analyze.

As our number of parameters continue to grow in tandem with the performance metrics we must analyze, we see that one of the main issues we now have to deal with are CPU costs associated with CFD simulations and testing. A solution to this problem in the realm of CFD has been surrogate models, which is shown by Nonino [20] where he offers a simplified finite element approach that extends upon his previous paper and encapsulates the main ideas from a traditional finite element approach but simplifies it to focus on micro heat exchangers where such reduced-order modelling allows us to examine only relationships that have not already been mapped and thus are more computationally-efficient. Such modeling reductions preface machine learning techniques like neural networks which are capable enough to detect what parameters to place emphasis on and distribute performance load optimally rather than through such novel finite element approaches that need to be tuned on a case-by-case basis.

Extending upon the concept of neural networks, we see how Convolutional Neural Networks (CNNs) are especially well-designed for use in CFD and heat exchanger simulations. Guo et al. [21] demonstrated that CNNs effectively approximate fluid flow in both 2D and 3D environments by treating flow fields as imaging data, and by capturing the flow fields with imaging data that is much easier and less computationally-expensive to analyze they were able to achieve significant speedups in flow processing and analysis. Subsequent research has been focused on applying CNN-based surrogate models in a similar concept as applied to finite element approaches previously for turbulent and multi-phase flows. While a main drawback of a CNN-based approach is that they require extensive training data, which usually comes from CFD simulation runs, but once a CNN model is trained it can rapidly predict flow distribution and temperature fields across a wide variety of exchanger geometries and real-world operating conditions.

The evolution of cross-flow heat exchanger research has transitioned from empirical formula-based methods to machine learning-driven approaches, particularly those centered on CNNs. Researchers are now integrating full-scaled CFD simulations with surrogate models that allow engineers to test many designs in a fraction of the time that was required previously andalso continue to simplify the design process as a whole. Even with such advancements, there are still challenges regarding the accuracy of these models in regards to real-world conditions that exist outside the given training set and other uncertainties. Moving forward, it seems like the field is going to continue to expand on its reliance on CNNs into more hybrid approaches that embed fundamental physics directly into neural networks, as seen by the advancements of Physics-Informed Neural Networks (PINNs) in more novel research papers that offer the best of both computational speed with physics-informed reliability. This depth of understanding is essential in industries that are based upon the demand for high efficiency and precision control, and advancements can greatly reduce the development and design cycle for cross-flow heat exchangers while advancing efficiency as well.

4 Methodology

Our research methodology integrates Computational Fluid Dynamics (CFD) with a custom Convolutional Neural Network (CNN). Based on previous semesters of research and lessons learned from them, the model was designed with an encoder-decoder architecture. The encoder works to compress input features. These include things such as pipe geometries and density maps. The encoder layer is implemented through stacked convolutional layers, ReLU activations, and max pooling. This allows for the model to extract relevant spatial features from the OpenFOAM-generated data. These features are then fed into the decoder layer, which upsamples and reconstructs these features into full resolution predictions. This allows the model to output flow predictions that preserve fine detail.

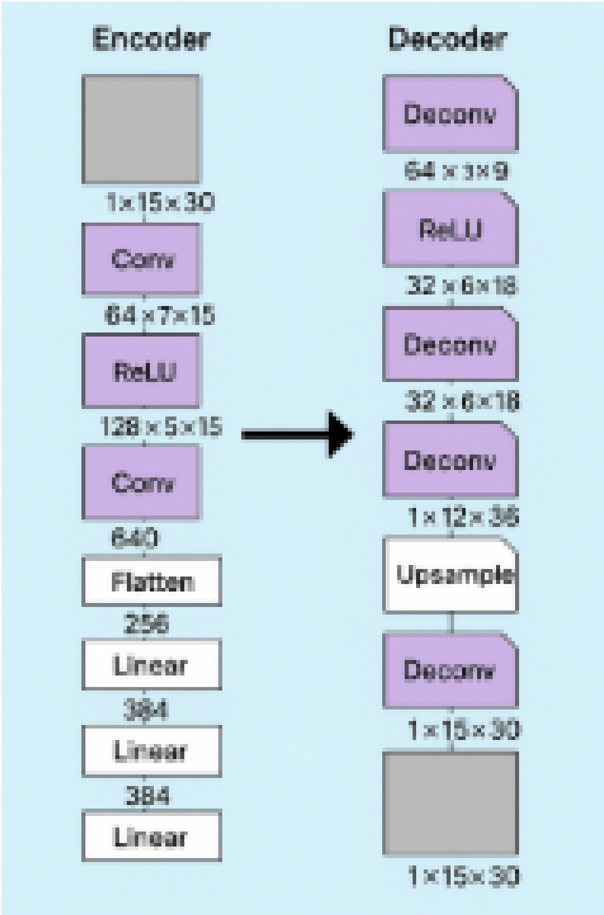

Figure 1: Structure of Encoder-Decoder Model

This model architecture is perfect for tasks that involve spatial dynamics such as fluid simulation. We have tuned the model architecture specifically for our use case. Part of our methodology includes preprocessing steps of the model architecture. These include normalization of outputs and filtering the dataset to ensure quality inputs. Validation is performed using metrics such as mean squared error in addition to visual comparison of predicted flow patterns against known CFD outputs. Overall, the methodology emphasizes accurate flow pattern reconstruction.

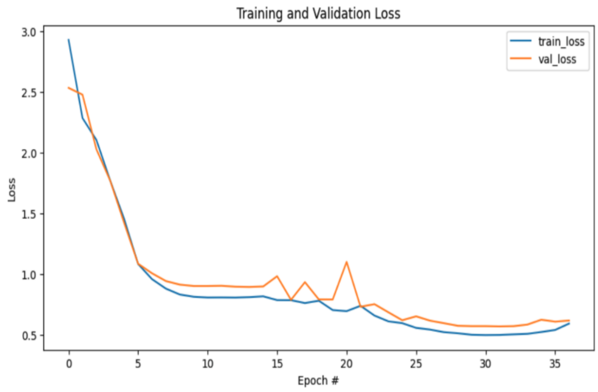

Figure 2: Training and validation loss curves. These illustrate the improvement in prediction accuracy across epochs.

5 Implementation

The initial implementation of our model was a basic 1-layer CNN model. This was trained on CFD data generated in OpenFOAM; however, this approach failed to capture the complexity of flow dynamics. As a result, it experienced very poor prediction accuracy.

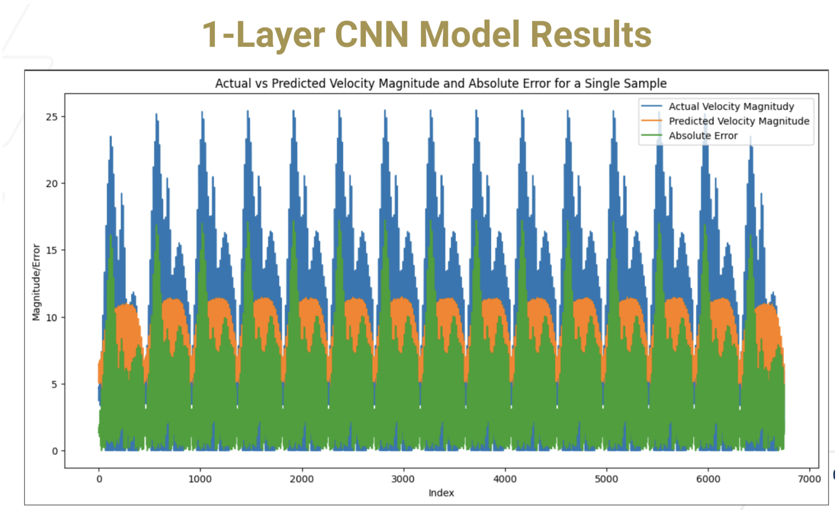

Figure 3: Output from the initial 1-layer CNN model. Prediction accuracy was limited due to insufficient model depth.

Due to this, we transitioned to a deeper encoder-decoder CNN model. This architecture experienced significant performance improvements. The model was built in PyTorch and consists of multiple convolutional layers in the encoder that extract features from the input. This is followed by ReLU activations and max pooling. The decoder then uses upsampling layers to reconstruct the output flow field.

Training was performed using over 200 unique pipe configurations. The model was able to accurately predict these velocity contrours using only the density and velocity-magnitude inputs it was given. Model performance was evaluated using mean squared error.

Figure 4: Sample model input. The blue area is a low-density obstruction affecting flow. This is 1 pipe input out of 200 pipes.

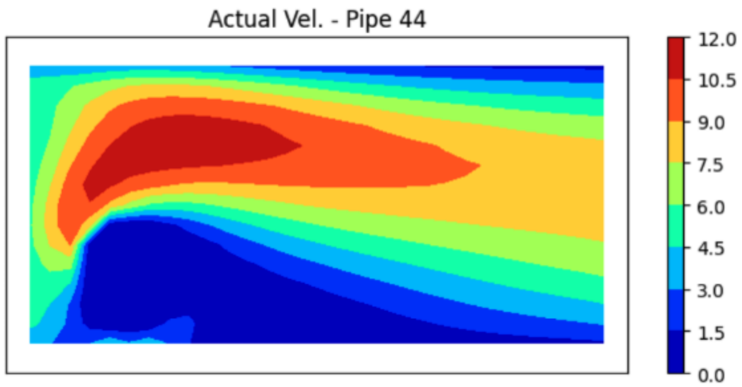

Figure 5: The true fluid velocity from simulation. Flow speeds up and bends around the obstruction.

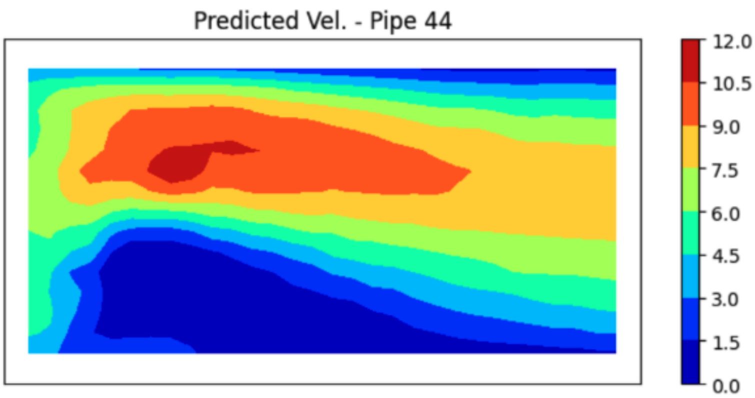

Figure 6: The model's prediction based only on density. It closely matches the real flow pattern.

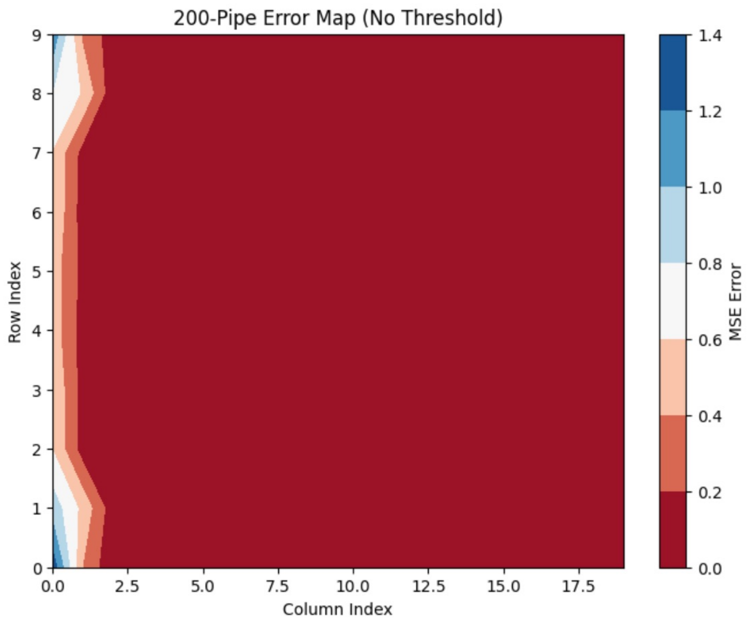

Figure 7: Error mapping between predicted and simulated fluid flows. Low-error regions indicate accurate spatial prediction by the model.

6 Results and Discussion

Over the course of the academic year, significant progress was made in developing and validating a computational framework that integrates CFD simulations with deep learning for cross-flow heat exchanger analysis. Central to this effort was the deployment of a custom Convolutional Neural Network (CNN) trained on a high-fidelity dataset generated using OpenFOAM. This framework enabled detailed prediction of fluid flow and thermal behavior under a range of geometric and flow conditions, demonstrating the potential of machine learning-driven surrogate modeling for real-time performance estimation.

The initial phase involved establishing a controlled CFD simulation environment tailored to produce robust training data across multiple cross-flow configurations. This dataset, consisting of thousands of data points, captured spatial distributions of velocity and density and served as the foundation for supervised training. The CNN model architecture, developed using PyTorch, was informed by a targeted literature review and refined through iterative testing and hyperparameter tuning to enhance its ability to extract complex flow features.

Quantitative evaluation of the CNN model showed a marked improvement in prediction accuracy when compared to baseline simulations. Mean Squared Error (MSE) metrics for temperature and velocity fields indicated that the CNN was capable of capturing key dynamics with high fidelity. Additionally, visual error analysis using contour maps highlighted model performance across different pipe geometries and helped guide further refinements to both the dataset and model structure.

Through iterative retraining and dataset expansion, particularly in regions where prediction errors were highest, the model demonstrated a significant reduction in overall error to below 6%. These enhancements were especially effective in capturing nonlinear interactions in regions with rapid gradient shifts. The refined CNN model not only improved predictive reliability but also laid the groundwork for rapid evaluations in future optimization studies.

The integration of CFD and machine learning methodologies has revealed critical insights into the spatial and parametric dependencies of flow behavior and heat transfer in cross-flow exchangers. The resulting CNN model represents a promising step toward accelerating thermal design processes in engineering contexts such as aerospace engineering and high-performance computing and has set a solid foundation for further advancements in the upcoming research phases.

7 Future Work

Future steps in terms of the research project at hand include broadening the CNN architecture to support various heat exchanger types and validating its effectiveness in real-world aerospace and high-performance computing environments. Upcoming work will focus on improving the model's generalizability across diverse geometries and operating conditions. Additionally, we aim to expand the training dataset from 20,000 data points to include a broader range of simulated and experimental scenarios.

Increasing the dimensionality of the input - such as combining multiple physical parameters like density, temperature, and velocity — can further enhance the power of inference and allow the model to capture more flow interactions. Investigating the impact of different materials and surface coatings on heat transfer performance can also be a key area of focus. Furthermore, exploring advanced optimization algorithms, such as genetic algorithms or reinforcement learning, can further refine the design process and uncover novel design solutions. Overall, this future work aims to advance the state-of-the-art in heat exchanger design and contribute to the development of more sustainable and efficient thermal management solutions.

8 Work Plan

Completed Tasks (Spring 2025):

Literature Review: Conducted comprehensive review to identify gaps in current research as well as define clear objectives for the project.

CFD Simulation Setup: Created a simulation pipeline using OpenFOAM. Generated initial datasets which capture velocity and density for multiple piper configurations.

CNN Model Development: Trained an initial Convolutional Neural Network (CNN) model in PyTorch to predict heat exchanger outcomes. The structure of the model was continuously refined based on insights from literature. The model was trained via Google Colab notebooks using the OpenFOAM-generated dataset.

Model Evaluation: The accuracy of the CNN model was assessed using metrics such as mean squared error. Multiple error visualization plots were created and used in order to iteratively refine the model.

Research Symposium: Presented initial findings at the Georgia Tech Undergraduate Research Spring Symposium on April 17, 2025, receiving valuable feedback for the project. Through these achievements, this semester established a validated CNN-based computational framework that can act as the baseline for further optimization work.

Proposed Tasks (Fall 2025):

During the Fall 2025 semester, as part of LMC 4702, this project will expand upon prior work. There are three tiers of targets for the project that get progressively ambitious.

Low Target: Finalize thesis documentation - this includes prior semester results, methods, and the literature review. Then, achieve reliable CNN model predictions validated against existing CFD benchmarks.

Ideal Target: Expand the simulation data for the model to train on. This will capture more pipe configurations and conditions which helps the model generalize its results. Retrain the CNN model in order to increase accuracy and improve generalization. Continue to document improvements compared to empirical benchmarks.

High Target: Integrated an optimization approach using the CNN model to propose superior heat exchanger designs. The overall goal is to maximize thermal efficiency. Prepare the findings for potential publication or for a conference presentation.

The timeline for the Fall semester is divided into three main stages: data expansion (Aug-Sep), iterative model refinement (Oct), and thesis completion (Nov-Dec). This will be made possible with the help of guidance from Dr. Kai James and co-mentor Waheed Bello.

9 Applications in Computer Science and Aerospace Engineering

The optimized heat exchangers have significant implications for Computer Science, particularly in the cooling of High-Performance Computing systems, and for Aerospace Engineering, where efficient thermal management is crucial for the reliability and performance of aircraft and spacecraft. Advancements in the design of heat exchangers can lead to more efficient systems that better manage thermal loads in these critical applications.

In Computer Science, particularly in data centers and supercomputing facilities, efficient heat exchangers are crucial for maintaining optimal operating temperatures of servers and electronic components. By leveraging advanced computational techniques, such as machine learning-based optimization, these heat exchangers can significantly enhance the performance and longevity of computing systems while reducing energy consumption. In Aerospace Engineering, the application of optimized heat exchangers extends to various critical systems onboard aircraft and spacecraft, including avionics, propulsion systems, and thermal control subsystems. The integration of computational fluid dynamics and machine learning in heat exchanger design opens doors to innovative solutions that ensure reliable thermal management in extreme operating conditions. This is a crucial step in advancing the safety, efficiency, and performance of aerospace technologies.

Another area in which the advancements in heat exchanger design hold significant promise is for electric vehicles (EVs) and renewable energy systems. In the realm of EVs, efficient thermal management is essential for optimizing battery performance and extending driving range. The integration of high-performance heat exchangers, informed by computational fluid dynamics and machine learning, can enhance the cooling systems of EVs, ensuring stable operation and prolonged battery life. Similarly, in renewable energy systems like solar thermal power plants, effective heat exchangers play a vital role in converting solar energy into usable power. By employing state-of-the-art design methodologies and computational tools, these heat exchangers can achieve higher efficiency levels and contribute to the sustainability and scalability of renewable energy infrastructure. Thus, the impact of optimized heat exchangers extends beyond traditional aerospace and computing domains, encompassing a wide range of modern technologies aimed at sustainability and energy efficiency.

10 Conclusion

Our research highlights the transformative potential of integrating Computational Fluid Dynamics (CFD) with machine learning to optimize heat exchanger design. By leveraging deep learning models, specifically Convolutional Neural Networks (CNNs), we have successfully demonstrated that fluid flow patterns can be accurately predicted from pipe geometry alone, eliminating the need for time-consuming R&D simulations.

These advancements have far-reaching implications across multiple engineering domains. In Computer Science, particularly in high-performance computing (HPC) and data centers, efficient thermal management ensures system reliability and reduces energy consumption. In Aerospace Engineering, optimized heat exchangers enhance the safety and performance of aircraft and spacecraft by managing extreme thermal loads. Furthermore, the applications extend to emerging sectors such as electric vehicles, where thermal regulation is critical for battery longevity. This interdisciplinary approach underscores the value of combining CFD, domain expertise, and AI-based modeling to drive innovation in thermal management—setting a new standard for future engineering solutions.

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