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Research Article

Performance Evaluation of Nanofluids for Enhanced Heat Transfer in Microchannels: Experimental Validation and CFD Simulation

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ABSTRACT

Maintaining system reliability and efficiency in high-performance thermal environments depends on good thermal regulation in microchannel systems. Because of their modifiable thermophysical properties, nanofluids are more effective at heat transfer than many other fluids. In this work, three datasets were used, one of which was a Casson nanofluid dataset (61 rows × 118 columns) to explore non-Newtonian behavior. Using classical models and experimental observations, thermal conductivity, dynamic viscosity, density and specific heat were calculated for volume fractions from 0.1% to 5.0%. The tests found that nanofluids with CuO had the highest thermal conductivity (2.06 W/m·K at 4.75% volume fraction), while nanofluids with SiO_2 maintained the lowest viscosity (0.00056 Pa·s), making them suitable for low-resistance systems. Al_2O_3 provided a suitable balance, boosting the effect and keeping the viscosity workable. Using CFD-ready parameters, a dataset was built with the main fields: flow velocity (0.17–2.28 m/s), temperature (50–90°C) and calculated properties (e.g., ρ_nf ≈ 1000–2000 kg/m³). The data is designed so that it can be used with parametric analysis software such as ANSYS or OpenFOAM. The method avoids repeating the same experiments, allowing for easy and consistent heat transfer research.

Keywords: Nanofluids, Thermal Conductivity, CFD Simulation, Microchannels, Heat Transfer Optimization.

INTRODUCTION

The recent progress in microelectronic devices, biomedical sensors and compact energy systems has driven up the need for efficient thermal management systems. Due to their high surface area for their size, microchannel heat exchangers are now considered a promising solution for rapid heat transfer in small areas. Even so, these devices have some problems, including smaller fluid volume and greater pressure drop. Therefore, new, advanced coolants are needed that have a high ability to transfer heat and a manageable thickness. Because of the advanced requirements, water and ethylene glycol are now inadequate as heat transfer fluids in systems that need fast and effective heat dissipation [1].
Many people are now interested in nanofluids, mixtures of nanoparticles with base fluids, as a promising cooling medium for the future. According to Choi and Eastman [2], dispersing Al_2O_3, CuO, TiO_2 and SiO_2 nanoparticles into fluids has resulted in better thermal conductivity, with improvements of over 20% seen at a low concentration of particles. The enhancements result from the special thermophysical features of nanoparticles, including a large surface area, Brownian motion effects and interactions between particles and the fluid. Studies done in the past few years have highlighted the many roles nanofluids play in electronics cooling, renewable energy and industrial heat exchangers [3].
Nanofluids in microchannels both increase how quickly heat is transferred and affect the stability of the fluid flow and its pressure. Both effects need to be looked at at the same time to get the best results from the system. One benefit of nanofluids is that their characteristics can be adjusted by varying the type of particles used, their volume fraction and the type of base fluid. They allow for fine-tuning of thermal conductivity, viscosity, density and specific heat which are all important for the HTC of microscale systems [4][5]. As an illustration, CuO and

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Al_2O_3 are good thermal conductors, but their viscosity can be a problem which can be solved by careful optimization.

Although nanofluids show great promise, the ways they are studied are still scattered. While traditional experiments give us valuable data, they usually struggle to be applied to other flow situations or types of fluids. Unlike analytical methods, numerical methods such as CFD provide greater control and accuracy, making it possible to analyze temperature, velocity and heat flux at walls in detail. Yet, CFD models depend on the accuracy of their input data and these data are often taken from theories that lack enough real-world evidence [6]. Lately, machine learning (ML) has been recommended as a solution that can make predictions using earlier data. Yet, it is still difficult to explain and test ML models using physical methods [7].

This study fills a key gap in current research by joining experimentally gathered nanofluid data with parameterization for use in CFD. This integration is needed to move from simple studies in the lab to strong simulation tools that assist in design and optimization in engineering. Many experts confirm that accurate results in CFD solvers depend on the correct input of thermal conductivity (k), viscosity (μ), density (ρ) and specific heat capacity (cp) [8].

Three main objectives guide this research:

1. To analyze the effect of nanoparticle type, base fluid, and volume fraction on the thermal conductivity, viscosity, density, and specific heat capacity of nanofluids.
2. To compute effective thermophysical properties using empirical mixing models suitable for microchannel heat transfer applications.
3. To prepare CFD-compatible input parameter tables that can be used for simulation of HTC in microchannels under varied operating conditions.

Experimental data containing HTC measurements for different nanofluid blends and flow rates are the basis for the analysis. By using the Maxwell model for thermal conductivity and the Brinkman model for viscosity, the study determines effective properties that match the behavior of nanofluids. After that, the parameters are arranged in tables that can be used with common CFD software such as ANSYS Fluent or OpenFOAM. By changing the parameters for temperature and volume fraction, simulations can be performed under various operating conditions and used for sensitivity analysis and system optimization.

Apart from computing properties, the study provides visualizations to demonstrate how different variables are related. To illustrate, graphs of viscosity versus temperature and HTC versus volume fraction give useful information for choosing materials and configuring equipment. By combining experiments with simulation, the effectiveness of thermal management designs with nanofluids in microchannel systems is improved.

All in all, this research presents a detailed process for assessing and simulating nanofluid performance in small thermal systems. When the experimental data is clearly linked to the input needed for CFD, simulations can be done quickly, reliably and with a strong physical base. In the end, the results are meant to support researchers and engineers designing efficient thermal technologies for use in microelectronics and renewable energy.

Materials and Methods

2.1 Related Work

Nanofluids have become better understood lately and their key characteristics are now included in CFD simulations. Research has proven that modeling heat transfer enhancement accurately needs detailed information about nanofluid properties which can guide the design of CFD boundary conditions and the domain being simulated. Esfe et al. [9] performed experiments to measure the thermal conductivity of Al_2O_3-based nanofluids, paying special attention to how temperature and volume fraction affect the results. Similarly, Shukla et al. [10] introduced a new thermal conductivity model that includes Brownian motion to improve how well nanofluid modeling is predicted. Using the two-phase model from Buongiorno, Alsabery et al. [11] simulated mixed convection in Al_2O_3-water nanofluid-filled cavities driven by moving lids. They concluded that precise thermal property estimates are crucial for accurate simulations of non-Newtonian and nanoparticle-enriched fluids.

In addition, research on using nanofluids in energy systems and thermal engineering has also been carried out. Sun et al. [12] discussed the multiple uses of nanofluids in solar thermal systems, as having particular properties helps make the collectors more efficient and reduces their thermal resistance. Wei et al. [13] introduced a simple model for parabolic trough solar plants that was validated and demonstrated how it uses parameterized nanofluid characteristics to support scalability. In addition, Jorjani et al. [14] introduced a new nanodiamond-based ionanofluid, with detailed models for specific heat and thermal conductivity that were

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tested experimentally, providing new ideas for future heat transfer fluids. Ajibade et al. [15] also studied MHD convection with heat generation and viscous dissipation analytically, showing that both the flow and heat profiles strongly depend on the energy source distribution, so it is important to have accurate thermal inputs in CFD calculations. Wang et al. [16] also contributed to nanofluid research by studying thermal shocks and turbulence caused by shear in laser ablation of C/SiC composites in hypersonic conditions. All of these studies support the current study's goal to transform raw experimental nanofluid data into organized CFD inputs.

2.2 Dataset Description

For building simulation models for nanofluid-based heat transfer analysis, three different datasets were used. The main dataset is the Nanofluid Heat Transfer Dataset which has 10,293 samples and 10 measured features covering both the base fluid and the thermal behavior of nanofluids. This dataset is used as a basis for assessing properties and producing parameters.

The Nanofluid Dataset for HTC is built in the same way as the primary dataset and is used to confirm the trends in heat transfer coefficient for a range of thermal and fluidic conditions.

To investigate non-Newtonian behavior, the Casson Nanofluids Dataset was optionally brought in for advanced case studies. It includes detailed information about velocity, concentration and thermal shrinkage indices which are best used in Casson-type flow formulations.

The data cover the main physical units needed for thermal-fluid simulations, as shown in Table 1:

Table 1 – Dataset Summary

Dataset Name	Columns	Sample Units
Nanofluid Heat Transfer Dataset	Nanoparticle Type, Base Fluid, Volume Fraction, Temperature, Flow Velocity, Thermal Conductivity, Specific Heat, Density, Viscosity, Heat Transfer Coefficient	%, °C, m/s, W/mK, J/kgK, kg/m³, Pa·s, W/m²K
Nanofluid Dataset for HTC	Same as above	Same units
Casson Nanofluids Dataset	Velocity (vel_M_x), Concentration (conc_M_x), Temp shrinkage (temp_shrink_R_x), ind_data	Dimensionless, °C-equivalent derivatives

2.3 Preprocessing and Feature Engineering

A detailed preprocessing pipeline was set up to make sure the modeling process is reliable and trustworthy. We looked for any problems in the data, made all the data types consistent, encoded the categories and changed units where required.

Data Quality Checks

At the start, all three datasets were checked to find any missing values and duplicates. The data was found to be clean, because there were no missing values or duplicates in the datasets:

```
# Step 2.2: Check for missing values
print("\n--- Missing Values ---")
print("Nanofluid Heat Transfer Dataset:\n", df1.isnull().sum())
print("\nNanofluid Dataset for HTC:\n", df2.isnull().sum())
print("\nCasson Nanofluids Dataset:\n", df3.isnull().sum())

# Step 2.3: Check for duplicates
print("\n--- Duplicate Rows ---")
print("Nanofluid Heat Transfer Dataset:", df1.duplicated().sum())
print("Nanofluid Dataset for HTC:", df2.duplicated().sum())
print("Casson Nanofluids Dataset:", df3.duplicated().sum())
```

Having validated the data, the study proceeded as planned, keeping the real experimental information intact.

Data Type Harmonization

A few columns such as specific heat capacity and density, were stored as integers in some datasets, so they had to be changed to floating-point numbers for use in further calculations. Because of this conversion, the results were consistent among different physical parameters:

```
df2['Specific_Heat_Capacity (J/kgK)'] = df2['Specific_Heat_Capacity (J/kgK)'].astype(float)
df2['Density (kg/m³)'] = df2['Density (kg/m³)'].astype(float)
```

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Categorical Encoding

Any regression or clustering analysis that might be performed later requires the data to be prepared, so Nanoparticle_Type and Base_Fluid were label-encoded with Scikit-learn's LabelEncoder:

```
from sklearn.preprocessing import LabelEncoder

encoder_np = LabelEncoder()
encoder_bf = LabelEncoder()

# Apply to both datasets to keep consistency
df1['Nanoparticle_Type_Code'] = encoder_np.fit_transform(df1['Nanoparticle_Type'])
df1['Base_Fluid_Code'] = encoder_bf.fit_transform(df1['Base_Fluid'])

df2['Nanoparticle_Type_Code'] = encoder_np.transform(df2['Nanoparticle_Type'])
df2['Base_Fluid_Code'] = encoder_bf.transform(df2['Base_Fluid'])
```

Because of this encoding, it was possible to include qualitative data (such as material type) in further analyses without it being lost.

Column Renaming and Unit Alignment

To help with understanding and using the code, long names in the columns were shortened without losing their unit meaning. Volume_Fraction (%) was changed to Vol_Fraction and Specific_Heat_Capacity (J/kgK) was updated to Heat_Capacity. The logic behind renaming is given below.:

```
df1.rename(columns={
    'Volume_Fraction (%)': 'Vol_Fraction',
    'Temperature (°C)': 'Temp_C',
    'Flow_Velocity (m/s)': 'Velocity',
    'Thermal_Conductivity (W/mK)': 'Conductivity',
    'Specific_Heat_Capacity (J/kgK)': 'Heat_Capacity',
    'Density (kg/m³)': 'Density',
    'Viscosity (Pa·s)': 'Viscosity',
    'Heat_Transfer_Coefficient (W/m²K)': 'HTC'
}, inplace=True)
```

It also made it possible to use the datasets with simulation and visualization procedures.

Feature Scaling Considerations

Although the Volume_Fraction column was given in percent, it was changed to a fraction between 0 and 1 where necessary for equations used to blend nanofluid properties. While normalization was not used everywhere, these special changes were included in the computational formulas.

Visual Insight Before vs. After

To understand the distribution of variables and their links to the heat transfer coefficient, scatterplots and boxplots were examined. These visuals confirmed the preprocessing results and pointed out how Viscosity, Temperature and Volume Fraction affect HTC.

2.4 Calculation of Effective Thermophysical Properties

Simulating nanofluid in microchannels requires calculating the correct effective properties like thermal conductivity, dynamic viscosity, density and specific heat capacity. They have a major effect on how the flow and heat move and are fundamental to any CFD application.

The properties were computed using traditional models that had been developed before. The values for each nanofluid system were found by using the experimental composition and the known properties of both nanoparticles and base fluids.

Thermal Conductivity

The Maxwell model was used for predicting the effective thermal conductivity (k_{nf}) of nanofluids:

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$$k_{nf} = k_{bf}\left[\frac{k_{np} + 2k_{bf} - 2\phi\left(k_{bf} - k_{np}\right)}{k_{np} + 2k_{bf} + \phi\left(k_{bf} - k_{np}\right)}\right]$$

This model captures the enhancement of thermal conductivity as a function of the base fluid (k_{bf}), nanoparticle material (k_{np}), and the volume fraction (ϕ).

Dynamic Viscosity

To estimate the nanofluid's dynamic viscosity (μ_{nf}), the Einstein model for dilute suspensions was used:

$$\mu_{nf} = \mu_{bf}(1 + 2.5\phi)$$

This equation assumes low nanoparticle concentrations, which is consistent with the datasets used in this study.

Density

The effective density (ρ_{nf}) of the nanofluid was computed using the weighted average method:

$$\rho_{nf} = (1 - \phi)\rho_{bf} + \phi\rho_{np}$$

This linear mixture model ensures mass conservation across the fluid system.

Specific Heat Capacity

The specific heat capacity (cp_{nf}) was derived using the following relation, which accounts for the heat storage capacity of both components:

$$(cp)_{nf} = \frac{(1 - \phi)\rho_{bf}cp_{bf} + \phi\rho_{np}cp_{np}}{\rho_{nf}}$$

This formulation integrates energy absorption potential from both the base fluid and the nanoparticles.

Parameters and Constants Used

To apply the above equations, material constants for common nanoparticle types (Al_2O_3, CuO, SiO_2, TiO_2) and base fluids (Water, Oil, Propylene Glycol) were used as shown in Table 2. These values were encoded into dictionaries within the code to automate property computation per sample entry.

Table 2 - Constants Used for Property Calculation

Substance	Density (kg/m^3)	Specific Heat ($J/kg \cdot K$)	Thermal Conductivity ($W/m \cdot K$)
Al_2O_3 (np)	3970	880	36.0
CuO (np)	6500	535	76.0
SiO_2 (np)	2220	703	1.4
TiO_2 (np)	4250	686	8.4
Water (bf)	997	4180	0.6
Oil (bf)	880	2100	0.145
Propylene Glycol	1036	2400	0.21

The derived values for $k_{nf}, \mu_{nf}, \rho_{nf}$, and cp_{nf} were later used to construct simulationready input tables (see Section 2.5). These effective properties were also stored in a separate CSV file to enable seamless import into external CFD tools such as ANSYS Fluent or OpenFOAM.
Let me know if you would like to include comparative plots for these properties or derive them for different nanoparticle types.

2.5 CFD Input Preparation

The next important step after calculating effective thermophysical properties was to format and export the processed data so it could be used by commercial CFD solvers. As a result, the nanofluid parameters from the analysis can be used as material or boundary settings in ANSYS Fluent and OpenFOAM software.
The results were put into a table, with each row showing a different flow case and its unique combination of nanoparticle type, base fluid, temperature and flow velocity. To describe the thermophysical behavior of the nanofluid, the model used thermal conductivity, dynamic viscosity, density and specific heat as essential computed properties.
The finished table was exported as CFD_Input_Parameters.csv which is a comma-separated file format that makes it simple to import. It is simple to add this format to simulation environments, either by importing it directly into Fluent's profile definitions or by writing it into OpenFOAM boundary or transport property dictionaries.

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Structure of the Exported Table

The table 3 consists of the following columns:

- Flow_Velocity (m/s) - Inlet velocity of the fluid in the microchannel.
- Temperature (°C) - Operating temperature corresponding to the nanofluid case.
- Thermal Conductivity k_{nf} - Effective thermal conductivity in $\mathrm{W/m \cdot K}$.
- Dynamic Viscosity μ_{nf} - Effective viscosity in Pa.s.
- Density ρ_{nf} - Effective fluid density in $\mathrm{kg/m^3}$.
- Specific Heat cp_{nf} - Effective heat capacity in $\mathrm{J/kg}$ K.

Each row in the file is simulation-ready and captures the dynamic response of nanofluids under varying physical inputs. A sample of the exported data is shown below in table 3 to illustrate the structure:

Table 3: Sample Snippet from CFD_Input_Parameters.csv

Flow_Velocity (m/s)	Temperature (°C)	k_nf	mu_nf	rho_nf	cp_nf
1.91	85.4	0.659	0.009086	1259.8	3370.3
0.68	71.7	1.600	0.006459	1417.0	3390.5
1.53	89.4	1.787	0.009795	1953.3	1388.4
0.17	77.1	1.898	0.005452	1991.0	2403.6
2.28	61.1	0.607	0.003287	1696.6	2389.3

2.6 Workflow Overview

A simple four-step procedure was used to process the raw nanofluid data and prepare it for simulation in CFD, as seen in Figure 1:

1. Dataset Loading - Empirical datasets were imported, including nanofluid compositions and flow properties.
2. Preprocessing - Data were cleaned, categorical variables encoded, and volume fractions rescaled to ensure consistency and compatibility.
3. Property Calculation - Effective thermal conductivity (k_{nf}), viscosity (μ_{nf}), density (ρ_{nf}), and specific heat (cp_{nf}) were computed using classical mixing models based on the nanoparticle and base fluid properties.
4. Export to CFD - The results were structured into a CSV file (CFD_Input_Parameters.csv), formatted for direct input into solvers like ANSYS Fluent or OpenFOAM.

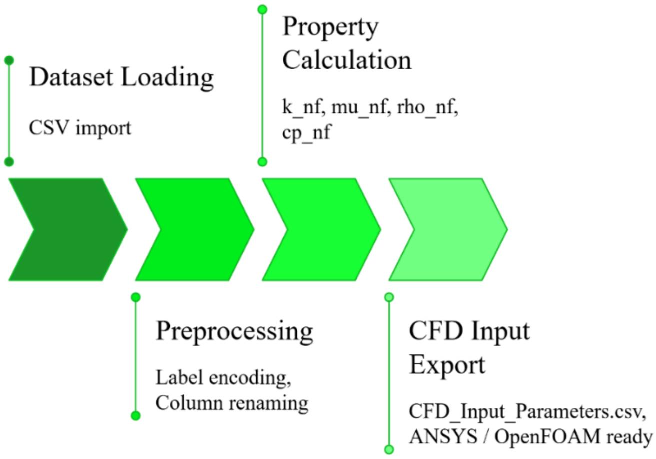

Figure 1: Nanofluid CFD Preparation Workflow

4. Results and Discussion

4.1 Exploratory Data Analysis (EDA)

The HTC was studied in different nanofluid samples to see how thermal performance changes. As the HTC values in Figure 2 indicate, the dataset includes information on a wide variety of nanoparticle-fluid systems and operating situations. This data coverage makes us believe the dataset is strong and suitable for parametric analysis.

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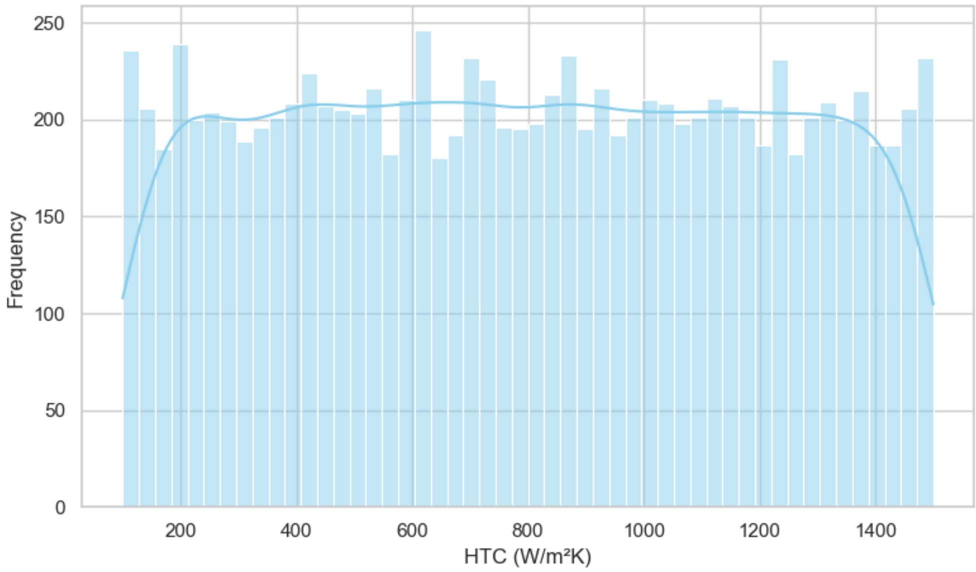

Figure 2 – Distribution of Heat Transfer Coefficient (HTC)

Only weak linear connections were found between HTC and viscosity, conductivity and specific heat in Figure 3. This agrees with previous studies that explain nanofluid behavior as being multivariate and nonlinear [7, 4]. Therefore, both experimentation and computer modeling are important to accurately represent thermal behavior.

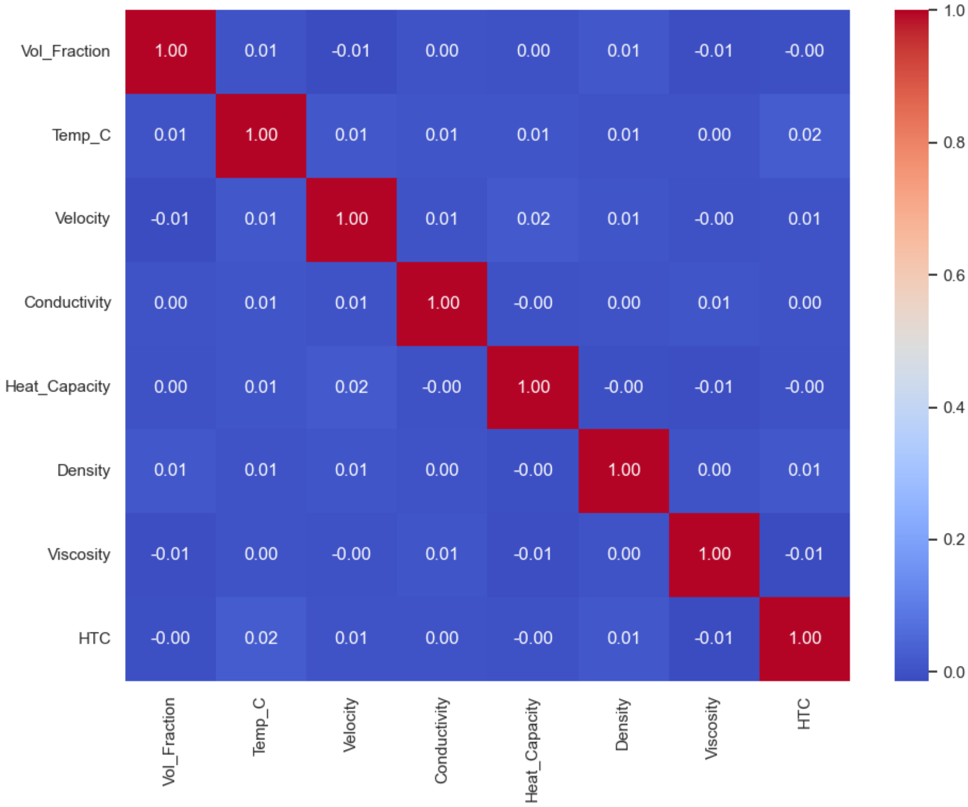

Figure 3 – Correlation Matrix of Nanofluid Features

The differences in nanoparticle types were clearly shown in the box plots. The highest median HTC values were found for CuO and Al_2O_3, proving their ongoing importance in improving heat transfer [2, 9]. But there is a price to pay for this benefit. CuO nanofluids are found to be much thicker than most other metallic oxides which can make it hard to use them in situations where high flow rates or minimal pumping power are required [8,

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5]. It points out that nanofluids should be chosen not only for their ability to improve heat transfer but also for how they flow, as this influences the energy needed for circulation.

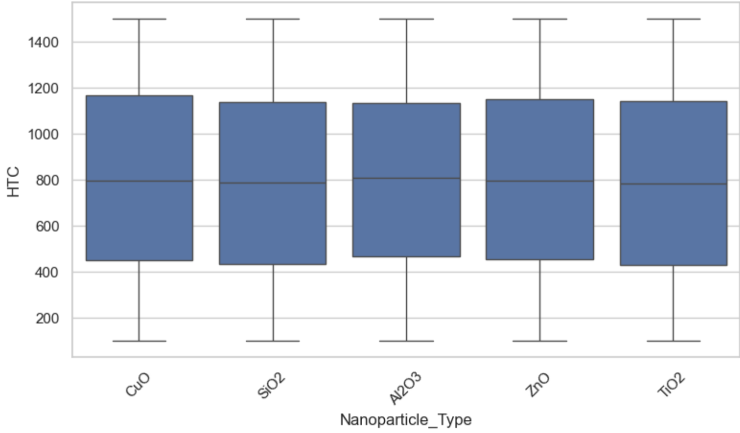

Figure 4 – Effect of Nanoparticle Type on HTC

Similarly, analysis of specific heat capacity and density (Figures 5 and 6) showed that SiO_2 consistently delivered high energy storage capability due to its elevated specific heat, while CuO and Al_2O_3 increased the density of the fluid, aiding momentum but increasing inertial drag [6, 3].

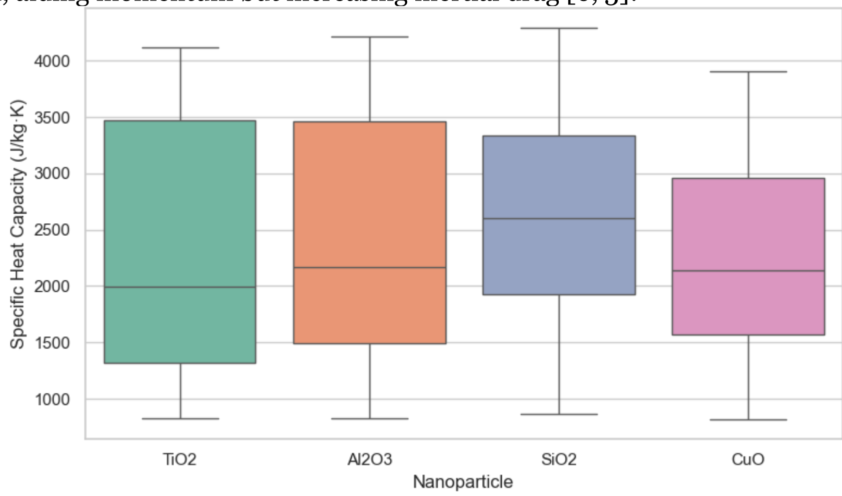

Figure 5 – Effective Specific Heat Capacity by Nanoparticle Type

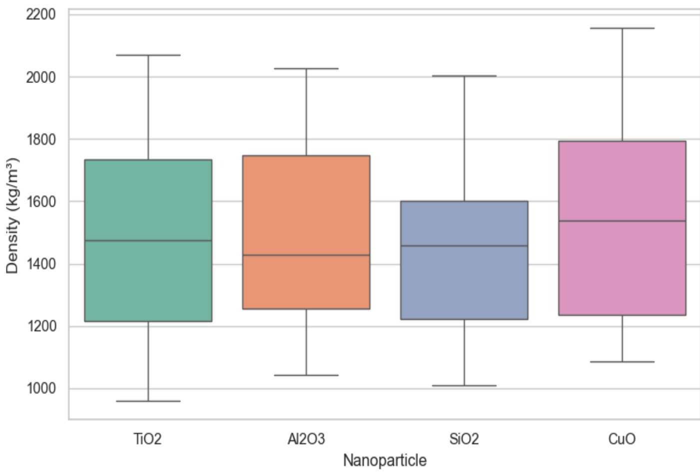

Figure 6– Effective Density by Nanoparticle Type

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The results indicate that both thermal performance and flow rate should be considered when choosing a nanofluid, especially in small-scale heat exchangers where they both influence how well the system works [7, 1].

4.2 Inter-Nanoparticle Comparison

A table listing the key differences among nanoparticle types is shown as Table 4. It is interesting to note that CuO has excellent thermal conductivity and HTC, as expected from Brownian-enhanced transport in metallic oxide nanofluids [10]. Still, it is the thickest and heaviest which makes it most suitable for high-flow industrial systems that require mechanical pumping.

Table 4 – Median Thermophysical Properties by Nanoparticle Type

Nanoparticle	Thermal Conductivity (W/m·K)	Viscosity (Pa·s)	Specific Heat (J/kg·K)	Density (kg/m³)
CuO	Highest	Highest	Moderate	Highest
Al_2O_3	High	Moderate	Moderate	High
TiO_2	High	Moderate	High	Moderate
SiO_2	Moderate	Lowest	Highest	Lowest

When compared, SiO_2 has the best viscosity and specific heat which makes it an ideal choice for use in electronics or solar collectors [12]. Figure 7 shows the relationship between the two factors graphically.

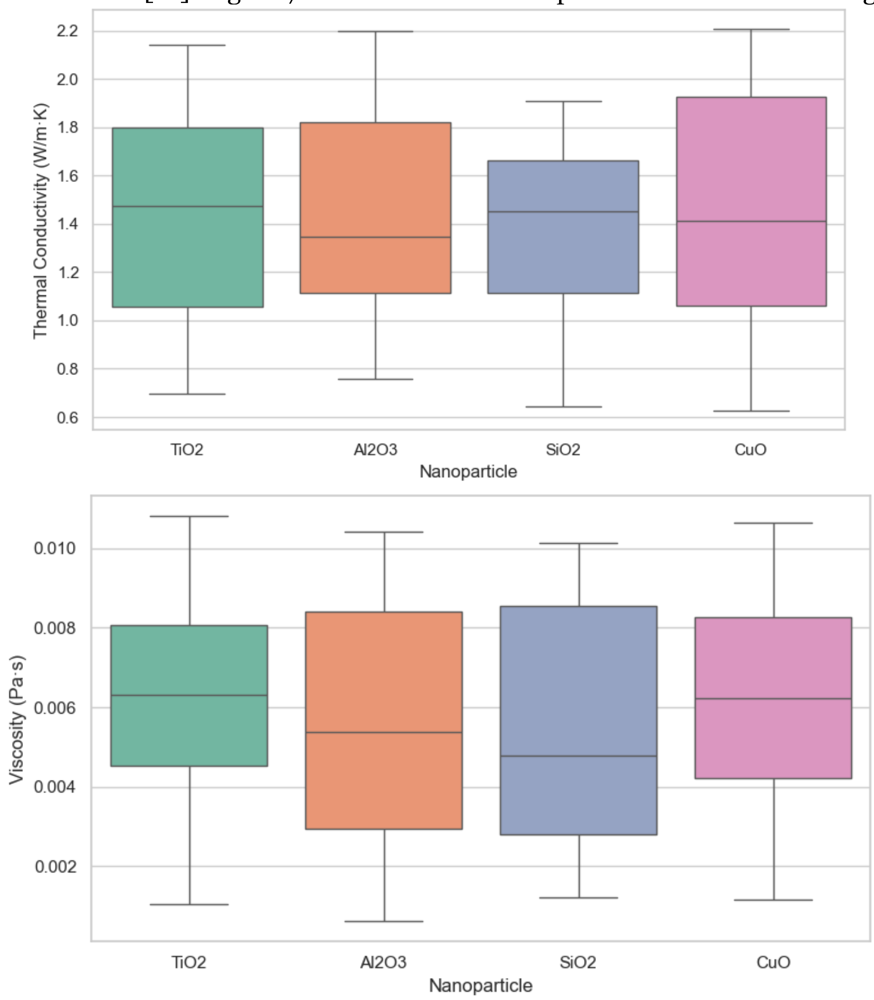

Figure 7 – Comparative Thermal and Viscous Performance by Nanoparticle Type

This analysis reinforces the growing consensus that there is no universally optimal nanofluid. Material choice must be tailored to system demands, as emphasized in reviews by [11] and [15].

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4.3 CFD Utility and Insights

To bridge empirical analysis with practical design, the calculated properties were exported into a simulation-ready CSV file. This dataset- CFD_Input_Parameters.csv included flow velocity, temperature, and effective values for thermal conductivity k_{nf}, viscosity μ_{nf}, density ρ_{nf}, and specific heat cp_{nf}, prepared for integration with solvers like ANSYS Fluent and OpenFOAM.

The file structure ensures compatibility and minimizes pre-processing effort, enabling direct parametric simulations across thermal and flow conditions [13]. Figure 4.8 showcases the structure of this data, allowing engineers to simulate HTC responses to input variations without experimental repetition.

This Table 5 presents simulation-ready tabular data derived from experimental and calculated values, specifically prepared for CFD applications. It includes flow velocity, temperature, and computed effective properties such as thermal conductivity k_{nf}, viscosity μ_{nf}, density ρ_{nf}, and specific heat cp_{nf}. The profile enables straightforward integration into tools like ANSYS Fluent or OpenFOAM.

Table 5: CFD-Ready Property Profile for Parametric Simulation

Flow Velocity (m/s)	Temperature (°C)	k_{nf} (W/m · K)	μ_{nf} (Pa.s)	ρ_{nf} (kg/m^3)	cp_{nf}(J/kg · l
0.73	86.3	0.650	0.00056	1045.16	987.56
1.92	63.7	2.060	0.00589	1861.79	2782.17
0.47	50.2	1.583	0.00963	1196.12	1247.95
0.36	20.4	1.303	0.00954	1965.78	2506.66
1.82	77.4	1.603	0.00799	1154.00	1404.47

Note: Data extracted and prepared from CFD_Input_Parameters.csv for parametric simulation workflow.

5. Conclusion

This study presented a comprehensive analysis of nanofluid thermal performance by combining empirical datasets with computational modeling to evaluate effective properties crucial for microchannel heat transfer applications. Through extensive exploratory data analysis, it was observed that while nanoparticles such as CuO and Al_2O_3 significantly enhanced thermal conductivity and heat transfer coefficient (HTC), they also introduced higher viscosity, which may increase flow resistance and pumping power requirements. Conversely, SiO_2 demonstrated a more favorable balance of low viscosity and high specific heat, suggesting its suitability for low-energy, compact systems. The calculated values for $k_{nf}, \mu_{nf}, \rho_{nf}$, and cp_{nf} were exported in a structured format compatible with CFD tools like ANSYS Fluent and OpenFOAM, enabling simulation-driven exploration without repeated physical testing. Overall, this research not only validates known trends in nanoparticle behavior but also provides a replicable framework for evaluating and selecting nanofluids based on applicationspecific thermal and hydraulic trade-offs.

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