AI-Driven Modeling of Hybrid Nanofluid Density Using a Novel Hybrid Deep Learning and Metaheuristic Optimization Framework

Nanofluids are a class of advanced fluids developed by dispersing nanoscale solid particles such as aluminum oxide (Al_2O_3), copper oxide (CuO), titanium dioxide (TiO_2), or silicon dioxide (SiO_2) into conventional base fluids like water, ethylene glycol, or oils. These suspensions exhibit superior thermophysical properties compared to their base fluids, including enhanced thermal conductivity, viscosity, and density. Such unique characteristics make them attractive for use in applications involving energy systems, electronics cooling, and material manufacturing. In recent years, hybrid nanofluids, prepared by dispersing more than one type of nanoparticle into a base fluid, have gained significant attention due to their synergistic effects, which provide better heat transfer, chemical stability, and flow performance. Among the various thermophysical properties of hybrid nanofluids, density plays a particularly crucial role as it directly influences flow dynamics, convective heat transfer, and pumping power requirements in engineering systems. Therefore, accurate prediction of nanofluid density is essential for designing efficient and reliable thermal systems.

Traditional approaches for predicting nanofluid density have largely relied on empirical or theoretical mixture models. These classical models, such as the weighted average or Pak and Cho equations, assume ideal dispersion and linear mixing between nanoparticles and base fluids. Although these correlations are straightforward, they often fail to capture the nonlinear and temperature-dependent interactions that occur in real systems, especially in the case of hybrid nanofluids where different types of nanoparticles interact in complex ways. Consequently, the accuracy of these empirical formulations deteriorates when the system deviates from ideal conditions or when nanoparticle concentrations increase. Furthermore, such models are often developed under narrow experimental conditions and lack the flexibility to generalize to diverse hybrid compositions.

Artificial Intelligence (AI) has revolutionized nanofluid research by enabling data-driven prediction of complex thermophysical properties. Machine Learning (ML) models such as Random Forests, Gradient Boosting, and Support Vector Regression have improved the accuracy of predicting viscosity, thermal conductivity, and density; however, they often depend on manual feature engineering and struggle with nonlinear or high-dimensional relationships. Deep Learning (DL), a more advanced branch of AI, overcomes these limitations by automatically extracting hierarchical features and modeling intricate nonlinear dependencies among variables like temperature, concentration, and particle type. Unlike traditional ML, DL can efficiently learn from large experimental datasets without explicit assumptions, making it particularly effective for capturing the complex, multivariable interactions governing the behavior of hybrid nanofluids.

Inspired by the demonstrated efficacy of these techniques, this research will develop a novel hybrid deep learning framework to accurately predict the density of hybrid nanofluids while ensuring physical consistency and reliability. A publicly available dataset will be collected, containing key experimental parameters such as temperature, nanoparticle type, size, concentration, and base fluid characteristics. The dataset will be preprocessed through cleaning, normalization, and encoding to maintain quality and consistency, followed by exploratory data analysis to identify key influencing factors and understand variable interactions. This research will introduce a novel deep learning and optimization framework that advances beyond existing empirical and machine learning approaches by integrating adaptive feature learning with automated hyperparameter tuning. The proposed hybrid deep learning framework will consist of multiple layers capable of learning nonlinear relationships and capturing both local and global dependencies among thermophysical parameters. It will employ advanced regularization techniques to avoid overfitting and enhance generalization across different fluid compositions. To further refine model accuracy, an intelligent metaheuristic optimization strategy will be incorporated to optimize network configuration and training dynamics, achieving an optimal balance between precision and computational efficiency. This integrated deep learning and optimization approach will offer a powerful, data-driven method for accurate and interpretable prediction of hybrid nanofluid density.

Model performance will be evaluated using multiple statistical metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). Comparative analyses will be performed against existing ML and DL models to validate the superiority of the proposed framework. The hybrid deep learning framework combined with metaheuristic optimization will enhance predictive accuracy, reduce training error, and improve computational efficiency. This research is expected to contribute significantly to the advancement of AI-driven thermophysical property prediction, enabling the development of intelligent and data-centric design strategies for hybrid nanofluid systems. In the long term, such approaches can serve as reliable tools for engineers and scientists to design thermally efficient systems, reduce experimental costs, and expand the practical implementation of hybrid nanofluids in industrial and energy applications.