Techno-computing Journal (2025), 1, (1)
https://doi.org/10.71170/tecoj.2025.1.1.1-13

Research paper

Deep learning LSTM and random forest ML-aided design tools for energy cooling capacity modeling

Ismail A. Mahmoud [1*], Almustapha A. Wakili [2], Abubakar M. Danjuma [3], AY Sada [4], Mahmud M. Jibril [5], and Zakiyyu I. Takai [6]

[1] *Department of Physics Education Faculty of Science and Technology Education, Kano University of Science and Technology Wudil, Nigeria*
[2] *Computer and Information Science Department Towson University, USA*
[3] *Materials Science and Engineering Department, King Fahd University of Petroleum and Minerals, Dhahran, Saudi Arabia*
[4] *Department of Electrical and Computer Engineering, Baze University Abuja, Nigeria*
[5] *Faculty of Engineering, Department of Civil Engineering, Kano University of Science and Technology, KUST, Wudil, Nigeria*
[6] *Department of Physics, Faculty of Science, Yusuf Maitama Sule University Kano, Nigeria*
**Corresponding Author Email: ismailaminumahmoud27@gmail.com*

Abstract

Cooling capacity (Qe) is a critical metric in cooling system design across commercial, residential, and industrial sectors. It represents the system's ability to remove heat and maintain a steady temperature, contributing to energy efficiency. This study employed two novel machine-learning approaches to model cooling system efficiency: long short-term memory (LSTM) and random forest (RF). At the outset, correlation, and fuzzy sensitivity analyses of dependent and independent variables were conducted. Based on the fuzzy sensitivity analysis results, three different modeling schemes (C1, C2, and C3) were developed, and the predictive models focused on data validation and calibration. Furthermore, the model's performance is evaluated using metrics such as correlation coefficient (R), coefficient of determination (R^2), mean square error (MSE), and root mean square error (RMSE). The results reveal that LSTM models demonstrated exceptional performance during training, achieving R values of 0.997 and R^2 values of 0.998, indicating a strong fit to the dataset. However, R values dropped to 0.796 during the testing phase, with corresponding R^2 values of 0.799. In contrast, the RF model exhibited superior generalization on the testing data, with an R-value of 0.933 and an R^2 value of 0.966. Although the MSE and RMSE values were slightly higher for the RF models than the LSTM models. The overall performance demonstrated the robustness of RF in predicting cooling system efficiency, with better generalization and lower error rates during testing. This indicates that the RF-M1 model achieved the best overall results due to its superior testing performance metrics.

Keywords: Artificial intelligence, Cooling system efficiency, Sensitivity analysis, Machine learning

1. Introduction

As global energy demands continue to rise and sustainability becomes a top priority, efficient cooling systems are more essential than ever. The cooling capacity (Qe) measures a system's ability to remove heat from its environment. Yet, it plays a crucial role in applications ranging from residential air conditioning to large-scale industrial facilities [1]. The Qe is a critical way of maintaining the functionality and efficiency of various industrial and commercial operations, such as data centers,

(Received 13 Nov 2024; revised 25 Nov 2025; accepted 28 Jan 2025; first published online 20 March 2025);
©Techno-computing Journal 2025. Journal homepage https://technocomputing.org/index.php/tecoj

manufacturing facilities, Heating, Ventilation, and Air Conditioning (HVAC) systems. These systems are designed to regulate temperature and humidity levels, ensuring that each equipment operates within safe thermal limits [2]. Predicting Qe performance involves using advanced algorithms and data-driven models to forecast key operational metrics, such as temperature trends and potential system failures [3]. Accurate predictions of Qe will optimize energy usage, improve system reliability, and extend equipment lifespans. In temperature-sensitive industries, such as semiconductor manufacturing and food storage, effective Qe prediction directly impacts product quality and operational costs [4]. One of the key challenges with Qe systems is their high energy demand to maintain optimal temperatures. Large-scale systems require significant energy, affecting environmental sustainability and increasing operational costs. Inconsistent maintenance practices can lead to equipment wear and tears, resulting in efficiency losses and unplanned failures. Environmental factors, such as seasonal changes, further complicate Qe performance by forcing systems to work harder, ultimately reducing operational efficiency [5]. Predicting Qe performance is challenging due to highly dynamic operating environments, where factors like fluctuating external temperatures and variable humidity levels can significantly impact efficiency [6]. Physical components, such as compressors, fans, and heat exchangers, also experience gradual wear, affecting system performance over time. Another challenge is data management complexity; Qe systems generate vast sensor data that may contain noise or missing values, making accurate data processing and interpretation difficult [7,8]. Traditional modeling methods often struggle to capture the nonlinear and time-dependent relationships inherent in Qe operations, leading to suboptimal predictions and increased operational risks [9]. Despite their importance in maintaining safe temperatures and equipment protection, Qe systems often face energy consumption and efficiency challenges due to fixed settings that cannot adapt to environmental changes or inconsistent demands in real time. This results in inefficient energy usage, frequent overcooling, and increased operational costs[10].

Applying artificial intelligence (AI) and machine learning (ML) methods to enhance Qe performance has become a prominent research area. Many studies, such as Zhang et al., have explored different models to improve efficiency. [11] which validated the use of Long Short-Term Memory (LSTM) models in forecasting cooling load demands, demonstrating their superiority over traditional regression models in accuracy. Similarly, LSTM models have been employed for temperature prediction within Qe systems, with their ability to capture long-term dependencies in data streams leading to more reliable predictions of peak loads, thereby enabling smoother energy distribution and reduced operational costs [12]. The studies highlighted LSTM's suitability for cyclical load requirements, showcasing its advantages in settings where demand fluctuates over time. In another study by Choubani et al. [13], explored the energy-saving potential of evaporative cooling systems, especially in arid climates. Lei et al. revealed significant reductions in energy consumption compared to conventional air conditioning systems [14], RF (Random Forest) models have been applied to analyze Qe data in commercial buildings, identifying key operational variables, such as ambient temperature and humidity, as critical factors influencing cooling performance; furthermore, Romdhane et al. [15] has discussed using phase change materials (PCMs) in cooling applications, showing that PCMs can enhance Qe efficiency by storing and releasing thermal energy during peak demand periods. A comprehensive review of vapor compression systems has emphasized the need for improved refrigerators and system designs to enhance performance while minimizing environmental impact.

Moreover, Li and Yao [16] have demonstrated the application of RF models in predicting cooling energy demand, indicating that RF models offer a cost-effective and interpretable solution for Qe prediction. Verma et al. [16] developed Qe as a sustainable approach to urban cooling, highlighting the benefits of centralized cooling plants in reducing overall energy consumption and operational costs across multiple buildings. Support Vector Machines (SVM) have also been utilized to identify anomalies in Qe operations, categorizing data patterns into normal and fault states, proving effective for early failure detection and timely interventions [17]. Integrating renewable energy sources, such as solar power [18], into Qe systems has significantly decreased reliance on conventional energy sources and reduced operational costs [19]. AI and ML models can optimize system performance and reduce energy waste by predicting cooling demands based on historical data. Implementing AI in Qe methods offers substantial long-term benefits, allowing businesses to reduce energy consumption, minimize environmental impact, and maintain precise temperature control for critical spaces, including laboratories. With AI integration, cooling systems evolve from static, one-size-fits-all solutions into intelligent systems capable of meeting specific cooling needs efficiently. Advancements in AI methods promise to transform Qe, setting new benchmarks for flexibility, competence, and cost-efficiency across various industries. AI models provide transformative techniques for Qe prediction and optimization. AI models can process large datasets through ML algorithms, including historical performance data, environmental conditions, and energy consumption data [20]. ML models can analyze complex relationships among factors to make highly accurate real-time predictions for cooling systems. This capability allows AI models to adjust cooling settings, adapt to changing demands, conserve energy, and reduce costs. The primary objective of the current study is to develop and validate ML models, including LSTM and RF, for precise modeling of cooling system efficiency using environmental data obtained from surveys based on a solar-powered vapor absorption refrigeration system (VARS) integrated with latent heat energy storage tailored to the Riyadh city climate. By reducing the need for extensive experimental work, applying Qe can be accelerated using computational methods such as ML approaches.

2. Material and Methods

2.1 Data Sources and Variability

It's paramount to understand that data pre-processing is a crucial first step to ensure the quality and reliability of the input data[21,22]. This includes handling the missing values, removing outliers, and encoding the selected variables if they are present. Ensure the research data is good, clean, and ready to take out the modeling of the employed models, RF and LSTM. Moreover, a fuzzy sensitivity analysis was conducted to determine the best model combination. The data used in the current study contains 8760 instances, and it was obtained through a survey based on a solar-powered vapor absorption system integrated with latent heat energy storage tailored in Riyadh city of Saudi Arabia. The current study comprises some key components like ambient temperature (TA), Relative humidity (Phi), Coefficient of Performance (COP), Efficiency of the absorber (effa), Efficiency of the desorber (effd), Mass flow rate(mu), specific temperature measurement point(T20), Water inflow rate (win), Mass flow rate of water (Mwater), and the target variable which is Cooling capacity of the evaporator (Qe).

2.2 Data Pre-processing and Sensitivity Analysis

Data pre-processing is crucial in every ML modeling technique; it allows raw data to be prepared for training in any network system[23,24]. The method involves data cleaning to understand the linearity and remove unnecessary variables from the data set. This study cleaned up data by classifying and eradicating unwanted columns. All the missing values were to be filed out, letting the category data change to a numerical set. The normalization equation is presented in Equation 1. The main idea is to use the input variables based on fuzzy sensitivity analysis to estimate the levels of the output variables accurately, while Table 2 presents the sensitivity analysis result.

$$y = \frac{x_{-}\ x_{minimum}}{x_{\mathrm{maximum}-}\ x_{minimum}} \tag{1}$$

where x is labeled as measured data, and x_{min}, and x_{max} are the minimum and maximum facts, singly. However, Equation 2 produces the input article grouping that will be used as inputs in the modeling RF and LSTM models. These combinations were selected based on correlation analysis, highlighting the significance of the exergy system. Thus, each of these combinations was trained and tested with both models.

$$Qe \quad = \begin{matrix} M1 = \ T20 + Phi + Cop \\ M2 = T20 + Phi + Cop + mu + effd + effa \\ M3 = \ T20 + Phi + Cop + mu + effd + effa + mwater + Ta + win \end{matrix} \tag{2}$$

However, a sensitivity analysis test is used to regulate how different input variables impact the output of a model. It helps identify which inputs are the most influential, how much uncertainty in the inputs affects the results, and whether the model is robust to changes in input values. Fuzzy Sensitivity Analysis is a technique used to understand how changes in the input variables of a fuzzy system affect its output. In different systems [25]. This is important for improving system performance and decision-making in uncertain environments, such as climate modeling, financial forecasting, or control systems. In fuzzy sensitivity analysis, one of the common approaches is to evaluate how small changes in the inputs lead to variations in the output [26]. Fuzzy sensitivity analysis can help determine how that change influences the fuzzy logic output, like a control signal for a Qe. Fuzzy sensitivity analysis is widely applied in engineering, economics, and environmental science, where systems have uncertain or imprecise data. It can be beneficial in systems like predictive maintenance for Qe, where inputs such as temperature, humidity, and pressure may not always be precise but still need to be considered for optimal performance [27]. However, sensitivity analysis, a measured method used to determine how different values of an input variable can impact an actual output variable under a given set of assumptions, is a critical tool for assessing the robustness and reliability of models and predictions.

3. Model Building

The AI models employed for Qe prediction involved a comprehensive approach, including model building, pre-processing, and normalization. The performance of these models was evaluated using various metrics such as the Coefficient of Determination (R^2), Correlation Coefficient (R), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The primary goal of the modeling techniques was to predict Qe with high accuracy and to serve as effective methods for enhancing Qe predictions. The current research utilized LSTM and RF algorithms due to their promising performance in handling large datasets and capturing complex relationships. The robustness of the prediction models was ensured through a process involving calibration and validation of the research data, where 80% of the data was used for validation and 20% for calibration. This approach aimed to maintain a balanced and unbiased evaluation of model performance. Pre-processing techniques were employed to remove noise and scale the data, thereby improving data stationary and enhancing model accuracy. Data pre-processing included techniques such as data normalization, missing value treatment, and noise reduction to ensure high-quality input for model training. The proposed modeling schema, as depicted in Figure 1, outlines the systematic data preparation and modeling process. The rationale for splitting the data into calibration and validation sets was to prevent data leakage and ensure that the models generate reliable and accurate predictions. By integrating the calibration and validation phases, this study developed a precise prediction model for Qe estimation, thereby minimizing over-fitting and improving the generalization capability of the models. This comprehensive approach allowed the LSTM and RF models to learn effectively from the data, providing robust and reliable Qe predictions that can be applied in various real-world scenarios.

3.1 Random Forest (RF)

RF is an ensemble learning method for classification and regression tasks. It builds multiple decision trees during training and combines their outputs to make more accurate and stable predictions see Figure 2. The core idea behind RF is to improve the performance and reduce the overfitting tendency of individual decision trees by aggregating their results [28]. This RF approach increases model robustness, particularly in handling large datasets with complex structures. RF operates using two main techniques: random feature selection and During the training phase, RF creates each decision tree using a different bootstrapped dataset sample, ensuring diversity among the trees [29]. Also, at each node split, only a random subset of. Each tree in the forest is trained on a randomly sampled subset of the training data, drawn with replacement. Moreover, when splitting nodes within a tree, Random Forest considers a random subset of features rather than all available features [30].

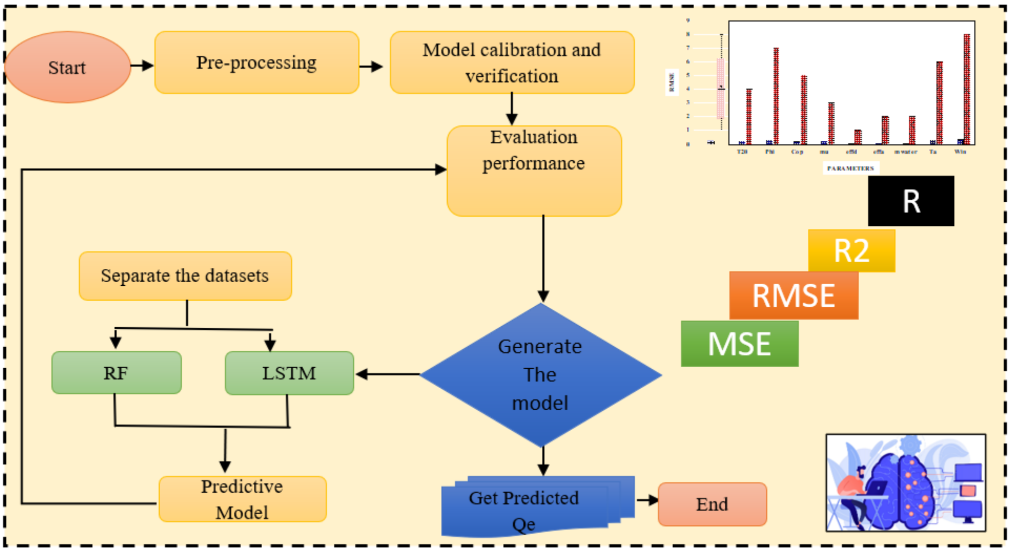

***Figure 1**: Proposed modeling schema involved in the current study.*

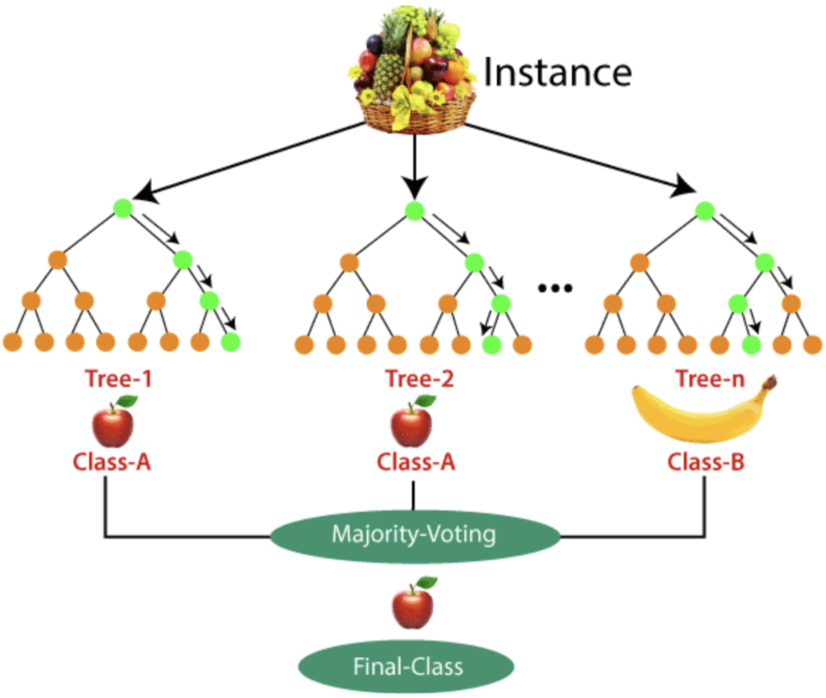

***Figure 2:** RF architecture.*

3.2 Long Short-Term Memory (LSTM)

LSTM networks are Recurrent Neural Networks (RNN) designed to learn and retain long-term dependencies in sequential data. Unlike traditional RNN, which struggles with disappearing and exploding gradient problems, LSTM uses a unique architecture that enables it to capture patterns over extended sequences effectively [31]. This makes LSTM mainly suitable for tasks where relationships between distant elements in a sequence are critical, such as time series predicting and natural language processing. LSTM has been widely applied in various fields, including speech recognition, financial modeling, and predictive maintenance (Figure 3). LSTM's ability to model long-term dependencies makes them particularly effective in Qe performance prediction, where historical data plays a significant role in forecasting future system behavior [32]. The LSTM architecture consists of memory cells and three gating mechanisms. The forgetting gate decides which information from the previous cell state should be discarded, while the input gate determines which new information should be added. The output gate controls what part of the current cell state is passed to the next hidden state [33].

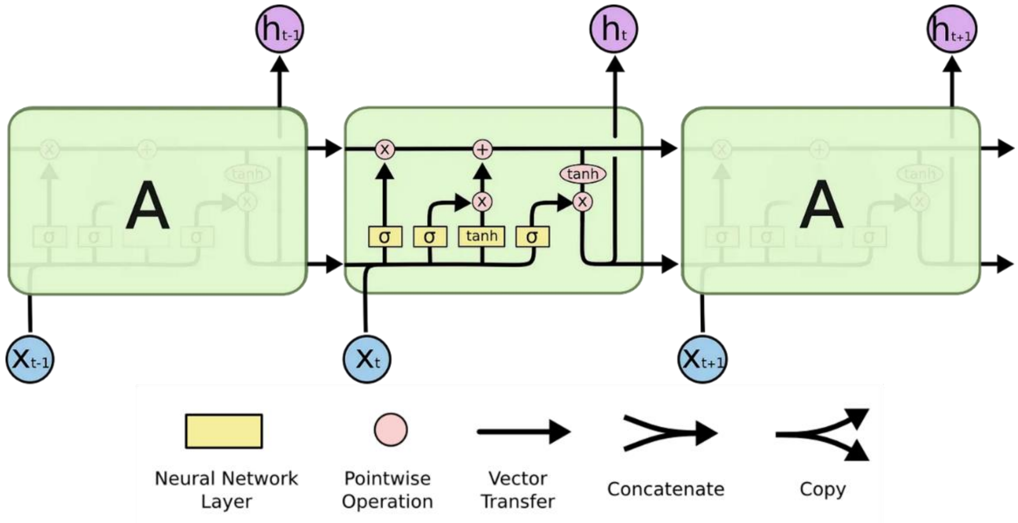

Figure 3: *Schematic architecture of LSTM.*

3.3 Model Validation and Performance Evaluation Criteria

The validation of AI models is crucial in ensuring that the employed models are reliable and capable of making accurate predictions on unseen data[34]. Effective model validation helps prevent overfitting and estimates how well the model will generalize to new datasets. This process establishes criteria and measurements to evaluate the models' predictive performance, efficiency, and quality. Such criteria form the basis for assessing model performance and assist decision-makers in making well-informed choices about model promotion or further improvements [35]. In the current study, various metrics were utilized to evaluate model performance. These metrics measured different aspects of the models, including accuracy, error, uncertainty, and the model's ability to generalize to unseen data. Four key statistical measures were employed: the R, R^2, MSE, and RMSE (Table 1). These metrics were chosen to comprehensively assess how well the models captured data trends, minimized prediction errors, and maintained reliability across different data segments. Table 1 presents the formulas for these performance criteria, illustrating the mathematical basis for evaluating model performance. Including these metrics ensures a robust evaluation framework, highlighting the strengths and areas for potential improvement within the predictive models. Using these statistical measures, the study could objectively assess the accuracy and reliability of the AI models, guiding further refinement and optimization to achieve the best possible predictive performance [36].

Table 1*: Performance evaluation indicators*

Name	Formula	Range
R^2	$1-\frac{\sum_{j=1}^{N}[(Y)_{obs.j}-(Y)_{com.j}]^2}{\sum_{j=1}^{N}[(Y)_{obs.j}-(\gamma)_{com.j}]^2}$	(− 1 < R< 1)
R	$\frac{\sum_{i=1}^{N}[[Y_{obs.i}-\overline{Y_{obs.i}}][[Y_{com.i}-\gamma_{com.i}]}{\sqrt{\sum_{i=1}^{N}[[Y_{obs.i}-\gamma_{obs.i}]^2[[Y_{com.i}-\gamma_{com.i}]^2}}$	(0 < R < 1)
MSE	$\frac{1}{N}\sum_{i=1}^{N}[Y_{obs.i}-Y_{com.i}]^2$	(0 < MSE < ∞)

RMSE	$\sqrt{\frac{\sum_{i=1}^{N}[Y_{obs.i} - Y_{com.i}]^2}{N}}$	$(0 < \text{RMSE} < \infty)$

where N provides the number of instances in the dataset, Y_{obsi} means the observed value, Y_{comi} designates the predicted value, and Y_{comi} is the predicted mean of the instances.

4. Applications Result and Analysis

However, Figure 4 presents the sensitivity analysis results using the Neuro-fuzzy Technique, whereby the first modeling schema Combination (C1) comprises T20, Phi, and Cop. However, the second modeling combination (C2) contained T20, Phi, and Cop, mu, effd, and effa. The third modeling combination is (C3), T20, Phi, Cop, mu, effd, effa, mwater, Ta, and win. Hence, this group of input variables was taken out based on the sensitivity analysis in the table below. Moreover, Figure 4 presents a sensitivity analysis ranking variables based on their RMSE, revealing the relative impact of each on model performance. The variable effd, with the lowest RMSE (0.005127), ranks first, indicating its high sensitivity and influence on prediction accuracy, while win, with the highest RMSE (0.304908), ranks lowest, suggesting minimal impact. The top-ranking variables, for instance, effd, effa, and mwater, demonstrate the most decisive influence on the model, making them critical for tuning efforts. Variables such as mu, T_{20}, and COP occupy the middle ranks, reflecting moderate sensitivity. In contrast, Phi, Ta, and Win have higher RMSE values, indicating they are less impactful. These findings suggest that optimizing low-RMSE variables would enhance model accuracy, while adjustments to high-RMSE variables would have a limited effect, thus prioritizing key variables for model optimization. The findings of this study can be applied to optimize energy-efficient cooling systems by prioritizing key variables that significantly impact performance. The sensitivity analysis helps refine control strategies for HVAC systems, ensuring improved energy management by focusing on critical parameters such as effd, effa, and mwater. Also, industries can leverage these insights to develop predictive maintenance models, enhancing system reliability and reducing operational costs. Lastly, the superior performance of the RF model suggests its potential application in smart building automation, where accurate cooling load predictions enable real-time energy optimization.

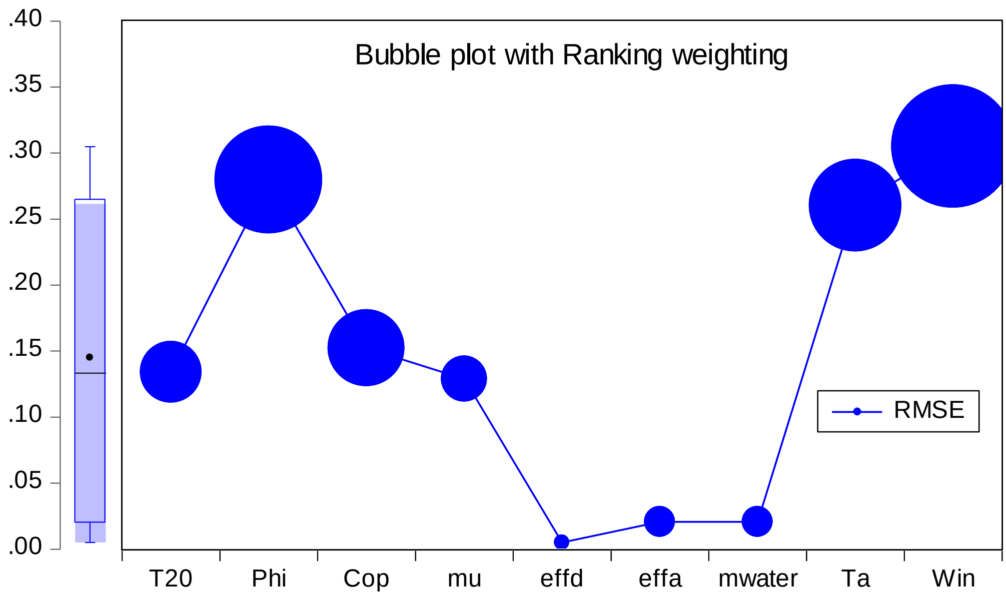

Figure 4. Sensitivity analysis graphical presentation based on their RMSE ranking

The boxplot shows the distribution and variability of different variables regarding their normalized sensitivity or predictive impact, providing visual insight into their range, central tendency, and spread (Figure 5a). Variables such as COP, effa, and effd exhibit a wide range with large interquartile spreads, suggesting significant variability in their influence on the model. Mwater and mu show relatively minor ranges, indicating more stable or consistent sensitivity. Phi, T20, Ta, and Win demonstrate moderate to high variability but with distinctive differences in their medians and outlier behavior. Notably, Win appears to have lower median sensitivity, further confirming its limited impact compared to other variables. The presence of outliers, especially for COP and effa, indicates instances where their impact deviated significantly from the typical range, emphasizing the need to explore potential causes of such behavior in model responses. Visualization highlights each parameter's diverse sensitivity and stability characteristics, guiding focus on more influential and consistent variables for model improvement.

Figure 5b shows the histogram plot that provides a comprehensive view of the distribution of various variables, offering insight into their frequency and concentration across different normalized sensitivity ranges. The distribution for COP shows a dominant peak at the lower end, suggesting a high frequency of low-sensitivity occurrences, indicating a limited impact on the model in most cases. The *effa* and *effd* exhibit more balanced distributions with higher frequencies in the middle ranges, implying a moderate but consistent influence across different instances. *Mwater, mu, phi,* and *T20* show a more dispersed distribution with smaller peaks across various intervals, highlighting their variable impact. The *ta* demonstrates a noticeable frequency peak, indicating a consistent influence around its sensitivity value. At the same time, *Win* has a skewed distribution towards lower frequencies, reinforcing its limited influence compared to others. The relatively flat distribution for Qe implies its spread of impact is more uniform across various levels. The distribution analysis helps understand the frequency and relative significance of each parameter's influence on model performance, guiding a more targeted approach for model enhancement and optimization.

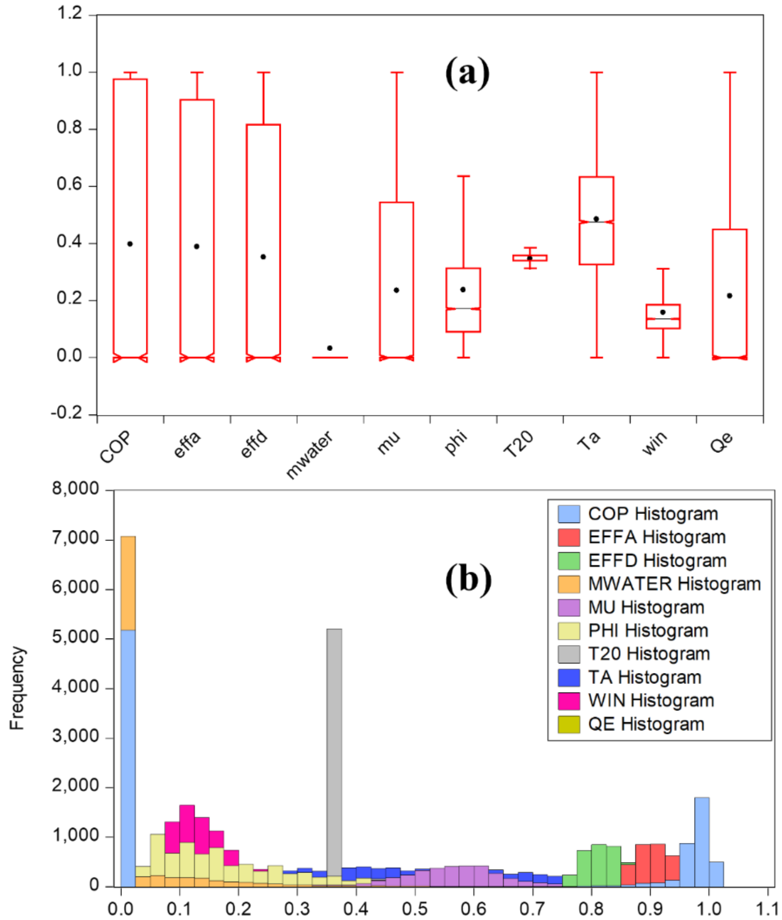

Figure 5: *(a) boxplot showing some of the statistical variables (b) distribution plot of the raw data used in this study*

4.1 Predictive Model Result

This study employed two ML models, RF and LSTM, to predict Qe. Each of these models was utilized with three different input combinations, designated as C1, C2, and C3, to enhance the robustness and accuracy of predictions. Data processing was conducted using E-Views 13.0, while the LSTM model was implemented through Python code due to its capacity to capture temporal dependencies. Conversely, the RF model was built using R Studio version 4.2.2, benefiting from its strength in handling non-linear relationships and reducing overfitting. Table 2 presents the models' calibration and verification phase results, with their performance evaluated using various metrics. These metrics offered insights into how well the models fit the data and their ability to generalize predictions across different data sets[37,38]. The results demonstrate each model's capability, highlighting strengths and areas for improvement in the predictive process. This comparative analysis supports ML approaches' optimal selection and refinement for accurate and reliable system predictions[39].

***Table 2**: Result of the ML models for both Calibration and verification.*

		Calibration Phase		
Models	R	R^2	MSE	RMSE
LSTM-M1	0.9970	0.9985	35.9373	5.9948
LSTM-M2	0.9976	0.9988	35.9416	5.9951
LSTM-M3	0.9976	0.9988	35.9504	5.9959
RFM-M1	0.9977	0.9988	35.9464	5.9955
RFM-M2	0.9977	0.9988	35.9479	5.9957
RFM-M3	0.9977	0.9988	35.9479	5.9957
		Verification Phase		
Models	R	R^2	MSE	RMSE
LSTM-M1	0.7961	0.8923	14.4328	3.7991
LSTM-M2	0.7987	0.8937	14.4244	3.7980
LSTM-M3	0.7994	0.8941	14.4299	3.7987
RFM-M1	0.9335	0.9662	14.4514	3.8015
RFM-M2	0.9333	0.9661	14.4505	3.8014
RFM-M3	0.9333	0.9661	14.4506	3.8014

The results indicate that the employed models, LSTM and RF, exhibited exceptional performance with high R and R^2 values during the training validation phase. Specifically, the LSTM model using combinations C1, C2, and C3 achieved R values ranging from 0.9970 to 0.9976 and R^2 values consistently above 0.9985, demonstrating a strong fit to the training data. Similarly, the RF model showed comparable performance with R values around 0.9976 and R^2 values close to 0.9988. These high values indicate that both models effectively captured the underlying patterns in the data with minimal error. Furthermore, the MSE and RMSE values for all models remained within a narrow range, with the lowest RMSE around 5.99, underscoring their high accuracy during training. The testing phase provided critical insight into the model's generalization ability to unseen data. In this phase, the RF model outperformed the LSTM model, achieving a higher R-value of 0.9661. In contrast, the LSTM models recorded R values ranging from 0.7961 to 0.7994, corresponding R^2 values between 0.8922 and 0.8941. Despite the lower R^2 values for the LSTM models during testing, their performance remained consistent, as evidenced by similar MSE and RMSE values across both training and testing phases. Figure 6 presents the cumulative probability graph between the observed and computed Qe in training and testing. Notably, the RMSE values for both models during testing were below 3.80, indicating good predictive accuracy. While both models demonstrated strong performance in training and testing, the

RF model showcased superior generalization capability. This advantage can be attributed to the ensemble nature of RF, which enhances robustness and mitigates over-fitting. On the other hand, the slightly weaker performance of the LSTM models during testing may be due to their sensitivity to hyperparameter tuning. Nonetheless, the comparable RMSE values of both LSTM and RF during testing suggest similar predictive accuracy. However, the analysis underscores that the RF model exhibits better generalization, making it more reliable for real-world applications where unseen data variability exists in cooling system prediction. Future research should focus on fine-tuning LSTM hyperparameters or integrating hybrid approaches to enhance model robustness and predictive accuracy. The radar plot illustrated in Figure 7 visually represents multivariate data on a two-dimensional chart, often called a spider chart. It consists of a series of equiangular spokes radiating from a central point, each representing a distinct variable. A shape is formed by plotting variable values along these spokes and connecting the data points, visually depicting relationships and patterns within the dataset. This graphical representation provides an intuitive overview of the model's performance and data variability.

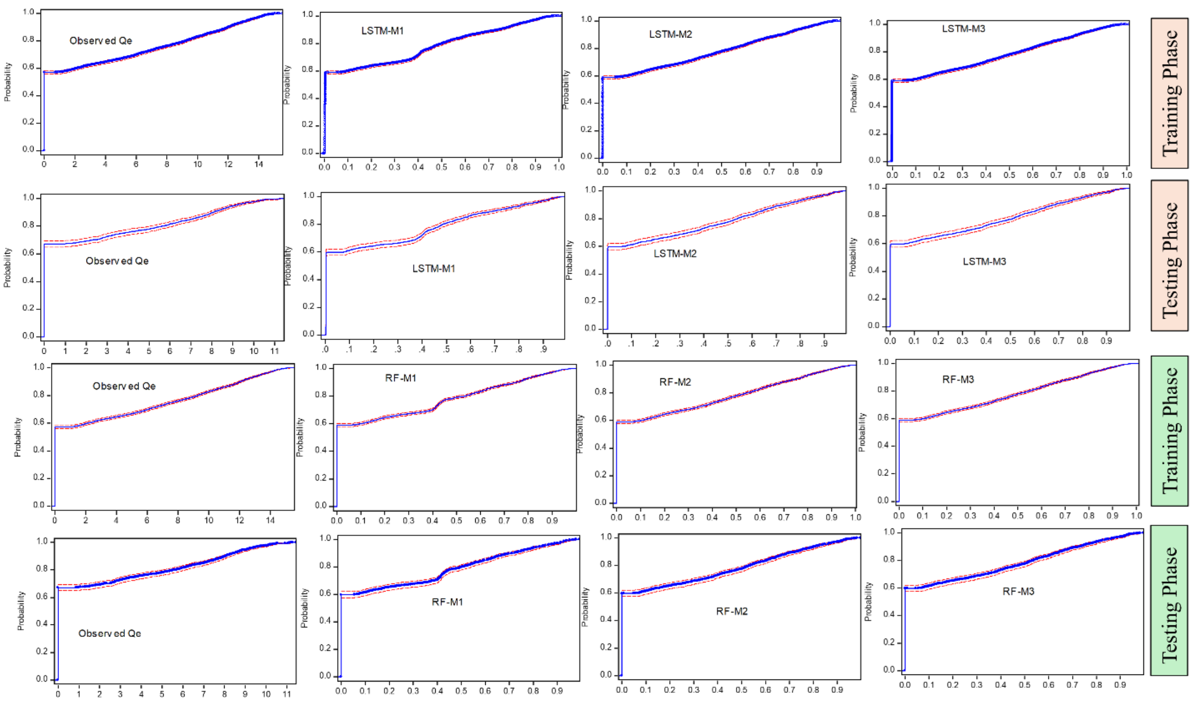

Figure 6: *Cumulative Probability graph for training and testing values.*

The RMSE values during the verification phase indicate the predictive accuracy and generalization capabilities of the LSTM and RF models when applied to unseen data. Among the LSTM models, LSTM-M2 had the lowest RMSE at 3.7980, closely followed by LSTM-M3 at 3.7987 and LSTM-M1 at 3.7991. This suggests that all three LSTM models had comparable performance, with slight variations indicating consistent accuracy in prediction but a tendency to underperform slightly relative to the RF models. The RF models (RFM-M1, RFM-M2, and RFM-M3) exhibited slightly higher RMSE values, ranging from 3.8014 to 3.8015. While these values are marginally higher than the LSTM models, the difference is insignificant. This minimal increase in RMSE suggests that the RF models maintain high predictive accuracy during the verification phase, with robust generalization capabilities. The RMSE values reveal that both the LSTM and RF models performed well in predicting unseen data, with a slight edge in accuracy for LSTM models based purely on RMSE. However, given the RF models' strong performance, their ensemble nature likely contributes to better stability and resistance to overfitting despite the minor difference in RMSE. This indicates that RF models may offer better reliability for practical applications in more complex or varied data scenarios.

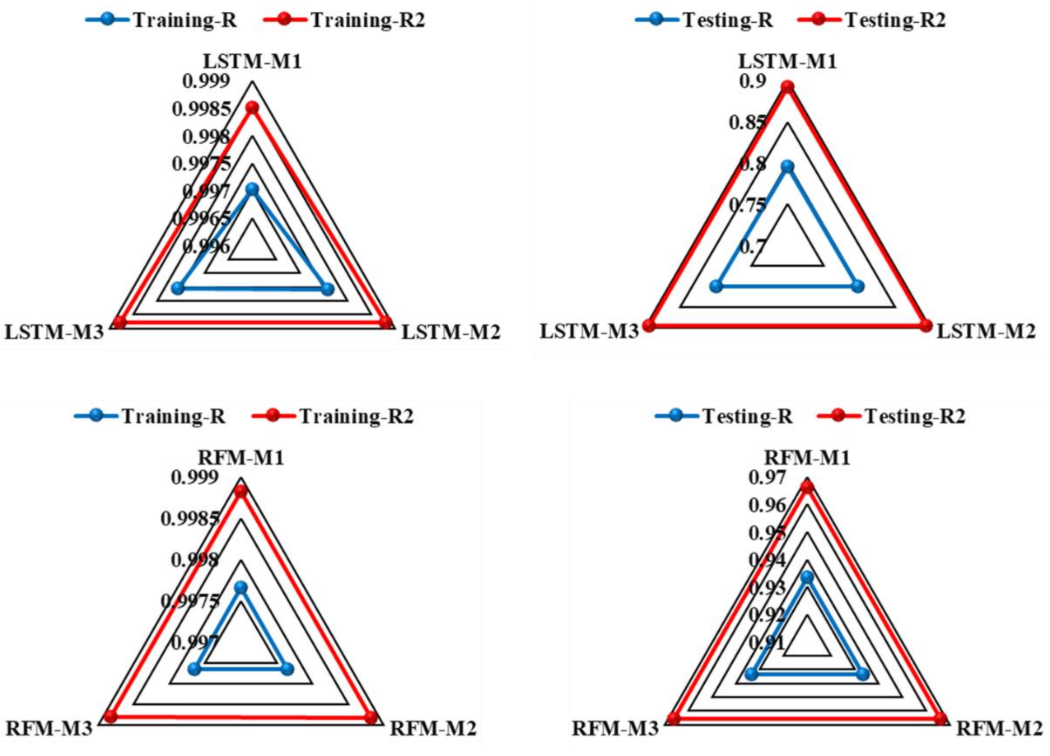

Figure 7: *Radar plots between the observed and computed values regarding goodness-of-fit criteria.*

5. Conclusion

This study investigated the predictive performance of LSTM and RF models for cooling capacity prediction. The models were evaluated using various performance metrics, including R, R^2, MSE, and RMSE, providing comprehensive insights into their effectiveness during calibration and verification phases. The results demonstrated that long short-term memory and RF models deliver high accuracy in modeling Energy Cooling systems, with strong correlations and low errors during training. However, during testing, the RF model consistently outperformed the LSTM model, particularly regarding its generalization ability to unseen data. This enhanced performance can be attributed to the ensemble nature of RF, which reduces the risk of overfitting and enhances robustness. While the sequential learning capability of the long short-term memory model makes it highly effective for capturing time-dependent patterns, its performance during testing was slightly constrained, indicating the need for further fine-tuning of hyperparameters to enhance its predictive accuracy with new data. Future research should focus on optimizing the long short-term memory model or exploring hybrid approaches that combine the strengths of both long short-term memory and RF models. Such hybrid solutions may offer improved predictive accuracy and adaptability in dynamic environments, ensuring enhanced modeling performance in complex real-world scenarios.

Competing Interests: The authors declare no competing interests.

Data Availability Statement: The supported data associated with this researcher is available upon request from the corresponding author.

References

[1] J. Lee, J. Ni, J. Sarangapani, Machine learning for predictive maintenance in industrial systems, J. Intell. Manuf. 30 (2020) 3155–3172.

[2] J. Chai, J. Fan, Advanced thermal regulating materials and systems for energy saving and thermal

comfort in buildings, Mater. Today Energy. 24 (2022) 100925. https://doi.org/https://doi.org/10.1016/j.mtener.2021.100925.
[3] N. Hajimirza Amin, A. Etemad, A. Abdalisousan, Data-driven performance analysis of an active chilled beam air conditioning system: A machine learning approach for energy efficiency and predictive maintenance, Results Eng. 23 (2024) 102747. https://doi.org/10.1016/j.rineng.2024.102747.
[4] C.-F. Chien, Y.-J. Chen, Y.-T. Han, Y.-C. Wu, Industry 3.5 for optimizing chiller configuration for energy saving and an empirical study for semiconductor manufacturing, Resour. Conserv. Recycl. 168 (2021) 105247. https://doi.org/https://doi.org/10.1016/j.resconrec.2020.105247.
[5] A. Al-Nini, H.H. Ya, N. Al-Mahbashi, H. Hussin, A Review on Green Cooling: Exploring the Benefits of Sustainable Energy-Powered District Cooling with Thermal Energy Storage, Sustain. . 15 (2023). https://doi.org/10.3390/su15065433.
[6] J. Cho, J. Woo, Development and experimental study of an independent row-based cooling system for improving thermal performance of a data center, Appl. Therm. Eng. 169 (2019) 114857. https://doi.org/10.1016/j.applthermaleng.2019.114857.
[7] Y. Qiao, T. Cao, J. Muehlbauer, Y. Hwang, R. Radermacher, Experimental study of a personal cooling system integrated with phase change material, Appl. Therm. Eng. 170 (2020). https://doi.org/10.1016/j.applthermaleng.2020.115026.
[8] M. Lillstrang, M. Harju, G. del Campo, G. Calderon, J. Röning, S. Tamminen, Implications of properties and quality of indoor sensor data for building machine learning applications: Two case studies in smart campuses, Build. Environ. 207 (2022) 108529. https://doi.org/https://doi.org/10.1016/j.buildenv.2021.108529.
[9] M.A. Saleh, H.M. Rasel, B. Ray, A comprehensive review towards resilient rainfall forecasting models using artificial intelligence techniques, Green Technol. Sustain. 2 (2024) 100104. https://doi.org/https://doi.org/10.1016/j.grets.2024.100104.
[10] A. Mohamed Mahmoud IBRAHIM, W. LI, A.-H. ISMAIL MOURAD, M.A.E. OMER, F.A. ESSA, A. Mustafa ABD EL-NABY, M. S.Al SOUFI, M.F. EZZAT, A. ElSHEIKH, Cooling and lubrication techniques in grinding: A state-of-the-art review, applications, and sustainability assessment, Chinese J. Aeronaut. 36 (2023) 76–113. https://doi.org/https://doi.org/10.1016/j.cja.2023.03.026.
[11] L. Zhang, X. Fu, D. Luo, L. Xing, Y. Du, Musical Experience Offsets Age-Related Decline in Understanding Speech-in-Noise: Type of Training Does Not Matter, Working Memory Is the Key, Ear Hear. 42 (2021) 258–270. https://doi.org/10.1097/AUD.0000000000000921.
[12] S.M. Al-Selwi, M.F. Hassan, S.J. Abdulkadir, A. Muneer, E.H. Sumiea, A. Alqushaibi, M.G. Ragab, RNN-LSTM: From applications to modeling techniques and beyond—Systematic review, J. King Saud Univ. - Comput. Inf. Sci. 36 (2024) 102068. https://doi.org/https://doi.org/10.1016/j.jksuci.2024.102068.
[13] K. Choubani, M.A. Almeshaal, M. Ben Rabha, Performance Analysis of a Solar-Powered Evapora-tive Cooling System, (2023). https://doi.org/10.20944/preprints202306.1052.v1.
[14] L. Lei, S. Shao, Prediction model of the large commercial building cooling loads based on rough set and deep extreme learning machine, J. Build. Eng. 80 (2023) 107958. https://doi.org/https://doi.org/10.1016/j.jobe.2023.107958.
[15] S. Ben Romdhane, A. Amamou, R. Ben Khalifa, N.M. Saïd, Z. Younsi, A. Jemni, A review on thermal energy storage using phase change materials in passive building applications, J. Build. Eng. 32 (2020) 101563. https://doi.org/https://doi.org/10.1016/j.jobe.2020.101563.
[16] V. Verma, A Centralized Cooling System As An Alternative To Conventional Air Conditioning: A Sustainable Transition Towards Green-Energy, Int. J. Res. Appl. Sci. Eng. Technol. 12 (2024) 1161–1170. https://doi.org/10.22214/ijraset.2024.58528.
[17] A. Ahmed Murtaza, A. Saher, M. Hamza Zafar, S. Kumayl Raza Moosavi, M. Faisal Aftab, F. Sanfilippo, Paradigm shift for predictive maintenance and condition monitoring from Industry 4.0 to Industry 5.0: A systematic review, challenges and case study, Results Eng. 24 (2024) 102935. https://doi.org/https://doi.org/10.1016/j.rineng.2024.102935.
[18] B.A. Aljashaami, B.M. Ali, S.A. Salih, N.T. Alwan, M.H. Majeed, O.M. Ali, O.R. Alomar, V.I. Velkin, S.E. Shcheklein, Recent improvements to heating, ventilation, and cooling technologies for buildings based on renewable energy to achieve zero-energy buildings: A systematic review, Results Eng. 23 (2024) 102769. https://doi.org/https://doi.org/10.1016/j.rineng.2024.102769.
[19] Z. Hou, Z. Lian, An Application of Support Vector Machines in Cooling Load Prediction, 2009. https://doi.org/10.1109/IWISA.2009.5072707.
[20] K. Elhabyb, A. Baina, M. Bellafkih, A.F. Deifalla, Machine Learning Algorithms for Predicting Energy Consumption in Educational Buildings, Int. J. Energy Res. 2024 (2024) 1–19. https://doi.org/10.1155/2024/6812425.
[21] U. Alhaji, E. Chinemezu, J. Nwachukwu, S. Isah, Prediction of energy content of biomass based on hybrid machine learning ensemble algorithm, Energy Nexus. 8 (2022) 100157. https://doi.org/10.1016/j.nexus.2022.100157.
[22] Q.B. Pham, S.I. Abba, A.G. Usman, N.T.T. Linh, V. Gupta, A. Malik, R. Costache, N.D. Vo, D.Q. Tri, Potential of Hybrid Data-Intelligence Algorithms for Multi-Station Modelling of Rainfall, Water Resour. Manag. (2019). https://doi.org/10.1007/s11269-019-02408-3.
[23] I. Abdulazeez, S.I. Abba, J. Usman, A.G. Usman, I.H. Aljundi, Recovery of Brine Resources Through Crown-Passivated Graphene, Silicene, and Boron Nitride Nanosheets Based on Machine-Learning Structural Predictions, ACS Appl. Nano Mater. (2023). https://doi.org/10.1021/acsanm.3c04421.
[24] J. Usman, S. Abba, F. Abdu, ... L.Y.-R., undefined 2024, Enhanced desalination with polyamide thin-film

membranes using ensemble ML chemometric methods and SHAP analysis, Pubs.Rsc.Org. (n.d.).
[25] G. Oluyemi, M. Vilela, A. Petrovski, Sensitivity analysis applied to fuzzy inference on the value of information in the oil and gas industry, Int. J. Appl. Decis. Sci. 13 (2020) 1. https://doi.org/10.1504/ijads.2020.10026404.
[26] J. Więckowski, W. Sałabun, Sensitivity analysis approaches in multi-criteria decision analysis: A systematic review, Appl. Soft Comput. 148 (2023) 110915. https://doi.org/https://doi.org/10.1016/j.asoc.2023.110915.
[27] C. Kahraman, E. Haktanır Aktaş, Fuzzy Sensitivity Analysis, in: 2024: pp. 145–156. https://doi.org/10.1007/978-3-031-54660-0_9.
[28] M. Schonlau, R. Zou, The random forest algorithm for statistical learning, Stata J. Promot. Commun. Stat. Stata. 20 (2020) 3–29. https://doi.org/10.1177/1536867X20909688.
[29] A.A. Khan, O. Chaudhari, R. Chandra, A review of ensemble learning and data augmentation models for class imbalanced problems: Combination, implementation and evaluation, Expert Syst. Appl. 244 (2024) 122778. https://doi.org/https://doi.org/10.1016/j.eswa.2023.122778.
[30] T.-H. Lee, A. Ullah, R. Wang, Bootstrap Aggregating and Random Forest, in: 2020: pp. 389–429. https://doi.org/10.1007/978-3-030-31150-6_13.
[31] M. Waqas, U.W. Humphries, A critical review of RNN and LSTM variants in hydrological time series predictions, MethodsX. 13 (2024) 102946. https://doi.org/https://doi.org/10.1016/j.mex.2024.102946.
[32] G. Van Houdt, C. Mosquera, G. Nápoles, A review on the long short-term memory model, Artif. Intell. Rev. 53 (2020) 5929–5955. https://doi.org/10.1007/s10462-020-09838-1.
[33] Y. Lu, F. Salem, Simplified gating in long short-term memory (LSTM) recurrent neural networks, 2017. https://doi.org/10.1109/MWSCAS.2017.8053244.
[34] H.U. Abdullahi, A.G. Usman, S.I. Abba, H.U. Abdullahi, Modelling the Absorbance of a Bioactive Compound in HPLC Method using Artificial Neural Network and Multilinear Regression Methods, Dutse J. Pure Appl. Sci. 6 (2020).
[35] A.G. Usman, S. Mati, M.M. Jibril, J. Usman, S.M.H. Shah, S.I. Abba, S.R. Naganna, Evidential Neural Network Model for Groundwater Salinization Simulation: A First Application in Hydro-Environmental Engineering, Water (Switzerland). 16 (2024). https://doi.org/10.3390/w16202873.
[36] I.A. Mahmoud, U.J. Muhammad, S.J. Kawu, M.M. Magaji, Machine Learning-Based Wind Speed Estimation for Renewable Energy Optimization in Urban Environments : A Case Study in Kano State , Nigeria, (2024). https://doi.org/10.52589/AJSTE-XKYBH2QI.
[37] M. Adamu, S.I.H. Salim, I. Malami, M.N.I.S.I. Abba, Y.E. Ibrahim, Prediction of compressive strength of concrete incorporated with jujube seed as partial replacement of coarse aggregate : a feasibility of Hammerstein – Wiener model versus support vector machine, Model. Earth Syst. Environ. (2021). https://doi.org/10.1007/s40808-021-01301-6.
[38] B. Musa, N. Yimen, S.I. Abba, H.H. Adun, M. Dagbasi, Multi-State Load Demand Forecasting Using Hybridized Support Vector Regression Integrated with Optimal Design of Off-Grid Energy Systems — A Metaheuristic Approach, (2021) 1–30.
[39] D.S. Aliyu, S.I. Malami, F.H. Anwar, M.M. Farouk, M.S. Labbo, S.I. Abba, Prediction of compressive strength of lightweight concrete made with partially replaced cement by animal bone ash using artificial neural network, 2021 1st Int. Conf. Multidiscip. Eng. Appl. Sci. ICMEAS 2021. (2021). https://doi.org/10.1109/ICMEAS52683.2021.9692317.