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Predicting Thermal Preferences - A Comparative Analysis of Machine Learning Algorithms using ASHRAE Global Thermal Comfort Database II

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ABSTRACT

Predicting thermal preferences and ensuring comfort through machine learning is a highly active research field that has attracted significant attention from researchers aiming to achieve accurate forecasting and a deeper understanding of human thermal comfort in buildings. The primary objective of this study is to develop machine learning models for predicting thermal preference using the ASHRAE Global Thermal Comfort Database II. Additionally, the algorithms developed in this study can serve as valuable groundwork for transferring the acquired knowledge to develop personalized machine learning models, thereby enhancing individualized comfort. To enhance the dataset's accuracy and reliability, rigorous data exploration and preprocessing were executed. A comparative analysis of diverse machine learning algorithms was conducted, revealing that ensemble-based methods, namely Random Forest, Extra Trees, LightGBM, CatBoost, Gradient Boosting Machine, and XGBoost, exhibited superior performance in predicting thermal preferences. The accuracy of these ensemble models was further refined through hyperparameter optimization using the Optuna framework. This optimization led to a notable improvement, increased the model accuracy from 65% for traditional machine learning algorithms to 70% for the optimized ensemble algorithms.

1. Introduction

The design and control of indoor environmental conditions play a crucial role in ensuring occupant comfort and well-being [1]. Thermal and comfort, in particular, is a crucial aspect of occupant satisfaction and directly impacts human productivity and building energy consumption [2]. Accurate prediction of thermal preference can enable effective temperature control strategies and improve comfort and energy efficiency. In recent years, machine-learning approaches have emerged as promising tools for modelling and predicting thermal preferences based on objective and subjective data [3].

Several studies have focused on predicting thermal comfort and preference using machine learning techniques. Konis *et al.,* [4] evaluated a smartphone and software service called the

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Occupant Mobile Gateway (OMG), which collected real-time subjective feedback and objective thermal environmental data to improve the understanding of occupant comfort. Hu *et al.,* [5] proposed a learning-based approach using machine learning and Internet of Things technologies to enhance thermal comfort modelling.

Cosma *et al.,* [6] introduced a technique that provides real-time feedback to an HVAC system based on occupant preferences to improve overall comfort. Luo *et al.,* [7] achieved accurate TSV prediction using an RF algorithm with a reduced feature set. Wang *et al.,* [8] analysed subjective thermal comfort metrics using machine learning, considering individual differences among occupants. Yoon *et al.,* [9] developed a Gaussian process regression model and a model predictive control system to improve indoor thermal comfort. Warey *et al.,* [10] used machine learning and computational fluid dynamics (CFD) to predict vehicle occupant thermal comfort. Shan *et al.,* [11] explored machine learning techniques using EEG measurements to classify real-time thermal comfort states.

Alhamayani *et al.,* [12] estimated energy savings in residences using machine learning models. Bai *et al.,* [13] emphasized the importance of dataset parameters in ensemble learning models for thermal preference prediction. Lala *et al.,* [14] applied multi-task learning to predict thermal comfort in naturally ventilated buildings.

Wu *et al.,* [15] explored the connection between the effectiveness of machine learning models and their hyperparameters using Gaussian processes. Kotthoff *et al.,* [16] presented an updated version of Auto-WEKA, a system designed to assist users in optimizing the performance of machine learning models. This is achieved by automatically exploring the combined space of WEKA's learning algorithms and their corresponding hyperparameter configurations using advanced Bayesian optimization techniques. Li *et al.,* [17] investigated a system for efficient parallel hyperparameter tuning, recognizing the challenges posed by the large hyperparameter spaces and lengthy training times of modern learning models. Wu *et al.,* [18] employed Gaussian processes to establish a link between the performance of machine learning models and the hyperparameters governing them.

While the field of predicting thermal preferences through machine learning is active, this study addresses a significant research gap by specifically analysing the ASHRAE Global Thermal Comfort Database II, aiming to understand the relationship between building occupants and indoor environmental conditions by analysing the ASHRAE Global Thermal Comfort Database II. Machine learning algorithms were developed to predict thermal preferences based on personal and environmental factors. The research involves comparing various machine learning algorithms to identify those that offer the highest accuracy in predicting thermal preferences. In addition, this study explores the optimization of ensemble machine-learning algorithms and the influence of different hyperparameter tuning techniques on their performance, including the choice of machine learning algorithm as a hyperparameter.

2. Methods
2.1 Dataset and Key Parameters

The selection of data sources and parameters is crucial for the development of machine learning algorithms to predict thermal preference. The quality of the dataset is necessary for accurate and reliable models. The ASHRAE Global Thermal Comfort Database II is an open-source research database launched in 2014 [19].

The database includes data from thermal comfort field investigations conducted worldwide from 1995 until the latest version on July 15, 2022. It comprises approximately 107,584 sets of objective indoor climatic observations, along with subjective evaluations provided by building occupants [20].

The selected features include thermal preference, Year, City, Season, building type, Outdoor monthly air temperature (C), Sex, Age, Air temperature (C), Clo, Met, Air velocity (m/s), Relative humidity (%), and Cooling strategy building level.

2.2 Data Preprocessing

Figure 1 illustrates the conceptual structure of the study's research framework, offering a visual representation of its fundamental organization. Data preprocessing is essential for data analysis or a machine learning pipeline. It involves transforming raw data into a clean, organized, and meaningful format that algorithms can effectively use.

Categorical data encoding is the process of converting categorical data into numerical data. This is often necessary for most machine learning algorithms. Techniques such as one-hot encoding, label encoding, and ordinal encoding are used. The study compares label encoding, which assigns unique integers to categories, with one-hot encoding, where binary digits represent categories in separate columns. Interestingly, the study finds no distinction in model accuracy between these two methods.

Z-score standardization involves transforming the data by subtracting the mean and dividing by the standard deviation. This process centres the data around a mean of 0 and scales it based on the standard deviation, enabling fair comparison and analysis across different data distributions.

2.3 Train/Test Split and Cross–Validation

The train/test split evaluates machine learning models by dividing the dataset into a training set for model training and a test set for performance evaluation. On the other hand, cross-validation enhances model performance by splitting the training data into multiple folds, training the model on some folds, and evaluating it on the remaining folds. Both the train/test split and cross-validation are crucial techniques for assessing model performance, preventing overfitting, and ensuring effective generalization of new data.

We conducted experiments using various k-fold cross-validation techniques, ranging from 3- to 10-fold, and tested a wide range of training proportions (50-100%). However, we observed no significant difference in the model accuracy. Therefore, we utilized the 80/20 train/test split with a fivefold cross-validation method.

2.4 Machine Learning Algorithms

The machine learning algorithms investigated in this study cover diverse techniques commonly used for classification tasks. Logistic regression fits a line or curve to the data and predicts the probability of a new data point belonging to a specific class. Linear discriminant analysis (LDA) aims to find a linear combination of features that maximizes class separation while minimizing within-class scatter. K–nearest Neighbors (KNN) assigns a class label to a data point based on the labels of its k nearest neighbours in the feature space. Decision trees create a tree-like model of decisions based on input features, providing interpretability and handling both categorical and numerical features. Gaussian naive Bayes (GNB) is a probabilistic classification algorithm assuming Gaussian distribution and statistical independence of features.

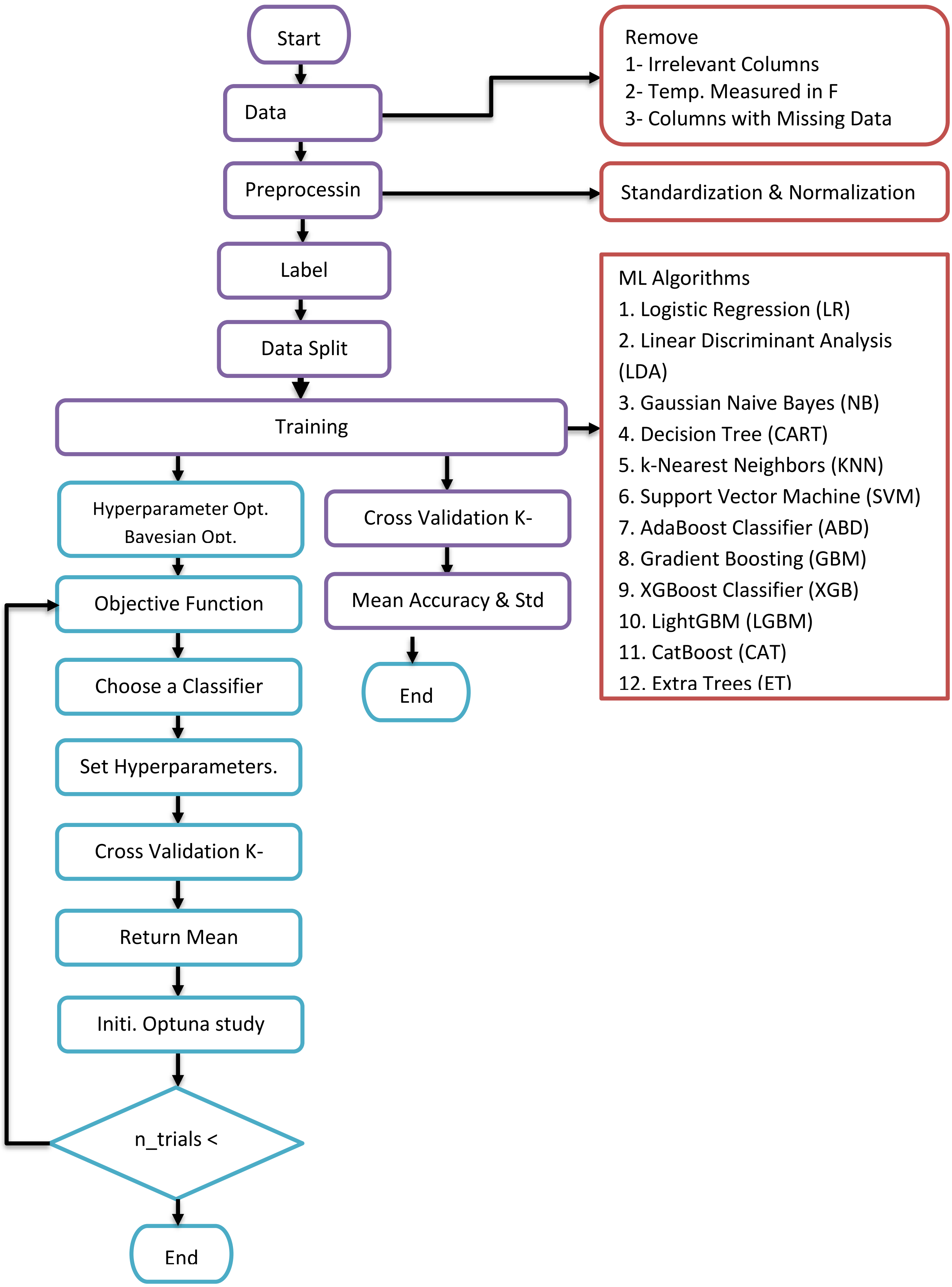

Fig. 1. Conceptual structure of the study

Ensemble methods such as Bagging, Boosting, and Random Forests combine multiple models for improved predictive performance. Random Forests create multiple decision trees and aggregate their predictions through voting. ExtraTrees further randomizes the tree-building process, making it computationally efficient and less prone to overfitting. AdaBoost assigns higher weights to misclassified samples to focus on complex examples. The gradient-boosting machine (GBM) combines weak learners, often decision trees, to create a robust predictive model. Notable implementations of GBM include XGBoost, LightGBM, and CatBoost. XGBoost offers scalability, performance, and regularization techniques. LightGBM is memory-efficient and fast, using a histogram-based approach. CatBoost handles categorical features effectively without explicit encoding [21]. Traditional GBM, available in libraries such as scikit-learn, provides effective gradient-boosting capabilities.

These machine learning algorithms were selected on the basis of their versatility, performance, and ability to handle various data types, aiming to develop accurate models for predicting thermal preference.

2.5 Bayesian Optimization

Bayesian optimization is a powerful technique for hyperparameter optimization that combines probabilistic modelling and an acquisition function to efficiently search for the optimal set of hyperparameters. Unlike grid search or random search, which require many iterations, Bayesian optimization intelligently selects the next set of hyperparameters to evaluate based on previous evaluations, gradually improving the model's performance [22].

This study uses Optuna [23] to implement Bayesian optimization, which offers support for continuous and discrete hyperparameters and dynamically adapting the search based on past evaluations. The Optuna framework, combined with the Bayesian optimization algorithm using Tree-structured Parzen Estimator (TPE) as the surrogate model and Expected Improvement (EI) as the acquisition function, allows for modelling the relationships between hyperparameters and the objective function and estimating potential improvements.

3. Results

3.1 Data Exploration

In order to enhance the quality and performance of the dataset, several unnecessary columns were excluded. These columns included the temperature measurements in Fahrenheit and those related to publication, data contributors, and comfort indices, except for the selected target index of Thermal Preference. In addition, columns with considerable missing data were removed to ensure data integrity and accuracy. In this study, we carefully selected 13 input features, as illustrated in Figure 2, to achieve better model performance.

Figure 2 shows a matrix plot of the missing values within the selected ASHRAE database II columns. This plot serves to identify patterns and pinpoint the locations where data are missing. Each column represents a variable, and each row corresponds to an observation. The matrix plot shows that the 'sex,' 'age,' and 'outdoor air temperature' columns contain a significant number of missing values. Given the size of our dataset, we decided to remove the rows that contain missing data.

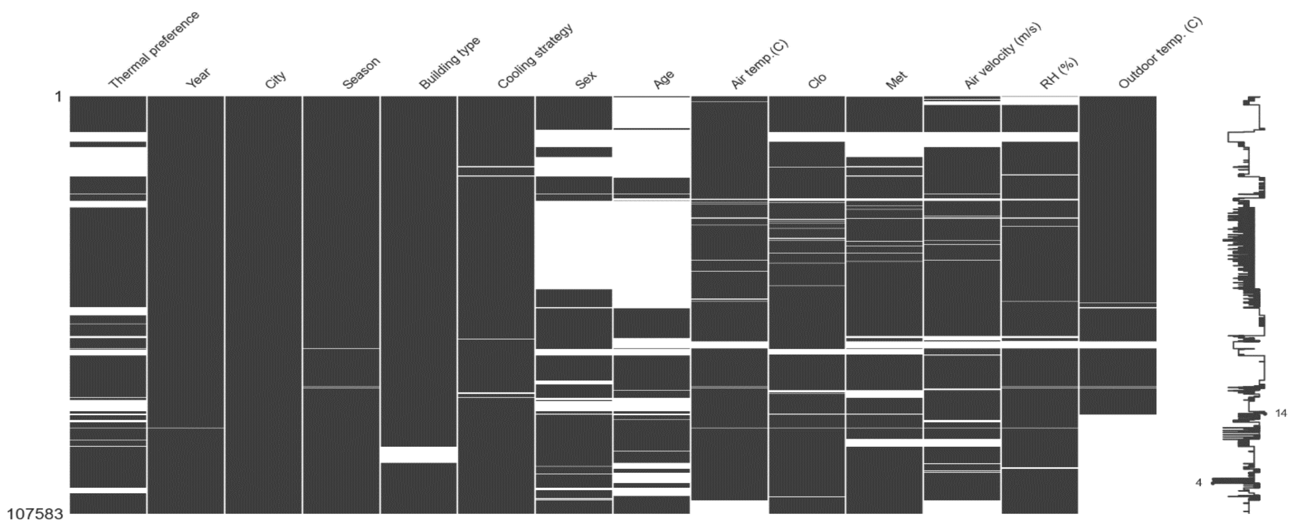

Fig. 2. Matrix plot of missing data in dataset variables

3.2 Data Normalization and Standardization

Data standardization is essential in machine learning to reduce the impact of scale-dependent factors. Figure 3 illustrates the distributions of the variables before and after standardization, providing a visual representation of the effectiveness of this procedure in ensuring a fair evaluation of the variables' impact on model performance. By standardizing the data, we removed the inherent scale differences among the variables, allowing for a more reliable and meaningful analysis of their contributions to the models.

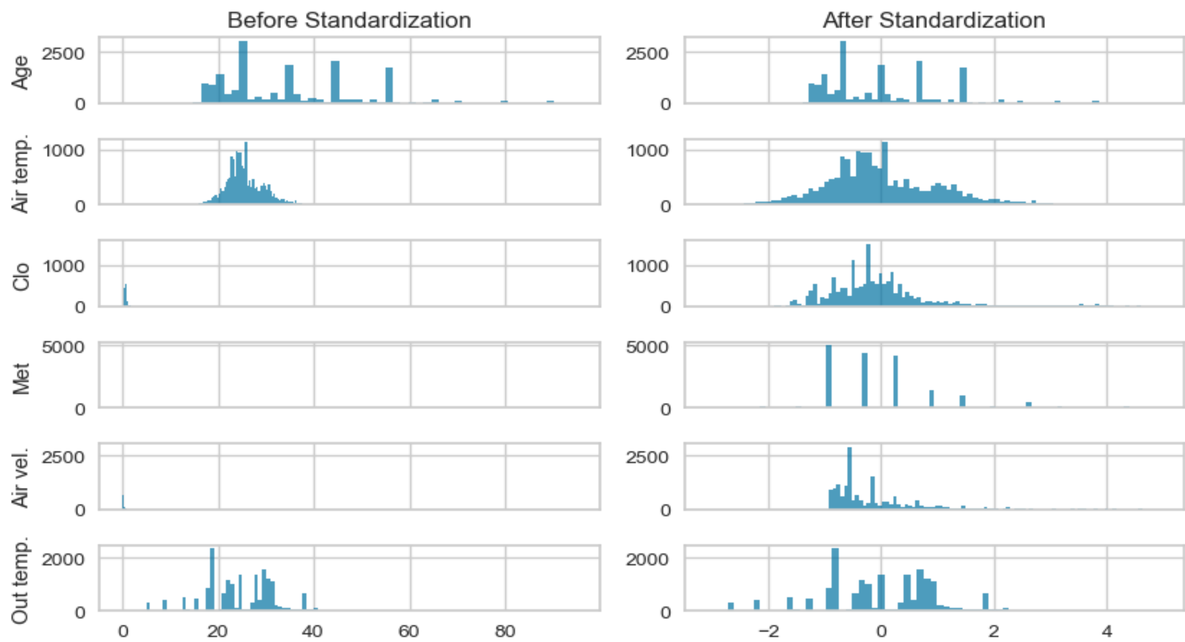

Fig. 3. Data before and after Z-score standardization

3.3 Comparative Analysis of Different Machine Learning Algorithms

A comparative analysis was conducted to evaluate the performance of different machine learning algorithms in predicting thermal preference. Figure 4 shows a box plot of the accuracy scores obtained for each algorithm and their corresponding standard deviations, providing valuable insights into their performance variability.

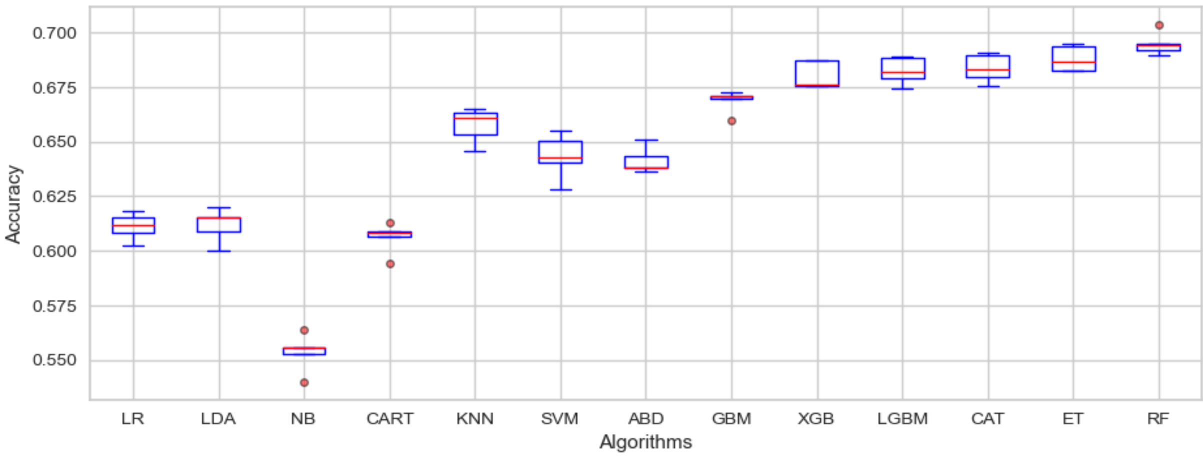

Fig. 4. Boxplot comparison of different machine learning algorithms

The evaluation of each model was performed using cross–validation with 5 folds. The accuracy scoring metric is used to assess the performance of the models. The code iterates over each model, applies cross-validation, and stores the results.

Linear Regression (LR) and linear discriminant analysis (LDA) demonstrated similar accuracies of approximately 61.1%, indicating moderate performance. Naive Bayes (NB) exhibited a lower accuracy of 55.4%, suggesting limited effectiveness compared with other algorithms.

Decision Tree (CART) achieved an accuracy of 60.6%, aligning with LR and LDA in terms of performance. K–nearest Neighbors (KNN) displayed improved accuracy at 65.8%, outperforming LR, LDA, NB, and CART.

The support vector machine (SVM) showed an accuracy of 64.3%, indicating competitive performance. AdaBoost (ABD) performed similarly with an accuracy of 64.1%.

Gradient Boosting Machine (GBM), XGBoost (XGB), LightGBM (LGBM), and CatBoost (CAT) delivered strong performances, with accuracies ranging from 66.9% to 68.4%. These algorithms demonstrated superior accuracy compared with LR, LDA, NB, CART, KNN, SVM, and ABD.

Among the tested algorithms, ensemble methods, specifically Extra Trees (ET) and Random Forest (RF), achieved higher accuracies of 68.2% and 69.1%, respectively. These results were supported by low standard deviations of 0.0047 and 0.0052, indicating consistent and reliable performance.

3.4 Comparison of Optimized Ensemble Learning Algorithms

In this section, we compare the performance of the optimized ensemble machine learning algorithms using Bayesian optimization implemented in the Optuna framework. We measured the performance of each optimized algorithm in terms of mean and standard deviation and also record the number of trials conducted. The comparison involves optimizing hyperparameters for different classifier algorithms within specific ranges, such as LightGBM, XGboost, RF, GBM, AdaBoost, ExtraTrees, and CatBoost. The objective of this study is to maximize the accuracy of the models.

Cross–validation is performed with 5 folds, and the accuracy scores are calculated using the "accuracy" metric. The Optuna framework conducts 50 trials to determine the optimal hyperparameter configuration with the highest accuracy. The optimization algorithm automatically selects the most promising ensemble method with its respective hyperparameters by iteratively evaluating the models with different hyperparameters.

The results demonstrate that the ensemble learning approach, with optimized hyperparameters, improves the performance of the machine learning algorithms, as shown in Figure 5. The LightGBM algorithm achieved the highest mean performance of 0.6997 after 26 trials, followed by ExtraTrees with 0.6842 after 12 trials. However, the remaining algorithms did not show promising results, indicating that the optimization algorithms did not explore many trials.

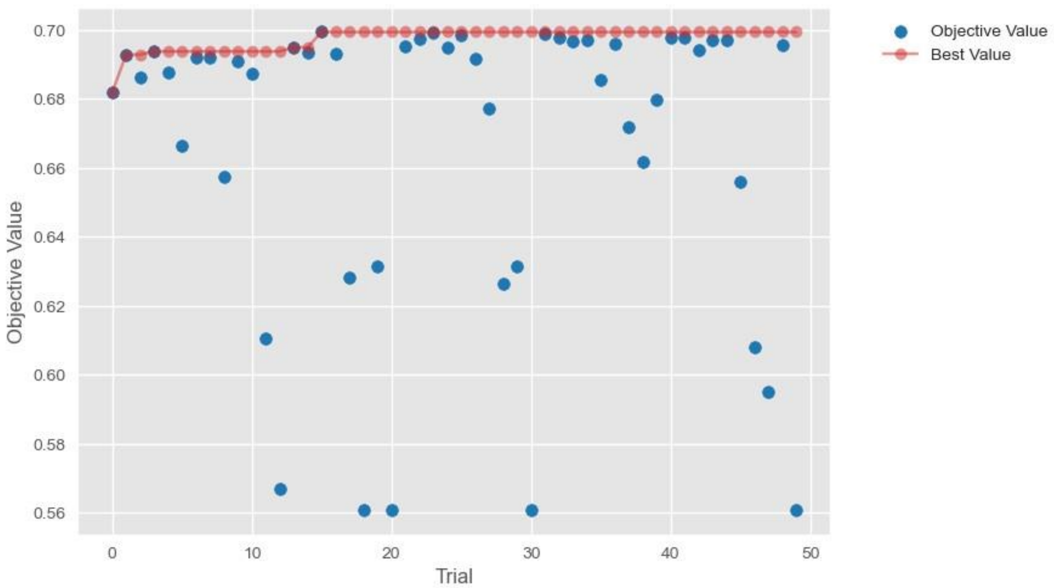

Fig. 5. Optimization history plot

3.5 Feature Importance

The comparison between Random Forest and XGBoost feature importance rankings shows that the two algorithms have different perceptions of feature importance as shown in Figure 6. While some features may have similar rankings in both algorithms (e.g., Air temp.(C) appearing in the top five for both), the overall rankings and the importance assigned to each feature vary.

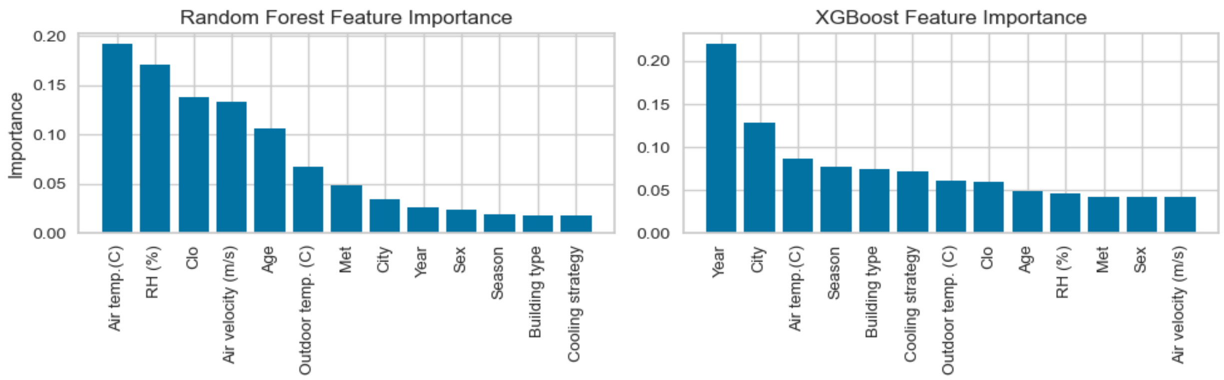

Fig. 6. Comparison of feature importance: random forest vs. XGBoosting

4. Discussion

The present study aimed to develop machine learning models for predicting thermal preference based on the ASHRAE Global Thermal Comfort Database II. Through data exploitation, we excluded unnecessary columns and removed those with missing data, ensuring the accuracy and reliability of the dataset. Additionally, data standardization was performed to eliminate scale differences among variables, enabling a fair evaluation of their contributions to the models.

The comparative analysis of different machine learning algorithms shows varying levels of performance. Linear Regression (LR) and Linear Discriminant Analysis (LDA) demonstrated moderate accuracies, while Naive Bayes (NB) exhibited limited effectiveness in predicting thermal preference. Decision Tree (CART) achieved a similar accuracy to LR and LDA, and K-Nearest Neighbors (KNN) outperformed several algorithms, including LR, LDA, NB, and CART.

Support Vector Machine (SVM) and AdaBoost (ABD) showed competitive performances, but the ensemble-based algorithms delivered the most robust results. Gradient Boosting Machine (GBM), XGBoost (XGB), LightGBM (LGBM), and CatBoost (CAT) consistently outperformed other algorithms, demonstrating their superiority in predicting thermal preference. This finding aligns with previous studies highlighting the effectiveness of ensemble methods in capturing complex relationships within the data.

Among the ensemble-based algorithms, Random Forest (RF) and Extra Trees (ET) achieved the highest accuracies, indicating their robustness and reliability. These algorithms performed consistently well across different iterations, as evidenced by their low standard deviations. The results suggest that RF and ET are particularly suitable for predicting thermal preference due to their ability to leverage the collective strength of multiple decision trees.

To further enhance the performance of the ensemble methods, we employed the Optuna framework for hyperparameter optimization. We identified the optimal configurations that yielded the highest accuracies by iteratively evaluating the models with different hyperparameters. The optimized ensemble learning algorithms, including LightGBM, XGBoost, RF, GBM, AdaBoost, ExtraTrees, and CatBoost, outperformed their non-optimized counterparts, emphasizing the importance of hyperparameter tuning in maximizing model performance.

The findings of this study have practical implications for the design and control of indoor environments. Accurately predicting thermal preference can improve occupant comfort and satisfaction, as well as energy efficiency. Building designers and facility managers can make informed decisions regarding temperature control and HVAC system optimization by leveraging ensemble-based algorithms, such as RF, ET, LGBM, CAT, GBM, and XGB.

5. Conclusion

In this study, machine learning models were developed to predict thermal preference using the ASHRAE Global Thermal Comfort Database II. Data exploration and standardization ensured the dataset's accuracy and reliability for meaningful analysis of variable impacts on model performance.

The comparative analysis of machine learning algorithms demonstrated that ensemble-based algorithms such as Random Forest (RF), Extra Trees (ET), LightGBM (LGBM), CatBoost (CAT), Gradient Boosting Machine (GBM), and XGBoost (XGB) consistently outperformed other algorithms in predicting thermal preference. This highlights the effectiveness of ensemble methods in capturing complex relationships and their suitability for this task.

We employed the Optuna framework for hyperparameter optimization to further improve ensemble methods, resulting in even higher accuracies. This emphasizes the significance of hyperparameter tuning in maximizing model performance.

The results of this study have practical implications for indoor environment design and control. Accurate thermal preference prediction can significantly enhance occupant comfort, satisfaction, and energy efficiency. Building designers and facility managers can utilize these insights to inform temperature control and HVAC system optimization decisions. Furthermore, the findings of this study can serve as a foundation for transferring the learned knowledge to develop personalized comfort machine learning models.

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