The prediction of thermal sensation in building using support vector machine and extreme gradient boosting

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ABSTRACT

The building has great potential for energy savings as one of locations that humans often occupy. In addition to energy efficiency, humans must consider environmental sustainability and comfort of building's occupants. Conditioning of indoor air quality, including those related to thermal comfort, continues to be pursued to be more economical, one of which is to utilize the prediction of occupants' thermal sensations. The prediction results can be utilized to adjust room air conditions more economically. This paper proposes using extreme gradient boosting (XGBoost) and support vector machine (SVM) to predict thermal sensation in the building. The built environment parameters are preprocessed, and the thermal sensation is predicted by intelligent systems. The ten variables that most influence the level of accuracy of this thermal sensation prediction system are thermal preference vote, indoor operative temperature, Griffith's neutral temperature, indoor globe temperature, mean radiant temperature, indoor air temperature, predicted mean vote, and outdoor mean temperature. SVM with four features, XGBoost and XGBoost with hyperparameter tuning, achieve an accuracy of 99.45%, 97.81%, and 98.08%, respectively. Regarding computational complexity, training an SVM system with the same number of features requires shorter time than XGBoost training. The same thing also happened with test of SVM system, which required shorter time compared to time for the examination of XGBoost system.

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1. INTRODUCTION

Energy is one of the vital needs of humans. With the increase in population, limited energy reserves encourage humans to continue striving to preserve the environment while saving energy [1], [2]. The building sector holds over 40% of the energy used [3]–[5]. The energy sector used in buildings has excellent energy-saving potential with environmental and economic aspects. Therefore, it is essential to improve energy use efficiency by implementing potential strategies to achieve sustainable and green buildings [6]. The most significant energy use equipment of any commercial building is air conditioning equipment, with an average energy use of more than 40% [7], [8]. Generally, the building may have one or two air conditioning systems: naturally ventilated and air-conditioned. Buildings with natural ventilation usually consume less energy when compared to air-conditioned buildings [9]–[11]. In energy-efficient buildings, efforts are made to reduce the use of heating ventilation and air conditioning (HVAC) but still pay attention to the comfort of the occupants. In addition to seeking energy savings, researchers have also sought to increase the use of renewable energy for sustainable development [12], [13].

Besides environmental and economic aspects, humans also need to pay attention to the sensation and comfort of building occupants [14]–[17]. The occupants' comfort in the room is related to the temperature set point and the thermal habits of the occupants. The strategy to determine the temperature set point is essential because although it affects energy use, it also affects the productivity of the room occupants [18]–[20]. Several researchers have tried to develop a thermal comfort control system based on artificial intelligence [21]–[25]. Thermal sensation prediction is also proposed using an intelligent face mask from exhaled breath temperature [26] and data-driven [27].

On the other hand, the outside temperature influences the energy used to adjust the room temperature to the set point. In cold weather (below 10 °C), an increase in temperature of one degree celsius reduces electricity consumption by 1% to 5% [28]. The opposite happens in warm weather (above 20 °C), where one additional degree of heating will increase electricity usage by 0% to 8%. Therefore, a better strategy is needed to efficiently determine the temperature set point, which saves energy but does not decrease the productivity of the occupants.

Several artificial intelligence methods have been used in various applications [29]–[33]. This paper proposes prediction methods of thermal sensation in a building using a support vector machine (SVM) and extreme gradient boosting (XGBoost) [34]–[38]. A multilayer perceptron-based transfer learning model has been implemented for thermal comfort prediction [39]. Other researchers applied a machine learning model based on convolutional neural network-long short-term memory (CNN-LSTM) transfer learning and random forest for building thermal comfort prediction [40]–[42]. Table 1 lists the machine learning model and its features in building thermal sensation prediction.

Table 1. Research about thermal sensation prediction

No	Research	Model	Feature
1	Salem and Mousa [6]	XGBoost	Temperature, CO_2, humidity, room occupancy, air flow velocity, and light levels
2	Jin *et al.* [43]	Random forest	
3	Gao *et al.* [39]	Transfer learning-based Multilayer perceptron	Air temperature, airspeed, mean radiant temperature, metabolic rate, relative humidity, and clothing insulation
4	Bai *et al.* [41]	Random forest, deep cascade forest	Age, sex, metabolic rate, clothing insulation, relative humidity, air temperature, air velocity, weight, and height
5	Our proposed system	SVM and XGBoost	Month, season, sex, air sensation vote, thermal preference vote, air preference vote, relative humidity sensation vote, relative humidity preference vote, comfortability, productivity, thermal acceptability, clothing insulation, upholstery, total clothing insulation, metabolism level, sweating/shivering, indoor air temperature, air movement, indoor globe temperature, relative humidity, percentage of people dissatisfied, predicted mean vote, Griffith's neutral temperature (r=0.50), mean radiant temperature, indoor temperature, outdoor mean temperature, outdoor running mean temperature (30 days), Griffith's neutral temperature (r=0.25), Griffith's neutral temperature (r=0.33)

2. RESEARCH METHOD

The proposed thermal sensation prediction system of a building using SVM and XGBoost is shown in Figure 1. The system consists of data collection, preprocessing, and classifiers of SVM and XGBoost [6]. The classifiers will predict the occupant's thermal sensation in the building.

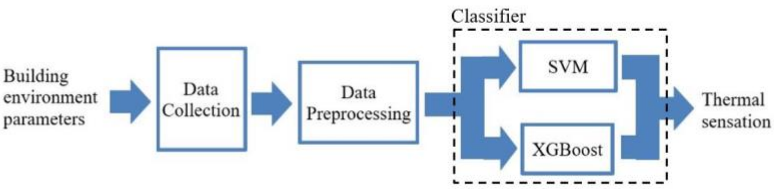

Figure *1*. The proposed thermal sensation prediction system of a building using SVM and XGBoost

2.1. Data collection

The data utilized in this study is a dataset of the thermal comfort responses in darjeeling district, India [44]–[47]. The dataset contains the thermal comfort response of 436 subjects in ten different buildings in five locations: Siliguri, Kurseong, Mirik, Sonada, and Tiger Hill. The data collection complied with the ASHRAE class II protocol, where indoor air temperature, air movement, relative humidity, and global temperature were measured 110 cm above the floor. All buildings are naturally ventilated with no cooling or heating. The buildings in Siliguri and Sonada are college buildings. The buildings in Kurseong and Tiger Hill are residential, while the building in Mirik is an office. Data collection is carried out monthly between January and December. The dataset has 2,608 responses with 30 features, as listed in Table 2.

Table 2. Variables of the thermal comfort dataset

No	Variable	Unit
1	Month	-
2	Season	-
3	Sex	-
4	Thermal preference vote	-
5	Air sensation vote	-
6	Air preference vote	-
7	Relative humidity sensation vote	-
8	Relative humidity preference vote	-
9	Comfortability	-
10	Productivity	-
11	Thermal acceptability	-
12	Clothing insulation	Clo
13	Upholstery	-
14	Total clothing insulation	Clo
15	Metabolism level	-
16	Sweating/shivering	-
17	Indoor air temperature	℃
18	Indoor globe temperature	℃
19	Air movement	m/s
20	Relative humidity	%
21	Predicted mean vote	-
22	Percentage of people dissatisfied	%
23	Griffith's neutral temperature (r = 0.50)	℃
24	Mean radiant temperature	℃
25	Indoor temperature	℃
26	Outdoor mean temperature	℃
27	Outdoor running mean temperature (30 days)	℃
28	Griffith's neutral temperature (r = 0.25)	℃
29	Griffith's neutral temperature (r=0.33)	℃
30	Thermal sensation vote	-

2.2. Data preprocessing and classifier

We designed data preprocessing, SVM, and XGBoost using Python with several libraries such as Numpy, Pandas, Scikit-learn, and Matplotlib [48], [49]. Data preprocessing is conducted to remove variability or unwanted effects of the data. Valuable information related to the desired property can be used for efficient modeling. The specific purpose of the preprocessing technique depends on the data type to be handled. The data preprocessing in this study includes cleaning data from noise in the form of outliers and not a number (NaN), as well as filtering data features that are adjusted to the Fanger parameters and the ASHRAE standard 55 for thermal sensation prediction. In the data reprocessing, we simplify the label features on the dependent variable of thermal sensation vote (TSV). The standard ASHRAE scale divides TSV into seven levels: hot, warm, slightly warm, neutral, slightly cool, cool, and cold.

There are two models compared in this study as the classifier of the system, namely SVM and XGBoost. This study also varies the features used for the two models. XGBoost is a machine learning type with an ensemble algorithm based on gradient-boosted trees. Output model tree pada XGBoost as (1) [6].

$$\hat{y}_i{}^t = \sum_{i=1}^{t} f_k(x_i) = \hat{y}_i{}^{(t-1)} + f_t(x_i) \quad (1)$$

Where $\hat{y}_i{}^t$ is the final three model; $\hat{y}_i{}^{(t-1)}$ is the previously generated tree model; t is the number of base tree models, and $f_t(x_i)$ is the newly generated tree model. SVM is a supervised artificial intelligence model for data analysis, regression, and pattern recognition. The approximated function in SVM as (2):

$$f(x) = \omega\varphi(x) + b \tag{2}$$

where $\varphi(x)$ is the higher-dimensional feature space converted from the input vector x [50].

3. RESULTS AND DISCUSSION

Figure 2 shows the feature importance of the thermal sensation prediction system variables using XGBoost. This feature importance order is used in feature selection in the prediction model. Figure 3 shows the accuracy of the thermal sensation prediction system using SVM, XGBoost, and XGBoost with hyperparameter tuning and feature variation [34], [35]. The accuracy of the methods has varying values depending on the number of features used in the model. The SVM prediction system achieved the highest accuracy of 99.45% when using four and five features. Because the number of features usually also affects computational complexity, the SVM with four features has lower computational complexity, so it was chosen as the best SVM model for this prediction system. Prediction systems using XGBoost and XGBoost with hyperparameter tuning show varied accuracy patterns depending on the number of system features but not more than the highest accuracy of the SVM model.

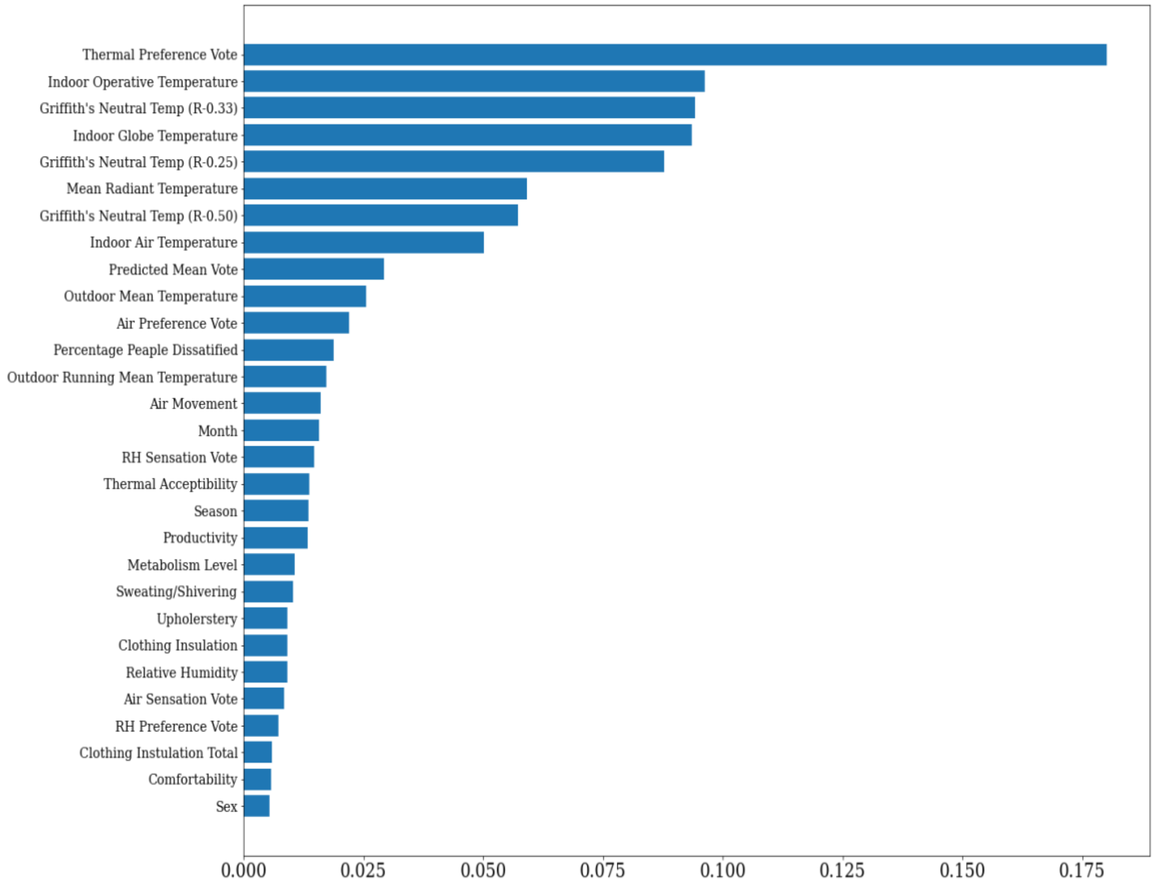

Figure 2. Feature importance of the variables of the thermal sensation prediction system using XGBoost

Figure 4 shows the thermal sensation prediction confusion matrix of the SVM system with four features. When using the SVM system with four features, two hundred and thirty-three thermal sensations are correctly predicted as "slightly cool." Two hundred and twenty-three thermal sensations are correctly predicted as "neutral." Furthermore, 165 thermal sensations are correctly predicted as "slightly warm.” "hot" and "cold" are more difficult to predict using SVM than other sensation classes. SVM systems usually have lower computational complexity than XGBoost systems with the same number of features.

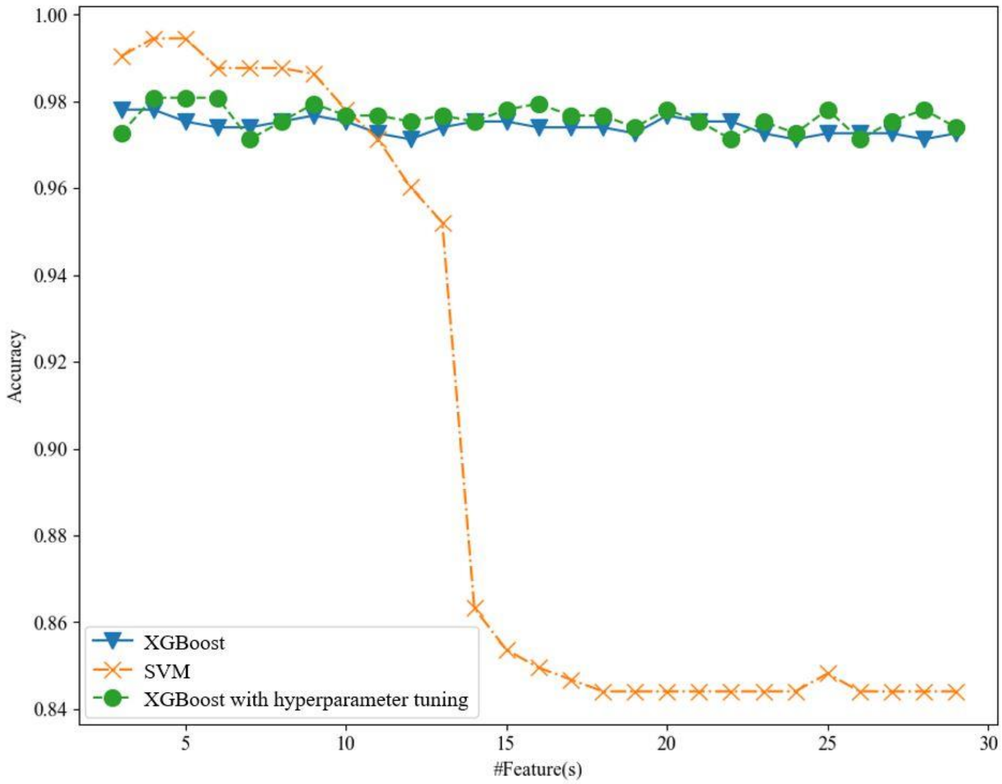

Figure 3. The accuracy of the thermal sensation prediction system using SVM, XGBoost, and XGBoost with hyperparameter tuning

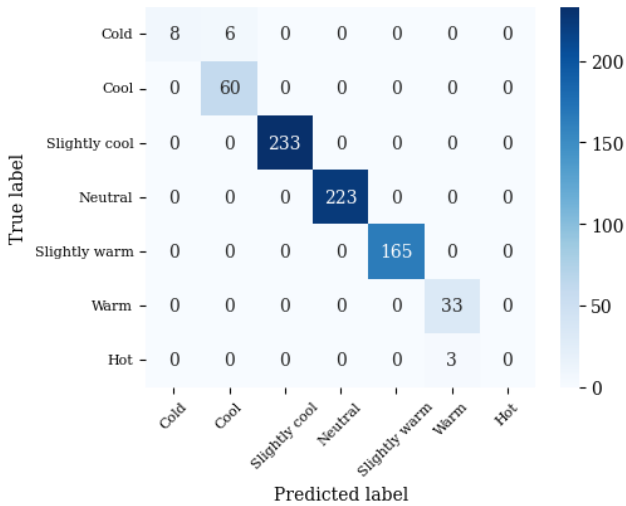

Figure 4. Confusion matrix of the thermal sensation prediction system using SVM with four features

4. CONCLUSION

We propose a thermal sensation prediction system in buildings using SVM and XGBoost. The experimental results show that the SVM prediction system outperforms the XGBoost system. SVM with four features, XGBoost and XGBoost with hyperparameter tuning, achieve an accuracy of 99.45%, 97.81%, and 98.08%, respectively. Regarding computational complexity, training an SVM system with the same number of features requires a shorter time than XGBoost training. The same thing also happened with the test of the SVM system, which required a shorter time compared to the time for the test of the XGBoost system.

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