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A Machine Learning-Based Thermal Comfort Prediction Model for Older Adults

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Abstract

Indoor thermal comfort plays a critical role in safeguarding the health and quality of life of older adults (aged 60 and above), whose thermoregulatory capacity is diminished compared with younger populations due to reduced basal metabolic rate, impaired vasomotor responses, and elevated thermal sensation thresholds. While the Predicted Mean Vote (PMV) model has long served as a benchmark for thermal comfort assessment, its parameters are calibrated predominantly on young, healthy subjects and thus produce systematic prediction biases for older adults. Data-driven machine learning approaches have emerged as promising alternatives; however, existing studies that advocate deep learning architectures for thermal comfort prediction are predominantly based on small-sample datasets (N<500), leaving their generalizability under large-scale data conditions unverified. This study systematically compares a Convolutional-Recurrent Neural Network (CRNN, comprising one-dimensional convolution and Gated Recurrent Unit layers) with three established machine learning algorithms—K-Nearest Neighbors (KNN), Gradient Boosting Decision Trees (GBDT), and Random Forest (RF)—using a dedicated dataset of 5 820 older adult samples constructed from the ASHRAE Global Thermal Comfort Database II. Model performance was evaluated across both regression (continuous thermal sensation prediction) and classification (discrete seven-level thermal sensation determination) tasks. Results demonstrate that RF outperformed all models: in regression, RF achieved a mean absolute error (MAE) of 0.597 3 and root mean square error (RMSE) of 0.842 7, approximately 13.1% and 15.1% lower than CRNN (MAE = 0.687 6, RMSE = 0.992 2), respectively. In classification, RF attained 78.0% accuracy and a weighted F1 score of 0.539, compared with 68.7% and 0.513 for CRNN. The CRNN exhibited pronounced overfitting and majority-class bias, attributable to an architectural incompatibility between its sequential modeling design and the non-temporal tabular nature of thermal comfort data. These findings provide evidence-based guidance for selecting models to construct individualized thermal comfort prediction systems for older adults and inform the development of intelligent age-friendly textile products.

Keywords: thermal comfort; older adults; machine learning; convolutional-recurrent neural network; random forest; prediction model

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1 Introduction

With the irreversible progression of global population aging, designing indoor living environments that balance health and comfort for older adults has become a critical interdisciplinary issue spanning environmental engineering and public health. Physiological research confirms that compared with younger populations, the thermoregulatory systems of older adults exhibit significant degenerative characteristics, primarily manifested as reduced basal metabolic rate, sluggish vasomotor responses, and pathological elevation of thermal sensation thresholds [1-3]. Specifically, older adults experience diminished peripheral vasoconstriction and vasodilation efficiency, leading to impaired heat dissipation and retention capacity; reduced metabolic heat production renders them more vulnerable to cold stress; and attenuated sweat gland function limits evaporative cooling under warm conditions [3, 4]. These age-related physiological declines substantially weaken older adults' adaptive capacity to adjust to fluctuations in the indoor thermal environment. They can readily trigger cascading health risks, including increased cardiovascular workload, respiratory infections, and sleep disorders [1, 5]. Consequently, indoor thermal comfort assessment for older adults requires methodologies that account for these population-specific physiological characteristics, rather than relying on models calibrated for younger, healthier populations.

For an extended period, indoor thermal comfort assessment has primarily relied on the Predicted Mean Vote (PMV) model proposed by Fanger [6]; however, this model exhibits significant theoretical deficiencies in its applicability to older adults. The PMV model is built on idealized assumptions of "human thermal balance" and a "steady-state environment", with its parameters predominantly calibrated from experimental data on young, healthy populations, failing to account for individual differences arising from aging, such as metabolic rate decline and diminished thermoregulatory capacity [7, 8]. Empirical studies demonstrate that direct application of the PMV model to older populations typically produces systematic prediction biases, often manifested as misjudgment of thermal sensitivity in older adults [9, 10]. This "misalignment" between physical models and human perception renders existing environmental regulation strategies inadequate to meet the thermal requirements of older adults.

Data-driven approaches represented by machine learning have gradually emerged as research hotspots due to their powerful nonlinear mapping capabilities. Early studies using traditional algorithms such as support vector machines and decision trees outperformed the PMV model in predictive accuracy [11]. In recent years, complex deep learning architectures have been introduced to this field, with some small-sample studies claiming their performance superiority over traditional models [12, 13]. Nevertheless, this conclusion lacks rigorous validation of generalization. First, deep models designed for image or time-series data may be structurally incompatible with typical thermal comfort datasets, which typically consist of discrete, non-temporal tabular data. Second, existing studies are mostly based on small sample sizes ($N<500$); under limited data scales, complex deep models are highly susceptible to overfitting, making their advantages in specific experiments difficult to replicate in practical engineering.

Meanwhile, the thermal comfort of clothing systems represents another critical dimension of the human thermal environment that directly influences model input parameters. Research has demonstrated that fabric properties significantly affect clothing thermal comfort performance under varying environmental temperatures [14], and clothing system design—including fabric structure, air permeability, and moisture transfer characteristics—plays a decisive role in the microclimate between the skin and the external environment [15, 16]. Furthermore, studies on heat and moisture transfer in human–clothing–environment systems have established that clothing insulation cannot be treated as a static parameter but varies with body movement, posture, and environmental conditions [17, 18]. The clothing insulation value (Clo), adopted as an input feature in thermal comfort prediction models, thus serves as a simplified yet essential proxy for these complex clothing–body interactions.

Addressing the aforementioned theoretical gaps, this study aims to systematically evaluate the performance differences between deep learning and traditional machine learning models for thermal comfort prediction in older adults (defined as individuals aged 60 years and above) through large-scale empirical analysis. Based on the ASHRAE Global Thermal Comfort Database II, a dedicated dataset comprising 5 820 samples was constructed—a scale far exceeding previous similar studies. A Convolutional-Recurrent Neural Network (CRNN) that combines one-dimensional convolutional and Gated Recurrent Unit layers was selected as the deep learning representative and compared with KNN, GBDT, and RF across both regression and classification tasks. By introducing large-scale data, this study examines whether deep learning architectures retain their reported advantages when applied to non-temporal tabular thermal comfort data and provides evidence-based guidance for model selection in age-friendly indoor environment regulation.

2 Methods

2.1 Dataset and Preprocessing

2.1.1 Data Source

The data used in this study originate from the ASHRAE Global Thermal Comfort Database II, published by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) [19]. The database represents one of the largest and most comprehensive public data resources in the thermal comfort research domain, encompassing environmental measurement data and subjective thermal sensation voting information across diverse climate zones, building types, and population characteristics.

2.1.2 Data Screening and Features

To construct the thermal comfort prediction model for older adults, samples were first screened from the original database, with records extracted for subjects aged 60 years and above. Subsequently, samples containing missing values and variables irrelevant to the research objectives were removed, forming the experimental dataset of 5 820 samples for model training and evaluation.

The model output variable was set as thermal sensation. Preliminary comparative experimental results informed this choice: under consistent input-feature conditions, models with thermal sensation as the target variable achieved approximately 5% higher prediction accuracy than those with thermal comfort. This finding is consistent with previous research confirming that thermal sensation voting data exhibit stronger statistical regularity and are more conducive to model learning than thermal comfort evaluations [11, 20].

Model input variables comprehensively consider environmental parameters, individual physiological characteristics, and clothing parameters. The selection of these features is grounded in established thermal comfort theory: environmental factors (air temperature, relative humidity, air velocity, and outdoor monthly air temperature) constitute the primary determinants of the thermal environment [6, 21]; individual characteristics (age, sex, and metabolic rate) capture physiological variability in thermoregulation [1, 22]; and clothing insulation (Clo) quantifies the thermal resistance of the clothing barrier between the skin and the environment [14, 23]. The specific composition and physical meanings of each input feature are presented in Table 1.

Table 1: Model feature input variables

Feature Category	Feature Name	Data Type	Unit
Environmental	Air temperature	float	°C
Environmental	Relative humidity	float	%
Environmental	Air velocity	float	m/s
Environmental	Outdoor monthly air temperature	float	°C
Individual	Age	integer	year
Individual	Sex	categorical	–
Individual	Metabolic rate (Met)	float	met
Clothing	Clothing insulation (Clo)	float	clo

Note: The categorical variable Sex is one-hot encoded during preprocessing, resulting in 9 input dimensions for the model.

2.1.3 Data Standardization

Given the significant differences in dimensions and numerical ranges among input features, this study employs the Z-score standardization method for all continuous numerical features:

$$z = (x - \mu)/\sigma \tag{1}$$

where x represents the original data point, μ denotes the mean, and σ represents the standard deviation. The categorical variable Sex was processed using one-hot encoding to convert it into binary numerical representations suitable for model input.

2.2 Model Architecture

2.2.1 Baseline Machine Learning Models

To establish an objective reference framework for evaluating deep learning model performance, this study selected three traditional machine learning algorithms as baselines, encompassing three mainstream paradigms: instance-based learning, Bagging ensemble, and Boosting ensemble.

K-Nearest Neighbors (KNN). As a typical non-parametric, instance-based learning algorithm, KNN makes no assumptions about data distribution. The algorithm performs weighted voting or regression by measuring Euclidean distances between test samples and the K nearest neighbors in the training set.

Gradient Boosting Decision Trees (GBDT). This represents the forefront of boosting ensemble strategies. The algorithm sequentially constructs a series of weak classifiers via gradient-based optimization in function space, with each new tree aiming to fit the residuals from the previous iteration.

Random Forest (RF). As the culmination of Bagging ensemble methods, Random Forest constructs multiple independent decision trees through Bootstrap sampling and random feature subspace selection. Compared to single models, RF significantly reduces model variance, exhibiting strong anti-overfitting capability and robustness.

2.2.2 CRNN Hybrid Deep Learning Model

The thermal sensation formation process involves the comprehensive interaction among multi-dimensional, heterogeneous information, including environmental, individual physiological, and clothing factors. Some existing small-sample studies suggest that hybrid architectures combining convolutional and recurrent neural network layers can achieve superior performance in thermal comfort classification tasks [12, 13]. However, these studies employed limited data scales (N<500) and architectures primarily designed for sequential data, leaving their applicability to large-scale, non-temporal tabular data unverified.

This study selects a Convolutional-Recurrent Neural Network (CRNN) as the representative deep learning model for systematic evaluation. The rationale for choosing this specific architecture is twofold: first, it enables direct comparison with prior claims of deep learning superiority in thermal comfort prediction [12, 13]; second, the CRNN represents a widely adopted hybrid architecture that combines local feature extraction (via convolution) with sequential dependency modeling (via recurrent layers), providing a strong test case for evaluating deep learning's suitability for tabular thermal comfort data.

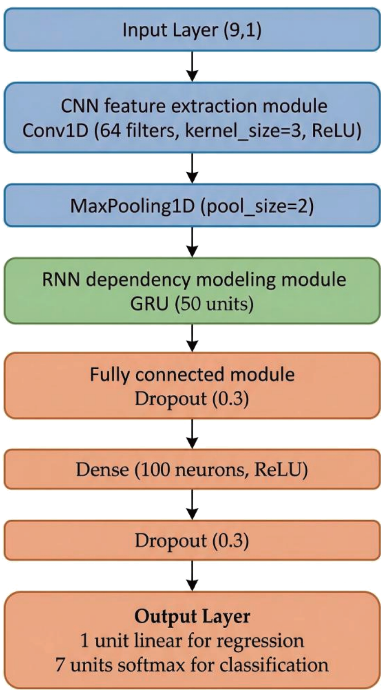

Fig. 1: CRNN model architecture diagram

Regarding the choice of Gated Recurrent Unit (GRU) over Long Short-Term Memory (LSTM) as the recurrent layer, GRU offers comparable modeling capacity with fewer parameters (two gates versus three in LSTM), resulting in improved training efficiency and reduced overfitting risk for the moderate data scale (N = 5 820) employed in this study.

The choice of Conv1D + GRU over alternative deep learning approaches such as Multilayer Perceptrons (MLPs) or Transformers was motivated by the study's objective: to evaluate whether hybrid architectures specifically designed to capture local patterns and sequential dependencies genuinely outperform simpler ensemble methods on thermal comfort data. An MLP would not test this specific claim. Transformers would face similar structural-mismatch issues with non-temporal data and would require substantially more training data.

The specific structural parameters of the CRNN model are shown in Table 2. The model receives the preprocessed 9-dimensional feature vector reshaped as a (9, 1) tensor. The convolutional layer with 64 filters and a kernel size of 3 (same padding) extracts local feature patterns, followed by max pooling (pool_size=2). The GRU layer with 50 hidden units models potential dependencies. Two Dropout layers (rate = 0.3) mitigate overfitting. The fully connected layer with 100 neurons performs a nonlinear mapping. For regression, the output layer uses linear activation; for classification, Softmax activation maps to seven thermal sensation levels (−3 to +3).

Table 2: CRNN architecture

Layer	Type	Parameters	Activation
1	Input	shape = (9, 1)	–
2	Conv1D	filters=64, kernel_size=3, padding='same'	ReLU
3	MaxPooling1D	pool_size=2	–
4	GRU	units=50	–
5	Dropout	rate=0.3	–
6	Dense	units=100	ReLU
7	Dropout	rate=0.3	–
8	Output	units=1 (reg) / units=7 (cls)	Linear / Softmax

2.3 Experimental Setup

All experiments were implemented in Python using scikit-learn for baseline machine learning models and TensorFlow/Keras for the CRNN model. The dataset was split into training and test sets at an 80:20 ratio using stratified sampling (random_state = 42) to ensure consistent class distribution across partitions. For the CRNN model, 10% of the training data was reserved as a validation set to monitor training progress.

Baseline models (KNN, GBDT, RF) were trained with scikit-learn's default hyperparameters to ensure a fair, reproducible comparison framework. The CRNN model was trained using the Adam optimizer with a mean squared error loss function for regression tasks and sparse categorical cross-entropy for classification tasks, over 1 000 epochs with a batch size of 64.

2.4 Performance Evaluation Metrics

To comprehensively quantify each model's generalization performance, this study establishes specific evaluation frameworks for two task types.

In regression prediction, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are employed as core metrics. MAE measures the average level of absolute deviation between predicted and actual values. RMSE assigns greater weight to larger prediction deviations via squared-error weighting, effectively assessing model sensitivity to extreme outliers.

In classification prediction, given that thermal comfort data often exhibits class imbalance, this study employs both Accuracy and Weighted F1-Score. The F1 score, as the harmonic mean of precision and recall, considers both precision and recall. A weighted strategy accounts for differences in sample quantities across thermal sensation levels.

3 Results

3.1 Comparison of Regression Model Performance

Under the regression modeling framework, quantitative evaluation metrics for each model are presented in Table 3. The Random Forest (RF) model exhibits optimal regression performance across all metrics, achieving an MAE of 0.597 3 and an RMSE of 0.842 7. Compared with the CRNN model (MAE = 0.687 6, RMSE = 0.992 2), RF reduced MAE by approximately 13.1% and RMSE by approximately 15.1%. This significant gap indicates that, when processing tabular thermal comfort data lacking temporal dependencies, CRNN failed to demonstrate the feature-extraction advantages expected of deep learning.

Table 3: Performance of regression-based prediction models

Model	MAE	RMSE
K-Nearest Neighbors (KNN)	0.642 9	0.895 3
Random Forest (RF)	0.597 3	0.842 7
Gradient Boosting Decision Trees (GBDT)	0.633 0	0.869 6
CRNN	0.687 6	0.992 2

The Random Forest scatter distribution is most compact, with the strongest linear trend along the y = x diagonal. In contrast, the CRNN model's scatter exhibits a notably diffuse distribution, particularly in regions of extreme thermal sensation.

The RF error distribution curve exhibits leptokurtic characteristics, with the highest and narrowest peak centered near 0. The CRNN error curve exhibits platykurtic characteristics, with a low, flat peak and a broad base.

3.2 Comparison of Classification Model Performance

The classification task discretizes thermal sensation into seven levels according to the ASHRAE scale (−3 to +3). Accuracy and weighted F1 scores are shown in Table 4. The RF model achieves

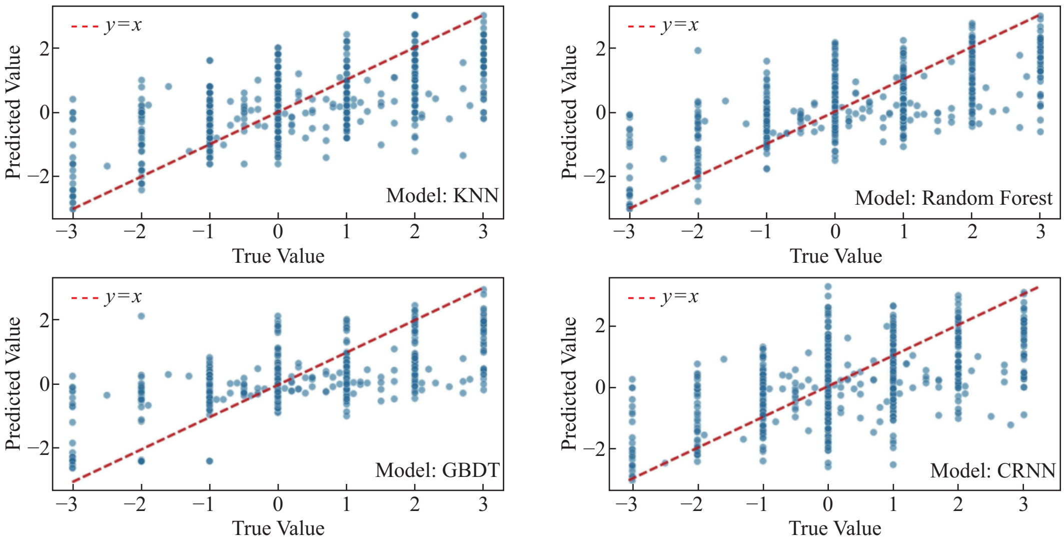

Fig. 2: Scatter plots comparing predicted versus actual values

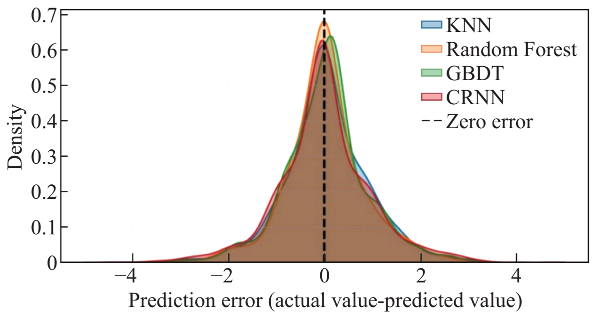

Fig. 3: Prediction error (residual) distribution

Table 4: Classification-based prediction model performance comparison

Model	Accuracy	F1 Score (Weighted)
K-Nearest Neighbors (KNN)	0.657	0.515
Random Forest (RF)	0.780	0.539
Gradient Boosting Decision Trees (GBDT)	0.677	0.501
CRNN	0.687	0.513

78.0% accuracy, significantly outperforming CRNN's 68.7%. RF's weighted F1 score (0.539) also outperforms CRNN (0.513).

4 Discussion

4.1 Analysis of Factors Influencing Model Performance Differences

Existing studies using small-sample data indicate that hybrid convolutional-recurrent architectures show potential for thermal comfort classification tasks [12, 13]; however, this study obtained different results on a large-scale dataset (N = 5 820). The CRNN model's overall performance failed to exceed the Random Forest model across both tasks.

First, the effectiveness of deep learning models depends heavily on the compatibility between their inductive biases and the data structure. The core advantage of the CRNN architecture (Conv1D + GRU) lies in its ability to capture local patterns and sequential dependencies. However, the dataset belongs to typical non-temporal tabular data, with samples being independently and identically distributed. Applying CRNN on such data compels the model to seek non-existent sequential patterns, introducing unnecessary noise fitting. In contrast, the tree-based partitioning mechanism of Random Forest is naturally suited for handling orthogonal splitting and nonlinear combinations in feature space.

Second, although the sample size of 5 820 exceeds prior studies, this scale remains relatively limited for the parameter-heavy CRNN. The learning curves (Fig. 4) reveal overfitting: training accuracy continues rising while validation accuracy stagnates or declines, with an expanding generalization gap.

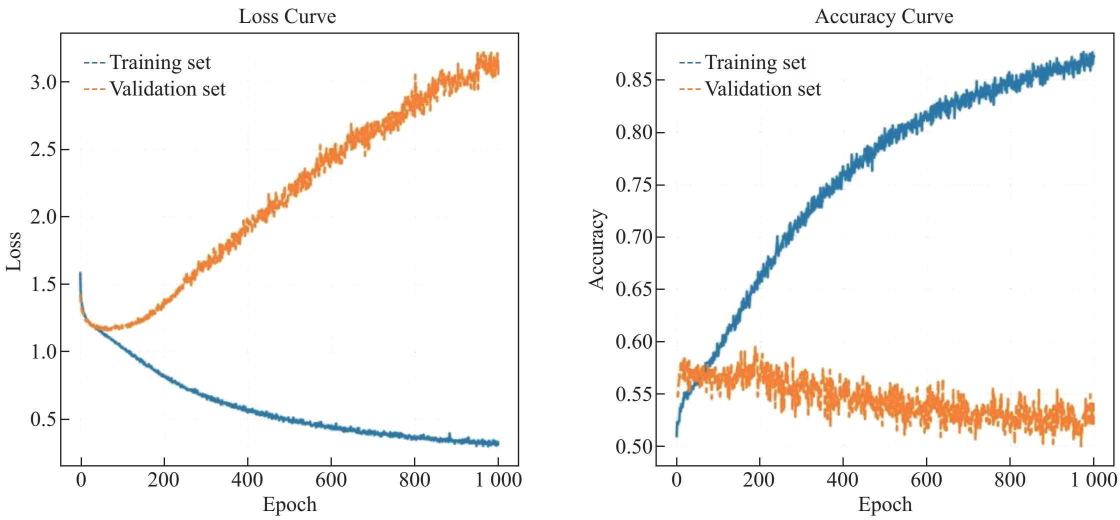

Fig. 4: CRNN classification model learning curves (1000 epochs)

Further analysis of the normalized confusion matrices (Fig. 5) reveals that CRNN's recognition accuracy for the neutral category remains only approximately 64%, significantly lower than RF's approximately 85%. Numerous samples from other categories are misclassified as neutral, indicating a pronounced majority-class bias.

4.2 Comparison with Existing Studies and Implications

The finding that Random Forest outperforms deep learning on tabular thermal comfort data is consistent with broader trends in the machine learning community. Li and Zhao [24] similarly demonstrated RF's effectiveness in indoor thermal comfort prediction. The present study extends this finding to the specific context of older adults using a substantially larger dataset.

The present results carry important implications for clothing and textile science. The model's input features include clothing insulation (Clo), which serves as a simplified representation of the complex heat and moisture transfer processes in the human–clothing–environment system.

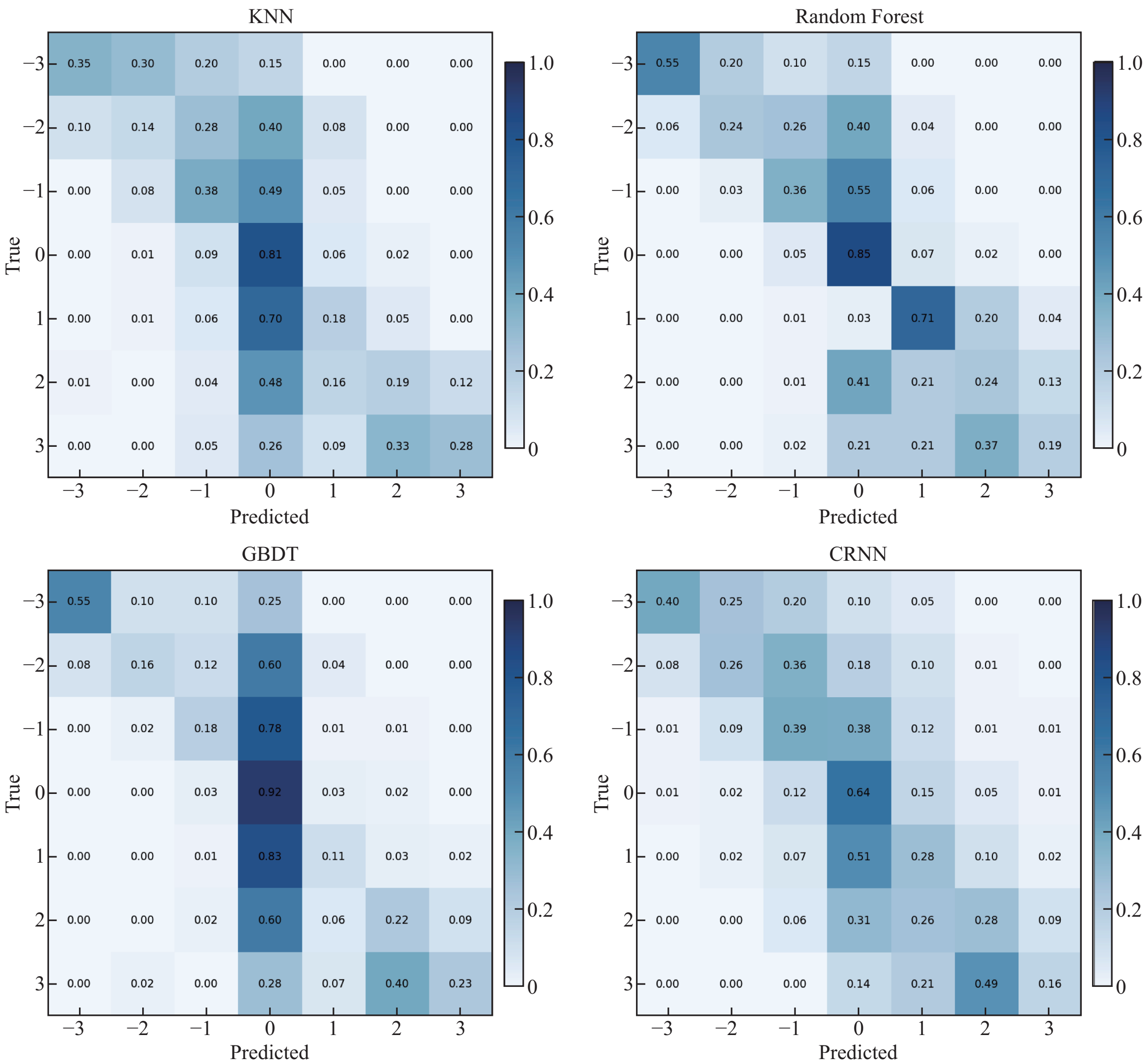

Fig. 5: Normalized confusion matrix comparison

Research on fabric properties and clothing thermal comfort has established that thermal performance is influenced by fabric structure, air permeability, and moisture management [14–16]. Studies examining temperature variation at the skin–clothing interface [17] and differences in convective heat transfer across body sizes [18] further underscore the multifactorial nature of clothing thermal comfort. The RF model's superior performance suggests that for practical applications in age-friendly smart textile design, ensemble learning approaches may provide more reliable thermal comfort predictions.

4.3 Limitations and Future Work

Several limitations should be acknowledged. First, the dataset is limited to the ASHRAE Database II and may not fully represent all climate zones and cultural contexts. Second, only one deep learning architecture (CRNN) was evaluated; other architectures, such as attention-based models or TabNet, may yield different results. Third, baseline models used default hyperparameters; systematic optimization could improve performance across all models. Fourth, while

Clo captures overall clothing insulation, it does not fully represent dynamic heat and moisture transfer properties.

Regarding transferability, the methodology is generalizable to other population groups. However, specific model parameters may differ across age groups. Future work should validate the RF model on prospective datasets and explore the integration of temporal data streams from wearable sensors, which would provide a more appropriate application scenario for recurrent neural network architectures.

5 Conclusion

This study systematically evaluated performance differences between a Convolutional-Recurrent Neural Network (CRNN) and ensemble machine learning models based on 5 820 older adult samples from the ASHRAE Global Database. The Random Forest model demonstrated comprehensive superiority: in regression tasks, RF achieved an MAE of 0.5973 (13.1% lower than CRNN) with leptokurtic error distribution; in classification tasks, RF achieved 78.0% accuracy (9.3 percentage points above CRNN) and a weighted F1 score of 0.539 versus 0.513 for CRNN. These results reveal structural misalignment between the CRNN's sequential modeling architecture and the non-temporal tabular nature of thermal comfort data. The findings provide algorithmic guidance for developing intelligent age-friendly textiles: the RF model's combination of high accuracy, low computational load, and interpretability makes it well-suited for integration into the embedded control systems of smart garments for active thermal management in older adults.

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