Original Article

Modeling Universal Thermal Climate Index Thermal Stress in Iran's Hot Zones Using Neural Networks and Naïve Bayes

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Abstract

Aim: This study aimed to assess the impact of heat stressors in various environments across the expansive hot regions of Iran, with the goal of supporting workforce health and well-being. **Methods:** This descriptive-analytical study was conducted in four main stages: (1) identifying and measuring factors influencing the Universal Thermal Climate Index (UTCI), (2) calculating the UTCI as the dependent variable, (3) applying neural network (NN) and Naïve Bayes (NB) algorithms to weigh and model the effective factors on the UTCI, and (4) evaluating the accuracy of each model. Data modeling utilized Python's scikit-learn package (version 3.7) and the Orange toolkit. **Results:** The average UTCI values in hot-dry and hot-humid regions were 30.49 and 39.48, respectively. In models for hot-dry regions, both algorithms identified dry temperature (T_a) as a significant factor. For hot-humid regions, the NB algorithm identified mean radiant temperature (T_{mrt}) as the primary factor, while the NN algorithm highlighted dry temperature (T_a). Model accuracy ranged from 74% to 94%, with NN algorithms demonstrating higher accuracy compared to NB algorithms. **Conclusion:** In the models for hot-dry regions, both algorithms predicted T_a and then T_{mrt} as the principal factors. For hot-humid regions, it was inferred that T_{mrt} is the main influencing factor on the UTCI.

Keywords: Hot dry, hot humid, Universal Thermal Climate Index, weighting

Introduction

In contemporary times, individuals are increasingly inclined to allocate significant portions of their time to outdoor environments. The quality of their engagement with the surroundings is notably shaped by factors such as air temperature (T_a), airflow velocity (V_a), relative humidity (RH), and radiation fluxes. These elements profoundly influence human thermo-physiological conditions, thereby exerting a substantial impact on individuals' thermal comfort.[1,2] Consequently, the interaction between environmental conditions and thermo-physiological parameters must be carefully considered when evaluating human comfort.[3]

Heat stress represents a prevalent workplace challenge that directly impacts individuals' performance and can even lead to fatalities. Prolonged exposure to excessive heat disrupts metabolism, elevates body temperature, increases heart rate and blood pressure, and contributes to disorders and illnesses. This heightened risk also escalates errors and accidents at work, alongside potentially causing neurological and psychological ailments, thus reducing overall work efficiency.[4] Heat-related disorders such as muscle cramps, heatstroke, and strokes result from imbalances in the body's heat regulation mechanisms. Consequently, these disorders pose significant health and safety risks to workers.[5] According to a 2004 report from the US Bureau of Labor Statistics, approximately 14 million workers were employed in US factories, with substantial incidences of heat-related effects documented across industries. This included reports of 18 deaths attributed to adverse thermal conditions in one specific sector.[6]

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Quick Response Code:	
	Website: https://journals.lww.com/IJEH
	DOI: 10.4103/ijehe.ijehe_21_24

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How to cite this article: Zare S, Esmaeili R, Hemmatjo R. Modeling Universal Thermal Climate Index thermal stress in Iran's hot zones using neural networks and Naïve Bayes. Int J Env Health Eng 2025;14:9.

Received: 18-04-2024, **Revised:** 27-08-2024,
Accepted: 28-08-2024, **Published:** 23-05-2025

Environmental monitoring and control, along with the assessment of heat exchange between the environment and workers, as well as monitoring certain human physiological parameters, have been suggested for evaluating heat stress in occupational settings.[7] The initial step in mitigating the adverse effects of workplace hazards, including heat, involves identifying high-risk environments and employing suitable devices to measure existing conditions. During the evaluation phase, measurement results are compared against established standards to accurately assess the situation.[8] Environmental factors such as air temperature, Wet Bulb Globe Temperature (WBGT), humidity, and airflow rate, coupled with individual activities and clothing type, significantly contribute to heat stress levels. To quantify heat stress, these prevailing conditions are synthesized into a numerical value, often referred to as the "thermal stress index."[9]

Throughout the last century, numerous evaluation methods have been developed in the form of various indicators to assess warm environments and manage heat stress while ensuring human thermal comfort.[6,10] The number of these indices has exceeded 45, with many being endorsed by the International Organization for Standardization. The earliest indicator, introduced by Hoghton in 1905, was based on Wet Bulb Temperature (WBT).[4,11,12]

The Universal Thermal Climate Index (UTCI) is a significant outdoor thermal index designed for assessing thermal comfort across various climatic zones and seasons. This index was developed using a multi-node model of human thermoregulation.[13] UTCI equivalent temperature values are available through software source code and executable programs downloadable from the project's website (www.utci.org).[2] Havenith *et al*. expanded on the UTCI-Fiala model by incorporating an adaptive clothing model in their research.[14]

Neural networks (NNs) serve as powerful tools for analyzing and simulating nonlinear and uncertain systems, particularly when interactions between system components and parameters are complex or not easily discernible.[15] Similar to the human brain, NNs are intelligent systems capable of learning from experimental data. They deduce rules and patterns by processing numerical data or examples, without the need for explicit statistical assumptions. NNs excel in learning directly from data to predict outputs corresponding to specific inputs, probing relationships between input and output sets without prior assumptions or predefined knowledge bases about parameter relationships.[16]

The Bayesian method is a classification technique that determines the likelihood of a phenomenon occurring or not occurring based on probability. Naïve Bayes (NB), leveraging fundamental principles of probability (particularly conditional probability), yields effective results with minimal initial training. It belongs to the category of supervised learning methods, where the model learns from observed data. In applications such as text categorization and medical diagnosis, NB demonstrates performance comparable to NNs and decision trees. At its core, Bayesian learning relies on Bayes' theorem, enabling the calculation of posterior probabilities from prior probabilities.[17]

Iran exhibits significant climatic diversity, with approximately 35.5% of its total area classified as completely desert, 29.2% as desert, 20.1% as semi-desert, 5% as temperate, and 10% as humid. Overall, 82% of Iran's territory falls within desert and semi-desert regions, predominantly located in the central and southern parts of the country, characterized by extremely hot summers.[18] Despite this climatic diversity, there has been a lack of comprehensive studies assessing heat stress and weighting the factors influencing it specifically in Iran's hot and dry, as well as hot and humid environments. To address this gap, this study aims to investigate the impact of heat stressors in these diverse environments, aiming to safeguard the health and well-being of the workforce. The general objectives of the study are to measure and calculate environmental parameters and the UTCI, to model predictor variables using NN and NB algorithms, and to determine the accuracy rate and area under the curve (AUC) of these algorithms.

Materials and Methods

Study design

In 2023, this cross-sectional descriptive study analytically examines and models the factors influencing the UTCI heat stress index in hot-dry and hot-humid regions of Iran, utilizing NN and NB algorithms. The study focuses on the southeastern region of Iran as a representative hot-dry area and the southern region as a hot-humid area. The research involves five main steps: first, selecting and measuring factors influencing the UTCI in both hot-dry and hot-humid climates; second, calculating the UTCI as the primary target variable for each climate region; third, applying the NN algorithm to weigh and model the factors affecting the UTCI in both climatic zones; fourth, utilizing the NB algorithm to assess and model these factors in the same zones; and finally, evaluating the accuracy and AUC of both models, followed by a comparative analysis.

According to the Köppen climate classification, Iran is categorized into 10 distinct climatic regions.[19,20] Approximately 80% of Iran falls under the hot climate category, with 16.7% classified as mild and 3.2% as cold regions.[21] Based on the classification by the Meteorological Organization of Iran [Figure 1], Kerman (representing hot and dry conditions) and Bandar Abbas (representing hot and humid conditions) were selected as the study locations.

Selecting factors affecting the Universal Thermal Climate Index and measuring them

Environmental parameters influencing the UTCI include air temperature (T_a), RH, radiant temperature (T_{mrt}), and airflow velocity (V_a). These factors were measured in various locations within the two selected regions according to the division of the Meteorological Organization of Iran. Specifically, Kerman was chosen to represent a hot and dry climate, while Bandar Abbas represents a hot and humid climate.[22] The study conducted measurements every half hour from 8 am to 11 pm over a period

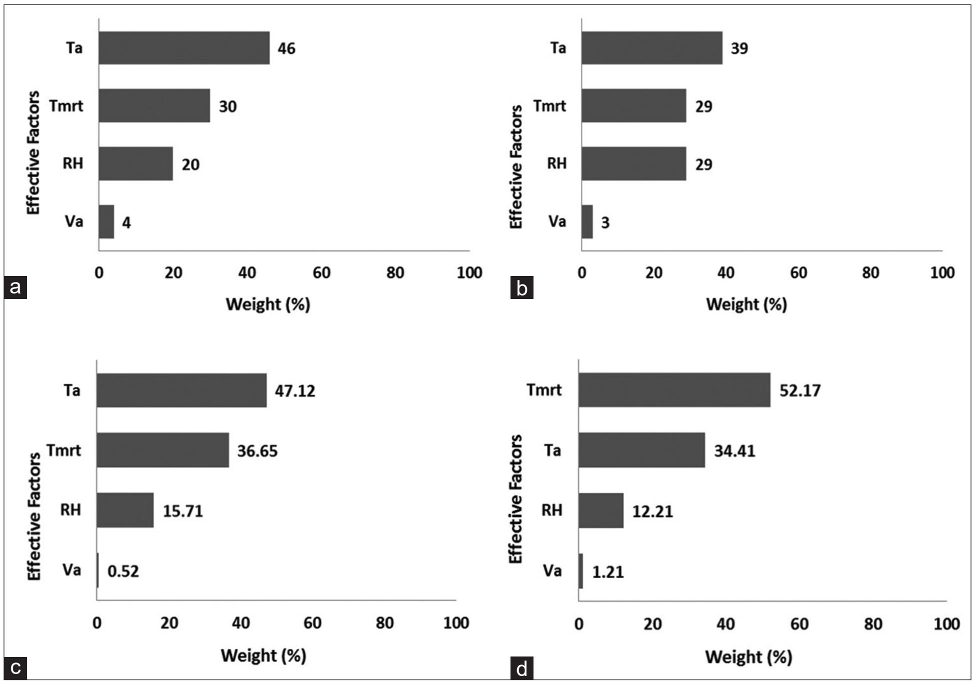

Figure 1: Modeling Universal Thermal Climate Index (UTCI) of hot-dry and hot-humid regions based on neural network and Naïve Bayes algorithms. (a) Modeling UTCI of hot and dry regions based on neural network algorithms, (b) Modeling UTCI of hot and humid regions based on neural network algorithms, (c) Modeling UTCI of hot and dry regions based on Naïve Bayes algorithms, (d) Modeling UTCI of hot and humid regions based on Naïve Bayes algorithms

of 15 days in each climatic zone during the summer season. The study aimed for a reliability of 95% and a test power of 80%. Based on previous studies and the scope of the current research, the minimum required sample size was determined to be 409 samples after adjusting for each region. In each location, devices specified in the manuscript were used to collect data on air temperature (T_a), RH, radiative temperature (T_{mrt}), and airflow velocity (V_a). These instruments were carefully selected to ensure accurate and consistent measurement of environmental parameters throughout the study period.

Dry temperature (T_a)

To measure the dry temperature, a mercury thermometer of Fisher model made in Japan with a measuring range (100°F−0°F) and reading accuracy of 0.1°F is used. The temperature is in Fahrenheit, which can be converted to Celsius (Equation 1).[23]

$$F = 1/8C + 32 \tag{1}$$

where F is Fahrenheit scale and C is Celsius scale.

Relative humidity

To measure RH, a calibrated WBGT effective (WBGTeff) meter manufactured by Casella (model Casella-1232342; Casella, UK) was utilized.[24] This instrument is specifically designed to accurately measure WBGTeff, which incorporates factors such as air temperature, humidity, radiant heat, and air movement to provide a comprehensive assessment of environmental conditions affecting human thermal comfort and heat stress.

Radiative temperature (T_{mrt})

A WBT thermometer with a measuring range (−20°C–100°C) with a reading accuracy of 0.1°C is used to measure the radiative temperature.[25]

Airflow velocity (V_a)

KIMO VT50 thermo-anemometer (manufactured in France) with a measuring range of 0.15–30 m/s was used to assess air velocity.[26]

Calculation of Universal Thermal Climate Index

The UTCI is considered one of the most comprehensive indices for evaluating outdoor heat stress. It represents the equivalent temperature of the environment relative to a reference condition. UTCI is derived such that the air temperature of the reference environment yields the same thermal strain index value experienced by a reference individual in the actual environment. The development of UTCI aimed to establish a standardized criterion for assessing heat stress based on human biometeorology. To compute UTCI, both meteorological (e.g., dry temperature, mean radiant temperature, and wind speed at 10 m elevation) and nonmeteorological data (e.g., metabolic rate and clothing thermal resistance) serve as input factors.[22] The UTCI is calculated using Equation 2, which integrates various environmental and physiological parameters:

$$UTCI = CalcUTCI(T_a, V_a, T_{mrt}, RH) \tag{2}$$

where is dry temperature, is airflow velocity, is radiative temperature, and is relative humidity.

In this study, the BioKlima software was utilized to calculate the UTCI. The software integrates values of air temperature (T_a), RH, mean radiant temperature (T_{mrt}), and wind speed (V_a) as inputs to compute the final UTCI value. This approach ensures consistent and accurate evaluation of heat stress based on established biometeorological principles and models incorporated into the software.

Weighting factors affecting Universal Thermal Climate Index by neural network and Naïve Bayes algorithm in two climatic zones

In the study, the data are initially classified and then subjected to analysis using a 70/30 ratio for training and testing, respectively. This means 70% of the data are utilized for algorithm training, while the remaining 30% are allocated for testing the model's performance. This process is repeated 200 times to ensure the robustness and reliability of the results.[27]

After training and testing the algorithms, factors gain ratios are computed to determine their relative importance or weight in influencing the UTCI. These gain ratios are crucial as they quantify the contribution of each factor (such as air temperature, RH, mean radiant temperature, and wind speed) to the overall UTCI value. The iterative nature of the analysis and the repeated evaluations enhance the statistical validity and confidence in the derived factors' importance in predicting heat stress levels in hot-dry and hot-humid environments.

Gauging the accuracy and area under curve stemming from neural network and Naïve Bayes algorithm

The classification algorithms in this study utilize various assessment criteria to categorize discrete output variables. Specifically, the study focuses on accuracy and AUC. Accuracy measures the proportion of correctly classified cases out of the total number of cases evaluated. AUC serves as a validation metric, indicating the model's ability to discriminate between classes, with higher values indicating better performance. These criteria are essential for evaluating the effectiveness of the classification algorithms in predicting outcomes related to UTCI and heat stress assessment[28] (Equation 3).

$$Accuracy = \frac{True\ Postive\ cases + True\ Negative\ cases}{All\ cases} \tag{3}$$

Data analysis and processing

The Statistical Package for the Social Sciences (SPSS) software version 20 made by SPSS Inc. in USA was used to analyze the mean and standard deviation of the environmental parameters and UTCI. Meanwhile, Python's scikit-learn package version 3.7 and the Orange toolkit were employed for weighting and modeling the influential factors on UTCI.

Results

Environmental parameters (effective factors)

Table 1 presents the mean and standard deviation of environmental parameters. In hot-dry regions, the mean values are 28.68°C for dry temperature, 1.96 m/s for air velocity, 31.88°C for radiant temperature, and 51.81% for RH. In hot-humid regions, the highest recorded values are 4.9 m/s for air velocity and 93.1% for RH.

Universal Thermal Climate Index heat index (target factor)

Table 2 illustrates the calculated results of the UTCI. In hot-dry regions, the mean UTCI is 30.49. Meanwhile, the minimum UTCI value observed in hot-humid regions is 25.

Weighting and modeling neural network and Naïve Bayes algorithms

In this section, the results of modeling the UTCI for each of the two different climatic zones are presented separately using the NN and NB algorithms. The results are reported as gain ratio, as depicted in Figure 1. Part A illustrates the gain ratio modeling of UTCI in hot-dry regions based on the NN. The most influential factor, with a gain ratio of 46%, is related to dry temperature (T_a), followed by mean radiant temperature (T_{mrt}) with 30%. Part B shows the gain ratio of UTCI modeling for hot-humid regions based on the NN. The most significant factor here, with a gain ratio of 29%, is related to T_{mrt}, followed by air velocity (V_a) with 3%. Part C displays the gain ratio of UTCI modeling for hot-dry regions using the NB algorithm. The predominant factor, with a gain ratio of 47.12%, is associated

Table 1: Measured values of environmental parameters

	Factors affecting heat stress index (environmental parameters)			
	T_a (°C)	V_a (m/s)	T_{mrt} (°C)	RH (%)
Hot-dry regions				
Mean	28.68	1.96	31.88	51.81
Standard deviation	3.6	1	5.67	9.96
Maximum	33.7	4.7	39.90	77.70
Minimum	17.50	0.6	18.60	31.90
Hot-humid regions				
Mean	35.33	2	37.09	61.11
Standard deviation	4.19	1	6.07	10.90
Maximum	47.80	4.9	52.50	93.10
Minimum	23.90	0.7	21.60	25.30

RH: Relative humidity

Table 2: Universal Thermal Climate Index results in hot-dry and hot-humid regions

	UTCI (°C)
Hot-dry regions	
Mean	30.49
Standard deviation	4.06
Maximum	37.60
Minimum	19.10
Hot-humid regions	
Mean	39.48
Standard deviation	6.41
Maximum	68.10
Minimum	25

UTCI: Universal Thermal Climate Index

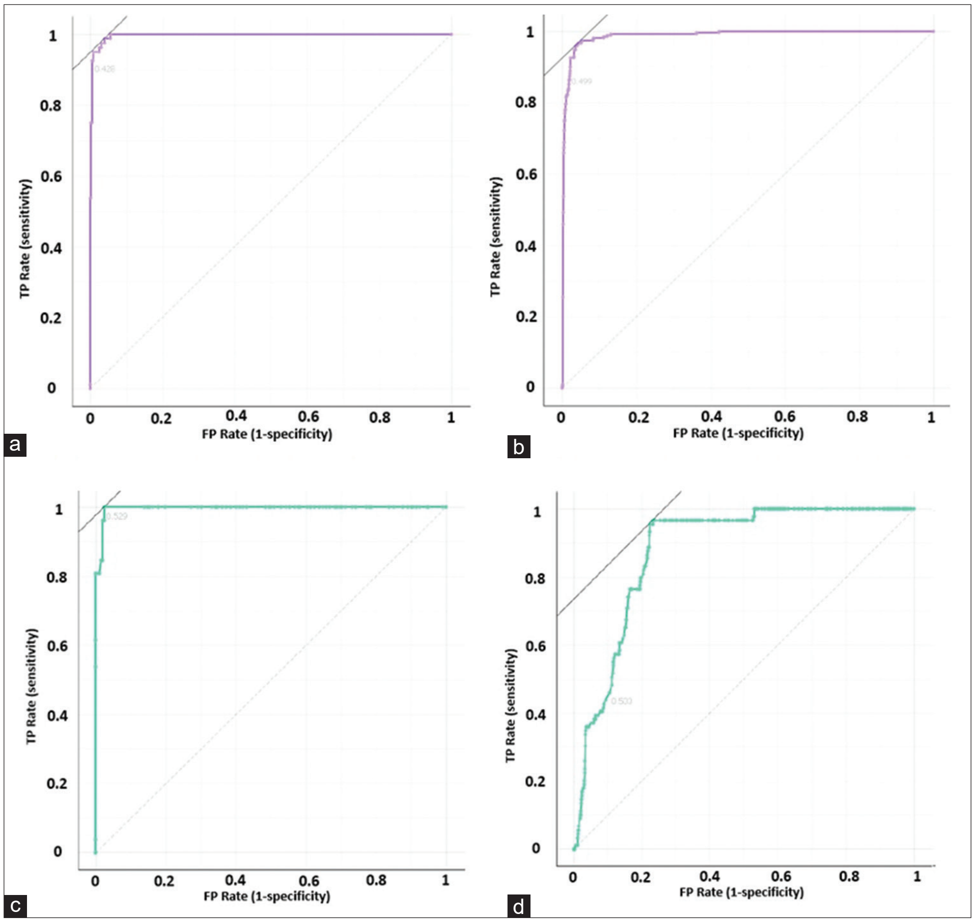

Figure 2: Receiver operating characteristic (ROC) curves of neural network and Naïve Bayes algorithms in Universal Thermal Climate Index modeling of hot-dry and hot-humid regions. (a) ROC curve of neural network algorithm for UTCI modeling of hot and dry regions, (b) ROC curve of neural network algorithm for UTCI modeling of hot and humid regions, (c) ROC curve of Naïve Bayes algorithm for UTCI modeling of hot and dry regions, (d) ROC curve of Naïve Bayes algorithm for UTCI modeling of hot and humid regions

with T_a, while V_a has the least effect, with a gain ratio of 0.52%. Part D depicts the gain ratio of UTCI modeling for hot-humid regions using the NB algorithm. T_a emerges as the most influential factor, with a weight of 34.41%, followed by RH at 12.21%. These gain ratios indicate the relative importance of each environmental parameter in influencing the UTCI in the respective climatic zones, providing insights into which factors have the greatest impact on thermal stress in hot-dry and hot-humid conditions.

Accuracy rate and area under the curve

Accuracy rate

Table 3 presents the accuracy rates of the four models mentioned. The NB algorithm exhibits the lowest accuracy rate at 74%, while the NN model for hot-humid regions achieves the highest accuracy rate at 94%.

Area under the curve rate

Figure 2 displays the AUC rates of the UTCI models categorized by algorithm: Part A exhibits the receiver operating characteristic (ROC) curve of the NN algorithm for modeling UTCI in hot-dry regions, achieving an AUC of 98%. Part B shows the ROC curve of the NN algorithm for modeling UTCI in hot-humid regions, with an AUC of 99%. Part C displays the ROC curve of the NB algorithm for modeling UTCI in hot-dry regions, achieving an AUC of 96%. Part D illustrates the ROC curve of the NB algorithm for modeling UTCI in hot-humid regions, with an AUC of 87%. These AUC values provide a measure of the models' performance in discriminating between different classes of UTCI values, demonstrating that higher values indicate better model discrimination and predictive capability.

Table 3: Accuracy rates of Universal Thermal Climate Index models

Algorithm	Climate region	Accuracy rate (%)
NN	Hot dry	93
	Hot and humid	94
Naïve Bayes	Hot dry	88
	Hot and humid	74

NN: Neural network

Discussion

This study aimed to analyze and model the factors influencing UTCI in hot-dry and hot-humid regions of Iran using NN and

NB algorithms. In hot-dry regions, the mean values of dry temperature, air velocity, radiant temperature, and RH were 28.68, 1.96, 31.88, and 51.81, respectively, while in hot-humid regions, they were 35.33, 2, 37.09, and 61.11, respectively [Table 1]. The mean UTCI values were 30.49 in hot-dry regions and 39.48 in hot-humid regions [Table 2]. In modeling UTCI for hot-dry regions using the NN, the most influential factor was dry temperature (T_a) with a weight of 46%, followed by mean radiant temperature (T_{mrt}) with 30% [Figure 1]. For hot-humid regions, T_a had the highest weight of 39%, while air velocity (V_a) had the lowest impact at 3%. When employing the NB algorithm for modeling UTCI in hot-dry regions, T_a had the highest weight of 46%, followed by RH at 15.71%, and V_a had the least impact at 0.52% [Figure 1]. In hot-humid regions modeled with NB, T_a was again significant with a weight of 34.41%, followed by RH at 12.21%. Both algorithms consistently identified T_a as a primary factor impacting UTCI in hot-dry regions, followed by T_{mrt}. In hot-humid regions, while NB emphasized T_{mrt} significantly, the NN indicated a closer influence between T_a and T_{mrt}.

In the study, the highest accuracy rate was achieved by the NN algorithm for modeling UTCI in hot-humid regions, reaching 94%. Generally, the accuracy rates of the NB models were lower compared to those of the NN models [Table 3]. Additionally, the AUC rates of the NN models were superior to those of the NB models, with rates of 98% for hot-dry regions and 99% for hot-humid regions [Figure 2]. In a study by Sung *et al.*, which compared UTCI with several other common heat indices, it was found that UTCI is highly sensitive to even slight changes in climate conditions and can be applied across a wide range of outdoor temperatures (cold, temperate, and hot). This sensitivity contrasts with other indices that are limited to specific temperature ranges.[29] In the current study, based on the mean UTCI values reported, it was observed that UTCI indicated similar levels of heat stress in both hot-dry and hot-humid climatic zones. This suggests that UTCI is suitable and applicable across diverse climatic conditions, as it accurately reflects thermal stress levels irrespective of specific temperature conditions in each zone.

Jiang and Yao focused on modeling personal thermal sensations using the C-Support Vector Classification algorithm. Their study aimed to learn individuals' thermal preferences based on feedback, environmental factors, and physiological and behavioral data. Validation of the modeling approach involved comparing actual thermal sensation votes with modeled predictions from 20 participants. They also compared the accuracy of their models with predictions from the predicted mean vote (PMV) model. Their study reported an average accuracy rate of 89.82% across all participants, with 17 out of 20 participants achieving accuracy rates over 80%.[30] In the current study, similar to Jiang and Yao's approach, the NN models achieved high accuracy rates of 93% for hot-dry regions and 94% for hot-humid regions. Conversely, the NB algorithm models showed lower accuracy rates of 74% for hot-humid regions and 88% for hot-dry regions. These findings demonstrate comparable high accuracy rates in modeling thermal conditions, akin to the results observed in Jiang and Yao's research.

Kariminia *et al*. conducted a study in Isfahan titled "A simulation model for visitors' thermal comfort at urban public squares using non-probabilistic binary-linear classifier through soft-computing methodologies." They assessed various environmental factors across four corners of two public squares, alongside administering surveys to gauge visitors' thermal sensation and collecting meteorological data. The study aimed to estimate visitors' thermal comfort levels based on thermal comfort indices entered into a computational model. They reported R^2 values for thermal sensation, PMV, physiologically equivalent temperature (PET), standard effective temperature, and T_{mrt} at 48%, 94%, 99%, 97%, and 84%, respectively.[31] In the current study, similar to Kariminia *et al*.'s[31] findings, the models achieved high accuracy rates. Specifically, the NN models attained accuracy rates of 93% and 94% for hot-dry and hot-humid regions, respectively. The NB algorithm models also demonstrated high accuracy rates, though specific values were not provided in the response. These results align with the rigorous validation and high accuracy observed in Kariminia *et al*.'s[31] study, reflecting the effectiveness of computational methodologies in modeling thermal comfort in different environmental conditions.

In the study by Megri and El Naqa (2016), the support vector machine (SVM) algorithm achieved a high correlation coefficient between 93% and 99%, indicating strong predictive performance.[32] Similarly, in the present study, the accuracy rates of UTCI modeling algorithms were evaluated. The NN algorithm models demonstrated accuracy rates close to 100%, resembling the high predictive capability observed in the SVM study. On the other hand, the NB algorithm models achieved accuracy rates ranging around 80%. These findings underscore the effectiveness of machine learning algorithms, such as NNs and SVM, in accurately modeling UTCI and predicting thermal comfort indices. The high accuracy rates suggest robust performance in capturing complex relationships between environmental parameters and thermal stress indices in different climatic conditions.

In Nasir *et al*.'s study (2019), the focus was on classifying thermally treated wood using machine learning techniques. They compared the performance of artificial neural networks, SVM, and NB classifiers for this purpose. Parameters such as moisture content, water absorption, swelling coefficient, color (specifically lightness parameter L*), hardness, and dynamic modulus of elasticity were measured to determine optimal wood categorization characteristics. The study found that as the feature dimension increased, the NB classifier outperformed SVM, achieving a robust accuracy rate of 0.99 based on certain parameters.[33] In the present study, similar to Nasir *et al*.'s[33] findings, the UTCI modeling algorithms demonstrated high accuracy rates. The NN algorithm models achieved nearly 100% accuracy, indicating strong predictive capability comparable to the robust classifiers observed in the wood classification study. On the other hand, the NB algorithm models exhibited accuracy rates of around 80%. These results suggest that while NNs excel in achieving high accuracy, NB also performs effectively in modeling UTCI, albeit with slightly lower accuracy compared to NNs.

In the study by Moustris *et al*., artificial NN models were employed to estimate a complex human thermal comfort index related to urban heat and cool island patterns. They utilized temperature data from a standard meteorological station and incorporated inputs such as air temperature, RH, wind speed, and radiation to model the PET. Their study reported high accuracy rates of 99% for hot periods and 97% for cold periods of the year.[34] Similarly, in the present study, the NN models achieved high accuracy rates, specifically 93% and 94% for hot-dry and hot-humid regions, respectively. This aligns with the robust predictive performance observed in Moustris *et al*.'s[34] work. On the other hand, the NB algorithm models in the present study achieved accuracy rates of 74% for hot-humid regions and 88% for hot-dry regions. While slightly lower than NNs, these accuracy rates still indicate the effective modeling capabilities of NB in capturing the relationships between environmental parameters and UTCI.

Conclusion

In both NN and NB models applied to hot-dry regions, the primary factors predicted were dry temperature (T_a) followed by mean radiant temperature (T_{mrt}). Conversely, in hot-humid regions, the models indicated that mean radiant temperature (T_{mrt}) predominantly influenced the UTCI. Given the high accuracy rates and AUC values obtained from these algorithms in the present study, the models developed can be considered reliable and robust. These findings suggest practical applications in improving workplace climatic conditions by effectively controlling the factors identified as significant contributors to UTCI. By understanding and weighing these factors, strategies can be implemented to mitigate heat stress and enhance the well-being and productivity of workers exposed to varying climatic conditions in hot-dry and hot-humid regions.

Acknowledgment

We are deeply grateful for the support provided by this center and the Research Deputy of Kerman University of Medical Sciences, Kerman, Iran.

Financial support and sponsorship

This study is the output of a research project Health Modeling Research Center at Kerman University of Medical Sciences, Research Grant # 97000855.

Ethics code

This study was approved as a research project in the Ethics Committee of Kerman University of Medical Sciences with code number IR.KMU.REC.1397.528. In the present study, all participants were above 18 years old and signed an informed consent form prior to taking part in the study.

Conflicts of interest

There are no conflicts of interest.

Authors' contributions

Sajad Zare: Conceptualization, methodology, project administration, validation, writing – review and editing; Reza Esmaeili: Conceptualization, formal analysis, methodology, supervision, writing – original draft, writing – review and editing, data curation, formal analysis, investigation, visualization.

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