# Chapter 14
# A Study on Thermal Comfort Assessment Frameworks and Models in Cities

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**Abstract** Considering the increasing trends of urbanization, climatic change, and air temperature in cities, the issue of urban heat island mitigation for ensuring thermal comfort is of high importance. Enhancing thermal comfort also has implications for human health, well-being, and productivity. In recent decades, several assessment frameworks and models have been proposed to measure and predict thermal comfort in cities. This chapter tries to explore major assessment frameworks and models that explain and measure thermal comfort in cities by considering physical, physiological, psychological, and behavioral dimensions. It shows that thermal comfort models could be divided into two major categories, namely, knowledge-based thermal comfort methods and data-driven thermal comfort models. Each of these two has subset models for thermal comfort testing in cities. The findings indicate that recent trends in measuring thermal comfort are focused on data-driven models based on simulation algorithms.

**Keywords** Climate change · Urban heat islands · Thermal comfort · Thermal comfort models

## 1 Introduction

The increasing trends of urbanization across the globe have caused tremendous pressure on the environment (Zhang, 2016). Such pressure shows itself as unsustainable pattern of urban growth (sprawl), the increasing number of cars, decreasing green

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space per capita, and huge amounts of energy consumption in the cities. These have led to a large-scale modification in urban land use and land cover pattern and, consequently, brought about adverse effects in cities (Mohan et al., 2020). All these, which threaten the health of citizens and urban sustainability, have caused concerns among researchers, policymakers, and urban planners (Bartholy & Pongrácz, 2018).

Recently, the significant growth of some concepts in the literature, such as ‘cool cities’, ‘urban heat islands’, and ‘thermal comfort’ are justified in line with the concern of climatic manifestations of urbanization (Qi et al., 2021; Taha, 2015). Among these, thermal comfort refers to the existence of a satisfactory temperature for individuals in urban spaces that does not lead to endangering their health (Ahmed, 2003). In fact, this matter is related to the quality of outdoor and semi-outdoor spaces in the city, such as parks, squares, pedestrian streets, public recreational spaces, residential areas, sports stadiums, etc., that assist in creating spaces for exercising and socializing of the citizens. The quality of design and placement of these spaces and the pattern of land cover significantly impact the city vitality and livability, especially individuals’ thermal comfort (Chen & Ng, 2012).

Considering the importance of urban sustainability, urban climate change adaptation, and urban health, many scholars have attempted to explain how to estimate and create manners to reach thermal comfort in the cities. In this road, particularly, numerous studies have sought to present and expand assessment tools and models to measure thermal comfort in cities. Concerning this matter, previous literature shows that thermal comfort models have mainly focused on two aspects, namely, knowledge-based thermal comfort methods and data-driven thermal comfort models. To this end, an effort has been made to describe these models and assessment tools in this chapter.

## 2 Knowledge-Based Thermal Comfort Models

Based on the literature, knowledge-based thermal comfort models are known as traditional models that are classified into heat balance models and adaptive models. In brief, heat balance models based on laboratory studies believed that thermal comfort could be obtained by holding body temperature in a narrow range, low skin moisture, and minimizing the physiological effort of regulation (De Dear et al., 2020). On the other side, adaptive models, based on field studies, claim that a variety of temperature ranges can be assumed comfortable for individuals because they can adapt to varying boundary conditions (Yao et al., 2009).

Some of the most famous models related to both aspects are described in the following.

## *2.1 Predicted Mean Vote (PMV)*

Predicted Mean Vote (PMV) has been proposed by Fanger in 1970 based on his laboratories and chambers studies (Yau & Chew, 2014). In this model, Fanger expanded a type of heat balance equation, which consists of a combination of six factors that affect achieving a thermal balance between the human body and the environment (Li & Liu, 2020). These factors include four primary and two personal factors shown in Fig. 1.

According to Yao et al. (2009) "The PMV model is based on extensive American and European experiments involving over a thousand subjects exposed to well-controlled, extensive and rigorous laboratory environments" (p. 2089). The PMV model estimates thermal comfort based on the six factors mentioned and quantifies the absolute and relative impact of the factors in light of what is thermally comfortable (Efeoma & Uduku, 2014). The equation of PMV model is shown below:

$$f = (TA, TM, VEL, RH, MET, CLO) = 0 \tag{1}$$

Based on the model equation, it is predicted that in terms of the skin temperature and sweat rate limits, a person will have thermal comfort when the thermal load of his body is equal to zero (Zhang & Lin, 2020). This model has been used widely and measures thermal comfort based on a seven-point scale (+3 = hot, +2 = warm, +1 = slightly warm, 0 = neutral, 1 = slightly cool, 2 = cool, 3 = cold) (Zheng et al., 2021). Practically, "PMV is also commonly interpreted by the Predicted Percentage Dissatisfied Index (PPD), which is defined as the quantitative prediction of the percentage of thermally dissatisfied people at each PMV value" (Chen & Ng, 2012, p. 129).

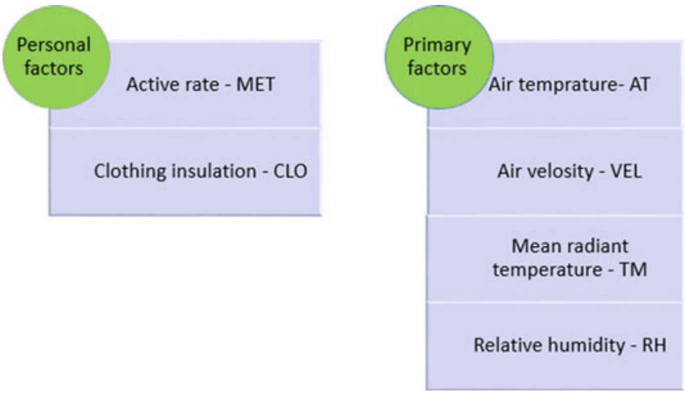


**Fig. 1** Constituent factors of PMV model—Modified from (Adapted from Efeoma & Uduku, 2014)

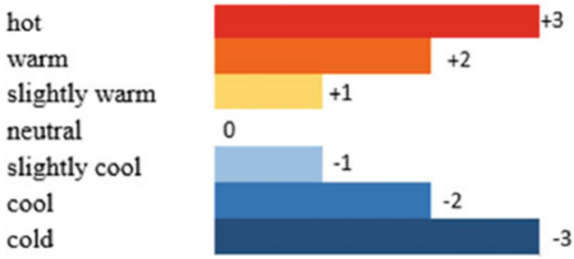


**Fig. 2** ASHRAE thermal comfort scale (Adapted from Lu et al., 2019)

### 2.1.1 ASHRAE

American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) gained considerable ground among researchers in the 1990s in terms of field studies (Toe & Kubota, 2013). The model is considered a method to fill the gap between comfort theory and practice. ASHRAE was developed by de Dear and Brager,"is based on the analysis of about 9,000 of the 21,000 sets of raw data compiled from field studies in 160 buildings located in diverse climatic zones around the world" (Carlucci et al., 2021, p. 2).

As shown in Fig. 2, this model measured thermal comfort based on a seven-point sensation scale, which runs from "cold" (–3) to "neutral" (0) to "hot" (+3) and is drawn from the PMV model of Fanger (1970) (Langevin et al., 2012). In the edited version of ASHRAE by Humphreys and Nicol, 2004, ASHRAE scale is from −3 (much too cool) to +3 (much too warm).

The Humphreys 1975–1981 database and the ASHRAE RP-884 database as a meta-analysis of a larger database in the context of field surveys were applied for developing ASHRAE adaptive standard. In between, the ASHRAE RP-884 database that could cover various climatic areas, such as hot–humid areas, has been applied by numerous studies (Farghal & Wagner, 2010; Schweiker & Shukuya, 2012; Toe & Kubota, 2013). This database was used as the basis for the development of ASHRAE standard 55: Thermal Environmental Conditions for Human Occupancy. Since then, "the adaptive thermal comfort model was first included in the 2004 edition of the ASHRAE Standard 55; and subsequent revision of the Standard thereafter" (Efeoma & Uduku, 2014, p. 403).

### 2.1.2 ISO 7730

The ISO 7730 standard is an adaptive thermal standard based on Frager's work with young Danish students on the PMV model (Ealiwa et al., 2001). This standard is presented to predict the general thermal sensation and degree of discomfort. It can analyze and interpret thermal comfort based on the PMV and PPD (predicted percentage of dissatisfied) and local thermal comfort (Zare et al., 2018).

Overall, The ISO 7730 standard was expanded in parallel with ASHRAE 55. This standard is part of a series of ISO standards (Such as ISO 7243, ISO 7933, and ISO/TR 14415) that are revised every 5 years and used in a range of thermal environments from mild to extreme (Wilde, 2020).

## 2.2 The Physiological Equivalent Temperature (PET)

The Physiological Equivalent Temperature (PET), which is known as a steady-state method, is a temperature dimension index based on degrees Celsius. PET has been formed considering Munich Energy-balance Model for Individuals (MEMI).The MEMI is defined according to the energy balance equation for the human body. Below, the structure of this equation and the definitions of its components are described (Matzarakis & Amelung, 2008):

$$M + W + R + C + E_D + E_{Re} + E_{Sw} + S = 0 \tag{2}$$

$M$: "the metabolic rate (internal energy production)";
$W$: "the physical work output";
$R$: "the net radiation of the body";
$C$: "the convective heat flow";
$E_D$: "the latent heat flow to evaporate water diffusing through the skin";
$E_{Re}$: "the sum of heat flows for heating and humidifying the inspired air";
$E_{Sw}$: "the heat flow due to evaporation of sweat";
$S$: "the storage heat flow for heating or cooling the body mass".

Two points is important in this equation. First, the unit of all heat flows is defined based on Watt, and second, "the individual terms in this equation have positive signs if they result in an energy gain for the body and negative signs in the case of an energy loss ($M$ is always positive; $W$, $E_D$ and $E_{Sw}$ are always negative)" (Matzarakis & Amelung, 2008, p. 165).

PET has been found suitable for the analysis of outdoor thermal comfort. As stated by Chen and Ng (2012) in this model, "the evaluation of a complex outdoor climatic environment translates to a simple indoor scenario on a physiologically equivalent basis" (p. 114) in an easy understanding and interpreting manner.

## 2.3 Black Box Theory

The black box theory, widely used in cybernetics, applies the variables, such as culture, climate, social, psychological, and behavioral adaptations that significantly impact thermal perception (Shooshtarian, 2019). The main point of this theory is to explore and assess the logical and statistical relationships between information that is applied in the box and instructions that are known as output (De Dear et al., 2020). The principles of this theory can be described as follows:

- Defining a deterministic stimulus for the black box that is the input of the system;
- Black box output and focus on establishing a meaningful statistical relationship between input and output;
- Using mathematical methods to express the relationship and develop the black box with a mathematical model (Yao et al., 2009).

## *2.4 Adaptive Thermal Comfort Standards*

Besides the models mentioned above related to knowledge-based thermal comfort models, adaptive standards have also had a key effect in expanding these kinds of models across the globe. In fact, adaptive standards have had a significant impact on the visibility of adaptive models since 2004. The trend of consideration of adaptive standards began from ASHRAE 55, elaborated in 2004. In addition to ASHRAE 55 and ISO 7730 described above, there are some major standards in expanding the adaptive models. These are briefly explained in the next section.

### 2.4.1 EN 15251

EN 15251, the European standard, which specifies the indoor environmental parameters, and its revision prEN 16798 are adaptive standards that were applied PMV and adaptive models in their structure (Carlucci et al., 2018). Presented in 2007, EN 15251 was formed based on empirical data obtained from close to 1,500 participants recorded in the pan-European Smart Controls and Thermal Comfort (SCATs) project (De Dear et al., 2020; Pozas et al., 2022).

The main aim of this standard was to reduce the energy usage by air conditioning systems through varying setpoint temperatures in line with outdoor temperature by applying an 'adaptive algorithm'. To this end, numerous physical measurements and subjective responses from numerous locations in France, Greece, Portugal, Sweden, and the UK were recorded. As pointed out by De Dear et al. (2020), to optimize the performance of the EN 15251 standard, "the Griffiths method rather than linear regression was applied to estimate the neutral temperature with Griffiths Coefficient of $G = 0.5$, meaning that thermal sensation votes were presumed to change at the rate of one vote (on the 7 point scale) per 2 K change in operative temperature" (p. 12).

### 2.4.2 Dutch ISSO 74-2004/2014

This is another adaptive standard used to assess thermal comfort in unconditioned, mixed-mode, and conditioned spaces (Hamdy et al., 2017). Like ASHRAE 55, ISSO is based on data from the RP-884 database. Moreover, the ISSO algorithm for thermal neutrality is in the same manner as the RP-884 project (De Dear et al., 2020).

ISSO followed two application scenarios, namely, Alpha-space and beta-space. The first one is "free-running situations in summer with operable windows and a non-strict clothing policy for the occupants", and the second one is related to those "which primarily rely on centrally-controlled cooling in summer." (De Dear et al., 2020, p. 14).

Compared to the 2004 version, in the 2014 version of ISSO, four types of changes were applied: (1) Considering specific interior spaces rather than the entire building. (2) Being based on a smaller and entirely European SCATs database. (3) Division of temperature conditions in four classes instead of three classes, and (4) Adopting a different method in calculating the outdoor temperature and adopting 7-day outdoor temperature horizon instead of 3-day temperature horizon (De Dear et al., 2020).

### 2.4.3 GB/T 50785

GB/T 50785 standard is a Chinese comfort standard for free-running buildings. This standard is based on a field study, and its data source comes from fourteen major cities in China with five climate zones (Li et al., 2018). The topology of the buildings assessed in this standard is public buildings, such as official and educational buildings, and multi-family residential buildings (De Dear et al., 2020; Xu et al., 2016).

The process of conducting field studies included 28,000 subjects by coverage of summer, winter, spring, and autumn seasons. In this standard, a graphical method has been applied for calculating neutral temperature, and for adopting a climate temperature index, a running mean temperature was used (De Dear et al., 2020). Using a graphical method to calculate the neutral temperature in this standard is an approach similar to that of ASHRAE 55-2013. Also, there are three categories for describing operative temperature: (I) "a still air comfort zone (<0.15 m/s)" (II) "the rest of the acceptable area", and (III) "unacceptable temperatures" (Khovalyg et al., 2020).

## 3 Data-Driven Thermal Comfort Models

Since the second decade of the twenty-first century, rapid advances in statistic science have brought new approaches and methods into the human thermal comfort field. Since 2016, using IoT sensing technologies, big data, machine learning, and deep learning techniques has been more popular among researchers to assess thermal comfort (Zhao et al., 2014). These models in the context of human thermal comfort are known as data-driven models (Gao et al., 2021). The ability to simulate different situations and use new methods in data management, classification, and analysis can be one of the advantages of data-driven models.

A variety of algorithms based on new analytical methods and tools can be seen in previous literature. In the next section some of the frequently used data-driven models that have been applied for assessing thermal comfort are described.

## *3.1 Gaussian Naïve Bayes (GNB) Algorithm*

This algorithm is a defined kind of naïve Bayes algorithm. This algorithm can be used in a situation where the requested variables (P) have non-interrupted values to solve. When we work with real-time data in thermal comfort analysis and have this assumption that the data (objectives) (x) associated with each class (y) is regularly distributed with a Gaussian distribution, we can use the GNB algorithm. In fact, this algorithm helps us to have a model with high-performance capability, high training speed, and the ability to correctly predict the characteristics of the data belonging to each class (Srivastava, 2020). At the following, Fig. 3 shows the function of GNB classifier.

According to Fig. 3 and as it has been stated by Raizada and Lee (2013), in the assessment process of GNB algorithm, "for each data point, the z-score distance between that point and each class-mean is calculated, namely the distance from the class mean divided by the standard deviation of that class " (p. 2).

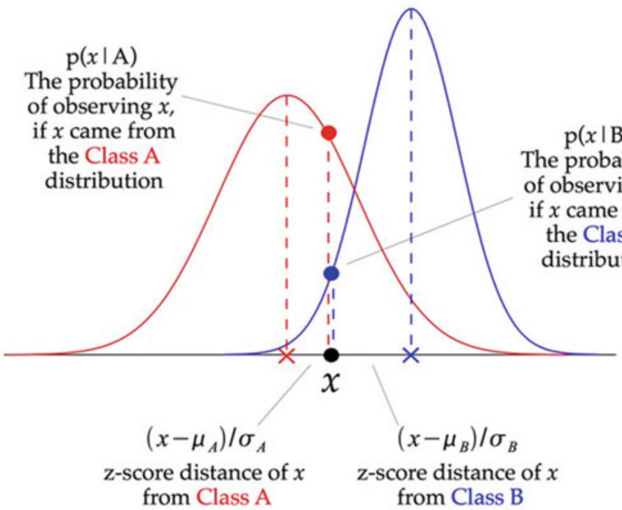


**Fig. 3** The function of GNB classifier (Adapted from Raizada & Lee, 2013)

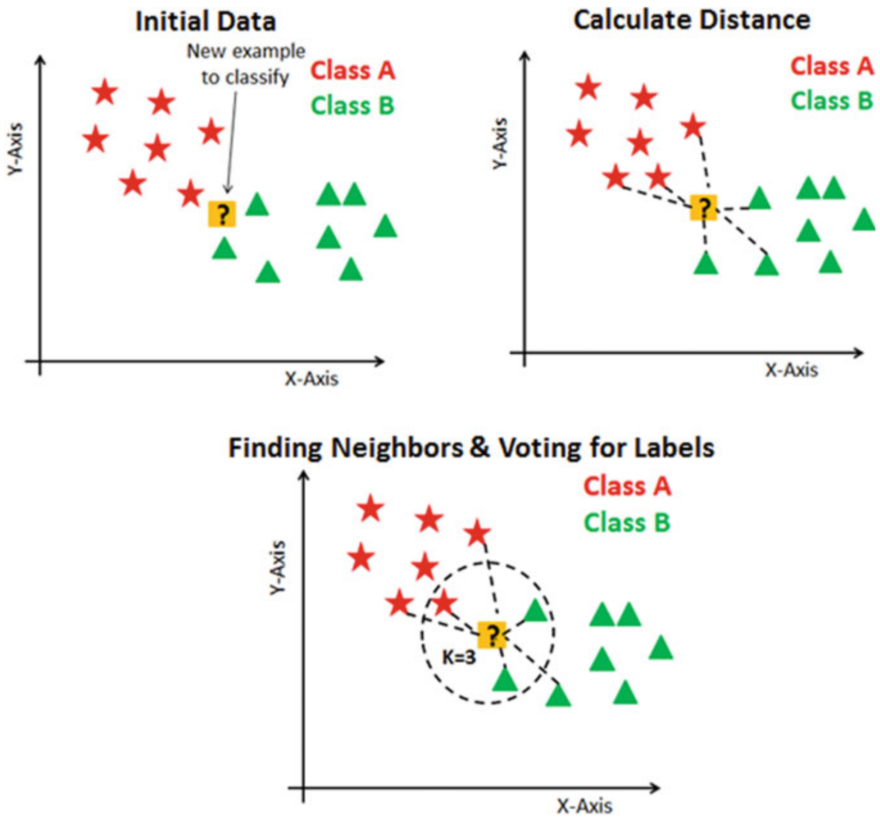


**Fig. 4** An example of KNN diagram[2]

## 3.2 *K-Nearest Neighbor*

K-Nearest Neighbor algorithm (KNN) is known as a supervised machine learning algorithm that can be applied to either classification or predictive regression problems (Xiong & Yao, 2021). The main assumption in this algorithm is that similar points can be placed next to each other (Wang et al., 2019). As can be seen in Fig. 4, for assessing classification problems, a class label is produced considering the majority vote. The meaning of "majority voting" is applying majority of over 50% of vote when just two classes have established the data.[1]

Besides the same manner as classification problems, for regression problems, it is important taking into account the average of the k (as a tuning parameter) nearest neighbors for creating a prediction about a classification (García-Laencina et al.,

[1] https://www.ibm.com/topics/knn.

[2] https://www.datacamp.com/tutorial/k-nearest-neighbor-classification-scikit-learn.

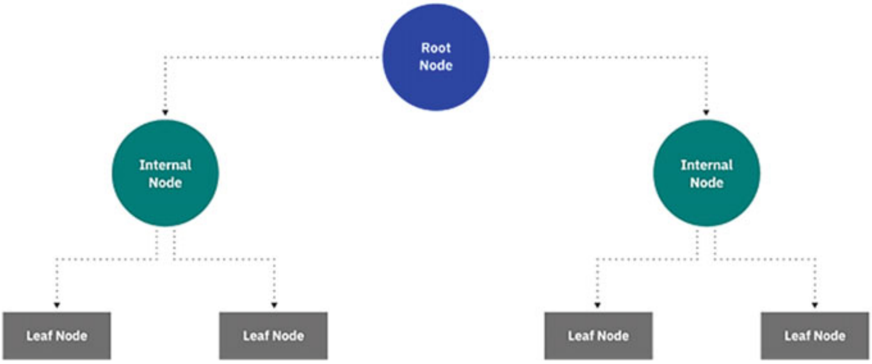


**Fig. 5** The structure of DT algorithm[3]

2015). Contrary to classification in which discrete values are used, it is considered continuous values for regression (Gu et al., 2018).

## *3.3 Decision Tree*

Known as a non-parametric supervised learning algorithm, Decision Tree (DT) is used for both classification and regression tasks (Ramosaj & Pauly, 2019). This algorithm advances the work of analysis by creating a hierarchical tree graph that expands the partition of a dependent or target variable by multiple independent variables. By this partitioning, the strength of relationships in a dataset is determined through the size of the split at each step (Vellei et al., 2017).

Based on Fig. 5, the structure of DT has been established by a hierarchical structure, which includes a root node, branches, internal nodes, and leaf nodes (Shorabeh et al., 2022).

The analysis process in this algorithm starts from the *root node* and the data space divides into several regions as new nodes. By repeating this process, some more new nodes are created. In the tree-shaped structure of the algorithm, each branch of the tree finishes in a *leaf node*. Leaf nodes provide categories that are the best interpretation of the state of the respective regions as long as the data cannot be further divided than the current state (Vellei et al., 2017).

[3] https://www.ibm.com/topics/decision-trees.

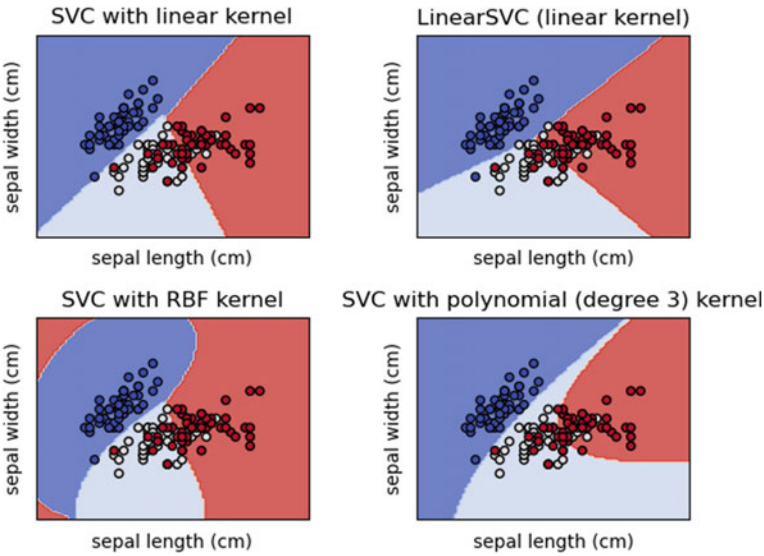


**Fig. 6** Examples of SVM outputs by using multiple kernel functions[4]

## 3.4 *Support Vector Machine*

Support Vector Machine (SVM) is a supervised learning model related to learning algorithms that analyze data for both classification and regression analysis. Due to generalization ability, SVM classifiers are widely used in the previous literature (Du et al., 2020).

Besides making linear classification, SVMs are able to accomplish a non-linear classification using kernel trick and mapping their data into high-dimensional feature spaces (Tiwari, 2022). in fact, The SVM algorithm can create a variety of learning machines by applying different kernel functions (Du et al., 2020). Figure 6 illustrates SVM classifier outputs by applying multiple kernel functions.

## 3.5 *Random Forest*

Random Forest (RF) is a commonly-used machine learning algorithm that provides a single result by the combination of multiple decision tree outputs. RF also handles both classification and regression problems. Regarding this, as stated by Vellei et al. (2017) RF "is an ensemble of tree-based models and can be used for classification tasks when the base models are classification trees, or regression tasks when the base models are regression trees" (p. 18).

[4] https://scikit-learn.org/stable/modules/svm.html.

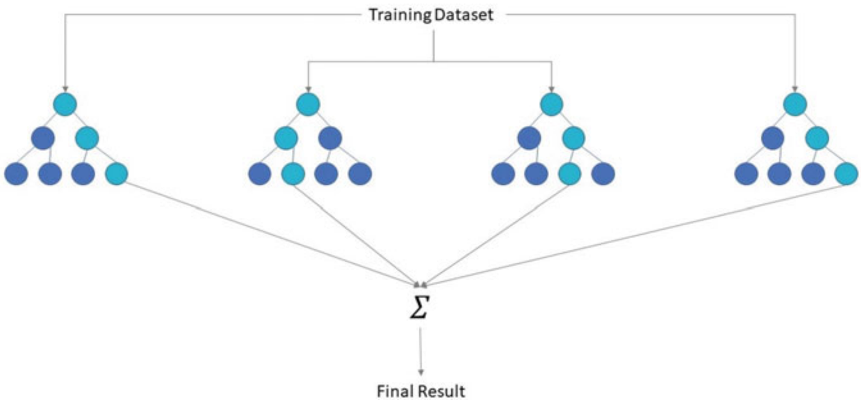


**Fig. 7** A diagram of RF[5]

Three main hyperparameters exist in RF: node size, tree numbers, and the number of features sampled (Lulli et al., 2019). Overall, the advantages of this algorithm include its use in big data, being resistant to outliers, dealing with simple and complex linear relationships, and creating competitive prediction accuracy in high-dimensional data (Han & Kim, 2021). Figure 7 shows a diagram of RF.

## 4 Comparison of the Knowledge-Based and Data-Driven Models

As revealed in this study, the models that are known as thermal comfort models are classified into knowledge-based models and data driven models. The knowledge-based models, called traditional models, started to apply in the thermal comfort analysis in 1970 (Carlucci et al., 2018). In between, the data-driven models became famous, especially since the last decade (Schwieker, 2022). Historically, these two kinds of models have been raised in different times. In fact, considerable advances in analytical and statistical tools make significant differences among them (Park & Nagy, 2018).

The main difference between these models is based on the methodological approach. In this regard, in the knowledge-based thermal comfort models, researchers use laboratory and field studies to obtain and analyze data (De Dear et al., 2020; Zheng et al., 2021). The data are also analyzed considering some pre-articulated standards for assessing the results (De Dear et al., 2020). The analysis process is time-consuming, and the accuracy of the results may be low. Moreover, these models use a series of mathematical deductions with certain inputs, for example, clothing thermal resistance, ambient temperature, and wind speed, to obtain outputs

[5] https://www.ibm.com/cloud/learn/random-forest.

(Zhao et al., 2021). Carlucci et al. (2018) state that despite promoting the uptake of knowledge-based models, especially adaptive comfort models by practitioners and designers, full exploitation of these models is impossible due to uncertainties related to their application.

On the contrary, data-driven models are flexible and utilize new advanced statistical tools and software (Feng et al., 2022; Park & Nagy, 2018). These models provide and facilitate using big data and simulating different and various situations in the thermal comfort analysis for researchers. This means that the data can be analyzed simultaneously in different and diverse conditions with several statistical methods, and a better comparison of the results can be obtained (Zhao et al., 2014, 2021). In fact, they are established based on big data, machine learning and deep learning algorithms, and neural network and provide high matching of input and output for assessing thermal comfort. Under this circumstance, the prediction accuracy is improved, and the possible errors are reduced (Feng et al., 2022; Zhao et al., 2021). As stated by Zhao et al. (2021) "data-driven models can make accurate and efficient prediction of individual thermal comfort, which will also make the thermal comfort model more practical and have more life-oriented applications" (p. 31).

Overall, compared to the inflexibility, relatively limited amount of data, time-consuming process, and the use of relatively old methods in knowledge-based models, data-driven models are flexible, use new and various methods and big data, and have high efficiency in complex conditions. All these conditions have caused researchers to benefit more from data-driven models in studies related to thermal comfort.

## 5 Conclusions

Considering the recent transformations of urbanization and the increasing trend of climate change in cities around the world, the issues of urban heat islands and moving toward cool cities and having thermal comfort are essential for urban dwellers. To reach and assess thermal comfort in cities, numerous models and assessment frameworks have been accomplished. According to the literature, there are two major classifications for describing thermal comfort assessment frameworks and models. They are knowledge-based models and data-driven models.

Knowledge-based models and tools are known as traditional methods that have gained their ground among scholars since 1970. These kinds of thermal comfort models obtain their data through both laboratory and field studies. They are divided into heat balance models and adaptive models. Adaptive models and standards have played a pivotal role in transformations and considerable development of thermal comfort models and assessment tools in the past three decades.

Since last decade and following massive transformations and advances in statistics and analytical tools, IoT and smart simulation algorithms based on deep and machine learning have been widely used for assessment of thermal comfort in cities. They are known as data-driven models, which use big data and simulate a variety of situations to analyze and explain an individual's thermal comfort. As we have shown in this study, data-driven models have some major advantages compared to knowledge-based models. These advantages are summarized as: the capability to use big data, the ability to achieve a high level of prediction, robustness to outliers, and the ability to deal withcomplex situations.

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