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A Systematic Approach to Optimizing Energy-Efficient Automated Systems with Learning Models for Thermal Comfort Control in Indoor Spaces

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Abstract: Energy-efficient automated systems for thermal comfort control in buildings is an emerging research area that has the potential to be considered through a combination of smart solutions. This research aims to explore and optimize energy-efficient automated systems with regard to thermal comfort parameters, energy use, workloads, and their operation for thermal comfort control in indoor spaces. In this research, a systematic approach is deployed, and building information modeling (BIM) software and energy optimization algorithms are applied at first to thermal comfort parameters, such as natural ventilation, to derive the contextual information and compute the building performance of an indoor environment with Internet of Things (IoT) technologies installed. The open-source dataset from the experiment environment is also applied in training and testing unique black box models, which are examined through the users' voting data acquired via the personal comfort systems (PCS), thus revealing the significance of Fanger's approach and the relationship between people and their surroundings in developing the learning models. The contextual information obtained via BIM simulations, the IoT-based data, and the building performance evaluations indicated the critical levels of energy use and the capacities of the thermal comfort control systems. Machine learning models were found to be significant in optimizing the operation of the automated systems, and deep learning models were momentous in understanding and predicting user activities and thermal comfort levels for well-being; this can optimize energy use in smart buildings.

Keywords: indoor air; thermal comfort; user occupation; artificial intelligence; machine learning; natural ventilation; building performance; building information modeling

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1. Introduction

Designing buildings with automated systems is emerging research; yet, further systematic approaches to the optimization of energy use and the deployment of the smart systems and learning models for thermal comfort control and well-being in indoor spaces are needed [1,2]. Smart systems and Internet of Things (IoT) technologies, which are used for energy-efficient buildings and environments, also have a rising impact on personal comfort systems (PCS) [3]. The seminal studies have investigated adjustable air-conditioning systems to meet the desired levels of thermal comfort and well-being with regard to user preferences [4–6]. Thermal comfort levels such as mean radiant temperature [4] have become significant in the exploration of the design and deployment of automated smart systems; this is especially the case with Fanger's approach, which applies the predicted mean votes of users [1]. Considering user preferences for thermal comfort and well-being also motivates this research to explore the systematic approaches and methods used in developing and improving the energy-efficient automated smart systems that are to be applied in indoor environments. Related articles also analyze the correlational changes in thermal comfort levels by controlling the automated heating, ventilation, and air conditioning (HVAC) systems through the use and levels of thermostats and fans [5], which are tested for different seasons [6].

In the control and regulation of the thermal comfort and well-being of users, a systematic approach is followed in this research in defining and optimizing the energy usage, power, workloads, and operation of the automated systems to be applied for ventilation, cooling, and heating in indoor environments. An open-source IoT-based dataset, including the voting of users acquired from the special care context in a residential building, is analyzed and processed in the experiments concerning the user occupation and predicted activities for thermal comfort and well-being. Therefore, this study aims to derive thermal comfort parameters, generate algorithms, and develop learning models in the optimization of smart systems and energy-efficient infrastructure that will be based on IoT data for thermal comfort and well-being in the contexts of designed indoor environments.

In configuring smart spaces and systems, digital simulations are crucial in the search for the technical possibilities and the limits of building performance evaluation and in the generation of contextual data and parameters for state-of-the-art smart systems for well-being and thermal comfort. In investigating the parameters for setting up energy-efficient IoT-based automation systems in smart buildings and environments, it also crucial for the streaming data to be integrated with the collaborative and common workspace platforms such as that of building information modeling (BIM) software. In this research, the critical parameters for thermal comfort and well-being are explored and investigated through BIM simulations, algorithms, and learning models using real-time IoT data from the conditioned experiment space.

Thus, the dataset from an experimental work was analyzed, where the IoT technologies were embedded within the specific physical configuration of the indoor space in an apartment flat in Ankara, Turkey, to achieve greater infection control during the pandemic for individuals who might suffer from COVID-19 or other ailments [3,7]. Additionally, real-time learning models were applied in that experimental work to produce big data about the categorized activities and the comfort levels of users after surveying the potential applications of sensors, IoT technologies, and learning models for healthcare and well-being [3]. The study was also significant in its integration of innovative research on real-time learning systems with indoor environments for monitoring and predicting thermal comfort levels and well-being. For instance, the concentration levels of CO_2 and the air quality are critical parameters, and their changes were observed through natural ventilation experiments [3]. In this research, these correlated factors are also analyzed, along with other thermal comfort parameters, user occupation patterns, and the voting of users.

This research proposes to explore and optimize the energy use, workloads, and operation of automated systems for thermal comfort control in indoor spaces. In that regard, the building performance of the indoor space is evaluated first, based on the existing dataset derived from the thermal comfort levels and optimal energy use for ventilation and air quality. BIM software is applied to simulate the experiment environment for heating and cooling to analyze the workloads in achieving thermal comfort levels. Similarly, energy optimization algorithms and models are explored, developed, and tested with regard to the inputs from natural ventilation experiments in optimizing the energy use for zero-energy building research to deploy minimum energy for air purification and ventilation as well as for the desired thermal comfort levels and well-being of users. The survey on the related literature and the outcomes of this research further showed that the learning models could improve the efficiency of smart systems in energy optimization. Thus, automated systems are proposed to achieve thermal comfort levels and to better meet the desired well-being of users by deploying black box learning models in indoor environments with smart technologies. Accordingly, the voting of users is examined by both including and excluding them from the dataset to observe the challenges in developing artificial intelligence (AI) models such as convolutional neural networks (CNN)s for automation systems.

In brief, this research is unique in comparison to that of the related literature and applies a systematic approach that deploys learning models to explore the optimal energy use and building performance of automated smart systems that are to be developed for thermal comfort and well-being in the context of indoor spaces. The research examines an open-source dataset that allows the evaluation of the facts about the building performance, natural ventilation, air quality, and user activities and the user voting acquired via PCS. The outcomes of this systematic approach also indicate that in deploying simulations and smart systems with learning models, it is crucial to derive and process the context-based data when optimizing the thermal comfort control for each specific condition. The simulation of the experiment area by BIM software allows the generation and evaluation of context-based information on building performance, power loads, and energy optimization parameters. The data from the environment were applied to develop algorithms and unique deep learning models for the operation of smart systems, and Fanger, as well as non-Fanger, approaches were examined in the optimization of the novel, lightweight, and efficient deep learning models for state-of-the-art automation systems. Briefly, the objectives and major contributions of the research can be highlighted as follows:

- BIM simulations and energy optimization algorithms are explored to provide context-based information about the energy use and capacities of the automated systems to be installed into the experiment environment.
- Machine learning models are applied in discovering the optimization of the operation of the automated systems for thermal comfort control in the context of indoor environments.
- Lightweight and efficient deep learning models are developed for understanding the user activity and thermal comfort levels in the context of the experiment environment, in which IoT-based smart systems for thermal comfort and well-being are installed.

This article proceeds as follows: in Section 2, the related works on thermal comfort control and well-being are surveyed with regard to the research on the building performance evaluation as well as natural and artificial ventilation, smart systems and buildings, and learning models. In Section 3, the article introduces the materials and methods of the systematic approach followed in this research. Section 4 presents the experiments and results that are followed in the order introduced in Section 3. Section 5 discusses the results and evaluates the facts with regard to the possible steps to be applied in developing and operating automated smart systems in indoor environments. Section 6 briefly concludes the research.

2. Related Works

The seminal articles have reviewed the literature and systems for thermal comfort control in buildings; they have also considered the occupation and well-being of users [1,2]. One of these articles proposes a combination of models, systems, and procedures for smart applications [1]. The research emphasizes that the predicted mean vote (PMV) is the main thermal comfort modeling approach in finding the correlation between the environmental parameters and the personal factors via the vote of occupants, in reference to Fanger's pioneer work in the 1970s [1].

Many articles also investigate zero-energy buildings, the building design, and its components with regard to thermal comfort parameters such as heating, cooling, natural and artificial ventilation, and air quality. For instance, Wei et al. used *CiteSpace* (5.8.R3 SE 64-bit) to discover the relevant literature, which was also categorized with respect to the different approaches to zero-energy building research [8]. Gassar et al. explore the performance optimization parameters and models during the design of buildings for energy-efficient heating, cooling, and lighting by surveying related articles and works in the literature [9]. In another seminal article, the façade performances of the buildings in Singapore were studied with regard to climate change by reporting the major factors, such as temperature, humidity, wind speed, corrosion, degradation, material use, and vegetation, which also influencing the building performance [10].

The seminal works also consider passive building design [11–13]. For instance, Eki-house is a solar house prototype for the Solar Decathlon Europe 2012 competition developed by examining the building design strategies for different seasons and with regard to the energy design optimization of a house in Madrid deploying photovoltaic systems [11].

Similarly, Lopez-Escamilla et al. conducted a study on a social housing prototype, which was first presented in the Solar Decathlon competition in 2015, by investigating the design of bioclimatic double skin in a tropical climate [12]. Santy et al. explored the standards for the design of a passive house, without using HVAC systems, by depending on the bioclimatic analyses of some regions in Indonesia [13].

Furthermore, the researchers have examined natural and artificial ventilation as significant thermal comfort parameters. For instance, the authors investigated the parameters that influence the optimization of energy use with regard to the specific atrium typology in buildings and divided the energy simulation periods in which the HVAC systems were applied [14]. The researchers have also explored using HVAC systems to meet thermal comfort levels in different seasons [5,6]. On the other hand, Abdullah et al. studied the performance of building components with regard to the design of windows for natural ventilation; they considered the analyzed parameters and evaluated their performance in relation to the environmental facts [15]. Similarly, window opening behavior (WOB) was inspected by Kim et al. in relation to environmental parameters of indoor and outdoor spaces; they also considered the occupant behavior and thermal comfort in "structural equation modeling" [16]. The paper argues that new human–technology relations should be followed in adopting advanced technologies and systems for successful energy-efficient design strategies [16]. In the experiments of that research, the collected data from the exterior and indoor spaces were processed with regard to temperature, CO_2 concentration, and solar radiation [16]. Monitoring the occupant behavior is also considered in the development of structural equation modeling with regard to WOB [16]. Window opening events were discretely evaluated, and the research concluded that occupant access to the systems can increase tenant satisfaction and reduce operational costs [16].

The air quality and air index values of indoor environments were also seen as equally significant in one of the recent articles, which considers the data on the air quality of indoor environments to develop learning models for health and well-being purposes [3]. In another research work, air conditioning design was studied by considering a building performance simulation of the air quality and thermal comfort of an indoor stepped hall [17]. The impact of the research on thermal comfort levels was explored by measuring the air velocity, temperature, and air change rate with the help of building modeling that simulated the airflow, temperature, and air velocity distribution in the different locations in that indoor space [17]. The user occupation patterns with the air index and gas sensor value (GSV) also provide substantial results for energy-dependent modeling in the performance evaluation of buildings and the development of IoT-based state-of-the-art HVAC systems [18,19].

There are also reviews on the related literature that evaluate the capabilities of BIM for managing the operation and maintenance of green buildings [20]. Many articles also review the smart systems and buildings with regard to digital twins and BIM in Industry 4.0 [21] and the use of neural networks to decrease errors in predicting the actual energy consumption rates in the building energy performance evaluation [22].

In another seminal research work, Lee et al. reviewed the major concepts of responsive architecture that can be evaluated within the scope of energy-efficient buildings and environments with smart systems [23]. Comprehensive surveys on smart building technologies, systems, and sensing technologies also aim to discover new approaches in human–building interactions with regard to energy use and occupation, as well as the features of buildings and components [2,14]. A deep survey was also made on the categorizing of the applied smart technologies in [2]; the work was similar to that in [24]. Correspondingly, Al-Obaidi et al. review the use of IoT technologies applied for energy-efficient buildings and cities with a comprehensive survey on the concepts of infrastructural development, models, technological potential, applications, and the challenges related to their use [25].

Sensor-based environments and IoT technologies in buildings have also increased considerably [24,26]. These technologies meet the requirements for special use and self-care [27,28], in addition to providing improvements in energy efficiency and crowdsourcing environmental data [24], which have led to an increase in the quality of smart homes [29].

They also have significant potential for smart decision making, which can be integrated into BIM platforms [30] in the monitoring of workflow and construction processes [31–33], as well as in building energy models, analyzing sensorial information [34], and energy management in smart house systems [35,36]. IoT and sensor-based technologies have also been employed for well-being and for the remote monitoring purposes of smart healthcare in buildings [24,26–29,37].

Occupant behavior and health in buildings are vital aspects that should be considered with the energy usage, well-being, and building performance evaluation [18,38–42]. There is also research on identifying the evaluation criteria of the smartness of buildings, which can be categorized into different groups with the use of scoring systems [43]. A seminal article also applied the voting system and the learning models together with data from the indoor working spaces of the Helios building with IoT-based sensors [44]. In assessing the votes, the mean and standard deviation were applied, in a similar manner to Fanger's approach [44]. Thus, predicting the complex user behavior and updating the existing dataset ubiquitously with regard to user activity remain developing research areas with higher potential. Architects continue to survey the demand for further design requirements and parameters that can be updated in real-time when considering user activities and thermal comfort levels [45,46]. Accordingly, Almusaed et al. inspected the smart building design concepts with regard to the rising impact of AI and digital twins [47]. In most recent applications, IoT technologies and AI have been used for real-time learning and monitoring [3].

The potential of smart systems was also discovered in related studies with overarching experiments using machine learning (ML) and real-time deep learning models [3]. In a comprehensive review article, the models were classified as white box, grey box, and black box models, such as machine learning models, artificial neural networks, and recurrent neural networks, which are deployed for predicting building energy usage [48]. In that research, the building envelope parameters, HVAC systems, and weather factors were surveyed accordingly [48]. Another survey was conducted on applying ML and AI models, as well those that do not apply black box models, in the estimation and prediction of thermal comfort in the classrooms of primary schools in Japan [49]. The research also conducted comprehensive analyses of the factors that define thermal comfort by considering the voting data from the occupants [49].

In another research work with a comprehensive review, the applications of machine learning and statistical models were analyzed in the evaluation of building energy performance and the prediction of energy-efficient retrofitting considerations [50]. In another study, machine learning models were applied in the generation of a design method to explore the optimal energy-saving residential form [51]. According to the research, machine learning models are used to compare and combine the results of energy optimization methods with regard to various performance indicators. These methods also aid in determining the best locations for energy-saving buildings [51]. In another related research work, machine learning models, such as Gaussian process regression (GPR), were applied in global sensitivity analyses for energy prediction and optimization by exploring the architectural typology of a courtyard house [52]. In another article, machine learning models were applied to predict building energy usage under different environmental conditions, with a greater concern for climate change and the difficulties in measuring its effects in different geographic regions and contexts [53].

Different studies also applied genetic algorithms, incorporated with neural networks, for green architecture by reviewing the studies in various research areas and different parts of buildings regarding energy usage and optimization in several countries [54]. Similarly, Fallah et al. applied artificial neural networks optimized with electrostatic discharge algorithms to calculate the parameters for evaluating the energy efficiency and thermal loads of residential buildings [55]. In another research work, artificial neural networks were applied in the prediction and analyses of the mean radiant temperature for the location of selected residential building in Sendai, Japan [56].

Accordingly, the systematic approaches are explored and deployed in our research through the surveyed thermal comfort parameters, BIM, algorithms, and learning models used in the improvement of the building performance evaluation, thermal comfort control, and well-being by the applied models and methods. The dataset from a unique experiment environment, in which IoT and smart sensor systems are applied, is processed by deploying the BIM software, energy-optimization algorithms, and step-by-step learning models that are proposed for use with state-of-the-art automation systems.

3. Materials and Methods

This article aims to derive a systematic approach to developing energy-efficient solutions for thermal comfort control and well-being in indoor spaces and to employ them in operating state-of-the-art systems. Thus, the research explores the thermal comfort parameters for the energy-efficient execution of the automated solutions by first considering the building performance and context-based data of indoor spaces. The thermal comfort parameters surveyed from the related literature that are to be explored in this research are briefly noted as follows:

- Temperature;
- Humidity;
- Air quality and CO_2 concentration;
- Airflow and ventilation;
- User occupation;
- User voting;
- Performance of the buildings and building components;
- The facts from indoor and exterior environments.

The study analyzes a dataset related to these parameters from the selected indoor experiment space and deploys the energy optimization algorithms as well as building performance evaluation models. The research also explores the performance and efficiency of "grey-box" and "black-box" learning models [48] and attempts to develop unique deep CNNs to increase the efficiency of smart systems deployment to predict the thermal comfort levels and well-being of users.

The open-source dataset used in acquiring the critical inputs about these parameters is based on the IoT cloud of the experiment environment, which has smart systems installed to acquire the user-rated well-being values with the help of personalized devices [3,7,57]. The experimental data of the observations were also processed and tested during the pandemic by the real-time learning models deployed to predict and monitor occupant behavior and well-being in the experiment environment [3].

In the parametrization of the state-of-the-art smart and automated systems for thermal comfort and well-being, the BIM simulations of this experiment environment were generated in this research using *Autodesk Revit Architecture 2023* and *Autodesk Insight* (for Revit 2023) software to evaluate the building performance and to calculate the energy use and workloads (Figures 1 and 2a). The components of the building were modeled, and their construction details and heat transfer coefficients were reported with the help of the BIM software *Autodesk Revit Architecture*, using Intel(R) Core(TM) i7-4700HQ CPU @ 2.40 GHz as the hardware resource with four cores and eight logical processors for computations, and NVIDIA GeForce 750 M as the Graphic Processing Unit (GPU) used in the simulations and renderings (Figures 1 and 2a, Table 1).

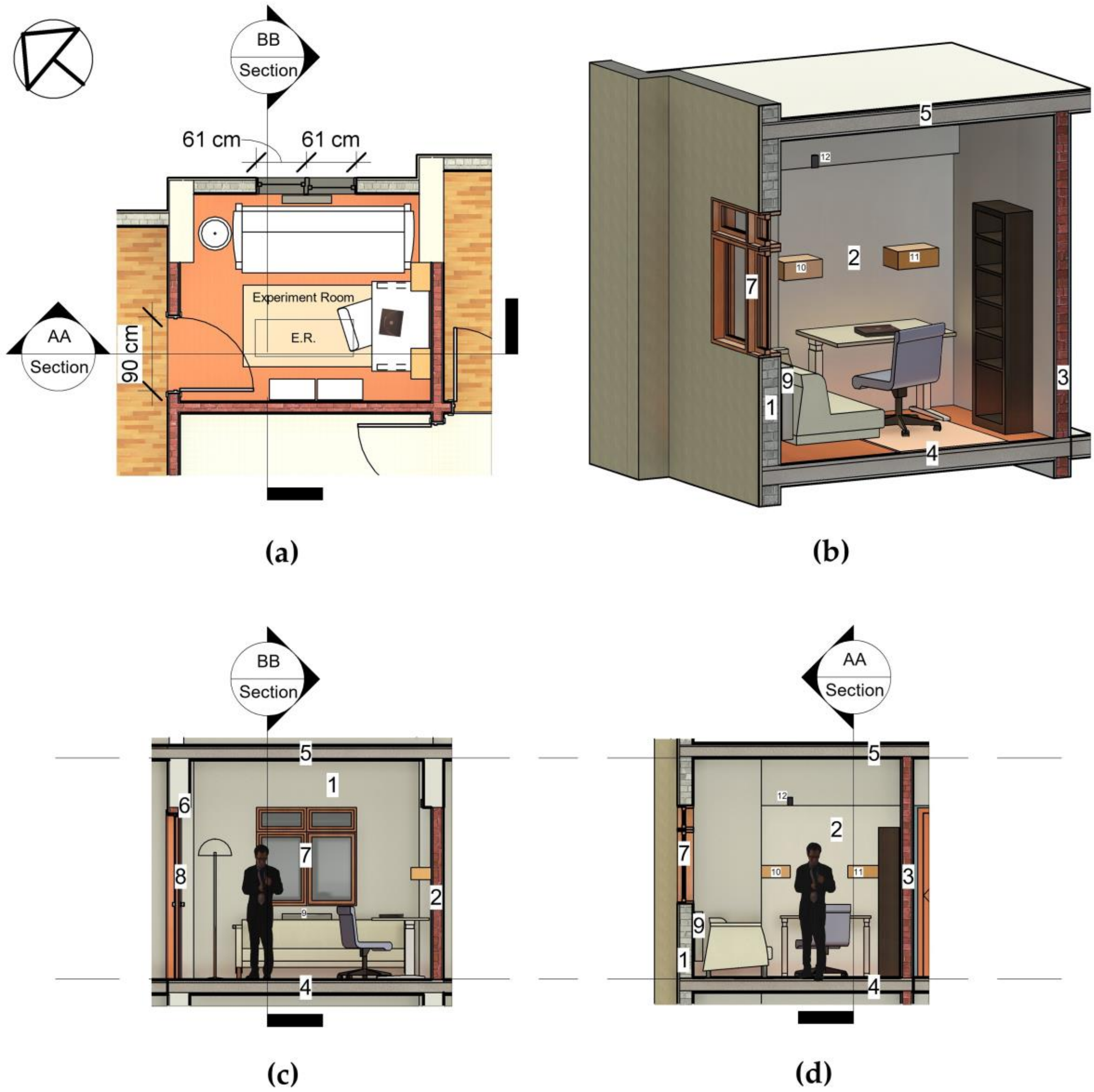

Figure 1. BIM simulation and the drawings of the experiment environment: (**a**) plan; (**b**) 3-dimensional drawing; (**c**) AA section; (**d**) BB section.

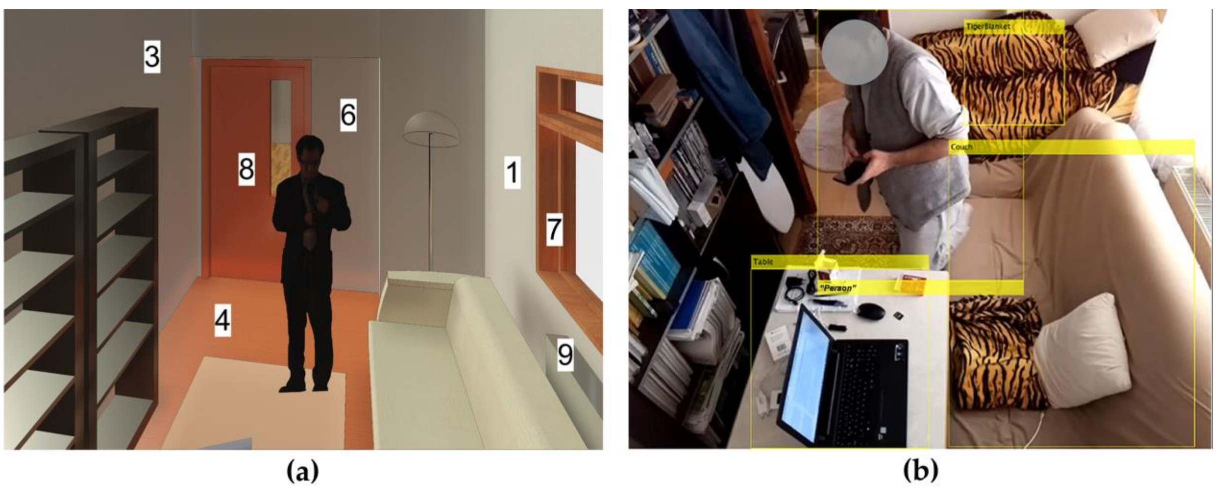

Figure 2. (**a**) Rendering from BIM simulation scene of the IoT-based camera; (**b**) faster R-CNN prediction applied in the experiment area [3].

Table 1. Building components and their features in the experiment area.

Component ID	Building Components	Dimensions		Heat Transfer Coefficient (W/(m^2·K))
		Area (sq·m)	Thickness (cm)	
1	Exterior wall	6.851	20	2.66
2	Interior wall	7.27	15	3.65
3	Interior wall	9.036	15	3.82
4	Floor	7.64	18	4.65
5	Ceiling	7.64	18	4.71
6	Interior wall	5	15	3.65
7	Exterior windows	1.45	1	3.69
8	Interior door	1.8	3.5	1.87
9	Radiator	0.366	10	-
10	Smart system	0.0875	15	-
11	Smart system	0.0875	15	-
12	IoT-based camera	-	-	-

Air index parameters that were highly related to thermal comfort levels were studied with regard to energy use and optimization through the derived models and energy optimization algorithms for smart systems that depended on the dataset from the experiment environment. The test dataset from the natural ventilation experiments was further processed to compare the results with the earlier observations and performances of the learning models with regard to the chosen parameters for thermal comfort.

Additionally, various machine learning and deep learning models were trained and tested, and their performances were compared to the training and test datasets to find the optimal learning models for the operation of smart systems based on the ventilation experiments. The dataset acquired from this experiment space also included the classified labels for user activities and thermal comfort levels. In that regard, novel and efficient deep CNNs were further developed, trained, and tested with these datasets in this research for state-of-the-art technologies which correlated with the thermal comfort and air quality levels, user activities, and user-defined voting values.

3.1. The Parameters for Models and Methods Applied in the Experiments

The challenges of the COVID-19 pandemic have inspired studies on the air quality and activity patterns of users who may require intensive care in indoor spaces [3,18,38]. The temperature, humidity, airflow, and air quality of indoor environments are absolutely vital for analyzing user occupation patterns and well-being [18,37,38]. Their parameterization for energy usage and behavior prediction through gaining knowledge about the user activity is also extremely important [18,37,38] and useful in developing the building performance evaluation models by applying BIM, energy optimization models, and algorithms and in the evaluation of advanced learning models using machine learning algorithms and even state-of-the-art deep learning models.

Since the 1970s, Fanger's approach has encouraged the processing of data about the well-being of users in spaces [1]. Thus, PMV has become the relevant method in modeling and assessing thermal comfort levels [1]. Similarly, related projects regarding thermal comfort and well-being have also considered the specific design of special care contexts for healthcare and infection control in buildings using innovative IoT technologies [3,7]. The developed projects provided big data about the activities and preferences of users, which can be processed for deciding on thermal comfort levels. Thus, the crowdsourced IoT data from indoor spaces were considered in the scope of user occupation patterns and thermal comfort parameters in this research, including the natural ventilation experiments for energy optimization methods and greater well-being at the residential scale.

3.2. The Experiment Environment and Its Simulation

During the COVID-19 pandemic, a room in a residential building in Ankara, Turkey, was designed as the experiment environment using IoT-based sensors and real-time learning models and aiming for the special care and well-being of the users [3,7]. The room that was used in the experiments has a 7.64 sq m floor area and a 2.7 m clear height from the floor to ceiling; thus, it is around 20.63 m^3. Accordingly, the BIM simulation of the experiment environment was modeled via *Autodesk Revit Architecture* to assess the building performance of the components and the thermal comfort conditions of this area (Figures 1 and 2a, Table 1).

3.2.1. Smart Systems Applied in the Experiment Environment

An IoT-based camera and smart systems (Figure 2b, Table 1) were installed in the experiment room and included ultrasonic sensors together with humidity and temperature sensors [3,7]. The smart systems also included an MQ-2 gas sensor to provide critical data regarding the air quality and the levels of particles, including carbon dioxide (CO_2) as well as butane (C_4H_{10}), liquefied petroleum gas (LPG), methane (CH_4), and smoke [3,7]. Additionally, a rating system was designed to be handled by the remote controller, enabling the users to vote on their well-being and comfort levels (Figure 3) [3,7]. Similarly, a web server based on the local area network (LAN) of this space was developed to collect the relative user data [3,7].

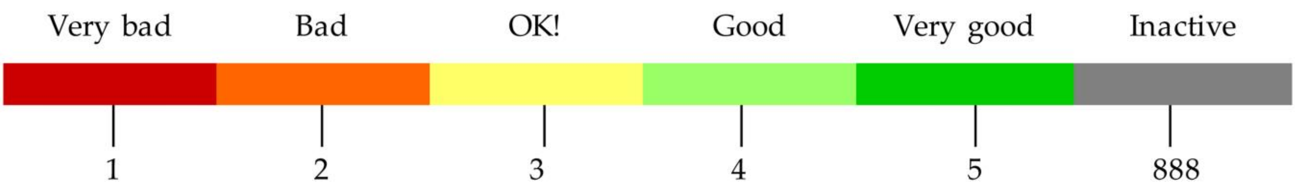

Figure 3. User-rated voting system for monitoring the well-being of the occupant.

Thus, the related parameters about the air quality and air index values, together with the recognized activities of the users and the user-rated data, were acquired as six different observations from different sensors simultaneously, generating the dataset, and fed to the IoT Cloud channel on *ThingSpeak*, the *MathWorks* IoT platform [57], via the system [3,7].

3.2.2. The Real-Time Learning System

The generated dataset from the sensors was acquired as the IoT data and used to develop a real-time learning system, including a CNN, which was trained, tested, and optimized for the monitoring and well-being of the users [3,7]. The developed real-time deep learning system predicted the labeled user occupation patterns and environmental data, including thermal comfort levels and critical behavior. It provided feedback about the user activity and critical circumstances for well-being in real-time [3]. The system also served to generate big data about the labeled predictions of user activities, which were applied as separate behavior labels; the system proved its efficiency with a 99.97% success rate in test accuracy and in real-time prediction and recognition of activity during the experiments [3]. Furthermore, faster R-CNN models were applied to recognize objects and people in the room using IoT-based imaging devices (Figure 2b) [3].

3.3. Dataset

The dataset, "IoT Channel for Real-Time Learning & Monitoring" [57], used in this research had 113.327 inputs, including sensor data and the predictions of the real-time learning system based on each sensor data item [3]. The last 100 inputs also served as open-source datasets on the public IoT channel [57]. The initially collected dataset from the IoT cloud included 2170 channel feeds; 1567 of these included raw data from the indoor environment. Six hundred and three inputs included six observation inputs about motion tracking, air quality, temperature, humidity, the well-being of users, and the correlated data about the user activities, as they were also used in training the real-time learning system in the related research [3]. The training dataset with six observations included ten categorized activities about the user occupation (1, 5, 6, 7, 9, 10) and thermal comfort levels in the indoor environment (2, 3, 4, 8), as illustrated in Table 2; these were recorded and predicted for thermal comfort and well-being.

Table 2. Examples from the dataset with ten classes.

Categorized Activities	Temperature (Celsius)	Humidity (Percent)	Gas Sensor Value (GSV)	User-Rated Well-Being	D1 (cm)	D2 (cm)
1. Visitor (or user) sits	24.6	58	502	888	41.1	57.2
	25.9	50	566	888	54.6	72.3
	25.9	50	566	888	66.27	84
	26.1	49	539	888	87.3	95
	26.1	49	536	888	87.3	98
2. Ventilation	25.4	36	481	888	76.59	78
	25.4	35	472	888	77.5	79
	25.4	36	468	888	77	80
	25.3	33	467	888	76.26	81
3. Cold, dry indoor air	25.2	33	472	888	77.02	81
	25.3	33	467	888	76.26	81
	20.6	32	469	888	76.46	81
	20.9	32	488	888	76.26	81
4. Hot, humid indoor air	26.1	49	533	888	78.31	88
	26.1	49	536	888	78.63	87
	29.8	51	502	888	69.6	86
	29.8	52	502	888	71.5	101.1
5. Going Out	26	50	542	5	88.8	124
	26	50	542	5	85.82	124
	26	50	542	5	86.25	131
	26	50	546	5	86.25	131
	24.6	48	542	5	102	149.5
	24.7	53	502	5	129	149
6. Entering In	26	48	541	888	98.43	134
	26	48	540	888	107.19	123
	27.1	50	502	888	127	143.3
	27.1	50	502	888	114.4	129.1
7. User moves into the bed	25.7	49	501	5	75.71	67
	25.8	49	424	4	78.26	69
	24.8	48	517	5	48.5	59.2
	25.3	49	502	4	23.1	33.2
8. Air quality and well-being correlation	25.8	50	556	2	75.61	102
	26	50	508	5	77.61	92
	24.5	48	555	5	75.3	94.3
	24.9	48	502	5	85.5	107.1
9. Two people move within the room	25.9	49	585	888	66.4	101
	25.9	49	578	888	66.4	103
10. User moves from the bed	25.9	49	425	4	77.83	68
	25.9	49	541	5	77.11	53
	24.5	48	552	5	34.1	42.2
	24.6	48	549	5	27.5	34.9

The dataset also included specific experiments on natural ventilation and observations on the changes in air index values and the air quality of the indoor environment. For example, changes in the room temperature, humidity, and GSV were observed by providing natural ventilation to the well-heated experiment room at noon on 18 November 2020 for 14 min 41 s, or 881 s, as shown in Figure 4, from moments A to B [3]. The average room temperature in the experiments was 25.9 °C, and the outside temperature in Ankara, Turkey, was 13.9 °C (Figure 4) [3]. There was 25–30 s period between the sensor observations, which were sent to the cloud and acquired in real-time, and 12–13 s for predicting each observation. Accordingly, the outcomes of the experiment provided a substantial basis for the evaluation of the energy-based modeling and building performance of the indoor environment. Thus, the observations on temperature, humidity, and GSV were also used as the training dataset in this research into developing machine learning and deep learning models based on these ventilation experiments (Figure 4).

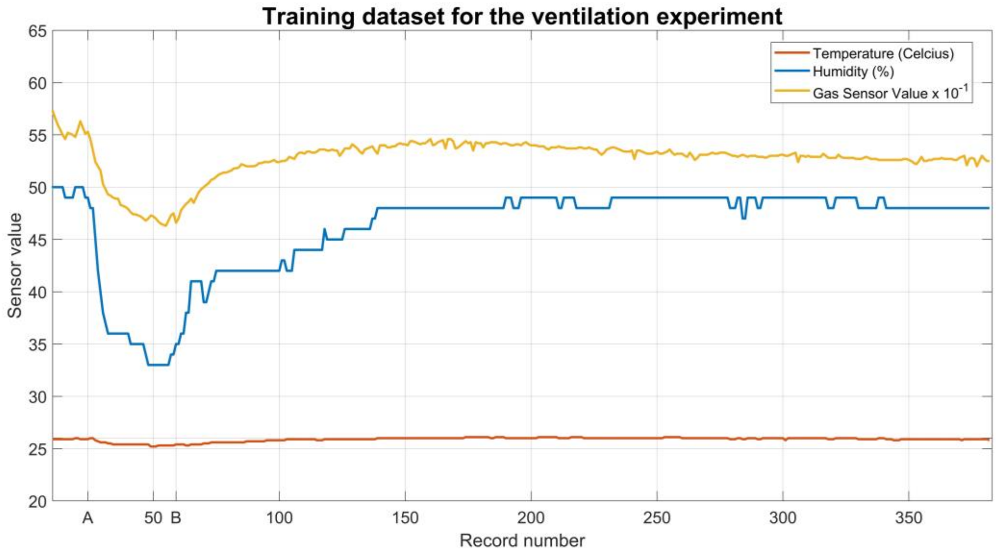

Figure 4. The training dataset for the ventilation experiment on November 18th [3,57].

3.4. Analyses of the Heat Losses and Power Loads to HVAC Systems

In the evaluation of the building performance and in finding the optimal energy use of state-of-the-art HVAC technologies, such as heaters, radiators, coolers, air conditioners, and air purifiers, building performance simulations were conducted first with the help of the BIM data of the experiment room. In the calculation of the heat losses and workloads that were observed in the simulations as well as in the real experiments, the heat coefficients of the building components in Table 1 were used, depending on the information from the BIM simulation. Thus, the power loads for the radiator or heater, to compensate for the heat losses from the exterior wall and windows in the experiment room at a given time, can be found by Equation (1).

$$H_{load} = h \times A \times (T_{out} - T_{in}) = h \times A \times \Delta T(\mathrm{t}), \quad (1)$$

where h is the heat transfer coefficient, A is the area of the building component (Table 1), and ΔT(t) is the temperature difference between the exterior (T_{out}) and indoor zones (T_{in}).

3.5. Algorithms for Optimizing the Energy Use of the Automated Thermal Comfort Systems for Ventilation

Given that the research investigated the optimization of energy use in buildings with automated systems, thermal comfort parameters such as natural ventilation were explored together with the contextual information from the experiment environment in deciding the sizing and capacities of the systems to be applied in the contexts of indoor spaces. This section aims to derive algorithms for deciding on the balanced energy levels and energy loss in the experiment environment during the natural ventilation experiments. Thus, the heating loads for the automated systems were aimed to be computed by comparing the used energy with regard to the heating and cooling in the experiment environment. The outcomes of the algorithms were assumed to derive critical energy levels and sensor values for automated systems. Thus, it was also significant to consider the values from the BIM simulations and the modeling in developing the algorithms and computing the building performance by learning the context-based data from the indoor environment to decide on the critical energy levels for the automated state-of-the-art smart systems.

The concern regarding the automated systems for thermal comfort control offers further potential for energy-efficient smart infrastructural developments. To this end, this study explored the design constraints and parameters for efficient automated systems based on energy optimization algorithms and optimized learning models developed with the datasets from the natural ventilation experiments together with the data provided by the BIM software *Autodesk Revit Architecture*.

Even though the flow of air by natural ventilation removes the number of particles with negative effects on the air quality and health, there is a compromise in the heat energy through the decrease in the temperature and humidity of the experiment room. Thus, novel algorithms were explored and applied to the training and test datasets to optimize the changes in GSV with regard to the energy change without directly changing and computing the room's temperature or the building components' heat constants. The energy loss or the amount of work to change GSV was correlated in this research to derive the optimal energy loss function that can be used for artificial systems to improve the air quality without decreasing temperature and heat energy.

In the development of the algorithms, thermal loads and temperature values in the experiment environment were considered balanced or in equilibrium at certain moments. Thus, Equation (2) was deployed for this analysis in the optimization of energy usage and energy loss for the conditioned areas in the buildings by natural ventilation and airflow, with decreasing GSV in the time interval from moments A to B.

$$\frac{\partial_{energy\ (per\ GSV)}}{\partial t} = \frac{H_{loss}\ |_B^A}{\frac{\partial_{GSV}\ |_B^A}{\partial t}} \tag{2}$$

The outcomes of Equation (2) can be defined with the units of '*Joule per GSV*'. Thus, the energy loss to decrease the gas level by artificial means can be optimized by Equation (2), which defines a gradient function for the optimal energy loss that is based on the change in GSV in the dataset. Using Equation (1), (A) denotes the infinitesimally thin and resisting surface area for the heat transfer, like a window opening for ventilation, and (t) is the duration of the natural ventilation experiment.

The heat loss from the wall is compensated for by heating the room with another energy source, the radiator (Figures 1 and 2, Table 1), as discussed, to keep the room temperature steady throughout the day. Thus, the heat loss during the ventilation of the room can be calculated as the direct heat transfer between the room and the exterior environment. Therefore, the heat loss during the ventilation experiments, from moments A to B (Figure 4), can be expressed in Equation (3).

$$H_{loss}\ |_B^A = h_{Air} \times A_{opening} \times \left|_B^A \begin{array}{c} ((T_{outA} - T_{inA})- \\ (T_{outB} - T_{inB})) \end{array}\right. \tag{3}$$

Thus, the changes in GSV can be calculated by Equation (4).

$$\frac{\partial_{GSV}\ |_B^A}{\partial t} = \nabla_{GSV} = \frac{|GSV_A - GSV_B|}{\Delta t\ |_B^A} \tag{4}$$

In this regard, it is significant to consider the outcomes of Equations (2)–(4) in defining and deciding the critical energy levels and optimizing the size, capacities, and energy that can be used by the smart systems in the regulation of the air quality and thermal comfort levels of indoor spaces.

3.6. Applying Machine Learning and Deep Learning Models on the Dataset

Machine learning and deep learning models have also been advanced for the recognition of human activity and thermal comfort levels; they are used in smart spaces, industrial applications, and energy-efficient smart infrastructure [7,24]. In this regard, machine learning and deep learning models were explored further in the ventilation experiments datasets to find the optimal learning models for the operation of energy-efficient and smart automated systems, such as air purifiers, by recognizing and predicting thermal comfort levels and well-being.

In the experiments of the related studies, the well-being values and GSV were also correlated with the air index values by exploring the real-time IoT data, which are considered critical for the user occupation [3]. This correlation is significant for building performance evaluation models trained through machine learning algorithms and artificial neural networks. Thus, the correlating changes in room temperature, humidity, and GSV were separately studied through ML and AI to develop the efficient and optimized learning models in this research.

The earlier related studies on the training dataset showed that the most efficient methods were applied through GPR algorithms [3]. Thus, GPR algorithms were also surveyed and applied in this research to the training as well as the new test datasets for the ventilation experiments. Accordingly, the kernel function for the exponential GPR model [58], which was applied in the experiments of this research, can be iterated in Equation (5).

$$k_e(x_n,\ x_m|\theta) = \sigma_f^2 \times exp\left(-\frac{\sqrt{(x_n - x_m)^T \times (x_n - x_m)}}{\sigma_l}\right) \tag{5}$$

In Equation (5), *theta* (θ) is the parametrization vector; x_n and x_m represent two different inputs in the training data as the observations of the measured sensor values to predict the following one with regard to the given parametrization vector. σ_l stands for the standard deviation between inputs, σ_f denotes the length scale, and T stands for the transpose operator.

The squared exponential kernel function is similarly expressed in Equation (6) [58].

$$k_{se}(x_n,\ x_m|\theta) = \sigma_f^2 \times exp\left(-\frac{1}{2}\frac{(x_n - x_m)^T \times (x_n - x_m)}{\sigma_l^2}\right) \tag{6}$$

Thus, the Matérn 5/2 GPR function can be defined as in Equation (7) [58].

$$k_{mtrn}(x_n,\ x_m|\theta) = \sigma_f^2 \times \left(1 + \frac{\sqrt{3\sqrt{(x_n - x_m)^T \times (x_n - x_m)}}}{\sigma_l}\right) \times \exp\left(-\frac{\sqrt{3\sqrt{(x_n - x_m)^T \times (x_n - x_m)}}}{\sigma_l}\right), \tag{7}$$

and the rational quadratic kernel function is expressed in Equation (8), where alpha (α) is the non-negative parameter of the covariance [58].

$$k_{rq}(x_n,\ x_m|\theta) = \sigma_f^2 \times \left(1 + \frac{\left|(x_n - x_m)^T \times (x_n - x_m)\right|}{2\,\alpha \times \sigma_l^2}\right),\ \alpha \geq 0 \tag{8}$$

In the experiments, the kernel functions and the standard deviation signals were calculated and assigned by MATLAB Regression Learner (in Statistics and Machine Learning Toolbox, Version 12.5, MATLAB R2023a) software. Thus, machine learning and deep learning models were employed using MATLAB Regression Learner (Table 3) and using the abovementioned equations on the training and test datasets.

Table 3. Learning models applied to the natural ventilation datasets.

Model Type	Number of Connected Layers	First Layer Size	Second Layer Size	Third Layer Size
GPR Squared Exponential	-	-	-	-
GPR Matérn 5/2	-	-	-	-
GPR Exponential	-	-	-	-
GPR Rational Quadratic	-	-	-	-
Neural Network—Narrow	1	10	-	-
Neural Network—Medium	1	25	-	-
Neural Network—Wide	1	100	-	-
Neural Network—Bilayered	2	10	10	-
Neural Network—Trilayered	3	10	10	10
Neural Network—Optimizable 1	1	10	-	-
Neural Network—Optimizable 2	3	10	10	10
Neural Network—Optimizable 3	3	10	10	10

In the experiments, GSV and the user activity were studied by further tracing the votes for well-being to find the optimal energy levels for the automated systems to be used for activating the ventilation and in deciding the grounding algorithms and learning models with regard to the standard deviation and mean values, as in Fanger's approach [48].

3.7. Development of Deeper and Efficient CNNs

Regarding the rising challenges in developing extremely small and efficient real-time learning models [59], the research developed novel artificial neural networks with increased depth and various kernel sizes of the CNN, which used the same dataset as that in related articles [3,7,57] (Table 4). Given that the dataset included tiny and compelling inputs about the user activities and thermal comfort levels, the kernel sizes of the neural networks needed to be adjusted to a very constrained dimension, and the models were supposed to be trained and to make fast predictions. Therefore, new deep learning models were developed to decrease the size and parameters of the CNN compared to the CNN applied in the real-time learning system in the related research [3] (Table 4). Increasing the depth and efficiency of the learning models was the research aim and the challenge of this research; the limits were overcome by adding convolution layers, increasing the channels, changing the kernel sizes of the convolution layers, and adding further global pooling layers, as illustrated in Table 4 and Figure 5. The developed neural networks were applied to the dataset with ten classes while only including the four related categories for the thermal comfort levels (2, 3, 4, and 8) in Table 1; this increased the difficulty of training the learning models and testing their performance compared to the earlier research [3]. The models are also compared to the non-Fanger and Fanger's approaches by excluding and including the user-rated well-being values in the dataset to understand the challenges and the potential of the user-defined values in developing the learning models for smart automation systems.

Table 4. Convolutional neural networks (CNNs), developed and applied to the dataset with ten classes.

Model	Number of Convolution Layers	Number of Layers	Number of Connections	Depth of Architectures	Kernel Sizes of Convolutions	Parameters	Model Size (kB)
CNN [3]	1	6	5	1	3×3	13,900	34.9
CNN-D3 (ours)	8	20	19	3	6×6 and 1×1	2500	15.9
CNN-D3_v2 (ours)	11	24	23	3	1×1 and 3×3	12,800	54.9

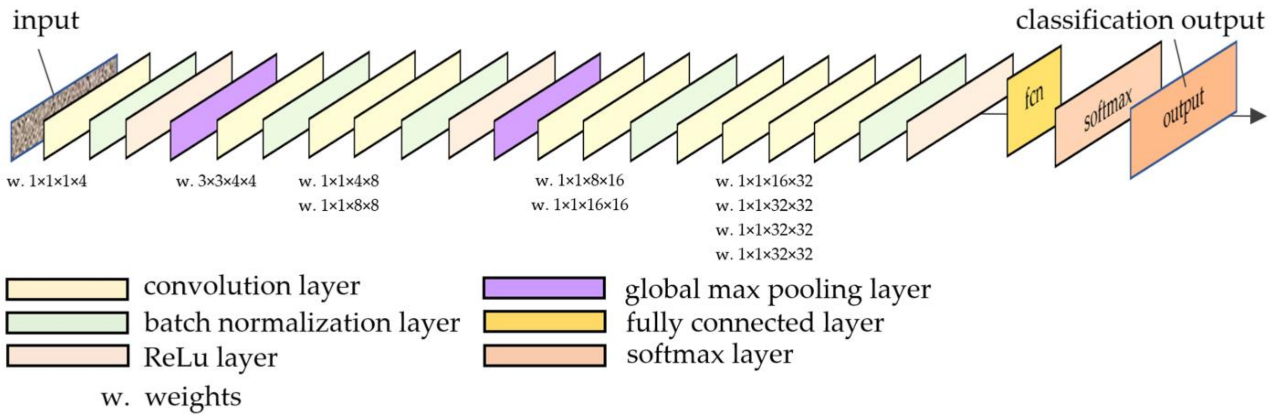

Figure 5. The network architecture of CNN-D3_v2.

4. Experiments and Results

Based on the chosen parameters, the experiments were conducted through BIM simulations, the developed algorithms, and learning models on the datasets in evaluating the building performance and thermal comfort levels with regard to the introduced systematic approach. The methods were applied in order to decide the optimization of the automated smart systems for thermal comfort control and well-being in indoor spaces and special care contexts.

4.1. Experiments and Results on the Heat Losses and Thermal Conductivity

In the experiments, BIM simulation and the insights for the heat losses and power loads were deployed first in order to have proper modeling parameters for the sizing of the HVAC systems. Depending on the digital model of the experiment room, developed via *Autodesk Revit Architecture*, *Autodesk Insight* software was applied to simulate the hottest and coolest days of one year and to calculate the peak loads for the cooling and heating of the location of the experiment area (Table 5).

Table 5. The calculated power loads and building performance analyses for thermal conductivity.

Experiment Conditions	Instant Sensible Load (W)	Delayed Sensible Load (W)	Power Load (W) (Heat Loss)
21 January at 00:15, outside: −8.0 °C, inside: 21.1 °C (Heating—BIM simulation)			
Glass—Conduction	−89	-	-
Wall	-	−102	-
21 July at 14:45, outside: 37.8 °C, inside: 23.9 °C (Cooling—BIM simulation)			
Glass—Conduction	12	-	-
Wall	-	132	-
18 November at 12:30, outside: 13.9 °C, inside: 25.9 °C (Ventilation—Real experiment)			
Glass—Conduction	-	-	−64.06
Wall	-	-	−218.68
14 March at 14:30, outside: 15.0 °C, inside: 26 °C (Ventilation—Real experiment)			
Glass—Conduction	-	-	−58.72
Wall	-	-	−200.46

A similar methodology was followed in the ventilation experiments to evaluate the building performance in real-world conditions (Table 5). Accordingly, the ventilation experiment, which was similar to the one on 18 November (Figure 4), was repeated on 14 March 2021. The experiments were conducted in the same room with an average room temperature of 26 °C and the outside temperature of 15 °C at noon, at 14:30 (Figure 6).

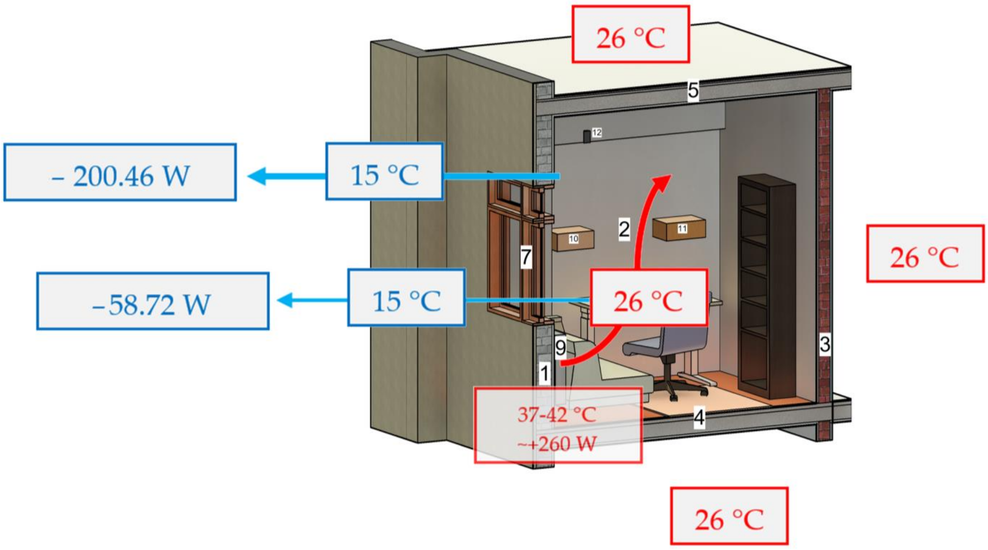

Figure 6. BIM visualization of the experiment room for simulating the building performance of thermal conductivity on 14 March.

In the calculations of the heat loads using Equation (1), it was decided that all the interior zones and other neighboring rooms would have the same temperature as the experiment room (Figure 6). Given that the heat coefficients for the building components were in Kelvin (K), the temperature values were converted into K during the calculations. As a result, the heating load for the radiator was found to be 259.18 Watts (W), at least, to compensate for the heat loss from the exterior wall, 200.46 W, and from the windows, 58.72 W, for this real experiment on 14 March (Table 5). Similarly, 282.74 W was needed for the radiator to compensate for the heat loss from the wall, 218.68 W, and the windows, 64.06 W, on 18 November.

The observations from the natural ventilation experiments on 14 March were also arranged as the test dataset, as illustrated in Figure 7, to examine the performance of the developed learning models. Thus, the observation values were also planned to derive the values of the minimal energy loss for a certain amount of betterment in the air quality.

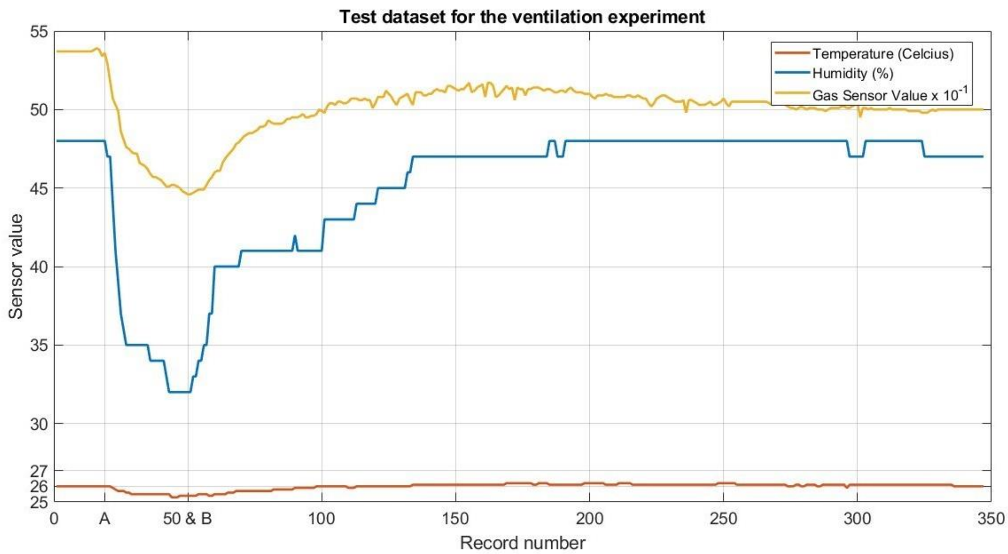

Figure 7. Test dataset for the ventilation experiments on 14 March.

4.2. Energy Optimization of the Automated HVAC Systems with Regard to the Energy Lost by the Natural Ventilation

In the calculation of the minimal energy loss for a certain amount of betterment in the air quality, the abovementioned Equations (2)–(4) were employed together on the given temperature and GSV acquired on 18 November and 14 March (Table 6). Accordingly, the temperature values given in Celsius were converted into K during the calculations (Table 6).

Table 6. Values from the natural ventilation experiments to calculate the energy loss.

Experiment Date	h_{air} (W/(m^2·K)) [60]	$A_{opening}$ (sq·m)	T_{outA} (K)	T_{outB} (K)	T_{inA} (K)	T_{inB} (K)	GSV_A	GSV_B	$\Delta t\|_B^A$·(s)
18 November [3]	25.5	0.48	287.05	287.05	299.05	298.45	557	463	881
14 March	25.5	0.48	288.15	288.15	299.15	298.55	536	446	828

Accordingly, the heating loads were both equal to −7.344 W (*Joule*/*s*) during the natural ventilation experiments. The energy used to improve the air quality in the experiments on 18 November was calculated as 6470.064 *Joule* and 68.831 *Joule per GSV*. Similarly, 6080.832 *Joule* of energy was used for the experiments on 14 March, resulting in 67.565 *Joule per GSV*, indicating the energy needed to decrease the GSV per unit.

4.3. Experiments on Machine Learning and Deep Learning Models

Given that the exact conditions were not purely linear and solvable by simpler equations, machine learning and deep learning models were further explored on the training and test datasets of the ventilation experiments (Figures 4 and 7). Thus, the aim was to optimize the operation of the smart systems, such as the air purifiers and conditioners, by deploying the learning models in controlling the thermal comfort and air quality and taking action before the needed energy and desired thermal comfort levels were exceeded. Accordingly, MATLAB Regression Learner software was run to deploy the learning models on the training and test datasets of the natural ventilation experiments that were executed when determining the best computation method for a precise calculation in simulating the thermal conductivity and change in thermal comfort levels. In all the experiments with the learning models, Intel(R) Core(TM) i7-4700HQ CPU @ 2.40 GHz was used as the hardware resource with four cores and eight logical processors. The use of a parallel pool was activated with four local parallel pool workers during the experiments. For the regression experiments, GSV or temperature was selected as the response value, and the remaining two observations, including humidity, were arranged as inputs. To prepare the training data, MATLAB Regression Learner was set through ten cross-validation folds; principal component analysis (PCA) was disabled, and the optimizer was not applicable.

Table 7 illustrates the results of the experiments on the selected machine learning and deep learning models applied to the partial training dataset, which only included the observation values from the sensors from moment A, when the natural ventilation was allowed, to moment B, when the natural ventilation was ended (Figure 4). In these experiments, the inputs were the temperature and humidity values to predict GSV as the response. Accordingly, Figure 8 illustrates the prediction results of the wide neural network on the partial training dataset.

The trained learning models were then tested through the test dataset (Figure 7, Table 7). Figure 9 illustrates the prediction results of the medium neural network, which was trained on the partial training dataset and tested on the partial test dataset and only included the observations from moments A to B (Figure 7).

Table 7. Training and test results of learning models on the partial training dataset for the ventilation experiment. Inputs: temperature and humidity. Response: gas sensor value (GSV).

Model Type	RMSE (Validation)	RMSE (Test)	Number of Iterations	Model Size (kB)	Training Time (s)	Prediction Speed (obs/s)
GPR Squared Exponential	0.477	1.648	-	9	19.113	410
GPR Matérn 5/2	0.446	1.802	-	9	18.398	660
GPR Exponential	0.445	2.004	-	9	17.857	850
GPR Rational Quadratic	0.459	1.846	-	9	17.237	720
Neural Network—Narrow	0.584	1.358	-	4	15.973	470
Neural Network—Medium	0.477	1.314	-	5	20.639	600
Neural Network—Wide	**0.441**	1.843	-	7	20.332	300
Neural Network—Bilayered	0.471	2.246	-	6	20.152	510
Neural Network—Trilayered	0.474	2.476	-	8	24.284	1200
Neural Network—Optimizable 1	2.503	1.793	30	4	33.325	880
Neural Network—Optimizable 2	0.602	**1.288**	30	76	250.21	640
Neural Network—Optimizable 3	0.612	1.405	100	4	406.3	720

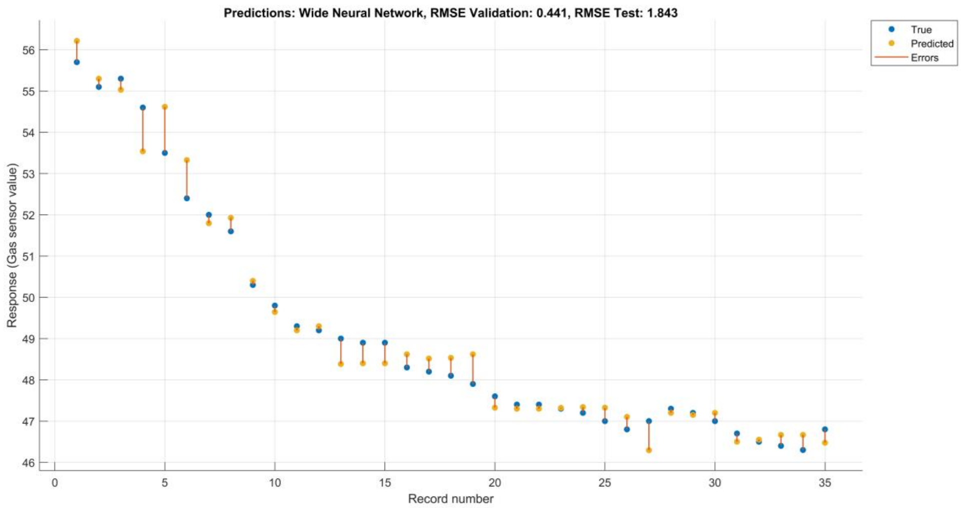

Figure 8. Prediction results of wide neural network on the partial training dataset for the ventilation experiment. Inputs: temperature and humidity. Response: GSV.

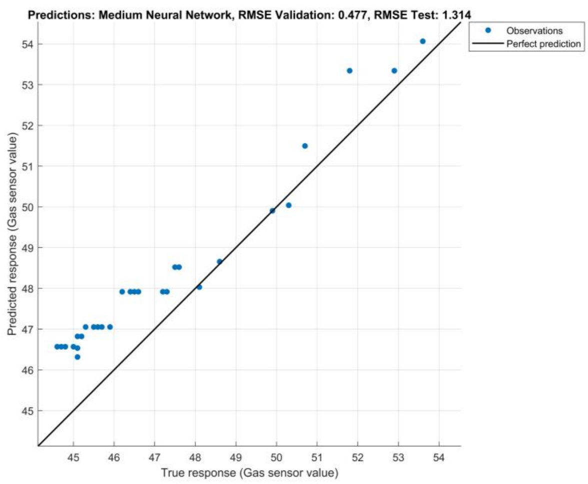

Figure 9. Prediction results of medium neural network on the partial test dataset for the ventilation experiment. Inputs: temperature and humidity. Response: GSV.

The developed learning models that were trained and tested on the selected datasets, and they were also utilized using randomly selected inputs to compare the prediction results with the ground truth (Table 8).

Table 8. Predicted GSV by the trained wide neural network.

Inputs		Output	Ground Truth
Temperature (°C)	**Humidity (Percent)**	**Predicted (GSV) ***	**Real (GSV)**
26	47	53.3	51.8
25.9	44	51.5	50.7
25.8	41	50.9	50.3
25.5	35	48.5	47.3
25.5	35	48.5	47.2

* error < 0.05.

Based on the same partial training dataset, all the selected learning models were also trained by setting the inputs as humidity and GSV in order to predict the temperature as the response (Table 9). The trained models were then tested on the partial dataset using the selected inputs. Figure 10 illustrates the prediction results of the trilayered neural network, tested on the partial test dataset for the ventilation experiment.

Table 9. Training and test results of learning models on the partial training dataset for the ventilation experiment. Inputs: humidity and GSV. Response: temperature.

Model Type	RMSE (Validation)	RMSE (Test)	Number of Iterations	Model Size (kB)	Training Time (s)	Prediction Speed (obs/s)
GPR Squared Exponential	0.056	0.119	-	9	3.9408	680
GPR Matérn 5/2	0.051	0.121	-	9	6.4251	670
GPR Exponential	0.060	0.137	-	9	5.7391	560
GPR Rational Quadratic	**0.052**	0.123	-	9	4.5206	760
Neural Network—Narrow	0.067	0.225	-	4	8.6182	760
Neural Network—Medium	0.067	0.236	-	5	9.5076	820
Neural Network—Wide	0.055	0.170	-	7	11.817	810
Neural Network—Bilayered	0.063	0.159	-	6	11.588	920
Neural Network—Trilayered	0.078	**0.112**	-	8	14.179	960
Neural Network—Optimizable 1	0.110	0.247	30	4	341.47	740
Neural Network—Optimizable 2	0.070	0.181	30	4	47.279	1500
Neural Network—Optimizable 3	0.591	0.652	100	112	185.44	1600

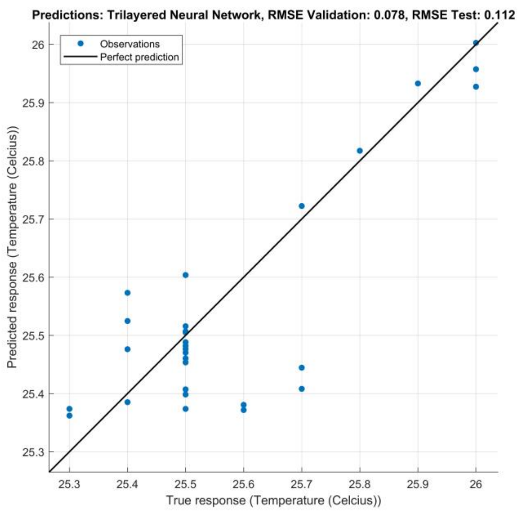

Figure 10. Prediction results of Trilayered Neural Network on the partial test dataset for the ventilation experiment. Inputs: humidity and GSV. Response: temperature.

All the selected learning models were also trained and tested on the whole training and test datasets (Figures 4 and 7) to observe the performances of the learning models in predicting the values for the ventilation experiments. Table 10 illustrates the results of the learning models on the training dataset by setting the inputs as temperature and humidity values and the response as GSV. Accordingly, Figure 11 illustrates the prediction results of the exponential GPR model on the selected training dataset.

Table 10. Training and test results of learning models on the training dataset for the ventilation experiment. Inputs: temperature and humidity. Response: GSV.

Model Type	RMSE (Validation)	RMSE (Test)	Number of Iterations	Model Size (kB)	Training Time (s)	Prediction Speed (obs/s)
GPR Squared Exponential	0.358	3.121	-	17	6.0042	4500
GPR Matérn 5/2	0.355	3.195	-	17	5.3396	5700
GPR Exponential	**0.346**	3.149	-	17	8.7419	6500
GPR Rational Quadratic	0.349	3.157	-	17	14.765	6400
Neural Network—Narrow	0.701	3.108	-	4	6.6549	7300
Neural Network—Medium	0.602	3.434	-	5	11.471	7500
Neural Network—Wide	0.390	3.401	-	7	17.75	9500
Neural Network—Bilayered	0.537	3.135	-	6	15.43	8200
Neural Network—Trilayered	0.431	3.312	-	8	19.729	13,000
Neural Network—Optimizable 1	0.973	**2.508**	30	4	45.322	14,000
Neural Network—Optimizable 2	0.734	2.863	30	4	236.92	14,000
Neural Network—Optimizable 3	0.703	2.858	100	11	599.37	17,000

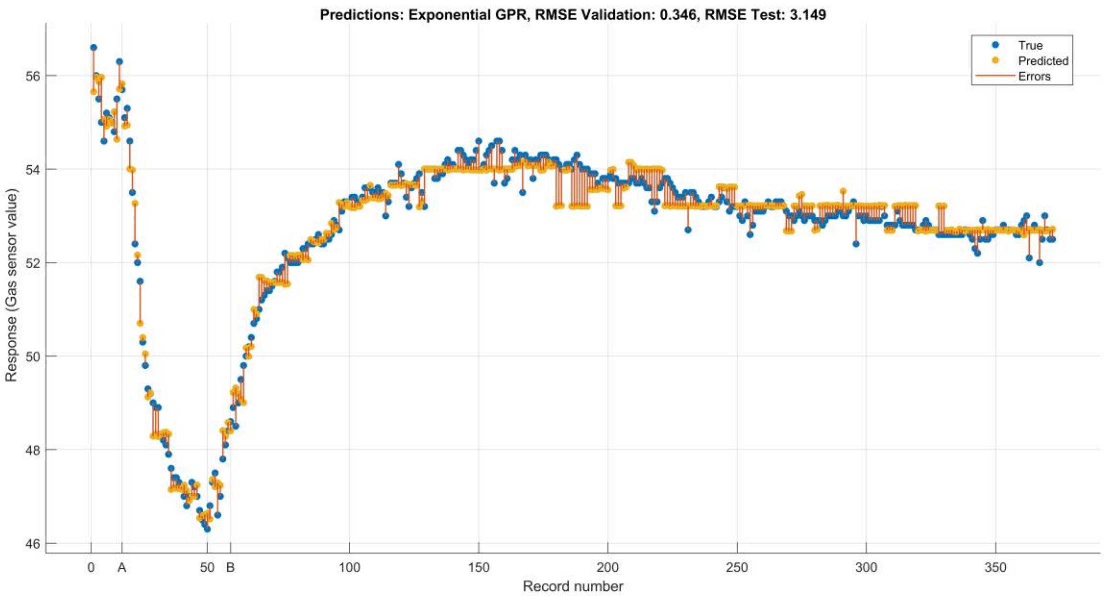

Figure 11. Prediction results of exponential GPR on the training dataset for the ventilation experiment. Inputs: Temperature and humidity. Response: GSV.

The whole training dataset was also prepared by setting the inputs as humidity and GSV in order to predict temperature as the response. The trained learning models were also tested on the test dataset with selected inputs and responses. Accordingly, Table 11 illustrates the training and test results of the learning models. The prediction results of the rational quadratic GPR on the training dataset are illustrated in Figure 12, and the prediction results of optimizable neural network 3 on the test dataset are illustrated in Figure 13.

Table 11. Training and test results of learning models on the training dataset for the ventilation experiment. Inputs: humidity and GSV. Response: temperature.

Model Type	RMSE (Validation)	RMSE (Test)	Number of Iterations	Model Size (kB)	Training Time (s)	Prediction Speed (obs/s)
GPR Squared Exponential	0.039	0.293	-	17	6.5397	8600
GPR Matérn 5/2	0.039	0.308	-	17	8.877	7500
GPR Exponential	0.039	0.335	-	17	9.6738	7900
GPR Rational Quadratic	**0.038**	0.324	-	17	14.116	7300
Neural Network—Narrow	0.061	0.251	-	4	12.466	8900
Neural Network—Medium	0.051	0.344	-	5	19.061	6200
Neural Network—Wide	0.041	0.244	-	7	23.841	11,000
Neural Network—Bilayered	0.052	0.437	-	6	21.347	10,000
Neural Network—Trilayered	0.073	0.389	-	8	26.61	11,000
Neural Network—Optimizable 1	0.301	0.393	30	4	43.231	15,000
Neural Network—Optimizable 2	0.070	0.246	30	13	88.246	19,000
Neural Network—Optimizable 3	0.099	**0.157**	100	4	360.81	17,000

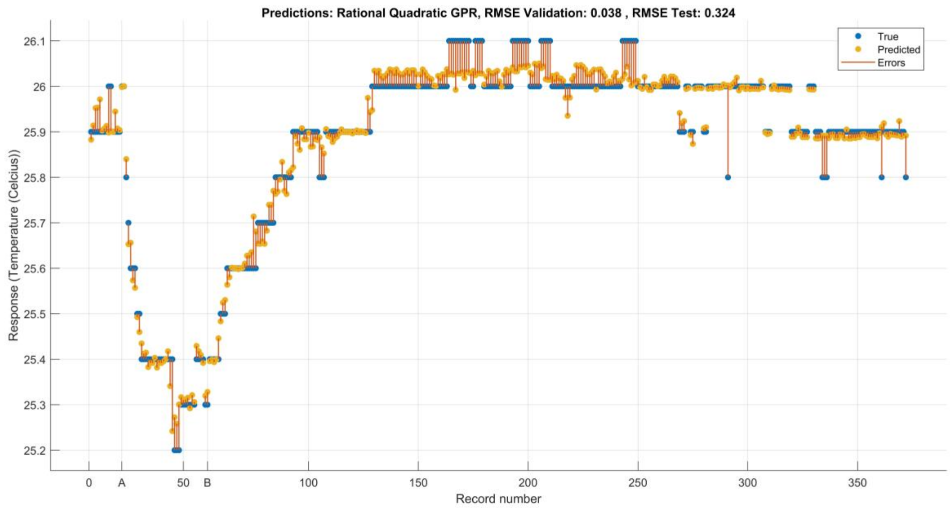

Figure 12. Prediction results of rational quadratic GPR on the training dataset for the ventilation experiment. Inputs: humidity and GSV. Response: temperature.

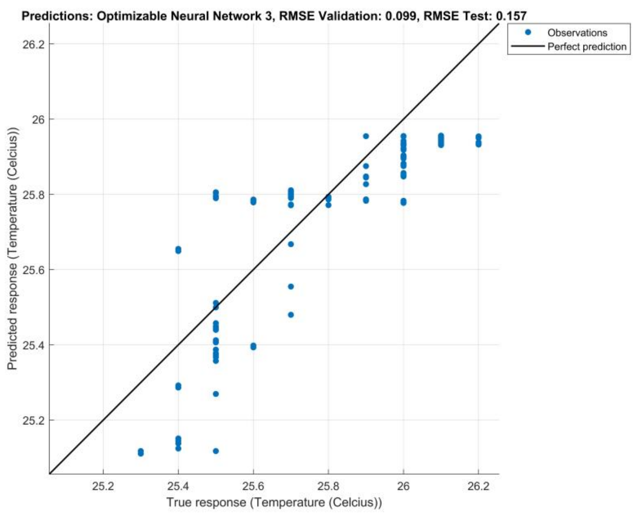

Figure 13. Prediction results of optimizable neural network on the test dataset for the ventilation experiment. Inputs: humidity and GSV. Response: temperature.

4.4. Experiments and Results of Deeper and Efficient CNNs on the Selected Datasets

The results of the natural ventilation experiments revealed that training precise learning models was another challenging task. Thus, the deep learning models were further developed by considering the complex datasets and inputs for smart systems and automated technologies using less energy to predict user activity and thermal comfort levels.

The developed deep learning models (Table 4), considering the challenges and needs related to efficient smart systems and the users' thermal comfort levels and well-being, were tested through the selected datasets. Table 12 illustrates the results of the developed neural networks applied to the dataset with four classes, excluding the user-rated well-being values. Table 13 illustrates the results of the same CNN models, which were also trained and tested to grasp the challenging role of Fanger's approach by including the user-rated well-being values in the training dataset with four classes, categorized by considering the user occupation and thermal comfort levels through six sensor observations for each input.

Table 12. Results of CNNs on the dataset with four selected classes without user-rated well-being values.

Models *	**Training Time (s)**	**Final Training Accuracy (Percent)**	**Validation Accuracy (Percent)**	**Test Accuracy (Percent)**	**Training Loss**	**Validation Loss**
CNN [3]	38	100	100	100	0.001300	0.001300
CNN-D3 (ours)	71	100	100	100	0.001500	0.001500
CNN-D3_v2 (ours)	88	100	100	100	**0.000485**	**0.000485**

* All models were trained for 5000 iterations with a 0.001 initial learning rate.

Table 13. Results of CNNs on the dataset with four selected classes, including the user-rated well-being values.

Models *	**Training Time (s)**	**Final Training Accuracy (Percent)**	**Validation Accuracy (Percent)**	**Test Accuracy (Percent)**	**Training Loss**	**Validation Loss**
CNN [3]	32	77.78	77.78	80	0.3967	0.3967
CNN-D3 (ours)	73	**100**	**100**	**100**	**0.0019**	**0.0019**
CNN-D3_v2 (ours)	88	**100**	**100**	**100**	**0.0301**	**0.0301**

* All models were trained for 5000 iterations with a 0.001 initial learning rate.

The results reveal that the accuracy of CNNs, used for the real-time learning system in the related studies [3,7], sharply decreased when including the user-rated voting values in the dataset (Tables 12 and 13). On the other hand, the CNNs that were developed specifically with regard to the size of the datasets in this research performed much better when compared to the earlier and shallower models, even if they were lightweight and smaller than 16 and 55 kB (Tables 4, 12 and 13).

5. Discussion

Automated systems in buildings are expected to be designed to be energy-efficient. The consideration of environmental facts in the development of energy optimization algorithms and computing technologies offers greater potential for automated systems. The energy-efficient automated systems with deep learning and real-time learning models, developed through the IoT data from the environments, are also gaining increasing attention. Regarding the related seminal works in the literature, this study aimed to deploy a systematic approach to discover the parameters and constraints in optimizing the energy usage of automated solutions for thermal comfort control. In this regard, building performance simulations, energy optimization algorithms, and grey box and black box learning models, such as ML and deep learning models, were explored for the control of thermal comfort and well-being. The chosen methods were conducted through BIM simulations in the evaluation of the building performance (Table 1, Figures 1 and 2), as well as for energy optimization in the heat loss and ventilation experiments via the equations and learning models developed through the IoT-based datasets, including the user-rated voting in accordance with Fanger's seminal approach (Figures 3, 4, 6 and 7, Table 2). Thus, the design of automated systems can be considered in relation to the parameters and the challenges of optimizing the cost of operations and energy usage, as well as the performance of the learning models in thermal comfort control (Tables 3 and 4).

Smart automation systems should consider the parameters for thermal comfort levels, such as temperature, humidity, and air quality. In this research, BIM software was used to derive context-based information about the building components and to simulate the thermal comfort levels with regard to the essential performance parameters. The building performance simulations (Figures 1 and 2, Table 1) for the evaluation of the energy loss and usage in the ventilation experiments (Figures 4 and 7) also made it possible to decide on the functional parameters and electricity features of energy-efficient air purifier and conditioner systems. Thus, based on the facts from the developed BIM simulations, using *Autodesk Revit Architecture* and *Autodesk Insight* software, calculations for the thermal conductivity of the building components and the peak loads of heating, cooling, and ventilation were made (Figures 1 and 2, Tables 1, 5 and 6). Thus, to keep the room temperature steady, the peak load to the HVAC system for cooling was calculated as 144 Won 21 July and 191 W for heating on 21 January, based on the BIM simulations and modeling (Table 5).

It can also be concluded from the experiments that 58.72 W of heat was calculated as being lost from the windows, and 200.46 W was calculated as the heat loss from the wall that the heater should compensate for in order to keep the room temperature constant during and after the ventilation experiments on 14 March (Table 5, Figure 6). Similarly, the experiments on 18 November revealed that the peak load to the radiator was calculated as 282.74 W; to compensate for the heat losses from the wall, it was as 218.68 W; and for the windows, it was as 64.06 W (Table 5). The attempt was made to further optimize the energy usage and the electricity features of the systems via Equations (2)–(4), without tackling the temperature and humidity changes in the experiment area. For instance, on 14 March, a state-of-the-art air purifier needed to have a lowest fan setting of at least 7.344 W (*Joule/s*) to take action instead of natural ventilation; thus, further energy loss from the openings and windows can be minimized by the system without decreasing the temperature of the indoor spaces (Table 6). If the purifier was allowed to apply 40 W for a maximum fan setting, then the system needed to run for at least 161.75 s for the conditions on 18 November and 152 s for the conditions on 14 March for the purification of the indoor air using the same energy as that lost during the experiments (Table 6).

The energy optimization algorithms were only expressed for the simpler solutions in deciding on the needed capacities of the smart systems, whereas the conditions were not purely linear in this research. Thus, the related real-time IoT data from the sensors on the thermal comfort levels were also processed through machine learning and deep learning models to decide on the optimization of the operation of the automated systems, which can be activated or stopped before the needed energy and desired values are exceeded. In other words, apart from the fixed algorithmic solutions, regression models such as machine learning and deep learning models were further explored in finding the optimal model to operate the automated systems (Table 3). A series of experiments was conducted by deploying MATLAB Regression Learner to develop machine learning and deep learning models and to predict the desired sensor values and states that could stimulate the systems to take action or to decrease and terminate the energy usage. Comparing the results of the root mean square error (RMSE) values of learning models revealed that the complex algorithms and deep learning models (Table 4) could be further evaluated for more sophisticated conditions and robust calculations in energy optimization (Tables 7–11).

For instance, in predicting the ventilation experiments, the wide neural network returned the best results for the partial training dataset (Figure 8), and the optimizable (2) neural network had the best performance for the partial test dataset once GSV was set as the response (Table 7). Thus, the wide neural network was also developed and tested to predict GSV by randomly selecting the given inputs (Table 8).

In the following experiments, however, the rational quadratic GPR returned the best RMSE result for the partial training dataset, and the trilayered neural network performed the best for the partial dataset once the temperature of the room was set as the response parameter (Figure 10, Table 9). In predicting the responses for a longer period, exponential GPR returned the best RMSE result for the training dataset (Figure 11), and the optimizable (1) neural network returned the best RMSE for the test dataset once GSV was set as the response (Table 10). By setting temperature as the response (Table 11), rational quadratic GPR returned the best RMSE for the training dataset (Figure 12), even though most of the neural networks also returned similar results. On the other hand, the test dataset allowed for a better examination of the efficiency of the trained networks, and the optimizable (3) neural network returned the best RMSE result by far for the test dataset (Figure 13, Table 11).

In brief, various machine learning and deep learning models yielded the best results for different datasets and response parameters. It can be concluded from these results that different learning models can be trained and optimized for each different action and parameter. On the other hand, it should be noted that most of the optimizable neural networks were more lightweight and returned more consistent results for the training datasets and better results in predicting the test datasets compared to the machine learning algorithms (Tables 7 and 9–11).

Better performance results for the unknown test datasets were much more significant for the real-time learning and real-world applications. Moreover, the prediction accuracies of the neural networks improved by increasing the depth and training iteration; they perform much better on complex test datasets with longer periods. They also had the potential to be improved by increasing the number of fully connected layers (Tables 10 and 11). In this regard, the novel deep neural networks were developed and further trained in this research for energy-efficient automated systems predicting thermal comfort levels and well-being (Table 4).

Regarding the user-rated well-being values and Fanger's approach, the attempt was made to advance the calculation methods by adopting the deep neural networks, such as CNN, in recognizing and correlating the thermal comfort levels and user activities in the datasets (Table 2, Figures 3, 4 and 7). On the other hand, it is observed from the results that developing learning models for ideal prediction is yet another challenge and a difficult research problem, as only a few learning models predicted the ideal responses in this research (Figures 9, 10 and 13).

Thus, the experiments were also conducted to develop new classification-based neural networks by increasing the depth of the learning models (Figure 5), and they were tested on the dataset with the classified user activities (Table 2). Accordingly, the new CNNs with different depths and the CNNs of the earlier related research [3] were used in the experiment on the training dataset by only including four classes of thermal comfort levels (2, 4, 5, 8 in Table 2). The networks were also trained with regard to both non-Fanger and Fanger's approaches by excluding and including the user-rated well-being votes in the dataset.

The results show that the earlier version of the CNN, used in the real-time learning system, needed more depth and accuracy in predicting the dataset with four classes and the user-rated well-being values (Tables 12 and 13). The experiments also revealed that involving the user-rated well-being values also increased the difficulty and challenges for the learning models. In this regard, it can be concluded that the consideration of Fanger's approach in developing deep learning models also needs novel and efficient solutions to be applied to energy-efficient automated systems; the attempt to investigate this was made in this research (Tables 4 and 13).

Limitations and Proposals of the Research

The limitations and future proposals of this work can be briefly discussed. There are still limited data about the building performance and natural ventilation experiments for the explored context. For instance, there are no data from other spaces as there is a lack of smart systems or corresponding IoT data. Thus, only hypothetical models could be developed with regard to the adjacent areas, with the help of BIM simulation; the heat coefficients of the building components of each area were simulated. On the other hand, the developed algorithms allowed the calculation of the optimization of energy use for natural ventilation without depending on the heat coefficients. Instead, machine learning and deep learning models were explored for the more complex conditions to be adapted to the internal dynamics and correlations among the indoor facts and usage patterns and were considered to be much more significant in this research.

Be that as it may, the usage of IoT systems can be encouraged and multiplied in various environments to calculate heat losses and energy efficiency in the surrounding areas. Additionally, the usage periods in this research were not divided into seasons as a limitation of the dataset once the related studies in the literature were considered [6]. Comprehensive datasets from the experiment environments with affordable new hardware resources and scalable computing technologies can be developed and trained for energy-efficient solutions and sustainable environments in different contexts for future work [24,61].

All in all, a systematic approach for defining the parameters and energy-efficient solutions for automated systems in thermal comfort control was explored and executed through the existing datasets in a special care context. The BIM simulations provided abundant resources about the context in evaluating the building energy performance, energy use, and optimization for heating, cooling, and ventilation of the experiment area. These provided the basis for the sizing and electrical features of the state-of-the-art automated systems to be applied in this context. The contextual data from the experiment area were also processed to develop energy-optimization algorithms, ML, and deep learning models in order to predict thermal comfort levels and classify activities so that the efficiency of the automated systems, by applying learning models, could be improved by decreasing the energy usage and the runtime needed to take action. In brief, from the experiments and results, a combination of different optimization methods, algorithms, and learning models can be proposed for developing and deploying energy-efficient state-of-the-art technologies to take action for thermal comfort control with regard to the specific context of indoor environments and the occupations of the users:

- BIM simulations should be encouraged in providing context-based information from the areas in which IoT-based smart systems are to be installed.
- Energy optimization algorithms should be explored and applied with regard to the thermal comfort parameters, such as air quality and context-based data, to be evaluated in the building performance, energy usage, and thermal conductivity when deciding on the optimal electricity features of the automated systems without changing other thermal comfort levels.
- Machine learning models that fit best when optimizing the energy use and operation of the automated systems should also be discovered and applied with regard to the thermal comfort parameters and contextual information.
- Finally, more complex, yet lightweight, deep learning models that are to be trained quickly and are good at accurate prediction should be explored and applied to smart systems that take action by recognizing the classified activities needed to control thermal comfort and well-being.

6. Conclusions

Smart systems and technologies in buildings offer well-being and thermal comfort control, and they have the potential to be developed systematically with regard to thermal comfort parameters, user preferences, and energy-efficient concerns. Based on the experiments conducted, it can be inferred that BIM simulations and IoT systems are highly effective in acquiring, generating, and processing comprehensive data from indoor spaces. Additionally, black box models were found to be highly useful for processing sensor data through advanced algorithms and learning models, thereby enabling effective thermal comfort control and enhancing overall well-being. These findings have significant implications for the development of advanced building management systems and can pave the way for more efficient and sustainable indoor environments in the future.

It is clear from the results that context-based information and the outcomes of computations of the building performances of indoor spaces, acquired with the help of BIM simulation and modeling, are absolutely crucial in the evaluation of the experiments related to thermal comfort parameters, such as natural ventilation, in order to develop zero-energy buildings as well as state-of-the-art and energy-efficient automated systems for thermal comfort control. Moreover, energy-optimization algorithms that are developed with the help of context-based information from BIM simulations and smart systems allow for a decision on the critical thermal comfort parameters, energy usage, and power loads for the capacities and electricity features of the automated systems. Nevertheless, the energy-optimization algorithms are only considered when the heating loads and thermal conditions are caught in a balance during the ventilation experiments, even though the phenomena of airflow and natural ventilation need to be considered through the changing states. In this regard, the development of machine learning and deep learning models is understood to be extremely significant in the optimization of the operation of energy-efficient automated systems that can predict the critical energy levels and user activity when the temperature and heating loads in the indoor spaces are changed and not in equilibrium, or once they cannot be resolved by simpler equations. The experiments on learning models showed that machine learning and deep learning models that fit best to the conditional changes might facilitate and optimize the operation of the automation systems efficiently with regard to the varying circumstances and might help to decide how and when these intelligent systems should take action. In this regard, the use of artificial intelligence models in the development of state-of-the-art automated systems is also seen as crucial in understanding user activity and thermal comfort levels in indoor spaces. Thus, user-defined ratings and Fanger's approach were considered in developing novel learning models to decide on the thermal comfort levels during the operation of smart systems, which were found to be absolutely crucial in recognizing and predicting the user activity and thermal comfort levels that can significantly decrease the energy used for thermal comfort control.

The systematic approaches applied in this research can enable the development of energy-efficient state-of-the-art smart systems for thermal comfort control and well-being. Consequently, thermal comfort levels in buildings can be optimized by the automated systems with regard to the contextual information about the building components and the evaluation of their performances and also by considering the user activities and preferences in indoor environments in designing energy-efficient buildings with smart systems.

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Abbreviations

AI	Artificial Intelligence
BIM	Building Information Modeling
°C	Celsius
CH_4	Methane
C_4H_{10}	Butane
cm	Centimeter
CNN	Convolutional Neural Network
CO_2	Carbon dioxide
GPR	Gaussian Process Regression
GPU	Graphic Processing Unit

GSV	Gas Sensor Value
HVAC	Heating, Ventilation, Air Conditioning
IoT	Internet of Things
K	Kelvin
kB	Kilobyte
LAN	Local Area Network
LPG	Liquefied Petroleum Gas
m	Meter
min	Minute
ML	Machine Learning
obs/s	Observations per second
PCA	Principal Component Analysis
PCS	Personal Comfort Systems
PMV	Predicted Mean Vote
R-CNN	Region-Based Convolutional Neural Network
RMSE	Root Mean Squared Error
s	Second
sq m	Square Meter
W	Watt
WOB	Window Opening Behavior

References

1. Grassi, B.; Piana, E.A.; Lezzi, A.M.; Pilotelli, M. A Review of Recent Literature on Systems and Methods for the Control of Thermal Comfort in Buildings. *Appl. Sci.* **2022**, *12*, 5473. [CrossRef]
2. Ji, W.; Yang, L.; Liu, Z.; Feng, S. A Systematic Review of Sensing Technology in Human-Building Interaction Research. *Buildings* **2023**, *13*, 691. [CrossRef]
3. Erişen, S. Real-Time Learning and Monitoring System in Fighting against SARS-CoV-2 in a Private Indoor Environment. *Sensors* **2022**, *22*, 7001. [CrossRef] [PubMed]
4. Xing, D.; Li, N. Numerical Prediction of Mean Radiant Temperature in Radiant Cooling Indoor Environments. *J. Therm. Sci.* **2022**, *31*, 359–369. [CrossRef]
5. He, Y.; Li, N.; Zhang, H.; Han, Y.; Lu, J.; Zhou, L. Air-conditioning use behaviors when elevated air movement is available. *Energy Build.* **2020**, *225*, 110370–110382. [CrossRef]
6. He, Y.; Li, N.; Lu, J.; Li, N.; Deng, Q.; Tan, C.; Yan, J. Meeting thermal needs of occupants in shared space with an adjustable thermostat and local heating in winter: An experimental study. *Energy Build.* **2021**, *236*, 110776–110790. [CrossRef]
7. Erişen, S. IoT-Based Real-Time updating multi-layered learning system applied for a special care context during COVID-19. *Cogent Eng.* **2022**, *9*, 2044588. [CrossRef]
8. Wei, J.; Li, J.; Zhao, J.; Wang, X. Hot Topics and Trends in Zero-Energy Building Research—A Bibliometrical Analysis Based on CiteSpace. *Buildings* **2023**, *13*, 479. [CrossRef]
9. Gassar, A.A.A.; Koo, C.; Kim, T.; Cha, S.H. Performance Optimization Studies on Heating, Cooling and Lighting Energy Systems of Buildings during the Design Stage: A Review. *Sustainability* **2021**, *13*, 9815. [CrossRef]
10. Chew, L.W.; Li, X.-X.; Chew, M.Y.L. Climate Change Projection and Its Impacts on Building Façades in Singapore. *Sustainability* **2023**, *15*, 3156. [CrossRef]
11. Irulegi, O.; Torres, L.; Serra, A.; Mendizabal, I.; Hernández, R. The Ekihouse: An energy self-sufficient house based on passive design strategies. *Energy Build.* **2014**, *83*, 57–69. [CrossRef]
12. Lopez-Escamilla, A.; Herrera-Limones, R.; Leon-Rodríguez, A.L. Evaluation of environmental comfort in a social housing prototype with bioclimatic double-skin in a tropical climate. *Build. Environ.* **2022**, *218*, 109119. [CrossRef]
13. Santy; Matsumoto, H.; Tsuzuki, K.; Susanti, L. Bioclimatic Analysis in Pre-Design Stage of Passive House in Indonesia. *Buildings* **2017**, *7*, 24. [CrossRef]
14. Ji, Y.; Xu, M.; Zhang, T.; He, Y. Intelligent Parametric Optimization of Building Atrium Design: A Case Study for a Sustainable and Comfortable Environment. *Sustainability* **2023**, *15*, 4362. [CrossRef]
15. Abdullah, H.K.; Alibaba, H.Z. A Performance-Based Window Design and Evaluation Model for Naturally Ventilated Offices. *Buildings* **2022**, *12*, 1141. [CrossRef]
16. Kim, A.; Wang, S.; Kim, J.-E.; Reed, D. Indoor/Outdoor Environmental Parameters and Window-Opening Behavior: A Structural Equation Modeling Analysis. *Buildings* **2019**, *9*, 94. [CrossRef]
17. Chen, R.; Liu, Y.-T.; Tsay, Y.-S. An Air Conditioning Design Strategy of the Stepped Hall Based on Building Performance Simulation. *Buildings* **2022**, *12*, 1269. [CrossRef]

18. Guerra-Santin, O.; Itard, L. Occupants' behaviour: Determinants and effects on residential heating consumption. *Build. Res. Inf.* **2010**, *38*, 318–338. [CrossRef]
19. Carpino, C.; Loukou, E.; Heiselberg, P.; Arcuri, N. Energy performance gap of a nearly zero energy building (nZEB) in Denmark: The influence of occupancy modelling. *Build. Res. Inf.* **2020**, *48*, 899–921. [CrossRef]
20. Cao, Y.; Kamaruzzaman, S.N.; Aziz, N.M. Building Information Modeling (BIM) Capabilities in the Operation and Maintenance Phase of Green Buildings: A Systematic Review. *Buildings* **2022**, *12*, 830. [CrossRef]
21. Hu, W.; Lim, K.Y.H.; Cai, Y. Digital Twin and Industry 4.0 Enablers in Building and Construction: A Survey. *Buildings* **2022**, *12*, 2004. [CrossRef]
22. Hammad, A.W. Minimising the Deviation between Predicted and Actual Building Performance via Use of Neural Networks and BIM. *Buildings* **2019**, *9*, 131. [CrossRef]
23. Lee, J.H.; Ostwald, M.J.; Kim, M.J. Characterizing Smart Environments as Interactive and Collective Platforms: A Review of the Key Behaviors of Responsive Architecture. *Sensors* **2021**, *21*, 3417. [CrossRef] [PubMed]
24. Erişen, S. Incremental transformation of spatial intelligence from smart systems to sensorial infrastructures. *Build. Res. Inf.* **2021**, *49*, 113–126. [CrossRef]
25. Al-Obaidi, K.M.; Hossain, M.; Alduais, N.A.M.; Al-Duais, H.S.; Omrany, H.; Ghaffarianhoseini, A. A Review of Using IoT for Energy Efficient Buildings and Cities: A Built Environment Perspective. *Energies* **2022**, *15*, 5991. [CrossRef]
26. Claypool, M.; Garcia, M.; Retsin, G.; Soler, V. Introduction: Architecture in the age of automation. In *Robotic Building. Architecture in the Age of Automation*; Claypool, M., Garcia, M., Retsin, G., Soler, V., Eds.; Detail Business Information GmbH: Munich, Germany, 2019; pp. 10–20.
27. Shang, C.; Chang, C.-Y.; Liu, J.; Zhao, S.; Roy, D. FIID: Feature-based implicit irregularity detection using unsupervised learning from IoT data for homecare of elderly. *IEEE Internet Things* **2020**, *7*, 10884–10896. [CrossRef]
28. Deen, M.J. Information and communications technologies for elderly ubiquitous healthcare in a smart home. *Pers. Ubiquitous Comput.* **2015**, *15*, 573–599. [CrossRef]
29. Kocaturk, T. Intelligent building paradigm and data-driven models of innovation. *Archit. Eng. Des. Manag.* **2019**, *15*, 311–312. [CrossRef]
30. Dave, B.; Buda, A.; Nurminen, A.; Främling, K. A framework for integrating BIM and IoT through open standards. *Autom. Constr.* **2018**, *95*, 35–45. [CrossRef]
31. Li, C.Z.; Xue, F.; Li, X.; Hong, J.; Shen, G.Q. An Internet of Things-enabled BIM platform for on-site assembly services in prefabricated construction. *Autom. Constr.* **2018**, *89*, 146–161. [CrossRef]
32. Louis, J.; Dunston, P.S. Integrating IoT into operational workflows for real-time and automated decision-making in repetitive construction operations. *Autom. Constr.* **2018**, *94*, 317–327. [CrossRef]
33. McGlinn, K.; Brennan, R.; Debruyne, C.; Meehan, A.; McNerney, L.; Clinton, E.; Kelly, P.; O'Sullivan, D. Publishing authoritative geospatial data to support interlinking of building information models. *Autom. Constr.* **2021**, *124*, 103534. [CrossRef]
34. Martín-Garín, A.; Millán-García, J.; Baïri, A.; Millán-Medel, J.; Sala-Lizarraga, J. Environmental monitoring system based on an Open Source Platform and the Internet of Things for a building energy retrofit. *Autom. Constr.* **2018**, *87*, 201–214. [CrossRef]
35. Pedrasa, M.A.A.; Spooner, T.D.; MacGill, I.F. Coordinated scheduling of residential distributed energy resources to optimize smart home energy services. *IEEE Trans Smart Grid* **2010**, *1*, 134–143. [CrossRef]
36. Al-Ali, A.; Zualkernan, I.A.; Rashid, M.; Gupta, R.; AliKarar, M. A smart home energy management system using IoT and Big Data analytics approach. *IEEE Trans. Consum. Electron.* **2017**, *63*, 426–434. [CrossRef]
37. Brookfield, K.; Fitzsimons, C.; Scott, I.; Mead, G.; Starr, J.; Thin, N.; Tinker, A.; Thompson, C.W. The home as enabler of more active lifestyles among older people. *Build. Res. Inf.* **2015**, *43*, 616–630. [CrossRef]
38. Roulet, C.-A.; Flourentzou, F.; Foradini, F.; Bluyssen, P.; Cox, C.; Aizlewood, C. Multicriteria analysis of health, comfort and energy efficiency in buildings. *Build. Res. Inf.* **2006**, *34*, 475–482. [CrossRef]
39. Eker, S.; Zimmermann, N.; Carnohan, S.; Davies, M. Participatory system dynamics modelling for housing, energy and wellbeing interactions. *Build. Res. Inf.* **2018**, *46*, 738–754. [CrossRef]
40. Sharpe, T. Mainstreaming building performance evaluation for the benefit of users. *Build. Res. Inf.* **2018**, *47*, 251–254. [CrossRef]
41. Tweed, C.; Zapata-Lancaster, G. Interdisciplinary perspectives on building thermal performance. *Build. Res. Inf.* **2018**, *46*, 552–565. [CrossRef]
42. Zhang, Y.; Tzortzopoulos, P.; Kagioglou, M. Healing built-environment effects on health outcomes: Environment-occupant-health framework. *Build. Res. Inf.* **2019**, *47*, 747–766. [CrossRef]
43. Gunatilaka, R.N.; Abdeen, F.N.; Sepasgozar, S.M.E. Developing a Scoring System to Evaluate the Level of Smartness in Commercial Buildings: A Case of Sri Lanka. *Buildings* **2021**, *11*, 644. [CrossRef]
44. Tardioli, G.; Filho, R.; Bernaud, P.; Ntimos, D. An Innovative Modelling Approach Based on Building Physics and Machine Learning for the Prediction of Indoor Thermal Comfort in an Office Building. *Buildings* **2022**, *12*, 475. [CrossRef]
45. Kim, T.W.; Kim, Y.; Cha, S.H.; Fischer, M. Automated updating of space design requirements connecting user activities and space types. *Autom. Constr.* **2015**, *50*, 102–110. [CrossRef]
46. Vischer, J. Towards a user-centred theory of the built environment. *Build. Res. Inf.* **2008**, *36*, 231–240. [CrossRef]
47. Almusaed, A.; Yitmen, I. Architectural Reply for Smart Building Design Concepts Based on Artificial Intelligence Simulation Models and Digital Twins. *Sustainability* **2023**, *15*, 4955. [CrossRef]

48. Yu, J.; Chang, W.-S.; Dong, Y. Building Energy Prediction Models and Related Uncertainties: A Review. *Buildings* **2022**, *12*, 1284. [CrossRef]
49. Lala, B.; Hagishima, A. A Review of Thermal Comfort in Primary Schools and Future Challenges in Machine Learning Based Prediction for Children. *Buildings* **2022**, *12*, 2007. [CrossRef]
50. Anastasiadou, M.; Santos, V.; Dias, M.S. Machine Learning Techniques Focusing on the Energy Performance of Buildings: A Dimensions and Methods Analysis. *Buildings* **2022**, *12*, 28. [CrossRef]
51. Guo, H.; Duan, D.; Yan, J.; Ding, K.; Xiang, F.; Peng, R. Machine Learning-Based Method for Detached Energy-Saving Residential Form Generation. *Buildings* **2022**, *12*, 1504. [CrossRef]
52. Guo, J.; Li, M.; Jin, Y.; Shi, C.; Wang, Z. Energy Prediction and Optimization Based on Sequential Global Sensitivity Analysis: The Case Study of Courtyard-Style Dwellings in Cold Regions of China. *Buildings* **2022**, *12*, 1132. [CrossRef]
53. Mohammadiziazi, R.; Bilec, M.M. Application of Machine Learning for Predicting Building Energy Use at Different Temporal and Spatial Resolution under Climate Change in USA. *Buildings* **2020**, *10*, 139. [CrossRef]
54. Elshafei, G.; Vilceková, S.; Zeleňáková, M.; Negm, A.M. An Extensive Study for aWide Utilization of Green Architecture Parameters in Built Environment Based on Genetic Schemes. *Buildings* **2021**, *11*, 507. [CrossRef]
55. Fallah, A.M.; Ghafourian, E.; Sichani, L.S.; Ghafourian, H.; Arandian, B.; Nehdi, M.L. Novel Neural Network Optimized by Electrostatic Discharge Algorithm for Modification of Buildings Energy Performance. *Sustainability* **2023**, *15*, 2884. [CrossRef]
56. Xie, Y.; Hu, W.; Zhou, X.; Yan, S.; Li, C. Artificial Neural Network Modeling for Predicting and Evaluating the Mean Radiant Temperature around Buildings on Hot Summer Days. *Buildings* **2022**, *12*, 513. [CrossRef]
57. IoT Channel for Real-Time Learning & Monitoring. Available online: https://thingspeak.com/channels/1229234 (accessed on 16 June 2023).
58. Zhang, N.; Xiong, J.; Zhong, J.; Leatham, K. Gaussian Process Regression Method for Classification for High-Dimensional Data with Limited Samples. In Proceedings of the 2018 Eighth International Conference on Information Science and Technology (ICIST), Cordoba, Granada, Seville, Spain, 30 June–6 July 2018.
59. Strickland, E. Andrew Ng, AI Minimalist: The Machine-Learning Pioneer Says Small is the New Big. *IEEE Spectr.* **2022**, *59*, 22–25. [CrossRef]
60. The Engineering Toolbox.com. Available online: https://www.theengineeringtoolbox.com/air-properties-viscosity-conductivity-heat-capacity-d_1509.html (accessed on 10 March 2021).
61. Emmitt, S. *Architectural Technology: Research & Practice*; Wiley-Blackwell: Chichester, UK, 2013.