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Review

The Role of Machine Learning and the Internet of Things in Smart Buildings for Energy Efficiency

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Abstract: Machine learning can be used to automate a wide range of tasks. Smart buildings, which use the Internet of Things (IoT) to connect building operations, enable activities, such as monitoring temperature, safety, and maintenance, for easier controlling via mobile devices and computers. Smart buildings are becoming core aspects in larger system integrations as the IoT is becoming increasingly widespread. The IoT plays an important role in smart buildings and provides facilities that improve human security by using effective technology-based life-saving strategies. This review highlights the role of IoT devices in smart buildings. The IoT devices platform and its components are highlighted in this review. Furthermore, this review provides security challenges regarding IoT and smart buildings. The main factors pertaining to smart buildings are described and the different methods of machine learning in combination with IoT technologies are also described to improve the effectiveness of smart buildings to make them energy efficient.

Keywords: machine learning; Internet of Things; smart buildings; challenges in smart buildings; IoT applications

Citation: Shah, S.F.A.; Iqbal, M.; Aziz, Z.; Rana, T.A.; Khalid, A.; Cheah, Y.-N.; Arif, M. The Role of Machine Learning and the Internet of Things in Smart Buildings for Energy Efficiency. *Appl. Sci.* **2022**, *12*, 7882. https://doi.org/10.3390/app12157882

Academic Editors: Luisa F. Cabeza and Salvatore Vasta

Received: 16 June 2022
Accepted: 11 July 2022
Published: 5 August 2022

1. Introduction

The Internet of Things has grown drastically to become one of the most significant inventions of the 21st century. The IoT consists of a collection of connected physical objects that are linked together by sensors, applications, and other technologies for data integration and exchange across devices and systems [1]. These devices connect using the Internet protocol (IP), which is the same technology that is used to recognize computers on the Internet and allows users to interact with one another via the Internet. The goal of the Internet of Things is to have devices that can self-report data and information regularly, enhancing efficiency and delivering essential information speedier than a system that is based on human input [2]. Smart buildings use connected technologies, devices, data analytics, and automation to control infrastructures, such as security, lighting, ventilation, heating, and air conditioning [3]. Smart heating, ventilation, and air conditioning (HVAC) controls can reduce HVAC usage, especially during peak energy demand periods, by limiting power consumption in unoccupied building zones, detecting and diagnosing issues, and limiting energy consumption.

Smart buildings offer great comfort and increase safety for building occupants, improve energy efficiency, and lower facility running costs via automation, sensors, and remote features. Smart buildings deploy IoT sensors to detect and analyze several factors in building parameters that can be used to improve buildings' environments and activities. Smart buildings, which use the Internet of Things (IoT) to connect building operations, and monitor building temperature, security, and maintenance, are easier to control via smartphones and tablets. Buildings are becoming smarter due to the IoT, which is capable of integrating thousands of sensors and enabling real-time data collecting and analysis, making them more efficient and user-friendly [4]. One of the most key technologies to consider when designing smart buildings is a fire alarm system. An IoT-based fire alarm system is essential to ensure the protection of people's lives and to reduce the amount of damage as much as possible. In [5] the author explained behaviors and energy consumption trends using the machine learning algorithm (also known as J48) and the Weka API and then classified it according to energy consumption. For home comfort, security, and energy-saving, HEMS-IoT, a smart energy management system that is based on the big data for the home and machine learning, was proposed. Machine learning and big data are crucial because they allow the system to track and classify energy usage efficiency, recognize user behavior patterns, and keep the buildings occupants comfortable. In [6] the authors start by exploring the numerous security issues that IoT applications face, second, to address current security concerns, the authors conducted a survey. Away for developing smart building applications that link the IoT with smart building web services is described in [7]. Ref. [8] demonstrate how the IoT can be applied to design smart buildings; the team employed a smartphone app and also open-platform servers. As a result, they devised a system for controlling the devices that included relays and a low-cost microcontroller Arduino board. An Android smartphone application is also included with the smart system, and users can interact with it.

Ref. [9] present an overview of the application of machine learning techniques for the achievement of a global implementation of the IoT. A discussion is performed on some of the essential strategic technologies and application fields that are supposed to drive Internet of Things research in future years. In [10] an intelligent controller for commercial and residential HVAC systems was developed by the authors using machine learning techniques. It is presented in [11] that IoT networks must make contextual and situational customized resources and managerial decisions regarding the allocation of resources difficulties. In comparison to conventional resource methods, such as optimization and heuristics-based methodologies, game theory, and cooperative methodologies, machine learning models can produce behaviors from the run-time context in response to changes in the climate, as well as reconfigure and retrain themselves. For IoT application environments that are large in scale, complicated, distributed, and continually changing, machine learning algorithms hold promise for independent resource analysis and decision making [12].

Many researchers have recently focused their studies on a variety of topics, such as smart buildings, sensor appliances, and building management systems, to raise the standard of living in smart buildings. The primary goal of the current research is to discover different aspects of IoT that affect smart buildings. Artificial intelligence combined with the IoT can bring a transformation of businesses and economic work. Artificial intelligence (AI) is used to create complicated algorithms to defend networks and systems, including IoT devices. With little or no human involvement, the IoT is powered by AI technologies that simulate intelligent behavior and assist in decision-making.

The current review highlights the relevant research dealing with the Internet of Things and machine learning technology and its involvement in smart buildings. Additionally, the challenges of the IoT technology in smart buildings as well as machine learning techniques and methodologies, and their characteristics and association with IoT, to improve the efficiency of smart buildings, are described in this review. Section 2 provides an overview of the relevant research on the role of IoT devices in smart buildings. The IoT platform and its components are also described in this section. Furthermore, the challenges in IoT-enabled smart buildings are described in the Section 2. In Section 3, we go through the most essential IoT-enabled factors in depth, which need AI integration to make smart buildings energy efficient. In Section 4 different machine learning algorithms are discussed in detail, which are very useful to make the smart building more efficient. Section 5 presents the conclusion.

2. The Role of IoT Devices in Smart Buildings

We investigated and analyzed prior material in the fields of machine learning and the IoT, and their role in smart buildings. The papers that made a substantial contribution to our research are included in the following paragraphs. In [13] it is stated that many smart devices, including sensing devices, cell phones, and other smart devices, are linked through the IoT. These devices can exchange information and interact with one another. The IoT is a technology that connects Internet-connected gadgets, and enables communication and interaction throughout the physical world, by extending the current Internet. In [11] according to the authors, agriculture, military, household appliances, and personal healthcare are just a few of the applications and services available through the Internet of Things. A new framework is presented by [14] for delivering and maintaining ubiquitous connectivity, real-time applications, and solutions for transport system requirements, based on machine learning and IoT capability.

An intelligent system was also created by [14] to enable real-time monitoring and operation of appliances in a smart house utilizing a low-cost IoT platform for the lab, which is a free and open-source Internet of Things platform. Data regarding the home, such as temperatures, light levels, and resident behaviors, are collected using installed sensors and cameras. If the data exceed the specified thresholds, the inhabitants of the home are notified via text messages/emails, allowing them to modify the environment by manipulating the gadgets. To detect aberrant situations, the system was programmed using artificial intelligence. With current developments, standard buildings can be changed into smart buildings at a reasonable cost by taking advantage of recent advances in machine learning (ML), sensor devices, large-scale data analytics, and the Internet of Things. Only minor infrastructure improvements are required [15]. A three-tier IoT-based extensible architecture for processing sensor data and identifying the most important clinical indicators to diagnose heart disease through the use of ROC analysis, the most important clinical markers that signal potential heart disease, are determined; this model is proposed by [16].

Smart lighting uses modern controls to eliminate over lighting by including day lighting and improved functions for detecting occupancy and dimming. Light level controllers for luminaries are rapidly evolving and gaining adoption throughout the industry. Step and continuous dimming control are rewarded in demand-response schemes [17]. Lighting management systems can be programmed to regulate smart lighting systems that are controlled wirelessly. Retrofitting is made easier with wireless controllers, while lighting management capabilities provide users with access to controls through web-based dashboards.

It is becoming increasingly common to install remote smart building monitoring systems to improve one's level of convenience and overall quality of life. To sense, transmit data, and exert power over the home's supplies, instruments, and surroundings, these systems require a network of intelligent Internet of Things sensors. For remote monitoring to be supported, the devices should have very low power consumption, and the network provider should cover a larger area. Figure 1 highlights the IoT-based systems in smart buildings.

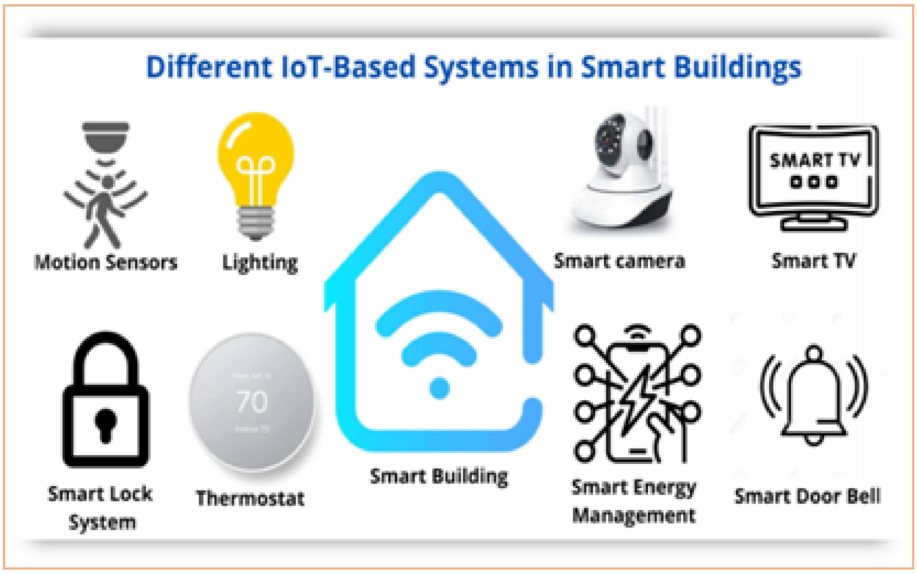

Figure 1. IoT-based systems in smart buildings.

2.1. The Platform and Components of IoT-Based Devices

The Internet of Things (IoT) is a network of interconnected devices that share, communicate, and use real-world data to deliver services to individuals, organizations, and society. The IoT is a technology that links physical devices to the Internet. The IoT platform connects devices and objects with built-in sensors, integrating data from huge devices and utilizing analytics to provide the most useful information [18]. IoT technologies have a variety of applications, such as detection systems, communications technologies, cloud technologies, and location technologies.

- **IoT sensors**:

The sensors save all of the information on the server and display it as required, for example, to draw energy consumption patterns of building workloads and minimize power usage [19]. This benefits customers and also improves the outside environment of the building. The main components of an effective IoT system are depicted in Figure 2.

- **IoT gateways**:

A gateway's principal function in telecommunications is to act as a link between different communications systems. With respect of communication options, interfaces, and protocols, these technologies can vary [20].

- **Cloud infrastructure**:

The importance of cloud infrastructure in IoT clouds for IoT services, such as vehicle-to-vehicle (V2V) connectivity, real-time health tracking, and commercial IoT, is higher than simple computing services [21]. The most popular endeavor is smart device scheduling. Smart device scheduling effectively controls device functionality for end-users and also saves money and energy. At the same time, it is guaranteed that the users' comfort is not endangered. In this case, the energy management system schedules the devices efficiently in response to the external data and user input [22].

- **Network infrastructure**:

In the coming years it is expected that cellular-based technologies that install low power wide area networks (LPWAN) would be important growth drivers in the Internet of Things connectivity of smart buildings. There are several different connectivity options available, such as LTE and LoRAWAN, which are cellular-based, as well as Wi-Fi-based options, that can be used to link Internet of Things devices to each other and the cloud.

These networks can function over a considerably greater distance and at much faster data speeds [23].

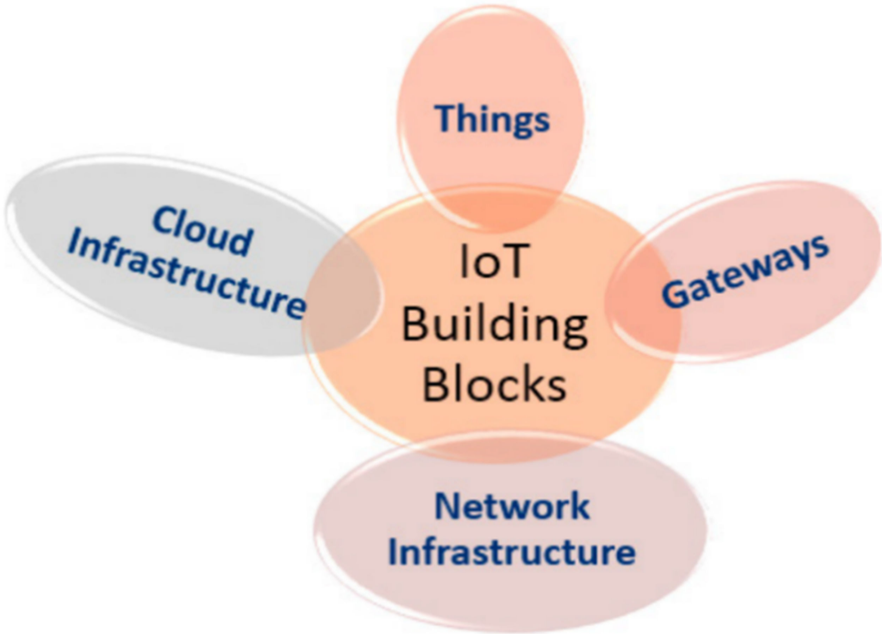

Figure 2. Basic components of an effective IoT system.

Smart buildings, which use the Internet of Things (IoT) to connect building operations, enable activities, such monitoring building temperature, safety, and maintenance, which are easier to control via mobile devices and computers. Building management systems, IoT sensors, artificial intelligence, and machine learning are some of the technologies that can be used in a smart building to regulate its operation.

- **Building management systems**:

Building management systems, often referred to as building automation systems, have an important part in energy management in commercial and industrial buildings [24]. Smart buildings provide better convenience for facility managers, increase safety and comfort for building occupants, and reduce facility running costs through automation, sensors, and remote features.

2.2. Challenges in IoT-Enabled Smart Buildings

A new industrial infrastructure built on cyber-physical technologies with embedded software that is linked to the real world via the Internet of Things is referred to as Industry 4.0 [25]. As part of the production process, this framework facilitates communication by incorporating machine learning (ML) as well as artificial intelligence (AI) [26]. Some societal uses of IoT include healthcare, home automation, entertainment, workplaces, and educational buildings. In smart buildings, for example, equipment and devices can be monitored and regulated to save energy and enhance tenant security and comfort. There are many challenges in smart buildings. Smart buildings can be made safer and much more secure via the application of careful planning, capable management, and sensible regulations [27]. Table 1 summarizes several challenges faced in smart buildings.

Table 1. Challenges in IoT-enabled smart buildings.

Sr. #	Challenges	Function and Role in IoT and Smart Buildings	Description	References
1	Big data analytics	In smart buildings, enormous amounts of data are generated every second and increase to crucial quantities.	The Internet of Things (IoT) generates vast quantities of constantly changing, high-resolution data that can be used for big data analytics. In the context.	[28]
2	Availability of services and networks	Intelligent buildings manage a complex network.	It is one of the big issues that intelligent buildings manage a complex network of connected functional entities across the building.	[29]
3	Cyber security concerns	Handle the increasing complexity of building operations.	Consumer IoT devices, such as IP cameras, are being integrated into building automation systems (BAS) to handle the increasing complexity of building operations. However, attack channels have grown, and attacks might potentially harm building residents, these changes raise significant cyber security issues.	[30]
4	System for controlling the energy use of a building	Building's energy management system which carries out critical energy management tasks.	It is necessary for the building's energy management system to carry out critical energy management tasks. It is a big challenge, namely, checking energy supply parameters, automated demand reaction, identifying energy consumption anomalies, and energy cost inspection.	[31]
5	Increase visibility	Visibility is required to detect misconfigurations.	With pervasive connectivity, visibility of resources entering and exiting the network is essential. Visibility is required to detect misconfigurations, errors, or anomalies that could result in a security flaw.	[32]
6	Manageability, connectivity, and programmability	Gives smart services to users while also maximizing resource utilization.	Applying IoT technologies to buildings can providesmart services to users while also maximizing resource utilization. There are various problems in designing apps for these two domains. Three significant issues are manageability, connectivity, and programmability.	[33]
7	Sensors range	Sensors are necessary in smart buildings to transfer data.	Limitations in the sensing range are expensive, especially for smart buildings.	[34]
8	Energy efficiency in smart buildings	It provides analytics that how energy is absorbed in smart buildings.	To achieve energy efficiency enhancement, the very first step is to identify the important parameters involved in the issue, this is followed by the formation of appropriate algorithms for processing the data and information that has been obtained based on the history and results of forecasting analytics of how energy is absorbed in smart buildings.	[35]

Table 1. *Cont.*

Sr. #	Challenges	Function and Role in IoT and Smart Buildings	Description	References
9	Data collection, processing, and storage	The system should be able to collect many kinds of information at the same time.	In IoT, data can be collected from the indoor/outdoor environments and building equipment structure. The system should be able to collect many kinds of information at the same time to ensure that correct data are obtained.	[36]
10	Recognizing and predicting resident behavior	In current buildings, current GPS systems do not offer the level of precision needed for navigation.	Understanding resident behavior is difficult, and finding them inside structures is a huge difficulty. Within buildings, current GPS systems do not offer the level of precision needed for navigation, and their primary purpose is to track geofences and other location-based applications.	[28]

3. Most Essential IoT-Enabled Factors Which Need AI Integration in Smart Buildings to Make Them Energy Efficient

People can feel safe and comfortable in smart buildings with the integration of AI and IoT. Data from a range of sensors are used by IoT-enabled smart buildings to reduce energy consumption and increase operational efficiency [37]. IoT devices installed in smart buildings help smart buildings to control their energy consumption [38]. The Internet of Things (IoT) detects and analyzes environmental impacts, such as humidity, temperature, and pressure, to reduce energy consumption in smart buildings. Smart buildings use IoT sensors to regulate and manage lighting by turning them on and off as needed. Emergency management and reaction can be improved with the usage of IoT technologies, resulting in considerably improved results. By connecting sensors and sending real-time information to managers, rescuers, and endangered people, the Internet of Things (IoT) has transformed our perspective regarding safety mechanisms [39]. The application of these technologies, as well as the utilization of recent advancements, has obvious benefits in smart building projects as shown in Figure 3. These use-cases can enhance structured smart functionalities and promote end-user comfort.

- **Building automation systems (BAS)**:

Building automation systems (BAS) are intelligent systems that aim to automate the management of multiple control functions and increase resources. Scalability issues include not just adding additional devices, but also managing them, as well as guaranteeing consistent and robust communication [40]. When comparing different IoT solutions, the amount of time it takes to install each sensor correlates directly to the entire cost [41]. BAS keep an eye on each utility's performance and potential problems and notify the building's managers if anything goes wrong.

- **IoT indoor localization**:

An IoT indoor localization algorithm that determines the position of things must be hybrid. A hybrid algorithm is a problem-solving algorithm that incorporates two or more different algorithms. Sensor-based indoor tracking and placement are frequently required in evolving IoT applications, and efficiency is considerably improved by detecting the nature of the nearby indoor environment [42].

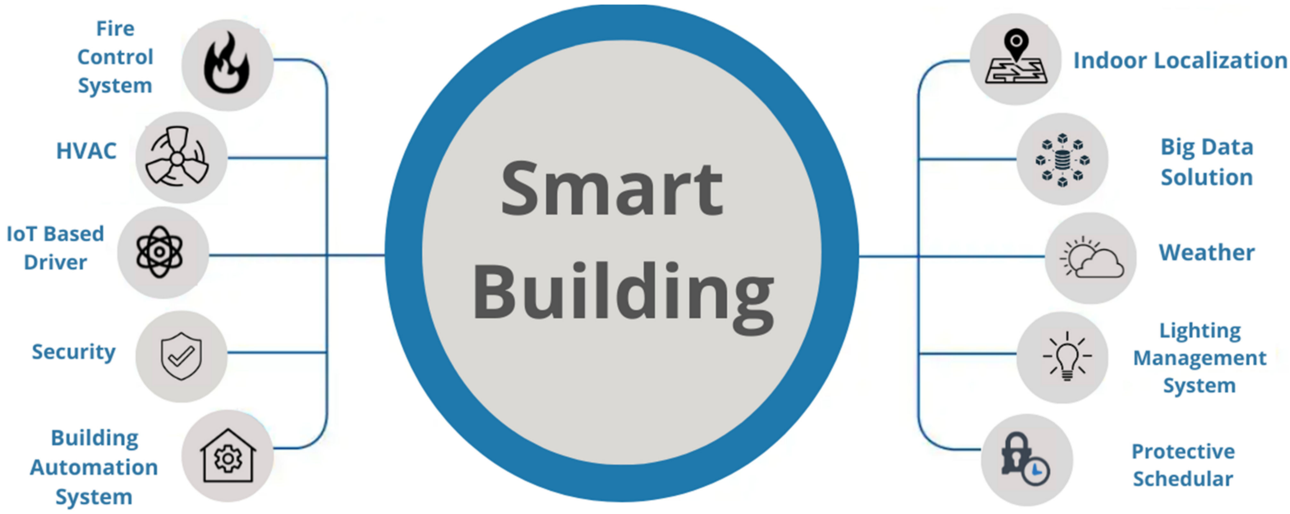

Figure 3. AI-based systems for smart buildings.

- **Lighting Management System**:

IoT-based lighting control is essential for smart buildings, to provide lighting control in buildings, and a range of vendor-specific approaches and technologies have been implemented. Visible light communications (VLC) solutions, which will become available in the next several years, are another breakthrough in Internet of Things (IoT) adoption [37]. Infrared transmission has been employed in systems (both outside and indoors the former is based on free-space optical communication systems). VLC is commonly assumed to include visible light produced by LEDs [43].

- **Protective Schedulers**:

Smart plug load controls are receptacles and power strips that automatically turn off power to equipment that can detect the major load, such as a computer, and adjust the operation of peripheral devices appropriately. Plug load schedules can be incorporated into lighting and buildings' management systems (BMS) for centralized control [44].

- **Large Amounts of Data**:

Different businesses face basic challenges in integrating and sharing large amounts of data. Traditional databases are merged with big data databases to generate meaningful results. Big data exchange among consumers, on the other hand, is seen as a major difficulty [45]. Furthermore, big data raises serious challenges, such as data privacy and security. The IoT with AI offers solutions to these problems, as IoT is being integrated into decentralized energy systems to enhance the environment by increasing energy efficiency and reducing waste [46].

- **Fire Control System**:

Only fire control systems that can deliver accurate and timely fire alarms that identify the specific location of the fire can be considered effective. Enhanced fire safety can be included in a smart building through the usage of app-based, cloud-based, and wirelessly connected system components. When integrated into a smart building, it is feasible to massively improve fire safety in a variety of ways, ranging from temperature sensors that can determine smoke alarms that can automatically activate in response to an emergency. In addition, fire protection and alarm systems have developed into highly advanced computer-based systems, which combine fire detection and disaster communication systems as an integral component of the entire operations [47].

- **Heating, Ventilation, and Air Conditioning (HVAC)**:

Intelligent heating, ventilation, and air conditioning make use of sensors that are integrated into the building automation system. These sensors compile information about the environment. HVAC equipment gives users the flexibility to fine-tune the heat, humidity, and airflow in several different zones. Early defect prediction and identification in heating, ventilation, and air conditioning (HVAC) systems have the potential to reduce the damage that can be caused to equipment, hence enhancing the dependability and safety of smart buildings [31].

- **Security**:

The development of so-called smart buildings has given rise to significant issues, including safety and the selection of an alarm verification service in order to be in compliance with regulations and produce an atmosphere that is significantly more comfortable, productive, and safe. The application of technology is required for the creation of user-centric smart buildings by organizations. These buildings must be able to keep people safe from physical threats, allow for a safe return to the workplace following a pandemic, and continue to operate normally in the event of Internet interruptions such as cyber-attacks [48].

- **Weather System**:

The term temperature refers to a physical quantity that indicates the relative levels of heat and cold; in the context of building control, it is a very important parameter. The ability of modern buildings to make temperature adjustments automatically has the potential to both make people's living and working environments more comfortable and save a significant amount of energy. The most typical being the wind that is cold in the summer and the wind that is warm in the winter. The primary purpose of the wind sensor is to determine the velocity of the wind within the ventilation ducts while also performing volumetric calculations on the air passing through it [49].

4. AI-Based Approaches in Smart Buildings

Smart building is a building that is equipped with automated control systems and makes use of information to increase the operation of the building as well as the level of comfort for its users. Artificial intelligence (AI) combined with buildings and IoT devices have the potential to improve inhabitant experience, operational efficiency, and space and asset utilization [50]. With the use of AI, building systems can now integrate excess data from IoT devices and occupant behavior independently to develop knowledge, optimize processes, and enhance environmental effectiveness.

IoT and AI platforms' learning capabilities allow for the creation of innovative new services for interacting with building occupants. Through automated operation processes, these technologies have the potential to decrease costs [51]. In smart buildings, energy consumption can be reduced by implementing AI technology for improved control, consistency, and automation. Different machine learning algorithms are compared and applied in smart buildings. In buildings' energy systems, AI-based techniques are being applied. Diesel generators (DGs), wind turbines (WTs), photovoltaic panels (PVs), thermal energy storage systems, electric energy storage systems, lighting systems, HVAC systems, window management systems, blind systems, electric vehicles (EVs), electric heaters (EWHs), gas boilers, and washing machines (WMs), are all examples of energy equipment used in smart buildings [52]. It is critical to schedule such equipment in a coordinated way because they have significant social, environmental, and economic implications [53].

4.1. Different Machine Learning Methods and Algorithms Which Can Be Integrated with IoT for Smart Buildings Energy Efficiency

The most used ML approaches that can be used with IoT to make smart buildings the most energy-efficient are detailed in the following subsections and highlighted in Figure 4.

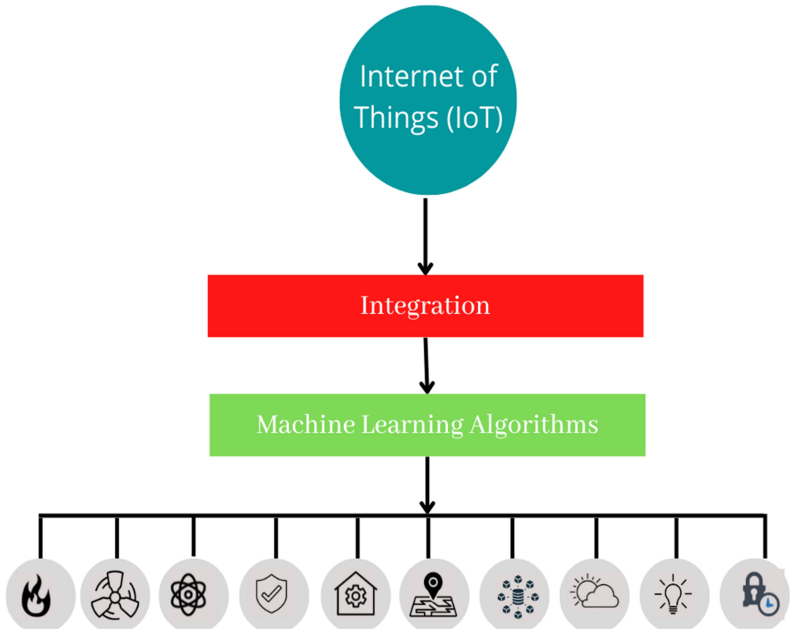

Figure 4. IoT integration with machine learning algorithms for smart building energy efficiency.

4.1.1. Artificial Neural Networks (ANNs)

Smart building strategies aim to reduce energy usage and improve client satisfaction and comfort. They are based on the use of intelligent sensors and software to analyze both external and indoor elements to provide comfortable monitoring, as well as safety devices for energy usage management. Artificial neural networks (ANNs) can learn the most important information trends in a multidimensional environment. ANNs have been used in the application of solar energy to estimate building heating needs [54]. ANNs are also being used in ventilation, solar radiation, air-conditioning technologies, power-generation modeling and control, load forecasting, and refrigerators. The random forest model was used to estimate energy consumption in residential structures, and the Bayesian regularized neural network (BRNN) approach is used to predict several building energy demands from an environment input data set [55]. The use of the ANN approach makes it possible to monitor in real-time, for example, an artificial neural network (ANN) can beused to estimate and forecast the temperature of a specific area in the building [56]. Many different scenarios can be simulated using the energy simulation software, Energy Plus, creating an abundance of data that can be used to train an ANN model and calculate energy usage [57].

Neural networks may not always produce the same results for the same input; neural network-based systems and solutions require extensive training [58]. The flow of input signal analysis to obtain energy estimation is contained in the signal. The outcome of the energy calculation from the input signal is widely used to obtain actions regarding hardware/software-based smart building functionalities. Mobile phones can also be used to acquire voice instructions to regulate the electrical appliances in intelligent buildings [59]. The user can use a mobile phone to enter voice commands, which are then shared with the building's energy management system via Bluetooth and Wi-Fi communication, and then analyzed to decode the necessary actions of electrical appliances.

4.1.2. Wavelet Neural Network

Building energy usage must be forecasted to achieve effective energy management and reduce environmental impacts. In variable air volume (VAV) technologies, a wavelet neural network is a fault detection solution for temperature, flow rate, and pressure sensors. Wavelet transforms and neural networks are combined in this method. It is possible to predict the reliance on renewable microgrid systems in time-series data using this method, which helps to reduce system costs while also maximizing battery charging time. The accuracy has been greatly enhanced by combining the two procedures [60].

A wavelet neural network approach was proposed by [61] for improving PID controller performance. PID stands for (proportional + integral + derivative) controller. [62] implemented neural network PID as the basis for a modern control system that is based on previous investigation. As it provides the closed-loop control system's predetermined value, the central control's brain is its control strategy management section. Therefore, an intelligent strategic control process is critical because it has the power of generating control logic; it is ideal for smart building technologies that are adaptive depending on the latest environmental parameters [63]. On/off, proportional (P), proportional + integral + derivative (PID), proportional/integral (PI), as well as control methods, are the most commonly used control techniques. The on/off control mode is frequently used in building lighting and shading systems. To monitor the set value, controllers using PI/PID models are widely utilized in the development of heating and ventilation systems. The self-learning and dynamic decoupled control characteristics of a neural network PID are excellent [64].

4.1.3. Deep Learning Algorithms

Deep learning approaches, such as unsupervised or semi-supervised extracting features, as well as hierarchical feature extraction, are some of the promising aspects of the field of deep learning algorithms. Recurrent neural networks (RNN), convolution neural networks (CNN), deep Boltzmann machine (DBM), stacked auto-encoders, and deep belief networks (DBN) are among the most often used deep learning (DL) techniques. Drop-out and convolutions are two approaches used by DL for models to learn quickly from large amounts of data. However, due to the orders of magnitude of parameters needed by the models, DL needs more data to learn than other algorithms [65]. Deep learning allows us to design next-generation smart sensors for sophisticated building automation with tremendous agility. We can instantly respond to new forms of data, adapt to new situations, and fully utilize computing capacity when they become accessible. Deep learning provides better performance over classical machine learning. DL allows achieving unprecedented levels of sensory and analytic intelligence using the most cost-effective and energy-efficient embedded processors [66].

4.1.4. Time Series Analysis

Time series forecasting is a very essential field of machine learning. Time series data sets often have high dimensionality. The elimination of dimensionality is one of the main goals of time series representations, the types of representation are classified as follows: non-data-adaptive depiction, model-based depiction, and data-adaptive depicting [67]. In smart buildings, [68] established a time series-based framework for deriving temporal principles from observable physical and instrumental activity. Using a combination of the fuzzy time series and universal harmonic search methods in conjunction with a support vector machine (SVM), [67] developed an electric load prediction model that can generate reliable prediction results. Data-driven methodologies for measuring building energy were evaluated by [69]. Their findings indicated that data-driven approaches include load predictions, energy pattern profiles, and retrofit options. The ANNs model was perhaps the most famous in a wide range of applications, from energy forecasting to retrofitting solutions [70]. SVM models were commonly used for large-scale building energy analyses because of their flexibility of training [71].

4.1.5. Regression

Finding a real-valued target function is the goal of a regression problem [72]. It describes the link between variables that are evaluated frequently using a degree of inaccuracy in the model's predictions [73]. Linear regression, regression analysis, and ordinary least squares regression are the most used regression algorithms. The orthogonal matching pursuit algorithm's regression approach was employed by [74] to discover the environmental and physical variables that contribute to smart building energy efficiency. In this study, researchers evaluated and explored the applicability of regression models for electrical load prediction in commercial buildings. They used datasets from real buildings to provide empirical comparisons between several models. Regarding other more complex ML models, the regression models behaved fairly well, according to the researchers [75].

4.1.6. Deep Reinforcement Learning

Reinforcement learning is a well-known machine learning subject that deals with systematic decision-making in the face of uncertainty [76]. In the case of reinforcement learning, the artificial object learns and predicts from experience and uses the trial-and-error method to update its impact. When the solution space for a building energy optimization process is extremely big, existing approaches cannot solve it in real-time. Traditional energy-management approaches have specific applicability requirements, indicating that they are limited in their adaptability when faced with a variety of building situations. Artificial intelligence technology is finding significant competency in management and optimization, due to the fast development of IoT technology and computing capabilities. Deep reinforcement learning (DRL) is a generic artificial intelligence technology that has the potential to address the difficulties of energy efficiency in smart buildings [77].

4.1.7. Decision Tree Classification Algorithm

As a result of the wide range of machine learning algorithms available, selecting the one that is best suited to the dataset and problem at hand is the most critical consideration when creating a model. Decision trees are intended to mimic human decision-making abilities, thus they are easy to understand [78]. Non-parametric supervised learning with decision trees can be used for both regression and classification. Decision trees are a type of predictive modeling that helps in mapping several decisions or solutions to a certain result. The decision trees are made up of different kinds of nodes. The root node is the starting point of the decision tree, which is often the entire dataset in machine learning. The endpoints of branching are referred to as leaf nodes. From a leaf node, the decision tree will not branch any further. The internal nodes in a decision tree in machine learning are the data's attributes, and the leaf node is the result [79]. Decision tree models have been applied in numerous areas in smart energy buildings, including predicting the danger of an outage and storing energy management and energy usage in smart buildings [80].

4.1.8. Genetic Algorithms and Their Use-Cases in Machine Learning

A genetic algorithm (GA) is an approach that can be used to solve a wide variety of optimization issues. GAs can be used to locate huge areas or multimodal spaces. In order to create a genetic algorithm (GA) to solve problems with search and optimization, a heuristic type of search strategy is applied [81]. This algorithm is a subclass of the evolutionary algorithms used in computing. To solve issues, genetic algorithms use the principles of genetics and natural selection. A genetic algorithm implements the concept of computation by representing chromosomes with arrays of bits or characters normally called binary strings [82]. Each string corresponds to a possible solution and the genetic algorithm then modifies the most probable chromosomes in pursuit of better results. TPOT (tree-based pipeline optimization) is an auto-ML system to improve machine learning pipelines through the application of genetic algorithms [83]. [20] developed a prediction-based power management system for reducing energy usage and enhancing user comfort in residential structures. To increase the overall performance of energy consumption reduction and optimize user pleasure, the researchers used data smoothing during the optimization procedure and employed a genetic algorithm for improving energy efficiency.

4.1.9. Support Vector Machines (SVMs)

Supervised learning algorithms include support vector machines (SVMs) that use vector support machines. By estimating the occupancy rate, their goal is to be able to predict the current state of the facility in terms of facility management, resident satisfaction, and overall security and safety [84]. Aiming to find the hyper plane with the highest margin of separation between two categories, the SVM algorithms attempt to divide the data into two groups: both occupied and empty [85]. To classify non-differentiable pair data, non-linear kernel functions, such as radial basic functions, can be utilized to describe the data in larger dimensions and subsequently be used for classification. Classifying data is the most typical use case for a support vector machine. Finding a function for all the training data, especially information regarding the target, is the primary goal of these techniques. Temperature, humidity levels, and the strength of the sun's radiation should all be taken into account.

In the following Table 2, different kinds of machine learning algorithms and the objectives of these algorithms are discussed with their use in IoT applications to make smart buildings more energy efficient.

Table 2. Machine learning algorithms, the objective of IoT technologies, and their domain in smart building applications.

Sr. #	Machine Learning Models/Algorithms	Objectives in IoT Technologies	Smart Buildings Applications Domain	Advantages	Disadvantages
1	ANNs	Forecasting and Modeling.	Reduce energy usage based on intelligent sensors.	Excellent accuracy and comfortable monitoring	Complex
2	WNN	Forecasting events based on time series data.	Used in building lighting and shading systems.	Excellent consistency	Low speed
3	Deep learning	It is helpful in both the prediction of data and the modeling of patterns.	Useful for designing and modeling energy-efficient systems.	High precision and acceptable speed	Very complicated
4	Time Series Analysis	High dimensionality.	Generates reliable prediction results for building energy.	Predict the Future	The observations are not independent of one another
5	Regression	Behavior prediction.	Discover the environmental and physical variables that contribute to smart building energy efficiency.	Rapid speed	Unreliable precision
6	Deep Reinforcement Learning	Systematic decision-making.	It has the potential to address the difficulties of energy efficiency in smart buildings.	Solve complicated tasks	Very complicated
7	Decision Tree Classification	Maps several decisions.	Predicts the danger of an outage and handles energy management and energy usage in smartbuildings.	Simple to understand	Relative inaccurate
8	Genetic Algorithms	Optimization of issues.	Managing loads optimally and enhancing energy efficiency.	Excellent accuracy	Low speed
9	Support vector Machines	The organization of data and the protection of it in IoT.	Prediction of the amount of energy used in buildings.	Excellent accuracy	It is complex and the speed is low

5. Conclusions

Researchers in the field of smart buildings are looking to machine learning approaches for managing, analyzing, and improving the energy efficiency of smart buildings. In this study, the most essential factors of smart buildings are discussed, with a special emphasis on what is currently required of smart building and why machine learning algorithms are important for integration with the IoT to make buildings energy efficient. The use of IoT technology in smart buildings provides numerous benefits, but it also has some challenges. In this review, an overview of the topic of Internet of Things technology, as well as its role in smart buildings has been described. The platform of IoT devices and their basic components are also presented. Internet of Things (IoT) devices in smart buildings present many challenges and those challenges need solutions.

We have shown many essential factors and characteristics of smart buildings, which are described above, and those factors require integration with machine learning to solve energy efficiency and other challenges. In this review, we outline the most common machine learning algorithms that can be combined with IoT to make smart buildings more energy-efficient. These machine learning methods can play a vital role with IoT to make smart buildings more energy efficient.

There are still a variety of challenges in smart buildings for energy efficiency, despite the fact that recent technological advancements in machine learning algorithms have made it possible to implement the concept of smart buildings. If we are able to find more solutions to the different challenges in a timely manner, it will be a tremendous driving factor for improvements in both the academic and industrial domains of smart building research.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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