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Review

Machine Learning Theory in Building Energy Modeling and Optimization: A Bibliometric Analysis

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Abstract
In recent decades, the machine learning theory has been developed in the field of artificial intelligence (AI), as it excludes all shortcomings of manpower, performs complex calculations without rest, and provides prediction benefits for projects. Machine learning models and algorithms extract natural models from the data set, which offers increased problem insight, better decisions, and more accurate predictions. Machine learning has a variety of methods, including supervised, unsupervised, and reinforcement learning, and has been used for building energy modeling in recent years. In this review paper, machine learning in building energy modeling was examined to demonstrate the publications in this area and the relationship between these topics. This paper investigated machine learning methods for building energy modeling using bibliometric analysis and data mining. Therefore, the objective of this research was to give insight into the status of machine learning uses for energy systems in the construction industry. Scientometric software was used for analysis. Deep learning is also a cutting-edge topic of machine learning in 2018 onwards, so a brief explanation in this research was provided to explore a proper connection between machine learning, deep learning, and construction energy modeling.

Keywords: machine learning, building energy modeling, futures studies, optimization

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1 INTRODUCTION

Given the high cost of energy and the vague picture of the process of return on investment in construction industry projects and optimization of energy consumption, accurate evaluation of strategies to reduce energy consumption before implementation is of great significance[1]. Given the wide range of energy consumption issues, energy simulation software is invariably engaged in the decision-making about design strategies and components. The lack of energy reserves on the planet has resulted in the exploration of various methods to reduce and optimize energy consumption[2]. Buildings are one of the largest sources of energy waste, and one of the most vital elements in the construction industry is the virtual modeling of energy consumption in terms of both economics and time. However, there is a dearth of in-depth research that has been conducted on energy consumption modeling. In construction industry, one small miscalculation will lead to catastrophic errors in the project, so considerable efforts have been made to obviate such errors[3]. Machine learning is an emerging tool that substantially contributes to controlling the modeling of energy systems in the construction industry[4].

During machine learning, data are imported into relevant mathematical models to facilitate decision-making as per the existing conditions[5]. Machine learning technology allows for enhanced automation and reduced breakdowns in construction. As a current example, new applications with machine learning technologies allow construction firms to observe the instrumentation ceaselessly on website and in real time. In the event of element failure or system failure, the system actively alerts the operator, which increases website safety and employee safety[6].

The integration of performance in style processes results in previous complexness in building style, which requires comprehensive reviews of the general performance of the building and system dependencies. General dependencies usually cross disciplinary boundaries and cause multidisciplinary interdependencies that interfere with overall performance. Thus, effective connections between several different disciplines are necessitated, for which. machine learning is contributory because the system starts when it receives the required algorithms[7]. Machine learning offers consistent prediction and simple parameter structures in the early stages of design, allowing designers and engineers to rapidly change their designs and the consequences of performance in the design space exploration (DSE) process[8].

Currently, physical modeling and simulation, also known as white box modeling, and machine learning models, or black box modeling, are two main approaches for performance prediction. The black box modeling examines the physicality of buildings and provides alternative statistical and machine learning models that predict energy performance in these complex conditions, design and engineering. Alternative models based on the response level an initial method is used to reduce the number of experiments with good predictions. Black box modeling performance is used to predict building energy performance[9].

Short-term and long-run assessment of building energy demand is crucial[10]. Energy demand statement is classical mistreatment building simulation tool or information-driven mensuration data. Engineering and benchmark supported simulation models are classical models that have been developed for mistreatment building physics. Classical modeling needs a particular quantity of building parameters to achieve a reliable demand forecast[11,12].

Given the spare quantity of historical information, applied math algorithms and machine learning may be classified as data-driven modeling that dependably predicts future demand without simulation, resulting in the trend in analysis to estimate the energy consumption of buildings mistreatment data-driven and statistics analysis strategies. In data-driven analysis, energy demand statement mistreatment historical energy consumption information of buildings and alternative connected parameters such as information Climate are carried out through a learning method[6,13].

Research has been actively conducted on the optimization of regional building operations and energy systems. There are square measure numerous objectives for optimizing these building operations, including price and energy savings. The social context of operations optimization analysis is that it reduces carbonic acid gas emissions and stabilizes the grid through demand-side management. The employment of optimum time period operations is considered inevitable because the replacement of fuel energy sources with renewable energy sources (RES) is necessary[14]. Studies on machine learning can be divided into 2 main clusters. The primary cluster focuses on the employment of solutions, such as applied math of advanced integers, and another cluster of non-model strategies, such as meteorology and machine learning, during which the most effective results are obtained through effective algorithmic programs[15].

To automatically control the operation of the building, the precise and two-way communication tool of the building includes an intelligent system for energy supply[16]. Consumption forecasting is considered an energy efficiency initiative, because it is a sustainable approach to energy management to minimize energy loss in smart energy consumption[17].

This paper analyzed the pros and cons of machine learning in building energy modeling to examine the relationship between the published articles and the amount of articles published and the time of the articles being published.

2 LITERATURE REVIEW

Alexander Orlova, Mikhail Ronyagina et al. studied load forecasting in broadcast systems. In the broadcast of an important social event (such as a popular boxing match or a football match), the load of broadcast on that system prior to the start of the event increases dramatically. Their research presented a new method for load forecasting in a broadcast system using data analysis from social network-based Machine learning and the new linear scalable architecture of the system. Using this method, the capacities with a load prediction module can be monitored and regulated[18].

Hadri and his team worked on a comparative study of load forecasting approaches in smart buildings. Efficient management of smart buildings mainly depends on monitoring the actual two-way flow of electricity information, coverage of electricity generation from RES, storage infrastructure, and electricity demand. For example, building load estimation through the collection of micro data on electricity consumption can be used to measure and manage microgrid systems (e.g., RES storage) to cover demand as well as predict fluctuations. In addition to generating electricity and residual charge, efficient network management of microsystems, also requires forecasting power consumption. As an example, a shape-based clustering method for predicting household electricity consumption is based on principal component analysis to reduce its rate. Machine learning theory and a combination of several classifiers, such as SVM, majority vote, and classification predict maximum demand and allow better management of load balance in the microgrid[19].

Nutkiewicz et al.[20] studied the machine learning towards advanced energy storage devices and systems. With economic process, world energy consumption has been surging over the past decade. For instance, world electricity and fuel consumption increased by 19.44 and 9.14 percent from 2010 to 2017 according to International Energy Agency statistics, which exacerbated energy shortages and carbon dioxide emissions. Carbon dioxide emissions increased by 22/2%, causing important challenges for ancient models and algorithms. The classical approaches need technology for larger accuracy, larger productivity, and higher optimization[20]. Machine learning, together with a massive body of information, has flourished in recent years. The introduction of human data to machine learning facilitates the interaction between humans and machine learning systems and creates machine learning selections apprehensible to humans[21].

Paudel et al.[22] studied machine learning to predict large-scale crop performance. Product performance forecasting is an important but complex issue that requires sustainable sustainability and efficient use of natural resources. It is valuable for food chain stakeholders, including farmers, commodity traders and policymakers. Field surveys, crop growth models, remote sensing, statistical models and their combinations are commonly used to predict crop performance. These methods eliminate slightly different aspects of the product, but the new methods rely on satellite imagery to record the current state of the products. Recent studies have been used to construct high-resolution remote sensing data and product modeling statistical models to predict actual performance. It also creats a framework for predicting potential performance for Canada, using remote sensing models, product modeling, Bayesian inference, and statistical models[8,22].

Zivkovic et al.[23] performed the prediction of COVID-19 using a combined machine learning and antenna search approach. COVID-19 is a new respiratory coronavirus that were identified in human in December 2019, in Wuhan, China. Since then, the virus has spread worldwide and affected more than 200 countries, with the number of reported cases increasing to more than 13 million. However, the magnitude of the COVID-19 outbreak may need months or even years to gather relevant information. Studies on the estimated number of infections, severe cases requiring intensive care, and the number of deaths in such studies are of substantial importance.

Ghannam et al. studied the approaches of AI and machine learning to respond to energy demand in a systematic review and concluded that the growing trend of RES and their rapid development in Recent years have posed major challenges for power system operators[24]. The majority of RES are characterized by intermittent variability, resulting in difficulties in the prediction of output power (i.e., depending on sunlight or wind speed). These features complicate the operations and power systems because more flexibility is required to protect their normal performance and stability. AI approaches are very important as a basic tool for identification[25]. AI can be used to predict electricity demand and production, optimize energy storage and use, better understand energy consumption patterns, and provide better power system stability and efficiency. AI also facilitates decision-making and manages the planning and control of many devices used[26].

Naganathan et al. conducted research on short-term factory-level load forecasting-the machine learning approach[27]. To increase energy efficiency in production environments, an increasing number of energy metering points are installed. In general, load prediction can be done with method-based and data-driven approaches, and model-based approaches include physical and statistical models[27].

Walker et al.[11] studied the accuracy of various machine learning algorithms and price superimposed predicting energy performance at the combined level of business buildings additionally, growing leverage in building integrated property energy sources, and energy conversion technologies need the pliability of energy systems. Model-based customary engineering calculations and simulations are classified in classical modeling and developed victimization building physics. Classical modeling needs an explicit quantity of building parameters to get a reliable demand forecast. Given the ample historical information of applied math modeling and machine learning algorithms which will be classified as data-driven, modeling will predict future demand with uncertainty[11].

Seyedzadeh et al. studied component-based machine learning to predict performance in building style[28]. Desegregation performance into style processes results in better style quality[28]. Thus, information on performance and interdependencies is needed for rising style use, and in specific areas with smart performance within the house exploration style method (to be obtainable quick enough and simply as massive as doable). Adequate for method of machine learning during this scenario offers the benefits of quick prediction and easy parameter structures to match the initial design stages in an exceedingly DSE method. However, current mil approaches are developed specifically for style conditions and require redevelopment[29].

The advantage and the novelty of this bibliometric method used in this paper are that in this study a bibliographic map is generated by using a VOS viewer[30], and different forms of the keywords have been merged and accounted as one general keyword. Irrelevant keywords were eliminated, and gaps of the field of study were drawn according to the strengths and weakness of the keywords' connections and neighbors.

3 METHODOLOGY

The thematic importance of data science and data analysis is open access. The most important types of data is the data obtained from research information. VOS viewer software is one of the most important and widely used scientometrics software to summarize data and draw maps from research-related data[31]. This software, can draw co-authorship maps, co-authorship due to the dependence of countries and organizations, citation maps, and bibliographic pairs.

In addition, with this software, key people and key magazines in a field can be identified. This software is favored by researchers due to its special graphic features and user-friendliness. Moreover, the software can identifie pristine research topics in various fields and create a thesaurus to unify the information[32].

The keywords related to the current research topic are identified, including Energy, Building energy, "Building energy", "Machine learning", Machine learning, Machin learning and energy, Machine learning in building energy modelling.

As shown in Figure 1, there is a large body of research on general topics such as energy, and the more limited the article topics, the smaller the number. In articles on energy, the number is disturbed due to the complexity of the topics and its scatter in the drawing.

Each of these keywords was searched separately in Scopus, and for each of them, 2,000 articles were ranked based on the most recent citations in CSV Excel format. This step was carried out on June 15, 2021, and the received articles had the most citations. The connection of the general topic of energy with other topics were displayed, and the Excel in VOS viewer software was downloaded to obtain the map from the data.

Simultaneous entry of keyword data allows the relationship to be displayed and provides insights into the strengths and gaps of research and future research trends, to find terms and technologies that can be used in machine learning research in building energy for further development and use. Flow diagram of the research model is shown in Figure 2.

4 RESULTS AND DISCUSSION

A general map of the energy subject is shown in Figure 3. Two series of articles were received, the best articles and the most popular articles given the large number of the studies.

This diagram shows all the cases with a wide range of topics, and in this figure, red is related to energy efficiency, yellow and green is related to energy research, and blue is related to energy factors[33].

Figure 4 shows that there is little communication in this area. This is the case and the number of articles presented compared to other cases in the field of energy and machine learning, which is yellow and is one of the new articles from 2018 onwards.

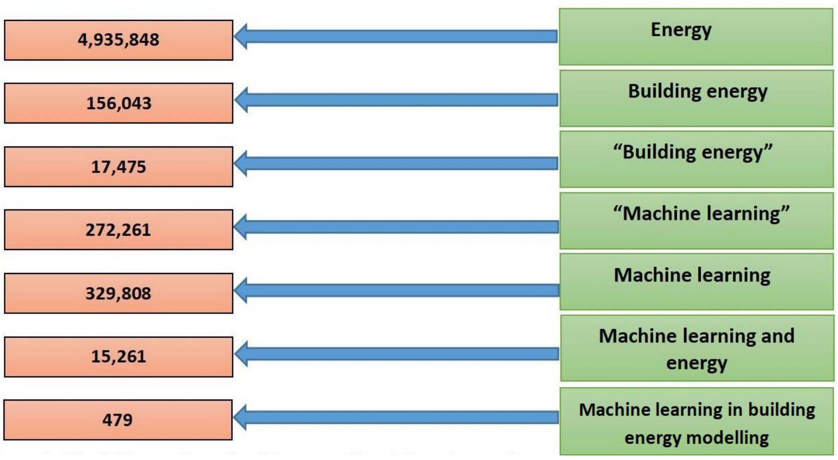

Figure 1. Check the number of articles according to how to search.

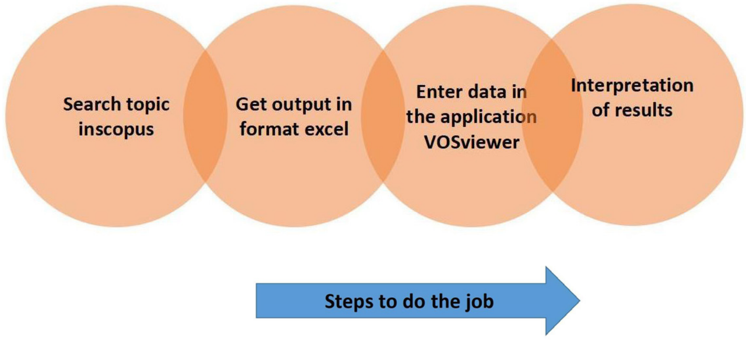

Figure 2. Steps for scientometrics of articles.

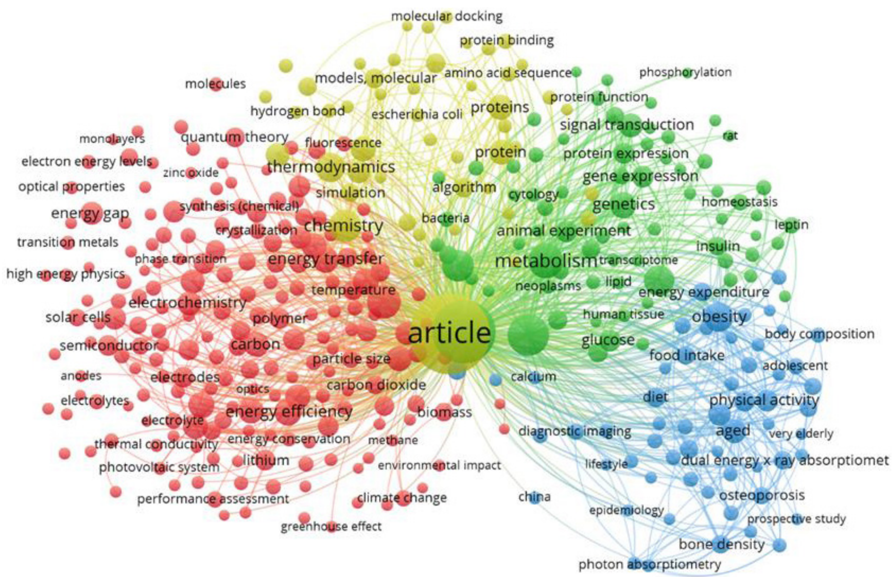

Figure 3. General diagram of the subject of energy.

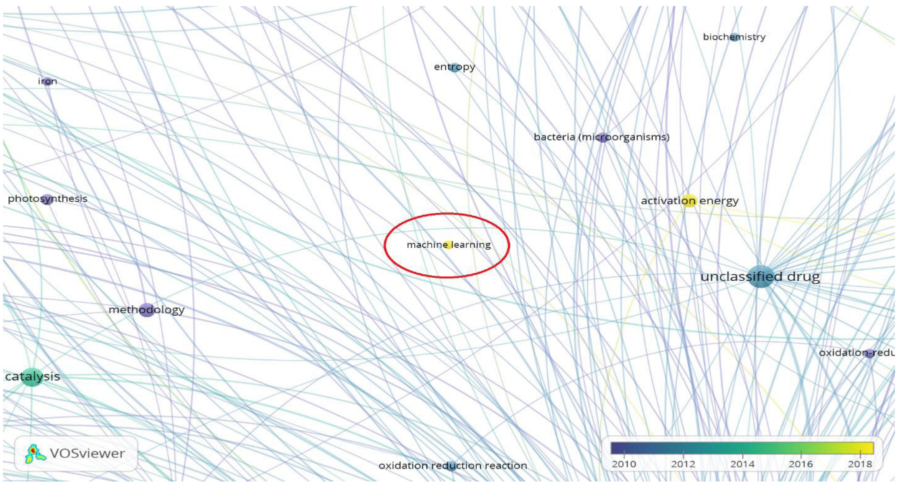

Figure 4. The relationship between machine learning and energy.

In Figure 5, the energy in the field of construction was examined, which shows that the number of articles is much more limited and is closer to the present research topic.

Figure 6 shows that machine learning, is strongly associated with energy and building. This topic is small and far in shape, indicating a new topic in this field with a low number of articles compared to other topics.

Figure 7 shows that the number of articles in the field of machine learning is extremely small and is shown in green.

Figure 8 examines machine learning communications with other fields. The two sets of two thousand articles

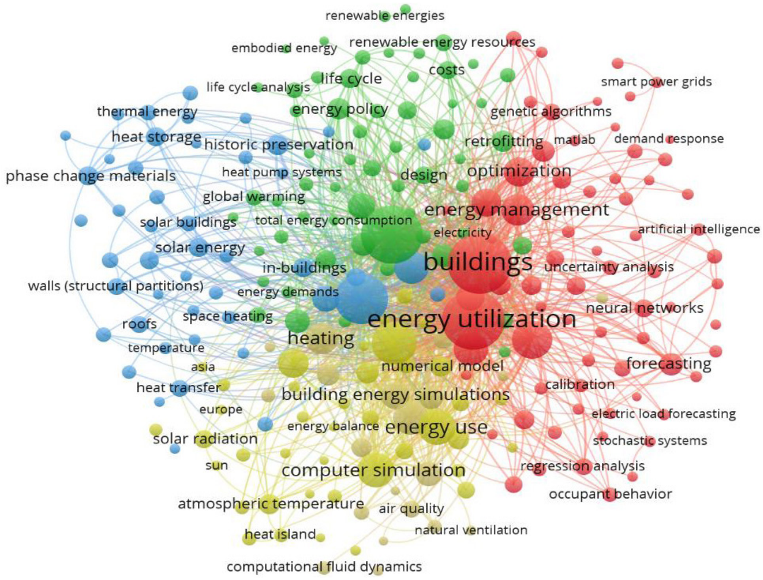

Figure 5. Energy in the field of construction. Red charts in the field of building energy consumption; green charts in the field of energy efficiency; blue charts in the field of energy conservation; and yellow diagrams in the field of energy simulation.

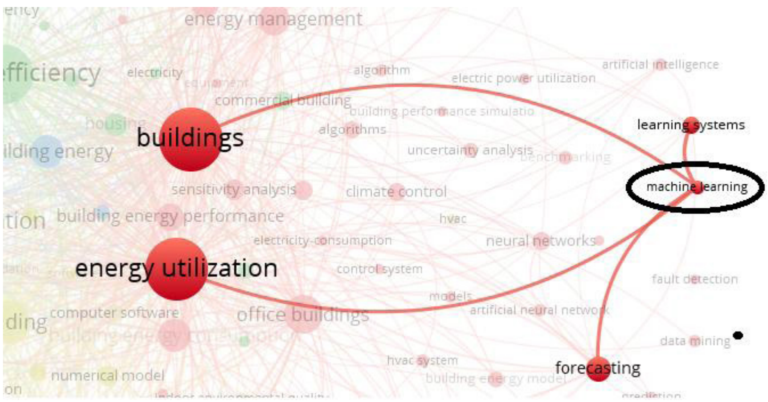

Figure 6. The relationship between machine learning and other things.

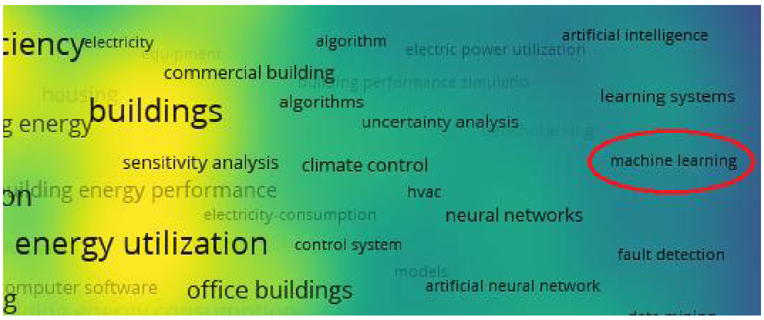

Figure 7. Examining the number of articles.

received in the field of machine learning, are the latest articles series, and the best articles were imported in the software, which shows the large volume of machine learning articles and its close relationship with machine learning, deep learning and AI.

The titles of AI, deep learning and machine learning are synonymous with each other and may cause related issues. AI means a computer that can study and learn from human behaviors. Machine learning is a type of artificial intelligence (AI) that allows software applications to become more accurate in predicting outcomes without the need for explicit programming. Deep learning is a type of machine learning and AI that imitates the way humans gain certain types of knowledge[6,34].

Initially, AI researchers worked on problems such as different types of games and solving math and logic problems

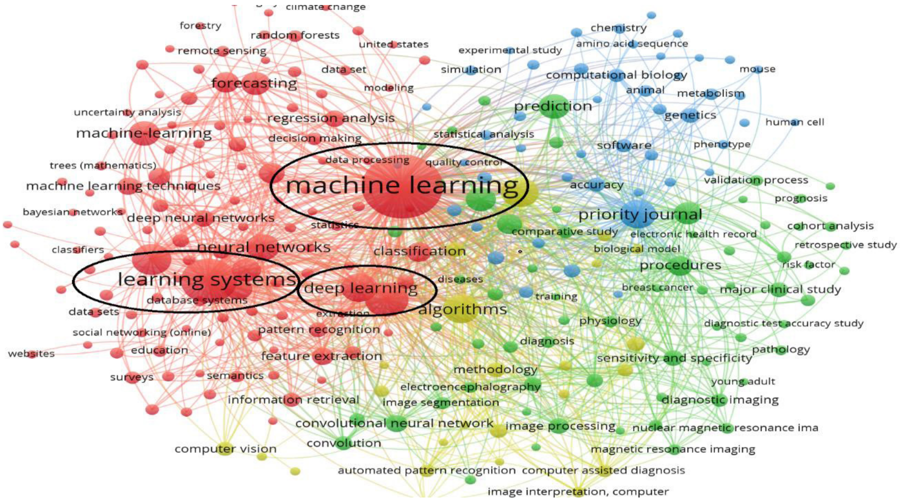

Figure 8. Examines machine learning communications.

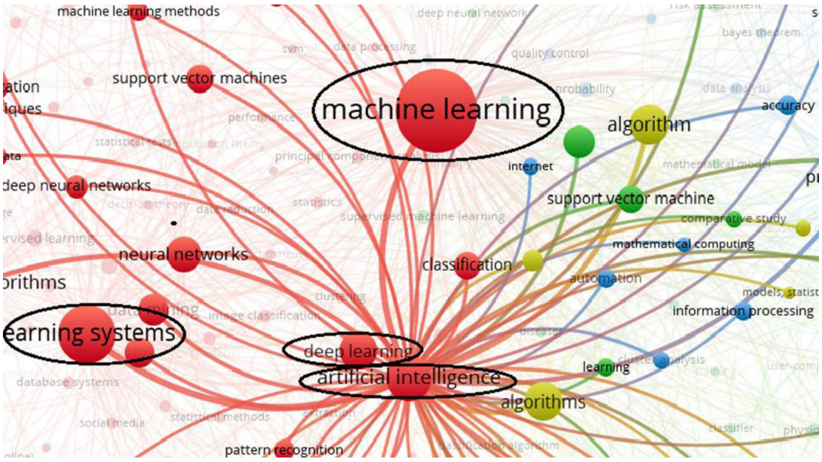

Figure 9. The relationship between AI and machine learning and deep learning.

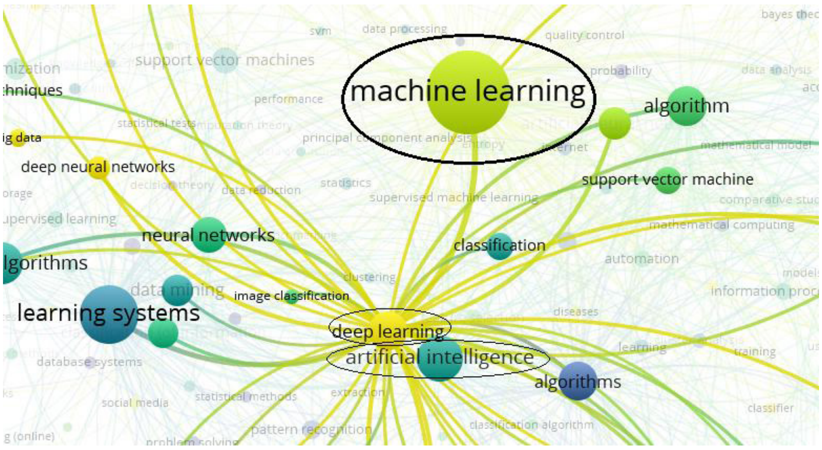

Figure 10. Duration of articles.

that were beyond human abilities[35]. There are many different techniques, such as expert or regular systems, and one of the most widely used methods in the 1980s is the machine learning machine[11].

However, some problems fail to be addressed simply by AI. For examples, specific-code algorithms or intelligent systems are unavailable for image recognition or meaning extraction. The starting point of technology designs then progressively switched from human behavior imitation (AI) to imitation of human learning As human process and master knowledge[34], which is the main theory of the educational machine[36]. The theory of victimization artificial neurons already exists, and software-simulated

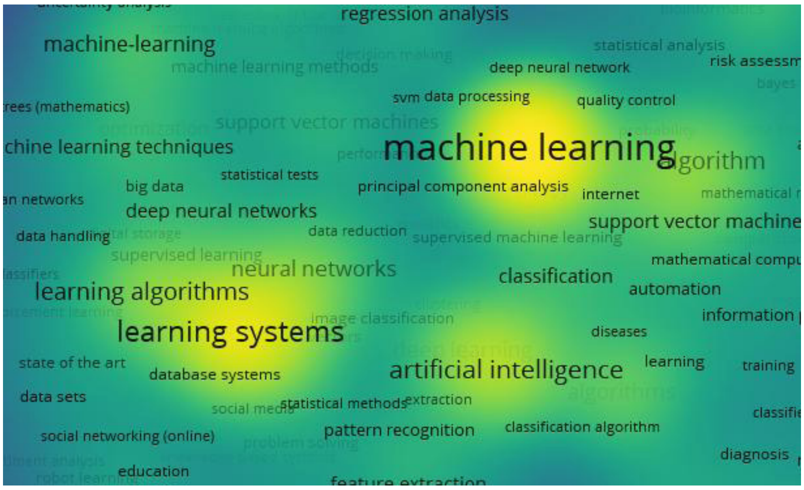

Figure 11. The number of articles published.

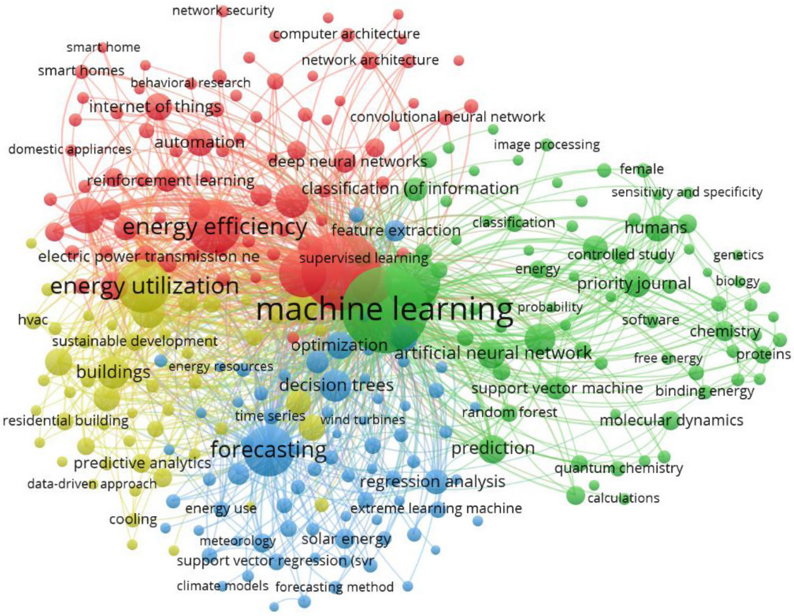

Figure 12. Machine learning in building energy.

neural networks are used to solve various issues, and manage complicated issues[37].

Deep learning imitation in the context of deep learning is merely an abstract imitation of the brain and its neural networks, suggesting that neurons is abstracted as a computational unit and neural network including different layers of computation for segmentation[38,39].

As can be seen in Figure 9, the relationship between machine learning and deep learning and AI was examined. It is quite clear that machine learning is a subset of AI and that deep learning is closely related to machine learning.

In Figure 10, the subject of machine learning is yellow and is a very new subject, and machine learning is light green with slightly longer development than deep learning, and AI is dark green with the longest development history among the three technologies.

Figure 11 exhibits a connection between these three issues, and the field of AI is dark green and has a medium circle, indicating a longer history of its relevant articles. Machine learning with a moderate number of publications is in light green in 2012 and shows a larger yellow circle after 2016[40].

The relationship between machine learning in energy was investigated, and the results showed a dearth of topic regarding machine learning[41].

In Figure 12, the news topics have been examined, and the connection is clear. Green section is related to the field of intelligent learning, the red part is related to the field of energy efficiency, the blue section is related to the optimization area, and yellow section is related to energy consumption.

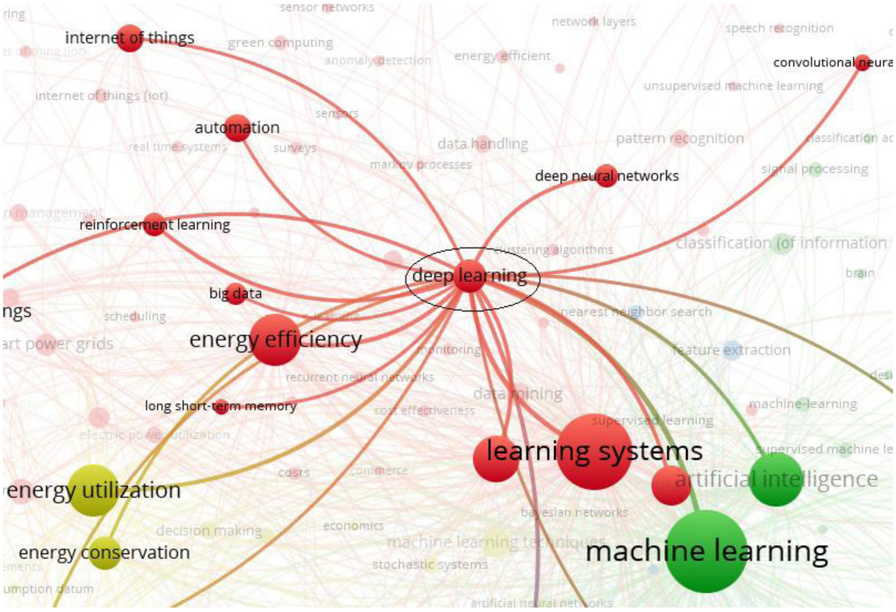

Figure 13. Deep learning relationship to other energy topics.

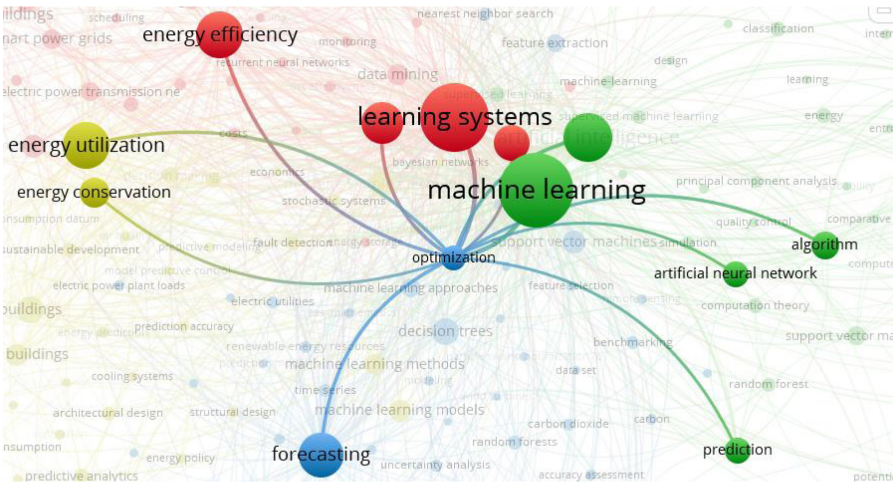

Figure 14. Optimization relationship to other energy topics.

The following part explored the relationship between deep learning and other topics.

Deep learning is a new topic, optimization involves many actors are involved, and energy efficiency plays an important role in obtaining and using energy[42].

In Figure 13, deep learning and its relationship to other topics such as energy efficiency and system learning and energy production and AI were examined.

In Figure 14, optimization is the main goal, which contributes to achieving high efficiency and less waste to optimize the energy use in the building.

Figure 15 displays the energy efficiency. Correct energy efficiency is important for the correct use of energy produced in the building, and the relationship between productivity and machine learning and deep learning was presented.

Keywords were used to identify topics with high relevance to machine learning. The articles about machine learning in building energy modeling were imported into the software, the associations among them were exhibited[43]. Figure 16 shows that the number of sections has increased and the cases that are related to each other are clearly identified.

System learning is displayed in Figure 17 and its relationship to energy efficiency and energy optimization and other concepts is observed.

Figure 18 examines the relationship between prediction and algorithms. To obtain the best efficiency and optimization for energy, prediction of multiple factors with machine learning was necessitated.

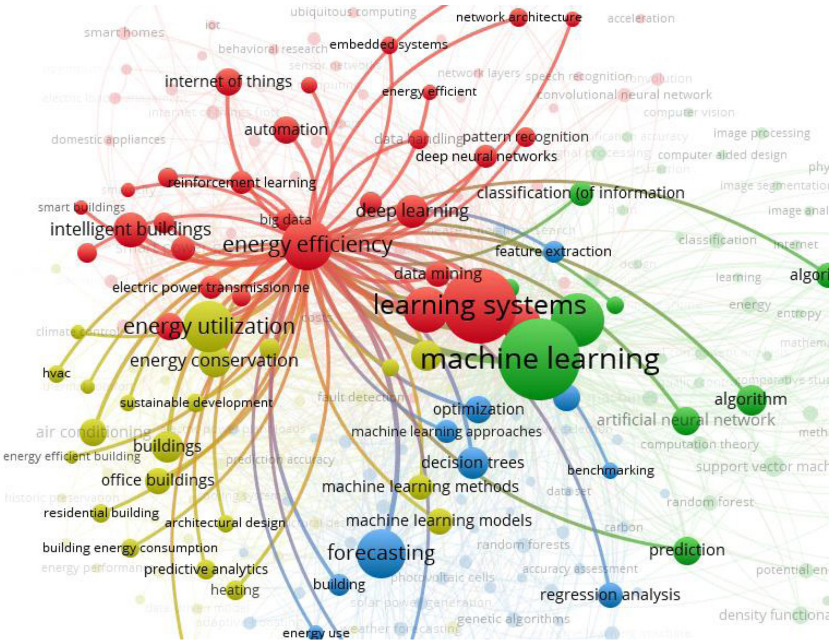

Figure 15. Energy efficiency relationship to other energy topics.

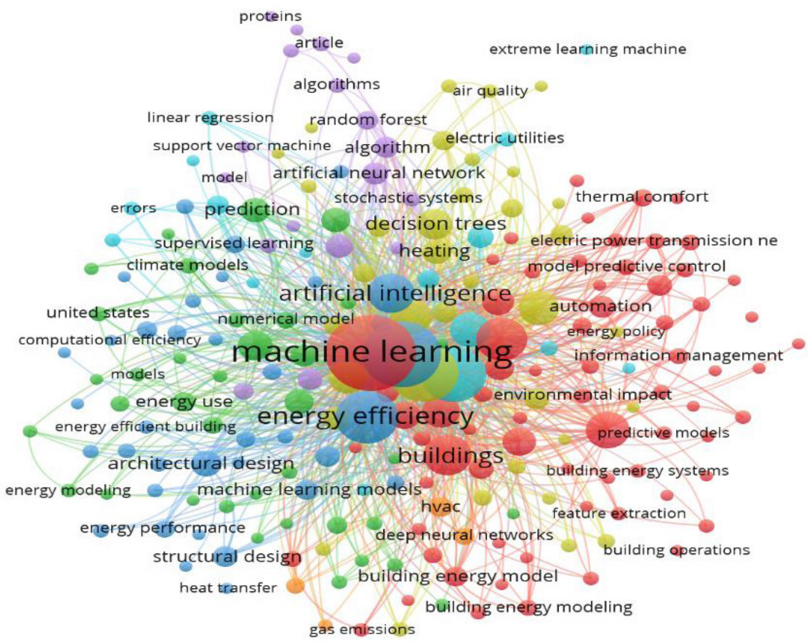

Figure 16. Machine learning in building energy modeling.

5 RESEARCH GAPS

To find research gaps in machine learning in building energy modeling area, a new bibliometric analysis based on co-occurrence data was done using the new keywords (research gaps) and the same steps as mentioned before and synthsized comprehensively in the following.

5.1 Optimization

Optimization reduces financial, energy, and time costs[44]. The intention of optimization herein refers to the energy optimization in the construction field[45].

This can be done using machine learning theory, but as long as there is sufficient energy at our disposal, the main goal is not to optimize or increase the efficiency, but only to use energy[15]. Figure 19 shows building optimization with machine learning links.

5.2 Energy Efficiency in the Building.

Improper use of energy results in various issues and slow technological advance[46]. According to Figure 20, little attention has been given to this issue.

5.3 Simulation

To increase the efficiency of the present research work, simulation is potentially beneficial for the proper use of

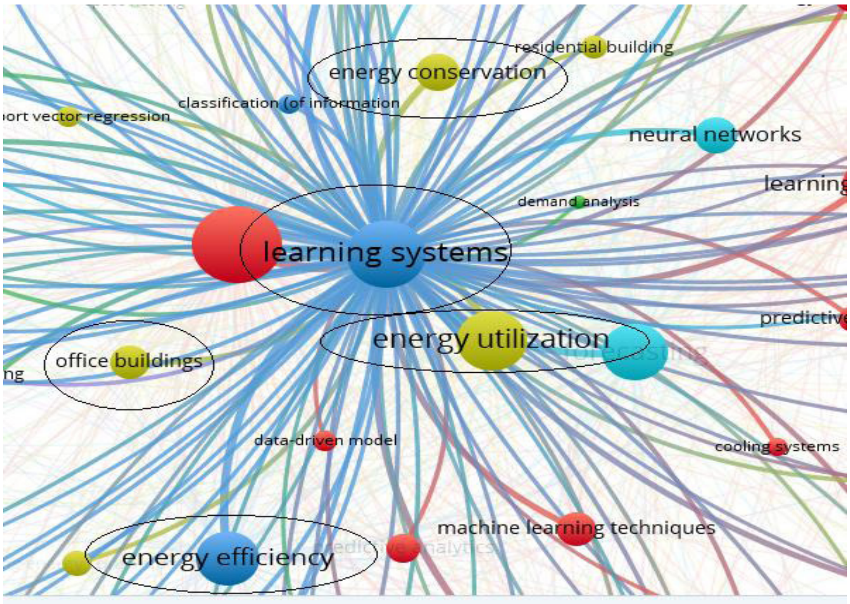

Figure 17. Machine learning connection.

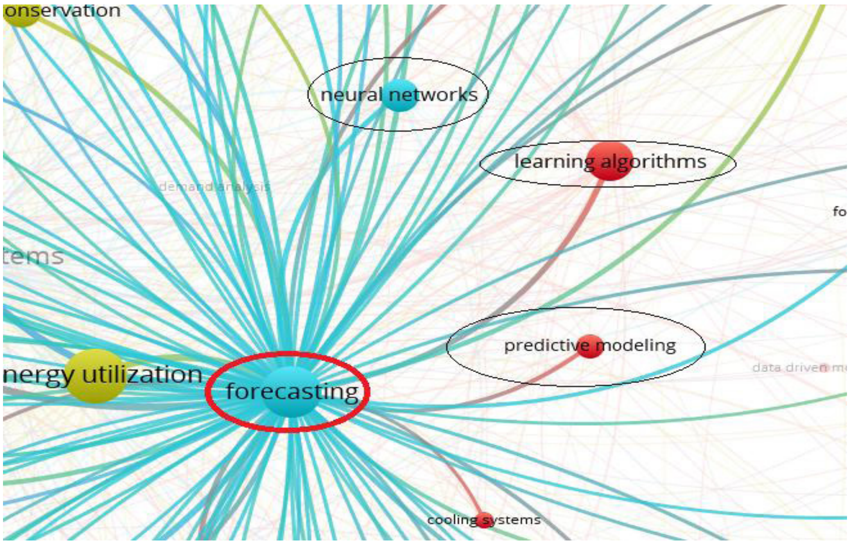

Figure 18. Communication between forecasting and algorithms.

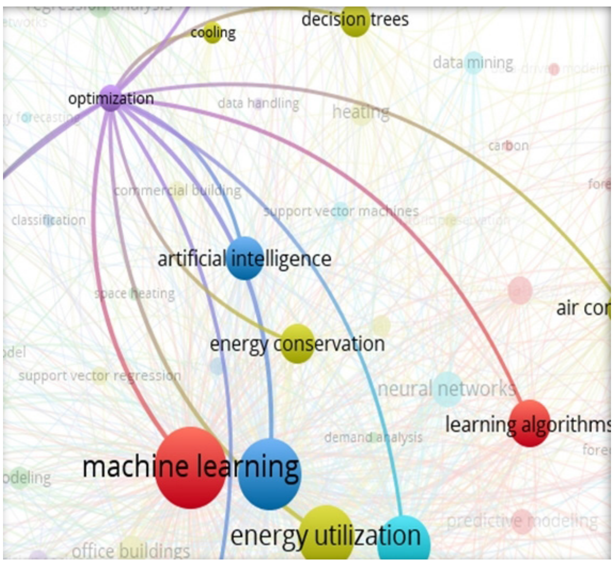

Figure 19. Building optimization with machine learning.

energy[38]. As shown in Figure 21, the number of articles discussed in the simulation discussion is small.

5.4 Methodology

To achieve the goal of energy modeling in the construction field using machine learning, the methodology is essential in completing the current work in simulation[38], and in Figure 22 shows that few articles has been published in this field.

5.5 Data Analysis

Valid and accurate data are significant to produce truthful and scientific conclusions[47]. In energy modeling, machine learning with valid data allows for better results[48]. It can be seen in Figure 23 that this issue has been marginally studied.

5.6 Building Energy Management

Appropriate energy management contributes to the sustainable development of society. Thus, new methods

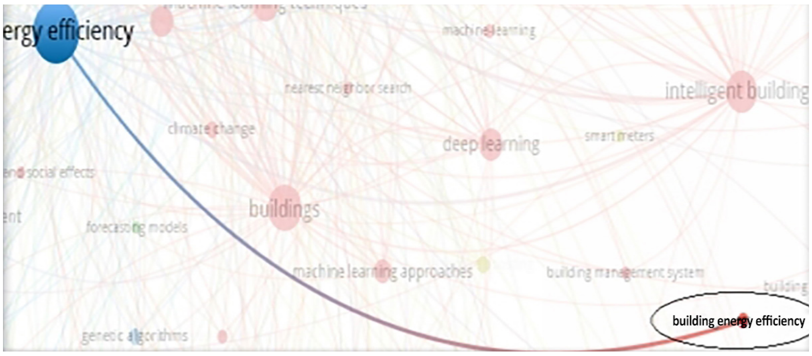

Figure 20. Energy efficiency in the building.

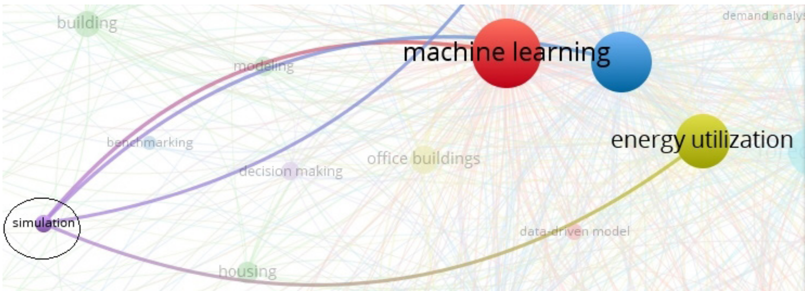

Figure 21. Simulation.

Figure 22. Methodologies.

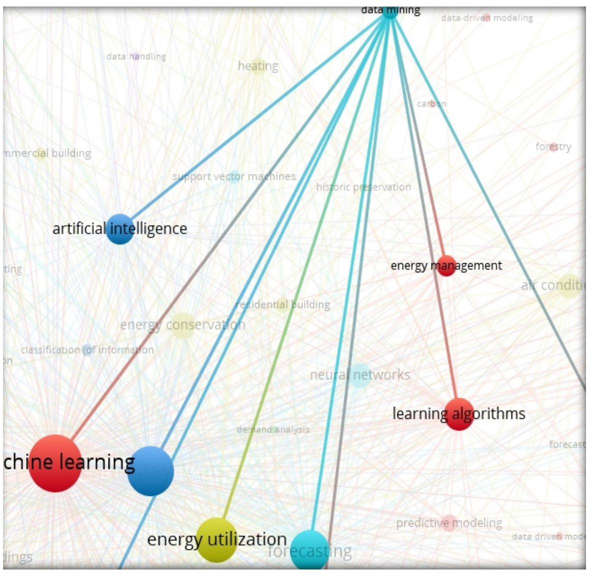

Figure 23. Data Mining.

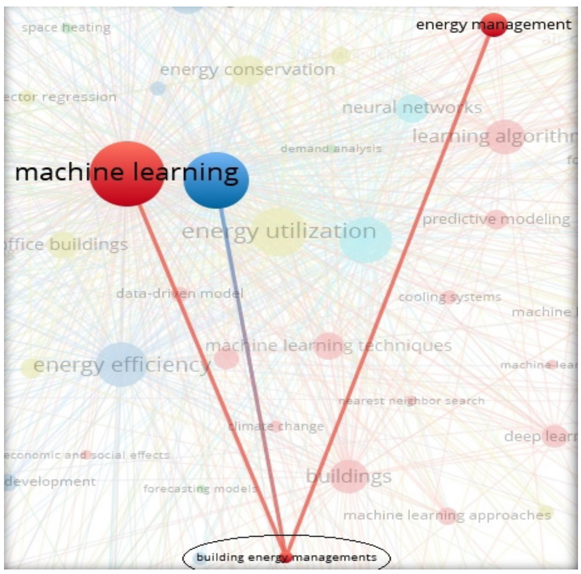

Figure 24. Building energy management.

such as machine learning can be adopted to achieve better energy management[42].

Figure 24 shows that few number of articles have been published in this field.

6 CONCLUSION

Articles using the Scopus site was collected. The relationship with all the topics was examined in the term of scientometrics. Due to its novelty and variety of topics in the field of machine learning, its association with other fields was week. The present study anticipated the trend, narrowed the topics, and examined machine learning in building energy. Furthermore, the weaknesses and gaps in the review of articles were presented. The important topic is energy efficiency in the construction field, which is also the subject of the present article. Building energy simulation is extensively used in various projects to avoid the waste of energy and time. Methodology and data mining is also important to better model the energy of the construction field with machine learning theory.

Proper energy management will prevent unnecessary use of energy to reduce costs. However, such issue has captured little attention. Herein, other issues mentioned include comparative studies, algorithms, data mining, trading, and feature extraction.

Moreover, deep learning is independent only in highly professional, advanced and equipped machines, while machine learning is compatible in most systems. Deep learning needs GPU to execute various and complex commands, suggesting that the information and knowledge received was used to reduce the complexity of the information and clarify the patterns of the training algorithms. This stage is the most costly and difficult stage and time-consuming. The degree of accuracy in the identification of features by the expert has a great impact on system performance. In deep learning, the computer is trained to automatically search the desired information and features. When using machine learning to solve a problem, it is suggested that the problem be first divided into several smaller levels and each part presented to the system separately. Finally, the obtained results are combined . Deep learning performs all these steps within the network without the need for human skill intervention. Thus, the joint use of machine learning and deep learning is encouraged to balance and optimize the energy modeling.

A feasibility study evaluates and analyzes the potential of the proposed project and is based on research and studies to support the decision-making process. In contrast, research gaps in multiple areas shows that machine learning and building energy modelling may have a promising future in the programs of energy and civil scientists, and further investigations are required in this field. The results showed a high connection between machine learning and energy efficiency. The following factors are the limitations of machine learning in building energy modeling.

Data collection: Machine learning requires a wide range of information for training, and this set of information must be comprehensive, impartial, quality, and perfect. To collect the vast number of data, auxiliary software like Design Builder are necessitated.

Time and resources: Machine learning is time-consuming in learning algorithms and requires many resource, which is indicative of more computer power for management.

Interpretation of results: Another important challenge is the ability to accurately analyze the results of algorithms. One of the mostly used algorithms for building energy modeling and forecasting is recurrent neural networks (RNN), which allows a faster and easier learning process of time-varying data, and gated recurrent unit (GRU) is recommended to overcome the issues of RNN.

High error sensitivity: Learning is a self-driving machine that also produces many errors. For example, an incomplete set of small data can lead to an inaccurate forecast. A single error in machine learning can have a ripple effect whose consequences may remain unknown for a long time, and the identification and correction of errors is even more time-consuming. Therefore, a high accuracy of at least more than 80% is required to overcome the exact demand and supply of energy to the construction industry.

Conflicts of Interest

The authors declared that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contribution

All authors contributed to the manuscript and approved the final version.

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Not applicable.

Abbreviation List

AI, Artificial intelligence
DSE, Design space exploration
RES, Renewable energy sources
ESS, Energy storage systems

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