Predicting The Energy Performance and Consumption of Buildings Using Machine Learning: A Review

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Abstract
As the world's population, urban infrastructure, and technological capabilities continue to expand at a breakneck pace, so too does the need for energy. As a result, improving the energy efficiency of the construction industry has become a critical goal in order to minimise greenhouse gas emissions and fossil fuel usage. One of the best ways to reduce down on carbon dioxide emissions and energy use from new buildings is to prioritise energy efficiency. However, the energy performance of the existing stock may be improved by effective energy management and clever renovations. For effective decision making, all these strategies need precise energy forecasting. Machine learning (ML) approaches have been suggested in recent years for energy consumption and performance predictions in buildings. All of these are discussed in this work as they relate to building energy forecasts. We present prior studies of these models and their respective applications.
Keywords: *Artificial intelligence, energy consumption predictions, energy performance, predictions etc.,*

1. Introduction

he global pace of development is skyrocketing right now, and more growth is inevitable. The world economy is expected to increase by 3.2% in 2022 and 2.7% in 2023, down from 6.0% in 2021[1] (www.imf.org). The global population is steadily increasing each year. A rising trend in human population suggests rising needs in areas such as housing, national development, and more. In tandem with these innovations, excess energy is required to fuel global demand while protecting the natural world. Additionally, industrial expansion is not the only factor in the rise in building energy consumption; fast residential and commercial development expansion also plays a role. While progress is being made, it is essentialto consider environmental concerns to lessen pollution, carbon emissions, and the greenhouse impact [2].

It is generally accepted that human population growth and the subsequent demands on municipal infrastructure for new building construction are the principal drivers of global warming. Increasing the construction sector's energy efficiency has become crucial to reducing petrol emissions and fossil fuel useo. However, the energy performance of the existing stock may be improved by effective energy management and clever renovations. All of these workarounds depend on precise energy forecasting for best choice-making. Forecasting building energy consumption and performance has been suggested as a use of AI (artificial intelligence) and, more specifically, machine learning techniques in recent years [3-7].

It is a critical and challenging for building experts to improve electricity end use and lower the amount of energy buildings use while yet keeping quality standards that are acceptable[8]. Commercial buildings have the most significant potential for power savings thus, it makes sense to invest in more efficient heating, ventilation, air conditioning, and lighting systems [9]. Several methods for increasing the efficiency of buildings and lighting systems in developing nations have been researched and identified [10,11]. However, in developing countries like India, there is a lack of systematic evaluations of the implementation and efficacy of these technologies.

Because the building energy efficiency measures created to date only attempt to enhance current methods and develop a methodology for their practical application, there is a continuing effort to define an extended period of energy strategy and systematic processes to achieve energy conservation[conservation [12]. Building design and operation methods can achieve more efficient energy utilisation and optimisation. Compared to earlier research, the behaviour of cooling and heating systems in controlling the interior temperature environment was studied under identical conditions in Seoul, Korea.[13]. The research found that people's perception of thermal comfort has changed due to the advent of HVAC systems, making them prefer warmer temperatures in the winter and summer that are significantly lower.

Smart buildings are an emerging idea that a new era of energy efficiency that it claims to usher in including sensors, artificial intelligence (AI) and big data (BD),. Better control, increased dependability, and automated systems are just a few ways AI technology in smart buildings may help reduce energy use. It is standard practice to apply AI controls for energy conservation purposes. Artificial intelligence (AI) can potentially have wide-ranging, demonstrable energy-saving impacts across various industries and settings. It was also unclear that AI-assisted control differed from conventional control in response [14, 15].

2.Energy Conservation/Efficiency

2.1. Global Perspective of Energy Conservation

The heating, cooling, and powering of buildings accounts for a significant fraction of the global total. Around thirty percent of this consumption might potentially be avoided by the implementation of energy efficiency measures, as well as the design, construction, and operation of sustainable buildings [19,20]. According to a number of studies[21], In many countries, building energy consumption accounts for close to 40% of total energy consumption. This suggests that the installation of air conditioning systems consumes more than 10% of the entire amount of energy produced across the globe. It indicates that building energy inefficiency is pervasive, and there is much room for improvement in this area.

If everyone made an effort to save energy, the amount of power needed to run air conditioners in buildings would drop by around 40%[22]. The construction and layout of the HVAC system should be part of the overall effort to reduce energy consumption. Therefore, it is important to take into account the management of the ventilation,heating, and air conditioning system while developing a thermal design tool for a structure.

2.2Energy Conservation in India

The increase in the need for electricity is outpacing the growth in the energy supply. As a result, reducing energy consumption is becoming a significant concern in India. Numerous international studies on energy efficiency have been conducted, and India has undertaken a few of its own. New building projects must shift away from the energy-intensive designs typical of western Western commercial structures in the 20th century; if the building industry will ever realise its full potential for reducing carbon dioxide emissions. According to the findings of this study, a completeanalysis of office buildings in India should be proposed. These buildings should be strategically stratified over energy intensities, each with a different environmental control system and design approach suitable for usage in a particular climatic zone. Climate-adaptive interior design temperatures will give a low-carbon development option for the commercial building sector in India without losing occupant comfort or workplace efficiency. In India, the commercial building industry is expected to expand at a rate of 7% in 2018[18].

2.3 Design of Buildings for Energy Efficiency

Facade, ventilation,heating, (HVAC), and building management and control system (BMS) design all influence how much natural ventilation helps a building [23]. Energy Concept Adviser is a tool developed by Erhorn et al. [24] to increase the efficiency of school buildings from an energy consumption standpoint. Most nations'educational buildings have revealed striking similarities in the tool's tool's operation, and upkeep depiction. Studies demonstrate that decision-makers seldom use energy-saving solutions during retrofits because they are unaware of the many options available. The ECA is a resource for decision-makers involved in the design phase of a school building project. Energy system recommendations and prospective design ideas for the design phase are provided in the ECA. The research by Wit et al. [25] dealt addressing doubts about the quantification of building performance and its potential influence on aesthetic decisions. When a design evolves, the design team makes a series of options based on feedback from a wide range of domain specialists. The findings shed light on the building domain knowledge accountable for the inputs that prolong sensible judgements about energy consumption, thermal comfort, HVAC system size, etc.

[Hui [26] argues that the study of how to make buildings more energy efficient requires the use of building energy modelling. The research defined energy simulation, its role in the design process, and the characteristics of simulation design tools. In the integrated building design systems framework, practical strategies for simulation have been studied..

In another study, the principles of sustainable development were applied to an overview of energy efficiency ideas. Optimising energy use is crucial, especially within the structure itself. It is evident from the results that designers and end users need access to computational tools that help them make the most efficient use of electric energy in buildings. The study analysed the computational resource critically and provided recommendations for modernising this computer source. Expert feedback reinforced the significance of computers to the progress of the project. Energy diagnosis, induced rationality in design requirements, and energy consumption are all possible thanks to the computing resources available for managing electric energy use in [buildings [27]. There has been a lot of interest in the idea of Zero Energy Buildings (ZEBs). recently and is now considered a desirable goal for the construction industry. A clear and consistent description of the ZEB concept and a widely acknowledged energy calculation technique is necessary before worldwide standards can be established. Possible solutions to the problems mentioned above have been studied and presented to pave the way for creating a unified definition of ZEB and a reliable energy calculation methodology [28]. Wilde et al. aimed to solve the issue of including building simulation technologies into the design process. The study detailed a method for using computational aid throughout the building design phase to make intelligent choices about which energy-efficient materials to include into construction plans. Prototype support environments have been proven effective in facilitating communication between architectural design and simulation [29].

2.4 Energy Efficiency in Commercial Buildings

Cost-effective energy retrofits and efficiency measures may be implemented in commercial buildings to reduce energy usage. By making the right adjustments to the building's energy systems, money may be saved on peak load costs and equipment replacements. When talking about structures, "energy conservation" means "preserving a precious resource"[16]. Energy saving will be the most important breakthrough of the new millennium.

According to the available research, commercial buildings in India have a lot of room to increase their energy efficiency. The energy efficiency of commercial buildings can be improved by at least 20% using proven, low-cost strategies. Energy-efficient lighting system management and operation, HVAC system design, and building envelope design are just a few of the methods that may be used. Energy efficiency measures for new construction are evolving in ways that are distinct from those used for retrofitting older structures. The strategy for new construction is to create structures that use little external energy sources. Efforts are made to increase efficiency in preexisting and older structures, and proper energy management practises and energy audits are encouraged to pinpoint problem areas. Good operating practises, replacement, and retrofitting are three of the most prominent and well-established trends for increasing energy efficiency.

With the aim of helping other developing nations, this case study sets out to pinpoint the primary uses of electricity among Amman's populace. The majority of Amman's energy use came from cooling the air (26%), cooling the food (19.1%), lighting (19%), and heating the water (13%). Water heating refrigeration and air conditioning use a significant amount of energy, but may be offset by the installation of hybrid systems that use solar and wind power[17].

This document summarises current research on estimating building energy usage using modelling. Engineering, statistics, and AI are all examples of these techniques. Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) are the most used AI techniques. Krarti and Dounis both presented comprehensive overviews of AI approaches to the field of building energy systems in 2003 (see [30]) and 2010 (see [31]). The paper's emphasis is on predictive usage. This study further analyses engineering and statistical techniques to enhance the material and give readers a comprehensive picture of numerous prediction methodologies. In addition, hybrid approaches, such as [32-34], integrate several models to improve forecast accuracy. This study provides a high-level overview of relevant applications, models, associated issues (such as data pre-processing), and potential future directions.

3 Machine Learning Techniques

The term "Machine Learning" refers to the process wherein a computer is taught to perform a task by being presented with a specific set of data. Smith et al.,[35] defined Machine Learning as a collection of computational algorithms that can quickly search and characterize patterns in data. According to (Mohri, et al.,[36] Machine Learning can be defined as "Computational methods using experience to improve performance or to make accurate predictions". Alpaydin [37] describes Machine Learning as a requirement for Artificial Intelligence. According to the author, a system can be called Intelligent, if it has the ability to learn and adapt with the changing environment. To some extent, Machine Learning can be seen as an offshoot of broader term Artificial Intelligence, that tends to construct a system that learns from data. Figure 1 below shows the relation between AI and ML .

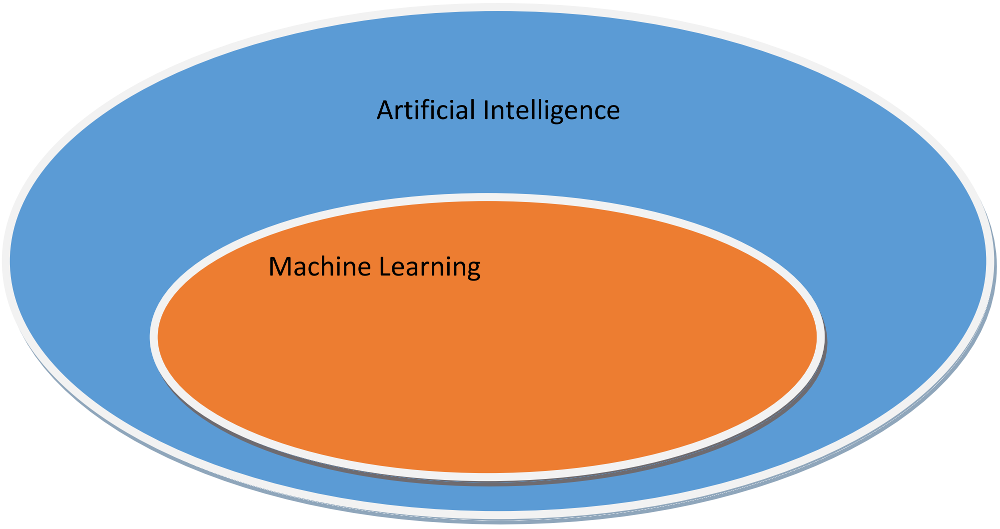

Figure 1: ML as a subset of AI

Machine learning (ML) is a common name for algorithms designed to learn from existing data sets. When it comes to learning processes, these algorithms frequently consume vast amounts of information while taking into consideration a limited number of input features. In the past several years, Many ML methods have been proposed for application in the construction sector for predicting heating and cooling loads, energy consumption, and performance under varying conditions.

There are a number of fields that are allied with Machine Learning, like Data Mining, Statistics, Control theory, Cognitive learning etc. Figure 2.lists some allied fields of Machine Learning, like Data Mining, Statistics, Control Theory, Databases, evolutionary models, Cognitive Science, Neuro Science, Decision Theory etc.

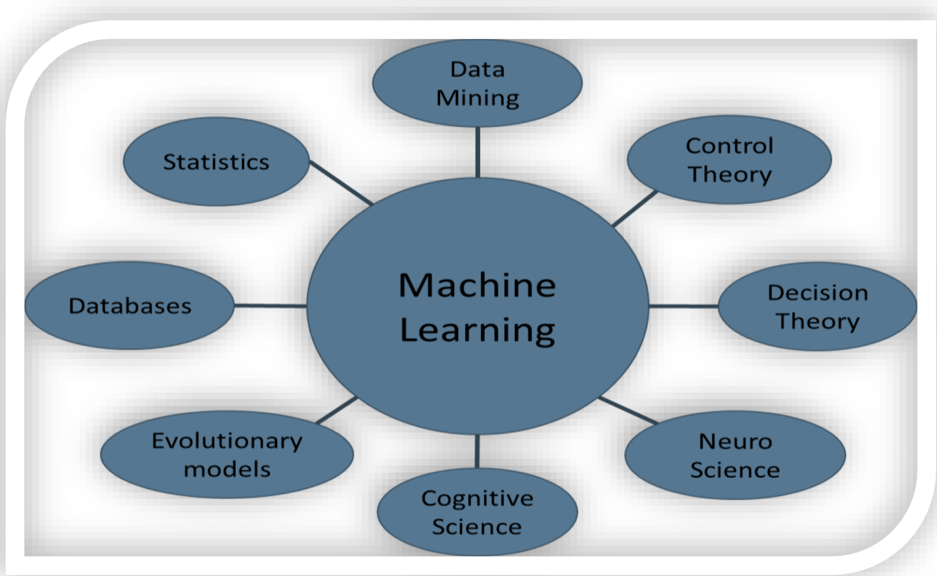

Figure 2: ML and allied fields

There are various techniques using which the machines can be made to learn. Figure 3 shows broad categories of Machine Learning techniques and some algorithms in each category. Two well-known techniques of ML are:

a) Unsupervised Learning

b) Supervised Learning

In Unsupervised Learning techniques there is no provision of labelled examples. Depending on the particular learning model that was applied, the results can be obtained in the form of patterns or groupings. Clustering is a frequent method used in unsupervised learning. In this method, a similarity measures are used to divide the dataset into a predetermined number of groups. The numbers items that are contained within the same cluster are more similar to one another than the data objects that are contained within other clusters.

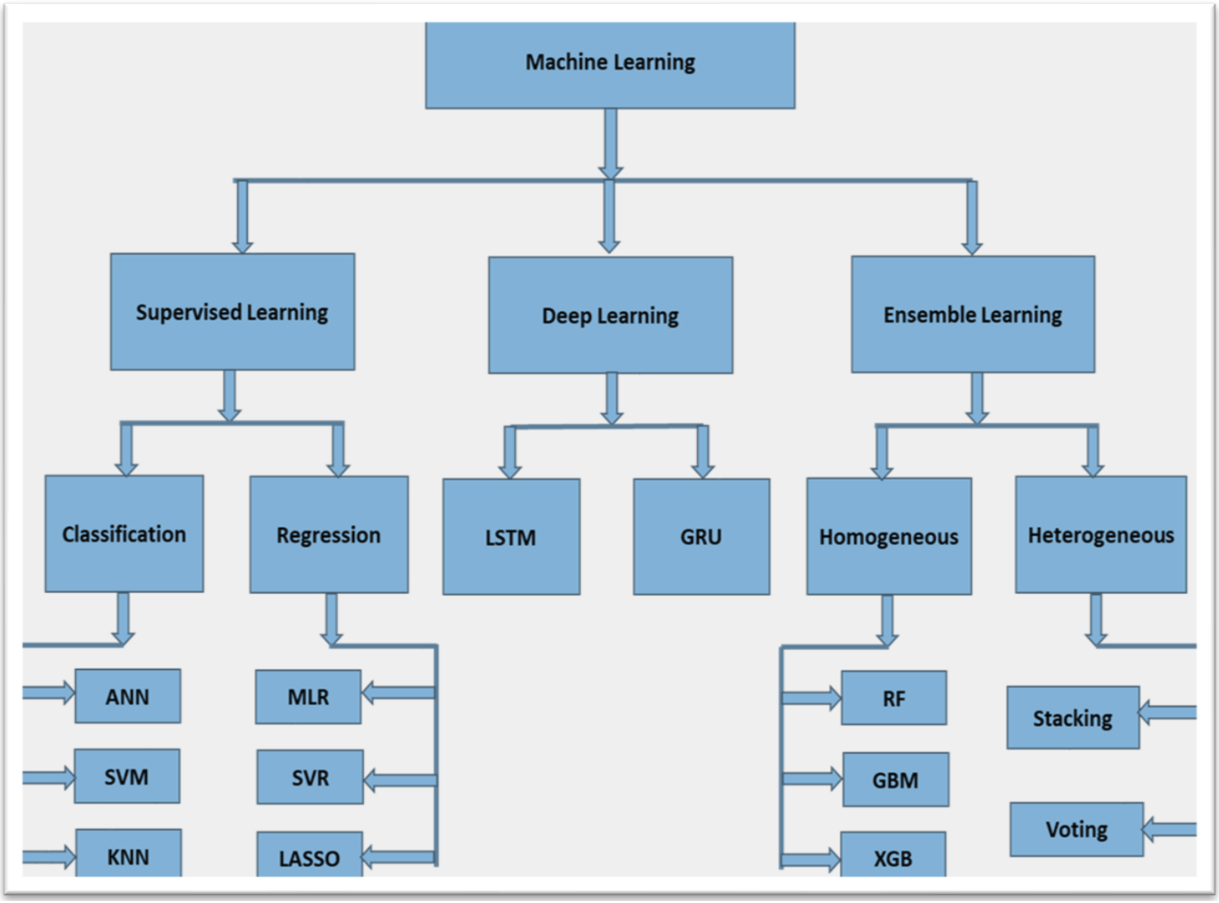

Figure 3: Machine Learning categories and related algorithms

During the process of supervised learning, the data that is being input is translated to the output that is sought by using a labelled set of training data. Classification and regression are two techniques that are frequently used in supervised learning. In Classification, the data objects are grouped into a finite set of classes. One statistical approach that is typically put to use for making numerical forecasts is called regression, which you may think of as a procedure. Regression can be broken down into two categories: a) Linear Regression, in which the goal is to find the optimal line for fitting two variables such that one of them, referred to as the Predictor, is independent and can be used to predict the other variable, referred to as the Response, which is dependent; and b) Non-Linear Regression, in which the goal is to find the best curve rather than the best line. Both of these types of regression require more complicated calculations. Polynomial Regression is a typical example that is used.

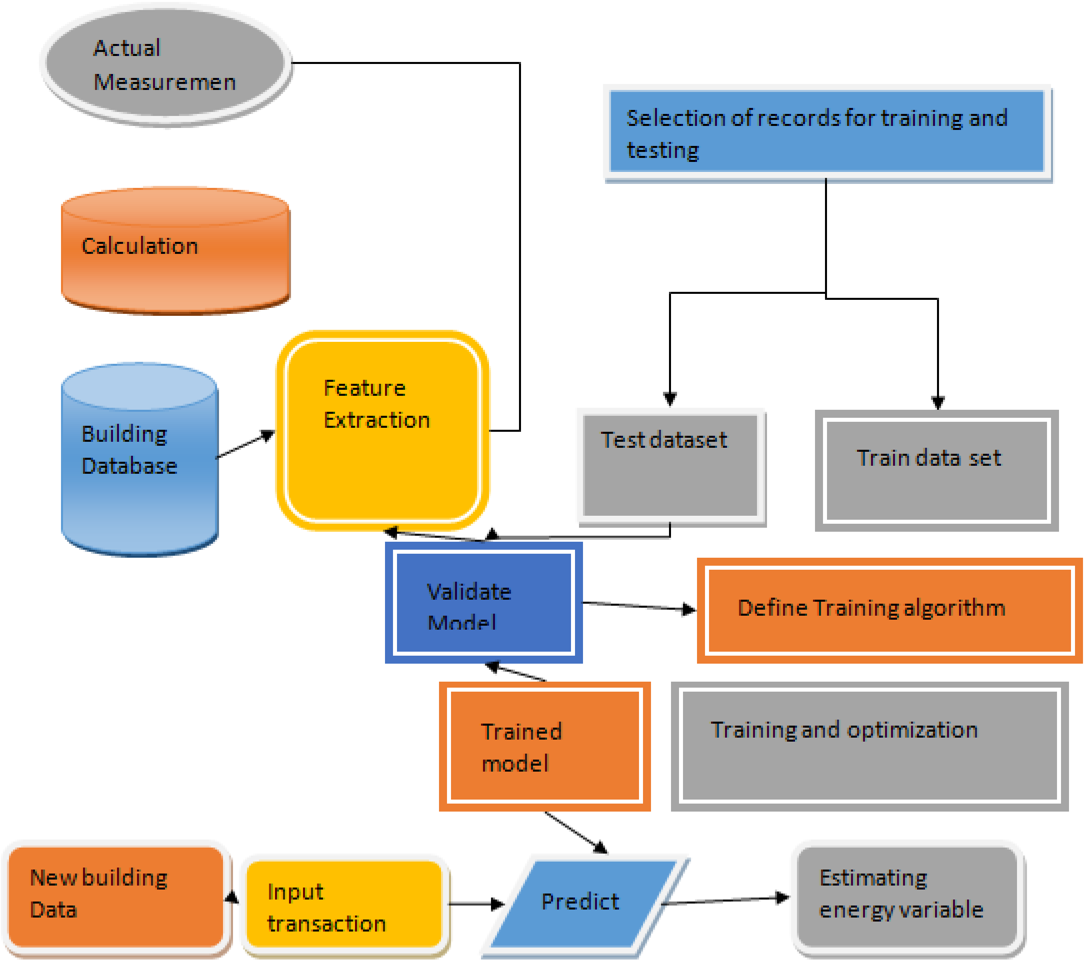

Figure 4: Supervised learning

Another class of Machine Learning techniques is Semi-Supervised Learning, which is a mixed-methods learning (both supervised and unsupervised). The Machine Learning model is built using both labelled and unlabelled data. All these Machine Learning techniques have a great potential to extract useful knowledge out of a given dataset in a particular domain.

One of the challenges in determining how much energy a structure uses is the most prominent machine learning (ML) approaches now in use is neural networks. They have been able to represent non-linear issues and complicated systems with great success. ANNs can learn to ignore errors and distractions [38] thanks to the use of a variety of methodologies, and they are also capable of understanding the fundamental configurations of physical structures..

The area of neurobiology provided the foundation for the principal idea of the ANN. A number of distinct varieties of ANN, including as FFN(feed-forward networks), RBFN(radial basis function networks), and RNN(recurrent networks), have been proposed for use in a variety of diverse applications. Each ANN is made up of multiple layers neurons and activation functions, the latter of which are accountable for the formation of connections between the neurons. There are at least two layers of neurons. Functions such as the linear, sigmoid, and hard limit functions are examples of those that are used frequently[39].The FFN model, the original and simplest neural network model, has one-way information flow and no feedback loops between input and output neurons. This ensures that the model is as simple as possible. A generalised construction of the FFN is depicted in Figure 5 and includes an input, an output, and one hidden layer. By enabling feedback loops from output nodes to input nodes, an RNN can learn from its previous experiences thanks to its own internal memory. RNNs have been conceptualised in a variety of architectural forms, including, but not limited to, long-term memory, recursion, and full connectivity. [40,41] This neural network type is commonly used to address very deep learning problems(those requiring a solution of more than a thousand layers)[40,41].

Within the context of RBFM, an application of As an activation function, a radial basis function might be used produces an output that is a linear combination of the neuron parameters and the inputs. When it comes to the estimation and prediction of time series, this kind of network is particularly efficient [42-44].

It is determined, what the structure will be depending on the situation and the degree of intricacy, work, and then by supplying activation function with the appropriate number of records, it will update the weights and bias.

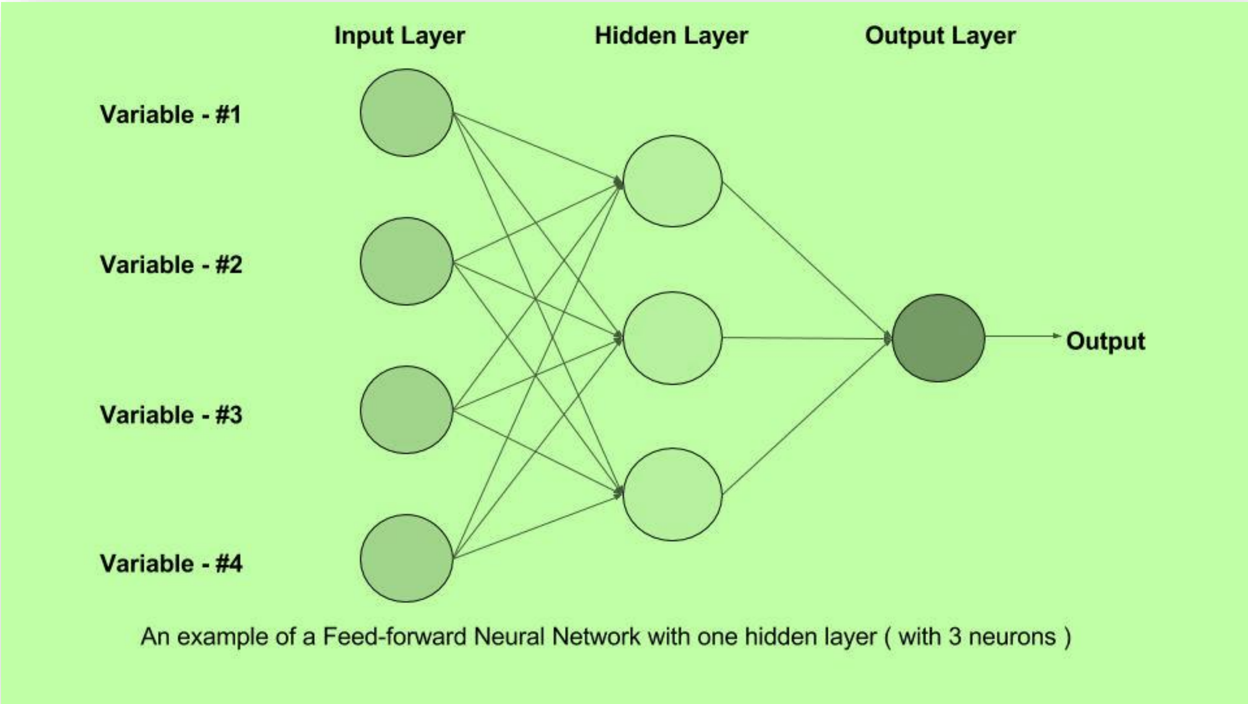

Figure 5: feed forward neural network

Table 1: An overview of machine learning methods for predicting building efficiency and energy use

Author	Target	Building case and data	Methods	Finding
D'Oca,& Hong, [45]	Building Energy Performance	Sixteen offices situated in Frankfurt Germany	Clustering (K means algorithm) and ARM (FP Growth algorithm)	People who work in buildings that rely on natural ventilation are able to tolerate a greater workers in buildings are subjected to a narrower range of temperatures that rely on air conditioning, according to the findings of a study. This research had some shortcomings, one of which was that the indoor environment and energy performance grew more dependent on the actions of the occupants.
(Xiao, & Fan[46]	Building Energy Performance	Tallest commercial building of Hong Kong.	K means algorithm and Apriori algorithm	The framework is appropriate for improving the operational performance of the building.

(Zhou, et. al.,2015[47]	HVAC	lab in a University in Singapore	K-Means Partitional clustering algorithm	Both the Predicted Means Vote model and the Extreme Learning Machine were utilised in order to get thermal comfort indices. The HVAC system in the room can be independently adjusted, allowing for more efficient use of the space overall.
(Zhao,.et. al.,2014)[48]	HVAC	Building of Pennsylvania in US	(SVM algorithms) and Regression (Linear Regression, Locally weighted Regression, SVR algorithms	The authors of the study highlighted the significance of occupancy pattern in determining HVAC energy use has substantial variances for buildings that are located in climate and environment conditions that are distinct from one another.
(Braun,. et. al.,2014)[49]	Building Energy Performance	UK Yorkshire and Humber region	Multiple Linear Regression technique	According to the findings, it is projected that the amount of electricity used will go up by 2.1%. Additionally, it is anticipated that the temperature will remain nearly the same as it was in 2012, however the humidity is anticipated to increase by 12%.
Candanedo,. et. al., [50]	Building Energy Performance	Residential building in Belgium	MLR, SVM, RF and GBM	Experiments showed that data collected from Living room, kitchen and laundry was highly important towards prediction. They ranked atmospheric pressure as the most important feature for prediction
Deb, et. al., [51]	Building Energy Performance	Buildings in Singapore	MLR and ANN	According to the findings, ANN is superior to MLP in terms of precisely forecasting the amount of money saved on energy. The fact that the data were confidential and site visits were not allowed was a limitation of this study, which made it more difficult than it would have been otherwise.
(Jain,et. al.,2014)[52]	Building Energy Performance	Residential building in the United States	Support vector regression	The authors conducted an investigation into the accuracy of the predictions by considering both time

				and location, and they discovered that hourly predictions made in relation to floor levels provided the best results. Coefficient of Variation achieved was 3.30%.
Kusiak,. et. al.,[53]	Building Energy Performance	IOWA Energy Center, Ankeny, IOWA	CART, CHAID, Boosting tree, RF, MARSplines, MLP, MLP ensemble and SVM	MLP ensemble model proved better than other models, with 7.66% total energy savings.
Manjarres, et. al., [54]	HVAC	Office building in Spain	Random Forests	Because of this, a significant amount of energy was saved, the heating process accounted for 48%, whereas the cooling process accounted for 39%.
Marasco & Kontokosta, [55]	Building Energy Performance	New York City including residential, office, hotel, warehouse buildings	Machine Learning classifier (Falling Rule List classifier)	The forecast that is made by this classifier will cut down on the time-consuming and expensive energy audits being required.
Park, .et. al., [56]	Building Energy Performance	official buildings in South Korea	decision tree method	The system that has been proposed is able to be utilised measuring a building's energy efficiency in relation to its actual energy use of the building. When compared to both the baseline and the traditional systems, it was clear that the new system was superior.
Rahman et. al.,[57]	HVAC	commercial building in Alexandria	Support Vector Machines, Discriminant Analysis, Decision Trees, and KNN	According to the findings, the K-nearest neighbour algorithm was the one that disaggregated power the most effectively.
Cho, et. al.,[58]	HVAC	office buildings in Korea	Decision Tree	According to the results, the HVAC system's air conditioning (AC) component has the greatest effect on costs, followed by heating (CP), and finally ventilation (WD).
Wei, et. al.,[59]	HVAC	Ankeny Iowa	Exhaustive Regression CHAID, Support Vector Machine Regression, Boosting Regression Trees, Random Forest Regression, MLP, MLP Ensemble, Standard Regression CHAID,	MLP ensemble model performed best

			MAR Splines for Regression,	
Bui,. et. al., [60]	Heating Load and Cooling Load	Residential building in Turkey and in Greece	ANN with Electromagnetism based Firefly optimization algorithm	Using the proposed approach, civil engineers can create structures that use less energy. When compared to other approaches, RMSE performs better (93.28%-98.50% better) and more quickly (5 and 7 times faster than ELM and GP, respectively) on dataset 1. Computing time was short, and RMSE, MAE, and MAPE were all lowest, for dataset 2.
Araya. et. al.,[61]	HVAC	school in Canada	Support Vector Regression and Random Forests	Canadian school HVAC power consumption data was used in a series of experiments, with EAD showing considerable improvement over CCAD-SW in terms of sensitivity and False Positive rate reduction.
(Fan,et. al.,[62]	prediction of cooling load	educational building in Hong Kong	The deep neural network was evaluated in comparison to conventional prediction methods such as MLR, EN, RF, GBM, SVR, XGBOOST trees	The cooling load prediction results showed that the Deep Learning method worked better. Furthermore, non-linear prediction methods outperformed linear ones. MAPE Next-day energy usage using ensemble models was 2.32%, and peak power demand was 2.85%.
Alanbar,. et. al., [63]	Building Energy Performance	building in Qassim University, Saudi Arabia	LSTM Deep learning technique	The model performed better than other models like ANN, BP, SVR with accuracy as high as 94.31% and RMSE as low as 0.045.
Almalaq, & Zhang[64]	Building Energy Performance	residential and commercial buildings	Genetic Algorithm with LSTM deep learning algorithm	The model was compared with ARIMA, Decision Tree, MLP, LSTM and GA-ANN and results showed a reduction of error by 17.319% and 10.669% in Residential building and Commercial building case studies respectively.

(Zhang, et. al., [65]	Building Energy Performance	public building in China	Long Short Term Memory networks with Artificial Neural Networks	The hybrid method is better than other data driven methods. MAE, RMSE, CV-RMSE and R Squared have been chosen as the evaluation metrics for model comparison. The hybrid methods outperform ANN, FR, SVR and GBT

Table 1 provides a summary of available ML methods, organised by use case. Prediction times, building study examples, energy consumption statistics, and model training features are all listed in the table below..

3Application of AI to Smart and Energy-Efficient Buildings

3.1 Use of machine learning tools in the study of energy utilisation in buildings

ANN, Polynomial Regression, Decision Trees and (SVM) [66-69] are examples of machine learning technologies used to analysethe Energy Performance of Buildings. In [66], the authors use ANN to assess the indications of a building's heat load. The authors have created a method, using ANN, to evaluate the energy-use behaviour of a building with little data. They are predicting future energy use via a back propagation network. For studying building energy consumption, recurrent neural networks have been employed, general regression neural networks have been used, and backpropagation neural networks have been used [70–74]. There are three main categories into which all current methods for predicting a building's energy use fall: (a) Physical (White Box) Models and (b) Data-Driven (Black Box) Models with Machine Learning Grey Box techniques (hybrid models that include elements of both physical and ML) [75,76].

Predicting building energy consumption [77,78], heating and cooling loads, indoor air temperature and relative humidity, modelling HVAC equipment behaviour, recommending energy retrofitting measures, etc., have all benefited greatly from AI techniques.

3.2 ANN in the prediction of energy use in buildings

Several types of neural network topologies are used in the study of energy. Energy consumption predictions for three buildings of varying shapes and sizes were made using a backpropagation ANN by Ekici and Aksoy [77]. The results of the ANN network were compared with those of the finite difference method's energy consumption estimations. The research suggests that ANN will be a n excellent resource for future building design and alterations to improve energy efficiency. There are, however, caveats to the study that the authors want to address in future publications. They have only accounted for the energy used for the heating load, not the lighting or cooling load.

3.3 ANN in the estimation of thermal loads of buildings

Using statistical machine learning methods, Tsanas and Xifara [79] offer an approach for accurately estimating residential structures' cooling and heating loads. Predictions for heating load and cooling load are made using eight input variables by the authors. The input variables are selected based on empirical evidence that they significantly impact the energy consumption of a structure. The density of the building, its surface area, the area of its walls and roof, its height, its orientation, the area of its windows, and the distribution of its windows are all input factors. The Ecotect programme was used to produce the construction data collection. According to the findings, RF performed much better than IRLS. Both models'efficacy was measured by using MAE, MSE, and MRE. The assumption of continuous climate and occupancy is a weakness of the research. Predictions for HL and CL will improve by adding these factors as input.

To estimate heating loads in commercial buildings, data-driven or black-box models have been built in work suggested in [80]. The information comes from BEMSs in the buildings themselves, as well as other sources like weather reports. The issue of missing information in BEMS data was addressed using an EnergyPlus-created reference building as a standard. The BEMS variables are collected from the building's sensors. The link between the input factors and the result was analysed statistically. Each model's accuracy was measured by calculating its Mean Absolute Error (MAE) as most significant and least projected values. Studies assessing the Pearson coefficient and the Spearman rank correlation found a meaningful relationship.The average accuracy of the regression models was 74.52%, whereas that of the ANN models was 83.31%. The generalised linear regression method yielded the most precise regression model (92.1%). The multilayer perceptron method produced the highest accurate ANN model (97% accuracy). Both models used outside relative humidity,outside air temperature, sun rays and the room's ambient temperature are taken into consideration. Models based on artificial neural networks outperformed regression-based models for predicting a building's heating load.

The authors in [81] have estimated building thermal loads using hybrid AI approaches. The information needed for the analysis may be found in [79]. The abc-ANN model has the lowest MAE (0.52) of all the ANN models. Both of the adaptive ANN models outperformed the abc-knn.In [82], the authors suggest using deep learning techniques to provide a 24-hour cooling demand prediction. "Deep learning" refers to a method combining many different types of machine learning algorithms into a single process. Deep learning algorithms can visualise complex patterns in large datasets. Both supervised and unsupervised applications of the deep learning approach are possible, with the former used to construct a forecasting model and the latter used to retrieve fundamental properties from raw data.
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As an initial step, feature extraction was performed on the building data to identify valuable properties that would later serve as inputs to the model. Necessary engineering, structural,statistical, and profound learning aspects were extracted from the building data using four feature extraction approaches. The feature extraction process exemplifies the unsupervised nature of deep learning. Seven different prediction methods are presented by different feature sets to create prediction models, highlighting the power of supervised deep learning. High-order linear regression, gradient-based decision trees, and gradient-boosting methods are all The Use of Support Vector Machines in Research, random forests, elastic netsand deep understanding are only some methods utilised to make these predictions. Multiple linear regression and net elastic models are the least effective of the ones proposed. Extreme gradient boosting produces the best-performing models compared to the other. Compared to nonlinear prediction methods, the results of utilising linear methods are shown to be shallow .

3.4 ANN in the prediction of indoor atmospheric conditions

The researchers of [83] used an ANN to hourly forecast the inside temperature and relative humidity of a building in a humid location. The most current measurements of the interior and outside temperatures, and the relative humidity are input into the neural network model. Before commencing the study, data on the relative humidity and temperature of the indoor air were gathered over twenty-four months before the start of the research. In light of these findings, we concluded that the most effective architecture for an ANN is a multilayer perceptron. There are hyperbolic tangents present in both the activation functions of the hidden layer as well as the activation functions of the output layer. Using the Lavenberg-Marquardt method, the model of the neural network is trained in MATLAB. The findings demonstrated that ANN is a viable approach for predicting the temperature and relative humidity of the air within a building.

4. Digital Twin Technology in Construction Technology

This section discusses how real-time updates and bidirectional coordination are now being used in digital twin applications in the construction sector. Despite the increasing prevalence of ""smart" "buildings equipped with ""smart" "automated equipment, the construction sector has lagged behind others in using digital twins. Nevertheless, the development of smart and intelligent building construction provides a strong basis for the wider application of digital twins. It is required to synchronise the systems so that actual and virtual structures (Cyber-Physical Systems) function in tandem in order to reap the full benefits of using DIGITAL TWIN in the building industry. Only then will it be possible to fully exploit the potential of this technology. Buildings that are both smarter and more technologically advanced can be created with the assistance of cyber-physical systems during the design and construction phases [88]. The physical assets in these structures may be monitored and managed thanks to automated sensors, actuators, and other technology. This is the groundwork for introducing digital twins. .

The digital twin concept relies on constant feedback and synchronisation in both directions [89]. A digital twin in technology is a dynamic model, and it's best to make one before building the real thing [90]. However, sensory data collected from the physical model is essential for developing a digital twin. Incorporating real-world asset information into a digital representation simplifies management and keeps everyone on the same page. Project managers or analysts may access the generated virtual model from their mobile devices [89]. Therefore, a building's tight synchronisation and efficient functioning may be ensured by creating a virtual duplicate before starting any major work. Over time, the volume of information acquired by digital twin technologies may optimise building operations and life-cycle management. The digital twin's information and data resulting from sensors implanted in the physical systems and operating over time. Keen [91] observed that a digital twin contains aspects such as information gleaned by AI and ML techniques, as well as operational data gathered by on-board sensors when designing and constructing a physical environment. These features may be found in a physical space's architecture. When these components operate as they should, building managers are provided withhave an all-encompassing view of the asset's systems, workspaces, and ensembles.The Frasers Tower in Singapore is a connected building designed for digital twins has already deployed the technology in the physical environment [92]. This project was a collaboration between Bentley Systems and Schneider Electric, and it included the use of 900 light, air quality, and temperature sensors in addition to 179 Bluetooth beacons installed in conference rooms. About 2,100 data points are generated by embedded sensors and telemetry and sent to the cloud through Microsoft Azure, allowing for comprehensive monitoring of the surrounding environment. Even considering the Singapore example, the construction sector is still lagging behind others in adopting digital twin solutions.

The use of digital twins is still in its infancy, but it shows great promise for the building sector. The authors have noted some positive outcomes from using digital twin technology. Using cost-benefit analysis throughout a facility's performance and operations is a crucial advantage of digital twins. While the initial cost of developing a digital twin may be high, its benefits to a system's ongoing maintenance and improvement are substantial [93]. Some of the many advantages provided by digital twins include streamlined data administration, anomaly detection for more efficient supervision, and centralised control and management of user access.

The concept of the digital twin has been applied to many different areas with impressive outcomes. When cCompared to manufacturing, construction's implementation of digital twin technology lags far behind. In addition, many technical and intricate processes are required to set up a DIGITAL TWIN so that it works. Setting up a digital twin necessitates a advanced data management system to control the model and the information required for the task.

5. Discussion and Prospects

The construction sector is the leading contributor to pollution and fossil fuel use, thus efforts to reduce these impacts via better building design and energy efficiency have received a lot of attention in recent years. As regulations tighten and fuel prices rise, building owners are under pressure to cut energy usage via measures like retrofitting and the installation of smart controls and sensors. This problem is more pressing in the commercial and industrial sectors due to the large amount of energy wasted as a result of incompetent management. This has led to the implementation of a number of smart technologies that reduce energy consumption. The proliferation of state-of-the-art tools including sensors, data, wireless transmission, network connection, cloud computing, and smart gadgets has resulted in an unprecedented avalanche of data. Traditional modelling of building energy using software and statistical methodologies falls short of delivering the timely and precise projections required for efficient decision-making systems. For a broad range of building types, ML models have shown impressive potential in the area of energy modelling and evaluation. In this study, we compared and contrasted the many ML models that have been used to the problem of calculating building energy requirements. Several pre-processing methods were also thoroughly examined for improving the models' capacity to anticipate outcomes.

Building energy forecasting is one area where ANN has found considerable application since its debut to the market in the 1990s. Accurate energy analysis and prediction in buildings may be achieved with the use of artificial neural networks (ANNs). However, they need cautious thought while choosing the network architecture and changing the training hyper-parameters. Since ANN suffer from a local minimum problem, their efficacy is uncertain. Many research have concluded that a significant number of training samples is required for ANN to attain good accuracy. In that case, even rudimentary MLR models could do better. That's why ANN could be the best choice for engineers who have backgrounds in areas like deep learning and statistical modelling.

Through the literature review, it is clear that several computations, at various scales (from sub-system to building to regional and national) are required to assess the energy system of a structure. There are situations in which each model excels beyond the others. Significant discrepancies may be seen in the engineering model. The process of creating this model might encompass a wide range of factors. It's possible that this model, if sufficiently detailed and complete, may be used to make precise computations. . On the other hand, with the proper simplification techniques, it may be reduced to a lighter model that is simple to construct without sacrificing accuracy. It is generally agreed that the excessive complexity and lack of input information make this sophisticated engineering model challenging to implement. The statistical model is simple to create, but has two significant flaws: it is rigid and cannot adapt to new data.

This report also included a summary of digital twin applications outside of the construction industry. It was discovered that digital twins might be helpful in many different ways during the lifecycle of an asset or facility. With digital twin technology, builders may accumulate data over time to sunderstand the investment and its parts in-depth. This may be utilised throughout an operation to track and manage assets and fine-tune procedures. The relevance of digital twin technology in physical facilities may be shown by looking at two examples: the first is predicting the life cycle performance of a facility, and the second is providing economic advantage by optimising future scenarios. This lifetime forecast makes it feasible to include a Condition-Based Maintenance (CBM) regime, which uses real-time data to prioritise and maximise the usage of maintenance resources. CBM stands for condition-based maintenance. Although the construction industry is one of the many that have used digital twins, the technology has not yet reached its full potential. In this article, we surveyed the current status of digital twins across many sectors, with a particular emphasis on the building and construction industry.

6.Conclusion

Recent research on forecasting energy use in buildings is summarised here. Many models were developed for this application with the goals of accurate, robust, and user-friendly prediction because of due to the complicated nature in terms of how buildings use energy and how variable external elements can be influence it. Applying standard models like machine learning (especially neural networks and support vector machines), engineering, statistics, and AI-based methods. models to novel prediction issues, enhancing the performance of the model by refining its parameters or input samples for maximum efficiency, streamlining the issues, or the construction of the models, and comparing the models under certain situations are the primary areas of research focus. It is difficult to determine which model is superior without conducting a comprehensive comparison under identical conditions, since each model being built has benefits and downsides. New and improved artificial intelligence technologies may provide alternatives to or perhaps breakthroughs in estimating a building's energy use. The report makes a few suggestions for future lines of inquiry.

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