

## Artificial Neural Networks for Predicting Energy Performance and Consumption in Buildings: A Comprehensive Review

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### Abstract

As the world's population, urban infrastructure, and technological capabilities continue to expand rapidly, so does the demand for energy. This paper aims to emphasize the importance of prioritizing energy efficiency in new buildings and enhancing the energy performance of existing structures. This study reviews various machine learning (ML) models and their applications in building energy forecasting, comparing and contrasting their effectiveness. In recent years, ML approaches, particularly Artificial Neural Networks (ANNs), have been proposed for predicting energy consumption and performance in buildings. This paper discusses these models in the context of building energy forecasting. Furthermore, it explores the application of digital twins beyond the construction industry, highlighting their potential benefits in asset lifecycle management and optimization. By providing a comprehensive reviews of ML models and exploring the potential of digital twins, this research contributes to developing effective strategies for reducing energy consumption in the building sector.

**Keywords:** *Energy Efficiency, Machine Learning Models, Building Energy Forecasting, Digital Twins, Construction Industry etc.*

### Introduction

The global pace of development is skyrocketing, and further growth is inevitable. The world economy is projected to grow, and the global population steadily increases each year. This rising population indicates increased needs in areas such as housing and national development. In tandem with these advancements, excess energy is required to fuel global demand while protecting the natural world. While progress is being made, it's crucial to address environmental concerns to mitigate pollution, carbon emissions, and the greenhouse effect. Population growth and subsequent demands on infrastructure for new building construction are major contributors to global warming. Increasing the construction sector's energy efficiency is essential to reducing petroleum emissions and fossil fuel use. Effective energy management and intelligent renovations can also improve the energy performance of existing buildings. Accurate energy forecasting is key to informed decision-making in all these strategies. In recent years, artificial intelligence (AI) and machine learning techniques have been proposed for forecasting building energy consumption and performance (Pang et al., 2020). Improving electricity end-use and lowering energy consumption in buildings while maintaining acceptable quality standards is a critical challenge for building experts. Commercial buildings offer the most significant potential for energy savings through investments in efficient heating, ventilation, air conditioning, and lighting systems. While various methods for increasing efficiency have been researched, there is a lack of systematic evaluations of their implementation and effectiveness in developing countries (Hussaini, 2019). Building design and operation methods can achieve more efficient energy utilization and optimization. Research has shown that the advent of HVAC systems has altered people's perception of thermal comfort, leading to preferences for warmer temperatures in winter and cooler temperatures in summer (Farmani, 2018). Smart buildings, incorporating sensors, AI, and big data, represent an emerging era of energy efficiency. AI technology in smart buildings can help reduce energy use through better control, increased reliability, and automated systems. AI controls are commonly used for energy conservation, and AI has the potential for broad, demonstrable energy-saving impacts across various

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industries. However, the difference in response between AI-assisted control and conventional control remains unclear (Jiao, 2020).

## **Energy Conservation/Efficiency**

### **Global Perspective of Energy Conservation**

Heating, cooling, and powering buildings account for a significant portion of global energy consumption. 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 (Bertagnolio et al., 2008). According study Bevington et al., (1990), 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% (Bureau of Energy Efficiency, 2011). 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.

### **Design of Buildings for Energy Efficiency**

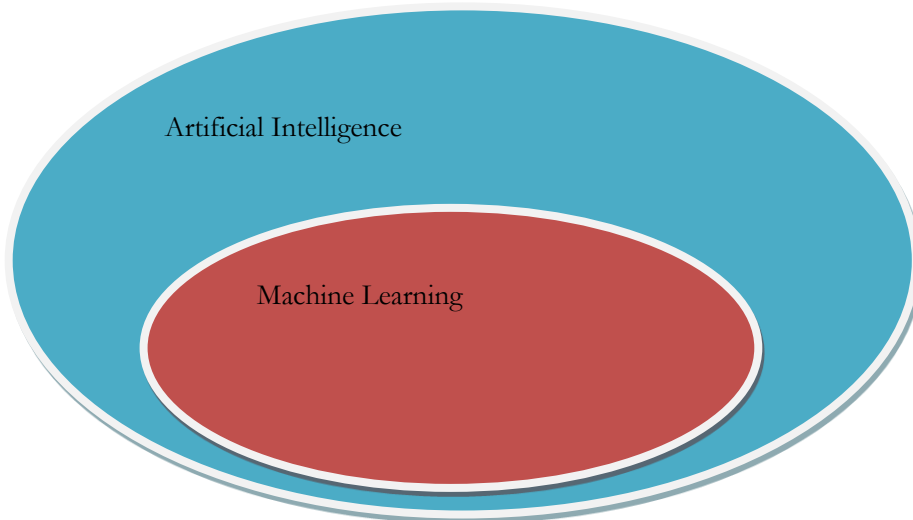
Facade, ventilation, heating, ventilation, and air conditioning (HVAC), and building management and control systems (BMS) all influence the effectiveness of natural ventilation in a building (Butala& Novak, 1999). Erhorn et al. (2008) developed the Energy Concept Adviser (ECA) to improve the energy efficiency of school buildings. The tool's operation and maintenance depiction showed striking similarities across most nations' educational buildings. Studies reveal that decision-makers often overlook energy-saving solutions during retrofits due to a lack of awareness. The ECA serves as a resource for decision-makers in the design phase, providing energy system recommendations and potential design ideas.

Wit et al. (2001) addressed concerns about quantifying building performance and its potential impact on design decisions. The research highlighted the building domain knowledge responsible for inputs that inform judgments about energy consumption, thermal comfort, HVAC system sizing, etc., during design evolution.

Hui (1998) emphasized the use of building energy modeling in energy efficiency studies. The research defined energy simulation, its role in the design process, and the characteristics of simulation design tools. Practical simulation strategies were explored within the integrated building design systems framework.

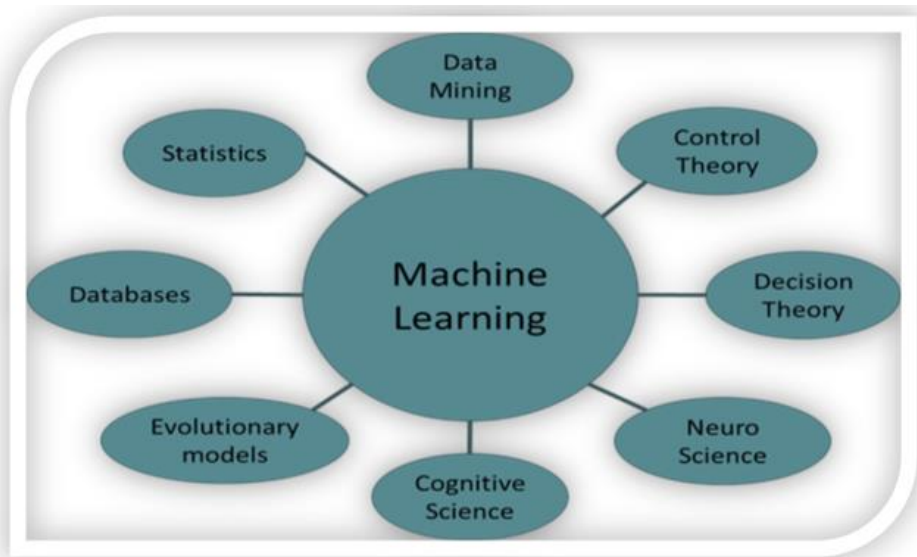
### **Machine Learning Techniques**

Machine Learning (ML) refers to the process of teaching a computer to perform tasks by feeding it specific data sets. Smith et al. (2016) defined ML as a collection of computational algorithms that can rapidly identify and characterize patterns in data. Mohri et al. (2018) described it as "computational methods using experience to improve performance or make accurate predictions." Alpaydin (2016) even considers ML a prerequisite for Artificial Intelligence (AI), suggesting that a system can be considered intelligent if it possesses the ability to learn and adapt to changing environments. In essence, ML can be viewed as a subset of AI, focusing on constructing systems that learn from data (Figure 1).



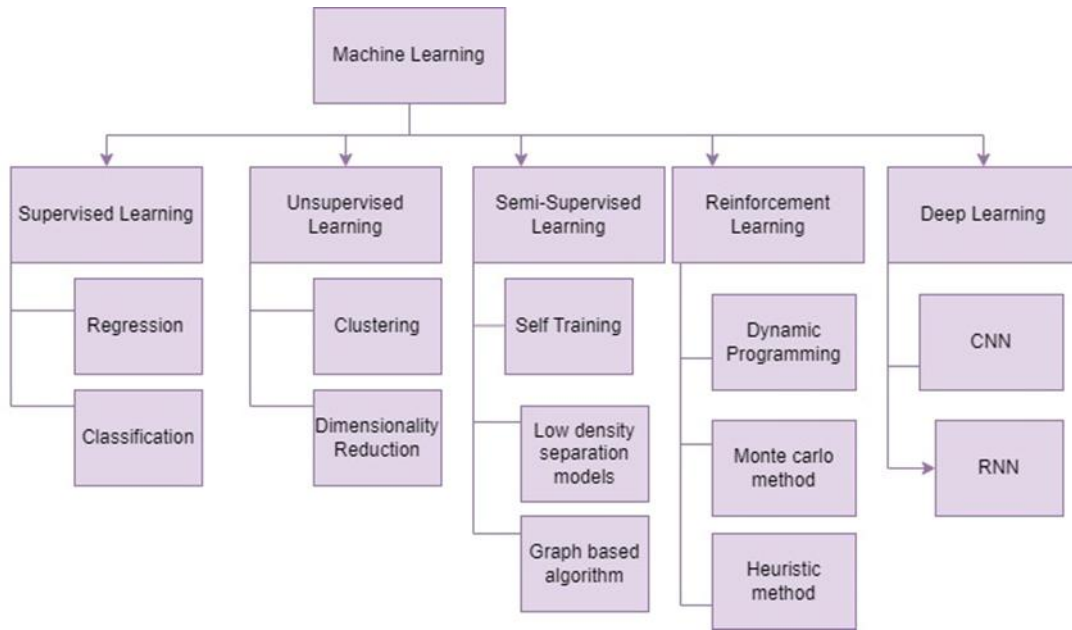
**Figure 1: ML as a subset of AI(Das et al., 2020)**

ML algorithms are commonly used to extract knowledge from existing data sets. They often consume vast amounts of information while considering a limited set of input features. In recent years, numerous ML methods have been proposed for applications within the construction industry, specifically for predicting heating and cooling loads, energy consumption, and performance under various conditions. Machine Learning intersects with various allied fields, including Data Mining, Statistics, Control Theory, Cognitive Learning, and more.



**Figure 2: ML and allied fields(Huang, 2022)**

Figure 2 illustrates some of these interconnected disciplines, such as Data Mining, Statistics, Control Theory, Databases, Evolutionary Models, Cognitive Science, Neuroscience, and Decision Theory.



**Figure 3: Machine Learning categories and related algorithms(Nassif et al., 2019)**

Figure 3 shows broad categories of Machine Learning techniques and some algorithms in each category.

One of the most prominent ML approaches used in energy consumption prediction is neural networks(NN). NN have demonstrated success in representing non-linear problems and complex systems. ANNs can be trained to disregard errors and noise (Tso &Yau, 2007) and understand the fundamental configurations of physical structure (Park &Lek, 2016).

RNNs, on the other hand, enable feedback loops, allowing them to learn from past experiences due to their internal memory. RNNs have been conceptualized in various architectures, including long-term memory, recursive, and fully connected networks. They are commonly used to address deep learning problems requiring solutions with over a thousand layers (Pérez-Ortiz et al., 2003).

**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, 2014)	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 worker 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, 2014)	Building Energy	Tallest commercial	K means algorithm	The framework is appropriate for improving the operational performance of the building.

	Perform ance	building of Hong Kong.	and Apriori algorithm	
(Zhou et al.,2015)	HVAC	lab in a University in Singapore	K-Means Partitional clustering algorithm	Both the Predicted Means Vote model and the Extreme Learning Machine were utilized 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)	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)	Building Energy Perform ance	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%.
(Candanedoet. al., 2017)	Building Energy Perform ance	Residenti al 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., 2018)	Building Energy Perform ance	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)	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., 2010)	Building Energy Performance	IOWA Energy Center, Ankeny, IOWA	CART, CHAID, Boosting tree, RF, MAR Splines, MLP, MLP ensemble and SVM	MLP ensemble model proved better than other models, with 7.66% total energy savings.
(Manjarres et al., 2017)	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, 2016)	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., 2016)	Building Energy Performance	official buildings in South Korea	decision tree method	The system that has been proposed is able to be utilized 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., 2018)	HVAC	commercial building in Alexandria	Support Vector Machines, Discriminant Analysis, Decision Trees, and KNN	According to the findings, the K-nearest neighbor algorithm was the one that disaggregated power the most effectively.

(Cho, et. al., 2018)	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., 2015)	HVAC	Ankeny Iowa	Exhaustive Regression CHAID, Support Vector Machine Regression, Boosting Regression Trees, Random Forest Regression, MLP, MLP Ensemble, Standard Regression CHAID, MAR Splines for Regression,	MLP ensemble model performed best
(Bui et. al., 2020)	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., 2017)	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., 2017)	prediction of cooling load	educational building	The deep neural network was evaluated in	The cooling load prediction results showed that the Deep Learning method worked better. Furthermore, non-linear

		in Hong Kong	comparison to conventional prediction methods such as MLR, EN, RF, GBM, SVR, XGBOOST trees	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., 2020)	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, 2018)	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., 2020)	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 summarizes available ML methods, categorized by use case, and includes information on prediction times, building study examples, energy consumption statistics, and model training features.

**Application of AI to Smart and Energy-Efficient Buildings**

Artificial Neural Networks (ANNs), Polynomial Regression, Decision Trees, and Support Vector Machines (SVMs) are examples of machine learning techniques used to analyze building energy performance (Tsanas, 2012; Chirag et al., 2016). Tsanas (2012) employed ANNs to assess a building's heat load indicators and developed a method to evaluate energy-use behavior with limited data using a back-propagation network to predict future consumption. Suthar et al. (2024) utilized machine learning to predict land surface temperature (LST) in Bengaluru, India, a city grappling with urbanization, air pollution, and temperature challenges. Recurrent neural networks, general regression neural networks, and back-propagation neural networks have been used to study building energy consumption (Ansett & Kreider, 1993).

Now a days, building energy prediction methods fall into three categories: (a) Physical (White Box) Models, (b) Data-Driven (Black Box) Models using Machine Learning, and (c) Grey Box techniques (hybrid models combining physical and ML elements) (Dastbaz et al., 2017; Underwood & Yik, 2008). AI techniques have significantly benefited various aspects of building energy management, including predicting consumption (Ekici et al., 2009), heating and cooling loads, indoor air temperature and relative humidity, modeling HVAC equipment behavior, and recommending energy retrofitting measures.

Various neural network topologies are utilized in energy studies. Ekici and Aksoy (2009) employed a backpropagation ANN to predict energy consumption in three buildings of different shapes and sizes. However, the authors acknowledge limitations, such as focusing solely on heating load and excluding lighting or cooling loads, which they intend to address in future research. Verma et al. (2021) developed an ANN-based data-driven model to predict energy consumption. This model, trained using deep learning and the Levenberg-Marquardt backpropagation algorithm, aims to achieve a global optimum between indoor comfort and energy consumption in India.

Jayakeerti et al. (2023) concluded that building information modeling (BIM) could significantly reduce energy costs based on energy analysis. They employed a neural network model, considering the life cycle cost of electrical and fuel for roof, wall, orientation, and HVAC.

Rajput and Thomas (2023) concluded that passive design solutions in buildings offer benefits such as increased thermal comfort and potential energy savings. However, simulation-based approaches to understand the impact of these solutions on energy needs and thermal comfort in tropical climates like India have been under-researched. The study aimed to develop a framework based on BESO and ANNs to enhance thermal comfort and building energy performance in Indian climates through passive design solutions and mixed-mode operation strategies.

Gunay et al. (2017) suggested using deep learning techniques for 24-hour cooling demand prediction. Deep learning combines multiple machine learning algorithms into a single process and can visualize complex patterns in large datasets. It can be used in both supervised (for building forecasting models) and unsupervised (for extracting fundamental properties from raw data) applications.

Mba et al. (2016) employed an Artificial Neural Network (ANN) to predict the hourly indoor temperature and relative humidity of a building located in a humid climate. The ANN model's inputs included the most recent measurements of indoor and outdoor temperatures and relative humidity. Prior to conducting the study, the researchers collected twenty-four months of data on indoor air temperature and relative humidity. Based on their findings, they concluded that the most effective ANN architecture for this purpose is a multilayer perceptron.

## **Conclusion**

In this paper, a detailed review of the deployment of ANN in forecasting of energy performance or energy utilization in buildings has been undertaken. Due to the presence of various external factors influencing building energy, the dynamics of building energy are complicated and diverse which reforms the importance of state-of-art models that could predict the energy consumption efficiently and effectively. ANN has turned out to be extremely useful in this regard, to be able to decode many factors and handle large sums of data in this subject area. Therefore, from the literature review it has been seen that ANNs have been used successfully for the prediction of energy consumption, thermal load and indoor environment parameters. However, it is informational to note some of the most important drawbacks of ANNs which are high computational cost, and sensitivity to the parameters' setting. The future research studies should be aimed at enhancing the performance of ANN tools to ensure that they are more accurate, reliable and easy to comprehend, formulate new multidirectional tools that involve ANN together with physical models, and solve the problems related to data limitation and reliability. Incorporating the strengths of ANNs and solving the problems faced while using them, will go a long way in improving the predictability and efficiency of the building's energy performance and hence the overall efficiency of the built environment.

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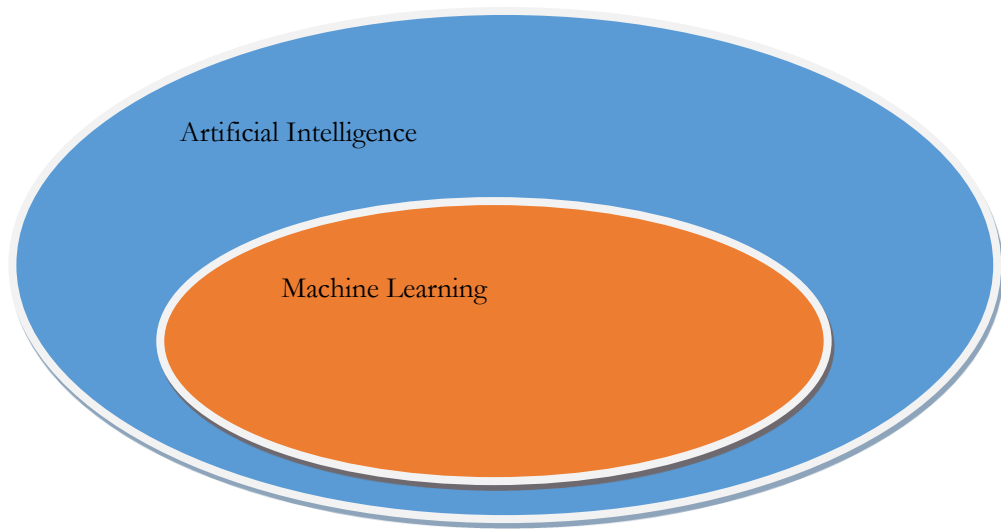


Figure 1: ML as a subset of AI(Das et al., 2020)

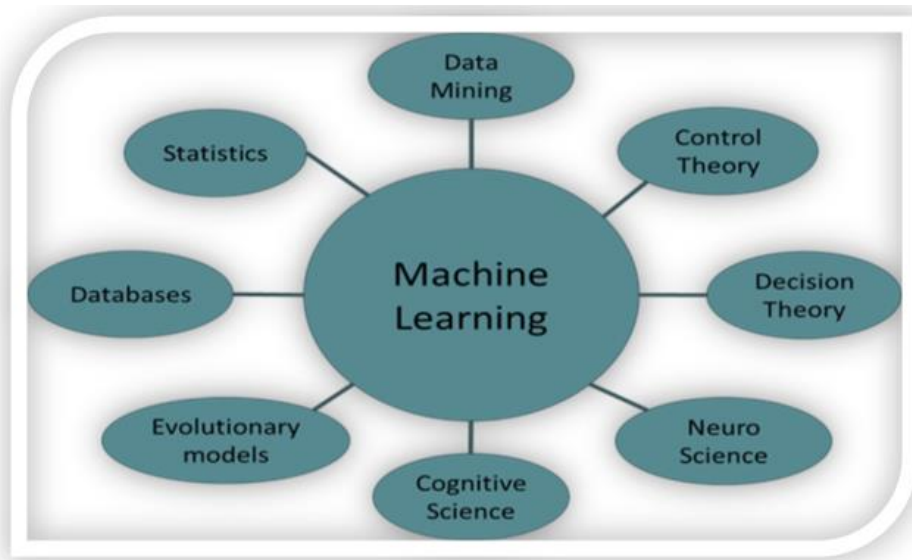


Figure 2: ML and allied fields(Huang, 2022)

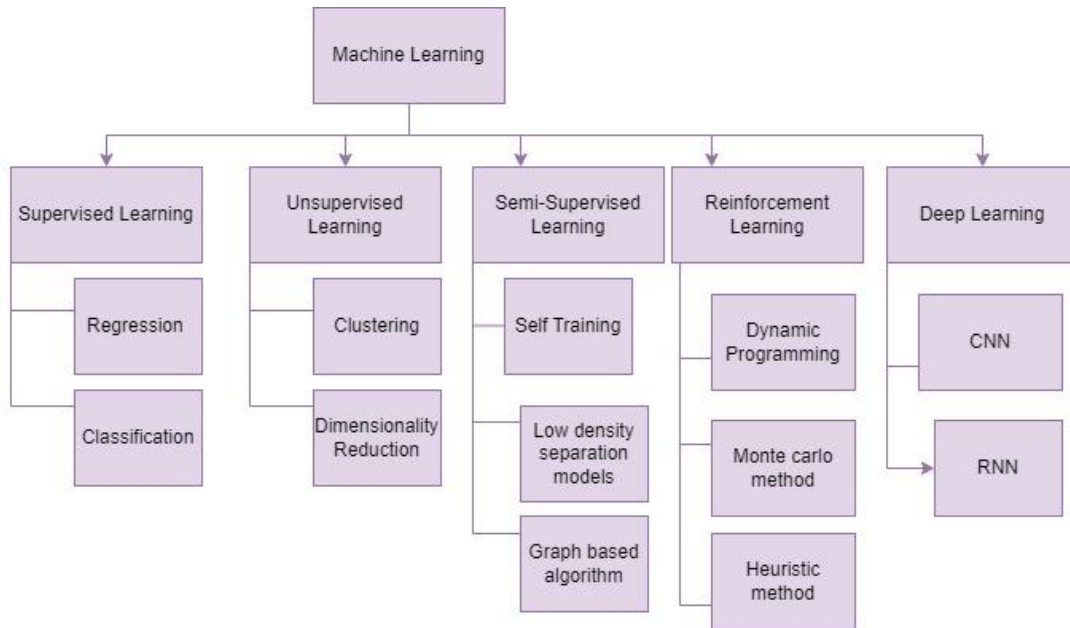


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