Investigating Machine Learning Algorithms within the Conceptual Design Phase, Analyzing Building Energy Consumption and Construction Phase

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Abstract

The application of computation in design domains has improved design process methodologies from CAD to BIM, leading to more efficient approaches to problem-solving and decision-making. In particular, machine learning algorithms are being used in the design process because of their efficient learning, analyzing, and prediction capabilities. The present study leverages machine learning in the context of built environments and explores the possible implementation of diverse ML methodologies throughout the conceptual design stage and building performance analysis. This article investigates the latest developments in machine learning and their applications to built environments and architectural design... The study also looks at new issues in the built environment and how machine learning ideas may be applied in the future to address them. The use of generative adversarial networks (GAN), convolutional neural networks (CNN), and deep neural networks (DNN) in the creation of floor plans, enhancement of energy efficiency, capturing architectural styles, defect assessment, and other applications is examined in this research study. Its ramifications are appropriate for reaching sustainable solutions for issues like energy use, preserving cultural heritage, etc. in the built environment. This research implies that these intelligent algorithms will enable the emergence of interdisciplinary strategies to evolve to address existing problems and find efficient solutions.

Keywords: Artificial Intelligence, Machine learning algorithms, Neural Networks, Generative Architectural design

Introduction

According to (X. Wang & Love, 2012) the technological advancements made the construction process into a high level of automation, and requires high integration of information and physical intensive resources. This paves the use of machine learning to augment existing design tools, allowing for a more efficient and informed design approach. Some of ML's learning algorithms uses logical inference based on observation and inference from what has been observed (Cramer and Kristensen 2000). ML has a lot of potential for improving the design process.

Conceptual design Phase

In the past, the application of machine learning methods for creating and assessing design models before their execution. With the extended applications in various fields, DNN has started growing in the field of architecture by a technique called style transfer where Neural networks discover the style of a famous architect and apply it to the freshly developed layer .The DNNs can analyse and recognize the patterns of the concepts and cultural expressions ,spatial configuration ,urban development and others (As et al., 2018) . Recent work has explored the application of Generative Adversarial Network (GAN) to generative design, which further automates the tedious task of manually implementing design rules. The technique has proven useful for creating floor plans, rendering, and style conversion. (Villaggi and Nagy 2017; Nagy et al 2017;Chaillou 2019).An improvised version of GAN is StyleGAN which has become as a prominent machine learning process in the field of Architectural design process.

ML Technique	Application
pix2pixHD - recognizes architectural drawings and generates them through machine learning.	This phenomena is promising and allows the algorithm to intelligently learn and support spatial decisions and cognition. (Huang and Zheng 2018)
Raster to Vector graphics Rasterized images limit further computing capacities due to the disregard of the semantic information behind the drawings. Also developed a method of conversion of Rasterised image to Vector graphics.	This allows for application in 3D models for interior space visualisation, remodelling of spaces , and also in data analysis(Liu et al.,2017)
GAN	By training and fine-tuning a range of models on specific styles, a basic floor plan can be replicated to the taught style such as Manhattan Unit, Baroque, Victorian and Row house. (Chaillou 2019)

pix2pixHD and CNNs (Convolutional Neural Networks)	To recognize and generate architectural drawings, color codification of rooms, and generate floor plans (Huang et al.(2018)
Tile-maps- Probabilistic machine learning model	Scope of inference design systems for architectural design (Koh et al. (2019)
Image classification neural network	To generate architectural design by transforming the three-dimensional model data into two-dimensional multi-view data **(**Kyle et al. (2019**)**

Table 1 : ML techniques in various processes of design.

Building Energy consumption

In 1995, the use of ANN in energy consumption prediction in buildings in tropical climates using a basic FFN model was carried out based on occupancy and temperature data.

The decision-making involves selecting the most optimal solutions where there are multi-objective optimisation (MOO) approaches were used (B. Wang et al., 2014).Machine learning models such as ANN have been used to estimate energy consumption (Ferlito et al. 2015), heating and cooling demands (Aydinalp et al. 2004; Li et al. 2009; Alam et al. 2016), space heating (Mihalakakou et al. 2002;Aydinalp et al. 2004) and energy efficiency (Cheng and Cao 2014)

ANN for Automated Fault Detection and Diagnostics (AFDD) has proven effective in a number of energy-saving building initiatives. (Magoulès et al. 2013), HVAC system (Du et al. 2013) . To provide automatic energy consumption control ANN is applied (Kalogirou 2000; Benedetti et al. 2016) and heating system optimization (Yang et al. 2003; Ahn et al. 2017) . In a residential building located in Athens, FFN and RNN used for the prediction of hourly electricity energy consumption (Mihalakakou et al. 2002). For commercial building in Hong Kong, ANN is used to asses dynamic energy performance (Wong et al. 2010) . A method is proposed to estimate the prediction of total heat loss coefficient, the total heat capacity and the gain factor (Lundin et al.2004).

Physical modelling and simulation and machine learning models are the two methodologies now available to forecast performance in building design.

Author	Research area
Zhao and Magoulès (2010)	Four methods for predicting building energy consumption are proposed: statistical techniques that use pertinent data to relate energy use to design features; engineering techniques that use physically-based simulations.
Foucquier et al. (2013)	Approaches to energy consumption prediction were physically-based white box method, zonal and nodal methods; statistical black-box method
Ahmad et.al., (2014)	Two methods for predicting energy use are hybrid approaches and MLAs, like ANN and SVM. Considerations included complexity, speed, input type, accuracy, and ease of use.
Fumo (2014)	A summary of various attempts was presented, emphasizing weather data, model verification, and whole-building energy. Four categories were used in the study to predict energy: hybrid, statistical, engineering, and steady-state or dynamic methods.
Wang and Srinivasan (2017)	Energy prediction techniques were found using white-, black-, and grey-box approaches, with an emphasis on black-box single algorithms and different ensemble algorithms.

Table 2: Summary of Research works related to ML in Energy consumption and Prediction

Construction phase

In the construction phase, analysis of cost, Management and documentation of construction, detection of construction defects and inspecting the structural constancy. Building information modelling and waste management during construction DES is capable of capturing the interplay and dependency between intricate construction processes. (Larsson et al., 2016) . DES is used in this integration framework to simulate the construction process and offers process data for calculating construction costs, schedules, and greenhouse gas emissions. Activity-Component-Resource-Action-Sequence (CARS), a construction production model, was developed to accurately simulate the features of the building process.

Author	Area of study
Tang et al.(2010)	Examined methods for automating the process of converting laser scanner data into as-built BIM.
Zhu and Brilakis (2008)	Used computer vision to identify issues automatically with the surface of concrete, such as damages and discolouration.
Jiang et al. (2008)	investigated methods for computer vision and image processing in order to see if they could be used to track structural testing and identify deformation in bridges.
Akinci et al. (2006)	CNN assisted in the development of an automated construction flaw identification and management strategy for construction quality control.
Kuritcyn et al. (2015)	This study suggested a technique that uses image recognition algorithms to automatically identify the Construction Demolition Waste classes.

Table 3 :Summary of research works related to application of ML in Construction

Post occupancy evaluation

The use of machine learning in post-occupancy building evaluation is a significant area of interest and research. The ability to analyze measurements of indoor environmental factors and survey data on occupant satisfaction and comfort creates new opportunities for architects and facility managers to address tenant concerns more effectively and maximize building performance. Both supervised and unsupervised learning techniques have been used for individual comfort learning (Chaudhiri et.al.,2018;Farhan et.al., 2015; chaudhiri et.al 2017; Dai et al., 2017; Ranjan et.al 2016; Peng et.al.,2017). These studies cover a wide range of topics, such as indoor air quality (IAQ), indoor environmental quality (which meets thermal, aural, visual, and spatial comfort needs), and occupant complaints. All of these factors have an impact on the security and well-being of the occupants. (Pin et.al.,2018) employed infrared thermography on human faces, they presented a learning technique based on hidden Markov models (HMM) for determining individual thermal comfort.(Ghahramania et al.,2017)proposed a method for modelling and assessing individual thermal comfort based on online learning. Kim et al.,2018 created a novel method for creating personal comfort models that, using information from occupant feedback and heating and cooling performance, predict a person's preferred temperature. Six machine learning algorithms are incorporated into the model, which is based on field data collected from 38 tenants in an office building. The data includes human control behaviour, environmental variables, and mechanical system settings.

Conclusion

Architects however adapted to the changes in the past, from manual drawing to CAD and mastered it. Likely, Artificial intelligence and machine learning started to support the architects in terms of generating ideas as well as enhancing the previous project. In this paper, we discussed the advantages of various Machine Learning Algorithms in design, modelling and optimization tasks like in the automatic generation of design solutions based on prompts, and images of buildings. Shortly, machine learning algorithms may be applied in Construction waste simulation tools, Energy Management and Analysis tools, Visual Analytics, and Resource Optimization can make the whole building industry more sustainable.

Despite its many applications, machine learning has certain drawbacks. One reason is that they need balanced training sets, which are hard to come by in the architecture field just yet. In fact, machine learning learners may develop biases towards particular patterns and exhibit poor generalization skills if they are given an unbalanced dataset. An additional challenge is the substantial volume of data required to guarantee optimal performance of any data-driven machine-learning method. The absence of vast volumes of data required to train the algorithms, the applicability of the trained algorithm to unexpected scenarios, and the black-box nature of the outcomes are all limitations of present research. Though the design criteria like quantitative like connectivity, visibility, daylighting etc. can be modelled. Qualitative factors like human preferences and experiences will be able to be quantified with the use of these algorithms shortly. Building information and codes are turning out to be more available, to the place where information-driven plans can introduce various chances to enhance customary guides. Future development in data-driven design should not only offer new design possibilities but also assist designers in better understanding their design challenges through human-computer interaction.

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