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Project 1

EC601

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Architect co-pilot

The architect co-pilot is focused on machine learning in building architecture, including designing floors and buildings and decorating a room. This project would discover how to implement the concept of machine learning models in the early building designs and discuss how the ML models reduce energy consumption.

First, a research paper about the early building design stage by Feng et al. (2019) develops a method to quantify and map uncertainty. Also, they use a machine learning algorithm integrating fuzzy C-means clustering. The FCM can fuzzily cluster samples and is applied in conjunction with a regression method to quantify uncertainty. Figure 1 shows the structure of trained ELM models for baseline regression and uncertainty mapping. There are 34 clusters, 30 neurons for uncertainty mapping, and 119 neurons for baseline regression to implement the platform and model establishment.

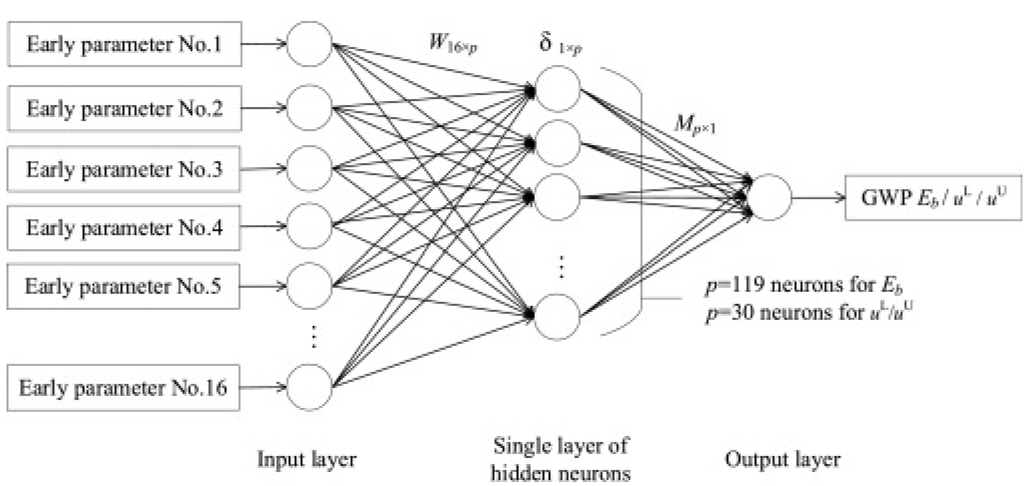

Figure 1: The structure of ELM models for baseline regression and uncertainty mapping

According to the research, machine learning applications for building structural design and performance assessment: State-of-the-art review is written by Sun, Burton and Huang (2020). They discuss how Machine Learning applications relate to the challenges and opportunities in architectural design. They also formulate machine learning algorithms and process the state of practice and research for machine learning applications into architect design. Unfortunately, they found that providing high-quality data sources for machine learning development is unreachable. They encourage that future studies should incorporate more knowledge-informed selection strategies. The reason is that the previous studies have not established general guidelines for selecting machine learning models.

To begin with, a general formulation of supervised learning (classification and regression) and unsupervised learning problems. Supervised learning aims to solve the general optimization problem by minimizing the empirical loss function defined by equation 1.

$$\underset{\theta}{argmin} \frac{1}{n} \sum_{i=1}^{n} \varphi(y_i, f(\boldsymbol{x}_i; \theta)) + \lambda \Omega(\theta) \tag{1}$$

$$\underset{\alpha}{argmin} \frac{1}{n} \sum_{i=1}^{n} \varphi(\boldsymbol{x}_i; \alpha) \tag{2}$$

The objective of unsupervised learning is to induce the basic structure and parameters of demonstration that created the information, which can, at that point, be utilized to gather the information into clusters, creating unused occasions and drawing inductions. Sun et al. (2020) show that equations 1 and 2 can be expressed into equation 3, which is the empirical loss over the training dataset by giving the model f. It assists in minimizing the loss function over the entire data space where p(x,y) is the theoretical joint probability density function of the feature (x) and response (y) variable over the entire data space, D.

$$\underset{\alpha,\theta}{argmin} L(f) = \int_{D} \varphi(y, f(\boldsymbol{x}))p(\boldsymbol{x}, y)d\boldsymbol{x}dy \tag{3}$$

Furthermore, Sun et al. (2020) present many methodologies of how to solve the SDPA (structural design and performance assessment), such as Linear regression, kernel regression, Tree-based algorithms, logistic regression, support vector machines, K-Nearest Neighbors, Discriminant analysis, and Artificial neural networks and its variants. This report will focus on the artificial neural networks and its variants. Sun et al. (2020) clarify that “it takes a set of features x as inputs and applies complex feature fusion operations through a series of layers.”

$$\boldsymbol{h}^l = a^l \left(\boldsymbol{W}^l \boldsymbol{h}^{l-1} + \boldsymbol{b}^l \right) \tag{4}$$

Equation 4 shows that the h^l represents the lth hidden layer and consists of p^l neurons. A linear combination of the neurons computes this. The ANN model is trained by backpropagation that calculates the error gradients over each model parameter. The variations of ANNs have been created to realize faster convergence, better forecast execution, and less memory utilization. At the end of the research, Sun et al. (2020) state that “This can be addressed by using importance testing to understand better the individual effects of features on the response variable. ” They clarify that the results from machine learning models are challenging to interpret. They highly recommend combining data-driven procedures with building SDPA domain knowledge for future studies.

Geyer and Singaravel (2018) discovered that machine learning is advantageous for using data analytics and predicting building performance. In this research, they introduced the component-based approach, enabling them to predict the performance and management complexity for sustainable buildings' design and energy efficiency. The method of artificial neural networks (ANN) has been used in this research, and it has a function to represent the components' behavior. It would deal with the flexibility problem when the machine learning model represents data regression.

Figure 2 shows that the static ML model focuses on the critical relationship between the components for the static prediction during the architecture of the neural networks. The input parameters are hidden neurons and training algorithms. It would be beneficial for building the static model and contribute to building the dynamic model shown in Figure 3.

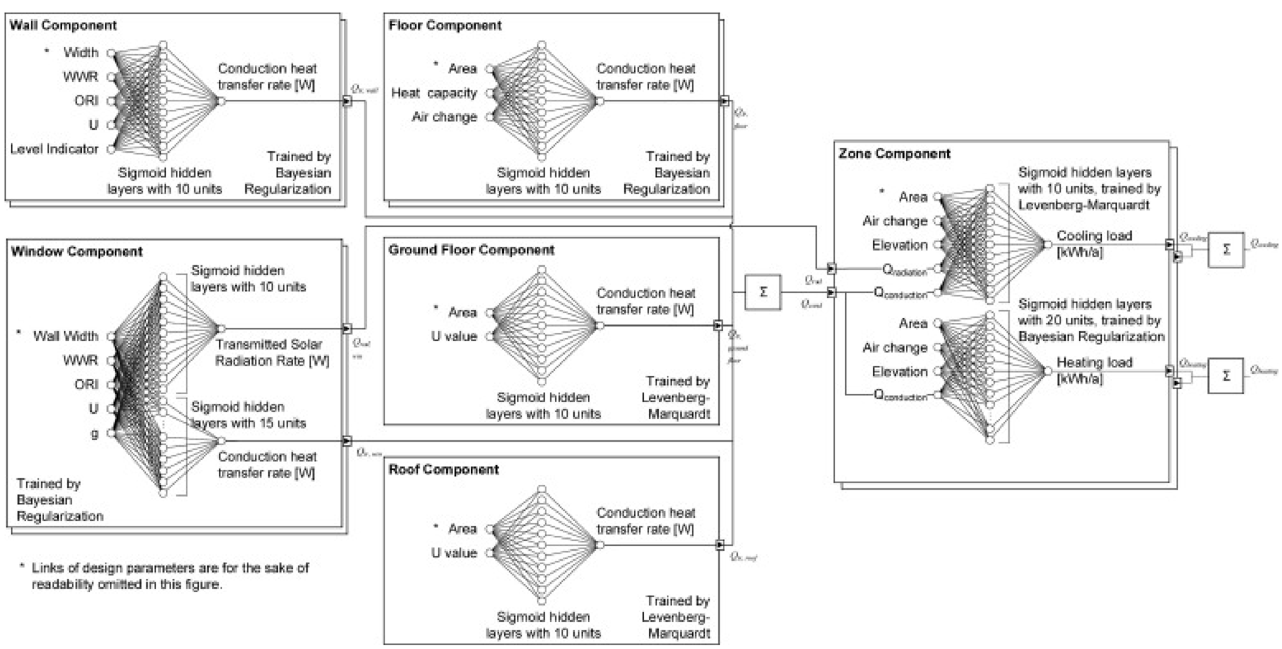

Figure 2: Neural network architecture for components for static prediction

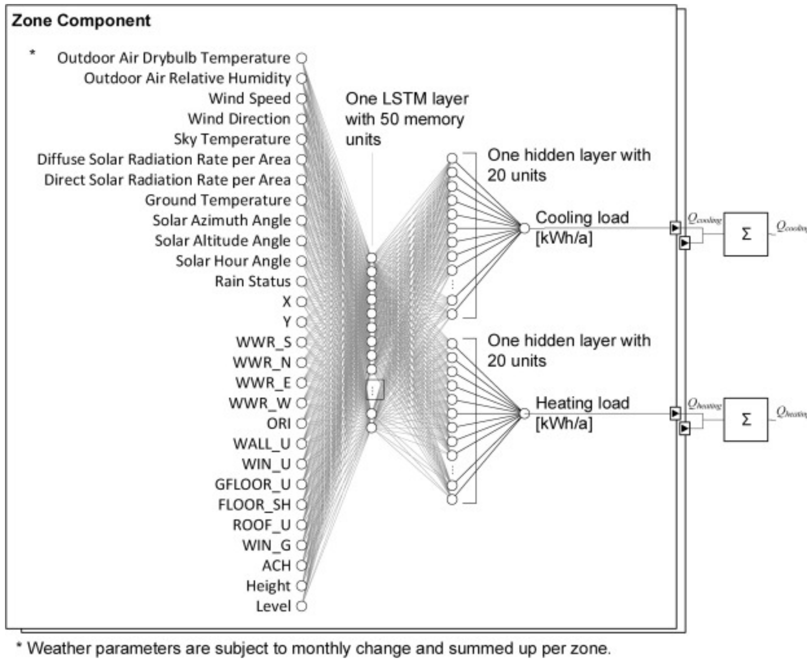

Figure 3: Dynamic model structure with LSTM layer to incorporate dynamic effects

The input variables of the dynamic model are from average weather data and design parameters. The dynamic model concentrates on the ML model's long short-term memory. It would save the storage of historical data and make current predictions. The benefit of using the LSTM layer is to capture dynamic interactions in the weather data based on the energy demand of a thermal zone. Figure 4 shows three tests that "provide valuable insight into the processes and flows between the components" Geyer and Singaravel (2018). When the complexity of the design and deviation of the training case is increasing, it will bring the positive slope of indication of the extensibility. Even Though the ML model has many advantages of predicting energy performance, it is only valid for cases covered by the training data.

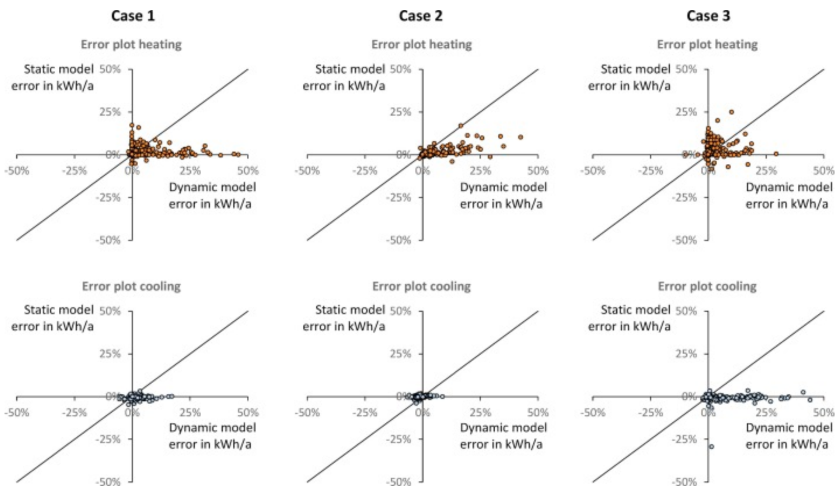

Figure 4: Error overview in relation to the maximum prediction for all cases and for the static and dynamic models

There is another research about the early predicting cooling loads for energy-efficient design in office buildings. As Ngo (2018) mentions, developing high-efficiency energy conservation for building design is imperative. In this study, he would build a machine-learning model based on the 243 buildings' cooling loads data set. Ngo (2018) presents one method of machine learning models shown in Figure 5. It shows the construction and evaluation process in three steps. Also, this method is applied to ANNs, CART, LR, and SVR models.

To begin with ANNs, ANNs implement the process of the brain to define complex patterns and solve prediction problems. It consists of three main layers: input, hidden, and output. Moreover, CART is to help the classification and regression tree. LR models define the relationship between a numerical response variable and more explanatory variables. Lastly, the SVR models are supposed to solve nonlinear regression problems. Table 1 shows the output of four methods of the model. After the comparison, the ANNs achieve the highest prediction accuracy in R and MAPE, representing the best performance.

Single machine learning models	**R**	**RMSE (kW)**	**MAE (kW)**	**MAPE (%)**	**SI (Ranking)**	**Computing time (s)**
ANNs	**0.99**	**176.32**	**139.08**	**8.67**	0.000 (1)	0.45
SVR	0.78	900.21	559.47	38.96	0.98 (4)	0.04
CART	0.98	268.84	178.89	9.33	0.08 (2)	0.01
LR	0.85	737.98	576.92	39.74	0.86 (3)	0.06

Note: Bold values denote the best performance measures among the models; (•) stands for model raking.

Table 1: Performance of single machine learning models for test data of cooling loads

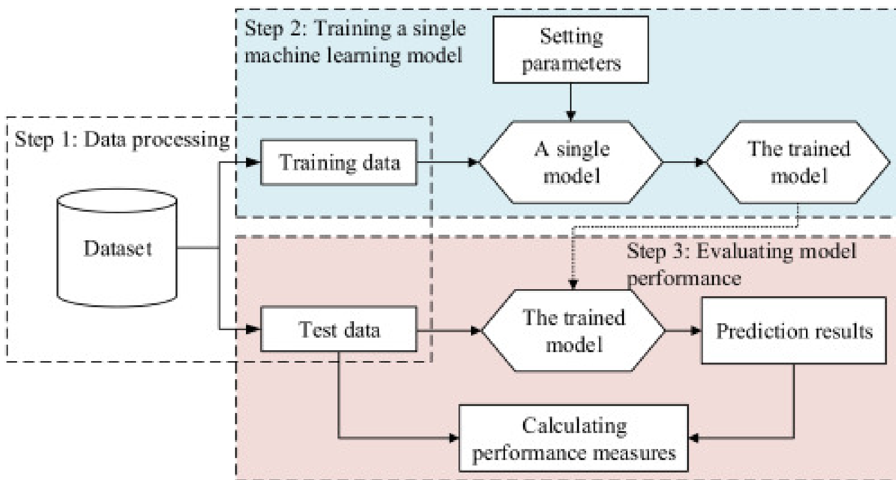

Figure 5: Construction and evaluation process for single machine learning models

Figure 6 shows the actual and predicted cooling loads from four different combinations of ML models from the Ngo (2018) research. After the comparison, the ANNs and CART present the most accurate prediction because all points are more dense than others. This result would be constructive for designers to use a tool to build the relationship between building cooling loads and building characteristics to enhance energy conservation.

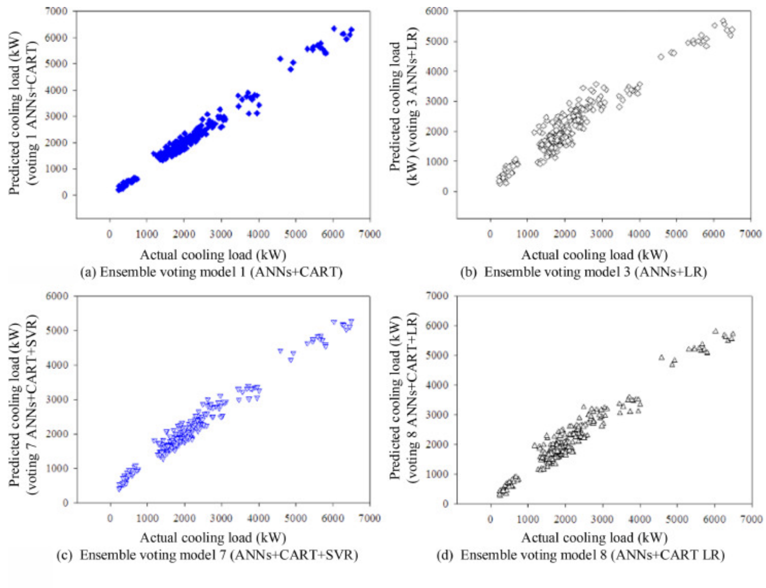

Figure 6: Scatter plot of actual and predicted cooling loads from ensemble voting models

Last but not least, there is an article that ChatGPT writes to discover the impacts and effectiveness of building design by using machine learning shown below the highlighted contexts. The ChatGPT stands on the designer's attitude; it discusses all the benefits of machine learning. ChatGPT states that the machine learning implementation while designing buildings is a revolutionary step. However, the CharGPT does not clarify more specific machine learning models and data processing methods.

Executive Summary

Architect Co-Pilot represents a groundbreaking development in the field of architecture, leveraging machine learning to redefine the architectural design process. This report explores the capabilities, applications, benefits, challenges, and the potential impact of this innovative technology in the domain of architectural design. By providing insights into how Architect Co-Pilot can revolutionize floor plan design, optimize building structures, and assist in interior decoration, this report highlights its transformative potential within the architectural industry.

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1. Introduction

The architectural industry is undergoing a profound transformation with the advent of machine learning technologies. Architect Co-Pilot is at the forefront of this revolution, offering architects, designers, and homeowners a powerful tool to enhance their creative processes. This report delves into the core functionalities and applications of Architect Co-Pilot.

2. Designing Floor Plans

2.1 Space Optimization

Architect Co-Pilot's ability to analyze available space and suggest optimal layouts is a game-changer. It takes into account crucial factors like natural light, traffic flow, and room functionality, ensuring efficient space utilization.

2.2 Style and Preferences

Users can input their design preferences, and Architect Co-Pilot generates floor plans aligned with these preferences, streamlining the design process and reducing manual work.

2.3 Iterative Design

The machine learning capabilities allow architects to experiment with multiple design options quickly, facilitating the exploration of different configurations and real-time adjustments.

3. Building Structure Optimization

3.1 Material Selection

Architect Co-Pilot recommends suitable building materials based on location, climate, and budget considerations, ensuring the construction is efficient and sustainable.

3.2 Load-Bearing Analysis

The tool performs load-bearing analysis, predicting structural performance under various conditions and recommending modifications when necessary.

3.3 Cost Estimation

Architect Co-Pilot provides accurate cost estimations, helping architects and builders stay within budget constraints.

4. Interior Decoration Assistance

4.1 Color Palette Selection

By analyzing room parameters and user preferences, the tool suggests color palettes that complement the space and create the desired ambiance.

4.2 Furniture Placement

Architect Co-Pilot proposes furniture layouts to maximize comfort, usability, and visual appeal within a room.

4.3 Accessory and Lighting Recommendations

The tool recommends suitable accessories and lighting fixtures to enhance the overall interior design.

5. Benefits and Challenges

5.1 Benefits

- Increased Efficiency: Architect Co-Pilot streamlines the design process, saving time and effort.
- Improved Design Quality: The tool's recommendations lead to more aesthetically pleasing and functional designs.
- Cost Savings: Accurate cost estimations help in staying within budget constraints.

5.2 Challenges

- Data Dependence: The tool relies on quality data for optimal performance.
- Integration and Learning Curve: Architects may require training to incorporate it into their workflows.
- Ethical Considerations: Privacy, data security, and algorithmic biases need to be addressed.

6. Conclusion

Architect Co-Pilot represents a revolutionary technology with the potential to reshape the architectural industry. By harnessing machine learning, it empowers architects and designers to create efficient, aesthetically pleasing, and cost-effective buildings and interiors. While challenges exist, the benefits far outweigh them, making Architect Co-Pilot an exciting development in the field of architecture. Its integration into architectural practices promises to enhance creativity, efficiency, and sustainability in the built environment, ultimately benefiting architects, builders, and homeowners alike.

Taking into account the multifaceted aspects and complexities of the matter at hand, many researchers present their analysis of how to build and create machine learning models, such as KNNs, LTSM, CART, LR, and SVR. Also, they apply many methods to process the data by using logistic regression, K-means, clusters, and others. However, many researchers declare that data and methods still need to be improved for future study, and the accuracy of the machine learning model could still be more accurate. The last part is using ChatGPT to solve the Architectural Machine Learning problems. ChatGPT discusses many benefits of designers utilizing the ML models in building design.

Reference

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