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Using Machine Learning for Sustainable Concrete Material Selection and Optimization in Building Design

MENG, Qian [1] **XU, Haoran** [2] **HE, Jingwen** [3*]

[1] University of Technology Sydney, Australia
[2] Columbia University, USA
[3] Washington University in St. Louis, USA

**** HE, Jingwen is the corresponding author, E-mail: jingwenhe@wustl.edu***

Abstract: This paper explores the application of machine learning (ML) in the selection and optimization of concrete materials for sustainable building design. It discusses how AI-driven platforms, such as Concrete Copilot and SmartMix, are revolutionizing concrete mix design by improving performance, reducing costs, and minimizing environmental impact. By leveraging ML techniques, these platforms enable real-time optimization of concrete ingredients, enhancing both resource efficiency and sustainability. The paper highlights the potential of machine learning to drive innovation in the concrete industry, contributing to the development of greener, more efficient building materials for future construction projects.

Keywords: Machine Learning, Sustainable Concrete, Material Optimization, Building Design.

Disciplines: Machine Learning. **Subjects:** Computer Application Technology.

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1 INTRODUCTION

With the development of artificial intelligence (AI) technology, the construction industry is undergoing unprecedented change. The introduction of AI not only improves the efficiency of the design process but also plays an important role in creative scheme generation, performance simulation, decision support, and so on. This paper discusses the application of AI in the architectural design industry, including concept generation in the early stage of design, the optimization of design parameters, and the role of design simulation and optimization. [1] Introduce the latest progress of AI-enabled automated design tools. Through the introduction of the application of artificial intelligence technology developed by independent innovation and the analysis of specific practical cases, demonstrate the application achievements and potential of the latest AI technology in actual architectural design projects [2-3]. Practice shows that artificial intelligence technology will bring a revolutionary impact to the engineering design industry and represents the new quality productivity of the engineering design industry. [4] At the same time, artificial intelligence technology can only play its great value if it is combined with the industry and the specific scene of the industry.

Huang et al. (2024), in their study Research on Multi-agency Collaboration Medical Images Analysis and Classification System, based on Federated Learning presented at the 2024 International Conference on Biomedicine and Intelligent Technology, demonstrate the effectiveness of federated learning in enabling secure, decentralized collaboration for medical image analysis[5]. This approach ensures privacy preservation while optimizing classification accuracy, showcasing how machine learning can address challenges involving distributed and sensitive datasets. Similarly, leveraging machine learning techniques to optimize material selection in sustainable building design requires managing diverse, often decentralized data sources. Huang et al.'s work provides valuable inspiration for implementing collaborative frameworks to improve data utilization and decision-making efficiency in sustainable construction.

Large-scale mining in the construction industry has caused serious waste of resources and environmental pollution, posing a major threat to biodiversity and human health. To address this issue, promoting the sustainability of buildings is a key measure to reduce their ecological footprint. [6-7] Among them, the use of construction waste instead of natural materials to prepare sustainable concrete is an effective means to reduce the environmental impact (EI) of concrete. With the application of new types of solid waste (auxiliary cementing materials, recycled aggregates, geopolymers, etc.), the complexity of sustainable concrete design increases. In addition, concrete contains a variety of components, the random distribution of aggregates, mortar, and pores will lead to the uneven distribution of components in the concrete. [8][9] The traditional method is mainly based on test and finite element simulation to establish a regression model to predict the performance of concrete, but it is not enough to evaluate the performance of multi-component materials such as concrete.

In recent years, various artificial intelligence (AI) techniques have been used to evaluate concrete performance.[10]AI technology has strong nonlinear processing capabilities and the ability to analyze high-dimensional variables, which can effectively analyze complex interaction mechanisms in concrete. Xu, Chen, and Xiao (2024), in their study A Hybrid Price Forecasting Model for the Stock Trading Market Based on AI Technique (Authorea Preprints), propose an innovative hybrid model that combines multiple AI techniques to improve stock price forecasting accuracy [11-13]. Their approach demonstrates the potential of integrating machine learning algorithms for handling complex, dynamic financial data, offering insights into predictive analytics that are highly relevant to enhancing decision-making in financial markets. However, there are still some problems to be improved. For example, how to build a database with strong correlation, determine the most suitable machine learning algorithm for predicting performance, and so on. [14-16] Solving the above problems can effectively improve the utilization rate of machine learning models. More importantly, analyzing the sustainable performance of concrete can fundamentally optimize the ratio of raw materials, reduce costs, and thus achieve sustainable development of the construction industry.

2 MACHINE LEARNING TECHNIQUES FOR MATERIAL SELECTION

AI, ML, and DL have numerous applications in the construction industry, most of which have become a reality in the past few years due to the increased computing power of high-performance graphics processing units (GPUs), the increased availability of advanced ML and DL algorithms, and the relative ease of implementing these algorithms using computer languages, ML and DL libraries, and software[17].

2.1 DETECTION OF DIGITAL IMAGES OF BUILDING MATERIALS BASED ON MACHINE LEARNING

Machine learning collected at construction sites through digital images and video clips is often used to extract useful information. Exploring new applications of image processing techniques in construction engineering and management is a growing area of research. One of the initial steps in various image processing applications is the automatic detection of various building materials on construction images. In this paper, the authors conducted a comparative study to evaluate the performance of different machine-learning techniques in detecting three common classifications of building materials: concrete, red brick, and OSB board[18-21]. The classifiers used in this study are Multilayer perceptron (MLP), radial basis function (RBF), and support vector machine (SVM).

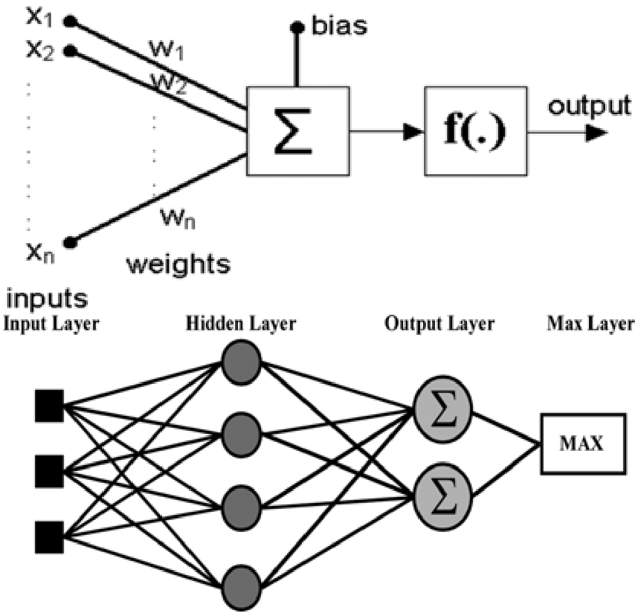

FIG. 1. DIGITAL IMAGE MODEL ARCHITECTURE FOR INSPECTION OF BUILDING MATERIALS BASED ON MACHINE LEARNING

To achieve this goal, the feature vectors extracted from image blocks by machine learning technology will be classified and the efficiency of these methods for detecting building materials will be compared. [22-23] The results show that the SVM model is superior to the other two techniques for all three materials in accurately detecting material texture in images. The results also show that the commonly used material detection algorithms perform well when detecting materials with different colors and appearance, such as red bricks; However, these machine learning models may be less accurate in detecting the performance of materials that have color and texture variations (such as concrete) and materials that contain color and appearance properties similar to other elements in the scene (such as ORB boards)[24].

2.2 MATERIAL FILTERING AND SELECTION BASED ON CONVOLUTIONAL NEURAL NETWORKS

A neural network (CNN) is a unique type of artificial neural network (ANN) that can be used to process data with a grid-like topology. CNNS are primarily used for classification using image and computer vision applications. CNN has three main types of layers in its architecture. They are the convolutional layer, the pooled layer, and the fully connected (FC) layer. ated its effectiveness in [25]. Its interconnected layers facilitate the seamless integration and processing of information from diverse sources. Inspired by the model structure presented in this paper, we found it highly effective for handling multivariable feature data in material-related machine-learning tasks. This model design provides valuable insights into a typical CNN, the convolutional layer is followed by a pooled layer or another convolutional layer, and finally the FC layer. The input layer of the CNN holds the input image data. The convolutional layer is the core building block of CNN, which uses several components such as filters/kernels/feature detectors and feature maps [26]. The feature detector/filter/kernel is a two-dimensional weight array smaller than the image size. Calculate the dot product between the pixel value of the image and the weight of the filter and input the result into the output array. This process is called convolution, and the feature detector moves over the entire image to perform this calculation and determine the features.

In this approach, all the neurons in one layer are not interconnected with the neurons in the next layer, as an NN would be. Only the neurons belonging to the filter are connected to the convolutional neurons of the next layer[27-28]. The output of this process is called a feature graph or activation graph, or convolutional feature, and this approach has revolutionized deep learning by reducing the connections between neurons, thereby reducing the memory and processing requirements for large inputs such as images, video, and audio. The depth of the convolutional layer output will depend on the number of filters. [29]After the convolution layer, the activation function is applied. The pooling layer is used to reduce the dimensionality of the image by obtaining the sum and average of the fields. [30-32]This process is also called downsampling. The fully connected layer is located at the end of the network, as shown in Figure 5, and the neurons in this layer are fully connected to the activation in the previous layer. Filter size, filter number, fill, and stride length are hyperparameters that determine the architecture of the DL algorithm. The cost function is then calculated based on the result compared to the actual value, and the kernel's weights are updated by backpropagating this error.

2.3 SELECTION OF BUILDING MATERIALS BASED ON GENERATIVE ADVERSARIAL NETWORK

Generative adversarial networks (Gans) are a deep learning algorithm that focuses on generating models to create images, video, and audio. Using Gans, you can create new data instances that are similar to the data in a training dataset. [33]Gans uses two types of deep neural networks in their architecture, called "generators" and "discriminators." The generator is responsible for creating new functionality similar to the trained data in the dataset, combined with feedback from the discriminator.

The discriminator is responsible for identifying the real data from the data created by the generator and providing feedback to the generator on the quality of the output image compared to the real image in the dataset. In the initial phase of training, the generator creates obvious false results that the discriminator can identify[34]. However, as training progresses, the generator can create results that can fool the discriminator, and if the training process is successful and the discriminator starts to classify fake data as real data, the accuracy of the discriminator decreases

In addition, there are many variations of Gans, Progressive GANs, Conditional GANs, Cycle GANs, Text-to-image GANs, Super Resolution GANs, InfoGANs, Progressive gans, conditional gans, cycle Gans, text-to-image gans, super-resolution gans, Infogans, DCGANs and Wasserstein GANs. Most of these algorithms have been used for generative design in the building and construction industry.

3 OPTIMIZATION OF MATERIAL PERFORMANCE

In the realm of sustainable building design, optimizing material performance is crucial for achieving both environmental and economic goals [35]. The selection of materials must consider a variety of performance criteria, such as energy efficiency, durability, cost-effectiveness, and environmental impact. Traditional material selection often involves trade-offs between these factors, making it challenging to find the optimal balance, The “Multi-Layer Data Fusion Architecture” demonstrated its effectiveness in . Its interconnected layers facilitate the seamless integration and processing of information from diverse sources. Inspired by the model structure presented in this paper, we found it highly effective for handling multivariable feature data in material-related machine-learning tasks. This model design provides valuable insights into the multifaceted characteristics of materials, leveraging large datasets of existing materials such as sustainable concrete.

However, machine learning techniques offer new possibilities for addressing these challenges. By leveraging advanced algorithms, we can perform multi-objective optimization that simultaneously considers multiple performance indicators, helping to select the best materials based on complex, often conflicting requirements. This approach not only enhances the sustainability of building projects but also improves the cost-efficiency of construction processes. One notable area of innovation is in the concrete industry, where AI technologies are driving transformative changes.

Through AI-driven material optimization, the concrete industry is becoming more sustainable, both in terms of resource usage and environmental impact. Below are some examples of how AI is changing the concrete sector, particularly in the context of optimizing its performance for sustainable building design.

3.1 ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE PERFORMANCE OPTIMIZATION IN THE CONCRETE INDUSTRY

In recent years, several technology companies have been leveraging AI to revolutionize the concrete industry by optimizing the material's performance and improving sustainability. One such innovation is Concrete Copilot, developed by Concrete.ai. This generative AI platform is capable of producing millions of potential concrete mix designs, allowing producers to quickly identify the best formulations for specific applications. By predicting ingredient performance in just seconds, the platform significantly reduces the time required for mix design, cutting down a process that would traditionally take weeks to just minutes. This not only saves time and money for manufacturers but also increases production efficiency and can reduce carbon emissions by up to 30%.

Another notable development is Giatec's SmartMix software, which consolidates all concrete production and quality data into a single platform. The system uses the Roxi AI engine to adjust mix proportions in real-time, ensuring optimal homogeneity. As the only solution of its kind for the ready-mix concrete industry, SmartMix gives manufacturers comprehensive control over their operations while optimizing material management through advanced AI insights. Recently, Giatec secured CAD 17.5 million from the Canadian government’s Strategic Innovation Fund to further develop SmartMix™. This funding supports the creation of the world’s first smart ready-mix concrete plant and aids Canada's goal of achieving net-zero emissions in the concrete sector by 2050.

Additionally, MIntelligent Feed, developed by Marcotte Systems (now part of Command Alkon), represents the world’s first AI-driven solution for real-time optimization of concrete production. The system dynamically adjusts according to changing plant conditions to ensure consistent concrete quality and optimal use of materials. By minimizing deviations and producing high-quality concrete that meets specifications, Intelligent Feed is helping producers maintain efficiency and reduce waste. Furthermore, AskConcrete, an AI-powered answer engine launched by the National Ready Mixed Concrete Association (NRMCA) in partnership with XBE, leverages hundreds of NRMCA publications to provide detailed answers about concrete and construction processes, making it a valuable tool for industry professionals seeking fast and reliable insights. These innovations demonstrate how AI is driving efficiency, sustainability, and quality in the concrete industry.

4 CONCLUSION

In a world of rapid technological development, artificial intelligence is profoundly changing the way we live and work. Among them, the construction industry is also receiving the baptism of this change. In the construction sector, the introduction of artificial intelligence is not only optimizing the design and construction process but is reshaping the future of building materials. AI can select and optimize material use through predictive models, as well as the potential to drive research and development of new materials, such as smart concrete and bio-based building materials. The use of these materials will greatly improve the environmental protection and durability of buildings. However, we must also face challenges such as data access and model accuracy. While there are still many challenges to overcome, the potential of AI in the field of building materials is indisputable. In the future, we have reason to expect a new era of AI-led and optimized building materials.

First, AI offers a new perspective on the selection and application of building materials. AI can use machine learning models to predict the performance of different building materials under various environmental conditions, which provides a huge help in the material selection process. For example, AI can predict which building materials will provide the best thermal efficiency, or the most durability, under different climatic and geological conditions. This predictive ability helps architects and engineers choose the most adaptable building materials, thereby improving the environmental protection and durability of buildings.

Second, AI can also help us make more efficient use of building materials. By optimizing the design and construction process, AI can significantly reduce the waste of building materials. AI algorithms can predict the number of materials needed, thereby reducing surpluses and shortages during construction. In addition, AI can optimize the distribution and use of materials through algorithms to ensure that each material can be used to maximum efficiency.

Overall, the impact of AI on building materials is changing the way we design and build buildings. Through AI, we can optimize the selection and use of materials, develop new materials, and improve the environmental protection and durability of buildings. Despite the challenges, the potential of AI in building materials is huge. The continued development of artificial intelligence will continue to drive innovation in building materials, bringing us safer, more efficient, and environmentally friendly buildings.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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ABOUT THE AUTHORS

MENG, Qian

School of Architecture and Design, University of Technology Sydney, Sydney, Australia, 2007, mengqian519@gmail.com.

XU, Haoran

Graduate School of Architecture, Planning and Preservation, Columbia University, New York, 10027, USA, hx2304@columbia.edu.

HE, Jingwen

Samfox School of Architecture, Washington University in St. Louis, California, USA, 94608, jingwenhe@wustl.edu.

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