Artificial Intelligence and Applications in Structural and Material Engineering

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Abstract. The integration of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has become a vital tool attributed to Structural and Material Engineering and developed the way engineers approach design analysis and optimization. This paper explores the principal models of ML and DL, such as the generative adversarial network (GAN) and the artificial neural networks (ANN) and, and discusses their impacts on the applications of material design, structure damage detection (SDD), and archtecture design. It indicates that the high-quality of database is the essential key to training the model. Thus, the data preprocessing is required for expanding the data source and improving the quality of data. In material design process, ML and DL models reduce the time to predict the properties of construction materials, which makes SDD realistic as well. For architecture design, GAN is used to generate image data, such as drawing of the floor plan and this could be helpful to reduce the labor resources. However, some challenges of ML and DL are found while applying the algorithms to real-life applications. For example, sufficient data is needed to train the DL models and the ethic aspect is also a concern when thinking of AI.

Keywords: Structural and Material engineering; Machine Learning; Artificial Intelligence.

1. Introduction

In an increasingly complex and data-rich world, technologies such as ML and DL have emerged as powerful tools to analyze data and process complex algorithms and models. AI is defined as a larger concept of creating systems through algorithms that can perform based on the predicting relationships or models by ML. Furthermore, ML and DL allow computers to learn from data and improve the performance of predicting outputs, which simplifies the processing of the optimized material design and further monitors the behavior. Especially for the field of biomedical material design, the ML and DL models such as convolutional neural networks (CNN) perform well in capturing the different hierarchical levels of material [1]. For example, the applications to the civilization field could be inspired because the materials are optimized for maximum strength with minimum resources. SDD techniques can be conducted by ANN by extracting the shape of bending structures and GAN is able to be applied to generate the architectural drawings. However, the difficulties of using ML and DL are not negligible, such as data source limitations and non-observable processing.

This paper delves into the primary ML and DL frameworks, including GAN and ANN, and evaluates their influence on material design, structural damage detection (SDD), and architectural design. The potential difficulties of using ML and DL methods in structural and material engineering are stated such as limited data resources and ethical issue, and some future suggestions are given to address the corresponding challenges

2. Artificial Intelligence Technologies

AI, ML, and DL are closely related fields, with ML being a subset of AI (Figure 1). As mentioned, AI have a broader range of systems that can operate the tasks that are normally required human's thinking. While, ML and DL focus on learning from data to process more specific tasks, which involves predicting outputs or relationships between input and output.

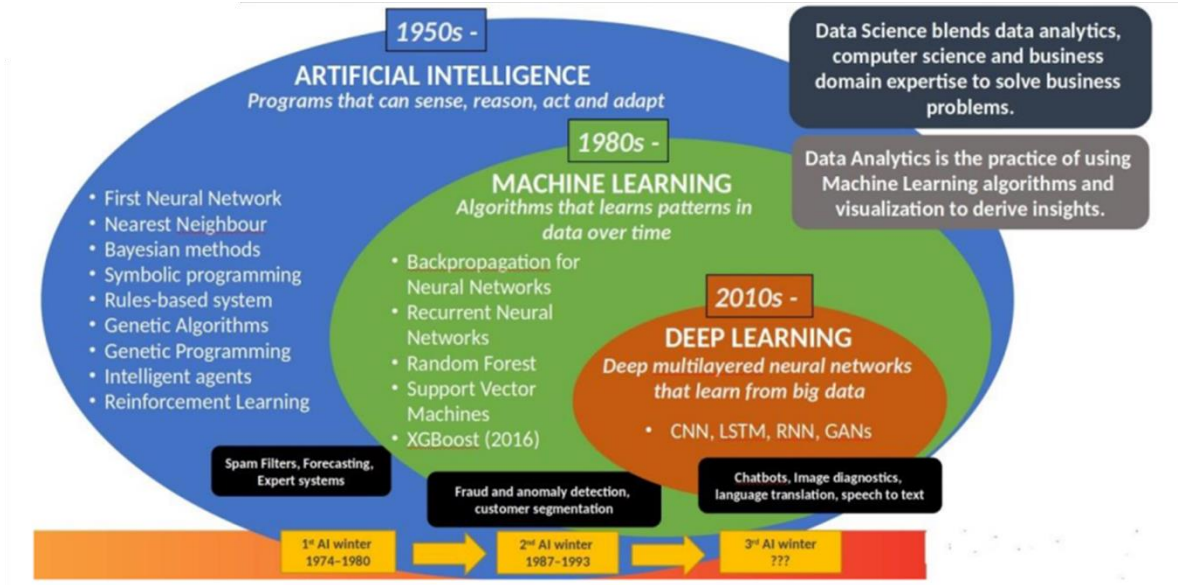


Figure 1. Classification of AI technologies.

2.1. Machine Learning

ML performs similarly to a simulator of AI and there are three main types of it, supervised model, unsupervised model, and enforcement model. Each model adopts different approaches to exploring the output of data, which generally could be a relationship or prediction.

Supervised learning involves training a model on the labeled datasets, where the output data (y) should have at least one input (x). The objective of the model is to analyze a relationship between inputs and outputs. Common algorithms in supervised learning include linear regression and backpropagation for neural networks (BPNN). BPNN is used in ANN for various tasks, such as classification, regression, and pattern recognition. This neural network perform well standings in the field of concrete structure design.

Unsupervised learning deals with datasets that are not labeled, meaning there are no explicit target outputs provided during training. The objective here is to find patterns, structures, or relationships within the data. For example, clustering and principal component analysis (PCA) are common unsupervised algorithms.

Reinforcement learning involves training an agent to make a sequence of decisions in an environment in order to maximize a cumulative reward. The agent learns through trial and error, receiving feedback in the form of rewards or penalties based on its actions. Reinforcement learning is commonly used in applications such as game playing, robotic control, and autonomous systems.

2.2. Deep Learning

DL is working on training ANNs to perform tasks by analyze a large amounts of input data, which is also known as a field of ML. It's inspired by the neural network of the human brains, where neurons are interconnected to process information. DL consists of multiple layers (deep architectures), enabling them to learn intricate and hierarchical microstructure patterns in data through autonomous microstructure search, which is suitable for material design [1].

ANN simply referred to as a neural network, are a class of ML models created from the inspiration of the human brains. They are a fundamental component of DL and it can have several specific networks, such as CNN and recurrent neural network (RNN). CNN as an example, is extracting the image feature by mathematically calculating convolutions. Convolution maintains the spatial connection among pixels and is computed by the multiplication of the image matrix and the filter matrix. Filters consist of adjustable weights that are optimized during training to extract features [1]. Through the combination of the convolution layers, it is perfectly fitting into the neural network working with DL. With the fact that it is image-based, the probability of using it to describe the

material becomes realistic. Another similar ANN model is an RNN. However, the difference is that RNN is designed to work with sequences of data. RNN can map input sequences to output sequences and it is useful while dealing with natural language processing (NLP). Moreover, there are advanced versions of RNN, designed to better capture and manage long-range dependencies in sequences, overcoming the vanishing gradient problem [2, 3].

GAN is a type of AI model within the realm of DL. A GAN consists of the generator and the discriminator, which are trained simultaneously through a competitive process. This competition between the generator and discriminator results in the generator becoming progressively better at creating data that is indistinguishable from real data [2]. GANs are widely used for generating realistic and high-quality synthetic data, images, videos, and audio [2].

2.3. Source of Data for ML and DL

Collecting input data for ML and DL involves gathering a large amount of relevant and representative data to train and evaluate the ML models. High-quality data is essential for building accurate and robust models. Thus, there are challenges in data collection as well, such as the limitation of data and the massive budget to obtain the data. The popular way is collecting from the database or literature as the appearance of high-throughput computational materials contributes to building the database, such as AFLOW and MATDAT [1]. The database records the mechanical properties of materials, which is further useful for structural analysis and material design. The labeled textual data can be collected by literature as well, and RNN can be useful in this case. As mentioned in the DL section, NLP collects and processes data from various sources to enable computers to understand, interpret, and generate human language. This method reduces manual operation to a large extent and allows a computer to obtain data automatically; however, there may be some input data preprocessing needed.

Data preprocessing is essentially important because it can organize input data to satisfy the need for data analysis. It involves cleaning and transforming raw data into a format that is suitable for analysis or training ML models. Effective data preprocessing enhances the quality of the data and improves the performance of models by removing noise, handling missing values, and standardizing the data. Nevertheless, DL can possibly require less manual feature engineering and data preprocessing compared to traditional ML due to feature extraction and data abstraction. DL model is beneficial from training and deals with data from simple to abstraction [1].

3. Applications of ML and DL

ML and DL have found various applications in the field of materials science and structural engineering, such as construction material design and structural design.

3.1. Construction Material Design

Construction material design is critically important, as it directly impacts safety, efficiency, and sustainability. Concrete, as a commonly used construction material, can be predicted compressive strength, tensile strength, and other properties by ML or DL. For instance, the challenges of construction material optimization can possibly be constrained by an objective [2]. The method of using ML and DL models can be extremely convenient while using optimization algorithms, such as nonlinear or linear regression programming. The neural networks are suitable for property predictions and material screening by using the capabilities of non-linear [4]. Concrete design could be a problem with predicting the specific strength, especially the compressive strength, roughness, and crack propagation. ML can be helpful in structural health monitoring (SHM), particularly the concrete structures [5]. For instance, using Extreme Gradient Boosting (XGBoost) and BPNN can identify the compressive strength of multiple types of concrete with given input values of w/c ratio, mortar, and ratio of fine and coarse aggregates [4,6]. XGBoost is a tree-based ML algorithm used for both classification and regression tasks and this model indicates an 85% accurate result to the experimental

result evaluated by Root Mean Square Error (RMSE) [7]. This feature also enables further applications. For example, damage detection and predictive maintenance become realistic as well based on the material properties and historical data with the combination of environmental conditions [1].

3.2. Structure Damage Detection (SDD) and Maintenance

A structural system is a critical aspect of civil and mechanical engineering that involves creating the framework, support systems, and overall configuration of a structure to ensure it can withstand the loads and environmental conditions it may be subjected to. As mentioned, the success of predicting the material properties proves the SDD and predictive maintenance feasibility. ML-driven parametric SDD techniques are introduced, wherein the feature extraction step involves the identification of specific modal parameters from the structural systems using either input-output or output-only modal identification methods. For example, a proficient ML classifier, after being skillfully trained, is employed to analyze the modal parameters to evaluate the structural soundness [8]. An ANN model is trained based on the shapes of the bending structure and Fourier coefficients are as a damage index to identify the positioning. Moreover, an advanced study states six hidden neurons of an ANN structure contribute to the accurate rate of SDD conducted by Bayesian Algorithms [8].

3.3. Architecture design

Architecture design is the process of planning, designing, and creating the physical spaces, structures, and environments that make up our built environment involves creating blueprints, drawings, and plans that guide the construction of buildings, landscapes, and urban areas. The generation of floor plans has been achievable by using DL. For example, CNNs and GANs can be used for house style recognition and indoor scene synthesis by a training model called ArchiGAN [2]. CNNs are suitable to process image-based data and GANs can lay out the floor plan. There is a software called pix2pix using GANs, which can process the input data and form a predicted draft image, and this software could generate construction figures based on the input prompts.

4. Discussion

4.1. Advantages and challenges

Design construction material using ML and DL models enables the material properties to be predicted accurately, which saves the budget of human labor, reduces the trial and error cost, and develops sustainable solutions for design purposes. XGBoost indicates the strong power in the regression process with highly accurate results. Compared to the traditional methods, the advantages are observable. Concrete design involves different admixtures, such as air-entraining, water-reducing, retarding, accelerating, and plasticizers, which makes the traditional method difficult to predict the exact properties [7]. ML can simply change the number of inputs and convert them to different algorithms. While ML and DL models can make accurate predictions, understanding the underlying causes of specific material properties or structural issues can be challenging. This lack of interpretability can hinder engineers' ability to make informed decisions based on model output.

SDD and maintenance are crucial aspects of ensuring the longevity and safety of civil and mechanical engineering structures. ML-driven parametric SDD techniques utilize modal parameters to identify potential damage, with advanced algorithms like ANN enhancing accuracy rates. However, SDD techniques are all based on supervised ML algorithms, which highly rely on labeled data for training purposes [8]. Thus, there can be some constraints, such as human labor to label the data and run the model and a lack of data on the failure structure. Limited data on the pre or post-damage structure can be captured unless testing material properties in laboratories [8, 9].

The field of architecture has witnessed a significant transformation with the integration of DL techniques, revolutionizing the process of designing physical spaces, structures, and environments.

This shift has not only streamlined architectural design but also opened up new avenues for creativity and efficiency. The GAN models show the powerful ability to generate and re-generating output, which is beneficial for planning because the client may ask for changes once viewing the draft planning [2]. In the comparison of hand-made drawing, the use of CNN and GAN save time and cost, increase efficiency, and further makes it easier to find optimized material for the design. However, the image-based database may need to be expanded for training the model. As ML and DL are applied to critical aspects of construction, ethical considerations regarding data privacy, bias, and fairness become paramount [10]. Ensuring that models do not reinforce existing biases or make decisions that have unintended ethical consequences is a significant challenge. Therefore, there are future considerations as references to the stated challenges and constraints.

The use of ML and DL models in construction material design has proven highly advantageous. It allows for the accurate prediction of material properties, leading to cost savings by reducing human labor and trial-and-error expenses. However, the lack of interpretability in ML and DL models can hinder engineers' decision-making. Supervised models heavily rely on labeled data for training, posing constraints such as the need for human labor to label data and limited data availability for damaged structures. Material property testing in labs can help overcome this limitation. DL models also save time and increase efficiency compared to hand-drawn designs. However, expanding image-based databases for model training may be necessary. Ethical considerations such as data privacy, bias, and fairness are crucial when applying ML and DL to construction. Ensuring that models do not perpetuate biases or have unintended ethical consequences is a significant challenge. Future efforts should focus on addressing these challenges and constraints in the construction and architecture fields.

4.2. Future Considerations

One of the primary limitations is the availability of high-quality data. ML and DL models heavily rely on data for training, and construction material properties datasets may be limited in size and diversity. Low-quality or incomplete data can lead to biased or inaccurate predictions. Data augmentation and generation are possible methods to overcome this challenge. Techniques such as rotation, flipping, cropping, and adding noise to images, or synthesizing new text data through paraphrasing or translation, can be used to generate additional training samples [1,2,9]. Data generation can be conducted by GAN models because GAN models perform well on generative data.

Another challenge that needs to be confronted is the ethical issue of AI technologies. Addressing ethical considerations in ML and DL applications in construction is crucial to ensure fairness, transparency, and responsible use of these technologies [10]. Anonymizing sensitive information in the data can be the solution to prevent privacy breaches, and continuously monitoring the performance is essentially vital to the ethical aspects of ML/DL models.

5. Conclusion

The integration of AI, ML, and DL technologies has ushered in a transformative across various domains, including material science, structural engineering, construction material design, and architecture design. These technologies offer unprecedented capabilities to analyze complex data, predict outcomes, optimize designs, and enhance the efficiency and sustainability of construction processes.

Data collection and preprocessing are foundational to successful ML and DL applications. In material science and structural engineering, ML and DL models predict material properties, enabling precise material selection, and XG boost and BPNN are suitable models for concrete design with parameter-based analysis. SDD techniques are successfully conducted by ANN and the optimized ANN structure is investigated through Bayesian Algorithms. In architecture design, DL models such as CNNs and GANs enable the recognition of architectural styles and the generation of floor plans. The marriage of CNNs and GANs in models such as ArchiGAN demonstrates how AI transforms indoor scene synthesis, opening new vistas for innovative design. In essence, the fusion of ML, and

DL holds enormous promise for the construction industry, propelling it toward data-driven decision-making, optimized designs, and sustainable practices.

As these technologies continue to evolve, they would reshape how to approach construction, material design, and architecture, ushering in a future where innovation and efficiency harmonize with the built environment's aesthetic and functional needs. While data collection can be challenging due to limitations and costs, databases and computational materials tools have become valuable sources of relevant data. The methods of data augmentation and generation provide the diversity and size of the database to ensure that the data is sufficient to process trained models. Moreover, the ethics of AI is discussed in this study. To address this challenge, data anonymization and continuous monitoring are required actions to protect privacy and evaluate the potential ethical impact. As these technologies continue to evolve, they will reshape how we approach construction, material design, and architecture, ushering in a future where innovation and efficiency harmonize with the built environment's aesthetic and functional needs.

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