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A Critical Review of Deep Learning Applications, Challenges, and Future Directions in Structural Engineering

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Abstract: Deep learning (DL), a major part of artificial intelligence (AI) is considered as a transformational technology in different areas of science, such as structural engineering. This critical review uncovers the potential contribution of deep learning in solving complex issues facing structural engineering, such as optimizing structural design, predicting and monitoring material behaviour, and monitoring in real-time the structural health. Through developed neural network architectures such as generative adversarial networks (GANs), recurrent neural networks (RNNs), and convolutional neural networks (CNNs), engineers can identify solutions based on traditional deterministic data extraction. However, issues like computational requirements, model interpretability and data scarcity are widely adopted. This review highlights recent advancements, practical applications, and the limitations of deep learning in structural engineering, proposing pathways for future research to enhance its efficacy and integration in real-world scenarios.

Keywords: Deep Learning, Machine Learning, Neural Networks, Structural Engineering, Structural Health Monitoring, Optimization of Structural Design.

Обзор применения глубинного обучения в строительном проектировании: проблемы и будущие направления

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Аннотация: Глубинное обучение (DL), основная часть искусственного интеллекта (AI), рассматривается как технология трансформации в различных областях науки, таких как строительное проектирование. Данный критический обзор раскрывает потенциальный вклад глубинного обучения в решение сложных проблем, стоящих перед строительным проектированием, таких как оптимизация конструкции, прогнозирование и мониторинг поведения материалов, а также мониторинг состояния конструкции в режиме реального времени. Благодаря разработанным архитектурам нейронных сетей, таким как генеративные адверсивные сети (GAN), рекуррентные нейронные сети (RNN) и конволюционные нейронные сети (CNN), инженеры могут находить решения на основе традиционного детерминированного извлечения данных. Однако при этом широко распространены такие проблемы, как вычислительные требования, интерпретируемость моделей и нехватка данных. В данном обзоре освещаются последние достижения, практические применения и ограничения глубинного обучения в строительном проектировании, предлагаются пути будущих исследований для повышения его эффективности и интеграции в реальные практические задачи.

Ключевые слова: Глубинное обучение, машинное обучение, нейронные сети, проектирование конструкций, мониторинг состояния конструкций, оптимизация конструкций

1. INTRODUCTION

Structural engineering has long relied on tried-and-error methods such as finite element analysis [1, 2], deterministic models [3], and material science [4] to design safe and reliable structures [5]. Yet, with increasingly complex infrastructures and unpredictable environmental factors, the limits of these traditional techniques are being tested [6]. Therefore, deep learning, a cutting-edge technology rooted in artificial intelligence (AI), offer a new paradigm for problem-solving in structural engineering [7]. However, employing deep learning in this field is still in its nascent stages, yet its potential to revolutionize the industry is significant [8]. From optimizing the structural design to predicting the behavior of materials under stress, deep learning provides a data-driven approach to challenges that have historically been difficult to model using traditional engineering tools.

This review will explore the current applications for deep learning regarding structural engineering, discuss the advantages and limitations of integrating AI technologies, and suggest pathways for future research.

2. OVERVIEW OF DEEP LEARNING

Being a branch of Machine Learning, Deep Learning employs neural networks to execute various assignment like regression, classification, and learning [9]. It is known by this term because it has many layers of neurons similar to those in the human brain. Thus, it can also be called 'Artificial Neural Networks' [See Figure 1]. Its foundation is rooted in 1943 when McCulloch and Pitts published a paper that introduced the neural network first mathematical model [10].

A method called threshold logic (a combination of algorithms and mathematics) was used to simulate the human brain thought process. Later in 1957, a simple version of deep learning called Perceptron was suggested by Frank Rosenblatt which can learn from experience and adjust its weights to make precise predictions [11]. The breakthrough came in 1986 when backpropagation was introduced by Geoffrey Hinton [12]. This algorithm efficiently computes the network's weights gradients. Thus facilitating multi-layer neural networks training. Another progress was achieved in 2006 when scientists began applying deep learning models on the GPUs (graphics processing units) of computers, which eventually, led to the application of Convolutional Neural Networks (CNNs) in image recognition [13]. Till now, the demand for Deep Learning is still increasing and still improving with the introduction of new algorithms [14].

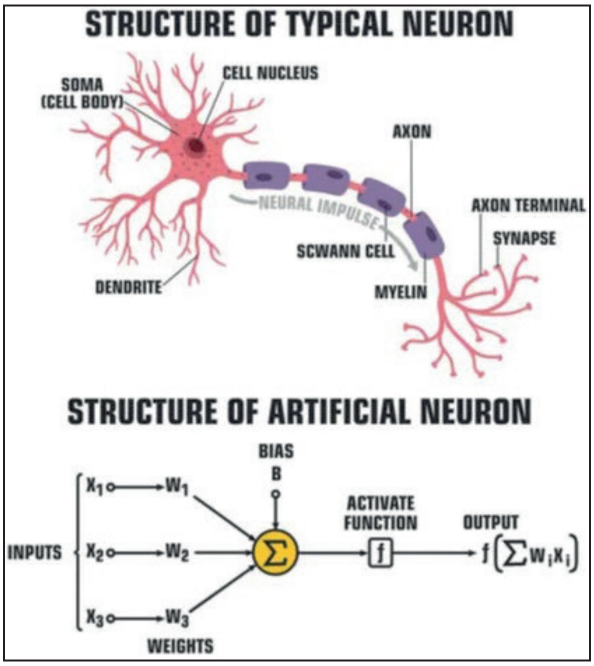

Figure 1. A compression between diagrams of biological neuron vs artificial neuron [14]

At its core, deep learning represents a dramatic departure from traditional machine learning techniques. While conventional machine learning algorithms require structured data and manual feature selection, deep learning models excel at finding patterns in large, unstructured datasets like images, sensor data, or time-series signals from infrastructure monitoring systems. This makes them particularly suited for applications in structural engineering, where the real world rarely conforms to neat, clean data inputs.

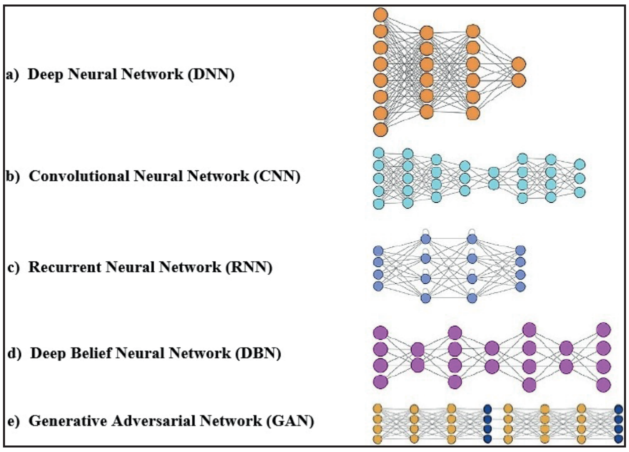

Figure 2. Different types of neural networks [15]

For instance, convolutional neural networks (CNNs) can detect minute cracks in bridges, while recurrent neural networks (RNNs) can forecast the behavior of buildings during seismic events. Moreover, generative adversarial networks (GANs) were utilized for generative design, automatically creating thousands of structural layouts that meet specific performance criteria. Figure 2 illustrates different types of neural networks used in structural engineering.

3. DEEP LEARNING APPLICATIONS IN STRUCTURAL ENGINEERING

3.1 Structural Health Monitoring

SHM has traditionally been a reactive process. However, deep learning is transforming it into a proactive discipline, using CNNs to process high-resolution images of structures to identify signs of damage such as cracks or corrosion. For instance, in Sydney Harbour Bridge, where CNNs were employed to analyze real-time sensor data, predicting damage before it occurs. These models can now offer early maintenance solutions, reducing downtime and enhancing infrastructure reliability [16, 17]. Dorafshan, Thomas [18] have conducted an image-based concrete crack detection by developing a Deep Convolutional Neural Network (DCCN). It was shown that it can predict and detect cracks better than the traditional edge detection methods (Gaussian, Butterworth Sobel, Prewitt, Roberts, and Laplacian of Gaussian).

Gao and Mosalam [19] have developed a Visual Geometry Group (VGG) based architecture to detect the damage in structural components [See Figure 3]. Furthermore, transfer learning was applied to obtain a robust recognition performance with a small training dataset, and collecting images for the training process was done by building an image dataset which is called Structural ImageNet. The acquired data have established the potential of using transfer learning in image-based structural damage recognition. Deng, Ju [20] have conducted an abnormal data recovery framework of an ancient palace wall by applying a gated recurrent unit (GRU). It was established that the selected method is adequate of obtaining accurate results of data recovery for ancient buildings.

3.2 Load Prediction and Structural Behavior Modeling

Several studies were conducted to determine the best AI techniques for forecasting loads. RNNs and long short-term memory (LSTM) models were found to be greatly adopted for load prediction, especially under dynamic conditions such as earthquakes. By analyzing historical data, these models can predict structural responses with high accuracy. This predictive power is crucial in regions prone to seismic activity, where deep learning has demonstrated an ability to improve the safety and resilience of buildings. Zhang, Chen [21] have employed a Deep LSTM to predict nonlinear seismic performance. Two different schemes (different input/output formats) were developed and it was shown that the proposed network provides a reliable and efficient solution for nonlinear structural response prediction. Another research has demonstrated the accuracy of the LSTM algorithm in predicting the thermal loading of a building [22, 23].

Other studies have determined the efficiency of CNN in predicting the strength of concrete [24]. For instance, Deng, He [25] have suggested developing a CNN using a SoftMax regression model to predict the recycled concrete compressive strength before construction. The software has been trained using characteristics such as the water-cement ratio, the replacement ratio recycled fine aggregate, coarse aggregate, the fly ash and their mixtures. The suggested model has demonstrated efficient results and precision. Other researchers have determined that employing CNNs provides accurate and reliable results regarding the dynamic structural performance of reinforced concrete (R.C.) slabs under blast loads [25, 26].

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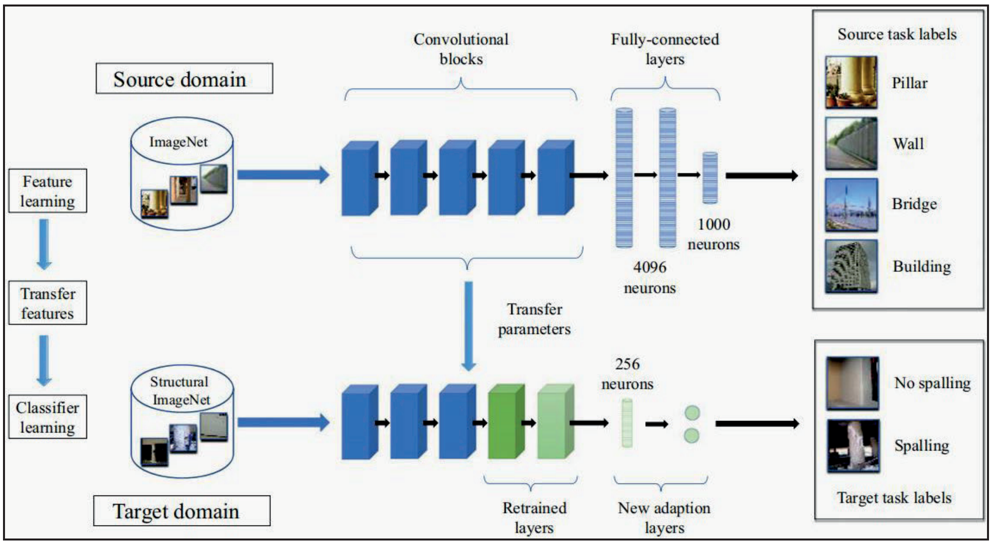

Figure 3. Detecting damage using Transfer Learning [19]

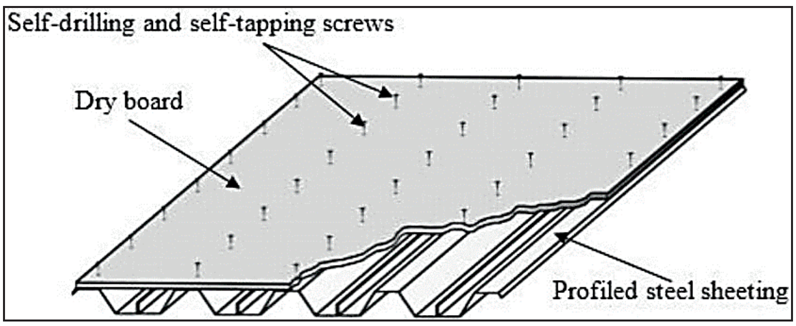

Figure 4. Typical PSSDB Floor panel [27]

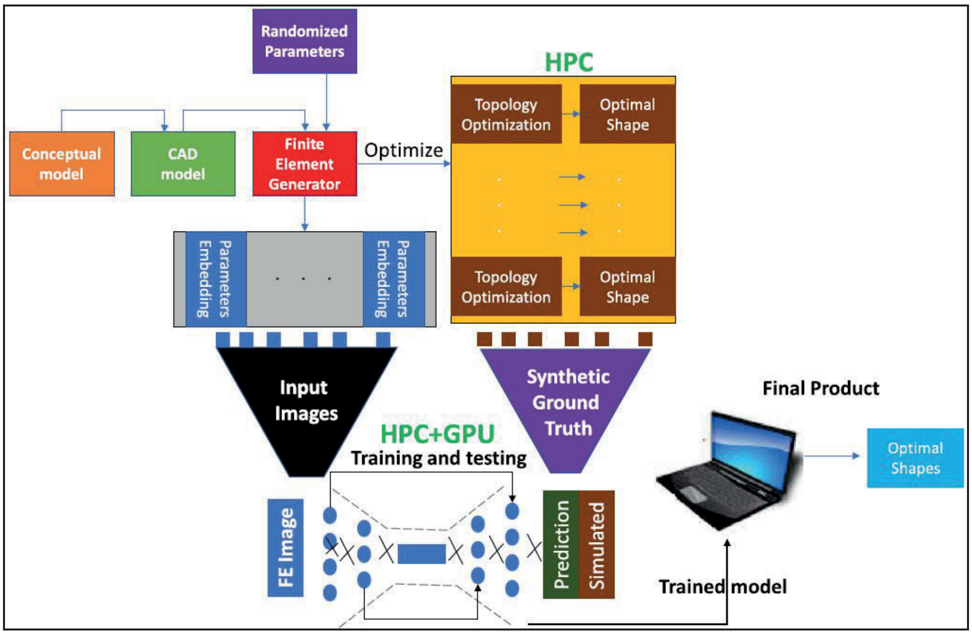

Figure 5. Flowchart used of CNN-based optimizer [28]

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3.3 Optimization of Structural Design

Optimization in design isn't just about making structures stronger; it's about making them smarter. Deep learning algorithms such as GANs enable engineers to generate and test thousands of design configurations in seconds, optimizing for parameters like material properties, load capacities, and cost constraints [29, 30]. A study conducted in 2018 by Vafa employed ANN to develop the optimum steel deck cross-sections for the Profiled Steel Sheeting Dry Board (PSSDB) floor panels [see Figure 4] [27]. Non-dominated Sorting Genetic Algorithm II (A multi-objective genetic algorithm) was employed for this research. It was shown the efficacy of ANNs in improving structural design [27].
Another study conducted by Ferreiro-Cabello, Fraile-Garcia [31] have employed deep learning techniques to develop metamodels with the aim to facilitate the optimization of one-way slabs. Five DNNs were developed which were capable of predicting CO_2 emissions, embodied energy, cost and deflection. The suggested method showed reliable results with only 0.5% error. Abueidda, Koric [28] have applied CNN to predict the optimized materials design subjected to small/large deformations (with/without stress constraints) Figure 5. The developed models demonstrate an accurate prediction of the optimized designs, and they can be employed in other design domains and nonlinear mechanics scenarios. Mai, Lieu [32] have applied a deep novel unsupervised learning (DUL)-based framework to optimize a truss structures design subjected to various constraints, and it was

shown that a computational cost in most problems can be saved using such algorithms.

4. CHALLENGES AND LIMITATIONS

Despite its potential, Deep Learning faces various challenges that can be summarized in the following:

4.1 Data Availability and Quality

High-quality and large datasets are essential for deep learning. Nevertheless, data scarcity is a major challenge in structural engineering, especially when it comes to rare events like structural failures [33]. Techniques like transfer learning, where models are adapted from similar domains, offer a potential solution [34].

4.2 Model Interpretability

One of the issues that discourage adapting deep learning in engineering applications is its "black box" nature [35]. Engineers must trust these models for safety-critical decisions, yet their inner workings are often opaque, making regulatory approval difficult.

4.3 Generalization and Scalability

Generalization to new environments and scalability to larger, more complex structures remain significant hurdles. Models trained on one type of structure may not perform as well on another, raising concerns about their robustness in real-world applications.

4.4 Underfitting & Overfitting

Both Overfitting & underfitting can pose an obstacle to deep learning. The former occurs when the models cannot capture the underlying patterns due to their simplicity, while the latter occurs when training the model demands a large amount of time and contains noisy data because of its complexity [36]. Therefore, it is important to provide an optimal solution by employing balanced-complex models to avoid either case Figure 6.

4.5 Ethical & Bias Issues

Biases can occur during the learning algorithm of the model to prioritize solutions with certain characteristics over others. Such an issue is considered unethical since it can cause unfair results. Thus, addressing such issues is essential to achieve fairness.

4.6 Hardware Limitations

High-performance CPUs are essential for training models. However, having access to such hardware is hard for many researchers.

5. FUTURE RESEARCH DIRECTIONS

5.1 Hybrid Models

Hybrid models that combine deep learning with traditional physics-based simulations hold significant promise for enhancing both accuracy and interpretability [37].

5.2 Transfer Learning

Transfer learning offers a way forward in addressing the issue of limited data availability, allowing models trained on one task to be adapted for another.

5.3 Real-Time Applications in Smart Cities

As cities become more connected, deep learning will significantly contribute in the real-time monitoring and management of infrastructure [38]. For instance, these models can optimize traffic flow or monitor structural health in real time. Consequently, decreasing the risk of catastrophic failures by capacitate predictive maintenance.

6. CONCLUSION

Deep learning is poised to transform structural engineering by improving prediction accuracy, optimizing designs, and enabling real-time monitoring. Although challenges remain particularly in data quality and model interpretability, the benefits of AI are too significant to ignore. As deep learning continues to advance, it will become even more integrated into the field, leading to smarter, safer, and more resilient infrastructure.

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