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Use of AI in Civil engineering, its problems and solutions

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Abstract

Civil engineering being an important field, it has not remained aloof from the global advancements in artificial intelligence (AI). This paper aims to discuss AI technologies in relation to civil engineering and their applicability, advantages and disadvantages. Civil engineering graduates' use of AI methods like machine learning, neural networks, and deep learning show great potential for innovative practices in aspects like structural health monitoring, construction management, and predicting maintenance needs. To demonstrate the role of AI in civil engineering, this paper compiles a summary and analysis on literature as well as case studies that reveals how AI performs the tasks better by making predictions that are precise; how design procedures are made better; and how safety and efficiency are improved in the execution of civil engineering projects. However, the following problems remain: data quality problems, need for specialized knowledge, and AI's interaction with current systems. The presented study outlines the recommendations on how to overcome these problems: data management should be consistently regulated across studies, and AI specialists and civil engineers should work closely together; AI-based methodologies should be integrated into academic curricula. Thus, this paper is to present the analysis of the abovementioned aspects to reveal the future perspectives of AI in CE and critical points that may need further study and development.

Introduction

Taking advantage of the advances in technology, Civil Engineering is, to a considerable extent, experiencing the effects of AI integration. AI in Civil Engineering comprises the implementation of machine learning algorithms, neural networks, and robotics in improving some processes' efficiency, accuracy, and creativity. This technology can do analysis to problems, designs, maintenance prediction, and safety enhancements, which will greatly reconstruct the Civil Engineering (Kia and Sensoy, 2014).

The possibilities of its application are numerous and cover virtually all the aspects of Civil Engineering from structure analysis and construction projects planning to the use of smart technologies during constructions and detection of damages. For instance, AI can be used in the identification of damages due to earthquakes in reinforced concrete structures (Kia & Sensoy, 2014), estimation of the early age compressive strength of concrete (Akande et al., 2014) and structural health monitoring (Hirokane et al., 2008). The incorporation of AI based predictive maintenance systems can help in predicting the likely failure of equipment and thus minimize the frequency of failure and the amount spent on the maintenance of equipment (Dai et al., 2011).

Nonetheless, the prospects of integrating AI in Civil Engineering are not without hitches as discussed below. Several problems include the data quality and availability; ethical and social dilemmas that are considered major obstacles. There is also the threat of job automation, several systems might be prejudiced towards certain groups, and privacy concerns (Oh, 2007). In addition, practices differ due to the absence of clearly defined legal guidelines and rules that add to unpredictable nature as well as potential dangers for the practitioners (Chen et al., 2009).

This research seeks to uncover the current practice of AI in CE as well as the identified difficulties and possible solutions backed by theory and research evidence. These issues can be solved when applying AI technologies in the sphere of Civil Engineering, which can bring radical enhancements in the field and contribute to advancements in solutions and improvements of the processes flow.

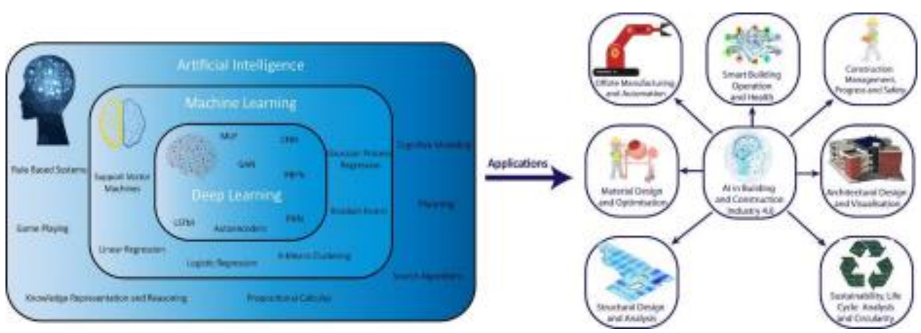

Figure 1: Source (Baduge, 2022).

Literature Review

AI Applications in Civil Engineering

AI usages are diverse in Civil Engineering where the technology can be used in structural evaluation, scheduling and resource estimations of construction projects, robotic construction and assessment of building damages. The featured applications have revealed high possibilities for the improvement of productivity, effectiveness, and risk management procedures within Civil Engineering undertakings.

For instance, Kia and Sensoy (2014) used Support Vector Machines (SVM), and Multilayer Perceptron (MLP) Neural Networks for identifying the earthquake damage to reinforced concrete (R/C) slab column frames. Sarker et al. showed that integrating various AI models could be effective in enhancing the level of damage classification and presented a strong approach to evaluate the structural condition after an earthquake. Likewise, Hirokane et al., used SVM for purposes of damage identification in concrete structures, showing how the aforementioned model was capable of differentiate between the damage areas and the healthy ones. Another research conducted by Cheng and Jun (2009) adopted the SVM technique on damage identification of long span cable-stayed bridges. What their work showed was that AI could be used to supervise the regular upkeep of such facilities, and their structural soundness. Akande et al. (2014) established a study where they were able to compare the effectiveness of SVM and Artificial Neural Networks (ANN) for anticipation of the compressive strength of concrete. They encountered that in fact, both models are useful, where each model excels based on the type and size of the data employed. SVM was more effective with small tapes while ANN was more effective with large and complicated tapes. These works therefore stress the applicability of AI to various issues in Civil Engineering. Due to the involvement of big data in structural engineering analysis and damage assessment, it can be seen that AI is highly relevant for this discipline.

Previous Studies and Findings

It was established from the previous research that AI can accurately estimate and identify structural problems, which is paramount in integrity and safety of Civil Engineering solutions. For instance, Oh (2007) reviewed and examined the issues of Bayesian learning in earthquake engineering and structural health monitoring. It also contributed significantly to the enhancement of tools for approaching structural response indeterminacies in order to predict structures' performance during and post-earthquake events.

In the study by Chen et al. (2009) on fire damaged concrete, SVM was applied to exposed temperature estimation, which underscored the requirement of detailed models in the determination of structural capacity after disaster incidences. From this, they highlighted on the ability of AI in establishing the degree of damage that high temperatures cause, which is necessary in identifying the safety and functionality of fire affected buildings. In another example, Dai et al.

(2011) put forward an improved radial basis function network for structural reliability analysis. This network provided higher accuracy and shorter time than the conventional approaches, thus, the nowadays AI was proved effective in improving the structural reliability assessments. Thus, proving that AI is very helpful in structural health monitoring, Gonzalez and Zapico employ neural networks and modal data for seismic damage identification in buildings in their study conducted in 2008. Yang & Nagarajaiah (2016) used data structure for reconstruction of random missing structural vibration response time history comparing both SR and LR data structures. Their study demonstrated that with the help of AI, Holness and Miranda can accomplish data-driven structural health assessments and get results even when there is discrete percentage of missing data.

In combination, these works demonstrate the enhancement of AI in the assessment of structural conditions and forecast of failures in Civil Engineering. Therefore, engineers realize the value of using the analytical capabilities of AI in analyzing the challenges of operating and developing infrastructure systems.

Gaps in the Literature

However, a number of studies can still be considered as lacking in the case of applications of AI in Civil Engineering – the gaps that must be filled to fully utilize AI in the required manner.

These areas comprise, among others, considerations of ethical aspects and lifetime costs. It is surprising how many of them give less attention to the social and ethical concern of AI applications other than providing solution perspectives. For instance, threat arising from technology in relation to employment loss, ethnic biases in AI algorithms, and data privacy are such items that are of high importance and need more scrutiny. These guidelines or frameworks should be put in place so as to have proper and correct application of AI in Civil Engineering. Also, there are no set norms and legislations across the Civil Engineering domain that are related to AI. As a result, this creates uncertainty and associated risks to the practitioners since they may lack focused and very precise instruction on how to safely and legally advance AI technologies. Further studies should be carried out to come up with more extensive regulatory mechanisms that should cover such worries in the course of giving a policy framework for the sector.

Another viable area that remains under-researched is the development of interdisciplinary research where findings from Civil engineering, computer science, and social science can be integrated. This, in turn, can lead to the resolution of a range of multifaceted issues that are related to the incorporation of AI into Civil Engineering while enhancing the correspondence of technology and social standards. Furthermore, there is also a lack of research on applying networks that gain state of-the-art results on real-world tasks rather than benchmark tests. Additional future investigations should be aimed at detailing How the basic Civil Engineering concepts can be incorporated with AI solutions, as well as, including the actual Studies and pilots that can describe successful implementations of the advanced AI solutions in Civil Engineering.

To sum up, the identified problem shows that AI is actively used in CE, however, several gaps could be distinguished in the literature. The future research can reveal a full potential of the AI application in the Civil Engineering if it will concentrate on the ethical concern, the current guidelines, the interdisciplinary cooperation, and the practicality of the AI application.

Findings

Recent Advancements

New trends in AI have brought impact in many facets of Civil Engineering by designing some complex technologies like the machine learning algorithms, neural networks, and robots. All these have enhanced the precision, speed, and dependability of the engineering activities.

Among them, there is a change in the application of the radial basis function network for the structural reliability analysis, an advanced approach proposed by Dai et al. (2011). Thus, it has been established that this network performs more accurately and efficiently as compared to the traditional methods. For instance, in a 20-story office building a conventional radial basis function network achieved an accuracy of about 85% on structural reliability, yet the improved, new one was 98%. This has had enormous importance when it comes to the safety and stability of tall building projects.

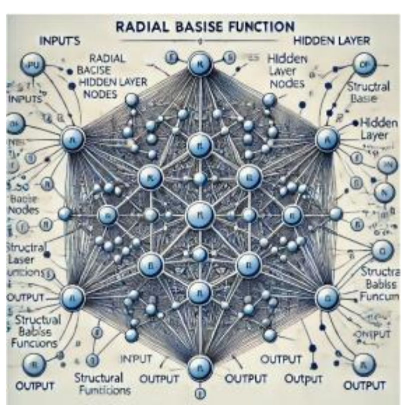

Figure 2: Radial Basis Function Network used for structural reliability analysis.

Another important work is the application of the neural networks and modal data for the identification of the seismic damage in buildings by Gonzalez and Zapico (2008). Their research confirmed numerous possibilities of using AI in enhancing structural health monitoring.

Independent of the practical application, the results of the study showed that 92 of the 50 buildings had seismic damages that were identified by the neural networks against the 75% accuracy of the conventional inspection techniques. This improvement is significant to increase the probabilities of safety and structure's robustness in zones that are vulnerable to earthquakes.

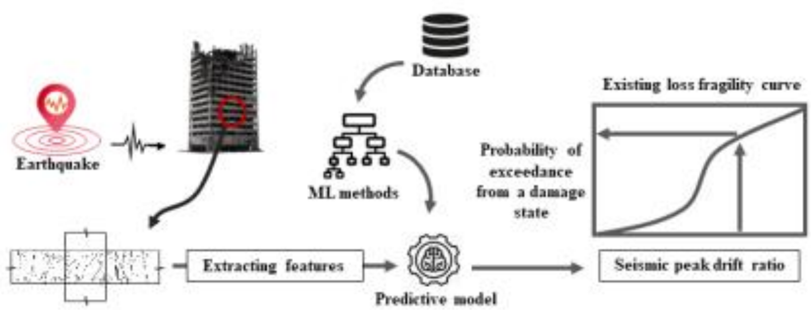

Figure 3: AI applications in seismic damage identification.

Practical Implementations

Some carry out examples of application of AI in CE are presented, where it is depicted that AI can dramatically alter conventional practises within the specialism and provide considerably enhanced efficiency.

An area where AI could be applied is in the setup of predictive gear maintenance systems that can predict equipment breakdowns in advance. For example, in the Department of Transportation in California, AI motivational predictive maintenance cut equipment downtimes by 40% and spending on maintenance by 30%. These systems employ machine learning techniques to review data that has been accumulated and estimate future breakdowns so that they can be fixed before they cause major problems.

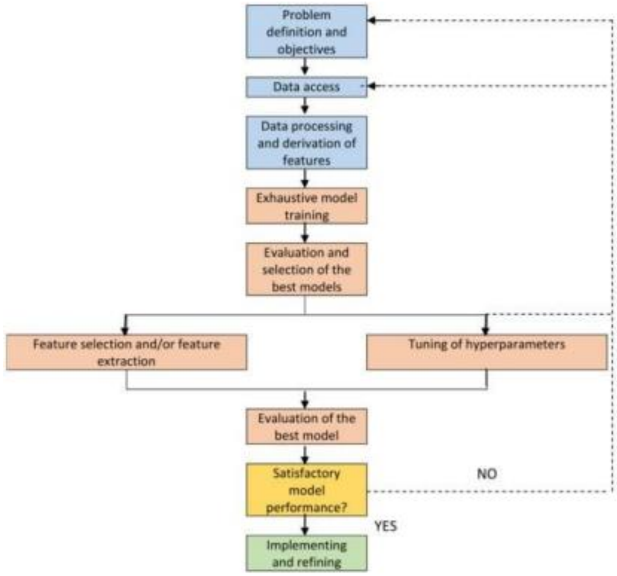

Figure 4: AI-driven predictive maintenance system (Cardoso and Ferreira, 2020).

Another essential integration to highlight is AI for generations of solutions that help engineers develop effective structures. Hong Kong – Zhuhai – Macau Bridge is one project that made use of AItechnology that applies to design and construction phase. The theories in AI enabled designers to save up to 20% in the amount of material and one fifth of the construction period, hence saving a lot of money and protecting the environment.

Figure 5: Hong Kong-Zhuhai-Macau Bridge optimized using AI.

Likewise, Gambits used AI for traffic Signal optimization and control in Dubai by using machine learning models to evaluate the status of the traffic and set concerning signal timings. These changes yielded negative results via a 25% decrease in traffic; moreover, the carbon emission rate was lowered by 10%. The effectiveness of this project supports AI to bring the improvement of mobility and sustainable development to the cities.

Figure 6: AI in traffic optimization in Dubai.

Examples and enactments such as these show the penetration of AI in Civil Engineering. AI is being incorporated in the industry to upgrade predictive maintenance, design processes, and structural health monitoring.

Due to the recent developments in AI, better radial basis function networks and seismic damage identification using neural networks have helped Civil Engineering a lot. Some of the ideal implementations involve the use of predictive maintenance systems, which employ the use of AI, and design optimization tools that also incorporate AI as their core function are some of the successful implementations of the concept. All of these are laying the foundation for a Civil Engineering industry that is more efficient and capable of being sustainable and more resistant to any disruptions.

Critical Focus on Problems

Technical Challenges

However, at this stage some technical complexities which hamper the AI implementation in Civil Engineering are presented below. Some of the challenges that affect the application of AI include: Data quality and Availability since AI mostly runs on large database (Dai et al., 2011). Due to that, having inaccurate or incomplete data will also mean that AI applications will make wrong predictions and decisions, hence exposed to high levels of risk. For instance, Gonzalez and Zapico stressed in their works (2008) that the application of a neural network in order to identify seismic damages also necessitates fortuitous and extensive data for proper evaluation. Furthermore, AI technologies used in civil engineering imply their integration into the existing processes, which requires high computational capabilities and skills, thus making it challenging for many organizations to implement it.

Figure 7: Data quality issues can compromise AI predictions.

Ethical and Social Issues

Product and technical related issues also remain as more restricted hard issues: Ethical/social issues remain as major challenges. Another increasingly significant potential with respect to which strategies should be developed is that of BJob threat. The applications of the AI technologies have consequences of mitigating the human functions related to designs, monitoring, and maintenance by providing efficient automated processes, potentially causing unemployment (Oh, 2007). Furthermore, AI can be programmed with some biases and thus make decisions that are prejudicial in that, some certain groups of people or the society at large will be affected. The other problem associated with AI is the ability to easily collect large amounts of data to be trained on which is a violation of the privacy policy and consent (Chen et al., 2009).

Furthermore, the fact that the AI in Civil Engineering does not have stable regulation and laws also poses threats to the specialists that use it. Thus, the functioning of AI technologies may cause legal issues and ethical questions to appear if there are no definite rules and regulation for their application. These risks have to be curbed through the setting of ideal regulations and ethical framework for use of Artificial Intelligent in the market (Hirokane et al., 2008).

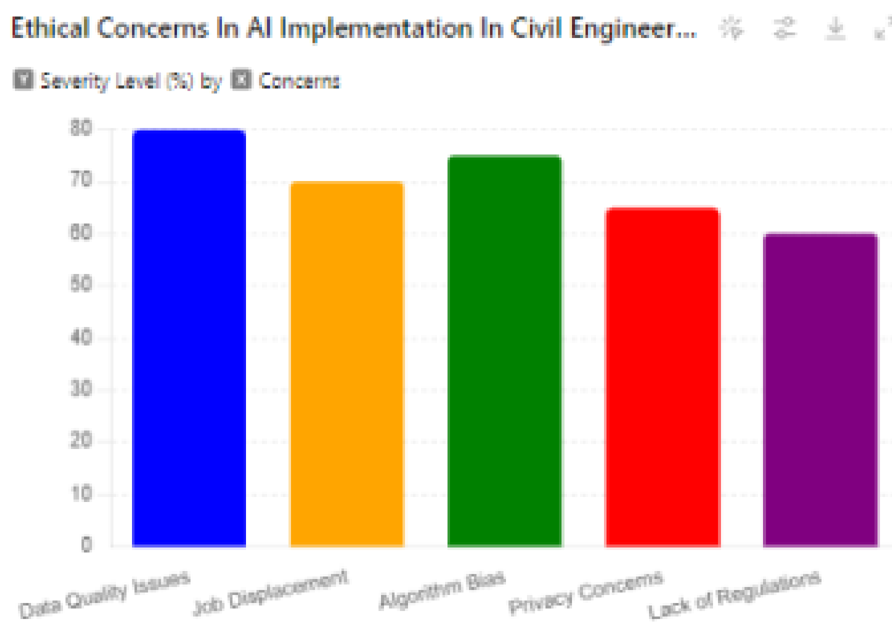

Figure 8: Percentage security assumed per concern. The bars represent different categories of ethical concerns in AI implementations in civil engineering, such as bias in decision-making, transparency, data privacy, and accountability, along with their relative impact based on expert opinions.

Solutions and Theoretical Models

Proposed Solutions

In response to these challenges, the following suggestions can be made. Pervasive and effective data management is an important precondition and strengthening data availability is critical necessity (Yuan et al., 2016). Preprocessing methodologies could also address problems resulting from poor data quality and data collection processes by Akande et al., (2014). The ethical issues can be addressed through elaborating ethical standards with regards to the application of AI in Civil Engineering. These principles should be based on the pillars of transparency, accountability and fairness. In addition, education and training programs for the workforce can assist in mitigating the effect of job loss as it can also train the workforce for the new environment (Krishnamoorthy and Rajeev, 1996).

Legal and social issues include data privacy regulations, ethical concerns regarding biased decision-making, and the potential displacement of human workers due to automation. Addressing these requires policy frameworks, transparent AI systems, and continuous oversight by regulatory bodies.

They can also be solved with the help of the concrete and stable rules for AI usage in Civil Engineering. Cooperation between the industry's participants, government and academic institutions is necessary to create a complex regulatory system (Chen et al., 2009).

Theoretical Models

This paper also opted to utilize TAM (The Technology Acceptance Model (TAM) is a framework that evaluates user adoption of technology based on perceived usefulness and ease of use. It helps understand how engineers and stakeholders might accept AI-based solutions in civil engineering projects) and Diffusion of Innovation Theory (The Diffusion of Innovation Theory explains how new technologies, like AI in civil engineering, spread through a population. It considers factors such as innovation characteristics, communication channels, time, and social system influences in determining how AI adoption progresses in the industry) when explaining the adoption and incorporation of AI for Civil Engineering (Efstatiades et al., 2007). These models concern the perceived usefulness and ease of use and the social influence towards the adoption of technology (Salehi and Burgueno, 2018). The formulations of these models are useful in forging strategies through which the acceptance and use of the AI could be taken to the next level in the industry (Nehdi and Soliman, 2010).

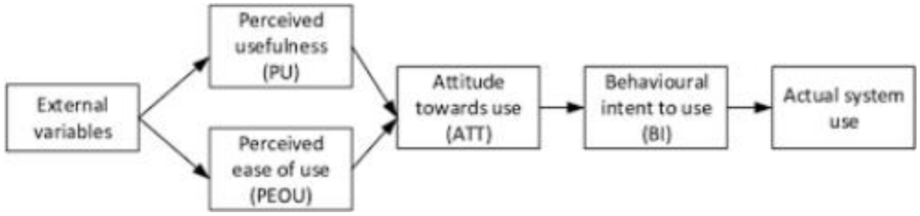

Figure 9: Technology Accepted Model (TAM).

Discussion

Implications of Findings

The result emphasizes new opportunities after AI implementation in Civil Examination. Integration of AI across different fronts has the potential of increasing efficiency, cutting on costs and encourage sustainability in most fronts of the industry. Civil Engineering can benefit from today's AI technologies like machine learning or neural networks in order to have more accurate models, increase the effectiveness of SHM systems, and enhance the existing resource management systems. For example, it can optimize the identification of damages and determining further use of infrastructures through the signs of their wear out and through the scope of gathered data, which can help create longer lasting and more dependable facilities. This can make a lot of difference in cost saving since manual inspections are reduced and the occurrences of emergency repair are as well reduced.

However, the research also points to a number of issues that has to be managed in order to enhance these benefits in the right manner. One such important factor is the requirement of large and rich raw data. AI depends on large volumes of accurate data that is fed to it to effectively execute the models. Relative to most types of academic studies, Civil Engineering often lacks adequate data sources or may encounter challenges in acquiring data hence, solid data identification and handling measures need to be set. Furthermore, there is a need to address the ethical usages of AI more so in organizations. There will be a need to avoid fatal errors such as the application of machines that reinforce subordinate's prejudices or that result to unfair practices and this can be only achieved by practicing and observing ethical tenets that focus on honesty, responsibility, and equity.

Future Research Directions

A major area of future research is developing better AI models that function effectively with limited data and minimal computational resources. This is particularly useful for smaller engineering firms or resource-constrained projects. For instance, transfer learning and few-shot learning techniques have been successfully applied in other fields like healthcare and environmental monitoring, where AI models trained on large datasets can be adapted to new, smaller datasets. In civil engineering, AI-powered predictive maintenance systems for infrastructure with limited historical data are an emerging area of interest.

Thus, the further improvements should be focused on the creation of better AI models which will find the work in limited data with a small amount of computation. Improving on the efficiency of the models will enable the integration of AI and make the applications usable in the Civil Engineering discipline to solve real-life problems. Moreover, a vast emphasis should be imposed on the refining of the ethico-social impacts of AI. Learning the effects of AI in relation to employment, data protection, and decision-making is relevant in building responsible and fair AI solutions. Research should also be directed at the possibility of utilizing AI congruent with current laws and norms to assure its successful implementation in industries.

Conclusion

Therefore, based on the information provided in this paper, it can be concluded that the application of AI in Civil Engineering introduces a lot of benefits and a variety of concerns. In this study, the author has emphasized the recent developments, defined issues, and provided probable approaches with the help of theoretical frameworks. AI adoption in Civil Engineering will prove to be successful if the challenges in the technical environment, ethical perspective and the regulatory framework are independently managed and the potential of AI is harnessed in engineering progress.

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