Approaches of Artificial Intelligence and Machine Learning in Smart Cities: Critical Review

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Abstract: Smart cities are aiming to develop a management system for growing urban cities, improve the economy, energy consumption, and living standards of their citizens. Information and communication technology (ICT) has a much more important place in decision making, policy design, and implementation of modern techniques to develop smart cities. This review aims primarily to investigate the role of artificial intelligence (AI) and machine learning (ML) in the development of smart cities. This survey leads to the systematic interpretation of current patterns in ICT-related information flow publications as well as to the identification of the usual technologies used to facilitate this communication. In this paper, we represent the detailed presentation of AI & ML in the intelligent transport system and the prediction of mix design and mechanical properties of concrete.

1. General introduction

Though urban areas occupy just 3% of Earth's land, 75% of the natural resources are consumed and 60% to 80% of world greenhouse gas emissions are produced. The urban population will rise to 70% by 2050 instead of more than 50% of the global amount of urban population [1], [2]. The rapid urbanization of countries will drastically impact the environment, security, and management of the urbanized cities. Many countries like the US, EU, Japan, etc. have been proposed the concept of smart cities to reduce optimized energy consumption and natural resources. Many countries worldwide have developed and adopted intelligent city programs to address future problems efficiently [3]. Innovative approaches are needed to improve production quality and sustainability and to reduce costs for intelligent production systems. It is important to note that in the 1990s, the father of artificial intelligence (AI), John McCarthy, described artificial intelligence as 'the science and engineering of smart machines, especially smart computer programs.' The word "AI" is used in general when a computer simulation works, like thinking and problem solving, which humans associate with another human mind [4]. Artificial intelligence is
divided into 16 different parts namely knowledge representation, natural language understanding, a theory of computation, reasoning, genetic algorithm, machine learning, artificial neural network (ANN), systems, expert systems, data mining, artificial life, programming, distributed artificial intelligence, theorem proving, belief revision and constraint satisfaction [5]–[11]. Today, AI has become a field of research that is necessary to expand globally in the engineering field, education, law, science. AI disciplines including machine learning, processing of natural languages, image processing, and data mining are now a major theme for modern technology leaders. ML is now very fast growing as an AI branch. The usage has gone to relevant disciplines, including digital learning machines, smart cities, medical science, agriculture, archaeology, sports, business, etc. [12]. A general thoughtful of AI & ML work and their variants have been provided in this article. This paper provides useful ideas and opportunities for undertaking AI and ML work.

The complexity of the projects and the individualistic nature of the infrastructure projects were responsible for delays and errors. The use of reports, Technical drawings, programs, and photographic records is still commonly used to plan and track building projects which makes the process inefficient. The impact on progressive improvements in construction on the integration of information and communication technology (ICT) is undeniable [13], [14]. A variety of technologies and systems have recently been introduced at building sites to enhance the connectivity, coordination, preparation, and monitoring of projects, including cloud computing, online technology, tracking technologies, and building information modeling (BIM) [15]. Such modern technologies are typically used for enhancing structural monitoring in different technical combinations and comparing the designed and constructed prototypes [16], [17]. The Unmanned Aerial Vehicles (UAV), Blockchain, Internet of Things (IoT), and the artificial intelligence, machine learning, and DRL-based technologies in numerous applications continue to be in the developmental stage of projects in smart cities and provide more possibilities for the future [3]. Figures1–3 are the key focus in such activities. AI is having a rising effect on our day-to-day activities. AI is quickly changing the complexity of our day-to-day work, affecting the conventional human thought approach, and engaging with the world. To efficiently classify and evaluate any criminal incident, researchers proposed an effective framework of smart city crime detection created on the neural networks (NN) and DRL [18]. Furthermore, an architecture based on the ML which can also be used before it happens to forecast incidents and generate answers [19].

In this art of literature, we've given the latest development in various smart city sectors regarding AI and ML related applications. We concentrated on assessing the role and impact of previous strategies on one of the most important aspects of the smart cities. The purpose of this paper is to represent previously published highlights of positions relating to AI in civil engineering. Such papers would supplement formerly published literature investigation articles that would deliver the theoretic
framework or may show a significant role in the advancement of AI in civil engineering. It reflects the rates and hotspots of recent AI work in civil engineering and will promote ongoing study. The remaining article is summarized as: Section 2 provides a description of civil engineering machine learning, Section 3 illustrates machine learning techniques in civil engineering under which we described application of ITS and concrete properties in civil engineering, and conclusions in Section 4.

2. Machine learning: an overview

Machine learning is one of the leading subfields of AI dealing with the design and creation of algorithms for the recognition and decision-making of complex patterns based on experimental data. Machine-based learning models may either be analytical to predict or descriptive to acquire information from data, or together [20]–[22]. The original goal of ML techniques was the automated development of Information for integration into structures of expertise. This generation was supposed to relieve the bottleneck in knowledge-acquisition often associated with the development of an expert program. ML techniques can not only be seen as tools for the generation of knowledge but more generally as tools for data analysis or information modeling similar to traditional statistical technology. ML and statistical techniques used as approximately the same functions. Nonetheless, ML approaches are non-parametric and allow fewer data assumptions, at the cost of additional calculations made possible by the increase in computing capacity [20]. ML development models have a small number of choices for design which are generally 1) training subset, 2) validation subset and 3) testing subset. The first is used for model training. Second, the software fit into training data is impartially evaluated and avoids the overfitting of the prototype by halting increments to the mistake. The model is ultimately used in the third phase to check data to determine the results [23]. Depending on the training resources, machine learning is considered into two groups as supervised and unsupervised learning.

Supervised learning: A collection of inputs & targets is used to train the AI network to map output data with a mapping function. The main aspect of supervised learning is the presence of a "teacher" and the input-output data for the instruction. It is further separated into regression and classification. Support vector machine, Random forest, and linear regression, are some examples of supervised learning.

Unsupervised learning: No guidance is available in unsupervised learning, only an unclassified and non-labeled input dataset is delivered for the training of the AI network in finding hidden patterns, responses, and distributions. Clustering and association are various types of unsupervised learning problems. Auto-encoder and k-means algorithms are typical examples of unsupervised learning.

An algorithm should be developed for problem-solving in machine learning methods. Machine learning algorithms adopt different approaches, such as statistics, data mining, pattern recognition, and signal processing in different fields. This helps the system to take advantage of efficiencies in all fields, which result in solid solutions using changed areas of expertise. Figure 4 offers some of its most
important algorithms used in supervised and unsupervised learning. It is also possible to notice that some types of algorithms work with different types of learning to solve several problems [24]. Machine learning is gaining popularity in many engineering techniques. Implementation of ML in the evaluation of properties of reinforced concrete structure and the service life is still controlled.

Figure 4. Types of machine learning with adopted algorithms.

3. Machine learning techniques in civil engineering

3.1 Application in intelligent transport system (ITS)

The intelligent transport system is a combination of smart sensors, control system and information and communication technology (ICT). Tomorrow's smart cities, ITS will be an essential part. Nonetheless, achieving the true potential of ITS needs accurate data and ultra-low latency analytical approaches, integrating in real time a heterogeneous combination of ITS network knowledge and its setting [25]. In order to track and estimate accurately real time circulation information in an urban environment, AI and ML technology are a key component of sustainable ITS [26], [27]. ITS required a reliable monitoring and management system to transmit or process various sensors. Traditionally, many mobile ITS sensors cause high delays, network traffic and network exhaustion [28]. Effective edge and analysis systems would therefore be recommended to procedure vast volumes of the information at the level of each single car and then submit the findings to the cloud to resolve the ITS inactivity and dependability issues. Deep-Learning (DL) techniques as artificial intelligence (AI) perform highly sophical functions such as speech and image recognition which cannot be analytically extracted [29]–[31]. Thus, DL techniques are an operative research for ITS if correctly applied, since they enable heterogeneous optimization and processing of ITS data [31]. Veres et al. carried out a detailed study examining the role of the DRL and ML as AI in various fields e.g. traffic flow assessment, fleet management, hunting of passengers, MEC channel estimation, accident estimation etc. on smart city Infrastructure [32].

The authors concentrated on the emergence of mobile edge computing (MEC) problems. A DRL based methodology is suggested to study about specific arguing potential over unattended learning to successfully deal with possible safety threats. The proposed model has been studied compared with the
present ML protocols. The result indicates an additional 6% improvement in accuracy in the technique proposed [33]. Innovative long-term short-term memory (LSTM) network prediction technology to predict numerous limitations for a wireless link, to confirm optimal device presentation. The LSTM network is able to organize promising data in an array which makes it easy to examine space-temporal correlations between different communications channel parameters. In the given instance, the simulation results verified the effectiveness of the proposed model [34]. A study for efficient use of Taxis GPS trajectory information in a passenger hunting field. The proposed effective and reliable (TRec) recommendation framework is based on the DNN structure. Take the following steps in the TRec search: taxi drivers are the stuff that can be identified, the status of the route expected and the net benefits determined. A real data collection that confirms its performance and quality, assessed the suggested framework of recommendations (TRec) [35].

![ITS architecture and components.](image)

The authors in this article have suggested improved decision-making in a driving activity in a heterogeneous DRL dependent environment. This refers to the data preprocessor that converts the information into the hyper-grid matrix. It consists of a two-stream DNN to remove the critical dormant functions and a DRL methodology to achieving the optimal strategy. Simulation tests using multiple traffic scenarios for linked vehicles confirm the efficiency of the proposed situation [36]. A DRL strategy for designing an intelligent vehicle edge computing offload system. The author has developed a finite Markov chain for the design of the communications and computer states and established a cooperative problem for improving the quality of experience (CQO) in order to enhance the mission and resource management. The NP-hard problem suggested is further split into two different problems which deal efficiently with it and numerical tests are used to validate its effectiveness [37]. The writers spoke about the use of UAVs for transmission link for full-performance vehicles. The model is based on the issue of Markov Decision Process (MDP) and addressed different transitional UAV and vehicle states. Deep Deterministic Policy Gradient (DDPG) algorithms were proposed to study efficiently the energy
consumption of flying UAVs based on three different techniques. In a more realistic scenario, the presentation of the suggested model is deliberate and simulations are checked [38].

For V2V contact, Ye et al. have developed a groundbreaking, decentralized DRL resource allocation framework that can be used in broadcast and unicast environments too. The projected practice allows an individual vehicle or v2v link, instead of waiting for global information to resolve on its individual to find an optimum electricity level for broadcast and the subcontracting. The results of the simulation show that each user or operator can resourcefully fulfill and optimize interference with contact V2I (car-to-infrastructure) with strict latency requirements on V2V links [39]. A traffic-aware technique that enables the implementation of UAVs to enhance the quality of service in a vehicle environment. In the traffic overcrowding and associated events setting, the UAVs used act as MEC nodes. Simulation results have validated the proposed protocol performance [40]. The stacked self-coding model is introduced and implemented to learn about various aspects of traffic flow and be trained in a greedy sense. The performance of the proposed traffic flow prediction technique has exceeded existing techniques' effectiveness. The rapid movement of UAS, its ease of deployment, the increased potential for payload, long resistance and low production cost made it an important part of intelligent city IT. From blood supply to parcel delivery, the preceding favorable aspects of UAVs have played its part in ITS. In optimizing ITS trajectory, energy consumption and performance of UAVs, ML and DRL technologies play an important part [41].

3.2 Application in Mix design and concrete properties

Concrete mix design is a preparation to produce the desired properties like workability, strength and durability. Traditional method of mix design produce lots of trial mixes and not cost effective. Conventional mix-proportion algorithms are only built on a generalization of previous experience often as empirical formula or tables. Because of the complexity of concrete materials, modern concrete algorithms are a check and error exercise, which results in additional costs and time. Modeling these properties has been exploited with the ability of machine learning algorithms to solve conventional empirical regression models. Development of trustworthy and precise model for assessing concrete properties and mix design will heighten time and cost by conveying engineers with critical data. To predict the mix design and properties of concrete, powerful models were developed using single or hybrid ML algorithms. A brief review of mix design and properties of concrete by ML techniques evaluated in Table 1. The review consists various ML techniques as support vector machine, fuzzy logic, neural network, fuzzy interface and combined models. The study reviewed in Table 1 concluded that ML approach is a powerful tool to evaluate properties of concrete without any influence of data complexity. This results to economic and ecological mix-design method by minimize the trial mixes [25-47]. Similarly, for saving time and costs, Mechanical strength and elasticity modulus of the concrete are measured in the form of linear or nonlinear regression equations using an empirical formula [42], [43]. Finding of modulus of elasticity is very time taking and complicated [44].
### Table 1: Review of ML techniques in mix design and mechanical properties of concrete.

| Concrete Type                                      | Problem                                | Algorithm                                      | References |
|----------------------------------------------------|----------------------------------------|-----------------------------------------------|------------|
| Normal and high strength                          |                                        | Neural network                                | [45]       |
| High performance                                   |                                        |                                               |            |
| Normal concrete with mineral fillers               |                                        | Artificial Neural network                     | [47]       |
|                                                    | **Prediction of compressive strength** |                                              |            |
| Self-compacting                                    |                                        | Neural network                                | [48]       |
|                                                    |                                        |                                               |            |
| Normal concrete                                    |                                        | Neural network & support vector machine       | [53]       |
|                                                    |                                        |                                               |            |
| High performance Concrete (HPC)                    |                                        | Hybrid of FL, SVM & GA                        | [56]       |
|                                                    |                                        | Combined model                                | [57]       |
|                                                    |                                        | Neural network & neuro-fuzzy approach         | [54]       |
|                                                    |                                        | Fuzzy-logic & support vector                  | [55]       |
| C&D waste concrete                                 |                                        | Neural network                                | [58]       |
|                                                    |                                        |                                               | [59]       |
| Concrete with agriculture and construction waste   |                                        | Neural network                                | [60]       |
|                                                    |                                        |                                               |            |
| FRP reinforced                                     |                                        | Neural network                                | [61]       |
|                                                    |                                        |                                               |            |
| High performance fibre reinforced concrete         |                                        | Finite Element                                | [52]       |
|                                                    |                                        |                                               |            |
| Geopolymer concrete                                |                                        | Support vector machine                        | [62]       |
|                                                    | **Prediction of splitting tensile strength** |                                        |            |
| High performance concrete                          |                                        | Neural network, genetic programing            | [63]       |
|                                                    |                                        |                                               |            |
| Concrete with agriculture and construction waste   |                                        | Neural network                                | [60]       |
|                                                    | **Prediction of modulus of elasticity** |                                        |            |
| Normal and high strength                           |                                        | Adaptive network-based fuzzy inference system  | [64]       |
|                                                    |                                        | Neural network                                | [65]       |
Conventional empirical models, based on limited experimental data and variables, were developed using a fixed equation to determine the mechanical properties of the concrete [68]. They are successful only in describing their own calibration experimental results. The model coefficients as well as the form of the equation will be modified if the original data has been updated [53]. The conventional models may not therefore be appropriate to find out the properties of the new concrete, because in some concrete types, the correlation between components and concrete characteristics is highly nonlinear [60].

4. Conclusions

A transitory study of the necessary ideas of artificial intelligence and machine learning techniques have been done in this paper. The complexity of the projects and the individualistic nature of the infrastructure projects were responsible for delays and errors. To minimize the time and cost, modernization will take place with many AI techniques. In this paper, we reviewed modern smart cities’ research tendencies and growth concerning many complex problems and applications skilled by academicians and industry. The increasing value for smart transport systems and concrete properties of the techniques described above. The ML models in AI were grouped into many algorithms as neural network, finite element, fuzzy-logic or fuzzy-interface, and support vector machine. These models application were used to predict the compressive strength, tensile strength, modulus of elasticity and mix design of concrete and also showed a significant role in the advancement of AI in civil engineering. Markov Decision Process (MDP) and Deep Deterministic Policy Gradient (DDPG) algorithms were proposed very efficient to the energy consumption of flying UAVs based intelligent transport system (ITS). In combination with the benefits and drawbacks of the ML tests, the analysis will assist engineers in selecting the best models to calculate the mechanical strength of concrete.

References

[1] Y. Liu, C. Yang, L. Jiang, S. Xie, and Y. Zhang, “Intelligent Edge Computing for IoT-Based Energy Management in Smart Cities,” IEEE Netw., vol. 33, no. 2, pp. 111–117, 2019.
[2] E. O’Dwyer, I. Pan, S. Acha, and N. Shah, “Smart energy systems for sustainable smart cities: Current developments, trends and future directions,” Appl. Energy, vol. 237, no. October 2018, pp. 581–597, 2019.
[3] Z. Ullah, F. Al-Turjman, L. Mostarda, and R. Gagliardi, “Applications of Artificial Intelligence and Machine learning in smart cities,” Comput. Commun., vol. 154, no. March, pp. 313–323, 2020.
[4] G. Nishika, “A literature survey on artificial intelligence,” Int. J. Eng. Res. Technol., vol. 5, no. 19, pp. 1–5, 2017.
[5] X. Chen and P. Van Beek, “Con ict-Directed Backjumping Revisited,” pp. 53–81, 2001.
[6] X. Zhou, B. Liu, Z. Wu, and Y. Feng, “Integrative mining of traditional Chinese medicine literature and MEDLINE for functional gene networks,” Artif. Intell. Med., vol. 41, no. 2, pp. 87–104, 2007.
[7] P. Stone, M. L. Littman, S. Singh, and M. Kearns, “ATTac-2000: An adaptive autonomous
bidding agent,” *Proc. Int. Conf. Auton. Agents*, pp. 238–245, 2001.

[8] J. Hong, “Goal recognition through goal graph analysis,” *J. Artif. Intell. Res.*, vol. 15, pp. 1–30, 2001.

[9] Y. Peng and X. Zhang, “Integrative data mining in systems biology: from text to network mining,” *Artif. Intell. Med.*, vol. 41, no. 2, pp. 83–86, 2007.

[10] J. Singer, I. P. Gent, and A. Smaill, “Backbone Fragility and the Local Search Cost Peak,” *J. Artif. Intell. Res.*, vol. 12, p. 235, 2000.

[11] D. Alexandrov, “Randomized Algorithms for the Minmax Diameter k-Clustering Problem,” *Proc. ECCO 13*, vol. 12, pp. 193–194, 2000.

[12] R. Cioffi, M. Travaglioni, G. Piscitelli, A. Petrillo, and F. De Felice, “Artificial intelligence and machine learning applications in smart production: Progress, trends, and directions,” *Sustain.*, vol. 12, no. 2, 2020.

[13] F. Pour Rahimian, S. Seyedzadeh, S. Oliver, S. Rodriguez, and N. Dawood, “On-demand monitoring of construction projects through a game-like hybrid application of BIM and machine learning,” *Autom. Constr.*, vol. 110, no. October 2019, p. 103012, 2020.

[14] R. A. Stewart, “IT enhanced project information management in construction: Pathways to improved performance and strategic competitiveness,” *Autom. Constr.*, vol. 16, no. 4, pp. 511–517, 2007.

[15] E. J. Adwan and A. Al-Soufi, “A Review of ICT Technology in,” *Int. J. Manag. Inf. Technol.*, vol. 8, no. 3, 2016.

[16] S. Alsafouri and S. K. Ayer, “Review of ICT Implementations for Facilitating Information Flow between Virtual Models and Construction Project Sites,” *Autom. Constr.*, vol. 86, no. October 2017, pp. 176–189, 2018.

[17] E. O. Ibem and S. Laryea, “Survey of digital technologies in procurement of construction projects,” *Autom. Constr.*, vol. 46, pp. 11–21, 2014.

[18] S. Chackravarthy, S. Schmitt, and L. Yang, “Intelligent crime anomaly detection in smart cities using deep learning,” *Proc. - 4th IEEE Int. Conf. Collab. Internet Comput. CIC 2018*, pp. 399–404, 2018.

[19] V. M. Karbhari and L. S. W. Lee, *Vibration-based damage detection techniques for structural health monitoring of civil infrastructure systems*. Woodhead Publishing Limited, 2009.

[20] S. Parsons, “Introduction to Machine Learning, Second Edition by Ethem Alpaydin, MIT Press, 584 pp., $55.00. ISBN 978-0-262-01243-0,” *Knowl. Eng. Rev.*, vol. 25, no. 3, pp. 353–353, 2010.

[21] W. Ben Chaabene, M. Flah, and M. L. Nehdi, “Machine learning prediction of mechanical properties of concrete: Critical review,” *Constr. Build. Mater.*, vol. 260, p. 119889, 2020.

[22] A. P. Mikhail Kanervski, Vadim Timonin, *Machine Learning for Spatial Environmental Data*. EPFL Press New York, 2009.

[23] A. Ferdowski, U. Challita, and W. Saad, “Deep Learning for Reliable Mobile Edge Analytics in Intelligent Transportation Systems: An Overview,” *IEEE Veh. Technol. Mag.*, vol. 14, no. 1, pp. 62–70, 2019.

[24] J. Zhang, Y. Zheng, and D. Qi, “Deep spatio-temporal residual networks for citywide crowd flows prediction,” *31st AAAI Conf. Artif. Intell. AAAI 2017*, pp. 1655–1661, 2017.

[25] Z. Zhao, W. Chen, X. Wu, P. C. V. Chen, and J. Liu, “LSTM network: A deep learning approach for short-term traffic forecast,” *IET Image Process.*, vol. 11, no. 1, pp. 68–75, 2017.

[26] Y. Lecun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[27] P. Papadimitratos, A. La Fortelle, K. Evenssen, R. Brignolo, and S. Cosenza, “Vehicular communication systems: Enabling technologies, applications, and future outlook on intelligent transportation,” *IEEE Veh. Technol. Mag.*, vol. 47, no. 11, pp. 84–95, 2009.
[30] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, “Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial,” IEEE Commun. Surv. Tutorials, vol. 21, no. 4, pp. 3039–3071, 2019.

[31] A. M. and G. H. Alex Graves, “Speech Recognition with Deep Recurrent Neural Networks,” Department of Computer Science, University of Toronto,” no. 3, pp. 6645–6649, 2013.

[32] M. Veres and M. Moussa, “Deep Learning for Intelligent Transportation Systems: A Survey of Emerging Trends,” IEEE Trans. Intell. Transp. Syst., vol. PP, pp. 1–17, 2019.

[33] Y. Chen, Y. Zhang, S. Maharjan, M. Alam, and T. Wu, “Deep Learning for Secure Mobile Edge Computing in Cyber-Physical Transportation Systems,” IEEE Netw., vol. 33, no. 4, pp. 36–41, 2019.

[34] G. Liu, Y. Xu, Z. He, Y. Rao, J. Xia, and L. Fan, “Deep Learning-Based Channel Prediction for Edge Computing Networks Toward Intelligent Connected Vehicles,” IEEE Access, vol. 7, pp. 114487–114495, 2019.

[35] Z. Huang, G. Shan, J. Cheng, and J. Sun, “TRec: an efficient recommendation system for hunting passengers with deep neural networks,” Neural Comput. Appl., vol. 31, no. s1, pp. 209–222, 2019.

[36] Z. Bai, W. Shangguan, B. Cai, and L. Chai, “Deep reinforcement learning based high-level driving behavior decision-making model in heterogeneous traffic,” Chinese Control Conf. CCC, vol. 2019-July, no. 3, pp. 8600–8605, 2019.

[37] P. Ning, H. Shi, P. Niu, T. Lu, and W. Wang, “Electric field analysis of auxiliary electrode in needle-free electrostatic spinning,” Ferroelectrics, vol. 548, no. 1, pp. 60–71, 2019.

[38] X. Zhu, Y. Hu, Q. Hu, and B. Li, “Analysis of electromagnetic performance of helix TWT with beam loaded,” 2018 IEEE Int. Vac. Electron. Conf. IVEC 2018, no. 6, pp. 383–384, 2018.

[39] H. Ye, G. Y. Li, and B. H. F. Juang, “Deep Reinforcement Learning Based Resource Allocation for V2V Communications,” IEEE Trans. Veh. Technol., vol. 68, no. 4, pp. 3163–3173, 2019.

[40] H. El-Sayed, M. Chaqfa, S. Zeadally, and D. Puthal, “A Traffic-Aware Approach for Enabling Unmanned Aerial Vehicles (UAVs) in Smart City Scenarios,” IEEE Access, vol. 7, pp. 86297–86305, 2019.

[41] F. Yisheng Lv, Yanjie Duan, Wenwen Kang, Zhengxi Li, and Fei-Yue Wang, “Traffic Flow Prediction With Big Data: A Deep Learning Approach,” IEEE Access, pp. 1–9, 2014.

[42] A. H. Gandomi and A. H. Alavi, “Applications of computational intelligence in behavior simulation of concrete materials,” Stud. Comput. Intell., vol. 359, no. Ci, pp. 221–243, 2011.

[43] P. of I. C. Proceedings and ICICE-2013, “INTERNATIONAL CONFERENCE ON Organised by,” Proc. Int. Conf. Innov. Civ. Eng. ICICE-2013, 2013.

[44] M. Y. Mansour, M. Dicleli, J. Y. Lee, and J. Zhang, “Predicting the shear strength of reinforced concrete beams using artificial neural network,” Constr. Build. Mater., vol. 26, no. 6, pp. 781–799, 2004.

[45] T. Ji, T. Lin, and X. Lin, “A concrete mix proportion design algorithm based on artificial neural networks,” Cem. Concr. Res., vol. 36, no. 7, pp. 1399–1408, 2006.

[46] M. I. Khan, “Mix proportions for HPC incorporating multi-cementitious composites using artificial neural networks,” Constr. Build. Mater., vol. 28, no. 1, pp. 14–20, 2012.

[47] R. Gujar and V. Vakharia, “Prediction and validation of alternative fillers used in micro surfacing mix-design using machine learning techniques,” Constr. Build. Mater., vol. 207, pp. 519–527, 2019.

[48] M. Uysal and H. Tanyildizi, “Estimation of compressive strength of self compacting concrete containing polypropylene fiber and mineral additives exposed to high temperature using artificial neural network,” Constr. Build. Mater., vol. 27, no. 1, pp. 404–414, 2012.

[49] B. K. R. Prasad, H. Eskandari, and B. V. V. Reddy, “Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN,” Constr. Build. Mater., vol. 23, no. 1, pp. 117–128, 2009.

[50] R. Siddique, P. Aggarwal, and Y. Aggarwal, “Prediction of compressive strength of self-compacting concrete containing bottom ash using artificial neural networks,” Adv. Eng. Softw.,
[51] W. J.-Z. Ni Hong-Guang, “Prediction of compressive strength of concrete using neural networks,” *Comput. Concr.*, vol. 10, no. 2, pp. 197–217, 2000.

[52] P. Jiao, M. Roy, K. Barri, R. Zhu, I. Ray, and A. H. Alavi, “High-performance fiber reinforced concrete as a repairing material to normal concrete structures: Experiments, numerical simulations and a machine learning-based prediction model,” *Constr. Build. Mater.*, vol. 223, pp. 1167–1181, 2019.

[53] D. C. Feng *et al.*, “Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach,” *Constr. Build. Mater.*, vol. 230, p. 117000, 2020.

[54] Dipro Dutta and Sudhirkumar V. Barai, “Prediction of Compressive Strength of Concrete: Machine Learning Approaches,” *Recent Adv. Struct. Eng.*, vol. 11, no. Part 1, pp. 19–33, 2016.

[55] Q. Zhou, F. Wang, and F. Zhu, “Estimation of compressive strength of hollow concrete masonry prisms using artificial neural networks and adaptive neuro-fuzzy inference systems,” *Constr. Build. Mater.*, vol. 125, pp. 417–426, 2016.

[56] M. Y. Cheng, J. S. Chou, A. F. V. Roy, and Y. W. Wu, “High-performance Concrete Compressive Strength Prediction using Time-Weighted Evolutionary Fuzzy Support Vector Machines Inference Model,” *Autom. Constr.*, vol. 28, pp. 106–115, 2012.

[57] J. S. Chou and A. D. Pham, “Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength,” *Constr. Build. Mater.*, vol. 49, pp. 554–563, 2013.

[58] A. T. A. Dantas, M. Batista Leite, and K. De Jesus Nagahama, “Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks,” *Constr. Build. Mater.*, vol. 38, pp. 717–722, 2013.

[59] Z. H. Duan, S. C. Kou, and C. S. Poon, “Prediction of compressive strength of recycled aggregate concrete using artificial neural networks,” *Constr. Build. Mater.*, vol. 40, pp. 1200–1206, 2013.

[60] M. A. Getahun, S. M. Shitote, and Z. C. Abiero Garay, “Artificial neural network based modelling approach for strength prediction of concrete incorporating agricultural and construction wastes,” *Constr. Build. Mater.*, vol. 190, pp. 517–525, 2018.

[61] H. Naderpour, A. Kheyroddin, and G. G. Amiri, “Prediction of FRP-confined compressive strength of concrete using artificial neural networks,” *Compos. Struct.*, vol. 92, no. 12, pp. 2817–2829, 2010.

[62] A. Nazari and J. G. Sanjayan, “Modelling of compressive strength of geopolymer paste, mortar and concrete by optimized support vector machine,” *Ceram. Int.*, vol. 41, no. 9PartB, pp. 12164–12177, 2015.

[63] A. Nazari and S. Riahi, “Prediction split tensile strength and water permeability of high strength concrete containing TiO2 nanoparticles by artificial neural network and genetic programming,” *Compos. Part B Eng.*, vol. 42, no. 3, pp. 473–488, 2011.

[64] B. Ahmadi-Nedushan, “Prediction of elastic modulus of normal and high strength concrete using ANFIS and optimal nonlinear regression models,” *Constr. Build. Mater.*, vol. 36, pp. 665–673, 2012.

[65] F. Demir, “Prediction of elastic modulus of normal and high strength concrete by artificial neural networks,” *Constr. Build. Mater.*, vol. 22, no. 7, pp. 1428–1435, 2008.

[66] K. Yan and C. Shi, “Prediction of elastic modulus of normal and high strength concrete by support vector machine,” *Constr. Build. Mater.*, vol. 24, no. 8, pp. 1479–1485, 2010.

[67] F. Demir and K. Armagan Korkmaz, “Prediction of lower and upper bounds of elastic modulus of high strength concrete,” *Constr. Build. Mater.*, vol. 22, no. 7, pp. 1385–1393, 2008.

[68] P. Chopra, R. K. Sharma, and M. Kumar, “Prediction of Compressive Strength of Concrete Using Artificial Neural Network and Genetic Programming,” *Adv. Mater. Sci. Eng.*, vol. 2016, 2016.