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A Selective Survey Review of Computational Intelligence Applications in the Primary Subdomains of Civil Engineering Specializations

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Abstract: Artificial intelligence is the branch of computer science that attempts to model cognitive processes such as learning, adaptability and perception to generate intelligent behavior capable of solving complex problems with environmental adaptation and deductive reasoning. Applied research of cutting-edge technologies, primarily computational intelligence, including machine/deep learning and fuzzy computing, can add value to modern science and, more generally, to entrepreneurship and the economy. Regarding the science of civil engineering and, more generally, the construction industry, which is one of the most important in economic entrepreneurship both in terms of the size of the workforce employed and the amount of capital invested, the use of artificial intelligence can change industry business models, eliminate costly mistakes, reduce jobsite injuries and make large engineering projects more efficient. The purpose of this paper is to discuss recent research on artificial intelligence methods (machine and deep learning, computer vision, natural language processing, fuzzy systems, etc.) and their related technologies (extensive data analysis, blockchain, cloud computing, internet of things and augmented reality) in the fields of application of civil engineering science, such as structural engineering, geotechnical engineering, hydraulics and water resources. This review examines the benefits and limitations of using computational intelligence in civil engineering and the challenges researchers and practitioners face in implementing these techniques. The manuscript is targeted at a technical audience, such as researchers or practitioners in civil engineering or computational intelligence, and also intended for a broader audience such as policymakers or the general public who are interested in the civil engineering domain.

Keywords: computational intelligence; machine/deep learning; fuzzy computing; data analysis; blockchain; cloud computing; Internet of Things; augmented reality; civil engineering

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1. Introduction

The modern era is characterized by rapid technological developments, resulting in the development of a new economy at a global level, where the most critical asset is data. The era of "big data" has given rise to the need to analyze it and extract the valuable hidden knowledge it contains [1]. More generally, the maximization of the production process in the modern era in sectors such as construction, and especially as the Industry 4.0 standard, promotes big data and requires the widespread use of cyber-physical systems that monitor and supervise physical processes, taking autonomous and decentralized optimal decisions [2].

The decisions in question are based on information collection and analysis procedures, which come from the continuous flow of data, giving an increasingly accurate picture of the system's effectiveness in production processes. This fact implies requirements for constant collection and analysis of large-scale data from heterogeneous sources.

The visualization of information and its diagnosis as to whether it is accurate, incomplete or inaccurate (veracity), determining its final value is a highly complex and demanding process, especially when real-time decision-making is required [3]. Large-scale data are considered as data that grow at high-speed rates as information arrives from multiple sources at high speed (velocity), which implies a change in the ways of collecting and storing this data (volume). Accordingly, various unstructured or semi-structured data forms are included, characterized by variability, as they change meaning or status over time and the environment in which they are found.

Intelligent large-scale data analysis systems based on artificial intelligence methods have the potential to provide machine-readable formats suitable for handling complex tasks by demonstrating logic, experiential learning and optimal decision-making capabilities without human intervention.

Artificial intelligence is an umbrella term to describe a machine's ability to mimic human cognitive functions, such as problem-solving, pattern recognition, learning and adapting to a dynamic, ever-changing environment [3]. Computational intelligence (CI) is the primary subdivision of artificial intelligence (AI) and deals with the theory, design, implementation and development of physiologically and linguistically inspired computational paradigms [4].

This paper's remaining sections are structured as follows: Section 2 presents the basic concept of computational intelligence (CI) which is the theory, design, application and development of biologically and linguistically motivated computational paradigms, including machine learning, neural networks, fuzzy logic and evolutionary computation. The applications of CI in civil engineering research domains and specifically in Architectural Compositions, Building Technologies and Materials, Geotechnical Engineering, Structural Construction, Computer Programming and Mathematics, Mechanics Engineering, Transportation Engineering, and Hydraulics and Water Resources Engineering are described in Section 3. Section 4 presents the context of Industry 4.0 and how it can extend the applications of civil engineering science to future research. Finally, Section 5 presents the conclusions of the research.

2. Computational Intelligence

CI is a developing field that includes computer paradigms such as ambient intelligence, artificial life, social learning, artificial immune systems, social reasoning and artificial hormone networks. Effective intelligent systems, such as cognitive developmental systems, require CI. A subset of CI is machine learning (ML) and deep learning (DL), which uses algorithmic techniques to enable information systems to learn from data without being explicitly programmed. CI is at the heart of some of the most effective AI systems as there has been a surge in research in DL (which is the primary approach for AI) in recent years. Their ability is constantly optimized as they receive more and more data, which requires the continuous and perpetual collection of information from each production stage to multifacetedly investigate the current but also historical situation of the processes being performed [5].

In CI, the basic concept of the function f, which implements a correspondence mapping each element p of the set P to a single element $f(p)$ of the set Q, is of fundamental importance as its practical advantage is that it can be implemented in practice with tangible results. Assuming a system datum as an input that implements a function, one and only one output datum is mapped to it. With this view, the goal of a computational intelligence algorithm is to estimate a function $f : R^N \rightarrow T$, where the domain R is a set of real numbers, while the domain T can be either $T = R^M$ in regression problems or a group of labels in classification problems.

The process of computing the function $f : R^N \to T$ given a set of pairs $(x_1, f(x_1)), \ldots,$ $(x_n, f(x_n))$, while computing the value $\hat{f}(x_0)$ for $x_0 \neq x_i, i \in \{1, \ldots, n\}$, is called supervised learning. The average ranking error of the training set points can be measured by the following function [6,7]:

$$R_{emp}(g) = \frac{1}{N}\sum_i L(y_1, g(\mathrm{x}_i))$$

Patterns in an input stream, that is, training data, are used when the classes are unknown, and the system makes predictions based on some distribution or some quantitative measures to evaluate and characterize the data's similarity to respective groups. The following function describes how to compute a process of this kind [8,9]:

$$SCORE(C,\ D) = \sum_{k=1}^{K} d(\mathrm{x}_i, c_k)$$

where $c_k = \frac{1}{n_k}\sum_{x \in c_k} x$ and $d(x,y) = \|x-y\|^2$.

One hybrid type of algorithm is semi-supervised learning, which is based on searching for a decision boundary with a maximum profit margin over the labelled data so that the decision boundary has maximum profit over the more general dataset. The loss function for the labelled data is $(1 - yf(x))_+$, while the loss function for the unlabeled data is $(1 - |f(x)|)_+$. The algorithm calculates the function $f^*(x) = h^*(x) + b$ by minimizing the normalized empirical risk as follows [5,10]:

$$f^* = \underset{f}{\mathrm{argmin}}\left(\sum_{i=1}^{l}(1 - y_i f(x_i))_+ + \lambda_1\|h\|_H^2 + \lambda_2\sum_{i=l+1}^{l+u}(1 - |f(x_i)|)_+\right)$$

The available data are delivered progressively in sequential order in this situation and utilized for training and prediction by computing the error at each iteration. This on-line/sequential learning approach aims to reduce the cumulative error throughout all iterations, as calculated by the formula below [5,11]:

$$I_n[w] = \sum_{j=1}^{n} V(\langle w, x_j\rangle, y_j) = \sum_{j=1}^{n}\left(x_j^T w - y_j\right)^2$$

In reinforcement learning, the algorithm learns to make decisions based on rewards or punishment. The method accepts as input the states $s \epsilon S$ of the agent. It has the action-state value function $Q(s, a)$ for each action $a\epsilon A(s)$ to maximize the rewards, correspondingly minimizing the punishments. The basic idea of the algorithm lies behind the repeated renewal of the equation:

$$Q_{i+1}(s,a) = E_{s'}\left\{r + \gamma \underset{a'}{max} Q_i(s', a') \mid s, \alpha\right\}$$

until a value is reached that is equivalent to the optimal one $Q*$, where $Q\imath \to Q*$ and $i \to\ \infty$.

A basic goal of any learning process is an acceptable ability to generalize [5,12].

The three primary foundations of CI have traditionally been neural networks, fuzzy systems and evolutionary computation. However, several nature-inspired computer models have emerged throughout time.

2.1. Neural Networks

The attempt to simulate the human brain and, by extension, the central nervous system constitutes the training of neural networks. It is an architecture that uses information processing (stimuli), the communication between neurons in parallel and distributed processing processes and the learning, recognition and inference capabilities that are integrated and processed in real-time [4,11].

Neurons are the building blocks and nodes of neural networks, with each node receiving a set of numerical inputs (input layer), either from other neurons or from the environment. Based on these inputs, a calculation (hidden layer) is performed, producing an output (output layer). These layers of neurons multiply their information by matching synaptic weights and totaling the results. This sum is fed as an argument to the activation function, which each node implements internally. The value the part receives for that argument is the neuron's output for the current inputs and weights [12,13].

More specifically, neural networks are clusters of neurons that have transfer functions and are hierarchically structured according to the levels above. They implement an $f : R^N \rightarrow T$ function using various architectures depending on the intended effect. The numerical inputs $x_1, \ldots, x_n$ are multiplied by the weights $w_1, \ldots, w_n$, respectively, and then summed, taking into account the bias constant β, which is the $n+1$ weight of the artificial neuron. Therefore, the output (σ) is calculated as follows [12,14,15]:

$$\sigma = \sum_{i=1}^{n} w_i x_i + \beta = \sum_{i=1}^{n} w_i x_i = w^T \cdot x$$

where $w^T \cdot x$ represents the inner product of the vector $x = (x_1, \ldots, x_n, 1)^T$ input of the artificial neuron on the vector $w = (w_1, \ldots, w_n, w_{n+1})^T$ weights. The weighted linear sum, σ, of the neuron's inputs is then fed into a non-linear distortion component, $f(\sigma)$, called the transfer function. Some of the more popular $f(\sigma)$ that have been proposed in the literature are presented below [4,5]:

1. Hyperbolic tangent:

$$f(\sigma) = \frac{1 - e^{-\sigma}}{1 + e^{-\sigma}}$$

2. Sigmoid:

$$f(\sigma) = \frac{1}{1 + e^{-\sigma}}$$

3. ReLU:

$$f(x) = x^+ = max(0, x)$$

Depending on how the layers are interconnected and how the nodes communicate, various architectures emerge, the most significant of which are the contemporary deep architectures, which can solve particularly complex problems. CNN, or ConvNet, is one of the most prevalent deep neural networks. Due to the convolutional layering of learned characteristics with input data, this architecture is suitable for processing 2D data such as images. CNNs eliminate the human supervision preprocess by automatically identifying and extracting image classification characteristics. The essential components of deep architecture neural networks are not pre-trained but learn as the network trains on a collection of patterns. Deep learning models are highly accurate for computer vision applications such as object categorization [4,5]. Figure 1 depicts the classification process of a CNN.

Filters are applied in the CNN architecture at varying resolutions to each training picture, and each convolved image's result serves as the next layer's input. Every feature map output is the result of applying a filter to the image. The new feature map is the next input.

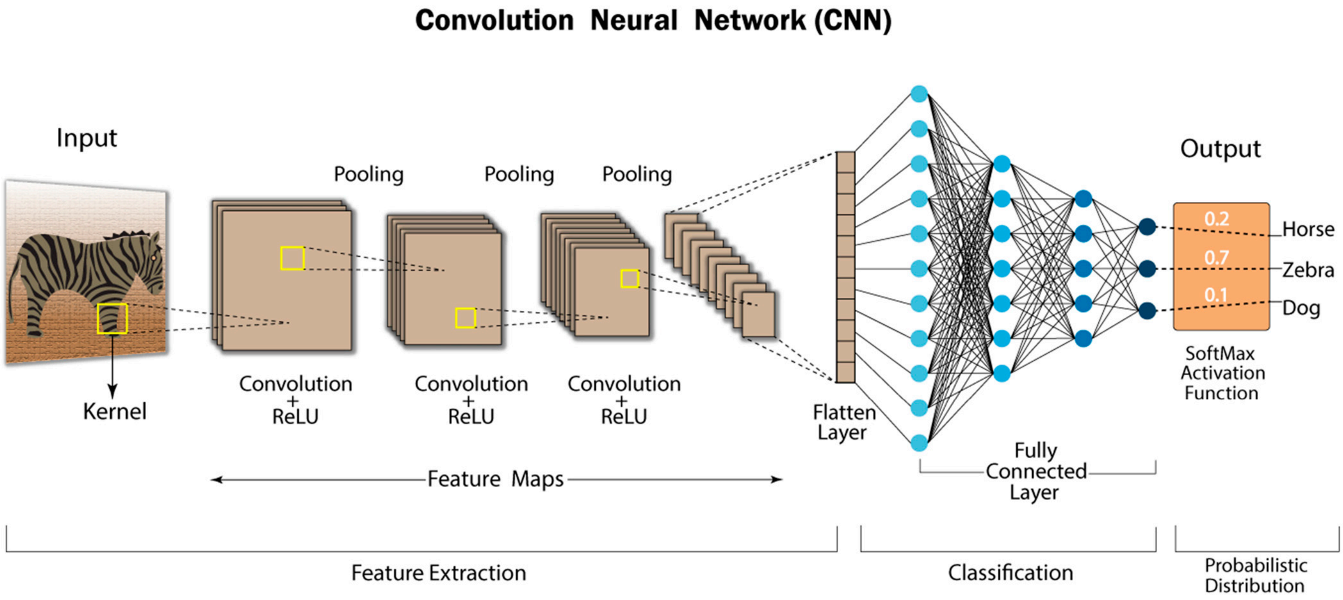

Figure 1. Example of a network with convolutional layers (https://developersbreach.com, accessed on 4 March 2023).

2.2. Fuzzy Systems

Fuzzy logic [16,17] is a unique form of intelligence related to decision-making methodology. It is based on the extension of the concept of the classical binary set $\{0,1\}$, in which the relation of "belongs to" $(\in)$ for a function $I_A(x)$ is generalized so that instead, x takes infinite values in the closed interval $[0,\ 1]$. In other words, it creates a new majority set A, where the transition from the category of elements of X that belong to the fuzzy set $\widetilde{A}$, to the type of elements of X that do not belong to A is not abrupt-unclear but gradual-unclear, as is usually the case in reality [16,18]. In this sense, the characteristic two-valued function $I_A(x)$ expresses a compact set A in the two-member domain $\{0,1\}$. It is included in the concept of the participation function, $\mu_{\widetilde{A}}(x)$, which expresses a fuzzy set at the extreme values of the infinite space $[0,\ 1]$ and uses functions such as $\mu_{\widetilde{A}}(x)$ [19]:

1. Triangular:

$$\mu_{A_i}(x) = \begin{cases} 0,\ x < a \\ \frac{x-a}{b-a}, a \le x \le b \\ \frac{c-x}{c-b}, b \le x \le c \\ 0,\ c \le x \end{cases}$$

2. Trapezoid:

$$\mu_{A_i}(x) = \begin{cases} 0,\ x < a \\ \frac{x-a}{b-a}, a \le x \le b \\ 1,\ b \le x \le c \\ \frac{c-x}{c-b}, c \le x \le d \\ 0, d \le x \end{cases}$$

3. Gaussian:

$$\mu_{A_i}(x) = exp$$

Among the fuzzy sets [18,20,21] (sets whose elements have degrees of membership), it is possible to perform certain operations such as [16,17,22]:

1. Fuzzy disjunction

$$\mu_{\widetilde{A}\cup\widetilde{B}}(x) = \mu_{\widetilde{A}}(x) \bigvee \mu_{\widetilde{B}}(x) = max[\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x)] \forall x \in X$$

2. Fuzzy conjunction:

$$\mu_{\widetilde{A}\cap\widetilde{B}}(x) = \mu_{\widetilde{A}}(x) \bigwedge \mu_{\widetilde{B}}(x) = min[\mu_{\widetilde{A}}(x), \mu_{\widetilde{B}}(x)] \forall x \in X$$

3. Fuzzy product:

$$\mu_{\widetilde{A}\cdot\widetilde{B}}(x) = \mu_{\widetilde{A}}(x) \cdot \mu_{\widetilde{B}}(x) \forall x \in X$$

4. Fuzzy complement:

$$\mu_{\neg\widetilde{A}} = 1 \neg \mu_{\widetilde{A}}(x)$$

Fuzzy reasoning is called the process of deriving fuzzy conclusions, a process which is based on three fundamental concepts of the theory of fuzzy logic [19,23] and specifically on fuzzy variables, inference rules and fuzzy relations, which can be combined through the process of composition with operations such as [18,24,25]:

1. Fuzzy composition max-min:

$$\mu_{R\circ Q}(x,z) = \max_{y\in Y}(\min(\mu_R(x,y), \mu_Q(y,z))) = \bigvee_{y\in Y} \left(\mu_R(x,y) \bigwedge \mu_Q(y,z)\right)$$

2. Fuzzy composition max-prod:

$$\mu_{R\circ Q}(x,z) = \max_{y\in Y}(\mu_R(x,y) \cdot \mu_Q(y,z)) = \bigvee_{y\in Y} (\mu_R(x,y) \cdot \mu_Q(y,z))$$

2.3. Evolutionary Computation

Evolutionary systems [26,27] work based on the Darwinian theory of the mechanism of natural selection through which evolution occurs, given that all life forms come from common ancestors and have been shaped over time. The application techniques of the mechanisms they use are inspired by the biological evolution of species, such as reproduction, mutation, recombination, natural selection and ultimately, survival of the fittest. Technically, they belong to the family of systems that operate with trial and error and can be considered stochastic optimization methods. This characteristic of these systems sets them apart. It makes them preferable to other classical optimization methods because they have little or no knowledge of the problem or function they are asked to solve [28–30]. The solution methods are not dependent or based on complex calculated parameters. These systems can evolve and adapt in a manner analogous to that of the organization they imitate, which is an optimal solution in cases of dynamic and rapidly changing environments [26,31].

The particle swarm optimization (PSO) algorithm [27,32,33] is a typical case of evolutionary algorithms. In PSO, a set of particles moves around a search space to find the optimal solution. The position of each particle represents a potential solution to the problem, and the velocity of the particle represents the direction and speed of movement, as depicted in the following Figure 2.

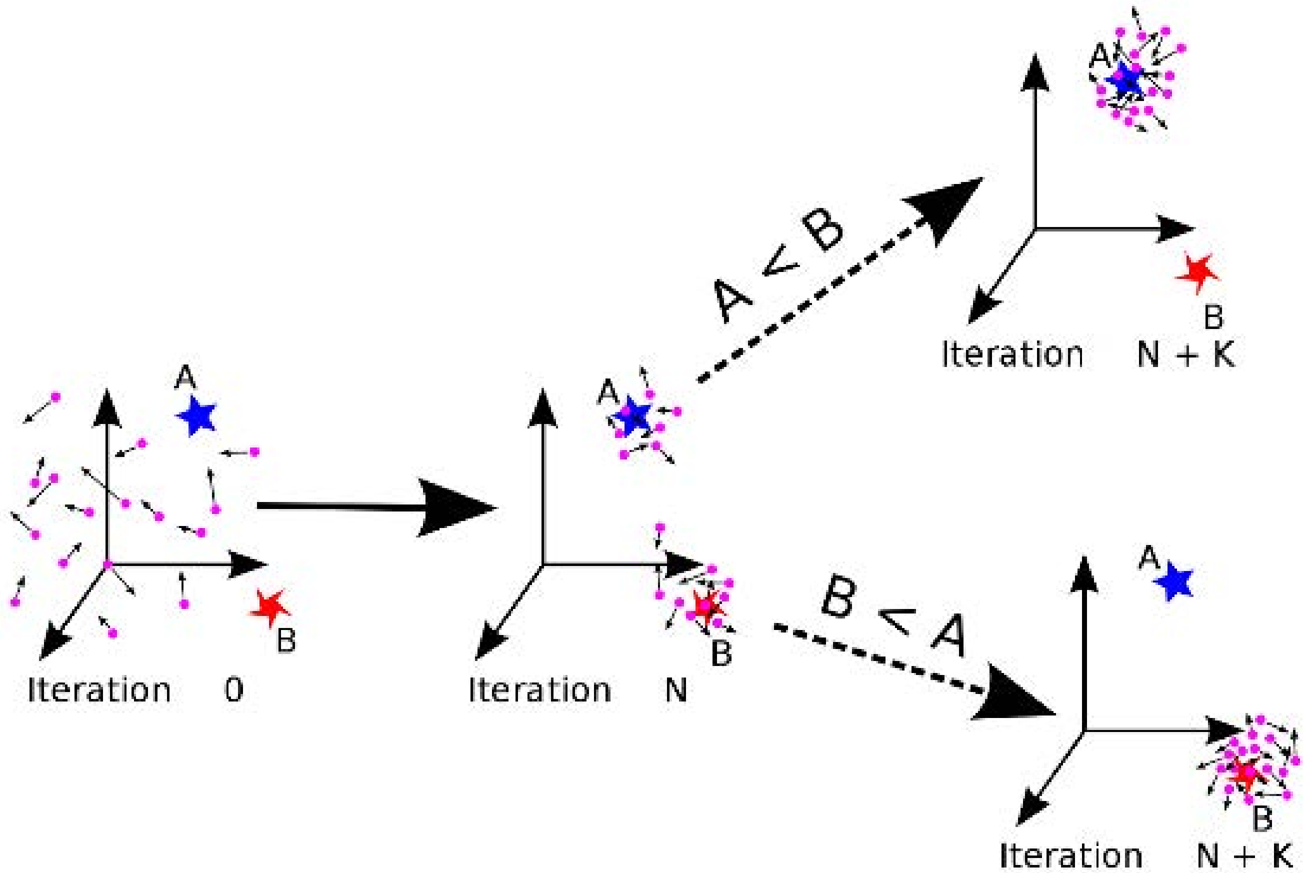

Figure 2. Particle swarm optimization algorithm.

The algorithm starts with an initial population of particles, which are randomly placed in the search space. Each particle is associated with two vectors: its position and velocity. The position and velocity of each particle are updated in each iteration based on the best solution found so far by the particle itself and its neighbors.

It is a straightforward algorithm because it does not use crossover and mutation mechanisms and it can be applied to many problems since it requires minimal parameters to be adjusted. It is also, in many cases, very fast as it uses random real numbers and communication between the entities of a swarm. Specifically, PSO investigates the space of an objective function by altering the paths of individual tracers known as particles. These trajectories produce semi-stochastic route segments. A swarm particle's motion is governed by a stochastic and a deterministic component. Each particle is drawn to the overall best location recognized by the swarm and the best place it has encountered while tending to wander randomly. When an entity discovers a better location than the previous one, it promotes it to the current best for track i. There is a current best for all n entities at each time t throughout the iterations. The aim is to find the optimum overall position until it can no longer be improved.

Let p and u be the position and velocity for an entity I, respectively. The following formula gives the new velocity vector [32,33]:

$$u_{n,m}^{new} = u_{n,m}^{old} + \Gamma_1 \times r_1 \times \left(p_{n,m}^{local_{best}} - p_{n,m}^{old}\right) + \Gamma_2 \times r_2 \times \left(p_{n,m}^{global_{best}} - p_{n,m}^{old}\right)$$

where $u_{n,m}$ is the velocity of the particle, r_1, r_2 are independent random numbers, $\Gamma_1,\ \Gamma_2$ are learning parameters, $p_{n,m}^{local\_best}$ is the local optimal solution and $p_{n,m}^{global\_best}$ is the overall optimal solution.

The PSO algorithm updates each particle's velocity component and then adds the velocity to the location component. This update is determined by the best solution/position obtained by the particle and the one discovered by the total population of particles. If a particle's optimum solution is better than the population's, it will eventually replace it. All particles' starting positions are evenly distributed to sample the majority of the search space. It is also possible to set an entity's initial vector to zero. The new location is described by the equation below [33]:

$$p_{n,m}^{new} = p_{n,m}^{old} + u_{n,m}^{new}$$

with u usually bound to the range $[0, u_{max}]$.

3. Applications of Computational Intelligence in Civil Engineering Research Domains

The potential applications of CI and its recent developments in the science of civil engineering are enormous, as, in the busy everyday life of the construction site, issues such as requests for information dissemination, dealing with open issues and the management of the construction of technical projects are present. Artificial intelligence can be the intelligent assistant that can optimally control and manage the vast amounts of data generated and alert managers to all the critical points that need their attention. In this way, the manufacturing sector within the framework of Industry 4.0 can make substantial innovative leaps, acquire significant extroversion and develop previously impossible activities [34,35]. This fact, and the general utilization of artificial intelligence in the science of civil engineering, is proven by the relevant research that has been published in the global literature.

3.1. Relevant Research Studies

In recent years, the need to model increasingly complex technical projects that the modern civil engineer is called upon to handle has highlighted the need to exploit artificial intelligence and integrate it increasingly more into the processes they apply. It is essential to mention that the research in this direction and the related fields show a constantly growing trend, which is strengthened by interdisciplinary research, continually offering new implementations that enhance the edge of the said field of knowledge. Presented below are indicative works of applied research in the area of civil engineering science.

3.1.1. Architectural Compositions, Building Technologies and Materials

The domain of architectural compositions, building technologies and materials covers architectural designs of building units or ensembles; construction art and systems and methods of construction works; the technology of construction materials; structural physics; and microclimate control and maintenance and restoration of old buildings and monuments.

The field in question can benefit significantly from using physics-based artificial intelligence models and implementing analytical differential equations or other mathematical models used to solve structural physics problems or simulations [13]. Concrete is the most widely used construction material, but it is also a recognized pollutant that causes significant sustainability issues in terms of resource depletion, energy use and greenhouse gas emissions. AI can lessen the environmental impact of concrete to increase its long-term sustainability. For example, the authors of [36] developed a model to forecast the compressive strength of various eco-friendly concrete mixtures, which may be used in the design process. A combination of recycled concrete and blast furnace slag is utilized to create the concrete. As a final step, a machine learning model was developed that accurately predicts the compressive strength of green concrete.

Self-healing concepts have not yet produced design solutions that reliably quantify their positive effects on structural performance, despite a vast body of literature [37]. Concrete and other cement-based materials have an inherent ability to self-heal [38]. It has been demonstrated that the effectiveness of concrete's self-strengthening and self-healing depends on several factors, the most significant of which are the type of exposure, the width of the crack and the presence of healing stimulants such as crystalline impurities [39]. Autogenous self-healing is largely unaffected by additional factors such as fiber count and additional cementitious materials. A related study [40] proposed, through a properly constructed neural network design and analysis diagrams, a simple input–output model for rapid prediction and evaluation of the self-healing effectiveness of cement-based materials. In particular, it uses AI techniques to quantify the performance of material recovery by displaying the quantitative correlations between mix ratios, exposure type and duration and initial crack width. Specifically, for ANN analysis, a back-propagation network was developed in this study. A single-layer feed-forward neural network was developed. In this network, the output and hidden layers are associated with biases. The training of data is performed by the method of supervised learning in this algorithm. The predicted output values are compared with the provided outputs and the associated error is calculated. The weights and biases of each neural network are adjusted based on this error. This process is iteratively carried out until the error is below the desired value or the maximum number of iterations is reached. In terms of assessing structural performance deterioration and significantly extending the life of reinforced concrete structures, this is the first systematic incorporation of self-healing principles into durability-based design methodologies.

3.1.2. Geotechnical Engineering

The domain of geotechnical engineering covers the subject of soil dynamics, geotechnical earthquake engineering, soil–foundation–structure interactions, soil improvement and reinforcement, analysis of the behavior of geostructures with simulations, deep foundations, geotechnical engineering of mining projects and environmental and geotechnical engineering.

Soil classification based on shared characteristics is a cornerstone of geotechnical engineering. Testing in the lab and the field, both of which may be expensive and time-consuming, has led to this categorization. Each construction site has ground studies, which must be completed before any technical project can be designed. Artificial intelligence may play a crucial role in cutting down on the time and money needed for a proper site inspection program. For example, [41] evaluated the essential ability of machine learning models to classify soils based on cone penetration tests (CPT). A dataset of 1339 representative CPTs was used to test 24 different machine learning models, based on three different algorithms. The applied algorithms were support the vector machine, artificial neural network and random forest algorithms; the input variables included tip resistance, sleeve friction, friction ratio and depth; and the output variables included total vertical stresses, effective vertical stresses and hydrostatic pore pressure. Soil classes based on grain size distributions and soil types based on soil behavior are often used as reference points in the literature. The accuracy of each model's predictions and the time it takes to train are compared. Notably, the algorithm with the highest predictive ability for grain size distribution soil classes obtained around 75% accuracy, while the algorithm with the best predictive power for soil classes achieved about 97–99% accuracy. The best results for all targets were obtained with models using a random forest classifier.

Evaluating soil liquefaction is challenging in geotechnical earthquake engineering. The capacity energy is related to initial soil factors such as the relative density, the initial appropriate confining pressure, fine contents and the soil textural properties, which have been the focus of several liquefaction evaluation processes and approaches. Traditional methods used to assess the liquefaction risk of sand deposits fall into one of three broad categories: stress, strain or energy. The energy-based approach has the edge over the other two because, unlike the focus- or stress-based methods, it accounts for the impacts of stress and strain concurrently. In [42], the amount of energy needed to cause liquefaction in the sand and silty sand was estimated by conducting comparative analyses of state-of-the-art artificial intelligence systems on suitable datasets. Specifically, analyses were carried out on a total of 405 previously published tests using soft computing approaches, including ridge, Lasso and LassoCV, random forest, eXtreme gradient boost (XGBoost) and multivariate adaptive regression splines (MARS) approaches, to assess the capacity energy required to trigger liquefaction in sand and silty sand. The performance measures for ridge and Lasso and LassoCV models were all below 0.6, reflecting the shortage of linear regression methods in handling the complex data mapping in high-dimensional datasets. RF, XGBoost and MARS models were capable of capturing the nonlinear relationships involving a multitude of variables with interaction among each other without making any specific assumption about the underlying functional relationship between the input variables and the response. Using the results of ridge, Lasso and LassoCV, random forest, XGBoost and MARS for a cross-validation, it can be found that the capacity energy, Log(W), was most sensitive to Dr, the relative importance of which was almost 100% for all five machine learning methods. The R^2 score of the testing set for the MARS model was the same as the XGBoost model, and even higher than the RF model. The relative importance obtained by the MARS model was quite close to the average value of the five models. In addition, compared to the black box model of RF and the XGBoost model, the MARS model had an advantage in the capacity to output explicit expressions. The results clearly prove the capability of the proposed models and the capacity energy concept to assess liquefaction resistance of soils.

3.1.3. Structural Constructions

The domain of structural constructions covers the subjects of applied methods of analysis and design of linear and surface carriers; reinforced concrete structures for everyday and seismic actions; prestressed concrete structures for normal and seismic activities; special reinforced and prestressed concrete structures; and control and interventions in structures, metal structures, metal bridges, wooden structures, light structures and masonry structures for every day and seismic actions.

Advanced machine learning algorithms have been successfully applied in many areas of modelling seismic structures and, more generally, in predicting structural damage from single earthquake events, ignoring the effect of seismic sequences. In [43], a neural network approach was applied to determine the expected ultimate structural damage of a reinforced concrete frame under natural and artificial ground motion sequences. Sequential earthquakes consisting of two seismic events were used. Specifically, 16 known measures of ground motion intensity and the structural damage caused by the first earthquake were considered characteristics of the problem. In contrast, the final structural damage was the goal. After the first seismic events and after the seismic sequences, the damage indices' actual values were calculated through a nonlinear time history analysis. The machine learning model was trained using the dataset generated from artificial arrangements, while the predictive ability of the neural network was approximated using the natural seismic lines. In this paper, a holistic single-hidden layer feed forward network (ShLFFN) shallow architecture approach with N neurons in the hidden layer, randomly chosen input weights and random values of bias constants on the hidden layer neurons was used, while the output weights were computed by a single matrix multiplication, which automates and optimally solves the problem. The proposed approach learns N samples with accuracy, while the learning speed was even thousands of times faster than conventional feed forward networks, as the training was not based on time-consuming, repetitive processes such as the back propagation algorithm, which changes the weights of the neural network by estimating the quadratic error between the target vectors and the actual network outputs for all training samples, which are entered into the network in a random serial manner and for many repetitions (epochs). An important advantage gained by the proposed system is the fact that it offers a more efficient and stable prediction model, since the overall behavior of multiple MLP ANNs is less noisy than a single one, and in any case, it reduces the overall risk of particularly inaccurate values. The study in question is a promising application of the method of modelling multiple seismic sequences for the final prediction of the structural damage of a building, offering highly accurate results [44].

Multiple nonlinear time history evaluations utilizing various incidence angles are necessary to determine the angle at which possible seismic damage is at a maximum (critical angle). Thus, the rise in seismic excitation is a crucial consideration in assessing the seismic response of structures. In addition, several accelerograms should be used to analyze the seismic reaction, as advised by seismic codes [45]. As a result, it takes longer to complete the project. [46] presented a technique for critical angle estimation that uses multi-layer neural networks to drastically cut down on computation time. The general concept is to identify situations in which the seismic damage category is higher due to the acute angle than it would be due to the application of seismic motion along the structural axis of the structure. This is accomplished by formulating and resolving the issue as a pattern recognition problem. Inputs to the networks were the ratios of seismic parameter values along the two components of the horizontal seismic files and correctly chosen structural parameters. The investigation findings demonstrate that neural networks can accurately identify situations when a necessary angle computation is required.

3.1.4. Computer Programming and Mathematics

The domain of computer programming mathematics covers the subjects of mathematics, natural sciences, informatics, system analysis and optimization methods, economic analysis and technical economics, project organization and planning, management and human relations, the mechanization of constructions, the management of the social and natural environment and the security and protection of complex systems.

In the subject matter of the specific field, multiple fields of application have been explored with a serious impact on the science of civil engineering [47–50]. For example, in [51], a thorough identification and risk assessment study was carried out for the construction of an underground tunnel passing under a river. Specifically, the risks associated with tunnel construction include environmental and technical ones. The environmental factors refer primarily to the geological conditions affecting the tunnel, such as the inclination of the surrounding rock and the burial depth. Technical factors refer primarily to design parameters and technical measures influencing the tunnel safety. In conjunction with the shield-tunnel construction analysis, the risk factors are the grade of surrounding rock, the burial depth, the water cover depth, the excavation method, the synchronous grouting, the strength of secondary grouting, the grouting pressure and the soil bin pressure. The "kill unit" was used to simulate the shield excavation, and surface forces were applied around the tunnel to simulate different grouting pressures. A thrust force was applied along the excavated face of the tunnel to simulate the soil chamber pressure.

The main risk events when the shield tunnel crosses beneath the river are landslides and water surges, so landslides and water surges were employed as composite risk indicators. Each risk that triggers the combined risk is treated as a separate indicator, and a two-level evaluation index system was established correspondingly. Numerical simulations were used to discover an initial link between the indicators impacting the construction in question, field measurements then validate the findings, and a collection of representative samples was developed. Fuzzy logic and a feed-forward neural network were used for the pieces under consideration to assess the risk level in light of changes to the pertinent indicators of interest. Consequently, the system in question is applied to the risk assessment of Line 5 of the Hangzhou Metro in China, and modifications to the concrete strength, grouting pressure and soil chamber pressure were recommended based on the findings.

In addition to safeguarding against physical hazards, there is an ongoing need to secure critical infrastructure from digital hazards [52,53]. Accordingly, the importance of big data analysis for the detection of online threats [54], but also in general the protection of sensitive information present in big data, is a constant demand of the research community. In particular, the analysis of big data related to the science of civil engineering [55], as well as the development of intelligent methods for monitoring the implementation of large-scale technical projects [56], is an important field of research in the field in question.

A characteristic example that incorporates current expertise in this specific field is the 3-year postdoctoral research carried out in the Department of Civil Engineering, Democritus University of Thrace, concerning the design and development of innovative intelligent information systems and the management and analysis of big data with the aim of the digital security of critical urban infrastructures [10,57].

3.1.5. Mechanics Engineering

The mechanics engineering domain covers continuum mechanics, solid body kinematics and dynamics, the strength of materials, experimental mechanics, fracture mechanics, the theory of plasticity and viscoelasticity and theoretical methods for calculating linear and surface vectors.

In particular, the modelling of fracture energy investigation methodologies utilized to investigate the fracture performance of concrete structures/beams is a hot topic of study because of the critical relevance of this topic to the practical implementation of concrete engineering works. While the fracture energy may be estimated and the fracture behavior of various concrete structures can be predicted, this is not always possible owing to the material's inherent properties and the intricacy of the fracture process. In [58], the researchers used various experimental methodologies, AI and associated optimization techniques to find a workable solution to fracture energy prediction issues. Multiple factors that influence the fracture energy and compressive strength of concrete were studied, and critical conclusions were gleaned for further study and experimental assessment. Specifically, in this study, artificial intelligence approaches were used to seek a feasible way to solve these prediction issues. Firstly, the ridge regression (RR), the classification and regression tree (CART) and the gradient boosting regression tree (GBRT) were selected to construct the predictive models. Then, the hyperparameters were tuned with the particle swarm optimization (PSO) algorithm; the performances of these three optimum models were compared with the test dataset. The mean squared errors (MSEs) of the optimum RR, CART and GBRT models were 0.0447, 0.0164 and 0.0111, respectively, which indicated that their performances were excellent. Compared with the RR and CART models, the hybrid model constructed with GBRT and PSO appeared to be the most accurate and generalizable, both of which are significant for prediction work. The relative importance of the variables that influence the fracture energy of concrete was obtained, and the compressive strength was found to be the most significant variable.

One of the most basic composite materials with excellent properties is fiber-reinforced concrete, the application of which is constantly expanding in multiple technical projects. However, its mixed design is mainly based on extensive experimentation, the effectiveness of which has been tested. For example, [59] deals with the concept of using metallic and non-metallic fibers in concrete. In this research, GI (galvanized iron) and chopped jute fibers were used to develop an FRC material to study the possible improvement in the 28 day strength. Clumping of fibers at high fiber amounts caused mixing and casting problems. These problems became even more severe when long fibers were used at a high fiber dosage amount. In this study, different compositions of jute (0.1%, 0.2% and 0.3%) and GI fibers (1%, 1.5% and 2%) with different lengths were added to concrete. Significant increases in compressive and tensile strengths between plane concrete and fiber-reinforced concretes were found. Accordingly, one of the main priorities of the field in question is the study of the mechanical properties of composite materials used in constructions, their conventional failure criteria and their possible deformation states.

Researchers in [60] implemented a machine learning model capable of predicting the fracture behavior of all possible subclasses of fiber-reinforced concrete, especially cementitious composites made with strain hardening. Specifically, five machine learning models were developed and their outputs were compared. These include artificial neural networks, the support vector machine, the classification and regression tree, the Gaussian process of regression and the extreme gradient boosting tree. The study evaluated 15 input parameters that included mix design components and fiber properties to predict the fracture behavior of concrete fiber matrices. Due to the small size of the available dataset, this article employed a unique technique called the generative adversarial network to build a virtual dataset to augment the data and improve the accuracy. The results indicated that the extreme gradient boosting tree model has the lowest error and therefore was the best mimicker in predicting fiber-reinforced concrete properties. This article is anticipated to lead to a considerable improvement in the recipe design of effective fiber-reinforced concrete formulations. The process results demonstrate that machine learning models significantly improve the design of adequate fiber-reinforced concrete formulations with their inherent properties of simulating and explaining their application modes.

3.1.6. Transportation Engineering

The domain of transportation engineering covers the subjects of road construction, pavements, traffic engineering, transport and terminal economics, transport statistics and error theory, airport planning, transport planning, railway, public transport evaluation, spatial planning, urban planning, city history, expropriations, cartography data, photogrammetry data and environmental impacts from the construction and operation of roads.

One of the central planning priorities of transportation projects is modeling short-term demand forecasts, which are usually focused on a horizon of less than one hour and are necessary for implementing dynamic transit control strategies. Suppose that airlines and other service providers have a good idea of how much demand they may anticipate. In that case, they can better prepare for demand spikes and mitigate their adverse effects on service quality and customer experience by using real-time management tactics. Predicting platform congestion and vehicle overcrowding is one of the most beneficial uses of transport demand forecasting models. This needs knowledge of origin and destination demands, giving a comprehensive picture of when, where and why customers join and leave a service. While some research has been performed in this area, it is limited and primarily concerned with forecasting passenger arrivals at stations. For many real-world uses, these data fall short [61,62].

In [63], using advanced AI patterns, a scalable, real-time framework for demand forecasting in transportation systems was created. The proposed model was divided into three distinct sections: a multi-resolution spatial feature extraction section for capturing local spatial dependencies, an auxiliary coding section for external information and an area for tracking the temporal development of demand. Specifically, the order required at any given time is a square matrix that is processed in two different directions. Using the first fork, we can see patterns in the data that were not apparent in the raw demand data by decomposing it into its component time and frequency variations. A three-layer convolutional neural network was utilized in the second route to understand the demand's geographical relationships. After that, the market's temporal development was captured using a convolutional network with short-term memory. Two months of automated fare data from the Hong Kong mass transit train system were used in a case study to assess the methodology, demonstrating the suggested model's evident superiority over the other benchmark approaches.

The flow of traffic is instantaneous. The notion of dynamic lane reversal (DLR), which allows vehicles to quickly switch lane directions to reflect their dynamics, has been tested on a broad scale in autonomously driven public transportation in recent years. DLR has been built to eliminate traffic bottlenecks, maximize the efficiency of road areas and prevent unused capacity. The effects of DLR and its ability to be implemented are, however, yet unknown.

In [64], an ideal DLR strategy for a road segment with bidirectional stochastic traffic flow was investigated using a lane-based directional cell transmission model to explore DLR's efficacy, practicality and application. A regression analysis was carried out based on the gathered data to determine the influences of directional flow rate and multiple lanes on DLR-induced delay reductions. The findings suggest that, compared to conventional reversible lane strategies, DLR deployment may drastically cut the overall queuing time. DLR also achieved a superior performance on longer, multi-lane stretches and in situations when traffic was moving in opposite directions but relatively close together. It is also important to highlight how the suggested method helped identify the previously undetectable pattern border.

Even though assessing the distribution of travel times across lanes and other vehicles, in addition to their predicted values, is crucial for high-level traffic control and management of urban roadways with unique lane-to-lane circumstances, it has received relatively little attention. In [65], the authors present a novel approach for estimating the lane-based distribution of trip times for various vehicles by comparing low-resolution video pictures received from conventional traffic surveillance cameras. The system utilized deep learning neural architectures in conjunction with bipartite graph matching. They used a case study of a crowded metropolitan street in Hong Kong. According to the findings, the suggested technique effectively calculates the travel time distribution along linked lanes according to the vehicle type.

3.1.7. Hydraulics and Water Resources Engineering

The domain of hydraulics and water resources engineering covers the disciplines of fluid mechanics, experimental and computational hydraulics, environmental hydraulics, marine engineering and port engineering, river hydraulics, hydrology and water resources management, hydraulic and hydrological engineering, engineering water supply and sanitation, sanitary engineering, water and urban wastewater treatment facilities, ecology and aquatic ecosystems.

In the field in question, there has been a lot of research for several years related to hydraulic devices [66,67], water resource management [68,69] and environmental hydraulics [70,71]. Despite all this, significant progress has recently been made in more specialized research fields. Cavitation, entrained air and foaming are all processes in which the deformation of air bubbles in a fluid flow field is of interest. This problem cannot be solved theoretically in complicated conditions, and a solution based on the precision of computational fluid dynamics is generally not acceptable. In [72], the authors suggest and describe a novel method for addressing this issue based on a hybrid sketch method for collecting experimental data and a comparison of machine learning algorithms for developing prediction models. The equivalent diameter and aspect ratio of air bubbles flowing near a sinking jet were predicted using three different models. The variables used by each model were unique. After constructing five various iterations of the additive regression of decision stump, bagging, K-star, random forest and support vector regression algorithms by adjusting their hyperparameters, the authors found that all five of them converged steadily.

Two models produced accurate estimates of comparable diameter using four distinct measures. Every configuration of the third model was offered at a discount from the second. Differences in the input variables to the prediction models exhibit a more substantial effect on the precision of the findings when trying to forecast the bubble aspect ratio. The suggested method has promise for tackling complex issues in investigating multiphase flows.

A typical example of the application of artificial intelligence in coastal engineering concerns methods such as artificial neural networks combined with fuzzy models, which are used to improve the prediction efficiency and reduce the time and cost spent on the experimental work of applying empirical formulas on the stability of breakwaters. Specifically, in [73], to predict the stability number of breakwaters, the least squares version of support vector machines (LSSVM) method was used, which takes seven independent variables (breakwater permeability, damage level, wave rate, slope angle, water depth, wave height and wave peak period) as inputs, and managed to predict the stability of breakwaters with an accuracy rate of 0.997.

4. Future Research

Taking a conceptual approach, Industry 4.0 can be seen as a new organizational level of automated value chain management methods, including the entire life cycle of processes, from raw materials to the final product. Including widespread use of modern technologies, such as artificial intelligence, data analysis, cyber-physical systems, the Internet of Things or the Industrial Internet of Things, cloud computing, blockchain and cognitive computing systems, leads to significant upgrades in modern production processes.

Indicatively, the use of artificial intelligence in the context of Industry 4.0 can extend the applications of civil engineering science as follows [74]:

1. Prevent cost overruns by analyzing factors such as the size of a project and the type of contracts and improving the skills of project managers and workers.
2. Improvement in the design and management of the construction of technical projects through building information modelling (BIM).
3. Reduction in the risks that can occur regarding a project's quality, safety, cost and construction duration.
4. Rational and realistic planning of a project with the development of algorithms that will learn from previous related projects.
5. More productive operation by handling repetitive machine tasks freeing human resources.
6. Increase construction site safety by using algorithms that aggregate data and images of the construction site and predict potential hazards.
7. Dealing with shortages of human resources and machinery through the proper management of the resources in question, depending on the progress of the individual contracts.
8. Implement a predictive maintenance plan based on real-time analysis from various parts of the construction site and with various means such as sensors, mobile devices, drones, information systems, etc.
9. Monitor engineering works in real-time, giving warnings about when and where repair is required, predicting and identifying damage that may occur, along with their location and their extent.
10. Improve productivity by using intelligent methods of scheduling, material requisitioning and implementing idle time reduction plans.
11. Determination of optimum concrete mix properties such as maximum dry density or ideal moisture content.
12. Management of technical projects with the ability to predict changes in costs based on raw material market prices and available stocks.
13. Modelling, analyzing and predicting destructive factors such as foundation subsidence, slope stability, seismic resistance, tidal events, etc.
14. Reduce project errors with automatic multivariate data analysis.
15. Solving complex problems at different project stages, such as design decision-making, foundation engineering, construction waste management, intelligent material handling, etc.
16. Design and development of innovative, intelligent information systems aiming at the digital security (cybersecurity) of critical urban infrastructures.

5. Conclusions

Considered a branch of computer science, artificial intelligence refers to the construction of intelligent machines capable of performing human tasks by imitating human characteristics, intelligence and logic, but without direct human intervention. It is considered the pinnacle of modern science, which makes it a promising subject in civil engineering science, as this area is characterized by the current need for improved planning and management of large-scale technical projects. From this point of view, the knowledge of the methodologies and ways of applying artificial intelligence is drawn up with the multiple requirements for processing large technical projects. In light of this, the modern civil engineer should be able to define the specifications, design constraints, preparation, operational procedures, testing and evaluation of intelligent solutions derived from artificial intelligence.

In the future, robotics, the internet and artificial intelligence can significantly reduce manufacturing costs and time. This will be achieved through the monitoring of work with cameras, the more accurate planning of the passage of electromechanical networks in modern buildings, the development of more effective safety systems on construction sites and, above all, the real-time interaction of workers with materials and machines to warn supervisors in time of potential manufacturing defects, productivity issues and safety issues.

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References

1. Cuzzocrea, A. Big Data Lakes: Models, Frameworks, and Techniques. In Proceedings of the 2021 IEEE International Conference on Big Data and Smart Computing (BigComp), Jeju Island, Republic of Korea, 17–20 January 2021; pp. 1–4. [CrossRef]
2. Lakshmi Patibandla, R.S.M.; Srinivas, V.S.; Mohanty, S.N.; Ranjan Pattanaik, C. Automatic Machine Learning: An Exploratory Review. In Proceedings of the 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 3–4 September 2021; pp. 1–9. [CrossRef]
3. Gasparin, A.; Lukovic, S.; Alippi, C. Deep Learning for Time Series Forecasting: The Electric Load Case. *arXiv* **2019**, arXiv:190709207. Available online: http://arxiv.org/abs/1907.09207 (accessed on 27 March 2022). [CrossRef]
4. Khan, A.; Sohail, A.; Zahoora, U.; Qureshi, A.S. A Survey of the Recent Architectures of Deep Convolutional Neural Networks. *Artif. Intell. Rev.* **2020**, *53*, 5455–5516. [CrossRef]
5. Alzubaidi, L.; Zhang, J.; Humaidi, A.J.; Al-Dujaili, A.; Duan, Y.; Al-Shamma, O.; Santamaría, J.; Fadhel, M.A.; Al-Amidie, M.; Farhan, L. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *J. Big Data* **2021**, *8*, 53. [CrossRef] [PubMed]
6. Raschka, S. An Overview of General Performance Metrics of Binary Classifier Systems. *arXiv* **2014**, arXiv:14105330. Available online: http://arxiv.org/abs/1410.5330 (accessed on 9 November 2021).
7. Yang, Z.; Zhang, T.; Yang, J. Research on classification algorithms for attention mechanism. In Proceedings of the 2020 19th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), Xuzhou, China, 16–19 October 2020; pp. 194–197. [CrossRef]
8. Kononenko, I.; Kukar, M. Chapter 12-Cluster Analysis. In *Machine Learning and Data Mining*; Kononenko, I., Kukar, M., Eds.; Woodhead Publishing: Sawston, UK, 2007; pp. 321–358. [CrossRef]
9. *Chapter 14. Clustering Algorithms III: Schemes Based on Function Optimization-Pattern Recognition*, 4th ed. Available online: https://www.oreilly.com/library/view/pattern-recognition-4th/9781597492720/kindle_split_151.html (accessed on 24 October 2021).
10. Demertzis, K.; Iliadis, L.; Bougoudis, I. Gryphon: A semi-supervised anomaly detection system based on one-class evolving spiking neural network. *Neural Comput. Appl.* **2020**, *32*, 4303–4314. [CrossRef]
11. Lobo, J.L.; Del Ser, J.; Bifet, A.; Kasabov, N. Spiking Neural Networks and Online Learning: An Overview and Perspectives. *arXiv* **2019**, arXiv:190808019. Available online: http://arxiv.org/abs/1908.08019 (accessed on 23 October 2021). [CrossRef]
12. Deng, B.; Zhang, X.; Gong, W.; Shang, D. An Overview of Extreme Learning Machine. In Proceedings of the 2019 4th International Conference on Control, Robotics and Cybernetics (CRC), Tokyo, Japan, 27–30 September 2019; pp. 189–195. [CrossRef]
13. Vadyala, S.R.; Betgeri1, S.N.; Matthews, D.J.C.; Matthews, D.E. A Review of Physics-based Machine Learning in Civil Engineering. *arXiv* **2021**, arXiv:211004600. Available online: http://arxiv.org/abs/2110.04600 (accessed on 10 February 2022). [CrossRef]
14. de Lima, T.F.; Peng, H.-T.; Tait, A.N.; Nahmias, M.A.; Miller, H.B.; Shastri, B.J.; Prucnal, P.R. Machine Learning with Neuromorphic Photonics. *J. Light. Technol.* **2019**, *37*, 1515–1534. [CrossRef]
15. Demertzis, K.; Iliadis, L.; Avramidis, S.; El-Kassaby, Y.A. Machine learning use in predicting interior spruce wood density utilizing progeny test information. *Neural Comput. Appl.* **2017**, *28*, 505–519. [CrossRef]
16. Venkata Subba Reddy, P. Generalized fuzzy logic for incomplete information. In Proceedings of the 2013 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Hyderabad, India, 7–10 July 2013; pp. 1–6. [CrossRef]
17. Subba Reddy, P.V. Fuzzy predicate logic for Knowledge Representation. In Proceedings of the 2013 International Conference on Fuzzy Theory and Its Applications (iFUZZY), Taipei, Taiwan, 6–8 December 2013; pp. 43–48. [CrossRef]
18. Chen, H.-P.; Yeh, Z.-M. Extended fuzzy Petri net for multi-stage fuzzy logic inference. In Proceedings of the Ninth IEEE International Conference on Fuzzy Systems. FUZZ- IEEE 2000 (Cat. No.00CH37063), San Antonio, TX, USA, 7–10 May 2000; Volume 1, pp. 441–446. [CrossRef]

19. Jang, J.-S.R. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
20. Georgopoulos, V.C.; Stylios, C.D. Fuzzy cognitive maps for decision making in triage of non-critical elderly patients. In Proceedings of the 2017 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS), Okinawa, Japan, 24–26 November 2017; pp. 225–228. [CrossRef]
21. Papageorgiou, E.; Stylios, C.; Groumpos, P. Fuzzy Cognitive Map Learning Based on Nonlinear Hebbian Rule. In Proceedings of the AI 2003: Advances in Artificial Intelligence; Gedeon, T.D., Fung, L.C.C., Eds.; Springer: Berlin, Heidelberg, 2003; pp. 256–268. [CrossRef]
22. Zhou, K.; Zain, A.M.; Mo, L. Dynamic properties of fuzzy Petri net model and related analysis. *J. Cent. South Univ.* **2015**, *22*, 4717–4723. [CrossRef]
23. Salleh, M.; Hussain, K. A review of training methods of ANFIS for applications in business and economics. *Int. J. u-e-Serv. Sci. Technol.* **2016**, *9*, 165–172. [CrossRef]
24. Hu, L.; Wang, L. H fuzzy filtering design via membership function dependent Lyapunov function. In Proceedings of the 2016 3rd International Conference on Informative and Cybernetics for Computational Social Systems (ICCSS), Jinzhou, China, 26–29 August 2016; pp. 348–353. [CrossRef]
25. Al-Gunaid, M.A.; Shcherbakov, M.V.; Zadiran, K.S.; Melikov, A.V. A survey of fuzzy cognitive maps forecasting methods. In Proceedings of the 2017 8th International Conference on Information, Intelligence, Systems Applications (IISA), Larnaca, Cyprus, 27–30 August 2017; pp. 1–6. [CrossRef]
26. Demertzis, K.; Iliadis, L. Adaptive Elitist Differential Evolution Extreme Learning Machines on Big Data: Intelligent Recognition of Invasive Species. In Proceedings of the Advances in Big Data, Thessaloniki, Greece, 23–25 October 2016; Angelov, P., Manolopoulos, Y., Iliadis, L., Roy, A., Vellasco, M., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 333–345. [CrossRef]
27. Lü, J.; Wang, P. Evolutionary Mechanisms of Network Motifs in PPI Networks. In *Modeling and Analysis of Bio-Molecular Networks*; Lü, J., Wang, P., Eds.; Springer: Singapore, 2020; pp. 295–313. [CrossRef]
28. Ghannoum, E.; Kieloch, Z. Use of modern technologies and software to deliver efficient design and optimization of 1380 km long bipole III ±500 kV HVDC transmission line, Manitoba, Canada. In Proceedings of the PES T D 2012, Orlando, FL, USA, 7–10 May 2012; pp. 1–6. [CrossRef]
29. Hao, J.; Luo, S.; Pan, L. Computer-aided intelligent design using deep multiobjective cooperative optimization algorithm. *Future Gener. Comput. Syst.* **2021**, *124*, 49–53. [CrossRef]
30. Anil, R.; Gupta, V.; Koren, T.; Singer, Y. Memory-Efficient Adaptive Optimization. *arXiv* **2019**, arXiv:1901.11150. [CrossRef]
31. Peters, G.; Lampart, M.; Weber, R. Evolutionary Rough k-Medoid Clustering. In *Transactions on Rough Sets VIII*; Peters, J.F., Skowron, A., Eds.; Lecture Notes in Computer Science; Springer: Berlin, Heidelberg, 2008; pp. 289–306. [CrossRef]
32. Anantathanavit, M.; Munlin, M.-A. Radius Particle Swarm Optimization. In Proceedings of the 2013 International Computer Science and Engineering Conference (ICSEC), Nakhonpathom, Thailand, 4–6 September 2013; pp. 126–130. [CrossRef]
33. Wu, X. A density adjustment based particle swarm optimization learning algorithm for neural network design. In Proceedings of the 2011 International Conference on Electrical and Control Engineering, Yichang, China, 16–18 September 2011; pp. 2829–2832. [CrossRef]
34. Velásquez Villagrán, N.; Pesado, P.; Estevez, E. Cloud Robotics for Industry 40-A Literature Review. In Proceedings of the Cloud Computing, Big Data & Emerging Topics, La Plata, Argentina, 8–10 September 2020; Rucci, E., Naiouf, M., Chichizola, F., De Giusti, L., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 3–15. [CrossRef]
35. Bogue, R. Cloud robotics: A review of technologies, developments and applications. *Ind. Robot Int. J.* **2017**, *44*, 1–5. [CrossRef]
36. Farooq, F.; Czarnecki, S.; Niewiadomski, P.; Aslam, F.; Alabduljabbar, H.; Ostrowski, K.A.; Śliwa-Wieczorek, K.; Nowobilski, T.; Malazdrewicz, S. A Comparative Study for the Prediction of the Compressive Strength of Self-Compacting Concrete Modified with Fly Ash. *Materials* **2021**, *14*, 4934. [CrossRef] [PubMed]
37. Romero, M.C.C.; Piraquive, F.N.D.; Nery, M.E.E. Evaluation of mechanical influence of different methods of encapsulation of bacillus subtilis bacteria in the manufacture of self-healing concrete-Systematic literature review. In Proceedings of the 2021 Congreso Internacional de Innovación y Tendencias en Ingeniería (CONIITI), Bogotá, Colombia, 29 September–1 October 2021; pp. 1–6. [CrossRef]
38. Galal, M.K.; Najjar, A.A.; Thaher, A.; Mustafa, A.; Sultan, M.; Awadi, A.A.; Shitole, S.; Mourad, A.-H.I.; Khaldi, V.N.A. Self-Healing Bio-Concrete: Overview, Importance and Limitations. In Proceedings of the 2022 Advances in Science and Engineering Technology International Conferences (ASET), Dubai, United Arab Emirates, 21–24 February 2022; pp. 1–6. [CrossRef]
39. Ratnayake, K.A.S.D.; Nanayakkara, S.M.A. Effect of Fly Ash on Self-healing of Cracks in Concrete. In Proceedings of the 2018 Moratuwa Engineering Research Conference (MERCon), Moratuwa, Sri Lanka, 30 May–1 June 2018; pp. 264–269. [CrossRef]
40. Gupta, S.; Al-Obaidi, S.; Ferrara, L. Meta-Analysis and Machine Learning Models to Optimize the Efficiency of Self-Healing Capacity of Cementitious Material. *Materials* **2021**, *14*, 4437. [CrossRef]
41. Rauter, S.; Tschuchnigg, F. CPT Data Interpretation Employing Different Machine Learning Techniques. *Geosciences* **2021**, *11*, 265. [CrossRef]
42. Chen, Z.; Li, H.; Goh, A.T.C.; Wu, C.; Zhang, W. Soil Liquefaction Assessment Using Soft Computing Approaches Based on Capacity Energy Concept. *Geosciences* **2020**, *10*, 330. [CrossRef]

43. Lazaridis, P.C.; Kavvadias, I.E.; Demertzis, K.; Iliadis, L.; Papaleonidas, A.; Vasiliadis, L.K.; Elenas, A. Structural Damage Prediction Under Seismic Sequence Using Neural Networks. In Proceedings of the 8th International Conference on Computational Methods in Structural Dynamics and Earthquake Engineering (COMPDYN 2021), Athens, Greece, 1–21 July 2021.
44. Lazaridis, P.C.; Kavvadias, I.E.; Demertzis, K.; Iliadis, L.; Vasiliadis, L.K. Structural Damage Prediction of a Reinforced Concrete Frame under Single and Multiple Seismic Events Using Machine Learning Algorithms. *Appl. Sci.* **2022**, *12*, 3845. [CrossRef]
45. Demertzis, K.; Kostinakis, K.; Morfidis, K.; Iliadis, L. An interpretable machine learning method for the prediction of R/C buildings' seismic response. *J. Build. Eng.* **2023**, *63*, 105493. [CrossRef]
46. Morfidis, K.; Kostinakis, K. Rapid Prediction of Seismic Incident Angle's Influence on the Damage Level of RC Buildings Using Artificial Neural Networks. *Appl. Sci.* **2022**, *12*, 1055. [CrossRef]
47. Li, X.; Lu, W.; He, Y. 3D Mechanical Characters and Their Fabric Evolutions of Granular Materials by DEM Simulation. *Math. Probl. Eng.* **2022**, *2022*, e4765887. [CrossRef]
48. Al-Akhras, N.; Othman, O. Bond behavior of NSM strips in corroded/cracked reinforced concrete. *Front. Built Environ.* **2022**, *8*. [CrossRef]
49. Hafiz, M.K.; Khan, Q.-Z.; Ahmad, S. Cyclic Behavior of Retrofitted Low- and High-Strength Concrete Scaled Bridge Piers under Quasistatic Loading. *Math. Probl. Eng.* **2022**, *2022*, e2141485. [CrossRef]
50. Hanandeh, S. Evaluation Circular Failure of Soil Slopes Using Classification and Predictive Gene Expression Programming Schemes. *Front. Built Environ.* **2022**, *8*. [CrossRef]
51. Liang, X.; Qi, T.; Jin, Z.; Qin, S.; Chen, P. Risk Assessment System Based on Fuzzy Composite Evaluation and a Backpropagation Neural Network for a Shield Tunnel Crossing under a River. *Adv. Civ. Eng.* **2020**, *2020*, e8840200. [CrossRef]
52. STODDART, K. UK cyber security and critical national infrastructure protection. *Int. Aff.* **2016**, *92*, 1079–1105. [CrossRef]
53. Toward a Safer Tomorrow: Cybersecurity and Critical Infrastructure. Available online: https://www.springerprofessional.de/en/toward-a-safer-tomorrow-cybersecurity-and-critical-infrastructur/11962790 (accessed on 10 February 2022).
54. Big Data Analytics for Network Intrusion Detection: A Survey. Available online: http://article.sapub.org/10.5923.j.ijnc.20170701.03.html (accessed on 10 February 2022).
55. Liang, Y.; Wu, D.; Huston, D.; Liu, G.; Li, Y.; Gao, C.; Ma, Z.J. Civil Infrastructure Serviceability Evaluation Based on Big Data. In *Guide to Big Data Applications*; Srinivasan, S., Ed.; Studies in Big Data; Springer International Publishing: Cham, Switzerland, 2018; pp. 295–325. [CrossRef]
56. Sabeur, Z.; Zlatev, Z.; Melas, P.; Veres, G.; Arbab-Zavar, B.; Middleton, L.; Museux, N. Large Scale Surveillance, Detection and Alerts Information Management System for Critical Infrastructure. In Proceedings of the Environmental Software Systems. Computer Science for Environmental Protection, Zadar, Croatia, 10–12 May 2017; Hřebíček, J., Denzer, R., Schimak, G., Pitner, T., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 237–246. [CrossRef]
57. Xing, L.; Demertzis, K.; Yang, J. Identifying data streams anomalies by evolving spiking restricted Boltzmann machines. *Neural Comput. Appl.* **2020**, *32*, 6699–6713. [CrossRef]
58. Xiao, Q.; Li, C.; Lei, S.; Han, X.; Chen, Q.; Qiu, Z.; Sun, B. Using Hybrid Artificial Intelligence Approaches to Predict the Fracture Energy of Concrete Beams. *Adv. Civ. Eng.* **2021**, *2021*, e6663767. [CrossRef]
59. Gupta, S.D.; Chayon, M.S.N.A.; Karmaka, C.; Zakaria, H.M. The Study of the Strength Properties of Galvanized Iron (GI) Fiber Reinforced Concrete. *J. Civ. Eng. Forum* **2020**, *6*, 285–294. [CrossRef]
60. Khokhar, S.A.; Ahmed, T.; Khushnood, R.A.; Ali, S.M. Shahnawaz A Predictive Mimicker of Fracture Behavior in Fiber Reinforced Concrete Using Machine Learning. *Materials* **2021**, *14*, 7669. [CrossRef] [PubMed]
61. Behrooz, H.; Hayeri, Y.M. Machine Learning Applications in Surface Transportation Systems: A Literature Review. *Appl. Sci.* **2022**, *12*, 9156. [CrossRef]
62. Akhtar, M.; Moridpour, S. A Review of Traffic Congestion Prediction Using Artificial Intelligence. *J. Adv. Transp.* **2021**, *2021*, e8878011. [CrossRef]
63. Noursalehi, P.; Koutsopoulos, H.; Zhao, J.; Zhao, J.; Zhao, J. Dynamic Origin-Destination Prediction in Urban Rail Systems: A Multi-resolution Spatio-Temporal Deep Learning Approach. *IEEE Trans. Intell. Transp. Syst.* **2020**. [CrossRef]
64. Fu, Q.; Tian, Y.; Sun, J. Modeling and simulation of dynamic lane reversal using a cell transmission model. *J. Intell. Transp. Syst.* **2021**, *0*, 1–13. [CrossRef]
65. Zhang, C.; Ho, H.W.; Lam, W.H.K.; Ma, W.; Wong, S.C.; Chow, A.H.F. Lane-based estimation of travel time distributions by vehicle type via vehicle re-identification using low-resolution video images. *J. Intell. Transp. Syst.* **2022**, *0*, 1–20. [CrossRef]
66. Daneshfaraz, R.; Aminvash, E.; Ghaderi, A.; Abraham, J.; Bagherzadeh, M. SVM Performance for Predicting the Effect of Horizontal Screen Diameters on the Hydraulic Parameters of a Vertical Drop. *Appl. Sci.* **2021**, *11*, 4238. [CrossRef]
67. Yang, H.-Q.; Chen, X.; Zhang, L.; Zhang, J.; Wei, X.; Tang, C. Conditions of Hydraulic Heterogeneity under Which Bayesian Estimation is More Reliable. *Water* **2020**, *12*, 160. [CrossRef]
68. El Baba, M.; Kayastha, P.; Huysmans, M.; De Smedt, F. Evaluation of the Groundwater Quality Using the Water Quality Index and Geostatistical Analysis in the Dier al-Balah Governorate, Gaza Strip, Palestine. *Water* **2020**, *12*, 262. [CrossRef]
69. Tu, H.; Wang, X.; Zhang, W.; Peng, H.; Ke, Q.; Chen, X. Flash Flood Early Warning Coupled with Hydrological Simulation and the Rising Rate of the Flood Stage in a Mountainous Small Watershed in Sichuan Province, China. *Water* **2020**, *12*, 255. [CrossRef]
70. Kimura, N.; Yoshinaga, I.; Sekijima, K.; Azechi, I.; Baba, D. Convolutional Neural Network Coupled with a Transfer-Learning Approach for Time-Series Flood Predictions. *Water* **2020**, *12*, 96. [CrossRef]

71. Neumayer, M.; Teschemacher, S.; Schloemer, S.; Zahner, V.; Rieger, W. Hydraulic Modeling of Beaver Dams and Evaluation of Their Impacts on Flood Events. *Water* **2020**, *12*, 300. [CrossRef]
72. Di Nunno, F.; Alves Pereira, F.; de Marinis, G.; Di Felice, F.; Gargano, R.; Miozzi, M.; Granata, F. Deformation of Air Bubbles Near a Plunging Jet Using a Machine Learning Approach. *Appl. Sci.* **2020**, *10*, 3879. [CrossRef]
73. Gedik, N. Least Squares Support Vector Mechanics to Predict the Stability Number of Rubble-Mound Breakwaters. *Water* **2018**, *10*, 1452. [CrossRef]
74. Giraldo, J.M.G.; Palacio, L.G. The fourth industrial revolution, an opportunity for Civil Engineering. In Proceedings of the 2020 15th Iberian Conference on Information Systems and Technologies (CISTI), Seville, Spain, 24–27 June; 2020; pp. 1–7. [CrossRef]