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Editorial

Artificial Neural Networks Applied in Civil Engineering

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1. Introduction

In recent years, artificial neural networks (ANN) and artificial intelligence (AI), in general, have garnered significant attention with respect to their applications in several scientific fields, varying from big data management to medical diagnosis. ANN techniques are already used in everyday applications, such as personalized advertisements, virtual assistants, autonomous driving, etc. The start of regeneration breakthroughs in ANNs can be traced back to the year 2005 and can be attributed to the development of novel learning architectures such as convolutional neural networks (CNN) and deep belief networks (DBN), with significant progress having been achieved so far and new methodologies having been proposed, such as generative adversarial networks (GAN). At present, ANN-based models are widely used in several forms of engineering applications.

This Special Issue was organized in the framework of the IMSFARE research project: "Advanced Information Modelling for SAFER structures against manmade hazards", aiming to collect state-of-the-art research studies on applications and advances of ANNs to civil engineering problems. This Special Issue contains the latest progress on the application of ANN-based models in civil engineering problems, promoting cross-fertilization between related scientific subjects. In particular, the focus of this Special Issue is on hybrid studies and applications related to structural engineering, transportation engineering, geotechnical engineering, hydraulic engineering, environmental engineering, coastal and ocean engineering, structural health monitoring, and construction management.

ANN-based models have found a wide range of uses and applications in engineering fields, including civil and structural engineering, with impressive results [1–3]. Figure 1 shows the research articles related to the development of ANN-based models published in the field of civil engineering. In particular, these research articles were obtained from the Scopus database (www.scopus.com) on 26 December 2022, using the query "*TITLE-ABS-KEY* ((*"neural networks"*) *and* (*"civil" or "structural" or "transportation" or "geotechnical" or "hydraulic" or "environmental" or "construction" or "shm" or "structural health"*)) *and* (*LIMIT-TO* (*SUBJAREA*, *"ENGI"*))*" and* (*LIMIT-TO* (*SRCTYPE*, *"j"*))", which returned 21,246 document results in total. The boost in publishing of ANN-related studies in civil engineering subjects is proof that such models are gaining momentum, and in the coming years, the growth is expected to continue, resulting into new improvements and applications.

The results of a co-occurrence analysis are also presented herein based on the top keywords, including author keywords and index keywords, of the 21,246 documents collected from the Scopus database. For the purposes of this analysis, we searched Scopus using the word "neural networks" within "Article title, Abstract and Keywords" and we limited the search to the "Engineering" field and to all years until 26 December 2022. Within the results, we found the top-50 keywords of the 21,246 articles. A network visualization of the co-occurrence of the top-50 keywords is presented in Figure 2, generated using VOSviewer software [4], with five clusters presented using different colors and a minimum strength equal to 60.

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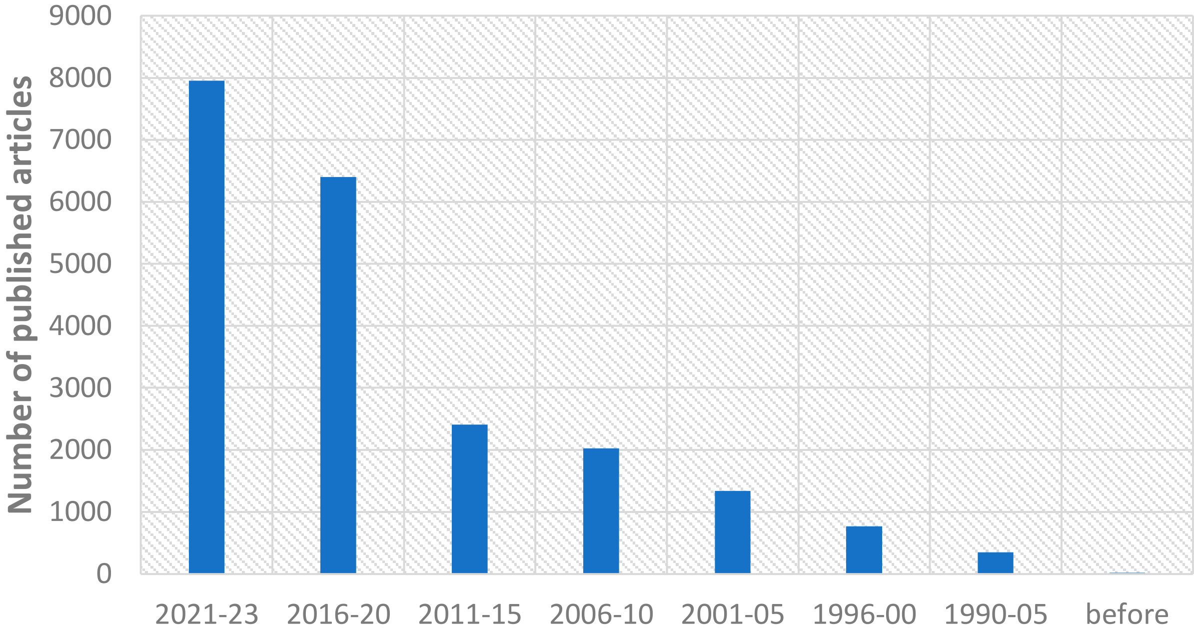

Figure 1. Published articles (in Scopus) where ANN-based models were applied to civil engineering-related subjects (until 26 December 2022).

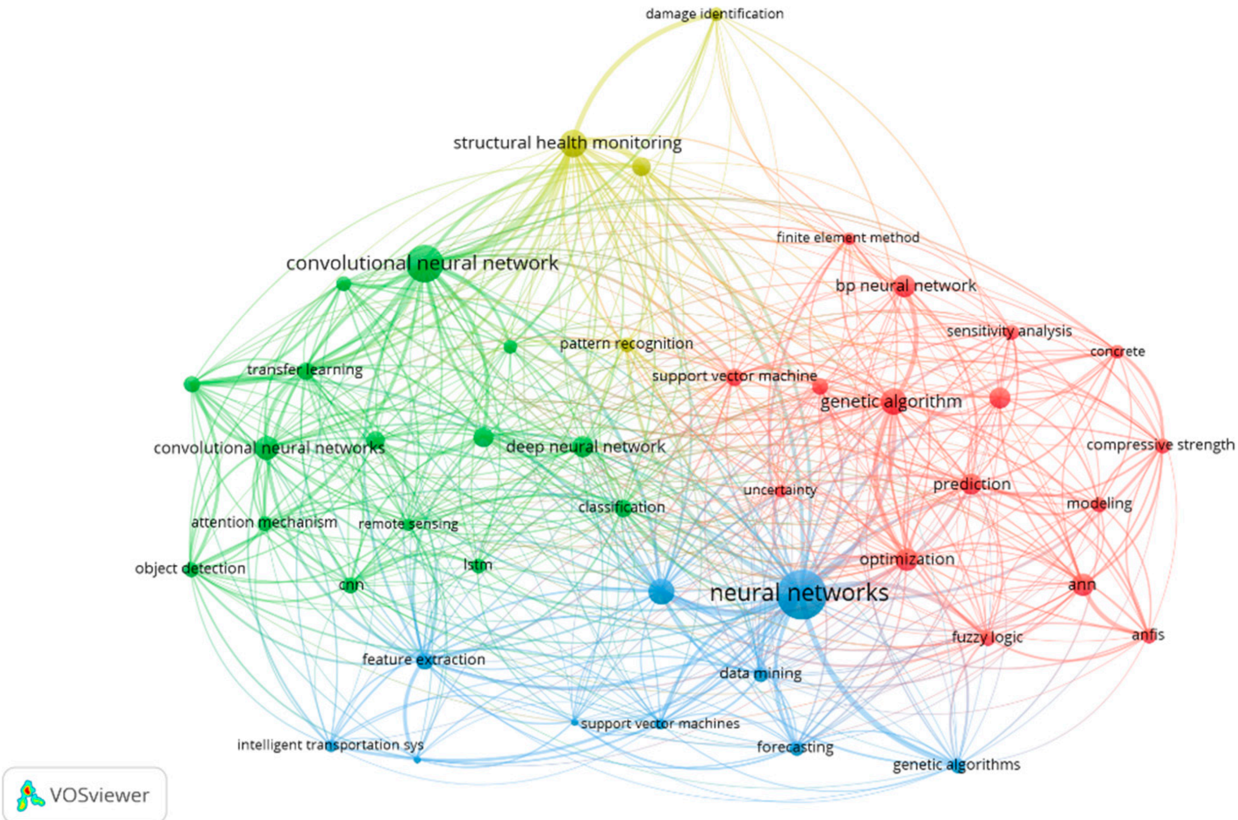

Figure 2. Bibliometric map of the co-occurrence of top-50 keywords of documents including "neural networks" in the "Engineering" field, in Scopus (until 26 December 2022).

The authors who published the most journal articles related to subjects in this Special Issue on "Artificial neural networks applied in civil engineering" are listed in Table 1:

Table 1. The authors with most journal articles related to "Artificial neural networks applied in civil engineering", in Scopus (until 26 December 2022).

Author	NoA	Author	NoA	Author	NoA	Author	NoA
Adeli, H.	48	Teng, S.	14	Shen, D.	11	Li, A.	9
Oh, S.K.	31	Jahed Armaghani, D.	13	Song, G.	11	Mahadevan, S.	9
Armaghani, D.J.	29	Jiang, X.	13	Vlahogianni, E.I.	11	Mohamad, E.T.	9
Kisi, O.	25	Khosravi, A.	13	Yuan, S.	11	Mohammed, A.S.	9
Ni, Y.Q.	25	Ko, J.M.	13	Zio, E.	11	Muhammad, K.	9
Worden, K.	25	Li, J.	13	Altabey, W.A.	10	Nehdi, M.L.	9
Lagaros, N.D.	22	Masri, S.F.	13	Bui-Tien, T.	10	Park, S.	9
Cheng, M.Y.	20	Nahavandi, S.	13	Cha, Y.J.	10	Pham, B.T.	9
Freitag, S.	19	Nourani, V.	13	Cheng, J.	10	Sadowski, Ł.	9
Hao, H.	19	Ran, B.	13	Chou, J.S.	10	Stoffel, M.	9
Pedrycz, W.	19	Tang, J.	13	Ebid, A.M.	10	Sun, X.	9
Asteris, P.G.	18	Zhou, J.	13	Foong, L.K.	10	Takuma, M.	9
Gholizadeh, S.	18	Buehler, M.J.	12	Giglio, M.	10	Tran, V.L.	9
Gopalakrishnan, K.	18	Gandomi, A.H.	12	Hakim, S.J.S.	10	Yu, B.	9
Moayedi, H.	18	Ghaboussi, J.	12	Kartam, N.	10	Zhang, W.	9
Moselhi, O.	18	Graf, W.	12	Koopialipoor, M.	10	Zhao, X.	9
Naderpour, H.	18	Hoang, N.D.	12	Lehký, D.	10	Abdel-Aty, M.	8
Papadrakakis, M.	18	Kaewunruen, S.	12	Li, H.	10	Arditi, D.	8
Samui, P.	18	Li, J.	12	Li, Q.S.	10	Attoh-Okine, N.O.	8
Wang, Y.	18	Markert, B.	12	Love, P.E.D.	10	Avci, O.	8
Hajela, P.	17	Meschke, G.	12	Manson, G.	10	Behzadan, A.H.	8
Hasanipanah, M.	17	Onyelowe, K.C.	12	Noori, M.	10	Bui, D.T.	8

2. Contributions

This Special Issue has been quite successful, gathering 19 contributions in total, with the research teams being from 21 different countries around the world and with a broad range of topics related to the applications of ANN in civil engineering being covered. This Special Issue belongs to the section "Civil Engineering". The articles are divided into four groups, as follows: (i) earthquake engineering and design codes (three articles), (ii) structural optimization and decision making (three articles), (iii) material properties and performance (eight articles), and (iv) geotechnical engineering (five articles). A brief description of each article, for every category, is presented in the following sections.

2.1. Earthquake Engineering and Design Codes

In the work by Mekaoui and Saito [5], a hybrid seismic analysis computing the full nonlinear response of building structures is presented and validated in various test cases. For these purposes, recurrent neural networks are trained to predict the nonlinear hysteretic response of isolation devices with deformation- and velocity-dependent behavior. Then, they are implemented in an explicit time integration method to perform time history analyses. A comprehensive framework is proposed to develop and test deep learning models considering data framing, the network architecture, and the learning behavior. Hybrid seismic analyses of three base-isolated building models subjected to four ground motions with different properties were performed to check their efficiency.

The work by Xiong et al. [6] introduces a multiple-input convolutional neural network (MI-CNN) model for the seismic damage assessment of regional buildings. First, ground motion sequences together with building attribute data are adopted as inputs of the proposed MI-CNN model. Second, the prediction accuracy of the MI-CNN model is discussed comprehensively for different scenarios. The overall prediction accuracy is 79.7%, and the prediction accuracies for all scenarios are above 77%, indicating a good prediction performance of the proposed method. The computation efficiency of the proposed method is 340 times faster than that of the nonlinear multi-degree-of-freedom shear model using time history analysis. Third, a case study is conducted for reinforced concrete (RC) frame buildings in Shenzhen city, and two seismic scenarios (i.e., M6.5 and M7.5) are studied for the area.

The extraction of regulatory information is a prerequisite for automated code compliance checking. Although several machine learning models have been explored for extracting computer-understandable engineering constraints from code clauses written in natural language, most are inadequate to address the complexity of the semantic relations between named entities. In particular, the existence of two or more overlapping relations involving the same entity greatly exacerbates the difficulty of information extraction. In the study by Li et al. [7], a joint extraction model is proposed to extract the relations among entities in the form of triplets.

2.2. Structural Optimization and Decision Making

Substantial computing resource requirements need to be met to address topology optimization problems and become prohibitive in cases with large-scale design domains discretized with fine finite element meshes. A deep learning-assisted topology optimization (DLTOP) methodology was previously presented [8] and employs deep learning techniques to predict the optimized system configuration, thus substantially reducing the required computational effort of the optimization algorithm and overcoming potential bottlenecks. Building upon DLTOP, the study by Kallioras et al. [9] presents a novel deep learning-based model upgrading (DLMU) scheme. The scheme utilizes reduced order (surrogate) modeling techniques, which downscale complex models while preserving their original behavioral characteristics, thereby reducing the computational demand with limited impact on accuracy.

The study by Roberts et al. [10] presents a roadmap to help these authorities by using flexible data analysis and deep learning computational systems to highlight important factors within road networks, which are used to construct models that can help predict future intervention timelines. A case study in Palermo, Italy, was successfully developed to demonstrate how the techniques could be applied to perform appropriate feature selection and prediction models based on limited data sources. The workflow provides a pathway towards more effective pavement maintenance management practices using techniques that can be readily adapted based on different environments. This is another step towards automating these practices within pavement management systems.

The number of construction site accidents can be reduced by taking proactive preventative steps using prediction models developed based on factors that influence the safety climate. In the study by Makki and Mosly [11], a prediction model of the safety climate observed by construction site personnel in Saudi Arabia was developed, identifying a set of significant safety climate predictors. The model was built with data collected from 401 active construction site personnel using a bootstrapped multiple ordinal logistic regression model. The model revealed five significant predictors: supervision, guidance, and inspection; social security and health insurance; management's commitment to safety; management's safety justice; and coworker influence.

2.3. Material Properties and Performance

In the study by Wu [12], a radial basis function (RBF) artificial neural network model for predicting the 28-day compressive strength of concrete was established. The database used in this study was the expansion to the one used in the author's previous work, with data added from other work. The stochastic gradient approach presented in the textbook was employed to determine the centers of RBFs and their shape parameters. With an extremely large number of training iterations and just a few RBFs in the ANN, all the RBF-ANNs converged to the solutions with global minimum errors. The results of the verification imply that the present RBF-ANN model outperforms the BP-ANN model in the author's previous work. The centers of the RBFs, their shape parameters, their weights, and the threshold are all listed in this article.

The objective of the study by Ahmad et al. [13] was to compare conventional models used for estimating the load-carrying capacity of reinforced concrete members, i.e., current design codes (CDCs), with the method based on different assumptions, i.e., the compressive force path (CFP) method and an ANN-based solver. For this purpose, four different databases and the details of their critical parameters were developed based on the data from available experimental studies. These databases obtained from the published experimental studies helped us to estimate the member response at the ultimate limit-state (ULS). The results show that the predictions of the CFP and the ANNs often correlate closer to the experimental data than to the CDCs.

The study by Rahman and Al-Ameri [14] on concrete and cementitious materials focused on finding sustainable solutions to address critical issues, such as increased carbon emissions, or corrosion attacks associated with reinforced concrete structures. This study examined the bond behavior of BFRP-reinforced SCGC specimens with variables such as bar diameter (6 mm and 10 mm) and embedment lengths. The embedment lengths adopted were 5, 10, and 15 times the bar diameter (db) and were denoted as 5 db, 10 db, and 15 db throughout the study. The result was then compared with the SCGC reinforced with traditional steel bars, in accordance with the ACI 440.3R-04 and CAN/CSA-S806-02 guidelines. A prediction model for bond strength was proposed using ANN tools, which contributes to new knowledge on the use of Basalt FRP bars as internal reinforcement in ambient-cured self-compacting geopolymer concrete.

Earth-based materials have shown promise in the development of ecofriendly and sustainable construction materials. However, their unconventional usage in the construction field makes the estimation of their properties difficult and inaccurate. To obtain more accurate properties, a support vector machine (SVM), ANN, and linear regression (LR) were used to predict the compressive strength of the alkali-activated termite soil. In the study by Mahamat et al. [15], factors such as activator concentration, Si/Al, initial curing temperature, water absorption, weight, and curing regime were used as input parameters due to their significant effect on the compressive strength.

An ANN model for predicting the compressive strength of concrete was established in the study by Lin and Wu [16]. A database of real concrete mix proportioning listed in earlier research by another author was used for training and testing the ANN. The results of the synaptic weights and the thresholds in the ANN are all listed. Therefore, the formulae expressed in this study can be used to predict the compressive strength of concrete according to the mix proportioning.

The standard design concept for CRCP has been modified through several changes made in the design parameters to eliminate the cluster of closely spaced crack patterns, since these crack patterns lead to the development of spalling and punch-out distresses in CRCPs. Despite adjusting the longitudinal reinforcement ratio, slab thickness, and addition of asphalt interlayer, the narrowly spaced cracks could not be effectively removed. The application of transverse partial surface saw-cuts significantly reduced the probability of randomly occurring cracks in the reconstruction project of the Motorway E313 in Herentals, Belgium. The field investigation has also indicated that the early-age crack induction in CRCP is quite susceptible to the saw-cut depth. The study by Kashif et al. [17] aimed to evaluate the effect of different depths and lengths of the partial surface saw-cut on the effectiveness of crack induction in CRCP under an external varying temperature field.

The damage investigation and inspection methods for infrastructures performed in small-scale (type III) facilities usually involve a visual examination by an inspector using surveying tools (e.g., cracking, crack microscope, etc.) in the field. These methods can interfere with the subjectivity of the inspector, which may reduce the objectivity and reliability of the record. Therefore, a new image analysis technique is needed to automatically detect cracks and to analyze the characteristics of the cracks objectively. In the study by Kim et al. [18], an image analysis technique using deep learning was developed to detect cracks and to analyze characteristics (e.g., length and width) in images for small-scale facilities. Three stages of an image processing pipeline were proposed for crack detection and to obtain its characteristics. In the first and second stages, two-dimensional convolutional neural networks were used for crack image detection (e.g., classification and segmentation). Based on convolution neural network for the detection, hierarchical feature learning architecture was applied into our deep learning network.

The fluid seepage in the saturated zone of the subgrade promotes the migration of fine particles in the filler, resulting in a change in pore structure and morphology of the filler and the deformation of the solid skeleton, which affects the fluid seepage characteristics. The muddy interlayer, mud pumping, and other diseases are then finally repeatedly formed. The research by Ding et al. [19] shows that the volume fraction of fine particles first increases, then decreases, and finally becomes stable with an increase in time due to the continuous erosion and migration of fine particles in the saturated zone of the subgrade. The volume fraction of fine particles for the upper part of the subgrade is larger than that for the lower part of the subgrade. The porosity, the velocity of fluid, the velocity of fine particles, and the permeability show a trend of increasing first and then stabilizing with time; the pore water pressure has no significant changes with time. The vertical displacement increases first and then decreases slightly with the increase in time, and finally tends to be stable.

2.4. Geotechnical Engineering

The paper by Azmoon et al. [20] presented a comparison study between methods of deep learning as a new category of slope stability analysis, built upon the recent advances in artificial intelligence and conventional limit equilibrium analysis methods. For this purpose, a computer code was developed to calculate the factor of safety (FS) using four limit equilibrium methods: Bishop's simplified method, the Fellenius method, Janbu's simplified method, and Janbu's corrected method.

For tunneling in urban areas, understanding the interaction and behavior of tunnels and the foundation of adjacent structures is very important, and various studies have been conducted. Superstructures in urban areas are designed and constructed with piled rafts, which are more effective than the conventional piled foundation. However, the settlement of a piled raft induced by tunneling mostly focuses on raft settlement. In the study by Oh et al. [21], raft and pile settlements were, therefore, obtained through 3D numerical analysis and the change rate of settlement along the pile length was calculated by linear assumption. Machine learning was utilized to develop prediction models for raft and pile settlement, and a change rate of settlement along the pile length due to tunneling.

Designing the structure based on the probability of failure leads to an economical design. Machine learning models used for predicting the factor of safety of the wall include emotional neural network, multivariate adaptive regression spline, and SOS–LSSVM. The first-order second moment method is used for calculating the reliability index of the wall. In addition, these models are assessed based on the results they produce and the best model among these is concluded for extensive field study in the future [22]. The overall performance evaluation through various accuracy quantifications determined SOS–LSSVM as the best model. The obtained results show that the reliability index calculated by the AI methods differs from the reference values by less than 2%. These methodologies have made the problems facile by increasing the precision of the result. Artificial intelligence has removed cumbersome calculations in almost all the acquainted fields and disciplines. The techniques used in this study are evolved versions of some older algorithms. The work by Mishra et al. [23] aimed to clarify the probabilistic approach toward designing these structures, using artificial intelligence to simplify practical evaluations.

An initial soil profile needs to be assumed at the beginning of the inversion analysis, which involves calculating the theoretical dispersion curve. If the assumption of the starting soil profile model is not reasonably close, the iteration process might lead to nonconvergence or take too long to converge. Automating the inversion procedure will allow us to evaluate the soil stiffness properties conveniently and rapidly by means of the SASW method. The multilayer perceptron (MLP), random forest (RF), support vector regression (SVR), and linear regression (LR) algorithms were implemented by Mitu et al. [24] to automate the inversion.

In the field of rock mechanics and rock engineering, the strength parameter that is considered to characterize the rock is uniaxial compressive strength (UCS). It is usually determined in the laboratory through a few statistically representative number of specimens, with a recommended minimum of five. UCS can also be estimated from the rock index properties, such as the effective porosity, density, and P-wave velocity. In the case of a porous rock such as travertine, the random distribution of voids inside the test specimen (not detectable in the density–porosity test but in the compressive strength test) causes large variations in the UCS value, which were found in the range of 62 MPa for this rock. Aiming to solve this problem, a statistical analysis and machine learning models (ANN) were developed by Saldaña et al. [25] to generate a reliable predictive model, through which the best results for a multiple regression model between uniaxial compressive strength (UCS), P-wave velocity, and porosity were obtained.

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