Scientia Iranica A (2020) 27(6), 2645–2656

SCIENTIA IRANICA

Sharif University of Technology
Scientia Iranica
Transactions A: Civil Engineering
http://scientiairanica.sharif.edu

Invited/Review Article

Machine learning in structural engineering

J.P. Amezquita-Sanchez[a,*], M. Valtierra-Rodriguez[a], and H. Adeli[b]

a. *ENAP-RG, CA Sistemas Dinámicos, Faculty of Engineering, Departments of Electromechanical, and Biomedical Engineering, Autonomous University of Queretaro, Campus San Juan del Rio, Moctezuma 249, Col. San Cayetano, 76807, San Juan del Rio, Queretaro, Mexico.*

b. *Department of Civil, Environmental, and Geodetic Engineering, The Ohio State University, 470 Hitchcock Hall, 2070 Neil Avenude, Columbus, OH 43220, USA.*

Received 14 November 2020; accepted 18 November 2020

KEYWORDS
Civil structures;
Machine learning;
Deep learning;
Structural engineering;
System identification;
Structural health monitoring;
Vibration control;
Structural design;
Prediction.

Abstract. This article presents a review of selected articles about structural engineering applications of Machine Learning (ML) in the past few years. It is divided into the following areas: structural system identification, structural health monitoring, structural vibration control, structural design, and prediction applications. Deep neural network algorithms have been the subject of a large number of articles in civil and structural engineering. There are, however, other ML algorithms with great potential in civil and structural engineering that are worth exploring. Four novel supervised ML algorithms developed recently by the senior author and his associates with potential applications in civil/structural engineering are reviewed in this paper. They are the Enhanced Probabilistic Neural Network (EPNN), the Neural Dynamic Classification (NDC) algorithm, the Finite Element Machine (FEMa), and the Dynamic Ensemble Learning (DEL) algorithm.

1. Introduction

Machine Learning (ML) is a key Artificial Intelligence (AI) technology that is impacting almost every field in a significant way from image recognition, e.g., pupil detection [1], multi-object tracking [2], video surveillance [3], multi-target regression [4], thermal infrared face identification [5], and human activity recognition [6], to various brain and neuroscience applications, e.g., building functional brain network [7], motor imagery brain-computer interface [8,9], mapping scalp to intracranial EEG [10], seizure detection [11], diagnosis of the Parkinson's disease [12], and characterization of the modulation of the hippocampal rhythms [13].

In general, an ML system consists of three components: inputs comprising a dataset of signals/images/features, the ML algorithm, and output which is associated with the phenomenon studied (see Figure 1). ML algorithms can be classified into three broad categories:

a) Supervised learning such as Support Vector Machine (SVM) [14], various neural network models, statistical regression, Random Forest (RF) [15], fuzzy classifiers [16], and Decision Trees (DTs);

b) Unsupervised learning such as various clustering algorithms, e.g., k-means clustering and hierarchical clustering [17], autoencoders, self-organizing maps, competitive learning [18], and deep Boltzmann machine;

c) Reinforcement learning such as Q-learning, R-learning, and Temporal Difference (TD) learning [19].

*. *Corresponding author. Tel.: +52 (1) 427 274 12 44*
E-mail address: jamezquita@uaq.mx (J.P. Amezquita-Sanchez)

doi :10.24200/sci.2020.22091

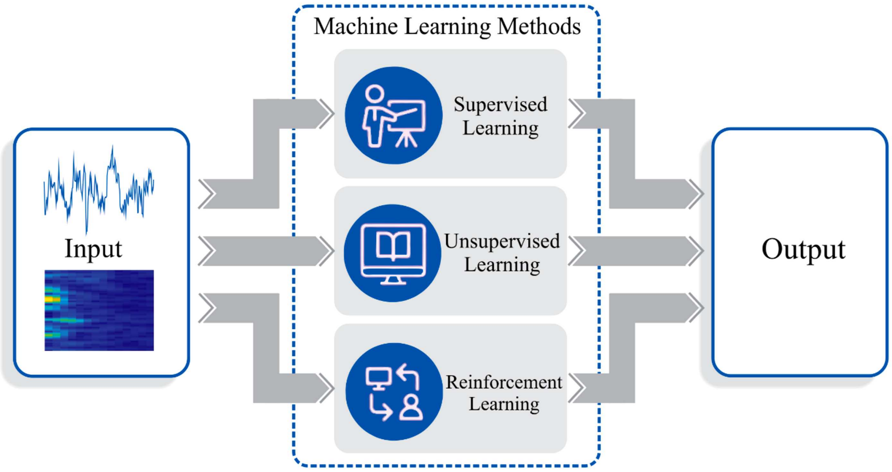

Figure 1. Components of an ML system.

The first journal article on civil engineering application of neural networks was published in 1989 [20]. Amezquita-Sanchez et al. [21] presented a review of research articles on neural networks in civil engineering published from 2001 to 2016. This article presents a review of selected articles on structural engineering applications of ML in recent years since 2017. It is divided into the following topics where most of the ML research in structural engineering is published: structural system identification, structural health monitoring, structural vibration control, structural design, and prediction applications. In addition, four novel supervised ML algorithms developed recently by the senior author and his associates with potential applications in civil/structural engineering are introduced.

2. Structural system identification

Structural System Identification (SSI) is an important topic in structural engineering as it allows constructing a mathematical model of a structural system from a set of input-output measurements generated by dynamic time series signals [22]. Perez-Ramirez et al. [23] presented a methodology for identification of modal parameters of structures using ambient vibrations and Synchrosqueezed Wavelet Transform (SWT). Jiang et al. [24] introduced a fuzzy stochastic neural network model for nonparametric identification of civil structures using the nonlinear autoregressive moving average with exogenous inputs model through the combination of two computational intelligence techniques, i.e., fuzzy logic and neural networks. The proposed model was validated using a 1:20 scaled model of a 38-storey concrete building and a benchmark 4-story 2×2 bay 3D steel frame.

Denoising a signal for an effective SSI scheme can represent a challenging task because this process can also inadvertently remove frequency components associated with the structural behavior. Amezquita-Sanchez et al. [25] presented a robust methodology for identification of modal parameters of large smart structures based on the adroit integration of the multiple signal classification algorithm, the empirical wavelet transform, and the Hilbert transform [26] and applied it to calculate the natural frequencies and damping ratios of a 123-story super high-rise building structure, the Lotte World Tower, the tallest building in Korea (see Figure 2), subjected to ambient vibrations. The results showed that the proposed approach could identify the natural frequencies and damping ratios of large civil structures with high accuracy.

For a more robust SSI strategy capable of dealing with the inherent noise, nonlinearities, and uncertainties present in the acquired samples, Perez-Ramirez et al. [27] combined the empirical mode de-

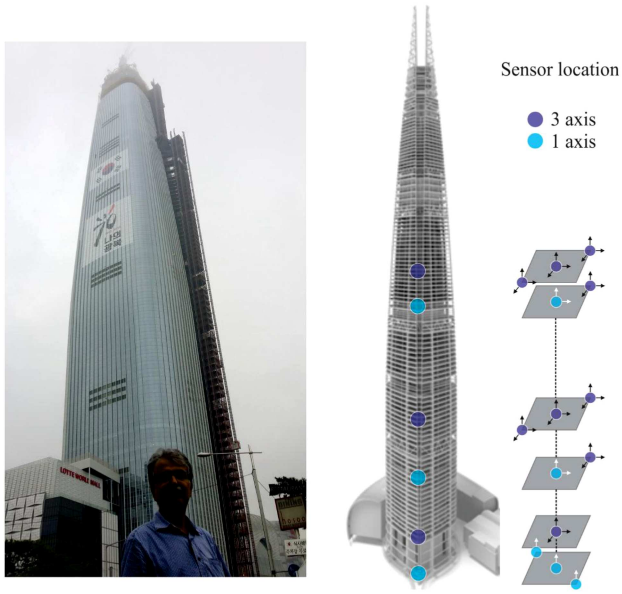

Figure 2. Lotte World Tower in Seoul, Korea.

composition [28–30], a recurrent neural network model, Bayesian training [31], and mutual information for response prediction of civil structures subjected to extreme loadings. The effectiveness of the proposed approach was validated using the experimental data of a 1:20-scaled 38-story high-rise building structure subjected to artificial seismic excitations and ambient vibrations and a five-story steel frame subjected to different levels of the Kobe earthquake.

Yao et al. [32] reported blind modal identification using limited sensors and a modified sparse component analysis. Yuen and Huang [33] introduced a Bayesian Frequency-domain substructure Identification. Yuen et al. [34] described self-calibrating Bayesian real-time system identification. Tian et al. [35] discussed system identification of pedestrian bridges using particle image velocimetry.

3. Structural Health Monitoring (SHM)

Structural Health Monitoring (SHM) continues to be the subject of intensive research in structural engineering. It can be divided into two categories of image-based SHM employing the computer vision technology and vibration signal-based SHM based on the signals obtained during dynamic events. The latter in turn can be divided into two general approaches: parametric system identification (modal parameters identification) and non-parametric system identification. ML algorithms have been used extensively in both types of SHM.

3.1. Vibration signal-based SHM

SHM based on the non-parametric system identification approach consists of two main stages of feature extraction/selection and classification. The feature/patterns identified in the first step are employed for designing and training a machine learning algorithm with the goal of determining the health condition of the structure in an automated manner.

Kostić and Gül [36] combined an autoregressive model with exogenous inputs with a Multi-Layer Perceptron Neural Network (MLPNN) for damage detection of a simulated footbridge structure at varying temperatures. Pan et al. [37] evaluated three time-frequency methods, Wavelet Transform (WT), Hilbert-Huang Transform (HHT), and Teager-Huang Transform (THT) for identifying features in measured signals in combination with SVM using a simulated cable-stayed bridge.

Incipient or light damage represents a challenge for identification. Yanez-Borjas et al. [38] proposed the fusion of statistical indices and a decision tree for detecting damage due to corrosion in a 3D 9-bay and 169-member truss-type bridge subjected to dynamic excitations. The authors reported that the proposal could identify light damage due to external corrosion, causing 1 mm reduction in the bar element diameter. Amezquita-Sanchez [39] integrated the Shannon entropy index with a decision tree for evaluating the measured responses of a 1:20 scaled model of a 38-storey concrete building structure under different levels of damage produced by cracks.

The aforementioned works have exhibited advances in SHM; however, they require a hand-crafted feature extraction approach to effective classification in the subsequent step [40]. In recent years, deep learning algorithms such as Convolutional Neural Networks (CNNs) have been employed for automatic feature extraction in SHM. In these methods, feature extraction and classification steps are performed in a single step to avoid the exhaustive tests between features and classifiers (see Figure 3) [41,42]. Abdeljaber et al. [43] explored a 1D-CNN for determining the condition of a benchmark 4-story 2×2 bay 3D steel frame subjected to ambient vibrations. Krishnasamy and Arumulla [44]

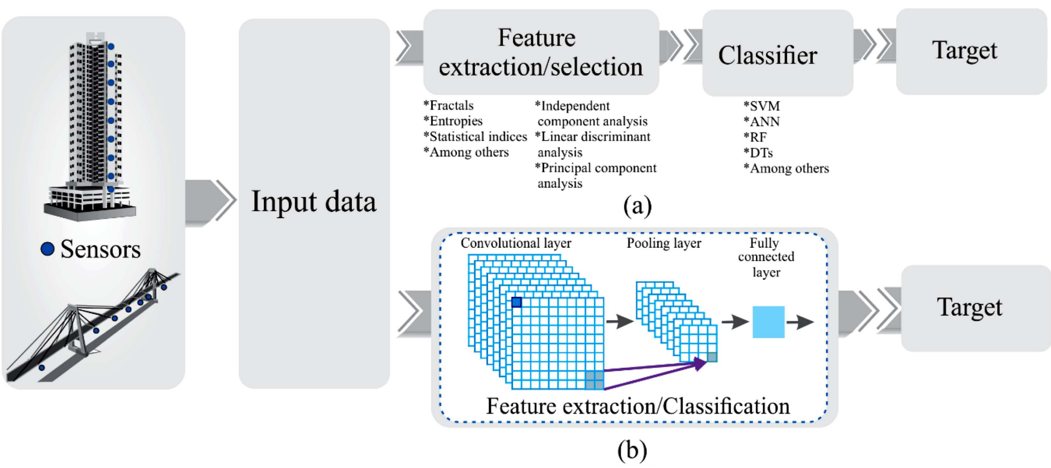

Figure 3. (a) Traditional machine learning and (b) deep learning.

combined a second-order blind identification with WT and autoregressive time series models for detecting minor incipient damage such as subtle cracks in a beam subjected to dynamic excitations.

The effective training of supervised ML approaches requires a large set of data from healthy and damaged structures. To overcome this limitation, unsupervised ML-based methods have been proposed recently because they do not require labeling the training data from different damage scenarios. Rafiei and Adeli [45] presented a novel unsupervised deep learning model for global and local health condition assessment of structures using ambient vibration response through integration of SWT, fast Fourier transform, and deep restricted Boltzmann machine. The model extracts features from the frequency domain of the recorded signals automatically.

Ibrahim et al. [46] compared the classification performance of three machine learning algorithms, SVM, K-Nearest Neighbor (KNN), and CNN, for evaluating the health condition of two simulated four- and eight-story building structures subjected to earthquakes. They reported that CNN outperformed SVM and KNN in terms of accuracy for damage detection. Zhang et al. [47] discussed vibration-based structural state identification by a one-dimensional CNN. Huang et al. [48] presented a multitask sparse Bayesian learning for SHM applications.

Wang et al. [49] described shear loading detection of through bolts in bridges using a percussion-based one-dimensional memory-augmented CNN. Naranjo-Perez et al. [50] presented a collaborative machine learning-optimization algorithm to improve the finite element model updating of structures. Their proposal consists of the harmonic search and active-set algorithms, multilayer perceptron neural networks, and the principal component analysis, where advantages such as the computation time, robustness and effectiveness of an actual steel footbridge model are obtained. From this work, it is observed that the combination of several machine-learning algorithms and other mathematical tools can lead to more powerful solution methods.

Wang and Cha [51] combined a deep auto-encoder, an unsupervised deep learning method, with a one-class SVM for vibration-based health monitoring of a laboratory-scaled steel bridge. The authors reported an accuracy rate of 91% for light damage detection. Sajedi and Liang [52] discussed the vibration-based semantic damage segmentation for SHM.

3.2. Image-based SHM

Cha et al. [53] presented the autonomous structural visual inspection using region-based deep learning for detecting different types of damage. Gao and Mosalam [54] employed a deep transfer learning for image-based structural damage recognition. Zhang et al. [55] described a context-aware deep convolutional semantic segmentation network for detecting cracks in structures. Wu et al. [56] discussed pruning CNNs for efficient edge computing in health condition assessment of structures. Nayyeri et al. [57] described a foreground-background separation technique for bridge crack detection.

Deng et al. [58] employed CNN for concrete crack detection with handwriting script interferences. Pan and Yang [59] described a post-disaster image-based damage detection of reinforced concrete buildings using dual CNNs. Liu et al. [60] reported an image-based crack assessment of bridge piers employing Unmanned Aerial Vehicles (UAVs) and 3D scene reconstruction. Jiang and Zhang [61] also discussed a real-time crack assessment using deep neural networks and wall-climbing UAVs.

Athanasiou et al. [62] outlined a machine learning approach to crack assessment of reinforced concrete shells using multifractal analysis as a feature extractor.

4. Vibration control of structures

Dynamic loadings such as traffic, wind, and seismic activity generate vibrational responses that can negatively affect the integrity of a structure. In order to decrease this negative impact, many efforts on research and technology development for structural vibration control have been proposed.

Figure 4 presents the four classes of vibration control technologies and a tabular summary of systems proposed in each category. Ying and Ni [63] reviewed applications of the magnetorheological visco-elastomer materials in structural vibration control. Lu et al. [64] reviewed various non-linear dampers. Deng and Dapino [65] reviewed magnetostrictive materials for structural vibration control such as Terfenol-D and Galfenol (alloy of iron and gallium). Elias and Matsagar [66] reviewed vibration control of structures using passive Tuned Mass Dampers (TMD) for wind- and earthquake-excited structures. Rahimi et al. [67] also reviewed the application of TMDs for vibration control of structures including the theoretical backgrounds for various types of TMDs and practical and economic aspects.

Computational intelligence approaches such as neural networks, fuzzy logic systems [68], and genetic algorithms [69] and their combination have played a significant role in the development of adaptive/intelligent control algorithms. Wang and Adeli [70] presented a self-constructing Wavelet Neural Network (WNN) for nonlinear adaptive control of structures based on integration of a self-constructing wavelet neural network developed specifically for structural system identification with an adaptive fuzzy sliding mode control approach. The authors note

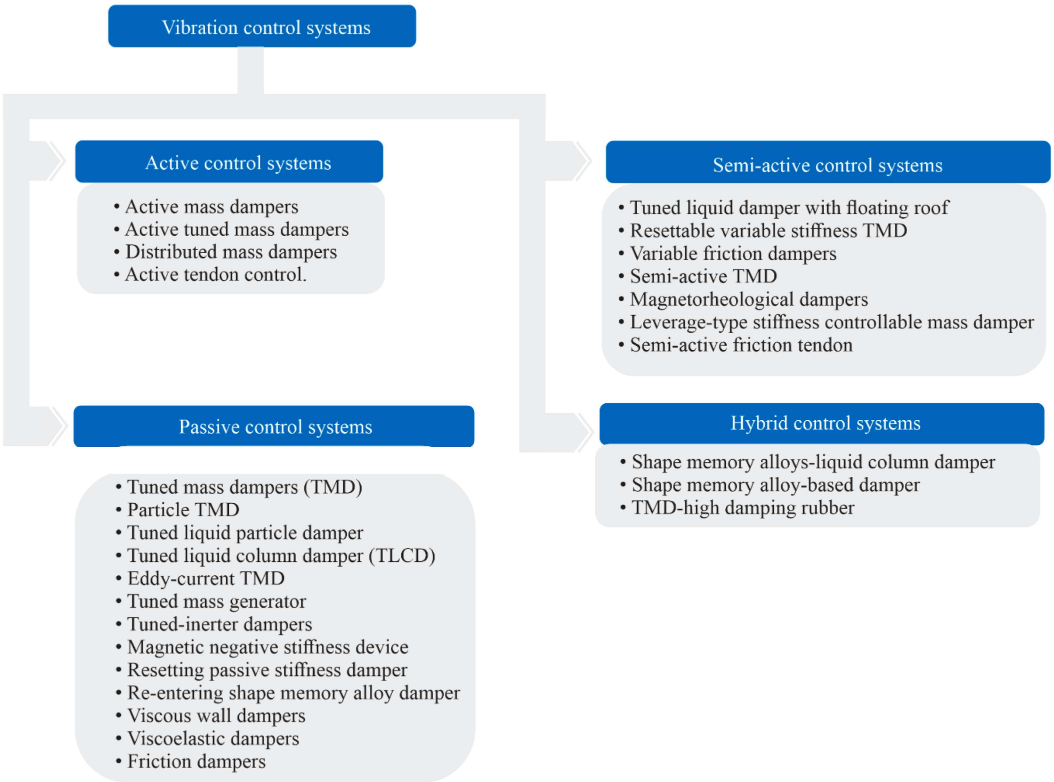

Figure 4. Classification of different vibration control systems.

"*the algorithm is particularly suitable when the physical properties such as the stiffnesses and damping ratios of the structural system are unknown or partially known which is the case when a structure is subjected to an extreme dynamic event such as an earthquake as the structural properties change during the event.*" A unique aspect of the algorithm is that the structural identification and control are performed simultaneously, which makes it adaptive and more suitable for real-life structures. A fuzzy compensation controller reduces the chattering and adaptive laws based on Lyapunov functions for finding the unknown parameters of the WNN provide control stability.

An adaptive WNN controller was introduced by Chen and Liang [71] to improve the performance of a pneumatic isolation system. Bui et al. [72] discussed a fuzzy controller for structural vibration control. Wang et al. [73] described a fuzzy finite-time stable compensation control considering different actuator failures. Fu et al. [74] described a fuzzy-neural network control for a magnetorheological elastomer vibration isolation system.

From the reviewed works, it is observed that neural network- and fuzzy logic-based approaches are the most common solutions for vibration control; yet, their combination yields more powerful results since the advantages of both computing approaches are exploited synergistically. For instance, neural networks provide the capability to deal with non-linear properties of different dynamic systems and fuzzy logic allows dealing with the information uncertainty usually existing in real-world problems.

Rahmani et al. [75] employed a reinforcement learning, Q-learning, method for controlling the vibration of a moment frame subjected to seismic loading. Lu et al. [76] proposed a vibration identification method based on a CNN to find the optimal parameters of Linear Quadratic Regulator (LQR) algorithm for vibration control of a single-degree-of-freedom linear system subjected to dynamic excitations. The authors note that the integration of CNN with LQR improves the performance of the LQR algorithm with fixed parameters; however, it requires collecting a large amount of vibration input data and its efficacy of real structures needs to be investigated.

5. Structural design

Application of machine learning in engineering design was pioneered by Adeli and Yeh [77] three decades ago. Rafiei et al. [78] presented a novel approach to concrete mixed design using the patented neural dynamics optimization model of Adeli and Park [79] and a classification algorithm used as a virtual lab to predict whether desired constraints are satisfied in each iteration of the design or not. The authors tested the model using three different classification algorithms: SVM, Probabilistic Neural Network (PNN), and Enhanced Probabilistic Neural Network (EPNN) to be described later. They reported EPNN with the highest accuracy.

Zheng et al. [80] proposed using neural network learning to accelerate the time-consuming 3D form finding and topological design of compression-only shell structures with planar faces.

6. Prediction applications

Greco et al. [81] used a genetic algorithm to predict seismic collapse of frame structures. Asteris and Nikoo [82] employed an artificial bee colony-based neural network to predict the fundamental period of infilled frame structures using a number of stories and spans, the span length, the infill wall panel stiffness, and the percentage of openings as the input of the neural network model. Luo and Paal [83] described a locally weighted SVM model to predict the drift capacity of reinforced concrete columns for seismic vulnerability assessments.

Deep learning approaches have also been reported for prediction tasks. Nie et al. [84] used a CNN for stress field prediction in cantilevered structures. Nguyen et al. [85] employed a deep neural network with high-order neuron to predict the compressive strength of foamed concrete where a cross-entropy cost function is used to enhance the model performance. Luo and Kareem [86] presented deep convolutional neural networks for uncertainty propagation in random fields and statistical characterization of the system responses under various spatially varying properties.

Oh et al. [87] employed a CNN to estimate the response of tall buildings due to wind loading. Similarly, Oh et al. [88] employed a CNN to predict the seismic responses of building structures. The viability of the CNN was validated using numerical simulation and experimental data obtained on a 3-story concrete structure subjected to seismic excitations. Zhang et al. [89] evaluated a deep learning approach called Long Short-Term Memory (LSTM) network [90] for nonlinear structural response prediction of a 6-story hotel building located at San Bernardino, California, subjected to seismic excitations. In addition, an unsupervised learning algorithm, K-means clustering, was employed to cluster the seismic inputs for:

1. Generating the most informative datasets for training the LSTM,
2. Improving the prediction accuracy with limited data.

They reported an accuracy rate of 90% for predicting the structural response. Gulgec et al. [91] also discussed the application of deep learning to strain estimation from acceleration data for fatigue.

7. New supervised learning algorithms

Deep neural network algorithms such as CNN have been the subject of a large number of articles in civil and structural engineering so much so that their applications are becoming almost routine. There are, however, other new and powerful supervised learning or classification algorithms with great potential in civil and structural engineering that are worth exploring. Four of them developed by the senior author and his associates are reviewed in this section.

7.1. Enhanced probabilistic neural network

Ahmadlou and Adeli [92] proposed a supervised classifier called Enhanced Probabilistic Neural Network (EPNN) to improve the accuracy and robustness of PNN by means of local decision circles with the purpose of incorporating the non-homogeneity often existing in a training population. They demonstrated that EPNN was superior to PNN by applying it to three different benchmark classification problems: iris data, diabetic data, and breast cancer data. Since then, EPNN has been demonstrated to be a powerful classification algorithm for diagnosis of various neurological disorders such as Parkinson's disease [93] and Mild Cognitive Impairment (MCI) [94] and prediction of sudden cardiac arrest [95]. To the best of the authors' knowledge, there is only one structural engineering application of EPNN, as described in Section 5.

7.2. Neural dynamic classification algorithm

Starting with the patented neural dynamics optimization model of Adeli and Park [79], Rafiei and Adeli [45] introduced a new supervised classification algorithm, called Neural Dynamic Classification (NDC), with the goal of uncovering the most effective feature spaces and finding the optimum number of features required for accurate classification. The algorithm is capable of solving highly complicated classification problems by employing a new feature space with large margins between clusters and close proximity of the classmates and a set of transformation functions. They compared the new classification algorithm with the Probabilistic Neural Network (PNN), EPNN, and SVM using multiple standard benchmark problems. They note "*NDC yields the most accurate classification results followed by EPNN. A beauty of the new algorithm is the smoothness of convergence curves which is an indication of robustness and good performance of the algorithm.*"

So far, NDC has been used successfully to solve two complicated structural engineering problems, that is, development of an earthquake early warning system [96] and damage detection in high-rise building structures [97].

7.3. Finite element machine for fast learning

Recently, Pereira et al. [98] proposed a new supervised pattern classifier, called Finite Element Machine (FEMa), with its research ideology and theoretical basis in the Finite Element Method widely used in numerical analysis and solution of numerous engineering problems. In this model, "*each training sample is the center of a basis function, and the whole training set is modeled as a probabilistic manifold for classification purpose.*" The algorithm is parameterless and does not require a training step, which can be a great advantage when the dataset is large, that is so-called the Big Data problems. FEMa has been shown to yield competitive results for classifying 23 different public benchmark datasets (e.g., breast data, wine data, diabetes data, among others) compared with nine other pattern classifiers such as DT, Bayesian [99], KNN, RF, Optimum-Path Forest (OPF), SVM with Radial Basis Function, SVM with a sigmoid function, and EPNN. The authors believe that FEMa has great potentials and should be explored for civil/structural engineering applications.

7.4. Dynamic ensemble learning algorithm

As noted in this article, many different ML algorithms have been developed over the past three decades. Ensemble ML methods employ multiple learning algorithms to achieve more accurate results than those obtained using any of the constituent learning algorithms [100–102]. Rokibul Alam et al. [103] presented a Dynamic Ensemble Learning (DEL) algorithm for designing an ensemble of neural networks. According to the authors, "*DEL algorithm determines the size of ensemble, the number of individual NNs employing a constructive strategy, the number of hidden nodes of individual NNs employing a constructive-pruning strategy, and different training samples for individual NN's learning.*" They introduced the concept of negative correlation learning to enhance the diversity in learning. The efficacy of the model has been verified by application to four medical and seven non-medical benchmark problems and datasets.

8. Conclusions

There has been a significant interest in the application of ML algorithms in structural engineering in recent years. Some of the recent structural engineering applications of ML algorithms were reviewed in this paper. The most common ML approaches used in structural engineering included SVM and deep learning algorithms such as CNN and LSTM. The latter has captured the imagination of structural engineering researchers in the past four years. There are, however, other ML algorithms with great potential in civil and structural engineering that are worth exploring. Four novel supervised ML algorithms developed recently by the senior author and his associates with potential applications in civil/structural engineering were introduced in this paper.

References

1. Vera-Olmos, F.J., Pardo, E., Melero, H., and Malpica, N. "DeepEye: Deep convolutional network for pupil detection in real environments", *Integrated Computer-Aided Engineering*, **26**(1), pp. 85–95 (2019).
2. Yang, T., Cappelle, C., Ruichek, Y., and El Bagdouri, M. "Multi-object tracking with discriminant correlation filter based deep learning tracker", *Integrated Computer-Aided Engineering*, **26**(3), pp. 273–284 (2019).
3. Benito-Picazo, J., Domínguez, E., Palomo, E.J., and López-Rubio, E. "Deep learning-based video surveillance system managed by low cost hardware and panoramic cameras", *Integrated Computer-Aided Engineering*, **27**(4), pp. 373–387 (2020).
4. Reyes, O. and Ventura, S. "Performing multi-target regression via a parameter sharing-based deep network", *International Journal of Neural Systems*, **29**(9), 1950014 (22 pages) (2019).
5. Wang, P. and Bai, X. "Regional parallel structure based CNN for thermal infrared face identification", *Integrated Computer-Aided Engineering*, **25**(3), pp. 247–260 (2018).
6. Rodriguez-Lera, F.J., Rico, F.M., and Olivera, V.M. "Neural networks for recognizing human activities in home-like environments", *Integrated Computer-Aided Engineering*, **26**(1), pp. 37–47 (2019).
7. Hua, C., Wang, H., Wang, H., Lu, S., Liu, C., and Khalid, S.M. "A novel method of building functional brain network using deep learning algorithm with application in proficiency detection", *International Journal of Neural Systems*, **29**(1), 1850015 (17 pages) (2019).
8. Gaur, P., McCreadie, K., Pachori, R.B., Wang, H., and Prasad, G. "Tangent space feature-based transfer learning classification model for two-class motor imagery brain-computer interface", *International Journal of Neural Systems*, **29**(10), 19500215 (17 pages) (2019).
9. Lozano, A., Suárez, J.S., Soto-Sánchez, C., Garrigos, J., Martinez-Alvarez, J.J., Ferrandez, J.M., and Fernandez, E. "Neurolight: a deep learning neural interface for cortical visual prostheses", *International Journal of Neural Systems*, **30**(9), 2050045 (19 pages) (2020).
10. Antoniades, A., Spyrou, L., Martin-Lopez, D., Valentin, A., Alarcon, G., Sanei, S., and Took, C.C. "Deep neural architectures for mapping scalp to intracranial EEG", *International Journal of Neural Systems*, **28**(8), 1850009 (2018).

11. Ansari, A.H., Cherian, P.J., Caicedo, A., Naulaers, G., De Vos, M., and Van Huffel, S. "Neonatal seizure detection using deep convolutional neural networks", *International Journal of Neural Systems*, **29**(4), 1850011 (20 pages) (2019).

12. Manzanera, M.O., Meles, S.K., Leenders, K.L., Renken, R.J., Pagani, M., Arnaldi, D., Nobili, F., Obeso, J., Oroz, M.R., Morbelli, S., and Maurits, N.M. "Scaled subprofile modeling and convolutional neural networks for the identification of Parkinson's disease in 3D nuclear imaging data", *International Journal of Neural Systems*, **29**(9), 1950010 (15 pages) (2019).

13. Park, S.E., Laxpati, N.G., Gutekunst, C.A., Connolly, M.J., Tung, J., Berglund, K., Mahmoudi, B., and Gross, R.E. "A machine learning approach to characterize the modulation of the hippocampal rhythms via optogenetic stimulation of the medial septum", *International Journal of Neural Systems*, **29**(10), 1950020 (21 pages) (2019).

14. Zhang, J., Xiao, M., Gao, L., and Chu, S. "Probability and interval hybrid reliability analysis based on adaptive local approximation of projection outlines using support vector machine", *Computer-Aided Civil and Infrastructure Engineering*, **34**(11), pp. 991–1009 (2019).

15. Yu, B., Wang, H., Shan, W., and Yao, B. "Prediction of bus travel time using random forests based on near neighbors", *Computer-Aided Civil and Infrastructure Engineering*, **33**(4), pp. 333–350 (2018).

16. Abbasi, H., Bennet, L., Gunn, A.J., and Unsworth, C.P. "Latent phase detection of hypoxic-ischemic spike transients in the EEG of preterm fetal sheep using reverse biorthogonal wavelets & fuzzy classifier", *International Journal of Neural Systems*, **29**(10), 1950013, (17 pages) (2019).

17. Chen, Z. and Liu, X.C. "Roadway asset inspection sampling using high-dimensional clustering and locality-sensitivity hashing", *Computer-Aided Civil and Infrastructure Engineering*, **34**(2), pp. 116–129 (2019).

18. Lopez-Rubio, E., Molina-Cabello, M.A., Luque-Baena, R.M., and Dominguez, E. "Foreground detection by competitive learning for varying input distributions", *International Journal of Neural Systems*, **28**(5), 1750056 (16 pages) (2018).

19. Sutton, R. and Barto, A., *Reinforcement Learning*, 2nd Ed., MIT Press (2018).

20. Adeli, H. and Yeh, C. "Perceptron learning in engineering design", *Computer-Aided Civil and Infrastructure Engineering*, **4**(4), pp. 247–256 (1989).

21. Amezquita-Sanchez, J.P., Valtierra-Rodriguez, M., Aldwaik, M., and Adeli, H. "Neurocomputing in civil infrastructure", *Scientia Iranica*, **23**(6), pp. 2417–2428 (2016).

22. Yuen, K.V. and Mu, H.Q. "Real-time system identification: an algorithm for simultaneous model class selection and parametric identification", *Computer-Aided Civil and Infrastructure Engineering*, **30**(10), pp. 785–801 (2015).

23. Perez-Ramirez, C.A., Amezquita-Sanchez, J.P., Adeli, H. Valtierra-Rodriguez, M., Camarena-Martinez, D., and Rene Romero-Troncoso, R.J. "New methodology for modal parameters identification of smart civil structures using ambient vibrations and synchrosqueezed wavelet", *Engineering Applications of Artificial Intelligence*, **48**, pp. 1–16 (2016).

24. Jiang, X., Mahadevan, S., and Yuan, Y. "Fuzzy stochastic neural network model for structural system identification", *Mechanical Systems and Signal Processing*, **82**, pp. 394–411 (2017).

25. Amezquita-Sanchez, J.P., Park, H.S., and Adeli, H. "A novel methodology for modal parameters identification of large smart structures using MUSIC, empirical wavelet transform, and Hilbert transform", *Engineering Structures*, **147**, pp. 148–159 (2017).

26. Karami, K., Fatehi, P., and Yazdani, A. "On-line system identification of structures using wavelet-Hilbert transform and sparse component analysis", *Computer-Aided Civil and Infrastructure Engineering*, **35**(8), pp. 870–886 (2020).

27. Perez-Ramirez, C.A., Amezquita-Sanchez, J.P., Valtierra-Rodriguez, M., and Adeli, H. "Recurrent neural network model with Bayesian training and mutual information for response prediction of large buildings", *Engineering Structures*, **178**, pp. 603–615 (2019).

28. Wu, W.H., Chen, C.C., Jhou, J.W., and Lai, G. "A rapidly convergent empirical mode decomposition method for analyzing the environmental temperature effects on stay cable force", *Computer-Aided Civil and Infrastructure Engineering*, **33**(8), pp. 672–690 (2018).

29. Zhang, S., Zhou, L., Chen, X., Zhang, L., Li, L., and Li, M. "Network-wide traffic speed forecasting: 3D convolutional neural network with ensemble empirical mode decomposition", *Computer-Aided Civil and Infrastructure Engineering*, **35**(10), pp. 1132–1147 (2020).

30. Saadaoui, F. and Ben Messaoud, O. "Multiscaled neural autoregressive distributed lag: a new empirical mode decomposition model for nonlinear time series forecasting", *International Journal of Neural Systems*, **30**(8), 2050039 (15 pages) (2020).

31. Wang, J., Liu, X.Z., and Ni, Y.Q. "A Bayesian probabilistic approach for acoustic emission-based rail condition assessment", *Computer-Aided Civil and Infrastructure Engineering*, **33**(1), pp. 21–34 (2018).

32. Yao, X.J., Yi, T.H., Qu, C., and Li, H.N. "Blind modal identification using limited sensors through modified sparse component analysis by time-frequency method", *Computer-Aided Civil and Infrastructure Engineering*, **33**(9), pp. 769–782 (2018).

33. Yuen, K.X. and Huang, K. "Identifiability-enhanced Bayesian frequency-domain substructure identification", *Computer-Aided Civil and Infrastructure Engineering*, **33**(9), pp. 800–812 (2018).

34. Yuen, K.V., Kuok, S.C., and Dong, L. "Self-calibrating Bayesian real-time system identification", *Computer-Aided Civil and Infrastructure Engineering*, **34**(9), pp. 806–821 (2019).

35. Tian, Y., Zhang, J., and Yu, S. "Rapid impact testing and system identification of footbridges using particle image velocimetry", *Computer-Aided Civil and Infrastructure Engineering*, **34**(2), pp. 130–145 (2019).

36. Kostić, B. and Gül, M. "Vibration-based damage detection of bridges under varying temperature effects using time-series analysis and artificial neural networks", *Journal of Bridge Engineering*, **22**(10), 04017065 (2017).

37. Pan, H., Azimi, M., Yan, F., and Lin, Z. "Time-frequency-based data-driven structural diagnosis and damage detection for cable-stayed bridges", *Journal of Bridge Engineering*, **23**(6), 04018033 (2018).

38. Yanez-Borjas, J.J., Valtierra-Rodriguez, M., Camarena-Martinez, D., and Amezquita-Sanchez, J.P. "Statistical time features for global corrosion assessment in a truss bridge from vibration signals", *Measurement*, **160**, 107858 (2020).

39. Amezquita-Sanchez, J.P. "Entropy algorithms for detecting incipient damage in high-rise buildings subjected to dynamic vibrations", *Journal of Vibration and Control* (In press) (2020). DOI: 10.1177/1077546320929145

40. Ettouney, M.M. and Alampalli, S., *Infrastructure Health in Civil Engineering: Theory and Components*, CRC press (2016).

41. Torres, J.F., Galicia, A., Troncoso, A., and Martínez-Álvarez, F. "A scalable approach based on deep learning for big data time series forecasting", *Integrated Computer-Aided Engineering*, **25**(4), pp. 335–348 (2018).

42. Valtierra-Rodriguez, M., Rivera-Guillen, J.R., Basurto-Hurtado, J.A. De-Santiago-Perez, J.J., Granados-Lieberman, D., and Amezquita-Sanchez, J.P. "Convolutional neural network and motor current signature analysis during the transient state for detection of broken rotor bars in induction motors", *Sensors*, **20**(13), 3721 (2020).

43. Abdeljaber, O., Avci, O., Kiranyaz, M.S., Boashash, B., Sodano, H., and Inman, D.J. "1-D CNNs for structural damage detection: Verification on a structural health monitoring benchmark data", *Neurocomputing*, **275**, pp. 1308–1317 (2018).

44. Krishnasamy, L. and Arumulla, R.M.R. "Baseline-free hybrid diagnostic technique for detection of minor incipient damage in the structure", *Journal of Performance of Constructed Facilities*, **33**(2), 04019018 (2019).

45. Rafiei, M.H. and Adeli, H. "A new neural dynamic classification algorithm", *IEEE Transactions on Neural Networks and Learning Systems*, **28**(12), pp. 3074–3083 (2017).

46. Ibrahim, A., Eltawil, A., Na, Y., and El-Tawil, S. "A machine learning approach for structural health monitoring using noisy data sets", *IEEE Transactions on Automation Science and Engineering*, **17**(2), pp. 900–908 (2019).

47. Zhang, Y., Miyamori, Y., Mikami, S., and Saito, T. "Vibration-based structural state identification by a 1-dimensional convolutional neural network", *Computer-Aided Civil and Infrastructure Engineering*, **34**(9), pp. 822–839 (2019).

48. Huang, Y., Beck, J.L., and Li, H. "Multitask sparse Bayesian learning with applications in structural health monitoring", *Computer-Aided Civil and Infrastructure Engineering*, **34**(9), pp. 732–754 (2019).

49. Wang, F., Song, G., and Mo, Y.L. "Shear loading detection of through bolts in bridge structures using a percussion-based one-dimensional memory-augmented convolutional neural network", *Computer-Aided Civil and Infrastructure Engineering* (In press) (2020). DOI: 10.1111/mice.12602

50. Naranjo-Pérez, J., Infantes, M., Jiménez-Alonso, J.F., and Sáez, A. "A collaborative machine learning-optimization algorithm to improve the finite element model updating of civil engineering structures", *Engineering. Structures*, **225**, 111327 (2020).

51. Wang, Z. and Cha, Y.J. "Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect structural damage", *Structural Health Monitoring* (In press) (2020). DOI: 10.1177/1475921720934051

52. Sajedi, S.O. and Liang, X. "Vibration-based semantic damage segmentation for large-scale structural health monitoring", *Computer-Aided Civil and Infrastructure Engineering*, **35**(6), pp. 579–596 (2020).

53. Cha, Y.J., Choi, W., Suh, G., Mahmoudkhani, S., and Büyüköztürk, O. "Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types", *Computer-Aided Civil and Infrastructure Engineering*, **33**(9), pp. 731–747 (2018).

54. Gao, Y. and Mosalam, K.M. "Deep transfer learning for image-based structural damage recognition", *Computer-Aided Civil and Infrastructure Engineering*, **33**(9), pp. 748–768 (2018).

55. Zhang, X., Rajan, D., and Story, B. "Concrete crack detection using context-aware deep semantic segmentation network", *Computer-Aided Civil and Infrastructure Engineering*, **34**(11), pp. 951–971 (2019)

56. Wu, R.T., Ankush Singla, A., Jahanshahi, M.R., Bertino, E., Ko, B.J., and Verma, D. "Pruning deep convolutional neural networks for efficient edge computing in condition assessment of civil infrastructures", *Computer-Aided Civil and Infrastructure Engineering*, **34**(9), pp. 774–789 (2019).

57. Nayyeri, F., Hou, L., Zhou, J., and Guan, H. "Foreground-background separation technique for road and bridge crack detection", *Computer-Aided Civil and Infrastructure Engineering*, **34**(6), pp. 457–470 (2019).

58. Deng, J., Lu, Y., and Lee, V.C.S. "Concrete crack detection with handwriting script interferences using faster region-based convolutional neural network", *Computer-Aided Civil and Infrastructure Engineering*, **35**(4), pp. 373–388 (2020).

59. Pan, X. and Yang, T.Y. "Post-disaster imaged-based damage detection and repair cost estimation of reinforced concrete buildings using dual convolutional neural networks", *Computer-Aided Civil and Infrastructure Engineering*, **35**(5), pp. 495–510 (2020).

60. Liu, Y.F., Nie, X., Fan, J.S., and Liu, X.G. "Image-based crack assessment of bridge piers using unmanned aerial vehicles and 3D scene reconstruction", *Computer-Aided Civil and Infrastructure Engineering*, **35**(5), pp. 511–529 (2020).

61. Jiang, S. and Zhang, J. "Real-time crack assessment using deep neural networks with wall-climbing unmanned aerial system", *Computer-Aided Civil and Infrastructure Engineering*, **35**(6), pp. 549–564 (2020).

62. Athanasiou, A., Ebrahimkhanlou, A., Zaborac, J., Hrynyk, T., and Salamone, S. "A machine learning approach based on multifractal features for crack assessment of reinforced concrete shells", *Computer-Aided Civil and Infrastructure Engineering*, **35**(6), pp. 565–578 (2020).

63. Ying, Z. and Ni, Y. "Advances in structural vibration control application of magneto-rheological visco-elastomer", *Journal of Theoretical and Applied Mechanics*, **7**(2), pp. 61–66 (2017).

64. Lu, Z., Wang, Z., Zhou, Y., and Lu, X. "Nonlinear dissipative devices in structural vibration control: A review", *Journal of Sound and Vibration*, **423**, pp. 18–49 (2018).

65. Deng, Z. and Dapino, M.J. "Review of magnetostrictive materials for structural vibration control", *Smart Materials and Structures*, **27**(11), 113001 (2018).

66. Elias, S. and Matsagar, V. "Research developments in vibration control of structures using passive tuned mass dampers", *Annual Reviews in Control*, **44**, pp. 129–156 (2017).

67. Rahimi, F., Aghayari, R., and Samali, B. "Application of tuned mass dampers for structural vibration control: a state-of-the-art review", *Civil Engineering Journal*, **6**(8), pp. 1622–1651 (2020).

68. Chiew, F.H., Ng, C.K., Chai, K.C., and Tay, K.M. "A fuzzy adaptive resonance theory-based model for mix proportion estimation of high performance concrete", *Computer-Aided Civil and Infrastructure Engineering*, **32**(9), pp. 772–786 (2017).

69. Padillo, F., Luna, J.M., Herrera, F., and Ventura, S. "Mining association rules on big data through mapreduce genetic programming", *Integrated Computer-Aided Engineering*, **25**(1), pp. 31–48 (2018).

70. Wang, N. and Adeli, H. "Self-constructing wavelet neural network algorithm for nonlinear control of large structures", *Engineering Applications of Artificial Intelligence*, **41**, pp. 249–258 (2015).

71. Chen, H.Y., and Liang, J.W. "Adaptive wavelet neural network controller for active suppression control of a diaphragm-type pneumatic vibration isolator", *International Journal of Control, Automation and Systems*, **15**(3), pp. 1456–1465 (2017).

72. Bui, H.L., Le, T.A., and Bui, V.B. "Explicit formula of hedge-algebras-based fuzzy controller and applications in structural vibration control", *Applied Soft Computing*, **60**, pp. 150–166 (2017).

73. Wang, J., Huang, Y., Wang, T., Zhang, C., and Liu, Y. "Fuzzy finite-time stable compensation control for a building structural vibration system with actuator failures", *Applied Soft Computing*, **93**, 106372 (2020).

74. Fu, J., Lai, J., Yang, Z., Bai, J., and Yu, M. "Fuzzy-neural network control for a magnetorheological elastomer vibration isolation system", *Smart Materials and Structures*, **29**(7), 074001 (2020).

75. Rahmani, H.R., Chase, G., Wiering, M., and Könke, C. "A framework for brain learning-based control of smart structures", *Advanced Engineering Informatics*, **42**, 100986 (2019).

76. Lu, X., Liao, W., Huang, W., Xu, Y., and Chen, X. "An improved linear quadratic regulator control method through convolutional neural network-based vibration identification", *Journal of Vibration and Control* (In press) https://doi.org/10.1177/1077546320933756 (2020). DOI: 10.1177/1077546320933756

77. Adeli, H. and Yeh, C. "Explanation-based machine learning in engineering design", *Engineering Applications of Artificial Intelligence*, **3**(2), pp. 127–137 (1990).

78. Rafiei, M.H., Khushefati, W.H., Demirboga, R., and Adeli, H. "Novel approach for concrete mix design using neural dynamics model and the virtual lab concept", *ACI Materials Journal*, **114**(1), pp. 117–127 (2017).

79. Adeli, H. and Park, H.S., *Neurocomputing for Design Automation*, Boca Raton, Florida: CRC Press (1998).

80. Zheng, H., Moosavi, V., and Akbarzadeh, M. "Machine learning assisted evaluations in structural design and construction", *Automation in Construction*, **119**, 103346 (2020).

81. Greco, A., Cannizzaro, F., and Pluchino, A. "Seismic collapse prediction of frame structures by means of genetic algorithms", *Engineering Structures*, **143**, pp. 152–168 (2017).

82. Asteris, P.G., and Nikoo, M. "Artificial bee colony-based neural network for the prediction of the fundamental period of infilled frame structures", *Neural Computing and Applications*, **31**(9), pp. 4837–4847 (2019).

83. Luo, H. and Paal, S.G. "A locally weighted machine learning model for generalized prediction of drift capacity in seismic vulnerability assessments", *Computer-Aided Civil and Infrastructure Engineering*, **34**(11), pp. 935–950 (2019).

84. Nie, Z., Jiang, H., and Kara, L.B. "Stress field prediction in cantilevered structures using convolutional neural networks", *Journal of Computing and Information Science in Engineering*, **20**(1), pp. 1–16 (2020).

85. Nguyen, T., Kashani, A., Ngo, T., and Bordas, S. "Deep neural network with high-order neuron for the prediction of foamed concrete strength", *Computer-Aided Civil and Infrastructure Engineering*, **34**(4), pp. 316–332 (2019).

86. Luo, X. and Kareem, A. "Deep convolutional neural networks for uncertainty propagation in random fields", *Computer-Aided Civil and Infrastructure Engineering*, **34**(12), pp. 1041–1054 (2019).

87. Oh, B.K., Glisic, B., Kim, Y., and Park, H.S. "Convolutional neural network-based wind-induced response estimation model for tall buildings", *Computer-Aided Civil and Infrastructure Engineering*, **34**(10), pp. 843–858 (2019).

88. Oh, B.K., Park, Y., and Park, H.S. "Seismic response prediction method for building structures using convolutional neural network", *Structural Health Monitoring*, **27**(5), p. e2519 (2020).

89. Zhang, R., Chen, Z., Chen, S., Zheng, J., Büyüköztürk, O., and Sun, H. "Deep long short-term memory networks for nonlinear structural seismic response prediction", *Computers and Structures*, **220**, pp. 55–68 (2020).

90. Wang, J., Zhang, L., Chen, Y., and Yi, Z. "A new delay connection for long short-term memory networks", *International Journal of Neural Systems*, **28**(6), 1750061 (2018).

91. Gulgec, N.S., Takáč, M., and Pakzad, S.N. "Structural sensing with deep learning: strain estimation from acceleration data for fatigue assessment", *Computer-Aided Civil and Infrastructure Engineering*, **35**(12), pp. 1349–1364 (2020).

92. Ahmadlou, M. and Adeli, H. "Enhanced probabilistic neural network with local decision circles: a robust classifier", *Integrated Computer-Aided Engineering*, **17**(3), pp. 197–210 (2010).

93. Hirschauer, T.J., Adeli, H., and Buford, J.A. "Computer-aided diagnosis of Parkinson's disease using enhanced probabilistic neural network", *Journal of Medical Systems*, **39**(11), p. 179 (2015).

94. Amezquita-Sanchez, J.P., Adeli, A., and Adeli, H. "A new methodology for automated diagnosis of mild cognitive impairment (MCI) using magnetoencephalography (MEG)", *Behavioural Brain Research*, **305**, pp. 174–180 (2016).

95. Amezquita-Sanchez, J.P., Valtierra-Rodriguez, M., Adeli, H., and Perez-Ramirez, C. "A novel wavelet transform-homogeneity model for sudden cardiac death prediction using ECG signals", *Journal of Medical Systems*, **42**(10), p. 176 (2018).

96. Rafiei, M.H. and Adeli, H. "NEEWS: A novel earthquake early warning model using neural dynamic classification and neural dynamic optimization", *Soil Dynamics and Earthquake Engineering*, **100**, pp. 417–427 (2017).

97. Rafiei, M.H. and Adeli, H. "A novel machine learning-based algorithm to detect damage in high-rise building structures", *The Structural Design of Tall and Special Buildings*, **26**(18), e1400 (2017).

98. Pereira, D.R., Piteri, M.A., Souza, A.N., Papa, J.P., and Adeli, H. "FEMa: a finite element machine for fast learning", *Neural Computing and Applications*, **32**(10), pp. 6393–6404 (2019).

99. Schetinin, V., Jakaite, L., and Krzanowski, W. "Bayesian learning of models estimating uncertainty in alert systems: application to aircraft collision avoidance", *Integrated Computer-Aided Engineering*, **25**(3), pp. 229–245 (2018).

100. Molina-Cabello, M.A., Luque-Baena, R.M., López-Rubio, E., and Thurnhofer-Hemsi, K. "Vehicle type detection by ensembles of convolutional neural networks on super resolved images", *Integrated Computer-Aided Engineering*, **25**(4), pp. 321–333 (2018).

101. Reyes, O., Fardoun, H.M., and Ventura, S. "An ensemble-based method for the selection of instances in the multi-target regression problem", *Integrated Computer-Aided Engineering*, **25**(4), pp. 305–320 (2018).

102. Hamreras, S., Boucheham, B., Molina-Cabello, M.A., Benıtez-Rochel, R., and Lopez-Rubio, E. "Content-based image retrieval by ensembles of deep learning object classifiers", *Integrated Computer-Aided Engineering*, **27**(3), pp. 317–331 (2020).

103. Rokibul Alam, K.M., Siddique, N., and Adeli, H. "A dynamic ensemble learning algorithm for neural networks", *Neural Computing and Applications*, **32**(10), pp. 6393–6404 (2020).

Biographies

Juan Pablo Amezquita-Sanchez graduated from University of Guanajuato in 2007 with a BSc degree in Electronic Engineering. He received his MSc degree in Electrical Engineering from University of Guanajuato and the PhD degree in Mechatronics from the Autonomous University of Queretaro, Queretaro, Mexico in 2009 and 2012, respectively. He was a Postdoctoral Visiting Scholar in The Ohio State University during 2013-2014. He is currently a full-time Professor at the Faculty of Engineering, Autonomous University of Queretaro, Campus San Juan del Rio, Queretaro, Mexico. He is a member of the Mexican National Research System (SNI), level 1. He has published papers in the areas of structural health monitoring, signal processing, and mechatronics.

Martin Valtierra-Rodriguez received the BE degree in Mechatronics Engineering and the ME degree in Electrical Engineering from the University of Guanajuato, Guanajuato, Mexico in 2008 and 2010, respectively, and the PhD degree in Mechatronics from the Autonomous University of Queretaro, San Juan del Río, Mexico in 2013. He is currently a Professor at the Faculty of Engineering, Autonomous University of Queretaro and a member of the Mexican National Research System (SNI, level 2). His current research interests include signal processing, expert systems, and applications of mechatronics.

Hojjat Adeli received his PhD from Stanford University in 1976 at the age of 26. He is currently an Academy Professor at The Ohio State University where he held the Abba G. Lichtenstein Professorship for ten years. He is the Editor-in-Chief of the international journals Computer-Aided Civil and Infrastructure Engineering which he founded in 1986 and Integrated Computer-Aided Engineering which he founded in 1993. He has authored over 600 research and scientific publications in various fields of computer science, engineering, applied mathematics, and medicine, including 16 ground-breaking high-technology books. He is the recipient of sixty-seven awards and honors including four Honorary Doctorates, and Honorary Professorship at several Asian and European Universities. In 2005, he was elected Distinguished Member, ASCE: "for wide-ranging, exceptional, and pioneering contributions to computing in civil engineering and extraordinary leadership in advancing the use of computing and information technologies in many engineering disciplines throughout the world." He is a member of Academia European, a corresponding member of the Spanish Royal Academy of Engineering, a foreign member of Lithuanian Academy of Sciences and Polish Academy of Science, and a Fellow of AAAS, IEEE, AIMBE, and American Neurological Association.