Structural Damage Diagnosis and prediction using Machine Learning and Deep Learning Models: Comprehensive Review of Advances

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The loss of integrity and adverse effect on mechanical properties can be concluded as attributing miro/macro-mechanics damage in structures especially in composite structures. Damage as a progressive degradation of material continuity in engineering predictions for any aspects of initiation and propagation, requires to be identified by a trustworthy mechanism to guarantee the safety of structures. Beside the materials design, the structural integrity and health are usually prone to be monitored clearly. One of the most powerful method for detection of damage is machine learning (ML). This paper presents the state of the art of ML methods and their applications in structural damage and prediction. Popular ML methods are identified and the performance and future trends are discussed.

Keywords: damage detection, machine learning, principal component analysis, composites, micromechanics of damage, continuum damage mechanics

Acronyms

ANN	Artificial neural network
ELM	Extreme learning machine
ML	Machine learning
SVM	Support vector machine
WNN	Wavelet neural networks
DL	Deep learning
ARIMA	Autoregressive integrated moving average
FFNN	Feed-forward neural networks
MLP	Multi layered perceptron

DT	Decision tree
RSM	Response surface methodology
BPNN	Back propagation neural network
CM	Centroid mean
ANFIS	Adaptive neuro fuzzy inference system
ANP	Analytic network process
RF	Random forest
NRTL	Non-random two-liquid
RNN	Recurrent neural network
PLS	Partial least squares
DA	Discriminant analysis
PCA	Principal component analysis
LDA	Linear discriminant analysis
SVR	Support vector regression
LS	Least-squares
SB	Sparse Bayesian
MCDM	Multi criteria decision making
GP	Genetic programming
MLR	Multi linear regression
SWARA	Step-wise Weight Assessment Ratio Analysis
MOORA	Multi Objective Optimization by Ratio Analysis
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1. Introduction

Structural damage diagnosis and prediction are of utmost importance in various scientific and engineering applications (Cha, Choi, Suh, Mahmoudkhani, & Büyüköztürk, 2018; Chen et al., 2019; Finotti, Cury, & Barbosa, 2019). Second paragraph on general damage detection methods and drawback to those methods (Hong et al., 2019; Huang & Wang, 2018; Jang, Lee, Park, & Baek, 2018; Kan et al., 2017; Krummenacher, Ong, Koller, Kobayashi, & Buhmann, 2018; Wang, Hu, & Zhai, 2018; Z. Zhang et al., 2019). Third paragraph on machine learning suitability and importance of machine learning and deep learning methods on this application (H. Li et al., 2019; Y. Z. Lin, Nie, & Ma, 2017; F. Ni, Zhang, & Chen, 2019; Patala, 2019; Pu, Apel, Liu, & Mitri, 2019; Quaranta et al., 2019). Fourth paragraph of this paper's contribution and the need for a comprehensive review. (Gordan, Razak, Ismail, & Ghaedi, 2017, 2018) reviews the general application of artificial intelligence methods including soft computing, data mining, optimization methods etc. However, there is a gap in research for a focused and comprehensive review on machine learning and deep learning models (S. Ren, Chen, Li, Chen, & Li, 2018; Salehi, Das, Biswas, & Burgueño, 2019).

There has been an enormous evolution in system modeling and intelligence after introducing the early models for deep learning. Deep learning methods very fast emerged and expanded applications in various scientific and engineering domains. Health informatics, energy, urban informatics, safety, security, hydrological systems modeling, economic, bioinformatics, and computational mechanics have been among the early application domains of deep learning. State of the art surveys on the data driven methods and machine learning algorithms, indicates that deep learning, along with the ensemble and hybrid machine learning methods are the future of data science. Further comparative studies report that deep learning models and hybrid machine learning models often outperform conventional machine learning models. Figure 1 represents the rapid rise in the applications of various deep learning methods during the past five years. Deep learning methods are fast evolving for higher performance. Literature includes adequate review papers on the progressing algorithms in particular application domains, e.g., renewable energy forecasting, cardiovascular image analysis, resolution imaging, radiology, 3D sensed data classification, 3D sensed data classification, multimedia analytics, sentiment classification, text detection, transportation systems, activity recognition in radar, hyperspectral, medical ultrasound analysis, image cytometry, and apache spark. However, a simplified list of deep learning methods has not been communicated so far. Thus, there is a gap in research in introducing the deep learning methods and summarize the methods and application in a brief, yet communicative paper. Consequently, this paper aims at providing a comprehensive list of the most popular deep learning methods and their notable applications. In every section, one deep learning method is introduced, and the notable applications related to that method are listed. The description of each deep learning method and the function of each building block is explained.

2. Survey methodology

The primary goal of this literature survey is to present the state of the art of ML models in the individual application areas of structural damage diagnosis. Accordingly, the research methodology has been developed to identify, classify and review the notable peer-reviewed articles in design and implementation of sustainable business models in top-level subject fields. The Web-of-Science and elsevier scopus are used for the implementation of the search queries of “defect or damage or crack” and “ml $method_{1\text{-}n}$” for title, abstract and keywords the relevant literatures are identified. the query of (title-abs-key (defect or damage or crack) and title-abs-key (ml $method_{1\text{-}n}$)) in addition to the query of (title-abs-key (defect or damage or crack) and title-abs-key (dl $method_{1\text{-}n}$)) would result in 21,933 documents. however, through auxiliary search keywords such as "mechanic* and structure*" in all fields of the paper we reduce the results to 4,669 documents making sure that the most relevant papers are identified, which forms our initial database. Reading in detail the articles’ relevancy downed the numbers to 150 articles for the final consideration.

The research methodology follows a comprehensive and structured workflow based on a systematic database search and cross-reference snowballing. The flowchart of the research methodology is presented in figure 1. The method is considered as a modified version of review proposed by Easterby-Smith et al. (2015). In the first step the search queries explore the Thomson Reuters Web-of-Science and Elsevier Scopus databases. In the second step the abstract and keywords of the identified articles are browsed to identify the relevant literature and exclude the irrelevant ones. In step three the database of the relevant articles is created. In step four, the article is carefully read, and the category of the application is identified accordingly. In this step the expert-based knowledge and the initial preferences would influence the number and the type of the categories. In step five we decide on generating a new category and export the article in a new table of application domain or pass the article to step six where a category would host an article in its table. Once a category is created for a new article, in step seven, we pass that article to that category. In step eight we save the content of our database in various categories, update the content of the tables, and review the papers. This workflow will be repeated until sorting out all the papers.

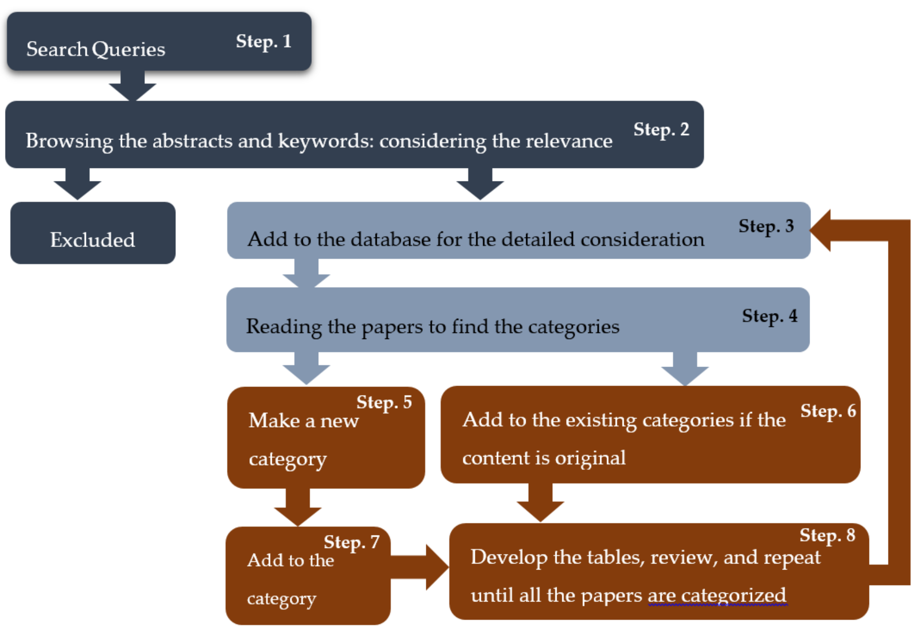

Figure 1. Flowchart of the methodology of research

3. Machine learning methods

The survey methodology classifies the machine learning methods in seven groups, i.e. ANN-based, SVM-based, Tree-based models, Ensembles, Bayesians, Logistic regressions, and Neuro-Fuzzy. The last group is deep learning which has been considered separately. The notable papers have been reviewed in individual classes.

3.1 ANN

ANN can prepare general frameworks for analyzing damaged induced materials. Due to the fact that artificial neural networks have various applications such as accurate prediction of complex material behavior, it could be applied for damage detection and structural integrities in corresponding multiple-variable problems.

Table 1. Notable ANN-based models for structural damage diagnosis and prediction

Reference	Year	Contribution	Application
Zhang Z., Hong Y., Hou B., Zhang Z., Negahban M., Zhang J.	2019	Accelerated discoveries of mechanical properties of graphene using machine learning and high-throughput computation	
Jafari-Marandi R., Khanzadeh M., Tian W., Smith B., Bian L.	2019	From in-situ monitoring toward high-throughput process control: cost-driven decision-making framework for laser-based additive manufacturing	Additive manufacturing (AM); Artificial neural networks (ANN); Porosity prediction; Self-organizing error-drive neural networks (SOEDNN); Thermal history
Gomes G.F., de Almeida F.A., Junqueira D.M., da Cunha S.S., Jr., Ancelotti A.C., Jr.	2019	Optimized damage identification in CFRP plates by reduced mode shapes and GA-ANN methods	Artificial neural networks; Composite plates; Damage identification; Inverse problem; Sensor placement optimization; Structural health monitoring
Finotti R.P., Cury A.A., Barbosa F.S.	2019	An SHM approach using machine learning and statistical indicators extracted from raw dynamic measurements	Computational intelligence; Damage identification; Dynamic measurement; Structural dynamic; Structural health monitoring; Vibration monitoring

Pu Y., Apel D.B., Liu V., Mitri H.	2019	Machine learning methods for rockburst prediction-state-of-the-art review	Artificial neural network; Burst liability; Deep learning; Rockburst prediction; Support vector machine
Wong E.W.C., Kim D.K.	2018	A simplified method to predict fatigue damage of TTR subjected to short-term VIV using artificial neural network	Artificial neural network; Current; Fatigue damage; Riser; Top-tensioned riser; Vortex-induced vibration
Nie W., Zhao Z.Y., Goh A.T.C., Song M.K., Guo W., Zhu X.	2018	Performance based support design for horseshoe-shaped rock caverns using 2D numerical analysis	Artificial neural network; Convergence confinement method; Rock cavern; Support design
Gedik N.	2018	Least squares support vector mechanics to predict the stability number of rubble-mound breakwaters	Least squares support vector mechanics; Particle swarm optimization; Rubble-mound breakwater; Stability number
Rezaniaiee Aqdam H., Ettefagh M.M., Hassannejad R.	2018	Health monitoring of mooring lines in floating structures using artificial neural networks	Damage diagnosis; Finite element method; Mooring lines; Radial basis neural networks; Structural health monitoring; Uncertainty
Cha Y.-J., Choi W., Suh G., Mahmoudkhani S., Büyüköztürk O.	2018	Autonomous Structural Visual Inspection Using Region-Based Deep Learning for Detecting Multiple Damage Types	
Wang Z., Hu M., Zhai G.	2018	Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data	Convolutional neural networks; Fruit quality detection; Hyperspectral transmittance image; Internal mechanical damage detection; Machine learning
Krummenacher G., Ong C.S., Koller S., Kobayashi S., Buhmann J.M.	2018	Wheel Defect Detection with Machine Learning	artificial neural networks; Machine learning; pattern analysis; railway accidents; railway safety; statistical learning; supervised learning; support vector machines; wavelet transforms
AminShokravi A., Eskandar H., Derakhsh A.M., Rad H.N., Ghanadi A.	2018	The potential application of particle swarm optimization algorithm for forecasting the air-overpressure induced by mine blasting	ANN; AOp; Blasting; PSO

Gordan M., Razak H.A., Ismail Z., Ghaedi K.	2018	Data mining based damage identification using imperialist competitive algorithm and artificial neural network	Artificial neural network; Damage detection; Data mining; Hybrid algorithm; Imperial competitive algorithm; Structural health monitoring
Ghritlahre H.K., Prasad R.K.	2018	Exergetic performance prediction of a roughened solar air heater using artificial neural network	Artificial neural network; Exergy analysis; Learning algorithm; Multi-layer perceptron; Solar air heater
Rojas-Moraleda R., Valous N.A., Gowen A., Esquerre C., Härtel S., Salinas L., O'Donnell C.	2017	A frame-based ANN for classification of hyperspectral images: assessment of mechanical damage in mushrooms	Artificial neural networks; Frame-based classification; Imaging spectroscopy; Mechanical damage; Salient point detectors
Lin Y.-Z., Nie Z.-H., Ma H.-W.	2017	Structural Damage Detection with Automatic Feature-Extraction through Deep Learning	
Çalık A., Yıldırım S., Tosun E.	2017	Estimation of crack propagation in polymer electrolyte membrane fuel cell under vibration conditions	Artificial neural network; Crack propagation; Mechanical vibration; Polymer electrolyte membrane fuel cell
Tan Z.X., Thambiratnam D.P., Chan T.H.T., Abdul Razak H.	2017	Detecting damage in steel beams using modal strain energy based damage index and Artificial Neural Network	Artificial Neural Network; Damage index; Damage location; Damage prediction; Damage scenarios; Damage severity; Failure prevention; Modal strain energy; Vibration based technique
Samareh H., Khoshrou S.H., Shahriar K., Ebadzadeh M.M., Eslami M.	2017	Optimization of a nonlinear model for predicting the ground vibration using the combinational particle swarm optimization-genetic algorithm	Artificial neural network; Blasting; Genetic algorithm; Geo-mechanics properties of rock mass; Ground vibration; Particle swarm optimization
Gordan M., Razak H.A., Ismail Z., Ghaedi K.	2017	Recent developments in damage identification of structures using data mining	Artificial neural network; Data mining technique; Genetic algorithm; Principal component analysis; Structural damage detection
Choi C.K., Kim J.S., Yoo H.H.	2016	Identification of location and size of a defect in a structural system	Active external moment; Artificial neural network (ANN); Fault

		employing active external excitation and hybrid feature vector components in HMM	diagnosis; Hidden Markov model (HMM); Structural system
Bissacot A.C.G., Salgado S.A.B., Balestrassi P.P., Paiva A.P., Zambroni Souza A.C., Wazen R.	2016	Comparison of neural networks and logistic regression in assessing the occurrence of failures in steel structures of transmission lines	Artificial neural networks; Fall of metal structures; Logistic regression; ROC curves; Transmission lines
Guruprasad R., Behera B.K.	2015	Comparative Analysis of Soft Computing Models in Prediction of Bending Rigidity of Cotton Woven Fabrics	ANFIS; ANN; Bending rigidity; BPNN; GANN
Alves V., Cury A., Roitman N., Magluta C., Cremona C.	2015	Structural modification assessment using supervised learning methods applied to vibration data	Damage assessment; Learning algorithms; Pattern recognition; SHM; Symbolic data
Güneyisi E.M., Mermerdaş K., Güneyisi E., Gesoğlu M.	2015	Numerical modeling of time to corrosion induced cover cracking in reinforced concrete using soft-computing based methods	Experimental database; Modeling; Reinforced concrete; Steel reinforcement corrosion; Time to cover cracking
Harish N., Mandal S., Rao S., Patil S.G.	2015	Particle Swarm Optimization based support vector machine for damage level prediction of non-reshaped berm breakwater	Berm breakwater; Damage level; Non-reshaped; PSO-SVM; SVM
Meruane V., Ortiz-Bernardin A.	2015	Structural damage assessment using linear approximation with maximum entropy and transmissibility data	Linear approximation; Maximum-entropy principle; Structural damage assessment; Supervised learning algorithms

ANN based models include a great deal of models for damage modeling. (Alves, Cury, Roitman, Magluta, & Cremona, 2015; AminShokravi, Eskandar, Derakhsh, Rad, & Ghanadi, 2018; Bissacot et al., 2016; Çalık, Yıldırım, & Tosun, 2017; Cha et al., 2018; Choi, Kim, & Yoo, 2016; Finotti et al., 2019; Gedik, 2018; Ghritlahre & Prasad, 2018;

Gomes, de Almeida, Junqueira, da Cunha, & Ancelotti, 2019; Gordan et al., 2017, 2018; Güneyisi, Mermerdaş, Güneyisi, & Gesoğlu, 2015; Guruprasad & Behera, 2015; Harish, Mandal, Rao, & Patil, 2015; Jafari-Marandi, Khanzadeh, Tian, Smith, & Bian, 2019; Krummenacher et al., 2018; Y. Z. Lin et al., 2017; Meruane & Ortiz-Bernardin, 2015; Nie et al., 2018; Pu et al., 2019; Rezaniaiee Aqdam, Ettefagh, & Hassannejad, 2018; Rojas-Moraleda et al., 2017; Samareh, Khoshrou, Shahriar, Ebadzadeh, & Eslami, 2017; Tan, Thambiratnam, Chan, & Abdul Razak, 2017; Wang et al., 2018; Wong & Kim, 2018; Z. Zhang et al., 2019)

Table. 2 Notable Support vectors (SVM) models

Authors	Year	Title	Author Keywords
Nair A., Cai C.S., Kong X.	2019	Studying Failure Modes of GFRP Laminate Coupons Using AE Pattern-Recognition Method	Acoustic emission; Failure mode identification; Glass fiber reinforced polymer (GFRP) laminate coupon; k - means clustering; Multilayer perceptron; Pattern recognition; Support vector machine
Zhang Z., Hong Y., Hou B., Zhang Z., Negahban M., Zhang J.	2019	Accelerated discoveries of mechanical properties of graphene using machine learning and high-throughput computation	
Nair A., Cai C.S., Kong X.	2019	Acoustic emission pattern recognition in CFRP retrofitted RC beams for failure mode identification	Acoustic emission; CFRP retrofitted RC beams; Failure mode identification; K-means clustering; Multilayer perceptron; Pattern recognition; Support vector machine
Forero-Ramírez J.-C., Restrepo-Girón A.-D., Nope-Rodríguez S.-E.	2019	Detection of Internal Defects in Carbon Fiber Reinforced Plastic Slabs Using Background Thermal Compensation by Filtering and Support Vector Machines	Background thermal compensation by filtering (BTCF); Carbon fiber reinforced plastic (CFRP); Feature selection; Infrared thermography (IT); Support vector machines (SVM)
Finotti R.P., Cury A.A., Barbosa F.S.	2019	An SHM approach using machine learning and statistical indicators extracted from raw dynamic measurements	Computational intelligence; Damage identification; Dynamic measurement; Structural dynamic; Structural health monitoring; Vibration monitoring
Pu Y., Apel D.B., Liu V., Mitri H.	2019	Machine learning methods for rockburst prediction-state-of-the-art review	Artificial neural network; Burst liability; Deep learning; Rockburst prediction; Support vector machine
Gedik N.	2018	Least squares support vector mechanics to predict the stability number of rubble-mound breakwaters	Least squares support vector mechanics; Particle swarm optimization; Rubble-mound breakwater; Stability number

Lin T.-K.	2018	An edge-feature-description-based scheme combined with support vector machines for the detection of vortex-induced vibration	Edge feature description; Hybrid vision-based method; Support vector machines; Vortex-induced vibration
Krummenacher G., Ong C.S., Koller S., Kobayashi S., Buhmann J.M.	2018	Wheel Defect Detection with Machine Learning	artificial neural networks; Machine learning; pattern analysis; railway accidents; railway safety; statistical learning; supervised learning; support vector machines; wavelet transforms
Rojas-Moraleda R., Valous N.A., Gowen A., Esquerre C., Härtel S., Salinas L., O'Donnell C.	2017	A frame-based ANN for classification of hyperspectral images: assessment of mechanical damage in mushrooms	Artificial neural networks; Frame-based classification; Imaging spectroscopy; Mechanical damage; Salient point detectors
Yi Q., Wang H., Guo R., Li S., Jiang Y.	2017	Laser ultrasonic quantitative recognition based on wavelet packet fusion algorithm and SVM	Dimension reduction; Laser ultrasonic; Quantitative recognition; SVM classification; Wavelet packet fusion
Alves V., Cury A., Roitman N., Magluta C., Cremona C.	2015	Structural modification assessment using supervised learning methods applied to vibration data	Damage assessment; Learning algorithms; Pattern recognition; SHM; Symbolic data
Lu S., Jiang M., Sui Q., Sai Y., Jia L.	2015	Damage identification system of CFRP using fiber bragg grating sensors	CFRP structural damage identification; Fiber bragg grating; Multi-class C-support vector classification; One-class support vector machines; Principal component analysis
Harish N., Mandal S., Rao S., Patil S.G.	2015	Particle Swarm Optimization based support vector machine for damage level prediction of non-reshaped berm breakwater	Berm breakwater; Damage level; Non-reshaped; PSO-SVM; SVM

SVM have gained popularity in modeling the damage. (Alves et al., 2015; Finotti et al., 2019; Forero-Ramírez, Restrepo-Girón, & Nope-Rodríguez, 2019; Gedik, 2018; Harish et al., 2015; Krummenacher et al., 2018; T. K. Lin, 2018; Lu, Jiang, Sui, Sai, & Jia, 2015; Nair, Cai, & Kong, 2019a, 2019b; Pu et al., 2019; Rojas-Moraleda et al., 2017; Yi, Wang, Guo, Li, & Jiang, 2017; Z. Zhang et al., 2019)

Tree-based models;

Decision trees (DTs), Classification and Regression Trees (CART)

Table 3. Notable tree-based models

Authors	Year	Source title	Author Keywords
Andrejiova M., Grincova A., Marasova D.	2019	Engineering Failure Analysis	Classification model; Damage; Decision tree; Regression analysis; Rubber-textile conveyor belt
Dia A., Dieng L., Gaillet L., Gning P.B.	2019	Heliyon	Acoustics; Materials science; Mechanical engineering
Bhowmik B., Krishnan M., Hazra B., Pakrashi V.	2019	Structural Health Monitoring	damage-sensitive features; real-time damage detection; Recursive singular spectral analysis; structural health monitoring; time-varying autoregressive modeling
Noori Hoshyar A., Samali B., Liyanapathirana R., Taghavipour S.	2019	Structural Health Monitoring	damage index; de-noising; mother wavelets; severity analysis; smart aggregate sensors; Structural health monitoring; wavelet de-noising
Egnew A.C., Roueche D.B., Prevatt D.O.	2018	Natural Hazards Review	
Pérez-Ruiz M., Rallo P., Jiménez M.R., Garrido-Izard M., Suárez M.P., Casanova L., Valero C., Martínez-Guanter J., Morales-Sillero A.	2018	Sensors (Switzerland)	Canopy volume; Fruit damage; Laser scanning; Monitoring; Olea europaea; Olive harvester
Wang Z., Hu M., Zhai G.	2018	Sensors (Switzerland)	Convolutional neural networks; Fruit quality detection; Hyperspectral transmittance image; Internal mechanical damage detection; Machine learning
Kim C.S., Hwang J.H., Jung J.T.	2017	Information (Japan)	3-point bending specimen; Buckling; CFRP; Damage; Restoration
Kabir G., Sadiq R., Tesfamariam S.	2016	Structure and Infrastructure Engineering	Bayesian belief network (BBN); Fault tree analysis (FTA); Fuzzy set theory; Linguistic variables; Oil and gas pipelines; Safety assessment; Uncertainty
Dorval A.D., Meredieu C., Danjon F.	2016	Annals of Botany	3D root architecture; Acclimation; Biomechanics; Flexural stiffness; Forest tree;

			Maximum tensile load; Pinus pinaster; Soil depth; Toppling; Tree anchorage; Windthrow
Favillier A., Lopez-Saez J., Corona C., Trappmann D., Toe D., Stoffel M., Rovéra G., Berger F.	2015	Geomorphology	Coppice stands; Dendrogeomorphology; Forest-rockfall interactions; French Alps; Recurrence intervals; Submontane broadleaved species
Alves V., Cury A., Roitman N., Magluta C., Cremona C.	2015	Engineering Structures	Damage assessment; Learning algorithms; Pattern recognition; SHM; Symbolic data

(Alves et al., 2015; Andrejiova, Grincova, & Marasova, 2019; Bhowmik, Krishnan, Hazra, & Pakrashi, 2019; Dia, Dieng, Gaillet, & Gning, 2019; Dorval, Meredieu, & Danjon, 2016; Egnew, Roueche, & Prevatt, 2018; Favillier et al., 2015; Kabir, Sadiq, & Tesfamariam, 2016; Kim, Hwang, & Jung, 2017; Noori Hoshyar, Samali, Liyanapathirana, & Taghavipour, 2019; Pérez-Ruiz et al., 2018; Wang et al., 2018; Z. Zhang et al., 2019)

Table. 4 Notable ensembles models including it includes boosting and bagging for making ensembles

Authors	Title	Year	Author Keywords
Mayer A.E., Mayer P.N.	Evolution of pore ensemble in solid and molten aluminum under dynamic tensile fracture: Molecular dynamics simulations and mechanical models	2019	Aluminum melt; Dynamic tensile fracture; High-rate stretching; Mechanical model; Molecular dynamics; Solid aluminum
Uzay C., Geren N., Boztepe M.H., Bayramoglu M.	Bending behavior of sandwich structures with different fiber facing types and extremely low-density foam cores	2019	ANOVA; Failure modes; Flexural properties; Sandwich structures; Ttree-point bending
Panettieri E., Leclerc G., Jumel J., Guitard J.	Mixed-mode crack propagation tests of composite bonded joints using a dual-actuator load frame – Constant and variable G II /G I conditions	2018	Composite bonded joints; Debonding; Dual-actuator system; Fracture toughness; Mixed-mode
Wang Z., Hu M., Zhai G.	Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data	2018	Convolutional neural networks; Fruit quality detection; Hyperspectral transmittance image; Internal mechanical damage detection; Machine learning
Fakih M.A., Mustapha S., Tarraf	Detection and assessment of flaws in friction stir welded joints using ultrasonic	2018	CT scanning; Finite element analysis; Friction stir welding; Lamb waves;

J., Ayoub G., Hamade R.	guided waves: experimental and finite element analysis		Structural health monitoring; Weld inspection
Froustey C., Naimark O.B., Panteleev I.A., Bilalov D.A., Petrova A.N., Lyapunova E.A.	Multiscale structural relaxation and adiabatic shear failure mechanisms	2017	adiabatic shear; dynamic loading; microdefects
Tanırcan G., Alçık H., Beyen K.	Reliability of MEMS accelerometers for instrumental intensity mapping of earthquakes	2017	
Li J., Zhang J.	Adaptive Multiscale Noise Control Enhanced Stochastic Resonance Method Based on Modified EEMD with Its Application in Bearing Fault Diagnosis	2016	
Yu J.-B., Lu X.-L., Zong W.-Z.	Wafer defect detection and recognition based on local and nonlocal linear discriminant analysis and dynamic ensemble of gaussian mixture models	2016	Gaussian mixture model (GMM); Manifold learning; Pattern recognition; Semiconductor manufacturing; Wafer defect
Sokovikov M., Bilalov D., Oborin V., Chudinov V., Uvarov S., Bayandin Y., Naimark O.	Structural mechanisms of formation of adiabatic shear bands	2016	Dynamic loading; Microdefects; Numerical modeling; Plastic strain localization
Ren Y.-C., Weng P.	Structural damage detection based on improved Hilbert-Huang transform	2015	Damage detection; Ensemble empirical mode decomposition; Hilbert-huang transform; Instantaneous frequency
Ovid'Ko I., Sheinerman A., Skiba N., Krasnitiskiy S., Smirnov A.	Twin boundary migration and nanocrack generation in ultrafine- grained materials with nanotwinned structure	2015	Cracks; Defects; Fracture; Modeling; Nanotwinned materials; Plastic deformation; Yield strength

(Fakih, Mustapha, Tarraf, Ayoub, & Hamade, 2018; Froustey et al., 2017; J. Li & Zhang, 2016; Mayer & Mayer, 2019; Ovid'Ko, Sheinerman, Skiba, Krasnitiskiy, & Smirnov, 2015; Panettieri, Leclerc, Jumel, & Guitard, 2018; Y. C. Ren & Weng, 2015; Sokovikov et al., 2016; Tanırcan, Alçık, & Beyen, 2017; Uzay, Geren, Boztepe, & Bayramoglu, 2019; Wang et al., 2018; Yu, Lu, & Zong, 2016)

Table 5. Notable Bayesians Models

Authors	Year	Author Keywords	Title
Sha G., Radzieński M., Cao M., Ostachowicz W.	2019	Bayesian data fusion; Damage growth monitoring; Damage localization; Relative natural frequency change; Severity estimation	A novel method for single and multiple damage detection in beams using relative natural frequency changes
Chattopadhyay P., Mondal S., Ray A., Mukhopadhyay A.	2019		Dynamic Data-Driven Combustor Design for Mitigation of Thermoacoustic Instabilities
Yang D.Y., Frangopol D.M.	2018	Bayesian network; crack growth; decision-making; Fatigue; influence diagram; life-cycle	Evidence-based framework for real-time life-cycle management of fatigue-critical details of structures
Ye D., Hong G.S., Zhang Y., Zhu K., Fuh J.Y.H.	2018	Additive manufacturing; Deep belief networks; Defect detection; Fast Fourier transform	Defect detection in selective laser melting technology by acoustic signals with deep belief networks
Ebrahimian H., Astroza R., Conte J.P., Papadimitriou C.	2018	Bayesian method; direct differentiation method; joint parameter and input estimation; nonlinear finite element model; output-only system identification; structural health monitoring	Bayesian optimal estimation for output-only nonlinear system and damage identification of civil structures
Wu X., Zeng X., Huang J., Song H.-Q.	2017	Bayesian network; Finite element analysis; Reliability growth; Solid rocket motor; Structure optimization	Research on Tail Structure Optimization for Solid Rocket Motor
Liu Y., Shuai Q., Zhou S., Tang J.	2017	Damage prognosis; finite element methods (FEMs); hierarchical Bayesian model; Markov	Prognosis of Structural Damage Growth Via

		chain Monte Carlo (MCMC) method; structural health monitoring	Integration of Physical Model Prediction and Bayesian Estimation
Ni Y., Lu X., Lu W.	2017	Bayesian; High-rise building; Modal identification; Shaking table test; Vibration test	Operational modal analysis of a high-rise multi-function building with dampers by a Bayesian approach
Ebrahimian H., Astroza R., Conte J.P., de Callafon R.A.	2017	Bayesian inference; Gradient-based optimization; Model updating; Nonlinear finite element model; Nonlinear system identification; Uncertainty quantification	Nonlinear finite element model updating for damage identification of civil structures using batch Bayesian estimation
Kabir G., Sadiq R., Tesfamariam S.	2016	Bayesian belief network (BBN); Fault tree analysis (FTA); Fuzzy set theory; Linguistic variables; Oil and gas pipelines; Safety assessment; Uncertainty	A fuzzy Bayesian belief network for safety assessment of oil and gas pipelines
Yazdanipour M., Pourgol-Mohammad M.	2016	Bayesian approach; Crack length distribution; Fatigue crack growth; Probabilistic modeling; Propagation of uncertainty	Stochastic fatigue crack growth analysis of metallic structures under multiple thermal-mechanical stress levels
Seuba J., Deville S., Guizard C., Stevenson A.J.	2016	Ceramics; Mechanical properties; Mechanical reliability; Porous materials; Weibull	The effect of wall thickness distribution on mechanical reliability and strength in unidirectional porous ceramics
Alves V., Cury A., Roitman N., Magluta C., Cremona C.	2015	Damage assessment; Learning algorithms; Pattern recognition; SHM; Symbolic data	Structural modification assessment using supervised learning methods applied to vibration data

Baneen U., Guivant J.E.	2015	Bayesian; Curvature mode shapes; Damage detection; Kernels; Plate-type structure.	A 2D Bayesian approach for damage detection in plate-type structures

(Chattopadhyay, Mondal, Ray, & Mukhopadhyay, 2019; Ebrahimian, Astroza, Conte, & de Callafon, 2017; Ebrahimian, Astroza, Conte, & Papadimitriou, 2018; Kabir et al., 2016; Liu, Shuai, Zhou, & Tang, 2017; Y. Ni, Lu, & Lu, 2017; Seuba, Deville, Guizard, & Stevenson, 2016; Sha, Radzieński, Cao, & Ostachowicz, 2019; Wu, Zeng, Huang, & Song, 2017; Yang & Frangopol, 2018; Yazdanipour & Pourgol-Mohammad, 2016; Ye, Hong, Zhang, Zhu, & Fuh, 2018)

Logistic regressions

Table 6. Notable logistic regressions

Authors	Title	Year	Author Keywords
Egnew A.C., Roueche D.B., Prevatt D.O.	Linking Building Attributes and Tornado Vulnerability Using a Logistic Regression Model	2018	
Jang D.-W., Lee S., Park J.-W., Baek D.-C.	Failure detection technique under random fatigue loading by machine learning and dual sensing on symmetric structure	2018	Dual sensing; Failure detection; Fatigue loading; Machine learning; Prognostics and Health Management (PHM)
Bissacot A.C.G., Salgado S.A.B., Balestrassi P.P., Paiva A.P., Zambroni Souza A.C., Wazen R.	Comparison of neural networks and logistic regression in assessing the occurrence of failures in steel structures of transmission lines	2016	Artificial neural networks; Fall of metal structures; Logistic regression; ROC curves; Transmission lines
Regan T., Canturk R., Slavkovsky E., Niezrecki C., Inalpolat M.	Wind turbine blade damage detection using various machine learning algorithms	2016	Health Monitoring; Logistic Regression; Machine Learning; Support Vector Machine; Wind Turbine Blades
Gauthier F., Hétu B., Allard M.	Forecasting method of ice blocks fall using logistic model and melting degree–days calculation:	2015	Degree–day; Ice avalanche; Ice blocks fall; Logistic regression; Predictive model

	a case study in northern Gaspésie, Québec, Canada		
Zhang W., Shen S., Basak P., Wen H., Wu S., Faheem A., Mohammad L.N.	Development of predictive models for initiation and propagation of field transverse cracking	2015	
Wazen R.N., Fernandes T.S.P., Aoki A.R., De Souza W.E.	Evaluation of the susceptibility of failures in steel structures of transmission lines	2013	Dropped structures; Logistic regression; Metallic structures; Rough sets; Transmission lines

(Bissacot et al., 2016; Egnew et al., 2018; Gauthier, Hétu, & Allard, 2015; Jang et al., 2018; Regan, Canturk, Slavkovsky, Niezrecki, & Inalpolat, 2016; Wazen, Fernandes, Aoki, & De Souza, 2013; W. Zhang et al., 2015)

Neuro-Fuzzy

Table 7. Notable ANFIS models

Authors	Title	Year	Author Keywords
Tran Q.T., Nguyen S.D., Seo T.-I.	Algorithm for estimating online bearing fault upon the ability to extract meaningful information from big data of intelligent structures	2019	adaptive neuro-fuzzy inference system (ANFIS)-based damage identification; AI for estimating damage; identifying bearing damage; singular spectrum analysis (SSA) for identifying damage
Naderpour H., Mirrashid M.	Shear failure capacity prediction of concrete beam-column joints in terms of ANFIS and GMDH	2019	Adaptive neuro-fuzzy inference system (ANFIS); Concrete beam-column joint; Group method of data handling (GMDH); Shear capacity; Soft computing; Vulnerability
Hashemineja d M.M., Sohankar N., Hajiannia A.	Predicting the collapsibility potential of unsaturated soils using adaptive neural fuzzy inference system and particle swarm optimization	2018	Adaptive neural fuzzy inference system; Collapsibility potential; Gaussian membership function; Particle swarm optimization; Soft computing
Aydin K., Kisi O.	Damage detection in structural beam elements	2015	Beam; Damage detection; Grid partitioning; Neuro fuzzy system; Subtractive clustering

	using hybrid neuro fuzzy systems		
Guruprasad R., Behera B.K.	Comparative Analysis of Soft Computing Models in Prediction of Bending Rigidity of Cotton Woven Fabrics	2015	ANFIS; ANN; Bending rigidity; BPNN; GANN
Nanda J., Das L.D., Das S., Das H.C.	Influence of multi-transverse crack on cantilever shaft	2015	adaptive neuro-fuzzy inference system; experimental analysis; mode shape; multiple cracks; natural frequency; shaft; Vibration
[No author name available]	3rd International Conference on Civil Engineering and Transportation, ICCET 2013	2014	
[No author name available]	2013 International Conference on Mechanical and Electronics Engineering, ICMEE 2013	2013	
[No author name available]	2013 2nd International Conference on Manufacture Engineering, Quality and Production System, ICMEQP 2013	2013	
Adoko A.C., Gokceoglu C., Wu L., Zuo Q.J.	Knowledge-based and data-driven fuzzy modeling for rockburst prediction	2013	ANFIS; Mamdani fuzzy inference system; Prediction modeling in rock engineering; Rockburst; Takagi-Sugeno fuzzy inference system

(Adoko, Gokceoglu, Wu, & Zuo, 2013; Aydin & Kisi, 2015; Guruprasad & Behera, 2015; Hasheminejad, Sohankar, & Hajiannia, 2018; Naderpour & Mirrashid, 2019; Nanda, Das, Das, & Das, 2015; Tran, Nguyen, & Seo, 2019)

Conclusions

Deep learning methods are fast-evolving. Some of them have advanced to be specialized in a particular application domain. However, there is a gap in research in introducing the deep learning methods and summarize the methods and application in a single paper. Consequently, this paper aims at providing a comprehensive list of the most popular deep learning methods and provide notable applications. CNN, RNN, DAE, DBNs, LSTM methods have been identified as the most popular deep learning method. The description of each deep learning method and the function of each building block of them is explained.

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Alves, V., Cury, A., Roitman, N., Magluta, C., & Cremona, C. (2015). Structural modification assessment using supervised learning methods applied to vibration data. *Engineering Structures, 99*, 439-448. doi:10.1016/j.engstruct.2015.05.003

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