State-of-the-Art Review

Machine Learning for Risk and Resilience Assessment in Structural Engineering: Progress and Future Trends

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Abstract: Population growth, economic development, and rapid urbanization in many areas have led to increased exposure and vulnerability of structural and infrastructure systems to hazards. Thus, developing risk-based assessment and management tools is crucial for stakeholders and the general public to make informed decisions on prehazard planning and posthazard recovery. To this end, structural risk and resilience assessment has been an ongoing research topic in the past 20 years. Recently, machine learning (ML) techniques have been shown as promising tools for advancing the risk and resilience assessment of structure and infrastructure systems. To date, however, there is a lack of a holistic review on ML progress across various branches of structural engineering; an in-depth analysis of literature that can provide a timely evaluation of risk and resilience assessment methods of the built environment, where different types of structural and infrastructure facilities are interconnected. For this reason, this study conducted a comprehensive review on ML for risk and resilience assessment in four main branches of structural engineering (buildings, bridges, pipelines, and electric power systems). To cover the crucial modules in the prevailing risk and resilience assessment frameworks, existing literature is thoroughly examined and characterized in terms of six attributes of ML, including method, task type, data source, analysis scale, event type, and topic area. Moreover, limitations and challenges are identified, and future research needs are highlighted to move forward the frontiers of ML for structural risk and resilience assessment. **DOI: 10.1061/(ASCE)ST.1943-541X.0003392.** *© 2022 American Society of Civil Engineers.*

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Introduction

Background and Motivation

Critical infrastructures are often regarded as vital national assets. They provide crucial services for prosperous development, resilient functioning, and long-term sustainability of communities (Biringe et al. 2013). In the context of structural engineering, critical infrastructure indicates the necessary structural and infrastructure facilities that form the built environment to support our society, mainly including (1) building structures used for residences, commerce, government administration, and healthcare services; (2) transportation infrastructures such as bridges, roads, and highways; and (3) lifeline infrastructures such as those built on pipelines for water and energy distribution and wire-based systems used for electrical power supply and telecommunication. As the vulnerability of structures has been increasingly witnessed under extreme events induced by natural or technological hazards or under operational conditions due to aging effects (Steinberg and Cruz 2004; Halkos and Zisiadou 2020), cutting-edge risk-informed assessment methods have attracted growing attention from stakeholders such as code developers, practitioners, and academic researchers (Ouyang 2014; Liu and Song 2020; Mottahedi et al. 2021).

In the domain of structural engineering, risk is commonly defined as the probability or rate of exceedance of a given extent of consequences on physical, environmental, economic, and/or social dimensions (Ghosn et al. 2019). The well-known performance-based earthquake engineering framework developed by the Pacific Earthquake Engineering Research (PEER) center (Deierlein et al. 2003) provides a viable path for risk quantification using a convolutional integral formulation that involves four main stochastic modules (i.e., hazard analysis, response prediction, fragility assessment, and consequence estimates). This framework has been transferred (with modifications) to other natural hazards including wind (Ciampoli et al. 2011), hurricanes (Barbato et al. 2013), tsunamis (Attary et al. 2017), and recently to coastal multihazard scenarios (González-Dueñas and Padgett 2021). While these frameworks successfully quantify risk to single or multiple events by quantitative indicators such as direct/indirect economic losses, down time, casualties, etc., they do not explicitly assess how the systems recover from the extreme events. For this reason, resilience assessment has become an emerging topic, as it quantifies the ability of a structural system to prepare and plan for, absorb, recover from, and

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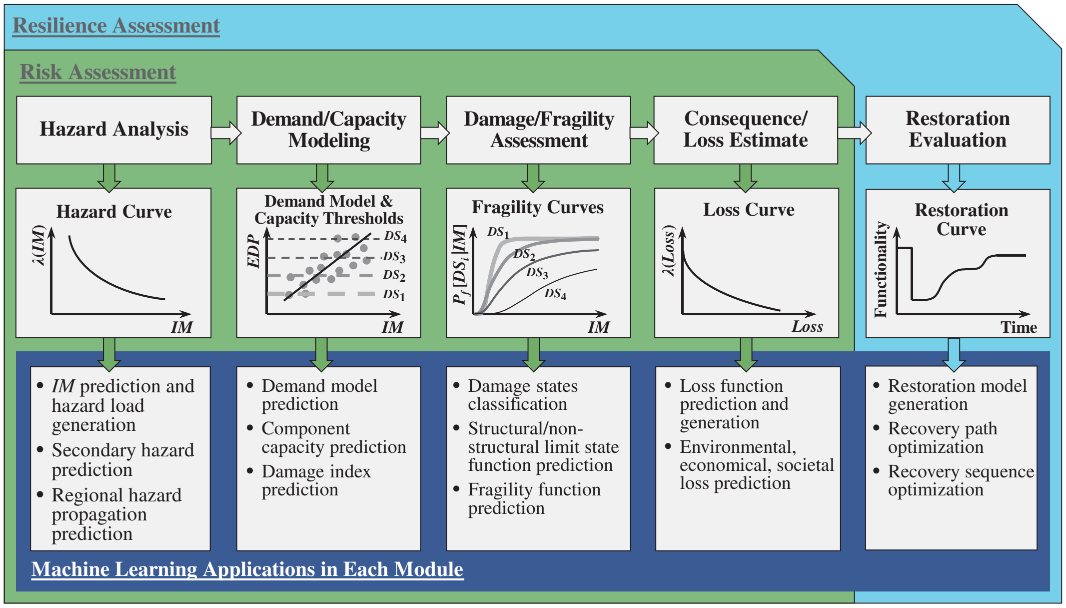

IM: Intensity measure
EDP: Engineering demand parameter
DS_i: *i*-th damage state
λ(IM): Annual rate of exceedance of hazard in terms of *IM*
$P_f[DS_i|IM]$: Probability of exceedance for DS_i given *IM*
λ(Loss): Annual rate of exceedance of consequence/loss

Fig. 1. Illustration of risk and resilience assessment frameworks and associated ML applications.

more successfully adapt to the adverse events (National Research Council 2012). Current practices of resilience assessment are normally rooted in risk assessment while introducing an additional module to characterize the time-evolving functionality loss and recovery of the structural system accounting for different mitigation measures and restoration trajectories (Cimellaro et al. 2010b; Ayyub 2015; Koliou et al. 2020; Pang and Wang 2021a, b). In other words, the restoration evaluation module together with the aforementioned four modules form the prevailing frameworks of risk and resilience assessment, as illustrated in Fig. 1.

Methodological developments for risk and resilience assessment for the five modules have focused mainly on field measurements and expert opinion surveys (Kawashima et al. 2009; Reuland et al. 2019; Mitoulis and Argyroudis 2021), elaborate laboratory experiments (Wang et al. 2019a, c; Astroza et al. 2021), and simplified/sophisticated numerical simulations (Li 2012; Xie et al. 2017; Wang et al. 2019b). However, such approaches have been recognized as resource and time consuming, such that they are not preferable for large spatial and temporal risk and resilience assessment (e.g., life-cycle assessment in regional scales). Data-driven methods incorporating machine learning (ML) have progressively emerged in the twenty-first century and provided powerful tools to each module of risk and resilience assessment, due to the expeditious development and applicability of artificial intelligence (AI), the accumulation of databases by the substantial experiments and physics-based simulation studies, as well as breakthroughs in structural health monitoring (SHM) fields in data acquisition theories, apparatus, processing, and transmission (e.g., Zimmerman and Lynch 2006; Farrar and Worden 2012). ML is recognized as a promising path to shift the structural engineering profession in the decades to come (Burton and Mieler 2021; Flah et al. 2021; Xie et al. 2022). Possible applications of ML methods in each module of the risk and resilience assessment frameworks are highlighted in Fig. 1. Details of these applications are discussed later in the paper.

Significant strides have been made in the past two decades in developing and advancing ML algorithms, models, and associated frameworks to boost the tangible application of ML in design, analysis, and management of structures and infrastructure systems. Several reviews on state of the art or practice were conducted on the application of ML in different branches of civil engineering. For example, Flood (2008) reviewed the development and applications of artificial neural networks (ANN), one of the most popular ML algorithms, in various branches of civil engineering. The review pointed to high capabilities of ANN and the benefits of integrating ANN with other computing paradigms such as generic algorithms. Salehi and Burgueño (2018) summarized the evolution of ML approaches in terms of supervised, unsupervised, and reinforcement learning and their implementation in SHM, optimization, and predicting mechanical properties of materials. Other recent relevant reviews have focused on the role of ML in structural design and performance assessment of buildings (Sun et al. 2021), ML-aided design and inspection of reinforced concrete (RC) bridges (Fan et al. 2021), and ML-assisted SHM for condition assessment and damage detection of bridges and structures (Sun et al. 2020; Sony et al. 2021). In addition, a few review studies covered the ML application in inspection, monitoring, and maintenance of pipeline systems (Rachman et al. 2021) and electric power systems (Cheng and Yu 2019; Ibrahim et al. 2020), merits and limitations of ML in seismology for earthquake early warning and ground motion predictions (Kong et al. 2019), and seismic hazard analyses and associated structural damage detection, fragility modeling, and seismic control and mitigation (Xie et al. 2020). However, there is still a lack of a comprehensive review of methodological developments and applications of ML from a broad view of structural engineering, which not only examines the technical background and development in each branch but also motivates integrated research on regional/community/city levels where various types of structures are interdependently involved. Furthermore, an understanding of current progress, challenges, and future research is needed on ML implementation in structural risk and resilience assessment toward reliable decision-making for stakeholders.

(1) ML Method	(2) Task Type	(3) Data Source	(4) Analysis Scale	(5) Topic Area	(6) Event Type
1a) RS and evolvements	2a) Regression	3a) Field measurement	4a) Component	5a) Response prediction	6a) Operational condition
1b) ANN	2b) Classification	3b) Laboratory test	4b) Structure	5b) Capacity modeling	6b) Earthquake
1c) DL	2c) Clustering	3c) Computational simulation	4c) Regional/ network	5c) Damage/fragility assessment	6c) Wind
1d) SVM	2d) Dimensionality reduction			5d) Consequence/ loss estimate	6d) Landslide
1e) DT and ensembles	2e) Decision-making			5e) Restoration evaluation	6e) Flood/scour
1f) Others					6f) Wave/surge
					6g) Fire/wildfire

Fig. 2. Attributes and associated subtraits used for characterizing publications. Note that "1f) Others" includes relatively less used ML methods for supervised learning (e.g., k-nearest neighbors, LR, Gaussian process, and naïve Bayes) than those for unsupervised/reinforcement learning.

Scope and Methodology

Considering the recency of existing ML/AI review papers on different structural engineering branches, this review focuses on (1) bridge infrastructure (141 papers surveyed in this review), (2) pipeline infrastructure used in energy, water, and wastewater systems (28 papers), and (3) electric power systems (26 papers), while the branch of building structures is investigated with emphasis on recent publications after the review work by Sun et al. (2021).

The knowledge of each reviewed publication is characterized using six attributes, each containing multiple subtraits, as displayed in Fig. 2. Specifically, the first three attributes and associated subtraits are set up based on taxonomies of prevailing ML methods, task types, and data sources detailed later, while the last three are characterized according to properties of study objects and problems. The topic area is one of the paramount attributes that uniquely accounts for the major modules of risk and resilience assessment frameworks, and facilitates summarizing the past and ongoing progress and identifying future research avenues. It should be noted that the module of *hazard analysis* is not assessed in the topic area because it is beyond the scope of this paper, and has been discussed in recent publications (Alimoradi and Beck 2015; Loridan et al. 2017; Xie et al. 2020).

The rest of this paper is organized into three sections: (1) drawing an overall picture on the taxonomy, progress, and popularity of ML methods in structural engineering and collecting accessible databases for the expediency of further research and education; (2) thoroughly analyzing research status and trends in buildings, bridges, pipelines, and electric power systems; and (3) discussing critical questions and challenges to highlight emerging research needs for ML-aided risk and resilience assessment in structural engineering.

ML Methods and Databases

Taxonomy and Application Trends of ML Methods

As a predominant subfield of AI, ML refers to a group of algorithms that can enable computer-aided models to successfully learn from existing data or past experiences (Hastie et al. 2009). Early practitioners in civil engineering divided ML methods into *supervised* or *unsupervised learning* based on the type of data (i.e., labeled or unlabeled) used for learning (Reich 1997). Rapid development of ML has led to another subdomain named *reinforcement learning* adept at decision-making tasks that cannot be well solved by the traditional supervised or unsupervised learning. It is worth noting that from a view of data type, reinforcement learning can be supervised or unsupervised, or even semisupervised where a mix of labeled and unlabeled data is involved. Fig. 3 illustrates the ML domains, together with the corresponding types of tasks and major algorithms. For clarification, supervised, unsupervised, and reinforcement learning are further discussed next with typical examples in structural engineering.

Supervised learning utilizes a labeled data set composed of known input and output variables to train a model that can best approximate the input-output relationship for regression tasks that fit the output variable with the input ones [e.g., developing prediction models for curvature responses of bridge columns under seismic loading using ANN, random forests (RF), response surface (RS), etc. (Wang et al. 2021c), and capturing force-displacement relations of RC columns under cyclic loads using a support vector machine (SVM) (Luo and Paal 2018; Huang et al. 2022)] or classification tasks that find boundaries in the data set so as to separate the data into a number of known classes [e.g., identifying the failure risk of pipelines as low, moderate, high, and severe utilizing a decision tree (DT), RF, and other ensemble methods (Mazumder et al. 2021a)]. By contrast, unsupervised learning explores an unlabeled data set consisting of known input and unknown output variables to learn a paradigm for clustering tasks that infer the underlying natural structures based on similarity/difference [e.g., clustering structural states into damaged or undamaged by learning structural vibration time-series data using the fuzzy c-means algorithm (da Silva et al. 2008), and diagnosing structural conditions using deep autoencoders (Jiang et al. 2021)], or dimensionality reduction tasks that reduce the number of input variables while retaining the crucial ones to keep as much relevant information as possible [e.g., reducing the structural vibration time-series data to extract the most influential factors using the principal component analysis (PCA) (da Silva et al. 2008)]. Reinforcement learning adopts a manually prepared space of actions and states to create a computational agent to learn to solve decision-making tasks for taking optimal actions through maximizing the rewards it receives for its actions [e.g., prioritizing posthurricane recovery trajectories for resilience enhancement of power distribution systems using the deep Q-learning algorithm (Dehghani et al. 2021a)].

To understand the application trend and popularity of ML methods in structural engineering, Fig. 4 shows annual publication records that highlight the development of the top five prevailing ML methods identified from the ML method attribute. Characteristics of these prevailing methods are described in the next section for the completeness of this paper. Before interpreting the figure, it is worth sketching the ML history. Since the origin of the terminology *machine learning* in the computer science field in the 1940s, ML methods practically remained out of interest in structural engineering for a long time until the 1980s. The following decades witnessed a lukewarm growth trend represented by a handful of studies limited to simple problems using supervised learning with a limited number of ML methods (mainly in ANN) until an outbreak starting from the mid-2010s for bridges [Fig. 4(a)], where ANN, deep learning (DL), and DT and its ensembles occupy

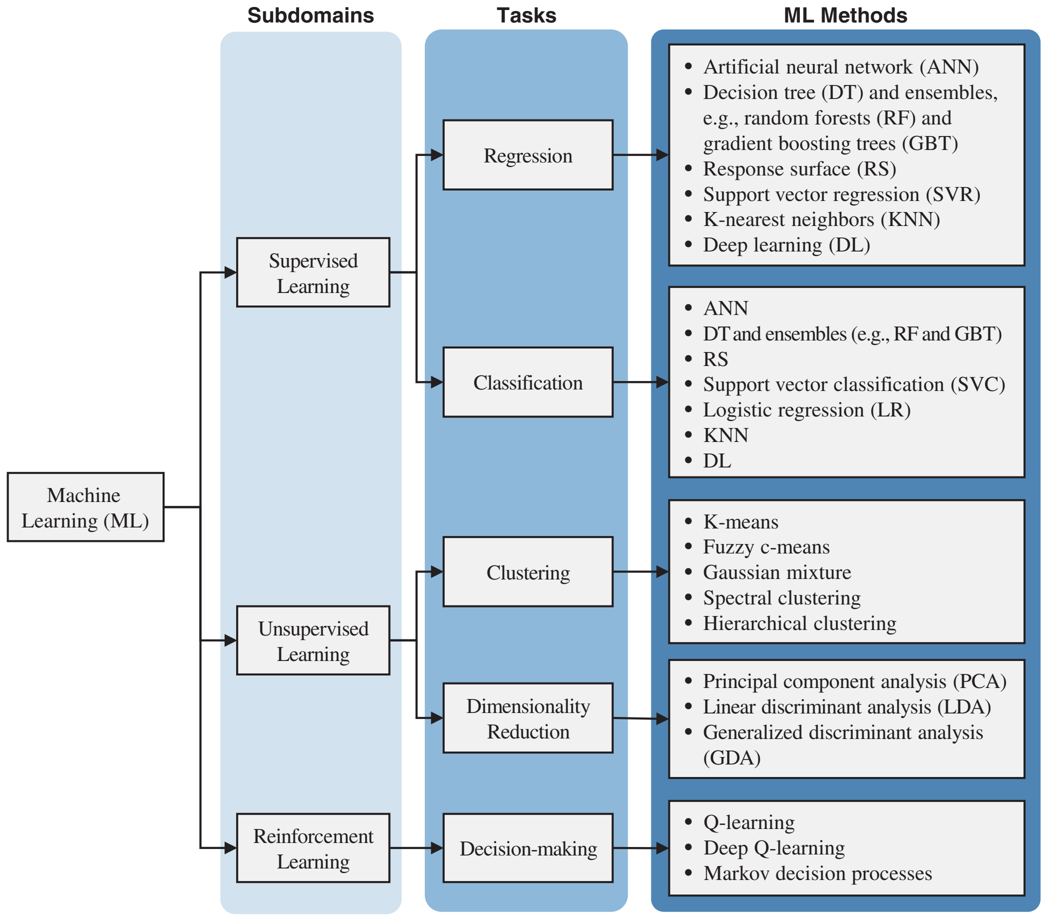

Fig. 3. The taxonomy of ML in terms of subdomains, tasks, and major methods.

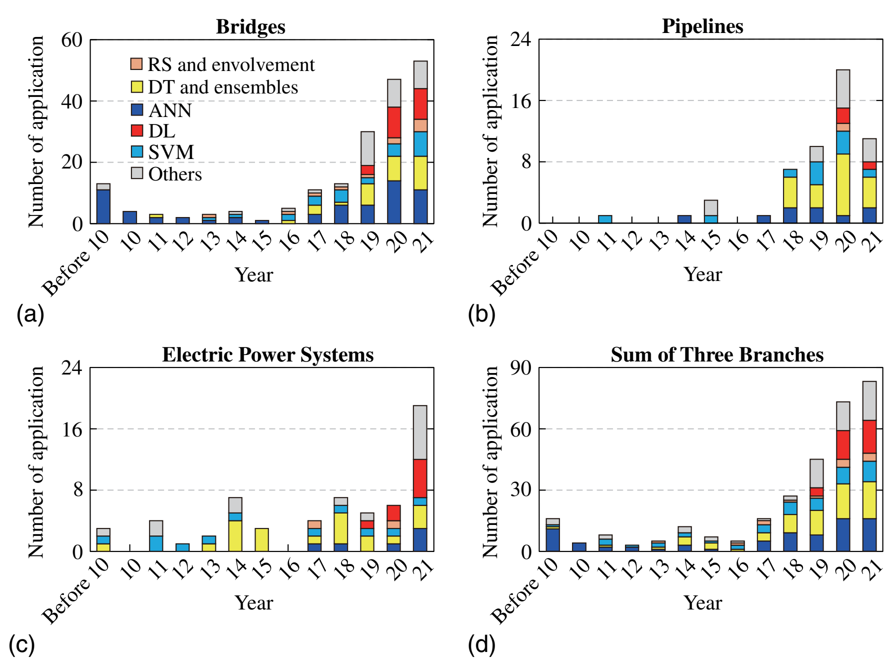

Fig. 4. Annual number of publications for ML in different branches of structural engineering: (a) bridges; (b) pipelines; (c) electric power systems; and (d) sum of these three branches.

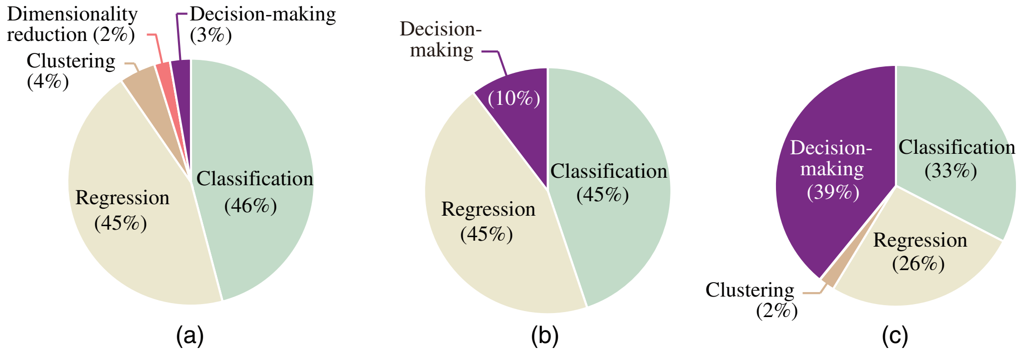

Fig. 5. Distribution of task types in different branches of structural engineering: (a) bridges; (b) pipelines; and (c) electric power systems.

the top three positions. A similar increase is noticeable in the pipeline branch in the later 2010s [Fig. 4(b)] with the predominant application of DT and its ensembles. Also, ML applications in electric power systems for structural risk and resilience assessment show an increasing trend [Fig. 4(c)], where DL and DT and its ensembles are the most popular and promising ones. The analysis of literature indicates a recent growth of other algorithms for supervised learning, e.g., k-nearest neighbors and logistic regression (LR), and for unsupervised/reinforcement learning, e.g., those shown in Fig. 3. A sum of the three branches [Fig. 4(d)] again demonstrates the rapid growth of ML applications in the past five years, where ANN, DL, DT and its ensembles, SVM, and RS are the top prevailing ML methods. For completeness, these methods are characterized in the next section from the view of the structural engineering field.

Using pie charts, Fig. 5 presents the distribution of task types for different branches of structural engineering. It is seen that classification and regression tasks (supervised learning) are predominant in both bridges and pipelines, while clustering and dimensionality reduction tasks (unsupervised learning) are rarely applied among all branches. By contrast, the decision-making task governs the ML applications in electric power systems (particularly for restoration evaluation as discussed later), while occupying relatively less in the pipeline and bridge branches.

Characteristics of Prevailing ML Methods Used in Structural Engineering

RS and Its Evolvements: Ridge, Least Absolute Shrinkage and Selection Operator, and Elastic Net

As a classical statistical method, RS explores the relationship of variables in a system to estimate its response. This approach has been widely used in many fields due to its simplicity, explicitness, interpretability, and transferability (Box and Hunter 1957). Because of these merits, RS is more often used for regression tasks. A series of basic functions are commonly adopted to explicitly describe the relationship between inputs and outputs. While high-order polynomials can be used as the basis functions, first- and second-order polynomials are preferable for data where the relationships are not complex. Regression coefficients are determined by minimizing a loss function that describes the difference of predicted and observed responses, as seen in Eq. (1). Here, the loss function is presented in the most popular form, i.e., the residual sum of squares

$$\hat{w} = \arg\min_{w}\left\{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2\right\} \tag{1}$$

where $\hat{w} = w_j$ ($j = 0, 1, 2, \ldots, m$) denotes the unknown m regression coefficients for predictors (i.e., input variables and/or their combinations); and y_i and $\hat{y}_i$ ($i = 1, 2, \ldots, N$) represent the ith observed and predicted responses, respectively, for a training set with N data. However, RS with this loss function has been found to trigger overfitting issues for relatively complex problems involving a large number of nonlinearly correlated or independent variables in particular. In that respect, the past few decades have witnessed the evolution of RS through applying regularization techniques that introduce a penalty term in the loss function to tune the model size, thereby avoiding or remitting overfitting. Featured by different penalty terms as given in Eqs. (2)–(4), the evolved RS methods mainly include ridge (Hoerl and Kennard 1970), least absolute shrinkage and selection operator (LASSO) (Tibshirani 1996), and elastic net (Zou and Hastie 2005)

$$\text{Ridge: } \hat{w} = \arg\min_{w}\left\{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda\sum_{j=1}^{m}w_j^2\right\} \tag{2}$$

$$\text{LASSO: } \hat{w} = \arg\min_{w}\left\{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda\sum_{j=1}^{m}|w_j|\right\} \tag{3}$$

$$\text{Elastic net: } \hat{w} = \arg\min_{w}\left\{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 + \lambda_1\sum_{j=1}^{m}w_j^2 + \lambda_2\sum_{j=1}^{m}|w_j|\right\} \tag{4}$$

where λ, λ_1, and λ_2 (all beyond zero) = penalty-related parameters that control the amount of reduction in model size. Therefore, the penalty-related parameters are key factors in these evolved RS methods, as listed in Table 1, and need to be tuned (i.e., optimized) through rigorous methods such as cross-validation. Note that LASSO not only helps in reducing overfitting but also can assist in variable-importance identification, as it reduces coefficients of unimportant variables to zero, whereas ridge only reduces these coefficients close to zero but not zero. By contrast, elastic net is particularly effective for high-dimensional data sets, especially when the number of input variables is much larger than the number of output variables.

ANN

As the most popular ML algorithm for both classification and regression tasks, ANN is inspired by the nonlinear bioelectricity transmission among neural cells (i.e., neurons) (Haykin 2008). ANN used in structural engineering is mostly represented by a fully connected multilayer feedforward perceptron that describes the relationship between the input and output variables. While some studies define ANN as a perceptron with one input layer, one hidden layer, and one output layer, a broader definition of ANN is a perceptron consisting of one input layer, a limited number of

Table 1. Key parameters in the prevailing ML methods used in structural engineering

ML method(s)	Key parameters
RS and its evolvements: Ridge, LASSO, and elastic net	• Penalty-related parameters in loss functions
ANN and DL: DNN, RNN, and CNN	• Number of hidden layers • Number of neurons in each hidden layer • Activation function • Learning rate or initial learning rate • Dropout rate • Number of convolutional layers (for CNN) • Size of convolving kernel in each convolutional layer (for CNN) • Maximum size of pooling window (for CNN)
SVM	• Kernel-related parameters for hyperplanes and margins • Penalty-related parameters in loss functions
DT and its ensembles: RF, GBT, and XGBoost	• Maximum number of features for splitting • Minimum number of samples in an internal node • Minimum number of samples in a leaf node • Number of DTs (for the ensembles) • Maximum depth for each decision tree

hidden layers, and one output layer, with each layer containing a limited number of neurons depending on the task complexity, as illustrated in Fig. 6(a). Each neuron in the hidden layer is computed via a two-stage process: (1) linear regression fitted using neurons in the previous layer, and (2) nonlinearity induced using an activation function (e.g., rectified linear unit, sigmoid, tanh, softmax, etc.) that feeds into the fitted regression. The stochastic gradient descent method (Amari 1993) is often used to iteratively adjust the weight coefficients in the linear regression process using backward chain-rule derivatives such that the prediction error represented by a loss function is minimized. As listed in Table 1, key parameters in ANN include the number of hidden layers and the number of neurons in each hidden layer, activation function, dropout rate that modifies the number of neurons in different hidden layers, and learning rate (or initial learning rate) that controls the step size at each iteration while moving toward a minimum of the loss function. These key parameters always need to be tuned (or optimized) for specific problems to avoid overfitting as well as underfitting issues. By reviewing the collected literature, current practices in structural engineering mostly apply ANN with less than five hidden layers.

DL

To distinguish from ANN, DL is basically a term used to describe more advanced neural networks, particularly for tasks with quite large and intricate data sets involving highly nonlinear relationships. DL methods that are successfully applied in structural engineering mainly include three types: (1) the deep neural network [DNN, as seen in Fig. 6(b)] that simply extends ANN by increasing the number of hidden layers (and neurons) [e.g., as many as 10 hidden layers or more as argued by Schmidhuber (2015)]; (2) the recurrent neural network (RNN) that cuts time-series data by steps and saves the output of each hidden layer at each time step and feeds it back to the previous layer for remembering and recalling the information [Fig. 6(c)], and thereby specializes in solving time-dependent regression problems [e.g., predicting seismic time-history responses of semiactively controlled buildings (Kim 2020)] as well as classification problems [e.g., estimating deterioration levels of constructed concrete bridges in long-term coastal and non-coastal environments (Miao et al. 2021)]; and (3) the convolutional neural network [CNN, Fig. 6(d)] that is powerful for processing intricate data [i.e., grid-like topological data such as images (Krizhevsky et al. 2012)] via a unique feature-extraction module involving multiple convolution and pooling operations that gradually transform the intricate data to legible tabulated data, which are taken as input to a followed ANN or DNN in the CNN architecture. Owing to these properties, CNN has shown promising capabilities in dealing with classification tasks with illegible data sets [e.g., detecting structural damage levels according to images of surface cracks (Cha et al. 2017)] as well as regression tasks [e.g., evaluating dynamic responses of steel frame structures (Wu and Jahanshahi 2019)].

SVM

SVM can be specifically called support vector classification (SVC) and support vector regression (SVR) according to the type of task. More specifically, SVC is a binary classification algorithm using kernel functions (e.g., linear, polynomial, Gaussian, etc.) that construct a hyperplane and associated support vectors to maximize the margin between them, such that the training data set can be effectively classified into two classes. Multiple binary SVC models are often used for training data sets with high-dimensional features. Typical applications of SVC in structural engineering include classifying types of bridges in the US National Bridge Inventory (NBI) database (Jootoo and Lattanzi 2017) and classifying potential failure levels of pipelines under operational conditions (Mazumder et al. 2021a). The application of SVR for regression tasks such as predicting vortex-induced vibration of a long-span suspension bridge against wind loads (Li et al. 2018) is commonly realized by introducing a unique region called the *ε-insensitive region* where ε is a threshold defined by users, within which the prediction error is ignored (Cortes and Vapnik 1995). In other words, as ε increases, the prediction becomes less sensitive to the error. Using nonlinear kernel functions, linear regressions are developed in the high-dimensional feature space.

DT and Its Ensembles: RF, Gradient Boosting Trees, and Extreme Gradient Boosting

DT, also called the classification and regression tree (CART), can be used for both classification and regression tasks. It is an algorithm that recursively splits input data (i.e., features represented by input variables) and defines a local model in each splitting region. As shown in Fig. 7(a), a DT is structured by a root node that is commonly split into two internal nodes in the first depth (or one internal node and one leaf node, or two leaf nodes in case the problem is relatively simple). The internal node can be regarded as a new root node in this depth and further split, while the leaf node

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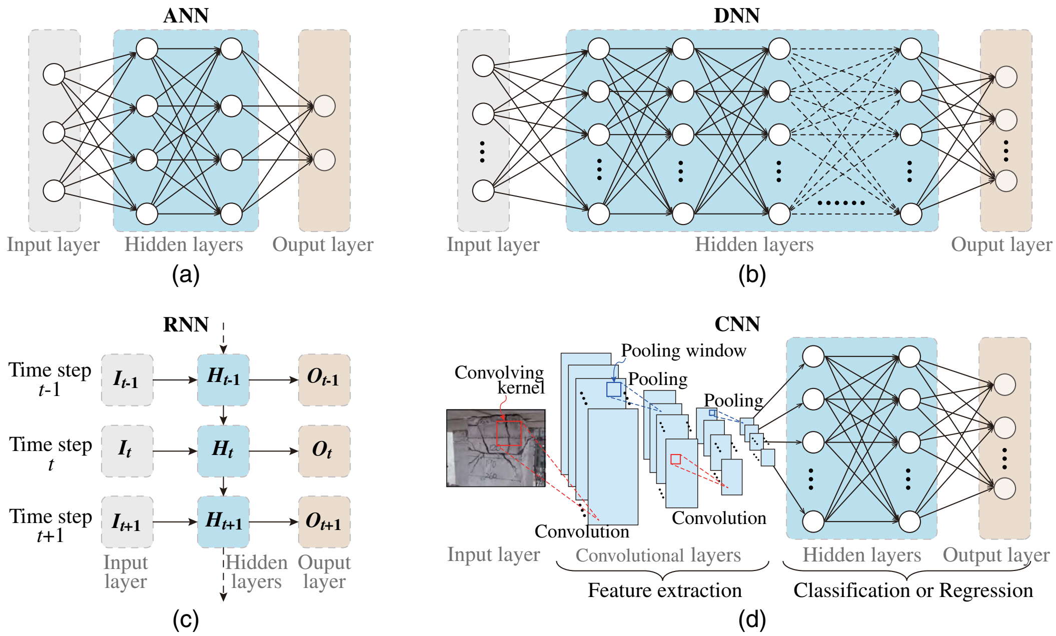

Fig. 6. Architectural illustration of neural network–based ML methods: (a) ANN; (b) DNN; (c) RNN; and (d) CNN. (Image reprinted from Wang et al. 2016, © ASCE.)

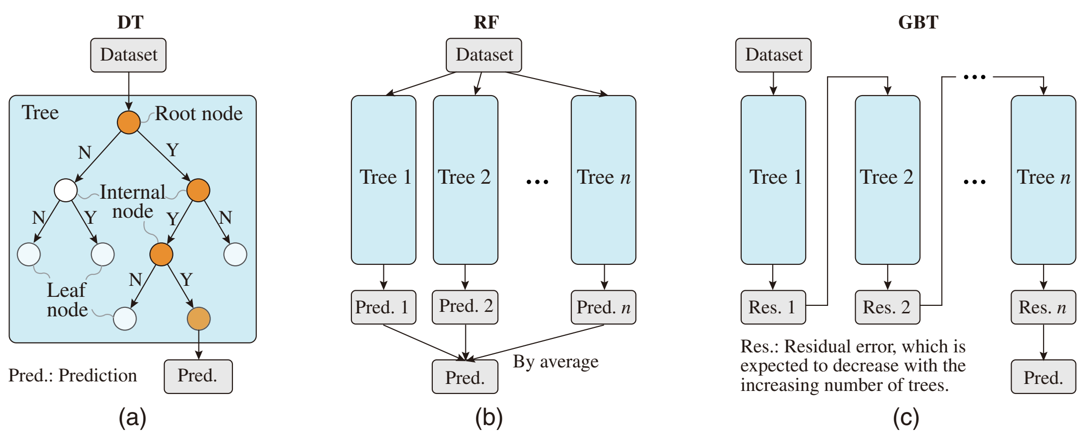

Fig. 7. Architectural illustration of tree-based ML methods: (a) DT; (b) RF; and (c) GBT.

represents a prediction that cannot be split. Key parameters in DT include the maximum number of features for splitting, the minimum number of samples in an internal node, the minimum number of samples in a leaf node, and the maximum depth for each tree, as listed in Table 1. Despite the fact that these parameters can be elaborately tuned, overfitting has always been a limitation in DT (Bramer 2020).

To overcome the overfitting as well as underfitting issues in DT, ensemble techniques that take advantage of multiple trees have been developed to extend DT to more advanced tree-based ML methods such as RF, gradient boosting trees (GBT), and extreme gradient boosting (XGBoost). Specifically, RF is a bagging-based ensemble algorithm by constructing multiple DTs in parallel (Ho 1995), as depicted in Fig. 7(b). The number of trees is a key parameter for the performance of RF. Bagging is built on the premise that it is unlikely for a weak learner, in this case a decision tree, to learn all patterns. Instead, weak learners fit to randomly select partial data sets in parallel. The learned patterns are then aggregated according to some predefined rules, such as the mean output of the individual trees. Owing to these merits, RF has been successfully implemented in risk and resilience assessment of structures (Wu and Baker 2020; Soleimani and Hajializadeh 2022).

GTB is developed based on another ensemble learning approach called *boosting*, where multiple models are aggregated in series rather than in parallel as in bagging (e.g., RF). More specifically, a series of decision trees is concatenated sequentially in GTB such that each tree learns the pattern between the input variables and the residual error in the previous tree, as illustrated in Fig. 7(c). In this manner, the residual error can be gradually reduced, finally resulting in a high-fidelity prediction. The number of trees is a critical parameter in GTB in addition to those in DT. To improve the generalization ability of GTB (i.e., reducing overfitting), Chen and Guestrin (2016) developed an extreme gradient boosting tree algorithm, called XGBoost, by optimizing the gradient boosting algorithm in GTB. Since its inception, XGBoost has noticeably shown better performance compared with other prevailing ML methods applied in structural engineering (Lim and Chi 2019; Nguyen-Sy et al. 2020; Feng et al. 2021c).

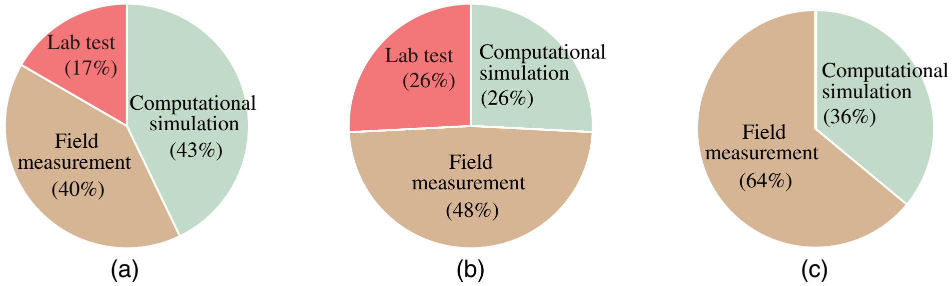

Fig. 8. Distribution of data sources in different branches of structural engineering: (a) bridges; (b) pipelines; and (c) electric power systems.

Data Sources and Accessible Databases

Fig. 8 illustrates the proportions of data sources (i.e., computational simulation, field measurement, and lab test) in different structural branches. It is found that computational simulation is the major source of data in the bridge branch [Fig. 8(a)], occupying 43% of all the reviewed literature, followed by field measurement (40%) and lab tests (17%). Field measurement, by contrast, is the predominant source of data in the electric power systems branch. It is also the predominant source in the pipeline branch, which may be attributed to the fact that sensors have been widely used in the pipeline field for pipe break monitoring and detecting (Xie and Tian 2018).

Though databases derived from computational simulation and field measurement are more prevalent than those from lab tests in general, many of them are not accessible. To facilitate further research and support educational activities such as ML course and syllabus development for structural engineering students, Table 2 summarizes publicly accessible databases, together with their properties in terms of the source and size of databases and the structure type. From Table 2, most of the accessible databases are from lab tests with sizes mostly in hundreds and from field records with sizes in thousands (especially for electric power systems), while very few are from computational simulation but with much larger sizes from thousands to tens of thousands.

Progress of ML for Risk and Resilience Assessment

To provide an overall look at the progress of ML applications for structural risk and resilience assessment, Figs. 9–11 present pie charts to populate the attributes of analysis scale, topic area, and

Table 2. Accessible databases for ML implementation in structural engineering

Author(s) (year)	Data source	Structure type	Database size	Description
FHWA (1995)	Field records	Bridge	Over 615,000	US NBI
Yeh (1998, 2008)	Lab tests	Building/bridge	1,030	Compressive strength of concrete
Berry et al. (2004)	Lab tests	Building/bridge	434	Failure modes and force-displacement relationships of RC columns under cyclic load tests
Ospina et al. (2015)	Lab tests	Building	519	Punching shear strength of flat slabs
Ning and Li (2016)	Lab tests	Building/bridge	133	Plastic hinge length of RC columns
Karanci and Betti (2018)	Lab tests	Bridge	180	Bridge cables corrosion
Lu et al. (2018)	Lab tests	Building	158	Shear strength of corroded RC beams
Feng and Fu (2020)	Lab tests	Building	86	Shear strength of internal RC beam-column joints
Huang and Burton (2020)	Lab tests	Building	264	Failure modes and shear strength of masonry infilled frames
Mangalathu et al. (2020b)	Lab tests	Building	393	Failure modes and shear strength of RC shear walls
Chen et al. (2021)	Lab tests	Building/bridge	520	Bond strength between fiber-reinforced polymer and concrete
Degtyarev and Naser (2021)	Numerical simulation	Building	3,512	Shear strength of cold-formed steel channels
Feng et al. (2021c)	Lab tests	Building	434	Shear strength of squat RC walls
Feng et al. (2021b)	Lab tests	Building	271	Shear strength of RC deep beams
Guan et al. (2021)	Field records	Building	621	Seismic design of steel moment-resisting frame buildings
Guan et al. (2021)	Numerical simulation	Building	12,000	Seismic responses of steel moment-resisting frame buildings
Vu et al. (2021)	Lab tests	Building/bridge	1,017	Uniaxial compressive strength of concrete-filled steel tubular columns
Xu et al. (2021)	Lab tests	Building/bridge	217	Concrete-to-concrete interface shear strength
Mazumder et al. (2021a)	Lab tests	Pipeline	92	Burst failure data of metallic pipes compiled from literature
Li et al. (2005)	Field records	Utility wood pole	13,940	Field test data including age, initial strength, and one measurement per utility wood pole
Cui et al. (2013)	Field records	Power transformer	1,542	Dissolved gasses concentration and oil test results for power transformers condition assessment
Leauprasert et al. (2020)	Field records	Power transformer	350	Technical data and test results of 350 units of power transformers

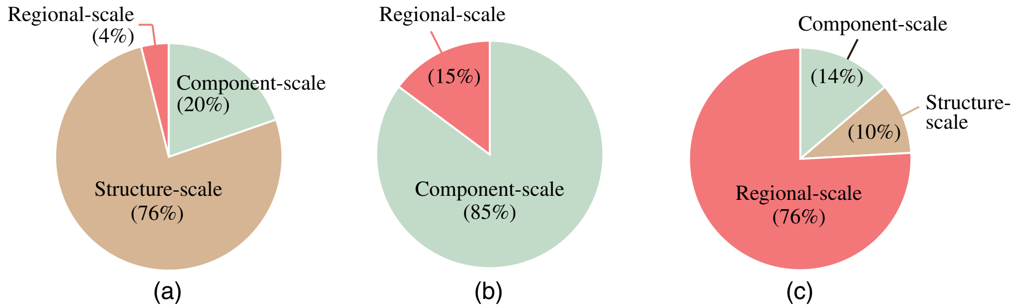

Fig. 9. Distribution of analysis scales in different branches of structural engineering: (a) bridges; (b) pipelines; and (c) electric power systems.

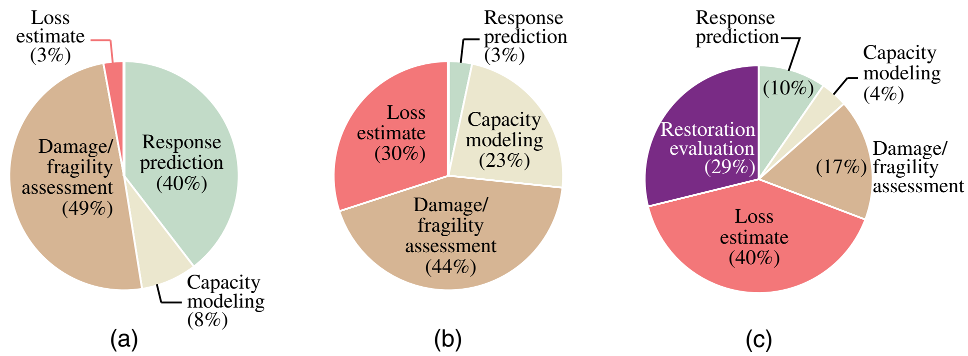

Fig. 10. Distribution of topic areas in different branches of structural engineering: (a) bridges; (b) pipelines; and (c) electric power systems.

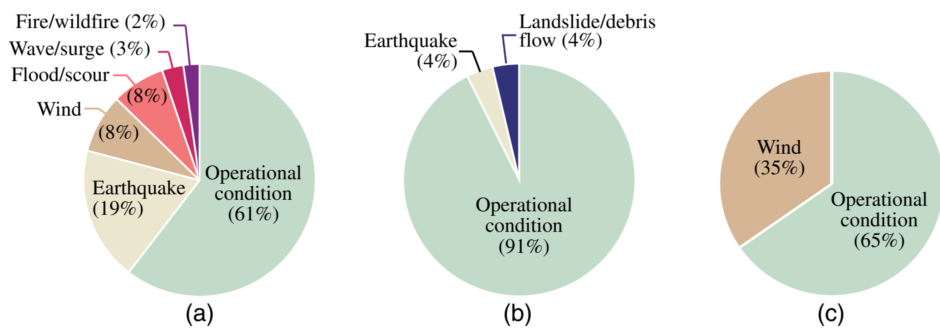

Fig. 11. Distribution of operational condition and extreme events in different branches of structural engineering: (a) bridges; (b) pipelines; and (c) electric power systems.

event type, respectively, in bridges, pipelines, and electric power systems. From Figs. 9 and 10, ML applications in bridges mainly fall into structure-scale studies on response prediction and damage/fragility assessment, while the majority of ML studies in pipelines are on component capacity modeling and associated damage/fragility assessment. ML-based loss estimation occupies 30% of the pipeline branch, but merely 3% in the bridge branch. Moreover, ML-based restoration evaluation is yet to be explored in both the bridge and the pipeline branches. By contrast, regional-scale loss estimation and restoration evaluation have been the main areas of ML applications in electric power systems. Regarding event types (Fig. 11), ML methods are more frequently applied under operational conditions (mainly for condition assessment) than extreme events, especially in the pipeline branch (91% of the ML applications are for the operational condition). As for extreme events, earthquakes are the major concern in bridges (followed by wind and flood hazards), while wind events (including hurricanes, typhoons, and cyclones) are all related to ML applications in electric power systems. The progress of ML in each structural branch is further discussed next.

Building Structures

As one of the oldest and most known branches in structural engineering, building structures' performance assessment has been intensively documented in the past two decades (Ezzeldin and El-Dakhakhni 2020). Sun et al. (2021) described that ML methods have been progressively applied for the design and analyses of buildings across the modules of the risk assessment framework, including (1) component and/or structure-level response prediction (e.g., Morfidis and Kostinakis 2017; Sun et al. 2019), (2) component-level capacity evaluation (e.g., Jeon et al. 2014;

Fu and Feng 2021), and (3) damage detection and fragility analyses of buildings (e.g., Kiani et al. 2019; Mangalathu et al. 2020c) using field, experimental, and computational data in different formats such as numeric data, images, videos, and written texts.

Other studies on ML-based risk assessment focusing on loss estimates are still rare and limited to earthquake events, e.g., (1) seismic collapse risk analyses of RC buildings in the US using various ML methods where the tree-based ensemble ones, XGBoost in particular, exhibit better performance (Hwang et al. 2021); (2) risk-informed seismic surrogate modeling of steel frame buildings in China using ANN, SVM, DT, and RF (Tang et al. 2021); and (3) seismic loss modeling of European building portfolios using ANN-based surrogate models that remarkably outperform the traditional probabilistic seismic demand models based on scalar intensity measures (IMs) (Kalakonas and Silva 2021). These studies used sophisticated numerical modeling and computationally cost analyzing processes for generating large-size databases that cover seismic hazard and structural features. Because of this time-consuming procedure for data preparation as well as the limitation of the developed ML models for specific types of building structures at specific earthquake-prone sites, the advantages of efficient ML-based risk assessment have not been fully utilized. In particular, a noted challenge is a scarcity of risk-informed databases. Therefore, more studies are warranted on various building portfolios with different construction materials and methods for developing, exchanging, and sharing the databases. Such research efforts would facilitate the emerging ML-aided regional-scale damage and risk assessment of building structures using active learning in particular to treat with extensively large data sets (Stojadinović et al. 2022; Tomar and Burton 2021). Different from ML applications in single-structure risk assessment (i.e., hazard, damage, and loss analysis modules), regional-scale risk assessment is characterized by the additionally unique module—exposure modeling that describes the quantity and distribution of buildings at risk in the regions of interest. Some ML progress for this module includes (1) utilizing DL techniques to scan streets to identify vulnerable soft-story buildings (Yu et al. 2020); (2) leveraging DL on stress and satellite images to rapidly extract building information (Gonzalez et al. 2020; Wang et al. 2021a); and (3) using ML classification algorithms to estimate the number of stories in houses for enriching the existing building inventory (Heresi and Miranda 2021).

ML techniques have also been applied in resilience assessment of building structures with an emphasis on the postdisaster recovery modeling. ML applications for this purpose evolve from early work on simply fitted RS models for postearthquake or posthurricane housing recovery estimates (Wu and Lindell 2004; Zhang and Peacock 2009) to recent progress on (1) fuzzy logic for postearthquake downtime estimates of building structures (De Iuliis et al. 2019); and (2) discrete state-dependent Markov process or continuous time-dependent stochastic process for postearthquake recovery time estimates of individual and/or portfolio-level buildings (e.g., Lin and Wang 2017; Kang et al. 2018; Dhulipala et al. 2021). A growing consensus is that recovery modeling of buildings needs to move forward toward the community and city scale and account for not only structural physical damage and resources for restoration, but also interdependent infrastructure facilities and associated environmental and socioeconomic factors (Costa et al. 2020). These factors are further discussed later as future research needs.

Bridge Infrastructure

Risk analyses of bridge infrastructure (from a single bridge to bridge portfolios, and to bridge-road networks) have been an active topic in the past two decades, especially for extreme events such as earthquakes (Sfahani et al. 2015), hurricanes (Balomenos et al. 2020), tsunamis (Akiyama et al. 2020), and scour (Briaud et al. 2014), as well as in a multihazard context (Li et al. 2012; Gidaris et al. 2017). Reliable risk assessment can provide quantitative consequence estimates that facilitate informed posthazard resilience assessment (Argyroudis et al. 2019; Banerjee et al. 2019). Fig. 12 shows the annual number of publications on ML applications for bridges under different extreme events. A noticeable increasing trend on both number of publications and hazard types is observed, indicating the growing interest in considering climate changes, especially for the extreme weather-related hazards such as wind and waves. These considerations will be further discussed in the next section.

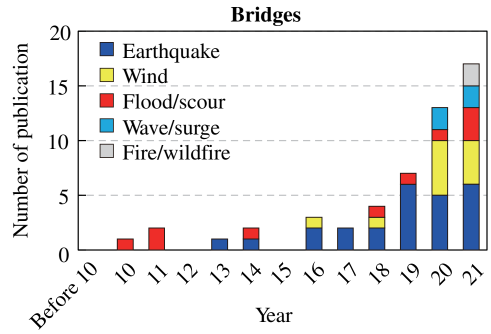

Fig. 12. Annual number of publications on ML applications for different extreme events in bridge infrastructure.

Similar to the building structure branch, ML applications in the risk assessment framework of bridge infrastructure mainly fall into the modules of response prediction (e.g., Du and Padgett 2020; Fang et al. 2020; Li et al. 2021; Wang et al. 2021c), component capacity estimates (e.g., Mangalathu and Jeon 2019a; Feng et al. 2020), and damage/fragility evaluation (e.g., Pang et al. 2014, 2021; Ataei and Padgett 2015; Mangalathu and Jeon 2019b; Kiani et al. 2019). The most popular and well-performed ML methods across these studies are ANN, SVM, and RF. In addition, there is a trend of increasing applications of other ensemble approaches such as XGBoost, owing to its outstanding performance on the prediction accuracy and the remarkable ability in interpretability of critical factors (e.g., Mangalathu et al. 2020a). Other ML-aided studies show a tendency on risk assessment and associated decision-making on optimal management of regional bridge infrastructure by leveraging, for instance, Markov decision processes (Fereshtehnejad and Shafieezadeh 2017; Tao et al. 2020), deep reinforcement learning that takes advantage of deep Q-learning (Andriotis and Papakonstantinou 2019), and active learning that are efficient for extensive data requirement scenarios (Mangalathu and Jeon 2020).

As for the resilience assessment of bridge infrastructure, applications of ML on recovery modeling are still limited. Nonetheless, it is worth mentioning the current prevailing practices that utilize traditional methods, including (1) expert judgment-based empirical recovery modeling using simple mathematical functions such as linear, exponential, and trigonometric functions (Shinozuka et al. 2003; Kafali and Grigoriu 2005; Cimellaro et al. 2010a); (2) field survey and expert questionnaire-based recovery trajectory modeling that account for resources for repair and restoration (Kammouh et al. 2018; Misra et al. 2020; Mitoulis et al. 2021); (3) simulation-based probabilistic recovery modeling elaborately considering impacts of the restoration construction process on traffic disruptions as well as resource availability from component to system levels (Karamlou and Bocchini 2017); and (4) search-based global optimization methods (e.g., genetic algorithm) for postevent recovery trajectory optimization of bridge-road networks (Zhang et al. 2017), and Markov decision process-based life-cycle seismic resilience assessment of bridges (Tao et al. 2021). These methods successfully facilitate the progress of resilience assessment in bridge infrastructure, although they have different levels of limitations, such as the simplification in early empirical models that accounts for limited information of the physical recovery process and the extensive computational burden in the traditional global optimization methods for preevent prediction in particular. More importantly, these studies have boosted the development of databases on recovery modeling (e.g., restoration construction methods, durations, trajectories, and traffic interrupts). Therefore, it is expected to see emerging and increasing ML applications in recovery modeling of bridge infrastructure in the very near future. In particular, recently advanced ML-based recovery modeling in other structural engineering branches such as electric power systems (Dehghani et al. 2021a), as interpreted next, can shed light on similar ML applications in bridge infrastructure.

Pipeline Infrastructure

ML and AI have been extensively applied for analyzing the performance of pipeline infrastructure systems (i.e., water distribution systems, oil and gas transportation systems). While the application of ML gained significant attention in recent years, most existing works focused on analyzing the performance of individual pipelines subjected to corrosion deterioration and leakage detection.

El-Abbasy et al. (2014) applied an ANN model to predict the failure of oil and gas pipelines using a data set of historical failures. This model can predict the failure types besides corrosion, such as mechanical, third party, natural hazard, and operational. Senouci et al. (2014) further applied fuzzy logic for predicting the failure types of oil and gas pipelines using the same data set. This study revealed that the fuzzy-based technique outperformed ANN models concerning model validity. Senouci et al. (2014) used five input features (i.e., type of transported product, pipeline location, pipeline age, land use, and pipeline diameter) as the ML models' input features to predict the pipeline's failure type. Five pipeline failure types are considered: mechanical failure, operational failure, failure caused by corrosion, failure caused by natural hazards, and failure caused by a third party. Rashid et al. (2015) applied smart wireless sensors for detecting leakage in long-range pipelines. Their model utilized wireless communication and ML to autonomously learn, make decisions, and report critical activities in the natural oil and gas pipeline. SVM, K-nearest neighbors (KNN), and naïve Bayes were used to analyze sensor data to identify leakage size and location.

Su et al. (2021) used DL algorithms to assess the influence of corrosion on the reliability of corroded pipelines. Failure pressures of pipelines were estimated using ASME (2009), DNV (2004), and PCORRC (Stephens and Leis 2000) standards and the finite-element method. A total of 150 groups of finite-element model–simulated and 142 groups of burst pressure test data were used for the training and accuracy testing of the DL algorithms. The DL algorithms showed high prediction accuracy. Li et al. (2019) compared ANN and SVM to evaluate the vulnerability of urban buried gas pipeline networks. The model selection phase for SVM was relatively simpler than designing ANN architecture, which led to an overfitting problem for ANN. Although both approaches provide similar and consistent outputs, the training output of SVM fitted better than ANN. Liu et al. (2019) modeled a leakage detection technique applying ML and wireless sensors. SVM was applied to enhance the precision and intelligence of leakage detection. This study suggested that the leakage identification method can effectively identify the leaks in water pipelines and has lower energy consumption than the conventional networking methods.

Kumar et al. (2018) developed a CNN to analyze inspection videos of sewer pipelines to detect three types of defects (i.e., deposits, root intrusion, and cracks) in sewer pipes. The outcomes of this study provide a good level of accuracy (about 87%) in defect detection. Similarly, Hassan et al. (2019) developed CNN to classify a large data set with 47,000 images of defects, debris silty, joint faulty, joint open, lateral protruding, and surface damage. Ouadah (2018) used ANN, DT, and the analytic hierarchy process for assessing the defect risk of pipelines.

Muhammad et al. (2021) applied an ensemble boosting ML algorithm to the pipeline failure data set to develop an effective ensemble prediction model capable of greater accuracy. The research experiments were conducted utilizing the Conservation of Clean Air and Water in Europe database. The proposed boosting model generated better results than other ML methods. Lu et al. (2021) proposed a new data-driven framework for predicting the residual strength of corroded pipelines. The prediction framework utilized PCA and SVM ML modules. PCA was used to reduce the dimensions of the existing data to determine the input-output structure of the prediction model. SVM was employed to predict the pipeline's residual strength. This framework showed good prediction accuracy and stability with burst failure test data. Xu and Sinha (2021) modeled pipe break data using survival analysis with ML imputation methods. Two ANN models are developed as imputation methods to calibrate the survival data. The authors concluded that the use of the imputation method improves the survival analysis results and mitigates the impact of left-truncated break records. Mazumder et al. (2021a) investigated the feasibility of ML techniques for predicting burst failure of steel oil and gas pipelines. The efficiency of eight ML techniques (i.e., KNN, DT, RF, naïve Bayes, and four boosting algorithms) was compared using a set of data derived from experimental burst failure tests. This study revealed that boosting algorithms performed better in burst failure risk detection of pipelines. The authors also showed that ML algorithms could predict the burst failure risk of pipelines with better efficiency and accuracy than physical models.

While most of the past studies applied ML for estimating the performance of pipelines under normal operating conditions, ML application for pipeline performance analysis subjected to natural hazards is rare. Ni et al. (2020) performed a fragility analysis of pipelines due to permanent fault displacement using LASSO regression. Multidimensional fragility curves were generated through LASSO regression, where the relative importance of risk parameters was determined. Prediction results suggested that the fault displacement and fault–pipe crossing angle are the most influential parameters in seismic risk analysis of pipelines in fault zones. Bagriacik et al. (2018) compared statistical and ML models to estimate seismic damage in water pipelines. The authors analyzed a large number of data sets of damaged water pipelines from the 2011 Christchurch earthquake. Three ML algorithms (i.e., LR, boosted regression trees, RF) and repair rate approaches are used in predicting pipeline damage. Although the boosted regression tree offers the best overall performance, LR offers the advantages of a closed-form solution and can compare pipe materials explicitly. The repair rate method is very good at predicting the total number of damaged pipes, though is less capable of predicting the failure of an individual pipe.

Electric Power Systems

Risk and resilience assessment and management of power systems involve modeling network reliability considering the impact of disruptive events such as natural hazards, intentional attacks, and accidental events. Change in network reliability due to a disruptive event is used to quantify risks to the network, plan resilience improvement and risk management actions, and evaluate the effectiveness of the actions. Methods for evaluating power system reliability can be broadly classified into connectivity- and flow-based models. Both models are complex and can be computationally prohibitive, especially for risk and resilience assessment, where all possible hazard events and intensities need to be considered. To avoid the complexity of network modeling, some researchers have proposed statistical methods mainly based on regression analysis to predict the magnitude, spatial variation, and duration of power outages, mainly considering weather-related events (Liu et al. 2005; Guikema et al. 2006, 2014; Guikema and Goffelt 2008; Han et al. 2009; Nateghi et al. 2011, 2014). Statistical methods, however, have resulted in models with insufficient accuracy (Kabir et al. 2019).

Recently, ML-based models have been proposed for power outage forecasting, reliability analysis, and resilience enhancement as an improvement to the accuracy of statistical methods. ML models for tropical cyclone-related power outage forecasting involve using storm event data, local weather data, and grid damage data from previous events to forecast the extent, duration, and spatial distribution of power outages. Classical ML algorithms such as boosting algorithms (Kankanala et al. 2013; Nateghi 2018), Bayesian network with Gaussian process algorithms (Lu and Zhang 2021), weighted extreme learning machine (ELM) and long short-term memory model (LSTM) (Oh et al. 2021), and cost-sensitive algorithms (Jufri et al. 2019) have been used to predict power outages. However, classical ML algorithms can lead to bias and inaccurate models because outage data are zero-inflated, and outages are stochastic with irreducible variability (Kabir et al. 2019). Hence, an ML model can show good accuracy by always predicting zero outages. To overcome such limitations, Kabir et al. (2019) proposed a two-stage model that solves the challenge of zero-inflated data by incorporating unbalanced learning techniques (resampling and cost-sensitive learning) into the model.

ML models for reliability analysis employ active learning techniques to overcome the computational complexity of flow-based reliability models. For example, Dehghani et al. (2021b) proposed an active learning approach for network reliability analysis that integrates Bayesian additive regression trees and Monte Carlo simulation. ML-based models for optimal power grid resilience enhancement decisions have also been proposed (Dehghani et al. 2021a). Optimization of long-term resilience enhancement decisions is often formulated as a combinatorial optimization problem that is difficult to solve due to its computational complexity. This challenge can be overcome by using reinforcement learning, which systematically and automatically learns from heuristics (Dehghani et al. 2021a). Recently, Assis et al. (2021) used three unsupervised ML techniques to reduce the computational effort of using nonsequential Monte Carlo simulation to evaluate the reliability of composite generation and transmission systems. Similarly, Duchesne et al. (2017) used supervised ML techniques to develop a simplified model for real-time power system reliability management. The developed model was able to identify the most relevant variables for reliability management and was shown to be able to predict the reliability level of the system accounting for uncertainties.

The use of AI for power system restoration has also been proposed in the literature (Nagata et al. 1995; Chin and Su 2005; Liu and Gu 2007; El-Werfelli et al. 2009). However, because reconfiguration for power system restoration results in a huge solution space, the problem is typically divided into two sequential stages to limit its complexity (El-Werfelli et al. 2009). The use of AI is limited to the first stage of determining an optimal reconfiguration for the system. The use of ML for detecting cyberattacks on power systems has also been investigated (Hink et al. 2014; Pan et al. 2015; Liu et al. 2020; Sayghe et al. 2020). Cyberattacks differ from other causes of disturbances such as natural hazards because there is an overt attempt to disguise the attack. Hence, ML can be a good approach to detect cyberattacks as it can simultaneously assess many variables related to the operation of the system and study behavioral patterns to detect malicious and anomalous events.

The use of ML for condition assessment of power system components is also becoming common in the literature. ML has especially been applied for condition assessment of transformers (Hao and Dong 2011; Ma et al. 2012; Cui et al. 2013; Leauprasert et al. 2020). This is because transformers are among the most critical assets in a power system, and their failure significantly impacts the reliable delivery of electricity. In the past, electrical and chemical techniques [e.g., polarization and depolarization current (PDC) measurements and dissolved gas analysis (DGA)] have been used for condition assessment of transformers. However, it is still challenging to accurately interpret measured data and explicitly infer a transformer's condition using such methods. ML techniques have been shown to have the potential to overcome such challenges (Ma et al. 2012). ML has also been used for condition assessment of power distribution cables using partial discharge, aging, and damage data (Mousavi and Butler-Purry 2009; Parrado-Hernández et al. 2018; Codjo et al. 2021). Additionally, ML methods have been used for the condition assessment of transmission towers and insulating systems considering weather-driven factors (Dehghanian et al. 2019). Data used in the models include condition monitoring data for insulators and conductors; inspection data and human judgment for tower structures, foundations, and auxiliaries; and line resistance data as a function of temperature.

One challenge to the application of ML for risk and resilience assessment of power systems is data sparsity. This is mainly because storm data and grid damage data are recorded by different entities that have different observation locations and use different time frames. Also, extreme events that cause widespread outages are rare; hence, adequate data on the behavior of power grids might not be available. More research on zero-inflated data is also needed to improve the accuracy of the ML techniques. Finally, power system variables (equipment, technology, operation), climate, and weather conditions that affect tropical cyclones, thunderstorms, and other hazards are changing (Kabir et al. 2019). Hence, more research is needed to account for the changing conditions and data.

Challenges and Emerging Research Needs

Data Availability, Quantity, Quality, and Model Interpretability

Data availability is an essential premise for ML model development, while the accessibility of ML models is a vital factor for the broad application of these models by users. Recalling Table 2, data availability has become less an issue under operational conditions owing to advancements in SHM theories and practices [e.g., the continuous expansion of the NBI data set (FHWA 1995)] and the accelerated development and increasing applications of emerging techniques such as smart wired/wireless data recording, transmission, and fusion techniques (Diego et al. 2015; Abas et al. 2018; Diez-Olivan et al. 2019), together with Internet of Things (IoT) (Din et al. 2019) that can facilitate the development of real-time data sets in large spatiotemporal scales for ML-based life-cycle risk and resilience assessment and unmanned aerial vehicles (UAVs)

(Morgenthal and Hallermann 2014) that can monitor structures and enable rapid damage assessment using ML-aided computer-vision techniques (Wang et al. 2021d), particularly for scenarios where human inspections are not feasible. Under extreme events, by contrast, data availability is still facing strong challenges for high-fidelity ML modeling for risk and resilience assessment purposes. ML-based high-confidence hazard analyses have been documented for earthquakes (Xie et al. 2020) based on the well-established strong motion databases such as the PEER NGA West2 database (Ancheta et al. 2014), while more research is warranted for other types of extreme events such as hurricanes (Szczyrba et al. 2021), storm surge (Lee et al. 2021), and wildfires (Jain et al. 2020). In this regard, a future research need is to establish, improve, and expand databases for these extreme hazards. An ongoing good example is the Severe Weather Data Inventory of the National Oceanic and Atmospheric Administration (Ansari et al. 2009). On the other hand, limited accessibility to the developed ML models has been a common problem in previous studies, particularly those before 2015. However, this problem is being gradually resolved following the development of cloud storage and cyberinfrastructure such as DesignSafe (Rathje et al. 2017) that allow users to upload, store, and share ML models.

Regarding data quantity and quality, an ideal data set shall have a sufficiently large size and cover all potential features, such that it can develop high-generality ML models. While a handful of studies have provided preliminary suggestions on the minimum size required with respect to the number of input variables for different kinds of engineering problems (Hastie et al. 2009), there is still a lack of recognized criteria to evaluate the quantity and quality of data sets. In that respect, it is vital to establish standards and criteria for data recording, storage, and sharing to ensure the quantity and quality across different structural engineering areas, such that it boosts an integrated study on community-level risk and resilience assessment by taking advantage of ML. In the meantime, developing high-fidelity predictive models using data sets with limited high-quality data, especially for strong nonlinear and high-dimensional problems, which are common situations in risk assessment of structures under extreme events, is still an emerging topic where more theoretical and practical studies are required (Li and Jia 2020; Chen and Feng 2022).

Model interpretability is attracting more and more attention to address the common critique of the black box feature in ML models (Mangalathu et al. 2020a, 2021; Feng et al. 2021c; Somala et al. 2021). The primary role of model interpretability for structural risk and resilience assessment is to elucidate relationships between the input and output variables, reveal sources of involved uncertainties and quantify their magnitudes so that stakeholders can make informed decisions based on the explainable ML models, and more importantly, identify scenarios where the ML models are not reliable. Across the surveyed literature, the most popular approach for ML model interpretability is SHapley Additive exPlanations (SHAP) (Lundberg and Lee 2017), while other approaches such as partial dependence plot (PDP) (Friedman 2001), local interpretable model-agnostic explanations (LIME) (Ribeiro et al. 2016), and accumulated local effects (ALE) (Apley and Zhu 2020) are relatively less used. Features and applicability of these approaches in earthquake engineering have been elucidated recently (Mangalathu et al. 2022), but there is no clear consensus on the applicability of these methods for other extreme events. Further, more efforts are needed to solve limitations in the existing approaches—for instance, the correlation-causality inconsistency, unintuitive explanation, and multicollinearity issues in SHAP, and the instability of the explanations in LIME.

Optimization and Evolution of ML Methods for Risk Assessment

As various sources of uncertainties exist and propagate throughout performance-based engineering frameworks (i.e., from hazard analysis to structural damage estimation, and to loss evaluation modules), it is paramount to increase the accuracy of ML models for reliable risk assessment. To this end, one prevailing path is the cross-validation-based optimization of ML algorithms in terms of architecture, kernel/activation function, and learning rate (Mangalathu et al. 2018; Wang et al. 2021c; Xu et al. 2021). However, such an optimization process is often treated as case-dependent and thereby time-consuming to some extent, which inevitably trades off the advantage of efficiency in ML modeling. Thus, it is crucial to explore universal solutions for the optimum parameters in ML methods for various structural engineering problems. Note that such universal solutions are reasonably viable for scaler data sets because regardless of problem types, they are always normalized or standardized to the same range (e.g., ranged in [0,1] by normalization or in a standard normal distribution by standardization) before ML modeling.

Other paths to increase the accuracy of ML models can be summarized as the evolution of ML methods, such as (1) improving loss functions in DL using physics-based information for the accurate prediction of time-history responses of structures under earthquakes (Zhang et al. 2020) or using knowledge-based information for accurate estimates of structural responses against wind loads (Wang and Wu 2020); (2) refining DL architecture through high-order transmission between hidden layers for highly nonlinear problems in developing ground motion prediction models (Ji et al. 2021); (3) developing hybrid ML models, for instance, by semisupervised learning to find optimum solutions for sensor placement and achieve high-confidence leakage detection of large spatial water distribution networks (Fan and Yu 2021), or by Bayesian model averaging techniques that take advantage of individual ML models to improve the prediction of plastic hinge lengths of RC columns (Feng et al. 2021a); (4) coupling ML-based data-driven prediction models with physics-based ones such as hysteretic models of structural components for highly efficient and robust seismic response estimates of structures (Luo and Paal 2021); (5) combining ML with digital twin to enhance data interpretation for real-time risk assessment and management of structures such as oil pipelines in a life-cycle context (Priyanka et al. 2021); and (6) enhancing data acquisition with geographic information and census systems to cover more features on engineering, geology, environmental, and socioeconomic dimensions for better understanding of risk to structural and infrastructure facilities and communities (Cardoni et al. 2021; Fan et al. 2022). The aforementioned evolution of ML methods can be enhanced and expanded further for advancing the risk and resilience assessment methodologies.

Interdependent Infrastructure Risk Assessment

The interdependency between complex critical infrastructure systems has increased with rapid urbanization, economic development, new technological innovation, and advancement in cyberinfrastructure management. The complex interdependency of critical infrastructure systems exists due to the input-output linkages, physical proximity, functional and logical linkages, and shared infrastructure resources (Rinaldi et al. 2001; Atef and Moselhi 2013; Mazumder et al. 2018). Failure in one critical infrastructure system often leads to functionality loss of dependent infrastructure systems, which may result in social and economic disruption in severe cases (Mazumder et al. 2021b). Most of the existing design standards provide guidelines for the design and assessment of individual components but do not provide a detailed guideline on analyzing interdependency between infrastructure systems (Ghosn et al. 2016; Mazumder et al. 2018). While interdependency in complex infrastructure systems has been long recognized (Dueñas-Osorio et al. 2007; Hernandez-Fajardo and Dueñas-Osorio 2013; Ghosn et al. 2016; Mazumder et al. 2018), an area that has received less attention is estimating functionality and resilience of infrastructure systems considering the complex effect of interdependencies and cascading failure in infrastructure systems. To the best of the authors' knowledge, recent advancements in ML and AI techniques have not been explored extensively for analyzing the interdependency between infrastructure systems. Limited efforts have been made in analyzing the resilience of interdependent infrastructure systems using ML and AI algorithms, such as reinforcement, DL, and network theory (Sun and Zhang 2020; Wang et al. 2021b; Mazumder et al. 2021b).

Risk analysis and risk management of infrastructure systems are often complicated by the infrastructure systems' interdependencies (Loggins and Wallace 2015). ML algorithms, particularly RF and boosting algorithms, have shown promise for predicting the performance of infrastructure components (DeRousseau et al. 2019). Applying ML, AI, and complex network theory, it is possible to quickly estimate damages to infrastructure components subject to extreme hazards and identify how damage propagates to other interdependent infrastructure systems. Modeling infrastructure damage and its cascading effect through a realistic testbed analysis can help to identify the critical components for risk mitigation planning.

ML techniques can perform infrastructure damage analysis significantly faster than the conventional physics-based models (Mazumder et al. 2021a). Hence, ML and AI can overcome the large computational cost required for complex and large infrastructure damage analysis for risk and resilience quantification. Although past studies have made significant progress toward risk and resilience assessment, most of them are focused on analyzing the interdependency between physical infrastructure systems. However, failure in infrastructure systems also disrupts social and cyberinfrastructure systems (Yagan et al. 2012; Tu et al. 2019). Understanding and modeling all dimensions of complex interdependencies are crucial for developing effective risk mitigation strategies. While modeling cyber-physical-social interdependencies is challenging using existing approaches, the application of ML and complex graph theory can be key enablers for future modeling of cyber-physical-social infrastructure systems.

Regional-Level Resilience Assessment

There is a growing need for the use of ML techniques to turn disaster data into practical and suitable tools for improving hazard resilience for large-scale natural hazards (Arslan et al. 2017). Such tools can facilitate predisaster resource allocation; minimize fatalities, injuries and economic impact; provide a better postdisaster response; and make communities more hazard resilient. For example, Yousefi et al. (2020) investigated models to predict multiple hazards including snow avalanches, landslides, wildfires, land subsidence, and floods using ML techniques (i.e., RS, SVM, and GTB). The predictive model can be used for improving hazard resilience at a regional scale. Sangeetha and Jayakumar (2018) used ML to predict flash floods using data from soil moisture and rainfall volume. Liu et al. (2017) examined the role of resolution of the satellite images or aerial imagery for the detection of flood extent in urban areas. Pyayt et al. (2011) proposed a method for monitoring flood protection systems (i.e., a dike) utilizing ML techniques from real-time measurements from the installed sensors.

What remains challenging is how to use ML to better predict future hazards from historical data and meet the needs of improved hazard resilience (Saravi et al. 2019). Furthermore, applying modern technical developments such as ML for ensuring resilience, particularly critical infrastructures, has not yet been fully utilized (Dick et al. 2019). So far, some examples of the progress in this aspect that have been made include data-driven power outage detection by social sensors to improve resilience to weather-related outages (Sun et al. 2016), ML-aided determination of structural integrity for structural engineering (Lee et al. 2018), and a summary of DL-based SHM of civil infrastructures (Ye et al. 2019). Hegde and Rokseth (2020) showed that even though there are about 30 different risk assessment techniques, very few have the ability of real-time risk assessment. As timely risk assessment is very important to regional-level resilience analysis for decision-makers, the increasing role of ML in facilitating such assessments in the near future can be expected.

Consideration of Climate Changes

Changes in climate patterns, especially weather extremes, have created a highly uncertain and increasingly volatile environment for infrastructure systems. Indeed, climate change is anticipated to impact many hazards to the built environment. As an example, projections indicate that the relative sea level along the coasts of the US may rise by over 14 in. by 2080 under a low global mean sea level rise scenario (Sweet et al. 2017), which is very likely to be exceeded under various climate change projections. This rise in relative sea level will increase the annual frequency of damaging flood events by 25 times (Wuebbles et al. 2017), which will have devastating impacts on buildings, energy and transportation infrastructure, and other critical built and natural systems in coastal regions, and will extend the reach of coastal flooding to areas further inland. While there are differences in the projected impacts, studies generally indicate that stresses to the built environment in the US will increase, and in some parts of the country the increase will be substantial (Wuebbles et al. 2017).

Understanding climate change and its implications for the built environment and developing effective strategies to tackle its adverse effects require transdisciplinary research that involves multiple disciplines (Bendito and Barrios 2016). For the purposes of this review paper that focuses on advancements and applications of AI and ML in structural engineering, this section presents a brief overview of research on climate change related to structural engineering applications using AI and ML methods. The areas of interest are categorized into modeling variations in loads on the built environment as the result of climate change and assessment of the impacts.

To improve short-term streamflow forecasting considering climate change effects, genetic programming and ANN models have been applied (Makkeasorn et al. 2008). Such models can be used in flood warning systems, and the longer projections can improve the understanding of future flood loads on structural components and infrastructure systems. This objective was pursued through the inclusion of sea surface temperature along with other meteorological data to forecast discharges in a watershed in south Texas. The genetic programming model was found to noticeably improve forecasting capabilities relative to other techniques. Sarzaeim et al. (2017) implemented several ML techniques including genetic programming, ANN, and SVM to project runoffs under climate change effects. SVM was found to outperform other techniques.

ML methods have been applied in several studies to project the state of the hazards that will impact the built environment under climate change conditions. Lin and Cha (2020) predicted hurricane characteristics for near- and long-term projections using nonlinear autoregressive ANN with exogenous input. Applying this approach, nonstationary hurricane parameters, including the central pressure difference and the ratio of the number of high-intensity hurricanes to the number of total hurricanes in a year, were derived. Based on these results, hurricane tracks were developed for multiple regions along the southeastern US coast, and hurricane risks to the building stock for current, near-term, and long-term projection scenarios were assessed. Snaiki et al. (2020) used a multilayer feedforward backpropagation network to associate peak storm surge to standard hurricane parameters including central pressure, translational speed, radius of maximum winds, and storm track. The large database of synthetic tropical storms developed by the US Army Corp. of Engineers was used to train the ML model. The projected effects of climate change on hurricane storm surge and winds were subsequently analyzed for coastal bridges in the northeast US coastline.

Areas that remain to further explore include integration of physics-based computational and data-driven approaches to increase the fidelity of projections of hazards and their impacts on structures and infrastructure systems under climate change scenarios, quantification of uncertainties, and development of adaptation and mitigation strategies. For the latter challenge, deep reinforcement learning methods provide a viable framework for decision-making under uncertainty that can be leveraged for planning and sequential decision-making problems that the society faces for mitigation and adaptation decisions.

Summary

This article provides a comprehensive review of ML applications for risk and resilience assessment in structural engineering in terms of four major branches: buildings, bridges, pipelines, and electric power systems. The reviewed publications are characterized by six attributes (i.e., ML methods, task types, data sources, analysis scales, topic areas, and event types) to understand the progress and the state of the art of ML for structural risk and resilience assessment. Accessible databases are tabulated for the sake of further research and education. Crucial challenges and future research needs are highlighted as follows.

Data scarcity and sparsity, especially the lack of precise field records for natural hazard events in large spatiotemporal scales, are still a noticeable challenge for ML modeling, validation, and verification toward risk- and/or resilience-informed high-fidelity inference and decision-support machines. Therefore, expanding existing databases and developing high-quality new databases are imminently warranted for future studies. Besides, developing ML models that can understand the underlying mechanisms of structure and infrastructure systems is another challenge. To this end, physics-guided ML modeling is an area where more studies are needed, particularly to fill a crucial research gap of how to ensure a positive contribution of the physical knowledge in ML modeling.

With growing concerns related to impacts of natural hazards on complex and interdependent civil infrastructure systems, risk and resilience analysis has become crucial in infrastructure asset management. Although ML application has gained considerable attention in the last decade due to its ability to handle large data sets efficiently, ML application on complex interdependency and cascading failure analysis of interdependent civil infrastructure systems is limited. Modeling complex interdependencies is crucial for effective planning of risk mitigation. Future applications of ML can be key enablers for resilience modeling of infrastructure systems.

Finally, as climate change continues to be a serious concern with the rise in greenhouse gas emissions, many weather-related hazards are anticipated to be affected. It is therefore necessary to develop the capabilities to forecast the characteristics of changing hazards in the future and effective mitigation and adaptation strategies to reduce future economic and societal risks. While ML methods have been used in the development of such capabilities, integration of data and physics models for improved long-term forecasting of weather and climate hazards as well as decision-making under deep uncertainty are among key areas where ML methods can make significant contributions in the future.

Data Availability Statement

Some or all data, models, and codes that support the findings of the study are available from the corresponding author upon reasonable request.

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