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Application of Machine Learning in Structural Engineering: A Review of Predictive Models and Design Optimization

Methal Qudori Ali[1], Eman Abbas Abood[2], Mohammed Hazim Mohammed[3]

[1]Iraqi Ministry of Higher Education and Scientific Research, Baghdad, Iraq
[2]The Higher Institute of Forensic Sciences/Department of Forensic Engineering, University of Al-Nahrain, Baghdad, Iraq
[3]Iraqi Ministry of Higher Education and Scientific Research, Baghdad, Iraq

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ABSTRACT

In the field of mechanical engineering served as a tool for addressing complex problems in the Structural Engineering due to enabling fact-pushed structural framework evaluation, prediction and optimisation. Different from different literature opinions in concentrating mainly around individual machine learning machine learning paradigm and individual structural application areas, right here we develop a unified and contrasting research for supervised, unsupervised and reinforcement learning methods in the context of structural engineering along with the current developments of physics-informed and hybrid learning frameworks for future Structural Engineering. In the present statistical era, and the advancements made in processing capacity, a mixed framework is examined with the less complex strategy to deal with established engineering solutions towards applying neighbourhood engineering for starting point and detailing the easy way of the examine gadget, and the supervised based totally on memorisation, unsupervised and the reinforcements for each one the paradigms within the Structural Engineering together with structural diagram automatic checks, optimisation, structural overall health tracking, and consequently on. Apart from the statistical efficiency of various gadgets concerning algorithmic intricacy, desirable characteristics, merits and demerits, comparison features related to style discovering of the multi machines also be examined; the content will straight handle with the main limitations of smart systems that prevent a widespread adoption in structural engineering research, the consequences of combination of physics based models with the artificial intelligence demonstrate a terrific prospect for enhancing performance in structural check, monitoring, style procedures, but, we highlight a need of hybrid approach in blending data driven methods along with customary engineering principles, with special reference to their relevance to use in the linear frameworks within the structure study.

1. Introduction

Machine learning (ML) has been one of the major technologies in Artificial Intelligence(AI) that have made substantial impact on various scientific and technological areas. Applications of machine learning (ML) technique are rapidly growing in the field of Structural Engineering in image analysis(ML), multi-object tracking, multi-target regression, detecting thermal infrared stress and estimating structural stress[1],[2],[3],[4],[5],[6]. In general, Machine Learning(ML) works by the fact that computer system applies various complex algorithms on data and reveals its intricate pattern with concealed association between them. More interestingly, ML system is capable to explore the hidden similar patterns

Corresponding author E-mail address: Mohammed_hazim2013@yahoo.com
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from data, even when there are not clearly-understood underlying physical phenomena.

ML technology has many advantage over any traditional model for many tasks, and in particular, ML algorithm can continuously improve over time by adapting its internal mechanism by incorporating more new coming information[8]. Essentially, ML algorithms have typically three input elements which is composed of input data, algorithm learning procedure and the output. Data is the most important part of machine learning applications. Typically, it is a set of observations representing different opportunities or object in the environment or system under study. Each observation has a set of characteristics, that we measure either together or infer from statistics and observations[7],[9],[10]. In view of the facts that each attribute can be measured with specific number in an attribute vector, increasing variety of applications generates a good dimension space, thus it has been necessary to resort to dimensional discount methods so as to manage the task efficiently [1],[11]. Supervised machine learning of smart objects(SML), unsupervised machine learning(UML), and reinforcement machine learning(RML) are three categories of which data acquiring approaches of smart objects largely classified into, which are neuronal networks[12], Guided vector machine[13], Random statistical models [14],[15],[16] , decision tree algorithm[17] are typical examples of supervisory expert algorithms; Deep Boltzmann machine [20], competitive learning algorithms[18],k-means clustering and hierarchical clustering algorithm[19] are typical examples of techniques in learning data without labels; algorithms like Q-learning[22] and temporal difference learning[23] are typical examples of Reinforcement Learning that specially focuses on learning the correct behaviors by interacting with environment [21]. The suitable smartphone to learn a pattern is highly dependent upon the application circumstances, and must be statistical. Supervised learning algorithms are generally utilized when a labeled dataset is available; in such circumstances, the learning algorithms enable the models to recognize the correlations among input attributes, as well as known output value, and then forecast unknown value [24].

This particular property makessupervised machine learning techniques broadly suitable for material characterization and health monitoring. Inversely, unsupervised learning algorithms are very appropriate for large number of unlabeled datasets; these models typically help the system identify hidden structures, groups, or patterns within the dataset, for which example applications include exploratory data analysis, anomaly detection, or clustering [25]. One area that is not so popularly considered in applications related to structural engineering is reinforcement learning, which trains an agent to learn by repeatedly taking actions that maximize a cumulative reward signal [26].

Such approach works particularly well for control problem where sequence of decision making is necessary,and through interaction and feedback, it may ultimately determine optimal policy in complex scenario.

The past few years have seen structural engineering move beyond black-box data-driven machine learning models toward a more hybrid approach integrating machine learning with physical knowledge, numerical simulation, and expert engineering practices. Physics-informed neural networks, hybrid finite element machine learning methods, digital twins, and transfer learning approaches have recently achieved improved robustness, interpretability and generalization compared with previous machine learning approaches. Yet, only a handful of review articles have taken a critical look at this paradigm transition and compared these new models to conventional ones on the basis of their benefits and limitations in diverse Structural Engineering applications. This paper takes such a step and provides a unified overview of traditional and next-generation machine learning methodologies.

There have been many machine learning applications developed in Structural Engineering, but the review literature is fragmented. Previous reviews usually address one particular machine learning methodology (e.g., supervised learning in structural health monitoring, deep learning in damage detection), but have limited discussion on other learning types such as unsupervised, reinforcement learning or newer hybrid approaches. Besides algorithmic performance, the majority of previous reviews fail to comprehensively discuss the practical issues and challenges, such as data sparsity, interpretability, computational efficiency, generalization and the incorporation with physical structure modeling. As a result, structural researchers and engineers do not have a consolidated review to rely upon, comparing machine learning paradigms from both computation and application perspectives.

Taking inspiration from the above challenges, this review aims to provide a systematic and critical comparison of supervised learning, unsupervised learning, and reinforcement learning paradigms in Structural Engineering.

The review summarizes representative applications for each paradigm and critically discusses their advantages, limitations, computational efficiencies, and practical feasibility in various fields such as structural health monitoring, structural assessment, structural design optimization, computational mechanics and smart infrastructure. In addition, this review highlights open issues (limited availability of labeled data, dependence on synthetic finite element data, transparency/explainability of models, physics-guided hybrid frameworks) and promising research directions towards building more reliable and deployable machine learning for Structural Engineering. Structure of the rest of this paper.

The fundamental concepts of various machine learning paradigms applied to structural engineering are introduced in Section 2. Recent applications of supervised, unsupervised, and reinforcement learning are surveyed in Sections 3–5, respectively. Section 6 compares various machine learning paradigms. Section 7 summarizes the research gaps, limits and challenges and offers some future directions. Section 8 discuss Emerging Trends and Comparative Perspective. Section 9 concludes this review.

2. Types of Machine Learning

2.1 Supervised machine learning

Machine learning has seen enormous use of this supervised learning algorithm. The basis of this paradigm is that learning occurs from experience or samples. We refer to this learning algorithm as “supervised” as labeled examples are provided in the course of the learning process which the algorithm use as a learning curriculum in the same sense as a teacher does. In this method, all of the training inputs have corresponding training output [28].

The learning algorithm identifies the relationship between these input and outputs [29].

Figure 1 illustrate how the algorithm can then analyze those inputs and outputs relationship to discern a set of patterns which map inputs to their associated outcomes. Following a training stage, a new set of unknown inputs are processed and output predictions are generated for those new inputs [29].

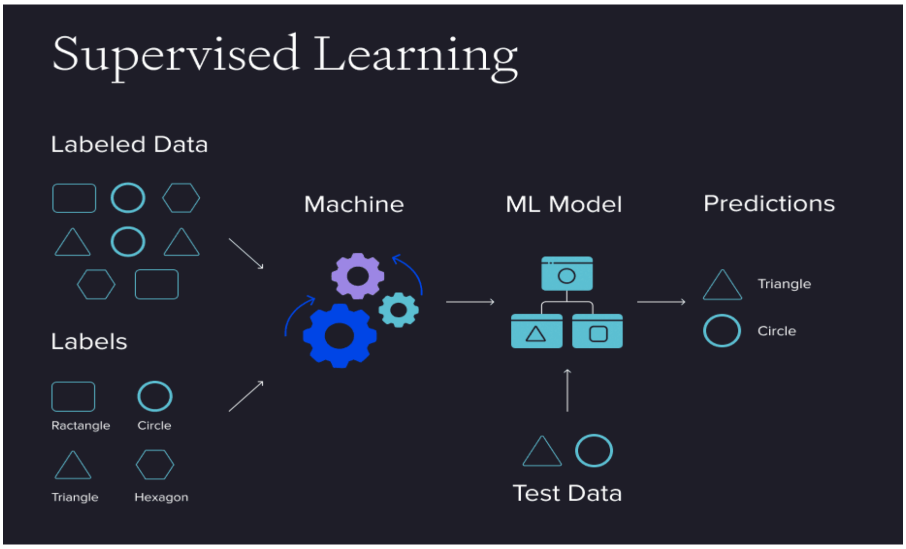

Figure 1. Supervised Machine Learning.

Typically, the purpose of the supervised learning models is to learn a function to estimate a relationship between input variables and a desired output [30]. Through the model's adjustment of its parameters based on existing patterns from the data set, a learning mapping function can be trained [31]. Similar methodology is commonly applied by most supervised learning systems [32]. Collected data is initially aggregated and prepared through cleaning, transformation, and normalization processes. Then, train and test data are extracted from the preprocessed set [33].

A suitable supervised learning strategy is subsequently identified to establish the prediction model after the preparation of data. In this training process, the machine is fed iteratively with training data to repeatedly tune its inner parameters [33]. During each iterative iteration, the model seeks to reduce prediction errors in a manner of a specified optimisation criteria, and training often continues to either a given number of iterations or a given stopping criterion [34]. The developed prediction model is then tested on a test data set for its predictive performance, and its areas of deficiency [33,34]. The overall cycle may take several iterations to come to an appropriately functioning model [35].

The supervised learning approach has two major rankings which are quadratic, and quadratic regression [36]. It is applied for ranking problems in the sense that it helps the machine to classify the samples solely depending on given classified samples [37]. Image pattern and equipment recognition, depending on some properties for illustration, serves as a prominent example of classification task. The established rule set provides a mapping between the measurable characteristics and corresponding classes in the training step.

Alternatively, regression approaches, however, can provide for an uninterrupted range of predicted value, where a correlation exists between some inputs variables and the targeted variables [38]. Common types of regression strategies to employ on the supervised framework are multiple regression run, bayesian regression run, and polynomial regression run, in which there does not necessarily have any correlation between the inputs and output, whereas the classification tree based algorithms construct a hierarchical model by means of sets of conditional rules [39,40]. Neural networks naturally have tendency for self tutoring in well estimated supervision; consequently, network of this kind will deliver value estimation of prediction through training that adjusts network parameters, to achieve largest weights and bias within the network communication level [41].

Most of supervised recognition algorithm encodes the input record in the form of featuresvector which consists of one vector for each sentence in dataset[42]. Then these vectors form the prepareddataset and for each observation; they can have the labels that are the output that one istrying topredict[25]. During training block, the designed feature, by model, is capable to predict outputusing only input feature.

At training, error from the predictionis reduced by optimization procedures iteratively.

Commonly inneural network models, back-propagation is used for optimizationalgorithm whichcomputes the derivatives for update of parameters of model[42]. The technique of gradientdescent[43]and second guess (ADAM) optimizations are frequently utilized in optimization techniques at one stag of training that improve convergence and balance in general[43]. ADAMoptimization technique combines elements ofmomentumbased methods [44] and mean square parameter based methods, and their techniques for effective updates Class-value [45].

2.2 Unsupervised machine learning

The machine learning method of unsupervised learning seeks to identify and extract interesting patterns in datasets that don’t contain clear classes. “The task is to discover from training examples that belong to groups whether there is any structure within the data that could lead to a parsimonious (simpler and thus more useful) representation of the information stored in the dataset [46],” (Han and Kamber, 2012). Since there are no goal outputs in unsupervised learning training data the algorithms are not capable of directly classifying or predicting data like in supervised machine learning. However, the algorithms collect similar data based on common attributes.

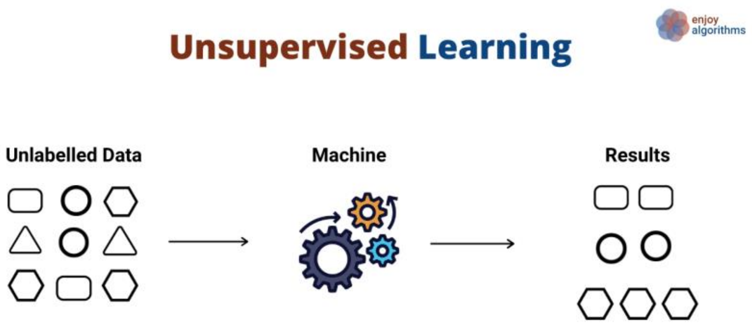

Figure 2. Unsupervised Machine Learning.

The first phase of unsupervised models involves observing the raw data, seeking to discover underlying relationships and patterns. In the subsequent phase, data instances which possess a correlation between them, are classified into certain groups, known as clusters, to uncover peculiar trends and patterns present in the raw data by adopting some algorithmic process, typically clustering algorithms, such as k-means clustering [46]. Since no defined outputs are supplied to the model in the unsupervised models for training purposes, the learning process relies solely on the inherent characteristics of the available data.

The three major categories of issues that supervised learning approaches primarily focus on include dimensionality reduction, clustering, and discovering associations. In the clustering process, the various instances observed are organized into various groups (clusters) whereby the entities (data points) located in the identical clusters feature related attribute(s). For that aim, usually mathematical metrics of similarity/dissimilarity are measured in order to classify the best related entity. Mathematical values derived by measuring the dissimilarity amongst instances on attributes helps to form better clusters [47], [48].

After having clustered the instances into several groups (clusters), the instances within each cluster (each instance represents a cluster) will often represent some sort of centroid that summarized the instances in a particular cluster. The quality of clustering, which measures the compactness of data instances in each cluster around their centroids, is commonly evaluated based on internal criteria. In most cases, an improvement in clustering results would indicate reduced within-cluster dispersion. The total clustering error decreases when number of clusters increases, although finding optimal number of clusters is still challenging [49].

2.3 Reinforcement machine learning

As in Figure 3,reinforcement machine learningis a learning method that applies learning by experiencing an environment to achieve a goal. This is often very successful for sequential decision-making in a dynamic and unstable environment. Trial and error in a fixed environment policy is the foundation of this type of learning[51].

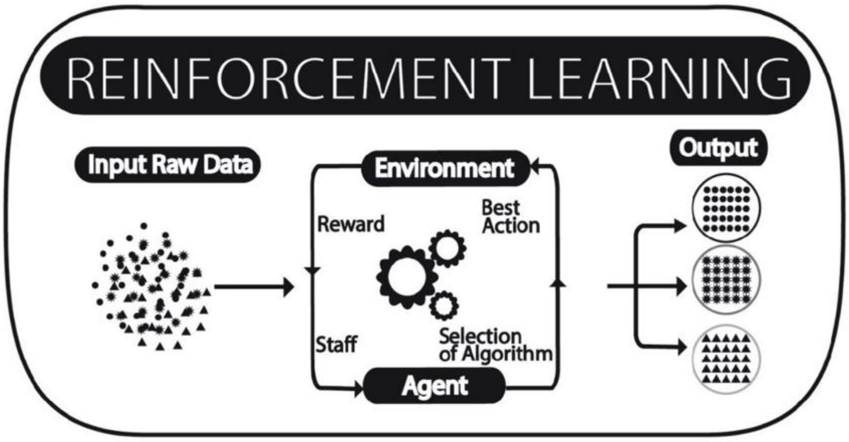

Figure 3. Reinforcement Machine Learning.

At its core, a reinforcement learning agent exists and interacts with an environment. During each time step, an agent takes specific action and this changes machine state, keeps that state positive within the environment [52]. Then, the machine receives a reaction from the environment which changes to a new state and provides a reward which shows the agent was good at what it chose to do [53].

Through positive reinforcement learning, attempt to strengthen gaining knowledge of ways to make such options involves considering the anticipated value of the various phases in a pleasant condition.

This differentiation accounts for both the instantaneous profits that arise from participating with both attention interests along with theanticipated long term rewards from subsequently derived situations [54], which therefore indicates that decisions consider both immediate periods of gains and potential profits for longer future times considering environmental confounders [55]. Temporal differences learning methods, gradientdescent type learning optimization, as well as Monte Carlo type learning, can all be leveraged to approximation the value capabilities [43].

3. Applications of Supervised Machine Learning

Supervised Machine Mastering (SML) increasingly emerged as a tool of prediction within the naming disciplines in engineering: Primarily within the realm of structural engineering; structural computer mechanics Even though excellent descriptive potential of the SML fashions used here can be mentioned, many have been referred to as “black subject programs”, The SML’s combination with numeric modeling strategy like Finite Element Method(FEM) is a recent development of scientific analysis area This combination’s fundamental aim is to cut back computational quantity without shedding the primary numeric accuracy [56]. Superior high quality and well-liked coaching data has vital impact to enhance efficiency of supervised studying fashions [57],[58]. Within the field of structural engineering the coaching data can be based mostly on the observations of building structure; beforehand distributed analytical works or actual experimental outcomes [59].

FEA simulation will be utilized to carry out a lot of the computations of building issues due to its capacity to determine complicated boundary circumstances and behaviors of construction.FEM is broadly adopted technique for a range of engineering challenges as a result of its excessive degree of versatility in managing intricate shapes and boundary conditions.

Though these complicated simulations could entail incredibly huge equation techniques, thus necessitating intensive calculation powers and time [61]. In such a context, effective SML fashions based on synthesized data set can function “surrogate models” or surrogates capable of predict the structural response beneath recent inputs data set below a substantially discounted calculation quantity [60],[62]. However, the highly effective studying fashions on synthetic data set will not be all the time able to make efficient transfer to actual situations [63]. Since numerical simulation could oversimplify the uncertainty and the complexity contained in actual engineering methods as a measure to enhance accuracy and dependability of models [63],[64].

Such type of the models when fully skilled, they can mimic the difficult building habits whereas minimizing the quantity of calculation powers required within the parameter exploration or the repetitive simulations.

SML models are being employed as substitutes for or accélérateurs for the traditional numerical simulation, particularly in the domain of the computational mechanics. There include knowledge-driven numerical solvers; improve of typical finite component formulations; discovery of multi-scale finite factors, etc.[61],[65].

As an illustration, machine learning approaches have been applied to formulate direct link between loads and structural Responses for eliminating inner displacement fields derived via recurrent numerical algorithms [61]. Neural community algorithms have additionally been efficiently utilized to approximation solutions of ordinary and partial differential equation typically require the usage of some numerical discretization approaches[66]. Because deep neural networks can approximation of physical fields contained in the area of calculations by minimizing the residuals which correspond to boundary situations and govern equations, they may be utilized as a predictive tool[67].

The performance of predictive models from supervised learning is significantly impacted by hyperparameter settings. Some common hyperparameter are the learning rate, mini batch size, depth of network, number of hidden neurons, activation function type, coefficient of regularization parameters, and selection of optimizer type. Rather than use these values empirically, recent investigations in Structural Engineering apply grid search, random search, Bayesian optimization or genetic algorithm type approaches for optimization or selection of optimal parameter sets for maximizing validation performance with least overfitting.

Decision of best model to choose is typically based on achieving minimum prediction errors e.g. Mean Squared Error (MSE), Mean Absolute Error (MAE) or maximum Coefficient of Determination (R^2) as desired for the given engineering problem.

One of the most significant obstacles to ML in computer mechanics is the demand for huge scale data sets. FEMs can be computationally high value for producing high-quality simulation data. With the use of physicsguided machinability techniques has been developed to lessen the information quantity required.

Methods that use governing equations or familiar physical laws to gather typer knowledge enable models to be really trained with far less data sets [68].

Knowledge framework reasoning mainly on physics can cut the need for the training data with considerable amount; at the same time them was relying on uniform physics. What's more, tool learning surrogate models were utilized to expect dynamic structural reactions, pressure vectors and time-dependent behaviors of structural part structures, such as, beams and trusses [69]. The general performance of the surrogate models is no the best motivation through theme knowledge approach but also engineering problem definition and expression [70].

Along with traditional train-test data splitting, some recent Structural Engineering works also perform models testing for robustness by using cross validation procedures and separate benchmark data collection sets. Several different statistical measures about prediction accuracy of model are used to evaluate model performance, such as MAE, RMSE, and R value for a regression problem, and precision, recall, and F value for a classification issue depending on whether the problem is predicting continuous values or classes. Using several different metrics together coupled with advanced validation methods will give a more validated comparison of the generalization ability of model than simply report the prediction accuracy of model.

Another general field where inspections have been utilised is SHM (structural health monitoring). The aim of these systems is to evaluate the condition of the structures by continuous monitoring and comparing obtained information [71]. The method is based on the gathering of structural response information, damage indicators and using particular statistical techniques or tools, related to information models, to detect structural changes [72]. This approach has been widely used in various infrastructure applications such as buildings, bridges, dams and tunnels and a reevaluation of the structural design and tunnels dynamic properties as well as vibrational properties and modal parameters [73].

The very beneficial of machine learning methods is that SHM can be viewed as a nuisance for statistical pattern recognition [71]. Supervised learning methods can be utilized to identify losses, detect them, discover their intensity, and forecast the Final service Life of structural structure [74]. Supervised learning works successfully in several researches to modify the structural behavior in edifices, bridges, and dams using metrics such as leakage, porosity [75]. Yet, for large infrastructure, acquiring classified damage data is a challenge, constraining the development of statistical-driven SHM models [76].

Transfer learning techniques for attack this project are saturating SHM applications. As a part of the transfer learning approaches, knowledge obtained from one structural element or dataset can be transferred to another similar problem. It decreases the school data statistics required for the target system [77].

Moreover, a population based full SHM scheme was available to enhance the damage detection for single system by utilizing data from a bank of related eta structures [67].

These approaches demonstrated how the integration of simulated data, physics-based models, and sparse field observations can significantly enhance tracking accuracy.

It is very related to physical twins, which are the digitally mirrored images of real structures that updated continuously by using real-time monitoring records [73]. Digital twin using the tools to improve the predictive talent and structural decision making. But there are some problems (quantification experiments, quantification of unknown etc.) and difficult to improvement [73].

Furthermore, the use of supervised machine learning in manufacturing and structural design has been reviewed. The structure design:manufacturing in Structural Engineering design has been constrained by building layout optimization, structural member size, structural configuration decisions [78]. In designing building layouts and structural floor plans early in the design process, some current research using deep learning architecture such as generative adversarial networks and convolutional neural network [79]. Other research has been reviewing automated structural design optimization based on shear wall layout, structural system, and reinforced concrete components design [80].

Machine learning has been applied in industry to model and predict complex machining operations. For example, by combining the numerical simulation with real-world data, a machine learning model has been constructed to predict the cutting force during milling [81]. Since bad machining conditions can cause bad tool wear, inaccurate production accuracy and surface quality, the prediction of the cutting forces are very important. Machine learning techniques were also utilized in additive manufacturing to predict the mechanical properties and behavior of components fabricated additively [82].

Stress analysis remains a further important use case for supervised learning. In many fields of engineering, such as aeronautics, automotive and biomedical engineering, finite element analysis is still the most popular approach to determine the stresses in complex structures [83]. However, the use of FEA to solve extremely nonlinear problems may require a high number of simulations.

Therefore, machine learning algorithms have been proposed as surrogate models aimed at predicting stress fields at a much lower computational cost [64], [66].

Such surrogate models for stress field prediction are also attractive for point-of-decision machines as they have been able to predict stresses in less than a second in a few studies [69].

Moreover supervision learning has also been used in the measurement of structural component fatigue and failure analysis. Based on stress environment and fracture topology, neural network was employed for fatigue life prediction of steel and reinforced concrete structures [84]. With moderate accuracy, they can replace time-consuming numerical calculations.

For probabilistic failure prediction of structural systems under unknown loading conditions, machine learning method was further combined with probabilistic methods, such as monotony of the Monte Carlo method [85].

Several approaches such as stand-ins neural networks, fuzzy good discrimination architecture and particle swarm optimization algorithms, for example, support vector machine were used for fatigue crack detection and prediction of growth [86].

A further success where supervised learning has been shown to excel is in content modeling.

From the simulated or experimental data, the ML models may directly learn the nonlinear material behaviors and imitate the complex stress-strain relationship [87]. The constitutive material behaviors can be expressed through the integration of such models into the finite element model. For example, the ML-based material models were constructed by representative space combination of microstructures to forecast fabric responses under single load condition [88].

The reliability of this kind model hinges on abundance of refined training data to decode fabric behaviors [87].

Hybrid data sets containing both experimental and simulated data set were created to improve the flexibility and “understandability" of ML-based material modeling [60].

Lastly, the system gradually becomes familiar to engineering optimization problems by acquiring knowledge about they could be tackled. Evolutionary algorithms including genetic algorithms were commonly implemented to optimize structural configurations or investigate the links between design parameters and functional parameters [89]. Genetic algorithms trade on numerous operational tactics including combination, insertion and inverse to imitate those in the evolution and present more suitable candidates.

They were efficiently used for structure design optimization and parameter identification of engineering structure [90].

Yet, the efficiency might be reduced by the invasion of the high dimensional solution space in complex engineering problems with randomness [91].

Population optimization methods, such as genetic algorithms (GA) and particle swarm optimization (PSO), have also received widespread usage in selecting hyperparameters of machine learning models in Structural Engineering domains. In place of manually choosing network architecture or optimization parameters, an set of candidate solutions is evaluated with an objective function-such as minimizing prediction error or maximizing structural performance metric-using global searching algorithms that iteratively modify candidates using evolution (GA) or cooperative behaviors of particles-PSO. The candidates are iteratively refined (or the algorithm stopped) by the optimization procedure after a specified number of generations or given improvements.

In summary, comprehensive capabilities have been identified in numerous technical domains for knowledge extraction from surveillance systems. Through the integration of record-pushing paradigm with classic physics-based techniques, green computing architectures have been invented for simulation improvement, structural control systems optimization and higher-level structural design optimization methodologies development.

While supervised machine learning has in some cases exhibited unprecedented predictive performance in Structural Engineering applications, they are subject to several caveats. For example, the majority of the published work has used either clean laboratory data or numerically simulated data to train their models. Quantities of interest may not be accurately predicted using measurements obtained in the real world (e.g., much greater variability, complex boundary conditions, sensor noise) and performance when trained on just simulation data has yet to be investigated fully. Published work has also prioritized prediction accuracy over interpretability, computational speed, uncertainty quantification, and stationarity.

Another notable phenomenon is the use of dissimilar data sets and evaluation methodologies when comparing between different types of supervised learning methods, which makes it infeasible to objectively compare the performance of different algorithms. As a result, no supervised learning method can be deemed the best for any Structural Engineering application. In fact, contemporary studies gradually indicate that hybrid processes combining supervised learning with physics based numerical models and expert domain knowledge have shown to be more robust and scalable than a purely data driven methodology. This review aims to focus on these experiments by bringing out not only the achievements but also the reasons of recurrent failures in scale-up.

4. Applications of Unsupervised Machine Learning

(UML) The interdisciplinary field of unsupervised learning in machine intelligence draws upon fields such as computer science, data, engineering and optimization to uncover effects within unclassified data Information ideas and Bayesian ideas are often utilized in UML technologies with respect to statistical modeling. The primary visualization of UML models are component estimation, unbiased goal estimation, Gaussian mixture model, goal analysis, statespace model, hidden Markov model Graphical models and approximate Bayesian techniques such as Markove Monte Carlo, fractional inference, expectative Centralization and Laplace Approximation In relation to deriving the arguments of model, the Expectation-Maximization technique is a significant tool [10].

In spite of their prevalent use, UML strategies are prone to scalability shortcomings for big data. For example, when uptrained on big data, the deep belief network (DBN) and sparse coding can have big value as computation [22]. Has created this problem by image processing engines (GPUs) to uptrain encoding processes and enormously parallel computing strategies, resulting in enormous speed enhancements compared to traditional CPU computing structures[15], dimensionality reduction strategies with locally linear embedding (LLE) non-linear high dimensional task optimization tip for the LLE needs utilizes global optimization with primary charge functions, and has been " widely used in clustering, nonlinear dimensionality reduction application" [92].

In practical applications for Structural Engineering under monitoring, the performance of LLE largely depends on the suitable set of hyper-parameters, especially the size of neighborhood (k) and the dimension of feature space. The neighborhood of too small size can cause broken local low-dimensional structures, while the too large region can also introduce an unwanted distortion of the data topology compared to the true structure of the structural response data which will not be suitable for the Structural Engineering applications. Therefore in many research a heuristic selection of the hyperparameters can be based on experimental or sensitivity analysis approach to gain a stable and physically meaningful feature for high dimension Structural Monitoring data according to a clustering quality index, reconstruction error or prediction accuracy.

Estimation of class at best may be a non-trivial set of packages of UML. No information-independent structures of cluster techniques which group observations according to similarity have a prior estimate of class categories are taken out any natural patterns in proportion [22]. The OK-path rule set is now one of the commonly used art for its high expert expectations and efficiency.

Clustering techniques being used widely, such as packages with field frequently used search engines.

Here, so-called unlabeled data, such as keyword and category hierarchies can be used to mechanically generate topic-based fully search structures. [93]. Moreover, hidden estimator use of elegant has been demonstrated to be synonym in some cases; as a consequence of discriminant based estimation, an option for traditional clustering techniques [93]. Probabilistic cryptographic estimation based on generative hidden object models and probabilistic composability decomposition has been successfully used here to enhance the choice of records mining [93].

UML methods are also often adopted into training games of information engineering. The data mining methods of clustering, visualization, outlier detection and dimensionality reduction are number one applied to uncover the structure of complex data sets [94]. By dividing observations of similar occupations into well grouped cluster with high internal similarity, these strategies can implement sample identification and exploratory solving [95]. UML methodology are widely utilized to pre-process raw multidimensional information to form relevant feature description to help follow-up works such as classification, interpolation or anomaly detection when classified statistics will not be accessible, UML approaches identify unknwon rule statistics [19], [96].

Feature engineering is another robust use for UML, particularly when it is difficult to "urh" classifier back to classified statistics. As a feature-subset selection procedure for unlabeled data [47], discovering an appropriate diversity of data clusters to produce an effective feature subset is broadly examined. Even though expectation maximization clustering techniques estimate the feasability for minimizing functions, it is negligible.

Automatic learning of feature detectors from unlabeled picture data has been applied in computer vision applications to lessen reliance on big human labeled datasets [10].

For example, to improve object recognition efficiency without significant human feature extraction by hierarchical matching pursuit combined with sparse coding has been developed to acquire hierarchical features of RGB-D data [97].

Since it is not possible to intentionally damage the structure for training, there is often a lack of labeled damage data in static health monitoring (SHM), another significant application of UML. In these situations, unsupervised models employ exogenous or anomaly identification techniques to recognize aberrations or inconsistencies from normal structural motion [97]. Loss-sensitive abilities are extracted from acoustic vibration data of

[98] via fractional autoregressive modeling and nearest neighbor algorithms.

The approaches enable simultaneous increase in pc power and retention of information regarding structural degradation while processing sensor data of high dimensionality.

Recent investigations have also utilized deep gain knowledge on techniques like transformer networks, graph convolution networks and others to assess time-series sensor data so as to successfully:

a- identify damage accurately

b- determine the location of damage instances

c- develop models capable of contrasting between multiple number of targets [98].

In commercial designs of structures, UML methodologies offer 'data-driven' efficient control and enhancement of availability. Industrial treatment methods that are rather advanced in fields such as shear manufacturing and stainless-steel fabrication provide a vast amount of sensor information. Data mining tools which include both supervised and unsupervised algorithms can generate 1st class predictions on the product, derive pertinent manufacturing factors and discover all operational trends through intermediate manufacturing stages. Damages can be spotted early and quality fluctuations can be identified quickly, thus encouraging a more environmentally sustainable and efficient manufacturing procedure and minimizing manufacturing losses [99].

Lastly, UML recently has been applied to other Structural Engineering problems such as physics constrained deep learning methods for solving partial differential equations (PDEs) [100]. These methods do not need labeled data; Instead, learned numerical solutions are obtained according to boundary conditions only. Further applications include the prediction of material properties, such as the compressive strength of high-performance concrete, and automated fatigue fracture identification using outlier analysis [101]. In addition, UML methods have been applied to structural optimization problems, such as the optimization of truss structure design [101].

In conclusion, these myriad applications demonstrate the necessity of the Web-based framework in extracting label information from unlabeled data, in diverse ranges of scientific and technical disciplines where labels are sparse or missing.

Unsupervised learning offers an appealing answer to Structural Engineering problems for which labeled data are difficult to obtain-for instance structural health monitoring and abnormalities detection. However, the practical understanding of the identified groups and of the features in the latent spaces remains a major drawback. Structural groups are generally identified from clusters that are optimized either mathematically or statistically-not engineering meaning-rendering the results hardly interpretable from an engineering point of view. Moreover, defining the clustering hyperparameters, latent space reduction methods and validation indices still requires specialist knowledge.

Recent literature suggests a growing inclination towards a hybrid scheme that "exploits the power of unsupervised feature extraction via various methods, integrated with a supervised classifier and physics-based constraints, in order to improve the interpretability and uniqueness of the solution and hence establish the reliability of the prediction". Instead of taking unsupervised approach as an independent methodology, most cited successful applications adopt it as an initial step for feature extraction followed by the predictive model. Here, this review stress on that subsequent research and application should concentrate on the "hybrid framework" under which the automatic discovery of meaningful pattern and engineering knowledge, along with the uncertainty-aware inferencing can be integrated together.

5. Applications of Reinforcement Machine Learning

In dynamic environments, optimality and sequential decision-making problems are particularly adapted to Reinforcement Machine Learning (RML). An agent interacts with its environment and learns its optimally by balancing exploration and exploitation, in order to maximize cumulative rewards [102]. Throughout its participation in the process, the agent refines its learning method and adapts its behavior to new environments.

The reinforcement learning framework under both deterministic and stochastic circumstances can be formalized as a Markov Decision Process, in which actions, states and rewards affect the learning process.

Transfer learning has been used to accelerate learning and reduce computation for complex and large or continuous state problems [77]. RML algorithms such as Q-learning, temporal-difference learning, adaptive dynamic programming, actor-critic networks and Monte Carlo techniques, are known to perform well for optimization and control problems in the presence of uncertainty [103].

Reinforcement learning mainly has the interaction with the environment instead of dedicated training data as it has in supervised learning, which requires label data. After trials and refinements, the agent discovers, and policy grows up by feedback with incentives [] []. Hence, in reinforcement learning algorithms, the optimal policy with minimum cost in long-term, i.e., within prediction horizon, are learned directly from interaction with the environment and might need very little amount of pre-existing data.

Most of the RL problems attempt to discover the policy that optimizes the expected long-term reward and are presented as Markov decision processes (MDPs) [102].

Model-free reinforcement learning techniques optimize policies without pre-existing knowledge of reward function and transition probabilities further [104].

In computational mechanics, RML methods have been employed to facilitate sophisticated steps such as mesh generation. Reinforcement learning has the potential to develop self-learning systems which can autonomously produce high-quality meshes for complex geometries bycasting the process of generating a mesh as an MDP. To generate a quad mesh for structural analysis problems, an advantage actor-critic reinforcement learning network has been proposed, which effectively decreases the computational expense and human involvement [102].

Another area widely studied with reinforcement learning is structural control. Hypothetical control problems were solved applying case-based reinforcement learning early [104], while more recent approaches, aiming at determining optimal control policies to dynamic systems, treat structural control problems as MDPs, or adopt approaches such as adaptive dynamic programming and other RLapproaches [11]. Several applications in civil engineering are known, including dynamic load management, flexible structures control, and vibration mitigation. Applications include water canal control systems [105], vibration mitigation in semi-active structures [105], flexible hinged plate control [106], bridge monitoring systems based on IoT [107], floating wind turbines [11] and seismic structural control [103].

The applications of reinforcement learning in seismic control were inspired by the randomness of earthquake loading. Reinforcement learning based control algorithms have been designed to adaptively control active mass drive system to reduce structural vibration under earthquake [108]. Dynamic state predictors can be integrated into these systems to reduce time-delay effects and improve controller quality of control.

Virtual scalable reinforcement learning control methodologies have been discussed to accommodate various structural responses and loading scenarios and different control implementations [103].

Besides the control designs, reinforcement learning has been adopted to carry out structure maintenance schedules planning and defect diagnosis, by learning optimal maintenance policies based on historical infrastructure data. Several comparison studies showed that actor-critic policy gradient algorithms often converge faster and exhibit higher stabilization performance than typical Q-learning algorithms in multiple control setting contexts [104].

RLs have also attracted significant interest for production optimization and structural design. Many manufacturing processes involve costly simulations or trial-based testing for optimization of operational procedures and parameter adjustments. RML algorithms offer an alternative, reducing computation and cost by directly learning successful strategies by interacting with simulation models [109].

Autonomous manufacturing systems may incorporate robotic operators with learned decision-making strategies for adapting to variations in human performance and environmental conditions [110].

Engineering design applications include structural design and aerodynamic shape optimization, which RLs often find to be more successful than traditional gradient-based, and gradient-free approaches [111].

In addition, RML is also being increasingly adopted in autonomous systems and intelligent infrastructure. Tasks related to decision making like resource management and congestion control in Internet of Things (IoT) enabled intelligent smart cities can make use of Reinforcement Learning. Online reinforcement learning algorithms were used to solve path planning and autonomous navigation problems.

Besides navigation and task planning in dynamic environments, where Reinforcement Learning-controlled aerial vehicles have been used to build three-dimensional structures [112], offline path planning in static environment was also used to be tackled with Q-learning [113].

Automated structural design with RL was touted as a way to improve the effectiveness of design automation with small and limited design data and historical records as it serves as a basis for data-driven design exploration and optimization [114]. Deep reinforcement learning was also used in the structural design with huge state spaces [115].

Another application of reinforcement learning showing promising results is in failure analysis of structural systems. When many potential failure modes are identified, the combinatorial explosion makes the analysis intractable, unless using a practical sampling approach to investigating the failure spaces. The failed component selection strategy has been formulated as a sequential decision making problem using the MDP framework within deep reinforcement learning [116]. It was tested on roof truss and bridge structure, showing that it can outperform typical Monte Carlo simulation type approaches with higher prediction accuracy and less computational expense [116].

Thirdly, materials modeling and design optimization have primarily used RL. The optimal material processing pathways giving excelled microstructures as well as matching mechanical properties are identified by the deep reinforcement learning algorithms such as deep Q-networks with prioritized experience replay [117]. Likewise, Q-detection has been carried out for optimizing microstructure of biostimulation composite materials to neglect high dimensional problems and complex behavior of tissue design Furthermore, probabilistic neural network methods combined with reinforcement learning provide insights into the predicting of disease prediction, for example, solid variation Caredi elect elimination strategy has utilized to enable the inclusion of uncertainty estimation in neural network algorithms [118].

This method inserts a neural network to model the epistemic uncertainty at some point within the forecast but remains limited in its ability to extrapolate beyond the training data set.

In summary, the reinforcement machine learning has been successfully developed into a rigorous and useful paradigm to solve tough engineering problems involved in sequential choice optimization, dynamic environment, and uncertainty become substantially more prominent.

Reinforcement learning presents distinct benefits for structural optimization, adaptive control, and sequential decision, as evidenced from its ability to improve the policy via learning through interaction with the environment. Its application within the fields of Structural Engineering, however, is still rather sparse when juxtaposed with supervised learning. The majority of the applications are verified using simulated environments as a proxy, while very few are proven on full-scale structural systems. This reliance on simulation imposes questions about policy transferability, computational cost, and robustness to uncertain real-world operating conditions.

One other challenge is the huge computational cost to train the RL agents, especially for large infrastructure systems with very high-dimensional state space. Recent researches show that reinforcement learning integrated with digital twins, physics-informed models, surrogate modeling, and transfer learning can greatly reduce training cost and enhance decision delivery reliability. This review hence concludes that hybrid reinforcement learning framework could be one of the most promising research directions for future intelligent Structural Engineering systems.

6. Comparison of Machine Learning Paradigms in Structural Engineering

The previous sections examined example applications of supervised, unsupervised and reinforcement learning separately. In order to compare the paradigms for prediction accuracy, computational efficiency, interpretability, data requirements, scalability and engineering relevance a synthesis of the literature review must be conducted as discussed in the next section.

The three main classes of tools for acquiring Knowledge Strategies used in Structural Engineering are supervised, unsupervised, and reinforcement learning models Each of this model type is good ideal for addressing some types of problems, and special types of data, strategies identify and machine requirements for implementation. Breadth validation of several designs is necessary to identify the best design for certain Structural Engineering jobs, including optimization and decision orbit. Control learning system dimension requires labeled datasets with identifiable input parameters and attributive aspire outputs. In Structural Engineering, this model is commonly used for forward modeling of dynamic observed issues (fabric property testing and damage classification), stress, and grip calculations, assessment of building fitness, since the model learns from direct exhibit-input guidance, near-by practice strategies is usually anticipates, while it can be found adequate class datasets and, consequently, presents a huge flaw, particularly in Structural Engineering programs, where testing and annotation may need to be intensive statistics worth, knowledge testing, or even endless observing.

In any case, and for any algorithm,well then, the hyperparameter optimization has become a crucial aspect of amodernic application in the Structural Engineering domain since the quality of the model obtained generally strongly depends on the specific parameter configuration, not only on the used learning algorithm.

Estimation: Unsupervised machine learning makes every effort to find these correlations in unlabelled data sets. For example, these effects make a common model because it can be a help on problems such as clustering structural response, detecting anearal adduction of action pattern and dimensionality reduction on large supervised database it can be helpful to recognize the unobserved, on the other hand it can be difficult to identify and test increasing convergence from different c with important structure.

Reinforcement for knowledge acquisition , in which the agent oscillates with the environment and discovers the optimum stroke direction and other direction of optimize reaches, is a entirely novel structure expertise in Structural Engineering, adaptive vibration mitigation, intelligent layout control challenge, dynamic network developing for utility appliance and so on. Since reinforcement learning can also fortify guidelines steadily through rowing, it is far favorable than supervised learning in circumstances of striding selections and change machine working. However, strengthening fashion cognition normally needs pas d school thread and huge laptop resources, particularly in the case when complex machine dynamics or actualistic simulation settings are hoped for.

The computing cost of learning normal fashion may be somewhat high for one human inspector depending on the chosen approach and the size of the data set. The training line is quickened by utilizing large classified data set, more complex fashion, and more profundas neural network such as these. Unsupervised learning techniques may also need iterative optimization strategy for clustering or dimension reduction when dealing with the high-dimension tracking data and can be computationally vamp (O models). Reinforcement learning has the most computational cost among about 3 models.

Each model would be appropriate primarily depending on the specific technical goal and the features of the data that maybe obtainable at present or at any point in time. Supervised skill could be effective if dependable labeled data and definitely one particular predictive model for the application space is available; unsupervised detection is of great support in interpreting wholesale swathes of tracking information for revealing inherent structural mode behaviors or challenging anomalies outside predefined classes; and, learning about reinforcement would be instrumental in manipulating, optimizing, and adaptive decision of structural system in action.

Table 1. Comparison of machine Learning paradigms in Structural Engineering.

ML Type	Data Requirement	Main Applications	Training Complexity	Inference Speed	Computational Cost	Advantages	Limitations
Supervised Learning	Labeled datasets	SHM, damage classification, stress prediction, material modeling	Moderate to High (depends on model complexity)	Fast after training	Moderate	High predictive accuracy, mature algorithms, straightforward evaluation	Requires large labeled datasets; risk of overfitting
Unsupervised Learning	Unlabeled datasets	Clustering, anomaly detection, feature extraction	Moderate	Fast to Moderate	Moderate	Discovers hidden patterns without labeled data	Difficult interpretation; parameter sensitivity
Reinforcement Learning	Interaction with environment and reward signals	Structural control, adaptive optimization, maintenance planning	High	Moderate	High	Excellent for sequential decision-making and dynamic systems	Long training time; computationally intensive; simulation-dependent

In addition to the prediction accuracy, computational efficiency has, in recent years, gathered great importance as a criterion for selecting the most suitable Machine Learning (ML) model in the field of Structural Engineering. Practical applications such as real-time structural health monitoring, Intelligent infrastructure management and digital twin frameworks demand prediction models capable of high inference speed at a reasonable computational cost. While deep neural networks and reinforcement learning models usually necessitate enormous training computational costs, their inference phase tend to be considerably faster, so that this trade-off favors their use for real-time applications once trained. On the contrary, conventional Machine Learning

Algorithms tend to be characterized by lower training complexity and lower hardware demands but have a tendency toward lower predictive capabilities when a structure exhibits highly non-linear behavior. For this reason, the selection of an appropriate learning paradigm should be based on other factors in addition to prediction capabilities including Computational complexity (scalability), memory demands, etc. And application latency constraints.

It should be noted that the computational efficiency also varies significantly with the specific algorithm and the extent of the engineering problem. Take the example of training a neural network. Convolutional neural networks and transformer-based architectures possessing large number of trainable weights usually demand GPU acceleration, while others such as decision trees, support vector machine and ensemble learning algorithms can often be trained reliably on generic computing devices.

Reinforcement learning algorithms generally require multiple simulated interaction cycles, hence they tend to take more time to train than supervised learning algorithms.

However, reinforcement learning algorithms could be advantageous for online adaptive control systems once suitable policies have been learned. Therefore, assessment of computational efficiency should account for offline training speeds as well as online inference costs rather than merely the prediction accuracy.

7. Problems and Limitations of Machine Learning in Structural Engineering

Even though there have been a lot of significant improvements in Structural Engineering, there are still many constraints and limitations to keep tool-mastery strategies do not work

Successfully implement in practical engineering settings One of the most leading motives behind these problems is the availability of data, data superstition, interpretability of the model, generalization, computational expenses, the growth of information mining and robust applicative machine learning to determine response to structural systems involving mixing with traditional and physics-based approaches. One main problem in the theory is due to the deficiency of Superdata, particularly labeled data set. Most of device-reservation approaches, especially the supervised device-reservation approaches demand huge quantity of labeled data for training phase.

For structural safety monitoring and damage detection in Structural Engineering applications, it is difficult to take hidden data set of structural damage because the actual structural fasteners or damage are rare and sometimes require a controlled laboratory experiment or expert specialist access and can be sensitive to keep.

Therefore, many existing data are limited as options and will not accurately represent the real system complex of behavior.

A number of recent approaches use rigorous validation methods in the development of Machine Learning models to ensure the precision and reliability of the trained models. K-fold cross-validation is perhaps the most popular validation method used by individual research efforts, because it divides the available data into many different training/validation sets and so is less dependent on any particular data set division. Other common validation methods that are often used include leave-one-out cross-validation, repeated random subsampling, and stratified cross-validation in cases of imbalanced data sets. Use of these validation techniques has been shown to give more accurate estimates of the predictive performance and to guard against over-fitting (when used with limited experimental data).

Apart from internal validation, external validation utilizing independent experimental datasets or field-monitoring measurements has also been considered as another potential must-have requirement for Structural Engineering studies. Since most of Machine Learning models are initially trained and validated with pre-created synthetic datasets via finite element simulations, there could be a significant gap between simulation and actual structural behaviors resulting from model uncertainties, environmental influences, sensor noises, and boundary condition effects etc. Recently, it is advised to incorporate numerical simulation results with experimental measurement data (through hybrid dataset, transfer learning, domain adaptation, physics-informed Machine Learning, etc.) to diminish the simulation bias with reducing overfitting, thus to promote the generalization capacity of the trained models for the real engineering structure applications.

The fact of large number of records raises another all-pervasive nuisance. Structural monitoring systems frequently rely on sensors for monitoring displacement, acceleration, pressure, vibration, etc. However, sensor statistics tend to contain noise originating from environments, limitations of instruments, signal coming from other sources.

Missed data caused from faulty sensors, improper connection and maintenance is also a factor having repercussion on system's verification method for the reason that many algorithms estimate the accuracy of the data entered and completeness of the data entered.

This weak data may lead to inaccurate structure predictions or to misinterpretation of structural behavior

Another desirable problem of engineering applications is model interpretability. Nowadays many sophisticated fashion recognition machines, especially architectural deep learning, work as do complex nonlinear systems with physiologically incomprehensible selection-design strategies. Those fashions can also have excellent prediction precision They are measurable and big models in engineering researches. Due to physiologically incomprehensiblity of record-drivenmodels, engineers may be much less probable to apply them.

A third challenge relates to the concept of generalization of the systems of fashion studies. Models are often trained to use simulated information derived from numerical fashions or extensive experimental data bases, but the actual system may respond very differently than fashions because of uncertainties in physical properties, boundary conditions, environmental impacts, and design variations as end products in actual systems do effectively generalize to the fashion systems is a major research undertaking.

The cost of computation is another disadvantage, particularly for deep learning with applications processing large amounts of records. Training of complex neural networks typically requires large memory sizes and high-end machines. In most situations it is necessary to employ professional devices such as graphics processing units (GPUs) to generate realistic examples. These laptop requirements can restrict the technology offered to "learn" complex concepts, particularly in engineering environments where computing power might be scarce.

Last but not the least, It is very stubborn to combine system learning techniques with classical physics based whole means technologies. Structural Engineering, as a representative subject of classical physics has relied on two most prominent theorist models: finite detail modeling and structural mechanics. Let's notice that because Machine Learning techniques are mostly registry-driven and has no explicit physiologic toformat speed rule, it's very difficult to merge the above two strategies to provide a reliable and consistent way. It's up to develope hybrid modeling techniques which learn from data while constrains by physics to realize revolutionary integration; this will provide intelligent knowledge with prediction agility but employing based techniques today.

Another important point, is an automatic Machine Identification has a tremendous power to investigate in further detail such complex Structural records over time, which can greatly support others SMART decision-making strategies, but solving these problems is important to ensure such strategies are effective and appropriately used in real Structural Engineering context; and efficiency in terms of processing technology, and minimum computational cost.

8. Emerging Trends and Comparative Perspective

The works surveyed in this paper demonstrate a clear trend of a gradual transition from traditional empirical data-driven Machine Learning frameworks toward hybrid and physics-informed learning systems. Structural Engineering applications are the most exhaustive, where supervised ML algorithms were adopted, trained on measured (or numerically simulated) data, to perform tasks as prediction and classification. While such approaches could reach high accuracy under ideal circumstances, their performance was disappointing in case where the structures interacted with different conditions than the learned ones. This is one of the drivers of the emergence of the hybrid approaches.

Physics-informed Machine Learning is one of the most promising recent innovations in computational Structural Engineering. Such approaches, instead of trained on experimentally determined data, also use governing equations, constitutive laws, equilibrium conditions or finite element formulations, during the optimization process. As a result, they need less training samples, have better physics-awareness and generalize well across structural environments. Hybrid finite element-Machine Learning frameworks also use numerical experiments and data trained surrogate models to dramatically speed up computations with acceptable engineering accuracy.

Another trend is incorporating Machine Learning into digital twin for real-time structural assessment. Digital twins-and similar approaches-keep the numerical models in “lockstep" with sensor measurements; the Machine Learning algorithms leverage the real-time data to revise predictions dynamically that reflect operating condition variations. These types of integrated approaches offer greater flexibility of real-time updating, uncertainty information, and decision support for maintenance planning and structural safety assessment compared with traditional static prediction models.

As shown from the reviewed literature, there is no one fits all structure ML paradigm for having the most effective application toward a given problem in Structural Engineering. Nonetheless, the recent literature worldwide appears to be converged to a growing body of evidence indicating that hybrid structures through synergizing different ML learning modes, backhuman knowledge & physics based modeling in one optimal framework would have better robustness, transparency, and efficiency in use. Hence, future direction in Structural Engineering research at large would be heading toward integrated intelligent system instead of standalone ML algorithms.

Table 2 Comparison between Conventional Data-Driven ML and Physics-Informed/Hybrid ML

Aspect	**Conventional Data-Driven ML**	**Physics-Informed / Hybrid ML**
Data Requirement	Large labeled datasets	Smaller datasets supplemented by physical laws
Generalization	Limited outside training domain	Better extrapolation to unseen structural conditions
Interpretability	Often considered black-box	Higher physical interpretability
Computational Cost	Lower model development complexity	Higher development complexity but improved prediction reliability
Dependence on FEM	Usually independent	Strong integration with FEM and structural mechanics
Engineering Reliability	Moderate	Higher due to physical consistency
Suitable Applications	Pattern recognition, classification	Structural analysis, digital twins, SHM, optimization

9. Conclusions

The Mechanical engineering technology has extended its hold in Structural Engineering Industrially, by providing record-saving prediction, monitoring, optimization and decision support tools. Knowledge of reinforcement-primary standards, common techniques and practices are described.

Supervised expertise approach generally is the most popular one. It is used extensively, thanks to its excellent prediction ability and the progress it makes on many tasks from fault prediction, fabric modeling, pressure forecast, structural condition monitoring to test unlabeled data in package clustering, anomalies detection, feature deflection are challenging. Through supervised data Fortification expertise, but less general, can to adapt a dynamic optimization and control problem, such as retrofit design, structural control and structural optimization in uncertain environments.

The evaluation shows the particular strengths and limitations of each tools,s expertise regime. Large data sets with classifiers can be hard to 'collect' for Structural Engineering programmes, and although supervised studies can instance highly accurate projection and they can also test for hidden styles in unremarked data to find the unobserved, there can difficulty in interpreting results. Reinforcement learning can cardilaginally excel in sequential decision making problems, but requires a sophisticated training regime and a high value computer system.

Yet, several limitations still exist for the nature of massively application of tool checking in Structural Engineering, such as lack of very good datasets, amplitude noise in monitoring systems, model interpretation problems, problems in the use of models from actual systems High computational complexity of the global integration with traditional physics-based whole strategies for all these challenging scenarios.

Future research efforts should focus more on rigorous validation protocols, such as field-monitoring based external validation, standardized benchmark dataset, and uncertainty-aware testing framework, so as to enable transferability of Machine Learning models from simulation to real structures.

In following studies should be more efforts on how to improve these hybrid modeling framework together with smart objects with known engineering understanding. All informations of the model should be considered and should develop algorithms that can effectively operate from imperfect or limited data. Use Machine Learning in Structural Engineering Technologies improvement in numerical Structural Engineering10, duplication high-performance and longer computing technologies might prove a feasible way to improve the efficiency, reliability, and intelligence of current structural analysis and design systems.

Future comparative studies should be supplemented with standardized comput engineeringmetrics such as training time, prediction latency, resource consumption, and energy efficiency to objectively compare various Machine Learning approaches in Structural Engineering.

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