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Applications of Artificial Intelligence in Structural Engineering: A Review

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Abstract: *Artificial intelligence (AI) is a computational approach that aims to mimic human-like thinking/cognitive abilities to tackle complicated engineering issues. AI is appropriate for engineering contexts with a large set of inputs. AI is a feasible alternative to traditional modelling and statistical techniques. Experimentation is a herculean task in the domain of structural engineering, so AI-based techniques are viable alternatives for the prediction of various engineering design parameters, such as structural response, compressive strength, etc. The goal of this research is to outline numerous applications of artificial intelligence in structural engineering that have emerged in recent years. Initially, a broad introduction to AI is provided, followed by a discussion of the relevance of AI in the field of structural engineering. Thereafter, a review of recent applications of AI techniques such as deep learning (DL), pattern recognition (PR), and machine learning (ML) in structural engineering is presented, and the ability of such techniques to meet the constraints of conventional models is explored. Furthermore, the benefits of adopting such algorithmic approaches are thoroughly addressed. Finally, future research areas and latest innovations by using deep learning, pattern recognition, and machine learning are given, along with their shortcomings.*

Keywords: *Structural Engineering, Artificial Intelligence, Machine Learning, Deep Learning.*

Abbreviations:
ISI: Indian Standards Institute
BIS: Bureau of Indian Standards
AI: Artificial Intelligence
DL: Deep Learning
ML: Machine Learning
PR: Pattern Recognition
ASTM: American Society for Testing and Materials
SHM: Structural Health Monitoring
ASCE: American Society of Civil Engineers
BPNN: Back Propagation Neural Networks
FFANN: Feed Forward Artificial Neural Network
IO: Immediate Occupancy
LS: Life Safety
CP: Collapse Prevention
RC: Reinforced Concrete
MDPI: Multidisciplinary Digital Publishing Institute
FRP: Fibre Reinforced Polymer
MLP: Multilayer Perceptron
BRB: Buckling-Restrained Braced
RSM: Response Surface Model
PSDM: Probabilistic Seismic Demand Model
LR: Logistic Regression
PGA: Peak Ground Acceleration
DSHA: Deterministic Seismic Hazard Analysis
PSHA: Probabilistic Seismic Hazard Analysis
CNN: Convolutional Neural Network
SVM: Support Vector Machine
AHP: Analytical Hierarchy Process
R2: R-squared (Coefficient of determination)
R: Correlation Coefficient
MAE: Mean Absolute Error
RMSE: Root Mean Square Error
MAPE: Mean Absolute Percentage Error
VEcv: Variance Explained by Cross-Validation

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I. INTRODUCTION

Engineers frequently develop experiments to investigate practical difficulties. However, such investigations are constrained in terms of the number of test/cube samples and variables used, as well as the research facilities available. To verify that tests are comparable, testing standards/guidelines, such as those developed by the Bureau of Indian Standards (BIS), the Indian Standards Institute (ISI), the American Society for Testing and Materials (ASTM), and the International Organisation for Standardisation, have been established.

For many experimental trials and situations, these guidelines include a specific statement regarding the testing process, technology, and technical requirements. In the Structural Engineering domain, research facilities are primarily available for the elemental response of different structural members. Engineers can utilise modern numerical methods, such as finite element analysis, instead of relying on experimentation. Machine learning (ML) is another promising new tool for addressing various practical difficulties in the structural engineering domain [1]. Artificial intelligence (AI) is a branch of computer science whose goal is to enable computers to do tasks that are similar to those performed by humans [2]. In contrast to statistical techniques, AI does not start with making assumptions about a phenomenon. AI, on the other hand, is a specially built computational technique aimed at replicating human-like thinking/cognitive ability to tackle complicated technical challenges. AI is well-suited to engineering scenarios involving a high number of inputs (random variables) and a non-linear relationship between random variables and output.

In many instances, AI utilises evolutionary algorithms that attempt to learn patterns concealed in random data points through systematic evaluation.

Once a pattern is discovered, this pattern turns into the main phase of solving the complex system through training and adaptive learning. An AI-based cognitive model made of multiple layers and processing units (neurons). These neurons are arranged in visible and hidden layers to create a model that resembles the human brain, in which neurons and layers communicate continuously. The input layer, which contains random variables (predictors), is linked to hidden layers that can create linear and non-linear models. On the other hand, the hidden layers are linked to the output layer, which includes the problem's outcome/target variable(s). In the 1980s, structural engineers began to investigate machine learning applications. In recent years, researchers have begun seriously exploring different ways in which AI techniques can be applied to the structural engineering domain to solve some challenging, untraceable problems [3]. This study reviews current and future applications of AI in the field of structural engineering. Also, it discusses opportunities & challenges which can be addressed if AI Applications are used effectively in structural engineering practice.

Table I: Summary of Some of the AI Models Developed by Different Researchers in the Domain of Structural Engineering in Recent Years, from 2018 to 2021

Reference	Type of Structure	Response Variables	Predictor Variables	AI Methods	Performance Parameters
P. Jeyer et.al. 2018 [4]	2 Storeyed Rect. Building, 8 Storeyed Box Building	Wind Speed, Wind Direction, etc.	Cooling load and heating load	Component-based ML	R2, prediction vs simulation results
M. Z. Naser et.al. 2019 [1]	Reinforced Concrete (RC) structural members	Geometrical & Material Properties of RC Beam and Columns	Thermal & Structural Response of Fire-Exposed RC Members	AI-based cognitive framework	R2, R, MAE
A. D. Pham et.al.2020 [5]	Reinforced Concrete (RC) Flexural Members	Geometrical Parameters, Moment, Stress, etc.	Long Term Deflections	Single, voting ensemble, bagging ensemble & Stacking ensemble ML models	R, RMSE, MAE, & MAPE, SI, Predicted Vs Actual Values
D. Thaler et.al. 2020 [6]	3 Storeyed Two Bay Frame Structure	Earthquake Features as Time period, acceleration, velocity, amplitude, etc.	Structural Response	Feed-forward neural network	NA
M. K. Almustafa et.al. 2020 [7]	RC Slab exposed to Blast Loading	Length, width, depth, type of slab, Concrete compressive strength, etc.	Maximum Displacement of RC Slabs	Hybrid classification-regression Random Forests algorithm	R2, VEcv, MAE
J. Won et.al. 2021 [8]	Building Structures	Seismic Response with SSI Effects	Seismic Performance Levels such as Immediate occupancy (IO), Life safety (LS), and Collapse prevention (CP) and Collapse (C)	Feed Forward Artificial Neural Network (FFANN)	MSE, R2, Relation between predicted and target values, Confusion Matrix
M. K. Almustafa et.al. 2020 [9]	Fibre Reinforced Polymer (FRP) Retrofitted RC Slab exposed to Blast Loading.	Slab Size, Bond Strength, FRP configuration, Steel yield strength, Steel rfn. Ratio etc.	Maximum Displacement of RC Slabs	Gaussian process regression algorithm	R2, MAE, MAPE
D. Birky et.al. 2021 [10]	Non-Linear Structural System	Geometrical & Material Properties of the cantilever beam	Dynamic Response	Deep Learning Neural Network	MAPE, Actual vs Predicted
D. C. Feng et.al. 2020 [11]	NA	coarse/fine aggregates, cement, water, additive, etc.	Compressive Strength of Concrete	ANN & SVM	R^2, RMSE, MAE, MAPE
C. J. Lin et.al. 2021 [12]	NA	Ingredients of Concrete	Compressive Strength of Concrete	Back Propagation ANN & Genetic Programming	Coefficient of Efficiency (C.E.)
G. Du et.al. 2021 [13]	NA	Ingredients of High-Performance Self-Compacting Concrete	Compressive Strength of High-Performance Self-Compacting Concrete	GA – BP Neural Network (BPNN)	Correlation coefficient (C), RMSE, MAE
K. Jadhav et. al. 2020 [14]	Existing Structures	02 different earthquakes	Seismic Hazard Safety	Multilayer Perceptron Network (MLP)	Confusion Matrix
B. Sun et. al. 2020 [15]	Large-scale steel BRB Frame	Ground motion records	Seismic Fragility Analysis	ANN	-
R. Segura et. al. 2020 [16]	Concrete Gravity Dam	Ground motion records	Maximum Relative Base Sliding	Metamodels	R^2, RMSE, RMAE
C. Long et.al. 2020 [17]	2D and 3D Truss structures	Cross-Section Areas of Bars	Optimised Cross-Section Areas with weight	Deep learning	-
J. Melchiorre et. al. [18]	Circular Arches	Geometrical Parameters	Quantity of material	Genetic Algorithm	-

II. METHODOLOGY

Articles/Journal papers/conference proceedings were collected randomly with keyword searches as "applications of AI in

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structural engineering", "AI in structural engineering", "ANN in structural engineering", "Machine Learning/Deep learning/Pattern Recognition Applications Structural engineering", "Prediction of compressive strength of concrete by AI techniques" from prominent and well-accepted academic databases as Scopus, Web of Science, American Society of Civil Engineers (ASCE) Library, Wiley Online Library, Sage, Science Direct, Multidisciplinary digital publishing institute (MDPI), Taylor & Francis Online and Emerald. The articles/Journal Papers/conference proceedings selected for review are from recent years, from 2018 to 2021. Randomly, 30 articles related to applications of AI in the structural engineering domain were selected for this study.

A. Applications of AI in Structural Engineering

With advancements in technology, AI plays a vital role in the sub-domains of Structural Engineering. Some of the most critical applications are as follows:

Structural Health Monitoring (SHM) is the process of implementing a damage detection and characterisation strategy for engineering structures. It involves monitoring of existing structures such as bridges, heritage buildings, etc., with the help of sensors from remote locations. As of today, one cannot monitor the health of structures from remote locations without sensors. Current practices to monitor/evaluate the performance of existing structures are the Visual Inspection Method and the Non-destructive method. As these practices have some limitations, such as being time-consuming and costly, working only in accessible regions of the structures, needing a high degree of expertise, etc [Y. Hooda, et al. [19]. It is challenging to detect damage to existing infrastructure by conventional vibration-based methods of SHM. Therefore, there is a need for alternative novel techniques. Various AI techniques provide advanced mathematical frameworks and algorithms that can help to discover and model the performance of a structure through deep mining of monitoring data collected from sensors [20]. M. Mishra et al. [21] carried out a systematic review to assess the health condition of heritage buildings using different emerging AI techniques, including ML, and also discussed the future scope and challenges of AI techniques related to heritage buildings. P. Singh et.al [22] carried out a literature review of various machine learning methods for monitoring of existing structures and also discussed current methods of SHM, such as vibration-based methods, Visual inspection, etc., and how to implement them with different machine learning techniques. O. Avci et.al. [24] reviewed vibration-based damage detection of civil infrastructures by using conventional methods as well as AI techniques such as ML and DL. As the structure becomes more complicated, the dependence on system physics for interpreting the observed sensor data becomes less (See Fig. No. 1), and a predominantly data-driven approach is adopted. For complex real-world structures, the preferred method must be data-driven, with system-physics/domain knowledge integrated in some way [14].

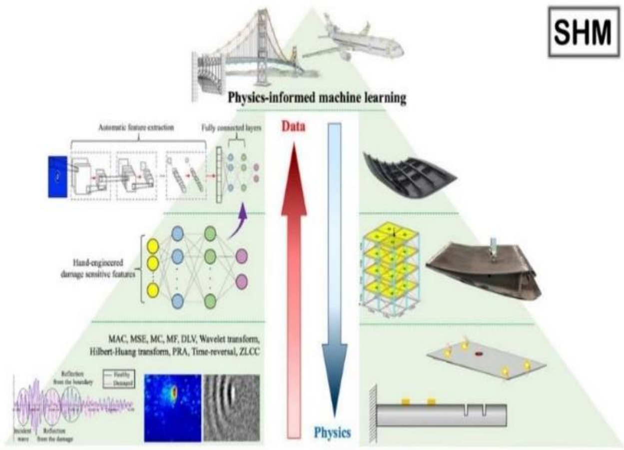
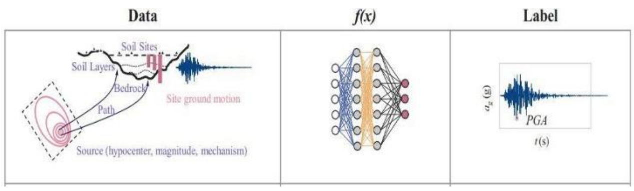


Fig.1: Structural Health Monitoring (SHM) [14]

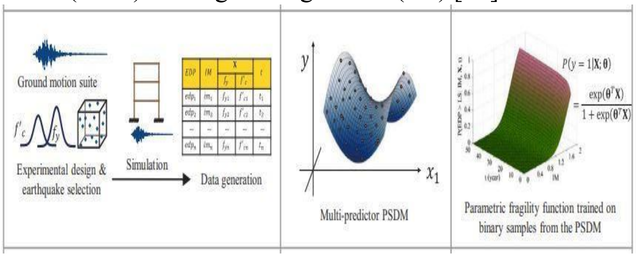
Seismic hazard analysis involves the quantitative estimation of ground shaking hazards at a particular area. Seismic hazards can be analysed in two ways: deterministically and probabilistically. When a specific earthquake scenario is assumed, deterministic seismic hazard analysis (DSHA) is carried out. When uncertainties such as earthquake size, location, and time of occurrence are explicitly considered, probabilistic seismic hazard analysis (PSHA) is carried out. A critical part of seismic hazard analysis is the determination of Peak Ground Acceleration (PGA) and response acceleration (spectral acceleration) for an area/site [25]. A schematic figure shows (See Fig.2) training an ANN to predict the PGA of ground motions using strong motion databases [14]. Kirti Jadhav et.al [14] developed a smartphone application for seismic hazard safety assessment of RC Buildings by using ML, and also developed an ML-based framework for the seismic hazard safety of RC Buildings and studied damage classification techniques, the efficacy of the Machine Learning (ML) method in damage prediction via a Support Vector Machine (SVM) model. R. Jena et.al [26] developed a convolutional neural network (CNN) model for earthquake probability assessment in NE India and conducted vulnerability assessments using the analytical hierarchy process (AHP), Venn's intersection theory for hazard, and an integrated model for risk mapping and also developed a CNN model for earthquake probability estimation & to identify the earthquake-prone areas at Palu, Indonesia.



[Fig.2: Structural Hazard Analysis (SHA) [14]]

Seismic fragility can be defined as the proneness of a structural component or a system to fail to perform satisfactorily under a predefined limit state when subjected to an extensive range of seismic action. In accordance with the above definition, seismic fragility analysis can be regarded as a probabilistic measure for seismic performance assessment of structural components or systems.

There are two different end products of seismic fragility analysis: a damage probability matrix and a fragility curve [16]. R. Segura Padgett et. al [16] developed metamodels by using different machine learning techniques to find the approximate seismic response of concrete gravity dams, and practical design guidelines were devised from analysis of metamodels. Sun et al. [15] established machine learning-based algorithms for seismic fragility analysis of steel buckling-restrained braced (BRB) frames. Following the figure number. 3 shows that the development of a multi-predictor probabilistic seismic demand model (PSDM) and a multidimensional fragility model through response surface model (RSM) and logistic regression (LR) [14].



[Fig.3: Seismic Fragility Analysis [14]]

Structural optimisation is crucial for improving the efficiency, cost-effectiveness, and environmental sustainability of built structures. Over the last few decades, structural optimisation has proved itself as an essential tool in the design process. The goal of the optimisation can be to minimise the stresses, amount of steel, overall cost, etc., for a given amount of material and boundary conditions. Structural Designs based on an optimal material distribution for the structural system are not only efficient and lightweight but are also often aesthetically pleasant from an architectural point of view [27]. L. Mei et al. [27] carried out a critical literature review on structural optimisation in the civil engineering domain. C. Long et. al [17] studied a novel approach for structural optimisation of 2D & 3D truss structures by using deep learning. Hao Zheng et.al [28] proposed a novel method by using machine learning techniques for topological design compression-only shell structures with planar faces, considering both structural performance & construction constraints. J. Melchiorre et al. [18] developed machine learning algorithms for the structural optimisation of circular arches with different cross-sections.

The strength of concrete is an important parameter to determine the performance of the material during service conditions. For the mix design of concrete, the strength is essential. Generally, concrete has high compressive strength and low tensile strength. Conventionally, statistical analyses such as linear & Non-Linear regression are critical tools to find the strength of concrete mixes. However, results obtained through statistical analyses are often inferior in most cases. In recent years, machine learning algorithms have drawn more and more attention because of their capability to deal with multivariable analysis [13]. G. Du et. al [13] developed a genetic algorithm to predict compressive strength of self-compacting concrete by using back propagation neural networks (BPNN). P.F.S. Silva et al. [29] developed three models, including Random Forest, ANN & SVM, for predicting the compressive strength of concrete. S. D. Latif [30] developed a prediction model for compressive strength using datasets obtained from a deep learning method, long short-term memory (LSTM), and a Support vector machine (SVM). Bhagat S.R. et. al [23] reviewed different AI techniques for forecasting pollution.

III. CONCLUSION AND FUTURE SCOPE

This research looked at how artificial intelligence (AI) can be used in the field of structural engineering. There are five critical areas, such as structural health monitoring (SHM), seismic hazard analysis, seismic fragility analysis, optimisation of structural systems/members & prediction of strength of concrete, in which one can apply various AI techniques. A summary of multiple AI techniques in the structural engineering field, as employed by researchers over the past three years, from 2018 to 2021, is presented in tabular form. The review demonstrates that various AI approaches like machine learning, pattern recognition, and deep learning have the capacity to understand nonlinear relationships among the contributing factors, allowing them to tackle a wide range of issues that are difficult or impossible to address using conventional approaches. The review further shows that various AI techniques have been applied to the computational structural analysis domain, such as in finite element analysis, to improve computational time. Numerous challenges must be addressed to apply various AI techniques in the structural engineering domain. The first challenge is obtaining sufficient, diverse, and high-quality data. The second difficulty is the black box character of some AI approaches. It is fair to advise structural engineers who are completely unaware of the AI algorithms not to utilise various AI approaches. The third issue, which seems to be a side effect of AI's massive popularity, is that it is sometimes extolled like a panacea for all challenges in different sectors. The fourth issue concentrates on assessing whether various AI algorithms are appropriate for specific problems in the structural engineering domain. The fourth issue focuses on evaluating whether various AI algorithms are suitable for particular problems in the structural engineering domain. In summary, the authors believe that there are several potential domains where AI algorithms might give substantial benefits to practising structural engineers.

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