Emerging Applications of Artificial Intelligence in Structural Engineering and Construction Industry

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Abstract. With the beaming concept of Construction 4.0, the disciplines of structural engineering and construction industry needs an advancement for the data collection, interpretation and analysis. Augmented Intelligence and its various disciplines find an impressive application in the field of civil engineering for data requisition, management and performance. This study focuses on how AI and its various principles can be blended with the emerging areas of structural engineering, and how it is shaping the construction industry by employing in the major areas of monitoring of structural health, assessment of damages and construction management.

1. Introduction
Artificial Intelligence or Augmented Intelligence is a technological revolution which allows the machines to work intelligent in a most efficient way. Artificial Intelligence is a way to encompasses the capabilities of human beings such that they can accomplish the tasks which neither humans nor machines can do individually. With the availability of the power of internet, we can access any information in lesser duration of time. Also, with the principles of Internet of Things (IoT) and Distributed Computing, an enormous amount of data can be collected and used in a particular application area. With the help of Augmented Intelligence, the structured information is available at the fingerprints of the user and thus, helps them in making the righteous decision with the background of data with solid evidences. AI works on the fundamental of the knowledge that is provided to them by the human beings by different means and examples. The humans deliver machines a skill to study the various examples and thus, generate the machine learning representatives based upon the inputs and anticipated outputs. The above process can be done in three different ways, i.e., by three types of learnings including: Unsupervised Learning, Supervised Learning and Reinforcement Learning. Also, AI can be defined in four different ways on the basis of its dimensions and application areas as Weak AI, Applied AI, Generalized AI and Super AI. Narrow or Weak AI is that type of AI which is only applied to a definite domain, the application areas include Intelligent Spam Filters, Self-driven cars, virtual assistant and many more. Applied AI is the one which ca perform definite tasks, make their decisions by considering the planned and automated algorithms and statistics. This type of AI doesn’t learn new algorithms to perform their tasks. Generalised AI, or sometimes known as Strong AI, is the type of AI which can function and perform a great diversity of individual or inter-related tasks. This type of AI is capable to learn new algorithms to perform and find the solution of the emerging innovative problems. Generalised AI can perform the mentioned tasks by instructing on its own the latest strategies. It is considered to be a mixture of many...
strategic disciplines of AI, which learn from experience and thus, is able to perform at a human level of intelligence. Conscious AI or Super AI, is that branch of AI which interact directly with the human – level consciousness. Since, the correct definition of the consciousness is yet to be coined, the Conscious AI will be considered as a futuristic AI.

The application of AI has been increasing as the technology advances and having a lot of dimensions. The first dimension includes the steps and procedures to make machines understand and do the appropriate act as human beings does. The second dimension is all about the sensory and cognitive capabilities of the machines, including the speech recognition and image processing, based on a particular pattern acknowledgement. And the third dimension consists of creating those innovative technologies which can replace what human beings can do. AI is not only related to the field of computer sciences; it is based on the principles of other scientific disciplines also. The area of Electrical Engineering and Computer Science Engineering focuses on the implementation of AI in hardware and software respectively. The disciplines of Statistics and Mathematics is used is the determination of the viable models and in the measurement of performance. Because of the fact that AI is programmed on the ability and the way brain works, the areas of Linguistics and Psychology plays an important role in the understating of working of AI. The ethical consideration was guided by principles of philosophy. The applications of AI are used worldwide on everyday basis, from one domain to another, having a huge impact on the lives of human beings as well as on the society in various meaningful and expressive ways.

Figure 1. Emerging AI Branches in Structural Engineering and Construction Industry.

Considering the various disciplines of AI such as Deep Learning, Pattern Recognition, Machine Learning, Fuzzy Logics, Swarm Optimization, Decision Trees and Evolutionary Computation; all can find their applications in the areas of construction industry structural engineering. Figure 1 shows the
increasing trends of the various disciplines of AI in the field of construction industry and structural engineering over the past decade. The main objective of PR or Pattern Recognition is the classification of the objects into different categories, classes or groups. The main reason behind the classification may depend on the application area, may consists of signals, speech, images, and so on [1,2]. The features in PR are signified by as a set of characteristics. Outcomings from the Statistical Decision Theory are used to produce the decisive boundaries among the pattern classes. Deep Learning, considering a branch of Machine Learning, I basically made up of several networks, made up of either unlabelled data or unstructured data. It is built in the principles of Deep Neural Networks. DL designs consists of Recurrent Neural Networks (RNN) and Convolutional Neural Network (CNN). CNN architectures is considered to be most useful in the application areas of Construction industry and structural engineering. The principle of CNN is inspired by the visual cortex of animals [3]. This technique has been used in computer science and engineering for the purpose of image recognition [4 – 9]. Due to the presence of sporadically connected neurons, CNNs are more capable in the process of capture the 2D topology of pixels than standard neural networks.

2. Application areas of AI in Civil Engineering:

With the advancement in the technology and considering the principles of Construction 4.0 and Industry 4.0, Augmented Intelligence (AI) plays an important role in the various sub – disciplines of Civil Engineering. Some of the most important applications includes:

2.1. Structural Health Monitoring (SHM):

Structural Health Monitoring or commonly known as SHM is defined as the process of executing a detection of damage and characterization approach for the engineered building and structures. It basically involves the process of Statistical Models Development, Data Feature Extraction, Operational Evaluation and Health monitoring. The objectives of SHM includes Assessment of post-earthquake structural integrity, monitoring of structures affected by external factors, decline in construction and growth in maintenance needs, the move towards performance-based design philosophy, Performance enhancement of an existing structure and Feedback loop to improve future design based on experience.

With the help of AI, many sensors and dampers are been designed and installed in the structures to perform the above stated objectives. In SHM, the approach used is known as a model – driven approach, which emphasis on the numerical modelling of a particular structure, on the basis of finite element modelling (FEM), which develop the relation between the discrepancies measured and the generation of model data for the purpose of detection of damage in a particular structure. With making the comparison between the model formed and measured data, the damage in a structure can be detected.

Sensors plays a vital role in the process in the collection of the data. The data – driven approach is worthy when 1. The structure is complicated to model because of its physical characteristic and 2. The data is huge. While considering the concept of Machine Learning in SHM, it deals with producing information form the earlier experiences, getting to know about the parameters of the model and then concentrating on forecasting latest and new data for input. The various learning schemes such as Unsupervised and Supervised Learning, have been used in the various applications of SHM. The algorithms include Artificial Neural Networks (ANN) [9], K – Nearest Neighbour Method (K – NN) [10] and Support Vector Machine [11].

Freshly, SHM community had adopted a new variety of Machine Learning Methods, which is known as Singular Value Decomposition and Low – Rank Matrix Decomposition. This class of ML is having the capability in dealing with incomplete and sparse data. A data matrix is used to represent the measurements of a structural response from the mounted sensors. Latest mathematical tools such as low – rank matrix decomposition and sparse representation are used to process the measurements for a structure with irregular data. The information shared [12] focused on how the application of statistical Methods and Low – Rank Matrix Decomposition is useful in the structural health monitoring and identification of the localised damage for plate structures. Nagarajaiah [11] offered a new model for the purpose of damage detection, which based on the low – rank data structures and modelling of the
structure. This method is widely used in the dynamics of the structure and also in the application areas which are related to data sensing, data and structural monitoring, and structural management. Yang et al. [13,14] worked on the decomposition of the low – rank matrix, in conjunction with the methods of norm minimization to get the responses of vibrations which occurred due to wind loading and seismic loading in cable – stayed bridges and stell tower. The study conducted by Mondoro et al. [15] showcased an ideology to determine the strategies regarding optimum risk – management. They considered these strategies only in case of bridges, in which all the uncertainties were associated with failure outcomes of the bridge under hurricanes and loading of the moving traffic, socially, economically and environmentally. Chatterjee et. al. [16] used an algorithm for the purpose of calibration of an ANN – Model to restrict the maximum as well as RMS error of the network.

2.2. Modular Construction Decision Making:
Neuro – Modex – Neural Network System for Modular Construction Decision Making helps in the process of decision making to choose either a conventional model or to go for some modification to the existing model for a particular project. This decision-making system works on some decision – making attributes, which depends on basic five disciplines: 1. Risk management in Project, 2. Characteristics of Project, 3. Availability of Labour, 4. Relation between Environment and Organisation, and 5. Location of Project. The neural network for making this particular model is created by collecting data from various construction and engineering industries, and also from some of the environmental – related industries.

2.3. Construction Management System:
Construction Management System consists the management of the construction project from the very first step of designing to the last step of handing over to the client. The initial model – designing plays an important role in the process of fusion of a finally acceptable result. The application of neural network forecasts a better design at the initial stage, which includes some various significant fields in construction industry such as calculation and determination of concrete mix grade, load calculations, determination of the tensile reinforcement and depth of the beam, and calculation of moment capacity. Artificial Intelligence finds its application for generation of plans in different stages of project, including the explanation of the actions used in the project management with their pros and cons, and how to determine and use the emerging actions into the project plan. With Construction 4.0, the application of Robotics has been started in the execution phase of the construction industry in various machineries related to work with concrete making, plastering, transportation of materials and with the latest, safety of the labours at the construction site. The application of Machine Learning used in the concrete production at the batching plant at construction site. After determining the various constituents of grade of the concrete used for a particular work, we just need to enter the values and the concrete of that mix is just made within a fraction of minutes. The application of AI is being vastly used in the determination of weak structural link in any structure. With the advancement in the technological software as well as the input methods in different mathematical software, the structure can be easily analysed and then we can predict that whether the structure is safe to withstand the hazardous effects of high intensity wind loads, seismic loading and impact loading as per the latest Indian Codal Provisions, issued by Bureau of Indian Standards (BIS). After performing the analysis, if the structure tends to fail or any structural member comes out to be a “weak” member, then we provide necessary rehabilitation or retrofitting techniques so as for the seismic strengthening of the structural element or structure.

In consideration with the management of the various activities at the construction site, again disciplines of AI play an important role for keeping the track on the same. With the application of ANN in the management related technical platforms, one can easily track down the progress of the project on daily, weekly, monthly or yearly basis. Also, with such applications, one can track down the location of the labours on the construction site by putting a GPS – chip in safety jacket or helmets of the labours. This will be helpful in gathering data regarding the presence of labours on the construction site, the movement of the labours on the construction site and if any causality happens, one can easily reach to the injured labour with the help of these chips inserted in their uniform.
Table 1. Domain Disciplines of AI in Structural Engineering and Construction Management.

| Domain Application | Disciplines of Structural Engineering | Method and Application of AI used | Reference No |
|---------------------|--------------------------------------|----------------------------------|--------------|
|                     | Bridge Structure                      | Autoregressive models            | 17, 18       |
|                     | Steel Frame Storey Structure          | ANN with Bayesian method          | 19, 20       |
|                     | Structure with steel beam             | Mahalanobis distance-based function | 21           |
|                     | RCC Frame Structure                   | Artificial Neural Network         | 22           |
|                     | Steel Structure made – up for Rail – Road Network | Mahalanobis squared distance | 23           |
|                     | RCC Frame structure                   | Analysis considering the concepts of Robust Regression and Principal component analysis | 24           |
| Structural Health Monitoring | Bridge Superstructure                | Pattern Recognition Approach      | 25           |
|                     | Bridge – Suspension Type Bridge       | ANN with concepts of Regression Tree, Random Forest and Support Vector Regression | 26           |
|                     | Gusset Plate Designing and Analysis for Bridge | Probabilistic neural networks & Bayesian approach | 27           |
|                     | Plate structures                      | 2DLDA and 2DPCA                   | 28 – 30      |
|                     | Analysis of a Stadium Structure       | Principal Component Analysis considering Autoregressive Modelling | 31           |
|                     | Metallic structures                   | Adaboost machine learning         | 32           |
|                     | Concrete structural components        | SVM                               | 33           |
|                     | Pipes (made up of steel)              | Adaptive Boosting and SVM         | 34           |
|                     | Meshed RCC structure                  | ANN                               | 35           |
|                     | Transportable – Type Bridge           | Robust Regression Analysis         | 36, 37       |
|                     | Cable – Stayed Bridge                 | Sparse Recovery with L – 1 Mechanism | 14           |
|                     | Steel Frame Building                  | Pattern Recognition Approach      | 38, 39       |
|                     | 3 – storeyed frame structure          | Vector Quantisation in Machine Learning | 40, 41     |
|                     | PSC flexural members                  | Pattern Recognition Approach with Euclidean and Mahalanobis functions | 42, 43     |
|                     | Space Truss and Bridge Slab           | Pattern Recognition Approach with an Auto - Regressive Modelling | 44           |
|                     | Plate with one end fixed and another end free | Multi – Layered ANN              | 45           |
|                     | Superstructure of bridge              | Symbolic Data Clustering with PCA | 46           |
|                     | Plate structures                      | Multi – Layered ANN               | 47           |
|                     | 3 – storeyed frame structure          | ANN                               | 48           |
|                     | Grid Steel Frame Structure            | Principles of ANN with SOM         | 49           |
|                     | Transmission Towers                  | PCA – Principal Component Analysis | 50           |
2.4. SHM System with IoT:
One of the chief concerns in the structural and construction industry is the property of durability of the structures. With the latest revisions in the Indian Standard Codal Provisions regarding new clauses and guidelines in the concrete production, calculation of wind loads and seismic vulnerability, the existing structures must be checked and analysed as per the latest revision provisions. This particular situation makes the construction industry to shift towards the concept and skills under Internet of Things. [75]. The concept of IoT finds application in the structural monitoring. This concept focuses on the enhancing the machine – to – machine communication with the help of integrated sensors, with main aim of efficiently and effectively monitoring of devices. Smart devices are used for the purpose of collection of data, transmission of information, processing information collaboratively using the techniques of cloud computing. In continuation, the concepts of Machine Learning and IoT can be combinedly used for SHM [76 – 78]. On contrary, one of the vital questions arises while performing SHM of the structures, commonly bridges, it is not so easy to timely monitor the sensors mounted as well as to compare the fresh readings with the previous data. Thus, it is a challenging job to monitor all the installed sensors, which are also may be geographically located at a certain distant from one another. Therefore, a new technology must be needed for this application in such a manner that it binds the sensors, such that the recordings from all the mounted sensors can be recorded at one single time. Furthermore, it is a must task to connect all the information which are received through the sensors via internet. For the same purpose, some of the discipline of AI and IoT can be effectively combined and
used. The data from the various sensors placed on a long – span bridge can be obtained by the means of IoT and then with the help of ML, one can do further structural analysis and explanation. With IoT, Structural Health Assessment provides an accurate, time – saving, economic and efficient solution. The blend of the application and concepts of IoT, SHM and Cloud Computing, a powerful database can be generated and analysed in comparison to the traditional way of performing structural health assessment. Moreover, the platform of cloud computing gives an advantage to the SHM system to stock the data and use them for the development and usage of the smart monitoring devices. The “health” status of the structure is sent to the server, and then the data is stored, can be remotely monitored with the help of mobile devices and can be interpreted with the help of ML.

2.5. Smart Cities with IoT:
With the beaming expansion of the industry focusing on the idea and application of smart cities in various engineering disciplines, IoT plays an important role for more research application [79 – 82]. The concept of smart cities comes with an idea of making better usage of services for the common public and simultaneously reduction in the operational costs. Thus, it can be considered as a discipline which focuses on the usage of the resources available efficiently and effectively. This particular agenda can be only achieved by proper instalment and data collection through the wireless sensors which can be installed at various places in a city. With the application of IoT with the concept of smart cities, the sensors are used for the data collection, interpretation and categorization. [83, 84].

![Figure 2. Branches of AI in Structural Engineering.](image-url)
Since the data collected from a particular city is vast, it is hard to maintain the record as well as to interpret the same. Also, one city is different from another, having their own specific problems, there is a must need for the development of technological advancements for data collection, classification and interpretation. DL architecture can be used for the collection and interpretation of the data in such situation. The concept of DL is used to train various systems for the purpose of recognition of the pattern for providing a wide variety of networks and also, provide the recognition which may develop due to network performance issues. DL architecture is found to be highly effective in sequential data analysis. Thus, this platform provides a solution to solve the problem related to optimization with respect to smart structures and cities. The belief behind smart city depends on the usage of the sensors to guarantee the safety, sustainability and efficiency of the city’s infrastructures. With the latest development in the field of nanotechnology, self-sensing materials are provided in a city for the purpose of monitoring the condition of the structures in a particular city. Another important emerging technology is Smart Concrete, which is having an ability of making any structure made up of concrete self-sustaining [85–86]. The monitoring of traffic and vulnerability assessment of the structures can be easily done by fabricating the concrete mix with sensors, made up of carbon nanotubes. Another noteworthy example is the development of new approaches for the detection of the corrosion in the concrete structures at very first stage. The reason behind this approach to monitor the concrete condition during its curing phase. The sensors embedded into the concrete also leads to monitor accurately the temperature of the concrete and strength of the concrete during its curing phase. The data regarding the same can be easily stored, and communicated with the help of smartphones through IoT. ML and DL are considered to be the two most application areas of AI for the purpose of data collection and interpretation for the assessment of structure.

3. Conclusion
This study focused on how the different disciplines of AI is useful in various areas of structural engineering and construction industry. It had been noted that to solve the structural problems, relates to health monitoring or damage assessment, the traditional methods are accompanied with the technological advancements in terms of sensors and algorithms for the collection of data, implementation and analysis. Also, whether related to construction management or structural designing and analysis, emerging applications of AI in civil engineering finds a worthy result. The usage of these advancements results in better performance and accuracy.

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