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Integration of Non-Destructive Testing Techniques and Machine Learning Algorithms for Enhanced Structural Health Monitoring of Bridges

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Author's contribution

The sole author designed, analyzed, interpreted and prepared the manuscript.

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Review Article

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ABSTRACT

Aim: To examine the integration of non-destructive testing techniques and machine learning algorithms in order to enhance structural health monitoring of bridges.
Problem Statement: Bridges are vital structures in civil engineering which have broad purposes and economic influence. However, they get expired over some period calling for their structural health monitoring from time to time to avoid any catastrophic event that may arise from their collapse.
Significance of Study: This technical review critically examines the need to adopt the use of non-destructive testing techniques and machine learning algorithms in order to enhance structural health monitoring of bridges.

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Methodology: Recent relevant published articles in the area of structural health monitoring of bridges, non-destructive testing techniques and machine learning algorithms were consulted.
Discussion: The advancement of technology has greatly influenced the incorporation of non-destructive testing techniques and machine learning algorithms to enhance structural health monitoring of bridges. This technically review has discussed the fundamental principles of structural health monitoring of bridges, non-destructive testing techniques and machine learning algorithms. Various non-destructive testing methods for SHM of bridges were highlighted and major emphasis was laid on visual testing, ultrasonic testing, liquid penetrant testing and radiographic testing. Their respective advantages and shortcomings were discussed. Application of machine learning in bridge SHM to improve the monitoring techniques was discussed. Different supervised and unsupervised learning algorithms that are applicable to the SHM of bridges are explained.
Conclusion: The incorporation of non-destructive testing techniques and machine learning algorithms to structural health monitoring of bridges is imperative to integrate and enhance the process.

Keywords: Machine learning algorithms; non-destructive testing techniques; structural health monitoring; bridges; supervised and unsupervised learning.

1. INTRODUCTION

In the modern era, structures of civil engineering are the results and outputs which are attributed with design solutions which are progressively complex. To attain this, the adoption of innovative materials and methods in new construction are often proposed by engineers. Materials performance and their potential to be resilient to different stresses are still of major importance [1]. Not only this, researchers are much concerned with the materials recycling and general sustainability with the major target of reducing the cost and construction time. To corroborate this, human population growth has greatly influenced the rise in the size of numerous civil engineering structures. Based on this fact, global records of increase in the dimensions of structures in terms of length for bridges and height for buildings are noticed. Thus, this ascertains the possibility of rise in challenges of handling these gigantic structures in terms of maintenance requiring high dependable monitoring with high level of accuracy which can majorly be achieved with the use of well-thought-out integrated techniques and higher number of sensors. The aforementioned structures irrespective of being old or new are subjected to the aging and get decayed over time as year progresses. Factors such as fatigue, cycling loading and corrosion are major determinants of the degradation of the structures over time. Asides this, sudden deterioration as a result of natural disasters such as earthquakes or collisions can be experienced unexpectedly. In theoretical consideration, factors such as poor management, technical problem and maintenance are the major causatives of bridge collapse. Fig. 1a is the pictorial presentation of a highly corroded cross beam in the Old Lidingö Bridge while Fig. 1b represents the installation of strain gauge in the Old Lidingö Bridge [2].

(a)

(b)

Fig. 1. Pictorial presentation of (a) highly corroded cross beam located in the Old Lidingö Bridge and (b) installed strain gauge situated at the Old Lidingö Bridge [2]

1.1 Bridges as Prominent Civil Engineering Structure

Bridges are the most prominent structures among other civil engineering structures and they have been identified as principal transportation infrastructure properties of a country which serve as stimulants to social and economic development and regional cooperation. For instance, many of the bridges existing today in the United States were constructed to have a lifetime of about 50 years before repair based on the standard set by the American Society of Civil Engineers (ASCE). However, the average age of many of the bridges in the United State are presently about 40 years. Additionally, one-third of the existing bridges of around 576,600 are either functionally obsolete (that is need to be replaced) or structurally deficient (that is need to be repaired) as it was estimated in 2014 by the US Federal Highway Agency (FHWA). Equally in Europe, Joint Research Centre (JRC) has alarmed the ageing condition of the transport infrastructure in critical condition [3]. It was reported that many of the road bridges with more than 100 meter long, found along the major European transport corridors in the Trans-European Transport Network, were constructed in the era of economic boom in 1950s. It was then noticed in 2019 that many of the aforementioned bridges are expired calling for either repair or replacement. Nonetheless, many of these bridges, as a result of general increase in axle loads and traffic volume, carry considerably larger loads more than what they were designed for originally [4-7]. All these factors have greatly influenced the requirement for inspection, maintenance and monitoring of bridges. Additionally, some recent tragic occurrences like the collapse of Morandi Bridge has greatly emphasized these needs. Thus, the structural health maintenance (SHM) of bridges is very paramount. Fig. 2 represents the schematic representation of the SHM of bridges [4].

There is need to adopt efficient techniques to enhance the structural health monitoring of bridges such as the use of non-destructive testing techniques and machine learning algorithms. The techniques of examining materials and their quality assurance are referred to as the Non-destructive testing (NDT) which are purposely to preserve the inspected materials integrity, assets and components. Non-destructive testing simply means the adoption of testing techniques that do not change any of the tested product properties [5]. These properties could be its integrity, strength, corrosion resistance, appearance, conductivity, toughness, wear resistance and many more. Non-destructive testing is also known as non-destructive analysis, non-destructive evaluation, non-destructive inspection and non-destructive examination. The material can still be used when it passes the NDT tests because the tests do not incur any detrimental effect on the material. This benefit makes non-destructive testing a very beneficial technique for products that are newly manufactured as well as for those that are in use already. The use of a single NDT process may be enough once the scope of work is not difficult. However, in cases where tangible information regarding the product properties is needed, combination of test methods and techniques are adopted [6].

1.2 Introduction to Destructive AND Non-Destructive Testing Methods

There are some similarities in the objectives of both destructive and non-destructive testing. However, significant differences exist in their application methods and core use cases. Factors that determine their objectives, similarities and differences include results reliability, time wastage, cost efficiency and safety. The main aim of each of the testing technique is the assurance of safe product [2]. The main objective of destructive testing is to determine the operational limits for a product via tests such as tensile tests and fatigue. On the other hand, already existing materials or those in service and manufactured ones are investigated to know if they are in good condition to satisfactorily function in their service environment using NDT. NDT can equally be adopted to assess the wear and tear extent of the materials such as the utilization of ultrasonic thickness evaluation for ships steel plating [3].

In terms of cost efficiency, non-destructive testing is more cost-efficient in two ways when compared with the destructive testing. Firstly, NDT does not alter the test specimen and the material remains as effective as it was after the evaluation via NDT and can thus be put into service without any delay. Secondly, NDT can easily recognize the potential challenges in machinery that is on operation like pressure vessel. Thus, recommendation can be made for the replacement before the occurrence of failure [7]. This thereby saves the breakdown costs which may be costlier than downtime that was temporarily planned for a single part replacement. With reference to time, NDT is more effective than the destructive technique. By nature, the processes involved in destructive methods are time-consuming than those of the NDT. This is primarily because the processes of destructive testing are often manual and only fewer components can be automated. Nonetheless, longer inspection and preparation times are required for destructive testing. On the other hand, NDT does not often require the need for parts removal from service thereby saving treasured time. In the case of destructive testing, downtime increases resulting from halting the work and stopping the machines for testing [8].

Machine learning algorithms are other crucial tools that are applicable in enhancing the structural health monitoring of bridges. The ability of a system to automatically develop knowledge from large-scale after being acquired and integrated is called machine learning. The acquired knowledge is autonomously expanded via the discovery of new information without being programmed specifically to execute such [9]. In short, the machine algorithms have found wide application in: (1) capturing event understating in model form, (2) detection of anomalous phenomenon behavior proactively such that suitable corrective actions can be taken, (3) a deeper cyber event understanding that led to data generation under study and (4) future values prediction that will be created by the event with reference to the constructed model. Machine learning is an evolutionary study having recent technological innovations especially with smarter algorithms development and advancement in storage systems and hardware. Thus, the performance of a large number of tasks more precisely and efficiently has become possible. In the last couple of decades, these were unimaginable. In the past few years, a specialized subset of machine learning called deep learning was evolved. It practically involves more sophisticated algorithms, architectures and models for the prediction of future outcomes with difficult events and handling of multifaceted problems [10].

Recent times are experiencing speedy advancement in machine learning algorithm systems most especially in natural language processing, speech, image processing, reinforcement learning, computer and robotic vision and emotional processing and understanding. There are many machine learning applications that have evolved or are springing up presently in numerous business domains

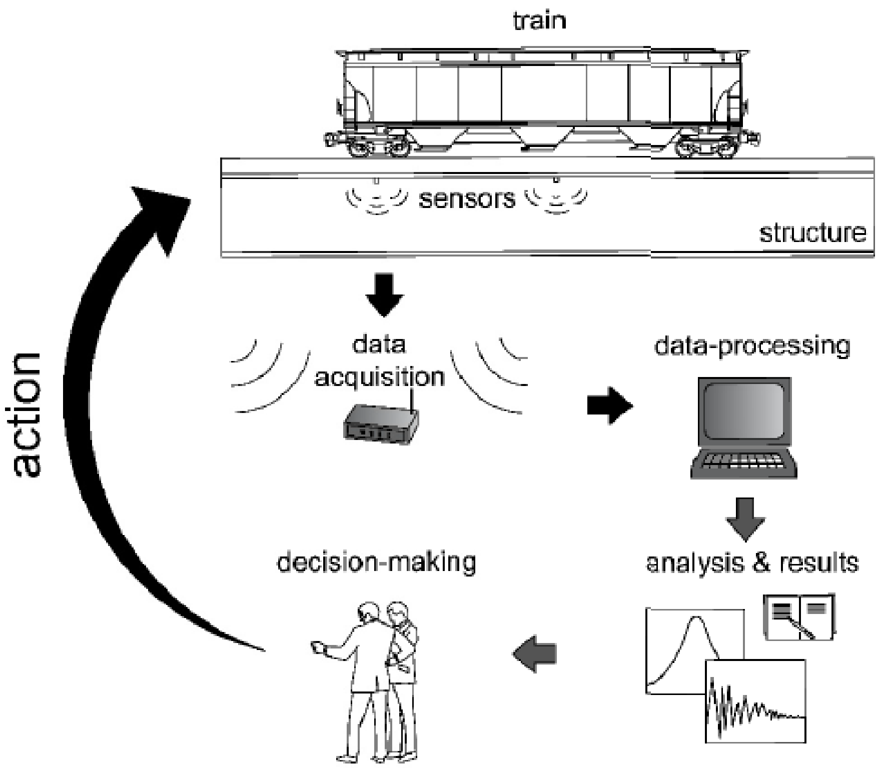

Fig. 2. Schematic representation of the SHM of bridges

such as human resources, sales and marketing, media and entertainment, finance and investment, medicines and healthcare, operations and supply chain, and many more [11]. Lately in the industry, the applied ML systems are showing some noticeable trends which adopt the power of artificial intelligence (AI) and ML systems to enhance benefits in business and society. Some of these trends are: (1) using reinforcement learning-based systems, (2) wide-spread usage of deep-learning solutions into all domains products and applications, (3) less volume of code and speedy execution of ML systems, (4) automatic codes generation for building of ML models, (5) few-shots evolution, if not systems of zero-shot learning-based, (6) designing of novel processes for the purpose of robust management and improvement of machine learning systems for improved efficiency and reliability, (7) rise in the utilization of light-weight systems appropriate for working on the resource-constrained internet of things (IoT) tools, (8) more importance of unsupervised learning-based systems that need less or no human intervention for the execution of their operations and (9)) rise in the adoption of generative adversarial networks (GAN)-based models for different image processing applications including image enhancement, image searching and so on [8].

2. NON-DESTRUCTIVE TESTING METHODS FOR SHM OF BRIDGES

Testing can be an effective means of inspecting and assessing bridge structures condition. With reference to their invasiveness degree, testing methods can be grouped into semi-destructive, destructive and non-destructive testing (NDT) methods. The destructive methods are made up of tests usually executed in laboratory under more or less controlled situations that may not the exact actual conditions usually experienced in the field. In addition, these tests can be rather costly as it is always necessary to alter the component or subject it to failure. The NDT methods are made up of a broad group of analytical techniques executed to determine the system, component or material properties, component without causing any form of damage [5]. This advantage is principally beneficial for examining in-service bridges, since the bridges can be left unharmed and open to traffic while they are still under the examination period and thus minimize the effect to the traveling public and the community in general. Some of the popular conventional NDT techniques used for damage detection in bridges are stated in Table 1 and their respective disadvantages and advantages have been published in the literature. Of these methods, the most common and peculiar ones for executing the SHM of bridges are the visual testing, ultrasonic testing, liquid penetrant testing and radiographic testing [2].

Visual testing remains the most common method of NDT for SHM of bridges. The method requires thorough examination of the bridge and detecting visible defects by naked eyes. It is a feasible and quick technique of product quality tracking at every single stage for which the specimen is in service. Defects such as cracks, deformation, corrosion and welding defects can be detected via visual inspections. To attain these, simple instruments like a camera, gauges or rulers are needed. In situations where inspectors cannot access dangerous environments or places, the use of drones is adopted. Many industries engaging in SHM of bridges usually incorporate machine learning and artificial intelligence to advance the visual inspection results. Benefits of visual testing are safety, portability, effectiveness, inexpensiveness, ease of training, little or no downtime and little or no part preparation is required. The shortcomings of visual testing include (1) it can work only with surface defects, (2) there is possibility of flaws in misinterpretation and (3) without additional optical instruments, it cannot detect minute defects [10].

After the visual inspection testing, the ultrasonic testing stands out as the most popular non-destructive testing method [11-12]. This method involves using generating a high-frequency sound wave via a transmitter which travels through the bridge under examination. The wave frequency usually ranges between 1 to10 MHz such that the wave is altered when experiencing a change in the material density. The alteration in the transmitted wave is absorbed by a receiver [12]. The received wave is then measured and analyzed by the equipment for better understanding of the depth and nature of the defects in the bridge. The thickness of the specimen can equally be calculated by the equipment via the division of the wave speed in the material by the time taken to travel. Various types of ultrasonic testing tools are already in existence based on their field of application and nuances which include immersion testing, phased array ultrasonic testing, pulse-echo testing and guided wave testing. Defects like thinning, abrasions, pitting, corrosion and cracks.

Ultrasonic testing is reliable, quick, portable, clean, accurate and sensitive, safe and easy to use, can detect subsurface and surface defects, can identify minor defects that are not visible to the naked eye and possesses the ability to gauge dense materials. However, ultrasonic testing is (1) difficult to use with thin materials (2) requires training (3) for accurate results, wave propagation speed in the examined material must be known (4) needs a smooth surface and (5) requires couplants for smooth wave transfer from the transmitter to the specimen [7].

Another prevailing non-destructive testing method that can be adopted in the identification of surface-level defects is the liquid penetrant testing. To execute this, the surface defects like fissures, cracks and voids are filled with a low-viscosity liquid called penetrant. The bridge section with defects is then left alone for some periods after the excess liquid has been wiped off. A developer which enables the penetrant to move towards the surface is then applied by the inspector [6]. The section of the bridge that has defects is left alone for a specified period of time after which the surface inspection is performed by the inspector. The inspection can be executed with the aid of naked eye in cases where the dye is visible. Black light is required for inspection in cases of fluorescent dyes. Surface discontinuities like porosity, laps, seams, leaks and cracks can be detected via this method. Liquid penetrant tests possess the following attributes as their benefits: (1) low cost, (2) portable, (3) works with numerous materials, (4) can test huge areas, (5) material properties such as conductivity, magnetism and metallic/non-metallic are not essential, (6) suitable for sophisticated part geometries, (7) Easy to use and, (8) tiny defects like hairline cracks can be spotted. The disadvantages are (1) the depth of defects is unknown, (2) inability to identify subsurface defects, (3) hazard of toxic fumes exposure and (4) incompatibility with porous materials [13].

Lastly, internal defects in parts can be spotted using radiographic testing with the aid of radiation. X-rays work perfectly with thinner materials in which the gamma rays are good for thicker materials. The mechanism involves placing the specimen between a recording media and the radiation source. The volume of radiation which exits the examined part in various locations is absorbed once the radiation falls on the part. The recording media is made up of either a digital detector or a physical radiography film. The test enables the evaluation of the size and shape of internal defects via changing the radiation exposure angle. Radiographic testing can be used to locate defects such as insufficient fusion, thinning, voids, corrosion, cracks, porosity, laps and excess root penetration [9]. Advantages of radiographic testing include: (1) ability to record subsurface and surface defects, (2) permanent documentation, (3) ability to test complex structures, (4) limited results misinterpretation, (5) can work with broad range of materials, (6) possibility of portability using gamma ray testing and (7) requires little surface preparation. The shortcomings of radiographic

Table 1. Various Non-destructive testing methods

Audio-visual methods	Visual inspection Chain drag Coin tap test
Stress-wave methods	Acoustic emission Impact echo testing Sonic testing Ultrasonic NDT Impulse response (IR)
Electromagnetic methods	Ground penetrating radar (GPR) Conductivity Half-cell potential Electrical resistivity measurement
Deterministic methods	Proof load test Coring
Miscellaneous tests	Dynamic vibration testing Infrared thermography Radiography

testing include (1) ineffective for surface and planar defects, (2) more expensive (3) requires skilled personnel for execution and accurate results interpretation, (4) radiation and high voltage can be detrimental to personnel and (5) requires two-sided access to specimen [3].

These NDT methods are usually incorporated with visual inspections which compensate for knowledge that may be impossible to infer or is excessively peculiar to those optical methods only. NDT methods are generally dependent on physical principles in which electromagnetics and acoustics play a very vital role. This strongly indicates that these methods can solely be adopted in damage detection on a local scale which is often on dangerous locations of the structure and access to particular components of the structure is required causing a cost-consuming and timely process [8]. Asides, the interpretation of the results are usually conducted by test technicians on an isolated basis without serious comparison of the obtained signals in the present inspection with the homologous ones generated from the past inspections. A means to lessen those shortcomings has arose with innovative materials and sensor techniques which enable sensors to be incorporated with structural components for continuous long-term usage and enabling NDT techniques to be adopted occasionally for initial examination and/or additional testing as and when necessary [14].

3. APPLICATION OF MACHINE LEARNING IN BRIDGE SHM

The advantage of Machine learning (ML) has been taken by data-based methods. The application of artificial Intelligence (AI) which provides systems with the capacity to automatically learn and improve based on experience without the need to explicitly program them to do so is referred to as machine learning. It focuses on the advancement of computer algorithms or programs that can access data and utilize it to learn for themselves which involves future predictions making without human assistance or intervention. The principle behind the use of data-based technique for SHM, and more precisely for the detection of damage in structures, is to utilize the data sets of feature signals gotten from a structure over time and to adopt soft computing techniques to warn about damage and its characteristics. Based on this and the ideology of ML, pattern recognition is a predominantly beneficial branch wherein labels, such as “damaged” or “healthy” are allocated to a given input value with the aid of an algorithm. Fig. 3 is the applicable machine learning algorithms for SHM of bridges [7]. Fig. 4 presents structural health monitoring for bridges as a four-part pattern recognition process which include (1) operational evaluation, (2) data acquisition, normalization and cleansing, (3) feature extraction and data compression and (4) statistical model development. Nonetheless, as shown in Fig. 3, ML can be classified into two types of learning for SHM of bridges which include supervised and unsupervised learning. Fig. 4 shows the four-part pattern recognition process for the structural health monitoring of bridges [10].

3.1 Supervised Learning Approach

The major goal of supervised learning algorithm is to usually get the computer to learn a classification system that was already created. Thus, supervised learning algorithm is justly general in classification problems. A typical example of classification learning is the digit recognition. Mostly, classification learning is suitable for any problem in which classification deduction is beneficial and the classification is not difficult to evaluate. It might not even be necessary in some situations to give predetermined classifications to all instance of a problem if the classifications can be worked out by the agent. This is a typical example of unsupervised learning in a classification perspective [13]. In supervised Learning, the probability for inputs is often left undefined. This model is not necessary since the inputs are accessible but it is impossible for anything to be inferred about the outputs if some of the input values cannot be found.

Supervised learning can be utilized for generalization from new illustrations. The process of applying supervised ML to a real world problem such as in the SHM of bridges is presented as Fig. 5. The collection of dataset is the first step. The selection of suitable applicable fields in terms of features and attributes is a function of the availability of a requisite expert. The most common approach for decision trees and neural networks training can be easily decided by the expert [15]. The gathered information from the pre-determined classifications determines the nature of the technique to be adopted. For neural networks, the classification is adopted to evaluate the network error and then adjust the network to reduce it while in decision trees, the classifications are utilized to recognize the kind of attributes that give the most information which can be utilized to tackle the classification puzzle. The examples stated here succeed based on some supervision in the form of pre-determined classifications. Inductive machine learning involves learning of a set of rules from instances like training of dataset and creation of a classifier that can be utilized for simplification from new instances [12].

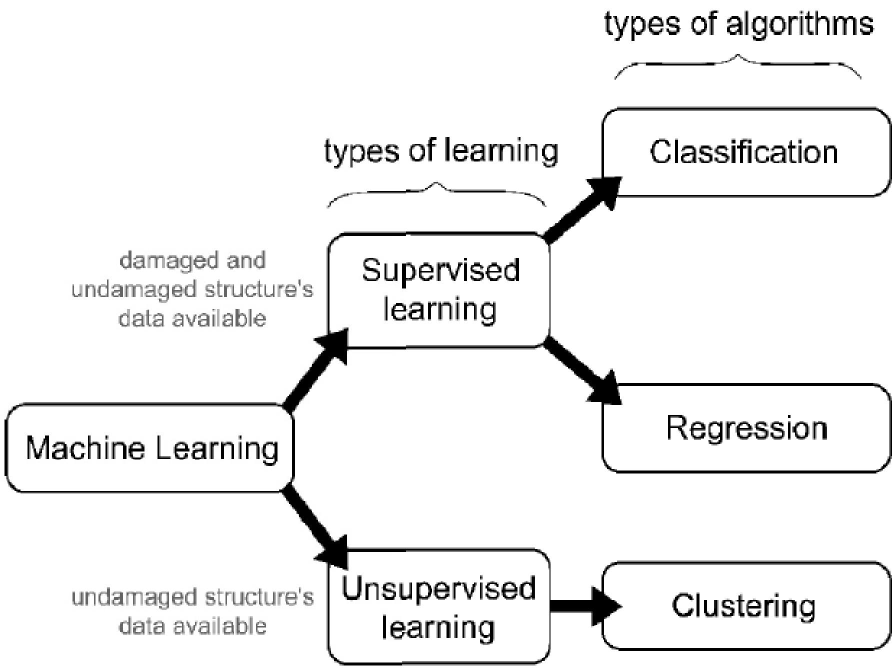

Fig. 3. Applicable machine learning algorithms for SHM of bridges

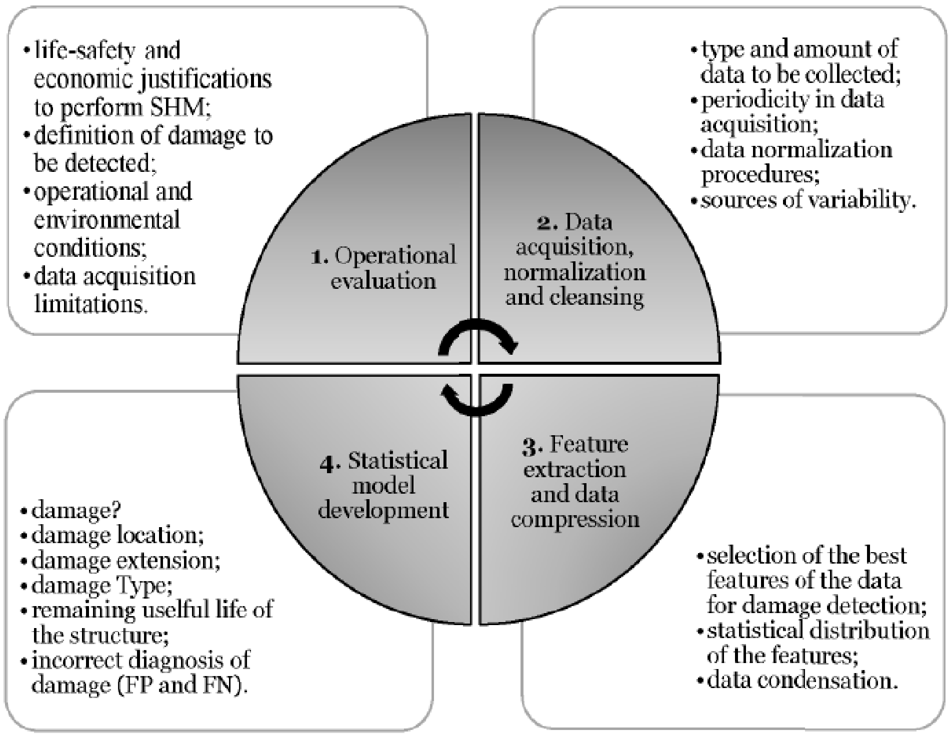

Fig. 4. Structural health monitoring for bridges as a four-part pattern recognition process

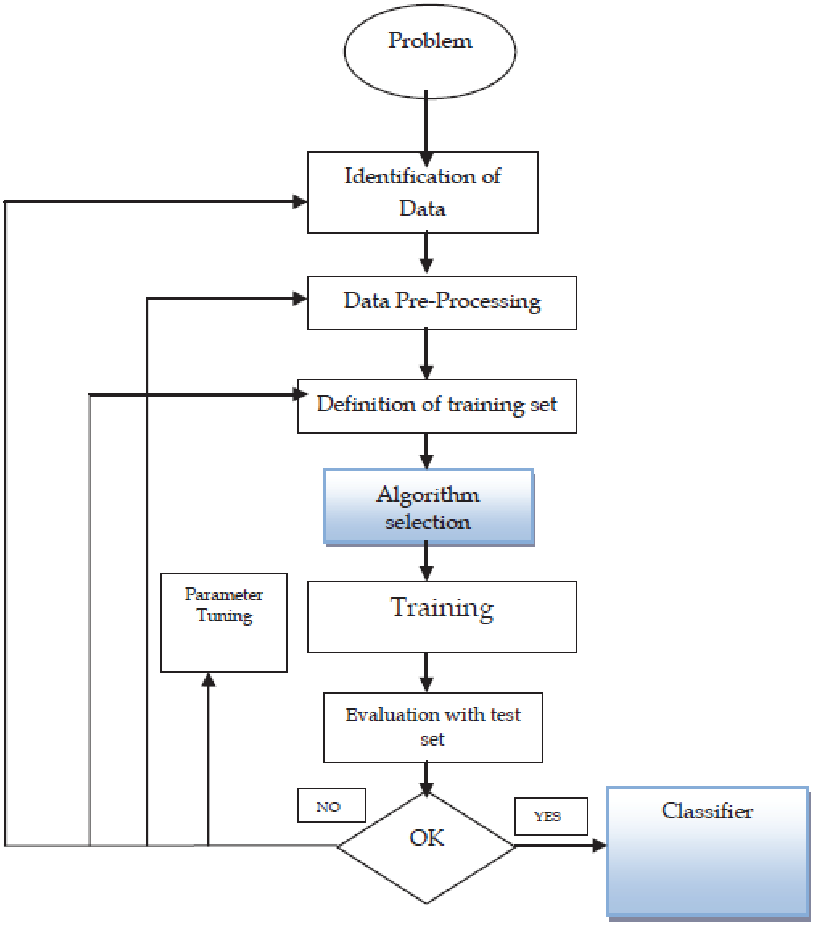

Fig. 5. Machine learning supervise process for SHM of bridges

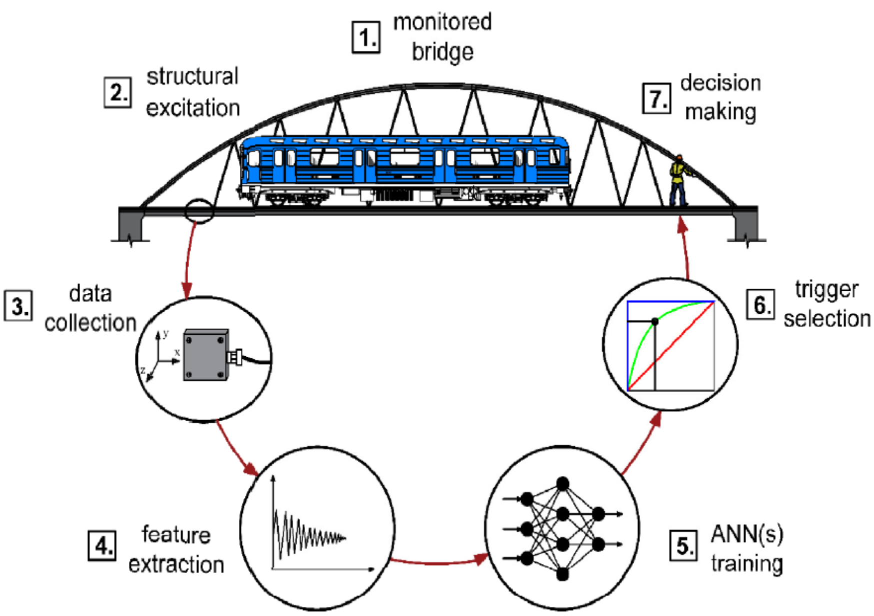

Fig. 6. Step by step approach to applying ANN as unsupervised learning algorithm tool for SHM of bridges

3.2 Unsupervised Learning Approach for SHM of Bridges

The main goal of unsupervised learning is to ensure the computer understands and learn how to perform a task which was not pre-trained initially. Two approaches on how unsupervised learning can be handled are discussed. The first approach is to teach the agent via the use of some kind of reward system to signify success and not via giving explicit categorizations. It should be noted that this kind of training will commonly be suitable into the decision problem framework. Under this, the main objective is for decisions making in order to optimize rewards and not to generate a classification [16]. The technique is general and gives room for agents to be rewarded for executing certain actions and punished for doing others. Usually, a kind of reinforcement learning can be utilized for unsupervised learning in which the agents focus on past punishments and rewards without essentially even learning any information regarding the exact routes via which its actions influence the world. The learning of a reward function makes the agent to simply know the task to execute without any processing and thus, makes all of the aforementioned information to be unnecessary. This is because the expected exact reward to be achieved for each task it could execute is already known [17]. This can be tremendously useful in situations where the calculation of every possibility consumes a lot of time. In another way, unsupervised learning approach for SHM of bridges can be extremely time consuming in terms of learning via trial and error. However, this learning type can be powerful based on the assumption that no pre-discovered classification of examples is executed. In some situations, classifications may not be the best adopted option. Fig. 6 is the diagrammatic representation of step by step approach to applying ANN as unsupervised learning algorithm tool for SHM of bridges.

Clustering is the second type of unsupervised learning in which the primary objective is to find relationships in the training data and not purposely to maximize a utility function. The assumption is based on the fact that the discovered clusters will reasonably match excellently well with an intuitive classification [18]. For example, clustering of individuals with respect to demographics might lead to wealthy clustering in one group and poor clustering in another. Although the algorithm might not have assigned names to these clusters, they can be generated and utilized to assign new examples into one or the other of the clusters. This is a data-driven technique that can work excellently when sufficient data is available. In some situations like social information filtering, the information regarding other members of a cluster can be enough for the algorithm to generate meaningful results [19-20]. Other cases may be such that the clusters are simply a beneficial instrument for a human analyst. Unsupervised learning in some cases suffers unfortunately from over-fitting problem during training of data. This challenging situation may be unavoidable because an algorithm requires powerful tool to learn from its inputs. Fig. 7 shows the algorithm for data collection for ANN training, validation and testing using data collected from both healthy and damaged bridges [21-23].

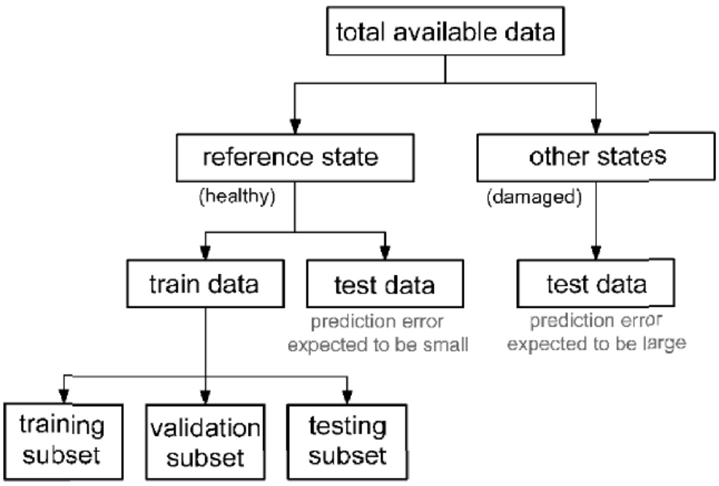

Fig. 7. Data collection for ANN training, validation and testing using data collected from both healthy and damaged bridges

4. CONCLUSION

One of the vital structures in civil engineering with wide applicability is bridge. Bridges are principal transportation infrastructure properties of a nation which acts like stimulants to social and economic development; and regional cooperation. However, they get expired over some period calling for their structural health monitoring from time to time to avoid any catastrophic event that may arise from their collapse. Thus, there is need to critically discuss structural health monitoring as a means to sustain both the healthy and damaged bridges. The advancement of technology has greatly influenced the incorporation of non-destructive testing techniques and machine learning algorithms to enhance structural health monitoring of bridges. This technically review has discussed the fundamental principles of structural health monitoring of bridges, non-destructive testing techniques and machine learning algorithms. Various non-destructive testing methods for SHM of bridges were highlighted and major emphasis was laid on visual testing, ultrasonic testing, liquid penetrant testing and radiographic testing. Their respective advantages and shortcomings were discussed. Application of machine learning in bridge SHM to improve the monitoring techniques was discussed. Different supervised and unsupervised learning algorithms that are applicable to the SHM of bridges are explained. In conclusion, the incorporation of non-destructive testing techniques and machine learning algorithms to structural health monitoring of bridges is imperative to integrate and enhance the process.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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