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Review paper

Implementation of digital twin and support vector machine in structural health monitoring of bridges

Asseel Za'al Ode Al-Hijazeen[1], Muhammad Fawad[2], Michael Gerges[3], Kálmán Koris[4], Marek Salamak[5]

Abstract: Structural health monitoring (SHM) of bridges is constantly upgraded by researchers and bridge engineers as it directly deals with bridge performance and its safety over a certain time period. This article addresses some issues in the traditional SHM systems and the reason for moving towards an automated monitoring system. In order to automate the bridge assessment and monitoring process, a mechanism for the linkage of Digital Twins (DT) and Machine Learning (ML), namely the Support Vector Machine (SVM) algorithm, is discussed in detail. The basis of this mechanism lies in the collection of data from the real bridge using sensors and is providing the basis for the establishment and calibration of the digital twin. Then, data analysis and decision-making processes are to be carried out through regression-based ML algorithms. So, in this study, both ML brain and a DT model are merged to support the decision-making of the bridge management system and predict or even prevent further damage or collapse of the bridge. In this way, the SHM system cannot only be automated but calibrated from time to time to ensure the safety of the bridge against the associated damages.

Keywords: structural health monitoring, bridges, damages, digital twin, machine learning, support vector machine

[1]MSc., Budapest University of Technology and Economics, Faculty of Civil Engineering, Műegyetem rkp. 3, 1111 Budapest, Hungary, e-mail: asseel.al-hijazeen@emk.bme.hu, ORCID: 0000-0001-5835-853X
[2]MSc., Eng., 1) Silesian University of Technology, Faculty of Civil Engineering, ul. Akademicka 2A, 44-100 Gliwice, Poland, 2) Budapest University of Technology and Economics, Faculty of Civil Engineering, Műegyetem rkp. 3, 1111 Budapest, Hungary, e-mail: muhammad.fawad@polsl.pl, ORCID: 0000-0003-4729-7289
[3]Associate Dean, University of Wolverhampton, Wulfruna St, Wolverhampton WV1 1LY, the United Kingdom, e-mail: michael.gerges@wlv.ac.uk, ORCID: 0000-0001-5986-7301
[4]Assoc. Prof., Budapest University of Technology and Economics, Faculty of Civil Engineering, Műegyetem rkp. 3, 1111 Budapest, Hungary, e-mail: koris.kalman@emk.bme.hu, ORCID: 0000-0002-6571-5555
[5]Assoc. Prof., Silesian University of Technology, Faculty of Civil Engineering, ul. Akademicka 2A, 44-100 Gliwice, Poland, e-mail: marek.salamak@polsl.pl, ORCID: 0000-0003-3602-0575

1. Introduction

The great importance of bridge structures results in high requirements for their reliable and long-term use [1]. Over the last 15 years, concerns about bridges' deterioration have increased significantly, as the existing bridge structures are subjected to numerous environmental and operational loads in daily operations [2]. The influences of these external loads are unfavorable and prone to accelerated structural damages. The probable reduction in bridge performance is the result of various factors such as weather, overloading by traffic, poor design work, motion excitation, fatigue cracking, construction deficiencies, and material deterioration [3, 4].

Extreme events, like earthquakes, may also be encountered throughout the bridge service life; for example, Baihua Bridge, an RC multi-span girder bridge located in the near-fault region, collapsed in the curved spans and was damaged significantly in the straight spans during the Wenchuan, China earthquake of May 12.2008 [5], where five spans collapsed utterly, Some columns suffered from shear cracking, crushing of concrete, and destruction of collar beams [6]. Deterioration rates of different RC bridge elements are influenced by the combined effects of several complex phenomena such as reinforcement corrosion, concrete degradation, creep, shrinkage, cracking, fatigue, etc. [7]. Rajeev et al. analysed bridge failures in 10 thousand bridges from 1977 to 2017 and found that the dominant causes include natural disasters at 80.30%, deterioration of the material at 10.10%, bridge overloading at 3.28%, and Human-Made disasters at 2.19% of all the failures of the studied bridges [8].

Finding and controlling the deterioration factors that damage bridges are as crucial to efficient bridge maintenance as repairing the caused damage. Identifying these factors will certainly help in the cause-and-effect analysis, damage diagnosis, modelling of bridge deterioration, improving prediction accuracy, and reducing bridge life cycle cost [9]. Traditionally, visual inspection plays an essential role in the detection of structural surface defects and assessing the structural condition. However, visual inspection is labour-intensive, time-consuming, and subjective even for well-trained inspectors, hence is unable to track condition variations in real-time. Structural health monitoring (SHM) techniques have been proposed and increasingly used in bridges in the past decades to address the problem [3, 10]. The core of a well-designed SHM system is a data acquisition system that relies on deployed sensors to initiate the information workflow from which ultimate decisions about operations, maintenance, and other life-cycle actions will be made [11].

Sensors are generally divided into two types, namely wired and wireless sensors [12]. Wired sensors are usually limitedly applied since they require installation during structure construction. The wiring could impact the function of the structure with a limited number of sensors. Therefore, with the development of wireless sensors, wireless monitoring has emerged in recent years as a promising technology that could significantly impact SHM [13]. Nevertheless, assessing civil structures is a complex task caused by the stochastic nature of the underlying deterioration processes and the loading demands [14]. Yet the contradiction is that this situation can lead to difficulties if, for example, no relevant information is extracted from monitored data. Hence, the critical issue associated with SHM techniques nowadays is how to extract relevant information that can be incorporated into the decision-making process relating to managing and maintaining civil infrastructure [15].

SHM approach is still facing some serious challenges in changing environmental (temperature, humidity, wind, etc.) and subjected operational conditions (live loads, etc.) of bridges [16]. These variations influence the measured signals, making data interpretation a complex task. Thus, it can be impossible to distinguish structural changes due to the failure to quantify the input-output relationship between environmental and operational conditions, on one hand, and on the other hand structural responses (e.g., strains and displacements) or derived quantities (e.g., natural frequencies) [17]. Several mathematical alternatives may be able to account for the environmental and operational effects, with regression analysis being a suitable tool in Machine Learning (ML) when there is a large quantity of data obtained under varying conditions [15].

Since modern monitoring systems provide large amounts of data, regression analyses have been explored in several SHM applications. Within a local approach to SHM, Guo et al. [18, 19] carried out a linear regression analysis to describe the pattern between monthly-averaged S-N fatigue damages (number of cycles to failure, N(S), when a material is repetitively cycled over a given stress range S), monthly-averaged temperatures, and traffic flow. Furthermore, [20], and [21] have used SHM systems to predict further damages or the bridge's collapse if an alarm system is established with a Digital Twin (DT). They can give the comparison phase threshold values for stresses and internal forces. DTs have two essential characteristics, interactive feedback, and self-evolution. They can realise intuitive observations and predictions of the working state, making operation and maintenance work more efficiently [22].

Further, it is analysed that Machine Learning algorithms are needed to drive the analysis and processing of the twin data platform. By analysing the data, DT can diagnose and predict the bridge's status [23]. The coupling mechanism of the DT and ML is now becoming the core of SHM monitoring [24]. Its primary function is to collect, process, and analyse data and then output diagnostic and predictive results to support the decision-making of related work and predict or even prevent further damage or collapse of the bridge [25].

Based on the above-mentioned literature authors have tried to present the technological advancements currently in use for SHM bridges and linked them with smart systems using DT technology and ML algorithms. Further, it is summarized how crucial it is to develop an automatic SHM methodology to detect damages in reinforced concrete bridges at their early stages. The presented methodology consists of three main segments; data collecting which is represented by sensors for the measurement of data, digital twin which is a 3D model identical to the physical bridge and helps to identify threshold values for some suggested parameters, and an artificial intelligence algorithm (SVM), that is based on the assigned threshold values, can detect the occurred damage, and predict the future behaviour of the bridge.

2. SHM of bridges

Most bridges are either coming to the end of their design life or are in poor situations. For example, the Canadian Infrastructure Report Card 2016 declared that 25% of the existing bridges are in poor condition. The equivalent value from the US Infrastructure Report Card highlighted that 9.1% (equivalent to 56,000 bridges) of the existing bridges are designated structurally deficient [26]. A bridge's deterioration can lead to functional or structural failure without appropriate monitoring and maintenance measures. SHM is a measuring system established to constantly monitor a structure's technical condition and behaviour. Housner et al. [27] defined SHM as using sensing techniques and structural characteristics analysis to detect structural damage or degradation. Aktan et al. [28] proposed that SHM should be considered within the domain of condition assessment; Farrar and Worden [29] regarded SHM as a damage detection process. In summary, SHM aims to assess the current structural health state to enable stakeholders to make informed performance, maintenance, or repair decisions, based on appropriate in situ measured data analyses [11].

SHM techniques have been applied in bridges by installing structural health monitoring systems for almost 40 years and have been increasingly used in long-span bridges worldwide [30]. These SHM systems have accumulated massive data after long-term measurement by numerous sensors with high sampling frequencies. Interpreting these data from the viewpoint of structure safety becomes a priority of SHM research [3]. SHM allows monitoring and measuring the physical quantities obtained from monitoring devices in a structure to check the assumptions made at the design stage; abnormalities are also correctly detected. Setting an appropriate alarm system in the SHM application minimises the possibility of damage and thus increases the structure's safety [31]. New-found structural health monitoring systems have been developed with different approaches, such as using wireless sensors with self-diagnosing and self-calibration to reduce data transmission and power consumption [31].

2.1. Existing issues in ordinary SHM

Throughout SHM of bridges, some problems may arise; for instance, large and heterogeneous datasets are obtained and are challenging to store, process, and interpret. Furthermore, low query efficiency of relevant data, as different data resources are stored in various management systems. In addition to this another concern is interoperability, it works across multiple software packages for different stages of a bridge project, so it is low due to inharmonious data file formats. Besides this, there is often a loss of data and information during project handover, in addition to low integration in various design and construction iterations and loss of historical data that can help to improve predictions. Four types of monitoring data can be gathered during bridge assessment; response-based data, such as strain, displacement, and inclination; geometry-based, such as conventional surveying and laser scanning; vision-based, such as image and video; and loading operational and environmental loadings [32].

Two main approaches for processing and interpreting bridge monitoring data can be used: a physics-based approach and a data-driven approach. A physics-based system correlates sensor measurements with previous physics-based model predictions like code formulas and finite element models; it explains any inconsistencies, thus implying actual structural conditions and performance. For example, Biliszczuk et al. [33] presented a structural health monitoring system and a finite element model-based force analysis assessment for stay cables. The system was designed to monitor the cables' health and detect any potential damage or deterioration. The force analysis assessment method was used to estimate the forces acting on the cables and to evaluate their structural integrity.

The current practice usually involves model updating, mainly by updating the parameters within the model to minimise the discrepancies and generate an "As-Is" model; the differences between model predictions and new measurements may indicate the existence of damages [3]. A data-driven approach is formulated based on data alone in statical models, which identify trends, patterns, and correlations inside the datasets and quantify structural conditions and performance uncertainties [32].

Automation of bridge inspection systems is challenging; the first phase involves developing a 3D digital geometry model, and input/output data processing must be controlled to decrease the propagation of errors. The second phase consists of the inspection process. Engineers can detect structural damages in real-time and have advanced functions for remote supervision by adapting a good machine vision concept. Inspection data can be perceived and directly uploaded onto the server through a mobile device or an uncrewed aerial vehicle (UAV), or another wearable/augmented reality (AR) device, and timely analysis to determine the crack profile, width, length, as well as propagation direction, significantly supports the decision-making process from a remote office [26].

3. Coupling of DT and ML in SHM

Structural Health Monitoring damage detection method driven by the combination of digital twinning and machine learning is the use of DT technology to realise the digitisation and visualisation of the critical elements of SHM in terms of geometry, structural behaviour, damages, and other aspects, and the analysis and prediction of future structural behaviour through machine learning algorithms, including the bridge's state prediction, residual life prediction, potential future damages or even collapse. Research on the combined application of DTs and AI technologies like machine learning is still in its infancy [34]. Machine learning integrated with twin modelling makes it possible to establish a synchronous operation in the digital space. A mechanism for the fusion of digital twins and artificial intelligence is built.

The basis of this coupling mechanism is collecting the structural and environmental information of the actual structure, such as strains, stresses, displacements, or temperature. In this study, sensors are used to collect information such as the environmental and mechanical properties of the structure, thereby providing a basis for the establishment and calibration of the structural digital twin. DT model is shown in Fig. 1.

The core of DT and ML integration systems is an information management and control platform based on machine learning. This platform is formed by fusing these two technologies, mainly consisting of two parts: an ML brain and a DT model, as shown in Fig. 1. Building an information management and control platform will make continuous structural health assessment and future damage detection possible. Also, direct sensor information

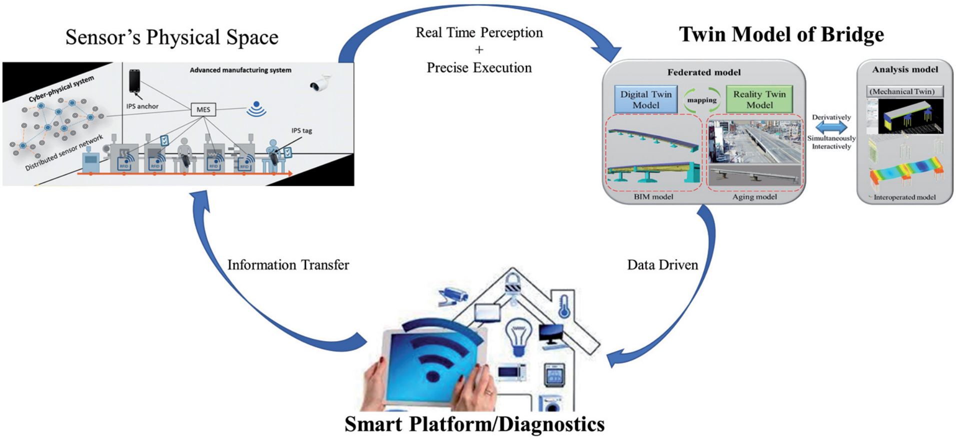

Fig. 1. Closed-loop of information management and control platform of bridge diagnostics

transmitting to ML algorithms will be sufficient for the structural evaluation. Moreover, the bridge's collapse can be avoided if an appropriate alarm system had been established.

4. Digital Twins

Digital twins are vital to adapt to changes in the twenty-first century, categorised as technology push (e.g., integrated sensing, Industrial Internet of Things) and demand-pull (e.g., change of use, climate change); virtualising bridges became important for improving their management and sustainability [32]. A DT is a digital replica of actual physical objects (processes, systems, etc.) in computers. It is considered a conceptual digital model of data and behaviour for structures of interest, attributing and operating through their life cycle [35, 36]. Digital twins must be the most realistic virtual representation of physical entities, including the digital model and all relevant information, and must be synchronised with those entities. One important characteristic of DT is self-evolution; they must change and evolve according to the actual situation while maintaining the contrast between physical and virtual spaces [23].

DTs are not just pure data; they contain algorithms that describe their real counterparts and decide an action in the production system based on this processed data [37]. A DT operates as a virtual representation of the physical bridge, which can be updated in near real-time as new data is collected, provide feedback to the physical twin, and achieve 'what-if' scenarios for assessing risks and predicting performance [32]. In 2002, the conception of a digital twin at the center of the fourth industrial revolution was first applied at the University of Michigan, US [35]. Ye et al. [38] investigated the digital twinning of two railway bridges in Staffordshire, the UK, with pervasive sensor networks installed. To manage the DT, a simulation model for the bridge, the interaction with the actual bridge, and the environment for simulation execution and visualisation must be established. From a practical point of view, the created numerical model must follow the real behaviour of the structure as closely as possible [39].

Furthermore, to maintain the safety of the real bridge despite changes during its life cycle, the DT must be updated to continuously apply the actual data generated from the real bridge. Accordingly, a digital twin requires combining a wide range of technologies, among which modelling and simulation are essential for the evolution of the DT [35]. The concept of digital twinning spread widely in the last two decades and is considered one of the top strategic technologies over time, where a DT model is paired with a physical entity and then represented for its existence. After that, the DT model can perform the functions of the monitoring system, aiming to catch and remove the problems even before they occur. Therefore, uncertainty risk can be prevented, and new challenges and opportunities can be assumed to determine the future through simulation [26]. Leser et al. [40] used DT technology for the health management of fatigue-critical structures. They observed that it has application potential in the operation and maintenance processes of multiple fields, from engineering to medical treatment. Ye et al. [41] built a digital twin model for structural monitoring.

4.1. Twin model concept for bridge maintenance

Three main tasks must be performed to apply the DT concept to a bridge maintenance system. First, a 3D geometry model, the so-called DT model, is generated based on the as-built documents of the existing bridge. Second, the reversed 3D surface model with the bridge's status, the so-called reality twin model, is created through the 3D scanning procedure, a combination of scanned photos using UAV of the lateral and top surface models and laser scanning cloud data for the bottom surface model. Finally, a federated model is developed between the DT model and the "reality twin model." [26]. The structural 3D model, the so-called mechanical twin model, can be directly derived from the DT model. Inspection data from the scanning procedure are automatically converted into technical damage reports based on image processing and image tracing technology and directly updated onto the initial model.

Furthermore, the environmental conditions, including temperature and humidity history, loading history, and monitoring data, are indispensable for predicting the consequent performance of the structural member. Briefly, DT model concept adoption helps engineers make a long-term strategy for the operation and management of the bridge, in other words, preventive maintenance. Automation of inspection, from the data capturing process to image processing and archive-data updating, is used instead of the traditional visual observation inspection. Thus, assessment is faster, more accurate, and can be scheduled frequently. Regarding the mechanical twin model, it continuously keeps tracking the changes in the bridge. Thus, engineers can assess the current behaviour of the structure and leave the basic assumption to the decision-making team.

To conclude, the DT model concept focuses more on capturing and storing the historical data of the asset and based on that, predicting the future behaviour of the asset. The general procedure for maintenance work is a closed loop of interactive processes, including inspecting, monitoring, and performing appropriate repair or rehabilitation work and upgrading the feedback to the database. Initially, the current condition of an individual structural member is observed and assessed. The repair or rehabilitation work is diagnosed and proposed if necessary. Subsequently, the best repair method is chosen and applied. Finally, all archived data, including inspection/monitoring data, date/method of repair work, and structural condition right after repair work, are upgraded into the database; this work is continuously repeated throughout the service life of the bridge. The DT model of the bridge (Fig. 2) is developed by creating a 3D mesh model of the bridge considering the existing damages and similar material laws to represent the actual behaviour of the structure as possible.

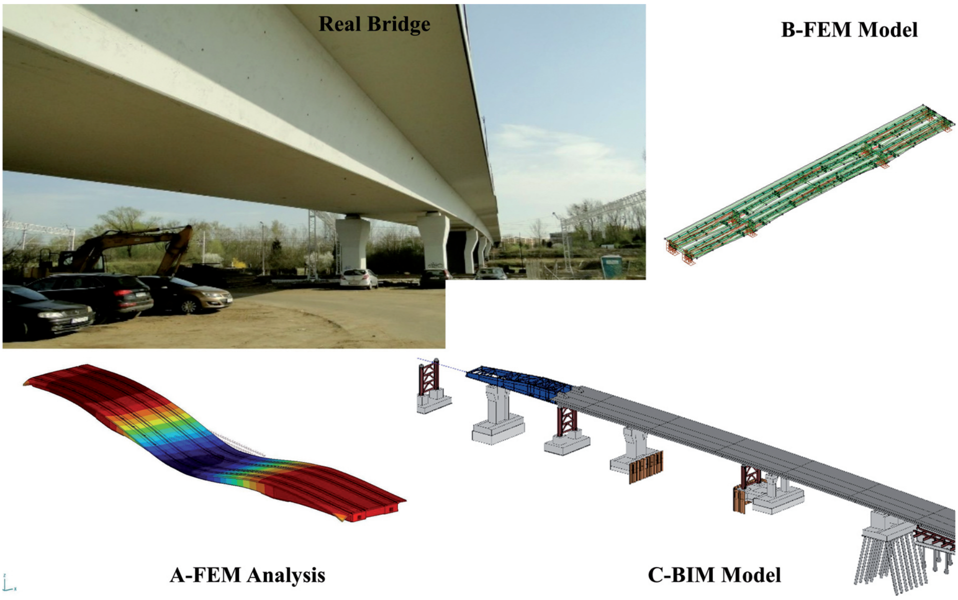

Fig. 2. 3D deformed shape model of the bridge (A), FE model of the bridge (B), digital twin representation (C)

5. Inventory system and object ID definition

The first main task for generating a 3D information model is creating the data schema for maintenance purposes. Therefore, each structural element needs to be identified by a specific ID. The final information model will be produced by assembling all members' specific IDs obtained using their orientation data, including coordinates and constraint information. Each structural element is categorised as a superstructure or a substructure in an inventory system. Note that structural elements should have similar characteristics and properties in one category. The 3D information model is generated based on the inventory system and ID identification. The database consists of attributes of each member and an archive of submitted documents, 'Attribute' information includes general information such as structure type, geometric shape, nominal size, or material property, and orientation information, including location and constraint.

In contrast, an 'Archive' includes an inspection plan, inspection manual or damage history, and repair record [26, 42]. The standard report form should be considered to make the archive data feature computer readable. This means it should be stored in primitive file formats such as .jpg for photo-checking reports, .avi for video-checking reports, or .pdf/.txt for document reports [26].

5.1. Information specification

Different levels of accuracy can be considered based on the anticipated Level of Detail (LOD) and the importance of the project [43]. The final goal of a DT model for bridge maintenance uses the highest of those levels; from this model, it is possible to derive the lower level of DT model, such as DT model for conceptual design, DT model for detail design, or structural analysis, and DT model for shop drawing or preassembly [26]. There are three maturity levels of digital twin models; the first is the partial DT model which contains only limited essential information like graphical design, structural analysis, or prefabrication. The second is called clone DT, which can be established by combining individual partial DTs. The highest level of DT maturity is the augmented DT, where the in-use data are enhanced by upgrading from derivative, analytics, or correlated data derived through the federated model [26, 44].

6. Machine learning in SHM of bridges

The pioneer described machine learning in 1959 as a "field of study that gives computers the ability to learn without being explicitly programmed" and is constructed to learn from data by automatically extracting patterns [25]. Machine learning techniques are helpful in various applications, including computer vision tasks, robotics, autonomous vehicle control, speech, natural language processing, and neuroscience research [45]. Conversely, AI has recently attracted the attention of civil engineering experts [46]. There are usually three types of machine learning: supervised, unsupervised, and reinforcement learning, as shown in Fig. 3. In the SHM domain, Supervised learning (SL) can be used, for instance, to detect the type and severity of damage [47]. As shown in Fig. 4, ML is a straightforward process, starting from the database input, passing through the selected algorithm, getting the output, and stopping or restarting the process by providing feedback. The end of the process is marked when getting an accurate and well-predicted result. A better understanding of the data can help select the suitable algorithm at the input stage. Some algorithms can operate well with smaller sample sets, while others require extensive samples. Also, some work better with a particular type of data than others.

As illustrated in Fig. 5, data need to be well understood and manipulated using mathematical tools, for example, data statistics and data visualisation, before using any machine

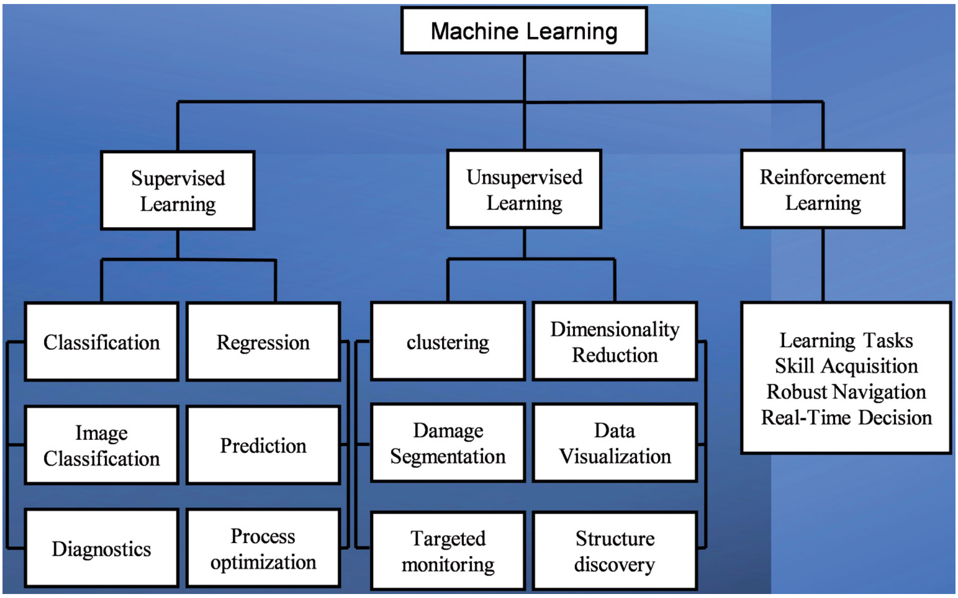

Fig. 3. ML classification [45]

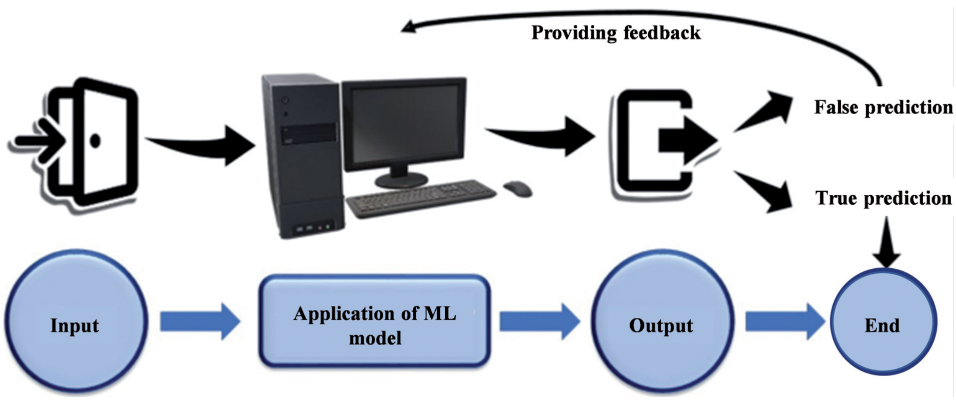

Fig. 4. Life cycle of ML [45]

learning algorithm. In data statistics, percentiles are used to identify the range, average, and median of data to describe the central tendency and correlations, also acquiring knowledge of how the data is linked together [45].

Nevertheless, density plots and histograms are used in data visualisation to show the data distribution and box plots to identify problems like outliers [48]. Then, data need to be 'cleaned,' which means dealing with missing values and outliers that can concern specific algorithms, decreasing output predictive accuracy. Finally, the data can be enriched to make the models easier to interpret, reduce redundancy and dimensionality, capture complex

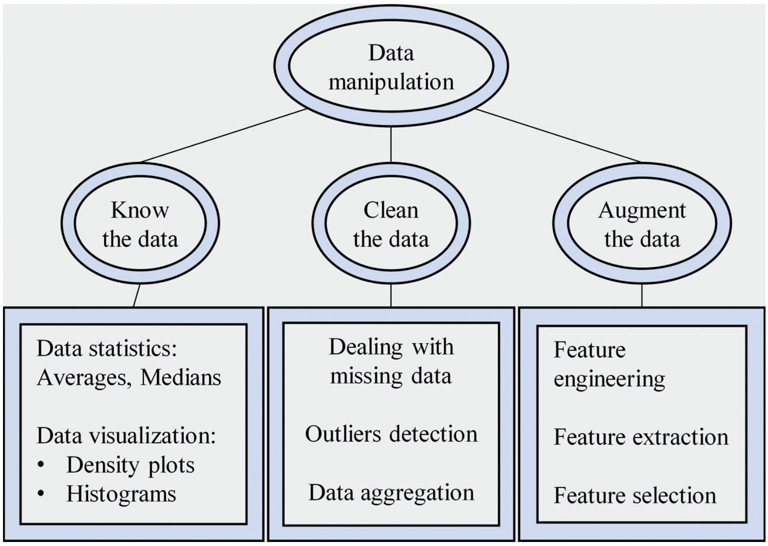

Fig. 5. Input configuration [46]

relationships, and rescale some variables [49]. After manipulating the data, the problem must be categorised following an input-output process. If the data is labelled for the input process, it will involve a supervised learning problem. However, if it is unlabelled, the learning problem is unsupervised. On the other hand, the output process is classified by task. If the output is a set of input groups, the problem can be recognised as a clustering problem.

Understanding the problem's constraints is also the main task in selecting an appropriate algorithm. Some conditions could be presented in an ML algorithm, starting from the awareness of the data storage capacity. Furthermore, prediction time can play a significant role in the selection process. For instance, some SHM problems need to be solved promptly. For example, real-time object detection problems must be super-fast to avoid wasting information during object recognition [50]. In addition, the model training process should learn quickly in cases where it is rapidly exposed to new data and must instantly process it. Other factors in selecting the appropriate algorithm, such as the accuracy and scale of the model, model pre-processing, and complexity in terms of features, included learning and predicting more complex polynomial terms, interactions, and computational overhead [49].

6.1. Support vector machine (SVM)

Support Vector Machine is a supervised learning technique with solid theoretical foundations based on the Vapnik-Chervonenkis theory [51]. It has a substantial regularisation property that can generalise the model to new data. These characteristics help it overcome overfitting, a common problem for neural networks. Furthermore, SVM can unify different discriminant functions in the same framework, such as linear, polynomial, and radial basis functions [52]. SVM has been widely used in bridge health monitoring applications to determine damage in the Hangzhou bridge using strain vibration, distortion, and cable tension [53]. Furthermore, SVM was attempted for crack detection in the Sydney Harbor Bridge, Australia, using inputs including force, acceleration, and time histories recorded during regular bridge operation [54].

SVM proved its effectiveness in binary classifications, training, building, and regression tasks. For instance, "L2 Regularization" is an essential feature of SVM, characterised by superior generalisation capability [49]. Another important part is that it performs well in non-linear data from different sensors installed on structures. It also has excellent stability in the case of a specific change in the data; in contrast, it is an obstacle for other kinds of neural networks. Nevertheless, using the SVM algorithm can be challenging since the filter or the kernel needs to be chosen appropriately to handle non-linear data. This can lead to generating too many support vectors, which will increase the calculation time. Moreover, the obtained data from sensors need to be scaled manually, reducing the time to effectively obtain classification and regression results. SVM is accurate enough to have a substantial margin of separation between classes (a safe structure and a damaged one). However, its application still depends on computation time, which is one of the most critical factors in AI tasks [49].

6.2. SVM methodology

The basic idea behind the SVM algorithm is to differentiate between groups of data features, called vectors which represent the available data (training data set) [55], The geometrical interpretation of SVM is that the algorithm seeks an optimal separating surface, i.e. a hyperplane (shown in Fig. 6) equidistant from the two classes and has a maximum margin [56].

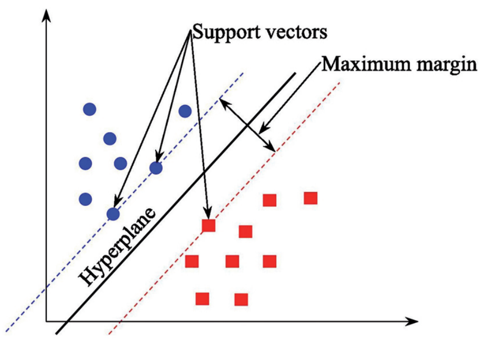

Fig. 6. Example of SVM for classification [55]

Denote x, a feature vector obtained from sensor data, $y \in \{-1, 1\}$ the label of x, where $y = -1$ means that x is recorded from a damaged bridge element and $y = +1$ implies that x is measured from a healthy component. A hyperplane with maximum margins separating the points with labels $y = +1$ from those with $y = -1$ should be determined [54]. The classification model is a function, $f\colon Rd \longrightarrow \{-1, 1\}$. Its form is: $f(\mathbf{x}) = \operatorname{sgn}(\mathbf{w} \cdot \mathbf{x} - b)$ where '$\cdot$' is the dot product, $\operatorname{sgn}(x) = +1$ if $x > 0$ and $\operatorname{sgn}(x) = -1$ otherwise. w and b are the parameters of the model and can be learned from a training process • can be obtained from the digital twin. Given a set of n training samples, $\left\{(\mathbf{x}_i, y_i)\right\}_{i=1}^{n}$, the training process defines the model parameters w and b by making sure that the classification error of the obtained model on the training set is minimised while still maximising the margin. Mathematically, the training process is equivalent to the following minimization problem:

$$\min_{w,\xi,b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \qquad [54] \tag{6.1}$$

$$\text{such that}\ \ y_i(w \cdot x_i - b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \ \ i = 1, \ldots, n, \qquad [54] \tag{6.2}$$

where ξ_i is a slack variable to control how much training error is allowed and C is the variable for controlling the balance between ξ_i (the training error) and $\mathbf{w}$ (the margin). The problem can be transformed into the dual form using the Lagrangian multiplier:

$$\max_{\alpha_1,\ldots,\alpha_n} \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j \mathbf{x}_i\mathbf{x}_j \qquad [54] \tag{6.3}$$

$$\text{such that}\ \ \sum_i \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C, \ \ i = 1, \ldots, \ \text{n.t} \qquad [54] \tag{6.4}$$

This problem can be solved using quadratic programming. After prepossessing the raw data, which is generated from the sensors by replacing any missing data for example, the SVM searches for the simplest solution that classifies the data correctly using Eq. (6.1). This means if we have two vectors of parameters, for example, temperature and horizontal elongation of the bridge, using the former equations we can predict new values after the classification model $f(\mathbf{x}) = \operatorname{sgn}(\mathbf{w} \cdot \mathbf{x} - b) = \operatorname{sgn}\left(\sum_i \alpha_i y_i \mathbf{x}_i \mathbf{x} - b\right)$ is learned, and a health score for a new data record, denoted as x_{new}, can be generated as $\sum_i \alpha_i y_i \mathbf{x}_i \mathbf{x}_{\text{new}} - b$.

7. Conclusions

This paper has carried out an extensive literature review of the Bridge Health monitoring system and the use of AI-based technologies for the assessment and monitoring of bridges.

This study has discussed the major concerns of the bridge health monitoring system, its fundamental principles according to different studies available online, the purpose of the SHM system, and its developments over a couple of decades. Further, it has highlighted several issues like large and heterogeneous datasets and their processing, low query efficiency of relevant data, interoperability of multiple software packages, and loss of data and information during project handover which makes the bridge SHM inefficient.

So, to overcome these issues of SHM systems, authors have critically analysed the AI-based modern techniques like SVM and their linkage with DT which can control the SHM system. In this way, it is observed that ML algorithms are needed to drive the analysis and processing of the twin data platform because. ML integrated with twin modelling makes it possible to establish a synchronous operation in the digital space giving rise to the fusion of digital twins and artificial intelligence. This fusion is the core of this paper. which integrates the information management system and control platform based on machine learning.

Further, this paper highlights the DT model concept that focuses more on capturing and storing the historical data of the asset and predicts the future behaviour of the asset. This DT model can be controlled by ML algorithms and the most efficient of them is the SVM-based regression algorithm. It is outlined in this article that an automated health assessment of bridges platform is built by the coupling of digital twins which work as a virtual representation of the physical bridge and can be updated in real-time as new data is collected by the sensors from the actual bridge, then implanted in vector support. It then trains data and can predict new outcomes, which will help in the decision-making and bridge management systems.

The major outcome of this study is the coupling mechanism of the DT and ML which is now becoming the core of SHM monitoring. Its primary function is to collect, process, and analyse data and then output diagnostic and predictive results to support the decision-making of related work and predict or even prevent further damage or collapse of the bridge. In this way not only the bridge's health is maintained against the associated damages but also the SHM system is calibrated against its defects.

8. Recommendations for future studies

To verify the presented methodologies, the authors will test this coupling methodology of DT and ML in the SHM system of the Soroksari bridge in Hungary. There is an existing sensory system on the bridge, since the measurement data are not enough to evaluate the structural behaviour of the bridge or predict future damages, the authors installed seven new strain gauges inside the bridge's boxes, this allows the usage of different complex ML algorithms for more accuracy. Moreover, the authors only developed the FE model-based DT model of a bridge (Fig. 2) in this research, but the validation of this model is not presented. For the validation of DT model, a field experiment is already planned through which data will be collected from the SHM system and will be directly linked to the DT model of the bridge for its automatic validation.

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