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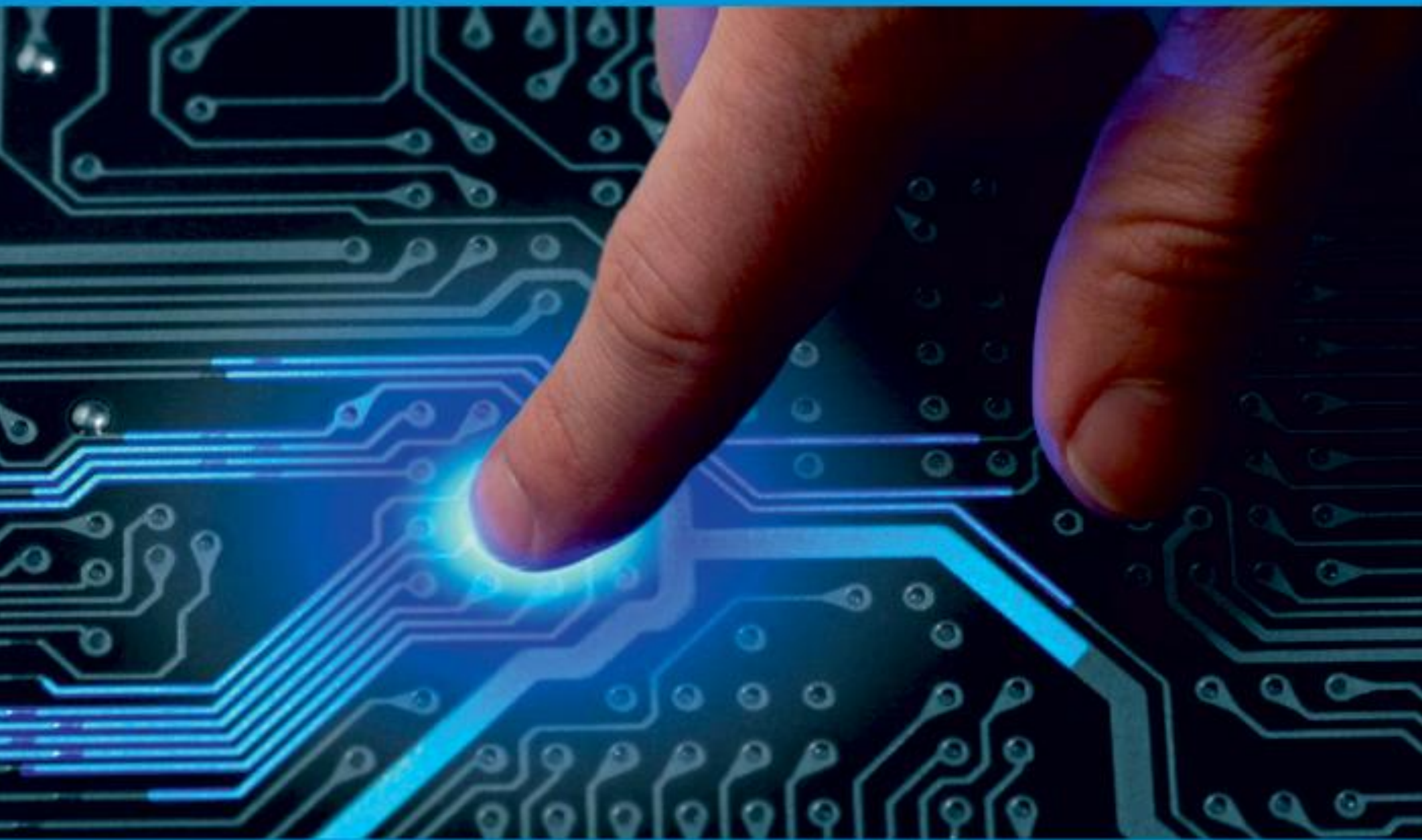

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Structural Health Monitoring Using Machine Learning

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ABSTRACT: The main aim of this paper is to produce This research focuses on advancing Building Damage Detection (BDD) through the application of deep learning methodologies. In the aftermath of natural disasters or incidents, prompt and accurate identification of structural damage is crucial for effective response and recovery. Leveraging the capabilities of deep neural networks, specifically convolutional neural networks (CNNs), our proposed model aims to autonomously detect and classify building damage from diverse data sources, including high-resolution satellite imagery and on-site photographs .The deep learning model is trained on extensive datasets, enabling it to learn intricate patterns and features associated with various degrees of structural damage. Through this learning process, the system becomes adept at distinguishing between undamaged structures, minor damage, and severe structural compromise. The utilization of CNNs facilitates spatial hierarchies of features extraction, enhancing the model's ability to capture nuanced information in complex images .The proposed BDD system offers a scalable and adaptable solution, capable of handling different types of disasters and imaging conditions. By automating the detection process, it significantly expedites the assessment of building damage, allowing for swift and informed decision-making in disaster response scenarios. This research contributes to the advancement of automated tools for building damage assessment, ultimately supporting more efficient and effective disaster management strategies.

I. INTRODUCTION

Machinery equipment and structures, particularly lifelines, fabricate the most critical components in this modern age, and they have become an indispensable part of the present day. In the case of utility lifelines, such as roadways, bridges, and powerlines, any threats that could cause a failure in any part of the system, no matter the extent, can eventually lead to the disruption of a whole city or a country. This means that if it was possible to predict future failures and detect the existing ones, this could potentially lead to a reduction in direct and indirect economic costs and human life fatalities. The key to doing so lies in identifying damage in structures. Damage is typically defined, in simple terms, as any change to the material or geometry, such as the boundary condition that can alter the dynamic properties or the response of the structure,1 thus adversely affecting the current or future performance of the system.2 In the past, identifying damage was only based on a periodical inspection either carried out using non-destructive testing /non-destructive evaluation (NDE) or by visual observation. The latter method, although it performs well for straightforward applications, is susceptible to subjectivity, human errors, prolonged duration, and occupant's safety for more complex systems. Prior knowledge of the damaged area is necessary for such techniques which would be impossible for small and unreachable regions without completely dismantling part of that area first. Such damage detection is localized, meaning it cannot represent the global behavior or the system's response.

The impracticality of visual inspection for large and complex civil infrastructures and long biennial inspection intervals has opened up the possibility of incorporating condition-based assessment techniques. As such, structural health monitoring (SHM) has emerged to provide the transition from offline damage identification to near real-time and online damage assessment. In layman's terms, SHM is a damage detection strategy that can observe a structure over a long period using a series of continuous measuring devices. Sensitive features extracted from these continuous measurements and the statistical analysis of such measures can provide the ability to assess the current performance of structures. Figure 1 represents the typical components of an SHM system. It starts with a selection of sensors and the placement of them in strategic locations on the structure. The collected data through the data acquisition system are transmitted to the processing unit and stored and managed in a database system. The evaluation of the collected data and the health state of the system is determined through several techniques and algorithms. In the end, based on the location and severity of the identified damage and how it can propagate in the future, inspection and maintenance during the decision-making process will be decided and carried out.

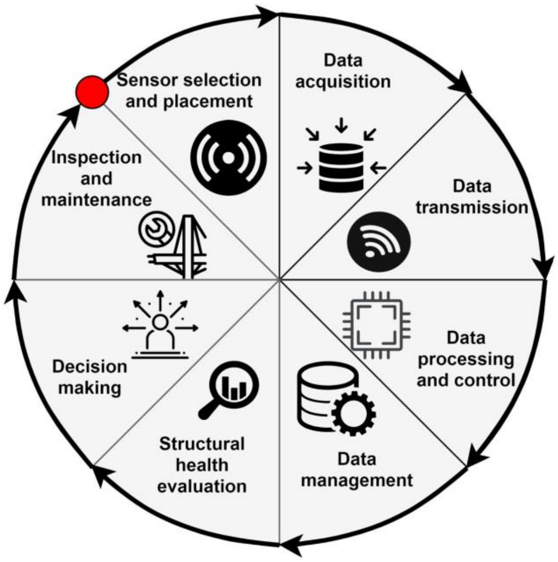

Figure 1.Typical components of SHM

II. MODEL-DRIVEN SHM VERSUS DATA-DRIVEN SHM

As stated earlier, to identify the damage, the undamaged state of the structure must either be assumed or developed. Similarly, the extent of the damage is nearly impossible to quantify or assess if the previous "undamaged state" is unknown. Therefore, the ability to identify damaged structure from the given measurements ultimately lies in realizing the previously recorded information and the pattern of changes it follows throughout the measuring period. In certain SHM applications, a prior model, typically the finite element model (FEM) of the structure, is useful as a baseline. Model updating is then performed, replacing the initial assumptions with the measured values. This is then considered as the original state of the structure. Further updating of the model can, therefore, identify the damage by considering the structural changes. This process of SHM implementation is a model-driven method. Therefore, an accurate analytical model of the structure is required.

There are numerous works related to model-driven SHM. To name a few, Cao et al.4 developed a piezoelectric impedance measurement for structural damage identification through an inverse analysis. Similarly, Moore et al.5 identified cracks in a thin plate by model updating. Generally, coming up with an accurate model is burdensome. Model discrepancies, especially for complex structures, are inevitable with little to no information about joints and bonds. Such an inverse problem is not well-posed6 and requires regularization and simplification.7 An alternative to a model-driven SHM system is a data-driven model. Other than relying on the physical model of the structure, the model construction is dependent on statistical pattern recognition (PR), which is usually applied by machine learning (ML) algorithms.

In contrast to having an FEM and updating the model later, the sensing devices' data from the structures are used more conveniently in the undamaged state and under few circumstances in the damaged state. In cases where insufficient labeled data exists, the data-driven approach can take an unsupervised form, or a hybrid model can be utilized for generating additional data. Augmentation of data-driven SHM systems with FEM can generate labeled datasets for training validation and testing phases. However, it is crucial to highlight that physical models are computationally intensive and need validation with experimental results.8 On the other hand, not every ML algorithm is capable of damage prognosis, meaning data-driven approaches are not always predictive models. Therefore, the decision between employing model-driven or data-driven SHM systems or both ultimately boils down to realizing (1) the proposed system's requirements, (2) the complexity of the application where the system is deployed, and (3) if the existing data and models can support and provide valuable inferences about the health state of the structure. For example, suppose one prefers a hybrid combination of the two methods. In that case, the system's predictive accuracy depends on the performance of the physics-based model and if the measured data from the data-driven approach is relevant and usable for training and validation.

Damage definition and identification

A vertical hierarchy is typically considered in order to identify damage. A pioneered damage typology scheme was offered by Rytter.9 Damage state was categorized into four levels, namely:
1. Existence of damage—Detection
2. Position of damage—Location
3. Severity of damage—Extent
4. Prognosis of damage—Prediction

In such a hierarchy, knowledge of the previous level is generally essential for complete damage identification. Thus, the success at each level is likely to depend on the performance of the lower levels. With the advent of ML and PR algorithms, a new level can be added to the above. Determination of the type or classification of damage is the level that is possible through the use of ML algorithms.10 This new step lies between steps 2 and 3 introduced above. Figure 2 depicts the 5-step hierarchical damage identification from detection to prediction transactions.

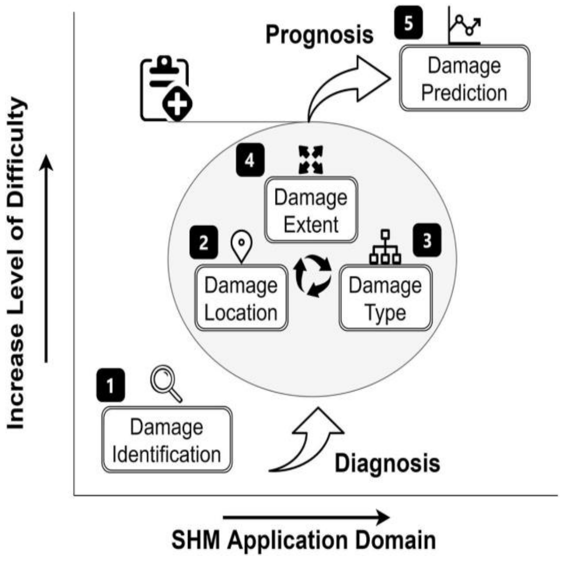

Figure 2. Five-step hierarchical damage identification scheme

Given that both damaged and undamaged information is available, a supervised learning algorithm can effectively go through all five damage detection levels. This, as explained before, requires extensive data to be readily available from the sensing systems, the physical-based models, or the experiments. Nevertheless, this is not possible in many cases, and the current information for damage state is limited, if not unavailable. For such situations, there exists a method called unsupervised learning. Instead of learning the models and train based on the data, a relatively simple approach, novelty, or outlier detection is applied.11 An initial baseline of the model is therefore created assuming normal operative conditions. Later, upon receiving new data from the sensing systems during the operation mode, the algorithm detects any outlier given the set threshold defined by the system.12 One example of an unsupervised algorithm was tested on an aircraft fuselage and multi-layered carbon fiber–reinforced plastic (CFRP) plate for damage detection.13

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III. OBJECTIVES OF THIS STUDY

The application of PR is not a new topic and dates back to the early 70s and 80s. In simple terms, PR is a tool to represent and recognize regularities in data. Sometimes, simple mathematical models based on a shared domain about a specific application can be used to infer patterns from a set of data and classify accordingly. During the 1990s, however, instead of relying on models derived by an expert (usually researchers) to classify data, machines were used to learn from the data, generate the most probable outcome, and validate the model based on unseen set data. The most likely outcome is a result of statistical PR algorithms, which are generally referred to as ML techniques.

This review aims to generalize these applications harmoniously using ML and SHM frameworks. Many methods with different results exist in the rich body of literature. Several approaches and techniques for feature extraction, data normalizations, and dimensionality reductions are employed for various civil infrastructures. This review brings a systematic collection of different SHM applications compatible with the statistical PR perspective. The readers, therefore, are introduced to the concept of ML and its utilization in the SHM paradigm. Moreover, model-driven and data-driven approaches in SHM will be discussed, but an emphasis will be placed on data-driven SHM approaches. In addition, tables and figures refine the ML taxonomy behind the vast SHM literature complementing the article. Next-generation SHM potentials such as unmanned aerial vehicle (UAV)-assisted SHM, mobile-SHM, and virtual/augmented reality–supported SHM are also addressed in this study together with the digital twin, smart city, and big data era.

For better readability, the abbreviations used in this survey, along with their definitions, are provided . In summary, the review aims to consider

1. The pipeline of ML in each component that makes up SHM systems.

2. The different tools and algorithms used in ML and DL processes for each level of SHM damage identification.

3. The different learning algorithms proposed for context-dependent applications.

4. Extension into IoT age-related and next-generation emerging technologies and data science prospects for SHM.

IV. DESIGN BUILDING DESCRIPTION

In this section, OLR was implemented with the CAV and $RCAV$ as features on Tai-Tung Fire Bureau (TFB) building located at Tai-Tung city in Taiwan. TFB was a four-story reinforced concrete building with a partial basement. The first story height for the building was 5 m (16.4 ft) which was taller than the other stories, 3.5 m (11.4 ft). Furthermore, the first story had fewer partition walls for the purpose of parking fire engines and other large equipment causing the first story to behave as a soft story. TFB was instrumented with 22 accelerometers located as shown in Figure 8. It experienced five earthquakes, listed in Table 6, and suffered from severe damage during the 2006 M 6.2 earthquake Several columns of the first story and partition walls on first and second stories experienced major damage. The building was deemed not feasible to repair and was subsequently demolished

V. FORMULAS

INPUT:

$$OD_j = \sum_{j=0}^{n-m} A_j$$

Where **'m'** is the number Reduced Features and total number of Features ID_{i} are 'n'.

OUTPUT:

Predicate the Damage grades in ID;.

STEP-1:
for each j=0ton-m
Find Hyperplane with m-dimensional
Minimize to:1/2||v||^2

Subject to : y_i (V ^ T .X_i +b)>=1, i = 1, 2 ,......m
$y_i \in \{1,-1\}$, $X_i, \in$ Rm

STEP-2:
for each j=0 to n-m
Draw Margin.

STEP-3:
If (Hyperplane== low Margin)
Miss-classification
Else
Perfect classification.

STEP-4:
Take and move with classification (Damage building data) to next step.

STEP-5:
Using FF-BPNN
Find the damage grades.

STEP-6:
For each neuron
Find HD*n* (y) = f [Neth (y)]

P(y) Input vector and y*th* pattern.
Now Net*h* is defined Net*h* = Σ Whi (y).P(y)

STEP-7:
For each neuron
find 1~LO_{o}(y)=f[Net_{o}(y)] .
Neto (y) = Σ Woh-f [Σ Whi (y) .Pi(y)]
STEP-8:
Estimate EF (0) = 1/2∑ [T*o* (y) - OL*o*(y)]²

STEP-9:
Predicate the Damage grades in *Id*i

STEP-10:
STOP.

VI. CONCLUSION

This article provided an extensive overview of the ML-engaged SHM systems with connections to the new technologies rapidly growing in the latest decade. A detailed breakdown of techniques, methods, and algorithms from the literature is presented and examined, emphasizing ML and the data-centric advancements occupying the current research trends. The survey included a systematic discussion of the steps taken to implement an ML model for SHM with pathways, taxonomies, and breakdowns. Moreover, the most common algorithms proposed for context-dependent applications were overviewed. The survey revealed that the extension of ML in SHM dramatically increased the system's capabilities, providing innovative solutions for different research challenges.

The ML pipeline and corresponding algorithms have the potential to uncover the influence of EOFs due to their multivariate encapsulation capabilities. EOFs, a long-lasting problem in the SHM community, is one step closer to a solution with ubiquitous data and their digital extensions. Moreover, ML solutions also draw a pathway to addressing nonstationary and nonlinear sources of variations, and compression/dimensionality reduction brings gigantic inverse problems into solvable stages.

Forthcoming mobile and noncontact technologies are arriving with their digital counterparts. They do not only offer new sources of physical parameters being observed, but also have their own embedded intelligence from consumer-grade smart devices to UAVs. Likewise, IoT is no longer a futuristic theme; it became a reality with the rapid distribution of low-cost headless computers all over the world. However, the community still has an unclear understanding of how these breakthroughs can serve the smart city agenda as well as sustainability on the monitoring side. The next decade is expected to provide alternative aspects, which attracted rare attention, such as visualization and interfaces.

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