Emergence of Machine Learning Techniques in Ultrasonic Guided Wave-based Structural Health Monitoring: A Narrative Review

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ABSTRACT

Identification of damage in its early stage can have a great contribution in decreasing the maintenance costs and prolonging the life of valuable structures. Although conventional damage detection techniques have a mature background, their widespread application in industrial practice is still missing. In recent years the application of Machine Learning (ML) algorithms have been more and more exploited in structural health monitoring systems (SHM). Because of the superior capabilities of ML approaches in recognizing and classifying available patterns in a dataset, they have demonstrated a significant improvement in traditional damage identification algorithms. This review study focuses on the use of machine learning (ML) approaches in Ultrasonic Guided Wave (UGW)-based SHM, in which a structure is continually monitored using permanent sensors. Accordingly, multiple steps required for performing damage detection through UGWs are stated. Moreover, it is outlined that the employment of ML techniques for UGW-based damage detection can be subtended into two main phases: (1) extracting features from the data set, and reducing the dimension of the data space, (2) processing the patterns for revealing patterns, and classification of instances. With this regard, the most frequent techniques for the realization of those two phases are elaborated. This study shows the great potential of ML algorithms to assist and enhance UGW-based damage detection algorithms.

1. INTRODUCTION

During the past decades a number of large structures, that our modern society is highly dependent on, have been built and manufactured covering a range of application fields – from civil engineering to aerospace and automotive industries. It is obvious that devising a strategy for prolonging the lifetime of those structures yields a massive save of natural as well as economic resources. This initiates the necessity of having a reliable approach for assessing the health condition of those structures.

Structural Health Monitoring (SHM), as a remedy for the described issue, has gained profound attention during the last two decades. The terminology of SHM describes the process of designing a paradigm, whose outcome is the determination of the health state of the structure. This process usually involves (1) the observation of the structure, (2) extraction of features that are sensitive to the damage, and at last (3) developing appropriate approaches for the final decision making about the presence of any damage, its location, and its severity. There are multiple choices for each of these steps, which also define the category of the conceived SHM scheme. For instance, the observation of a structure can be carried out by means of different sensory technologies such as accelerometers, laser Doppler vibrometers (LDVs), piezoelectric transducers, etc. The nature of the observation, and the diagnosis signal, bring the discussion to a well-known category of the SHM techniques, namely, UGW-based methods. In this family of methods, the diagnosis signal is usually a guided wave that is propagated through the structure. The interaction of the propagated wave and the damage in a structure introduces some sort of fingerprints in the captured signals. With the help of proper signal processing methods, those fingerprints can be accentuated as features. A detailed discussion on different types of techniques for performing a UGW-based SHM can be found in (Giurgiutiu, 2007) and (Zhongqing SU, 2009). The characteristics extracted from processing of the raw signals can then be put into decision-making algorithms to determine if the structure is damaged. The latter step can be performed by using physical models (Barthorpe, Hughes, & Gardner, 2021) of the structure, or statistical data-driven models mainly based on ML techniques (Farrar & Worden, 2012). It is important to emphasize that model-driven procedures need manual work from professionals with an in-depth

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understanding of the complicated system's physical, mechanical, electrical, data flow, or other relevant components. As a result, experienced specialists are often limited and costly resources, and they are also prone to human mistakes. The most significant disadvantage is that human-centric modeling takes a long time.

The hierarchy of the damage detection paradigm stated by (Rytter, 1993), outlines the prognosis of the damage in four steps, namely, (*Level 1*) Detection, (*Level 2*) Localization, (*Level 3*) Assessment, and (*Level 4*) Prediction. It was argued by (Worden & Manson, 2006), that the ML can offer a robust and reliable framework to address levels 1 to 3 of these steps. However, in the previous decade, the applicability of ML in damage detection was not fully feasible. This was due to a lack of data from the structures, which should be provided into the ML algorithms. However, during the past 10 years, we are observing the era of "big data". Accordingly, in the field of SHM, due to embedded sensory technologies with structures, more and more data can be available. Also, the maturity of machine learning technologies, as well as advancements in IT infrastructure and requisite technology, make applying machine learning approaches into SHM more feasible. ML algorithms give mathematical tools for linking the system's input, which is the measured signal, and the output, which is the structure's health state. In a closer look, the entire scheme can be outlined as obtaining the diagnosis signals, extracting and selecting features, and classifying the instances of the problem based on the defined classes.

In recent years, several review studies have been performed to provide a state-of-the-art of ML application in SHM. For instance, (Gordan, Razak, Ismail, & Ghaedi, 2017) carried out a review of the data mining methods in damage detection, where they have considered several classifications and regression methods such as Artificial Neural Network (ANN), Support Vector Machine (SVM), Bayesian analysis (Adeli, Rosić, Matthies, Reinstädler, & Dinkler, 2020a, 2020b), etc. Moreover, the drawbacks and limitations of the reviewed methods are also discussed. In another recent review article performed by (Avci et al., 2021), the application of machine learning algorithms in vibration-based SHM is investigated. This comprehensive work has reviewed articles exclusively with application in civil structures. Furthermore, review articles presented in (Flah, Nunez, Chaabene, & Nehdi, 2020; Martinez-Luengo, Kolios, & Wang, 2016; Mishra, 2020; Toh & Park, 2020) have considered also the application of ML in vibration-based SHM. Yet, the void of performing a review study on the application of ML techniques in UGW-based SHM can be observed. To this end, the current study outlines the state-of-the-art in the field of UGW-based damage detection by the utilization of ML techniques.

Based on the reviewed studies, an overview of performing UGW-based damage detection on an arbitrary type of structure by means of ML algorithms can be described by Figure 1. The flowchart depicted in this figure shows that the input to this system is a set of UGW signals, which at the first step required to be pre-processed. According to the reviewed articles, two useful techniques to perform this task are listed. In the next station, according to the nature of the problem, it is needed to generate features and afterward apply the dimension reduction, or the other way round. The options for performing this step are listed as well in the corresponding boxes at the mentioned stages. Subsequently, the obtained features from the previous step should be fed into a classification algorithm for the determination of the health state of the structure. In a similar way, other multi-class classification algorithms can be employed to localize damage on the structure. Alternative to classification algorithms, it is possible to employ clustering algorithms where no labeled data is available, and a so-called unsupervised learning task should be performed. The current paper is structured based on the main steps represented in Figure 1; accordingly, section 2 elaborates the scheme of conventional UGW-based damage detection algorithms by expressing their building blocks. The main part of the current study is represented in section 3, where two main aspects of performing ML algorithms, namely, feature extraction and pattern recognition are discussed. In this section, the most frequent algorithms concerning those two main aspects are selected. After a brief explanation about each of the methods, the associated studies, in which those techniques have been implemented are presented. Lastly, in section 5, the main findings of the study are described, and an outline for future works is stated.

1.1. Search methodology and selection criteria

ML can be designated as one of the most rapidly expanding research fields nowadays. Its emerging expansion affects all fields, not avoiding also SHM and NDE. Therefore, selection of the reviewed field and its narrowing in order to address specific classes of interest for a predestinated readership plays an important role. In order to carefully select a reviewed field of interest a thorough analysis was performed, that can be summarized as follows.

- The search in the framework of this study was performed based on the entries in referent data bases that are acknowledged in the scientific community and are set as a standard for evaluating the impact of publications. Science Direct, ASCE library, Web of Science, Scopus, SAGE Publication, and Wiley Online Library databases are utilized to search for the reviewed articles in the current study.
- The search was performed based on the following keywords: "Machine learning", "Damage detection", "Structural health monitoring", "Guided wave", "Artificial intelligence", "Deep learning", and "Ultrasonic guided wave damage detection".

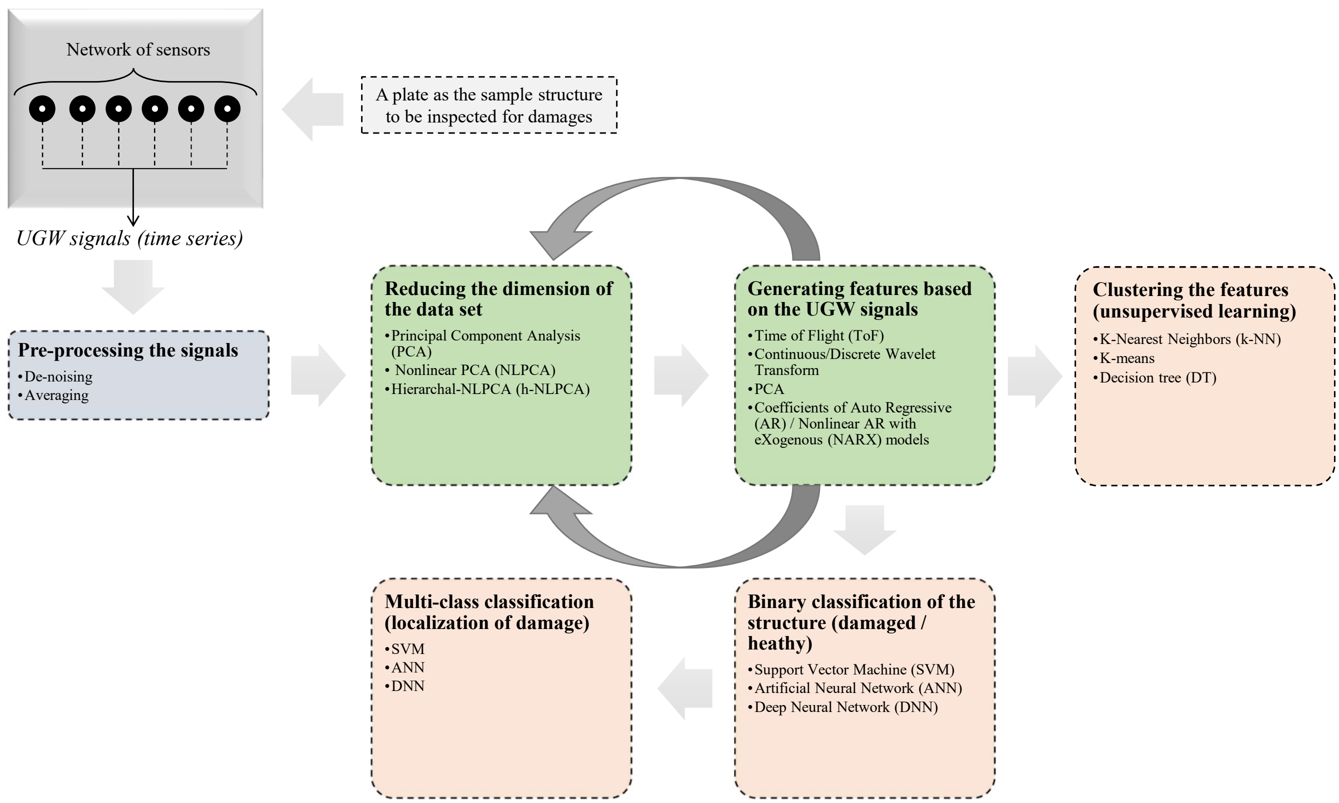

Figure 1. An overview for performing UGW-based damage detection along with implementation of machine learning algorithms.

- After a first broader selection based on keywords and thorough consideration of the abstracts and the methodologies applied in the papers, in the next step the field designated for the survey was further narrowed by excluding those papers which have employed the data from images, vibration signal, acoustic emission, and other sources, rather than UGW signals, resulting in the references reported in this work.

Although a thorough search has been performed with the aim to observe most of the published papers in line with the scope of this investigation, another even more important goal of this study is to find out the most unique works with versatile employment of ML methods. To this end, each selected article is studied carefully to obtain the key points with regard to employed feature extraction, dimension reduction, and pattern processing techniques. This approach attempts to present a well-documented guideline for future works on the implementation of ML in UGW-based damage detection techniques.

2. UGW-BASED DAMAGE DETECTION

The use of UGWs for SHM has been thoroughly discussed in several review papers (Mitra & Gopalakrishnan, 2016; Z. Su, Ye, & Lu, 2006; Raghavan & Cesnik, 2007; J. L. Rose, 2002; Chimenti, 1997; J. Rose, 2000; Lee & Staszewski, 2003). The current study does not aim to go deeply into the different classes of UGW-based methods and their principles. However, this section tries to elaborate the matter briefly, so that the readers can comprehend the next sections without the need of reviewing other publications. UGW-based methods for SHM have been implemented and developed widely in the last two decades. The evolution of this category of methods has been originated from the conventional Nondestructive Inspection (NDI) and Nondestructive Testing (NDT). In an SHM approach for utilization of UGWs, no large and expensive ultrasonic transducers are required and mostly piezoelectric sensors are employed for actuation/sensing of waves. Five main advantages of UGW-based methods are (1) cheap and normally lightweight transducers, which can be easily mounted on the structure, (2) the capability of scanning a large area even with a limited number of transducers, (3) due to high-frequency content of the excitation signal, even small damages in the structure can be detected, (4) low-frequency vibrations, which are largely caused by the environment, do not interfere with the UGWs and may be effectively separated during signal processing step, and (5) due to utilization of the transient part of the signal for this method, the effect of structural damping is not prominent (Mitra & Gopalakrishnan, 2016).

Lamb wave, named after a British applied mathematician Horace Lamb (Lamb, 1917), is one of the most utilized types of waves in UGW-based methods. They are guided between the upper and the lower or the inner and the outer surfaces of a plate or cylindrical shell, respectively. Therefore, they are the most qualified candidate to be employed in thin-walled structures. There are two basic types of Lamb waves, namely symmetric and antisymmetric. Each of these wave types can possess several modes. Accordingly, their propagation is multi-modal and dispersive. The principle, which enables the UGWs to reveal the damage, is the change of the properties of the structure at a local and global scale after the presence of any abnormality in the structure. These abnormalities can be induced in a structure due to a crack, corrosion, delamination, or other possible factors. These imperfections are prone to be seen in the dynamical responses of a structure. The aim of the UGW-based methods is to capture these introduced changes in the dynamical response of the structure and to interpret their physical relevance. Particularly, there exists valuable information in the scattered waves by the damage, which is a result of the interaction between Lamb waves and structural damage. Three essential steps can be named, that make the detection of damage using UGWs possible:

1. Activation of the favored UGW by employing the appropriate transducers, and capturing the scattered wave by means of a configuration of sensors;
2. Processing the captured signals to evoke and assess their characteristic;
3. Definition of damage indices by establishing a correlation between the extracted features and physical or data-driven models.

Point (1) can have an experimental or numerical realization. The necessity to have a reliable model for the structure to describe the propagation of the wave or to prepare a robust and reliable experimental setup plays a substantial role in the accuracy of the implementation of the next steps. Due to the focus of the current study on the implementation of ML methods in UGW-based SHM, this point is not explained in the current work and further information can be found in (Zhongqing SU, 2009). However, points (2) and (3) have more importance in this context and require elaboration on them. The flowchart for performing a classical damage detection task is presented in Figure 2. According to this flowchart, selection and deployment of the sensors' network is the first step. Afterward, through pre-processing, and feature extraction steps, the required data for revealing the patterns are provided. In the data fusion step, the information for making the ultimate decision about the presence of the damage is combined. This information has two sources. First, the damage detection database which concerns prior measurement on a pristine structure, as well as other damage scenarios. The second source is the engineering knowledge that originates from the available physical models for the structure.

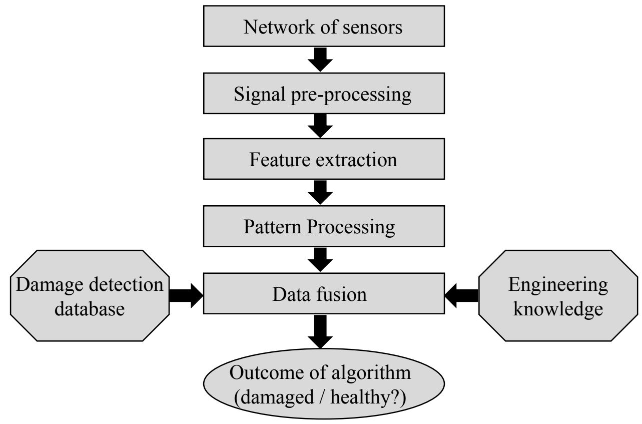

Figure 2. Flowchart of performing damage detection by means of UGW signals

2.1. Processing of UGW signals

There is a high correlation between the accuracy of a chosen damage detection algorithm and the processing of the signal. Different damage detection algorithms need specific processing approaches. A common categorization of the signal processing methods can be carried out based on the domain, in which the processing is performed. This approach divides the signal processing methods into three categories: 1) time domain, 2) frequency-domain, and 3) joint time-frequency-domain analyses. These three main realms of categories are elaborated in this section. However, a thorough study on the signal processing methods, which are beneficial for the damage detection algorithms can be found in (W. J. Staszewski & Worden, 2003; W. Staszewski, 2002).

2.1.1. Time domain methods

By considering this point that a Lamb wave is recorded as a time-series, several time-domain-based characteristics can be obtained from it. One of the frequent methods to extract the energy distribution of a lamb wave is the Hilbert transform. The Hilbert transform is defined as (Pandey, 1996):

$$H(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{f(\tau)}{t-\tau}\, d\tau \tag{1}$$

where $H(t)$ is the Hilbert transform of the signal $f(t)$. Based on $H(t)$ and $f(t)$ a so-called analytic signal $F_A(t)$ can be constructed:

$$F_A(t) = f(t) + iH(t) = e(t).e^{i\phi(t)} \tag{2}$$

here $e(t)$ and $\phi(t)$ denote the module and instantaneous frequency of $F_A(t)$. Furthermore, the envelope of $e(t)$ shows the distribution of the energy in time domain.

(W. J. Staszewski & Worden, 2003; Coverley & Staszewski, 2003; Michaels, 2008; Michaels & Michaels, 2007a; Konstantinidis, Drinkwater, & Wilcox, 2006; Sattarifar & Nestorović, 2021) can give examples for the application of Hilbert transform in a damage detection context. Correlation analysis is another algorithm, which can provide a good comparison between two states: healthy and damaged. For instance, (Z. Su, Wang, Chen, Ye, & Wang, 2006) has used the auto-correlation algorithm to provide the information required for the assessment of a carbon fiber/epoxy woven plate's delamination. There are several other criteria that can be defined in the time-domain such as Root Mean Square (RMS), standard deviation, Time-of-Flight (ToF) of the signal, etc. All of these parameters assist different damage detection methods to reveal the presence of the damage. The detail of these characteristics and their examples can be found in (Z. Su & Ye, 2009; Mitra & Gopalakrishnan, 2016).

2.1.2. Frequency domain methods

Frequency-domain methods can reveal certain characteristics of the signal which are not prominent in the time-domain. In order to transfer the recorded time-series into the frequency-domain Fourier transform is often used. However, it should be noted that due to the discrete nature of the captured time-series, discrete Fourier transform (DFT) is required to be employed. By using DFT, a signal can be expressed in frequency-domain, and information such as its frequency content can be demonstrated. The mathematical formulation for DFT of a discrete function $x[n]$ is shown in equation (3).

$$X_k = \sum_{n=1}^{N} x_n e^{-\frac{2\pi i}{N} kn} \quad (k = 1,\ 2, ...,\ N), \tag{3}$$

where X_k is the transformed value of the time-domain function into the frequency-domain and N is the number of samples of the time-series.

Using frequency-domain methods enables several possibilities. For instance, through this transformation digital signal filters can be applied to the signal. This filtering process often helps to isolate the band of interest for damage identification from the original signal (Michaels, Lee, Croxford, & Wilcox, 2013; Sattarifar & Nestorović, 2019). Furthermore, spectral analysis can be performed to obtain a damage index. With this regard, (Kedra & Rucka, 2017) considered the use of power spectral moment as a quantitative indicator for comparing the UGW signals measured in healthy and damaged states of a structure. The employment of transfer functions is another option for working with transformed data in the frequency-domain. Recently (Tan et al., 2022) has employed the transfer function technique for damage detection in carbon fiber-reinforced polymer (CFRP) plates.

2.1.3. Joint time-frequency domain methods

This family of methods by combining the analysis performed in time and frequency-domain avoids losing the important information carried by the original signal. Short-time Fourier transform (STFT), Wigner-Ville distribution (WVD) and wavelet transform (WT) are the three main algorithms that are employed in a joint time-frequency domain. The outcome of these algorithms reflects the information regarding the frequency content of a signal and the time of its occurrence simultaneously in a plot. Among these three algorithms, WT has captured most of the attention in the SHM community, due to its applications in de-noising and filtering (Chen et al., 2013), as well as detection of ToF (Perelli, Marchi, Marzani, & Speciale, 2014). Further explanation on the WTs can be found in section 3.1.2; in addition, a detailed mathematical description of WTs can be obtained in (Chui, 1997) as well.

2.2. Damage Index

All of the analyses explained in section 2.1 should serve the problem of damage detection. The final purpose of signal processing methods is to reveal the changes which can be present between two states of a structure, i.e damaged and healthy. Observing and quantifying these changes require the definition of features which should be extracted from the signal. Similar to the processing methods that are explained in time, frequency, and joint time-frequency-domain, damage indices (DIs) or sensitive features to damage can be defined as well in these three domains.

Peak-to-peak amplitude (Betz, Staszewski, Thursby, & Culshaw, 2006), signal variance, ToF (Betz et al., 2006; Sattarifar & Nestorović, 2019; Sharif-Khodaei & Aliabadi, 2014), wave energy (Michaels & Michaels, 2007b) are the main features which can be defined in a time-domain based method. ToF has shown itself to be one of the most employed features among all of the mentioned characteristics of the signal. The use of DIs based on the statistical indicators is also exploited by many researchers. In a work performed by (Sattarifar & Nestorović, 2021), the statistical indicators such as mean, max, kurtosis, skewness, root mean square, etc. are used to generate scalar features from a time-series. The definition of features in frequency-domain is also in a close correlation with the processing methods defined in this domain. Accordingly, the most applicable features are: spectral density, FFT coefficients, and Figure-of-Merit (FoM) (Tracy & Chang, 1998). Similarly, DIs can be defined in a joint time-frequency-domain analysis based on WT coefficients. Comparison of measured signals from a healthy structure and a damaged one can also contribute to generation of new features. Several DIs based on the cross correlation between the signals from the intact and damaged models are implemented in a study by (Mechbal & Rebillat, 2017) to show to what extent a structure is damaged. Further DIs can be defined by taking into the account the path between the transducers (Olisa, Khan, & Starr, 2021). Moreover, (Xu, Yuan, Chen, & Ren, 2019) has employed other DIs such as spatial phase difference, spectrum loss, differential curve energy, normalized correlation moment, etc. based on the comparison between the signals obtained from the damage state and the intact state.

In recent years, other novel damage indices also have been proposed by many scholars. For instance, (Cantero-Chinchilla et al., 2021) introduced an index that by using fuzzy logic basics, measures the time-of-flight mismatch of sequential ultrasonic guided-wave data. Also, there are other indices that can be generated according to ML principles (K. Wang et al., 2021), which can also be considered as features. More explanation of them is available in section 3.1.

2.3. Assortment of UGW-based damage identification algorithms

After obtaining and extracting the proper features out of the signals, it is time to aggregate and interpret these features. There are multiple algorithms that can facilitate this job. In this section, the most common ways of their classification are presented. Moreover, for selected categories, examples are provided.

Based on the characteristic of information that damage detection algorithms can provide to the user, they can be categorized at three levels:

1. **Identification**: at this stage only the presence of the damage in the structure can be diagnosed;
2. **Localization**: at this level the spatial coordinate of the present damage in the structure can be predicted;
3. **Quantification**: at this level not only the location of the damage but also the severity of it can be detected.

Dependence of a damage detection method on the baseline data (data from the healthy state) provides another option for categorizing them:

1. Baseline dependent
2. Baseline independent

In a baseline-dependent method, an array of transducers is employed at two states (healthy and damaged) of the structure to detect the damage. One of the most implemented techniques in this category of methods is regarded as the probability-based imaging algorithms, where the generated image reflects the probability of the presence of the damage at specific locations on the structure (Figure 3). The creation of such images is based on multiple time-domain features such as ToF, and amplitude of a specific wave mode. Lamb wave tomography which is regularly employed in conventional ultrasonic testing is one of the most classical examples of this family of methods (McKeon & Hinders, 1999; Jansen, Hutchins, & Mottram, 1994). A comparative study of several tomographic algorithms can be also found in (Zhao, Royer, Owens, & Rose, 2011). Alternatively, a correlation-based imaging technique has been presented in (Quaegebeur, Ostiguy, & Masson, 2014). The principle of this technique relies on the correlation of the measured signals with dictionary signals. There are research that have considered Bayesian methods to perform the damage detection. For instance, (Cantero-Chinchilla, Chiachío, Chiachío, Chronopoulos, & Jones, 2019) were able to reconstruct the damage localization within a metallic plate without having to assume a specific a priori time-frequency transform model. This was done by predicting ToF and using it as an input to the Bayesian inverse problem of damage localization. The application of Bayesian inference problem to identify damage is also investigated in (W.-J. Yan, Chronopoulos, Papadimitriou, Cantero-Chinchilla, & Zhu, 2020).

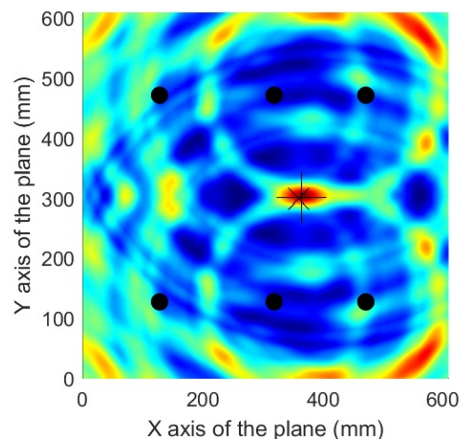

Figure 3. An example of the generated contour plot in delay and sum imaging technique (simulation and analysis performed by authors)

Although baseline-dependent techniques are popular and well-known, nevertheless they possess their limitations. First of all, the availability of the pristine signal cannot always be guaranteed. For instance, an aging structure can exhibit different behavior in comparison to the healthy state, although there is no damage present. Moreover, environmental and conditional changes can also lead to a deviation in the captured signals from a healthy state. Both of these cases result in the generation of a false alarm. Baseline-free methods are developed to address these limitations. One of the first implementations of such techniques dates back to the concept of time reversibility in general acoustics (Fink et al., 2000). Based on this motivation, time-reversal methods based on Lamb waves for detection of damages in an aluminum plate were also proposed in (C. H. Wang, Rose, & Chang, 2004). Moreover, another comprehensive study has been performed

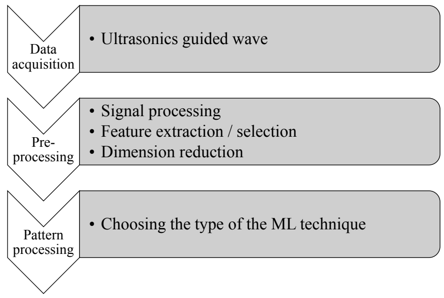

Figure 4. The flowchart for performing damage detection based on ML

by (Poddar, Kumar, Mitra, & Mujumdar, 2011), in which the effect of different parameters such as transducer size, frequency, and pulse frequency bandwidth on the quality of a reconstructed input signal has been investigated.

3. EMERGENCE OF MACHINE LEARNING IN UGW-BASED DAMAGE DETECTION

ML techniques have proven themselves to be beneficial for modeling complex linear and nonlinear phenomena in the presence of uncertainty. Furthermore, due to the immense potential of ML methods to generate data-driven models, their implementation in damage detection algorithms is getting more and more attention. The goal of the current study is not to mention the different categories of ML methods and their definition and limitation. Rather, it is intended to illustrate the required steps to carry out UGW-based damage identification by using ML algorithms. Based on this fact, the next sections of this work are organized based on the depicted flowchart in Figure 4. According to this figure, which is inspired by the waterfall model (Bedworth & O'Brien, 2000), the implementation of ML in a damage detection task should be followed in three main steps.

In the first step, the data acquisition for the problem should be performed. Due to the intention of the current study to confine itself to UGW-based damage detection methods, Lamb waves or other UGWs should be solely utilized as the diagnosis signal. Furthermore, the propagated waves measured at several locations of the structure are the acquired signals. Nevertheless, it should be noted that the way the UGW signals are excited and recorded has many possibilities that can be found in many sources such as (Mitra & Gopalakrishnan, 2016) and (Z. Su & Ye, 2009). The data acquisition step shown Figure 4 corresponds to the *"sensing"* step in the waterfall diagram presented in (Bedworth & O'Brien, 2000).

Afterward, the acquired data needs to be processed to prepare as an input for the chosen ML technique. The pre-processing step can be divided into three main phases, namely, signal processing, feature extraction/selection, and dimension reduction. Different possibilities for processing of a signal are already discussed in section 2.1. However, the elaboration of algorithms concerning feature extraction/selection as well as the dimension reduction will be presented in the corresponding section. Accordingly, studies relevant to the mentioned algorithms will be demonstrated.

The last step of the Figure 4 concerns the selection of the proper ML technique. Accordingly, in section 3.2, the discussion about selection of the pattern processing algorithms will be brought up. Moreover, by referring to the associated publications, the implementation of different ML techniques in UGW-based damage detection will be reviewed.

3.1. Feature extraction / selection and dimension reduction

As it is outlined in Figure 4, the type of data that is used in a UGW-based damage detection is mostly time series. This type of data requires special treatments which are introduced in section 2.1. Ultimately, the processed UGW signals require to be employed as the input of the pattern processing schemes. However, one of the difficulties in using time-domain signals is the magnitude and quantity of data that is frequently collected through sensor networks or many sensors. In order to address this issue, those features that represent the maximum dynamic (variance) of the data should be extracted. Moreover, in the case of damage detection using UGWs, it is often the case that the input space is shaped by time series containing a high number of samples. Hence, before applying feature extraction techniques, the dimension of the input space needs to be reduced. To this end, multiple techniques concerning extracting features from the raw data and addressing the curse of dimensionality are devised. The analysis of the selected papers for the current investigation reveals that there are three families of algorithms, which are mainly employed as feature extraction and dimension reduction techniques. These techniques are Principal Component Analysis (PCA), Wavelet Transform (WT), and Autoregressive models (AR). Accordingly, the mentioned methods are elaborated and associated researches, in which the mentioned techniques have been implemented, are described.

3.1.1. Principal component analysis (linear/nonlinear)

Principal component analysis (PCA) is a well-known multivariate analysis that is capable of reducing the size of a complex data set (Jolliffe, 2002). Furthermore, by decreasing the dimension of the input data (for instance, in the context of UGW-based damage detection algorithms, time series with a high number of samples), the hidden trends of the signal can be revealed. The unveiling of these underlying patterns helps the learning algorithms to be trained faster and more efficiently. Applying PCA to a signal re-expresses the original data set in a new space, in which the most prominent dynamics of the signal are retained. Therefore, PCA analysis can be employed to generate proper features for a chosen classification algorithm. Moreover, it can be used as a dimension reduction tool. In order to be able to apply PCA on a set of data, particular steps should be followed (Mujica, Rodellar, Fernández, & Güemes, 2010):

1. The recorded signals should be arranged in a matrix **S**. The matrix **S** has a dimension of $n \times m$, where n represents number of performed experiments and m is the product of number of samples in each experiment times the number of measurement points (sensors).
2. Calculating the covariance of matrix **S**:
$$\mathbf{C}_s = \frac{1}{n-1}\mathbf{S}^T\mathbf{S}. \tag{4}$$
3. Obtaining the eigenvalues and the eigenvectors of the covariance matrix:
$$\mathbf{C}_s\tilde{\mathbf{V}} = \tilde{\mathbf{V}}\Lambda \tag{5}$$
where the diagonal components of Λ represents the eigenvalues of $\mathbf{C}_s$, and columns of $\tilde{\mathbf{V}}$ are the eigenvectors of covariance matrix.
4. The most prominent features of the data are described by those eigenvectors whose corresponding eigenvalues have the highest amount. Hence, columns of $\tilde{\mathbf{V}}$ should be sorted by descending order according to the associated eigenvalues. By selecting a reduced number of components ($d < n$) from the sorted $\tilde{\mathbf{V}}$, a new matrix **V** can be formed. Matrix **V** is called the PCA model of the original data set.
5. As a geometrical interpretation the original signal can be projected toward the direction of the principle components as:
$$\mathbf{T} = \mathbf{S}\mathbf{V} \tag{6}$$
where **T** demonstrates the score matrix.

There have been numerous deployments of PCA in the field of UGW-based damage identification. (D. A. Tibaduiza, Mujica, Rodellar, & Güemes, 2016) employed PCA to define patterns associated with the healthy and damaged states. In order to have a quantitative comparison between those two states, Q-$statisitic$ and Hotelling's T^2-$statisitic$ have been utilized. The formulation of these two indices can be obtained from (Yue & Qin, 2001) and (Mujica et al., 2010). In this work, several structures, such as aircraft turbine blades and aircraft skin panels have been equipped with lead zirconate titanate (PZT) transducers. Several actuation phases, each from a specific bounded PZT on the structure have been considered. Based on the collected data from each actuation phase, a PCA model has been generated for each of the states, i.e damaged and healthy. Accordingly, the generated PCA models serve as a classifier, where the outputs of it are the score matrices and damage indices. (Murta, Vieira, Santos, & de Moura, 2018) proposed a technique based on PCA for the detection of welding defects in a plate. The required data for PCA are obtained through a numerical simulation of ultrasound wave propagation. The welding imperfection has been modeled as a discontinuity in the numerical simulation. The outcome of each simulation is an A-scan signal that can be fed into the PCA. Similarly to (D. A. Tibaduiza et al., 2016), here PCA has been used as a classifier as well. The implementation of PCA for this problem is based on the technique adopted in (Vieira, de Moura, & Gonçalves, 2010). The work performed by (Arcos Jiménez, Gómez Muñoz, & García Márquez, 2019) concerned the detection of dirt and mud on the blade of a wind turbine. The authors have utilized PCA to extract features and to reduce the dimension of the data set. Furthermore, for the generation of guided waves Macro Fiber Composites (MFC) transducers have been deployed. The generated features by PCA are then fed into multiple classifiers. (Miorelli, Kulakovskyi, Mesnil, & D'Almeida, 2019) considered the use of PCA for dimension reduction of the data set generated by a guided wave imaging algorithm. The aim of this study is to identify damage in an aluminum panel. The PCA has been applied to a 600×600 pixel image. This synthetic data set is obtained from CIVA SHM forward solver (Mesnil, Imperiale, Demaldent, Baronian, & Chapuis, 2018), and the post-processing of the signals is based on Excitelet algorithm (Quaegebeur, Masson, Langlois-Demers, & Micheau, 2011). (Ghrib, Rébillat, Vermot des Roches, & Mechbal, 2019) proposed a nonlinear model-based feature for increasing the performance of the classification. These nonlinear features are computed based on Hammerstein (Bakir, Rebillat, & Mechbal, 2015) models, which itself these models are identified with an exponential sine sweep signal. PCA is utilized in this work to examine if the reduction of input data dimension helps the classifier to work more robustly. The preliminary signals in this work are generated via numerical simulations as well as performing experiments on a composite aeronautic plate. In the work presented by (Sen et al., 2019), the health monitoring problem of the pipes was regarded. The required data for their work has been acquired from experimental works. In the experiments, the responses of guided waves are captured based on a pitch-catch configuration. PCA is used in this study to decrease the dimension of the samples. The captured samples in this work have a size of 2500, which through the utilization of PCA is reduced to 150 principal components. Furthermore, it is shown that the use of the first two principal components has described the most prominent trends of the data. Therefore, they can be used as features yielding to the classification of the health state of the pipe. In a study carried out by (Sbarufatti, Manson, & Worden, 2014), PCA is utilized for the reduction of input space. Their study concerned damage detection in an aluminum plate. Moreover, PZT transducers have been mounted on the plate to generate and record the propagated guided wave. In this study, 516 damage cases have been considered.

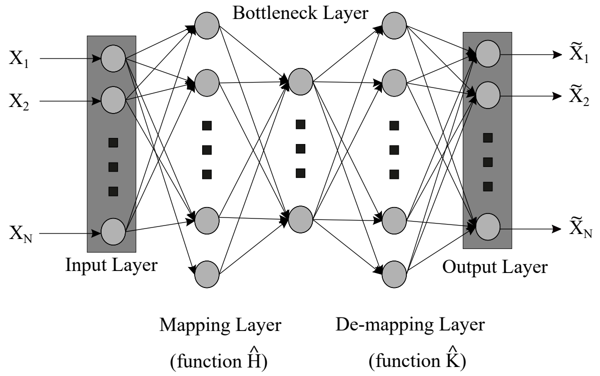

Figure 5. The architecture of a NLPCA network (Kramer, 1991)

Moreover, for each damage scenario, 30 damage indices are defined that are originated from the 30 available paths defined by the configuration of transducers. Hence, the input space has a dimension of 30×516. The utilization of PCA in this study has reduced this dimension into 15×516. This dimension reduction has been performed due to the fact, that the first 15 principal components of the data set in this study represent 95% of the total variance. Here the dimension reduction through PCA has resulted in eliminating half of the paths. This reduction can be an obvious effect of the reciprocating nature of the signals between two sensor points. But, still due to the simplicity of PCA algorithm, its use can be justified. An overview of the analyzed references in this section is shown in Table 1. This table represents the number of data points before applying PCA to them as well as the retained number of PCA components. Further, the achieved variance in each study also is listed in Table 1. It should be noted that those references containing this information are just considered for this table.

Nonlinear principal component analysis (NLPCA) is outlined as a nonlinear generalization of the conventional PCA. The idea behind this technique is to consider curves instead of lines for finding the most important dynamics of the data. The conventional nonlinear PCA was proposed by (Kramer, 1991), and is based on a multi-layer perceptron (MLP) with an auto-associative topology. The identity mapping is done by employment of a square error. This mapping is performed through a connection of inputs and output in the auto-associative architecture. The network architecture is shown in Figure 5. In the presented network layout five layers can be seen. Three of them are hidden layers, and two of the layers are the input and the output layers. The decision about the number of nodes is associated with the complexity of the nonlinear function that can be generated. There should be a compromise between the accuracy and the over-fitting problem in choosing the number of nodes. It is recommended by (Kramer, 1991) to constraint the number of nodes in the network layout, proportional to the number of data set. Unlike PCA, mapping into feature space in a NLPCA approach can be generalized to let arbitrary nonlinear functions to be employed. The mapping in a NLPCA scheme is performed by equation (7):

$$\hat{\mathbf{T}} = \hat{\mathbf{H}}\mathbf{X}_j \tag{7}$$

where $\hat{\mathbf{H}}$ is a nonlinear vector containing N individual nonlinear functions: $\hat{\mathbf{H}} = \{\hat{\mathbf{H}}_1, \hat{\mathbf{H}}_2, ..., \hat{\mathbf{H}}_N\}$. Furthermore, $\hat{\mathbf{T}}$ and $\mathbf{X}_j$ are analogous to $\mathbf{S}$ and $\mathbf{V}$ in equation (6). The inverse transformation which corresponds to the de-mapping step in Figure 5 can be obtained by equation (6):

$$\tilde{\mathbf{X}}_j = \hat{\mathbf{K}}\hat{\mathbf{T}} \tag{8}$$

where the nonlinear function $\hat{\mathbf{K}} = \{\hat{\mathbf{K}}_1, \hat{\mathbf{K}}_2, ..., \hat{\mathbf{K}}_N\}$ is responsible for the transformation.

As an extension to the conventional NLPCA, (Scholz & Vigário, 2002) developed hierarchical-NLPCA (h-NLPCA). The proposed technique is based on a hierarchical type of learning. In a h-NLPCA scheme output ($\tilde{\mathbf{X}}$) is forced to be equal to the input ($\mathbf{X}$). This aim is fulfilled through minimization of the Squared Reconstruction Error (SRE) stated by the equation (9)

$$SRE = \frac{1}{jn}\sum_{j=1}^{J}\sum_{n=1}^{N}\Big(\mathbf{X}_{j,n} - \tilde{\mathbf{X}}_{j,n}\Big)^2 = 1 \tag{9}$$

Unlike the NLPCA, in an h-NLPCA implementation components of the input space are ordered hierarchically, i.e the first n components contain the maximum variance of the data. Selection of h-NLPCA over conventional PCA can be justified in problems, where different features have a nonlinear correlation with respect to each other. However, the reviewed studies do not show any particular advantage of h-NLPCA over PCA, in the context of UGW-based damage detection.

There have been multiple implementations of h-NLPCA in the context of UGW-based damage detection. (D. Tibaduiza et al., 2018) have investigated the damage identification based on UGW data collected from a carbon fiber-reinforced polymer (CFRP) sandwich and composite plate. The acquisition of the data is carried out through PZT transducers. The arrangement of the data is similar to a prior work performed in (D. A. Tibaduiza et al., 2016). In this study ((D. Tibaduiza et al., 2018)) h-NLPCA is applied to the data from the input space at each actuation phase. Afterward, nonlinear components can be obtained, that are deployed for the training of multiple classification algorithms. This study has just considered the first thirty components yielded from the h-NLPCA technique. The implementation of h-NLPCA in this study has contributed significantly to decreasing the dimensions of the input space, so that the dimension of the raw data has been reduced to 150×30 from an original value of 150×180000. (Jiménez et al., 2019) compared the use of linear and nonlinear features for a classification problem with an objective of

Table 1. An overview of the utilized PCA configurations and performances in the selected articles

Scholars	No. of data points	No. of PCA components	achieved variance
(D. A. Tibaduiza et al., 2016)	140	2	80%
(Murta et al., 2018)	108	12	71%
(Miorelli et al., 2019)	500	4	—
(Ghrib et al., 2019)	1820	3	94%
(Sen et al., 2019)	2500	150	—
(Sbarufatti et al., 2014)	516	15	95%
(D. Tibaduiza, Torres-Arredondo, Vitola, Anaya, & Pozo, 2018)	60000	30	—
(Jiménez, García Márquez, Moraleda, & Gómez Muñoz, 2019)	—	5	—
(Sattarifar & Nestorović, 2021)	240	2	—

determination of ice on the wind turbine blades. MFC transducers are employed in a pitch-catch configuration for the purpose of wave generation and sensing on the structure. Furthermore, a six-cycle Hanning-windowed signal at four different center frequencies (20 kHz, 30 kHz, 50 kHz, 100 kHz) is used as the excitation signal of the structure. This study has considered h-NLPCA, and PCA as the nonlinear and linear feature extraction techniques, respectively. The chosen architecture for the h-NLPCA is a network consisting of 12 hidden nodes in the mapping and de-mapping layers. Furthermore, five nodes have been considered for the bottleneck layer. The precision of different classification algorithms by using the linear features extracted from PCA, and nonlinear features obtained from h-NLPCA, does not show any significant difference in this study.

3.1.2. Continuous / Discrete wavelet transform

Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) have been employed widely as signal processing and pre-processing tools in the SHM community (Z. Su & Ye, 2009). As it is mentioned in previous sections, these two methods belong to the joint time-frequency-domain methods. The comprehension of CWT and DWT applications in feature extraction of UGWs requires a preliminary understanding of these two methods, as well as their formulation. Therefore, in this section, a brief theoretical background of both techniques is presented, and subsequently, the required steps for their implementation are expressed.

CWT was initially proposed by (Daubechies, 1990) and (Newland, 1994) to address limitations concerned with using a short-time Fourier transform (STFT). By means of the STFT technique, the spectrogram of a nonstationary signal can be obtained. However, there are limitations with regard to controlling the resolution of frequency of the time and frequency in the obtained spectrogram, as well as the inability to inverse the time-frequency map. Using the Wavelet Transform (WT) addresses both of the issues. A wavelet by definition is a waveform with an average amplitude of zero and a limited duration. By applying a WT on a signal, the original signal is expressed using two parameters, namely, scale and a translational value, indicated by a and b, respectively. Principally, WT is a windowing technique, whose window size is variable.

In the CWT implementation, a dynamic signal $f(t)$ is windowed by an orthogonal wavelet function $\Psi(t)$, yielding the converted quadratic form as (Z. Su & Ye, 2009):

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t).\Psi^*(\frac{t-b}{a}).dt \qquad (10)$$

where $W(a,b)$ denotes the CWT coefficients. This parameter can also be interpreted as a series of band-pass filters, whose central frequencies and bandwidths are dependent on the scale and $\Psi(t)$. Furthermore, $\Psi^*(t)$ represents the complex conjugate of $\Psi(t)$ in equation (10). The output of this formula depicts the energy spectrum of the original dynamic signal $f(t)$. Hence, the total energy of the signal can be expressed as (Z. Su & Ye, 2009):

$$E = \int_{b\geqslant 0}^{+\infty} \int_{a\geqslant 0}^{+\infty} |W(a,b)|^2.da.db \qquad (11)$$

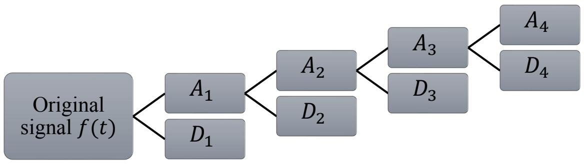

Figure 6. A four-level DWT-based signal decomposition

DWT algorithm enables the decomposition of a dynamic signal into associated sub-bands of it; those are the bands with higher and lower frequencies with certain cut-off frequencies. Apart from the application of DWT in feature extracting, it can be as well beneficial for de-noising the signal. By applying the DWT on a signal, based on the favored level of the hierarchy, it is separated into *approximations* and *details*. The former notion (approximations, A_i) represents the low-frequency components of the signal, whereas the latter one (details, D_i) describes the high-frequency content. An example based on a four-level hierarchy of DWT algorithm is depicted in Figure 6

The utilization of CWT and DWT as a feature extraction technique has been embodied in multiple investigations. (Atashipour, Mirdamadi, Hemasian-Etefagh, Amirfattahi, & Ziaei-Rad, 2012) proposed the deployment of CWT for extracting the ToF of the Lamb waves. In particular, a CWT-based Scale-Averaged wavelet Power (SAP) is employed, whose maximum corresponds to the arrival time of the wave packet. The SAP metric for a discrete signal $f(n)$ with N samples is defined as:

$$SAP(n) = \frac{1}{M} \sum_{i=1}^{M} |W(a_i, n)|^2 \tag{12}$$

where M is the largest scale of the CWT. Furthermore, by using the envelope of the SAP, the input vector of the ANN is formed. In a similar way, (G. Yan, 2013) employed the CWT technique to capture the ToF of the incidents waves. However, in this study, a Bayesian approach for the localization of the damage is followed. In a research performed by (Liew & Veidt, 2009), using the DWT for extracting features from the measured UGWs is investigated. Due to the phase discrepancy of UGWs, and a large number of the sampling points in the time domain, it is often impractical for pattern recognition methods to use such signals directly as the input. This study has addressed both of these issues by the deployment of DWT. The obtained wavelet coefficients from each level of the signal decomposition are fed into the ANN as the input of the system. Furthermore, it is shown that through the use of DWT, the computational time of the network has been reduced. The implementation of DWT was realized in this study by selecting an 8^{th} order Daubechies wavelet. In another work carried out by (D. Tibaduiza et al., 2018), it is shown in a similar study to (Liew & Veidt, 2009), how the DWT can be used to extract features from recorded UGWs. In this study, the decomposed signals calculated by applying the DWT on them are directly used as the input for several classification algorithms. Likewise, (Virupakshappa & Oruklu, 2019) employed DWT to decompose the captured signal into approximations and details. Due to the distinguishable signal-to-noise ratio in the low pass components of the decomposition (A_i components), they are selected as the input feature for multiple unsupervised ML algorithms. (Ewald, Groves, & Benedictus, 2019) proposed a novel method by incorporating the CWT and Convolutional Neural Network (CNN). In this study, through applying the CWT on the dynamic signals the wavelet coefficients matrix (WCM) is determined. The excitation signal selected to be propagated through the plate is a 5-cycled Hanning-windowed toneburst. Due to the similarity of the described excitation signal to Morlet wavelet, this type of wavelet is used for the CWT analysis. Subsequent to obtaining the WCM through CWT, it is fed into the devised CNN. Afterwards, by training the CNN, the neural weights are obtained.

3.1.3. Autoregressive and nonlinear autoregressive with exogenous models

Autoregressive (AR) models are another well-known technique that enables feature extraction from a time series. An AR model articulates the current output of a system as a linear combination of the past outputs. In other words, the variable is regressed on itself. equation (13) defines the formulation of an AR model:

$$Y[t] = c + \sum_{j=1}^{p} c_j y[t-j] + \psi[t] \tag{13}$$

where p denotes the order of the model and illustrates the dependency of the current measurement on the p previous measurements. $Y[t]$ denotes the captured time series, and ψ is white noise. Moreover, c_j are the AR coefficients and c can be defined as:

$$c \equiv (1 - \sum_{j=1}^{p} c_j)\mu \tag{14}$$

where μ is the mean of the input signal.

Estimation of the AR model coefficients is mostly performed by the Yule-Walker method (Box, 2008). These coefficients serve as the extracted feature from a time series based on an AR model. Furthermore, multiple techniques can aid the selection of model order. Akaike's information criterion is commonly employed for this purpose (Farrar & Worden, 2012). More precisely, this issue has been investigated for an SHM case study in (Figueiredo, Figueiras, Park, Farrar, & Worden, 2010).

The nonlinear implementation of an AR model is usually expressed as Nonlinear Autoregressive models with Exogenous

(NARX). NARX models have found their first applications in system identification of nonlinear dynamic systems. This technique is initially proposed by (Leontaritis & Billings, 1985). A NARX model is capable of predicting the output of the system from its input by means of a nonlinear function. A NARX model with polynomial terms up to an order of three can be expressed as:

$$y(t) = \sum_{i_1=1}^{M} y(t-i_1)\theta_{i_1} + \sum_{i_1=1}^{M}\sum_{i_2=i_1}^{M} y(t-i_1)y(t-i_2)\theta_{i_1 i_2} + \sum_{i_1=1}^{M} \dots \sum_{i_l=i_{l-1}}^{M} y(t-i_2)\dots y(t-i_2)\theta_{i_1 \dots i_l} \tag{15}$$

where $y(t)$ and $y(t-i_1)$ represent the original and delayed data samples, respectively. The exact polynomial terms for an example with 4 samples are described in (X. Zhang, Zou, He, & Sun, 2016). Furthermore, the feature vector is composed of the NARX coefficients (θ). The mathematical formulation that yields the θ coefficients is presented in (Jiménez et al., 2019).

The employment of AR and NARX have been observed in several studies. (Jiménez, Gómez Muñoz, & García Márquez, 2018) have proposed the use of AR for feature extraction from the guided waves. The aim of classification in this work concerns with identification of delamination in wind turbine blades. In this study, the AR coefficients are obtained based on Levison-Durbin algorithm (Castiglioni, 2005). The research carried out by (Arcos Jiménez, Zhang, Gómez Muñoz, & García Márquez, 2020) concerns the use of nonlinear features and their comparison with linear ones. AR and NARX have been selected to provide nonlinear features. It has been shown in this study that the selection of NARX over AR has a significant positive effect on the outcome of the damage detection problem. The high number of generated features through the NARX method is one of its drawbacks. To tackle this issue, neighborhood component analysis has been employed to select the most prominent features and reduce the dimension of the input space. Furthermore, similar studies presented in (Arcos Jiménez et al., 2019) and (Jiménez et al., 2019) have considered the NARX and AR as a feature extraction tool for UGW-based damage detection.

3.2. Pattern processing

The damage detection problem outlines itself as a task, in which the state of the structure should be classified. In conventional UGW-based methods, by defining some sort of Damage Indices (DIs), specific thresholds are set, so that the user can be aware of the probable damaged state of the structure. The definition of the DIs as well as the threshold from which the structure can be considered as damaged, are often case-oriented tasks, and there is no possibility of generalization by following conventional algorithms. However, in an ML-based damage detection scheme, it is the machine itself that recognizes the patterns and classifies the structure with regard to its health condition. Evidently, the perception of the trends in the data should be facilitated through multiple classifications and clustering techniques, which are elaborated in sections 3.2.1, 3.2.2 and 3.2.3. The selection of the methods to be explained in this section is justified due to the frequency of the occurrence in the reviewed articles. The details for the share of each single pattern processing method in the reviewed articles are outlined in section 4.

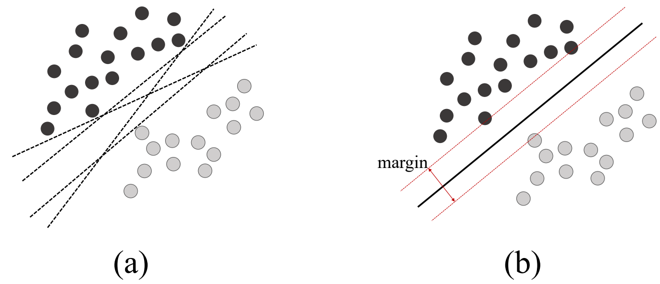

Figure 7. (a) Arbitrary decision boundaries (b) Decision boundary obtained by SVM

3.2.1. Support vector machine

SVM is an effective and powerful ML technique, which is capable of linear and nonlinear classification, regression as well as outlier detection. This algorithm is initially proposed by (Vapnik, 1995). The fundamental idea behind the SVM algorithm can be well outlined through Figure 7. The two classes represented in Figure 7 can be separated with the dashed lines. These dashed lines are perfectly classifying the two classes. However, these classifiers will have poor performance with regard to new instances that are close to the decision boundaries. In contrast, the decision boundary depicted by the solid line in Figure 7(b) represents the classification by SVM. The latter decision boundary guarantees a rich performance even for new instances since it stays as far as possible to the closest training instance (Géron, 2019). Therefore, it can be stated that the goal of an SVM classifier is to determine such a decision boundary (hyperplane), which can classify the given data in the optimal form. In order to express the mentioned optimization problem mathematically, the following equation should be outlined.

Let D be the input space of the problem, which contains both classes:

$$D = \{(x_i, y_i),\ x_i \in \Re\ and\ y_i \in +1\ or\ -1\} \tag{16}$$

here x_i and y_i represent the data and the class vector, respectively. Assuming the values of y_i to be $+1$ or -1. Then, the decision boundary of the described data set can be obtained by equation (17).

$$y(Wx - b) \geqslant 1 \tag{17}$$

where W describes a vector normal to the hyperplane, and b represents the offset from the origin. W is obtained by utilization of quadratic programming and b can be determined by having the values for x, y, and W. The Lagrange multiplier α is used in the quadratic programming, and for the optimization as well, with the condition of maximizing the α. Furthermore, in the SVM algorithm two other parameters, namely, C and ξ, which account for soft margin optimization, respectively should be regarded. The optimization equation and its constraints are represented in equation (18) and 19, respectively.

$$argmin_{W,\xi,b}\{\frac{1}{2}||W||^2 + C\sum_{i=1}^{N}\xi_i\} \tag{18}$$

$$0 \leqslant \alpha \leqslant C,\ \xi \geqslant 0 \tag{19}$$

The decision boundary obtained by equation (18) is able to classify a linear separable input space. However, in the case of a nonlinear relation between input and output, a Gaussian kernel function is required to be deployed. The kernel function determines a linear function by mapping the input space into a higher-dimensional space. The selection of the kernel type and its parameters plays an important role in the accuracy of the classification. As examples, linear, quadratic, polynomial, multilayer perceptron, and Gaussian Radial Basis Kernel Functions (GRBF) can be named. A detailed discussion on the mapping process of kernel functions can be found in (Cristianini & Shawe-Taylor, 2000).

Due to SVM's great capability in learning and classifying unique patterns, numerous studies have employed this technique for damage detection. One of the earliest works concerning the deployment of SVM in UGW-based damage detection is performed by (Dackermann, Skinner, & Li, 2014). In this study, by using UGW and SVM, a novel technique for the in-situ health assessment of timber utility poles is proposed. The selected features to be fed into the SVM are obtained from coefficients of the AR model. The devised technique in this study yielded an accuracy of $95.7 \pm 3.1\%$ for the prediction of the health state. (Agarwal & Mitra, 2014) used SVM for detection of damage in a metallic plate. This study proposed the utilization of the matching pursuit technique to prepare the input vector for the SVM. It is shown that the SVM outperforms ANN, and has a robust performance in the presence of the noise. The trained classifier based on the SVM technique showed an accuracy of 95% in detecting the damage. Furthermore, apart from damage detection, the authors have devised a technique to localize the damage on the structure. In an investigation carried out by (Virupakshappa & Oruklu, 2015), the SVM classifier is deployed for detection of a flaw in a steel block. The A-scan data is utilized in this study as the preliminary form of the input vector. However, a novel technique is proposed to decompose the signal into sub-band frequencies, and the latter feature is fed ultimately to the SVM classifier. The research performed by (Eybpoosh, Berges, & Noh, 2017) concerns the utilization of the SVM technique for damage detection in pipelines. In this work, a pitch-catch data acquisition scheme is used for collecting the required data of the classifiers. Furthermore, a novel feature extraction algorithm is devised to obtain a sparse vector of coefficients from the energy of the arrival signals. This study employs the SVM not directly for identifying the damage in the pipeline, but to reveal the capability of the proposed feature in dividing the data into two classes. Due to the necessity of having a nonlinear decision boundary for classifying the instances, GRBF is used as the kernel function. It is also demonstrated in this research that the implemented method has an acceptable performance even under varying environmental and operational conditions. Additionally, this paper has analyzed the feasibility of a real-time configuration for detecting damage. (Dib et al., 2018) proposed a one-class implementation of SVM as an unsupervised classifier to determine the damage caused by an impact on a metallic plate. The required data for this work is obtained through an analytical model as well as experimental results. Furthermore, a voting system is developed based on an ensemble of classifiers. The proposed method has the advantage of requiring only a limited number of baseline signals since each classifier is trained based on a different segment of the signal. The application of SVM as a nonlinear classifier for detection of ice as well as mud on the wind turbine blades is demonstrated in studies performed in (Jiménez et al., 2019) and (Arcos Jiménez et al., 2020), respectively. The implementation of SVM as a classic classifier has been challenged in a study carried out by (Melville, Alguri, Deemer, & Harley, 2018). Their investigation has demonstrated that using a more sophisticated ML technique (Deep Learning) yields a higher accuracy in comparison to the SVM. Apart from the mentioned works, the deployment of SVM as a classifier for detection of damage in a UGW-based damage detection scheme has been considered in (Ghrib et al., 2019), (D. Tibaduiza et al., 2018), (Mardanshahi, Nasir, Kazemirad, & Shokrieh, 2020), and (Li, Gu, Hu, & She, 2019) as well.

3.2.2. Artificial neural network

In this section of the paper, one of the oldest learning techniques is discussed. Artificial Neural Networks (ANNs) can be argued to be the origin of the ML discipline. The raise of the ANN began with the leading work on the structure of neurons in the 1910s (Ramón y Cajal, 1910). However, the initial ANN algorithm has been introduced by the work carried out by (McCulloch & Pitts, 1943), in which a simplified mathematical model for the way that animal brains works is proposed. Despite the early attention that the ANN algorithm gained, it was only during the last two decades, that a massive

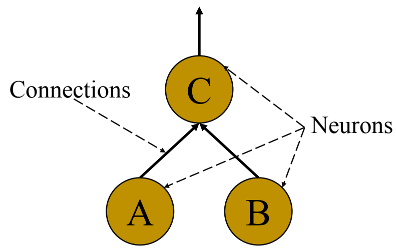

Figure 8. McCulloch-Pitts neuron, representing a simple architecture performing the *"AND"* logical computation

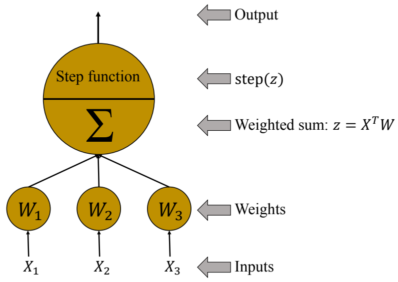

Figure 9. Computation of weighted sum and applying a step function on it in a Threshold Logic Unit (TLU) neuron

wave of interest was flooded toward this ML technique.

The building block of nearly each ANN is the artificial neuron. By receiving a set of inputs, these neurons generate a single output. One of the early models for the neurons, which is called McCulloch-Pitts (MCP), considers the neurons to have binary inputs and outputs. The structure of an MCP neuron consists of two blocks, namely, summation and activation. Figure 8 depicts a network of binary neurons performing the logical *"AND"* operation, where both the A and B neurons should be activated in order to activate the neuron C.

It should be noted that the described MCP neurons did not end up with a network implementation. The pioneering initial study on the networks of artificial neurons was performed by (Rosenblatt, 1958). He proposed the perceptron architecture, which is based on an artificial neuron called Threshold Logic Unit (TLU). In opposite to the binary neurons, the input and the output of the TLU neurons are real numbers. Furthermore, each input connection of a TLU is associated with a weight (Géron, 2019). Afterwards, a step function is applied to the summed weighted inputs, and the output is generated (Figure 9). Common step-functions utilized in the perceptron are Heaviside and sign functions.

After a rigorous investigation carried out by (Minsky, 1969), it was revealed that the described architecture has limitations regarding the complexity of the problem. Furthermore, it was concluded that using a threshold prevents finding a learning rule. Hence, the hard thresholds were substituted with continuous functions such as Sigmoid or hyperbolic tangent functions.

Generalization of the described perceptron architectures yields to the Multilayer Perceptron (MLP). A complete discussion on the matter can be found in (Haykin, 1994) and (Bishop, 1995). In a feedforward MLP architecture, values of the input pass through the input layer and hidden layers. Ultimately, the result of the network becomes known at the output layer. Similar to the TLU neurons, in this architecture, at each node of the hidden layers a weighted sum is performed, and the result is passed through the next layer. Establishing the proper values for the weights of the signal is the training phase of the network (Farrar & Worden, 2012). With the described introduction on the origin and principles of the method, the discussion will be followed by the application of ANN in the context of SHM and particularly, UGW-based damage detection.

ANNs can aid in multiple fashions to resolve the problem arising in performing damage detection. For instance, ANN can be beneficial in reconstructing signals from the noisy input, regression problems (finding associated output for a given input), classification of the input data, etc. The most desired application among mentioned examples would be the classification, which assists in determining the damaged state of a structure.

One of the early implementations of ANN in the context of SHM and UGW-based damage detection dates back to a study performed by (Z. Su & Ye, 2004) in the year 2004. A novel technique named as Intelligent Signal Processing and Pattern Recognition (ISPPR) was developed in this study, to extract features and identify damage in a composite plate. The data acquisition is carried out by using 8 PZT transducers on the plate. The ISPPR algorithm extracts features by performing several steps on the raw measured signals. First, by using DWT, signals were decomposed to several sub-band frequencies. This step helps to extract components of the signal which are in correlation with the actual excitation function. Afterwards, CWT is applied to the selected sub-band from DWT analysis, so that the energy of the signal can be allocated over time-scale space. Furthermore, the digitized features are fed into a multilayer feedforward ANN to be used as the training data. Accordingly, the trained ANN network can obtain the location of the damage on the structure. (Dworakowski, Ambrozinski, Packo, Dragan, & Stepinski, 2014) took advantage of ANN to devise a classifier for the assessment of the structural condition. Four damage indices were defined based on the time-domain signals and are considered as the input of the ANN. The selected ANN consists of two hidden layers, plus one input, and one output layer. The output of the network is a linear neuron returning numbers between 0 and 1, representing the state of the structure to be healthy until fully damaged, respectively. The structure used in this study is an aircraft panel, and for generating the data set, artificial damages are introduced. The developed method in a study performed by (Seno, Sharif Khodaei, &

Aliabadi, 2019) suggests the utilization of ANN for feature extraction and classification. The followed goal in this study concerns localizing the impact image in a composite plate. The inconsistency of the input feature, which occurs due to variation in size of the damage or environmental conditions, is an important issue which reduces the accuracy of the implemented ML technique. A novel technique is proposed in this study to tackle this problem. To this end, special treatments for pre-processing of the time signals and extraction of the time of arrivals (ToAs) are considered. Ultimately, the ToAs are used as the input of the ANN. One hidden layer is considered for the network, and the output consists of two neurons returning the (X, Y) coordinate of the impact damage. (Hesser, Kocur, & Markert, 2020) proposed the use of ANN for active source localization in an aluminum plate. The internal damages and imperfections are mostly responsible for the presence of the active sources in the wavefield. The required data for training the ANN network is collected by means of experimental and numerical studies. The outcome of the classification through ANN showed an acceptable performance with regard to source localization. Apart from the mentioned articles, further references can be obtained in Table. 2. Due to similarity in the way ANN is employed in those studies, it is omitted to mention them explicitly.

3.2.3. Deep learning

Despite the great potential of ANN for tackling complex classification problems, it has limitations regarding the number of layers to be selected. This hinders the training of a deep network, for instance, for problems concerning input data with high-resolution pictures. The described issue is possible to be addressed through the deployment of deep neural network (DNN) algorithms. However, the possibility of utilizing deep layers was not alone responsible for the emergence of the DNN techniques in recent years; rather, it was the increase of computational power and the amount of the training data, that resulted in the flourishing of this technique. Nevertheless, by selecting a DNN technique, multiple issues regarding the training of the network can arise. Vanishing/exploding gradients, the lack of adequate amount of data for a large network, slow training, and overfitting are examples of the problems one could face by implementing a DNN. A detailed discussion on addressing these issues can be found in (Géron, 2019). There are several DNN techniques such as Convolutional Neural Network (CNN), autoencoders, Wavelet Neural Network (WNN), and Long Short-Term Memory-Neural Networks (LSTM–NN) which have been used in recent years in the context of the UGW-based damage detection. Due to the diversity of the methods, each algorithm is briefly explained by mentioning the associated examples.

In a CNN, the input layer and rest of the associated convolutional layers can be represented in $2D$. Unlike the conventional ANNs, in CNN, the neurons of the first layer do not connect to all of the neurons from the input layer, but to the pixels of the input in their receptive field. The size of this receptive field is called "$stride$". A similar procedure called "$Max\ Pooling$" can be performed on the input data for reducing computational effort and memory usage. By max-pooling a layer, each neuron is connected to the neurons of the previous layer in the receptive field (defined by the stride). However, the maximum value of the selected pixels in the stride is transferred to the next layer. Moreover, analogous to the weights that were applied in a conventional ANN, in a CNN the set of weights are called filters or convolution kernels. Each convolutional layer has multiple filters, which results in obtaining one feature map per filter (Géron, 2019). Convolution layers, Pooling layers, fully-connected layers, and an output layer are common components of a CNN. Different CNN architectures are obtained from different combinations of those layers. The fully-connected layer is a standard neural layer that isn't convolutional and the output layer is the point where the output of the network is determined. In a binary classification, the output layer includes only one neuron that indicates whether or not the passed training sample corresponds to a given class, with a "one" indicating "true" and a "zero" indicating "false". A thorough theoretical discussion on the definition of these layers and their mathematical formulation can be obtained in (Goodfellow, 2016).

One of the first applications of deep learning in UGW-based damage detection was proposed in a research carried out by (Melville et al., 2018). In this study a deep learning algorithm is used, to assess the full wavefield data collected from laser Doppler vibrometer and PZT transducers. The obtained data sets are recorded from four different metallic plates, with different thicknesses and material properties. Each full wavefield yields 100×100 signals, bringing the total number of signals obtained for one plate to be 10000. Each of the recorded signals has a length of 3000 samples. Hence, each wavefield matrix has a dimension of 100000×3000, where nearly 88% of it is used as the training data and the rest as the testing signals. The utilized network in this study consists of 4 hidden layers, from which two are convolutional and two fully-connected. The employed convolutional layer in (Melville et al., 2018) has a window size of 10×1, a stride length of 1×1, 16 feature maps, and the max-pooling layer of the network has a stride size of 10×1. It is shown in this study that through the implementation of the described network a maximum accuracy of 100% can be reached for the classification of damaged plates from the healthy ones. Further details regarding the employed architecture of the network in this study can be found in (Krizhevsky, Sutskever, & Hinton, 2012).

(Virkkunen, Koskinen, Jessen-Juhler, & Rinta-Aho, 2019) developed an algorithm for detecting flaws of a welded steel pipe by using deep learning and particularly CNN. The architecture of the employed CNN is based on the VGG16 net-

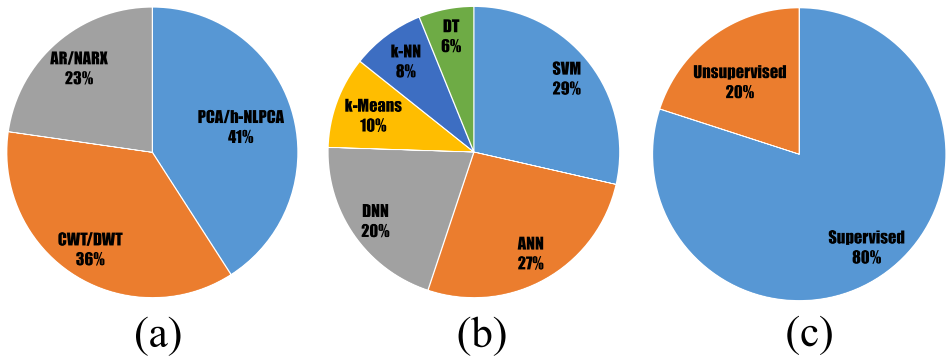

Figure 10. (a) Frequency of the feature extraction methods in the selected articles for the current review paper, (b) Frequency of the pattern recognition/clustering methods in UGW-based damage detection based on the reviewed articles in the current study, (c) Contribution of the supervised and unsupervised method in UGW-based damage detection based on the reviewed articles in the current study

work proposed in (X. Zhang et al., 2016). The results of this study show the reliability of deep learning in damage detection in comparison to human performance. The VGG-16 architecture is used in the work carried out by (Liu & Zhang, 2020) as well. The aim of this study is to detect the crack in a thin metallic plate by using deep learning. The input of the CNN is the pre-processed UGWs measured with PZT transducers. For pre-processing of the data, STFT is applied to the raw UGW signals. Furthermore, SoftMax with cross-entropy is employed as the cost function of the network. A similar deployment of the CNN in the context of UGW-based SHM can be found in (Ewald et al., 2019) as well. In another investigation performed by (Liao, Ou, & Xu, 2020) by incorporating a CNN into the ultrasonic imaging approach sub-wavelength super-resolution defect images are generated. The considered case study in this research is the damage detection in anisotropic composite aircraft laminated structures. One of the main goals of this work is to provide an computationally efficient scheme that enables its online implementation. (Tabian, Fu, & Khodaei, 2019) introduced a CNN-based metamodel for detecting, localizing, and characterizing impacts on complex composite structures. As an input for the metamodel, this work utilised ultrasonic waves generated by external impact events to generate 2-dimensional (2D) images. The accuracy of detection was evaluated on a composite fuselage panel and found to be more than 94%. Furthermore, the scalability of this metamodeling technique was investigated by training CNN metamodels with data from a stiffened panel piece and evaluating their performance on other portions of equivalent shape. Another piece of work by (Xu et al., 2019) involves the diagnosis of a fatigue crack utilizing damage indices (DIs) received from various guided waves exciting-acquisition channels. In addition, they created a CNN and trained it to extract high-level features from a variety of DIs, then utilized the feature fusion to evaluate cracks. The proposed method is validated by conducting fatigue tests on a typical kind of airplane structure. (C. Su et al., 2019) presented a method based on UGW and CNN for concurrently localizing and assessing damage in composite plates. The sensor array in their technique records UGWs reaction signals as training data. The damage detection model is built using the spectrum comprising damage characteristics and related damage modes as input and output of a CNN, respectively.

The study performed by (Marino, Virupakshappa, & Oruklu, 2019) considers an ensemble of deep learning techniques to propose a novel classifier for UGW-based SHM. The designed network reckons two LSTM-NNs for time analysis (downsampling and denoising) of the signal, a WNN for prediction of properties and function estimation, and a CNN for feature extraction. More information on the LSTM-NN and WNN algorithms can be found in (Hochreiter & Schmidhuber, 1997) and (Antonis K. Alexandridis, 2014), respectively.

(C. Su et al., 2020) suggested the utilization of stack autoencoder (SAE) and CNN algorithms for damage identification and localization in a composite plate. The Lamb wave is used as the diagnostic signal to be propagated in the plate. Furthermore, FFT is applied to the time-domain signals to obtain the required features for the SAE. This study concluded that both the SAE and CNN algorithms yield the same accuracy for recognition of the damage. Nevertheless, it is shown that using SAE results in nearly 13% reduction of the training time. Details on the type of the architecture and the required steps to train the network can be also found in (Pathirage et al., 2018).

The implementation of CNNs in UGW-based SHM has been further investigated recently. (Mariani, Rendu, Urbani, & Sbarufatti, 2021) employed a casual dilated CNN to find faults in UGW-inspected plates. They demonstrated how their technique mitigates the issue of feature engineering, which should be undertaken by human operators. (Zargar & Yuan, 2021) presented a hybrid CNN-recurrent neural network (RNN) to handle the spatiotemporal information extraction challenge in an impact damage detection problem. They verified their suggested approach by generating simulated wavefields using a five-bay stiffened aluminum panel finite element analysis (FEA). The use of a WT for generating a 2D image, which later should be utilized as an input for the CNN, was considered in a study carried out by (Azuara, Ruiz, & Barrera, 2021). They successfully predicted the distance of a damage to the transmitters using their proposed algorithm.

The assessment of papers reveals a significant trend toward employing deep learning-based classification algorithms for UGW-based SHM using 2D-CNNs, with an image (2D array) serving as the input of the network. However, it is obvious that the raw signals acquired by a UGW-based technique, are by definition 1-dimensional (1D) arrays. To that goal, the signals must be transformed into a 2D array using techniques such as time-frequency analysis introduced in section 2.1.3 or reshaping 1D arrays into 2D ones. Furthermore, the usage of 2D-CNNs necessitates substantial computing resources, rendering it unsuitable for real-time SHM applications with stand-alone processing units that demand low-power/low-memory devices. To alleviate the aforementioned drawbacks, 1D-CNNs have recently been used to perform UGW-based damage detection. In a paper presented by (Kiranyaz et al., 2021), a comprehensive evaluation of 1D-CNNs and its use in defect detection can be found.

Following scholars have considered the use of 1D-CNNs for UGW-based SHM. In a research performed by (Rai & Mitra, 2021) a 1D-CNN architecture capable of operating directly on raw time-domain UGWs recorded from a thin metallic plate is described. The 1D-CNN architecture presented in this work consists of two parallel 1D-CNN layers, that can learn higher order damage-related features and improve the classification performance. Further, (Cui, Azuara, di Scalea, & Barrera, 2021) implemented a 1D-CNN algorithm for damage detection and localization in stiffened composite panels. In another study performed by (Rautela, Senthilnath, Moll, & Gopalakrishnan, 2021) UGWs were used to detect and locate damage on a composite panel. They presented a physical-informed machine learning approach in which domain information and expert supervision are used to aid the learning process of a 1D-CNN architecture.

3.2.4. Other classification and clustering techniques

Apart from the elaborated methods in previous sections, there have been several other algorithms, that have aided the UGW-based damage detection. According to the analysis performed in Figure 10(b), k-nearest neighbors (k-NN) and k-means have attracted the most attention after SVM, ANN, and DNN techniques. For instance, (Virupakshappa & Oruklu, 2019) considered the flaw detection by using three different unsupervised ML algorithms, namely, k-means, Gaussian mixture modeling, and mean-shift clustering. These techniques are

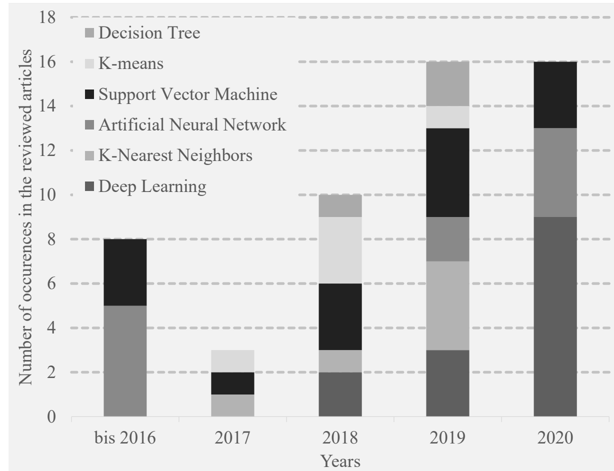

Figure 11. Number of occurrences of the pattern recognition/clustering methods in UGW-based damage detection with respect to different years based on the reviewed articles in the current study

implemented to find the centroids of the input data, which should divide the data set into two classes of flawed and not-flawed. This paper shows how clustering methods may be utilized to categorize the flaw vs. no-flaw classification scenario. In this study, through the proposed technique an accuracy of over 90% was achieved. (Murta et al., 2018) considered as well the use of k-means for clustering the data to classify a welding defect. An example of the implementation of k-NN as a classifier can be found in the work performed by (Vitola, Pozo, Tibaduiza, & Anaya, 2017). In this article, six different schemes of k-NN, such as fine k-NN, cosine k-NN, weighted k-NN, etc. have been regarded. Furthermore, the precision of each K-NN scheme is described by using confusion matrices. This study showed that through the utilization of k-NN technique three different configurations of damages can be classified with an average true positive rate (TPR) of 84%. Other examples for implementation of k-means can also be found in 2.

4. OVERVIEW AND SUMMARY OF THE METHODS

This section attempts to provide an overview over the previous sections. For this purpose, several figures concerning the frequency of the occurrence of different algorithms and techniques reviewed in the current study are represented. Further, studies concerned with the utilization of a specific method with regard to feature extraction, and pattern processing are summarized in Table 2 and Table 3. The information presented in this section should assess wrapping up the current study as well as providing voids for future works.

Table 2. A summary of the employed pattern recognition methods and their associated examples in the reviewed papers

Scholars	**Name of the ML algorithm**	**Compared algorithm(s)**	**case study**	**Input data type and source**	**ML performance index**
(Dackermann et al., 2014)	SVM	—	Timber utility poles	Time-domain stress wave signals (in situ data)	Accuracy
(Agarwal & Mitra, 2014)	SVM	ANN	Plate with a notch	Lamb wave velocity signals (simulation)	Accuracy, κ (κ: a single value metric to compare two confusion matrices)
(Virupakshappa & Oruklu, 2015)	SVM	—	Steel block	Subband-filtered waveforms from A-scan (simulation)	Accuracy, confusion matrix
(Eybpoosh et al., 2017)	SVM	k-means	Steel and Aluminum Pipelines	Guided waves generated by PZT transducers (experiment)	Accuracy, FPR, FNR
(Dib et al., 2018)	SVM	—	Glass fiber composite plate	Guided waves (Analytical model and experiment)	Accuracy
(Jiménez et al., 2019), (Arcos Jiménez et al., 2020)	SVM	DT, discriminant analysis (DA), k-NN, ensemble classification	wind turbine blade	Ultrasonic signals (experiment)	Precision
(Ghrib et al., 2019)	SVM	—	Cantilever beam and composite plate	Exponential sine sweep signal (simulation and experiment)	Accuracy
(D. Tibaduiza et al., 2018)	SVM	k-NN, DT	carbon fiber reinforced polymer (CFRP) sandwich structure, CFRP Plate	Ultrasonic signals (experiment)	Accuracy, confusion matrix
(Mardanshahi et al., 2020)	SVM	ANN	Laminated composite	Ultrasonic signals (experiment)	Accuracy, confusion matrix
(Li et al., 2019)	SVM	ANN	Stator bar	Ultrasonic signals (simulation and experiment)	Accuracy
(Z. Zhang, Pan, Wang, & Lin, 2020)	SVM	—	Aluminum beam	Ultrasonic signals (simulation)	Accuracy, confusion matrix
(Hoshyar, Samali, Liyanapathirana, Houshyar, & Yu, 2019)	SVM	k-NN, ensemble classification	Concrete beam	Ultrasonic signals measured under a three-point and four-point bending test (experiment)	Accuracy

Table 2. (continued)

Scholars	**Name of the ML algorithm**	**Compared algo-rithm(s)**	**case study**	**Input data type and source**	**ML performance index**
(Z. Su & Ye, 2004)	ANN	—	Composite plate	Ultrasonic signals (simulation and experiment)	Mean squared error (MSE)
(Garg, Mahapatra, Suresh, Gopalakrishnan, & Omkar, 2004)	ANN	—	Composite plate	Ultrasonic signals (simulation)	MSE
(Atashipour et al., 2012)	ANN	—	Thick steel beam	Ultrasonic signals (simulation and experiment)	MSE
(Sbarufatti et al., 2014)	ANN	—	Aluminum skin	Ultrasonic signals (simulation and experiment)	MSE
(Dworakowski et al., 2014)	ANN	—	Aircraft wing panel	Ultrasonic signals (simulation and experiment)	Confusion matrix
(Seno et al., 2019)	ANN	—	Composite plate	Ultrasonic signals (simulation and experiment)	Precision
(Xiao, Gao, Tian, Gang Cai, & qing Wang, 2020)	ANN	—	Thin-walled tubes	Ultrasonic signals (experiment)	—
(Hesser et al., 2020)	ANN	—	Aluminum plate	Ultrasonic signals (experiment)	MSE
(Qian et al., 2020)	ANN	—	Composite plate	Ultrasonic signals (experiment)	MSE
(Hesser et al., 2020)	ANN	—	Aluminum plate	Ultrasonic signals (experiment)	MSE
(Qian et al., 2020)	ANN	—	Composite plate	Ultrasonic signals (experiment)	MSE
(Melville et al., 2018)	CNN	—	Aluminum plate	Ultrasonic signals (simulation and experiment)	Accuracy
(Virkkunen et al., 2019)	CNN	—	Welded Pipe	Ultrasonic signals + data augmentation (experiment)	Accuracy
(Marino et al., 2019)	Long short-term memory NN (LSTM-NN)	Wavelet Neural Network	—	Ultrasonic signals (simulation and experiment)	Accuracy
(C. Su et al., 2020)	Stack autoencoder	CNN, ANN, SVM, Naïve Bayesian classifier	Composite plate	Ultrasonic signals (simulation and experiment)	Accuracy

Table 2. (continued)

Scholars	Name of the ML algorithm	Compared algo-rithm(s)	case study	Input data type and source	ML per-formance index
(Ewald et al., 2019)	CNN	Several CNN architectures	Aluminum plate	Ultrasonic signals (simulation and experiment)	Accuracy
(Liu & Zhang, 2020)	CNN	ANN	Aluminum plate	Ultrasonic signals (simulation and experiment)	Accuracy
(Pathirage et al., 2018)	Sparse autoencoder	Two other autoencoder architectures	Steel frame and concrete bridge	eigenfrequencies of the structure (simulation and experiment)	MSE
(S. Zhang, Li, & Ye, 2021)	1-D CNN	—	Aluminum plate	Ultrasonic signals (simulation and experiment)	Accuracy
(Dabetwar, Ekwaro-Osire, & Dias, 2020)	CNN	—	CFRP plate	Ultrasonic signals + X-ray images (NASA Prognostics Data Repository for CFRP)	Precision, Recall, F1-score, Confusion matrix
(Liao et al., 2020)	CNN	—	Airplane laminated L-joint	Ultrasonic signals (simulation and experiment)	MSE
(Z. Wang & Cha, 2020)	Autoencoder integrated with one-class SVM	—	12-story building model and steel bridge	acceleration of structure (simulation and experiment)	Accuracy, MSE
(Tabian et al., 2019)	CNN	—	Composite fuselage panel	UGW generated by external impact events and recorded by piezoelectric sensors	Accuracy
(Xu et al., 2019)	CNN	—	Aircraft structure	Several DIs	Accuracy
(C. Su et al., 2019)	CNN	—	Composite plates	UGWs generated and recorded by piezoelectric sensors	Error rate
(Mariani et al., 2021)	Causal dilated CNN	—	Steel plate	UGWs generated and recorded by piezoelectric sensors across a 50° range of temperature	Accuracy, loss
(Zargar & Yuan, 2021)	CNN-RNN	—	Five-bay stiffened aluminum plate	Numerical simulation and wavefield captured by a high-speed camera	Accuracy
(Azuara et al., 2021)	CNN	—	Composite plate	2D images obtained as the WT of the acquired experimental signals	Accuracy, confusion matrix

In section 3.1, it was mentioned that according to the reviewed papers for extracting features and reducing the dimension of the input space, there are three families of methods, that have been mainly used in the literature. Figure 10(a) shows the share of each of those methods in the analyzed publications. According to this figure, PCA and h-NLPCA methods have been employed in 41% of the works. The second most implemented category of algorithms for generating features is the CWT/DWT-based methods. AR/NARX models with a share of 23% belong to the third most employed techniques. Furthermore, Table 3 outlines corresponding references for each of the mentioned feature extraction or dimension reduction algorithms.

Figure 10(b) provides the statistic regarding the popularity of the pattern processing algorithms in the reviewed papers. According to this figure, SVM, ANN, and DNN are employed in nearly 75% of the selected references. Moreover, Figure 10(c) depicts that more than 80% of the implemented ML methods belong to the family of supervised learning algorithms. Analyzing the occurrence of the pattern processing methods with respect to years (Figure 11) also supports the fact that the mentioned three ML techniques have a great contribution to the reviewed papers. Additionally, Figure 11 outlines the rising of a new wave concerning the application of ML methods in UGW-based damage detection. This point articulates once more the necessity of performing the current study.

Table 2 presents a comprehensive summary of the references. These research items are categorized based on the ML techniques utilized in them. This table also provides the name of other ML algorithms that are used in associated papers. Based on the fact that the main emphasis of each paper is on which ML method, it is decided to consider that technique as the main one and the others as the compared algorithms. Further, the presented case study in each of the papers is shown. As it is mentioned at the beginning of the current work, this study has attempted to narrow the scope of the reviewed article based on the input signals that have been used in them. Accordingly, Table 2 also describes the type of input utilized in each study. Moreover, it is specified if the data came from an analytical model, a numerical simulation, the authors' own experimental setup, or an external database. Also, it is shown which performance indices for assessing the ML algorithms are considered. The definition of those indices are available in most of the ML textbooks such as (Goodfellow, 2016) or (Géron, 2019).

As shown in Table 2 and also Figure 10, neural network-based methods (ANN, CNN, ...) are major techniques for UGW-based damage detection. This trend is more dominant in recent years as it is depicted in Figure 10. Another intriguing point observed in Table 2 is the lack of variety in performed case studies. As can be seen, most of the studies have considered a thin-plate to inspect for damages. Although this is an obvious outcome of the selected niche (UGW-based SHM) in the current work; nevertheless, more complicated structures such as curved plates, plates with other welded parts, etc. should be regarded for the direction of future works.

5. CONCLUSION

The importance of early damage detection has brought the UGW-based family of methods to the center of the SHM community's attention. Numerous studies have been carried out, in which novel techniques for the identification of damage by utilizing UGWs have been proposed. In the past decade, ML techniques have shown great effectiveness in evolving the conventional SHM techniques to a new level. In this study, by reviewing a broad range of articles, the significance of the ML techniques in the context of UGW-based SHM was presented. The current review paper showed to what extent the ML algorithms could be beneficial for the conventional SHM methods. It was shown that the employment of ML could express the damage detection in two main steps, namely, feature extraction, and pattern processing. According to the reviewed articles, it was concluded that PCA/h-NLPCA, CWT/DWT, AR/NARX are the main methods that have been used for feature extraction and dimension reduction. With regard to pattern processing techniques, it was shown that the supervised learning algorithms with a share of 79% have been mostly used. The unsupervised techniques or clustering algorithms have been mostly implemented through the use of K-means method. Clustering of instances can assist novelty detection. Furthermore, it was concluded that ML techniques based on SVM, ANN, and DNN are the most employed techniques, in the context of UGW-based damage detection. The current study showed that methods based on deep learning were less frequent than their conventional ML rivals. However, it was observed that during recent years, the application of deep learning techniques is getting more attention. The following points can be recognized as challenges and areas that require more investigations based on the analyzed studies for this review paper:

- Regardless of whether ML approaches are incorporated in SHM or traditional UGW-based damage detection algorithms are used, the resilience and durability of sensors, cables, and connections under operating conditions are still issues that require more studies.
- Localization and quantification still remain difficult tasks due to the unavailability of a range of various damage situations from a genuine structure. Future research should concentrate on determining the required data, that represent various damage types and locations from operational infrastructure.
- Multiple structural damage identification is not investigated thoroughly in many articles so far and requires ad-

Table 2. (continued)

Scholars	**Name of the ML algorithm**	**Compared algorithm(s)**	**case study**	**Input data type and source**	**ML performance index**
(Rai & Mitra, 2021)	1D-CNN	—	Aluminum plate	Signals generated by numerical simulation as well experiment	Accuracy, confusion matrix
(Cui et al., 2021)	1D-CNN	—	Stiffened composite with a stinger	UGWs generated and recorded by piezoelectric sensors	Accuracy, recall, F1-score, precision
(Alguri, Melville, & Harley, 2018), (Alguri, Melville, Deemer, & Harley, 2018)	k-means	Dictionary learning	Aluminum and steel plate	Chirp signal sweeping from 1kHz to 150 kHz – (simulation and experiment)	—
(Virupakshappa & Oruklu, 2019)	k-means	Gaussian mixture modeling and mean shift clustering	—	A-scan	Accuracy
(Murta et al., 2018)	k-means	k-NN	Welded plate	Ultrasonic signals (simulation)	Confusion matrix
(Vitola et al., 2017)	k-NN	—	Aluminum beam, Aluminum, and composite plates	Ultrasonic signals (experiment)	Confusion matrix
(Arcos Jiménez et al., 2019)	k-NN	DT, SVM, DA	Wind turbine blade	Ultrasonic signals (experiment)	Recall, F1-score

ditional work.

- There has been already a number of in-service real-time damage detection schemes presented in reviewed papers. However, minimizing the computational effort of the model to enable its online implementation is still a challenge, which should be addressed in future works.
- Unsupervised methods only have a minority of the share in the reviewed articles. Hence, their potential for novelty detection still should be exploited.
- Deep learning algorithms have shown considerable power in generalizing the SHM techniques. However, still not too many studies have considered their potential in the context of UGW-based damage detection.
- Using a combination of the data from a real-life structure, and the numerical models require further investigation. This helps for having extensive datasets, that can aid in much more reliability of ML techniques.
- Despite the rising number of ML applications in UGW-based damage detection, they are mostly concerned with more established ML algorithms. However, utilization of peculiar ML techniques such as reinforcement learning, or transformers is still not popular in the SHM community. It is beyond doubt that the employment of such novel ML techniques can advance the fronts of the damage detection algorithms.

ACKNOWLEDGMENT

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Table 3. Summary of the employed feature extraction methods in reviewed papers

Name of the feature extraction method	**Reference examples**
Principle Component Analysis (PCA) and hierarchical-nonlinear PCA (h-NLPCA)	(D. A. Tibaduiza et al., 2016), (Murta et al., 2018), (Arcos Jiménez et al., 2019), (Miorelli et al., 2019), (Ghrib et al., 2019), (Sen et al., 2019), (Sbarufatti et al., 2014), (D. Tibaduiza et al., 2018), (Jiménez et al., 2019),(Sattarifar & Nestorović, 2021)
Continuous / Discrete wavelet transform (CWT/DWT)	(Atashipour et al., 2012), (G. Yan, 2013), (Liew & Veidt, 2009), (D. Tibaduiza et al., 2018), (Virupakshappa & Oruklu, 2019), (Ewald et al., 2019), (Z. Zhang et al., 2020), (Hoshyar et al., 2019)
Linear and nonlinear autoregressive models	(Jiménez et al., 2018), (Arcos Jiménez et al., 2020), (Arcos Jiménez et al., 2019), (Jiménez et al., 2019), (Dackermann et al., 2014),

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